A Survey on Context-aware Recommender Systems Based on Computational Intelligence Techniques

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Abstract

The demand for ubiquitous information processing over the Web has called for the development of context-aware recommender systems capable of dealing with the problems of information overload and information filtering. Contemporary recommender systems harness context-awareness with the personalization to offer the most accurate recommendations about different products, services, and resources. However, such systems come across the issues, such as sparsity, cold start, and scalability that lead to imprecise recommendations. Computational Intelligence (CI) techniques not only improve recommendation accuracy but also substantially mitigate the aforementioned issues. Large numbers of context-aware recommender systems are based on the CI techniques, such as: **(a)** fuzzy sets, **(b)** Artificial Neural Networks (ANNs), **(c)** Evolutionary Computing (EC), **(d)** Swarm Intelligence (SI), and **(e)** Artificial Immune Systems (AIS). This survey aims to encompass the state-of-the-art context-aware recommender systems based on the CI techniques. Taxonomy of the CI techniques is presented and challenges particular to the context-aware recommender systems are also discussed. Moreover, the ability of each of the CI techniques to deal with the aforesaid challenges is also highlighted. Furthermore, the strengths and weaknesses of each of the CI techniques used in context-aware recommender systems are discussed and a comparison of the techniques is also presented.

Keywords: Computational intelligence, context-aware recommendation personalization, user preferences.

1. Introduction

Recommender systems have attained widespread acceptance and have attracted the increased attention by the masses for over a decade. Recommender systems alleviate the complexities of products and services selection tasks and are meant to overcome the issues of information overload [1]. Recommender systems collect information about the preferences from the users, sift through the huge volumes of information scattered around the Web, and select the information that best suites the user preferences. Generally, the recommender systems obtain information from the users either explicitly or implicitly [2, 3]. The information extracted through the user ratings of various items is considered as explicit information extraction while the information obtained by observing the user behaviors during interaction with the recommender systems is considered as the implicit information extraction. However, the ubiquitous information processing demands in the recommender systems have called for the use of information retrieval techniques that not only offer context-aware recommendations but also are scalable. In this regard, an offshoot of the Artificial Intelligence (AI) discipline called Computational Intelligence (CI) coined by John McCarthy in 1956 not only exhibits the aptitude to adapt to the changing situations but also possesses the attributes for generalizing, discovering, reasoning, and association [4]. In literature there are different definitions for the CI and computationally intelligent systems. For example, according to Bezdek [5], computationally intelligent systems use numerical data, have pattern recognition capabilities, exhibit computational adaptivity and fault tolerance, and their error rates approximate the human performance. Alternatively, Eberhart *et al.* [6] articulated that the CI and adaptation are synonymous.

The CI techniques, such as, **(a)** fuzzy sets, **(b)** Artificial Neural Networks (ANNs), **(c)** Evolutionary Computing (EC), **(d)** Swarm Intelligence (SI), and **(e)** Artificial Immune Systems (AISs) have exhibited significant potentials to make recommender systems more robust, effective, and context-aware [7, 8]. Consequently, the CI techniques have been used to design intelligent and context-aware algorithms to incorporate the aforementioned features [4]. In contrast to the traditional AI-based systems, the CI techniques do not require the construction of precise models to deal with the imprecise, incomplete, and uncertain information. Therefore, the CI techniques have widely been used in the design and implementation of a variety of intelligent systems to solve problems where formalized models are difficult to establish [7]. Major application domains of the CI include context-aware recommendation, [9], consumer electronics [10], medical diagnosis [11], scheduling of industrial processes [12], product design engineering [13], robotics [14], patent analysis [15], cryptology [16], e-learning [17], tourism recommendations [18], and numerous others. Each of the above application domains uses particular CI technique(s) to operate effectively and to fulfill the desired objectives.

Keeping in view the widespread use of the CI techniques in recommender systems, we present an overview of the recent context-aware recommender systems based on the CI techniques. We discuss the recently developed recommender systems based on the CI techniques employed in different business domains, such as e-commerce, venue recommendation, TV program guides, research resources recommendations, and business partner recommendation systems. We also discuss the effectiveness of algorithms based on the CI techniques to offer contextual recommendations.

A few prior studies have presented the state-of-the-art in context-aware recommender systems. For example, Lu *et al.* [2] present discussion on the recommender system applications and challenges with focus on the similarity methods. Ref. [19] presents state-of-the-art in recommender systems, identifies their limitations, and also highlights some possible research directions for the future. A detailed discussion on filtering methods and traditional recommendation models with their interrelationships is presented in [3]. Besides discussion on recommender systems' evaluation, Ref. [3] also highlighted a few recommender systems using the CI techniques. Park *et al.* [20] presented a survey on recommender systems research. However, the focus of the survey is mainly on classification framework for application fields and data mining techniques with a nominal emphasis on the use of CI techniques in recommender systems. The authors in [21] discussed recommendation approaches, such as collaborative filtering, content based filtering and hybrid filtering and also identified their limitations. Ref. [4] presented the personalization efforts carried out using the CI techniques and also highlights the key features and limitations of each of the techniques. However, the survey does not provide detailed discussion on the presented systems.

On the other hand, our survey is focused on most recent context-aware recommender systems based on the CI techniques. The survey highlights the significance of applying the CI techniques in context-aware recommender systems. We present taxonomy of the CI techniques and also discuss the challenges being faced by the recommender systems, such as sparsity, cold start, and scalability. Moreover, the effects of the aforesaid challenges on the system performance in terms of accuracy and the capabilities of each of the CI techniques to deal with the challenges are also highlighted. Furthermore, the strengths and weaknesses of each of the CI techniques employed in recommender systems are presented and some possible suggestions to deal with the challenges are also underlined. We believe that the survey will be a useful source for the researchers in finding the recent research carried out on recommender systems based on the CI techniques. Figure 1 presents the taxonomy of the CI techniques.

The paper is organized as follows. Section 2 discusses the basic concepts of context-aware recommender systems and also highlights the associated challenges. Some recent recommender systems based on the CI techniques along with their key features are presented in Section 3. Section 4 presents discussion on the CI techniques and Section 5 concludes the survey.

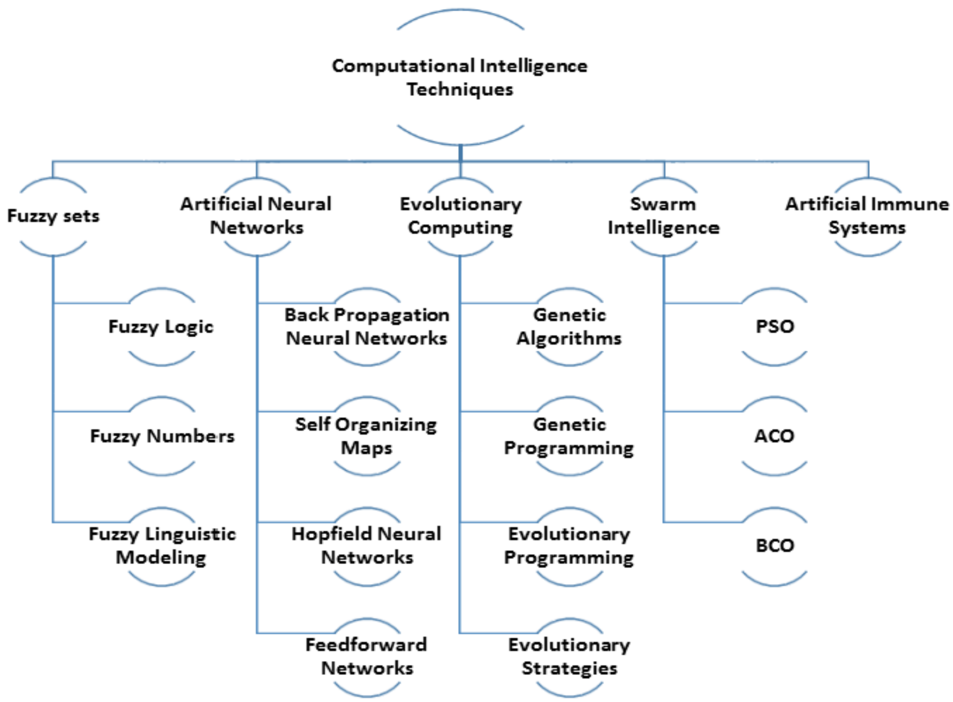

Figure 1: Taxonomy of Computational Intelligence Techniques

2. Context-aware Recommender Systems

The concept of recommender systems was introduced to deal with the challenges of information overload, to scrutinize the large information sets, and to retrieve the most relevant information [22]. Recommendations can be about any product, locations, and services, for example books, videos, music, TV programs, documents, research resources, and websites [3, 20, 23]. Through personalized recommendations, users are suggested about the items or services on the basis of purchases of similar products or services by the other customers. To accomplish the task of recommendations, the recommender systems usually employ any of the following recommendation approaches: **(a)** Collaborative Filtering (CF), **(b)** Content Based (CB) filtering, and **(c)** hybrid filtering [24].

The CF approach operates on the basis of observed behaviors of the users while interacting with the systems and filters out those with the similar behavior [19]. The CF technique has been used in different types of recommender systems, such as e-commerce, e-learning, and tourism [24]. The CF based approaches are further categorized into memory based and model based algorithms. Memory based algorithms operate on the user rating matrix and make recommendations based on the items rated by the users in the past. On the other hand, the model based algorithms use the user ratings to learn the model that subsequently are used to perform the task of prediction [19], [25]. Figure 2 presents an illustration of the CF method.

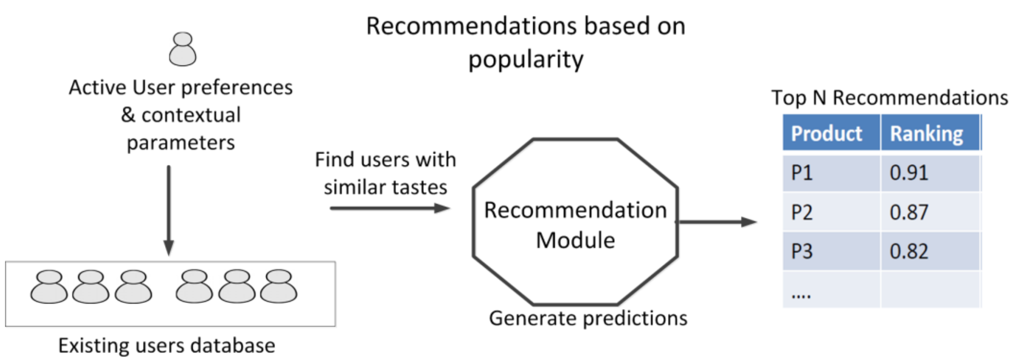

Figure 2: A Generic Example of Collaborative Filtering

Content based filtering approach provides recommendations based on the content items that were targeted by the users in the past searches. By comparing various candidate items with the items rated in past by different users, the best matching items are recommended [26]. Recommender systems that use a combination of two or more filtering techniques are called hybrid systems. Such systems are claimed to have improved recommendation accuracy by overcoming the drawbacks of individual approaches. The system proposed in [27] is an example of hybrid system that employs the content based and collaborative filtering. Figure 3 presents an illustrative example of content based filtering.

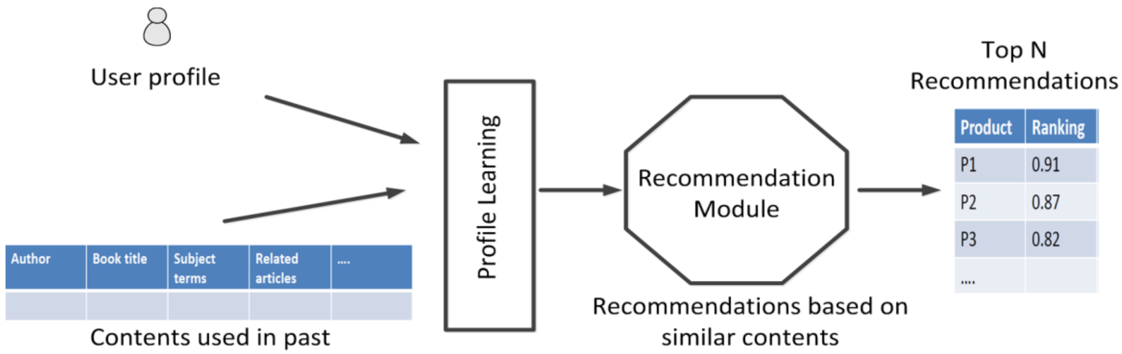

Figure 2: A Generic Example of Content Based Filtering

Recommender systems offer recommendations by considering the appropriate context [25]. Generally, context is an information halo that is used to characterize the situations pertaining to the objects of interest, such as places, events, people, things, media, and information. Recommender systems use contextual data, such as temporal, spatial, sentimental, social, and environmental data [28]. However, there are certain challenges particular to the context-aware recommender systems that affect the quality of recommendation [29]. The challenges are detailed below.

Sparsity: The sparsity issue in recommender systems occurs due to the scarce data points required to describe the exact context. Typically the number of items rated by each customer may be limited that eventually results in a smaller set of ratings by overall users [2]. The data sparseness issues arise irrespective of the types of the recommender systems. For example, the data in MovieLens is represented as a user-item matrix. The matrix is populated by the ratings assigned to the movies. As the number of user ratings increases the matrix dimensions grow and the major reason for data sparseness is that the majority of the users do not rate the items because of the large pools of items that eventually results in data sparseness [21]. Recommender systems that employ collaborative filtering come across the sparsity issues because this technique heavily depends on the rating matrix [29]. Various approaches have been used to overcome the issue of data sparseness in recommender systems. Dimensionality reduction techniques, such as Singular Value Decomposition (SVD), matrix factorization, and Latent Semantic Index (LSI) have been used in the recommender systems to handle the sparsity problem [2].

Cold start: Cold start is another challenge that recommender systems come across and it occurs for users or items that are new to the system and also because of the insufficient information. The variations of the cold start problem are new user problem, new item problem, and new system problem. The new users or new items do not have sufficient rating information in the system at the start. Consequently, for the new user or new items there may be insufficient records in the system to compare the similarity that eventually can result in zero similarity [29]. Most of the CF based recommendation systems come across the cold start problem and therefore, lack in offering accurate recommendations [30]. The cold start problem has been addressed by using content based approaches using cross level association rules and hybrid (CF and CB) approaches.

Scalability: Scalability refers to the capability to handle huge volumes of data in efficient and effective way. However, for the contemporary recommender systems enriched with gigantic data volumes, the scalability issues not only result in increased processing time but also cause reduced accuracy [29]. The neighborhood based similarity approaches and the memory based collaborative filtering approaches face the problem of scalability because they require parsing thousands of users in rating matrix that not only results in inefficiency but also causes the scalability problem. Different approaches have been employed to tackle the issue of scalability. For example, perturbation techniques may be effective in handling the scalability issue by using the algorithms incrementally over the huge datasets and slightly adjusting the recommendations in situations when additional data is received [2]. Dimensionality reduction approaches have also proved effective to handle the scalability issue as well. However, the matrix factorization step in dimensionality reduction approaches is computationally expensive. Sarwar *et al*. [31] used incremental SVD technique to pre-compute the SVD for existing users. Besides the dimensionality reduction techniques, memory based CF approaches using Pearson correlation also effectively deal with the scalability issue by performing similarity computations between the co-rated items instead of similarity calculations on all pairs of items. The model based clustering CF approaches solve the scalability problem by searching the smaller and similar clusters instead of searching the entire database. The user based *Top-N* recommendation approaches are less scalable. However, the item based *Top-N* recommendation algorithms address the issue by initially finding *k* most similar items and subsequently removing the items that are already purchased by users [32]. Memory based CF approaches have scalability issues because such approaches are largely dependent on user ratings.

The performance of recommender systems is generally evaluated in terms of prediction accuracy and quality. The prediction metrics include Mean Absolute Error (MAE), Root of Mean Square Error (RMSE), Normalized Mean Average Error (NMAE), and the coverage [33], [2]. However, the MAE is the commonly used predictive metric that calculates the average deviation between the true rating and the predicted rating [34]. Likewise, the recommendation quality metrics include the precision, recall, and F-measure. These metrics are being used as quality metrics since a long time. Interested readers are encouraged to consult [1], [2], and [32].

3. Recent Recommender Systems Based on the CI Techniques

In this section we discuss some recent recommender systems based on each of the CI techniques. The key feature(s) of each of the systems are highlighted. Moreover, we also indicate that what types of challenges are dealt by each of the CI techniques. The symbol "✓" in each of Table 1—Table 5 represents that a technique addresses a particular challenge, whereas the symbol "✗" means that the authors do not address/discuss the particular challenge.

3.1 Recommender Systems Based on Fuzzy Set Theory

First introduced by LotfiZadeh in 1965 [35], the fuzzy set theory is applicable in domains and situations where the information is incomplete or imprecise [8]. The need for a framework capable of dealing with uncertainties motivated the evolution of the fuzzy logic. In a broader sense, fuzzy logic has largely been used for analyzing the vague situations of the natural language. In a narrow sense, fuzzy logic is characterized as a symbolic logic with the notion of many-valued logic. Recommender systems based on the fuzzy set theory are presented below.

A hybrid approach to deal with the issues of uncertainty and data sparsity in the customer and product data for telecom products and services is presented in [36]. The approach employs the fuzzy set technique in conjunction with user based and item based filtering to deal with the fuzzy product similarities. The prediction accuracy of the system is evaluated using the MovieLens 100 K dataset comprising of 100,000 rating records from 943 users for 1682 items. To overcome the sparsity issue, the authors applied item based CF to construct a dense user-item rating matrix. The missing sparsity rate of 94.96% in the dataset was calculated. The rate was in between 94.64% and 95.59% presented in [37]. Although the approach is useful to mitigate the cold start problem, the authors mainly focused on sparsity problem. Moreover, the approach is less scalable because of incompetence of user based *Top-N* recommendation algorithms.

Ref. [38] presented an approach to offer personalized business partner recommendations for Small and Medium Businesses (SMBs). To mitigate the sparsity and cold start, the product similarity analysis is combined to evolve a product semantic relevance approach. Each business company is considered as an item and its similarity with the other items is determined. The ratings from the business users and domain experts using fuzzy linguistic terms are obtained followed by the calculation of item-based fuzzy CF and item-based fuzzy semantic similarities between businesses. Subsequently, the prediction values for the fuzzy set based ratings are computed and fuzzy closeness coefficient values to generate the list of *Top-N* relevant business are calculated. With the increase in sparsity level, the MAE decreases while the values for coverage, precision, recall, and F-measure increase. The MAE and coverage on a different number of ratings of cold start items also revealed that the approach performed significantly better as compared to the algorithms proposed in [39] and [40].

The authors in [41] proposed a fuzzy linguistic recommender system that operates in university digital library environment and disseminates the stored information to users working in similar domains. The tool is based on the concept of Google Wave, which provides a common space by permitting the users and resources to work together. The approach deals with the cold start problem for new users. To enter in the system, the new users need to define their profiles by selecting a two-tuple linguistic value. The new user's preferences are represented as a vector that subsequently is compared with the other vectors to determine the similarity. The process of insertion of a new resource is similar to that of new user insertion process. The average values for precision, recall, and F-measure were 0.8674, 0.8734, 0.8693, respectively.

A hybrid recommender system to facilitate the employees of technology transfer office and to mitigate the cold start problem is proposed in [42]. Fuzzy linguistic modeling to disseminate the research resources and to enhance the information discovering properties in an academic setting is applied. To overcome the cold start problem the authors employed a technique similar to that used in [41]. For the new user, the authors applied a CF based approach that employs a nearest neighbor algorithm to generate recommendations in accordance with the preferences of nearest neighbors. However, a limitation of the approach is that to avoid ambiguities and to establish the internal representation of the user profiles, continuous interaction with the domain experts is required.

A trust-based Recommender System for Peer Production Services (TREPPS) that takes into account the trustworthiness of the recommendation sources and user profile is proposed by Li *et al.* [43]. The recommendation task comprises of selecting the service providers that match the requestors' needs. Afterwards, the recommendations are aggregated from the experienced users and a ranking of the recommendations is provided. Moreover, the authors applied a fuzzy Multi

Criteria Decision Making (MCDM) approach to find the most optimal recommendations for the peer services. The experimental results exhibited that the TREPPS effectively improves the peer production services quality and minimizes the information overload as compared to the other approaches. However, the TREPPS and other similar trust based systems generally are not applicable to explicit trust filtering techniques that affects the scalability of such systems.

A fuzzy linguistic modelling based recommendation framework that utilizes both the subjective and objective information is presented in [34]. The subjective information comprises of expert opinions whereas the objective information is constituted based on the preferences of similar users and their past experiences. The approach deals with the cold start and sparsity issues by first obtaining the prediction information about the unrated relevant items of a new user and subsequently *Top-N* recommendations are derived. The active user's preferences are defined as a fuzzy number and the task of generating the relevant items for new users is accomplished by calculating the preferences of neighbors to generate a prediction value. The approach was applied on one rich and one sparse dataset and tested the effects of neighborhood size and recommendation size on system accuracy. The authors claimed that the accuracy of their proposed approach was not much influenced by the sparsity problem because of annexation of subject users' information that is always sufficient in making recommendation.

Table 1: Recommender systems based on fuzzy sets

Work	CI Technique(s)	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[36]	Fuzzy set theory	Deals with fuzzy similarities in customer and product data	✓	✓	✗
[38]	Fuzzy set theory	Fuzzy similarity based predictions to find potential partners	✓		✗
[41]	Fuzzy linguistic modeling	Suggests research resources to the researchers with similar interest	✗	✓	✗
[42]	Fuzzy linguistic modeling	Flexible for selective dissemination of knowledge	✗	✓	✗
[43]	Fuzzy set theory and linguistic modeling	Enhances the quality and veracity of peer production services	✗	✓	✗
[34]	Fuzzy linguistic modeling	Uses subjective information for recommendations	✓	✓	✗

3.2 Recommender Systems Based on Artificial Neural Networks (ANNs)

The ANNs comprise of interconnected group of artificial neurons and a computational model for processing. Among the various types of ANNs, the Back Propagation Neural Networks (BPNN), Kohonen Self Organizing Maps (SOMs), Hopfield networks, and Feedforward networks are the few names. The ANNs have the ability to learn, memorize, and to establish the relationships among the input data and are also capable of modeling the non-linear dependencies [44]. The recommendation systems based on ANNs are presented below.

A context-aware recommender system for TV program recommendation is presented in [10]. The available TV programs are represented in adjacent vector space and subsequently a genre transform is applied to minimize its dimension. To estimate whether a certain TV program is of significant interest to the user or not, a Feedforward neural network is applied. The cold start problem in the approach is overcome by learning the TV viewing habits of the viewers. The temporal context along with the program data is fed into a single hidden layer Feedforward neural network. The contextual information is retrieved from the system clock and is further provided to the neural network by introducing additional input nodes. Testing the approach with one hidden node trained on four past user interactions revealed accuracy over 92%. However, the system was tested on a small scale. Increasing the number of nodes at all the layers requires weight adjustment that is not desirable at large-scale.

Chou *et al*. [45] proposed a technique to offer personalized recommendation based on the notion that user with similar navigation behaviors have similar interests. A BPNN training model is used to enhance the recommendation accuracy by classifying the users into groups with the similar navigation behavior. The user navigation behaviors are further analyzed by extracting the navigation pattern through the unsupervised Web mining approach. To evaluate the validity of the proposed approach, the authors selected a successful website selling soap and skin care products. The classification accuracy was observed best with the eight nodes in the hidden layer. However, the system might come across the scalability problems because it is not certain how to determine the number of intermediate nodes. Moreover, for the users and items with the fewer occurrences, the system was unable to offer the accurate recommendations.

A content recommendation tool for Web personalization based on the ANNs and Kano's method [46] is proposed in [47]. The online shopping behaviors of the users belonging to different clusters were analyzed through the demographics data and the pattern for internet use.

The approach overcomes the cold start problem by applying the ANN to the user clustering instead of conventional clustering methods, such as the *k*-means. However, the approach seems deficient in dealing with the sparsity as it initially requires the dense data sets and sufficient number of user ratings.

Biancalana *et al.* [48] developed a movie recommendation approach based on the assumption that the events occurring over time may influence the recommendations. The user data were pre-processed by grouping the number of ratings of movies by a given user in predefined time intervals, such as one day, one week, or one month. Afterwards, the authors used neural networks to determine the user ratings. The neural network was trained on the following input parameters: **(a)** distribution of number of users rating for a movie per week and per day of week, **(b)** rating submission date, and **(c)** the total number of ratings given to a movie. Testing the neural network on training sets and testing sets of almost equal sizes, the classification accuracy of around 71.9% was observed.

An approach to alleviate the issues of sparsity and cold start in recommender systems is proposed in [49]. Probabilistic Neural Networks (PNNs) are employed for the calculation of trust among the users on the basis of rating matrix. The presented approach is effective in smoothing the sparse rating matrix by using the values of calculated trust. The trusted clusters and the trust values for users in those clusters are identified using the PNN. For sparsity problem, the proposed system performs better with the increase in sparsity level. However, at 50% sparsity level, the Pearson performed well. When tested for the cold start problem, the proposed algorithm significantly performed better than the cosine and Pearson with an error of 0.2 in contrast to the average error of 0.4 of the other systems. The performance of the proposed system in terms of MAE was also observed better than the other approaches. Table 2 summarizes our findings about the recommender systems based on ANNs.

3.3 Recommender systems based on Evolutionary Computing (EC)

Evolutionary Computing (EC) is a CI paradigm that focuses on biologically inspired algorithms following the notion of evolution. Evolutionary computing algorithms have several variants namely, Genetic Algorithms (GA), Genetic Programming (GP), Evolutionary Programming (EP), and Evolutionary Strategies (ES) [50]. The EC is based on computing models, such as natural selection, survival of the fittest, and reproduction. The evolutionary

Table 2: Recommender systems based on the ANNs

Work	CI Technique(s)	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[10]	ANN	Personalized program recommendation by considering users' interests	×	✓	×
[45]	ANN	Uses customers' knowledge to offer personalized recommendations	×	✓	×
[47]	ANN	Effective in personalized provision of web contents considering the online shopping behaviors of users	×	✓	×
[48]	ANN	Focuses on temporal aspects for movie recommendation	×	×	×
[49]	PNN	Uses trust ratings to recommend the items	✓	✓	✓

algorithms are conceptually simple, broadly applicable, robust to dynamic changes, and possess the ability to solve the problems that are difficult to solve otherwise. The EC based recommender systems are effective in dealing with situations when the product categories are scalable. Recommender systems based on the EC are presented below.

A recommender system using the GA and *k*-means clustering collectively called (GA K-means) for an online e-commerce environment is presented in [51]. The approach utilizes the features of the GA to determine the nearest clusters for the target customers and subsequently searches for the most similar neighbors. The recommendations are generated based on the nearest neighbors' purchased items. The intra-class inertia which is the mean of the distance between the cluster center and the sample data was used to evaluate the system performance. The value of intra-class inertia for the GA-K algorithm was observed the least as compared to the simple *k*-means and SOMs. However, the numbers of clusters were set arbitrarily to five that may or may not be an optimal number. Therefore, the performance in terms of recommendation for any other metrics, can be extremely different from the one used by the authors.

Ref. [52] also used the GA to improve the collaborative filtering recommendation process for movies recommendation. The method efficiently selects the items that best match the user preferences. To determine similarities, the approach uses different sets of weights as population of the GA while the optimal similarities are achieved through a fitness function. The authors claimed that using a more simple formula to calculate the similarities as compared to traditional similarity measurement approaches makes the recommendation process efficient. The proposed model based approach addresses the sparsity problem by calculating the *k* similar neighbors of a user and the predictions for that user are calculated subsequently. The experiments were conducted using the MovieLens and FilmAffinity by the comparing the proposed GA method with the Pearson correlation, cosine, and Mean Square Difference. The MAE for the proposed GA was significantly less than the three methods used for comparison.

Another GA based approach for movie recommendation is presented in [53]. The system collects, disseminates, and uses the ratings of other users to recommend movies. The user preferences are utilized by the GA for feature selection and the features are weighted and those with the higher weights are regarded more important than others. The authors coded an additional preference component and also used most similar features to determine the neighbors with the similar tastes. This eliminates the sparsity and cold problems and is also scalable. The performance of the proposed GA based approach was compared to a collaborative filtering based method using the Pearson coefficient. The average fitness of the proposed approach was observed 18.21% higher than that of the Pearson algorithm. However, the processing time of the proposed approach was increased gradually with the increase in neighbor set that might be a bottleneck in case of larger neighbor sets. The fitness of the GA method remains constant with the increase in neighbor size that is an evidence of the scalable nature of the method.

Al-Shamri and Bhardwaj [54] proposed a fuzzy-genetic approach to offer accurate recommendations. The approach first develops a concise user model to enable the hybrid filtering for minimizing the system complexity and the user item matrix sparsity. The features specified in user preferences are assigned weights based on user ratings. The similarity among user preferences is calculated using a fuzzy distance function. The sparsity problem is overcome by developing a set of hybrid features that combines the properties of both the users and the items. The information integrated from various sources results in minimizing the scalability issue. The complexity of the approach was observed significantly less than the Pearson algorithm. Moreover, the MAE for the proposed approach was smaller than the PRS for all the five splits that is an evidence for the prediction accuracy of the system.

A recommendation model called Context-Aware Collaborative Filtering using Genetic Algorithm (CACF-GA) is presented by Dao *et al.* [55]. The model provides location based advertisements based on the preferences indicated by the users and interaction context. To develop the context-aware recommendation model, initially discrete contexts were defined and subsequently, the notion of context similarity was applied on a collaborative filtering mechanism. The optimum similarity values between the contexts were assigned using the GA. The authors implemented the prototype system and collected inputs, such as latest day of visit, time, and the specific need types, for instance shopping places, and restaurants from the users. The average MAE with the proposed approach was observed lowest in comparison to the conventional collaborative filtering algorithms. However, the approach was tested on a dataset with insufficient ratings that elevates the sparsity problem. Table 3 summarizes our findings about the recommender systems based on the EC approaches.

Table 3: Recommender systems based on the EC methodologies

Work	CI Technique(s)	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[52]	Genetic Algorithm	Mitigates the need of hybrid models	✓	×	×
[53]	Genetic Algorithm	Uses a hybrid filtering mechanism to recommend new items on the basis of previous likings and ratings	✓	✓	✓
[51]	Genetic Algorithm	Segments the shopping market into clusters to offer accurate recommendations	×	×	×
[54]	Fuzzy-Genetic approach	Effective in minimizing the system complexity	✓	✓	✓
[55]	Genetic Algorithm	Provides location based advertisements based on user preferences and interaction context	×	×	×

3.4 Recommender systems based on Swarm Intelligence (SI) Techniques

Swarm Intelligence (SI) techniques, such as Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO), and Ant Colony Optimization (ACO) are specifically used for optimization [8]. The concept of SI originates from the swarms of social organisms [56]. The PSO is a stochastic approach for optimization that uses a population based search methodology. The individuals in the swarm are considered as particles and a set of local rules applies to each of the particles [57]. The ACO is also nature inspired algorithm in which the ants form a network of paths that connects their nests with the sources of food [58]. A few recent recommender systems based on the SI techniques are presented below.

The authors in [59] developed a recommender system called Trust based Ant Recommender System (TARS) that uses the ACO to provide neighborhood recommendations based on similarity. In the given scenario, the ACO is effective in making better decisions by using the items and the number of neighbors involved to predict the ratings. Moreover, the dynamic pheromone update strategy that defines the users' popularity as a recommender is useful to alleviate the cold start issue for the new users. The TARS deals with the sparsity issue by combing the similarity measure used to determine the similarities between the two users with another measure called confidence in partner profile while forming a directed trust graph for each of the users. The continuous update of trust between the users results in more accurate recommendations. When compared with traditional CF approach using the MovieLens dataset and Jester dataset, the TARS exhibited improved results for precision, recall, and F-measure.

Nadi *et al.* [60] used the ACO in combination with the fuzzy logic to recommend the well matching URLs to the users with the similar interests. The users' navigational behavior is used for accurate and relevant predictions by locating the users in appropriate classes. A user-item matrix is created to determine similarities among the users and the items recommended by these users. Moreover, the distance between two users is calculated through a fuzzy set that is subsequently used for fuzzy ant based clustering. The pheromone of each cluster is calculated and updated based on the recommendations made for active users. The updated pheromone is used to recommend items in the future to the new users thereby reducing the cold start problem. Although the approach appears quite effective in approximating the solutions, it is not applicable to the situations requiring the exact solutions due to the sparse user-item matrix in the start.

Hsu *et al.* [61] proposed a personalized and scalable system to recommend auxiliary learning materials on Facebook using the Artificial Bee Colony (ABC) algorithm. The approach recommends learning materials on the basis of difficulty level of the auxiliary materials, the number of "*likes*" for a particular learning material, learning styles of individuals, and the course topics. The ABC algorithm is analogous to the random food search operations by bees where the nectar amount found at each food source is regarded as the fitness value. The learning material in response to a search query is considered as a food source. The learning contents that best match the query and the ones liked by most people are recommended to the users. The average fitness values and average execution time of the proposed ABC algorithm with the random search algorithm were found near optimal within reasonable computation time.

Ujjin and Bentley [62] used the PSO to build the user profiles and to subsequently determine the similarities of the active user with the others. To deal with the data having sparse attributes, the PSO is applied. The recommendations regarding the movies are provided to the current user based on the feedback of other users. The performance of the proposed system was observed better than the recommender systems based on the GA and non-adaptive recommender system using the Pearson algorithm.

The authors in [29] used the ACO to develop a cloud based context-aware recommender system called Omnisuggest for venue selection. The Omnisuggest used a model-based Hyperlink- Induced Topic Search (HITS) approach to overcome the issues of cold start and data sparseness by recommending venues to the new users by utilizing the opinion of experienced users (called hubs) and through similarity computation with conditional probabilities between the preferences elicited by the new users and the hubs. The approach addresses the scalability issue by deploying the system as a cloud based architecture. The authors evaluated the performance of the system on Foursquare dataset by comparing with the Single Value Decomposition (SVD) matrix factorization method and the popularity based method. Omnisuggest performed better as compared to the SVD. However, the performance of the Omnisuggest and the popularity based algorithm was observed almost equivalent because of their least sensitivity to data sparseness. Table 4 summarizes our findings about the recommender systems based on the SI techniques.

Table 4: Recommender systems based on SI techniques

Work	CI Technique(s)	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[62]	PSO	Recommendations based on profile similarities	✓	✗	✓
[59]	ACO	Neighborhood recommendations based on item similarity	✓	✓	✗
[60]	Fuzzy sets and ACO	Models the users' navigational behavior offline for recommendation tasks	✗	✓	✓
[61]	BCO	Uses social media to recommend learning materials to the users	✗	✗	✓
[29]	ACO	Uses the opinion of the experienced users to recommend items	✓	✓	✓

3.5 Recommender systems based on Artificial Immune Systems (AISs)

The AIS is another CI technique that is quite feasible for Web based systems because of the capability of adaptation to the ever changing Web environment. Inspired by natural immune systems, the AISs are adaptive in nature and have been used for pattern recognition, classification, data clustering, security, scheduling, anomaly and Web mining [63]. Morrison and Aickelin [64] developed a website recommender system using the immune networks. Cayzer and Aickelin [65] used the AIS to develop a movie recommender system. To introduce diversity in the immune repertoire, both systems use idiotypic network approach. The objective of both the systems is to estimate the active users' interests on a different set of neighbors. The AIS based systems are useful in dealing with the sparsity issue and scalability issues. Recommender systems based on the AIS are presented below.

Acilar and Arslan [66] proposed a method for collaborative filtering based on Artificial Immune Network (aiNet). The authors claimed that aiNet is efficient enough in sparsity reduction and also enables the dataset scalability by describing the data structures with the spatial distribution and the cluster interrelations. The task of finding similar users becomes easier because of the approximated completeness of the datasets. To overcome the sparsity problem, the authors used implicit ratings that are generated by applying the hyper-mutation mechanism of the aiNet. The experimental results show that the average sparsity rate of the dataset was reduced to the 13.13% from 94.96 percent through the hyper mutation mechanism on the proposed algorithm. To overcome the scalability issue the authors used a hybrid approach by first using a dimension reduction approach through network suppression mechanism for aiNet and then the reduced dataset was clustered as a model based approach through the *k-means* algorithm.

A CF based film recommendation system using the AIS is presented in [67]. The approach attempts to find a subset of matches using the idiotypic effects. The concentration of antibodies varies with the variation in population if interaction among them is allowed. The same concept when applied in recommender systems results in more adaptive recommendations because the neighborhood choices and the neighbor weights highly influence the recommendation accuracy. The algorithm is applied by further multiplying the correlation with the concentration of the antibodies (neighbors in this case). The approach was evaluated by recording the user votes for movies. The AIS based algorithm performed almost analogous to the Simple Pearson Predictor and the authors' further argued that the proposed method for neighbor selection can be generalized to form ad-hoc communities.

A recommender system to offer personalized recommendations on news articles using the AIS and danger theory is presented in [68]. The approach works by analyzing and tracking users' interaction behaviors, such as browsing and navigation. The user preferences are also obtained and knowledge about the objects of interest is also associated with the user profile. The proposed AIS based approach ranks the incoming news articles based on the affinity of features with the profiles of the users that eventually help in mitigating the cold start problem. An antigen feature vector is used to match the features with the stored features in the user profiles. Testing the approach on a small scale exhibited prediction accuracy similar to the naive Bayesian classifier. Table 5 summarizes our findings about the recommender systems based on AISs.

Table 5: Recommender systems based on Artificial Immune Networks

Work	CI Technique(s)	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[66]	AIS	Reduces sparsity and enhances scalability	✓	✗	✓
[67]	AIS	Uses idiotypic effects to find the matches among the neighbors	✓	✓	✗
[68]	AIS	Tracks user interaction behavior with the system to make recommendations	✗	✓	✗

4. Discussion

The CI techniques presented in Section 3 enable the recommenders systems to offer personalized recommendations. The recommendation accuracy and the user satisfaction through the CI approaches have been observed to a reasonable level. Moreover, the discussed CI techniques exhibit the capability to handle one or more design challenges highlighted in this survey. Nonetheless, the CI techniques also appear deficient in certain respects. Fuzzy logic for example, may not always provide definite recommendations because there are various ways to interpret the fuzzy rules. Additionally, combining and defuzzifying the outputs from numerous fuzzy rules can be difficult to implement because of the diverse user needs, different system behaviors, and multiple dimensions of data. Further, the fuzzy logic based solutions are difficult to generalize because they rely on the rule base [15]. Despite the abilities to effectively handle the imprecise information and resolve ambiguities in user stated inputs, the fuzzy based approaches are limited in efficiently handling the sparsity, cold start, and scalability issues. The reason is that the fuzzy set theory used in recommender systems mostly utilizes the user profile based collaborative filtering that not only is less scalable but also is less immune to the sparsity and cold start. Using the fuzzy set theory in conjunction with content based filtering approaches can reduce the sparsity, cold start, and scalability issues to a reasonable level.

Likewise, the limitations of ANNs, such as over fitting and inefficiency to learn new data may result in incorrect recommendations because satisfying large number of parameters and re-learning are predominantly multifaceted tasks. Hybrid filtering approaches using the ANNs and fuzzy genetic algorithms have proved quiet effective to reduce the cold start problem. The approaches combine the content based and collaborative filtering and successfully generate recommendations for the items that have never been used or are relatively newer. Model based hybrid approaches using the ANNs are in some way effective for cold start problem. However, these approaches have shown limited potential to deal with the sparsity issues.

The EC based approaches also come across the issues that might lead to inappropriate context interpretations. Among the few that lead to the sub-optimal solutions are the deceptive fitness functions and premature convergence of the evolutionary algorithms. Using certain hybrid approaches that combine each of the GA and ANNs with the fuzzy sets can possibly alleviate the associated problems. The GAs prove useful in reducing the sparsity, cold start, and scalability. Nonetheless, the heuristics used in the GAs can cause in elongated time to converge the results that in turn results in increased computational complexities.

The SI techniques also come across an important issue of stagnation due to absence of centralized control. Consequently, the recommendation mechanism may trail a sub- optimal path every time that eventually results in irrelevant recommendations. However, a careful setting of the SI system parameters can reduce the probability of stagnation [69]. Another limitation of the SI techniques is that these techniques are not well suited to situations requiring exact solutions. Consequently, it becomes difficult for the SI based approaches to model the context properly in most of the scenarios, particularly for venue recommendations. Another interesting observation about the SI based techniques is that these approaches are substantially capable of dealing with the issues of cold start, scalability and sparsity.

Although, the AIS based recommender systems are fairly useful in disambiguating the noise from the web contents, there are some limitations associated with them. For example, they only extract information from hypertext documents. Moreover, the traditional approaches to extract the metaphor from the AIS based systems are naive that have driven away the AIS based approaches from their immunological roots [70]. Another challenging problem for the AIS based approaches is profile adaptation. Furthermore, an important limitation of the AIS systems is their computational complexity that makes them less feasible for the practical use.

Table 6: Strengths and weaknesses of the CI techniques

CI Technique	Strengths	Weaknesses	Application in recommender systems
Fuzzy logic	• Effective for identification of ambiguities and uncertainties • Deals with fuzzy product similarities	• Requires continuous interaction with domain experts to resolve ambiguities • Difficult to combine outputs from multiple rules due to diversified user needs	• Resolving the ambiguities between the precisely stated attributes of the product and the linguistic user inputs • Processing user profiles with fuzzy inference
ANNs	• Effectively identify users with similar behaviors • Effective in accurate context elicitation	• Limited interpretation and explanation of results	• Used to analyze product ratings for personalization
EC	• Accurate context computation • Useful for document search, query optimization, and personalization	• Premature convergence • Computationally expensive	• Used to identify the neighbors with the similar tastes. • Optimization of personalized search tasks
SI	• Highly adaptive and evolvable • Require less memory	• Not suitable for problems requiring exact solutions • Fall into inactivity due to absence of centralized control	• Personalized content sequencing • Web usage mining
AIS	• Maintain immunological memory of past encounters, continuous learning of new encounters • Remove noise from Web contents	• Profile adaptation in practice is challenging • Uses naïve approaches to extract traditional metaphors	• Used to handle the problem of preference matching • Web personalization

Large numbers of context-aware recommender systems based on the CI techniques are the evidences of their widespread and cross domain applicability. However, scalability is still a major challenge that most of the presented techniques in this survey fail to handle. Using the CI techniques in conjunction with other machine learning approaches can not only help in the improved quality of retrieved information but also can be useful in dealing with the challenges, such as sparsity, cold start, and scalability. Table 6 presents a comparison of the general CI techniques, such as the fuzzy logic, ANN, EC, SI, and AIS. Table 7 also presents a comparison of the various recommendation systems based on the CI techniques. The comparison has been made on the basis of parameters, such as Data present in databases, filtering approach, recommendation algorithm, similarity measures, prediction metrics (MAE and coverage), recommendation quality metrics (precision, recall, F-measure), and the objective achieved by a particular technique. Due to space limitations, the following abbreviations are used for Table 7.

User rating: UR, Item Rating: IR, User Profile: UP, Filtering Approach: FA, Collaborative Filtering: CF, Content based Filtering: CB, Hybrid Filtering: HF, Similarity Measure: SM, Memory based: MM, Model based: MB, Pearson Correlation: PC, Euclidean Distance: ED, Cosine Similarity: CS, Prediction Metrics: PM, Precision: P, Recall: R, F-measure: F, Top-N recommendations: T, Predictions: P.

5. Conclusions

In this survey, we presented a state-of-the-art in context-aware recommender systems based on the CI techniques, such as the fuzzy sets, ANNs, EC, SI, and the AISs. Besides discussion on context-aware recommender systems based on each of the aforementioned CI techniques, we also highlighted the key feature(s) of each of the systems. Moreover, we also discussed the major design challenges being encountered by recommender systems and also reported the types of challenges being met by each of the presented approaches. Interestingly, it is observed that each of the CI techniques is capable of dealing with one or more challenges. Although the SI and the AIS are relatively new as compared to the rest of CI techniques, their capabilities to offer personalized recommendations and to meet the challenges, such as sparsity, cold start, and scalability are a predictor of their widespread use in the future research on context-aware recommender systems. In general, the CI techniques have been proved effective not only in context-aware recommender systems but also in context-aware searching. However, these systems still have to go a long way and possibly need to utilize the CI techniques in conjunction with each other to entirely deal with the challenges stated in this survey.

Table 7: Comparison of different CI based approaches

Ref.	Data	FA	Algorithm	SM	Evaluation metrics					Objective achieved (T/P)
					PM	Recommendation quality metrics				
						P	R	F	Others	
[36]	UR	HF	MM, MB	PC	MAE (0.784929)	-	-	-	-	P
[38]	UR	CF	MM	PC	MAE(0.5) Coverage (0.90)	-	-	-	-	P
[41]	UP	HF	MB	CS	-	0.864	0.8734	0.8693	-	T
[42]	UP	HF	MM	ED	MAE (0.7471)	67.42	69.03	68.11	-	P,T
[34]	UR	CF	MM, MB	ED	-	0.73	0.75	0.75	-	T
[45]	UP	HF	MB	-	-	-	-	-	Type I and Type II errors	P
[10]	UR, UP	CF	MB	PC	-	-	-	-	71.9% prediction accuracy	P
[47]	UP	CF	MB	*k*-means	-	-	-		Average difference in satisfaction score	
[49]	UR	CF	MB	CS	-	0.98	0.98	0.98	-	T
[48]	UR	CF	MB	PC	MAE (0.03)	-	-	-	-	P
[51]	UP	HF	MB	*k*-means		-	-	-	Intra-class inertia (2.128)	P
[52]	UR	CF	MB	GA based similarity function	-	0.73 0.79	0.38 0.38	0.80 0.78	-	T
[53]	UR, UP	CF	MB	ED	-	-	-	-	Average fitness value (81.77%)	P
[54]	UR, IR, UP	HF	MM	PC	MAE (0.675) Coverage (97.56)	-	-	-	-	P
[55]	UR, IR, UP	CF	MM	PC	MAE(0.9122)	-	-	-	-	P
[59]	UR, IR, UP	CF	MM	PC	MAE (73%) MAE (77.6%)	24.33 31.4	36.5 44.34	-	-	P,T
[60]	UP	HF	MB	Jaccard Coefficient	MAE (0.56)	0.17	-	-	-	T
[61]	UP	CF	MB	-	-	-	-		Average fitness (0.260)	T
[62]	UR, IR, UP	CF	MB	ED	-	-	-		Prediction accuracy (90%)	P
[29]	Up, social relationship	CF/Social filtering	MM, MB	PC	-	0.03	0.5	0.05	-	T
[66]	UR, IR, UP	CF	MM, MB	PC	MAE (0.82)	-	-	-	-	T
[67]	UR, IR, UP	CF	MB	PC	MAE (0.90)	-	-	-	-	P,T
[68]	UR, IR, UP	HF	MB	CS	-	-	82.80	89.49	86.06	T

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