CHAPTER

3

Complexity science for urban solutions

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Introduction

Everyone who lives in an urban environment is (consciously or not) affected by its planning and design. Cities have now been recognized as nuclei for innovation, expertise, and opulence; they can be considered as "concentrations of social interactions in space" (Garfield, 2019). As cities grow larger in population and size, they exhibit three key characteristics—complexity, diversity, and intelligence (Güell, 2006; Camagni, 2003; Fernández-Güell et al., 2016)—that offer a glimpse of both the potential of cities and the problems that they face today.

Many urban issues, ranging from wealth inequity to environmental sustainability, are usually tackled independently of each other (Bettencourt and West, 2010) despite their obvious interdependencies. This practice continues the convention of disciplines following a centralized order, which was largely the norm up to the 19th and 20th centuries (Batty and Marshall, 2012). Urban planning in the 20th century was characterized by a rigorous top-down approach, despite notable critics, including Christopher Alexander, who railed against the simplistic urban models of "tree-like" hierarchies and Jane Jacobs, who called for more diversity and citizen-centric design that reflected the realities of urban life. Facing today's climate emergency, it seems clear that such outdated planning and design strategies are ineffective in satisfactorily addressing many of today's problems.

The need for cities to become smarter in problem-solving cannot be overstated. It is important that concurrent trends in urbanization, economic growth, technological progress, and environmental sustainability act as drivers in urban planning and design thinking processes (Naphade et al., 2011). Batty et al. (2012) call for an "integration that enables system-wide effects to be tracked, understood and built into the very responses and designs that characterize the operations and functions of the city." Christopher Alexander, in "Notes on the Synthesis of Form," details the "use of a structure-preserving mathematical decomposition of complex

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design problems into hierarchies of simpler problems which could be readily solved, then recomposed into a complex solution" (Taylor, 2019). His proposed methodology of automating the deconstruction processes based on a holistic and comprehensive understanding of all the factors (Doug, 1994) has influence on and applications in both the computation and design fields. His intent is similar to that of (Bettencourt and West, 2010), whose approach to the study of cities is to "understand their dynamics, growth and evolution in a scientifically predictable, quantitative way." This highlights the need for and potential of artificial intelligence (AI) in urban planning and design today.

Internet of Things (IoT) technology is already ubiquitous in many cities worldwide, with wide-ranging applications in urban planning and design that are based on real-time data collection. In a more dominant role, AI tools and techniques can be tapped into for tackling multiple issues across urban scales, to integrate a conscious top-down approach to planning with site-specific bottom-up solutions. In the following, we detail a complexity science-based methodology that employs machine learning (ML) to quantitatively analyze spaces and activities in high-density urban built environments, with the goal of understanding the efficacy of their use and shortcomings to inform better future planning and design decisions.

Artificial intelligence (AI) in the built environment

Digitization, through the installation of sensors, computational cores, and different telecommunication systems (Alvarez, 2017), has resulted in an unprecedented scale of urban data generation. It is predicted that by 2023, machine-to-machine (M2M) connections, such as smart meters, video surveillance, healthcare monitoring, transportation, and package or asset tracking, will be 14.7 billion in number or 50% of the total devices and connections (Cisco, 2020). AI can be used, beyond processing such large amounts of data, for cognitive computing integration (Allam and Dhunny, 2019), which makes it pervasive in urban environments and led to the "smart city" concept.

The idea of the "smart city" has accompanied the rise of IoT. Harrison et al. (2010) essentially view it as information and communication technologies that can help cities to address their problems as well as increase their competitiveness and efficiency (Batty et al., 2012). Kitchin (2014) provides one definition of the smart city as "the prioritization of data capture and analysis as a means for underpinning evidence-informed policy development, enacting new modes of technocratic governance, empowering citizens through open, transparent information, and stimulating economic innovation and growth." In the smart city framework, AI can inform urban planning and design processes, e.g., in transport planning, with progress in intelligent transport systems (ITS) and the exploration of automated vehicle technology. AI helps account for unpredictability in transport planning, where users' behavior is too difficult to model by traditional analytical methods (Abduljabbar et al., 2019; Gopalakrishnan et al., 2021). Intelligent prediction methods are used in ITS subsystems such as advanced traveler information systems, traffic management systems, public transportation systems, and commercial vehicle operations (Mahamuni, 2018; Abduljabbar et al., 2019). They are based on the use of historical data that has been extracted from sensors on roads, which is input to ML and AI algorithms (Mahamuni, 2018). AI is also used by ride-sharing service companies such as Uber and Didi Chuxing to predict passenger demand (Yao et al., 2018). Through avoiding empty vehicles, the use of AI in this context can help to reduce energy consumption and traffic congestion. In the long run, the use of AI in smart city planning and design is expected to generate many important benefits for the urban environment and its socioeconomic development.

The use of AI is currently being explored in urban planning and design in many ways. Incorporating ML in cloud-based platforms such as Google Earth Engine and ArcGIS Cloud aCarto has enhanced urban analytical methods through satellite imagery (Goldblatt et al., 2018). AI is also a powerful tool that can support decision-making; through the lens of generative urban design, AI can be used to model processes that lead to a solution to many problems. Quan et al. (2019) have argued that the system as a "smart design framework" has four main components: human problem initialization stage (problem clarification), human-system interface stage (mathematical representation of the problem dimensions), system optimization stage (computational algorithms that drive design exploration) and human-system interaction stage (result interpretation and visualization), in which heuristic algorithms (such as genetic algorithms, simulated annealing, tabu searches, etc.) and other AI search techniques can be used for optimization. Although they are applied more commonly in architectural than in urban design due to the dynamic and complex nature of urban problems (Quan et al., 2019), they allow for providing the planner and designer with multiple urban form iterations to intuit (Gopalakrishnan et al., 2021). For example, street network generation using deep learning techniques has been experimented with (Hartmann et al., 2017). This can influence methods of urban visualization but is currently not widespread in the industry due to the difficulties in interpreting the results (Miao et al., 2020).

AI-aided urban planning and design is both an important tool for improving existing cities as well as a tenet for future cities. A popular example of the use of AI in the generation of a masterplan is Masdar City in the United Arab Emirates, where the planning of personal rapid transit and autonomous vehicle systems was coupled with the planning and design of spaces from the very beginning of the project. Future cities such as Neom in Saudi Arabia and Beiyang AI Town in China will intrinsically link the emergent urbanism and lifestyle with AI techniques (Cugurullo, 2020; Gopalakrishnan et al., 2021).

At the architectural scale, the exploration of AI began with early efforts to use computation for generative form compositions and representation (Stiny and Gips, 1972). The evolution of AI led to integrated building systems documentation, complex formal representations, and experiments in decision support systems based on multiobjective optimization engines resulting in a wider design space (Keough and Benjamin, 2010). Decades of computational advancement, recent open-source sharing, and the availability of distributed cloud computing have rapidly increased the experimental creation of tools with analytical, optimization, and generative design capabilities. The advent of IoT devices with embedded sensors has allowed for the sensing and responding to the built environment and human activity in complex spatial networks at many scales (Gopalakrishnan et al., 2021; Manivannan et al., 2020).

As computational systems have emerged as a fundamental keystone in architectural design, they have extended the capacity of traditional processes, while challenging design conventions and praxis (Rocker, 2006). The development of computational design tools has changed the way machines can inform and actively interact with the design process. Computational systems have greatly reduced labor time, improved design quality, and reduced cost by helping planners and designers to work more efficiently. The progressive adoption of technological solutions has transformed the architecture, engineering, and construction (AEC) industry in many ways: first by introducing computer-aided design (CAD) software, then by exploring new construction techniques through parametric tools, and now by introducing statistical computing capacities such as big data and AI.

AI techniques can be applied to several design problems such as building massing, orientation, façade design, thermal comfort, daylighting, life cycle analysis, structural design analysis, energy, and cost (Machairas et al., 2014). Recent examples include the linking of CAD packages to simulation engines, such as the DIVA plug-in that links the Rhinoceros software to the Radiance software (Lagios et al., 2010) or design tools that integrate solar radiation, energy and wind flow analysis modules, such as project Vasari by Autodesk Labs (Gopalakrishnan et al., 2021).

Current planning and design research has also explored the development of new interfacing tools and ML models. For example, a multicriteria genetic algorithm was used to optimize architecture desk layouts in offices by evaluating existing office design (Anderson et al., 2018). These heuristic algorithm-based optimizations can influence the design of a building's envelope according to simulated energy performance (Tuhus-Dubrow and Krarti, 2010) as well as expected energy performance (Chronis et al., 2012). Heuristic algorithms are also useful for geometrical form optimization, and for accounting construction costs (Rudenauer and Dohmen, 2007) and real-estate value (Alfaris and Merello, 2008). In this context, AI has been employed to optimize structural geometry and was able to identify the optimum solution out of approximately 30,000 possible designs (Flager et al., 2009; Gopalakrishnan et al., 2021).

Recent projects by research groups at Autodesk, including Project Discover and Autodesk@MarRS, have explored the use of computational systems in urban planning and design as part of a "generative design" process by using computational capabilities to generate feasible solutions and to explore larger solution spaces based on robust and rigorous models that meet required design conditions and performance criteria. A number of tools are now available for planners and designers who seek to incorporate genetic algorithms in the design process, most notably Galapagos for Rhino Grasshopper (Rutten, 2013) and Optimo for Revit Dynamo, where traditional parametric 3-D modeling programs can be augmented by libraries that add ML capabilities (e.g., artificial neural network, nonlinear regression, k-means clustering, etc.) to be used in conjunction with spatial data modeling (Gopalakrishnan et al., 2021).

Complexity science and urban systems

In the 21st century, the rise of the smart city paradigm has significantly contributed to the understanding of the intrinsic complexity (Naphade et al., 2011) of urban environments. The complexity of cities makes an interdisciplinary approach to the planning and designing of cities and their dynamics increasingly imperative, as argued by Batty and Marshall (2012), who evince that the idea of a bottom-up approach became important at the same time as the notion that "many different systems being claimed by different disciplines were part of a more generic whole." The need for a holistic approach to problem-solving in the context of urban planning and design calls for an understanding of the complex patterns that are visible in the city as we study social networks, transportation networks, spatial networks, etc., through the lens of complexity science (Batty, 2009; Gopalakrishnan et al., 2021; Manivannan et al., 2020). Mitchell (2014) states: "The 'study of complexity' refers to the attempt to find common principles underlying the behavior of complex systems—systems in which large collections of components interact in nonlinear ways. Here, the term nonlinear implies that the system cannot be understood simply by understanding its individual components; nonlinear interactions cause the whole to be 'more than the sum of its parts.'"

One way to understand this is to view the city as a network of resource flows (Kennedy et al., 2011) and its buildings as a network of interconnected programmatic spaces and circulatory paths, or nodes and links, within the superstructure of the urban spatial network (Gopalakrishnan et al., 2021).

Key aspects of spatial network analysis

Scale of spatial networks

Scale is a fundamental concept in all space-related analysis (Sheppard and McMaster, 2008; Jiang and Anders Brandt, 2016; Boeing, 2018). In studies of social interactions, population movements and urban structure, two of the most common types of spatial networks, include two scales, between and within cities. The analysis of intercity networks is focused on the interactions and connectivity between cities within a region. This type of analysis treats every city as a single node. The information on the city is gathered and aggregated as an indivisible object (Alderson and Beckfield, 2004; Neal, 2011). The intracity spatial network analysis is focused on the heterogeneity within a city, that every part of a city could have different urban functions or roles (Jiang and Claramunt, 2004; Chin and Bouffanais, 2020). Thus, these analyses allow us to understand and uncover the underlying structure of the city. Examples for intercity and intracity networks are shown in Fig. 3.1.

Fig. 3.1A and B are examples for intercity and intracity networks. The colors show the community detection result (modularity-based) and sizes of nodes indicate betweenness centrality. Both community detection and betweenness centrality are network analysis techniques, which will be discussed in the next section of this chapter (Section: Analysis of spatial networks). Fig. 3.1A shows the airline network in Southeast Asia. Each node is an airport and represents a city. The large nodes include SIN (Singapore), CGK (Jakarta, Indonesia), KUL (Kuala Lumpur, Malaysia), MNL (Manila, Philippines), RGN (Yangon, Myanmar), and SGN (Ho Chi Minh, Vietnam). Fig. 3.1B shows the public transport (including train and bus) network between subzones (an administrative level) in Singapore. The community detection result returned five communities that grouped the subzones according to their physical locations, e.g., the light green subzones at the bottom left corner are mainly located in the western part of Singapore, whereas the majority of orange subzones at the bottom right corner are located in the eastern part. The other three communities at the top (green, blue, and purple, gray, light gray in print version) contained other subzones that were located in the northern, central, and northeastern parts. The mixed patterns in community detection results indicated strong connectivity between these regions.

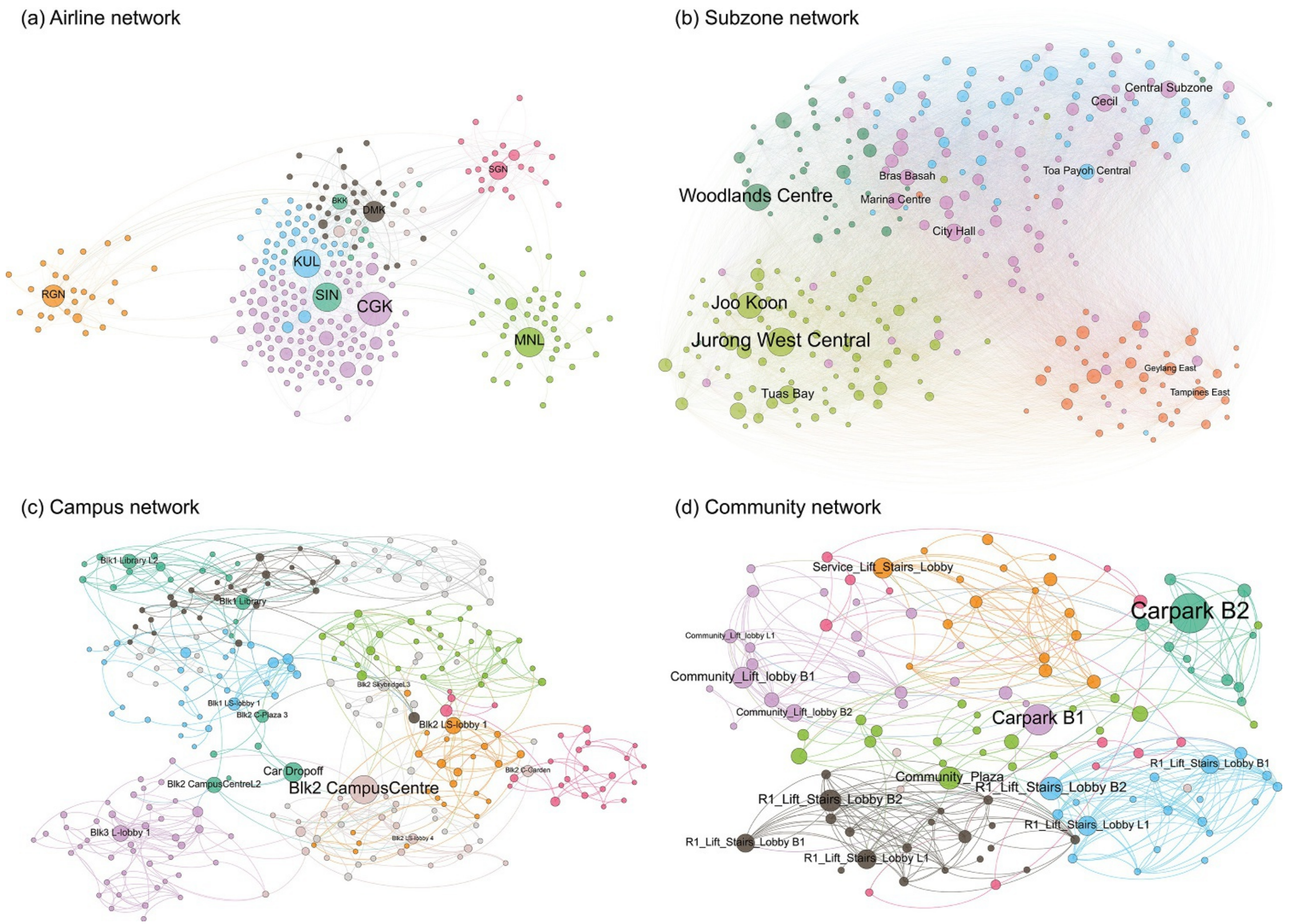

FIG. 3.1 Spatial network examples of three different scales: (A) an airline network, where cities are nodes; (B) a public transportation network within a city, where nodes are the subdistricts (subzones); (C) a university campus network, where nodes are the spaces within the buildings; and (D) a vertically integrated building, where nodes are spaces of different programs. Sizes of nodes indicate the community detection and betweenness centrality results. *The calculations and figure generations were generated in Gephi.*

As many cities are increasingly arranged vertically, urban space should be analyzed in a higher resolution because different types of space could be vertically overlapped. For example, in Singapore, there are residential towers that were built on top of bus interchanges. In this situation, the horizontal subdivision of space (such as the subzones in Singapore, Fig. 3.1B) is not suitable for the analysis of space. In a vertical urban space, the subdivision could be even smaller spaces with distinguishable functions, i.e., micro-spaces, e.g., shops, lift lobbies, gardens, classrooms, or houses. The focus of the analyses of these micro-space networks is on understanding their microlevel spatial interactions and structure. For example, how people move between the shops, or which locations are more accessible. Fig. 3.1C shows the adjacent relationships between micro-spaces of the Singapore University of Technology and Design (SUTD) Campus. The campus is designed in a way that fosters connectivity between the various buildings and programs, e.g., through multiple sky-bridges at different levels. The community detection result of the campus (Fig. 3.1C) shows block structure, i.e., most of the communities (nodes with the same color) are formed by spaces in the same block. At the same time, the whole campus network also shows a strong connectivity between blocks. Fig. 3.1D shows an example of a spatial network in a vertically integrated building, Kampung Admiralty, a high-density mixed-use development for the elderly in Singapore. The two groups of nodes at the bottom (gray at the bottom left and blue, light gray in print version, at the bottom right) indicate the two residential towers of Kampung Admiralty, which are separated from the public spaces and facilities of the development to maintain the privacy of the residents. The towers are only connected to the public spaces and facilities and to each other on Level 6 (Sky Garden) and on the ground level; the green nodes, gray in print version (center) are the community spaces that are mainly located on the ground level, whereas the orange nodes, gray in print version (top middle) are the public spaces at Level 6, which include a sky garden, a playground, and walkways that connect the residential and commercial spaces; nodes at the top right corner are mainly composed of the basement car park, whereas the top left corner contains the nodes of the central service lift lobbies. These examples show that a basic network analysis of space networks can reveal the structure of the functions in the buildings.

Similar to geographical and spatial studies, in spatial network analysis, the concept of scale is important for the identification of the research question and the study of object definition processes: in other words, what spatial unit is appropriate for accessing a specific research problem, and what unit would then lead to the questions of what can be explained and to what extent the results can be interpreted. In addition, the scale of study also implies the spatial boundary, i.e., what the limits of the study are. Therefore, it also indicates the edges of the cases and where edge effects may occur.

Common types of spatial networks

A spatial network (graph) can be defined as $G\ (V, E)$, where V is a set of nodes (also known as vertices), and E is a set of links (also known as edges). In addition, a spatial network can be categorized by its links' direction (i.e., undirected vs directed) and links' weight (i.e., unweighted or weighted); by the definition of connectivity (topologically adjacent, accessibility, or visibility); and if it is a dual representation network.

Directional and weighting

While the analysis of spatial networks applies concepts from network analysis and graph theory, there are several ways to define a spatial network. Direction and weightings are two main aspects of a network. An undirected network means that the links are mutual, i.e., two nodes are connected bidirectionally, e.g., the accessible network is established by a network without any one-way connections. For a directed network, the links are shown as arrows, indicating that each link only flows in one direction, e.g., space users can go from one node to another through a directed link, but not in the opposite direction ; if the flows are accessible between two nodes, two links with opposite directions are needed. Weights could be added to links and nodes, but usually they are used to describe the links' weight. An unweighted network means that the weights of links are the same. On the other hand, a weighted network is used to describe links that are not uniform, i.e., some links have higher weights than others. The weight of links can be used to describe the intensity, cost, and capacity between connected nodes.

Adjacency, accessibility, and visibility

Three basic types of relationships are commonly used to represent the interaction of spaces. The spatial adjacency network is the most intuitive network. It defines each space as a node and a link is generated between every two directly connected spaces. In other words, a link in the adjacent network indicates that the two nodes are not only next to each other but also connected (e.g., through an open door or a hallway). An example is given in Fig. 3.2A. It shows the adjacency network of an integrated community building. Accessibility is one of the important relationships in spatial network analysis studies. The accessibility in this form of analysis is defined through a cost function, i.e., a threshold in distance, moving time, or transport fare: for example, the accessibility from residential blocks to medical facilities, which can also be described as the accessibility between different building programs. Fig. 3.2B shows the 50-m reachable network of a community building. In addition to accessibility, visibility network analysis is a method to access the intervisibility relationship between nodes that has been developed from the spatial analysis theories of space syntax (Turner et al., 2001; Jiang and Claramunt, 2002).

Dual representation

Dual representation networks (also known as dual graphs) focus on the relationship of the connections (Añez et al., 1996; Batty, 2013). Technically, the dual representation of a network converts the links to nodes and establishes links through the relationships of node-sharing in the original network. For example, in a typical street network, the streets are represented as links and the intersections (endpoints of streets) as nodes. A dual representation of the street network would be a network with streets defined as nodes, and links represented as the relationship between streets, i.e., street-street connectivity networks (Jiang and Liu, 2009). While the dual representation network focuses on the relationships between the connections, it is useful for the analysis of the linkages themselves, e.g., the evaluation of traffic in connections (Hu et al., 2008), or the assessment of the attractiveness of each connection (Wen et al., 2017). An example for dual representation in a community building is shown in Fig. 3.2C.

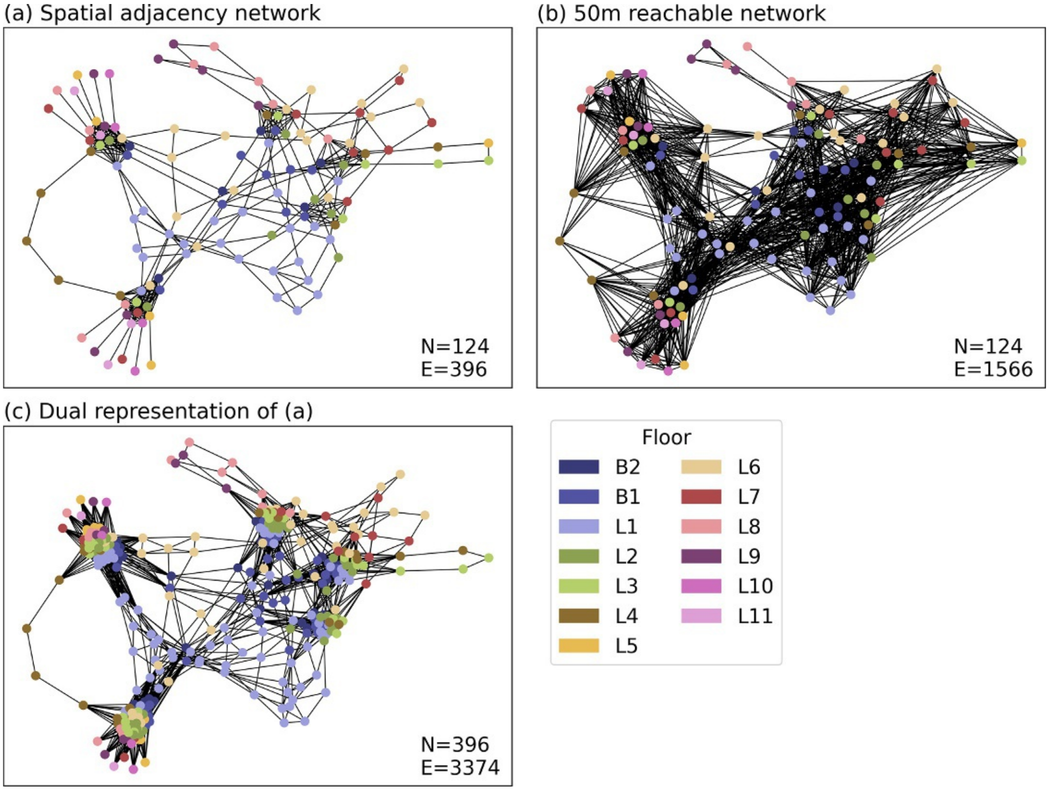

FIG. 3.2 Three types of commonly used spatial networks in Kampung Admiralty, Singapore: (A) spatial adjacency network, (B) reachable network, and (C) dual representation network. *Networks were generated and visualized in Python.*

Analysis of spatial networks

The analysis of complex networks is a combination of methods and algorithms used to uncover their structure. A complex network is composed of two main elements—the nodes which act as agents, and the links which capture the complex relationships or interactions between the nodes. Three basic and classical analyses of complex network studies include the measurement of the importance of nodes, measurements of the criticality of links, and the identification of communities.

Measurements of the importance of spatial nodes

The main purpose for measuring the importance levels of nodes is to identify the key players exhibiting significant influence as a result of complex interactions. Using different definitions of “main players” or “significance,” there are three basic centrality measurements that have been frequently discussed in the relevant literature, including “degree,” “closeness,” and “betweenness” (Barrat et al., 2004). Fig. 3.3 shows an example of the three centrality measurements for the SUTD Campus network.

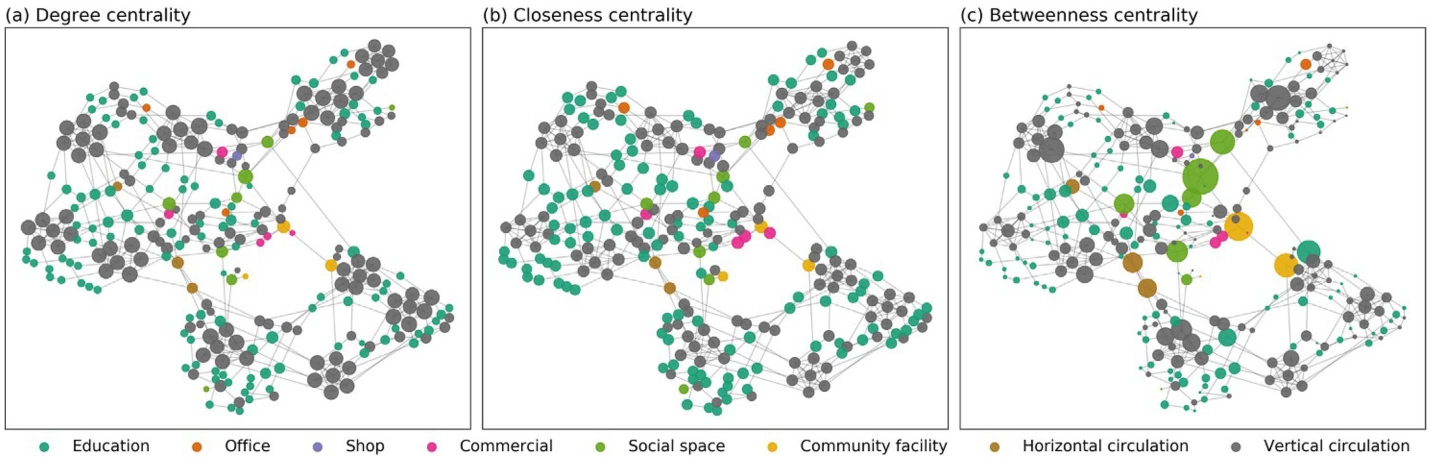

FIG. 3.3 The demonstration of (A) degree centrality, (B) closeness centrality, and (C) betweenness centrality for the SUTD Campus network. The calculation of the shortest path in (B) and (C) have considered the actual distance between the centroid of the spaces. *Calculated and visualized in Python.*

Degree centrality is the most basic measurement of a node's significance. By definition, it is the number of neighbors a node has. The higher the degree centrality, the more neighbors a given node has, hence the more influencing power it potentially holds. This measure is useful in finding the most connected spaces or influential individuals within a spatial or social network by ranking all nodes within a network. The calculation of degree centrality can be useful for the effective planning of active social spaces that act as critical connectors in the built environment.

Closeness centrality measures the distance from one source node to all other nodes, i.e., how close a node is to all others. The Small World Problem, a famous experiment conducted by Milgram (1967), stated that every two people in the United States can be connected through approximately three friendship links, meaning that on average, everyone can reach everyone else through two people. Thus, the question about heterogeneity between people arises, i.e., is any of them closer to everyone else? The calculation of closeness centrality first determines the step counts of the shortest path from one source node to all other nodes (namely farness). The inverse of the summation of farness is closeness. A node with high closeness can reach the whole network with the least efforts (steps). So, closeness centrality can help in identifying spatial clusters within a building or any spatial development, highlighting the spatial influencing power of distribution of nodes. For example, an international airport is connected to more places in fewer steps (transfers) than a domestic airport in the same country, because domestic airports rely on the former to reach international destinations.

Betweenness centrality is identifies the "bridge-like" nodes within a complex network. A node with high betweenness centrality acts as a "broker." It controls the connectivity of some nodes that "hide" behind it. For example, a bridge between two islands would have high betweenness because all flows from one island will need to go over the bridge to reach the other other. Technically speaking, betweenness measures the levels of criticalness of a node in terms of being "in between" all pairs of nodes. The calculation of this measurement needs to identify the shortest path of all pairs of nodes and count the number of nodes appearing in these shortest paths. Previous studies used betweenness as a measurement of vulnerability (Ducruet et al., 2010). The concept behind this is that when high betweenness nodes are removed (e.g., because they malfunctioned or are attacked), the network could break into pieces or the connection could be increased as the flows would need to be rerouted to a new shortest path structure. In the context of studying human movement, a high betweenness centrality measure (e.g., Fig. 3.4) indicates that a node is part of many shortest routes, which typically translates to increased human movement and interactions.

Other than the centralities measurements, there are two groups of advanced algorithms that are frequently used for assessing the importance of nodes. The first group is used to uncover the core and peripheral structure of complex networks. One of the most recognized methods in this area is the so-called *k-shell decomposition* (Carmi et al., 2007; Kitsak et al., 2010). The concept of *k-shell decomposition* is that core nodes have links to each other; thus, if a node's neighbor is a peripheral node, there is a high probability that it is also a peripheral node. Technically, the calculation process starts by setting the k-value to 1, and iteratively removing nodes with degree equal to k, until all nodes' degree centrality is higher than k; all the removed nodes belong to the k-shell group; then, the k-value is increased by 1 and the nodes removal and k-shell assigning process is repeated until all nodes are processed. The k-shell values can be used to differentiate the nodes from core, periphery, or any hierarchy of levels

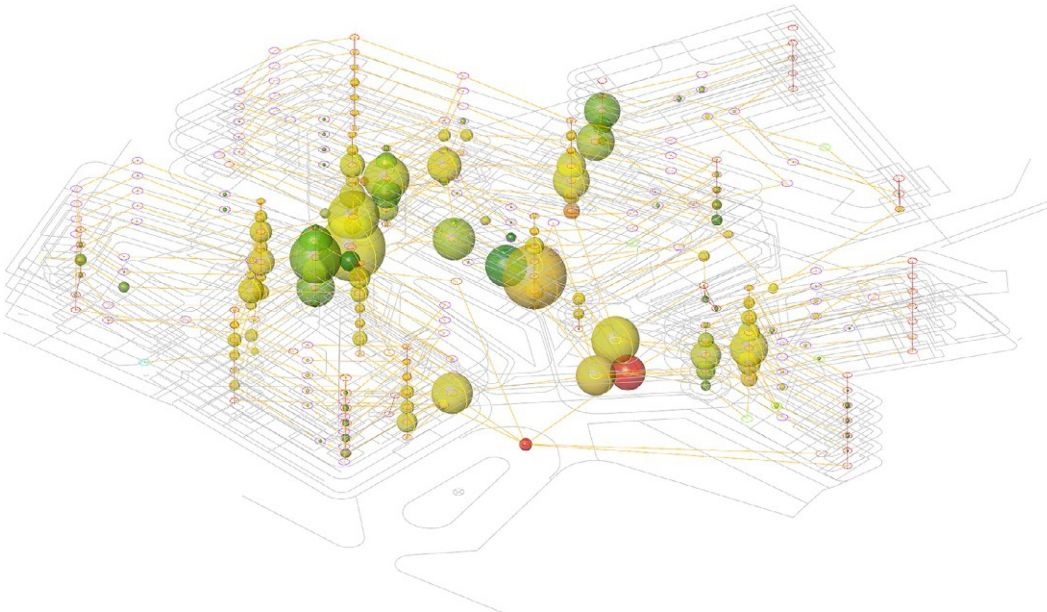

FIG. 3.4 Betweenness centrality diagram of the SUTD Campus network. The calculation of betweenness centrality includes the actual distance in searching for the shortest path. *Calculated in Python and visualized in Rhinoceros, Grasshopper.*

in between, i.e., nodes with higher *k*-shell values have a larger probability to be cores, and vice versa. In a spatial network, the top-level core nodes are the nodes surrounded by second-level core nodes, hence, they can be used to identify the regional cores or the most influential nodes (Kitsak et al., 2010; Chin and Bouffanais, 2020).

The second group of advanced algorithms is utilized in iterative process calculations to penetrate networks. It includes Google's *PageRank* algorithm (Brin and Page, 1998) and the Hyperlink-Induced Topic Search (HITS) algorithm (Kleinberg et al., 1999). The reason for developing these advanced algorithms was to improve the measurements of the importance of nodes at a global level through the penetration of the whole network and the consideration of the direction of edges (for directed networks). These algorithms were developed for the identification of key webpages in the World Wide Web. PageRank uses a large number of "random surfers" who move within a network and count them on each page in every step. After surfers move randomly for a certain time, the number reaches an equilibrium state that indicates the constant number of surfers appear at each page. The mathematics of the PageRank algorithm is closely related to that of a Markov chain process. In spatial network analysis, PageRank has been used and modified in previous studies. Modifications include Place Rank (El-Geneidy and Levinson, 2011) that considers the flow of population, EpiRank (Huang et al., 2019a,b) and Geographical PageRank (Chin and Wen, 2015) that considers the distance decay effect.

Measurements of the criticalness of links

In the discussion of the significance of links, previous studies focused on the criticalness of each link within the network, i.e., which links are more critical than others (Barrat et al., 2004; Onnela et al., 2007; Papakyriazis and Boudourides, 2001). The concept of criticalness and vulnerability of links are related to the concept of strong and weak ties in social network analysis (Granovetter, 1973). A strong tie (bond) in a social network indicates a strong bonding between a group of people—everyone knows everyone else in the group very well—whereas a weak tie (bridge) indicates more potential opportunities—a person with more weak ties indicates that he/she knows more people from outside the groups, which results in more information from other groups (Granovetter, 1973; Hansen, 1999; Gee et al., 2017). This is similar to the concept of betweenness centrality; thus, the most intuitive way to measure the criticalness of links is through applying the betweenness centrality measurement to them, namely edge-betweenness (Girvan and Newman, 2002; Newman and Girvan, 2004).

A link is more critical or vulnerable than others if its removal would break the network into two components or increase the separation of nodes (e.g., diameter, average closeness). These critical link have been defined as "bridges" (or "global bridges") in previous studies (Bollobás, 1998; Huang et al., 2019a,b). On the other hand, if the removal of a link would not separate the nodes at the two ends, i.e., the alternative path to connect the two nodes is short, then it is less vulnerable and is known as "bond." To inspect the hierarchical structure from bridge to bond, previous studies have also defined a multilevel local bridge (Huang et al., 2019a,b; Huang and Chin, 2020). The hierarchical structure is determined through the length of the alternative path after the removal of the target link, i.e., if the alternative path is as long as the average path length of all pairs of nodes, the link is assigned as a global bridge (highest level); if the alternative path length is shorter than that, it is considered as the second highest local bridge, etc.

Detection of community structure

Besides the analysis of nodes and links, one of the other main analyses for network structure is community detection (Girvan and Newman, 2002). Similar to the clustering analysis in spatial analysis that aims to find points that are near to each other, the main purpose of detecting communities is to identify nodes that are densely connected to each other. Some examples are shown in Fig. 3.1. For instance, in the airline network of airports in Southeast Asia (Fig. 3.1A), domestic airports are usually connected to each other but not linked to those in other countries. This forces them to form a densely connected structure within their country and only link to airports outside through brokers (international airports). For example, the green nodes at the bottom right corner of the network are the airports in the Philippines, the red nodes at the top right are the airports in Vietnam, and the orange nodes on the left are airports in Myanmar.

In order to detect communities in a complex network, the measurement of modularity is introduced (Newman and Girvan, 2004; Newman, 2006). Qualitatively, modularity is a measurement for the quality of nodes partition. Quantitatively, modularity compares the number of links in a community (both ends are in the same community) to the distribution of links at random (in the same community on the basis of chance). The modularity measurement is typically used along with a heuristic algorithm for nodes grouping (Clauset et al., 2004;

Guimera et al., 2004, 2005; Blondel et al., 2008). The Louvain method—the currently most popular modularity-based community detection method—is a greedy algorithm that iteratively merges the communities and calculates the changes of modularity (Blondel et al., 2008). Using a simulated annealing heuristic algorithm, Guimera et al. (2004) developed another way to detect the optimal partitions of nodes with a fluctuation process.

Due to the limitations of the modularity calculation, the modularity-based methods do not capture the effects of direction and flow structure in a directed network. Therefore, the MapEquation algorithm has been introduced to better understand the effects of flow in a directed network (Rosvall et al., 2009). Similar to PageRank, MapEquation uses a random surfer process in the calculation. In other words, the partition results of MapEquation tend to maximize the flows of random surfers more within and less in between partitions. Since the concept of the MapEquation algorithm is more aligned with the nature of population flow, it can delineate better partitioning results in a transportation flow or population movement network (Zhong et al., 2014; Chin and Bouffanais, 2020).

Computational social science and its AI applications

Comparing and correlating the various importance measurements and empirical statistics data (e.g., actual population flow, socio-demographic, disease cases) allows for the identification ofthe significance of spaces regarding their programs and locations. Several previous studies have been conducted to analyze population movements at the urban scale. For example, Wen et al. (2017) integrated a genetic algorithm to analyze the traffic flow data and the dual representation of the road network structure using a modified PageRank algorithm to obtain a spatial distribution of spatial attractiveness. The results were subsequently used to discuss traffic congestion and delineate the traffic impact area (Wen et al., 2016). Other research has studied daily round trip commuting patterns and integrated the data with several infectious diseases, including 2009 H1N1 influenza, enterovirus cases, and 2003 Severe Acute Respiratory Syndrome, to assess the disease spreading risk of the two directions of commuting, i.e., from home to the workplace and back (Huang et al., 2019a,b; Chin and Huang, 2020). In a study of a campus network, researchers used the class attending timetable data of individual students to establish a flow network in between campus buildings. The study delineated the campus into multiple zones using community detection methods and analyzed the separation levels through a campus isolation scenario simulation process to access the effects of campus isolation to control the spreading of diseases (Wen and Chin, 2015).

These computational analyses of network measures and empirical statistics allow for the identification of parameters for the planning and design of size, colocation, and placement of social spaces within larger building or spatial developments. Combined with the nodes' spatial attributes such as floor area, height, openness, visibility, etc., it allows for the further identification of the factors that influence the effectiveness of these spaces in terms of their use. The many possibilities and parameters of spatial distributions at multiple scales can benefit from complexity science-based methods that map and analyze spatial networks with greater quantitative measures, types of intelligence, and a rich collation of data sources. In addition, a variety of datasets from different fields of research as well as the ubiquity of smart IoT devices provide the basis for new methods of sensing and analyzing actual space use in the built environment.

The study of space use is interdisciplinary in nature and also draws from computational social science. The latter is a subfield of the social sciences that uses computational methods to study social phenomena. To evaluate urban and architectural space use, these include the tracking of human activities in the built environment to better understand intertwined social, spatial, and temporal behaviors. The computational methods employed in this context are mainly based on algorithms that allow for the building of predictive models that use tracking data. In addition, statistical techniques and simple computational processes are employed to study the relationship between humans and the built environment they inhabit (Alessandretti et al., 2018).

ML is considered to be a subset of AI and it can be applied in two important ways: (a) human activity recognition (Lara and Labrador, 2013), and (b) location prediction (Zafari et al., 2019). Both of these applications are based on supervised methods that use training data to predict the class of interest, e.g., running, walking, or specific locations (rooms, etc.). This can be done offline (passive prediction after data collection is complete) or online (active prediction during data collection). Online predictions, on the one hand, are helpful for active interaction with the user or for real-time decision-making. However, they are computationally intensive and rely on real-time and incomplete data. Offline predictions, on the other hand, allow researchers to analyze the complete dataset and provide the flexibility of tweaking models for better prediction accuracy. Offline methods are therefore more suitable for researchers who study long-term behavior of humans that requires devices to be energy efficient. However, unsupervised ML methods such as clustering and pattern recognition can also be useful for the understanding of human activity patterns such as the

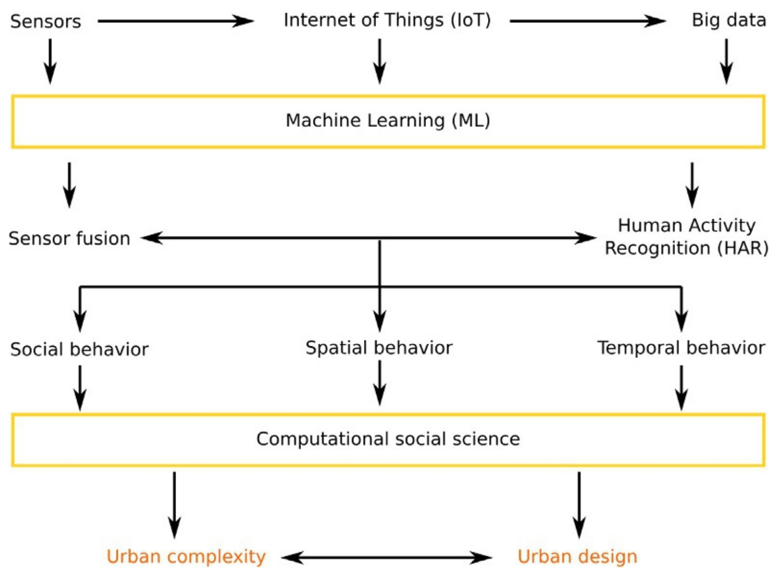

FIG. 3.5 Application of ML in studying the social and spatiotemporal behaviors of humans in the built environment.

identification of important nodes or attractive places and the delineation of traffic impact areas (Wen et al., 2016, 2017).

Wearable devices, including mobile phones, smart watches, and smart glasses, have become an important part of our everyday life. Social science researchers and urban planners have used large-scale availability of big data generated by these mobile devices to track humans and to study their behavior in the built environment. The study of human mobility has led to important developments in our understanding of human behavior, including the descriptions of their daily mobility patterns in cities, "burstiness" of individual and collective behavior, and simple mathematical models of their displacement (Barthélemy, 2011; Manivannan et al., 2020). All of these have helped to inform the planning and design of cities, e.g., through the appropriate placement of facilities and the provision of connections between important places.

Mobile sensors (e.g., inertial measurement unit, IMU) that consist of an accelerometer and gyroscope along with a barometer and magnetometer, are the predominantly found built-in sensors in mobile phones (Lara and Labrador, 2013; Manivannan et al., 2020). The data from these sensors can be processed and used to recognize many activities, such as running, walking, standing, sitting, sleeping, climbing stairs, etc. The identification of these activities within the context of their location can help to understand how a particular space is used. Barometer sensors are sensitive to change in elevation and have been used to recognize vertical displacement through elevators, escalators, and stairs (Manivannan et al., 2020). The identification of vertical mobility can indicate the choice of users regarding vertical mobility modes and their time of use during the day can, e.g., help to avoid vertical traffic congestion, and the average vertical displacement height can help make decisions about the allocation of facilities on appropriate building levels (Manivannan et al., 2020).

Location-based sensors including GPS, Bluetooth, Wi-Fi access points, and Radio Frequency Identifier (RFID) can be used to identify the location of users in indoor or outdoor environments (Zafari et al., 2019). Peer-to-environment sensing systems developed using these sensors can be used for tracking and navigation. Due to the environmental obstacles (such as walls, plants, etc.), the receive signal strength indication (RSSI) measured at the receiver end from these sensors is unreliable as an indicator of distance (Zafari et al., 2019). Hence, ML is used to convert the radio signal available in each location and is studied over time and the revealed patterns of these signals can be used with supervised ML algorithms to predict their corresponding location.

The application of ML can thus be used to study the socio-spatial behavior of humans in the built environment and inform urban planning and design. As such, it can be an integral part of evidence-based approach. The framework shown in Fig. 3.5 summarizes the application of tools and techniques from computational and information science to understand social and urban structures and to facilitate urban development. The first layer consists of (big) data from the built environment and human activities, which were collected by sensors and the IoT. The ML methods are applied to these data to identify patterns, leading to sensor fusions and HAR. Further analyses can provide a deeper understanding of space users in terms of their social, spatial, and temporal behaviors. The integration of these analyses can also contribute to computational social science which then can help to further develop urban applications of complexity science (Manivannan et al., 2018; Bouffanais and Lim, 2020; Chin and Bouffanais, 2020).

Summary

In this chapter, we described a new complexity science-based approach to the understanding of the dynamics, growth, and evolution of cities in a scientifically predictable, quantitative way. We discussed innovative AI-aided urban planning and design methods and tools and how these have already been and can be applied in the future. We further described spatial network analysis and common types of spatial networks as well as computational social science and its application to urban planning and design problems. The complexity science-based approach to analyzing the dynamics of cities described in this chapter allows us to uncover and understand their underlying structure and can lead to more informed urban planning and design decisions in the future.

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