Relation-aware Graph Convolutional Networks for Library Book Recommendation

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Abstract. In response to the issues of sparse borrowing relationship data, shifting content interests, and recommendation cold start in university library, this paper proposes a personalized book recommendation method based on Graph Convolutional Networks (GCNs). This method possesses conventional prediction and inductive capabilities by constructing a global tripartite graph of borrowers, books, and subjects and training a relation-aware GCN on local subgraphs. Additionally, a temporal self-attention (TSA) mechanism is proposed to encode long-term and short-term temporal patterns of borrower preferences, overcoming the variations and decay of interests over time. Experimental results conducted on two datasets demonstrate the advanced performance of our method, which is further validated through testing with real library data. Our proposed method effectively addresses the recommendation cold start problem, and places greater emphasis on the recent borrowing interests of readers, thereby improving the accuracy of recommendations.

Keywords: Graph Convolutional Networks, Relational Attentive, Book Recommendation, Library

1 INTRODUCTION

The book recommendation system in university libraries aims to provide reasonable book recommendations to borrowers by analyzing massive library data and reader's historical behavior, thus efficiently meeting their personalized needs. This has a positive impact on improving the efficiency of library collection utilization and user satisfaction. However, the majority of current recommendation systems rely on sparse matrices of book-reader correspondences, where the increase in the number of books does not proportionally match the increase in the number of readers. Furthermore, users without historical behavior cannot be recommended, resulting in the cold start problem. Additionally, borrowers tend to change the number and types of books borrowed based on recent courses, majors, and other requirements. Moreover, there is a general trend of decreasing interest in a certain category of books over time. Simply relying on linear extraction from existing user's historical behavior makes it difficult to achieve good recommendation performance.

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Early collaborative filtering algorithms have been widely used in various recommendation scenarios [1]. Traditional collaborative filtering algorithms often result in a high proportion of popular items in the recommendation results. However, users prefer to be recommended items that they are not familiar with, so addressing the dominance of popular items is a challenge that traditional collaborative filtering algorithms need to overcome [2]. Recently, the advances in GCNs have also had a significant impact on the field of recommender systems, and especially on collaborative filtering [3]. The principle of GCNs for user-item recommendation is to establish user and item nodes and represent their relationships through edges. GCN-based recommendation systems represent a continually evolving and innovative field [4]. However, a limitation that still needs to be addressed is establishing effective links between recommending new users and recommended items without the need for retraining and modeling.

Considering the aforementioned factors, we have incorporated domain constraints into the graph construction process. Specifically, we establish a reader-subject-book tripartite graph and train the GCN to focus on relationship attention. To address interest decay, we encode both long-term and short-term temporal patterns of user preferences using a proposed sequential self-attention mechanism. The contributions of this paper are summarized as follows:

1. We propose a novel relation-aware GCN architecture to address the problem of book recommendations in university libraries, i.e., RAGCN, which constructs a graph and learns its feature representation by leveraging the original embeddings of readers, subjects, and books.

2. We design a TSA layer to model the temporal patterns of user preferences, which updates the item embeddings within different time frames, enabling the extraction of long-term and short-term context-aware subgraphs for each target object.

3. Comparative experiments on two public dataset demonstrate that our RAGCN outperforms existing state-of-the-art approaches. Furthermore, we conduct tests using library-specific data, which validate the applicability of our method.

The reminder of this article is organized as follows. Section 2 introduces our RAGCN and the design details, and the extensive experimental results and analysis are reported in Section 3. Section 4 concludes this article.

2 METHODOLOGY

The overall architecture of our RAGCN is depicted in Figure 1, which consists of four stages. We begin by performing shallow feature extraction of input vectors using a single hidden layer feed-forward network (FFN). Then, we pair the interaction content within different time frames to extract long-term and short-term subgraph embeddings for each target object. Next, we employ the RAGCN to learn the representation relationships among readers, subjects, and books. Finally, we utilize a TSA layer to model user preferences and update the embeddings. With these embeddings, we make predictions.

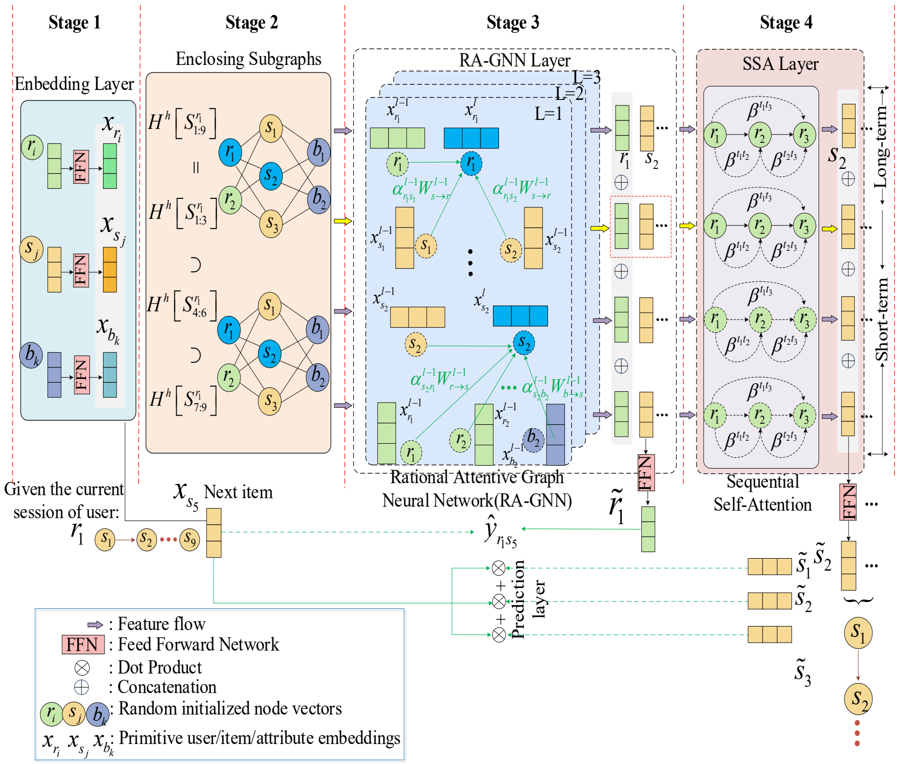

Fig. 1. The overall pipeline of the RAGCN. The symbols r_i, s_i and b_i denote the nodes in the reader set $\mathcal{R}$, subject set $\mathcal{S}$, and book set $\mathcal{B}$, respectively.

2.1 Data Preprocessing and Subgraph Embedding

Firstly, the basic information of borrowers is organized, including their ID, gender, category, department affiliation, and research areas, which is used to construct user behavioral profiles, analyze reader preferences, and establish user feature models. Next, the basic information of books is collected and organized, including the book title, ISBN, publisher, author, and classification number. The borrowing behavior relationship between readers and books is then recorded, where each sample represents a reader's borrowing behavior towards a book.

By feeding the randomly initialized vectors into the FFN, low-dimensional dense real-valued vectors are obtained. We refer to these dense vectors as raw embeddings, denoted as $\boldsymbol{X} \in \mathbb{R}^{d \times q}$, where d represents the embedding dimension and q is the sum of the number of readers, subjects, and books in the training data. A global tripartite graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is constructed to represent the relationships between borrowers, subjects, and books, where the introduction of subjects aims to reduce the initial cold start error for new users. The node set $\mathcal{V}$ is the union of the reader set $\mathcal{R}$, subject set

$\mathcal{S}$, and book set $\mathcal{B}$, i.e., $\mathcal{V}=\mathcal{R}\cup\mathcal{S}\cup\mathcal{B}$. The edge set is $\mathcal{E}=\mathcal{E}^{\mathcal{RS}}\cup\mathcal{E}^{\mathcal{RB}}$, where $\mathcal{E}^{\mathcal{RS}}$ represents the edges connecting readers with subjects, and the edges in $\mathcal{E}^{\mathcal{RS}}$ provide a degree of content-based filtering. $\mathcal{E}^{\mathcal{RB}}$ represents the edges connecting readers with books, which reflects the effectiveness of collaborative filtering, determining whether to recommend books to borrowers. The construction of $\mathcal{G}$ allows our model to perform inductive learning and transfer learning. The relationship from readers to books can be categorized into four types, denoted by variable $n_r = 1 \text{ or } 2 \text{ or } 3 \text{ or } 4$. It should be noted that G is different for variable a and b.

2.2 RAGCN

The specific feature fusion process in RAGCN is accomplished by designing adjacency matrices. In this propagation, our objective is to describe each user and item using high-order paths connected to other books, readers, and subjects. The $\mathcal{V}$ and $\mathcal{E}$ at the lth layer are represented by a symmetrical adjacency matrix $\boldsymbol{A}^{(l)}\in\mathbb{R}^{d\times q}$, and the element $a_{ij}^{(l)}$ is defined as the edge weight between the connected nodes v_i and v_j , which is formulized as

$$a_{ij}^{(l)}=\frac{\exp\left(dis\left(v_i,v_j\right)\right)}{\sum^{d\times q}\exp\left(dis\left(v_i,v_j\right)\right)} \tag{1}$$

where $dis(*)$ is the Euclidean distance between nodes.

In order to achieve relationship awareness, we define a weight matrix $\boldsymbol{W}_r^{(l)}\in\mathbb{R}^{d\times 1}$ to differentiate between different layers. Additionally, we define a weight $\boldsymbol{W}_o^{(l)}\in\mathbb{R}^{d\times 1}$ to represent self-attention. The update of the feature vector in the next layer of node v_i can be represented as follows:

$$x_i^{(l+1)}=\sigma\left(\boldsymbol{W}_o^{(l)}x_i^{(l)}+\sum_{n_r}\sum_{j=1}^{d\times q}\tilde{a}_{ij}^{(l)}\boldsymbol{W}_r^{(l)}x_i^{(l)}\right) \tag{2}$$

where $\sigma(*)$ is the nonlinear activation function. $\tilde{a}_{ij}^{(l)}$ is the element of the symmetric normalized adjacency matrix $\tilde{\boldsymbol{A}}^{(l)}$, which can be obtained by

$$\tilde{\boldsymbol{A}}^{(l)}=\left(\boldsymbol{D}^{(l)}\right)^{-1/2}\boldsymbol{A}^{(l)}\left(\boldsymbol{D}^{(l)}\right)^{-1/2} \tag{3}$$

where $\boldsymbol{D}^{(l)}=\operatorname{diag}\left\{d_1^{(l)},\cdots,d_i^{(l)}\right\}$ is a diagonal matrix.

RAGCN can ultimately generate effective user and item representations by encoding high-order relationships between user preferences and item relevance.

2.3 TSA

To consider the temporal factor and improve recommendation accuracy, we propose a TSA mechanism to generate item representations with temporal information, and its input is the sequence of embeddings obtained from RAGCN, denoted as $\boldsymbol{T}_{a:b}^{u}=\left[t_a,t_{a+1},\cdots,t_b\right]$, where $t\in\mathbb{R}^{d}$. The output is denoted as $\boldsymbol{Z}_{a:b}^{u}=\left[z_a,z_{a+1},\cdots,z_b\right]$, where $z\in\mathbb{R}^{d}$. The queries, keys, and values embeddings of the self-attention mechanism are calculated by the above embeddings, and the transform weight matrixes are denoted as $\boldsymbol{W}_q\in\mathbb{R}^{d\times d}$, $\boldsymbol{W}_k\in\mathbb{R}^{d\times d}$, and $\boldsymbol{W}_v\in\mathbb{R}^{d\times d}$. Moreover, the attention weight matrix $\beta_{a:b}\in\mathbb{R}^{m\times m}$ is introduced to represent the calculation of temporal sequence awareness, where $m=a-b+1$. The TSA is applied to the projected value matrix to generate the output embedding matrix $\boldsymbol{Z}_{a:b}^{u}$, which can be formulated as

$$\boldsymbol{Z}_{a:b}^{u}=\beta_{a:b}\left(\boldsymbol{T}_{a:b}^{u}\boldsymbol{W}_v\right) \tag{4}$$

$$\beta_{a:b}^{\left(t_i,t_j\right)}=\frac{\exp\left(e^{\left(t_i,t_j\right)}\right)}{\sum_{k=1}^{m}e^{\left(t_i,t_k\right)}} \tag{5}$$

$$e^{\left(t_i,t_j\right)}=\frac{\left(\left(\boldsymbol{T}_{a:b}^{u}\boldsymbol{W}_q\right)\left(\boldsymbol{T}_{a:b}^{u}\boldsymbol{W}_k\right)^{\mathrm{T}}\right)_{t_i,t_j}}{\sqrt{d}}+I_{t_i,t_j} \tag{6}$$

where I_{t_i,t_j} is the element of the mask matrix $\boldsymbol{I}\in\mathbb{R}^{m\times m}$, and its value follows the following rule:

$$I_{t_i,t_j}=\begin{cases}0 & \mathit{if}\ a\le t_i\le t_j\le b\\ -\infty & \mathit{otherwise}\end{cases} \tag{7}$$

3 EXPERIMENTS

We compare the proposed RAGCN with several state-of-the-art methods and baselines, including CTR [5], CDL [6], ConvMF+ [7], DIEN [8], HGAN [9], MAGNN [10] and GCMC [11]. Two widely popular real-world datasets, namely Book-Crossing and Goodbooks-10k, were used to evaluate the proposed model in the experiments. Four evaluation metrics were used for performance comparison: Precision@k (P@k), Recall@k (R@k), NDCG@k (N@k), and Mean Reciprocal Rank (MRR).

The quantitative comparison results of all methods on the two datasets are shown in Table 1, where the best values are indicated in bold, and the second-best values are underlined. We can observe that the proposed RAGCN outperforms all competing methods in terms of performance. The Goodbooks-10k dataset has a very high sparsity, approaching 99%, which affects the performance of collaborative filtering methods like

CTR and CDL. The user latent vectors learned by ConvMF+ do not accurately represent user features in the dataset. The heterogeneous graph neural network MAGNN is the second-best model. Due to its inability to capture sequential patterns of user preferences in the given view, IGMC performs worse than our RAGCN. MAGNN and GCMC also have lower performance than RAGCN because their embedding generation methods do not consider the impact of long-term sequences on the association between readers and books. Our RAGCN performs better on extremely sparse datasets compared to other methods. The Book-Crossing dataset has lower sparsity compared to Goodbooks-10k, resulting in slightly improved recommendation performance for PMF, CTR, and CDL methods, but still far below our RAGCN.

Table 1. Quantitative comparison results of various methods for the two public datasets.

Method	Goodbooks-10k				Book-Crossing			
	MRR	P@10	R@10	N@10	MRR	P@10	R@10	N@10
CTR	1.345	0.124	0.134	0.122	0.894	0.028	0.096	0.042
CDL	1.254	0.135	0.168	0.136	0.874	0.046	0.105	0.049
ConvMF+	1.233	0.143	0.156	0.137	0.784	0.047	0.114	0.058
DIEN	1.586	0.145	0.154	0.139	1.325	0.062	0.106	0.063
IGMC	1.785	<u>0.164</u>	0.165	0.144	1.467	0.058	0.112	0.069
MAGNN	1.665	0.153	0.167	<u>0.153</u>	1.456	<u>0.064</u>	0.123	0.070
GCMC	<u>1.867</u>	0.158	<u>0.179</u>	0.135	<u>1.754</u>	0.061	<u>0.143</u>	<u>0.071</u>
RAGCN	**1.966**	**0.166**	**0.185**	**0.159**	**1.766**	**0.067**	**0.165**	**0.075**

Another test experiment involved evaluating the performance of recommendation quantity using actual books from a university library. The data used in this experiment consisted of 23924 borrowing records, 32 subjects, and 3532 readers. The aforementioned data underwent preprocessing before being used for testing. We set the number of recommended books to 5, 10 and 15, respectively. The MRR metric for different methods is shown in Figure 2. As the number of recommendations increases, our RAGCN exhibits a significant improvement in accuracy compared to traditional user-based collaborative filtering algorithms. This suggests that our model, due to the introduction of self-attention mechanism, has a more accurate grasp of reader preferences, leading to improved performance.

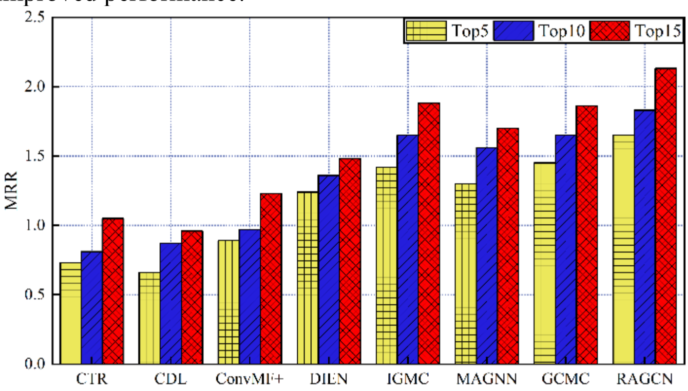

Fig. 2. Comparison of MRR for different recommendation lengths.

4 CONCLUSION

The proposed RAGCN in this paper enables personalized book recommendations in the context of university libraries. It can achieve this without relying on content or auxiliary information, effectively addressing the challenges of recommendation cold start and interest decay. The developed model is based on GCN and incorporates relationship-awareness, allowing for the learning of relationship attention matrices within closed subgraphs centered around reader-subject-book pairs. The performance of RAGCN has been evaluated on both the public dataset and real-world data, demonstrating its exceptional performance.

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