GroRec: A Group-Centric Intelligent Recommender System Integrating Social, Mobile and Big Data Technologies

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Abstract—In recent years, an extensive integration of cyber, physical and social spaces has been occurring. Cyber-Physical-Social Systems (CPSSs) have become the basic paradigm of evolution in the information industry, through which traditional computer science will evolve into cyber-physical-social computational science. Intelligent recommender systems, which are an important fundamental research topic in the CPSS field and one of the key techniques for the implementation of personalized and intelligent computing, have great significance in CPSS development. This paper proposes a group-centric recommender system in the CPSS domain, which consists of activity-oriented group discovery, the revision of rating data for improved accuracy, and group preference modeling that supports sufficient context mining from multiple sources. Through experiments, it is verified that the proposed recommender system is efficient, objective and accurate, thereby providing a strong foundation for personalized computing in the CPSS paradigm.

Index Terms—Big data, data analysis, data fusion, cyber-physical-social systems, recommender services

1 Introduction

With the explosion of Social Network Services (SNSs), increasing amounts of data from physical, social and cyber spaces are being generated and disseminated through social networks [1]. Currently, we live in a world that involves physical enjoinment, social activities, and cyber resources, with which we engage through multidimensional comprehensive systems that provide computing, communication, control, commerce, etc. In particular, through advanced mobile and sensing technologies, social data can easily be collected as records of social events, which can be analyzed to yield a better understanding of users' daily activities, social circles, living habits, etc. Hence, various studies have been performed with a focus on developing community-centric applications based on data analysis that integrates social, mobile and big data technologies, such as Cyber-Physical-Social Systems (CPSSs) [2], [3]. Intelligent recommender systems are a key technology and a typical class of applications for providing personalized and intelligent services in the CPSS paradigm [4]. Unfortunately, because of concerns related to Volume, Variety, Velocity and Veracity (the 4 Vs) [5], the adequate and efficient analysis of the big data collected in CPSSs to provide intelligent recommendations faces the following challenges [6].

- **Efficiency**: In a CPSS, a recommender system must analyze high-dimensional, multi-source and heterogeneous data collected from cyber, physical and social spaces. However, conventional recommenders provide individual services to each user, meaning that significant amounts of storage, computing and network resources will inevitably be required for individual preference modeling. With the individual-centric approach, it is difficult to provide users with timely and suitable recommendations in a CPSS.
- **Objectivity**: Social data are an important supplement to context analysis in a recommender system, but they include various types of emotional information that influence the objectivity of the recommendation results. For example, Fig. 1 presents three user reviews and ratings posted on Yelp. Although all three users rated the reviewed establishment with the full five stars, they were not completely content with the products or services offered, as implied by the highlighted reviews. We define this phenomenon as *emotional offset*.
- **Sufficiency**: Assisted by the Internet of Things (IoT), mobile networks, SNSs and other advanced technologies, increasingly extensive data are becoming available for recommender systems. However, because of the discontinuous nature of the data collection, the problem of sparsity is common in CPSSs and it is difficult to analyze users' preferences and behavior patterns.

To address these challenges, this paper proposes a group-centric intelligent recommender system named GroRec, which integrates social, mobile and big data technologies to provide effective, objective and accurate recommendation services in CPSSs. Specifically, this article makes the following contributions.

- To decrease the complexity of conventional individual-centric recommender systems, we propose a group-centric approach. From the high-dimensional data available in a CPSS, groups are discovered based on the similarity of user behavior.

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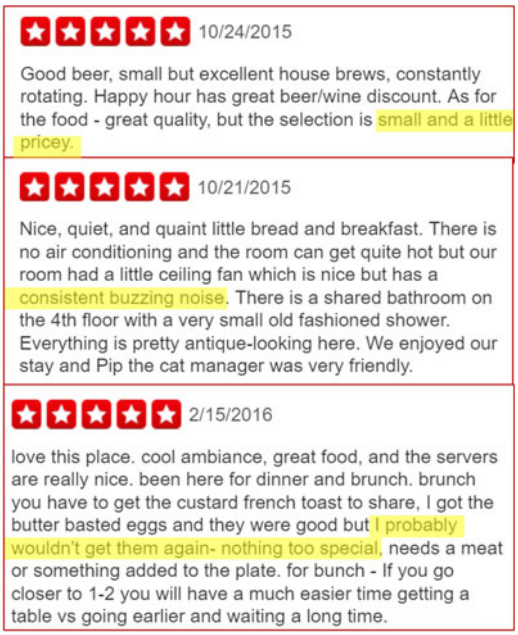


Fig. 1. Emotional offset between ratings and reviews.

- We propose a quantitative method of assessing emotional offset, which is based on sentiment analysis, to revise user ratings to improve the objectivity of context data.
- We propose a comprehensive approach based on three aspects, i.e., ratings, interests and social relationships, to discover the preferences of groups of users.

2 Related Work

In brief, there are three kinds of efforts involved in our work: group recommendation, emotion-aware recommendation and multidimensional preference modeling. We review previous works on these topics in this section.

2.1 Group Recommendation

Group recommendation is an approach that has been proposed to provide similar users with the same recommendation services, with the intent of satisfying more users' personalized demands while requiring fewer resources. Conventionally, group recommendation, as an extension of individual recommendation, provides a constant user group with recommendation results that represent a compromise based on the features of each individual. For example, Yen-Liang et al. proposed an algorithm based on collaborative filtering (CF) and a genetic algorithm to predict the ratings of all individuals in a group and thus to generate the most appropriate recommendation for that group [7]. With the rapid development of SNSs, various approaches integrated with social data have been proposed. In [8], Amirali et al. proposed preference-oriented social networks with the ability to generate group decisions or recommendations even when the preferences of some group members are unobserved. Most group recommendation approaches serve groups that consist of permanent members; however, their accuracy may be affected by differences in individual preference. Hence, in [9], Ludovico et al. proposed a clustering-based approach to discovering groups for providing group recommendations based on the similarity of individuals' preferences. Generally, considerable progress has been made in reaching agreement regarding certain issues related to group recommendation. In particular, it is universally accepted that group recommendation is more economical and effective than individual recommendation. However, existing approaches are still based on low-dimensional rating data, which are not directly available for use in CPSSs.

2.2 Emotion-Aware Recommendation

With the rapid development of cognitive neuroscience, computational neuroscience, brain-computer interfaces, neural engineering and other interdisciplines, emotion-aware systems are becoming an important field of research in cognitive science and intelligence science. Hence, many researchers have attempted to incorporate emotional factors into recommender systems [10]. In [11], Jia-Ching et al. proposed an emotion-profile-based music recommender system, in which a recognized emotion, an emotion profile, and personal historical query results are fed into the recommendation module to generate a recommended music list. In [12], Claudia et al. explored the role of emotions in short films and proposed a method of automatically extracting affective context from user comments associated with short films available on YouTube, which can then be leveraged for emotion-aware film recommendation. However, all existing emotion-aware recommender systems focus on the emotional requirements of the user, whereas none of them is concerned with the influence of emotion on the objectivity of recommendation results, as exemplified in Fig. 1. Therefore, the ability to quantify emotional offset in recommender systems is an issue of great importance.

2.3 Multidimensional Preference Modeling

Data sparsity poses a considerable challenge in recommender systems because of the difficulty of extracting user preferences from limited data. In CPSSs, the fusion of data from multiple sources provides recommender systems with richer user data, such as implicit feedback [13] and SNS records [14], but the modeling of user preferences from sparse multidimensional data remains an intractable problem. To address this issue, approaches based on dimensional reduction are often applied to map sparse multidimensional data to a denser low-dimensional domain. In [15], Jian et al. proposed an approach based on Markov chains for robust multi-view spectral clustering via low-rank and sparse decomposition. In [16], Qiang et al. proposed a method of incremental matrix factorization via feature space re-learning for recommender systems, which can facilitate more accurate recommendation based on the analysis of multidimensional data. Although dimensional reduction is effective for alleviating the sparsity problem, the proposed approach can only be applied to analyze data in a specific context, which are not available in CPSSs. Therefore, there is an urgent need to develop the ability to comprehensively extract user preferences from the multidimensional context data available in CPSSs.

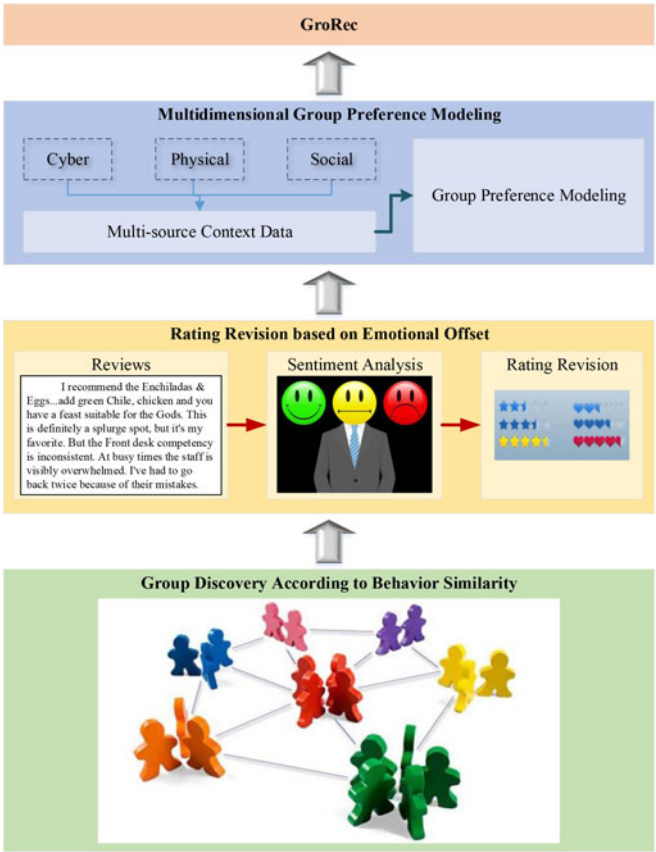


Fig. 2. System architecture.

3 Proposed System Architecture and System Model

3.1 Proposed System Architecture

The proposed GroRec system is expected to be able to provide effective, objective and accurate recommendations in CPSSs. As illustrated in Fig. 2, GroRec consists of the following modules.

- **Group Discovery Based on Behavioral Similarity**: To address the issue of the explosion of context data available in CPSSs, a group-centric approach is applied to decrease the computational complexity of the recommender system. However, conventional group discovery methods are based on the clustering of low-dimensional data and thus are not applicable for CPSSs. In GroRec, the group discovery module is designed to rapidly and accurately discover groups from high-dimensional data based on the similarity of user behavior.
- **Rating Revision Based on Emotional Offset**: As shown in Fig. 1, there can be a significant offset between user reviews and ratings, which can lower the accuracy of recommendation results. In GroRec, rating data are revised in accordance with their emotional features, which are extracted from user reviews through sentiment analysis. The rating revision module is the foundation for ensuring the objectivity of the recommender, thereby improving the accuracy of the recommendation results.
- **Multidimensional Group Preference Modeling**: In a CPSS, extracting user preferences from multi-source, heterogeneous and high-dimensional context data is a highly challenging task, especially given the sparsity caused by the uneven distribution of user data. Hence, the multidimensional preference modeling module in GroRec is designed to comprehensively analyze user preferences to provide more intelligent recommendation services.

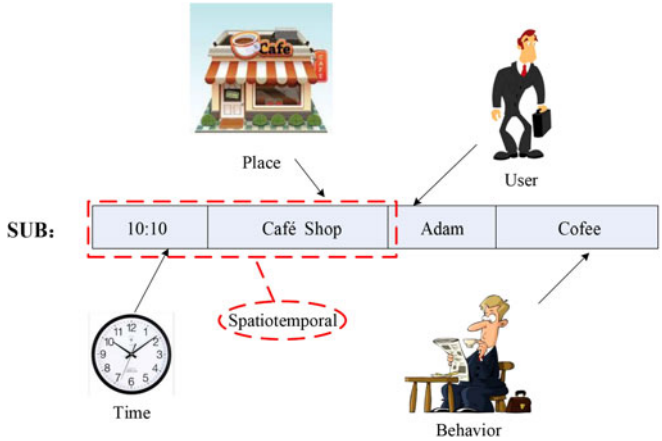


Fig. 3. SUB model.

3.2 System Model and Problem Formulation

The proposed GroRec system consists of three modules, i.e., group discovery, rating revision and multidimensional preference modeling, to separately address three underlying problems: 1) user classification based on behavioral similarity, 2) quantification of emotional offset in user reviews, and 3)comprehensive group preference modeling.

3.2.1 *User Classification Based on Behavioral Similarity*

The purpose of group discovery is to classify users based on behavioral similarity. In a CPSS, the available user behavior data consist of four elements, i.e., time, place, user, and behavior. Generally, the time and place information can be merged for dimensional reduction. Therefore, we define user behavior data using a Spacetime-User-Behavior (SUB) model. However, the SUB model is merely a data structure; it must be represented using a proper mathematical approach.

A tensor is able to represent multidimensional arrays [17] and thus is a suitable means of representing the SUB model, which describes three-dimensional data. Hence, the SUB model can be represented by a 3rd-order tensor, as shown in Equation 1, where I_S, I_U and I_B represent the vector spaces of spacetime, user and behavior, respectively. Specifically, $a_{ijk} = 1$, where $a_{ijk} \in A_{SUB}$, represents that user j exhibits behavior k at the spacetime point i, whereas $a_{ijk} = 0$ otherwise

$$\begin{cases} A_{SUB} \in R^{I_S \times I_U \times I_B} \\ a_{ijk} = \{0, 1 | a_{ijk} \in A_{SUB}\}. \end{cases} \tag{1}$$

Furthermore, we apply Tucker decomposition, which is a method of high-order principal component analysis, for further dimensional reduction. As shown in Equation (2), the initial tensor, $A \in R^{I_1 \times \ldots \times I_N}$, is decomposed into a core

tensor, i.e., $B \in R^{R_1 \times \ldots \times R_N}$, and a series of matrix multiplication patterns, i.e., $U^{(n)} = [u_1^{(n)}, \ldots, u_{R_n}^{(n)}] \in R^{I_n \times R_n}$, through Tucker decomposition [18]

$$\begin{aligned} \underline{A} &\cong \sum_{r_1=1}^{R_1} \cdots \sum_{r_N=1}^{R_N} b_{r_1 \cdots r_N} (u_{r_1}^{(1)} \circ \cdots \circ u_{r_N}^{(N)}) \\ &= \underline{B} \times_1 U^{(1)} \cdots \times_N U^{(N)} = [\![\underline{B}; U^{(1)}, \ldots, U^{(N)}]\!]. \end{aligned} \tag{2}$$

In particular, if $r < R_N$, then the approximate tensor of the SUB tensor, which is a high-order compression of the initial tensor, can be calculated using Equations (1) and (2) as

$$A'_{SUB} = B \times_1 U_r^{(S)T} \times_2 U_r^{(U)T} \times_3 U_r^{(B)T}. \tag{3}$$

Through Tucker decomposition, the volume and dimensionality of the user behavior data are reduced, but more importantly, the sparsity is alleviated to some extent because the approximate tensor is a densified approximation of the initial tensor.

3.2.2 Quantification of Emotional Offset in User Reviews

Considering that user reviews can include a significant emotional offset, sentiment analysis is an important means of calculating this offset to revise the original ratings.

Suppose that there are i words in subsentences sub; then, we can calculate the sentiment value using as

$$Pol(sub) = \begin{cases} -1 & \text{odd-numbered negative words} \\ 1 & \text{even-numbered negative words} \end{cases} \tag{4}$$

$$Sen(sub) = Pol(sub) \left(\sum_{w_i \in sub} SentiWordNet(w_i) \right). \tag{5}$$

Here, $Pol(sub)$ represents the polarity of sub and $SentiWordNet(w_i)$ represents the sentiment value of word i as calculated according to SentiWordNet 3.0.[1]

However, user reviews can significantly differ in length, and the emotional offset of a longer review is likely to be higher than that of a shorter one. To balance the influence of different review lengths on the overall variance, normalization is essential when calculating the overall emotional offset of user reviews.

Suppose that there are j subsentences in review re, including n sentiment words; then, we can calculate the emotional offset using as

$$Offset(re) = \frac{\sum_{sub_j \in re} Sen(sub_j)}{n}. \tag{6}$$

Obviously, the emotional offset of each user review falls in the range of $[-1, 1]$; this fact is used to revise the original rating by means of Equation (7), where $R(re)$ is the rating corresponding to review re and ρ is a value that is determined through training and is used to adjust the relative weights of the original rating and the emotional offset

$$R_{rev}(re) = \rho R(re) + (1 - \rho) Offset(re). \tag{7}$$

1. http://sentiwordnet.isti.cnr.it/

3.2.3 Comprehensive Group Preference Modeling

Preference modeling is the most important issue for a recommender system. In GroRec, we propose a comprehensive approach to extracting group preferences from ratings, interests and social relationships. Considering the high dimensionality of the context data available in a CPSS, matrix factorization (MF) is a suitable means of mapping the complex relationships between users and items into a low-dimensional space of latent factors. Through MF, users and items are mapped to a low-dimensional latent factor space that explains the user ratings of the items, and the user-item rating matrix is regarded as the product of the users and items, as presented in Equation (8). Here, k represents the number of selected latent factors and P and Q represent the weights of each user and item, respectively, with respect to each characteristic in the latent factor space, which are the results of factorizing the rating matrix R and are used for rating prediction. Notably, some latent factors can typically be ignored; therefore, $k < m, n$

$$R_{m \times n} = P_{m \times k} * Q_{k \times n}. \tag{8}$$

Generally, Stochastic Gradient Descent (SGD) [19] is often applied to minimize the loss function, which is presented in Equation (9), for the calculation of P and Q. In this function, $\lambda(\|P\|_F^2 + \|Q\|_F^2)$ is a bias unit to avoid over-fitting, λ is the regularization parameter, and $\|P\|_F^2$ and $\|Q\|_F^2$ are Frobenius norms. Specifically, the minimization of Equation (9) is equivalent to the parameter training of the partial derivatives presented in Equation (10)

$$J = \sum_{R_{ui} \in train} (R_{ui} - P_u Q_i^T)^2 + \lambda(\|P\|_F^2 + \|Q\|_F^2) \tag{9}$$

$$\begin{cases} \frac{\partial J}{\partial P} = -2 \sum_{R_{ui} \in train} (R_{ui} - P_u Q_i^T) Q + 2\lambda P \\ \frac{\partial J}{\partial Q} = -2 \sum_{R_{ui} \in train} (R_{ui} - P_u Q_i^T) P + 2\lambda Q. \end{cases} \tag{10}$$

Because of the good performance of MF, many researchers have attempted to extend this model by incorporating information other than rating data, such as social network data [20] and even multidimensional context data [21], to provide more accurate recommendations. In GroRec, we propose a comprehensive preference model based on multidimensional MF.

4 Prototype Implementation and Detailed Methodology

4.1 Group Discovery Based on Behavioral Similarity

In a CPSS, the available user behavior data are four-dimensional, including time, place, user and behavior information. In GroRec, we propose to represent user behavior data in tensor form, analyze the behavioral similarity of users via Tucker decomposition, and discover groups via clustering. Fig. 4 illustrates the flowchart of the group discovery process in GroRec. Specifically, group discovery in GroRec consists of the following steps.

1) **Tensor-based Representation of User Behavior**: As introduced in Section 3.2.1, the SUB model is used to represent the user behavior data in the form of the

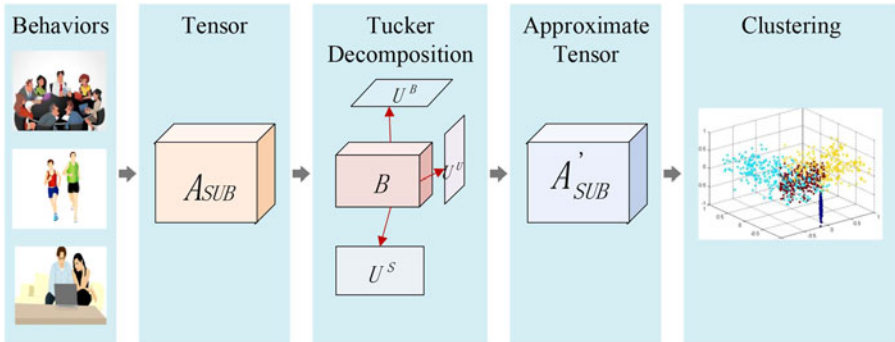


Fig. 4. Group discovery flowchart.

tensor A_{SUB}, the structure of which is schematically illustrated in Fig. 5.

2) **Behavioral Similarity Analysis via Tucker Decomposition**: As shown in Fig. 6, the approximate tensor A'_{SUB} can be calculated via Tucker decomposition. According to the definition of the approximate tensor, it is known that A'_{SUB} is an approximate representation of user behavior, whereas $a \in A'_{SUB}$ describes the probability of a specific user behavior, which can be used to analyze behavioral similarity.
3) **Group Discovery via Clustering**: In Fig. 7, the structure of the approximate tensor A'_{SUB} is illustrated in three-dimensional coordinates. This approximate tensor can be used to identify groups via clustering algorithms. In the proposed scheme, the approximate tensor A'_{SUB} is clustered using the K-Nearest Neighbors (KNN) algorithm [22] after normalization.

4.2 Rating Revision Based on Emotional Offset

In GroRec, the emotional offset is calculated through sentiment analysis and used to revise the corresponding rating data to improve the objectivity of user evaluations. Specifically, we calculate the emotional offset using a non-supervisory learning method based on a sentiment lexicon as follows:

1) **Text Preprocessing**: The reviews, which predominantly consist of text, must be preprocessed, including word segmentation, morphological normalization, and the removal of stopwords and punctuation.
2) **Emotional Offset Calculation**: Using Equations (4), (5) and (6), the emotional offset of each review can be calculated.
3) **Rating revision**: Based on the corresponding calculated emotional offset, each rating is revised using Equation (7).

4.3 Multidimensional Group Preference Modeling

In the proposed GroRec system, a comprehensive group preference model is built that integrates ratings, interests and social relationships. Fig. 8 presents the flowchart of the preference modeling process in GroRec, which consists of group-centric data fusion and group preference modeling.

4.3.1 *Group-Centric Data Fusion*

Through data fusion, the context of each member is merged into a group-centric context. Considering the different weights of each member in a group, linear superposition is not suitable for group-centric data fusion. As shown in Figs. 5 and 6, it is obvious that the elements in the approximate tensor A' are different from the elements in the initial

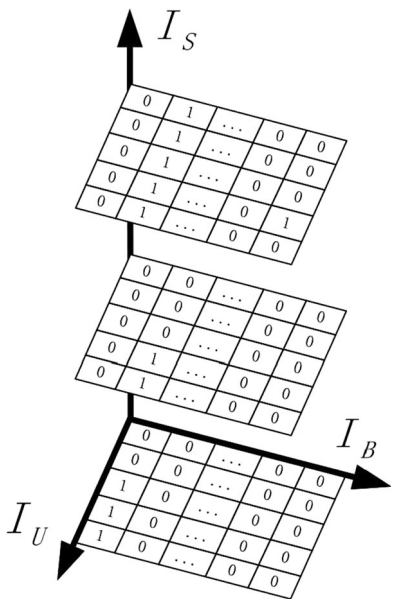


Fig. 5. Tensor-based representation of user behavior data.

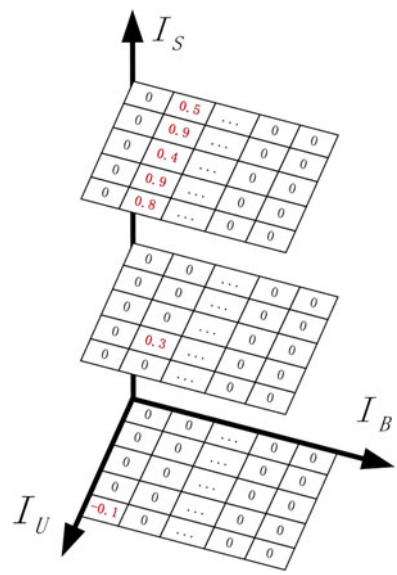


Fig. 6. Behavioral similarity analysis via tucker decomposition.

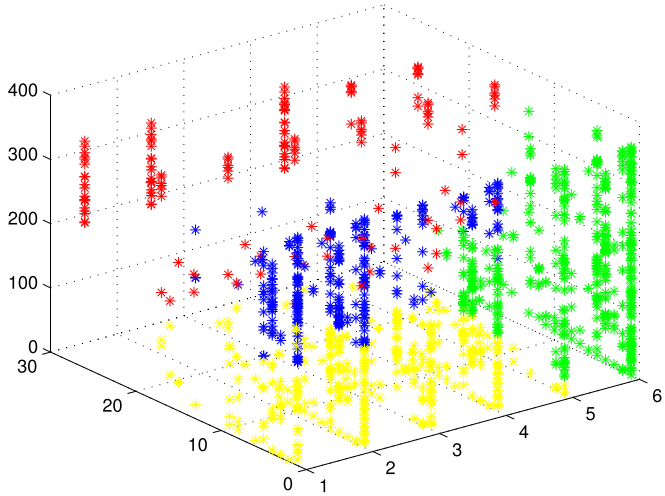


Fig. 7. Group discovery via clustering.

tensor A. In accordance with the significance of the approximate tensor, an element in the approximate tensor represents the prevalence of the corresponding behavior in a group. Moreover, as shown in Fig. 7, group discovery is performed based on the approximate tensor. Therefore, the weight of each behavior can be calculated using Equation (11), which is the foundation of group-centric data fusion

$$W_b = \frac{a_b}{\sum_{i \in group} a_i}, a_i \in A'. \tag{11}$$

Here, a_b is the element corresponding to behavior b in the approximate tensor A' and $\sum_{i \in group} a_i$ is the sum of all elements included in a group. Hence, through group-centric data fusion, the behavior data of all members are integrated the form of individual data. In other words, the group as a whole is treated as an individual user.

4.3.2 Group Preference Modeling

The purpose of group preference modeling is to extract preferences from ratings, interests and social relationships, each of which must be modeled separately.

- **Rating-based Matrix Factorization (RMF)**: As described in Section 3.2.2, the rating data are revised to obtain more objective user evaluations of items. The RMF process is a basic MF procedure, which can be applied using Equations (9) and (10).
- **Interest-based Matrix Factorization (IMF)**: To integrate user interests into the preference model, the generally accepted approach for discovering interests is used, namely, Latent Dirichlet Allocation (LDA) [23]. Specifically, the distributions of interests and items associated with a group are extracted through LDA, i.e., the interest matrix G and the item matrix I are calculated. Based on the extracted distributions of interests and items, IMF is performed using the loss function presented in Equation (12) and the partial derivatives presented in Equation (13). Here, α and β are the weights of the user interests and item features, respectively, and A is the latent-topic-mapping matrix of the latent-factor-rating matrix.

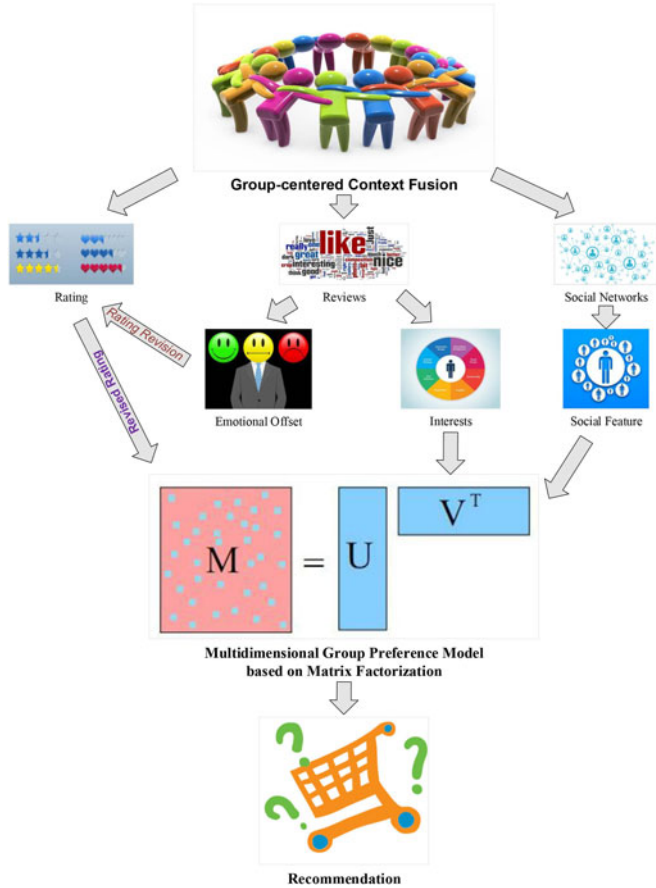


Fig. 8. Flowchart of multidimensional group preference modeling.

$$\begin{aligned} J = &\sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T)^2 \\ &+ \alpha \sum_{R_{gi} \in train} (G - P_g A^T)^2 \\ &+ \beta \sum_{R_{gi} \in train} (I - Q_i A^T)^2 \\ &+ \lambda(\|P\|_F^2 + \|Q\|_F^2 + \|A\|_F^2) \end{aligned} \tag{12}$$

$$\begin{cases} \dfrac{\partial J}{\partial P} = -2 \sum\limits_{R_{gi} \in train} (R_{gi} - P_g Q_i^T) Q \\ -2\alpha \sum\limits_{R_{gi} \in train} \alpha (G - P_g A^T) A + 2\lambda P; \\ \dfrac{\partial J}{\partial Q} = -2 \sum\limits_{R_{gi} \in train} (R_{gi} - P_g Q_i^T) P \\ -2\beta \sum\limits_{R_{gi} \in train} \alpha (I - Q_i A^T) A + 2\lambda Q; \\ \dfrac{\partial J}{\partial A} = -2\alpha \sum\limits_{R_{gi} \in train} (G - P_g A^T) P \\ -2\beta \sum\limits_{R_{gi} \in train} \alpha (I - Q_i A^T) Q + 2\lambda A. \end{cases} \tag{13}$$

- **Social-based Matrix Factorization (SMF)**: Various recommender systems exploit social network

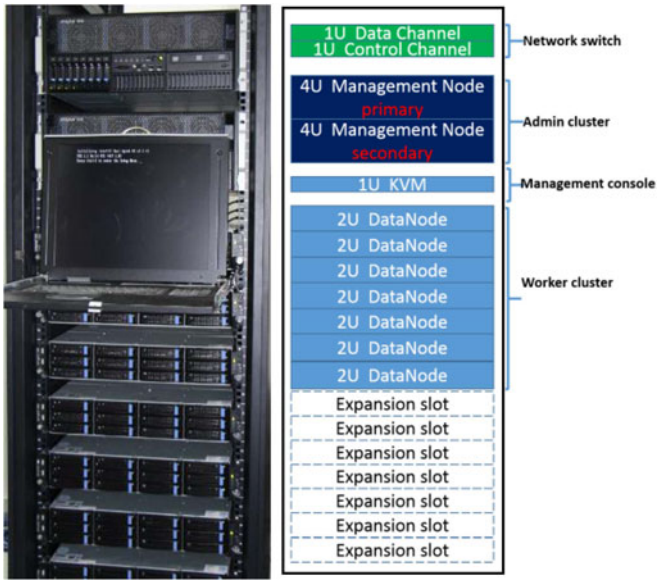


Fig. 9. Inspur in-cloud smartData appliance.

records to alleviate sparsity and improve accuracy. In the proposed GroRec system, a friend group g' is defined based on the friendships of each member in group g. Then, the similarity between g and g' can be calculated in terms of the Pearson Product-Moment Correlation Coefficients (PPMCCs) for ratings and interests as presented in Equation (14), where P_{rat} is the rating-based PPMCC of g and g', P_{int} is the interest-based PPMCC of g and g', and ε is an adjustment factor for the weights of P_{rat} and P_{int}

$$Sim(g, g') = \varepsilon P_{rat}(g, g') + (1 - \varepsilon) P_{int}(g, g'). \tag{14}$$

Based on the similarity of the friend group, social factors can be integrated into the group preference model. Specifically, SMF is performed using the loss function presented in Equation (15) and the partial derivatives presented in Equation (16)

$$\begin{aligned} J = & \sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T)^2 \\ & + \gamma \sum_{j \in g'} sim(g, g') \|P_g - P_j\|_F^2 \\ & + \lambda(\|P\|_F^2 + \|Q\|_F^2) \end{aligned} \tag{15}$$

$$\begin{cases} \dfrac{\partial J}{\partial P} = -2 \displaystyle\sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T) Q \\ + \gamma \displaystyle\sum_{j \in g'} sim(g, g') P - g - P_j + 2\lambda P; \\ \dfrac{\partial J}{\partial Q} = -2 \displaystyle\sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T) P + 2\lambda Q. \end{cases} \tag{16}$$

Based on the RMF, IMF and SMF procedures, the loss function and partial derivatives for group preference modeling based on MF can be derived as

$$\begin{aligned} J = & \sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T)^2 \\ & + \alpha \sum_{R_{gi} \in train} (G - P_g A^T)^2 \\ & + \beta \sum_{R_{gi} \in train} (I - Q_i A^T)^2 \\ & + \gamma \sum_{j \in g'} sim(g, g') \|P_g - P_j\|_F^2 \\ & + \lambda(\|P\|_F^2 + \|Q\|_F^2 + + \|A\|_F^2) \end{aligned} \tag{17}$$

$$\begin{cases} \dfrac{\partial J}{\partial P} = -2 \displaystyle\sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T) Q \\ \quad -2\alpha \displaystyle\sum_{R_{gi} \in train} \alpha (G - P_g A^T) A \\ + \gamma \displaystyle\sum_{j \in g'} sim(g, g') P - g - P_j + 2\lambda P; \\ \dfrac{\partial J}{\partial Q} = -2 \displaystyle\sum_{R_{gi} \in train} (R_{gi} - P_g Q_i^T) P + 2\lambda Q; \\ \dfrac{\partial J}{\partial A} = -2\alpha \displaystyle\sum_{R_{gi} \in train} (G - P_g A^T) P \\ -2\beta \displaystyle\sum_{R_{gi} \in train} \alpha (I - Q_i A^T) Q + 2\lambda A. \end{cases} \tag{18}$$

5 Experiments and Evaluations

5.1 Experimental Data and Evaluation Standards

The experimental data used in this paper were obtained from an open data set provided by the crowd-sourced review website Yelp.[2] In these experiments, approximately 80 percent of these data were randomly selected for training, and the remaining data were used to verify the performance of the proposed system. The experimental data set included information about local businesses in 10 cities across four countries. Specifically, the data set included 2.2 M reviews and 591 K tips provided by 552 K users for 77 K businesses and involved a social network of 552 K users, for a total of 3.5 M social edges.

The hardware environment used in our experiments was an Inspur In-Cloud SmartData Appliance (SDA) provided by the Embedded and Pervasive Computing Lab at Huazhong University of Science and Technology. As illustrated in Fig. 9, this SDA consists of two main clusters: 1) an admin cluster with two nodes, providing 64 CPU cores, 256 GB of RAM and 3.6 TB of storage, and 2) a worker cluster with seven nodes, providing 84 CPU cores, 336 GB of RAM and 252 TB of storage.

Generally, the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) are the most important indicators for the evaluation of recommender systems. Moreover, the Recall, Precision and F1 Score are the typical indicators used to evaluate clustering-based recommendations [24]. Therefore, we evaluated the performance of the group discovery module in terms of the Recall, Precision and F1 Score

2. http://www.yelp.com/dataset_challenge/

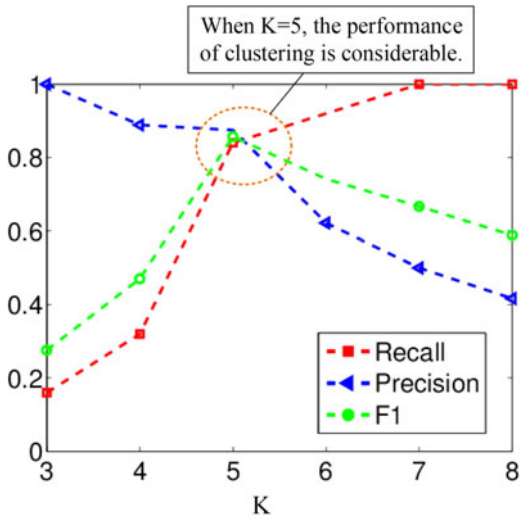


Fig. 10. Evaluation of group discovery performance.

and evaluated the recommendation performance of GroRec using the RMSE.

5.2 Evaluation of Group Discovery Performance

As stated in Section 4.1, in GroRec, group discovery based on behavioral similarity is performed using the KNN clustering algorithm. Because of its simplicity and suitability, KNN is often used to cluster low-dimensional data. In the proposed group discovery scheme, the volume and dimensionality of the context data are effectively compressed and reduced, allowing these data to be processed using the KNN algorithm. To simplify the evaluation of the proposed scheme, we selected approximately 6,000 behavior data corresponding to 57 users at similar times and places from the experimental data. The Recall, Precision and F1 Score, which were calculated using Equations (19), (20) and (21), respectively, were selected as the evaluation indicators for this experiment. In these equations, TP represents the number of true positives, TN represents the number of true negatives, and FP represents the number of false positives

$$Recall = \frac{TP}{TP + TN} \tag{19}$$

$$Precision = \frac{TP}{TP + FP} \tag{20}$$

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}. \tag{21}$$

Fig. 10 illustrates the evaluation of the proposed KNN-based group discovery procedure for several values of K. It is seen that when K is small, FP is small but FN is relatively large; therefore, the Recall is low and the Precision is high. By contrast, when K is large, FP is large but FN is relatively small, resulting in a high Recall and a low Precision. When $K = 5$, the Recall, Precision and F1 Score are all high. Therefore, the experiment confirms that the proposed group discovery scheme is suitable for discovering groups based on the behavioral similarity among users.

TABLE 1
Parameters to Be Determined

Parameter	Significance	Optimal Value
η	learning rate	0.001
λ	regularization parameter	0.1
N	number of iterations	100
M	number of latent factors	15
ρ	weight of original rating	0.7
K	number of latent topics	30
α	weight of user interests	0.1
β	weight of item features	0.1

5.3 Evaluation of the Recommendations Provided by GroRec

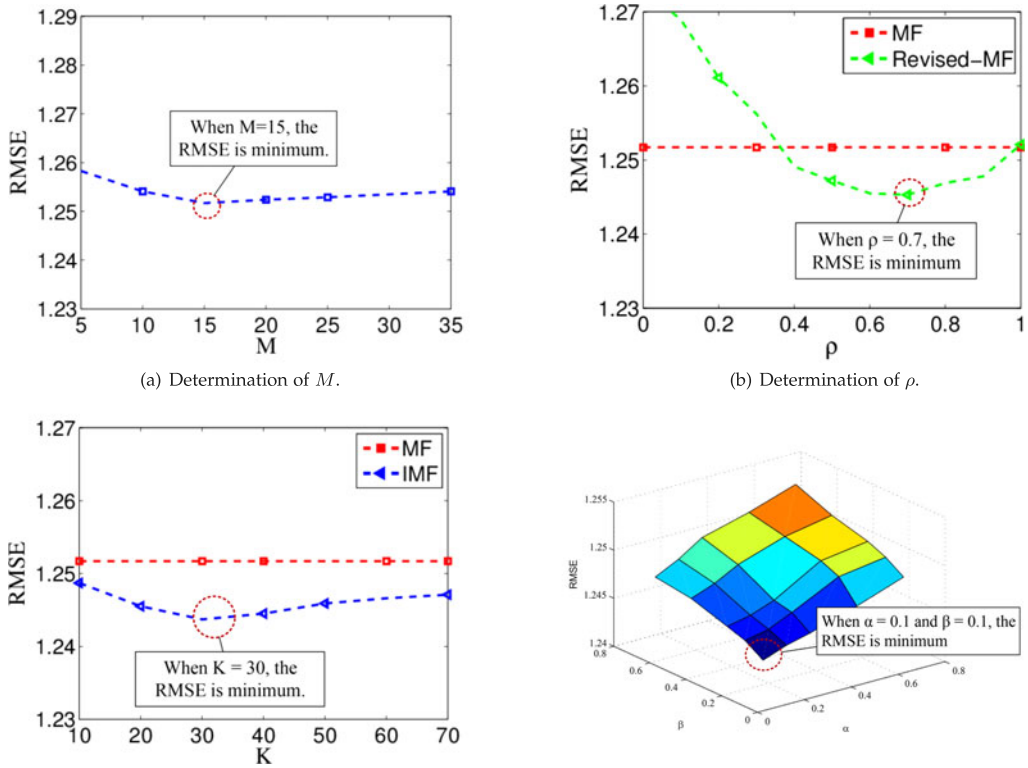
Using Equation (22), the RMSE between the predicted ratings and the actual ratings can be calculated. A smaller RMSE indicates a better recommendation performance. In this equation, n is the number of records in the test data set, p_i represents a predicted rating calculated by GroRec, and r_i represents the corresponding actual rating from the data set

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - r_i)^2}. \tag{22}$$

The experiment reported here was designed to compare our proposed GroRec system with typical systems for item-based CF [25], user-based CF [26] and MF-based recommendations [19]. As described in Section 4.3, the parameters summarized in Table 1 should be determined before the comparison.

In Table 1, η, λ and N are the three basic SGD parameters for MF. Through simple substitution, the results can be found to be satisfactory when $\eta = 0.001$, $\lambda = 0.1$, and $N = 100$. The other optimal parameters were determined as follows. ρ, K, α and β are used only in HMF, and we determined the optimal value for each of these parameters by fixing the other three.

1) M: The determination of M is essential for all MF-based recommendations. Based on the basic MF loss function presented in [19], we evaluated the RMSE for $M = [5, 10, \ldots, 30, 35]$. As shown in Fig. 11a, when $M = 15$, the RMSE reaches its minimum. Therefore, the number of latent factors in the evaluation was determined to be 15.
2) ρ: In the simulation, we set $K = 20$, $\alpha = 0.1$ and $\beta = 0.1$ and attempted to minimize the RMSE with $\rho = [0, 0.1, \ldots, 0.9, 1]$. Here, $\rho = 0$ indicates that only the emotional offset is used for rating prediction, whereas $\rho = 1$ means that only the original rating is used. Fig. 11b shows that when $\rho = 0.7$, the RMSE of the MF calculated based on the emotional-offset-revised ratings (Revised-MF, green line in Fig. 11b) reaches a minimum. The RMSE of the basic MF (MF, red line in Fig. 11b) is also shown as a constant value, corresponding to a special case of the revised MF with $\rho = 1$. The findings indicate that the weight of the emotional offset should be smaller than that of the original rating, because the original rating is usually submitted after some deliberation and is reasonably representative of the user's intent.



(a) Determination of M.

(b) Determination of ρ.

(c) Determination of K.

(d) Determination of α and β.

Fig. 11. Determination of the optimal parameters.

3) K: In the simulation, we fixed $\rho = 0.7$ and set $\alpha = 0.1$ and $\beta = 0.1$. Fig. 11c presents the experimental results for the RMSE of the IMF (blue line in Fig. 11c) as calculated for $K = [10, 20, \ldots, 60, 70]$, revealing that the RMSE reaches its minimum when $K = 30$. If K is too small, the topic distributions of the user interests and item features cannot be sufficiently represented in the MF. Conversely, when K is too large, the degree of fusion of the user interests, item features and latent factors is too low to achieve a small RMSE.

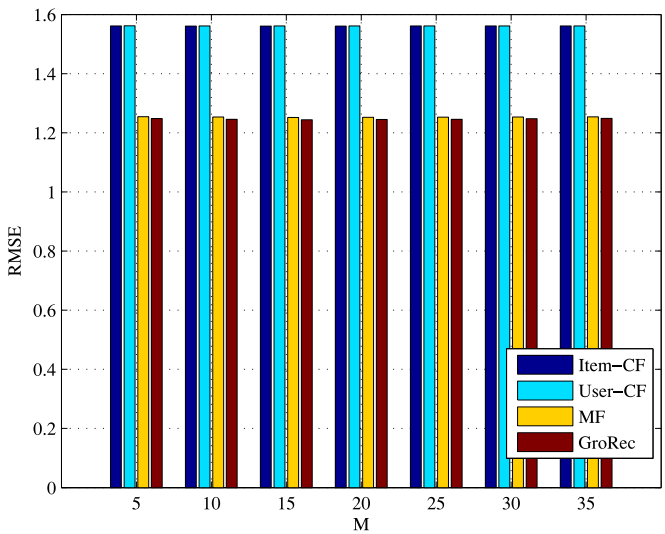


Fig. 12. Comparison between GroRec and conventional recommender systems based on CF and MF.

4) α and β: Based on the parameter determination results presented above, the final parameters to be determined were α and β. We attempted to optimize $\alpha, \beta \in [0, 1]$ through a grid search; as shown in Fig. 11d, the RMSE reaches a minimum when $\alpha = 0.1$ and $\beta = 0.1$. These results indicate that the weights of the user interests and item features, which are used to revise the basic MF to achieve more accurate recommendations, should be rather small.

Using the determined optimal parameters, we evaluated the performance of the proposed GroRec system. In Fig. 12, it is obvious that the RMSE of GroRec is lower than that of MF, which indicates that GroRec is able to provide more accurate recommendations. Furthermore, considering the similarity between the number of latent factors in MF (i.e., M) and the number of neighborhoods in CF, which is one of the most common techniques used in recommender systems, it is reasonable to include the results for item-based CF and user-based CF in the comparison, with the finding that the RMSE of conventional CF-based recommendation is higher than that of MF-based recommendation.

6 Conclusion

At present, CPSSs are evolving rapidly and becoming widely accepted. However, the theoretical foundations of recommender systems are immature, presenting great challenges in improving the sufficiency, objectivity and accuracy of such systems in CPSSs. To address this need, we propose a group-centric intelligent recommender system named GroRec, which integrates social, mobile and big data technologies to provide effective,

objective and accurate recommendation services in CPSSs. Specifically, a group-centric approach based on the behavioral similarity among users is proposed to decrease the complexity of conventional individual-centric recommender systems; a method of quantifying emotional offset based on sentiment analysis is proposed to revise user ratings for improved objectivity of rating data; and a comprehensive approach based on three aspects, i.e., ratings, interests and social relationships, is proposed to comprehensively extract group preferences. Furthermore, experiments verify that the performance of the proposed GroRec system is superior to that of the conventional CF-based and MF-based approaches. However, the proposed scheme can still be further improved, considering that the KNN-based group discovery module has limited processing power. Therefore, in our future work, we will attempt to develop a deep-learning-based approach to improve the efficiency and accuracy of group discovery.

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