



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

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1. Motivation

- When visiting a new city, tourists often ask “what to visit next”.
 - identify Points of Interest (POIs) from a huge set of choices
- “Experiences” from past users can help current users to solve their problems¹.
 - More and more GPS trajectories are created.
 - How can we make use of these highly available GPS datasets?

A promising technique

- Collaborative filtering (CF): “Amazon-like recommendation”
 - “People who ... also” : recommending items that people with similar preferences liked in the past
 - Often employed for movie, product recommendation
- CF in LBS
 - Often using explicit ratings: requiring users’ active involvement
→ impractical for LBS
 - Providing context-aware CF is still very challenging.

Research goals

- Designing context-aware CF methods
 - to make use of the highly available GPS trajectories
 - for providing contextual “Amazon-like” POI recommendations in mobile guides
- Vision: “in similar context, after visiting POI A, other people similar to you often went to POI B.”

2. Key issues of context-aware CF

- Building contextual user profiles
- Measuring usefulness of other users' "opinions"
- Making recommendations
 - Aggregating "useful opinions"

2.1 Building contextual user profiles

- Extracting visited POIs (stops) from trajectories
 - User profile: a set of visited POIs
- Labeling user profile with “context of the visit”
 - Which context parameters are relevant and thus needed to be modeled?

Identifying relevant context parameters

- A two-stage method
 - Identifying an initial set of candidate context parameters from literature or experts.
 - Refining the initial set according to the collected data
 - *If tourists in different weather conditions behave differently, “weather” is a relevant parameter.*

2.2 Measuring usefulness of other users' "opinions"



- Measuring usefulness of other users' profiles in making recommendation for the current user in the current context
 - **Preference-based user similarity**: measured by comparing the POIs they visited

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

- **Context similarity**: the similarity between other users' context and the current user's context

Context similarity measure

- Statistic-based approach (SBA)
 - *If visits in a context (situation) are similar to visits in another situation, these two situations can be considered as similar.*
 - Similarity between two situations
 - Measuring the “distance” of visits in these two situations.
 - Transforming the “distance” into similarity

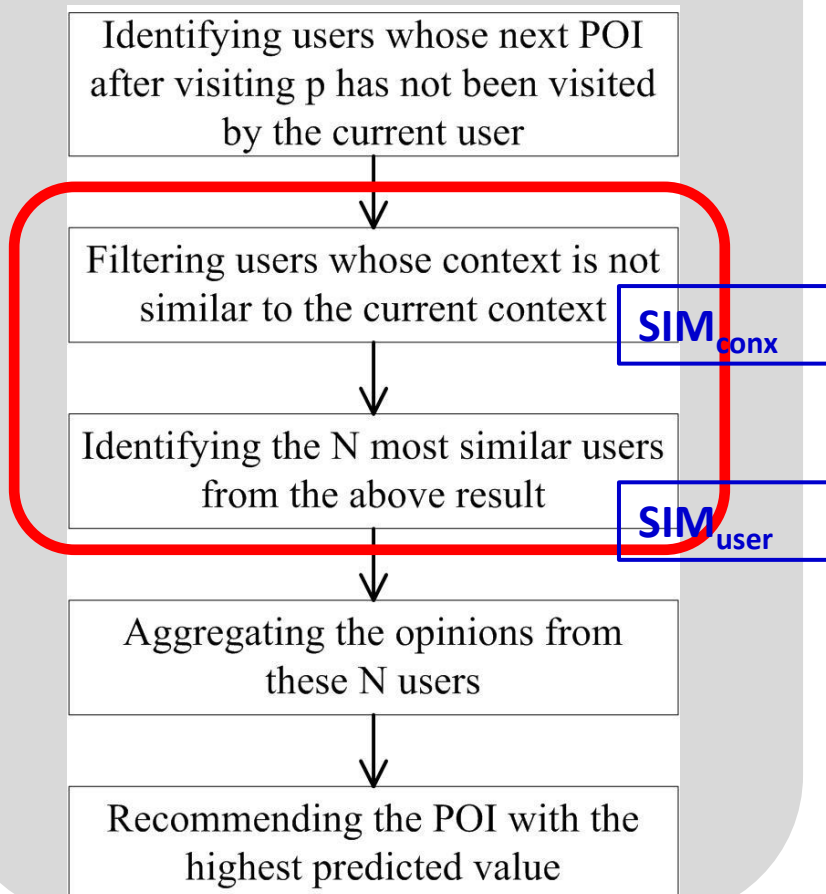
$$Dist(A, B) = \sqrt{\frac{\sum_{p \in P} \frac{1}{F_p} * (A_p - B_p)^2}{\sum_{p \in P} \frac{1}{F_p}}}$$

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

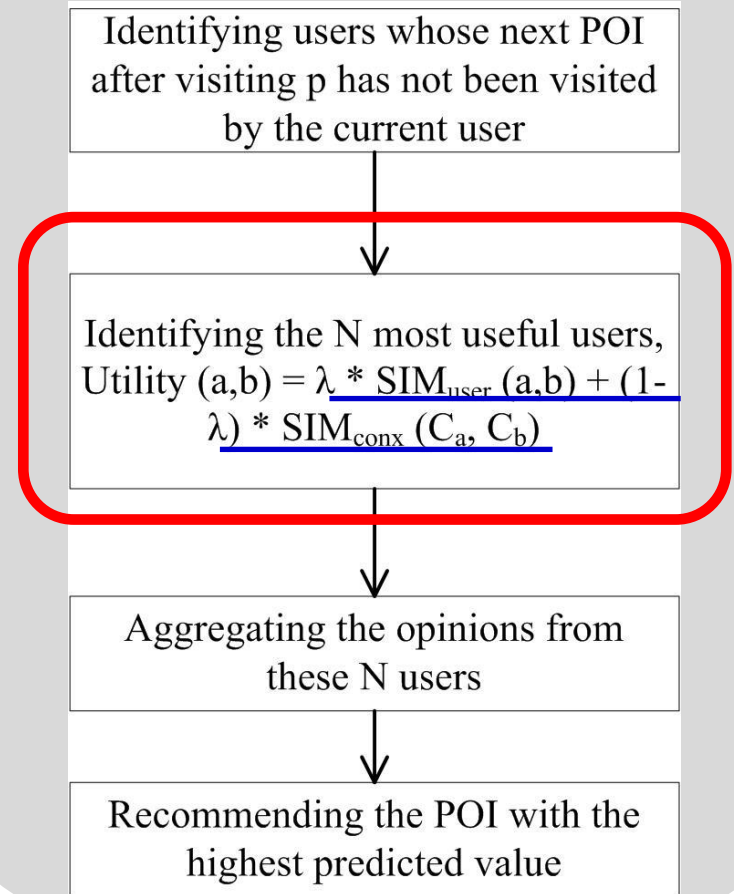
2.3 Making recommendations

- Two ways of combining user similarity and context similarity to identify “useful” users

M1. Contextual pre-filtering (SBA_CP_CaCF)



M2. Contextual modeling (SBA_CM_CaCF)



3. Evaluation

- GPS trajectories collected in Vienna zoo
 - Extracting a set of visited POIs (stops) from each trajectory to build user profiles
 - Only considering trajectories with at least 6 POIs
 - 41 trajectories in total
- Some additional information
 - weather (sunny/rainy), age (≥ 45 , < 45), time limit(Y/N), year ticket(Y/N), first visit to the zoo (Y/N), with baby (Y/N)
 - The initial set of context parameters

3.1 Identifying relevant context parameters

- How do tourists' visits differ among different conditions for each candidate 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)

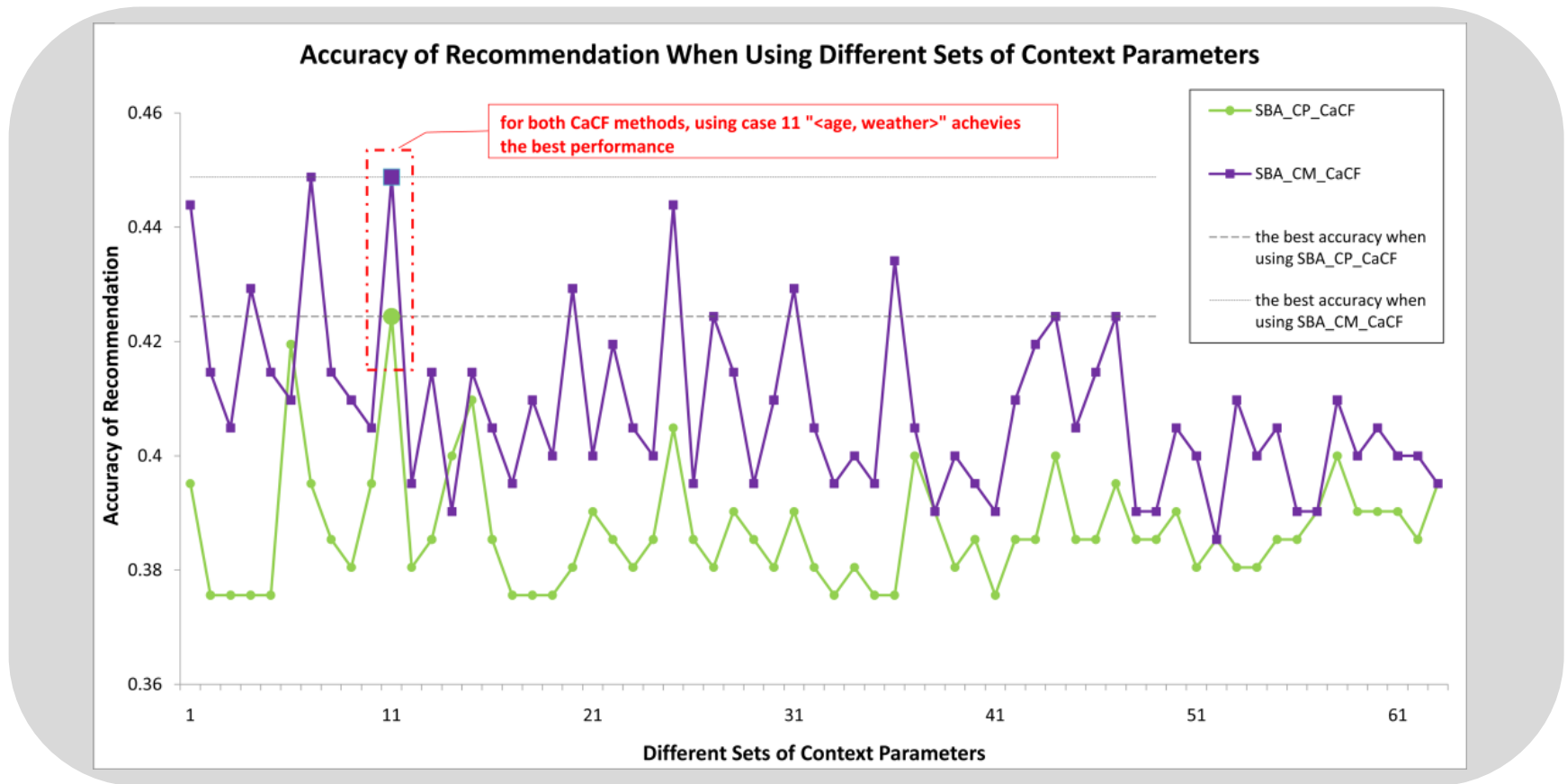
- The final set of context parameters:
 - <age, weather>

3.2 Experimental evaluation

- Leave-one-out evaluation
 - Using 40 of the 41 trajectories (visitors) to predict for the remaining one.
- Predictive accuracy
 - If the predicted POI is actually visited by the user, the recommendation process is considered as successful.

Results (1):

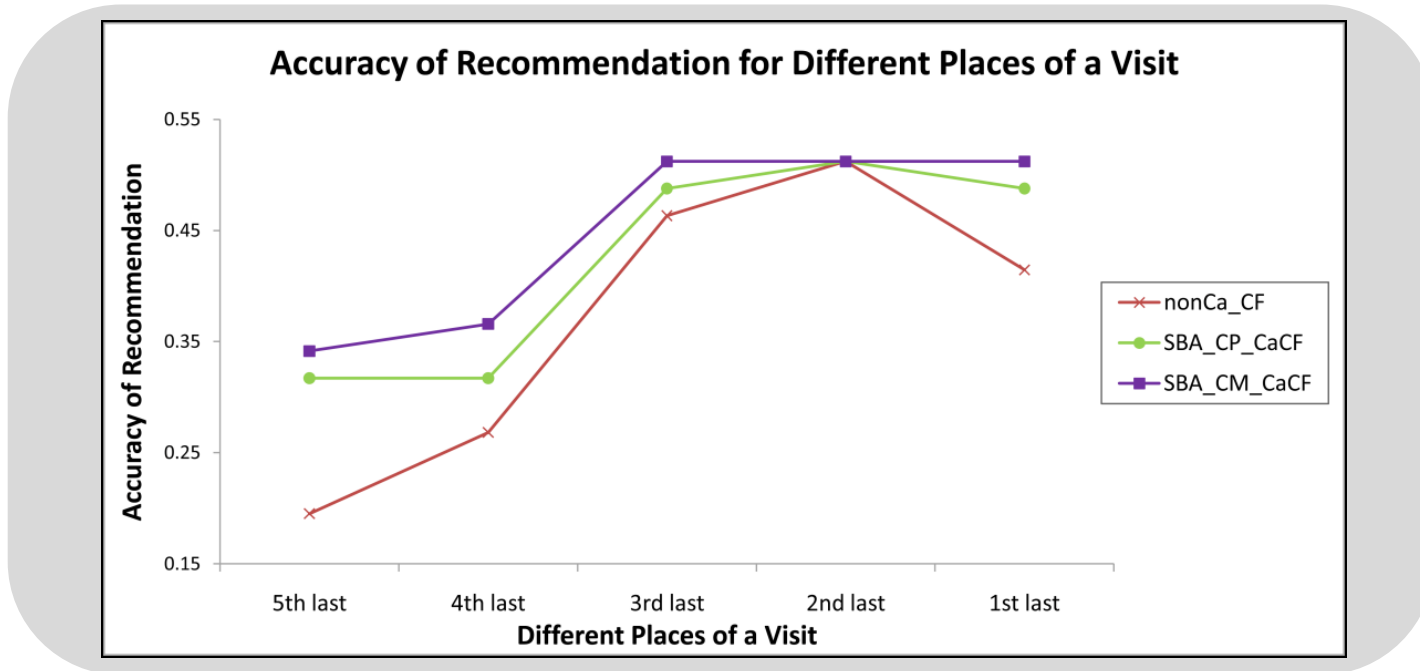
How do the performances of the CaCF methods change when using different sets of context parameters?



... choosing a suitable set of relevant context parameters is very important and may affect the recommendation performance.

...Using the proposed set of context parameters performs the best: *the two-stage method is feasible and useful for identifying relevant context parameters.*

Results (2): How do the CaCF methods perform differently when making recommendations for different places of a visit?



... a upward trend for the accuracy of all CaCF methods and the nonCa_CF when the positions of the predicted POI increase.

...the performance of contextual modeling approach is at least as good as the performance of contextual pre-filtering approach.

... the CaCF methods perform considerably better than the non-contextual CF method: ***including context information in a CF for mobile guides can improve the recommendation performance.***

4. Conclusions

- Two context-aware CF methods are designed to mine GPS trajectories to provide users with contextual “Amazon-like” POI recommendations.
- The evaluation shows that
 - The two-stage method can help to identify relevant context parameters.
 - **Including context information into CF can provide users with more appropriate recommendations.**

5. Work in progress

- Evaluated with different kinds of data
 - Data from Vienna zoo, city center, city-wide
- Exploring more complex CaCF methods
 - Considering different types of context information



Thank you!
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Comments?

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