A Framework of a Personalized Location-based Traveler Recommendation System in Mobile Application

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Abstract

In this era of evolving technology, there are various channels and platforms through which travelers can find tour information and share their tour experience. These include tourism websites, social network sites, blogs, forums, and various search engines such as Google, Yahoo, etc. However, information found in this way is not filtered based on travelers' preferences. Hence, travelers face an information overflow problem.. There is also increasing demand for more information on local area attractions, such as local food, shopping spots, places of interest and so on during the tour. The goal of this research is to propose a suitable recommendation method for use in a Personalized Location-based Traveler Recommender System (PLTRS) to provide personalized tourism information to its users. A comparative study of available recommender systems and location-based services (LBS) is conducted to explore the different approaches to recommender systems and LBS technology. The effectiveness of the system based on the proposed framework is tested using various scenarios which might be faced by users.

Keywords: *Personalized recommender system, Tourism industry, Location-based service, Mobile application*

1. Introduction

Tourists can find tourism information on blogs, forums, websites of points of interest etc. However, information overflow can occur on the internet as there is still a lack of focus on the use of recommender technology in the tourism field, especially in the area of personalized information [1]. In the tourism industry, mobile tourism is emerging [2]. During a trip, tourists need to be able to obtain tour information in a timely manner whenever there are any changes in their planned trip [3]. Personalized recommendation of tour information is vital for mobile users, as the screen size is small and demands a nice presentation of relevant information [4]. For the PLTRS mobile application to succeed, it must be able to provide tourism information based on the user's preferences and current location. The objectives of this study are:

- To compare the features and functions of different types of recommender system
- To examine existing location-based services and identify the main issues/problems encountered.
- To propose a framework for a Personalized Location-based Traveler Recommender System for mobile application.

2. Types of Recommender System

The function of a recommender system is to give predictions, suggestions, and opinions according to the user's configured data or any other necessary criteria (Annika Hinze, 2005) [5]. There are three types of recommender systems: collaborative filtering, content-based and knowledge-based recommendation.

2.1. Collaborative Filtering Recommendation

A collaborative filtering recommender system displays recommendations based on the preferences of similar users [5]. The results are based on the feedback from users who are similar to the target user instead of on the target user's own past preferences [6]. The accuracy of a collaborative filtering method depends on the number of items which can be associated with certain users [5]. There are many tourism systems using collaborative filtering; one of them is the Multichannel Adaptive Information Systems (MAIS) project [4].

Techniques used in collaborative filtering include memory-based collaborative filtering and model-based collaborative filtering [7]. Memory-based collaborative filtering, also called user-based collaborative filtering, uses statistical techniques to find users surrounding or near the target user, and forecast results according to those users who have similar preferences [8]. This algorithm is based on users' voting (or rating) patterns and the correlations between them [9]. There are scalability problems with this method [9]. The model-based collaborative filtering technique is widely used as it is scalable with huge databases [9]. Its algorithm uses clustering techniques to cluster users into highly similar groups and makes recommendations based on the group into which the target user is clustered [7]. This method solves the scalability problem as the recommendation process seeks the user rating only from the clustered group instead of from the whole database [7]. In addition, new items or information added to the database are neglected by the recommender system as there is no initial rating for the item [4]. These scalability, accuracy and "cold start" problems of a collaborative filtering recommender system are issues to be concerned about, especially in a mobile application. Figure 1 shows the architecture of a collaborative filtering recommender system used in tourism [10].

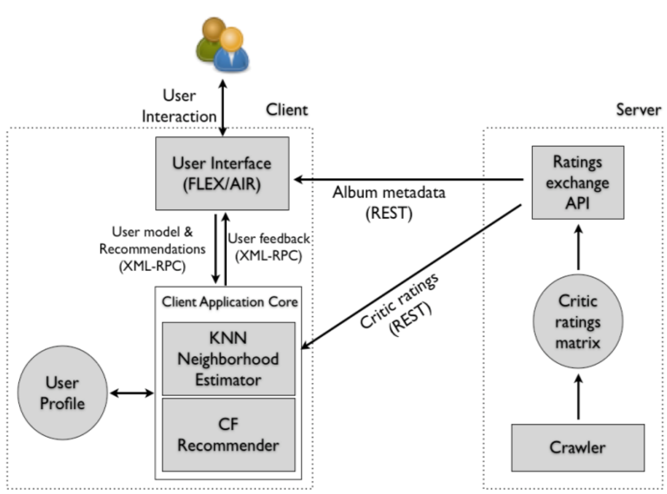


Figure1. Collaborative Filtering Recommendation Architecture [10]

It uses the neighborhood estimator compared with a target user profile to produce recommendations. The recommender system gathers rating data from a ratings database and user profile data from a user database. These data are used to estimate the neighborhood which shares the most similar characteristic with the target user.

2.2. Content-based Recommendation

Content-based recommendation suggests to the user items similar to their past experience and preferences [5]. No other parties' feedback or preferences are involved. This is an advantage in serving the person who has unique interests and who does not need feedback from similar users. Content-based recommendation systems begin the recommendation process by obtaining data regarding item features and the user's profile. These data are used to calculate the similarity of an item's features with the user's profile. The system then selects the items which have the highest similarity with the user's preferences [11]. The filtering process applies the algorithms of either information retrieval or item attribute-based filtering [12]. There are two ways to obtain profile data: through explicit sources such as a form which users fill out upon signing up for the service, or through implicit sources such as the user's browsing history and the history of their interaction with the recommendation system [13, 14].

Content-based recommendation systems use the feature weighting method to filter out items which possess features matching the users' stated preferences and their historical profile [11]. The technique most often used in the features weighting method is Term Frequency-Inverse Document Frequency (TF-IDF) [14]. TF-IDF looks to see whether the users' profile has the same indicators (terms) as those in the item description keywords [11]. Content-based recommendation systems do have some limitations. The user can only get recommendations based on his or her own preferences, without taking into account other users' ratings and feedback [5]. In addition, there are cold start issues since the recommendations will lack accuracy in the beginning, when users first join, until interaction between user and system can enrich the data stored in the user's profile [14]. According to Chen Jian, automated content-based recommendation using the clustering technique is the solution to the cold-start problem [15]. By clustering users, a content-based recommendation system can make recommendations to a user even when there is no past input or history for that user.

2.3. Knowledge-based Recommendation

Knowledge-based recommendation systems recommend to users according to both the user's preference and the characteristics of the required item [5]. Navigation aids are used to get information about the user's preferences, which is not stored for later use. The analysis of the characteristics of items currently preferred by the user and the item descriptions is crucial for a knowledge-based recommendation system to make accurate recommendations [16]. Knowledge-based filtering collects data explicitly during each interaction of a user with the system. The collected data is stored in the form of statements, rules or ontologies [12] using one of two methods: case-based reasoning and rule-based reasoning [17].

Case-based reasoning refers to applying past history (cases) in order to solve new cases [8]. It is analogy based and uses an inductive approach to come up with a solution for new cases [17]. The needed knowledge is drawn from the case database [18], meaning that this method requires less knowledge input from the user in order to come up with a solution. Rule-based reasoning involves a domain application which stores the knowledge needed to solve the problem in the form of rules applicable to a specific domain [17]. Knowledge inside the domain application is decomposed by domain experts into rules [19]. The relations between extracted rules are analyzed to come up with a solution for a given problem. Rule-based reasoning uses a deductive approach to emulate human experts' problem solving behavior to produce a solution [17].

3. Location-Based Services (LBS)

Location Based Services (LBS) solutions deliver relevant information according to the user's current location using position information and intelligent applications [20]. LBS can retrieve the user's location through any Global Positioning System (GPS)-enabled mobile phone, through the location services provided by the mobile operator, or through WiFi positioning technologies. The technologies involved in LBS are positioning technology, Geographic Information System (GIS) technology and Location Management Functions. [21]. Positioning technologies are used to identify the position of the client-side device. GIS provides map and geographical data such as the locations of buildings, streets, mountains, rivers, etc. Location management functions manage and process the position information and GIS data [21].

The LBS components and information flow are shown in figure 2. Figure 3 shows the architecture of A-GPS, which is the combination of GPS satellite and cellular network navigation. Basic components of the LBS are mobile device, positioning, communication network, and service provider or content provider [22]. Mobile devices can be categorized as GPS-enabled phones and non-GPS-enabled phone. Assisted Geographical Positioning System (A-GPS) enabled phone is a mobile phone which supports GPS technology while non-GPS-enabled phones do not. Positioning technology can be categorized as basic positioning, satellite positioning and positioning in 3G networks [23].

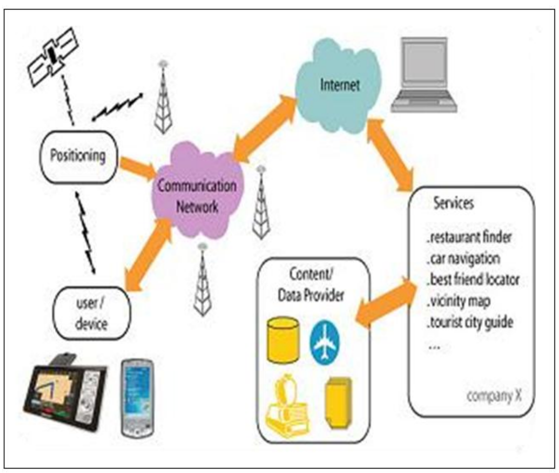


Figure 2: LBS Components and Information Flow [22]

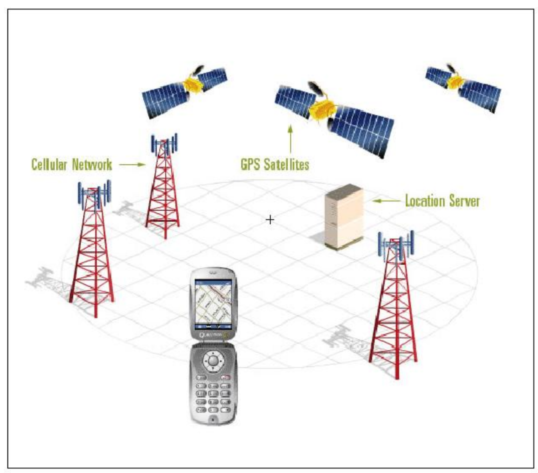


Figure 3: Assisted GPS (A-GPS) Network Architecture [25]

Basic positioning uses the cell phone signal to determine location information. Satellite Positioning uses satellite technology to determine location information, while 3G networks use mobile-based data technologies to identify the location. GPS positioning is the most common use of positioning technology [22]. However, GPS positioning methods have trouble with indoor positioning accuracy as the signal reception may be blocked by the buildings [24]. Assisted Geographical Positioning System (A-GPS) is a technology which enhances the performance of GPS by enabling the 3G network as well as the GPS navigation [24]. Advantages of A-GPS over GPS are faster location acquisition, lower processing power for devices, and higher accuracy for indoor positioning [25]. Thus, A-GPS is the most suitable positioning method to use for PLTRS.

Hence, using A-GPS can determine the position, whether outdoors or indoors, more precisely. Wireless communication networks are used to transfer data and requests from a mobile device to the content provider/service provider and vice versa [22]. There are threetypes of communication networks, each of which has a different coverage area and data transfer rate. The first is Wireless Wide Area Network (WWAN) such as GSM and GPRS; it has the largest coverage, ranging from 100m to 35km.

The second is Wireless Local Area Network (WLAN) such as IEEE 802.11a; this has a medium coverage area but the highest data transfer rate, ranging from 11 Mbps to 100 Mbps. The third is Wireless Personal Area Network (WPAN) such as Bluetooth and Infra-red, which has the most limited coverage and an average data transfer rate [22]. The application of wireless communication network in LBS depends on the location and mobile specifications of its users.

LBS play an important role in the development of the mobile tourist industry [26]. LBS which provide the user's current location are a significant source of data which a recommender system can use to filter personalized tour information more precisely. The search and filter process is simplified by having the user's location information [26]. Thus, LBS should be embedded within the recommender system to enable it to come up with personalized tourist information for users.

4. Proposed Framework for PLTRS Mobile Application

Figure 4 shows the proposed framework for the PLTRS mobile application. This framework incorporates location-based service, user positioning information, user profile database, tour information database, and usage log which track a user's interaction with the system. These data are used by the content based recommendation system for first time filtering. The recommended data and the data from the user rating database are fed into a second round of filtering, which uses the collaborative filtering recommendation system.

4.1. TF-IDF Content-based Recommender System

This filtering process uses the features weighting method known as Term Frequency-Inverse Document Frequency (TF-IDF) for its content-based recommender system. This method filters the data set for items which have keyword(s) in their descriptions which match the user’s profile indicators. The TF-IDF content-based recommender system will match the indicator “Chinese food” with the keyword descriptions of restaurants in the tour information database and recommend those that match. Figure 5 shows the workflow for the TF-IDF content-based recommender while figure 6 shows the workflow for the model-based collaborative filtering recommendation method.

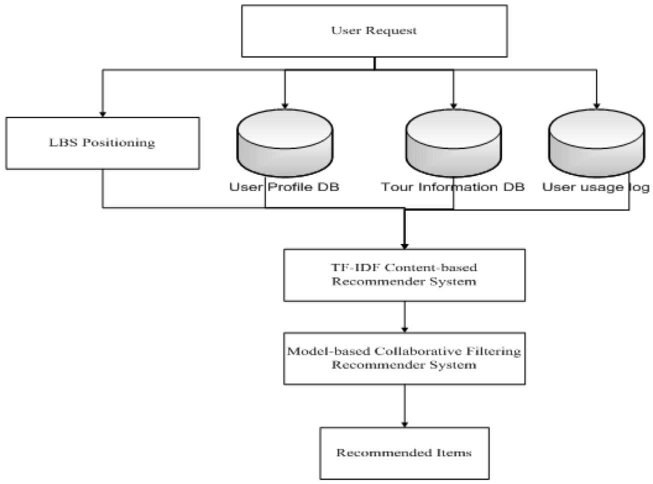
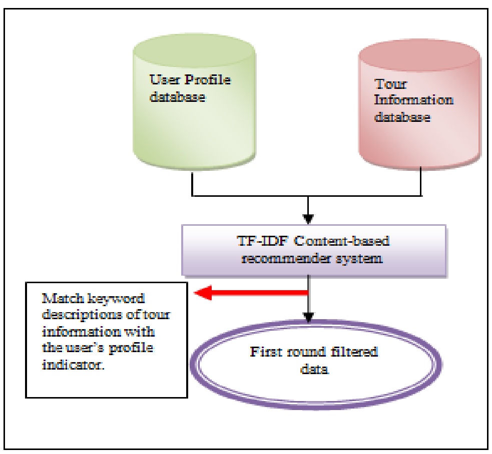


Figure 4: Proposed Framework for PLTRS



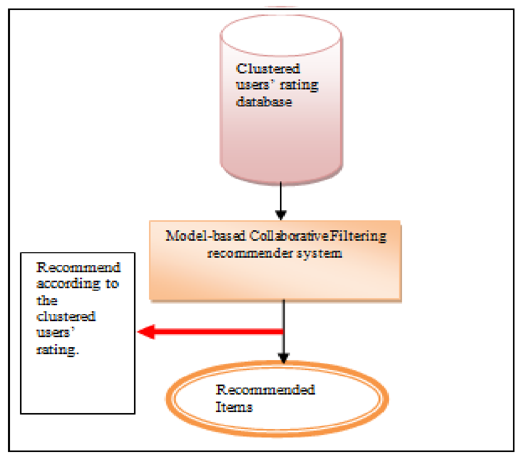


Figure 5: TF-IDF Content-based Recommendation

Figure 6: Model-based collaborative Filtering Recommendation System

4.2. Model-based Collaborative Filtering Recommender System

A model-based collaborative filtering recommendation method makes recommendations based on the user's ratings. Users whose profiles are similar to that of the target user are clustered. The ratings of this group of users are used to generate recommendations for the target user. The PLTRS mobile application uses the cascade hybrid method for the first round of filtering using the TF-IDF content-based recommendation method. The first-round filtered data then undergoes a second filtering using the model-based collaborative filtering recommendation method. The PLTRS mobile application returns recommendations based on the user's current location and preferences and on similar community ratings.

If users are new to the system, the content-based filtering merely uses the profile which the user input upon SignUp; otherwise, content-based filtering uses a combination of the usage log and user profile as indicators to match with the tour information description keywords. Each time the user interacts with the system, the usage log is updated. First round filtered data is fed into the second recommendation method which uses model-based collaborative filtering. If the first-time recommended items have no community rating record, the system displays the first-round filtered data and updates the user rating database. If user ratings do exist for the recommended items, the display is sorted in descending order of user rating.

5. Conclusions

The Personalized Location-based Traveler Recommender System (PLTRS) mobile application is a unique service which can recommend to users' personalized tour information during a trip via their mobile phone. The PLTRS mobile application is a new combination of existing technology which could increase patron satisfaction in the tourism industry.

This study reviewed existing recommender systems and identified the most suitable for use in PLTRS. Based on this comparative study of the techniques involved in the PLTRS mobile application, PLTRS should adopt a hybrid recommender system. Even though the research evaluation is based on several assumptions, the output of the recommendation has shown that the hybrid recommendation method is best able to recommend personalized tour information for users. Hence, we conclude that the PLTRS mobile application would be able to provide personalized tour information for users under any conditions.

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