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METHODS OF BUILDING RECOMMENDATION SYSTEMS IN E-COMMERCE

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Abstract. The purpose of this article is to study the main approaches and algorithms for building recommendation services in online trading systems. Recommendation systems optimize the sales process by identifying interesting and relevant products or services for users and offering them personalized recommendations, and serve to increase sales in e-commerce systems. In this article, the capabilities of the main techniques of recommendation systems, such as collaborative filtering, content-based approaches and hybrid models have been analyzed. A comparative analysis of the effectiveness of these methods and algorithms is carried out, their advantages and disadvantages are identified. The paper concludes by suggesting theoretical and practical frameworks for future advancements in recommender systems.

Keywords: recommendation systems, e-commerce, collaborative filtering, content-based recommendation, hybrid model, TF-IDF model, personalized recommendation.

1. Introduction

In recent years, with the development of the digital economy, e-commerce systems have become an integral part of our lives, radically changing the sphere of trade and service. Every day, thousands of users visit online platforms and search for the products or services they need. It is the e-commerce systems that have simplified the purchase of various goods and services and created a wide choice for consumers. Therefore, recommendation systems have become an integral part of e-commerce, simplifying the purchasing process by suggesting suitable products or services to consumers. Recommendation systems are software products (mechanisms, modules, or services) that provide users with personalized recommendations based on their needs, interests, and past actions [1],[2]. While they speed up the product discovery process for users, they also

significantly benefit commercial platforms. In particular, it increases the volume of sales, strengthens the positive attitude of customers towards the e-commerce system, and ensures the satisfaction of users' needs.The development of recommendations in e-commerce systems is an important tool of providing personalized service in e-commerce systems, which serves to anticipate the needs of customers, offer them suitable products, and facilitate and speed up the purchase process. Recommendation systems not only provide convenience for customers, but also allow platform owners to increase revenue, create positive customer attitudes toward the system, and gain competitive advantage.

This article aims to study the main approaches and algorithms for the building recommendation services in e-commerce systems. In general, recommendation systems can predict users' interests and offer them suitable products and services, which further improves the user experience. The main goal of the article is to recommend solutions aimed at improving recommendation systems based on modern technologies and increasing their effectiveness in e-commerce. At the same time, the article will be useful not only for scientific analysis, but also for practicing programmers and commercial experts. It should be noted that this article analyzes Collaborative filtering, Content-based and Hybrid models. Advantages and disadvantages of each model have been studied [2].

2. Literature review

Recommender systems in e-commerce are algorithms or software systems that help users find interesting and relevant content based on their interests, behaviors, or information from other users [3]. Such systems are widely used in many online services such as streaming platforms (services that transmit video, audio or other types of data in real time over the Internet), online stores, social networks, and educational platforms. [1]. The theoretical foundations of recommender systems have been extensively researched by various authors. For example, the book "Recommender Systems Handbook" [4] describes in detail the basic concepts and methods of recommendation systems, as well as their application areas. This book is very useful for learning the scientific basis of recommender systems. It takes a broad look at the content-based and collaborative sorting and hybrid systems that form the basis of today's recommendation systems.

Collaborative filtering is one of the oldest and most common methods of recommender systems. Sarwar, Karypis and other scientists have carried out several scientific studies in this field and in the article "Collaborative Filtering for Recommender Systems" [5], they analyzed the methods of using cosine similarity and correlation coefficient to determine user and product similarity. This article focuses on the advantages and limitations of collaborative filtering, as well as ways to improve its effectiveness.

Research papers written by Lops, de Gemmis, and Semeraro are widely used in

the field of content-based recommendation. The article "Content-Based Recommender Systems" [6] explains algorithms for matching product or service recommendations with user interests, such as TF-IDF and Vector Cosine Similarity. This paper presents the ways and limitations of using content-based recommendations effectively. This research is an important resource for learning how content-based systems work and how they benefit more informed users.

In order to improve the effectiveness of recommendation systems, hybrid recommendation systems (a combination of collaborative filtering and content-based approaches) have been widely studied by researchers. Robin Burke in his article "Hybrid Recommender Systems: A Review and Experiments" [7] discusses the different forms of hybrid systems, their effectiveness, and their applications. This article explains how hybrid recommenders can provide more accurate recommendations to the user and how this method can help make recommendations more accurate.

3. Recommendation systems

3.1. Collaborative filtering-based recommendation systems

There are mainly 2 types of collaborative filtering-based recommendation systems: User-based and Item-based collaborative filtering.

User-based collaborative filtering: Recommends products that the user is interested in from similar users. For example, for two users who like the same books, other similar books are recommended. If the user has purchased a book, books related to the genre, author, or topic of that book are recommended. In this approach, the interests of other users similar to the user are studied.

Cosine similarity is used to calculate the similarity between two users:

$$CosineSimilarity(u,v) = \frac{\sum_{i=1}^{n} R_{u,i} \cdot R_{v,i}}{\sqrt{\sum_{i=1}^{n} R_{u,i}^2} \cdot \sqrt{\sum_{i=1}^{n} R_{v,i}^2}} \quad (1)$$

where $R_{u,i}$ and $R_{v,i}$ are the ratings of product i as rated by users u and v. The result is between 0 and 1, with higher values indicating similar users.

Item-based collaborative filtering: When a user purchases a particular product, similar products that are highly rated by other users are suggested to them. Similarity between products is considered to recommend similar products based on the products the user is interested in.

Cosine similarity is used to calculate the similarity between two items:

$$CosineSimilarity(i,j) = \frac{\sum_{u=1}^{m} R_{u,i} \cdot R_{u,j}}{\sqrt{\sum_{u=1}^{m} R_{u,i}^2} \cdot \sqrt{\sum_{u=1}^{m} R_{u,j}^2}} \quad (2)$$

where $R_{u,i}$ is the rating given to product i by user u.

3.2. Content-based recommendation systems

Content-based recommendation is based on the specific characteristics of

products and user interests. The main advantage of this approach is that it increases efficiency when there is a lot of information about the products. However, these systems tend to recommend items similar to those a user has already interacted with, leading to a lack of novelty and surprise. Users may get stuck in a "filter bubble" where they only see recommendations aligned with their existing preferences. Detailed information on the advantages and limitations of this method is given in [6]. In a content-based approach, recommendations are formed by examining the main features of the product and selecting products with features that match the user's interests.

In these systems, the TF-IDF (Term Frequency-Inverse Document Frequency) model is used to represent product features (attributes).

$$\mathrm{TF}-\mathrm{IDF}=\mathrm{TF}_{i,j}\cdot\mathrm{IDF}_i \qquad (3)$$

where $\mathrm{TF}_{i,j}$ is the term frequency, the frequency of the i -th term in product j. IDF_i is the inverse document frequency, which can be calculated as follows:

$$\mathrm{IDF}_i=\log\left(\frac{N}{n_i}\right) \qquad (4)$$

N is the total number of documents, n_i is the number of documents in which the i-th term appears.

In content-based recommendation systems, recommendations are generated when a user profile matches product features.

3.3.Hybrid recommendation systems

Hybrid systems improve recommendation performance by combining collaborative filtering and content-based recommendation approaches. This method allows the limitations of one approach to be compensated for by the other, which helps to increase the accuracy of the system. The following formula can be used to generate recommendations in a hybrid method:

$$FRS=\alpha\cdot CFS+(1-\alpha)\cdot CBS \qquad (5)$$

where *FRS* is the Final Recommendation Score, *CFS* is the Collaborative Filtering Score, *CBS* is the Content-Based Score, α is the weight factor (a value between 0 and 1) emphasizes one of the recommendation systems.

4. Result analysis

Precision and Recall are important criteria for measuring the effectiveness of recommendation systems. Table 1 presents the performance metrics for 3 different recommendation models. The results presented in Table 1 demonstrate that the hybrid model achieves the highest results. The Precision values range from 0.74 to 0.82, indicating the accuracy of the recommendations made by these models. The Recall values range from 0.65 to 0.76, reflecting the completeness or coverage of the recommendations provided by these models.

Table 1. Performance metrics of different models

Model	Precision	Recall
Collaborative filtering	0.78	0.68
Content-based	0.74	0.65
Gibrid model	0.82	0.76

In recommendation systems, Click-through Rate (CTR) and Conversion Rate (CR) play an important role in assessing the effectiveness of the system. These indicators allow system to measure user engagement and their transition to real action (purchase or other targeted action). These metrics shown in Table 2 provide insights into the effectiveness of the different recommendation approaches in terms of user engagement and driving desired actions.

Table 2. Click-through Rate and Conversion Rate

Model	CTR	CR
Collaborative filtering	12 %	4.5 %
Content-based	10 %	3.8 %
Gibrid model	15 %	6.2 %

The results of the study showed that the hybrid model achieved high CTR and CR results, which allows it to provide highly relevant recommendations for the user. The table shows that the Collaborative filtering model has the highest Click-through Rate at 12%, followed by the Gibrid model at 15% and the Content-based model at 10%. In terms of Conversion Rate, the Collaborative filtering model has the highest rate at 4.5%, followed by the Content-based model at 3.8% and the Gibrid model at 6.2%.

From the above results, we can see that Collaborative Filtering is based on user experience and takes into account social factors, and in this case, users who are using the system for the first time may face the problem of lack of information [8]. Content-based recommendation reflects personal interests well, but users may suffer from a lack of diversity. The hybrid model is a more effective and universal approach than “Collaborative Filtering” and “Content-based recommendation”, and can meet the needs of different users, but due to its complexity, it is not necessary to implement such filtering on small platforms.

5. Conclusion

Recommendation systems in e-commerce are an integral part of the modern digital economy and play a key role in optimizing interactions between consumers and commerce platforms. This article analyzed the main methods and algorithms for building recommendation systems, including the effectiveness of collaborative filtering, content-based approaches, and hybrid models. Their role in ensuring user satisfaction and increasing sales is widely covered. The research found that each method and algorithm has its own strengths and weaknesses. For example, collaborative filtering is effective in identifying

similarities between users, but suffers from the problem of a lack of information. While content-based approaches are good at identifying individual user needs, they suffer from a lack of diversity. Hybrid systems, on the other hand, have been shown to successfully overcome these shortcomings and improve their recommendation performance.

Currently, e-commerce systems are becoming more advanced, and the increase in data and the use of artificial intelligence and machine learning technologies to act on them are playing an important role in advancing recommendation services to the next level. Deep learning and big data analytics techniques can be successfully used to generate personalized recommendations in real-time. At the same time, protecting user privacy and ensuring privacy were highlighted as key issues in improving recommendation systems. In our future work, we will cover the methods and algorithms for applying artificial intelligence technologies in recommendation systems.

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