The Status and Development of E-commerce Platform Recommendation Systems Based on Artificial Intelligence Technology

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Abstract: This paper focuses on discussing the recommendation system of e-commerce platforms that use artificial intelligence technology. It summarizes the topic by exploring various aspects such as application, technical principles, performance evaluation indicators, application cases, development trends, challenges, and future research directions. It introduces recommended systems that utilize collaborative filtering and content-based filtering technologies. The technical principles behind these systems include user interest modeling and product feature extraction. And, it introduces performance evaluation indicators such as accuracy and coverage. It also discusses the application and effects of recommended systems in well-known e-commerce platforms both domestically and internationally. Additionally, the paper analyzes the challenges of data sparsity and cold start problems in e-commerce platform recommendation systems and provides relevant solutions. Finally, the paper proposes future research plans in this field.

Keywords: E-commerce; Recommendation system; Artificial intelligence.

1 Introduction

The e-commerce industry is rapidly growing, resulting in an increase in the number of commodities available on their platforms[1]. However, this growth has led to a significant problem of information overload for users. Therefore, to meet the needs of customers, e-commerce platforms have made it imperative to offer personalized recommendation services. The advent of artificial intelligence technology has opened up new avenues for the development of e-commerce recommendation systems[2][3]. This paper will explore the utilization of artificial intelligence technology in e-commerce platform recommendation systems. It explores the use of artificial intelligence technology in e-commerce platform recommendation systems. It provides examples of well-known e-commerce platforms both domestically and internationally that have successfully implemented recommendation systems. The paper also discusses the current development trends and challenges facing recommendation systems in e-commerce

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platforms. The ultimate goal is to identify future research directions for recommendation systems in e-commerce platforms. The purpose of this paper is to thoroughly investigate the usage and advancement of artificial intelligence technology in e-commerce platform recommendation systems. Our goal is to offer valuable insights and inspiration for the research and development of these systems.

2 E-commerce platform recommendation principle

The e-commerce platform recommendation system is an application of artificial intelligence technology, which can make personalized recommendations to users based on the user's historical data, and increase the sales conversion rate. This section will introduce the technical principle of the e-commerce platform recommendation system, including three aspects: user interest modeling, commodity feature extraction, and recommendation algorithm.

2.1 User interest modeling

User interest modeling plays a crucial role in the recommendation system of e-commerce platforms. Its primary objective is to model and describe user interests. Typically, the system depicts user interests by user historical behavior data. In this section, we take Alibaba's DIN (Deep Interest Network) as an example. The algorithm utilizes the concept of Attention in modeling the expression of user interest, as given by formula 1[1]. This involves calculating the Attention Weighted score using the target item and the item in the user behavior sequence, resulting in a user interest model that is oriented toward the target item. Besides, to improve the prediction success rate of sequential recommendations related to user behavior time series, Alibaba has implemented a time interval-aware data augmentation method[2].

$$V_u = f(V_a) = \sum_{i=1}^{n}(w_i * V_i) = \sum_{i=1}^{n} g(V_i, V_a) * V_i \tag{1}$$

Among them, V_u represents the user prediction vector, V represents the target item prediction vector, V represents the prediction vector of the i-th behavior of the user, and w_i represents the weight, which is determined by the relationship between V_i and V_a, that is, g(V_i, V_a) in the above formula.

2.2 Product feature extraction

Product feature extraction is the process of transforming product information into computable feature vectors. In e-commerce recommendation systems, this information typically includes the product name, description, picture, and price. These data points are then converted into a vector form that can be processed by a computer. Commonly used methods for feature extraction include text, image, and price feature extraction.

2.3 Recommendation algorithm

The recommendation algorithm is the central component of the e-commerce platform's recommendation system. Its primary function is to provide personalized recommendations to users based on their interests and the characteristics of the products they are viewing. The algorithms include various techniques, such as collaborative filtering, content-based filtering, and other technologies[3][4]. Collaborative filtering (given by formulas 2 and 3) is a commonly used recommendation algorithm that identifies the potential interests of users by analyzing similarities between them. It recommends products that are similar to the ones that users have shown interest in.

$$\mathrm{sim}(i.j) = \cos(i,j) = \frac{N_i * N_j}{|N_i| * |N_j|} = \frac{\sum_{k=1}^{n}(R_{ik} * R_{jk})}{\sqrt{\sum_{k=1}^{n} R_{ik}^2} * \sqrt{\sum_{k=1}^{n} R_{jk}^2}} \tag{2}$$

Among them, N_i and N_j represent the item sets that users i and j contact, $|N_i|$, $|N_j|$ represent the number of items that users i and j contact, R_{ik} represents the user *i*'s evaluation of item *k*, and R_{jk} represents the user *j*'s evaluation of item k. The closer the calculation result is to 1, the higher the similarity between users *i* and *j* is.

$$p_{ik} = \frac{\sum_{Ni \in N(u)} Sim(i,j) * r_{jk}}{\sum_{Ni \in N(u)} Sim(i,j)} \tag{3}$$

Among them, p_{ik} represents the user i's preference for item k, r_{jk} represents the user j's evaluation of item k, and Sim(i,j) represents the similarity between user *i* and user *j*.

3 System performance evaluation index

3.1 Accuracy

Accuracy is a fundamental performance indicator of a recommendation system, measuring the extent to which the products suggested by the system match the products that interest the users. This section presents the accuracy evaluation metrics typically adopted in recommendation systems, such as prediction precision and recall. The website typically offers a personalized recommendation list known as Top-N recommendation. The accuracy of its predictions is typically evaluated using either precision (given by formula 4) or recall metrics (given by formula 5).

$$\mathrm{Recall} = \frac{\sum_{j \in J} |R(j) \cap T(j)|}{\sum_{j \in J} |T(j)|} \tag{4}$$

$$\mathrm{precision} = \frac{\sum_{j \in J} |R(j) \cap T(j)|}{\sum_{j \in J} |R(j)|} \tag{5}$$

Among them, *j* represents a certain user, R(j) represents the predicted recommendation list of the user, and *T(j)* represents the behavior list of the user on the recommendation list. The values of precision and recall are between 0 and 1, and the closer the value is to 1, the better the system is.

3.2 Coverage rate

In recommendation systems, the coverage rate is an indicator of the system's ability to recommend a diverse range of products, including those that are less popular or niche. This is commonly known as the 'long tail' of items. It can be formulated as:

$$C = \frac{\left|\bigcup_{u \in U} R_{(u)}\right|}{|I|} \tag{6}$$

Among them, I represents all item sets, U represents user sets, and $R_{(u)}$ represents the set of recommended items for each user, and the higher its value, the wider the coverage of the recommendation system.

3.3 Diversity

Diversity refers to the degree of difference between the products recommended by the recommendation system, which can measure the diversity and novelty of the recommendation results. Diversity types are broadly classified into user diversity and timing diversity. User diversity refers to the diversity of recommendations provided to different users, also known as the concept of 'thousands of people and thousands of faces'. The Hamming distance (given by formula 7) algorithm is commonly used to measure user diversity.

$$H_{ij} = 1 - \frac{Q_{ij}}{L} \tag{7}$$

Among them, L is the length of the recommendation list, and Q_{ij} is the number of identical items in the two recommendation lists recommended by the system to users i and k. H_{ij} measures the difference in recommendation results among different users, and the larger the value, the higher the degree of diversity among different users. Temporal diversity, in the context of recommendation systems, refers to the dynamic evolution of user interests and their time-varying context. It measures the diversity of new recommendations as compared to past recommendations and is quantified using the SSD (Self-System Diversity) algorithm, as outlined in formula 8.

$$\mathrm{SSD}(R|u) = \frac{|R/R_{t-1}|}{|R|} \tag{8}$$

Among them, R_{t-1} is the last recommendation of R, SSD refers to the proportion of the recommendation list that is not included in the previous recommendation list, and examines the timing diversity of the recommendation results. The smaller the value, the timing diversity of the recommendation lists the better. To improve the diversity of recommendations, the recommendation results of different recommendation algorithms are usually combined, such as MRR, DPP, PRM, and other methods.

4. Applications

The e-commerce industry has seen significant growth in recent years, and with it, the recommendation system has become a crucial component of e-commerce platforms. This section will focus on the application and impact of the recommendation system in popular e-commerce platforms worldwide, providing insights into its practical use.

Table 1 presents an analysis of the impact and effectiveness of recommendation systems on various domestic and international e-commerce platforms, including an evaluation of performance indicators. The objective is to provide a better understanding of the significance and potential applications of recommendation systems within the e-commerce industry.

Table 1 Application and performance indicators of recommendation systems on e-commerce platforms.

Platform		Application situation and effect.	Indicators
Domestic	*Tao Bao*	Using a two-layer retrieval and ranking paradigm, and using the PURS model[5] and self-attention Transformer model[6], to ensure the novelty of recommendation results.	Accuracy Recall
	Pin Duo Duo	Launched ‘Thousands of People and Thousands of Faces’, according to product categories, product attributes, etc., make directional recommendations, and make redirection tags.	Immediacy Accuracy
	Jing Dong	Adopt a business architecture including system architecture, model service, machine learning, and data platform.	Immediacy Recall
International	*Ama-Zong*	Using item-based collaborative filtering algorithm. The recommended catalog is constantly changing over time [7].	Accuracy Diversity
	e-Bay	Collaborative filtering, content recommendation, and other algorithms are used to analyze users’ historical shopping records and bidding behaviors.	Accuracy Diversity Immediacy

After analyzing the recommendation systems of popular e-commerce platforms, it was found that domestic platforms focus on models based on user interests, while foreign platforms prioritize algorithms such as item collaborative filtering. This divergence may be attributed to cultural and consumption habit disparities, as well as differences in data diversity.

This section introduces the practical application of recommender systems on e-commerce platforms and the differences between recommender systems on different e-commerce platforms. It helps to better understand the importance and application prospects of recommendation systems in the e-commerce industry.

5 Existing problems and solutions.

5.1 Data sparsity.

E-commerce platforms have a wide variety of products and a huge amount of user behavior data. However, users' behaviors such as evaluating and purchasing products on the e-commerce platform are not continuous. For instance, on *Taobao*, users tend to focus on purchasing products during major promotions, resulting in a sudden decrease in purchasing behavior post-promotion. Recommender systems frequently encounter the issue of data sparsity. To address this problem, the recommendation algorithm can be fine-tuned to enhance its sophistication and intelligence.

5.2 Cold start problem.

The cold start problem in recommender systems arises when there is insufficient user behavior data or when new users register, making it difficult to provide accurate product recommendations. To overcome this challenge, recommendation systems can leverage linked open data sets and use personal information, to enrich user data for better recommendations [8].

5.3 Interpretability problem.

Recommendation systems on e-commerce platforms often lack transparency and are difficult for users to trust. These algorithms are typically black boxes and do not provide explanations for their recommendations. For instance, *JD*'s recommendation system continues to suggest products based on a user's past purchase behavior, even after they have made numerous purchases. This lack of transparency and explainability can be a barrier to meeting user needs and building trust. For this issue, the system needs to explain the recommendation.

5.4 User privacy protection issues.

To provide personalized recommendation services, the recommendation system requires collecting users' personal information and behavior data. When recommending products based on a user's historical behavior, the recommendation system analyzes user data. However, this can lead to the identifier that identifies the user's identity leaking their privacy information [9][10]. To protect the privacy and rights of users, the recommendation system needs to adopt more effective user privacy protection technologies, such as differential privacy.

6 Conclusion

This paper presents a review of the recommendation system utilized in e-commerce platforms through the application of artificial intelligence technology. The introduction outlines the significance of artificial intelligence technology in the recommendation system of e-commerce platforms and highlights the research purpose and significance of this paper. Then, the technical principle of the system is expounded, and the performance evaluation index of the system is discussed. What's more, it introduces the application and effect of recommendation systems on well-known e-commerce platforms. And the development trends and challenges of the systems for e-commerce platforms. It proposes future research directions. To sum up, this paper provides a comprehensive overview of the recommendation system of an e-commerce platform based on artificial intelligence technology and looks forward to the future development direction.

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