Social Context Contribution to Group Recommender Systems

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***Abstract*—There are several factors that influence the group decision making process. The individual's personality and the group's social context play a role in the group's decision and the individual's satisfaction with it. Group recommender systems, which offer support to group decision making can offer better results by incorporating such factors. In this paper, we present a social context-aware group recommendation platform which takes into consideration several of the social factors between the group members in the recommendation process. We examined the effect of multiple social factors independently and collectively on the recommenders' outcomes. Our analysis shows the superiority of social-context aware group recommenders compared to a collaborative filtering group recommender baseline approach.**

Keywords–recommender systems; group recommendation; collaborative filtering; social networking; social context; tie strength; social hierarchy

I. INTRODUCTION

The need for recommender systems is increasing as they facilitate decision making processes in multiple domains. They provide users with individualized recommendations or predicted ratings based on different factors such as the preferences to users with similar tastes or domain-based contextual information. There is a growing interest in group recommender systems as they additionally help with group decision making. They provide recommended items to groups or group predictions taking into consideration the preferences of each individual group member. In one variety of group recommenders, recommendations are generated for individual group members and these recommendations are aggregated to form recommendations for the whole group. In another variety, the individual preferences or ratings of the group members are aggregated into a group model and recommendations are then generated to the model. In both cases, an aggregation strategy determines how to aggregate either individual recommendations or individual preferences [1].

Group recommender systems cover multiple domains. Such as music [2] [3], movies [4], and travel [5] [6]. As the group decision making is a complex social exercise, incorporating social factors in group recommenders became an interesting research area. Delic et al. [7] show through an empirical study, how the social relationships between the group members can be used to predict the members' satisfaction with the group's decision. They conclude that social relationships should be included in the preference models used in group recommender systems. Previous research has considered incorporating several social factors in group recommenders. One of these social factors is trust, which was indicated to influence the group recommendation results. Quijano-Sanchez et al. [8] describe a group recommender system based on trust and personality type, while Wang et al. [9] determine the trust factor from more than one source and uses it to determine the group predictions. A trust-based group recommender system is presented in [10], where a movie ratings dataset was created which also includes pairwise user trust ratings.

Social influence is another social factor that has been used to improve group recommenders' performance. In [11], social influence is determined by identifying the dominators and the followers in the group. The group predictions are determined as the average predictions of the group's dominant members. In [12], the social influence metric is introduced to quantify and measure the member's contribution to the group decision.

In this paper, we introduce a social context-aware group recommender for restaurants based on 8 different social factors in addition to the individuals' personality types. We examine the effect of each of the 8 social factors individually on the group recommender's results as well as the effect of combining the 8 social factors together forming a representation of what we call the long-term social context between the group members. We built a platform for the creation and the evaluation of social context-based group recommendation algorithms, and we used our platform to build different group recommenders based on different social factors and compared their results with a baseline item-item collaborative filtering group recommender. Additionally, we built a restaurant rating and social network platform using which we collected a dataset that includes individuals' and groups' restaurant ratings, and – using a pairwise user evaluation feature - a social network that captures the groups' social contexts.

The rest of the paper is organized as follows: Section II provides a description of the social network and the restaurant rating platform we used to collect our dataset. Section III describes our approach to social context-based group recommendation for restaurants and explains our group recommendation platform and the different recommendation algorithms we built with it. Section IV outlines the experiment setup we used to collect the dataset. We present our findings in Section V.

II. SOCIAL NETWORK AND RESTAURANT RATING PLATFORM

"Social context refers to characterizing the social nature of the situation a user is currently in" [13]. It is represented by the models of any aspects of social interaction having a relation

 ISBN: 978-1-61208-797-9

to IT systems. Long term social context can be described, on a high level, by the dense social network groups the user is part of, and on a low level, by friendship on a social networking platform. Examples of the social factors that contribute to long term social context, which have significance over long durations, are the level of established trust, the duration of the relationship, and the frequency of the interaction. Short term social context, on the other hand, is represented on a high level by social situations whose validity has a temporal scope of minutes to hours and is characterized by social signals and the socially relevant emotions resulting during co-activity social situations. On a low level, the short term social context can be described by sensor data or signals, for example a set of identifiers of persons in bluetooth range.

The interactions between the users of modern social networking platforms either establish or describe long-term social contexts between them. In this paper, we study the influence of long-term social context awareness on the quality of group recommendation. Therefore, the first step is to collect a dataset of individual and group ratings, which also includes the groups' long-term social context information.

Building a real dataset for group recommendation is often regarded as a challenging task [14]. We built our social network and restaurant rating platform to collect the aforementioned dataset. The main requirements for our platform were to:

1) capture the user's personality traits, which may influence how the user may behave during a decision-making process that involves several participants
2) store social network and long term social context information by allowing users to form groups among themselves and perform pairwise social attributes' evaluations
3) elicit the users' individual preferences in restaurants, by allowing the users to rate restaurants as individuals
4) elicit the group preferences in restaurants, by allowing the users to rate restaurants as groups

Our social network and restaurant rating platform is a web application whose use cases and interactions are explained as follows:

Personality Test: The Thomas-Kilmann Conflict Mode Instrument (TKI) [15] quantifies the behaviour of an individual during a conflict, by identifying five different styles of personalities: competing, avoiding, accommodating, collaborating, and compromising. TKI was successfully used in the context of group recommendation as the personality type was shown to be a significant factor in determining the social influence of each of the group members in the decision-making process [16]. After registration, the user answers the TKI personality questionnaire which is composed of 30 double statements in the form of two columns to choose from: A or B. For each statement, the user has to choose between either column A or column B depending on which statement of the two columns she finds more descriptive of her behaviour or personality.

User Rating: In the next step, the user can choose other users of the platform and evaluate them according to 8 social context attributes. The social context attributes are: relationship, social capital, tie strength/trust, social similarity, social context similarity, social hierarchy, and domain expertise. Table I describes each of the social context attributes. As shown in Figure 1, the relationship attribute is a free text

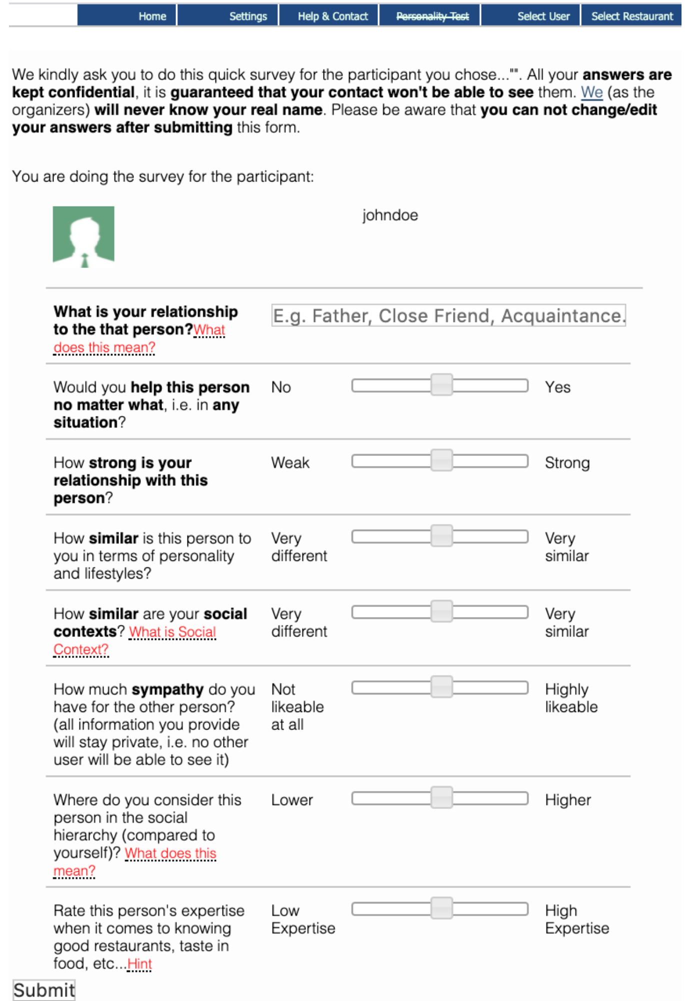

Figure 1. User can rate another user according to eight different social context attributes.

where the user freely enters a description of the nature of her relationship with the rated users. For the other social context attributes, the rating is done using sliders.

Individual Restaurant Rating: In the next step, the user chooses restaurants that she knows and rates individually. To facilitate the process to the user, we integrated a Google Maps widget [17] to our platform. The user can search for restaurants and pick them from the map, as shown in Figure 2. The user is invited to rate at least 5 restaurants, but there is no upper limit to the number of restaurants that a user can rate. When the user picks the restaurants on the map, some metadata about the restaurant will appear in a small popup, which also contains a button to review the restaurant. The restaurant review screen is shown in Figure 3, which provides the user with 8 metrics to rate a restaurant: Hipness, price, order, service, food taste, location, social overlap (which means: to which extent the user and the user's friends share the same opinion about this restaurant and how it suits them as a group), and finally enabling the user to write additional comments. We chose to provide the user with several metrics to rate a restaurant as opposed to a single rating because it captures more accurate opinions.

TABLE I. SOCIAL CONTEXT ATTRIBUTES CAPTURED BY THE SOCIAL NETWORK AND RESTAURANT RATING PLATFORM.

Social Context Attribute	Description
Relationship	A free text description of the relationship with the rated user
Social Capital	Identifies to which extent the user will be willing to help the rated user, which we consider an accumulation of a social capital built from the interaction between the two persons over time.
Tie Strength/Trust	Represents how the user sees the strength of the relationship with the other user. It's also an indication of how much the user trusts the rated user in general.
Social Similarity	Identifies how the two users are socially similar in terms of interests and lifestyle as perceived by the rating user.
Social Context Similarity	Social context is defined by the social setting the users are living in, e.g. sharing the same workplace, school, course, friends, etc. with a friend would imply similar social contexts.
Sympathy	indicates the level of sympathy towards the rated user.
Social Hierarchy	A person who holds a higher position in the social hierarchy is a person who is held in greater respect. For example: a parent, an older person, a person who has some influence, excels at something, or regarded as a role model.
Domain Expertise	A rating for the other user's expertise when it comes to knowing good restaurants, or that this person is famous for having a good and trusted taste in food.

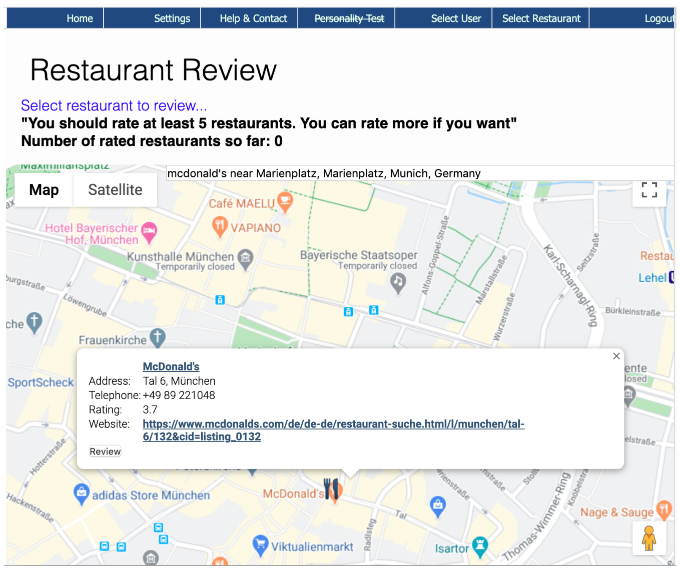

Figure 2. Restaurant picking tool. User/Group can search for any restaurant to review.

Group Formation: A user can instantiate groups with other users of the platform. The user who creates the group is called the group master. The group members should evaluate each other according to the 8 social context attributes described in Table I.

Group Restaurant Rating: Similar to individuals, groups should also rate restaurants. The group restaurant rating is a collaborative process. The group members have to meet, either in person or via a communication medium, search for restaurants and discuss on how to rate restaurants as a group. The group master, finally, executes the group decision and enters the group ratings to the platform. The pairwise user evaluations and the instantiated groups data is a representation of a social network where the nodes are the users and the edges are the relationships between the users in the groups. The weights of the edges are identified by the ratings the users gave each other according to the eight social context attributes. This social network also stores information about the users' personalities as described by their answers to the TKI questionnaire, as well as information about their personal preferences in restaurants represented by their individual restaurant ratings and their group preferences in restaurants represented by their groups' restaurant ratings. The data collected by our social network and restaurant rating platform serve as ground truth data which can be used to evaluate restaurant group recommenders in general, but especially our social context-aware group recommender system.

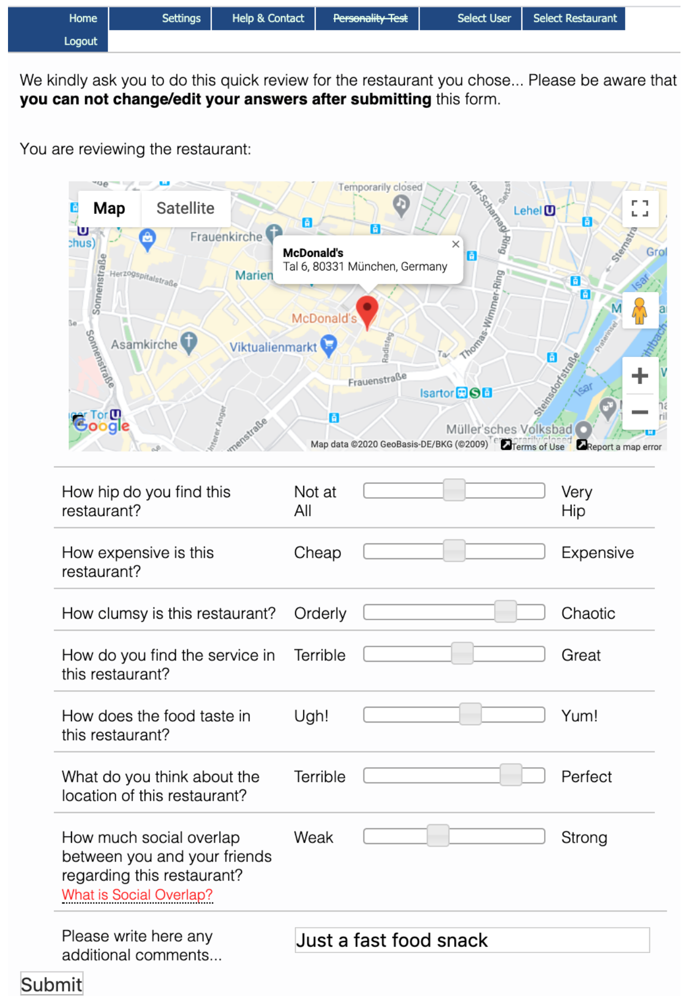

Figure 3. User/Group rates restaurants according to eight different rating metrics using sliders

III. SOCIAL CONTEXT-AWARE GROUP RECOMMENDER SYSTEM

Deciding what to recommend to a group of individuals is a challenging task. Not only individuals' preferences should be taken into consideration during the recommendation process, but also how to aggregate those preferences using a model

 ISBN: 978-1-61208-797-9

that collectively represents the group's preferences should be considered. Such an aggregation should reflect the group decision making process, so that the list of recommended items to the group results in the highest satisfaction to the majority of the group members. Group decision making is a complex process that is largely influenced by the group dynamics characterized by the individuals' personalities and the degree of influence they may impose on each other either generally or during the decision making process [18]. The social influence is part of the group's social context, which is in the long term defined by the history of the members' relationships and in the short term resulting from the group formation and the social dynamics surrounding the decision making process. In this paper, we introduce a framework to build long-term social context-aware group recommenders that incorporate different social context attributes together with the individuals' personalities to improve the group recommendation results.

The social choice theory which has been studied in many disciplines such as economics, politics, and sociology covers the group decision making process or the study of what is best for a group given the opinions of its members [19]. There are different strategies to aggregate individual user preferences into group preferences and presenting a list of recommended items to the group accordingly. Those strategies which are based on the social choice theory can generally be classified into 3 categories [20]:

1) *Majority-based Strategies:* strategies that focus on recommending to the groups the most popular choices among the individuals. The Plurality Voting Strategy [19] is a an example of this category.
2) *Consensus-based Strategies:* which generally attempts to average the individuals' preferences into group preferences. E.g. averaging strategies [19]
3) *Role-based Strategies:* where the group preference is determined based on the preferences of some of its members, depending on their roles or how influential they are in the group. For example, dictatorship strategies [20]

The group recommendation process consists of three main steps. The first step is to generate predicted ratings to the individual users (group members) using a single-user recommender system. The second step is, using one of the mentioned social choice theory-based aggregation strategies, to aggregate the individuals' predicted ratings into group predicted ratings. Finally, the list of recommended items which consists of the items with the highest predicted rating values is presented to the group. The choice of the aggregation strategy largely depends on the group recommendation problem and domain. For our use case, which is group recommendation of restaurants, we built and evaluated our recommenders based on 4 different aggregation strategies: *Average, Least Misery, Most Pleasure, and Dictatorship.*

For the *Average aggregation* strategy, the individuals' predicted ratings of an item are calculated, and the average is taken of all predicted ratings of that item for all the group members. The average value will be the group's predicted rating for that item.

For the *Least Misery* aggregation strategy, the degree of group satisfaction of an item is be determined by its least satisfied member. For each item, the group predicted rating for the item will be the smallest predicted rating for that item among the group members.

For the *Most Pleasure (Maximum Satisfaction)* aggregation strategy, the group predicted rating of an item is the highest rating for that item by any of the group members. Hence, the group's predicted rating for the item is dominated by the most satisfied member of the group of that item.

For the *Dictatorship (Single User)* aggregation strategy, the group's predicted rating for an item is the predicted rating of the group's dictator. The choice of the dictator can be based on different factors. For example, the group's dictator can be chosen to be the most influential member, the oldest or the most respected member of the group, etc..

We built our group recommendation and evaluation framework based on Lenskit [21]. Our framework is largely configurable and highly extensible, which easily allows to add new recommendation algorithms, aggregation strategies, and evaluation methods. Using our group recommendation framework, we built different group recommender systems for restaurants based on a dataset that we collected with our social network and restaurant rating platform.

We built different social context-based group recommenders and compared each with a baseline group recommender. The baseline group recommender is based on an item-item collaborative filtering single user recommender [22] [23]. For both the baseline recommender and the various social context recommenders, we applied the 4 aforementioned aggregation strategies.

The social context-aware recommenders are based on the 8 different social context attributes described in the previous section. The social context attributes are used either individually or collectively in the recommendation process. We define two types of social context-aware recommenders. The first is the *single social context attribute-based group recommender systems*. Those are the recommenders that are based on single social context attributes such as: trust or social hierarchy. For this type of group recommenders, we generalize the delegation-based method [8] which employs both the personality type and the trust in the recommendation model so that we can weigh the single user predicted rating by any of the social context attributes:

$$pred_{soc}(u,i) = \frac{1}{\left|\sum_{v \in G} attr_{u,v}\right|} \sum_{v \in G \wedge v \neq u} attr_{u,v} \cdot (\mathrm{pred}(v,i) + p_v) \quad (1)$$

where $pred_{soc}(u,i)$ is the social context influenced predicted rating of item i for user u. $attr_{u,v}$ is the social context attribute value rated by user u towards user v (e.g. the value of tie strength or sympathy rated by user u towards user v). $pred(v,i)$ is the predicted rating of user v for item i. p_v is the personality value of user v. We created 8 recommenders based on each the 8 social context attributes.

The second type is the *full social context recommender*, where the single user predicted ratings are influenced by all of the 8 available social context attributes present in the social network. The single user full social context predicted rating in this case is calculated as follows:

$$pred_{fullsoc}(u,i) = \frac{1}{\left|\sum_{v \in G}(\sum_{attr \in soctxt} attr_{u,v})\right|} \cdot \sum_{v \in G \wedge v \neq u} \left[(\sum_{attr \in soctxt} attr_{u,v}) \cdot (\mathrm{pred}(v,i) + p_v) \right] \quad (2)$$

Where $soctxt$ is the set of the 8 social context attributes in the social network, $attr$ is a social context attribute value rated by user u to user v. As in the previous equation, p_v is the personality value of user v

For both types of social context-aware recommenders, group predictions are generated according to the 3 aggregation strategies: Average, Least Misery, and Most Pleasure. For the Dictatorship strategy, the social context is not used to generate single user predictions, instead they are generated, as for the baseline recommender, using the single-user Item-item collaborative filtering algorithm. The group prediction is calculated as the dictator's predicted rating for the item. The social context attributes are then used to elect the dictator. For example: if the Dictatorship recommender is based on the social context attribute "domain expertise", then the dictator of the group will be elected as the group member with the highest total domain expertise value as rated by the other group members.

We used our group recommendation platform to build and evaluate 38 different group recommender systems. They represent the combination of recommendation algorithms based on different social context attributes and aggregation strategies. They are classified as follows: The baseline recommender, 8 social context-aware recommenders based 8 different individual social context attributes, and a full social context recommender based on the aggregation of the individual social context attributes. Each of those algorithms is combined with the 3 different aggregation strategies: Average, Least Misery, and Most Pleasure. For the Dictatorship aggregation strategy, only the individual social context recommenders are combined with it and they are compared with a baseline item-item collaborative filtering recommender that uses the Average aggregation strategy.

IV. EXPERIMENTAL SETUP

We set up an experiment using our social networking and restaurant rating platform with the goal of building a dataset of restaurant ratings both from individuals and groups and capturing the participants' social contexts. The dataset serves as the ground truth against which we can evaluate our social context-aware group recommenders.

Our experiment participants are the students of the Social Computing class offered by the department of Informatics at the Technical University of Munich [24]. We asked our students to participate in the experiment as part of the course activities so that the students could test social computing concepts using their "own" data. The experiment consisted of the 4 following phases: In Phase 1, the students register to the social networking and the restaurant rating platform and answer the TKI personality questionnaire. In Phase 2, we asked the students to use the platform's restaurant search tool to choose and rate restaurants as individuals. We instructed the students to balance their selections between restaurants they favoured and those which they didn't have good experiences with. In phase 3, we asked the students to form groups among themselves, and use the platform's user evaluation tool to evaluate their co-group members. These evaluations are elements of the social context as discussed below. During the same phase, we encouraged the students to invite external participants to the experiment, e.g. their family members, partners, relatives and friends. The external participants were also asked to answer the personality questionnaire, rate restaurants as individuals, and evaluate other users - normally the members of their inviting students' groups- according to the social context attributes. In phase 4, the students were instructed to create the groups – they already formed offline - in the platform. The students were instructed to sit together, choose and rate restaurants collaboratively as a group using the restaurant search and rating tools. The group restaurant ratings are entered into the tool by the group master, which is a role that any group member can assume. Students formed groups with the external participants whom they invited to the experiment, this constellation resulted in two types of groups and restaurant ratings.

Internal Groups: are the groups that exclusively consist of students. Since the number of participants in this class is rather large and the students do not necessarily know each other very well, these groups are characterized by relatively weaker social ties or weaker long-term social contexts. The second type is the *External Groups*, which are the groups that contain both class students and external participants. Stronger social ties between the groups' members or stronger social contexts generally characterize this type of groups. We isolated external groups in our analysis to evaluate the effect of stronger social contexts on the social context-aware recommenders results.

Each phase of the experiment's 4 phases lasted for about one week. The overall number of participants was: 363. 178 participants were students and the rest were externals. 246 of them were males and 117 females. Participants were from 37 different countries; 235 participants were from Germany (about 64.5%). 356 of the participants submitted their birthdates, among them, 101 participants were less than 25 years old, 171 participants aged between 25 and 35 years, 4 participants were between the age of 35 and 45, and 80 participants were older than 45 years. 340 participants (about. 93.7%) have answered the TKI personality questionnaire. The participants submitted 1480 individual restaurant ratings. 137 groups were created, 45 of them were students' groups (internal groups) and the rest (92) were external groups which contain both students and the students' external invitees. The maximum number of participants per group is 5, the minimum is 3, and the average group participation is 3.2 participants. The groups submitted 656 restaurant ratings, where 218 ratings were submitted by internal groups, and 438 ratings by external groups. The anonymized dataset we gathered from the experiment consisted of the following:

Personality Data: The participants' TKI personality test scores. Each record consists of a user Id and a personality score with the value between 0 and 1. The smaller values describe more cooperating personality types while higher values describe more competing ones. The mapping of the TKI questionnaire answers single value on the cooperativeness-competitiveness scale was presented in a previous work [25] and is implemented according to Recio-Garcia et al. algorithm [26].

Social Contexts Data: Captures the participants' social context, as it contains the user-to-user ratings values according the 8 different social context attributes. Each record consists of two attributes: from (user Id) and to (user Id) which indicate the rating direction. The values of the social context attributes are in the range from 0 to 1. As mentioned earlier, the social context attribute "relationship" is presented as a free text field. We manually mapped the textual descriptions to values between 0 and 1. To do that, we clustered all the textual descriptions entered by the users into 8 different categories. We assigned each category a value between 0 and 1. The higher the value the more intimate is the relationship. We mapped each of the user descriptions to one of the 8 categories and therefore a numerical value. The categories are:

- *Unknown:* A person barely known. Value: 0
- *Adversary:* A person identified as a competition by the rating person. Value: 0
- *Acquaintance:* Value: 0.25
- *Strong Acquaintance:* A person who is well known or admired by the rating user, yet is not considered a friend. Value: 0.5
- *Friend:* Value: 0.5
- *Close Friend:* Value 0.75
- *Partner:* Life partner or spouse. Value: 1.0
- *Family:* Family member. Value: 1.0

Individual Ratings: Contains the restaurant ratings by individual participants. Each record consists of a user Id, restaurant Id, and a single valued restaurant rating between 0 and 5. The rating value is calculated as the average of the 7 numerical restaurant rating metrics values described earlier. *Group Ratings:* Similar to the individual ratings, but for groups. Each record consists of a group Id, restaurant Id, and a single valued restaurant rating. *User/Groups:* Contains the membership information of users in the groups. Maps user Id to a group Id. We ran our group recommender algorithms both on the full dataset and on the external group ratings dataset. The next section provides a detailed description of our experimental results..

V. Experimental Results

We compare the results of our social context-based group recommenders with a baseline item-item collaborative filtering group recommender. For both types, we experimented with 4 different aggregation strategies: Average, Least Misery, Most Pleasure (Maximum Satisfaction), and Single-User (Dictatorship).

For the social context-based group recommendation, we built a group recommender based on each of the social context attributes separately and compared each with the baseline using the restaurants' dataset. We built a social context recommender based on the aggregation of all the social context attributes and we call it the *full social context recommender* and compared it to the baseline. We ran the full social context recommender on two different datasets: the full dataset and the external groups' dataset. As explained earlier, the latter dataset is characterized by stronger social relationships.

Since recommendation is often interpreted as a ranking problem [27], we chose classification metrics and ranking metrics to compare our recommenders. We used 3 different evaluation metrics to compare the results: Precision@n, and Recall@n as classification metrics, and the Normalized Discounted Cumulative Gain (NDCG) as a ranking metric. We define "n" as the number of the recommended items, and we ran the recommenders and evaluated the results for 4 different values of n: 100, 10, 5, and 3.

The NDCG takes into account the order of the item in the recommendation list so that the items that appear lower in the recommendation list have less relevance value compared to those that appear on the top [27]. We used the DCG implementation in the Lenskit package [21]:

$$\mathrm{DCG@n}(g) = \sum_{i=1}^{n} \frac{r_{gi}}{\log_2(1+i)} \tag{3}$$

Where g represents the group for which the recommendation list is generated, i is the ith recommended item, n the number of recommended items, *rgi* the predicted rating of item i for the group g. The normalized discounted cumulative gain is calculated by comparing the DCG to the ideal DCG represented by the ordered list of favourite items by the group according to the groups actual rating list, which is shown by the following equation: [27]

$$NDCG@n(g) = \frac{DCG@n(g)}{iDCG@n(g)} \tag{4}$$

The Precision@n is calculated as the ratio between the number of relevant items in the recommendation list to a group and the total number of recommended items. It is calculated as follows [27]:

$$\text{precision@n}(g) = \frac{\text{predicted }_n(g) \cap \text{ relevant }(g)}{n} \tag{5}$$

And finally, the Recall@n is calculated as the ratio between the number of relevant items in the recommendation list to a group and the total number of relevant items for that group. The following equation shows how Recall@n is calculated [27]:

$$\text{recall@}n(g) = \frac{|\text{predicted}_n(g) \cap \text{relevant}(g)|}{|\text{relevant}(g)|} \tag{6}$$

For both Precision@n and Recall@n, the set of relevant items $relevant(g)$ are the items that were actually rated by the group.

Figure 4 shows the results of comparing individual social context attributes-based group recommenders to the baseline using each of the aggregation strategies. The social context-based recommenders are named after their corresponding social attributes: domain expertise (domex), social hierarchy (hierch), relationship (rel), social sapital (socap), social similarity (socsim), social context similarity (soxsim), sympathy (symp), and trust (trst). The baseline recommender (ii) is named after item-item collaborative filtering. The social context-based recommenders outperform the baseline for all the metrics for all the aggregation strategies except for the Dictatorship strategy where the performance of the baseline is comparable to the social context recommenders. At n=10, however, the social context recommenders still outperform the baseline for the Dictatorship strategy. While we cannot conclude that there is one social context attribute that consistently outperforms all other attributes for all metrics and for all strategies,

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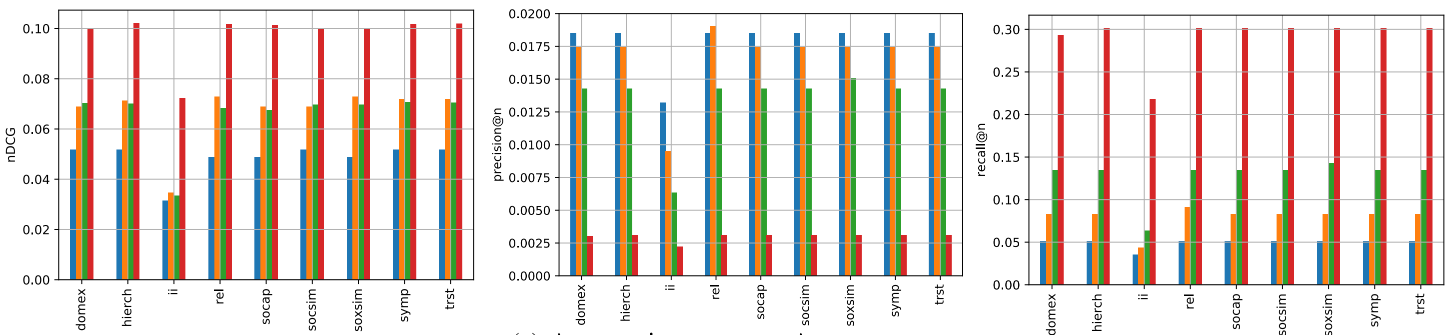
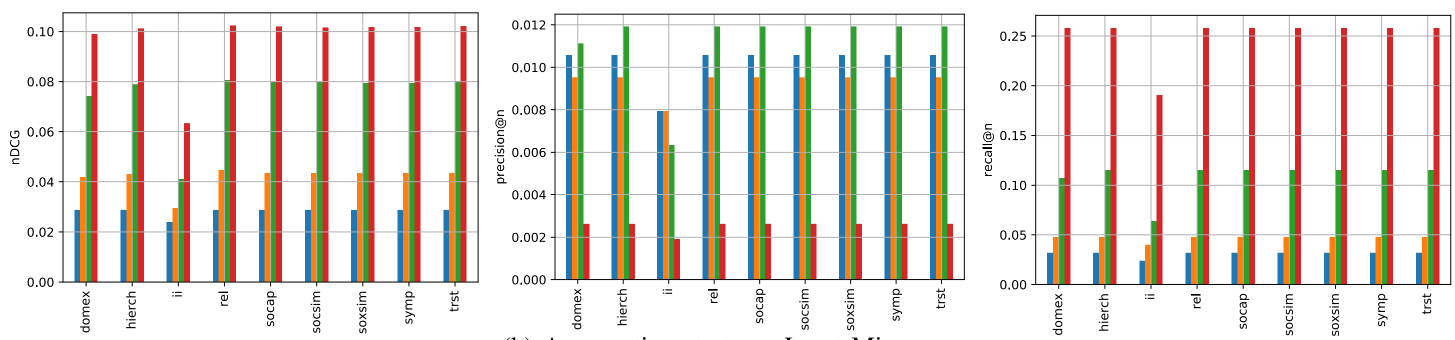
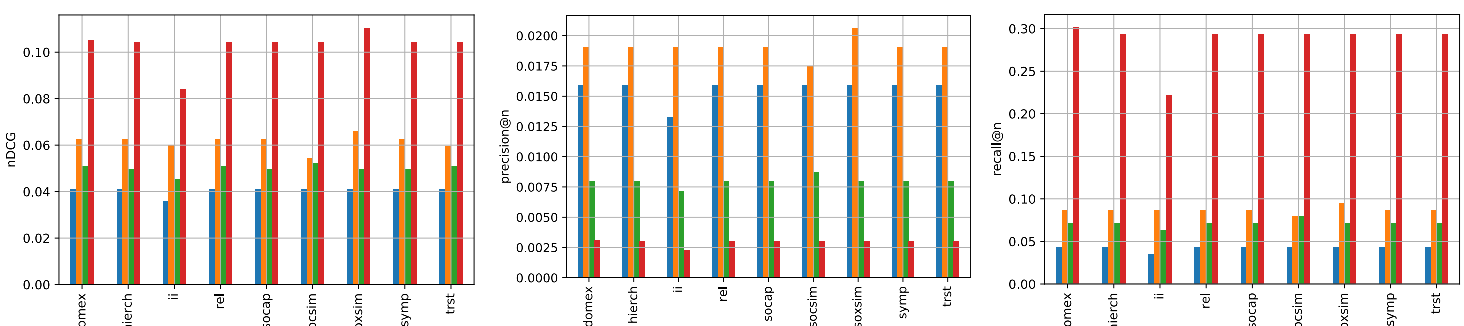


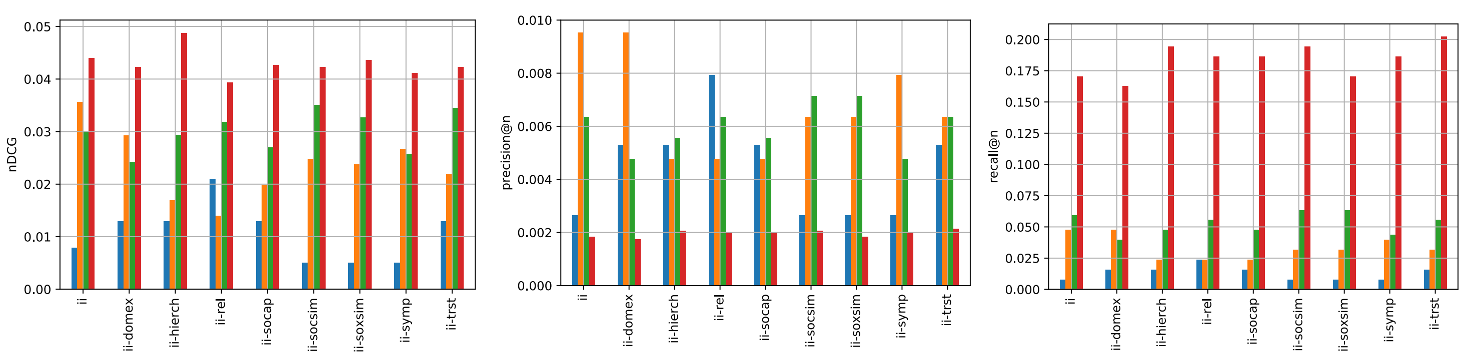
(a) Aggregation strategy: Average



(b) Aggregation strategy: Least Misery



(c) Aggregation strategy: Most Pleasure



(d) Aggregation strategy: Dictatorship

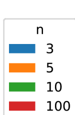
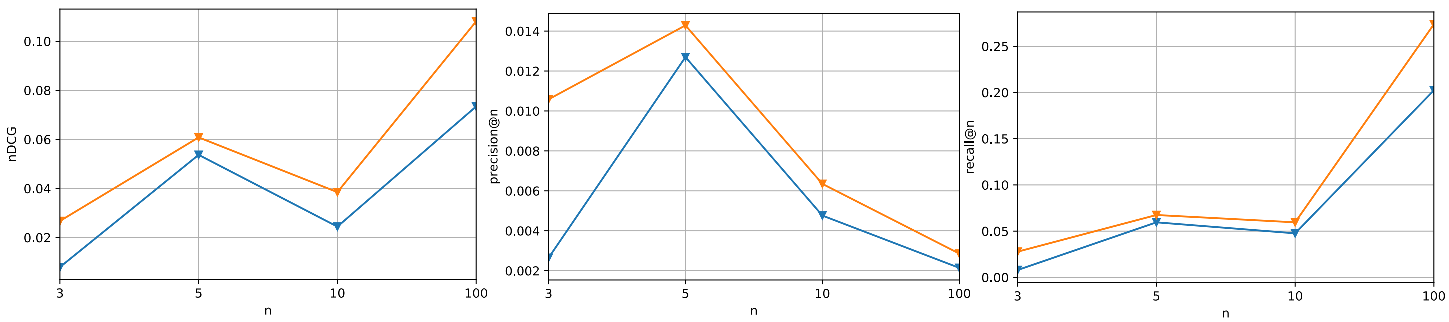
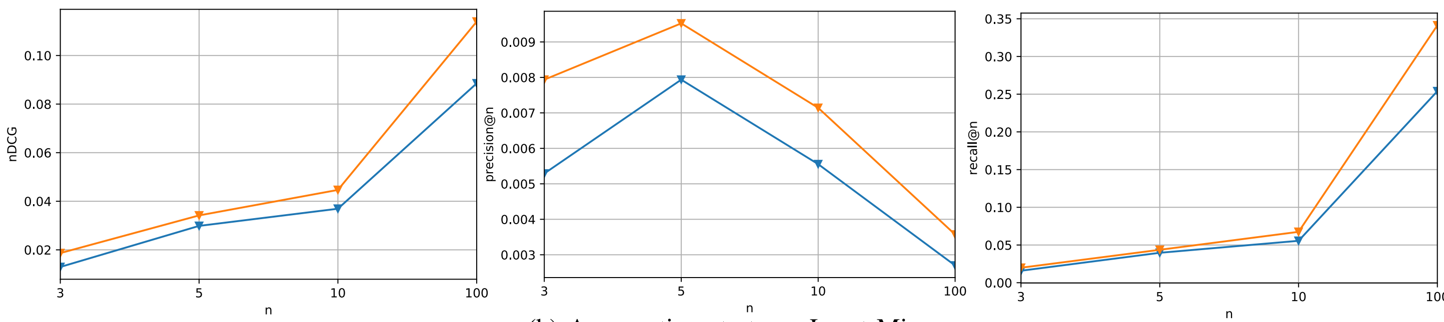


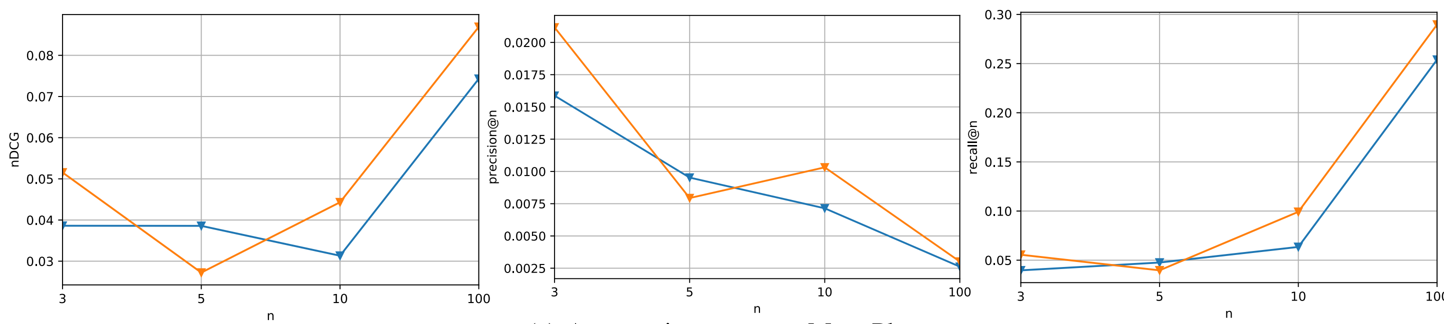
Figure 4. nDCG, precision@n, and recall@n resulting from group recommenders based on the baseline item-item collaborative filtering algorithm and the prediction algorithms based on 8 social context attributes. Group recommendations are generated based on the aggregation strategies: Average, Least Misery, Most Pleasure, and Dictatorship



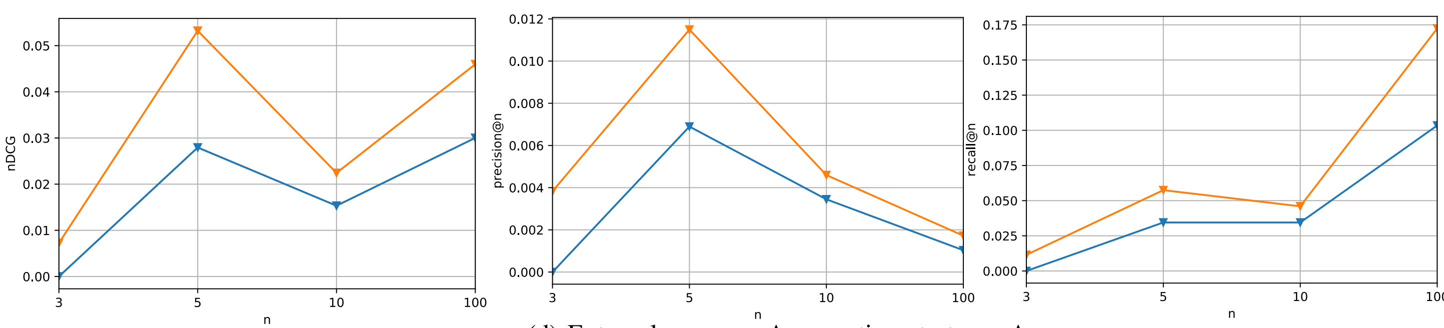
(a) Aggregation strategy: Average



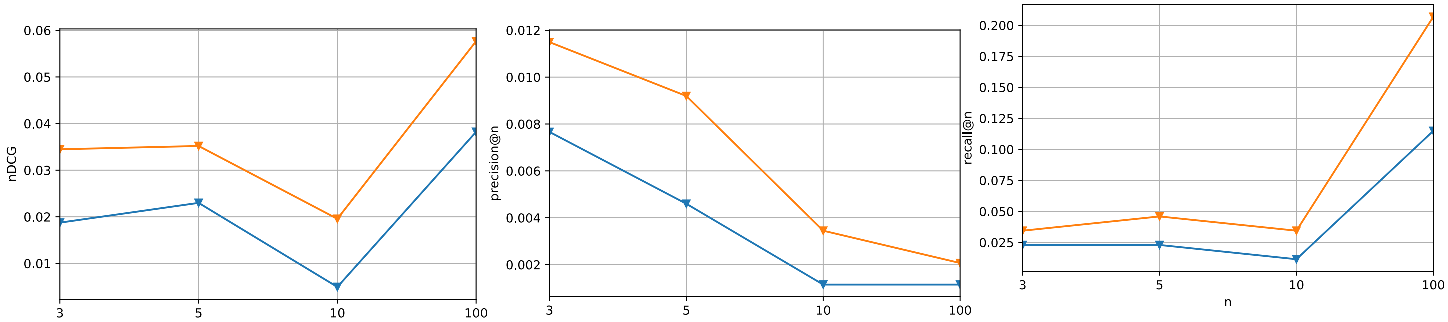
(b) Aggregation strategy: Least Misery



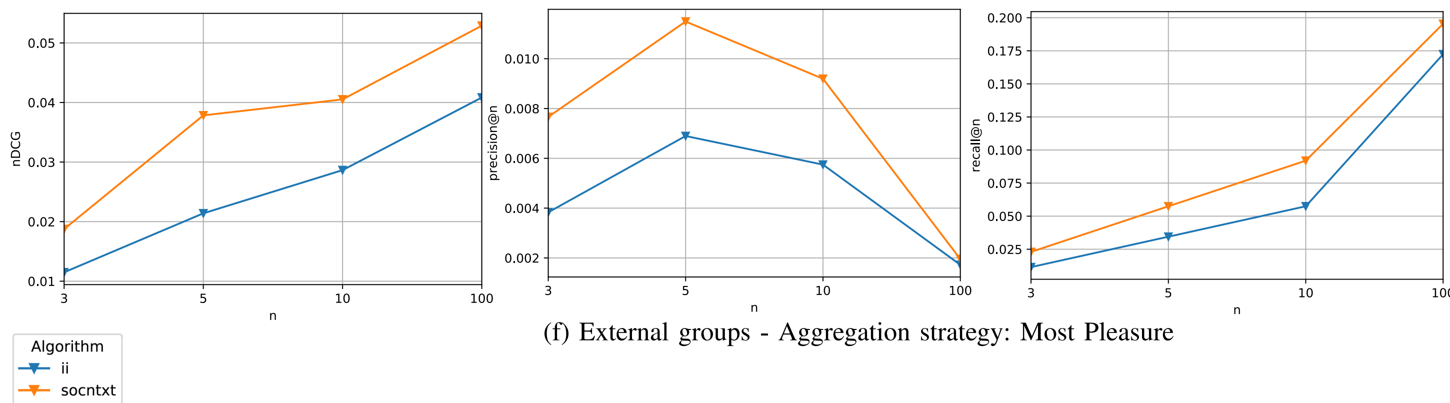
(c) Aggregation strategy: Most Pleasure



(d) External groups - Aggregation strategy: Average



(e) External groups - Aggregation strategy: Least Misery



(f) External groups - Aggregation strategy: Most Pleasure

Figure 5. nDCG, precision@n, and recall@n resulting from group recommenders based on the baseline item-item collaborative filtering algorithm and the full social context prediction algorithm. Group recommendations are generated based on the aggregation strategies: Average, Least Misery, and Most Pleasure. Sub-figures a, b, c are the results of the full dataset, and sub-figures d, e, f are the results of the external groups' dataset

the noticed trend is that trust and relationship-based social context recommenders are generally performing better than the other recommenders. One of them is among the top 3 performing algorithms with respect to the average values of NDCG, Precision@n, and Recall@n for all values of n and for all aggregation strategies. The social context similarity-based recommender has on the average the best values of all metrics for the Most Pleasure aggregation strategy. And we notice that for the Dictatorship strategy, the baseline's average NDCG value is higher than all that of the social context-based recommenders and it ranks third for the average Precision@n.

Figure 5 compares the *full social context recommender*, which is based on the aggregation of all the social context attributes, to the baseline recommender. The evaluation is for both the full data set Figure 5 (a, b, c), and for the subset of external groups (d, e, f). For both datasets, the *full social context recommender* consistently outperforms the baseline for almost all aggregation strategies at all values of n. The only exception is for the full dataset with the Most Pleasure strategy at n=5 where the baseline outperforms the *full social context recommender* for all the metrics. For the full dataset, the *full social context recommender* with the Average aggregation strategy performs better than all other strategies with respect to the average NDCG, precision@n, and recall@n for all values of n. It is also the most outperforming *full social context recommender* compared to the baseline with 57.16% higher average NDCG, 72.41% higher average precision@n, and 57.83% higher average recall@n.

For the external groups' dataset, the *full social context recommender* with the Most Pleasure aggregation strategy has the best metrics values by comparing the average NDCG, precision@n, and recall@n for all n values. In terms of outperforming the baseline, the *full social context recommender* based on the Average aggregation strategy performs best with 75.87% higher NDCG, 90.23% higher precision@n, and 66.67% higher recall@n. We notice that the outperforming percentages of the full social context recommenders for the external group's dataset compared to the baseline are significantly higher than those for the full dataset. This behaviour is consistent with our hypothesis that for groups characterized by stronger relationships, the social context influence on the results of group recommendation is relatively stronger.

VI. Conclusion and Future Work

In this paper, we presented a platform that incorporates the long-term social context in group recommendations. The presented platform allows to easily configure, implement and evaluate social context-aware recommenders using different social choice theory aggregation strategies. We also present a social networking and restaurant rating platform using which we raised an experimental dataset of individuals and group ratings of restaurants. The dataset also includes the participants' long-term social contexts by allowing them to evaluate each other according to different social context attributes.

While previous research shows the influence of social factors such as trust and behavioural factors such as the personality type on group recommendation quality, in our research we investigated 8 different social context attributes together with the personality type. We examined the effect of each attribute alone on the recommendation quality and also aggregated the 8 attributes together in what we call the full social context. Our analysis shows the superiority of the social context-aware recommenders in general over a baseline recommender. This was proven both for the *individual social context attributes-based recommenders* and for the *full social context-aware recommender* using most of the group recommendation aggregation strategies. We evaluated the group recommenders on the full dataset, and on a subset of groups characterized by more intimate relationships. We prove that for the latter dataset where the group members have stronger social contexts, the influence of the long-term social context on the quality of group recommendation is even stronger.

As a future work, we intend to continue exploring the contribution of the social context to group recommendation by studying the effect of short-term social context. We intend to build a solution that detects the group members spatial-temporal social situations before the recommendation act. It will also allow the system to interactively get users feedback on the results. Such a setup will enable us to build a larger and denser ground truth dataset The incorporation of both long-term and short-term social contexts into group recommendation as well as the live user feedback will help to build a more real-life application and will allow for a larger study of the social context contribution to the group recommendation.

 ISBN: 978-1-61208-797-9

REFERENCES

[1] J. Masthoff, "Group recommender systems: Combining individual models," in Recommender systems handbook. Springer, 2011, pp. 677–702.

[2] Q. Li, S. H. Myaeng, and B. M. Kim, "A probabilistic music recommender considering user opinions and audio features," Information processing & management, vol. 43, no. 2, 2007, pp. 473–487.

[3] J. F. McCarthy and T. D. Anagnost, "Musicfx: an arbiter of group preferences for computer supported collaborative workouts," in Proceedings of the 1998 ACM conference on Computer supported cooperative work, 1998, pp. 363–372.

[4] M. O'connor, D. Cosley, J. A. Konstan, and J. Riedl, "Polylens: a recommender system for groups of users," in ECSCW 2001. Springer, 2001, pp. 199–218.

[5] L. Ardissono, A. Goy, G. Petrone, M. Segnan, and P. Torasso, "Intrigue: personalized recommendation of tourist attractions for desktop and hand held devices," Applied artificial intelligence, vol. 17, no. 8-9, 2003, pp. 687–714.

[6] T. Mahmood, F. Ricci, A. Venturini, and W. Höpken, "Adaptive recommender systems for travel planning," in ENTER, vol. 8, 2008, pp. 1–11.

[7] A. Delic, J. Masthoff, J. Neidhardt, and H. Werthner, "How to use social relationships in group recommenders: empirical evidence," in Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization, 2018, pp. 121–129.

[8] L. Quijano-Sánchez, J. A. Recio-García, and B. Díaz-Agudo, "Group recommendation methods for social network environments," in 3rd workshop on recommender systems and the social web within the 5th ACM international conference on recommender systems (RecSys' 11), 2011, pp. 24–31.

[9] H. Wang, D. Chen, and J. Zhang, "Group recommendation based on hybrid trust metric," Automatika, 2020, pp. 1–10.

[10] G. Fang, L. Su, D. Jiang, and L. Wu, "Group recommendation robotics based on external social-trust networks," in 2nd EAI International Conference on Robotic Sensor Networks. Springer, 2020, pp. 59–73.

[11] Y. Zheng, "Identifying dominators and followers in group decision making based on the personality traits." in IUI Workshops, 2018.

[12] Y. et al., "Social influence-based group representation learning for group recommendation," in 2019 IEEE 35th International Conference on Data Engineering (ICDE). IEEE, 2019, pp. 566–577.

[13] G. Groh, "Contextual social networking," habilitation, Technische Universität München, 2011.

[14] M. Rijlaarsdam, S. Scholten, and C. C. Liem, "Towards creating a non-synthetic group recommendation dataset." in ImpactRS RecSys, 2019.

[15] K. W. Thomas, "Thomas-kilmann conflict mode instrument," in Tuxedo, NY XICOM 1974, 1974.

[16] J. A. Recio-Garcia, G. Jimenez-Diaz, A. A. Sanchez-Ruiz, and B. Diaz-Agudo, "Personality aware recommendations to groups," in Proceedings of the third ACM conference on Recommender systems, 2009, pp. 325–328.

[17] Google, "Google maps," retrieved: August, 2020, from https://www.google.com/maps.

[18] G. Stasser and J. H. Davis, "Group decision making and social influence: A social interaction sequence model." Psychological Review, vol. 88, no. 6, 1981, p. 523.

[19] I. Cantador and P. Castells, "Group recommender systems: new perspectives in the social web," in Recommender systems for the social web. Springer, 2012, pp. 139–157.

[20] S. et al., "Analysis of strategies for building group profiles," in International Conference on User Modeling, Adaptation, and Personalization. Springer, 2010, pp. 40–51.

[21] M. D. Ekstrand, "The lkpy package for recommender systems experiments," Boise State University, Computer Science Faculty Publications and Presentations 147, Aug 2018, retrieved: August, 2020. [Online]. Available: https://md.ekstrandom.net/pubs/lkpy

[22] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Item-based collaborative filtering recommendation algorithms," in Proceedings of the 10th international conference on World Wide Web, 2001, pp. 285–295.

[23] M. Deshpande and G. Karypis, "Item-based top-n recommendation algorithms," ACM Transactions on Information Systems (TOIS), vol. 22, no. 1, 2004, pp. 143–177.

[24] "Tum department of informatics," retrieved: August, 2020, from https://www.in.tum.de.

[25] G. Semmler, "Long Term Social Context in Group Recommender Systems," Master's thesis, Technical University of Munich, Germany, 2017.

[26] J. A. Recio-Garcia, G. Jimenez-Diaz, A. A. Sanchez-Ruiz, and B. Diaz-Agudo, "Personality aware recommendations to groups," in Proceedings of the third ACM conference on Recommender systems, 2009, pp. 325–328.

[27] A. Felfernig, L. Boratto, M. Stettinger, and M. Tkalčič, "Evaluating group recommender systems," in Group Recommender Systems. Springer, 2018, pp. 59–71.