Group recommendation method combining short-term interest and long-term preference

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Abstract: Based on self-attention and outer product-based neural collaborative filtering, this paper proposed a SLAR model. The model uses the recent interaction information of each user in the group and self-attention mechanism to obtain the short-term interest vector of the group. The attention mechanism and self-attention mechanism are used to calculate the influence of each user and the influence between members during the interaction between the target group and item, so as to aggregate them into the long-term preference vector of the group, and then the sum of short-term interest and long-term preference is input into ONCF model as the embedding vector of the group to mine the interaction between the group and the project from the data, and finally complete the group recommendation. Compared with the traditional group fusion strategy on CAMR2011 data set, the experimental results show that SLGR model achieves better results.

1. Introduction

With the rapid development of modern information technology, the amount of data transmitted on the Internet is becoming larger and larger, and people are facing a severe problem of information overload. The birth of the recommendation system alleviates the problem of information overload to a certain extent. The recommendation system selects items that users may be interested in from a large amount of data, provides personalized services for consumers, helps businesses adjust strategies to create new business opportunities, and effectively solves the long tail effect.

However, the current research on recommendation system mainly focuses on personalized recommendation for a single user. In fact, people make decisions in the form of a group in many scenes, such as class travel and family members watching movies together. In this case, the traditional recommendation system for individuals can not play its role. Therefore, it is necessary to study a more efficient group recommendation algorithm to apply to group recommendation scenarios.

Most of the existing group recommendation methods use predefined fixed strategies to integrate the preferences of group members[1]. In practical application, these methods do not make good use of the relationship and influence of group members, and are not enough to capture the complex and dynamic group decision-making process. To solve this problem, this paper proposes to use self-attention mechanism and attention mechanism to construct the short-term interest and long-term preference of the group, and obtain the embedding vector representing the group in a learnable way. Then an improved neural collaborative filtering model is used, which can make the group embedding vector...
and user embedding vector cross repeatedly, and the convolution neural network is used to predict the score of the group on the item. The main work of this paper includes: a) learning group representation from the perspective of short-term interests and long-term preferences; b) modeling the interaction between groups and items by ONCF model; c) experiments on data sets show that SLAR achieves better results.

2. SLAR

In order to obtain the group representation from the joint consideration of short-term interest and long-term preference, so as to predict the group preference, this chapter first formally describes the problem, and then describes the group recommendation algorithm proposed in this paper in detail.

2.1. Problem description

Firstly, there are user set $U = \{u_1, u_2, ..., u_{|U|}\}$, item set $I = \{v_1, v_2, ..., v_{|I|}\}$, group set $G = \{g_1, g_2, ..., g_{|G|}\}$, interaction matrix $Y$ between group and item, interaction matrix $R$ between user and item, and interaction time matrix $T$ between user and item in the model. The goal is to obtain an embedded representation of a group.

2.2. Group preference fusion strategy

This paper defines the preference vector of group $g_l$ for item $v_j$, which is composed of the long-term preference of $g_l$ and the short-term interest of $g_l$, as $g_l(j)$.

$$ g_l(j) = q_{ls} + q_{ls} $$

In the above formula, $q_{ls}$ represents short-term interest of group $l$ and $q_{lt}$ represents long-term preference of group $l$.

2.2.1 Group short-term interest

Unlike the basic attention model, which learns the representation under limited background knowledge, self-attention can maintain the sequence information of the context and capture the relationship between the elements in the sequence, regardless of the distance between them[2]. The Figure 1 shows the self-attention module that reflects the group's short-term interests in the article.

![Figure 1. Short-term interest structure of target group](image_url)
We assume that each user's short-term interest comes from $N$ recent interactive items. Therefore, we can obtain the nearest $N$ interactive items of each user in the target group through matrix $T$. As shown in the figure above, in order to obtain the group's short-term interest, the specific calculation process is as follows.

1) For the target group, we first obtain the item vector of his nearest $N$ interactive items with length $k$ for the first user in the group.

2) Then, the matrix $Z$ formed by the interactive items is used as the input Query, Key and Value of the self-attention module.

3) The nonlinear function $\text{RELU}$ is used to project Query and Key to $Q'$ and $K'$.

$$Q' = \text{RELU}(Z \cdot W_Q)$$

$$K' = \text{RELU}(Z \cdot W_K)$$

4) Multiply $Q'$ and $K'$ and normalize them to output the weight matrix $M$.

$$M = \text{softmax} \left( \frac{Q' \cdot K'}{\sqrt{k}} \right)$$

5) Multiply the weight matrix $A$ by Value to obtain the weighted output of the self-attention module. Then average the $N$ user attention representations as the user's short-term interest representations.

$$A = S \cdot Z = \left[ a_{1,1}, a_{1,2}, \ldots, a_{1,N} \right]^T$$

$$s_{l,1} = \frac{1}{N} \sum_{i=1}^{N} a_{1,i}$$

6) Repeat the operations from 1) to 5), calculate the short-term interest of each user in the target group $l$, and then aggregate it into the group short-term interest.

$$q_{l,k} = \sum_{i=1}^{N} s_{l,i}$$

2.2.2 Group long-term preference

Considering that each member of the group has different influence on the specified items, and the members have mutual influence, we use the attention mechanism and self-attention mechanism to construct the group's long-term preference.

The construction process of group membership vector is the same as that of user short-term interest. However, here we input the user vector in the target group. For the specific acquisition process, please refer to the short-term interest module above. Finally, we can get the membership vector $e_l$. In order to
construct the user aggregation vector, we take the user vector in the group as the key, input the target  
item as the query into the neural attention network, obtain the influence of each member in the group  
for the target item, and then weighted sum the user vector with these weights to obtain the user  
aggregation vector. The specific calculation steps are as follows.

\[ e_{i,j} = \text{softmax} \left( h^T \text{RELU}(P_v v_j + P_u u_i + b) \right) \]  
\[ f_{i,j} = \sum_{l=1}^{[g_{i,j}]} e_{i,l} u_i \]  
\[ P_v \text{ and } P_u \text{ represent the weight matrix corresponding to } v_j \text{ and } u_i, h^T \text{ is a weight matrix for mapping.} \]

Finally, we get the expression of group long-term preference in the form of the sum of \( f_{i,j} \)  
and \( e_{i,j} \), that is \( q_{ii} \).

3. Learning strategy based on ONCF model

The general neural collaborative filtering model uses multi-layer perceptron to replace the inner  
product operation of user hidden vector and item hidden vector in traditional matrix decomposition\(^{[3]}\),  
but the feature intersection of NCF in the interoperability layer is not sufficient. ONCF has improved  
on this basis\(^{[4]}\). In group recommendation, we have carried out the outer product operation of group  
embedded vector and item embedded vector, Then the convolution neural network is used to predict  
the score of the group to the item. Figure 3 illustrates the ONCF Learning framework.

**Representation Layer.** \( g_l(j) \) and \( v_j \) are the embedding vectors of group \( l \) and item \( j \) respectively,  
which are equivalent to the implicit vectors in the traditional matrix decomposition.

**Outer Product Layer.** The outer product operation is performed on \( g_l(j) \) and \( v_j \), so that the vector  
after the outer product becomes a matrix \( E \) that can describe the relationship between each dimension.

\[ E = g_l(j)v_j^T \]  

**Hidden Layers.** Then, CNN is used on this characteristic interaction matrix to carry out high-order  
interaction for each dimension locally and globally. The output vector predicted by CNN is \( f(E) \).

**Prediction Layer.** The final prediction score of the group is obtained by using the fully connected  
network, the weight of the connected network is \( W \), and we optimize the parameters by minimizing  
BPR loss where \( \theta_d \) are parameter specific regularization hyper-parameters to prevent over-fitting,  
and \( D \) denotes the set of training instances.
\[ y_{t,j} = W^TE \]  
\[ L(\Delta) = \sum_{l,j \in D} - \ln \sigma(y_{t,j} - y_{t,j}^*) + \theta \| \Delta \|^2 \]  

4. Experiments

In this paper, the experiment is carried out on the CARM2011 data set, and the leave one out method is used for evaluation. 100 items without interaction with the group are randomly selected, and the test items are sorted in these 100 items. HR\[^5\] is used to measure the recall rate and NDCG\[^6\] is used to measure the ranking quality of the list. The larger the index, the better the effect. By comparing the experimental results of traditional fusion strategy and SLAG, it is found that the effect of our SLAG model is better.

| Table 1. Experimental results |
|-----------------------------|
| NCF+AVG | NCF+LM | AGREE | SLAG |
| HR (k=5) | 0.5376 | 0.5296 | 0.5679 | 0.5796 |
| NDCG (k=5) | 0.3694 | 0.3668 | 0.3876 | 0.3962 |
| HR (k=10) | 0.7429 | 0.7411 | 0.7621 | 0.7732 |
| NDCG (k=10) | 0.4397 | 0.4403 | 0.4512 | 0.4616 |

Figure 4. Performance comparison when k takes different values

5. Conclusions

This paper constructs the slag model from the perspectives of short-term interest and long-term preference, and then recommends the group through the ONCF model. Compared with the traditional fusion strategies, the slag model has a better effect.

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