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Investigating urban metro stations as cognitive places in cities using points of interest

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ABSTRACT

The significance of urban metro stations extends beyond their roles as transport nodes in a city. Their surroundings are usually well-developed and attract a lot of human activities, which make the metro station areas important cognitive places characterized by vague boundaries and rich semantics. Current studies mainly define metro station areas based on an estimation of walking distance to the stations (e.g., 700 m) and investigate these areas from the perspectives of transportation and land use instead of as cognitive places perceived by the crowd. To fill this gap, this study proposes a novel framework for extracting and understanding the cognitive regions of urban metro stations based on points of interest (POIs). First, we extract the cognitive regions of metro stations based on co-occurrence patterns of the stations and their surrounding POIs on web pages by proposing a cohesive approach combined of spatial clustering, web page extraction, knee-point detection, and polygon generation techniques. Second, we identify the semantics of metro stations based on POI types inside the regions using the term frequency-inverse document frequency (TF-IDF) method. In total 166 metro stations along with more than one million POIs in Shenzhen, China are utilized as data sources of the case study. The results indicate that our proposed framework can well detect the place characteristics of urban metro stations, which enriches the place-based GIS research and provides a human-centric perspective for urban planning and location-based-service (LBS) applications.

1. Introduction

Urban metro stations play significant roles in major cities. They are important transport nodes that carry a huge amount of intra-urban trips (Gong, Lin, & Duan, 2017; Ma, Zhang, Ding, & Wang, 2018). Moreover, their surroundings are usually well-developed with high-density businesses, residences, and public facilities, which make the areas vibrant and attract a lot of human activities (Lai, Cheng, & Lansley, 2017; Zhou, Fang, Zhan, Huang, & Fu, 2017). Given these reasons, metro station names are frequently mentioned in our daily discourse, especially when describing location references, such as "*Alice lives near the SanLiTun Station*." People who are familiar with the city usually have unique impressions on various stations. Taking the metro stations of Beijing as an example, one would think of various shopping malls when mentioning “XiDan Station” and associate “GuoMao Station” with a cluster of dense and tall modern office buildings. In this context, urban metro stations are typical cognitive places perceived by the crowd through interacting with the surrounding society and environment (Blaschke et al., 2018; Filomena, Verstegen, & Manley, 2019; Lynch, 1960; McCunn & Gifford, 2018; Merschdorf & Blaschke, 2018; Shaw & Sui, 2019), which are characterized by vague boundaries and rich semantics (Gao, Janowicz, McKenzie, & Li, 2013; Hu et al., 2015; Liu, Yuan, Xiao, Zhang, & Hu, 2010; Montello, Goodchild, Gottsegen, & Fohl, 2003).

Extracting and understanding the cognitive regions of metro stations provide important values in many aspects. Given that metro systems have an important role in shaping metropolitan areas, geographical information can be integrated into a station-area level to help tourists, new immigrants, and nonnative merchants to learn about the city quickly. LBS and web mapping services can be enhanced by integrating the transportation functions of metro stations with their activity characteristics of places. Furthermore, urban planners can evaluate the development of current metro station areas based on their cognitive ranges and attached semantics, so as to make human-centric urban planning and design.

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Existing studies on metro station areas mainly come from the transit-oriented development (TOD) domain, which dedicates to offer a strategy to integrate land use and transport systems by developing high-density, mixed-use, and pedestrian-friendly areas around the transportation nodes (Higgins & Kanaroglou, 2016; Lyu, Bertolini, & Pfeffer, 2016). The TOD precincts (i.e., station catchment areas) are generally defined according to an understanding of how far people are willing to walk to take public transport, and 10- min is generally considered as an acceptable walking time. Specifically, a buffer zone of 700 m is usually used to delineate TOD precincts in European cities (Reusser, Loukopoulos, Stauffacher, & Scholz, 2008; Vale, 2015; Zemp, Stauffacher, Lang, & Scholz, 2011), buffers between 400 and 800 m are adopted for American cities (Atkinson-Palombo & Kuby, 2011; Austin et al., 2010), and buffers of 500 m are generally used for Asian cities (Sung, Choi, Lee, & Cheon, 2014). Based on these definitions, TOD studies have explored the station catchment areas based on their land use density and diversity, property value, population and employment density, walk score, and street connectivity, and investigated their interactions, associations and the coordinated developments with the public transport (Bertolini, 1999; Higgins & Kanaroglou, 2016; Lyu et al., 2016; Reusser et al., 2008).

Different from the TOD studies, this study aims to investigate metro station areas as cognitive places. Specifically, we intend to extract the vague cognitive regions of metro stations perceived by the crowd and identify the semantics of the regions that can reflect the crowd's impressions and perceptions.

For cognitive place studies, human-participant surveys have been widely used to extract the boundaries of vague places in GIScience and in spatial cognition studies (Montello et al., 2003; Montello, Friedman, & Phillips, 2014). A classic study is that Montello et al. (2003) recruited a group of participants to delineate the range of "downtown Santa Barbara" on a map. However, such experiments are time-consuming and labor-intensive. In recent years, the widely available geotagged data collected from social media (e.g., Twitter and Flickr) provide promising opportunities for place-based studies. Using such crowd-generated, semantically-rich and location-determined geotagged points, researchers have proposed various approaches to extract and understand the vague places (Gao, Janowicz, Montello, et al., 2017; Hu et al., 2015; Li & Goodchild, 2012; Liu et al., 2010; Grothe & Schaab, 2009). For example, using datasets collected from Flickr, Instagram, Twitter, Travel blogs, and Wikipedia, Gao, Janowicz, Montello, et al. (2017) introduced a data-synthesis-driven approach to extract the boundaries and thematic characteristics of places and compared their derived vague cognitive regions of “Northern California” and “Southern California” with those extracted from the human-participants study by Montello et al. (2014). The results using the data-synthesis-driven approach got a good concordance with that from the traditional survey. Hu et al. (2015) presented a coherent framework for extracting and understanding urban areas of interest (AOI) based on geotagged photos sourced from social media. Minimum bounding polygons (Gao, Janowicz, Montello, et al., 2017; Hu et al., 2015), kernel-density analysis (Grothe & Schaab, 2009; Li & Goodchild, 2012; McKenzie & Adams, 2017), and machine-learning classification algorithms (Grothe & Schaab, 2009) are generally used to delineate the boundaries of vague cognitive regions. The natural language processing (NLP) methods, such as topic modeling (Adams & McKenzie, 2013; Gao, Janowicz, Montello, et al., 2017) , the term frequency-inverse document frequency (TF-IDF) model (Hu et al., 2015; Ramos, 2003), and modified word2vec models (Yan, Janowicz, Mai, & Gao, 2017; Zhai et al., 2019) are creatively introduced to derive the semantics of cognitive regions from the textual tags.

Despite having significant value in extracting and understanding cognitive places, geotagged data are not ideal for studying the metro station areas owing to issues of completeness and biases (Li, Goodchild, & Xu, 2013; Yue et al., 2017). People usually prefer to mark and tag attractive places, such as famous cities, scenic spots, and top universities, while metro station names are less likely to be discussed and tagged on social media. Therefore, instead of using the geotagged social media data, this study utilizes the points of interest (POI) data and acquires the cognitive relationships of POIs and metro stations from the web pages (Hu, Ye, & Shaw, 2017; Jones, Purves, Clough, & Joho, 2008; Liu, Wang, Kang, Gao, & Lu, 2014; McKenzie, Liu, Hu, & Lee, 2018; Sanderson & Kohler, 2004; Wu, Wang, Shi, Gao, & Liu, 2019). Assuming that frequently co-occurred place names on web pages implies a strong relatedness between them, researchers have investigated the relationships between geographical entities, such as cities (Hu et al., 2017) and provinces (Liu et al., 2014), and extracted the cognitive regions of vague places by those with precise locations (Jones et al., 2008). Following the same assumption, this study considers a metro station and a POI to be vaguely related in cognition if they co-exist on a number of web pages.

A novel framework is proposed to extract and understand the cognitive regions of urban metro station areas. First, we extract the cognitive regions of metro stations based on the counts of co-occurrences of station names and POI addresses on web pages. A cohesive approach that combined of spatial clustering, web page extraction, knee-point detection, and polygon generation techniques is proposed. Then, we identify the semantics of metro stations based on POI types inside the cognitive regions using the TF-IDF method. The framework is also applicable to metro stations in other cities or other similar kinds of cognitive places (e.g., urban landmarks).

The following of the paper is structured as follows. Section 2 introduces the framework and the datasets in this study, including the data preprocessing steps. Section 3 presents the extraction of the cognitive regions of urban metro stations. Section 4 presents the identification of the semantics of metro station areas. Section 5 presents discussions and Section 6 concludes this work.

2. Framework and datasets

2.1. Framework

The framework of this study is shown in Fig. 1. The metro stations (including locations and names) and POIs (including coordinates, addresses, and types) are used as data sources. In this framework, address-format unification and DBSCAN clustering techniques are conducted to pre-process the POI data. Web page extraction, knee-point detection, and polygon generation, constitute a cohesive approach to delineate the cognitive regions of metro stations. Finally, a TF-IDF method is applied to identify the semantics of the station areas.

2.2. Datasets and preprocessing

2.2.1. Metro stations

The case study is conducted in the city of Shenzhen, China, which is located at the southern part of China. Since its establishment in 1979 as a Special Economic Zone (SEZ), Shenzhen has become one of the largest and most developed cities in China. It has approximately a 20 million daily population according to a statistic derived from the mobile phone data at the end of 2017 by the China Mobile company.

As shown in Fig. 2, as of 2018, Shenzhen had 8 metro lines (Line 1–5, 7, 9, and 11) that were operated across 166 stations in six of the ten administrative districts, namely, Baoan, Nanshan, Futian, Luohu, Longhua, and Longgang.

Fig. 3 demonstrates the distance between each station and its spatially nearest station. We can observe that except 14 stations located at the suburbs of the city, the distances of most stations with their nearest stations are less than 1500 m. Therefore, to reduce the computational cost, this study only considers POIs within a radius of 1500 m for each station, which is a large spatial extent to investigate the cognitive relations between the metro stations and their surrounding POIs.

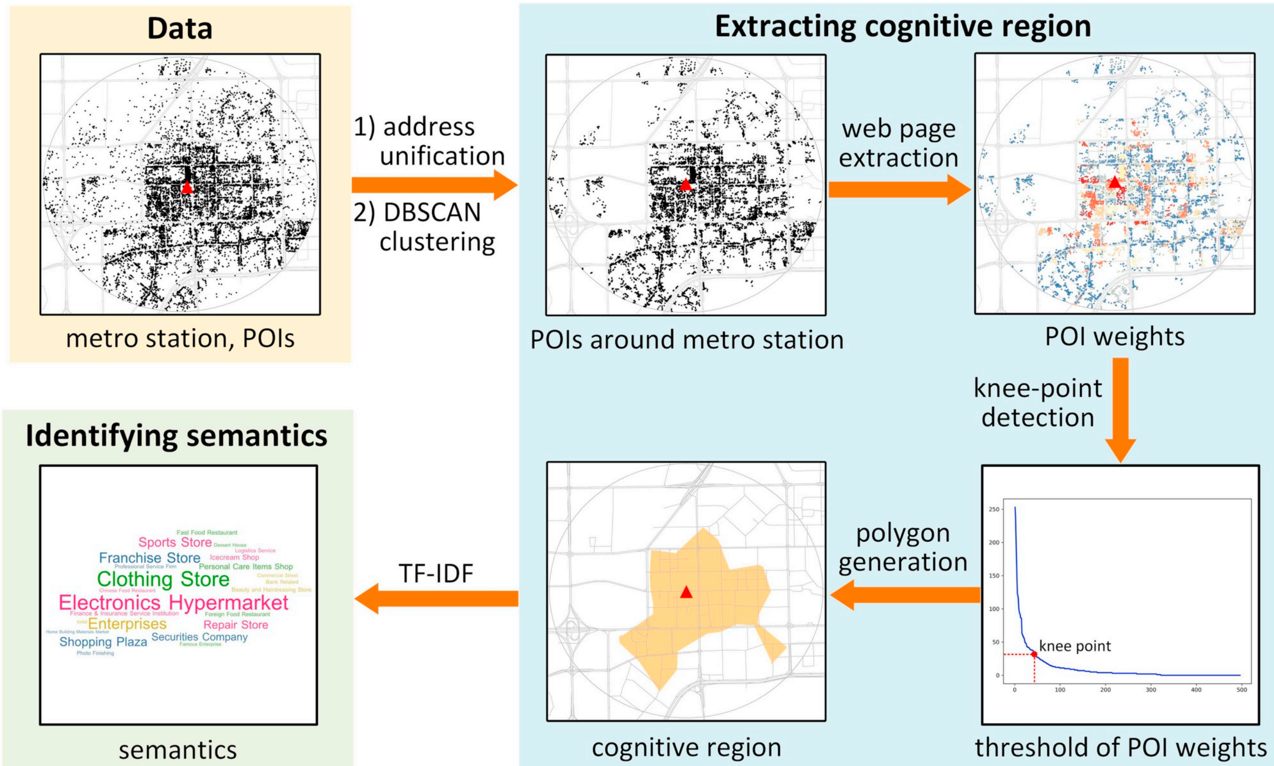


Fig. 1. The proposed framework for extracting and understanding the cognitive regions of urban metro stations.

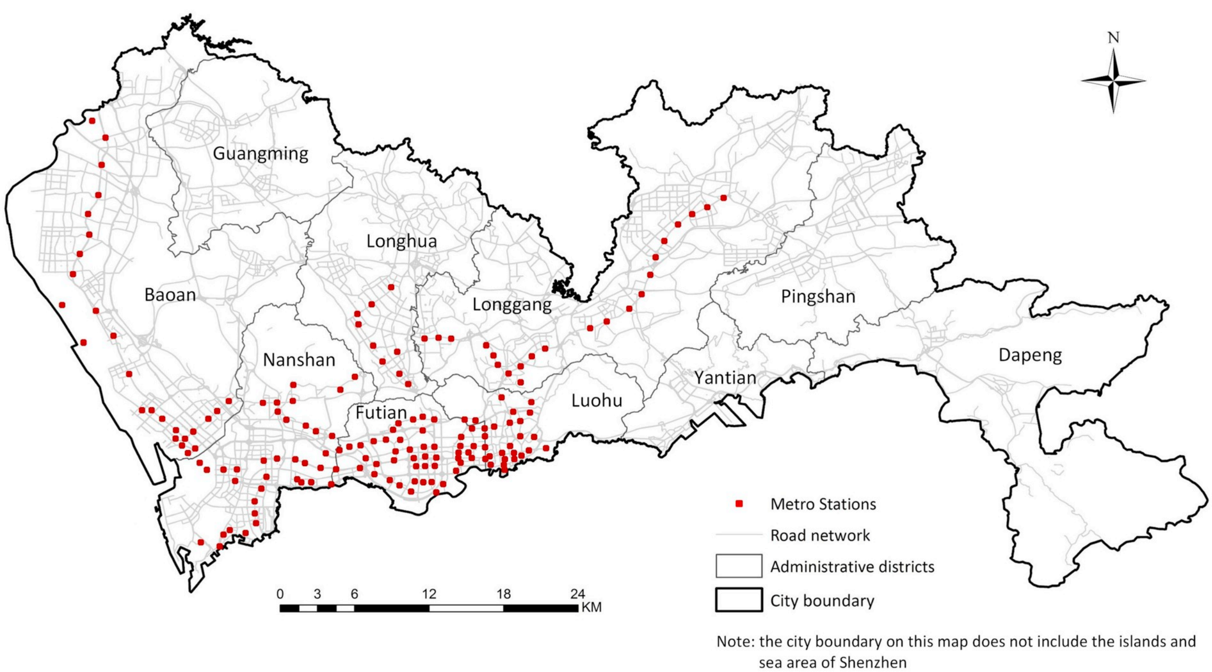


Fig. 2. The 166 metro stations in Shenzhen, China.

2.2.2. *Points of interest*

Compared to conventional land use data, POIs can depict places and human activities in a much finer spatial and taxonomic granularity (Yue et al., 2017). Existing POI-based studies have mainly used POIs from check-ins or geo-tagged photos in social media (Yan, Janowicz, Mai, & Gao, 2017; McKenzie & Adams, 2017; Gao, Janowicz, & Couclelis, 2017; Liu & Long, 2016; Hu et al., 2015), which have incompleteness or sampling bias issues (Li et al., 2013; Yue et al., 2017). For example, people usually prefer to record their locations and activities in tourist attractions and restaurants rather than in hospitals and metro stations.

Therefore, this study uses a set of POIs collected through the open API[1] of the Gaode Maps[2] (also known as the AutoNavi Maps), which is

[1] https://lbs.amap.com/api/webservice/guide/api/search
[2] https://www.amap.com/

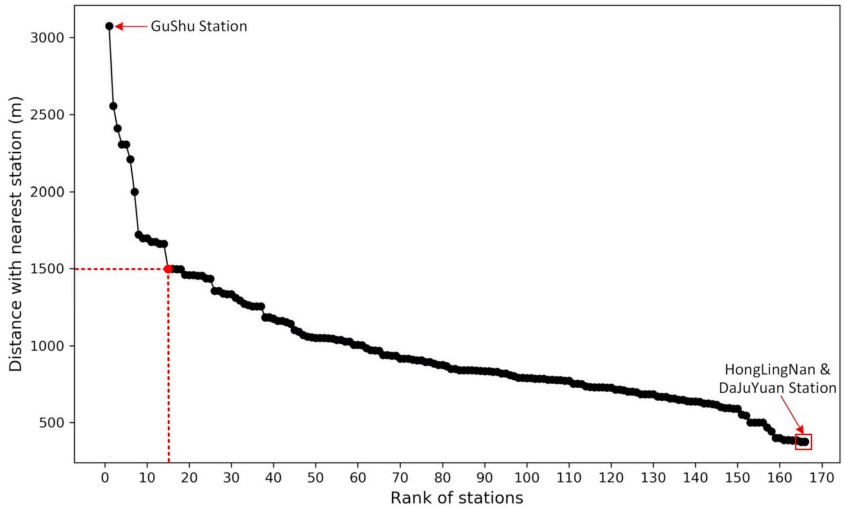


Fig. 3. Distance between each station and its nearest station.

one of the largest web mapping, navigation, and LBS platforms in China. More than 1.7 million POIs in Shenzhen were collected at the end of September 2018.

The collected POIs belong to 126 subtypes of 14 primary place types, including “Food & Beverages”, “Shopping”, “Daily Life Service”, “Sports & Recreation”, “Medical Service”, “Accommodation Service”, “Tourist Attraction”, “Commercial House”, “Governmental Organization & Social Group”, “Science/Culture & Education Service”, “Transportation Service”, “Finance & Insurance Service”, “Enterprises” and “Public Facility”. The 126 subtypes (e.g., Chinese Food Restaurant, Foreign Food Restaurant, Coffee House, and Sports Store) are used in this study to identify the semantics of station areas.

We perform two preprocessing tasks prior to using the dataset. The first task aims to unify the format of POI addresses to better serve as query terms for web document searching. The second task aims to remove the unusual points, given that POIs with address or coordinate errors would affect the shapes and ranges of the generated cognitive regions.

- Preprocessing task I – Address format unification

Addresses are used as query terms to search the web. However, many addresses contain sub-district or building names, and even floor and room numbers, which are too detailed and may affect the search results. Therefore, this study unifies all addresses into a simplified format of “HOUSE_NUMBER STREET_NAME” (i.e., “~路/街/道~号” in Chinese) using the regular expression matching technique in NLP.

Table 1 shows some examples of the addresses before and after the preprocessing of format unification. The unified addresses can better serve as search engine query terms.

Table 1
Examples of addresses before and after format unification.

Before	After
“宝安南路3063号茂源大厦1层103室” “3063 BaoAnNan Rd, MaoYuan Building, Floor 1, Room 103”	“宝安南路3063号” “3063 BaoAnNan Rd”
“东滨路3129号(兰园大厦一层商铺)” “3129 DongBin Rd (shops inside LanYuan Building, Floor 1)”	“东滨路3129号” “3129 DongBin Rd”
“龙岗街道嶂背路9号” “9 ZhangBei Rd, LongGang Sub-district”	“嶂背路9号” “9 ZhangBei Rd”
“深圳市福田区福星路96号” “96 FuXing Rd, FuTian District, Shenzhen”	“福星路96号” “96 FuXing Rd”

- Preprocessing task II – DBSCAN clustering

As the boundaries generated from POIs are sensitive to the correctness of POI coordinates, we perform a preprocessing to remove outliers based on a fact that one address is usually attached with multiple spatially aggregated POIs with correct coordinates, as the example shown in Fig. 4. For each address, we utilize the density-based spatial clustering of applications with noise (DBSCAN) algorithm (Ester, Kriegel, Sander, & Xu, 1996) to group and retain the POIs that are closely packed together in space. Then we mark and remove the outliers that lie alone in low-density regions.

The DBSCAN clustering algorithm requires two parameters: *Eps*, which is the search radius, and *MinPts*, which is the minimum number of points required to form a dense region within the search radius.

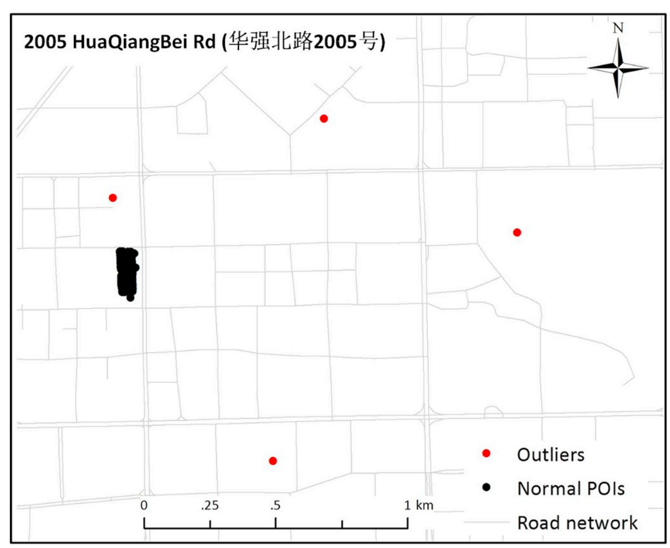


Fig. 4. POIs that share the same address.

These two parameters define a minimum density threshold, and clusters are identified at locations where the density of points is larger than the threshold. Considering that POIs sharing the same addresses are usually located in the same buildings, we set *Eps* = 45 m, and *MinPts* = 2. Fig. 5 shows an example of POIs around the HuaQiangBei Station before and after the preprocessing of DBSCAN clustering, and the remaining POIs without outliers can be more confidently used to extract the cognitive regions.

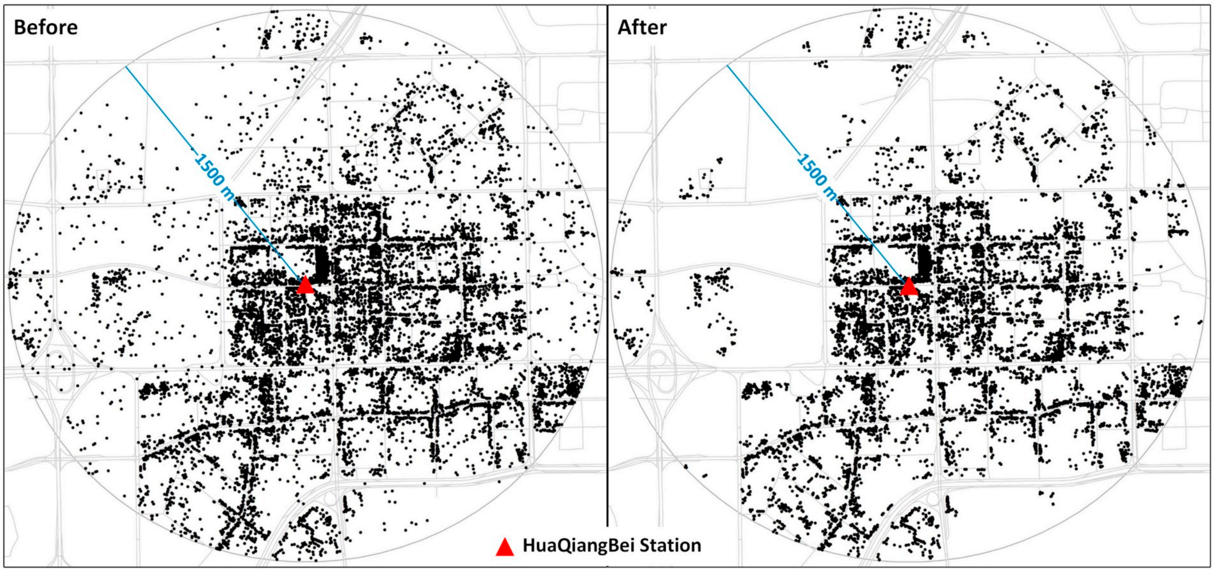


Fig. 5. POIs around HuaQiangBei Station before and after DBSCAN clustering.

3. Extracting cognitive regions of metro stations

Following the assumption that frequently co-occurred place names on web pages imply a strong relatedness between them, this study proposes a cohesive approach to extract the cognitive regions of metro stations using their surrounding POIs. Concretely, the cognitive relations between a metro station and each of its surrounding POIs is measured by the count of their co-occurring web pages, the threshold of co-occurring count is set using a knee-point detection method. And the POIs with co-occurring counts above the threshold are selected to generate the cognitive region for a metro station.

3.1. Measuring cognitive relations between metro stations and POIs

To acquire the cognitive relationships of metro stations and their surrounding POIs, a web script crawler called HtmlUnit[3] is used to automatically retrieve the search result pages by submitting co-occurrence queries [“Station_name station” “POI address”] (e.g., [“华强北地铁” “中航路1号”]) to the Sogou search engine[4] (one of the major Web search engines in China). Each search result page includes the information of how many web pages that contain both the station name and the POI address having been found. For example, the result page shows as “About 458 results are found” (i.e., “找到约458条结果”).

The word “station” (i.e., “地铁”) is fixed (i.e., must-be-included) in the query terms to avoid ambiguity of other homonymous place names with the station names. The POI addresses instead of the POI names are used as queries, because addresses have been used in a long period, while POI names often alter over time, which are different from other types of place names (e.g., city names and province names) (Gao, Janowicz, Montello, et al., 2017; Hu et al., 2017; Liu et al., 2014; Montello et al., 2014). Besides, when the creators of the web contents describe a place, the address of the place may be attached, while the nearby metro station is very likely to be mentioned as a travel guidance when public transportation is accessible. Note that the nearby metro station is not necessarily the spatially nearest one, but usually the one with nearest cognitive distance in individuals' perceptions (Briggs, 1973; Montello, 1991). This makes station names and POI addresses frequently appear in the same web pages, and their co-occurring counts can be considered as a vote of the POI belonging to the metro station area.

Through this way, we obtain the weights (i.e., co-occurring counts) of POIs around each metro station. Fig. 6 displays the weights of POIs around six metro stations, namely, BuJi, BuXin, HouHai, HuaQiangBei, ShenDa, and ShiMinZhongXin. Using HuaQiangBei Station as an example, the characteristics of the cognitive relations between metro stations and their surrounding POIs are analyzed as follows.

First, POI weights are related to the popularity of the POIs. As shown in Fig. 7(1), we revisit the dominant POIs with high weights and find that they are usually popular and long-standing places such as shopping malls, multifunctional buildings, and famous hotels, which can be considered as “landmarks” in the metro station areas.

Second, POI weights are related to the popularity of the metro stations. As shown in Fig. 7(2), we select the overlapping POIs of two adjacent stations, i.e., HuaQiangBei and YanNan, and calculate the differences between their POI weights. It shows that more POIs have closer relations to the more famous station (i.e., HuaQiangBei Station), even though some of the POIs are spatially nearer to the less famous one (i.e., YanNan Station).

Third, dominant POIs with high weights show the distance-decay effect. Fig. 7(3) displays the relation between the weights of POIs and their Euclidean distances to the HuaQiangBei Station. It indicates that most POIs have low weights regardless of their distances to the station. Meanwhile, the weights of dominant POIs decrease with increase in the distances to the station, implying that dominant POIs with higher weights are generally nearer to the metro station.

3.2. Selecting dominant POIs with close relations to metro stations

We make statistics toward the weights of POI addresses around each metro station and find that their Rank-Weight distributions are all with long tails (as shown in Fig. 8), showing that a minority of addresses have high weights, while a majority of addresses have low weights.

To delineate the cognitive regions of metro stations perceived by the crowd instead of the minority, dominant POIs with closer cognitive relations to the metro stations need to be selected, while non-dominant POIs with very low weights in the “tail” of the distributions should be filtered out. To achieve this goal, a knee-point detection method is introduced to find the breaking point between the “head” and the “tail” of each Rank-Weight distribution.

The knee-point detection method provides a mathematical solution to identify the “right” operating point in the computer system behavior

[3] http://htmlunit.sourceforge.net/

[4] http://www.sogou.com

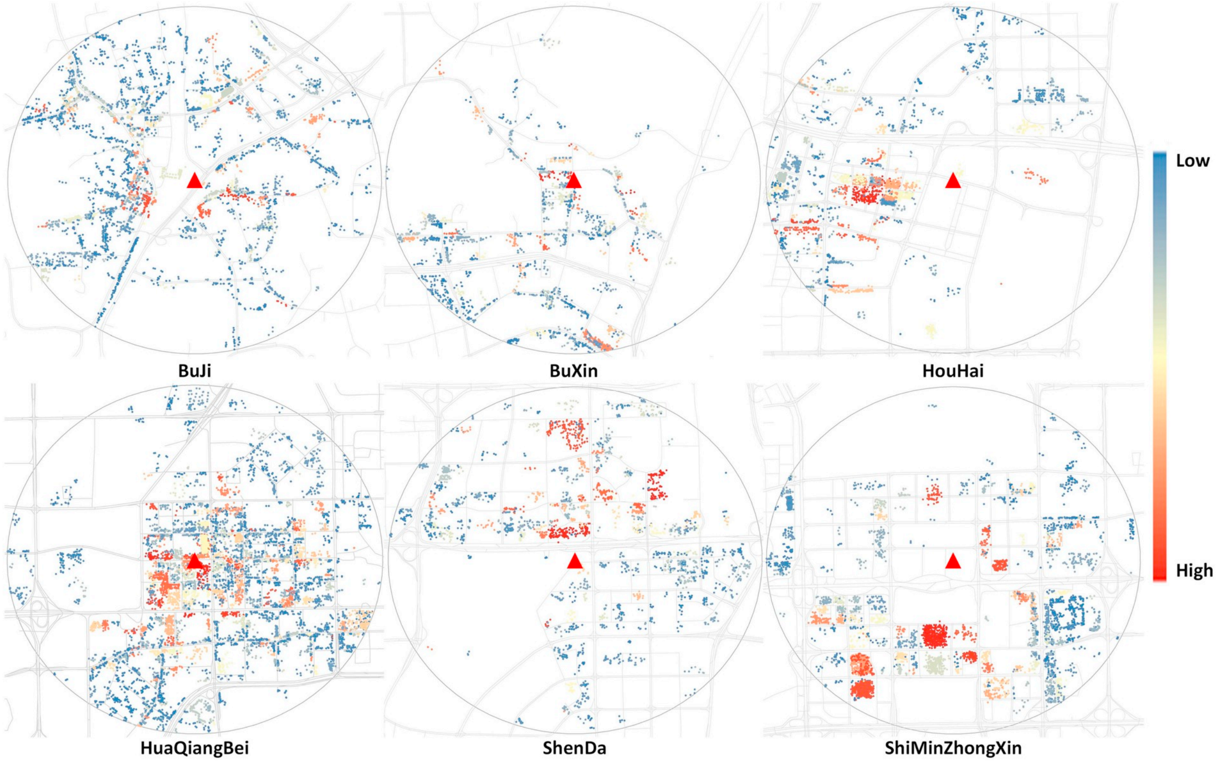


Fig. 6. The spatial distributions of the weights of POIs around six metro stations.

(Satopaa, Albrecht, Irwin, & Raghavan, 2011). As shown in Fig. 9, in this solution, a line is drawn from the first point on the curve to the last. The point on the curve, which has the largest distance from the drawn line, is considered as the knee point of the curve. As shown in Fig. 9, to find the knee point, first, the distance of each point on the curve to the line (i.e., *d*) is calculated using some geometric vector operations. Then, the point with maximum *d* is considered as the knee point of the curve.

Using this method, we can identify the threshold and select the dominant POIs for each metro station. Fig. 10 shows the knee-point detection result of the HuaQiangBei Station. The Fig. 10(1) indicates the location of the detected knee point, while Fig. 10(2) shows the POIs around the station with weights above the knee point, which are dominant POIs cognitively related to the metro station and will be used for extracting the cognitive region of the station.

3.3. Delineating vague boundaries of metro station areas

The cognitive regions of metro stations are extracted by delineating the minimum bounding geometries of the identified dominant POIs.

Convex hull (Preparata & Hong, 1977), circle, rectangle and envelope are the typical methods for finding the minimum bounding geometry enclosing the inputted points, which are also deployed in many GIS tools such as ArcGIS. However, these geometries are unsatisfactory in accurately depicting the shapes of point sets, because they usually contain large empty areas that are not occupied by the original point set (Akdag, Eick, & Chen, 2014). To fill this gap, Duckham, Kulik, Worboys, and Galton (2008) proposed an algorithm called Chi-shape to generate the concave hull of given point set. Hu et al. (2015) utilized the Chi-shape algorithm to construct urban areas of interest (AOI) from crowdsourced point sets collected from social media, and released the programming code for implementing the algorithm on GitHub.[5]

The Chi-shape algorithm first constructs a Delaunay triangulation based on the point set, which is a convex hull. Then, it erodes the initial boundary by deleting its edges in the order of edge length until the longest edge of the boundary is shorter than a threshold. A normalized length parameter λ_P in the [1, 100] range determines the threshold of the longest edge of the generated concave hull. Different λ_P values can derive different concave hulls from the same point set. As shown in Fig. 11, polygons with $\lambda_P = 1$ are closest to the original point set but with very spiky edges, while polygons with larger λ_P values are less complex and also contain more empty space inside. To generate a concave hull with balanced complexity and emptiness, Akdag et al. (2014) proposed to find the optimal λ_P by minimizing the fitness function:

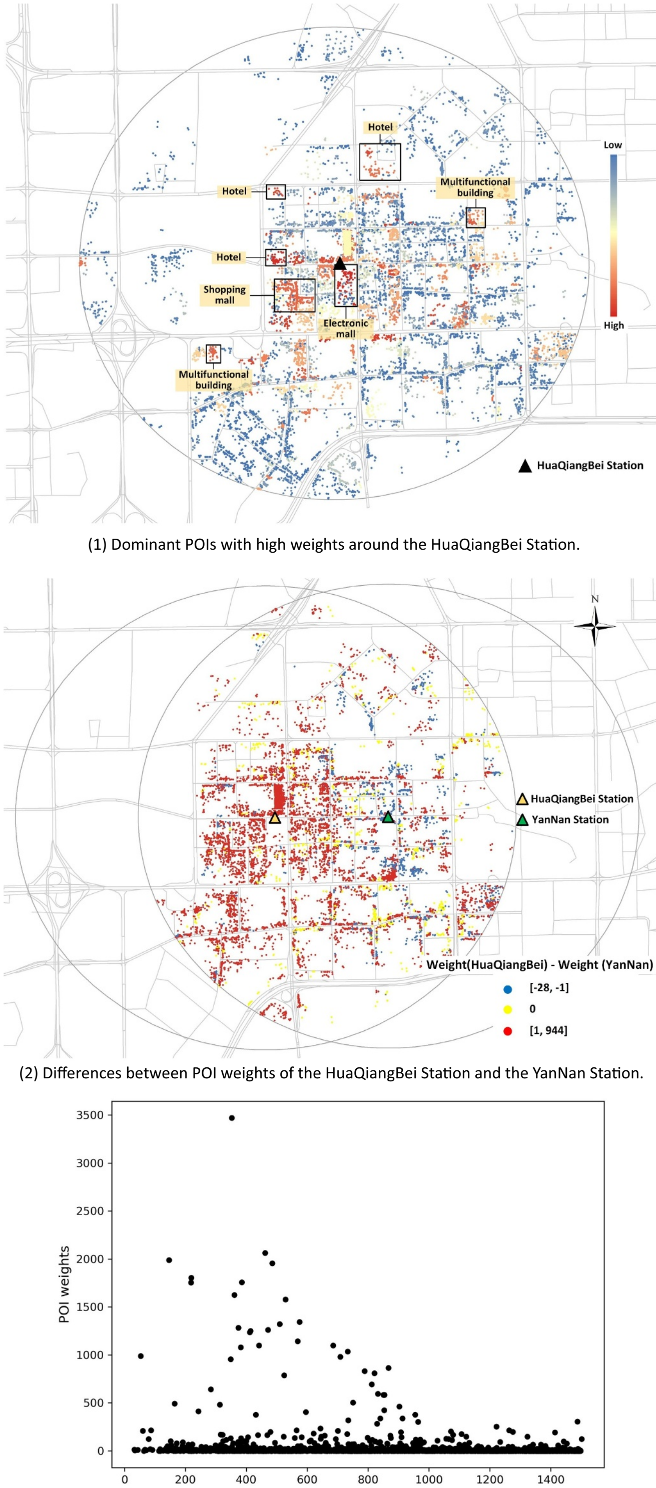
$$\varnothing(\mathrm{P}, \mathrm{D}) = \mathrm{Emptiness}(\mathrm{P}, \mathrm{D}) + \mathrm{C} * \mathrm{Complexity}(\mathrm{P}),$$

where *P* represents the concave hull generated from the point set; *D* is a set of Delaunay triangles generated from the same point set; *C* is a parameter that balances the relative weights of polygon complexity and polygon emptiness. *C* varies in the [0, 1] range, and a larger *C* value will prefer to derive less complex polygons. This study sets $C = 1$ to generate concave hulls with smoother boundaries.

Different λ_P values will lead to different fitness scores $\varnothing$, and a λ_P corresponding to a minimum fitness score is the optimal parameter for generating the concave hull. Fig. 12 shows the relations between $\varnothing$ and λ_P when employing the Chi-shape algorithm to the dominant POIs around the metro stations of HuaQiangBei and YanNan. Accordingly, the optimal λ_P values are picked when the $\varnothing$ values touch the bottoms of the curves.

Under the optimal λ_P values, we generate the concave hulls (i.e., cognitive regions) for all metro stations. Fig. 13 shows the cognitive regions of six metro stations, which are in different shapes and areas, and protrude in different directions. This finding indicates that a unified radius (e.g., 500 m) cannot precisely capture the cognitive regions of metro stations. As shown in Fig. 13, the cognitive region of "ShiMinZhongXin Station" occupies a larger area because it is the core of downtown Shenzhen. We also observe the "needle" shapes in some polygons. We revisit the POIs that cause these needles and find that

[5] https://github.com/YingjieHu/BalancedConcaveHulls



(1) Dominant POIs with high weights around the HuaQiangBei Station.

(2) Differences between POI weights of the HuaQiangBei Station and the YanNan Station.

(3) Relation between the weights of POIs and their distances to the HuaQiangBei Station.

Fig. 7. Characteristics of POI weights around metro stations.

they are not errors or outliers, but famous activity places. For example, the needle tip in the polygon of "ShiMinZhongXin Station" is a multi-functional building called "No. 1 World Plaza", which may have close relations to the station in the people's perceptions. Meanwhile, the left-bottom needle tip in the polygon of "ShenDa Station" represents a few POIs indicating Shenzhen University. This is a limitation of using point-based data that when the POI itself represents a relatively large region (e.g., a university), the whole extent of the region cannot be included in the cognitive region.

We upload the cognitive regions of the 166 metro stations in Shenzhen, China to ArcGIS Online and share them publicly.[6] Given that a POI may be dominant to more than one metro station, the cognitive regions of the nearby stations may be overlapping with each other.

4. Identifying semantics of metro stations

As typical places, metro station areas usually imply rich semantics in relation to people's perceptions, impressions and even emotions (Ballatore & Adams, 2015; Hu, Deng, & Zhou, 2019; Kovacs-Györi et al., 2018; McKenzie & Adams, 2017), which can be well depicted by the types of places inside the station areas. For example, people who are familiar with Beijing would think of various shopping malls when mentioning the "XiDan Station" and associate the "GuoMao Station" with a cluster of dense and tall modern office buildings.

Therefore, this study aims to understand the semantics of urban metro stations by the types of the POIs inside the station areas. Calculating the proportions of POI types inside each area is a commonly used method to achieve this goal. However, some general POI types (similar to the stop words in linguistic texts), such as Chinese restaurant and fast-food restaurant, would account for high proportions in many station areas, which cannot reflect the unique characteristics of the individual stations.

To highlight the specific and unique POI types in each station area and lower the role of those common types, we adopt the TF-IDF method, which has been widely used in information retrieval (Salton & Buckley, 1988) and text-based recommender systems (Beel, Gipp, Langer, & Breitinger, 2016). The weight of the POI type j in station area R_i can be calculated as follows:

$$TFIDF_{ij} = TF_{ij} \times log_2 \frac{N}{DF_j},$$

where TF_{ij} is the proportion of POIs on type j among all POIs in R_i; N is the number of station areas in the city; and DF_j is the number of station areas that contain type j. By integrating the IDF_j term (i.e., $log_2 \frac{N}{DF_j}$), the weights of the common types that appear in a number of metro station areas can be lowered.

Fig. 14 shows the identified semantics of six metro stations. The sizes of POI types in each word cloud are proportional to their TF-IDF weights. The detailed analysis toward the results are as follows.

- "HuaQiangBei" has been famous as an electronic market for decades, and now it is also one of the largest and most popular commercial areas in Shenzhen. The identified POI types with high TF-IDF weights, such as "Electronics Hypermarket", "Clothing Store", and "Enterprises", accurately depict the characteristics of the station area.
- "ShenZhenBeiZhan" means "Shenzhen North Station", which is also a large high-speed rail station in Shenzhen. The homonymic metro station is exactly located inside and connects to the railway station. The prominent key word "Railway Station" accurately describes the semantics of the station area.
- "ShaoNianGong" means "children's palace", which is a public facility in China where children engage in extra-curricular activities. This area has gathered various science, education, and culture related activity places. Therefore, the key words of "Theatre and Cinema", "Cultural Palace", and "Exhibition Hall" well describe the key characteristics of the station area.
- "ShenDa" is an abbreviation of Shenzhen University, which is one of the top 100 universities in China and a large research institution in Shenzhen. Except for the university, the top Internet Corporation, Tencent, as well as some high-tech parks also gather around this

[6] https://arcg.is/KyiP8

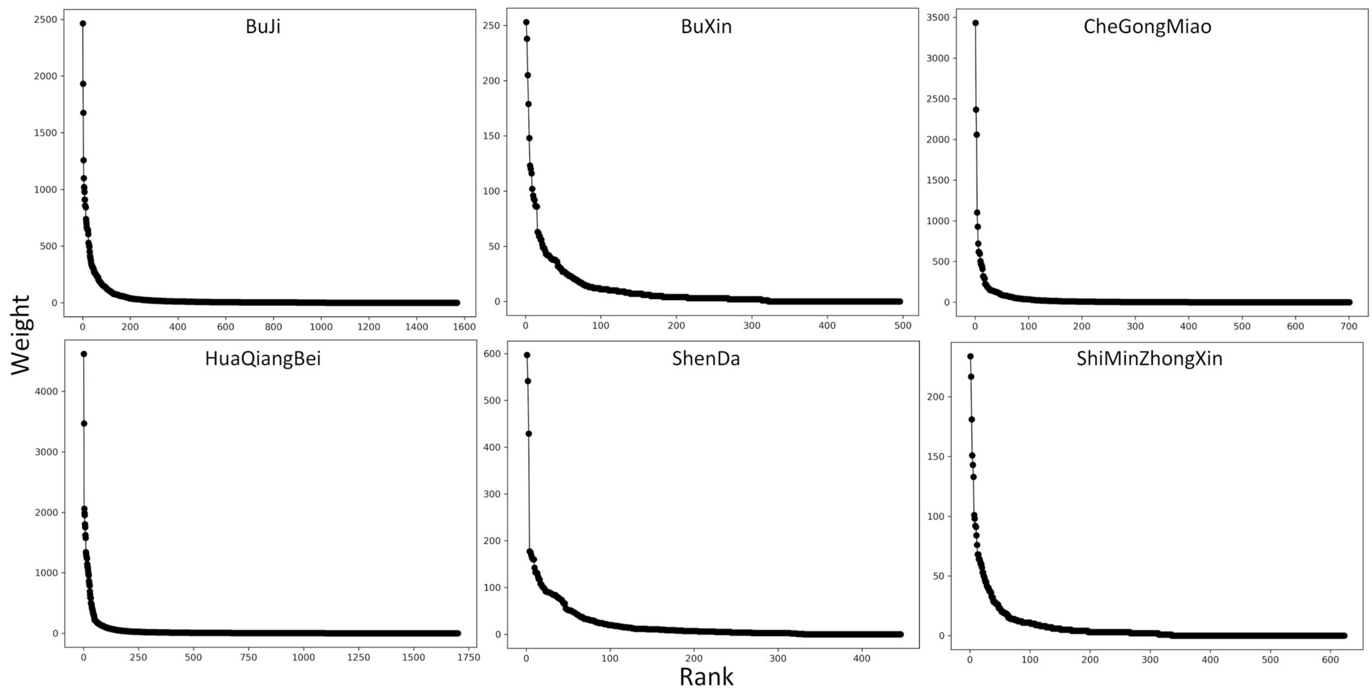


Fig. 8. Rank-Weight distributions of POI addresses around six metro stations.

station. Therefore, our identified high-weighted POI types depict this station area accurately.

- "HuaQiaoCheng Station" is surrounded by several scenic spots, such as the "Splendid China Folk Village", "Window of the World", and "Happy Valley". Therefore, the area can be well described by the dominant type "Tourist Attraction".
- "ShiMinZhongXin" means "civic center", which is located at the center of the city. The station is surrounded by various financial companies in tall and modern office buildings. The dominant POI types, such as "Securities Company" and "Finance & Insurance Service Institution", well reflect the semantics of station area.

Overall, the TF-IDF method performs quite well in identifying the specific place semantics of individual metro station areas. The semantic analysis can help better understand the driving force of co-occurrence patterns between the POIs and the metro stations in different contexts.

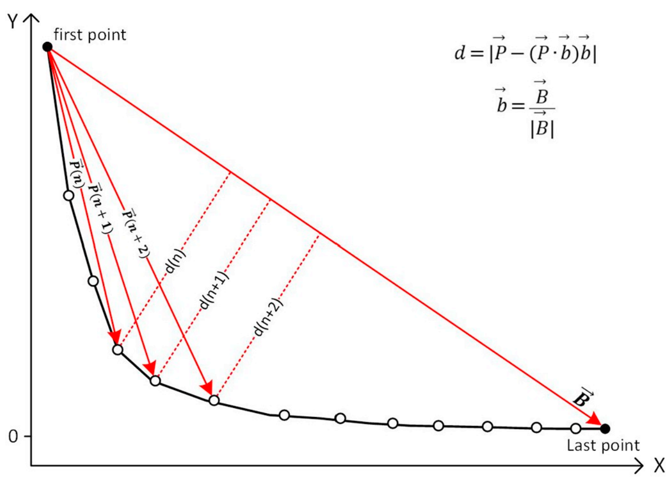


Fig. 9. Illustration of the knee-point detection method.

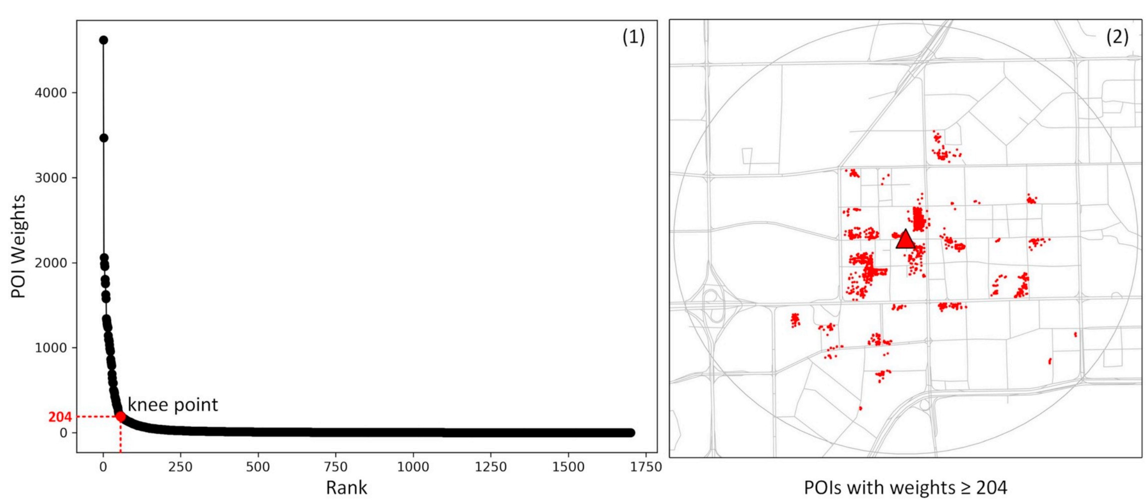


Fig. 10. Knee-point detection for POIs around the HuaQiangBei Station.

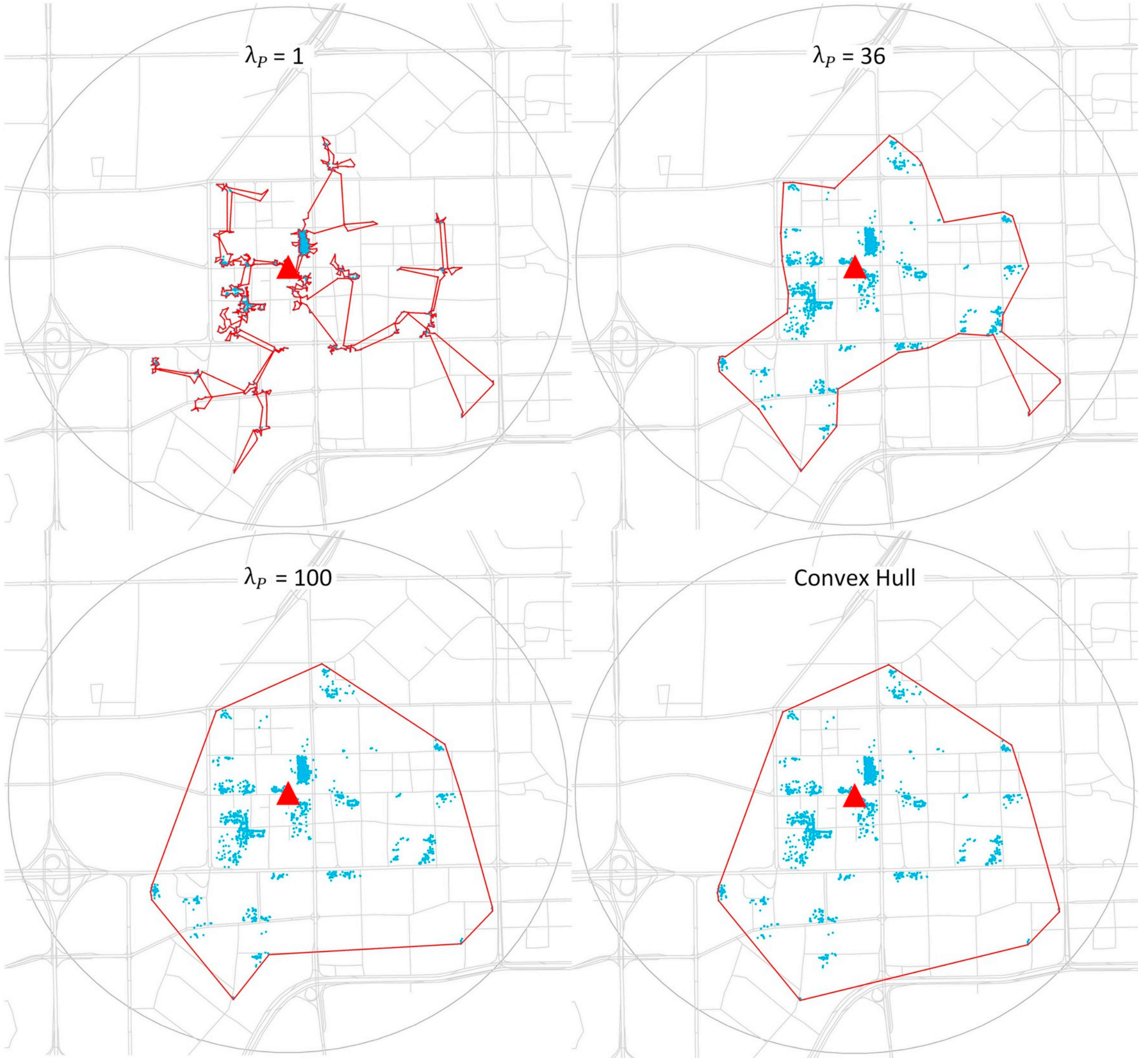


Fig. 11. Concave hulls generated under different λ_P values and the convex hull generated from the same point set.

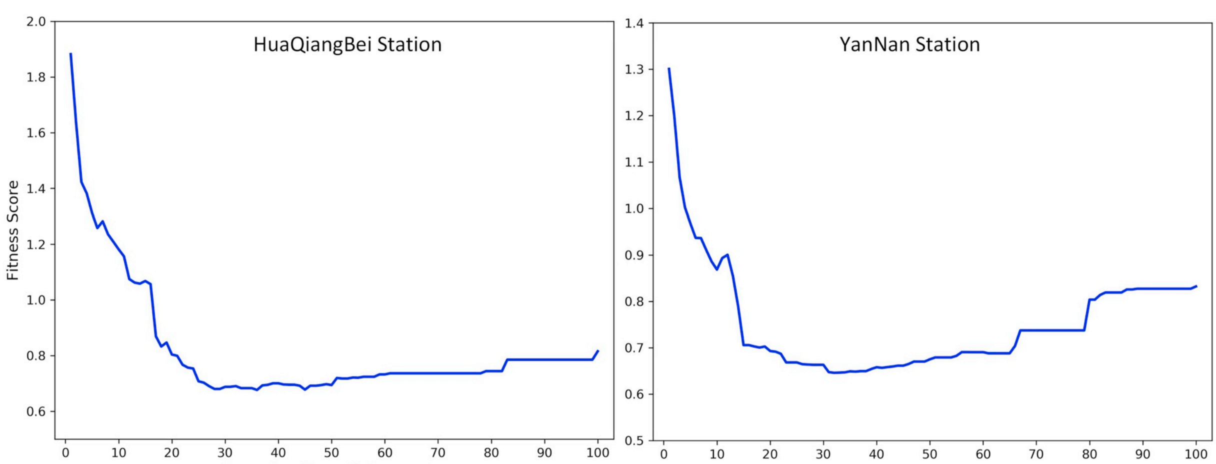


Fig. 12. Finding the optimal λ_P based on its relation with fitness score $\varnothing$.

5. Discussion

5.1. Potential applications

This study may provide significant values for potential applications.

For instance, the static map shown in Fig. 15 can be developed into a searchable, interactive, and dynamic web map, where the place characteristics of metro stations and their transportation functions can be integrated to provide more comprehensive geographic information. Geographic information retrieval can be made at the station-area level

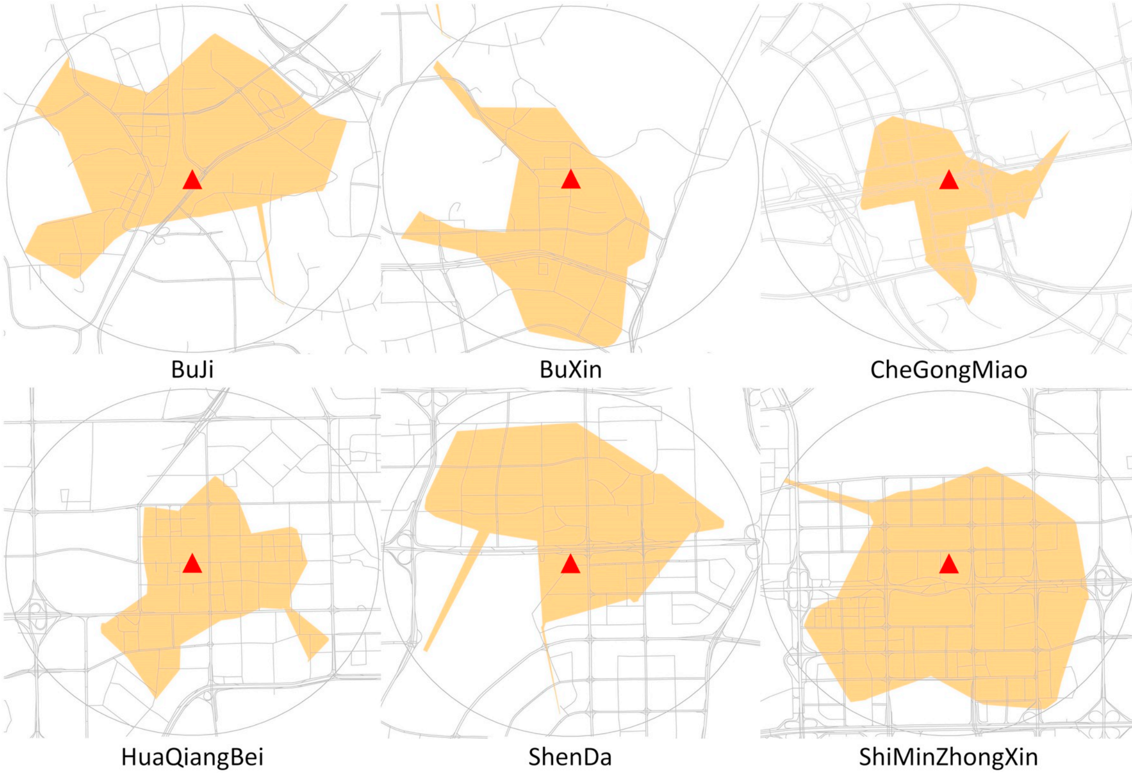


Fig. 13. Extracted cognitive regions of six metro stations in Shenzhen, China.

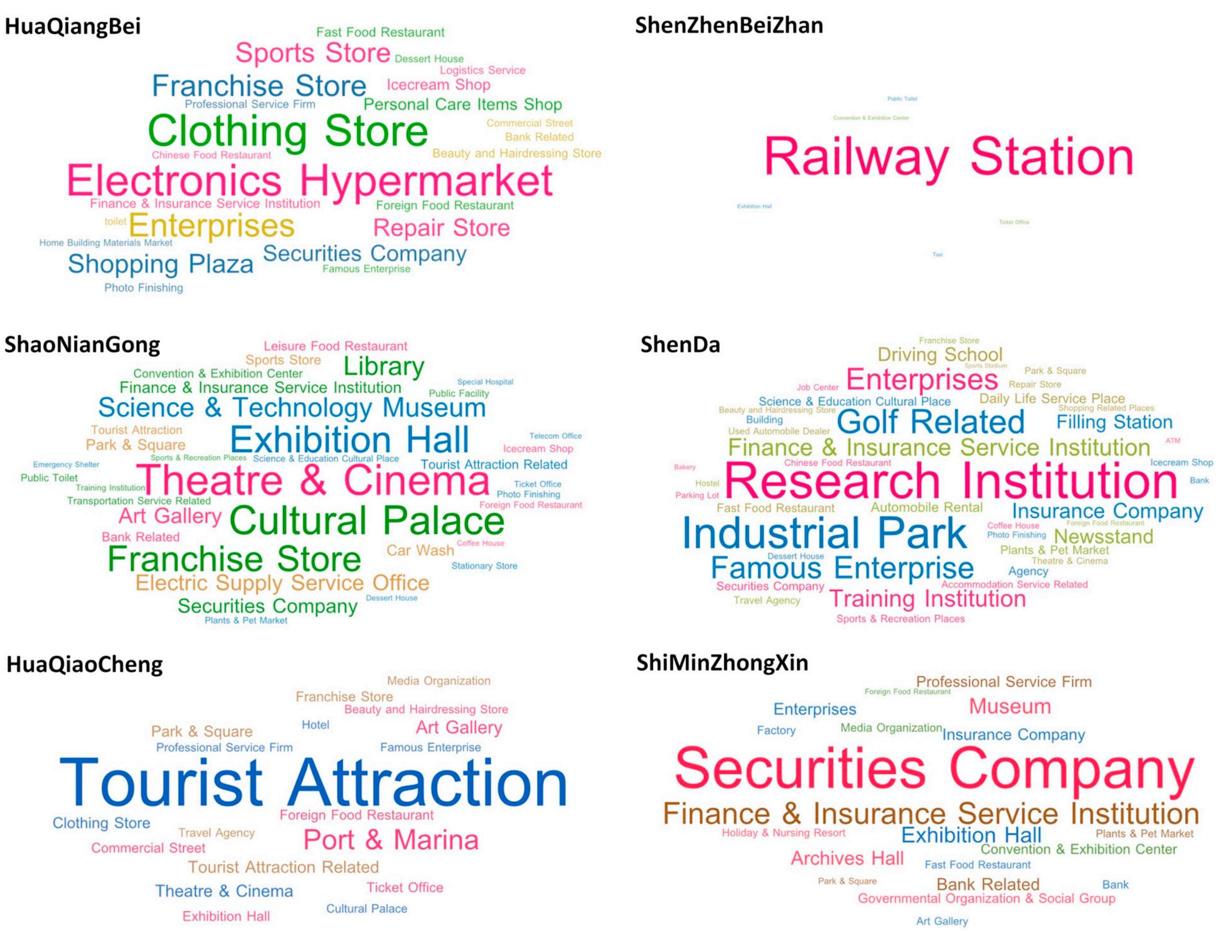


Fig. 14. Identified semantics of six metro stations in Shenzhen, China.

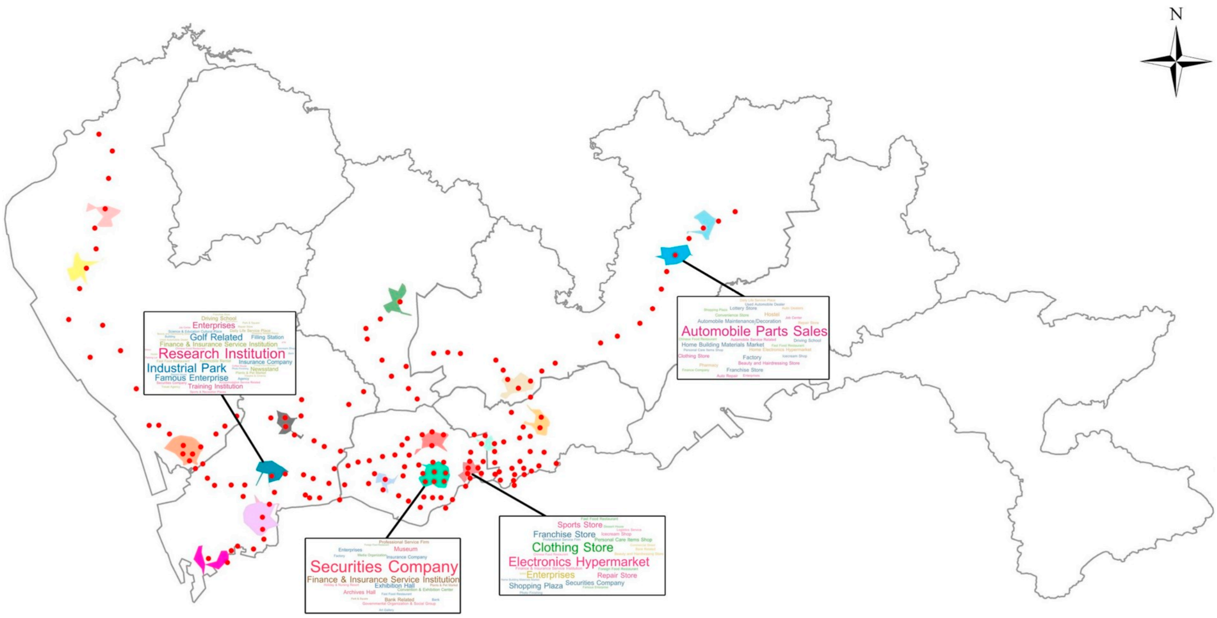


Fig. 15. Urban metro stations as cognitive places displayed on a map.

to better meet the users' requirements. In many situations, what a user need is not a specific POI, but a functional region to conduct a series of similar activities (Gao, Janowicz, & Couclelis, 2017). For example, when a person wants to go shopping, a region contains plenty of shops with convenient public transportation would be expected. When a person plans to meet friends dispersed throughout the city, a metro station area that is spatially accessible to all of them and characterized by various restaurants and cafés would be desirable.

Moreover, our identified cognitive regions and semantics can help evaluate the developments and function complementarities of existing metro stations, especially when combining the smart card data (Ren et al., 2019), which would be beneficial for the modeling of passenger flow, site selection of new stations, and urban planning.

5.2. Implications for urban planning

As Kevin Lynch stated in *The Image of the City* (Lynch, 1960), the skeleton of individuals' mental images is formed by five types of elements in the city: paths, edges, nodes, districts and landmarks, which mediates in the interaction between humans and their environment. The first thing we want to emphasize in this study is that urban metro stations are also one type of such cognitive elements (i.e., landmarks) in cities; their properties as cognitive places should be considered in urban planning and design so as to match people's cognition. In addition, our extracted cognitive regions of urban metro stations show diverse and irregular shapes, which indicates that unified physical distances frequently used in existing studies and planning practices cannot precisely define TOD precincts perceived by humans. To this end, what we suggest in this study is that urban planning practices should attach importance to "cognitive place" and "cognitive distance", which load human experiences and perceptions toward the environments (Briggs, 1973; Montello, 1991). This is also coincident with the ultimate goal of urban planning, urban design, and smart-city construction, i.e., making better human societies and improving human lives (Shaw & Sui, 2019).

5.3. Contributions

The main contributions of this study are summarized as follows.

First, existing studies have investigated metro stations and their attachment areas from the transportation and land-use perspectives, while this study explores their characteristics as cognitive places with human spatial cognition and perception on urban environments being considered, which to our knowledge, is the first attempt.

Second, this study proposes a novel approach for extracting the cognitive regions of metro stations and identifying the semantics of the station areas. The generalized framework is also applicable to metro stations in other cities or other similar kinds of cognitive places (e.g., urban landmarks).

Third, this study enriches place-based GIS research and provides a human-centric perspective for urban planning and LBS applications.

5.4. Limitations and potential improvements

The main limitation of this study may be that there is no ground truth to quantitatively verify the accuracy of our delineated cognitive boundaries, but we make efforts to guarantee the effectiveness of the derived results by assuring the quality of the data and rationality of the approach. Moreover, the analysis toward the characteristics of POI weights in Section 3.1 can also indirectly demonstrate the reasonability of the results.

Another limitation may be that the sharp boundaries of the cognitive regions are irregular and do not fit the regular shapes of the buildings or roads in the real world. Potential improvements can be made in the future by aggregating POIs inside buildings or blocks and using the footprints of buildings or blocks rather than the point-based locations to generate more reasonable and practical cognitive regions.

6. Conclusion

The areas around urban metro stations are usually well-developed and attract plenty of human activities, which make the areas as typical cognitive places that shape people's knowledge, impressions, and experiences in the city. This study proposes a new framework for extracting and understanding the cognitive regions of metro stations using POIs. First, the cognitive regions of metro stations are extracted based on the co-occurring counts of station names and POI addresses on web pages. Then a cohesive approach combined of spatial clustering, web page extraction, knee-point detection, and polygon generation techniques is presented. Moreover, the semantics of metro stations are identified based on POI types inside the regions using a TF-IDF based method. In summary, this study proposes a novel and effective framework for investigating urban metro stations as cognitive places, which enriches the research of place-based GIS and provides a human-centric perspective for urban planning and LBS applications.

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