Extracting Area Characteristics from People Flow and POI Data Using Graph Neural Networks

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Introduction

Urban mobility patterns modeled with Graph Neural Networks (GNNs) support land use mapping, demand forecasting, and policies against commercial decline. Yao et al. have shown that metro stations, business districts, and residential areas can be identified from the mobility data alone [1]. Yet most models are dependent on biased samples or auxiliary labels, and to our knowledge, no other study has reconstructed citywide functional similarity in a fully unsupervised way. Data granularity and personal privacy remain major barriers.

In this study, we examine whether embeddings from a mobility graph alone can capture commercial similarity defined by Point of Interest data (POIs) of Tokyo. Using a nationwide origin–destination network, we train an unsupervised Graph Convolutional Network (GCN) and compare embeddings with POIs. Building on advances in heterogeneous graph learning [2] and the GCN framework [3], we demonstrate that People Flow Dataset (PF) can capture citywide functional similarity.

Methodology

We use anonymized PF data within the study area, Tokyo Metropolis, Japan, and focused on trips that were made only by rail transport, including trains and subways. We divide the study area into 500 m × 500 m mesh cells [4] and tallied the POIs within the corresponding cells. Nodes correspond to the mesh cells that appear as origins or destinations. Undirected edges from node i to node j aggregate population counts having internal transitions removed. To stabilize heavy-tailed flows and to reduce the influence of very long trips without parameter tuning, we define a distance attenuated weight as follows,

$$w_{ij} = \log(1 + F_{ij})/((1 + d_{ij})/\tau) \ ,$$

where suffix i and j denote the node index. F_{ij} and d_{ij} denote the OD (Origin Destination) flow count from cell $i$to cell j and the centroid distance [km], respectively. The τ is the median of d_{ij} across all OD pairs. We then rescale weights so that their mean equals 1, yield a directed, weighted graph. Each node's features are two probability vectors over all (time × age × gender) combinations: an outgoing mix based on departures from the node and an incoming mix based on arrivals to it. Weights of unobserved category cells are set to 0.

Embeddings are learned with a graph auto-encoder whose encoder is a two-layer GCN that consumes the weighted edges and the decoder uses inner products. Training optimizes an edge-reconstruction objective on the directed graph. The resulting embeddings are clustered with k-means such that for each cluster we compute the relative POIs composition and compare it with the grouping derived from PF to benchmark how far PF alone recovers commercial-function similarity across Tokyo.

Results

Table 1 shows the relative composition of POIs categories in each cluster. Taken together, the embeddings learned solely from PF recover a structure of the core, inner ring, and periphery that aligns with commercial functions defined by POIs.

Future directions

This study is ongoing, and we plan to further extend it in several ways. By incorporating richer POIs to reflect commercial functions more directly, we aim to refine the correspondence between embeddings derived from PF and urban commercial structure. At the same time, the current analysis has not yet included a systematic evaluation, so we will compare our approach against baseline models to assess its effectiveness and limitations.

References

[1] Yao Z., Fu Y., Liu B., Hu W., and Xiong H. "Representing Urban Functions through Zone Embedding with Human Mobility Patterns." In: Proceedings of the 27th International Joint Conference on Artificial Intelligence (2018), pp. 3919-3925.
[2] X. Zhai, J. Jiang, A. Dejl, A. Rago, F. Guo, F. Toni, and A. Sivakumar "Heterogeneous Graph Neural Networks with Post-hoc Explanations for Multi-Modal Land-Use Inference." In: Information Fusion 120 (2025) 103057, pp. 1-25.
[3] Kipf T. N. and Welling M. "Semi-Supervised Classification with Graph Convolutional Networks." Published as a conference paper at ICLR (2017) 1-14.
[4] Website of the Statistics Bureau of Japan. https://www.stat.go.jp/data/mesh/pdf/gaiyo1.pdf. Online. Accessed 9 September 2025.

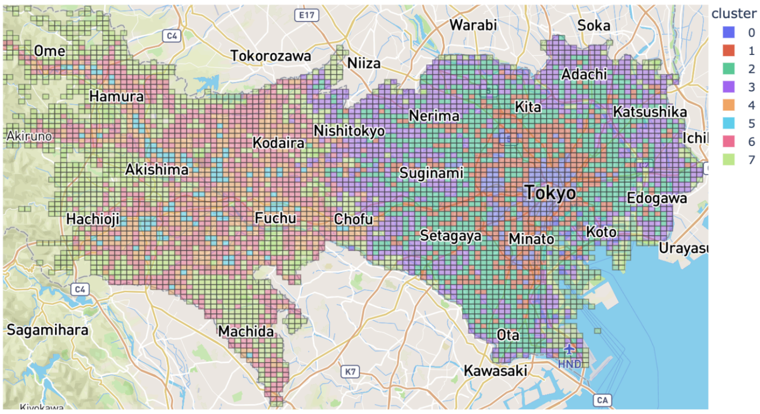

Figure 1. **Spatial distribution of embedding clusters obtained solely from PF information in Tokyo (k=8).**
Each mesh cell is colored by its k-means Cluster index (0-7) computed from an unsupervised graph auto-encoder on PF.

Cluster	Metro	Dense Urban	Urban	Suburban	Country	Rural	Null
0	**0.86**	0.08	0.02	0.00	0.00	0.00	0.03
1	0.17	0.27	**0.45**	0.00	0.00	0.01	0.09
2	0.02	0.08	**0.73**	0.02	0.01	0.00	0.13
3	0.02	0.01	**0.63**	0.09	0.03	0.01	0.22
4	0.00	0.01	**0.47**	0.27	0.05	0.00	0.19
5	0.06	0.10	**0.57**	0.15	0.03	0.00	0.09
6	0.00	0.00	0.26	**0.33**	0.15	0.02	0.25
7	0.04	0.00	0.09	0.15	0.16	0.14	**0.40**

Table 1. **POIs composition by PF-only clusters (k=8).**
For each cluster, the entries give the fraction of mesh cells labeled as each POIs-defined area type ("Metro", "Dense Urban", "Urban", "Suburban", "Country", "Rural"). "Null" marks cells with no POIs coverage. Row totals sum to 1 up to rounding. Cluster indices (0-7) correspond to the clusters in Fig. 1.