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A Hybrid Approach for Group Profiling in Recommender Systems

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Abstract: Recommendation is a significant paradigm for information exploring, which focuses on the recovery of items of potential interest to users. Some activities tend to be social rather than individual, which puts forward the need to offer recommendations to groups of users. Group recommender systems present a whole set of new challenges within the field of recommender systems. In this paper, we present a hybrid approach based on group profiling for homogeneous and non-homogenous groups containing a few distant individual profiles among their members. This approach combines three familiar individual recommendation approaches: collaborative filtering, content-based filtering and demographic information. This hybrid approach allows the detection of those implicit similarities in the user rating profile, so as to include members with divergent profiles. We also describe the promising results obtained when evaluating the approach proposed in the movie and music domain.

Key Words: Group Profiling, Group Recommender Systems, Aggregate Ratings, Hybrid Recommender Systems, Group Heterogeneity
Category: I.2.1, I.2.6, L.2.2, L.2.7, L.6.2

1 Introduction

Recommender systems appeared because of the need to provide assistance to users of domains with a wide variety of potentially interesting items. These systems identify items that match users' preferences and needs. Recommendation focuses on the recovery of items of potential interest to users, such as movies, music, tours [Rodriguez et al., 2010, Noguera et al., 2012], among others. There is extensive research focused on satisfying individual users' needs [Ricci et al., 2011, Boratto and Carta, 2011]. Highly sophisticated individual recommender systems are able to interpret users' preferences and provide recommendations based on personalization techniques. These systems implement several approaches to generate suggestions, such as content-based recommendation, collaborative filtering or demographic information; some systems even combined these methods to result in hybrid techniques [Schiaffino and Amandi, 2009].

The content-based approach is based on the notion that each user exhibits a particular behavior under a given set of circumstances, and that such behavior is repeated under similar situations. A content-based recommendation system learns the users' profiles observing the items classified as "interesting", either explicitly or implicitly. On the other hand, collaborative filtering predicts a user's behavior by identifying similarities with other users. This technique compares the evaluations given by an active user with those ones given by other users, to find users with similar tastes, and generate suggestions derived from similar users' evaluations. Finally, the filtering techniques based on demographic information aim to categorize the users according to their personal information and generate suggestions based on their demographic category. For example, attributes such as age, gender, education and location could be used in the classification process. There are few purely demographic recommender systems due to the users' unwillingness to share large amounts of personal data with the systems. Nowadays, with the exponential growth of social networks the situation is changing to a wider perspective, with users more confident to share personal information.

Activities in online social networks, such as Facebook[1] or Twitter[2], have increased exponentially and some recommender systems have used information derived from these social networks to generate more accurate recommendations. For example, in [Pham et al., 2011] it is proposed a clustering approach that is based in users' social information to identify the neighborhood of the users. In [Carrer-Neto et al., 2012] the authors propose a hybrid recommender system based on knowledge and social information, which makes use of an ontology to structure the semantic of the domain. Related approaches are proposed by [Blanco-Fernández et al., 2011], in which it is considered that time influences the individual preferences, and by [Ting et al., 2012] in which the suggestions are based on data from micro-blogs.

Within some domains, activities tend to be social, which puts forward the need of adaptation of the classic recommender systems, since the end user of the suggestion is a group formed by individual users with particular preferences. For example, domains such as restaurants, TV programs, movies or music [Christensen and Schiaffino, 2011], tend to be used more frequently by groups rather than by individuals. Group recommendation expands recommender systems research area, as the idea of generating a set of recommendations to satisfy a group of users with possible competing interests is a significant challenge. In [Jameson and Smyth, 2007] this challenge is organized in terms of four sub-tasks that could be carried out by group recommenders: obtaining information about users' preferences, generating recommendations, explaining these recommendations and helping users to reach consensus. Generating recommendations is the sub-task that has concentrated most researchers' attention.

There are three basic approaches to generate group recommendations: merg-

[1] http://www.facebook.com
[2] http://www.twitter.com

ing individual recommendations, aggregation of individuals' ratings, and construction of a group profile. Some of the techniques applied to aggregate individuals' ratings are multiplication, maximizing average satisfaction and minimizing misery, among others. A comparative analysis of these techniques has shown that multiplication and maximizing satisfaction are the most successful to achieve individual satisfaction [Christensen and Schiaffino, 2011].

This paper presents an approach to generate recommendations based on group profiling for both homogeneous and heterogeneous groups. The proposed technique combines the best-known individual recommendation approaches, collaborative and content-based filtering, to detect implicit similarities within the user rating profiles and allow the inclusion of members with distinctive and/or conflicting preferences (or "*outliers*[3]"). The heterogeneity of the group is analyzed to identify these *outliers* and to define a homogenous subgroup with the remaining members to create a *core* profile. The group profile will be enriched with *outliers*' preferences to allow the integration by considering the principles of the content-based filtering. After this process, the group collaborative profile is composed by items provided by the individual profile with high collaborative similarity and also items belonging to members with low collaborative similarity (*outliers*) but high content-based similarity. The demographic information of the members is then aggregated to create the demographic group information. Finally, we utilize collaborative and demographic filtering to generate the suggestions for the group.

The rest of the paper is organized as follows: Section 2 describes the hybrid group profiling technique proposed in this work. In Section 3 we describe an illustrative example of the group profiling process. Section 4 presents the experimental results obtained when analyzing the technique. Section 5 mentions some related works. Finally, Section 6 presents our conclusions and the future works.

2 Hybrid Group Profiling

Many existing techniques to generate group recommendations are based only on the rating-based collaborative preferences, i.e. the profile that contains the ratings given by users. To create a list of recommended items for a group, these techniques estimate the rating for unevaluated items and aggregate these ratings to obtain a single one that represents the whole group. In this context, the insufficient overlap between users' profiles is a hindrance to make high quality recommendations.

In group recommendation, the user profile is used to generate suggestions based on the aggregation approach; this approach is limited to members' evaluations and fails to consider a group profile that may be enriched with several

[3] We called "*outliers*" to the members with distant profiles from the rest of the group.

characteristics, either by the domain as member, group or even subgroups of users. Moreover, most research on group recommendation has been developed under the assumption that groups are homogeneous, i.e. group member profiles will have similar preferences. The evaluations are carried out with homogeneous groups for which most aggregation preferences techniques aim at satisfying all individual members. Upon the analysis of how groups are composed, it could be observed that they may vary from formally established, long-term groups to "ad-hoc" collections of individuals who use a system together on a particular occasion [Boratto and Carta, 2011]. Furthermore, if the degree of group homogeneity decreases, the individual satisfaction obtained from the suggestions generated by any of the above techniques can be expected to decline for all group members. The application of these techniques is successful in achieving high levels of satisfaction for homogeneous groups, but hinders overall group satisfaction in the case of heterogeneous groups.

Creating a group profile is the most suitable approach to model group's preferences regarding different aspects. The group profile may include information related to users' evaluations of items, as well as demographic information about users, usability preferences of the system, domain knowledge, among others. A user profile may consist of any information deemed relevant at the time of personalizing the system. The main challenge of creating a group profile lies in identifying the set of items that should be considered as preferences of the group as a whole. Considering that difficulty, in this work we present a hybrid approach to generate group recommendations based on group profiling that contemplates both homogeneous and non-homogeneous groups. This approach differs from the existing approaches in that it aims at finding implicit similarities between the members' rating profiles, combining three individual recommendation techniques: collaborative filtering, content-based filtering and demographic information. As shown in Fig. 1, the approach analyzes the degree of homogeneity of the group by calculating the similarity among group members to identify the *outliers* and the homogeneous subgroup. The inclusion of the *outliers* is done by using a content-based filtering technique. Considering that the *outliers* are members with distinct preferences than the homogeneous subgroup, the approach includes them so that no preference (of the homogeneous majority) is affected. Only those items with a high total similarity to the items previously included in the *core* profile are considered to form the *peripheral* profile.

In order to formalize the definition of *core* and *peripheral* profiles we assume a set of U users $\{1,...,U_{max}\}$ and a set of I items $\{1,...,I_{max}\}$. Eq. (1) presents a formal definition of a user profile M_u (u represents an individual user), which is a set of 2-tuple of an item i and an assignment of a rating $r_{u,i}$ to the item i for the user u. In this case, I_u represents the set of items that have a rating assigned by the user u. In this work, the proposed approach specifies a profile

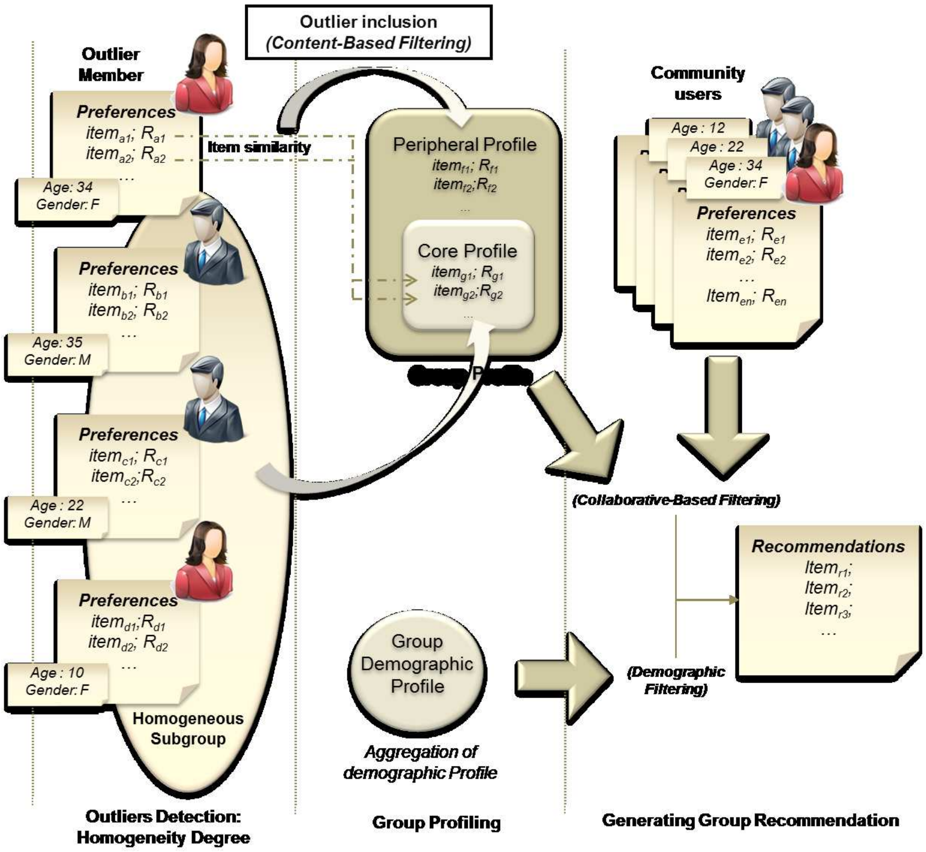


Figure 1: Flow to create the group profile

M_g (represented by Eq. (2)) for a group g as a conjunction of a *core* profile M_{g_c} and a *peripheral* profile M_{g_p}. The *core* profile M_{g_c} is determined by the set of items I_{g_c} that represent preferences in the subgroup members' profiles and the *peripheral* profile is determined by the set of items I_{g_p} detected in the outliers inclusion process (which is presented in detail in Section 2.3). Eq. (3) formalizes the group *core* profile M_{g_c}, which is also represented by a set of 2-tuple of an item i and an assignment of a rating $r_{g,i}$ to the item i for the group g. The rating $r_{g,i}$ is an aggregated value ($aggregation(\{r_{u,i}\})$) calculated from the individual ratings $r_{u,i}$ of all group members u. Similarly, Eq. (4) formalizes the group *peripheral* profile M_{g_p}, which is represented by a set of 2-tuple of an item i and an assignment of a rating $r_{g,i}$ to the item i for the group g. The rating $r_{g,i}$ is also calculated by aggregating ($aggregation(\{r_{u,i}\})$) the individual ratings of all group members. The methodology utilized to calculate this $aggregation(\{r_{u,i}\})$ for both profiles (M_{g_c} and M_{g_p}) is presented in Section 2.

$$M_u = \{< i, r_{u,i} >: i \in I_u \wedge r \in \mathbb{R} \wedge I_u \in I\} \quad (1)$$

$$M_g = M_{g_c} \bigcup M_{g_p} \quad (2)$$

$$M_{g_c} = \{< i, r_{g,i} >: i \in I_{g_c} \wedge r_{g,i} = aggregation(\{r_{u,i}\}), \forall u \in g\} \quad (3)$$

$$M_{g_p} = \{< i, r_{g,i} >: i \in I_{g_p} \wedge r_{g,i} = aggregation(\{r_{u,i}\}), \forall u \in g\} \quad (4)$$

Eq. (5) and Eq. (6) describe the sets of rated items for the *core* profile (I_{g_c}) and the *peripheral* profile (I_{g_p}), in which S is the homogeneous subgroup, I_s is the set of rated items of this subgroup, O is the set of the *outliers* members, I_o is the set of rated items of the *outliers* members, $\bigcup_{\forall u \in S} (\bigcup_{\forall u \in I_u} j)$ represents the union of all the items j included in all the individual models I_u of the users of the subgroup S, $\bigcup_{\forall u \in O} (\bigcup_{\forall u \in I_u} j)$ represents the union of all the items j included in all the individual models I_u of all users u that were classified as outliers O, $totalSimilarity(j, I_{g_c})$ is the similarity between item j and the items included in the *core* profile and d_i is a similarity threshold (these topics will be further developed in Section 2.3). The set O is described by Eq. (7), which establishes that it is formed by all the users included in the group g who have more than m neighbors ($neighbors_{u,g}$) in the whole group (Section 2.2 explains this in detail). The value m is a threshold which is set in the experimental phase (see Sections 4.2.1 and 4.3.1). Moreover, Eq. (8) formalizes the homogeneous subgroup which is formed by all the users of the group g who do not belong to the set O. To sum up, these formalizations establish that the *core* profile is formed by all the items rated for subgroup members, and the *peripheral* profile is formed by only those items from the *outliers*' profiles that are similar (considering the content of the items) to the items included in the *core* profile.

$$I_{g_c} = \{i : i \in I_s \mid I_s \in I \wedge I_s = \bigcup_{\forall u \in S} (\bigcup_{\forall u \in I_u} j)\} \quad (5)$$

$$I_{g_p} = \{i : i \in I_o \mid I_o \in I \wedge I_o = \bigcup_{\forall u \in O} (\bigcup_{\forall u \in I_u} j) \wedge totalSimilarity(j, I_{g_c}) \geq d_i\} \quad (6)$$

$$O = \{u : u \in g \wedge neighbors_{u,g} < m\} \quad (7)$$

$$S = \{u : u \in g \wedge u \notin O\} \quad (8)$$

Additionally, the demographic information is aggregated to complete the group profile. The methodology for aggregating individual demographic profiles into a single group profile representing the demographic information of the group depends on the information obtained by the recommender system. In this case, we utilize the age and the gender of the group members. The information about the age is divided into a set of ranges of values representing all the possible values of the dataset utilized and each user belongs to a single range. For the groups, the individuals' ages are aggregated by determining a single range that includes the age of the group majority. To obtain the gender that represents the group, we consider the predominant gender; i.e. the gender of the group majority. Finally, the whole group profile is contrasted with the community user's profiles by applying collaborative and demographic filtering.

The following subsections describe the full process to create the group profile. Sub-section 2.1 presents different ways to combine individual techniques and the one used in this work. Sub-section 2.2 exposes the process to analyze the group's homogeneity degree in order to detect the outliers members. Sub-section 2.3 explains how the outliers are included in the final group profile. Moreover, sub-section 2.4 details the method to create the group profile. Finally, sub-section 2.5 describes the process to generate group recommendations.

2.1 Filtering Combinations

In the area of individual recommendation, several ways to combine the filtering techniques have been researched. In [Burke, 2002] a survey of different recommendation techniques was presented, in which seven hybridization methods were described: (1) Weighted: the score of several techniques are combined to produce a single recommendation; (2) Switching: the system switches between different techniques; (3) Mixed: the system presents the recommendations generated by different techniques; (4) Feature combination: the features from different recommendation data sources are thrown together into a single recommendation algorithm; (5) Cascade: one recommender refines the recommendations given by another; and (6) Feature augmentation: the output from one technique is used as an input feature to another; and (7) Meta-level: The profile learned by one recommender is used as input to another.

In a more abstract description we can identify three instances that comprise these methods. Most commonly, collaborative filtering is combined with some other techniques, such as content-based filtering, compensating each other's downsides. In the first combination content-based filtering processed sequentially after collaborative filtering. This combination seeks to solve the first-rater problem, which is associated with the collaborative filtering approach. The following combination analyzes the content-based user profiles, and then applies collaborative filtering techniques to generate suggestions. Item descriptions and *Feature*

Selection should be considered when designing content-based systems. In both combinations, if unsatisfactory recommendations are submitted onto the next stage their low-quality will naturally propagate onto the next stage, meaning that the second technique could hardly generate high-quality recommendations. Consequently, a parallel combination might be more effective than a combination in series, as in the third combination (which analyzes profiles merging both item descriptions and ratings at the time of generating the final recommendations).

These hybrid approaches, which combine filtering approaches in different ways, have been widely implemented in individual recommender systems. In this work, we applied a *cascade combination*: firstly, ratings and items' attributes (content-based filtering) are analyzed in *parallel*, and then, when the group profile is consolidated, a collaborative filtering technique is applied in order to generate the group suggestions. We combine three filtering techniques in order to overcome the drawbacks of each technique by taking advantage of the benefits of the others. Despite the fact that collaborative filtering is one of the most successful approaches [Su and Khoshgoftaar, 2009], as it recommends items based on users' past preferences, new users will need to rate a sufficient number of items (cold start problem) to create a profile rich enough to be compared to other community profiles. In this work, we also considered the demographic filtering to support the collaborative filtering when the members have sparse (or none) profiles. Thereby, members with a low number of preferences provide their demographic information to detect neighbors with similar characteristics. On the other hand, content-based filtering is utilized to detect similarities between users' profiles that the *outlier detection technique* fails to detect, i.e. the content of the items is analyzed to include in the *peripheral* profile only those items that are similar to the items previously included in the *core* profile.

2.2 *Outliers* Detection: Homogeneity Degree

As mentioned above, the proposed recommendation process firstly needs to detect the members whose preferences are distant from the rest. Hence, it is necessary to calculate a cross-correlation of group members. A confidence factor is included in the correlation calculation. This factor is determined by the number of overlapped items among user's profiles. We applied this confidence factor in the calculations because we think it is important to identify different degrees of similitude between each pair of users. This similitude or commonality is given by the overlap between the users' profiles, in other words the quality of the similarity value depends on the number of common evaluations. However, in order to create the set of qualified user-neighbors we determined a minimum number of overlapping. Eq. (9) calculates the correlation between two users u_i and u_j, where Ov is the number of overlapping items, r_{max} is the maximum rating domain value (for example, in movie recommendations it could be a range that varies between 1 to 5 stars, then r_{max} is 5), $r_{i,x}$ is the rating given by user i to item x, and $r_{j,x}$ the rating given by user j to item x.

$$similarity(u_i, u_j) = \frac{(Ov * r_{max}) - \sum_{x=1}^{Ov} |r_{i,x} - r_{j,x}|}{Ov * r_{max}} \tag{9}$$

We utilized an *outlier* detection technique to identify members whose profiles contain divergent preferences. Specifically, we use a proximity-based technique introduced by [Knorr and Ng, 1998]: if the *similarity values* (given by Eq. (9)) between the target user and m of the k nearest neighbors (where $m < k$) lie within a specific distance threshold d_m 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 neighbors inside the distance threshold then the exemplar is an *outlier*. In other words, if the similarity of a target user with other member is higher than the threshold d_m then they are considered as neighbors; if the target user has more than m neighbors in the group, then the target user is classified as normal, otherwise the user is an outlier. The value of the threshold d_m is calculated by analyzing the dataset utilized for evaluation, which is presented in Section 4.

With those members that are not *outliers* we formed a homogeneous subgroup to construct the *core* group profile. Once the homogeneous subgroup has been formed, the *core* profile is defined, i.e. the main characteristics of the members belonging to this subgroup are identified. The items included in the profiles of subgroup members become part of the *core* of the group profile.

2.3 *Outliers* Inclusion: Content-Based Filtering

In order to include the *outliers* and their preferences in the group profile we consider the content of the items included in the members' profiles. For this purpose, the profile of each *outlier* is analyzed and items that present higher content similarity with the items added to the *core* profile are included in the *peripheral* group profile. 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 d_i. Eq. (10) describes the total similarity, in which I_{g_c} is the set of items included in the *core* profile. The threshold d_i is determined by analyzing the dataset utilized for evaluation. In Section 4 we describe the methodology applied to determine this value.

$$totalSimilarity(i, I_{g_c}) = \frac{\sum_{\forall j \in I_{g_c}} similarity(i, j)}{|I_{g_c}|} \tag{10}$$

Item correlation is calculated with Eq. (11), where N_a is the number of attribute types, w_x is the weight of the attribute type x, and $f(A_{x,i}, A_{x,j})$ is the similarity between the attribute x for item i and the attribute x for item j.

Type	Type of Attribute	Similarity Measure
Date (Year) -Y_n	$YYYY$	$\frac{(Dif_{max}-\lvert Y_1-Y_2\rvert)}{Dif_{max}}$
String -S_n	Known set of values (only one)	$S_1 = S_2 ? 1 : 0$
(String)* - S_n^*	Known set of values (subset)	$\frac{\lvert S_1^* \cap S_2^*\rvert}{S_{max}^*}$
Integer - I_n	Numerical range of values	$\frac{I_{max}-\lvert I_1-I_2\rvert}{I_{max}}$

Table 1: Similarity measures for the attributes types

This similarity equation is determined by the type of attribute, for example, if the attribute type is *String* then the similarity would be 1 whether it is exactly the same string or *0* if it is not. Table 1 shows the similarity equations for the different attribute types: *Date*, for attributes that describe years; *String*, for attributes that represent a string holding only one value among several known; *(String)** for attributes that hold a subset of known values; and *Integer*, for attributes that describe a range of numeric values. The similarity equations for these attributes types were normalized in order to be within the range [0,1]. These equations were adapted from the work presented by [Debnath et al., 2008].

$$similarity(i_i, i_j) = \sum_{x=1}^{N_a} w_x * f(A_{x,i}, A_{x,j}) \tag{11}$$

In some domains there are attributes that require a special processing. For example, the attribute *title* in movie domains could be considered as a simple *String*, but it would not be of major importance in the final equation of similarity, since this equation would contribute with a similarity value only in the case that two movies have exactly the same title. In this work, we assumed that this type of attributes (such as *title* of a movie or a book) could provide more information if the text is analyzed. For that reason, the similarity between two attributes of this type is obtained through text processing techniques, by removing the stop words, as articles, pronouns, prepositions and symbols (like ":", or "-"), which do not provide any information to the ultimate meaning of the text.

The calculation of item cross-correlation in the *core* group profile and the items associated to the *outliers*' profiles allows the inclusion of preferences, not visible a priori, in the user rating profile. These items are included to the group profile with the procedure described in Section 2.4.

The feature weighting process utilized in this work is an adaptation of the process presented by [Debnath et al., 2008], in which the weights are derived from a set of linear regression equations. A social network graph is created to reflect the users' criteria to determine the similarity between the items. The evaluated items $(I_1, I_2, ..., I_n)$ are the nodes and the weight of the edges is the number of users that evaluate each pair of items $(\#u\{(I_i, I_j)\})$. The linear regression equations are derived from this social network graph by equaling the Eq. (11) to the weight of each edge (see Eq. (12)).

$$w_0 + w_1 * f(A_{1,i}, A_{1,j}) + ... + w_n * f(A_{n,i}, A_{n,j}) = \#u\{(I_i, I_j)\} \qquad (12)$$

2.4 Group Profiling

In this procedure, we applied the well-known rating matrix for individual collaborative recommendations, which represents the users' evaluations of the items (in which the intersection between row i and column j contains the evaluation of user i for item j). If the cell is empty, it means item j has not been evaluated by user i. In particular, the sub-matrix that includes group members and the items from both *core* and *peripheral* profiles are analyzed in this work.

The group profile is obtained by combining two aggregation techniques, which are described in [Jameson and Smyth, 2007]: Maximizing Average Satisfaction and Ensuring Some Degree of Fairness. Applying these techniques we obtain a group evaluation R_i for each item, which is composed of a conjunction of the group average and a penalty term that reflects the amount of variation among the predicted ratings. We utilized a neighborhood technique (*K-NN*) to find similar users who rated the target item. The evaluation is derived from the weighted average of the ratings given by neighbors.

This is represented by Eq. (13), in which G_m is the number of group members, i is the item to be evaluated and σ is the standard deviation with a weight w that reflects the relative importance of fairness.

$$R_i = \frac{1}{G_m} * \sum_{j=1}^{G_m} r_{i,j} - w * \sigma(\{r_{i,j}\}) \qquad (13)$$

2.5 Generating Group Recommendations

Upon creating the group profile it is possible to generate recommendations with a collaborative filtering technique, looking for users with similar profiles to the target group within the community. The similarity among users is calculated by analyzing the collaborative similarity and the demographic similarity. The similarity factor is composed by the weighted sum of both collaborative and demographic similarity, as it is shown in Eq. (14), where α and β are the weights for each similarity ($\alpha > \beta$ and $\alpha + \beta = 1$).

$$similarity(g, u_j) = \alpha * similarity_c(g, u_j) + \beta * similarity_d(g, u_j) \qquad (14)$$

$$similarity_d(u_i, u_j) = similarity_{age} + similarity_{gender} \qquad (15)$$

The demographic similarity is defined by the users' age and gender (see Eq. (15)). The similarity by age has a maximum value of *0.5* and it is calculated by Eq. (16), where $\#range_{max}$ is the number of the major range, $\#range_i$ is the number of the range of the user i, $\#range_j$ is the number of the range of the user j and the multiplication by *0.5* is to normalized the value. The similarity by gender is simply *0.5* ($similarity_{gender} = 0.5$) if both have the same gender; otherwise the demographic similarity would exclusively depend on the similarity by age, i.e. $similarity_{gender} = 0$.

$$similarity_{age}(u_i, u_j) = (\frac{\#range_{max} - |\#range_i - \#range_j|}{\#range_{max}}) * 0.5 \qquad (16)$$

The collaborative similarity between the group profile and another user within the community is calculated using a variant of Eq. (9) presented in Section 2.2, which considers the overlap between the two profiles.

The group prediction is obtained considering the nearest neighbors and Eq. (17), which was adapted to group recommendations and where g is the target group, i is the item to receive an estimated evaluation, k is the number of neighbors, $r_{j,i}$ is the evaluation given by the neighboring user j for the item i, and $similarity(g, u_j)$ is the correlation between a group and a neighboring user.

$$prediction(g,i) = \frac{\sum_{j=1}^{k} r_{j,i} * similarity(g, u_j)}{k} \qquad (17)$$

The recommendation process concludes with the estimations for each candidate item, suggesting those items with highest estimations. The recommended items would be presented as an ordered list from highest to lower estimated values; i.e. the top-n candidates items. Algorithm 1 presents a pseudo-code of the main methods of the approach. This combination is performed, firstly, when the group profile is created by applying the content-based filtering in order to detect the items with similar content to those ones included in the *core* profile, and, secondly, when the group recommendations are generated by considering a hybrid similarity calculation for the detection of the neighbors in the community of users, which combines collaborative filtering and demographic filtering approaches.

3 An Illustrative Example

In order to clarify the process previously described, in this section we present a simple and illustrative example created for a group with 3 members whose preferences are shown in Table 2.

As an initial step, to detect the *outliers* we need to calculate the cross-correlation among all group members. Table 3 presents the users correlation

Algorithm 1 Pseudo-code of the proposed approach's main methods

```
//Core profile
for each member m in subgroup s
  for each item i in the profile of m
    core <- i
//Peripheral profile (Outlier Inclusion)
for each member outlier o
  for each item i in the profile of s
    if i is Content-Based Filtered
      peripheral <- i
//Profiling group
profile = core U peripheral
//Estimate ratings for the group profile
for each item i in the profile
  r = estimate rating for i
  profile <- (i,r)
//Generate recommendations
for each candidate item c
  n = get neighbors of group g //CB and DF similarity
  estimation <- average of the ratings of n
recommendation <- candidates items with highest estimation
```

Movie	$r_{1,x}$
Avatar (A)	5
Titanic (B)	2
The Lord of the Rings: The Return of the King (C)	5
Pirates of the Caribbean: Dead Man's Chest (D)	4
Toy Story 3 (E)	3
Alice in Wonderland (F)	4

(a) u_1's profile

Movie	$r_{2,x}$
C	4
D	2
E	5
F	4
Harry Potter and the Order of the Phoenix (G)	3
The Lord of the Rings: The Two Towers (H)	5

(b) u_2's profile

Movie	$r_{3,x}$
A	1
B	5
G	5
H	1
Star Wars: Episode I - The Phantom Menace (I)	3
Harry Potter and the Goblet of Fire (J)	5

(c) u_3's profile

Table 2: An example of users' profiles

	u_1	u_2	u_3	#N
u_1	-	0.75	0.3	1
u_2	0.75	-	0.4	1
u_3	0.3	0.4	-	***0***

Table 3: An example of collaborative similarity matrix

MOVIE	A	B	C	D	E	F	G	H
u_1	5	2	5	4	3	4	-	-
u_2	-	-	4	2	5	4	3	5

Table 4: Example of *core* profile

matrix, which contains the similarity between each pair of members and the number of neighbors (N) for each particular member. These values were calculated by applying the user correlation calculation (see Eq. (9)). Assuming a threshold value $d_m = 0.6$ and $m = 0.33$ (at least one neighbor) to determine the users' neighborhood, we obtained that member u_3 is an *outlier* for this particular group. Therefore, the homogeneous subgroup includes members $u_1$and u_2.

Table 4 shows the sub-matrix formed by the items from the members' profiles of the homogeneous subgroup (*core* profile), with the real values for each member. Then, we need to calculate the cross-correlation among all the items included in the *core* profile and those included in the *outliers'* profiles. Table 5 presents an example of the similarity calculation between two items by analyzing the correlation value $f(A_{x,i}, A_{x,j})$ for each particular attribute type, according to the equations presented in Table 1. To simplify this example, we only focused on the following movie attributes: release date (year), actors and genre; and we determined for each of them the relevance weight (w_x) as follow: $w_{genre} = 0.5$, $w_{actor} = 0.2$ and $w_{releaseDate} = 0.3$. Table 6 shows the correlation values between the items included in the *core* profile and the items belonging to the *outlier* member. In this case, if we consider a threshold $d_i = 0.5$, we include into the group profile only the movie *"Harry Potter and the Goblet of Fire"*.

Finally, we create the group profile with the selected items by calculating the group estimations. Table 7 shows the group profile with the aggregation (group rating) values for each item of the profile.

With this process we finally obtain a group collaborative profile, in which we included items provided by the individual profiles with high collaborative similarity and also items belonging to members with low collaborative similarity but high content-based similarity. To generate predictions for the group as a whole, this group profile will be considered in conjunction with the demographic information, as mentioned in Section 2.5.

Pirates of the Caribbean: Dead Man's Chest	Pirates of the Caribbean: At World's End	$f(A_{x,i}, A_{x,j})$
2006	2007	***0.98***
Johnny Depp | Orlando Bloom | Keira Knightley | Bill Nighy | Stellan Skarsgard | Alex Norton	***Johnny Depp | Orlando Bloom | Keira Knightley*** | Geoffrey Rush | ***Bill Nighy*** | Chow Yun-Fat | ***Stellan Skarsgard*** | Christopher S. Capp	***0.62***
Action| Adventure| Fantasy	Action| Adventure| Fantasy	***1***

Table 5: Example of content-based similarity

		Peripheral profile	
		I	*J*
Core profile	*A*	0.56	0.53
	B	0.41	0.28
	C	0.53	0.41
	D	0.63	0.60
	E	0.21	0.34
	F	0.37	0.68
	G	0.44	0.95
	H	0.73	0.56
	Total Similarity	**0.49**	**0.54**

Table 6: Example of *outliers* inclusion

4 Experimental Results

We carried out four different experiments within the movie and music domain to evaluate the precision of the approach. In the first experiment of each domain (see Section 4.2.2 and Section 4.3.2) we analyzed the prediction for how each member of the group g would rate a subset of items for which the real individual evaluation is known, measuring the individual satisfaction related to the group satisfaction. Then, in the second experiment in the movie domain (see Section 4.2.3) we analyzed the prediction for how the group g would rate a subset of items for which the real evaluation of the group is known, measuring the group satisfaction. Finally, the second experiment in the music domain (see Section 4.3.3) analyzes the accuracy of the approach by varying the group' heterogeneity degree.

We utilized the error metrics most often used in the recommendation literature: *mean absolute error* (*MAE* - Eq. (18)) and *root mean squared error* (*RMSE*

MOVIE	A	B	C	D	E	F	G	H	J
u_1	5	2	5	4	3	4	-	-	-
u_2	-	-	4	2	5	4	3	5	-
u_3	1	5	-	-	-	-	5	1	5
$r_{g,x}$	**2.8**	**3.35**	**4.45**	**2.9**	**3.9**	**4**	**3.9**	**2.8**	**5**

Table 7: Example of group profile

- Eq. (19)). Given a test set τ of user-item pairs (u,i) with ratings $r_{u,i}$, and the predicted ratings $\bar{r_{u,i}}$, *MAE* and *RMSE* determine the error distance between the estimated rating and the real one. *RMSE* penalizes large errors more severely than *MAE*. Since our numerical rating scale gives ratings over the range [1,5], we normalized to express errors as percentages of full scale: *Normalized MAE (NMAE)* and *Normalized RMSE (NRMSE)*.

$$MAE = \frac{1}{|\tau|} \sum_{(u,i)\epsilon\tau} |\bar{r_{u,i}} - r_{u,i}| \tag{18}$$

$$RMSE = \sqrt{\frac{1}{|\tau|} \sum_{(u,i)\epsilon\tau} (\bar{r}_{u,i} - r_{u,i})^2} \tag{19}$$

All the experiments compare the error produced by our hybrid approach with two well-known aggregation techniques: maximizing average satisfaction and ensuring some degree of fairness. The goal of maximizing average satisfaction can be achieved by an aggregation function that computes some sort of average of the predicted satisfaction of each member. On the other hand, the goal of ensuring fairness is to satisfy everyone just about equally well and is in general combined with some other goal. For example, it could be combined with maximizing average satisfaction with a penalizing term that reflects the amount of variation among the predicted ratings (see Eq. (13)).

4.1 Datasets

The "Yahoo! Webscope™ Program" is a reference library of scientifically useful datasets for non-commercial use by academics and other scientists. We utilized the data generated by Yahoo! Movies [Yahoo! Academic Relations, 2006] and Yahoo! Music [Yahoo! Academic Relations, 2003]. In the Yahoo! Movies Dataset, the *training* data contains 7,642 users, 11,915 movies, and 211,231 ratings. The *test* data contains 2,309 users, 2,380 items, and 10,136 ratings. Besides this, the dataset provides complete movie descriptive content information (29 fields per movie). We focused on 7 of them: title, running time, release date, genres, directors, crews and actors. Moreover, the Yahoo! Music Dataset contains over 717 million ratings of 136 thousand songs given by 1.8 million users of Yahoo! Music services. Each song in the dataset is accompanied by artist, album, and genre attributes. In this case, the Yahoo! Music Dataset does not provide demographic information about users.

In order to analyze the group satisfaction in the movie domain, we used the group feedback obtained from a set of 44 System Engineering students at UNCPBA[4]. The students were organized in 9 groups with different sizes (between 3 and 6 users per group). Each group would choose a subset of items, which were used in the second experiment as a real evaluation, which allows us to compare with the evaluation predicted for our approach. These profiles were included as part of the Yahoo! Dataset[5].

4.2 Experiments in the Movie Domain

We carried out two experiments in the movie domain to analyze the individual and the group prediction error when group recommendations are generated with the hybrid approach. We analyzed the error values obtained with the hybrid approach and the aggregation techniques.

4.2.1 Experimental Settings

The experiments were carried out under a set of assumptions derived directly from the procedure proposed. Firstly, the computation process to obtain the demographic similarity between two users suggests the necessity of sorting out the users' ages in ranges. For the experiments, the users' age was divided in six different ranges: 1) 15 to 24 years old, 2) 25 to 34 years old, 3) 35 to 49 years old, 4) 50 to 64 years old, 5) 65 to 74 years old; and 6) 75 years old or more.

Moreover, the approach applies a neighborhood technique, which requires the definition of the maximum number k of neighbors used for estimation. In the experiments below, we considered k=60, as it is suggested by [Herlocker et al., 2002]. Besides, the *outlier* detection process is sensitive to the use of the thresholds of minimum distance d_m between two members to be neighbors and the minimum number m of neighbor members to determine the homogeneous subgroup (if a group member has fewer neighbors than the threshold then it is an *outlier*). In that case, we considered that the minimum distance d_m is dependent on the domain and data. In statistics, a distance value within the range $[media_{s_u} - \theta_{s_u};media_{s_u} + \theta_{s_u}]$ is considered as "*normal*". A value below that

[4] http://www.unicen.edu.ar

[5] Dataset's users domain data and the student profiles used to form the groups in all the experiments, are available at: http://users.exa.unicen.edu.ar/~ichriste/projects_en.html

range is considered "*outlier*". Therefore, we calculated the mean and the standard deviation (θ_{d_m}) of the distances among all users. We analyzed the cross-correlations among users in the Yahoo! Movie Dataset and we obtained a threshold $d_m = 0.6$. After identifying the value of d_m, we tested the approach by varying the minimum percentage of neighbor members to determine that m representing a 21% have shown acceptable results identifying *outliers*. Then, we needed to select a value for the threshold d_i that determines the minimum distance between two items for the process to include *outliers*. As for the distance between members, we considered the distance values between items within the range $[media_{s_i} - \theta_{s_i}; media_{s_i} + \theta_{s_i}]$ as "*normal*". Hence, we calculated the mean and the standard deviation (θ_{d_i}) of the distances among all items and we obtained a value $d_i = 0.28$.

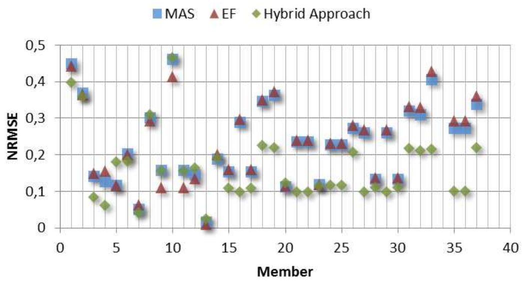
The aggregation technique used to estimate the evaluation for the items in the group profile depends on a weight w that represents the relevance of the standard deviation. If we choose a high value for w, we may obtain a recommendation that makes everyone equally miserable. Because of that, we pick w=*0.1* to give certain relevance to the fairness, but not too much.

The approach proposes a methodology to include the *outliers*, considering the content of the items by weighting the attributes. The weights used in the experiments were empirically evaluated by applying the featuring weighting process presented in the Section 2.3. We defined these weights as follows: $w_{title} = 0.121$, $w_{releaseDate} = 0.008$, $w_{runningTime} = 0.39$, $w_{genres} = 0.42$, $w_{directors} = 0.01$, $w_{crews} = 0.001$ and $w_{actors} = 0.05$,

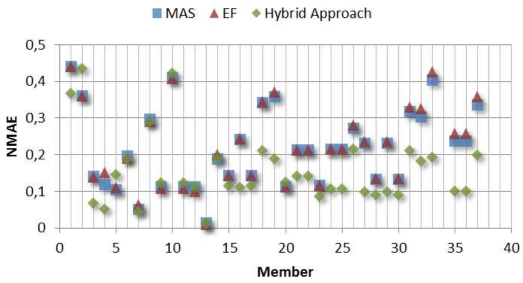
4.2.2 Experiment 1 - Individual Satisfaction Analysis

The first experiment aims to analyze the *NMAE* and *NRMSE* values, focusing on the individual users (not group). In order to achieve this, we created 10 groups with a total of 38 users from the Yahoo! Dataset and we recommended a set of items included on the *test* dataset for each group. The groups were formed with 3, 4, 5 or 6 users with at least one *outlier*. We computed the *NMAE* for each member of the groups, measuring the prediction error for the individual members against the group as a whole. With this experiment we expected to analyze the effectiveness of the technique when it predicts ratings for the group by comparing with the real rating given by each individual member, especially, *outliers* members. We compared the results obtained by our approach with the results obtained by the aggregation approach.

Fig. 2 shows the *NMAE* and *NRMSE* values obtained for each of the 38 users by our approach in comparison with the aggregation techniques: maximizing average satisfaction (MAS) and ensuring fairness (EF). As shown in this figure, most of the values obtained by running the hybrid approach (represented by



(a) NMAE



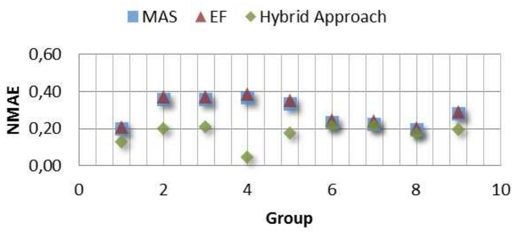
(b) NRMSE

Figure 2: Experiment 1 (movie domain): Individual analysis

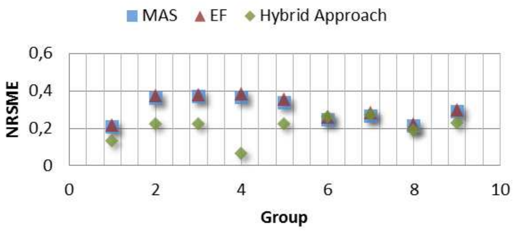
diamonds) are lower than the values obtained with the aggregation techniques (squares for MAS, and triangles for EF).

4.2.3 Experiment 2 - Group Satisfaction Analysis

This experiment aims to analyze the *NMAE* and *NRMSE* values of the approach presented in this work in comparison with two well-known aggregation techniques for group recommendation. With this purpose, we analyzed the feedback obtained from a set of 44 System Engineering students at UNCPBA. As a requirement of an Artificial Intelligent course they had to implement a simple aggregation technique and compare the results with a subset of items from Yahoo! Dataset that they would choose as a group. This subset was used in this experiment as a real evaluation by each group, which allows us to compare with the evaluation predicted for our approach. The students were organized in 9 groups with different sizes (between 3 and 6 users per group). On average, each student evaluated 20 movies. These profiles were included as part of the *training* Yahoo! Dataset, and the users' profiles included in this dataset were considered



(a) NMAE



(b) NRMSE

Figure 3: Experiment 2 (movie domain): Group Analysis

as community users' profiles in collaborative techniques. The feedback from the students was included in the *test* Yahoo! Dataset for the evaluation.

Fig. 3 shows the *NMAE* and *NRMSE* values obtained for each group of users by the three different techniques: maximizing average satisfaction (MAS), ensuring fairness (EF) and the hybrid approach proposed.

4.3 Experiments in the Music Domain

We carried out two experiments in the music domain to analyze the individual prediction error and the impact of varying the amount of *outliers* when group recommendations are generated by utilizing the hybrid approach. We analyzed the error values obtained by the hybrid approach and the aggregation techniques.

4.3.1 Experimental Settings

The experiments were carried out on the music domain under a set of assumptions derived from the procedure proposed. Firstly, we could not consider the demographic similarity in these experiments since the Yahoo! Music Dataset does not provide demographic information about users.

As in the experiments on the movie domain, for the neighborhood technique, which requires the definition of the maximum number k of neighbors, we considered k=60. The threshold $d_m = 0.45$ was obtained as for the movie domain, considering the average and the standard deviation. After identifying this threshold, we tested the approach by varying the minimum percentage of neighbor members to determine that m representing a 36% have shown acceptable results identifying *outliers*. Then, the threshold d_i was defined as $d_i = 0.13$ by analyzing the Yahoo! Music Dataset. In the estimation process we considered a value w=0.1 for the penalization in the aggregation technique.

Finally, the weights of the attributes were obtained considering the feature weighting process presented in Section 2.3. We defined them as follows: $w_{album} = 0.36$, $w_{artist} = 0.04$ and $w_{genres} = 0.6$.

4.3.2 Experiment 3 - Individual Satisfaction Analysis

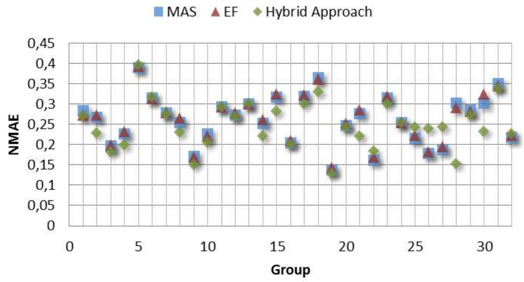
This experiment aims to analyze the *NMAE* and *NRMSE* values, focusing on the individual members of the groups. In order to achieve this, we created 32 groups with a total of 330 users from the Yahoo! Dataset and we recommended a set of items included on the *test* dataset for each group. The groups were formed with 3 to 55 users with at least one *outlier*. We computed the *NMAE* and *NRMSE* for each member of the groups, measuring individual prediction error. With this experiment we expected to analyze the effectiveness of the approach when it predicts ratings for groups by analyzing the real ratings given by each individual member, especially, by *outliers* members. We compared the results obtained by our approach with the results obtained by the aggregation approach.

Fig. 2 shows the *NMAE* and *NRMSE* values obtained for each of the 32 groups by our approach in comparison with the aggregation techniques: maximizing average satisfaction (MAS) and ensuring fairness (EF). As shown in this figure, most of the values obtained by running the hybrid approach (represented by diamonds) are lower than the values obtained with the aggregation techniques (squares for MAS, and triangles for EF).

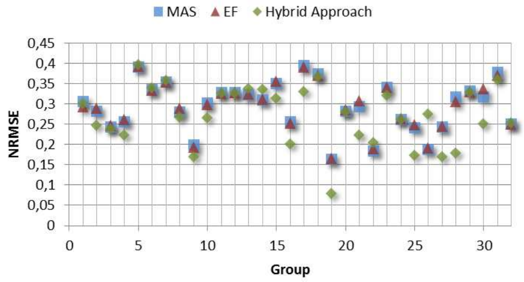
4.3.3 Experiment 4 - Varying the Amount of *Outliers*

This experiment aims to analyze the accuracy of the approach by focusing in the variation on the group's heterogeneity degree. Therefore, we considered 9 groups with different number of members and, particularly, we observed the percentage of *outliers* of each group. Thus, it is analyzed the impact of the heterogeneity degree variation in the group satisfaction. Since the difficulties of the generation of recommendations to large groups could indistinctly impact on members' satisfaction we considered groups with a similar amount of members. Table 8 summarizes the main characteristics of the groups analyzed in this experiment.

Fig. 5 shows the *NMAE* and *NRMSE* values obtained for each of the 10 groups by our approach in comparison with the aggregation techniques: maximizing average satisfaction (MAS) and ensuring fairness (EF).



(a) NMAE



(b) NRMSE

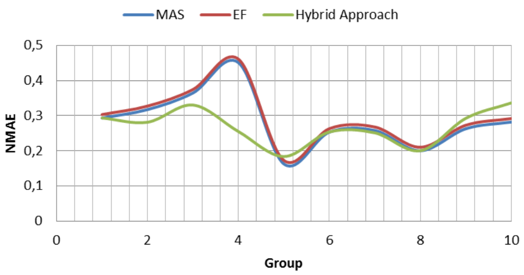
Figure 4: Experiment 3 (music domain): Individual Analysis

#Group	1	2	3	4	5	6	7	8	9
#Members	10	6	4	3	5	6	7	5	5
#Average of preferences	132	75	131	114	78	106	110	76	330
%Outliers	10	17	25	33	40	50	57	60	80

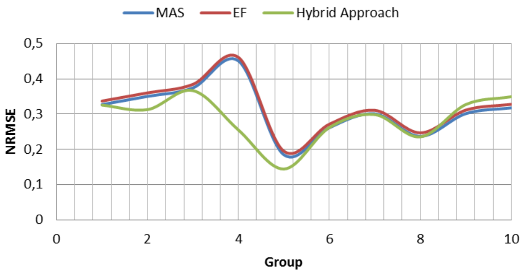
Table 8: Groups' characteristics for the experiment 4 (music domain)

4.4 Discussion and Analysis

In order to analyze the effectiveness of our approach we considered as baseline two of the most known and frequently-used techniques designed to generate group recommendations: maximizing average satisfaction and ensuring some degree of fairness. Despite the fact that these techniques are simple aggregation techniques, they are considered the cornerstones of group recommendation research area since they were the first approaches to solve the change of paradigm from an individual to a group of users. We compared the prediction values generated for different items using these two aggregation techniques and our hybrid approach. Accuracy results are summarized in Table 9. This table is organized



(a) NMAE



(b) NRMSE

Figure 5: Experiment 4 (music domain): Varying the amount of *outliers*

considering the different perspectives of the analysis conducted during the experiments. We summarized the error values (*NMAE* and *NRMSE)* obtained for each technique by analyzing the group satisfaction (experiment 2), the individual satisfaction (experiments 1 y 3) and, finally, the *outliers'* satisfaction (experiments 1, 2 y 3). These error values (*NMAE* and *NRMSE*) indicate that predicted ratings values will be within roughly 31% of the true ratings values for each algorithm. In all cases our approach improved the results of the two other aggregation techniques.

The results obtained in the experiments that analyze individual and group satisfaction show that the hybrid approach was more accurate at making recommendations than the other aggregation techniques, either satisfying the group as a whole or each individual member (including *outliers*). Furthermore, experiment 2 shows that, fulfilling our main initial requirement, our approach includes the members whose profiles are distant improving the results obtained with aggregation techniques, which focus on satisfying only the majority homogeneous. In experiment 4 we analyzed the impact of varying the number of *outliers* on the satisfaction of each group member. As we expected, in this experiment the individual satisfaction for the hybrid approach decreases as the number of *out-*

	Hybrid	EF	MAS
Group Satisfaction			
NMAE	***0.17***	*0.3*	*0.28*
NRMSE	***0.2***	*0.31*	*0.29*
Individual Satisfaction			
NMAE	***0.22***	*0.26*	*0.26*
NRMSE	***0.24***	*0.29*	*0.29*
***Outliers*' Satisfaction**			
NMAE	***0.23***	*0.28*	*0.28*
NRMSE	***0.21***	*0.29*	*0.29*

Table 9: Summarized results for experiments 1, 2 and 3

liers increases, i.e. the error difference between the hybrid approach and the aggregation techniques is reduced.

5 Related Works

Some aggregation techniques have been utilized in individual recommender systems to adapt their results to the requirements of group recommendation. As regards to the approach used, there are even more possible methods for the construction of group profiles than for the aggregation of individual ratings, since group profiles can take many different forms [Jameson and Smyth, 2007]. For example, [Kim et al., 2010] present a method to generate group recommendations that consists of two phases. The first phase includes a filtering method based on the group profile, so as to satisfy most members. The second phase includes a filtering method based on individual profiles, so as to reduce the number of unsatisfied members. Another example of this approach is described by [Garcia et al., 2011], in which a tourist web-based recommender system is presented; this system, named e-Tourism, also provides recommendations to groups of users by applying aggregations techniques. Furthermore, [Garcia et al., 2012] describe a domain-independent group recommender system that can be used with any ontology-based application domain as well as with several group profiling strategies. In [Senot et al., 2010] the authors present a preliminary evaluation made on a real large-scale dataset of TV viewings, showing how group interests can be predicted by combining individual user profiles through an appropriate strategy.

Most of the systems mentioned above use techniques to generate group recommendations that are based only on members' given ratings and fail to consider a group profile that may be enriched with several characteristics, either by the domain, as member, group or even subgroups of users. Moreover, even if the technique is based on the approach that defines a group profile, all of them have been developed under the assumption that groups are homogeneous, i.e. their profiles will have similar preferences. The evaluations are carried out with homogeneous groups for which most aggregation preferences techniques aim at satisfying all individual members. In this work a hybrid approach is presented, which considers rating, item-content and demographic information to generate recommendation for homogeneous and heterogeneous groups.

6 Conclusions and Future Works

In this paper, we have described a new approach for group profiling, which combines collaborative filtering, content-based filtering and demographic information to recommend items to group of users. This combination of techniques is exploited so as to include those members whose profiles are distant from the rest of the members. The results obtained when evaluating the approach demonstrated that the combination of the three approaches and the consideration of the *outliers* in the group profile overcomes the results obtained with the well-known aggregation techniques, since we provide an alternative to make recommendations for a group containing a few distant individual profiles among their members. Besides, with the combination of the most popular filtering techniques we provide an approach that suggests items both when no information about previous evaluations is available and when no similar users can be found. In addition, the precision of the recommendations made was higher for the hybrid technique than with each aggregation technique. However, it is important to mention that the approach proposed requires a greater effort by developers and designers of group recommender systems, than the simple aggregation techniques. Also, the experiment that analyzed the accuracy of the approach by focusing in the variation on the heterogeneity degree of the groups showed that the approach generate more accurate predictions when the amount of *outliers* in the group does not exceed 80% of the group. Besides, the various tasks involved in the approach, such as *outlier* detection process, construction of a *core* profile, feature weighting process, among others, demand time/resources that derive in an higher computational cost. As future work, we are planning to consider evaluating this approach in another domain, such as recommendation of tourist attractions.

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