RUICP: Commodity Recommendation Model Based on User Real Time Interest and Commodity Popularity

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***Abstract*—At present, the recommendation of massive commodities mainly depends on the short-term click through rate of commodities and the data directly browsed and clicked by users. This recommendation method can better meet the shopping needs of users, but there are two shortcomings. One is to recommend homogeneous commodities to long-term shopping users; second, we can't grasp the real-time changes of users' interests, and can only recommend results similar to the recently clicked products. Therefore, this study intends to establish a time-varying expression method of users' interest intensity to solve the deviation of real-time recommendation content, and propose a recommendation model RUICP based on users' time-dependent interest and commodity heat. Firstly, the user's basic data and cumulative usage information are used for portrait, specifically, the user's usage data is divided into isochronous and deep-seated semantic feature analysis, the model is optimized and the user's long-term interest intensity is obtained after parameter estimation; Then, the user's short-term interest is obtained by splitting the user's short-term use data, and the user's final interest is calculated by combining the short-term interest and the user's long-term interest intensity; Then calculate the product popularity score by adding the repeated click through rate of products, and then update the ranking of products; Finally, the classic item based collaborative filtering algorithm is used to calculate the matching degree of user interest and goods, and then recommend. The results of simulation experiments show that compared with other methods, RUICP has higher recommendation accuracy for old users and has certain value for solving the cold start problem.**

Keywords*—*User real time interest; commodity popularity; recommend

I. Introduction

According to the "48th Statistical Report on Internet Development in China," with the development of mobile internet, China has reached 1.007 billion mobile internet users, and the scale of online shopping users has reached 812 million, with an internet penetration rate of 80.3%. In the vast sea of users and commodities, personalized recommendation systems play an extremely important role. They can meet the personalized needs of users, quickly and accurately find products, on the other hand, help high-quality products be discovered by more users, thus benefiting merchants and achieving a win-win situation for both users and merchants.

The commodity recommendation system will establish a corresponding interest model according to each user's basic information, likes, browsing and other operations, and can recommend commodities with corresponding topics according to the model. This model is based on the stability of user interest, that is, the overall interest of users does not change much with time, and then adjust the interest direction. According to partial feedback, many scholars also put forward corresponding models based on this, relying on matrix decomposition technology [1] to learn the potential characteristics of users and projects. He et al. [2] established the NCF model, and the neural network method is used for the interaction between users and project features of the recommendation system, making the recommendation officially enter the research field with deep learning as the main technology.

However, in practical use, user interests change over time. The time sequence of interactions between users and items can reflect changes in user interests. Commodity recommendation systems achieve real-time recommendation based on this principle. However, existing hardware computing power is limited, and recommendation systems based on long sequence information of users often suffer from slow computation or sacrifice a certain degree of accuracy for computational speed. Regardless of the method chosen, it results in poor user experience. To address this challenge, some scholars have begun to study recommendation systems based on short sequence information. This approach focuses on the activities of users in the recent past, modeling user short-term interests through actions such as browsing and liking, to capture short-term changes in user interests. This method not only avoids the high time complexity of processing long sequence information but also allows for real-time tracking of user interest changes, thereby achieving precise recommendations in the short term. However, this approach also has significant limitations in capturing user interests and preferences over long periods.

In response to the aforementioned issues, this paper conducts an in-depth analysis of the shortcomings in existing research and proposes a recommendation model named RUICP, based on real-time user interest and commodity popularity. This model not only captures the characteristic of user interests changing over time and adjusts recommendations in real-time to meet personalized user needs but also effectively addresses the cold start problem by introducing the factor of commodity popularity. Through this research, we aim to provide new ideas and methods for the development of recommendation systems, further promoting innovation and

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application of personalized recommendation technology. The main contributions of this paper are as follows:

- Proposed a method for calculating long and short-term user time-sensitive interests, which can more accurately capture changes in user interests.
- Designed a new method for calculating commodity popularity, taking into account user repeat click rates, resulting in more scientifically derived results.
- Empirical evidence demonstrates that the proposed method in this paper has certain accuracy advantages and provides valuable insights for addressing the cold start problem.

The rest is as follows: Section II discusses related work. Section III introduces the model of this article in detail. Section IV evaluates the method proposed in this article. Section V concludes the study and outlines future work.

II. Related Work

In the field of commodity recommendation, scholars have explored various methods, primarily focusing on user behavior, commodity attributes, and their interactions. For instance, Wang et al. [3] introduced a recommendation algorithm that emphasizes user click behavior, inferring preferences by analyzing user browsing patterns to identify points of interest. Similarly, Ficel et al. [4] utilized the relationship between users and commodities for recommendations. They first modeled articles based on freshness and popularity then inferred user preferences based on personal information and browsing history, and finally recommended commodities by integrating the two pieces of information. Experimental results show the reliability of this method. However, while these methods provide valuable insights into user behavior and preferences, they may overlook certain temporal dynamics, failing to capture the essence of changes in user interests over time. Mookiah et al. [5] modeled commodity relationships using a heterogeneous graph approach, capturing key commodities for filtering, which is effective for users with low interactivity, particularly in specific scenarios for precise recommendations, but lacks universality. Sung et al. [6] investigated the attractiveness of commodity titles and keywords to users, simulating user perception from the perspective of commodity titles to recommend commodities with attractive titles, thereby increasing click-through rates. Although this method enables rapid recommendations, it may lead to the problem of homogeneous commodities. Han et al. [7] personalized commodity recommendations by analyzing user browsing records, employing an improved association rule combined with collaborative filtering algorithms. While this method offers stable overall performance and considers multiple factors for recommendations, it may be constrained when dealing with complex user behavior patterns and may not adequately address the cold start problem for new users.

In recent years, scholars have begun researching recommendation methods based on deep learning. Zheng et al. [9] proposed a recommendation framework based on Q-Learning to simulate feedback after clicks, searching for attractive commodities for users based on feedback information, but requires large amounts of data and computational resources for model training and optimization. Epure et al. [10] studied changes in browsing interests over time, dividing interests into short-term, medium-term, and long-term levels, concluding that a combination of long-term and short-term recommendations achieves the highest accuracy. Recommendations based on a combination of medium-term and short-term interests may increase the variety of commodities but may not be significant for some users with less obvious changes in interests over different periods. Qi et al. [11] investigated popular commodities to address the cold start problem and insufficient diversity in recommendation systems, combining personalized matching scores with commodity popularity to calculate recommendation rankings. This method innovatively proposes a popularity calculation method but overly relies on popularity factors, resulting in personalized recommendations lacking diversity. Ji et al. [12] studied the dynamic characteristics of interaction times between users and commodities, utilizing a time-sensitive heterogeneous graph neural network based on commodity recommendation, improving recommendation accuracy and providing better interpretability compared to traditional neural network methods. Meng et al. [13] studied the importance of commodity lifecycle, integrating user preference attention and commodity lifecycle, modeling the dual impact of user clicks on commodities. Ji et al. [14] used commodity click-through rates to measure commodity popularity. Wu et al. [15] employed attention mechanism networks to learn commodity and user representations. Despite significant progress in recommendation systems, existing methods still have some limitations. Firstly, existing methods often struggle to accurately capture and model the dynamic nature of user interest changes, resulting in recommendations deviating from actual user needs. Secondly, existing methods often have difficulty fully considering the diversity of commodity attributes and the complexity of user preferences, limiting the accuracy and personalization of recommendations. Additionally, the cold start and diversity problems in recommendation systems remain significant challenges. Therefore, we conducted this work and proposed RUICP, hoping to explore more accurate and personalized recommendation methods by deeply studying the dynamic interactions between users and commodities.

III. Calculation Model

The RUICP model proposed in this paper, as illustrated in Fig. 1, introduces innovative designs at several key steps.

Firstly, RUICP leverages user basic data and accumulated usage information to construct refined user profiles. By partitioning user usage data into equal time intervals and conducting in-depth semantic feature analysis, the model can more accurately capture users' long-term interest intensity. Next, the model focuses on short-term changes in user interests. By splitting short-term usage data, the model can quickly capture users' short-term interest points. Additionally, by combining short-term interest with long-term interest intensity, the model can comprehensively consider users' stable and temporary interests, generating recommendations that better fit current needs, forming the final interest.

In addition to considering user interests, the model innovatively introduces commodity repeat click rates to calculate commodity popularity scores. This metric reflects the actual attractiveness of commodities and user attention, providing a more reasonable basis for ranking commodities. By updating commodity rankings, the model ensures that high-quality and popular commodities receive more exposure opportunities. Finally, RUICP employs the classic model-based collaborative filtering algorithm [8] to calculate the matching degree between user interests and commodities. This algorithm comprehensively considers user historical behavior, commodity attributes, and user-commodity interaction relationships, providing users with more accurate and personalized recommendations. By combining user profiles and commodity rankings from the aforementioned steps, the model can present users with a rich and diverse recommendation list.

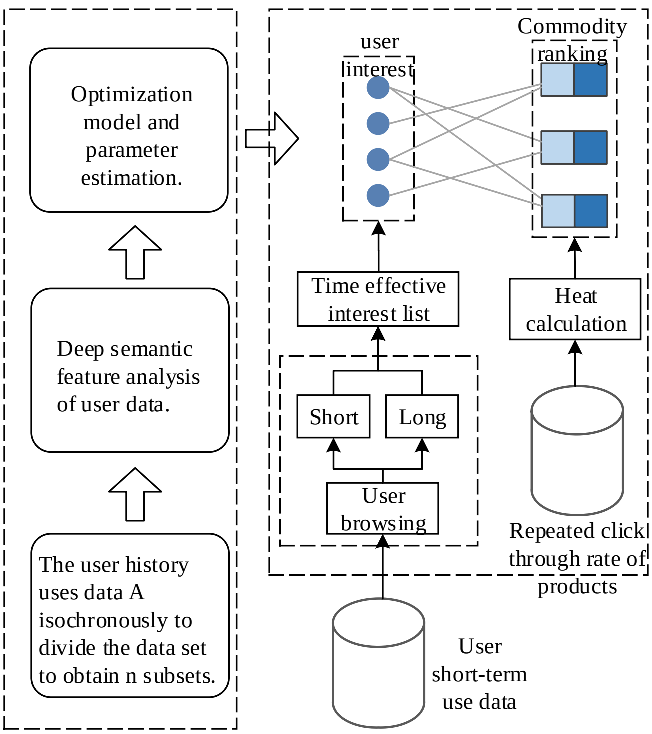

Fig. 1. Product recommendation model.

A. User Portrait

Constructing user profiles is a crucial step in recommendation systems, revealing users' interests and preferences through in-depth exploration of user basic data and accumulated usage information. In the recommended model proposed in this paper, the construction of user profiles is particularly refined and comprehensive.

Firstly, RUICP fully utilizes user basic data, which hides users' points of interest. For example, geographic location information can reflect users' regional consumption habits; for instance, users in the northern regions may be more inclined to purchase garlic and kang tables, whereas users in the southern regions may not be interested in these commodities. Furthermore, RUICP divides user usage data into time periods and deeply analyzes users' behavioral patterns during each period. By calculating the number of clicks C_u and browsing duration L_u in each period, RUICP can further characterize changes in user interests.

It is worth noting that this paper does not include shopping cart information when constructing user profiles. This is because many users do not have the habit of adding items to their shopping carts, or only add items to their shopping carts before checkout, after which they no longer pay attention to these items. Moreover, shopping cart information often has strong interest tendencies. If incorporated into the recommendation system, it may cause the system to repeatedly recommend items that users have added to their shopping carts, causing inconvenience to users. Additionally, adding shopping cart information increases data dimensions, leading to increased computational difficulty, which is not conducive to real-time recommendations. To avoid these problems, we adopt a more reasonable interest prediction method. During the model parameter estimation phase, we introduce a smoothing parameter G and set it to 10. The introduction of this parameter helps smooth changes in user interests, making the prediction results more stable and accurate. Finally, we calculate the user's interest prediction value according to Eq. (1), which provides an important basis for subsequent commodity recommendations.

$$U_i = \frac{\sum\left(\sum_{n\in t} C_n \times \frac{\alpha C_i + \beta L_u}{C_{total}} \times p^t + G\right)}{\sum_{n\in t} C_n} \quad (1)$$

where, U_i represents the user's interest in topic i, α and β are set to 0.5 and 0.3 respectively, $\sum_{n\in t} C_n$ is the total number of clicks by the user during period t, p^t is the probability of the user clicking on item i during period t, and C_{total} is the total number of clicks during the user's usage period.

B. User Real-Time Interest

During the entire browsing process, users may be attracted by promotional activities or exquisite products, resulting in continuously changing real-time interests. Traditional recommendation methods often overlook the rapid changes in user interests within a very short period, or use commodity similarity as a substitute for these changes. Many studies assume that when a user clicks on a product, it indicates their interest at that moment, and therefore recommend similar products. However, this approach has two problems: 1) Users may be recommended similar products after accidental clicks; 2) Users may click on a product out of curiosity, without genuine interest, yet the recommendation system still relies on browsing history to suggest similar products. Therefore, this paper investigates user real-time interests and proposes a method to capture them. The core idea of this method is to differentiate between users' long-term and short-term interests based on their usage duration and click behavior, and adjust the recommendation strategy accordingly.

Firstly, RUICP categorize user behavior into long-term and short-term types based on their usage duration. Lengthy browsing typically reflects the types of products that users have long-term interest in, which is crucial for determining their long-term interests. We calculate the user's long-term interest U_L by weighting the user's dwell time on each product. In contrast, short-term browsing may more likely reflect users' temporary needs or curiosity, with a lower contribution to short-term interest U_S. Next, we further divide users' short-term behavior. By partitioning short-term click behavior based on the time of clicking, we obtain U_{s1}, U_{s2}, and so on. We then use the cosine similarity formula to calculate the similarity between these products. If the similarity between products is high and the user has made a purchase, we consider this click as not representing the user's genuine interest but possibly due to accidental clicks or curiosity. Conversely, if the similarity between products is low, the categories to which these products belong are more likely to be the user's short-term interest points U_S. To more accurately measure the user's real-time interest intensity, we propose a comprehensive calculation formula that combines the user's long-term interest and short-term interest, considering the impact of the interest factor d, as shown in Eq. (2).

$$I_u = 1 - d + d(\alpha U_L + \beta \sum U_{si}) \tag{2}$$

where, $\sum U_{si}$ represents the comprehensive weight of similar products, and dd represents the interest factor. By adjusting the value of the interest factor, we can control the weight of long-term and short-term interests in the final recommendation, thus flexibly adapting to the personalized needs of different users.

Furthermore, when calculating product similarity, we adopt the classic TF-IDF method. Considering that users with a wider range of interests may behave more randomly without clear objectives, we adjust their contribution to similarity calculation based on their behavior quantity. The more behaviors a user have, the lower their contribution, to avoid the excessive influence of random behaviors on similarity calculation. The specific calculation is as shown in Eq. (3) and Eq. (4).

$$Sim^W(i,j) = \frac{\sum_{u \in U} w_u \delta(i,j)}{\sum_{u \in U} w_u} \tag{3}$$

$$w_u = \frac{1}{\log I_u + 1}\ , \delta(i,j) = \begin{cases} 1, i \in I_u \, and \, j \in I_u \\ 0, else \end{cases} \tag{4}$$

Where U is the set of all users, U_i is the set of users interested in product i, W_u represents the contribution of user u to similarity, and I_u is the user's real-time interest intensity.

C. Commodity Heat Calculation

Commodity hotness is a crucial indicator of the popularity of products. Accurately calculating commodity hotness is essential for improving the accuracy and timeliness of recommendations in recommendation systems. Traditional methods for calculating commodity hotness are typically based on factors such as product attributes, click-through rates, and release time. However, these methods may not fully reflect the actual popularity of products, especially for those products that have been on the market for a long time but maintain stable sales.

In China's leading online shopping platform, Taobao, products are classified into 15 major categories. For international understanding and analysis, this paper integrates them into 10 major categories. Moreover, based on the "Analysis of Major Category Transaction Data on Taobao - 2019Q1" report, we accurately calculate the influence factors of various product categories, as shown in Table I.

TABLE I. INFLUENCE FACTORS OF PRODUCTS

Classification	Influence Factor	Classification	Influence Factor
Clothing	0.85	Snacks	0.85
Beauty Makeup	0.76	Digital	0.76
Ingredients	0.63	Home Furnishing	0.63
Medicine	0.56	Luxury Goods	0.56
Vehicle	0.24	Other	0.24

Based on these influence factors and considering practical life scenarios, we propose a new method for calculating commodity hotness to more accurately reflect the actual popularity of products. Firstly, we consider the basic attributes of products, such as product type, and set different influence factors for different types of products. For example, products with high consumption frequency, such as clothing and snacks, have relatively high influence factors, while products such as cars and other special types have lower influence factors. This approach allows for consideration of the differences in basic market demand for different types of products. RUICP integrates user interaction data for products to calculate commodity hotness H, as shown in Eq. (5).

$$H = \frac{W+K}{(T+1)^G} \tag{5}$$

W is the normalized sum of product views, comments, likes, etc., to eliminate dimensional differences between different data sources and enable comparison and weighting. K is the influence factor of the product. T is the time since the product was released. G is a smoothing parameter used to control the rate of decay of commodity hotness over time. By adjusting the value of G, the balance between freshness and historical popularity of products can be controlled, allowing the recommendation results to reflect both currently trending products and maintain attention to classic products.

However, considering only the above factors may still not fully reflect the true hotness of products. As shown in Table I, in fact, some products, despite being on the market for a long time, maintain very high sales due to their excellent quality or unique value, and their hotness does not significantly decay over time. If traditional hotness calculation methods are used, the hotness of these classic products may be severely underestimated. Therefore, we further consider the repeat click rate D of users and propose a new hotness calculation method, using it as an important indicator to measure commodity hotness. The repeat click rate can reflect users' sustained interest in products and is an effective indicator of the persistence of product hotness, as shown in Eq. (6).

$$H = \frac{\max(W,D)+U}{(\frac{T}{\log D}+1)^G} \tag{6}$$

By comprehensively considering the repeat click rate and other relevant factors, we can more comprehensively evaluate the hotness of products, thereby providing consumers with more accurate and valuable recommendations. This method not only helps improve the shopping experience for users but also provides businesses with a more scientific approach to product management and marketing strategies.

IV. Experimental Settings and Evaluation Indicators

A. Dataset and Experimental Setup

The dataset used in this experiment is from the KDD Cup 2020 Track-B, which is a publicly available dataset covering user-clicked behaviors over ten days. It contains over 1 million click records, involving 100,000 commodities and 30,000 users. Such scale ensures that our research has sufficient breadth and depth to fully reflect the diversity and complexity of user behavior. Considering that the original dataset may contain some missing and redundant information, we conducted disambiguation and deduplication processes to ensure the accuracy and effectiveness of the data.

User Features: Include user ID, age group, gender, and city hierarchy.

Commodity Features: Include features of the commodities, represented as 128-dimensional text features.

Training Set: Records the user's historical click behavior, excluding the latest 10 clicks.

Validation Set: Contains the historical click behavior of users to be predicted, consisting of the latest 10 clicks for each user.

In the dataset, user features are a crucial part for understanding user preferences and behavior patterns, while commodity features can better characterize the attributes and characteristics of commodities. These features can effectively depict the diversity and differences of commodities, contributing to improved recommendation accuracy and personalization. In terms of experimental settings, we divided the dataset into training and validation sets. The training set is mainly used to calculate the strength of user interest, from which we can derive the representation of interest strength for each user by mining patterns and information in their historical click behavior. Additionally, the training set is used to extract the number of clicks and non-clicks of commodities within the last 30 minutes to calculate commodity popularity. The validation set is used to evaluate the performance of the model, consisting of the latest 10 click records for each user, which will be treated as the user's historical click behavior to be predicted. By comparing the model's predicted results with the actual click behavior; we can assess the accuracy and effectiveness of the model. Table II details the specific statistics of the dataset.

TABLE II. DATASET STATISTICS

Users	Commodities	Training Records	Validation Records
6,737	117,538	174,414	67,370

To comprehensively evaluate the performance of the model, we selected AUC, nDCG@5, and nDCG@10 as evaluation metrics. A higher AUC value indicates better classification performance of the model, while values of nDCG@5 and nDCG@10 closer to 1 indicate higher quality of recommendation ranking in the Top-K recommendation results. These metrics provide a comprehensive and objective method for evaluating the performance of the recommendation system.

In terms of selecting comparison methods, we chose several excellent methods in the field of commodity recommendation as benchmarks. These methods include DRN [9], which recommends commodities by simulating feedback after clicks, DCAN [13], which integrates user preference attention and commodity lifecycle, CTR [14], which measures popularity based on click-through rate, and NPA [15], which learns commodity and user representations using attention mechanism networks. By comparing with these methods, we can objectively and accurately evaluate the performance and advantages of our proposed RUICP algorithm in the experiment.

B. User Cold Start

To comprehensively evaluate the effectiveness of RUICP in addressing the cold start problem, we designed a series of rigorous validation measures. Firstly, we simulated scenarios with new users and conducted four experiments, recommending commodities after 1, 3, 5, and 7 clicks respectively. The aim was to explore the recommendation performance of RUICP under different numbers of clicks. With this carefully designed experiment, we were able to systematically observe and analyze the performance of RUICP during the cold start phase for new users. The specific results are shown in Fig. 2.

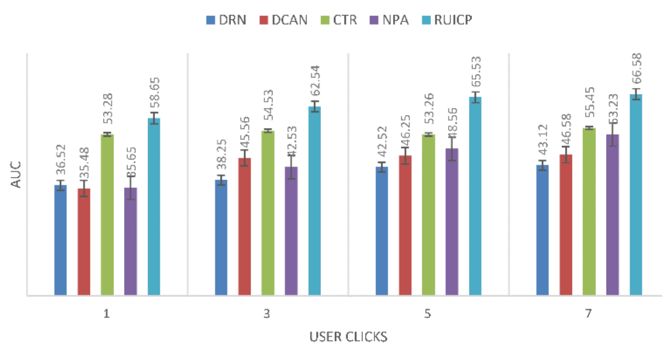

Fig. 2. New user recommendation results.

Fig. 2 clearly demonstrates the recommendation results for new users. From the figure, we can observe that RUICP has advantages over other methods in metrics such as AUC, nDCG@5, and nDCG@10. Particularly in the scenario with new users, RUICP exhibits significant advantages in addressing the cold start problem. Compared to traditional recommendation methods, RUICP introduces commodity popularity as an important metric, calculating commodity popularity based on recent click rates of other users, which enhances its timeliness and universality. During the cold start phase, when users lack relevant data, RUICP can more accurately capture users' latent interests and provide personalized recommendations that align with user preferences. Additionally, compared to other methods, RUICP not only relies on interactions between users and commodities but also comprehensively considers commodity popularity and user interest strength, thereby more comprehensively addressing users' actual needs in the recommendation process. Furthermore, compared to methods like CTR, which rely heavily on click-through rate for measuring popularity, RUICP can better reflect users' interest strength, avoiding inaccuracies in recommendation results caused by excessive reliance on popularity calculated through click rates.

In summary, RUICP exhibits significant advantages in addressing the user cold start problem and holds promising applications in recommendation systems.

C. Recommendation Accuracy

In this section, experiments were conducted to evaluate the accuracy of RUICP for recommending to existing users. The dataset mentioned in Table II was used for training, and the performance of various recommendation methods was analyzed by comparing them with the validation set. After two repeated experiments, we obtained average results and standard deviations, as shown in Table III. These experimental results provide us with an intuitive comparison of the performance of different recommendation algorithms.

TABLE III. EXPERIMENTAL RESULTS

Methods	AUC	nDCG@5	nDCG@10
DRN	52.45±0.00	25.46±0.16	28.18±0.16
DCAN	57.26±0.02	28.26±0.03	28.35±0.11
CTR	63.51±0.15	31.25±0.00	37.56±0.01
NPA	66.17±0.00	32.56±0.02	38.51±0.13
RUICP	69.23±0.15	36.66±0.18	45.26±0.15

From the experimental results, it can be seen that RUICP exhibits significant advantages over other methods. Specifically, while DRN and DCAN have their own characteristics, they both fail to fully consider the real-time changes in user interests. DRN overly relies on feedback after user clicks, making it prone to the recommendation dilemma of homogeneity, while DCAN, although combining user preferences and item lifecycles, lacks the ability to capture real-time interests, resulting in often outdated recommendations. The CTR method improves recommendation accuracy by introducing the commodity popularity factor, but its popularity calculation method is relatively simple and overlooks personalized user needs and real-time interest changes, thus failing to fully consider the differences between different users. Although NPA optimizes the interaction representation between users and commodities using attention mechanisms, it also fails to capture the rapid changes in user short-term interests. In contrast, the advantage of RUICP lies in its ability to capture and reflect changes in user interests in real-time. By comprehensively considering user interest strength, commodity popularity, and real-time interaction information, RUICP not only improves recommendation accuracy but also ensures recommendation timeliness and personalization. In summary, RUICP exhibits significant advantages in addressing real-time recommendation problems for existing users, better meeting users' personalized needs, and improving user satisfaction and click-through rates.

V. CONCLUSION AND FUTURE WORK

This paper proposes a dynamic representation method of user interest intensity by accurately capturing changes in user interests over time, aiming to address the bias issue in real-time recommendation content. Building upon this, we innovatively introduce the RUICP recommendation model based on user temporal interest and commodity popularity. By analyzing user behavior patterns, emotional tendencies, and other relevant information, we can accurately understand users' psychological states and needs. Based on this information, our method can provide recommendation content that matches the user's current psychological state, helping users better satisfy their psychological needs. For example, in the analysis of user behavior patterns, we consider not only user clicks but also analyze browsing history, purchase records, and other information to fully understand user interests and preferences. In emotional tendency analysis, we use sentiment analysis techniques to identify the emotional states that users exhibit during interactions, further accurately capturing users' psychological needs. The comprehensive application of these technologies and strategies enables RUICP to better understand and satisfy users' psychological needs, thereby improving user experience and psychological enjoyment.

In experiments, by simulating real-time user click experiments, the recommendation effects of RUICP in new and existing users were comprehensively verified. Experimental results show that compared to other methods, RUICP not only significantly improves the recommendation accuracy for existing users but also effectively addresses the cold start problem for new users.

In conclusion, the RUICP model proposed in this paper demonstrates significant advantages in improving recommendation system accuracy and increasing user effective clicks. This method provides new ideas for addressing user stickiness and advertising efficiency issues, with important practical value. In the future, we plan to apply the RUICP model to more related fields to achieve more in-depth and comprehensive research results.

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