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Article

Optimization and Innovation of AI-Based E-Commerce Platform Recommendation System

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Abstract: With the rapid advancement of artificial intelligence (AI) technology, recommendation systems on e-commerce platforms have become essential tools for enhancing user experience and optimizing sales strategies. This study systematically investigates the optimization and innovation of AI-based recommendation systems, identifying key challenges in data quality, algorithmic accuracy, and system adaptability in current platforms. To address these challenges, we propose integrated strategies involving big data analytics, deep learning models, and data fusion techniques to improve the precision and personalization of recommendations. Additionally, the exploration of emerging technologies, such as natural language processing and graph computing, highlights the potential for more context-aware, interpretable, and scalable recommendation frameworks. By leveraging these approaches, intelligent recommendation systems can provide more diversified, user-centric services, thereby promoting higher engagement and supporting the sustainable development of e-commerce ecosystems.

Keywords: AI recommendation system; big data; deep learning; personalized recommendation; social recommendations

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1. Introduction

Personalized recommendation has become a core technology for e-commerce platforms to enhance user experience and increase conversion rates. By analyzing users' browsing behavior, purchase history, and preference patterns, recommendation systems can deliver targeted content and product suggestions, thereby improving user engagement and platform profitability. However, traditional recommendation algorithms often face limitations, such as low data quality, insufficient feature representation, and restricted algorithmic accuracy, which hinder their ability to provide precise and personalized recommendations [1].

The integration of artificial intelligence (AI) technology into recommendation systems offers promising solutions to these challenges. AI techniques, including machine learning, deep learning, and natural language processing, can optimize algorithmic performance, enhance data processing efficiency, and support the construction of more intelligent, context-aware recommendation frameworks. Furthermore, AI-based approaches enable platforms to better handle large-scale and heterogeneous data, improve predictive accuracy, and adapt to dynamic user preferences in real time. In addition, advanced AI models provide opportunities to strengthen user privacy protection while maintaining recommendation effectiveness, addressing growing concerns over data security.

This study aims to explore the optimization and innovation paths of AI in recommendation systems on e-commerce platforms. By systematically examining current challenges and emerging AI-driven solutions, this article seeks to provide theoretical guidance for the development of more intelligent, scalable, and user-centric recommendation technologies. Ultimately, the research contributes to the understanding of how AI can support the sustainable growth of e-commerce ecosystems while delivering a superior user experience [2].

2. The Role of AI in Recommendation Systems for E-commerce Platforms

Artificial intelligence (AI) technology leverages large-scale data analysis and continuous algorithmic optimization to deliver personalized content, thereby enhancing user interaction and improving platform operational efficiency. By applying AI, intelligent recommendation systems can integrate multi-dimensional information, including user behavior records, preference patterns, and online browsing habits, to construct detailed user profiles, predict potential user needs, and provide targeted product or service recommendations.

This process relies heavily on AI technologies such as deep learning, machine learning, and intelligent algorithms to accurately process and interpret complex and heterogeneous data. AI-driven recommendation systems possess strong adaptability and high accuracy, forming their core competitive advantage and surpassing traditional rule-based recommendation models. These systems continuously analyze user behavior patterns and feedback, dynamically adjust and optimize recommendation algorithms, and align content delivery more closely with actual user needs. As a result, conversion rates and user engagement are significantly enhanced [3].

Moreover, AI enables platforms to process large volumes of data in real time, facilitating instantaneous personalized content delivery. This capability not only improves management efficiency but also drives increased business revenue and platform profitability. By incorporating AI into recommendation systems, e-commerce platforms can achieve a balance between operational scalability, personalization accuracy, and user satisfaction, ultimately supporting sustainable growth and competitive advantage in an increasingly data-driven market environment.

3. Problems with E-commerce Platform Recommendation Systems

3.1. Data Quality Issues

One of the primary challenges faced by e-commerce platforms in implementing personalized recommendation algorithms is the issue of low-quality data. User behavior data often exhibits uneven distribution, particularly for newly registered users or recently launched products, which makes it difficult for the system to accurately infer users' true preferences from limited information. This limitation directly impacts the precision of recommendation results [4].

Data incompleteness is another common problem. Many users do not provide comprehensive personal information, and some user behaviors may not be fully captured by the platform, restricting the recommendation system's ability to gain a thorough understanding of user needs. Additionally, datasets often contain a significant amount of noisy data, which may originate from recording errors, atypical user interactions, or automated bot activity. Such noise not only undermines data reliability but also disrupts the training of recommendation algorithms, reducing the system's overall effectiveness. Consequently, low-quality data can significantly weaken the performance of recommendation systems, limiting both the accuracy and practical utility of the recommendations provided to users [5].

3.2. Accuracy and Diversity Issues of Recommendation Algorithms

In many e-commerce platforms, collaborative filtering and content-based methods are commonly employed for product recommendation. However, these traditional algorithms often struggle with data sparsity when handling large volumes of user and product information, leading to decreased recommendation accuracy. Furthermore, algorithms that primarily rely on historical user behavior tend to reinforce existing preferences, which reduces the diversity of recommended content and limits users' exposure to new or less familiar products.

A recommendation system that overemphasizes past behavior may generate a narrow, predictable user experience, neglecting users' potential interests in other product categories. Striking an effective balance between recommendation accuracy and content diversity remains a key challenge, as focusing solely on precision can lead to monotonous recommendations, while emphasizing diversity without sufficient personalization may reduce user satisfaction. Addressing these challenges is crucial for enhancing the overall performance and user engagement of e-commerce recommendation systems [6,7].

4. Optimization Strategies for AI based Recommendation Systems

4.1. Big Data and Deep Learning Optimization Recommendation Algorithm

In the practical application of recommendation systems, deep learning technology plays an extremely important role in improving recommendation accuracy, especially by integrating big data processing capabilities and complex neural network models. In order to further optimize recommendation algorithms, deep learning techniques such as neural network-based collaborative filtering models and deep autoencoders have been widely adopted [8]. These algorithms can more effectively explore users' deep preferences and diverse behavioral patterns, thereby enhancing the accuracy of recommendations. The neural network collaborative filtering algorithm, with the help of deep learning architecture, can automatically extract low-dimensional representations of users and products from large amounts of data, effectively addressing data sparsity and cold-start problems for new users or products. The optimization objective of this algorithm is to reduce the difference between the predicted score and the actual score, and the mean square error is usually used as the loss function to evaluate the prediction accuracy:

$$L = \frac{1}{N}\sum_{i=1}^{N}(r_{ui} - \hat{r}_{ui})^2 \quad (1)$$

In formula (1), r_{ui} is the actual rating of i $\hat{r}_{ui}$ is the predicted rating value, N is the total amount of rating dataset, and the loss function aims to adjust the weights within the neural network, with the goal of making the predicted rating value closer to the actual rating value. For example, extracting user behavior data from e-commerce platforms, which involves users' rating information for diverse products, is applied to neural network-based collaborative filtering technology to construct a latent feature model between users and products. In the experimental design, arrange 20 training cycles and record the value of the loss function (MSE) at the end of each cycle. The fluctuation of the loss function (such as mean square error MSE) during the tracked training process is shown in Figure 1, in order to monitor the dynamic optimization of the model.

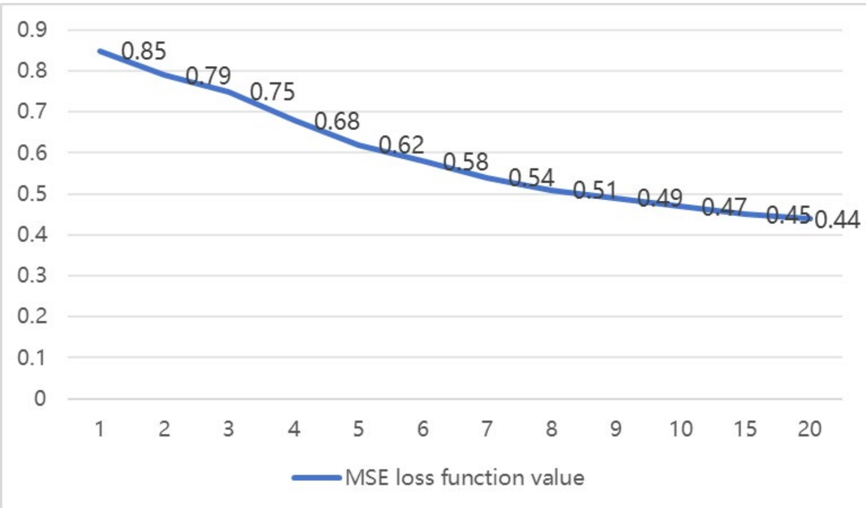

Figure 1. Trend of Loss Function Changes.

As shown in Figure 1, during the initial stage of training, the value of the loss function decreases rapidly, indicating that the model is effectively learning and optimizing the recommendation output. As training progresses, the model parameters gradually approach an optimal and stable state, and the rate of decline in the loss function begins to slow down. At this stage, the effect of model adjustment becomes increasingly stable. If training continues, the value of the loss function will eventually reach a lower level and remain unchanged, suggesting that the model has converged and further performance improvement is minimal. At this point, the recommendation system is capable of accurately extracting users' implicit preferences from large amounts of data, thereby further improving the accuracy of recommendation results.

4.2. Intelligent Recommendation and Personalized Optimization

Intelligent recommendation algorithms commonly employ trained neural networks or reinforcement learning models to enhance their effectiveness. For example, deep neural networks (DNNs) are used to capture user preferences and integrate various behavioral data, such as clicks, browsing history, and purchase records, to achieve personalized recommendations.

4.2.1. Personalized Recommendation Modeling in Deepening Learning

Firstly, in terms of embedding user and item attributes, the system maps the attribute vectors of users and items into a low-dimensional space and extracts latent feature vectors through the embedding layer. For specific users u and items i, the latent feature vectors in the low-dimensional space are denoted as u and i, respectively. These vectors can be obtained and represented through the embedding layer in the neural network:

$$u = \text{Embedding}_u(\text{user features});\ i = \text{Embedding}_i(\text{item features}) \quad (3)$$

Secondly, regarding the prediction mechanism of the user-item interaction model, the system fuses the low-dimensional embedding vectors of users and items and inputs them into a neural network for nonlinear transformation. In this way, the user's preference for a specific item can be estimated. The estimated result can be expressed as the user's predicted rating or the recommendation probability for that item:

$$\hat{r}_{ui} = f(u, i, \theta) \quad (4)$$

In formula (4), f is a non-linear mapping such as a multi-layer neural network in deep learning, and θ represents the adjustment parameter of the network $\hat{r}_{ui}$ represents the estimated value of user u for product i. In intelligent recommendation systems, the core pursuit is to reduce bias in the recommendation process, and Mean Squared Error (MSE) is commonly used as the standard for the loss function. For the optimization of personalized recommendation models, the system adopts efficient algorithms to iteratively update the model parameters to ensure that the accuracy of recommendation results matches user preferences. By continuously adjusting the model parameters, the value of the loss function is reduced, thereby improving the personalization of recommendations [9].

4.2.2. The Policy Gradient Process of Reinforcement Learning

In the field of reinforcement learning, the recommendation mechanism aims to maximize cumulative rewards. Its core lies in constructing a policy π that determines recommendation actions capable of achieving long-term benefit optimization. The iterative update of the policy can be expressed as follows:

$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta J(\theta) \quad (5)$$

In formula (5), α is the learning rate, $\nabla_\theta J(\theta)$ is the gradient of the strategy, and $J(\theta)$ is the expected reward function. With this strategy, the recommendation system can track and adapt to the evolution of user preferences, and output customized recommendation results in real-time. This process not only improves the accuracy of recommendations, but also enhances the adaptability and variability of the system, allowing users to experience a recommendation experience that is more tailored to their individual needs.

5. Innovative Application of E-commerce Platform Recommendation System Driven by AI Technology

5.1. Intelligent Recommendations Based on Natural Language Processing

Natural language processing (NLP) converts textual information into a machine-understandable format, enabling the system to extract valuable insights from various text sources such as product descriptions, user reviews, and social media posts, and to recommend relevant products to users [10].

NLP models typically involve several key technologies, including word vector representation (Word Embeddings), keyword extraction (TF-IDF), and sentiment analysis. These technologies play a significant role in improving product recommendations. Sentiment analysis, in particular, enables the system to identify positive or negative feedback from users, thereby enhancing the accuracy and relevance of the recommended results.

The structure of the natural language processing model is illustrated in Figure 2.

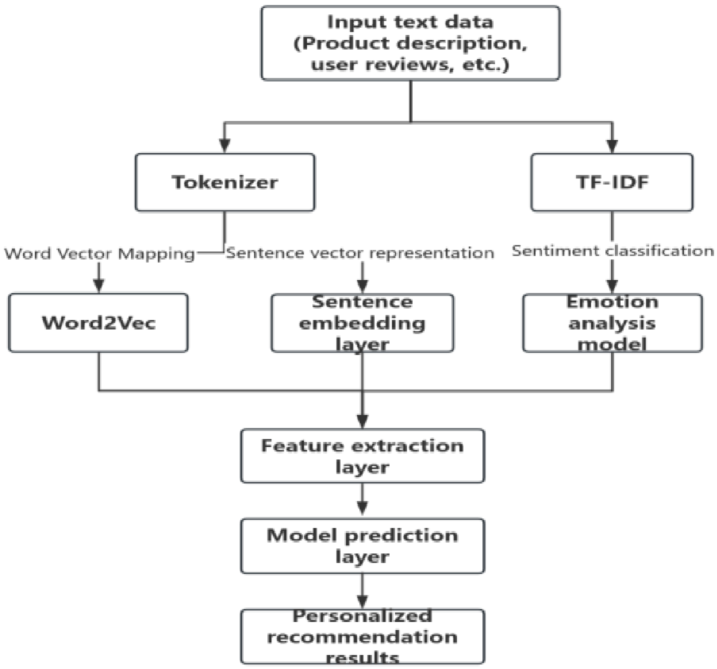

Figure 2. NLP model structure.

As shown in Figure 2, this structure illustrates in detail the application of advanced natural language processing techniques, including Word2Vec, TF-IDF, and sentiment analysis, to extract and process textual data and integrate the processed results into an intelligent recommendation system. Each stage is designed to enhance the system's understanding of the semantic content of the text, thereby achieving more refined and personalized recommendation objectives. Based on this framework, the recommendation system can combine diverse textual resources such as product descriptions and user feedback, while incorporating sentiment analysis strategies to deliver more accurate and personalized product recommendations to users.

5.2. Graph Based Social Recommendation System

In the recommendation mechanism of social networks, interactions between participants and products are represented as edges and nodes within a graph, where nodes correspond to either users or products. By applying graph algorithms, the system can effectively explore the complex relationships among users and generate personalized recommendations based on these connections. For instance, the system may recommend products favored by a user's friends based on their proximity within the social network, or suggest behaviors and preferences similar to those of other users with shared interests. In the graph-based recommendation system, the critical step involves extracting meaningful information from the social network graph. The primary technical applications related to this process are presented in Table 1.

Table 1. Main Technologies of Graph based Social Recommendation System.

technical method	Main application scenarios	advantage
Graph based collaborative filtering	Calculate similarity through user item graph and recommend items to users	Ability to improve recommendation relevance based on neighbor recommendations
pagerank algorithm	Analyze the weight relationship between users and items, and recommend items with high importance	Capture global influence, suitable for large-scale social networks
Community Discovery Algorithm	Recommend items with similar interests by dividing user groups	Improve recommendation accuracy based on user group behavior patterns
Graph Convolutional Network (GCN)	Using graph structures and deep learning methods for recommendation	Capable of handling complex graph structures and capturing nonlinear relationships

As shown in Table 1, graph-based collaborative filtering technology explores the intrinsic connections between users and products, enabling the accurate recommendation of relevant items. This approach is particularly effective in social network scenarios with rich interaction data. The PageRank algorithm evaluates the influence of users and products within the network and recommends key items based on node weights. Community detection algorithms further enhance recommendation accuracy by leveraging the similarity of preferences within user groups. Graph Convolutional Networks (GCNs) incorporate deep learning concepts to process complex graph-structured data, uncover non-linear relationships between users and products, and improve both personalization and recommendation accuracy. Overall, graph computing technologies have significantly enhanced the performance of recommendation systems by deeply mining users' social connections and behavioral patterns.

5.3. Integration of AI and Real time Recommendation System

In the dynamic recommendation mechanism, artificial intelligence technology is combined with real-time data stream analysis to provide immediate responses to user behavior and deliver customized, real-time recommendation content. This approach leverages streaming data processing capabilities to analyze users' dynamic behaviors as they occur, while employing self-updating models to maintain recommendation accuracy. For real-time data processing, systems typically utilize models such as Recurrent Neural Networks (RNNs), which can predict users' future preferences based on their current behavior sequences and enable the completion of real-time recommendation tasks.

5.3.1. Real Time Streaming Data Update Formula

The system dynamically updates the user's interest graph based on their real-time behavior data at a specific time point, following the mathematical model below:

$$R_u(t+1) = R_u(t) + \alpha \Delta R_u(t) \tag{6}$$

Among them, Ru(t) represents the interest vector of user u at time t, ΔRu(t) denotes the fluctuation of user interests during this period, and α is the learning rate, which determines the speed of updates to the interest graph. The learning rate αcontrols the magnitude of interest graph adjustments, ensuring that the system responds sensitively to new user behaviors while avoiding instability caused by excessive changes. Through continuous iteration and updates, the model can capture changes in user interests in real time and continuously optimize the performance of the recommendation system.

5.3.2. Real Time Recommendation Based on RNN

Recurrent Neural Networks (RNNs) can effectively process time-series data, particularly when real-time performance is required in recommendation systems. In a real-time recommendation algorithm utilizing RNN technology, the system predicts the user's next behavior b_{t+1} based on the sequence of past behaviors {b1, b2, ..., bt} and the current behavior b_t. The update formula is as follows:

$$h_t = \sigma(W_h \times h_{t-1} + Wx \times b_t);\ \hat{b}_{t+1} = W_o \times h_t \quad (7)$$

Among them, h_t is the output of the RNN hidden layer, W_h, W_x, W_o are the weight matrices, and$\sigma$is the activation function. To evaluate the effectiveness of the AI integrated real-time recommendation system, four different recommendation algorithms were selected for comparison, aiming to explore their advantages and disadvantages in real-time recommendation and recommendation accuracy. The dataset used covers 2 million behavioral records of approximately 100000 users. This experiment simulates a real-time recommendation scenario, dividing the dataset into a training set (historical behavior data) and a real-time set (behavior records from the last 24 hours). During the testing process, each recommendation algorithm underwent corresponding training and validation. By implementing cross validation methods, the effectiveness of various recommendation algorithms was comprehensively evaluated to ensure the accuracy and credibility of the results obtained. The experimental comparison results are shown in Table 2.

Table 2. Performance Comparison of Real time Recommendation Systems.

Recommended system type	**Response time**	**Recommendation accuracy**	**Real time update capability**	**Applicable scenarios**
Traditional recommendation system	3-5	75%-85%	Lower	Static data recommendation, offline recommendation
Real time recommendation system based on AI	1-3	85%-95%	tall	Dynamic user behavior analysis and personalized recommendations
Hybrid recommendation system	2-4	80%-90%	medium	Based on multiple algorithms
Deep Learning Recommendation System	1-2	90%-98%	tall	Based on multiple algorithms

From the data comparison presented in Table 2, it is evident that integrating AI technology with real-time recommendation systems significantly improves both the accuracy of recommendations and the system's real-time responsiveness. The application of deep learning algorithms in recommendation systems, with their advanced data processing capabilities, not only enhances the precision of recommendation results but also demonstrates high efficiency in handling real-time information. In practical scenarios, AI-based real-time recommendation systems are particularly well suited for e-commerce and social networking platforms that require rapid adaptation to changes in user behavior.

6. Conclusion

In the collaborative development of data processing and algorithm design, artificial intelligence has become a powerful driving force in advancing recommendation systems toward greater efficiency, precision, and personalization. Optimization through big data and deep learning, precise enhancement via multimodal data fusion, intelligent recommendation, and personalized adjustments make product recommendations on e-commerce platforms more targeted and effective. Additionally, by integrating technologies such as natural language understanding and graph computing, recommendation algorithms exhibit strong adaptability and scalability when processing complex information. Looking forward, with the continued advancement of technology, AI-driven recommendation systems are expected to play a central role in diverse scenarios, delivering higher economic benefits to the e-commerce industry.

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