# Chapter 27
# Graph Neural Networks in Urban Intelligence

Yanhua Li, Xun Zhou, and Menghai Pan

**Abstract** In recent years, smart and connected urban infrastructures have undergone a fast expansion, which increasingly generates huge amounts of urban big data, such as human mobility data, location-based transaction data, regional weather and air quality data, social connection data. These heterogeneous data sources convey rich information about the city and can be naturally linked with or modeled by graphs, e.g., urban social graph, transportation graph. These urban graph data can enable intelligent solutions to solve various urban challenges, such as urban facility planning, air pollution, etc. However, it is also very challenging to manage, analyze, and make sense of such big urban graph data. Recently, there have been many studies on advancing and expanding Graph Neural Networks (GNNs) approaches for various urban intelligence applications. In this chapter, we provide a comprehensive overview of the graph neural network (GNN) techniques that have been used to empower urban intelligence, in four application categories, namely, (i) urban anomaly and event detection, (ii) urban configuration and transportation planning, (iii) urban traffic prediction, and (iv) urban human behavior inference. The chapter also discusses future directions of this line of research. The chapter is (tentatively) organized as follows.

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## 27.1 Graph Neural Networks for Urban Intelligence

### *27.1.1 Introduction*

According to the report (Desa, 2018) published by the United Nations in 2018, the urban population in the world reached 55 percent in 2018, which is growing rapidly over time. By 2050, the world will be one-third rural (34 percent) and two-thirds urban (66 percent). Moreover, thanks to the fast development of sensing technologies in recent years, various sensors are widely deployed in the urban areas, e.g., the GPS sets on vehicles, personal devices, air quality monitoring stations, gas pressure regulators, etc. Stimulated by the large urban population and the wide use of the sensors, there are massive data generated in the urban environment, for example, the trajectory data of the vehicles in ride-sharing services, the air quality monitoring data. Given a large amount of heterogeneous urban data, the question to answer is what and how can we benefit from these data. For instance, can we use the GPS data of the vehicles to help urban planners better design the road network? Can we infer the air quality index across the city based on a limited number of existing monitoring stations? To answer these practical questions, the interdisciplinary research area, *Urban Intelligence*, has been extensively studied in recent years. In general, *Urban Intelligence*, which is also referred as *urban computing*, is a process of acquisition, integration, and analysis of big and heterogeneous data generated by a diversity of sources in urban spaces, such as sensors, devices, vehicles, buildings, and humans, to tackle the major issues in cities (Zheng et al, 2014).

Data analytics (e.g., data mining, machine learning, optimization) techniques are usually employed to analyze numerous types of data generated in the urban scenarios for prediction, pattern discovery, and decision-making purposes. How to represent urban data is an essential question for the design and implementation of these techniques. Given the heterogeneity of urban big data, various data structures can be used to represent them. For example, spatial data in an urban area can be represented as raster data (like images), where the area is partitioned into grid cells (pixels) with attribute functions imposed on them (Pan et al, 2020b; Zhang et al, 2019, 2020b,a; Pan et al, 2019, 2020a). Spatial data can also be represented as a collection of objects (e.g., vehicles, point-of-interests, and trajectory GPS points) with their locations and topological relationships defined (Ding et al, 2020b).

Moreover, the intrinsic structures of many urban big data enable people to represent them with graphs. For instance, the structure of urban road network helps people model the traffic data with graphs (Xie et al, 2019b; Dai et al, 2020; Cui et al, 2019; Chen et al, 2019b; Song et al, 2020a; Zhang et al, 2020e; Zheng et al, 2020a; Diao et al, 2019; Guo et al, 2019b; Li et al, 2018e; Yu et al, 2018a; Zhang et al, 2018e); the pipeline of gas supply network enable people to model the gas pressure monitoring data with graph (Yi and Park, 2020); people can also represent the data on the map with a graph by dividing the city into functional regions (Wang et al, 2019o; Yi and Park, 2020; Geng et al, 2019; Bai et al, 2019a; Xie et al, 2016). Representing urban data with graphs can capture the intrinsic topological information and knowledge in the data, and plenty of techniques are developed to analyze the urban graph data.

*Graph Neural Networks* (GNNs) are naturally employed to solve various real-world problems with urban graph data. For example, Convolutional Graph Neural Networks (ConvGNN) (Kipf and Welling, 2017b) are used to capture the spatial dependencies of the urban graph data, and Recurrent Graph Neural Networks (RecGNN) (Li et al, 2016b) are for the temporal dependencies. Spatial-temporal Graph Neural Networks (STGNN) (Yu et al, 2018a) can capture both spatial and temporal dependencies in the data, which are widely used in dealing with many urban intelligence problems, e.g., predicting traffic status based on urban traffic data (Zhang et al, 2018e; Li et al, 2018e; Yu et al, 2018a). The traffic data are modeled as spatial-temporal graphs where the nodes are sensors on road segments, and each node has the average traffic speed within a window as dynamic input features.

In the following sections, we first summarize the general application scenarios in urban intelligence, followed by the graph representations in urban scenarios. Then, we provide more details on GNN for urban configuration and transportation planning, urban anomaly and event detection, and urban human behavior inference, respectively.

### 27.1.2 Application scenarios in urban intelligence

The diverse application domains in urban intelligence include urban planning, transportation, environment, energy, human behavior analysis, economy, and event detection, etc. In the following paragraphs, we will introduce the practical problems and the common datasets in these domains. The problems and examples highlighted below are not exhaustive, here we just introduce some critical problems and typical examples from literature, which are summarized in Table 27.1.

Table 27.1: Application domain and examples in urban intelligence.

| Application domain | Example task | Example data source |
|---|---|---|
| Urban configuration | Estimate impact of construction(Zhang et al, 2019c) | Taxi GPS, road network. |
| | Discover functional regions(Yuan et al, 2012) | Taxi GPS, POIs. |
| Transportation | Improve efficiency of taxi drivers(Pan et al, 2019) | Taxi GPS, road network. |
| Environment | Infer air quality(Zheng et al, 2013) | Air quality data from monitor stations, road network, POIs. |
| Energy consumption | Estimate gas consumption(Shang et al, 2014) | Taxi GPS. |
| Human behavior | Estimate user similarity(Li et al, 2008) | GPS data from phones. |
| Economy | Place retail store(Karamshuk et al, 2013) | POIs, human mobility data. |
| Public Safety | Detect anomalous traffic pattern(Pang et al, 2011) | Taxi GPS, road network. |

**1) Urban configuration.** Urban configuration is essential for enabling smart cities. It deals with the design problem of the entire urban area, such as, the land use, the layout of human settlements, design of road networks, etc. The problems in this domain includes estimating the impact of a construction (Zhang et al, 2019c), discovering the functional regions of the city (Yuan et al, 2012), detecting city boundaries (Ratti et al, 2010), etc. In (Zhang et al, 2019c), the authors employ and analyze the historical taxi GPS data and the road network data, where they define the off-deployment traffic estimation problem as a traffic generation problem, and develop a novel deep generative model TrafficGAN that captures the shared patterns across spatial regions of how traffic conditions evolve according to travel demand changes and underlying road network structures. This problem is important to city planners to evaluate and develop urban deployment plans. In (Yuan et al, 2012), the authors propose a DRoF framework that Discovers Regions of different Functions in a city using human mobility between regions with data collected from the GPS set in Taxis in Beijing and points of interest (POIs) located in the city. The understanding of functional regions in a city can calibrate urban planning and facilitate other applications, such as choosing a location for a business. In (Ratti et al, 2010), the authors propose a model to detect the city's boundary by analyzing the human network inferred from a large telecommunications database in Great Britain. Answering this question can help the city planner get a sense on what the exact range the urban area is within as the urban area changes fast over time.

**2) Transportation.** Transportation plays an important role in the urban area. Urban intelligence deals with several problems regarding the transportation in the city, e.g., routing for the drivers, estimating the travel time, improving the efficiency of taxi system and the public transit system, etc. In (Yuan et al, 2010), the authors propose a T-Drive system, that provides personalized driving directions that adapt to weather, traffic conditions, and a person's own driving habits. The system is built based on historical trajectory data of taxicabs. In (Pan et al, 2019), the authors propose a solution framework to analyze the learning curve of taxi drivers. The proposed method first learns the driver's preference to different profiles and habit features in each time period, then analyzes the preference dynamics of different groups of drivers. The results illustrate that taxi drivers tend to change their preference to some habit features to improve their operation efficiency. This finding can help the new drivers improve their operation efficiency faster. The authors in (Watkins et al, 2011) conducted a study on the impact of providing real-time bus arrival information directly on riders' mobile phones and found it to reduce not only the perceived wait time of those already at a bus stop, but also the actual wait time experienced by customers who plan their journey using such information.

**3) Urban Environment.** Urban intelligence can deal with the potential threat to the environment caused by the fast pace of urbanization. The environment is essential for people's health, for example, air quality, noise, etc. In (Zheng et al, 2013), the authors infer the real-time and fine-grained air quality information throughout a city based on the (historical and real-time) air quality data reported by existing monitor stations and a variety of data sources observed in the city, such as meteorology, traffic flow, human mobility, structure of road networks, and POIs. The results can be used to suggest people when and where to conduct outdoor activities, e.g., jogging. Also, the result can infer suitable locations for deploying new air quality monitoring stations. Noise pollution is usually serious in the urban area. It has impacts to both the mental and physical health of human beings. Santini et al (2008) assess environmental noise pollution in urban areas by using the monitoring data from wireless sensor networks.

**4) Energy supply and consumption.** Another application domain of urban intelligence is energy consumption in the urban area, which usually deals with the problem of sensing city-scale energy cost, improving energy infrastructures, and finally reducing energy consumption. The common energy include gas and electricity. Shang et al (2014) inferred the gas consumption and pollution emission of vehicles traveling on a city's road network in the current time slot using GPS trajectories from a sample of vehicles (e.g., taxicabs). The knowledge can be used not only to suggest cost-efficient driving routes but also to identify the road segments where gas has been wasted significantly. Momtazpour et al (2012) proposes a framework to predict electronic vehicle (EV) charging needs based on owners' activities, EV charging demands at different locations in the city and available charge of EV batteries, and design distributed mechanisms that manage the movements of EVs to different charging stations.

**5) Urban human behavior analysis.** With the popularization of smart devices, people can generate massive location-embedded information every day, such as, location-tagged text, image, video, check-ins, GPS trajectories. The first question in this domain is estimating user similarity, and similar users can be recommended as friends. Li et al (2008) connects users with similar interests even when they may not have known each other previously, and community discovery, which employs the GPS trajectories collected from GPS equipped devices like phones.

**6) Economy.** Urban intelligence can benefit the urban economy. The human mobility and the statistics of POIs can reflect the economy of the city. For example, the average price of a dinner in the restaurants can indicate the income level and the power of consumption. In (Karamshuk et al, 2013), the authors study the problem of optimal retail store placement in the context of location-based social networks. They collected human mobility data from Foursquare and analyzed it to understand how the popularity of three retail store chains in New York is shaped in terms of number of check-ins. The result indicates that some POIs, like train station and airport, can imply the popularity of the location, also, the number of competitive stores is an indicator for the popularity.

**7) Public safety.** Public safety and security in the urban area is always attracting people's concerns. The availability of different data enable us to learn from history how to deal with public safety problems, e.g., traffic accident (Yuan et al, 2018), large event (Vahedian et al, 2019; Khezerlou et al, 2021, 2017; Vahedian et al, 2017), pandemic (Bao et al, 2020), etc., and we can use the data to detect and predict abnormal events. Pang et al (2011) detects the anomalous traffic pattern from the spatial-temporal data of vehicles. The authors partition a city into uniform grids and counted the number of vehicles arriving in a grid over a time period. The objective was to identify contiguous sets of cells and time intervals that have the largest statistically significant departure from expected behavior (i.e., the number of vehicles).

### *27.1.3 Representing urban systems as graphs*

Various data structures and models can be employed to define the spatial settings of urban systems. For example, a simple model is a grid structure, where the urban area is partitioned into grid cells, with a set of attribute values of interest (e.g., average traffic speed, number of taxis, population, rainfall) associated with each cell. While such a model is simple to implement, it ignores many intrinsic and important relationships existing in urban data. For example, a grid structure may lose the information of road connectivity in the underlying traffic system of the city. In many scenarios, instead, graph is an elegant choice to capture the intrinsic topological information and knowledge in the data. Many urban system components can be represented as graphs. Additional attributes may be associated with nodes and/or edges. In this section, we introduce graph representations of various urban system scenarios, which are summarized in Table 27.2. The application domains covered include **1)** Urban transportation and configuration planning, **2)** Urban environment monitoring, **3)** Urban energy supply and consumption, **4)** Urban event and anomaly detection, and **5)** Urban human behavior analysis.

Table 27.2: Graph representations in urban systems

| Application domain | Nodes | Edges | Examples |
|---|---|---|---|
| Transportation & configuration planning | Road segments | Intersections | Traffic flow prediction (Xie et al, 2019b; Dai et al, 2020) (Cui et al, 2019; Chen et al, 2019b) (Song et al, 2020a; Zhang et al, 2020e) (Zheng et al, 2020a; Diao et al, 2019) (Guo et al, 2019b; Li et al, 2018e) (Yu et al, 2018a; Zhang et al, 2018e) |
| | Functional zones | Road connections | Learning road network representation (Wu et al, 2020c) |
| | POIs | Road connections | Parking availability prediction, POI recommendation (Zhang et al, 2020a; Chang et al, 2020a) |
| Environment monitoring | Monitoring sensors | Proximity | Air quality inference (Wang et al, 2020h) (Li et al, 2017f) |
| Energy supply & consumption | Regulators | Pipelines | Gas pressure monitoring (Yi and Park, 2020) |
| Event & anomaly detection | Urban regions | Proximity | Traffic accident prediction (Zhou et al, 2020g,h; Yu et al, 2021b) |
| Human behavior analysis | Sessions, locations, objects | Event stream | User behavior modeling (Wang et al, 2020a) |
| | Urban regions | Proximity | Passenger demand prediction (Wang et al, 2019o; Yi and Park, 2020) (Geng et al, 2019; Bai et al, 2019a) (Xie et al, 2016) |

**1) Urban transportation and configuration planing.** Modeling urban transportation system as a graph is widely used in solving real-world urban intelligence problems, e.g., traffic flow prediction (Xie et al, 2019b; Dai et al, 2020; Cui et al, 2019; Chen et al, 2019b; Song et al, 2020a; Zhang et al, 2020e; Zheng et al, 2020a; Diao et al, 2019; Guo et al, 2019b; Li et al, 2018e; Yu et al, 2018a; Zhang et al, 2018e), parking availability problem (Zhang et al, 2020a), etc. The graphs are usually built based on the real-world road network. To solve the problem of ***traffic flow prediction***, in (Cui et al, 2019), the authors employ an undirected graph to predict the traffic state, the nodes are the traffic sensing locations, e.g., sensor stations, road segments, and the edges are the intersections or road segments connecting those traffic sensing locations. Xie et al (2019b); Dai et al (2020) model the urban traffic network as a directed graph with attributes to predict the traffic speed, the nodes are the road segments, and the edges are the intersections. Road segment width, length, and direction are the attributes of the nodes, and the type of intersection, and whether there are traffic lights, toll gates are the attributes of the edges. For ***urban configuration,*** Wu et al (2020c) incorporates a hierarchical GNN framework to learn Road Network Representation in different levels. The nodes in the hierarchical graph include road segments, structural regions, and functional zones, and the edges are intersections and hyperedges. There are some works about ***predicting parking availability***. Zhang et al (2020a) models the parking lots and the surrounding POIs and population features as a graph to predict the parking availability for the parking lots. The nodes are the parking lots, and the edges are determined by the connectivity between each two parking lots whose on-road distance is smaller than a threshold. Context features, e.g., POI distribution, population, etc., are the attributes of the nodes.

**2) Urban environment monitoring system.** People model the air quality monitoring system as a graph to forecast the air quality in the urban area(Wang et al, 2020h; Li et al, 2017f). For example, Wang et al (2020h) proposed the PM2.5-GNN to forecast the PM2.5 index in different locations. The nodes are locations determined by latitude, longitude, altitude, and there exists an edge between two nodes if the distance and difference of altitudes between them are less than threshholds respectively (e.g., distance $< 300$ *km* and difference of altitudes $< 1200$ *m*). The node attributes include Planetary Boundary Layer (PBL) height, K index, wind speed, 2m temperature, relative humidity, precipitation, and surface pressure. Edge attributes include wind speed of source node, distance between source and sink, wind direction of source node, and direction from source to sink.

**3) Urban energy supply and consumption.** GNN is also employed in analyzing urban energy supply and consuming systems. For example, Yi and Park (2020) proposed a framework to predict the gas pressure in the gas supply network. The gas regulators are considered as the nodes, and the pipelines that connect every two regulators are the edges.

**4) Urban event and anomaly detection.** Urban event and anomaly detection is a hot topic in urban intelligence. People employ machine learning models to detect or predict the events occurring in the urban area, e.g., traffic accident prediction(Zhou et al, 2020g,h; Yu et al, 2021b). In (Zhou et al, 2020g), the authors proposed a framework to predict traffic accident in different regions of the city. The urban area is divided into subregions, i.e., grids, and if the traffic elements within two subregions have strong correlations, there is a connection.

**5) Urban human behavior analysis.** Studying human behavior in urban region can benefit people in many aspects, for example, demographic attribute prediction, personalized recommendation, passenger demand prediction, etc. Some works proposed GNN to study ***Human behavior modeling*.** Human behavior modeling is essential for many real-world applications such as demographic attribute prediction, content recommendation, and target advertising. In (Wang et al, 2020a), the authors model human behavior via a tripartite graph. The nodes include user's sessions, locations and items. There exists an edge between a session node and a location node if the user started the session at this location. Similarly, there exists an edge between a session node and an item node if the user interacted with this item within the session. Each edge possesses a time attribute indicating the temporal signal of the interaction between two nodes. Another application of analysing human behavior is ***passenger demand prediction*.** Understanding human behavior in daily transits can help improve the efficiency of urban transportation system. For example, predicting the passenger demand in the ride-sharing system can help the ride-sharing company and the drivers improve their operation efficiency. And in recent publications, many researchers employ graph neural networks to solve the problem of predicting human mobility (Wang et al, 2019o; Yi and Park, 2020; Geng et al, 2019; Bai et al, 2019a; Xie et al, 2016), and usually the nodes of the graph are subregions of the city, and the edges are usually defined based on spatial proximity.

### *27.1.4 Case Study 1: Graph Neural Networksin urban configuration and transportation*

Urban intelligence can help urban planners design urban configuration, and benefit the urban transportation system from different perspectives, e.g., operation efficiency, safety, environmental protection, etc. To enable urban intelligence in urban configuration and transportation planning, researchers developed practical machine learning approaches, including graph neural networks (GNN), to deal with real-world problems. In this section, we introduce some state-of-the-art (SOTA) designs of GNN targeting on solving the real-world urban configuration and transportation problems.

**Urban traffic prediction.** Predicting traffic status, e.g., speed, volume, is important in enabling urban intelligence. The traffic prediction problem is a typical time-series prediction problem:

**Definition 27.1. Urban traffic prediction problem.** *Given* historical traffic observations and context features of the road network, *predicting* the traffic status (e.g., speed, flow, etc.) in future time slots over the road network.

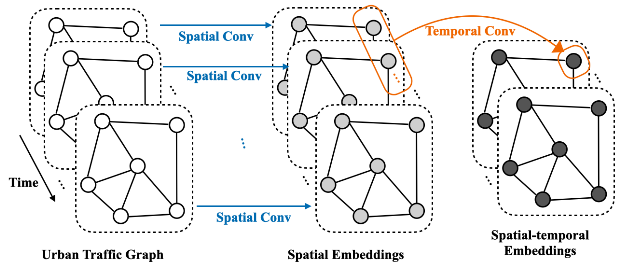


Figure 27.1: CNN-based STGNN

To address the traffic prediction problem, Spatial-temporal Graph Neural Networks (STGNN) are usually employed. The road segments are the nodes, and the traffic status is the attributes of the nodes. The traffic status in different time slots are corresponding to the temporal dynamics of the graph. Usually, graph convolution operation is used to capture the spatial dependencies among the nodes, and a 1D-convolution operation is then employed to capture the temporal dependencies among different time slots. The framework of CNN-based STGNN is illustrated in Fig.27.1. The spatial-temporal embeddings can be used to predict the traffic status.

Another design of STGNN is based on Recurrent Neural Networks (RNN), which can also predict traffic status in Spatial-temporal graphs. Most RNN-based approaches capture spatial-temporal dependencies by filtering inputs and hidden states passed to a recurrent unit using graph convolution operations. The basic RNN can be formulated in Eq. (27.1).

$$H^{(t)} = \sigma(WX^{(t)} + UH^{(t-1)} + \mathbf{b}), \tag{27.1}$$

where $X^{(t)}$ is the node feature matrix at time step $t$. $H$ is the hidden state. $W$, $U$, and $\mathbf{b}$ are the network parameters. Then, the STGNN based on RNN can be formulated as Eq. (27.2):

$$H^{(t)} = \sigma(Gconv(X^{(t)}, A; W) + Gconv(H^{(t-1)}, A; U) + \mathbf{b}), \tag{27.2}$$

where $Gconv(\cdot)$ is the graph convolution operation, and $A$ is the graph adjacency matrix. Both designs of STGNN can be employed to predict the node attributes, i.e., traffic status, given the spatial-temporal graph of traffic.

**Urban configuration.** An urban road network is a vital component in urban configuration. How to represent it is essential for many analyses and researches related to real-world applications. As a real-world road network is a complex system with hierarchical structures, long-range dependency among units, and functional roles, it is challenging to design effective representation learning methods. The road network representation learning problem can be defined like this:

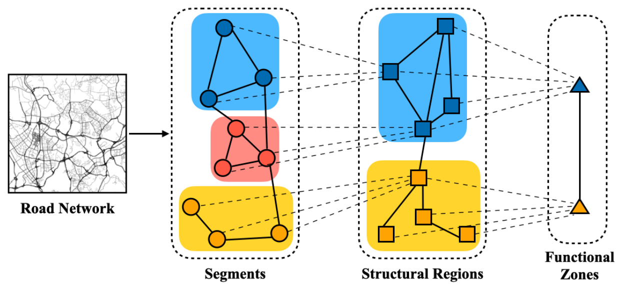


Figure 27.2: Hierarchical road network graph

**Definition 27.2. Road network representation learning problem.** *Given* a road network, the *target* is to construct the corresponding graphs that can represent the structure and topological information of the road network.

Benefit from the topology of graph, we can represent road network with hierarchical graphs. In (Wu et al, 2020c), the authors propose to represent urban road networks with a hierarchical graph with three levels, and the node in each level corresponds to road segments, structural region, and functional zone, respectively, as illustrated in Fig.27.2. The structural region is the aggregation of some connected road segments, which serves as some specific traffic roles, e.g., intersection, overpass. And functional zone is the aggregation of structural regions, which can represent some functional facilities in the city, e.g., transportation hub, shopping area. To learn the hierarchical graph representation, the road segments are first represented by contextual embedding, e.g., road type, lane number, segment length, etc. Then, graph clustering and network reconstruction techniques are employed to form the structural region graph. And vehicle trajectory data is employed to capture the functional zones over structural regions.

### *27.1.5 Case Study 2: Graph Neural Networks in urban anomaly and event detection*

Public safety and security in the urban area always attracts people's concerns. The availability of different data enables us to learn from history how to deal with public safety problems, e.g., traffic accidents, crime, large events, pandemic, etc., and we can use the data to detect and predict abnormal events.

**Traffic accident prediction.** Traffic accident prediction is of great significance to improve the safety of the road network. Although "accident" is a word related to "randomness", there exist a significant correlation between the occurrence of traffic accidents and the surrounding environmental features, e.g., traffic flow, road network structure, weather, etc. Thus, machine learning approaches, like GNN, can be

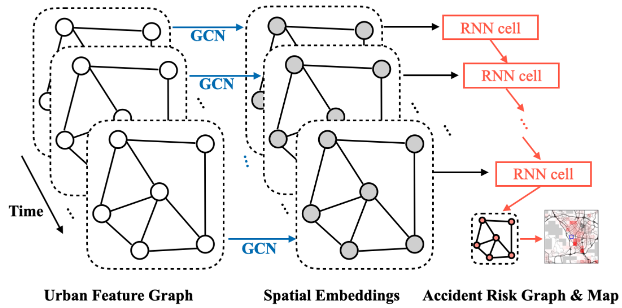


Figure 27.3: Example GNN framework for traffic accident prediction.

employed to predict or forecast traffic accidents over the city, which can help enable urban intelligence.

The problem of traffic accident prediction is as follows:

**Definition 27.3. Traffic accident prediction problem.** *Given* the road network data and the historical environmental features, the *target* is to predict the traffic accident risk over the city in the future.

The environmental features include the traffic conditions, surrounding POIs, etc. In recent publications (Zhou et al, 2020g,h; Yu et al, 2021b), GNN is employed to solve this problem.

The graphs in solving traffic accident problem are usually constructed based on dividing the urban area into grids, and each grid is considered as a node. If the traffic conditions between two nodes have a strong correlation, there is an edge between them. The context environmental features are the attributes with each grid. After the graphs are constructed in different historical time slots, graph convolutional neural networks (GCNs) are usually used to extract the hidden embedding in each time slot. Then, methods dealing with time-series inputs can be employed to capture the temporal dependencies, e.g., RNN-based neural networks. Finally, the spatial-temporal information is used to predict traffic accident risk over the city. Overall, the solution framework can be considered as an STGNN as illustrate in Fig. 27.3. For more details, please refer to (Zhou et al, 2020g,h; Yu et al, 2021b).

### 27.1.6 Case Study 3: Graph Neural Networks in urban human behavior inference

Human behavior analysis plays an important role in enabling urban intelligence, for example, studying the behavior of drivers can help improve the efficiency of urban transportation system, analysing passenger behaviors can help improve the operation efficiency of the drivers in taxi or ride-hailing services, and understanding user behavior pattern can help improve personal recommendation of commercial

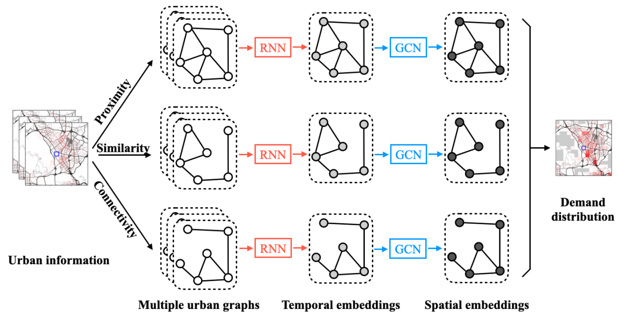


Figure 27.4: Example STGNN framework for passenger demand prediction.

items, which will benefit the urban economy. In this section, we demonstrate how GNN works in analyzing urban human behaviors via two real-world applications, i.e., passenger demand prediction and user behavior modeling.

**Passenger demand prediction.** Passenger demand prediction is mostly conducted at the region-level, i.e., the urban area is divided into small grids. The problem can be defined as follows:

**Definition 27.4. Passenger demand prediction problem.** *Given* the historical demands and context features distributions, the task is to *predict* the passenger demand in each region.

Different from most traffic graphs which construct the graphs with road segments as nodes, here in passenger demand prediction problem, people usually construct the graph with grids as the nodes. The edges, i.e., the correlations between each pair of nodes, are determined by spatial proximity, similarity of contextual environment, or road network connectivity for distant grids.

Spatial-temporal Graph Neural Networks (STGNN) are the most popular GNN models employed in predicting passenger demand. In (Geng et al, 2019), the authors propose the spatiotemporal multi-graph convolution network (ST-MGCN) to predict the passenger demand in the ride-hailing service. The overall framework can be illustrated as in Fig.27.4. First, multiple graphs are constructed based on different aspects of relationships between each two grids, i.e., proximity, functional similarity, and transportation connectivity. Then, a RNN is used to aggregate observations in different times considering the global contextual information. After that, GCN is used to model the non-Euclidean correlations among regions. Finally, the aggregated embeddings are used to predict the passenger demand over the city.

**User behavior modeling.** Modeling human behavior is important for many real-world applications, e.g., demographic attribute prediction, content recommendation, and target advertising, etc. Studying human behavior in the urban scenario can benefit urban intelligence in many aspects, e.g., economy, transportation, etc. Here, we introduce an example of modeling spatial-temporal user behavior with tripartite graphs (Wang et al, 2020a).

Take the urban user online browsing behavior as an example, the spatial-temporal user behavior can be defined on a set of users $U$, a set of sessions $S$, a set of items $V$, and a set of locations $L$. Each user's behavior log can be represented by a set of session-location tuples, and each session contains multiple item-timestamp tuples. Then a user's spatial-temporal behavior can be captured via a tripartite graph as illustrated in Fig.27.5. The nodes of this tripartite graph include user's sessions $S$, locations $L$, and items $V$. The edges include session-item edges and session-location edges.

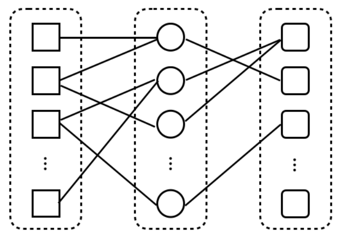


Figure 27.5: Spatial-temporal user behavior graph

To extract the user representation from each user's spatial-temporal behavior graph, GNN can be employed. The idea is to extract session embeddings from the items within each session, and RNN can be employed to aggregate the information of items. Then session embeddings are further aggregated into temporal embeddings of different time span, e.g., day, week. Also, the session embeddings and locations are composed to produce the spatial embeddings. Last, the spatial and temporal embeddings are fused into one embedding which can represent the user's behavior. For more details, we would like to refer you to (Wang et al, 2020a).

### 27.1.7 Future Directions

It is inspiring that GNNs have obtained significant achievements on urban intelligence. For future research, we envision that there exist several potential directions as following.

**Interpretability of the GNNs model on urban intelligence.** The applications of GNNs on urban intelligence are closely related to real-world problems. Besides improving the performance of the GNNs model, it is necessary to enhance the interpritability of the GNNs model. For example, in the application predicting traffic flow, it is important to identify hidden factors (e.g., structure of road network) that can affect the traffic flow. These hidden factors may also help urban planners better design road network to balance the traffic flow.

Recent advances in interpretable AI and machine learning research have led to the development of numerous intrinsic or post-hoc interpretable graph neural network models (Huang et al, 2020c). However, few of them are designed for GNNs on urban problems. Designing interpretable urban GNNs is non-trivial due to the unique properties of urban big data. For example, urban data are usually heterogeneous, i.e., the interpretation of learned relationships between the input features and target variables vary over space. For example, the risk factors for traffic accidents may shift when moving from a densely populated area to a non-residential area. Also, the interpretation model of GNN at nearby locations (e.g., neighboring nodes) share similarities due to the auto-correlation of spatial data (Pan et al, 2020b). These factors should be considered when designing interpretable urban GNNs.

**New applications for GNNs on urban intelligence.** As introduced above, GNNs have demonstrated their effectiveness and efficiency in many applications domains in urban intelligence, e.g., transportation, environment, energy, safety, human behavior. There exist potential applications of GNNs on urban scenario, such as, improving urban power (electricity) supply, contact tracing of patients of infectious diseases (e.g., COVID-19), and modeling responses to complex environmental and climate events (e.g., flood, Hurricane, etc).

**Editor's Notes**: Urban intelligence covers a wide range of macro-scale physical networks such as transportation networks and power grids. They are typical cases of spatial networks, which are networks whose nodes and edges are embedded in space probably under spatial constraints (e.g., planarity). So it is not a surprise that urban intelligence could largely benefit from deep learning techniques for spatial data and network data. Different from most of the application domains introduced in Chapters 19-27, there are usually well-designed computational models for many subareas in urban intelligence, so it is important to explore how deep graph learning techniques can contribute and compensate for the weakness of the existing strategies.