Multi-Level Crowd Estimation with Limited Data

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Abstract Data scarcity is one of the main challenges for real-world crowd estimation tasks, as most of the existing (deep) machine learning approaches rely on having sufficient training data. This study proposes a graph-based multi-task learning model to address data insufficient scenarios for multi-level crowd estimation. In a case study, we first illustrate the utilization of potential open datasets for data augmentation and then implement the proposed model for crowed estimation at neighbourhood and node levels. In comparison with baseline models and single task learning approaches, we illustrate how multi-task learning enables knowledge-sharing that maximum feature learning when data is limited. We also analysis the performance under various percentage of missing data to gain insights into which levels of data absence critically impact the estimation accuracy.

Keywords Crowd estimation, multi-task learning, data scarcity

1 Motivation and Approach

Crowd estimation is one of the crucial tasks for safety management and traffic optimization. Efficiently modelling and forecasting crowd density and flows supports mitigating congestion and optimizing resource allocation [1]. For special events which often bring a sudden surge within a short period, precise crowd estimation will provides authorities sufficient response time and early warnings in emergencies to ensure public safety.

Recent studies on crowd estimation use machine learning and deep learning methods on multiple resources such as sensors, road networks, and GPS data. However, the performance of these methods is highly dependent on the availability of sufficient training data, which is often difficult to obtain in real world scenarios [2]. *Data scarcity* is a common problem in reality as data collection can be time-consuming, expensive, or privacy-limited. Lack of sufficient data will model accuracy and reliability, thus brings difficulties in estimating crowd variations in extreme scenarios, making emergency response systems less effective [3].

To address the data challenge mentioned above, this study proposes a graph-based multi-task learning integration of data augmentation to enhance crowd estimation performance under data scarcity scenario (Fig 1 (a)). The utilization of potential open data not only increase the amount of available datasets but also reduce the cost with data insufficiency. The implementation of multi-task learning enable knowledge-sharing to maximize the available features across related tasks with limited data. We validate the proposed framework for multi-level crowd estimation at Scheveningen area in Netherlands.

2 Case Study

The case study at the Scheveningen area of The Hague, Netherlands is focused on the crowd estimation at both neighbourhood level and node level. Available data has been used in the neighbourhood level which contains hourly and daily visit volumes at 16 neighbourhoods, shown in the grey boundaries in Fig 1 (b). For the node level, we only have three parking lots data that contains hourly parking occupancy and occupancy percentages within the case study area. To enrich node level data, we collect open Points of Interest (POI) data from Google Place API. The POI data contains 265 points with static features (categories, ratings, check-in number, etc) and dynamic features (average and live popularity times). We use popularity time to present crowd density levels from 0 to 100 for which 0 represents the closed hour, 1 and 100 are the percentages of the lowest and highest visits per hour. The standard popularity time represents the average density over the past few weeks and the live popularities is the real-time crowd density that updates hourly. We visualize the case study area and crowd density spatial-temporal variances within a week in Fig 1 (b).

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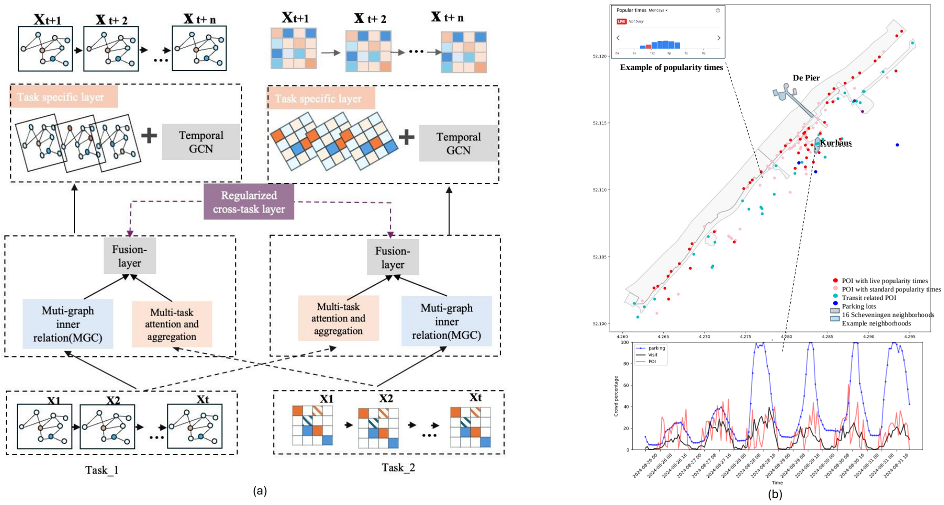

Figure 1: Left: Approach. Right: Data of case study.

Fig 1 (a) illustrates our proposed framework for the multi-level crowd estimation. For the case study, task 1 refers to node-level (POI and parking) crowd estimation and task 2 is neighbourhood-level hourly visits estimation. The experiment conducted from 1 July 2024 to 1 October 2024. As crowd-related data inherently multi-dimensions (spatial, temporal, contextual), we first model them as graph data to represent heterogeneous spatial dependencies (geographic, semantic). After acquiring the inner-task graphs and cross-task graphs, we integrate them using multi-graph convolution with self-attention fusion methods that developed from the Graph Convolution Network (GCN) [4]. After acquiring the multi-relation features in the shared layer, the Temporal GCN is then used for task specific layer. To investigate the performance of our proposed framework on different data insufficient scenarios, we evaluate the model by masking 10% to 40% percentage of training data as missing values for each task. We compare our proposed model with the baseline model: LSTM, GCN, STGCN [5] and MRGCN [6] and implement the ablation analysis to evaluate performance between single task learning and multi-task learning.

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Bibliography

[1] Jiang, H., Gai, Z., Wang, Z., Wang, C., Fan, Z., Chen, Q., Tsubouchi, K., Song, N., and Shibasaki, R., *DeepCrowd: A deep model for large-scale citywide crowd density and flow prediction*, IEEE Transactions on Knowledge and Data Engineering **35**(1), 177–190, 2021.

[2] Mustapha, S., Kassir, A., Hassoun, K., Dawy, Z., and Abi-Rached, H., *Estimation of crowd flow and load on pedestrian bridges using machine learning with sensor fusion*, Automation in Construction **112**, 103092, 2020.

[3] Poon, W. H., Wong, P. K. Y., and Cheng, J. C. P., *Long-time gap crowd prediction using time series deep learning models with two-dimensional single attribute inputs*, Advanced Engineering Informatics **51**, 101482, 2021.

[4] Kipf, T. N. and Welling, M., *Semi-supervised classification with graph convolutional networks*, arXiv preprint arXiv:1609.02907, 2016.

[5] Han, H., Zhang, M., Huo, M., Zhang, F., Wang, Z., Chen, E., Wang, H., He, X., and Liu, Q.,*STGNN: a spatial-temporal aware graph learning method for POI recommendation*, Proceedings of the 2020 IEEE International Conference on Data Mining (ICDM), 1552–1557, 2020.

[6] Huang, Z., Li, X., Ye, Y., and Ng, M. K., *MR-GCN: Multi-Relational Graph Convolutional Networks based on Generalized Tensor Product*, In Proceedings of the 20th International Joint Conference on Artificial Intelligence (IJCAI), 1258–1264, 2020.