Analysis of a context-aware recommender system model for smart urban environment

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ABSTRACT
Recommender systems, deployed on the web and in mobile devices, help users in finding services and products that are addressing their needs, based on their profile. On the other hand, such systems help also organizations in promoting their products or services to a targeted market. Users in mobility in smart urban spaces are surrounded with products and services, such as mobile device applications. In this paper, we are presenting the result of a survey, where participants had to give their opinions on recommendation modalities in several scenarios of context-aware service recommendation in urban environments. These results are followed by an analysis and a discussion.

General Terms
Experimentation, Human Factors

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI) : Miscellaneous

Keywords
Recommender systems, Context-awareness, Smart city, Survey

INTRODUCTION
The integration of recommender systems in the software used in our daily living activities is more and more pervasive. The first services to integrate such systems were websites of retail products such as eBay, Amazon or iTunes. Today, we can find recommender systems in most software, where users have to browse through an extended content: You Tube, Google Play, Netflix, etc. The vast majority of these recommender systems are using the users' behaviors or interests such as collaborative filtering, with algorithms like Slope-One [1] or Hidden Markov Model based algorithms [2].

On one hand, with the current capabilities of the mobile devices to capture contextual information about their surrounding environment and the deployment of wireless sensors in smart urban environments, there is a growing interest in using the contextual information to improve the services/products recommendation [3]. For instance, it is possible to use the user's current location, related information to the location (e.g. shop, school, restaurant, etc.) and profile of the other people around, to propose new services (e.g. mobile apps) or products to the context.

On the other hand, we previously worked on providing services to people with special needs in smart spaces based on the context of the spaces and the users' profile [4]. Therefore, we are interested in extending our work around the context-aware service delivery in smart urban environments by taking into account an approach based on the service recommendation.

In this paper, we present the result of a survey that presented, to 55 participants, five scenarios of service recommendation in urban environments. For each scenario, we asked to the participants their opinion about the behavior of a context-aware recommender system and which context modalities should have priorities in proposing services to the users. The focus of the survey was mobile application recommendation, according to our research objectives.

The first goal of our work is to collect information on the required modalities of a context-aware recommender system in the context of user mobility in smart urban environment. As the amount of contextual information is really important in an urban settings and the inter-relation between these information can be complex, the results of the survey will help us in the up-coming phase of our work, by giving the guidelines around the required functionalities and to which degrees these functionalities should be implemented. Our second goal is to gather data on the users' opinions on context-aware recommender system in urban environment, which the literature currently lacks.

Therefore, in the next section, we present a review of the related work (Section Related Work), followed by a description of the survey (Section Description of the study). Then, we present the collected results, followed by a discussion about the results (Section Results). Finally, we conclude this paper by presenting our future work based on the result of this paper.

RELATED WORK
The context-aware recommender system as a field of research is relatively new. It emerge from the fusion of different research project on the context-awareness, such as the work of Dey et al. on the Context Toolkit [5], from context-aware application such as the Cyberguide project from Abowd et al. [6] and from

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recommender systems such as the work of Alabanovic and Shoham [7] on the content based, collaborative filtering "Cross-domain Topic Learning (CTL) model to confirm patterns compared to traditional collaborations in the same domain".

However, one of the first research teams to introduce the topic of the context-aware recommender system was Adomavicius et al. [9] which work on integrating contextual information in a multidimensional analysis of the users' ratings. However, the contextual information used in their work is limited to the time or the period of the day. For instance, in [3], Adomavicius et al. propose several solutions to the integration of context-awareness to the recommender systems, which will help us in the implementation of our future system.

On the other hand, some works has been done on location-based recommender system. For instance, Levandoski et al. [10] propose a solution based on three types of location ratings (spatial rating for non-spatial item, non-spatial rating for spatial item, and spatial rating for spatial item). The approach of Levandoski et al. is similar to the work of Adomavicius, where they used four-tuples of five-tuples to qualify the ratings and use multidimensional analysis techniques to compare ratings, but whith an extended definition of the context.

Yang et al. [11] propose also a framework to recommend e-commerce contents to users during a shopping experience in physical stores. The focus their work is to use the recommender system as a marketing tool to inform potential customers of promotion and new products. Moreover, Yu et al. [12] proposes a platform for media recommendation on smart phones, which uses a hybrid approach based on an analysis of similarity between media content, a Naïve Bayesian classifier and semantic rules for the analysis of the contextual information.

In the current state of the art, most of the work focuses on providing solutions to context-aware recommendation problems without involving potential users in the work. Throughout our study, we used a approach to involve users from the beginning of our work, by integrating them in the modeling part of the recommendation modalities.

DESCRIPTION OF THE STUDY

As we introduced in the previous section, the goal of our work was to get a first look about the opinion of potential users on modalities around the service recommendation in smart urban environments. Thus, we built a survey where we asked to the participant to give their opinions about the service recommendation in five different scenarios and a series of general questions. The main objective being to gather data that will used to bootstrap the development of our prototype, based on the users' points of view.

The survey begins with a series of questions about the participant profile (e.g. sex, age, occupation, environment where they are living and working, etc.), followed by questions about their uses of mobile devices such as smart phones. Then, we presented to the participants five scenarios, in which they are set in five specific contexts of service recommendation: in a restaurant, in public transportation, while they are shopping, at their home and during a trip/vacation.

For each scenario, we asked to the participant to rank which contextual information, related to the scenario's environment, should be processed in priorities by the recommender system. For instance, in the restaurant scenario, the participant had to rank which of these information that should affect more the system: (i) user interaction history related to the location (e.g. services used in the same location), (ii) services most used by other users in the same location, (iii) service related to the ongoing activity, (iv) service related to similar location, (v) service related to similar context (e.g. time, day, public spaces?) and finally, (vi) service related to the users' preferences and scores attributed to similar services (i.e. non context-aware recommender system).

We concluded the survey with a series of general questions where we asked to participants to choose between two mobile apps to recommend with different context settings. For instance, we asked to users which app should be prioritized between an app A used 50% of the time in a specific location and an app B used 75% of the time by the other users in the same location. The answers to these questions will help us in giving the general reasoning modalities for our future recommendation algorithms.

RESULTS

We used the social networks (e.g Facebook, Twitter) and a French mailing list on HCI to publicize our survey. 55 participants completed the survey with 37.25% of male participants and 62.75% female. Concerning their utilization of mobile technologies, 73% of the participants are owners of smart phones and among the smart phone owners, 71% have Android OS phones. Moreover, concerning their utilization of mobile applications or services, 13% are frequent users of mobile apps (several times an hour) and 25% of smart phone owners have more than 40 apps on their phone. Finally, 36% of participants are living in urban environment with more than 800,000 inhabitants (70% for urban environments with more than 100,000 inhabitants), while 40% are working in urban environments with more than more than 800,000 inhabitants.

The average age of the participants is 33 years old with a standard deviation of 10 years. Moreover, 32% of the participant was from Canada, 57% from France and the rest from other countries (Luxemburg and Morocco). We decided on purpose to focus the participation to the survey to French speaking participants (survey is in french), as our next evaluations will also include mostly French-Canadians and French people. Moreover, the number of participants is relatively low for an opinion survey. We feel that including more participants to the study will not improve significantly the results (while reducing error margins) and we collected enough written feedback to proceed to the next project phases. Moreover, the results will be corroborate (or not) with our future evaluations.

The Table 1 presents the results related to the five scenarios that we presented to the participants, where they had to rank which recommendation modalities have priority over others. The results can be classified in three classes, the first tier: the services linked to the location and to the interaction history; the second tier: services related to the ongoing activity and to similar categories; and the last tier with services most used by other users, in similar context and related to the user preferences. Prior to the survey, one of our hypotheses was that participants would rank the modality related to the services used by other users in a same location higher than other modalities.

Table 1 : Average Ranking of the recommendation modalities related to the user's context, where ranking was ranging from 1 to 7 (1 ranked first and 7 ranked last)

Scenarios/ Modalities	Interaction History	Services …					
		Linked to location	Most used by other users in the same location	Related to the ongoing activity	Related to a similar location (categories)	Used in similar context	Related to the user preferences
Restaurant	3.05	**2.47**	5.37	3.77	4.33	4.86	4.11
Public transportation	2.78	**1.09**	5.42	4.69	3.93	5.09	4.96
Shopping	-	**1.62**	4.15	3.9	2.56	4.81	3.94
Home	**1.5**	-	4	3.43	4.45	4.13	3.47
Trip	-	**1.58**	2.49	4.49	2.73	4.96	4.73
Average	**2.4**	**1.69**	**4.3**	**4.1**	**3.6**	**4.777**	**4.24**

Moreover, we were surprised to see that the recommendation related to the user preferences was not ranked higher too, as it is equivalent to the current recommender system in services such as Google Play. However, our hypotheses were respected with the interaction history and the service linked to the location being ranked first. Moreover, we can see that these two modalities were mostly ranked first and second for the five scenarios. The third most important is less emerging, but would be the services related to a similar location (categories), which is similar to a content-based filtering such as in Amazon or Netflix recommendations.

In the general questions section, we asked a series of questions in general settings without scenarios or explanation on the context of recommendations. For instance, we asked to the participants which modalities, in a general context of service recommendation in a smart urban environment, should have the highest impact on the recommendations. The Table 2 presented the results to this question. The participants ranked first the contextual information (e.g. time, location, day, public places?), a contradiction with their answers in the scenarios section. However, they ranked last the other users interaction history, a similar ranking to the previous questions.

Moreover, we presented to the users several mobile applications and related contextual information. The users had to choose which mobile applications should be recommended to the users considering the context. The participants' answers to these questions confirmed their previous answers in the scenarios section, where the application related to the users' history and the application linked to specific locations were considered more valuable.

Finally, after each scenario and at the end of the survey, we asked to the participants to provide written feedback about the context-aware service recommendations in urban settings. Several participants expressed their concerns about the intrusion of such system in their privacy. From their point of views, being tracked by a context-aware system, which it uses their location, ongoing activities and possibly share these data (even if it's anonymized) with other systems, is an important threat. The privacy in context-aware recommender system must be managed with caution, as security breach, even when the contextual information is anonymized, is a high risk.

On the other hand, some users expressed their tepidness about receiving recommendation notifications too often on their mobile devices. Of course, some mechanisms must prevent users of being flood with notifications while their context is changing rapidly. For instance, it is a non-sense to trigger notifications about mobile applications available each time users are walking on the front of a store, especially when users are in commercial centers with hundred of stores and available services. About the responsiveness of a context-aware recommender system, we asked to the participants what should be the value that would trigger a notification about an available service. 74% of participants found that a notification should be triggered when the current context and the user profile match between 80% and 90% of a service description, history of use, context of use, service profile etc.

Table 2 : Ranking of the recommendation modalities in general context

Modalities/ Ranking	1 (most important)	2	3	4 (least important)
Interaction history	20.75%	33.96%	43.40%	1.89%
Contextual information	45.28%	30.19%	16.98%	7.55%
User preferences	28.30%	20.75%	32.08%	18.87%
Other users interaction history	5.66%	15.09%	7.55%	71.70%

DISCUSSION

As we wrote previously, the rating the participants gave to the modality around the other users' interaction history surprised us. Most of the popular recommendation systems, using collaborative filtering approaches, are using other interaction history, ratings and comments to build content or service recommendations.

Many of these systems use their users' interaction history to feed their recommender system at the discretion of the average users that are unaware of this technique. Even if the public is more and more confronted to data mining in their daily life activities, most of the users are unaware that most of the transactions they are doing on the web are logged and used to increase the precision and responsiveness of their requests. Therefore, it is reasonable to attribute their low rating to this modality, to the fact that they think that acceding to other users' history is a privacy violation. This hypothesis is corroborated by the users' comments in the survey.

To have a better overview of the rating the participants gave to each context-aware recommendation modalities, we matched the result from the Table 1 and Table 2 by computing the average ratings for each modality. As the Table 1 shows more modalities than Table 2, we regrouped *Service related to the location, Service related to the ongoing activities, Service used in similar context and Service related to similar categories,* by computing the average rating and matching it with the *Contextual Information* from Table 2. The Figure 1 presents the results of this match, where the numbers from 1(most important) to 4 (least important) represent the average rating attributed to the modalities. The intersection of the two tables confirmed the overall appreciation of the users for the interaction history and the contextual information (e.g. current activities, location, time, etc.) modalities. However, these results bring several other questions.

For instance, there is a clear appreciation for recommendations provided from the user's interaction history. If this modality can provide pretty accurate service recommendations to the users, it can reduce also the possibility to recommend new and genuine services that users did not used previously. Therefore, the weight of the interaction history must be managed in a smart way, for instance by presenting to users a "Top 3" recommendation, where other recommended services are new services.

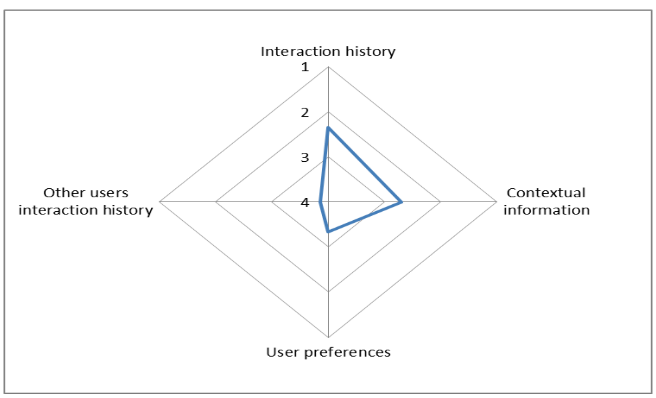

Figure 1: Average rating for the recommendation modalities in general scenarios and specific scenarios

FUTURE WORKS

First, we believe that a high quality recommendation should include three things: what the user wants, what the user desires, and what the user needs. Another important element that should be added to study: is the user trusts the system. For example, we can analyze the restaurant and event domains, which would require an engine recommendation system optimization in a cross-domain. We could use a hybrid approach combining collaborative filtering and content-based filtering, with the integration of the concept of context to increase the acuteness of the engine.

Engine system recommendation would allow optimal recommendation identified with the user. We have considered avoiding the past history of the user, by analyzing recommendation only at time t (neither at time t-1 or t+1). This hybrid system would automatically propose recommendations to the user unbeknownst to himself or herself. Furthermore, the recommendation would integrate a tinge of emotions to give the user the feeling that his or her desires are being met.

About the concept of emotion in recommendations, we plan to compare a recommender system that takes into account a tinge of emotions to a system with doesn't integrate a tinge of emotions, both within the context awareness. Second, we will study how to better implement marketing algorithms in the engine system recommendation. Third, since users have patterns in their behavior and mental processes, we will work on predicting recommendations based on machine learning techniques and Bayesian approaches (e.g. Bayesian network).

Finally, we worked previously on the intelligibility of context-aware system [13], an approach where systems with embedded "intelligence" have mechanisms to describe to users the way they are working and computing results. We plan to use this approach to provide useful information to users on how our future recommendation algorithms will work, which, we expect, will give users more trust in the system.

CONCLUSION

This paper has provided positive survey results and different perspectives on context-aware recommendation systems for urban environment scenarios. Based on these results, we can do various kinds of recommendation systems. We have confirmed that the contextual information is perceived as must for a recommendation system dedicated to providing services in urban environments. On the other hand, taking into consideration the interaction history of the users is ranked as well as the context. Moreover, in concordance with related works, the user's location as a recommendation modality is highlighted in the presented results.

Today, recommendation systems are based mainly on social web data and user's service rating. By integrating contextual information and a more in depth description of the users, recommendation systems will be improved. We propose that next recommendation algorithms will be based on the user trust of the user to the system, on user's profile, on service profiles and the users' context. We believe that this would increase the quality of the recommendation.

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