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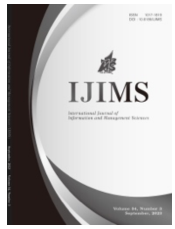

E-commerce Marketing Program Design based on LightGBM and Weighted Hybrid Recommendation Algorithms

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Keywords

Lightweight Gradient Boosting Tree; Collaborative Filtering Algorithm; Weighted Hybrid Recommendation Algorithm; E-commerce Platform; Marketing Strategy

Abstract

For decreasing the operating cost of merchants and ensure the competitive vitality of the e-commerce market, the study designs a consumer coupon issuance and product personalized recommendation model applicable to e-commerce marketing on the ground of lightweight gradient boosting tree and weighted hybrid recommendation algorithm. The experiment showcases that when the weighted hybrid recommendation algorithm is applied to e-commerce marketing, the recommendation effect evaluation indexes are all in good performance, in which the maximal coverage rate reaches 0.926. The mean inverse rank fetch reached 0.90 level, the recommendation hit rate increased from 47.65% to 81.31%, and the normalized discount cumulative gain increased from 38.18% to 67.26%. The coupon placement accuracy under this marketing program application is high, user purchase rate is up to 50%, user clicks fluctuate in the range of 75.0%-94.0%, and cost-effectiveness reaches 51.3%. This study improves the effectiveness of e-commerce marketing methods, helps to expand the target user group, and improves the conversion rate of user purchases.

1. Introduction

E-commerce (EC) is a form of commercial trade utilizing computer technology and the Internet platform, including online shopping, online payment, online marketing and other business activities. EC is not subject to time and geographical constraints, and compared with the traditional brick-and-mortar business model, EC has the advantages of globalization, low cost and high efficiency. EC provides users with a wider choice of goods and a more convenient shopping experience, and at the same time provides merchants with broader market opportunities (Zhang & Dwivedi, 2022; Guo & Zhai, 2022). In order to attract more potential customers and increase the conversion rate and repurchase rate of goods, the design and level of marketing programs are very critical. Nevertheless, as the growth of various EC platforms, the network information overload has weakened the adaptability of traditional marketing

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methods, and merchants and users need to spend more time and energy on brand promotion and product comparison and selection. On the ground of this market environment, the competition among EC companies has intensified, and the operating costs have increased significantly. Facing the severe situation of information overload on the Internet, EC platforms need more skillful and unique marketing methods to adapt to consumer demand and market changes (Kumar et al., 2022). Relying on the development of computer technology, customer precision marketing on the ground of big data and artificial intelligence (AI) has become a mainstream marketing method (Chen & Chen, 2022; Cao et al., 2022). In this regard, the study selects two key marketing links, namely, promotion precise push and personalized product recommendation, and designs a coupon precise placement model for EC platform using Light Gradient Boosting Machine (LightGBM); and designs a personalized recommendation model (PRM) for EC platform on the ground of weighted hybrid recommendation algorithm, completing the design of EC precise marketing program design. The study consists of four parts: firstly, an overview of the current status of research around the world on EC informative marketing related technologies is conducted; then, the design of the marketing scheme on the ground of the precise placement of EC platform coupons and the PRM is elaborated; then, the designed marketing model is evaluated in terms of its performance and application effect analysis is carried out; and finally, the results of the research experiments are summarized and concluded. The realization of this research is expected to provide a more concise and intuitive shopping environment, increase users' willingness to buy, and improve EC business conditions.

2. Related Works

The emergence of EC facilitates people's shopping, promotes the development of economy and society, and receives extensive attention from all walks of life. In order to further enhance the consumption potential of EC platforms and the shopping experience of consumers, scholars at home and abroad have carried out a series of studies on the informatization marketing of EC platforms. Internet technology provides customized marketing methods for EC platforms, and the design and page display of EC products are closely linked to sales. Yazdani et al. (2022) chose ten different meta-heuristic algorithms to conduct a comparative analysis of EC performance, and the experimental structure showed that the ant-lion optimization algorithm had a normalized objective function of 77%, and the moth-flame optimization algorithm had a normalized objective function of 81%. This research enriches the theory and practice of EC body of knowledge. In order to increase the sales profit of EC, it is important to accurately predict the customer purchase pattern and mine the relationship between customers and goods. Alghanam et al. proposed a data mining model to improve the prediction accuracy of the frequent item set with the ability to mine the association rules; and utilized K-means clustering algorithm on the dataset to improve the efficiency of the model operation. The experimental structure shows that when the number of clusters is 8, the accuracy of the model reaches 95.2%, which can accurately predict the purchase behavior (Alghanam et al., 2022). EC marketing needs personalized marketing strategy, Pan et al. (2022) designed a personalized marketing method on the ground of mining algorithm by calculating frequent closed itemsets and positive and negative sample support numbers that can calculate marketing success rate. By comparing EC performance, the marketing strategy designed by this method improved by 8%; the marketing success rate increased from 2.72% to 6.31% after application in telecommunication companies, and this study verified the role of data mining algorithms in online marketing. In order to improve the marketing effect of EC products, Cui et al. (2021) constructed an EC product marketing model on the ground of the improved Q-learning algorithm, and used the mean normalization method to reduce the noise effect of the unfixed time interval between the decision points on the reward signals; they also combined with the idea of hybrid model, and designed a deep reinforcement learning dual network for observing the customer state in the direct marketing scenario. The algorithm is evaluated by combining the public dataset with the example model, and the precision marketing model constructed by the research has good results. The design of precision marketing scheme for agricultural products on the ground of Internet EC is still in the exploratory stage, Gao (2022) precision marketing of agricultural EC, an improved k-nearest neighbor algorithm is used to classify users on the ground of personal information such as geographic location, occupation, and behavioral preferences. The study shows that this method can greatly promote the development of agricultural EC in China.

Consumer shopping satisfaction is closely relevant to EC marketing activities, Li et al. (2023) analyzed the impact of online EC interactions on consumer satisfaction on the ground of big data, constructed an interaction and trust association model, and investigated the intrinsic impact mechanism of online interactions on online shopping consumer satisfaction. The research results show that personalized recommendation can improve consumer satisfaction. In order to enhance the competitiveness of EC and help EC companies to develop appropriate marketing strategies, Diwandari and Hidayat (2022) evaluated customer satisfaction and designed marketing strategies by analyzing consumer preferences and clickstream data. The decision tree algorithm is utilized to achieve dynamic mining and page interest estimation, and the experimental results show that the method performs well in user interest assessment, and the accuracy can be further improved by using it in conjunction with other methods. For promoting the utilization of AI in the field of EC, Xie et al. (2022) designed an AI personalized preference recommender system, and the experimental results show that AI recommendation makes consumers have higher levels of cognitive conflict; compared with artificial recommenders, AI recommenders are more efficient, and this research is of great significance to the theory and practice of EC and marketing communication. The growth of massive data on the Internet increased the difficulty of EC preference recommendation to the existing recommender systems are still facing the issue of cold start and data sparsity, in this regard, Gulzar and Alwan (2023) on the ground of the algorithm of ordered clustering designed a new clustering technique to utilize collaborative filtering strategies for EC recommender systems for the clustering of users with similarity of user preferences, and the experiment verified the efficiency of the method.

In summary, there have been many studies related to EC computer marketing programs, and the usefulness of computer technology in EC marketing and promotion have been verified. However, most of the research focuses on the design of personalized and preference-recommended marketing methods, and there are relatively few studies on the precise placement of promotional activities and coupons. In this study, the precise placement of promotional activities and personalized recommendation of products are considered simultaneously, and the study is aimed at the design of a more complete EC marketing plan.

3. EC Marketing Model Design on the Ground of Lightgbm and Personalized Recommendation Algorithm

The design and implementation of EC marketing program is essential for the development of EC business. For enhancing the sales profit of EC platform, the study explores the issuance of EC coupons and personalized recommendation in the EC marketing link, and designs a marketing plan applicable to the EC platform.

3.1 LightGBM-based EC coupon accurate placement model design

EC business marketing concepts, methods and traditional brick-and-mortar marketing methods are quite different, with the gradual maturation and landing of big data, cloud computing, AI and other technologies, EC marketing programs are gradually moving in the direction of information and digitalization. Coupon is a common preferential means of business promotion, and the precise placement of EC consumer coupons is a concentrated manifestation of the personalized care of the enterprise, which helps to help EC enterprises establish a good brand reputation and word of mouth. Precise placement can effectively stimulate customers' desire to buy, reduce unnecessary marketing costs and improve the efficiency of marketing activities (Daskalakis et al., 2022). In the process of precise placement of consumer coupons, it is necessary to analyze and gain insight into customers' preferences, purchasing habits and behaviors, and the collection and analysis of big data on shopping behavior is also conducive to the personalized recommendation of EC companies, the study uses the idea of classification integrated learning to design a precise placement model of EC coupons, and the pattern of placement is shown in Fig. 1.

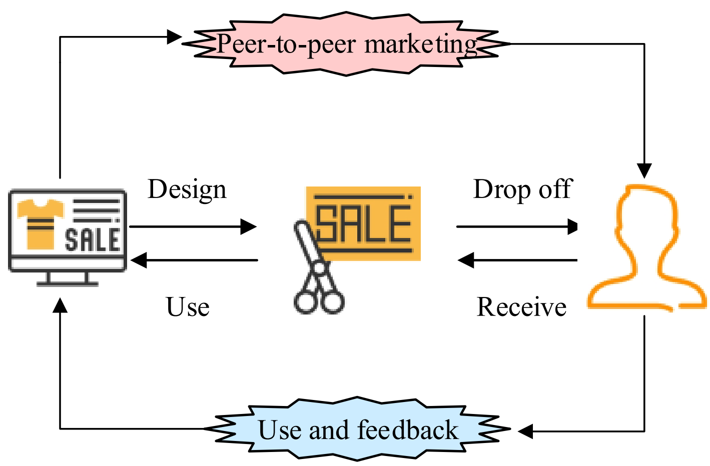


Fig. 1 *Precise Delivery Mode of Coupons*

Firstly, the data of EC platform, such as user consumption records and purchasing behaviors, are processed with missing values and data coding. Then the data are feature-constructed according to industry experience and business logic to mine the effective features of the original data. The study analyzes the statistical features of the data, the ratio features of users' consumption coupon use, the time dimension features of users' consumption and the rule features, and judges the users' consumption preference, users' consumption activity, etc. on the ground of the constructed features (Salem et al., 2023; Wu et al., 2021). In addition, the study chooses the feature selection algorithm integrating random forest and Pearson correlation coefficient for measuring the importance of model features. The importance is calculated according to the Random Forest Out Of Bag (OOB) error rate $E_i^{(OOB)}$, and the calculation process is shown in Equation (1). In Equation (1), m_j^o denotes the amount of OOB data of the j tree; Y_p denotes the value of the p sample; Y_p^j, Y_{p,π_i}^j denote the predicted value of the j tree on the p sample before and after the OOB perturbation, respectively; I denotes the schematic function.

$$E_i^{(OOB)} = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{m_j^o}\left(\sum_{p=1}^{m_j^o} I\left(Y_p = Y_p^j\right) - \sum_{p=1}^{m_j^o} I\left(Y_p = Y_{p,\pi_i}^j\right)\right) \tag{1}$$

The covariance between features can easily lead to the over-fitting phenomenon of the model, and the introduction of the Pearson correlation coefficient ρ_{xy} can maximize the exclusion of features with large correlation, and the calculation process is shown in Equation (2). In Equation (2), X, Y denotes different random variables, and Cov, D denote the covariance and standard deviation, respectively. The joint use of Pearson's correlation coefficient and Random Forest can differentiate the correlation and importance of the features, and complete the feature selection.

$$\rho_{xy} = \frac{Cov(X,Y)}{\sqrt{D(x)}\sqrt{D(x)}} = \frac{\sum_{n}^{i=1}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{n}^{i=1}\left(X_i - \overline{X}\right)^2}\sqrt{\sum_{n}^{i=1}\left(Y_i - \overline{Y}\right)^2}} \tag{2}$$

Classification integrated learning is a learning method that constructs and combines multiple learners to complete the learning task, and there are two main combining strategies: averaging and voting, and classification integrated learning improves the generalization ability and stability of the model. The study selects LightGBM in the serial integrated learning algorithm boosting to construct the coupon placement model. LightGBM is an efficient parallel algorithm on the ground of the gradient boosting tree implementation, which has the advantages of lower memory consumption, higher accuracy, and stronger robustness. The decision tree growth strategy of LightGBM is to divide the dataset by leaf splitting, which divides the dataset into smaller subsets to produce a tree is grown by selecting the leaf node with the largest splitting gain among all the leaves for splitting, and the growth principle is showcased in Fig. 2. In addition, in order to prevent over-fitting phenomenon during leaf splitting, the study sets the maximum depth limit of the decision tree.

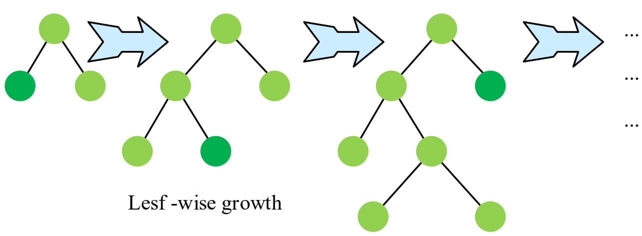


Fig. 2 *Leaves Split the Growth Principle*

The LightGBM algorithm contains two important optimization steps, Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). Excessive samples contain more redundancy and noise, which increase the computational complexity. GOSS improves the model training speed by retaining only the samples with larger gradient through sample weighting, which greatly reduces the computation and memory consumption. EFB bundles the features with the same or related features, which decreases the dimensionality of the features, and enhances the prediction performance and training speed of the model.

Raw shopping consumption data positive and negative samples are usually looking for extreme imbalance phenomenon, the study uses the integrated learning algorithm Easy ensemble on the ground of random under sampling for solving the imbalance of the original consumption samples (Wu et al., 2022). Easy Ensemble repeats the combination of positive and negative samples many times to train multiple classifiers for integrated learning, and the entire coupon placement algorithm's workflow is shown in Fig. 3.

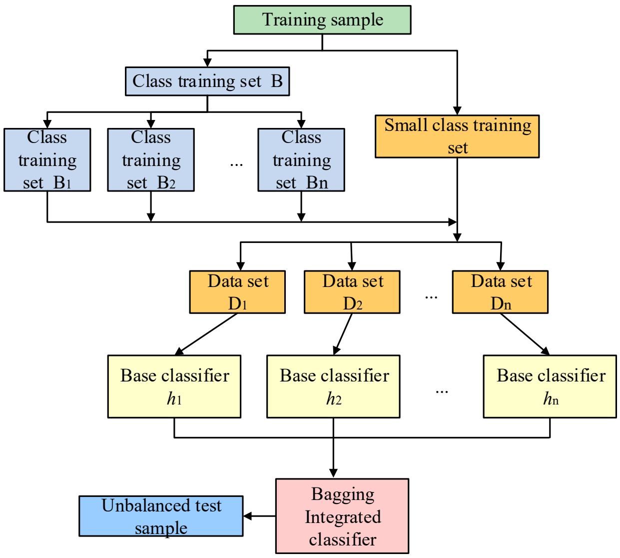


Fig. 3 *Workflow of Coupon Delivery Algorithm*

The calculation process of voting categorization prediction for the classification problem is shown in Equation (3). In Equation (3), $y^{(j)}$ denotes the predicted value of a particular sample; n denotes the number of LightGBM-based classifiers; and 0.5 denotes the critical value of positive and negative samples.

$$\frac{y_1^{(j)} + y_2^{(j)} + \ldots + y_n^{(j)}}{n} \geq \frac{1}{2} \tag{3}$$

3.2 Design of personalized hybrid weighted recommendation model for EC on the ground of scoring matrix

On the basis of accurate placement of coupons, further implementation of accurate personalized recommendation is a key link in EC marketing. The purpose of personalized recommendation is to recommend possible purchases for the user, to help the user quickly and accurately find products to meet the needs of the platform, which greatly improves the shopping experience and increases the willingness to make decisions on purchases, and the process of implementation of personalized recommendation provides a strong support for the decision-making of EC enterprises (Fkih, 2022).

Collaborative Filtering (CF) recommendation algorithm is a common and effective recommendation algorithm that mainly uses user behavioral data (e.g., ratings, clicks, browsing, etc.) to discover user's interests and behavioral patterns, so as to recommend unknown but potentially interesting items for the user (Jain et al., 2022). Collaborative filtering mainly includes. User-based Collaborative Filtering (UserCF) and Item-based Collaborative Filtering (ItemCF), the working principle of the recommender system is shown in Fig. 4.

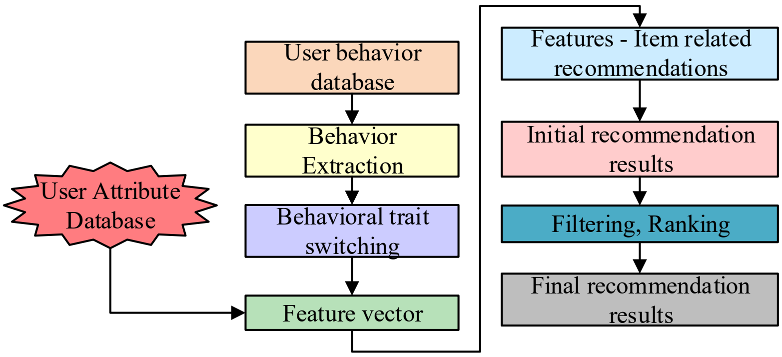


Fig. 4 *Working Mechanism of Recommendation System*

UserCF is an algorithm for recommendation by calculating the similarity between users. The main process of UserCF is roughly divided into four steps: establishing user-item rating matrix, calculating similarity between users, determining nearest neighbor set, and determining item ratings by weighted average or voting. The flowchart of user-based collaborative filtering algorithm is shown in Fig. 5.

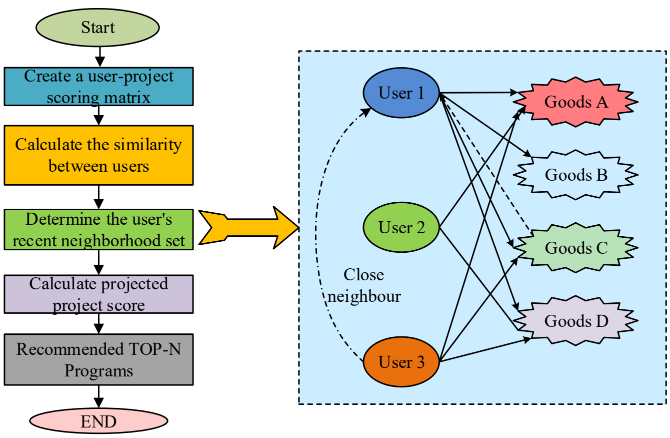


Fig. 5 *User-Based Collaborative Filtering Recommendation Algorithm*

The user-item rating matrix definition equation is shown in Equation (4), in Equation (4), U,I denotes the user, item full set respectively. r_{ij} serves as the rating of i user on j item.

$$R_{U,I}=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{4}$$

The set of nearest neighbors of UserCF can be obtained by calculating the similarity between users through the user-item scoring matrix. The similarity between users is also calculated using the Pearson correlation coefficient, and the calculation process is shown in Equation (5). In Equation (5), $I_{1,2}$ serves as the set of items rated by different users; $\overline{r_1}$, $\overline{r_2}$ denote the average ratings; r_{1i}, r_{2i} denote the ratings of items by user u_1,u_2.

$$sim(u_1,u_2)=\frac{\sum_{i\in I_{1,2}}\left(r_{1i}-\overline{r_1}\right)\left(r_{2i}-\overline{r_2}\right)}{\sqrt{\sum_{i\in I_{1,2}}\left(r_{1i}-\overline{r_1}\right)^2}\sqrt{\sum_{i\in I_{1,2}}\left(r_{2i}-\overline{r_2}\right)^2}} \tag{5}$$

The process of calculating the user's favorite degree of the item is shown in Equation (6), where U_k denotes the set of k nearest neighbors of the target user u. Then the item ratings are determined by weighted average or simple majority voting to generate recommendation results.

$$p(u,i)=\frac{\sum_{I\in U_k} sim(u_1,u_2)*r_{1i}}{\sum_{I\in U_k} sim(u_1,u_2)} \tag{6}$$

The key to ItemCF is to compute item attributes and find similar items on the ground of the target item. The similarity between different items is calculated on the ground of the user-item rating matrix, and the set of k nearest neighbors of the items is determined. The user's favorite degree of the item is calculated in Equation (7), in which r_{uj} represents the user's u rating of the item j; I_u serves as the set of items with which the user has had exchanges; I_k represents k items that are similar to the target item i; and $sim(i,j)$ serves as the degree of similarity between different items.

$$p(u,i)=\frac{\sum_{j\in I_u\cap I_k} sim(i,j)*r_{uj}}{\sum_{j\in I_u\cap I_k} sim(i,j)} \tag{7}$$

The key of UserCF is to calculate the degree of matching between the content and the user's interest, but the number of users on EC platforms is much larger than the number of items, and the user's interest is not easy to be captured, so there are difficulties in the application of UserCF on EC platforms. In contrast, the key of ItemCF is to calculate the attributes of items, which is more adaptable to the characteristics of EC platforms. However, ItemCF has a cold-start problem for new items, with poor recommendation effect, and it is not easy to mine users' new interests. Therefore, the study introduces a trust relationship and weighted hybrid approach to improve the fusion of UserCF and ItemCF, and the working mechanism of the hybrid weighted recommendation algorithm improved on the ground of the trust mechanism is shown in Fig. 6.

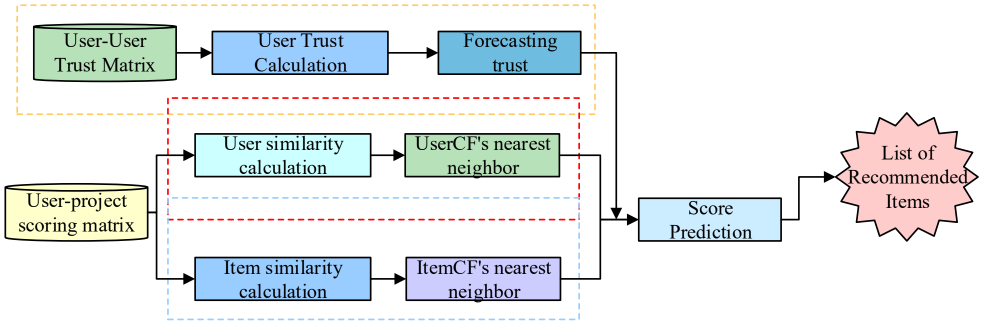


Fig. 6 *Improved Hybrid Weighted Recommendation Algorithm on the Ground of Trust Mechanism*

The improved method locks the set of nearest neighbor items I_k in ItemCF into the set of user rated items I_u, and the process of calculating the user's favoriteness rating of the items changes to Equation (8).

$$p(u,i)=\frac{\sum_{j\in I_k} sim(i,j)*r_{uj}}{\sum_{j\in I_k} sim(i,j)} \tag{8}$$

In the face of massive product information and user purchase data on EC platforms, user evaluation information is relatively sparse. Common similarity calculation methods cannot accurately reflect the similarity of users or items in the face of data sparsity, resulting in poor recommendation results. The study introduces trust relationship to improve collaborative filtering algorithm on the ground of the nearest neighbor set calculated by trust degree. The degree of trust is the degree of trust between users in terms of similarity, interaction history, and social relationship metrics, and the calculation of the degree of trust can assist the coordinated filtering recommendation algorithm in filtering and adjusting the recommendation results.

The study chooses the asymmetric trust factor to measure the trust between users, and the calculation process is shown in Equation (9). In Equation (9), θ_{ab}, θ_{ab} represent the trust factors of user a to b and user b to a, respectively; I_a, I_b represent the items rated by user a and b, respectively.

$$\begin{cases}\theta_{ab}=\dfrac{I_a\cap I_b}{I_a}*\dfrac{I_a\cap I_b}{I_a\cup I_b}\\[2ex] \theta_{ba}=\dfrac{I_a\cap I_b}{I_b}*\dfrac{I_a\cap I_b}{I_a\cup I_b}\end{cases} \tag{9}$$

The calculation of trust also requires the specific score of the scoring item to calculate the user's trust in the item, and the process of calculating the trust is shown in Equation (10),

$trust(a,b) \in [0,1]$. In Equation (10), $value(a,b,i)$ denotes the size of user a's trust in user b on item i; and n serves as the number of items that user a has scored.

$$trust(a,b) = \frac{\sum_{i=0}^{n} value(a,b,i)}{n} \tag{10}$$

There are also large differences in the scoring criteria of different users, and the calculation of scoring similarity needs to take into account the user gap, the user difference sim_{AB} Calculation process is shown in Equation (11), Equation (11), Max, Min respectively, represents the maximum and minimum values of user scores.

$$sim_{AB} = \frac{\sum_{i=1}^{N} \left(1 - \frac{\overline{r_A} - \overline{r_B} + r_{BI} - r_{AI}}{2(Max - Min)} \right)}{|I_A \cap I_B|} \tag{11}$$

The process of calculating the trust level of the integrated user gap is shown in Equation (12), where r_{ai}, r_{bi} denote the ratings of user a,b on item i, respectively.

$$value(a,b,i) = \frac{(r_{ai} - r_{bi})^2}{2(Max - Min)} \tag{12}$$

The process of calculating the finalized trust level by combining the trust level with the asymmetric trust factor is shown in Equation (13).

$$\begin{cases} sim_t(a,b) = trust(a,b) * \theta_{ab} \\ sim_t(b,a) = trust(b,a) * \theta_{ba} \end{cases} \tag{13}$$

The TOP-N sorting method is used to determine the nearest neighbor sets of similar users and items, UserCF and ItemCF generate recommendation results individually, and finally mixed weighting is performed, the calculation process is shown in Equation (14), which a represents the weight ratio.

$$preference = a \cdot pref_{UserCF} + (1-a)\, pref_{ItemCF} \tag{14}$$

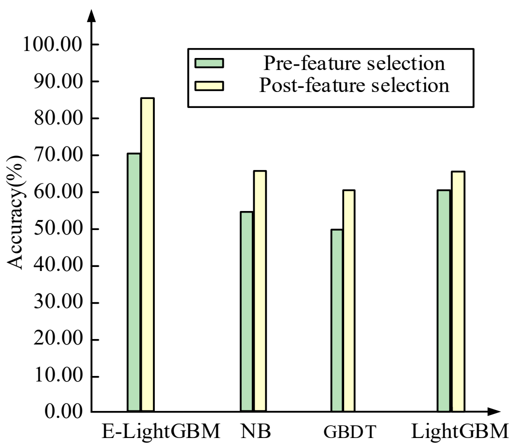
4. EC Marketing Model Performance Testing and Program Application Effect Analysis

For verifying the effectiveness of the coupon placement model and PRM designed by the study, the study designed performance test experiments and application effect analysis experiments, and the results were analyzed and discussed.

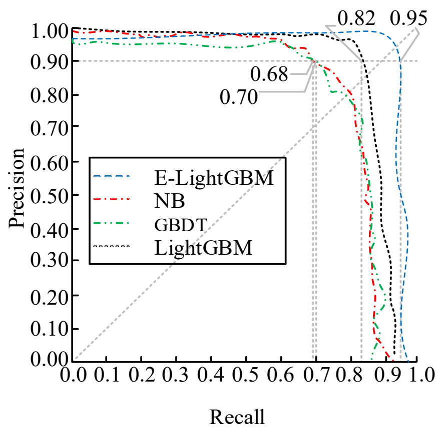
4.1 Performance test of improved LightGBM model with weighted hybrid recommendation algorithm

Taobao user behavior data is selected as the test experiment dataset. The Taobao user behavior dataset includes 3623 different product categories and four shopping behaviors: click, buy, like and add. The data required for the experiments are divided into training set and test set according to the ratio of 8:2.

In order to accomplish the performance testing of different model algorithms, programs were written in C++ to implement the algorithms required for testing. Easy Ensemble-LightGBM (E-LightGBM), traditional LightGBM, and Naive Bayes (NB) were selected first, Gradient Boosting Decision Tree (GBDT). LightGBM is a gradient boosting algorithm based on decision trees for classification and regression problems. E-LightGBM is a gradient boosting decision tree that integrates two techniques, EasyEnsemble and LightGBM, for category imbalance problems. NB is a classification algorithm based on Bayes' theorem and the assumption of conditional independence of features. GBDT is a model for classifying problems by iterative training of multiple decision trees model for classification problems. The effect of feature selection algorithms was verified; and the performance of the research-designed method was compared with the traditional classification model, and the accuracy, precision and recall were chosen as the evaluation indexes of the model, and the statistical results of the accuracy and Precision-Recall curves (PR) are shown in Fig. 7. As can be seen in Fig. 7(a), the feature selection of Random Forest combined with Pearson correlation coefficient effectively increases the accuracy of the algorithm, and the accuracy values of different classification models using this method are all greater than those before feature selection, and the accuracy of the E-LightGBM model designed in the study is most obviously improved. As can be seen in Fig. 7(b), the PR curve of the E-LightGBM model is located in the rightmost upper corner of the coordinate axis, and the curve area is the largest. When the precision rate takes the value of 0.90, the recall rate takes the value of 0.95, while the recall rate of Bayesian algorithm in the same experimental environment is only 0.68, which shows that the E-LightGBM model has the optimal ability to categorize and find positive examples.



(a) Accuracy

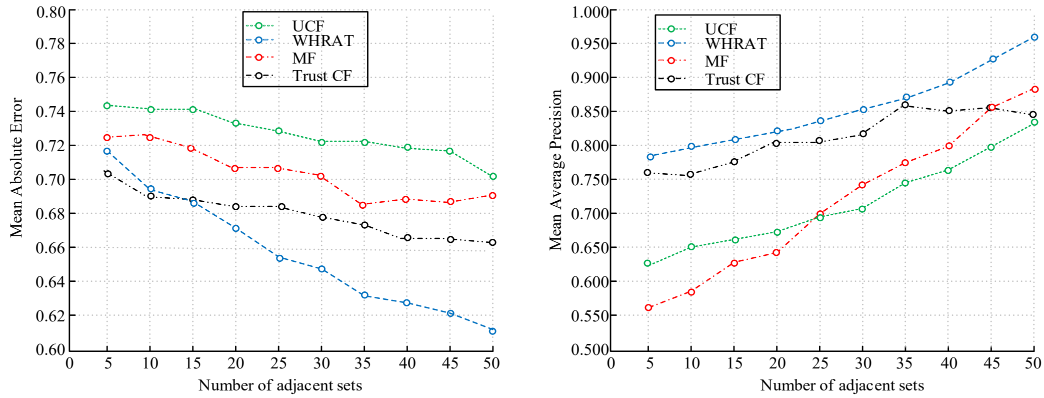


(b) PR

Fig. 7 *Verification of Feature Selection Effect and Comparison of Algorithm Performance*

Movie Lens is chosen as a test dataset for the recommendation model. Movie Lens contains various movie ratings covering 27,000 movies and contains genre information and user application tags. The Weighted hybrid recommendation algorithm on the ground of trust (WHRAT) designed in the study is compared with other recommendation models: traditional User Collaborative Filtering (UCF), Trust CF, Recommendation Algorithm On the ground of

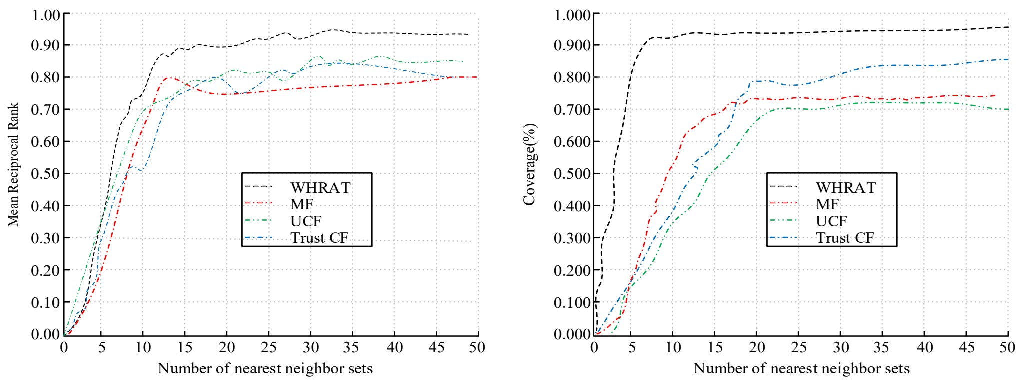
Matrix Factorization (MF). UCF is an algorithm that uses behavioral data between users to make recommendations by measuring the similarity between users to predict their preferences for unrated items. Trust CF builds on UCF by taking into account the trust relationship between users. MF is a decomposition of the user-item ratings matrix into two low-rank matrices, and recommendations for completing a task are represented by learning the factors of the matrices. The results of Mean Absolute Error (MAE) and Mean Average Precision (MAP) of different recommendation algorithms are shown in Fig. 8. As seen in Fig. 8, the MAE values of different recommendation algorithms differ significantly, and the MAE of the research-designed WHRAT algorithm converges below the minimum value of 0.62. The MAP value of the WHRAT algorithm reaches the highest value of 0.961, and the traditional UCF precision value is the worst, and when the set of nearest neighbors reaches 50, the MAP takes the value of 0.842. It can be seen that the research-designed WHRAT algorithm is very effective in the enhancement of recommendation precision, effect is remarkable.



(a)MAE (b)MAP

Fig. 8 *Different Recommendation Algorithm Error and Precision of the Contrast*

4.2 Analysis of the marketing effect of precise placement of coupons and personalized recommendations



(a)MRR (b)Coverage

Fig. 9 *Comparison of Recommendation Effects of Different Recommendation Algorithms*

All the sales data and user behaviors of an EC platform in the past year are selected as the dataset for performance testing, and a total of 275,614 data are collected after preprocessing operations. The Mean Reciprocal Rank (MRR) and coverage rate are used as the evaluation indexes of the algorithm, and the experimental statistical outcomes are showcased in Fig. 9, from which it can be seen that, with the increase of the number of nearest neighbors, the MRR value and coverage rate of different algorithms are on the rise, and the WHRAT algorithm designed in the study considers the similarity value from the aspects of scoring trustworthiness and weighted mixing, which improves the algorithm's recommendation accuracy. The coverage rate indicates the percentage of the number of goods recommended to the user by the recommender system, and the WHRAT algorithm has the largest recommendation breadth, with the maximum coverage rate reaching 0.926, while the other three algorithms have a maximum coverage rate of below 0.850 MRR is an index that measures the effect of sorting, and the higher the inverse rank of the mean value is, the better the effect of sorting is indicated. It can be seen that WHRAT algorithm has better recommendation effect.

The Hits Ratio (HR) of the evaluation index k and the Normalized Discounted Cumulative Gain (NDGG) of the evaluation index are selected to evaluate the performance of the recommendation algorithms, and the experimental statistics are shown in Table 1. Both HR and NDGG are metrics for evaluating the ranking performance of a recommender system. HR measures how many items of interest to the user are hit in the first K recommendation results. NDGG is calculated based on the ranking and relevance of the recommendation results and measures the ranking quality and relevance of the recommendation results. As can be seen from Table 1, the HR and NDGG of each recommendation algorithm show an increasing trend with the increase of k-rank. When the number of ranks is the same, the WHRAT algorithm takes the highest value of the indicator, the HR value rises from 47.65% to 81.31%, and the NDGG value rises from 38.18% to 67.26%. HR indicates the ratio of the number of hits of the user's favorite items to the total number of items, and the higher the value takes means the more excellent the accuracy of the recommendation; and the higher the NDGG is means the better the quality of the recommendation list, which can be seen that the WHRAT algorithm is well applied in EC marketing recommendation.

Table 1 *Comparison of Recommendation Effects of Recommendation Algorithms*

Evaluating indicator		WHRAT	UCF	MF	Trust CF
$k\#5$	HR	47.65%	39.44%	42.47%	34.88%
	NDGG	38.18%	36.77%	37.47%	31.26%
$k\#10$	HR	67.06%	49.09%	51.28%	54.88%
	NDGG	49.21%	37.52%	39.96%	36.25%
$k\#15$	HR	81.31%	72.22%	62.34%	72.29%
	NDGG	67.26%	49.09%	51.28%	54.88%

The statistical results of coupon placement accuracy and purchase rate for target users are shown in Fig. 10. As seen in Fig. 10, under the research-designed coupon placement model for EC marketing, with the increase in the type of coupon placement for the same user, the placement accuracy for the target user rises significantly and is much higher than other models. At the same time, with the increase of coupon placement types, the increase of placement accuracy also improves the user's shopping conversion rate, and the research-designed method achieves more than 50% of the user's purchase rate in the case of 10 types of coupons placed at one time.

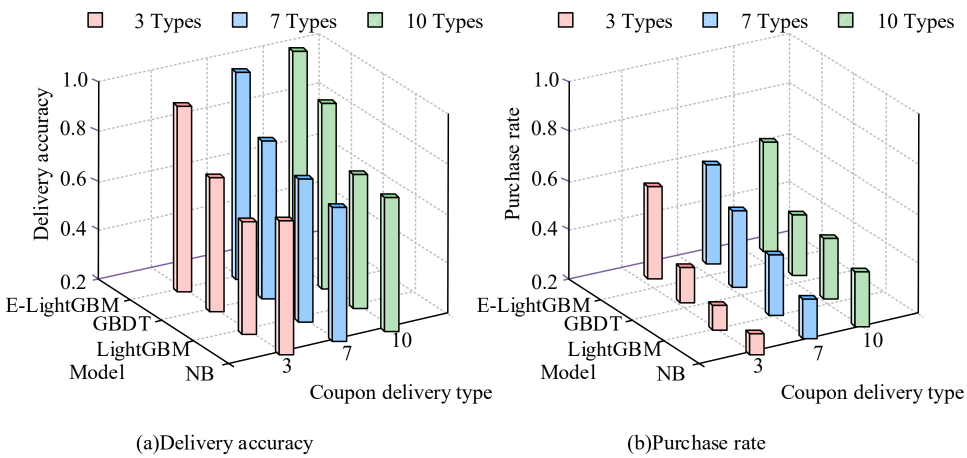


Fig. 10 *Comparison between Coupon Delivery Accuracy and Purchase Rate*

Finally, the user clicks and cost effectiveness were selected to evaluate the research-designed EC marketing program, and the experimental results are shown in Fig. 11. As seen in Fig. 11, the platform was effective before and after the use of the research-designed marketing program during the test cycle. The number of user clicks increased substantially after use, and the fluctuation range was roughly maintained in the range interval of 75.0%-94.0%; the cost-effectiveness had a downward fluctuation, but the overall trend was upward, and the highest cost-effectiveness reached 51.3%.

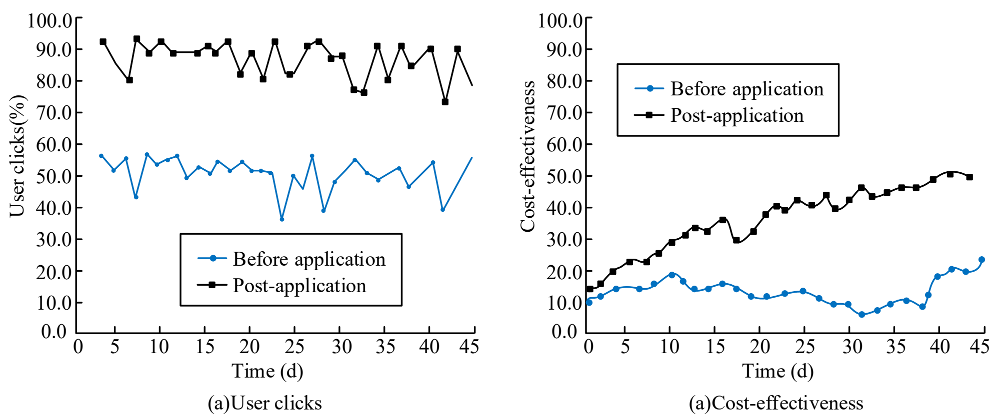


Fig. 11 *Comparison of User Clicks and Cost-Effectiveness*

5. Conclusion

The rise and popularization of Internet technology accelerates the development and change of EC, facing the severe situation of network information overload, and actively responding to the challenges of EC marketing strategy, the research designed a consumer coupon placement model and a product PRM for EC marketing program design on the ground of LightGBM and hybrid weighted recommendation algorithm. The experimental results show that the research-designed E-LightGBM model has the largest PR curve area, when the precision rate takes the value of 0.90, and the recall rate takes the value of 0.95, which is better than other algorithms in the same experimental environment. The MAE and MAP of the WHRAT algorithm outperforms the other recommendation algorithms, with the convergence value of the MAE being at 0.62, and the MAP reaches the highest value of 0.842.The maximum coverage reached 0.926 and MRR took the maximum value, which is better than the other three algorithms. Meanwhile, the HR and NDGG metrics of this algorithm take the optimal values at different values of k. The HR value rises from 47.65% to 81.31%, and the NDGG value rises from 38.18% to 67.26%. In the actual operating environment of e-commerce, e-commerce enterprises can accurately deliver personalized coupons to users based on their behavioral data, purchase history, preferences and other information. At the same time, the attributes and hotness of the products are integrated to generate personalized generated recommendation results. This application improves user experience, facilitates purchasing decisions, and increases the click and purchase conversion rate of users on recommended products, thereby boosting revenue. The marketing program has a high precision of coupon placement during the marketing of the EC platform, and the user purchase rate can reach 50% when there are more types of coupon placement. The number of user clicks after marketing fluctuated in the range interval of 75.0%-94.0%, and the cost-effectiveness reached 51.3%. The consumer coupon placement model and product PRM designed in the study can better cope with the Internet information overload problem, which is significant for the improvement of EC marketing scheme and conducive to the further utilization of computer technology in personalized marketing and business model innovation. E-commerce platforms use personalized recommendation models to help users quickly find products of interest, providing a more proactive business service. At the same time, the placement of consumer vouchers allows merchants to better adapt to shifts in market development trends and enhance their marketing capabilities. Consumers also get more economical personalized services in the process. However, subsequent research can further enhance the operation of the algorithm for strengthening the shopping experience.

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