Dynamic Urban Function Representation: Learning Urban Characteristics from POI, Land Use, and Human Mobility Patterns

Author: Chung-En Tsern[1], Supervisors: Prof. Elsa Arcaute[1], Cristobal Montt[2]
[1] University College London, [2] Virgin Media O2 & GHD

Back Ground and Motivation

Conventional land-use and census classifications provide essential baselines for urban analysis but remain static, slow to update, and unable to reflect the temporal rhythms of contemporary cities.

This study develops a spatiotemporal embedding framework to delineate urban functions in Greater London by integrating POI distributions, land-use proportions, and anonymised mobile phone mobility data, aggregated into the H3 hexagonal grid. By moving beyond static "snapshots" toward dynamic, data-driven functional clustering, this framework provides a scalable and interpretable basis for adaptive urban planning.

Data and Methods

This study draws on four datasets: (1) Points of Interest (POI) from the CDRC UK POI package, (2) Virgin Media O2's Motion RTLI mobility data, consisting of anonymised device records aggregated at five-minute intervals with demographic attributes and home/work/visitor/International labels, (3) Verisk UKLand v2024 land-use with 27 classes, and (4) the London Output Area Classification (LOAC), which is used as an external baseline for validation.

The workflow proceeds in four stages (Figure 1) : (1) Data collection, where land use, POI, and mobility data are gathered as complementary views of the urban environment; (2) Spatial aggregation, where all datasets are converted into H3 hexagonal grids at resolution 9; (3) Feature embedding, where spatial (land use and POI) and temporal (mobility) attributes are embedded and fused using self-attention to capture dynamic urban characteristics; (4) Functional delineation, where clustering is applied to the spatiotemporal vectors to identify distinct urban zones.

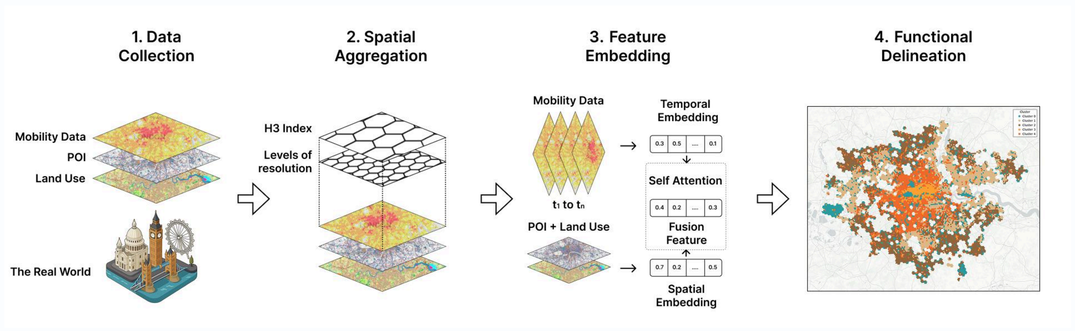

Figure 1: Dynamic urban function representation framework.

Key Findings

After fusing spatial and temporal data with self-attention, we clustered London into five groups (Figure 2): Cluster 3 covers the city centre, Cluster 4 dense mixed-use zones, Clusters 1 and 2 suburban residential areas, and Cluster 0 leisure/tourist sites such as airports, parks, and riverfronts. Areas without data reflect gaps in Virgin Media's H3-9 coverage.

For temporal variation (Figure 3), Cluster 3 shows sharp midday peaks and evening declines, with lower weekend and Friday activity, consistent with commercial districts and remote working pattern. Cluster 4 maintains stable levels due to mixed land-use. Clusters 1 and 2 peak in the evening, with Cluster 1 denser than Cluster 2. Cluster 0 attracts daytime visitors but is quiet at night.

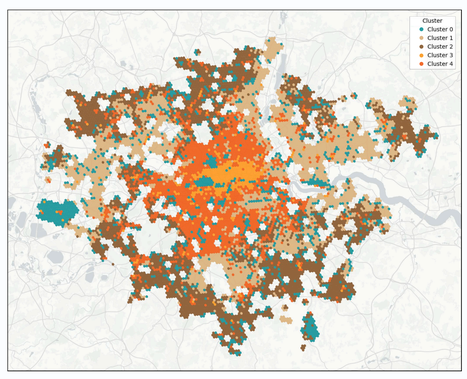

Figure 2: Spatial distribution of Clustering.

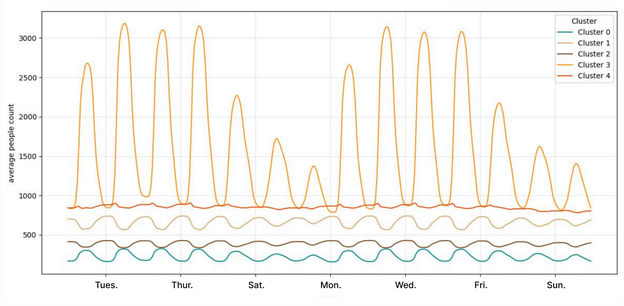

Figure 3: Average population variation by cluster.

We further analysed the age, activity, and socio-economic profiles of each cluster (Figure 4). Cluster 2 is the oldest, with 52% aged over 50, while Cluster 3 is the youngest, with higher proportions aged 15–29. Clusters 0, 1, and 4 show no major age differences. In terms of activity, Clusters 0 and 3 attract the most visitors and international populations; Clusters 1 and 2 are mainly residential with little visitor activity; and Cluster 4 (mixed-use) shows a balance of residential and visitor presence. Socio-economic results show Cluster 1 with nearly 30% DE (more disadvantaged), Cluster 2 with the lowest DE (most affluent), and Clusters 1, 3, and 4 dominated by AB/C1, indicating middle- to high-income groups.

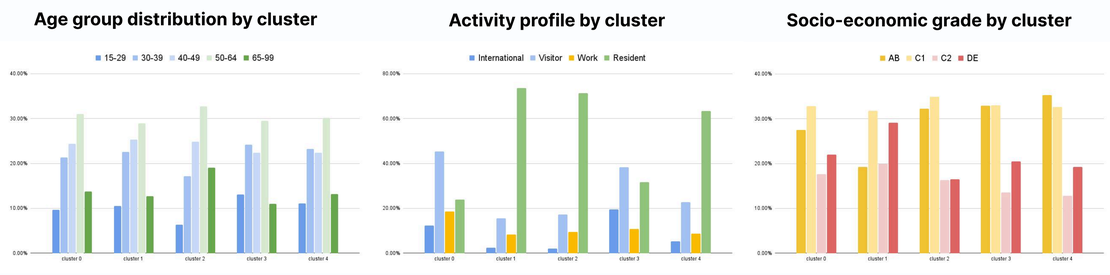

Figure 4: Demographic distribution of Clustering.

The analysis identifies five functional types across London: leisure/tourist zones (cluster 0), emerging (Cluster 1) and affluent residential suburbs (cluster 2), city centres/sub-centres (Cluster 3), and mixed-use inner urban areas (Cluster 4).

Value of the research

This study shows that embedding POIs, land-use, and mobility data provides a finer representation of urban functions than static land-use maps. For example, Ealing's land use is largely residential with retail (79%) and transport (15%), making it difficult to classify as a city sub-centre based on land-use and POIs alone. By incorporating temporal patterns, the model identifies these hexagons as city centres/sub-centres (Cluster 3), a result further validated by satellite imagery showing dense high-rise buildings (Figure 5). This demonstrates how spatiotemporal fusion uncovers insights that static data cannot. Importantly, these patterns align with LOAC, reinforcing the reliability of the approach while highlighting its added value in capturing urban dynamics. By dynamically delineating functional zones through spatial and temporal features, this approach supports transport, infrastructure, housing, and social policy planning, offering decision-makers a richer toolkit for managing urban complexity.

Figure 5: Integrated view of Ealing combining satellite imagery, land use, POIs, and functional characteristics.