Learning from Location History for Location Recommendation in LBS

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Abstract. Location recommendation is one of the most important components in many Location Based Services (LBS), especially in mobile guides. Currently, providing relevant location (e.g., Point of Interest, POI) recommendation is still very challenging. This paper aims to investigate how location histories can be used for making POI recommendation in LBS. A collaborative filtering–based approach is proposed, which consists of three steps: user profiling from location history, measuring user similarity, and making recommendations. With this, smart services like "after visiting..., other people similar to you often went to ..." can be provided in LBS.

Keywords: Location Based Services, Location Recommendation, Location History

1. Introduction

Recent years have seen an increasing interest in Location Based Services (LBS) with the continual evolution of mobile devices and communication technology. Location recommendation is one of the most important components in many LBS applications, especially in mobile guides. Current LBS applications mostly rely on an adaptation engine to determine the appropriateness of locations (Points of Interest, POIs) for meeting users' needs and interest (Huang and Gartner 2012). However, building the adaptation engine has to undergo a long process of knowledge acquisition, which is very time-consuming and impractical for many LBS applications.

Additionally, the increasing ubiquity of GPS-enabled devices and other tracking devices has led to the accumulation of large location history datasets, such as GPS trajectories. Research on mining location histories often mainly focuses on identifying behaviour patterns (Giannotti et al. 2007, Zheng et al. 2009). However, these location histories may also reflect the perspectives and experiences of other people who solve their spatial tasks (e.g. choosing which POI to visit next) in this situation. Aggregating these location histories may help to provide current user with smart location recommendations. However, little research has been done this aspect.

Collaborative filtering (CF, "Amazon-like recommendations") is a promising solution for the above problems. It uses "opinions" of similar users to help the current user efficiently identify information of interest (Resnick & Varian 1997). Therefore, it can be applied to aggregate location histories for POI recommendations. Currently, CF is often applied in Web-based applications, such as movie recommendations (Adomavicius and Tuzhilin 2005), and product recommendations (see Amazon.com). A comprehensive investigation of how CF can be used to make POI recommendation from location histories is still missing.

This paper aims to investigate how CF can be employed to derive POI recommendation from location histories. A methodology is introduced in section 2. In section 3, we evaluate the proposed method with some real location history datasets.

2. Methodology

The process of CF often includes three key stages (Adomavicius and Tuzhilin 2005): building user profile, identifying similar users, and aggregating "opinions" from the N most similar users for recommendations. In the following, we introduce a methodology to address these three stages.

2.1. User Profiling from Location Histories

Based on the stop-move conceptual model developed by Spaccapietra et al. (2008), we model a user profile, which is extracted from a location history, as a sequence of stops and moves. Stops and moves can be enriched with different attributes. An example of a user profile is presented in Figure 1.

In order to extract user profiles from raw location histories, a time-threshold-free spatial join approach is developed. The approach requires a set of pre-defined geographic areas (i.e., "candidate stops") as input. If an object has stayed in an area for duration longer than the time threshold, it is considered to have stopped at this area, and therefore, a stop is extracted. The time threshold of each candidate stop is dynamically learned from the characteristics of the user itself (reflected by the average duration of the user at all the pre-defined areas she/he visited) and the characteristics of the intersected geographic area. With this, a set of stops and moves and their corresponding attributes, such as stop durations, move durations can be extracted to build user profiles.

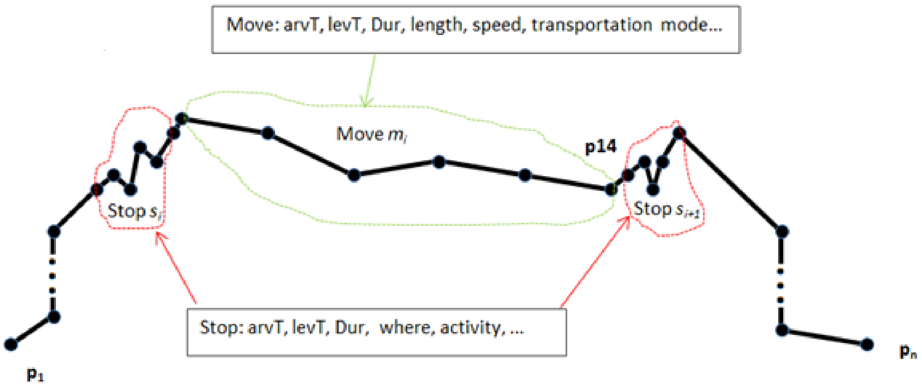

Figure 1. An example of a user profile: a sequence of stops and moves

2.2. Measuring User Similarity

The key in CF is to locate other users whose opinions can be used for generating recommendation for the current user. In this paper, we identify these users in terms of their similarities with the current user, and similar users are defined as users having similar patterns in visiting POIs.

When designing user similarity measure, four aspects are considered: sequential relationships (i.e., the order of visited POIs), POI popularity (two users accessed a POI visited by a few people might be more correlated than others shared a POI history accessed by many people), durations at POIs (users spending similar time at POIs are more similar to each other), and transits between POIs (users having similar transits between POIs are more similar to each other).

2.3. Making Recommendations

With the user similarity measure, the N most similar users (i.e., "neighbors") for the current user can be identified. We can then aggregate these neighbors' next POI after visiting the current POI (considering the user similarity value). Finally, the POI with the highest predicted value will be recommended to the current user.

3. Evaluation

The proposed methods are evaluated with three location history datasets: Vienna zoo dataset (with 209 valid GPS trajectories), Delft dataset (with 255 valid GPS trajectories), and Vienna city dataset (extracted from Flickr datasets, with 112 valid trips).

To evaluate the predictive performance of the proposed CF methods, a location-based method (LBM) is implemented as a benchmark. The LBM randomly recommends user with the closest POI which has not been visited by the current user. A simple CF based approach, which measures user similarity by counting the number of POIs commonly visited by both users, is also implemented as a benchmark.

We use the leave-one-out validation. Accuracy is used to evaluate the performance of the methods, and is defined as the ratio of the number of corrected recommendations (i.e., the predicted POI is actually viewed immediately by the current user) and the number of recommendation processes. Figure 2 depicts the results.

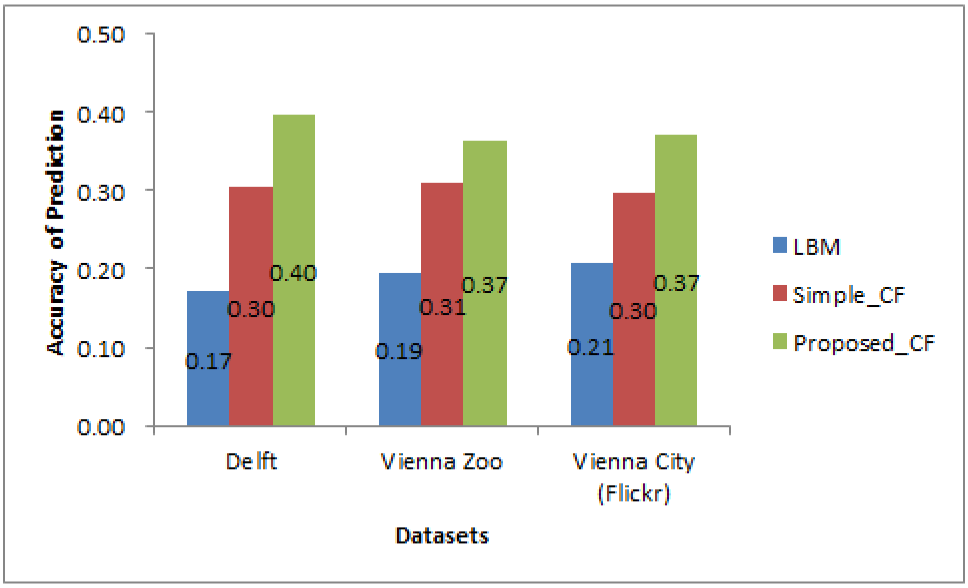

Figure 2. The predictive performance of the proposed CF method, the LBM and the simple CF

Figure 2 shows that the proposed CF method is feasible to derive POI recommendation from location histories in LBS. More importantly, for all three datasets, the proposed CF method always performs considerably better than the LBM and the simple CF.

4. Conclusion and Future Work

In summary, the proposed CF method can provide more accurate POI recommendations than simple location-based method in LBS. Also considering sequential relationships, visit frequencies of POIs, durations at POIs, and transits between POIs into the CF process can improve the predictive performance.

Our next step is to introduce context-awareness into the proposed method. We expect context-aware CF will further improve the predictive performance.

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