User-Centered Evaluation of Strategies for Recommending Sequences of Points of Interest to Groups

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ABSTRACT

Most recommender systems (RSs) predict the preferences of individual users; however, in certain scenarios, recommendations need to be made for a group of users. Tourism is a popular domain for group recommendations because people often travel in groups and look for point of interest (POI) sequences for their visits during a trip. In this study, we present different strategies that can be used to recommend POI sequences for groups. In addition, we introduce novel approaches, including a strategy called *Split Group*, which allows groups to split into smaller groups during a trip. We compared all strategies in a user study with 40 real groups. Our results proved that there was a significant difference in the quality of recommendations generated by using the different strategies. Most groups were willing to split temporarily during a trip, even when they were traveling with persons close to them. In this case, *Split Group* generated the best recommendations for different evaluation criteria. We use these findings to propose improvements for group recommendation strategies in the tourism domain.

CCS CONCEPTS

• **Information systems → Recommender systems**.

KEYWORDS

Recommender System; Group Recommendation; Sequence; Preference Aggregation; Social Choice Strategy; User Study

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1 INTRODUCTION

Most recommender systems (RSs) in tourism provide support to travelers by suggesting lists of points of interest (POIs) that best satisfy their contextual needs, such as visiting a restaurant or a museum [4]. However, when exploring a new city, tourists often look for a sequence of POIs that they can visit along a route during a specified period of time. The problem of determining trips that are composed of multiple POIs is called the Tourist Trip Design Problem (TTDP) [25].

It is challenging to recommend good sequences of items, especially to groups of users. The recommended sequence needs to satisfy all the group members; however, the satisfaction with a sequence also depends on the order of the recommended items [16]. In this regard, tourist trips are a special case of item sequences. The order of POIs in a trip is not very flexible because the location of the recommended items becomes a limiting factor. Furthermore, a number of other factors determine if and when a POI can be visited during a trip, such as the time left, the weather, and the opening hours. Consequently, a recommended tourist trip cannot always contain the POIs with the highest predicted user ratings.

A number of studies have been conducted on group recommendation strategies in various domains; however, to the best of our knowledge, there are no user studies that evaluate different group recommendation strategies to solve the TTDP. In this study, we introduce two novel group recommendation strategies: *Split Group* and *Connect Segments*. *Split Group* allows groups to split temporarily and rejoin later. For instance, if a few persons in a group want to go shopping during a trip but the rest prefer to do some outdoor activity, the group can split and meet again subsequently for another combined activity. *Connect Segments* combines the various parts of each group member's individual recommendation to create a sequence for the group. Furthermore, we apply established group recommendation strategies (*aggregating profiles of users (AP)* and *aggregating recommendations (AR)* [6]) to the TTDP and compare all the strategies in a user study with 40 real groups.

The remainder of this paper is organized as follows. In Section 2, we summarize related work. We present different strategies to recommend tourist trips to groups in Section 3. The results of our user study in which we evaluated these strategies are presented in Section 4. The paper concludes in Section 5.

2 RELATED WORK

Early RSs in tourism use content-based filtering and case-based reasoning to propose POIs or travel plans composed of multiple travel items, such as destinations, hotels, and means of transport [13, 21, 22]. In the last few years, there has been an increasing trend of using collaborative filtering for tourism recommendations [4]. Furthermore, recent approaches are increasingly using the data collected from location-based social networks [3], such as features extracted from images to recommend POIs [26] or geotagged photos to extract real-life travel sequences and information

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about POI popularity and user preferences [14]. A few RSs have been developed to recommend travel-related items to groups. The investigated use cases are recommendations of lists of POIs [2, 19], event venues [28], restaurants [10, 17], and ski packages [18].

Many algorithms and heuristics have been developed to solve the TTDP, and most of these solutions are based on the Orienteering Problem (OP) and other similar optimization problems [9]. In the last few years, researchers developed the first practical applications to evaluate the recommended trips from a user's perspective [8, 11, 24]. Until today, very few works have solved the TTDP for user groups. Anagnostopoulos et al. [1] introduced TourGroup, an extension of the OP, which aims to generate tours that satisfy all group members by finding a compromise route. They present different formulations of the problem, and the objective functions of these problems are derived from preference aggregation strategies inspired by the social choice theory. In addition, they developed different algorithms that solved the TourGroup problem. Sylejmani et al. [23] introduced another extension of the OP by taking into account the social relationships between the different group members. One of the approaches they presented is similar to our *Split Group* strategy; however, they consider every group member for separation from the current group at every POI of every trip. Consequently, the average execution time is high (around 20 s for the *fast mode*), which makes their solution more suitable for pre-trip planning. Our approach considers only POIs with a low profit for a user as candidates for splitting the group. Therefore, it is faster and more suitable for usage in practical applications. Both [1] and [23] evaluated their approaches in experiments using data sets but created synthetic groups.

In this research, we present different types of strategies to solve the TTDP for groups; we include a novel strategy that allows groups to split temporarily. We conducted a user study with 40 real groups to evaluate all strategies from a user's perspective.

3 GROUP RECOMMENDATION STRATEGIES FOR THE TOURIST TRIP DESIGN PROBLEM

In this section, we introduce TourRec, a mobile tourist trip RS that we used as the basis for the development of our group recommendation strategies. Then, we show how to apply *AP* and *AR* strategies to solve the TTDP for groups and introduce our two proposed strategies termed *Split Group* and *Connect Segments*.

3.1 TourRec – a Mobile RS for Tourist Trips

We integrated our recommendation algorithms into TourRec, a mobile RS for Android devices we developed [11]. The group recommendation strategies that we propose in this study extend the recommendation algorithm for single users, as applied in TourRec. Every request in TourRec is composed of the user's travel preferences, a starting point, a destination, a starting time, and a time budget. Travel preferences are specified by rating five POI categories (e.g., *Arts & Entertainment* and *Food*) on a scale ranging from 0 (not interested in this category) to 5 (strongly interested in this category). To specify travel preferences more precisely, each category has multiple subcategories (e.g., *Art Museum* and *French Restaurant*) that users can rate. In this study, a user profile is composed of 42 subcategories. The RS retrieves POIs around and between the start and destination from Foursquare and calculates the POI profits based on the user preferences and the context factors. Then, a graph is drawn with the POIs as vertices and the connection between the POIs as edges. A routing algorithm based on Dijkstra's algorithm is used to find a trip that maximizes the collected profits while respecting the time budget [27]. Instead of finding the shortest path, the adapted algorithm tries to maximize the total profit. The recommended trip is eventually displayed on the mobile device.

3.2 Aggregating Profiles of Users (AP)

The goal of *AP* is to create a common user profile that reflects all the preferences of all the group members. Social choice strategies can be used to aggregate the profiles of the group members [15].

We are interested not only in the relative positions of the ratings in each individual's category preferences, but also in the strengths of preferences. Therefore, we use the *Average*, *Average without Misery*, and *Most Pleasure* strategies as examples of *AP* strategies in this study. These strategies performed well in previous experiments, whereas other strategies, such as *Least Misery*, performed poorly [15]. The *Average* strategy calculates the average of the individual ratings of all group members for every category. The *Average without Misery* strategy filters all the categories with at least one rating below a threshold. The *Most Pleasure* strategy uses the maximum individual rating as a group rating.

The group profile is then used together with the context ratings to calculate the profit of every POI before executing the Dijkstra-based tourist trip algorithm.

3.3 Split Group

One disadvantage of *AP* is that it can undermine individual preferences because every group member has to use the same recommendation. Therefore, we present an extension of the *AP* approach, which allows every user to visit important POIs based on their personal recommendations. Figure 1 visualizes our proposed approach. First, the POI profits for all users are determined and aggregated to recommend a mutual trip for the group. Our implementation uses the *Average* strategy; however, it is also possible to use other suitable social choice strategies. Then, an individual recommendation is made for each user. The algorithm checks if POIs from the mutual trip could be replaced with the POIs from the individual trip for every group member. To determine the best replacement for a POI in the mutual trip, the profit of every candidate POI (i.e., every POI in the individual trip) is divided by the overall distance that the user needs to walk from the previous POI to the candidate and to the following POI. If the profit of a candidate is higher than the current POI's profit, it replaces the POI, that is, the user leaves the group to visit this POI. Only POIs with a profit below a threshold t can be replaced because we believe that no group member should leave the group if the mutual recommendation is already satisfying for the group member. Figure 2 shows a trip generated by *Split Group*.

3.4 Aggregating Recommendations (AR)

AR means that a recommendation is generated for every group member individually before the recommendations are combined into one group recommendation [6]. In our approach, we apply a social choice strategy on the POIs that are part of at least one of the

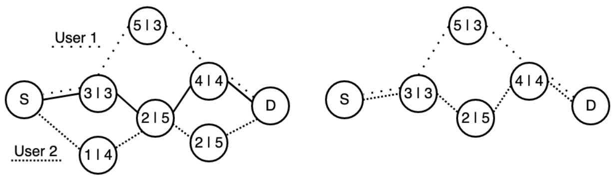

Figure 1: Visualization of *Split Group* with two users and a threshold $t = 3$ for replacing POIs. The profits for each user are displayed in the vertices in the format (user 1 | user 2). The left side shows the mutual trip (solid line) and the individual trips (dotted lines). The final recommendation on the right side is the mutual trip for both users; however, user 1 visits one POI from the individual recommendation before rejoining user 2 at the last POI.

individual trips to aggregate recommendations. The profit of a POI is increased by the factor of n^2, where n is the number of individual routes that contain the POI. The idea is to make it more likely that the POIs that are part of multiple individual recommendations appear in the group recommendation. In this study, we used the *Average* strategy to test this approach.

3.5 Connect Segments

Connect Segments is a variation of *AR* that follows the idea that during a trip, every group member can visit their favorite POIs for a specified period. For instance, in the morning, the group visits a museum that user A likes the most, then they have lunch at user B's favorite restaurant, and so on.

In this study, groups visit a segment of two POIs from a group member's individual recommendation before the next two POIs are taken from another group member's individual recommendation. The order of the group members in this process is determined randomly. This procedure continues until either the end of all individual recommendations is reached or no more time is left.

4 USER STUDY

We evaluated the recommendation techniques in a user study.

4.1 Participants

The participants were made to register for the study as a group of three people because we wanted to conduct our user study with real, non-synthetic groups. In total, 120 participants (40 groups) participated. The participants were in the age ranges of 18–24 years (60 %) and 25–34 years (40 %), 50.8 % were females and 48.3 % were males. One participant preferred to not specify the gender. The participants were mainly composed of students and alumni. 62.4 % called their group "close friends" or "family", 31.7 % called them "student fellows", and 3.3 % did not know the other group members prior to the study.

We asked the participants if they appreciate splitting during a trip on a 5-point Likert scale. This question received contradictory

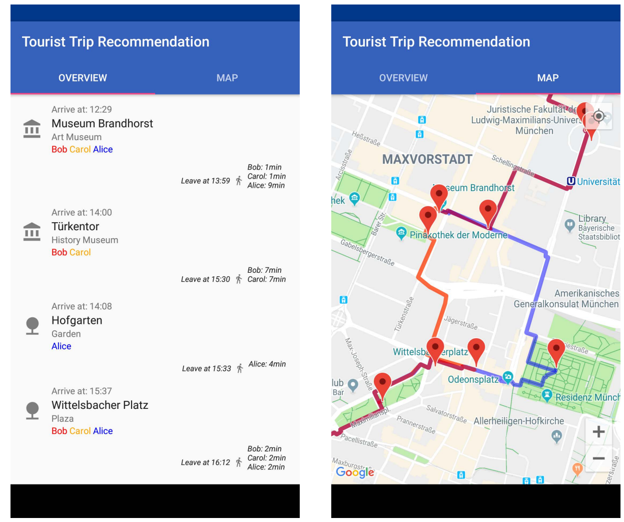

Figure 2: Extract from a recommendation generated by *Split Group*. After visiting an art museum, Bob and Carol visit another museum while Alice spends some time in a garden before rejoining Bob and Carol at a plaza.

responses ($\overline{x} = 3.58$, $s = 1.31$). Many participants stated that splitting was acceptable, even when traveling with close friends. However, 25 % of the participants felt that splitting should be avoided (response 2 or lower).

4.2 Recommendation Strategy Evaluation

During the user study, we generated three trip recommendations for each of the six recommendation strategies presented in Section 3. Consequently, the participants received and rated 18 trips. The order of the strategies was randomly chosen for every group to reduce the learning effect on the results. To reduce the number of independent variables, the trips came with fixed conditions. Every recommendation strategy was used to generate trips with three pre-defined start and destination pairs in the city center of Munich, Germany, a touristic area that offers of a wide range of POIs. All the trips had the same maximum duration (8 h). The weather during each trip was set to sunny, and the group size was set to three, similar to previous group recommendation research [15].

Every participant was equipped with an Android smartphone with the extended TourRec application. The participants entered their travel preferences separately in their own devices. The connection between the smartphones was hard coded. The recommended trip was displayed on all smartphones on a map and as a list with additional information, such as arrival times (see Figure 2).

After examining the recommendations, the participants were asked to rate five statements that we adapted from the ResQue questionnaire [20] on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree):

(S1) The recommended trip matched my personal interests.
(S2) The attractions in the recommended trip are diverse.

(S3) The order of attractions in the trip is satisfactory.
(S4) The recommended trip is feasible for a walking tourist.
(S5) I would make this trip when traveling with my group.

In a previous study, we showed that decisions made by groups are often dominated by few group members [12]. In this study, we were interested in the individual satisfaction with the recommended trips and therefore did not ask for actual group decisions.

Table 1 shows the average responses for all recommendation strategies and whether there is a significant difference between the strategies based on the Friedman tests that we conducted.

Table 1: Average responses for all scenarios on a 5-point Likert scale (Note. *p < 0.05; **p < 0.01; ***p < 0.001).

Q	Avg	AwMi	MoPl	Split	AR	CoSe	Sig.
S1	3.74	3.73	3.48	**3.88**	3.56	3.52	***
S2	3.71	3.44	3.46	**3.85**	3.52	3.49	***
S3	3.64	3.60	3.51	**3.72**	3.56	3.39	***
S4	3.98	**4.03**	3.96	3.99	4.02	3.84	**
S5	**3.49**	3.43	3.19	3.48	3.32	3.21	***

The results show that there is a significant difference between the strategies with regard to each of the five criteria. *Split Group* performed the best in three out of five criteria, and it had a score similar to the *Average* strategy and the *Average without Misery* strategy for S4 and S5. Conover's post-hoc tests [5] show that *Split Group*:

- matches the personal interests of the participants significantly more than the *Most Pleasure* strategy, *AR*, and *Connect Segments*,
- generates a significantly higher diversity of the trips than all the other strategies except for the *Average* strategy.
- ensures a significantly better ordering of items in the trip than the *Most Pleasure strategy*, *AR*, and *Connect Segments*,
- creates trips that are significantly more feasible for walking tourists than *Connect Segments*, and
- creates trips that the participants would much rather make when traveling with their groups than the trips generated by the *Most Pleasure* strategy and *Connect Segments*.

Only in the *Average* strategy our tests did not reveal any significant difference from *Split Group* in any of the five statements. The trips generated by the *Average without Misery* strategy were similarly rated by the participants; however, the diversity of these trips was significantly less than the diversity of the trips generated by the *Average* strategy and *Split Group*. The worst strategies in our experiment were *Most Pleasure* and *Connect Segments*. *Average*, *Split Group*, and *Average without Misery* created trips that the users would much rather make than the trips generated by the *Most Pleasure* strategy. Trips generated by the *Connect Segments* strategy had the worst performance with regard to the order of POIs. This was expected because our first implementation of the *Connect Segments* strategy combined parts of different trips without a post-hoc optimization of the order of the POIs in the new trip.

We analyzed whether the willingness to split and the trip ratings generated by *Split Group* depended on the group type. Using the self-assessment of our participants, we clustered our groups into 17 primary groups (i.e., groups in which members shared a close relationship, such as family) and 23 secondary groups (i.e., groups which are often created in goal-focused situations, such as colleagues) [7]. Our results indicated that there was no significant difference between both the group types. We thus concluded that the type of relationship does not influence the willingness to split during a trip. This was also confirmed by comments received from many participants after the study; these participants explained that they would split temporarily, even when traveling with a very close person, if this satisfies everyone's needs.

Finally, we compared the ratings of *Split Group* provided by people who were willing to split during a trip with the ratings given by people who thought that splitting should be avoided or is not an option at all; the result of the Wilcoxon rank sum test shows that there is a greater possibility that the former group would make a trip generated by *Split Group* rather than the latter ($p = 0.007$).

5 DISCUSSION AND CONCLUSION

In this study, we adapted *AP* and *AR* strategies to solve TTDP for groups and introduced two novel strategies for this purpose. We compared the recommendations generated by these strategies in a user study with 40 real groups.

Our study revealed that many people were willing to split for some time during a daily trip even when they were traveling with a primary group, such as close friends and relatives. Furthermore, the option to split during a trip can improve the quality of the recommended trips. However, 25 % of the participants wanted to avoid splitting, or they completely rejected the idea. User interfaces in practical RSs should allow users to specify if they are willing to split during a trip. For those who prefer to travel together, another strategy, such as the *Average* strategy, could be used to generate recommendations of a similar quality.

The *Connect Segments* strategy that we proposed is another way to ensure that every group member can visit their preferred POIs. However, our user study revealed that groups were less satisfied with trips that were generated using this strategy because it led to a suboptimal order of POIs in a trip. To overcome this problem, we suggest extending this algorithm by using a post-hoc optimization phase and evaluating the extension in a subsequent study.

In this study, we set the group size to three to reduce the number of variables. Although many people were open to the idea of splitting during a trip, certain participants stated that they would not be willing to split into smaller groups because they did not want to travel alone. Therefore, we believe that the *Split Group* algorithm would perform even better in large groups; we will verify this in our future studies. Furthermore, our algorithms did not consider the POI categories when suggesting a group to split. In a few cases, a group was supposed to split for lunch or for dinner. The feedback we received from these groups was that splitting was not an option during such activities, even when the group members had different food choices. In addition, the groups did not prefer to split when the categories that the subgroups were supposed to visit were similar, for example, a garden and a park. In our future work, we will determine the categories that would be optimal for splitting, and we will use our findings to optimize our *Split Group* algorithm. We also plan to apply our strategies in scenarios other than the TTDP.

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