Review on Recommender System and Architecture

Mehrdad Mollanoroozi
Department of Engineering, Isfahan Branch, Islamic Azad University, Iran
Email: mollanoroozim@yahoo.com

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ABSTRACT:
Today, global information societies are increasingly producing a mass of information, which makes it difficult to access relevant and useful information at the moment. In the meantime, there are many services and products that need to be filtered and presented based on the priorities of users. Recommender systems emerged as a tool to deal with the mass of data to respond to the existing need. These systems collect user information or information that helps users to provide a list of items explicitly or implicitly to suggest to users. With the flourishing of electronic commerce, the use of recommender systems in various aspects of online business has revolutionized electronic commerce.

1. INTRODUCTION

The use of recommendation system has many advantages for both the service provider and the user. The service provider can achieve a higher percentage of sales by quickly processing data and suitable offers, and the user can find products suitable for his taste or need in the shortest time. observes [4 and 5]. Since the beginning of the presence of recommender systems on the Internet, extensive research has been done in order to improve them and overcome the existing challenges, because these systems play an important role in personalization and e-commerce decisions, and researchers are still trying to improve them. The improvement of recommender systems can be implemented in different phases. Any initiative in architecture and information acquisition techniques, creativity in design techniques, development of implementation methods and algorithms, improvement of evaluation criteria and measurement techniques, etc. can be an effective step in improving these systems [3].

In the following chapter, the concepts and terms of recommender systems are presented first. In the following, the approaches of these systems, the challenges in each approach and the history of the research conducted to improve them will be examined. The FCM clustering algorithm will be introduced in this chapter, and at the end of the introduction of the optimization algorithms, the binary adaptive wall algorithm will be discussed.

2. CONCEPTS AND TERMS OF RECOMMENDER SYSTEMS

2.1. An introduction to recommender systems

In the past, recommender systems were considered a part of data mining and information filtering until in the late 1990s, they emerged as an independent research field and attracted the attention of researchers in various fields such as machine learning, information retrieval, and human-computer interactions. Recommender systems are powerful software for filtering information and showing suggestions to the user that the user may prefer to visit. These suggestions can be from any field, for example suggest to watch this movie, which song you will probably like, what online news to read or what products to buy according to your taste. With the flourishing of electronic commerce, companies use recommender systems in order to achieve their electronic business goals [15]. These systems are embedded in online environments as a decision-making strategy to show targeted suggestions to the user from the multitude of available information. At present, big companies like Google, Facebook, YouTube, Amazon, etc. rely on the systems of recommending their products and services to the users, which has caused a significant increase in income. The Amazon website is the most famous example of the use of these systems, which displays items to the user based on the purchase history, visit history, and the item the user is viewing. We can also mention Netflix, which is a large company that produces television and film collections and provides its services and products to 190 countries online with the extensive use of these systems [16].

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2.2. Comparison of recommender systems and decision support systems

Although there are many similarities between these two systems, there are also differences between them, the most important of which is that the end user in decision support systems are senior or middle managers of an organization, while in recommender systems, the use of the system is limited to a certain level. It is not possible and the system is in common use. But the main similarity of these two systems is also based on the fact that recommender systems, apart from the point of view of user levels and technically, are considered a subset of decision support systems. Both of them help the user in making decisions, and both of them are information systems that have a knowledge base, a database, a user interface, etc. [17].

2.3. Objectives of recommender systems

The main goal of recommender systems is the ability to adapt the suggestions provided to the needs and interests of users. Identifying and recognizing the needs and tastes of users can be predicted based on the knowledge obtained from them. Usually, by analyzing the knowledge obtained, the common interests of a group of users with similar tastes can be found, and the results can be used to provide personalized suggestions. In line with the goals of these systems, the following can be mentioned: [11]

- Increasing sales of various items
- Reduce search time
- Increasing user satisfaction
- Increasing customer loyalty
- Better understanding of customer needs
- Finding popular items and managing them [18]

2.4. Principles of recommender systems

Recommender systems collect and process various types of data in order to generate recommendations. The data is mainly related to the item, the user and the relationships between the user and the items. In each system, the method of collecting data from users is examined, and in general, the data is divided into two categories: the first category is data extracted from users' behavior, which is used in some implementations of collaborative filtering because it is easily possible to receive ratings from users. The data provided by the user while viewing the pages cannot be used to provide suggestions; such as the process of visiting pages and the duration of viewing various items presented on the website. The second category is the data received from the user himself, which users may allow the recommender system to provide them with more accurate suggestions by specifying their interests when purchasing previous products and giving points to each item. In other words, when users buy, they register their opinion about that product in the form of feedback (which is usually done through rating) in the system. The data extracted from the user himself is much more accurate than the data extracted from the user's behavior because the user declares his opinion accurately [19].

In the process of designing and implementing the recommender system, different types of information sources are used. This information can be points of users to items, personal information of users, content related to system items, communication in social networks and information related to the user's position. It is natural that in the process of designing a recommender system, much attention should be paid to the type of available data. In the process of designing and implementing a combination of a recommender system, the following considerations are taken into consideration [18]:

- The type of data available in the database (privileges of users to items, information entered by users during their registration, features and content of existing items, information extracted from social networks and user's location, social relationships between users, etc.) Each system's database stores different data based on the type of system operation, which changes the way the system works based on the type of available data.
- Algorithms used for filtering (filtering algorithm based on demographic factors, content-based filtering algorithm, collaborative filtering algorithm, concept-based filtering algorithm, combined filtering algorithms and filtering algorithm based on social networks)
- The method chosen for how to use the data
- Techniques used (probabilistic approaches, Bayesian networks, nearest neighbor algorithm, algorithms inspired by biology such as neural networks, genetic algorithm and fuzzy models, etc.)
- The level of dispersion of the database and the expected scalability of the system.
- Optimum performance of the system in terms of memory and time consumption
- The goals that have been considered
- The desired quality of the presented results (the obtained results should have the desired quality in terms of innovation, coverage, accuracy, etc. [20]).

3. APPROACHES IN RECOMMENDER SYSTEMS

The situation, situation and conditions of the user, his needs and also the knowledge that the system has of the user, each of them is the basis for the creation of one of the types of recommender systems. The approaches in recommender systems can be defined as follows [21]:

- Collaborative filtering approach
- Content-based filtering approach

• The approach of combined methods
• Approach based on demographic information
• Knowledge-based filtering approach
• Filtering approach based on social networks

3.1. Collaborative filtering approach

Collaborative filtering approach, abbreviated as CF, is the most widely used and popular filtering algorithm, and it works in the same way that people usually do in their daily decisions. This means that it uses the opinions and experiences of others (which are registered as points in the system) to suggest items. In this approach, users can rate items such as goods, movies, music, books, etc. With this, enough information is stored in the system to suggest users who are similar to each other. Therefore, keeping in mind the privileges of other users to an item and the degree of similarity of the current user with other users, the items are suggested to the current user. Among the successful examples of this approach, Amazon.com and grouplense.org can be mentioned [22].

The basis of the work in the cooperative approach is based on the calculation of the similarity between users and items, and based on the calculated similarity, neighborhoods are created. To calculate the degree of similarity, a criterion of similarity is needed. Traditional methods used ratings as a criterion in such a way that users who gave similar ratings to similar items were placed in a neighborhood group.

• Factoring matrix: while user-based and item-based methods are simple, usually the factoring matrix-based method is more effective. Because these methods make it possible to discover the hidden features that exist between the interactions of users and items. They use this method to predict scores in collaborative filtering and divide the user-item interaction matrix into two square matrices. For example, two users may give high marks to certain items and the reason for this may be because of the actor, director or genre of those movies. By correctly identifying these hidden features, the scores can be predicted based on the user and specific items. In this solution, the system ranks the items based on the scores and suggests items with the highest scores to the user [27].

3.2. Content-based filtering approach

In the content-based filtering approach, suggestions are given to the user based on his past choices. For example, in web-based e-commerce recommender systems, if the user has bought a movie in the past, and now there are movies for sale on the website that the user has not yet bought, then the system will recommend those movies to the user. In fact, interests, likes, and experiences The user in the past is the basis of suggestions for the future. In this method, it is necessary to analyze and analyze the contents and information related to users and items, so that with the help of this work, the degree of similarity between users and items can be calculated. Another important thing in this method is to determine a suitable similarity criterion because in this algorithm, items are suggested to the user that are more similar to the items that the user liked in the past. In order to be able to calculate the degree of similarity between different items, we need to extract the attributes and characteristics of the items from different sources. This work requires a solution that can automatically retrieve these attributes to compare and determine the degree of similarity between the data and information available in the system. This work becomes very difficult and complicated in some cases [28].

The big problem that this algorithm has is that because this algorithm tries to suggest items that the user has seen in the past, and the only thing it considers is the user's past records, activities, and choices, therefore, it cannot make a suggestion outside of the user's past vision. In slow production, there may be an item that the user is interested in and has not seen, and it is not similar to the items that he has seen in the past, and this item will remain open. Another problem that this method has is that it is not possible to receive feedback from its users, the main reason is that in the systems that use this algorithm, unlike the systems that use the collaborative algorithm, users usually do not rate the verses and this issue It causes the system to not be able to determine whether it had a correct offer or not. These problems have caused that this algorithm is usually not used alone and is mostly used as a combined system with other methods and algorithms. One of the best existing combinations is content-based filtering with social media filtering. The combination of these two makes it possible to use, in addition to the given ratings, information that exists in social networks such as comments, posts, communication between friends, followers and followers, likes and tags to increase the accuracy of suggestions [29].

Content-based filtering algorithm includes three steps:

- Extracting attributes related to items:
- In order for a system based on CBF to work well, attributes related to items are first extracted. In general, most of the attributes are explicitly included with the items in the system; Therefore, the extraction of such traits does not face any particular problem; But there are another group of traits that, based on the scope of the system, special techniques must be used to extract them. For example, in systems where the items are text documents, classical information retrieval methods are used [30].
- Comparing the attributes of the items with the user's preferences:
- After the attributes of the items have been extracted, it should be determined to what

extent the items in the system match the user's taste. This step uses methods such as exploratory methods or clustering algorithms.
- Suggesting items more similar to the user's preferences

This demographic information algorithm refers to information such as (gender, nationality, age, place of residence, occupation, etc.) They are in the same age range and their jobs are related to each other (they probably have similar interests and needs [31].

3.3. combined approach

In the combined approach, the previous approaches are combined to achieve the highest performance. A hybrid system tries to use the advantages of one approach to compensate for the shortcomings of the other approach. For example, a collaborative filter is unable to process new items without ranking, while a content-based approach does not encounter new items. , because the suggestions are based on the desired features that are easily available [32].

3.4. Filtering approach based on demographic information

This approach classifies users based on demographic characteristics obtained from the user profile. This approach is very similar to filtering

3.5. knowledge-based filtering approach

Knowledge-based recommender systems are a new generation of recommender systems that are based on existing knowledge about users and items. Such systems provide their suggestions based on their interpretation and inference of the user's tastes and needs, and from a theoretical point of view, they have more accuracy and quality than the other mentioned methods[18]. It is natural that for the implementation of such systems, there is a need for a platform and structure based on knowledge. In this type of recommender system, the raw material used to produce a list of suggestions is the system's knowledge about the customer and the product. Knowledge-based systems use different methods that can be used to analyze knowledge, which are common methods in genetic algorithms, fuzzy algorithms, neural networks, etc. Also, in such systems, decision trees, example-oriented reasoning, etc. can also be used. The method based on self-knowledge is divided into two methods based on limitation and based on case. Both methods are the same in terms of the proposal process, i.e. first, a user must state his request accurately, then the system tries to give a diagnosis solution. The system can even give a short explanation of why it suggested an item. But these two methods are different in terms of knowledge acquisition. The case-based method suggests similar items using similarity, but the constraint-based method performs the recommendation process according to the recommendation rules that have been explicitly embedded in advance [33].

3.6. Filtering based on social networks

With the expansion of social networks, a group of researchers went to use the information available in these networks (such as tags, friends, followers, messages, etc.) in recommender systems. This information may be collected explicitly or implicitly. Based on the results of using this information, it has been determined that this work has improved the proposed results. In the field of using social networks in recommender systems, studies and scientific researches are divided into two categories. A group sought to use the information available in these networks to improve the efficiency of the existing systems, and the results of their work prove the positive effect of this information on the proposed systems. On the other hand, another group of researchers went towards creating a new recommender system based on social filtering. This group no longer seeks to combine social networks with other recommender systems. Rather, they intend to use the potentials in such networks to create an independent system [34].

4 PROBLEMS AND CHALLENGES OF THE RECOMMENDER SYSTEM

Nowadays, numerous recommender systems have been improved for different domains, however, these systems are not accurate enough to meet the information needs of users. Therefore, it is necessary to create very high-quality systems. In the design of recommender systems, designers are faced with issues and challenges that need to be taken into consideration.

4.1. Cold start challenge

This problem happens when new users enter the system or new items are added to the website catalog. In this case, the taste of new users cannot be predicted, nor can the score of new items be evaluated. The problem of the cold start challenge can be solved in different ways. For example, at the beginning, about the items, ask the user a number of questions, directly ask the user's taste, or give him suggestions based on the user's demographic information. Demographic information can be location, gender, age, etc.[20]. The challenge of cold start is of two types: cold start of the user and cold start of the item. In the cold start of a new user, a new user is introduced to the system, who the system does not know about him, and therefore he has a problem to provide suggestions. In the cold start of an item, a A new item is added to the system, and because the scoring rate for the new item is low and the data related to it is sparse and scattered, the system is delayed in offering this item. Because the cold start of the user is more difficult, extensive studies have been conducted in this field. In fact, the main cause of this problem is the lack of sufficient information for the system, and the presented approaches are trying to collect this information. The information can be collected directly by asking the user or indirectly by using the available information. Therefore, the approaches can be classified into two groups based on the way of collecting this information [35]. Depending on the nature of information collection, there are different techniques for collecting information:

The accuracy of the suitable offer: an offer is suitable when it is in accordance with the user's taste. Different criteria can be considered to measure the accuracy. This parameter can be used to evaluate the effectiveness and also the usefulness of the system. However, learning the user profile may reduce the accuracy of the system. The solutions must maintain the overall accuracy. A way to Doing this is choosing the minimum number of search items with the best information content [7].

Reduction of favoritism and bias: Scoring between users and items is expected to be accurately recorded. However, some ratings are independent of interactions. For example, popular items tend to have high scores. Such biased scoring, personalizing the system's recommendations disrupts [36].

Compatibility: It is desirable that the solutions are compatible. There are different filtering strategies and ranking formats that can be used by a recommender system.

Diversity: usually there are different areas of items, such as in the electronic market, electronic appliances, home appliances, clothing, etc. A good recommender system should suggest items that cover all areas. learned [36].

4.2. Scalability

Due to the fact that the number of users and items in recommender systems is increasing, therefore, the systems must provide algorithms to be able to provide their suggestions quickly. In fact, the system must have the ability to work in the face of large scale data. In a site like Amazon, which has more than 18 million products and services and more than 20 million customers, clustering and dimensionality reduction techniques and Bayesian networks are used to deal with this problem [37].

4.3. lack of comments

On the other hand, users often do not want to give their opinion about the goods, as a result, many houses will remain empty in the evaluation matrix [37].

4.4. Thin and scattered data

Dealing with a very large amount of information about the verses in the website catalog and the reluctance of users to rate the items reduces the accuracy of the recommender systems. When the system adds more items and the number of users rating the items is small, the data is scattered and thin. occurs [37].

4.5. privacy

It is true that by entering the user's personal information, the recommender system can provide better suggestions, but to what extent can we trust the security of privacy and the security of the entered data. Internet users are usually worried about their information being compromised. Therefore, a collaborative recommender system must ensure the security of users' privacy and data. Recommender systems use information encryption mechanism to solve this problem [20].

4.6. gray sheep

Sometimes in cooperative systems, the opinions of a user do not correspond to any group, as a result, the system gets confused to provide suggestions. This problem is solved by filtering the user's personal information from his profile or his opinion about various items. The use of clustering methods such as K-means or FCM can reduce the percentage of errors in suggestions and improve the performance of the system [38].

4.7. Validity of data over time

Users' tastes can be changed over time, some needs are short-term and some are long-term. Therefore, considering time and removing old patterns is one of the important issues. Therefore, one of the challenges that collaborative filtering

4.8. The problem of synonymous names

This problem occurs when an item is displayed with one or more synonymous names. In such a situation, the system cannot determine whether it is dealing with different items or similar items. For example, when the collaborative recommender system faces two words "comedy movie" and "comedy film", the recommender cannot distinguish whether it is facing different terms or not. Therefore, the excessive use of synonymous words and terms can make CF performance difficult in providing suitable suggestions. Since the content of the item is completely ignored, therefore the recommender does not consider the hidden relationship between the items and new items are not suggested until the users' rating reaches a certain level. To eliminate the problem of synonyms, ontology, singular value analysis (SVD) and latent concept indexing (LSI) methods are used [39].

4.9. trusting recommender systems

Most of the users want to know what criteria are considered in the proposal that is presented to them. As a result, collaborative filtering systems should convince their users with appropriate reasons, in other words, how to choose criteria for providing suggestions plays a very vital role in recommender systems [39].

4.10. Trusting the data available in the recommender systems

Entering incorrect data by the owners of goods can derail the proposal process. Collaborative filtering systems should be designed so that profit-seeking people cannot influence users with false data [39].

4.11. Shilling attacks

What happens if a malicious user or adversary gets into the system and starts giving false ratings? Such attacks can threaten the level of trust in the provider, its performance, popularity and efficiency. The destructive effects of these attacks can be greatly reduced by predicting the cause of the attack, the amount of information needed to start the attack, etc. [39].

4.12. Limited content and Over-specialization

Content-based recommender systems rely on data processing related to items or users, which is realized by using information retrieval techniques. Therefore, limited content can be problematic. This problem occurs when the system only suggests items that the user has seen or have a high score. That is, items with a high score become stronger and items with a low score become weaker [39].

4.13. user environment

Recommender systems should have a very good appearance so that the user can better receive the suggestions and choose them.

4.14. clustering

Cluster analysis is a method for grouping data or observations according to their similarity or degree of closeness. Through cluster analysis, data or observations are divided into homogeneous and distinct categories. In the clustering method, there is no pre-existing category and in fact the variables are not divided independently and dependently. Rather, in clustering, we are looking for groups of data that are similar to each other, and by discovering these similarities, we can better identify behaviors and act based on them to get better results. In some cases, clustering is used for data that are significantly different from the rest. For example, a series of customers, all of them have purchases above one hundred dollars per month, except one. The clustering method is an indirect method; This means that this method can be used even when we do not have any previous information about the internal structure of the database. This method can be used to discover hidden patterns and improve the performance of direct methods. This method is easy to use and can be used for most types of data. Clustering can be considered as the most important issue in unsupervised learning. Clustering looks for a structure within a set of unlabeled data. A cluster is a set of data that are similar. In clustering, we try to divide the data into clusters that maximize the similarity between the data in each cluster and minimize the similarity between the data in different clusters [40].

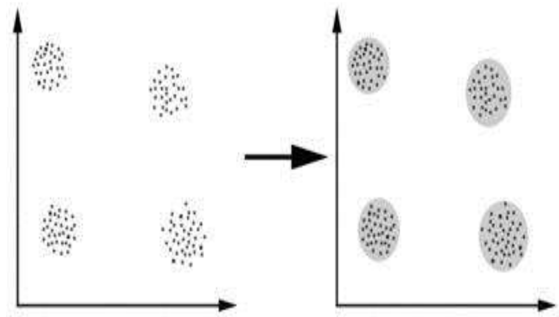

Fig.1. Clustering [28].

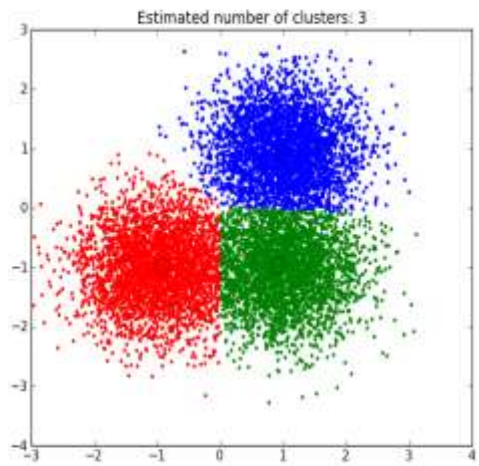

Fig. 2. Clustering Graph [41]

Fig. 2 shows an example of applying clustering on a set of data, which uses the distance criterion as dissimilarity between data.

5. CONCLUSION

Clustering and its methods are not similar to classification. In fact, the difference and similarity of clustering and classification is like the difference and similarity between chemical composition and physical composition of materials. In chemical combination, a new substance is produced and a new substance is created according to the primary materials, and in physical combination, only materials are physically combined, but both of these processes are among the basic processes of chemistry. In clustering, we divide them into groups only based on the similarities of objects (referring to data records), but in classification (classification) we use existing records to solve another problem.

Data clustering is one of the first and most important processes in data analysis and data mining. Currently, one of the important discussions is designing a suitable and strong algorithm for clustering data types. Clustering is a process for classifying components or patterns into clusters so that similar patterns are placed in the same cluster [42]. In general, there are two types of clustering: hard clustering and soft or fuzzy clustering. In hard clustering, each point can only be in one cluster. Therefore, the result is wavy. However, in many real conditions, the presence of resolution limitation, poor contrast, multiplicity of interference, noise and non-uniformity of illumination will reduce the performance of hard clustering. Fuzzy theory proposes membership theory by a membership function. Fuzzy clustering is considered as a soft segmentation method. According to the fuzzy clustering method, the FCM algorithm is a common method in data clustering because it has strong features for fuzzy points and can retain more information than hard clustering. Conventional FCM algorithm works well on noise-free images. This method is very sensitive to noise and fake images [43].

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