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上下文感知推荐系统：挑战和机遇

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【摘要】该文梳理了社会和科学领域中上下文感知推荐系统的主要概念、技术、挑战和未来趋势；其次，分类介绍了可用于基于上下文的推荐的一系列技术和主要框架。除了经典的基于内容、基于协同过滤和基于矩阵分解的技术之外，调研了最近的研究方向，即基于深度学习和基于模糊逻辑的方法。最后，描述了在推荐过程中利用上下文信息的潜在研究机会。

关　键　词　推荐系统；上下文感知；上下文获取；上下文整合

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Context-Aware Recommender Systems: Challenges and Opportunities

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Abstract In this review, we attempt to highlight major concepts, techniques, challenges and future trends of context-aware recommender systems in social and scientific domains. The primary objective of this paper is to sum up the most recent developments in this rich knowledge area. A set of techniques and major frameworks available for context-based recommender systems are classified and introduced. Along with classical content-based, collaborative filtering and matrix factorization based techniques, we investigate the most recent research areas, i.e., deep learning and fuzzy logic based methodologies. Finally, we close by portraying potential future research opportunities with respect to utilizing context information in recommendation process.

Key words　recommender systems;　context-aware;　context elicitation;　context integration

1　Introduction

The massive adoption of the internet has caused the exponential growth of products and services on the World Wide Web. Now, an individual consumer has been indulged into this leisure of service and is allowed to make reasonable choices saving time and money. Companies such as Amazon, Taobao, Jingdong, and Netflix have to face considerable competition, and they are looking for technology-aided ways to increase revenue and customer satisfaction. Most of the commercial objectives are to target the right products or services for an individual consumer and this has introduced a new field full of challenges, i.e., personalized recommendation. Recommender systems are designed to provide personalized recommendations. In other words, they are the filtering engines that aggregate opinions to help decision-making processes. They are used so broadly as to bring a considerable influence on the daily life of almost everyone in different domains such as social media, public health, e-commerce, education, advertisement and entertainment, etc. The efficient generation of relevant recommendations in large-scale systems is a very complex task. In order to provide personalized recommendations, these engines and algorithms need to capture users' varying interests and find mostly nonlinear dependencies between them. Enormous data

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sparsity and ambitious real-time requirements make such recommendations challenging in dynamic real-life situations. Context-aware recommender systems come up with an innovative utilization of dynamic context (or situation) information such as user behavior, changing weather conditions, government policies, and cultural habits[1]. It has been proved that additional context information is highly supportive for about all types of recommender systems[2] and it boosts up the recommendation process. To support this claim, we reviewed academic literature published during the last ten years on the three most trusted academic web databases, Google scholar, Web of Science and dblp.org. Trends in Fig. 1 and Fig. 2 shows the continuously increasing interest of researchers in context-aware recommender systems. In this paper, we present an overview of the existing literature in context-aware recommender systems and a brief understanding about the state-of-the-art approaches. We attempt to cover all aspects from the past, present, and future directions of context-aware recommender systems that can act as a benchmark for next-generation researchers to understand this hot domain.

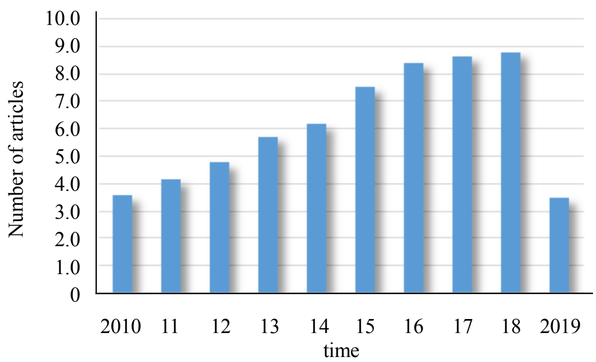

Fig. 1 Year-wise peer review articles as reflected by Google Scholar

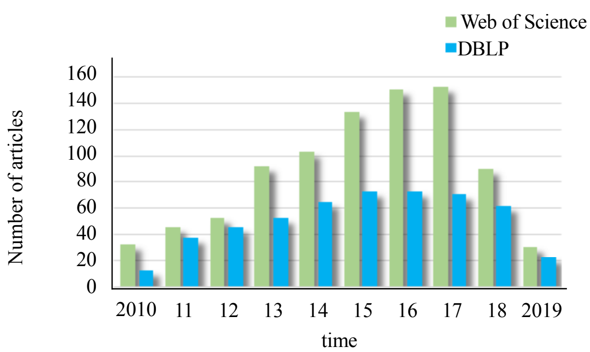

Fig. 2 Year-wise peer review articles as reflected Web of Science and dblp.org

1.1 Background

Context information is a concept that can have different definitions depending on the area where it appears. The most widely used definition was suggested by Ref. [3]: “Context is any information that can be used to characterize the situation of an entity. An entity can be a person, a place, or an object that is considered relevant to the interaction between a user and an application, including the user himself/herself and the applications themselves”. This has been proved in academic literature that correctness of recommendation may highly be affected by context information[4-8]. For example, a customer could be more or less interested in a particular movie depending on the day of the week or the weather condition or the mood he/she has on some specific day. Context information can be static or dynamic. In the case of static context, recommender system assumes that this information is constant over time. For example, the birthday of a user or a festival with the year span. On the other hand, dynamic context means the variating conditions over time, and therefore it is more complex to handle and has a deep impact on the performance of recommender system.

The user context information can be categorized into many types. Most reviewers[2-4], [9-10] categorize context information in five general categories: individual, location, time, activity, and relational. Here, we focus on five general categories of context classification presented in Ref. [11].

Individual context: The context information related to independent entities (e.g., users/items) that have similar features is considered as individual context. The individual context is sub-divided into human, artificial, natural, and groups of entities. Natural context means the natural occurrence of living or non-living entities, i.e. without human involvement. For example, dynamic weather conditions, infusion and user health context etc. are common natural contexts. The human context concerns the user behavior and preferences, for example, user preference related to payment, size, design or quality of product. Artificial context illustrates the attributes that come from human actions, synthetically generated or inferred through some other activities. Finally, the groups of entities context describe common features of any group of objects. For example, categorical detail about shopping stores according to the user's preferences.

Location context: The location context means the location or place associated with an entity, e.g., the city where a specific product is being manufactured or the theater where a specific movie is being inaugurated. It is observed that location context is also sub-classified either as physical (the physical location of a user) or virtual (IP address of a mail server, MAC address of network node).

Time context: Time is another important class of context. It is the information related to the time like cultural seasons of the year, day of the week, starting time of a movie show etc. Time context is sub-classified as definite and indefinite time. The definite time means the time with absolute starting and ending points, while indefinite time context refers vice-versa.

Activity context: The activities that are performed by entities or players involved in recommendation process are considered as activity context. For example, shopping, watching a movie or any other task a user does at a particular time.

Relational context: The relationships that come from different situations in which actors of the system are involved with other objects are considered as relational context. Relational context can be social or functional. Social means interpersonal relations such as affliations or associations while functional refers to the usage of an entity with another entity.

1.2 Data collection

Data collection is an important aspect for writing a quality review article. We conducted a bibliographic search of top ranked conference proceedings and journals. Especially, papers published in IEEE and ACM Transactions and particularly we analyze data from Science Direct, Elsevier, and Springer etc. Fig. 3 represents the overall temporal frequency of the articles selected for this review, while Fig. 4 shows the categorical detail of journal and conference articles selected for this literature review.

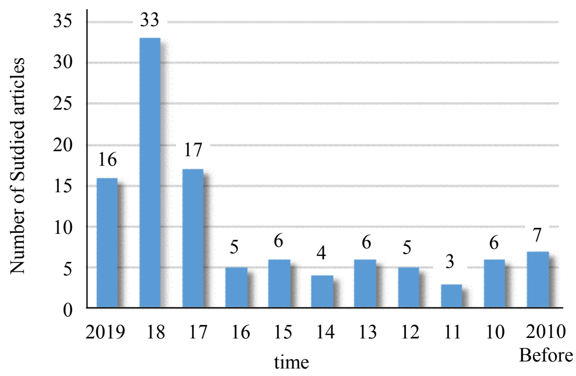

Fig. 3 Overall temporal frequency of selected articles

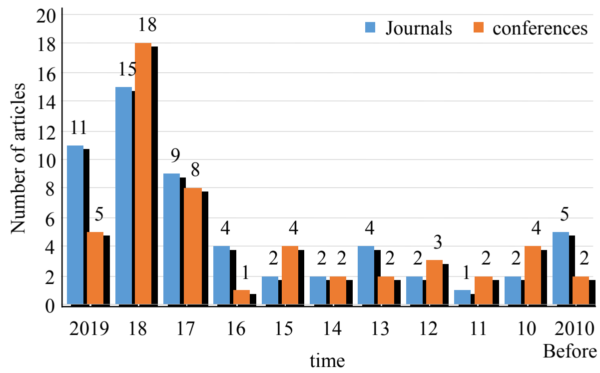

Fig. 4 Categorical detail of journal & conference articles

2 Contributions and Related Work

Context-based recommender systems have more than a decade of history in data mining and data analytics literature. There has been a growing interest of researchers towards context-aware recommender systems over the past few years.

2.1 Related Work

A comprehensive study on context based recommender systems was proposed by Ref. [12] with a multidimensional recommendation model that extends the user-item interaction with contextual data. The proposed methodology is somehow similar to the OLAP-based models widely used in data warehousing applications related to databases. Besides using manual approach to deal with the context relevance, there are some data mining and machine learning algorithms that help us to detect and model contexts automatically. Ref. [13] integrated comprehensive literature on automatic context detection techniques for movie recommender systems. Ref. [12] advised that an expert should suggest some contextual features as a candidate; then, by means of statistical methods the most relevant context should be extracted. For example, they perform a pairwise t-test among candidate features. Karatzoglou *et al*. proposed a tensor factorization based multiverse recommendation model[14]. The model utilizes different type of context as an additional dimension in the representation framework of data in the form of data tensors. Another unique way to get the relevance of a context was suggested in Ref. [15] in which some imaginary contextual preference model should be offered to users to observe the opinion. Then, the users should be asked to respond against these questions, and in this way they collect useful context information. Finally, the authors showed that their system outperformed a recommender system that does not use the context. Similarly, a contextual video recommendation was presented by Ref. [16], they proposed a contextual model based on multi-modal content relevance and user feedback. Reference [17] proposed a model for tweet recommendation that incorporates contextual attributes to improve the recommendation quality. The proposed method outperforms by modeling contextual attributes, such as the tweet topic level, user social relations, authority of the tweet author and the quality of the tweet. A personalized news article recommendation model was proposed in Ref. [18]. This model recommends articles to users based on the accompanying context information, while simultaneously adapting the article selection strategy based on the user click feedback. The contextual recommendation is also prevalent in music recommendation. A study conducted by Ref. [19] performed emotional allocation modeling by characterizing the mood of the user based on the web pages the user visited. This emotional context is used to recommend music to the user. Later on, the emotional context utilization has been a key focus of attention by many researchers in recommendation literature[20-23].

Context information is also predominant in event recommendation due to the availability of many contextual attributes, such as venue, time-of-day, event popularity and geographic distance. Reference [24] considered temporal and spatial context to estimate event attendance. Similarly, Ref. [25] proposed a concept of social event radar, which is basically a bilingual context mining and sentiment analysis summarization system for event prediction in social networks. Reference [26] discussed a brief overview of several factors that impact on user’s event preferences. The study showed that the proposed model can dynamically predict event occurrence for the user in a close environment. Also, they proposed a context-aware approach[27] by exploiting various contextual features (attributes) including social signals based on group memberships, temporal signals derived from the users’ time preferences and location signals based on the users’ geographical preferences. Ref. [28] proposed a social event recommendation method that exploits user's social interaction relations and collaborative friendships. Reference [29] performed group recommendations for events by exploiting matrix factorization to model interactions between users and groups. By considering both implicit patterns (e.g., feedback and profile details) and explicit features (e.g., location and social features), the proposed approach shows significant improved performance for group recommendations.

2.2 Recent Research Trends

More recently, Reference [30] introduced a context-aware advertisement recommendation on twitter through the theory of rough sets. The proposed model analyzes the users’ tweets during timeline by means of interpreting the personal interests of the given user through rough sets. On the same stream, Ref. [31]. presented a brief review of recent developments, processes and future research directions of the context-aware recommender system. Reference [32] presented a comprehensive review of techniques and recent research opportunities in mining user behavioral rules for context-aware intelligent mobile applications. A context-aware reinforcement learning-based mobile cloud computing framework for tele-monitoring was presented in Ref. [33]. The proposed model is capable of finding an optimal action-selection policy by utilizing Q-learning for task scheduler, proficient to determine the most-optimal offloading strategy under the changing operational and environmental conditions. Reference [34] illustrated tourist trip recommendations based on context information. They utilized additional context information in tourism, such as weather, location, or opening/closing hours, etc. They focus on two context factors that are highly relevant when recommending a sequence of POIs: time of the day and previously visited point of interest. Ref. [35] suggested a framework to use context factors for smart self-management of knowledge workers. With this framework, they first devised a scenario to show how such a system could positively contribute to self-management via a set of interventions based on sensor data. Then, they presented an architecture that conceptualizes a context-aware system integrating several data sources along with descriptions of implementation options of such a system. Reference [36] introduced a transfer learning algorithm for context-aware question matching in information-seeking conversations in e-commerce.

Reference [37] introduced a systematic framework for attentive long short-term preference context modeling for personalized product search. The proposed model employs a neural network approach to learn and integrate the long and short term user preferences with the input query for the personalized product search. Specifically, two attention networks were designed to differentiate the features in the short-term as well as in the long-term user preferences. Reference [38] presented a context-aware recommender system by combining community-based knowledge with association rule mining to alleviate the cold start problem. This is basically a hybrid model that combines four key factors: 1) community created knowledge, 2) ontologies, 3) association rule mining, and 4) an innovative scoring function based on probability metrics to handle the cold-start problem in context-aware recommender systems. During the last couple of years, group recommendation systems have gain lot of commercial interest by mega production companies. Ref. [39] introduced a novel context-aware group recommendation for the point-of-interest generation.

Collaborator recommendation is a useful application; it is one of the most popular area of research in academic recommender systems. Reference [40] proposed a novel context-aware academic collaborator recommender model which is capable of recommending potential new collaborators. Reference [41] introduced the use of context in Recurrent Neural Network (RNN) for efficient recommendation process. The authors portrayed an empirical analysis on classical feature collection approaches and demonstrated that this schemes are unfit in capturing the most significant feature crosses. Finally, they applied RNN to improve the efficiency of recommender algorithm. To overcome the citation recommendation issues, a context-aware model with BERT and graph convolutional neural networks was designed in Ref. [42]. This model is a deep learning based model that utilizes graph convolutional network and bidirectional encoder representations (a pre-trained model for textual data) for more relevant paper citation recommendation.

Another reshape of collaborative filtering for utilizing context information is a graph-based context-aware collaborative filtering approach[43]. The proposed method exploits the transitivity of the interactions between users and items on the user-item graph to enlarge the direct interactions, thus reducing the negative effect of sparse data. Based on graph transitivity the proposed model introduces a new graph-based association measure that can be used to measure the similarity between two users or two items in nearest neighbor recommendation methods. For realizing the significance of event prediction, a semantic-enhanced and context-aware hybrid collaborative filtering model for event recommendation was proposed in Ref. [44]. The proposed model combines semantic content analysis and contextual event influence for user neighborhood selection. At the initial layer, the proposed model exploits the latent topic model for analyzing event description text and establish each user a long-term interest model and short-term interest model from user event registration history. At next, the model establishes each event an influence weight to jointly represent its social impact among users and its semantic uniqueness among events.

3 Context Integration

Recommender systems emerged as a hot research area since early 1990s, when information retrieval results from search engines are overwhelmed practitioners and researchers started thinking on building recommendation engines that have the capability to narrow information flood according to user needs. For example, in case of an item recommender system, Ali may assign a rating of 7 (out of 10) for the item “Mobile”, i.e., set

$$R_{\text{Item}}(\text{Ali,Mobile}) = 7 \tag{1}$$

Most of the times, the recommendation process starts with an initial rating specification that is either collected explicitly (provided by the user itself) or a system generated rating matrix implicitly (i.e., inferred rating by some environmental variables). Once initial ratings are computed, the system estimates the rating function R

$$R : \text{User} \times \text{Item} \to \text{Rating} \tag{2}$$

Here, R is the rating function that has two input variables, i.e. User and Item while Rating is the output matrix or an ordered set of integers or real numbers within a specific range. The recommender system takes the highest rated item from rating matrix and recommends it for the users. This classical recommender system with two input variables (i.e., User and Item in any form) is known as traditional or two-dimensional (2D) recommender system. On the other hand, a context-aware recommender system utilizes additional context information into recommendation process. It helps to narrow down the retrieved information very close to the user needs with reference to the current context. In this case rating furcation R can be summarized as:

$$R : \text{User} \times \text{Item} \times \text{Context} \to \text{Rating} \tag{3}$$

As stated above, R is the rating function with input variables User, Item and an additional Context for context information (representing a specific situation or state in which User and Item can have a good match). The context variable acts as an additional filter to choose the most relevant information for recommendation algorithm. For example, reconsider the above example of recommending electronic items to users, where users are the set of any end-users that are using the recommender system and items are described as any set of purchasable electronic accessories (such as mobile phone, laptop, tablet, etc.) while context is the additional information that is incorporated to filter out the most relevant information (such as season, budget, the time when user is going to buy the item, etc.). The decision of the user to buy the item is highly dependent on three described attributes (season, budget, and time). The rating matrix is accordingly calculated and Top-N items are recommended to the given user.

Here, articles selected for this literature review are classified into ten broad categories and presented the count for each category in Fig. 5. Contextual pre-filtering is the most common technique used by most of the practitioners in context-aware recommendation paradigm. In this paradigm, the context information is incorporated with input data, and then it is passed to the recommender algorithm. Afterwards, the recommender algorithm can predict the ratings using any traditional 2D recommender algorithm. Opposite to this, contextual post-filtering passes the input data directly to conventional 2D recommender algorithm and gets conventional recommendations, and after that in presence of context information the recommended results further filter down for close relevance. Although, this paradigm exists but it is most limited in use as shown in Fig. 5. Finally, contextual modeling is the third recommendation paradigm for context information integration. Context information is directly modeled as part of recommendation algorithm. This facilitates the rating estimation process and make possible the maximum use of context information.

3.1 Context Elicitation

Context elicitation refers to the process of acquiring context information from the user’s environment. This is one of the prime important activity in context-aware recommender systems’ life cycle and one of the active research area in this domain. According to the available academic literature[4], the context information can be obtained through one of the following ways:

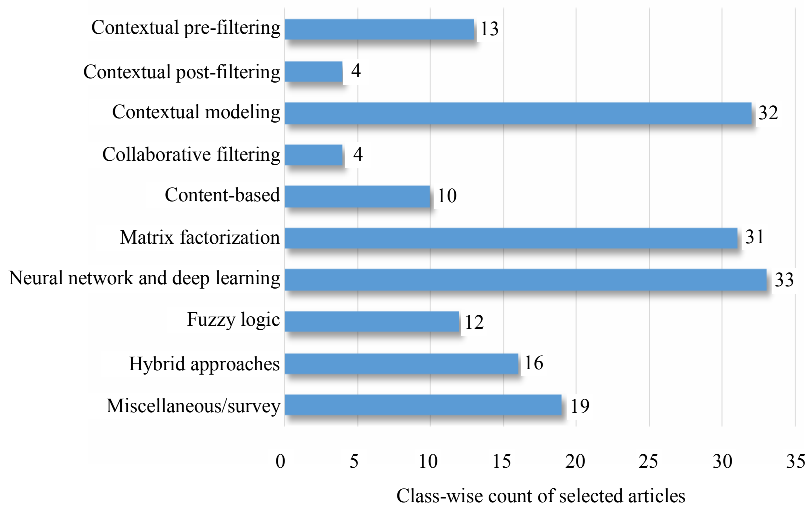

Fig. 5 Class-wise count of selected articles presenting the significance of each approach

- **Explicitly:** Explicit context gathering means collecting context information directly from the user by approaching relevant information sources. For example, a website may collect context information by restricting someone to answer a specific set of questions or fill out a form before providing access to specific web pages.
- **Implicitly:** Implicit context gathering means collecting context information indirectly. For example, a change in user's location could be obtained from its mobile network operator. Alternatively, temporal context details can be obtained from the timestamp of a transaction. The implicit context information might be dynamic that may change over time, and this makes it much more complex and challenging in practical applications.
- **Inferring context variables:** We can infer the context information by means of statistical and data mining techniques. For example, the household identity of a user (male, female, high budget, low budget, etc.) on retailer website like Amazon could not be directly or indirectly identified on a browser scrolling, but it can be inferred by what kind of items are being focused on a specific time and decision could be injected accordingly.

Dynamic context acquisition is one of the most active research areas. It is challenging to model dynamic context information, especially in streaming data such as the purchase intents of users in a retailer environment or time and location dependent users' choice of movies in a ticketing selling app. The context elicitation and integration require an automatic framework to detect context sources available for all stakeholders at runtime and streamline the sensors compulsory to gather this information. The key challenges in acquiring context information are as follows: 1) attaining the context information from non-implicit and non-explicit context sources, e.g., to list-down the user intents and motivations for a specific item in a specific situation, and 2) an interface development that can acquire context consistently from the user environment. To some extent its static versions are commercially available with many retailers like Taobao, Amazon, and Jingdong, etc., but it is still challenging to have an interface that fulfill the dynamic needs of a user.

3.2 Context Integration

Integration of context information in recommendation process is an important step. It has long roots in recommender systems' literature, e.g., Herlocker and Konstan introduced a framework[45] to incorporate the knowledge about user's activity (context information) in recommendation process. For example, if we want to recommend movies to a user, then we should be aware about the list of movies the user has already seen or the detail of user's companion (girlfriend/boyfriend, alone or colleagues), because this information is highly influential for right recommendation to the end user. It is important to consider that this approach works within the traditional

2D User×Item space, since the activity details for a particular user consist of a list of sample items. However, this acts as a foundation milestone for incorporating additional relevant information (context information) into the standard collaborative filtering paradigm. Since the early time of context information integration, different approaches have been there in practice to bind context information with recommendation process such as recommendation via context driven querying and search, recommendation via contextual preference elicitation and contextual modeling are the most common ones. More specifically, Ref. [46] classified the context utilization in recommendation process in three abstract ways.

3.2.1 Contextual pre-filtering

The contextual pre-filtering approach integrates context information with input data and makes it as contextualized input to the recommender algorithm. One of the key benefits of this framework is that it allows any of the previously proposed recommendation technique to be easily adopted in pre-filtering context integration. For example, context utilization for a Top-*N* item recommendation system, if a user wants to see a list of specific items on Sunday, only item ratings for Sunday should be utilized to generate the Top-*N* items. Therefore, another important advantage of the contextual pre-filtering approach is that we can take benefit of all the previous researches in a 2D recommender system to make more robust methods in context-aware recommendation paradigm. More formally, let $R^S_{\text{User}\times\text{Items}}: U\times I \to \text{Rating}$ be any 2D rating prediction/estimation function with existing rating *S* (i.e., *S* contains tuples as <user; item; rating> for all the pre-determined ratings) can calculate a prediction for any rating, e.g., $R^S_{\text{user}\times\text{terms}}(\text{Ali},\text{iPhone})$. On the other hand, a 3D rating prediction function consists of an additional attribute (i.e., time) that can be illustrated as:

$$R^S_{U\times I\times T}: U\times I\times T \to \text{Rating} \tag{4}$$

where *S* contains tuples like (user; item; time; rating) for the user-specified ratings. Then, this 3D rating prediction function could be presented by means of a 2D rating prediction function in several ways like:

$$\forall(u,i,t)\in U\times I\times T \quad R^S_{U\times I\times T}(u,i,t) = R^{S[\text{Time}=t]}_{U\times I}(u,i) \tag{5}$$

Here, [Time = *t*] presents a simple time-dependent variable *t* (or contextual pre-filter condition) and *S* denotes a predefined rating dataset obtained by selecting only the records time *t* precondition and keeping in view of the values only for User and Item dimensions. More specifically, the concept of context generalization was applied for an adequate pre-filtering approach[12]. For context generalization, let us define $c'=(c'_1,c'_2,c'_3,\cdots,c'_k)$ as generalized form of some real world situations (context) and $c=(c_1,c_2,c_3,\cdots,c_k)$ if and only if for every $(c_i \to c'_i)$ for i = 1, 2, ···, k for every context situation there exists a generalized context in the corresponding context hierarchy. We can use c' (instead of *c*) for querying data to obtain contextualized ratings.

Among some recent developments, Ref. [4] broadly summarized the state-of-the-art pre-filtering based context utilization methodologies and deeply illustrated the use and significance of this knowledge domain in recommendation process. Also, Ref. [5] presented the most recent uses of deep learning based contextual pre-filtering approach in different context-aware recommender systems and pre-filtering based techniques for general recommender systems. Similarly, the significance of pre-filtering based context integration in recommendation process was categorically illustrated in Ref. [1].

Moreover, a personalized pre-filtering based re-ranking model for e-commerce recommender systems was proposed in Ref. [47]. This model can be easily deployed to end user as an independent working module and can be directly ranked by means of existing feature vectors of ranking. It can directly optimize the entire recommendation list by adopting a special structure to efficiently encode the context labeling with the input information of all items in the list. Reference [8] proposed a probabilistic model to find the mapping between users' annotated tags and locations' taste keywords. Reference [48] proposed a context-aware item representation framework for the next basket of items recommendation, entitled as "Encoder Representations from Transformers". The proposed methodology trains deep item representations conditioning on their transaction contexts. A novel approach to reduce the cold-start problem was presented by means of pre-filtering based technique inspired from association rule mining[38]. It combines the available ontologies, community generated knowledge with association rule mining by a scoring function based on probability metrics. The authors validated the results on state-of-the-art and real-user datasets and present encouraging performance output. Table 1 presents the summary of class-wise count that depicts the significance of pre-filtering approach.

3.2.2 Contextual post-filtering

As the name implies, in contextual post-filtering framework, initially the context information is ignored and input data is directly passed to the standard recommendation algorithm. When the recommendation algorithm generates recommendations the context information is incorporated to filter-out Top-N recommendations and/or to boost user's relevance with the given task. The contextual post-filtering approach has to adjust the obtained list from recommender algorithm for each user according to the given context information. This adjustment can be either made by filtering out recommendations that are less relevant (in a given context) or ranking the list based on the given context information. This makes it computationally expensive and difficult to manage.

Table 1 Key findings: Summary of the discussed techniques as appeared in the article classification title

Techniques	Short Description	Appeared in selected literature
Contextual pre-filtering	Integrating context information with input data and then passing it to recommender algorithm.	[1, 4, 8,12, 14, 24, 26, 27, 29, 46, 47, 57, 91]
Contextual post-filtering	Passing input data directly to recommender algorithm and then applying context information.	[4, 5, 17, 43]
Contextual modeling	Intelligently modeling context information with recommendation algorithm. The most active approach in studied literature.	[7, 8, 11-13, 16, 18-21, 23, 28, 30, 34-38, 40, 46-48, 52-55, 59, 91, 92, 101, 110, 111]
Collaborative filtering based recommenders	Most basic classical group of frameworks for making recommendations. The items are selected with collaboration of other user preferences.	[14, 17, 43, 44],
Content-based recommenders	Another classical recommendation framework, which utilizes the content of each item for recommendation purposes. Principally, these approaches have the capability to add-up additional information for recommendation process.	[94, 91, 51, 45, 29, 27, 26, 25, 18, 15],
Matrix factorization based recommenders	One way of collaborative filtering, finding a pair of low rank 2D matrices instead of the input matrix.	[8, 14, 24-27, 50-59, 60-62]
Neural network and deep learning based recommenders	Designing an intelligent network that can independently, automatically and dynamically learn user preference from input data.	[5, 14, 33, 35-37, 41, 42, 47, 48, 58, 63-77, 93, 97, 99, 102, 111-113]
Fuzzy logic based recommenders	Utilizing, the magical power of fuzzy logic for learning more micro level details of context enrichment.	[22, 78-87, 109]
Hybrid approaches	Mixing two or more approaches to make a new one.	[38, 39, 42-44, 52, 54, 57, 84, 88-90, 97, 100, 101, 111]
Literature reviews, books or book chapters	Doctoral dissertations, various literature reviews or surveys, books or book chapters, and highly cited technical reports.	[1-6, 9, 10, 31, 32, 49, 50, 56, 78, 96, 105-107, 114]

Due to inherent complications, contextual post-filtering is less popular among state-of-the-art context integration methodologies. This fact is also considered by certain recent review articles[1], [4-5] However, just like the contextual pre-filtering approach one major advantage of post-filtering approach is that it is flexible to accommodate various traditional 2D recommendation algorithms. Also, incorporating context generalization in contextual post-filtering approach can open new gateways of research context-aware recommendation research.

3.2.3 Contextual modeling

Contextual modeling is the third recommendation paradigm for context information integration. Here, context information is directly modeled as part of recommendation algorithm. This facilitates the rating estimation process and makes possible the maximum use of context information. Unlike pre-filtering and post-filtering approaches that can utilize classical 2D recommendation algorithms, the contextual modeling approach makes possible the actual maximum utilization of context information which principally represents predictive models (such as regression, decision tree, Bayesian or probabilistic models) or heuristics that integrate context details with the user and item data, i.e. $\text{Rating} = (\text{User}, \text{Item}, \text{Context})$. During last decade, significant number of the contextual modeling approaches have been introduced based on a variety of predictive modeling approaches as well as heuristics based techniques. As per this literature review is concerned, Fig. 6 and Table 1 present the significance of contextual modeling and categorical distribution of the selected literature for this article.

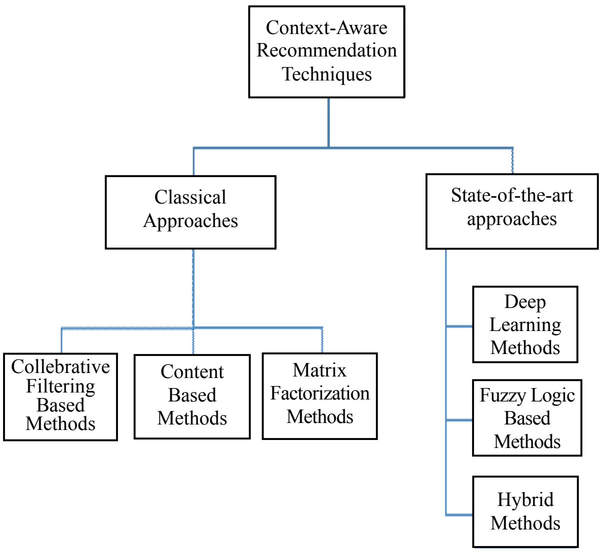

Fig. 6 Classification of context-aware recommender system techniques

4 Classification of Methodologies

Context-aware recommender systems have been a key research area for a couple of decades and various research communities are consistently trying to build up intelligent models for efficient processing. Methods proposed for context integration and context modeling belong to vast and diverse scientific domains, and that is why it is extremely difficult to draw a clear line that categorizes these approaches in a standard way. Also, usage of hybrid models makes it difficult to uniformly classify these approaches in a unique standard. However, according to recent literature, we summarize and present context based recommender system approaches as a high-level abstraction presented in Fig. 6. Overall, we divide context based recommender systems into two broad categories, i.e., the classical approaches and the state-of-the-art approaches. The classical approaches are further categorized into three subsets, i.e., content-based methods, collaborative filtering based methods and matrix factorization based methods. Since available recent literature reviews[1], [4-6],[49] are the witness of this fact that classical approaches have been broadly studied and rapidly discussed in academic literature, we are omitting the detail of these approaches form the undergoing discussion. In addition, we highlight the most recent developments in modern state-of-the-art approaches, i.e., deep learning methods, fuzzy logic based context-aware recommender systems techniques, and finally some hybrid methods. An overview of recent developments in these categories is presented below.

4.1 Classical Approaches

In this section, we will discuss the classical context collection and integration approaches for recommendation process. Intentionally, we consider only content-based, collaborative filtering based and matrix factorization based methods and introduce their basic semantics. We will not deeply describe these techniques as substantial research has been already done on these classical techniques.

4.1.1 Collaborative filtering based methods

Collaborative filtering based recommender systems are the most basic form of recommendation methodologies. In this type of methods, the items are selected with collaboration of other user preferences from a large set of alternative items. The basic assumption in the collaborative filtering approach is that the two users with the same preference in the past will also have an interest in the future as well. For example, if a user X and user Y have similar shopping interest, and user X has recently bought iPhone X which user Y still does not have, then the idea behind collaborative filtering is to recommend iPhone X to user Y as well. With respect to context information, it has been observed that most of the collaborative filtering based approaches utilize contexts like time, location, social interaction and activities as the leading factors. In addition, restaurants, music, movies, points of interests, social networks and e-retailing are the most common application areas.

4.1.2 Content-based methods

The concept of content-based context utilization is not new in recommender systems. It has adopted from traditional 2D recommender system approaches. The basic idea behind these techniques is to utilize the content of each item for recommendation purposes. Inherently, these approaches have the capability to add-up additional information in recommendation process, the same thing that we do in context integration. This property makes the content based approaches more flexible and convenient to adopt in context-based recommender systems. Table 2 shows the categorical distribution of reviewed articles including content-based context-aware recommendation approaches.

4.1.3 Matrix factorization based methods

Standard matrix factorization and context-aware matrix factorization models typically predict a single user-item matrix under a single and or multiple context factors for true rating prediction. Matrix factorization has very long roots in statistical analysis, data mining and classical 2D recommender systems. The basic idea behind matrix factorization is that when a user gives feedback to a certain movie they watch, this feedback information is sparse (as all users did not bother to give feedback) but can be represented in a form of a 2D ($M_{\text{users}}\times N_{\text{items}}$) matrix. Then, there exists a shorter matrix P ($M\times K$) and Q ($N\times K$) that truly represent the semantics of the original ($M_{\text{users}}\times N_{\text{items}}$) matrix. To our concern with matrix factorization, the context-aware matrix factorization techniques introduced in Ref. [50] are the non-probabilistic linear models that decompose the rating matrix into a product of two smaller matrices with integrating context factors. On the other hand, probabilistic matrix factorization describes users and items by means of n-dimensional latent vectors. It can be further extended to learn various social contextual factors like latent vectors as supposed by Ref. [51] for the review rating prediction problem. Context- aware matrix factorization is proved as one of the most common techniques for number of applications such as: online social recommendation[14, 52], Point-of-Interests (POI) recommendations[8], [53-55], item recommendation[56-59], event recommendation, and event prediction[24-27, 60-62] and this list is too long. A major strength of context-aware matrix factorization approach is that it can flexibly accommodate implicit feedback, the dynamic information that is not directly derived but can be indirectly inferred through analyzing user behavior.

Table 2 Publically available benchmark datasets for context-based recommender systems

Dataset	Precise Description	Subject Domain	Contextual Attributes	Appearance
MovieLens	Information about movies, ratings, and users	Movies	Human(age, gender, Profession) Time(D, M, Y, h, m, day, type) Location (Social, neighbor dist.)	[2, 9, 12, 13, 45, 46]
DePaulMovie	Data from different surveys with random users that rated movies in different contexts	Movies	Human, Social, Time, Mood, Location	[17, 91-94]
Netflix	One of the largest movie dataset for movie recommendations	Movies	Human, Social, Location	[4, 78, 95-99]
FourSquare	Dataset acquired from FourSquare that contains information about user visited places	POI	Social, Location, Time	[38, 54, 100]
TripAdvisor	Data collected for TripAdvisor location-based app	POI	Human, Location, Social, Time	[1, 8, 100-103]
InCarMusic	Data collected for InCarMusic location-based app	Music	Mood, natural, traffic, weather	[15, 50, 104]
Yahoo	Dataset with over ten million ratings of musical artists provided by Yahoo labs	Music	Natural, mood, location, human	[31, 95]
Twitter	Well-known social media tweet analysis dataset	Social Media	Time, Location, Social	[24, 26, 99, 105-108]

4.2 State-of-the-Art Approaches

Machine learning and deep neural network have revolutionized the classical data mining and information retrieval techniques. Similarly, they have a great impact on context-aware recommender systems as well. As observed, the above-mentioned classical approaches focused primarily on the prediction by means of handcrafted feature learning to make better recommendations. While most of the state-of-the-art techniques focused on dynamic feature learning and learning-to-rank like style instead of optimizing a model for its quality using some ranking function. There is a big pool of these techniques, and various measures and correlations can be used to classify these approaches. Simply, we classify these approaches into three abstract categories, i.e., deep learning based methods, fuzzy logic based methods, and hybrid methods.

4.2.1 Deep learning-based methods

Deep learning has revolutionized existing analytical and predictive models, and its inherent capability to work as a black box automatic learner is highly suitable with our concern for context aware systems where recommendations are dynamic as per changing contexts. The academic literature is a vital witness that numerous deep recommendation approaches have been proposed in a short span of past few years. Before diving into the details of recent advancements, it is important to look at the key reasons for applying deep learning framework for context-aware recommender systems. At this tangent, it would be congruous to consider the most inspiring properties of neural architectures: firstly, they are end-to-end differentiable[63]; secondly, they provide suitable learning bias catered to the input data type. For example, if we have an inherent structure that the model can utilize, then the given network could be useful. Similarly, rapidly generating sequential structures of click-logs or web sessions are strongly apt for the learning biases provided by convolutional or recurrent[64-65] models. Moreover, deep networks are also competitive as they are composited of multiple neural building blocks. Here, the key advantage regarding context based recommender systems is that multiple building blocks can independently focus on a specific context situation. For a similar objective, a brief and comprehensive summary of four concrete strengths of deep neural networks for recommender systems is recently reported in Ref. [5].

- **Nonlinear transformation:** The deep neural networks can proficiently model the nonlinearity in the data with nonlinear activations such as sigmoid, ReLU and tanh, etc. This property makes possible to uncover hidden and complex user/item interaction patterns. Classical methods like collaborative filtering, factorization machines, and sparse linear model are primarily linear in nature and have their own limitations[14, 66-75]. This facilitates the neural networks to approximate any continuous function by varying the possible combinations and activation choices.
- **Representation learning:** Deep neural networks are efficient for learning and especially reliable learning. Commonly, a huge volume of sparse information about users and items are available in real-world applications. The model or network needs to make use of this information to produce valuable decision support knowledge in an automatic way. The deep neural networks are capable in assisting representation learning on two strong arguments. Firstly, its automatic feature learning capability can cut-down the cost of hand-crafting feature design. Secondly, it permits the recommendation models to utilize heterogeneous and dynamic context information such as time, location and activity, etc.
- **Sequence modeling:** The ability of sequence modeling has made it successful in many real-world practical applications (context gathering, context integration, machine translation, natural language processing, and speech recognition, etc.). RNN and CNN both have played an important role in structural enhancement of context utilization in recommendation process.
- **Flexibility:** Deep neural networks are flexible to all kinds of machine learning applications, especially with the advent of Keras, TesnsorFlow, Caffe, Theano and PyTorch all kinds of analytical tools are flexibly available under the same umbrella.

More recently, Ref. [76] proposed a novel deep neural network based recommendation model entitled as Convolutional and Dense-layer Matrix Factorization (CDMF) for context-aware recommendation that has basically combined multi-source item information with the tag details. A convolution neural network is used to extract hidden features from the item description and then merge it with tag information via a full connection layer. Similarly, a deep joint network for the recommendation of session-based news with contextual augmentation is proposed in Ref. [77]. Basically, it combines the user's click activities with the session information and news contextual features. Both the methods use a deep joint network to predict next click behavior of a user.

4.2.2 Fuzzy logic based methods

Primarily, the fuzzy set theory was introduced in 1965. Since its inception, it has been applied in a variety of disciplines such as logic, decision theory, operations research, computer science, artificial intelligence, pattern recognition and robotics, etc. Especially, during last few years, it has revolutionized various information storage and retrieval disciplines including recommender systems[22, 78]. One of the early contributions on fuzzy based recommendations was introduced in Ref. [79], introducing fuzzy logic methods for the development of recommender systems. The proposed methods regarding reclusive modeling are closely connected to the content-based recommendation that deals with user preferences, item profiling and object representation and domain expert prototypes. Additionally, a fuzzy Bayesian network with utility theory for context-aware music recommender system was introduced in Ref. [80]. Similarly, closer frameworks for the same objective were reported in Ref. [81-82].

Recently, Ref. [83] reviewed the recent trends and future directions of context utilization by means of fuzzy logic recommender systems. Reference [84] proposed a hybrid fuzzy approach, Reference [85] introduced neuro-fuzzy classification method, Reference [86] used fuzzy rules for pre-filtering based context-aware recommender system, and Reference [87] proposed framework for modeling context information in student group recommendation. All these are the recent milestones toward context based recommender systems.

4.2.3 Hybrid methods

Hybridization is one of the most frequent tools in modern research. A variety of algorithms have been proposed for context-aware recommendation during last few years, including collaborative filtering, content-based, factorization based, machine learning based and the list of these classes is too long to discuss here. Each of these classes has its own merits and demerits, and we can flexibly mix-up the stronger part of each technique to form a hybrid method. We have observed from the considered literature that most of the hybrid methods combine content-based and collaborative filtering techniques for creating new methods. However, this is not a uniform claim regarding hybridization. There are also combinations of other approaches such as reported in [84] and [44].

More recently, various hybrid models in recommender systems emerged in literature, such as hybrid collaborative filtering[44], hybrid e-learning system for sequential pattern mining[88], artificial neural network based hybrid recommender system[89], and hybrid model for Top-N context-aware recommendations[90].

5 Benchmark Datasets

Datasets act as a backbone in modern machine learning based research. The significance of datasets in any research paradigm may lead to their emancipation into an essential part of research infrastructure. Context-aware recommendation research has multidimensional frameworks of institutional methodologies that need well-organized datasets for testing new methodologies. We found a considerable gape on the availability of state-of-the-art datasets for context-aware recommender systems. Here, we discuss some most commonly used datasets to evaluate context-based recommendation algorithms. Table 2 shows 8 different publically available datasets supporting context-based recommendation.

6 Research Directions

Here we will discuss major future research directions in context-aware recommender systems. We characterize the challenges and future research opportunities into six sub-classes, i.e., context collection, dynamic context management, context integration, availability of context-oriented datasets, recommender system's own intrinsic issues and uniform validation criteria for context-aware recommender systems.

6.1 Context Collection

Collecting dynamic context information from the real world is a challenging task, especially in a streaming environment. Most of the existing context elicitation algorithms[1-2, 4, 7, 15, 20, 32, 38, 109] produce optimum performance only with a piece of hypothetical static context information. Practically and principally, context is dynamic and its elicitation requires an automatic mechanism so that it could be maximally utilized in recommendation process. For this purpose, two mainstream areas were highlighted in Ref. [4]: first, the acquisition of context information from non-traditional and non-explicit context sources, and second, the development of a user interface that supports to collect context information from multiple and suitable sources.

6.2 Dynamic Context Management

Dynamic context management is one of the most active research challenges in the context-aware recommender system because of the fact that most of the commercial objectives are still associated with this research question. It is a challenge to model dynamic context information especially in streaming data such as the purchase intents of users in a retailer environment or time and location dependent user choice of movies in a ticketing selling app etc. To deal with this dynamic nature of context, the recommender system must be furnished with an adaptive mechanism to segregate the relevance and irrelevance of context and integrate it with the recommendation process automatically. It means that the recommender system should be able to intelligently and independently manage the entire life cycle of context information at runtime, for example, calculating the phenomenon that specific context variables are relevant or irrelevant and treat them accordingly, also, adopting a particular framework according to the given context dynamics that may be relevant to the users' current interests.

6.3 Context Integration

Modeling contextual factors in recommendation algorithm is also a key challenge for researchers and practitioners. Currently, pre-filtering, post-filtering and contextual modeling are the three major paradigms to integrate contextual factors in recommendation process. We deeply investigated different tools and techniques[4, 8, 11, 12, 35, 37, 46, 50, 51, 83, 90, 97, 101, 103, 110-113] and found that contextual modeling is the most potential knowledge area for practitioners in this domain.

6.4 Availability of Context Oriented Datasets

The significance of datasets in any research paradigm may lead to their emancipation into an essential part of research infrastructure. Context-aware recommendation research as multidimensional framework needs well-organized datasets for testing new methodologies. As shown in Table 1, we consider only a few of publically available ones.

6.5 Handling Intrinsic Issues in Recommender Systems

Recommender systems have some inherent problems like cold-start, sparsity of the input data, scalability, and some performance issues such as acceleration of output results, novelty, trust, and privacy of the user data, diversification, risk and adoptability. Although a substantial amount of research effort has been made in these areas, we found that a considerable research gape is still there as highlighted by most of the researchers[5, 46, 96, 99, 100, 114] in term of performance and computational tradeoffs.

6.6 Uniform Validation Criteria for Context-Aware Recommender Systems

Increasing user satisfaction level is definitely the ultimate goal of research in recommender system. In order to compute this satisfaction level, most of the researchers have established their own measures which may be correct under a bounded environment but may not universally applicable. It might be possible that one set of measures such holdout or cross-validation, K-fold cross-validation, bootstrapping and/or simulation may accurately work for specific circumstances but may differently perform under other conditions. This rises a need for the uniform validation criteria for context-aware recommender systems.

7 Conclusion

In this paper, we present a comprehensive literature review on context-aware recommender systems. The study is primarily conducted to help the research community, especially young researchers to understand the fact that how context information can improve the recommendation process. We started by understanding principal concepts of context and its significance in recommendation process, and the major types of context were then illustrated. The main focus of our paper is to sum up the most recent developments regarding context integration in the recommendation process. We uncovered various methodologies, estimating (tailoring/partly observed or unobserved) context information to learn user profiles, context integration strategies including pre-filtering, post-filtering, and contextual modeling. Approaches were classified (as shown in Fig. 6) into two mainstream areas, i.e., classical and state-of-the-art methodologies. The classical (content-based, collaborative filtering and matrix factorization based) approaches were less focused as they have been discussed in academic literature. We investigated the most recent research directions, i.e., deep learning and fuzzy logic based methodologies. Finally, we close by illustrating potential future research directions in this active area.

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