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Social influence in group recommender systems

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Abstract

Purpose – The purpose of this paper is to propose an approach to generate recommendations for groups on the basis of social factors extracted from a social network. Group recommendation techniques traditionally assumed users were independent individuals, ignoring the effects of social interaction and relationships among users. In this work the authors analyse the social factors available in social networks in the light of sociological theories which endorse individuals' susceptibility to influence within a group.
Design/methodology/approach – The approach proposed is based on the creation of a group model in two stages: identifying the items that are representative of the majority's preferences, and analysing members' similarity; and extracting potential influence from members' interactions in a social network to predict a group's opinion on each item.
Findings – The promising results obtained when evaluating the approach in the movie domain suggest that individual opinions tend to be accommodated to group satisfaction, as demonstrated by the incidence of the aforementioned factors in collective behaviour, as endorsed by sociological research. Moreover the findings suggest that these factors have dissimilar impacts on group satisfaction.
Originality/value – The results obtained provide clues about how social influence exerted within groups could alter individuals' opinions when a group has a common goal. There is limited research in this area exploring social influence in group recommendations; thus the originality of this perspective lies in the use of sociological theory to explain social influence in groups of users, and the flexibility of the approach to be applied in any domain. The findings could be helpful for group recommender systems developers both at research and commercial levels.

Keywords Social networks, Social influence, Group aggregation, Group recommender systems, Social centrality, Social interactions

Paper type Research paper

Introduction

Recommender systems have become essential tools in most e-commerce sites and thereby have captured the attention of researchers in the last decades. As a first approach most recommendation techniques focused on satisfying individual users by analysing their revealed preferences and past activities. Nevertheless in some domains users tend to perform activities collectively, as in the case of a group watching a movie (Christensen and Schiaffino, 2011), eating out or planning a holiday (Ardissono *et al.*, 2003); this particular market niche demands the adaptation of classic recommender systems to cater for both individual and common preferences (Jameson and Smyth, 2007).

For all intents and purposes group recommender systems could be classified into two main categories:

(1) those which perform an aggregation of individuals' preferences to obtain a possible group evaluation for each candidate item; and

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(2) those which perform an aggregation of individuals' models into a single group model and generate suggestions based on this model (Ortega *et al.*, 2013).

Some of the techniques applied to aggregate individuals' ratings are multiplication, maximising average satisfaction (MAS), and minimising misery. To create a group model reflecting the preferences of most of a group, the systems aggregate group members' revealed preferences. Suggestions are generated for the "virtual user" constructed upon the group model, by applying a classic recommendation technique for individual users.

Nowadays most recommender systems are integrated into web sites that are often connected to social networks, providing access to users' profiles and interactions in those sites. Data analysis of social network information has thus become an extra resource to upgrade recommendations. The initial use of such data has been applied in individual recommender systems, also known as social recommender systems, as they assumed trusted relationships (TR) might affect individual preferences. These systems analyse social interactions to identify strong relationships or "trusted-friends" of a target user (Massa and Avesani, 2004), or detect specific users whose opinions may influence others' behaviour (Ye *et al.*, 2012; Subramani and Rajagopalan, 2003). This original application of social network information has also been utilised to upgrade group recommendation systems.

Group recommender systems were first applied in contexts closely related to leisure activities, such as movies, music, or travelling. Although recommendations have traditionally been based on individual preferences, and/or group profiles, an important aspect of collective activities seems to have been neglected: the need to reach consensus. In non-virtual environments consensus results from negotiation among group members, who are frequently willing to modify initial individual opinions for the sake of the common enjoyment of the group as a whole. Therefore the inclusion of social influence as a variable in group recommender systems is a natural evolutionary stage in the field, as the analysis of some social factors might allow the system to predict, to some extent, group members' potential to influence and be influenced, in an attempt to replicate the power of personal interaction in non-virtual contexts. This is an innovative line of investigation that has begun to be explored in recent years (Cantador and Castells, 2012).

Social influence has been studied by various authors in an attempt to identify interpersonal factors that could be understood as indicators of opinion changes (Friedkin and Johnsen, 2011; Crandall *et al.*, 2008). For instance Young and Srivastava (2007) describe an overview of the impact of social influence on e-commerce and explain that central nodes in a social network could represent influential consumers, while TR could be used to increase the accuracy of suggestions. Additionally Bonhard *et al.* (2006) demonstrate users' interests, not only users' ratings, are important to decision-makers when choosing items. Moreover a thought-provoking sociological analysis is presented by Friedkin (2006) who investigated three bases of interpersonal power among group members that can be retrieved from social networks: cohesion, similarity, and centrality. He 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 and affective relations. Furthermore Friedkin describes social similarity (SS) as the similarity of actors' profiles. Finally he claims central actors are likely to be more influential because of their greater access to information and efficiency in communicating opinions.

In view of these analyses we propose an approach to generate group suggestions based on a group model created by aggregating influenced individual preferences (IIP) derived from individual members' roles and social interactions. This approach analyses TR expressed by members, SS among members and social centrality (SC) of each group member. A TR reflects the cohesion between two members by analysing their affective relation. SS reflects the likeness between members, i.e. shared activities, likes, friends, or interests. SC reflects members' reputations in the social network. These factors are considered to determine the social impact of the others' opinions in each individual member's opinion. Additionally group structure and degree of heterogeneity among members are examined to detect items suitable to be included in the group model, by applying the two best-known individual recommendation techniques: collaborative and content-based filtering.

The paper is organised as follows. The next section presents an overview of the proposed approach. The following section explains the method that obtains the items to include in the group model. The subsequent section mentions the social factors considered in this work and the mechanisms utilised to extract them directly from the social network. Then we describe how our approach executes the IIPs' aggregation process by considering those social factors. After that we explain how the final group suggestions are generated. Next we present our findings and the experimental results obtained when we evaluated the approach within the movie domain in the context of Facebook. Then some related works are summarised, and the final section presents our conclusions, implications of our research, and proposes lines for future research.

Overview of the approach

We propose an approach to generate group suggestions based on the aggregation of individuals' models into a single group model; in this context there are two important factors to consider:

(1) which items (of the individuals' models) to include in the group model; and

(2) how to aggregate individuals' preferences about those items to obtain a possible collective preference.

In order to identify items to include in the group model, we developed a hybrid approach incorporating the items of each member's models by analysing the degree of heterogeneity within a group (Christensen and Schiaffino, 2012). This approach combines two familiar individual recommendation approaches – collaborative and content-based filtering – to allow the detection of implicit similarities between members' rating models.

In this paper to aggregate individuals' preferences we present a technique that considers social factors directly extracted from an analysis of interactions within the social network. The main goal of this analysis is to detect group dynamics, styles, and members' roles to identify the degree of influence among group members and evidence of possible changes in preferences. The work is based on the assertion that an individual's opinion could be altered when a person is part of a group cooperating for a shared goal. The closer the relationship between members, the higher the influence on each other's opinions, i.e. for the sake of consensus they would be willing to revise opinions.

This approach bases the analysis of social influence on three tenets:

(1) the relationships between members as expressed by themselves;

(2) the SS and shared interests; and

(3) the SC and reputation in the social graph, to model the bases of interpersonal power introduced by Friedkin (2006).

Figure 1 presents a general schema of the whole group recommendation approach, in which a group and the social network graph are the inputs and the recommendation list the final output. Group formation is analysed to determine items for the group model and the social network is examined to detect members' relationships, SS, and SC. This information is considered together with individual preferences for the selected items resulting from the aggregation to estimate a single group preference. Finally the group model obtained becomes an individual model by implementing a traditional collaborative filtering technique in order to produce a list of suggestions for the group.

Detection of the group model's items

Creating a group model is the most suitable approach to recognise group preferences (Jameson and Smyth, 2007); the main challenge lies in identifying items that should be considered as collective preferences. In the light of that difficulty, we propose a hybrid approach to generate group recommendations based on group modelling for both homogeneous and heterogeneous groups, which are conceived as distributed in a centre-periphery structure. This approach, presented in detail in our previous work (Christensen and Schiaffino, 2012) integrates three different user models (individual models, core group model, and extended group model) and can be characterised in three main steps, as shown in Figure 2: outliers detection, outliers inclusion, and group preference aggregation.

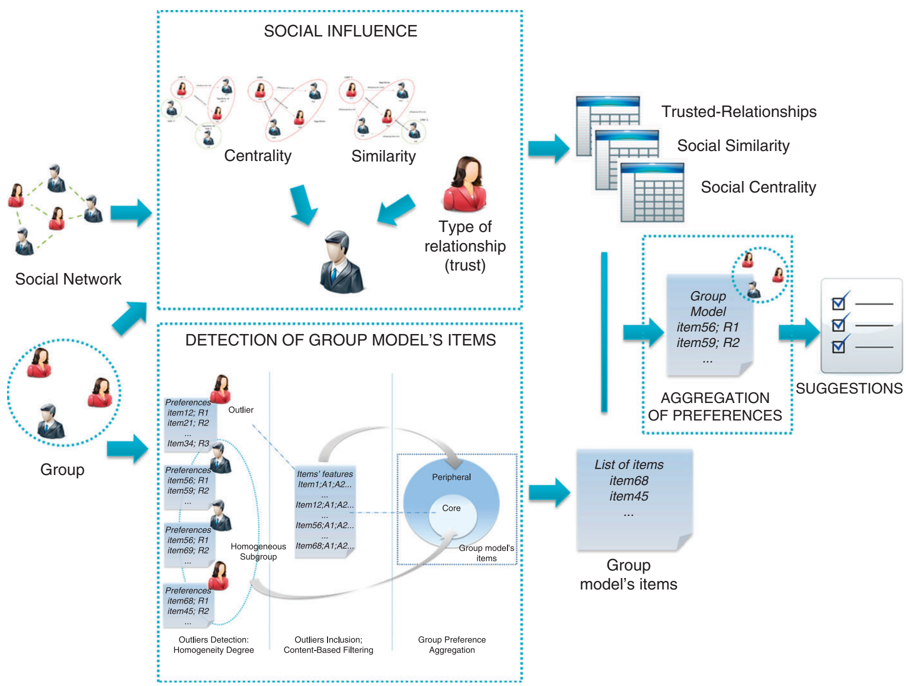

Figure 1.
General schema of the proposed approach

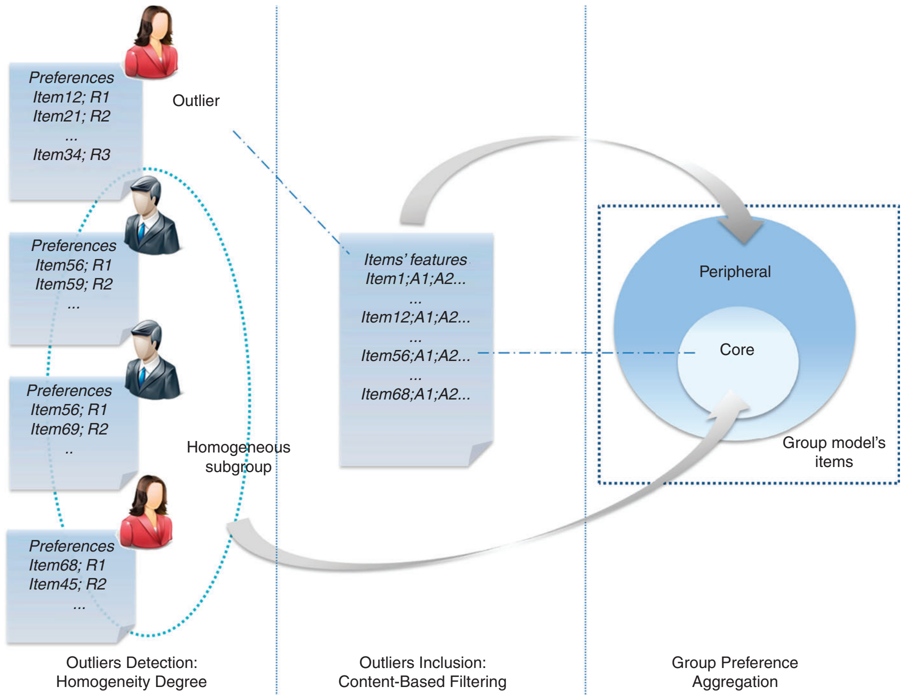

Figure 2.
Hybrid approach for the detection of group model's items

In the outliers detection process, members with markedly dissimilar models are detected and a homogeneous subgroup is formed with core members. Specifically we use a proximity-based technique: if the similarity values between the target user (a group member) and m of the k-nearest neighbours (where $m < k$) lie within a specific distance threshold d then the exemplar is deemed to lie in a sufficiently dense region of the data distribution to be classified as normal. However, if there are less than m neighbours inside the distance threshold then the exemplar is an outlier. Therefore to detect all the outlier members and construct the homogeneous subgroup a cross-correlation calculation among all group members is required. This process ends with the construction of the core profile, in which the items in the member's models of the homogeneous subgroup are incorporated as part of the core group model.

Once outlier members have been detected, the homogeneous subgroup identified and the core group model constructed, items in the individual outliers' models are included by comparing their content-similarities with items in the core group model; only items with high content similarity are included in the peripheral group model. In other words the approach considers only those items (rated by the outliers) whose total similarity with the whole set of items in the core is higher than a given threshold t. At the end of this process the group model is constructed with all the items included in the core and peripheral group model.

Since our goal is to analyse the relevance of social factors in the aggregation process, the third step that implies the group preference aggregation (i.e. the aggregation of the individual preferences to determine a single group preference for each item in the group model) has been modified to include the variations produced by social influence exerted among group members (see section below on aggregation of preferences).

Social influence

Social influence, that is, the degree of influence that one individual may have on another, may be measured by analysing various social factors. In this paper we consider three of those factors: the TR expressed by members, SS, and SC of each individual member. Examples of social influence based on TR occur daily 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. TR 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, or 7 = unknown.

The present research work explores the application of social recommender systems within the particular domain of movies, a social context typically related to personal or leisure activities that users might engage in with friends, family, or acquaintances. Thus each type of relationship is replaced with a weight that represents its relevance, by utilising a simple discretisation technique in which the closest relationship (couple) receives the highest weight. Finally a matrix $TR_{i,j}$ $(U \times U)$ is obtained in which U is the set of users and each intersection $TR_{i,j}$ is the weight that represents the type of relationship between user i and user j. Relationships can be specified by users or obtained from social interactions. In a different context, different relationships and weights might be considered.

Social influence is also affected by SS as in some situations individuals tend to reproduce the behaviour of those with whom they share activities, likes, friends, or interests, and whose opinions are usually in sync with their own. In this case we consider a set of social aspects extracted from social networks to define SS among members (see Table I).

In view of the infinite variety of users' interests, the analysis of the factors that determine a SS value between two members is challenging. We tackle this challenge by combining 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 utilising a classical distance metric, which combines the structural distance ($d_s(i,j)$) and the attribute distance ($d_a(i,j)$) (Zhou *et al.*, 2009). In this attribute-social graph (ASG) users and attributes – such as activities, likes, friends, or interests – are represented by nodes and interest relationships between users and attributes are represented by edges. First the ASG is examined in order to remove irrelevant attributes from the graph. We utilised a measure of a node's centrality in a graph, referred to as betweenness centrality, which counts the number of shortest paths between a pair of nodes in which node i resides. All the attributes nodes with

Activities	Groups	Groups in which both users are members
	Games	Games that both users play
Tastes	Likes	Same pages liked
	Books	Books read by both users
	Music	Artists, songs, or albums that both are interested in
	Movies	Movies that both users watched
	Favourite teams	Same favourite teams
	Favourite athletes	Same favourite athletes
	Favourite TV shows	Same TV shows

Table I.
List of social aspects that define social similarity

betweenness centrality equal to zero are discarded from the graph as they fail to provide relevant information about the users' similarity (as in the case of attributes linked to a single user). Then we calculate the distance between each pair of users over the ASG, which is determined by the simple equation: $d(i,j) = \alpha \times d_s(i,j) + \beta \times d_a(i,j)$, in which $0 < \alpha, \beta < 1$, and $\alpha + \beta = 1$. The structural distance is defined with the cosine similarity resulting from the total number of shared neighbours (friends) divided by the square root of the product of the total of neighbours of i and j. The attribute distance is calculated by applying the min similarity to generate a representative value considering the large amount of data. Min similarity results from the number of total shared attributes divided by the minimum value between the attributes of i and j. Finally a matrix $SS_{i,j}$ $(U \times U)$ is obtained in which U is the set of users and each intersection $SS_{i,j}$ is the weight that represents the type of relationship between user i and user j. Notice that this matrix is symmetric, i.e. $SS_{i,j}$ is equal to $SS_{j,i}$.

As a final stage in this process, social influence is also considered as a centrality issue, i.e. central nodes are assumed to be more influential than peripheral nodes. To detect this type of social influence we define the term SC as a measure that determines the nodes that are in the centre of the network. There are different approaches that define centrality in a graph and all of them have the same goal: distinguishing "important" nodes. The most popular are: first, degree, which determines that the nodes with the highest number of ties are the most important; second, closeness, which attributes high node centrality to a node which is relatively close to all other nodes; and third, betweenness, which considers a node important if it lies on communication paths because it can control communication flow. Each of these measures is normalised and the average is calculated to obtain a unique centrality value for each member.

Aggregation of preferences

Once we have obtained the items for the group model, it is necessary to define an aggregation value for those items so as to reflect the possible rating of the group as a whole. For this aggregation process, individual expressed opinions are incorporated in the matrix of ratings traditionally utilised in classic recommender systems, in which the intersection of row i and column j stands for value $r_{i,j}$ given by user i for item j. 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.

Figure 3 presents a visual comparison of the classical social recommender systems and our approach. Traditionally social recommender systems incorporate a trust matrix ($T_{u,v}$) in the ratings estimation calculation, in which each intersection of row i with column j is a weight that reflects the trust between user i and user j. This trust weight is mostly given by users and reflects a degree of reliance between each pair of users. As shown in Figure 3, these systems analyse the rating matrix ($R_{i,j}$) to detect users' similarities ($S_{u,v}$) to estimate unknown ratings ($E_{i,j}$) by weighting the opinions of the members based on the relationships. Unlike other social approaches that are based only on the user trust matrix, our approach creates three matrices ($TR_{u,v}$, $SS_{u,v}$, and SC_u) – one for each social factor extracted from the social network – and then develops a social influence matrix ($SI_{u \rightarrow v}$), which will modify the individual ratings at the time of estimation. We create a group model which could be treated as an individual user model, by incorporating it as a new column in the different matrices.

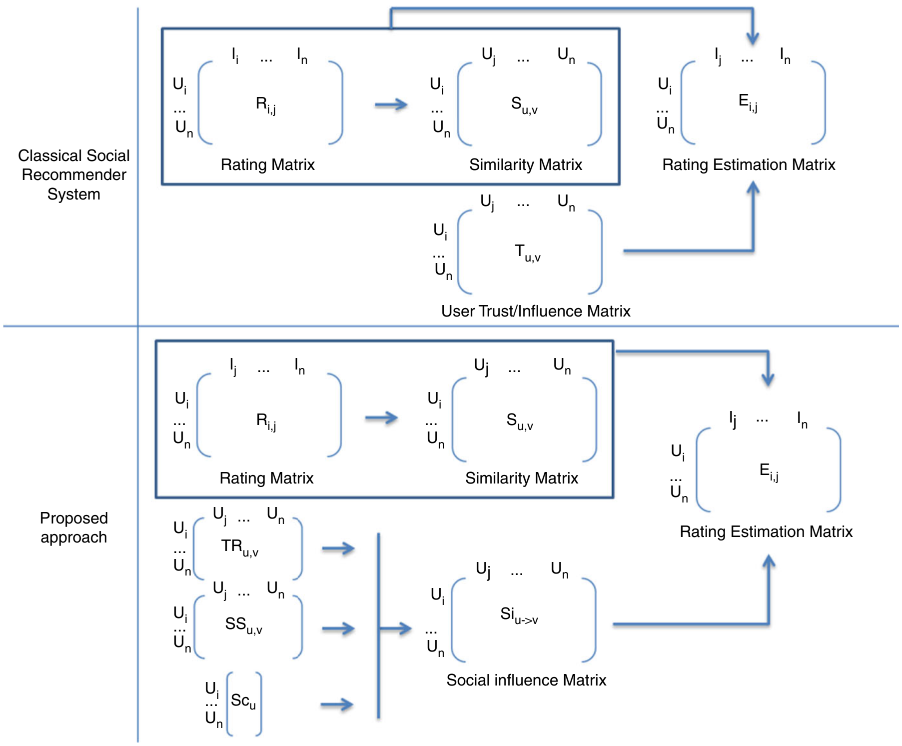

Figure 3.
A visual comparison between classical RS and our proposed approach

IIP

In order to find evidence of social influence among group members, individual opinions are modified by equation 1, in which $SI_{v\rightarrow u}$ is the value of the social influence exerted by user v on user u, $r_{v,i}$ is the expressed individual opinion of 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 $SI_{v\rightarrow u}$ value is obtained by Equation (2), in which $TR_{v,u}$ is the social influence value 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 SS, and SC_v is the social influence value exerted by user v on user u because of 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}):

$$IIP_{u,i} = r_{u,i} + \frac{\sum\limits_{v\in G\wedge v\neq u} SI_{v\rightarrow u} \times (r_{v,i} - r_{u,i})}{|G| - 1} \tag{1}$$

$$SI_{v\rightarrow u} = w_{TR} \times TR_{u,v} + w_{SS} \times SS_{u,v} + w_{SC} \times SC_v \tag{2}$$

Group preferences

Once IIP has been obtained, the aggregation process is performed to determine the possible group ratings for the items in the group model. Although in this work we applied an individual model aggregation approach, it is feasible to adapt the traditional techniques of the aggregation of individual opinions (or ratings) approach, in order to reap their benefits. 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 the value $IIP_{u,i}$ indicating how m_u would rate c_i (considering the social influence), and then compute an aggregated value $IIP_{g,i}$ from the set $\{IIP_{u,i}\}$, to finally recommend the candidates with highest estimated rating $IIP_{g,i}$. One of the main benefits of this approach is that only a simple aggregation calculation is required, and there is no need to process members' preferences before this calculation. Nevertheless all these computations are executed when the target group asks for suggestions, i.e. only in an online phase. Usually the estimation process to determine the unknown individual ratings has an extremely high computational cost due to the huge amount of individual profiles in the data set and users will presumably require a suggestion within minutes or seconds.

In view of this drawback, we decided to apply an aggregation of individual models approach, which counters the computational cost issue by taking advantage of the simplicity of applying a technique derived from the aggregation of individual preferences approach, but processing this information in an offline phase, when the group model is created. To adapt the aggregation of individual preferences approach to the needs of the aggregation of individual models approach, we consider as a base only the items included in the group model I_i, instead of all the candidate items, and for each group member m_u an IIP $IIP_{u,i}$ is estimated to obtain a single group preference $IIP_{g,i}$ from the set $\{IIP_{u,i}\}$.

The computation of the aggregated values could be performed through numerous aggregation techniques, each with a specific goal as mentioned in the introduction. The main goal of this work is to reveal the social influence on individual opinions, which is considered in the estimation process. For that reason we used the MAS technique whose purpose does not modify or interfere with our main goal.

Group suggestions

Since the aggregation of individual models approach has been applied, it is possible to generate group suggestions from the classical individual recommendation techniques. We consider the most frequently used individual technique, known as collaborative filtering (Schafer *et al.*, 2007), which traces users whose preferences are similar to the target users, within the community. In the estimation process for candidate items, a collaborative similarity between the target group's model and the community users' models is obtained based on the real evaluations. The collaborative similarity is calculated by applying the Pearson correlation. A K-nearest neighbours algorithm is performed to obtain the group estimation value for each candidate item through a weighted average of the individual ratings given by the selected neighbours. The group estimation ratings are obtained for each candidate item and those with the highest values will be suggested to the group.

Experimentation and evaluation

We carried out the experiments utilising a Facebook application developed especially for this purpose. The application, named SocialGR (http://apps.facebook.com/socialgr/) – see Figure 4 – is a social recommender system for movies, which extracts both the individual preferences and social factors from the social network. We initially developed SocialGR as a research system with the promise of being an actual application that can be used for anyone as a Facebook application. It is available online but it is still in an exploratory stage, in which all its features are evaluated to improve the recommendations' quality as well as the user's experience. This application was

Figure 4.
SocialGR, a social recommender system for Facebook users

utilised in this case to collect individual users' profiles with real ratings about movies. The system offers a friendly home screen that allows users not only to rate different movies but also to analyse the movie's descriptions – title, year, and link to IMDb (www.imdb.com) – and the movie's trailer. With the individual evaluations, SocialGR can generate individual recommendations by applying a classical collaborative algorithm. In this work we only need the individual profiles and a list of movies that represent the groups' selections (with the respective evaluations). The individual profiles will be part of the training data set, i.e. with these evaluations we train the different techniques. The groups' selection lists will be part of the test data set, i.e. with the trained techniques we estimate a rating for each known rating in the groups' selections and we calculate the error produced by each technique. SocialGR utilises the movies and the evaluations (individual profiles) included in the MovieLens Dataset (distributed by the Grouplens group at the University of Minnesota and available at: www.grouplens.org/) as a basis to generate suggestions.

Data sets

The data set utilised to evaluate the proposed approach consists of two parts:

(1) the data set generated with SocialGR, which involves users' evaluations, users' social profiles, groups' information and groups' evaluations; and

(2) the MovieLens Dataset that was utilised to generate the suggestions with the collaborative filtering technique.

The SocialGR Dataset contains 198 systems engineering students at UNCPBA (www.unicen.edu.ar/) with their social information (groups, interests, activities, among others), 12,967 individual users' evaluations, 52 groups (two to six users in each) and 518 groups' evaluations with a total of six couples, 116 friends, 67 present co-workers or partners, 49 past co-workers or partners, 53 acquaintances and 28 unknown. In this case there was no relationship of the family type. Moreover on average each student's social profile has a total of 25 activities or tastes to analyse. Furthermore 82.6 per cent of the students were male, only a 17.3 per cent were female, and the ages varied from 21 to 26 years old.

Movies in the MovieLens Dataset were used for both individuals' and groups' evaluations by the 198 users, allowing us to extend the MovieLens Dataset with the data set generated by SocialGR, i.e. the individual profiles generated with SocialGR are incorporated as part of the MovieLens Dataset. We decided to perform this extension because the MovieLens Dataset provides a set of real individual profiles that can be used as a substantial set of community users when calculating similarities between users and finding neighbours to generate estimations.

The MovieLens Dataset contains 71,567 users, 10,681 movies, and 10,000,054 ratings. The data set provides movie descriptive content information, title, and genres.

Methodology

In order to evaluate our approach, we developed an experiment to separately analyse the impact of the different social influence aspects on group satisfaction. First the proposed hybrid approach is executed in two different ways:

(1) HY-TR-SS-SC: IIP calculated with TR, SS, and SC values ($w_{tr} = w_{SS} = w_{SC} = 1/3$); and

(2) HY-NSI: without social influence ($w_{SS} = w_{SC} = w_{tr} = 0$).

All of these variants of the comprehensive approach were juxtaposed with one of the most used and best performing (Christensen and Schiaffino, 2011; Ortega *et al.*, 2013) group recommendation techniques by varying the three social aspects considered in this work:

(1) MAS-NSI: a simple MAS technique, without social influence consideration;

(2) MAS-TR-SS-SC: MAS, IIP calculated with TR, SS, and SC values ($w_{tr} = w_{SS} = w_{SC} = 1/3$);

(3) MAS-TR-SS: MAS, IIP calculated with TR and SS values ($w_{tr} = w_{SS} = 1/2$ and $w_{SC} = 0$);

(4) MAS-TR-SC: MAS, IIP calculated with TR and SC values ($w_{tr} = w_{SC} = 1/2$ and $w_{SS} = 0$);

(5) MAS-SS-SC: MAS, IIP calculated with SS and SC values ($w_{SS} = w_{SC} = 1/2$ and $w_{tr} = 0$);

(6) MAS-TR: MAS, IIP calculated with TR values ($w_{tr} = 1$ and $w_{SS} = w_{SC} = 0$);

(7) MAS-SS: MAS, IIP calculated with SS values ($w_{SS} = 1$ and $w_{tr} = w_{SC} = 0$); and

(8) MAS-SC: a MAS technique, IIP calculated with SC values ($w_{SC} = 1$ and $w_{SS} = w_{tr} = 0$).

The variations without consideration of social influence (MAS-NSI and HY-NSI) are the first baseline techniques; MAS-NSI is a classic group recommendation technique based on the aggregation of individual preferences approach and HY-NSI is a variation of the aggregation of individual models approach, both with no consideration of social influence. Moreover MAS-TR is also a baseline because most of the social recommendation techniques apply only the TR to analyse social influence. The main goal of these experiments is to evaluate the performance of our approach and analyse social influence when generating group recommendations, i.e. we expect to improve the performance of the baseline techniques because of the inclusion of three different social factors: TR, SS, and SC.

Since our approach creates a group model in order to avoid expensive online computation and construct a richer group model, the variation of the social influence aspects (TR, SS, and SC) exhibits slight differences in the final evaluation; this occurs because the group model is used to search for similar profiles in the community and to estimate a rating for each candidate item, which entails some loss of information. Unlike the aggregation of group model approach, when the aggregation of individual preferences approach is modified by varying social influence weight, the differences are more substantial.

SocialGR was presented to about 200 users, who were required to complete their profiles by evaluating no < 20 movies. Then these users were invited to create groups and evaluate a set of movies by exchanging opinions with other group members. In order to evaluate the approach, we utilised the error metrics most used in the recommendation literature: mean absolute error (MAE) and root mean squared error (RMSE). Given a test set τ of user-item pairs (u,i) with ratings $r_{u,i}$, and the estimated ratings $\bar{r}_{u,i}$, MAE and RMSE determine the error distance between the estimated rating and the real one. RMSE penalises wide variation more severely than MAE. We normalised these metrics to express errors as percentages of full scale: normalised mean absolute error (NMAE) and normalised root mean squared error (NRMSE).

Experimental results

This experiment aims to analyse the NMAE and NRMSE values of the approach presented in this work by varying the importance of the social influence factors (TR, SS, and SC) considered in comparison with a classical aggregation technique: MAS. With this purpose, we analysed the feedback obtained from 198 users organised into 52 groups. The students' models were included as part of the training MovieLens Dataset and the users' models included in this data set were considered as community users' models in collaborative techniques. The feedback from the students was included in the test MovieLens Dataset for evaluation.

Figures 5 and 6 present the NMAE and NRMSE values, respectively, for our approach and the variations of MAS.

Discussion and analysis

In order to analyse the effectiveness of our approach and the importance of the inclusion of social influence factors in the aggregation calculation, we carried out an experiment for which we developed ten different variations of the techniques: two for our approach (with and without social influence) and eight for the MAS technique, in

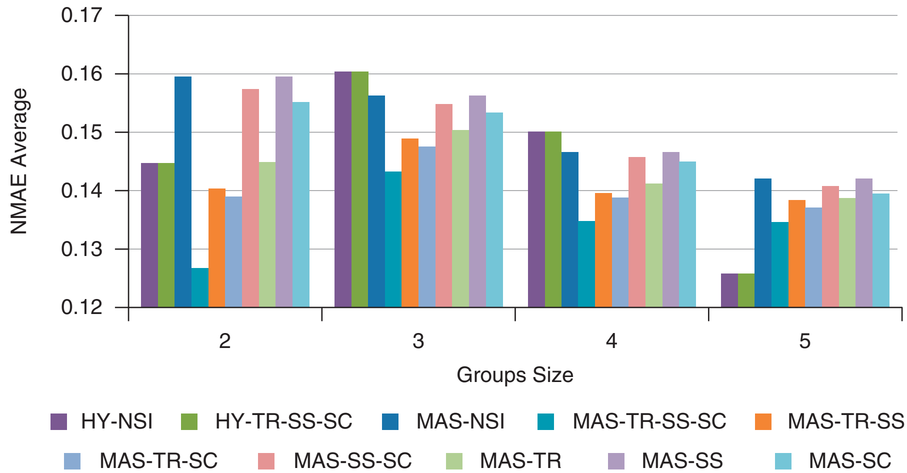

Figure 5.
NMAE average for the different groups' size

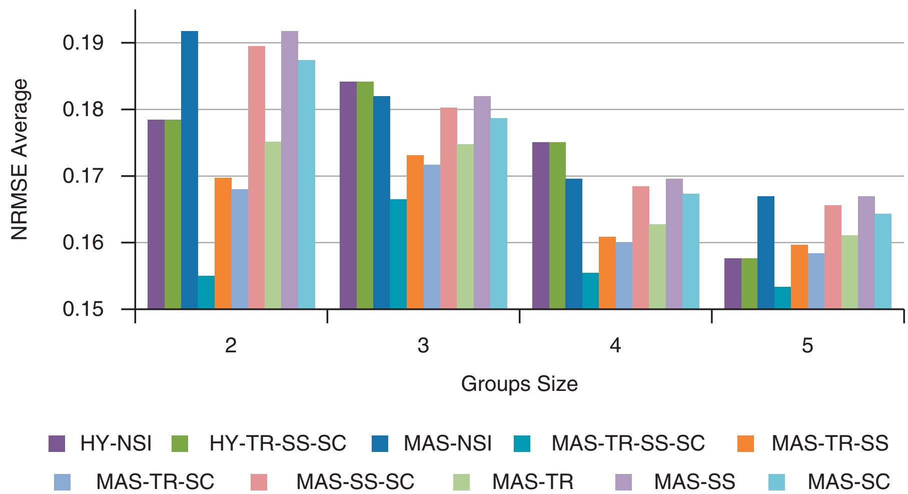

Figure 6.
NRMSE average for the different groups' size

which the relevance (or weight) of the three factors considered were varied: TR, SS, and SC. These variations also include the baseline techniques when no social influence is considered (HY-NSI and MAS-NSI) and also the classical technique widely applied in social recommender systems that only analysed trusted-relationships (MAS-TR). Therefore, as a first goal of this experimentation, we analysed the results of both approaches, aggregation of individual preferences (MAS) and aggregation of individual models (HY), when a social influence analysis is performed (HY-TR-SS-SC and MAS-TR-SS-SC), in contrast with the results obtained without social influence consideration (HY-NSI and MAS-NSI). As a second goal of the experimentation we proposed to analyse the baseline technique extensively applied in social recommender systems, which is based on trusted-relationships (MAS-TR); since one of the social factors considered in this work is TR, we utilised the variation that only considered TR to contrast the results obtained by our proposed social influence analysis (MAS-TR-SS-SC), which considered three different social factors. Finally another objective of this experimentation is to analyse the relevance of each social factor included in the social influence calculation, i.e. we contrasted the different variations of the social influence analysis in order to have a clearer idea of the impact of each of them in the final results. The variations of the social influence factors were calculated considering the MAS technique because in spite of its simplicity this aggregation technique was one of the first to both solve the change of paradigm (from an individual to a group of users) and produce highly accurate suggestions, thus becoming the cornerstone group recommendation method. Moreover when a group model is created the minimal changes that could be generated by the variation of the social influence hardly modify the final group recommendations; this could be appreciated in the final results, in which there are no error differences between HY-NSI and HY-TR-SS-SC.

Figures 5 and 6 present NMAE and NRSME organised by groups' size. The first apparent result of these figures is that for most of the techniques, accuracy improves with large groups. Another noteworthy result is that the introduction of social factors in the MAS technique implies a substantial improvement in accuracy. Furthermore, when applied to groups of three or four users the hybrid approach produced mixed results, but for two or five users the approach yields encouraging results. Nonetheless, in the summarised results presented in Table II, it is noticeable that even though the hybrid approach fails to achieve the lower error values, it outperforms the classic aggregation technique (MAS-NSI). This is one of the advantages of construction of a group model over the aggregation of individual preferences approach (MAS-NSI), together with the benefits of creating it in an offline phase to save time and computational cost, and the inclusion of further details that could be used to tailor the recommendation technique to a specific domain (such as genre, birth, information about past activities, among others).

Table II sums up the error values (NMAE and NRMSE) obtained for each technique by analysing the estimated values in contrast with the real ones. These error values (NMAE and NRMSE) indicate that estimated ratings values produce an error of approximately 18 per cent of the real ratings values for each algorithm. With regard to the first goal, the results revealed that, in the case of the hybrid approach (HY-NSI and HY-TR-SS-SC), there was no difference when the social influence was considered at the moment of creation of the group model. This is because when a group model is created the subtle differences of the preferences derived from social influence among members are not reflected when generating group recommendations. In contrast the results

	NMAE	NRMSE
HY-NSI	0.1503	0.1854
HY-TR-SS-SC	0.1503	0.1854
MAS-NSI	0.1527	0.1878
MAS-TR-SS-SC	0.1338	0.1662
MAS-TR-SS	0.1418	0.1743
MAS-TR-SC	0.1407	0.1732
MAS-SS-SC	0.1514	0.1863
MAS-TR	0.1444	0.1774
MAS-SS	0.1527	0.1878
MAS-SC	0.1501	0.1849

Table II. Summarised results

suggest that when the aggregation of individual preferences approach is applied the difference is more obvious; all the variations which consider some type of social factor (to describe social influence among members) significantly improve the classical techniques (MAS-NSI). Moreover the central technique of our proposal, which applies all the three social factors to determine social influence (MAS-TR-SS-SC), was the one with the lowest estimation errors, and in contrast with the classical social recommendation technique, in which only trusted-relationship (MAS-TR) is considered, our technique significantly reduces the estimation error. Moreover these results suggest that the social factors considered have dissimilar impacts. For example the MAS technique with consideration of SC and trusted-relationship (MAS-TR-SC) yielded higher accurate values than SS and SC by themselves (MAS-SS-SC). The most accurate technique was MAS with all the social factors (MAS-TR-SS-SC). Then when each social factor was separately evaluated it is evident that the factor with more impact on the final accuracy is TR (see MAS-TR, MAS-SS, and MAS-SC) and it is also observable that SC outperforms SS.

Related work

Generating recommendations to customise and satisfy the interests of individual users has been an active research area since the mid-1990s. Several recommendation techniques have been proposed ranging from content-based similarity analysis (Pazzani and Billsus, 2007), collaborative filtering techniques which try to find similar users in the community (Linden *et al.*, 2003), to hybrid techniques that combine different approaches (Burke, 2002).

In view of the exponential growth of the available information generated by social networks, researchers in the area of recommendation have begun to analyse this context to exploit the users' information to generate more accurate recommendations. These systems are known as social recommender systems and their study has recently begun. For example Ma *et al.* (2008) propose a matrix factorisation model for improving recommender systems by incorporating social network information. Moreover the work presented by Massa and Avesani (2004) proposes an algorithm that replaces the phase of finding neighbours by applying a trust metric that propagates trust over the network. Furthermore social information has been utilised by some authors to alleviate the classical problems of the collaborative recommender systems, such as data sparsity (Ma *et al.*, 2011; Pitsilis and Knapskog, 2012). Some social recommender systems analyse the influence of various social factors in the target user's opinion (He and Chu, 2010).

The issue of generating recommendations to groups is a relatively new research field (Boratto and Carta, 2011) although it has produced a number of techniques aimed at meeting the needs of groups in a plethora of domains such as music, movies (Christensen and Schiaffino, 2011), and TV shows (Yu *et al.*, 2006). Nonetheless few studies link social influence and social networks with group recommendation. Cantador and Castells (2012) revise the state of the art in group recommender systems and present open research problems to be considered in this research area, especially related to the social web and social dynamics, among others. However, there are only a few works that include proposals that analyse social factors to anticipate the social influence exerted among group members in the decision-making process in the group recommendation context. For example Gartrell *et al.* (2010) proposed the use of three descriptors of the group members to generate recommendations: a social descriptor, which gives a weight of 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. Additionally Quijano-Sanchez *et al.* (2013) propose a method to generate suggestions for groups of users which includes an analysis of group personality composition, a test designed to measure the behaviour of people in conflictive situations, and assesses trust among group members by analysing a set of social factors in order to detect tie strength. The aforementioned literature explores the importance of social factors in group recommender systems, given that one of the constituent characteristics of groups is the pursuit of a common goal and it is natural to assume that social interactions may have an impact on both individual opinions and final consensus. Unlike the previous research works, which based the analysis of social influence on intuitive measures, we construct an innovative social recommender approach based on Friedkin's sociological theory, which exploits the structural foundations of social networks to detect social influence in groups by identifying and assessing TR, SS, and SC (Friedkin, 2006; Friedkin and Johnsen, 2011); the applicability of that theory is evident in the extensive analysis of social networks dynamics by Crandall *et al.* (2008), Snijders *et al.* (2007), and Yang and Leskovec (2010). For that reason, in comparison with the previous works, our approach not only analyses more factors of the social interactions but it also extracts them in an implicit way. For example the approach presented by Gartrell *et al.* (2010) analyses three descriptors that are only derived from the users' evaluations and the expressed members' relationships. At this point the results obtained with our approach show that the inclusion of social factors other than the members' relationships (such as SS and SC) significantly improves the accuracy of the group recommendation techniques. Moreover the approach proposed by Quijano-Sanchez *et al.* (2013) analyses a set of social factors extracted from social networks to determine the trust between each group member, but it also considers personality composition that is derived from a test that the users have to complete before asking for recommendations. This test, known as the Thomas-Kilmann Conflict Mode Instrument, consists of 30 different situations with two possible answers, which requires a considerable effort from each user.

Conclusions, limitations, and future work

We presented an approach to generate group recommendations which, based on a sociological theory, considers social factors extracted from the social network. Moreover we presented an analysis of the impact of these social factors on the state-of-the-art aggregation technique with the highest performance: MAS. The promising results obtained when evaluating the approach in the movie domain reflect that individuals tend to alter their preferences when they are organised in groups, due to social factors such as interpersonal relationships, SS, or SC as endorsed in aforementioned sociological theory. Furthermore we found that these factors affect final group satisfaction in a variable manner, with TR being the most relevant aspect, but together, significantly improve the baseline techniques.

The first conclusion drawn from the results is that, with respect to the aggregation of individual models approach, the small changes in individual preferences given social influences exerted by members of the group are not significant enough to produce noteworthy improvements in the final groups' estimations. This is because of the creation of the group model as a prelude to the aggregation of individual preferences, so there is some loss of information which is then reflected in the estimation process.

Nevertheless we believe this approach is one of the most important in the group recommendation research area, since it is the one with the most flexibility regarding the information that can be incorporated into a group model, and also this approach allows a pre-processing offline stage. Consequently it saves timeout response from the user, which is impossible with the aggregation of individual preferences approach, in which the calculations must be performed when the group requests the recommendations. However, the results obtained with our approach to aggregating individual models outperform the classical approach of aggregation of individual preferences. The results obtained from the different variations of the aggregation of individual preferences approach reveal the importance of the inclusion of social influence in the group recommendation process. In this approach small variations in individual preferences proved to be highly relevant to generate estimations that represent the opinion of the group as a whole.

The proposed approach can be used in any domain in which ratings are considered in the process of group recommendation and could include further meaningful information to generate the suggestions. There is limited research in this area exploring social influence in group recommendation; thus the originality of this perspective lies in the use of sociological theory to explain social influence in groups of users, and the flexibility of the approach to be applied in any domain. In particular our findings can be helpful to group recommender systems developers, both in the research and commercial fields, that would like to consider social relationships within their systems. An example of such a system might be a site that sells tours to groups of users. Such a system would benefit from including our approach and findings in the recommendation process. Furthermore we implemented this approach as part of a framework that includes various group recommendation techniques (Christensen and Schiaffino, 2011). Therefore, to utilise our approach, a recommender system can extend this framework, which needs as input the individuals' profiles (evaluations and interests), group members, and social relationships.

There are some limitations in our approach that should be mentioned. First in order to weigh the different types of relationships we had to determine some standard criteria. Considering that in this work we applied our approach in an entertainment context, we decided to establish an order in which affective relationships have more relevance than business relationships. This probably needs to be modified in other recommendations domains. Moreover a list of only nine social aspects was extracted from Facebook to determine SS among group members. The values of SS between each pair of users can be improved if more social aspects are considered, for example photos in which both users are tagged, posts in common, shared videos, among others.

A line of research worth pursuing further is the evaluation of this approach and the impact of social influence in group recommendation by applying different social network analysis approaches, in order to extract more accurate information about interpersonal relationships, considering complexity and interaction effects. Moreover we are identifying other evaluations which involve a change of domain and an extended data set.

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