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Identifying Street-Character-Weighted Local Area using locally weighted community detection methods

The case study of London and Amsterdam

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ABSTRACT

Previous research suggests that community detection methods, which defines subgraph that maximises internal ties and minimise external ties, can be applied on the street network dual graph in identifying Street-based Local Area (Law et al 2016; Law 2017). The method was successful in identifying isolated local area but were unsuccessful in identifying local area that was less driven by the grid but more from other urban factors. This research attempts to address this problem by embedding street characteristics in community detection to define Street Character Weighted Local Area (St-W-LA). The idea is that street neighbourhoods are not only defined by the topology of the street network but also by the morphology of the built form. In particular, we adopted Spacemate Building Density Metric in defining Density-based local area for Amsterdam in the Netherlands and Space Syntax angular choice metric in defining angular-choice-based (note. for simplicity reasons we term this betweeness-based) local area for London in the UK. We compared the results of the community detection with user defined local area through visual analysis. In general, we found the weighted and the unweighted street-based local areas to be similar. This suggests that neighbourhood characteristics (morphology) follow neighbourhood topology where areas that were built in similar times with similar density and building type were also better connected internally. However, we also found notable differences between the two methods where the weighted local area seems better in capturing the user defined local area in more continuous grids. Further empirical research employing mental map studies and intra-cluster analysis are needed to validate the method.

KEYWORDS

Community Detection, Neighbourhoods, Modularity, street networks, space syntax

1. INTRODUCTION

The concept of a local area or a neighbourhood is complex and fuzzy, which involves spatial, historical, socio-economic and perceptual characteristics that change and overlap over time and geography. Previous research suggests that community detection methods, which defines subgraphs that maximises internal ties and minimise external ties, can be applied on the street network dual graph in identifying

Street-based Local Area (Law et al 2016; Law 2017). These methods were successful in identifying isolated local area such as the Isles of Dogs that are based purely on the topology of the street network in Greater London. The rationale here is that people experience the urban local area along a street network. Therefore, a local area defined by street network will be able to capture subtle differences in street topology. However, the use of Street-based Local Area (St-LA) has many limitations. The key limitation is that using only the street connectivity matrix in defining neighbourhoods is contrary to the belief that neighbourhoods are made up of many overlapping factors. For example, a local area can be identified from its architectural style, its land use, or its built form of the area. This paper attempts to address this by embedding different street characteristics in community detection to define Street-Character-Weighted Local Area (St-W-LA). The idea is that street neighbourhoods are not only defined by the topology of the street network but also by its morphology and character of the built form. We will apply a weighted community detection method in identifying street character weighted local area (St-W-LA). We will demonstrate the usefulness of the method through a qualitative assessment comparing a weighted approach and an unweighted approach for two distinct case studies in both London and Amsterdam. Two separate sets of weights namely density and angular choice will be used for the two case studies as examples of this methodological exploration.

2. RELATED WORKS

There is a long history in the research of local areas or neighbourhoods, which ultimately facilitated the creation of terms that are used interchangeably in the regional science literature. The concept of locality or neighbourhood is complex and fuzzy, full of idiosyncrasies; it encompasses spatial, historical, socio-economic and perceptual inner characteristics that change and overlap according to the geographical scale and point in time (Galster, 2001). According to Lynch (1967), a city district is an area of homogeneous character (physical, social or functional) within and heterogeneous between districts. The more these characters, and environments overlap, the more unified the district becomes. The term ‘local area’ is used in this paper to represent a geography with similar characteristics that is larger than a property but smaller than a city. The definition of local area is an important topic in region sciences for example in housing submarket definition (Orford, 2001). Census tracts, which are often used as local area units, have been criticised for their arbitrary definition and inconsistent results (Orford, 1999; Goodman, 1978; Leishman, 2009).

An early enquiry in defining a local area through its spatial morphology emerged from the field of space syntax. One of the earliest observations was made by Hillier et al. (1987). The authors found that the correlation between spatial configuration and pedestrian movement differ between local areas. Penn (1998) called these local areas ‘correlation detectors’. Peponis (1988) made the observation that highly accessible routes act as natural boundaries between neighbourhoods. Read (1999) observed that neighbourhoods are often found in places of high local integration. The former observation can be interpreted as neighbourhoods being divided by high movement corridors, while the latter suggests that the heart of the neighbourhood has greater node density than its edges. These emerging ideas led to the concept of syntactical local area from Yang’s (2007) embeddedness measures and Dalton’s (2006) point intelligibility measures. The former focused on the node count density differences between two radii. The latter focused on defining a local version of intelligibility to identify syntactic neighbourhoods.

Law et al. (2016 and 2017) then extended these efforts by applying community detection, which defines subgraphs that maximises internal ties and minimise internal ties, on the spatial dual graph to identify Street-based Local Area (St-LA). These methods, based purely on the topology of the street network, were successful in identifying disconnected cognitive local area such as the Isles of Dogs in Greater London. Despite the conceptual elegance of the method in capturing isolated local areas, the use of St-LA has many limitations. The key limitation is that using only the street connectivity matrix in defining neighbourhoods is contrary to the belief that neighbourhoods are made up of multiple factors. A neighbourhood isn't only defined by its connectivity to the surrounding area but also by its built form, its architecture and its character. This research intends to address this limitation by applying a locally-weighted community detection on the spatial dual graph in identifying street-character-weighted local area (St-W-LA).

3. METHOD

We will use the weighted modularity optimisation on the dual graph representation to identify street character weighted local area (St-W-LA). The following section describes the graph representation of the street network followed by a description of weighted modularity optimisation.

3.1 STREET NETWORK GRAPH REPRESENTATION

A graph G=(V,E) is given by two sets V,E such that element of edge e is an ordered pair of vertices v. The adjacency matrix A (V*V) is often used to represent a graph where the elements in the matrix indicate whether pairs of vertices are adjacent (a_ij=1) or not adjacent (a_ij=0). There are two generic representations for a street network graph. In the primal representation, the node of the street network is the junction and the edge is the connection between the junctions. In a primal representation, the connections are physical. In the dual representation, the node of the street network is the street and the edge is the incidence between the two streets (Batty, 2004; Porta et al., 2006). This research will follow the space syntax literature in using the dual representation in identifying street-based local areas. Figure 1 illustrates these two types of graphs.

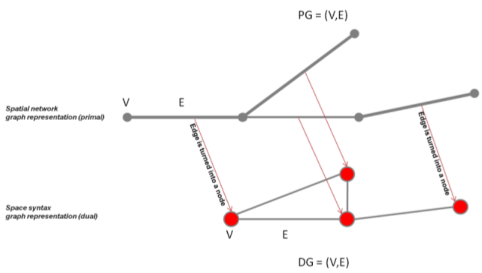

Figure 1 The spatial network graph definition.

a. Primal graph representation at the top.

b. Dual graph representation at the bottom.

3.2 WEIGHTED MODULARITY OPTIMISATION

We will use the weighted modularity optimisation in identifying street-character local areas (Girvan and Newman 2002). Modularity is the most popular quality function used in community detection which calculates the difference between the observed number of edges within a subgraph and the expected number of edges. The greater the observed number of edges relative to the expected number, the higher its modularity. Modularity Q is defined where W is the weighted adjacency matrix, m is the total number of edges in the graph, ki and kj are the degrees for vertex i and vertex j. The weighted version of the modularity quality function simply replaces the adjacency matrix A with the weighted adjacency matrix W. In this case the standard modularity is used where the expected number of edges is defined by the configuration null model.

$$Q = \frac{1}{2m}\sum(W - k_i k_j/2m\,)\delta(C_i, C_j)$$

Q is modularity index

W is weighted the adjacency matrix

m is the total number of edges

k_i and k_j are the degree for the two subgraphs i,j

Equation 1 (Girvan and Newman, 2002).

It is currently impossible to use optimisation against the above function to solve for large datasets. As a result, a number of approaches have been implemented for finding an approximate optimal subgraph (Girvan and Newman, 2002). One method is to apply a multi-level approach (Blondel et al., 2008) otherwise known as the Louvain method to optimise against the modularity function, as illustrated in Figure 2.

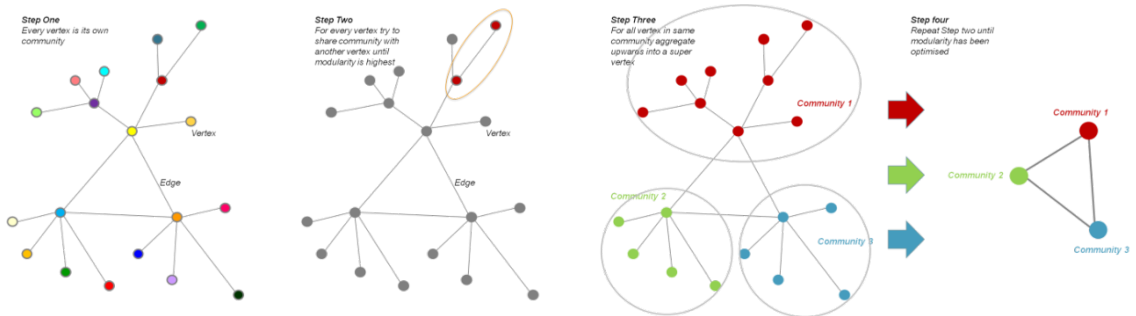

Figure 2 Diagram illustrating the modularity optimisation algorithm. The algorithm starts where every vertex is a community. Every vertex shares community membership with the neighbour that attains the highest modularity. Vertices in the same membership gets aggregated into a super vertex (right). This cycle continues until modularity can no longer be optimised (diagram produced by the author).

The modularity optimisation algorithm starts where every vertex is a subgraph. Every vertex then shares a subgraph membership with the neighbour that attains the highest modularity score. This procedure repeats for all vertices. After all of the vertices are traversed, the vertices within the same subgraph are aggregated into a new super vertex. The super vertices again aggregate with their neighbours, and this continues until modularity can no longer be optimised. The next section describes how the weighted adjacency matrix is constructed.

4. STREET-CHARACTER-METRICS

We adopt two different sets of urban characteristics in defining two types of St-W-LA. The first is the density-weighted street neighbourhood where we use the Spacemate building density metric (Berghauser Pont and Haupt, 2010) as weights for the Amsterdam case study. The second is the Betweenness-weighted street neighbourhood where we use space syntax angular choice (Hillier and Iida 2005) as weights for the London case study. Density is incorporated as a similarity measure where the weights between streets are higher when density is more similar. Betweenness is incorporated as a penalty measure where higher betweenness is inversely related to its connectivity. The section below describes these two sets of weights in more detail.

4.1 DENSITY-WEIGHTED MODULARITY (SPACEMATE DENSITY)

Spacemate density uses two metrics to measure density and from that, generate density types. Ground Space Index (GSI), the first metric, describes the use of the ground in two dimensions (i.e. coverage), and Floor Space Index (FSI)3, the second metric, describes the intensity of the use of the ground floor by stacking floor space in the third dimension. Berghauser Pont and Haupt (2010) have shown that by measuring density with these two metrics, it is possible to make a distinction between different building types, which the variables separately were incapable of making (ibid.; Steadman, 2014). Spacemate density (i.e. FSI and GSI) is measured for a 500 meter network buffer around each building that has been proven to still describe building types whereas, at larger scales, this relation would get lost (Berghauser Pont and Marcus, 2014).

For the density calculation, first, gross floor area (GFA) for each building polygon is calculated by multiplying the average building height with the built area (BA). Next, accessible GFA and accessible BA is calculated using the equation for Attraction reach (AR), using the street segment as origin (software PST[1]):

$$AR(o) = \sum_{a \in A} (f(a) w\big(D(o,a)\big))$$

f(a) = attractions value associated with GFA and BA respectively

D(o,a) = shortest distance from origin o to attraction a

w(x) = attenuation function (not used; 1)

Equation 2

[1] Place Syntax Tool PST is a plugin software to QGIS; documentation available at https://www.smog.chalmers.se/pst.

FSI(o) and GSI(o) are then calculated as follows where Area(o) is the area of the convex hull connecting all endpoints of the street segments that are reached within 500m.

$$FSI(o) = \frac{AR(o,GFA)}{Area(o)}$$

Equation 3

$$GSI(o) = \frac{AR(o,BA)}{Area(o)}$$

Equation 4

To develop the density types, supervised k-means clustering is used (Song and Knaap 2007), where the numbers of clusters (k) and the cluster centres were predefined, based on earlier work by Berghauser Pont and Haupt (2010). This results in six clusters in the case of Amsterdam (Berghauser Pont et al. 2017). Density is incorporated into the adjacency matrix by calculating a similarity measures between streets. The weights between each street and its connected street is simply the inverse of its density difference. These weights are then used in the calculation of the density-weighted modularity.

4.1 BETWEENNESS-WEIGHTED MODULARITY (SPACE SYNTAX ANGULAR CHOICE)

Space syntax angular choice or angular betweenness centrality in graph theory (Hillier and Iida, 2005) measures the sum of the weighted shortest path (θ) overlap for a particular segment i between all pairs of origins s and destinations t. Betweenness centrality captures the through-movement potential of a street segment (Freeman, 1977; Hillier and Iida, 2005) and is represented by the following equation:

$$bc_i = \sum_{s \neq i \neq t} \frac{\theta_i(st)}{\theta(st)}$$

bc_i is the measure of betweenness centrality at i

θ (st) are all shortest paths between s and t

θ_i (st) are all the shortest paths between s and t that overlaps at i

Equation 5

Betweenness is then incorporated into the adjacency matrix as a penalty between streets. We first calculate the weights between each street and its neighbour as the inverse of the junction betweenness it traverses. We then apply a step function that magnifies the difference between the highest percentile betweenness street with the rest of the streets. The motivation being that it is much harder to cross a high betweenness street as compare to a medium or low betweenness street. These weights are then used in the calculation of Betweenness-weighted modularity. Further research is envisaged to test how the weights can be incorporated into community detection methods.

5. DATASETS AND CASE STUDIES

5.1 AMSTERDAM

Amsterdam in the Netherlands is used as the first case study in testing the density-weighted street local area. The extent of the study area is presented in Figure 3, where the black lines indicate the 99 administrative boundaries of quarters (wijken) of Amsterdam (https://maps.amsterdam.nl/gebiedsindeling/).

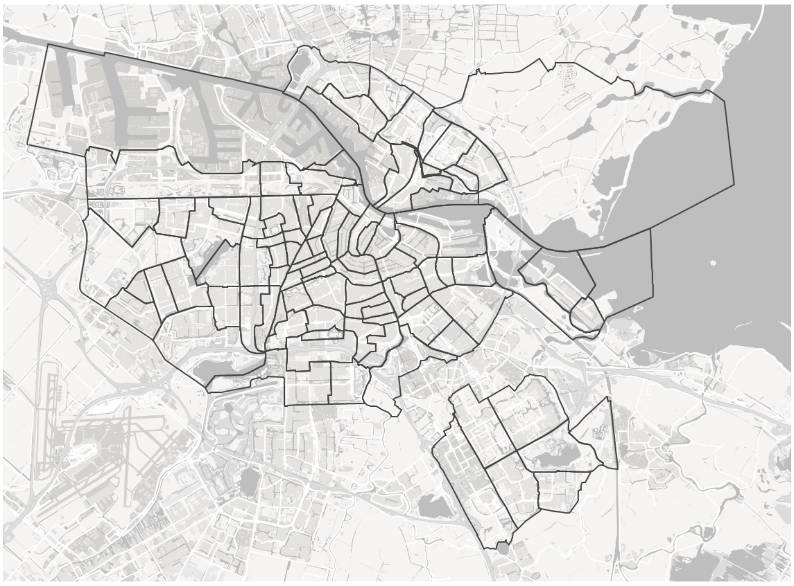

Figure 3. Amsterdam Study area boundary.

To test to what extent the algorithms can capture urban districts, two masterplans are compared to the generated area boundaries by juxtaposition. Two areas are selected in Amsterdam: Plan Zuid (1915) and Bos en Lommer (1935) (Figure 4).

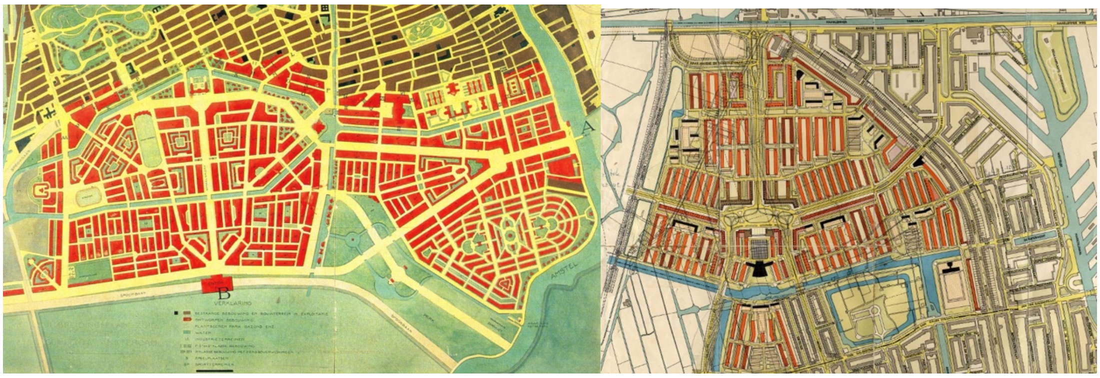

Figure 4. Amsterdam case studies

a.Plan Zuid (left)

b.Bos en Lommer (right).

Figure 4a shows Plan Zuid, an urban development plan of Amsterdam South, designed by H.P. Berlage thatcovers the area between the Cornelis Krusemannstraat, Amstelveenseweg, the current southern ring road (A10) and the Amstel. Most of the plan was realized according to Berlage’s design, except for the area south of Zuider Amstelkanaal where today, the Zuidas, a rapidly developing business district can be found.The plan correspond to three named (administrative) areas, Stadionbuurt, Apollobuurt and Rivierenbuurt, of which we will focus on Stadionbuurt and Apollobuurt that covers the western part of Plan Zuid.

Bos en Lommer (figure 4b), located between the Haarlemmerweg, Westelijk Marktkanaal, Jan van Galenstraat en Ceintuurspoorbaan, was part of the larger expansion area for Amsterdam West, designed by C. van Eesteren. It is the first large scale experiment with open blocks in the Netherlands, following the ideas of CIAM, the International Congresses of Modern Architecture. The plan was realized after WWII and instead of a continuous urban fabric, the area was split in two parts, divided by the ring road, highway A10. Where the road passes Bos en Lommer, it is realized as open tunnel to ensure continuity at the urban fabric level. This has been strengthened by more recent developments along the Bos en Lommerweg when buildings were added on top of the highway.

5.2 LONDON

The Greater London Area in the UK is used as the second case study in comparing the standard street based local area and betweenness-weighted local area. The extent of the study area is presented in Figure 5, where the black line indicates the study boundary, the red line denotes the 33 administrative borough boundaries of Greater London (ONS, 2014) and the grey line signifies the OS meridian line street network.

Figure 5. Study area boundary.

To compare the algorithms, two named urban areas in London were juxtaposed, namely Hampstead Garden Suburb (1906), and Soho district in Central London (1600). These areas were selected to represent two types of distinct named areas in London. This type of visual comparison had been used in previous syntactical studies (Dalton 2006; Yang 2007).

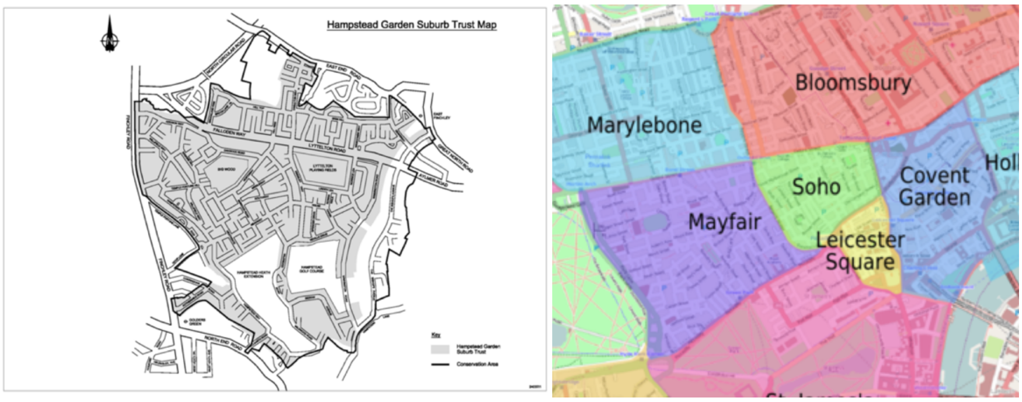

Figure 6. London case studies

a. Hampstead Garden Suburb in London (left).

b. Soho District in Central London (right).

Figure 6a shows the Hampstead Garden Suburb in Outer London which lies between East End Road in the north, Finchley Road to the west, Bishops Avenue to the east and North End Road in the south. Hampstead Garden Suburb represents the archetypal planned community in the early 20th century where a single developer and single architect planned the whole district. Figure 6b shows the districts in Central London where Soho lies between Oxford Street in the north, Regent Street to the west, Shaftsbury Avenue to the south and Charring Cross Road to the East. Soho represents a district in Central London which grew organically from the 1600 encompassing a continuous urban grid.

5.3 LONDON INTRA-CLUSTER HOUSE PRICE ANALYSIS

To better understand the boundary effects on socio-economic outcomes, an exploratory intra-cluster house price analysis is conducted in London. This research conjectures that house prices (per sqm) are more similar within a local area cluster than between clusters, both visually and statistically. An analysis of variance (ANOVA) is employed to test whether the house price variation between the local area differs from the variation within the local area. The null hypothesis is such that the mean house price of the sample is the same for all of the local area. In the ANOVA, the F-test statistics is calculated by dividing the between group variability (Bms) by the within group variability (Wms). The null hypothesis is rejected if the p-value from the statistical test is less than 0.01.

$$F = \frac{B_{ms}}{W_{ms}}$$

where B_ms is the between group variability

W_ms is the within group variability

Equation 6

6. RESULTS

6.1 AMSTERDAM RESULTS (DENSITY-WEIGHTED MODULARITY)

Figure 7. Comparing Connectivity-weighted local area (left) and Density-weighted local area (right) for Plan Zuid in Amsterdam

Figure 8. Comparing Connectivity-weighted local area (left) and Betweenness-weighted local area (right) for Bos en Lommer in Amsterdam.

Figure 7 shows the Plan Zuid area and Figure 8 shows the Bos en Lommer area. On the left it shows the communities found from the connectivity-weighted modularity and on the right it shows the communities obtained from the density-weighted modularity. Each colour represents a different membership, with the named local urban area boundary shown in black. The results show that the density-weighted algorithm was more accurate than the connectivity-weighted modularity algorithm for both named areas. The results also show that the connectivity-weighted modularity algorithm does not account properly for continuity in the building type characteristics. For example, Bos en Lommer is separated by a major ring road that resulted in two local areas on each side of this route when using the connectivity-weighted modularity algorithm, despite the fact that these areas hold the same building types, are designed by the same architect and built in the same period. Recent new development in the area where the ring road is covered by buildings has further contributed to the sense of local neighbourhood that is not captured by the connectivity-weighted modularity, while the density-weighted modularity was able to accurately define the named area. A small area in the south-west of the local areas is, according to the density-weighted modularity, not part of the local area. Interestingly, this area has recently been redeveloped and is of a totally different building type, which is accurately captured by the density-weighted modularity. The same result is found in Plan Zuid where the connectivity-weighted modularity algorithm divides the named area in two local areas and connect these, to areas in the north and south respectively, even including part of the Zuidas, the new business district of Amsterdam with high rise office buildings. The density-weighted modularity algorithm is clearly more accurate in detecting the named areas in line with the design of Plan Zuid by Berlage.

6.2 LONDON RESULTS (BETWEENNESS-WEIGHTED MODULARITY)

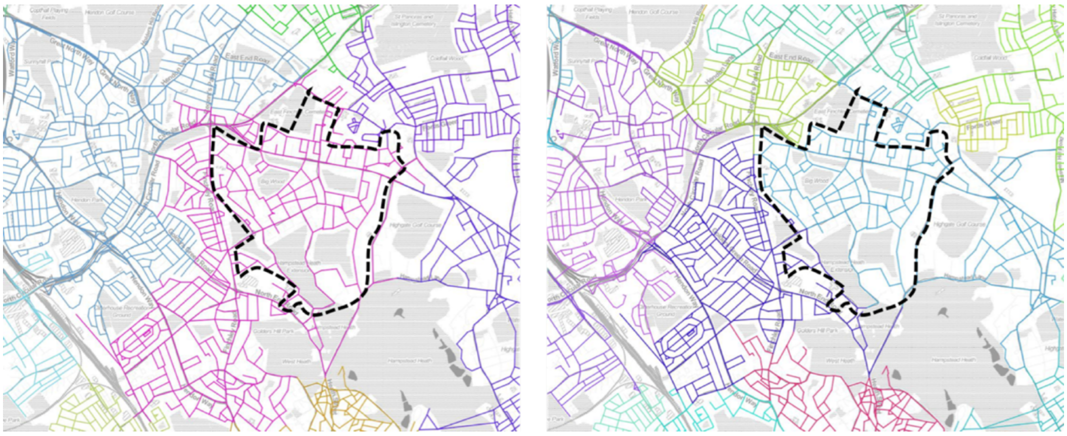

Figure 9. Comparing Connectivity-weighted local area and Betweenness-weighted local area for Hampstead Garden Suburb in London.

Figure 10. Comparing Connectivity-weighted local area and Betweenness-weighted local area for Soho in London.

Figure 9 shows the Hampstead Garden Suburb and Figure 10 shows the Soho District. On the left it shows the communities found from connectivity-weighted modularity and on the right it shows the communities obtained from betweenness-weighted modularity. Each colour represents a different membership, with the named local urban area boundary shown in black.

The results show that the connectivity-weighted modularity is able to capture the Hampstead Garden Suburb as a single neighbourhood. In contrast, the algorithm isn't able to capture Soho as a single neighbourhood. The results arenot surprising as the Hampstead Garden Suburb were planned by a single developer/architect with minimal connections to the surrounding neighbourhoods, while Soho has been developed more organically with a porous grid that connects to the surrounding area.

On the other hand, the betweenness-weighted modularity algorithm is able to capture both Hampstead Garden Suburb and Soho as a single neighbourhood. Betweenness-weighted modularity is able to capture both the disconnectivity of the grid and the disconnectivity caused by high movement (betweenness) routes. Due to greater movement-demand, high betweenness routes have often wider carriageway thereby multiplying disconnectivity at the local level. For example in the Hampstead Garden Suburb, Finchley Road was identified as a seperator when applying the betweenness-weighted modularity but not identified when applying the connectivity-weighted modularity.

The betweenness-weighted modularity thus enables to capture the differentiation when crossing a high betweenness route in Soho which is separated by three high betweenness routes namely Oxford Street and Regent Street. However, the algorithm fails to find the eastern boundary bordered by Shaftsbury Avenue. This result aligns with Peponis' (1988) observation where high accessibility route can serves as a natural boundary between neighbourhoods.

6.3 HOUSE PRICE ANALYSIS

Table 1 illustrates the ANOVA results, which tested whether the 2011 house price variations of the connectivity-weighted local area and the betweenness-weighted local area differed from the within variations. The p-value was statistically significant, at a 0.01 level. These initial results showed, quantitatively, house prices in London were significantly more similar within each local area as defined by both algorithm than between.

Figure 11 shows on the left the house price per sqm (interpolated) of North London in 2011 where green is higher house price and orange is lower house price and on the right the neighbourhoods identified from the betweenness modularity algorithm for the same area. The result shows that there are clear house price differences between some neighbourhoods, for example between Crouch Hill and Green Lanes and between Stamford Hill and Tottenham. However, these differences between neighbourhoods are not homogenous suggesting that there are different levels of severance and fuzziness between neighbourhoods that are not captured by the analysis.

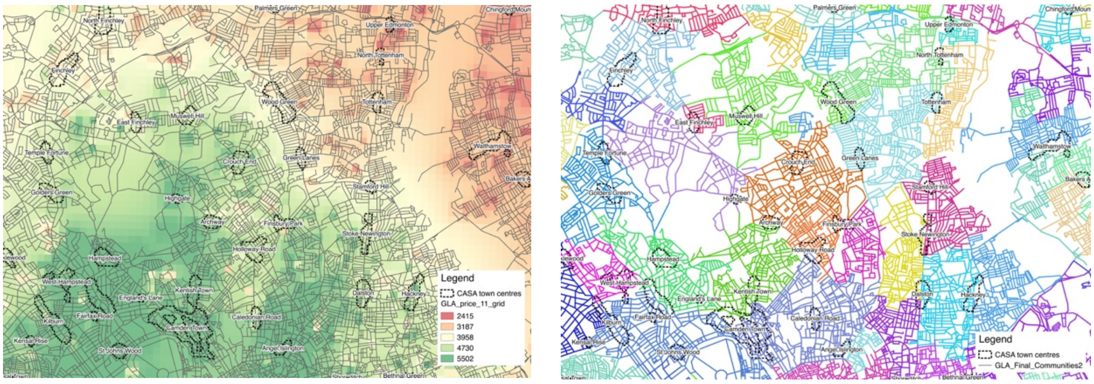

Figure 11. Comparing house price per sqm (left) and Betweenness-weighted local area for north London (right).

Conn_mod	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Between groups	169	8,287,569,304	49,038,871.6	69.930	0.000
Within groups	6051	4,243,269,311	701,250.9		

BC_mod	**Df**	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Between groups	307	8632426580	28118653.4	42.649	0.000
Within groups	5913	3898412034	659295.1		

Table 01. ANOVA tests for connectivity-weighted local area (top) and betweenness-weighted local area (bottom).

7. CONCLUSIONS

Through the two case studies, this research demonstrates the usefulness of applying weighted-community detection approach in defining different types of street neighbourhoods. Density and Betweenness Weighted modularity is useful for identifying local areas with a porous grid structure such as Central London and Amsterdam. These porous urban areas are less separated by the connectivity of the street grid but more by local differentiation such as movement of the road network or the density and character of the built form.

The result shows that the 'street-based local area' and the 'street-character-weighted local area' have notable similarities and differences between them. The similarity suggests that neighbourhood character such as density likely follows neighbourhood topology as areas that were built in similar times are likely to be better connected. However, we also found notable differences between the two methods suggesting that some neighbourhoods are less driven by the grid but more by its urban characteristics. The result are most apparent for Soho in Central London which is separated by the betweenness of the roads bordering the neighbourhood rather than by the connectivity of the district to its surrounding. The research also shows there are clear house price differentiation at the boundaries of some neighbourhoods but not all. The result suggests boundaries between neighbourhoods are not all the same where some are fuzzier than others.

This proof-of-concept study is not conclusive but it rather provides useful evidences for further research in the use of community detection methods for street networks. Future research should attempt to holistically aggregate different sets of weights in defining neighbourhoods with multiple overlapping factors. This is important in developing a universal method to identify multi-factor multi-level street neighbourhoods. There are many consequent questions methodologically, namely how should the weights be aggregated and which weights should be prioritised. These questions can potentially be studied using data-driven and machine learning approaches. Other factors can include urban characteristics retrieved from street imagery or socio-economic characteristics retrieved from census data.

To conclude, weighted modularity optimisation is an appropriate method for identifying street-character-weighted local area that encompasses street connectivity, street density and street centrality. The method produces visually useful partitions with great computation efficiency. Due to the small sample size of this pilot study, further research is required to test different sets of weights for different neighbourhoods and different cities. More empirical work is needed quantitatively to validate the method. Further research can include incorporating the method in identifying spatial housing submarkets and to tests the extent these street neighbourhood partitions relate to human perceptual neighbourhoods by overlapping them with mental maps.

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