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Recommender System: Design and Opportunity in the Development of Information Systems

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Abstract: This paper investigates the design and opportunity of recommendation engines in developing information systems. The essential characteristics of the recommendation system, technological tools for monitoring and collecting user activities, and the method of generating recommendations are defined. The main focus is on the basic concepts, different types of recommendation systems, and their practical application in different technological fields and industries. Also, the paper analyzes the most used algorithms for generating recommendations and various metrics for evaluation. It shows the most common problems faced by system recommendations, the most important of which are the problems of cold start, sparse data, and changes in user behavior. Applied recommendation systems in current areas such as e-commerce, video streaming platforms, and social networks are discussed. At the end of the paper, the future development of the recommendation system, the future direction of research within information systems, and the potential improvement of user experience within various information systems were discussed. The paper aims to provide a clearer insight into recommendation systems and their increasingly pronounced impact on users' online activities.

Keywords: recommender systems, applied recommender algorithms, personalized systems, hybrid recommendation, performance evaluation

1. Introduction

With the ever-increasing volume of information, recommender systems have long been an effective strategy for overcoming such information overload [1]. The applicability of recommendation systems is crucial, considering their wide application in many information systems [2]. Recommender systems are among the most influential applications in smart environments, aiming to indicate potential content of greater interest to users [3]. For example, in today's e-commerce field, almost all e-commerce sites use recommendation systems to help users find suitable products [4,5]. Thus, they not only help users overcome information overload but can also significantly contribute to the business success of service providers [3–6]. In many practical applications, recommendation systems monitor user behavior and activities and generate customized recommendations based on the collected information. Although this approach is beneficial, the limitations may occur when users have just started using an information system that applies a personalized recommender algorithm. In that case, the system does not have enough information about the user, and for this reason, it occurs cold start and spars data. To overcome this problem, researchers develop various techniques and algorithms [7–9].

This paper defines the concept of a recommendation system, investigates various algorithms used in practice to generate content, presents solutions for potential problems such as cold start faced by recommender engines, and shows various applications and future developments of these systems.

2. Defining Recommender systems

The recommendation system is an advanced technology that uses machine learning and data analysis elements to generate user recommendations. These systems represent software components, usually belonging to a more extensive information system, but can also be stand-alone tools.

Recommendation systems use different algorithms and techniques to collect, analyze, and filter data based on which they generate relevant user recommendations. This way, recommendation systems improve user experience within various information systems and online platforms. Recommendation systems can be divided into non-personalized and personalized recommendation systems [10,11].

3. Non-personalized Recommender systems

Non-personalized recommendation systems are tasked with providing recommendations to users without considering their individual preferences and behaviors. Unlike personalized recommendation systems, these systems do not rely on the unique characteristics of users but take into account general data within information systems. In this way, the system offers recommendations even if the user has yet to have the opportunity to use the system so far.

The disadvantage of this approach is that users will not receive recommendations according to their preferences but will receive recommendations based on general information within the information system. For this reason, these systems are often used as an initial step in implementing a recommendation system within a more extensive information system. A non-personalized system usually represents the best-selling or most famous content within the information system [10–12].

4. Personalized Recommender systems

Personalized recommendation systems are designed to generate customized user recommendations based on their preferences, past behavior, and demographic information. These systems track the user's online activities, such as purchases and rated content, and based on this, they try to predict and understand which items and content the user will be potentially interested in. It is often said that a good recommendation is characterized by variety, personalization, and timeliness.

Using efficient and accurate recommendation techniques is very important for a system that will provide excellent and valuable user recommendations. This explains the importance of understanding the characteristics and potential of different recommendation techniques [5, 10–12].

Figure 1 shows the structure of different recommendation filtering techniques.

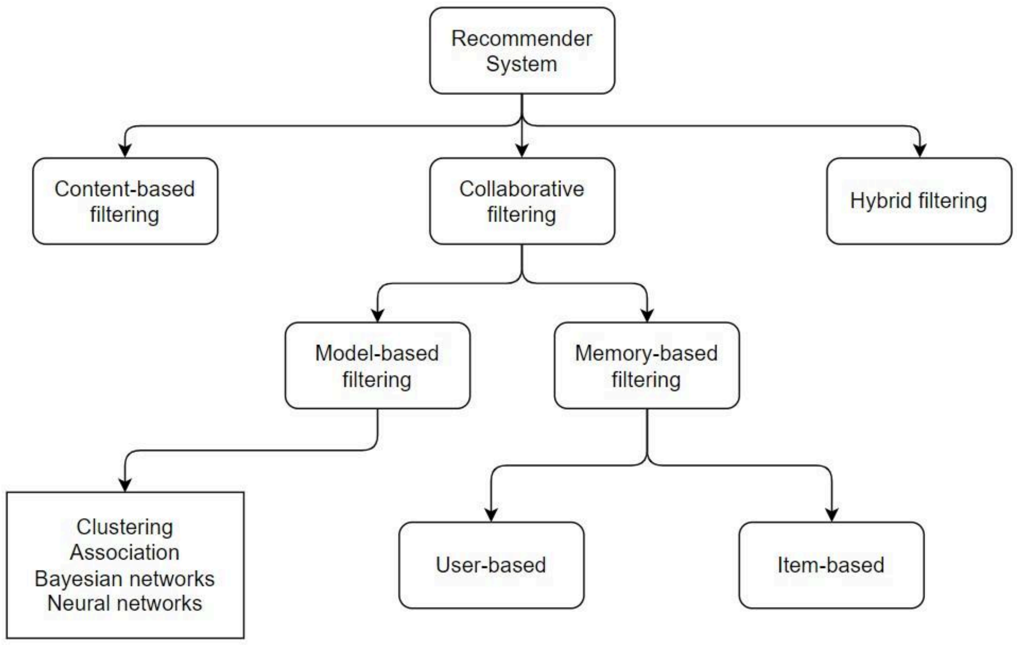

Figure 1 – The structure of different filtering techniques for generating recommendations, adapted from [13].

The most common and most used algorithms for a personalized recommendation system are:

- Content-based filtering;
- Collaborative filtering;
- Hybrid filtering.

4.1. Content-based filtering

Content-based filtering is a domain-specific algorithm that emphasizes the analysis of item attributes to generate predictions. This technique generates recommendations based on user characteristics gathered by analyzing content the user has rated in the past. The items that the user rated best are taken as recommendations. Content-based filtering uses machine learning models to generate meaningful and relevant recommendations. The most used machine learning models are the Naive Bayes classifier, decision tree, and neural networks. This technique does not require collecting other users' information because they do not influence the recommendations. Also, if there is a sudden change in user profile and activity, the content-based filtering technique has the potential to adjust recommendations in a short period [10–12].

For example, if the user has purchased a product within the information system, the system assumes that the user prefers that product category. Considering this information, it is likely that the user will buy a similar product in the future use of the system [5].

The main advantage of this recommendation system lies in the user's understanding of the recommendation. A user can infer that their past activities have influenced their current recommendations, which can reduce data privacy concerns. On the other hand, the biggest drawback of this system is the excessive specialization of recommendations. In most cases, the system will offer the user recommendations based on previous activity and content, limiting the ability to recommend content outside of the user's known preferences. Also, a limitation of content-based recommender systems is the cold start problem. Due to the way the system works, the user must evaluate a sufficient number of contents so that the system can give appropriate recommendations [6,7].

4.2. Collaborative filtering

Collaborative filtering is a system that predicts a valuable product for a user based on other users within an information system. Although the term collaborative filtering has been around for over ten years, this method draws its roots from something people have been doing for centuries - sharing ideas with others.

Unlike content-based filtering, the system determines users based on similar preferences of the target user. Then, it compares users with similar interests and preferences, calculating similarities between their profiles to provide recommendations. In this way, the user receives recommendations for a product that he has not previously evaluated but has already been positively evaluated by similar users [5,14]. Colloquially, similar users can also be called "neighborhood" [10–12]. Recommendations generated by collaborative filtering can be in the form of predictions or recommendations. Approaches to collaborative filtering differ precisely in how similarity between users is determined.

Collaborative filtering systems can be classified into two basic principles [5]:

- User-based collaborative filtering
- Item-based Collaborative Filtering

In user-based collaborative filtering, the target user's product preferences and evaluations are compared with other users' evaluations to identify a group of similar users. After identifying similar users, the system recommends products that other users rated with the highest ratings. In this way, the target user receives recommendations that make preferences similar to his. However, in item-based collaborative filtering, recommendations are generated by identifying similar products that the target user has previously purchased or rated. When determining the similarity between items, the preferences of the observed user are compared with other users of the information system. In both of the mentioned collaborative filtering approaches, the user's generated recommendation depends on the preferences of other users, which is the core of this recommendation system. The advantage of this recommendation system is compelling personalization and the possibility of unexpected discoveries - the system can recommend content that differs from the content in which the user has shown interest. This overcomes the problem of excessive personalization. On the other hand, the lack of this system represents a cold start problem and sensitivity to sparse data. For collaborative filtering, it is necessary to provide sufficient data on user interactions within the information system [5,10–12].

4.3. Hybrid filtering

Hybrid Hybrid or mixed system filtering represents a combination of several different approaches and techniques for generating recommendations to provide more precise, diverse, and practical recommendations. These systems are often used in practice because they can provide more precise and adaptive recommendations. The most significant advantage of the hybrid filtering system is that it improves the quality of the recommendation by combining the advantages of different recommendation systems. Also, this system increases flexibility and reduces the limitations of individual recommendation systems. Finally, hybrid systems overcome the most common problems that recommender systems face, which is most often the problem of a cold start and excessive specialization of recommendations. On the other hand, the disadvantage of these systems is the increased complexity and effort in developing the recommendation system and the need for a large volume of data. Although hybrid recommenders offer significant advantages regarding recommendation quality and flexibility, resource requirements should be carefully considered when deciding on system implementation [5, 10–12].

5. Performance evaluation of the Recommender system

Evaluation of the performance of the recommendation system is a critical process in the development of the recommendation system. This process includes evaluating the accuracy of the recommendation and measuring the effectiveness of the content generated by the recommendation system. In this way, it is determined to what extent the system meets the user's needs and how relevant the generated recommendation is to the user.

Three types of experiments are conducted when evaluating a recommendation system, namely:

- Online – uses datasets and protocols replicating user activity and measuring prediction accuracy;
- Offline – evaluating the use of the referral system in real-time;
- User studies – based on using the recommendation system by a limited number of users and analyzing their feedback.

The choice of system and algorithm is based on evaluation metrics. The most common evaluation metrics are Recall, Precision, Root Mean Squared Error – RMSE, Mean Absolute Error – MAE. The recall evaluation metric evaluates the accuracy of the system's recommendation based on user preferences – the higher the response, the more accurate the recommendation. Precision measures the percentage of user ratings in all possible recommendations. The square root of the root mean square error measures prediction errors that should ideally be low. These are just some metrics for evaluating the accuracy of recommender systems in use today. It is essential to understand that the success and accuracy of the recommendation system largely depend on the accuracy and quality of the data used [15,16].

6. Application of Recommender systems

In the modern technological age, recommendation systems have become an inevitable tool for personalizing the user experience and improving user engagement. Recommender systems applications can be seen in various business areas. Of these, the most significant are e-commerce [4,5], cloud gaming services [17–19], streaming platforms [20,21], social networks [22,23], and the fields of education [3,24,25].

In e-commerce, recommendation systems recommend relevant products and content to the user, achieving user satisfaction and promoting better product sales in an information system [5]. Also, the application of these systems can be seen in the field of streaming platforms, which include platforms like Netflix, Spotify, and YouTube. Recommendation systems recommend content to users based on their previous preferences and searches. Social networks use recommendation systems to suggest new friends, groups, and pages that might interest users.

In education, these systems are becoming more and more accessible. They adapt teaching material according to individual needs and learning styles, providing a customized learning approach to the user [3].

7. Future directions and development of Recommender systems

Recommendation systems have focused on attracting potential customers, but future systems will have a broader impact on our daily lives. They will become indispensable tools that will act as personal advisors in all aspects of life, not just limited to buying and selling products. Future recommendation systems are expected to be based on data from the Internet of Things (IoT), Internet of Everything (IoE), and big data, using it intelligently [26]. They will overcome the cold start problem by gathering information from other sources [3], such as social networks [22,23] and the Internet of Everything [27]. Future systems will be more user-centric, providing recommendations that better reflect customer preferences. Analysis of personal characteristics and behavior will enable more personalized recommendations. These systems will expand their influence by becoming a part of everyday life, tracking users' activities, and providing recommendations that include health care, emotional state, and other aspects of life. Future recommendation systems are expected to be applied more ethically, offering users recommendations only when needed [1,3,28].

8. Conclusion

One of the key challenges in implementing a recommendation system is balancing user privacy and personalization. The need for personalized recommendations is growing, which includes tracking user activity, while on the other hand, the question of how to protect data from misuse is also raised. As a solution to this problem, more and more work is being done to develop technologies such as differential privacy and federated learning. These technologies indicate the possibilities of overcoming these challenges and enable the implementation of a recommendation system without compromising user privacy. We also had the opportunity to see the key role of machine learning in the accuracy of recommendations of recommender systems, allowing them to adapt to changing user preferences. However, we also recognized that it is important to continuously monitor system performance, and evaluate and update algorithms to maintain their accuracy and relevance.

In the coming period, an expansive development of the recommendation system can be expected, including new technologies such as deep learning and artificial intelligence, to understand the user's preferences and needs even more precisely. Understanding the user's habits and activities will be crucial for creating trust among users.

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