Papers recommendation with Item-level Collaborative Memory Network

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Abstract. The recommendation system can recommend information to users personally and efficiently, which satisfies the user's demand for information in the information age, and has become a hot topic in the current era. In the recommendation system, users and items and the interaction of their own information has a crucial impact on the efficiency and accuracy of the recommendations. However, most of the existing recommendation systems usually design the systems as user-base only, considering the user's influence on the item in the recommendation, which to some extent blurs the interaction between items and users at the item level, unknown and potential connections between items and users are not well considered. In this paper, we developed a collaborative memory network that can focus on the potential relation between items and users, and consider the impact of items' characteristics on user behavior. Experiments have shown that our improvement is better than the original method.

Keywords: Recommendation Systems, Memory Network, Collaborative Filtering.

1 INTRODUCTION

In the context of the era of big data, modern recommendation systems undoubtedly become an indispensable part of people's needs in their life. As an application that filters a large amount of information, the recommendation system can collect historical behavior data of the users, process the data through various processing methods or using relevant recommendation technologies, in order to obtain personalized recommendation for ~~the~~ users and recommend information or items such as movies, music, books, news, etc. to users that users may be interested in or ~~like~~. The data of the recommendation system includes explicit data and implicit data, the explicit data can more accurately reflect the user's real preference on the items, such as user rating, etc., and the implicit data can reflect the user's preference after being analyzed and processed such as user clicks, watch time, etc. However, there are a large number of data and information that can be selected by users. The effective recommendation system can provide the most relevant content for users under the premise of large data volume, improve the efficiency and accuracy of the recommendation, and optimize the user experience.

The recommendation system ~~base~~ on collaborative filtering can analyze the dependence between users and items, and use the similarity information between users to recommend content that users are interested in [1,2.3]. The recommendation method also has a high degree of personalization and automation, at the same time, feedback can be used to speed up learning. Collaborative filtering technology is one of the most classic and mainstream technologies in recommendation systems[4,5]. In real life, the user's rating data is very rare, that is, explicit data is much less than implicit data, so how to add implicit data to the model becomes a problem. SVD++ integrates the user's implicit behavior into the Singular Value Decomposition (SVD) [6] model, enhancing the user's implicit feedback [7].

Another recommended system algorithm is the K-nearest neighbor classification algorithm (KNN). The core idea of KNN is to find the majority of the *k* most neighboring samples in a features space, if most of these samples belong to a certain categor~~ies~~ [8], then the sample also belongs to this categor~~ies~~ and has the characteristics of all samples in this categor~~ies~~. When determining the classification, the KNN method only determines the category to which the sample to be classified belongs according to the categories of the nearest one or several samples. When making the categor~~ies~~ decision, it is only related to a very small number of adjacent samples, and is more suitable for a set of samples to be classified that intersect or overlap in a categories.

Recently, Tay et al. [9] proposed a flexible adaptive metric learning algorithm for collaborative filtering and ranking. By learning the adaptive relationship vector between users and items interaction, find an optimal translation vector between each user-item interaction pair, while introducing a relational vector to simulate the potential relationship between users and items. Hseih et al. [10] revealed the potential impact of internal products to simulate user-item relationships. Inspired by the memory network, Ebesu et al. [11] presented Collaborative Memory Network (CMN),they used the memory module as the nearest neighbor model of similar users, and used the attention mechanism based on specific users to learn the adaptive nonlinear weighting of the user neighborhood, while utilizing the adaptive neighborhood state and a nonlinear interaction between users and items memory to generate recommendations.

Despite the success of CMN, it ignore~~d~~ some content. Each item has a connection with a group of users, and similar items do not necessarily have the same appeal to the same user [12]. When considering the relevance between a item and a user, the CMN only considers the construction of neighborhood representation with similar users. However, in general, the problem of collaborative ranking has many-to-many nature, the item will also have a certain degree of impact on the user's choices and preferences, which may cause ~~in~~ changes in the user's preferences. CMN ignores the potential relationships between items and users, especially those related to large data sets.

To solve this problem, we propose a network called Item-level Collaborative Memory Network (ICMN) for ranking and recommendation, which can fully consider the distribution of potential relationships between items and users and strengthen the relationship between specific item and neighborhoods, it can take into account the impact of users and items on each other and their neighborhoods. Specifically, in order to be able to take into account the potential relationship between items and users, we adopt a higher-order method to obtain the weighted sum of the relationship between the specific item and the user and the neighborhoods they forms. Undoubtedly, our work has been inspired by the latest developments in NLP and recommendation systems [13,14,15]. The experimental results show that our method is better than CMN and can capture the hidden semantics between implicit interactions.

Our contributions are summarized as follows:

- We propose ICMN, a new type of network that takes into account the potential relationship between items and users, used to generate rankings for recommendations. For the first time, we have fully considered the distribution of potential relationships between items and users on CMN, and strengthened the relationship between specific items and neighborhoods.
- We evaluate~~d~~ our proposed ICMN on a public dataset. Experiments have shown that our proposed ICMN is not only superior to CMN, but also superior to many other powerful baselines with improved performance.
- We also consider the impact of items and users on each other and their neighborhood, and neurological attention provides greater insight and interpretability for this model.

2 RELATED WORK

2.1 Collaborative Filtering

The rapid development of the Internet era and the construction of a large number of information systems, resources, and websites has enabled people to enjoy the rapid way of obtaining information, but they also have created the confusion of how to obtain the information they need efficiently and accurately. At the same time, users have also created more personalized needs, and recommendation systems have emerged. The recommendation system can ~~solve~~ the need ~~for~~ users to quickly and efficiently obtain the required information. While improving the quality of service, the system provides users with more personalized services, the collaborative filtering recommendation algorithm is the most classic and widely used algorithm in the recommendation system currently. It can also be divided into explicit collaborative filtering and implicit collaborative filtering. The former learns the user's explicit information such as rating, score, etc., while the latter involves the user implicit interaction data.

Usually, in implicit collaborative filtering, if there is an interaction between the user and the item, it is recorded as 1, otherwise 0 [16]. However, this does not indicate that the feedback between the user and the item that generated the interaction is positive or negative.

In a traditional data-based approach, all unobserved interactions are treated as negative samples and have the same weight, but unobserved interactions and data may be positive or missing data [17], and also have different weights. To this end, some recent efforts [18,19] have focused on weighting schemes and have considered whether unobserved samples are indeed negative. For example, certain non-uniform weighting schemes on negative samples, such as user-oriented and item popularity orientation, have been proposed and proven to be more effective than uniform weighting schemes [20].However, one major limitation of the non-uniform weighting method is that the weighting scheme is defined based on the hypothesis proposed by the authors, which may not be correct in the actual data. He et al. [21] weighted missing data according to item popularity. Gu et al. [22] use supervisory methods to optimize global term weights for specific recommended domains.

2.2 Attention Mechanism

The attention mechanism has a great improvement effect on the sequence learning task. The attention model can perform data weighted transformation on the data sequence. Xu et al. [23] proposed two attention modes, one is hard attention and the other is soft attention~~,~~ hard attention only pays attention to a certain position of the model sequence at each moment, ~~and~~ soft attention takes care of all the positions at a time, and the weight of each position is different. Luong et al. [24] proposed two improved attentions, namely global attention and local attention. Among them, local attention can be regarded as a mixture of hard attention and soft attention. Unlike hard attention, local attention can be differentiated almost everywhere and easy to train, it only focus on a small part of the source position at a time, and global attention needs to scan all source hidden states each time.

2.3 Deep Learning

Deep learning stems from the research of artificial neural networks, is one of the latest trends in artificial intelligence and machine learning research, and is one of the most popular scientific research trends today. It combines low-level features to form more abstract high-level way to represent attributes categories or features to discover the distributed feature representation of the data [25].The deep learning approach has brought historic progress to machine learning. In the study of machine learning, the motivation of deep learning lies in the establishment and simulation of a neural network for the analysis and learning of the human brain. It can mimic the mechanism of the human brain to interpret data such as images, sounds and texts, etc.

In the recommendation system, the general idea of common algorithms is to convert high-dimensional discrete features into fixed-length continuous features through the embedding layer, then pass through multiple fully connected layers, and finally convert to a 0-1 value through a sigmoid function to representing the probability of clicks [26].This method can fit high-order nonlinear relationships through neural networks while reducing the workload of artificial features. Recently, Zhou et al. [27] proposed a Deep Interest Evolution Network (DIN) for click-through rate prediction, ~~it~~ adaptively learns the representation of user interest from the historical behavior of an advertisement by designing a local activation unit.

2.4 Collaborative Memory Network(CMN)

CMN is a recent deep architecture that demonstrates excellent and competitive performance in several baseline tests. In this network, memory components and neural attention mechanisms are merged into neighborhood components to learn about the user's specific neighborhood. The ranking score is generated by the neighborhood and user memory [11].At the same time, the network can stack multiple memory modules together to create a more complex architecture for capturing deep and complex user-item interactions.

CMN focuses its attention on users' information, which leads to the neglect of information about items. In the process of user interaction with the item, in addition to the explicit relationship, there is an implicit relationship. At the same time, in addition to the users' influence on items, the items also have a non-negligible connection with users. Similar items do not necessarily have the same appeal to the same user and items that have not interacted with the user will also affect the user's choice to some extent.

In real life, the channels through which users can accept item information are diverse, which means that different information will make the characteristics of the item have different effects on users. At the same time, it also shows that CMN cannot flexibly recommend in the case of huge data volume and dense dataset.

3 OUR MODEL

In this section, we will introduce CMN and our network model ICMN that can focus on the item's attractiveness and potential relationships to users. The overall architecture and construction process of our network model has shown in Figure 1.

3.1 Collaborative Memory Network

The CMN combines the memory component and the neural attention mechanism to form a neighborhood component that learns the user's specific neighborhood [11]. The model ~~that~~ stacking of the four memories enables them to obtain a deeper relationship between users and items. In a single-layer memory, given a user u, a preference vector q_{ui} for a particular user v is formed, and then a similarity q_{uiv} of a particular user to a user in the user neighborhood is derived, which is represented by $q_{uiv} = m_u^T m_v + e_i^T m_v$.When constructing the final neighborhood representation, the CMN constructs a neighborhood representation p_{uiv} for a particular user for subsequent operations. We focus on items information and their features, embedding users and items, and using different methods to get the final neighborhood s_{iu} for a particular item. On this basis, we get the final ranking score.

3.2 User and Item Embedding

The input users and items information are embedded in the memory component of the user and the item respectively. The user's memory component is M, and the item's memory component is E, where $M \in R^{P \times d}$, $E \in R^{Q \times d}$, P, and Q are the number of users and items, d is the dimension of the memory. The users preferences（用户的偏好） are stored in the user memory component slice m_u, and the features of the item i are stored in e_i of the item memory slice to get the similarities a_{iut} for a particular item and a particular user in their given neighborhood:

$$a_{iut}=m_u^T e_t+e_i^T e_t \qquad \forall t \in N(u) \tag{1}$$

Where t is a specific item in the item neighborhood with implicit feedback.

3.3 Item Neighborhood Attention

In order to focus on the influential set of items and users in the neighborhood, the attention mechanism can learn the adaptive weighting function, which is different from the traditional neighborhood method used in Pearson correlation or cosine similarity [28], the function does not need to set the number of users or items. At the same time, we do not need to pre-define or set the weighting function based on past experience in the learning process of the whole attention mechanism. In this way, we can better learn the unique contribution of items:

$$x_{iut}=\frac{\exp(a_{iut})}{\sum_{g \in N(u)} \exp(a_{iut})} \qquad \forall t \in N(u) \tag{2}$$

Among them, the generated neighborhood distribution can be dynamically assigned to specific item.

Then, by using the weights formed by the attention mechanism, the weights are manipulated with the neighborhood to form the neighborhood representation:

$$s_{iu}=\sum_{t \in N(u)} x_{iut} \times f_t \tag{3}$$

Where f_t is the vector of another embedded matrix of items, × is the operation at the matrix level. Focusing on the characteristics of items, the weights formed by the attention mechanism are selectively weighted to items and their neighborhoods in different ways to obtain the final weighted neighborhood.

This not only consider the impact of items on users, but also strengthens the relationship between the specific item and the neighborhood, taking into account the distribution of the potential relationship between items and users [29].

3.4 Memory Stack

Throughout the model building, we operate with a stack of four memories that capture deeper and broader information between items and users, improving the efficiency and performance of the entire model. Through the stacking of memories, it can dynamically assign weights to items, and capture the appeal of the item to users more comprehensively and in detail. Using the s_{iu}^y generated by the upper memory, a nonlinear mapping z_{iu}^y between the memories can be formed for next memory, and then a_{iut}^{y+1} can be obtained by updating with the item neighborhood, and finally, after the four layers of memory components, the final neighborhood representation is obtained:

$$z_{iu}^y=\emptyset\left(W_{a_{iu}^y}^y+s_{iu}^y+\mathrm{b}\right) \tag{4}$$

$$a_{iut}^{y+1} = \left(z_{iu}^{y}\right)^{T} e_t \quad \forall t \in N(u) \tag{5}$$

Where y is the number of memory layers, and W is a weight matrix that maps the features of the items to the potential space, combined with the information of the previous layer.

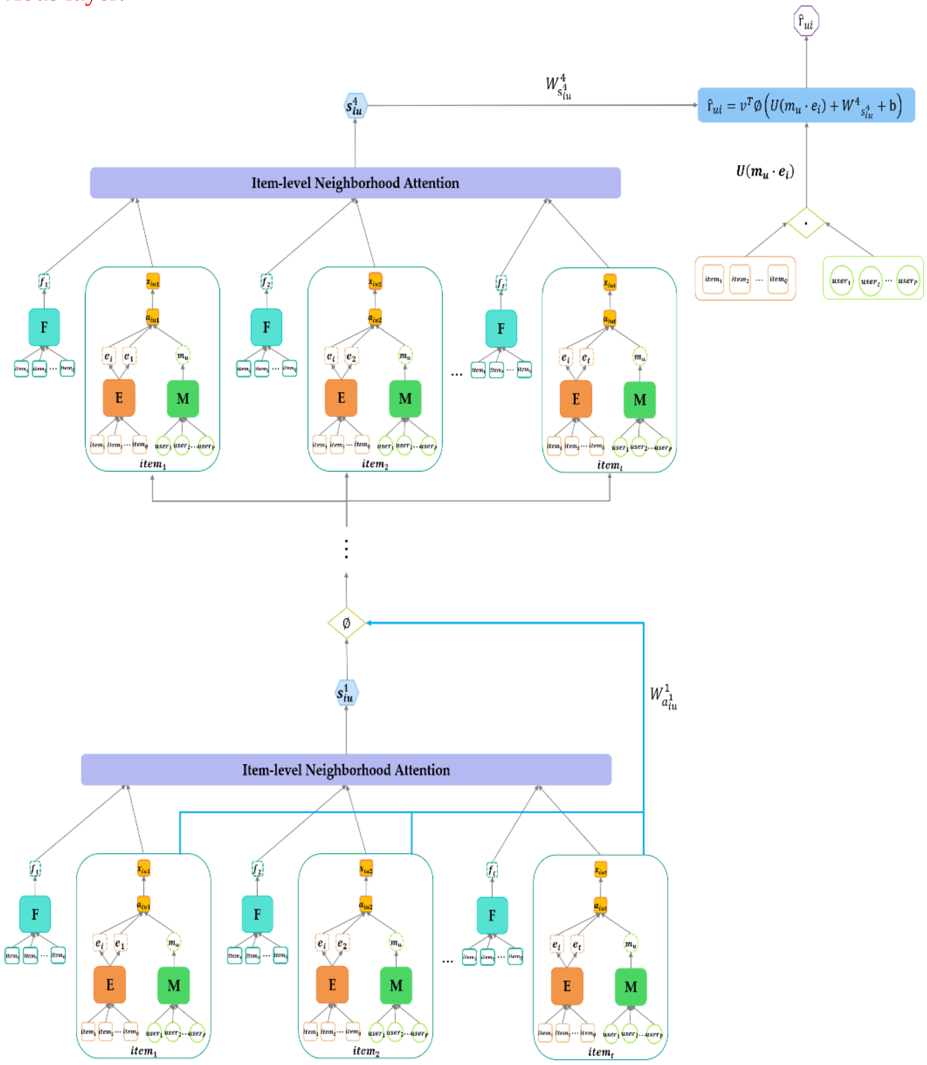

Fig. 1. Our model structure. This model can focus on item information and build with four layers of memory components.

3.5 Output

~~Capture~~ the local structure of items and users' neighborhood and the global interaction information between items and users, items and users have established a deeper and wider relationship, and then through a non-linear approach, the potential relationship between items and users can be more fully reflected to generate a ranking score that focuses on the items' influence:

$$\hat{r}_{iu} = v^T \emptyset \left(U(m_u \cdot e_i) + W^4{}_{s^4_{iu}} + b \right) \tag{6}$$

Where $\cdot$ is the operation of the element level. After obtaining the product of items and users, we learn the neighborhood representation and parameters by linear projection. We use the nonlinear activation function $\emptyset(x) = max(0, x)$, which can improve the expressive ability of the model [30,31] , the overall structure of the model ~~is~~ shown in Figure 1.

3.6 Parameter Estimation

We use the Bayesian Personalized Ranking (BPR) optimization standard [34] as our loss function:

$$L = \sum_{(u,i^+,i^-)} \log \sigma\left(\hat{r}_{i^+u} - \hat{r}_{i^-u}\right) \tag{7}$$

Where $\sigma(x) = 1/(1 + exp(-x))$ is a logical sigmoid function.

4 PERFORMANCE EVALUATION

In this section, we will introduce the dataset and baseline settings used in the experiment.

4.1 Dataset

The dataset we use is the citeulike-a dataset [33], an online service collected from CiteULike, which allows users to create their own collection of articles. Each article has a summary, title and label, and the user provides a digital catalog to save and share academic papers~~, the~~ dataset has 204,987 ratings ~~and~~ 5,551 users and 16,980 items.

4.2 Baselines

In this section, we will present the key baselines for comparison with our proposed ICMN.

SVD ++: SVD ++ [7] is a hybrid model that combines neighborhood-based similarity and latent factor model.

GMF: The Generalized Matrix Factorization (GMF) [32] model is a nonlinearly extended potential factor model.

KNN: KNN [8] is a neighborhood-based method for calculating cosine item-item similarity.

BPR: Bayesian Personalized Sorting (BPR) [34] is a matrix factorization model of implicit feedback.

NeuMF: Neural Matrix Factorization (NeuMF) [32] is a matrix factorization model for item ordering through a multilayer perceptron model.

CDAE: Collaborative Denoising Automatic Encoder (CDAE) [35] is a item-based deep learning model.

FISM: Factored Item Similarity Model (FISM) [36] is a neighborhood-based model that can decompose the similarity matrix of item-item pairs and optimize the loss function.

CMN: Collaborative Memory Networking [11] is a model that fuses memory components and attention mechanisms and is the source of our ideas.

In addition, we set the number of negative samples as 4 and initialize in pre-training. In pre-training, l2's weight decay is set to 0.001. During training, l2's weight decay is set to 0.1, the embedded size *d* of the memory is set to 50.

We use two common ranking evaluation metrics Hit Ratio(HR) and Normalized Discounted Cumulative Gain(NDCG) [37] as the basis for the evaluation of experimental results. HR can measure the presence of the positive item within the top N and NDCG can measure the items position in the ranked list and penalizes the score for ranking the item lower in the list.

Table 1. Citeulike-a dataset experiment results.

	HR@5	HR@10	NDCG@5	NDCG@10
SVD++	0.6952	0.8199	0.5244	0.5649
GMF	0.7271	0.8326	0.5689	0.6034
KNN	0.6990	0.7348	0.5789	0.5909
BPR	0.6547	0.8083	0.4858	0.5357
NeuMF	0.7629	0.8647	0.5985	0.6316
CDAE	0.6799	0.8103	0.5106	0.5532
FISM	0.6727	0.8072	0.5106	0.5545
CMN	0.7959	0.8921	0.6185	0.6500
ICMN	**0.8044**	**0.8934**	**0.6434**	**0.6726**

4.3 Baseline Comparison

The data in Table 1 shows the experimental results of our model and each baseline model. At the same time, we also show the results of our model and other baseline models on four indicators in a more intuitive way in Figure 2. It can be seen that our results have good results and performance on these four indicators.

ICMN can consider the impact of the relevant information and characteristics of the items on user preferences, and prove the importance of the items' own information in the recommendation process. The stacking of four layers of memories further optimizes performance, and the dynamic processing of weights by the attention component enables the model to focus on deeper information. The results prove that our model is superior to all baseline models.

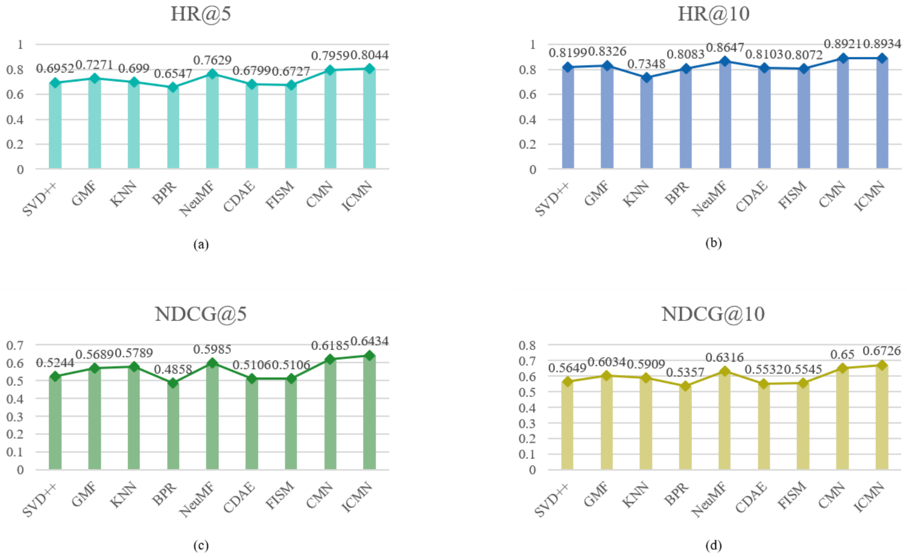

Fig. 2. Visualization of experimental results. (a)(b)(c)(d) are the results of our and other baseline models in the Citeulike-a dataset with HR@5, HR@10, NDCG@5 and NDCG@10 as the evaluation indicators.

5 CONCLUSION

In this paper, we propose an item-level collaborative memory network (ICMN) that can focus on the impact of the item level, which not only takes into account the attractiveness of items to users, but also fully considers the distribution of the potential relationship between items and users to strengthen the relationship between specific items and neighborhoods and enables our network to perform well on larger data sets. Attention mechanisms can also handle items features more rationally and dynamically to obtain more comprehensive user preference information. In future work, we want to add time information or other information that can more fully reflects the relationships between users and items to our network.

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