Chapter 13
Outlook and Next Steps: Integrating Social Network and Spatial Analyses for Urban Research in the New Data Environment

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13.1 Introduction

As illustrated by the previous chapters in this edited volume, the interactions between spatial and social dimensions of the built environment have both conceptual and practical significance. However, many previous studies have adopted social network and spatial analyses separately to understand the built environment. In this book, we hope to put forward a discussion regarding how social network and spatial analyses could be combined for a more refined understanding of the built environment.

The need for such an integration takes places in a new data environment. Urban studies and planning might be approaching a 'technological inflection point' with the rise of information and communications technologies (ICT), smart cities initiatives, and powerful computing devices (Batty 2013; Rabari and Storper 2014;

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Ruths and Pfeffer 2014; Shaw and Sui 2018). The combination of smart cities, open data and open government initiatives, ubiquitous computing, broadband internet, linked sensors, location-based services, and digitally enabled devices has turned the city into a data pool, creating a new data environment for urban research (Offenhuber et al. 2012; Batty 2013; Liu et al. 2015; Shaw et al. 2016; Ye and Liu 2018). This new urban data environment includes open data, big data, as well as emerging data infrastructures (Kitchin 2014). Datasets about urban dynamics are being produced at very fine spatial and temporal scales, oftentimes as ‘data exhaust’ during the operation of websites (e.g., Internet search and online shopping records), social media applications (e.g., Facebook and Instagram), service providers (e.g., mobile phone data), government and non-government agencies (e.g., open government initiatives) (Shaw et al. 2016).

These new urban datasets provide us with useful information to better link urban dynamics in and across physical, social, and virtual spaces. This new urban data environment could provide alternative ways of characterizing theoretical constructs (e.g., urbanity, place, and community), enable new approaches to urban planning and management, and inform new pathways towards urban development and sustainability (Shaw et al. 2016). Although it will not solve all urban problems on its own, this new data environment would help characterize urban dynamics and inform policy and planning at finer spatiotemporal resolutions than before (Glaeser et al. 2016).

Furthermore, the promises and limitations of integrating social network and spatial analyses (with or without the new data environment) have been reflected in related fields, such as sociology (Adams et al. 2012), public health (Emch et al. 2012; Perez-Heydrich et al. 2013), GIScience (Andris 2016), and organization science (Wineman et al. 2009; Sailer and McCulloh 2012). In this short concluding piece, we attempt to discuss the potential for integrating spatial and social network analyses for urban research and try to cover the theoretical, methodological, data, and applied aspects. While we have offered some initial thoughts in a related editorial (Ye and Liu 2018), we would like to further elaborate here the potential and challenges for such integration in the new data environment.

13.2 Possibilities for Integration

13.2.1 Integration of Conceptualizations

A first step in integrating social network analysis and spatial analysis requires the conceptualization of the built environment in terms of nodes (vertices) and links (edges). Nodes and links are the most basic building blocks in network research (Andris et al. 2018; Ye and Liu 2018). As suggested by Poorthuis and Van Meeteren (2018), this entails a ‘nodalization’ process, whereby a complex built environment is rendered "a discrete set of nodes between which interactions are modelled as edges is crucial". For example, in the analysis of networks at the inter-city scale (e.g., the world city network (WCN) approach developed by the Globalization and World Cities Research Network; Taylor and Derudder 2016), individual cities are treated as 'nodes', where flows of goods, information, and people between cities are deemed 'links' between cities. Similarly, road junctions and segments are conceived as 'nodes' and 'links' in the study of street patterns, as evidenced in the Space Syntax literature (Hillier and Hanson 1984).

The key theoretical concern is therefore with the analytical unit, i.e., what are the 'nodes' in the network (van Meeteren et al. 2016; van Meeteren and Poorthuis 2017). More specifically, "the main debates … concerns the choice of 'appropriate' spatial units and the relevance of 'interaction' between these spatial units" (van Meeteren et al. 2016, p. 61). On the one hand, the integration of these two types of analyses needs to be conceptualized and performed on the same analytical units. Spatial analysis tends to focus more on what happens within these analytical units, whereas social network analysis can more aptly analyze the interactions between these units. If spatial and social network analyses are based on different analytical units, we are likely to encounter issues such as the uncertain geographic context and modifiable analytical unit problems (Kwan 2012). On the other hands, the interactions between 'analytical units' must be relevant. In other words, we need to be clear about what the 'network' is and should not use social network analysis for its own sake. Van Meeteren et al. (2016, p. 61) demonstrate these two conceptual issues within the context of urban economics, and post the question that "are cities, regions, or other types of agglomerations the crucial geographical units of analysis if we want to understand economic development or is it better to focus on the interactions between these units, that is, networks of regions, cities and agglomerations, to fathom this conundrum?" Relatedly, in line with the call for 'use-inspired basic research' (Stokes 1997), having analytical units that are commonly understood and used by researchers and practitioners/professionals may ease knowledge exchange and facilitate research impacts.

The discussion about analytical unit has significant theoretical implications, as different analytical units essentially speak to different bodies of theoretical literature (Burger and Meijers 2016). For example, in the discussion of urban systems, Poorthuis and Van Meeteren (2018) suggest that "what we nodalize as a 'city' in urban network models is in fact a complex field of nested and imbricated, yet relatively autonomous, urbanization processes", and that these different nodalizations are respectively in line with different classical theories about the organization of the urban space, such as the daily urban system (Coombes et al. 1979) and Central Place Theory (See also Derudder and Taylor 2017). By the same token, Space Syntax's conceptualization of streets and plans is closely related to the observation that urban form and activities tend to overlap, especially in 'old cities' (Hillier and Hanson 1984).

13.2.2 Integration of Analytics and Methods

With recent ICT advancements, new data sources emerge that are able to capture different types of interactions among people and places. These data sources (e.g., mobile phone and social media data) have provided new opportunities for integrating spatial and social network analyses. At the beginning of this century, debates have emerged regarding how information and communication technologies may (re)shape the relationship between geography and human interactions (Cairncross 2001; Xu et al. 2017). As a result, many studies have started to examine the geographic properties of different social networks. We will narrow our scope here and demonstrate several major empirical ways of combining spatial and social network information. Our examples will mainly be drawn from the emerging field of human dynamics (Shaw et al. 2016).

One common approach is associating individuals within a social network to locations in geographic space (Liben-Nowell et al. 2005; Andris 2016). These locations usually refer to places where individuals' daily activities occur (e.g., home). By doing so, different types of social relationships can be analyzed from a spatial point of view. For example, many studies have found that there are distance decay effects in friendship or the connection strength of members within a social network (Backstrom et al. 2010; Goldenberg and Levy 2009; Xu et al. 2017). By embedding social networks into physical space, these studies have provided empirical evidence regarding how geographic distance and proximity shape social network structures.

Human is the central element that connects spatial and social networks. The behavioral dynamics of human in one type of network is highly related to that of the other. This has inspired researchers to investigate the interaction between social relations and activities of individuals in physical space. By using mobile phone data, Toole et al. (2015) suggest that the visitation patterns of individuals are much more similar to those of their social acquaintances than those of strangers. In another mobile phone based research, Calabrese et al. (2011) find that people who contact each other frequently are more likely to co-locate in space at the same time. Given the strong connection between human mobility and social relations, new methods can be proposed to predict the structure of one network type based on that of the other. For example, relationships of social contacts are proved to provide additional capability of predicting human movements in physical space (Cho et al. 2011). On the other hand, human movements in spatial networks can be used to better predict the formation and evolution of social links (Wang et al. 2011). In other words, spatial and social networks are two interconnected components that continuously shape each other.

Recently, another strand of research has focused on using information in social networks to enrich the semantics of entities in spatial networks. For example, Hristova et al. (2016) propose a framework of interconnected geo-social networks to quantify individual urban locations' social diversity. The approach makes it possible to distinguish places that are attended by diverse groups of individuals from those are frequented by regulars. In another research, Xu et al. (2017) propose two metrics, namely bonding and bridging capabilities, to identify places in cities that bring friends together versus those that facilitate chance encounters among strangers. By integrating social network and spatial analyses, these studies have shed light on the social dimension and roles of places in cities, which will be useful to urban planning (e.g., evaluating people's use of public space) and management.

13.2.3 Integration of Software Environments

Our discussion differentiates several major types of software environments: (1) those developed to handle 'spatial networks' (Barthélemy 2011); (2) those designed for 'social network' analysis; and (3) those generally developed for handling spatial information (e.g., Geographical Information Systems; GIS). Unlike social networks, the nodes and/or links in spatial networks are geographically bounded (Barthélemy 2011). Consequently, there have been different software and tools that handle these two types of networks. Each set of software was developed to solve specific research questions. From the perspective of spatial networks, the theory of space syntax has inspired the development of software for analyzing urban networks (Hillier et al. 1976; Hillier and Hanson 1984; Sailer and McCulloh 2012). Tools such as Axwoman and AxialGen were developed to describe the spatial configuration of complex urban spaces. These tools are often used to assist particular applications in urban design and planning. On the other hand, software such as UCINET and Gephi have been widely applied to visualize and analyze social network structures. Through the usage of these tools, the networks and their structural properties (e.g., small-world and scale-free networks) can be effectively revealed. There are also tools that are capable of analyzing both types of networks. Tools such as igraph and NetworkX have been broadly adopted to analyze network properties at the nodal level (e.g., betweenness and centrality) and to uncover hidden interaction communities (i.e., community detection). Unfortunately, there have been a shortage of tools and research that couple spatial and social network analysis (Ye et al. 2018).

Furthermore, current GIS functions are limited in dealing with network analysis (Andris 2016). For example, ArcGIS—which is developed by ESRI—has been widely used in academia, industry, and government sectors. Although it has incorporated certain functions of network analysis, those functions are designed to solve typical GIS problems such as way finding and vehicle routing. The abilities to reveal properties and dynamics of spatial networks remain quite limited. It is therefore important to identify key research questions that would drive the development of network analysis functions. For example, many mobility datasets such as floating car data and smart card transactions have been used to better understand urban spatial structures (Li et al. 2017). How to effectively measure these urban spatial structures from a network perspective? How to properly represent the urban hierarchy? These are all questions worth investigating. Also, there is a need to incorporate functions into GIS systems that could spatialize different types of social networks (Andris 2016). The functions should also be determined based on critical research questions. For example, critical questions include but are not limited to: how could urban researchers become literate about these new tools and datasets? How are social connections of cities related to other spatial processes (e.g., migration)? In sum, much work remains to be done to define standards and key functions for spatial and social network analyses, and eventually, the integration of the two.

13.2.4 Integration Beyond Spatial and Social Network Analysis

Having highlighted new data and methods for integrating spatial and social network analysis, we want to emphasize that there are opportunities for the integration beyond these quantitative analyses (Ye and Liu 2018). This is most evident in the recent call for integrating quantitative and qualitative studies in the world city network research (Watson and Beaverstock 2014). World city network research concerns both processes within individual cities that have given rise to their world/ global city status as well as the connections between key cities (Sassen 2001; Coe et al., 2010). WCN within the Globalization and World Cities research network (Taylor and Derudder 2016) have been adopting spatial and social network analytics, which range from geospatial visualization, network centrality measures, to generative network models (Liu et al. 2013; Hennemann et al. 2015; Martinus et al. 2015). Recent studies have argued that such 'top-down' and 'structural' approaches to modeling intercity relationships have reached their theoretical impasses (Watson and Beaverstock 2014). Consequently, Watson and Beaverstock (2014, p. 412) have suggested "a move away from structural approaches in which the firm is the main unit of analysis, towards qualitative approaches in which individual agency and practice are afforded greater importance". Although such critiques can be made about any type of quantitative study, they do highlight the importance and possibilities of combining both quantitative and qualitative approaches. That being said, we should be aware of the pros and cons of quantitative analysis of the built environment. Instead, mixed methods might be needed to characterize the complexity of our human-environment interactions.

13.3 A SWOT Analysis of Integration

Next, we would like to offer a SWOT analysis of the integration within the broader context of the new urban data environment. Strength: We may be gradually heading towards the post big data era (Shaw et al. 2016; Ye 2018). Datasets that used to be considered as "emerging" are nowadays available to many institutions and researchers. The volume and diversity of new data, especially produced in urban settings, are continuously enriched by ubiquitous sensing technologies (Xu et al. 2017; Zhang et al. 2018). The emergence of new data sources is also related to a new science of cities, which analyzes urban systems through the analytical lens of networks, interactions, and flows (Batty 2013). Various analytical methods, such as spatial interaction models, scaling, and machine learning, have been used to address questions in global migration (Simini et al. 2012), prediction of social interactions (Wang et al. 2011), and socioeconomic segregation (Le Roux et al. 2017). There have been increasing efforts across different fields (e.g., GIScience, computer science, and statistical physics) to couple big data and relevant techniques/theories for integrated social network and spatial analyses. The integration of the two, however, is still at an early stage and should be motivated by key questions and challenges that we need to address in the contemporary world (e.g., aging population, sustainable urban development, social stratification).

Weakness: While there are many insightful discussions about the consequences of emerging data sources, we would like to highlight that the rise of the new urban data environment is accompanied by an increasingly multi-disciplinary workforce in studying and transforming the built environment (Kitchin 2014; Ruths and Pfeffer 2014; Shelton et al. 2015). For example, major data and information technologies companies are devising 'smart city' toolkits for cities across the world. Internet giants are transforming urban landscape with driverless automobiles and super-fast Internet. Still, major international development agencies are promoting 'big and open data' as the frontier of urban planning and management. This is also related to the many research challenges and opportunities of conceptualizing, visualizing and analyzing new spatiotemporal data (Ye and Rey 2013). On the one hand, the new urban data environment and the increasingly multi-disciplinary workforce make it necessary to remind ourselves of some methodological issues that have be long-researched in urban studies and planning (e.g., bounded rationality, rational planning, and the use of models; Lee 1973; Wegener 1994). On the other hand, as implied above, the inter-disciplinary nature of urban research opens new opportunities for cross-fertilization. For example, O'Sullivan and Manson (2015) have reflected what geographers can learn from geographical research conducted by physicists, and how geographers can build upon the model- and data-driven approaches.

However, different research fields often entail different research methods and subsequent different required skill sets. Researchers in the urban discipline (e.g., urban geography, urban studies, urban planning, and urban design) may need to at least inform themselves about techniques to make use of the new urban data environment. However, critical questions include but are not limited to the following: how could urban researchers become literate about these new tools and datasets? How good a data analyst urban researchers need to become? How could urban researchers best use the new data sources and analytics (see for example, Shearmur, 2015)? How to balance the focus on domain knowledge on the one hand and new datasets and techniques on the other hand, considering the fact that the latter is evolving (Ye 2018)? As an anecdotal evidence, similar questions have raised much discussions at the first ‘Future of Urban Network Research’ Symposium that the first authors has attended.

Opportunity: As hinted above, free access to and wide distribution of the data and source codes facilitate the dialogue and cooperation among computational scientists, urban researchers and the general public, in order to coordinate innovative efforts and advances in theoretical perspectives, analytical approaches, and outreach (Ye 2018). The data-driven urban science’s self-correction power largely rely on the ability of research outcome reproducibility based on the open data and codes of such integration (Ye et al. 2018). The capability of recording individual’s digital footprints has been growing in the emerging open culture. With the growing popularity of smart phones, citizens are acting as ‘sensors’ to synthesize and interpret information from many layers and sources about both the spatial and social dimensions of the built environment (Goodchild 2007). For example, such human behavior can be used to demonstrate how a specific location at a given time period might be attractive and accessible to various groups of people, which is labelled as urban vibrancy (Wu et al. 2018). The relationships between urban vibrancy (through open data such as social media check-in records) and spatial network (such as land-use configurations) can support real-time urban decision making with fine-scale spatial and temporal resolutions. The combination of open data sources and open source codes will set up a rich empirical context in front of our eyes for urban research and policy interventions towards ever-increasing size and diversity of urban data (Ye and He 2016).

Threats: A major downfall of using big data and ‘digital skins’ (Rabari and Storper 2014) to study urban social space may be the over-representation of communities with a sophisticated infrastructure and financially well-off young people. It is noted that there exist many depressed neighborhoods with limited infrastructure and low-income population producing under-represented amounts of digital signals (Ye and He 2016; Ye 2018; Ye and Liu 2018). Hence, the spatial dynamics (ranging from daily to long-term activity) of such biased digital landscape might negatively affect the reliability of information and knowledge retrieved from the new (big) urban data. The integration also faces the challenges of the noise and uncertainty embedded in spatial social network data, which would even increase the chances of misusing or abusing such integration to address specific urban tasks (Shaw et al. 2016). Ye and He (2016) express the concerns towards blindly big-data-driven research, arguing that the embedded uneven local contexts must be considered. Because the integrated analysis of human activities, dynamics, and interactions across social, virtual and physical spaces will possibly raise many concerns in the data security and privacy issues, more ethnical, legal, and technological efforts are urgently needed to avoid a number of threats released by the power of such integration (Shaw et al. 2016). Still, there are legitimate concern regarding confidential information which might be revealed due to spatial and social network analysis integration, especially for those disadvantaged communities and populations (Curtis et al. 2006).

13.4 Conclusion

This century has experienced tremendous strides in physical and virtual interactions across spatial scales. At the same time, the world has been witnessing a growing population size in many urban areas at an unparalleled scale and speed. New theoretical arguments, data sources, and analytical approaches have shaped the restless landscape for bridging spatial and social network analyses of the urban environment in a transdisciplinary and cooperative manner. The research agenda has been markedly transformed and reshaped in light of the cutting-edge information technology and new (big) data. Tracking the dynamics and interactions of spatial system and social system in a joint fashion will facilitate the early detection of events and phenomena in and across the communities. A better understanding of such integrated systems can help predict possible events and their outcomes/impacts in the urban setting. It offers new insight into more meaningful and reasonable policy formation of a livable and sustainable city. For example, policy makers and urban professionals can be better informed about resource allocation and sustainable design of communities (Wu et al. 2018).

With the rise of the new urban data environment, many dimensions and scales of emerging spatial social network data present both challenges and opportunities for the design, implementation, and evaluation of urban policies. However, it is difficult for most urban researchers to use cutting-edge methods due to the lack of the ability to retrieve and process such unstructured large data, let alone being unfamiliar with the open source environment where various contributed toolkit codes can be collected and modified to reflect the need of integrating spatial and social network analytics. Such weakness could become obstacles for promoting spatial-social network thinking, collaboration, and education in respective contexts (Ye 2018). In addition, the changing urban contexts necessitates innovative spatial and network thinking to provide suggestions and strategies for sustainable development (Ye and Liu 2018; Ye 2018).

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