International Journal of Information Technology, Research and Applications (IJITRA)
Vol.1, No.2, August 2022, pp. 1~8

Recommendation Systems: Different Techniques, Challenges and Future Directions

Mahesh T R[1], Vivek V[1], V Vinoth Kumar[1]
[1]Department of Computer Science and Engineering, JAIN (Deemed-to-be University), Bengaluru, India

Article Info

Article history:

Received June 04, 2022
Revised June 12, 2022
Accepted July 14, 2022

Keywords:

Recommendation Systems
Challenges
Collaborative Filtering
Hybrid Filtering
Future Directions

ABSTRACT

As a major research interest, the Recommender Systems (RS) has evolved to help consumers locate products online by offering recommendations that closely fit their interests. This article presents a comprehensive study of accomplishments and the future direction in the field of Recommender Systems. It was thought that helping users cope with the issue of data overload was the original role of information retrieval systems or search engines, but what separates suggested systems from the existing search engines is the requirements for personalized useful and interesting. The "intelligence" aspect is what suggests more interesting and useful. Intelligence is one of the main routes of personalization to know the interests of the user, anticipate the unknown favorites of the user, and eventually provide suggestions by matching the question and the content beyond a basic search. This analysis has resulted in many important results, which will allow current and the next generation researchers of RS to evaluate and set the roadmap of their research in this field.

Corresponding Author:

Mahesh T R
Department of Computer Science and Engineering
JAIN (Deemed-to-be University)
Bengaluru
India
Email: trmahesh.1978@gmail.com

1. INTRODUCTION

Which four-wheeler should I buy? "Which restaurant am I supposed to see visit weekend?" "Where do my family have to go to spend the holidays?”, These are a some of the examples of very normal questions for which our friends and acquaintances frequently seek suggestions. Unfortunately, almost every one of us has observed that these nice recommendations are not always successful in many situations, even with their best intention, as the taste of others does not always mean harmonizing with that of ours. Sometimes these suggestions are biased as well. Really, RS is a significant insightful computer-based method that forecasts and helps them select things from a large pool of online stuff on based on the consumer adoption as well as usage. Most of the Internet users depend upon the RS in one or the other way. For example, prospective friends are recommended by Facebook, videos in accord are recommended by you tube agreement, Matching jobs are recommended by Glass doo, Trip Advisor suggests us appropriate vacation destinations, good reads suggest the books which are interesting and so on. E-Commerce sites (Examples, Amazon, eBay etc.) use RSs to draw consumers by using the goods that customers are likely to want. This has allowed them to achieve an immense sales increase. These are not restricted for online businesses only, but also there are many applications which eventually take benefits of RSs, to mention a few, social networks, entertainment sites, news through online portals and many other applications for knowledge management. In the communication approach between users as well as the service providers, RSs have engendered a new dimension.

Many businesses are now implementing RS approaches as an additional benefit to enrich their customer services. While the RS implementation depends upon the unique recommendation methodology followed by the application and, the core work of the recommendation systems for all applications remains more or less the same. The main objective of recommendation systems is to assist users in helping them in the process of decision-making to select an item via online by promoting high precision recommendations in-hand [1]. People from different fields like data processing, data retrieval, knowledge discovery, theory of approximation, theory of forecasting, artificial intelligence, information retrieval, business, marketing etc., have made substantial contributions to various research approaches [2]. The research group has done a great deal of work to improve applicability as well as efficiency of RSs in the past few years [3]. To overcome many of the technical challenges, new methodologies have been developed, such as providing more reliable recommendations while minimizing online computing time. A broad range of Artificial Intelligence methods have been introduced into suggested system study, including (ML) machine learning, data science, user simulation, as well as case-based reasoning. The notion of a smart machine that can think as well as learn as a human being has led to most of the humanized techniques which is called as Computational Intelligence (CI).

While Graundy [4], a computerized librarian, can be seen as an early move towards automated RS [4], in the early '90s, the concept of accruing opinions from millions of users who are online to get more relevant and attractive material arose. A manual CF framework, Tapestry [5], allowed customers to retrieve for objects via online knowledge domain. And GroupLens [6] has used a similar strategy by using Usenet articles to define the interest of the individual user and to include a customized suggestion based on the user's behaviour.

Social networking platforms (For example, Twitter, Facebook etc.,) have now emerged as a major forum for the application of RSs. Of course, these famous sites are taken as the main source of people-related knowledge and thus to be a great choice for exploiting modern and creative approaches to the recommendation, backing the old methods, to improve accuracy [7].

2. DIFFERENT PHASES OF RECOMMENDADTION SYSTEMS

There are different phases in the process of Recommendation systems as shown in the figure 1.

2.1 Phase 1-Information collection

Gathering the specific user information to build a profile of a user or say a model for purpose of prediction tasks, that includes features of activities of the user, or resources that are being obtained by user is done in this phase. Till the profile of the user or model of the system has been well built, an agent of recommendation cannot work sent percent accurately. To make an open-ended suggestion right away from the start, the system requires understanding from the user as much as possible it can. Recommendation systems depend on various types of inputs, like the very much convenient feedback taken explicitly which are of standard quality, that includes input which are straight forward from users regarding their attentiveness in products or feedback which is implicit by implicitly inferring user likings via user behaviour observation [9].

Explicit Feedback: To create and refine its model, the system typically reminds the user via the interface of the system to present ranks for objects. The recommendation accuracy really is dependent on number of user ratings or ranks issued. The one and only shortfall of this approach is that it needs user effort and users as such are not always ready to provide adequate details. It is even now observed as providing more accurate data, although more user effort is required for explicit feedback and presents clarity in recommendation process.

Implicit Feedback: Automatically, the system gathers the tastes of the user by trailing different user behaviour, namely purchase history, history of browser, time consumed on some web pages, email content, and clicks of buttons. Implicit feedback decreases the force on web users by inferencing the desires of their users from their device actions. This method is less accurate compared to explicit feedback; however, no effort is required by the user.

Hybrid Feedback: To mitigate their shortcomings and get a better functioning system, the benefits of implicit as well as explicit feedback, both can be merged in a system called hybrid. This is done by making use of implicit data as an explicit rating audit, or by making users to provide explicit input only when showing explicit interest.

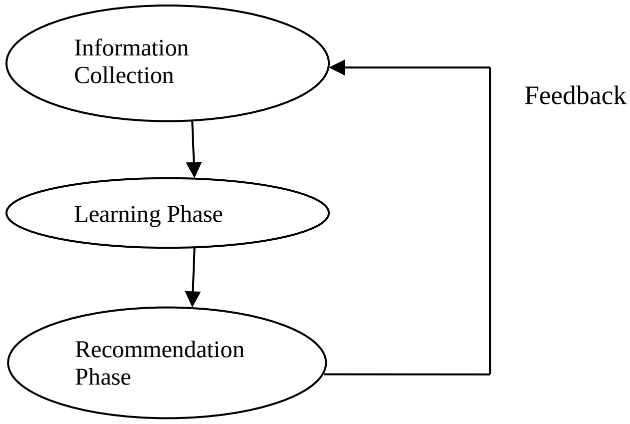

Figure 1: Recommendation process: Different phases

2.2 Phase 2-Learning Phase

This phase uses any of the learning algorithms to clear and to make use of the characteristics of the web users through the feedback received in the gathering procedure of data.

2.3 Phase3-Prediction Phase

This suggests or forecasts what kind of products or items that the users would prefer. SO, this is achieved directly on grounds of data set received in the information gathering process that may be either model-based or may be memory-based by the user's noted activities of the system.

3. DIFFERENT FILERING TECHNIQUES FOR RECOMMNEDADTION SYSTEMS

To a system which can offer good and practical guidance to the system's individual users, use of appropriate and correct recommendation methods is very critical. This illustrates the value of recognizing the characteristics and potential of various methods of recommendation. Figure 2 illustrates the anatomy of various methods for filtering recommendations.

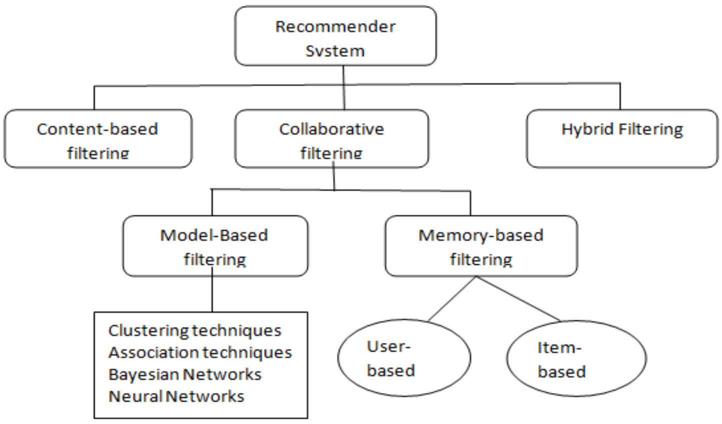

Figure 2: Different filtering techniques for Recommendation

3.1 Content-based Filtering (CBF)

Content-based recommender system works with user provided information directly or indirectly. A user profile is created based on that information, that is utilized to present suggestions to the users. The engine happens to be more detailed since the consumer provides more inputs or acts on the suggestions. In information recovery systems and content-based filtering mechanisms, the principles of WF i.e., Word Frequency and IDF i.e., Inverse Document Frequency are used. They are used to assess the relative value of a text / post / news storey / film etc. In a document, TF is the word frequency. Out of the entire pool of documents, the IDF is the inverse of the document frequency. "TF-IDF is mainly used for two reasons: Suppose that on Google we look for "the hike of critics'. It is definite that "the" would occur more often than "critics," but critics' relative meaning is greater than perspective of the search query. In such situations, the weighting of TF-IDF nullifies the impact of words having high-frequency on the value of an object. But the log of course is used to diminish the influence of terms having high frequency when measuring TF and IDF. TF = 4 versus TF = 5 is very different when compared TF =20 versus TF = 2000, for instance. Alternatively, the meaning of a particular word in a text cannot be calculated as raw count simply and so we have the following equation (1).

$$W_{t,d} = \begin{cases} 1 + log_{10} tf_{t,d} & if\, tf_{t,d} > 0 \quad otherwise\ 0 \\ o, & \end{cases} \qquad (1)$$

3.2 Challenges of Content-based Filtering

Recycling of news stories to be proposed is the greatest obstacle in news recommendations. Readers of the news tend to read about recent happenings. Recommending the most important articles news and new or fresh news in place of old news articles is therefore a major challenge. The new articles news are more very much relevant than the old ones, in few cases it might be appropriate to present the old or previous news to the reader depend upon the context or perspective of current happenings in order to gain detailed details and understanding of the topic. News readers tend to read the articles related to news from numerous outlets to obtain detailed knowledge of an incident that has occurred or the current progress of a news storey or different opinions and points of view. It is a daunting job to have related news articles written in another journal regarding the same case without sufficient system recommendations. Recommendation systems for the presentation of news articles written in only one language, from one source are typically developed. Recommendation of multi-lingual articles related to news from different outlets and deploying productive news articles using similarity methods are a difficult job for proper recommendation.

3.3 Collaborative filtering

Collaborative filtering uses similarities between users and objects simultaneously to provide recommendations to get rid of the shortcomings of content-based filtering. This allows for serendipitous recommendations which are based on likings of a similar user B, collaborative filtering models will recommend an object to user A. In addition, without relying on hand-engineering of functionality, the embeddings can be automatically taught. The technique of collaborative filtering executes by constructing a database of user likings or preferences for objects. Then, users are matched with appropriate interests and likings or preferences to make recommendations by measuring the user profiles similarities [12]. A user provides suggestions for some certain things which has not been rated before, however, those users in their neighbourhood have been positively rated positively already. Recommendations produced by CF are either predictive or recommended. Prediction is actually a numerical value, Rij, for the web user i expressing the item j's predicted score, where as Recommendation is record of the top N things that the web user likes most, as mentioned in below diagram Fig. 3'.

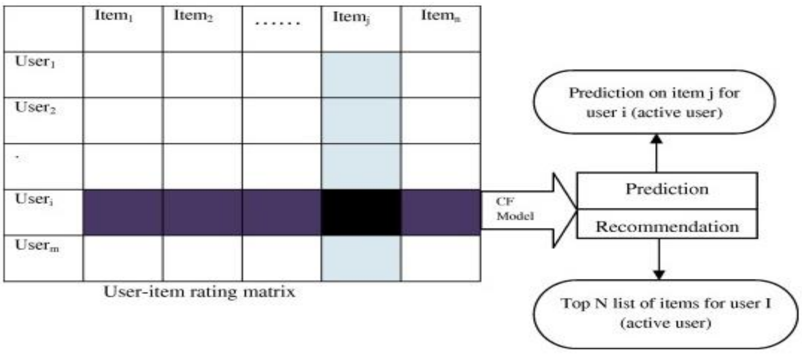

Figure 3: Collaborative Filtering Technique

Collaborative filtering approach is being categorized into 2 classifications: memory-based as well as model-based.

3.3.1 Memory based technique

In searching for a neighbor who shares recognition with him, the things which were already valued by the consumer before play an appropriate role [13,14]. When a neighbor of user is found, various algorithms are employed to merge neighbours' preferences to produce recommendations. Widespread popularity was gained in real world applications due to the efficacy of these techniques. User-based as well as item-based techniques, are the two ways using which memory-based CF can be accomplished. Firstly, their ratings or rankings on the identical item are compared. The user-based method computes the resemblance between users. Secondly, the item-based method determines the predictions considering the similarities among the objects but not that of users.

3.3.2 Model based technique

To enhance the efficiency in Collaborative filtering, this method uses the previous rankings for learning a model. Using the techniques like machine learning or data mining methods, the process of building the model can be completed. In fact, by making use of pre-computed model, really can easily suggest a collection of items and in fact have been proven to deliver recommendation results which are close to neighbourhood-based methods of recommendation. Learning algorithms have evolved a lot and have changed the way how recommendations are made, to recommend what consumers should consume, to recommend when a product should be consumed. Therefore, it is important that the remaining learning algorithms which are employed in these model-based recommendation systems are examined:

- Association rule: These algorithms [15] bring out the rules which predict the presence of an object based upon the existence of other objects in any transaction.
- Clustering: In various fields, clustering approaches have been used, namely pattern recognition, digital image processing, analytical data, and information discovery [16]. To identify meaningful classes which exist among them, the clustering algorithm aims to divide a collection of data based on the similarity features into several sub-clusters [17].
- Decision tree: The method is modelled as per the tree graph technique that is developed by evaluating a collection of training samples for which we define the labels for the class. Then, there are applied to identify examples previously not seen. If training is done on a very good quality of data, then accurate predictions can be expected [18].
- Regression: This technique is employed when a linear relationship is assumed to consistently link two or more variables. It is a powerful process of diversity to evaluate associative relationships among a dependent variable as well as one or many independent variables. Regression uses curve fitting, estimation, and very systematic hypotheses among relationships between evaluations of variables.
- Artificial Neural network (ANN): This is a composition of several linked neurons (nodes) that are organized in systemic ways in layers. Depending on the quantity of influence that one neuron has with another neuron, the connections among neurons will have weights linked with them. In some special problem cases, the use of neural networks has some benefits. For example, an ANN is very much robust against noisy as well as data sets which are erroneous since it contains several neurons, also it allocates weight to every connection [19].
- Link Analysis: This is a and method of creating interconnected object networks in order to investigate trends and patterns [20]. It has created tremendous potential for improving the efficiency in web searching. Link analysis includes algorithms for Page Ranking as well as HITS. A web page is treated by most of the link analysis algorithms as an individual node in the graph of web [21].

3.3.3 Hybrid Filtering

To get better device optimization, the hybrid filtering technique incorporates various techniques of recommendation to avoid certain disadvantages and problems faced by some pure or clear recommendation systems [25,26]. The concept behind hybrid techniques is that algorithms are combined to provide recommendations that are more accurate and efficient when compared to that of a single algorithm, as one algorithm can resolve the limitations of another algorithm [27]. In a combined model, using several recommendation techniques will suppress the limitations of a single technique. In any of the following ways, the combination of methods is done: separate implementation of the algorithm and outcome combination, using few content-based filtering methods in collaborative mode, or using few collaborative filtering methods in content-based technique by creating a single recommendation framework that brings all approaches together.

3.3.4 Challenges of Hybrid Filtering

When the sparsity increases, a greater number of items are introduced to the scheme, this issue will be more prevalent in the news domain, for instance, in a continuation fashion, latest news when published online and the number of news items increases rapidly.

Commercial websites are increasingly implementing the suggested systems since they can be used to dramatically boost the profitability of vendors without scrupulous intervention. The suggested systems are being used to highly rate their own items or product of their own and there are chances of showing very less ratings of other competitor products and other forms of attacks, such as shilling attacks [28] or attacks by profile injection [29].

3.4 Challenges of Collaborative Filtering

Since embedding is learned automatically, we do not need domain information. The model will help users identify new interests. The ML framework does not know whether the user is really interested in a given item in isolation, but the model may still suggest it because that item is of interest to similar users. To some degree, a matrix factorization model needs only the feedback matrix to be trained by the method. The framework doesn't require contextual features. This can be seen in practice as one of the many candidate generators. For a given (user, item) pair, the model prediction is the dot product of the corresponding embeddings. So, if an object is not seen during training, it cannot be embedded by the system and cannot question the model for this item. The cold-start issue is also called this problem [22-24].

It is difficult to observe or understand the reader's satisfaction with the storey, to know whether the user is really liked the article or not, without clear news reader feedback [25]. By using collective or CB-filtering techniques, the explicit input of a user can exhibit a vital role in accurate recommendations of the article to users who are the same news readers.

Predicting the future interest of the user is quite challenging and extremely complex in the domain of news for all forms of user-based recommendations. While some of the events occurring [26], e.g., some news, the desires of the consumer may be altered. Readers may be interested in reading articles about a World Cup season football match.

4. FUTURE DIRECTIONS

Nearly all RSs have been developed to date for sellers, suppliers, and those who provide services probably they are intended to attract possible customers. We assume that not only future RSs are going to be restricted to industry, but they are going to have high impact on our day to day lives [30]. These systems can become completely universal and become an important tool in day-to-day life every everybody. Future RSs are not going to be tied merely to only those applications were buying as well as selling are required; rather it can become a personal advisor for everyone to assist in every aspect of our life by providing guidance and suggestions [31]. Future RSs should sense need of ours and instinctively suggest it, even though if we don't articulate it directly. The demarcation between search and suggestions would become blurred by future RSs. RS would, in turn, be an important part of search engine for the future that can deliver personalized search. However, it is going to be very challenging for consumers to discover the reasoning and logic or the reason behind the suggestions they get [32]. It'll be more available to the RSs. In the case of merging recommendations along with searching, it is particularly important. If individuals understand the trend of the advice, they can check more carefully.

IoT, IoE and Big Data will drive the RSs primarily. Ubiquitous data's Intelligent use would be the big distinguishing aspect in the future RSs. Data can simply be obtained, evaluated, and analyzed from anywhere and for everything [33]. By gathering relevant and implied information from other online sources, future RSs would be able to come out of of 'cold start ' issue [34]. The primary enabler for this is social networks, Internet of everything and every possible means of omnipresent communication [35].

Usually, current RSs are centric towards seller, meaning users receive suggestions for only certain items that the sellers wish to sell [36]. This limits the independent interests of the buyers. By being more buyer-centric, potential RSs should suit buyers better. Sophisticated tools for data analytics can motivate dealers by helping them to evaluate and discover a valuable trend in the online shopping habits of people. For the goods they are interested in the beginning and ultimately what is that they are going to purchase, and they will catch the apparent pattern of the consumers.

They would also use the details that consumers put in their carts of goods and among those that are ultimately purchased and are not [37]. Based on these findings, the recommendation would give consumers an improved shopping experience. Through IoT, manufacturers can obtain, for each consumer, products/services usage metrics and change their products or even services and strategies of pricing accordingly [38]. For example, a person without right hand should get right product suggestions that are correct for him.

By evaluating personal patterns and behaviours, suggestions would be more personal and individualized. Digital reality that will involve consumers in more customized shopping will be used by RSs. Future RSs are going to very smarter, immediate responsive, linked, and safe with the ease technologies like virtual reality and potential of data [37]. The RS of the future will join our everyday lifestyle. By monitoring our everyday activities, like walking, talking, breathing, sleeping, eating, and gathering relevant data, they will keep a record of our behaviours [38].

5. CONCLUSION

It will always be a tough and confusing job to make a choice between various choices based on tremendous amount of data available online. Recommendation systems (RS) through online help us to solve this. RSs incorporate effective information extraction and filtering processes to do their job competently and accurately. In this article, we provided the context knowledge of recommendations systems, broad classifications, sub-categories, their challenges along with future directions. The research methodology, data collection approach, inclusion & exclusion criteria were comprehensively illustrated. This paper's main objective and main emphasis is to monitor the developments in RS research. A few interesting figures have emerged. Most RS analysis, for example, focuses on collaborative filtering and knowledge-based approaches. We are hopeful that many new and creative avenues of technologies such as Cognitive Computing, Artificial Intelligence, Internet of things and many more cutting edges will be seen in future RS research.

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BIOGRAPHIES OF AUTHORS

	T. R. Mahesh is serving as Associate Professor and Program Head in the Department of Computer Science and Engineering at Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bengaluru, India. Dr. Mahesh has to his credit more than 40 research papers in Scopus and SCIE indexed journals of high repute. He has been the editor for books on emerging and new age technologies with publishers like Springer, IGI Global, Wiley etc. Dr. Mahesh has served as reviewer and technical committee member for multiple conferences and journals of high reputation. His research areas include image processing, machine learning, Deep Learning, Artificial Intelligence, IoT and Data Science.
	V. Vivek is having 13 years of experience in teaching and research domains. His area of expertise includes Distributed Systems, Cloud Computing, Computer Networks, Agent-based Computing. He has completed his Master's and Doctoral degrees from the School of Computer Science and Technology, Karunya University, INDIA. He has received the CISCO certification in CCNA (Cisco Certified Network Associate) from CISCO Systems. He is also a part of the CSICO Networking Academy team as a CISCO Certified Instructor for more than eight years. He has published research articles in leading journals (SCI, and Scopus) and was a resource person for various guest lectures. He is also actively involved in signing academic MoU's with Infosys, CISCO, and Microsoft and organized various technical FDP's, workshops and hands-on training. Recently has been elevated as IEEE senior member by IEEE. He has worked for universities like Karunya University – Coimbatore and Alliance University- Bangalore and currently working as an Assistant Professor and Program Coordinator in the Department of Computer Science and Engineering (AI & ML) at JAIN (Deemed to be University), Bengaluru.
	**V. Vinoth Kumar** is an Associate Professor at Department of Computer Science, JAIN (Deemed-to-be University), Bangalore, India. His current research interests include Wireless Networks, Internet of Things, machine learning and Big Data Applications. He is the author/co-author of papers in international journals and conferences including SCI indexed papers. He has published as over than 35 papers in IEEE Access, Springer, Elsevier, IGI Global, Emerald etc.. He is the Associate Editor of International Journal of e-Collaboration (IJeC), International Journal of Pervasive Computing and Communications (IJPCC) and Editorial member of various journals.