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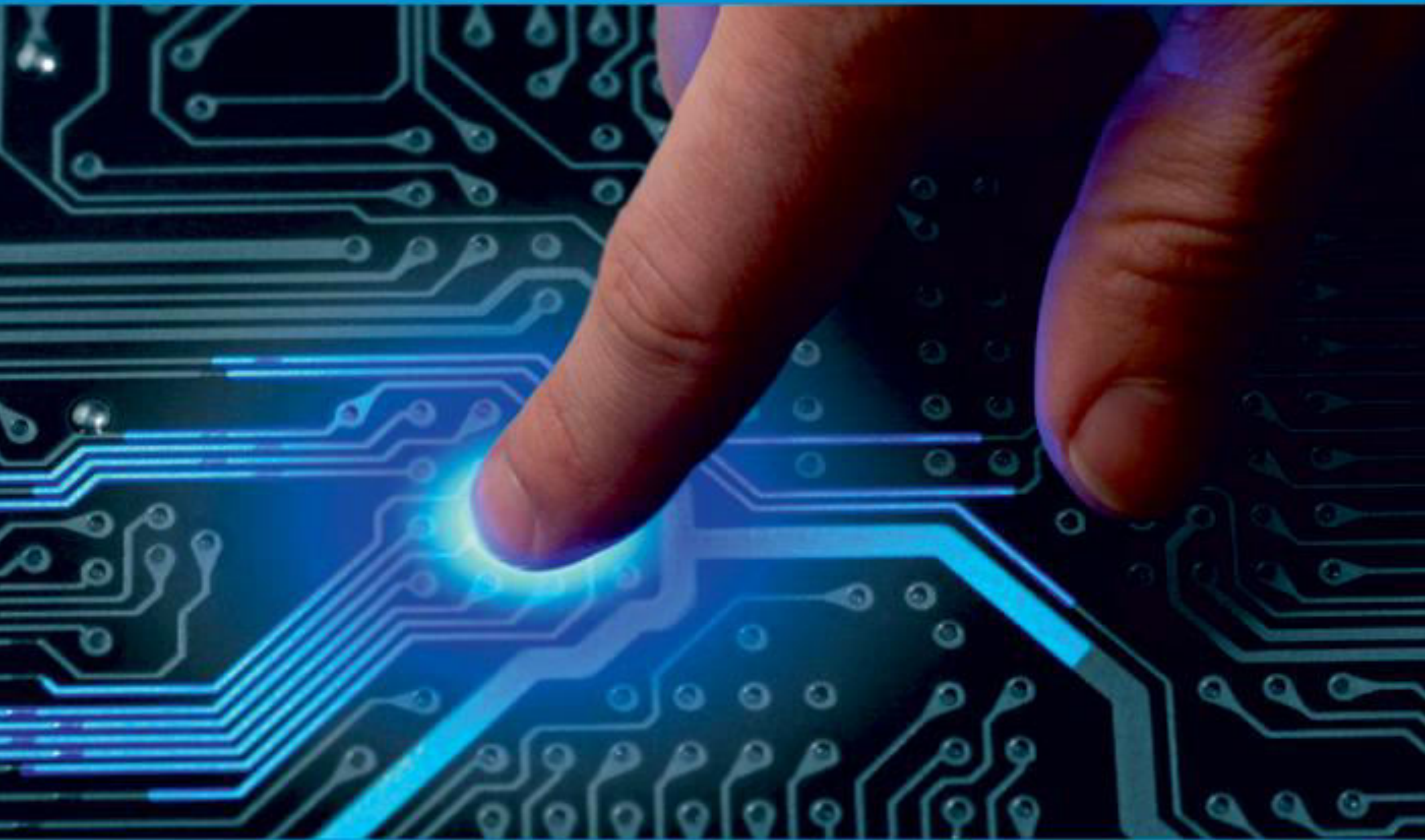

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A Survey on Recommendation System Methods and Challenges

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ABSTRACT: Recommendation system has become a crucial part of almost every online platform. The large sparse amounts of data available on the internet make it more challenging. The human-computer interaction nowadays is more like human-human interaction. Humans nowadays ask suggestions and advice on these platforms without thinking of it as a machine. E-commercial sites, OTT platforms cannot survive without these recommendation systems. The recommendation systems allow the user to discover new items that match their taste and it makes the system to target the items to the right users. Now filters like a content-based filter, collaborative filter and hybrid filter are used for these recommendation problems. This paper investigates and reports the current trends, issues, challenges, and research opportunities in developing high-quality recommender systems. If properly followed, these issues and challenges will introduce new research avenues and the goal towards fine-tuned and high quality recommender systems can be achieved.

KEYWORDS: Recommendation System,Content-based filtering, Collaborative filtering, Hybrid filtering.

I. INTRODUCTION

In the modern world, the explosive growth in the amount of available digital information and the number of visitors to the Internet have created a potential challenge of information overload which hinders timely access to items of interest on the Internet. Information retrieval systems, such as Google,DevilFinder and Altavista have partially solved this problem but prioritization and personalizing of information were absent. This has increased the demand for recommender systems more than ever before. Recommender systems are information filtering systems that deal with the problem of information overload by filtering vital information fragment out of large amount of dynamically generated information according to user's preferences, interest, or observed behavior about item [1]. Recommender system has the ability to predict whether a particular user would prefer an item or not based on the user's profile.

Recommender systems are beneficial to both service providers and users [2]. They reduce transaction costs of finding and selecting items in an online shopping environment. Recommendation systems have also proved to improve decision making process and quality. In e-commerce setting, recommender systems enhance revenues, for the fact that they are effective means of selling more products. In scientific libraries, recommender systems support users by allowing them to move beyond catalog searches. Therefore, the need to use efficient and accurate recommendation techniques within a system that will provide relevant and dependable recommendations for users cannot be over-emphasized.

Recommender systems are used in various domains including products, videos, images, articles, news and books. In spite of numerous research and development, interest in this area is still broader because of its demand. It is therefore necessary to build high-quality recommender systems for providing fine-tuned recommendations to users in a wide range of daily-life applications In this regard, researchers and industry practitioners need to come forward and work on some of the prominent issues and challenges in the area of recommendation system. The objectives of this paper is to present the general concept and methods behind the recommender systems and the issues and challenges related to it.

II. GENERAL CONCEPT AND PHASES OF RECOMMENDATION PROCESS

Recommender systems handle the problem of information overload that users normally encounter by providing them with personalized, exclusive content and service recommendations. Recently, various approaches for building recommendation systems have been developed, which can utilize either collaborative filtering, content-based filtering or hybrid filtering. Collaborative filtering technique is the most mature and the most commonly implemented.

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Collaborative filtering recommends items by identifying other users with similar taste; it uses their opinion to recommend items to the active user. Collaborative recommender systems have been implemented in different application areas. On the other hand, content-based techniques match content resources to user characteristics. Content-based filtering techniques normally base their predictions on user's information, and they ignore contributions from other users as with the case of collaborative techniques. The hybrid system are combination of both content and collaborative filtering and to improve the system different context is also added.

A. Recommendation system phases.

Figure 1 shows the general block diagram of recommendation system. It consist of three processes; the information collection phase, learning phase and the recommendation phase [1]. For each recommendation feedback is collected to improve the recommendation accuracy of the system.

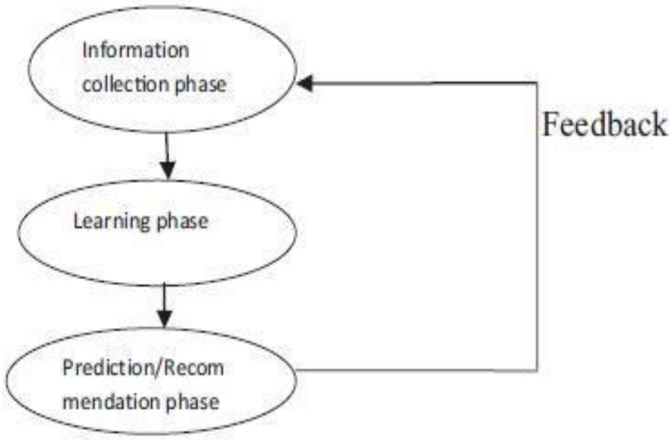

Figure 1Basic block diagram

1. Information collection.

This collects relevant information of users to generate a user profile or model for the prediction tasks including user's attribute, behaviors or content of the resources the user accesses. A recommendation agent cannot function accurately until the user profile/model hasbeen well constructed. The system needs to know as muchas possible from the user in order to provide reasonablerecommendation right from the onset. Recommender systemsrely on different types of input such as the most convenienthigh quality explicit feedback, which includes explicit inputby users regarding their interest in item or implicit feedbackby inferring user preferences indirectly through observing userbehavior. The success of any recommendation system dependslargely on its ability to represent user's current interests.Accurate models are indispensable for obtaining relevant andaccurate recommendations from any prediction techniques.

2. Explicit and Implicit feedback.

The system normally prompts the user through the system interface to provide ratings for items in order to construct and improve his model. The accuracy of recommendation depends on the quantity of ratings provided by the user. The only shortcoming of this method is, it requires effort from the users and also, users are not always ready to supply enough information. Despite the fact that explicit feedback requires more effort from user, it is still seen as providing more reliable data, since it does not involve extracting preferences from actions, and it also provides transparency into the recommendation process that results in a slightly higher perceived recommendation quality and more confidence in the recommendations. The system automatically infers the user's preferences by monitoring the different actions of users such as the history of purchases, navigation history, and time spent on some web pages, links followed by the user, content of e-mail and button clicks among others. Implicit feedback reduces the burden on users by inferring their user's preferences from their behavior with the system [10]. The method though does not require effort from the user, but it is less accurate.

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3. Learning phase and recommendation phase.

It recommendsor predicts what kind of items the user may prefer. This can be made either directly based on the dataset collected in information collection phase which could be memory based or model based or through the system's observed activities of the user.

III. RECOMMENDATION FILTERING TECHNIQUES

The use of efficient and accurate recommendation techniques is very important for a system that will provide good and useful recommendation to its individual users. This explains the importance of understanding the features and potentials of different recommendation techniques. Figure. 2 shows the anatomy of different recommendation filtering techniques.

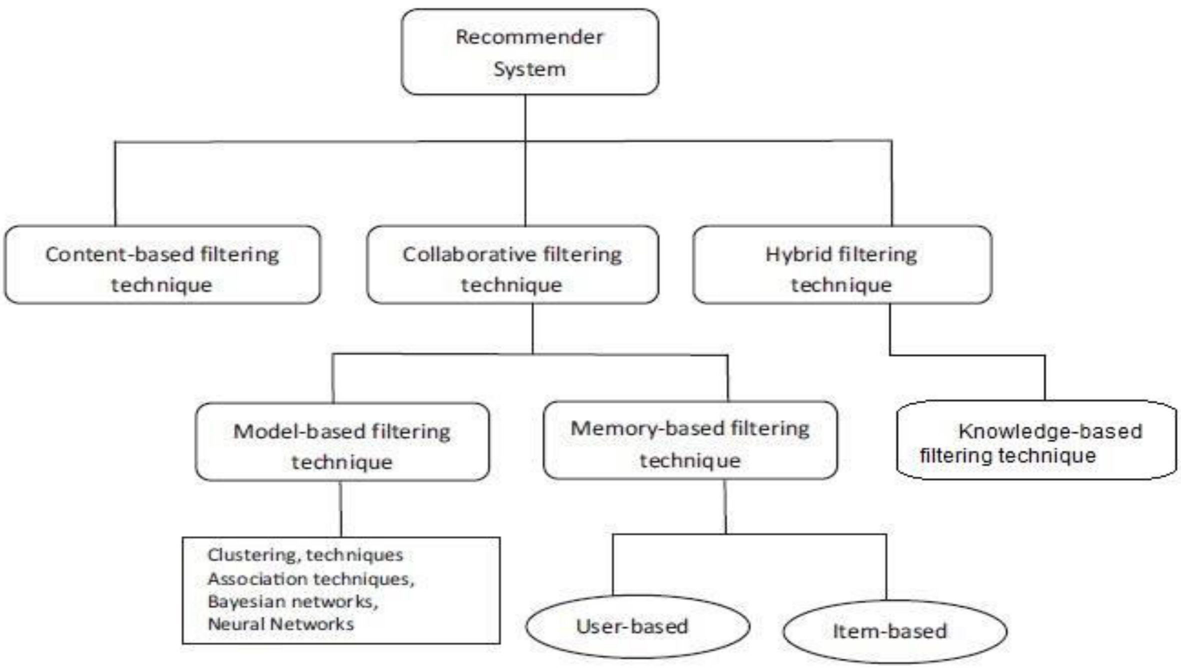

Figure 2Basic block diagram

A. Content Based filtering

Content-based technique is a domain-dependent algorithm and it emphasizes more on the analysis of the attributes of items in order to generate predictions [3]. When documents such as web pages, publications and news are to be recommended, content-based filtering technique is the most successful. In content-based filtering technique, recommendation is made based on the user profiles using features extracted from the content of the items the user has evaluated in the past. Items that are mostly related to the positively rated items are recommended to the user. They have the ability to recommend new items even if there are no ratings provided by users. So even if the database does not contain user preferences, recommendation accuracy is not affected.

B. Collaborative filtering.

Collaborative filtering is a domain-independent prediction technique for content that cannot easily and adequately be described by metadata such as movies and music [3]. Collaborative filtering technique works by building a database (user item matrix) of preferences for items by users. It then matches users with relevant interest and preferences by calculating similarities between their profiles to make recommendations. Such users build a group called neighborhood.

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A user gets recommendations to those items that he has not rated before but that were already positively rated by users in his neighborhood.

Recommendations that are produced by CF can be of either prediction or recommendation. Prediction is a numerical value, Rij, expressing the predicted score of item j for the user i, and while Recommendation is a list of top N items that the user will like the most. The technique of collaborative filtering can be divided into two categories: memory-based and model based.

In the memory-based approach the items that were already rated by the user before play a relevant role in searching for a neighbor that shares appreciation with him. Once a neighbor of a user is found, different algorithms can be used to combine the preferences of neighbors to generate recommendations. Due to the effectiveness of these techniques, they have achieved widespread success in real life applications. Memory-based CF can be achieved in two ways through user-based and item based techniques.

The model-based technique employs the previous ratings to learn a model in order to improve the performance of Collaborative filtering Technique. The model building process can be done using machine learning or data mining techniques. These techniques can quickly recommend a set of items for the fact that they use pre-computed model and they have proved to produce recommendation results that are similar to neighborhood-based recommender techniques. Examples of these techniques include Dimensionality Reduction technique such as Singular Value Decomposition (SVD), Matrix Completion Technique, Latent Semantic methods, and Regression and Clustering. Model-based techniques analyze the user-item matrix to identify relations between items; they use these relations to compare the list of top-N recommendations. Model based techniques resolve the sparsity problems associated with recommendation systems.

Collaborative Filtering has some major advantages over Content Based Filtering in that it can perform in domains where there is not much content associated with items and where content is difficult for a computer system to analyze.

C. Hybrid filtering

Hybrid filtering technique combines different recommendation techniques in order to gain better system optimization to avoid some limitations and problems of pure recommendation systems. The idea behind hybrid techniques is that a combination of algorithms will provide more accurate and effective recommendations than a single algorithm as the disadvantages of one algorithm can be overcome by another algorithm. Using multiple recommendation techniques can suppress the weaknesses of an individual technique in a combined model [4]. The combination of approaches can be done in any of the following ways: separate implementation of algorithms and combining the result, utilizing some content-based filtering in collaborative approach, utilizing some collaborative filtering in content-based approach, creating a unified recommendation system that brings together both approaches.

1. Knowledge Based Filtering.

A recommender system is knowledge-based when it makes recommendations based not on a user's rating history, but on specific queries made by the user. It might prompt the user to give a series of rules or guidelines on what the results should look like, or an example of an item. The system then searches through its database of items and returns similar results [5]. Here the context of the search plays an important role different similarity measures are used to identify the required item.

IV. ISSUES AND CHALLENGES

A. Pros and Cons of collaborative filtering techniques.

Collaborative Filtering has some major advantages over CBF in that it can perform in domains where there is not much content associated with items and where content is difficult for a computer system to analyze (such as opinions and ideal). Also, CF technique has the ability to provide serendipitous recommendations, which means that it can recommend items that are relevant to the user even without the content being in the user's profile. Despite the success of CF techniques, their widespread use has revealed some potential problems such as follows.

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- Cold-start problem. This refers to a situation where a recommender does not have adequate information about a user or an item in order to make relevant predictions. This is one of the major problems that reduce the performance of recommendation system. The profile of such new user or item will be empty since he has not rated any item; hence, his taste is not known to the system.

- Data sparsity problem. This is the problem that occurs as a result of lack of enough information, that is, when only a few of the total number of items available in a database are rated by users. This always leads to a sparse user item matrix, inability to locate successful neighbors and finally, the generation of weak recommendations. Also, data sparsity always leads to coverage problems, which is the percentage of items in the system that recommendations can be made for.

- Scalability. This is another problem associated with recommendation algorithms because computation normally grows linearly with the number of users and items [67]. A recommendation technique that is efficient when the number of dataset is limited may be unable to generate satisfactory number of recommendations when the volume of dataset is increased. Thus, it is crucial to apply recommendation techniques which are capable of scaling up in a successful manner as the number of dataset in a database increases. Methods used for solving scalability problem and speeding up recommendation generation are based on Dimensionality reduction techniques, such as Singular Value Decomposition (SVD) method, which has the ability to produce reliable and efficient recommendations.

- Synonymy. Synonymy is the tendency of very similar items to have different names or entries. Most recommender systems find it difficult to make distinction between closely related items such as the difference between e.g. baby wear and baby cloth. Collaborative Filtering systems usually find no match between the two terms to be able to compute their similarity. Different methods, such as automatic term expansion, the construction of a thesaurus, and Singular Value Decomposition (SVD), especially Latent Semantic Indexing are capable of solving the synonymy problem. The shortcoming of these methods is that some added terms may have different meanings from what is intended, which sometimes leads to rapid degradation of recommendation performance.

V. CONCLUSION AND FUTURE WORK

Recommender systems open new opportunities of retrieving personalized information on the Internet. It also helps to alleviate the problem of information overload which is a very common phenomenon with information retrieval systems and enables users to have access to products and services which are not readily available to users on the system. This paper discussed the two traditional recommendation techniques and highlighted their strengths and challenges with diverse kind of hybridization strategies used to improve their performances. Various learning algorithms used in generating recommendation models and evaluation metrics used in measuring the quality and performance of recommendation algorithms were discussed. This knowledge will empower researchers and serve as a road map to improve the state of the art recommendation techniques.

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