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Towards a Viewpoint of Context-Aware Recommender Systems (CARS) and Services

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***Abstract*— Recommender Systems have been/are being researched and deployed extensively in various disciplines such as tourism and education. Most traditional recommender systems such as *Collaborative Filtering (CF)* and *Content-Based Filtering (CBF)* generate recommendations by using two main attributes, namely; users and items i.e. recommendations are generated based on a user having an interest or preference of a particular item resource. It has however been recently realized by researchers that it is important to incorporate context as part of a recommendation process in order to generate accurate and efficient recommendations for users of a particular system. Context such as location, time, activity, physical conditions, social interaction etc. according to research are very important and can be used in addition to users and items to generate trustworthy and accurate recommendation. Location and time context for examples are important in mobile computing recommendations, due to the fact that a user may require a recommendation at a particular location in a particular time. Such scenarios have introduced *Context-Aware Recommender Systems (CARS)* for further open research issues and challenges. This paper initially presents Background of *CARS*, specifically from the perspective of context types, context modeling architectures and algorithms. Furthermore, the paper, presents an overview of the state-of-the-art research in the area of *CARS*, and finally discusses relevant open issues of *CARS*.**

***Index Terms*— Context-Awareness, Context-Aware Recommender Systems (CARS), Context and Services**

I. INTRODUCTION

THE importance of contextual information has been recognized by researchers and practitioners in many disciplines, including e-commerce personalization, information retrieval, ubiquitous and mobile computing, data mining, marketing, technology enhanced learning and management [1]-[6]. While a substantial amount of research has already been performed in the area of recommender systems, most existing approaches focus on recommending the most relevant items to users without taking into account any additional contextual information, such as time, location, or the company of other people (e.g., recommendations for watching videos/films/movies or dining out) [1]-[6]. Recommender systems have been researched and deployed extensively over the last decade in various application areas, including e-commerce and e-learning. Several recommendation algorithms, such as *Content-Based Filtering (CBF)* [7]-[9], collaborative filtering [8]-[12], knowledge-based filtering [13]-[15] and hybrid recommendations [8], [9], [16] are widely discussed in the literature and in several surveys of the state-of-the-art [6], [11]. In [1]-[6] the authors argue that relevant contextual information does matter in recommender systems and that it is important to take contextual information into account when providing or generating recommendations. According to [2], recommender systems for Technology Enhanced Learning (TEL) try to address these challenges - i.e. they attempt to filter content for different learning settings which involve different contexts [2]. The majority of existing approaches to recommender systems focuses on recommending the most relevant items to individual users. In other words, traditional recommender systems deal with applications having only two types of entities, users and items, and do not put them into a context when providing recommendations [1]-[6]. However, in many applications, such as recommending a holiday package, personalized content on a web site, or an academic video for a mobile learner, it may not be sufficient to consider only users and items – it is also important to incorporate the contextual information into the recommendation process in order to recommend items to users under certain *circumstances* [1]-[6]. For example in [17], the authors used a combination of social affinity information and spatio-temporal context of users and historical responses, to further refine a set of recommendations and to decide when a recommendation would be sent [17]. Another example observed by [1] involved a travel recommender system that provides a vacation recommendation in the winter can be very different from a recommendation in the summer because of location and weather contexts [1].

Among others, and due to the advancements of network and mobile services and the growing tool and device landscape, the notion of context has started to attract significant attention in this research, as indicated by contributions to a recent special issue on context-aware recommender systems [5]. From an operational perspective, context is often defined as an aggregate of various categories that describe the setting in which a recommender is deployed, such as the location, current activity and available time of the user [2]. Similarly, in the case of personalized content delivery on a web site for a user/customer, it is important to determine what content needs to be delivered (recommended) to a user/customer and when [1]. More specifically, on weekdays a user might prefer to watch world news (e.g., CNN or BBC) on TV when he/she logs on to the TV in the morning and the stock market report on weekends, and on weekdays to watch film/movie reviews and do shopping [1]. According to [1], [6], such recommendation observations are consistent with the findings in behavioral research on consumer decision making in marketing that have established that decision making, rather than being invariant, is contingent on the context of decision making.

Therefore, accurate prediction of consumer preferences certainly depends upon the degree to which the recommender system has incorporated the relevant contextual information into a recommendation method [1]. The main contribution of this paper is to outline the state-of-the-art of research and open research issues in the area of context-aware services and recommender systems, specifically from the perspective of context types, context modeling architectures and algorithms. The rest of the paper is structured and organized as follows: Section II presents a Background of Context-Aware Recommender Systems, Section III discusses Existing Research, Section IV elaborates on relevant Open Issues of Context-Aware Recommender Systems and Section V finally concludes the paper.

II. BACKGROUND OF CONTEXT-AWARE RECOMMENDER SYSTEM (CARS)

A. Definition of Context

Dey et al. [18], one of the most cited definitions of context, defines context as *"any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves*". The definition by Dey et al. [18] has been used comprehensively within various application domains, including researchers in Technology Enhanced Learning (TEL) [2], [19], [20]. Dourish [21] advocates that context has a dual origin: (1) social science based and (ii) technical. From a social science viewpoint, Dourish argues that context isn't something that describes a setting or situation but rather a feature of interaction. From a technical viewpoint, according to Dourish [21], context needs to be defined in a more specific through an operational term [22].

In order to operationalize context from a technical viewpoint, researchers including Schilit et al. [23] and Adomavicius and Tuzhilin [1] have attempted to define context in different ways by enumerating different categories. Adomavicius and Tuzhilin [1] argue that context is a multifaceted concept that has been studied across different research disciplines, including computer science (primarily in artificial intelligence and ubiquitous computing), cognitive science, linguistics, philosophy, psychology, and organizational sciences. Adomavicius and Tuzhilin [1] further discuss that since context has been studied in multiple disciplines, each discipline tends to take its own idiosyncratic view that is somewhat different from other disciplines and is more specific than the standard generic dictionary definition of context as "conditions or circumstances which affect something".

B. Categories and Types of Context

A previous work by Schilit et al. [23] divided context into three different types and categories, namely: *Computing Context*, *User Context* and *Physical Context*. *Physical Context* includes: *lighting*, *traffic conditions*, and *temperature*, *weather* and *noise levels*. *User Context* is made up of: *location*, *user*, *social affinity*, *social situation* and *people nearby*. *Computing Context* consists of *network connectivity*, *communication costs*, *communication bandwidth* and nearby resources such as *workstations*, *printers* and *scanners*. Chen and Kotz [25] realized the importance of *time* as a context category and Schmidt et al. [26] added *task* category comprising of: *user*, *tasks*, *location*, *infrastructure*, *physical conditions* and *time*. Zimmermann et al. [27] listed: *activity*, *location*, *individuality*, *time*, *location* and *relations* as basic context categories. According to Zimmermann et al. [27], individuality context is subdivided into four elements, namely: *human entity*, *artificial entity*, *natural entity* and *group entity*.

C. Context in Recommender Systems

Adomavicius and Tuzhilin [1] emphasize on the fact that since the general concept of context is very broad, the focus of context should be directly related recommender system fields such as data mining, e-commerce personalization, databases, information retrieval, ubiquitous and mobile context-aware systems, marketing, and management. The need to define and model a context in recommender systems through a consistent way or procedure has been identified by several researchers [1]-[5], [17], [24], [28], [29]. According to Verbert et al. [2], a precise definition and model of context can facilitate the identification of what does and what doesn't constitute context and can enable reuse and exchange of contextual data across applications. Descriptions of various context categories and types applicable in recommender systems are elaborated below:

1) Physical Conditions: The physical condition context describes the environmental situations of the user or the system at a particular location. Physical conditions context commonly includes attributes such as light, heat and sound. According to Verbert et al. [2], physical conditions context has been researched extensively in home automation research, however its' use in TEL is limited.

2) Computing: Computing context has been researched extensively by Ricci [4] and the pervasive and mobile learning research community [30]. Computing context characteristics can be classified into the following:

- *Hardware:* is made up of input and output capabilities of devices, storage (RAM, hard disk) and CPU capabilities etc.
- *Software:* describes whether the delivery context supports certain document formats, Application Program Interfaces (APIs) and Operating Systems etc.
- *Network:* Network comprises of the availability of appropriate bandwidth, coupled with static and dynamic

properties of the network that is being used by the recommender system. It is important to acquire the necessary computing context to support intelligent interfaces that can select and recommend suitable resources of a recommender system.

3) Location: Location context has dominated in the research of context-aware mobile computing to a large extent [4], [26], [31]-[34]. Different models of location have been proposed and implemented to capture geographic and human-readable information about objects, which include devices, persons and relationships between objects [1], [2]. The models include: (1) Orientation that can for example indicate which display device a user is looking for, (2) proximity of objects within space and lastly (3) communicative ability. An example is location contexts such as classroom, home and outdoor, that are often referenced by a learning application [2], [35], [36], [37].

4) Time: Time context comprises of date and time information that usually involves minutes, hours, weeks, months, semester, quarter of a year etc. Time is often and usually combined and used in conjunction with other context categories such as location, either as a time span or timestamp. Time context indicates an instance or period during which contextual information is needed, known or relevant to the user of the recommender system [2], [18].

5) User: The person who makes use of a recommender system or who recommendation resources are generated for is classified as a user. For example users in electronic learning (e-learning) are e-learners and would require a learning model in order to generate accurate and trustworthy recommendations. According to [2], learning models have been researched extensively in educational adaptive hypermedia and the educational modeling research areas. The user context of an appropriate recommender system framework for TEL, according to [2] and [79] comprise of basic personal information of the learner, knowledge/performance of the learner, learner interests, learning goals, learning and cognitive styles of the learner and learner's background.

6) Social Relations: Social relations describe social circles, associations, connections, affiliation and affinity between two or more persons. For example, social relations can be information about friends, neutral persons, neighbours, co-workers, enemies and relatives. Other researchers have identified community as an important context dimension [2].

7) Activity: The activity context depicts the tasks, objectives and actions of the recommender system user. For instance, in the scenario example used in Ramaswamy [17] replicates the fact that the user (Ram) who is interested in the restaurant would like to actively recommend the restaurant to his friend within his social circle or association context.

D. Context Sensors and Acquiring Contextual Information

According to Adomavicius and Tuzhilin [1] and Verbert et al. [2], contextual information can be obtained in a number of ways, including:

Explicit: The explicit procedure involves directly approaching relevant people and other sources of contextual information and explicitly gathering this information either by asking direct questions or eliciting information through other means. For example, an Electronic Learning Management System (eLMS) may obtain contextual information by asking the e-learner to fill out an interactive eLMS form or to answer some specific questions before he/she will be provided access to certain pages of the LMS.

Implicit: The implicit procedure involves observing user behaviour, relevant data or the environment. An example is a change in location of the user detected by a telecommunication company. Alternatively, temporal contextual information can be implicitly obtained from the timestamp of a transaction. In the cases of implicitly acquiring information, nothing needs to be done in terms of interacting with the user or other sources of contextual information – the source of the implicit contextual information is accessed directly and the data is extracted from it.

Inferring: The inferring procedure involves acquiring the context using statistical or data mining methods. For instance, the household identity of a person flipping the satellite video channels (husband, wife, son, daughter, etc.) may not be explicitly known to a satellite company; but it can be inferred with reasonable accuracy by observing the satellite video programs watched.

Context for recommendations are usually acquired through different context sensors. These context sensors are briefly explained below:

1) Location Context: Location context is often sensed through implicit procedures coupled with Location Based Services (LBS). Examples of these sensors include Global Positioning System (GPS) or Wireless Fidelity (Wi-Fi) locations sensors or sometimes a combination of both. Location-awareness through LBS is the procedure of discovering and knowing the user's physical position at a particular time. Such discovery and knowledge can be exploited as an important source of information to adapt the information delivered by the system and hence influence the generation of a recommendation. Location context is required in environments such as museums and tourist sites. In museum environment, precise and accurate description of the location is required to identify the object that is closest to the user. Some other systems that require accurate location information often rely on explicit methods, described above. Such explicit methods require the user to scan and RFID (Radio Frequency Identification) a tag [38]. TenseITS in Cui and Bull [39] relies on an explicit procedure where by a user is asked to input the location type, such as university, town, transportation or home.

2) Computing Context: Computing context is sensed implicitly by the surveyed systems [2]. Information about the computing device is often transmitted by including the identifier of the device in the Hyper Text Transfer Protocol (HTTP) request [40]. This identifier of the computing device is then used to retrieve relevant information about the device from a source of computing device profiles. Alternatively, if no information about the computing device is available in the source, information such as screen size and processing speed are sometimes captured in the request header [2], [41], [42].

3) Time Context: Time interval data, such as available study time, is entered explicitly in work of Cui and Bull [39], Berri et al. [41] and Schmidt [19]. In Yau and Moy [44], a learning schedule is used that enables users to explicitly enter such data in a schedule that they can use to plan their learning activities [2]. In most/all cases timestamp data is captured implicitly.

4) Physical Conditions Context: The physical conditions context is usually captured implicitly from the environment or explicitly from the user. The current prototypes available usually implement noise level indicators. Systems such as Yau and Moy [44] use a microphone to automate physical context acquisition. Cui and Bull [39] for example, rely on manual input to acquire contextual information from the user.

5) Activity Context: To acquire activity context, many recommender system rely on explicit procedure of user interactions to capture information. These user interactions could involve manual text input, scanning or RFID tagging [2]. In TEL recommender systems such as the ones in Schirru et al. [45] and Stern et al. [46], the activity context of a learner is inferred with tools and resources such as classification algorithms based on a task model created by an expert.

6) User Context: Depending on the type of information at stake and the type of recommender system, information about a user is captured in different way. Interests of a user are captured explicitly through rating modules or registration or implicitly through interactions and behaviour of the user with the system or sometimes a combination of explicit and implicit methodologies/approaches.

7) Social Relation Context: According to [2], in order to capture the context of social relations, explicit procedures are employed through a manual representation of a group structure [47] or the organization in corporate environments [48]. On the other hand, in order to capture context of social relations implicitly, the data from the recommender system is used.

E. Modeling Contextual Information in Recommender Systems

Recommender systems begun as an independent research area in the mid-1990s, when researchers and practitioners started focusing on recommendation problems that explicitly rely on the notion of ratings as a way to capture user interests and preferences for different items [1]. For example, in a case of a music recommender system, Dennis Coleman may assign a rating of 6 (out of 10) for the music “Viva Forever,” i.e., set R_{music}(Dennis Coleman, Viva Forever)=6.

The recommendation process typically starts with the specification of the initial set of ratings that is either explicitly provided by the users or is implicitly inferred by the system [1-5], [17], [28], [29].

Once these initial ratings are specified, a recommender system tries to estimate the rating function *R*,

R: User×Item→Rating, for the (user, item) pairs that have not been rated yet by the users. The rating in the above function is a totally ordered set (e.g., non-negative integers or real numbers within a certain range), and User and Item are the domains of users and items respectively. Once the function *R* is estimated for the whole *User* × *Item* space, a recommender system can recommend the highest-rated item (or k highest-rated items) for each user [1], [6], [8], [9].

According to [1], such systems are called traditional or two-dimensional (2D) since they consider only the User and Item dimensions in the recommendation process. The estimation of ratings for recommender systems is usually based on the ratings given by this user to other items, ratings given to this item by other users, and possibly on some other information as well (e.g., user demographics, item characteristics). Adomavicius and Tuzhilin [1], however noted that, while a substantial amount of research has been performed in the area of recommender systems through users and items, it is very important, relevant and imperative to explore the area of Context-Aware Recommender Systems (CARS), which deal with modeling and predicting user tastes and preferences by incorporating available contextual information into the recommendation process as additional explicit and implicit categories of data [1]-[6], [17], [28], [29]. These long-term preferences and tastes are usually expressed as ratings and are modeled as the function of not only items and users, but also of the context. Therefore, ratings are defined with the rating function as *R: User×Item×Context→Rating*, where User and Item are the domains of Users and Items respectively, Rating is the domain of Ratings, and Context specifies the contextual information associated with the application [1], [3].

To exemplify these concepts, an example in accordance to [1] is elaborated below. Consider the application for recommending films to users, where users and films are described as relations having the following attributes:

Film: The set of all the films that can be recommended; it is defined as **Film** (FilmID, Title, Cast, Length, Release Year, Director, Genre).

User: The people to who films are recommended; it is defined as **User** (UserID, Name, Address, Age, Gender, Profession).

Additionally, the contextual information consists of the following three categories below that are also defined as relations having the following attributes:

Cinema: The cinema that will show/broadcast the film; it is defined as **Cinema** (CinemaID, Name, Address, Capacity, City, State, Country).

Time: The time when the film can be or has been watched; it is defined as **Time** (Date, Day-of-Week, Time-of-Week, Month, Quarter, Year). In such a scenario the attribute Day-of-Week has values Mon, Tue, Wed, Thu, Fri, Sat, Sun, and attribute Time-of-Week has values “Weekday” and “Weekend”.

Companion: Companion represents a person or a group of persons with whom the user can watch the film. It is defined as **Companion** (companionType), where the attribute CompanionType has values “alone”, “family”, “girlfriend/boyfriend”, “friends”, “co-workers”, and “others”.

The ratings that are therefore assigned to a film by a person also depends on where and how the film has been watched, with whom, and at what time. For example, the type of film to recommend to university student Jacqueline Brooks can differ significantly depending on whether she is planning to watch it on a Sunday night with her family or on a Friday night with her boyfriend [1], [3].

F. *Algorithms in CARS*

Algorithms for CARS are classified into three main categories, namely: contextual modeling, contextual pre-filtering and contextual post-filtering. The contextual modeling approach of systems uses contextual information *directly* in the recommendation function as an explicit predictor of a user's rating for an item. The contextual modeling approach gives rise to truly multidimensional recommendation functions, which principally represent predictive models that are built using probabilistic models, regression, decision trees or other techniques or heuristic calculations that incorporate contextual information in addition to the user and item data, i.e., *Rating* = *R* (*User, Item, Context*). In the contextual pre-filtering algorithm scenario, information drives data selection or data construction for that specific context. In other words, information about the current context *c* is used for selecting or constructing the relevant set of data records (i.e., ratings). Then, ratings can be predicted using any traditional 2D recommender system on the selected data [1]-[3].

In the contextual post-filtering algorithm scenario, contextual information is initially ignored, and the ratings are predicted using any traditional 2D recommender system on the *entire* data, then the resulting set of recommendations is adjusted (*contextualized*) for each user using the contextual information [1], [6].The three paradigms for context-aware recommender systems (contextual modeling, pre-filtering and post-filtering) offer several different opportunities for employing combined approaches just like combination of other traditional recommender systems [8], [9], [11], [12], [16]. One possibility is to develop and combine several models of the same type. For example, Adomavicius et al. [3] followed this approach to develop a technique that combines information from several different contextual pre-filters.

III. CONTEXT-AWARE SERVICES AND RECOMMENDER SYSTEMS

A. *Context-Aware Services*

For a number of years the Information and Communication Technology (ICT) industry has been motivated by the forecasts of both mobile and ubiquitous computing. Mobile devices such as laptops, notebooks, Personal Digital Assistant (PDAs), smart phones have really freed individuals from the technological restraints of non-portable PCs such as desktops [49]. One of the most appealing aspects of mobile computing is the innovations of performing different functions in different locations Figure 1. Mobile device users may now choose to use social online networking sites for communication, exchange e-mails, use mobile multimedia such as audio and video, access business proposal, electronically submit and buy product orders, track shipments online and interact with coworkers in real-time from home or a distant site such as the beach, at the train station, bus station etc. and in many other locations. Figure 1 depicts the scenario of mobile devices being used for different functions in different contextual locations to provide services.

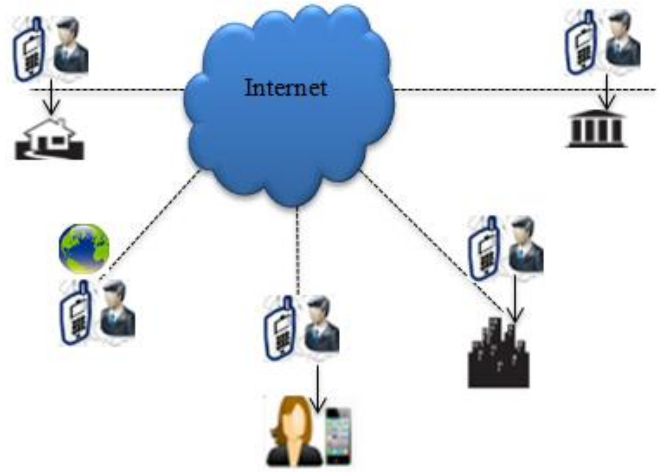

Fig. 1: Mobile Computing Innovates Functions from Different Locations

Not very long ago, these functions pertained with mobile device usage were performed at workstations and desktop PCs in fixed locations. This innovation would not be possible without near-ubiquitous internet communications. Certain mobile computing applications have taken advantage of changing user location. For example, geospatial databases through Location Based Services (LBS) are now consistently used to answer interrogations for the "nearest Bank of a customer", "directions to the airport/bus station/train station" and many others. Mobile computing context-aware services take advantage of information about current location that is available to the mobile application—mostly from sensors reacting to local wireless network towers or satellite signals [1], [4], [49].

1) Becoming Context-Aware

Information about the current location for a mobile user (or more correctly about the device being used) is an example of information taken from the physical "context" of that user and his device [1], [2], [4], [49].

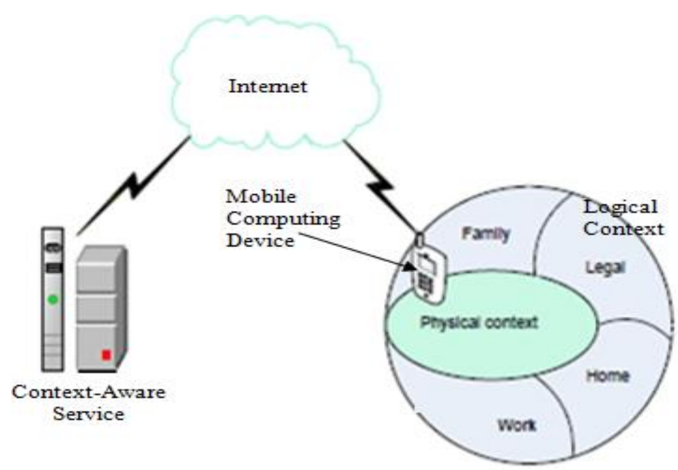

Fig. 2: Mobile Computing Device User Context

Figure 2 below depicts a Mobile Computing Device User Context. Recent trends in mobile computing are extending this concept of context to include many other facets of the user's physical environment. Mobile computing device characteristics, such as screen size, communications capabilities, keyboard configuration, accelerometers, satellite sensors, network identity and many others are being added to more accurately characterize the physical and computing context within which applications are being used [2], [49]. In more general terms, according to Jones [49] "context" may refer to any aspect of the situation within which an entity (person, place, or computational object) may invoke computational functionality.

As shown in Figure 2, any given context may comprise information about the physical world (location, movement, device characteristics, and so on) and about the logical domain neighboring the service consumer. This logical world contains information about personality, preferences of users, and relationships in different domains, such as friends, work, family, and others. Even historic information about any of these features might be incorporated. For example, work address might be contained in the service consumer's logical context. It is possible to collect contextual data about the physical world in real-time from detective sensors available in modern mobile devices, such as a smart phone or PDA.

The necessary contextual information about the logical world is however collected directly from the mobile device users/participants or gathered from interactions and communications the user has made with service providers. Whatever the nature of such information, context may come from different ways and has a relatively temporary lifetime. Context-Aware Services have been studied with example such event navigation [50], tourist guidance [51], [52] and context-aware messaging such as W-MAIL [53], GeoNotes [54], and E-graffiti [55].

B. Context-Aware Recommender Systems (CARS)

Several contextual recommender systems have been researched and developed to use contextual paradigms in various application domains. Examples include context-aware recommender systems that suggest gas stations to a driver of a car [56], contextualized media delivery systems [57], [58] and intelligent tourist guides [1]. For example, COMPASS [59] is a mobile multimedia recommender system that uses a *context-driven querying and search* approach to provide a tourist with information about nearby monuments, hotels and people. The evaluation experiment in [59] used time and location to contextualize and generate recommendations. Amusingly, the authors in [59] report that 'last time visited' had a negative influence on the perceived usefulness of the system. These results illustrate that careful analysis of data that is taken into account is necessary when deploying contextualization algorithms [1], [2], [4], [59]. Context-aware computing is becoming a wide research area and recently is gaining more and more attention in recommender systems [1]-[6], [56]-[59]. In order to generate effective and accurate recommendations, context –dependent techniques are most of the time combined with traditional recommender systems such as Collaborative Filtering (CF). For instance, Adomavicius et al. [6] elaborate on a search procedure performed to identify the segments of contextually tagged ratings that must be considered when a CF based prediction is computed for a particular context-dependent target situation.

The idea of using the location of the user to tune the user-to-user similarity function has also been exploited by Horozov et al. [60]. The restaurant recommender system in "*Geowhiz"* assumes that people who live in the same neighborhood are likely to visit the same nearby places. Hence, since people can be correlated in CF only if they have co-rated items, they [60] infer that there is a higher probability of correlating people who live close to each other than correlating people who live further apart.

Ramaswamy et al. [17] presented a social network-based recommender system that has been explicitly designed to work even with devices that just support phone calls and SMS. The design of the social network based recommender system incorporates three features that complement each other to derive highly targeted advertisements, namely: social affinity, spatio-temporal context and social affinity computation with spatio-temporal contextual association.

Yong et al. [61] proposed a personalized recommendation scheme which considers the activities of the user at runtime and the information on the environment around the user. The proposed system in Yong et al. [61] allows efficient operation in mobile device, and interoperability between the TV multimedia metadata and ontology. The accuracy of the proposed scheme in was evaluated by an experiment, which reveals a significant improvement compared to the existing schemes.

The large amounts of multimedia contents often cause the problem of information overload. To tackle this problem, it is necessary to develop personalization techniques to recommend most suitable contents to users. Kao-Li et al. [62], therefore develop a new social tag-based method for the recommendation of multimedia items, and compare it with several often-used methods. A context-aware platform is also implemented that takes into account different environment situations in order to make the most sensible recommendations in [62].

Lu et al. [63] presented a context-awareness multi-agent-based mobile educational game that can generate a series of learning activities for users doing On-the-Job training and make users interact with specific objects in their working environment. Lu et al. [63] revealed Multi-Agent Architecture (MAA) into the mobile educational game design to achieve the goals of developing a lightweight, flexible, and scalable game on the platform with limited resources such as mobile phones.

In Said [64], research involving context identification and the concepts related to hybrid and context-aware systems was presented. Furthermore, a conceptual architecture for a context-aware recommender system for movies and TV shows was introduced. The system consists of a number of processes for context identification and recommendation. The main focus of the research in was the identification of context, which in turn is used for recommendation. The approach in [64] was incorporated and evaluated in the recommendation engine of movie recommendation web-site Moviepilot.

Eliciting requirements on-site is challenging as analysts have to simultaneously observe the environment, interact with people and operate Requirements Engineering (RE) tools. Seyff et al. [65] explored the use of context-aware technologies to provide better guidance and support for on-site analysts. The context-aware Mobile Scenario Presenter tool in [65] guides analysts by automatically highlighting scenario events relevant to the currently observed work task.

The study in [66] describes the project SNOPS, a smart-city environment based on Future Internet Technologies. The authors focused on the context-aware recommendation services provided in the platform, which accommodates location dependent multimedia information with user's needs in a mobile environment related to an outdoor scenario within the Cultural Heritage domain. In particular they describe a recommendation strategy for planning browsing activities, exploiting objects features, users' behaviors and context information gathered by apposite sensor networks. Preliminary experimental results, related to user's satisfaction, have been carried out and discussed.

TABLE I
SOME EXISTING AND RELATED WORK IN CONTEXT-AWARE RECOMMENDER SYSTEMS (CARS)

		Possible Context Sensors						
Existing Research and Related Work	Recommender System	L	T	C	PC	A	SR	U
Amato et al. [66]	CARS	√		√	√	√		√
Bader et al. [56]	CARS	√	√	√				√
Boutemedjet et al. [67]	CBF and CARS	√	√	√	√			√
Cui and Bull [39]	CARS	√	√		√		√	√
Elahi [70]	CBF and CARS			√			√	√
Horozov et al. [60]	CF and CARS	√	√		√		√	√
Kao-Li et al. [62]	CF and CARS				√	√	√	√
Park et al. [58]	CARS	√	√	√				√
Petersen et al. [47]	CF and CBF	√		√			√	√
Ramaswamy et al. [17]	CF and CBF	√		√		√	√	√
Rendle et al.[71]	CARS	√	√	√		√		√
Said [64]	CARS	√	√	√	√			√
Schirru et al. [45]	CARS	√		√	√	√		√
Setten et al. [59]	CARS	√	√	√	√	√		√
Seyff et al. [65]	CARS	√	√	√	√			√
Stern et al. [46]	CARS	√		√		√		√
Woerndl et al. [69]	CF and CARS	√	√	√	√			√
Yau and Joy [44]	CARS		√	√	√			√
Yong, et al. [61]	CARS	√	√	√	√			√
Yu et al. [57]	CARS	√	√	√				√

(CF – Collaborative Filtering, CBF – Content-Based Filtering, KBF – Knowledge-Based Filtering and CARS – Context-Aware Recommender System, L- Location, T-Time, C-Computing, PC-Physical Conditions, A-Activity, SR-Social Relations, U- User)

Boutemedjet et al. [67] proposed a new framework for context-aware recommendation of visual documents by modeling the user needs, the context and also the visual document collection together in a unified model. Boutemedjet et al. [67] also addressed the user's need for diversified recommendations. Their pilot study in showed the merits of their approach in content based image retrieval.

Verbert et al. [2] presented a context framework that identifies relevant context dimensions for TEL applications and elaborated an analysis of existing TEL recommender systems along these dimensions.

Adomavicius and Tuzhilin [1] introduced three different algorithmic paradigms: contextual pre-filtering, post-filtering, and modeling – for incorporating contextual information into a recommendation process and discuss the possibilities of combining several context-aware recommendation techniques into a single unifying approach using a case study.

Lima et al. [68] presented a recommendation system approach for information systems based on user behavior and information context in which the users are located. The recommendation system in [68] has been defined and deployed through filtering processes (content-based, collaborative and hybrid). The behavior is defined by the events and the actions that comprise the user activities. The experimental results in [68] indicated that: (i) a more dynamic and autonomic mechanism for authenticating users in a pervasive mobile environment, and (ii) an efficiency improvement is needed in detecting anomalies on authentication by using a similarity model and space-time permutation.

Woerndl et al. [69] presented a model for proactivity in mobile recommender systems. The model in [69] relies on domain-dependent context modeling in several categories. The recommendation process is divided into two phases to first analyze the current situation and then examine the suitability of particular items. Woerndl et al. [69] implemented a prototype gas station recommender and conducted a survey for evaluation. Results showed good correlation of the output of the system in [69] with the assessment of users regarding the question on when to generate recommendations.

Elahi [70] presented a demo on a context-aware recommendation system. The system in [70] mines data from user's web searches and other sources to improve the presentation of content on visited web pages. While user is browsing the internet, a memory resident agent records and analyzes the content of the webpages that were either searched for or visited in order to identify topic preferences. Then, based on such information, the content of requested web page is ranked and classified with different styles. The demo in [70] shows how a music weblog can be modified automatically based on user's affinities.

Rendle et al. [71] proposed to apply Factorization Machines (FMs) to model contextual information and to provide context-aware rating predictions. This approach in [71] resulted in fast context-aware recommendations because the model equation of FMs can be computed in linear time both in the number of context variables and the factorization size. For learning FMs, Rendle et al. [71] developed an iterative optimization method that analytically finds the least-square solution for one parameter given the other ones.

IV. DISCUSSION AND OPEN ISSUES

A research major issue for the successful design of CARSs is the discovery of the contextual factors that are worth considering when generating and predicting recommendations. Such a problem is not easy to solve. It requires formulating informed estimations about the influence of certain factors before collecting data in naturalistic environments [72]. It is a kind of active learning problem, where the significance of the data to acquire must be estimated to minimize the cost of the real data acquisition phase [73]. The procedures researchers will use to estimate the relevance of contextual factors is the initial open research issue of building CARSs.

After a meaningful set of contextual conditions are identified, a predictive model that can predict how the evaluation of an item changes as a function of the contextual factors must be further researched and developed. This model is then used to select items given a target context. This step requires the collection and utilization of explicit ratings for items under several distinct contextual conditions. The acquisition of a representative sample of in-context item ratings is another issue [72], [74].

After the model is developed, a complete context-aware recommender system can be produced. By virtue of this scenario, a complete human–computer interaction layer can be designed and implemented on top of the core predictive model [72]. The user should be able to query the system for recommendations, specifying preferences and contextual conditions, and should receive useful suggestions that will be actually acted on [75]. Furthermore, in a mobile event guide application, for example, the user may request recommendations adapted to a precise conference/meeting, a specific conference/meeting location, and the fact that he/she has research/academic interests in Artificial Intelligence Conferences/Symposiums/Workshops. Computing good, trustworthy and efficient recommendations on the basis of a given predictive contextual model is also an open issue of CARSs.

Furthermore, the system must adapt the recommendations to this request and provide an effective visualization of the recommendations, including useful item descriptions and recommendation explanations [76]-[78]. Visualization and related problems for the user interface are also open research issues for CARSs.

Additionally, it is also very important to develop simple, friendly, and expressive User Interfaces (UIs) for supporting flexible but sometimes complex contextual recommendations [1]. High-quality UIs should reduce the complexity and simplify interactions between the end-users and the recommender system and make them available to wider audiences. Developing such UIs constitutes a topic of future research [1]. Other open research issues and challenges of CARS, include: Evaluation challenges, Dataset sharing challenges, Privacy challenges and Interaction challenges [2].

V. CONCLUSION

Recommender Systems since the 1990s have been very important and useful tools for filtering relevant information needs of users in domains such as education, entertainment, restaurant activities, tourism activities as well as museum activities. Recommender Systems literature however shows that individual recommender systems such as *CF* and *CBF*, recommend to users through user interests/ratings and items only. Recent research and development in Recommender Systems has delved into the fact that contextual information is relevant and important in generating recommendations in certain *circumstances* such as mobility and ubiquity. Through relevant literature, this paper therefore delved into a viewpoint of *CARS* Research specifically from the perspective of context types, context modeling architectures and algorithms as well as the existing research and ascertained for a fact that context indeed is important and relevant for recommender systems and should be adopted when a system is generating recommendations. There are however some open research issues and challenges that have been enumerated in Section IV of this paper, that still need to be tackled in order to gain more accurate, trustworthy and efficient recommendation through relevant CARS.

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