Multi-Behavior Hypergraph for Social Recommendation

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Abstract: With the rapid development of social networks and online platforms, social recommendation has become an important task in personalized recommendation systems. Social relationships have a significant impact on users' decisions, and recommendations from friends play a substantial role in whether a user purchases a particular item. Users' browsing, bookmarking, adding to cart, and purchase behaviors contain a wealth of information. Traditional recommendation models only focus on either users' social relationships or individual behaviors without connecting them. In this paper, we introduce a social recommendation model called MBSR, which utilizes graph convolution to extract users' social relationship lists and constructs multiple hypergraphs by combining a user's behavioral sequences. Different hypergraphs reflect users' different behavior patterns towards various items, ultimately predicting user ratings for items. Experimental results on a dataset demonstrate that the proposed model effectively improves recommendation performance.

1. Introduction

Over the past decade, with the rapid development of the internet and social media, people have generated a vast amount of digital footprints and social connections in their daily lives. These data encompass not only users' historical interaction behaviors, such as purchase records, viewing history, and ratings, but also social relationships among users[1-3], such as friendships, followings, and shared interests. These data contain rich information that can be utilized for the improvement and optimization of personalized recommendation systems.

Personalized recommendation systems aim to provide users with personalized recommendations that align with their interests and preferences. Traditional recommendation algorithms primarily rely on users' historical behaviors[4] for recommendations. These methods often overlook the influence of social relationships among users on the recommendation results. For instance, on social media platforms, users are more likely to be interested in content that their friends or followed individuals are interested in. Therefore, incorporating social relationships into the recommendation model can enhance the accuracy and personalization of recommendations. Additionally, besides purchase behaviors, users' browsing, bookmarking, and adding to-cart actions also impact the final recommendation accuracy. Extracting different behavior patterns from the sequence of hypergraphs can enrich users' feature representations.

2. Related Techniques

Graph Convolutional Neural Networks (GCN) as a powerful machine learning tool[5-6] have achieved significant advancements in graph data analysis and mining tasks. Graph neural networks capture complex patterns and structural features in graph data by learning relationships and information propagation between nodes. This makes them an ideal choice for handling recommendation data that includes user interactions and social relationships[7-8]. Graph convolutional operations are the core components of graph convolutional neural networks, used to aggregate neighbor information and update node representations. Specifically, graph convolutional operations utilize the information from a node's neighbors to update its feature representation, allowing for a better reflection of the node's position and relevance within the graph structure[9].

Hypergraphs are a more flexible and powerful graph model compared to traditional graphs, capable of capturing more complex relationships among users. In a hypergraph, nodes can belong to multiple edges simultaneously, allowing for a better representation of high-order relationships among users and capturing their shared interests and similarities.

A hypergraph describes the logical relationships between a set of meta-paths that have the same destination node (e.g., temporal order, spatial order, and topological order), and multiple hypergraphs with the same source node form a hypergraph.

3. Multi-Behavior Hypergraph Social Recommendation Model (MBSR)

3.1 User Feature Aggregation

The structure diagram of the MBSR model is shown in Figure 1. Based on the interactions between users and items, corresponding hypergraphs can be constructed, which encompass users' historical behaviors such as browsing before purchasing, adding to a cart, etc. These three types of behaviors are represented as three meta-paths used to capture the features between nodes. The combination of these three meta-paths forms a hypergraph, defined as follows:

$$HG_i^j=(u_j,(r_a,r_b,\ldots,\ r_c),v_i) \tag{1}$$

The behavior sequence (ra, rb, ..., rc) is sorted in chronological order, representing the rc interactions that user uj has with item vi in the past.

The graph encoder employs graph convolutional neural networks (GCN) to learn embedding representations for each behavior pattern. GCN can utilize neighbor information in the graph structure to capture relationships between nodes. By integrating embeddings from different behavior patterns and utilizing a multi-layer perceptron, the unified behavior model embedding for user uj can be obtained.

For aggregating user social relationships, GCN is used to extract representations and embeddings of user relationship lists[10-12]. It can extract user features from a social friend perspective and capture contextual information through information propagation between nodes, considering the influence of user social relationships on their interests and preferences. Then, a pooling layer is employed to reduce information redundancy. Through max-pooling operations, nodes or subgraphs with the maximum feature values are selected, focusing on the most informative parts[13-15]. This allows for varying weights between different friends, ultimately obtaining user embeddings that incorporate social information.

3.2 Item Information Aggregation Module

For users with limited social information, there can still be inherent interests and preferences associated with purchasing the same item. In the case of item information, we consider users who have purchased the same item. Using GCN, this information is encoded into item interaction vectors and aggregated with the item itself to generate the final representation vector for the item. This approach is beneficial for addressing cold-start problems and sparse data issues.

3.3 Forward Propagation and Loss Function of the MBSR Model

During the forward propagation process of the MBSR model, the user's multi-behavior hypergraph embeddings and social connection information are fed into the user encoder module. These two embeddings are fused to obtain the user's final embedding representation. For items, the item's embedding representation generated by the item information aggregation module is merged with the item's embedding to generate the final representation. The aggregator utilizes the ReLU function as the activation function, which performs a nonlinear transformation on the output of the neural network, effectively reducing computational complexity and model complexity while increasing the model's expressive power.

Next, the similarity score between the user and item embedding representations is calculated using dot product, which is used to predict the user's preference for the item, thereby generating personalized recommendation lists for the user. Finally, a loss function is utilized to measure the difference between the predicted results and the true labels, and the model parameters are optimized through an optimizer during training.

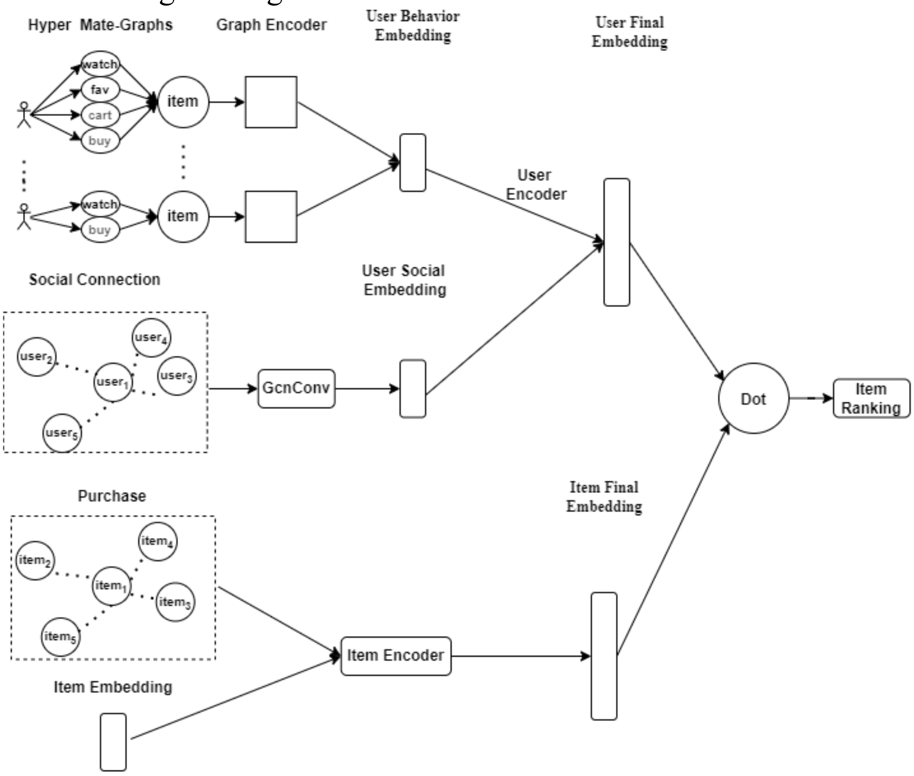

Figure 1 MBSR model structure diagram.

4. Experiments and Result Analysis

4.1 Experimental Environment

In this study, the code was written in Python version 3.8. PyTorch, a deep learning framework version 1.11.0, was used for modeling. The operating system used was Ubuntu 20.04, and the computations were performed on an RTX 4090 graphics card. The IDE used for development was PyCharm.

4.2 Experimental Dataset

Real-world datasets were used for experimental evaluation, obtained from an e-commerce website, Taobao. These datasets include users' historical interaction data and social connection information. By comparing the MBSR model with other benchmark models such as RGCN and HMG-CR, the performance of the MBSR model can be assessed in terms of prediction accuracy and recommendation effectiveness. The preprocessed data for specific data types are shown in Table 1.

Table 1 Experimental dataset.

Column name	Number
Users	57,994
Items	262,024
Behaviors	1,150,807
Social connections	641,284

4.3 Evaluation Metrics

To evaluate the quality of the recommendation algorithm, two commonly used metrics were employed. Recall@10 measures the proportion of correctly identified positive samples out of all true positive samples. NDCG@10 is used to evaluate the performance of ranking algorithms and considers the quality of the ranking within the top 10 items or results.

4.4 Experimental Results

Table 2 Comparison of experimental results.

Model	Recall@10	NDCG@10
GraphSAGE	0.3826	0.2312
RGCN	0.3767	0.2285
NMTR	0.3781	0.2012
HMG-CR	0.4464	0.2926
MBSR	0.4937	0.3281

The same dataset as above was used to conduct experiments on various recommendation algorithms in the article, and the results are shown in Table 2. The experimental results indicate that the MBSR model achieved good performance in social recommendation tasks. Compared to single social recommendations or methods that only consider user multi-behaviors, the MBSR model can better capture user interests and social relationships, thereby improving the accuracy and effectiveness of personalized recommendations.

5. Conclusion

This paper introduced a social recommendation method called MBSR, which is based on multi-behavior hypergraphs. By leveraging multi-behavior hypergraphs and social networks to extract user interests and social relationships, the MBSR model can provide more accurate and personalized recommendation results. The multi-behavior hypergraph captures user-item behavior dependencies more precisely and learns better user features. It effectively alleviates the problem of data sparsity caused by insufficient user-item interactions, thereby improving the recommendation performance for cold-start users. Experimental results demonstrate significant improvements in the MBSR model in user behavior and social recommendation tasks. Future research can explore other multi-behavior and social models and optimization algorithms to further enhance the performance and effectiveness of recommendations.

References

[1] Yu J, Yin H, Li J, et al. Self-supervised multi-channel hypergraph convolutional network for social recommendation[C].Proceedings of the web conference 2021, 2021: 413-424.

[2] Fan W, Ma Y, Li Q, et al. Graph neural networks for social recommendation[C].The world wide web conference, 2019: 417-426.

[3] Yu J, Yin H, Gao M, et al. Socially-aware self-supervised tri-training for recommendation [C]. Proceedings of the 27th ACM SIGKDD conference on knowledge discovery & data mining, 2021: 2084-2092.

[4] Yang H, Chen H, Li L, et al. Hyper meta-path contrastive learning for multi-behavior recommendation[C].2021 IEEE International Conference on Data Mining (ICDM). IEEE, 2021: 787-796.

[5] Huang C, Xu H, Xu Y, et al. Knowledge-aware coupled graph neural network for social recommendation[C].Proceedings of the AAAI conference on artificial intelligence, 2021, 35(5): 4115-4122.

[6] Xiao F, Li L, Xu W, et al. Dmbgn: Deep multi-behavior graph networks for voucher redemption rate prediction[C].Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, 2021: 3786-3794.

[7] Chen C, Ma W, Zhang M, et al. Graph heterogeneous multi-relational recommendation [C]. Proceedings of the AAAI Conference on Artificial Intelligence, 2021, 35(5): 3958-3966.

[8] Xia L, Huang C, Xu Y, et al. Knowledge-enhanced hierarchical graph transformer network for multi-behavior recommendation[C].Proceedings of the AAAI Conference on Artificial Intelligence, 2021, 35(5): 4486-4493.

[9] Wang W, Zhang W, Liu S, et al. Incorporating link prediction into multi-relational item graph modeling for session-based recommendation[J].IEEE Transactions on Knowledge and Data Engineering, 2021.

[10] Zhang J, Gao C, Jin D, et al. Group-buying recommendation for social e-commerce[C].2021 IEEE 37th International Conference on Data Engineering (ICDE), 2021: 1536-1547.

[11] Song C, Wang B, Jiang Q, et al. Social recommendation with implicit social influence [C]. Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval, 2021: 1788-1792.

[12] Pang Y, Wu L, Shen Q, et al. Heterogeneous global graph neural networks for personalized session-based recommendation[C].Proceedings of the fifteenth ACM international conference on web search and data mining, 2022: 775-783.

[13] Pan Z, Cai F, Chen W, et al. Collaborative graph learning for session-based recommendation[J].ACM Transactions on Information Systems (TOIS), 2022, 40(4): 1-26.

[14] Deng Z H, Wang C D, Huang L, et al. G^ 3SR: Global Graph Guided Session-Based Recommendation [J]. IEEE Transactions on Neural Networks and Learning Systems, 2022.

[15] Z. Cui, H. Chen, L. Cui, S. Liu, X. Liu, G. Xu, and H. Yin, “Reinforced kgs reasoning for explainable sequential recommendation,” World Wide Web, 06 2021.