A LOCATION-AWARE TOURISM RECOMMENDER SYSTEM BASED ON MOBILE DEVICES

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Recommender systems (RS) have been successfully used in different personalization issues. One of the most interesting applications is tourism (hotels, restaurants, monuments, etc.) where users can obtain personalized recommendations according to their profiles. Recently, the increasing use of mobile devices drives RSs to a new trend based on context-awareness. In this contribution we take advantage of mobile devices in RSs and propose a location-aware RS for tourism that provides recommendations to users not only based on their profile but also taking into account their current location.

1. Introduction

Personalization [6] has recently been recognized by experts as a critical factor of e-tourism companies to be successful. Up to date, recommender systems (RS) are the most successful personalization technique [1]. These systems lead users to suitable products by using different information filtering techniques, hence limiting the effects of information overload.

Recently, the fast development and adoption of ubiquitous computing technologies has fostered a considerable interest in the field of recommender systems for mobile devices. This kind of devices (e.g. smartphones, tablets, etc.) provide some unique features that are very appealing for e-tourism, namely, their ubiquity and the possibility of introducing context-awareness capabilities in their recommendations [11].

In this contribution we aim at exploiting these features by presenting a new mobile location-aware RS. This proposal emerges from a complete revision of our previous classic recommender system REJA [12] for restaurants that will be adapted to an ubiquitous environment. First, we extend our system to include user's context information such as distance from the user's current location to

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the points of interest (POIs) considered in the recommendation process. Second, we employ a mobile-friendly user interface for providing georeferenced recommendations on a 2D map.

The rest of the paper is organized as follows. Section 2 provides a necessary background about recommender systems. Section 3 presents our proposal of a location-aware hybrid recommender system designed for mobile tourism. Finally, Section 4 concludes the paper.

2. Preliminaries

Recommender Systems assist people to find out suitable products in e-shops with large databases of items according to their necessities and tastes. There exist different types of RSs depending on the information source and the technique used to rank items. According to recent research, collaborative filtering [5] is the most successful recommendation technique up to date [8, 10]. These systems use customer's ratings to categorize users in groups according to their affinity. Recommendations are then inferred by taking into account ratings of users' in the same group [1].

Despite the success of such techniques, they still present some weakness, mainly the cold start problem [9]. This problem refers to the difficulty to either make recommendations to new users or to recommend new items. Different proposals have been developed to smooth such problem [3, 4, 7, 12].

The advent of ubiquitous computing has motivated a new trend of research in this field. Context-aware recommender systems (CARSs) take full advantage of the unique attributes provided by mobile computing to provide users with relevant information according to their physical context and preferences. This is a very active research field, and we refer the reader to the recent surveys published in [2, 11]. Also, the nature of handheld devices arises unprecedented usability issues that require new technical solutions to tackle the small display sizes and limited input technologies of these devices [11].

3. A collaborative Location-aware Recommender System

In this work, we extend the REJA schema [12] from a web-based system to a map-based mobile location-aware RS. Originally, REJA was formed by a commutation hybridizing system with collaborative and knowledge filtering. Our aim is to integrate context information based on user's location following two different approaches [2], as shown in Figure 1:

1. *Location-aware recommender system:* First, a contextual pre-filter is used to reduce the number of items considered for the recommendation according

to the user's location. These items are used by our RS to generate a top-N list of items potentially interesting for the user.

2. *Distance based re-ranking:* A contextual post-filter re-ranks the previous top-N list according to the physical distance from the user to each item.
3. Following sections present in further detail these two phases, and also describe our client-server implementation and the proposed user interface.

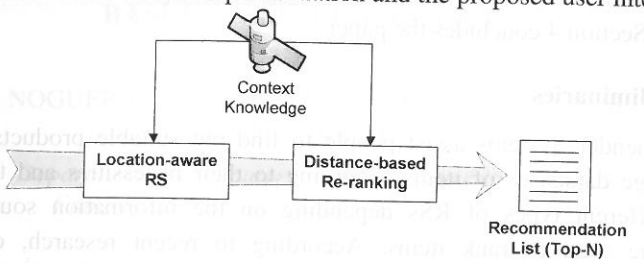


Figure 1. Location-aware Recommender System.

3.1. *Location-aware Recommender System*

We propose a contextual pre-filter that reduces the number of items considered by the RS to provide recommendations. When tourists are visiting a scenic place, they usually move around a limited area that will depend on their transportation (walking, car, bus, etc.). Our system fixes a circular area of radius R_{out} centered on the user's current location. This radius establishes the limits where the items might be recommended. This parameter that can be either user-defined or automatically inferred according to the user's form of transportation.

We assume that our RS deals with a set of recommendable items, $A=\{a_1,...,a_n\}$, geographically located. Therefore, the parameter R_{out} will be used to compute a subset, $A' \subseteq A$, that includes those items that could be suitable to be recommended to the user according to her current location, and ignoring the remaining ones because they are too far away from the user.

This set A' of nearby items is provided to a collaborative-based RS. This system groups all registered users according to their preferences and then computes a prediction for every item $a_i \in A'$ that has not been yet experienced by the user. Following, these predictions are used to generate a top-N list of items located close to the user's current location that can be potentially interesting for her. However, if the resulting list is empty or too short (e.g., the user is new and therefore could not be grouped), we are under a cold-start situation. In this case, our system discards this list and provides a new one composed of all the items of A'. In either case, the resulting list is sent to the following phase of our system, see Section 3.2.

3.2. *Distance-based Re-ranking*

In this phase, we apply a contextual post-filtering process that re-ranks the list of top-N recommended items provided by the previous phase using contextual information, in our case, the distance from the items to the user.

Specifically, this filter works as follows. Let $RL=\{(a_i,v_i)\ ,\ i=1,...,N\}$ be a recommendation list of N items where v_i is an estimation of the interest rate of the item a_i for the target user. The distance-based re-ranking filter receives this list as an input and modifies the interest rates v_i according to the distance from each item a_i to the user. The new interest rate after the distance-based re-ranking, w_i, is computed as: $w_i=v_iDD(u,a_i)$, where $DD(u,a_i)$ is the *distance decay function* for the item a_i and the user u. This decay function depends on the parameter R_{out} and may have different forms. We propose a simple to compute lineal decay function as follows:

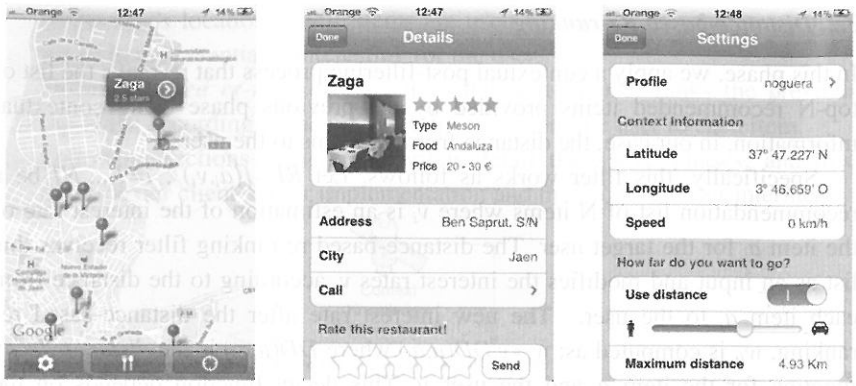
$$DD(u,a_i)=\begin{cases} 0\ if distance(u,a_i)\geq R_{out} \\ 1-\dfrac{x}{R_{out}}\ if distance(u,a_i)<R_{out} \end{cases} \quad (1)$$

Therefore, the recommendation list will be re-ranked according to the new values w_i, in descending order, giving a new list $RL'=\{(a_i,w_i)\ ,\ i=1,...,N\}$. This final list will be shown to the user.

3.3. *Software Design and User Interface*

User interface is an important issue when targeting mobile devices because of the limited screen size and user input. Here, we describe a mobile application that implements the recommendation model proposed in previous sections. Figure 2 shows some screenshots of our prototype under iOS, whose goal is to recommend restaurants in the province of Jaén (Spain).

After start-up, our mobile application shows the user a 2D map centered around its current physical location. The *Google Maps* API is used for this purpose. The location is obtained from the built-in GPS receiver currently included in most mobile devices. A network connection is then established with a remote web-server that implements the proposed hybrid RS described in Section 3.1. Both the user's *id* and current *location* are provided to the server, which in response sends a selection of nearby restaurants depending on the user's profile and location. The initial list of items provided by the server is then re-ranked by the mobile device as explained in Section 3.2. Finally, these items are portrayed on the map, see Figure 2a. The recommendation list is updated in *real-time* as the user moves around the environment.



a b c

Figure 2.Screenshots of the implemented mobile recommender system.

Touching a POI displays its recommendation value w_i according to a 5-stars scale. A descriptive screen with further information about the restaurant is also provided, which allows the user to emit votes, see Figure 2b. The user is also allowed to select a R_{out} value according to her desires, as shown in Figure 2c.

4. Concluding Remarks

Mobile devices are becoming a primary tool for accessing to information services and e-tourism. In this paper we have described the design of a ubiquitous location-aware recommender system tailored to mobile touristic purposes. Our proposal allows on-the-move tourists to download on-demand recommendations on their mobile devices according to their current location and personal tastes. Information is provided by means of a user-friendly interface based on a map.

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