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Using a Rich Context Model for a News Recommender System for Mobile Users

Alisa Sotsenko, Marc Jansen, Marcelo Milrad

Linnaeus University, Media Technology, Växjö, Sweden
{alisa.sotsenko, marc.jansen, marcelo.milrad} @lnu.se

Abstract. Recommender systems have become an important application domain related to the development of personalized mobile services. Thus, various recommender mechanisms have been developed for filtering and delivering relevant information to mobile users. This paper presents a rich context model to provide the relevant content of news to the current context of mobile users. The proposed rich context model allows not only providing relevant news with respect to the user's current context but, at the same time, also determines a convenient representation format of news suitable for mobile devices.

1 Introduction

Nowadays, people use mobile devices in very different situations independent of time and space in order to search and to retrieve relevant information about their needs and interests. Recommendation systems have become more and more popular for mobile devices due to the use and availability of various mobile information services [1]. Here, modern mobile devices provide a profound set of sensors and, together with Internet connectivity, rich possibilities to present relevant information with respect to the users' current context. Several studies have been conducted in order to provide personalized news recommender systems [2,3]. However, a number of challenges have been identified related to the accuracy of the news with relation to the mobile user´s context and the proper format in which this content should be delivered. Most systems have limited information about the context of the mobile users and they require explicit data input about the features of the mobile device without taking into account mobile limitations (e.g. screen size, connectivity type, battery status). Work carried out by [4] shows that recommender systems can provide better quality of news and movies recommendations if additional contextual information is taken into consideration. Therefore, one of the key challenges for providing relevant news in a convenient representation format within different mobile user's environments is to conceptualize a rich context model. From this perspective, we agreed with the research efforts carried out by [5] that claim that context models should be generic and abstracted in order to reuse it in different recommendation domains.

This contribution presents a rich context model for mobile users to be applied for news recommender systems. The paper is organized as follows. Section two describes which contextual information can be used in order to describe the rich context of

mobile users. Additionally, it describes how different content of news might or might not be relevant for mobile users in a variety of contexts, also with respect to their representation format. In Section three we describe the context model for handling the rich context information. Finally, our last section concludes the paper and describes future lines of work.

2 Defining Rich Context for Mobile Users

We understand the term *rich context* as data received from different mobile sensors and how this data can be enhanced by using external Web Services (e.g. Google Place API) in order to retrieve more detailed information including among others the current location (e.g. place, environmental information, etc.). Rich contexts may also include personal information like topics of interests, hobbies, profession, etc. The information about the user's interests and hobbies can be used to describe his/her topics of interests of news items. Additional contextual information could consist of the noise level in the place where the user is currently located and his/her movement status (e.g. sitting, walking, etc.) can be used to decide about the most convenient representation format related to the news content that best suit mobile devices. For instance, if the user is walking to his/her job place listening to an audio stream provided by a text to speech API reading out the news and listening to with headphones can be more convenient in comparison to reading on the mobile device screen. Furthermore, information about the platform of the mobile device allows providing relevant news information to the user's device. For instance, if users A and B share the same interests e.g. for mobile games, if user A has an Android based device while user B has an iPhone, the news about upcoming games for the Android platform will be more relevant to user A than user B.

We classify the current context of the user into three major dimensions: the *environment context* (e.g. place, noise level, date and time, etc.), his/her *personal context* (e.g. topics of interests, hobbies, profession, etc.) with information about the activity in which the user is currently involved (e.g. doing sport, working, etc.) and/or *device context* (e.g. information about device platform). All these dimensions of rich contextual information, as illustrated Table 1, can be extracted with help of mobile sensors and existing additional Web Services.

Table 1. Dimensions of rich contextual information.

Personal Context	Environment Context	Device Context
Topics of interests	Place	Platform
Hobbies	Direction	Battery Status
Country	Movement	Internet connectivity
Activity	Noise level	
Language	Date	
	Time	

For instance, the location can be gathered from GPS sensor and the current user's location could be identified by using Web Services like the Google Places API. Another example of using GPS sensor is getting local news related to the user nearest

place by using additional web service e.g. YourStreet API or Google News API. The information about the platform of the mobile device can be obtained by using e.g. Cordova API. Information about user's hobbies, age, language, country, profession can be collected from the different social network API's, e.g. through a social network login, in order to provide better recommendation results.

All the data sets described in Table 1 are used to represent the *rich context* of mobile users. The context model supports extendability of the sub-dimensions of the context information described in Table 1 and can therefore be used in different recommendation domains by considering different context parameters. The amount of relevant news related to one topic could be different in different contexts, e.g., if the user is sitting on a train, then he/she might want to read among a number of different news sources, while during a physical exercise (e.g. jogging) the user might want to get the news just from his/her favorite news site. An algorithmic and model based approach for handling rich context information of mobile users, the *Rich Context Model (RCM),* is described in the next section.

3 Description of the Proposed Rich Context Model

RCM is a context model for the handling of *rich context* information provided by mobile users. As described in our previous work on context modeling [6], we decided to use a *multi-dimensional vector space model* (MVSM) as the approach for modeling rich contexts of mobile users. The context in which some news are suitable for a particular situation needs to be calculated. For instance, this could be done by pre-executed evaluation where the users in different context have consumed different news. Afterwards, the users' context information of consumed news is stored in the MVSM. Then, each news item could be represented as a vector in the MVSM (e.g. News1, News2). Furthermore, each context dimension is in itself multidimensional in order to allow the description of an almost unlimited amount of dimensions in the RCM, e.g. environment context includes information about the place, noise level and user movement, etc.

In this model, we considered two requirements: the first one is to provide news content that is better suited to the user's current context and the second one is the representation format of the news that is most convenient to mobile users, again, according to his/her current situation. In order to identify the relevant content of news, the *similarity* is measured between two different vectors: the vector describing the *current rich context* of the user and other vectors describing the different available news items. The similarity between vectors can be calculated by e.g. Euclidian distance, Jaccard and cosine metrics. Based on our previous efforts [6], we consider the combination of *cosine* and *Jaccard* similarity metrics in order to match the *current rich context* of the user to the content and representational format of the news. Here, we differentiate Boolean data type of the contextual information e.g., if the user is currently moving (e.g. the user is siting in the library – 0; the user is running or walking in the park – 1) or outside/inside (e.g. the user is inside of the café, library or outside in the park, stadium, etc.). For this kind of Boolean data we propose to calculate the Jaccard similarity metrics to define similar user's environment context.

The cosine metrics, which we propose for non-Boolean data, defines how similar the current context of the user to another context in which some news was consumed. Since we need to use different similarity measures, for Boolean and non-Boolean data types, we end up have a value for the similarity that is a vector itself. Thus, the final step for the identification of the news items to recommend is to calculate the closest distance to the point of the *current rich context* of the user and all available news items.

The outcomes from the proposed *rich context model* could be used for organizing relevant data with other tools to provide some classification and sentiment analyses (e.g. clustering relevant topics or categorizing users by their interests in Tweeter [7]). Especially, it allows for a flexible definition of what kind of context dimensions should be considered. Furthermore, the proposed contextualized approach allows a real time recommendation of news. The mobile application will collect the user's current context information, analyze it and recommend relevant news accordingly in real-time. Hence, the pre-executed evaluation of news should be performed before the usage of the news recommendation application.

4 Conclusions and future work

In this paper we have presented an approach for providing news recommendations based on the current context of mobile users and the format in which the news items can be represented. The proposed rich context model supports the adaptation of relevant information delivered to users of mobile devices. Our future research will be focused on the evaluation of the proposed approach in a number of practical scenarios.

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