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Chapter 9

Using Context-Aware Collaborative Filtering for POI Recommendations in Mobile Guides

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Abstract

Mobile guide is one of the most popular Location Based Services. Currently, providing context-aware services/information is still very challenging in mobile guides. Collaborative filtering (CF), known as "Amazon-like recommendations", is a promising solution for providing context-aware recommendations. The paper investigates how context-aware CF (CaCF) can be introduced into mobile guides. Specifically, we focus on applying CaCF methods on the highly available GPS trajectories to enhance visitors with context-aware POI (Point of Interest) recommendations.

After analysing the key issues of CaCF, we present a methodology for addressing them. Firstly, a two-stage method is proposed to identify context parameters which are relevant and thus needed to be modelled in a CaCF application. After identifying relevant context parameters, we explore a statistic-based approach (SBA) to measure similarity between different contexts (situations). In considering two different ways of incorporating context information into the CF process, two CaCF methods are designed: SBA_CP_CaCF (using SBA and contextual pre-filtering), and SBA_CM_CaCF (using SBA and contextual modelling). With these CaCF methods, smart services like "in similar contexts, other people similar to you often …" can be provided.

Finally, the proposed methods are evaluated with some real GPS trajectories collected from Vienna Zoo (Austria). The results of the experiments show that the proposed CaCF methods are feasible and useful for providing context-aware POI recommendations in mobile guides. More importantly, we show that

including context information in the CF process can improve the recommendation performance.

Keywords: Location Based Services, mobile guides, context-aware recommendations, collaborative filtering, GPS trajectory

9.1 Introduction

Recent years have seen an increasing interest in Location Based Services (LBS) with the continual evolution of mobile devices and communication technology. Mobile guide is the largest group of LBS applications (Raper et al. 2007). One of the key goals of mobile guides is to provide users with relevant information/services for satisfying their needs, e.g. recommending some Points of Interest (POIs) to visit.

Providing context-aware POI recommendations in mobile guides is still very challenging. Currently, in order to provide context-awareness, mobile guides mostly rely on an adaptation engine to determine the appropriateness of POIs for satisfying users' needs and context. However, building the adaptation engine has to undergo a long process of knowledge acquisition, which is very time-consuming and impractical for many mobile guides.

Additionally, the increasing ubiquity of GPS-enabled devices has led to the accumulation of large spatio-temporal datasets, such as GPS trajectories. These trajectories may reflect the perspectives and experiences of other people who solve their spatial tasks (e.g. choosing which POI to visit next) in this situation. It is obvious in daily life that experiences from past users (especially similar users) in similar contexts can help current users solve their own problems efficiently (Wexelblat 1999). Therefore, by aggregating the trajectories, mobile guides can provide users with smart services, such as providing "social advice" for making decisions. However, little research has addressed these considerations.

Collaborative filtering (CF, "Amazon-like recommendations") is a promising solution for the above problems. It uses "opinions" of similar users in similar contexts to help the current user efficiently identify information of interest (Resnick & Varian 1997). As a result, by incorporating CF into mobile guides, relevant information (e.g. POIs) matching the user's current situation can be identified (by aggregating opinions from similar users in similar contexts).

The goal of this paper is to investigate methods of introducing context-aware CF (CaCF) into mobile guides to provide context-aware recommendations. Specifically, we aim at applying CaCF methods on the highly available GPS trajectories to enhance visitors with context-aware POI recommendations. With CaCF, smart services like "in similar contexts, other people similar to you often visited POI A" can be provided in mobile guides.

The rest of this paper is structured as follows. In *Section 9.2,* we outline related work. *Section 9.3* identifies the key issues of incorporating CaCF into mobile guides. In *Section 9.4,* a methodology for addressing these issues is presented. In *Section 9.5,* the proposed methods are implemented and evaluated with GPS trajectories collected from Vienna Zoo (Austria). Some major results are also discussed in *Section 9.5.* Finally, we draw conclusions and present future work in *Section 9.6.*

9.2 Related Work

The research concerns how CaCF can be incorporated into mobile guides for providing context-aware POI recommendations. It integrates several mainstream trends and concepts, such as POI recommendations in mobile guides, CF in LBS applications and trajectory mining. From these aspects, we summarize the related work.

9.2.1 POI Recommendations in Mobile Guides

To provide context-aware POI recommendations, current mobile guides mainly rely on knowledge about POIs (domain model, DM), knowledge about the user (user model, UM) and her/his context (context model, CM). An adaptation engine is also employed: It measures the appropriateness of objects (DM) for satisfying a user's needs and context (UM and CM), and returns the relevant objects.

UM includes information about users' interests, preferences, and needs. It can be static (Baus et al. 2001, Kray 2003) and dynamic (Cheverst et al. 2000, Wiesenhofer et al. 2007). For building DM and the adaptation engine, a long underlying learning (knowledge acquisition) process has to be carried out in the field, which is often very time-consuming and impractical for many mobile guides. More importantly, current mobile guides are unable to effectively provide users with context-aware services in unseen situations or situations with little previous knowledge. However, real-world applications often need to operate in these kinds of situations.

In contrast to the above approaches, we aim to use CF to providing context-aware recommendations. In the following, we analyse CF's potential in solving the problems of current context-aware recommendation systems (i.e. a long process of knowledge acquisition in providing context-awareness).

One of the key goals of context-awareness in mobile guides is to provide a user with relevant information according to her/his context. This goal matches with the aim of CF, especially CaCF, which aggregates opinions of similar users in similar contexts to help individuals efficiently identify interesting information (Resnick & Varian 1997). Opinions from other users may reflect their perceptions on the fitness/

appropriateness of a particular item (information) for their contexts. If similar users in similar contexts like that item, this item can be considered as a matching item for the current user in the current context. As a result, CaCF can be viewed as a real-time underlying learning process of building DM and UM, and an automatic engine for identifying relevant information. Moreover, as CF solely relies on user feedback (i.e. trajectories in this paper) and requires no previous domain knowledge, mobile guides employing CF will be able to effectively provide context-aware services in dynamic environments and unseen situations. Therefore, CaCF can be a novel method of providing context-aware recommendations in mobile guides.

9.2.2 CF in LBS

CF is often applied in Web-based applications, such as movie recommendations, and product recommendations (see Amazon.com). Currently, context-aware CF in Web-based applications is still very challenging (Adomavicius & Tuzhilin 2010).

There are some tries on applying CF in LBS, such as restaurant recommendations (Horozov et al. 2006), event recommendations (de Spindler et al. 2006, Li et al. 2009), shop recommendations (Takeuchi & Sugimoto 2006), recommendations in museums (Bohnert et al. 2008), and POI recommendations for tourism (van Setten et al. 2004). However, most of the researches only employed location as contextual factor, and did not consider other contextual factors which are also relevant for generating recommendations, e.g. weather and companion (with whom).

Context-awareness is a key element when introducing CF into LBS. For example, recommending a place for the same person to visit may vary according to different weather conditions and different companion conditions (alone or with children). “There is more to context than location” (Schmidt et al. 1999). When incorporating more context information into CF for LBS, the problem becomes very challenging. A comprehensive investigation of how context can be incorporated into LBS-based CF is urgently needed. It is also important to note that none of the research focused on experimentally studying whether including context information in a CF for LBS can improve the recommendation performance.

9.2.3 Trajectory Mining

With the increasing ubiquity of GPS-enabled devices, more and more people start to record their travel/sport experiences with GPS loggers. Therefore, large spatio-temporal datasets (e.g. trajectories) are created every day, or even every hour. Recently, mining these kinds of user-generated GPS data is receiving considerable attention.

There are researches focusing on mining personal location history based on individual trajectories, e.g. detecting significant locations of a user, predicting a user’s behaviour among these locations, identifying a user's spatio-temporal behaviour patterns, and recognizing a user's activities on each location (Li et al. 2008). In the meantime, many other researches mined multiple users' trajectories to understand mobility-related phenomena, e.g. Giannotti et al. (2007) aggregated many users' trajectories to identify spatio-temporal behaviour patterns. Zheng et al. (2009a) mined interesting locations and travel sequences from multiple users' trajectories. Li et al. (2008) proposed a user similarity measure based on different users' trajectories; however, they did not incorporate the similarity measure into the CF process.

There are also some researches focusing on using trajectories for recommendations. Takeuchi & Sugimoto (2006) recommended shops to users based on their individual preferences and needs, estimated by analysing their location history (i.e. GPS trajectories). Bohnert et al. (2008) developed a system for exhibit recommendations based on users' trajectories in a museum. However, it is necessary to note that context information (except location) was not considered in these researches.

In contrast to the above researches, this paper aims at designing context-aware CF methods to utilize trajectories for context-aware POI recommendations. Incorporating context information into the CF process for LBS applications is the main research focus.

9.3 Key Issues of Context-Aware CF

CaCF aggregates what similar users chose in similar contexts for recommendations. Several key issues have to be considered when providing CaCF in LBS: annotating user profiles with context, measuring similarities between contexts and similarities between users, and incorporating context information into the CF process.

1) Annotating user profiles with context: In CaCF, user profiles (e.g. trajectories[1]) should be annotated with context. A context (situation) can be characterized by a set of context parameters. Not all context parameters are relevant for generating recommendations. In order to annotate user profiles with context, a main question has to be answered: Which context parameters are relevant and thus needed to be modelled. Many researches chose some features of the world as context parameters from their own views (e.g. Panniello et al. (2009), and Adomavicius et al. (2005)). What is missing, however, is a method of identifying relevant context parameters for CaCF.
2) Measuring context similarity and user similarity: The goal is to determine which ratings (or user profiles, i.e. trajectories in this paper) are more relevant for the

[1] Raw trajectories can be processed and enriched with some semantic information to generate meaningful user profiles (e.g. places where users visit). Alvares et al. (2007) proposed a method on this aspect.

current user in the current context (i.e. more useful for making recommendations for the current context).

3) Incorporating context information into the CF process: Adomavicius & Tuzhilin (2010) proposed three approaches to incorporate context information into CF: 1) contextual pre-filtering: filter out irrelevant ratings (i.e. trajectories in our case) before using non-contextual CF method (i.e. the traditional method); 2) contextual post-filtering: use the traditional CF method, and then filter the results with context information; 3) contextual modelling: use context information directly inside the recommendation process. Currently, the approaches have not been applied to provide CaCF in LBS. How these approaches can be combined with the other key issues to provide CaCF in LBS should be carefully investigated.

9.4 Methodology

In this section, we explore some methods to address the key issues identified above.

9.4.1 Identifying Relevant Context Parameters

As mentioned before, context-dependent user profiles are important for context-aware recommendations. For annotating user profiles with context, we have to answer the question: Which context parameters are relevant and thus needed to be modelled.

We adopt an "interactional perspective" on context (Dourish 2004). Something is context (parameter) only if users' decision-making (e.g. choosing which POIs to visit), interaction with the system, or the behaviour of the system depends on it, otherwise it is just a feature of the world (Winograd 2001, Huang & Gartner 2009). For example, the temperature of the room is a relevant context parameter only if the adaptation of the interaction between human and the current system depends on it (or the behaviour of the system depends on it, e.g. when the temperature is higher than 30°C, start the air-conditioner), but otherwise it is just a feature of the world.

Based on this understanding, a two-stage method to identify relevant context parameters is designed:

1) A preliminary set of context parameters can be identified from literature or brainstorming. Data from users are then collected in different situations characterized by the preliminary set of context parameters.
2) The final set of context parameters can be created by refining the preliminary set according to the collected data. The basic strategy of refining is to analyse how some key aspects (e.g. the number of visited POIs, length of visit, and duration

of visit) of users' trajectories differ with different values of each context parameter in the preliminary set. If context parameter *c1* has *n* values, and the differences of the key aspects of visits are significant among these *n* values, then the current context parameter is relevant and thus needed to be modelled, otherwise it is irrelevant. T-test or analysis of variance (ANOVA) can be employed to test the significance. For example, if context parameter *"weather"* has two values *"sunny"* and *"rainy"*, and the difference between the key aspects of visits (e.g. the number of visited POIs) in *"sunny"* and the key aspects of visits in *"rainy"* is significant (i.e. "people behave differently in different weather condition"), then *"weather"* is relevant and thus needed to be modelled for CaCF, otherwise it is irrelevant.

It is necessary to note that we do not need to consider location as a relevant context parameter when annotating user profiles (trajectories) with context. The reason is that users' current location and location history are already stored in their trajectories. A trajectory includes a series of different stops (i.e. POIs). Every POI has a location. When recommending a POI for the current user, his/her current location (POI) is used to select relevant POIs which are *"close"* to the user (see step 1 of SBA_CP_CaCF in *Section 9.4.4)*.

9.4.2 Measuring User Similarity

For each user, a series of stops[2] (POIs) visited by him/her can be identified from his/her trajectory, e.g. using the SMoT method developed by Alvares et al. (2007). Therefore, a simple user similarity measure is adopted. It compares the POIs visited by the two users. It is obvious that two users accessed a POI visited by a few people might be more correlated than others who share a POI history accessed by many people (Zheng et al. 2009b). As a result, the visited popularity of a POI is considered when measuring similarity between users. Following is the proposed user similarity measure:

$$SIM_{user}(a,b) = \frac{\sum_{p \in POIS_{a,b}} \frac{1}{F_p}}{\sqrt{(\sum_{p \in POIS_a} \frac{1}{F_p}) * (\sum_{p \in POIS_b} \frac{1}{F_p})}}$$

where $POIS_a$ and $POIS_b$ are the set of visited POIs of user *a* and user *b*. $POIS_{a,b}$ is the set of POIs which are visited both by user *a* and user *b*. F_p is the visited popularity of POI *p* considering all the trajectories.

[2] When a visitor has stayed in a certain distance threshold over a time period, we consider him/her has a stop. Visitors tend to have a longer stay at a POI if they are interested in it. Therefore, in this paper, the time threhold is set big enough to eliminate POIs which were passed and not liked by the visitor.

9.4.3 Measuring Context Similarity

The similarity between the context (situation) in which the visit (trajectory) was made and the current context of the active user (who asks for recommendations) determines the usefulness of the trajectory in recommending POIs for him/her. In the following, we explore a statistic-based approach (SBA), which adopts a machine-learning technique.

With the method proposed in *Section 9.4.1,* relevant context parameters can be identified. By varying values for each parameter, all different situations can be identified. In the following, we propose an approach to measure the similarity between any two situations.

We assume that if visits in a situation (e.g. A) are similar to visits in another situation (e.g. B); these two situations can be considered as similar. Therefore, similarity between different contexts (situations) can be measured as some statistical metrics.

1) Measuring the distance of visits in situation A and visits in situation B:

$$Dist(A,B) = \sqrt{\frac{\sum_{p \in \bar{P}} \frac{1}{F_p} * (A_p - B_p)^2}{\sum_{p \in \bar{P}} \frac{1}{F_p}}}$$

$\bar{P}$ is the set of all POIs. A_p and B_p are the visit frequencies of POI p in situation A and B. F_p is the visited popularity of POI p considering all the trajectories.

2) Translating the distance measure into a similarity measure:

Shepard (1987) proposes that distance and perceived similarity are related via an exponential function. As a result, the following context similarity measure is designed:

$$SIM_{conx}(A,B) = e^{-Dist(A,B)}$$

With these two steps, similarity between any two situations can be calculated.

9.4.4 Making Recommendations

As mentioned in *Section 9.3,* context information can be incorporated into CF by contextual pre-filtering, contextual post-filtering, and contextual modelling. In this paper, we mainly focus on contextual pre-filtering and contextual modelling. As a result, two kinds of CaCF methods are designed. The steps of each method are as follows. We assume that the current user u is finishing the current POI p, and asking “which POI to visit next”.

SBA_CP_CaCF: Using SBA and contextual pre-filtering

1) Identifying users whose next POI after visiting *p* has not been visited by the current user.
2) Filtering users whose context similarities with the current user do not exceed a threshold δ. Context similarity is measured by the SBA method.
3) For the results of step 2, identify the N most similar users. The user similarity measure proposed in *Section 9.4.2* is employed.
4) For the N most similar users, aggregating every similar user's next POI after visiting *p* (considering user similarity values).
5) Selecting the POI with the highest predicted value, and recommending it to the current user.

SBA_CM_CaCF: Using SBA and contextual modelling

1) The same as step 1 in SBA_CP_CaCF.
2) For the results of step 1, identify the N most useful users. The usefulness is measured by considering both context similarity and user similarity.

   $$Utility(a,b) = \lambda * SIM_{user}(a,b) + (1-\lambda)SIM_{conx}(C_a, C_b)$$

   where C_a and C_b are the contexts of user *a* and *b*. $SIM_{conx}(C_a, C_b)$ is calculated using the SBA method in *Section 9.4.3.*
3) For the N most useful users, aggregating every useful user's next POI after visiting *p* (considering usefulness values).
4) The same as the step 5 in SBA_CP_CaCF.

With the above CaCF methods, context-aware recommendations can be provided in mobile guides.

9.5 Evaluation and Discussion

In this section, we discuss some experimental evaluations. The data collection and processing are discussed in *Section 9.5.1*. *Section 9.5.2* employs the proposed method in *Section 9.4.1* to identify relevant context parameters for the CaCF methods. We describe the experiment setting in *Section 9.5.3.* The evaluation and results are presented and discussed in *Section 9.5.4,* and summarized in *Section 9.5.5.*

9.5.1 Data Collection and Processing

Thanks to a cooperation with Vienna Zoo (Tiergarten Schönbrunn), we collected trajectories in the zoo in the first half of 2010. We encouraged visitors to carry GPS loggers with them while walking through the zoo. Before they start, we recorded some additional information (e.g. context information) about them and their visits, i.e. weather condition (sunny or rainy), age (>=45 or <45), time limit (Yes or No), annual ticket (Yes or No), first time in the zoo (Yes or No), and companion with small children (Yes or No). In total, we collected 53 valid trajectories of all kinds of visitors in different situations. For every trajectory, we extracted the following information: visited POIs and their orders, duration of visit, and length of visit.

We employed the SMoT method developed by Alvares et al. (2007) to identify stops from every trajectory. To simplify the process of identifying the visited POIs from every trajectory, 36 POIs (candidate stops) were defined in the zoo by considering the layout of the zoo and GPS accuracies. When a user's stop is within a defined POI, the user is considered to have been visited the POI. With this, a series of POIs which users visited can be identified. Therefore, for every trajectory, the following information was modelled:

> *<ID, visited POIs and their orders, the number of visited POIs, length of visit (km), duration of visit (hour), age, first time in the zoo, companion with small children, time limit, annual ticket, weather>*

We only considered trajectories with at least 6 POIs for the experimental evaluations. In total, we had 41 valid trajectories. The average number of POIs visited was 13.9 (ranging from 6 to 23), with a standard deviation of 4.

9.5.2 Identifying Relevant Context Parameters

The recorded context information (i.e. < "age", "first time in the zoo", "companion with small children", "time limit", "annual ticket", "weather">) was the preliminary set of context parameters. We applied the proposed method in *Section 9.4.1* to identify relevant context parameters from this preliminary set.

We mainly compared the follow key aspects of visit among different situations: the number of visited POIs, length of visit, and duration of visit. In order to test whether the differences among different conditions for each context parameter were significant, we employed the independent group two-tailed t-test. Due to the small size of the dataset, $p < 0.2$ was used to denote statistical significance. *Table 9.1* shows the results of the comparison. Each data cell in *Table 9.1* contains the following information: p-value of t-test, mean of condition1, and mean of condition2.

The t-tests indicated that the numbers of visited POIs among different "age" conditions were significantly different. Similar results can be found for length of

Table 9.1. How visits differed among different conditions for each context parameter.

	The number of visited POIs	Length of visit (km)	Duration of visit (hour)
Age (>=45, <45)	**p=0.18 (15.45 vs. 13.23)**	**p=0.19 (4.56 vs. 3.09)**	**p=0.16 (2.88 vs. 2.01)**
First Visit (Yes, No)	p=0.52 (14.46 vs. 13.56)	p=0.26 (4.19 vs. 3.18)	p=0.30 (2.58 vs. 2.08)
Annual Ticket (Yes, No)	p=0.63 (13.50 vs. 14.77)	p=0.79 (3.66 vs. 3.41)	p=0.28 (2.62 vs. 2.05)
Companion (Yes, No)	p=0.93 (13.88 vs. 14.00)	p=0.71 (3.39 vs. 3.89)	p=0.74 (2.30 vs. 2.03)
Time Limit (Yes, No)	p=0.29 (13.00 vs. 14:32)	p=0.31 (2.98 vs. 3.74)	p=0.60 (2.10 vs. 2.32)
Weather (Sunny, Rainy)	**p=0.01 (15.07 vs. 11.64)**	**p=0.04 (4.01 vs. 2.52)**	**p=0.01 (2.62 vs. 1.52)**

visit in different "age" conditions, and duration of visit in different "age" conditions. In other words, people at different "age" groups visited the zoo differently. Similarly, for different "weather" conditions, people also behaved differently (see the bold parts in *Table 9.1).* Therefore, "age" and "weather" were considered as relevant, and taken as the final set of context parameters. In *Section 9.5.4,* we provide an evaluation to test the correctness of this decision.

9.5.3 Experiment Setting

We used the dataset in *Section 9.5.1* to evaluate the recommendation performance of SBA_CP_CaCF and SBA_CM_CaCF. In order to experimentally study whether including context information in a CF can improve the recommendation performance, we also implemented a non-contextual CF method (nonCa_CF, i.e. SBA_CP_CaCF ignoring step 2) as a benchmark.

Due to the small size of the dataset, we used a leave-one-out validation. We trained the recommendation models on 40 of the 41 visitors (trajectories) in the dataset, and tested them on the remaining visitor (the active user). We used accuracy to evaluate the performance of the CaCF methods, and accuracy was defined as the ratio of the number of correct recommendations (i.e. the recommended POI was actually viewed immediately by the active user) and the number of recommendation processes (i.e. 41 in our dataset).

In order to identify optimized values for different parameters in the proposed CaCF methods, we evaluated several thousand parametrisations (i.e. varying the threshold in SBA_CP_CaCF, and the important weights in SBA_CM_CaCF), and used the best-performing one for the final experiments.

Two evaluations were performed. The first evaluation studied whether using the proposed set of context parameters *"<age, weather>"* can achieve the best recommendation performance. As we had 6 preliminary context parameters (candidates), in total we had another 62 ($=C_6^1+C_6^2+C_6^3+C_6^4+C_6^5+C_6^6-1$) possible sets of context parameters. The proposed CaCF methods using different sets of context parameters were compared when making recommendations for the last 5 POIs of every trajectory (we used the average accuracy of the 5 POIs). This evaluation is very useful for testing the effectiveness of the method proposed in *Section 9.4.1* and *Section 9.5.2* (i.e. identifying relevant context parameters).

The second evaluation focused on how the recommendation performances of the proposed CaCF methods differed when making recommendations for different places of a visit (i.e. from the 1st last to the 5th last). *"<age, weather>"* was used as the set of relevant context parameters. nonCa_CF was implemented as a benchmark. This evaluation can help us answer the following questions: 1) Does including context information in a CF for LBS improve the CF recommendation performance (context-aware CF vs. non-contextual CF)? 2) How do the recommendation performances of the proposed methods change when making recommendations for different places of a visit?

9.5.4 Results and Discussion

9.5.4.1 Making Recommendations with Different Sets of Context Parameters

Figure 9.1 shows how the recommendation performances of the proposed CaCF methods changed when using different sets of context parameters.

Using different sets of context parameters: *Figure 9.1* shows that among all the possible sets of context parameters, both CaCF methods using the proposed set "<age, weather>" achevied the best recommendation performances. Therefore, the proposed method (*Section 9.4.1* and *9.5.2)* to identify relevant context parameters is feasible and useful.

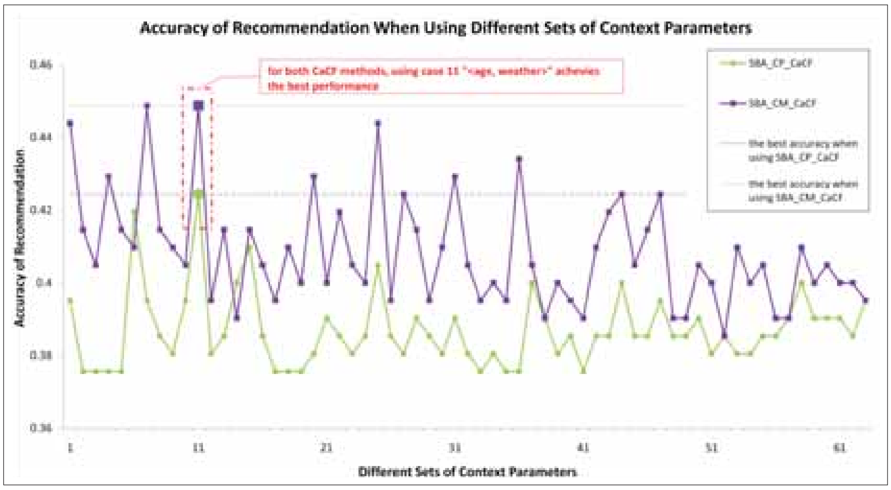

Fig. 9.1. The recommendation performances of the proposed CaCF methods changed when using different sets of context parameters (when predicting for the last 5 POIs of every trajectory).

In the meanwhile, It is also important to note that incorporating more context parameters into the CF process did not mean an improvement of performance. This can be explained by the increasing difficulty of developing an accurate context similarity measure when using more context parameters, and the increasing demand of data.

Contextual modelling vs. contextual pre-filtering when using different sets of context parameters: For most different sets of context parameters, the performance of SBA_CM_CaCF was at least as good as the performance of SBA_CP_CaCF. The two-tailed t-test showed that the difference between performance of SBA_CM_CaCF and that of SBA_CP_CaCF was statistically significant ($p=2.08E-15 << 0.01$). An explanation for this would be: The latter suffered from the problems of sparsity as lots of trajectories were filtered out, while in contextual modelling, more users (trajectories) were involved in making recommendations.

9.5.4.2 Making Recommendations for Different Places of a Visit

Figure 9.2 shows the results of how the recommendation performances of the CaCF methods changed when making recommendations for different places of a visit (i.e. from the 1st last to the 5th last). The proposed set of context parameters *("<age, weather>")* was employed.

non-contextual CF vs. context-aware CF: when making recommendations for different places of a visit, the performances of CaCF methods (i.e. SBA_CP_CaCF, and SBA_CM_CaCF) were considerably better than the performances of non-contextual CF method (i.e. nonCa_CF). This is consistent with what we expected: as CaCF methods were aware of the context (suitation) the user was in, they might generate more appropriate recommendations.

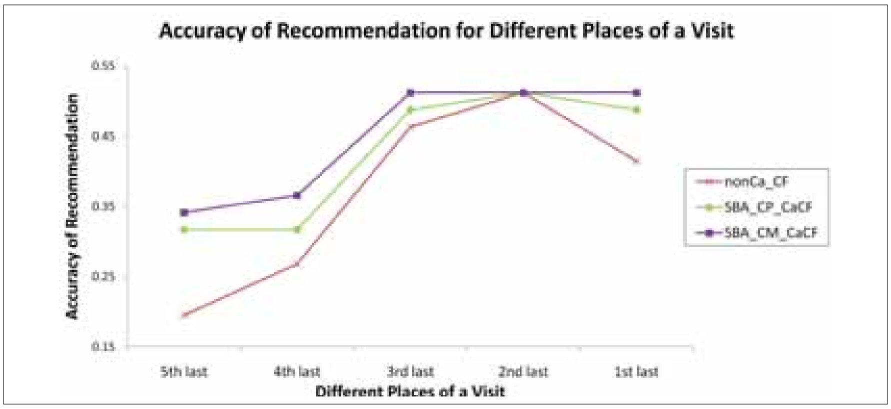

Fig. 9.2. The recommendation performances of the proposed CaCF methods changed when making recommendation for different places of a visit (using "<age, weather>" as relevant context parameters).

Making recommendations at different places of a visit: Different places (positions) reflect the different amount of information available about a visitor. *Figure 9.2* shows an upwards trend for the accuracy of all CaCF methods and the nonCa_CF when the positions of the predicted POI increased. This is consistent with our expectation: with the increase of the positions of the predicted POI, more information about a visitor was available for the recommendation methods, and therefore the recommendation performances were improving.

Contextual modelling vs. contextual pre-filtering when making recommendations for different places of a visit: When making recommendations for different places of a visit, the performance of contextual modelling approach (i.e. SBA_CM_CaCF) was at least as good as the performance of contextual pre-filtering approach (i.e. SBA_CP_CaCF). Similarly, this might be explained by the sparsity problem as lots of trajectories were filtered out in the contextual pre-filtering approach.

9.5.5 Summary

In summary, the main findings of the experiments are as follows:

1) When including context information in the CF process, choosing a suitable set of relevant context parameters is very important and may affect the recommendation performance.
2) The proposed method to identify relevant context parameters is feasible and useful, and using the proposed "<age, weather>" can achieve a higher recommendation accuracy for all the designed CaCF methods.
3) The recommendation performance of contextual modelling approach is at least as good as the performance of contextual pre-filtering approach.
4) Most importantly, the proposed CaCF methods can provide better recommendation performance than non-contextual CF, which means including context information in a CF for mobile guides can improve the recommendation performance.

9.6 Conclusions and Future Work

Currently, providing context-aware services/information is still very challenging in mobile guides. In this paper, methods of introducing CaCF into mobile guides were proposed. To be more specific, CaCF methods were applied on the highly available GPS trajectories to enhance visitors with context-aware POI recommendations in mobile guides.

The main contributions are as follows:

1) Key issues of incorporating CaCF into LBS applications (e.g. mobile guides) were identified.
2) A two-stage method was designed to identify relevant context parameters for CaCF.
3) A statistic-based approach (SBA) was proposed to measure context similarity.
4) In considering two different ways (i.e. contextual pre-filtering, and contextual modelling) of incorporating context information into the CF process, two CaCF methods were designed for LBS applications: SBA_CP_CaCF, and SBA_CM_CaCF.
5) Experimental studies were designed to evaluate the proposed methods. The results of the experiments show that the proposed CaCF methods are feasible and useful for providing context-aware recommendations in mobile guides.

From the experiments, following conclusion can be drawn: including context information in the CF process can provide more appropriate recommendations to users.

Our next step is to collect more trajectory data in both outdoor and indoor to evaluate the methods. We propose that with more trajectories available, the recommendation performances of CaCF methods will be improved and will have a significant difference with that of non-contextual CF methods. We are also interested in exploring more complex CaCF methods in considering different types of context information.

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