TourWithMe: Recommending peers to visit attractions together

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ABSTRACT

When a user travels alone or in a small group, usually likes to share the experience of visiting different attractions in a larger group. This article propose TourWithMe, our first approach to the problem of recommending peers to visit attractions in a city together. To this aim, TourWithMe automatically learns the user's interests from previously visited attractions, that are then combined with explicit preferences provided by the user to find compatible tourists in the city. TourWithMe recommends to the user different groups and, for each group, attractions that they would enjoy visiting together.

CCS CONCEPTS

• **Information systems → Recommender systems**; **Social recommendation**; *Crowdsourcing*.

KEYWORDS

group recommender system; tourism; crowdsourcing; user modeling

1 INTRODUCTION

Visiting a new city is always a challenging experience. Among the set of touristic attractions available in the city, tourists have to select, and usually prioritize, those that are more appealing according to their interests, available time and budget. In consequence, planning a holiday is usually a stressful activity and travellers relay in the use of different applications that may support their decision-making processes.

Recommender systems for tourism arisen to cope with the information overload to which tourists face when visiting a new city. In this regard, recommender systems have focused on different aspects of the domain, such as recommending hotels [1, 25], routes [10, 16], restaurants [9], itineraries [7, 15], and attractions [13, 33, 34].

A hot topic in recommender systems research is the recommendation of items to groups of users, since recommendations need to satisfy a group of users as a whole, instead of individual users [5, 6]. In the field of tourism, recommender systems for groups have been proposed for users who travel with a predefined group (for example, a group of friends or family travelling together) [2, 11].

To the best of our knowledge, none of the existing approaches considered the proposal of groups to visit different attractions together. This kind of recommender system might be extremely useful for users who visit a destination alone or in a small group (for example, with his/her couple) and who want to meet peers to share the experience of touring together. The need of this kind of service becomes clear given the existence of many websites [1,2,3] and social network groups [4,5,6] dedicated to people who wants to meet other people and form groups for tourism.

In this context, the popularization of mobile devices brings forward new challenges and opportunities for the implementation of personalized applications and location-aware services. Particularly, mobile devices enable to capture the user's mobility history and taking advantage of geographic proximity of other users to enhance the user experience [14].

In this article, we present TourWithMe, a recommender system in the tourism domain that takes advantage of mobile devices for recommending travellers to form groups to visit attractions or points of interest (POI) together. Our approach considers geolocalization provided by mobile devices in two ways. On the one hand, the approach implicitly learns the user's interest from the places he/she visits, the amount of time spent in each place, and the time spent travelling to those places. In this way, users do not have to manually check-in every place they visit or to explicitly provide their interests, as required by most of the current approaches. On the other hand, the approach finds other tourists in the proximity of the user and suggests forming a group with those users who have similar interests. Once a group is formed, the approach suggests to visit nearby venues that the whole group would enjoy visiting.

The remainder of this paper is organized as follows. Section 2 discusses related works about recommenders system for tourism. Section 3 presents the proposed approach for recommending travellers forming groups to visit attractions together. Finally, Section 4 presents conclusions and future works.

2 RELATED WORK

Recommenders System for tourism is a hot topic that has been addressed in several works in the last years. These works proposed approaches to recommend users to visit a nearby POI or even a tour itinerary. To carry out this task, proposed approaches used different information, such as the user's current location, information about nearby POIs, user preferences and interests, current day and time, temporal restrictions, etc. The kind of information used and the way in which this information is obtained vary depending on the approach.

In [31] and [19], authors asked users to manually provide their interest and preferences. Both approaches recommend a personalized tour itinerary that fits the user's interests. To carry out this

[1] https://www.yourtravelmates.com/
[2] https://www.workaway.info/
[3] https://www.couchsurfing.com/
[4] https://www.facebook.com/groups/altmtl/
[5] https://www.facebook.com/groups/1157818554266712/
[6] https://www.facebook.com/groups/travellinks/

task, [31] used a Greedy algorithm while [19] used an evolutionary algorithm. The main disadvantages of these works are that manually introducing interests may be a stressful task for users, and they tend to be reluctant to explicitly provide this kind of information [26]. For this reason, some works in the literature proposed to automatically infer the user's interests by analyzing the previously visited POIs.

To address this task, some works used check-ins made by user in location based social networks (LBSN) [17, 35] and geotagged photos from social networks [4, 20, 21] in order to reconstruct the history of visited POIs. In [4, 17, 20], authors proposed approaches that infer the interests of the user for each POI category according to the number of visited POIs belonging to that category. These approaches use these interests to generate a ranking of possible POIs to be visited by the user. In [35], authors proposed a similar approach that infers the user's interest from Jiepang check-ins data. As the user's interests may change according to the time of day, this approach also divides the day into six time slots and calculates the user's interests for each time slot separately. In [21], authors proposed an approach that calculates the duration of each visit by considering the timestamps of the first and the last photos took in the visited POI. The approach uses this information to estimate the user interest for a POI category. For example, if the user spends more time in museums than the average time spent by other users, the approach infers that the user is interested in museums.

As some tourists tend to travel in group, recommending POIs to a group of users instead of to a single user is a useful feature in the tourism domain. Some approaches in the literature address this feature by combining the users' profiles into a single group profile [12, 27]. In this way, approaches designed for recommending POIs to a single profile (usually a user profile) can recommend also POIs to a group by taking the group profile as input. There are two main approaches to combine user profiles: aggregation, when the resultant group profile is the union of all the group members preferences; and intersection, when the resultant group profile is the intersection of all the group members preferences. The approach presented by [5] used an hybrid approach for generating recommendations to groups of tourists, which combines the demographic information of users, the ratings of the community and the content-specific information about the items. The individual ratings inferred from the hybrid profile are weighted according to a fixed set of social relationships among the members of the group. Finally, the influenced individual ratings of all members of a group are combined to estimate a group rating for different items.

To the best of our knowledge, none of the existing approaches considered the proposal of groups to visit different attractions together. The most similar approach to the one presented in this article is the one presented in [22]. In this work, authors proposed an approach oriented to assisting travel agencies for grouping tourists. The approach uses K-means algorithm to cluster a predefined set of users into K groups. Each resultant group contains users with similar interest. Then, the approach assigns a tour itinerary from a set of predefined tour itineraries to each group of users. However, this approach is not useful for a tourist who is alone in an unknown city and wants to meet peers to visit POIs together.

3 SYSTEM DESIGN

Figure 1 shows a high-level diagram of TourWithMe. As shown in the diagram, the approach consists of three steps. In the first step (A) the approach infers the user's interests from the geolocation data of the user. By knowing the POIs visited by the user, the time spent in each place, and the time spent travelling to those places it is possible to estimate the interest of the user in such places. This step is detailed in Section 3.1. In the second step (B), when a user requires it, the approach proposes forming a group with nearby users. The approach uses the profile information of each user to form a cohesive group of users with similar interests. In this sense, there is more chance of finding a POI that is attractive to everyone in the group. This step is detailed in Section 3.2. Finally, in the third step (C), the approach recommends the top-five POIs to the group by considering the interest information of each user in the group. This step is detailed in Section 3.3.

3.1 Inferring the user's interests

This step consists of analyzing the mobility data of the user in order to infer his/her preferences. In order to carry out this task, TourWithMe takes advantage of modern mobile devices. These devices are equipped with several sensors that allow estimating the location of the user. For example, it is possible to estimate the user location by knowing the nearby WiFis or by using the GPS of the smartphone. By tracking the user location, TourWithMe detects visits to places, also named stay points. A stay point is defined in the literature as a geographic region where the user stayed over a time threshold T_s within a distance threshold D_s [24, 29, 32]. In particular, TourWithMe detects a visit when the user stays for more than 5 minutes within a distance of 50 meters. Each visit is represented as a tuple (C, T_i, T_e), where C is the centroid of the geographic area where the user stayed, T_i is the start time of the visit and T_f is the end time of the visit.

When a visit is detected, TourWithMe identifies the POI visited by the user, if any. To carry out this task, TourWithMe relies on public data extracted from OpenStreetMap[7] (OSM). In particular, TourWithMe uses the Overpass Turbo API[8] to query POIs that are less than 50 meters away from the visit. If there are no nearby POI, it is considered that the user stayed in some other place (e.g. in a store). If there is more than one nearby POI, TourWithMe selects the POI with the highest score according to Equation 1. This equation compares the duration of a visit V of user U and the average time of visit for a POI P. The average time of visit for P is computed from previous visits of other users to the same POI. It is important to notice that the user can manually modify the visited POI if needed.

$$score(V, P) = 1 - \frac{|avgDurationOfVisit(P) - duration(V)|}{avgDurationOfVisit(P)} \quad (1)$$

Once the visit has an associated POI, TourWithMe estimates the interest of the user in that POI. The interest of the user in a POI is a real value between 0 and 1 where 0 means that the user is not interested in the POI and 1 corresponds to the maximum interest. This value is computed according to Equation 2 and considers the

[7] https://www.openstreetmap.org/
[8] http://overpass-turbo.eu/

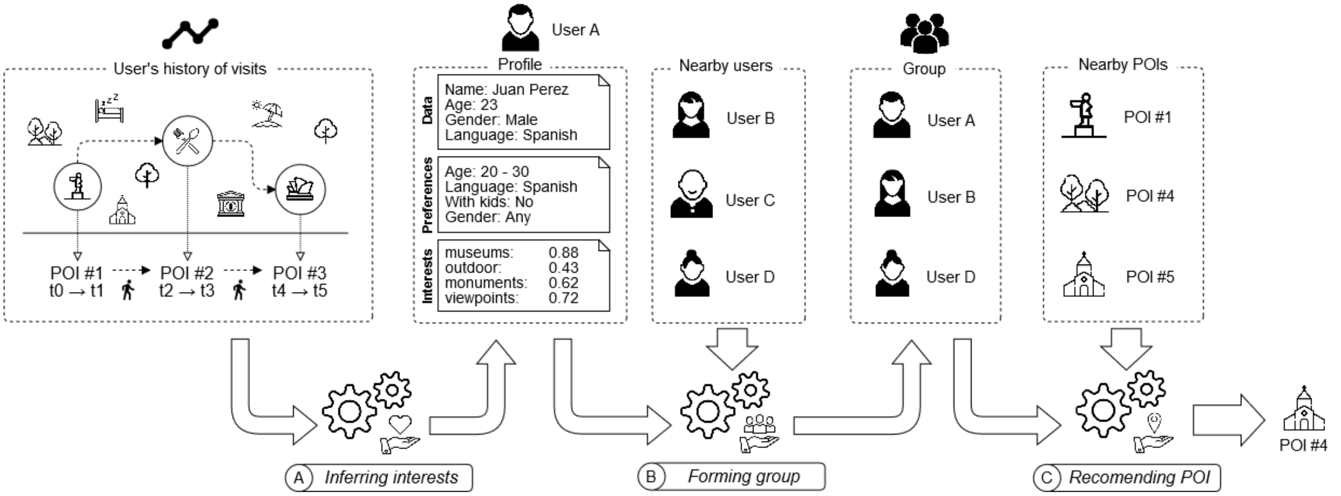

Figure 1: TourWithMe approach

time that the user spent in the POI ($int_{visit-time}$) and the time of the travel T to that POI ($int_{travel-time}$).

$$int(T,V,P) = \frac{int_{visit-time}(V,P) + int_{travel-time}(T,P)}{2} \quad (2)$$

To compute the first term of the equation, in [21] authors proposed to compute the ratio between the time spent by the user in the POI and the average duration of visits to that POI. However, this approach is not useful when a POI has different groups of users who visit the POI with different average times. For example, a museum can offer 1-hour and 2-hours guided tours. An average of 1.5 hours is then not representative for a user taking the 1-hour tour nor to a user taking the 2-hours tour. Furthermore, computing the interest of a user in a POI in this way doesn't give a normalized value of the user interest. To overcome the above-mentioned problems, TourWithMe uses the cumulative percentage of duration of visits. Equation 3 shows how the approach computes $int_{visit-time}(V,P)$ for a visit V to a POI P. For example, if spent 14 minutes in P, and 60% of people stayed less than 14 minutes in P, then the interest of the user in P is 0.6.

$$int_{visit-time}(V,P) = \frac{\sum_{d=0}^{duration(V)} V_{d,p}}{|V_p|} \quad (3)$$

where $V_{d,p}$ is number of visits to POI p with a duration d, and V_p is the number of visits to POI p.

The second term of Equation 2, $int_{travel-time}(T,P)$, compares the time spent by a user in a POI with respect to the time spent travelling to that POI. In [8] authors proposed travel-time ratio as a way to calculate how much time a user is willing to travel to perform an activity. In [30], authors found higher travel-time ratios for activities in which users are interested, such as sport and recreation activities. Mapping the conclusions arrived in the above-mentioned research to the tourism domain, we can assume that if a user travels a long time to visit a given POI, he/she has a great interest in that POI. Equation 4 details how to calculate this ratio for simple journeys in which the user goes to a POI and then returns to his place of lodging. The way to calculate the time ratio for journeys in which the user visit several POIs before returning his/her place of lodging is detailed in [30].

$$int_{travel-time}(T,V) = \frac{duration(T)}{duration(T) + duration(V)} \quad (4)$$

By knowing the interest of the user in each POI he/she visited, it is possible to estimate his/her interest for each POI category. As POIs are extracted from OSM, they have different pairs of key-value describing them. For example, {"*tourism*" : "*museum*"}, {"*name*" : "*Le Louvre*"}. These pairs of key-value are used to label the POI with POI categories. For example, "Le Louvre" is categorized as a "museum". To calculate the interest of a user for a specified POI category C, TourWithMe calculates the average interest of the user in every POI p belonging to C that he/she previously visited (Equation 5).

$$int_{inferred}(U,C) = \frac{\sum_{p \in C} interest(U,p)}{|C|} \quad (5)$$

3.2 Forming groups

For suggesting groups to a user, TourWithMe considers three factors: geolocalization, user's preferences and similarity between users' interests regarding POIs categories. When the user asks for suggestions or when he/she arrives to a new city, TourWithMe first find the set of users S_R within a parameter radio R from the user's current location. If R is not set by the user, TourWithMe considers the set of users visiting the same city. S_R contains then the set of candidate users near to the user's location.

Once the set of candidate users is obtained, it is filtered by the user's preferences. User's preferences are a list of restrictions that the user is able to manually fill in his/her profile, and indicate the system what kind of users are expected to be recommended to the target user. These preferences, which are all optional, include:

- age range: indicates the minimum and maximum age of other users in the group
- sex: preferred sex of people in the group (male, female, any)

- languages: a list of languages that users in the group should speak
- country of residence: if the user prefers other users from specific countries
- children preference: users can indicate whether they prefer tourists traveling with children or not.

Then, if a user established in his/her profile that he/she prefers other tourists aging between 20 and 30, any candidate whose age is outside those limits is removed from the set of candidates. The resulting set S_f contains the set of compatible candidates with the user's preferences.

Other kind of preferences included in the user profile are the following:

- a list of categories of interest: an explicit list of the POI categories in which the user manually indicated interest. Categories are taken from the OpenStreetMap Semantic Network [3].
- budget: indicates the amount of money the user expects to spend while visiting attractions. This variable is discretized in four values (0, $, $$, $$$), indicating free, cheap, moderate, and expensive POIs, respectively

The list of categories manually defined by the user and the inferred interests (which were obtained as described in Section 3.1) are combined to define the real interest of a user U in a category C (Equation 6). If user U explicitly indicated interest in C (by adding it to his/her list of interests), then $int(U,C)$ is the average between 1 and $int_{inferred}(U,C)$. Otherwise, $int(U,C)$ is equals to $int_{inferred}(U,C)$.

$$int(U,C) = \begin{cases} \frac{1+int_{inferred}(U,C)}{2}, & \text{if } U \text{ is interest in C} \\ \\ int_{inferred}(U,C), & \text{otherwise} \end{cases} \tag{6}$$

In the current implementation of TourWithMe, each candidate user v in S_f is ranked by computing the soft cosine similarity with respect to the target user U (Equation 7). This similarity measure does not assume that features in the space model are independent and then introduce the similarity of features into the equation of the traditional cosine similarity.

$$soft\_cosine(U,v) = \frac{\sum_{i,j}^{N} s_{ij} U_i v_j}{\sqrt{\sum_{i,j}^{N} s_{ij} U_i U_j} \sqrt{\sum_{i,j}^{N} s_{ij} c_i v_j}} \tag{7}$$

where U_i is the ith feature for user U, v_i is the ith feature for user v, and s_{ij} is the similarity between the ith and the jth features. The similarity between features i and j, s_{ij}, is computed by using the semantic similarity of OSM tags [3]. The set $S_C \subset S_f$ with the K most similar users is considered for forming groups in the next step.

When a user U asks for a group recommendation, he/she must define a preferred group size Z (where $Z < K$). Then, from S_c, all possible groups of size Z including the target user U are computed, and a cohesion score is assigned to each of them. Cohesion is computed as the average similarity between each pair of users in the group. Groups are finally sorted by the cohesion score.

3.3 Recommending POIs

Although groups are formed by finding tourists with similar interests, different users always will have some different interests. To address these diverse interests, most approaches in the literature build a group interest profile by aggregating or by intersecting the preferences of all group members [11, 13, 27, 28]. From these two options, aggregating preferences is preferable since it allows introducing serendipity in the recommendations enabling the user to discover attractions that may not be recommended by a recommender system for individuals. Serendipitous items are items that users would not find by themselves or even look for, but that would enjoy consuming. The introduction of serendipity in recommender systems is fundamental to avoid users losing the interest in recommendations due to a overspecialization of the system in the user's already-known interests [18]. This overspecialization, avoids the recommender system to learn new interests of the user, and enables the user to be able to predict by themselves what items would be recommended by the system, reducing in consequence the user's satisfaction with the recommendations.

For example, Figure 2 shows a group of three users with their respective interests. By aggregating user interests, the interest of the resultant group profile in a category C_i is the average interest of the three users in C_i. In the literature, this is known as *average aggregating strategy* [23]. As the interest of user B in C_2 is not defined, the interest of the whole group in C_2 is calculated by considering only users A and C. Thus, the resultant group profile has a high interest in category C_2. In this way, if the approach recommends a POI of C_2, it will encourage User B to visit a new kind of POI. Instead, by intersecting user interests, the resultant group profile will not have any interest value defined for C_2, since not all users of the group have an interest defined in C_2. Thus, the approach will encourage users to continue visiting the same kind of POIs they already visited before.

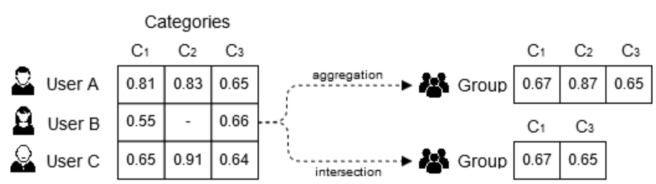

Figure 2: Aggregation vs. intersection of interests

TourWithMe builds a group interest profile based on the average interest preference of all group members. Given a group $g = u_1, ..., u_k$, the group interest in a cagetory c is defined according to Equation 8.

$$int(g,c) = \frac{1}{|g_c|} \sum_{u \in g_c} int(u,c) \tag{8}$$

where $g_c \subset g$ are the members of g for which the interest $int(u,c)$ is defined.

Then, the interest of a group g in a given POI p is computed according to Equation 9.

$$int(g,p) = \frac{\sum_{c \in C_p} int(g,c)}{|C_p|} \tag{9}$$

where C_p are the categories associated to POI p.

Continuing with the example of Figure 2, by using the average interest of all the group members not necessary may lead to making the best recommendation. For example, Figure 2 shows that the group profile has an interest of 0.67 for C_1 and 0.65 for C_3. Thus, recommending a POI belonging to C_1 would be preferred than recommending a POI belonging to C_3. However, the variation of interests for this category is very high: User A has an interest of 0.81, while User B has an interest of 0.55. Thus, visiting a POI belonging to C_1 seems to be *unfair* for User B. Moreover, User A will want to stay in the POI a longer time, while user B will want to leave before. Instead, when visiting a POI belonging to C_3, the three users will have a similar interest in the POI and there are more chances that they will agree about how long to be in that place.

To considering this situation, TourWithMe looks for recommending the POI that best fits the group profile at the same time that it reduces the variation of interest among users for the recommended POI. Equation 10 shows how TourWithMe score a POI p for a group g. All POIs in the user's neighbourhood are ranked according to this equation, and the top-5 POIs are assigned to each group as recommendations.

$$score(g,p) = int(g,p) - \frac{maxInterest(g,p) - minInterest(g,p)}{|g|} \quad (10)$$

where $maxInterest(g,p) - minInterest(g,p)$ is the maximum variation of interest between the members of group g for POI p.

Along to each recommendation TourWithMe computes the estimated time that the group would spend in each POI by using the cumulative percentage of duration of visits, as detailed in Equation 3. In this case, if the group interest in the category of a POI p is, for example, 0.6 and the time spent by 60% of the people at the given POI is t, we assign t as the estimated time that the group would spend at p.

4 CONCLUSIONS AND FUTURE WORK

In this article we presented TourWithMe, a first approach to the problem of recommending peers to visit different attractions in a group. We believe that our approach might appeal tourists traveling alone or in small groups to enhance the experience of enjoying the attractions offered by a new city.

TourWithMe is currently in a prototype stage, and is developed as a native Android application. This application tracks user location and detect visits when the user stays for more than 5 minutes within a distance of 50 meters. Then, TourWithMe associates each visit to a POI extracted from OpenStreetMap when possible. In addition, TourWithMe identifies the transport mode of each travel, which in the future may be a useful feature for POI recommendation. For example, if user moves by car, it is possible to recommend more distant POIs than if he/she moves on foot.

The next step in our research is to evaluate our approach with a benchmark dataset. As there is no benchmark dataset available for POI recommendation for group of users, most works in the literature use datasets with individual ratings and simulate groups. The rating of a simulated group for a POI may be estimated as the average ratings of the group members. The main challenge after evaluating the proposed approach with a simulated dataset will naturally be the validation with real users.

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