# Leveraging Context-Aware Recommender Systems for Improving Personal Knowledge Assistants by Introducing Contextual States

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**Abstract**

During the last decades, recommender systems have played a remarkable role in putting one step further toward making content platforms more intelligent in a wide variety of domains ranging from music and movies to books and documents. Notwithstanding the various applications of recommender systems, not many contributions have been made regarding their potential capabilities in the domain of personal knowledge management. Hence, it has been tried in this study to shed new light on an innovative application of recommender systems to improve personal knowledge assistants by making them capable of providing knowledge workers with useful information through every single situation during their daily work. This paper provides a comprehensive research tree involving the key information about state of the art approaches with a focus on the three most relevant categories to this research including knowledge-based, sequential, and session-based recommender systems. Furthermore, the idea of the contextual states is introduced as the first step of a promising direction toward collecting the required multi-dimensional information for making such helpful recommendations.

**Keywords**

recommender systems, context awareness, knowledge assistants, contextual states, information re-finding, proactive information delivery



## 1. Introduction

Recommender Systems (RS) have been attracting more and more attention these days due to the rapid growth of products the customers are provided with by various suppliers and services. The customers are surrounded by millions of choices for almost every single type of product. The main job of RS is to sort or filter these numerous items in a way that suits the users' needs and preferences as precisely as possible. Their applications include various areas ranging from recommending movies, music, television programs, books and documents to websites, conferences, tourism scenic spots, and learning materials. These wide applications have been classified into eight categories including e-commerce, e-business services, etc [1].

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Bringing context information into the play can move forward the capability of the RS from capturing the long-term static preferences of the users to a whole new level in which capturing also the short-term dynamic user needs becomes possible. This generation of such systems is usually known as the context-aware recommender systems (CARS) which are capable of leveraging the value of recommendations by exploiting context information that affects user preferences and situations [2]. CARS have also been broadly developed in diverse application domains such as in movies, music, e-commerce, news, and research papers [3].

### 1.1. Motivation and Research Goal

Notwithstanding such extensive developments of CARS in a wide variety of domains, not many contributions have been made in leveraging their potential power in combination with personal knowledge assistants (PKA) owing to the fact that context-awareness can play a remarkable role in such systems for knowledge work [4]. Hence, this research aims to present an innovative application of CARS as a useful tool for improving PKA by introducing the idea of contextual states (CS) which will be thoroughly discussed in section 3.

In contrary to the common target users of CARS which are mainly customers of various products, in the PKA domain introduced as a new application of such systems in this research, the target users mainly include knowledge workers (KW). KW are workers whose main capital is knowledge [5] (e.g., programmers, physicians, pharmacists, architects, engineers, scientists, design thinkers, public accountants, lawyers, and academics) and are often perceived as human subjects whose cognitive dimension is targeted with knowledge management systems and can be considered as investors of knowledge and energy in an organization [6].

Having such CARS embedded in the work environment, KW could be continuously provided with the most relevant and useful information based on their changing needs during daily tasks. It is justifiable to expect that such systems can lead to a significant increase in the productivity of KW since they spend almost 38 percent of their time searching for information [7].

### 1.2. Hypothetical Scenario

Let's take a scenario into consideration about a hypothetical researcher named Alice to clarify how such CARS could help KW in different ways through their activities on a daily basis. Alice wants to (co-)author a paper about personal information management (PIM). A smart recommender engine embedded in her work environment is expected to be capable of helping her with various useful recommendations adjusted to the information need of every single phase through her authoring task. For instance, recommending all the relevant previously viewed articles by Alice based on their relevance to her current topic PIM in the literature study phase, suggesting contact information of her colleagues sorted by their research and work experience in PIM in case she needs some kind of consultation for her research, recommending the top suitable visualization tools when she wants to represent her results via diagrams (such as matplotlib, seaborn, plotly, etc., provided that the system is aware of not only her current situation and need but also her static long-term preferences like favoring python among other programming languages), and also providing her with the top relevant upcoming conferences in the submission phase. However, all these examples cover only a few potential aspects of how such smart assistants could be capable of helping the KW theoretically. In order to make developing such systems practical, many essential questions should be tackled. For instance: What kind of recommendations can lead to productivity improvement during KW's daily tasks? How to recognize their situations and estimate the most important needs based on them? How the most relevant information must be retrieved in different scenarios and what data sources must be included? And finally, how the performance of such systems should be evaluated?

## 1.3. Research Scope and Challenges

In addition to the application domain, what also differs CARS for PKA from the existing systems is the research scope in terms of width and depth of the user-item interaction data by which the number of users and required insights per user's data are meant respectively. Let's take Spotify[1] as an example for more clarification. A well-known streaming service, of which providing music recommendations is a key feature. This service contains millions of active users leading to the effectiveness of famous methods like collaborative filtering (CF) [8] due to the high enough number of users leading to the capability of gaining useful insights about similarities among items (in item-based CF) or users (in user-based CF) based on the derived user-item interaction data [9]. In personal knowledge management scenarios, on the other hand, utilizing such user-item interaction data with a high number of users is almost impractical due to either too few active users or restrictions of using all the captured personal information owning to privacy policies. However, what compensates for the short width of the input data (i.e., number of users) in such scenarios is the depth of input data from which the required insight must be gained. In other words, the RS for PKA can reach a satisfying performance only on the condition that deep enough insights are captured from the user's dynamic situations among which even a very detailed action such as scrolling a document, changing the file directory, or switching between the browser tabs can be of great importance in making the right recommendations in every single situation. Besides, although it seems impractical at the first glance to use the well-known methods like CF for such RS due to the fewness of users, a new approach is proposed in section 3.2 that enables using the core idea of CF for PKA with some modifications.

Considering further dimensions of these CARS in knowledge management scenarios, there are some notable challenges in addition to typical challenges of RS (e.g., cold start problem [10]) that are worth mentioning. First of all, the candidate items for the recommendation of the aimed RS are not limited to a specific type (like music tracks for Spotify or movies for Netflix[2]) but are in fact heterogeneous items (such as articles, people, tools, conferences regarding the discussed scenario in section 1.2). Moreover, the volatility of user's needs and the high frequency of context switching [11] makes efficient real-time recommendation challenging since a deep understanding of the user's mental model needs to be captured in a pretty short amount of time for each specific situation that might last less than a few minutes. Besides, the dissimilar behavioral patterns of users can result in the inefficiency of applying a model which was trained by a group of specific users to another group. And the final issue to be addressed here is the possible lack of user's explicit feed-backs in such systems contrary to some other services in which the user-item rankings data can be derived from the rates each user gives to an item (e.g.,

[1]https://www.spotify.com/
[2]https://www.netflix.com/

like/dislike a recommended music or giving 1-5 stars to a movie). It's not judicious to expect users to give explicit feed-backs to such a substantial number of recommended items they are provided with continuously. Therefore, such systems should be possibly evaluated through either objective criteria or based on some implicit feed-backs extracted from user's activities.

Having covered the introductory discussion in this section, the paper continues by discussing the related work in section 2, followed by the proposed approach in section 3 containing an introduction to CS and how to use them as a key concept for making recommendations, coupled with useful concepts as the foundations for making CARS in PKA a more practical idea. Finally, the paper is concluded in section 4 along with briefly illustrating the prospects for future works.

## 2. Related Work

Since not many contributions have been made in using RS coupled with PKA, studies in which this idea has been explicitly discussed can not be easily found. However, a considerable number of contributions have been made to related research fields which either share many principal problem characteristics with the aimed RS in this research or discuss quite similar ideas through some different terminology. In what follows, the two mentioned groups of related work are investigated in subsections 2.1 and 2.2.

### 2.1. Recommender Systems with Similar Principal Characteristics

Before discussing how some principal problem characteristics are shared with the aimed RS, it is necessary to explain some aspects of the input data from which the user's situation is extracted in more detail. One of the most important parts of input data is the sequence of the computer interaction events containing every basic event from which the user's behavior can be extracted. This stream of basic events mainly consists of the user interactions with the keyboard, mouse, applications, and other resources of personal computer annotated with the corresponding timestamps like the dataset provided by Sánchez et al. [12]. The sequential characteristic of this event stream that is one of the main sources for capturing the required context information for giving recommendations, makes the challenge considerably similar to a specific category of RS known as the **sequential RS**. This type of RS on which a systematic review has been provided by Wang et al. [13] mainly model the sequential dependencies over the user-item interactions making these systems capable of capturing both dynamic and short-term preferences of users in contrast to the traditional RS in which only general static preferences are captured. This capability is of vital importance for the aimed RS in this research.

However, the RS with this capability are not limited to sequential RS. Another category of RS named the **session-based RS**, comprehensively discussed by Wang et al. [14], is associated with an underlying assumption that all of the historical interactions of the users are not of equal importance to their current preferences leading to the capability of such systems to capture short-term dynamic preferences evolving over time to provide more accurate recommendations sensitive to the evolution of their session contexts.

In addition to the two mentioned categories of RS, which are strongly linked to this research topic due to the sequential characteristic of the event stream and the importance of capturing the session sensitive preferences, another important category of the RS worth investigating here – owing to its potential capability for handling heterogeneous items and their relationships – is the **Knowledge Graph-based RS**. Using knowledge graphs (KG) in which the information is represented through a semantic graph as side information for the RS has attracted a significant attraction among the researchers recently [15]. Furthermore, the great potential of KG for information retrieval seems undeniable [16] making them so advantageous for personal information management as well [17]. Engaging KG in RS makes the possibility of not only involving various types of items but also representing more complex relations among them. It is worth mentioning that the entities of KG used in RS are not necessarily limited to recommendation items and can also contain the users and any other type of entity having some kind of relation to either items or users. Therefore, it is justifiable to consider the KG as a remarkably promising way of representing information in RS for PKA due to the need of handling heterogeneous resources and complex relations.

Combining the session-based and sequential RS leads to improvements in capturing dynamic preferences [18] and using the KG can make the RS more suitable for complex real-world use cases [19]. Combining these three research fields can result in effective hybrid methods provided that their various dimensions are exploited properly. Hence, putting the key information (e.g., challenges, approaches, and future directions) of the three mentioned categories together in a single diagram can provide a helpful general picture of the related state of the art. Therefore, a comprehensive research tree (presented in Figure 1) has been created during this research considering the recent surveys on the sequential session-based, and KG-based RS [13, 14, 15].

#### 2.1.1. KG-based Recommender Systems

As shown in the diagram, KG-based RS have been using mostly public cross-domain knowledge bases like YAGO, Freebase, DBpedia, and Wikidata as a side information source coupled with datasets included in one of the seven categories movie, book, music, product, point of interest, news, and social platform among which the personal knowledge management applications based on exclusive KG (like the exclusive KG data structure used by Forcher et al. [20] in music domain) seem to be missing in Guo et al. [15]. An interesting point to be mentioned here is the first future direction in KG-based RS stated by Guo et al. [15] which is capturing dynamic preferences rather than modeling static preferences. From the other RS categories aspect, the sequential and session-based approaches can provide the RS with such capability as previously discussed. From the knowledge base point of view and especially in personal/organizational knowledge management domain, the concept of evolving knowledge spaces introduced by Sauermann et al. [21] can be also helpful for making RS capable of dynamic recommendations.

#### 2.1.2. Sequential Recommender Systems

In the domain of sequential RS, various approaches have been proposed that can be categorized into three groups of traditional sequence models, latent representation, and deep neural networks. These approaches are capable of handling the main existing challenges of sequential data characteristics classified into five categories containing sequences with long length, flexible order, noise, heterogeneous relations, and hierarchical dependencies [13].

### 2.1.3. Session-based Recommender Systems

The emerged challenges from data characteristics in the domain of session-based RS share some categories with sequential RS such as challenges associated with length and order coupled with further challenges related to action type, anonymity, and session structure. The developed approaches in this domain not only share a considerable number of models with the sequential models namely latent representation models and Deep Neural Networks (NN) like Recurrent NN and Convolutional NN, but also contain further advanced models in Deep NN such as Graph NN, Attention Models, Generative Models, and Reinforcement Learning [14]. The discussed promising prospective research directions in session-based RS by Wang et al. [14] worth a brief mentioning due to their alignment with the prospects of this research. These aligned directions include capturing general long-term preferences (in addition to dynamic short-term ones), considering more contextual factors, using cross-domain information, considering more user behavior patterns, and online/streaming recommendation [18].

## 2.2. Similar Concepts with different wording

Some quite similar concepts to this research have been also studied through a little different terminology. For instance, the idea of *proactive information delivery* support into an organization is realized through a bottom-up strategy by Holz et al. [17]. The resulting system of this research allows for a task-oriented view of an office worker's personal knowledge space in order to realize proactive and context-sensitive information support during daily knowledge-intensive tasks. Although the mentioned information support for KW shares the key idea with this research, the term RS has not been used directly in this domain and situations within the same context have not been taken into account.

Last but not least is the quite recent study by Sappelli et al. [22] under the title *Evaluation of context-aware recommendation systems for information re-finding* which is considerably close to the topic of this research and can be considered as a primary direct contribution to this research domain. In this study, four criteria have been identified for evaluating the quality of KW support followed by applying three recommendation methods on a collected dataset of information behavior in context presented by Sappelli et al. [23]. This dataset which is named the SWELL dataset is created for stress and user modeling research by Koldijk et al. [24] and is mainly used in stress-related fields rather than personal knowledge management and PKA.

Notwithstanding the notable contribution of the mentioned research, especially for proposing the evaluation criteria for such RS and also providing an accessible dataset, many further steps are still to be taken toward bringing such RS to real-world applications. An essential step which is of great importance is moving from the simple characterization of context by Sappelli et al. [22] which is actually limited to eight predefined topics, to more complex models of context provided by Schwarz et al. [4, 25] beyond which the innovative self-organizing contexts (briefly discussed in section 3.1 as a useful concept) has also been proposed by Jilek et al. [26].

Besides, the recommendation candidates can not be annotated with useful information unless the mental model of the KW is captured properly [21, 27]. This capability becomes practicable provided that the user's personal knowledge space is modeled through a semantic desktop (by Sauermann et al. [28]) which is also introduced in section 3.1 as another helpful approach.

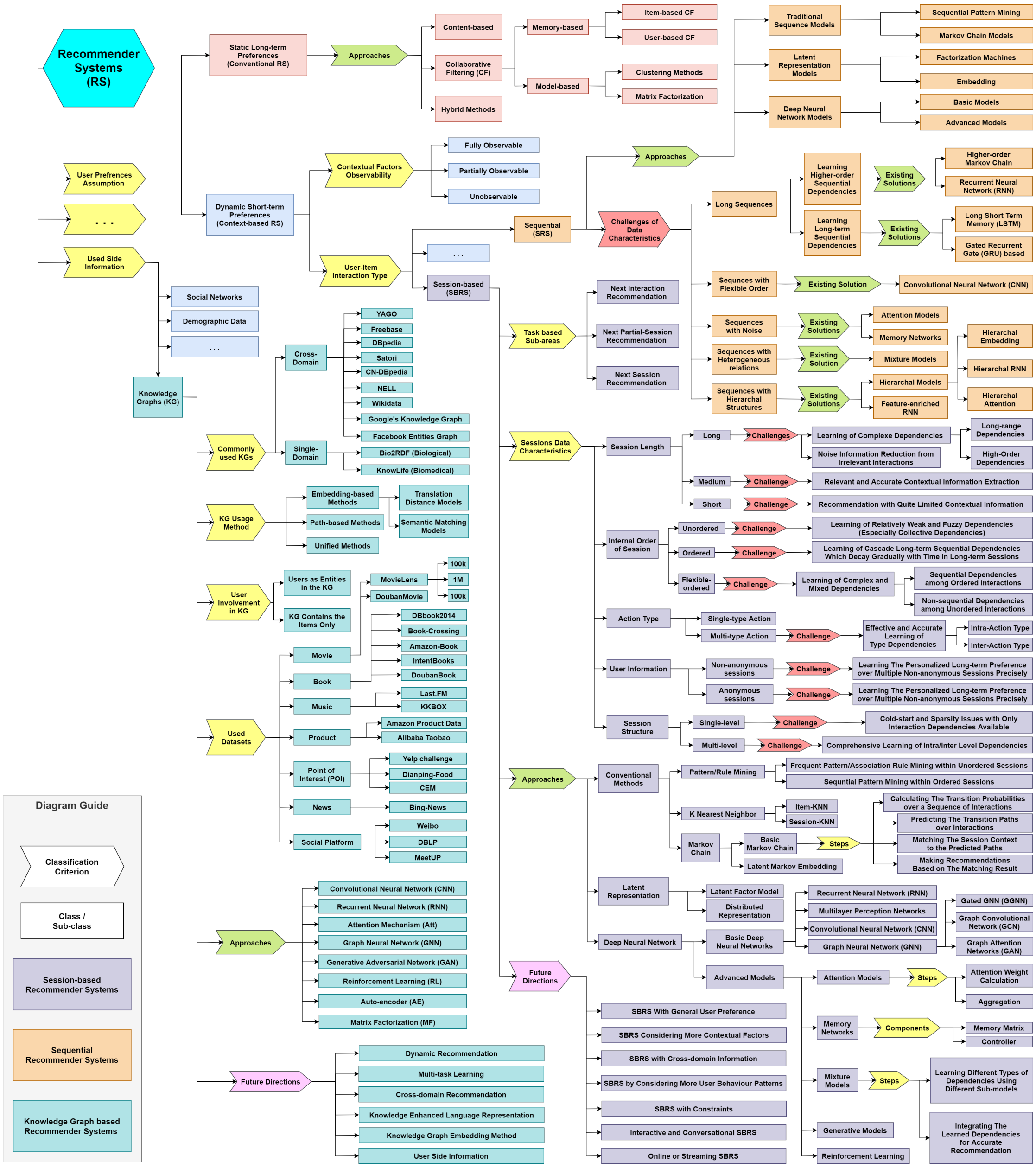


**Figure 1:** Recommender systems state of the art with focus on the three most relevant categories. (high-resolution version available online: https://www.dfki.uni-kl.de/~bakhshizadeh/lwda2021/)

Moreover, many other dimensions of each individual situation in which KW are supposed to be recommended by useful context-based information should be taken into consideration to reach a comprehensive model. The key steps toward capturing the mentioned various dimensions for providing the PKA with efficient recommendations are presented in the following section.

# 3. Proposed Approach

After discussing some of the fundamentals for making CS practical for real-life scenarios, this key idea toward leveraging RS to improve PKA is introduced in more detail through this section along with briefly discussing two approaches for making CS-based recommendations.

## 3.1. The Foundations for Enabling Contextual States

During the last decades, many notable concepts have been developed that can promote the CARS for PKA in terms of performance and feasibility of implementation. **Adaptive knowledge assistants** as, e.g., provided by Biedert et al. [29], are great platforms for embedding such CARS. The **semantic desktop** has proven to be a good solution for semantifying the work environment for KW [30], making the semantic dimension of CS practical. As defined by Sauermann et al. [28], a semantic desktop is an enlarged supplement to the user's memory in which an individual stores all her digital information like documents, multimedia, and messages interpreted as semantic web resources forming a KG using an individual vocabulary consisting of, e.g., topics, persons, events, and tasks embedded on the desktop (like provided by Maus et al. [31]). The performance of KG-based recommendations basically depends on the construction quality of such KG beneath the system which can be evaluated through innovative methods like proposed by Schröder et al. [32]. Moreover, the concept of **self-organizing contexts** can be a big step toward reaching the ability to recognize the user's needs in various situations by enriching CS with a more advanced representation of context in knowledge scenarios [26]. Furthermore, to broaden the richness to describe KW's activities and resources in terms of the organization, a corporate memory[3] is able to provide rich organizational KG to be used in the work environment. Finally, the idea of **intentional forgetting** worth mentioning due to its capability of managing information overload [34] resulting in more adequate recommendations.[4]

## 3.2. An Introduction to Contextual States

RS follow three main phases for the recommendation process including the information collection, Learning, and Prediction/Recommendation phase [35]. The information collection phase without which the next two phases would become useless is of great importance and should be considered as the prerequisite of such systems. The aimed RS in this study are clearly no exception. Thus, recommending suitable items that meet the user's exact needs considering both long and short-term preferences in all the possible situations can not be practical unless the user's state is observed and investigated from every single related perspective. In addition to time and activities which are two categories of contextual information already used in CARS, the further required information puts the RS for PKA in the multi-dimensional information category regarding the categorization provided by Sassi et al. [36] based on the nature of contextual factors in RS. The term CS proposed in this research refers to these multi-dimensional sessions of the KW in which all the required contextual information for recognizing the user's needs is considered. In other words, the contextual state of the KW in each moment involves all the

[3] This work is based on the corporate memory CoMem; see e.g. [33]; https://comem.ai

[4] This research is conducted in the project SensAI; https://comem.ai/sensai/

necessary insights derived from the available information gathered from either the historical data sources or the work environment real-time capturing tools. The required data in such PKA scenarios can be collected from three main sources including the event stream, the local files (e.g., documents, notes, slides, etc.), and also the KG on which the system is based provided that the work environment is enriched with semantification tools as discussed above.

Holding the view provided above and based on the conducted investigations during this research, seven dimensions have been assigned to the discussed CS including:

- **Role:** The role of KW affects their information need. For instance, a learner might be interested in educational sources whereas a networker should be provided with related people through the recommendation process. A comprehensive typology of knowledge worker roles and their corresponding expected actions is proposed by Reinhardt et al. [6]. According to this typology, roles are classified into ten categories including controller, helper, learner, linker, networker, organizer, retriever, sharer, solver, and tracker. This dimension can be considered as a factor influencing either long or short-term preferences as KW can be either assigned to a fixed role or play different roles during their tasks.
- **Action:** KW should be provided by different types of information support during different kinds of actions. As discussed by Reinhardt et al. [6], these actions consist of acquisition, analyze, authoring, co-authoring, dissemination, expert search, feedback, information organization, information search, learning, monitoring, networking, and service search.
- **Task:** Many actions are usually involved in accomplishing a task. Some simple examples are writing a report, preparing a presentation, replying to an email, etc. Furthermore, the task might be part of a larger process and – as often is the case in knowledge work – evolving with varying activities, resources, requirements, and outcome (e.g., [17, 37]).
- **Files and apps:** All the involved files and applications during a session should be taken into consideration as they usually contain useful information about other dimensions. For instance, starting with an empty PowerPoint could be an indicator for recognizing the task of preparing a presentation. Besides, the content of the included files (like documents, web pages, etc.) may be sometimes a good source for extracting the topic of the task.
- **Interaction behavior:** The data derived from hardware interfaces like keyboard and mouse events (i.e., clicks, movements, scrolls, etc.) from which useful information like dwell time can be extracted and result in improving session recommendation [38].
- **Semantics:** Much deeper understanding of the states can be gained from the semantic representation of the concepts involved in viewed files during a session rather than a plain text. Leveraging such a valuable dimension of contextual information has become promising due to the recent developments in ontology-based named entity recognition by practical methods for real-time applications like the one provided by Jilek et al. [39]. This dimension can enhance the system remarkably through the capability of measuring semantic distance between CS by using such methods as proposed by Zhu et al. [40].
- **Topic:** This dimension of CS can play a significant role in the recommendation results. The important point is that the assigned topic to CS can be defined through different levels of complexity ranging from simple static contexts [22] as mentioned in section 2.2 to more advanced contexts introduced by Jilek et al. [26]. Such complex models can improve the system exceedingly as long as the related challenges are handled properly.

After collecting the required contextual information from various dimensions in the first phase, the recommendations are made based on the extracted CS from the work environment. It could be judicious to follow the RS classic methods before heading towards the modern approaches based on NN [41]. The key idea is to consider CS as user contemporary profiles (rather than static profiles in content-based methods) and dynamically annotate the recommendation candidates regarding all the mentioned dimensions. The candidates can be sorted afterward based on the similarity between the annotation multi-dimensional vectors and CS during each session. The CF method can be also used with an innovative approach: Instead of a user-item interaction matrix which is the core of CF methods, a CS-items matrix can be formed to measure the relevance of items for each situation based on the similarity among CS assuming that if a user (let's say U) in a situation similar to some other situation (S) in which other people (P) were in the past, U is likely to find the items that P have viewed in S interesting.

## 4. Conclusion and Outlook

The contribution of this study is to present the potential strength of CARS for enhancing personal assistants to support the KW by providing them with useful recommendations based on their current information needs in every situation. Although the knowledge management domain is a pretty new direction for RS, it has been tried to provide a comprehensive literature study containing a considerable number of related researches that share the key characteristics. Then, holding the view that information collection is the first and principal phase of RS, the idea of CS has been introduced as multi-dimensional sessions through which all the required contextual information for recognizing the user's needs is considered. The very first steps of developing the next-generation RS have been taken by briefly discussing two approaches for using CS motivated by classic RS methods. The next step is to provide a practical model using CS coupled with the approaches proposed in the three discussed category of RS to overcome the existing challenges mainly emerged from the necessity of handling heterogeneous items with complex relationships (by leveraging KG-based RS) and capturing short-term dynamic needs of the KW (using sequential and session-based RS) in addition to general long-term preferences.

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