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Predict Sales Demand from People Flow Data and Point of Interest Data using Spatio-Temporal Graph Convolutional Network

Keywords: people flow, spatio-temporal graph convolutional network, sales demand, urban analytics,multi-layered graph

Introduction

In cities or urban environments, Human Mobility drives commercial revenue, where sales are modulated by where the people go, what surrounds them, and how they feel about the place [1]. To investigate this relationship, we consider cities as a dynamic network of spatial mesh cell nodes, linked by the daily flow of people from one cell to another [2]. Then, on top of this network, we build a Retail Arrival Potential (RAP) from the People Flow Dataset (PF) [4] and Point of Interest Data (POI). With this combination, we deliver forecasts with explanations of why some spatial mesh cells show higher commercial activity.

Methodology

The PF Dataset (PF) provides anonymized counts of movements between cells at 24-hour resolution. Each mesh cell (500 m × 500 m) [5] is enriched with Point of Interest Data (POI), which contains detailed information about each unique mesh cell, combining building, demographic, and landmark attributes. Each record includes identifiers such as mesh codes, building type and use (e.g., Apartment, Business), structural dimensions (area, floors), and geographic characteristics like elevation and topography. It also incorporates contextual data on urban density and notable landmarks (e.g., shopping malls, train stations, convenience stores).

Following the approach of Spatio-temporal Multi-Graph Convolution Network (ST-MGCN) [3], we model the city as a multi-layered graph over the same nodes. Instead of a single adjacency, we build three complementary graphs that capture geography, movement, and commercial function. Each graph is sparse, normalized, and passed to the ST-MGCN as a separate support.

Spatial adjacency graph (G^s) contains undirected edges connecting bordering cells to capture short-range spatial movements as well as spillovers. *Mobility flow graph (G^m)* contains directed edges, encoded to observe origin to destination trips from the records of the PF Dataset, exposing commuter corridors and transient hubs which a purely spatial graph misses. *POI similarity graph (G^p)* is built using cosine k-NN over standardized numeric attributes (households, area, floors, volume, radius, occupants, elevation) concatenated with building/landmark categories, and then symmetrically normalized.

At each layer, the model performs message passing separately on G^s, G^m, and G^p, producing three intermediate updates which are then combined through learned mixture weights so the model learns, per time step and location, whether geography, movement, or functional similarity is more informative. The model places two temporal 1-D convolution blocks around a multi-support graph convolution with a learnable per node, per time mixture gate over G^s, G^m, and G^p, to yield predictions and interpretable support weights.

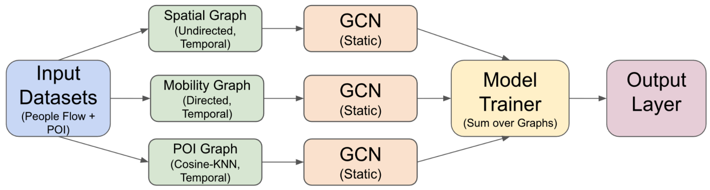

Fig1. Model Architecture

Result

Geographical representation of the predicted arrival value for the next 24 hours shows concentration in central Tokyo, a region characterized by high commercial density and intense population activity relative to adjacent mesh cells. Analysis of the learned support weights reveals that the model relies predominantly on the Functional/POI layer (G^p). Of all the land use categories in the POI Data, the functional layer weight is largest on nodes with retail and services oriented categories. These findings highlight that elevated human mobility patterns align with spatial concentration of commercial activity in central Tokyo.

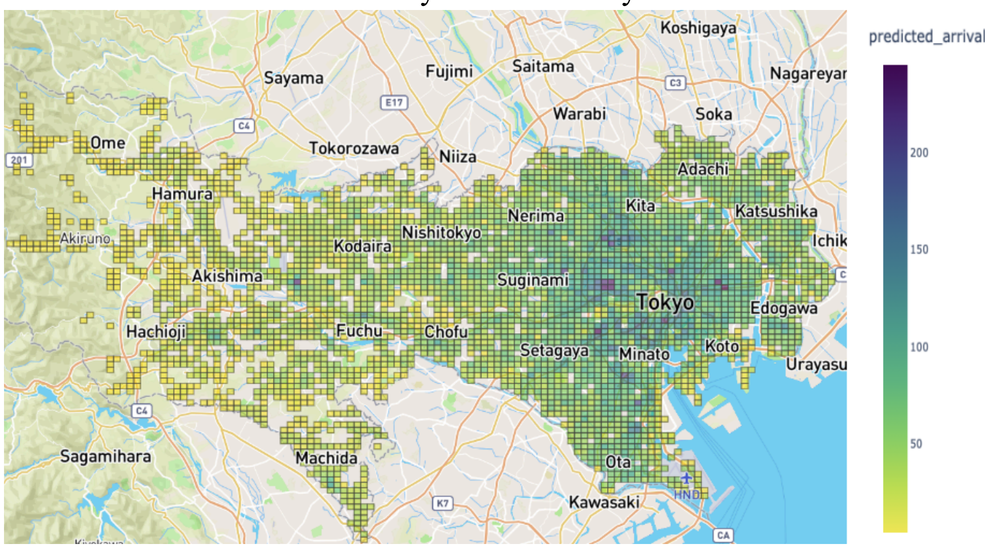

Fig2. The map illustrates the predicted number of people expected to arrive in each mesh cell of Tokyo Prefecture over the subsequent 24 hours. The predicted_arrival values are represented on a continuous color scale ranging from yellow (lower arrivals) to purple (higher arrivals).

References

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