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Spatial Attention Based Grid Representation Learning For Predicting Origin–Destination Flow

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Introduction

In this study, we proposed a deep graph model to learn meaningful OD information on grids within a city. We constructed a spatial attention-based deep graph network to generate grid representations and used them to predict the OD volumes. These representations also apply to other downstream tasks.

Methodology

We maintained an encoder–decoder framework for OD volume prediction. Urban indicators such as facility distributions and night population from open data serve as initialization for the embeddings.

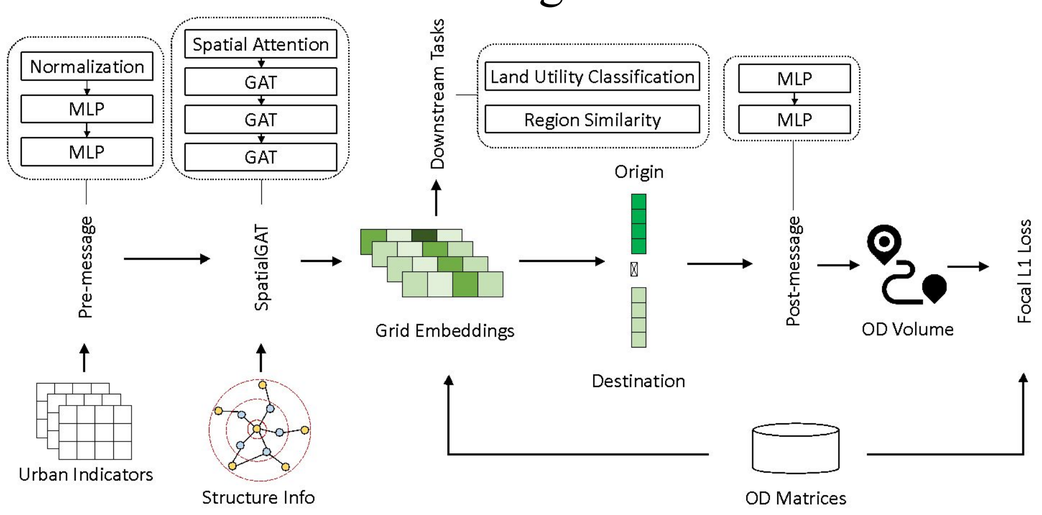

Fig. 1. Overall structure of this research.

Experiment

We performed an experiment in Shizuoka Prefecture in central Japan. We selected six areas with different characteristics: Aoi ward, Suruga ward, and Naka ward are typical city areas of relatively large, medium, and small sizes, respectively. Similarly, Fuji city, Numazu city, and Susono city are local areas of different sizes.

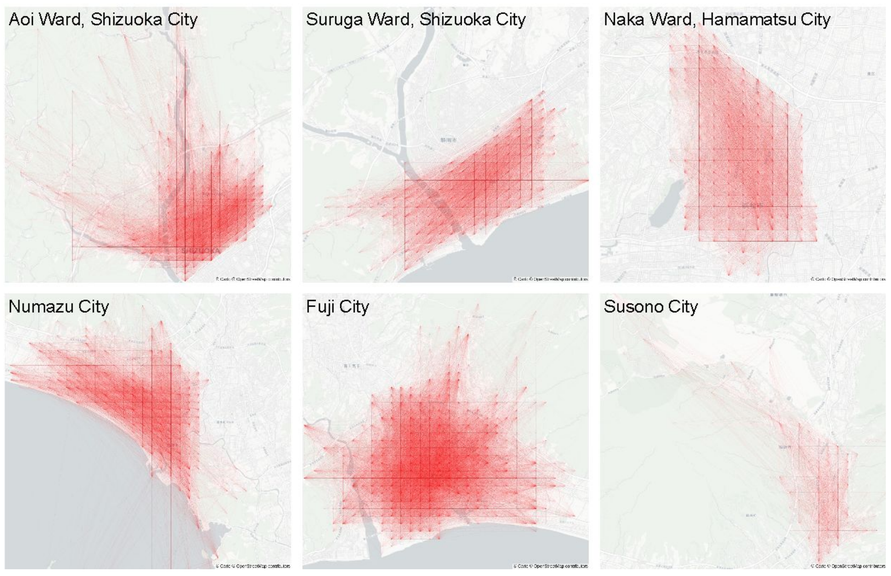

Fig.2. Six target areas in Shizuoka Prefecture.

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 COR focuses on the overall prediction.

Model	Area								
	Aoi Award, Shizuoka City			Suruga Ward, Shizuoka City			Naka Ward, Hamamatsu City		
	RMSE	MAE	COR	RMSE	MAE	COR	RMSE	MAE	COR
Gravity Model	153.39	68.93	0.04	149.39	121.21	0.09	438.66	406.93	0.15
Decision Tree	191.15	50.84	0.13	146.51	50.38	0.15	184.83	65.30	0.29
Random Forest	137.74	42.45	0.09	109.05	43.22	0.13	128.31	59.28	0.22
Gradient Boosting	137.84	42.14	0.19	106.00	41.30	0.27	119.97	55.46	0.39
2-Layer MLP	146.61	58.39	0.15	128.67	93.27	0.15	127.74	63.88	0.23
GraphSAGE	75.31	22.23	0.48	99.44	33.62	0.35	**75.30**	**21.82**	0.47
SpatialGAT	**67.34**	**21.40**	**0.64**	**79.18**	**22.95**	**0.58**	91.64	35.33	**0.72**

Model	Area								
	Numazu City			Fuji City			Susono City		
	RMSE	MAE	COR	RMSE	MAE	COR	RMSE	MAE	COR
Gravity Model	229.19	166.11	0.11	87.78	77.23	0.04	123.22	93.25	0.27
Decision Tree	189.47	49.07	0.11	86.56	29.18	0.08	148.91	46.87	0.06
Random Forest	106.88	40.31	0.09	57.27	21.93	0.12	97.45	39.03	0.20
Gradient Boosting	111.47	39.75	0.13	56.65	21.47	0.18	94.75	36.25	0.29
2-Layer MLP	113.69	52.21	0.22	75.49	56.95	0.11	99.02	56.22	0.28
GraphSAGE	**50.65**	**22.00**	0.38	50.59	22.97	0.39	88.15	30.12	0.39
SpatialGAT	108.80	24.45	**0.48**	**45.26**	**14.31**	**0.58**	**69.53**	**25.89**	**0.62**

Table 1. Result of baseline models and proposed model.

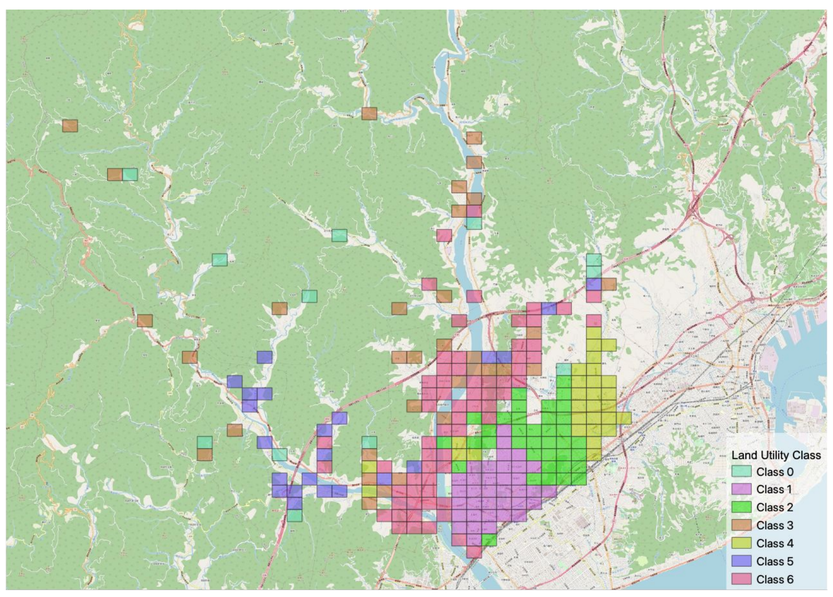

Fig. 3. Downstream task: land utility classification.

We used land utility classification as one downstream task. The classification is extremely accurate for the differentiation between rural and downtown areas.

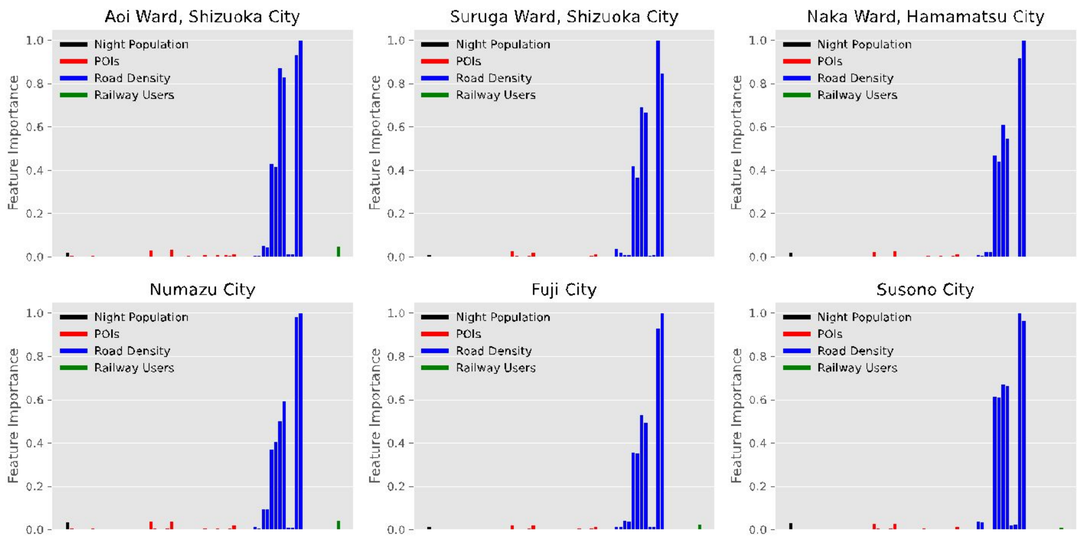

Fig. 4. Feature importance analysis of urban indicators.

We also conducted an indicator importance analysis to understand which indicator plays a more important role.

Conclusion

In conclusion, our proposed model can capture the major patterns of daily OD flow, and the results can be utilized in other downstream tasks.