Learning urban form through unsupervised graph-convolutional neural networks

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Abstract. Graph theory has long provided the basis for the computational modelling of urban flows and networks and, thus, for the study of urban form. The development of graph-convolutional neural networks offers the opportunity to explore new applications of deep learning approaches in urban studies. In this paper, we propose an unsupervised graph representation learning framework for analysing urban street networks. Our results illustrate how a model trained on a 1% random sample of street junctions in the UK can be used to explore the urban form of the city of Leicester, generating embeddings which are similar but distinct from classic metrics and able to capture key aspects such as the shift from urban to suburban structures. We conclude by outlining the current limitations and potential of the proposed framework for the study of urban form and function.

Keywords: Graph neural networks · Street network · Urban form.

1 Introduction

The analysis of street networks in the context of the study of urban form has largely focused on predefined measures of street network connectivity and structure to understand the nature of the underlying structures of cities [5]. However, recent studies have explored the potential of Graph Neural Networks (GNNs) to generate numerical representations (embeddings) of street networks that have been used to study road types [8] and homogeneity [18].

In this paper, we take a step further and adopt a similar graph representation learning approach to explore the broader study of urban form [1]. Our work is theoretically grounded in an understanding of urban locations not as having necessarily intrinsic characteristics per se but as anchors of flows and networks [2], and thus, we focus on street junctions as anchors of their local street network, as places of flow. However, rather than searching for underlying structures or processes generating such forms, we seek to relate the street network of one city (Leicester, UK) to a geographical context (the rest of the UK). We do not aim to create a universal model of urban form but rather to provide a lens into Leicester's urban form as a relationship to the rest of the UK.

The interest in the study of urban form is driven by its relationship with urban function, as the design and layout of a city are among the factors that influence human activity patterns [16]. Modelling the accessibility, connectivity, efficiency, and aesthetics of the built environment can support the design of harmonious environments that support diverse functions for residential, commercial, cultural, and recreational activities, promoting walkability, sustainability, and well-being. The emergence of OpenStreetMap[4] and the development of packages such as OSMnx [3] have enabled easier access to both street network data and analysis tools, facilitating insights into urban form [17].

Recent years have also witnessed increasing interest in adopting GNNs for urban-related studies [13], from traffic [10] to crime modelling [19], from social media [14] to mobile phone data [12]. The key driver behind the adoption of GNNs is the fact that they allow the creation of spatially-explicit models [13,15] due to their ability to algorithmically process graph-structured data. As street networks can be represented through their corresponding graph or its line graph, and GNNs can be used to learn numerical representations (embeddings) of nodes (or graphs), GNNs hold the potential to enable a numerical analysis of urban form through the encoding of the street network graph into an embedding space.

In this paper, we suggest that we can obtain a numerical representation of urban form through deep learning by training a Graph AutoEncoder (GAE) [11] based graph-convolutional layers on street network graphs. We start from the hypothesis that the number and lengths of street segments emanating from a junction and their respective connectivity can tell us something about the junction and its role as a place of flows through the street network. We thus train our model on a sample of junctions from UK cities and then explore the embeddings generated by the model for the city of Leicester as a case study.

2 Methods

Our objective was to create a model able to generate embeddings representing the topological position of a street junction in the context of its local street network. To minimise our assumptions and the complexity of the model, we took into account only the number of street segments connected to a street junction and the length of street segments and relied upon an unsupervised approach.

We used the data made available by Boeing [4], which include simplified street networks of 138 cities in the UK derived from OpenStreetMap. To train our model, we randomly sampled 1% of the nodes from 137 cities in the UK, leaving Leicester as a case study to explore the effectiveness of our model. For each node, we generated an ego-graph (a graph created starting from a single node)

[4] https://www.openstreetmap.org

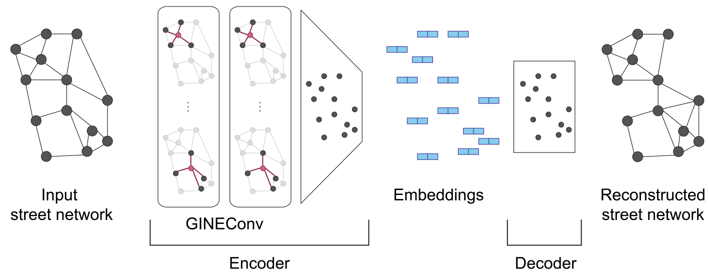

Fig. 1. Outline of the GAE model used to generate node embeddings.

including all nodes within 500 meters of street distance, only retaining graphs with at least 8 nodes. Each ego-graph included street junctions as nodes with the number of street segments emanating from each node as a node attribute, using a bounded min-max normalisation with $min = 1$ and $max = 4$ segments, and street segments as edges with their lengths as an edge attribute, using a bounded min-max normalisation with $min = 50$ and $max = 500$ meters.

We developed a GAE model using PyTorch Geometric [6], as illustrated in Figure 1. Within the GAE, the encoder learns to generate embeddings representing the input graph's nodes and their role within it so that the decoder is then able to use them to recreate a graph which should be as similar as possible to the original one. In our model, the encoder is composed of three layers. The first two layers use modified graph isomorphism operators [9] designed to incorporate the edge attributes in the aggregation step of the convolution, using 64 hidden features. We then designed our third layer as a simple linear one reducing the 64 hidden features to a very low dimensional space composed of 2 embeddings, which will allow for a simple visual exploration of the patterns. We use the decoder based on an inner product operator and the graph reconstruction loss functions as defined in the original GAE model by Kipf and Welling [11]. We trained the GAE for 1000 epochs using an AdamW optimiser with a 0.0001 learning rate on a randomly selected 80% of the dataset of ego-graphs described above. We then tested the model on the remaining 20% of the dataset, obtaining a similar loss, indicating that the model was not overfitted to the training data.

To evaluate the model, we used it to generate embeddings for all street junctions in Leicester, representing their role within their ego-graph. We also combined the model with an additional global mean pooling layer to obtain pooled embeddings of the node's ego-graph, representing a combined neighbourhood-level quantification of urban form.

First, we qualitatively explore the expressiveness of the model through a series of plots and maps. Figures 2a and 2b both illustrate the node embeddings obtained for street junctions in Leicester, encoding the first embedding on the x-axis and the second embedding on the y-axis. The difference is in the use of colour. Figure 2a encodes the three quantiles of each embedding dimension into a 3×3 bivariate colour scheme which is then replicated in Figure 2c to illustrate how the bivariate quantiles are spatially distributed in Leicester. The same approach to bivariate mapping is used in Figure 3 to illustrate the ego-graph pooled embedding. In Figure 2b, we instead use colour to illustrate eight clusters of node embeddings obtained using DBSCAN ($eps = 0.11$, $min = 300$), which are then similarly replicated in the maps in Figures 2d-f.

We then quantitatively compare the embeddings with closeness and betweenness centrality, both based on the whole city graph and based on the node's ego-graph, as well as basic statistics (as provided by OSMnx) for each node's ego-graph, as reported in Table 1.

3 Results

The main pattern emerging from Figure 2 is that a large portion of the information encoded in the second embedding dimension represents the shift from urban to suburban form (see, e.g., Spatial Signatures of Great Britain [7]). Low values (mid-light shades of blue in Figures 2a and 2c, and blue in Figures 2b and 2d-f) are concentrated in the first outer ring of the city, between the city centre and the suburbs, mostly characterised by Victorian terrace houses. Higher values (mid-dark shades of red in Figures 2a and 2c; in green, red and brown in Figures 2b and 2d-f) are concentrated in the suburbs, mostly characterised by detached and semi-detached houses built in the second half of the twentieth century.

The length of street segments seems to play an important role, as areas of Victorian terrace houses characterised by longer streets and surrounded by green spaces seem to be classified alongside suburban areas. Moreover, Figures 2d and 2e illustrate how roundabouts – described in the dataset as a set of junctions connected by very short street segments – are frequently characterised by nodes found in the purple cluster in Figure 2b. End-of-the-road nodes are frequently found in the yellow (mostly urban, near the blue) and red (mostly suburban, near the green) clusters in Figure 2b.

The results presented in Table 1 illustrate how the two embedding dimensions have a weak or moderate correlation with most of the classic measures (see the two central columns in Table 1). The first embedding dimension seems to display stronger correlation values when compared to the edge length and street segment length of the node's ego-graph. That is consistent with the findings of the qualitative analysis outlined above and illustrated by roundabout nodes being part of the purple cluster on the left in Figure 2b.

The two right-most columns in Table 1 show how most classic measures better correlate with the ego-graph pooled embeddings (illustrated in Figure 3) rather than with the node embeddings. Closeness centrality seems to correlate better with the ego-graph pooled embeddings rather than with the node embeddings, while betweenness centrality seems to correlate better with the node embeddings, although showing overall weaker correlations. The strongest correlations involve the number of streets per junction and the length of edges and street segments, as one would expect, as they are closely related to the values used as node attributes and edge attributes in the model.

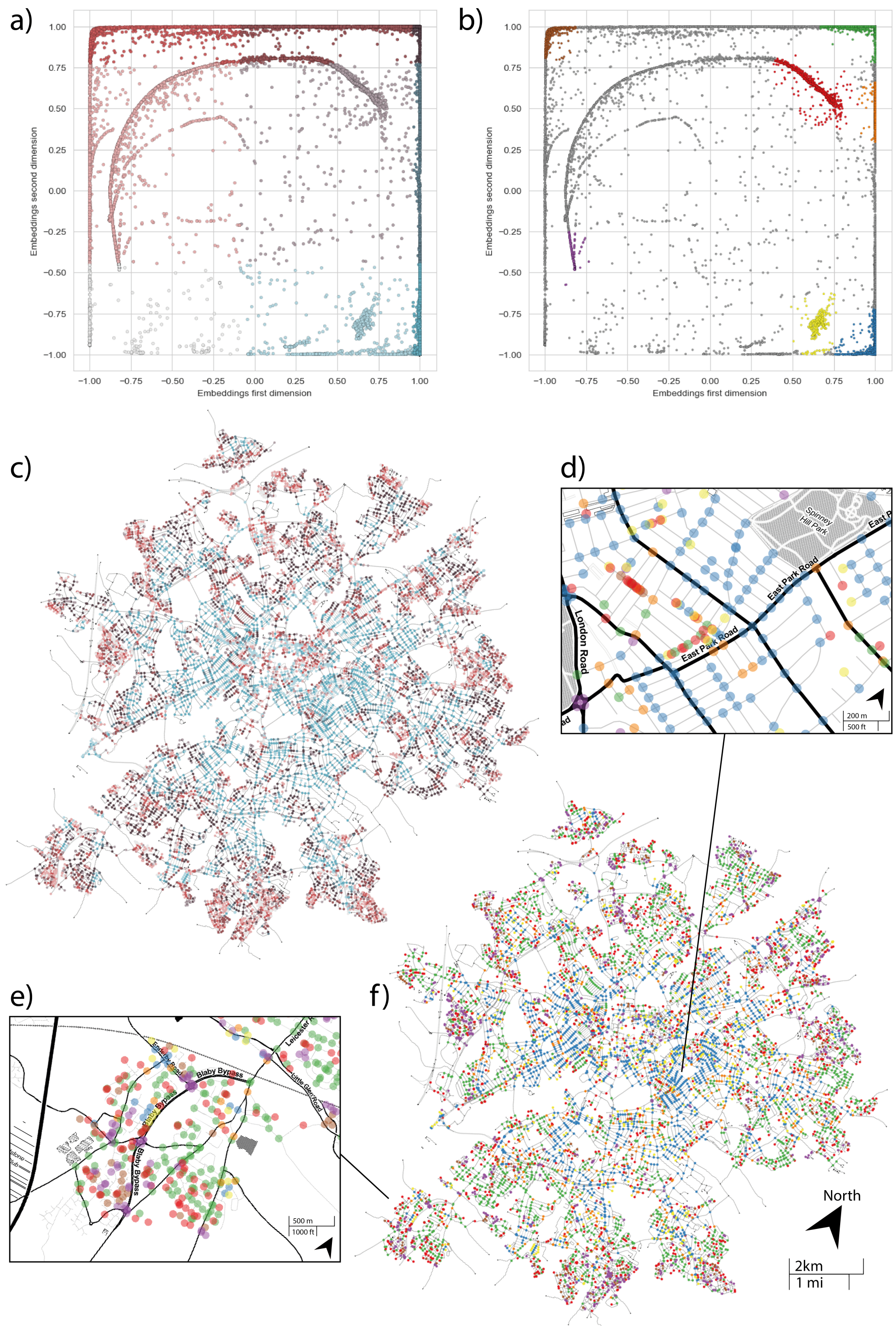

Fig. 2. Embeddings generated for Leicester, visualised as scatterplots illustrating 3×3 bivariate quantiles (a) and main clusters (b), as well as maps presenting the same 3×3 bivariate quantiles (c) and clusters (d, e and f). Data by OpenStreetMap, under ODbL, and by Boeing [4], under CC0 1.0. Map tiles by Stamen Design, under CC BY 3.0.

Table 1. Kendall's rank correlations between the embeddings generated by the model here presented and the node and ego-graph base statistics obtained using OSMnx [3]. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

	Node embeddings		Ego-graph pooled embed.	
Measure	Fist dim.	Second dim.	Fist dim.	Second dim.
Node in city graph				
closeness centrality	0.262***	-0.194***	**0.365*****	**-0.337*****
betweenness centrality	0.242***	-0.026***	0.117***	-0.155***
Node in ego-graph				
closeness centrality	0.296***	0.135***	**0.335*****	0.202***
betweenness centrality	0.260***	0.097***	0.125***	-0.017**
Ego-graph				
count of nodes	-0.033***	-0.104***	-0.138***	-0.226***
count of edges	0.013*	-0.101***	-0.068***	-0.213***
average node degree	0.261***	0.005	**0.377*****	0.037***
total edge length	0.210***	-0.131***	0.208***	-0.246***
average edge length	**0.370*****	-0.045***	**0.580*****	-0.022***
average streets per node	0.280***	-0.232***	**0.431*****	**-0.421*****
count of intersections	0.047***	-0.144***	-0.019***	**-0.302*****
total street segment length	0.192***	-0.163***	0.190***	-0.315***
count of street segments	0.009	-0.134***	-0.070***	-0.285***
average street segment length	**0.365*****	-0.044***	**0.589*****	-0.015*
average street circuity	-0.028***	0.131***	-0.066***	0.225***

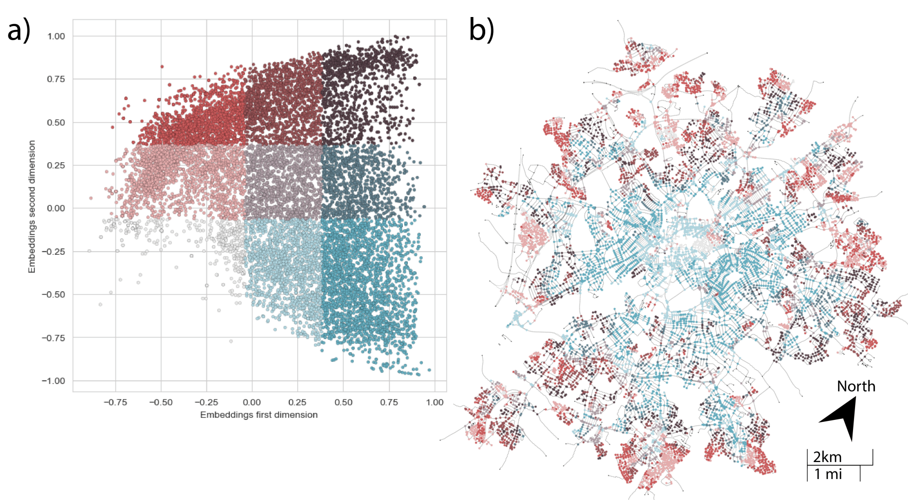

Fig. 3. Ego-graph pooled embeddings generated for Leicester, visualised as a scatterplot (a) and map (b) illustrating 3×3 bivariate quantiles. Data by OpenStreetMap, under ODbL, and by Boeing [4], under CC0 1.0.

4 Discussion and conclusions

The results presented above illustrate how GNNs can be used as an unsupervised framework to capture and explore urban form. Our quantitative analysis shows that the embeddings generated for Leicester by a GAE trained on samples from across the UK are broadly similar to but different from classic measures, while our qualitative analysis illustrates how those embeddings represent meaningful and consistent properties of Leicester's street network.

However, this is merely a first exploratory study. Most of the decisions that went into creating the model were based on our own previous experience in working with similar models and data, the literature discussed above, and a limited amount of testing. It is plausible that a larger sample of nodes, a different size of ego-graph, a different number of minimum nodes, a different data preprocessing or longer training might produce better results. Furthermore, the design space for the GAE architecture is vast, including the number of layers, the number of features for each layer and the type of graph-convolutional layer, alongside many other hyperparameters. The results presented here, obtained using a simple model, only demonstrate the viability of the framework, but a more thorough exploration of the design space is necessary. Moreover, a systematic approach to testing such a model – although that can be particularly challenging with unsupervised models which do not rely on "ground-truth" labels – and comparing it against a wider range of measures and classifications will be necessary. One option might be to rely on an F1-Score [8], another to crowdsource "ground-truth" labels and a third to test our results with local residents and city planners.

Beyond the computational aspects outlined above, in our future work, we aim to expand the use of our framework in three aspects. First, we aim to explore the adaptability and usefulness of our approach through space, time and scale, testing how models behave when using a continental or global dataset for training, including past street networks or limiting the training to cities of the same scale as the target one(s). Second, we will explore how to encode places beyond junctions, including buildings or points of interest. Third, we will explore how to encode flows beyond networks, including commuting or communications.

Acknowledgements and code

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References

1. Arribas-Bel, D., Fleischmann, M.: Spatial signatures - understanding (urban) spaces through form and function. Habitat International **128**, 102641 (2022). https://doi.org/10.1016/j.habitatint.2022.102641

2. Batty, M.: The new science of cities. MIT press (2013)
3. Boeing, G.: OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Computers, Environment and Urban Systems **65**, 126–139 (Sep 2017). https://doi.org/10.1016/j.compenvurbsys.2017.05.004
4. Boeing, G.: Global Urban Street Networks GraphML (2020). https://doi.org/10.7910/DVN/KA5HJ3
5. Boeing, G.: Street network models and indicators for every urban area in the world. Geographical Analysis **54**(3), 519–535 (2022). https://doi.org/10.1111/gean.12281
6. Fey, M., Lenssen, J.E.: Fast Graph Representation Learning with PyTorch Geometric (May 2019), `https://github.com/pyg-team/pytorch_geometric`
7. Fleischmann, M., Arribas-Bel, D.: Geographical Characterisation of British Urban Form and Function using the Spatial Signatures Framework (9 2021). https://doi.org/10.6084/m9.figshare.16691575.v1
8. Gharaee, Z., Kowshik, S., Stromann, O., Felsberg, M.: Graph representation learning for road type classification. Pattern Recognition **120**, 108174 (Dec 2021). https://doi.org/10.1016/j.patcog.2021.108174
9. Hu, W., Liu, B., Gomes, J., Zitnik, M., Liang, P., Pande, V., Leskovec, J.: Strategies for Pre-training Graph Neural Networks (Feb 2020). https://doi.org/10.48550/arXiv.1905.12265
10. Jiang, W., Luo, J.: Graph neural network for traffic forecasting: A survey. Expert Systems with Applications **207**, 117921 (2022). https://doi.org/https://doi.org/10.1016/j.eswa.2022.117921
11. Kipf, T.N., Welling, M.: Variational graph auto-encoders (2016)
12. Li, M., Gao, S., Lu, F., Liu, K., Zhang, H., Tu, W.: Prediction of human activity intensity using the interactions in physical and social spaces through graph convolutional networks. International Journal of Geographical Information Science **35**(12), 2489–2516 (2021). https://doi.org/10.1080/13658816.2021.1912347
13. Liu, P., Biljecki, F.: A review of spatially-explicit GeoAI applications in urban geography. International Journal of Applied Earth Observation and Geoinformation **112**, 102936 (2022). https://doi.org/10.1016/j.jag.2022.102936
14. Liu, P., De Sabbata, S.: A graph-based semi-supervised approach to classification learning in digital geographies. Computers, Environment and Urban Systems **86**, 101583 (Mar 2021). https://doi.org/10.1016/j.compenvurbsys.2020.101583
15. Mai, G., Janowicz, K., Hu, Y., Gao, S., Yan, B., Zhu, R., Cai, L., Lao, N.: A review of location encoding for GeoAI: methods and applications. International Journal of Geographical Information Science **36**(4), 639–673 (2022). https://doi.org/10.1080/13658816.2021.2004602
16. Rapoport, A.: Human aspects of urban form: towards a man—environment approach to urban form and design. Elsevier (2016)
17. Tang, V., Painho, M.: Exploring the relationships between perceived neighborhood boundaries and street network orientation. Transactions in GIS **27**(3), 877–899 (2023). https://doi.org/10.1111/tgis.13058
18. Xue, J., Jiang, N., Liang, S., Pang, Q., Yabe, T., Ukkusuri, S.V., Ma, J.: Quantifying the spatial homogeneity of urban road networks via graph neural networks. Nature Machine Intelligence **4**(3), 246–257 (Mar 2022). https://doi.org/10.1038/s42256-022-00462-y
19. Zhang, Y., Liu, P., Biljecki, F.: Knowledge and topology: A two layer spatially dependent graph neural networks to identify urban functions with time-series street view image. ISPRS Journal of Photogrammetry and Remote Sensing **198**, 153–168 (2023). https://doi.org/10.1016/j.isprsjprs.2023.03.008