Multi-objective Optimization for Guaranteed Delivery in Video Service Platform

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ABSTRACT

Guaranteed-Delivery (GD) is one of the important display strategies for the IP videos in video service platform. Different from the traditional recommendation strategy, GD requires the delivery system to guarantee the exposure amount (also called impressions in some works) for the content, where the amount generally comes from the purchase contract or business consideration of the platform. In this paper, we study the problem of how to maximize certain gains, such as video view (VV) or fairness of different contents (CTR variations between contents) under the GD constraints. We formulate such a problem as a constrained nonlinear programming problem, in which the objectives are to maximize the total VVs of contents and the exposure fairness between contents. In order to capture the trends of VV versus the impression number (page views, PV) for each video content, we propose a parameterized ordinary differential equation (ODE) model, and the parameters of the ODE are fitted by the video historical PV and CLICK datas. To solve the constrained nonlinear programming, we use genetic algorithm (GA) with a specific design of coding scheme considering the ODE constraints. The empirical study based on real-world data and online test on Youku.com verifies the effectiveness and superiority of our approach compared with the state of the art in the industry practice.

CCS CONCEPTS

• **Mathematics of computing** → **Non-parametric optimization**; **Ordinary differential equations**.

KEYWORDS

Guaranteed-Delivery strategy; video service platform; ordinary differential equation; nonlinear programming; genetic algorithm

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1 INTRODUCTION

For online video providers, e.g., Netflix, Youku, etc., there is usually one widget/drawer that needs to distribute the new-released or hot video contents (generally means TV dramas and varieties). The overall user visits of that drawer during one day will not change much due to the fact that the total number of daily active users (DAU) for a video service platform is relatively stable over a period. Therefore, the crucial problem for the widget is how to allocate limited impressions to the given video contents, so as to assure enough impression and fairness for them. The drawer should concern the business requirements or contract requirements for the new-released or hot video, i.e. guarantee the certain number of impressions for each content. This becomes a typical Guaranteed-Delivery system. Thus only relying on recommendation system, which is individual-oriented, is not enough. To solve this issue, an effective impression resource allocation system which plans the impression resources in a certain period before every operation period is essential. Generally, the operation period can be one day or every several hours, which depends on the specific requirement. Impression resource is first planned for each content at the beginning of the period considering all the requirements, then the dispatching system (typically the recommendation system) will take the impression amount allocated for each content as reference and try to find the most suitable users. Thus the whole system can balance both the business requirements and users' personal requirements.

However, the impression allocation before each operation period is complicated because of many constraints involved. Currently, the impression system is operated manually, which highly depends on the experience of human, and thus is definitely sub-optimal. On the one hand, the actual impression delivered for a video content in the widget mostly is determined by its click-through rate (CTR) empirically, but manual allocation strategy cannot precisely predict the contents' CLICK under a given impression. On the other hand, it is even hard for humans to design an allocation strategy that can also achieve high click number, fairness (which is a common object for this scenario) without violating all the constraints for each video. A typical scenario is that different video contents behave differently in terms of page views (PV) and video views (VV) because of the differences of content properties. Some video contents might achieve high clicks using less impressions while the others might consume more. If we assign too many impressions to these contents, the overall CTR might be at a lower level. Although several impression allocating algorithms for ads (also called guaranteed delivery algorithm) have been proposed, to the authors' knowledge, there is no existing algorithm proposed for contents' impression allocating problem. The contents' GD allocation problem has its speciality in the following two aspects. 1) For video content delivery, especially for IP video, content platform needs to expose those contents repeatedly to the target consumers because of the limited number of contents compared with ads or commercial products. Moreover, the contents generally have large varieties of potential consumers and repeated exposure has much more probability than ads to bring more potential consumers to watch the video. Thus CTR (the effectiveness metric) trends with PV is the key factor that contents delivery should be considered; 2) modeling the impression allocating problem for contents considering CTR trends as constraints poses a new challenge for both model and solution.

In this paper, to address the above challenges, we design a two-stage framework. The first stage is forecasting, and the second is allocating. In the forecasting stage, we seek to develop effective predictive model with the goal of forecasting click behavior of users on each content given their daily historical PV and CLICK records. Specifically, to describe CTR trends with respect to PV, a prediction model (called pv-click-ctr model) based on ordinal differential equation (ODE) is proposed. And then in the allocating stage, we provide a multiple objective nonlinear programming (NLP) model subject to the CTR trends and other constraints. Accordingly, to solve the NLP with ODE involved, a GA allocating algorithm is developed.

Combining CLICK forecasting model and allocating model provides us with a solution to handle content Guaranteed-Delivery (GD) problem. We carried out extensive offline and online experiments, which show the superior of proposed solution, on both model performance and system efficiency. To the best of our knowledge, this is one of the first industrial solutions that are capable of handling content Guaranteed-Delivery (GD) problem. It should be admitted that there are many other related factors, such as the location impact of impression within the widget, the performance of recommendation system for each content, etc. Currently we do not consider those factors since they will make the problem further intractable and leave them as future work. The main contributions of our work can be summarized as follows:

- We propose a parameterized pv-click-ctr prediction model to describe the CTR trends with PV.
- We design a framework that can maximize certain objectives, such as the VV of contents, fairness for each content, under the Guaranteed-Delivery (GD) constraints considering the CTR trends of each video content and impression resource limitation.
- Comprehensive offline and online experiments are conducted to verify the effectiveness of the proposed pv-click-ctr model as well as Guaranteed-Delivery strategy.

The rest of the paper is organized as follows. In Section 2, we provide related work. We describe the proposed pv-click-ctr prediction model and the optimization framework formulation in Section 3. In Section 4, based on the pv-click-ctr model and impression allocation model, the GA allocating algorithm is proposed. The online experiment for the pv-click-ctr model and the A/B test performance of the proposed allocating algorithm are illustrated in Section 5. Section 6 gives the conclusions of this paper.

2 RELATED WORK

In this section, we review two related research directions, the modeling of click behavior and Guaranteed-Delivery (GD) Strategies.

2.1 Click Prediction Model

Predicting the probability of a specific user response, e.g., CTR or Conversion Rate (CVR), is a core problem for performance-driven online advertising [7]. Logistic regression is the most widely used model, normally trained by stochastic gradient descent (SGD). The authors in [18] proposed to use an online learning algorithm called follow-the-regularized-leader (FTRL) to train logistic regression from the streaming data. The model successfully bypasses the learning rate update problem in SGD and it empirically works effectively. Bayesian probit regression [11] is another linear model for online learning where the feature weights are modeled with a distribution and the model learning is via updating the weight posterior. Binary naive Bayes [7] is also a popular linear model, by assuming the features are conditionally independent.

Building the model describing the CTR trends versus PV is similar to CTR prediction, which is a classic problem in both recommendation system and online advertisement domains. Typical methods involve both shallow and deep methods [5, 6, 10, 12, 14, 16, 17, 21, 23, 24, 26, 28, 30, 31]. They generally use item/commodity's features and users' features to predict the CTR of each item for each user. There are also some works that use bayesian smoothing method to estimate CTR [29]. However, those methods cannot be directly applied in our scenarios. In the GD scenario, we put more emphasis on the platform consideration compared with the typical personal recommendation scenario. We need to repeatedly exposure the content to assure the guaranteed exposure amount considering the facts that the content needs exposure to attract more customers. Thus no individual profiles need to be considered here. Moreover, we should assure the effectiveness and fairness of the impressions for those contents. Optimal allocation cannot avoid the evaluation of CTR under different impressions for each video. Thus we need to model the CTR trends versus PVs of each video content.

2.2 Guaranteed-Delivery (GD) Strategies

Optimization techniques have been successfully used in solving various decision problems, such as the advertisement (ad) allocation problem. In general, an ad allocation problem is similar to a mathematical transportation problem, which can be modeled as a bipartite graph with supply and demand nodes that represent viewer types and ad campaigns. Mihiotis and Tsakiris [19] studied the problem of finding the best possible combination of placements for an advertisement. The problem was modeled as an integer program (IP) with the objective of the highest rating and subject to the limitation of the advertising budget. Bollapragada et al. [3, 4] considered the commercial scheduling problem of a single advertiser. In order to meet all the requirements by automatically scheduling the commercials, the problem was formulated as an integer program (IP). Bollapragada et al. [2] then studied the problem of scheduling a set of commercials on a set of available slots, such that multiple airings of the same commercial are as much evenly spaced as possible. Mixed integer program (MIP) was used to formulate this issue and a branch and bound algorithm was developed to solve it. Kimms and Muller Bungart [15] described a planning problem at a broadcasting company, where advertisers place orders for advertisements and their airdates are not fixed by the advertisers. The TV channel has to decide simultaneously which orders to accept or to reject and when advertisements from accepted orders should be broadcasted. Pereira et al. [22] developed a decision support system to plan the best assignment for the weekly promotion space of a major TV station. The aim of this heuristic based scheduling software system was to maximize the total viewing for each product within its target consumers while fulfilling a set of constraints defined by advertisers. A differential game model for media budgeting and allocation is presented by Fruchter and Kalish [9]. Chickering and Heckerman [8] use hierarchical linear programming (LP) to produce a uniformly-spread schedule with maximum overall CTR and demonstrate the effectiveness of this approach through experiments on msn.com. Turner [27] defines Guaranteed Targeted Display Advertising (GTDA) as a class of media vehicles that include webpage banner ads, video games, electronic outdoor billboards, and the next generation of digital TV. They formulate the GTDA planning problem as a transportation problem with quadratic objective. Bharadwaj et al. [1] consider CPM contracts and minimize a weighted objective composed of linear under-delivery and quadratic spreading metrics. They develop an efficient algorithm, called SHALE, to solve their formulation with minimal memory usage and better run-time.

3 THE IMPRESSION ALLOCATING MODEL OF CONTENTS

In this section, we firstly give some preliminary notations of the Guaranteed-Delivery strategy for contents, and afterwards formulate the pv-click-ctr prediction model, which is the essential step in Guaranteed-Delivery strategy. Then we derive the PV allocating strategy, and take a discussion on the characteristics of the allocating strategy.

3.1 Preliminaries

We only consider the drawers that need the GD strategy, which are denoted as $\mathbf{S} = \{s_j, j \in \mathbb{Z}_n\}$, where $\mathbb{Z}_n$ means the integer sets from 1 to n; n is the total number of the drawer. The position set in the drawer s_j is denoted as $\mathbf{D}_{s_j} = \{d_{jk}, j \in \mathbb{Z}_n, k \in \mathbb{Z}_{\Theta(s_j)}\}$, where $\Theta(s_j)$ refers to the number of positions in drawer s_j. Denote the content set that needs to be considered in those drawer as $\mathbf{Q} = \{q_i, i \in \mathbb{Z}_m\}$, where m is the number of content. The overall daily PV limitation for each position d_{jk} is denoted as $\mathbf{C}(d_{jk})$. Without loss of generality, we denote the PV value as x and CLICK value as y, with certain subscripts added when needs in the following.

Considering resource capacity of each drawer and position, as well as CTR trend of each content, our goal is to find the appropriate daily PV for each content that can maximize the overall channel VV while avoiding the "over-exposure" and "under-exposure" as much as possible. Therefore, the main problem of Guaranteed-Delivery strategy is to estimate the click value y of a content with regard to the given PV value x. Formally speaking, the click prediction model is a "mapping" function which learns the patterns within the historical daily PV and CLICK datas and predicts the click value of one day.

3.2 The pv-click-ctr Prediction Model

The CTR trend of each content involves many factors and it is difficult to enumerate all of them to build the model based on its historical datas. Thus we investigate this issue from another viewpoint.

Generally, CLICK always comes from impression. More impressions will bring more CLICK numbers in most cases. However, the total number of target consumers for each content is limited. Repeated impressions for the same consumer cannot bring more CLICKs in statistics when the impression amount is too large. This "saturation" phenomena can be seen from the historical datas in our product, which is also similar to the population model in ecology system. Inspired by [13], we could introduce a parametric model that could capture the above insights.

To be specific, let $y(x)$ denote the CLICK value corresponding to a PV value x for one content in one day, Δx is the PV increment, and Δy is the CLICK increment corresponding to Δx. r is the relative growth rate coefficient. The relative growth rates for different contents are different since it mainly depends on the content quality etc.

If the PV value x is small, we could regard the CLICK growth rate proportional to PV, since more impression generally bring more CLICKs, that is,

$$\frac{y(x+\Delta x) - y(x)}{\Delta x} \approx r y(x) \tag{1}$$

However, when the PV value x is large, CLICK will have "saturation" effect and the growth rate will decrease. Formally it can be written as

$$\frac{y(x+\Delta x) - y(x)}{\Delta x} < 0 \tag{2}$$

Analogous to [13], we use a linear decreasing function of $y(x)$ to describe the "saturation" effects, i.e.

$$\frac{y(x+\Delta x) - y(x)}{\Delta x} = r\left(1 - \frac{y(x)}{y_m}\right) y(x) \tag{3}$$

where y_m is called the pivot CLICK value. When PV exceeds the amount of PV corresponding to y_m, the relative growth rate will be negative, i.e. if $y(x) > y_m$, $1 - \frac{y(x)}{y_m} < 0$. Both r and the the pivot CLICK y_m are the key content-based parameters representing the content's properties.

Let $\Delta x \to 0$, then the Equation (3) will be an ordinary differential equation model between CLICK and PV

$$\frac{\mathbf{dy}}{\mathbf{dx}} = r\left(1 - \frac{\mathbf{y}}{y_m}\right)\mathbf{y} \tag{4}$$

The solution of the Equation (4) is

$$\mathbf{y} = \frac{y_m y_0}{y_0 - (y_0 - y_m)e^{-r(\mathbf{x}-x_0)}} \tag{5}$$

where x_0 and y_0 represent initial PV and CLICK, respectively. If $y_0 < y_m$, the CLICK value grows, approaching y_m asymptotically as $x \to \infty$, if $y_0 > y_m$, the CLICK value decreases, again approaching y_m asymptotically as $x \to \infty$. In fact, $y = y_m$ is an equilibrium of Equation (4). Thus, the positive equilibrium $y = y_m$ of Equation (4) is globally stable, that is, $\lim_{n\to\infty} y(x) = y_m$ for solution $y(x)$ of Equation (4) with any initial value x_0.

To describe the CTR trends for each video content, the parameters r and y_m in Equation (5) are needed to be fitted by the historical daily PV and CLICK datas. We attribute all the content-related factors to those parameters, expecting them to represent the content's own CTR trends. We use least square fitting method to estimate the parameters.

3.3 Impression Allocating Model Formulation

Based on the pv-click-ctr prediction model proposed in the subsection 3.2, this subsection aims to develop an optimization programming model for the PV allocating problem. Let x_{ijk} represent the PV value of content q_i obtained from position d_{jk}, and $f(x_{ijk})$ is the CLICK value corresponding to x_{ijk}, which can be computed by using Equation (5). Our aim is to maximize the total video views (VV) and to minimize the CTR variance by optimizing x_{ijk}. By analyzing the optimization objectives and constraints, the allocation problem can be formulated as follows.

$$max\ \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij} f(x_{ijk}), k \in \mathbb{Z}_{\Theta(s_j)} \tag{6}$$

$$min\ \frac{\sum_{i=1}^{m}(p_i - P)^2}{m-1} \tag{7}$$

$$p_i = \frac{\sum_{j=1}^{n} f(x_{ijk})}{\sum_{j=1}^{n} x_{ijk}}, \forall i \in \{1, 2, ..., m\}, \forall k \in \mathbb{Z}_{\Theta(s_j)} \tag{8}$$

$$P = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ijk})}{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ijk}}, \forall k \in \mathbb{Z}_{\Theta(s_j)} \tag{9}$$

s.t.

$$\sum_{i=1}^{m} x_{ijk} < \mathbf{C}(s_j), \forall j \in \{1, 2, ..., n\}, \forall k \in \mathbb{Z}_{\Theta(s_j)} \tag{10}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ijk} < R, \forall k \in \mathbb{Z}_{\Theta(s_j)} \tag{11}$$

$$\begin{gathered} x_{ijk} < max\{\mathbf{C}(d_{jl}), l \in \mathbb{Z}_{\Theta(s_j)}\ \}, \\ \forall i \in \{1, 2, ..., m\}, \forall j \in \{1, 2, ..., n\}, \forall k \in \mathbb{Z}_{\Theta(s_j)} \end{gathered} \tag{12}$$

$$\begin{gathered} \left|\mathbf{C}_{jk}\right| \le k, \mathbf{C}_{jk} = \{x_{ijk} | x_{ijk} \ge \mathbf{C}(d_{jk}), 1 \le i \le m\}, \\ \forall j \in \{1, 2, ..., n\}, \forall k \in \mathbb{Z}_{\Theta(s_j)} \end{gathered} \tag{13}$$

where r_{ij} is the positive correlation coefficient between CLICK and VV for the content q_i in drawer s_j; $\mathbf{C}(s_j)$ is the total PV resources of drawer s_j; R is the total available resources for drawer set $\mathbf{S}$. The optimization objective expressed in Equation (6), is to maximize the overall VVs over all the drawers. The other optimization objective is to minimize the CTR variance between different contents formulated in Equations (7) – (9). The constraint expressed in Equation (10) means that the resources allocated to content set $\mathbf{Q}$ in drawer s_j cannot exceed its resource capacity, while the Equation (11) represents the resource constraint of drawer set $\mathbf{S}$. Equation (12) is the position resource constraint, which states that the resource allocated to a content in any drawer can not exceed its maximum position resource capacity. Equation (13) ensures that there must be one and only one position of a drawer allocated to a content, that is to say, we cannot display identical content to user at the same time.

4 A GA BASED ALLOCATING ALGORITHM FOR CONTENTS

In order to obtain the optimal or sub-optimal solution of the allocation problem modeled in Section 3, a GA allocation algorithm is proposed, which is an iterative algorithm where the pv-click-ctr prediction model is embedded.

Note that the PV allocating problem expressed in Equations (6) – (13) corresponds to a multi-objective constrained optimization problem (MCOP), whose optimal solution is extremely difficult to find. In general, a MCOP can be converted to a single-objective optimization problem by weighting method, then the PV allocating problem is stated as follows.

$$max\ g(\mathbf{X}|\lambda) = \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij} f(x_{ij}) + \lambda \frac{1}{\frac{\sum_{i=1}^{m}(p_i - P)^2}{m-1}} \tag{14}$$

$$p_i = \frac{\sum_{j=1}^{n} f(x_{ij})}{\sum_{j=1}^{n} x_{ij}}, \forall i \in \{1, 2, ..., m\} \tag{15}$$

$$P = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} f(x_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij}} \tag{16}$$

s.t.

$$\mathbf{X} \in \Omega \tag{17}$$

where λ denotes the weight parameter, Ω is the decision (variable) space described by Equations (10) – (13), and $g(\mathbf{X}|\lambda)$ is the objective function. It should be noted that the allocation problem modeled by Equations (14) - (17) is a combinatorial optimization problem, and it is non-linear and non-smooth. The combinatorial optimization involves problems in which their set of feasible solutions is discrete. The problem falls into NP completeness problem, which is quite difficult to be solved for global optima in polynomial time. Search algorithms such as branch and bound may degenerate to complete enumeration, and the CPU time needed to solve them may grow exponentially in the worst case [20]. To practically solve these problems, one has to be satisfied with finding good and approximately optimal solutions in reasonable, that is, polynomial time. As a classic algorithm for searching for an approximately optimal solution, GA provides an alternative approach. Different from the generic GA, Our proposed GA framework consists of the following two main components: Coding scheme considering ODE constraints, local search operations (selection with elitist strategy, crossover and mutation).

4.1 Coding Scheme and ODE-based Fitness

Following the typical framework of GA, the solution for the allocating problem is a chromosome or individual. Specifically, the chromosome in our problem is a matrix, where the elements are PV values allocated from the corresponding positions of drawers. The chromosome is generated in two steps: 1) For any content q_i, generate a permutation $\mathbf{x}_i$ with PV values, $\mathbf{x}_i = [x_{i,1}, x_{i,2}, ..., x_{i,n}]$, where the length of $\mathbf{x}_i$ is n. 2) Merge all of the permutations for different content to form the final formulation of chromosome $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_m]$.

The value of fitness function of each individual in GA, i.e. the fitness, is highly correlated to the probability of survival. Highly fitness individuals relative to the whole population have a high probability of being selected for mating whereas less fitness individuals have a correspondingly low probability of being selected. Specifically, the fitness function of the individual $\mathbf{X}$ in this problem is equal to the objective function defined in Equation (14). It should be noted that the crucial part of Equation (14) is $f(x_{ij})$. As mentioned above, $f(x_{ij})$ is a CLICK value corresponding to PV value x_{ij}, and it can be obtained by pv-click-ctr model proposed in Section 3.2. Suppose that the fitness function of individual $\mathbf{X}$ is $F(\mathbf{X})$, let $\mathbf{U} = \{u_1, u_2, ..., u_l\}$ and $\mathbf{V} = \{v_1, v_2, ..., v_l\}$ respectively denote the set of historical daily PV and CLICK datas. Since two parameters defined in Equation (4) are fitted by using datas from $\mathbf{U}$ and $\mathbf{V}$, it is assumed that $l \geq 4$. For a PV value $x_{i,j} \in \mathbf{X}$, find an element $u_k \in \mathbf{U}$ such that

$$u_k = \arg\min_{u_{\tilde{k}}} \|u_{\tilde{k}} - x_{i,j}\|, u_{\tilde{k}} \in U \tag{18}$$

According to Equation (3), we can obtain a corresponding CLICK value of $x_{i,j}$ as

$$f(x_{i,j}) = v_k + r(1 - \frac{v_k}{v_{max}})v_k(x_{i,j} - u_k) \tag{19}$$

where r and v_{max} are the parameters fitted by taking datas from $\mathbf{U}$ and $\mathbf{V}$ as input. $v_k \in \mathbf{V}$ represents the CLICK value corresponding to u_k. Then according to Equation (14), the fitness function $F(\mathbf{X})$ can be obtained as

$$F(\mathbf{X}) = g(\mathbf{X}|\lambda) \tag{20}$$

4.2 Local Search Operations with Elitist Strategy

The local selection operation involves a serial of operations, such as selection, mutation and crossover. The main purpose is to inherit the high-quality genes to the next generation, further to improve the efficiency of calculation and the probability of global convergence.

In the selection stage, we use elitism strategy to remains the "good" genes to the follow generations. Concretely, suppose $\mathbf{X}_u^k$ is the individual in the $k-th$ generation, the next generation corresponding to $\mathbf{X}_u^k$ is stated as follows:

$$\mathbf{X}_i^k = \begin{cases} \mathbf{X}_u^k, & F(\mathbf{X}_u^k) \geq F(\mathbf{X}_i^{k-1}) \\ \mathbf{X}_i^{k-1}, & otherwise \end{cases} \tag{21}$$

That means we only keep the individual of high fitness value to the next generation.

Crossover operator randomly crosses the genetic segments of individual of high-quality. The range of cross probability is generally recommended as 0.4-0.99. We use the Order Crossover (OX) [25] strategy in this paper.

Mutation operator has exploring effects in GA, which is expected to achieve globally optima with high probability. By mutation, a new chromosome is generated by changing the encoding of some genes in the chromosome after crossover. In order to ensure the stability of population evolution, the mutation probability generally takes smaller values. This paper uses an adaptive mutation probability, as shown below

$$p_m = \begin{cases} \frac{p_{max}(p_{max}-p_{min})(F-F_{avg})}{(F_{max}-F_{avg})}, & F \geq F_{avg} \\ p_{max}, & F < F_{avg} \end{cases} \tag{22}$$

where p_{max} and p_{min} represent the maximum and minimum mutation probabilities, where 0.05 and 0.01 are taken respectively in this paper. F is fitness function and F_{max} and F_{avg} are the largest and average value of fitness function for current population respectively.

Table 1: Basic information for offline and online experiments

	Offline Experiment	Online Experiment
Duration (days)	30	60
♯ contents	9	25

5 EXPERIMENTS

In this section, we conduct experiments with the aim of answering the following questions:

- Does the proposed pv-click-ctr model outperform the "smoothing CTR method" in CLICK prediction problem?
- How is the impact of elitist strategy in GA?
- How does the impression allocation algorithm perform in comparison with state-of- the-art manual strategy?

To answer these questions, we conduct extensive experiments on real-world datas from one of the top video service platforms, including offline and online experiments.

5.1 Experiment Settings

In order to test performance of both the ODE model and the proposed GA allocating algorithm, We carry out offline and online experiments. Both the offline and online experiment are carried out on the "Latest Hits" drawer of episode channel in Youku.com. For the offline experiment, the datas are constructed from real traffic logs of "Latest Hits" drawer. Due to the huge amount of online data, only one-month data is utilized. For the online experiment (A/B testing), we deploy our model online to serve 30% of the PVs and use manual allocation for 60% of PVs as control group. Table 1 summarizes the statistics about the configurations.

5.1.1 Parameter Settings. Table 2 shows the settings of all parameters, and the default one is highlighted in bold. Here the total available resource of drawer is denoted as R. Pop is the population size used in GA, and θ is used to control the termination condition. λ is the parameter in GA that balance the two objectives. In particular, the parameter α is used in least squares fitting method to reduce overfitting. In all experiments, we only vary one parameter and keep the rest by default.

5.1.2 Evaluation Metrics and Methods for Comparison. To evaluate the performance of pv-click-ctr model, we exploit Root Mean Square Error (RMSE) as well as the absolute percentage error (APE) as

Table 2: Paramter Settings

Parameter	Values
R	**7160482**
Pop	**80**
θ	**200**
λ	**1.0**
α	0.006, 0.008, **0.01**, 0.05, 0.1

evaluation metrics,

$$RMSE(\mathbf{y}, \hat{\mathbf{y}}) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{23}$$

$$APE(y_i, \hat{y}_i) = \frac{\|y_i - \hat{y}_i\|}{y_i} \tag{24}$$

where $\hat{y}_i \in \hat{\mathbf{y}}$ denotes the prediction PV value or CLICK value for a video content in one day, $y_i \in \mathbf{y}$ is the corresponding actual PV value or CLICK value, and N denotes the number of tested days.

5.2 Offline Experimental Results

5.2.1 Performance of pv-click-ctr model. To answer the first question, we use 9 online video contents shown in Table 1 to test the performance of pv-click-ctr model proposed above. To the best of our knowledge, this is the first work studying CTR trends with PVs. Despite that, we choose the “smoothing CTR method” proposed in [29] as baseline. Here “smoothing CTR method” utilizes the natural data hierarchy with an empirical Bayes method. The experiment results in terms of RMSE are given in Table 3.

Before the parameter fitting for pv-click-ctr model, the historical daily PV and CLICK datas and parameters should be preprocessed. (i) Sample filtering. Select the largest incremental subsequence in the daily history PV and CLICK data sequences respectively. (ii) Parameter preprocessing. Since the magnitude of the CLICK saturation value y_m is usually large, and the correlation coefficient r is usually of a small magnitude, in order to avoid the phenomenon of "large numbers eating decimals", data transformation is performed on these two parameters respectively, that is, $y_m \to log_{10}y_m$, $r \to e^r$. (iii) Sample preprocessing. In order to avoid falling into local optimum when parameters fitting is performed, data transformation is performed on historical samples, that is, $x \to log_{10}x$, $y \to log_{10}y$.

The click prediction curves of 9 contents in historical consecutive days are given in Figure 1, where “REAL” means true value and “MEAN” is the prediction result obtained from smoothing CTR method. We could clear see that the CTR has certain trends with PVs and our model can capture this pattern qualitatively. Quantitative evaluations are shown in Table 3, where pv-click-ctr performs better compared with smoothing CTR method in the given contents.

5.2.2 Hyper-parameter Sensitivity. We evaluate how different choices of hyper-parameter α in parameter fitting affect the performance of pv-click-ctr model using the offline data. Here we use the initial 5 days data to estimate the initial parameters for each content and then estimate the following days' results. All data for this content before the day to be predicted will be used. The choice of the parameter α is set to be $\alpha \in \{0.006, 0.008, 0.01, 0.05, 0.1\}$. We can see in Table 4 that the best average value of RMSE is at $\alpha = 0.01$ for all tested contents.

Table 3: Comparison between pv-click-ctr model and smoothing CTR method on online data

content index	♯ days	RMSE	
		pv-click-ctr model	smoothing CTR
1	15	0.0752	0.40144
2	19	0.13875	0.18118
3	27	0.12788	0.24273
4	10	0.04989	0.20967
5	32	0.15736	0.29446
6	16	0.11209	0.22749
7	24	0.13558	0.13774
8	21	0.10277	0.18685
9	15	0.04226	0.09936

Table 4: Hyper-parameter sensitivity analysis results

content index	RMSE				
	$\alpha = 0.006$	$\alpha = 0.008$	$\alpha = 0.01$	$\alpha = 0.05$	$\alpha = 0.1$
1	0.1785	0.1679	0.1583	**0.0964**	0.1120
2	0.0838	0.0817	**0.0800**	0.0918	0.1198
3	0.1084	0.1060	0.1039	**0.0925**	0.1091
4	0.1669	0.1474	0.1313	**0.0635**	0.0885
5	**0.0706**	**0.0706**	**0.0706**	0.0708	0.0714
6	**0.1102**	0.1117	0.1133	0.1479	0.1873
7	**0.0828**	0.0904	0.0985	0.2044	0.2554
8	0.1453	0.1455	0.1456	0.1447	**0.1435**
9	**0.1452**	0.1464	0.1480	0.1863	0.2069
Average	0.1213	0.1186	**0.1166**	0.1220	0.1438

Table 5: Comparison of online data and GA results

content index	vv			pv		
	REAL	GA	APE	REAL	GA	APE
1	50079	48123	3.907%	1575906	1475113	6.396%
2	28762	28077	2.382%	2190789	2257795	3.059%
3	18213	16139	11.388%	652690	620341	4.956%
4	56581	56727	0.258%	1457541	1327932	8.892%
5	38978	38492	1.246%	2379646	2152768	9.534%

5.2.3 Evaluation of the GA algorithm. We compare the GA offline experiment results with online data in terms of VV and PV. The result of the online performance is shown in Table 5, where “REAL” is online data. It is observed from Table 5 that, for the five given contents, GA achieves mean APE of 3.836% in VV, which demonstrates the efficacy of the pv-click-ctr model in GA.

5.2.4 Impacts of elitist strategy in GA. To answer the second question, we conduct experiments to show the elitist strategy impacts on GA. In the following, GA/E refers to GA without elitist strategy. We run the proposed algorithm GA and GA/E all ten times

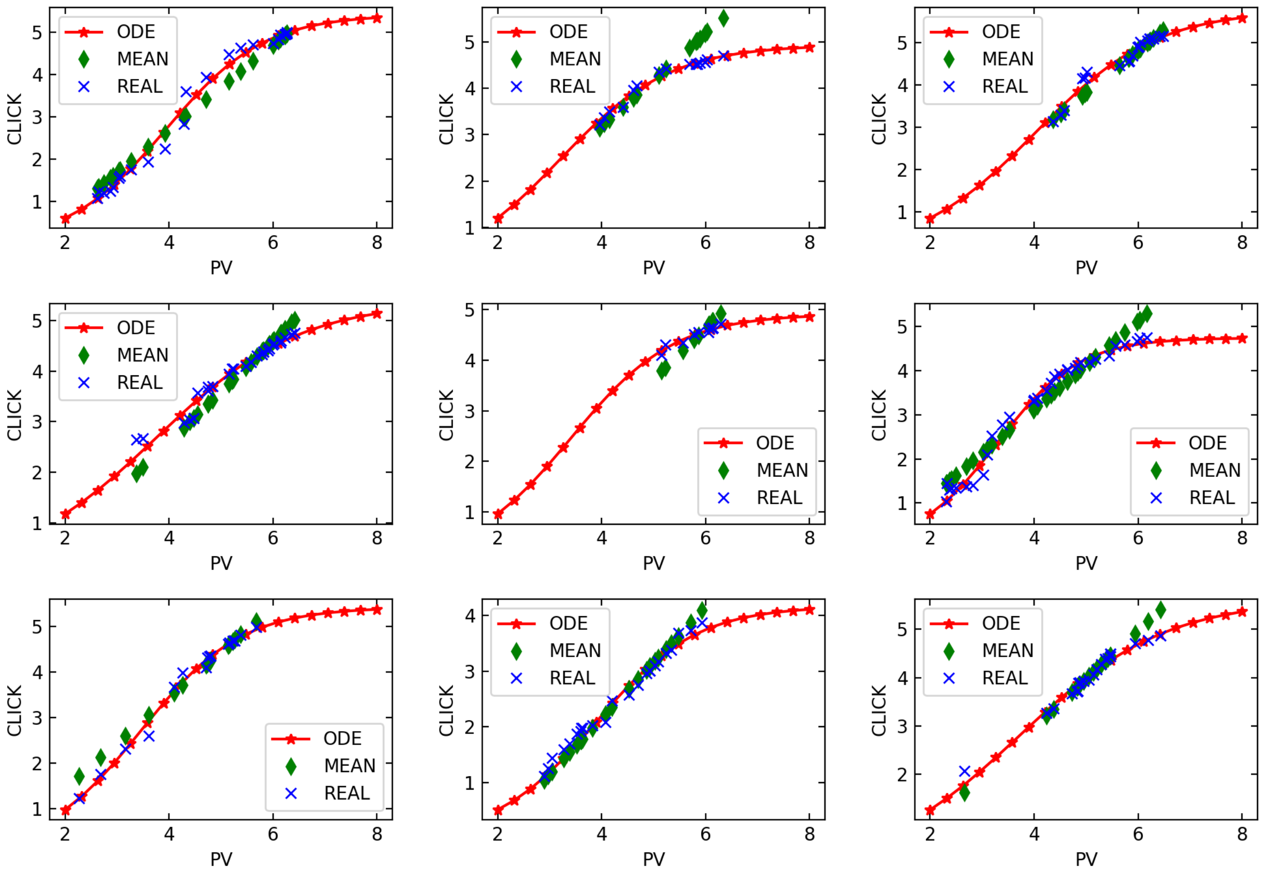

Figure 1: The click prediction curves of 9 contents by pv-click-ctr model and smoothing CTR method.

by using online historical datas. Experiment results are shown in Table 6, where obj, vv and var respectively mean objective function value, total VV of contents and CTR variance. From the results, we observe that the elitist strategy has an important impact on the performance of GA, as GA outperforms GA/E on obj values and vv values in 10 runnings. GA also gets a better CTR variance than GA/E since it obtains small var values in 6 runnings out of 10. This is reasonable since elitist strategy preserves the best solution for the next generation which improves the GA to a greater extent. This also illustrates the potential of elitist strategy, whose performance can be further enhanced by more carefully designed models.

The objective value evolution process for index 1 in Table 6 is given in Figure 2. From Figure 2, we find that the current best solution increases with the number of generations. That empirically means our algorithm converges toward the optimal solution as the search goes on.

Table 6: Experiment results by different search strategies

run index	GA			GA/E		
	obj	vv	var	obj	vv	var
1	4362	4159	0.4900%	4273	4143	0.7633%
2	4253	3971	0.3534%	4172	4022	0.6621%
3	4292	4045	0.4032%	4255	4076	0.5531%
4	4089	3832	0.3884%	4066	3917	0.6661%
5	4226	4040	0.5333%	3927	3696	0.4315%
6	4285	4115	0.5829%	3988	3741	0.4025%
7	4347	4076	0.3669%	4266	4055	0.4725%
8	4211	4001	0.4736%	4151	4000	0.6555%
9	4268	4107	0.6202%	4086	3885	0.4940%
10	4294	4103	0.5224%	4215	4045	0.5858%

5.3 Online Experimental Results

To answer the third question, the online experiments are conducted. We deploy the pv-click-ctr model and the proposed optimization framework in online system parallel with the existing GD system, which is operated manually by operation specialist. We concern with two metrics in the online experiments, i.e. CTR variance, total CTR, which are consistent with our problem formulation in section 3.3 , where total CTR is given by

$$CTR = \frac{\sum_{i=1}^{m}(click_i)}{\sum_{i=1}^{m}(pv_i)} \tag{25}$$

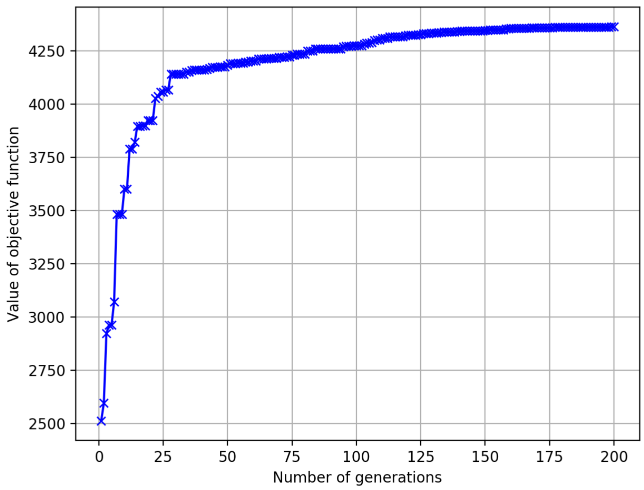

Figure 2: Changing trend of the current best solution.

where pv_i and $click_i$ denote the daily PV and CLICK of the content q_i, respectively. The system keeps running till now and we only show the first 7 weeks online performance after the system deployed.

To illustrate the comparison in detail, Table 7 shows a snapshot of the first 30 days of the results. For sake of data security, the data is desensitized using some transformations without impacts on the result comparison. From Table 7 we observe that GA outperforms manual strategy both in CTR variance and total CTR within 30 days. Note that GA achieves significant improvements on total CTR, this illustrates the advantage of pv-click-ctr model.

We also provide statistics comparison results over 7 weeks as seen in Table 8. It is observed that the improvements on CTR variance is remarkable (more than 50% averagely). Both the detailed and overall results show that the GD model for contents proposed in this paper can help us to make more informed and effective decisions in practical content GD system, which is superior to the current practical solutions.

6 CONCLUSION

In this paper, we study the model and algorithm for the video content Guaranteed-Delivery system with multiple objectives in video service platform. As far as we know, such a problem has never been reported in the existing literature. To solve it, we propose a novel algorithm framework that generates efficient solutions with GD constraints. There are two main components in the proposed framework. Firstly, the CLICK value for each content is forecasted by an ODE model (pv-click-ctr prediction model), which is used for describing the CTR trends with respect to PV. Then the Guaranteed-Delivery problem is formulated as an optimization problem constrained by the learned pv-click-ctr prediction model. The optimization problem can be solved by GA. This framework is easy to implement and has been successfully applied to many scenarios in practice. The results of both offline experiments and online A/B testing demonstrate its effectiveness. Cold-start problem for the pv-click-ctr model and incorporating more related factors into the model require future research. Also for practitioners, we should also investigate more sophisticated accelerating algorithm to solve the complicated optimization problem with ODE constraints. Potential direction might involve sequential quadratic programming etc.

Table 7: A/B test result during 30 days for optimization strategy and manual strategy

day index	var		CTR		
	manual	GA	manual	GA	%Lift
1	0.0333%	0.0166%	2.35%	3.03%	+28.94%
2	0.0301%	0.0259%	2.26%	2.82%	+24.90%
3	0.0492%	0.0261%	2.70%	2.88%	+6.82%
4	0.0544%	0.0432%	2.69%	3.48%	+29.33%
5	0.0347%	0.0201%	2.52%	2.96%	+17.74%
6	0.0447%	0.0238%	2.35%	2.99%	+27.53%
7	0.0369%	0.0198%	2.50%	5.35%	+114.43%
8	0.0423%	0.0266%	2.61%	3.32%	+26.91%
9	0.0439%	0.0332%	2.63%	4.36%	+65.70%
10	0.0570%	0.0469%	2.96%	4.09%	+38.14%
11	0.0604%	0.0575%	2.72%	3.32%	+22.32%
12	0.0669%	0.0154%	2.69%	2.82%	+4.98%
13	0.0319%	0.0058%	2.00%	3.12%	+56.18%
14	0.0593%	0.0073%	2.50%	2.58%	+3.50%
15	0.0566%	0.0031%	2.14%	2.54%	+18.70%
16	0.0636%	0.0269%	2.72%	2.91%	+7.27%
17	0.0564%	0.0015%	2.58%	2.82%	+9.12%
18	0.0460%	0.0025%	2.35%	2.65%	+13.01%
19	0.0212%	0.0067%	1.72%	2.47%	+43.92%
20	0.0433%	0.0173%	2.31%	2.40%	+3.90%
21	0.0637%	0.0458%	2.10%	2.80%	+33.35%
22	0.0365%	0.0182%	2.13%	2.68%	+26.13%
23	0.0584%	0.0168%	2.61%	2.73%	+4.40%
24	0.0428%	0.0261%	2.20%	2.92%	+32.70%
25	0.0761%	0.0585%	2.97%	3.44%	+15.53%
26	0.0529%	0.0361%	2.58%	4.80%	+85.80%
27	0.0578%	0.0531%	2.62%	4.39%	+67.42%
28	0.0800%	0.0300%	3.10%	4.63%	+49.65%
29	0.0552%	0.0264%	2.57%	4.62%	+79.41%
30	0.0737%	0.0214%	2.95%	3.82%	+29.60%

Table 8: A/B test result during 7 weeks for optimization strategy and manual strategy

week index	var (%Reduce)	CTR (%Lift)
1	+79.21%	+13.96%
2	+74.80%	+20.93%
3	+78.93%	+45.23%
4	+52.14%	+18.41%
5	+66.98%	+39.29%
6	+22.63%	+60.59%
7	+33.60%	+51.59%
Average	+58.33%	+35.72%

REFERENCES

[1] Vijay Bharadwaj, Peiji Chen, Wenjing Ma, Chandrashekhar Nagarajan, John Tomlin, Sergei Vassilvitskii, Erik Vee, and Jian Yang. 2012. SHALE: An Efficient Algorithm for Allocation of Guaranteed Display Advertising. *CoRR* abs/1203.3619 (2012). arXiv:1203.3619 http://arxiv.org/abs/1203.3619

[2] Srinivas Bollapragada, Michael R. Bussieck, and Suman Mallik. 2004. Scheduling Commercial Videotapes in Broadcast Television. *Operations Research* 52, 5 (2004), 679–689. https://doi.org/10.1287/opre.1040.0119 arXiv:https://doi.org/10.1287/opre.1040.0119

[3] Srinivas Bollapragada, Hong Cheng, Mary Phillips, Marc Garbiras, Michael Scholes, Tim Gibbs, and Mark Humphreville. 2002. NBC's Optimization Systems Increase Revenues and Productivity. *INFORMS Journal on Applied Analytics* 32, 1 (2002), 47–60. https://doi.org/10.1287/inte.32.1.47.19 arXiv:https://pubsonline.informs.org/doi/pdf/10.1287/inte.32.1.47.19

[4] Srinivas Bollapragada and Marc Garbiras. 2004. Scheduling Commercials on Broadcast Television. *Operations Research* 52, 3 (2004), 337–345. https://doi.org/10.1287/opre.1030.0083 arXiv:https://doi.org/10.1287/opre.1030.0083

[5] Olivier Chapelle. 2014. Modeling Delayed Feedback in Display Advertising. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '14)*. ACM, New York, NY, USA, 1097–1105. https://doi.org/10.1145/2623330.2623634

[6] Olivier Chapelle. 2015. Offline Evaluation of Response Prediction in Online Advertising Auctions. In *Proceedings of the 24th International Conference on World Wide Web (WWW '15 Companion)*. ACM, New York, NY, USA, 919–922. https://doi.org/10.1145/2740908.2742566

[7] Olivier Chapelle, Eren Manavoglu, and Romer Rosales. 2015. Simple and Scalable Response Prediction for Display Advertising. *ACM Trans. Intell. Syst. Technol.* 5, 4, Article Article 61 (Dec. 2015), 34 pages. https://doi.org/10.1145/2532128

[8] David Maxwell Chickering and David Heckerman. 2003. Targeted Advertising on the Web with Inventory Management. *INFORMS Journal on Applied Analytics* 33, 5 (2003), 71–77. https://doi.org/10.1287/inte.33.5.71.19248 arXiv:https://pubsonline.informs.org/doi/pdf/10.1287/inte.33.5.71.19248

[9] Gila E. Fruchter and Shlomo Kalish. 1998. Dynamic promotional budgeting and media allocation. *European Journal of Operational Research* 111, 1 (1998), 15 – 27. https://doi.org/10.1016/S0377-2217(97)00315-9

[10] Kun Gai, Xiaoqiang Zhu, Han Li, Kai Liu, and Zhe Wang. 2017. Learning Piece-wise Linear Models from Large Scale Data for Ad Click Prediction. arXiv:stat.ML/1704.05194

[11] Thore Graepel, Joaquin Quinonero Candela, Thomas Borchert, and Ralf Herbrich. 2010. Web-scale bayesian click-through rate prediction for sponsored search advertising in microsoft's bing search engine. Omnipress.

[12] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. 2017. DeepFM: A Factorization-Machine based Neural Network for CTR Prediction. arXiv:cs.IR/1703.04247

[13] Ferenc Hartung, Tibor Krisztin, Hans-Otto Walther, and Jianhong Wu. 2006. Chapter 5 Functional Differential Equations with State-Dependent Delays: Theory and Applications. Handbook of Differential Equations: Ordinary Differential Equations, Vol. 3. North-Holland, 435 – 545. https://doi.org/10.1016/S1874-5725(06)80009-X

[14] Xinran He, Junfeng Pan, Ou Jin, Tianbing Xu, Bo Liu, Tao Xu, Yanxin Shi, Antoine Atallah, Ralf Herbrich, Stuart Bowers, and Joaquin Quiñonero Candela. 2014. Practical Lessons from Predicting Clicks on Ads at Facebook. In *Proceedings of the Eighth International Workshop on Data Mining for Online Advertising (ADKDD'14)*. ACM, New York, NY, USA, Article 5, 9 pages. https://doi.org/10.1145/2648584.2648589

[15] Alf Kimms and Michael Muller-Bungart. 2007. Revenue management for broadcasting commercials: the channel's problem of selecting and scheduling the advertisements to be aired. *International Journal of Revenue Management* 1, 1 (2007), 28–44. https://ideas.repec.org/a/ids/ijrevm/v1y2007i1p28-44.html

[16] Kuang-chih Lee, Burkay Orten, Ali Dasdan, and Wentong Li. 2012. Estimating Conversion Rate in Display Advertising from Past Erformance Data. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '12)*. ACM, New York, NY, USA, 768–776. https://doi.org/10.1145/2339530.2339651

[17] Qiang Liu, Feng Yu, Shu Wu, and Liang Wang. 2015. A Convolutional Click Prediction Model. In *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management (CIKM '15)*. ACM, New York, NY, USA, 1743–1746. https://doi.org/10.1145/2806416.2806603

[18] H Brendan McMahan. [n. d.]. Follow-the-Regularized-Leader and Mirror Descent: Equivalence Theorems and L1 Regularization. ([n. d.]).

[19] A Mihiotis and I Tsakiris. 2004. A mathematical programming study of advertising allocation problem. *Appl. Math. Comput.* 148, 2 (2004), 373 – 379. https://doi.org/10.1016/S0096-3003(02)00853-6

[20] H. Mühlenbein, M. Gorges-Schleuter, and O. Krämer. 1988. Evolution algorithms in combinatorial optimization. *Parallel Comput.* 7, 1 (1988), 65 – 85. https://doi.org/10.1016/0167-8191(88)90098-1

[21] Richard J. Oentaryo, Ee-Peng Lim, Jia-Wei Low, David Lo, and Michael Finegold. 2014. Predicting Response in Mobile Advertising with Hierarchical Importance-aware Factorization Machine. In *Proceedings of the 7th ACM International Conference on Web Search and Data Mining (WSDM '14)*. ACM, New York, NY, USA, 123–132. https://doi.org/10.1145/2556195.2556240

[22] Paulo A. Pereira, Fernando A. C. C. Fontes, and Dalila B. M. M. Fontes. 2008. A Decision Support System for Planning Promotion Time Slots. In *Operations Research Proceedings 2007*, Jörg Kalcsics and Stefan Nickel (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 147–152.

[23] Yanru Qu, Han Cai, Kan Ren, Weinan Zhang, Yong Yu, Ying Wen, and Jun Wang. 2016. Product-based Neural Networks for User Response Prediction. arXiv:cs.LG/1611.00144

[24] Lili Shan, Lei Lin, Chengjie Sun, and Xiaolong Wang. 2016. Predicting ad click-through rates via feature-based fully coupled interaction tensor factorization. *Electronic Commerce Research and Applications* 16 (2016), 30 – 42. https://doi.org/10.1016/j.elerap.2016.01.004

[25] Nitasha Soni and Dr. Tribhuwan Kumar. 2014. Study of Various Crossover Operators in Genetic Algorithms.

[26] A. Ta. 2015. Factorization machines with follow-the-regularized-leader for CTR prediction in display advertising. In *2015 IEEE International Conference on Big Data (Big Data)*. 2889–2891. https://doi.org/10.1109/BigData.2015.7364112

[27] John Turner. 2012. The Planning of Guaranteed Targeted Display Advertising. *Operations Research* 60, 1 (2012), 18–33. https://doi.org/10.1287/opre.1110.0996 arXiv:https://doi.org/10.1287/opre.1110.0996

[28] Flavian Vasile and Damien Lefortier. 2016. Cost-sensitive Learning for Bidding in Online Advertising Auctions. *CoRR* abs/1603.03713 (2016). arXiv:1603.03713 http://arxiv.org/abs/1603.03713

[29] Xuerui Wang, Wei Li, Ying Cui, Ruofei Zhang, and Jianchang Mao. 2011. Click-through rate estimation for rare events in online advertising. In *Online multimedia advertising: Techniques and technologies*. IGI Global, 1–12.

[30] Weinan Zhang, Tianming Du, and Jun Wang. 2016. Deep Learning over Multi-field Categorical Data: A Case Study on User Response Prediction. arXiv:cs.LG/1601.02376

[31] Guorui Zhou, Chengru Song, Xiaoqiang Zhu, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2017. Deep Interest Network for Click-Through Rate Prediction. arXiv:stat.ML/1706.06978