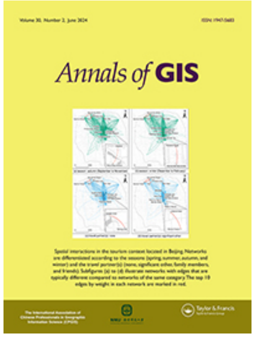

Annals of GIS

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tagi20

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To cite this article: Yu Liu, Shengyin Wang, Xuechen Wang, Yunhao Zheng, Xiaojian Chen, Yang Xu & Chaogui Kang (2024) Towards semantic enrichment for spatial interactions, Annals of GIS, 30:2, 151-166, DOI: 10.1080/19475683.2024.2324392

To link to this article: https://doi.org/10.1080/19475683.2024.2324392

Published online: 06 Mar 2024.

ANNALS OF GIS
2024, VOL. 30, NO. 2, 151–166
https://doi.org/10.1080/19475683.2024.2324392

Towards semantic enrichment for spatial interactions

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ABSTRACT
Various big geo-data provide a social sensing approach to measure spatial interactions. Existing studies often aggregate individual-level movement trajectories or social ties to obtain the interaction intensity between places, neglecting the detailed meanings (i.e. the semantics) behind spatial interactions. However, such meanings help to understand the relationship between two places, and consequently, the characteristics of both places. We argue that semantics can be extracted from spatial interactions through features of space, time, symmetry, and individual-based statistics. Whereafter the calculation and applications of the features are given. Furthermore, we discuss the construction of spatial interaction networks with semantics, as well as approaches to representing places according to spatial interactions. Finally, we illustrate the potential value of spatial interaction semantics in facilitating decision-making through an example in the context of tourism planning.

ARTICLE HISTORY
Received 23 June 2023
Accepted 21 February 2024

KEYWORDS
Spatial interaction; semantics; big geo-data; social sensing

1. Introduction

Spatial interaction is a classic research topic in human geography (Fotheringham 1981; Roy and Thill 2004; Ullman 1980). It focuses on inter-place relationships that can be measured by flows of people, freight, services, energy, or information (J. Wang 2017). Based on observed spatial interactions, we can identify the underlying spatial structure that consists of the linkages, nodes, hinterlands, and hierarchies (Taaffe 2001). On the one hand, spatial interactions connect separated places in geographical space into a system with a certain structure and function. On the other hand, spatial interactions keep changing, reflecting the evolution of geographical features and their spatial structure. Due to the high storage complexity, $O(n^2)$, of spatial interaction data, traditional data collection methods are with higher costs, thus limiting the in-depth analyses and applications. Leveraging multi-source social sensing data, we can conveniently quantify the spatial interaction intensity (Y. Liu et al. 2015). This brings new opportunities for understanding spatial interactions, as well as the networks consisting of multiple places and the underlying geospatial patterns.

In general, two approaches are available to obtain spatial interactions. First, we can extract individual granular movement trajectories based on data such as mobile phone data and taxi trajectories, and then calculate the total flow between every pair of spatial units as the intensity of spatial interaction. Second, we can estimate the interaction intensity by aggregating social ties observed from mobile (or landline) communication and social media friendship (Y. Liu et al. 2020). In practice, the former approach has gained more attention due to richer data sources. For simplicity, we refer to a movement as a flow, which can be abstracted as a vector from starting point $<x_1, y_1>$ to endpoint $<x_2, y_2>$. If the starting and ending times are recorded, it can also be represented as a vector in a three-dimensional space of time and space. As a comparison, spatial interaction refers to the inter-place connections, including flows and social ties, obtained based on aggregation (Figure 1).

As big geo-data have provided great conveniences for quantifying spatial interactions, spatial interaction recently becomes a hot topic in geographical studies. Various data have been used to measure the interaction intensity between geographical units with different spatial scales. Studies based on interaction intensities include identifying the underlying spatial structure behind observed interactions, revealing the driving factors such

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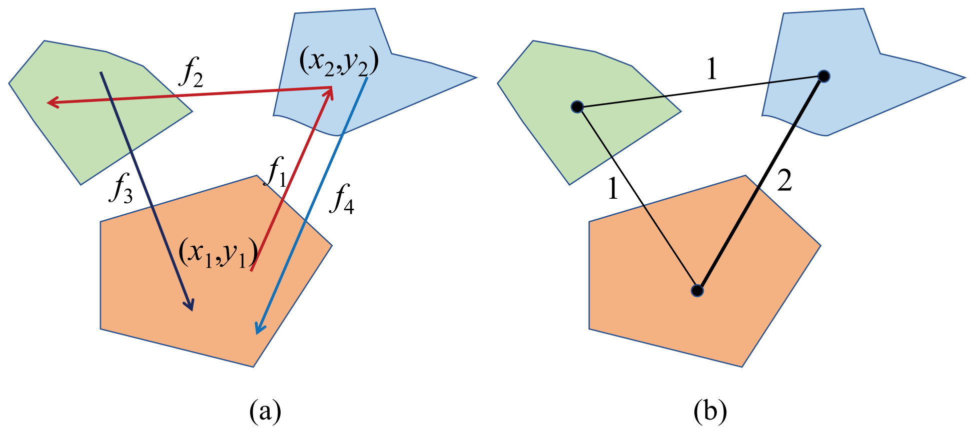


Figure 1. The relationship between flows and spatial interactions. (a) Four individual-level flows between three places. (b) Measuring spatial interaction intensities by aggregating flows. Arrows indicate the direction of flow, and if there are arrows at both ends, it indicates bidirectional flow. The thickness of the line indicates the magnitude of flow, that is, the intensity of spatial interaction. Line colors indicate different types of flows or spatial interactions. These apply to all figures.

as spatial proximity and socio-economic conditions, depicting the dynamic evolution along the temporal dimension and making predictions, and finally applying them to fields such as urban planning, traffic management, and public health. For example, the community detection methods borrowed from network sciences are widely used to uncover the spatial structure of a certain area. Guimera et al. (2005), Ratti et al. (2010), Liu et al. (2014), and Chi et al. (2016) employed the community detection methods to delineate the spatial structure of regions with different scales, ranging from the global to nationwide, provincial, and intra-urban levels. The data sources of these studies cover flight data, mobile phone communication data, social media data, and taxi trajectory data. Regarding constructing models (such as the gravity model and the intervention opportunity model) to explain and predict the interaction intensity between two locations, there are investigations about the distance effect (Liben-Nowell et al. 2005), the radiation model proposed by Simini et al. (2012), and the comparison between the radiation model and the gravity model (Masucci et al. 2013). In a recent study, Ren et al. (2020) quantified the impact of inter-place functional complementarity on spatial interactions.

When aggregating flows based on individuals' trajectories, the time and frequency distributions of these flows are of great significance. Unfortunately, most existing spatial interaction research pays much attention to collective interaction intensities (as depicted in Figure 1), while ignoring the detailed information that can be extracted from fine-grained big data. Hence, it is difficult to deeply understand the attributes of places at both ends of the interaction. We can use social networks as an analogy to illustrate this point. Suppose two pairs of individuals both have 5 phone calls in one month with different temporal distributions. The calls occur on the same day for the first case while evenly distributed within a month for the second one. Clearly, the corresponding interpersonal relationships differ. The former roughly corresponds to two people who communicate due to temporary matters, while the latter often implies a stable and close relationship. Similarly, given two pairs of places, even if the interaction intensity is the same, the differences in semantic features, such as temporal distributions, can distinguish the relationship between places and reveal the attributes of participating places.

Scholars have explored detailed semantics of spatial interactions using different social sensing methods. Kang et al. (2015) investigated the diurnal variations of intracity interactions between traffic analysis zones (TAZs) using Beijing taxi data, and conducted clustering to identify several types of meaningful spatial connections, such as commuting and entertainment. Each type is associated with certain temporal curves of interaction intensity. Schläpfer et al. (2021) delved into the frequency characteristics of spatial interactions and pointed out that they are related to the hierarchical level of urban facilities. However, there is still a lack of comprehensive and systematic understanding of spatial interaction semantics. Therefore, this study proposes the concept of spatial interaction semantics (SIS) and summarizes the computation methods of SIS from various aspects, including space, time, symmetry, and individual-based statistics. Furthermore, we discuss how to characterize places based on SIS and further construct semantic spatial interaction network analysis methods. The proposed SIS framework can serve as a guiding principle for spatial interaction sensing studies and applications supported by big geo-data.

2. Spatial interaction semantics

In the field of linguistics, semantics refers to the meanings contained in language (Kroeger 2018). Regarding information systems, it usually refers to the meanings of a concept (such as the city) or a data set (such as an image). Given that the spatial interaction between two places reflects their relationship, the underlying semantics in spatial interactions help us to understand the meanings of such inter-place relationships derived from flows of people and goods. For example, the relationship between residential areas and workplaces can be represented by commuting flows. Clearly, if the meanings of two inter-place relationships are different, we should observe different spatial interaction patterns. Since semantic features and semantic relations are essential to represent the meaning of a concept (Maggo and Garg 2022), it is valuable to extract spatial interaction semantics from the features of such flows, with the support of big geo-data. Note that the interpretation of semantics depends on users' background knowledge. In other words, the derived semantics vary from person to person. Also, such semantics are application specific. With the same observed features, different semantics may be derived in different applications (e.g. transportation planning or tourism management).

The significance of SIS for geographic analysis is twofold. First, it helps to comprehensively depict the relationship between two locations. Analogous to social networks, two individuals are linked if they have certain relationships. Suppose with more observations, we can somehow determine the concrete social tie types (e.g. kinship and colleagueship) and measure the relationship strength between two individuals, then the social network is with semantics. In other words, the network contains much richer meanings. Second, based on the semantics of all spatial interactions between a place and other places, the characteristics of the place can be comprehensively understood. The above procedure can be formalized as follows. Given places P_i and P_j, the spatial interactions can be represented as a mapping $P_i \times P_j \rightarrow v$, if only the volumes (or interaction intensities) V are considered. However, when interaction semantics are obtained, the range of the mapping is a set of vectors, that is, $P_i \times P_j \rightarrow v, s_1, s_2, \ldots, s_n$. Based on the n-dimensional vectors, the spatial interactions can be classified into m categories, $C_i, i = 1\tilde{m}$. Consequently, employing these categorical labels that align closely with a shared understanding facilitates a clearer interpretation of the characteristics of different places. This procedure embodies a saying in social networks, i.e. 'you can better know a person according to his/her friends'.

While traditional data can only quantify interaction strength, big data can extract rich semantics due to its merit of fine granularity. Especially, spatial interactions measured by human movements contain much more detailed information. A related concept is semantic trajectory (Parent et al. 2013). An ordinary trajectory can be expressed as a sequence of space-time points. In contrast, a semantic trajectory records information such as travel purposes, travel modes, speed, geographical environments, and the demographical properties of the traveller such as gender and age. Hence, it is convenient to extract interaction semantics (Figure 2). Detailed travel information is often obtained using costly travel survey methods. Although big geo-data provide a promising approach to semantic enrichment, they unfortunately belong to a type of 'thin data' compared to travel survey data (Y. Liu 2016) and lack explicit information such as travel purposes. For example, precise pick-up and drop-off locations and times can be

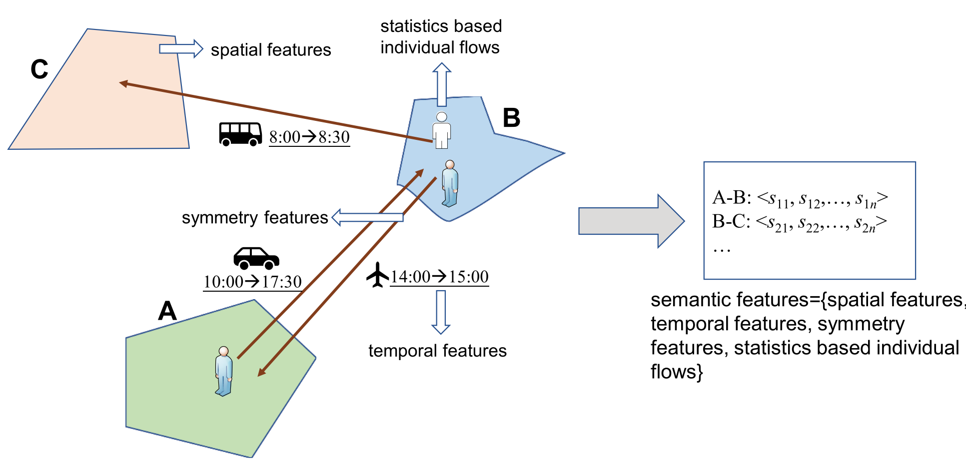


Figure 2. Deriving semantic features of spatial interactions by aggregating semantic trajectories. By considering different aspects of flows, a framework including four types of semantic features can be established.

obtained from taxi trajectories, but the travel purposes keep unknown. A challenge is to infer detailed information utilizing additional clues such as land uses and POI distributions around the drop-off points (Gong et al. 2016).

3. Enriching spatial interaction semantics

Comprehensive analyses of interaction patterns rely on detailed semantics. As shown in Figure 2, we argue that SIS are derivable from the following features besides intensity: spatial features (including distance and direction), temporal features, symmetry features, and statistical distributions of flows (based on different travel purposes, traffic modes, and even demographical characteristics of travellers). Note that the calculation of these features encounters the modifiable areal unit problem, since spatial interactions are generally obtained by aggregating flows between places. The derived semantics are inevitably affected by the places' spatial extents (and time resolution when considering temporal features). The issue is important but not the focus of this research.

3.1. Spatial features

A spatial interaction connects two separate locations, thus endowing the semantic dimension from a spatial perspective. The SIS from locations mainly includes two aspects, namely the distance and direction features derived from the spatial configuration of the two places, and the contextual features obtained from the geographical attributes of the two places, such as similarity and complementarity. It is worth noting that these semantic features are often used to construct interaction models to predict the intensity of interaction between places (Simini et al. 2021). A typical example is the gravity model, which uses the populations of the two end locations to enrich the semantics and then predict the strengths of spatial interactions.

Distance is the fundamental attribute of spatial interactions since it is always related to the cost factor. Generally, the interaction cost between two places is positively related to distance, and thus the intensity will decrease with increasing distance. This is the phenomenon of the distance decay effect (Miller and Miller 2004). The distance decay effect can be quantified by decay parameters, such as β in the power law decay function $d^{-\beta}$. Given a place, the stronger the distance decay effect of its association interactions, the more likely the place is to be connected to nearby places. Conversely, the weaker the effect, the wider the range of the place's influence area. For example, in a city, a large stadium generally shows weaker decay in spatial interactions and wider influence area than a grocery. Hence, the decay parameter serves as a good indicator for evaluating the relative importance of the place. Another important indicator for measuring interaction distance is 'effective distance', which represents the fact that flows and spread of things do not always follow the same distance attenuation law. For example, in the spread of the epidemic, areas with stronger spatial interaction will be more vulnerable, leading to earlier outbreaks. Therefore, the effective distance represented by interaction strength can be used as a substitute for traditional Euclidean distance. This transformation changes previous methods of establishing spatial weight matrices simply dominated by geographical proximity, and improves the accuracy of predicting the outbreak time of infectious diseases (Brockmann and Helbing 2013).

The directional distribution of interactions can be represented by the angles of the directed lines between all pairs of locations. Given a place, such directional distribution reflects its relative location inside a city or a region. In general, the closer a location is to a hot spot or centre of a city, The more even the directional distribution is. If a place is in the outer suburbs or at the city boundary, the associated interactions are anisotropic, i.e. concentrated within a specific orientation range. Hence, interaction directions can help to better understand a location (Yao et al. 2019), and play an indicative role in revealing multiple centres of a city.

The place pair at both ends of a spatial interaction form the 'container' for the interaction. Hence, building second-order measures based on the geographical information of these two places, can define contextual features of the interaction and explain the intensity and other attributes of the interaction. For example, by constructing second-order association measures between venues (such as job-residence complementarity, trade complementarity, urban functional differences, etc.), empirical analyses can be conducted to reveal the internal driving forces and inherent mechanisms of interactions, and consequently, quantify the impacts of different measures on the changes of interaction intensity. For example, Y. Wang et al. (2021) considered the relationship between population migration versus urban development measured by industrial upgrading, and built indicators of similarity and complementarity of industrial structures to estimate the industrial structure impacts on population migration. Ren et al. (2020) introduced functional complementarity indicators into the human movement prediction model. They effectively improved the accuracy of interaction intensity prediction and confirmed the impacts of functional complementarity between place pairs on spatial interactions.

3.2. Temporal features

Features of spatial interactions usually change over time. Taking the intensity of interaction from location A to B as an example, its dynamics can be expressed as $\mathbf{v}_{A\to B} = \left[v^1_{A\to B}, \cdots, v^t_{A\to B}\right]$. The temporal variation of interactions is an important component of SIS. Previous studies have paid much attention to the diurnal cycle of intraurban interactions. Due to the regularity of human mobility, the interaction intensity between different places exhibits stable fluctuations within 24 hours of a day. The temporal patterns are related to the purposes of travels that constitute an interaction, such as commuting to work mostly occur in morning time, and the volume of leisure and entertainment travels is high in evening time (Kang et al. 2016). Hence, the temporal features of an interaction reflect land use properties of the origin and destination, as well as the similarity and complementarity of such properties.

Given a directed spatial interaction, the peak in the temporal curve during the morning indicates 'residence to workplace' or 'residence to school' movements. On the contrary, the peak in the evening implies that the interaction is more likely to belong to 'workplace to residence', 'school to residence', or 'workplace to leisure or entertainment place' travel modes Figure 3(a). If two places exhibit bimodal characteristics during the morning and evening periods, it can be attributed to the following two situations. First, both peaks are for commuting purposes and are generated by two different groups of people. The morning peak indicates that one group of people move to their workplaces from places of residence, and the evening peak indicates that this group returns from their workplaces to their residences. This clearly reveals the phenomenon of home-work separation, which can be measured by excess commuting. Second, the two peaks are generated by different populations and mixed with different interaction purposes. The morning peak mainly comes from the commuting relationship between residence and workplace, while the evening peak corresponds to a mixture of various relationships such as 'workplace to leisure and entertainment place', 'leisure and entertainment place to residence', and 'workplace to residence' Figure 3(b). Understanding the dynamic patterns of inter-place interactions helps to reveal urban spatial structures. For example, Chen et al. (2022) distinguished periodic and non-periodic patterns based on intensity measures within a day, and extracted temporally stationary interactions. Based on these interactions, they constructed a recurrent interaction network to detect the spatial structure within the city (Chen et al. 2022).

In addition to diurnal temporal features, the long-term temporal semantics focus on the interaction changes between two places over a longer time span (such as several years or even decades). While high-frequency spatial interaction changes within a city reflect a relatively stable relationship between two places, long-term and low-frequency semantic features represent the evolution of urban land uses and spatial structures, or the rise and fall of cities at the regional scale. Taking the interaction pattern of Beijing as an example, the Daxing Airport, which began its operation in 2019, has attracted a significant number of flows that were originally headed to the Capital Airport. This resulted in a sharp decrease of flows between the Capital Airport and other places. Meanwhile, the introduction of subway lines connecting the city centre and suburbs typically prompts people to migrate from the centre area to the suburbs due to lower housing prices. Hence, much research has paid attention to long-term changes of spatial interaction networks. For example, Sun et al. (2015)

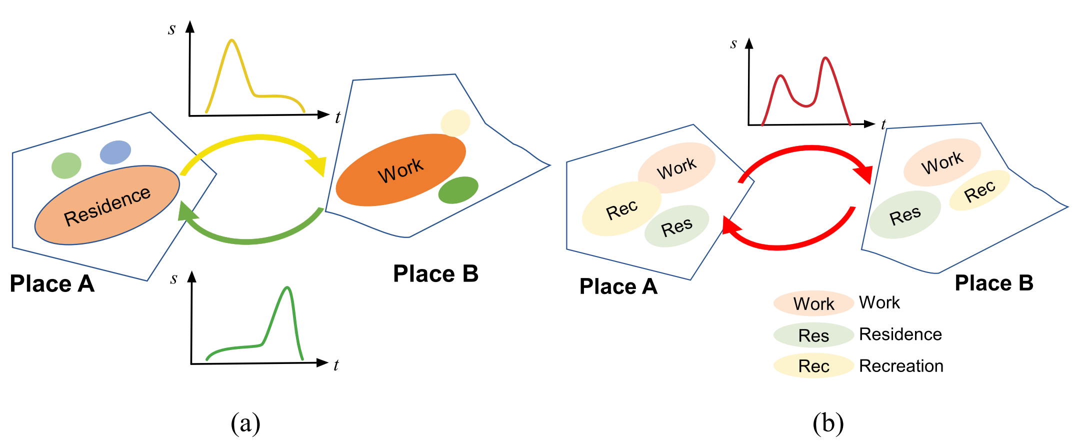


Figure 3. The relationship between temporal features, represented by curve plots, and urban land uses. (a) A relatively ideal case that demonstrates the spatial interactions between residential areas and workplaces. In each one-direction diurnal spatial interaction intensity curve, there is only one peak. (b) In complicated cases with two (or more) peaks, we can identify situations such as home-work separation or mixed land uses.

conducted community analysis on interaction networks spanning multiple years and found significant changes in the urban spatial structure before and after the completion of the expansion project of the Singapore Ring Metro Line. Zhong et al. (2014) conducted a comparative analysis of traffic card data in Singapore from 2010 to 2012, revealing a trend of multi-centre development in the city and the emergence of new sub-centres. These findings reflect the rapid response of spatial interactions to the changes of urban spatial structure.

3.3. Symmetry features

When considering bidirectional spatial interactions between two locations, the symmetry of interaction volume is an important feature. Interactions measured by flows of goods and funds often exhibit asymmetry or even unidirectionality. Given two places, the interaction volumes along the two directions are usually unequal due to the inequality in economic development and industrial structure. In extreme cases, such as the flow of agricultural products, it is generally unidirectional from rural areas to urban areas. Thus, the asymmetric characteristics reflect functional differences or even complementarities between the two locations involved in the interaction Figure 4(a). In addition to the flow of goods, Guo et al. (2022) used web search records to measure the interaction intensity between cities in China, which also exhibited asymmetry.

Regarding human movements, such asymmetry also exists. However, it can be slightly complicated and dependent on the spatio-temporal scale. For example, inter-city movements within a short interval (e.g. 10 days) often exhibit symmetry. This is because most

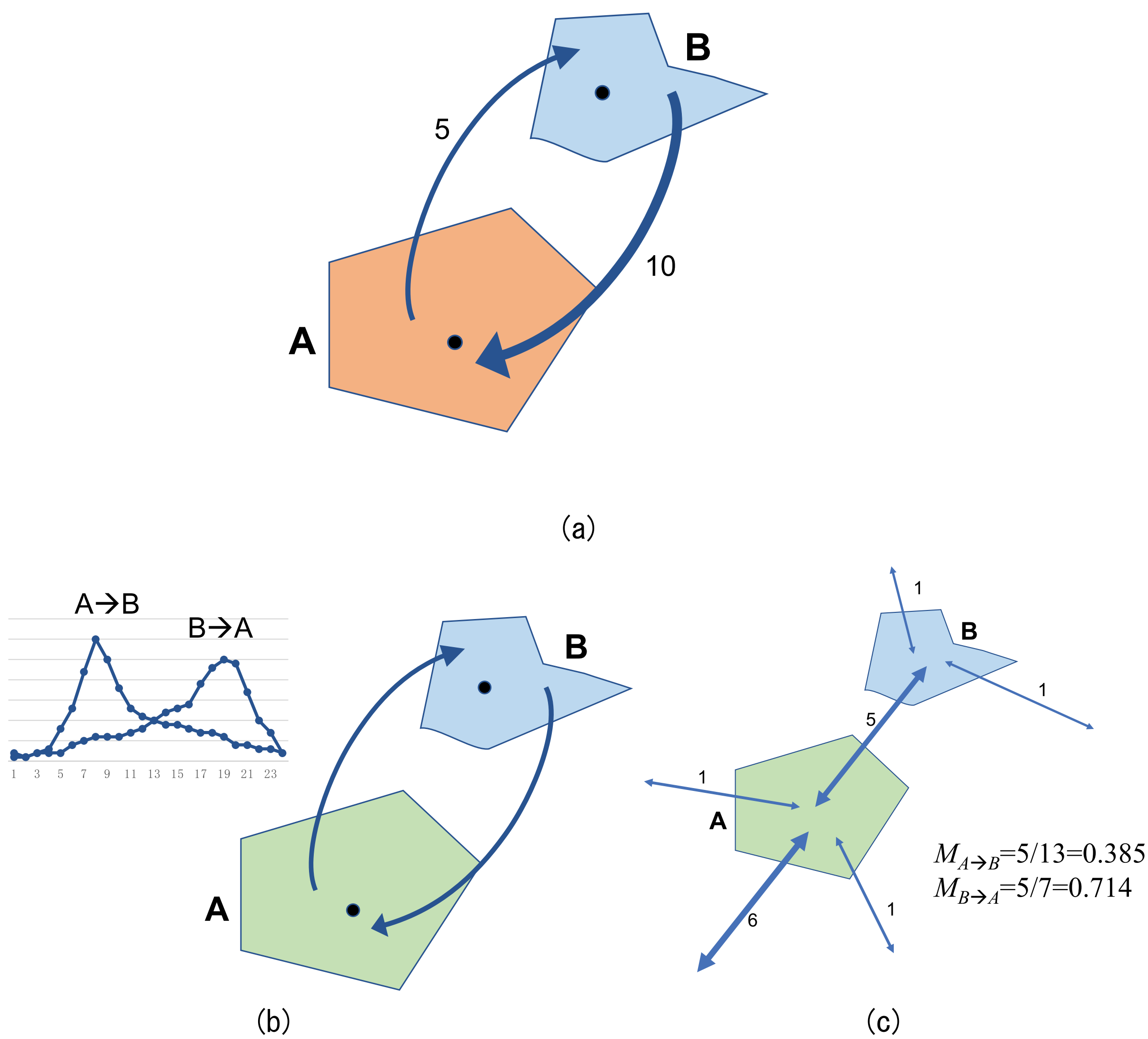


Figure 4. Different types of asymmetric spatial interactions. (a) Asymmetric in total volume; (b) symmetrical total volume but asymmetric in certain time periods; (c) asymmetric relative importance.

intercity trips for purposes such as business, tourism, and family visits often return within a relatively short period. This symmetry indicates a rough balance of flows in both directions. However, when examining the interactions between cities over a long time span (e.g. 10 years), the asymmetric trend of intercity migrations may be observed by identifying areas with net outflow and inflow.

The symmetry features of intracity flows also relates to time scales. Most movements inside a city are round-trips and completed within one day. A typical example is commuting flows (Schneider et al. 2013). If a 24-hour observation interval is applied, the two-way flows between the two locations are roughly equal. However, it is easy to find asymmetry if we focus on specific periods (such as morning and evening peaks). That is, the flow from residential areas to workplaces in the morning is higher than the reverse flow, and this asymmetry will flip during the evening Figure 4(b). With the support of big data, high-frequency human movements can be well observed, thus enable fine time scale analyses of symmetry semantics. Considering the characteristics of residents' travel and the nature of big data, there are three main reasons for asymmetric spatial interactions on a daily scale. First, the travel is not a round-trip (e.g. 'A-B-A'), but rather an 'A-B-C-A' or more complex circular travel chain. In general, the proportion of complex travel chains is relatively low. Second, travels targeting intercity transportation facilities such as airports and train stations may lead to asymmetry, since people leaving the city by plane or rail usually will not return on the same day. Such asymmetry may be more significant during a certain period such as the Spring Festival Holiday. Last, in some special cases, a round-trip travel accomplished by different transportation modes (e.g. taxis and buses) also leads to asymmetry if a single big data type (such as taxi trajectories) is used to extract trips. Liu et al. (2012) found a significant difference in the total number of arrivals and departures in a day between Hongqiao and Pudong airports, using the trajectory of taxis in Shanghai. This suggests that people tend to take taxis to the airport but choose transportation modes to leave, which may be attributed to the longer waiting time for taxis at the airports.

In addition to absolute symmetry based on interaction intensity, the relative importance of the interaction at both ends can also be measured based on the proportion of interaction intensity to the total interaction volume at the two participating locations, which is usually asymmetric. As shown in Figure 4(c), without considering directionality, the interaction strength between A and B is 5, but this interaction is relatively more important for B compared to place A.

3.4. Statistics based individual flows

Since social sensing big data include individual-level mobility data (Y. Liu et al. 2015), the interaction obtained by aggregating individual movements can contain statistical distribution features of different trip attributes, if the information corresponding to each trip is available. Such statistics can be used to analyse the correlation and even causal relationship between different interactions, which further characterizes a comprehensive picture of the relationships between places (Wesolowski et al. 2014; Yue et al. 2018). The travel information includes, but is not limited to: users ID, demographic characteristics (such as gender and age), purpose of travel, mode of transportation, accompaniers.

Among individual flow based statistics, the frequency distribution characteristics of individual trips in an interaction have received a great deal of attention in recent years because of the information they imply about the purpose of people's trips. For example, within a week, the total number of flows between two locations in the city is 1,000 person-times. Whether these 1,000 flows are completed 5 times by 200 persons on average, or once by 1,000 persons, the corresponding specific travel purposes may be very different. The former usually corresponds to commuting behaviour, while the latter is related to general leisure and recreational activities. This is because trips for different purposes have different frequency characteristics for a person: trips such as buying daily necessities may be made once every few days; trips such as watching sports events are reduced to once every few months; while for commuting trips, the frequency is usually higher than for non-commuting trips. Schläpfer et al. (2021) systematically illustrated the importance of individual trip frequency in spatial interactions and found that visitor traffic in an area is inversely proportional to the product square of trip distance r and trip frequency f (i.e. $(rf)^2$). This finding suggests that traffic between two locations within a city can be divided into 'short distance-high frequency' and 'long distance-low frequency' interactions. From an individual perspective, this also suggests that the energy of human travel is conserved: the distance and frequency of people's travel is a process of mutual constraint and optimization. To explain the above findings, the authors introduced a preference exploration mechanism based on the preference return model, i.e. people tend to explore popular locations, thus reproducing the above 'frequency-distance' law and also obtaining an urban spatial structure that conforms to Zipf's law (Batty 2008; Rozenfeld et al. 2011). These results are not only used to predict visitor flows between the two locations, but also validate the well-known central place theory of traditional geography (Batty 2013) and Weber's theory of emergent optimality (Weber and Friedrich 1929).

However, due to user privacy issues, sometimes individual information in social sensing big data is not directly accessible (Kang et al. 2020). A large number of researchers have also sought to infer attribute and travel-related information about individuals through their spatio-temporal distribution of trips (Gong et al. 2016; Schneider et al. 2013; Wu et al. 2019; Y. Zhong et al. 2015), thus indirectly ensuring the richness of interaction semantic information at the individual level.

4. Leveraging semantics in network analysis

Spatial interaction describes the interplay between different objects embedded in geographical space. A spatial network consists of all spatial interactions in a given geographical area, within which each spatial object is taken as a node and the interaction between two different spatial locations is taken as an edge. As such, if two spatial interactions share a node, they generate a connected component. If all nodes are connected, they generate a spatial network Figure 5(a). At the beginning, the topological adjacency is the most commonly used spatial relationship to define the edge in a spatial network. That is, edges only exist between adjacent spatial locations and the entire spatial network is unweighted. In such a simplified representation of spatial network, the complex forms of spatial interaction as well as their rich semantics are not fully considered. Later, the contextualized interactions beyond the topological relationship are utilized to define weighted edges in spatial networks. For example, the intensity of spatial interactions is spatially sensitive, as the connections between certain spatial locations are tighter (Barrat, Barthélemy, and Vespignani 2005). In recent years, as the scale of the complexity, diversity and semantics of spatial interactions revealed in big geo-data increases, spatial network analysis has witnessed many developments that go beyond the paradigm of social network analysis. Apart from the interaction intensity, the purpose, means, speed and context of spatial interactions from a social sensing perspective, as well as the demographic characteristics of the actors in the spatial interaction systems are considered as meaningful for understanding spatial interaction networks. Since different layers of spatial networks can be derived from the

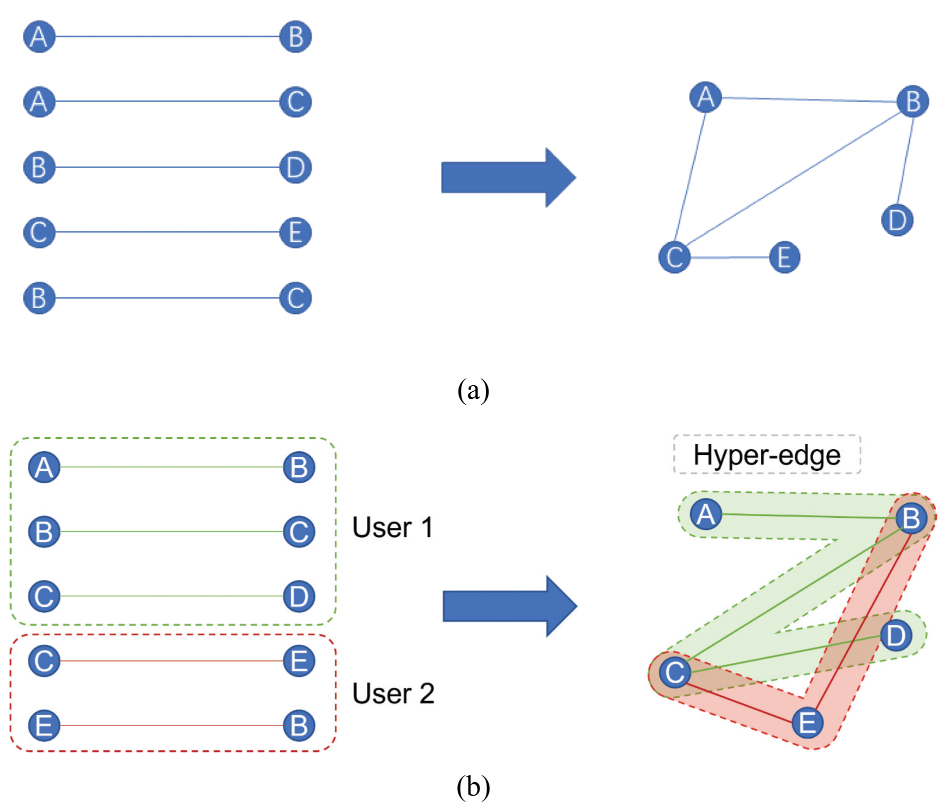


Figure 5. Two approaches to constructing networks from spatial interactions. (a) Place perspective, where two places are linked if there are flows between them. (b) Moving object perspective, where two places are linked if they are visited by the same moving object, such as an individual. In the manner, a hypergraph is constructed.

different forms, contexts and semantics of spatial interactions, the interplays between spatial objects can be more comprehensively analysed. The multi-layer spatial networks that capture the spatial interactions across different time periods and different interaction forms are widely used tools for the analysis of such complex spatial interaction systems. For example, a sequence of spatial networks can be built in consecutive time periods (such as by hours, days, months, and years) to uncover the spatio-temporal dynamics of spatial interactions (Kang, Jiang, and Liu 2022). The interplays between different forms of transport interactions (including taxis, buses and subways) can decouple the substitution, competition, and/or complementation relationships between them in space and time (Yue et al. 2018). Such complex, multi-layered spatial networks have already drawn growing attention in recent years. Additionally, socially sensed big geo-data also showed an ability to capture the complete, continuous trajectories of the moving actors in a spatial interaction system. It thus provides a human-mobility-centric perspective of understanding the spatial interactions between locations. A hyper-edge between multiple locations can be defined if they are visited by a moving subject Figure 5(b). A network that consists of such hyper-edges is termed a hyper-graph that characterizes flow-based semantics of spatial interactions. Moreover, in a spatial interaction system in the form of hyper-graphs, the node can also be defined in varying spatial scales, by aggregating adjacent locations into a hyper-node. By applying network models of hyper-nodes and hyper-edges, it becomes more flexible to address certain fundamental issues in geographical analysis, including the ambiguity of defining spatial entities and the complexity of defining high-order relationships (Kang and Qin 2016; Kang, Jiang, and Liu 2022).

5. Deriving place characteristics

Given the attributes of places and the distances between them, we can predict the strength of spatial interactions. On the other hand, the observed strength and semantic information of spatial interactions also promote our understanding of place characteristics (Batty 2013). Earlier studies achieve this goal through reversely fitting gravitational models, i.e. estimating place repulsiveness and attractiveness according to the strength of inter-place spatial interactions and geographic distances (O'Kelly et al. 1995; Xiao et al. 2013). If we can observe more abundant semantic information beyond the interaction intensity, undoubtedly, the characterization of places will be more precise and comprehensive.

There are two main approaches to characterizing place attributes according to the semantics of spatial interactions. The first approach is to aggregate all relevant interactions for a given place and interpret place attributes with statistical measures Figure 6(b). For example, Kang et al. (2015) found that the temporal distributions of spatial interactions for nightlife places (e.g. Sanlitun) show a significant increase at night from the taxi trajectory data of Beijing. Yao et al. (2019) argued that the average distance of spatial interactions associated with the Capital International Airport is longer than that with other places, and most of the spatial interactions are in the 'southwest-northeast' direction. Such findings are consistent with the geographical fact that the airport is located in the northeast of Beijing's main urban area. In this direction, the flow-based I-index proposed by X. Wang et al. (2021) deserves to be mentioned. If the index of a place is i, it means that there are i flows whose origins are at least αi metres away from the place, while the origins of the remaining flows are no more than αi metres (α is a predefined parameter). Thus, the higher the I-index of a place is, the more attractive the place is. Moreover, a place with a higher I-index also means that it can attract long-range trips, which corresponds to a larger impact area.

The second approach involves learning place representations from spatial interaction networks. Representation learning is a set of machine learning techniques that aims at extracting significant patterns from raw data to create more interpretable features (Bengio et al. 2013). Thus, the learned place representations are supposed to contain features explaining the driving factors of the observed spatial interactions, specifically those associated with place attributes Figure 6(c). In data-sufficient cases, some studies also consider multiple spatial interaction semantics by constructing spatiotemporal interaction networks, aiming to capture more comprehensive representations of places. For instance, Zhou and Huang (2018) introduced the SkipGram (Mikolov et al. 2013) model to learn place representations from manually defined spatiotemporal contexts of places. Results show that features explaining functional attributes of places are extracted from spatial interactions and taking into account more spatial interaction semantics can perform better. Wang and Li (2017) constructed a spatiotemporal interaction network based on taxi flow data and took the inter-place distances into account through a spatial graph. Place representations learned from the graphs above contain information on various place attributes (e.g. crime rates, per capita income, and housing prices).

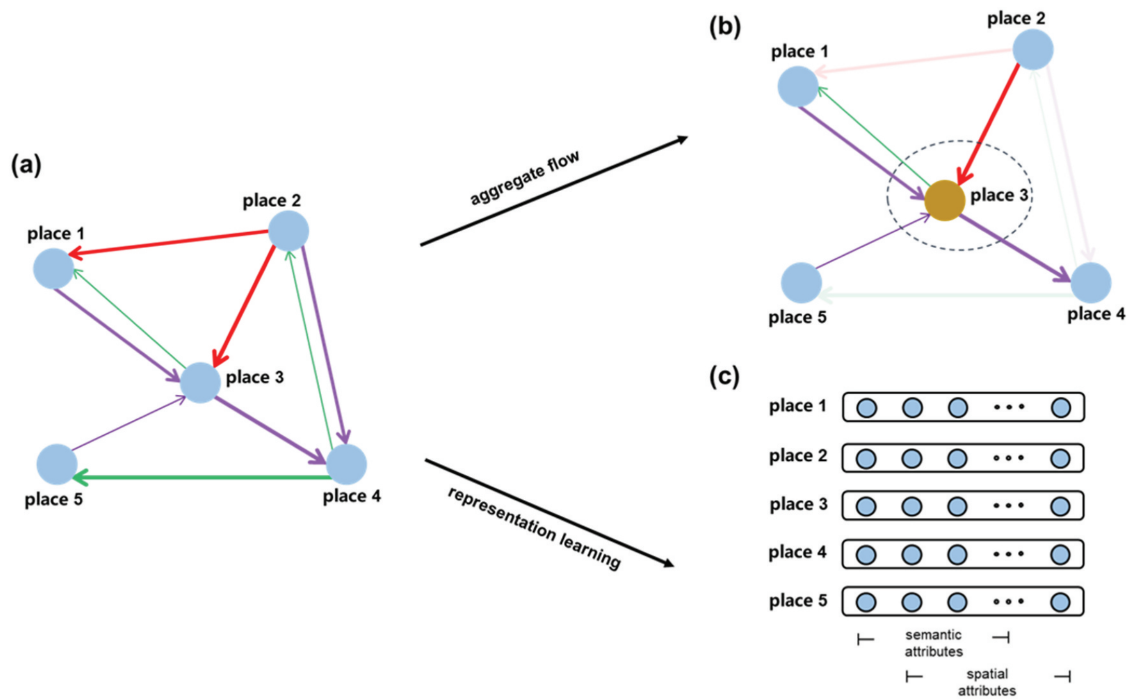


Figure 6. Two main approaches to characterizing place attributes according to the semantics of spatial interactions. (a) A simplified schema of inter-place spatial interaction network. (b) Approach #1: aggregating all relevant interactions (even individual-level flows) for a given place and characterize each place with statistical measures. (c) Approach #2: extracting features that can explain place attributes from spatial interactions with representation learning.

6. Case studies

We present two cases to demonstrate the extraction of semantics from spatial interactions. Both datasets are collected in Beijing. In the first study, we obtained interaction data with temporal stamps between 1418 traffic analysis zones (TAZs) within the 6^{th} ring road area of Beijing. This dataset was provided by China Unicom, one of the largest mobile phone operators in China, and was collected from 7.48 million local users over a three-month period spanning July, August 2018 and May 2019. We retained a total of 14,186 pairs of TAZs' interactions for further analysis, focusing on instances where the daily average intensity exceeded 100, aiming to identify typical temporal patterns. For each pair, the bidirectional interactions generally exhibit different diurnal temporal curves. A typical example is the commuting flows between residential areas and workplaces (Figure 7(a). These flows demonstrate notable asymmetry, with morning peak and the evening peak corresponding to home-to-work and work-to-home commuting flows. Through a deeper examination on the temporal curves, spatial interactions with richer semantics can be identified. Figure 7(b,c) depict two special examples. In general, the morning peak for home-to-work commutes occurs around 8 am Figure 7(a). However, some commuting flows exhibit morning peaks around 10 am, as shown in Figure 7(b). It has been proven that most destinations of these flows are hi-tech firms, which allow employees to adopt flexible working hours. In Figure 7(c), the peak appears around 12 pm, representing spatial interactions between tourist spots, such as the Summer Palace and the Temple of Heaven. The temporal patterns reveal a simple fact that many tourists visit two places in one day and transfer at noon time.

In tourism research, spatial interaction semantics are valuable to understand tourist mobility between attractions. In the second case study, we collected geo-located travel blogs from Qunar.com (https://www.qunar.com/). The website requests travel bloggers to manually input POIs to record the places they visit during their travels. The background information, such as departure date, duration, partners, and consumption, is also recorded in the blog data. Semantics related to spatial features, temporal features, symmetry features, as well as statistics based individual flows can be clearly highlighted through the tourist mobility analysis using the data set.

Regarding temporal features, four spatial interaction networks of different seasons were built according to the departure dates recorded in travel blogs. A noteworthy interaction comes from Prince Gong's Mansion to the

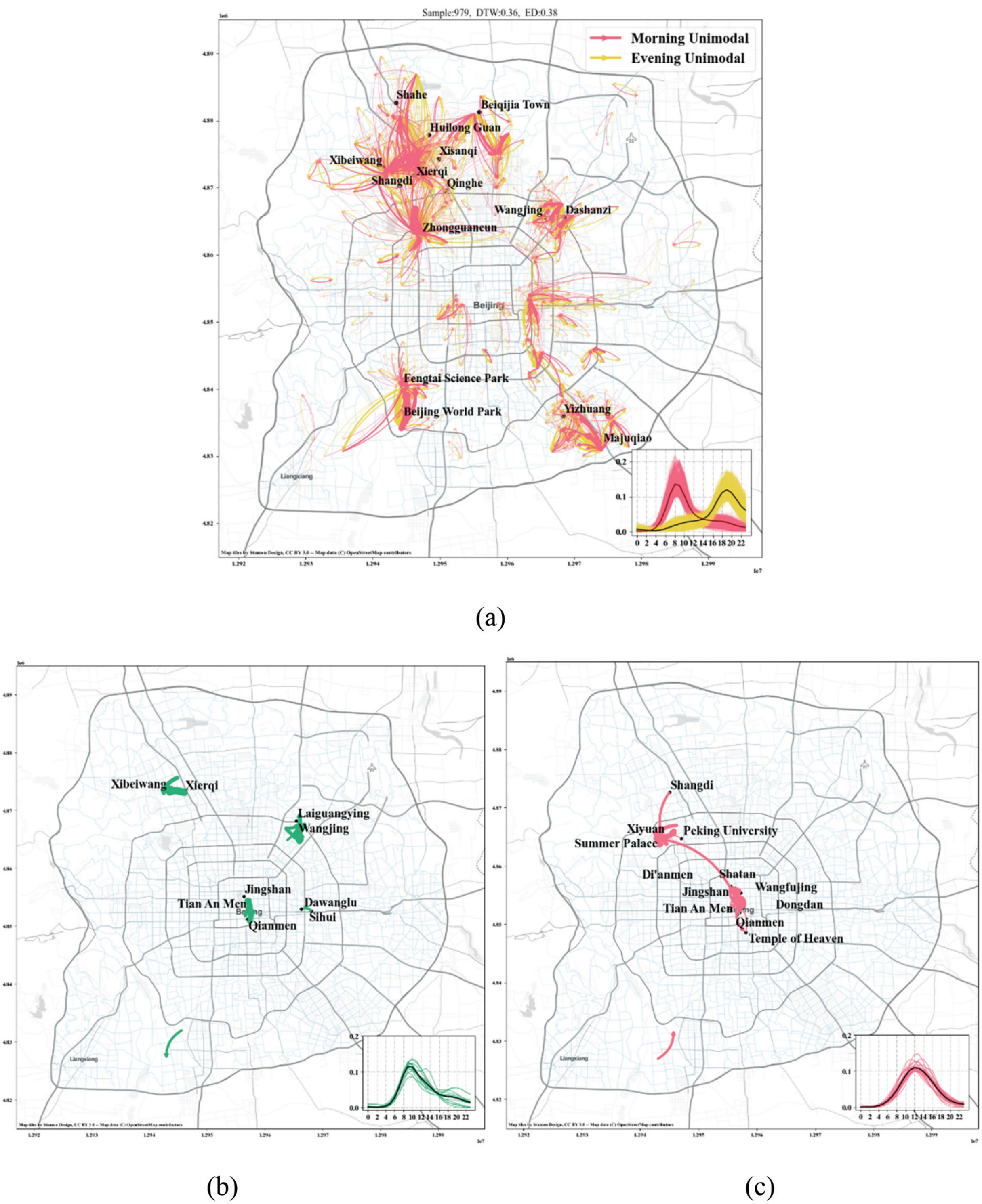
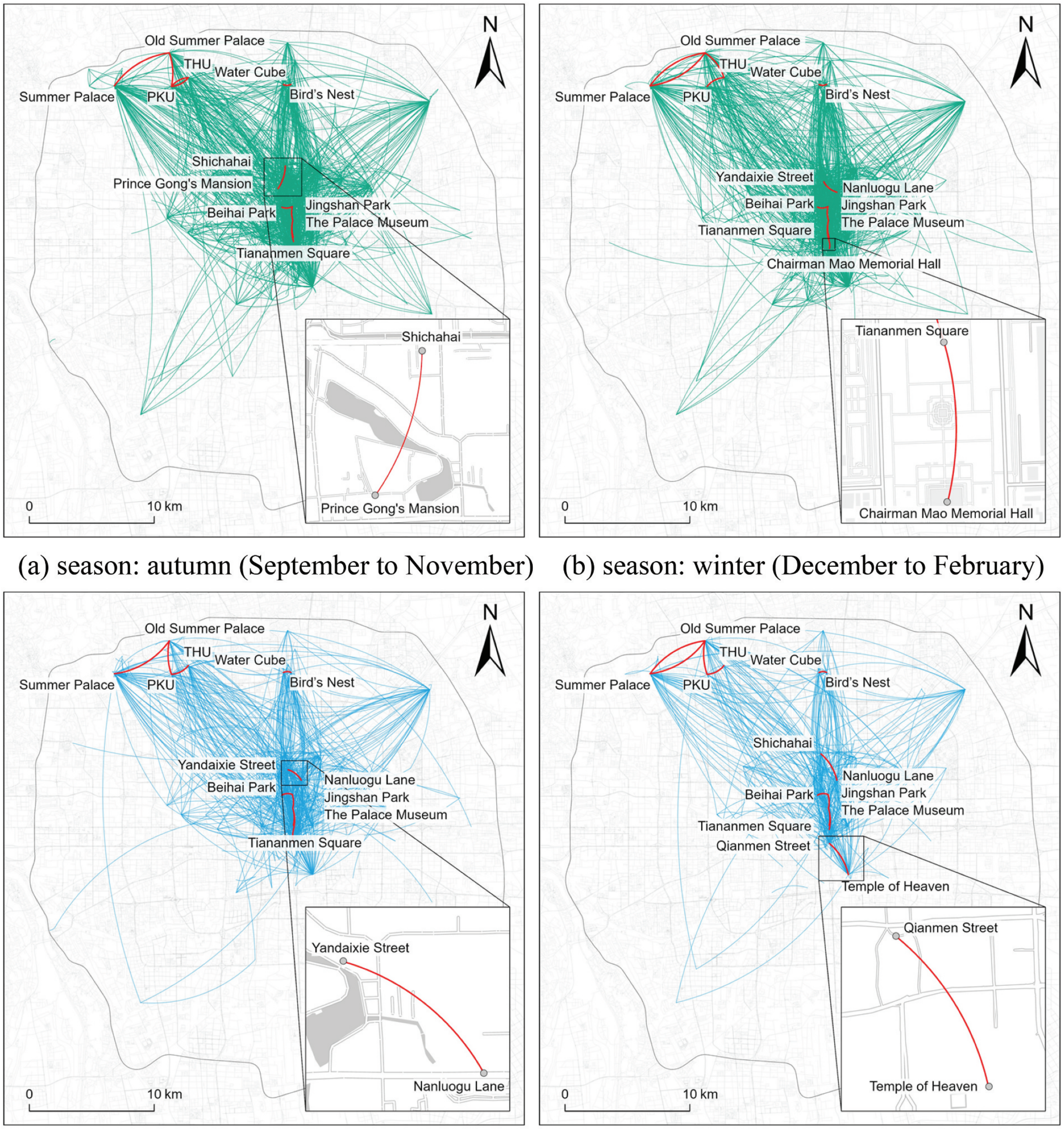


Figure 7. Understanding spatial interaction semantics from a diurnal variation perspective. Given a spatial interaction between two places, the occurrence time of maximum flow volume is an important semantic feature for understanding the spatial interaction as well as the two places.

Shichahai (Park) in the 'autumn' network see Figure 8(a). Both of these locations are famous for viewing the fall scenery (e.g. remnants of lotus) in Beijing. Another special interaction comes from the Chairman Mao Memorial Hall to Tiananmen Square in the 'winter' network see Figure 8(b). Chairman Mao's birthday anniversary is in winter, when many tourists come to the Memorial Hall to pay their respects. This evidence allows the Memorial Hall to interact more strongly with the neighbouring popular attraction Tiananmen Square in winter.



(a) season: autumn (September to November) (b) season: winter (December to February)

(c) travel partner(s): none (d) travel partner(s): significant other

Figure 8. Spatial interactions in the tourism context located in Beijing. Networks are differentiated according to the seasons (spring, summer, autumn, and winter) and the travel partner(s) (none, significant other, family members, and friends). Subfigures (a) to (d) illustrate networks with edges that are typically different compared to networks of the same category. The top 10 edges by weight in each network are marked in red.

We also built four spatial interaction networks according to the bloggers' travel partner properties. These networks can be used to demonstrate how the spatial structure differs when considering SIS expressed by travel partners. For example, the route from Nanluogu Lane to Yandaixie Street is popular among solo travellers see Figure 8(c). The two related attractions are both 'Hutongs' (a special type of narrow alley or lane built in ancient Beijing), which are quite suitable for a solo stroll to soak up the city's atmosphere. Additionally, the movements from Qianmen Street to the Temple of Heaven are highlighted in the 'couples' network see Figure 8(d), while this interaction is not prominent in the other networks. In the real world, the two places involved in this interaction are all popular tourist hotspots for couples.

Empirical tourism research relies on capturing implications from case studies to assist tourism stakeholders, particularly marketers, in their decision-making. Obviously, SIS extracted from tourism flows can effectively help stakeholders improve their decisions. Specifically, the semantics of the spatial interactions between tourism attractions are valuable in designing combined marketing or precise marketing strategies (Mou et al. 2020). Such strategies may be put into practice in the aforementioned case by opening some 'love hotels' as necessary between Qianmen Street and the Temple of Heaven. In Autumn, the visual marketing of fall scenery should be enhanced at attractions with natural landscapes such as Shichahai (Park). It is worth noting that marketers are not the only type of tourism stakeholders, and the same spatial interaction may also have different 'semantics' for different types of tourism stakeholders. For example, for (potential) tourists, spatial interaction analysis can help their route planning by enabling them to know which routes are popular or unpopular for others. Tourism managers might be more concerned with easing and regulating the travel flows corresponding to high-intensity spatial interactions rather than recklessly attracting more visitors therein.

The SIS can also be extracted from spatial and symmetry features in the second case. Figure 9 shows the distribution of the geographical distance and the (directed) spatial interaction intensity between the attractions. The figure demonstrates that the spatial interactions with larger intensities are often relatively short in length, indicating that the spatial interactions in the tourism context are likely to be influenced by the distance decay effect. Additionally, the intensity correlation coefficient for spatial interactions with the same connection nodes but different directions is 0.417, showing the asymmetry feature of spatial interactions. This may be due to the following facts: (1) the ease of access or transportation options may vary in different directions, affecting how tourists visit attractions; (2) tourists have the consistency to follow a particular movement pattern, leading to variations in the number of tourists at attractions in different directions; and (3) different directions have unique platial characteristics that attract tourists.

Similar to our findings in the tourism applications, Leung et al. (2012) pointed out that the structure of the attraction interaction network presented by overseas tourists in Beijing has changed significantly due to the holding of the Beijing 2008 Olympic Games. Zeng (2018) found that the destination interaction networks presented by free independent tourists (FITs) and group package tourists would have different structural patterns. In addition, many scholars have also identified other potential impacts of spatial interaction semantics in tourism research. For instance, Jin et al. (2018), Liu et al. (2023), and Xu et al. (2021) found that spatial interaction networks in the tourism context vary by tourists' trip lengths, modes of transportation, and nationalities. These studies confirmed the value of SIS in tourism studies.

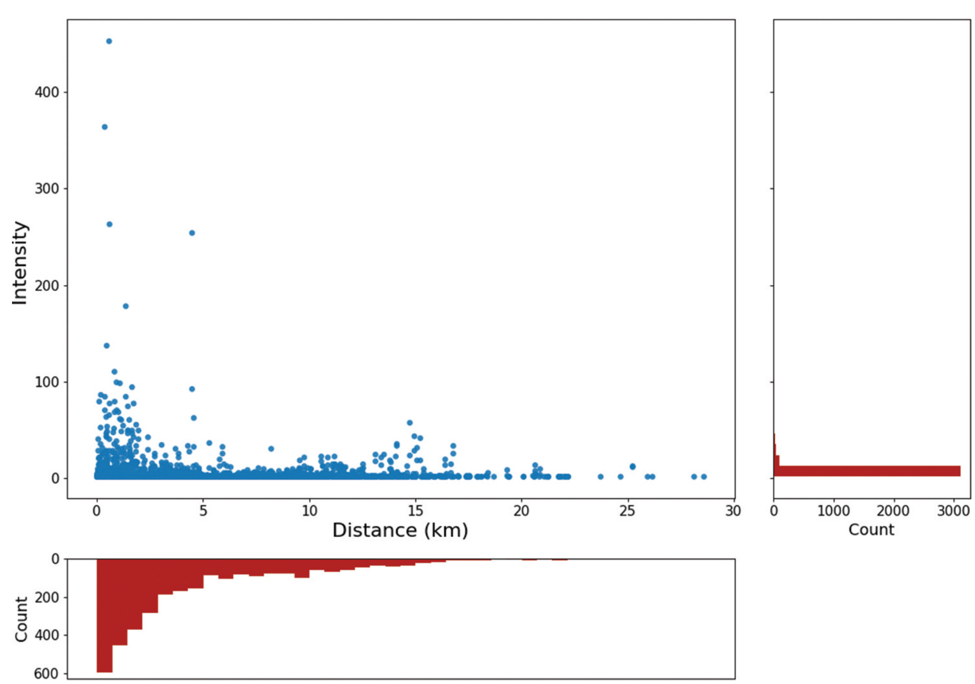


Figure 9. Distance-intensity distribution of spatial interactions.

7. Conclusions

Spatial interaction is a classic topic in geographical studies. Because the storage complexity is $O(n^2)$, the cost of collecting spatial interactions is high, which limits its application in fine spatio-temporal resolution scenarios. The approach of social sensing offered by multi-source big data supports fine-grained measurement of space interactions. However, existing studies often aggregate individual-level movements or connections to obtain the interaction intensity between two places, which aligns with the traditional representation and analysis methods of macro-level interactions. For example, using trajectories extracted from social media data, it is possible to measure the interaction intensity between two cities, yielding results that coincide with spatial interactions constructed using traditional data sources (e.g. air passenger flows) in terms of data models and analysis methods. The drawback of this aggregation approach is the omission of detailed interaction semantic information, thereby not fully leveraging the advantages of big data.

This research calls attention to spatial interaction semantics, which play a significant role in providing a detailed characterization of spatial interactions and even the attributes of places. For instance, when two pairs of places have an equal interaction intensity based on human movements, the differences in various features such as the time of travel (morning or afternoon), purpose and mode of travel, age composition of travellers, and travel frequency, can help us to infer the underlying semantics, which deepen our understanding of the relationships between and attributes of the places. We therefore emphasize the importance of SIS and suggest that when measuring spatial interactions based on social sensing data, it is beneficial to enrich SIS from multiple perspectives, including spatial, temporal, symmetry, and micro-statistical features, in addition to intensity. Notably, many trajectory datasets are 'thin data' and lack semantic information. It is thus necessary to infer additional information using appropriate machine learning methods and construct semantic trajectories to enrich SIS. Although this research pays more attention to spatial interactions measured by human movements, which are in general much richer and valuable, displacements of any objects such as goods or traffic flows (c.f. the example in Section 3.3), and 'movements' in virtual spaces, can also enrich SIS, following the proposed framework.

Based on SIS, a spatial interaction network with semantics can be constructed. Compared to conventional binary 0/1 topology networks or weighted networks based on interaction intensity, it provides a more comprehensive representation of spatial interactions, enabling the analysis of correlations between different features, such as the relationship between travel purpose and travel frequency. Furthermore, by aggregating the SIS of a place or introducing representation learning methods based on the interaction network, we can vectorize places' properties, thereby supporting specific application scenarios.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

National Natural Science Foundation of China [No. 41830645]

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