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Uncovering inconspicuous places using social media check-ins and street view images

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ABSTRACT

There is a Chinese proverb, "if your wine tastes really good, you do not need to worry about the location of your bar (酒香不怕巷子深)", which implies that the popular places for local residents are sometimes hidden behind an unassuming door or on unexpected streets. Discovering these unassuming places (e.g. restaurants) of a city will benefit the understanding of local culture and help to build livable neighborhoods. Previous work has been limited by the lack of appropriate data sources and efficient tools to evaluate the popularity, ambiance and physical surroundings of places in large-scale urban areas. In addition, how to characterize places with respect to different groups of people remains unclear. In this work, we propose a data-driven approach using social media check-ins and street-level images to compare the different activity patterns of visitors and locals, and uncover inconspicuous but interesting places for them in a city. We use check-in records as a proxy of the popularity of a particular type of place, and differentiate visitors and locals based on their travel and social media behaviors. In addition, we employ street-level images to represent the physical environments of places. As a result, we discovered a number of inconspicuous yet popular restaurants in Beijing. These restaurants are located mostly in deep alleys of Old Beijing neighborhoods, where the physical environments are not particularly appealing; however, these places are frequently visited by locals for social engagements. We also discovered beautiful but unpopular outdoor places in Beijing. These places are potential recreational areas for all groups of people and could be improved regarding urban design and planning to make these public infrastructures more attractive. This work demonstrates how multi-source big geo-data can be combined to build comprehensive place-based representations for different groups of people.

1. Introduction

Places are where people live, perceive, and interact with each other (Tuan, 1979). A place provides basic physical settings for human activities and human interpret a place with different sentiments through their experiences and activities (Agnew & Livingstone, 2011; Couclelis, 1992). Understanding how people use places and how a place affects people's activities is essential to making a place livable. A place and its meanings are intrinsically vague and subjective (Blaschke et al., 2018; Jones, Purves, Clough, & Joho, 2008). Nevertheless, the development of GIScience and the emergence of big geo-data bring unprecedented opportunities to create computational characterization of places (Goodchild, 2011; Liu et al., 2015; Purves, Winter, & Kuhn, 2019; Winter, Kuhn, & Krüger, 2009).

Appropriate data sources and effective tools are now available for representing places from different perspectives. Regarding place boundaries, social media corpus and topic modeling techniques are used to estimate vague cognitive regions and spatial hierarchies among vague places (Gao et al., 2017; Hong & Yao, 2019; Vasardani, Winter, & Richter, 2013). To enrich place semantics, researchers adopt points-of-interest (POIs) and human positioning data to identify different functions and types of places (McKenzie, Janowicz, Gao, Yang, & Hu, 2015, Liu & Long, 2016, Tu et al., 2018, Papadakis, Resch, & Blaschke, 2019, a, Dong, Ratti, & Zheng, 2019). In terms of assessing place locales (the physical setting of a place (Agnew & Livingstone, 2011)), scene elements extracted from street-level imagery are used for place locale

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representation (Zhang, Zhang, Liu, & Lin, 2018). In addition, online neighborhood reviews, geotagged social media photos, street-level imagery and machine learning-based methods are employed to derive human perceptual evaluations of place locales (Hu, Deng, & Zhou, 2019; Kang et al., 2019; Wang et al., 2019; Zhang et al., 2018). These works advance our understanding of place-based GIS and provide insights into how place can be formalized using big geo-data and state-of-the-art computational tools (Blaschke & Merschdorf, 2014; Goodchild, 2007; Li et al., 2016). Characterizing place from multiple dimensions and perspectives is of great importance to our comprehensive understanding of a place (Papadakis, Gao, & Baryannis, 2019; Zhu et al., 2020) . However, most existing literature focuses on characterizing one aspect of a place, such as measuring place activities(Hollenstein & Purves, 2010), representing place locales (Zhang, Zhang, et al., 2018), and extracting the vague cognitive regions of a place (Wu, Wang, Shi, Gao, & Liu, 2019). Few studies have linked or integrated all three basic elements of a place—locale, semantics, and associated human activities—in a data-driven approach.

Another important research gap arising from this issue is the lack of a framework to characterize and identify places for different groups of people. Place has been defined as “a spatial location that has been given meaning by human experiences” (Tuan, 1977). The meanings of a place for people vary between groups. For example, the “sense of place” for locals and tourists is significantly different for the same place (Kianicka, Buchecker, Hunziker, & Müller-Böker, 2006). In addition, local residents may prefer a small peaceful and lively square, a street corner or an unassuming restaurant for social interactions, while tourists tend to visit famous and remarkable sites and attractions (Kaltenborn & Williams, 2002). More generally, different groups of people, visitors and locals, for example, behave differently and have their own ways of using and experiencing the place. However, approaches to identifying places for different groups remain scarce, due to the lack of a holistic picture of a place.

To address the above issues, we propose a data-driven framework to characterize places considering four aspects: type, popularity, locale, and groups. The framework is driven by two big geo-data sources, social media check-in data and street-level imagery. Social media check-in data contain geo-locations, in terms of coordinates or POIs, at which people use particular apps or post social media messages with a mobile phone. The check-in number reflects the intensity of human activities in a place (location or POI), and check-in type indicates the place type (restaurant, park, etc.). Social media check-in data have been widely used to capture the intensity of social and economic activities and serve as a proxy for urban vibrancy (Huang et al., 2019; Jia, Du, Wang, Bai, & Fei, 2019), for example, modeling urban diurnal activities (Tu et al., 2017), predicting land use patterns, and extracting place semantics and urban functions (Gao, Janowicz, & Couclelis, 2017). In addition, street-level imagery is the natural images and photos taken along streets, providing detailed visual information on the physical environment and covering urban street networks densely. Street view imagery comprises the images provided by web-based map services such as Google Street View (GSV) (Ma, Wang, Zhang, Shim, & Ratti, 2019; Naik, Kominers, Raskar, Glaeser, & Hidalgo, 2017), Baidu Street View (BSV) (Zhang, Wu, Zhu, & Liu, 2019) and Tencent Street View (TSV) (Long & Liu, 2017) and photos from online photo sharing services such as Flickr (Kang et al., 2019) and Panoramio (Zhang, Zhou, Ratti, & Liu, 2019). Currently, more than half of the world's population is covered by these data sources (Goel et al., 2018), which have been extensively used for infrastructure auditing (Kang, Körner, Wang, Taubenböck, & Zhu, 2018), greenery calculation (Branson et al., 2018; Cai, Li, Seiferling, & Ratti, 2018), solar energy estimation (Liu et al., 2019) and social-economic factor prediction (Ilic, Sawada, & Zarzelli, 2019; Suel, Polak, Bennett, & Ezzati, 2019), etc. In this work, social media check-ins and street-level imagery are used to represent place types, human activity intensities of places, and place locales. Based on social media check-in behaviors, the user residences are identified according to the locations of their frequent posts. Then, the places for different groups of people are characterized based on the visiting ratio of locals to visitors. Furthermore, different types of inconspicuous places can be uncovered by jointly considering the human activity intensity (check-in numbers), physical surroundings (perception scores for street view images), and groups of people (i.e., locals or visitors).

We demonstrate the framework with two examples. First, we discovered a number of unassuming restaurants in Beijing, most of which are located in deep alleys of old neighborhoods, where the neighborhoods are visually ordinary or even boring in street view images, but are frequently visited by local people. These restaurants are places that promote and accommodate social engagements and reflect local cultures. Second, we mined beautiful but unpopular outdoor places (e.g. parks and plazas) of Beijing, whose physical surroundings are well maintained and beautiful but whose overall check-in numbers are low. These places should receive attention and can be further studied regarding urban design and management. In general, the framework characterizes and identifies inconspicuous places depending on place types, place locales, associated human activities and groups. This work offers insights into how multi-source big geo-data can be combined in a place-based GIS to enrich place semantics, characterize the meaning of place and uncover places for different groups of people.

2. Framework for characterizing places using social sensing data

“Social sensing” data refer to the big geo-data collected from social media and other user-generated content, to record human behaviors, identify place semantics, and reflect socioeconomic characteristics (Liu et al., 2015). Fig. 1 depicts the conceptual framework for characterizing places and identifying inconspicuous places using social sensing data. The framework is composed of two levels. At the first level, social sensing data are employed to create effective computational representations for places from four aspects, namely place locales, place types, place activities and place groups. Place locales can be represented by street-level imagery and potentially evaluated by individuals and computer vision. For example, a pretrained deep convolutional neural network (DCNN) is able to extract high-level street view imagery features to characterize place locales. These features contain not only overall information of cityscapes (e.g, level of naturalness, land use type, human perception) (Cordts et al., 2016; Zhou, Lapedriza, Khosla, Oliva, & Torralba, 2017) but also details of place semantics (traffic, grocery, park, etc.) (Zhang, Zhang, et al., 2018). By linking the image features and human perceptions, the place locale can be generally evaluated using publicly available street-level imagery. Similarly, information about place types and activities can be derived from check-in records (Tu et al., 2017), POIs (Gao, Janowicz, & Couclelis, 2017), and human trajectories (Xu et al., 2019). In addition, places visited by different groups of people can be identified according to empirical practice and theories on how different groups of people interact with places and how a place attracts different groups of people. The groups can be defined based on residency, i.e., locals and visitors, or other aspects of social mixing within a city. The preference of different groups for certain places may vary. Identifying places for these groups would facilitate the understanding of spatial heterogeneity and socioeconomic segregation of a city (Clark, 1991; Prestby, App, Kang, & Gao, 2020; Xu, Belyi, Santi, & Ratti, 2019). As an implementation, place group information can be derived from individual behavior data of different groups of users from social media platforms. For instance, based on the locations where users post messages, we can identify their origins and further differentiate whether they are visitors or locals. Hence, the group of a place can be characterized by obtaining the places' visiting percentages for different groups of people. At the second level, different types of inconspicuous places can be identified based on the computational representations of places. We define an “inconspicuous place” as a place either with a visually unassuming physical environment (i.e., a low locale evaluation score) or ignored by certain

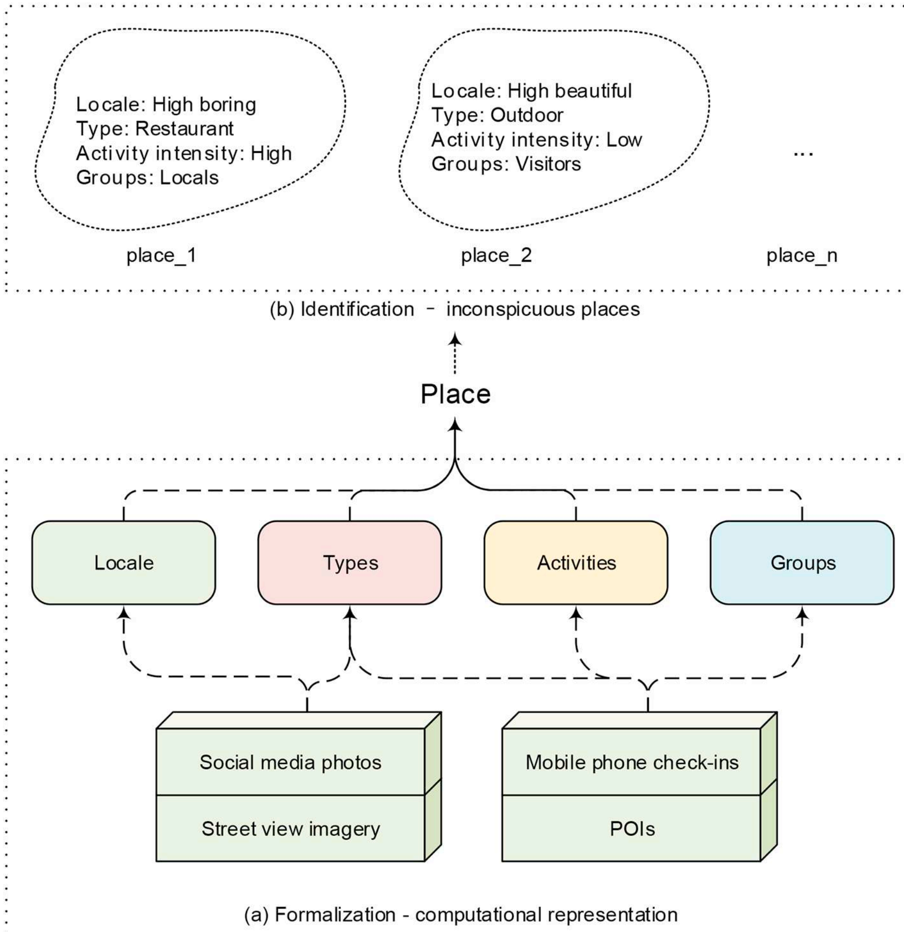

Fig. 1. The framework for characterizing places and identifying inconspicuous places using social sensing data.

groups of people (locals vs. visitors).

In the remainder of this paper, we first introduce the data and methods for characterizing the four dimensions of places: types (Section 3.1), popularity (Section 3.1), groups (Section 3.2), and locales (Section 3.3). Second, we present an implementation of uncovering inconspicuous places based on the framework with two case studies in Section 4.2 and Section 4.3. The first case study discovered unassuming restaurants where human activities are high but the physical appearances are poor. These places are popular with locals. The second case study identified inconspicuous outdoor places with good scenery but low human activity. These are potential recreational places for all people.

3. Characterizing places regarding type, human activity, group and locale

In this section, taking Beijing as the research area, we present the data and methods for creating computational representations of places in Beijing. To clarify, in this work, by “place type” we refer to the type of a POI (e.g. restaurant or park), “place popularity” is represented by the visit intensity of a place, “place locale” refers to the physical surroundings of a place depicted in street-level imagery, and “place group” indicates the percentage of different groups of people (e.g. visitors and locals) who visit a place.

3.1. Deriving place types and associated human activity intensities

We use social media check-in data to represent the human activity intensity of a place. The dataset was collected from one of the most popular social media platforms in China, Sina Weibo,[1] a microblogging service with an active user base approaching a half billion people, commonly referred to as “Chinese Twitter”. When users post a message with their mobile phones, check-in records are generated, which include the time, geo-locaiton and the attached point of interest (POI). We obtained the data from Weibo in two steps. First, we collected all the records from Beijing in 2016, which contains approximately three million records and 20,000 POIs from more than 800,000 users (note that these users consist of both visitors and locals). Second, to identify the actual residences of the users, we retrieved all the records from these users, regardless of what time and from which city their records were generated; these records contain those generated in other cities and earlier than 2016. In total, our dataset contains nearly 12 million records from 2014 to 2017.

The study area is within the 5^{th} Ring Road of Beijing: a historical, cultural and populous city in China. In Fig. 2A, we present the spatial distribution of the six types of POIs within the 5^{th} Ring Road of Beijing, namely, *dining* (7975), *residence* (3980), *business* (1867), *recreation* (1672), *transport* (965), and *outdoors* (749). The colored polygons are calculated via kernel density estimation, indicating the different patterns of the POI types. For example, the *work* places are concentrated in the northwest (Zhongguancun, often referred to as “China's Silicon Valley”) and east (Guomao, the center of the Beijing central business district) of Beijing. *Housing* and *traffic* places are uniformly distributed across Beijing. Fig. 2B shows the distribution of check-ins of all the POI types along streets. The numbers of check-ins are aggregated from the

[1] https://www.weibo.com/

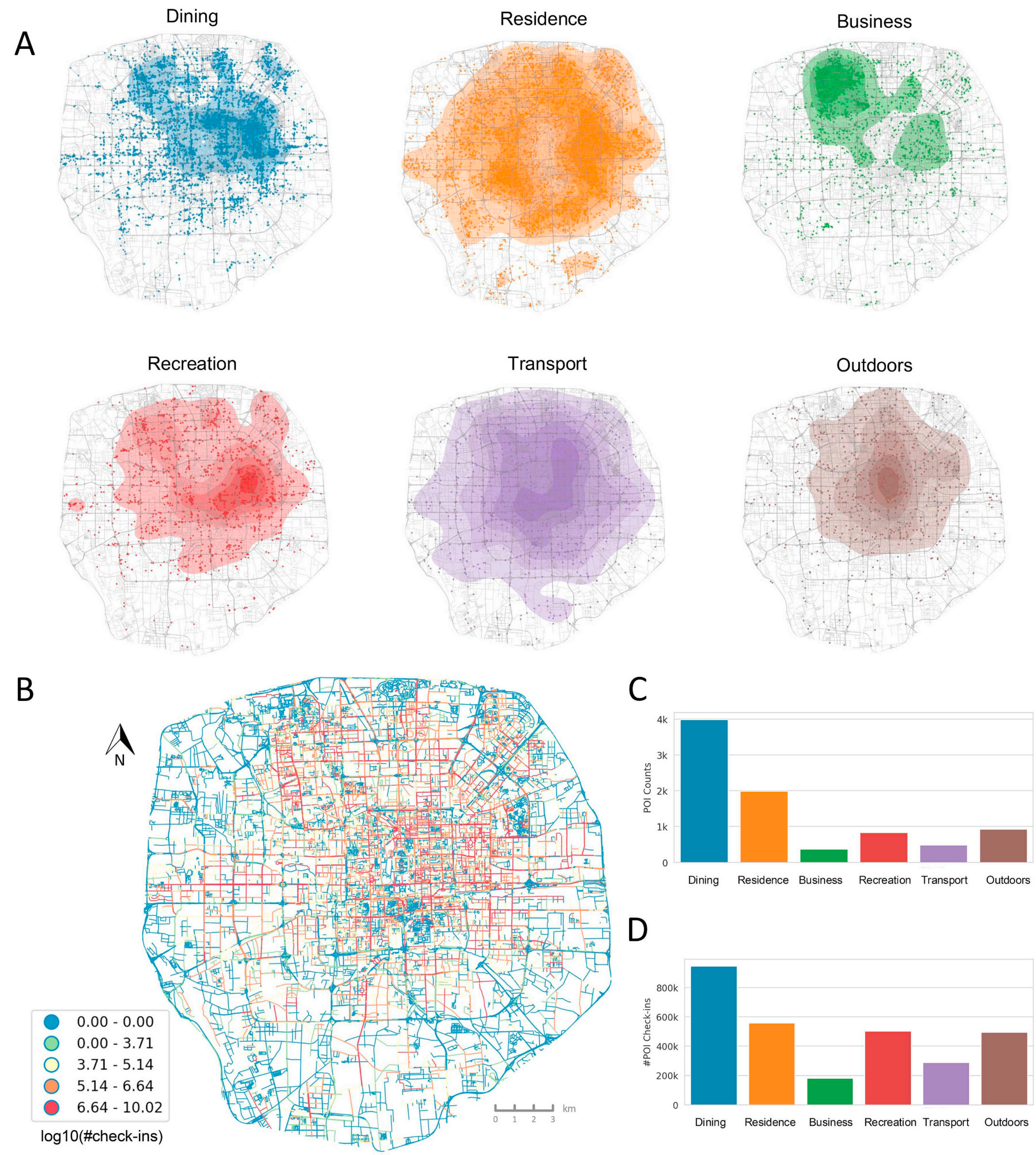

Fig. 2. Point-of-interest (POI) types and statistics in Beijing in 2016. (A) Spatial distributions of the six POI types. The densities are calculated using kernel density estimation. (B) TAZ-level POI check-in numbers (sum of all the types). (C) Counts of the six POI types. (D) Numbers of check-ins for the six POI types.

POIs to their nearest streets. As shown in the figure, human activities are more concentrated between the 2nd and 4th Ring Roads of Beijing. The results are also consistent with a previous work demonstrating the street-level human activity intensity pattern of Beijing (Zhu, Wang, Wu, & Liu, 2017).

3.2. *Deriving place groups - visitors and locals*

3.2.1. *Recognizing user's origin*

To understand the different activity patterns and places popular with visitors and locals in Beijing, it is necessary to recognize whether a user is a visitor or local resident. In this case, inspired by previous works (Gao et al., 2019; Li, Zhou, & Wang, 2018; Liu, Wang, & Ye, 2018), we recognize the user's city of residence based on their spatio-temporal behaviors from all the Weibo records. Since the data include the time and location of a user's posting message, we can build a posting sequence (*Seq*) for the user as $Seq = \ < C_{r1}, C_{r2}, \ldots, C_{ri} >$, where C_{ri} indicates the particular city in which the Weibo record r_i was generated, and i refers to the total number of records for the user.

Here, we define the users' origin as the city of residence where they live and stay for most of their time. Hence, it is reasonable to assume that a Weibo user's city of residence is the city where the user posts most messages. Based on this assumption, the number of posts in city k can be calculated as N_{Ck}, and the user's city of residence can be predicted according to $max\{N_{C1}, N_{C2}, \ldots, N_{Ck}\}$.

In addition, a person will usually return to his/her city after a trip. From another perspective, the user's origin can also be predicted based on the city frequency in his/her travel trajectory *Traj*, which can be obtained by removing the repeated sequential city entities in *Seq*. The trajectory is denoted by $Traj = \ < C_0, C_1, \ldots, C_m >$, where C_m refers to the m_{th} city in the user's travel trajectory. Based on this assumption, the user's city of residence can be obtained by calculating the most frequently visited city in round trips *Traj*.

The two above algorithms contribute to recognizing users' cities of residence, which can either be adopted to validate each other or be combined together for high performance with a higher accuracy. In the experiment, to guarantee the recognition precision, we first remove the users who have fewer than five records (approximately 11% of the total numbers of records) and obtained a total of 664,449 users. Second, we perform the two algorithms individually and remove the records of users with inconsistent predictions (2.3% of the users were removed). The result shows that for all the users who posted at least one Weibo message in Beijing, there were 256,983 non-local people, accounting for 39.56% of the total. In Fig. 3A, we present the spatial distribution of their residences. Basically, the number of user distribution fits with the distance decay effect. Most non-local users are from Beijing's neighboring provinces, including Hebei, Shandong, Shanxi, Liaoning, etc. Others may come from populous and developed regions, such as Guangdong, Zhejiang and Jiangsu Provinces.

Fig. 3B and Fig. 3C demonstrate the distributions of local people's and visitors' activities in Beijing, respectively, which suggest remarkably different patterns between locals and visitors. In detail, the local users are distributed evenly around the central and northern Beijing, with the center of Haidian District and Chaoyang District as the densest areas. The visitors are concentrated in several hot spots in Beijing, such as tourist attractions (Tiananmen Square and the Forbidden City), the central business district (Guomao and Zhongguancun), and transportation hubs (the Beijing Capital International Airport and Beijing West Railway Station).

3.2.2. Identifying popular restaurants and outdoor places frequented by visitors and locals

Furthermore, we focus on two types of Weibo users' locations, namely, "dining" and "outdoor". In Fig. 4A-D, we present the distribution of visitor and local users' activities at "dining" and "outdoor" POIs. Marked differences were observed between the behaviors of local people and visitors for both "dining" and "outdoor" POIs. Generally, there are clear patterns in the places popular with visitors clustered around Beijing, while the place popular with locals are more scattered around the city. Regarding "dining" places, those visited by locals and visitors are similar, but the former is more widely distributed. Houhai, Sanlitun and Qianmen are places where both locals and visitors prefer to go. In addition, Wudaokou, Zhongguancun, Xidan and Wangjing are frequent "dining" places only for locals. In terms of the "outdoor" POIs, visitors' popular places are mainly located among the top famous attractions of Beijing, such as the Forbidden City, Olympic Forest Park, Yuanmingyuan Park, and the Summer Palace, while locals' popular places include Chaoyang Sun Park, Beijing Zoo, Yuyuan Pond, 798 Art Zone, and Happy Valley Beijing.

We go further into identifying the POI-level places, i.e., particular restaurants and outdoor sites, for locals and visitors. Here, we evaluate whether a place is a local place by calculating the ratio of its number of visits by locals to its number of visits, and the POIs with $R_p > 0.5$ are considered local places:

$$R_p = \frac{N_{local}}{N_{local} + N_{visitor}} \tag{1}$$

where N_{local} and $N_{visitor}$ are the number of local check-ins and visitor check-ins, respectively. Note that we skip the consecutive repeated check-ins for the same user at the same place to eliminate potential bias caused by abnormal user behaviors (some users may post numerous messages at a place at one time).

We obtain the top 50 local restaurants/outdoor sites for locals/visitors by ranking the R_p (descending order for locals and ascending order for visitors). Fig. 5 presents the word-cloud visualizations of the 50 most frequently visited POI-level place names for locals and visitors using the *wordcloud* Python library. A larger size of font indicates a larger number total visits at the place. In Table 1, we list the most frequent names (in Chinese) in each word-cloud image with their English translations.

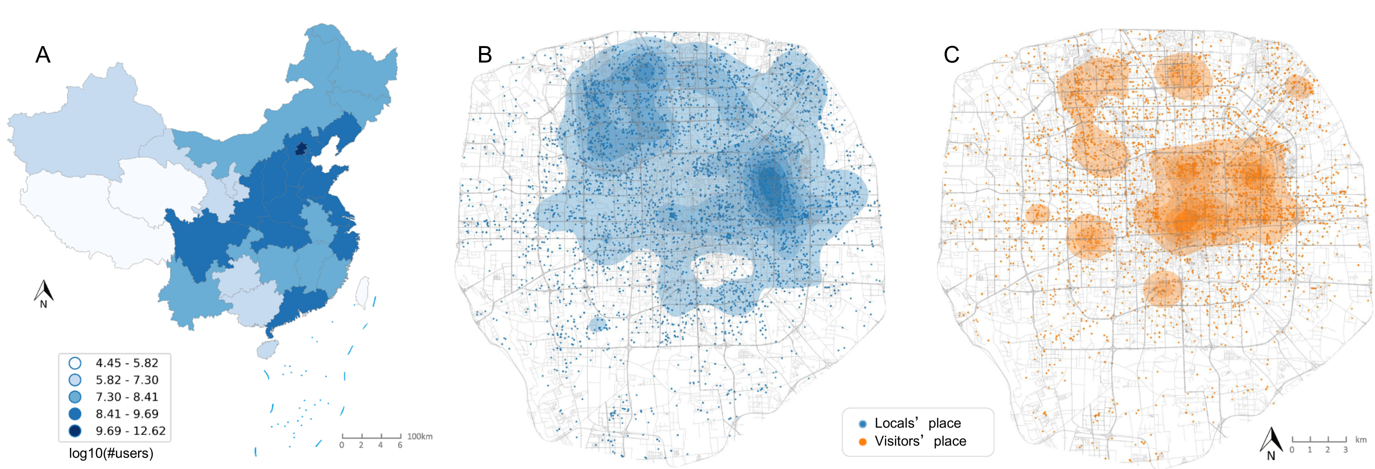

Fig. 3. Who posts Weibo in Beijing? The Weibo users' origins are recognized based on their frequently visited locations. (A) The residence of users who post at least one Weibo check-in in Beijing; 39.56% of the users are from non-Beijing regions. (B) Local users' activity pattern in Beijing. (C) Visiting users' activity pattern in Beijing.

Fig. 4. The places popular with locals and visitors in Beijing. (A) The dining places for locals. (B) The dining places for visitors. (C) The outdoor places for locals. (D) The outdoor places for visitors.

In general, there are a few predominant places for visitors regarding both restaurants and outdoor sites. Visitors' favorite cuisines include Peking roast duck, Peking copper pot shabu-shabu, and Peking noodles with soybean pasta. Indeed, these foods are among the most famous and featured traditional diets of Beijing. The Palace Museums, Tiananmen Square, The Summer Palace, the Temple of Heaven, etc., which are landmark tourist attractions, as expected, are listed to be the most frequently visited outdoor sites by visitors. By contrast, almost none of these restaurants or outdoor sites are among the locals' frequented visited places. For locals, their favorite places are generally diverse and dispersed. In terms of "dining", the post popular places include several popular Chinese food brands such as Haidilao hotpot, Maan Coffee, and Happy Duck House. In addition, there are many restaurant names containing English letters, indicating that some local people prefer more modern and Western food. This finding agrees with the theory of food and drink culture that local people's dining experience is improved by constantly seeking the newest and most exotic meals (Everett, 2016). For outdoor places, dozens of parks, such as Olympic Forest Park and Chaoyang Sun Park, are the favorite places for locals. In addition, Weiming Lake at Peking University, Happy Valley Beijing and Beijing Zoo are listed.

These results demonstrate the different preferences between locals and visitors for different types of activities. However, these places are derived based merely on their check-in records, while overlooking an important dimension for characterizing places - physical settings.

3.3. Deriving place locale evaluations using street-level imagery

We take street-level imagery as the proxy of place locales. Our street-level imagery dataset is composed of two data sources, i.e., street view images and social media photos. In total, 1,024,356 street view images and 355,709 social media photos were collected from Tencent Maps and Panoramio, respectively. Tencent Maps, launched in 2012, is a map service platform providing digital map and street view service in China, covering more than 290 Chinese cities, and Panoramio, which was launched in 2005 and discontinued in 2016, is a crowdsourcing, photo-sharing platform that contains geo-tagged photos taken from all around the worlds. Most images we obtained are taken during 2015–2016. Details about the two datasets can be found in (Zhang, Zhou, et al., 2018) and (Zhang, Zhou, et al., 2019). Fig. 6 presents the spatial distribution and samples of these two image datasets. The street view images cover the street network of Beijing densely and evenly, while the social media photos are mainly distributed around famous attractions in Beijing such as parks, scenic spots and historical sites. In terms of the image content, street view images focus on describing the streetscape while social media photos are more diverse, containing not only street views but also views inside blocks, squares and parks. In this study, we take full advantage of the characteristics of both street view

Fig. 5. Word-cloud visualizations of the frequently visited place names for locals and visitors. (A) Frequently visited "dining" places of locals. (B) Frequently visited "dining" places of visitors. (C) "Outdoor" places frequently visited by locals. (D) "Outdoor" places frequently visited by visitors. Table 1 lists the most frequent names with their English translations.

Table 1
Chinese/English names of the frequently visited places (from Fig. 5).

	Local Chinese	Visitor English	Chinese	English
Dining	海底捞火锅	Haidilao Hotpot	全聚德烤鸭	Donglaishun Roast Duck Restaurant
	漫咖啡	Maan Coffee	大董烤鸭店	Dadong Roast Duck Restaurant
	金钱豹美食	Golden Jaguar Buffets	东来顺饭庄	Donglaishun Copper Pot Shabu-shabu
	金鼎轩	Happy Duck House	海碗居炸酱面	Haiwanju Noodles With Soybean Pasta
	星巴克	Starbucks	簋街胡大麻小	Huda Spicy Crayfish
	花厨	Tomacado	后海酒吧	Houhai Bars
Outdoor	奥林匹克森林公园	Olympic Forest Park	故宫博物院	Forbidden City - Palace Museums
	北京大学未名湖	Weiming Lake at Peking University	天安门广场	Tiananmen Square
	北京欢乐谷	Happy Valley Beijing	颐和园	Summer Palace
	朝阳公园	Chaoyang Sun Park	毛主席纪念堂	Chairman Mao Memorial Hall
	北海公园	Beihai Park	什刹海	Shichahai Lake
	北京动物园	Beijing Zoo	天坛	Temple of Heaven

images and social media photos by combining the two image datasets together to represent the place locales comprehensively.

Here, we introduce a computer vision and machine learning-based approach to derive people's perceptual evaluation of a place's locale. We obtain the training dataset from the "Place Pulse" platform[2] from the MIT Media Lab (Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016; Salesses, Schechtner, & Hidalgo, 2013). The dataset contains more than 100,000 Google Street View images across 56 global cities and their corresponding perceptual scores (0–1) rated by more than 80,000 online volunteers. The perceptual ratings were collected through a web-based survey, in which the participants were asked to compare two street view images and respond to questions such as "which place looks more safe/beautiful/depressing/lively/wealthy/boring?" The details of the dataset is described in (Dubey et al., 2016; Salesses et al., 2013). A number of works have employed the "Place Pulse" dataset as a machine learning training set to train computer vision models (Dubey et al., 2016; Ordonez & Berg, 2014; Porzi, Rota Bulò, Lepri, & Ricci, 2015; Zhang, Zhou, et al., 2018). Consequently, these models are able to evaluate any street view image with six dimensions, namely, "safe", "lively", "beautiful", "wealthy", "boring" and "depressing". However, most of these previous methods require training models for each of the

[2] http://pulse.media.mit.edu/

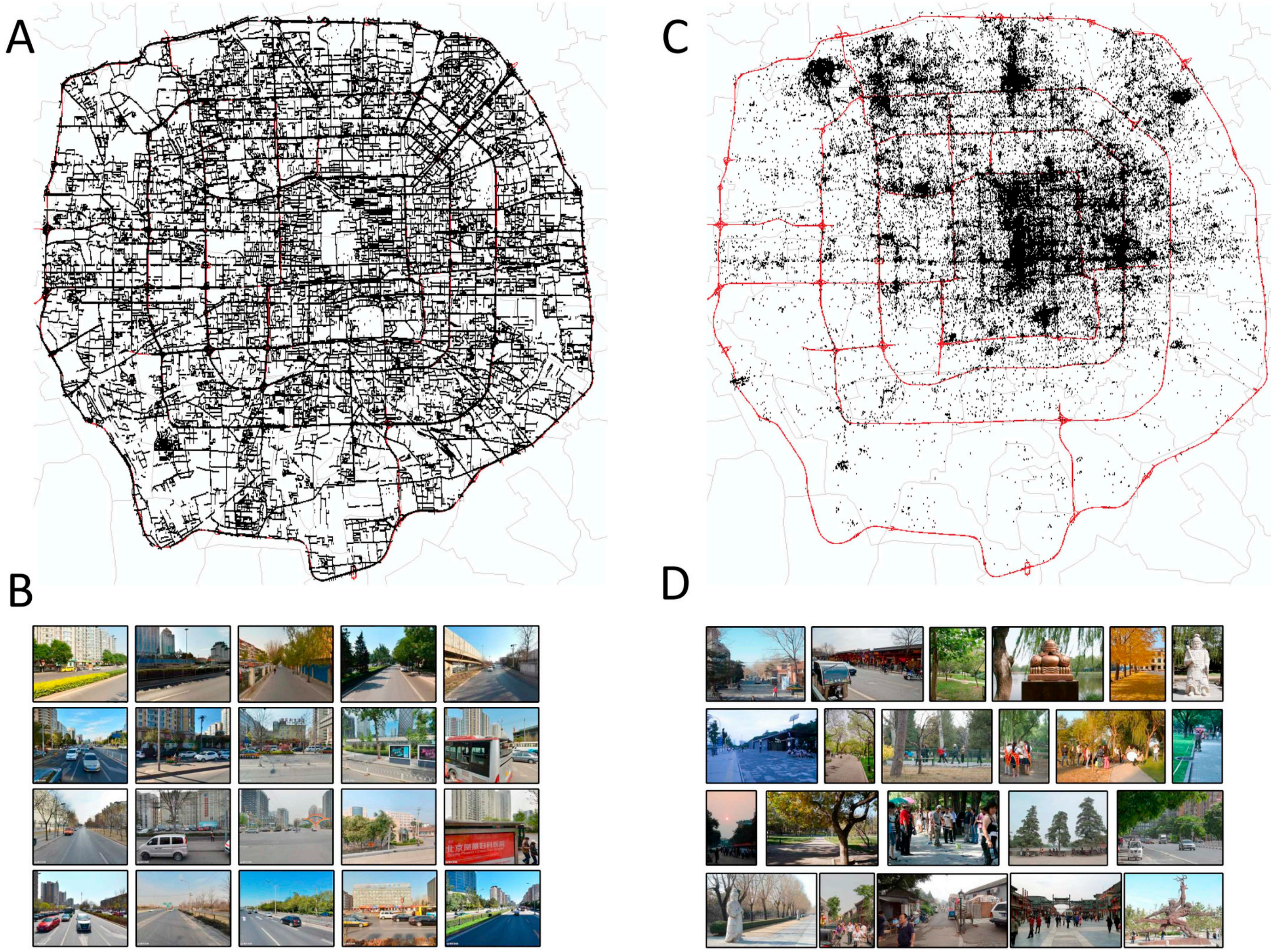

Fig. 6. Street-level imagery in Beijing. (A) Spatial distributions of the street view images from Tencent Maps. (B) Example street view images. (C) Spatial distributions of the social media photos from Panoramio. (D) Example social media photos. Images courtesy of Tencent Maps and Panoramio.

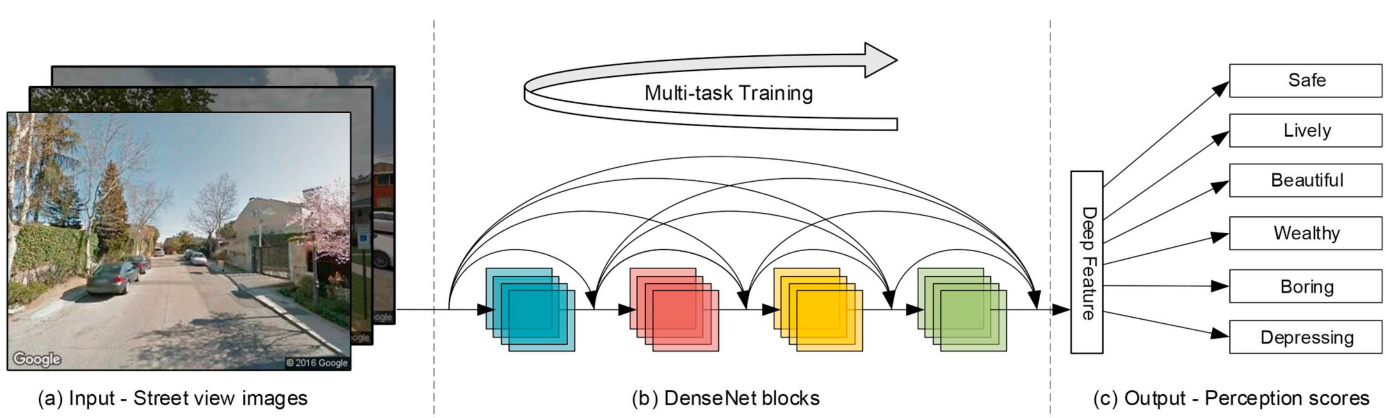

Fig. 7. Multi-task deep learning model for place locale evaluation using street view images. The model is able to predict the perceptual scores of the six dimensions simultaneously (images courtesy of Google Maps).

six perceptual dimensions individually.

Building upon these previous works, we propose a multi-task deep learning model to predict the perceptual scores of the six dimensions simultaneously. As presented in Fig. 7, we take DenseNet-121 (7b) as the main architecture of the model. DenseNet is a state-of-the-art DCNN architecture that has been widely used in various computer vision tasks (Huang, Liu, Weinberger, & van der Maaten, 2017; Zhang, Wu, et al., 2019). Given an input street view image (Fig. 7a), our proposed model is expected to simultaneously predict the scores of the six perceptual dimensions (Fig. 7c). The whole training work flow is similar to that in (Zhang, Zhou, et al., 2018), except for the loss function. To implement the multi-task training process, the loss for the perceptual dimension n

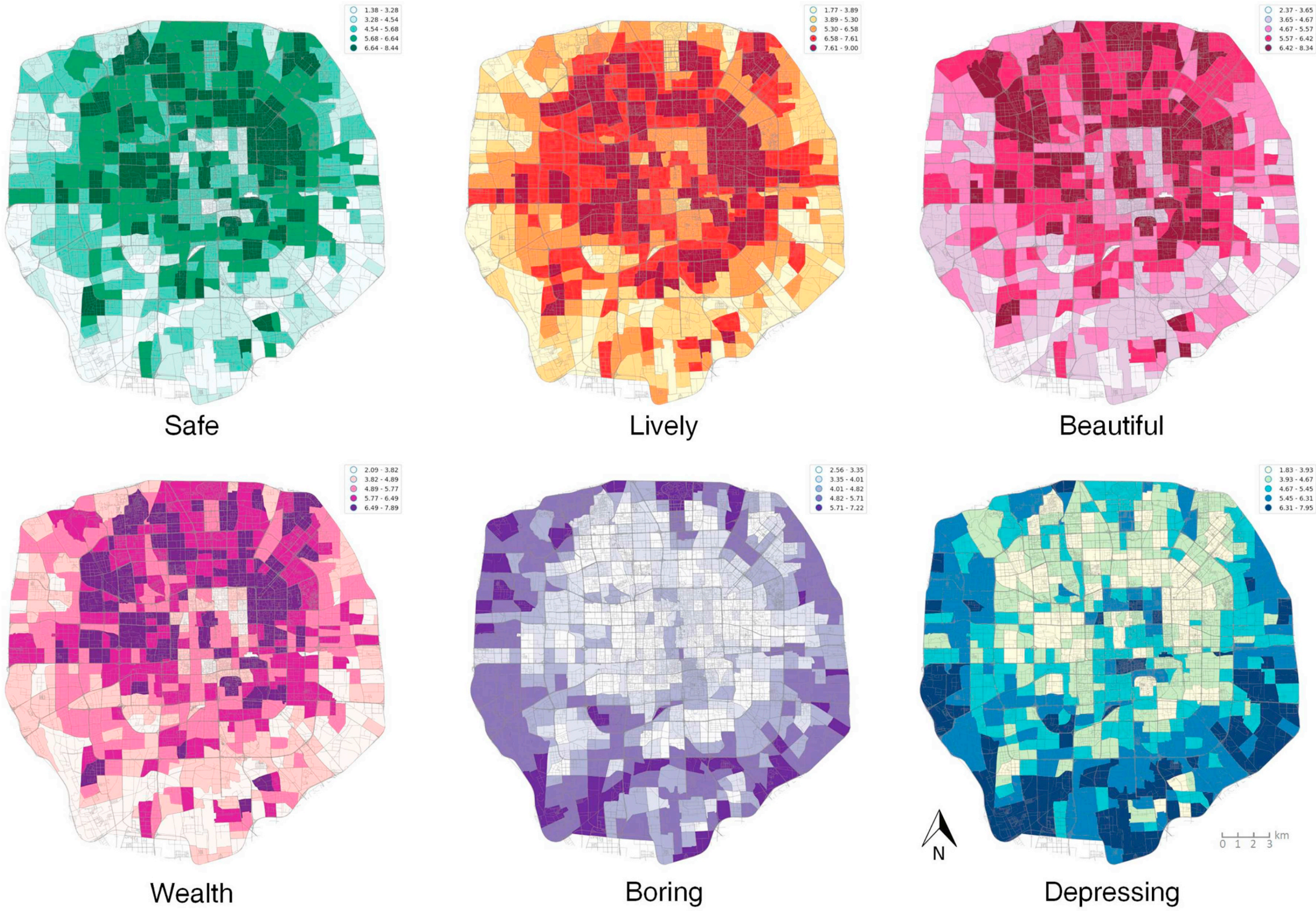

Fig. 8. The spatial distributions of the human perceptions to the place locales in Beijing. The evaluation dimension are "safe", "lively", "beautiful", "wealthy", "boring" and "depressing". The perception scores were predicted by the pre-trained multi-task deep learning model.

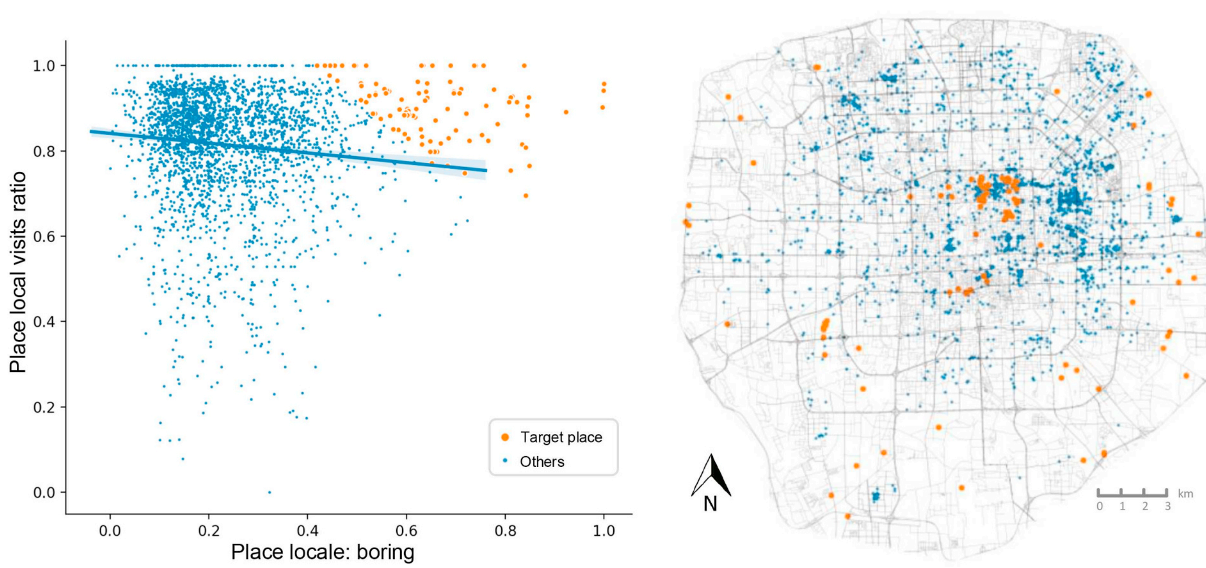

Fig. 9. Scatter plot between the place locales and place visits of restaurants (left) and the mapping of the restaurants in Beijing (right). The top 100 unassuming restaurants (orange) and others (blue) are grouped. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 10. Top 100 unassuming restaurants (orange stars) and eight examples with street-level imagery (purple stars) in Beijing. These restaurants have high social media check-in numbers but low image perceptual scores and are places where locals gather. Images courtesy of Tencent Maps and Panoramio. ©CARTO ©OpenStreetMap. Tile image map tiles by CartoDB under the CC BY 3.0 license. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

is defined as $\mathscr{L}_{\mathbf{n}}(w)$, where $n \in \{safe, lively, beautiful, wealthy, boring, depressing\}$. The training target is defined as:

$$\min_{w}\{\sum \mathcal{L}_{safe}(w) + \mathcal{L}_{lively}(w) + \mathcal{L}_{beautiful}(w) + \mathcal{L}_{wealthy}(w) + \mathcal{L}_{boring}(w) + \mathcal{L}_{depressing}(w)\} \tag{2}$$

The detailed parameter configuration for model training was introduced in (Zhang, Zhou, et al., 2018). After training, we applied the model to all of the street-level imagery in Beijing. Fig. 8 displays the spatial distributions of the six human perceptual dimensions to the place locales in Beijing. The results are consistent with those in (Zhang, Zhou, et al., 2018). Overall, mid-level roads and downtown areas are more "beautiful" and less "boring" than ring roads and suburbs, respectively. However, several small alleys and hutongs inside Beijing's 2^{nd} Ring Road are predicted to be "depressing" and "boring", where there are a considerable number of old and historical houses and buildings.

In the two case studies of this work, we mainly focus on the "boring" and "beautiful" dimensions for characterizing the locales of places.

4. Uncovering inconspicuous places of a city

In this section, we present the way to uncover two types of inconspicuous places in a city. First, we define an unassuming local restaurant as a place where local people visit frequently, but its physical environment is visually ordinary or even boring. These restaurants reflect locals' food and diet culture. Second, we define an inconspicuous outdoor place as where the surrounding scenery is appealing but is barely visited by people. These places should either receive better urban design and management attention or can be potentially recommended to locals and visitors for recreation.

Fig. 11. Scatter plot between place locale scores and place activity of the outdoor places (left) and the mapp of the outdoor places in Beijing (right). The top 100 inconspicuous outdoor places and the others are represented by the orange and blue dots, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.1. Problem formalization

Here, we formalize the problem of uncovering inconspicuous places for different groups of people. For a place P, let C_p denote the **type of the place**, V_p be the **total visit intensity of the place**, R_p be the **local visit ratio of the place** (refer to Eq. 1), and $E_p{}^n$ be the **perceptual score** of the place in dimension n, where $C \in \{dining, residence, business, recreation, transport, outdoors\}$, $V \in (0, \infty)$, $R \in (0,1)$, $E \in (0,1)$, and $n \in \{safe, lively, beautiful, wealthy, boring, depressing\}$. A place can hence be characterized as a four-dimensional vector $P = \ < C, V, R, E >$.

Hence, according to the local visit ratio of a place, an unassuming local restaurant can be identified as:

$$P_{catering} = < C_p, V_p, R_p, E_p > \quad \text{subject to} \quad \begin{cases} C_p = \langle catering \rangle \\ R_p > \mathcal{T}_R \\ E_p^{boring} > \mathcal{T}_E \end{cases} \tag{3}$$

where $\mathcal{T}_R$ represents a threshold of the local visit ratio (e.g. 0.5), and $\mathcal{T}_E$ is the threshold of the image perception score.

Then, we define the inconspicuous outdoor places for visitors in Eq. 4. These outdoor places present wonderful physical settings (high score on "beautiful" dimension) but rarely host communal activities (i.e., with low check-in numbers). They are of high quality yet ignored by people for some reason; we believe these areas are "potential" recreational places and can be used more efficiently through better design and improvement.

$$P_{outdoor} = < C_p, V_p, R_p, E_p > \quad \text{subject to} \quad \begin{cases} C_p = \langle outdoor \rangle \\ V_p < \mathcal{T}'_V \\ E_p^{beautiful} > \mathcal{T}'_E \end{cases} \tag{4}$$

where $\mathcal{T}'_V$ and $\mathcal{T}'_E$ are the thresholds of check-in number and image perception score respectively.

Accordingly, we construct metrics for both types of places that measure the "inconspicuous" degree:

$$S_{re} = R_p^{catering} * E_p^{boring}$$
$$S_{ot} = (max(V) - V_p^{outdoor}) * E_p^{beautiful} \tag{5}$$

A larger score indicates a higher "inconspicuous" degree of a place.

4.2. Inconspicuous restaurants

Fig. 9 plots the association between restaurants' locale score and their local visit ratios (left) and their spatial distribution in Beijing (right). The top 100 unassuming restaurants are discovered according to the S_{re} of the restaurants and are represented by orange dots in the figure. The blue dots indicate the other restaurants. We find a very weak correlation between the human perceptual scores of place locales and place-associated human activities at the city-level ($r < 0.01$). In addition, most of the unassuming restaurants are located in deep alleys of old neighborhoods and concentrated inside the 2^{nd} Ring Road of Beijing. These typical alleys are known as "hutong"(Tang & Long, 2019). In Old Beijing, a neighborhood was formed by one siheyuan, which is a courtyard surrounded by buildings on all four sides, and a hutong was formed by joining one siheyuan to another. Hutongs are the basic living units of residents of Old Beijing. More importantly, they are valuable cultural assets for tourism development and historical research (Gu & Ryan, 2008). From these results, the unassuming restaurants help us understand the local culture from a dietary perspective.

Fig. 10 shows the spatial distribution of the top 100 unassuming restaurants in Beijing (orange stars). Most of these restaurants serve local, traditional foods, such as Peking duck, Peking noodle and mongolian barbeque, but are different from the branded restaurants that tourists frequently visit. Fig. 10 also displays several samples of the unassuming restaurants (purple stars) with their street view images and social media photos. Although there are numbers of old houses in disrepair, these restaurants, people, cars and other details enliven the otherwise drab places. The short streets, small blocks and dense street network lead to lively and livable neighborhoods in Beijing, which is also consistent with the theory proposed by Jane Jacobs on the perspective of urban design (Jacobs, 1992).

4.3. Inconspicuous outdoor places

Fig. 11 shows the relationship between place locale scores and place visits of the outdoor places in Beijing on the left, and their spatial distribution on the right. The top 100 inconspicuous outdoor places (orange) are identified based on the S_{ot} metric and are distributed evenly across Beijing. There is a weak positive correlation between place locale scores and place visits for the outdoor places ($r = 0.15$), implying that a beautiful outdoor place will generally be popular.

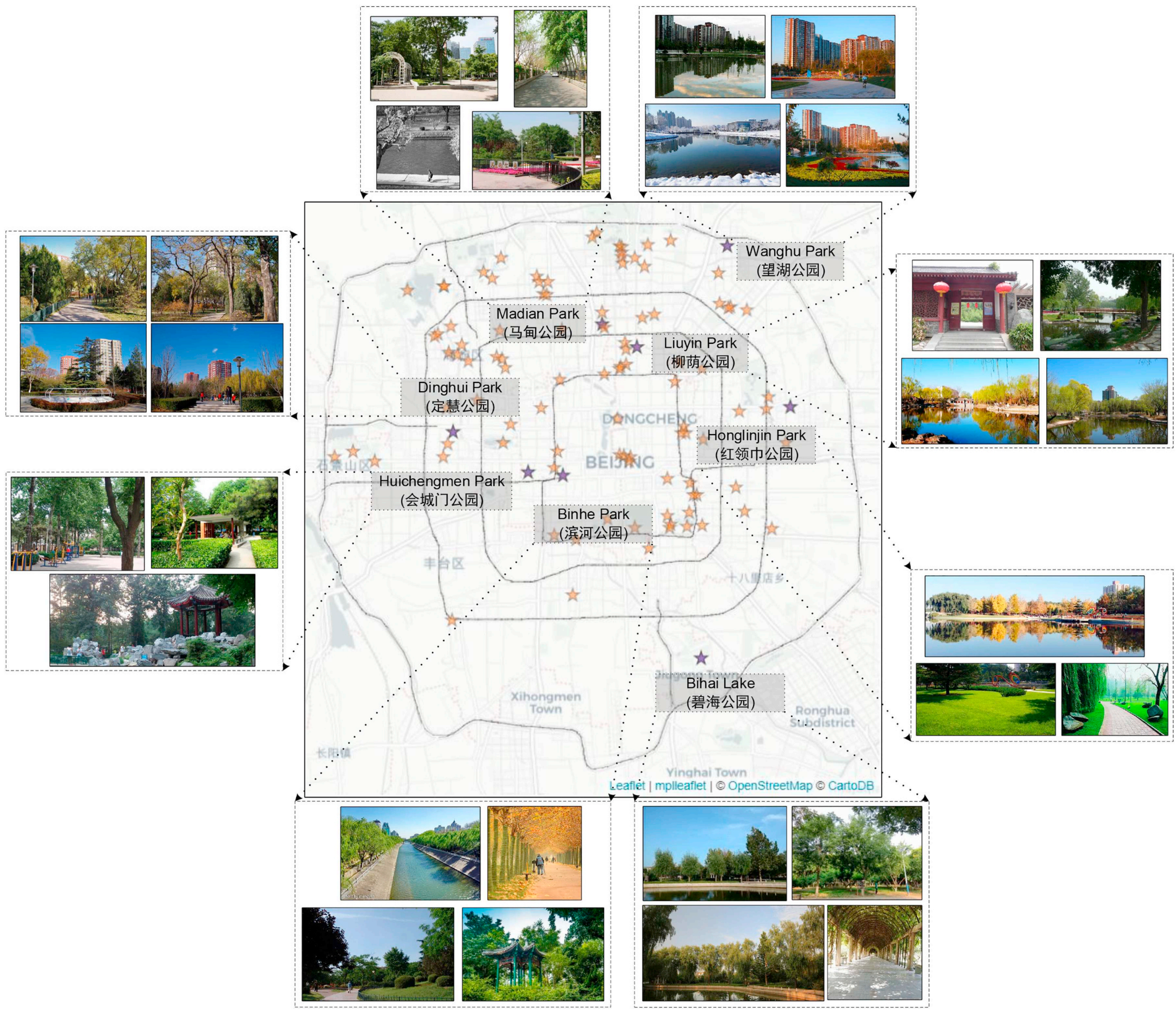

Fig. 12. Top 100 inconspicuous outdoor places (orange stars) and eight examples with street-level imagery (purple stars) in Beijing. These outdoor places have high scores on the "beautiful" dimension but low social media check-in numbers. Images courtesy of Tencent Maps and Panoramio. ©CARTO ©OpenStreetMap. Tile image map tiles by CartoDB under CC BY 3.0 license. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Nevertheless, beautiful yet unpopular outdoor places should receive attention.

Fig. 12 demonstrates the locations of the top 100 inconspicuous outdoor places in Beijing (orange stars), which are mostly parks and plazas. Their perceptual scores are high because of the pretty gardens, natural landscape, and unique landmarks. Despite their high quality, they are ignored by people for some reason, e.g., accessibility to the facility for visitors, low walkability for locals, and lack of visibility. As important public infrastructures, these outdoor places have the potential to become popular and be used more efficiently through place-making, public engagement and shared governance.

5. Discussion

Spatiotemporal urban big data are being generated at an unprecedented speed, which creates new opportunities to investigate human dynamics and the urban physical environment from multiple perspectives. Nevertheless, how can we integrate big geo-data from different sources well and how to build place-based representations linking and combining place locales and human activities has not been fully investigated. In this study, we show how digital representations of places can be created from different aspects and for various groups. This work may have the following implications.

First, understanding a place requires multiple perspectives. The various state-of-the-art artificial intelligence tools offer not only opportunities to mine deep representations of data but also platforms to integrate multi-source and heterogeneous data together to comprehensively understand space, place, and human dynamics. Second, "lively" and "vibrant" are the essential principles to make a high-quality place (Whyte, 1980). "Unpopular" outdoor places provide valuable references for understanding why some places work and others do not and how can we build human and livable neighborhoods through place-making. Third, a city is shaped heterogeneously by the differences in landscape, culture, history and interactions with residents over a long-term human settlement. Understanding the heterogeneity of a city should not merely focus on landmarks but should also pay attention to hidden places. For instance, unassuming local restaurants are ordinary or even visually boring from the outside but are inherently valuable cultural resources containing local customs, habitudes, and histories. Characterizing places comprehensively is essential to explore these unknown corners of a city. Last but not least, different groups of people, in terms of income, age, etc., behave differently and have their own ways of using the same place. In the process of rapid global urbanization, this situation causes or exacerbates certain issues, e.g., the physical separation and inequality of social groups, which has been called “urban and social segregation”. Characterizing places used by different groups will benefit the identification and evaluation of segregation and gentrification to further inform urban planners and decision makers in the process of urban development.

The major limitation of this work lies in the representativeness and bias of big data. Using social media check-ins to represent the popularity of places is biased (Yuan et al., 2019), since the user distributions of different groups are inconsistent. For instance, visitors are more likely to generate a check-in record than locals in a particular place. As a potential alternative, using mobile phone positioning data or integrating multi-source human activity data can mitigate this issue. In addition, how to involve the uncertainty of samples in further analysis is worth discussing. Owing to the rapid development of machine learning methods, many studies employ the data yielded from a machine learning model and attempt to explore the associations between predicted data and others. In that case, taking uncertainty of the predicted data into account is vital and necessary. More attention should be paid to this issue in future work.

6. Conclusion

Place-based GIS aims at formalizing place in the digital world and bridging the gaps between the informal world of human activity and the formal world of digitally represented geography (Blaschke et al., 2018; Goodchild, 2011). Appropriate data sources and effective tools are currently available. In this work, we propose a data-driven framework for place characterization with the support of multi-source social sensing data. The framework focuses on characterizing places from four essential aspects: place type, place popularity, place locale, and groups. As a demonstration, we employ street view images, social media photos and social media check-in data to implement the framework, and explore a number of “inconspicuous” places in Beijing. A number of unassuming but popular restaurants were explored, most of which are located in deep alleys of old neighborhoods, where local social interactions take place. In addition, we discovered a few well-maintained outdoor places, that are probably ignored by people. These places can potentially be studied as typical cases in urban design and place-making to learn from failure and to build public space to promote engagement, happiness, and well-being.

Declarations of Competing Interest

The authors declare that there is no conflict of interest.

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