CLG-REJA: A Consensus Location-aware group recommender system for Restaurants

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ABSTRACT

The need of support by users for finding out right items in overloaded search spaces is very important in many activities nowadays. One of the activities in which such support is highly demanded is in tourism because tourists visit new scenic places and want to get the best experiences in a limited time. For supporting such needs the use of Recommender Systems have provided good results, but due to the fact that tourism is usually a social activity tourists visit places in groups and demand items and information everywhere and any time. Therefore, the support demanded to Recommender Systems has evolved to Context-Aware and Group Recommendations Systems that is much more challenging. The group recommendations should satisfy all group members, though most proposals do not guarantee that the group recommendation has a high agreement level amongst the group members. Therefore in this contribution is proposed a location-awareness group recommender system that provide recommendations according to the location context of the group and additionally such recommendations are computed to obtain a high agreement among the group members by using a consensus reaching process. The system is implemented by extending a restaurant recommender system REJA (REstaurants of JAén).

Keywords

Group recommender systems, tourism, consensus reaching processes, group decision making, context awareness

Categories and Subject Descriptors

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

1. INTRODUCTION

People's interest in spending their spare time at visiting places for leisure has lead to an economy based on tourism in certain countries, such as those with relevant cities, cultures, religions or natural environment. The exploitation of tourist attractions, specially in cities, makes it necessary to help tourists at choosing among many tourism related choices, as it is the case of restaurants. The overloaded choice space and the limited time that tourists can spend to select a choice that meets their preferences leads to a sub-optimal final selection. To overcome this limitation, recommender systems (RS) arose as a successful tool for supporting tourists in their choices with a personalization process by filtering the items according to their interests and needs. Therefore, the RS recommends a reduced set of relevant items to the user.

Classically RS address recommendations about items to individuals. However, there are items such as, restaurants, travels, etc., that have a social component and they are usually enjoyed by groups of people. Group recommender systems (GRS) aims groups of users at finding interesting items among a set of overloaded choices that satisfied the group preferences. There are different approaches to generate the group recommendations [1]. Regardless the technique used, the aim of group recommendations is to satisfy all members and minimise their possible disagreement regarding the recommended products. The basic approaches to produce recommendations without members' disliked items are the *least misery* [2] and *average without misery* [3] methods. Although these methods achieve fairness, they do not guarantee a high level of agreement among the group members over the recommendation. Therefore, our aim in this contribution is to produce group recommendations that not only satisfy members preferences but also have a high degree of agreement.

To increase the agreement of recommendations it is studied the processes of Group decision making (GDM) problems in which agreed solutions are obtained by applying consensus reaching processes (CRP) [4, 5]. A CRP introduces a negotiation process in which the experts modify their initial preferences to bring them closer to the group. Therefore our proposal will apply a consensus-based recommendation approach [6] to achieve a high agreement on the group recommendations.

Additionally to the agreement on recommendations, tourists demand recommendations adapted to their current situation. In these cases, context-aware recommender systems (CARS) [7] are a trend of RS that focuses on delivering recommendations tailored not only to the users' preferences, but also to the circumstances in which the recommendation is requested. Therefore, it is necessary to include their context in order to improve recommendations, in our proposal is used as context the *location* though other context could be included.

Eventually, our proposal of a consensus location-aware recommendation will be integrated in the RS REJA (REstaurants of JAén) [8, 9, 10, 11], a system that recommends restaurants of the province of Jaén, that will combine a consensus driven group recommendation approach [6] with a location-awareness process in order to improve the satisfaction with group recommendations and increase the utility of the recommendations.

The remainder of the paper is structured as follows. First, Section 2 reviews the required background for our proposal. Section 3 describes REJA and extends it to provide context-aware and agreed group recommendations. Finally, Section 4 concludes the contribution.

2. PRELIMINARIES

This section reviews several basic concepts about Recommender Systems, Group Recommender Systems, Context-Aware Recommender Systems, Group Decision Making and Consensus Reaching Processes that are necessary to understand the performance of our proposal.

2.1 Recommender systems and Group recommender systems

A Recommender System (RS) can be described as *"any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options"* [12]. RSs have two main tasks: (i) to gather information about the users, the items and users' needs and interests over the items, and (ii) to recommend products in a personalised way to the users, taking into account the users' preferences.

Formally, the recommendation problem can be defined as finding the most useful item (or set of most useful items) among a large set of choices. To find the best item, a prediction function is approximated by the RS:

$$Recommendation(I,u) = \arg\max_{i_k \in I}[Prediction(i_k,u)] \qquad (1)$$

To obtain the recommendations, the RSs may use information over the users ($U = \{u_1,\dots,u_m\}$), the items ($I = \{i_1,\dots,i_n\}$) and the users' ratings over a set of items ($R \subseteq U \times I \rightarrow D$), among other. Depending on how the information is used to recommend, there are different types of RSs:

- Demographic RS [13]. This kind of RS relies on users' demographic attributes, such as the age, gender, or zip code. Most of these systems categorise users regarding their personal information and make recommendations based on the user's class.
- Content-based RS (CBRS) [14]. CBRSs rely on items' information, which can be a textual description or metadata (items' features) [15]. They also need users' feedback over the items and they recommend items that are similar to the ones that the user already experienced and/or liked.
- Knowledge-based RS (KBRS) [16]. In KBRS, the system holds and uses any kind of additional knowledge, such as a user model created from some items that are given as an example of a good item [17], a tweak over the features of a given recommendation (critique-based), or domain specific knowledge that describes items' features and their relations (ontology-based)
- Collaborative filtering RS (CFRS) [18]. Among the different types of RSs, the most successful approach is CFRS, which analyse users' preferences to recommend. This feature makes them able to recommend complex items, because they do not need any item knowledge to produce high quality recommendations.

Due to the fact that our proposal targets recommendations for groups of users and in RS the recommendations are tailored to individuals, it is necessary the use of Group Recommender Systems (GRS) that extends traditional RS to recommend to a target group of users ($G = \{g_1,\dots,g_r\}$) whose members can have different or even conflicting preferences [19].

In group recommendations, as stated by Jameson in [19], there exist four basic recommending subtasks: (i) acquiring members' preferences, (ii) generating the recommendations, (iii) explaining group recommendations, and (iv) aiding to make the final choice. Formally, a GRS tries to find the item (or set of items) that maximises the prediction for a group of users among a set of available items, similarly to individual RS (see Eq. 2).

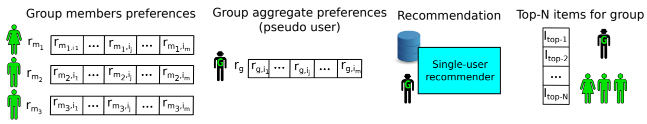


Figure 1: Rating aggregation approach for group recommendation.

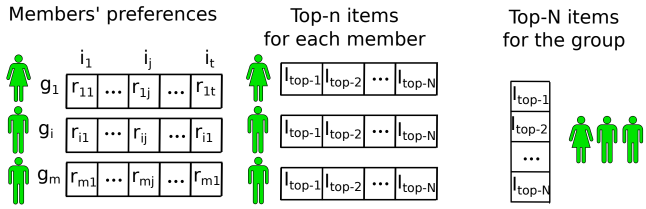


Figure 2: Recommendation aggregation approach for group recommendation.

$$Recommendation(I,G) = \arg\max_{i_k \in I}[Prediction(i_k,G)] \qquad (2)$$

A widespread approach to generate the group recommendations is to apply a single user RS and aggregate the information to produce the group recommendation [1]. Two approaches have been considered in the literature:

- Rating aggregation (see Fig. 1). A group profile is generated from the members' preferences by aggregating them. This pseudo-user profile represents the group preferences and it is used as input of a single user RS to produce the recommendations targeted to the group.
- Recommendation aggregation (see Fig. 2). For each group member it is generated a recommendation. These recommendations are aggregated to produce a single one, which is the recommendation targeted to the group.

Our proposal will use a recommendation aggregation approach that needs to use a single user RS to produce the individual recommendations, in the proposal is used the user-based k-nearest neighbours (UBNN) [20], which recommends items by looking for relations between users' preferences to predict unknown users' ratings (see Fig. 3) according to the following phases: (i) The similarity between the target user and each other system's users is computed, (ii) the most similar users are selected to form the neighbourhood of the target user, (iii) the neighbours' ratings are aggregated to predict the rating for the target user over all unseen or not experienced items, and (iv) the items with the highest prediction are recommended.

2.2 Context-aware recommender systems

Previous RSs assume that the user's satisfaction towards the recommendations is only dependent of his/her preferences, thus finding the best item or set of items can be done by analysing the ratings solely. But in some scenarios, the user's satisfaction with a given recommendation can depend on the items recommended and also other factors, such as the time when the recommendation is requested, the item's location, or the user's circumstances.

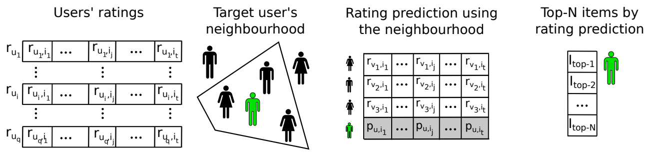


Figure 3: Single user recommendation through user based collaborative filtering.

Context-aware recommender systems (CARS) [7] are an extension of traditional RS that include contextual information in the recommendation calculus. The contextual information describes the context in which the recommendation is requested or presented to the user.

Several alternatives to include context-awareness in a RS have been proposed. These proposals can be classified into three approaches [7]:

- Contextual pre-filtering. It selects only the users' ratings that were generated in the target user's context.
- Contextual post-filtering. It modifies the ratings prediction regarding their suitability on the target user's context.
- Contextual modelling. The context is used in the prediction function as an input, added to the target user and item.

Researchers have found that none of these approaches completely dominates the other ones [7], therefore a study on the concrete system must be done to determine the best approach on the target recommendation scenario.

In tourism RS, different authors have pointed out the relevance of different contextual dimensions [21]. An important contextual information is the users' and items' location, which can influence the prediction or filter out items that are too far to reach from the user's location. Other important contextual dimension is the time, given that the recommendation of a set of tourist activities should be different if it is for summer or for winter. Other relevant contextual information are the weather, local time, user's mood, or companion, among others. In our proposal the context will be defined by the location of users and items.

2.3 Consensus Reaching Processes in Group Decision Making

In Group Decision Making (GDM) [22] problems, a set of experts ($E = \{e_1, \ldots, e_p\}$) tries to find the best solution among a set of alternatives ($A = \{a_1, \ldots, a_q\}$). There are different contexts in which the decision can occur, such as certainty, risk, and uncertainty. Most of the decisions in the real world occur in uncertainty context. To manage the uncertainty, the most used structure is a fuzzy preference relation.

A fuzzy preference relation [23] P_i given by an expert e_i is defined by a membership function $\mu_{P_i} : A \times A \to [0,1]$. This function is represented by a matrix of size $q \times q$, and each μ_i^{kl} denotes $\mu_{P_i}(a_k, a_l)$, this is, the preference degree of the alternative a_k over a_l, regarding the expert e_i. This preference degree can be less, equal, or greater than 0.5, indicating the degree to which a_k is preferred, are indifferent, or the degree to which a_l is preferred, respectively.

Once the experts have expressed their individual preferences, a selection process is performed to obtain a solution set of alternatives. However, this process does not guarantee an agreement on the solution and then experts might feel that their opinion has been overlooked or even that they reject the selected solution. To avoid

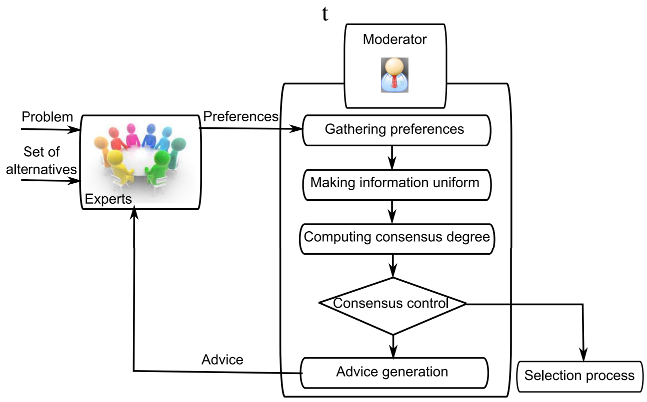


Figure 4: Scheme of resolution of a group decision making problem with a consensus reaching process.

the previous problem, Consensus Reaching Processes (CRP) [24] were introduced in GDM to achieve agreed solutions. It means that there exists a mutual agreement between the group member and each individual opinion has been taken into account to maximise the group satisfaction [25]. A CRP aims to reach a given agreement level before making the final selection of the alternative by means of an iterative discussion process among experts until they meet the consensus condition (see Fig. 4) [26]:

- Consensus measure: Using the preferences of each expert, the consensus degree of the group $cr \in [0,1]$ is calculated.
- Consensus control: Being μ the consensus degree required, it is checked if $cr > \mu \in [0,1]$. If it does, the consensus degree meets the requirement and the process ends. To avoid that the CRP takes too many rounds, a maximum number of rounds can be established. This finalises the process although the consensus degree required has not been reached.
- Consensus progress: If the consensus degree required has not been reached, the moderator communicates to each expert the preference modification that they should consider to reach the consensus degree.

A CRP is usually supervised by a moderator through the following functions, which in some cases can be automated [27]:

- Assess the agreement level of the experts.
- Find alternatives far from consensus.
- Advice the experts the preference changes that they should consider to increment the consensus.

2.4 Consensus driven group recommendation

Due to the fact, that this contribution aims at obtaining agreed recommendations for groups, it will implement the consensus-driven GRS approach [15] that applies an automatic CRP [28] in the recommendation aggregation process to improve the satisfaction of the members towards the group recommendation. The general scheme of the consensus-driven GRS follows these phases:

- Individual recommendation phase: First, the system uses the individual ratings over the restaurants to produce a recommendation tailored to each member.
- Consensus phase: An automatic consensus reaching process is applied to the individual recommendations. This process updates the individual recommendations in several iterations

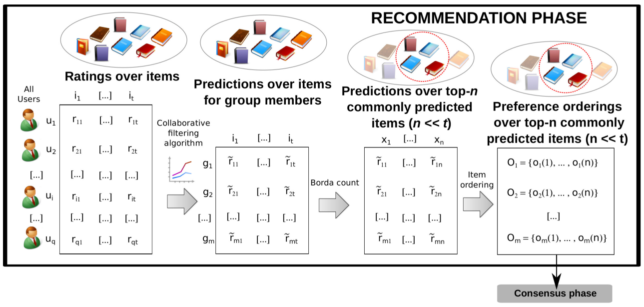


Figure 5: Recommendation phase scheme.

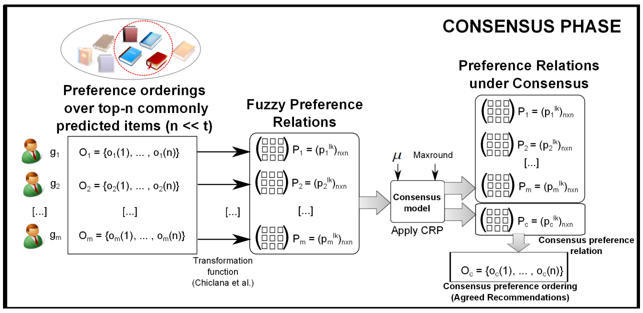


Figure 6: Consensus phase scheme.

until the consensus degree reaches an acceptable level and generates the collective recommendation.

These phases are described in further detail in the remaining of this section.

2.4.1 *Individual Recommendation phase*

In the individual recommendation phase (see Fig. 5), members' recommendations are computed using a single user RS, which produces an ordered list of items for each member. A subset of items is selected from the set of items recommended to all members. The orderings that the subsequent CRP uses are given on the subset selected.

Specifically, the recommendation phase is composed of the following steps:

1. The individual recommendations for each member are generated in the individual recommendation phase. To do so, a single user RS predicts the rating of unseen items for each member:
$$\tilde{r}_{g_i i_k} = Prediction(g_i, i_k) \qquad i_k \in \{i_l \in I \mid \forall g_i \nexists r_{g_i i_k}, g_i \in G\} \tag{3}$$
2. Once the predictions are generated, it is needed to take into account that, for some items, it might not be possible to predict a rating. For this reason, we consider only the items for which the system is able to produce a prediction for all the group members. Therefore, a subset of items is built and only the items in I^G set are taken into account in the next phase:
$$I^G = \{i_k \in I \mid \forall g_i \exists \tilde{r}_{g_i i_k}, g_i \in G\} \tag{4}$$
3. A total order of the items in I^G set is obtained for each group member regarding the prediction value:
$$O_{g_i} = \{o_{g_i}(i_1), \ldots, o_{g_i}(i_k), \ldots, o_{g_i}(i_s)\}, \quad i_k \in I^G \tag{5}$$
4. A reduced subset of items $I_t^G \subseteq I^G$ is built, composed of the t best products for the group using the Borda count over all members O_{g_i}. A total order $\tilde{O}_{g_i}$ over I_t^G set is built for each member, keeping the same order that the items had in O_{g_i}:
$$\tilde{O}_{g_i} = \{\tilde{o}_{g_i}(i_1), \ldots, \tilde{o}_{g_i}(i_k), \ldots, \tilde{o}_{g_i}(i_t)\}, \quad i_k \in I_t^G \tag{6}$$

2.4.2 *Consensus phase*

In the consensus phase (see Fig. 6), the individual recommendations of the members are combined to produce the group recommendations. A CRP then tries to obtain an agreed recommendation list for the group. This is done by applying an automatic CRP, which generates a recommendation list with a high consensus level among the members.

Specifically, the consensus phase is composed of the following steps:

1. Each total ordering $\tilde{O}_{g_i}$ is transformed into a fuzzy preference relation by using the following equation [29]:
$$p_{g_i}^{lk} = \frac{1}{2}\left(1 + \frac{\tilde{o}_{g_i}(i_k) - \tilde{o}_{g_i}(i_l)}{t-1}\right), \quad i_k, i_l \in I_t^G \tag{7}$$
where $\tilde{o}_{g_i}(i_k)$ and $\tilde{o}_{g_i}(i_l)$ are the position of items i_k and i_l for user g_i, respectively. An example is provided in order to clarify the behaviour of eq. (7). Let $I_t^G = \{i_1, i_2, i_3, i_4, i_5\}$ and $\tilde{O}_{g_1} = \{1, 5, 4, 3, 2\}$. The fuzzy preference relation for member g_1 is:
$$P_{g_1} = \begin{pmatrix} 0.5 & 1 & 0.88 & 0.75 & 0.63 \\ 0 & 0.5 & 0.38 & 0.25 & 0.13 \\ 0.13 & 0.63 & 0.5 & 0.38 & 0.25 \\ 0.25 & 0.75 & 0.63 & 0.5 & 0.38 \\ 0.38 & 0.88 & 0.75 & 0.63 & 0.5 \end{pmatrix}$$
where $p_{g_i}^{12} = 1$ indicates that item i_1 is totally preferred to i_2. The fuzzy preference relation is symmetric, hence $p_{g_i}^{21} = 0$ and indicates the same. When $p_{g_i}^{kl} = 0.5$, both items are equally preferred. When $i_k = i_l$ the preference is also 0.5, which is shown in the main diagonal of P_{g_1}.
2. Once the fuzzy preference relations are generated, an automatic CRP is applied over them. The CRP is composed of the following phases [26]:
   - Consensus measure: The similarity matrix of each pair of members is obtained from the similarity between their fuzzy preference relationships.
   $$SM_{g_i g_j} = (sm_{g_i g_j}^{i_k i_l})_{t \times t} \tag{8}$$
   $$sm_{g_i g_j}^{i_k i_l} = 1 - |(p_{g_i}^{i_k i_l} - p_{g_j}^{i_k i_l})| \tag{9}$$
   After this, the group's consensus matrix is generated from all the similarity matrices of all members:
   $$CM = (cm^{i_k i_l})_{t \times t} \tag{10}$$
   $$cm^{i_k i_l} = OWA_W(\cup_{g_i g_j} sim_{g_i g_j}^{i_k i_l}) \tag{11}$$
   where OWA_W is an Ordered Weighted Average operator [30] whose behaviour is determined by W.
   With CM matrix, $cr \in [0,1]$, is computed, which is the consensus level of the group:
   $$cr = \sum_{i_k \in I_t^G} \frac{ca^{i_k}}{t} \tag{12}$$

$$ca^{i_k} = \sum_{i_l \in I_t^G - \{i_k\}} cm^{i_k,i_k} \quad (13)$$

- Consensus control: In this step it is checked if $cr \geq \mu \in [0,1]$, being μ the required consensus degree. If $cr \geq \mu$, the consensus is reached and the collective preference is generated.
- Advice generation: If the consensus level has not reached the required consensus degree, the individual preferences are updated in a way that the further preferences of the group are modified automatically to bring them closer to the group preference. Specifically, the advice generation is done in the following way:
  - The collective preference P_G is computed.
  - The proximity matrix PP_{g_i} between each member g_i and P_G is computed:

$$pp_{g_i}^{i_k i_l} = 1 - |(p_{g_i}^{i_k i_l} - p_G^{i_k i_l})| \quad (14)$$

  - The pairs of items whose consensus degrees ca^{i_k} and $cr^{i_k i_l}$ are not enough are identified:

$$CC = \{(i_k, i_l) | ca^{i_k} < \mu \wedge cr^{i_k i_l} < \mu\} \quad (15)$$

  - The experts whose preferences over the pairs in CC should change are identified by checking if the proximity of the expert is lower than the average proximity.
  - The modified preferences are computed using the following equation:

$$\tilde{p}_{g_i}^{i_k i_l} = \begin{cases} \max(p_{g_i}^{i_k i_l} + 0.1, 1) & if \quad p_{g_i}^{i_k i_l} < p_G^{i_k i_l} \\ p_{g_i}^{i_k i_l} & if \quad p_{g_i}^{i_k i_l} = p_G^{i_k i_l} \\ \min(p_{g_i}^{i_k i_l} - 0.1, 0) & if \quad p_{g_i}^{i_k i_l} > p_G^{i_k i_l} \end{cases} \quad (16)$$

3. When the CRP ends, a fuzzy preference relationship with a high consensus is obtained. Then, the group recommendation is computed using the non-dominance degree of each alternative that expresses to what extent an alternative is non-dominated by the rest [31]:

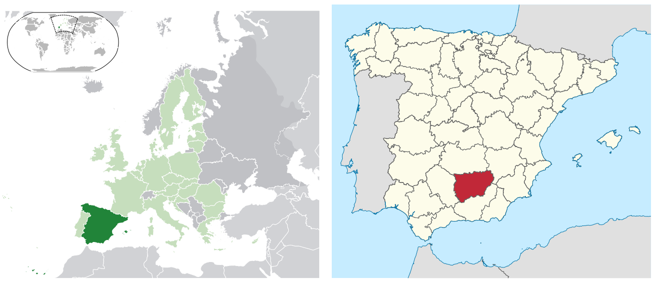
$$p^{ND}(i_k) = 1 - \sup_{i_l \in I_t^G} p^s(i_l, i_k) \quad (17)$$

where $p^{ND}(i_k)$ is the non-dominance degree of item i_k and $p^s(i_l, i_k)$ is:

$$p^s(i_k, i_l) = \begin{cases} p(i_k, i_l) - p(i_l, i_k) & if \quad p(i_k, i_l) \leqq p(i_l, i_k) \\ 0 & otherwise \end{cases} \quad (18)$$

3. CLG-REJA: A CONSENSUS LOCATION-AWARENESS GROUP RECOMMENDER FOR RESTAURANTS

This section introduces the consensus location-awareness group recommender scheme that is implemented on an app restaurant recommender system REJA. Therefore, first it is described the basic data and performance of REJA and later on it is described the performance of the location awareness and consensus recommendations to conclude with the interface of the app that can be used to obtain such a type of recommendations.



(a) Spain (b) Province of Jaén

Figure 7: Province of Jaén, area of interest of REJA

3.1 Restaurants of Jaén Recommender System: REJA

Even though there are different alternatives to search and check restaurants using widespread applications such as Yelp or TripAdvisor. However, location specific applications provide an added value over general ones. REJA[1] (REstaurants of JAén) [8, 9, 10, 11] is a system developed by Sinbad[2] Research Group at the University of Jaén (Spain) and it is focused on the recommendation of restaurants located in the province of Jaén.

Before describing REJA, it is interesting to provide some data about the environment of this system. The province of Jaén population is 664,916, distributed in 13,496km^2. The most important economic activity is olive oil production, which occupies around 80% of the cultivable land. Other important features related to tourism are that it has 4 nature parks, the preservation of a number of castles in different towns, and the preservation of a number of renaissance monuments, such as churches and palaces. This makes that, added to other tourism facilities, there are a number of restaurants distributed along the province.

REJA is a system that supports users at finding restaurants in the province of Jaén. It relies on explicit ratings over the restaurants. The restaurant database has 516 restaurants and holds additional information over them such as location, phone number, type of cuisine, and other relevant information over the restaurant facilities.

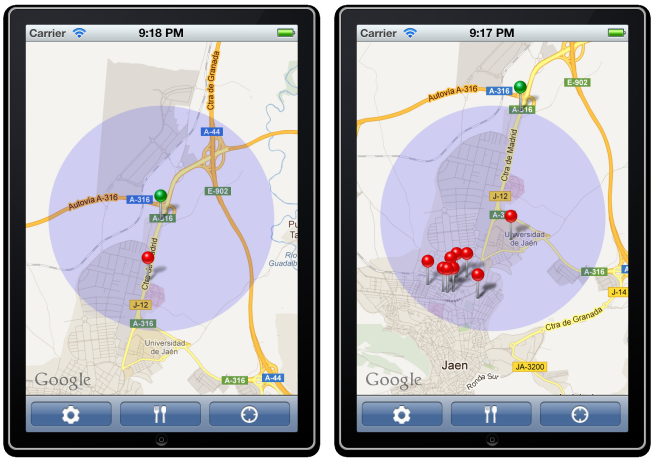
It may provide recommendations for anonymous users, REJA produces non-personalised recommendations such as most-liked and most popular restaurants and also enables the search of similar restaurants to a given one. However for registered users, REJA provides ***collaborative recommendations*** (CFRS). To obtain recommendations, a registered user must provide enough ratings about the restaurants known by her (at least 20 ratings). This information is used to build and modify the user's profile and to compute suitable recommendations for her.

When REJA is used by a user with a small amount of information, such as a novel user, CFRS face the problem of cold-start, which makes that the system cannot generate the recommendations or it produces low quality ones. To overcome this limitation and produce recommendations for such users, it implements a commuted hybrid recommender system [9] that hybridize the former CFRS and a knowledge-based system.

3.2 Including context awareness for recommendations on the move.

The previous functionalities of REJA [9] are targeted to users that interact with the system through a web interface at home. How-

[1] http://sinbad2.ujaen.es/reja



(a) On site request (b) On-the-move request

Figure 8: Area of interest for different user's contexts.

ever, users' interaction with the systems is done mostly through mobile devices in spite of their limitations such as screen size and battery duration. However, most of them have built-in sensors, such as barometer, accelerometers, wireless communication interfaces, compass and Global Positioning System (GPS), that can automatically gather information, which simplifies user's interaction. For this reason, users' interaction through mobile devices provide valuable information, which can be used to produce recommendations tailored to the specific user's context. Thus, REJA was extended to allow users access through mobile devices and enabled the possibility of users requesting restaurant recommendations to REJA, with the *location-awareness* requirements. So REJA integrates a CARS that takes into account the user's location and speed [10] that are used in a fuzzy system to adjust the parameters of an area of interest.

In the example depicted in Fig. 8 the user's location is represented with the green pin. As she is travelling to the city, the restaurants that he already left behind her are no longer interesting, and makes all the restaurant ahead a better option than the restaurants that the user has already left behind.

3.3 Location-awareness and consensus driven group recommendation

So far, REJA recommends restaurants for individual users using different approaches, such as hybridised or context-aware recommendation, among others. However, as it has been pointed out restaurant are social items enjoyed generally by groups. Therefore the restaurant recommender systems are used by groups. For this reason, this contribution adds to the location-aware REJA system a group recommendation approach based on consensus, not only to cope with the social requirement but also to provide highly agreed recommendations that provide satisfaction to the whole group.

Therefore, in the process of generating the group recommendations it is necessary to adjust them to the specific group's context. In the case of REJA, the context considered is the location of the different items and the position of the group members. From the three approaches to integrate context-awareness into a recommender system (see section 2.2). The approach used in this proposal is *contextual post-filtering*, which allows to filter and re-rank the items after they are recommended according to the items' and the user's context. Given that the context considered in REJA is the location of the different items and the position of the group members. Therefore, the items far from the users are penalised.

To integrate location-awareness in the consensus-driven GRS [6], the system has been modified to include the group's context. For this reason, in the integration of the model in CLG-REJA it is necessary to include a contextualisation phase. Therefore, the scheme for the consensus location-awareness group recommender system is composed of the three following phases (see Fig. 9):

1. Individual recommendation phase: The system generates the members' individual recommendations using a single user RS.
2. Recommendation contextualisation phase: The recommendations are post-filtered to incorporate the location information and produce localised individual recommendations.
3. Consensus phase: The contextualised individual recommendations are fed to the automatic consensus module that produces the group recommendations.

The phases of the system are described in further detail in the remaining of this section.

3.3.1 *Individual recommendation phase*

The individual recommendations for each member are generated in the individual recommendation phase. To do so, a single user RS produces a list of items, which are new for all members, sorted by their rating prediction (see Eq. 3).

Once the predictions are generated, it is needed to take into account that, for some items, it might not be possible to predict a rating for all members. These items are excluded from the recommendation (see Eq. 4).

3.3.2 *Recommendation contextualisation phase*

The individual recommendation phase output is the predictions for all the items with a prediction for all group's members. In this phase, these predictions are modified to exclude elements that are far from the group's location, therefore the items are re-ranked regarding their distance.

The items' re-ranking is performed by using a fuzzy method to allow certain flexibility. Thus, the group manager needs to establish a parameter δ, which is the distance that the group is willing to move to reach the item recommended. With this information, the system modifies the predictions of the items to discard those that are too far to reach, maintains the predictions of the items that lie within δ and modifies in a soft way the items that lie outside but near of δ:

Therefore, a modification is applied to the prediction of each item regarding their respective distance to the group:

$$\tilde{r}'_{g_i,i_k} = r_{g_i,i_k} * w_{G,i_k} \qquad ,w_{G,i_k} \in [0,1] \tag{19}$$

$$w_{G,i_k} = \begin{cases} 1 & if \quad d(G,i_k) \leq \delta \\ 1 - \frac{d(G,i_k)-\delta}{\delta'-\delta} & if \quad \delta \leq d(G,i_k) \leq \delta' \\ 0 & if \quad d(G,i_k) \geq \delta' \end{cases} \tag{20}$$

where $d(G,i_k)$ is the distance between the group and the item, δ is defined by the group manager, and δ' value is defined from δ:

$$\delta' = \delta * (1+\alpha), \qquad \alpha \in [0,1] \tag{21}$$

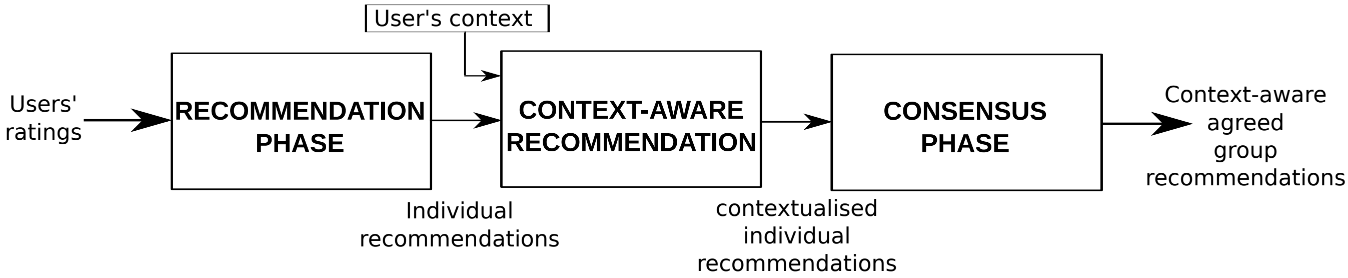


Figure 9: General scheme of the context-aware group recommender of REJA

where α is a parameter that defines how flexible is the contextual filtering. In REJA, α is set to 0.2, but it might be different in other recommendation domains.

After the contextualisation is done, it is needed to transform the contextualised predictions to a preference relation, in order to be used in the consensus phase. Similarly to the consensus-driven GRS, the total order for each member is obtained regarding the contextualised prediction value (r'_{g_i,i_k}):

$$O'_{g_i} = \{o'_{g_i}(i_1), \ldots, o'_{g_i}(i_k), \ldots, o'_{g_i}(i_s)\}, \quad i_k \in I^G \tag{22}$$

3.3.3 *Consensus phase*

The preference relation obtained in the previous phase describes the members' initial preferences over the items. However, to use them in a CRP, the number of items must be reduced. This reduction is done using the Borda count to select t items and compose I_t^G. After that, $\tilde{O}'_{g_i}$ are built maintaining the order in $\tilde{O}_{g_i}$:

$$\tilde{O}'_{g_i} = \{\tilde{o}'_{g_i}(i_1), \ldots, \tilde{o}'_{g_i}(i_k), \ldots, \tilde{o}'_{g_i}(i_t)\}, \quad i_k \in I_t^G \tag{23}$$

The total orderings $\tilde{O}'_{g_i}$ are transformed into fuzzy preference relationships [29] using the following equation:

$$p_{g_i}^{lk} = \frac{1}{2}\left(1 + \frac{\tilde{o}'_{g_i}(i_k) - \tilde{o}'_{g_i}(i_l)}{t-1}\right), \quad i_k, i_l \in I_t^G \tag{24}$$

Once the fuzzy preference relations are generated, an automatic CRP [24] is applied over them, as explained in steps 2 and 3 of the Consensus phase described in section 2.4.2

3.4 A Consensus Location-awareness group recommendation app for REJA

An operational prototype that implements the system described in section 3.3 has been developed with the aim at studying the performance of our proposal under real world contextual conditions. Our prototype aims at providing group restaurant recommendations in the province of Jaén.

The architecture of the prototype (see Fig. 10) follows the client-server paradigm that comprises two elements: the mobile clients and the remote server. On one hand, the mobile clients consists of a mobile application that is installed on the mobile devices. The application is in charge of creating the group, gathering the contextual knowledge, provide the server the group's information, and display the group recommendations. On the other hand, the remote server provides a web service that allows to the group creator to send the group's information to the server and request group recommendations generated with the system described in section 3.3.

Therefore, the users of the system are required to install a mobile application on their devices. Once the application is launched,

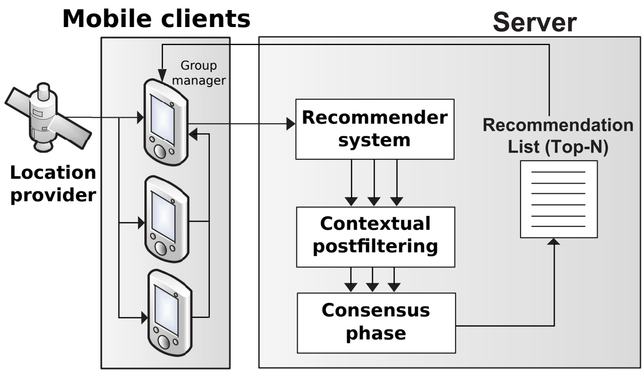


Figure 10: Architecture of the prototype for location-aware consensus-driven group recommendations.

the users are requested to provide their log-in data. Figure 11 depicts the log-in interface of the prototype and the initial screen for a logged user.

After this task is completed by all the group members the group that later on wants to request the recommendation is created. The aim of this task is to specify the users that belong to the group. Figure 12 illustrates how the prototype allows group creation. To perform this task minimising the group's members interaction with their mobile devices, the specification of the group members is done by the user with a special user role, the *group creator*. therefore, the group creator, added to the creation of the group, has the task of adding members to the group.

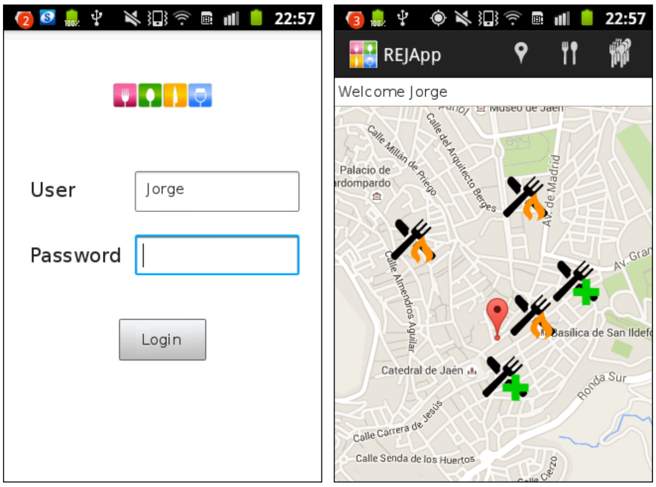
Once the group creation is done, the system allows the group creator to request the recommendations (see Fig. 13a). Before the actual group recommendation request, the group creator needs to express how far the group is willing to move to reach a good restaurant. For this, the interface provides a slider in which the group creator picks the desired value for δ.

When the system generates the recommendations, the mobile device presents the recommended items in the map, together with the group location (see Fig 13b). The map visualisation allows them to make the final decision taking into account the closeness of the restaurants recommended.

4. CONCLUDING REMARKS

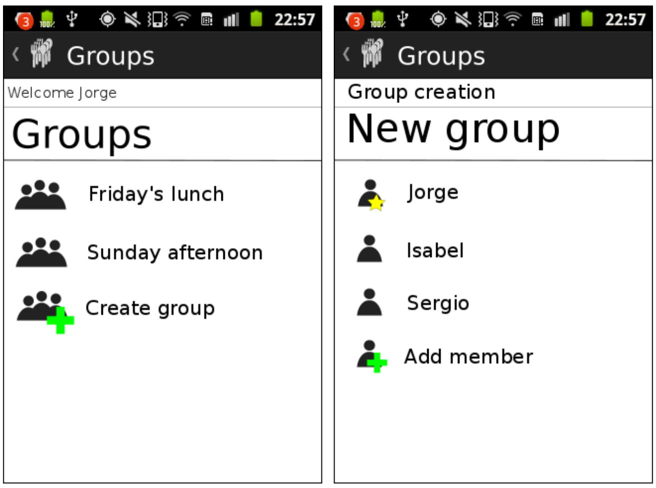
In this contribution, the improvement of classical recommender system for tourist purposes has been considered, taking into account two important issues within tourism namely, the ubiquity and social feature that involves tourism activities.

Therefore, a general recommendation scheme has been introduced, which is able to deal with context awareness and agreed group decisions. It has been implemented in a restaurant RS so-



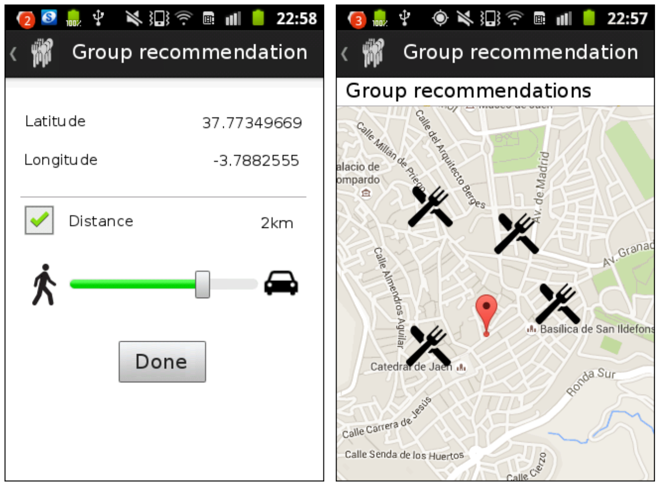
(a) Login page. (b) Logged user screen.

Figure 11: Screens of the prototype for the login task.



(a) Group creation. (b) Members specification.

Figure 12: Screens of the prototype for the group creation and members specification tasks.



(a) Recommendation request. (b) Map visualisation.

Figure 13: Screenshots of the recommendation request and visualisation.

called REJA by means of a mobile app.

As future work, we plan to develop a study of how the users perceive the utility of this kind of recommendation compared to others. Also we plan to develop an user study to evaluate the interaction of the users with the system and the satisfaction with the recommendations.

Other interesting future work is to integrate additional contextual dimensions additionally to the location, such as the climate or the week-day. These contexts are particularly interesting given that certain restaurant's facilities could change their influence on users' satisfaction in certain contexts. An example of this situation might be the availability of a terrace in a rainy day on winter.

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