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Identifying Urban Morphology from Street Networks with Graphlet Analysis

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Summary

Urban street networks contain repetitive structures that reflect human needs as cities expand and evolve. To identify and understand these building blocks of cities, we propose the use of graphlet-based methods–that is, focusing on small, connected subgraphs of these networks. Looking at graphlets of up to 4 nodes in the street networks of New York City, we identify local structures such as gridded patches through spatial auto-correlation statistics. This methodology can be quickly applied to any city in the world, helping researchers classify local street structures and identify common urban development trends across many cities.

KEYWORDS: street networks, urban morphology, graphlets, planning

1. Introduction

Network models of street patterns offer a robust way to formalize and scale the analysis of urban morphology (Boeing, 2017). Local network structures are central to this discipline. The inherent modularity of spatial networks (Gilarranz, 2020) and the recurrence of identifiable street patterns such as grids, cul-de-sacs, and long roads (Moosavi, 2017) suggests that street networks may be composed of several juxtaposed, wired-together local structures. Thinking about urban morphology as modular and identifying the function of local street structures in the city would support planners in designing replicable solutions to common urban issues or neighborhood goals (Dennemark et al., 2017).

Common tools from network science cannot be immediately used to identify these structures. Despite the existence of many complex network analysis techniques, spatial constraints to street networks steer structural analysis away from typical local indicators such as degrees, node correlations, and betweenness centralities (Akbarzadeh et al., 2018; Jiang et al., 2014). And, while scaling relationships are found on the network as a whole and correlated datasets to describe urban growth (Bettencourt et al., 2007; Boeing, 2021), they do not offer a precise description of *local* street structures. Attempts to classify local building blocks of cities often rely on planarity assumptions (Louf and Barthelemy, 2014) or data beyond the street network (Fleischmann et al., 2021).

We study street networks using graphlet analysis. A *graphlet* is a small, connected subgraph in a network. Graphlets were proposed to be simple building blocks of complex networks: Each of these local structures represents a different function in ecological, metabolic, online, trade, transportation, and social networks (Milo et al., 2002; Charbey and Prieur, 2019). These local measurements also provide a robust way to compare different networks structurally (Sarajilić et al., 2016; Tantardini et al., 2019). Existing studies of street networks with graphlet analysis focus on global graphlet counts rather than local assessment of the graphlets' role as building blocks (Topirceanu et al. 2014; Yu et al., 2019).

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2. Methodology

We consider graphlets of 2, 3, and 4 nodes on undirected street networks. There are exactly 9 such non-isomorphic graphlets. Within a certain graphlet, nodes might have different connectivity properties. To account for this, we define *automorphism orbits* (Pržulj, 2007) as follows: If there is a permutation of the vertices and edges of the graphlet which preserves neighbor relations (an isomorphism to itself) that relates two specific nodes, we say that these two nodes belong to the same orbit. The 9 graphlets and 15 orbits are labelled in **Figure 1**.

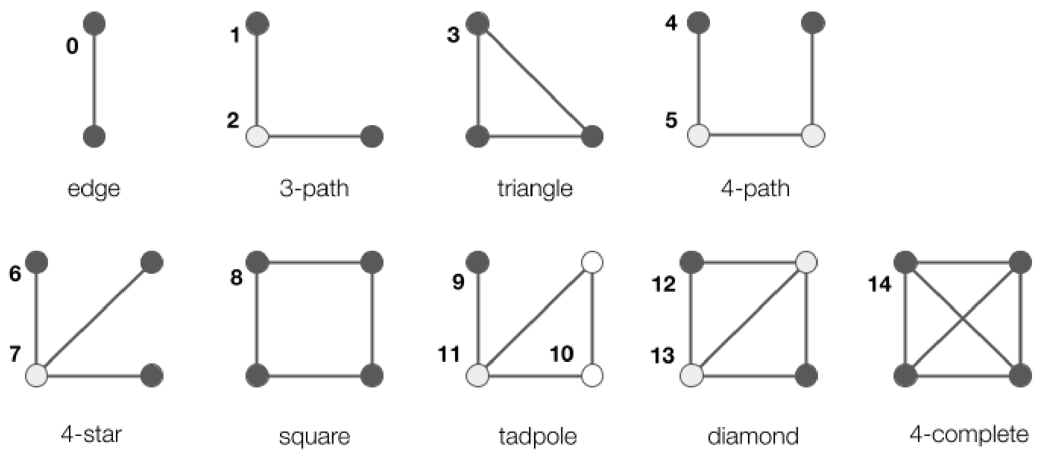

Figure 1. All 9 undirected graphlets of 2, 3, and 4 nodes with human-readable names and their orbits, labelled 0, . . . 14. In a certain graphlet, nodes with the same color belong to the same orbit, that is, are indistinguishable since there is an automorphism—a symmetry—of the graphlet permuting them.

Orbit 0 corresponds to an edge of a network. The count of graphlets in which a node corresponds to orbit zero is then the (trivial) degree of that node in the network. The idea of a degree can be extended to all other 14 orbits, so that for each node its *n-degree* counts the number of orbits n that it belongs to. Generalizing the degree distribution, we can define 15 *graphlet degree distributions* (GDDs) measuring structural properties of a network (Pržulj, 2007).

We compute the GDDs for New York City. Data is obtained from OpenStreetMap via OSMnx (Boeing, 2017). We selected only driveable streets–walkable streets include paths in parks and courtyards which do not represent well the urban street structure. We simplified the networks to perform meaningful graphlet analysis as follows: Edges were made undirected, multiple-node intersections were consolidated in a single node, and parallel edges and self-loops were removed. Using the orbit counting algorithm (Hocevar and Demsar, 2014), we computed the graphlet degrees of each node in the network.

The degrees were considered as categorical variables for two main reasons. First, the GDDs are concentrated in few values because street networks are constrained by space. Second, normatively ordering the n-degrees requires an analysis of functionalities associated with morphology. We computed entropy-based local indicators of spatial autocorrelation (ELSAs) for each node and for each of the 15 distributions (Naimi et al., 2019).

3. Results

We show results for the orbits 0 (the trivial degree) and 8 (the square degrees). We chose these two orbits for they represent a basic network indicator and a pervasive higher-level structure respectively. The degree distributions of New York are shown in **Figure 2**.

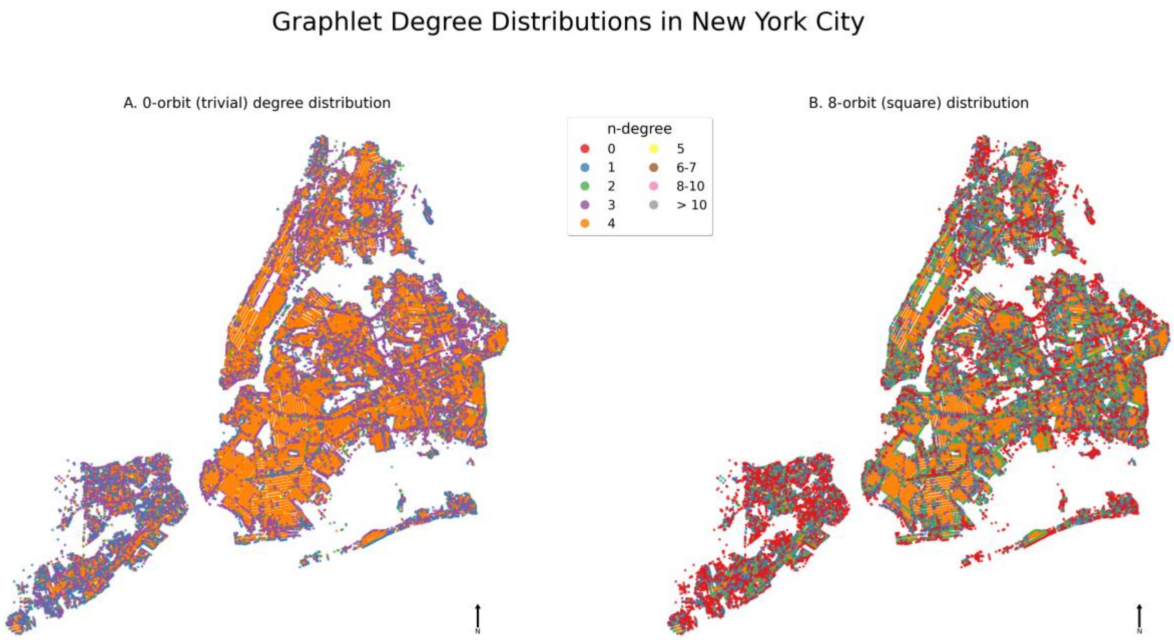

Figure 2. Distributions of graphlet degrees for orbit 0 and orbit 8 in New York City.

The GDDs, in both cases considered, have few possible and noticeably spatially clustered values. The trivial degree, as expected, is predominantly 4, which represents a natural crossing of two streets. The most common square degree is also 4. A group of nodes touching 4 squares can be thought of as a gridded street plan, so that the result is expected for the morphology of Manhattan and parts of Brooklyn and Queens. On the other hand, few nodes which have 0-degree equal to 4 in Staten Island (island in the bottom left of the map) also have 8-degree equal to 4. This gives us empirical evidence that the dependency between 8-degrees and 0-degrees in the other boroughs is not a mathematical artifact, but a product of urban morphology. Regions where nodes with 0-degree equal to 4 are likely to also have 8-degree equal to 4 are gridded urban regions.

For the spatial autocorrelation analysis, we focus on the entropy term of the ELSA statistics to highlight regions with diverse morphology (Naimi et al., 2019). These values are mapped in **Figure 3**.

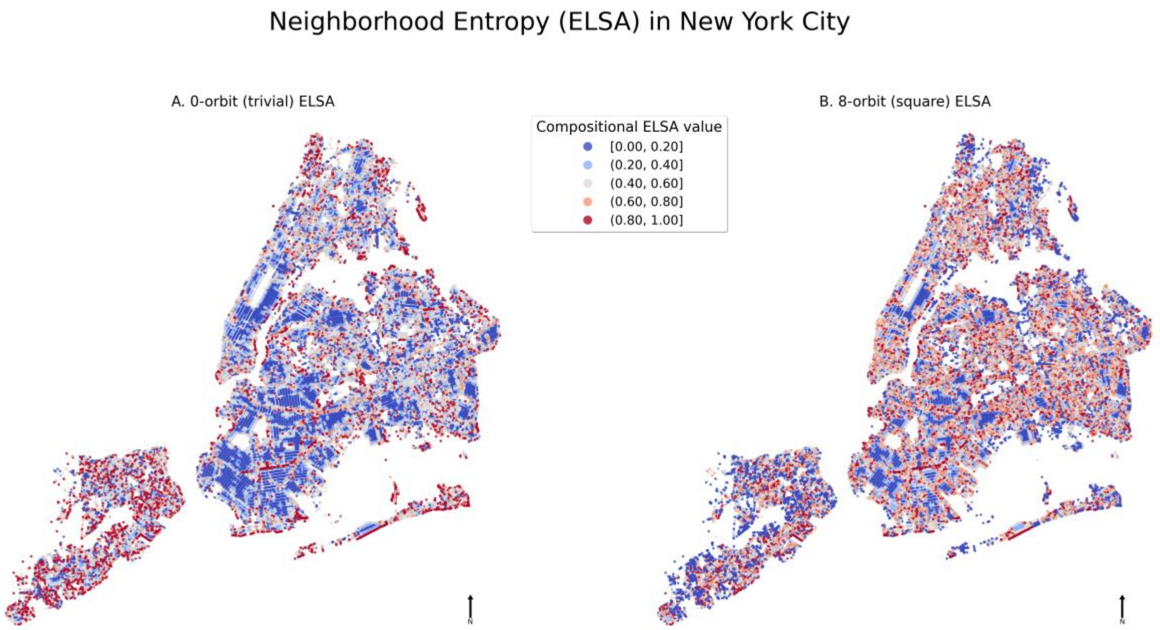

Figure 3. Compositional ELSA term for orbit 0 (left) and orbit 8 (right) in New York City. This

statistic–a value between 0 and 1–measures the diversity of graphlet degrees around a particular node. Nodes with the value close to zero, colored in dark blue, have little diversity so that their neighborhood is very homogeneous.

Through spatial autocorrelation analysis we can further identify gridded patches in the street network of New York. Regions colored dark blue in the maps define contiguous groups of nodes of predominantly the same graphlet degree. Comparing these maps to those in **Figure 2B**, we draw attention to regions of low degree diversity (dark blue in Fig. 3B) which also have square degree equal to 4. These regions correspond to gridded areas of the city.

We notice that in the square ELSA map (**Figure 3B**), dark blue regions are scarcer than in the trivial degree ELSA map (**Figure 3A**). This happens because the square degree equality defines a more restrictive condition than the trivial degree. Morphologically, these regions are "perfect" grids, whereas many of the homogenous regions in the trivial degree sense are grids broken apart by transverse streets, corners, or roundabouts.

4. Conclusions

In this research we sketched a framework to express morphological characteristics of a city from street networks. Our framework is based on graphlets, thus tying the study of cities to network methods common in the biological and social sciences. The graphlet degree distributions also naturally extends notions of degrees and connectivity to higher-level structures. We showed that these high-level structures represent the local morphology in New York City, and that morphological regions of the city can be identified with spatial autocorrelation statistics.

This work serves as a proof-of-concept that graphlets analysis can be leveraged in the study of urban morphology. Our approach can be applied to any city or region with a street network present in OpenStreetMap. Currently, we are improving the rigour behind the autocorrelation analysis to understand how identifying these morphological structures can improve our understanding of street networks.

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Biographies

Gabriel Agostini (he/him) is a student at Columbia University. He holds a Bachelor of Science in Applied Mathematics and is pursuing a Bachelor of Arts in Urban Studies. Through his research, he seeks to integrate network science, computational topology, and machine learning methodologies in the design of more equitable cities.

Juliana Goncalves (she/her) is a postdoc researcher at the Centre for Urban Science and Policy (CUSP) and the TPM AI Lab, within the Faculty of Technology, Management and Policy at TU Delft. Her research seeks to understand the socio-spatial dimension of the urban environment to support integrated decision-making in cities.

Trivik Verma is an Assistant Professor at Delft University of Technology. His research focusses on tackling challenges of urbanisation in an equitable and just manner. Specifically, he is using methods in spatial data science, complex network analysis and participatory mapping to develop computational tools for advancing the theories and practices of urban science.