Matrix Factorization in Social Group Recommender Systems

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***Abstract*—Traditionally, Group Recommender Systems (GRS) apply an aggregation approach, which computes a group rating for each item by estimating unknown individual ratings; for which has been demonstrated that matrix factorization (MF) models are superior to classic nearest-neighbor techniques in individual recommender systems. Moreover, when people are in a group making a choice from alternatives, they tend to change their opinions accordingly to the social influence exerted by others' group members. Sociological analyses suggest that some social factors express social influence in a group, such as, cohesion, social similarity and social centrality. In this work, we combine a MF model to estimate unknown ratings with a social network analysis (SNA) to evidence possible social influence. Firstly, we present an analysis of the relevance of social factors detected in relation with the members' opinions and, then, we describe the results obtained when comparing the proposed technique with the classic group recommender technique.**

***Index Terms*—group recommender systems; social recommender systems; matrix factorization;**

I. Introduction

Recommender systems are useful tools to help users make effective decisions based on their preferences and interests. Within some domains, recommender systems need to adapt the classic collaborative filtering technique to generate suggestions to groups of users with individual (and possible conflicting) interests. Examples of those domains are systems suggesting movies [1], holiday destinations [2] or songs to play in a shared room [1]. One of the firsts approaches applied in the initial group recommender systems (GRS) was aggregation of individual preferences [3], in which the members' ratings are aggregated to determine a group rating for each candidate item. Some of the techniques applied to aggregate individuals' ratings are multiplication, which calculate a single group value by multiplying the individuals' ratings; maximizing average satisfaction, which calculates an average among members' individual ratings and minimizing misery, which considers the minimum individual rating as a group evaluation based on the theory that the group will be as dissatisfied as the least dissatisfied member [4].

User-based or item-based collaborative filtering techniques are the most used, simple and intuitive to generate individual suggestions [5]. Nevertheless, there is a novel approach that could replace the collaborative filtering, named matrix factorization (MF) approach, which usually is more effective in underlying the interactions between users and items. Recently, some works have applied this approach in order to generate individual recommendations [6].

In addition, most of the recommendation techniques assume users as independent individuals, ignoring social interactions. With the extensive use of social networks, there are new openings to analyze people's behavior in social contexts. Nowadays, most users of those social networks express their interests and preferences in the social profiles and interact with other people as a daily habit. Social recommender systems incorporate the social information to improve the suggestions by identifying trusted-friends of a target user [7], or to detect specific users whose opinions may influence others' behavior [8], [9]. Social influence becomes more significant when the target of the recommendations is a group in which individual users' opinions present varying weight depending on their role or position within the group. In [10] the authors study state of the art approaches to group formation, modeling and recommendation, and present challenging problems to be included in the group recommender system research agenda in the context of the Social Web. In terms of analyzing social influence in groups of users, a sociological analysis is presented by Friedkin [11] who investigated three bases of interpersonal power among group members that can be retrieving from social networks: cohesion (or affective relationships), similarity and centrality.

In view of these previous analyses, in this paper we propose the incorporation of the MF model when group suggestions are generated by aggregating individual influenced preferences (IIP) derived from members' roles and social interactions. This approach analyzes trusted-relationships (TR) expressed by members (cohesion), social similarity (SS) and members' social centrality (SC).

The paper is organized as follows. Section 2 summarizes some related works. Section 3 presents an overview of the proposed technique. Section 4 describes the incorporation of the matrix factorization approach in group recommender systems. Section 5 explains the method to extract social factors directly from the social network. Section 6 describes how the individual influenced preferences' aggregation process is determined by considering the social factors. Then, Section 7 explains the aggregation process which aims to generate the

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final group suggestions. In Section 8, we present our findings and the experimental results obtained when we evaluated the approach within the movie domain in the context of Facebook. Finally, Section 9 presents our conclusion and proposes lines for future research.

II. Related Works

The issue of generating recommendations to groups is a relatively new research field [12], [13]; although, it has produced a number of techniques aimed at meeting the needs of groups [1], [14]. The exponential growth of the social networks caught the attention of the researchers in the area of recommendation and they have begun to analyze this contextual information in order to exploit the users' information to generate more accurate recommendations [15], [16]. Social recommender systems focused on groups of users have started to emerge in recent years [10]. In [17] the authors proposed the use of a social descriptor, which gives a weight representing importance to relationships between members, depending on frequency of daily contact; a descriptor of experience, which determines the experience or knowledge of the members in the domain; and a dissimilarity descriptor, which describes the degree of disagreement between any pair of group members. Moreover, in [18] the authors propose an analysis of group personality composition and trust among group members considering a set of social factors in order to detect tie strength. Additionally, matrix factorization model has demonstrated to be more effective to discover the latent features underlying the interactions between users and items within individual recommender systems [6]. Moreover, some of these works consider social influence as a part of the matrix factorization process [19]. Nonetheless, matrix factorization models have not yet been used in group recommender systems.

III. Overview of the Proposed Technique

This paper proposes a novel technique that combines matrix factorization model and social influence to generate group suggestions. The matrix factorization (MF) model, which is used to discover latent features caused by user-item interactions, is included in the aggregation process when the estimation of unknown ratings is required. This approach replaces the classical k-nearest neighbor (KNN) approach in which users with similar preferences in the community are used to estimate unknown ratings. MF models (presented in detail in Section IV) decompose the rating matrix in two different matrices to discover those latent features allowing the creation of an approximated matrix with values in all cells.

Once the estimation process is performed and the group estimation is required for each candidate item, the resulting values of the MF model are modified according to the social influence exerted for each group member. Social influence among members is represented in a matrix SI_{ij}, with intersection between row *i* and column *j* as social influence value exerted by user *i* over user *j*. In order to determine the social influence matrix, we base our technique in the aforementioned sociological theory proposed by Friedkin. In this theory, Friedkin highlights that members of a cohesive group are likely to be aware of each other's opinions, and describes cohesion as a multidimensional phenomenon entailing structural relations, affective relations and frequent interpersonal communications. Examples of social influence based on cohesion daily occur in situations in which a group is engaged in a collective activity, but the satisfaction of some members is perceived as a primary objective by other members who, due to their closeness, would willingly alter their immediate preferences. Furthermore, the author describes social similarity as the similarity of actors' profiles. In some situations individuals tend to reproduce the behavior and opinions of those users with whom they share activities, likes, friends or interests, among others and whose opinions are usually in sync with their own. Finally, he mentions that central actors are likely to be more influential because they have greater access to information and can communicate their opinions to others more efficiently. In this work, we based social influence in the detection of those three factors from the social network: (1) trusted-relationship (TR) reflects the *cohesion* between two members by analyzing their affective relation (type of relationship); (2) social *similarity* (SS) reflects the likeness between members, i.e. shared activities, likes, friends or interests, among others; and (3) social *centrality* reflects the reputation of each member in the whole social network. These factors are considered to determine the social impact of the others' opinions in each individual member's opinion. The process to extract these factors from the social network is explained in Section V. Figure 1 presents an overview of the proposed technique, in which for each member a social network analysis (SNA) is performed in order to determine the social influence exerted by others members (depending on TR, SS and SC), then the matrix factorization model creates a representation of the rating matrix in which all the unknown ratings are specified. This matrix is used to modify the individual members' opinions before the aggregation of individual preferences which determine the group suggestions based on the highest aggregated values.

IV. Matrix Factorization Model

Matrix factorization (MF) is basically used to factorize a matrix, i.e. to determine two (or more) matrices so that the multiplication is equal to the original matrix. It can be used to discover latent features underlying the interrelations between users and items in order to predict unknown ratings from the known ratings in the matrix ratings. Hence, if those latent features could be discovered, unknown ratings could be predicted with respect to a certain user and a certain item, because the features associated with the user should match with the features associated with the item. To formalize the MF model, we assume a set of users *U* and a set of items *I*. Let M (*UxI*) be the matrix that contains all the ratings given by individual users, and *K* the number of latent features to discover, we need to find two matrices *P* (*UxK*) and *Q* (*KxI*) such that their product approximates *M* ($M \approx PxQ^T = \bar{M}$).

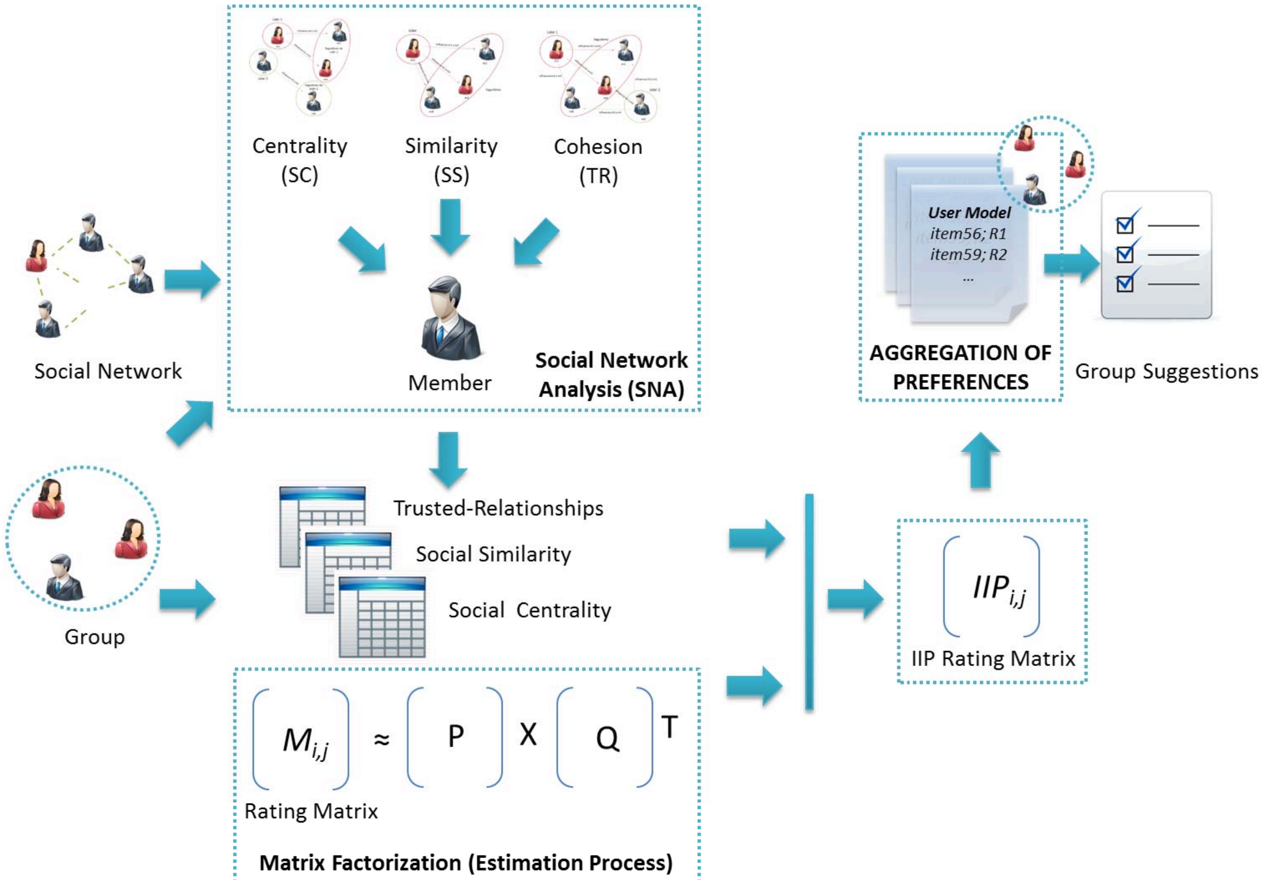


Figure 1. Overview of the proposed technique

P's rows represent the strength of the associations between a user and the features. Q's rows represent the strength of the associations between an item and the features. The estimated rating for an item i by the user u is calculated with the dot product of the two vectors corresponding to u_u and item i_i, as is presented in equation 1.

$$\bar{r}_{u,i} = p_u q_i^T = \sum_{k=1}^{K} p_{u,k} q_{k,i} \tag{1}$$

$$e_{u,i}^2 = (r_{u,i} - \bar{r}_{u,i})^2 = (r_{u,i} - \sum_{k=1}^{K} p_{u,k} q_{k,i})^2 \tag{2}$$

One approach to find the Q and P matrices is known as gradient descent, which first initializes the two matrices with random values, determines the distance (or error) of their product with M, and then tries to iteratively minimize this error. This error is determined by the difference between the estimated rating and the real rating, and it is calculated by equation 2. In order to minimize this error, it is necessary to know the direction to modify the values of $p_{u,k}$ and $q_{k,i}$, i.e. the gradient at the current values (equations 3 and 4).

$$\frac{\partial}{\partial p_{u,k}} e_{u,i}^2 = -2(r_{u,i} - \bar{r}_{u,i})(q_{k,i}) = -2 e_{u,i} q_{k,i} \tag{3}$$

$$\frac{\partial}{\partial q_{k,i}} e_{u,i}^2 = -2(r_{u,i} - \bar{r}_{u,i})(p_{u,k}) = -2 e_{u,i} p_{u,k} \tag{4}$$

Having obtained the gradient, it is possible to formulate the update rules for both $p_{u,k}$ and $q_{k,i}$ (equations 5 and 6, in which α is a constant whose value determines the rate of approaching the minimum). Using these update rules, the operation is iteratively performed until the error converges to its minimum. The overall error is calculated using the equation 7.

$$p'_{u,k} = p_{u,k} + \alpha \frac{\partial}{\partial p_{u,k}} e_{u,i}^2 = p_{u,k} + 2\alpha e_{u,i} q_{k,i} \tag{5}$$

$$q'_{k,i} = q_{k,i} + \alpha \frac{\partial}{\partial q_{k,i}} e_{u,i}^2 = q_{k,i} + 2\alpha e_{u,i} p_{u,k} \tag{6}$$

$$E = \sum_{(u_u, i_i, IIP_{u,i}) \epsilon T} e_{u,i} = \sum_{(u_u, i_i, IIP_{u,i}) \epsilon T} (r_{u,i} - \sum_{k=1}^{K} p_{u,k} q_{k,i})^2 \tag{7}$$

A traditional extension to this algorithm is to introduce regularization to avoid overfitting by adding a parameter β and modify the squared error as in equation 8, in which the new parameter β is used to control the magnitudes of the user-feature and item-feature vectors such that *P* and *Q* would give an effective approximation of *M* without having to contain large numbers. The new update rules for this squared error can be obtained by a procedure similar to the one described above (equations 9 and 10)

$$e_{u,i}^2 = (r_{u,i} - \sum_{k=1}^{K} p_{u,k}q_{k,i})^2 + \frac{\beta}{2}\sum_{k=1}^{K}(||P||^2 + ||Q||^2) \quad (8)$$

$$p'_{u,k} = p_{u,k} + \alpha\frac{\partial}{\partial p_{u,k}}e_{u,i}^2 = p_{u,k} + \alpha(2e_{u,k}q_{k,i} - \beta p_{u,k}) \quad (9)$$

$$q'_{k,i} = q_{k,i} + \alpha\frac{\partial}{\partial q_{k,i}}e_{u,i}^2 = q_{k,i} + \alpha(2e_{u,i}p_{u,k} - \beta q_{u,k}) \quad (10)$$

V. Detecting Social Influence Using SNA

In order to incorporate social influence, we consider three different social factors derived from the sociological analysis presented by Friedkin: the trusted-relationships (TR) expressed by members, social similarity (SS) and social centrality (SC) of each individual member. Trusted-relationships among members have been retrieved from the type of relationship stated by each user in the social network; therefore TR may take one of the following values, representing the closeness of the relationship: (1) couple, (2) family, (3) friends, (4) present co-workers or partners, (5) past co-workers or partners, (6) acquaintances, and (7) unknown. A matrix TR_{ij} (*UxU*) is obtained in which *U* is the set of users and each intersection TR_{ij} is the weight that represents the type of relationship between user *i* and user *j*.

Additionally, the social aspects considered to define the SS among group members are described as follows:

1) **Groups** in which both users are members.
2) **Games** that both users play.
3) Same **pages** liked.
4) **Books** read for both users.
5) **Artists, songs or albums** that both are interested in.
6) **Movies** that both users watched.
7) Same **favorite teams**.
8) Same f**avorite athletes**.
9) Same **TV shows**.

We analyze all of those aspects to determine a social similarity value through a combination of graph augmentation and distance metrics, i.e. we insert a set of nodes representing all possible attributes into the social graph, and determine the distance between each pair of users by utilizing a classical distance metric given by the equation: $d(i,j) = \alpha * d_s(i,j) + \beta * d_a(i,j)$, which combines the structural distance ($d_s(i,j)$) and the attribute distance ($d_a(i,j)$). In this attribute-social graph (ASG) the users and the attributes, such as activities, likes, friends or interests, are represented by nodes and the interest relationship between users and attributes are represented by edges. Firstly, all the non-relevant attributes from the graph are removed by calculating the *betweenness centrality*, which counts the number of shortest paths between a pair of nodes in which nodes *i* resides on. All the attributes nodes which have a *betweenness centrality* equal to zero are discarded from the graph as they fail to provide relevant information about the users' similarity. In this case, d_s is defined with the cosine similarity resulting from the total number of shared neighbors divided by the square root of the product of the total of neighbors of *i* and *j*. On the other hand, d_a is calculated by applying the *min similarity* which results from the number of total shared attributes divided by the minimum value between the total of attributes of *i* and *j*. Finally, as a result of this whole process, a matrix SS_{ij} (*UxU*) is obtained in which *U* is the set of users and each intersection SS_{ij} is the weight that represents the type of relationship between user *i* and user *j*.

As a final stage in this process, the central nodes are assumed to be more influential than peripheral nodes. Therefore, we utilize three different approaches to determine users' centrality in the graph: (1) *degree*, which determines that the nodes with the highest number of ties are the most important, (3) *closeness*, which attribute high node centrality to that which is relatively close to all other nodes and (3) *betweenness*, which considers a node as important if it lies on communication paths because it can control communication flow. Each of these measures is normalized and then the average of the three values is calculated in order to obtain a unique centrality value for each individual user.

VI. Individual Influenced Preferences

To reflect the possible rating of the group as a whole it is necessary to define an aggregation value for each candidate item. For this aggregation process, expressed individual opinions are incorporated in the matrix of ratings *M* traditionally utilized in classic recommender systems [5], in which the intersection of the row *u* and column *i* stands for value $r_{u,i}$ given by user *u* for item *i*. A special feature of this process is that before aggregating individual opinions, a social influence coefficient (extracted *TR*, *SS* and *SC*) is applied to obtain a possible group opinion for a candidate item.

$$IIP_{u,i} = r_{u,i} + \frac{\sum_{v \epsilon G \wedge v \neq u} SI_{v \to u} * (r_{v,i} - r_{u,i})}{|G| - 1} \quad (11)$$

$$SI_{v \to u} = w_{TR} * TR_{u,v} + w_{SS} * SS_{u,v} + w_{SC} * SC_v \quad (12)$$

In order to evidence social influence among group members, individual opinions are modified by equation 11, in which $SI_{v \to u}$ is the value of the social influence exerted by the user *v* to the user *u*, $r_{v,i}$ is the expressed individual opinion of the user *v* about item *i*, $r_{u,i}$ is the rating for the item *i* given by user *u* and |*G*| is the group size. The $SI_{v \to u}$ value is obtained by the application of the equation 12, in which $TR_{v,u}$ is the weight of the social influence exerted by user *u* on user *v* because of the type of relationship between them; $SS_{v,u}$ is the weight of the social influence exerted by user u on user v because of their social similarity, and SC_v is the weight of the social influence exerted by user *v* on user *u* because of the *v*'s centrality. Each type of social influence is weighted to determine a degree of relevance in the final equation (w_{TR}, w_{SS} and w_{SC}). Therefore, the values $r_{u,i}$ in the matrix ratings $\bar{M}$ are transformed with the individual influenced preference value $IIP_{u,i}$ when a group suggestion is required.

VII. Aggregation Process

Once $\bar{M}$ has been obtained, the aggregation process is performed to determine the possible group ratings for the items in the group model. The most classical application of the aggregation of individual ratings approach is based on the notion that for each candidate item c_i and each member m_u, the technique can estimate how m_u would rate c_i. One of the main benefits of this approach is that only a simple aggregation calculation (for example, ratings' average) is required, and there is no need to process members' preferences before this calculation. In order to adapt the aggregation of individual preferences approach to the needs of the inclusion of social influence, for each group member an individual influenced preference is estimated (*IIP*) in order to obtain a single group preference for each candidate item and, then, the candidates with highest groups values are recommended to the group.

The computation of the aggregated values could be performed through numerous aggregation techniques, each with a specific goal as mentioned in Section I. We used the maximizing average satisfaction technique whose is the most used and with the highest performance [3].

VIII. Experimental Results

We carried out the experiments utilizing a Facebook application, named *SocialGR*[1], which is a social recommender system for movies developed by us, and extracts both the individual preferences and social factors from the social network. So as to evaluate our technique, we developed two experiments to separately analyze the impact of the inclusion of the matrix factorization (MF) model and also the impact of the different social influence aspects on group satisfaction. *SocialGR* was presented to 198 users, who were required to complete their profiles by evaluating no less than 20 movies. Then, these users were invited to create groups and evaluate a set of movies by exchanging opinions with other group members. Once the groups' evaluations were obtained, we asked each individual user to complete a survey in which they had to assign a value to others group members that represents how influenced he/she was by that person in the movie selection process.

The first experiment evaluates the impact of the different social factors included to determine social influence in a group by calculating for each pair of users *(u,v)* the estimated social influence (SI) value, by using SNA and then comparing this value with the real one given by each user. In this case, the calculation of the SI estimated value was calculated by varying the relevance of the different social factors, i.e. we compared seven different scenarios:

1) **TRSSSC**: IIP calculated with TR, SS and SC values (w_{TR}=w_{SS}=w_{SC}=1/3);
2) **TRSS**: IIP calculated with TR and SS values (w_{TR}=w_{SS}=1/2 and w_{SC}=0);
3) **TRSC**: IIP calculated with TR and SC values (w_{TR}=w_{SC}=1/2 and w_{SS}=0);
4) **SSSC**: IIP calculated with SS and SC values (w_{SS}=w_{SC}=1/2 and w_{TR}=0);
5) **TR**: IIP calculated with TR values (w_{TR}=1 and w_{SC}=w_{SS}=0);
6) **SS**: IIP calculated with SS values (w_{SS}=1 and w_{TR}=w_{SC}=0);
7) **SC**: IIP calculated with SC values (w_{SC}=1 and w_{SS}=w_{TR}=0).

The second experiment evaluates the accuracy of the proposed technique. For that purpose, the maximizing average satisfaction (MAS) technique was executed in four different fashions:

1) **MAS-MF**: IIP calculated with TR, SS and SC values (w_{TR}=w_{SS}=w_{SC}=1/3). Estimation process with MF;
2) **MAS-KNN**: IIP calculated with TR, SS and SC values (w_{TR}=w_{SS}=w_{SC}=1/3). Estimation process with KNN;
3) **MAS-KNN-NI**: the classical MAS technique; without social influence consideration. Estimation process with KNN;
4) **MAS-MF-NI**: MAS technique without social influence consideration. Estimation process with MF.

Both experiments utilized the error metrics most used in the recommendation literature: mean absolute error (MAE) and root mean squared error (RMSE). Since our numerical rating scale gives ratings over the range [1-5], we normalized to express errors as percentages of full scale: Normalized Mean Absolute Error (NMAE) and Normalized Root Mean Squared Error (NRMSE).

A. Dataset

The dataset utilized to evaluate the proposed approach consists of two parts:

1) The dataset generated with *SocialGR*, which involves users' evaluations, users' social profiles, groups' information and groups' evaluations;
2) The *MovieLens*[2] dataset was utilized to generate the suggestions with the collaborative filtering technique.

The *SocialGR* dataset contains 198 System Engineering students at *UNCPBA* with their social information (groups, interests, activities, among others), 12967 individual users' evaluations, 52 groups (2-5 users in each) and 518 groups' evaluations. Movies in the *MovieLens* dataset were used for both individuals' and groups' evaluations by the 198 users. On the other hand, the *MovieLens* dataset contains 71,567 users, 10,681 movies, and 10,000,054 ratings. The dataset provides movie descriptive content information: title and genres.

[1]apps.facebook.com/socialgr/

[2]*http://www.grouplens.org/*

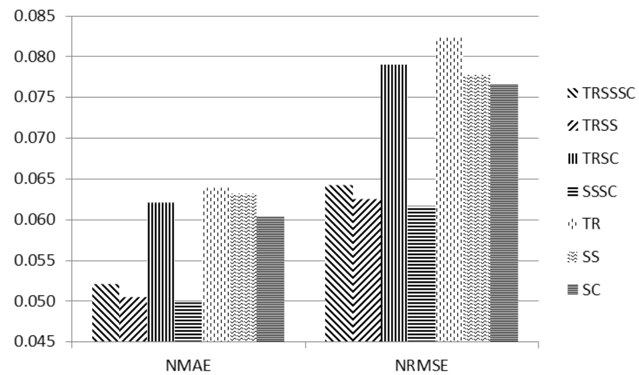
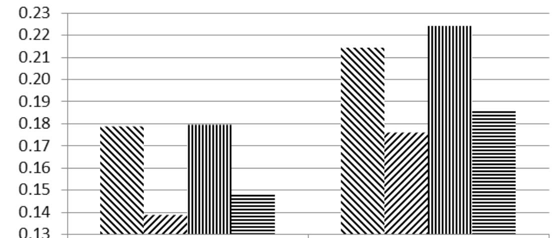


Figure 2. NMAE and NRMSE of the different ways to calculate social influence



	NMAE	NRMSE
MAS-KNN	0.178	0.214
MAS-MF	0.138	0.176
MAS-KNN-NI	0.179	0.224
MAS-MF-NI	0.148	0.186

Figure 3. NMAE and NRMSE of the different MAS techniques

B. Experiment 1: Results

This experiment aims to analyze the NMAE and NRMSE of the social influence estimation process proposed when SNA is used by varying the importance of the social influence factors (TR, SS and SC). With this purpose, we analyzed the feedback obtained from 198 users organized in 52 groups. The values of the influence given by users were utilized to evaluate the technique. Figure 2 presents, the NMAE and NRMSE values for the different variations of the process. This figure shows that, in general, the SNA performed to determine social influence among group members, achieve *SI* values that are drastically close to the real ones (explicitly given by group members), with an error less than 0.085. Moreover, the results suggest that the social factors extracted has a dissimilar impact, being social similarity and social centrality the most relevant factors to improve the accuracy when social influence is detecting. Then, when each social factor was separately evaluated it is noticeable that the factor with more impact in the final accuracy is SC (see TR, SS and SC).

C. Experiment 2: Results

This experiment aims to analyze the NMAE an NRMSE of our technique (MAS-MF) compared with the classical aggregation technique (MAS-KNN), and, also aims to compare these variations without modifying individual ratings with the social influence exerted by members (MAS-KNN-NI and MAS-MF-NI) . In this case, we also analyzed the feedback obtained from 198 users organized in 52 groups. Figure 3 presents, the NMAE and NRMSE for each technique. These error values (NMAE and NRMSE) indicate that estimated ratings values has a difference (or error) of approximately 22% of the real ratings values for each algorithm. A noteworthy aspect of these figures is that in all cases the introduction of the social factors and the matrix factorization model in the maximizing average satisfaction (MAS) technique implies a substantial improvement of the accuracy. The most accurate technique was MAS with consideration of the social influence and matrix factorization model (MAS-MF).

IX. Conclusions and Future Work

We presented a variation of the classical aggregation technique to generate group recommendations that considers social factors extracted from the social network (using SNA) based on a sociological theory and also utilizes the matrix factorization model to estimate the unknown individual ratings. Moreover, we present an analysis of the impact of these social factors in the influence values given by the group members. The results obtained when evaluating the analysis of the social network and social interaction to detect social influence are promising because the errors values obtained when the estimated SI is contrasted with the real SI given by users are fairly low (less than 0.09). Furthermore, we found that these factors do not have the same impact on the final group satisfaction, being social similarity the aspect with the more impact reducing the errors values. Moreover, in experiment 2 we found that when matrix factorization is used to estimate the unknown ratings the technique generate more accurate suggestion for the groups and, also, it is observable that the most accurate technique was MAS with the inclusion of social factors (to detect social influence) and matrix factorization model (to estimate unknown ratings).

There are few works which consider social influence in group recommender research area. This work differs from those in which it is based in a sociological theory which explains social influence in groups of users and those aspects are extracted directly by a social network analysis (SNA) and also in this work we replace the classical K-NN estimation process for the MF model which demonstrates to be more accurate to generate suggestions. As future work, we are planning other evaluations which involve a change of domain and an extended dataset.

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