International Journal of Information Technology and Web Engineering
Volume 19 • Issue 1

Personalized Recommendation Method of E-Commerce Products Based on In-Depth User Interest Portraits

Jingyi Li, Chongqing City Vocational College, China
Shaowu Bao, Anhui Agricultural University, China*

ABSTRACT

In dynamic e-commerce environments, researchers strive to understand users' interests and behaviors to enhance personalized product recommendations. Traditional collaborative filtering (CF) algorithms have encountered computational challenges such as similarity errors and user rating habits. This research addresses these issues by emphasizing user profiling techniques. This article proposes an innovative user profile updating technique that explores the key components of user profile (basic information, behavior, and domain knowledge). An enhanced kernel fuzzy mean clustering algorithm constructs a dynamic user portrait based on domain knowledge mapping. This dynamic portrait is combined with e-commerce personalized recommendation to improve the accuracy of inferring user interests, thus facilitating accurate recommendation on the platform. The method proposed in this article greatly improves the overall performance and provides strong support for developing smarter and more personalized e-commerce product recommendation systems.

KEYWORDS

Clustering, Collaborative Filtering, Knowledge Graph, Recommendation Algorithm, User Portrait

INTRODUCTION

In today's digital age, the e-commerce industry is booming, offering users convenience. However, the vast selection of products can pose challenges for users. A key considering when solving this problem lies in helping users find products that match their interests and needs within the huge product catalog. This is achieved through intelligent personalized recommendation systems (Esmaeili et al., 2020). However, traditional recommendation methods are revealing their limitations when confronted with large-scale and high-dimensional user data. It forces users to seek out more innovative and precise recommendation solutions (Zheng et al., 2021).

An effective recommendation method can help users quickly obtain high-quality information, thereby enhancing the user experience (Lestari & Sudarma, 2017). From the perspective of user demand, group user profiling helps e-commerce platforms grasp the probabilistic behavior of users

DOI: 10.4018/IJITWE.335123
*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

in different scenarios. With time, users' interests and preferences change (Vavliakis et al., 2019). For this reason, this article proposes a method to construct a dynamic group user portrait that adapts to users' needs in different scenarios.

Meanwhile, to solve the data sparsity problem in recommendations, a recommendation algorithm, dynamic portrait and intra-group collaborative filtering (DUCF), is introduced and successfully applied to e-commerce platforms. This approach facilitates a personalized recommendation application, providing scientific services for enterprises (Guo et al., 2017).

This research is devoted to the study of group dynamic user portraits. The authors established a domain knowledge graph from the perspective of user needs and generated user labels by analyzing consumers' historical information on e-commerce platforms, employing methods like data mining (Wu & Yin, 2019). In the construction of user profiles, the authors conducted experimental validation. The results showed that the group user profiles constructed in this article achieved significant improvements in both accuracy and recall (Xiang & Zhang, 2020).

Furthermore, the authors designed and implemented a personalized recommendation system based on dynamic user profiling and a collaborative filtering (CF) recommendation algorithm (Heinrich et al., 2021). Through a detailed analysis of the system's functionality and strategically designing the database, the authors developed a personalized recommendation function module to ensure a smooth shopping experience using the Django framework (Koniew et al.,2020). This system aims to provide a more scientific service, allowing users to navigate the platform with ease and efficiency. This allows the users to realize the effectiveness of personalized recommendations, improving the overall shopping experience.

Compared to prior studies that highlight the deep mining of user interests, this study employs deep learning techniques to build user profiles. It also underscores the application of personalized recommendation methods on e-commerce platforms. This approach implies a more comprehensive and accurate gathering of user interest information, aimed at achieving a better personalized recommendation effect. The goal is to elevate the user experience of e-commerce platforms through advancements.

RELATED WORKS

Xia (2016) supposed that if two users share a similar interest, it is very possible for them to select similar products. Thus, Xia designed an e-commerce product recommendation algorithm based on a CF model to compute the recommendation score. Ishida et al. (2017) contributed by showing the review to influence the user's decision-making process. This unique system can generate a recommendation sentence aligned with the user's preferences from a user profile that contains the product tag data.

Recommender systems help users find relevant items of interest, particularly on e-commerce or media streaming sites. Given the practical relevance of the problem, there has been an increased interest in session-based recommendation algorithms, which aim to predict the user's immediate next actions. Ludewig and Jannach (2018) presented the results of an in-depth performance comparison of several such algorithms using a variety of datasets and evaluation measures.

Chen et al. (2019) explored a novel approach to generate personalized product descriptions by combining the power of neural networks and a knowledge base. They proposed a knowledge-based personalized (KOBE) product description generation model in the context of e-commerce. The concept of e-commerce recommendation can be divided into the recommendation based on correlation and recommendation based on causality. Xu and Cui (2022) selected three representative consumer psychologies—consumer motivation, consumer attitude, and consumer interest—to explore product recommendations that consider multiple consumer psychologies.

Understanding the significance of item presentation in gaining and maintaining user attention, Sulikowski et al. (2022) conducted a task-based user eye-tracking study with 30 participants. They examined two variants of an online fashion store—one based on aesthetic rules and one defying them—and investigated their relationship to user attention through gaze fixation, tracking user interest, and conducting a supplementary survey.

Foreign scholars researched user portrait algorithms, forming relatively mature ideas (Requena et al., 2020). Domestic scholars have also achieved substantial progress in the field of user portrait research (Chehal et al., 2021). Based on the research and application-related work on user portraits at home and abroad, the methodologies for user portraits can be divided into four schools: (1) behavior school; (2) user interest preference school; (3) domain ontology school; and (4) social network school (Xiao et al., 2020).

Wu et al. (2021) used behavior data generated by users accessing academic resources. They extracted behavior labels and research interest labels from the data, constructing academic user portraits with these two label systems to satisfy the library's recommended service requirements (Kasap et al., 2017).

The goal of CF recommendation algorithms is to score recommended or predicted items based on user feedback from previous interaction items (Xu & Wang, 2022). By analyzing user feedback information, the most similar items and user groups are screened from the website. Then, it selects the item with the highest score from the user group with the most similar interests for recommendation.

CF includes memory and model recommendation methods, using machine learning algorithms to predict data and achieve predictive scoring for users (Wang & Zhang, 2021). The CF method includes various techniques like clustering, Bayesian network, latent semantic model, deep learning, and the Markov decision process (MDP). However, the performance of the CF recommendation method tends to deteriorate with sparse scores, often leading to cold start problem in systems (Wu et al., 2022).

The calculation of attribute values in this method holds particular importance, with each attribute representing the importance of an item to users (Huang & Ying, 2021).

There are many techniques for calculating attribute values; however, it is a challenge to collect user portraits based on the CB method (Guo et al., 2018). Most data pertaining to user portraits on e-commerce platforms belongs to personal privacy data, and building a user portrait model using this method is complicated with the user's labels are too sparse (Huo, 2021).

MATERIALS AND METHODS

User Portrait Update Technology

Static portrait models and dynamic portrait models are two types of user portrait models. As user preferences evolve, failing to update the portrait can cause errors in corresponding recommendations. Dynamic portrait models address this by ensuring timely updates to user information. However, static portrait models are based on offline data, using elements like the user's personal information and demographic data (Tian & Wang, 2021). While static data like the user's name and gender will remain unchanged, their dynamic data, such as hobbies, will fluctuate in varying time spans.

Combining time series data with static user portraits allows the label system of static user portraits to undergo dynamic updates according to different time series. This resolves the problem of delayed updates to user dynamic data, preventing insignificant recommendation effects. It also allows for the exploration of changes in user interests and hobbies, contributing to the construction of an enhanced user label system (Guan et al., 2019).

The time series forecasting method is a regression-based approach that predicts the future development trend by analyzing the changing laws of historical information. This method identifies accidental events that have existed through the analysis of historical data and reduces the probability of these events predicting future trend changes, thereby improving the accuracy and stability of predictions. A time series consists of discrete time data, which is generally composed of two aspects. This first is the current time point of the researched entity. The second is the observation value corresponding to that point in time. Time series data are affected by various factors, with differences in fields, backgrounds, and spaces where things are located. This will impact the representation of time series patterns.

The authors designed the following formula to represent the time series model:

$$S = T * J * C * R \tag{1}$$

Among them, S represents the time series model, T represents the long-term trend feature, J represents the seasonal change factor, c represents the periodic change, and R represents the random disturbance factor.

Next, they used the most basic averaging method to forecast the time series model, setting the time series as:

$$S_1, S_2, S_3, \cdots, S_{n-1}, S_n \tag{2}$$

where n is the number of samples and St is the observed value at time t. The authors conducted the experiment with T as the period and calculated the average Y of the T period as the predicted value for the T + 1 period (denoted by Ft + 1):

$$\bar{Y} = \sum_{t=1}^{T} \frac{Y_t}{T} = F_{T+1} \tag{3}$$

They used e T + 1 as the error at time T + 1 based on the observations at time T + 1, which can be expressed as:

$$e_{T+1} = Y_{T+1} - F_{T+1} \tag{4}$$

Then, the predicted value at time T + 2 is:

$$F_{T+2} = \bar{Y} = \sum_{t=1}^{T+1} \frac{Y_t}{T+1} = \frac{T \times F_{T+1} + Y_{T+1}}{T+1} \tag{5}$$

The error value of period T + 2 is:

$$e_{T+2} = Y_{T+2} - F_{T+2} \tag{6}$$

According to these formulas for multiple prediction values and errors, the authors can express the prediction value FT + n and prediction error eT + n at time T + n:

$$F_{T+n} = \bar{Y} = \sum_{t=1}^{T+n-1} \frac{Y_t}{T+n-1} = \frac{(T+n-2) \times F_{T+n-1} + Y_{T+n-1}}{T+n-1} \tag{7}$$

$$e_{T+n} = Y_{T+n} - F_{T+n} \tag{8}$$

As the time span continues to increase, early data may have an impact on the accuracy of future forecast values. To eliminate this possible error and ensure the accuracy of forecast values, the authors need the moving average (MA) to arrange the timing step. This is expressed with the following formulas:

$$F_{T+1} = \bar{Y} = \frac{1}{T}\left(Y_1 + Y_2 + \ldots + Y_T\right) \tag{9}$$

$$F_{T+2} = \bar{Y} = \frac{1}{T}\left(Y_2 + Y_3 + \ldots + Y_{T+1}\right) \tag{10}$$

$$F_{T+n} = \bar{Y} = \frac{1}{T}\left(Y_{T-n-1} + Y_{T-n-2} + \ldots + Y_{T+n-1}\right) \tag{11}$$

$$F_{T+n} = F_{T+n-1} + \frac{1}{T}\left(Y_{T+n-1} - Y_{n-1}\right) \tag{12}$$

From the above four formulas, the predicted value at time Ft + 1 can be obtained:

$$F_{t+1} = \frac{1}{T}\left(Y_{t-T+1} + Y_{t-T+2} + \ldots + Y_t\right) \tag{13}$$

$$F_{t+1} = F_t + \frac{1}{T}\left(Y_t - Y_{t-T}\right) \tag{14}$$

Finally, the authors considered a crucial point: if the research subject itself has periodic characteristics, the period of the moving average method should be calculated based on its own period. In addition, the authors generally used the mean square error (MSE) of the method to test the rationality of period selection. Period T was selected based on the smallest MSE value, expressed by the following formula:

$$MSE_{(T)} = \frac{1}{N-1}\sum_{i=T+1}^{N}\left(Y_i - F_i\right)^2 \tag{15}$$

Fuzzy Cluster Analysis

Cluster analysis is a statistical concept that refers to the use of complex mathematical calculations to classify data and group similar data into specific categories. Traditional cluster analysis follows a hard division technique, which classifies items according to certain standards, characterized by clear boundaries and high recognition. However, many real-world items are better suited for soft division, as their boundaries are often blurred, and they exhibit intermediate forms and attribute, better reflecting the characteristics of real life.

Fuzzy clustering analysis is a soft segmentation technique, allowing data points to belong to multiple clusters with certain probabilities rather than being forced into unique clusters. This method is more flexible in capturing similarities and differences between data points by considering their affiliation with the center of each cluster. In fuzzy clustering analysis, different objects are compared in terms of their similarity to the same cluster, accurately reflecting the true distribution of a sample and achieving effective clustering results. Thus, this method has become a key research direction in modern cluster analysis.

Fuzzy clustering methods (FCM) are roughly divided into two categories. The first is a hierarchical clustering method, which is based on fuzzy equivalence relation. The second is a progressive clustering method based on fuzzy partition. The FCM algorithm assumes that there is a data set $X = \left\{x_1, x_2, \ldots, x_n\right\}$

in which the data set fuzzy set c is represented by a matrix $U = \left[u_{ij}\right]$. In addition, the formula uij refers to the membership degree of the jth class, which should meet the following conditions:

$$\forall j, \sum_{i=1}^{c} u_{ij} = 1; \forall i, j, u_{ij} \in [0,1]; \forall i, \sum_{i=1}^{n} u_{ij} > 0 \tag{16}$$

Next, the limit of the intra-class weighted sum of squares error is considered:

$$(\min) J_m(U,V) = \sum_{j=1}^{n} \sum_{i=1}^{c} u_{ij}^m d_{ij}^2 \left(x_j, v_i\right) \tag{17}$$

V is specified as the cluster center and m is the weighting parameter $d_{ij}\left(x_j, v_i\right) = \left\|v_i - x_j\right\|$. Next, the desired objective function is found using the pull multiplier method, obtaining the optimal solution for U and V:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}} \tag{18}$$

$$v_i = \frac{\sum_{j=1}^{n} x_j u_{ij}^m}{\sum_{j=1}^{n} u_{ij}^m} \tag{19}$$

Finally, the values of U and V are repeated until the objective function reaches a steady state. There are many applications of fuzzy clustering analysis method. Thus, it plays an important role in image processing, weather forecasting, pattern recognition, neural network, medical treatment, and other domains.

Personalized Recommendation Algorithm Related Technologies

The recommendation algorithm aims to infer the content of a user's potential interest through a mathematical model. As the volume of user data increases with the expansion of the internet, the challenge lies in finding the user's points of interest from the massive data and providing timely recommendations. It is crucial for internet companies seeking to enhance the user experience and product engagement. With the advancement of recommendation algorithms, personalized recommendation algorithms have emerged as a mainstream technology for internet companies. These algorithms contribute to user stickiness, extend the time users spend with each product, explore long-tail content, and improve the overall experience. The following outlines the three recommendation algorithms.

CB Recommendation

The working process of CB recommendation methods relies on information retrieval technology. It hinges on the attributes of the item, obtaining item tags and calculating the similarity between two items based on these tags. Thus, it recommends other items to the user according to their distinct interests. While this method can recommend personalized products, there are still some limitations.

For example, the CB recommendation method pushes product information within a limited range, predominantly relying on the user's previously browsed information. Therefore, the user may receive recommendations similar to their prior information, limiting exposure to new information.

In addition, CB recommendation methods extract simple feature information and processing text-based information. However, they do not impact audio information, video information, and picture information. Therefore, the CB recommendation method is an effective text feature recommendation method.

Recommendation Based on CF

As the most important and widely employed technology, the CF recommendation algorithm solves the recommendation problem by predicting that users with similar historical behaviors have similar interests. The traditional CF recommendation algorithm is divided into two parts: the memory recommendation method (memory-based CF) and the model recommendation method (model-based CF). In the memory-based recommendation algorithm, preferences of users with similar interests are computed, and recommendations are then made to the target users. Similarity computation (between users or items) plays a key role in memory-based approaches, leading to the formulation of various similarity measures. These measures include the Pearson correlation coefficient (PCC), cosine similarity (COS), and several other heuristic similarity measures that apply domain-specific meanings to the rating data.

Hybrid Recommendation

A single recommendation algorithm may encounter challenges due to its singularity, data sources, and limitations of its own algorithm, leading to issues like the "cold start" problem, sparsity problem, Matthew effect, gray sheep effect, and portfolio effects. In response to these limitations, hybrid recommendation algorithms consist of multiple recommendation algorithms. A single recommendation algorithm has shortcomings; thus, the hybrid algorithm leverages the strengths of multiple algorithms. Typically, hybrid recommendation algorithms yield superior results.

Research should follow privacy regulations, using techniques like anonymization and desensitization to protect personal data privacy. The principles of data minimization and transparency should be followed, guiding the collection of only necessary information and communicating data processing practices to users through a clear privacy policy. Security measures must be emphasized during processing to ensure data confidentiality.

To address the challenge of label scarcity, this research applies an approach that integrates semi-supervised learning, active learning, transfer learning, and generative adversarial networks. This strategy maximizes the utilization of both labeled and unlabeled data. This comprehensive approach not only improves the efficiency of label utilization but also serves as a significant solution for maintaining data privacy.

RESULT ANALYSIS AND DISCUSSION

Experiment Results of Group Dynamic User Portrait

In this thesis, product data was collected from e-commerce platforms using web crawler technology and processed based on user requirements. The sorted CSV data was then imported into the database. To construct a dynamic user portrait model based on the knowledge graph of agricultural products, user behavioral data were first extracted and quantified with labels. The user's behavioral keywords were matched with the knowledge graph, and after extracting the labels, different weights were assigned according to different behaviors. For example, purchase behavior received the highest weight of 40, followed by add-to-cart, favorites, and browsing with weights of 30, 20, and 10, respectively. The proposed user profile updating method was then employed to predict labels weights, ensuring the continuous update of users' interest in agricultural products.

Unlike user behavior data, basic user information (for example, gender) can be represented by 0 or 1. These data do not change much. Thus, predicting these values may not require frequent updates.

The data source for an e-commerce platform's order data was selected from user behavior records during the period of January to June 2023. The statistical orders revealed 18,973 records of data, involving a total of 1,532 available users. Information heat was quantified based on the user profile labeling system, using criteria like gender, age, and region for user categorization.

Before the experiment, raw data was processed into labels, which were then quantified. The processed label weights, or smoothed values, were used to form a prediction model. This model compared the true values with the calculated smoothed value, facilitating the update of label weights. Triple exponential smoothing was employed, treating the weighted average of historical data as the future forecast result. The number of smoothings was determined by analyzing historical time series data. The initial value was set as the average of the first three data points in the series, and exponential smoothing calculations were then performed.

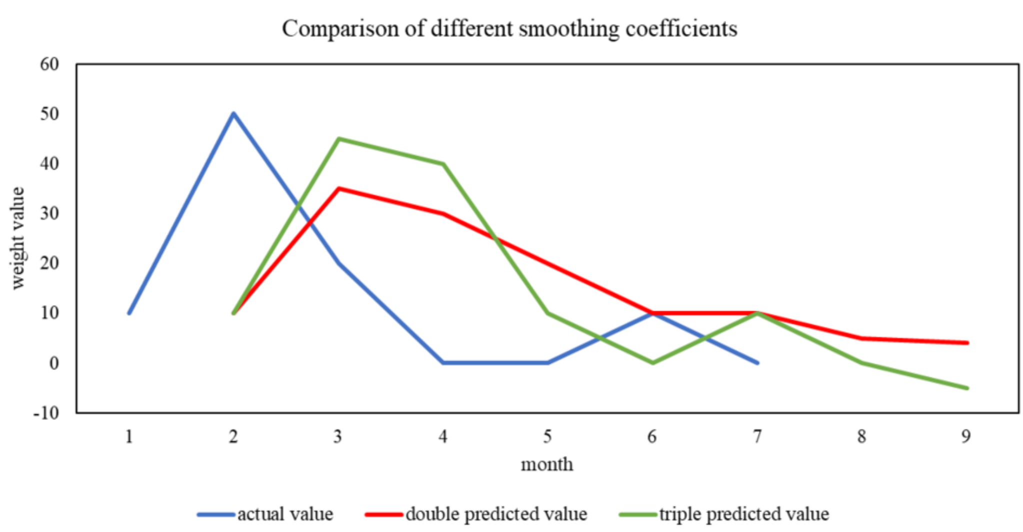
The selection of the smoothing coefficient depends on the data fluctuation. A small fluctuation in historical data suggests a stable trend in the user's interest degree. Thus, the smoothing coefficient should take a small value. On the contrary, a large fluctuation indicates significant changes in the user's interest degree, requiring a larger value at this time. In this article, the analysis of the sample sequence selected led to the best coefficient value, $\alpha = 0.3$, $\alpha = 0.5$, $\alpha = 0.6$, and $\alpha = 0.9$ were selected to compare the MSEs.

According to Figure 1, when α is 0.6, the prediction accuracy is higher than 0.3 and 0.9. In addition, the fitting is the highest. Thus, the fixed value $\alpha = 0.6$ is used to update the weight of the user portrait.

Recommendation Experiment Results Based on Dynamic User Profile and CF

This article first compares the relationship between time series and accuracy, focusing on two algorithms: the static user portrait recommendation algorithm and the dynamic user portrait recommendation algorithm. Additionally, the DUCF hybrid recommendation algorithm proposed in

Figure 1. Comparison of different smoothing coefficients α



this article is experimentally compared with both the traditional CF recommendation algorithm and the static user portrait and CF hybrid (UCF) recommendation algorithm.

Time Series and Accuracy Experimental Results

The relationship between time series and accuracy under two recommendation algorithms is studied. The experimental results are shown in Figure 2.

The recommendation method based on static user portraits follows a CB recommendation approach. In the initial stages of the recommendation model, all user historical data is fed to the model for training, resulting in better accuracy compared to dynamic portrait recommendation results, especially in the beginning. Dynamic portraits, trained in time segments, exhibit a lower accuracy initially (Figure 2).

However, with the passage of time, user interests evolve, leading to an increasing trend in prediction accuracy in recent months. As the training set accumulates, the trend begins to stabilize. The overall recommendation accuracy, while showing improvement over time, is not ideal. It is important to consider that the data set is this article is small, leading to fluctuations in the experiment, as shown in Figure 2. The data set analyzed here may include different seasons in terms of time series, and the platform's rapid data updates contribute to more fluctuations in user interests, impacting the accuracy of the results.

For subsequent experiments, this article begins by analyzing each vacant item on the original matrix and fills the value with the average score. The calculation result indicates that the recommended neighbors have a greater influence, and the number of related recommended neighbors is regarded as an important influencing factor directly affecting the recommendation algorithm's effectiveness. To test the MAE values of CF, UCF, and DUCF algorithms, different values of K (number of neighbors) are tested to observe the relationship between recommended quality and the generated neighbors. The experimental results are shown in Figure 3.

Figure 3 reveals that as the number of K values of the nearest neighbors increases, the traditional CF algorithm shows more obvious disadvantages in terms of the MAE values. Comparing the performance of different recommendation algorithms, the DUCF algorithm, on the whole, outperforms the CF algorithm. Notably, when $K \leq 30$, the MAE values of the three algorithms continue to

Figure 2. Accuracy under different time series

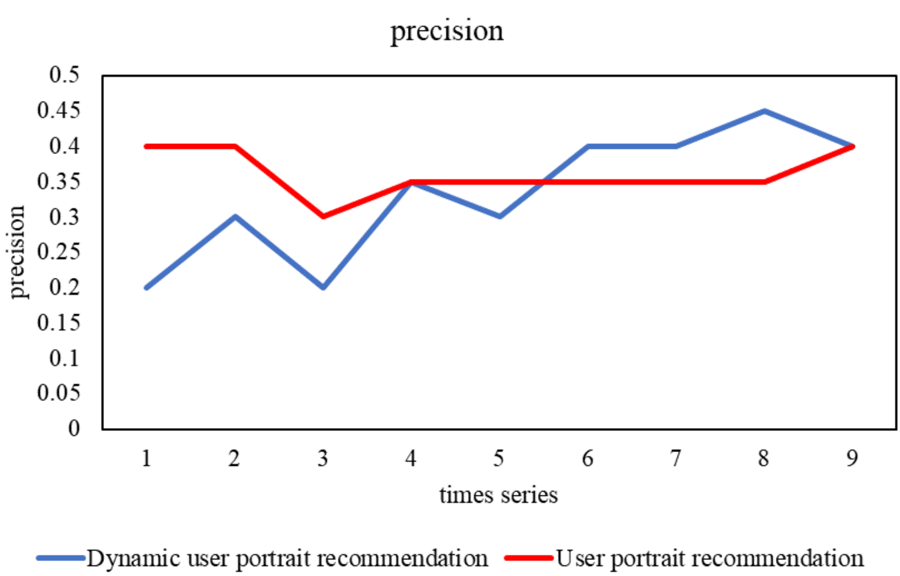
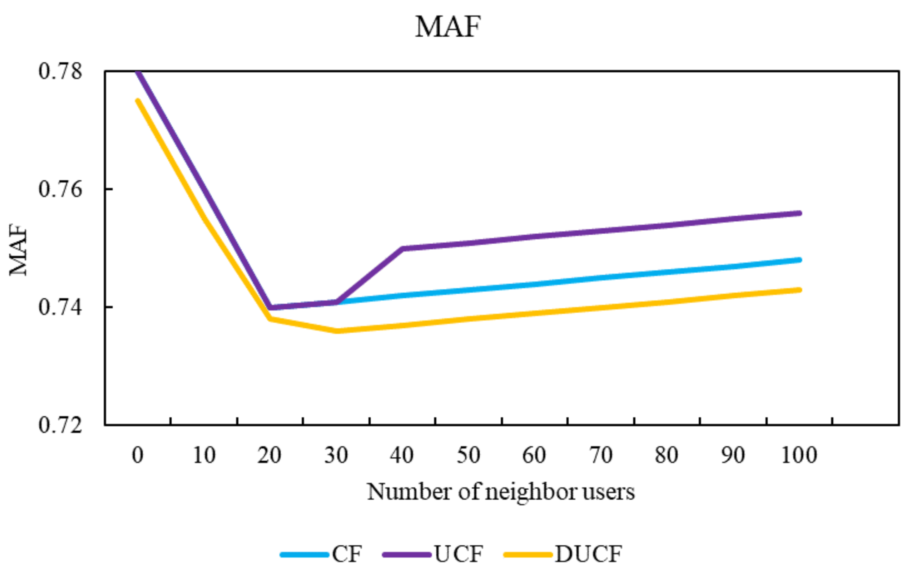


Figure 3. MAE values under different neighbor K



decrease as the number of neighbors increases. However, when K > 30, the performance of the three recommendation algorithms shows a decrease from the beginning and then stabilizes.

Comparison of Recommended Results

To fully verify the superiority of the improved algorithm, the experimental design compares different recommendation effects using precision rate, recall rate, and F1 value as standards in the recommendation experiment process. The experimental results are illustrated in Figures 4, 5, and 6, showcasing the changing trends of the recall rate, accuracy rate, and F1 value of the three algorithms, respectively.

As shown in Figure 4, the recall rate trends of the three algorithms first show an increase followed by constant change. Notably, the algorithm proposed in this article has obvious advantages, with the DUCF hybrid recommendation algorithm being the most effective. The ranking of the recall rate for the three algorithms, from highest to lowest, is DUCF > UCF > CF.

As shown in Figure 5, as the value of K increases, the accuracy rate undergoes a decreased followed by stabilization for the three recommendation algorithms. The accuracy and recall rate in personalized recommendation are inconsistent; therefore, the combination of UCF and CF is significantly better than the DUCF recommendation algorithm in recall rate. However, UCF and CF are more accurate than the DUCF hybrid recommendation algorithm.

From the experiments in Figures 4 and 5, it is observed that the trends of precision and recall rate changes are opposite, and the proposed recommendation algorithm in this article shows a greater advantage in recall but a lower precision rate, aligning with real-world scenarios. In such cases, evaluating the quality of the recommendation requires considering both recall rate and accuracy rate, requiring the uses of the F1 value for a comprehensive value. Figure 6 shows three types of algorithms.

As can be seen from Figure 6, as the number of nearest neighbors K increases, both the DUCF and UCF recommendation algorithms significantly outperform the CF recommendation algorithm in the F1 value. Considering MAE, precision rate, recall rate, and F1 value, the recommendation algorithm proposed in this articles demonstrates ideal results in comparison to the traditional algorithm.

Figure 4. Recall rate under different neighbors K

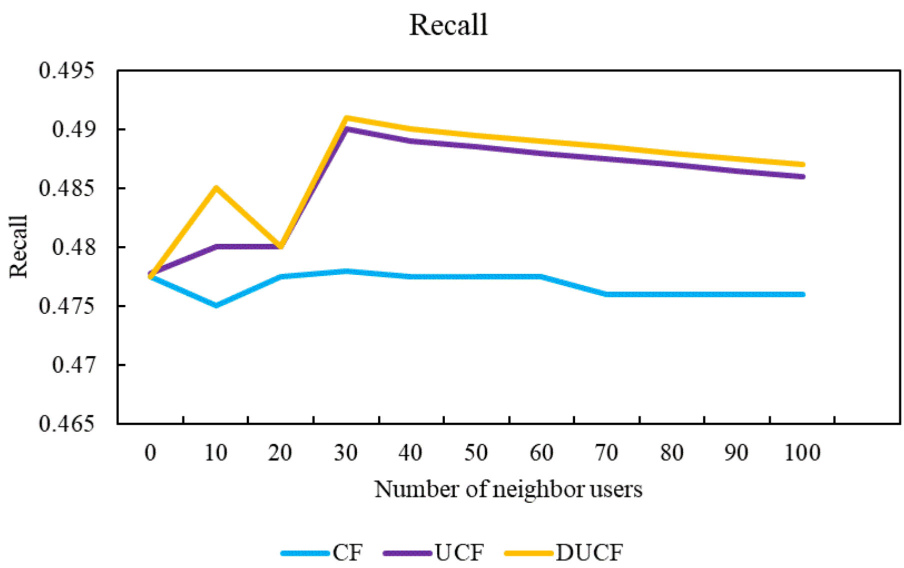
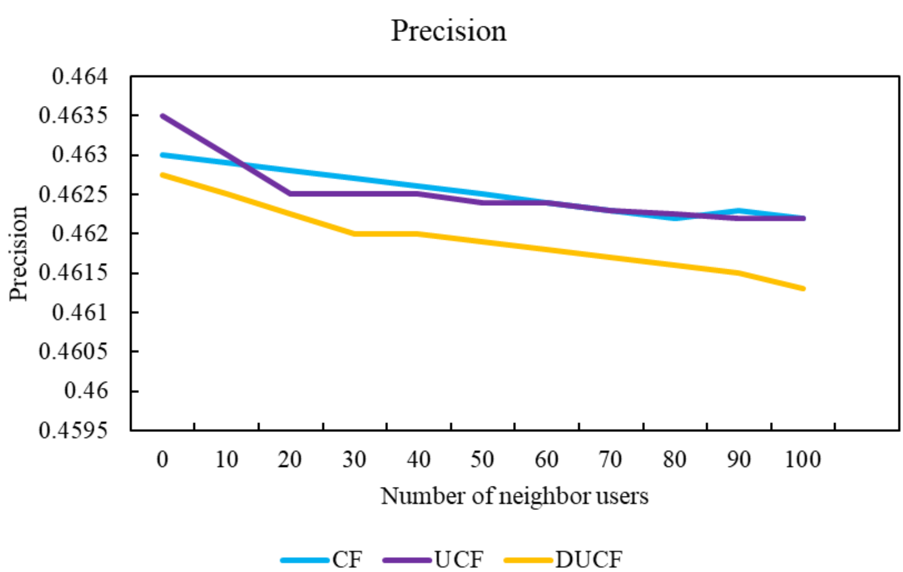


Figure 5. Accuracy under different neighbor K

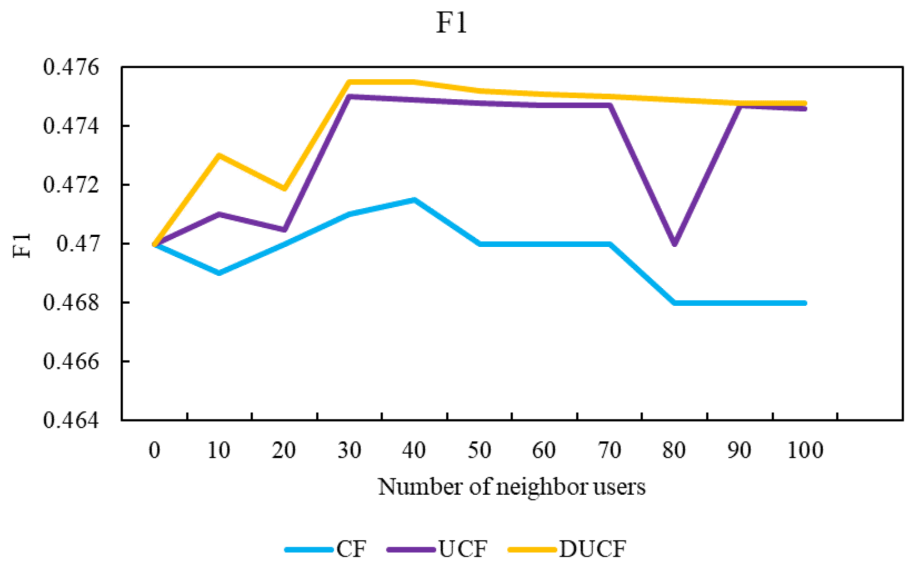


Design and Implementation of E-Commerce Recommendation System

This article introduces a user portrait design updated in time series to address issues like the cold start problem by recommending portraits. It offers a comprehensive analysis of time series issues, including practical concerns like data sparseness and cold start. By combining dynamic user portraits and choosing a hybrid recommendation method based on DUCF, the research aims to overcome these challenges.

The design considers user needs and analyses specific functions of each module, leading to the development of a database. Finally, a personalized e-commerce recommendation system is

Figure 6. F1 value under different neighbor K

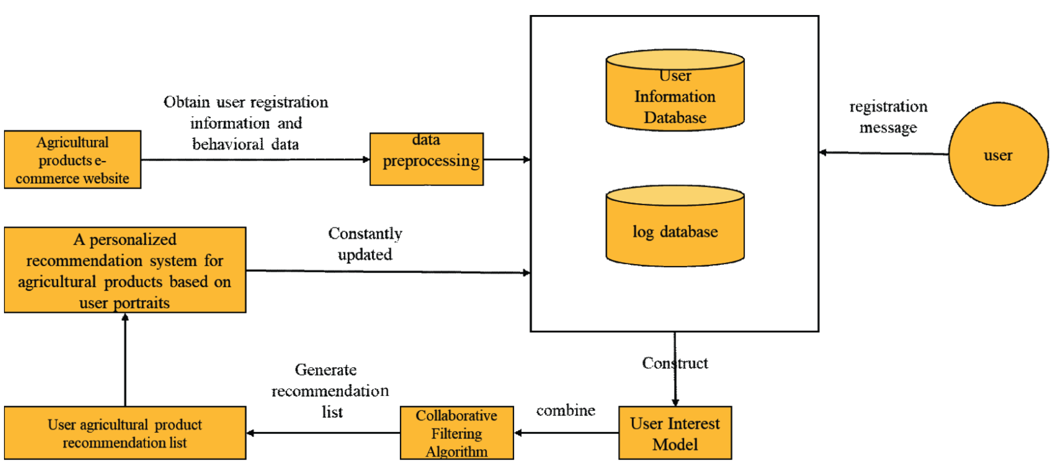


implemented, successfully completing user recommendation functions and achieving positive outcomes. The e-commerce recommendation method based on user portraits includes constructing a user interest recommendation model. Finally, recommendations are generated through the hybrid recommendation algorithm of DUCF, resulting in the creation of a top-n recommendation list.

The architecture of the personalized e-commerce recommendation system is shown in Figure 7.

The recommendation system needs a flexible recommendation strategy to cater to diverse user scenarios. For users who have not logged in, a mode of online browsing on the website's homepage is available, allowing them to explore the products they wish to purchase. When the system cannot obtain the real-time user portrait data, no personalized recommendations will be generated. Instead, popular products corresponding to the user's selected type preference will be highlighted. Registered users who have logged in and saved historical data, the recommendation system can accurately calculate

Figure 7. Architecture diagram of personalized e-commerce recommendation system



recommended content based on their historical behavior and other information. This tailored approach improves the overall user experience. It is important to note that different users may specify different recommended methods based on their preferences or interactions with the system.

CONCLUSION

This study successfully designed and implemented a personalized e-commerce recommender system featuring time-series updated user profiles and dynamic user models. The introduction of time-series dynamics enables a more precise capturing of changes in user interests, thus improving the flexibility and accuracy of the recommendation system. The proposed hybrid recommendation algorithm combines dynamic user profiling and CF techniques, demonstrating favorable performance in metrics like recall, accuracy, and F1 value. This approach is more suitable for personalized recommendation compared to traditional algorithms.

The e-commerce recommender system architecture constructed in this study successfully applies personalized recommendation strategies to real-world contexts. It intelligently selects recommendation strategies based on users' login status and historical behaviors, contributing to improved user satisfaction on e-commerce platforms. This research provides an innovative approach to recommender system optimization and establishes a foundation for future research and applications in related fields.

The study also presents opportunities for potential research directions and acknowledges limitations. Future research directions include deep mining of user behavioral features, introducing deep learning techniques, considering multimodal data, and emphasizing user privacy protection. These directions are expected to further enhance the performance and applicability of personalized e-commerce recommender systems, aligning them more closely in line with real-world scenario requirements.

For future research, it is important to adopt larger and more diverse datasets, conduct validation in more adequate experimental environments, compare the performance of different recommendation algorithms, and conduct further validation in real-world applications. This comprehensive approach will assess the feasibility and practical effects of personalized e-commerce recommendation systems.

DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

FUNDING STATEMENT

This work was supported by Project results of Collaborative Innovation Center of Smart Retail of Chongqing City Vocational College,Platform No.: KYPT202200003

ACKNOWLEDGMENT

The authors would like to show sincere thanks to those techniques who have contributed to this research.

REFERENCES

Chehal, D., Gupta, P., & Gulati, P. (2021). Implementation and comparison of topic modeling techniques based on user reviews in e-commerce recommendations. *Journal of Ambient Intelligence and Humanized Computing*, *12*(5), 5055–5070. doi:10.1007/s12652-020-01956-6

Chen, Q., Lin, J., Zhang, Y., Yang, H., Zhou, J., & Tang, J. (2019, July). Towards knowledge-based personalized product description generation in e-commerce. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 3040-3050). ACM. doi:10.1145/3292500.3330725

Danaa, A. A. A., & Sappor, E. D. (n.d.). *Accessing the impact of information and communication technology (ICT) on the performance of banks in Ghana: A case study of Ghana Commercial Bank Limited*.

Esmaeili, L., Mardani, S., Golpayegani, S. A. H., & Madar, Z. Z. (2020). A novel tourism recommender system in the context of social commerce. *Expert Systems with Applications*, *149*, 113301. doi:10.1016/j.eswa.2020.113301

Guan, Y., Wei, Q., & Chen, G. (2019). Deep learning based personalized recommendation with multi-view information integration. *Decision Support Systems*, *118*, 58–69. doi:10.1016/j.dss.2019.01.003

Guo, Y., Wang, M., & Li, X. (2017). Application of an improved Apriori algorithm in a mobile e-commerce recommendation system. *Industrial Management & Data Systems*, *117*(2), 287–303. doi:10.1108/IMDS-03-2016-0094

Guo, Y., Yin, C., Li, M., Ren, X., & Liu, P. (2018). Mobile e-commerce recommendation system based on multi-source information fusion for sustainable e-business. *Sustainability (Basel)*, *10*(1), 147. doi:10.3390/su10010147

Heinrich, B., Hopf, M., Lohninger, D., Schiller, A., & Szubartowicz, M. (2021). Data quality in recommender systems: The impact of completeness of item content data on prediction accuracy of recommender systems. *Electronic Markets*, *31*(2), 389–409. doi:10.1007/s12525-019-00366-7

Huang, H., & Ying, L. (2021, March). Research on consumer psychology modeling and intelligent recommendation of e-commerce users. In *2021 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)* (pp. 473-476). IEEE. doi:10.1109/ICITBS53129.2021.00121

Huo, Y. (2021). Agricultural product e-commerce recommendation system based on neural factorization machine in smart cities. *Internet Technology Letters*, *4*(1), e216. doi:10.1002/itl2.216

Ishida, Y., Uchiya, T., & Takumi, I. (2017). Design and evaluation of a movie recommendation system showing a review for evoking interested. *International Journal of Web Information Systems*, *13*(1), 72–84. doi:10.1108/IJWIS-12-2016-0073

Kasap, Ö. Y., & Tunga, M. A. (2017). A polynomial modelling based algorithm in top-N recommendation. *Expert Systems with Applications*, *79*, 313–321. doi:10.1016/j.eswa.2017.03.005

Koniew, M., Hapiffah, S., Sinaga, A., Oladiipo, A. F., Taiwo, O. M., Emmanuel, A. A., & Khuhro, M. A. (2017). *International Journal of Information Engineering and Electronic Business*. IJIEEB.

Lestari, N. M. A., & Sudarma, M. (2017). Perencanaan search engine e-commerce dengan metode latent semantic indexing berbasis multiplatform. Lontar Komput. *J. Ilm. Teknol. Inf*, *8*(1), 31.

Ludewig, M., & Jannach, D. (2018). Evaluation of session-based recommendation algorithms. *User Modeling and User-Adapted Interaction*, *28*(4-5), 331–390. doi:10.1007/s11257-018-9209-6

Requena, B., Cassani, G., Tagliabue, J., Greco, C., & Lacasa, L. (2020). Shopper intent prediction from clickstream e-commerce data with minimal browsing information. *Scientific Reports*, *10*(1), 1–23. doi:10.1038/s41598-020-73622-y PMID:33046722

Sulikowski, P., Kucznerowicz, M., Bąk, I., Romanowski, A., & Zdziebko, T. (2022). Online store aesthetics impact efficacy of product recommendations and highlighting. *Sensors (Basel)*, *22*(23), 9186. doi:10.3390/s22239186 PMID:36501888

Tian, G., & Wang, J. (2021). Recommendation algorithm for mobile e-commerce based on cone depth learning. *International Journal of Computers and Applications*, *43*(9), 897–902. doi:10.1080/1206212X.2019.1649346

Vavliakis, K. N., Katsikopoulos, G., & Symeonidis, A. L. (2019). E-commerce personalization with elasticsearch. *Procedia Computer Science*, *151*, 1128–1133. doi:10.1016/j.procs.2019.04.160

Wang, J., & Zhang, Y. (2021). Using cloud computing platform of 6G IoT in e-commerce personalized recommendation. *International Journal of System Assurance Engineering and Management*, *12*(4), 654–666. doi:10.1007/s13198-021-01059-1

Wu, J., Li, Y., Shi, L., Yang, L., Niu, X., & Zhang, W. (2022). ReRec: A divide-and-conquer approach to recommendation based on repeat purchase behaviors of users in community e-commerce. *Mathematics*, *10*(2), 208. doi:10.3390/math10020208

Wu, W., & Yin, B. (2019). Personalized recommendation algorithm based on consumer psychology of local group purchase e-commerce users. *Journal of Intelligent & Fuzzy Systems*, *37*(5), 5973–5981. doi:10.3233/JIFS-179179

Wu, X. Q., Zhang, L., Tian, S. L., & Wu, L. (2021). Scenario based e-commerce recommendation algorithm based on customer interest in Internet of things environment. *Electronic Commerce Research*, *21*(3), 689–705. doi:10.1007/s10660-019-09339-6

Xia, J. (2016, August). E-commerce product recommendation method based on collaborative filtering technology. In *2016 International Conference on Smart Grid and Electrical Automation (ICSGEA)* (pp. 90-93). IEEE. doi:10.1109/ICSGEA.2016.81

Xiang, D., & Zhang, Z. (2020). Cross-border e-commerce personalized recommendation based on fuzzy association specifications combined with complex preference model. *Mathematical Problems in Engineering*, *2020*, 1–9. doi:10.1155/2020/8871126

Xiao, L., Lu, Q., & Guo, F. (2020). Mobile personalized recommendation model based on privacy concerns and context analysis for the sustainable development of m-commerce. *Sustainability (Basel)*, *12*(7), 3036. doi:10.3390/su12073036

Xu, Q., & Wang, J. (2022). A social-aware and mobile computing-based e-commerce product recommendation system. *Computational Intelligence and Neuroscience*, *2022*, 1–8. doi:10.1155/2022/9501246 PMID:35345796

Xu, Y., & Cui, W. (2022). Commodity recommendation model integrating user psychological data analysis. *Frontiers in Psychology*, *13*, 907865. doi:10.3389/fpsyg.2022.907865 PMID:35712193

Yu, C. C., & Chang, H. P. (2009). Personalized location-based recommendation services for tour planning in mobile tourism applications. In *E-Commerce and Web Technologies: 10th International Conference, EC-Web 2009* (pp. 38-49). Springer Berlin Heidelberg. doi:10.1007/978-3-642-03964-5_5

Zheng, J., Li, Q., & Liao, J. (2021). Heterogeneous type-specific entity representation learning for recommendations in e-commerce network. *Information Processing & Management*, *58*(5), 102629. doi:10.1016/j.ipm.2021.102629

Jingyi Li (1990.2-), male, Han nationality, is a native of Qijiang, Chongqing, a master's degree student of Northwestern Polytechnic University in the United States, and an associate professor of the Business School of Chongqing City Vocational College, with the main research direction: marketing.

Shaowu Bao, School of Information and Computer, Anhui Agricultural University, Hefei Anhui 230000