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Analysis and Research on the Information Narrowing in Personalized Recommendation Systems

Xiangzheng Li

School of Information Science and Engineering, Dalian Polytechnic University, Dalian, China
robotlxz@163.com

Abstract. In the information age, personalized recommendation systems play a crucial role in addressing the problem of information overload. As deep learning technology has been applied in recommendation systems, the issue of homogeneous content recommendations has become increasingly severe, leading to the phenomenon of information narrowing. In particular, the filter bubbles generated by the computation and decision-making of deep learning algorithms are a typical manifestation of this type of problem. The emergence of filter bubbles limits the diversity of information accessible to users and may influence the quality of their final decisions. Existing studies reveal that introducing models with richer entity representations, like knowledge graph technology, can effectively address the lack of information and sparsity in recommendation systems, while mitigating filter bubble issues. Thus, this paper proposes a multimodal knowledge graph convolutional network model, inspired by knowledge graph convolutional networks. By leveraging entity neighborhood aggregation and introducing the concept of multimodality, using movie recommendations as an example, it enhances the entity representation in recommendations, thereby alleviating the information narrowing problem. The results indicate that the optimized model performs well in terms of recommendation accuracy and also increases the diversity of recommended content, thus providing users with a broader information perspective.

Keywords: Recommendation system, Information narrowing, Multimodal recommendation, Knowledge graph convolutional neural network

1. Introduction

In today's rapid development of information technology and intelligence, information overload has become a common problem in people's daily life and work [1,2]. With the rapid growth of Internet data, users face an ever-increasing amount of information, which makes information filtering more and more challenging. And this has made personalized recommendation systems crucial in helping users make informed choices. These systems originated from spam filtering technology and were later widely used in short videos, e-commerce platforms, social media and entertainment software, significantly enriching users' digital life experience [3]. However, deep learning has led to content homogenization, with users complaining about monotonous recommendations, which thus hampers long-term system development. At present, research has acknowledged this issue and introduced the concept of "information narrowing," including phenomena like filter bubbles, echo chambers, and

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information cocoons. Among them, deep learning-driven recommendation systems are considered to exacerbate these problems [4]. Although the introduction of knowledge graphs and multimodal technologies helps increase content diversity, how to solve the problem of information narrowing while boosting recommendation accuracy still needs further exploration [5-7]. This paper proposes an improved Multimodal Knowledge Graph Convolutional Network (MKGC) model, seeking to mine high-order attributes and latent semantic information of entities through knowledge graphs and combine multimodal data techniques to enrich entity representations, enhance recommendation diversity, and alleviate the problem of information narrowing. And this model optimizes the balance between accuracy and diversity in recommendation systems via feature fusion and convolutional neural network training, thereby improving the coverage and accuracy of recommendations. This study provides a new solution to the diversity problem in current recommendation systems, offering optimization suggestions for future development, especially in improving computational efficiency and addressing data sparsity.

2. Methodology

2.1. Experimental design

This model takes movie recommendation as an example. First, it enriches entity representations using movie tags and other attributes from the Movielens-20M dataset. Then, leveraging multimodal techniques and fusion strategies, it further enhances the potential semantic information of entities using poster image data corresponding to the movie entities. For the original dataset, a knowledge graph is constructed, and a fixed receptive field is used to aggregate entity neighborhood features to obtain a preliminary entity neighborhood representation. Next, a convolutional neural network is used to extract features from the image data, and then a dimensionality-reduced representation of the image features is obtained by modifying the fully connected layers of the neural network. Finally, using Movie IDs from the dataset as indices, an association between image data and user historical preferences is established. Based on this, an early fusion strategy is used to aggregate movie poster data features with the neighborhood aggregation features of entities in the knowledge graph and the entity's own feature representation, resulting in a further refined movie entity feature vector. Finally, the obtained new entity representation is fed as a new input into the knowledge graph convolutional neural network to generate predictions.

2.2. Data resource and pre-processing

This paper uses the MovieLens-20M dataset, collected and established by the GroupLens research group at the University of Minnesota. It contains six data files: "genomescores.csv", "genome-tags.csv", "links.csv", "movies.csv", "ratings.csv", and "tags.csv" . Furthermore, this paper employs web scraping technology for automated data collection , gathering the necessary data from the internet to supplement existing datasets that do not contain complete multimodal representations . By constructing a suitable neural network model, data from different modalities such as images, text, and videos are fused to obtain a more comprehensive and accurate movie entity feature table.

Data preprocessing mainly includes key steps such as data augmentation, handling missing values, data enhancement, selection of positive and negative samples, and data segmentation.

This paper introduces multimodal techniques to combine movie poster image data obtained through web crawling with other movie attribute information, thereby providing a richer and more comprehensive entity feature representation. For modal processing of the image data, a pre-trained

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ResNet-50 model is used. Before directly using the model for image feature extraction, the parameters of the pre-training data are first unfrozen, and the image data is split in an 8:2 ratio. The dataset is then trained and fine-tuned using 80% of the training set, and the parameters are then refrozen for feature extraction. After modal fusion, the MovieLens dataset is again split in an 8:2 ratio, with 80% used for training the recommendation task and the remaining 20% used to test model performance.

This paper employs a negative sampling strategy, using samples with a rating score of 1 as negative samples. Negative sampling is a technique for training classifiers, applicable when the number of positive samples far exceeds the number of negative samples. In this paper, negative sampling refers to randomly selecting a subset of items that the user has never interacted with as training negative samples. This improves the model's generalization ability and avoids overfitting caused by imbalanced data samples.

To meet the requirements of the model input, the image needs to be cropped in the middle to become a 224*224 pixel image, and data augmentation work such as grayscale processing needs to be performed.

2.3. Model training

For a given training set, the loss function of MKGC is defined as follows:

$$\mathscr{L}=\sum_{i\in\mathscr{I}}\left(\sum_{j\in J_i}\mathrm{CE}(y_{iv},\hat{y}_{vi})-\sum_{l=1}^{p_i^u}\mathrm{E}_{v_i-p(l)}\left(\mathrm{CE}(y_{iv},\hat{y}_{vi})\right)\right)+\lambda\|\mathrm{CE}\|_2^2 \tag{1}$$

Where CE is the cross-entropy loss function, P is the negative sample sampling distribution which follows a uniform distribution, T^u is u the number of negative samples for each user, and in this paper, a negative sample is defined as a movie with a user rating of 1. λ is the normalization coefficient, and the last part of the formula is an L2 regularization.

The algorithm describes the main training process of MGCN. For a given user-item pair (u,v), Y the entity importance score is calculated through its interaction matrix π_r^u to obtain a linear combination of its neighborhoods $v_{N(v)}^u$. The image features are then fused into the representation of the domain entities $v_{N(v)}^u$. By controlling the number of iterations H and the receptive field range M, H-order aggregation of the entity neighborhood is performed. Steps 2-4 are the modality-based domain entity fusion, step 5 limits the number of entities in the receptive field set, and steps 6-10 calculate the feature representation of the target entity after H iterations. Finally, the prediction is output, and the parameters are updated using gradient descent based on the loss function.

2.4. Evaluation indicators

MKGC aims to observe the impact on recommendation accuracy by supplementing entity representations and improving recommendation diversity. This paper uses Normalized Discounted Cumulative Gain (NDCG@k) and Entity Coverage@k to evaluate model performance, where k EC@k is the length of the recommendation list. EC@k, or Entity Coverage, is calculated based on the relevant entity coverage of the top k items in each user's recommendation list, given a set of recommended items from users. Higher coverage indicates richer and more diverse recommendations. Given a user's recommendation list: 1 2

$$R_\alpha=[r_1,r_2,...,r_\alpha] \tag{2}$$

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Here, the list consists of r recommended items k for the user , and the length of the list is [length missing u]. A dictionary is created E that maps each recommended item to a set of related entities, $E(r_i)$ which is the set of entities associated with the recommended item r_i . The calculation formula is as follows:

$$\mathrm{EntityCoverage@k}=\sum_{i=1}^{k} E(r_i) \tag{3}$$

NDCG@k: Normalized Discount Cumulative Gain is typically used to assess the quality of a recommendation list. If the system can prioritize items that a user likes based on their interests, the NDCG value will be higher. It can be used to evaluate the consistency between the recommendation results and the user's actual preferences. The specific calculation formula is as follows:

$$\mathrm{DCG@k}\sum_{i=1}^{\frac{2^{n_i}}{4}} \frac{1}{\log(i+1)} \tag{4}$$

$$\mathrm{IDCG@k}=\sum_{i=1}^{k} \frac{2^{n_i}}{\log(i+1)} \tag{5}$$

$$\mathrm{NDCG}(\bar{\alpha};k)-\frac{\mathrm{DGC}(\bar{\alpha};k)}{\mathrm{IDCG}(\bar{\alpha};k)} \tag{6}$$

In the implicit feedback recommendation scenario discussed in this paper, for any item, if the user has interacted with it, the gain value of that item in the relevance evaluation rel_i is set to 1; otherwise, it is 0. Furthermore, to consider the score reduction of items at different positions in the recommendation list, a reduction coefficient is introduced $\log_2(i+1)$. This coefficient represents i the ratio of the score at the i-th position to the score at the previous positions. All recommended items are sorted in an ideal order to obtain the recommendation list $|REL|$. In this list, k the cumulative gain of the previous items is defined as IDCG@ k , and the final value of NDCG@ is the ratio of k DCG@ k to IDCG@ k .

3. Experimental results

This paper compares the performance of all methods on the MovieLens20M dataset, using Top-k recommendation results and intuitively comparing the accuracy and diversity of each model on the MovieLens20M dataset through NDCG and EC metrics for different recommendation list lengths.

Table 1. Comparison of experimental model results

	NDCG@20	NDCG@40	EC@20	EC@40
MF	0.0923	0.1049	293.4026	465.7683
LightGCN	0.1251	0.1446	289.7449	459.9921
DirectAU	0.1311	0.1507	285.2685	455.7642
KGAT	0.1064	0.1210	287.6159	456.5071
DGCN	0.0839	0.0896	287.3097	451.5965
KGCN	0.0997	0.1222	296.6096	470.8185
KGdiverse	0.1294	0.1496	297.0598	468.9185
MKGC	0.1259	0.1491	302.1074	476.8222

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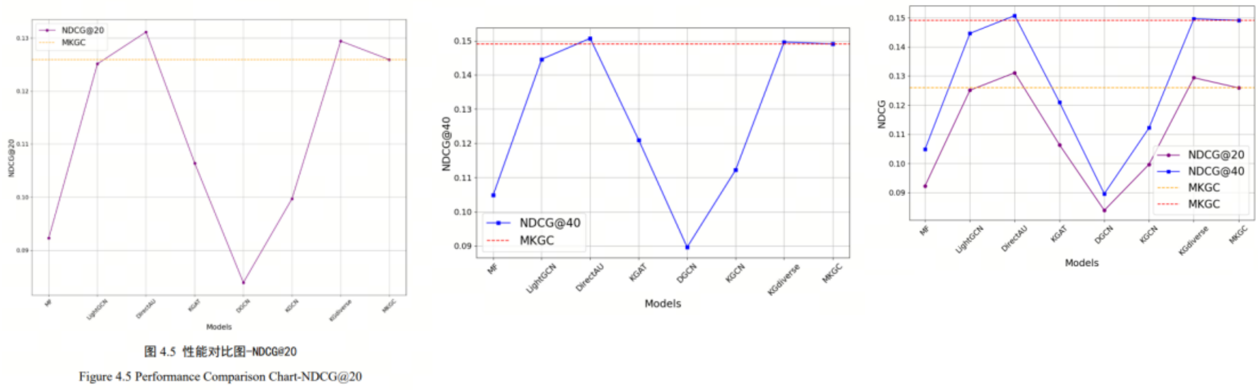
3.1. NDCG index

Figure 1(a) shows the comparison results of all models when the recommendation list length is 20. As can be seen from the figure, under the accuracy metric—normalized loss cumulative gain—the performance of this model is not optimal. The best performing model is the Direct-AU model, which is an enhancement of the traditional collaborative filtering algorithm and does indeed have impressive accuracy performance. However, it is worth noting that although the MGCN proposed in this paper aims to improve diversity performance, its recommendation accuracy is not low at a list length of 20. Another noteworthy point is the DGCN model, which proposes using GCN to increase recommendation diversity, but it is clear that simply adjusting its neighborhood distribution and increasing negative sampling will significantly reduce recommendation accuracy.

Figure 1(b) shows the performance of each model under a recommendation list of length 40. It can be seen that as the list length increases, models using knowledge graph technology, such as MKGC and KG-Diverse, achieve better recommendation performance. This is because knowledge graphs can more fully mine neighborhood entity information, allowing the model to better analyze and understand user preferences. Furthermore, at this point, the performance of the MKGC model is very close to the previously better-performing model, as shown in Figure 1(c) . Comparing the models with the two recommendation list lengths side-by-side, it can be seen that all models improve to some extent as the recommendation list length increases, but the model using knowledge graphs shows a significantly greater improvement. This is likely due to the rich entity association attributes in the knowledge graph; this implicit semantic information may be more helpful for the model to learn user preferences.



(a) NDCG@20 (b) NDCG@40 (c) NDCG

Figure 1. Performance comparison chart NDCG

3.2. EC indicators

Figure 2(a) shows the EC performance of each model when the recommendation list length is 20. It is clear that the MKGC model proposed in this paper improves the diversity recommendation performance to a certain extent, increasing the EC value by approximately 1.6%. This indicates that incorporating multimodal feature representations can indeed improve the model's diversity recommendation capability. Figure 2(b) compares the models when the recommendation list length is 40. The MKGC model still exhibits the best diversity recommendation performance. It is noteworthy that, under the EC metric, the MF model, which does not perform well in accuracy, possesses good diversity recommendation performance. This suggests that insufficient accuracy in

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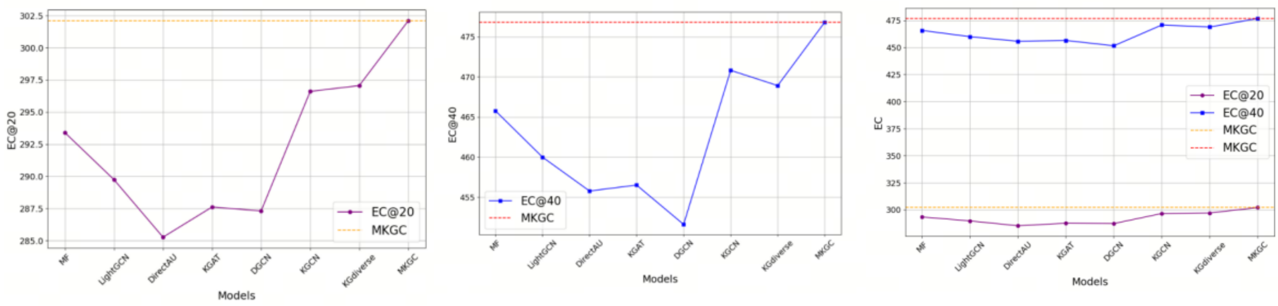
traditional recommendation models may lead to inaccurate category recommendations, covering more categories, but this is achieved at a significant sacrifice of recommendation accuracy. As shown in Figure 2(c) , when the recommendation list length increases, the entity EC values of all models are greatly improved. This is because the longer recommendation list allows for more types of entities within the list, thus covering more neighboring entities. Such improvements are generally determined by the complexity of the relationships or categories between entities within the data.



(a) EC@20 (b) EC@40 (c) EC

Figure 2. Performance comparison chart-EC

3.3. Analysis

The comparative experiments above validated the effectiveness of the proposed MKGC model in improving recommendation diversity. Notably, this model effectively enhances recommendation diversity without sacrificing significant accuracy. Compared to DirectAU, the model with the best recommendation accuracy, there is only about a 1% performance gap when the recommendation list is long. However, in terms of diversity, MKGC achieves the best performance among all tested models, improving coverage by approximately 1.7%. Compared to the KG-Diverse model, which also uses knowledge graph technology to improve recommendation diversity, our model shows only a 0.3% difference in accuracy. This difference may be due to the sparse semantic information of the image data, but simultaneously, our model achieves better diversity recommendation results.

4. Conclusion

This paper proposes a multimodal knowledge graph convolutional neural network (MKGC) to increase recommendation diversity. The model primarily integrates two modalities: conventional data constructed from a knowledge graph and image modal data with features extracted using CNNs. First, this paper elucidates the entity neighborhood aggregation concept in KGCN and improves upon it by integrating the extracted image data features into the entity feature representation within the knowledge graph, further enriching the latent semantic information of entities. Then, comparative experiments verify the model's effectiveness, demonstrating its ability to improve diversity in personalized recommendations and alleviate the problem of information narrowing to some extent. Intuitively, increased recommendation diversity generally leads to decreased recommendation accuracy; however, experimental results show that models utilizing knowledge graphs and other technologies can better uncover the correlations between entities within a project, thereby enabling better analysis and understanding of user profiles based on user interaction data. Algorithms with this capability can, to some extent, simultaneously improve recommendation diversity and accuracy.

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