An Multi-Aspect Attentional Model To Capture Multistratal Influence In Social Group

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***Abstract*—The recommendation system is an effective means to handle "information overload", and it is also one of the most common applications of big data technology. As an important sub-field in recommendation algorithms, social recommendation effectively enhances performance via using social relationships in online social network platforms. However, there are still two problems in the existing social recommendation models: Firstly, user's preference for item has multiple aspects of information, and its social neighbors only match or influence the target user's preferences in some aspects; Secondly, different friends have varied and dynamic influence on user at target item. To solve the problems, we propose a novel social recommendation model: SMAAM (Social-aware Multi-Aspect Attentional Model). We designed a multi-layer attention mechanism to capture the different levels of influence of social neighbors on users and their multiple aspects of views of items, and then select the most valuable friends and aspect information to model user preferences. The experimental results on two different public datasets explain that our model has more stable and excellent performance than some previously published models. In addition, we have also done some visualization of experimental process data to verify the effectiveness and correctness of the model on learning process and design ideas.**

Keywords- Social Recommendation; Multi-Aspects; Attention Mechanism

I. INTRODUCTION

In the era of information explosion, users would like to receive more valuable information in e-commerce and social media platforms. In order to solve the problem of information overload and generate personalized recommendations, recommender system was proposed. However, in the actual application scenarios of recommendation, due to the insufficiency of user's own interactive behavior and the information cocoon effect caused by excessive focus on the historical behavior of user, it is difficult for traditional recommendation algorithms to make more accurate and diverse recommendations. At present, many recommendation algorithms are based on Collaborative Filtering (CF), and the latent space modeled on this method has achieved great success. However, due to the scarcity of user-item interaction history, recommender system based on CF always could not obtain a satisfied performance.

On e-commence sites, users like to spread their preferences for goods into their social relationships. On the one hand, we can use the interactive information provided by friends to enhance the performance of recommendation; on the other hand, we can regularize users' underlying preferences via social information. Generally, there are two categories in social relationship: equal social relationships in undirected graph and follower-followee relationships in directed social graph. From the perspective of the content of datasets and training target, our work is based on undirected social networks.

At present, there are two problems in the existing algorithms of social recommendation that have not been fully studied. First, user only shows similar preferences in certain aspect with his friends. For example, user B and C both in A's social group. Although they like listening to songs, A and B pay more attention to the style of the song, and A and C have similar attention to the author of the song. Because user preference inference is usually complex and non-linear [5], aspect-level variance is difficult to capture by traditional CF models.

The second problem is that the mutual influence between social groups is different and dynamic. For example, if a user likes classical music, he will exchange opinions with a friend who likes classical music, but when a singer he likes releases a new song, he will go to other friends who also like the singer share it. In the traditional CF model, social influence is usually set to be equal, or rely on a predefined static function.

Inspired by the above questions, we propose a new social recommendation model that combines multiple latent aspect representation modules and multi-layer attention modules to improve the effect of recommendation.

In summary, our main contributions are as follows:

1. We propose a novel model for social recommendation. This model also considers the differences in views on item among user's friend and the differences in friend-level influence.

2. As far as we know, we apply aspect-level difference modeling to the item side for the first time, model the feature information of item into multiple different feature vectors, and finally use the attention mechanism to integrate them. At the same time, in user-side modeling,

we also utilize the multi-aspect feature information of the item.

3. We employ our model on two public datasets and validate that SMAAM has a consistent performance and better than state-of-the-art models.

II. Related Work

A. Traditional Collaborative Filtering

Matrix Factorization is one of the most popular methods among traditional CF methods, which is also the basis of many efficient recommendation models [13,14]. The early matrix factorization method aims to model user's explicit feedback by mapping users and items to the latent factor space [15], so that relationship between user and item can be obtained through the dot item of its latent factors (usually expressed as a score). Recently, some researchers have designed more advanced neural models based on latent factor models and matrix factorization. For example, NCF [1] models the complex relationship between users and item through using neural network structure. Although these deep embedded models have improved performance compared to previous shallow models, this model still fails to get rid of the problems caused by data scarcity. Because of the lack of user historical interaction data, although the powerful nonlinear relationship learning ability of neural networks can be used to try to model user preferences, compared to those models that can effectively use user social relationships, this type of simple recommen-dation model could not achieve a better performance.

B. Social Recommendation

In the past few years, most studies assume that users' decisions will be affected by the views and consume behaviors of their friends. For example, in the study of [12], they assumed that users might see the goods consumed by their friends, and expanded BPR by changing the negative sampling strategy. Jamali [2] designed a model based on social influence communication (SocialMF). Later, a new model based on influence was proposed, which used the embedded information in user's social network and the social influence of friends to recommend.

The SAMN model [5] proposed in 2019 mentioned multiple perspectives and designed a two-level attention mechanism to model social influential information, but the model ignored the multi-aspect feature modeling of item, resulting in insufficient item features.

In the same year, there was also the use of graph structure network to model complex and non-linear social relations work published [4], this model has achieved quite successful results through graph neural network modeling of social relations, and has implications for later related research directions. Certain reference significance. But it still failed to consider the issue of aspect level differences.

To the best of our knowledge, among all the published research results of social recommendation, there are few neural network structures that pay attention to the difference on the opinion level of friends and the aspect level of items, which is the main concerns of our work.

III. The Proposed Model

In this section, the proposed Social-aware Multi-Aspect Attentional Model (SMAAM) is introduced. First, we will briefly show the overall design and structure of our model. Then, we will present detailed formulations of each important module. Lastly, optimization details of SMAAM that we adopt are going to be introduced.

A. Problem Formulation

In our recommendation model, we have a user set **U** with N users and an item set **V** with M items. User's rating of items is given in the user-item matrix $\mathbb{R}^{N \times M}$. In the scoring matrix, r_{ij} indicates whether there is any interaction between the i-th user and the j-th item. Existence is set to 1, otherwise it is 0. At the same time, we define Social(i) and H(i) to represent the set of social neighbors of user i and the set of items he interacted with.

B. Architecture of SMAAM

The goal of our model is to make recommendation based on implicit feedback and social network information. Both aspect-level and friend-level information can be used to improve model's performance and capability of generalization.

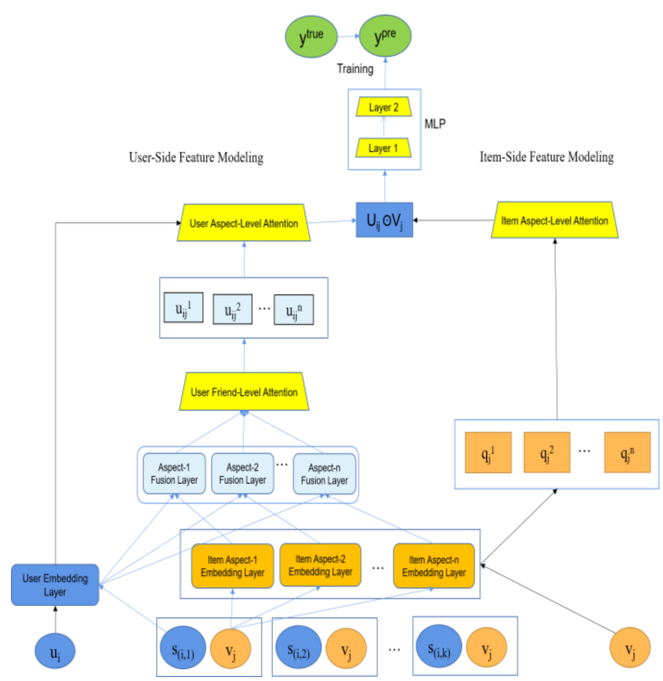


Figure 1. The framework of SMAAM

From Figure 1, we can briefly summarize our model: (1) Use the embedding layer to transform users and items into a dense matrix representation, and the items are projected into different latent spaces through multiple embedding layers. (2) The model is divided into two parts of the user side and the item side. On the user side, multiple embedding vectors of the item and the user's embedding vector are respectively integrated, and at the same time, multiple friends of the user who have also interacted with the item are input as social information. (3) There are two levels of attention on the user side to model the information difference between the aspect level and the friend level, and a layer of attention is set on the item side to get the final item feature representation. (4) The model is optimized through paired ranking and negative sampling strategies.

TABLE I. SUMMARY OF NOTATION

Symbols	*Definition and Descriptions*
U	set of users
V	set of items
R	user-item interaction matrix
Social(i)	set of user i's friends
H(i)	set of user i's items
p_i	the primary embedding of user i
q_{ij}^n	the n-th embedding of item j which friend i has interact with
f_{ij}^n	the n-th embedding of friend i on item j
u_{ij}^n	the n-th embedding of user i on item j
U_{ij}	the final representation of user i
V_i	the final representation of item i

C. Multi-Attentional User-Side Feature Modeling

Most social recommendation models will use embedding layer to learn the representation of the underlying relationship between users and users and items. We use p_i to represent the initial feature vector of the i-th social neighbor of the target user, and q_{ij}^n to represent the initial feature vector of the j-th item interacted by the i-th social neighbor in the n-th latent aspect.

We input the embedding feature vectors of user's friends into the fusion layer, which is implemented by a multi-layer perceptron. In the fusion layer, we merge the user's embedding vectors and the embedding vectors of each aspect of the item to form multiple different feature vectors to represent user's preference information in multiple aspects. Eq. (1) show output of aspect-n fusion layer.

$$\mathrm{f}_{\mathrm{ij}}{}^{\mathrm{n}} = g(W_f * [p_i, q_{\mathrm{ij}}^n] + b_{ij}^n) \tag{1}$$

After we obtain the fusion vector of each friend i in aspect n, the first attention layer learns different information among social group in each aspect. Each component of the attention's output is marked as:

$$\mathrm{e}_{tj}^n = W_2^T \sigma(W_1(W_{\mathrm{u}} f_{tj}^n \oplus W_v q_j^{\mathrm{n}}) + b_1) + b_2 \tag{2}$$

$$\alpha_{tj}^n = \frac{\exp(e_{tj}^n)}{\sum_{s \in Social(i)} \exp(e_{sj}^n)} \tag{3}$$

In this step, we use the embedded feature vector in one aspect of item as a query vector. Finally, the weighted feature vectors of the social group joined with the embedding vector of user i to get the feature vector of user in one aspect:

$$u_{\mathrm{i}j}^n = \sum_{t \in Social(i)} \alpha_{tj}^n f_{tj}^n + \mathrm{p}_i \tag{4}$$

In the user aspect-level attention, we use the self-attention mechanism to fuse the target user's feature information in multiple aspects. After the softmax function, the feature vector of each aspect is weighted and summed to obtain the final user-side representation (U*ij*):

$$\alpha_{\mathrm{ij}}^{\mathrm{n}} = soft\max((Wu_{ij}^n + b)^T h) \tag{5}$$

$$U_{ij} = \sum_{k=1}^{n} \alpha_{ij}^k u_{ij}^k \tag{6}$$

D. Multi-Aspect Item-Side Feature Modeling

On the item side, an item j is inputted into multiple embedding layers to obtain embedding vectors in multiple aspects. At the same time, these embedding vectors are also shared to the user side, ensuring the consistency of item feature learning. Then use a self-attention layer to merge the embedding vectors of multiple aspects of the item to obtain the final feature representation (V*j*).

E. Learning

Prediction. Our recommendation task is designed as a ranking problem based on estimated score of the whole item set. After completing feature modeling for both user and item, we use a multi-layer perceptron to make the final prediction score.

First, we will concatenate the final representation of user (U*ij*) and the item (V*j*) that we have obtained to form a vector F*ij*. Finally, we input this final vector into a 2-layer fully connected neural network, and get user's estimated score for item.

$$F_{\mathrm{ij}} = [U_i, V_j] \tag{7}$$

$$y_{ij}^{pred} = W_{n+1}{}^T(\sigma(W_n^T F_{ij} + b_n)) \tag{8}$$

Using a standard multi-layered perceptron (MLP) makes SMAAM more flexible and gain non-linear ability to learn the relationship between user and item.

Optimization. Our prediction part is based on implicit feedback, which is more common in practice, and can be automatically collected [16] (such as the number of clicks, the amount of consumption, whether to browse). For this reason, we opt the BPR loss function as the optimization objective, which is the commonly used pair-wise objective function in many previous similar optimization tasks [6].

For each positive user-item pair, a random sampling strategy is used. multiple negative samples from items are opted from those items which user has no interaction, which is denoted as k∈Neg$_{ij}$. The BPR loss function is as follows:

$$L_{BPR} = \sum_{(i,j,k)\in D} -\log(sigmoid(y_{ij}^{pred} - y_{k}^{pred})) + \lambda \quad (9)$$

We utilize mini-batch training combined with Adam as the main optimizer to optimize the objective function. Its main advantage is that in the training process, the learning rate can be adjusted adaptively, which makes the pre-setting of the learning rate less critical, and at the same time makes the speed of convergence faster [7].

IV. EXPERIMENTS

A. Experimental Settings

1) **Datasets**. In our experiments, we prepared two publicly accessible datasets for training and evaluating our model: FilmTrust [10] and Ciao [11]. We briefly introduce the two datasets:

- **FilmTrust**: This is a small dataset crawled from the entire FilmTrust website in June 2011. It contains users' ratings of movies and the trust between users [18].
- **Ciao**: Ciao is a dataset of the entire DVD category of UK websites in December 2013, crawled from dvd.ciao.co.

Characteristics of the two datasets are presented in Table 2.

TABLE II. CHARACTERISTICS OF THE TWO DATASETS

	#User	***#Item***	***#Interaction***	***#Social Link***
FilmTrust	1508	2071	35497	1853
Ciao	7375	105114	284086	111781

2) ***Baselines***. To evaluate the overall performance of our model, SMAAM was compared with the following baselines. Note that all models are trained by optimizing the same pairwise ranking loss of BPR for fair comparison.

- **SVD++** [3]: This a classic model based on latent factori-zation, which only uses user-item interaction history without other auxiliary information.
- **SocialMF** [2]: This is a classic social recommen-dation model based on collaborative filtering, while the influence is simply set equally for each friend.
- **SAMN** [5]: This is a recently proposed novel deep learning model which considered multi-level social influence.
- **DiffNet** [4]: This method utilized gragh neural network to model social relationship. It outperformed a lot of traditional social-aware recommendation models.

3) ***Evaluation Metrics***. For the TOP-K ranking problem, we opt two widely used indicators: HR and NDCG[8,9]. Specifically, HR measures the percentage of gains and losses among the top K popular items, while NDCG pays more attention to the top-ranked items [17].

$$HR@K = \frac{\sum_{i=1}^{N} Hit_i @K}{\sum_{i=1}^{N} NumInTest_i};$$

$$DCG@K = \sum_{j=1}^{K} \frac{2^{rel_j} - 1}{\log(j+1)}; \quad NDCG@K = \frac{DCG@K}{IDCG@K} \quad (10)$$

Since we pay more attention on the performance of the top-K of large item sets, we randomly selected 1,000 unrated items that users have not interacted with to evaluate their performance. Then, we mix these negative samples with positive samples in the test set to select the Top-K potential candidate items. The average result of 5 times repeated process was used to reduce the uncertainty in this process,

4) ***Experiments Details***. We randomly divide the data set into training set (70%), validation set (20%) and test set (10%). We used verification set to adjust the hyperparameters, and the performance comparison is applied on the test set. The parameters of the four comparison models have been initialized in their corresponding papers, and then carefully adjusted to achieve the best performance. The learning rates of all models are adjusted between [0.005, 0.01, 0.02, 0.05]. For the batch training process, we select the test batch size in [64,128,512]. For the dimension of the latent factor, we test in [32,64,128]. In order to prevent overfitting, we set offsets of different sizes to regularize.

B. Overall Comparision

Below we give the experimental results of SMAAM and four different models on two data sets in the Table 3. From the results in Table 3, we can get following conclusions:

- Methods that use social information generally perform better than methods that do not use social information. For example, SVD++, which does not use social information, performs far worse than other social-aware models on the two datasets.
- Neural network-based models usually obtain better performance than traditional methods due to advance nonlinear modeling in the feature interaction stage. Among all of baselines, the model based on graph neural network can usually achieve better performance on most indicators, which shows that the application of graph neural network in modeling high-order relationships between users is reasonable. This provides possible ideas for future improvements of our model.
- Our model SMAAM can always outperform other comparative models in all indicators on the two datasets, including SAMN and DiffNet. Although they can get a relatively ideal score in all indicators than other competitive models, our model can still maintain an improvement effect of more than 3% in most cases.

TABLE III. EXPERIMENTAL RESULTS FOR DIFFERENT MODELS ON FILMTRUST AND CIAO. THE BEST RESULTS ARE MARKED RED AND THE SECOND-BEST RESULTS ARE MARKED IN BLUE.

FilmTrust	HR@10	HR@20	HR@30	NDCG@10	NDCG@20	NDCG@30
SVD++	0.1284	0.2049	0.2101	0.1064	0.1241	0.1656
SocialMF	0.3515	0.4111	0.4474	0.2913	0.3085	0.3258
SAMN	0.5395	0.7806	0.8409	0.4587	0.5724	0.5927
DiffNet	0.5307	0.7721	0.8597	0.4631	0.5690	0.5968
SMAAM	0.5519	0.7878	0.8661	0.4836	0.5819	0.6183
%Improv	2.30%	0.92%	0.74%	4.43%	1.66%	3.60%

Ciao	HR@10	HR@20	HR@30	NDCG@10	NDCG@20	NDCG@30
SVD++	0.0598	0.0650	0.0692	0.0389	0.0408	0.0652
SocialMF	0.1035	0.1265	0.1485	0.0095	0.1082	0.1152
SAMN	0.1788	0.2043	0.2397	0.1501	0.1612	0.1693
DiffNet	0.1763	0.2102	0.2417	0.1621	0.1688	0.1759
SMAAM	0.1857	0.2266	0.2598	0.1773	0.1895	0.1922
%Improv	3.86%	7.80%	7.49%	9.38%	12.26%	9.27%

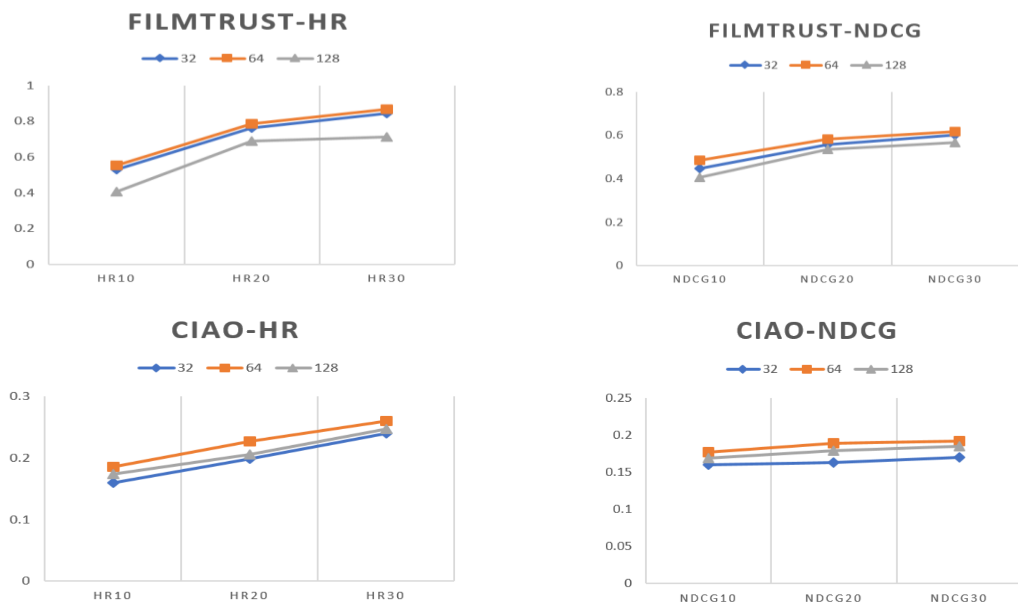


Figure 2. Performance comparison on two datasets and empoly different embedding sizes (validation sets)

- Since all models have been modified to TOP-K tasks, they must be modified to a same loss function. Based on this, improvement in performance is attributed to the capture of aspect-level and friend-level differences, as well as multi-aspect feature modeling on the item side. Because modeling information at a finer granularity can achieve better performance.

C. Feature Dimension Selection

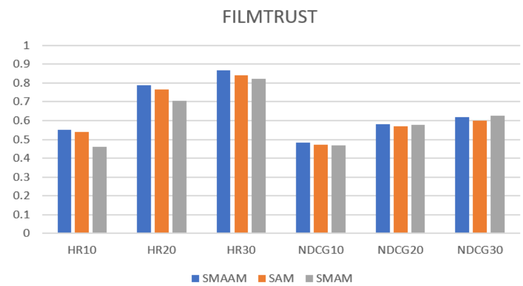
We did experiments on validation set in different size of feature dimension and results are showed on Figure 2. From the experimental results, on FilmTrust and Ciao, 64 as the feature dimension of the embedding layer to obtain better performance. At the same time, because the Ciao dataset user-item interaction and social information are more abundant than FilmTrust, 128 as dimension size originally performed the worst on FilmTrust can have relatively better performance on Ciao.

D. Effect of Multi-Aspect Item Embedding and Aspect-Level Attention Components

There are two key information modeling components in the SMAAM we proposed: the multi-aspect embedding feature of the item, which can model the feature information of multiple aspects of item by setting multiple embedding feature vectors; the multi-layered attentional layers for difference capturing, using Multi-layered attention captures the difference information at the aspect level and the user level in turn. In this section, we do some experiments on following variants of the SMAAM to validate effects and importance of each component.

- SAM: This variant model only sets up an item embedding layer, which can be seen as modeling information only from one aspect.
- SMAM: This variant model cancels the second layer of attention on user side. It directly averages the opinion information of all social neighbors instead of using the self-attention layer to capture differences.

Figure 3 presents results of comparison between SMAAM and its variants.



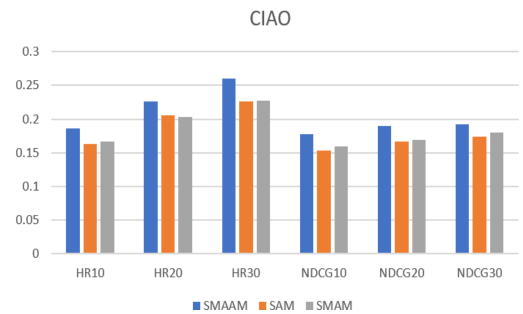


Figure 3. Effect of multi-aspect item embedding and aspect-level attention components

It can be seen from the results that the SMAAM has a relatively leading performance for all indicators on the FilmTrust data set, but the trend is not obvious. On Ciao, SMAAM has a better performance. Over all, the SAM variant has slightly better performance on FilmTrust than SMAM, but SMAM can perform better on Ciao. This may be because FilmTrust has limited data volume and user-commodity pairs are not enough to form sufficient multi-aspect feature modeling. On Ciao, the number of social relationships far exceeds FilmTrust, and a good amount of information can still be captured by averaging social neighbor information.

V. Conclusion

To the best of our knowledge, we are the first to utilize multi-embedding combined attention mechanism to model multi-aspect difference in social group. And we also adaptively measure the different influence in social group via self-attention. Through extensive experiments, we can get the following conclusions: (1) Social information plays a significant role in enhancing the performance of the recommender system; (2) The capture of differentiated information has a very important meaning in social recommendation, and effective capture can greatly improve model performance; (3) It is not easy to select too many or too few feature dimensions. Too much will cause the model to overfit and the training convergence speed will decrease. But lack of modeling space will not be possible to obtain the feature information completely.

In the future, we will explore the use of graph structure networks to improve the performance of our model. At the same time, the distribution of multi-polar views in social groups is also an interesting research direction. We can consider using it as additional information to optimize social recommendations.

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