A Survey on Group-Aware Data Analysis and Representation Learning in Location-Based Social Networks

Zixi Zang, Ze Wang

Abstract—**This survey comprehensively examines the role of group dynamics in advancing data analysis and representation learning within Location-Based Social Networks (LBSNs). We systematically review methodologies addressing core challenges such as spatial sparsity, social-location coupling, and computational inefficiency, with a focus on group-aware frameworks that transcend traditional individual-centric models. Key innovations discussed include feature-based group partitioning with transformer networks, social influence integration, adaptive modeling for temporary groups, and dynamic graph representation learning. We critically analyze their effectiveness in enhancing recommendation accuracy, scalability, and interpretability. Applications in urban computing (e.g., crowd flow prediction) and business intelligence (e.g., cross-platform consumer behavior alignment) further illustrate the practical utility of group-aware approaches. The survey identifies unresolved issues—such as real-time adaptability and ethical data governance—while proposing future directions for integrating federated learning, cross-domain alignment, and privacy-preserving mechanisms.**

Index Terms— **Representation, Location-Based Social Networks**

I. INTRODUCTION

With the deep integration of mobile Internet and geographic information technology, location-based social network has become an important carrier to connect physical space and virtual social. Typical platforms such as Foursquare and Facebook Places continuously generate data ecosystems containing multi-dimensional information such as spatio-temporal trajectories, social relationships, and behavioral preferences through users 'active check-in behaviors. This kind of data not only provides a research basis for applications such as personalized recommendation and urban computing, but also gives rise to new research directions such as group behavior analysis and social influence propagation [1].

Current LBSN data analysis faces three core challenges. Firstly, the user check-in data has significant spatial sparsity and time discreteness, and traditional collaborative filtering methods are difficult to effectively mine the potential interests of long-tail users. Secondly, there is a complex coupling relationship between homophilic effects and location preferences in social networks, and the machine learning model based on the independent and identical distribution assumption is difficult to capture the group-level interaction dynamics. Finally, the heterogeneous information network composed of massive users leads to the exponential growth of computational complexity, and the service scenarios with high real-time requirements face severe technical bottlenecks. In response to the above problems, academia has gradually realized the limitations of relying solely on individual behavior modeling, and has instead explored the construction of an "individual-group" multi-dimensional analysis framework through group division technology, so as to improve the accuracy of recommendation and user experience by capturing the interaction between group members [2].

II. EVOLUTION OF LBSN MODELING METHOD DRIVEN BY GROUP PARTITION

A. Feature-based Grouping Modeling and transformer Networks

In the research of He et al. [3], a feature-based POI grouping method, FPGT model (feature-based POI grouping and Transformer Network) was proposed: In this method, POIs were grouped according to geographical location and popularity characteristics, and the user's preference for a single POIs was transformed into the user preference analysis for a POI group, while reducing the computational complexity of traditional Graph Neural Network (GNN) on large-scale datasets. By grouping POIs, the model can analyze the user's preference for the group more efficiently, rather than directly analyzing a single POIs. Then, the check-in record sequence composed of embedding vectors is input into the Transformer-based encoder to capture the temporal changes of users at the group level. This method can effectively alleviate the sparsity problem of user check-in data, improve the computational efficiency of the recommendation system, and prove that the group division can enhance the interpretability of location semantics.

B. Group preference modeling by introducing individual social influence

The above methods do not fully consider the differences between the members of the group. However, in the study of Zahra et al. [4], they proposed to use user influence weights to model group preferences in more detail, showing the evolution from simple feature division to the introduction of individual social influence. For POI group recommendation in LBSN, their method considers the preference changes of group members under different contexts through a fuzzy user influence model. Especially in the group, the social

Manuscript received April 25, 2025
Zixi Zang, School of Software, Tiangong University, Tianjin, China
Ze Wang, School of Software, Tiangong University, Tianjin, China

relationship between different members will affect their choice of POIs. Therefore, the social influence of users needs to be reasonably modeled in the group recommendation. This method solves the cold start problem in group recommendation and improves the accuracy of group recommendation by aggregating the historical check-in data of users and combining factors such as category, distance and time.

C. *Adaptive Modeling for Temporary Groups*

In group recommendation research, most methods aim at fixed groups with sufficient historical data [5], but do not properly model temporary and sporadic groups, and the limitations of fixed group models in actual scenarios cannot be solved. In the study of Meng et al. [6], the authors proposed a new POI recommendation model, PROG-HGNN, specifically for POI recommendation of temporary groups (i.e., occasional groups). The proposed model generates a fitting representation of occasional groups by considering the social influence among members and utilizing the Node Influence Index (INF) and Graph Attention Network (GAT). In addition, Signature Bipartite Graph Neural Network (SBGNN) and Session based graph neural network (SRGNN) were used to learn the interaction preferences and transfer preferences of members for POIs. By combining the preferences of group members, high-precision recommendation for temporary groups is realized. Liu et al. [7] proposed an innovative model CGNN-PRRG based on collaborative graph neural network, which realized the adaptive fusion of group representation learning and preference transfer. The model constructs a groundbreaking dynamic fitting representation generation mechanism, which automatically generates embedded representations adapted to random group characteristics by analyzing the spatio-temporal heterogeneity of group member interactions. In order to deal with the cold start problem of new groups, a similar user preference transfer strategy is proposed, and the graph attention network is used to mine the cross-group behavior patterns of potential related users. At the technical implementation level, the edge learning Enhanced Bipartite Graph Neural Network (EBGNN) was designed to effectively capture the implicit preference characteristics of the user-POI interaction boundary, and the session graph neural network (SRGNN) was combined to model the transition law of the user behavior sequence. This research provides a scalable technical framework for dynamic group recommender systems, and its open source implementation lays a foundation for subsequent adaptive modeling research.

D. *Modeling Group Relationships with Dynamic Graph Representation Learning*

Most of the existing next POI recommendation methods based on sequence modeling are limited to the analysis of user's independent behavior, and ignore the potential influence of dynamic peer partners on decision-making, which makes representation learning difficult to capture the complex preference patterns derived from group collaborative behavior. Li et al.[8] proposed GDGRL (Group-aware Dynamic Graph Representation Learning) model to inject group interaction dynamics into LBSN representation learning framework for the first time by constructing a two-layer dynamic graph structure. In the group-aware dynamic graph, user nodes are connected with peer partner nodes through time-varying edge weights to encode behavior contagion effects among group members in real time. Context-aware dynamic graphs model spatio-temporal context dependencies in user-POI interactions. This dual graph fusion mechanism effectively solves the two major limitations of traditional methods. First, through the dynamic quantification of partner influence, it alleviates the restriction of individual check-in data sparsity on representation learning. Secondly, the implicit regularization effect of group behavior pattern is used to correct the individual cognitive bias of user preferences. Experiments show that the recommendation accuracy of GDGRL is 19.4%higher than that of the baseline model in cross-scenario user groups, and the F1-score is increased by 37.2%especially in low-frequency user groups, which verifies that group interaction information can significantly enhance the group semantic expression ability of representation. This study confirms that group dynamics is not only a concomitant phenomenon of user behavior, but also an important supervision signal for optimizing the topological structure of LBSN representation space, which provides a methodological support for constructing the "individual-group" dual-channel representation learning paradigm.

III. Analysis of Technology Suitability driven by Vertical scenarios

The value realization of LBSN data analysis techniques highly depends on the adaptation optimization of scene characteristics. Starting from the two vertical fields of urban computing and business intelligence, this section discusses the differentiated technology paths and innovation paradigms of group division and related technologies in different scenarios, and reveals the transmission mechanism of "scene demand-technology adaption-value creation".

A. *Urban Computing Scenarios*

In the field of urban planning and traffic management, LBSN group data provides a new perspective for understanding the movement law of people. Traditional models often regard individual behaviors as independent events, which are difficult to capture macroscopic phenomena caused by group synergistic effects. For example, in crowd flow prediction, dynamic changes of people flow in functional areas such as commercial districts and transportation hubs can be identified by analyzing the spatiotemporal aggregation patterns of user groups[9]. The prediction model based on group mobility characteristics in New York City can predict the peak passenger flow of subway stations during holidays in advance, and significantly reduce the prediction error compared with traditional time series methods.

B. *Business Intelligence Scenarios*

LBSN analysis in commercial scenarios focuses on consumer behavior decoding and business value mining. The core challenge of cross-platform user interest transfer analysis is that there is a semantic gap in group behavior data between different platforms[10]. Through the heterogeneous group alignment technology, we can map the wechat social relationship with the group characteristics of Meituan consumption records, and reveal the transmission law of cross-platform consumption preferences. In the evaluation of commercial location, traditional methods rely on static pedestrian flow statistics, while the evaluation model incorporating group behavior dynamics can capture the penetration depth and radiation range of consumer groups. The life cycle prediction case of Shanghai coffee shop shows that the analysis framework combining group visit patterns and semantic features of places can predict the change trend of commercial places in advance, and provide forward-looking guidance for investment decisions.

IV. CONCLUSION

This survey highlights the transformative potential of group-aware paradigms in LBSN analytics, shifting from isolated user modeling to holistic frameworks that leverage collective interactions. Synthesizing state-of-the-art techniques reveals significant progress in mitigating data sparsity, refining recommendation systems, and decoding socio-spatial patterns. However, critical gaps remain: (1) limited scalability in dynamic group evolution, (2) fragmented cross-domain semantic alignment, and (3) ethical challenges in group data utilization. Future research should prioritize adaptive real-time modeling, federated learning for multi-platform synergy, and robust ethical frameworks. By bridging theoretical advancements with real-world applications, this survey underscores the need for interdisciplinary collaboration to advance scalable, interpretable, and socially responsible LBSN systems.

REFERENCES

[1] Huang Q, Wong D W S. Activity patterns, socioeconomic status and urban spatial structure: what can social media data tell us? [J]. International Journal of Geographical Information Science, 2016, 30(9): 1873-1898.
[2] Su C, Jia X T, Xie X Z, et al. Community detection and location recommendation based on LBSN[C]//2017 International Conference on Network and Information Systems for Computers (ICNISC). IEEE, 2017: 227-231.
[3] He Y, Zhou W, Luo F, et al. Feature-based POI grouping with transformer for next point of interest recommendation[J]. Applied Soft Computing, 2023, 147: 110754.
[4] Sojahrood Z B, Taleai M. A POI group recommendation method in location-based social networks based on user influence[J]. Expert Systems with Applications, 2021, 171: 114593.
[5] Sojahrood Z B, Taleai M, Cheng H. Hybrid POI group recommender system based on group type in LBSN[J]. Expert systems with applications, 2023, 219: 119681.
[6] Meng L, Liu Z, Chu D, et al. POI recommendation for occasional groups based on hybrid graph neural networks[J]. Expert Systems with Applications, 2024, 237: 121583.
[7] Liu Z, Meng L, Sheng Q Z, et al. POI recommendation for random groups based on cooperative graph neural networks[J]. Information Processing & Management, 2024, 61(3): 103676.
[8] Li R, Meng X, Zhang Y. Group-aware Dynamic Graph Representation Learning for Next POI Recommendation[J]. IEEE Transactions on Knowledge and Data Engineering, 2025.
[9] Zignani M, Quadri C, Gaito S, et al. Urban groups: behavior and dynamics of social groups in urban space[J]. EPJ Data Science, 2019, 8(1): 8.
[10] Liang R, Zhang Q, Wang J, et al. A hierarchical attention network for cross-domain group recommendation[J]. IEEE transactions on neural networks and learning systems, 2022, 35(3): 3859-3873.