P-022

USING TRAJECTORIES FOR COLLABORATIVE FILTERING BASED POI RECOMMENDATIONS

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BACKGROUND AND OBJECTIVES

Mobile guide is the largest group of Location Based Services (Raper et al. 2007). One of the key goals of mobile guides is to provide users with relevant information/services for satisfying their need, e.g., recommending which Points of Interest (POIs) to visit.

Currently, POI recommendation in mobile guides often relies on knowledge about POIs (domain model), knowledge about the user (user model), and an adaptation engine. However, building these models and the adaptation engine usually has to undergo a long process of knowledge acquisition that is very time-consuming and impractical for many LBS applications. Additionally, in our daily life, we often employ social navigation strategy, i.e., using cues from “the behavior [opinions] of other people” to manage our activities (e.g., choosing where to go) (Höök 2003). Social navigation can enable users to gain more efficient and more satisfying answers to their problems (Wexelblat 1999). However, little work has been done on incorporating social navigation into LBS. What’s more, recently, more and more user-generated content (UGC, e.g., trajectories) is created in LBS. However, there is little work focusing on aggregating UGC to provide smart services in LBS.

Collaborative filtering (CF, known as Amazon-like recommendation) is a promising solution for the above problems. This paper investigates methods of incorporating CF into mobile guides to provide POI recommendations. Specifically, we aim at applying CF methods on the highly available GPS trajectories to enhance visitors with Amazon-like POI recommendations, i.e., “after visiting POI A, other people similar to you often went to POI B”.

APPROACH AND METHODS

User-based CF is employed in mining trajectories for Amazon-like POI recommendations. It includes three stages: building user profiles, computing of user similarities, and aggregating of ratings from the N most similar users for recommendation.

For each user, a series of stops (where he/she has stayed within a certain distance threshold over a time period) can be identified from his/her trajectories. If a stop is near/within a defined POI, the user is considered to have been visited the POI. As a result, for each user, a set of POIs visited by him/her can be extracted from his/her trajectory. The POI set can be viewed as his/her preference profiles.

For the second step, three kinds of user similarities are proposed: simple_USim (a simple user similarity measure), freq_USim (a user similarity measure considering visit frequencies of POIs), and freq_seq_USim (a user similarity measure considering preferences and spatio-temporal behavior). For the aspect of spatio-temporal behavior, we mainly focus on the sequence relationship between visited POIs (i.e., the ways in which POIs are visited). The Longest Common Subsequence (LCS) approach is employed to measure the similarity based on sequence relationship.

The next step is to employ the above three user similarities to select the most similar users (neighbors) whose opinions can be used for generating recommendations for the current user. We aggregate every similar neighbor’s next POI after visiting p (considering the user similarity value). Finally, the POI with the highest predicted value will be recommended to the current user.

With the above three steps, Amazon-like POI recommendations can be provided in mobile guides.

EVALUATION AND RESULTS

Thanks to the cooperation with Vienna Zoo, we collected trajectories in the zoo. We encouraged visitors to carry GPS loggers with them while walking through the zoo. In total, 56 trajectories of different kinds of visitors were collected.

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 one of the POIs which are close to the current location, and have not been visited by the current user.

Due to the small size of our dataset, 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 recommedations (i.e., the predicited POI is actually viewed immediately by the active user) and the number of recommendation processes.

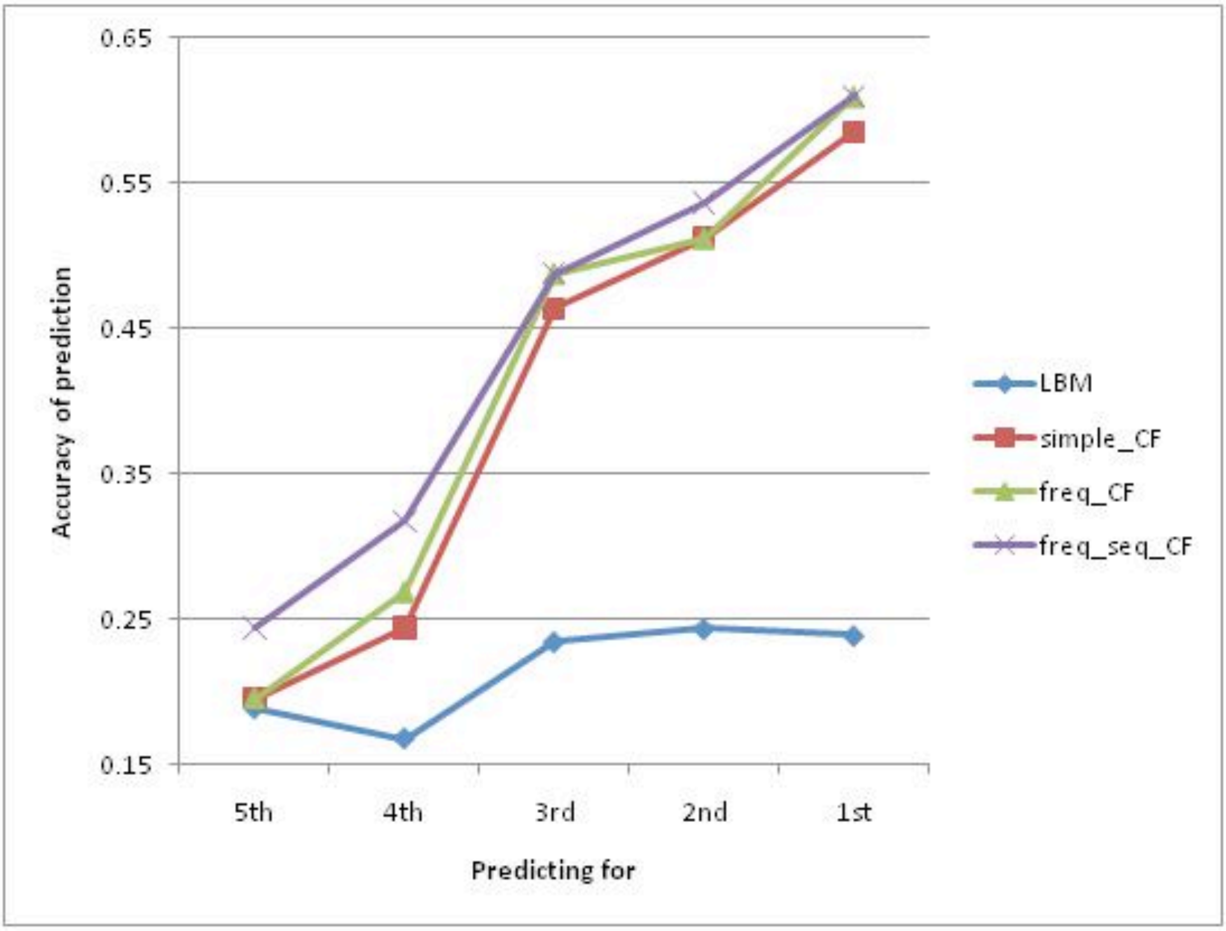

Figure 1. The predictive performance of the proposed CF methods changes when predicting POIs at different places of a trip (i.e., the 1^{st} last, the 2^{nd} last, the 3^{rd} last, the 4^{th} last, and the 5^{th} last).

Figure 1 shows that when predicting POIs at different places of a trip, the proposed CF methods always perform considerably better than the LBM. It also shows that, among different CF methods, freq_seq_CF always performs the best, following by freq_CF, and finally simple_CF.

CONCLUSION AND FUTURE WORK

In summary, the proposed CF methods can provide more accurate POI recommendations than simple location-based method in mobile guides. Also considering visit frequencies of POIs and spatio-temporal motion behavior (mainly the ways in which POIs are visited) into the CF process can improve the predictive performance.

Our next step is to evaluate the proposed methods with different kinds of trajectories. As context-awareness plays a key role in LBS, some context-aware CF methods will be also explored to provide more accurate recommendation.

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