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# Urban function classification at road segment level using taxi trajectory data: A graph convolutional neural network approach

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ABSTRACT

Extracting hidden information from human mobility patterns is one of the long-standing challenges of urban studies. In addition, exploring the relationship between urban functional structure and traffic spatial interaction pattern has long been of interest. Recently, vehicle GPS trajectory data emerged as a popular data source for revealing human mobility patterns and urban functions. However, few studies have fully leveraged traffic interaction information that is hidden in human mobility patterns to identify urban functions at the road segment level. To address this issue, a geo-semantic analysis framework was introduced in this study to model the relationship between traffic interaction and urban functions at the road segment level. First, a Road-Trajectory corpus was built and trained to obtain the semantic embedding representation of road segments. Then, considering topological connections between road segments, we used a graph convolutional neural network model to process the contextual and topological information to classify social functions along streets. A case study in Beijing, China, using a large volume of real-world taxi trajectories data, was conducted. The results show that our proposed methods, with relative less loss and high accuracy, outperform other comparative methods for classifying urban functions at the road segment level. This work contributes to the assessment of urban functional structure, and further aiding urban planners in designing better urbanization strategies with regard to traffic interaction and urban space structure.

## 1. Introduction

Extracting hidden information from human mobility and activity data is one of the long-standing challenges in the fields of urban geography (Gonzalez, Hidalgo, & Barabasi, 2008; Huang, Li, Liu, & Ban, 2015), land use planning (Castro, Zhang, Chen, Li, & Pan, 2013), and traffic planning (Jiang, 2009). Recently, numerous in-depth discussions have been conducted to explore urban land use and urban functions via human mobility and activity information (Barbosa et al., 2018; Gao, Janowicz, & Couclelis, 2017; Wu et al., 2020). As one of the conceptual and practical themes in human mobility, traffic interaction patterns are closely related to urban functions. They indicate the routes and purposes of the trips that people take in cities at the individual level and the spatial interaction patterns between urban regions from the collective perspective (Yang, Stewart, Tang, Xie, & Li, 2018; Zheng, Capra, Wolfson, & Yang, 2014). The exploration of traffic interaction patterns not only helps to understand urban structures but contributes to characterizing the activity of a city and getting a sense of its urban dynamics (Liu et al., 2015).

The proliferation of crowdsourcing technology and location-based services and the emergence of individual-level trajectory data create unprecedented opportunities for researchers to better understand human mobility and the social functions of urban regions (Zheng et al., 2014). Human activity trajectory data containing valuable information on how urban spaces are used are generated by people in their daily lives. Generally, this type of trajectory data includes vehicle GPS records (Yang et al., 2018), mobile phone positioning data (Pei et al., 2014), and social media check-in data (Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2019). A GPS-enabled taxi is flexible and its movements are usually widely covered in urban regions. Such data has much higher precision than other data sources. The related research scale and throughput have not been limited by the accessibility of qualified data and privacy issues. Due to its powerful ability to aid the monitoring of real-time traffic situations and the sensing of spatial interaction patterns, taxi GPS data

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has attracted much attention and it has been used with great success in multiple domains (Chen, Tao, Li, & Zhuo, 2016; Li et al., 2016; Siła-Nowicka et al., 2016; Yuan, Zheng, Zhang, & Xie, 2012).

Attempts have also been made to understand urban structures and social functions using taxi GPS records data. For instance, Zheng, Yanchi, Jing and Xing (2011) first introduced taxi GPS records to detect and evaluate the effectiveness of urban land use planning. Liu, Wang, Xiao, and Gao (2012) employed seven-day taxi records to depict intra-urban land use from travel behavior patterns. This study borrowed the "source to sink" concept from the field of ecological studies, investigating the temporal variations of pick-ups and drop-offs to characterize daily travel patterns and attempting to reveal their association with urban land uses in the city of Shanghai, China. Yuan, Zheng, and Xie (2012) proposed a DRoF (Discovers Regions of different Functions) framework, which uses a topic-based inference model based on features extracted from taxi GPS trajectories data and points of interest (POIs) data. In particular, the DRoF model featured the function of an urban parcel by using the temporal statistics of pick-up and drop-off locations within this parcel. Also, Liu, Gao, and Lu (2019) attempted to measure and incorporate spatial interaction patterns in classifying and understanding urban land use. In sum, these studies mainly use temporal or spatial variations (such as pick-up and drop-off frequencies) to highlight the potential role of taxi GPS records in monitoring people's travel patterns and revealing urban functional structure. In general, a taxi travel route is consecutive and consists of the pick-up location, several intermediate GPS records and the drop-off location. Pick-up and drop-off locations represent the travel purposes of people, while intermediate GPS records also contain valuable information, such as the movement flows and traffic states, which have not been thoroughly explored (Zheng et al., 2014).

The momentum to collect geo-spatial data at a large volume, and the proliferation of new methods in machine learning and deep learning bring unprecedented opportunities to explore the implicit information from geo-enriched trajectory data. By converting from original vehicle route GPS records into consecutive tracking sequences, several in-depth studies have been conducted to leverage the route records to explore sequential information on trajectories, which have a significant correlation with traffic interaction. For example, taking language as an analogy and regarding the mobile user anchor sequence (mobile user trajectory) as sentence and areal research unit as word, Li, Fei, and Zhang (2019) introduced a novel regionalization approach based on Word2Vec model, a representation learning model in the field of natural language processing (NLP), for portioning and grouping spatial parcels in an urban area. Embracing the same idea, Zhang et al. (2020) proposed the Traj2Vec model to classify urban land use type and measured the degree to which urban land use is mixed. However, different with mobile user trajectories analysis on areal units, vehicle movements are carried along the streets and constrained by urban road networks (Liu, Gao, & Lu, 2019; Zhu, Wang, Wu, & Liu, 2017). Therefore, many researchers have attempted to investigate traffic interaction at the road segment level along the urban road network (Chu et al., 2014; Zhang et al., 2016).

In an urban road network, roads are not isolated but connected. Existing studies usually assume that roads within a certain spatial or topological distance are correlated with each other. However, the studies in spatial heterogeneity of traffic impacts are still insufficient, and their potential remains to be tapped (Cheng, Haworth, & Wang, 2012; Wang, Wei, He, Gong, & Wang, 2014; Zou, Yue, Li, & Yeh, 2012). For example, upstream road traffic flows usually do not spread uniformly to its neighborhood roads (e.g., downstream and bidirected roads), but are concentrated in specific directions. The operation of a large number of motor vehicles in the urban road network generates traffic flow, while the different driving behavior of different vehicles result in diverse traffic interaction patterns. Since roads are adjacent and topologically connected, referring to the contextual relationship between words and documents in NLP (Bengio, Ducharme, Vincent, & Jauvin, 2003; Zhang et al., 2020), contextual and topological information can be employed to indicate traffic interaction pattern hidden in trajectories. Exploring this contextual and topological information is of great significance.

Road segments have geographical and topological association with other road segments, especially its neighbors. Road segment classification task is dependent on both the characteristics of that road segment, and its connected ones (Kwan, 2007). Therefore, a spatial prediction model is needed that can consider connections and integrate the characteristics of its neighbors. Moreover, vehicles moving within a city are naturally constrained by urban roads. As a typical graph structure in complex network study, urban road networks have been widely explored in urban studies and planning (Zhao et al., 2020). With powerful modeling ability for graph-structured data, graph convolutional neural networks (GCNN) has received much attention from researchers (Defferrard, Bresson, & Vandergheynst, 2017; Yan, Ai, Yang, & Yin, 2019; Zhu et al., 2020). By representing an urban road network as a road graph and aggregating characteristics of neighboring nodes, the contextual and topological information hidden in roads can be explored at a deeper level with a GCNN model. GCNN can handle the urban road network, which is structured for spatial interactions among irregular geographical units (Zhu et al., 2020).

In this study, we presented a geo-semantic analysis framework to investigate the traffic interaction patterns at a fine scale and evaluate the relationship between traffic interaction and urban functions. First, by analogizing road segments and taxi GPS trajectories (traffic elements) to words and sentences (linguistic terms in NLP), we built a Road-Trajectory corpus and learned a geo-semantic embedding representation from training a Word2Vec model. Then we introduced a GCNN model to classify the social functions of road segments based on the extracted geo-semantic embedding features. The purpose of this study is to address these issues:

- Classifying urban functions at the road segment level using traffic interaction information extracted from taxi GPS trajectories data;
- Presenting a GCNN model with geo-semantic embedding representation to improve the performance of urban function prediction task.

The remainder of this paper is organized as follows. The presented framework, including study materials and methods, is introduced in Section 2. The implementation and findings are then discussed in Section 3. Discussion and potential limitations of this work are outlined in Section 4. The conclusions are drawn in Section 5.

## 2. Framework

### 2.1. Overview

In this study, a geo-semantic analysis framework to investigate the linkage between traffic interaction patterns among road segments and urban functions is proposed (Fig. 1). Geo-semantic analysis takes advantage of semantic embedding technology (Bengio, Courville, & Vincent, 2013; Mikolov, Chen, Corrado, & Dean, 2013) in the field of NLP, analogizing traffic (or spatial) elements to NLP terms and then building high dimension embedding vectors to quantitatively represent the traffic elements, thereby investigating potential information in geographical data (Liu, Pelechrinis, & Labrinidis, 2019; Yao et al., 2017; Zhai et al., 2019). We start with collecting multi-sourced datasets, including taxi trajectory data, urban road network data, and POIs data within the research area. Then, we build geo-semantic embedding features/vectors and obtain urban functions a road segment perspective by using the auxiliary data of POIs. Specifically, we build a Road-Trajectory corpus based on the geo-semantic analogizing assumption and employ a Skip-gram based Word2Vec model to learn geo-semantic embedding features. At the last step we introduce a GCNN model and evaluation metrics using the features constructed.

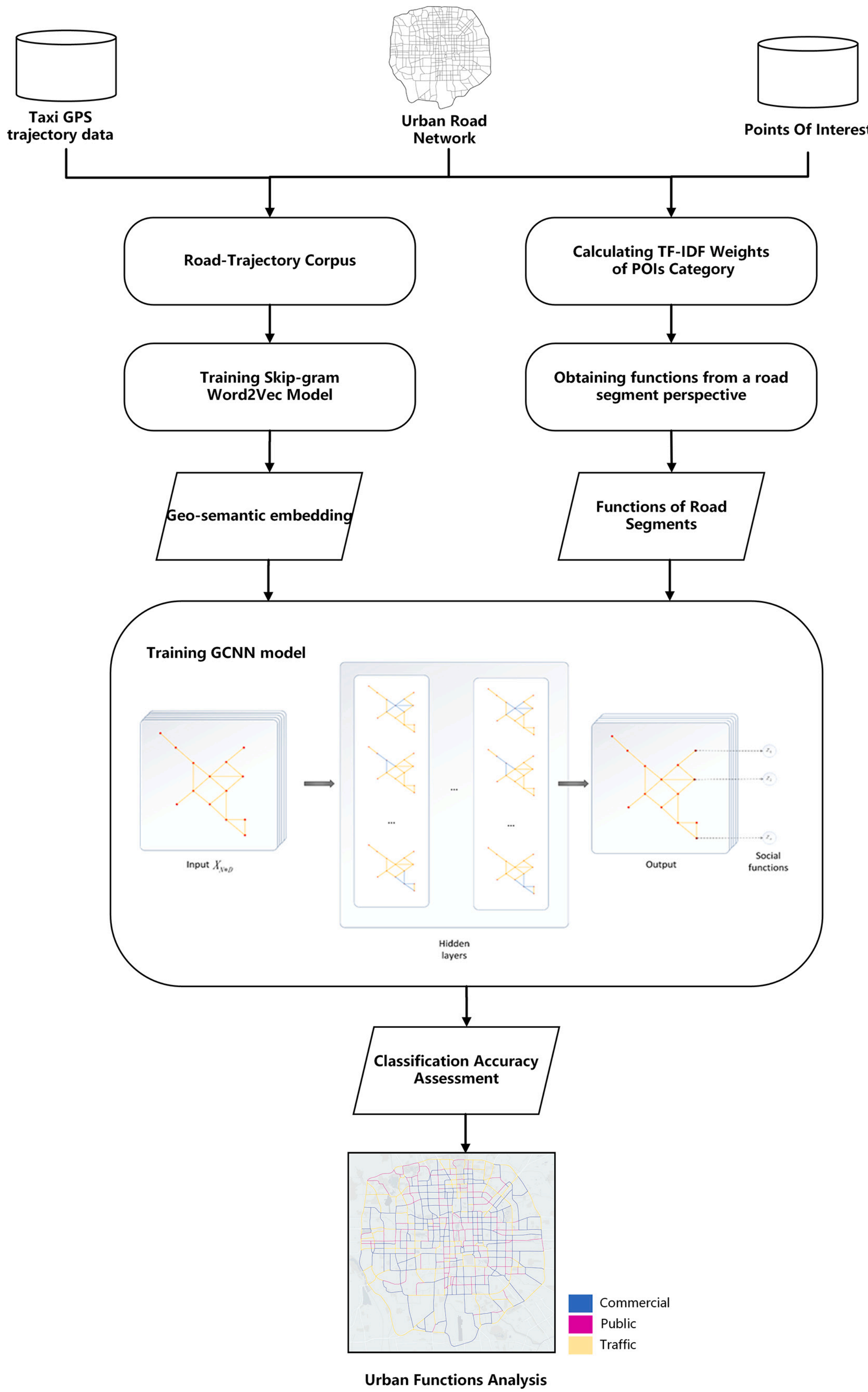


**Fig. 1.** An overview of the proposed framework.

### 2.2. Feature construction

#### 2.2.1. Building the road-trajectory corpus

In the field of NLP, based on a large-scale semantic corpus, we can effectively train the language model and mine the potential semantic representations or relationships. This corpus typically contains many documents and each document consists of many words (Stefanowitsch & Gries, 2007). Similarly, a geographical contextual corpus can be built in the research field of geo-semantic mining (Hu et al., 2020; Yao et al., 2017). In this study, we assumed that the traffic interaction pattern reflects the characteristics of the travel activities of urban people and that this pattern is closely related to the urban spatial structure. A Road-Trajectory corpus was developed on that basis. We divided the city's main roads into road segments based on the significant traffic nodes (such as intersections and T-junctions) within the road network. We analogized road segments to NLP words, the trajectories (or routes) of vehicles to documents, and the study area to a corpus. The aim of building such a corpus was to mine the traffic interaction patterns and potential contextual semantic relationships between road segments. It is worth noting that semantic relationship is expressed in two ways in the NLP: one is the co-occurrence relationship between words, such as phones and laptops, which often appear concurrently in technical documents; the other is the semantic similarity relationship between words, such as laptops and desktops, which typically have identical semantics (Katukuri, Raghavan, & Xie, 2013). In this study, the spatial semantic relationship referred to co-occurrence relationships. A strong similarity between two road segments suggests that both segments typically co-occur along travel routes or that they share either upstream or downstream segments along the travel routes (Liu et al., 2017).

As an essential mode of transportation for urban people, taxis operate in the urban road network. Taxi routes hold valuable information about human activity and the traffic flow. For one taxi route, it usually includes the pick-up location, drop-off location, and intermediate GPS points. By means of a map matching algorithm (C. Yang & Gidofalvi, 2018), GPS records were mapped to urban road segments. Each taxi travel route can be represented as the sequence of unduplicated and consecutive road segments (Fig. 2). Using these sequences, the final documents of the Road-Trajectory corpus for the geo-semantic training area were constructed. Note that we excluded vacant GPS data from this study.

#### 2.2.2. Training geo-semantic embedding model

The geo-semantic mining method transforms the geographical (or spatial) elements (such as urban functional parcels, POIs) to NLP elements, and then represents the spatial relationship or patterns between elements as semantic information, to support various geographic applications. Word embedding is a popular geo-semantic representation method that represents spatial elements as high-dimensional semantic embedding vectors and is widely applied to geographical clustering and classification studies. Word embedding has proved to be an effective and practical approach in geographical semantic representation and urban functional structure mining (Yuan et al., 2014; Zhang et al., 2020). In this study, we introduced the Word2Vec model for the semantic representation of spatial elements. Specifically, we took the Road-Trajectory corpus as an input; by training the Skip-gram based Word2Vec model (Goldberg & Levy, 2014), contextual information and traffic interaction patterns can be investigated, and each road segment symbolizes a high-dimensional feature vector. By entering the documents composed of road segment sequences, the optimization goal of the Word2Vec model is to minimize the information loss function; that is, to maximize the probability of the occurrence of a trajectory route that connects those road segments. The likelihood function of the Skip-gram model is as follows:

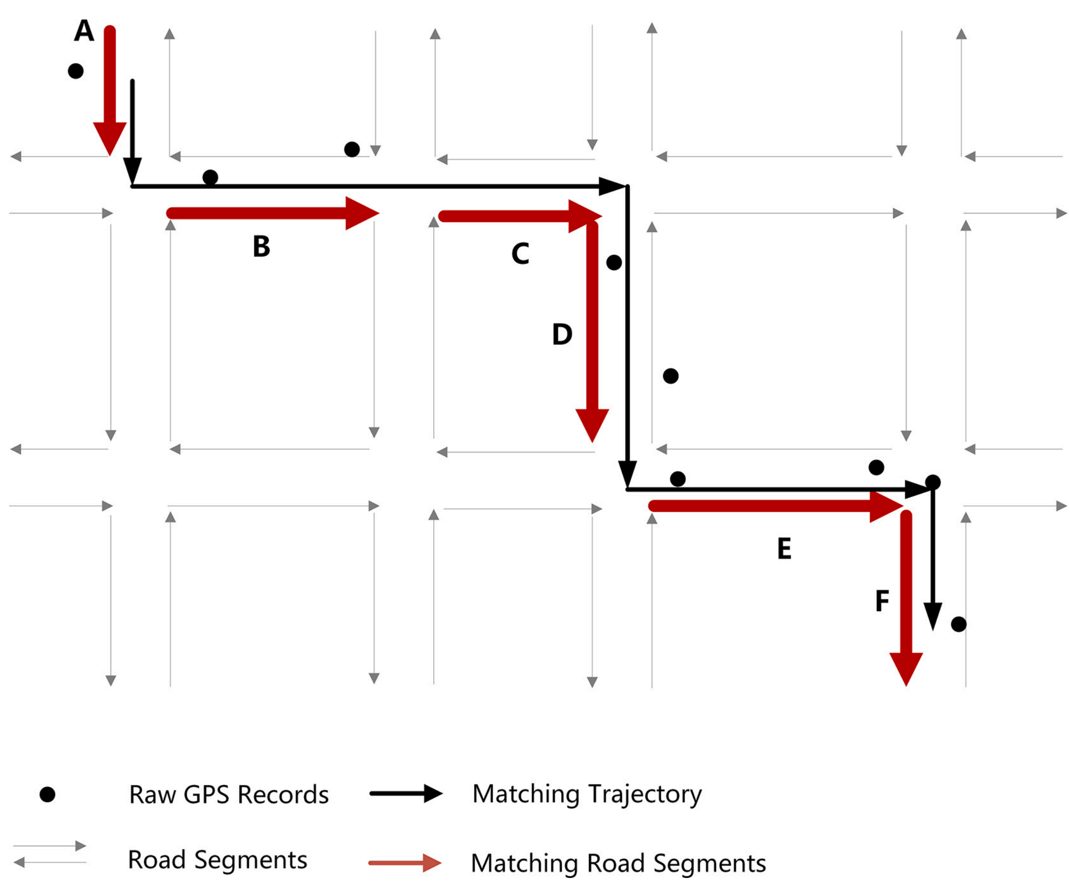


**Fig. 2.** Mapping raw GPS records to a road segments sequence.

$$L(\theta) = \prod_{i=1}^{N} \prod_{-m \le s \le m, j \ne 0} p\left(r_i \middle| r_{i-s}^{i+s}\right) \tag{1}$$

Where $N$ refers to the number of road segments, $s$ denotes the window size, and $r_{i-s}^{i+s}$ represents context road segments of target road segment $r_i$. The conditional probability of generating the context road segments for the given target road segment $p(r_i| r_{i-s}^{i+s})$ can be obtained by performing a softmax operation:

$$p\left(r_i \middle| r_{i-s}^{i+s}\right) = \frac{exp\left(r_i, r_{i-s}^{i+s}\right)}{\frac{1}{N}\sum_{i=1}^{N} exp\left(r_i, r_{i-s}^{i+s}\right)} \tag{2}$$

Finally, we characterize each road segment in the road network as a high-dimensional geo-semantic embedding vector. This vector implicitly contains deep traffic interaction information. The implementation of Word2Vec relies on the tools of genism (Rehurek & Sojka, 2010) in Python.

### 2.2.3. Obtaining urban functions from a road segment perspective

Because POIs can be used to infer areas of land with complex functions and have a high availability from map services, such data is of practical significance in the study of urban spatial and social structures (Zheng et al., 2014). Inspired by prior studies that employed POIs data to investigate urban functional structure (Gao et al., 2017; Hu et al., 2020; Zhai et al., 2019), our method assumes that social functions at the road segment level, such as residential, commercial, and transportation (Table 1), can be represented by the auxiliary data of POIs. As indicated by existing studies, POIs data has become a promising source to represent urban functional structure in the absence of urban functional ground truth, especially in China (Wu et al., 2020; Zhang et al., 2020; Zhang & Du, 2015).

Specifically, to classify the social functions of each road segment, the functions depending on the associated POI categories were grouped into three categories: commercial, public, and transportation (Table 2). Then, the Term Frequency-Inverse Document Frequency (TF-IDF) method (Ramos, 2003) was employed to calculate the weight of POI categories inside the buffer area of one road segment (in this paper, 100 m was employed as the buffer size). TF-IDF is an effective metric to identify semantics and urban functions (Liu et al., 2020). The urban function of a road segment can be subsequently identified by POI categories with a high weight.

$$\mathrm{w}_{rj} = tf_{rj} \times idf_{rj} \tag{3}$$

Where $\mathrm{w}_{rj}$ denotes the weight of POI category $j$ for the road segment $r$; $tf_{rj}= n_{r,\,j}/n_r$ means the term frequency; $idf_{rj} = \log\,(N/N_j)$ means the inverse data frequency. Note that a greater value of $\mathrm{w}_{rj}$ indicates the POIs category $j$ is more important in a road segment $r$.

**Table 1**
Functional Terminologies used in this study.

| Terminologies | Meaning |
|---|---|
| Traffic roads | Traffic roads are used to handle the link between the various functional parcels in the city and their connection with the city's external transportation hub. They are distinguished by high traffic speed, wide lanes and few pedestrians. |
| Commercial roads | Commercial roads are made up of shops on one side or both, and are the most common type of shopping space. Diversified roles, protection, comfort and facilitation of pedestrian activities characterize them. |
| Residential roads | Residential roads are primarily linked to residential clusters for walking bicycles and some motor vehicles, and a quiet environment should be preserved by such roads. According to the concept of pedestrian priority, the spatial environment should be organized, conducive to human activity and able to facilitate people contact. |
| Public roads | Public roads are designed to meet the needs of living activities within the functional areas of the city, which are characterized by low traffic speed. The lane can be slightly narrower, and both sides are usually configured for public buildings, parking lots, and living services. |

**Table 2**
Mapping POI categories to the social functions of road segments.

| No. | POI category | Count | Social function |
|---|---|---|---|
| 1 | Car service | 10,821 | Traffic |
| 2 | Daily life service place | 68,240 | Public |
| 3 | Sports/recreation | 19,308 | Public |
| 4 | Public facility | 19,370 | Public |
| 5 | Corporate business/factory | 48,416 | Commercial |
| 6 | Medical service | 17,426 | Public |
| 7 | Road facility | 2387 | Traffic |
| 8 | Governmental and public organizations | 45,848 | Public |
| 9 | Residential | 21,148 | Public |
| 10 | Science and education | 49,655 | Public |
| 11 | Shopping mall | 116,345 | Commercial |
| 12 | Transportation facilities | 69,473 | Traffic |
| 13 | Business building | 34,911 | Commercial |
| 14 | Bank/financial | 24,275 | Commercial |
| 15 | Tourist attraction | 8628 | Public |
| 16 | Food and beverage place | 56,989 | Commercial |

## 2.3. GCNN prediction model

In the above steps, a road segment in the road network is characterized as a geo-semantic embedding feature, which can be used to estimate the association between traffic interaction and urban functions at a street level. Road segments are not isolated in the urban road network but are linked topologically to each other. The estimation of a road segment, therefore, depends on the features of both this road segment and its connected road segments. Considering the influence of topological adjacency of road segments, this study introduced a well-established semi-supervised classification neural network model (GCNN) (Bruna, Zaremba, Szlam, & LeCun, 2013; Zhu et al., 2020) to classify the social function of road segments based on high-dimensional embedding vectors.

First, we used the road network to construct a bidirectional dual graph $G \equiv (V, E)$, consisting of a set of vertexes V that connect edges E (Porta, Crucitti, & Latora, 2006). Vertexes V refers to road segments and edges $E$ refers to the topological connection between adjacent road segments (Fig. 3). Each vertex $k$ has a feature vector $x_k$, which is summarized in a vector matrix $X_{\mathscr{n}*\mathscr{d}}$. where $\mathscr{n}$ represents the number of vertexes, and $\mathscr{d}$ represents the dimensions of the feature vector. Furthermore, the graph structure is described in a binary adjacency matrix A.

Second, the GCNN model was constructed based on an urban road graph G (Zhao et al., 2020). The GCNN model is designed as a multilayer neural network structure referred from traditional convolutional neural networks (CNNs). However, since graph structure is structured in the irregular spatial domain, CNNs cannot directly handle the urban road graph. For the road graph structure, the most straightforward way to construct a neural network is to expand all the nodes, with each node acting as a neuron processing unit, using the same weights and operations as in the multilayer perceptron (MLP) neural network. But information about the connections between nodes in the road graph, i.e., the road topology, is missing. To address this issue, Graph convolutional filter is introduced to transform urban road graph to the spectral domain and therefore the convolutional network structure is applied to handle with complex network issues. Fig. 4 displays the proposed architecture of GCNN with geo-semantic embedding.

In this work, The GCNN model was introduced to classify urban functions at the road segment level using geo-semantic embedding features. GCNN has a typical three-level network architecture: an input layer, two hidden layers and an output layer. Given an urban road graph G, the GCNN model inputs G with geo-semantic embedding vector matrix $X_{\mathscr{n}*\mathscr{d}}$, iteratively forward propagation operates with graph con-

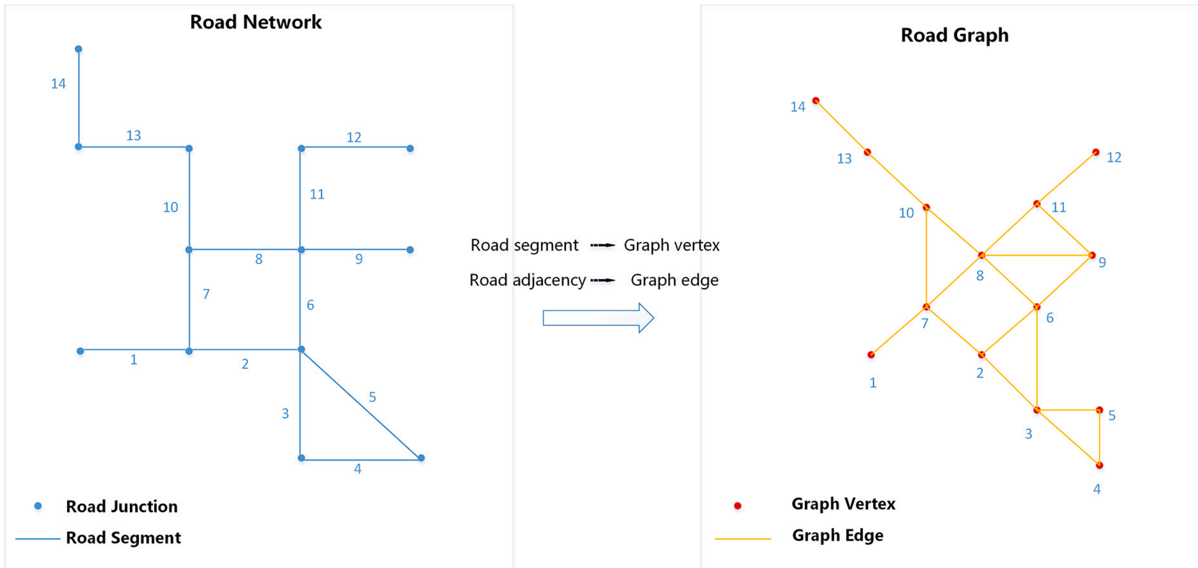


**Fig. 3.** An example of converting road network sample to a dual graph representation.

volutional filter in hidden layers, and finally outputs the node-level road graph G with the probability distribution of social functions P. The hidden layer can be described as a non-linear function:

$$H^{l+1} = f(H^l, A) \tag{4}$$

where $H^l$ denotes the $l^{th}$ neural network layer, especially $H^0 = X_{n*d}$ is the input layer, and $H^L = \mathrm{P}$ is the output layer, $l$ being the number of layers. Specifically, the GCNN follows a layer-wise propagation rule $f(\cdot,\cdot)$, which can be expressed as:

$$f(H^l, A) = \sigma\left(\widehat{D}^{-1/2}\widehat{A}\widehat{D}^{-1/2}H^lW^l\right) \tag{5}$$

where $\sigma(\cdot)$ denotes the non-linear activation function. In this paper, a Rectified Linear Unit (ReLU) was adopt to introduce nonlinearity into the hidden layers (Glorot, Bordes, & Bengio, 2011). $\widehat{D}^{-1/2}\widehat{A}\widehat{D}^{-1/2}$ denotes the normalized Laplacian matrix, which making GCNN taking advantage of neighboring characteristics and fully leveraging geographical information. $W^l$ is the weight matrix for the $l^{th}$ layer. More details about the GCNN model can be found in Kipf's work (Kipf & Welling, 2016).

### 2.4. Evaluation indictors

We compared the cross-entropy loss and prediction accuracies of different methods. The evaluation indictors are defined as follow:

#### 2.4.1. Cross-entropy loss:

$$loss = -\sum_{c=1}^{M} y_c log(p_c) \tag{6}$$

where $M$ is the number of social function class $c$ (In this paper, $M = 3$, i.e., commercial road, public road, and traffic road). $y$ is the binary indicator, $y = 1$ if road segment is correctly classified, otherwise $y = 0$. $p$ is predicted probability calculated by Softmax function.

#### 2.4.2. Accuracy:

$$acc = \frac{1}{N}\sum_{n=1}^{N} y_c \tag{7}$$

Where $N$ is the size of the test set. Note that the prediction accuracy is the major evaluation metric and the cross-entropy loss is only used as a complementary indicator for model comparison.

## 3. Implementation and results

### 3.1. Study area and data description

China's capital, the city of Beijing is the center of politics, culture, science, technology, and international exchange. Beijing has the largest urban built-up area and road traffic system in China. In recent years, with the acceleration of urbanization, new requirements have been put forward for road spatial planning and urban functional structure. The study area was the central urban area within the 5th Ring Road of Beijing (Fig. 5.a), characterized by a diverse urban morphology and elevated mixed land use rates. Taxis play an important role in intra-urban transportation in Beijing. The dataset, collected GPS trajectories of more than 12,000 taxis from November 1, 2011–November 14, 2011 in Beijing. The format of a GPS record comprises of taxi ID, longitude, latitude, timestamp, direction, speed, and status (vacant or occupied). The sampling frequency of the GPS track is about 30 s.

The primary road network and POIs data of the study area were collected from the Beijing City Lab (https://www.beijingcitylab.com/), which is an innovative research community that exploring urban dynamics quantitively and offering new insights for urban planning and governance for sustainable urban development in China. The lab also actively shared and released valuable urban geographical datasets, which have been widely used in many types of research (Long, 2016). In this study, the road network data covers the main roads in the study area (Fig. 5.b), including primary, secondary, and other driven roads. Meanwhile, due to the complexity of urban functional structure and the lack of urban land use ground truth, we employed the POIs data as auxiliary data to obtain the social function of each road segment. Fig. 5.c maps the kernel density distribution of POIs data. In these POI records, in addition to the basic information (e.g., POI name, address, geographical coordinates, and district name), multilevel category information, including top-level category, second-level category and third-level category is also included. The top-level category allowed us to infer urban functions. In this study, WGS84 geographic coordinate system was adopted.

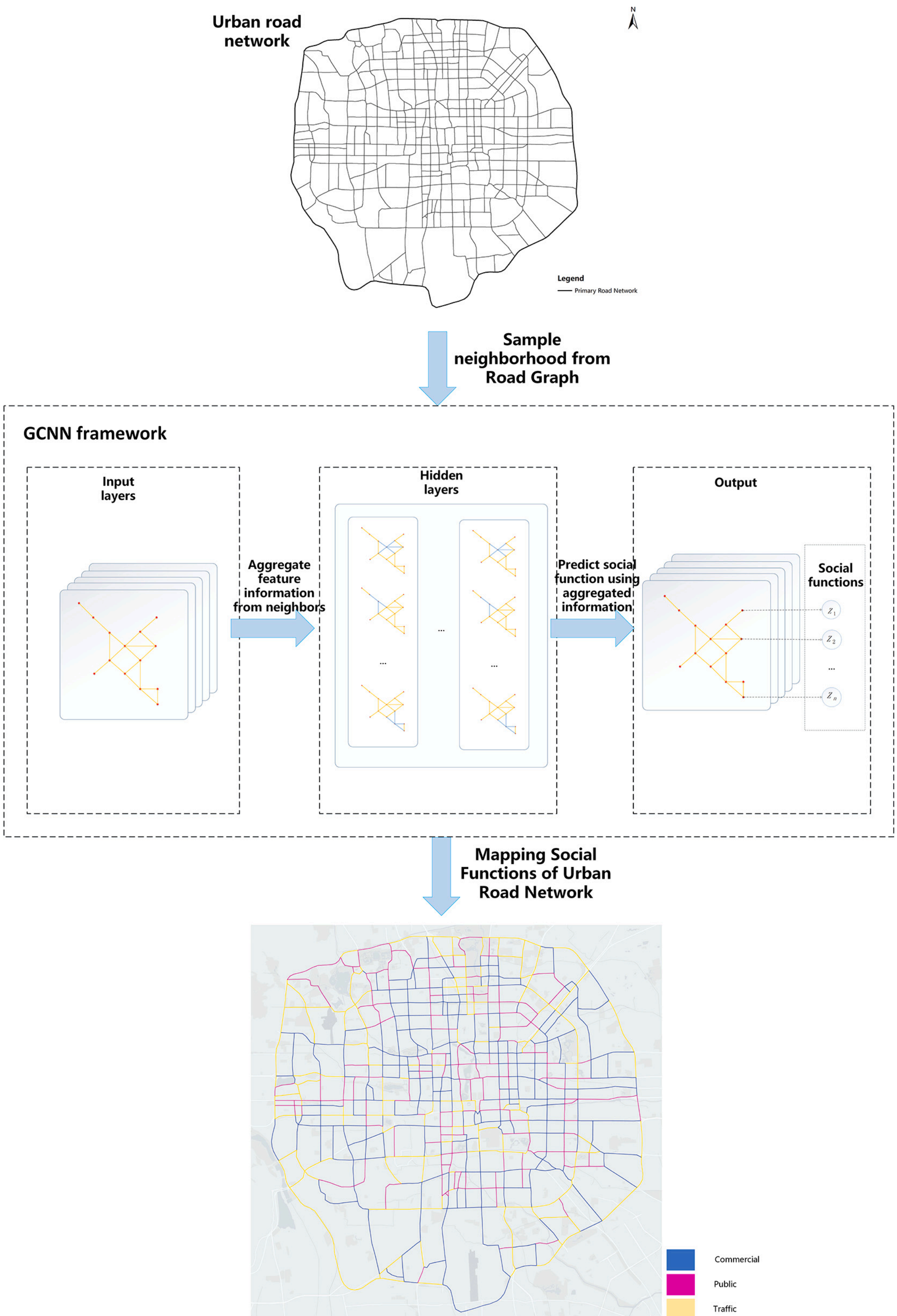


**Fig. 4.** The proposed architecture of GCNN.

*3.2. Geo-semantic embedding representation*

*3.2.1. Parameters setting in Word2Vec*

In this study, we extracted the main traffic roads in the study area and divided them into 1514 road segments. By inputting the Road-Trajectory corpus and training the Word2Vec model, each road segment can be represented as a high-dimensional vector, which contains important traffic interaction information and can be easily used in the downstream neural network models.

The parameter sensitivities of Word2Vec have been widely discussed in recent exploratory studies. Considering the computational cost of the Word2Vec model and the volume of the real taxi GPS trajectory data,

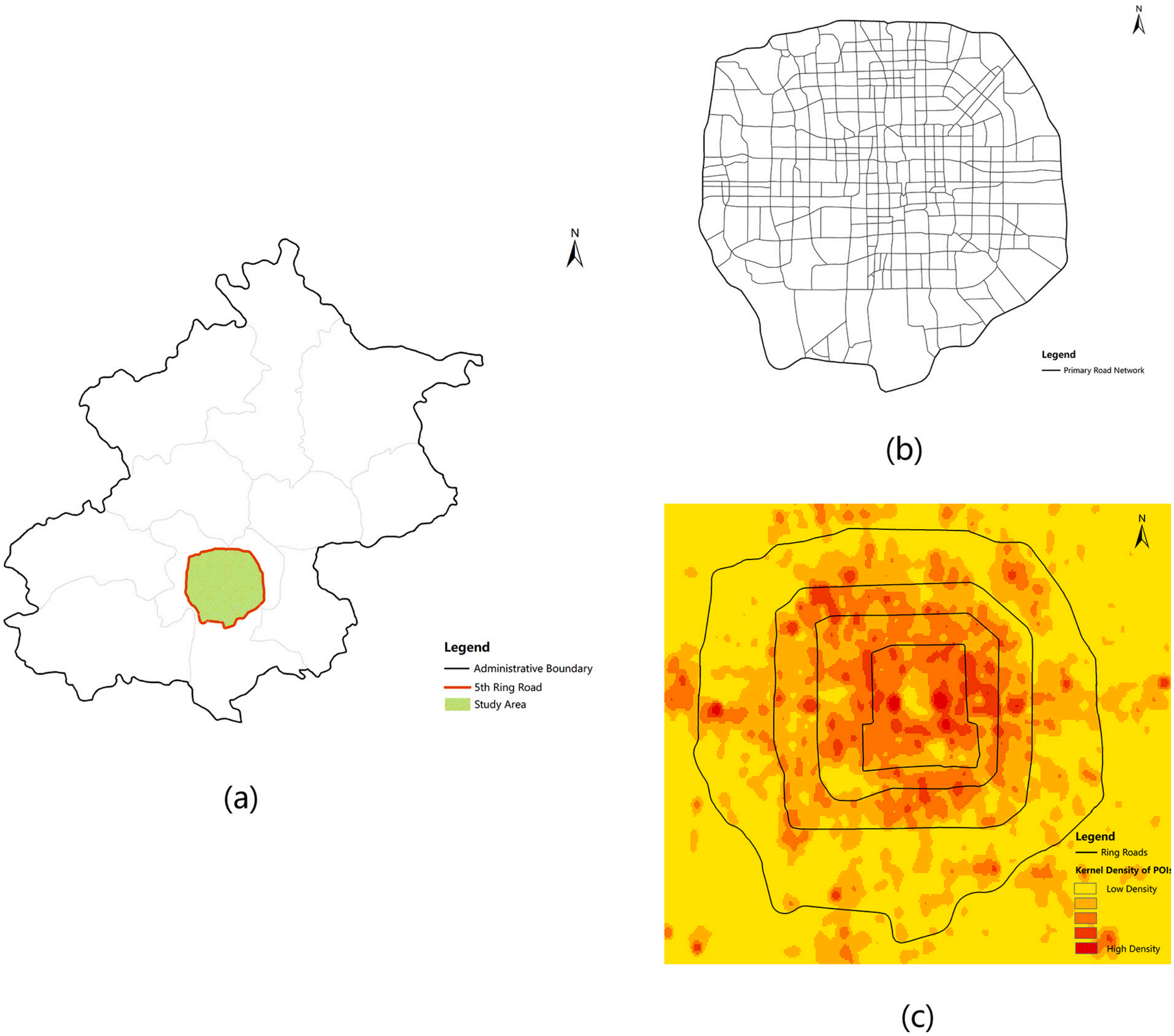


**Fig. 5.** Study area and data schema. (a) Study area – the central urban area of Beijing City. (b) The primary road network in the study area. (c) Kernel density distribution of POIs data.

most of the parameters were set to recommended or default values. Inspired by existing exploratory studies (Liu et al., 2017; Yan, Janowicz, Mai, & Gao, 2017), the vector dimension in the Word2Vec model was set to 128 and the scanning window was 6. However, an uncertain parameter still existed, namely the number of iterations $k$, which may have an impact on the final results. This uncertain parameter is usually

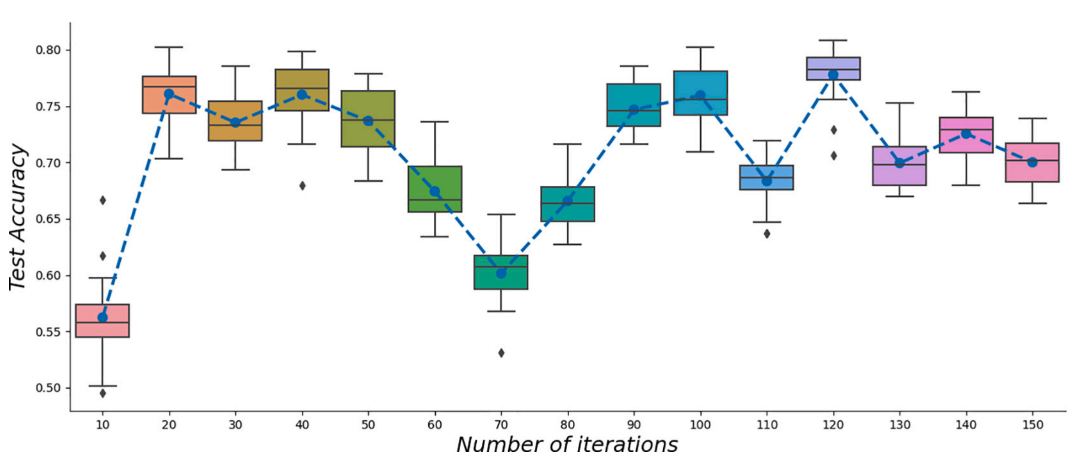


**Fig. 6.** Change of the testing accuracy of prediction assessment with increases in the number of iterations in Word2Vec. The box plot in each iteration dedicates the distribution of test accuracy of 20 times running, while the blue dot line dedicates the change of the mean value of test accuracy. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

determined by different geo-semantic tasks. In this study, a few trials were performed to determine the appropriate $k$ value in the Word2Vec model, which was achieved by running the GCNN prediction task with different numbers of iterations (ranging from 10 to 150 with intervals of 10, each iteration running 20 times to ensure the stable accuracy) and evaluating the testing accuracy. As depicted in Fig. 6, the mean value of testing accuracy peaked at about 0.76 when the number of iterations was set as 20, 40, 100, and 120. However, the box plots show that the distribution of test accuracy was uneven, and outliers existed when $k = 40$ and $k = 120$. Therefore, we set the number of iterations to 20 and 100 respectively in the following analysis.

### 3.2.2. Correlation analysis

In order to verify the effectiveness of the geo-semantic embedding vector of a road segment, we selected a road segment of interest: the FuCheng Road in Xidan district to visually estimate its traffic interaction and similarity among neighboring roads. We obtained the semantic embedding vector of FuCheng Road and its neighboring road segments. Then, we calculated the cosine similarity metric between them and explored the traffic interaction in the road network. As depicted in Fig. 7, the cosine similarity between FuCheng Road and its neighboring road segments in Xidan district were spatially heterogeneous. The maximum cosine similarity was 0.69, occurring between FuCheng Road and its downstream road segment, i.e., Tiyuguan South Road – road segment 1 in Fig. 7. However, the similarity value between FuCheng Road and its adjacent road segment, i.e., West 3rd Road—road segment 6 in Fig. 7—was only 0.029, meaning that there was less traffic interaction. Meanwhile, the similarity value between FuCheng Road and its bidirected road segment—road segment 3 in Fig. 7—was also small, only 0.036. We believe that this result is primarily related to the social function of a road segments and/or its spatial interaction with other road segments. For example, a typical taxi trip would not include FuCheng Road as well as road segment 3 because that would require making a U-turn at the end of one road segment and then going to the opposite direction, which does not happen very often with taxi trips. However, as the topological distance between FuCheng Road and its neighboring road segments increases, the similarity value between them becomes smaller, resulting in a weaker traffic interaction.

## 3.3. Spatial distribution of social functions

Considering the weight and proportion of POI categories along and near each road segment, the social function of road segments was divided into three types: commercial, public and traffic. Commercial POI dominated streets were the largest proportion at 37.8%, while public and traffic POI dominated streets account for 36.6% and 25.6%, respectively. As is shown in Fig. 8, commercial POI dominated streets are located in several popular business centers and market districts, such as Xidan, Wangfujing, and Shijiecheng commercial streets. Traffic POI dominated streets typically comprise ring roads, carrying the function of transportation, such as commuting between downtown and suburban areas. Public POI streets mainly comprise public services streets, distributed in scenic areas, public services areas, and residential areas.

## 3.4. Validation of GCNN prediction model

### 3.4.1. Comparative methods

A MLP neural network model (Pal & Mitra, 1992) was introduced to compare with the proposed GCNN prediction model. As one of the commonly applied feed-forward neural networks, MLP has various characteristics, such as fast operation, ease of implementation and smaller training set requirements. In addition, for a better understanding of the effectiveness and strength of semantic embedding features, a vector consisting of pick-up and drop-off features was implemented for comparison. Researchers have verified that the urban functions of a certain urban area can be characterized by the temporal and spatial dynamics of the number of taxi pick-ups or drop-offs (Liu et al., 2012; Pan, Qi, Wu, Zhang, & Li, 2013). For comparison purpose, we extracted similar features at the road segment level, i.e., the number of pick-ups per hour, the number of drop-offs per hour, and the difference between these two numbers from the real taxi GPS trajectory data set. Then, we concatenated the above features and generated a 72-dimensional Origin-Destination (OD) feature vector. All compared methods are listed as follow:

a) semantic embedding features with $k = 20$ + GCNN model ($SE_{20} + GCNN$);
b) semantic embedding features with $k = 20$ + MLP model ($SE_{20} + MLP$);
c) semantic embedding features with $k = 100$ + GCNN model ($SE_{100} + GCNN$);
d) semantic embedding features with $k = 100$ + MLP model ($SE_{100} + MLP$);
e) pick-up and drop-off features + GCNN model ($OD + GCNN$);
f) pick-up and drop-off features + MLP model ($OD + MLP$).

In the above methods, different feature vectors were fed into the GCNN model and MLP model, and the urban functions of each road segment were predicted. Additionally, by setting the random seed, we randomly split the dataset into the training dataset, the validation dataset, and the testing dataset with ratios of 60%, 20%, and 20%, respectively. The validation dataset was used to validate the model at each epoch while the training and the testing datasets were used to evaluate the final overall accuracy. The learning rate was set to 0.01; the number of hidden units was set to 64; and other parameters were set to the default values. The maximum number of training epochs was set to 1000 to fit the GCNN model sufficiently. The dropout mechanism (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014) and weight decay regularization were introduced to prevent overfitting in training process. To ensure a reliable and stable estimation of the prediction accuracy, each model was run 20 times with different random seeds.

### 3.4.2. Prediction performance

In this subsection, we discuss the performance of proposed GCNN model and comparative methods on the real taxi GPS trajectory data in Beijing. Table 3 shows the comparative results for the performance. We found that (1) our proposed methods (identifier a and c in the Table 3), with relative less loss and high accuracies, outperform other comparative methods (identifier b, d, e and f) for classifying urban functions on a very large volume of real-world taxi trajectories; (2) MLP-based methods (b, d and f) drop behind GCNN-based methods (a, c and e) as they ignore contextual information in geographic contexts in an urban road network, so compared with GCNN-based methods, MLP-based methods may suffer from the issue that how to fully leverage geographical influence; (3) semantic embedding based methods (identifier a, b, c and d) obtain much better performance than pick-up and drop-off based methods (e and f), indicating that modeling the underlying traffic interaction information extracted from taxi GPS trajectories is important for classifying urban functions at the road segment level.

To summarize, with semantic embedding features, our proposed GCNN model is able to learn and better leverage traffic interaction information extracted from taxi GPS trajectories data and significantly improve the performance of social function prediction task along road segments in urban areas.

# 4. Discussion

## 4.1. Semantic embedding features and model selection

In this study, we constructed semantic embedding features to represent traffic interaction characteristics among road segments by

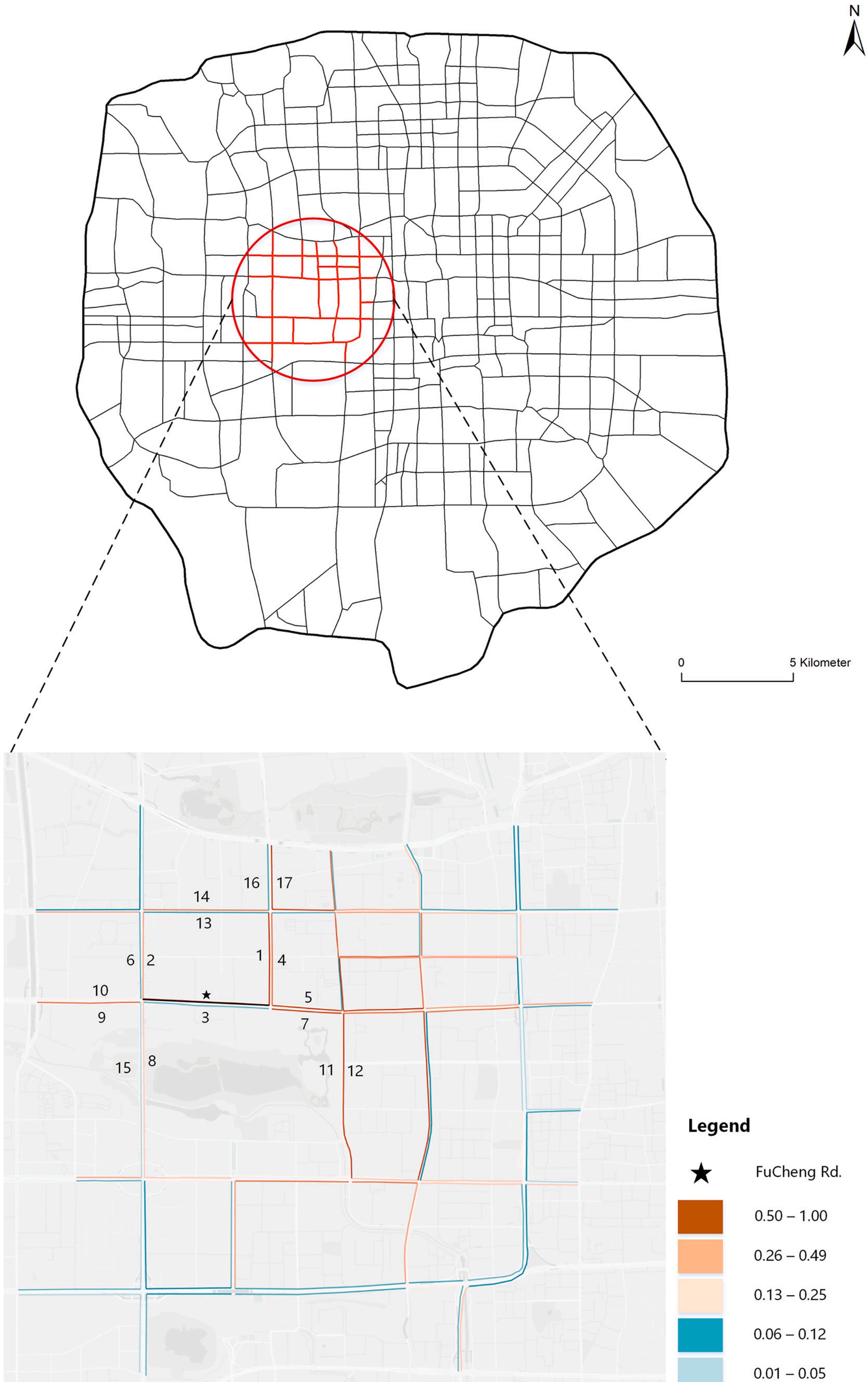


**Fig. 7.** Cosine similarity between FuCheng Road and neighboring road segments in Xidan district.

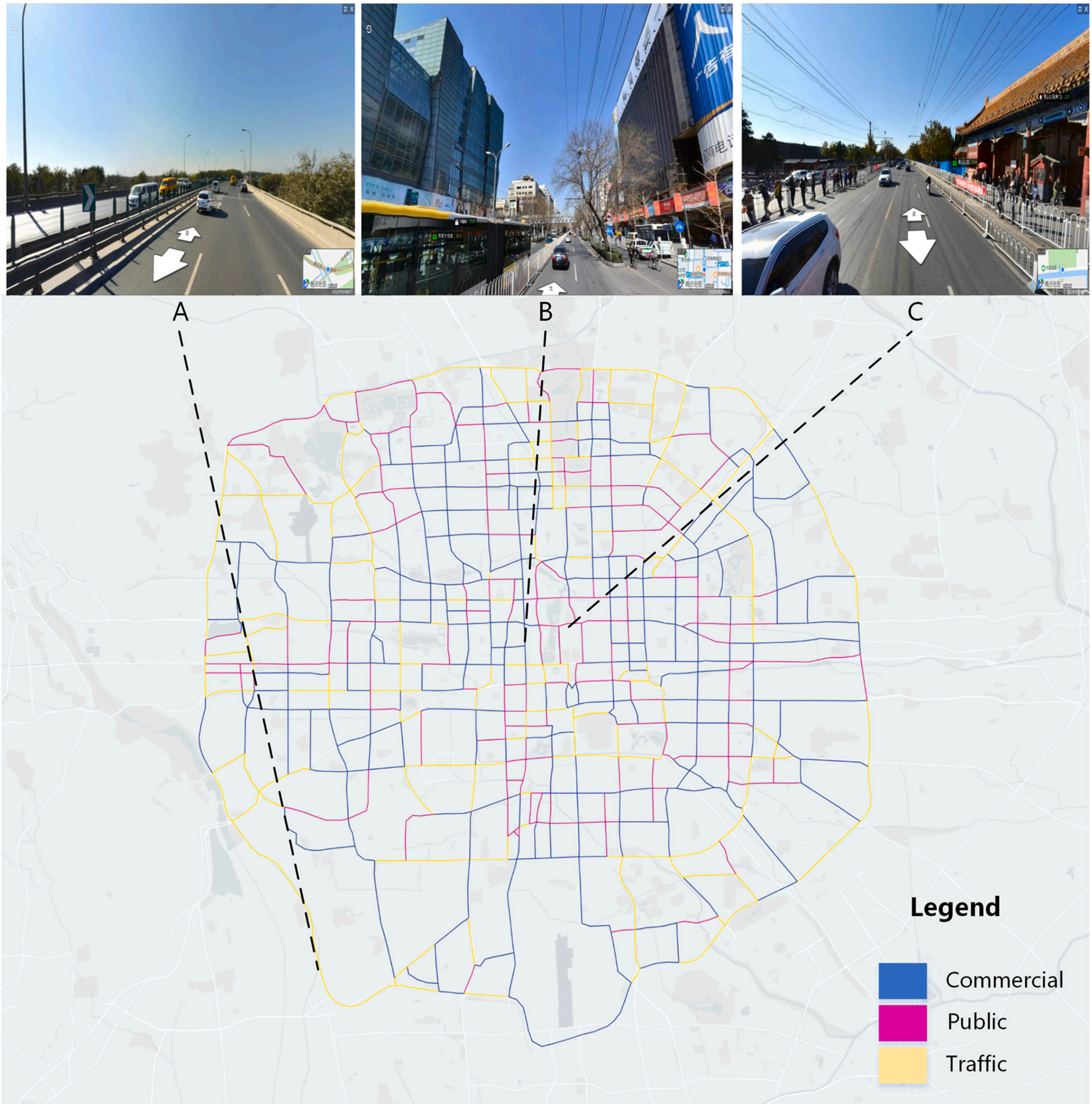


**Fig. 8.** The social function distribution of road segments. The three subfigures above the map are street view images of three interest road segments: A. South 5th Road (Traffic); B. Xidan South Street (Commercial); C. Jingshan Street (Public).

**Table 3**
Test assessment of compared methods.

| ID | Method | Loss | | | | Accuracy | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | Max. | Min. | Std. | Mean | Max. | Min. | Std. |
| a) | *$SE_{20}$ + GCNN* | 0.842 | 1.070 | **0.612** | 0.115 | **0.761** | **0.802** | 0.702 | 0.027 |
| b) | *$SE_{20}$ + MLP* | 1.116 | 1.609 | 0.953 | 0.197 | 0.528 | 0.571 | 0.452 | 0.036 |
| c) | *$SE_{100}$ + GCNN* | **0.786** | **0.988** | 0.664 | 0.084 | 0.759 | 0.802 | **0.710** | 0.026 |
| d) | *$SE_{100}$ + MLP* | 1.092 | 1.878 | 0.964 | 0.202 | 0.546 | 0.601 | 0.485 | 0.033 |
| e) | *OD + GCNN* | 0.981 | 1.012 | 0.946 | 0.021 | 0.532 | 0.581 | 0.495 | 0.022 |
| f) | *OD + MLP* | 1.032 | 1.069 | 0.993 | 0.017 | 0.491 | 0.436 | 0.538 | 0.029 |

Bolded score indicates relatively fit value in the corresponding column.

geo-semantic training in the Word2Vec model based on a Road-Trajectory corpus. Furthermore, urban function prediction results indicate that our proposed GCNN model outperformed traditional methods in comparative trials. Compared with existing methods, the proposed method has the following advantages. First, without considering traffic interaction correlations, the OD-based method merely leverages temporal and spatial activity variations and frequencies to classify urban functions, which may miss the contextual and underlying spatial interaction information. Liu, Kang, Gong, and Liu (2016) have revealed that urban land use is intricately linked to traffic behaviors, and a lack of information on spatial interaction creates a barrier for the improvement of classification accuracy in urban functional studies. Our study resonates with Liu's work and shows that semantically embedding features considering traffic interaction patterns can significantly improve the performance of modeling urban function prediction.

Second, how to learn effective data representation automatically becomes a key issue in machine learning and geo-semantic studies (Bengio et al., 2013). Early representation approaches, such as features extraction and features selection, both incorporate certain subjective learning assumptions and easily ignore potential information. Geo-semantic embedding features take advantage of potential information learning and inner spatial interaction, integrating a GCNN model that considers the influence of topological adjacency of road segments, thereby reducing manual intervention.

Third, although geo-embedding techniques, such as topic modeling and Word2Vec, have been investigated in urban road networks to certain degree, the advances for geo-embedding representation remains a key challenge, especially when integrating advanced deep learning methods with large geo-enriched movement data. Liu et al. (2017) presented a Road2Vec model to reveal traffic interaction pattern using vehicle travel routes. They used artificial neural network and support vector machine model to a short-term traffic forecasting task. The results showed that geo-embedding features can reveal implicit traffic relationship among roads and have a good performance in traffic forecasting. However, how to effectively leverage non-linear traffic interaction information hidden in geo-semantic embedding still needs further research. In this study, a semi-supervised GCNN model was introduced to integrate with geo-semantic embedding features of road segments. Enabled by the unique advantages of graph convolutional neural networks in dealing with an unstructured road graph, the potential of geo-semantic embedding features can be further explored. Our experimental results also revealed that the GCNN model with semantic embedding features obtains less information loss and higher prediction accuracies, and outperform comparative MLP-based methods.

In addition, GCNN was selected as the machine learning model to classify urban functions with regard to the characteristics of traffic spatial interactions among road segments. Geo-embedding representation has been shown to be an effective property that can describe the uniqueness and similarity of a road segment. However, roads are connected but are not isolated in urban road networks. GCNN adopt an aggregation strategy in which each road segment aggregates its topologically neighbors' embedding characteristics to learn the contextual and geographical information. Therefore, it is ideal for modeling urban road networks. Our results also showed that the GCNN-based method can perform better than other comparative methods.

### 4.2. Comparisons with popular machine learning methods

Moreover, comparisons with popular machine learning methods (Jordan & Mitchell, 2015) have also been employed to validate the performance of our proposed GCNN model. To ensure a reliable and stable estimation, a powerful toolkit for hyper parameter optimization and model compression- NNI (Neural Network Intelligence)-was utilized to obtain the best parameters (https://github.com/microsoft/nni). For comparative machine learning methods including linear regression (LR), k-nearest-neighbors (KNN), support vector machines (SVM), and random forest (RF), each model was run 100 times using semantic embedding features with $k = 20$ with different random seeds. Results are summarized in Table 4. Reported numbers denote the classification accuracy on the test set. We found that our proposed method, overall, outperforms other popular machine learning methods. The maximum accuracy of our proposed method is a little bit lower than the other three methods (KNN, SVM, and RF), but the mean accuracy and minimum accuracy are better than the other methods, while our method has a smaller standard deviation. This result indicates that our proposed method has better stability and robustness using the same features for geographic knowledge discovery.

### 4.3. Contributions and limitations

The contributions of this study can be summarized as following three aspects:

- Taxi GPS trajectory data have been widely employed in the related studies of investigating urban functional structure. Extracting pick-up and drop-off positions and then measuring the proportions inside each region is a commonly used method to characterize urban functional regions. However, intermediate GPS records of each trajectory also contain valuable information, such as the movement flows and traffic states, which have not been thoroughly explored. To address this issue, an analogizing strategy was presented and the Word2Vec model in NLP was employed to learned a geo-semantic embedding representation of road segment. Via geo-semantic embedding features, not only can we characterize urban traffic elements using representation learning, we can quantitatively investigate and measure the traffic interaction between road segments by correlation analysis;
- Vehicles moving within a city are naturally constrained by urban roads. As a typical graph structure in complex network study, urban road networks have been widely explored in urban studies and planning. Road segments have geographical and topological association with other road segments, especially its neighbors. Road segment based classifying task is dependent on both the characteristics of that road segment, and the characteristics of road segments to which it is connected. Therefore, a GCNN model was introduced to classify the social functions of road segments and improve the classification accuracy;
- Finally, this work makes a contribution by enhancing the understanding of the urban functional classification at the road segment level in a large-scale urban environment in an automatic and efficient way by using GCNN and taxi GPS trajectory data. This method can be done reproducibly and applicable with readily available trajectory data, OSM road network data and POIs data in many other urban areas.

The limitations of this study should also be noted and paid more attention to in future research. First, the social function of each road segment was identified, and these were divided into only three types. A real-world urban area, however, is characterized by more complex and

**Table 4**
Summary of results with compared machine learning methods.

| Method | Mean | Max. | Min. | Std. |
|---|---|---|---|---|
| LR | 0.561 | 0.573 | 0.551 | 0.007 |
| KNN | 0.543 | 0.821 | 0.435 | 0.116 |
| SVM | 0.682 | 0.834 | 0.338 | 0.164 |
| RF | 0.671 | 0.834 | 0.327 | 0.164 |
| GCNN (Our Proposed) | 0.759 | 0.802 | 0.710 | 0.026 |

Note: LR-Linear Regression Classification, KNN-K Nearest Neighbor Classification, SVM-Support Vector Machine Classification, RF-Random Forest Classification.

diverse urban functional structures and elevated mixed social functions. The next work on this issue is to integrate the mixture natures of urban land uses and POI data to reflect the diversity and mixture of social functions. Second, future research is anticipated to use more features in the GCNN-based prediction, such as physical characteristics from remote sensing and street view data. Third, it needs to be further explored that whether we should consider longer distance range of interactions rather than the directly connected neighbors when using graph-based deep learning models to study urban functions.

## 5. Conclusion

In this study, we proposed a novel framework for sensing the relationship between traffic interaction patterns and urban functions from a road segment perspective. Considering traffic interaction information, geo-semantic embedding features can be learned from the proposed Road-Trajectory corpus by training the Skip-gram Word2Vec model. Moreover, the social function of each road segment can be identified by integrating the auxiliary data of POIs and the TF-IDF weighting method. Finally, because road segments are topologically connected, we introduced a GCNN to classify the urban functions of road segments. This work was implemented using extensive taxi GPS trajectory data in Beijing. The result shows that our proposed GCNN model with geo-semantic embedding features outperform other comparative methods. We subsequently discussed the advantages of geo-semantic embedding representation and the potential improvement of the proposed framework. The framework and methods proposed in this study can be applied to other urban areas as well, which can be done reproducibly with readily available datasets. This study contributes to urban study and GIScience literature by building a Road-Trajectory corpus using vehicle GPS trajectory data and investigating social functions based on geo-semantic embedding features from a road segment perspective using deep learning techniques.

## Conflict of interest statement

No potential conflict of interest was reported by the authors.

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