

Hierarchical Graph Representation Learning for Large-Scale Origin–Destination Flow Prediction

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Introduction

In this study, we proposed a heterogeneous graph model to learn hierarchical embeddings in a prefecture to maintain the large-scale origin-destination matrix. We constructed a heterogeneous graph transformer-based network to extract multi-level representations and used them to predict cross-level OD volumes.

Methodology

Urban indicators such as facility distributions and night population from open data are used for model learning. Different OD matrices determined by types of edges and vertices serve as parts of multi-task learning.

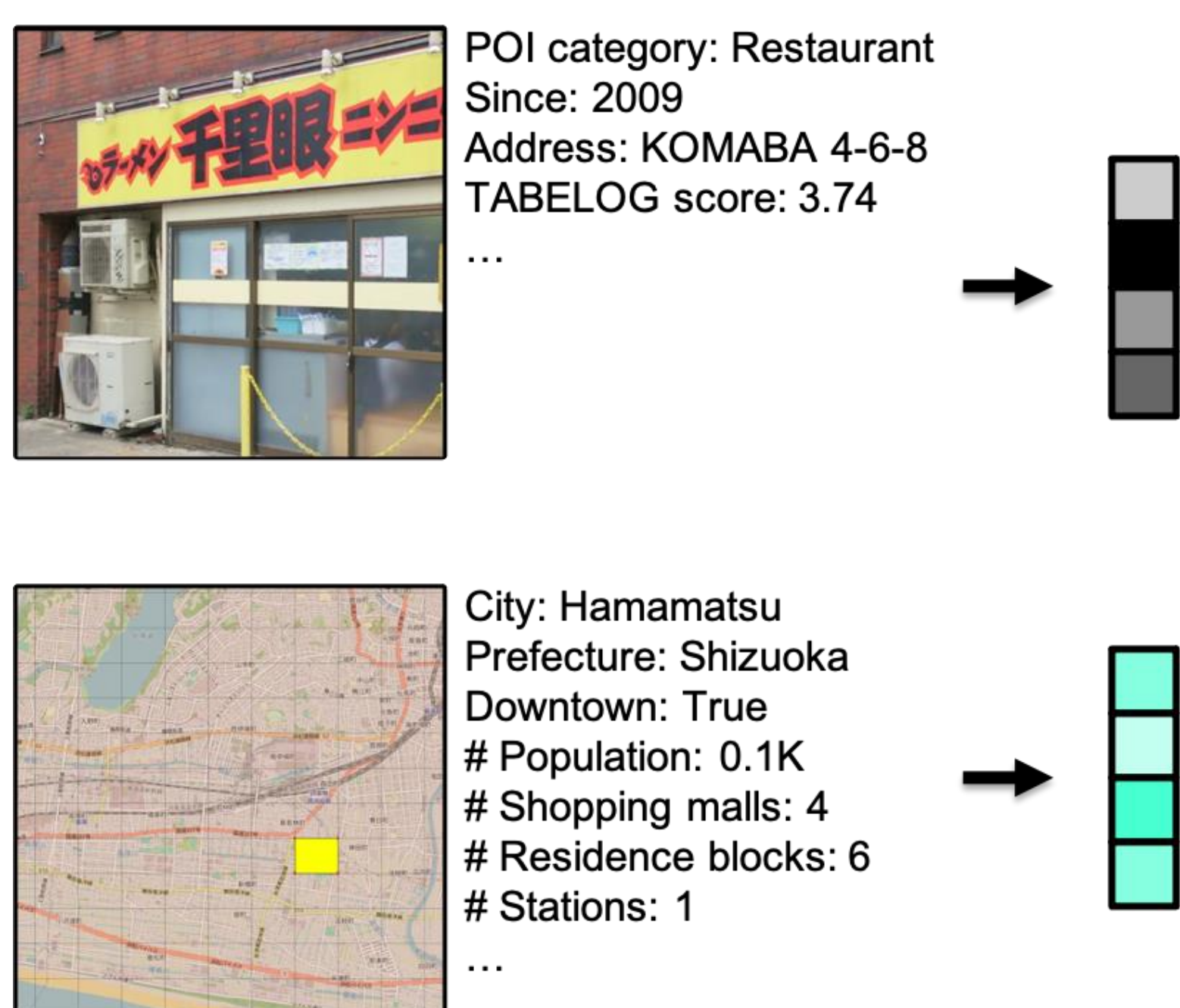


Fig. 1. Extraction of representations from urban indicators

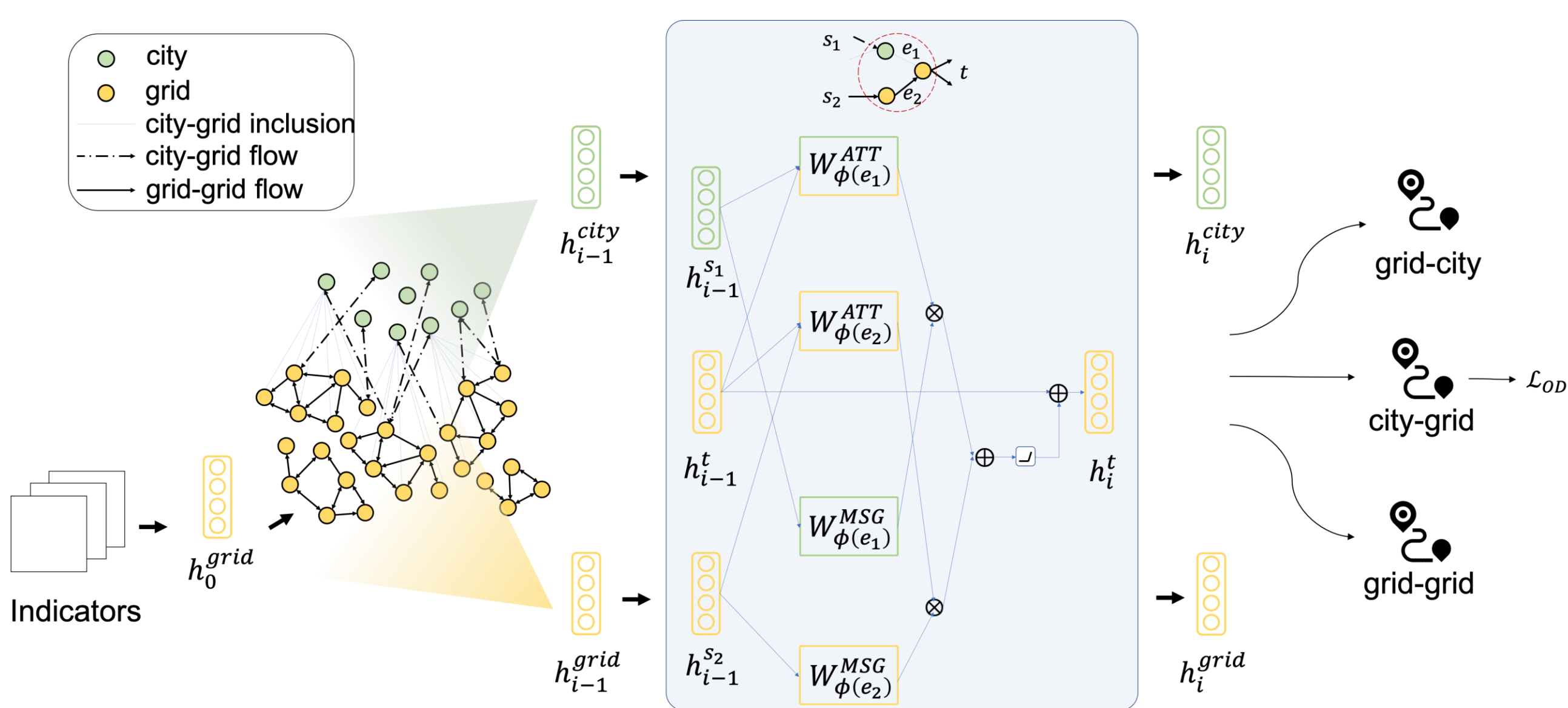


Fig. 2. The framework of the proposed model.

Experiment

We performed an experiment in Shizuoka Prefecture in central Japan. The target area includes 43 cities and affiliated mesh grids. The number of OD pairs is around 300K. We used CDR data from SoftBank Group Corp. as the ground-truth.

Discussion

This study proposes a heterogeneous graph based model to describe urban areas on a large scale. In future work, we will consider more types of spatial units and the relationships between units at different levels to comprehensively illustrate urban semantics.

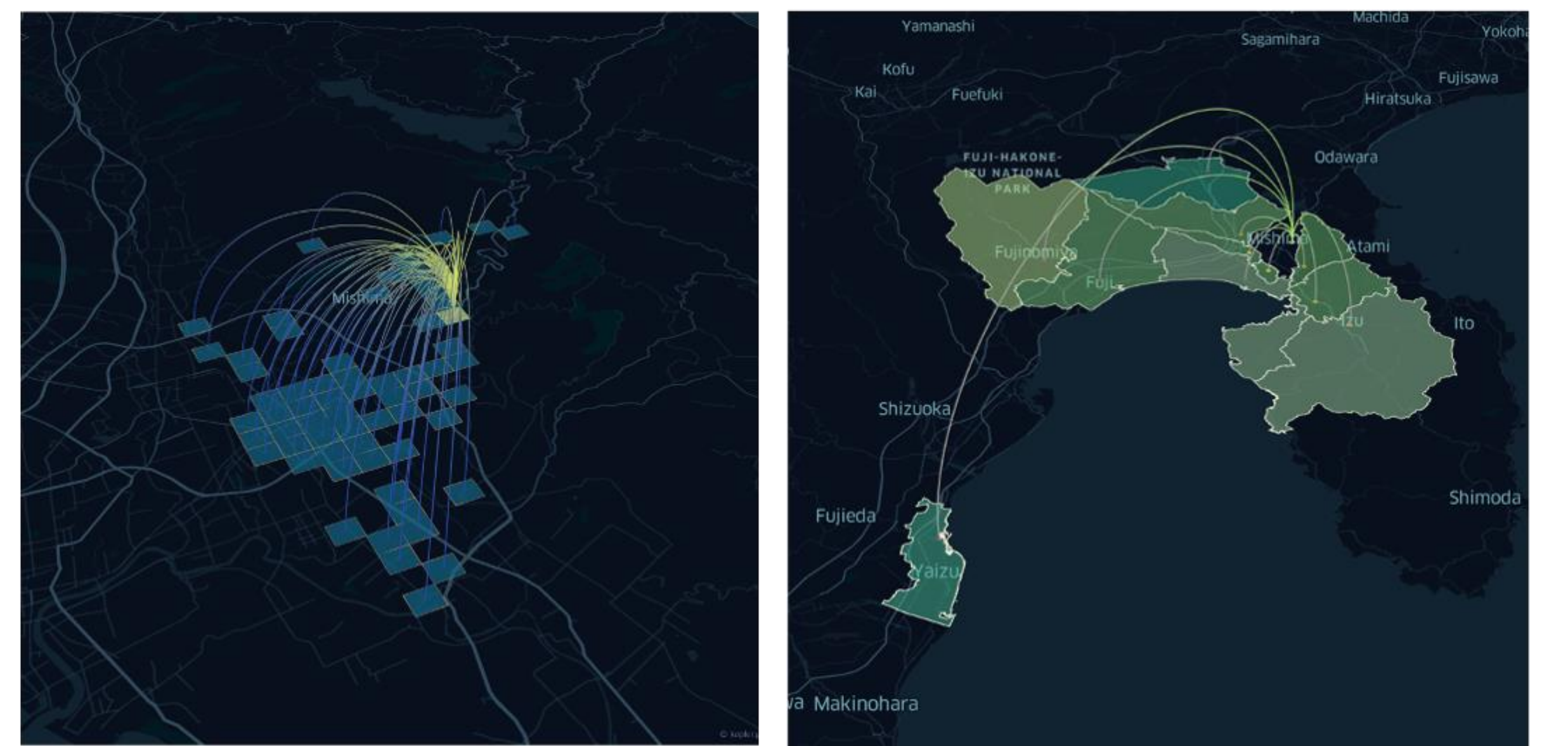


Fig. 3. Intra-level and inter-level people flows.

Result

We compared our model with several baseline models. The performance of the regression problem is measured with three metrics: RMSE and MAE emphasize the individual mesh grid prediction, whereas the correlation of coefficient focuses on the overall prediction.

Model	Grid to Grid			Grid to City			City to Grid		
	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
Gravity model	136.61	54.09	0.00	385.42	128.102	0.00	390.06	127.56	0.00
Decision tree	199.23	54.09	0.21	319.98	90.34	0.26	337.71	93.11	0.26
Random forest	159.63	44.67	0.06	263.20	81.59	0.20	273.85	81.21	0.16
Gradient boosting	158.26	43.89	0.15	255.27	77.61	0.31	265.55	76.84	0.29
Multi-layer perceptron	158.81	47.08	0.13	261.64	91.99	0.25	273.22	98.60	0.25
GMEL	122.96	44.15	0.01	328.84	84.13	0.05	318.23	80.54	0.05
HCM_{GAT}	<u>106.92</u>	<u>37.09</u>	0.32	214.44	<u>59.02</u>	0.43	246.15	<u>62.69</u>	0.36
HCM_{HGT}	131.15	50.47	<u>0.36</u>	<u>207.78</u>	65.42	<u>0.62</u>	<u>196.50</u>	65.60	<u>0.57</u>

Table. 1. Performance of the proposed model.