Recommendation Systems: Techniques, Challenges, Application, and Evaluation

Sandeep K. Raghuwanshi and R. K. Pateriya

Abstract With this tremendous growth of the Internet, mobile devices, and e-business, information load is increasing day by day. That leads to the development of the system, which can filter and prioritize the relevant information for users. Recommendation system solves this issue by enabling users to get knowledge, products, and services of personalized basis. Since the inception of recommender system, researcher has paid much attention and developed various filtering techniques to make these systems effective and efficient in terms of users and system experience. This paper presents a preliminary survey of different recommendation system based on filtering techniques, challenges applications, and evaluation metrics. The motive of work is to introduce researchers and practitioner with the different characteristics and possible filtering techniques of recommendation systems.

Keywords Collaborative filtering · Content-based filtering · Recommendation system

1 Introduction

Multiple choices lead confusion to a human being about what item is right for them or fulfill their requirements. This causes inception to develop a system which could help human being for the selection criteria and eliminate the dilemma. In present or past, human always relies on the suggestions from the outside for one purpose or other. Based on this, recommender system becomes the tools that shrink our options and present most suitable suggestions as per the requirements and our taste. The huge volume of information and user preferences increase the demand for new and

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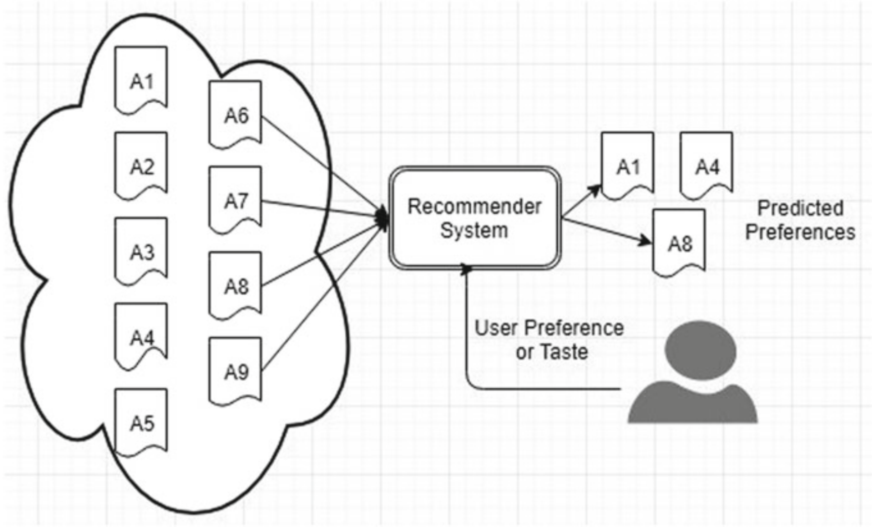

Fig. 1 Recommendation system

effective recommender system in the current age. Isinkaye et al. [1] with this RS must act as information filtering system that urges to predict preferences that user might have for an item over other and predict whether a particular item would prefer or not by him. A precise definition of a recommender system is given as (Fig. 1): A recommender system or a recommendation system (sometimes replacing the system with a synonym such as a platform or an engine) is a subclass of information filtering system that seeks to predict the rating or preference that a user would give to an item [2].

The existence of recommender system had been identified in the late 1970s, ever since many researchers have proposed various approaches to develop efficient recommender system. The first computer-based recommendation system was developed in 1992 by Goldberg et al. [3]. It was called Tapestry, a mail recommender system which was developed at the Xerox Palo Alto Research Centre [3]. Tapestry is an experimental information filtering system that manages the huge incoming stream of documents such as e-mail, news stories, and articles. It predicated documents on the belief that information filtering can be more effective when humans are involved in the filtering process. The primary motivation behind the development of RS is to reduce information load and processing cost by working on personalized information and data through analyzing the interest and behavior of the user to guess his/her preferences over the item. It is beneficiary for both users and service providers [4]. Presently, many organizations such as Google, Twitter, LinkedIn, Netflix, Amazon use recommendation system as a decision maker to either maximize its profits and minimize the risk possibility [5, 6]. Most popular recommender systems of today are Group Lens recommender system, Amazon.com recommender system, Netflix movie recommender system, Google News personalization system, Facebook friend recommendations, link prediction recommender system.

2 Filtering Techniques

Various methods are being proposed to develop an effective recommendation system out of them, two form the basis for the development of other approaches. These methods are content filtering, collaborative filtering [1]. Further, these techniques are extended and in present RS techniques are classified as (Fig. 2):

2.1 Content Filtering Recommendation System

Content-based (CB) techniques use feature list of the item and compare it with items preferred by a specific user previously. The items which match in similarity are recommended to the user. The essential function of content-based filtering works in two steps: It stores a user profile based on item features which are most commonly preferred by the user. These features are used to map the similarity of one item with other by similarity equation. After that, it compares each item's features with the user profile and recommends those who have a high degree of similarity [7]. For content-based system, one has to construct item profile, which is a record of essential characteristics of that item. These characteristics are discovered easily like in a movie the record may contain a list of actors, director, year of release, and genre (Fig. 3).

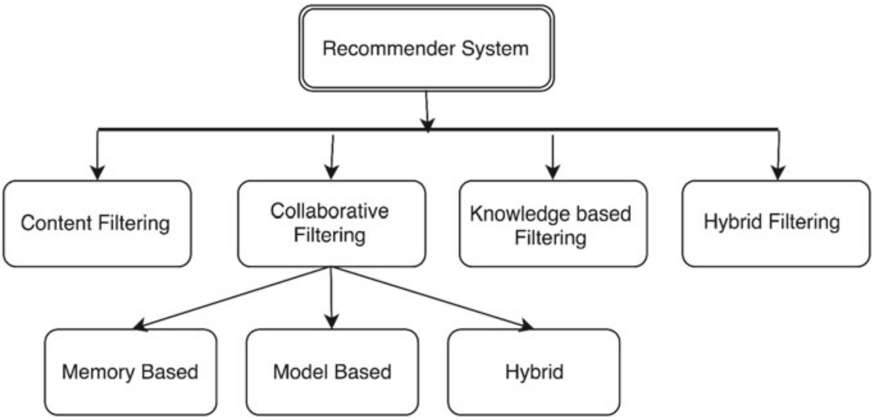

Fig. 2 Classification of recommendation systems

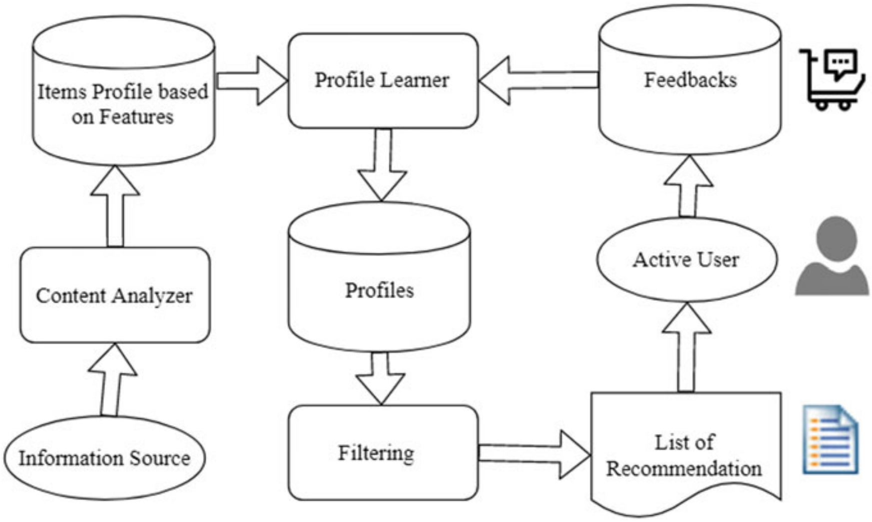

Fig. 3 Content-based filtering

CB filtering is most simple and natural approach to adopt as a recommendation it does not require any feedback from the user. Sometimes a single preference is enough to recommend many items to the user. This approach also extends naturally to the cases where item information is well organized and available such as movies, songs, products, and books. But at the same time, it also comes as a limitation of content-based filtering as item description is not always present in all cases that create difficulty in measuring the similarity between items. These recommendation systems have limitations to produce similar results and are static over the time.

2.2 Collaborative Filtering (CF)

CF is the most popular and used recommendation technique. The basis for collaborative filtering is that users with similar interest are inclined to give same preference for the new and future items. This technique works on two points. First, it serves as a criterion to select a group of similar people whose opinions will be accumulated as a basis for a recommendation (nearest neighbors). Second, it also uses these opinions to form a bigger group and have a greater impact on the recommendation [8]. Collaborative filtering techniques involved very large data sets and applied in diverse application areas like finance, weather forecasting, environmental sensing, e-commerce.

Collaborative filtering techniques make use of a data set of preferences/ratings given by the users for items to predict additional items that an active user might like. The model can be expressed as a preferences/rating matrix of order $m \times n$,

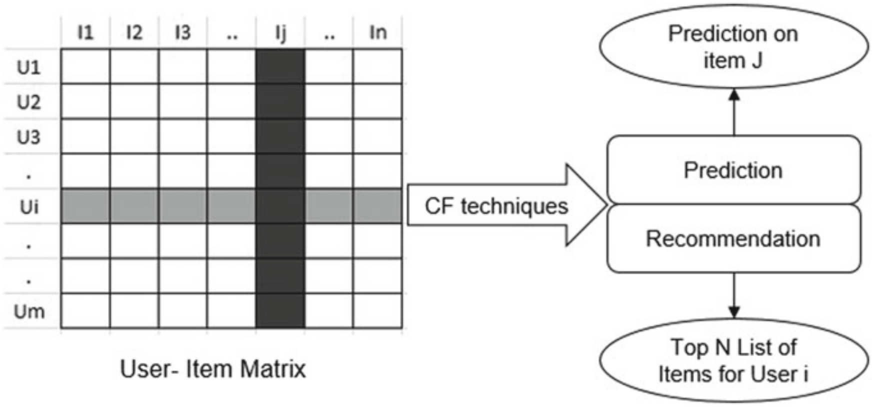

Fig. 4 Collaborative filtering [1]

where m is the number of users ($U_1, U_2, U_3, \ldots, U_m$) and n is the number of items ($I_1, I_2, I_3, \ldots, I_n$), rated by the users. The cell value ri, j of the matrix is the rating of item j was given by user i. These ratings can be either implicit (such as purchase for an item) or explicit (feedback by the user on a scale of k). The outcome of collaborative techniques can be of two types: First is the prediction of r_{ij}, a numerical value shows the preference of user I over item j, and second is the recommendation list of top N items that user might like the most [1, 9] and (Fig. 4)

The primary function of recommendation is to predict the utility of an item for a user. The recommendation system is characterizing as a user u is interested in item i with some degree of preference or rating $r(u, i)$. Each user has user profile of his taste, likes, dislikes, or sometimes a rating or feedback is given to a particular item. Each item is characterizing by its feature set such as for a movie the feature set may include movie Id, actors, director, release date, genre. Predicted preference of an active user a, for an item j, is calculated as:

$$P_{a,j} = \overline{r_a} + k \sum_{i=1}^{n} S_{(a,i)} \times r_{i,j} - \overline{r_i} \tag{1}$$

where r_a: the mean rating of user $a \cdot n$: the number of users in the database with nonzero $r_{i,j} \cdot S_{(a,i)}$: Similarity between the active user and each user $i \cdot k$: a normalizing factor such that the absolute values of the weights sum to unity.

There are many techniques used to compute the similarity between the users. Each one has its pros and cons in their areas some of them are:

i. Pearson Correlation Similarity: Pearson correlation defines the linear correlation between two vectors and has a value between −1 and 1. The similarity between the two vectors u and v is defined as:

$$S_{Cosine}(u, v) = \frac{\sum_{i=1}^{n}(r_{u,i} - \overline{r_u}) \times (r_{v,i} - \overline{r_v})}{\sqrt{\sum_{i=1}^{n}(r_{u,i} - \overline{r_u})^2 \times (r_{v,i} - \overline{r_v})^2}} \tag{2}$$

ii. Cosine Similarity: Cosine is one of the most popular methods of statistics to find similarity between two nonzero real values' vectors. It looked for an angle between two vectors in n-dimensional space and defined as:

$$S_{Pearson}(u, v) = \frac{\sum_{i=1}^{n}(r_{u,i}) \cdot (r_{v,i})}{\sqrt{\sum_{i=1}^{n}(r_{u,i})^2 \times (r_{v,i})^2}} \tag{3}$$

Collaborative techniques are grouped into memory-based techniques, model-based techniques, and hybrid techniques.

2.2.1 Memory-Based Filtering

Memory-based methods are straightforward and easy to implement. The best-known technique used is memory-based neighborhood-based filtering, which predicts preferences by referring to users who are similar to queried user or to items that are similar to queried item. The accuracy and efficiency of neighborhood technique are profoundly affected by how the similarity between users or items is calculated. This technique can be further extended with default votes, inverse user frequency, and case amplification [10, 11]. These techniques are further classified as user-based filtering techniques and item-based filtering technique.

User-Based Filtering technique computes the similarity between users by comparing their preference over the same item and calculates the predicted preference for items for the active user [1].

Item-Based Filtering techniques calculate predictions using similarity between items. The technique works by retrieving all the items rated by an active user and determines similarities of retrieved items with target item. It then selects top N most similar items to predict the preference of the active user for the target item [1].

2.2.2 Model-Based Filtering

Model-based techniques make use of data mining and machine learning approaches to predict the preference of a user to an item. These techniques include association rule [12], clustering [13], decision tree [14], artificial neural network [15], Bayesian classifier [16], regression [17], link analysis [18], and latent factor models. Among these latent factor models are the most studied and used model-based techniques. These techniques perform dimensionality reduction over user–item preference matrix and learn latent variables to predict preference of the user to an item in the recommendation process. These methods include matrix factorization [19], singular value decomposition [20], probabilistic matrix factorization [21, 22], Bayesian probabilistic matrix factorization [22], low-rank factorization [23], nonnegative matrix factorization [24], and latent Dirichlet allocation [25].

2.2.3 Hybrid Filtering

Some applications combine the advantages of memory-based and model-based approaches to form a hybrid filtering system. It results in better prediction and efficiency. A proper combination can overcome the limitation of collaborative filterings such as sparsity and diversity [9].

2.3 Knowledge-Based Filtering

Knowledge-based filtering uses back-end knowledge or information of users, items, and their relationship. These systems describe how a particular item meets the requirement of the user. The technique requires domain-specific knowledge of users and items. The most traditional knowledge-based system is the case-based system [26].

2.4 Hybrid Filtering

Hybrid filtering techniques is one which combines the advantages of two or more filtering techniques and overcomes their limitations. These techniques provide more effective and enhance results of recommendation [27]. Hybrid techniques can adopt one of the following strategies to develop a hybrid filtering method:

1. Use content-based and collaborative-based filterings to produce separate recommendation, and then use a linear combination of this two recommendations to provide a single recommendation [28].
2. Collaborative filtering can be used with content-based characteristics to calculate the similarity between users and find out neighbors to predict the recommendation [29].
3. Content-based techniques can be added to collaborative filtering characteristics, such as latent factor model with the content-based approach [30].
4. A conventional probabilistic method for combining collaborative and content-based technique to predict recommendation [31, 32].

Burke [33] performed over hybrid recommender systems and grouped them into seven classes as weighted hybridization, switching hybridization, mixed hybridization, feature-combining hybridization, cascade hybridization, feature-augmenting hybridization, and meta-level hybridization.

3 Challenges

3.1 Data Sparsity

Many e-commerce and shopping Web sites use recommender system and evaluate a very large item sets. With large item sets, the user–item metric becomes sparse and results as a limitation to many recommender systems. Few values of ratings/preferences in user–item metric lead to poor predictions. New items cannot be recommended until some users rate them, and similarly new users are also not getting good recommendations due to lack of their preference history. To deal with data sparsity problem, many techniques have proposed out of them dimensionality reduction like singular value decomposition [20], probabilistic matrix factorization [21, 22], and hybrid techniques such as content boosted are popular and mostly used (Table 1).

3.2 Scalability

Scalability has always been the challenge for recommendation systems. The performance of mostly traditional CF algorithms started to suffer from the increase of size in users and items. The tremendous increase in a database leads to a poor performance of algorithm as computational capabilities went beyond the practical limits [34].

3.3 Cold Start

Business adhered with recommendation systems has a cold start. Initially, for a new user case, do not have sufficient information. A considerable amount of time is required to lure a user and getting them know. However, many networks promote users to fill information to provide them more options. Items also have cold start when they are not rated [35].

3.4 Gray Sheep

User whose opinions do not consistent with any group of people is known as gray sheep. These users do not support the smooth functioning of collaborative filtering [28]. On the other, a special class of users known as Black sheep whose idiosyncratic behavior makes recommendations nearly impossible. With an optimal combination of content-based and collaborative filtering (hybrid techniques) is helping to solve gray sheep problem [36].

Table 1 Comparison of different recommendation systems

Filtering technique comparison

Filtering technique		Method	Advantages	Limitations
Content-based filtering		Use implicit and explicit feedback of users	• User independence • Transparent • Easy to recommend new items	• Hard to learn user preference • Limited degree of novelty • Static
Collaborative filtering	Memory-based	Neighbor-based approach	• Easy implementation • Does not need user profile and item features • Scalable with co-rated items • New data can be added easily	• User preference is needed • Performance decreases with sparsity • New user problem
	Model-based	Data mining, machine learning, dimensionality reduction	• Work well with sparse data • Scalable • Better prediction performance	• Loss of information due to dimensionality reduction • Trade-off between prediction performance and scalability
	Hybrid	Combine memory and model-based	• Improved prediction performance • Overcome problems such as sparsity and gray sheep	• Complex • Expensive implementation • Sometimes need explicit information
Knowledge-based filtering		Case-based, constraint-based, ontologies	• Improved personalized prediction • Handle new user and cold start problem well	• Expensive and complex • Need external domain-specific knowledge
Hybrid filtering		Combine two or more filtering techniques	• More accurate and effective recommendation • Suppress the limitation of individual techniques	• Expensive and complex

3.5 Synonymy

Synonymy refers to the tendency of a number of the same or very similar items to have different names or entries. Most recommender systems are unable to discover this latent association and thus treat these products differently [37, 38].

3.6 Privacy Breach

Recommendation system anyways leaks the information to users. The best example of this is the people you may know feature of Facebook. The issue of trust arises when evaluating a customer [39].

3.7 Shilling Attack

The recommendation is a public activity, so peoples get biased for their feedbacks and give millions of positive reviews for their products or items and sometimes negative views for their competitors. So, it becomes necessary for the system to incorporate a kind of mechanism to discourage this sort of phenomenon [40].

4 Applications

Recommender system applications are now ranging in personal, social, business services. All these areas have their practical applications in human life and have a great impact too. Researchers paid more emphasis over business applications and improved them a lot in recent past. The primary objective of research involves a practical aspect of implementation and effectiveness of recommendations. Mainly recommendation system applications are classified as:

E-commerce/E-shopping: The system was developed to provide guidelines for online customers. It is most popular and specialized field and employed through ratings/preference, which subsequently use to make recommendations. Tagging and reviews are other ways to connect user–item relationship. iTunes, Amazon, and eBay are some of the popular recommendation systems of the e-commerce world.

Entertainment: With the extensive growth of movies, videos, and music, users get frustrated while searching for the right content of their taste. This leads to the development of more effective and personalized recommendation system. Collaborative filtering has mostly used the technique in these systems. For videos content such as TV(Netflix) and YouTube, social and context-aware techniques play an effective role in traditional content-based and collaborative methods.

Contents: In recent years, recommender system has become the key of the e-content system to locate information and knowledge in the digital library. It covers personalized Web pages, a new article, e-mail filtering, etc.

Service Oriented: The Internet and mobile devices open a great opportunity to access various types of information. That also gives essence for the development of many service-based recommendation systems such as tourist recommendation, travel services, matchmaking services, consultation services.

5 Evaluation

The quality of recommendation system is measured through various types of evaluation metric based on the accuracy of prediction and coverage. The selection of metric depends on filtering technique, features of data set, and the task of recommendation system. According to Herlocker [41], evaluation metrics are categorized as prediction accuracy metrics (MAE, RMSE) and classification accuracy metrics (precision, recall, F-measures).

MAE: Mean Absolute Error is the average of the absolute difference between the predictions and actual values.

$$MAE = \frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{n}|r_{(i,j)} - \widehat{r_{i,j}}| \tag{4}$$

RMSE: Root Mean Square Error is computed by the square root of the average of the difference between predictions and actual values. Lower the RMSE is better the recommendation.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{m}\sum_{j=1}^{n}|r_{(i,j)} - \widehat{r_{i,j}}|^2} \tag{5}$$

Classification accuracy metrics are used to measure the performance of recommendation system based on classification techniques. These metrics are computed on confusion metric of predicted and actual values of classification (Table 2).

Table 2 Confusion metric

	Predicted values		
Actual values		Positive	Negative
	Positive	TP	FN
	Negative	FP	TN

Precision: A measure of exactness determines the fraction of relevant items retrieved out of all items retrieved.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall: A measure of completeness determines the fraction of relevant items retrieved out of all relevant items.

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

F-measure: Harmonic mean of precision and recall to get a single value for comparison purpose.

$$F - measure = \frac{2(Precision * Recall)}{Precision + Recall} \tag{8}$$

6 Conclusion

Recommender systems are the part of everyone's daily life. With the tremendous growth of information and knowledge over the Internet, it is become necessary to have more and more effective and efficient recommendation systems. These systems enable their users to access services and products of their taste, which are not readily available. This paper discusses and highlights various recommendation system with their techniques, challenges, applications, and their evaluation metrics. Presently, different hybridization techniques are used to develop recommendation systems required on task and user personalized basis. The paper helps the researcher to understand and improve the state of current recommendation system.

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