Evaluating Urban Accessibility: Comparative Representations of Street Network Topology Using GNNs

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Abstract

This study investigates the efficacy of graph neural network (GNN) information embeddings in analysing urban street network topology and its correlation with amenity access, compared with traditional measures of connectivity used in urban studies, in hopes of better informing the development and redevelopment of '15 minute cities', highly walkable neighbourhoods. Urban street networks and amenity accessibility profoundly influence urban livability, yet traditional analytical methods often oversimplify the complexity of these networks and their influence. This research employs GNNs to capture these complex interactions within urban environments, attempting to provide a better understanding of how street network design affects amenity access.

The research methodology involves training and testing multiple potential graph convolutional layers and hyperparameters, determining which is most capable of capturing street network topology in order to predict the number of amenities accessible for MSOA residents within a fifteen minute walk. The model's predictions are investigated with the use of GNNExplainer in order to open the 'black box' of machine learning prediction, and understand street network topologies that the model finds to predict high or low walkable amenity access. Mult-dimensional street network encodings for all urban and suburban MSOAs in England are then captured from both the pre-trained predictive model and a separately trained autoencoder using the same convolutional layers. These embeddings are further investigated with clustering, trait analysis, and plotting. Finally, their predictive capabilities are compared against those of traditional connectivity metrics through Spatial Error Models.

The study's findings suggest a nuanced and nonlinear relationship between connectivity and accessibility, influenced by factors such as the historical development of street networks, broader connectivity of train networks not captured by street topology, and the surrounding population density. Though requiring more complex pre-processing, findings demonstrate that GNNs provide superior predictive accuracy and analytical depth compared to conventional methods, with further investigation of their encoded data revealing complex dependencies that are crucial for informed urban planning and development.

This research contributes to the field of urban studies by introducing a methodological innovation and by refining our understanding of the dynamics between urban topology and functionality. It offers valuable insights for urban planners and policymakers aiming to enhance urban livability and implement 15-minute neighbourhoods through more informed, data-driven decision-making. Future research directions include expanding the application of GNNs to encompass additional urban characteristics and integrating more diverse datasets to further enrich the graph embeddings.

Code repository link:
https://drive.google.com/drive/folders/1Vvm0Jkt3ohkvwi2JFguVwZzsltgqY1MH?usp=sharing

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1 Introduction

Urbanisation is an ever-increasing reality as more and more of the world's population moves to expanding cities; as of 2020, approximately 56% of the global population lived in urban centres, a figure projected to rise to over 67% by 2050 (Shi et al., 2023). However, this process is neither uniform nor equal. Global urban studies have shown vastly different patterns in how urbanisation occurs, affected by many different factors. Fast-growing cities undergoing natural expansion are likely to beget tangled networks of slums, informal living conditions with prominent examples on the margins of Cape Town, Rio de Janeiro, and Mumbai. In contrast, regions with the finances and foresight for urban planning often manufacture (or bulldoze slums into) orderly, gridded streets, seen in both ancient ruins around the world, such as Rome and Mohenjo-Daro, and modern urban metropoli of the 19th century, including Chicago and Barcelona. (Xue et al, 2022).

These two broad patterns have been established since the first cities were built; however, newer shapes have more recently emerged. The advent of the automobile in the early 20th century created major shockwaves in the development of cities across the world and particularly in the West, prioritising car-centric planning characterised by sprawling suburbs, low-density housing reachable only through winding roads, cul-de-sacs, and dead end streets (Mees, 2009). Today, urban planners are still dealing with the aftermath of these planning choices forcing residents to rely on driving, which exacerbates social inequality by reducing access of residents without cars to essential services and social networks (Lucas et al, 2016), negatively affects public health by causing declines in daily walking (Daumann et al., 2015), and increases carbon footprints (Barrington-Leigh & Millard-Ball, 2019). Multivariate linear regression research using representations of the topological attributes of street networks has shown that the broad variety of potential forms of urbanity define innumerable aspects of life for their inhabitants, and shows that from them we can learn and learn to predict much (Ewing & Cervero, 2010; Barrington-Leigh & Millard-Ball, 2019).

Defined by urban planner Carlos Moreno in 2016, the idea of the '15 minute city' has quickly made its way from niche urban studies into popular culture as many cities attempt to reshape car-focused urban and suburban infrastructure into places more accessible for pedestrians

(Marchigiani & Bonfantini, 2022). These 15 minute cities are defined as urban areas within which all essential needs can be met within a 15 minute walk from home, increasing physical health, reducing carbon emissions, and supporting local economic sustainability (Moreno et al, 2022). Independent studies have established clear relationships between rates of pedestrianism and distance to amenities, with proximity, diversity, and supply of amenities being key factors in reducing driving rates (Elldér et al 2022; Olsen et al 2024). Further research has illustrated clear connections between street network topology and the locations of amenities, with streets and intersections that are more connected to their surrounding street network experiencing increased numbers of shopfronts. It is no surprise that they thrive in these areas; increased connectivity raises the number of shortest-path routes that pass through these areas, putting these amenities in the paths of more potential customers (Porta et al, 2012). These connectivity metrics not only gauge neighbourhood walkability, or the likelihood of residents being able to access essential amenities within a fifteen minute walk, but also can be used to predict residents' travel mode choices and even health outcomes. Understanding the implications of street network topology on urban accessibility is crucial; a deeper knowledge of these relationships can guide the development and redevelopment of healthier neighbourhoods, including 15-minute cities. Developing tools to plan these changes and model their impacts can significantly enhance the effectiveness of these urban improvements, leading to healthier communities and more sustainable urban environments. This research aims to inform successful strategies for increasing walkability in urban development and redevelopment.

Previous research of urban studies making predictions on urban characteristics based on street networks, particularly predictions of neighbourhood amenity accessibility, typically follow one of two related approaches. Within the first, space syntax is used, a process focusing on streets and intersections within the context of a broader street network graph to quantify their relative significance upon several measures; most importantly their *betweenness centrality*, or how likely the street or intersections is to be part of a shortest path between two other points, and their *degree centrality*, or the number of connections the intersection has (Freeman, 1977). In the second approach, predictions are made for a larger graph using overall representations summing up or averaging qualities of connectivity across the network, focusing on the quality of degree centrality across the nodes. Though consistency in these representations is lacking, common aspects used in this vein include proportions of nodal degrees, or what proportion of intersections are four-way, three-way, two-way, or dead ends, as well as ratios of streets to intersections. Though these methods may appropriately measure overall connectivity, there are still a vast number of possible graphs within each average measurement, each with potentially different ramifications towards residents.

Recent advances in data science, particularly within the field of machine learning, have made it possible to gain insights from large-scale datasets with complex variables interacting across spatial fields in non-linear ways. With the use of machine learning, broad varieties of information can be fed through algorithms to automatically pick out relevant data for the creation of representations of core distinguishing aspects, rather than going through extended feature engineering processes to determine and extract these distinguishing characteristics. These relevant representations are stored in low-dimensional latent feature representations, also known as embeddings, and can be used in further data analysis for predictive modelling, cluster analysis, or other research, often with much higher performance than traditional feature selection and representation. Among the newest applications of machine learning to urban studies are graph neural network models, which are capable of integrating into their analysis and representation of data not just the data objects themselves, but also the links between them, including specific qualities of those links. This process allows for the creation of detailed representations of complex networks, which has been increasingly used in recent years for urban analysis at the street network level.

Previous studies of effects of street network topologies upon neighbourhood walkability have used non-standardized connectivity measurements incapable of fully conveying the complex structure of the street network graphs. These methods are limited by the loss of granular data within these averaged measurements, as well as by the lack of standardised measurements across the field of street network topological study. By using recently developed graph neural network model methods to explore two ways of creating latent feature representations of street network topology, this study hopes to measure whether they can outperform traditional connectivity measurements in accurately predicting amenities available within fifteen minutes' walk with multivariate spatial error model, while also attempting to understand which topological graph features the models have found relevant to these predictions. This embedding strategy, if successful, could be deployed in further studies to incorporate more detailed data on a spatial scale defined not by geographical distance but by human-travelled connecting links of roads or other transportation routes.

1.1 Aims, Hypotheses

Aim: To evaluate and compare the effectiveness of traditional graph connectivity measures vs experimental graph neural network embeddings in predicting neighbourhood amenity accessibility based on street network topology, with an emphasis on the accuracy of predictions and the ability to identify critical spatial features that enhance accessibility.

Hypothesis 1: The graph convolutional neural network model embeddings will provide a higher predictive accuracy for fifteen-minute amenity access compared to traditional average connectivity metrics due to their abilities to capture complex topological features of street networks.

Hypothesis 2: Specific street network configurations significantly influence the availability of essential amenities within a fifteen minute walk, thereby impacting neighbourhood accessibility.

2 Literature Review

Urban street networks fit into the category of "complex systems" along with ecosystems, economic systems, and social networks; all of which have intricate internal features and topology affecting their characteristics and outcomes. These systems are inherently difficult to model and understand, but have huge influence over the people living within them. An early work popularising the idea of studying and quantifying this influence of urban street networks was the book *The Social Logic of Space* (Hiller & Hanson, 1984), which presented both the idea of the connection between space and society, and Space Syntax, new methodological tools for analysing these connections. Among the now-fundamental ideas proposed in this work was the concept of a mutually dependent relationship between space and society; that the creation of spatial layouts is greatly influenced by existing social behaviours, and that spatial layout greatly influences ongoing individual and collective behaviours.

Studies show that while the locations of primary economic activities typically initially define street networks, the locations of local secondary economic activities actually have a stronger tie to the layouts of these networks. Though roads are built to facilitate travel to major centres of economic output, the locations of local necessities are defined by these street networks and the ways that people move through them (Porta et al, 2012). One aspect of layout is particularly influential; the levels of connectivity between streets and their surrounding network. Well-connected streets are more likely to be included in shortest-path routes as they are more likely to link origin to destination (Hillier et al, 1993), attracting more people to pass through them and more businesses hoping to serve these passers by. Street networks do not only define where people go, but also how they get there; a multitude of studies have shown strong correlations between neighbourhood network layouts and the choices of their inhabitants to walk, cycle, or drive to reach daily activities (Ewing & Cervero, 2010)**.** This may be linked to street networks defining the locations of amenities; with amenities drawn to areas of high betweenness centrality, residents of less connected areas could face longer distances to reach amenities and thus choose to drive. Street network structures, amenity accessibility and travel mode choice are linked through the social-spatial connection. In order to understand and improve the accessibility of neighbourhoods, thus increasing rates of walking and biking over driving, it is necessary to examine and compare patterns in the street networks of neighbourhoods with high and low walkability.

In studying street networks and their connections to phenomena of urban life and public health, researchers have used strategies from other areas of general network science, to quantify and measure connectivity and disconnection, in particular centrality measures and nodal degree proportions. These measurements highlight different aspects and scales of network efficiency and connectivity, with both successfully used to reveal important information on street network patterns and their effects. Centrality measures provide understanding of how individual streets or intersections influence traffic flow, accessibility and connectivity within the network. While the betweenness centrality method uses network information to examine specific streets, measurements of nodal degree centrality distribution are used to quantify broader topological patterns of connectivity for a macroscopic view. Nodal degree distribution is defined as the proportion of nodes connected to a certain number of edges to the total number of nodes. Within the context of street networks, this is more easily understood as the proportion of intersections within an area that are four-way intersections, three-way, two-way (very unusual), or dead ends.

Using measurements of nodal degree distribution, studies have isolated common patterns of street network topology for comparison on their outcomes. Graphs where nodal degrees of 4 or more are more common indicate well integrated networks with extensive interconnectivity, such as gridded neighbourhoods and old mediaeval centres. Conversely, networks characterised by a prevalence of nodes with fewer connections indicates increased occurrences of dead ends, cul-de-sacs, and poorly-connected streets. These factors indicate properties of dendricity, or tree-like-ness, wherein successions of branching streets mean that many nodes can only be reached using one path. All street network types exist somewhere on this spectrum of connectivity between gridded and dendritic patterns. Studies on the two major morphologies indicate that network efficiency and robustness are strongly correlated with higher proportions of high nodal degrees indicating interconnectivity (Buhl et al, 2006). Measures of circuity and sinuosity measuring the directness of travel routes indicate that travel efficiency is higher in more connected networks where roads of high betweenness centrality provide best shortest-path routes (Barrington-Leigh & Millard-Ball, 2019). Highly interconnected networks are also less susceptible to failure; if a street is blocked or traffic is bad, there are other routes to reach the destination. In a disconnected dendritic network, a single street being blocked can isolate an entire neighbourhood, potentially causing huge safety issues in the cases of emergency vehicles needing access or natural disasters such as wildfires that must be escaped (Buhl et al, 2006).

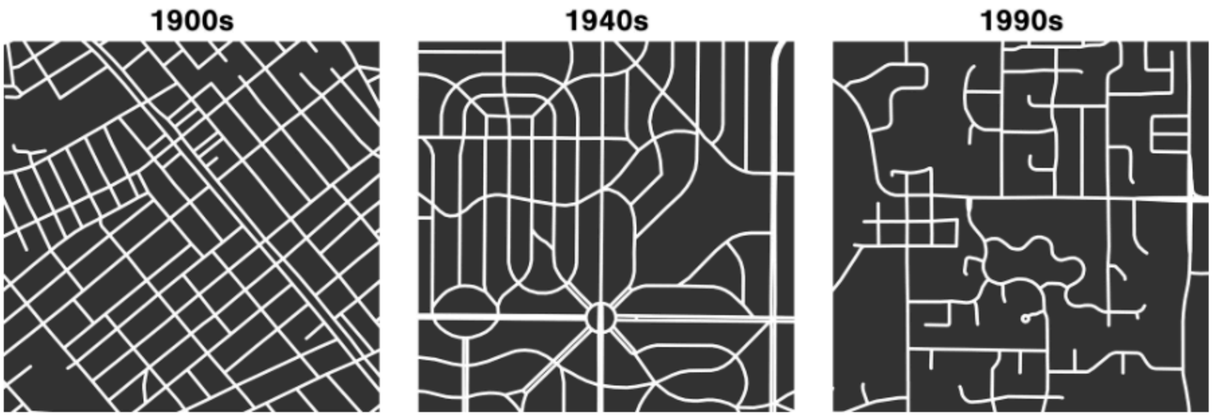

Figure 1. Real-world example street patterns from grid-based to dendritic. (Boeing, 2021)

As previously mentioned, connectivities of neighbourhoods and their associated topologies have significant effects on the locations of local amenities and the travel strategies used to reach them. Studies of local commerce agree that shops and restaurants do best in areas of high connectivity, such as town centres, areas often passed through due to high betweenness centrality. This increased exposure to potential customers gives businesses a higher chance of success than they would have in an area less travelled, and often results in increased urban vitality and the attraction of more visitors and more businesses (Porta et al, 2012).

Many studies on urban street networks have shown the statistical significance between street connectivity and transportation choice. Marshall and Garrick have found through multivariate regression models that people living in areas with high rates of connectivity are more likely to walk, cycle, or use public transportation on day to day journeys, while people in less connected urban areas are more likely to own and use cars (Marshall & Garrick, 2012). These studies used the average connectivity measurement of edge-to-node ratio, intersection density, and multiple street design variables compared to dependent variables of travel mode choice, with the 2010 study also incorporating socioeconomic census data and traffic data. Other studies, such as Boarnet, Nesamani, & Smith's 2004 land use analysis, as well as Cervero & Kockelman's 1997 research used measurements of proportion of four-way intersections to predict vehicle miles travelled per household with linear regressions (Boarnet, Nesamani, & Smith, 2004; Cervero & Kockleman, 1997). Both studies found that driving decreased within street networks with higher proportions of four-way intersections. It is possible that the discrepancy in travel mode choices between highly connected and disconnected neighbourhoods is influenced by residential self-selection bias caused by people who wish to walk or bike choosing to live in connected neighbourhoods where it is possible to do so, thus increasing rates of walking and biking there and decreasing them in other neighbourhoods. However, studies accounting for this bias still show that the street network has a stronger influence than self-selection; that environment is more influential on travel mode choices than individual choices (Ewing & Cervero, 2010). As humanity urbanises at increasing rates and it becomes necessary to expand cities and increase population density in suburban areas, it is important to build a stronger understanding of what topological factors make areas walkable, in order to design and build environments that reduce reliance on cars.

The vast majority of studies found measuring the effects of topology upon travel mode choice, amenity count, or public health outcomes do so with multivariate linear regression models. These models include a measure of street network structure, either, as previously mentioned, the proportion of intersections that are four-way; average nodal degree - the number of edges multiplied by two and divided by number of nodes; or edge-to-node ratio - the number of edges divided by the number of nodes. Little consensus exists deciding should be universally used. Some peer-reviewed studies, including Marshall, Piatkowski & Garrick (2014) have gone even further and performed manual classification upon street networks according to their visual resemblance to several predefined types, a laborious approach likely to invite human error or unconscious bias. Other studies, such as Barrington-Leigh and Millard-Ball's (2019) study of suburban sprawl, incorporate new structural and geographical measures of dendricity, circuity, and sinuosity, in order to create a Street-Network Disconnectedness index (SNDi) for classification and clustering of street networks. These different measures of street topology - average connectivity, manual classification, percentage of four-way intersections, and SDNi - are capable of measuring overall attributes of a system, as shown by the success of these studies in calculating effects of these topologies upon travel mode choice. However, they can only capture average attributes, not the specific topologies and subgraph patterns unique to individual graphs that may play large roles in dictating variable outcomes.

Graph Neural Networks (GNNs) are a powerful class of neural networks designed specifically for interpreting and making predictions on data that is structured as graphs. In order to capture the local and global structural information of graphs, GNNs use a technique known as message passing, whereby nodes in the graph aggregate information from their neighbouring nodes through layers of the network. Each node updates its state by combining its own features with the aggregated features of its neighbours, enabling the GNN to learn complex patterns across the entire network and allowing for both node-level and graph-level predictions (Kipf & Welling, 2016).

GNNs have fairly recently begun to be used in the context of urban street network analysis. An early primary use of GNNs in this field has been in traffic analysis and outcome prediction, with many studies deploying the network-based structures to simulate traffic flows over spatio-temporal graph neural networks (Jin 2023). GNNs can analyse the connectivity and flow between intersections to forecast traffic congestion, travel times, and potential bottlenecks. This capability allows town planners to make informed decisions about traffic light timings, road expansions, or public transport enhancements. Liu, Zhang, & Biljecki (2024) proposed a traffic volume prediction model combining graph convolutional networks with graph-based explainable AI method, called GNNExplainer, emphasizing the importance of understanding machine learning predictions. This capacity for analysing traffic flow arises from the ability of graph neural networks to capture the details of the street networks that traffic moves through in complex street network representations. Within street network representation, autoencoders are used to learn latent representations of street patterns which can then be clustered into different classifications or regressed against potential outcomes. These latent representations are created by compressing the high-dimensional input data (such as topological or geometrical features of the street network) into a lower-dimensional, encoded space. This process involves training the autoencoder to minimise the reconstruction error, which encourages the encoded space to retain as much of the significant information from the original data as possible, while discarding noise and redundant information (Kipf & Welling, 2016).

Neira & Murcio (2022) used these capabilities of encoders in their employment of Variational Autoencoders (VAEs) to model urban networks, capitalising on their ability to condense graphs of complex street networks into low-dimensional representations for clustering and analysis while also generating new, realistic urban configurations. Their findings demonstrated that VAEs could effectively extract key urban topologies, thus providing valuable insights into urban morphology and facilitating the analysis of previously unseen urban environments. This approach underscores the potential of autoencoder models in urban analytics, particularly in capturing the intricate topological features of urban layouts that traditional methods may overlook. Xue et al. (2022) also implemented graph autoencoders in order to quantify the spatial homogeneity of urban road networks using GNNs, revealing their ability to capture complex spatial patterns that are critical for urban planning, and discovering economic similarities between urban regions sharing similar road network structures. Zheng et al (2023) showed the potential of graph machine learning to inform urban redevelopment by applying reinforcement learning approaches to graph representations of the complex street networks of inaccessible slums, in order to propose new road infrastructure that could most efficiently serve disadvantaged urban residents.

Collectively, these studies highlight the transformative impact of machine learning techniques, particularly GNNs and autoencoders in advancing urban data science and enhancing the analytical capabilities of urban researchers by providing advanced representations of big complex data. As more urban data becomes available through increasing data capture and Internet of Things (IoT), networks of interconnected devices and sensors embedded across urban infrastructure and objects, machine learning will become essential to parse such massive datasets for meaning and insight for urban planners and managers (Hu & Shu, 2023). This study aims to compare topological representations created by predictive GNNs, autoencoders, and traditional metrics in their success in encoding interpretable data for analysis.

The connection between structure and property within street structures cannot be clearly labelled as causative. Relationships between amenities and street networks can run both ways; a density of amenities in one area creating more traffic and more incentives to increase connectivity and create clear through-routes; or a connected neighbourhood increasing pedestrian flow down certain streets and incentivising the establishment of more amenities. It should not be taken from this study that certain areas have been built wrongly (though some may be sub-optimal), only that from seeing a structure, we may hope to guess its properties, and perhaps vice-versa. Previous studies have shown that, although not universally clearly delineated, there is a causative relationship between an area's street network structure and the lives of its occupants, and by understanding what a walkable street network looks like, we may be able to build and rebuild our environments for better public health.

3 Data

3.1 Selecting Study Regions

This study was performed at the Medium Super Output Area (MSOA) level across all urban and suburban areas of England. MSOAs, each of which are built out of 3-5 adjacent Lower Super Output Areas (LSOAs), are defined by the population size within them, requiring a minimum population of 5,000 residents and a maximum of 15,000 residents, with most MSOAs having a population between 7,000 and 10,000. MSOA was selected for the level of study both their size and available data. While lacking the fine-grained data of LSOAs, they are large enough to demonstrate significant street network patterns within, unlike LSOAs which often are too small to show more than 5 streets. However, unlike Wards, LSOA-level data can still be accurately aggregated to the MSOA level, providing valuable insights on these regions.

As this study draws mostly upon urban research, it was necessary to first exclude rural MSOAs. This was done using the Spatial Signature dataset created by Urban Grammar project through application of machine learning clustering upon satellite imagery (Fleischmann & Arribas-Bel, 2022). Sixteen spatial signature typologies are defined, ranging from "Hyper concentrated urbanity" to "Wild countryside". Their data used in this research consisted of a dataframe for which each row represented an LSOA and each column the percentage of LSOA covered by each spatial signature type. These LSOA labels were aggregated to the MSOA level through area-weighted averaging in order to find what percentage of the MSOA consisted of each type of spatial signature. The spatial signature percentages were summed into either the urban and suburban category or the rural category, and MSOAs where a majority of the area was classified as rural were excluded from the dataset. MSOA and LSOA boundaries and population data were retrieved from Office for National Statistics' Open Geography Portal (Office for National Statistics, 2011).

3.2 Street Network Data

After isolating the MSOAs to be used in the study, the next step was to extract their street networks to be turned into graphs. This was done through use of Open Street Maps (OSMnx), an open-source mapping tool created by volunteers to record routes and features across the world (OpenStreetMap contributors, 2015). For each MSOA in England, geographical boundaries were created as a polygon and lists of street and intersection data within the polygon downloaded. Though this project focuses on walkability, the 'drive' network was used (showing all publicly accessible drivable routes) rather than the 'walk' network, as previous tests showed that the latter included many redundancies and fine details not representative of overall neighbourhood structure, such as driveways or both pavements on each side of a road. This may introduce inaccuracies if, for example, MSOAs had drive networks associated with inaccessible neighbourhoods but also had walkpaths 'unseen' by the graphs that introduced more walking accessibility. Future iterations of this research could attempt to use the walk travel mode for graphs by introducing further filters upon the links included, or by including edge type as an edge attribute. Edge attributes were not included in this research due to their incompatibility with several convolutional layer types and also with GNNExplainer. The information used from these extractions were lists of node (intersection) ID's, their coordinates, and lists of edges (roads) connecting each node.

One potential issue arises during graph extraction. Because the graphs, by necessity, are cut off at the borders of the MSOA, the edges of these graphs may not always reflect the true roads they represent. For example, a busy street heading towards a major intersection would be transformed to a dead end road when sliced short along MSOA boundaries, or a 4-way intersection transformed into a 2-way junction. Smaller MSOAs may face this issue more intensely than larger ones, as their perimeter increases in ratio to their internal area. In light of this issue, further research could consider studying city-wide graphs rather than subsectioning them.

Graphs as data objects are formed from three primary tensor components; 'x', a matrix holding rows of node feature data; 'edge_index', a 2-dimensional tensor holding the source and target nodes of edges defining the connections between nodes for messages to be passed along; and 'y', which contains the target labels or values for graph- or node- level prediction tasks. This analysis relied exclusively on graph topology to predict accessibility, and so no external data was taken from Open Street Maps other than lists of nodes, or intersections and the edges representing the streets, roads, or paths connecting them. Node feature data consisted of only an array of 1's, one for each node, in order for them to have something to aggregate during the message passing phase of the convolutional layers.

Within the message passing layers of a graph neural network, positional encodings can allow the model to weight and prioritise the incoming messages based on node positions, introducing anisotropy, or properties of directional dependence, into an otherwise isotropic or directionally homogenous process. This leads to more precise and context-aware updates during the message aggregation phase. Two sets of UK graphs were created, one with positional encodings also incorporated into nodal attributes and one with only the array of ones, in order to test whether positional encoding could contribute to increased understanding of topology.

3.3 Amenity Availability Data

This study in its investigation of the topology of fifteen-minute cities seeks to elucidate further upon the relationship between amenity availability and street topology, which has been previously found to show positive correlations between street betweenness centrality and presence of secondary economic activities. By gaining a better understanding of the relationship between street network topology and amenity access through topology embedding analysis, this study hopes to identify street network patterns that could promote increased amenity access and decrease daily use of cars, increasing public health In order to better understand these relationships, the availability of amenities within a fifteen minute walk must first be established for each MSOA. Walk mode analysis was chosen over public transit or bikes, all of which fit into the 15 minute city theory, in order to equalise access measures across populations which may have varying physical or financial restraints on bicycling, or urban areas that may have varying budgets for public transportation.

The essential amenities included within this study fall within seven categories, consisting of primary schools, secondary schools, further education, general practitioners (GPs), hospitals, food stores, and job centres, which here are classed as MSOAs with 5000 or more jobs. This data was collected and preprocessed to the LSOA level by the Department for Transport (DfT) at the Census Output Area (OA) level across England for their Journey Time Statistics 2019 data series (Department for Transport, 2021). For each of the 171,372 OAs, a road network point closest to the OA centroid was defined as the starting point, the road network distances to the nearby amenities was calculated, and the number of each amenity type within 15 minutes walk found assuming a walk speed of 4.8km per hour, just below the average person's walk speed. Road links were converted to straight lines before finding these routes, which could potentially cause data accuracy issues for any areas with excessively winding roads between intersections. OA data was then aggregated by DfT to the LSOA level using population-weighted aggregation. This process used a road network that included both driving and walking paths, differing from the drive-only street network used to create this study's MSOA street network graphs. Though unfortunate, the decision was made to retain this inconsistency due to the previously mentioned issues with the walk network topology, and to keep it in mind during analysis of results. One other potential issue introduced by the differences between the street network graph data and the amenity data is temporal; while the street network graph data is current, the amenity data is from 2019, the most recent iteration of DfT's Journey Time Statistics. This could result in inconsistencies from amenities opening or closing in the 5 intervening years, or construction changing street network topology. Efforts were made to download a 2019 version of the street networks from Open Street Maps to rectify this, but were ultimately unsuccessful.

Creating a truly accurate accessibility index would be a herculean task well worthy of its own dissertation. In this project, a simple cumulative index will instead be used to sum up the potential amenities accessible within a fifteen minute walk for the average resident of each MSOA. Inaccuracies in this method may arise from the equal weighting of each amenity, though not all amenities are truly equal. For example, an MSOA with four coffee shops would receive a higher score than an MSOA with a local supermarket and a primary school, even though the latter may likely generate more walkability for many of its inhabitants. However, without well-validated walkability indexes to draw from or extensive research on the relative importance of different amenity types, this cumulative measure was chosen as the least biased path.

Testing each variety of amenity independently was also considered, but as the 'count' of amenities within fifteen minutes maxes out at 10, MSOAs with the densest amenities had artificial caps placed on their scores, particularly within the 'food shop' category within central London where such amenities abound. By combining the different amenity types, MSOAs scoring high in a variety of amenities could be appropriately represented as higher-scoring.

As the data was originally downloaded from the DfT datasets at the LSOA level, it first had to be aggregated to the MSOA level. For each LSOA within an MSOA, the number of amenities within each amenity type was summed up, multiplied by the percentage of the MSOA population represented by the LSOA, and then added to the counts of other population-weighted LSOAs within the MSOA. Population weighted-averages were found rather than sums or regular averages in order to avoid double-counting any amenities and to ensure that LSOA with lower populations did not have outsized effects on overall results. This is the same process used by DfT to aggregate from OA to LSOA.

The resulting data consisted of the average number of amenities that each resident of the MSOA was able to access within a fifteen minute walk from the centroid of their OA. 3903 MSOAs were included in analysis, for which the average number of amenities within fifteen minutes was 6.984, with a standard deviation of 3.733.

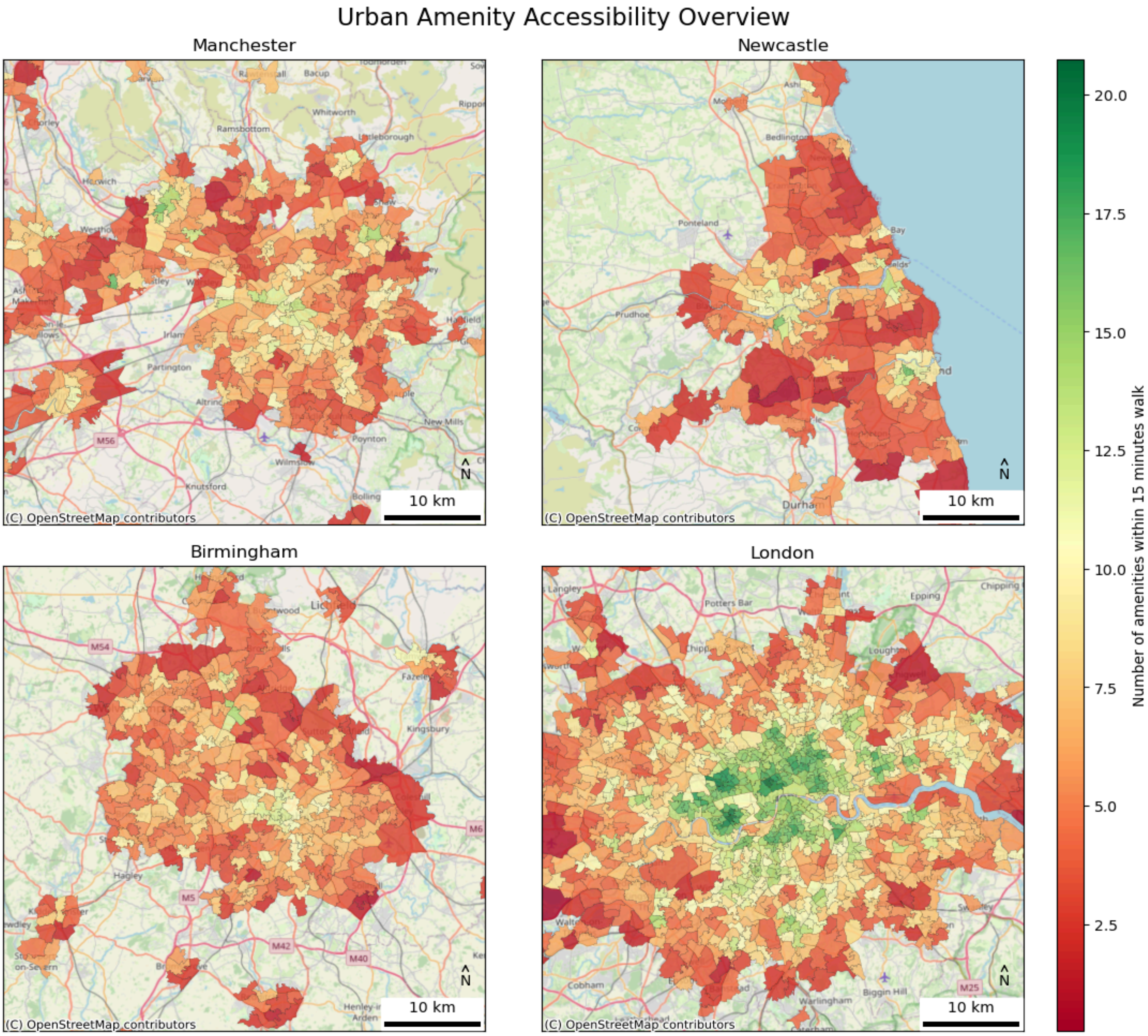

Figure 2: Plot of number of amenities accessible within 15 minutes walk for MSOAs within major urban areas in England

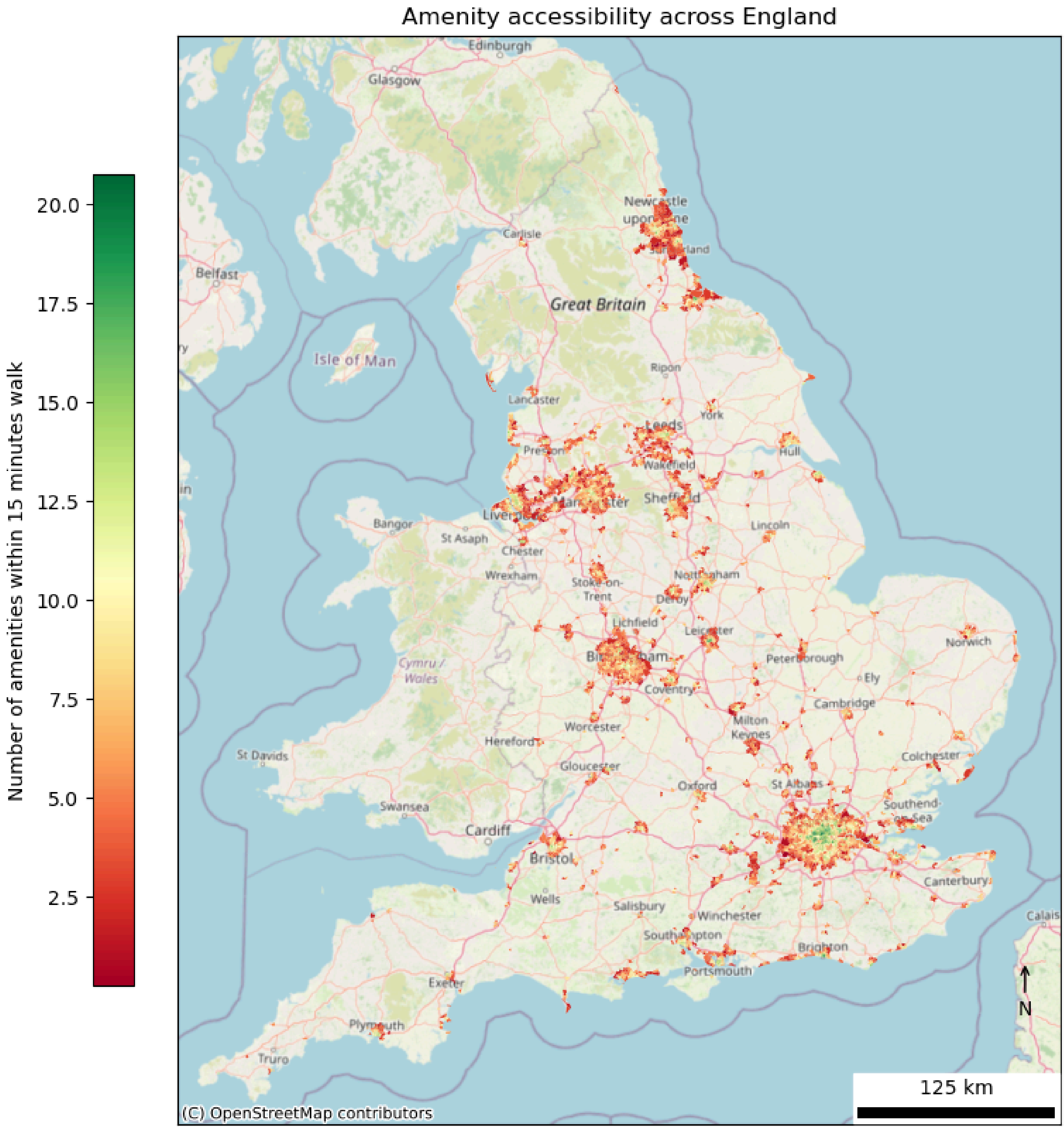

Figure 3: Plot of all urban and suburban MSOAs analysed with number of amenities within 15 minutes walking distance

4 Methodology

4.1 GNN Graph Prediction Model

Convolutional graph neural networks (CGNNs) operate similarly to traditional neural networks, consisting of interconnected layers of neurons that process and pass data. Each neuron is equipped with weights, internal parameters that determine which information is propagated to subsequent layers. These parameters are dynamically adjusted based on the network's performance during training to enhance prediction accuracy. Models leverage the trained parameters to convert input data into embeddings—multi-dimensional vectors that encapsulate the most salient features for making accurate predictions. The embeddings generated from the input data are subsequently processed through additional non-convolutional layers, which transform them into the final output predictions.

However, while traditional neural networks apply the same transformation across all parts of the input, CGNNs perform convolutions that account for the nodes' connectivity patterns. This allows CGNNs to aggregate information from a node's neighbours dynamically, updating node features based on both their direct attributes and their connections within the larger network each time embeddings are passed through a convolutional layer. These adaptations make CGNNs well suited for tasks where data relationships are explicitly defined by connections between elements.

Four different graph neural network models were built in order to test the efficacy of the methods of different message-passing layers; Graph Convolutional Network (GCN) (Kipf & Welling, 2016); Graph Isomorphic Network (GIN) (Xu et al, 2018); Graph Sample and Aggregation (GraphSAGE) (Hamilton, Ying, & Leskovec, 2017); and Dynamic Graph Attention Network (GATv2) (Shaked, Alon, & Yahav, 2021). Each model was built with the same architectural framework, differing only in the type of convolutional layer applied to the data. These layer types take different approaches in order to process, weight, and aggregate data from neighbouring nodes.

The initial linear layer transforms the graph data object into multidimensional node embeddings. The following convolutional layers aggregate data across the nodes in layers, to each node passing from the previous layer the information from that same node and its neighbours. By repeating this process across multiple convolution layers, nodes integrate information from broader topological contexts, enabling the network to capture complex patterns within the graph's structure. This is combined with the activation function ReLU (Rectified Linear Unit), introducing non-linearity into the function by neutralising negative inputs. ReLU was chosen for its success in speeding up the training process without penalties to accuracy and relative lack of vanishing gradient issues found with other activation functions like sigmoid or tanh (Nair & Hinton, 2010).

After the convolutional stages, a global pooling layer aggregates node features across the entire graph into a single multidimensional encoding of vectors. This encoding is the graph embedding, which after training can be extracted for prediction. The aggregated encoding is then passed through two fully connected linear layers, which include ReLU activations and dropout for regularisation, preparing the data for the final prediction output. After each epoch, the convolutional layer parameters are updated to change the relative valuation of different data and improve model accuracy.

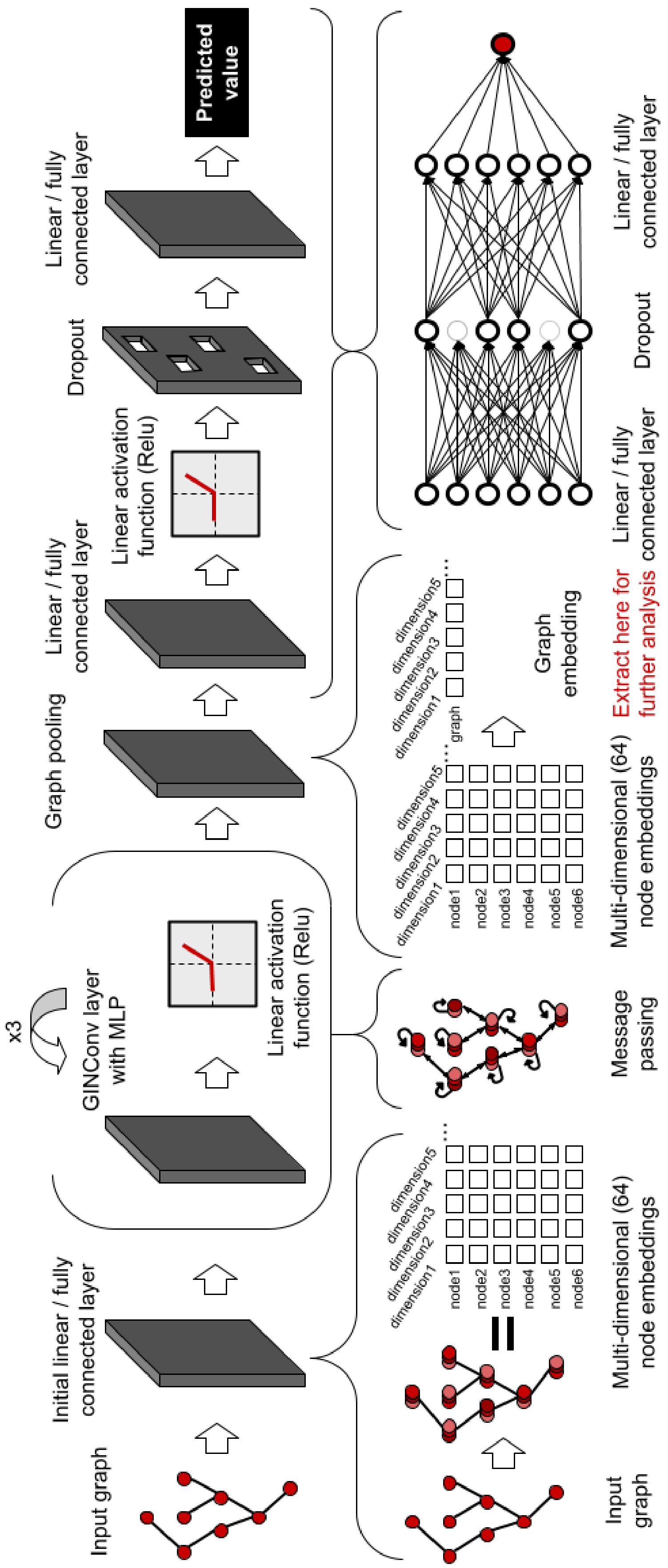

Figure 4: Schematic of the most successful graph convolutional neural network architecture used in this study with graph isomorphic network convolutional layer.

In the comparative study of four graph models, each model is designed to be as similar as possible in structure, employing layers that capture and integrate information across graph nodes to predict outcomes based on node and graph-level features. However, the GIN model differs in its use of a Multi-Layer Perceptron (MLP) within each convolutional layer, as shown in Figure 3. Unlike other models in this study using linear transformations or direct aggregation methods, GIN requires MLP to mimic the Weisfeiler-Lehman graph isomorphism test, a method known for its ability to distinguish graph structures (Xu et al, 2019).

$$h_v^{(k)} = MLP^{(k)}\left(\left(1 + \epsilon^{(k)}\right) \cdot h_v^{(k-1)} + \Sigma_{u \epsilon N(v)} h_u^{(k-1)}\right)$$

This equation from the original GIN paper by Xu, Hu, Leskovec and Jegelka (2019) represents the process by which GIN updates node representations, wherein $h_v^{(k)}$ represents the feature vector of node v at the k-th layer of the GNN. As nodes gather information from their neighbours one layer at a time, k also represents the number of neighbouring nodes, $N(v)$, that have had their information integrated into node h. $\epsilon^{(k)}$ is the learnable parameter that adjusts the weighting of the node's own features relative to its neighbours.

The models were trained with Mean Squared Error (MSE) loss function to calculate the difference between the real and expected values for the initial regression task, and the Adam optimizer with a learning rate of 0.01 for adjusting the parameters based on the first and second moments of the gradients (Kingma 2014). In the initial model comparison, each model was trained with a single layer for 50 epochs. Loss was reported for both training and testing as the average error per graph. All models except for GIN showed strong signs of underfitting during the tests, with little to no variation in the predicted values.

After selecting the model with the lowest loss between the true and predicted scores, the optimal number of convolutional layers was determined by comparing the 1-layer loss to 3, 5, and 10 layer model losses. Though it was marginally outperformed by the 10-layer model, the three-layer version was chosen for increased processing speed. Further research with greater computational resources could feasibly increase the number of layers along with accuracy. Increasing the number of convolutional layers in a GNN enables the model to aggregate information from a broader scope of the graph with each additional layer. This expansion through successive layers allows nodes to gather and process data from a wider network context, capturing more complex patterns and higher-order interactions between nodes that are not direct neighbours. As a result, deeper GNNs can develop more sophisticated representations, increasing their ability to predict outcomes based on comprehensive graph-wide data. However, deeper networks also risk overfitting and vanishing gradients.

Tests were conducted to find the most effective number of hidden channels, the number of dimensions of the feature representations that hold node and later graph data at each stage of the neural network. Each hidden channel captures a different aspect of the node's information or neighbourhood context. Increasing the number of hidden channels can allow GNNs to capture more complex patterns, but also increases computational requirements and can risk overfitting. The three-layer GIN model was tested with 32, 64, and 128 hidden channels and found the model with 64 layers to perform best. Test data consistently received lower loss scores than the training data, possibly due to increased variation of the y-value within the training data. However, it indicates that overfitting is not occurring within the models. The results of these initial tests can be seen in Table 1.

Conv. Layer	Layers	Channels	Train MSE loss	Test MSE loss
GCN	1	32	14.39	12.71
GIN	1	32	10.15	10.95
GraphSAGE	1	32	14.71	12.70
GATv2	1	32	14.66	12.71
GIN	3	32	9.63	7.76
GIN	5	32	9.08	11.48
GIN	10	32	9.28	7.34
GIN	3	64	9.66	7.84
GIN	3	128	10.06	8.19

Table 1: Standard data, no positional encoding, random test-train split, 50 epochs

Further tests were performed on this model to check its viability and attempt to improve its performance, the precise results of which are within Table 2. Instead of leaving the node values holding only 1's, five positional encoding values were added to each node. Positional encodings derived from Laplacian eigenvectors can help GCNNs better interpret and exploit the structural information in graphs. These encodings give each node a unique signature based on the node's position in the graph's embedding space, reflecting how nodes are connected and positioned within the larger network. In this case, though the positionally encoded data model achieved lower test and training losses than the model with regular data, examining the projected predictions and data distributions showed that the former exhibited less variance with poorer data distribution than the latter. Finally, a spatial dependency test was run, training the model on data excluding the West Midlands and then testing solely on the West Midlands, as seen in Figure 4. This spatial dependency test accounts for the possibility that the model is recognizing specific patterns in the randomly chosen training set MSOAs and applying its predictions to immediately neighbouring MSOAs in the test dataset, which may share the same patterns due to their adjacency. By spatially separating the training and testing sets, the test ensures that only overall patterns are being learned and applied. Finally, the best-performing model with 3 GIN convolutional layers and 64 hidden channels was trained for 150 epochs to optimise its learning, the parameters and results of which can be seen in Table 3. It was frozen in this state, all graphs passed through and the embeddings extracted for later spatial error model analysis.

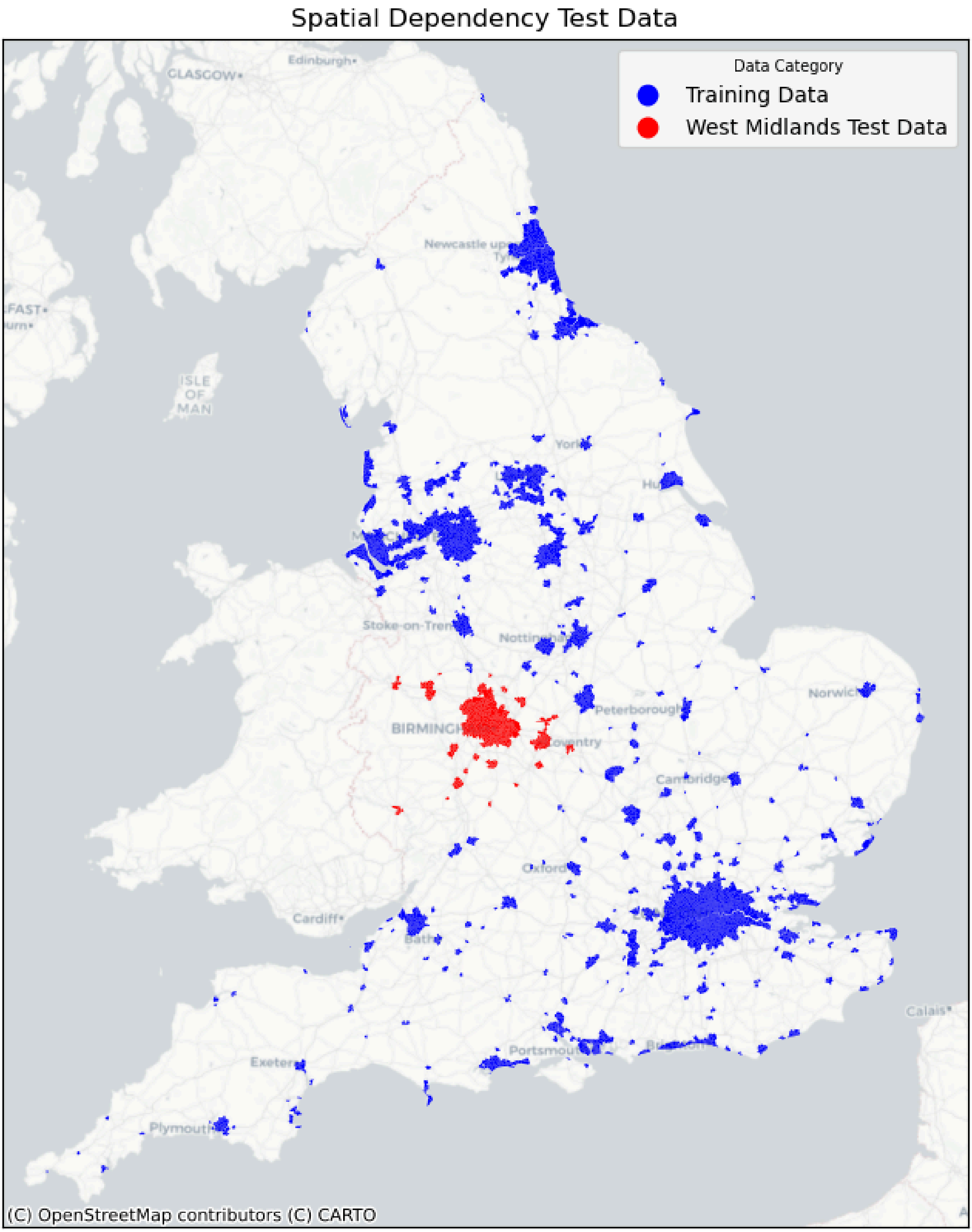

Figure 5: Spatial dependency test data

Data	Train MSE Loss	Test MSE Loss
Positional Encoding	9.46	10.30
West Midlands split	8.82	4.79

Table 2: Alternate Data Tests

Conv. Layer	Layers	Channels	Epochs	Train MSE	Test MSE
GIN	3	64	150	8.66	7.39

Table 3: Final Model Specifications

After successfully setting up and training the models on the different y-values, a GNNExplainer was built in order to explain the predictions made. GNNExplainer works to identify the most relevant nodes and edges that models base their predictions from, providing insights into how and why a GNN makes specific predictions (Ying et al, 2019). By optimising a mask over the input features and the graph structure, GNNExplainer effectively isolates selective parts of the graph and measures which information is necessary for the model to reach the same prediction as it would with the entire graph. After isolating these most informative streets and intersections, they were projected onto the original street maps for better visual understanding. The highest and lowest predictions made by the model were selected and projected in order to potentially gain understanding of qualities the model judged to be important in predicting amenity access.

4.2 Graph Autoencoder

After establishing the most effective convolutional layer and hyperparameters for number of layers and number of hidden channels during GNN training, this knowledge was applied to the creation of an autoencoder. A graph autoencoder is a type of neural network designed to learn efficient representations of graphs. It consists of two main components, an encoder and a decoder. The encoder maps the input graph's node and edge data into a latent space to create a compact vector representation. This embedding is intended to preserve the structural and feature data of the graph in a compressed form. Once encoded into the latent space, the decoder attempts to reconstruct the original graph structure from these embeddings in a link prediction problem. The encoder uses the latent representations to predict adjacency relationships between nodes in an attempt to reconstruct the adjacency matrix of the original graph. The performance of the autoencoder is assessed with Receiver Operating Characteristic (ROC) Area Under Curve (AUC) score, which sums up how well a model can distinguish between positive and negative instances in classification tasks. In this model, true links are defined as positive instances and false ones as negative. Unlike the previous GNN training, this task is one of unsupervised learning. The objective is not to understand specific qualities associated with high or low amenity access but to compress and isolate the underlying structure of the graphs. The model received a ROC AUC score of 0.92 on the testing and training data.

After training the autoencoder on all non-rural English MSOA graphs, the model was frozen, the graphs passed through once more and the embeddings extracted. Another unsupervised learning task was performed with k-means clustering upon the embeddings in order to map graphs with similar structures. These clusters were visually compared against amenity count data along with other social and topological variables to identify patterns between the topological similarity of the graphs and these additional variables.

4.3 Comparative Spatial Error Models

The first phase of this study established a baseline of commonly used methods of identifying amenity accessibility from graph structure to which to compare the performance of the final model. For each MSOA, the average nodal degree was calculated, or the average number of edges emanating from each node, a feature equivalent to twice the number of edges divided by the number of nodes. This feature was chosen for its previous usage in research on effects of street network graph topology on accessibility, health, and transport choices. Higher average nodal degrees indicate higher average connectivity, with more 4-way intersections, connecting streets, grid shaped networks, and many potential routes through a graph. Lower average nodal degrees, on the other hand, indicate lower connectivity, with more dead ends and dendritic patterns, where fewer possible routes through the graph exist.

Next, multivariate linear regression was run to establish whether residuals were spatially correlated before running spatial error models. Principal component analysis was performed upon the embeddings to extract 8 vectors with the most variation, avoiding excessive collinearity. Global Moran's I test was run on the residuals of the three models, and each demonstrated the required spatial correlation for spatial error model. Spatial error model was chosen in order to factor the topology of nearby non-rural MSOAs into predictions, as nearby street networks are likely to make an impact on amenity counts, particularly as MSOA amenity access overlap most likely exists for residents near the edges of MSOAs. Future spatial prediction tests on this topic could also experiment with spatial lag models in addition to spatial error models, as there is likely overlap and influence between both the independent and dependent variables in this scenario. For each model the R^2 score, representing the proportion of variance of true amenity counts explained by each model, was recorded and compared, as were the coefficient values for the average nodal degree and each PCA-selected vector of two embeddings sets. The final residuals were projected to visualise areas of high or low accuracy, and the predictions of the models compared.

5 Results

5.1 GNN Predictions and Explanations

Best Performing Model Predictions

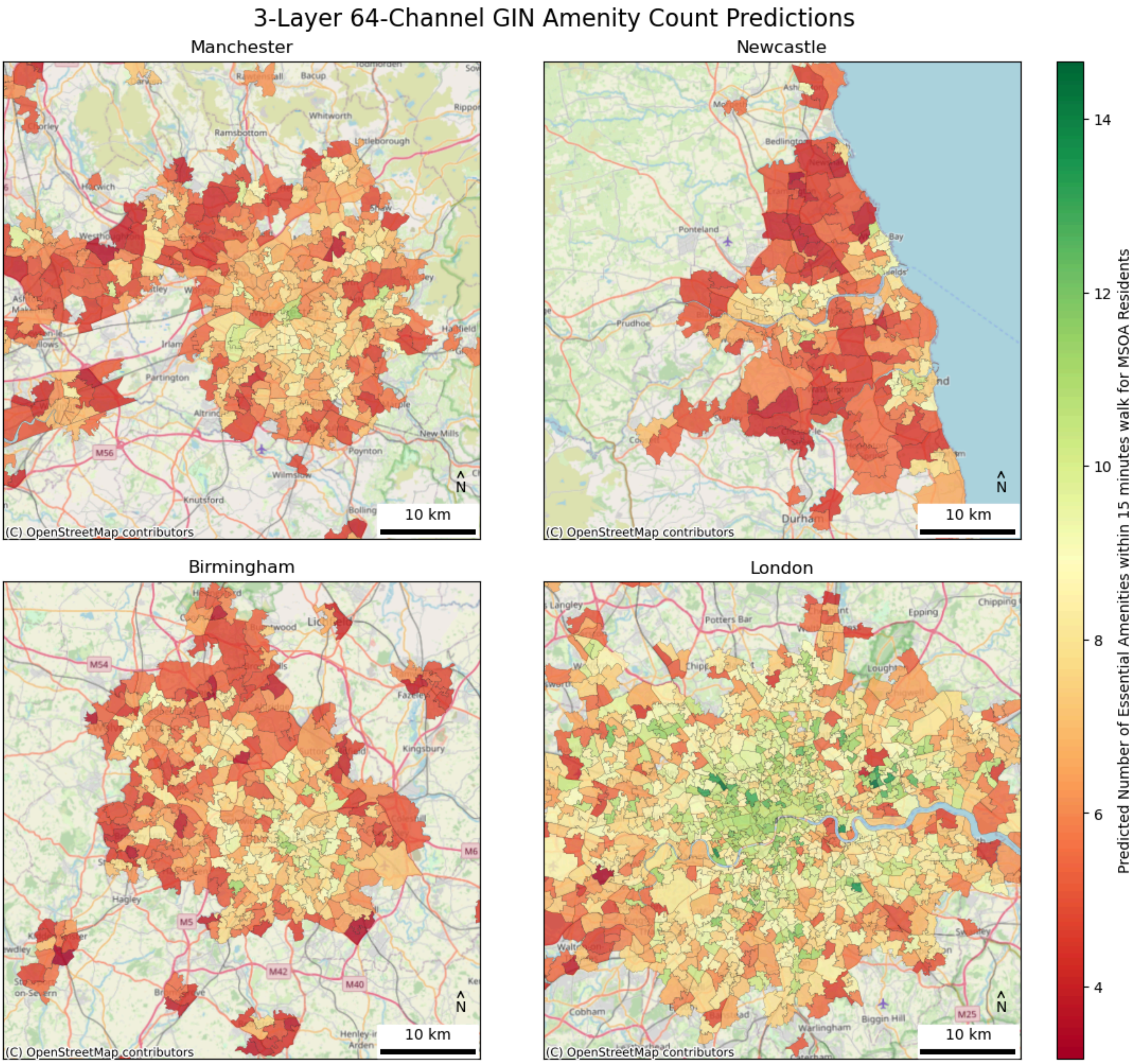

Figure 6: 3-layer 64-channel GIN amenity count predictions

GNN Explanations for 2 highest predictions

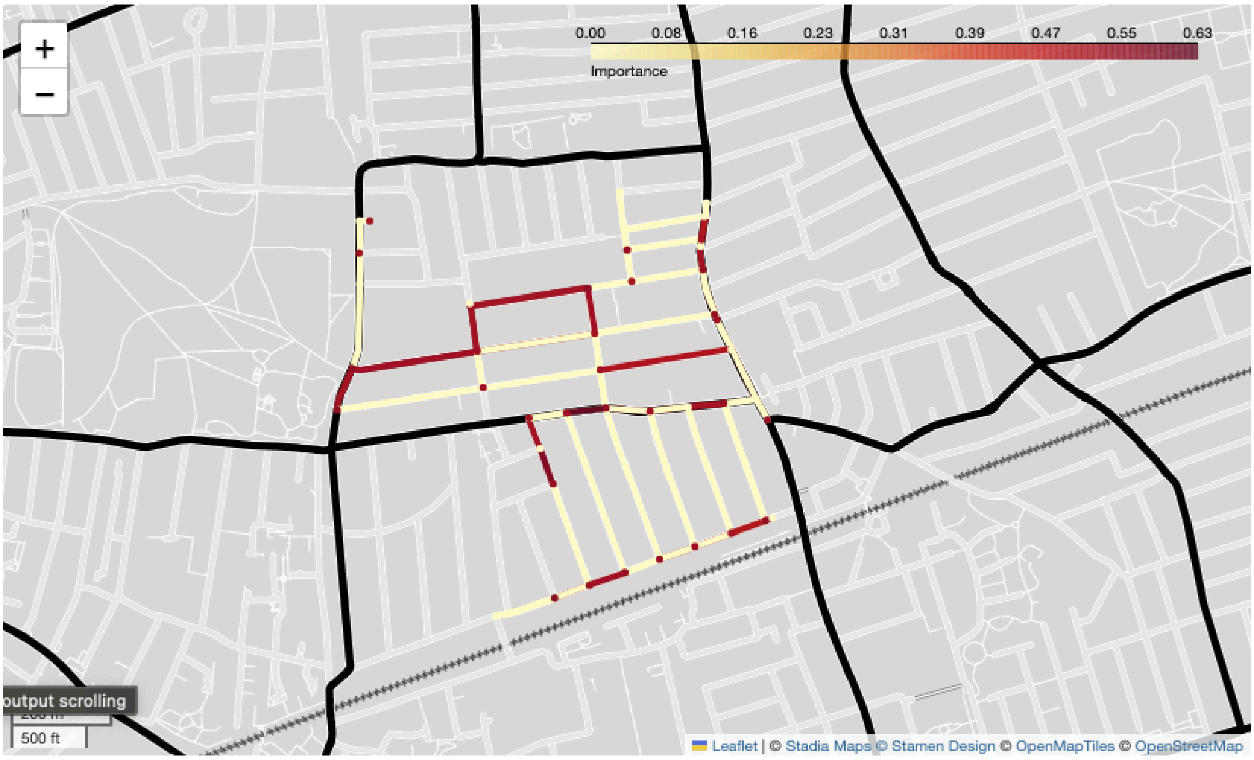

Figure 7: MSOA E02000730 in Newham

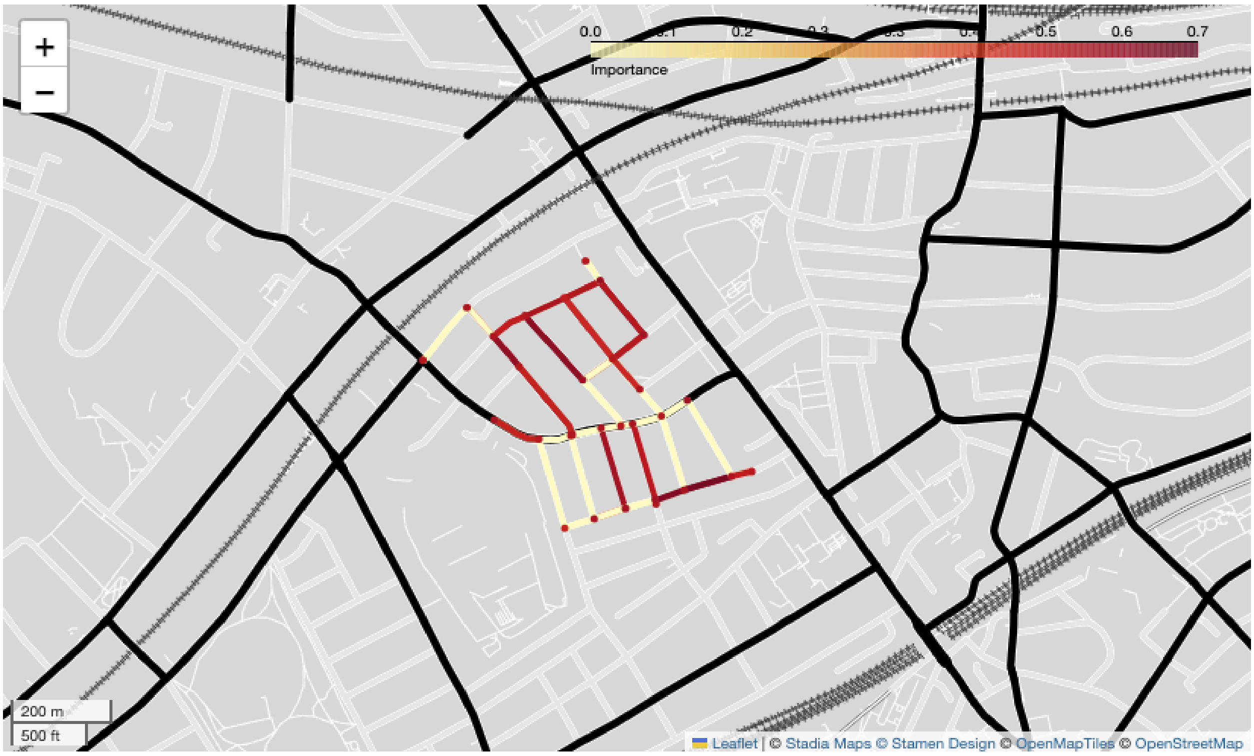

Figure 8: MSOA E02000120 in Brent

GNN Explanations for 2 lowest predictions

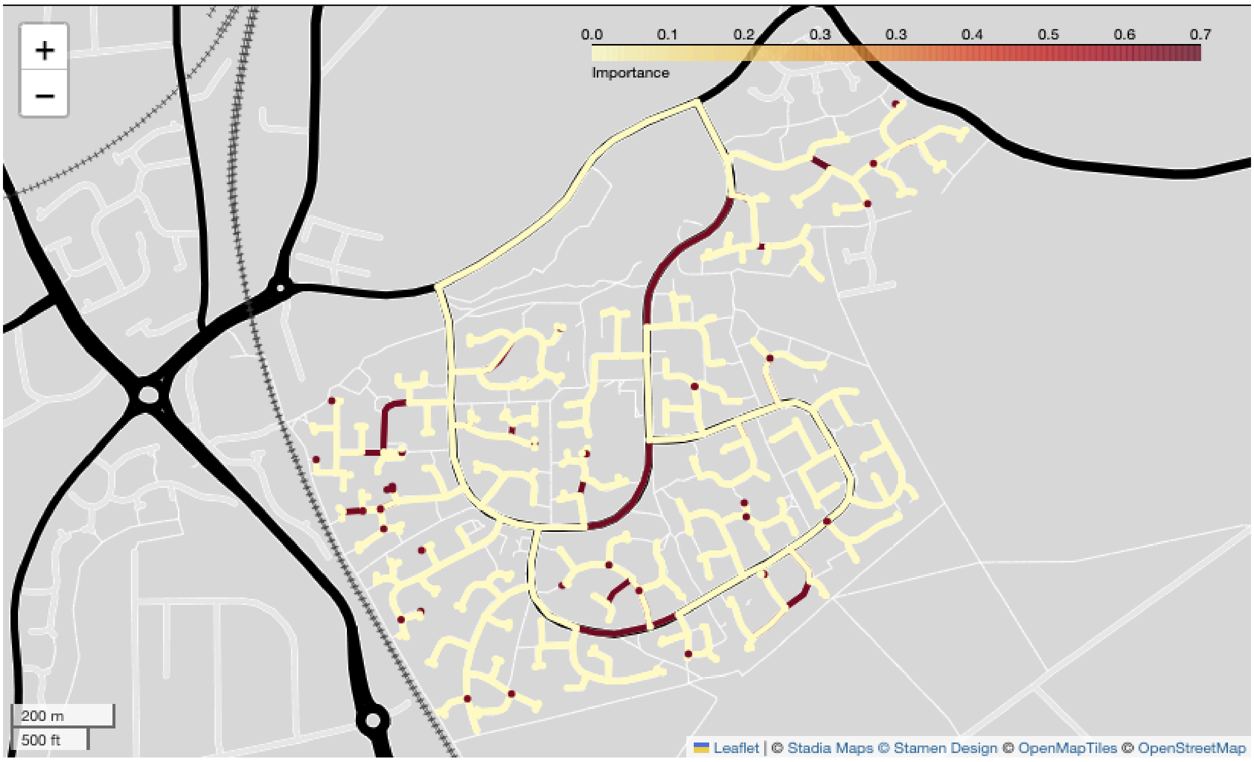

Figure 9: MSOA E02006776 in Wyre Forest

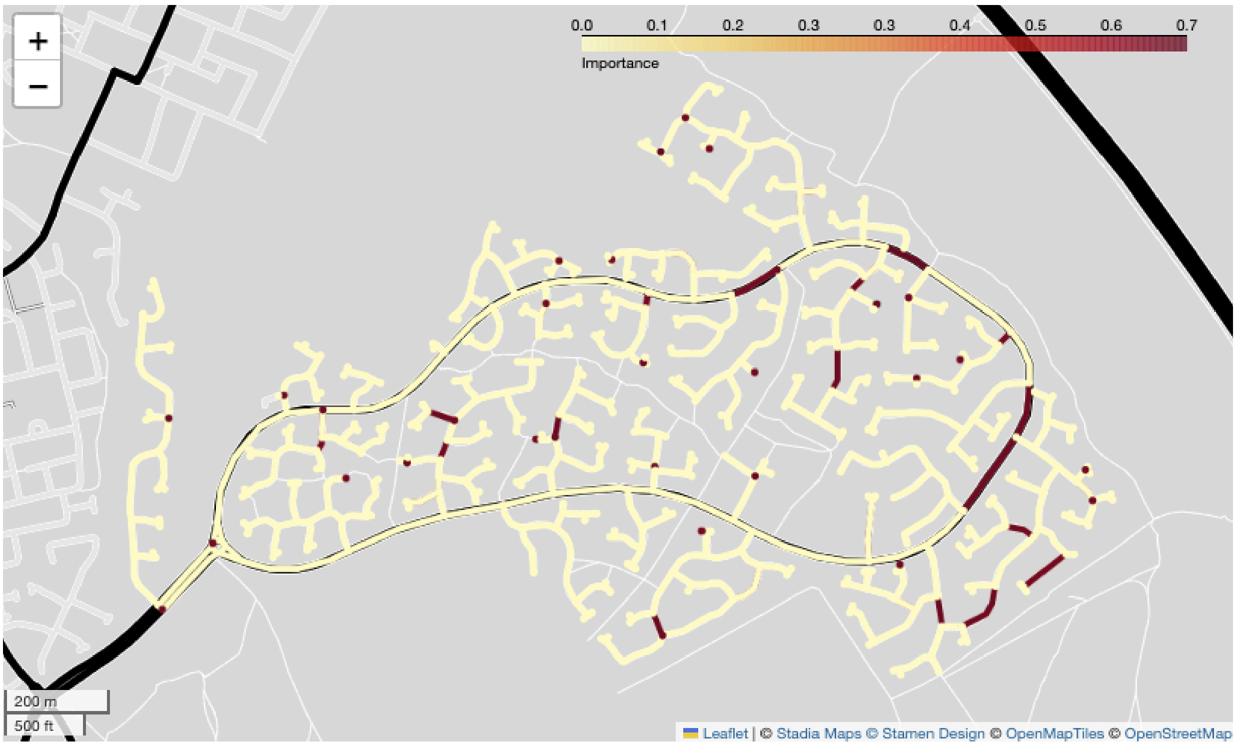

Figure 10: MSOA E02001353 in Liverpool

As shown in the projected predictions in Figure 5, the GNN model was broadly accurate in its predictions of high or low amenity access, with the highest predictions in city centres and the lowest within outskirts. Notably, however, it made few predictions of very high amenity access, potentially indicating a lack of differentiation in topology between MSOAs containing between 12 and 20 walking-distance amenities. While clear visual similarities exist between the projections of the highest and lowest predictions in Figures 6-9, with the former favouring grid shaped topology and the latter more dendritic, few clearly intuitive patterns emerged from the nodes and edges indicated to be important by the GNNExplainer.

5.2 Graph Autoencoder Clusters

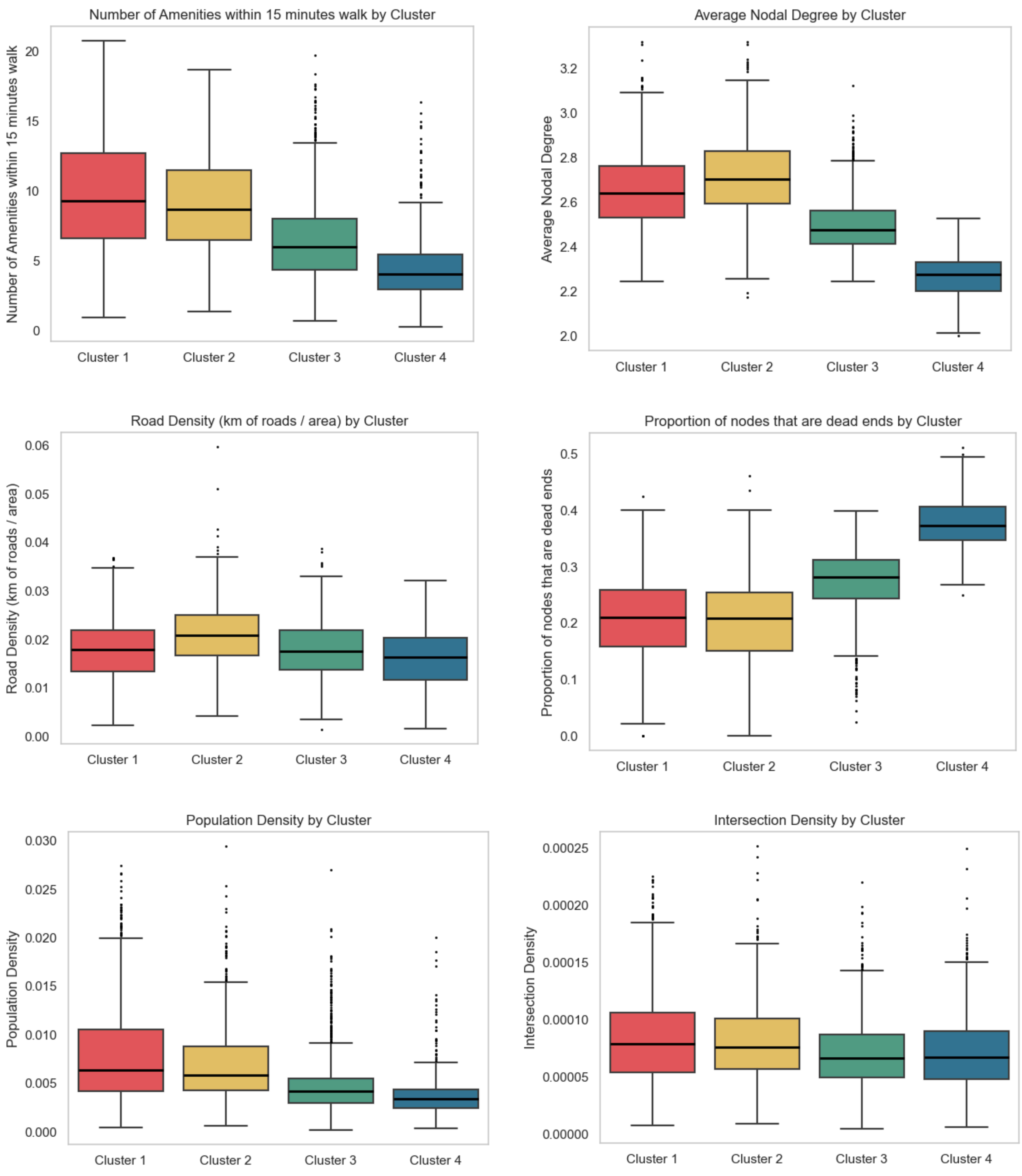

Figure 11: Autoencoder Embedding Cluster Traits

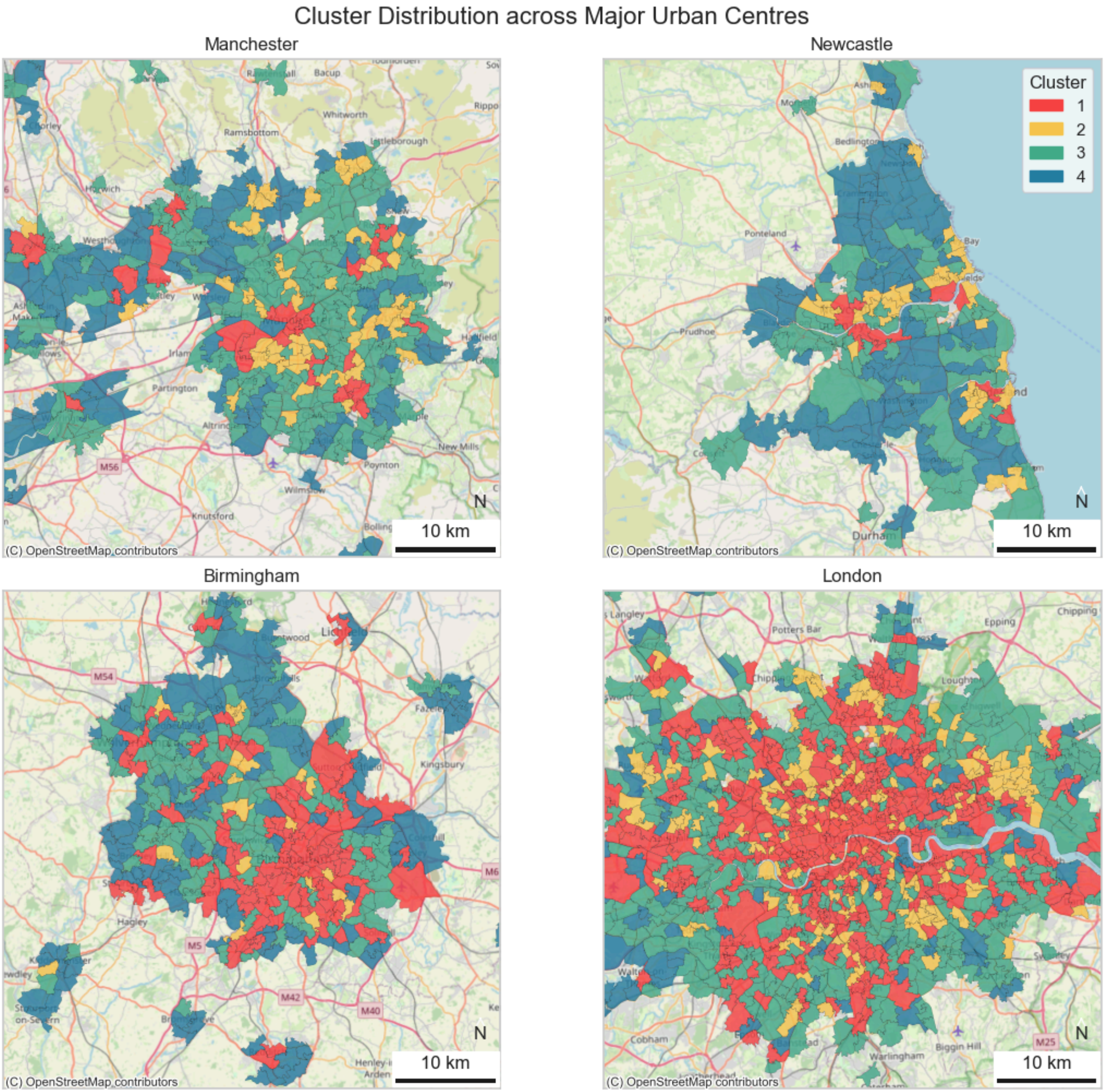

Figure 12: Cluster distribution across major urban centres

Cluster attribute analysis shows interesting patterns between cluster types as shown in Figure 10, with two main patterns appearing. The first pattern, appearing in amenity count data and population density, shows the first cluster as having the highest values in both, with clusters 2, 3, and 4 showing successively smaller values, indicating that the first cluster has the highest population density and the most amenities within walking distance. The second pattern, appearing in average nodal degree and road density, shows the second cluster having the highest values, followed by clusters 1, 3, and 4, indicating the second cluster has the highest nodal degree and road density. The third pattern matches the second but due to the nature of the data appears reversed, with the second cluster having the lowest values in proportions of dead-end intersections, indicating decreased numbers of dead-end roads in the second cluster. Major overlap appeared between the clusters in several categories including road density. Clusters 1 and 2 in particular had the strongest overlaps in many categories, with cluster 4 with the least overlap, particularly in average nodal degree and proportion of dead ends, which are related categories.

Projecting the clusters over maps of major cities in Figure 11 showed cluster 1 to appear the most strongly in city centres, accompanied more sparingly with cluster 2. Cluster 3 tended to border these areas, with cluster 4 in the further periphery. Newcastle in particular showed strong spatial clustering of the cluster types, while London had more of a mix of types.

5.3 Comparing Spatial Error Model Fits

Pseudo R-squared	0.317		Log Likelihood	-9186.155
Sigma-square ML	5.626		Akaike info criterion	19376.310
S.E of regression	2.372		Schwarz criterion	18388.849
Variable	Coef.	Std. Error	z-Statistic	p-value
Constant	6.722	0.102	65.981	0.000***
Average Nodal Degree	1.268	0.047	26.941	0.000***
Lambda	0.658	0.012	54.908	0.000***

Table 4: Average Nodal Degree Spatial Error Model Summary

Pseudo R-squared	0.409		Log Likelihood	-9002.958
Sigma-square ML	5.178		Akaike info criterion	18023.916
S.E of regression	2.276		Schwarz criterion	18080.341
Variable	Coef.	Std. Error	z-Statistic	p-value
Constant	6.779	0.093	72.707	0.000
PC1	1.585	0.046	34.454	0.000
PC2	-0.014	0.038	-0.376	0.707
PC3	-0.013	0.039	-0.329	0.743
PC4	0.038	0.037	1.042	0.298
PC5	0.042	0.035	1.184	0.236
PC6	-0.027	0.037	-0.719	0.472
PC7	-0.047	0.036	-1.311	0.190
PC8	-0.079	0.036	-2.176	0.030
Lambda	0.638	0.013	51.004	0.000

Table 5: Trained GNN Embeddings Spatial Error Model Summary

Pseudo R-squared	0.410		Log Likelihood	-8982.127
Sigma-square ML	5.112		Akaike info criterion	18023.916
S.E of regression	2.261		Schwarz criterion	18080.341
Variable	**Coef.**	**Std. Error**	**z-Statistic**	**p-value**
Constant	6.781	0.094	72.517	0.000
PC1	1.555	0.047	34.851	0.000
PC2	-0.015	0.038	-0.373	0.710
PC3	0.308	0.039	7.926	0.000
PC4	-0.131	0.037	-3.537	0.000
PC5	0.0577	0.038	1.511	0.131
PC6	0.0586	0.037	1.637	0.101
PC7	0.205	0.036	5.630	0.000
PC8	-0.015	0.035	-0.410	0.682
Lambda	0.642	0.012	51.757	0.000

Table 6: Autoencoder Embeddings Spatial Error Model Summary

The models of GNN-trained embeddings and autoencoder embeddings outperformed the basic connectivity model measuring average nodal degree, with pseudo R^2 scores of 0.409 and 0.410 compared to 0.317. The autoencoder embeddings marginally outperformed the GNN-trained embeddings in pseudo R^2 score and other overall metrics. While the GNN trained embeddings only had one primary component found to have sufficient probability (<0.005), the autoencoder had four primary components with sufficient probability. Lambda remains significant across all models, indicating significant spatial correlation in amenity presence.

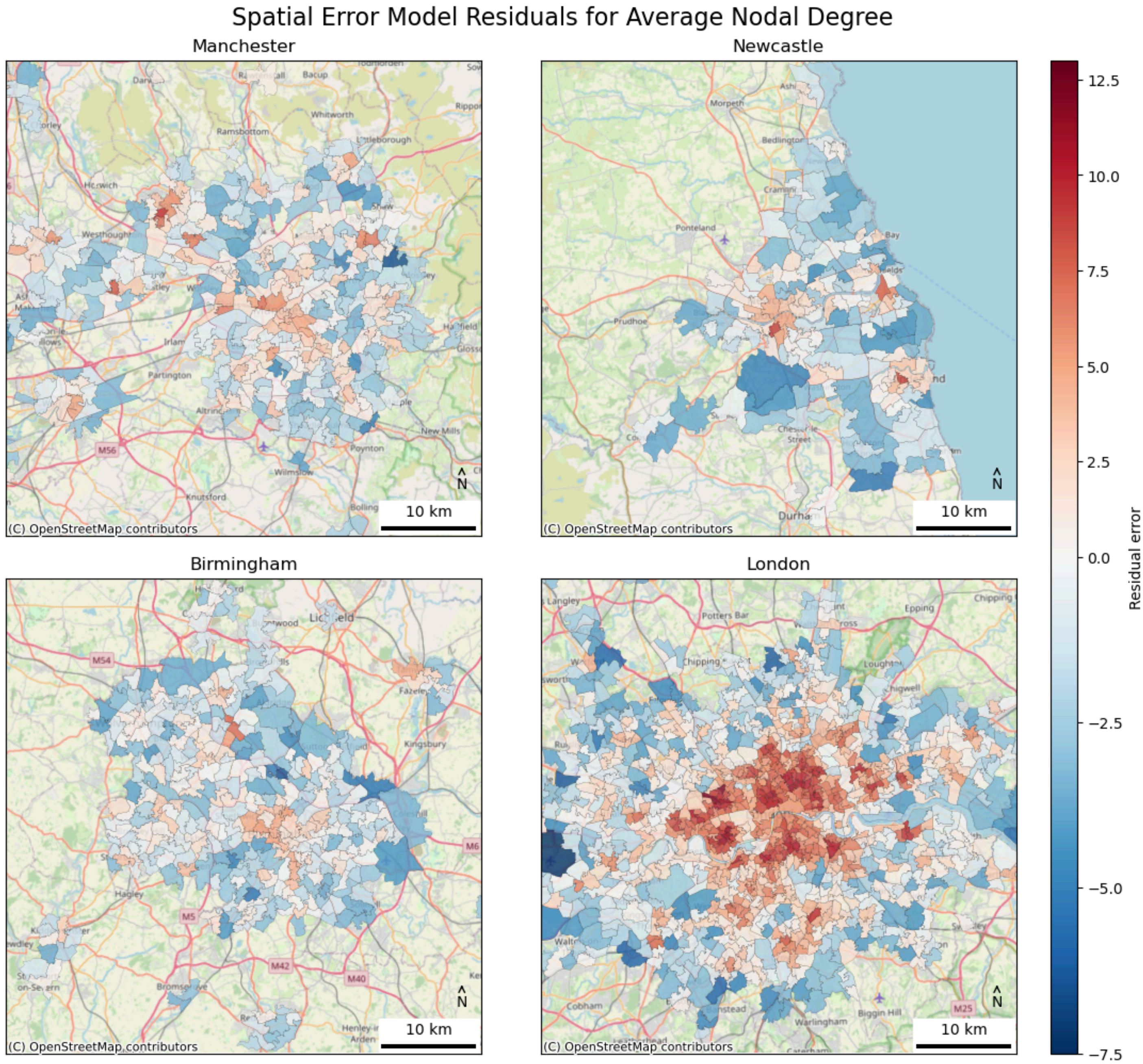

Figure 13: Spatial error model residuals for average nodal degree

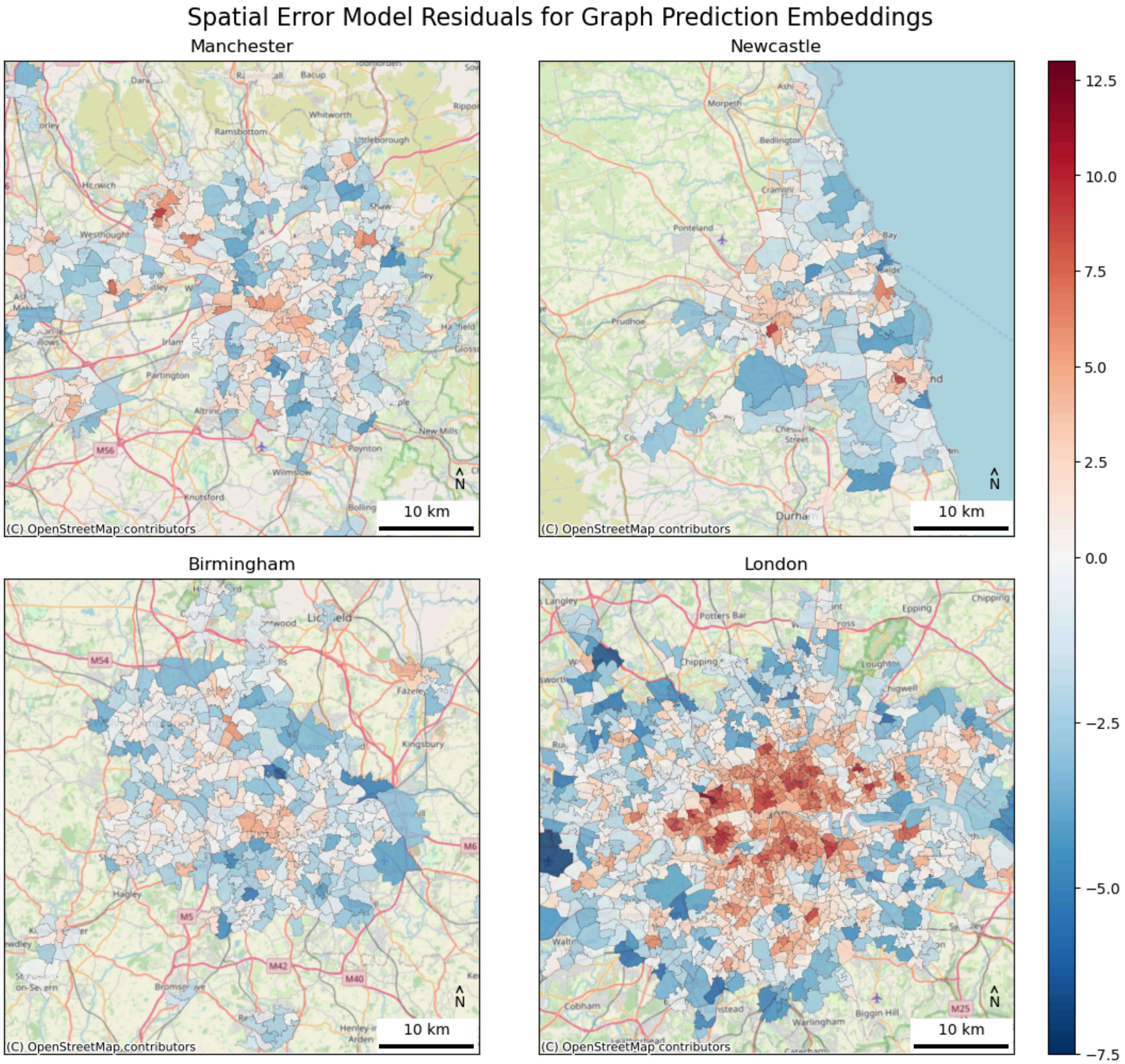

Figure 14: Spatial error model residuals for graph prediction embeddings

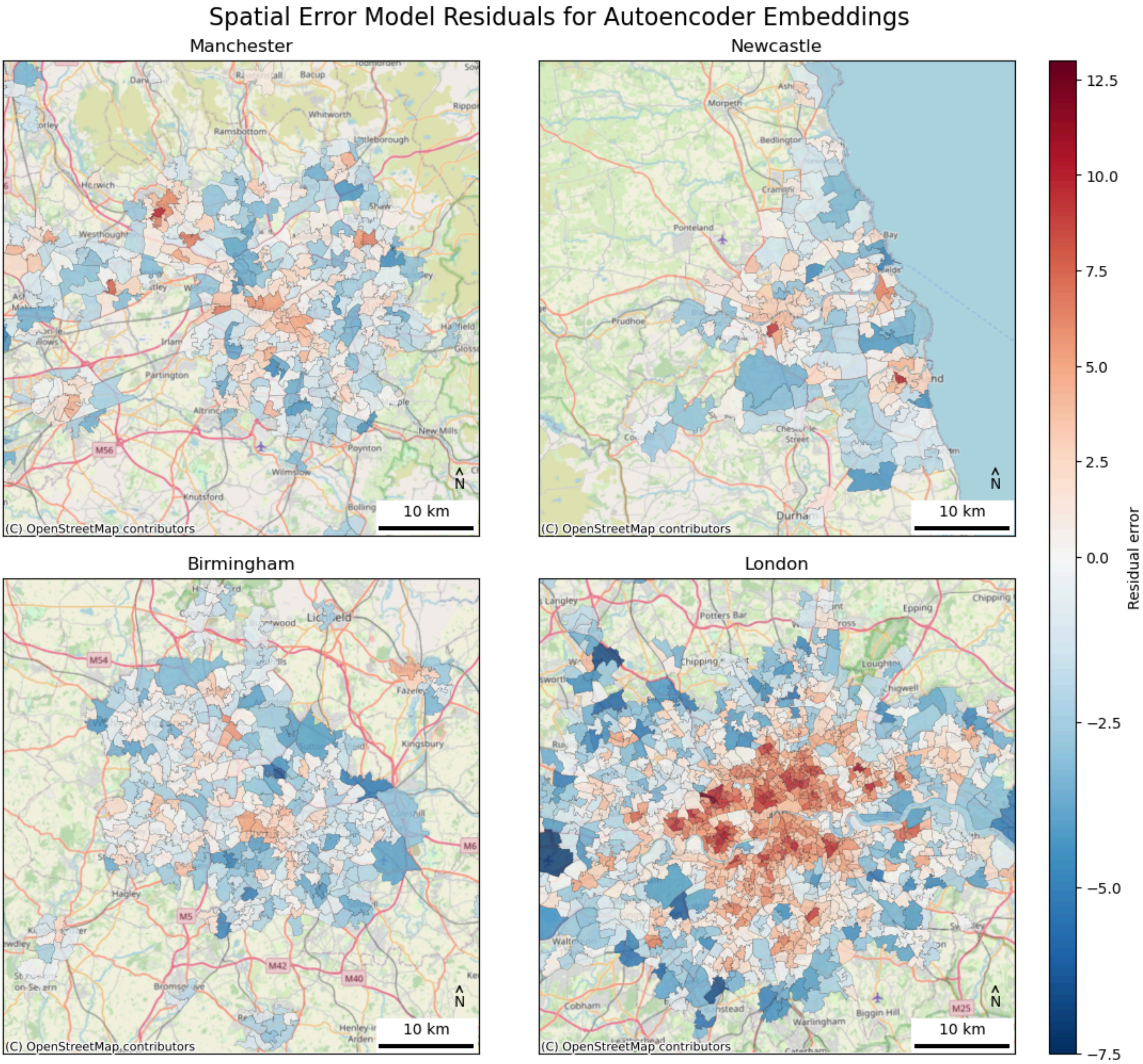

Figure 15: Spatial error model residuals for autocoder embeddings

All three models had similar spatial patterns across residuals, with central areas having strong underprediction of amenity presence and outer MSOAs experiencing milder overprediction. Predictions in central London were more underpredicted by average nodal degree than they were by embeddings.

6 Discussion

The GIN layer, which was more focused on topological traits than the GNN, GraphSAGE, or GATv2 layers it was compared with, emerged as the most effective in analysis, aligning with the expectation that topology-specific models perform better when graphs are primarily designed around topological data. However, notable limitations were observed here and with the autoencoder model embeddings as well as the basic connectivity predictions in recognition of areas with the highest amenity counts. This suggests that beyond a certain threshold, the influence of topology on amenity access diminishes, and other factors begin to play more significant roles. Though visualising its guesses made clear the broader patterns of grid shapes in MSOAs predicted high in amenity access and dendritic ones in MSOAs predicted with few walkable amenities, GNNExplainer module did not produce recognizable patterns within its explanations for nodes and edges found important in these predictions. It is possible that this tool is more attuned to finding nodes with specific attributes important to predictions, rather than selecting subpatterns important to topology. These findings suggest that for future iterations of this specific study, more diverse data types should be incorporated into graphs or other parts of analysis, to better capture the multifaceted nature of urbanity.

Analysis of the autoencoder's performance revealed interesting patterns, particularly in how it clustered data. There appears to be a slightly non-linear relationship between average nodal degree and amenity count, with Cluster 1 displaying the highest average nodal degree yet only the second-highest amenity count. This again points to complex interactions within the urban fabric that are not solely dependent on straightforward measures of connectivity. Additionally, the autoencoder showed that there was very little variation in road density, suggesting that population density, which had less intense overlap and the cluster relationship most similar to amenity count data, is the more important density metric for amenity access. Future exploration of autoencoder topological embeddings could involve visualisations of graphs before and after being passed through the autoencoder; however in this study, the process of being passed through the autoencoder meant that they lost their original indexes linked to the OSMnx maps, and the complexity of the graphs made them difficult to otherwise visualise.

The spatial error model using embedding vectors from the autoencoder demonstrated slightly higher accuracy and relevance than the trained GNN prediction model's embedding vectors, with three significant vectors compared to only one. Both of these models outperformed the model based on average nodal degree as a representation of connectivity. It should be noted that there are more topological variables than just average nodal degree that could be included to boost the connectivity models' scores, such as node-edge ratio or the specific proportions of each nodal degree's occurrence, but these were excluded from the final analysis due to high Variance Inflation Factor (VIF) scores indicating excessive collinearity. Likewise, the number of vectors included from the embeddings was reduced from the original 64 to just 8 after high VIF scores and low probability ratings indicated collinearity between many of the embeddings. This also suggests that in future iterations, the number of vectors output from the GNN or autoencoder modules could be reduced to cut down processing time while maintaining accuracy scores. It is intriguing that the autoencoder embeddings slightly outperformed the embeddings of the model trained to retain specific information related to amenity counts, suggesting that core topological traits best informed these predictions and not any specific substructure patterns. Overall, it can be concluded that both variable-trained and auto encoded graph neural network models were more successful than average connectivity traits in predicting amenity presence, fully capable of learning topological traits, embedding them into vectors and applying this embedded information towards further prediction tasks.

This research highlights the nuanced understanding of urban street networks and amenity access that emerges from employing graph neural networks compared to traditional metrics. Previous studies using these traditional metrics emphasise the correlation between high connectivity, increased pedestrianism and decreased car usage which is broadly supported by these findings linking increased amenity availability to these regions of high connectivity. However, examining the traits and projections of the autoencoder clusters shows further interesting patterns. Central London is by far the most amenity-dense area in England, which combined with plentiful public transport has allowed a far lower car ownership rate than anywhere else in the country (Whelan, 2007). Yet despite the fact that amenity density is typically correlated with high average nodal degree, which measures network connectivity, almost all of Central London's MSOAs fall into Cluster 1, which has only the second highest average nodal degree. Despite having less internally connected street networks, Central London is far more amenity-dense.

Though Cluster 2 has a higher average nodal degree than Cluster 1, they have almost precisely equal proportions of dead ends, suggesting that the decreased average nodal degree of Cluster 1 does not arise from increased dead ends but more likely from a higher rate of 3-way intersections rather than 4-way ones. That this disparity exists without observed negative consequence in amenity density suggests that the use of average nodal degree is perhaps not appropriate for street network research; if 3-way and 4-way intersections introduce roughly the same amount of pedestrian flow, it could instead be the ratio of these more complex intersections to dead-end, 1-degree nodes that matters more at the topological level. In this aspect,, Clusters 1 and 2 are equal. All of the clusters are remarkably similar in road density and intersection density, suggesting that building denser road networks and smaller lots may not increase amenity accessibility. Where cluster differences most match the disparities seen in amenity availability is in a non-topological trait; population density. Potentially, a lack of internally well-connected streets for pedestrians to be funnelled down to create specific attractive areas for amenities could be made up for in sheer volume of population. And in pedestrian volume city centres like Central London can rely on more than just residents; with most major tourist attractions and Airbnbs concentrated in the city centre, additional footfall is awarded to these most central amenities (Ye, Clarke, & Newing, 2021).

Many limitations and challenges were faced during data collection and assembly phases as well as in later methodology phases. The issues observed in the 'walk' network of OSMNx made it a poor fit for topology analysis, introducing a mismatch between the amenity walking distance measured by DfT and the 'drive' network graphs used within this analysis. Thus the output is more aligned with what 'drive' networks look like in walkable neighbourhoods than what 'walk' networks look like. Future iterations should attempt to resolve walk network data and include that, as well as other important data related to walkability, such as the presence of sidewalks, crosswalks, or shade, within edge data. Variable data was also imperfect, with lack of a well-validated amenity access index. The original development of this study aimed to test the vector embeddings trained on amenity access against transport mode and health variables. This approach intended to combine and replicate earlier research exploring the effects of street network topology and amenity access on these variables. However, lack of access to health and transport choice data as well as the growing complexity of the project refocused the aim upon understanding the embeddings, finding the best way to go about creating them, comparing their accuracy to established methods, and theorising further ways forward in spatial analysis using human topology. Typical black box issues with neural networks made it difficult to determine precisely which topological attributes were associated with higher or lower amenity access, and GNNExplainer did not provide much clarification. However, visualisations of clusters and average cluster traits did provide some further insights. Ultimately the topology embeddings were found to have a significant effect on amenity availability, but with the model fit score of 0.41, it is clear that the complexity of urban environments brings other factors in play which should be considered and included into the embeddings for improved prediction. Still, the performance of the GNN models indicates high potential for future research.

Further research into the applications of graph neural networks upon social and geographic research should focus upon applying these methods to networks of human connectivity, including drivable, walkable, or bikeable roads, or even to public transportation routes for buses or trains. The topologies of these networks may have more significant implications upon their effects on humans traversing them than previously accounted for in research. Suggested dependent variables to explore include route or transport mode choice, health outcomes, or economic trends, all of which can be connected to topological influence. By embedding knowledge into link-based networks rather than geographic planes, the relationships between points can be more accurately reflected and accounted for while making predictions. Out of the two methods used in this study for creating these topological embedding vectors, this study proposes autoencoders to be more useful, as they only require training once for application to many studies, rather than being trained each time on separate variables for prediction. Autoencoders are not currently eligible for the GNNExplainer due to their lack of a single output variable, but as the GNNExplainer does not seem to produce significant findings at this time this is not a significant downside. Future studies could research adding dense social or environmental data for effective embedding, potentially incorporating the Graph Isomorphism Network with Edge Weights (GINE) convolutional layer which incorporate edge data as well as node data, though a custom decoder model for the autoencoder may have to be built for this purpose. Both supervised and unsupervised tasks can be explored through this methodology. Finally, in future research, broader connections than those contained within single MSOAs should be studied. The most central urban regions, which are more connected through roads and public transport to surrounding regions than any other, had the highest and most underpredicted amenity counts. Finding ways to include the weights of these broader connections and interactions would be an important route for further research.

7 Conclusion

Graph neural network analysis of MSOA street network topology and its correlation with 15-minute amenity access confirmed the first hypothesis that GNN embeddings would improve predictive accuracy for amenity access compared to traditional average connectivity metrics. Trait analysis of clustered autoencoder embeddings showed that four-way intersections were not necessarily more indicative of increased accessibility than three-way intersections, and that decreased rates of dead ends were more important. This suggests a less linear connection between average nodal degree and the connectivity of an area than found in previous street network studies. However, beyond the relative importance of three- and four-way intersections, the second hypothesis of specific street network configurations influencing amenity availability could not be confirmed within this study. Further analysis on the graph embeddings also demonstrated the influence of non-topological features such as population density upon amenity accessibility, emphasising the potential for future studies to incorporate more socioeconomic variables into embeddings for increased analysis potential and the development of more accurate models.

Though major metropolitan areas such as Central London were correctly classified by the autoencoder as having high local connectivity and low proportions of dead-end streets, the embeddings still underpredicted amenity accessibility, suggesting that after peak local connectivity has been reached, further increases in amenity accessibility arise from other factors. Though socioeconomic variables likely play a role in this underprediction, it is also possible that broader patterns of connectivity are present but on too large a scale to be captured within MSOA topology; London's public transport network of underground and overground trains. Central London is far more connected to the rest of London than any other section of the broader city, with huge amounts of this connectivity arising from overground and underground trains not accounted for on these graphs.

Conversely, neighbourhoods designed with limited entry and exit points, exhibiting low connectivity, intentionally discourage through traffic and consequently the establishment of amenities. This bias against car-based through-traffic is understandable; as stated in the beginning of the paper, such traffic increases noise, pollution, and the likelihood of accidents. A common method of fifteen-minute city initiatives is remarkably similar, limiting car traffic in and out of neighbourhoods by instead routing them around larger super-blocks (Mueller et al, 2020). By decreasing car-based connectivity, pedestrianism becomes easier and safer, directing more people and financial resources towards local amenities rather than far-flung ones. But while these cities have become more walkable through such tactics, suburbs have become unwalkable, as their population density is too low to sustain essential amenities, particularly without individuals commuting into the area or visiting tourists. Making these neighbourhoods walkable is a difficult issue to solve without fundamentally changing them with the addition of connected through-paths to funnel more people through the neighbourhood, or conversion to more high-density housing, both of which are solutions likely to be majorly unpopular with existing residents.

Answers to this difficult question may again lie on larger scales than an MSOA-based analysis can understand, possibly with methods of interspersing roads of high car- or public transport-based connectivity between enclaves of low car access, increased walking connectivity. The analysis and optimal calculation of such complex patterns are certainly appropriate for future graph neural network study, particularly in models that can include multiple travel-type options along edge attributes. It is also clear that more factors play into effective fifteen-minute cities than just topology, such as population density, economic power, and cultural importance. All these and more can be encoded into street network graphs, capturing cities across nodes and links. By creating these dense and informative informational embeddings on the networks that we live on, graph neural networks have created the potential for us to gain a far better understanding of our urban worlds, even if it is sometimes necessary to dig a little deeper into the answers they provide.

Auto-Critique

When I began this project I knew I wanted to work with applying graph neural networks to street networks. I'd recently read about Harry Beck's creation of the Tube map in the early 20th century, which discarded the tradition of plotting the accurate locations of stations' geographical coordinates in favour of simply showing where they were in relation to each other linked by the tube lines, reasoning that only their relative positions mattered to the people travelling between them.

Going through this research project was a huge learning process, as I've not worked with complex machine learning processes very much before, only once with convolutional networks, and never with graph neural networks. Because of this I spent most of my time on this project figuring out how to build my original prediction models and convert the OSMnx maps into a graph dataset. Looking back, I would have tried to spend more time cleaning and building my graph datasets and amenity datasets. I wanted to remain focused on the topology aspect of the project, and so was initially hesitant to incorporate a broad array of data into the models, as it would be impossible to determine how much of the predictions were being determined by topology. However, making predictions from such broad arrays are where the real strengths of machine learning lie, and I think that the project could have been more informative by taking that approach and spending more time interpreting predictions. My advisor Dr Stephen Law's original proposal for the project was for the use of an autoencoder to determine topological types for different cities in the UK, and I do think that ultimately the most interesting and informative part of my project was the use of the autoencoder and the investigation of the different topologies of the MSOA cluster types.

There are many things I would like to do differently, but ultimately, I feel like this is a project I could have spent years on, and at some point it was necessary to accept the limitations of a MSc thesis and put the code down. I am very grateful for this project and all that it taught me.

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