Papers recommendation with Item-level Collaborative Memory Network

First Author[1[0000-1111-2222-3333]] and Second Author[2[1111-2222-3333-4444]]

[1] Princeton University, Princeton NJ 08544, USA
[2] Springer Heidelberg, Tiergartenstr. 17, 69121 Heidelberg, Germany
lncs@springer.com

Abstract. The recommendation system can provide users with personalized and efficient recommendation information, 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, the interaction of users and projects and their own information has a crucial impact on the efficiency and accuracy of the recommendations. However, most of the existing recommendation systems often only design the user as the main body, considering the role of the user's influence on the project in the recommendation, which to some extent blurs the user level at the project level. Interactivity, not well thought of the unknown and potential connections between users and projects. In this article, we're working on a collaborative storage network that can focus on the potential links between projects and users, and consider the impact of projects 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 life.As an application that filters a large amount of information and information, the recommendation system can collect historical behavior data of the user, process the data through various processing methods or using relevant recommendation technologies, in order to obtain personalized recommendation for the user, and the user Information or items that may be of interest or preference, such as movies, music, books, news, etc., are recommended to the user.
The data of the recommendation system includes explicit data and implicit data, wherein the explicit data can more accurately reflect the user's real preference for the item, such as user rating, etc., and the implicit data can reflect the user's after being analyzed and processed. Preferences, such as user clicks, watch time, etc.However, there are a large number of data and information that can be selected by the user. The effective recommendation system can provide the most relevant content for the user

under the premise of large data volume, improve the efficiency and accuracy of the recommendation, and optimize the user experience.

The recommendation system based on collaborative filtering can analyze the dependence between users and projects, and use the similarity information between users to recommend content that users are interested in. The recommended personalization and automation are also high, and feedback can also be passed. Information to speed up learning.Collaborative filtering technology is one of the most classic and mainstream technologies in recommendation systems. At the same time, applying matrix decomposition (MF) to collaborative filtering technology is one of the most popular methods. Many improvements are based on this. ongoing.Singular value decomposition (SVD) is a matrix decomposition method. Unlike eigen decomposition, SVD does not require that the decomposed matrix must be a square matrix. It can use a smaller and simpler matrix of smaller and simpler sub-matrices. Multiply, these sub-matrices describe the important characteristics of the original matrix, which has the advantage of simplifying the data, removing noise points, and improving the effect of the algorithm.However, 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 SVD model, enhancing the user's implicit feedback.

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 feature space, if most of these samples belong to a certain A category, then the sample also belongs to this category and has the characteristics of all samples in this category.The KNN method determines the category to which the sample to be classified belongs according to the category of the nearest one or several samples in determining the classification decision. When making the category 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 category.

Recently, Tay et al. proposed a flexible adaptive metric learning algorithm for collaborative filtering and ranking. By learning the adaptive relationship vector between user and project interaction, one is found between each user-project interaction pair. The best translation vector, while introducing a relational vector to simulate the potential relationship between the user and the project.Hseih et al. [9] revealed the potential impact of internal products to simulate user-project relationships. Inspired by the memory network, Ebesu et al. used the memory module as the nearest neighbor model of similar users, and used the attention mechanism based on specific users and projects to learn the adaptive nonlinear weighting of the user neighborhood, while utilizing the adaptive neighborhood state and A non-linear interaction between the user and the project memory to generate recommendations.Their proposed network, Collaborative Memory Network (CMN) demonstrations highly competitive performance on many benchmark datasets.

Despite the success of CMN, it ignored some content. Each project has a connection with a group of users, and similar projects do not necessarily have the same appeal to the same user.CMN considers the similarity of users to construct domain representation when considering the relationship between project and user. However, in general, the problem of collaborative ranking has many-to-many nature, and the project will have certain choices and preferences for users. The extent of the impact may result in a change in the user's preferences.CMN ignores the potential relationships between projects 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 projects and users, while strengthening specific projects and neighbors. The relationship between domains can take into account the impact of users and projects on each other and their respective neighborhoods.Specifically, in order to be able to take into account the potential relationship between the project and the user, we adopt a higher-order method to obtain the weighted sum of the relationship between the specific project and the user and the fields it forms.In addition, we have separately considered the individual results of focusing on specific users and focusing on specific projects. At the same time, we also considered the combination of focusing on specific users and focusing on specific projects.Undoubtedly, our work has been inspired by the latest developments in NLP and recommendation systems. 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 projects and users, used to generate rankings for recommendations. For the first time, we have fully considered the distribution of potential relationships between projects and users on CMN, and strengthened the relationship between specific projects and neighborhoods.
- We evaluated 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 users and projects on each other and the neighborhood, and combine the focus on specific users and modules that focus on specific projects to demonstrate the importance of the project's impact on users. At the same time, neurological attention provides greater insight and interpretability for the model.

2 RELATED WORK

2.1 Collaborative Filtering

The rapid development of the Internet era, the construction of a large number of information systems, resources, and websites has made people enjoy the rapid way of obtaining information, but at the same time, they have created the confusion of how to obtain the information they need efficiently and accurately. 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, and provides users with more personalized services.The collaborative filtering recommendation algorithm is the most classic and currently the most widely used algorithm in the recommendation system. It can also be divided into explicit collaborative filtering and implicit collaborative filtering. The former learns the user's explicit information such as rating, rating, 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 project, it is recorded as 1, otherwise 0.However, this does not indicate that the feedback between the user and the project that generated the interaction is positive, nor does it prove that the feedback between the user and the project that did not interact is 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, and also have Different weights.To this end, some recent efforts [21, 27] 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 [27] and project popularity orientation [21], have been proposed and proven to be more effective than uniform weighting schemes.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. weighted missing data according to project popularity. Yuan et al. used the richness of content information in social media to improve the accuracy of Single Collaborative Filtering (OCCF) for users with missing information-projects to find potential content.

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. [5] 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 t, and soft attention takes care of all the positions at a time, and the weight of each position is different.Luong et al. [6] 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 is almost everywhere. Easy and training, 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.

The traditional encoder-decoder structure relies on the limitation of an internal fixed-length vector in encoding and decoding, and shows very effective results in various machine learning tasks.

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 representation attributes. Category or feature to represent the distributed characteristics of the data [7].The deep learning approach has brought historic progress to machine learning.In recent years, the world has made many major breakthroughs in this field.The convolutional neural network proposed by Lecun et al. [8] is the first true multi-layer structure learning algorithm that uses spatial relative relationships to reduce the number of parameters to improve training performance.In the study of machine learning, the motivation of deep learning lies in the establishment and simulation of the 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.Like machine learning methods, in-depth machine learning methods also have supervised learning and unsupervised learning. Supervised learning is applied when data markers, classifier classifications, or numerical predictions.Unsupervised learning When the input data is not marked, features can be extracted from the data and sorted or tagged.

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-coupled layers, and finally convert to a 0-1 value through a sigmoid function, representing clicks. Probability [8].This method can fit high-order nonlinear relationships through neural networks while reducing the workload of artificial features.Recently, Zhou et al. [9] proposed a Deep Interest Evolution Network for Click-Through Rate Prediction, and proposed a Deep Interest Network (DIN) to adaptively derive historical behavior from an advertisement by designing a local activation unit. Learning the expression of user interest to address this challenge.

2.4 Collaborative Memory Network(CMN)

CMN is a recent deep architecture [10] 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 the user's For a particular neighborhood, the ranking score is generated by the neighborhood and user memory.At the same time, the network can stack multiple memory modules together to create a more complex architecture for capturing deep and complex user-project interactions.

However, CMN is not without defects. CMN focuses its attention on the user's information, which leads to the neglect of information about the project.In the process of user interaction with the project, in addition to the explicit relationship, there is an implicit relationship. At the same time, in addition to the user's influence on the project, the project also has a non-negligible connection with the user. It must be equally attractive to the same user, and projects that have not interacted with the user will affect the user's choice to some extent.

In real life, the channels through which users can accept project information are diverse, which means that different information will make the characteristics of the project 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 data set, and this inflexibility will cause adverse impact on CMN.

3 OUR MODEL

In this section, we will introduce ICMN, our network model that can focus on the project's attractiveness and potential relationships to users.First, we will introduce the general collaborative memory network (CMN) and explain the motivation of the model.After that, we will introduce the overall architecture and construction process of our network model, as shown in Figure 1, which includes the part of the project.Finally, we will introduce the relevant content that combines the user and the project's impact on each other and their neighborhoods to show the project's own influence, as shown in Figure 3.

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. The stacking of the two memories enables them to obtain a deeper relationship between the user and the project.In a single-layer memory, given a user u, a preference vector q_{ui} for a particular user is formed, and then a similarity q_{uiv} of a particular user to a user in the user domain 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 project information and features, embedding users and projects, and using different methods to get the final neighborhood s_{iu} for a particular project. On this basis, we get the final ranking score.

3.2 User and Item Embedding

The input user and project information are embedded in the memory component of the user and the project respectively. The user's memory component is M, and the project'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 projects, respectively, d is the dimension of the memory. The user's preferences are stored in the user memory component slice m_u, and the specific features of the project are stored in e_i of the project memory slice to get the similarities a_{iut} and q_{uiv} for a particular project and a particular user in their given neighborhood:

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

$$q_{uiv} = m_u^T m_v + e_i^T m_v \quad \forall v \in N(i) \tag{2}$$

Where v is a specific user in the user's neighborhood with implicit feedback, and t is a specific item in the project neighborhood with implicit feedback.

3.3 ICMN-User and Item Neighborhood Attention

In order to focus on the influential set of projects and users in the field, the attention mechanism can learn the adaptive weighting function, which is different from the traditional neighborhood method used in Pearson correlation or cosine similarity [11], adaptive weighting. The function does not need to set the number of users or projects. 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 the project. And the unique contributions of users:

$$x_{iut}=\frac{\exp(a_{iut})}{\sum_{g\in N(u)}\exp(a_{iut})} \qquad \forall t\in N(u) \tag{3}$$

$$p_{uiv}=\frac{\exp(q_{uiv})}{\sum_{k\in N(i)}\exp(q_{uik})} \qquad \forall v\in N(k) \tag{4}$$

Among them, the generated neighborhood distribution can be dynamically assigned to specific users and projects.

The weights are then manipulated with the neighborhood by using the weights formed by the attention mechanism to form the final neighborhood representation.

$$s_{iu}=\sum_{t\in N(u)} x_{iut}\times f_t \tag{5}$$

$$o_{ui}=\sum_{v\in N(i)} p_{uiv}\cdot c_v \tag{6}$$

Where f_t is the vector of another embedded matrix of the project, c_v is the vector in the user's other embedded matrix, $\times$ is the operation at the matrix level, and $\cdot$ is the operation at the vector level, focusing on the respective characteristics of the user and the project, the attention mechanism The resulting weights are selectively weighted in different ways to the user and the project and its neighborhood to obtain the final weighted neighborhood.

This not only takes into account the impact of the project on the user, but also strengthens the relationship between the specific project and the neighborhood, taking into account the distribution of the potential relationship between the project and the user, as shown in Figure 1.

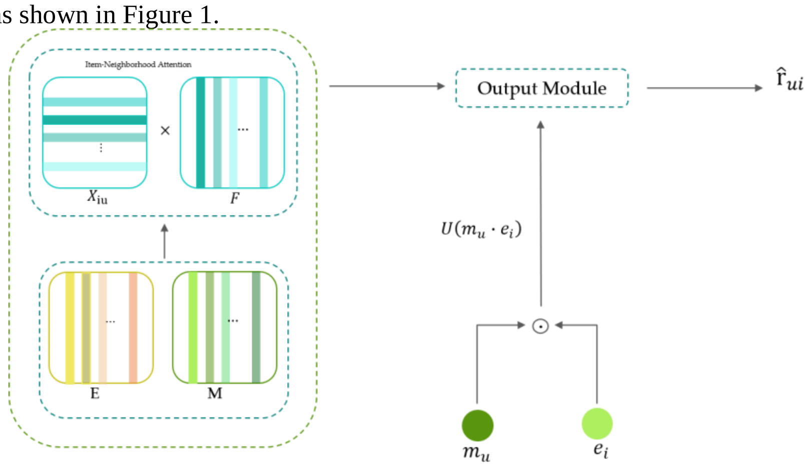

Fig. 1. A layer of memory structure about the project. Our model can focus on the project's attractiveness and potential relationships to users, and enhance the project's appeal to users.

3.4 Output Module

In the capture of the local structure of the project and the user's neighborhood and the global interaction between the project and the user, the project and the user have established a deeper and wider relationship, and then through a non-linear approach, can more fully reflect the project A potential relationship with the user to generate a ranking score that focuses on the impact of the project:

$$\hat{r}_{iu}=v^{T}\emptyset\left(U(m_u \cdot e_i)+W^2{}_{s_{iu}^2}+b\right) \tag{7}$$

Where · is the operation of the element level. After obtaining the product of the item and the user, we operate the neighborhood representation and parameters obtained by learning in a linear projection manner. We use the nonlinear activation function $\emptyset(x) = max(0, x)$, which can better play the role of the whole model [7,10]. In addition, when user information is added to take into account the impact of the project and the user on the other party and its neighbors, the ranking score becomes:

$$\hat{r}_{iu}=v^{T}\emptyset\left(U(m_u \cdot e_i)+W^2{}_{s_{iu}^2}+W^2{}_{o_{ui}^2}+b\right) \tag{8}$$

3.5 Parameter Estimation

We use the Bayesian Personalized Sorting (BPR) optimization standard [25] as our loss function:

$$L=\sum_{(u,i^+,i^-)}\log\sigma\left(\hat{r}_{i^+u}-\hat{r}_{i^-u}\right) \tag{9}$$

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

3.6 Memory Stack

In the concrete model construction, we use a stack of two memories to operate, the stacked memory can capture a deeper and wider information between the project and the user, improve the efficiency and performance of the entire model, as shown in Figure 2. Through the stacking of memories, you can dynamically assign weights to projects, and capture the appeal of the project to users more comprehensively and in detail.

3.7 Integrated User and Item

Throughout the construction of the model, we not only focus on the project, but also consider the unique information of the project itself and the impact of the project on the user's appeal. At the same time, we also combine the user and the project's influence on each other and their neighborhoods. Building a model, such a way to clear the project can show the non-negligible influence of the project itself, as shown in Figure 3.

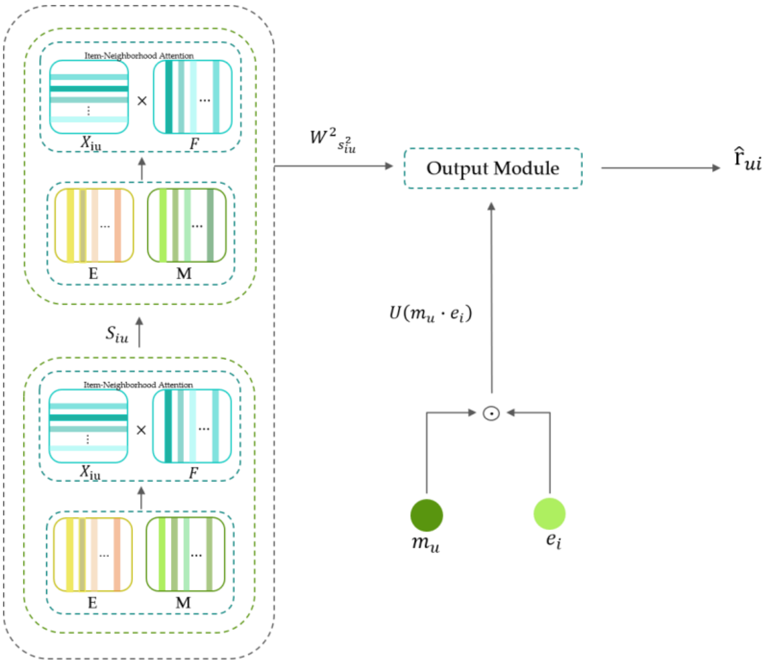

Fig. 2. Two memory stack. The stacking of the two memory components allows us to dynamically obtain the weight information generated by the attention mechanism.

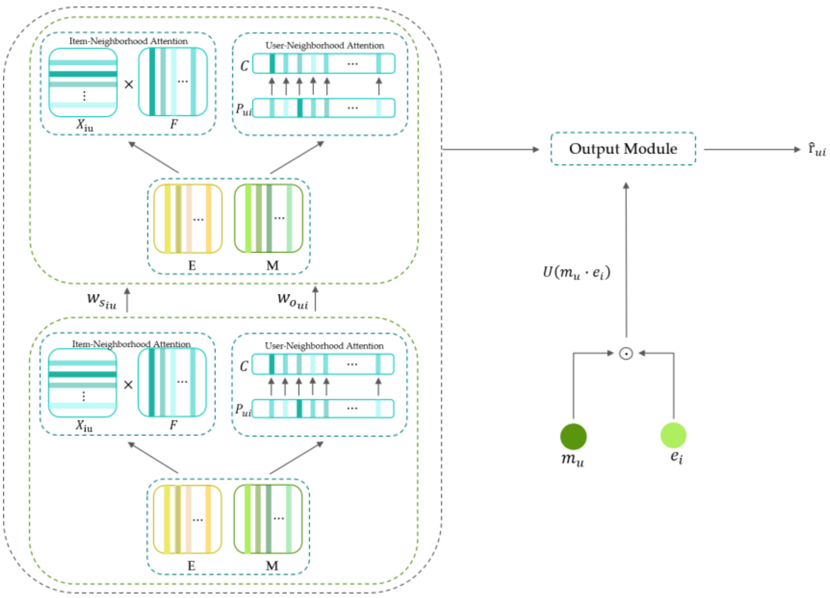

Fig. 3. Join the model of user information. Comparing with the original model after adding user information can clearly reflect the importance of project information and the non-negligible impact on users.

4 PERFORMANCE EVALUATION

In this section, we will introduce the data set and baseline settings used in the experiment, and experiment with the graphical data of the form.

4.1 Dataste

The dataset we use is the citeulike-a dataset, 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 specific information is shown in Table 1.

Table 1. Citeulike-a dataset information.

Ratings	Users	Items
204,987	5,551	16,980

4.2 Baselines

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

SVD ++: SVD ++ [17] is a hybrid model that combines neighborhood-based similarity and latent factor models.

GMF: The Generalized Matrix Factorization (GMF) [11] model is a nonlinearly extended potential factor model.

KNN: KNN [26] is a domain-based method for calculating cosine project-project similarity.

BPR: Bayesian Personalized Sorting (BPR) [25] is a matrix decomposition model of implicit feedback.

NeuMF: Neuromolecular Factorization (NeuMF) [11] is a matrix decomposition model for project ordering through a multilayer perceptron model.

CDAE: Collaborative Denoising Autoencoder (CDAE) [37] is a project-based deep learning model.

FISM: Factority Similarity Model (FISM) [15] is a neighborhood-based model that can decompose the similarity matrix of project-project pairs and optimize the loss function.

CMN: Collaborative storage networking 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 to 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, memory embedding. The size d is set to 50.

Table 2. 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	**0.8031**	**0.8932**	**0.6372**	**0.6666**
ICMN-u	0.7977	0.8879	0.6308	0.6603

4.3 Baseline Comparison

The data in Table 2 shows the experimental results of our model and each baseline model. Among them, ICMN-u adds the user's influence on the project, considering the impact of the project and the user on the other party and the neighborhood. We considered HR@5, HR@10, NDCG@5 and NDCG@10 were used as the basis for the evaluation of experimental results.It can be seen that our results have good results and performance on these four indicators. The improvement of ICMN performance not only indicates the optimization of the performance brought by the memory component, but also the processing of the weight by the attention component enables the model to obtain information more dynamically. More, the information and characteristics of the project itself are different for the user. The extent of the impact that cannot be ignored and the potential link between the project and the user.The experimental results show that our model is superior to all baselines. The experimental results of combining the project and user information into the model show that although superior to the CMN model, it is slightly insufficient compared with the model that focuses on project information.

5 CONCLUSION

In this paper, we propose an item-level collaborative memory network (ICMN) that can focus on the impact of the project level, which not only takes into account the attractiveness of the project to the user, but also fully considers the distribution of the potential relationship between the project and the user. To strengthen the relationship between specific projects and neighborhoods, in addition, we also consider the impact of users and projects on each other and the neighborhood.This enables our network to perform well on larger data sets.The attention mechanism also enables more rational, dynamic, and personalized processing of project features to obtain more comprehensive user preference information.We compared the other eight baselines on the citeulike-a dataset.In future work, we want to add time information or other information that more fully reflects user and project relationships to our network.

References

1. Author, F.: Article title. Journal 2(5), 99–110 (2016).
2. Author, F., Author, S.: Title of a proceedings paper. In: Editor, F., Editor, S. (eds.) CONFERENCE 2016, LNCS, vol. 9999, pp. 1–13. Springer, Heidelberg (2016).
3. Author, F., Author, S., Author, T.: Book title. 2nd edn. Publisher, Location (1999).
4. Author, F.: Contribution title. In: 9th International Proceedings on Proceedings, pp. 1–2. Publisher, Location (2010).
5. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
6. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
7. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
8. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
9. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
10. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
11. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
12. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
13. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
14. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
15. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
16. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
17. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
18. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
19. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
20. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
21. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
22. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
23. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
24. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
25. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
26. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
27. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
28. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
29. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
30. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
31. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
32. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
33. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
34. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
35. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
36. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
37. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
38. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
39. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
40. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
41. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
42. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.
43. LNCS Homepage, http://www.springer.com/lncs, last accessed 2016/11/21.