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# Optimization of Online Advertising Decision Combination Based on the Attribution of Consumer Behavior Big Data

***Abstract:* -** In the field of internet advertising, associated products based on various big data algorithms are widely presented on consumers' browsing pages in order to increase their purchasing interest. With the help of computer big data processing, online advertisers can better grasp the shopping needs of consumers. This study proposes a chance constrained programming optimization model (CC-PR) for budget allocation of advertisers in a dynamic and complex consumer behavior context, based on the premise of analyzing consumers' shopping journey from the perspective of the attribution of consumer behavior effects. It models different online behaviors generated by consumers' interest transfer at different shopping stages. The characteristic of this method is to simulate changes in consumer psychology, overcome the difficulty of predicting multi-stage behavior of consumers, and extract a model of dynamic generalizable laws of consumer psychology. It dynamically adjusts advertising strategies based on changes in consumer tendencies at different stages. In order to verify the effectiveness of the proposed strategy, this paper introduces batch data from large shopping platforms and compares our method with the baseline method through experiments. The results show that the CC-PR method proposed in this paper has superior performance. A large amount of consumer behavior data can help advertisers make more accurate advertising decisions, and the method proposed in this article is also a good example of the application of computer big data processing in the field of online advertising.

***Keywords:*** Online Advertisement, Consumer Behavior Big Data, Product Recommendation, Chance Constrained Programming.

## I. INTRODUCTION

In the business field, big data technology helps advertisers analyze potential customers by recording consumer behavior, market trend prediction, product development, supply chain management, and other aspects. By analyzing customer behavior data, enterprises can more accurately understand customer needs and provide customers with more personalized products and services. On internet shopping platforms, consumers can freely search for online product information whatever they need. However, products displayed in the user's field of vision are not naturally generated. In order to cater to consumers' shopping preferences, online merchants widely use recommendation systems based on various big data algorithms to display products that attract consumers [1, 2]. Usually, consumers start their online shopping journey with vague ideas, and in the subsequent product page browsing, they will capture information, continuously compare and gradually clarify their shopping goals [3]. In order to increase consumers' purchasing interest, their browsing pages will display other associated products at appropriate times [4]. Current studies have shown that if these associated products can better meet consumers' tastes, the likelihood of online conversion will greatly increase [5-7]. Therefore, these products recommended to consumers through page links need to be consistent with their interests, this can provide consumers with multiple product choices, making it more likely to make a purchase.

At present, research on associated product recommendation based on various big data algorithms usually uses collaborative filtering algorithms to specify consumers' interest, classify and model consumers based on their interests through cookies analysis in the backend of shopping websites [8]. Collaborative filtering is a recommendation algorithm based on user behavior, which simulates consumer preferences by analyzing users' historical behavior and preferences. Previous studies have typically used collaborative filtering methods to classify consumers, which may classify users with similar online behaviors as having similar consumption preferences. The advantage of this method is that it can discover non popular and novel products or projects, while the disadvantage is that as users and the number of products increase, the computational complexity becomes very large [9]. Project based collaborative filtering: analyzes users' evaluations and preferences for products or projects to recommend products or projects similar to those they have already evaluated to target users. It is based on the assumption that if two products or projects are evaluated by many users as similar, they may have similar attributes or features. The

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advantage of this method is that it can generate accurate recommendations based on users' actual evaluations and preferences, while the disadvantage is that as the number of users and products increases, the computational complexity also becomes very large. The advantage of collaborative filtering is that it can simulate consumer preferences based on their actual behavior, thereby generating accurate recommendations. However, its disadvantage is that as the number of users and products increases, the computational load becomes very large, requiring efficient algorithms and data structures to optimize performance. In addition, collaborative filtering also has a cold start issue, where it is difficult to effectively recommend new users or products due to a lack of sufficient behavioral data. Considering the diversity of consumer behavior and the instability of interest changes during the shopping process, there are still challenges that require more innovative exploration to understand which factors drive these psychological changes.

Aiming at this problem, this study proposes a chance constrained programming optimization model (CC-PR) for budget allocation of advertisers in a dynamic and complex consumer behavior context, which helps the recommended related products on the online page more accurately match consumers' shopping preferences. The CC-PR method can be used in dynamic and complex consumer behavior environment, iterating continuously to gradually approach the potential consciousness of consumers, and measuring the authority and importance of a product or project by constructing a hierarchical sequence of underlying consciousness requirements. For example, if a product is linked to more important products and triggers more consumer likes, favorites, or purchases, the importance of the product may be higher and more likely to meet the actual shopping needs of consumers. Based on the CC-PR method, it simulates consumers' constantly adjusting shopping thoughts, overcomes the difficulty of predicting multi-stage behavior of consumers, and refines the laws of dynamic changes in consumer psychology. It describes the potential consumer interest changes in multiple stages, and identifies strategies for dynamically detecting hidden interest and psychological changes in consumers. A large amount of consumer behavior data can help advertisers make more accurate advertising decisions, and the method proposed in this article is also a good example of the application of computer big data processing in the field of online advertising. The method proposed in this article reflects that big data technology is an important driving force for business innovation and transformation. It is reshaping the decision-making, operation, and management models of enterprises, driving continuous innovation and optimization, and gaining competitive advantages.

## II. Research Foundation

In recent years, online shopping has attracted the attention of businesses and consumers, and is also a research focus in the business field both domestically and internationally, but current research mainly focuses on the interests of online shopping platforms and the study of online user behavior. However, some small and medium-sized enterprises often lack the ability to explore online user behavior and complex algorithm rankings. At present, there is relatively little research from the perspective of advertisers, and it focuses on extracting or generating recommended products from different media, mainly including advertisers' landing pages or search engine query logs [10]. However, the recommended products generated through this method cannot guarantee that the number and relevance can meet the needs of advertisers [11]. Therefore, it is necessary to generate highly correlated, profitable, and well structured recommended products [12]. Part of the existing work is based on the statistical co-occurrence relationship between network content and search engine query logs to measure the correlation between recommended products, which ignores semantic information and easily ignores some low co-occurrence but semantically related recommended products. Product recommendation methods based on semantic information often lack timeliness and cannot be updated in a timely manner [13]. In the era of the internet, the speed of information updates is very fast, and people's names for the same thing may change at any time [14]. Moreover, popular online terms continue to appear, and consumer names for such recommended products are highly characteristic of the times. How to accurately understand and effectively utilize these new names has also become a problem that this article needs to address. Simply recommending products from the perspective of relevance cannot guarantee that the selected recommended products have commercial value, that is, it cannot be determined that users who have a demand for the recommended product query have the intention to purchase the product.

## III. Method

Consumers who shop on e-commerce platforms usually just stroll around at first, but may be attracted to a certain product during the browsing process; Consumers may also have a vague intention to browse shopping platform websites and gradually clarify your shopping goals by comparing multiple indicators such as price, appearance, and performance during the process of searching for product information.

Therefore, the shopping process of consumers is often a gradual process of clarification and adjustment. On e-commerce platforms, consumers experience a process of distraction and gradually focusing on their choices. During this shopping journey, consumers may be attracted to certain products or brands, generating a certain level of interest and attention. Consumers will also search and compare information at any time, and the ultimate shopping goals may gradually become clear, in order to find the products that best meet their needs and budget. In addition, consumers' shopping decisions may also be influenced by other factors, such as evaluations, recommendations, and word-of-mouth from other users. This information may affect consumers' purchasing intentions and decisions, further affecting their shopping behavior and preferences.

When consumers browse online shopping platforms, the various products presented on the same page will have an impact on their psychology. Under marketing budget constraints, it is necessary for advertisers to comprehensively analyze the effects of different product combinations presented on the same page. This research group proposes an investment portfolio optimization model for budget allocation based on the actual decision-making situation of online advertising.

In the Internet shopping platform, few consumers browse only one product advertisement and immediately purchase. More commonly, consumers will browse several similar products before making the final purchase. In view of this, advertisers usually place advertisements for different products in multiple advertising spaces in bulk, with each product's advertising page having recommended links to each other, in order to facilitate recommending other products to consumers for selection. In this case, advertisers need to allocate advertising budgets for numerous products. In fact, consumers are diverse, and their online browsing behavior is different. In the shopping platform, which usually charges advertisers based on the number of ad impressions, consumers who are active and enjoy browsing different products have relatively high final purchase costs (i.e. conversion costs). Therefore, if consumers can quickly and accurately grasp their shopping preferences and avoid ineffective product recommendations, it can help advertisers achieve higher profits while reducing advertising costs. Therefore, we propose an improved model based on the actual situation and explore how to classify consumers with active shopping behavior in existing large online shopping platforms according to their shopping preferences, more accurately place advertisements on them, and allocate budgets for advertising spaces for each product on this basis, thereby improving the overall revenue of advertisers.

We consider this problem as a Stackelberg game model, where the advertiser is the leader and the consumer is the follower. Advertisers first determine the budget allocated to each advertising space. Consumers can obtain product information by browsing advertisements and categorize them based on their past browsing and shopping behavior. Using the probability information of whether a product in a certain advertising space meets the shopping needs, and within a limited budget, decide which type of consumers to push advertisements to separately. For consumers, browsing advertisements online incurs time costs, with the goal of buying the most anticipated product (i.e. maximizing revenue) with minimal expected loss (i.e. time cost) during the shopping journey. Advertisers aim to achieve higher advertising revenue while minimizing the maximum expected loss caused by ineffective advertising.

Define the set of all consumer types as K, where each type of consumer is indexed by k. For K-class consumers, the required cost (including the total cost of consumers browsing new product advertisements through recommended links multiple times) is $c_k$. The probability of successful passage for consumers in the k-th category who choose product i as the starting product for online browsing before the advertiser allocates budget is $p_{ik}^0$, and the expected loss caused by clicking on the next product advertisement $ih$ is $d_{ihk}$. Based on the actual situation, the more picky consumers are, the higher their conversion cost, initial click through rate, and cost of clicking on the next product advertisement. Therefore, $p_{ik}^0 e^{-\lambda_i x_i}$, which is the probability of successfully clicking on the next product advertisement in the k-th category after budget allocation is obtained.

Define decision variables $x_i$ to represent the budget allocation of advertising i by advertisers. Assuming that each advertisement i is allocated a budget with a lower and upper bound, denoted as $\mathrm{L_i}$and$\mathrm{U_i}$, respectively. In addition, $y_{ihk}$ is a 0-1 decision variable, for whether consumers click on the next product advertisement. When the link h on the advertising page i is clicked by the k-th consumer, it is 1, otherwise it is 0.

Based on the above description, we establish the following 0-1 bilevel integer programming model:

$$\min_{\mathrm{W,x_i}} \ \mathrm{W} \tag{1}$$

$$\mathrm{s.t.} \sum_{\mathrm{i \in I}} \mathrm{x_i} \le \mathrm{B_G}\,, \tag{2}$$

$$\mathrm{L_i} \le \mathrm{x_i} \le \mathrm{U_i}, \forall \mathrm{i} \in \mathrm{I} \tag{3}$$

Wherein

$$W = \max_{y_{ihk}} \sum_{i\in I} \sum_{h\in H} \sum_{k\in K} p_{ik}^{0} e^{-\lambda_i x_i} d_{ihk} y_{ihk} \tag{4}$$

$$\text{s.t.} \sum_{i\in I} \sum_{k\in K} y_{ihk} \leq 1,\ \forall h \in H, \tag{5}$$

$$\sum_{i\in I} \sum_{h\in H} \sum_{k\in K} c_k y_{ihk} \leq B_T, \tag{6}$$

$$y_{ihk} \in \{0,1\},\ \forall i \in I, h \in H, k \in K. \tag{7}$$

In the upper level of planning, advertisers want to minimize the maximum expected loss W caused by ineffective advertising. Constraint (3.2) ensure that the total budget allocated to all advertisements does not exceed the budget limit B (G); Constraint (3.3) is the boundary constraint, which ensures that the budget allocated for each advertisement i is within its corresponding range. In the lower planning, consumers maximize the expected shopping revenue they can get. Constraints (3.5) ensure that each advertisement is viewed at most once by a single consumer. Constraints (3.6) Ensure that the total shopping cost does not exceed the consumer's cost limit B_T. The constraint (3.7) is a 0-1 constraint.

## IV. Application, Validation and Simulation

Based on the above research on consumer behavior budget allocation strategies for online shopping platforms, specifically in various purchasing channels, consumers usually click on several related recommended products before making a purchase decision (conversion). For a conversion, we realize that there are usually multiple consumer visits from different related recommended products before the conversion, and all these related recommended products have their own contributions to the final conversion result. And the advertiser needs to bid for a single associated recommended product, so the advertiser needs to allocate the conversion credit to each associated recommended product, and then determine the bid amount for each associated recommended product. Based on this, we propose an attribution based association based recommended product bidding strategy.

First, advertisers can delimit the feasible area of the final effect of advertising, $D = \{\bar{O}_1 > d_1, \bar{O}_2 > d_2, \bar{O}_3 < d_3, \bar{O}_4 > d_4, \bar{O}_5 = d_5\}$， where $O_1$ represents the set of keyword display, click rate, click price per unit, conversion rate and attribution proportion respectively， $d_i (i = 1, \cdots 5)$ are constants. Given the set of recommended products K associated with the advertiser (the bidder i in the auction), the consumer clicks on each associated recommended product before a conversion, $K_l \in K, l = 1, \cdots n$. The time interval between each click on the associated recommended product and the final conversion is $t_l$, then $t_1 > t_2 > \cdots t_n$. Firstly, this study introduces a time exponential decay part with a decay factor $\lambda$ (positive value) to represent the reduction in the conversion contribution of associated recommended products ( $h_l$ represented by the proportion of conversion values of associated recommended products in the conversion), which decreases over time, i.e $h_l \propto e^{-\lambda t_l}$; Secondly, this study considered the consumer click through situation of related recommended products. The higher the click through volume $c_l$, the higher the possibility of conversion of related recommended products, i.e $h_l \propto \frac{c_l}{\sum_{k=1}^{n} c_k}$. Taking into account the above two points, the conversion of the associated recommended products is represented as

$$h_l = \frac{\alpha e^{-\lambda t_l} + \beta \frac{c_l}{\sum_{k=1}^{n} c_k}}{\sum_{l=1}^{n} \alpha e^{-\lambda t_l} + \beta} \tag{8}$$

If the conversion value is H, the conversion value of the associated recommended product $K_l$ is $H \cdot h_l$. Considering all conversions $N_l$ related to the associated recommended product $K_l$ between two auctions (the previous auction and the current auction), we obtain the conversion value of the associated recommended product $K_l$ as $\widehat{H}_l = \sum_i \sum_{k=1}^{N_l} H_k \cdot h_{lk}$. Further, we obtain the attributable proportion of the keyword k in the keyword set as follows $Weight_k = \frac{\widehat{H}_k}{\sum_{j\in K} \widehat{H}_j}$.

Use the random maximum chance planning model (Chance Constrained Programming, CCP). The maximum chance planning model based on the random bid set seeks a random bid set that gives all keywords at least the minimum feasible reliability and maximizes the revenue per unit budget,

$$\operatorname{argmax}_{b_k} \sum_k \bar{f}_k$$

$$\text{s.t. } P\left\{D, \bar{O}_{4,b_k} \geq \bar{f} \,\middle|\, b_k, k\right\} \geq \alpha_k, k \in K. \tag{9}$$

For the above solution, namely, the optimal keyword bid set for the keyword set $\{b_k, k \in K\}$.

During search advertising and social media advertising promotion, advertisers need to adjust the keyword bids in a keyword set, regularly or even in real time. Each keyword corresponds to a bid $b_k$. At any moment, there can be an adjustment a, the feasible strategy space is: to increase the keyword bid by $\Delta$, or to reduce the keyword bid by $\Delta$, $\Delta \geq 0$. Suppose that the current bid status of the keyword set is $S_t$, the adjustment of the current moment t includes two ways: (1) $a(t) = A_1(k)$， to increase the bid of the keyword k by $\Delta$; (2) $a(t) = A_1(k)$, to reducing the keyword k by $\Delta$. The state transfer equation for the keyword set bid state can be expressed as:

$$S(t+1) = f(S(t), a(t)) = \begin{cases} S(t+1)|b_k' = b_k + \Delta, b_k \in S(t), b_k' \in S(t+1) \\ S(t+1)|b_k' = b_k - \Delta, b_k \in S(t), b_k' \in S(t+1) \end{cases} \tag{10}$$

The instantaneous value $\tau(S, a, t)$is known from the change in the revenue gain (after removing the noise expectation) brought about by the adjustment operation.The moment the advertiser starts is $t_0 = 0$.And give a virtual adjustment to this moment, remember the end of the promotion plan as T, then the objective function of the whole optimization problem can be defined as the total revenue of each adjustment, $J = \sum_{t=0}^{T} e^{-rt}\tau(S(t), a(t), t)dt$, wherer $\in (0,1)$ is the discount factor. To avoid the dimension disaster, we implement an evaluation network to approximate an objective function J through the BP neural network, and study the adjustment strategy of the keyword bid by using adaptive dynamic programming. The original problem can be converted to minimization$\|e_q\| = \sum_l e_q(j) = \sum_l [\tilde{J}(l) - \tau(l) - r\tilde{J}(l+1)]^2$, which is the sum of each adjusted TD error. Training the evaluation network Nc approximation, training the executive network is used to solve the Na of the minimized evaluation network.

The experiment collected the real-world data sets of a group of sportswear advertisers from Tmall, which is a large online shopping platform of Alibaba Group. Then we designed a corresponding advertising decision combination experiment scenario. The experiment obtained marketing, promotion, and sales data for 2616 products from 124 advertisers on e-commerce platforms Tmall from January 2022 to December 2022. Both datasets record a large number of specific consumer behaviors on shopping platforms, including consumer accounts, browsing product names, browsing duration, whether to place an order, leaving comments in the comment section, and other interactions.

In the following experiments, in order to ensure the objectivity and effectiveness of the results and avoid external interference, 10 cross validation tests were conducted in the experiment. The dataset is divided into a test set and an experimental set. Before the experiment started, we randomly divided these data into 10 shopping trips and randomly selected a group as the test set. The final result was taken as the average of the 10 tests. The final result of the experiment is to determine which method can better predict which product consumers will ultimately choose. Given the top-K highest scoring products by the methods, the experiments used two metrics, HR@K and NDCG@K, to measure their recommendation accuracy and ranking performance, respectively.

For the performance evaluation of CC-PR, the experiments compared it with 4 baseline recommendation methods. Among them, there are LBCNN [15], TagMF [16], Kernel-CF [17], and APR (combination of content-based and collaborative filtering) [18]. Based on the real dataset of Tmall, this method and four benchmark methods were used in the experiment to generate the top 10 product recommendation lists for the last behavior in each testing process after model training. This experiment uses the last product of actual consumer interaction on the Tmall platform as the correct recommended answer. Table 1 summarizes the performance of the method using 10-fold cross-validation.

Table 1: Comparison of Experimental Results of Four Methods

| | Tmal | |
|---|---|---|
| | HR@10 | NDCG@10 |
| LBCNN | 0.2193 | 0.1635 |
| TagMF | 0.2286 | 0.1837 |
| Kernel-CF | 0.2729 | 0.2218 |
| APR | 0.2796 | 0.2346 |
| CC-PR | 0.3126*** | 0.2553*** |

*, **, and *** Statistical significance at the 0.1, 0.05, and 0.01, levels, respectively.

The results show that CC-PR outperforms all the baseline methods. First, due to the fact that the CC-PR method is based on the observation and simulation of real consumer behavior, it has obvious advantages in personalized recommendations, which are very intuitively reflected in both accuracy and ranking than other baseline methods.

Second, CC-PR method, as an integrated dynamic method using deep learning, can demonstrate more general advantages than static methods, fully demonstrating the good performance of integrated dynamic methods in advertising recommendation.

Third, CC-PR method outperforms the ordinary deep learning–based baseline methods. Since the recommendation algorithm based on deep learning has been used in online advertising, the effectiveness of recommendation has been improved. However, these existing methods do not provide detailed analysis of the complex online browsing and shopping processes of consumers, as well as the multi-layer changes in consumer psychology during the process. By extracting generalizable rules from the psychological dynamics of diverse and sparse consumer behaviors, CC-PR method improves performance through a relatively simple model structure

## V. CONCLUSIONS

This study proposes a chance constrained programming optimization model for budget allocation of advertisers in a dynamic and complex consumer behavior context, based on the premise of analyzing consumers' shopping journey from the perspective of the attribution of consumer behavior effects. This paper designs an experimental scenario. First, a large-scale real-world data set is obtained through Tmall, and then the model is used to maximize the objective function value of advertisers and find budget investment portfolio optimization strategies in complex online shopping platform consumer behavior. Finally, the experimental results are verified and evaluated. The experimental results show that the performance of the product recommended is better than other methods within the budget range.

This method avoids the waste of advertising content caused by recommending unsatisfactory products to consumers, and can also improve consumer choice satisfaction. Tested in real advertising push service can be a good combination of advertisers, users, operators demand advertising tripartite advertising push.

In the follow-up work, further work can be improved: (1) refine the model and train it to be suitable for personalized product promotion across different product categories; (2) future research can conduct more detailed research on consumers' personalized interests by obtaining and integrating richer observational attributes/factor information of consumers, such as interpersonal relationships, shopping history, etc.

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