Properties of Context-Aware Recommender Systems: A Survey

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ABSTRACT
Recommender systems provide personalized recommendation for their users. These systems are still needed to be optimized to provide more effective recommendations. In some models the context of user and the item is considered during the recommendation process so that it would be possible to make a better estimation of the user's rating. In this article context aware recommender models are addressed. Also the properties of each one of these systems are specified based on the general characteristics of the context aware recommender systems. Finally a general comparison of the level of utilization of these characteristics in the context aware models is done.

General Terms
E-Commerce, Social Networking

Keywords
Recommendation system, Social network, Context awareness

1. INTRODUCTION
Recommender systems automatically determine the information about a specific user, which is trained by the existing data including user activity and user profiles [1]. Recommender systems are often classified according to the recommendations to be made. Two main methods of generating recommendation are collaborative filtering and content-based recommendation. Collaborative filtering assumes that the behavior of the customer is similar to the behavior of other customers and content-based recommendation extracts favorite properties of the interested item and recommends the products with those properties [2].

The classic recommender systems rely on user profiles that reflect the user's personal taste, but ignore other criteria such as temporal, geographical and emotional features. However, individual preferences vary throughout the day. For example, in the morning, most people do not want to see the movie, but instead prefer to see the daily news or the weather forecast. In addition, their habits are different at the weekends. People prefer different matters at work, home, etc. [3]. Various dimensions are considered in the design of recommender systems because in addition to customer and products' specifications other factors are involved in the purchase those are called the context. Context is expressed as a set of features that represent the characteristics of the user such as the reason of purchase, time and place of the purchase [4]. In addition to user profiles, user context history can affect the user's preferences. For example, a person may prefer a particular place for a summer vacation, but he may not choose that place for winter holidays. For example, there are various contexts for a place such as time, location, weather and other cases [5, 6]. In fact, context is any information that could be used to characterize the situation of an entity. An entity is a person, place, or object that is dependent on the interaction between a user and an application, including the location, time, activity and preferences of each of the entities have been considered [7].

The rest of the article is organized as follows. Section 2 introduces context aware recommender systems. Section 3 describes the features of the context aware recommender models. In section 4 a literature review on context aware recommender systems is done and these systems based on their various features are compared. Section 5 provides the discussion and conclusion.

2. LITERATURE REVIEW
Context aware recommender systems deal with modeling and prediction of user interests and preferences, according to context information in the process of recommendation as a classification of explicit additional data. The scores are introduced with ranking function as R:User×Item×Context→Rating in which User is the user domain, Item is the product domain, Rating is the scores domain and context specifies the context based information with their applications [8, 9].

In the literature on context aware systems, context has been defined as user location, surrounding objects and changes in these elements [10]. Other factors were added gradually. Brown et al., add Date, temperature and season [7]. Ryan et al. added the interested physical and conceptual state of a user [11]. Dey et al. added the emotional conditions of the user and expanded the definition into any information that could be specified regarding the interaction between the user and applications [12]. In fact a context aware system is able to extract, interpret and use the context data and comply its performance with the recent interested context of use [13].

The importance of using context data in the recommender systems is represented in Adomavicius et al and a multidimensional perspective is provided that can provide recommendations based on the context recommendation in many tools. They also showed that the context information in recommender systems is important and helps to improve the quality of recommendations in specific cases [14]. Similarly Oku et al. use of additional fields (e.g. time, and weather) in the recommendation process and use machine learning techniques to make recommendations on a restaurant's recommender systems [15]. Prahalad mentions that the ability to contact and touch the customers in any time and place means that the companies not only provide the competitive products but also unique ones (which is shaped by the moment customer experience by his context experience)[16]. Also Palmisano et al. uses the purpose of purchase in an e-commerce tool as context information. Different purchasing goals may lead to different types of behavior (purchasing for different reasons) [17].

3. PROPERTIES OF CONTEXT-AWARE RECOMMENDER SYSTEMS

Context aware recommender systems models can be examined from different perspectives. In this section, each of these approaches is introduced and their properties are described.

3.1 Classification of context

In order to organize different approaches, two methods are introduced that according to, the contexts can be categorized as Interactional and Representational approaches [18].

- Representational: In this approach, a context with a predefined set of observable characteristics and the structure does not change significantly over time, are defined. In other words, representational approach assumes that the contextual features are identifiable and predictable, and therefore can be collected and used within the context aware applications
- Interactional: This approach assumes that the user behavior induced by a main context, but the context is not necessarily visible.

3.2 Receiving context information

Context information can be obtained by explicit, implied or inferred methods to be taken. Each of these methods is described below [8].

- Explicit method: the information is obtained through direct connection with people and other context information or through asking directly or other methods of data extraction.
- The implied method: the information is implicitly obtained the data or the environment such as the location which is extracted by the mobile phone. Alternatively, when the implied data can be implicitly derived from the timestamp of the transaction. In this case, it is not necessary to interact with the user or other sources of field information. Implicit context data source is directly available and the data are extracted.
- The inferred method: In this method, the context is derived using statistical methods and data mining. For example, the identity of the person in a family who changes the TV channels (husband, wife, son, daughter, etc.) may not be clear to the cable TV company, but it can be derived with acceptable accuracy through observing the viewed television programs and channels by various data mining techniques. To infer the field data, creating a predictive model and its training with adequate data is necessary.

3.3 Combination of context in Recommender systems

The involvement of knowledge about the user's task in recommendation algorithm in personal usage can lead to better recommendation [19]. Different approaches to implement context information in the recommendation process can be classified in two groups:

- Recommendation via Context_driven querying and search: The Context_driven querying and search approach has been used in wide areas of mobile phones and tourist Recommender systems. The system that use this approach use the context information (obtained either directly from the user, for example, to determine the status or recent interest or the environment, for example, to obtain regional time, weather or last places) to query about a specific reference sources (e.g. restaurants) and providing the best matching source (e.g., nearest restaurant which is now open) to user.
- Recommendation via contextual preference elicitation and estimation: The contextual preference elicitation and estimation approach to use the context information in the recommendation process indicates the recent trend in the literature on the context-aware recommendation systems. Techniques that follow this approach are intended to model and learn the user's priorities for example through observing user interaction with the system or by obtaining feedback from the user's preferences on recently recommended goods. For modeling the priorities sensitive to the context and production of recommendations these techniques usually use one of the collaborative filtering, content-based or combined methods for the recommended settings or employ different techniques of intelligent data analysis.

3.4 Using context in various components

In the traditional two-dimensional User×Item, Recommender System acts as a function that takes the user preference data as an input and creates a list of recommendations for each user. In fact the traditional two-dimensional process contains three components: the data (input), the two-dimensional Recommender System (function) and the recommendation list (output). Using the context data on each of these components leads to a different pattern for context aware recommendation systems. Context aware Recommender process which is based on contextual preference elicitation and estimation can have the following forms based on the use of context in the components: Contextual pre-filtering, Contextual post-filtering and Contextual modeling [8].

- Contextual pre-filtering: In this approach the information about the current context are used to select or build a set of data records. Then the records are predicted using the traditional two-dimensional Recommender systems on selected data. Contextual pre-filtering approach uses the context information to selection or construction of two-dimensional data for recommendations. One of the major advantages of this approach is to allow the use of any of the numerous techniques of traditional recommendations.
- Contextual post-filtering: In this view, the context data are not considered and the scores are predicted using traditional two-dimensional Recommender systems on the input data. Then the resulting set of recommendations for each user is set using the context data.
- Contextual modeling: In this view, the context data are directly used in the modeling techniques as part of the predicted points. The contextual modeling uses the context data directly in the recommendation function as an explicit predictor of users score for a item while the Contextual pre-filtering and Contextual post-filtering approaches can use the traditional two-dimensional recommendation functions, the contextual modeling leads to a real multi-dimensional function.

3.5 Context generalization

Adomavicius et al [14] introduce the concept of Context generalization pre-filtering that allows the query about the filtering of the obtained data on a specific context. On the basis of formulation suppose that $\acute{C}=(\acute{c}_1,\ldots,\acute{c}_k)$ is a generalized context of $C=(c_1, \ldots, c_k)$ if and only if $c_i \rightarrow \acute{c}_i$ for every i=1,…, k in terms of hierarchy. Then $\acute{C}$ (instead of C) it can be used as a data query to obtain the data rates.

Usually there are several different possibilities for generalization so choosing the generalized pre-filtering is important. There are two solutions for this issue:

- Manual: it is a manual approach derived from expert opinion, as always certain days of the week in general can be extended to weekdays and weekends.
- Automatic: Another possibility is to use automatic approach that can measure the performance of the Recommender System on the input data set obtained from a generalized pre-filtering experimentally and then automatically choose the pre-filtering with best performance.

4. LITERATURE REVIEW AND COMPARISON OF CONTEXT-AWARE RECOMMENDER MODELS

Various context-based recommendation systems have been designed. In this part these models are reviewed and then the properties of these models are analyzed. Ahn et al. [20] have recently extended a technique similar to Contextual post_filtering to suggest the advertisements to the cell phone users' trough obtaining their interests, location and regional time and Lombardi et al. [21] have measure the impact of context data that have used the pre-filtering method on the data obtained from a retail store. Also Baltrunas and Ricci [22] have considered a different viewpoint on the Contextual post_filtering in representing and examining the advantages of products splitting that each product is divided into several different areas on the basis of various contexts in which the products can be used. Also Baltrunas and Amatriain [23] introduced the micro-profiles (or user splitting) in which they divide the user's profile into many micro profiles (that may have shared points) that each given user is presented in a particular context. Oku et al. [15] suggest the combination of classical context dimensions (e.g. time, and weather) directly on the recommendation space and use the machine learning techniques in the Recommender System of a restaurant.

Following the pre-filtering method a reduction based approach is presented in Adomavicius et al. that reduces the multi dimensional recommendation into two dimensional spaces of the user and product [14]. Also in another paper by Adomavicius et al. [8] the possibility of combining several context-aware recommendation systems in a single approach is discussed and a model is presented based on the combination of several pre-filtering. Kahng et al. [24] presented a new model to context aware recommendation that combines several sorting model and then they assessed this model on two real data sets and obtained better results than the previous methods [24].

Baltrunas et al. presented a context aware recommendation algorithm that expands the matrix analysis and the represented solution has the advantage of low computational cost [25]. In order to use the raw data in the context recommendation Shin et al. summarized the raw context data into a conceptual level [26]. The provided model in Bogers [27] paper uses the connections between the objects in various contexts on the website and then makes a random walk on the graph to generate a probability distribution over the unwatched movies of the user [27].

Table1. Properties of context-aware models

References	Receiving context information			Data types		Combination of context in Recommender systems		Using context in various components			Context generalization	
	Explicit	Implied	Inferred	Real data	Artificial data(Simulated)	Contextual preference elicitation and estimation	Context-driven querying and search	Contextual pre-filtering	Contextual post-filtering	Contextual modeling	Manual	Automatic
Adomavicius and Tuzhilin[8]	✓	×	×	✓	×	✓	×	✓	×	×	×	✓
Adomavicius et al. [14]	✓	×	×	✓	×	✓	×	✓	×	×	×	✓
Sim et al. [6]	×	×	×	×	✓	✓	×	✓	×	×	×	×
Kahng et al. [24]	×	✓	×	✓	×	✓	×	×	×	✓	×	×
Baltrunas et al. [25]	×	✓	×	✓	✓	✓	×	✓	×	×	×	×
Shin et al. [26]	×	✓	×	✓	×	✓	×	×	×	✓	×	✓

Akther et al. [5]	×	×	×	×	✓	✓	×	×	×	✓	×	×
Bogers [27]	×	✓	×	✓	×	✓	×	×	×	✓	×	×
Karatzoglou et al. [28]	×	✓	×	✓	✓	✓	×	×	×	✓	✓	×
Gantner et al. [29]	×	✓	×	✓	×	✓	×	✓	×	×	✓	×
Hong et al. [30]	×	✓	×	✓	×	✓	×	×	×	✓	×	×
Shi et al. [31]	✓	✓	×	✓	×	✓	×	✓	×	×	×	×
Kim et al. [32]	✓	×	×	✓	×	✓	×	×	✓	×	×	×
Huang et al. [33]	✓	×	×	✓	×	✓	×	✓	×	×	×	×
Keikha et al. [34]	✓	×	×	✓	×	✓	×	✓	×	✓	✓	×

The model presented in Karatzoglou et al. which is based on context modeling is a generalization of the matrix analysis that make a flexible and general context data integration possible with the data modeling [28]. Also Shi et al. provide a new movie recommendation algorithm based on matrix decomposition [31]. Gantner et al. offer a method for personalized tag recommendation method to model the context [29].

Using the context history in extracting the previous patterns to provide a user based recommendation is addressed in Hong et al. [30]. In the study by Kim et al. a product recommendation model using the context data is expanded [32]. Also, Huang et al. provide context aware Recommender System using extraction, measurement and composition of the context data in the recommendations that are based on Rough sets and collaborative filtering [33]. In Keikha et al. a trust-based context-aware recommender system is introduced that use context data to provide better recommendation to users [34]. Table 1 shows the characteristics of the studies.

Table 1 shows the characteristics of various context aware recommendation models. As seen in this table, some of the models are tested on artificial data (simulation), and some of them are tested using real data. These real context data are sometimes explicit, but in most cases the context data are implicit in the system and extracted for use in Recommender Systems.

As you can see, in all of the models recommendation is created by contextual preference elicitation and estimation. As mentioned before the context can be used in various components of the recommendations. As seen in the table, in most of these models the recommendation process is based on Contextual pre-filtering and Contextual modeling. In some of these models the Context generalization is used either automatically or manually.

5. DISCUSSION AND CONCLUSION

The classical recommender systems estimate the priority of products based on rates that other users have given to products. In some models in order to improve the recommender systems the context of the item and user are considered to recommendation of the item into the user. But the use and loading the context data in the recommendation process is different in these models. Generally according to the type of available context data and how to use and incorporate them in recommender systems, different features can be identified for these systems.

In this paper a review on the literature on the context aware recommender systems has been conducted. Also base on the available context data and how to use the data to make recommendations, context aware recommender models are divided into different categories. Finally, with respect to the categories and features the characteristics of each of these systems have been identified and are displayed on a table together.

According to the present study, most of these systems have been tested on real data that have been implicitly available and in all these cases the recommendation is created through contextual preference elicitation and estimation. Also it was observed that the contextual post-filtering method is rarely used and mostly the context data are used as contextual pre-filtering or contextual modeling in the recommendation process and in some cases these recommender models have also used the context generalization as well.

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