Users' Satisfaction in Recommendation Systems for Groups: an Approach Based on Noncooperative Games

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ABSTRACT

A major difficulty in a recommendation system for groups is to use a group aggregation strategy to ensure, among other things, the maximization of the average satisfaction of group members. This paper presents an approach based on the theory of noncooperative games to solve this problem. While group members can be seen as game players, the items for potential recommendation for the group comprise the set of possible actions. Achieving group satisfaction as a whole becomes, then, a problem of finding the Nash equilibrium. Experiments with a MovieLens dataset and a function of arithmetic mean to compute the prediction of group satisfaction for the generated recommendation have shown statistically significant results when compared to state-of-the-art aggregation strategies, in particular, when evaluation among group members are more heterogeneous. The feasibility of this unique approach is shown by the development of an application for Facebook, which recommends movies to groups of friends.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information Filtering

General Terms

Algorithms, Experimentation

Keywords

Group Recommendation, Game Theory, Nash equilibrium

1. INTRODUCTION

Traditional recommendation systems do perform personalized suggestions of items and that are of potential interest for a system's user [22, 6, 1, 8]. A recommendation system generates an item suggestion to a user based on a profile of interests. Such profile is automatically built from the individual items evaluation made by this user. Based on this interest profile, similarity analysis techniques between users, known as collaborative filtering [11] or between items, known as content-based filtering [20], are used to generate the recommendation. In recent years alternative approaches to generating recommendations for individuals have emerged, such as those based on personality analysis [18, 12], context-based [2], knowledge-based [6], demographic-based [6], and utility-based [2].

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The scientific literature related to recommendations for individuals is actually fairly wide. However, some scenarios require for recommendations for group of people and the techniques mentioned so far do not solve this new problem. As an example scenario of recommendation for groups are recommending repertoire of songs for a party, recommending a restaurant for a business lunch, a travel destination for family and movies for a group of friends.

Among the difficulties that arise in a group recommendation system is the need for an aggregation strategy for the generation of the recommendation. Recent scientific literature has enumerate three possible types of aggregation strategies [13, 5, 16]: (*i*) merge the lists of individual recommendations obtained for each individual member in a single list for the group, (*ii*) aggregate the individual preferences of all group members to particular items using some strategy traditionally based on the *Social Choice Theory* [3, 23, 21], or (*iii*) create a unique profile to the group as a whole.

The choice of aggregation strategy best suited to the recommendation system for groups is not a trivial task. This strategy needs to consider that group members wish to meet their own preferences. At the same time, it has to prevent that certain users keep always dissatisfied with the recommendation they receive (*misery*) and must ensure fairness in the recommendation for the group [15]. In specific contexts, where groups are formed randomly and, thus, the chances for heterogeneity are increased, this task is especially hard. Indeed, the tentative to solve such a conflict by means of some cooperative approach which try to reach a consensus in heterogeneous random groups may result in a negotiation agreement failure. Examples of such cooperative approaches are presented in [4], [26], [10]. The work of [25] shows that the increase in the number of group members leads to decreased satisfaction average for the group's recommendation.

We argue that a rational way of solving conflicts of interest between members of heterogeneous random groups should arise from *Non-Cooperative Game Theory* [Von Neumann and Morgenstern, 1947].

This paper thus proposes an innovative approach based on *noncooperative games* for recommending items to a group. Members are the players of the game, the items are modeled as game actions and the recommendation itself is modeled as a problem of finding the Nash equilibrium, performing a rational selection of the items set. Considering a stable strategy profile, the Nash equilibrium means that considering that the other players will not modify their own strategies, the current player has no incentive to change its own. Modeling recommendation for groups as a noncooperative game can meet the need for a balance between satisfying the own preferences of a member of the group and avoid the dissatisfaction of other group members through justice in the recommendation. Although users have their own interests, there will always be at least one Nash equilibrium, so the system can always make a recommendation to the group. This paper extends previous work [7], where the game actions had been defined from the result of the aggregation strategies of individual preference.

Specific goals are twofold: (i) provide proper formalization to the problem and (ii) develop a movie recommendation system for groups that runs on Facebook.

Section 2 reviews recommender systems for groups. In Section 3, we define formally the problem of recommendation for groups as a noncooperative game. Section 4 presents an illustrative example of the functioning of the approach to a small number of users in a group. Section 5 discusses experimental results with MovieLens datasets and presents the movie recommendation system developed as a Facebook application. Finally, section 6 presents some concluding remarks and future work.

2. GROUP RECOMMENDER SYSTEM

Although recommendation systems traditionally recommend items for individual users, there is an increasing amount of research focused on recommendation for groups of users [16, 13]. In such case, recommendations aim to satisfy a group of users with potentially conflicting interests.

The need for choosing a method of aggregation to generate recommendations is the key characteristic of group recommendation. Although different aggregation strategies differ in the way they manipulate and represent users' preferences, virtually all of them adopts one of three schemes: (1) aggregates a single set of individual recommendations, (2) builds a unique representation model for the group, or (3) aggregate the ratings/preferences for particular items.

Average, *Least Misery* and *Plurality Vote* are three of the main aggregation strategies studied in the related scientific literature. *Average* strategy assumes equal importance to group members and computes the average of the group evaluation for the items. The disadvantage of this strategy is due to the heavy reliance on group size. For groups with fewer members, for instance, each member opinion has a greater impact on the average. *Least Misery* strategy considers the evaluation made by the less satisfied group member as the satisfaction value for the whole group. The disadvantage of this strategy is that an item in which most members are little satisfied will probably be recommended rather than a item to which just one member is very unsatisfied whereas the others are pleased, for instance.

In the aggregation strategy *Plurality Vote*, each group member votes on the item with the highest individual preference. Although such strategy fulfills most of the group, the minority gets unsatisfied, eventually.

According to [24], aggregation strategies can be divided into three categories:

- **strategies consensus-based**: considers the preferences of all group members. Among the strategies in this category are *Average*, *Average without Misery*, *Fairness* and *Multiplicative*.

- **majority-based strategies:** uses the most popular items among group members. Among the strategies in this category is *Plurality Voting*.

- **borderline strategies**: consider only a subset of items in individual profiles based on user roles or any other relevant criteria. In the *Dictatorship* strategy, for instance, a single member imposes his taste for the rest of the group. *Least Misery* and *Most Pleasure* strategies consider only the lowest and highest level of interest, respectively, among the group members.

Aggregation strategies may be evaluated according to a sort of different metrics [13]:

- **Maximize average satisfaction**: a function that computes some kind of average predictions of satisfaction for each member to use as the basis for the selection of candidate items;

- **Minimize misery**: a function that measures the level of dissatisfaction of one or more members;

- **Ensure some degree of fairness**: a function that measures how balanced is the level of satisfaction among members of the group concerning the given recommendation.

Different kind of groups affect the way users evaluate the result of the adopted aggregation strategy. In Polylens [19], which consists of *permanent* groups, recommendation provided by *Least Misery* strategy had been accepted by 77% of the users. The fact that members get to know each other in advance contributes to minimize misery, for instance. As stated before, homogeneity or heterogeneity levels also affect recommendation quality. In the evaluation of YU's TV Recommender [26], the *Average* strategy achieved good performance for homogeneous groups. In contrast, the result worsened significantly as the group was getting closer the complete heterogeneity.

3. PROBLEM DEFINITION

Let $I = \{i_1, i_2, ..., i_n\}$ and $U = \{u_1, u_2, ..., u_k\}$ be the set of all items and all users, respectively. Consider a set G of all groups with at least two members that may be formed by U and so, $|G| = 2^k - k - 1$. Consider, finally, $g \in G$ and $|g|$ defined as the number m of group members g. If, for instance, a group consists of users u_1, u_2 and u_3, thus this can be expressed as $g = \{u_1, u_2, u_3\}$ and $|g|$.

Let us assume $p(u, i)$ as the evaluation for the item i user-supplied u, and $p(u, i) = 0$, if user u did not evaluate the item i. Consider $\hat{p}(u, i)$ as the predictive evaluation of item i for user u. The predicted evaluation $\hat{p}(u, i)$ is obtained from a prediction function $\hat{p}$ which considers, in turn, the similarity between items $s : I \times I \rightarrow \mathbb{R}$ or the similarity between users $s : U \times U \rightarrow \mathbb{R}$.

The items to be potentially recommended for each group belong to the set of items that have not been evaluated by any group member. These items are obtained from the intersection of the lists of items to which no member of the group has provided an evaluation (equation 1).

$$H = \bigcap_{u \in g} \{ i \mid \hat{p}(u,i) \neq \varnothing,\ i \in I \} \quad (1)$$

The group recommendation problem is modeled as a non-cooperative game in the *Normal Form* and the items to be recommended to the group are those in Nash equilibrium.

A game in the *Normal Form* is a tuple (m, A, f), where:

- m is the number of players (group members), indexed by j;
- $A = A_1 x ... x A_m$, with A_j being a finite set of actions available to the player j. A vector $a = (a_1, ..., a_m) \in A$ is known as *actions' profile*.
- $f = (f_1, ..., f_m)$, with $f_j : A \to \mathbb{R}$ being an utility function that computes a *payoff* for player j.

We have fixed a set of three possible actions to be available to a player in the action set A_j. These actions concern the three items with higher predicted values. The *payoff* function for each player considers the union of the item chosen as game action for each player j to form a actions' profile (equation 2).

$$R = \bigcup_{j=1}^{m} a_j \quad (2)$$

The *payoff* function (equation 3) calculates the predicted satisfaction of the member u from the result of the actions chosen by all players in a given game strategy.

$$f(u) = \frac{\sum_{i \in R} \hat{p}(u,i)}{|R|} \quad (3)$$

Intuitively, the player wants to find the aggregation strategy that maximizes the result of its *payoff* function. A Nash equilibrium is a stable strategy profile: it means that considering that other players will not modify their own strategies, the current player has no incentive to change its owns. In case of the existence of more than one Nash equilibria for the group, the choice of which of these will be recommended is accomplished by a harmonic mean (equation 4). This function performs the calculation based on the preferences of the group members for all of the items from each of the found Nash equilibria. The set with the highest harmonic mean is chosen. Since the harmonic mean prioritizes sets of values with smaller variance, it encourages *justice* in the recommendation. An experiment conducted by Masthoff [15] with volunteers has shown that group members are concerned about the balance between justice and meet their own preferences.

$$harmonic(x) = \frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}} \quad (4)$$

The proposed approach is illustrated in figure 1.

4. ILLUSTRATIVE EXAMPLE

Consider the preference of two members of a group to a set of five items (table 1).

Table 1: Individual preferences.

	A	B	C	D	E
Peter	10	4	3	8	6
Jane	1	9	8	5	4

Table 2: Payoff matrix to the game in the normal form.

	B	C	D
A	(7.0, 5.0)	(6.5, 4.5)	(9.0, 3.0)
D	(6.0, 6.5)	(3.5, 6.5)	(8.0, 5.0)
E	(5.0, 6.5)	(4.5, 6.0)	(7.0, 4.5)

The actions of player Peter have been chosen among the items A, D and E, once these had been the three better evaluated items by this user. The lines in the *payoff* matrix represent the actions. B, C and D are the items for player Jane and are properly represented as game actions in the columns of the same *payoff* matrix (figure 2). The *payoff* values for each player have been calculated by equation 3.

This *payoff* matrix has a single Nash equilibrium with strategy (A, B), where A is the item which represents the action to be chosen by Peter and B is the item which represents the action to be chosen by Jane. 7.0 (seven) is thus the payoff value for Peter and 5.0 (five) the payoff value for Jane. In case there were others Nash equilibria, the harmonic mean would be used, as stated before.

The strategy (A, B) has been selected as the only Nash equilibrium of this example. The reason is that if Peter chooses action A, Jane would have no benefit in changing her action from B to C or D, since the payoff would decrease. Likewise, considering that Jane chooses action B, Peter would have no benefit to change the action from A to D or E. This situation only occurs with the couple of actions (A, B).

5. EXPERIMENTS

Experiments have been performed in order to compare the proposed approach with three different state-of-the-art aggregation strategies: *Least Misery* (LM), *Average* and *Plurality Vote* (PV). Each strategy belongs to a different aggregation category according to [24].

Two different experimentation scenarios have been set, varying the levels of homogeneity among group members.

5.1 Dataset

The MovieLens [1] datasets are widely used in group recommendation research even though they do not actually provide information on groups. This is due to the complete lack of other well established and more suitable bases. The chosen dataset consists of 943 users, 1,682 movies and 100,000 movie ratings in the [1, 5] interval.

5.2 Experimentation Setup

For the first experimentation scenario, a list of rating predictions to every movie not yet seen by neither user in a group has been generated from individual evaluations $p(u, i)$

[1] http://www.grouplens.org/node/73/

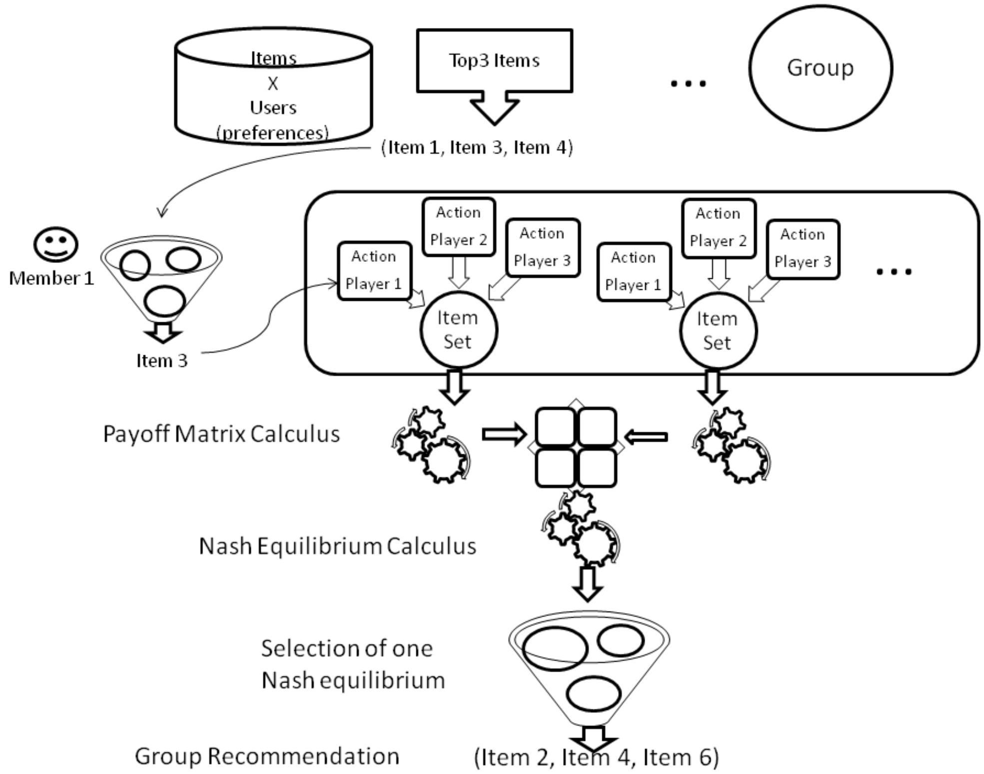


Figure 1: New Approach Overview

existent in the dataset. The rating predictions were generated by means of a collaborative filtering algorithm based on KNN (*K-Nearest Neighbor*) [9]. The histogram of figure 1 shows the distribution for the first experimentation scenario. Predictions have a mean value of 4.01 and low standard deviation of 0.41.

The second scenario concerns an artificial distribution built upon evaluation values randomly generated so as to compose a scenario with evaluation values more dispersed. The histogram of Figure 3 shows the correspondent distribution. Predictions have a mean value of 2.5 with standard deviation of 1.01.

In order to deal with the absence of groups in the MovieLens dataset, the users have been automatically grouped with K-Means clustering [14], with $K = \sqrt{943}$ and randomly generated initial centroid. Users of these clusters were randomly selected to form two kind of groups: (i) homogeneous group, with users from same cluster and (ii) heterogeneous group, with users from different clusters. A total of 28 groups with 3, 5 and 7 members have been generated for each kind, for a total of 336 groups.

The three actions available to each player were chosen among the items with the highest player rating prediction from the list of potential recommendations (list of items not yet evaluated by any group member). The tool Gambit [17] was used to set the games in the normal form and compute the Nash equilibria.

5.3 Evaluation Metric

We compared the result of the aggregation strategy based on the theory of non-cooperative games and Nash equilibrium with other state-of-the-art aggregation strategies. A prediction function for group satisfaction for recommended items has been used to evaluate the result (equation 5).

$$S(g,R) = \frac{\sum_{u \in g} S(u,R)}{|g|} \tag{5}$$

This function is constructed from the average of individual satisfactions of each group member to the list of recommended items (equation 6).

$$S(u,R) = \frac{\sum_{i \in R} \hat{p}(u,i)}{|R|} \tag{6}$$

The maximization of $S(g,R)$ means maximizing average satisfaction of the group members to the list of recommended items. The comparison between the aggregation strategies for predicting average satisfaction of the group is performed based on the *paired samples 2-tailed t-test* with confidence interval of 95%, where the value of the result to be considered statiscally significant must provide $p < 0.05$.

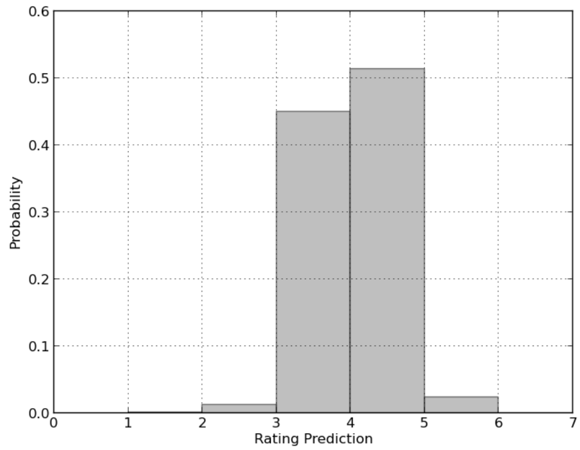


Figure 2: Histogram of predicted evaluation for the first experimentation scenario.

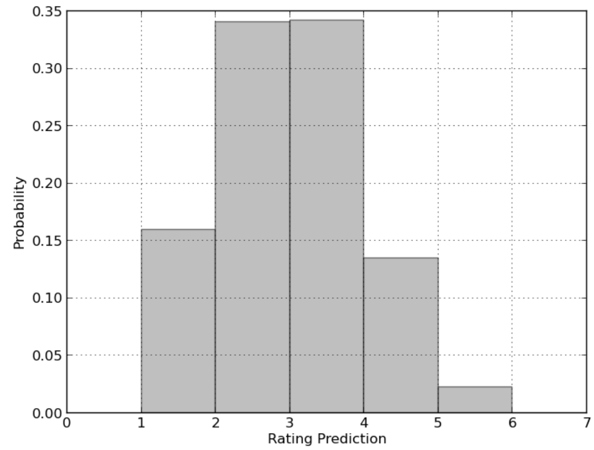


Figure 3: Histogram of predicted evaluation for the second experimentation scenario.

5.4 Experimentation Results

The results for the first experimentation scenario are presented in tables 3, 4, 5 and 6. Tables 7, 8, 9 and 10 concern the results for the second experimentation scenario.

Table 3: Prediction of average satisfaction for homogeneous groups (first experimentation scenario).

Size		LM	Average	PV	Equilibrium
	μ	4.62	4.65	4.61	4.56
3	σ	.13	.11	.12	.15
	Sig.	.008	.000	.028	
	μ	4.46	4.51	4.43	4.42
5	σ	.026	.027	.037	.028
	Sig.	.010	.000	.600	
	μ	4.36	4.41	4.27	4.34
7	σ	.16	.14	.21	.15
	Sig.	.070	.000	.030	

In table 3, for homogeneous groups, the results of Equilibrium strategy was worse than other strategies if we consider a maximum of 5 members per group. With 7 members, instead, Equilibrium strategy has performed better than Plurality Vote. Results also do not show statistically significant differences between Equilibrium strategy and the Least Misery strategy. Experiments with heterogeneous groups show very similar results (table 4).

Table 6 shows the correlation between the number of group members and the results of different strategies. It confirms that the strategy Equilibrium is the one that has the least negative correlation between the satisfaction of the group members and group size. The same occurs for heterogeneous groups in the first scenario.

Table 5 summarizes the comparison between strategies for both homogeneous and heterogeneous groups, regardless the number of members in the group. The Equilibrium strategy shows better results if compared to the Least Misery strategy for homogeneous groups.

The difference between tables 5 and 9 shows that groups tend to be more heterogeneous in the second scenario, highlighted by the prediction of satisfaction with lower values if compared to the first scenario for the outcome of all strategies. Also, it is possible to note that the strategy *Average* achieved the highest satisfaction values in both scenarios.

Table 4: Prediction of average satisfaction for heterogeneous groups (first experimentation scenario).

Size		LM	Average	PV	Equilibrium
	μ	4.58	4.62	4.55	4.53
3	σ	.12	.11	.15	.17
	Sig.	.004	.000	.229	
	μ	4.41	4.48	4.38	4.40
5	σ	.13	.12	.19	.14
	Sig.	.517	.000	.238	
	μ	4.32	4.36	4.21	4.32
7	σ	.14	.14	.15	.14
	Sig.	.714	.000	.000	

Table 5: Prediction of average satisfaction for both homogeneous and heterogeneous groups (first experimentation scenario).

Type		LM	Average	PV	Equilibrium
	μ	4.44	4.49	4.38	4.42
Ho.	σ	.17	.16	.21	.17
	Sig.	.01	.00	.00	
	μ	4.48	4.52	4.44	4.44
He.	σ	.17	.17	.23	.18
	Sig.	.00	.00	.88	

Table 6: Correlation between the number of group members and the results of strategies for the first experimentation scenario.

Type		LM	Average	PV	Equilibrium
Ho.	Corr.	-.634	-.659	-.663	-.496
	Sig.	.00	.00	.00	.00
	N	84	84	84	84
He.	Corr.	-.604	-.619	-.619	-.539
	Sig.	.00	.00	.00	.00
	N	84	84	84	84

Table 7: Prediction of average satisfaction for homogeneous groups (second experimentation scenario).

Size		LM	Average	PV	Equilibrium
3	μ	3.34	3.69	3.35	3.42
	σ	.53	.55	.56	.56
	Sig.	.28	.00	.32	
5	μ	2.93	3.25	3.09	3.07
	σ	.46	.48	.47	.47
	Sig.	.02	.00	.41	
7	μ	2.77	3.00	2.89	2.91
	σ	.37	.30	.39	.28
	Sig.	.00	.00	.50	

Table 8: Prediction of average satisfaction for heterogeneous groups (second experimentation scenario).

Size		LM	Average	PV	Equilibrium
3	μ	3.39	3.68	3.43	3.42
	σ	.26	.20	.32	.28
	Sig.	.677	.00	.80	
5	μ	2.85	3.12	2.97	3.01
	σ	.34	.25	.24	.26
	Sig.	.00	.00	.27	
7	μ	2.63	2.82	2.68	2.78
	σ	.30	.22	.30	.21
	Sig.	.00	.00	.43	

Tables 7, 8 and 9 summarize the outcome of the second scenario for both homogeneous and heterogeneous groups. The strategy Equilibrium performs better than the strategies *Least Misery* and *Plurality Vote*.

Tables 6 and 10 present the results of the correlation between the number of group members and the prediction of satisfaction for every aggregation strategy. In the fist scenario, the number of group members has the smallest negative correlation in the strategy *Equilibrium*. In the second scenario, Equilibrium has the second smallest negative correlation. The negative correlation between the amount of group members and average group satisfaction is also confirmed in another study [25]. This is due to a decrease in group consensus regarding the recommended items once you increase the number of members.

Table 9: Prediction of average satisfaction for both homogeneous and heterogeneous groups (second experimentation scenario).

Type		LM	Average	PV	Equilibrium
Ho.	μ	3.01	3.32	3.11	3.13
	σ	.51	.54	.51	.49
	Sig.	.00	.00	.00	
He.	μ	2.96	3.21	3.03	3.07
	σ	.44	.42	.43	.37
	Sig.	.00	.00	.00	

Table 10: Correlation between the number of group members and the results of strategies for the second experimentation scenario.

Type		LM	Average	PV	Equilibrium
Ho.	Corr.	-.712	-.837	-.734	-.723
	Sig.	.00	.00	.00	
	N	84	84	84	84
He.	Corr.	-.463	-.530	-.377	-.427
	Sig.	.00	.00	.00	
	N	84	84	84	84

5.5 Developed Application

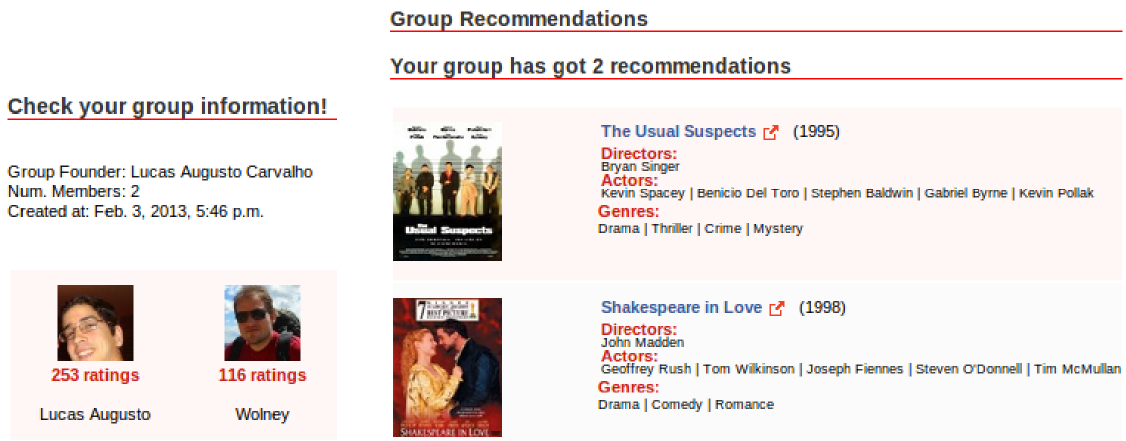
The proposed approach has been applied to the development of a real movie recommendation system for groups as a Facebook application. Table 11 displays some statistical information on the usage of the so-called MyPopCorn[2] group recommendation system, such as the number of users, number of provided movies ratings, number of individual recommendations performed, number of formed groups, and number of movie recommendations generated for groups.

Table 11: Usage numbers for MyPopCorn system.

Users	Ratings	Rec.	Groups	Group Rec.
168	15.900	2.906	5	10

The application has been developed in Python[3] with Django[4] framework and MySQL[5] database. The Apache Mahout[6] tool has been also used to provide individual predictions for items. Finally, Nash equilibrium has been achieved by means of the Gambit[7] tool. Figure 4 brings a screenshot of one of MyPopCorn's pages.

[2] http://mypopcorn.info
[3] http://python.org/
[4] http://www.djangoproject.org/
[5] http://www.mysql.org/
[6] http://mahout.apache.org/
[7] http://www.gambit-project.org/



(a) (b)

Figure 4: "Group Recommendation" page on MyPopCorn.

6. CONCLUSION

In this paper the problem of recommending items to groups of people has been modeled as a noncooperative game. Related work has shown that the resolution of such a conflict by means of a cooperative approach can result in a negotiation failure. In our approach, Nash equilibrium computation is used for rational selection of the set of items to be recommended for the group based on the individual preferences of its members. Group members are self-interested players of a noncooperative game in a normal form. The modeling of the recommendation strategy for groups like a noncooperative game meets the need for a balance between satisfying members' own preferences and avoid the dissatisfaction of other group members, through justice in the recommendation for the group. Furthermore, there will always exist at least one Nash equilibrium, i.e., the system can always make a recommendation to the group.

Experiments with a MovieLens dataset have shown satisfactory and promising results in comparison with other state-of-the-art aggregation strategies, such as the *Average* aggregation strategy, which is widely used in group recommendation research works. Compared to other aggregation strategies, the proposed approach has shown a smaller decrease in the average group satisfaction when the group becomes more heterogeneous and wider. The Equilibrium strategy performs better if compared to the aggregation strategies Least Misery and Plurality Vote under these conditions.

A group recommendation system, called MyPopCorn, has been developed as an application for Facebook. MyPopCorn's usage numbers indicates that the application is promising and proves the feasibility of the proposal.

As a future work, we intend to use a dataset from MyPopCorn to evaluate the approach. We also intend to provide an alternative approach based on the cooperative game theory, which compute the Shapley value for the group members in order to proper define the fairest set of recommended item for that group.

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