Recommending a Sequence of Points of Interest to a Group of Users in a Mobile Context

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ABSTRACT

Recommender systems (RSs) recommend points of interest (POIs), such as restaurants, museums or monuments, to users. In practice, tourists often travel in groups and want to visit a sequence of POIs along an enjoyable route. Recommending such a sequence of items to a group complicates the problem of travel recommendations because the preferences of all group members have to be taken into account. In this work, we want to examine how a RS can solve the so-called Tourist Trip Design Problem (TTDP) for a group of users. We present the most important components of our work and the research questions we want to be answered. We summarize the results we achieved so far and outline future work.

KEYWORDS

Group Recommender System; Tourist Trip Design Problem; Sequence; Point of Interest; Algorithm; User Interaction

1 INTRODUCTION AND MOTIVATION

Most Recommender Systems (RSs) provide personalized recommendations for single items, such as movies, books or points of interest (POIs). When planning a trip, tourists usually want to visit a sequence of POIs along an enjoyable route. The problem of finding such a tourist trip is called the Tourist Trip Design Problem (TTDP) [18]. Applications solving the TTDP for single users already exist but in practice, tourists often travel in groups. A Group RS (GRS) for tourist trips has to consider the preferences and constraints of all group members.

Different strategies exist for recommending items or sequences of items to groups. Basic approaches, such as calculating the average of the users' preferences, are easy to implement but might not be optimal. For example, if one user really dislikes a certain item, this item should not be recommended even if the majority of group members likes the item. It should be noted that there is no perfect way to aggregate the individual preferences. Instead, the group's intrinsic characteristics and the problem's nature have to be considered [4].

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In this PhD work, we want to examine how to recommend a sequence of items to a group of users, which is still an unexplored topic [13]. Our work focuses on tourist trips, sequences of POIs along enjoyable routes. Compared to other sequences of items, tourist trip recommendations are a more complex issue. The order of POIs in a trip is not very flexible because the recommended route should avoid disproportionate detours. Furthermore, it is likely that some POIs cannot be visited, for example, if they are too expensive or if the remaining time is insufficient. Recommending tourist trips to a group of users is a particular challenge. So far, no research has been done to evaluate which group recommendation strategies work best for recommending tourist trips. Simply combining existing preference aggregation strategies with TTDP algorithms for single users might not guarantee a high group satisfaction or work at all. An average strategy cannot be implemented when some POIs, e.g., bars or night clubs, are not suitable for special group members such as children. It is also conceivable that new group recommendation strategies have to be developed for the tourist trip scenario. For example, if the group members have very different travel preferences, the group could split up during the trip and meet again at a later point of time to avoid dissatisfaction.

The overall research question we want to answer in this work is: *How can RSs solve the TTDP for a group of users?* We want to investigate the problem from two perspectives: how to generate a recommendation for a group and how a group can interact with a tourist trip GRS. The rest of this paper is organized as follows: Section 2 summarizes related work. In Section 3, the different components of our work and research questions we want to be answered are presented. We outline our first results in Section 4. We describe our evaluation methodology and present an outlook on future work in Section 5. This work finishes with a short conclusion.

2 RELATED WORK

Early travel RSs suggested single items such as hotels and destinations or bundled such items to travel plans [16] [19]. They did not recommend items to a group of users or suggested a sequence of POIs along enjoyable routes.

Recommending sequences of items has been researched in different domains, such as music or television [13]. Algorithms solving the TTDP represent one solution to recommending sequences of POIs. Many algorithms and heuristics solving different variants of the TTDP have been developed over the past years. Some researchers integrated their algorithms in practical tourist trip applications. The City Trip Planner is a web-based tourist trip RS recommending single and multi-day trips [17]. CompRecTrip is another similar system recommending either sets or sequences of POIs [21]. The web and mobile application called DailyTRIP, presented by Gavalas et al. [6], can recommend multi-day trips around a common start/end point but it was evaluated with a simulation and a focus on efficiency only. The presented applications show how the TTDP can be solved in practical applications but none of them recommends trips to a group of users.

A few GRSs in tourism exist but to the best of our knowledge, no GRS generates tourist trips composed of multiple POIs. INTRIGUE recommends a list of POIs the user should visit but without combining them along a route [2]. The Travel Decision Forum supports users in agreeing on attributes of a trip, such as desired room facilities or leisure activities [8]. CATS is a case based RS proposing ski packages consisting of several attributes such as the locations, ski lift systems or hotel features [14]. Another GRS recommending single POIs is STSGroup [15].

In contrast to previous work, we want to show how to recommend sequences of POIs to a group of users. We will present solutions how to generate tourist trip recommendations for groups and develop different interaction styles. We want to integrate our findings in a practical application and evaluate them with real groups in user studies.

3 RESEARCH QUESTIONS

Jameson and Smyth [9] present four subtasks that have to be performed by a GRS:

(1) The system acquires information about the members' preferences.
(2) The system generates recommendations.
(3) The system presents recommendations to the members.
(4) The system helps the members arrive at a consensus about which recommendation (if any) to accept.

In the following, we present our research questions for each of the four subtasks. We outline how to evaluate the research questions in user studies in Section 5.

3.1 The System Acquires Information about the Members' Preferences

A GRS can either generate individual recommendations for all group members and combine them to a group recommendation or aggregate the users' preferences to create a virtual group user and recommend an item to this virtual user [13]. A user's preferences depend on the preferences of other group members and the group itself. In some scenarios, a user might accept a recommendation to do a close person a favor. Furthermore, a user might not want other group members to know which POIs she or he likes or dislikes. Revealing preferences to other users in a GRS may allow users to better understand what the best choice for the group is but this knowledge also enables manipulation [8].

Research questions we want to answer in this subtask:

(1) Which group types exist and which information about the group and its members is relevant for a tourist trip GRS?
(2) Which recommendation strategies work best when recommending tourist trips to a group of users?
(3) Which preferences should be revealed to other group members to maximize the quality of the recommendations without enabling manipulation or social embarrassment?

3.2 The System Generates Recommendations

TTDP algorithms perform two steps: At first, POIs are fetched from a data source and assigned a score. Then, a route containing some of the POIs and maximizing the total score of the trip without violating constraints has to be found [20]. Experiments showed that consuming recommended items can have a large impact on the ratings of other items in the same sequence [12]. While this has been proven for news recommendations, we assume that this is even more critical for POI recommendations. For example, when recommending two restaurants in a row, the second restaurant will not be appreciated by the users. Tourist trip algorithms have to identify appreciated and unwanted combinations of POI and consider them during the recommendation process [7].

Research questions we want to answer in this subtask:

(1) Which TTDP algorithms recommend the trips with the highest user satisfaction?
(2) How can the selection and order of POIs in tourist trips be optimized?
(3) How can existing TTDP algorithms be extended to generate recommendations for groups?

3.3 The System Presents Recommendations to the Members

Different approaches to presenting item sequences to users exist. In a tourist trip GRS, either the whole trip or only the upcoming POI can be presented. Travelers often change their plans spontaneously, e.g., stay longer at a POI. In this case, the rest of the trip has to be adapted accordingly. Using a conversational approach by proposing different alternatives successively and collecting feedback on every suggestion can help to better understand the user's preferences and improve the recommendation even after the trip has started. Some GRSs use public screens to present recommendations and to interact with the users. The advantage of such a screen is that it provides an extensive overview of the recommendations for all group members at the same time. On the other side, the use of public screens in recommendations raises privacy issues [1]. People may not like their recommendation to be seen by a broad audience. User interfaces for tourist trip GRS have to find a compromise between privacy and transparency and hide parts of the recommendation from the group or the public.

Research questions we want to answer in this subtask:

(1) How can tourist trip recommendations be presented to a group on mobile devices?
(2) How can public displays be integrated into the recommendation process to improve the user experience?
(3) How do the composition of the group and the relations between the group members influence the individuals' requirements towards privacy and transparency?

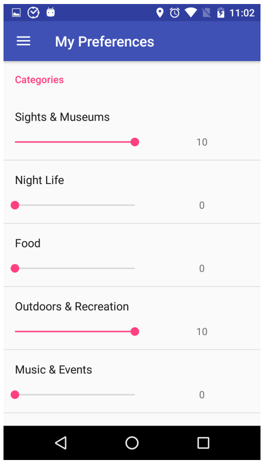

Figure 1: Travel preferences elicitation

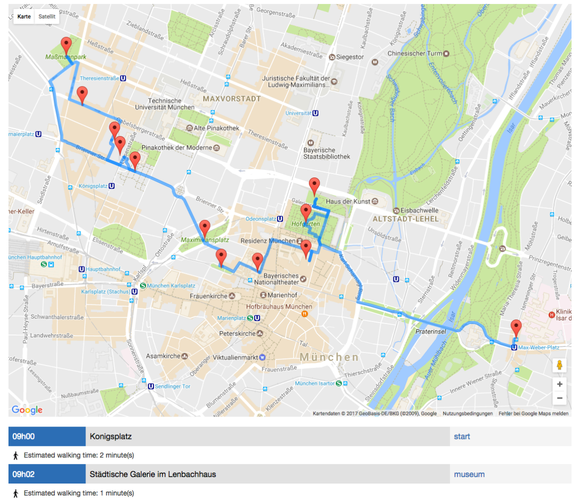

Figure 2: TourRec recommendation

3.4 The System Helps the Members Arrive at a Consensus about which Recommendation to Accept

In our scenario, users receive a recommendation with explanations and can provide feedback on the recommended trips by either using a personal device or a public screen, or both. Again, a good compromise between privacy and transparency has to be found. Users might feel more comfortable sharing their feedback on their personal devices but transparent explanations and open debates about the recommendations can help users to understand the preferences of other users and thus support them in finding a consensus.

Research questions we want to answer in this subtask:

(1) How can tourist trip recommendations be explained to a group?
(2) How much information can be revealed to ensure a high transparency while not violating the users' privacy?
(3) How can the group members provide feedback on a trip using their personal device or a public screen, or both?

4 RECENT RESULTS

We started to develop and evaluate first components of a tourist trips GRS.

4.1 Preference Elicitation

Figure 1 shows a basic approach we implemented to elicit a user's travel preferences [11]. This approach is limited to single users and works solely on the user's personal device.

A user interface as illustrated in Figure 1 allows users to easily indicate their travel preferences. One drawback is that this approach allows only to elicit very basic travel preferences, in this case, how much the user likes very general categories such as *Sights & Museums*. We are currently developing conversational interfaces to elicit the user's travel preferences in a more precise manner.

4.2 Tourist Trip Algorithms

We developed three tourist trip algorithms. The first approach (DB) is an extension of the algorithm presented in [20]. It uses Dijkstra's algorithm to maximize $\frac{total\ score}{distance}$ for each subpath. We developed an extension of this algorithm considering the distance to the destination for each subpath (DBDD). The third algorithm is a Greedy Randomised Adaptive Search Procedure (GRASP), a metaheuristic that performs a number of independent iterations to eventually return the best iteration results [5].

All algorithms were extended by item dependencies because the score of each POI is dependent on the presence or absence of other POIs in the same trip. In addition, we consider suitable times for visiting POIs. For example, a restaurant receives a higher score when recommended for lunch or dinner than in the afternoon. In a small pilot study, we compared our algorithms to our previous solution presented in [20]. A few users tested our system and emphasized that item dependencies and suitable times improve the recommendations by optimizing the ordering of POIs. Venues, such as restaurants or bars, are recommended at more appropriate times of the day.

Furthermore, we developed a responsive web application to evaluate our three TTDP algorithms in a preliminary user study. Every time a user requests a recommendation, one of the three algorithms is randomly chosen and a tourist trip as illustrated in Figure 2 is presented to the user on a map and as a list with arrival and walking times. After every recommendations, the users were asked to rate the following statements on a 5-point Likert scale (1: strongly disagree, 5: strongly agree):

(S1) Overall, I am satisfied with the recommended trip.
(S2) The number of places in my route is well chosen.
(S3) The selection of different categories in the trip is satisfying.
(S4) Places are suggested at the right times during the trip.
(S5) The route is feasible for a walking tourist.

During the preliminary user study, our tourist trip planner suggested 62 trips which were rated by the participants. Table 1 shows the average ratings for every statement.

Table 1: User study results

Algorithm	∅S1	∅S2	∅S3	∅S4	∅S5	# responses
DB	3.33	3.22	3.44	3.28	3.33	18
DBDD	3.13	3.33	3.29	2.88	4.08	24
GRASP	3.10	3.15	3.15	3.25	3.35	20

The results in Table 1 and the feedback we received from the participants show that the users like the general idea of the RS and are mainly satisfied with the recommendations. The average ratings of S5 show that routes generated by the DBDD algorithm are more feasible for walking tourists. This algorithm considers the distance to the final destination before adding a POI to the trip and therefore allows a more even distribution of POIs along the route. By contrast, the DB algorithm and GRASP tend to recommend trips where the majority of POIs are located in a small area. This is recommended for trips in small areas with many POIs, such as city centers. Otherwise, the connection to the final destination can be perceived as too large.

4.3 An Architecture for Tourist Trip Recommender Systems

We developed a multi-tier architecture which is partitioned into a presentation tier, an application logic tier and a data tier [11]. This architecture is the basis for our developments. The main advantages of this architecture for our work are:

- Reusability of functionality. For example, when developing new components such as clients, we do not have to re-implement the whole application logic.
- Modularity. Our system is composed of individual modules such as dedicated microservices for each TTDP algorithm. This architecture allows us to easily add, exchange or remove POI sources, algorithms and clients. Figure 1 and Figure 2 show the two clients our RSs currently uses to recommend tourist trips to single users.
- Developer friendliness. Single modules are easier to understand and teams can work on different components at the same time.
- Scalability. The modular design facilitates scalability.

5 EVALUATION METHODOLOGY AND FUTURE WORK

In this section, we summarize the next steps of our research and explain how we want to evaluate the different parts of our work. As explained, we want to investigate the problem from the two perspectives algorithms and user interaction and will therefore conduct user studies for both parts.

We will continue the user study described in Section 4.2 over a longer period of time to gather more feedback on the developed TTDP algorithms. In this study, the manipulated variable is the selection of the algorithm. Each user request is handled by a randomly selected algorithm. Apart from the different recommendations, the user is not able to distinguish between the algorithms as the other test conditions remain the same. The dependent variables are the answers to the questions S1 to S5 in Section 4.2 and will be extended by some implicit feedback, e.g., if the user exports or saves a recommendation. The gathered feedback will help us find out which algorithms promise the highest user satisfaction and how we can improve them to optimize the sequences.

Furthermore, the TTDP algorithms for single users will serve as a baseline for the evaluation of the TTDP group recommendation algorithms we develop. The simplest approach is to execute the single user TTDP algorithms with the aggregated group preferences. As explained, more sophisticated approaches should be evaluated when recommending tourist trips to different types of groups. We will develop alternatives approaches considering, for example, split groups and compare them against the baseline. The dependent variables are the individual's satisfaction with the recommendation (as in the single user study) as well as the perceived group satisfaction since group members have to compromise when using a GRS.

Our clients currently work for single users only. We will extend them to support group recommendations. This can be done by connecting multiple mobile devices, using a public display or combining both approaches. We will conduct usability tests to evaluate which of these interaction types is preferred by the users in the scenario of tourist trip planning. The manipulated variable in this scenario is the selected interaction type. The dependent variables are the time a group needs to find a tourist trip, the number of clicks and how many errors the users make. In addition, questionnaires such as the SUS can be used to measure usability [3]. Another manipulated variable in this user study is, besides different options for providing feedback on the different devices, the selected explanation style. We will investigate if a higher privacy level has a significant influence on the user experience.

User studies with groups of three to five users require a higher number of participants than studies with a single user. This is why we choose an within-subject design where each participant is exposed to all conditions of the manipulated variable [10]. We will randomize the order of the selected interaction type in each test to minimize the learning effect. We will perform a power analysis to determine the number of participants we need for our studies [10].

A major drawback of previous research in the field of GRS is that studies were either conducted on a small scale, in a contrived setting or used synthetic groups which can lead to falsified results [13]. This is why we want to conduct user studies with real groups and reach as many groups as possible. We want to achieve this goal by placing a public screen at a crowded place, among other things.

6 CONCLUSION

Recommending a sequence of items to a group of users remains a big challenge. Tourist trip recommendations are a particularly complex example of a sequence of items and will hence be the focus of our work. We want to tackle the problem from two perspectives: algorithms and user interaction. Therefore, we will develop new strategies for recommending tourist trips to groups as well as user interfaces for different devices. We will evaluate our results in user studies with real groups.

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