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Review Article

Classifications of Recommender Systems: A review

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Abstract

This paper presents the state of art techniques in recommender systems (RS). The various techniques are diagrammatically illustrated which on one hand helps a naïve researcher in this field to accommodate the on-going researches and establish a strong base, on the other hand it focuses on different categories of the recommender systems with deep technical discussions. The review studies on RS are highlighted which helps in understanding the previous review works and their directions. 8 different main categories of recommender techniques and 19 sub categories have been identified and stated. Further, soft computing approach for recommendation is emphasized which have not been well studied earlier. The major problems of the existing area is reviewed and presented from different perspectives. However, solutions to these issues are rarely discussed in the previous works, in this study future direction for possible solutions are also addressed.

Keywords: recommender systems, collaborative filtering, reclusive methods, knowledge based recommender systems, hybrid recommender systems, context aware recommender systems.

1. Introduction

The recommender systems (RS) have grown exponentially in recent few years and its applications have spread over various domain of life including online shopping of books, home appliances, movies, electronic gadgets, recommendation of doctors and hospitals for patients, institute recommendation for students and teachers, hotel recommendations for tourists and so forth. The philosophy behind the success of recommendation technology is the fact that it is human tendency to rely upon experiences of their neighbors and friends prior to making decision of any kind, especially regarding purchase of any items, taking admissions in institutes for higher education, opting an apartment for rent or buying it, spending weekend at some holiday places, etc.

The advancement of Internet technologies has caused data overload due to which the buyers face more difficulties in finding the exact destination which meet their needs out of a huge collection of the available options. If a student who wishes to spend his/her vacations at some hill stations and would like to stay in a hotel with peace and calm, there would be thousands of places all around the world which might come to him/her as options. In such a situation recommender systems can provide a better option according to the need and requirement of the user and depending upon his/her prior preferences.

Although there are several definitions which researchers have suggested for recommender systems, we define recommender systems as –

"*Recommender systems try to identify the need and preferences of users, filter the huge collection of data accordingly and present the best suited option before the users by using some well-defined mechanism*."

A formal definition for RS can be stated as;

Let 'S' be the set of users and 'I' be set of all items that fall under their preference category. Let $\boldsymbol{R \subseteq I}$ is the ranked list of items which is in some desired order, and r is an item in list R, i.e. $\mathbf{r \in R}$. The recommendation problem is to choose an $\mathbf{r \in R}$ such that it satisfies the users and also meets their need. Let 'E' be the evaluation metric to measure user satisfaction for some real number 'z', then we can assume user satisfaction is achieved only if **E • z**.

Mathematically, if '**f**' defines the function of recommending 'r' items to 's' users, our problem can be formulated as:

f (r,s) • z (1)

In this Paper, we have reviewed more than 200 articles related to recommender system including the manuscript in which very first existence of collaborative filtering has reported in mid 90s [1], [2].

2. Previous Review Studies

The first paper on collaborative filtering (CF) was introduced in mid of 90s [2], [3]. The proposed CF technique provided a platform to design recommender system and laid a strong foundation for the development of such recommender systems. The work in the concerned area has been reviewed extensively in the literature. The study of the surveys and reviews of recommender systems helps in establishing a better understanding of the subject and gives a holistic picture of the technology used in the field along with

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various aspects related to the topic. In this section, we have tried to include major review/survey papers on the related work and discussed their contributions. As the origin of the recommendation techniques are in mid 1990s, it seems adequate to include papers from 2000 onwards.

In 2000, B. Sarwar et al. [4] has analyzed the effectiveness of recommender systems on actual customer data from an e–commerce site and compared several recommender algorithms with respect to their performance [5]. In 2001, Schafer et al. [6] have examined traditional marketing methods and provided a foundation for the growth of recommender systems as a marketing tool for e-commerce. They have also presented taxonomy for recommender system and identified five models of recommender applications. One of the excellent contribution of the Schafer et al. was their exploration of four different domain for future study based on the taxonomy that have not been adequately explored by the existing applications, then. They have suggested following four area of research for recommender systems; non-personalized, attribute based, item-to-item correlations, and people-to-people correlations.

In 2002, R. Burke [7] investigated possible extent of hybrid recommender systems and provided quantitative results for relative comparisons. Burke [8] has also contributed for the researchers by surveying the hybrid recommender systems. He has made comparison between different recommendation techniques and hybridization strategies. Four techniques for recommendation and seven strategies of hybridization were considered. He also has included 41 hybrids with some new combination of that time. The attraction of the researchers towards recommender system has been noticed increasing rapidly in early decay of the millennium. The generations of recommendation by early decay of the millennium has been reported in [2]. The authors have also presented an overview of recommender systems with the discussion of the limitations, and possible enhancement for the solution of existing issues.

In 2007, Candillier et al.[9]has reviewed the primary collaborative filtering based systems and done an extensive comparison using MovieLens data set. Their study identifies advantages and drawbacks of the approaches under evaluation. However, there was no much discussion about the various issues encountered in the collaborative filtering based approaches. The issues like data sparsity, shilling attacks, synonymy, scalability, etc. are discussed comprehensively by X su and Khoshguftaar[10]. They have proposed possible solutions for the existing issues as well. The authors have also presented a comprehensive survey for collaborative filtering techniques, categorized collaborative filtering algorithms and analyzed their predictive performance in addressing these issues. The evaluation of the recommender system has been discussed in [11]. The authors have discussed the ways to compare recommenders based on the basis of a set of properties and described how can recommender systems' performance be compared for the relevant area of application. They have described experimental background suitable for deciding preferences between several algorithms. They have also discussed how to draw reliable conclusions from the conducted experiments.

In 2012, Park et al.[12] and Zhou et al. [13] have done a good work. Park et al. reviewed 210 research articles related to recommender system and examined the research trends in the concerned area by observing publication of the paper year-wise and journal-wise. The effort helps the interested people with insight for future research direction. Zhou et al. 2012 also presented an overview of state-of-the-art for developing personalized recommender systems in social networking environment in the same year. The work provides a research direction to address user profiling and cold start problems.

The maximum number of research papers for the survey has been included by Bobadilla in his tremendous work [14]. They have proposed a method which gives a criterion for the inclusion of research papers of the concerned field. They have discussed the overview of recommender systems and collaborative filtering methods. They have also provided original classification of recommender systems, suggested area of future research including bio inspired approaches for recommender system.

However, they have not discussed about the timing-factor in recommendation and a little was touched about fuzzy approaches in the recommendation. J Lu et al. in 2015 have systematically examines the reported recommender systems through four dimensions: Provides an understanding of developments in recommender system applications.

We have tried to include the discussion on the issue of time-constraint for recommender systems and also have discussed the fuzzy approaches for the recommendation of items. We have summarized the work in a tabular form and shown in Table 1.

Table 1. A glance of the review studies on Recommender Systems

Serial no.	Author & Year	Primary Contribution	Citation on Google Scholar as on February 2017
1	B. Sarwar et al. (2000)	• Analysis of effectiveness of RS • comparison of recommendation algorithm	2235
2	J. B. Schafer et al. (2001)	• Provided a foundation for the growth of RS as a marketing tool in e-commerce • Five models of applications and four domain of future work are explored.	1954
3	R. Burke (2002)	• Investigated possible extent of hybrid recommender systems • Provided quantitative results for relative comparison.	3153
4	G.Adomavicius and A. Tuzhilin (2005)	• Generation of RS is discussed • Limitations and possible enhancement are mathematically modeled	7777 (Most cited article on RS)

5	L. Candillier et al. (2007)	• Reviewed the primary collaborative filtering based systems • An extensive comparison using *MovieLens* data set.	150
6	X Su & T. M. Khoshguftaar (2009)	• Issues like data sparsity, shilling attacks, synonymy, scalability, etc. are discussed, and their possible solutions are proposed. • Comprehensive survey for CF techniques is performed, categorized CF algorithms and analyzed their predictive performance.	1974
7	G. Shani & A. Gunawardana (2011)	• Compared RS on the basis of characteristics and application both. • Described experimental background suitable for deciding preferences between several algorithms. • Discussed method of drawing reliable conclusions from the conducted experiments.	709
8	D. H. Park et al. (2012)	• Reviewed 210 research articles • Examined the research trends in the concerned area year-wise and journal-wise. • The effort helps the interested people with insight for future research direction.	284
9	X. Zhou et al. (2012)	• An overview of state-of-the-art for developing personalized recommender systems in social networking environment. • The work provides a research direction to address user profiling and cold start problems.	124
10	J. Bobadilla et al. (2013)	• An overview of recommender systems and collaborative filtering methods are discussed over 253 articles. • Provided original classification of recommender systems • Suggested area of future research including bio inspired approaches for recommender system.	683 (Most cited article since 2011, Elsevier)
11	J Lu et al. (2015)	• It systematically examines the reported recommender systems through four dimensions:recommendation methods, recommender systems software, real-world application domains and application platforms. • Provides an understanding of developments in recommender system applications.	102

3. Types of Recommender Systems

The recommender systems can be categorized on several bases. In the literature, the categorization of the recommender systems are usually found [2] on the following bases;

- *Approaches used*
- *Area of application for which recommendation is made*
- *Data mining techniques applied, etc.*

In [2], RS is categorized in 3 different criteria based on approaches, 1) Content-based recommendations, 2) Collaborative recommendations and 3) Hybrid recommendations. Bobadilla et al. [14] have suggested four categories on the basis of filtering algorithms, Content-based filtering, collaborative filtering, hybrid filtering and demographic filtering. Burke [7] have categorized 5 types of the recommender systems based on the approaches. The categories are; Collaborative based recommendations, Content- based recommendations, Demographic based recommendations, Utility based recommendations and Knowledge based recommendations.

We have categorized 8 types of recommender systems (RS). These categories broadly cover the techniques which have been used by the masses or the current generation researchers are frequently applying it.

1. Collaborative Filtering based recommender systems (C.F)
2. Reclusive methods based recommender systems (R.M)
3. Demographic Filtering based recommender systems (D.F)
4. Knowledge based recommender systems (K.B)
5. Hybrid Recommender systems (H.R)
6. Context Aware Recommendation System (CARS)
7. Social network based recommender systems
8. Soft Computing techniques based Recommender Systems

3.1 Collaborative Filtering based Recommender Systems

It is the most successful and frequently used recommendation technique discussed in the literature [15], [4], [16] since the appearance of first recommender system in mid 1990s. The collaborative approach makes use of the recommendation from other customers whose choices are similar to the target customers (i.e. customer for whom the recommendation is made). The customers with similar choices are termed as neighbor.

Thus, two major tasks are being performed in collaborative filtering; 1) finding the neighbor of a customer and 2) exploring the preferences of the neighbors of a target customer or user. The neighbor of a user can be formed by analysing the past purchasing behavior of the user and calculating the similarity scores between the choices of these users. Whereas the recommendation of the neighborhood customers can be obtained either explicitly in terms of rating which are numerical values within a specified range, or implicitly with some defined measures. Implicit recommendations also involve customer’s feedback. The customer’s feedback can be their behavior noticed by the user’s log information or it can be users’ sentiments expressed in terms of their reviews.

e.g. to understand better how items are recommended using C.F, we give a basic assumption which is supported by a diagram presented in Fig. **1** and illustrated in Table 2.

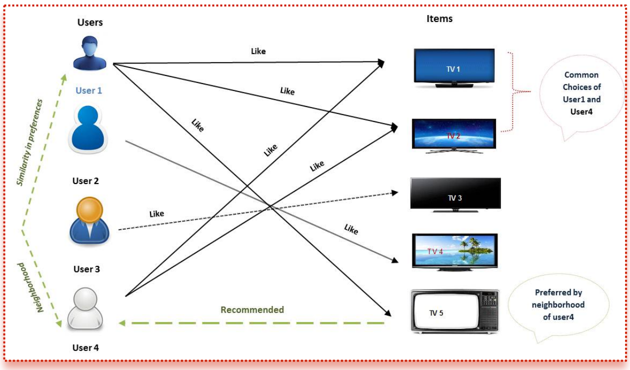

Fig. 1. Collaborative Filtering Approach

Table 2. Collaborative Approach illustration

Users	***Items***	***Purchase***
User1	*Tv1*	✓
	Tv2	✓
	Tv3	×
	Tv4	×
	Tv5	✓
User2	Tv1	×
	Tv2	×
	Tv3	×
	Tv4	✓
	Tv5	×
User3	Tv1	×
	Tv2	×
	Tv3	✓
	Tv4	×
	Tv5	×
User4	*Tv1*	✓
	Tv2	✓
	Tv3	×
	Tv4	×
	Tv5	*recommended*

Assumption for C.F: if user1 and user2 have similar ratings of item1, item2 … item 'n', they must have similar ratings for item 'n+1' also. In other words, if user1 has high rating for item1, item2 & item3, and user2 too has high rating for item1 and item2 then user2 must have high rating for item3 also.

The researchers have defined C.F differently and categorized in different criteria based on approaches and algorithms used. Adomavicius and Tuzhilin[2] expressed C.F in terms of a utility function which tries to predict utility of the items based on the rating given to the item by other customers having similar preferences as the target user. They have divided C.F algorithm in two categories. 1) Model based and 2) heuristic based. The same categorization has been reported in [17]. However, candillier et al. [9] have given three categories of collaborative approaches. a) User based, b) model-based and c) item-based.

In user based approach, a set of nearest neighbors is associated to each user, and by using nearest neighbors' ratings on that item, user's rating is predicted for the item. In model-based approach, a set of users groups are constructed and ratings of members of its group are explored. By using these ratings of an item, user's rating on an item is predicted. Usually in this CF technique, models are created for recommendation. These models are designed to produce accurate prediction on real data. However, in item-based approaches, a set of nearest neighbors is associated to each item, and by using rating of users on items' nearest neighbors, the rating on an item by users are predicted.

Researchers have applied these C.F to design RS for various applications such as recommending music, movie, web pages, articles and products for online shopping, etc. [18], [19]. Further, there are several techniques within the above three categories which researchers have worked on. The work can be classified further on the basis of different methods and algorithms. The respective criteria and related work is described in the following section.

3.1.1 Item based and User based CF techniques

Item based and User based recommendation are usually performed by exploiting –

- *Association rule mining between preferences of neighbor of users*
- *Rating*
- *Choice of individuals for varied items*
- *Similarity in the preferences of different users for common items*
- *Tagging*

3.1.1.1 Association rule mining between preferences of neighbor of users

Association rule mining has been used extensively in collaborative recommendation. An association rule based recommendation technique was proposed by Sarwar et al. [4]. The authors have suggested some association rule for exploring the association between user's purchase behaviors towards items and accordingly the items are recommended to users. The authors in [20] have investigated the possibilities of inclusion of association rule mining for collaborative filtering based recommendations. Since collaborative recommender exploit how similar are the customers' preferences, it is easy to make personalized recommendations.

However, association rule mining algorithms are designed by keeping in mind the concept of market basket analysis. Such algorithms are not useful for collaborative recommendation as there are enough rules which these methods need to mine, which may and may not be fruitful for the user. Also, other criteria of association rule mining often lead to create huge number of rules or some time very few rules which have a negative impact on the performance of the system. The authors have designed a collaborative recommendation technique to mine association rules for this purpose. The associations between users as well as associations between items, both are considered. In [21] authors have proposed scalable techniques based on association rule. The rules are discovered from usage data for personalization of web to users.

Sandvig et al. have presented a collaborative recommendation algorithm based on association rule mining in 2007 [22]. They have used k-NN algorithm to prevent profile injection attack. Their results indicate that the proposed methods have shown significantly improved performance.

3.1.1.2 Rating based recommendation

Since a general trend in recommendation is to get rating from a user for available items which in turn, support other users to find better items. This trend of recommendation is simply termed as rating based collaborative filtering. However, rating based recommendation is used in model based recommendation as well, which shall be discussed in its appropriate place (see section 2.3.1.2).

PolyLens[23], an extended version of MovieLens, is very helpful in group creation and management. Basically, PolyLens is designed for smaller group to recommend movie. Several factors have been considered while designing PolyLens, like generating group recommendation, evolution of group and its formation, and the nature of the group to which a user belongs. It uses the nearest neighbor methods and presents the sorted list according to lowest ratings.

RACOFI (Rule Applying Collaborative Filtering) is proposed in [24] which is a multi-dimensional rating system. The authors implemented RACOFI Music for assistance of users who usually prefers to listening music on-line. Their implementation helps in recommending and rating audio. Authors have categorized five features of music which generally have impact on users. They have made their system available on-line since August 2003 at [http://racofi.elg.ca].

Rating system is also used in TiVo [25] which uses 100 million ratings. These ratings are provided by approximately 30,000 users of different TV shows and movies. The TiVo recommends the different TV programs to viewers.

Since a general trend in recommendation is to get rating from a user for available items which in turn eventually support other users to find better items. The authors have presented [26] a database-driven approach which makes use of the ratings in item-to-item CF technique. The authors have claimed the ease of implementation and its applicability in vast range.

3.1.1.3 Choice based recommendation

In choice based recommendation, items are recommended by using similarity in the preferences of a single user for different items. Hayes and Cunningham [27] developed a music application, ‘smart radio’ at Trinity College, Dublin in 2001. The music application is a web-based which allows users to share music programs. The authors have used collaborative recommendation techniques and applied streaming audio technology. The controlled distribution of music on web by the operators is studied in their work and smart radio is designed to personalize the music programs. The idea of collaborative filtering is introduced to swap the music programs by observing the similarities between the users’ choice. The smart radio is currently working and has the permission from Irish music rights organization (IMRO).

Iman et al. Presented [28] a choice based technique that makes use of CF method and extract latent knowledge from user ratings, and ask the user to prefer one of the two sample items iteratively presented before them. The technique tries to place the user in the latent factor space, and those items are selected for recommendation which is near to the user position. The authors showed their results present better recommendations. Since, the authors have used latent factor as well, this CF technique can also fall in model based recommendation, if perceived otherwise.

As online radio has become popular, the authors have designed [29] a mechanism by which playlist in real-time of listening the audio can be tailored according to the musical tastes of the listener. The authors have used CF techniques to generate a playlist in real time. The audience usually has listening history of the music before listening to a particular one. On the basis of history of the listener, playlist is recommended to the listener. They have also described the details of the implementation of the technique.

A choice-based interface is studied for preference evocation during the cold start phase [30]. The interface is compared with an existing rating-based system. The authors have shown results which indicate that rating-based interface take more effort whereas choice based system provides more satisfying recommendations.

3.1.1.4 Recommendation based on similarity in the users’ preferences for common items

GroupLens[18] is one of the earliest developed collaborative filtering based system which provides filtered online news to member of a group. It eases the process of finding news articles which a user might like from huge amount of available news articles.

Pazzani in 1998 [31] has discussed how to learn profile of user interests and how it could help in the recommendation of web pages or news articles. The author has mentioned the collaborative approaches and their pros and cons in the recommendation of information sources to users by taking examples of restaurants.

In 2001, G Karypis[32] has suggested an item based personalized information filtering technology to explore a set of N items. These N items are matched with the interest of certain users. The authors have presented a method that first determines the similarities between the various items and then the similarity is used for final recommendation of items. The author has shown that the experimental evaluation on five different datasets is 27% better. The standard collaborative filtering techniques face great challenges in terms of scalability and performance, especially when there is a lack of explicit user ratings. To improve the scalability of collaborative filtering, web usage mining techniques can be used. However, it affects the recommendation accuracy.

An improved FolkRank by using item based CF method is proposed by Gemmell et al. [33]. They came up with a conclusion that item-based CF if mixed with traditional graph-based approach could enhance the performance in FolkRank. Thus, it is evident from the work that CF, especially item-based collaborative filtering, could be proved an excellent way to enhance the performance of a recommender system [34].

3.1.1.5 Tagging based recommendation

A recommendation approach based on tagging, ‘FolkRank’, was proposed in [35], [36]. Authors have calculated the distance from the uploaded resource. These distances serve as a base in exploring the tag recommendations.

Another tagging based recommendation approach is presented by Zheng and Li [37][38]. The system is based on CF. Their research has highlighted the importance of tag and time in the process of recommendation. In general, rating matrices are used in traditional systems based on CF; however, unlike others they used matrices based on tag and time relations. The similarities are obtained by calculating tag-weight and time-weight. The similarity index helps in identifying new neighbor which in turn give the prediction on the basis of recommendation they made.

3.1.2 Model based CF techniques

Model based CF techniques as described earlier used to develop models using several techniques including machine learning, Bayesian classification, ordering, clustering, latent information utilization, graph model, etc. Goldeberg[1] have presented a model based personalized book recommendation technique. The authors have applied association rule mining and BNs for personalized books recommendation. The association rule mining is used for exploring the association between user's preferences by observing the borrowed books. The BNs are implemented is designing the personalization of the RS.

However, the rating is also used in the model based recommendation. A User Rating Profile model (URP) for rating-based collaborative filtering is [39] presented. The URP is designed to assign one rating to each item for each user. The author introduced a generative latent variable model. Each user is represented as a mixture of activities of the user by generative latent variable model. User's actions help in generating the rating for each item by observing activity of a user towards an item. A preference pattern is associated with each activity of the user which supports in rating of the items.

The author [40] analyzed existing methods in 2004 from machine learning perspective to predict the rating. The author has shown that many existing methods which were designed to fulfill the task are simply modified machine learning techniques. The basic operations like dimensionality reduction, clustering, classification, regression, and density estimation are performed. New prediction methods are developed by the author. Marlin introduced a new experimental procedure which has not been used previously.

The Kim et al. have proposed a machine learning technique to extract the marketing rule for personalized recommendation. They have used tree induction techniques, which can be incorporated with data mining techniques to match the customer's demographic details. The proposed methodology helps in fetching the rules for personalization of advertisement to a buyer shopping on the Internet [41].

One of the issues with collaborative filtering technique is that they are not portable and is successful for an Internet environment with large computers. Miller et al.[42] presented 'PocketLens', a promising collaborative system that works on connected servers with even palmtop and the results are no more less than the other competitive techniques. PocketLens is based on CF algorithm which finds neighbor by the use of 5 peer to peer architectures. A shopbot is presented [43]. Shopbot is basically a comparison shopping search engine which is designed in such a way that it can exploit freebies to consumers without paying any extra fee. The authors have suggested an item-item similarity method by using CF techniques. They have considered the additional provision of providing the cost of the product as well as their benefit from saving point of view to customers for recommendations.

Bayesian networks (BNs) is used [44] as a classifier for CF. Binary-class data have been major focus for researchers in earlier model to perform CF task, however, the authors have applied advanced classifier based on BNs. Moreover, they have not worked on traditionally synthetic binary data; instead they have used real-world multi-class CF. they have showed by their experimental results that their proposed CF model has the performance better than the traditional CF algorithm, especially when rating data have relatively more missing rates. Also BNs based CF is robust as it does not degrade with increase of sparseness.

One of the fastest methods to improve the prediction accuracy without affecting the running time is presented by [45]. Previously, the adopted approaches used to compute interpolation priorities separately; however, Bell and Koren optimized the problem in a way that they computed interpolation weights simultaneously for neighbor. This method can generate a prediction in about 0.2 milliseconds. And is equivalent efficient for large scale applications. The Netflix dataset is used for evaluation.

In 2012, Sahoo et al. [46] developed a personalized recommendations to help the user when their preference might change with time. The authors have argued that user's behavior is not static and changes over time. They have proposed a hidden Markov model. The model performs personalized recommendations by correctly interpreting the behavior of a user in selecting the product. The preference of a user is modeled as a hidden Markov sequence. Authors claim that the proposed model outperforms the existing algorithms when the data is less sparse and the user preference is changing.

In 2013, Yue Shi et al. [47] introduced ranking in recommendations. Due to the rise of collaborative filtering (CF), the need of learning to rank has emerged. For improving the ranking of the top-N recommendations, the ranking method could contribute significantly. The authors have presented the key ideas of different categories of learning to rank approaches, and illustrated how these techniques can be extended to specific CF methods.

CF techniques follow the philosophy of one to one, i.e. every user is independent and uses a single account. However, in a case where multiple users share a same account may trouble the recommendation using CF. if context is available then CARS could solve the issue. But it needs context to be illustrated and explained [48]. Author proposed a solution to solve the issue without being aware of the context, by using top N shared accounts, an item-based top N collaborative filtering recommender system. The method gives the recommendations according to the binary positive feedback. The experimental results show that their techniques can tackle the issues regarding shared accounts of various datasets.

ExcUseMe[49] is the only pure CF based recommender system which tries to avoid cold start problem without combining content filtering or context details. The authors have presumed that the arrivals of users for purchase is randomly sequenced and certainly system takes the decision about the possibilities of new user participation in the exploration of newly launched items. The users which are possibly interested in new items are revealed by ExcUseMe gradually. The new items are modeled according to the user's preferences. The provable guarantee for cold start problem is assured by [28]. The authors have used matrix factorization. The theoretical prove of the error estimate is also given [49].

3.2 Reclusive Methods based Recommender Systems

It is clear from the above discussion that collaborative filtering is based upon finding similarities between users. It does not need any representation of the objects to be recommended. Unlike collaborative filtering, reclusive approach exploits the features of the objects and requires its representation [50]. The reclusive methods are considered as complementary to collaborative techniques. And it emphasizes on finding similarities between objects, i.e. items rather than finding the similarities between users.

Let us consider the example illustrated by using Fig. 2. There are five different TVs for which reclusive approach is described for a user. The user has preferred TV1, TV2 and TV3 either by purchasing or by putting it into cart. TV4 and TV5 are newly launched items. The features of TV5 are similar to TV1, whereas TV4 has different representations in terms of its characteristics. Thus reclusive approach which is also referred as 'content based or feature based recommendation' would recommend TV5 to user and not TV4.

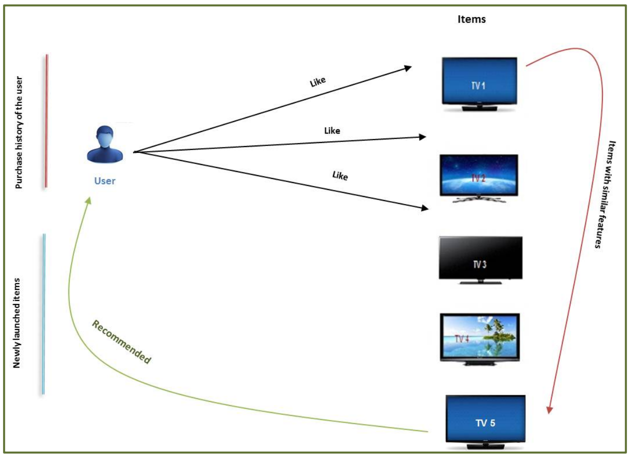

Fig. 2. Reclusive Approach for Recommendation

Reclusive recommendation or content-based Recommendation [51] mainly came from the concept of information accessing and is a kind of recommendation method based on comparing users' preferences and associating contents between items in order to provide recommendations to users. This content-based method is also called Feature-based Recommendations [52] that judges and find out items users are possibly interested in by analyzing the attributes and characteristics based on User Profile. The results are then recommended to users. It could even further assign different weights [53], [1] based on the degree of association between user's preferences and targeted contents in order to better fit users' requirements [54].

Like CF techniques, the recommendation approach for Reclusive techniques can also be categorized in the three types, i.e. 1) Heuristic based, 2) Model-based and 3) Web mining based. By the use of model based approaches, reclusive method tries to exploit different machine learning algorithms, classification techniques like Bayesian networks (BNs), probabilistic approaches, to group the preferences of users based on the content of the items purchased. Whereas, heuristic approaches uses different data mining techniques like clustering, decision tree, rule induction, etc. to fetch the product's features and recommend the one which is closest to the preferences of a user. A category, opinion mining, is explicitly classified as it has been used frequently in characterizing the items' features. Customer's reviews and their log information helps in making a consensus about the features of an item whether it could suit the users preferences or not?

3.2.1 Heuristic based Reclusive Recommendation

The Kim et al. [41] used decision tree to personalize the web advertisement for a user. The authors have proposed personalized recommendation techniques for the customers based on their past purchasing behavior. User profile is maintained to observe the attitude of a user towards similar products. The authors [55] presented a technique that combined the feature of classification; user based collaborative filtering and association rule mining. The classification technique is used to mine the book with respect to book's features. The latter two techniques are used to know the user's requirement for recommending highly rated books. A book recommendation system based on digital signage system has been proposed by the authors in [56]. The books are recommended for particulars by identifying age and sex of the users. Here books recommendation approach is confined and very limited. It cannot be spread to a big community or universities but only for few magazines for the user aged 19-21 of same located schools.

In [57], James and Nick have developed a recommender agent for the recommendation of movie (available at www.filmrecommendations.co.uk). The proposed approach make predictions based on content that relates the features accompanying in a movie like, actors, directors, stories, etc. new movies are included for making recommendation to users. The authors have improved the accuracy by their pure reclusive approach.

Kazai et al. have presented a mobile app which is enough intelligent to learn the user's interest from the past purchase history or activity knowledge of user at social network sites [58]. The app provides users with crowd curated content. The app is also capable of providing users with the knowledge of contents like by the user of twitter followed by them.

3.2.2 Model based Reclusive Recommendation

The researchers have usually utilized users profile to model it for storing their preferences. These preferences are matched with the feature or contents of the items. If there is a match between user interests and product's features, the item is recommended to the user. K. Lang [59] has sorted the user dependence problem in profiling user's preferences. Lang has proposed 'Newsweeder', a technique that has the provision for users to rate the news they have read in 1-5 rating scale. This helps in recommendation of next news for the user. Pazzani [31] has proposed a model based reclusive approach for fetching the user profile about their purchase. The authors have also suggested CF and demographic technique and combination of trio for a better recommendation.

Books, journals and research papers recommendations have helped a lot the people to fulfill their need and get benefited of the recommendation for their study of course. Mooney [60] proposed a content based book recommendation technique, called LIBRA (Learning Intelligent Book recommendation Agent) that utilized information extraction and a machine learning algorithm to explore the features of the books in recommendation. Jomsri [61] proposes a library book recommendation system based on user profile loaning and association rule. This system is useful for particular resides in the same institute within the same library and campus. The experiment is performed for the specific university only.

A user interface is designed for wireless information devices [62] by using user feedback. User interests learning model are framed for the current events through news. Machine learning methodology based on reclusive approach is developed. The authors have claimed their system can adapt according to the interests shown by the users. Also, the information size is reduced by the methods; as a consequence, users can save for obtaining the relevant information.

Since, reclusive approach tends to recommend those items which user has already aware of. This leads to the problem of overspecialization. The authors [63] have presented mechanism that overcomes overspecialization. Firstly, by exploring knowledge of user's preferences, then matching the preferences with launched items at shopping sites.

Bansal has proposed content driven user profiling [64]. The system provides recommendations for news and blog articles. The recommendation is supported by Comment-valued approach using topic modeling. A novel hierarchical Bayesian modeling approach is combined with classical recommendation technique. The content based solution also exploits user profiles which are enough influential in providing personalized ranking for users of comment-worthy articles. The system handles with cold-start issue with no extra requirement of meta-data.

Table 3. Recommender Systems, Categories and Techniques

S.No	**Types of Recommender System (RS)**	**Sub-category**	**Techniques**	**Research Papers**
1	Collaborative Filtering (CF) based RS	Item based	Association rule mining between preferences of neighbor of users, Rating, Choice of individuals for varied items, Similarity in the preferences of different users for common items, Tagging.	[156], [2], [17], [119], [157], [158], [159], [55], [45], [57], [157], [160]–[163], [8], [9], [30], [43], [165],[219]
		User based		
		Model based	Bayesian networks, clustering, Machine learning, Graph modeling	[49], [28], [49], [1], [39], [40], [41][44][46][43][45][47][42], [48].
2	Reclusive Methods (RM) based RS	Heuristic method	Rule induction, nearest neighborhood, Rocchio's algorithm, tagging, rating, etc.	[59], [105], [156], [15], [62], [165]–[169], [41], [55],[56][57], [58].
		Model based techniques	Bayesian networks, clustering, Machine learning, Graph modeling	[167],[50], [170]–[172], [173], [52], [174], [59], [31], [60], [61] ,[62][63][64].
		Web mining	Opinion mining, web usage mining, etc.	[65], [21], [66], [67], [68], [69], [70][71][72][38][73][57][74][220] [221][222]
3	Hybrid recommender systems	CF dominated RM	Techniques of CF, RM applied with each other in different combinations	[7], [175], [106], [8], [176], [177], [178], [179],[180], [181], [182], [57], [116], [161]
		RM dominated CF		
		CF and RM coalesced into one		
		Subsequent Integration of separately applied CF and RM		
		Integration of CF and RM with (KBS)	Techniques of CF and RM are applied with KBS, and other fuzzy, social network, etc.	[183], [94], [184]–[187], [180], [188], [161], [175], [177], [189],
		Integration of CF with other than RM		
		Integration of RM with other than CF		
4	Demographic filtering based RS	-	Correlation, similarity measures, etc.	[75], [187] , [190], [191], [75], [192], [31], [76],[193], [194]
5	Knowledge based Recommender System (KBS)	Constraint based	Machine learning, Bayesian network, AI, etc.	[92], [195], [96], [196], [97], [197], [93], [198], [98], [99] , [78], [82], [199]–[201], [91], [202], [203], [200], [90]
		Case based		

6	Context Aware Recommender System	Location aware, Temporal, Trust aware	User feedback, AI techniques, machine learning, etc.	[204], [205], [206], [207], [136], [138], [189], [127], [139], [208], [209], [142], [145], [143], [128], [210]–[212]
7	Social network based RS	Foafing, trade relationship, etc.	Similarities measures, user profiling, etc.	[213], [214], [215], [80], [148]
8	Soft Computing techniques based RS	Fuzzy genetics, fuzzy linguistics,	OWA, ORWA, fuzzy model, etc.	[153], [154], [216], [150], [217], [123], [155]

3.2.3 Web Mining based Recommendation

Since, web mining techniques are sensibly useful in processing the web data for extracting the desired information and performing operations according to the need of the problems. Web usage mining, web content mining and link mining i.e. web structure mining; all three leading web mining techniques are used in recommender technology recently. Since reclusive approach, mostly referred as content based approach, exploits user profiles and items descriptions to guess what user could like in future, depending upon the past preferences of a user, irrespective of the choices made by other users. Most content-based recommender systems encounter those ambiguities which usually a natural language suffers. The authors [65] have presented comprehensive methodology to overcome the issues which is associated with keywords based approaches.

Cho et al. [21] proposed a personalized recommendation system which is based on Web usage mining. They have suggested an improved collaborative recommendation methodology which can enhance the quality of recommendation for an Internet shopping mall. Further, sparsity and scalability are addressed well here to overcome the poor recommendation problems. Another personalized recommendation based on Web usage mining is proposed by Kim et al. [66]. Their method is mainly targeted the problem of helping customers to achieve recommendation only about the products they wish to purchase. Kim et al. have experimentally evaluated the proposed methods by applying it on a shopping mall of Korea.

A detailed discussion about the development of a personalized product recommendation system based on customer's click streams is performed in [67]. The authors have proposed a recommender system based on web mining to overcome the problem of data overload so that satisfactory recommendation can be made for users. Web mining techniques are used to observe the purchase behavior of the users and adopt the change in the users' preferences dynamically.

Although there have been good number of studies on opinion mining, however few of them lead to products recommendation. User feed-back based recommendation for electronics items are performed by the authors in [68][69], [70]. Liu et al. [71] proposed a novel product recommendation methodology by combining group decision making and data mining techniques. It addresses the customer lifetime value (CLV) to a firm. The authors in [72] recommended books for online shopping using web mining technique where they categorized the features from the reviews of the users available online and recommended top computer science books by assigning weights to these features and scoring these values. The authors in the paper searched the book on a specific topic using Google search. The top links are stored and the reviews of the readers for all the stored results are assessed. The features are extracted from the user's review and accordingly the books are ranked.

The reclusive methods are very effective in recommending TV program [38] as the content of a TV program can easily be traced by the features of programs like time of program being telecasted and characters involved in the programs, etc. The reclusive approaches can be a solution to sparsity and cold start problems to an extent. Authors have suggested reclusive approaches in music recommendation to overcome these issues. In [73] reclusive approaches are proposed to overcome the sparsity while authors [57] used reclusive methods to solve the cold start issues. There is few music systems developed to recommend music to a particular group [74].

3.3 Demographic Filtering based Recommender Systems

The recommender systems based on demographic filtering also use similarity measures as a metric. But instead of finding similar rated items by neighbor users, it tries to find the similarity between users' demographic information like, age, sex, occupation etc. In this approach, the system stores the demographic information of the customers and whenever a new user comes to merchandisers' site for the purchase of any product, the system identifies the similarity between user's demographic information. According to the preference of the customer, the system recommends alike items to new user having similar age, sex, occupation etc. to customer. A typical recommendation approach of demographic filtering based recommender system is shown in Fig. 3

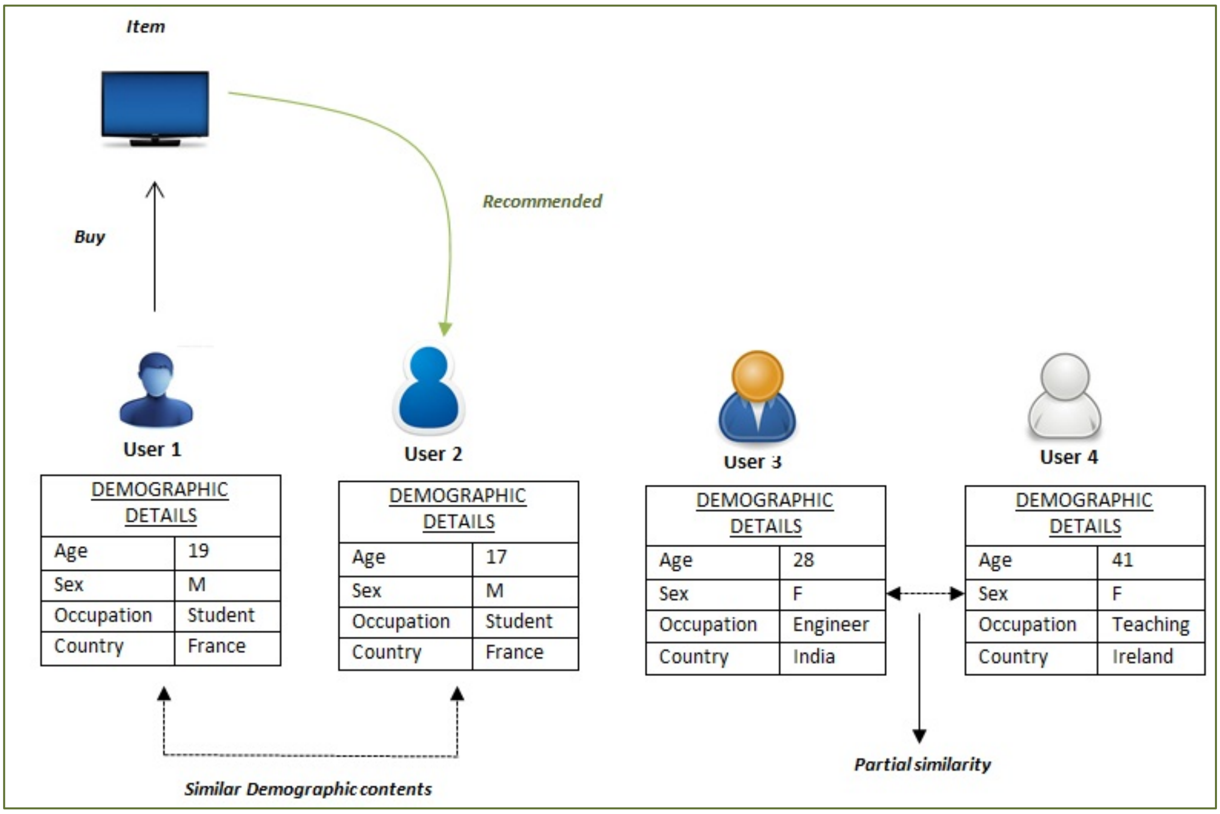

Fig. 3. Demographic Filtering based Recommendation Approach

In the figure, four different users are shown, user 1 and user2 are from same region, they both are teenager students from France, i.e. both the users have almost same demographic values. Whereas user3 and user4 are from different region with different occupation and they belong to different age group. However, both are females. Thus user 3 and user 4 differ significantly from each other as well as from user 1 and user 2. Hence, once the purchase and demographic record of user 1 is stored, the system would likely to recommend same item to a new user (say user 2) who is common in various or all aspects with user 1. Also, it is important to decide what types of similarities between the users are desirable. As we have seen above there is significant difference between user 3 and user 4. However, both are female and hence they may have similar choices of buying a product (like clothes, food products, etc.).

Thus, the choice of one of the users can be recommended to another on the basis of partial demographic similarities. Demographic information can be useful in finding the category of users whose choices are similar for certain objects. Krulwich et al. proposed LifeStyleFinder [75] and have used 62 clusters of users which were pre-existed and has made recommendations to users on the basis of other users belong to the defined clusters. Pazzani [31] attempted to apply minimal effort for collecting information of users, and classified users using text classifications. They have used hybrid techniques including collaborative, content and demographic information for making recommendation of Restaurants. They have come out with a conclusion that demographic methods can help in finding evenness in the descriptions of users that have similar choices of the restaurants. Content-based methods find evenness among the details of restaurants preferred by a particular user. However, collaborative method helps in finding correlation between the user's ratings of a particular restaurant and the user's ratings of other restaurants. Their experiment demonstrated that the consensus-based method is effective than any one of the individual method discussed above. Usually demographic filtering based recommendation technique when hybridized with collaborative or reclusive recommender approach is found to be more effective. We call it as hybrid techniques. The hybrid technique is discussed later in the section. These combinations can work well and may solve cold start problems to an extent.

Laila et al. [76] presented a solution to cold start problems which occur while using rating history of the user as a base for recommendation. They have used user's demographic details and combined it with reclusive and collaborative approach to provide recommendation for new users with no prior preference and rating details. A significant impact of demographic information of users for recommending research papers have been reported in [77]. Kim et al. [41] have suggested demographic filtering based recommender system. The filtering is based on decision tree induction and machine learning techniques.

3.4 Knowledge based Recommender Systems

The recommender system has much of its emergence due to the initial involvement of collaborative filtering methods. However, later a good amount of work is contributed using reclusive methods too. The early implication of collaborative and reclusive approaches to the recommendation technology has given a distinguished identity to the above two techniques in the categorization of recommender systems. As recommender system is a knowledge based approach, thus all the different categories are based on knowledge filtering techniques. The reason behind keeping reclusive and collaborative as a separate category is its familiarity and domination from early days of evolution of recommendation technology.

Apart from the above two techniques, collaborative and reclusive, any recommender technique by default may be inferred as a knowledge based approach. However, demographic filtering is based on collaboration of users' demographic knowledge; it seems adequate to keep it as a different criterion. The idea which differentiates knowledge based systems from other systems, is the degree of importance it gives to the following two domains –

a) user's requirement
b) Characteristic of the recommended items.

The above area of expertise helps in achieving users' satisfaction by fulfilling their needs. Certainly, an approach for building recommender system which needs either explicitly defined set of recommendation rules or some sort of similarity measures from prior purchase history of the users is perceived as knowledge based approach for recommender system. It is important to know the knowledge sources while categorizing a recommender system. It is more difficult to concisely typify knowledge based system than collaborative or reclusive systems. However, the recommender systems that use supplementary knowledge sources which are not exploited by collaborative and reclusive recommendations can be characterized as, "knowledge based systems". These systems depend more upon knowledge sources, while others frequently-used techniques do not depend highly upon such sources of knowledge.

Towle and Quinn [78] have argued that an additional information provided by the user could help in overcoming the sparse related problem as well as cold start problems. Hence, instead of 'rating' based recommendation, which is an implicit approach, they have suggested explicit model for recommendations. The authors have configured three major retardant in the sensible success of recommender systems. First, customers show reluctance for receiving recommendation if there is not up to the mark recommendation constantly, second, the constant arrival of new items and third, all the products do not have same characteristics. Thus, explicitly asking the requirement and choices from the user would allow training the system according to the user's need.

Knowledge based approach is applied in [79] for recommending programs on TV to a group. Since most of the RS need explicit ranking from the users. Merging these individuals ranking to one consensus ranking so that it may suit all member of a group well is a tough job. The authors proposed a method which learns the family preferences separately. On one hand the method keeps the privacy of the family preferences and on other hand it adapts to the changed preferences of a family. The classifier is applied to adapt the preferences of each family separately. A recall of 0.57 and precision of 0.30 have been achieved by the author's suggested work, although not much description of the Meta data was provided.

A similar approach is presented by Yu et al. in 2006 [80]. The authors have provided recommendation mechanism for TV programs for a group by exploiting user profile. The selected strategy first merges all user profiles to construct a common user profile, and then uses a recommendation approach to generate a common program recommendation list for the group according to the merged user profile. The total distance minimization is used for evaluation of the results. The system works well for group of users viewing the TV together.

For tourism recommendation; aspects like the charming of a place, ease of accessibility and accommodation, and well-furnished restaurants are often seen as important factors. Entrée, a FindMe driven system proposed by Burke et al. [81], [82] to recommend restaurants by using knowledge based approaches. The authors have clubbed concepts of several retrieval strategies involving knowledge based to fetch the destined information. RentMe system is designed which follow the guidelines of FindMe system for the recommendation of apartments in Chicago on rent.

To explore the best suited locations of restaurants for a group of people, a recommender system, 'Pocket-Restaurant-finder' is suggested in [83]. It incorporates the choices of the associates of a group. Furthermore, the application developed can help the group members in real life and have been designed to run at any kiosk to help a group in finding the restaurant of their mood. A system, Collaborative Advisory Travel System (CATS), has been presented as a solution for the recommendation of holidays. The system also tells the area where these holidays can be engaged.

SPETA [84] is a recommender system behaves like a guide that provides the service to tourist by observing their past preferences and locations. The suggested system makes use of the knowledge of user associated information like current and past locations and preferences. The information for the user is extracted which is integrated with innovative techniques to provide pleasant experiences to tourists. E-learning courses have been recommended with different techniques, proposed by authors in [85]–[89]. In these works authors have proposed recommendation methodology for courses to graduate students at university level and for online learning environment. A course recommendation for open university of China is proposed in [87]. In [90] authors have used machine learning technique to recommend courses for new enrolled students.

Further, two different types of knowledge based systems are reported in literature [91], [92], [93], [82], [94].

- *Case based recommender system.*
- *Constraint based recommender system*

These recommender systems are described below.

3.4.1. Case-based Recommendation:

In case-based approach, recommendation is largely perceived as a problem of evaluating resemblance of a product with user's preferences. The approach employed in Case-based recommendation is somewhat similar to reclusive approach in an exceedingly sense that both the approaches need detail descriptions of the products' features. In turn, these features are matched with the user's preferences to best suites their requirement and provide a high level of user satisfaction. Since the requirements and preferences of users aren't well outlined, hence, similarity-assessment method helps in up the standard of the recommendations, this is why case-based approach has gained a great success in e-commerce [95].

Let us consider an example [96]. If I go to market for buying refrigerator, the seller may and may not be acquainted with my preferences depending upon whether I have made my purchase from there before or not? Obviously, if I have purchased refrigerator before, why should I go again? That is seller is not aware of my preferences, right? Now, if there is description of the products like company to which it belongs, size of the refrigerator, color, power consumption and warranty durations, it will help the seller in providing the closest to choice object for customer. Let I was provided an item whose similitude to my preferences are high but I dislike the color. "*Everything is fine but may please you show me a blue* *of it?*" it would be my request from the shopkeeper to give me an item with similar features but the color should be blue, with this additional explicit knowledge provided an exact recommendation can be made with less effort and time. This is what a case based recommendation does in recommending the items to users. Case-based recommendation treats recommendation as primarily a similarity-assessment problem. How can the system find a product that is most similar to what the user has in mind, with the understanding that what counts as similar will often involve domain-specific knowledge and considerations?

In product recommendation, decision trees have been used extensively. McSherry [97] has come up with an idea of treating the decision tree as an identification method which identifies an item as an object for recommendation and stores it in case library as a single case. The authors have tried to reduce the complexity in acquiring the explicit knowledge from user for case based recommendations. McSherry in another work [98] has talked about how recommender system is affected by incremental query elicitation. Generally, obtaining the additional knowledge from the users, hinder in obtaining quality solution. The context for which the dialogues can be stopped without any loss in quality of solution is explained by the authors. It is suggested by the authors that destination-oriented technique in which number of cases gets dominance over target case, would provide a better solution. Further, it is noticed that the strategy costs less in computation as well. The authors have evaluated their results on Travel case library (TCL). TCL is a standard benchmark which contains more than 1,000 cases. It is found that their method reduces the average length of argument better than others.

The explanation of recommendation that briefs the user why recommendations have been made would attract the users and might satisfy for a good extent [99]. With this principle in mind, authors have not tried to justify the specific suggestion but rather explained the reason of suggestion. The philosophy also helps users in knowing the further opportunities in a case when the recommended items dissatisfy them. The compound critiques are trained to work as a form which may generate feedback. The authors have claimed explanation-rich critiques improve recommendations for users.

3.4.2. Constraint based Recommendation:

To understand constraint based recommendation, let us consider an example of how recommendations are made for web hosting services [92]. The personal preferences regarding cost, bandwidth, visitors count, etc. are required to be provided with users. The recommender suggests the users and explains the reason of recommendation on the basis of the preferences of the users observed. If no solution can be acquired by the recommender, a replacement is required to be provided for users, in order to save the users from going into a dead end situation. The above example is a better explanation for a constraint based recommendation [100]. In these recommender systems, features of the product and association of user's requirement with these features, both are modeled in the form of a constraint. Constraint-based approaches help in purchasing the items which are not frequently purchased. Constraint-based recommenders support customers in a deadly scenario where no other solution is provided by automatically suggesting options for remedies and explaining technicalities with the items' features.

The application of constraint-based recommenders for financial services is presented in [101]. Another financial application of constraint based is reported in [102]. The authors [103] present an approach to enhance the recommendation for multimedia. The additional feature for component visualization is associated with constraint based. It enables users to interact the virtual product directly. Visualization functionalities provide substantial contributions to user-friendly interfaces boosting the acceptance of recommenders.

Knowledge-based recommender technologies [101] enable customers and sales executives to identify the appropriate products and services. These knowledge engineering are also useful for complex and high involvement products such as cars, computers, or financial services. The authors have presented the VITA (VirtualisTanacsado) financial services recommendation environment which has been deployed for the Fundamenta building and loan association in Hungary.

The effective integration of configuration system development with industrial software development is crucial for a successful implementation of a mass customization strategy. On the one hand, configuration knowledge bases must be easy to develop and maintain due to continuously changing product assortments. On the other hand, flexible integrations into existing enterprise applications, e-marketplaces and different facets of supply chain settings must be supported. The authors have designed a model-driven architecture (MDA) for model development and interchange, and sensibly argued how the industrial configuration can serve as a foundation for standardized configuration knowledge representation; thus providing knowledge sharing in heterogeneous environments. [102].

The problems with DVR and catch-up TV has been resolved by methods proposed by [104]. The challenges and solution regarding personalizing the topic have been illustratively explained in this work. The author has concluded that there are the contents which are absorbed sequentially trends of seasonal dynamics is observed with these contents. If new content arrives just after broadcasting of any content, it would lead dynamic stream of data. And there may be repetition of similar data for different services simultaneously.

3.5 Hybrid Recommender Systems

Though Collaborative Filtering (C.F) and (R.M) are the most frequently used techniques in designing Recommender Systems (RS) but they inadequately provide any explanation of why the specific recommendations have been made to particular user along with recommendation, hence, they fail in fulfilling the explanation in various scenarios. These shortcomings of the both leading technologies can be overcome by the use of the combination of duo. The various combinations of these techniques have been presented in the literature. These combinations are termed as 'hybrid technique'. We have categorized seven types of hybrid recommender systems based on different combinations.

i) *Hybrid Recommender Systems based on Collaborative Filtering (CF) dominated Reclusive Method (RM)*
ii) *Hybrid Recommender Systems based on RM dominated CF techniques*
iii) *Hybrid Recommender Systems based on unified RM and CF techniques*

iv) Hybrid Recommender Systems based on Subsequent Integration of separately applied CF techniques and RM
v) Hybrid Recommender Systems based on Integration of CF and RM with knowledge based system (KBS)
vi) Other Hybrid Recommender Systems using CF techniques
vii) Other Hybrid Recommender Systems using RM

The work which incorporates these combinations has a wide range and has been applied over various applications. The techniques of the hybridization are described in the following section.

3.5.1. Hybrid Recommender Systems based on Collaborative Filtering dominated Reclusive Method

Incorporating components from CF and RM lead to form a hybrid recommender system. These hybrid recommender systems help in dealing with the above said shortcomings. The researchers have started to explore the frequent occurring problems with these two techniques, namely overspecialization and cold start problems. The hybrid technique, composed of the combination of these techniques in various suitable combinations is proposed, and a new approach for recommender system is perceived. It is noticed that various aspects which should be retained in the designing of recommender systems, are ignored. Not considering these aspects may dissatisfy the users and the ultimate goal of the recommender system cannot be achieved. The advantage of employing hybrid system is the power of assimilation of these methods in integrating the collaborative and reclusive approaches by contemplating the best of the two without considering the drawbacks of the either [105].

Mooney et al. have [60] presented an effective methodology combining content and collaboration. The content is used in enhancing user data whereas personalization of recommendation is made through collaborative filtering. The hybrid system performs better than pure CF technique or Reclusive Method [73].

Content with collaboration are elegantly combined in [73]. The authors used reclusive approach to design feature-based predictor for boosting the user profile. CF techniques have been utilized further to provide personalized recommendations. The authors have shown that Collaborative Filtering dominated reclusive methods outperforms the pure reclusive recommendation, pure collaborative filtering techniques, and simple hybrid approach.

The Good et al. have come up with a conclusion that CF techniques can be combined with content based agents, which in turn gives the best recommendations than any combination or separate techniques would produce. They designed the system in such a way that users need not to choose best in agents, instead, the CF framework recommends best ones for them [5].

A clustering technique has been presented [106] as a solution to cold start problems. Item-based CF techniques make use of clustering strategies. The comprehensive idea of integrating the content information into the CF has been explained. The authors have used MovieLens data for experiments. The results evinced the improvement for cold start problem.

The method to combine features of human personality into the traditional rating-based approach for CF systems is presented by Hu and Pu [107]. The rating based system usually computes similarity of the users' preferences with its neighbor and a naïve user may not find good recommendation due to lack of exploration about their past preferences. Combining human characteristics with CF techniques provides better recommendation for new users whose past rating preferences are not well formed.

3.5.2. Hybrid Recommender Systems based on Reclusive Method dominated Collaborative Filtering Techniques

RM dominated CF techniques implies those hybrid systems which incorporate CF techniques into Reclusive approaches. The basic philosophy of reclusive approaches is retained and collaborative techniques are applied over there. A technique for the purpose of text filtering by combining collaborative and content methods are presented in [108]. The latent semantic technique is used for storing user profiles. The RM dominated CF techniques performs well than the simple reclusive approaches.

Since, collaborative filtering methods are treated as a base in recommendation technology. It utilizes the recommendations based on other users' preferences. By contrast, reclusive approach is powerful enough to make recommendations by obtaining details about an item. Thus, reclusive approach can recommend items which are not previously rated by user. The additional feature of CF techniques for getting user profile stronger can boost the recommendation process if the two techniques are combined [73] . The authors have presented the results which demonstrate that RM dominated CF techniques can give correct recommendations [60].

A combination of RM and CF [109] is used to recommend TV program to viewers of Ireland and Britain by collecting their rating and reviews. The authors have discussed a content personalization system which selects the most suitable contents from an individual by reclusive dominated collaborative approach. The key to address the issue is the exposure of a learned user profiles. The duo combination provides a vigorous personalization solution.

3.5.3. Hybrid Recommender Systems based on unified Reclusive Method and Collaborative Filtering Techniques

Several authors have integrated CF and RM in many ways [14] . However, coalescing the two methods into one, is proposed by Ansari et al. [110]. As the brand online retailers like Amazon, eBay and Yahoo! use CF or Reclusive methods for the process of recommendation of various products and services to their users, unifying the duo could enhance the recommender strategies [66]. The authors have described a Bayesian model to sort out the preferences by categorizing the information into five different types of knowledge associated with the characteristics of the recommender system concerned. Markov chain Monte Carlo methods used to recommend movies. The Monte Carlo model works in all circumstances whether CF technique are able to be employed or not. Thus, in general, a recommender system can predict whether a particular product or service may fall into the preference category of a user, in addition it can guess for a user the movie he would be interested in, for sure. The inductive learning method [112] is proposed which incorporates the characteristics of the artifact, which is utilized by the recommender systems in making predictions.

A novel approach for the recommendation of on-line academic research papers based on ontology to help in boosting the user profiling is discussed [113]. The authors collect feedback for users' profiles by utilizing a novel approach based on profile visualization. The ontology of the research papers topic support in categorizing the papers which in turn serve as a base for collaborative recommendation. The users who have similar preferences in browsing the research papers of same interest are stored and accordingly the recommendations are made.

A unified framework for collaborative and reclusive recommendations based on probabilistic method is discussed [114] which is an extension of Hofmann's aspect model [115]. The method assimilates item's content with users and items which is generated by data source itself, and provides a solution in recommendation when data are prevailed by sparsity.

3.5.4. Hybrid Recommender Systems based on Subsequent Integration of separately applied Collaborative Filtering Techniques and Reclusive Methods

The separate implementation of RM and CF are applied in [108] and [116] where the authors have discussed the improvement in quality of recommendation. Kim et al. [117] have proposed a book recommender system for the validation of their method which was designed for an online community. They tried to satisfy the minor members of group which are left unsatisfied although the majority may have satisfaction due to the differences in preferences.

The recommendation technologies have been useful for recommending courses as well as utilizing the courses for other library management program. In [118] authors have used academic courses to generate data for library planning purposes.

Billsus and Pazzani have proposed the induction of hybrid user models. The hybrid model comprised of separate models for RM and CF techniques. The detail description of the implementation of these algorithms for addressing the issues booming in recommendation technology is done [119]. The CF and RM are also integrated and discussed from the restaurants recommendation perspectives and illustrated the advantages of the combination over separate implementation of either of the techniques [31].

3.5.5. Hybrid Recommender Systems based on Integration of Collaborative Filtering and Reclusive Methods with Knowledge based System

The use of combination of CF techniques and RM with knowledge based systems (KBS) has been reported in literature. The authors [120] have suggested a recommendation technique which identifies sets of rule and deduce the recommendation upon these rules. This recommender system provides accurate and cheap clinical examination to patients. A recommender system which provides personal health information of users is designed by Lee at al. [121]. It uses profile of users and accordingly the information is provided for the better services of patients. Wiesner et al. [122] kept the fact that physical activities are very important for fitness and health, so, they have designed a physical activity recommender system that tells the exercise time useful for people. Recommendation of nutritious diets have been suggested in [123]. They have used user ratings for the nutrition needed accordingly provided the nutritious diets to users. The usage of RS in health has been explored by Fernandez et al. in [124], where a detail of RS and their extensive uses in the domain of Health and care is discussed.

A recommender system has been suggested in [84] for e-business by introducing computational ecologies. This system supports recommendation based on negotiation which also inspires ecosystems monitor [125] .

For private banking, a recommender system 'PB-ADVISOR' for multi investment has been framed. The system addresses the issues of recommendation with explanation, in addition it also generates several packages and has the ability to suggest best services for customers with appropriate explanations [126].

3.5.6. Other Hybrid Recommender Systems using Collaborative Filtering Techniques

Knowledge-based (KB) and collaborative-filtering (CF) recommender systems, both have equally contributed online recommendation for users to find products close to their choices out of a huge data with large varieties. R Burke in 1999 has explicitly described in detail the pros and cons of these two [94]. The author has outlined the chances of collaborative and knowledge based hybrid recommender system. In the suggested methodology knowledge-based techniques and CF techniques both work as a complementary for others. KB technique bootstraps the CF engine, and the CF filters the KB recommendations.

A film recommender agent expands and fine-tunes collaborative-filtering results according to filtered content elements - namely, actors, directors, and genres. This approach supports recommendations for newly released, previously unrated titles. Directing users to relevant content is increasingly important in today's society with its ever-growing information mass [57]. Tang et al. [127] have suggested QoS services by using a hybrid techniques which combines CF method with location aware approach.

The use of CF techniques with temporal dynamics [128] is studied. The authors have presented a hybrid recommender system comprised of CF techniques and graph based model [129]. The graph-based approach has already been proven superior to other methods by experimental results. In other words, what information has been conveyed by other techniques is already suggested graph based model. An extensive evaluation has been performed by authors.

3.5.7. Other Hybrid Recommender Systems using Reclusive Method

The CF and RM are the base technologies in recommendation. The most of the technology either use both techniques in any combination or combine either of the technique with other methods like knowledge based approaches, context aware approaches, etc. since contents are used in reclusive approach to extract the features associated with the items in consideration, it would be a powerful combination if reclusive methods are combined with knowledge based approaches. A personalized recommendation could be a solution in providing user the matching items to their preferences out of the huge data available. A hybrid method which combines the reclusive approach with knowledge-based methods to enhance the recommendation performance is presented [130]. Explicit and implicit feedbacks are taken from the users for recommendation process. Optimized weight vectors and preference matrix (PM) are used for exploiting implicit and explicit attributes respectively. The hybrid system gives better results in reducing cold-start and sparsity.

The reclusive approach is able to recommend users the product which have been already searched or visited by them and cannot predict about one which has no past record. However, in many cases users may wish to go for purchasing a new item they never have seen before, as the unheard items may be of interest for a user. The situation is termed as serendipity. Incorporating serendipitous recommendation strategy with reclusive methods alleviate the over specialization problems in recommendation [131]. The authors have suggested hybrid recommendation approach to recommend surprisingly the new items to users. The hybrid methodology is comprised of reclusive and serendipitous approaches.

In [132] the authors have tried to use sematic web structure and text mining techniques for providing users the risk that may occur if the ignorance are kept alive. Thus these risks are advertised on social networks, etc. A hybrid music recommendation system which handles the issues encountered with collaborative and reclusive approaches has been reported [133]. The authors have utilized the rating as well as content of data by using a Bayesian network. The approach solved the problems of collaborative approach of not being capable of recommending music for which no ratings have been recorded. In addition, it also resolves the issue in studying the artist varieties. Latent variables are used to explore the solutions [134].

3.6 Context Aware Recommender Systems

Context aware recommender system though can be perceived as a special kind of knowledge based system, when context is involved as knowledge, required for recommendation. However, the high inclination of the recommender system research community towards recommender system for learning has provided a platform that compels us to keep CARS as a different category, and not a type of KBS.

The ultimate goal of recommender system is to achieve user satisfaction. And user can only be assured for their satisfaction if they are delivered with the exact recommendations that meet their needs. The user's requirement is not static and may vary time to time depending upon various social and other factors affecting their purchasing trend. Hence, Fig. 4shows a context aware recommender system (CARS) which takes into account the context in which user goes for some specific item. And different varieties of the items can affect the user's demand significantly.

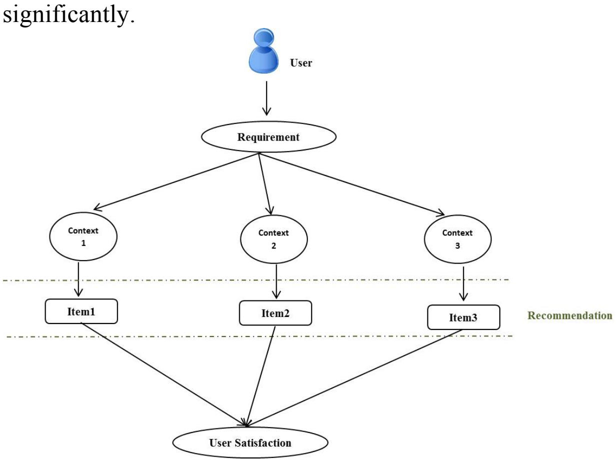

Fig. 4. Context Aware Recommender Systems Overview

We illustrate the example with the help of Fig. 5. Let us consider that user needs to buy clothes from a cloth merchandiser, obviously the demand of cloth for the type it belongs must depend upon the season and weather. In winter season user must be asking for the woolen cloth. Now, if we consider the reclusive approach it would be recommending woolen-like clothes to the specified user always, irrespective of the context. In collaborative approach, the system would go to observe the user's neighbors preference, eventually in the scenario, the probable recommendation may be clothes similar to woolen.

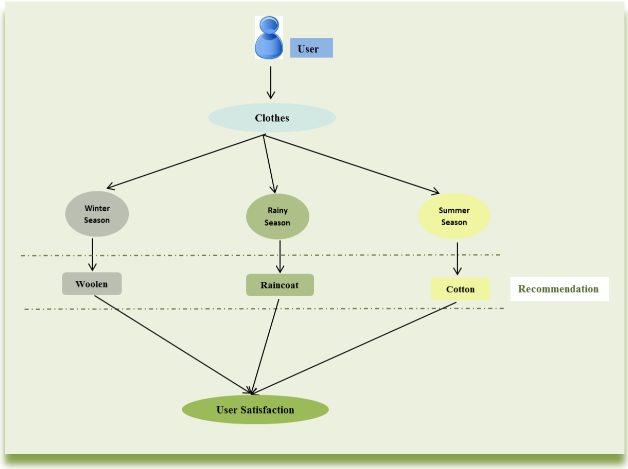

Fig. 5. Example for Context Aware Recommender Systems using season based clothes

The context aware recommendation is necessary to understand the user's delicate preferences and exploiting the complications in their requirement explicitly. It is shown in the Fig. 5 that how a CARS would care for user's choices. A Context Aware system would explore the situation in which the user's purchase is noticed, and tries to filter the recommendation accordingly. Thus, in a summer season, CARS can never recommend a woolen cloth to user. However, in the same scenario, the other systems may exhibit false positive error. False positive employs the recommendation of an item to user while the item is not needed to be recommended and not preferred by the users.

In mobile environments there can be various contexts needed to be considered while making any recommendations. The considerable context can be weather, time, route, location, ad transportation means, etc. before making any recommendation in such scenario recommendations should be designed context-aware for guiding the users on mobile path. A context based travel-related information for mobile systems are proposed [135]. Recommendations of restaurants in Taipei in a mobile device are performed.

Woerndl et al. [136] tries to incorporate contexts in recommender systems to make it applicable in mobile domain. The approach helps users to get aware of what have been installed in mobile of their neighbor; accordingly they may get recommendations for their mobile.

Though there are various techniques which have been classified as a separate category of RS, however, we classify the following different recommendation procedure as a part of context aware recommendation. Somehow, these are the contexts which may affect the recommendations from both seller and buyer point of view.

- *Location aware RS*
- *Trust aware RS*
- *Temporal RS*

Brunato and Battiti[137] realized the need of pilgrims and suggested mobility-aware recommendation system by fetching the location of the users. The authors have calculated a preference metric which answers the queries of the users for their needs of resources while making any pilgrimage. Mobility scenarios are introduced to better appropriate and more reliable predictions of user requirements.

Levandoski et al. [138] utilized location based ratings for recommendation and presented 'LARS', a location-aware recommender system. User partitioning is used to explore the location based ratings. The technique produces quality recommendation; in addition it maximizes the scalability of the system [139].

Yang et al. [140] has identified the need of the customers and sellers both for promotional selling and has presented a location based recommender system for online shopping which gives the best recommendation by fetching the sales and promotions which are location dependent. Tang et al. [127] has presented a location aware system which also incorporate collaborative techniques to produces QoS web based services. The web recommendations are made based on collaboration of user's locations.

A Bayesian Networks (BN) influenced map-based customized RS is proposed [141]. The system utilizes contextual knowledge including location and time. The contexts like weather and user request automatically collected from mobile devices are used to recommend appropriate item to users which match to their preferences.

Temporal recommender systems are meant to recommend items for users when time is required to be kept an essential component in decision-making process. A system is designed to recommend ranked cafes to customers [142] according to their preferences, explored by their preference's knowledge, characteristics of the cafes', specific situations, requirements, as well as the time of intended recommendation.

Queue Lee et al. [143] suggested a collaborative filtering-based recommender system using implicit feedback. Since the system does not use explicit feedback, it had relied upon pseudo rating observed from implicit feedback. The time of user's purchase and launch of an item are used to construct pseudo rating matrixes which in turn increase recommendation accuracy.

Lathia et al. [144] have shown how the temporal diversity can affect the recommendation specially the behavior of CF techniques in recommendations. Since the user's rating serve as a base in CF techniques. It is shown in their work that CF data changes over time and a user may not always rate the item each time he/she comes to shop online.

The authors in [145] presented a hybrid recommender system that not only incorporates the demographic details of users but also the temporal information. The results of the experiments has supported that temporal knowledge may enhance the performance.

3.7 Social Network based Recommender Systems

The detail of the RS applied over social networking environment has been extensively studied and presented by Zhou et al. [13]. The authors have tried to explore the pros and cons and the opportunities of social network based RS.

An overview of the Foafing the Music system is presented [146], [147]. The system used the text from RDF Site Summary (RSS) and Friend of a Friend (FOAF). The Foafing based system predicts music to a user that matches to his essence of music listening. Music information is collected from RSS feeds, music related blogs, upcoming albums and 'mp3' audio files at different music containing sites. The system discovered music with the help of user profiling, information and descriptions based on context supported ontological details of music domain.

Hu has presented a new paradigm of recommender systems. The RS can make use of social networks (SN) based information. This information can be the preferences observed for users, usual inclination of users towards a product or service, influenced and influencing entities, like friends and acquaintances. A probabilistic model is designed for personalization of the suggestion from these inferences. The real data from online SNs are extracted. With their experiment, the author has concluded that there is a strong similarity in the preferences of friends. Experimental results on this dataset show that proposed system improves the performance [148].

To make use of social network where private or personalized data of an individual is easily accessible for recommendation of items to new users are presented [107]. Human personality characteristics are integrated with rating given by them in the recommendation process.

A social network based recommender system which exploit [149] the trading relationships has been proposed. The system proposes the ways to compute the degree of recommendation for trusted online auction sellers. The authors have utilized network structure which is formed by history the transaction performed by user.

3.8 Soft Computing Techniques based Recommender Systems

The soft computing techniques have now been increasingly used in recommender systems for incorporating collaborative recommendations, reclusive recommendations and hybrid recommendations. To deal with the uncertainty in various business marketing affairs, Cornelis et al. [150] make use of fuzzy relations to model the degree of similitude between items and users. They also proposed a novel hybrid CF–CB approach whose rationale is concisely summed up as "recommending future items if they are similar to past items that similar users have liked". A hybrid fuzzy logic-based recommendation framework [151] was then developed to improve the trade exhibition recommender system for e-government. Zhang et al.[152] has developed a telecom recommender system using fuzzy techniques. The authors have used fuzzy on item based similarity approaches. The have applied fuzzy set techniques on mobile product and service recommendation. They have designed system referred as Fuzzy-based Telecom Product Recommender System (FTCP-RS).

A soft computing technique is applied for the recommendation of the books for university graduates by the authors [153] where they have incorporated the vagueness in the preferences of the books and aggregated the score of the books using OWA technique. Similar work has been suggested using ordered ranked approach in [154].

Hybrid approach using fuzzy-genetic to exploit the use of its varieties to address sparsity and scalability is addressed. But CF techniques face the issue of accuracy and sacability both. To overcome the problems of accuracy and scalability with memory based and model based CF techniques, respectively. The proposed system reduces sparsity and complexity; while retaining the neighbor recommendations perspective [155].

Fuzzy logic based RS is presented as a solution to issues encountered by CF techniques for some specific situations regarding those items which are brought into market rarely and not necessarily be repetitively put on sale [151]. The employed fuzzy technique recognizes the uncertainty in the information. The method can be helpful in various scenarios like trade exhibition recommendation.

The problem with CF technique and RM is that both of them fail in representation of explanation of relationship between users' feedback and features of items as they are subjective and uncertain. The authors have presented Fuzzy set theoretic method (FTM) [217] which identifies the application of fuzzy method presented by Yager [50]. The FTM makes use of aggregation which finds confidence score for recommendation. The techniques also utilize the various statistical measures to evaluate the RS.

The authors have suggested how to automatically recommend newly launched items to user which have no prior rating. Only with the users past history of purchase, the new items are recommended to users. The combination of Bayesian networks and Fuzzy Set Theory are used to enhance the system performance [218].

3.9 Solution to the existing problems

Various threatening issues have been discussed throughout this paper. The efforts of the researchers for these issues have also been discussed adequately. However, we have suggested different directions for these problems. The future solutions are summarized below.

- It is evident that prior to designing a recommender system one must understand the characteristics of the recommendation which can please the users. User's feedback directly reflects their priorities, likes and dislikes. Therefore, explicit or implicit feedback from the users to know the characteristics of their past preferences as well as to predict the future behavior is pragmatically important. A recommendation procedure which can exploit the feedback from users that directly convey the preferences of the users could be a better option. This procedure would provide a recommendation on consensus basis which overcomes the prevailing issues with Reclusive Method and Collaborative Filtering techniques.

- The cold start problem can be tackled by using consensus ranking from users for those items which suits majority of the group to which user belongs. However, there are two important aspects in it, first, to know similar-like user surroundings and second it may not be personalized recommendation. However, this approach may save time and ease the complexities involved in the recommendation. Suppose we have to recommend books for graduate students of any university. Finding each user's preferences and providing personalized recommendation all is time consuming and efforts are required in it. Also, cold start issue will remain a threat forever. As a solution, all the graduate students of same course in a University can be considered as member of one group. Top N books amongst several universities can be obtained by observing – a) what the best universities are recommending and, b) what the students have their opinion about these books. By finding the best book with some experimented suggestible approach, a good recommendation can be provided to large user without unknown prior preference (UPP) problem.

- In section 3.8, it is discussed how the soft computing have emerged and its employment in recommendation technology is seen increasing rapidly. A method which utilizes soft computing techniques and makes possible use of it to outstretch the satisfaction level of users can be framed. The various linguistic quantifiers with its different combination can be used to aggregate the users' preferences where not enough ratings are available or choices are not clearly defined.

- It is also revealed that rating scale proves handicap for several occasion, like when no ratings are available or rating scale lacks standard. Since the merchandiser and users have their own rating scale and own perception and understanding for rating scale. Hence, there is no standard rating parameter and lack of rating standard affects the recommendation badly. Some of the sites use 5 rating scale whereas others have 10 rating scales. So if we consider only how much star has been awarded by the user for a particular item, it would be confusing. A product is rated 6 out of 10, and another is rated 4 out of 5, it is obvious the latter is best rated but the system which only asks number of rating or rating points, it would opt for former. Thus we need some aggregation operator that can fit the difference in one view. Also, rating scale gives a relative preference idea and not absolute ranking. Hence, a user while reading a book gives 4 stars on amazon while the quotes from the user is indicating that the book is not up to the mark, however is well. That is 4 stars for a user means different from other. Different users perceive rating differently. Sometime a user gives 3 star to the best books he has ever been read. Whereas another user might have rated 4 stars to an average book, thus, there is a need of some operator that can eliminate the difference and project the rating absolutely and not relatively.

- Opinion mining could help better recommendation where rating scale might not have done well. Opinion mining could provide the recommendation by finding user's requirement according to their reviews, and matching it with characteristic of the product, hence, recommending the exact items to users. Opinion mining based recommendation seems to be one of the best alternatives. The opinion mining based recommendation is believed to be a realistic one adequate for the users' satisfactions. It also reflects the preference of a user better than the rating prediction. Opinion mining avoids user's rating and rather it emphasizes on user's reviews. Thus, opinion mining can be a good solution to deal with the issues those have been encountered with rating based recommendations.

3.10 Conclusion

The comprehensive survey of the recommender system is presented in this paper. With the help of the study conducted in the paper, we have concluded that there is an exponential growth of the research in the field of RS. Researchers have shown a great interest towards this area. The application area of RS has covered diverse field of daily life. It includes academia, health and care, business using e-commerce and e-shopping sites, etc.

Various techniques have been used to meet the demand for these applications. We have categorized 8 different types of RS which is further broken into 19 sub categories based on techniques and filtering algorithms used. The Collaborative Filtering (CF), most influential recommender technique, has largely used by the researchers but still fails to produce satisfying solution due to major drawbacks like cold start problem for new users and sparsity, as stated in section 3.1. The leading technique next to CF widely used in the literature is 'Reclusive Method' (RM) or 'Content based filtering'; the technique also suffers from the same complications. No technique alone can sensibly be considered as a solution to these problems, instead hybrid approach may fulfill the requirement. Thus, a more robust hybrid method which incorporates the best of these techniques without being affected by their worst may produce satisfying results.

We have also suggested some possible directions in overcoming problems like cold start and lack of rating standards in rating based recommendations, etc. One of the critical finding of the study is that personalized recommendation can be replaced by consensus based ranking to for situations where interest of users coincide, i.e. for the people which can be classified as a member of same group.

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