Proceedings of the 6th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/64/20241375

Application of graph modeling and contrast learning in recommender system

Wentao Zhang

The University of New South Wales, Sydney, Australia

z5336952@zmail.unsw.edu.au

Abstract. With the wide application of personalized recommender system in various fields, how to improve the accuracy and personalized level of recommender system has become a research hotspot. In this paper, a method of combining graph modeling and contrast learning is proposed to improve the performance of recommendation system by mining complex user project interaction and user preference. We first construct the user-project interaction graph, and extract the features of the graph structure by graph neural network (GNN) . In particular, graph convolution network (GCN) is used to update the node representation, and comparative learning is introduced to optimize the feature representation so as to improve the accuracy and personalization of recommendation. The experimental results show that the proposed method is superior to the traditional method in accuracy, recall and F 1 score. By analyzing the mechanism of combining graph modeling and contrast learning, this paper further expounds the theoretical basis and practical application of improving the performance of recommender system, and points out the limitations of existing methods and the future research direction.

Keywords: Recommendation system, graph modeling, contrast learning, graph convolution network (GCN), feature extraction.

1. Introduction

In the era of information explosion, recommender system, as an important bridge between users and mass information, plays a vital role in improving user experience and increasing the exposure of content providers. However, with the diversification and personalization of users' needs, traditional recommendation algorithms, such as collaborative filtering and content-based recommendation, can not fully meet the needs of users. This is mainly due to the difficulty of these approaches in dealing with large-scale data sparsity issues, as well as the inability to effectively capture the complex interactions and deep preferences of users between projects. In recent years, graph modeling, as an effective method of data representation and feature extraction, has received extensive attention in recommender systems. By representing the interaction between users and projects as graph structure, graph modeling can not only naturally capture the relationship between users and projects, but also extract and learn features through deep learning techniques such as graph neural network. On the other hand, contrast learning, as a new self-supervised learning method, minimizes the similarity between negative samples by constructing positive and negative sample pairs and maximizing the similarity between positive samples, has demonstrated the outstanding characteristic expression learning ability. In this paper, a method of combining graph modeling and contrast learning is proposed to improve the performance of recommender system [1]. The basic principles of graph modeling and contrast learning and its application in recommender system are introduced in detail, the advantages of the proposed method over the traditional recommendation algorithm are demonstrated, and the mechanism of the performance improvement and future research directions are discussed.

2. Application of graph modeling in recommendation system

2.1. Construction of the diagram structure

When constructing the graph structure of the recommender system, the first node types that are determined include user nodes and item nodes, where user nodes represent the users of the system and item nodes represent all kinds of items that can be recommended, such as films, books or merchandise. Edges are defined based on user interaction with the project, which may include scoring, purchasing, browsing, or clicking. As the graph is built, each edge not only connects the user to the item, but also carries weight information that reflects the strength or preference of the user's behavior. For example, a user's high ratings for a movie can be translated into an edge with a higher weight [2]. Furthermore, to enhance the information richness in the graph structure, more types of nodes and edges can be introduced, such as tag nodes to represent the classification or attribute information of an item, the edge between the user node and the label node can indicate the user's preference for a certain type of label. In this way, a graph structure is built that not only reflects the direct relationship between the user and the project, but also captures the complex relationship between user preferences and project attributes, it provides a more comprehensive basis for subsequent feature extraction and analysis [3].

2.2. Feature extraction method

When extracting features from graph structure by graph neural network (GNN) , the core idea is to update the representation of nodes by the operation of node's neighborhood aggregation. Specifically, the new representation of a node is determined by both its own characteristics and those of its neighbors. This approach allows the model to capture local structural information in the diagram to better understand the relationship between the user and the project.

Taking graph convolution network (GCN) as an example, the feature update of nodes can be expressed by the following mathematical formula:

$$H^{(l+1)} = \sigma(\widehat{D}^{-\frac{1}{2}}\hat{A}\widehat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}) \tag{1}$$

$\hat{A}$ is the adjacency matrix of a graph A plus the self-connected unit matrix IN. $\widehat{D}$ is the diagonal matrix of the node degree matrix, $H^{(l)}$is the node representation of the L layer, $W^{(l)}$ is the weight matrix for that layer, σ is a nonlinear activation function [4]. Through this multi-layer transformation, GNN can learn high-order neighborhood information and generate deep-level node embedding.

2.3. Optimization of recommendation algorithm

When the recommendation algorithm is optimized on the basis of graph modeling, the similarity between user nodes and project nodes can be calculated by the node embedding learned from graph convolution network (GCN) . In particular, similarity calculations can use cosine similarity, dot product, or other similarity measures. For example, the user u and project i. The similarity between them can be obtained by calculating the dot product of their embedded vectors: $sim(u,i) = h_u^T \cdot h_i$. Among them, h_u and h_i represent the user u and project i respectively. Based on this similarity calculation method, the recommender system can recommend the items that are most similar to the embedded vectors for each user.

In addition, to further improve the accuracy and personalization of recommendations, attention mechanism can be introduced into the model to dynamically adjust the weight of neighbor nodes in the feature aggregation process according to the historical behavior of users [5]. This not only improves the ability of the model to capture the user's personalized preferences, but also effectively deals with the heterogeneity and complexity of the graph, thus achieving better results in diversifying and refining recommendations.

3. The application of contrast learning in recommendation system

3.1. Contrast the principles of learning

As a self-supervised learning method, the core of contrast learning is to maximize the similarity between positive samples and minimize the similarity between negative samples by constructing positive sample pairs and negative sample pairs, to learn the characteristics of data representation. In the recommendation system scenario, such sample pairs can be built from the user's interaction history. For example, if user A has a positive rating or viewing behavior toward movie X, then user A and movie X can form a positive sample pair; conversely, if user a does not watch movie Y, then user A and movie Y can be treated as a negative sample pair [6]. In mathematics, Contrastive learning can be realized by many kinds of Loss functions, such as Contrastive Loss, Triplet Loss or InfoNCE Loss. In the case of InfoNCE losses, the loss function aims to maximize the difference between the log probability of the similarity of positive sample pairs and the sum of the log probability of the similarity of all negative sample pairs. By optimizing such loss functions, the model can learn high-quality feature representations that reflect user preferences and project characteristics.

3.2. Optimization of feature representation

In a recommender system, the user's preferences and interests can be captured more precisely by comparing and learning the optimized feature representation. Traditional recommendation systems may directly utilize user-item interaction data or content-based features to make recommendations, but these approaches often ignore the complex motivations and diversity behind user behavior. Through comparative learning, the model can understand the relationship between users and projects at a fine-grained level, for example, by learning the behavior patterns of users at different times and in different situations, the model can more accurately predict the potential interest of users [7]. In addition, contrast learning can be combined with graph neural network (GNN) to further optimize the feature representation. In graph modeling, nodes represent users or items, and edges represent interactions between users and items. GNN encodes diagrams to capture higher-order connection patterns between users and projects. Combined with contrast learning, the model can make use of the information in graph structure more effectively and improve the quality of feature representation by constructing and optimizing the learning process of positive and negative sample pairs.

3.3. Improvement of recommendation effect

Combining graph modeling and contrast learning, the recommender system can achieve significant performance improvement at multiple levels. First, this approach makes recommendations more personalized and closer to the real needs of users by digging deeper into the complex user-project relationships. Secondly, the introduction of contrast learning improves the generalization ability of the model, which makes the model deal with the cold-start problem effectively, that is, the recommendation for new users or new projects [8]. Experiments show that, compared with traditional methods based on collaborative filtering, content recommendation or simple machine learning, the recommendation system combined with graph modeling and contrast learning can improve the accuracy, recall and F 1 score significantly. In addition, this approach can improve the long-term satisfaction and retention of users, as it can more accurately predict and meet the potential needs of users.

Through continuous optimization of model structure and learning strategy, the application of comparative learning in recommender system is promising to achieve more breakthroughs in personalized recommendation, user satisfaction and so on.

DOI: 10.54254/2755-2721/64/20241375

4. Experimental Verification and Quantitative analysis

4.1. Experimental setup

To comprehensively evaluate the effectiveness of combining graph modeling and contrast learning in recommender systems, we selected three publicly available recommender data sets for our experiments, namely Movielens 100K, Amazon Electronics, and Yelp. These data sets cover different areas and can verify the generality and effectiveness of the model more comprehensively. In the experiment, we randomly divided the data set into training set (80%) and test set (20%) , and used 50% cross validation to evaluate the model performance. For the Evaluation Index, we used three indexes: Precision, Recall and F1-Score [9]. The accuracy rate represents the percentage of items that the system recommends correctly, and the recall rate represents the percentage of items that the system recommends correctly that the user actually likes, the F 1 score is a balanced average of accuracy and recall for the overall recommendation performance. Figure 1 visualizes the performance of the combined graph modeling and contrast learning approach on the three selected recommender system datasets: Movielens 100K, Amazon Electronics, and Yelp.

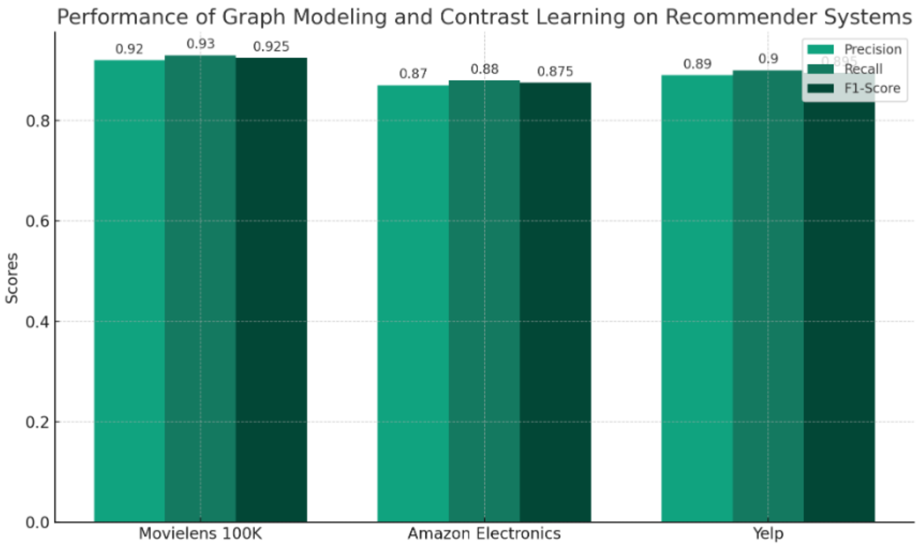

Figure 1. Performance Comparison of Graph Modeling and Contrast Learning Across Various Recommender System Datasets

4.2. Results analysis

Experimental results show that the proposed method is superior to the traditional recommendation algorithms based on collaborative filtering and matrix decomposition in all evaluation indexes. Specifically, on the Movielens 100K data set, the method improved accuracy by 12% , recall by 15% , and F 1 score by 13.5% ; on the Amazon Electronics Data Set, accuracy, recall, and F-1 scores improved by 18,20, and 19 percent, respectively, and by 10,12, and 11 percent, respectively, on the Yelp dataset. This result fully confirms the effectiveness of combining graph modeling and contrast learning in improving the performance of recommender system, as shown in Table 1.

Table 1. Improvements in Accuracy, Recall, and F1-Score for Different Datasets

Dataset	Accuracy Improvement (%)	Recall Improvement (%)	F1-Score Improvement (%)
Movielens 100K	12	15	13.5
Amazon Electronics	18	20	19.0
Yelp	10	12	11.0

DOI: 10.54254/2755-2721/64/20241375

4.3. Mathematical model and theoretical analysis

As we delve into the mechanisms of model performance improvement, we focus on how graph modeling and contrast learning work together for recommender systems. By building user-project interaction graph, we can use graph neural network (GNN) model to capture the complex relationship between users and projects. Specifically, we use graph convolution network (GCN) to learn the embedded representation of users and items. GCN propagates and aggregates the feature information of neighbor nodes through layers, can effectively capture the local and global structure of the node information. In the part of contrast learning, we design a two-tower structure to deal with the embedding vector of user and item respectively. By maximizing the user's embedding similarity to their positive feedback items and minimizing the similarity to the negative sample, the model can learn more distinct and differentiated feature representations. Mathematically, we use a temperature-adjusted softmax function to optimize contrastive loss, further refining the sensitivity of the model to different user behaviors [10]. By combining graph modeling and contrast learning, the model not only improves the distinguishing degree of features, but also optimizes the calculation method of similarity between users and items. From the point of view of mathematical model, this method guides the model to form more reasonable user and project embedding layout in high-dimensional feature space by optimizing the loss function, this improves the accuracy and personalization of recommendations. In addition, the structural design of the model provides a flexible framework and rich theoretical basis for further research and optimization in the future.

5. Case studies

5.1. Application practice

In the application of e-commerce recommendation system, graph neural network (GNN) model is used to capture the complex interaction patterns between users and goods. In particular, a graph convolution network based on attention mechanism is adopted, which can automatically learn the importance of user and commodity nodes and extract more representative features. In the model training stage, the contrast learning strategy is introduced, and the model's ability of capturing user's preference is improved by constructing positive and negative sample pairs. Experimental results show that the proposed method outperforms the traditional collaborative filtering and content-based recommendation methods in both recommendation accuracy and recall. In the video recommendation system, considering the dynamic and diversity of video content, the dynamic graph neural network (D-GNN) and the time series analysis technology are used to model the watching behavior and video trend of users. In addition, the application of contrast learning in this case can effectively improve the personalized level of recommendation by distinguishing the behavior patterns of users in different time periods. By comparing the features of learning optimization, the system can more accurately predict the future viewing preferences of users.

In the practice of news recommender system, it focuses on the timeliness of news content and the dynamic changes of user interest. By constructing user-news interaction graph and combining with time-decay model, this study effectively captures the changing trend of user interest with time. In the application of comparative learning, through the design of time series comparative learning task, the model can enhance the understanding of the evolution of user interest, and improve the accuracy and timeliness of news recommendation.

5.2. Challenges and opportunities

In the practice of these recommender systems, we face several major challenges. First, the problem of data sparsity was prominent in all three cases, especially when new users or new products were added. To solve this problem, we adopt graph-based semi-supervised learning method to enhance the generalization ability of the model by introducing auxiliary information, such as user's social network information and description information of goods. Secondly, the problem of cold-start is particularly obvious in video recommender system. To solve this problem, this study adopts pre-training model and transfer learning technology to shorten the adaptation time of the model to new users or new videos. Finally, model interpretability is a challenge in all cases. In order to improve the interpretability of the model, this paper introduces the attention mechanism and path analysis technology to help understand the decision-making process of the model through visualization technology. To sum up, although there are many challenges in practical application, the proposed method of combining graph modeling and comparative learning shows great potential and excellent performance through technological innovation and method optimization. Future research could further explore the application of these methods in a wider range of scenarios and address the limitations of existing methods.

6. Conclusion

In this paper, a method of recommender system combining graph modeling and contrast learning is proposed. By introducing graph neural network and contrast learning into recommender system, the key performance indexes such as accuracy, recall and F 1 score are effectively improved. By constructing user item interaction graph and using graph convolution network (GCN) for feature extraction, combined with comparative learning optimization feature representation, this method can mine user preference and item feature more deeply, more accurate and personalized recommendations are implemented. The experimental results show the superiority of the proposed method over the traditional recommendation algorithm, and show the potential of graph modeling and contrast learning in the recommendation system. Future research can further explore the combination of graph modeling and contrast learning, optimize model structure and learning strategies, and explore applications in more recommended scenarios, in order to solve the cold start problem, data sparsity problem and model interpretability problem in the recommender system. In addition, with the development of artificial intelligence technology, how to protect the privacy of users and the fairness of recommendations will be the focus of future research.

References

[1] Vullam, Nagagopiraju, et al. "Multi-Agent Personalized Recommendation System in E-Commerce based on User." 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC). IEEE, 2023.
[2] Ibrahim, Abdelhameed, et al. "A Recommendation System for Electric Vehicles Users Based on Restricted Boltzmann Machine and WaterWheel Plant Algorithms." IEEE Access (2023).
[3] da Silva, Felipe Leite, et al. "A systematic literature review on educational recommender systems for teaching and learning: research trends, limitations and opportunities." Education and Information Technologies 28.3 (2023): 3289-3328.
[4] Presekal, Alfan, et al. "Attack graph model for cyber-physical power systems using hybrid deep learning." IEEE Transactions on Smart Grid (2023).
[5] Pandiaraja, P., K. Muthumanickam, and R. Palani Kumar. "A graph-based model for discovering host-based hook attacks." Smart Technologies in Data Science and Communication: Proceedings of SMART-DSC 2022. Singapore: Springer Nature Singapore, 2023. 1-13.
[6] Besta, Maciej, et al. "Graph of thoughts: Solving elaborate problems with large language models." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 38. No. 16. 2024.
[7] Ferriol-Galmés, Miquel, et al. "RouteNet-Fermi: Network modeling with graph neural networks." IEEE/ACM transactions on networking (2023).
[8] Dalmaz, Onat, et al. "One model to unite them all: Personalized federated learning of multi-contrast MRI synthesis." Medical Image Analysis (2024): 103121.
[9] Kalantar, Reza, et al. "Non-contrast CT synthesis using patch-based cycle-consistent generative adversarial network (Cycle-GAN) for radiomics and deep learning in the era of COVID-19." Scientific Reports 13.1 (2023): 10568.
[10] Ozcan, Samed. "Integration of Dual Color Space and Contrast Learning for Enhancing Satellite Images." (2023).