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Group recommendation based on hybrid trust metric

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ABSTRACT

Group recommendation is a special service type which has the ability to satisfy a group's common interest and find the preferred items for group users. Deep mining of trust relationship between group members can contribute to the improvement of accuracy during group recommendation. Most of the existing trust-based group recommendation methods pay little attention to the diversity of trust sources, resulting in poor recommendation accuracy. To address the problem above, this paper proposes a group recommendation method based on a hybrid trust metric (GR-HTM). Firstly, GR-HTM creates an attribute trust matrix and a social trust matrix based on user attributes and social relationships, respectively. Secondly, GR-HTM accomplishes a hybrid trust matrix based on the integration of these two matrices with the employment of the Tanimoto coefficient. Finally, GR-HTM calculates weights for each item in the hybrid trust matrix based on weighted-meanlist and proceeds to group recommendation with a given trust threshold. Simulation experiments demonstrate that the proposed GR-HTM has better performance for group recommendation in accuracy and effectiveness.

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KEYWORDS
Hybrid trust metric; Tanimoto coefficient; group recommendation

1. Introduction

With the rapid development of information technology, services computing has become the default discipline in the modern services industry and has been integrated into a great many aspects in our daily life [1,2]. As one of the hottest topics in the field of web services [3,4], the demand for non-functional recommendation service [5] which mainly serves groups is increasing day by day. Group recommendation (GR) deals with a lot of user behaviour and emotional consensus problems [6], which can be summarized as group trust-based decision problems. Traditional trust-based recommendation methods simply divide users into trusted and untrusted by matrix decomposition [7] and focus on similarity between users [8], or design an online social network architecture based on users' social relationships [2]. All these above methods measure trust degree on other users in accordance with their ratings on the same items, completely ignoring the complexity of trust sources. Essentially, none of them provide an explicit expression for group trust. However, a reliable group recommendation is decided on the interaction of user preferences, social relationships and other related parameters, where trust metric is very essential.

1.1. Motivation and contribution

Nowadays, many applications, such as CloudMusic and Douban, provide music recommendation services to users. In trying to achieve successful recommendation, one of the difficulties faced by these recommendation platforms is precise similarity computing [9] which can mine the trust relationships between users. As a group, music recommendation scenario shown in Figure 1, assumes that there are m users and n types of music in this group. For each user, he/she has his/her own favourite type of music, which can be expressed as an explicit preference vector. For example, the user u_4 has her own preference vector P_{u_4}, i.e. u_4 favours M_4. Each user may have trust relationships with other users in the group. As Figure 1 depicts, u_4 has a trust relationship with u_3 and u_m. Both u_3 and u_m favour M_3 according to P_{u_3} and P_{u_m}. As a result, it is highly possible for u_4 to choose M_3 as a favourite music because of her trust on u_3 and u_m.

In this paper, we investigate how to integrate user preferences with trust relationships and also commence deep mining of an effective solution to group recommendation with mutual action of user cognitive behaviours and emotional factors.

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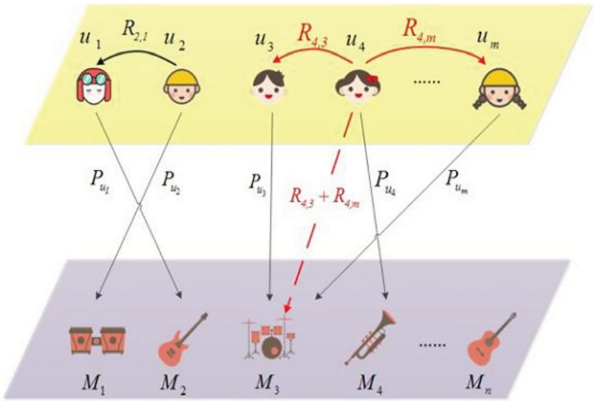


Figure 1. Group recommendation scenario based on trust relationship.

The main contribution of this paper is listed as follows:

1. To the best of our knowledge, this paper is the first to tackle the problem of diverse sources of trust within-group recommendation. We create an attribute trust matrix based on user attributes together with a social trust matrix based on social relationships between users.
2. We propose a hybrid trust metric model based on the integration of these two matrices by the employment of the Tanimoto coefficient. And we proceed to group recommendation after the decision of weights for each item based on weighted-meanlist.
3. Simulation experiments are conducted on public datasets to show that our proposed GR-HTM has improved the accuracy and effectiveness of group recommendation.

1.2. Organization

This paper is organized as follows: in Section 2, related works including recommendation and trust are given. In Section 3, our proposed method is described in detail. Experiments and analysis are discussed in Section 4. Conclusions and future works are discussed in Section 5.

2. Related works

In this section, we briefly review related work from three aspects: group recommendation, social recommendation and trust metric.

2.1. Group recommendation

GR is an important application problem in many social activities and industries, such as online shopping, music sharing and group travelling. GR belongs to social services [10], so it inevitably emphasizes the service quality (QoS) [11], and privacy preservation and dynamicity [12]. Service recommendation research has a long history, along with personalized recommendation technology, such as collaborative filtering (CF) [13], matrix decomposition (MF) [14] and deep learning (DL) [15] have been widely studied and the research on group recommendation is still very limited. Kyoungsoo Bok et al. [16] used the collaborative filtering to screen out similar profiles of other users in the group to implement GR. Ruibin Xiong et al. [17] implemented recommendation based on the collaborative filtering algorithm and text content application in the deep neural network. The existing group recommendation methods are mainly divided into preference fusion method and score fusion method. The preference fusion method is based on the preferences of all group members to provide group recommendation [18]. Tong Wu et al. [19] considered the trust of social, behavioural factor and proposed a two-stage trust network partition algorithm to reduce the complexity of LGDM problems. Greeshma Lingam et al. [20] first designed a recommendation-based online social network architecture by incorporating trust information (direct trust and indirect trust), relevance degree and recommended influence value. Then, they proposed a high-quality social trust associated model for evaluating a recommended trust path.

2.2. Social recommendation

The social recommendation has attracted considerable research attention in recent years as it effectively addresses data scarcity and cold start issues in traditional recommendation algorithms. One major assumption in the social recommendation is that users' behaviours in a social network are heavily affected by their social relationships. Social behaviour choice is an important embodiment of user emotion.

Alistair et al. [21] conducted relevant research on the role of SBH online and offline social activities in social relationships, and the experiment showed that the satisfaction of group members in social activities increased with the increase in intimacy. Lara Quijano-Sanchez et al. [10] gave comprehensive consideration to the satisfaction of the group and the friendly relationship within the group and put forward a personalized group recommendation method (personalized social individual explanation). Yue Ding et al. [22] calculated the influence value of users through the social interaction information of users in the group and the similarity relationship between users and then used the regularization classification method to deal with the problem of different preferences among users in the group. Xiao et al. [23] proposed a semi-supervised feature selection algorithm for customer classification, which could use tagged and untagged samples at the same time. Rui Chen et al. [24] proposed a novel social matrix factorization-based recommendation method which is proposed to improve the recommendation quality by fusing the user's social status and homophily. User's social status and homophily play important roles in improving the performance of recommender systems. Sajad Ahmadian et al. [25] proposed a novel social recommendation method which is based on an adaptive neighbour selection mechanism. In their proposed method, an initial neighbours' set of the users is calculated using the clustering algorithm.

In this paper, we propose a novel approach to explore the correlation between user's relationship and trust measure from the perspective of group user cognitive behaviour and emotional factors deeply and apply it to group recommendation.

2.3. Trust metric

Trust is one of the most important concepts in social networks. It is an important social element which can rapidly affect users' decisions [26]. People use the trust to help decide the extent to which they interact with others. Based on this, decision support systems work as a tool to support decision-making processes. It also makes use of the information of trust between users to help users make decisions in the social network more effectively. In particular, most successful recommendation systems consider trust relations and recommend items to a target user from their trusted users [27]. It has been shown that incorporating trust into recommendation systems can improve the quality and coverage of recommendations [28].

To simulate the uncertainty environment in the group, the interval trust function was constructed based on the common recognition and harmony degree between members [29]. Ximeng Wang [30] proposed a virtual GR algorithm, which integrates trust aggregation and file configuration at the same time and builds a user virtual coordinator to solve the preference conflict. Chen [31] analysed the similarity between other users under the same trusted user and minimized the difference between similar users by CosRA+T. Yin [32] proposed two trust recommendation algorithms – CFRAT and HRAT, which solve the problems of data sparsity and social trust metric, respectively. Trust metrics, the main current mainstream approach to group recommendation, is based on considering the user trust.

3. Group recommendation based on a hybrid trust metric

In this section, we propose a group recommendation method based on a hybrid trust metric (GR-HTM). The implicit trust is extracted by the relationships in the group. The hybrid trust metric is a trust mechanism formed by group users' attributes and relationships. It is different from the traditional concept of user similarity. Generally speaking, the proposed model GR-HTM includes two parts: (1) hybrid trust metric based on group members; (2) group recommendation based on weighted-meanlist.

3.1. GR-HTM model

The specific process of the HTM model is shown in Figure 2. The main steps include: (1) filter similar attributes of users according to historical data together with implementing trust metric based on such attributes; (2) create a social relationship topology, with the topology being updated by semi-supervised learning to obtain a matrix based on social relationships; (3) the above matrix fuses to obtain a hybrid trust matrix.

3.1.1. Trust metric based on attribute similarity

Shared content in social groups may reflect group preferences effectively as user attributes can also clearly identify the user's cognitive choice in behavioural preference. With preferences defined as using similar attributes, the trust matrix with similar attributes is created as follows:

$$Att\_Data \in R^{N\times D}$$

represents the attribute characteristic matrix of all members in a given group. These attributes are classified by extracting items from the group history that attract common attention among group members, where N represents the number of group members, and D represents the number of extracted attributes. Then, the matrix $Att\_Data_i = (Att_1, Att_2, \cdots, Att_D)$ is created, where i is the i $(i \in \{1, 2, \ldots, N\})$ member in the group, $Attribute_d$ $(d = \{1, 2, \ldots, D\})$ represents the dimension of attribute feature.

For uniform distribution of matrix, the RBF is employed and the smoothness estimation can be achieved. The calculation approach based on similar attributes between every two members is as follows (1):

$$Att\_Trust_{ij} = \exp(-||Att\_Data_i - Att\_Data_j||_2^2)/\sigma^2 \tag{1}$$

where Att_Trust_{ij} represents the trust between the user i and j based on the similar attributes (when $i = j$, $Att\_Trust_{ij} = 1$). σ is the kernel radius, which indirectly determines the performance of the classifier. If it is too small, it will lead to an appearance of overfitting. If it is too large, it will lead to the loss of the expansion of the classifier (therefore, σ is the maximum in this model).

The attribute similarity trust matrix $Att\_Trust \in R^{N\times N}$ is as follows:

$$\begin{bmatrix} a_{11} & \cdots & a_{1k} & \cdots & a_{1M} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ik} & \cdots & a_{iM} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{Nk} & \cdots & a_{NM} \end{bmatrix} \tag{2}$$

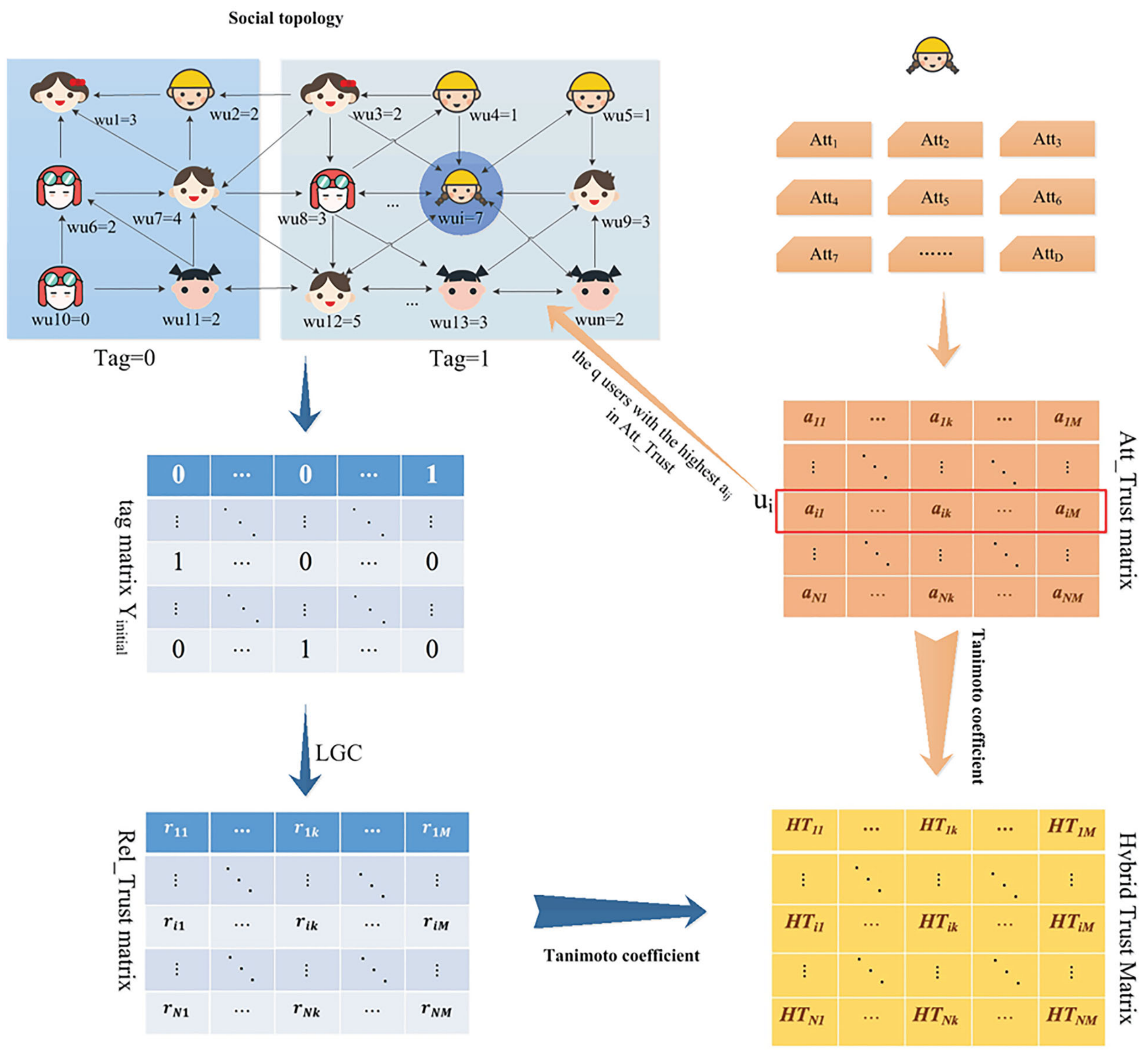


Figure 2. Hybrid trust model.

where $a_{ik} = Att\_Trust_{ij}$ represents the attribute similarity between group members with the same attributes. If i is in the group and has similar attributes with k in the friend set, then $a_{ik} = 1$; otherwise $a_{ik} = 0$.

3.1.2. Trust metric based on relationship similarity

We create the group social topology T with a huge user group of online social platform and consider extracting trust metrics by the relationships in the group. The node connection represents the relationship between members; the weight of each connection represents the strength of membership in the user group [33]. We employ semi-supervised learning by taking the user name as the key tag from a novel perspective. Then we acquire the potential trust relationship by considering the interaction relationship between tags, which is as follows:

(a) Given initial tag matrix

Given the group G and a group social topology T, the social weight of the user i in the topology is represented by wui. Usually, it is given in the data sets initially. It indicates the number of connections between user i and other users in the topology T. As illustrated in Figure 2, $wui = 7$ there are seven connections around user i. First, the user i with the highest weight who is recognized as trusted in the social topology is tagged as 1. Then, q users with the highest trust are selected from the corresponding trust matrix $Att\_Trust_i \in R^{N \times N}$ and tagged as 1, while the remaining are tagged as 0. Then we created the initial tag matrix Y_{initial};

(b) Trust metric with graph-based semi-supervised learning

The matrix Y_{initial} is inevitably sparse due to the changes in social relations within groups. The classical algorithm in the semi-supervised learning LGC [34] is employed, whose main idea is to make the tag information of each sample iteratively spread smoothly to the adjacent sample. This is helpful for us to get a good category accuracy.

First, the given group user dataset $X = \{X_1, X_2, \cdots, X_n\}$ defines a social relation matrix W_{ij}, where $i = 1, \cdots, n$; $j = 1, \cdots, m$. If the sample x_i was tagged, then $W_{ij} = 1$, otherwise $W_{ij} = 0$. The regular category function of LGC is given as follows:

$$E(F) = \frac{1}{2}(\sum_{i=1}^{N}\sum_{j=1}^{M} W_{ij} \left| |\frac{1}{\sqrt{D_{ii}}}F_i - \frac{1}{\sqrt{D_{jj}}}F_j \right| |^2 + \mu \sum_{i=1}^{N} ||F_i - Y_{\text{inital}}||^2) \tag{3}$$

where D is the diagonal matrix, $D_{ii} = \sum_{j=1}^{M} W_{ij}$; F_i is the value of the interaction between user i and the other. The second item $\mu \sum_{i=1}^{N} ||F_i - Y_{\text{initial}}||^2$ represents the label constraint, which enables the tagged nodes to be anchored in the classification.

Then the Laplacian matrix of the regularized social topology is calculated:

$$S = D^{-\frac{1}{2}} W D^{-\frac{1}{2}} \tag{4}$$

Each node updates its tag according to the following classification function:

$$F(t+1) = \alpha SF(t) + (1+\alpha) Y_{\text{initial}} \tag{5}$$

where $\alpha \in (0,1)$ represents the connection between the current node, its initial tag and its neighbour nodes. We iterate this step until F converges to a certain value, and each user matrix iterates the result to form a new label matrix Y.

According to the matrix Y, the trust metric based on the social relationship between users is shown in formula (6):

$$Rel\_Trust = (1 - \alpha S)^{-1} Y \tag{6}$$

where I is the identity matrix. The matrix represents the fiducial probability of each node (all users), with a range of [0,1].

In summary, we update the initial tag matrix through the LGC and get the trust matrix based on the social trust of the selected user, denoted as $Rel\_Trust \in R^{N \times M}$, as follows:

$$\begin{bmatrix} r_{11} & \cdots & r_{1k} & \cdots & r_{1M} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{i1} & \cdots & r_{ik} & \cdots & r_{iM} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{N1} & \cdots & r_{Nk} & \cdots & r_{NM} \end{bmatrix}$$

3.1.3. Hybrid trust metric matrix

To implement a good trust metric representation, we propose a hybrid trust metric model, as follows:

Tanimoto coefficient is employed to calculate the interaction between the two trust matrices mentioned above. The range of the coefficient is [0,1], which is conducive to the stability of the trust metric model and avoids the overload:

$$\begin{aligned} Trust_{(i:\ )} &= F(m, n | Att\_Trust_{(i:\ )}, Rel\_Trust_{(i:\ )}, Q) \\ &= \frac{Att\_Trust_{(i:\ )} \times Rel\_Trust_{(i:\ )}}{\left||Att\_Trust_{(i:\ )}\right||^2 \times \left||Rel\_Trust_{(i:\ )}\right||^2 - Att\_Trust_{(i:\ )} \times Rel\_Trust_{(i:\ )}} \\ &\quad + \frac{a}{2}||Q||_2^2 \end{aligned} \tag{7}$$

where $i \in m$ and $(i:\ )$ represent the values from the first column to the last column in row i. n is the dimension of the matrix columns. F is a non-linear interactive function. The first item

$$\frac{Att\_Trust_i \cdot Rel\_Trust_i}{||Att\_Trust_i||^2 \times ||Rel\_Trust_i||^2 - Att\_Trust_i \cdot Rel\_Trust_i}$$

employs the Tanimoto coefficient to acquire the interaction between two matrices; in the second item, α is the regularization parameter and Θ is the weight parameter of a given user i. Then, the hybrid trust metric is created as follows:

$$\begin{aligned} Trust^{Att} &= f(Trust_{i,M}(\cdots f(Trust_{i,1} F(t+1) + b_{1,1}) \cdots) + b_{1,M}), \\ Trust^{Rel} &= f\left(Trust_{i,M}\left(\cdots f\left(Trust_{i,1} \begin{bmatrix} Att^k & x^m \\ Rel^k & x^n \end{bmatrix} + b_{1,1}\right) \cdots\right) + b_{1,M}\right), \\ \hat{Trust}^{HT} &= s\left(Trust_{i,M}\left(\cdots f\left(Trust_{i,1} \begin{bmatrix} Trust^{Att} \\ Trust^{Rel} \end{bmatrix}\right)\right)\right) \end{aligned} \tag{8}$$

where $Trust^{Rel}$ and $Trust^{Att}$ represent the corresponding attribute similarity trust and social relationship trust, respectively. And $b_{i,(N/M)}$, $(i = 1, \ldots, (N/M))$ represents the correction matrix. $\hat{Trust}^{HT}$ represents a hybrid trust in, $Att^k$and Rel^k, respectively, represent the corresponding trust metric matrix, x^m and x^n are the corresponding input user matrix. Based on the above, the process of the HTM algorithm is given as follows:

Algorithm 1. The HTM algorithm

Input: G-given target social group, u_i-users in G,($i = 1, 2, \cdots, n$), social topology-T,

Output: the matrix of hybrid trust: $\hat{Trust}^{HT}$

/* Attribute similarity trust */

1: **for** each user u_i in G with the same attribute **do**

2: calculate *Att_Trust* via *RBF*

3: **end for**

/*Social trust*/

4: select u_i from topology T via weight u_i

5: **for** the first-q user in the matrix *Att_Trust* **do**

6: $Y_{initial} \leftarrow q_{u_i} / * q_{u_i} \in Att\_Trust * /$

7: **end for**
8: get Y by updating $Y_{initial}$ via LGC
9: **for** each user u_i in Y **do**
10: calculate social trust Rel_Trust
11: **end for**
/*Hybrid Trust Metric*/
12: **for** each user u_i in Att_Trust **do**
13: **for** each user u_i in Rel_Trust **do**
/*Tanimoto coefficient*/
14: compute $Trust_{(i,i)}$ according to Eq.(7)
15: compute $\hat{Trust}^{HT}$ according to Eq.(8)
16: **end for**
17: **end for**
18: **return** $\hat{Trust}^{HT}$

Taking the stability of the HTM model into consideration, trusted users are further screened and the trusted *threshold* is introduced as a formula (9):

$$\begin{aligned} threshold &= \max(\hat{Trust}^{HT}) - std(\hat{Trust}^{HT}) \\ &= \max(\hat{Trust}^{HT}) - \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{Trust}_i^{HT} - \mu)} \end{aligned} \tag{9}$$

where $\max(\hat{Trust}^{HT})$ represents the maximum of the hybrid trust matrix $\hat{Trust}^{HT}$; $std(\hat{Trust}^{HT})$ represents the standard deviation of the hybrid trust matrix $\hat{Trust}^{HT}$, and N represents the number of hybrid trust matrices.

The threshold is used to classify users and add labels continuously. And U represents the set of trusted users in the group. When $\hat{Trust}^{HT}$ is bigger than or equal to *threshold*, user i ($i \in U$) in the group is trusted. The setting of the threshold is not only a simple indicator to judge whether a group member is trusted [35] but also an important node to assign trust weight to members.

3.2. Group recommendation based on weighted-meanlist

In this part, we consider each trusted member in the group for their influence on recommendation (i.e. weight). The weighted average weakens the influence of historical data. At the same time, it enhances the noise which is in the data set [36]. The weighted process is implemented through the ensemble classification of group's preferences and social relationships and improved through the robustness of GR-HTM.

Let the item set of all trusted users in U be *List*, and *List* includes m recommended items $item_l (l = 1, 2, \cdots, m)$, the recommendation items of the member i ($i \in U$, which is tagged trusted) be $list_i$:

$$X_{il} = \begin{cases} 1, & if\ item_l\ in\ list_i \\ 0, & otherwise \end{cases} \tag{10}$$

If the item l exists in $list_i$ of i ($i \in U$), then $X_{il} = 1$, otherwise $X_{il} = 0$.

The weight w_l of the recommended $item_l$ in the whole group is shown in formula (11):

$$w_l = \frac{\sum_{i \in U} F_i \frac{X_{il}}{\sum X_{il_{i \in U}}}}{\sum_{i \in U} F_i} \tag{11}$$

where F_i is the fiducial probability that if the member i mentioned above belongs to the trusted category which is the weight of the member i ($i \in U$) in the group and the weight of its recommendation $list_i$ in the group.

We sort the items in descending order according to w_l in the whole group, and the top p recommended items are finally selected as the final recommendation list of the group.

4. Experiments and analysis

In this section, we conduct several experiments to compare the recommendation performance of our GR-HTM algorithm with the CosRA+T [31], the CFRAT and the HRAT [32]. The experimental environment is an Intel Core i7 6700HQ processor with a GPU of Nvidia GTX960M and a memory of 12 GB. The system is Ubuntu16.04LTS.

4.1. Algorithm baseline

To demonstrate improvements in the proposed approach, we compare performance against several representative baselines. These baselines cover trust-based group recommendation algorithms:

- *HRAT*: A hybrid recommendation algorithm based on trust and similarity (HRAT). The basic idea is to calculate the similarity between the target user and other users in the user data according to the user-item matrix, and then use the trust model to calculate the trust of the target user and other users.
- *CFRAT*: A recommendation algorithm based on the trust in sociology (CFRAT). The basic idea is to find the nearest neighbour set of the target user according to the user behaviour data collected by the recommendation system, and then select the item that the nearest trusted neighbour has to be selected as the recommendation of the target user.
- **CosRA+T:** A trust-based recommendation method, named CosRA+T, after integrating the information of trust relations into the resource-redistribution process. Specifically, a tunable parameter is used to scale the resources received by trusted users before the redistribution back to the objects. Interestingly, we find an optimal scaling parameter for the proposed CosRA+T method to achieve its best recommendation accuracy.

Table 1. Last.fm dataset.

Field	Value
Group members	1872
Number of groups	500
Artists	17,632
Group member and friend relations, i.e. 25,434 pairs	12,717
Weight of group members on artists, i.e. tuples (group member, artist, listening_Count)	92,834
Tags of artists	11,946
Tags of group members on artists, i.e. tuples [group member, tag, artist]	186,479

4.2. Dataset

We consider the effectiveness and accuracy of GR-HTM in the trust information of groups, last.fm dataset [37] was selected in this paper, which mainly collected the information of users listening to music. Related data statistics are shown in Table 1.

In the experiment, information of the target user and its social circle were selected. Five hundred groups of the user's social group were first selected as the training set. Then, 10 groups with high intimacy with the selected user were selected as the verification set to verify the performance of the algorithm in accuracy and recall rate.

4.3. Evaluation criteria and objects

We adopt two commonly used metrics to measure the performance of the GR-HTM algorithm, including precision [38] and recall [39]:

$$\text{precision}\,(p) = \frac{|\text{top} - p\text{ items} \cap \text{favorite items}|}{|\text{top} - p\text{ items}|} \tag{12}$$

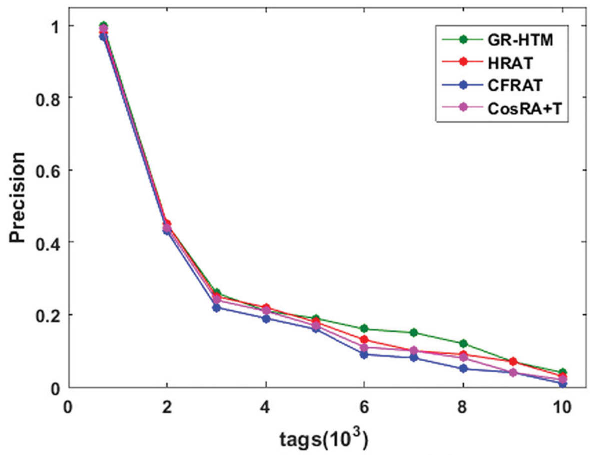
$$\text{recall}\,(p) = \frac{|\text{top} - p\text{ items} \cap \text{favorite items}|}{|\text{favorite items}|} \tag{13}$$

where top $-\,p$ items represents the first p recommended items of the groups and favourite items represents the items that required for the group members.

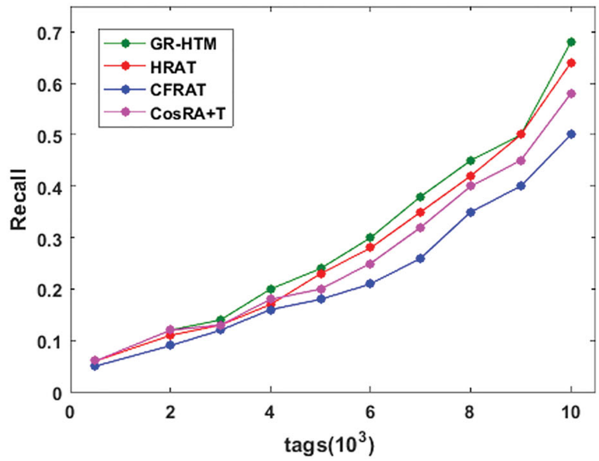
4.4. Experimental results and analysis

(1) Performance comparison of precision and recall (P–R)

In this section, we present the experimental results of GR-HTM and three baseline methods. Table 2 is the percentage representation of precision and recall based on the number of tags in a dataset. And Figure 3 is the chart representation of experimental results. In addition, Figure 4 shows the comparison of experimental results of precision and recall.



(a) Comparison of Precision



(b) Comparison of Recall

Figure 3. Verify the relationship between precision and recall. (a) Comparison of precision. (b) Comparison of recall.

Precision indicates the user's interest item in the recommendation list. The overall prediction shows a downward, but it can be seen that the accuracy of the GR-HTM is still slightly higher than the other three methods.

Recall indicates the probability that user's favourite items are recommended to the right user. The overall trend in Figure 3 is upward; the GR-HTM shows an advantage of faster rise, that is, the higher the dimension of the user group, the better the performance of the GR-HTM in filtering target users.

Table 2. P–R of group recommendation methods in different tags.

	Precision				Recall			
Tags	GR-HTM	HR-AT	CFRAT	CosRA+T	GR-HTM	HR-AT	CFRAT	CosRA+T
2	0.43	0.45	0.45	0.44	0.13	0.13	0.09	0.11
4	0.22	0.22	0.19	0.21	0.18	0.16	0.15	0.16
6	0.16	0.13	0.11	0.09	0.3	0.28	0.18	0.25
8	0.12	0.09	0.05	0.08	0.45	0.4	0.3	0.38
10	0.04	0.03	0.01	0.02	0.68	0.6	0.47	0.55

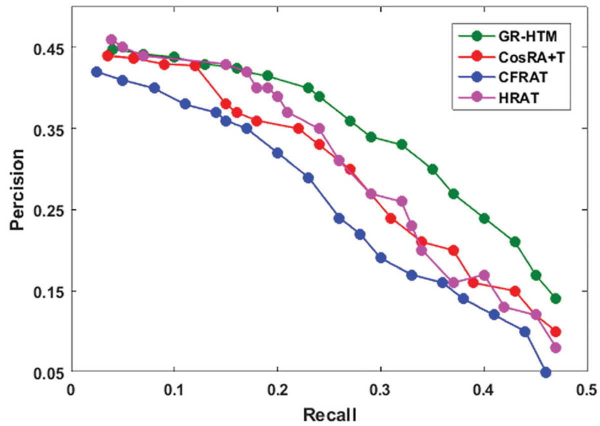


Figure 4. Comparison of P–R curves.

As illustrated in Figure 3(a), we can see that the GR-HTM has a higher precision than other baselines when the number of tags is above 2000. As can be seen from Figure 3(b), the GR-HTM has a better recall rate than the other three methods as the number of labels increases. Superiority is obvious when the number of tags reaches 7000 and 10,000.

A comprehensive analysis of Figure 3 fully shows the advantages of the GR-HTM algorithm in creating hybrid trust model by integrating the user behaviour preference and social relationship within the group. It not only makes up for the lack of timeliness of historical attribute but also reveals the implicit connection between the social relationship and the trust. Most importantly, the GR-HTM provides an effective solution to the group preference trade-off problem.

We compare the algorithm through different tags and neighbour numbers as the parameters. And the experimental results are displayed by the P–R curve.

As shown in Figure 4, the overall trend of precision seems to decrease. In essence, when the recall increases, the advantage of the GR-HTM becomes more and more obvious than other algorithms.

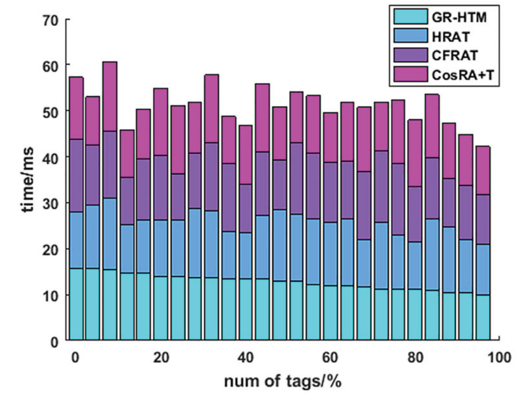
The results of experiment 1 show that the GR-HTM has a better performance in terms of precision and recall than the other three baseline methods.

(2) Performance comparison of stability and threshold

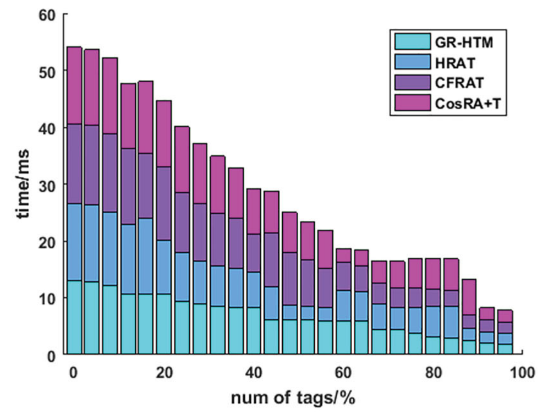
In this section, we present the experimental results of four comparison algorithms under different threshold conditions and the experimental diagram of the relationship between threshold, tag number and algorithm accuracy of the GR-HTM algorithm.

The experimental results above highlight the effectiveness of the GR-HTM algorithm in execution time and threshold setting.

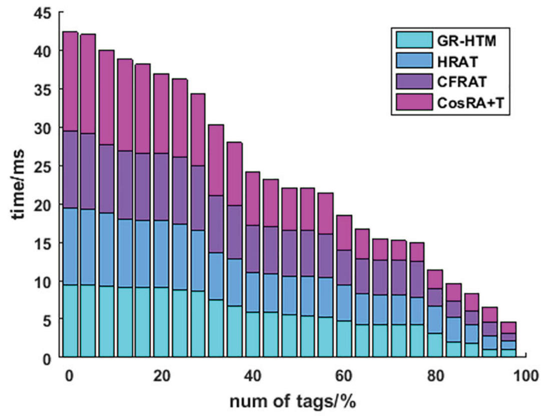
According to Figure 5, when the threshold is less than 0, the label classification effect is almost non-existent. We can see the fluctuations of the other three



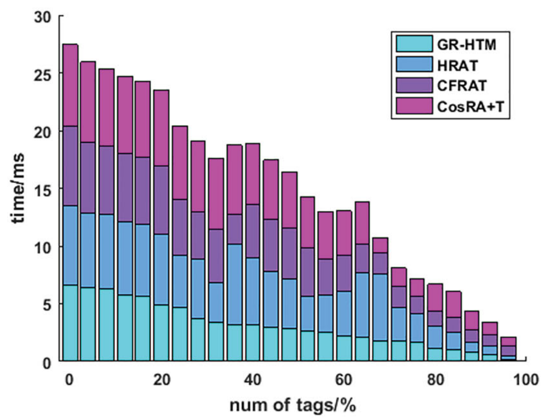
(a) Threshold=-0.5



(b) Threshold=0



(c) Threshold=0.5



(d) Threshold=0.85

Figure 5. Execution time comparison in different thresholds.

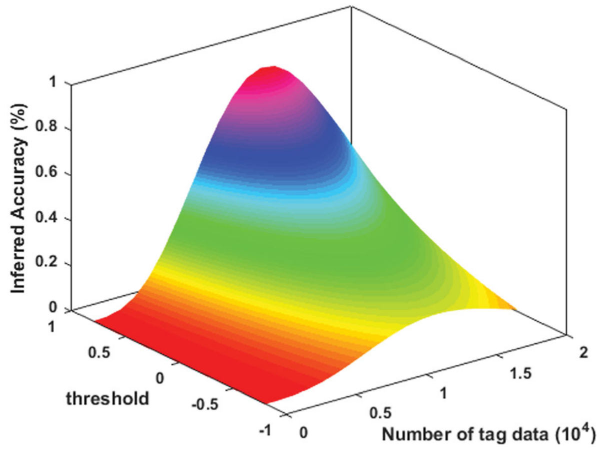


Figure 6. Validation of the threshold.

baseline methods when the threshold value is less than 0. However, the GR-HTM is the most stable one. With the increase of the threshold, it is obvious that the execution time of the GR-HTM is significantly reduced. Besides, it still maintains good stability.

As illustrated in Figure 5, when the value of the threshold is constant, the execution time of the GR-HTM is always the lowest (less than 20 ms). As the threshold increases, the execution time of the GR-HTM decreases gradually.

However, the above experiments only show the advantages of the GR-HTM in execution time and stability. As the value of the threshold is set, the number of tags retained in the dataset becomes smaller and smaller. Therefore, Figure 6 is given, and we can intuitively find the recommendation accuracy of the GR-HTM under the conditions of different threshold and number of tag data.

Observing the changes of threshold and inferred accuracy with the number of user tags in Figure 6, we can see that when the inferred accuracy reaches a certain peak, 0.95, there will be a downtrend afterwards. That is to say, the threshold is not positively correlated with the inferred accuracy. Therefore, to achieve an appropriate accuracy, we need to adjust the value of the threshold appropriately.

5. Conclusion

This paper proposes a group recommendation approach based on hybrid trust metric (the GR-HTM), which filters the historical attribute preferences of a group to generate trust measures and also analyses the social relationship to get the trust measure. Finally, the GR-HTM creates the hybrid trust matrix metric by fusion. We considered the potential trust information of the group comprehensively to modify the group preference and made a breakthrough in fully mining the complex trust relationship of the group.

At present, our work mainly focuses on the sort of items across the whole group. However, in practical applications, there are usually many subgroups within the group, and users do not only exist in only one subgroup. We will focus on the potential influence of subgroups on group recommendation results in our future work.

Disclosure statement

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