An Extensive Review of Machine Learning Models in Recommendation System

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Abstract— Recommender systems (RS) uses different method for recommending products or services to the interested users. Presently, RS has been employing machine learning (ML) models under the domain of artificial intelligence. On the other hand, selecting an appropriate ML method for a RS is a tedious task and the choice of ML algorithm plays a vital role which greatly influences the performance of a RS. The researchers and professional doing works on RS are having only less information about the present techniques in-algorithm usage. Furthermore, the design of RS using ML techniques always suffers from difficulties which need to be solved. So, in this paper, a detailed survey is made which reviews the various technologies exists in the RS and identifies many open issues and challenges. At the end of paper, a detailed comparison is made between the reviewed approaches.

Keywords— Recommendation system; Machine Learning; e-commerce

I. INTRODUCTION

In modern age, massive quantity of digital data is generated and the number of users visited to the Internet have posed a significant confront of information overload which delays the faster access of interested items on the Internet. Some of the information retrieval models like Google, DevilFinder, etc has resolved this issue, but the prioritization and customization (where a model performs mapping existing content to the interested users and favorite) of information are not available. It has raised the requirement of RS ever increasing. RS are considered as information filtering models which dealt with the issue of information overload [1] by extracting important information fragments from massive quantity of lively created data based on the preference of the user, interests or nature of the item [2]. RS has the capability of predicting that a specific user will prefer a product or not based on the customer's details. The RS will be advantageous for both service providers and customers [3]. They minimize the cost for transaction by identifying and choosing precuts in an online shopping platform [4]. It is also ensured that the RS leads to enhanced decision making process [5]. In e-commerce systems, RS improves the revenues, so that it is efficient by means of selling many products [3]. For technical libraries, RS helps customers by enabling them to go ahead of catalog searches. So, the requirement to utilize effective and precise RS in a system will give related and dependent recommendations for the customers which cannot be exaggerated. RS can be termed as a decision making strategy for customers under complicated information environments [6]. In the aspect of e-commerce, the RS can be defined as a tool which assists customers while searching the records of knowledge relevant to their interests and preferences [7]. It is a way of helping and recording the social process utilizing the other's recommendation for making choices in case of in sufficient personal details or experience of the alternative items [8]. RS manages the issue of information overload where the customer usually faces by giving them customized, that users normally encounter by providing them with personalized, special content and service recommendations. In recent days, different methodologies for building RS has been proposed, which utilizes any one of the following methods include collaborative, content-based and hybrid filtering [9–11].

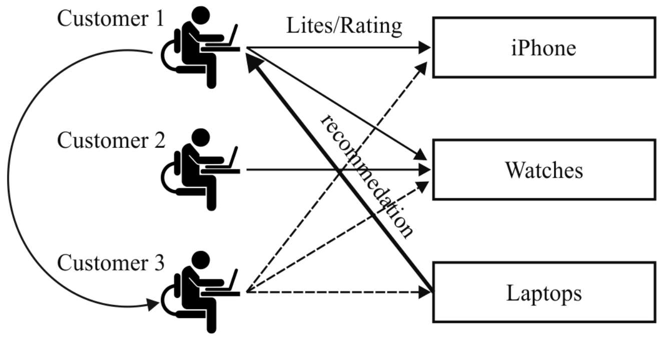

Fig. 1 Collaborative filtering

Collaborative filtering approach is the matured and widely employed method. It models the system by the consideration of the history of the customer (reviews posted to products, purchased or selected products) and an in addition to identical decisions made by various customers and then utilizes the model to determine the product or else rating in which the customer might be interested. User-based Collaborative filtering methods give recommendations by the consideration of the users with same kind of interests. It interlinks the user based on the rating given to the purchased product. As given in Fig. 1, the customer 1 recognized the customer 3 rather than customer 2 due to the fact that the rating given by customer 1 and customer 3 are similar. So, the product 3 will be recommended to the customer. Alternatively, the collaborative filtering suggests the products by the identification of another customer with same taste; it makes use of their views to suggest products to the current user. The collaborative RS has been developed in various application domains.

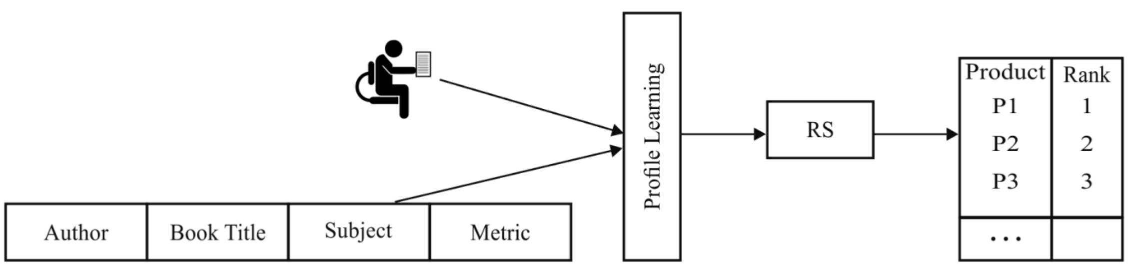

Fig. 2 Content based filtering

At the same time, the content-based method matches the content resources to the user's features. It simply eliminates the contributions from other users as with the case of collaborative methods [12, 13]. An illustration of content filtering is shown in Fig. 2. The major difference between the content and collaborative filtering methods is illustrated in Fig. 3. Fab strongly based on the ratings of various users for creating a training set and it is an exemplary of content-based RS. Few of the models use this method for helping the users to identify the information on the Internet such as Letizia [14]. This method employs a user interface which helps the customers while browsing Internet; it has the capability for tracking the browsing pattern of a customer for predicting the interested pages. Jennings and Higuchi [15] describe a neural network that models the interests of a user in a Usenet news environment. The difference between collaborative and content based filtering is illustrated in Fig. 3. ML models are being utilized in RS to provide better suggestions to the customers. But, the ML domain does not have a proper classification model for its techniques due to the fact of large number of methods exist in the literature. So, it is not easier to select a ML mode which is appropriate for the RS. The absence of detailed survey on the ML methods on the RS motivates us to perform this study.

So, in this paper, a detailed survey is made which reviews the various technologies exists in the RS and identifies many open issues and challenges. In this paper, we have reviewed the RS model under the classification of fuzzy logic, CI, EC and SI techniques. At the end of paper, a detailed comparison is made between the reviewed approaches. The upcoming portion of the study is arranged as follows: Section 2 explains the different stages involved in RS. A review of different models of RS is done in Section 3 and some conclusions are drawn in Section 4.

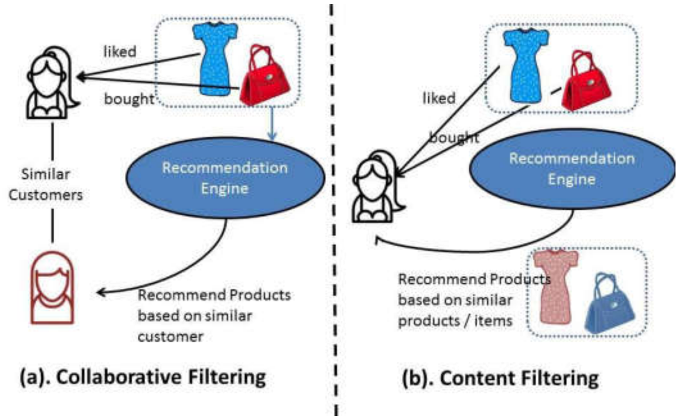

Fig. 3 Difference between collaborative and content filtering

II. STAGES OF RECOMMENDATION PROCESS

A. Information collection stage

In this stage, related user information will be collected for the creation of user profile or defines the prediction process including user's attribute, actions or content of the resources the user accesses. An agent from RS fails to operate precisely till the user profile has been well organized. The model should know more information from the customer for suggesting better products. The RS usually depends on various kinds of input like quality explicit feedback, which incorporates clear input by customers for their interest in the product or implicit feedback by analyzing the preferences of the customer in an indirect way by the observation of the customer actions [16]. A Hybrid feedback is also attained by the integration of implicit as well as explicit feedback. In the e-learning environment, a customer profile contains a set of personal data linked with a particular user. This information may include cognitive skill, intellectual ability, learning models, interests, preference and interaction with the system. The customer profile will be used for the retrieval of required data for the construction of a model of the customer. So, the customer profile defines a simple user model. The achievement of any RS mainly depends on its capability to indicate the present interest of the customers. Some precise models are needed to obtain proper and precise recommendations from any prediction techniques. While constructing a system from user's actions, a differentiation is always made among explicit and implicit forms of data acquisition. Some instances of explicit data gathering are listed below.

- Requesting a customer for rating a product
- Requesting a customer to search.
- Requesting a customer for ranking a set of products based on their favorite
- Giving two products to a customer and telling them to select the better choice
- Requesting a customer for creating a wish list

Some instances of explicit data gathering are listed below.

- Following the products that a customer visits in the website
- Investigating the number of times that the product has been visited by the customer
- Maintaining a record of the products that a customer bought online.
- Getting a list of products that a customer visited
- Searching the customer's account on social media for their likes and dislikes

The RS undergo comparison with the gathered data to the identical and non-identical data gathered from other customers a make a list of recommended products for the intended customer.

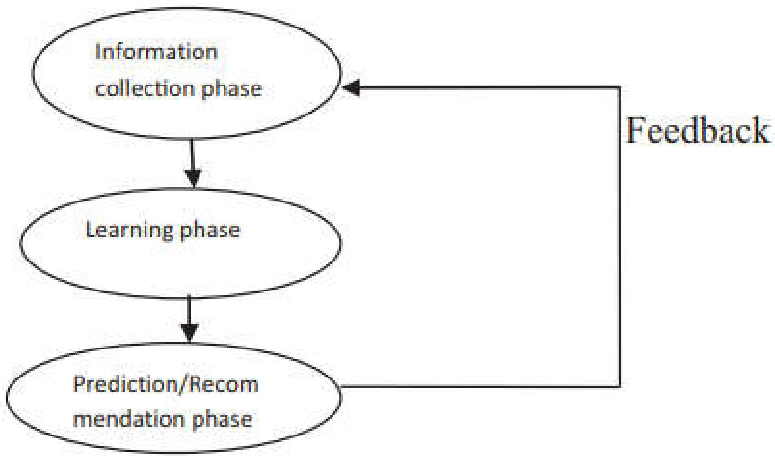

Fig 4 Recommendation phases

B. *Learning stage*

It employs a ML technique to identify and make use of the customer's characteristics from the collected feedback from the previous stage.

C. *Prediction/Recommendation stage*

It suggests the type of products in which the customer will choose. It can be decided straightly from the dataset gathered in the first stage which is saved in the memory based or model based or using the model's observed actions of the customer.

III. REVIEW OF RS BASED ON MACHINE LEARNING MODELS

A. *Rs based on Fuzzy set Theory*

When the data given is partial otherwise vague [17], fuzzy set theory is suitable in the areas in these circumstances, introduced by LotfiZadeh in 1965 [18]. There is a requirement for a structure which can deal with uncertain situation ignited the fuzzy logic progression. Fuzzy logic is majorly employed for circumstances that are uncertain of the actual language in a broad sense. When from a narrow sense, the concept of many-value logic is known as fuzzy logic which comes under symbolic logic. RS depended fuzzy set theory is demonstrated as follows.

To deal with the problems of vagueness in addition to data sparsity within the data of customer and product for telecom services, a hybrid approach is needed [19]. This approach combines the customer based and the product-based filtering using fuzzy set method to deal the similarity in fuzzy products.

By employing the Movie Lens 100 K dataset which contains 1 lakh rating records from 943 customers for 1682 products, the prediction accuracy of the system is examined. To avoid the problem of sparsity, the authors applied product based collaborative filtering to build a solid customer-product rating matrix. The sparsity rate which is missing is estimated as 94.96% in the dataset. The estimated value lies between 94.64% and 95.59% in [20]. Even though this method is helpful to reduce the cold start issue, the major focus of the authors is overcome the sparsity issue. Due to the ineffectiveness of the customer depend on *Top-N* recommendation algorithms, this method is less scalable.

A method projected in [21] to provide a recommendation which is a personalized one to the business partners for Small as well as Medium Businesses (SMBs). The analysis of product similarity is merged to develop a relevance based semantic procedure to reduce the issues of sparsity and cold start. Every organization is assumed as a product in addition their own similarities along with the products are determined. The fuzzy linguistic term is obtained by the rating from business customers in addition to the field experts followed by an estimation of resemblance between product-based fuzzy collaborative filtering as well as product-based fuzzy semantic approach. The estimations of the closeness of fuzzy coefficient rates to produce the list of relevant *Top-N* business and rates that are predicted for the rating of fuzzy set are calculated. When the rates of coverage, precision, recall, and F-measure increases, MAE decreases with increase in the level of sparsity. It revealed that the method performed fine when contrast between the algorithms projected in [22] and [23].

To various customers who are going through the same area in university digital library, aRS is presented using a fuzzy linguistic system [24]. The tool which offers a general space by allowing several customers as well as resources to operate in a simultaneous manner based on the idea of Google Wave. This method easily deals with the cold start issues of fresh customers. The fresh customers required to describe the profile via choosing a rate two-tuple linguistic to enter into the system. The priorities of a fresh customer is demonstrated by a vector which consequently compare itself to the another vectors to estimate the similarities. The procedure of inserting of a fresh resource is same as the procedure of inserting a new customer. The rates 0.8674, 0.8734, 0.8693 are the average of precision, recall and F-measure correspondingly.

In [25], hybrid RS for the workers of technology transfer office is offered and eliminates the cold start problem. To improve the properties of data discovery in a study purpose set and to divide the study resources, fuzzy linguistic modeling is employed. The author used a method as same as employed in [8] to avoid the issue of cold start. The authors used the method of collaborative filtering which uses a closest neighbour algorithm to produce recommendation in order to the priorities of closest neighbours for the fresh customers. But, the constraint of the method is to overcome the confusions in addition to create an internal organization of the customer profile, interaction among the field experts constantly is needed.

The trust worthiness of the sources of the recommendation and also for customer profile for trust-based RS for Peer Production Services (TREPPS) is projected in [26]. Choosing a service provider which is similar to the requestor requirements are the tasks of recommendation. Subsequently, the recommendation is grouped out off the rank order of recommendation and customers who had experienced. However, to search the best optimised recommendation for peer services, the author applies a fuzzy Multi Criteria Decision Making (MCDM) method. The outcomes show that TREPPS proficiently enhances with the quality of peer production services and reduces the data overload when contrast between the other methods. But, these systems are commonly suitable to external trust filtering methods which affect the system's scalability.

[27] projected a recommendation structure which depends on fuzzy linguistic modelling which employs together the objective and subjective data. The expert choices such as the object data is built depending upon the priorities of similar customer and the experiences which is contained in subjective data. Initially, by getting the data that is predicted regarding the relevant products that are unrated of a fresh customer, this method deals with the cold start and after that the derivations of *Top-N* recommendation are obtained. The process of recommending the products which are relevant to the fresh customers is done through estimating the priorities of neighbours to create a predicted value and the customer's priorities are described by a fuzzy number. This method is tested over dataset of one rich and one sparse to obtain the effect of neighbourhood volume and recommendation volume based on the accuracy of the system. Due to the annexation of subject customer's data which is at any moment proficient in creating recommendation, the author claimed that through the issue of sparsity, the accuracy of the projected method is not that much influenced.

B. *Rs Based on Artificial Neural Networks (ANNS)*

ANN contains a collection of interlinked artificial neurons and a computation design to process the data. From the diverse kinds of ANN, Back Propagation Neural Networks (BPNN) and Feedforward networks (FFNN) are widely used. The ANN has the capability of learning, memorizing and also establishing a relation between the input data and also has the capability to model the non-linear dependencies [28]. The RS based on ANN is shown in Fig… A context-aware RS for suggesting the TV programs are devised in [29]. The existing TV programme is indicated as adjacent vector space and consequently a genre transform is employed for minimizing the dimensions. For assessing whether a specific TV program is popular among the viewers or not, a FFNN is used. The cold start issue in the technique is resolved by analyzing the patterns of the programs watched by the viewers. The temporal context is given to the single hidden layer of FFNN with the program data. The contextual information gets retrieval from the system clock and is additionally given to the NN by giving extra input nodes. The validation of the method using one hidden node which undergone training using 4 past user interactions reported an accuracy of approximately 92%. On the other hand, the model is validated on small scale also. The increment in the number of nodes at every layer needs an adjustment of weights which is undesirable in large scale. [30] Projected a method which offers customized suggesting using the notion that the customer with identical navigation actions with same interest. A BPNN training method is employed for enhancing the accuracy of the RS by the classification of customers into groups with the identical navigation actions. The actions of the customer navigation are additionally investigated by the extraction of navigation patterns suing unsupervised web mining techniques. For the evaluation of the presented method, a famous soap and skin care products are used. The classification accuracy is found to be superior by the use of 8 nodes in the hidden layer. In addition, the model may face the scalability issues due to the fact that is uncertain to compute the number of intermediate nodes. Furthermore, for the customers and products with less number of occurrences, the model cannot able to provide precise suggestions.

A content recommendation tool for the customization of websites by employing ANN and Kano's technique [31] is presented in [32]. The purchasing patterns of the customers from various groups are identified using the demographics data and the patterns from internet usage. This method resolved the cold start problem using the application of ANN to the customer clustering rather than the traditional clustering techniques like k-means. But, this technique is found to be lacking when dealt with sparsity since it needs dense dataset as well as more number of customer rating at the starting stage. [33] Presented a RS for movies by considered that the actions occurred for a time period has impact on the suggestion of movies. The customer data undergo pre-processing step by the process of clustering the number of ratings of movies by a particular viewer in fixed time duration like one day or week or month. Then, NN will be applied to find the rating of the viewers.

For training purposes, the list of input parameters used are (a) distributing the number of viewers rating for a movie in every week as well as every day, (b) date of the rating given and (c) the sum of the ratings given to a movie. The training and testing set of NN is of identical sizes and the accuracy of approximately 72% is attained.

To overcome the problem of sparsity and cold start in RS, a probabilistic NN (PNN) is applied to calculate the trust level among the customers using a rating matrix [34]. The introduced method is efficient in smoothing the sparse rating matrix through the computed trust values. The trusted clusters as well as the trust values for the customers in those customers are found by PNN. Interms of sparsity, the PNN is effective and attained increased sparsity level. For cold start problem, the proposed PNN outperforms the cosine and Pearson with an error of 0.2 whereas compared method attains an error of 0.4. In addition, the results are analyzed interms of mean absolute error (MAE) where the PNN performs well interms of MAE also.

TABLE I
COMPARISON OF REVIEWED RS MODELS

Reference	Methodology	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[19]	Fuzzy	Deal with fuzzy resemblances in customer and product data	□	□	□
[21]	Fuzzy	Fuzzy resemblance based predictions for identifying potential partners	□	□	□
[24]	Fuzzy	Recommend research resources to the researchers with same taste	□	□	□
[23]	Fuzzy	Adjustable for selective dissemination of knowledge	□	□	□
[26]	Fuzzy	Improve the quality and reliability of peer production services	□	□	□
[27]	Fuzzy	Employs subjective information for suggestions	□	□	□
[29]	ANN	Customized program suggestion by the consideration of customer interests	□	□	□□
[30]	ANN	Employs customer's knowledge to provide customized suggestions	□	□	□
[32]	ANN	Efficient to customized distribution of web contents by considering the online shopping patterns of the customers	□	□	□□

Reference	Methodology	Key Feature(s)	Ability to deal with design challenges		
			Sparsity	Cold start	Scalability
[33]	ANN	Concentrates on temporal aspects for movie recommendation	□	□	□□
[34]	PNN	Employs trust ratings to suggest the products	□	□	□□
[37]	GA	Mitigates the requirement of hybrid models	□	□	□
[38]	GA	Employs a hybrid filtering scheme to suggest fresh products using the past likes and ratings	□	□	□
[36]	GA	Organizes the shopping market to clusters for providing precise suggestions	□	□	□
[39]	Fuzzy-GA	Efficient in the reduction of complexity level	□	□	□
[40]	GA	Gives location based advertisements using the customer choices and interaction context	□	□	□
[47]	PSO	Suggestions on the basis of profile similarities	□	□	□
[45]	ACO	Neighbourhood suggestions using product resemblance	□	□	□
[46]	Fuzzy sets and ACO	Employs the customer's navigational action offline for recommendation process	□	□	□
[48]	ACO	Utilize the opinion of the experienced users to suggest products	□	□□	□□

C. *Rs Based on Evolutionary Computing (EC)*

Several EC algorithms are Genetic Algorithms (GA), Genetic Programming (GP), Evolutionary Programming (EP), and Evolutionary Strategies (ES) [35]. The idea of evolutionary algorithm (EA) is very easy, versatile to different applications, flexible to rapid which are tedious to solve by other methods. The EC based RS are efficient when dealt with scenarios when the categories of the products are countable. Some of the ES using EC are reviewed in this section.

A RS using the GA and k-means clustering named as (GA-K means) for an e-commerce platform is proposed in [36]. This method employs the characteristics of GA to identify the closest clusters for the intended customers and consequently look for the similar customers in the closer area. The suggestions are made using the products purchased by the closest neighbors. Here, the cluster count is set randomly upto 5 which might or might not be an optimal number. [37] utilized GA for improving the collaborative filtering process to recommend movies. This method effectively chooses the products for better match to the preference of the customers. This method effectively chooses the products which are better matched with the preference of the customer. For determining the resemblance, this method uses a collection of weights as the population of GA whereas the optimal resemblance is attained by a fitness function. It is reported that a simple calculation can be used for the calculation of resemblance compared to conventional resemblance matching method makes the suggestions effective.

This method resolves the sparsity issue by the calculation of k identical neighbors of a user and the guessing for that user are computed successively. The experiment is conducted by the use of MovieLens and FilmAffinity making a comparison of presented GA with Pearson correlation, cosine, and Mean Square Difference. The MAE for the presented method is lesser than the compared techniques.

In [38], a GA based movie RS is introduced which gathers, distribute and utilizes the viewers rating to recommend movies. The first choices of the viewers are used by GA to select features. The features are weighted and the features with more weights are considered as important features. An extra preference component is employed to identify the nearby viewers with identical taste. It removes the sparsity and cold issues as well it is found to be scalable. Though the average fitness of the GA is better than the Pearson method, its computation time is increased with an increase in neighbour set which may leads to a bottleneck problem for larger neighbour sets. [39] devised a fuzzy-genetic method which offers precise suggestions. Initially, a proper customer model is designed which enables the hybrid filtering process to minimize the complexity level of the system as well as customer product matrix sparsity. The features denoted in the customer choices are allocated weights on the basis of the customer rating. The resemblance among the customer choices are computed by a fuzzy distance function. The sparsity issue is overcome by deriving a collection of hybrid features which combines the properties of customers as well as products. The information gathered from different sources leads to the decrease in the scalability problem. The computational complexity of the fuzzy genetic is lesser than the Pearson method. In addition, the MAE of the presented method is lesser than the PRS for all the five splits.

Context-Aware Collaborative Filtering using Genetic Algorithm (CACF-GA), a RS is introduced [40]. The CACF-GA gives location oriented advertisements using the choices given by the customers and some interaction context. For developing a context-aware RS, discrete contexts are defined and consequently, the notion of context similarity is employed on a collaborative filtering process. The optimum resemblance values among the context are allocated by GA. A prototype model is developed and gathered inputs like recent visit, time and particular requirements (hotel, movies) from the customers. The obtained MAE of the presented method is much lower the traditional methods. In addition, it is validated using a dataset with sparse rating which creates the issue of sparsity.

D. *RS based on Swarm Intelligence (SI) Techniques*

The idea behind ST begins the group of living organisms [41]. Particle swarm optimization (PSO) is a meta-heuristic method which employs a population based searching technique. The individuals in the group are treated as particles and a collection of local rules are applied to every particle [42]. Ant colony optimization (ACO) is also a bio-inspired method where the ants build a network of routers which connect the nest and food source [43]. Some of the RS based on SI techniques are discussed here.

In [44], Trust based Ant Recommender System (TARS) is proposed which employs ACO to give neighbour's suggestion using resemblance. In this case, ACO provides the suggestions by taking effective decisions using the produces and neighbour count used for the rating prediction. Furthermore, the dynamic pheromone updating features which defines the customer's popularity as a recommender, which will be helpful to eliminate the cold start problem for the recent customers. The TARS dealt with the sparsity problem by integrating the similarity measured employed to compute the resemblance among two customers with other metric known as confidence in partner profile during the formation of directed trust graph for every customer. The uninterrupted updation of trust level among the customer leads to precise suggestions.

On comparing with conventional approaches using benchmark dataset, TARS outperforms the other methods interms of precision, recall, and F-measure. Nadi et al. [45] uses ACO with fuzzy logic to suggest the matching URL to the users with identical tastes. The navigational pattern of the user can be utilized for precise and related prediction by the location of proper classes. Furthermore, the distance between two users is determined by fuzzy set which is successively employed for fuzzy ant based clustering. The pheromone level of every cluster is measured and gets updated using the suggestions made for the current users. The updated pheromone level can be employed for the product recommendations in the upcoming days for the new customers and hence cold start issue can be easily reduced. But, it is inapplicable to the situations which needs proper solutions because of sparse user-item matrix.

Hsu et al. [46] presented a customized and scalable model for the recommendations of the secondary learning in Facebook by the use of Artificial Bee Colony (ABC) algorithm. This method suggests study materials based on the difficulty level, "likes" for a specific study materials, course contents, etc. The ABC algorithm is similar to the randomized food searching operation of bees in which the attained nectar quantity of every food source is considered as the fitness value. The study material in response to a search query is treated as the food source. The study material with best match with the query and the one liked by many readers are suggested to the intended reader the fitness value and the computation time of the ABC algorithm with the random search algorithm is found to be near optimal. Ujjin and Bentley [47] employed PSO for developing customer profiles to successively identify the resemblance of the active customer with the others. For dealing with the data having sparse parameters, PSO is employed. The recommendations for movies are given to the present user using the feedback from the other viewers. The results of the PSO based RS is found to be efficient than the GA and Pearson algorithm. [48] make use of ACO to construct a cloud based context-aware RS known as Omnisuggest to select venues. It uses a Hyperlink- Induced Topic Search (HITS) method to eliminate the cold start and sparsity issues by suggesting venues to the customers using the choice of previous customers and by the similarity computation. The problem of scalability is resolved by the cloud based architecture. Table 1 summarizes the comparative analysis of the reviewed RS.

IV. CONCLUSIONS

RS can be termed as a decision making strategy for customers under complicated information environments [6]. In the aspect of e-commerce, the RS can be defined as a tool which assists customers while searching the records of knowledge relevant to their interests and preferences. In recent days, different methodologies for building RS has been proposed, which utilizes any one of the following methods include collaborative, content-based and hybrid filtering. ML models are being utilized in RS to provide better suggestions to the customers. In this paper, we have reviewed the RS model under the classification of fuzzy logic, CI, EC and SI techniques. Also, a detailed survey is made which reviews the various technologies exists in the RS and identifies many open issues and challenges.

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