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Social Sensing: A New Approach to Understanding Our Socioeconomic Environments

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The emergence of big data brings new opportunities for us to understand our socioeconomic environments. We use the term *social sensing* for such individual-level big geospatial data and the associated analysis methods. The word *sensing* suggests two natures of the data. First, they can be viewed as the analogue and complement of remote sensing, as big data can capture well socioeconomic features while conventional remote sensing data do not have such privilege. Second, in social sensing data, each individual plays the role of a sensor. This article conceptually bridges social sensing with remote sensing and points out the major issues when applying social sensing data and associated analytics. We also suggest that social sensing data contain rich information about spatial interactions and place semantics, which go beyond the scope of traditional remote sensing data. In the coming big data era, GIScientists should investigate theories in using social sensing data, such as data representativeness and quality, and develop new tools to deal with social sensing data. **Key Words:** GIScience, place semantics, social sensing, spatial interaction, temporal activity pattern.

大数据的兴起，对理解我们的社会经济环境，带来新的契机。我们使用“社会感知”之概念，称呼此般个人层级的广大地理空间数据及相关的分析方法。“感知”一词，意味着数据的两种本质。首先，它们可被视为遥测的模拟与补充，因为大数据可以有效捕捉社会经济特征，而传统的遥测数据则不具此一优势。再者，在社会感知数据中，每个个体，皆扮演着感应器的角色。本文在概念上，将社会感知与遥测进行连结，并指出应用社会感知数据及相关分析方法时的主要问题。我们同时主张，社会感知数据，包含了有关空间互动与地方语义学的丰富信息，并超出传统遥测数据的范畴。在即将来临的大数据时代中，地理信息科学家，应该探讨使用社会感知数据的理论，例如数据再现性与质量，并发展应对社会感知数据的崭新工具。 **关键词：** 地理信息科学，地方语义学，社会感知，空间互动，即时活动模式。

La aparición del concepto de los *big data* [grandes datos, o datos masivos] nos brinda otra perspectiva para entender mejor nuestros entornos socioeconómicos. En este contexto, utilizamos los términos percepción social para distinguir aquellos datos geoespaciales masivos a nivel individual y los métodos de análisis asociados. La palabra percepción sugiere datos de doble naturaleza. Primero, estos pueden verse como una analogía y complemento de la percepción remota, en la medida en que los datos masivos pueden captar bien los rasgos socioeconómicos, en tanto que los datos convencionales de la percepción remota no tienen tal privilegio. En segundo término, en los datos de la percepción social, cada individuo juega el papel de un sensor. Este artículo enlaza conceptualmente la percepción social con la percepción remota e identifica las cuestiones mayores cuando se aplican datos de percepción social y la ciencia del análisis asociada. También sugerimos que los datos de percepción social contienen una rica información acerca de las interacciones espaciales y la semántica del lugar, que llegan más allá del ámbito de los datos tradicionales de la percepción remota. En la era de los *big data* que se avecina, los científicos de la información geográfica deberán investigar las teorías sobre el uso de datos de percepción social, tales como representatividad de los datos y calidad, y desarrollar nuevas herramientas para lidiar con los datos de la percepción social. **Palabras clave:** SIGciencia, semántica del lugar, percepción social, interacción espacial, patrón de la actividad temporal.

The last five decades have witnessed the fast development of remote sensing techniques, of which a major objective is to reveal the physical characteristics of the Earth's surface, such as land cover features. Conventional land cover classification

methods take spectral and textual properties as the major evidence (P. Gong and Howarth 1990). Uncovers land uses from only remotely sensed imagery, however, is rather difficult, as socioeconomic features are not directly related to the spectral reflectance that

can be detected by various sensors (S.-S. Wu et al. 2009). Much literature introduces auxiliary information and domain knowledge for inferring land use (or social function) schemes (Liu, Guo, and Kelly 2008; Platt and Rapoza 2008; S.-S. Wu et al. 2009; Meng et al. 2012; Hu and Wang 2013). These methods do not always yield ideal results, though. Although remote sensing data can to a certain extent capture urban and suburban landscape and infrastructure (e.g., buildings and street networks; Jensen and Cowen 1999), remote sensors have limited capability to extract socioeconomic attributes and human dynamics such as movements and daily activities.

Recently, with the rapid development of information and communications technology (ICT), the impacts of ubiquitous big data on geography have been widely recognized (Graham and Shelton 2013), although there is not a clear and widely accepted definition of big geospatial data (Batty 2013a). Several types of geospatial big data are available to capture the spatiotemporal patterns of human activities and thus provide an alternative approach to uncovering land uses and exploring how cities function in a fine temporal resolution. Such big data include taxi trajectories, mobile phone records, social media or social networking data,¹ smart card records in public transportation systems, and so on (Lu and Liu 2012). Much research has been conducted to obtain land use characteristics using mobile phone data (Ratti et al. 2006; Toole et al. 2012; Pei et al. 2014), taxi data (Qi et al. 2011; Liu, Wang, et al. 2012), and smart card data (Y. Gong et al. 2012). The primary assertion of such studies is that different land uses are associated with different temporal rhythms of activities (Sevtsuk and Ratti 2010).

Considering that remote sensing data have been widely and successfully used to map physical features of our world, in this article we introduce the term *social sensing* for the previously mentioned geospatial big data, as such data have some features in common with the conventional remote sensing data and reveal socioeconomic characteristics as a complement to remote sensing data. We use social sensing to emphasize that geospatial big data can be viewed as an analogue of remote sensing data in social science research. By adopting the methods developed in remote sensing applications, social sensing provides a promising approach to understanding our socioeconomic environments, alone or integrated with remote sensing data. Additionally, social sensing data in general contain rich information, such as spatial interaction and place semantics, that go beyond the scope of

traditional remote sensing data. This article summarizes the properties of social sensing data and puts forward a research agenda for applying them in geographical analyses.

Social Sensing

In this section, we introduce two data sets to demonstrate the concept of social sensing. One data set is composed of taxi trajectories and another is of social media check-in records, both of which were collected in Shanghai, China. The taxi trajectory data set covers seven days in 2009 and includes pick-up points (PUPs) and drop-off points (DOPs; a description of this data set can be found in Liu, Kang, et al. 2012; Liu, Wang, et al. 2012). The check-in data contain about 100,000 check-in records collected over the course of one year. A check-in record is a spatiotemporally tagged text message posted by a user using a mobile device. From the data set, we can extract different places such as workplaces, hotels, parks, and restaurants (see L. Wu et al. [2014] for details about this data set). The study area (Figure 1A) is rasterized into 28,000 (140 rows and 200 columns) $250 \times 250 \text{ m}^2$ squares so that we can count the numbers of PUPs, DOPs, and check-ins in each pixel.

Figures 1B, 1C, and 1D depict the spatial distributions of the three activities, checking in, picking up, and dropping off. It is natural that the three distributions are positively correlated with the population distribution (Figure 1E, represented by the Landsat data with a spatial resolution of 1 km^2). The frequency distributions of the three activities have a heavy-tail characteristic (Figure 1F).

Much literature has paid attention to the temporal activity rhythms extracted from different data sources (Sevtsuk and Ratti 2010; Kang, Liu, et al. 2012; Liu, Wang, et al. 2012; Toole et al. 2012; Shen, Kwan, and Chai 2013; Pei et al. 2014). Because human activities have a clear daily periodicity, we can aggregate the actual data set covering a long period by computing the number of activities recorded for each hour of the day. Figure 2A depicts the averaged and normalized diurnal variations of the three activities across the entire study area. The check-in curve has two clear peaks, corresponding to 1 p.m. and 7 p.m. It is natural that the check-in probability is high during nonworking hours, especially when people have lunch or dinner. Although the curves representing pick-up, drop-off, and check-in behavior diverge during the day, the

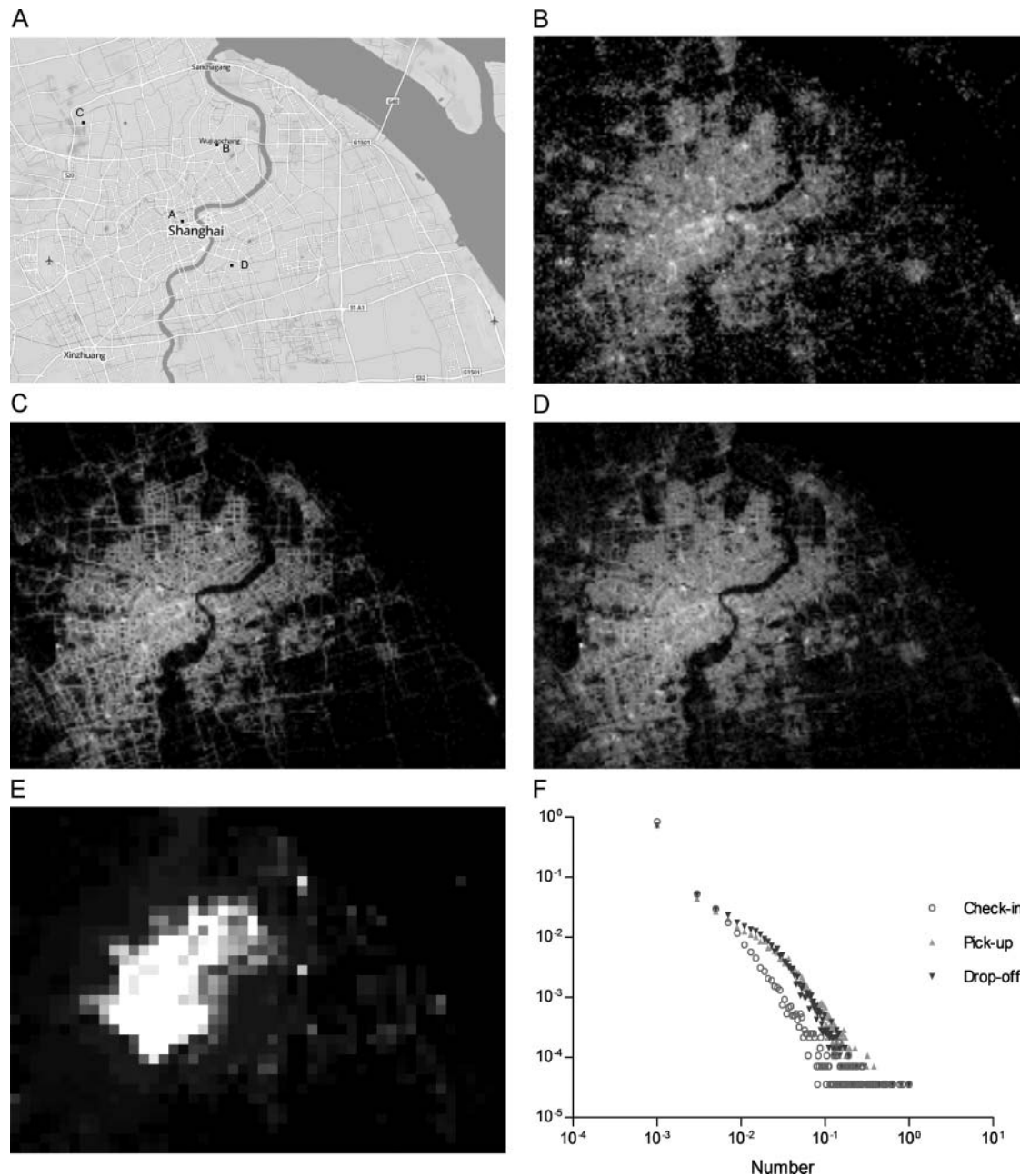


Figure 1. (A) Urban area of Shanghai; (B) spatial distribution of check-in points in about one year; (C) spatial distribution of pick-up points in seven days; (D) spatial distribution of drop-off points in seven days; (E) population density represented using Landsat data; (F) frequency distributions of the three activities. Note that B, C, and D are obtained using logarithmic transformations.

three curves exhibit a similar trend from 10 p.m. to 9 a.m. of the next day. Note that the temporal resolution for computing activity frequencies has been set as one hour. A different temporal resolution (e.g., 0.5 hours) will yield different curves, but the basic trend does not change much. Hence, in the following sections, we use one hour as the default time interval.

Compared with the global temporal patterns, given a data source, we are more interested in local temporal

patterns because different places (cf. points A and B in Figure 1A) are associated with different temporal signatures (Figure 2B). Furthermore, these varying temporal signatures are themselves dependent on the underlying land use features. Hence, a number of studies have focused on classifying land use features from taxi data (Liu, Wang, et al. 2012) and mobile phone data (Toole et al. 2012; Pei et al. 2014). The basic idea of such classification research is that the temporal

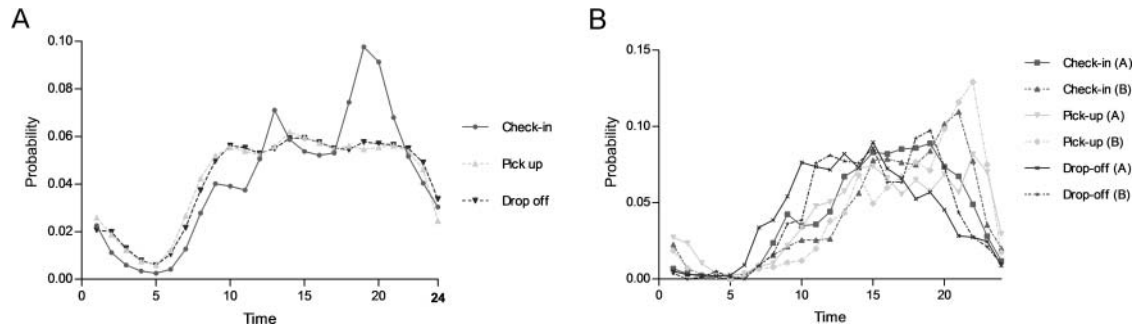


Figure 2. Normalized temporal variations of different activities extracted from taxi trajectories and social media check-in records. (A) Global patterns; (B) local patterns associated with two places.

curves, as shown in Figure 2B, can be viewed as the signatures of various land uses. This reminds us of the foundation of photometer remote sensing image classification, which generally extracts land cover information according to the electromagnetic spectral curves of different features such as forest, water, and barren land. Conventional remotely sensed data have been successfully applied in revealing physical geographical characteristics. On the contrary, current geospatial big data capture human activities better and are thus more sensitive to our socioeconomic environments. We thus use the term social sensing for various spatiotemporally tagged data sources and the associated analysis methods.

Linking Social Sensing with Remote Sensing

The temporal variations depicted in Figure 2 suggest that different places exhibit different responses to a certain activity. Meanwhile, given a place, the temporal variations of different activities captured by various social sensing data are also different. Hence, for each piece of social sensing data, by setting the spatial and temporal resolutions, we can obtain a series of

images, which are similar to different bands of remote sensing imagery. In this sense, different social sensing data can be viewed as the analogues of different remote sensing data. We compare social sensing data with remote sensing data in Table 1. It is clear that these two data sources share some common characteristics, such as containing multisensor, multiresolution, multitemporal information, but capture different aspects of a geographical environment.

The similarities between remote sensing data and social sensing data suggest that we can introduce conventional image processing methods to analyze geospatial big data. For example, we can view the activity density maps as different bands of images and generate false color composite images. The two subfigures in Figure 3 correspond to 8:00 a.m.–9:00 a.m. and 8:00 p.m.–9:00 p.m. The composition scheme is that check-ins, pick-ups, and drop-offs are represented by red, green, and blue channels, respectively. From the false color images, the spatiotemporal characteristics of the three activities can be clearly identified. The region color in white is the core area of Shanghai, where the densities of the three activities are all high. For the two time intervals, the red dots in the suburban areas indicate that the activity density of check-ins is higher than the other two activities. In the first image, the

Table 1. Comparisons between remote sensing and social sensing

	Remote sensing	Social sensing
Data source	Remote sensed data collected from various sensors, such as radiometer, radar, and LiDAR	Spatiotemporally tagged data collected from different location-aware devices, such as mobile phone, Global Positioning System
Major objective	Physical features of Earth's surface	Socioeconomic features of Earth's surface
Processing method	Correction and calibration, fusion, classification, and so on	Geocoding and preprocessing, fusion, classification, and so on
Signal for classification	Electromagnetic spectra	Temporal variation of activities

Note: Li DAR = light detection and ranging.

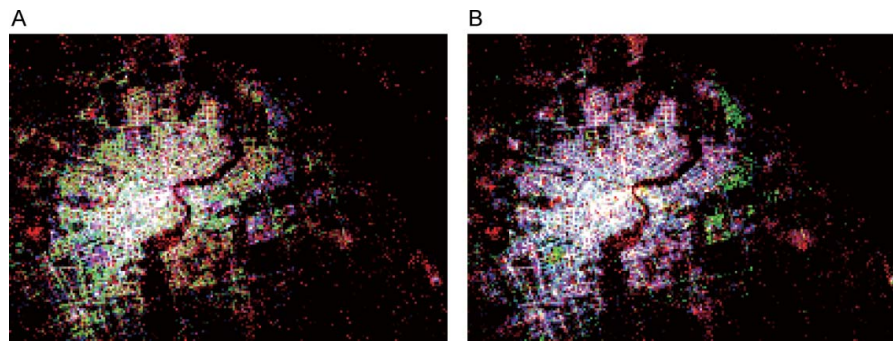


Figure 3. False color composition of three social sensing data source during different times: (A) 8:00 a.m.–9:00 a.m.; (B) 8:00 p.m.–9:00 p.m. (Color figure available online.)

green zones correspond to residential areas, where people leave home in the morning. These zones are purple or blue in the evening, indicating that both check-in and drop-off activities are high. Such synthesized images provide much land use information besides the previously mentioned patterns. Hence, we can use supervised or unsupervised classifiers to extract land uses, which we suggest are more reliable than those obtained from remotely sensed data because the source data directly capture human activities. A number of studies have been conducted in this vein (Liu, Wang, et al. 2012; Toole et al. 2012; Pei et al. 2014), but most of these studies focus on single-source data and do not take into account the fusion of multisource data.

Figure 3 demonstrates the similarity between social sensing and remote sensing. It suggests that well-developed remote sensing techniques can be applied in processing social sensing data and these two data sources can be integrated to gain a complete picture of

geographical environments. For the first aspect, in addition to aforementioned classification studies, other remote sensing methods such as calibration and enhancement, feature selection, data fusion, and image segmentation have the potential to be applied to social sensing data. For example, principal component analysis (or the Karhunen–Loève transform) has been used for finding the major components, which depict different land use aspects of the study area (Reades, Calabrese, and Ratti 2009; J. Sun et al. 2011). Besides directly providing methods, remote sensing is also a source to enlighten us to conduct similar studies. For example, numerous indexes such as the normalized difference vegetation index (NDVI) have been proposed. Accordingly, we can estimate happiness index (Mitchell et al. 2013) and demographical properties (L. Li, Goodchild, and Xu 2013) from social sensing data. Here we list only a few examples and believe that more analytical methods will be developed for social sensing data.

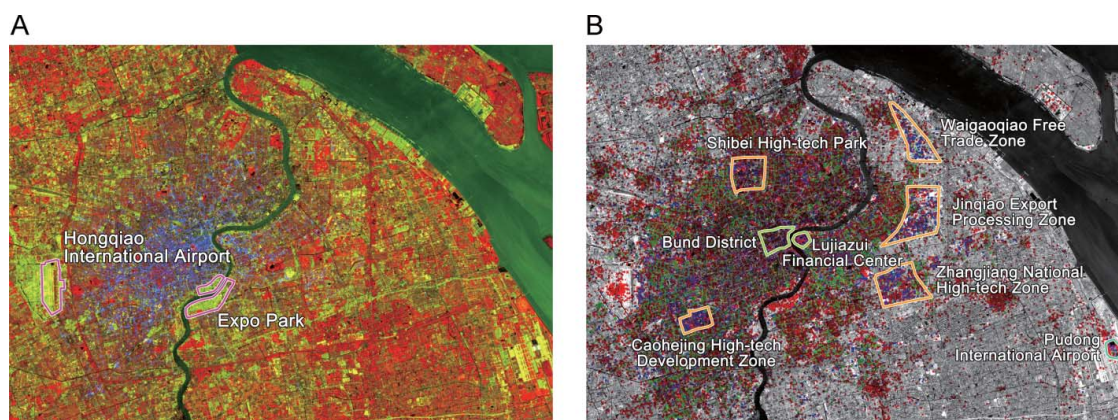


Figure 4. (A) False color composite imagery of 2010 ETM data of Landsat 7 and taxi drop-off data, where band 4, band 3, and drop-offs are represented by red, green, and blue channels, respectively. (B) Fused imagery by color transformation method: The low-resolution data are the RGB image composed of check-ins, pick-ups and drop-offs from 8:00 to 9:00 in the morning, and the high-resolution data are a Landsat 7 panchromatic image. RGB = red, green, blue. (Color figure available online.)

Second, social sensing helps to solve the problem of “inferring land uses from land cover characteristics” in remote sensing applications. We can get land cover information according to the spectral characteristics from remote sensing data and human activities and movements from social sensing data. Information extracted from the two different data sources can validate each other to yield more precise results. With regard to integrating social sensing data with remote sensing data, the conventional approach for fusing remote sensing data and non-telemetric data is taking non-remotely-sensed data as a band of remote sensing image. Figure 4A is a false color composite image with the combination of ETM4, ETM3, and drop-offs from 8:00 a.m. to 9:00 p.m. The regions in red are covered by plants and the purple built-up areas are high activity densities. It is interesting that the yellow zones are in general built-up areas with low activity densities denoted by drop-offs and thus highlight certain regions with special functions, such as Hongqiao Airport and Expo Park. When we analyze social sensing data, the spatial resolutions are generally ranging from tens of meters to hundreds of meters, which are relatively lower than high-spatial-resolution remote sensing data. Hence, we can merge high-resolution panchromatic imagery with social sensing data to increase their spatial resolution. An illustration is visualized in Figure 4B. We get a new RGB image based on Figure 3A with the spatial resolution of 90 m and use a color transformation method to fuse the Landsat 7 panchromatic image with the RGB imagery. From the fused imagery, we can clearly find some regions with high densities of check-ins and drop-offs, whose colors are mixtures of red, blue, and purple. They are generally big development zones, commercial areas, and public transportation facilities.

Issues in Using Social Sensing Data

Conventional remote sensing data suffer from the limitation of capturing human factors when used in socioeconomic applications. Such a limitation can be compensated for by integrating remote sensing data with social sensing data. A number of issues should be paid attention to when using social sensing data, however.

First, to compute the temporal variations of activities, the study area should be discretized into regular or irregular units. Although some research based on mobile phone records directly deals with Voronoi

polygons generated from base towers, many existing studies use regular rasterization with a coarse spatial resolution—for example, 0.25 km^2 (Reades, Calabrese, and Ratti 2009) and 1 km^2 (J. Sun et al. 2011; Liu, Wang, et al. 2012; Toole et al. 2012)—to investigate land uses. The resolutions are much lower than those of widely used remote sensing data. Unfortunately, increasing the spatial resolution will bring difficulties in analyzing social sensing data. As an extreme case, Figure 5A depicts a high-spatial-resolution remote sensing image of Pudong Airport and vicinity in Shanghai, China. A 1 km^2 square is drawn using thick red lines, and the size of each small square is $250 \times 250 \text{ m}^2$. It is natural that human activities should be linked with buildings, the size of which is close to 1 km^2 . When using taxi data to measure activities in this area, however, both PUPs and DOPs concentrate in a relatively small area. If adopting a spatial resolution of 250 m, a discontinuous result will be obtained. For pixels corresponding to the building, some contain high activity frequencies but others are blank. Figure 5B illustrates a fictitious urban environment, where four activities, including mobile phone calls, taxi pick-ups and drop-offs, bus pick-ups and drop-offs, and social media check-ins, exhibit greatly different distribution patterns. For example, both pick-ups and drop-offs can only occur in streets. Additionally, it is natural that bus pick-ups and drop-offs are more concentrated. On the contrary, mobile phone calls frequently occur within workplaces, and social media check-ins often occur at entertainment and dining establishments. In sum, the local spatial heterogeneity of different activities leads to sharp distribution gradients and makes the regularities unclear if a high spatial resolution is adopted. Hence, we should choose a coarser resolution to smoothen the activity distributions.

Second, the spatial distributions of most activities extracted from social sensing data are positively correlated with population density (Kang, Liu et al. 2012). As shown in Figure 1F, the spatial distributions of human activity frequencies suggest that most activities are concentrated in a small area, which roughly corresponds to the downtown of Shanghai. Hence, the data in Figures 1B, 1C, 1D, 3A, 3B, and 3C are all obtained using a logarithmic transform for better visualization. In urban fringe areas or rural areas, however, the activity density is relatively low and thus leads to the problem of small numbers. In such areas, the temporal variations are rather random, and we cannot find a representative pattern after normalization. Figure 6A

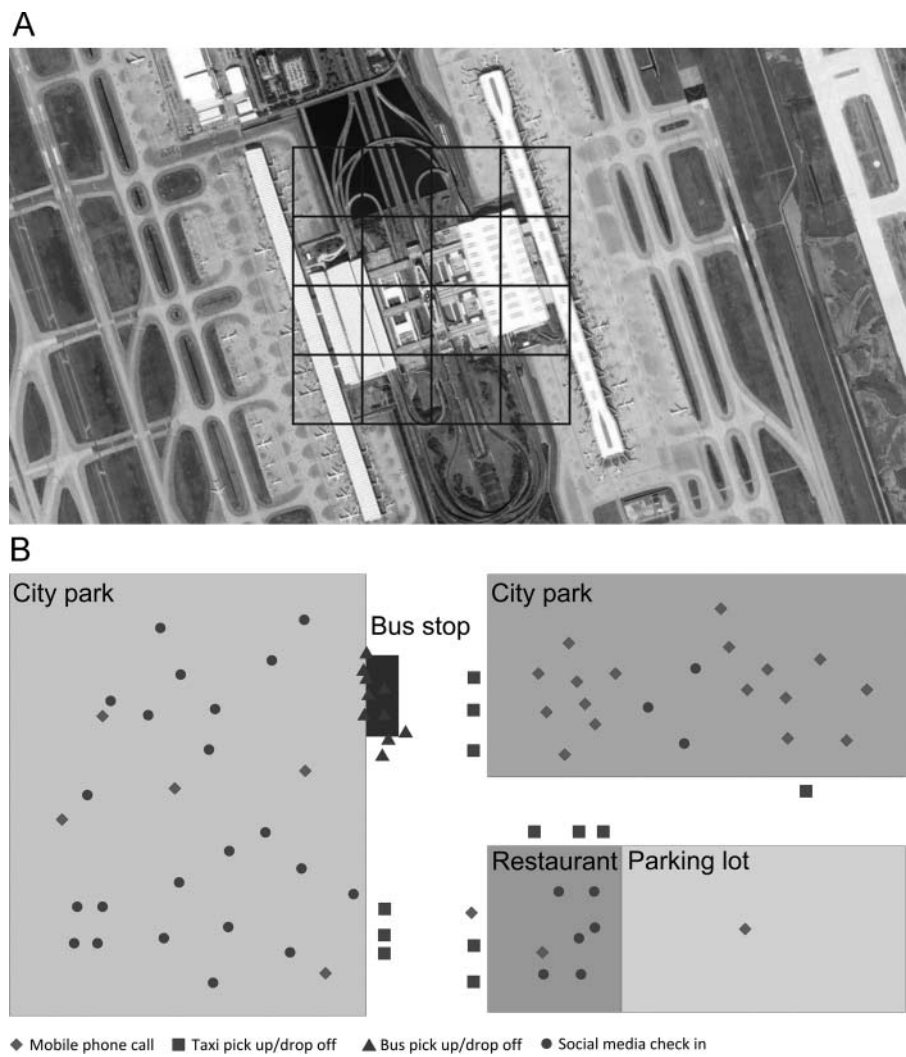


Figure 5. Spatial resolution issue of social sensing data. (A) A case of Pudong Airport, Shanghai. (B) Local spatial heterogeneity of activities captured by different social sensing data.

depicts the normalized temporal variations of check-ins inside two pixels in suburban areas (cf. points C and D in Figure 1A). The two curves are quite different, so the two points are likely to be categorized into

two land uses. When compared with pixels in urban areas, however, the absolute numbers of check-ins are very small, meaning that the two curves are flattened and it is difficult to find meaningful temporal patterns

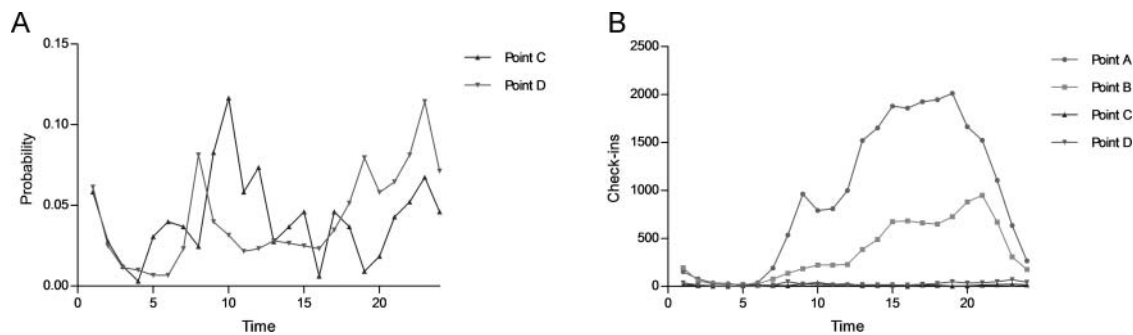


Figure 6. (A) Normalized temporal variations of check-ins inside two pixels in suburban areas. (B) Absolute temporal variations check-ins inside four pixels, two in urban areas and two in suburban areas.

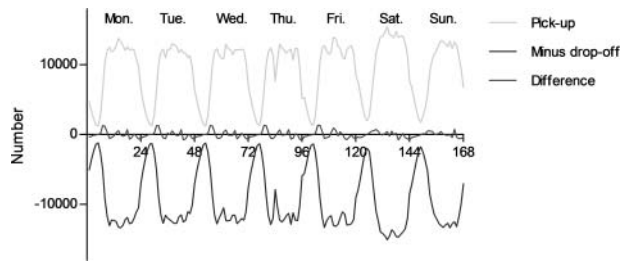


Figure 7. Global temporal variations of pick-ups and drop-offs in seven days. Because the two curves of pick-ups and drop-offs are quite similar, we use negative drop-off volumes to differentiate them.

(Figure 6B). Figure 6 demonstrates that both the relative and absolute temporal patterns can be used to reveal the underlying land uses. Pei et al. (2014) provided a good example of combining the two types of temporal variations. As a general rule, the total activity numbers reflect land use intensities and the temporal patterns depend on land use categories. Figure 6 also suggests that in rural areas, where human activity density is relatively low, social sensing data are not an effective measure of human activity. Last, considering such a spatial distribution, a varying resolution tessellation scheme might be more reasonable, although most existing studies have adopted regular rasterization. Future studies might adopt a fine resolution scheme in urban areas and a coarse one in suburban or rural areas.

Third, social sensing data might also encounter temporal issues. Current land use classification research is founded on the idea that land parcels classified in the same use category exhibit similar diurnal patterns of activities. Additionally, given a place, it is assumed that the temporal curves on different days are also similar and exhibit high regularity. Hence, most studies compress the data spanning a long period into a twenty-four-hour curve (cf. Figure 2). The assumption generally holds true. Slight differences, however, can still be found from day to day. Figure 7 plots the global temporal curves of Shanghai pick-ups and drop-offs in seven days. Some outliers exist, although the periodicity is rather clear. For example, there are more taxi trips on Saturday and people begin their trips a bit late on Sunday. These two tendencies make sense given the common weekend habits of many people. On Thursday, the number of trips rapidly declines in the morning after 9:00 a.m.; we have not found a reasonable explanation for this anomaly but suspect that it might be caused by a special event. Outliers can be identified from global patterns, not to mention local

patterns, which are less stable. The day-to-day changes in trip volume can be attributed to two aspects: special events and long-term dynamics. It is natural that in different seasons, the activity rhythms are different. Additionally, urban evolution, which includes sprawl and land use transition, influences local temporal patterns. Averaging diurnal patterns can filter noise in the data set but ultimately fails to capture these two dynamics. For many geographical applications, the latter aspect is more important. **We need to decouple short-term variations and long-term variations in social sensing data.** The data sets used in most current research cover a short period such as one month and thus the problem is not serious. With the accumulation of various big data, we can reveal regional evolution in addition to land use distributions.

Fourth, most existing temporal pattern studies are conducted based on the data collected in a single city such as Rome (Reades, Calabrese, and Ratti 2009), Shanghai (Liu, Wang, et al. 2012), or Boston (Toole et al. 2012). Little attention has been paid to intercity comparisons. Can we set up a uniform temporal signature database that stores the “standard” temporal curves associated with different land uses, just as we have done for remote sensing data processing? The answer is, unfortunately, negative. Given a city, the overall rhythm depends on its social, cultural, and economic features. The temporal signature of a particular activity is constrained by the overall rhythm. As shown in Figure 8, the diurnal activity variations of various cities are not identical, although some common patterns can be found. For example, the curves of most cities have two clear “peaks,” corresponding to 12:00 p.m.–1:00 p.m. and 6:00 p.m.–7:00 p.m. Such a pattern has also been reported by Cheng et al. (2011). Given a land use category, the difference between two cities might be more significant than those between different land uses inside one city. This makes it difficult to extract universal classification roles across cities. For this reason, unsupervised classification methods are widely preferred over supervised classifiers for social sensing data. Another difficulty for supervised classification is that delineating training areas from activity distribution maps such as Figures 1 and 2 is difficult due to the lack of standard temporal signatures. The differences between cities’ temporal signatures suggest that we should rely on spatial distributions of activities instead of temporal variations when the study area is expanded to a region containing multiple cities. A recent good study was reported by L. Li, Goodchild, and Xu (2013). They

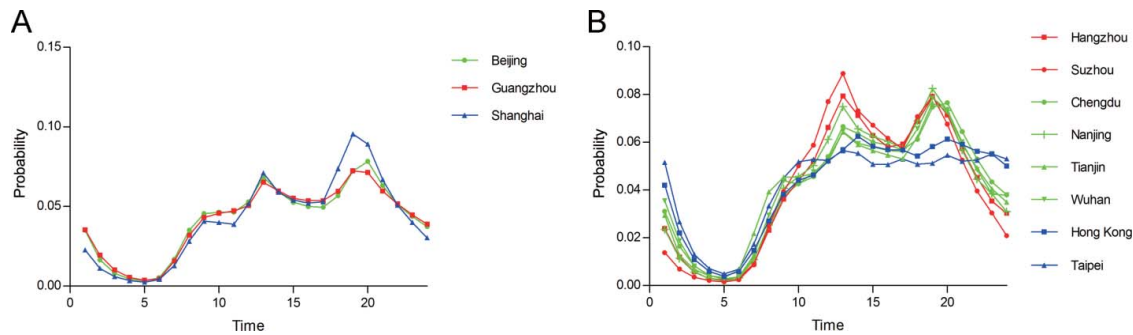


Figure 8. Diurnal variations of check-in activities in eleven top cities in China. The nine cities in mainland China exhibit similar patterns. Slight differences can still be found. For example, the evening check-in probability in Shanghai is high, indicating more night-life activities. In Hangzhou and Suzhou, there are maximum check-ins during noontime. It is interesting and reasonable that the diurnal variations of Hong Kong and Taipei are similar but different from those of mainland cities. (Color figure available online.)

introduced Twitter and Flickr data to investigate socioeconomic features in California.

Fifth, people's actual activities cannot be acquired directly from most kinds of social sensing data. The need to participate in activities generates travel demands (Kitamura 1988; Axhausen and Gärling 1992), and thus detailed activity information is very important in studying human travel behaviors, traffic engineering, and urban planning. The observed activities obtained from social sensing data are “proxy activities” such as checking in on social media Web sites, making phone calls, or boarding a taxi. Thus, compared to conventional travel survey data, most social sensing data contain much less information about people's actual activity types. For example, one could make a mobile phone call when he or she is working, shopping, or at leisure. From the mobile phone data, the user's actual activity when making the call is unknown. Hence, the observed spatiotemporal patterns are composed of patterns of different actual activities, such as in-home activities, work-related activities, and entertainment. Clearly, different activities exhibit different patterns (L. Wu et al. 2014). Decomposing existing social sensing data into actual activities can significantly improve our understanding of human mobility and consequently the underlying socioeconomic environments. Although previous studies have devised methods to infer individuals' actual activities from trajectories based on point of interest (POI) data (Alvares et al. 2007; Huang, Li, and Yue 2010; Phithakkitnukoon et al. 2010; W. Zhang, Li, and Pan 2012; Furletti et al. 2013; Schaller, Harvey, and Elswiler 2014), **uncertainty problems exist and make the related efforts challenging.** On the one hand, it is difficult to ensure the destinations according to the locations where proxy activities

occur, as there are generally many points of interest nearby. On the other hand, the same POI might be associated with different activities. For example, some people go to shopping malls to buy clothes and other goods, but others might want to have meals or meet friends. Additionally, the mapping from actual activities to proxy activities is rather complex. Given a spatial unit and a time interval, suppose there are N persons with M different activities. The numbers of the M activities are denoted by A_1, A_2, \dots, A_m . For a proxy activity denoted by j (e.g., a mobile phone call), the occurrence number is $D_j = A_1P_{1j} + A_2P_{2j} + \dots + A_mP_{mj}$, where P_{mj} denotes the probability of proxy activity j during actual activity m . P_{mj} heavily depends on the actual activity m . For example, people might make many phone calls but seldom check in during work time. Figure 9 plots the temporal curves of different activities extracted from the check-in data. People are more likely to check in during dining and entertainment, and the numbers of check-ins during other activities such as work are considerably small.

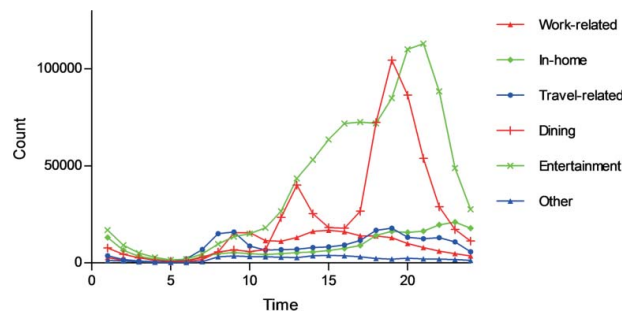


Figure 9. Temporal variations of activities extracted from check-in data in Shanghai. The check-in data explicitly record the type (e.g., restaurant, shopping mall) of place where a user checks in so that we can infer the activity information. (Color figure available online.)

Researchers have also suggested that the temporal signature characteristics of check-in data can help differentiate the POI types (Ye et al. 2011). The preceding equation does not take into account population heterogeneity. Even with the same actual activity, the likelihood that different individuals will complete the same proxy activity varies widely. For example, young people are more likely to check in on social media.

These issues remind us to pay close attention to the representativeness of social sensing data. Different social sensing data capture different aspects of the ground truth, just as in the parable of the blind men and the elephant. We suggest that integrating multi-source data, including survey data, can lead to a better understanding of actual activity patterns.

Beyond Capturing Activities

Besides complementing remote sensing data from the temporal activity variation perspective, social sensing data can be used to extract movements, social ties, and spatial cognition (primarily from social media data) of individuals. At the collective level, social sensing data provide an approach to revealing spatial interactions and place semantics.

Sensing Spatial Interactions

Large volumes of spatiotemporally tagged social sensing data have led to the upsurge of human mobility research (Calabrese et al. 2011; Lu and Liu 2012; Yue et al. 2014). Different patterns have been identified from various data sources and numerous models were constructed to interpret the observed patterns (e.g., Brockmann, Hufnagel, and Geisel 2006; González, Hidalgo, and Barabási 2008; Jiang, Yin, and Zhao 2009; Liu, Kang, et al. 2012; Noulas et al. 2012). It is accepted that human mobility patterns are influenced by factors including distance decay effect, spatial heterogeneity, and population heterogeneity. At the collective level, we can aggregate individuals' or vehicles' trajectories to obtain traffic flows between places. Besides movement, when all individuals have been georeferenced, their connections like mobile phone calls and social ties can be summed up to measure spatial interactions from a new perspective. For example, we can measure the interaction strength between two cities using the number of follower and followee pairs extracted from a social network site. Hence, geospatial big data generated by ICT also have

the capacity to capture spatial interactions. Such a property is different from conventional remote sensing data, in which connections between pixels are not represented. Figure 10 depicts the top twenty-five trip flows originating from point A and Hongqiao Airport computed using the taxi data. The flow volumes represent well the spatial interactions between places, which are $250 \times 250 \text{ m}^2$ pixels.

There is a long tradition of research on spatial interaction in geography. Additionally, data sources such as taxi data were used to measure spatial interactions as early as 1970 (Goddard 1970). Large volumes of social sensing data obviously produce new opportunities for this topic. Studies aggregating individual movements to analyze regional structure from the collective level have also been boosted. Recent literature can be categorized into two spatial scales: intracity scale (Roth et al. 2011; Gao et al. 2013) and intercity scale (Thiemann et al. 2010; Peng et al. 2012; Liu et al. 2014). At the intracity scale, the interactions between land parcels are influenced by the urban geographical environment. People travel in a city from place to place for certain objectives, suggesting that both the relationship between locations and their land uses can be revealed from spatial interactions and temporal activity variations. At the intercity scale, interactions extracted from big data help us to uncover regional structures.

Given a data set, if we partition the study region into areal units, a spatial interaction network can be formed (Batty 2013b). Within this network, areal units can be treated as nodes, and interactions between units are denoted by weighted edges. A number of network science methods including centrality computation and community detection have been developed and introduced to analyze spatial interaction networks. One of these methods, community detection, can identify meaningful subnetworks (subregions for spatial networks) with relatively dense connections. For regional or national-scale data, community detection studies have found that subregions are consistent with administrative boundaries (Ratti et al. 2010; Thiemann et al. 2010; Montis, Caschili, and Chessa 2013; Liu et al. 2014). Community detection methods can also be used to detect highly interactive subregions of a city. Figure 11A illustrates the community detection results of the network based on discretized 1 km^2 grids and the taxi trip flows between them. Most communities are spatially connected, indicating the cohesiveness of each zone with strong internal linkages. Additionally, the spatial continuity of subnetworks can be attributed to the

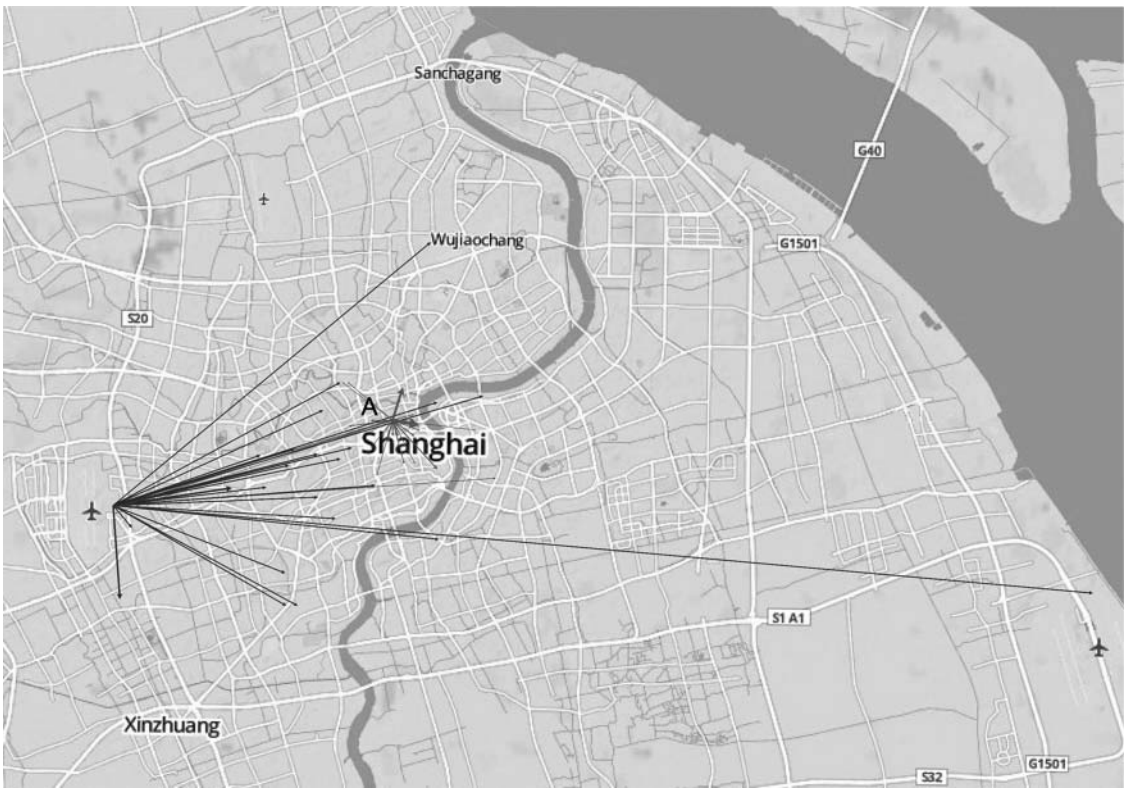


Figure 10. Spatial interactions extracted from taxi trajectories in Shanghai. The top twenty-five trip flows originate from two points: One is point A in Figure 1A within downtown and the other is Hongqiao Airport.

distance decay effect (Liu et al. 2014), which exists in almost all spatial interactions.

We can compare the community detection results with the classification result (Figure 11B) using the methods mentioned in the second section. Both approaches divide the study area into subregions but are conducted based on different measures: similarity and association. The two measures capture different aspects of the relatedness between places and are thus

widely used in regionalization. This case suggests that social sensing data provide more information than temporal variations. Let us revisit the discussion on land use at the beginning of this article. **Spatial interactions can also help improve land use classifications.** Except for temporal activity variations, land parcels of different land use types typically have different interaction patterns. Take residential land parcels, for example: They might have intense interactions with

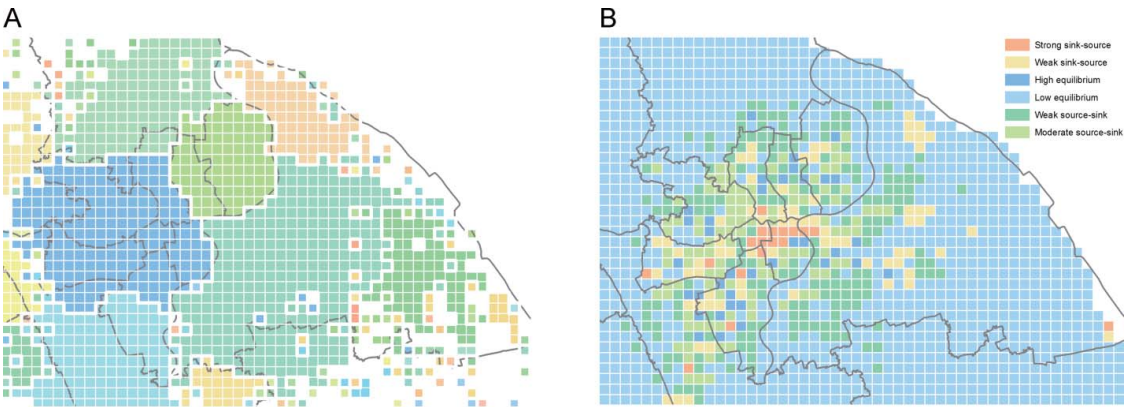


Figure 11. (A) Community detection result of network formed by all taxi flows. The subregions have strong internal interactions. (B) Classification result using temporally sequenced images of taxi pick-up and drop-off distributions (reproduced based on Liu, Wang, et al. 2012). (Color figure available online.)

[illegible]

business land parcels in the morning given that people are moving to their workplaces. These types of spatial interactions could reduce misclassification, particularly for pixels with low activity densities or similar temporal patterns.

Traditionally, human geographers, anthropologists, sociologists, and urban planners have been studying a variety of meanings of space and place to particular people (Tuan 1977; Hubbard, Kitchin, and Valentine 2004). The concept of sense of place indicates a unique identity that is deeply felt by local residents and outside tourists. With the wide use of the Internet (documents, blogs, photos, and videos), a vast amount of user-generated social sensing data with geospatial components has been shared by millions of volunteers (Goodchild 2007). Such big data offer good opportunities for researchers to study how humans perceive,

experience, and describe the world and consequently to represent place semantics (Rattenbury and Naaman 2009). For instance, Crandall et al. (2009) analyzed 60 million geotagged Flickr photos to identify the top-ranked landmarks on Earth and introduced integrated classification methods for prediction locations from visual, textual, and temporal features of the photos. Adams and McKenzie (2013) applied topic modeling on a lot of travel blogs to identify the thematic descriptions that are most associated with places around the world. Similar places can be derived based on the extracted thematic topics. A traditional challenge work of POI matching (or geospatial conflation) from different data sources can be facilitated by integrating multiple spatio-temporal-semantic attributes (McKenzie, Janowicz, and Adams 2014). Using Foursquare check-in data, it is possible to explore neighborhood dynamics (Cranshaw et al. 2012) and city-to-city similarity measures (Preoȕiuc-Pietro, Cranshaw, and Yano 2013) analogue to the use of remote sensing and landscape metrics to describe similar urban structures.

Furthermore, analytics of geotagged tweets offer new insights on the geographical distribution of human sentimental expressions on places and the temporal changes compared with demographic and health characteristics (Dodds et al. 2011; Mitchell et al. 2013; Yang and Mu forthcoming). Compared with capturing activities and spatial interactions where individuals play a passive sensor role, in sensing place semantics, each individual is actively uploads and shares his or her environmental perceptions, which is also helpful to model both activities and social ties.

The collected geotagged photos provide new evidence of the social perspective that few predominant semantic tags have characterized a sense of city. Figure 12A visualizes the 200 most frequent tags extracted from about 384,000 Flickr photos in Paris. These tags demonstrate how people perceive and annotate the characteristics of Paris (e.g., art, architecture, museum, and vacation). Table 2 shows the top twenty frequent geotagged tags in Paris grouped into geographical context, landmark names, place characteristics, urban functions, and time based on their different semantic meanings. Figures 12B and 12C depict the kernel density estimation (KDE) of the geotagged photos associated with the Eiffel Tower and the Seine River. It is clear that the heat maps outline the two places’ influence areas. Such an approach can help to understand the place semantics of cities; that is, we can not only get the spatial footprints of places from geotagged photos but also can derive human cognitive and hierarchal relationships between places that are captured in such social sensing data.

Goodchild (2011) discussed the idea of formalizing place in the digital world and addressed the relationship between the informal world of human discourse and the formal world of digitally represented geography. He argued that “perhaps a new field will emerge at this intersection between digital technology, social science, and digital data. If it does, the concept of place will clearly occupy a central position” (32). The proposed idea of social sensing might be a potential candidate.

Related Concepts

At present, a number of similar but different big-data-related concepts have been proposed, such as volunteered geographical information (VGI; Goodchild 2007), crowdsourcing geographical information (Goodchild and Glennon 2010), and urban computing (Zheng et al. 2014). Aggarwal and Abdelzaher (2011, 2013) used the term social sensing for data collected from location-aware devices, such as Global Positioning System (GPS)-enabled vehicles or individuals. Additionally, some scholars have coined alternative terms, such as people-centric sensing (Campbell et al. 2008) and urban sensing (Lane et al. 2008), that have similar meanings. In this section, we would like to discuss these concepts to highlight the value of social sensing in the context of geographical studies.

Goodchild (2007) introduced the term VGI for geographical data “provided voluntarily by individuals” via Web 2.0 techniques. The term highlights the fact that citizens have become participants in Web content contributions and play the role of sensor. In 2007, smartphones were not widely used and there were few location-based apps. In the 2007 article, the two example VGI applications were Wikimapia and OpenStreetMap, both of which are Web-based. At present, various mobile apps, such as apps for Twitter and Flickr, make it more convenient for individuals to contribute geographical information (Elwood, Goodchild, and Sui 2012; L. Li, Goodchild, and Xu 2013). When uploading VGI, an individual plays the role of an active sensor. For some social sensing data like mobile phone records, however, all individuals’ roles are passive. VGI includes conventional spatial data such as street lines and POI, which contain little human behavior information and are thus excluded from social sensing data. Compared with social sensing, VGI emphasizes a new data collection approach instead of mining socioeconomic characteristics. With regard to crowdsourcing geographical information, we suggest that it is a subset of VGI and is always

Table 2. The top twenty frequent tags extracted from geotagged Flickr photos in Paris

Groups	Tags (count)
Geographical context	France (15,373), Europe (3,909), Île-de-France (1,862), city (1,249), street (923), Disneyland (759)
Landmark names	Louvre (1,174), Eiffel Tower (868), Montmartre (755), Seine (721), Notre Dame (692)
Place characteristics	Architecture (1,486), art (1,406), travel (1,341), vacation (801), French (689)
Urban functions	Museum (1,253), concert (1,097), church (795)
Time	Night (864)

associated with particular objectives such as disaster response (Goodchild and Glennon 2010).

Urban computing is the umbrella term of Microsoft Research Asia for a series of studies that use data generated inside cities. According to Zheng et al. (2014), the data used in urban computing include geographical data, traffic data, mobile phone signals, commuting data, environmental monitoring data, social network data, and data about economy, energy, and health care. The list obviously covers almost all possible data sets, including social sensing data, for studying urban problems. It does not focus on human behavior characteristics. As the term itself implies, urban computing pays more attention to various techniques such as data acquisition, data management, and service providing. A system implementing urban computing is actually a geographical information system (GIS) for a certain city. On the contrary, social sensing roots in geography and thus supports intercity and regional studies (Ratti et al. 2010; L. Li, Goodchild, and Xu 2013; Liu et al. 2014), which are outside the scope of urban computing.

In the field of information technology (IT), **social sensing refers to the integration of social and sensor networks** (Aggarwal and Abdelzaher 2011, 2013). It pays much attention to hardware platforms for data collection techniques such as energy-efficient design. From a geographical perspective, the concept of social sensing extends its implications from the original IT implications to include data management, data analysis, and applications, in addition to data acquisition. The narrow sense of social sensing is obviously the foundation of the broad sense of social sensing due to its capacity of providing various data sources.

After comparing related concepts, we can list some properties of social sensing. First, social sensing data compose an important sector of big data. They capture three aspects of individual-level behavior characteristics: activity and movement, social ties, and emotion and perception. Hence, for a particular person, detailed behaviors could be exposed from geospatial big data. It raises privacy concerns: does big data mean big brother? (Lesk 2013). It is therefore important for researchers who use social sensing data to adopt appropriate protocols to ensure the protection of individual privacy in their studies. The three aspects affect each other and are all influenced by socioeconomic environments (Cho et al.; Eagle and Pentland 2006). Second, at the collective level, we can use social sensing data to uncover the geographical impacts that influence the observed patterns. Current research focuses on land uses (or social functions), spatial

interactions, and place semantics. Hence, social sensing also implies a series of methods for mining different geospatial big data. In this article, we list several methods for analyzing temporal signatures, interactions, and spatial embedded networks. Third, given that social sensing data contain rich temporal information, we can monitor temporal variations from the collected data and identify particular events (Crampton et al. 2013; Croitoru et al. 2013; Tsou et al. 2013). Last, social sensing serves geographical research at different spatial scales. **It indicates that some core theoretical concepts such as scale, spatial heterogeneity, and distance decay should be taken into account when dealing with social sensing data.**

Figure 13 demonstrates a framework of social sensing applications. The inner ring denotes the individual-level human behavior patterns, and the outer ring contains the collective level patterns. Note that the ecological fallacy should be addressed when extending collective-level patterns to individual-level patterns because a big data set covers large volumes of individuals (Liu et al. 2014). Collective-level patterns reflect properties of geographical environments well. The linkages between the two rings suggest that social sensing might provide a new insight into human–environment interactions, the fundamental research topic of geography.

In sum, **social sensing refers to a category of spatio-temporally tagged big data that provide an observatory for human behavior, as well as the methods and applications based on such big data.** The major objective of

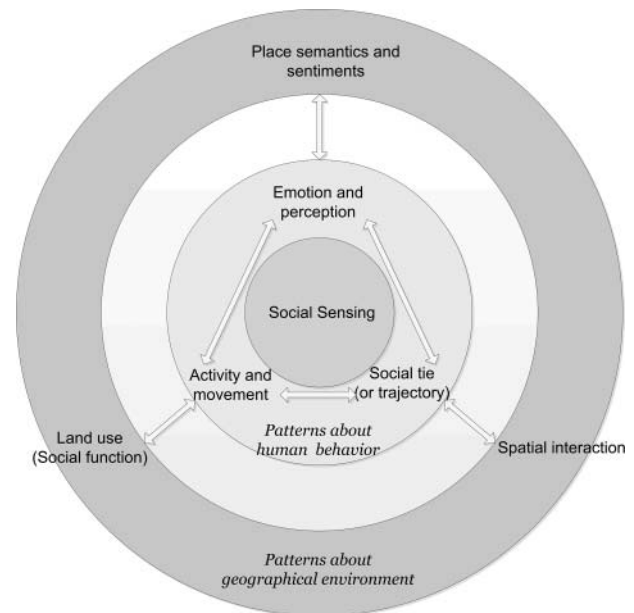


Figure 13. A framework diagram of social sensing applications.

Table 3. Characteristics of four social sensing data sources

Data	Activity	Movement	Social tie	Emotion and perception
Mobile phone records	Mobile phone call	Long-term (e.g., one month) trajectory of individuals; stops are locations where users make calls and the sampling rate is low	Caller and callee	N/A ^a
	Ratti et al. (2006), Toole et al. (2012), T. Sun et al. (2011), Kang, Liu, et al. (2012)	González, Hidalgo, and Barabási (2008), Kang, Ma, et al. (2012)	Onnela et al. (2007), Kang, Zhang, et al. (2013), Gao et al. (2013)	
Taxi trajectories	Pick up, drop off	Detailed short-term (e.g., half-hour) trip trajectory of individuals	N/A ^b	N/A ^a
	Qi et al. (2011); Liu, Wang, et al. (2012)	Jiang, Yin, and Zhao (2009), Liu, Kang, et al. (2012), Yue et al. (2012)		
Public transportation card records	Pick up, drop off	Origin and destination of an intraurban trip	People sharing a same bus or metro car	N/A ^a
	Chen, Chen, and Barry (2009), Y. Gong et al. (2012)	Roth et al. (2011), Long, Zhang, and Cui (2012)	L. Sun et al. (2013)	
Social media check-in records	Check-in	Long-term trajectory of individuals; stops are locations where a user posts geotagged entries and the sampling rate is very low	Friendship, follower, and followee	Textual expressions that contain emotion and perception information
	Cranshaw et al. (2012), L. Li, Goodchild, and Xu (2013)	Cheng et al. (2011), Noulas et al. (2012), Liu et al. (2014); L. Wu et al. (2014)	Liben-Nowell et al. (2005)	Rattenbury and Naaman (2009), Dodds et al. (2011), Mitchell et al. (2013), Gao et al. (forthcoming)

^aData do not contain textual expressions.

^bIndividual-level interactions cannot be extracted from taxi data because passengers are without identifiers.

social sensing is to detect socioeconomic characteristics in geographical space, and it can thus be viewed as a complement to remote sensing. Table 3 lists and compares four types of social sensing data that have been widely applied toward understanding behaviors. Besides the four types of data, a few studies have also introduced bank note records (Brockmann, Hufnagel, and Geisel 2006; Thiemann et al. 2010) and credit card records (Krumme et al. 2012) to extract movement information. Additionally, business world including both conventional retail and e-commerce has been taking advantage of big transaction data to analyze, predict, and customize sales. Therefore, relevant parties can better know purchase patterns and economic statuses in varied geographic regions and different seasons, as well as establish profiles for customer groups or individual customers.

Conclusions

The emergence of big data brings new opportunities and challenges to both GIScience and geography. Kitchin (2013) categorized geospatial big data into directed, automated, and volunteered. In all types of geospatial big data, individual-level information is recorded. The term social sensing proposed in this article has two aspects of meaning. First, it follows the concept of VGI, where each individual plays the role of a sensor (Goodchild 2007). Second, it can be viewed as an analogue of remote sensing that excels at collectively sensing our socioeconomic environments. Social sensing shares much in common with remote sensing. For a social sensing data set, after simple preprocessing, we can obtain a set of temporally sequenced images so

that conventional remote sensing methods can be used. Additionally, because social sensing data and remote sensing data capture different aspects of geographical environments, integrating these two types of data will be an attractive research topic.

In terms of individual-level behaviors, from social sensing data we can extract information about emotion and perception and social ties in addition to activity and movement. These three aspects cover an individual's doing, feeling, and social relations. From a collective perspective, however, land uses (or social functions), semantics, and spatial interactions of places can be obtained. The three aspects interact with each other at both the individual and the collective level. Mining the underlying patterns and revealing the geographical impacts form two major directions of social sensing applications, which in consequence raise several theoretical topics. We suggest that the following aspects are of top priority: data quality and representativeness (Goodchild 2013b), location anonymization and privacy conservation, spatiotemporal scale, combining multisource social sensing data, and linking individual versus collective-level patterns.

From the perspective of GIS, social sensing brings three new data types. The first is temporal images, which can be used to uncover land uses. Second, large volumes of trajectories can be extracted from social sensing data. Although this data type is not emphasized in this article, much research has been conducted for analyzing and visualizing trajectories (e.g., Kwan 2000; Lee, Han, and Whang 2007; Kwan, Xiao, and Ding 2014; J. Li and Wong 2014). Finally, interactions between individuals or places help us to construct spatially embedded networks so that network science methods can be borrowed to analyze them. These three data types all contain temporal semantics and thus form a key component in the space-time integration of GIS and geography (Richardson 2013). A rich number of analytical functions as well as data management and visualization tools are in need for GIS. First, although image processing and complex network methods can be introduced to images and networks derived from social sensing data, we still lack tools supporting trajectories analyses (Goodchild 2013a). Second, even for images and networks, due to the characteristics of social sensing data, existing methods sometimes cannot be directly used. For example, current network tools seldom take into account node locations. Last, the volumes of social sensing data are large and thus raise requirements for high-performance computation (Kwan 2004). A number of emerging

information technologies such as massive parallel-processing distributed databases and cloud-based infrastructure will definitely benefit the use of social sensing data.

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Note

1. From their original meanings, social media and social networking are distinct. In general, social media services (e.g., Twitter) focus on sharing information but social networking services (e.g., Facebook) pay much attention to connecting with others. Both of them provide similar functions, such as posting contents with locational information and maintaining relationships among users. In this article, we simply use social media for these services.

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