Influencing Factors for User Context in Proactive Mobile Recommenders

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Abstract

Proactive recommender systems break the standard request-response pattern of traditional recommenders by pushing item suggestions to the user when the situation seems appropriate. To support proactive recommendations in a mobile scenario, we have developed a two-phase proactivity model based on the current context of the user. In this paper, we explain our approach to model context by identifying different components: user and device status, and user activity. We have conducted an online survey among over 100 users to investigate how different context attributes influence the decision when to generate proactive recommendations. Thus, we were able to acquire appropriateness factors and weights for the context features in our proactivity model.

1   Introduction

Traditional recommender systems usually follow a request-response pattern, i.e. these systems only return item suggestions when a user makes an explicit request. Proactivity means that the system pushes recommendations to the user when the current situation seems appropriate, without explicit user request. In mobile recommender systems, users cannot easily browse through many search results and suffer from other restrictions in the user experience, because of limitations in the user interface such as small display sizes or missing keyboards. In addition, cognitive load and limited attention spans of users while moving also add to the need of adapted information access. Therefore, user experience could possibly be improved by delivering recommendations proactively in mobile environments.

Consider the following scenario: a tourist is visiting a city with a smartphone. She is walking around for two hours, has her phone not in silent mode and is not using an app at the moment. The user is walking near a café that fits her preferences well. The system determines that the situation calls for a break based on the available context information and proactively notifies the user about the recommended café nearby.

To support such a scenario, we have developed a two-phase proactivity model (Woerndl et al. 2011). The approach analyzes the current context and calculates a score that determines not only the best item(s) in a given situation, but also whether the situation warrants a recommendation at all. In this paper, we explain factors about the current context that influence the decision to generate proactive recommendations. The approach is supported by a survey we conducted among over 100 users.

The rest of the paper is organized as follows. First, we discuss some related work and explain our proactivity model. Then, we describe the context model in more detail in Section 4. Section 5 presents the results from a survey on influencing factors for user context. We conclude our paper with a brief summary and outlook.

2   Background

2.1   Related Work

A lot of work exists on context-awareness in interactive systems; see the survey (Baldauf et al. 2007) for an overview, for example. Context can be defined as characterizing the situation of entities that are relevant to the interaction between a user and an application (Dey et al. 2001). General principles and paradigms of context-aware recommender systems have been discussed and analyzed in (Adomavicius & Tuzhilin 2010). However, proactivity has not gained much attention in personalization and recommender systems research and has rarely been applied in practical recommender applications. (Tennenhouse 2000) considers the notion of proactive computing as a shift from human-centered to human-supervised computing, where connected systems monitor the physical environment and react to it without explicit user triggers.

As one example of proactivity in an existing system, (Hong et al. 2009) proposed an agent-based framework for proactive personalization services. This approach proposes a model according to which a user profile is deduced from a user's context history. The model enables proactive recommendations in the future. Another example of a proactive recommender system in ubiquitous computing can be found in (Sae-Ueng et al. 2008). The authors developed an apparel shop equipped with a large number of different sensors, like cameras and RFID sensors. They captured actions applied to items (viewing, touching, carrying, and fitting) by the customer. Based on this data, preferences of the customer were determined, which were in turn used to proactively recommend items to the customers.

Ricci discusses proactivity in his survey on mobile recommender systems (Ricci 2011). Some systems make use of the current user behavior, position and other context information to improve personalization on mobile devices and in ubiquitous computing in general. But Ricci concludes that "none of the existing reviewed systems is capable to proactively interrupt the user activity with unsolicited but relevant recommendations" although "[proactive recommendations] can revolutionize the role of recommender systems from topic

oriented information seeking and decision making tools to information discovery and entertaining companions" (Ricci 2011, 224).

2.2   Two-Phase Proactivity Model

To handle proactivity in mobile recommender systems, we propose the following two-phase model (Woerndl et al. 2011). In the first phase, the system determines whether or not the current situation warrants a recommendation (cf. Figure 1). To do so, the system calculates a score S1 which is a number between 0 and 1. If S1 exceeds a threshold T1, the second phase will be initiated. If S1 = 1, the highest possible value, then a recommendation will be triggered in any case. If S1 = 0, the recommendation process is aborted without considering items for recommendation. An example for S1 = 0 is when the users just had lunch, then no restaurant recommendation will be generated at this time. The calculation of S1 is based on context attributes that will be explained in detail in Section 3 of this paper. The first phase is executed periodically in the background or when relevant context attributes have changed, e.g. the user has moved according to the GPS or other sensors.
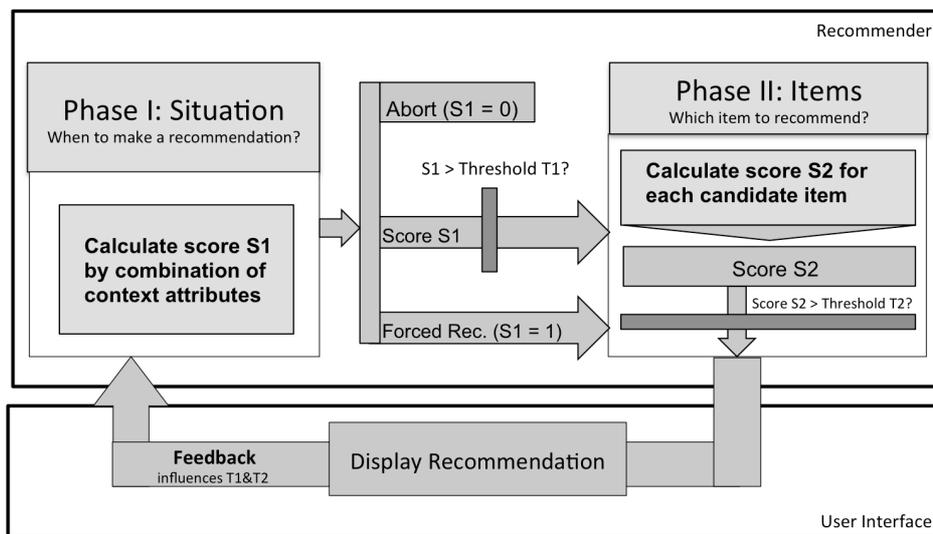

Figure 1. Proactivity Model

The second phase takes the suitability of particular items into account. If one or more items are considered good enough in the second phase (individual item score S2 > threshold T2), the recommender system communicates it to the user. The score S2 is the result from any contextual or non-contextual recommender system, e.g. the normalized predicted rating of a collaborative filtering algorithm for an item. After the recommended items are communicated to the user, she can optionally give feedback on the recommendations and also on the point in time of the recommendation.

3 Modeling Context for the Proactivity Model

3.1 Context Model for Phase I

Figure 2 illustrates the components of context in our model for the first phase (situation assessment). The focus in this paper is on the "user context".
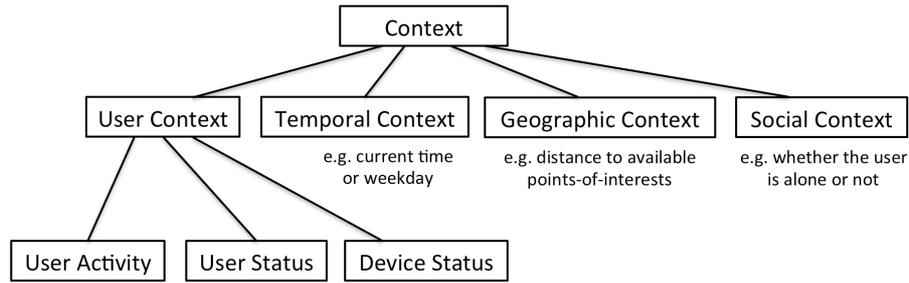

Figure 2. Context Components

In each of the four main categories, several context attributes can be modeled to collectively determine the score S1. The attributes are evaluated to value on a range from 0 to 1. The higher the score for a context attribute is, the higher the indication that a proactive recommendation could be useful. For example, if the current time is right around when the user usually has lunch, the corresponding temporal context attribute will be close to 1. Each attribute is weighted depending on the relative importance of the parameter to the recommendation process. In Section 4, we show how to determine appropriateness factors and weights for user and device status. In this paper, we focus on user context, but parameters for the other categories can be derived accordingly. Next, we will explain the components for user context in more detail.

Name / Key Question	Values
Telephony Status Is the user using the telephone?	idle, calling, receiving call, talking
Calendar Entry Does the user have a calendar entry (at present)?	entry at present, no entry for the next n minutes/ hours/days
Use of App Is the user using an app?	using an app, not using any app
Messaging Is the user involved in a messaging process?	currently receiving a message, received a message n seconds/minutes/hours ago

Table 1. Features of user status

3.2   User Status and Device Status

In our model, the user context is categorized into "user activity" (see chapter 3.3.), "user status" and "device status" (cf. Figure 2). User status model features describe the interaction of the user with the smartphone (e.g. whether she is using an application) and other related information (cf. Table 1).

The device status is structurally very similar to the user status, but incorporates different features, for instance the state of connectivity (cf. Table 2). Based on the scores of the modeled components, the overall user context score can be calculated by linearly combining the single values allowing for different weights, for example. The resulting user context score indicates how appropriate a recommendation in the current situation is. This information can then be used together with other context information in the first phase of the two-phase proactivity model to decide whether to generate a recommendation or not.

Name	Values
Display	on, off
Airplane Mode	on, off
Car Mode	on, off
Ringer	on, off
Wifi	connected, not connected, connection available
Mobile Data	connected, not connected

Table 2. Features of device status

3.3   User Activity

User activity describes what the user is doing right now, usually inferred from sensor data such as GPS or acceleration sensors. In the tourist scenario from the introduction for example, it is interesting to find out whether the user is "walking" or not. The assumption is that a user who is walking around a city will be more interested in a proactive recommendation. In this case, the classification ("walking", "not walking") yields a binary value, but can be mapped to a value between 0 und 1 by taking the duration of the activity into account.

We have conducted an analysis of GPS log data of twelve people to determine user activity in an online fashion, i.e. finding out whether the user is "walking" in real-time, without much delay on the smartphone. The twelve test users generated over 75000 location points. Results show an activity classification accuracy of over 85%. We were applying an approach from the literature for segment-based activity classification. More details about the algorithm and the study can be found in (Lerchenmueller & Woerndl 2012).

4   A Survey on Influencing Factors for User Context in Our Mobile Scenario

In this section, we describe a survey we have conducted in order to determine concrete values for the appropriateness factor of every feature of user status and device status that was listed in the previous section, and for the individual weights.

4.1   Goals and Structure of Survey

In Section 3, we presented a model for inferring the appropriateness of a proactive recommendation based on various context features. While the features and their possible values are constituted by the hard- and software sensors of the user's device, it is yet to be determined how a value of a feature translates to a quantification of appropriateness. For example, if the screen (= feature) of the device is on (= value), how appropriate is a recommendation judging only by this feature? Also, a weight needs to be determined for every feature as, for example, a silenced ringer may have a higher influence on the final context score as an activated Wifi connection. We determined quantifications of the appropriateness factors and the weights in our model through a user survey.

Feature value	Avg.	Median	Feature value	Avg.	Median
Telephony state			*Display*		
Idle	3.72	4	On	3.45	4
Calling	1.46	1	Off	2.97	3
Talking	1.45	1	Airplane mode		
Receiving call	1.45	1	On	1.81	1
App usage			Off	3.48	4
Using an app	2.26	2	*Car mode*		
Not using any app	3.84	4	On	2.25	2
Calendar entry			Off	3.35	3
At present	2.19	2	*Ringer*		
In 15 minutes	2.57	2.5	On	3.41	4
In 30 minutes	2.90	3	Off	2.93	3
In one hour	3.31	3	*Wifi*		
In 90 minutes	3.43	4	Connected	3.57	4
Two hours +	3.54	4	Not connected	3.28	3
No entry for the day	3.83	4	Connection available	3.27	3
Reception of messages			*Mobile data*		
At present	2.35	2	Connected	3.53	4
20 seconds ago	2.60	2.5	Not Connected	3.07	3
One minute ago	2.85	3			
Five minutes ago	3.28	3			
Ten minutes ago	3.50	4			
Ten minutes +	3.58	4			

Table 3: Appropriateness factors for the user status (left side) and the device status (right side)

Participants were asked to indicate the appropriateness of a recommendation for each feature value by a set of bipolar adjective pairs. A 5-point rating scale was applied (neutral middle desired), where the values represented a classification from 1 – *not at all appropriate* to 5 – *definitely appropriate*. Having indicated the appropriateness of each feature value, the

participants were asked to rate the importance of each feature on a 6-point scale, where 1 represented *not important* and 6 stood for *very important.*

4.2 Results

The survey was conducted online and participation was anonymous. 101 people completed the survey.

4.2.1 Appropriateness Factors

Table 3 shows all feature values the participants were asked to evaluate. The majority (53%) of the average values for user status features lies below 3 with an overall average of 2.85. Contrary to that, for the device status only 4 out of 13 values (31%) are below three, indicating that no recommendation is desired for the respective feature value. Here, the overall average is 3.11.

4.2.2 Weighting of Factors

The goal of the next part of the survey was to determine the weight or importance of each feature by assigning a number between 1 (not important) and 6 (very important). As already described in Section 3, the weight represents the influence of a concrete feature value on the decision process. The results are illustrated in Figure 3.
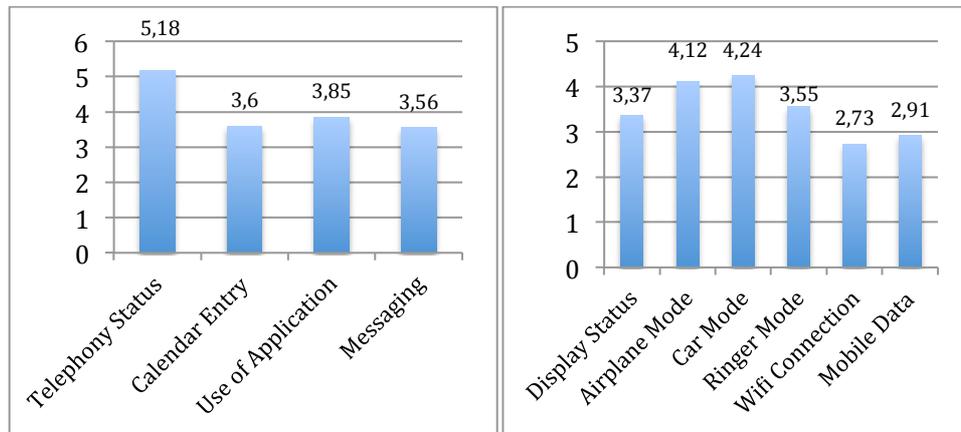

Figure 3. Results of the survey on factor weights for the user status (left) and the device status (right).

As can easily be seen, the telephony status marks the central point for determining the appropriateness of a recommendation. As for the device status, the features that clearly suggest a situation where no interruption is tolerable (airplane mode, car mode) are emphasized in their importance. Having collected appropriateness factors and weights for the features in our model, we can use those as parameters for the context features in the first phase of our proactivity model.

5 Conclusion

In this paper we have presented a model for user context with the goal to determine when to generate a proactive recommendation in a mobile scenario. We have investigated the influencing factors for such a model by means of an online survey. The next step is to integrate the different model components, implement proactivity in a prototype mobile recommender application, and evaluate the complete approach from the users' perspective. One option for future work is to investigate dynamic appropriateness and weight factors based on observing the user. Another area of ongoing research is to investigate the power usage of such a system to make it work in practice. In particular, it is interesting to balance the trade-off between context information gain and power consumption of various sensors which are available in a smartphone.

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