An Attention-Based Friend Recommendation Model in Social Network

Chongchao Cai[1, 2], Huahu Xu[1, *], Jie Wan[2], Baiqing Zhou[2] and Xiongwei Xie[3]

Abstract: In social networks, user attention affects the user's decision-making, resulting in a performance alteration of the recommendation systems. Existing systems make recommendations mainly according to users' preferences with a particular focus on items. However, the significance of users' attention and the difference in the influence of different users and items are often ignored. Thus, this paper proposes an attention-based multi-layer friend recommendation model to mitigate information overload in social networks. We first constructed the basic user and item matrix via convolutional neural networks (CNN). Then, we obtained user preferences by using the relationships between users and items, which were later inputted into our model to learn the preferences between friends. The error performance of the proposed method was compared with the traditional solutions based on collaborative filtering. A comprehensive performance evaluation was also conducted using large-scale real-world datasets collected from three popular location-based social networks. The experimental results revealed that our proposal outperforms the traditional methods in terms of recommendation performance.

Keywords: Friend recommendation, collaborative filtering, attention mechanism, deep learning.

1 Introduction

With the rapid development of the Internet and the popularization of smartphones, social networks have proliferated inevitably, affecting their users' way of thinking, behaviors, and habits greatly. It becomes more and more difficult for users to find friends with similar interests or buy products meeting their needs. Friend and/or product recommendations can be made through some attention mechanisms or keywords/labels collected from social media to improve the social experience of users. Thus, recommendation systems are crucial to solve the problem of information overload, where the methods based on social networks come to the forefront. Particularly, friend recommendation systems can suggest potential friends for users according to their current

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[1] School of Computer Engineering and Science, Shanghai University, Shanghai, 200444, China.

[2] College of Logistic and Information Engineering, Huzhou Vocational & Technical College, Huzhou, 313000, China.

[3] Google, New York, USA.

[*] Corresponding Author: Huahu Xu. Email: xuhuahu123@outlook.com.

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friends and past behaviors to enhance the stickiness between users and social networks [Shih, Lee and Chen (2018)]. The traditional collaborative filtering algorithm [Hu, Koren and Volinsky (2018); Koren (2018)] predicted user preferences based on their past behaviors while neglecting the relationships between users. In social networks, the relationships between users and items, published by users, are usually highly related [Ren, Liang, Li et al. (2018); Yang, Lei, Liu et al. (2018); Mnih, Heess and Graves (2018)]. In other terms, users tend to interact with other users with similar interests.

Although the social network-based recommendation systems include the relationship between users, they do not fully consider that different users may have different perceptions on the same topic. Therefore, this paper focuses on how to introduce the attention mechanism to solve the problem of different weight proportions in social networks.

The attention-based model is inspired by the human brain's attention model of cognitive psychology. Google Mind [Chorowski, Bahdanau, Serdyuk et al. (2015)] employed the attention mechanism for the first time to classify images in the RNN (Recurrent Neural Network) model. Subsequently, the attention mechanism achieved satisfactory results in NLP fields, such as machine translation and text summarization [Rush, Chopra and Weston (2018)], which was also introduced into the social network-based recommendation systems. For example, Chen et al. [Chen, Zhang, Liu et al. (2018)] revealed that the item expressed by users in social networks was based on different themes, and the weight of different stakeholders for different themes on the user impact was different. Hence, it was shown that the attention mechanism could improve the accuracy of the recommendation system.

Traditional recommendation algorithms typically use a certain feature, such as rating, user topic, and location information. However, the impact of attention on the relationship between the users has not been investigated in-depth yet. For example, a movie recommendation system has to utilize various types of feature data, such as followers, influence, and types, for in-depth mining of user behaviors [Cheng, Koc and Harmsen (2018)].

In the light of above-summarized literature, this paper proposes an attention-based friend recommendation (ABFR) system based on user relationships and user items. First, user and item feature representations are obtained, respectively. Using the attention mechanism, users' specific feature preferences are learned from their historical behaviors based on a multi-layer perceptron neural network. Then, the different roles of a specific user are learned from its historical behavior to predict the new item that the user may publish and acquire the user's preferences for each behavior. The user-friend feature representation is considered, and two layers of the attention network are used to model the different influence intensities between users and friends. Finally, these three parts are integrated through an end-to-end training process to support each other. The effectiveness of our model is validated by the experimental results.

The main contributions of this paper are summarized as follows.

1) For the first time in the literature, we used attention model and deep learning to improve the recommendation performance.

2) We construct user preferences from historical behaviors and integrate the user-friend preference relationship into the recommendation model.

3) Extensive simulations conducted on benchmark datasets demonstrate that our proposal, ABFR, outperforms the state-of-the-art models.

2 Related works

We categorize the existing studies under three groups that are relevant to our work: i) a social recommendation system, ii) a social recommendation system based on attention mechanism, and iii) an attention mechanism regarding social influence.

2.1 Social recommendation system

With the widespread utilization of social networks and related applications, there are more and more studies on friend and item recommendations. In social networks, user preferences and interests are dynamic. Song et al. [Song, Xiao, Wang et al. (2018)] constructed a neural network based on a dynamic attention graph to form user influences according to their current interests in items. Sun et al. [Sun, Wu and Wang (2018)] proposed that user preferences are determined by dynamic and static concerns of their published content, and thus constructed an RNN mechanism. Besides, Wang et al. [Wang, Wu, Sun et al. (2019)] established a trust-aware collaborative de-noise auto-encoder (TDAE) for deep learning using the scoring matrix and the user trust relationship. Furthermore, Lu et al. [Lu and Feng (2020)] introduced the concept of the adversary network model in deep learning.

2.2 Social recommendation system based on the attention mechanism

Seo et al. [Seo, Huang, Yang et al. (2018)] used a dual attention mechanism to separately build a parallel user feature network and a project feature network, predicting the possible project scores provided by specific users. Additionally, Wang et al. [Wang, Yu, Ren et al. (2018); Zhang, Chang, Yan et al. (2019)] introduced the single attention model into news recommendation. The input of the model was plain text and the category information of articles, and the output was 0/1, indicating whether the input news was selected. Chen et al. [Chen, Sun and Bing (2018); Ren, Zhu, Sharma et al. (2020)] put forward a special topic emotion analysis based on the attention memory network, which combined multiple location attention mechanisms in a non-linear way. Their model was able to deal with sentences that are more complex.

The attention mechanism was introduced into the neural networks, machine translation, and natural language processing by Google Mind [Chorowski, Bahdanau, Serdyuk et al. (2015)] for the first time in literature. Recently, various recommendation systems have also utilized the attention mechanism and achieved satisfactory results. In these studies, items and historical behaviors published by users were divided into two layers: category and feature. Regardless of the category or feature, the weight was always considered the same in the previous studies. However, both categories and features had different preferences when the attention mechanism was introduced. Experimental results indicated that the attention mechanism was effective in terms of recommendation performance. After the mechanism has been proved to be effective, it has been widely used in tag recommendation [Li, Liu and Hu (2018); Li, Song, Gao et al. (2019); Yang, Zhu and Li (2018)], POI recommendation [Ye, Yin, Lee et al. (2011)], friend recommendation [Song, Xiao, Wang et al. (2018); Chen, Wang, Shi et al. (2018); Liu, Zhang, Fu et al. (2018)].

3 Preliminaries

3.1 Matrix factorization model

Matrix factorization [Koren, Bell and Volinsky (2018)], widely used in recommendation systems, is based on dividing the original larger matrix into two small matrices. If the user content rating matrix A is of $m \times n$ dimensions, it means that there are m users and n items. Through a set of an algorithm, matrix A is transformed into two matrices, u and v. The dimension of matrix U is $m \times K$ and matrix V is $n \times K$, i.e.,:

$$A_{m*n} = \mathrm{U}_{m*k} V_{n*k}^{t} \tag{1}$$

Boutsidis et al. [Boutsidis and Gallopoulos (2018)] mapped the users and objects into a k-dimensional space, which is called the latent factor. The loss function of the basic matrix decomposition algorithm SVD can be expressed as:

$$\min_{p,\mathrm{q}} = \sum_{i=1}^{U} \sum_{j=1}^{T} (R_{i,j} - p_i^T q_j)^2 + \lambda(\left\|p_i\right\|^2 + \left\|q_j\right\|^2) \tag{2}$$

The matrix factorization algorithm follows the steps below:

1) Prepare the matrix of use items;

2) Initialize the element values of the matrix;

3) Calculate the predicted score with matrices U and V;

4) Calculate the error using the predicted and the actual scores;

5) Change the element values in matrices U and V according to the direction of the gradient.

3.2 Convolutional Neural Network (CNN)

This paper adopts CNN [Luo, Qin, Xiang et al. (2020); Li, Cao, Chen et al. (2017); Sun, Shi, Yin et al. (2019)] as the deep learning model, where the input is often identified by a matrix in the NLP task. The output vector processed by word2vec is named as word-embedding. Besides, CNN is used to extract the data features for the processed matrix. Fig. 1 illustrates how CNN is adopted into the recommendation system.

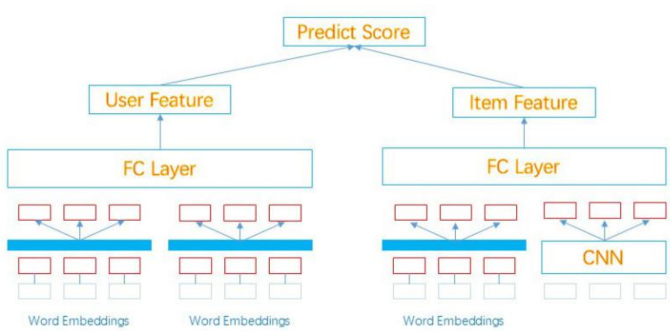

Figure 1: The CNN model

The first layer of the network is the word-embedding layer, which is a matrix composed of embedding vectors of each word. In the second layer, the embedding matrix is convoluted by using several convolution kernels with different window sizes.

4 Attention-based friend recommendation model

In social networks, users and items have different influences. For the same content, the items published by users with more fans will be recognized more, receiving more attention. Considering that the influence of attention among users is not the same as their interests and emotional tendencies, an attention mechanism is introduced into the friend recommendation system in this paper, and the attention-based friend recommendation (ABFR) model is developed. We first constructed the user and item matrices via CNN [Wang, Jiang, Luo et al. (2019)], and then introduced the attention mechanism. The first layer focuses on the user preferences for the item features, the second layer explores the user preferences for different items, and the third layer highlights user preferences for different friend characteristics. Our model adopts matrix factorization as the objective function, which can be defined as:

$$\hat{R}_{i,j} = (\mathrm{u}_i + \sum_{l \in S_i} \alpha_{(i,l)} \beta_{(i,l)} f_{(i,l)})^T v_j \tag{3}$$

4.1 Layer 1: Learning user features for different items and calculations

The social network recommendation system mainly considers users and their items.

Def 1: The item features of users include gender, number of fans (the people who pay attention to them), and the topics of interest. The user feature set can be defined as $u_f = \{u_{f_1}, u_{f_2}, \ldots u_{f_n}\}$.

Def 2: The items published by users include several features, such as emotional tendencies, number of evaluations, likes, and shares. Hence, the theme features can be expressed as $t_f = \{t_{f_1}, t_{f_2}, \ldots t_{f_n}\}$.

The calculation process of the first layer is as follows:

1) Input user and item into the embedding layer, and obtain the vector representation of the corresponding features;

2) Using CNN, obtain the feature representation of user and item, namely U_f and M_f, respectively;

3) Introduce the attention mechanism to dynamically allocate the weight;

4) Acquire the user's learning preference for the item.

Currently, ReLU [Hinton (2018)] is the most popular activation function in the world, which is used in almost all CNN and deep learning algorithms.

$$\alpha^*_{i,f} = \mathrm{Re}\,LU(w_i S_{i,f} + b_f) \tag{4}$$

where $S_{i,f}$ is the first topic feature in the content published by user $\boldsymbol{I}$, and $\boldsymbol{W_i}$ and $\boldsymbol{B_i}$ are the parameters that can be learned. The weight can be obtained by using ReLU [Hinton (2018)] as the activation function, i.e.:

$$\alpha_{i,f} = \frac{\exp(\alpha^*_{i,f})}{\sum_n \exp(\alpha^*_{i,f})} \tag{5}$$

Through the above-explained learning mechanism, we can obtain user preferences for item features and understand user behavior in social networks. Hence, the attention mechanism is used to designate user preferences for the "different" items.

4.2 Layer 2: Learning user preferences for different items

The calculation process of the second layer is described as follows:

1) Acquire the topic from the user's behavior;

2) Take the user's preference and topic from the first layer as the input layer;

3) Process the features through the embedded layer;

4) Introduce the attention mechanism and output the user's preference for the topic type.

The user UI's preference for the first topic can be expressed as:

$$\beta^*_{i,1} = \mathrm{Re}\,LU(W_1 u_i + W_2 \alpha_{i,1,f} + b) \tag{6}$$

where ReLU is the activation function, $\boldsymbol{U_i}$ is the first topic published by the user, $\boldsymbol{f}$ is the preference in the first topic, and W_1, W_2, and b are the parameters that can be learned. The influence of the weight and the bias of the current topic to be predicted and recommended are provided in (6), which can also be expressed as:

$$\beta_{i,1} = \frac{\exp(\beta^*_{i,1})}{\sum_n \exp(\beta^*_{i,1})} \tag{7}$$

Through the above-explained model, user preferences for different types of items can be learned as the next network input layer.

4.3 Layer 3: Learning different preferences between friends

In this part, we use the attention mechanism to learn user preferences for items. In social networks, different friends have different influences on users with the same attention relationship. Considering that, the attention mechanism is introduced to learn user preferences for different friends, which is combined with topic preference attributes. The objective function can be expressed as:

$$f^*_{i,1} = \mathrm{Re}\,LU(W_1 u_i + W_2 \beta_{i,1} + b) \tag{8}$$

where $\beta_{i,1}$ represents the user's preference attribute for the topic, and W_1, W_2, and b are the parameters that can be learned. The normalization is performed as:

$$f_{i,l} = \frac{\exp(f^{*}_{i,l})}{\sum_{n} \exp(f^{*}_{i,l})} \tag{9}$$

The weight preference of each friend can be obtained through the above-given learning mechanism. Hence, the end-user i can be expressed by:

$$\mathrm{U}_i = \mathrm{u}_i + \sum_{l \in S_i} \alpha_{(i,l)} \beta_{(i,l)} f_{(i,l)} \tag{10}$$

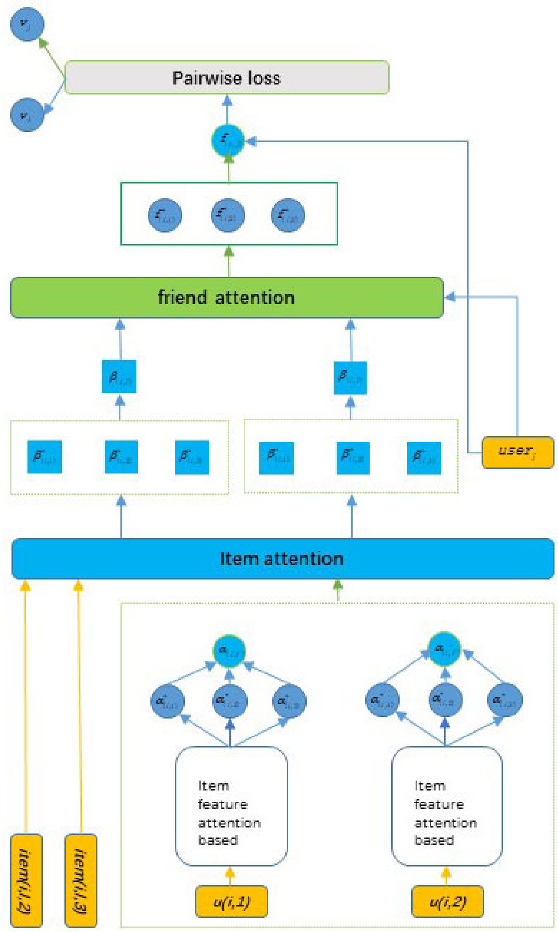

Figure 2: Illustration of our attention-based friend recommendation module

5 Experiments

5.1 Experimental datasets

We used three publicly available datasets, namely Delicious, Douban, and Epinions, in our experiments to evaluate the model performance. The details of each dataset are provided below:

Delicious: contains social connections, bookmarks, and tag information of 2000 users extracted from Delicious.com. It is simply an online bookmarking system, in which users can store, share, and discover web bookmarks, besides assigning various semantic tags to them.

Douban: is a popular website, allowing its users to watch movies, listen to music, and read books. The dataset includes user identities (in the movie community), movie reviews, and the social networks of users. The data collection time spans from December 2008 to January 2016.

Epinions: is a website, where users can review products. It allows users to register for free and start writing subjective reviews about any item possible.

The statistical details of these datasets are presented in Tab. 1.

Table 1: The statistical details of the datasets used

	Delicious	**Douban**	**Epinions**
Users	1,521	29,325	27,086
Items	1,202	12,282	18,785
Events	8,397	599,821	409,782
Social links	10,401	292,345	373,415

5.2 Baselines

The effectiveness of our proposed method is validated through comparisons with the following methods:

1. User CF [Gurini, Gasparetti, Micarelli et al. (2018)], which constitutes personalized recommendation lists.

2. SocialMF [Jamali and Ester (2018)], which considers the user association relationships in the recommendation system. Although it does not fully consider user preferences, it achieves good results.

3. SBPR [Guo, Zhang, Zhu et al. (2018)], which uses Bayesian maximum posterior estimation to find the total ordering relationship between the user-friend pairs.

4. SoReg [Ma, Zhou, Liu et al. (2018)], which uses social networks to regularize the latent user factors of matrix factorization.

5.3 Evaluation metrics

The effectiveness of our proposed method is validated through three evaluation dimensions: MAE, Recall@K, and NDCG@K.

MAE evaluates the difference between the ratings predicted by the recommendation system and given by the users, which can be formulated as:

$$MAE = \frac{1}{|R|} \sum_{r_{(u,j)} \in R} \left| r_{u,i} - \hat{r}_{u,i} \right| \tag{11}$$

DCG evaluates the results of the recommendation system. Its basic idea is that the documents should appear on the top position of the return list if the correlation between the documents in the return list and the input documents is strong. DCG can be defined as:

$$DCG_u = \sum_{k=1}^{N} \frac{2^{r_k} - 1}{\log(k+1)} \tag{12}$$

where K is the location of the items in the recommendation list, and R_k is the correlation between the items sorted by K and the input items in the recommendation list. NDCG can be defined as the cumulative gain of the impairment, i.e.:

$$NDCG_u = \frac{DCG_u}{IDCG_u} \tag{13}$$

5.4 Experimental results

MAE is utilized to compare the recommendation performance of the method proposed in this paper and the existing SocialMF, CF, SBPR, and SoReg. Fig. 3 illustrates the results obtained with three datasets.

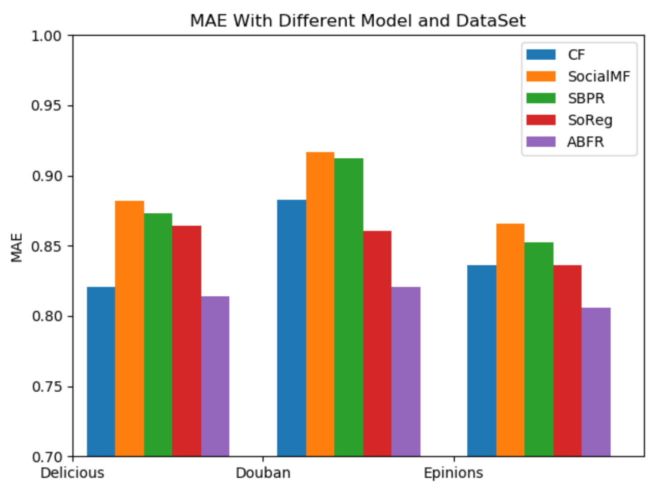

Figure 3: MAE results for different datasets

As demonstrated in Fig. 3 the error of SocialMF in terms of MAE is relatively small while that of the traditional CF is the worst. Besides, the social network-based method SocialMF alleviates the problem of data sparsity in the recommendation system. Considering the features of social networks, such as items' emotional tendencies, the performance of MAE can be improved. For the best performance, however, the attention mechanism needs to be integrated into the recommendation system.

Table 2: Performance comparison of all methods for three datasets

Delicious	**Recall@10**	**Recall@20**	**NDCG@10**	**NDCG@20**
CF	0.1177	0.1429	0.0711	0.0826
SocialMF	0.1182	0.1454	0.0732	0.0851
SBPR	0.1238	0.1514	0.0747	0.0855
SoReg	0.1173	0.1446	0.0739	0.0847
ABFR	**0.1265**	**0.1532**	**0.0794**	**0.0868**
Douban				
CF	0.1375	0.1718	0.0817	0.1041
SocialMF	0.1392	0.1734	0.0835	0.1174
SBPR	0.1445	0.1798	0.0848	0.1202
SoReg	0.1413	0.1766	0.0842	0.1176
ABFR	**0.1495**	**0.1812**	**0.0898**	**0.1276**
Epinions				
CF	0.0664	0.0816	0.0388	0.0518
SocialMF	0.0697	0.0842	0.0437	0.0547
SBPR	0.0746	0.0892	0.0467	0.0556
SoReg	0.0721	0.0883	0.0451	0.0548
ABFR	**0.0798**	**0.0921**	**0.0557**	**0.0577**

It can be observed from Tab. 2 that the accuracy of recommendation increases with increasing K, while the performance of the traditional CF algorithm gets worse. Therefore, it is evident that the relationships between users in social networks must be considered for recommendation performance. Despite used commonly, SocialMF and SBPR do not consider that different weights of different friends have varying influences on the users. Thus, their recommendation accuracies are lower than the ABFR algorithm.

The following observations can be drawn from the results: i) the methods using social information usually outperforms the methods without social information; ii) our method, ABFR, is consistently and significantly superior to all baselines with high-performance gains of other indicators; iii) since ABFR has the same loss function as other baselines, we can attribute the performance improvement to the proposed attention-based memory module and friend level attention.

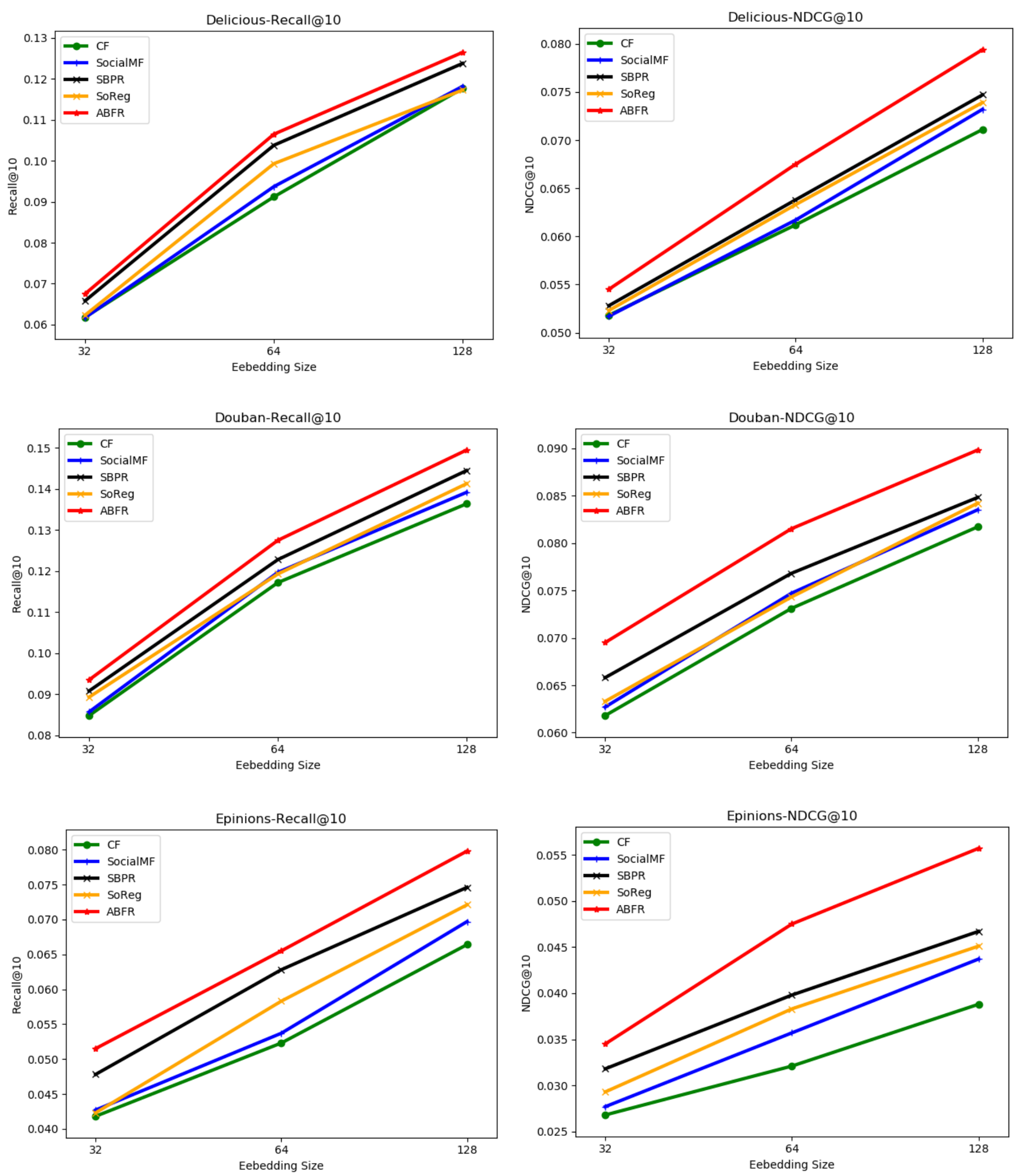

Figure 4: Performance comparison of datasets with different embedding sizes

We also performed experiments to test the influence of latent factor size d on the validation sets. The results of three datasets on Recall@10 and NDCG@10 metrics are presented in Fig. 4. As seen, our model outperforms the other models with different values of d. Furthermore, the performance of all models improves as the latent dimension size increases. This indicates that a larger dimension can capture more hidden factors of both users and items.

6 Conclusions

In social networks, the relationships between users play a crucial role in the accuracy of friend recommendation. Since different users have different preferences for items, the weight of users interacting with each other will be also different. Therefore, a friend recommendation system is designed in this paper based on a multi-level attention mechanism. First, the relationships between users and item features are used to obtain user preferences for item features. Then, the relationships between the users and each topic in the content are used to acquire user preferences. Finally, the relationships between users and friends are inputted into the model to learn the preferences between friends. Compared to the traditional recommendation algorithms, the three evaluation metrics, MAE, Recall@K, and NDCG@K, have been significantly improved. Our future studies will focus on the weak ties between users and friends in social networks and investigate how the attention-based mechanisms can improve the accuracy of the friend recommendation process.

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