A Systematic Review on Recommender System Models, Challenges, Domains and Its Perspectives

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Abstract. The accelerated tremendous reach of web applications substantially raises the demand for effective recommender systems to examine and filter required content from the vast quantity of information. Recommender systems have evolved in this digital arena as a way to aid users by giving them possibilities among acceptable and relevant items by analyzing user interests. In this system, the preferences as well as prior behavior patterns of the users, have been utilized to give a recommendation. The utilization of recommendation models became a crucial component in digital marketing strategy. It also plays a vital role in areas such as streaming services (movies, music, and books), social networking systems, e-governance, e-commerce (shopping), e-library, e-learning, tourism, resource services, any group activities and much more. Recently it has been inducted into healthcare, education and a wide variety of user's needs, to help the users in discovering and fetching related interests. However, the main challenges like cold start, sparsity, grey sheep, starvation, and shilling can degrade the performance of the recommender system. Research on recommender system has raised significantly to make the system overcome the challenges and enhance the accuracy of predictions. This article aims to provide a comprehensive review on the main models, challenges, evaluation methods, and metrics of the recommender system. Also aimed to provide a glimpse of the domains and tools concerning the recommender system. Future prospects were also to explore additional insights, and unresolved concerns in the area of RS to support future researchers.

Keywords: Recommender system · Model · Domains

1 Introduction

The recent developments and advancements in digital technologies have led to the growth of different domains. This leads to the production of a large quantity of data [19]. It makes it tougher for internet users to pick their interests out of the huge volume of data [20]. So, recommender systems (RS) as an essential part of the Web overcome the information overloading problem [21] The recommender system is a subset of the information filtering system that can deal with the abundance, of unstructured-natured

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data extracted from the web user's data [19]. The approach recommender system is similar to the ones that the user or neighbors that have recommended an item or an interest to the next one based upon the similarities of interest [21]. A recommender system is a well-growing information filtering system that suggests things to the user based upon the 'ratings' or 'preference' acquired from the user from the previous interactions with the system [1]. The basic impetus of an RS is to provide a list of possibly preferred things as suggestions to assist users shop, which is useful to the vendor as well [17]. The suggestions generated by the system are called as recommendations which play a major role in the different decision-making processes, such as products to buy, visual content to watch, and news article to read [35]. In the recommender system "item" is a common term that is used to indicate what RS recommends to the user [68]. The growth and development of cyberspace and smart appliances have led to increase usage of web applications, and social network systems (SNS) [36]. As a result, these services are gathering an expanding amount of digital data that may reflect consumers' preferences [37]. Consequently, web applications and SNS Portals have identified as a key source for acquiring various kinds of user's data [3]. Just not simply explicit data that was primarily given by the user include likes and ratings, that were predominantly used in current RS as well as the user's implicit data such as navigations and clicks on the web applications or portal visit data collected which indicating the user's activity patterns (like records), could be leveraged in RS [4].

1.1 Primary Functions

In a RS, the machine learning (ML) algorithms are very much useful to build a function that going to anticipate an item of user choice to the user based upon two primary functions prediction, and ranking.

- Prediction: In this approach, there is a need for finding out the rating value of an item from the user, and the user and item's (u $\times$ i) previous interaction. It is assumed that training data is provided that demonstrates user interest and preferences. Given U users and I items, this equates to an imperfect u $\times$ i matrix, at which supplied values are utilized for training. Where missing values are predicted according to the learned preferences which got from the u $\times$ i interactions [4].
- Ranking: In order to give recommendations to users it's not really essential to anticipate the ratings of users for particular items. But the vendor who is selling the items wants to pick up the top N times from the list of items to recommend to the active user. It is assumed that it is always needed to find out the top N items from the list than top users. It is assumed that the first function is necessary because the ranking for an item can be derived from the prediction function where the user and item interactions were predicted [4].

1.2 Goals of Recommender System

To achieve this objective, the RS needs to achieve operational and technical goals.

- Relevance*:* The RS needs to suggest the relevant item to an active user which matches to interest and regular needs of a user from the list of previous interactions [2].

- Novel*:* Sometimes it is very necessary to suggest an item that was never witnessed by the user such as some recent hit movie genre that was never chosen by the user. Novelty sometimes gives positive results to the vendor sometimes it is treated as introducing the new user to a specific new genre [17].
- Serendipity: Sometimes the recommendations are serendipitous when the suggestion of the item is positively surprising and make the user, felt lucky to have that item be on the list of suggestions. Serendipity seems to have a beneficial influence mostly on sales and helps uncover new areas of the user's interest [18].
- Diversity*:* Encouraging recommendation diversity gives a better result because the recommender systems often propose top-N items in the list. If the list of items were similar to the earlier one, sometimes the user gets bored and does not like any of the items from the list, which leads to a negative impact. It is suggested that the recommendation list must contain a different type of item which were top in particular criteria, if so there may be a probability that the user could show interest on least one item from the recommendation [17].

2 Models and Challenges

2.1 Recommender System Models

In order to present a basic overview of the main models in RSs, the standard approach to differentiating between six distinct kinds of recommendation models is as follows [5].

2.1.1 Content-Based Filtering

In the Content-Based (CB) model, the RS recommends an item to the user which was similar to the item liked by the user in the past [69]. Here the similarity of the items was calculated by taking into consideration of the features which was allied with compared items [70]. If the user positively responded with item 'i' with features 'f' then the system will recommend the items which match the features 'f' of the item 'i' [5]. (see Fig. 1), briefs the CB model used in movie recommendation system.

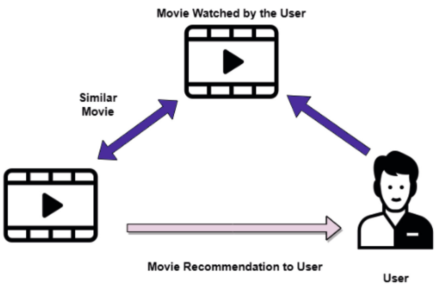

Fig. 1. Content-Based Filtering Model

Suitable techniques for describing the items and creating user profiles are required as well as a few strategies for making comparisons the user profile to the item description [38]. The recommendation procedure is divided into three parts, each of which is addressed by a different component. They are Content Analyzer, Profile Learner and Filtering Component [83].

- Content Analyzer: When information coming from different sources is in unstructured format, to extract structured meaningful information, some sort of pre-processing is necessary. The primary task of content analyzer's is to represent information in a suitable format for further processing [85].
- Profile Learner: This component attempts to create a user profile by using ML algorithms and based on user preferences and items liked or disliked by the user in the past [86].
- Filtering Component: This component recommends products based on a comparison of the user profile and the item description [85].

To predict user interests, CB filtering relies on classification learning algorithms like Decision Trees (DT), Nearest Neighbor (NN) Methods and Naïve Bayes (NB) Classifier. CB uses classification learning methods such as DT, NN Methods, and NB classifiers to predict user interests [84].

2.1.2 Collaborative Filtering

Collaborative-filtering (CF) model is quite different from CB filtering. CF is based on the user's similarity in interest rather than item features similarity which was the main focus of CB filtering. In CF, the items suggested to the user from the list of items user which was liked by another user who has a similar interest [71].

Figure 2 briefs the representation of CF. If the user 'A' has a taste to take burger and pizza along with coke then the system will suggest the coke to the user who orders burger and pizza in a similar pattern [39]. It represents that the fundamental principle of CF approach is that users who have similar interests would consume comparable items. In the recommender system, the collaborative model is the most prominent approach in recommending an item to the user [6].

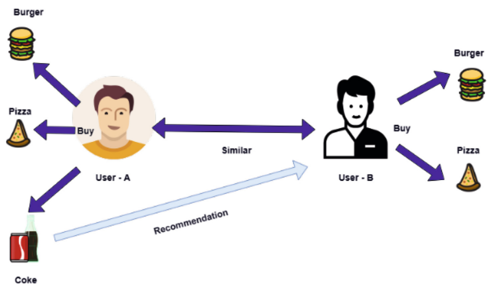

Fig. 2. Collaborative Filtering Model

This model may be subdivided into Memory-Based CF and Model-Based CF [6]. The memory-based technique predicts the target user based on user-item rating data [40]. In general, the memory-based technique makes use of neighborhood algorithms to find the neighbors who are the most similar. The target user's tastes are predicted based on the preferences of his or her neighbors. Various correlation measures, such as Cosine Similarity, Pearson Correlation Coefficient (PCC), and Spearman Coefficient, can be used to calculate user similarity. It is frequently used on a few e-commerce sites, such as Amazon. [84].Memory-Based CF may be further separated into User-Based CF and Item-Based CF [3].

User-Based CF is a model that examines similarity across users, identified by examining the data of each user with the same item It then develops and recommends a list of top N products that meet the interest based on the rating of each item by a similar group of users [73]. Spearman Coefficient, Pearson Correlation Coefficient, and Cosine Vector Similarity methods are used to determine similarity [84].

Instead of detecting similar users, the similarity between items is assessed in item-based CF. The item's profile is considered [84]. A suggestion is made to the target user based on the similarity of items. These types of recommender models were used in eCommerce applications [74].

Whereas the model-based technique trains a model using existing rating data by utilizing data mining and ML techniques like rule-based and clustering approaches and Bayesian networks, [34, 84].

2.1.3 Knowledge-Based System

Knowledge-based systems (KBS) model is used especially in the case of things that are not bought very frequently such as expensive luxury items, real estate, automobiles, tourist demands, and financial services which bought by the user very rarely, as a consequence the adequate rating not gone through the recommendation system to fetch a suggestion [3, 76]. Moreover, the pattern of consumer preferences may vary over time when working with such goods. For example, the model and features of mobile phones may change significantly over the years, in due connection with the preferences of the consumer also changes [41]. Sometimes it is also difficult to assess consumer interest with empirical data. These kinds, of circumstances, may be handled using knowledge-based RS, in which ratings are not engaged in the provision of suggestions [4].

Knowledge-based recommender system proposes items based on assumption of user's requirements and interests [42]. This information will sometimes involve specific functional knowledge about how particular product features fulfill user demands [78]. KBS consists of two categories-Case Based and Constraint Based [84]. The process of addressing new issues based on previous resolutions to similar scenarios used on similarity metrics is called as Case-based [86]. In case-based similarity recommendation algorithm was used for the recommendation of restaurants, fuzzy scoring scheme for diet planning, threshold retrieval for resource planning and knn was utilized for music recommendation [85]. In the constraint-based RS the system suggests solutions to the user along with parameters that influence the recommendation which has been retrieved based on a set of user preferences. If the item was not found according to the user requirements (the estimated similarity value crosses a specified threshold). In such cases, the minimum number of adjustments was suggested to the user to change the requirements in order to find a solution [86]. Multi-Attribute Utility Theory and Correlation Measures was utilized to retrieve the recommendation in KBS [84].

2.1.4 Demographic Based System

The demographic-based system (DBS) model generates the recommendation which was based on the demographic information of the user stored on their profiles [43]. Several web Portals adopt simple and efficient customization options depending on demographic information [76]. Figure 3 Pictorial representation of Hybrid recommender system.

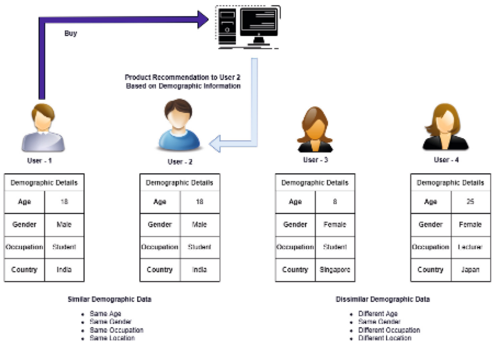

Fig. 3. Demographic-based system

For Example, recommendations may vary according to the age of the user, and the default language of the browser may change according to the country from where the user is browsing [5]. Researchers often use ML methods such as NB, Bayesian networks (BN), and Support Vector Machines (SVM) [89].

2.1.5 Community-Based System

Community-Based System (CBS) system model recommends an item to the user depending upon the preferences of the user's acquaintance such as friends and family who are treated as a community [44]. Rather than searching the items in the whole list of items, the user may check the items picked by the family and friends in same community [77]. The rising popularity of public social networks is boosting the importance of CBS. The recommendations generated through the CBS were not efficient when compared with the recommendations which were generated through approaches such as CB and CF systems unless in certain scenarios, such as when user evaluations of a given item are substantially a great deal [5].

The goal of community identification approaches is to uncover subgroups among participants where the quantity of interaction inside the group is greater than the amount of contact outside the group [45]. Several statistical and graph-based approaches have recently been utilized for community discovery. Such as Bayesian generative models [88], graph clustering methodologies, hierarchical clustering, and modularity-based algorithms were utilized [87].

2.1.6 Hybrid Systems

The term hybrid system (HS) model is used to derive any RS that unites with other recommendation methods together to achieve its result [78]. The benefit of this approach is that sometimes the CF method suffers from the rating deficit drawback when the item is subject to be new it suffers from a lack of user rating in connection with this the CF is not able to direct those items towards the recommendation whereas this doesn't really restrict CB techniques as the estimates for new products is dependent on their features seem to be normally freely accessible [46]. Thus, the incorporation of the above-stated methods can lead to a hybrid RS [79]. It was assumed that CF and CB are two methods, both CF and CB try to utilize the benefits of CF to remediate the flaws of CB. Numerous strategies were offered for integrating to develop a new hybrid system. Based on a review conducted by Robin Burke, HS can be classified into seven categories [78].

- Weighted: The outcomes of many RS are combined to provide a single recommendation [31, 32].
- Switching: The system switches between suggestion models depending on the circumstances [31–33].
- Mixed: Recommendations from different recommender models are presented together [31, 32].
- Feature combination: Features from various recommendations data sources are combined together into a single RS [32].
- Cascade: One recommender model refines the recommendations offered by another [31, 32].
- Feature augmentation: One model's output is used as an input to another [31–33].
- Meta-level: The model learned by one recommender model is utilized as input to another [31].

Table 1 shows some of the combination methods that have been employed.

Table 1. Exisiting systems in Hybrid Recommender model

Hybrid Method	Model Used	Machine Learning Technique Utilized	Recommends	References
Weighted	CB, CF	Cosine similarity, Data Mining, Hybrid Matrix factorization	Places of interest, Healthcare, Music	[10, 78, 90, 96]
Switching	CB, CF	Naive Bayes Classifier	News, Movie	[10, 78, 90, 96]
Mixed	CB, CF	Multi-granular Fuzzy linguistic	Research resource, Restaurant, and Movies	[10, 78, 90, 96]

(*continued*)

Table 1. (*continued*)

Hybrid Method	Model Used	Machine Learning Technique Utilized	Recommends	References
Feature combination	CB, CF	fuzzy c-means clustering	Music, Movie and Books	[10, 78, 91, 96]
Cascade	CF, CB, DBS	Clustering, Boosted Similarity	Websites, movies, restaurants	[10, 78, 92, 96]
Feature augmentation	CF, CB	Bayesian Network	Text Classification, Movies and Books	[10, 78, 93, 96]
Meta-level	CF through CB	Naive Bayes	Restaurant, Text analysis and Music	[10, 78, 90, 96]

2.2 Challenges of Recommender System

However, there are certain challenges associated with the use of a recommender system.

2.2.1 Cold Start Problem

The recommender system sometimes suffers from a lack of enough data about the user and item. These sorts of issues arise when the new user was signup into the system, in that connection RS doesn't have any information which relates to the user preference [4]. Likewise, when a new item was appended to the list of products the system suffered from a lack of rating, resulting in less efficient recommendations being made [80].

2.2.2 Sparsity

During and over a decade of investigation on RS, sparsity remains the chief obstacle and downs the effectiveness of the RS [6]. The CF mainly depends upon the user rating of an item and it is also considered to be extreme convergence between user preference similarity to imply them as closest in preferences of users [7]. Lack of user rating on the items which are available in the database leads to sparsity. In such cases, it is very difficult to find out the correlation between the user and the item, this leads to the poor quality of recommendations [81].

2.2.3 Gray Sheep

Due to user behavior dissimilarities, the CF method doesn't really function with similar efficiency for all the users. Depending upon the user behavior, users are separated into two categories such as white sheep and gray sheep. The users who have the highest similarity value with another user in the system are treated as white sheep in contrast the user who has a peculiar behavior pattern are treated as gray sheep [8].

These gray sheep users contrast with the other users they neither agree nor disagree with the other user's interests, these users have a very low association relationship with other users. Due to this gray sheep behavior of the user, the system doesn't have any benefit. Moreover, existence significantly reduces the quality of the suggestions offered to the rest of the users in the system. The unexpressed interest and preferences of the gray sheep users tend to the major drawback of the RS [82].

2.2.4 Starvation

In CF, the user usually recommended the items which are rated highly by more number of users, and the items with the lowest rating remain undiscovered this leads to starvation of undiscovered items and also might affect a decrease in sales for undiscovered items [9].

2.2.5 Shilling

The RS becomes reliable to the users if and only if it gives an unbiased recommendation. But, the pity is that the recommended system is sometimes attacked by the fraudsters who purposefully manipulate ratings in the system to diminish or boost the reputation of a specific items [5]. Sometimes the seller of the online store compromises the retailer recommended system by intentionally generating various user profiles for providing ratings that fit with the interests of its potential customers, subsequently utilizing these profiles to award high ratings to the seller items and poor rankings to competing companies' products. The above problem emerges in CF and matrix factorization but maybe not for CB models [9].

3 Overview of Domains

3.1 Streaming Services (SS)

Previously, individuals mostly watched visual content, such as films, at movie theaters or in television. However, a significant amount of visual content is being watched through SS such as Netflix, Disney +, and YouTube. Listening music is increasingly shifting away from downloading to streaming services like Swan and Spotify [22, 23]. Table 2 summarizes the RS is utilized in the field of SS.

Table 2. RS used in the SS field

SS	RS Model	Reference
Visual Content	Collaborative Filtering	[47, 48]
	Hybrid System	[49, 50]
Audio	Content Based	[51]
	Collaborative Filtering	[52]
	Hybrid System	[53]

3.2 Social Network Service (SNS)

In this era of digitalization, the online SNS have a major role in sharing the everyday activities, hobbies, interests, etc. of the users it also provides means to interact with other users on the same platform [94]. The large expansion in the usage of SNS was also increase data which was collected from users. The information gathered is not just used to provide suggestions inside SNS, it is also used in the RS for other organizations [24]. Table 3 summarizes the RS used in the SNS field.

Table 3. RS used in the SNS field.

SNS	RS Model	Reference
Followers or Item Recommendation	Collaborative Filtering	[54]
	Hybrid System	[55]
Information Recommendation	Content Based	[56]
	Collaborative Filtering	[24]
	Hybrid System	[57]

3.3 E-Commerce Service(e-CS)

E-commerce provides customers with many goods and numerous options in the online environment, making it simpler for sellers to sell items [95]. Customers were prohibited from walking outside, particularly during COVID-19 lockdown measures. Due to their inability to visit physical stores, mostly shoppers are turned towards online vendors. The service anticipates user choice by examining additional user data, like gender and age group, and the users' preferences was utilized in item suggestion [25]. Table 4 summarizes the RS used in the e-CS field.

Table 4. RS used in the e-Cs field

e-CS	RS Model	Reference
Web Application	Collaborative Filtering	[58]
	Hybrid System	[59]
Mobile Application	Hybrid System	[60]

3.4 Health Care (HC)

As people become more concerned about their health, the number of people who utilize smart wearable gadgets has also increased. These types of wearable gadgets collect a great quantity of user biometric information through sensors and update the information to the related application for monitoring the health conditions of the user. Moreover, it has been beneficial in study that suggests therapy [26]. Table 5 summarizes the health care service field.

Table 5. RS used in the HC service field

HC	RS Model	Reference
Medical Treatment or Diet Recommendation	Content Based	[61]
	Collaborative Filtering	[62]
	Hybrid System	[63]
Recommendation Using E-Health	Content Based	[64]

3.5 Education Service (ES)

A modern education, known as Smart Learning, has developed from the old type of education in the classroom or lecture hall to e-learning, in which learning is done in an online environment [27]. In order to provide students with an efficient and successful learning experience, the area of education services using the RS provides resources taking into account the students' learning styles and levels of knowledge and skills [28–30]. Table 6 summarizes the education service field.

Table 6. RS used in the ES field

ES	RS Model	Reference
Customized Learning	Content Based	[30]
	Collaborative Filtering	[65]
	Hybrid System	[66]
Course Recommendation	Hybrid System	[67]

4 Conclusion

Making a decision from a variety of possibilities and huge quantity of web data is always going to be challenging and complicated for the decision-makers. Hence online RS assists in overcoming the above problem statement. RSs employ effective information retrieval and filtering mechanisms in order to complete the tasks competently and accurately. An extensive study has been conducted in this work to present the numerous recommended methods and methodologies. Also, an overview of the different recommendation models used in RS, challenges, evaluation metrics, and a summary of domains, tools familiar with the recommender system was discussed briefly. Based on the review, the scope of the study will be expanded in the near future to compass the development of new RS that are suitable for a wide range of applications and to fulfill the requirements of humankind.

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