Hierarchically Constrained Adaptive Ad Exposure in Feeds

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ABSTRACT

A contemporary feed application usually provides blended results of organic items and sponsored items (ads) to users. Conventionally, ads are exposed at fixed positions. Such a fixed ad exposure strategy is inefficient due to ignoring users' personalized preferences towards ads. To this end, adaptive ad exposure is becoming an appealing strategy to boost the overall performance of the feed. However, existing approaches to implement the adaptive ad exposure strategy suffer from several limitations: 1) they usually fall into sub-optimal solutions because of only focusing on request-level optimization without consideration of the application-level performance and constraints; 2) they neglect the necessity of keeping the game-theoretical properties of ad auctions, and 3) they can hardly be deployed in large-scale applications due to high computational complexity. In this paper, we focus on the application-level performance optimization under hierarchical constraints in feeds and formulate adaptive ad exposure as a Dynamic Knapsack Problem. We propose Hierarchically Constrained Adaptive Ad Exposure (HCA2E) that possesses the desirable game-theoretical properties, computational efficiency, and performance robustness. Comprehensive offline and online experiments on a leading e-commerce application demonstrate the performance superiority of HCA2E.

CCS CONCEPTS
- Information systems → Computational advertising.

KEYWORDS
Adaptive Ad Exposure, Dynamic Knapsack Problem, Hierarchically Constrained Optimization

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CIKM ‘22, October 17–21, 2022, Atlanta, GA, USA  
© 2022 Association for Computing Machinery.  
ACM ISBN 978-1-4503-9236-5/22/10 . . $15.00  
https://doi.org/10.1145/3511808.3557103

1 INTRODUCTION

Nowadays, many online applications such as e-commerce, news recommendation, and social networks organize their contents in feeds. A contemporary feed application usually provides blended results of organic items (recommendations) and sponsored items (ads) to users [3]. Conventionally, ad exposure positions are fixed for the sake of simplicity in system implementation, which is known as fixed ad exposure (left part in Figure 1). However, such a fixed exposure strategy can be inefficient due to ignoring users' personalized preferences towards ads and lacks the flexibility to handle changes in business constraints [6, 25]. For example, there are more active users during e-commerce sale promotions, and thus exposing more ads than usual time could be more favorable. To this end, adaptive ad exposure (right part in Figure 1), dynamically determining the number and positions of ads for different users, has become an appealing strategy to boost the performance of the feed and meet various business constraints.

However, there are several critical challenges in implementing the adaptive ad exposure strategy in large-scale feed applications. First, adaptive ad exposure is a multi-objective optimization problem. For example, it needs to strike a balance between recommendation-side user engagement and advertising-side revenue, because more ads will generally increase ad revenue at the cost of user engagement. Thus, the performance of feeds with adaptive ad exposure should be Pareto efficient [11]. Second, business constraints, usually consisting of both request-level constraints (for a single user request) and application-level constraints (for all the requests over a period), should be taken into account due to the business nature. At the fine-grained request level, ad positions are constrained (e.g., not too dense) for a good user experience [23]. At the application level, the monetization rate, indicating the average proportion of ad exposures, should be constrained by an upper bound [21]. It is difficult to optimize the adaptive ad exposure strategy under the entanglement of hierarchical constraints. Third,
some desirable game-theoretical properties of ad auctions should be guaranteed. For example, Incentive Compatibility (IC) [19] and Individual Rationality (IR) [14] theoretically guarantee that truthful bidding is optimal for each advertiser, which is important for the long-term prosperity of the ad ecosystem [1, 12, 22]. Fourth, the adaptive ad exposure strategy must be computationally efficient to achieve low-latency responses and be robust enough to guarantee the performance stability in the ever-changing online environment [23].

A few efforts have been made to study adaptive ad exposure. Lightweight rule-based algorithms [20, 23, 24] are designed to blend organic items and ads following a ranking rule with some predefined re-ranking scores. However, they focus on the request-level optimization without consideration of application-level performance, resulting in sub-optimal performance of the feed applications under hierarchical constraints. Learning-based methods [10, 21, 26, 27] mostly employ reinforcement learning (RL) [17] to search for the optimal strategies and perform well in offline simulations. However, since RL models heavily rely on massive training data to update the parameters, they are neither robust nor lightweight to deal with the rapidly changing online environment. We also note that most works leave out the discussion of the necessity to guarantee desirable game-theoretical properties.

In this work, towards improving application-level performance under hierarchical constraints, we formulate adaptive ad exposure as a Dynamic Knapsack Problem (DKP) [5, 8] and propose a new approach Hierarchically Constrained Adaptive Ad Exposure (HCA2E). More specifically, to alleviate the difficulties in handling the hierarchical constraints, we design a two-level optimization architecture that decouples the DKP into request-level optimization and application-level optimization. In request-level optimization, we introduce a Rank-Preserving Principle (RPP) to maintain the game-theoretical properties of the ad auction and propose an Exposure Template Search (ETS) algorithm to search for the optimal exposure result satisfying the request-level constraints. In application-level optimization, we employ a real-time feedback controller to adapt to the application-level constraint. Moreover, we demonstrate that the two-level optimization is computationally efficient and robust against online fluctuations. Finally, comprehensive offline and online experimental evaluation results demonstrate that HCA2E outperforms competitive baselines.

The main contributions of this paper are summarized as follows:

- We formulate adaptive ad exposure in feeds as a Dynamic Knapsack Problem (DKP), which can capture various business optimization objectives and hierarchical constraints to derive flexible Pareto-efficient solutions.
- We provide an effective solution: Hierarchically Constrained Adaptive Ad Exposure (HCA2E), which possesses desirable game-theoretical properties, computational efficiency, and performance robustness.
- We have deployed HCA2E on Taobao, a leading e-commerce application. Extensive offline simulation and online A/B experiments demonstrate the performance superiority of HCA2E over competitive baselines.

## 2 BACKGROUND

In this section, we first present a system overview of a typical feed application. Then, we make necessary descriptions of major objectives and constraints of the performance optimization. We note that the introduced system framework, objectives, and constraints are applicable in various feed applications.

### 2.1 Feed Application System

As illustrated in Figure 2, a typical feed application has three parts:

- **Recommendation System (RS).** The running of RS consists of three cascading phases: 1) Rec-Matching server retrieves hundreds of candidate items according to the relevance between users’ preferences and items. 2) Rec-RTP server predicts multiple performance indicators for each candidate, such as $pXR$ (short...
for predicted $X$ rate, where $X$ can be click-through, favorite, conversion, etc.). 3) Rec-Ranking server sorts candidate items to maximize the expected recommendation utility, such as user engagement in social networks and gross merchandise volume in e-commerce feeds.

- **Advertising System (AS).** AS has three similar phases to RS. However, due to the advertisers’ participation, several differences exist: 1) Besides user-item relevance, Ad-Matching server needs to take advertisers’ willingness (e.g. bids and budgets) into account [9]. 2) Different from the Rec-Ranking server, Ad-Auction server should follow a certain auction mechanism, including the rules of ad allocation and pricing. With the predicted performance indicators, the ad allocation rule ranks candidate ads by descending order of effective Cost Per Mille (eCPM) to maximize the expected ad revenue [28]. The pricing rule determines the payment for the winning ads, such as the critical bid in the Generalized Second Price (GSP) auction [22].

- **Merging Server (MS).** Given two ranked lists of recommendation and ad candidates, MS combines them according to an exposure strategy that determines the order of exposed items for each request. Corresponding to the business requirements of the application, MS is desirable to achieve flexible Pareto-efficient solutions to trade off recommendation-side and advertising-side objectives. In addition, the computational complexity of MS should be enough low to ensure low latency.

### 2.2 Performance Objectives

The major performance objectives of the feed application contain **recommendation utility** and **advertising utility**. Recommendation utility (from recommendations) could have different interpretations in different feed applications. For example, user engagement, driven by users’ effective activities (e.g., clicks, favorites, comments, and shares), is widely used in social networks and news recommendations. In e-commerce feeds, gross merchandise volume (GMV), relevant to users’ clicks and further conversions, is the key indicator to measure the total amount of purchased commodities over a period. Advertising utility includes not only the above performance indicators (from ads) but also ad revenue. The advertising revenue is a common metric to represent the total payment of exposed or clicked ads over a specific period.

### 2.3 Business Constraints

Without loss of generality, in this paper, we consider the following crucial business constraints:

- **Application-level Constraint.** At the application level, the constraint of monetization rate is concerned. The monetization rate represents the proportion of ad exposures over total exposures (both recommendations and ads) within a period. As a key metric to quantify the supply of ad resources, the monetization rate should be constrained by a target value for two reasons: 1) fluctuating supply of ad resources might cause instability to the auction environment; 2) a too large proportion of ads could damage the recommendation utility.

- **Request-level Constraints.** To prevent some unintended results from harming the user experience, the ad exposure strategy should be further restricted by some request-level constraints.

Similar to [23], the following two constraints are considered: 1) top ad slot (TAS) defines the allowed highest exposure position of ads among all items to be exposed; 2) minimum ad gap (MAG) defines the allowed minimum position distance between two adjacent ads.

### 3 PROBLEM FORMULATION

Within a period (e.g., one day), we consider all the user requests as a sequence $\mathcal{S}$. For a request $s \in \mathcal{S}$, an ad exposure strategy $\pi_s$ determines the placement (positions and orders) of ads. Under $\pi_s$, the request-level expected utility $U(s|\pi_s)$ is determined by all items to be exposed on $s$, and should be a trade-off between expected recommendation utility $U^{rec}(s|\pi_s)$ and ad utility $U^{ad}(s|\pi_s)$, calculated as follows:\footnote{\(U^{rec}\) and \(U^{ad}\) are consistent with the ranking scores of RS and AS, and could be quantified by different performance metrics according to the business requirements.}:

$$U(s|\pi_s) = U^{ad}(s|\pi_s) + \alpha \times U^{rec}(s|\pi_s),$$

where $\alpha$ is an adjustable trade-off hyper-parameter. We optimize $\pi$ by maximizing the accumulative utility over $\mathcal{S}$, and the optimization should be constrained as described in Section 2.3. At the application level, the monetization rate $m(S)$ should be constrained by a target value $m^*$, i.e.,

$$m(S) \leq \frac{\sum_{s \in S} N^{ad}(s|\pi_s)}{\sum_{s \in S} N(s|\pi_s)} \leq m^*, \quad (2)$$

where $N^{ad}(s)$ and $N(s|\pi_s)$ denote the number of ads and all items respectively. At the request level, ad positions are restricted by the top ad slot and minimum ad gap. Thus, the overall optimization problem could be formulated as:

$$\max_{\pi_s} \sum_{s \in \mathcal{S}} U(s|\pi_s) \quad (3)$$

subject to

$$\sum_{s \in \mathcal{S}} N^{ad}(s|\pi_s) \leq m^* \times \sum_{s \in \mathcal{S}} N(s|\pi_s),$$

where $\pi_s \in \Pi_{TAS} \cap \Pi_{MAG}^*$, where we use $\Pi_{TAS}$ and $\Pi_{MAG}$ to denote the strategy space satisfying the request-level constraints of top ad slot (TAS) and minimum ad gap (MAG).

### 4 HIERARCHICALLY CONSTRAINED ADAPTIVE AD EXPOSURE

#### 4.1 Dynamic Knapsack Problem

4.1.1 **Strategy Decomposition.** The optimization problem (3) is challenging due to several reasons: 1) The optimization variable $\pi$ indicating different ranking results is discrete, and thus the optimization objective could be non-convex. 2) The optimization of $\pi$ is hierarchically constrained, i.e., real-time exposure on a single request needs to take into account the application-level constraint across all requests in $\mathcal{S}$. 3) $\pi$ should also guarantee the auction
mechanism properties and high computational efficiency. Thus, it is hard to directly optimize $\pi$. To tackle these challenges, we consider designing a hierarchical optimization approach, where we decompose the strategy over $S$ into two levels:

- **application-level selection strategy** $x = \{x_s\}_{s \in S}$ where $x_s = 1$ as $s$ is selected to expose ads and $x_s = 0$ otherwise.
- **request-level exposure strategy** $\pi$ determining how the candidate ads are exposed on a selected request.

Specially, we denote the exposure strategy without ads by $\pi^0$, and $\pi_s = \pi^0$ if $x_s = 0$ given a request $s$. Hence, the optimization problem (3) could be considered as a Knapsack Problem [15].

### 4.1.2 Request Description

From the perspective of a Knapsack Problem, each request is treated as an object with individual value and weight. For a request $s$ selected to expose ads, the real value produced by an exposure strategy $\pi_s$ should be the incremental utility of $\pi_s$ to the no-ad strategy $\pi^0$. Accordingly, we define the value of $s$ under $\pi_s$ as:

$$v(s|\pi_s) \triangleq U(s|\pi_s) - U(s|\pi^0).$$

(4)

Here, $U(s|\pi^0)$ is fixed given request $s$ since the expected recommendation utility $U_{rec}(s|\pi^0)$ only depends on the recommended items ranked in RS. Meanwhile, exposing ads could occupy a proportion of ad resources given the monetization rate constraint. Then we consider the weight of $s$ under $\pi_s$ to the knapsack, i.e.,

$$w(s|\pi_s) \triangleq N_{ad}(s|\pi_s).$$

(5)

Specially, for $s$ under $\pi^0$, we have $v(s|\pi^0) = 0$ and $w(s|\pi^0) = 0$.

### 4.1.3 Knapsack Description

Next, we consider a knapsack to accommodate the requests under the capacity constraint. The knapsack value $V$ is defined as the total value of requests selected in the knapsack, i.e., $V \triangleq \sum_{s \in S} x_s \times v(s|\pi_s)$. According to Equation (2), accumulative request weight in the knapsack (i.e., total ad exposures within $S$) should not exceed an upper bound, i.e., $\sum_{s \in S} N_{ad}(s|\pi_s) \leq m^* \times \sum_{s \in S} N(s|\pi_s)$. The accumulative request weight $W \triangleq \sum_{s \in S} N_{ad}(s|\pi_s)$, and the knapsack capacity could be expressed as

$$W^* \triangleq m^* \times \sum_{s \in S} N(s|\pi_s).$$

(6)

In this work, we consider that $W^*$ is constant within $S$ because the target monetization rate is predetermined and $\pi$ could rarely affect total exposures within a specific period.

#### 4.1.4 Optimization Objective

Based on the above descriptions, the goal is to maximize the knapsack value under the capacity constraint and aforementioned request-level constraints. The optimization problem (3) could be further expressed as:

$$\begin{align*}
\text{maximize} & \quad \sum_{s \in S} x_s \times v(s|\pi_s) \\
\text{subject to} & \quad \sum_{s \in S} x_s \times w(s|\pi_s) \leq W^* \\
& \quad \pi_s \in \Pi_{TAS} \cap \Pi_{MAG}.
\end{align*}$$

(7)

Different from a classic knapsack problem [15], since both the value and weight of each object (request) depend on $\pi$ and thus are variable, Formulation (7) is a Dynamic Knapsack Problem (DKP).

We handle the DKP by the following steps: 1) We design a two-level optimization architecture, consisting of application-level optimization and request-level optimization. 2) To maintain the game-theoretical properties and the independence/flexibility of AS and RS, we preserve the prior order from AS/RS, termed as Ranking-Preserving Principle, which also reduces the optimization complexity. 3) Based on the above designs, we use two lightweight algorithms to effectively solve the application-level optimization and request-level optimization respectively. We summarize our solutions as a unified approach: Hierarchically Constrained Adaptive Ad Exposure (HCA2E). We also reveal the implementation details of HCA2E for large-scale online services.

### 4.2 Hierarchical Optimization Formulation

#### 4.2.1 Application-level Optimization

We first consider optimizing the application-level selection strategy $x$ under the determined $\pi$, i.e., $v(s|\pi_s)$ and $w(s|\pi_s)$ of any $s \in S$ are determined. The Greedy algorithm [4] has been proposed to solve such a static 0-1 Knapsack Problem, where 

$$\rho(s|\pi_s) \triangleq \frac{v(s|\pi_s)}{w(s|\pi_s)}.$$
Specially, we note that $\rho(s|\pi^0) = 0$ as $v(s|\pi^0) = 0$. The basic idea is to greedily select the requests by descending order of $\rho$. As illustrated in Figure 3, we rank the requests and select the top requests until the cumulative weight exceeds the capacity $W^*$. However, ranking all the requests could be impractical in large-scale industrial scenarios. From Figure 3, we selected the requests depend on a screening threshold $\rho_{\text{THRES}}$: the requests with larger $\rho$ than $\rho_{\text{THRES}}$ will be selected into the knapsack. If $\rho_{\text{THRES}}$ is determined, we can obtain $x_\pi$ for $s \in S$ as:

$$x_\pi = 1 \left[ \rho(s|\pi) > \rho_{\text{THRES}} \right],$$

where $[\cdot]$ is the indicator function. Thus, the optimization of $\pi$ can be transformed as determining the 1-dimension variable $\rho_{\text{THRES}}$.

### 4.2.2 Request-level Optimization

We then fix $\pi$ to optimize the request-level exposure strategy $\pi$. For a selected request $s$, we consider two different ad exposure strategies $\pi^1_s$ and $\pi^2_s$. As illustrated in Figure 4, if the exposure strategy is changed from $\pi^1_s$ to $\pi^2_s$, $s$ will have a request-level value change, i.e., $\Delta v = v(s|\pi^2) - v(s|\pi^1)$, and a request-level weight change, i.e., $\Delta w = w(s|\pi^2) - w(s|\pi^1)$. Since requests are selected in the descending order of $\rho$, if the request weight changes, some requests near $\rho_{\text{THRES}}$ (represented by the blue shaded area in Figure 4) would be squeezed out (if $\Delta w > 0$) or selected (if $\Delta w < 0$) to satisfy the capacity constraint. Accordingly, the knapsack value change resulted by these requests is $\Delta v = \rho_{\text{THRES}} \times (-\Delta w)$. Thus, if $\pi^2_s$ outperforms $\pi^1_s$ with increasing knapsack value, we then have $\Delta v + \Delta w > 0$, i.e.,

$$v(s|\pi^2) - \rho_{\text{THRES}} \times w(s|\pi^2) > v(s|\pi^1) - \rho_{\text{THRES}} \times w(s|\pi^1).$$

According to the strategy improvement condition (10), we can acquire the optimal ad exposure strategy with a given $\rho_{\text{THRES}}$ as:

$$\pi^*_s = \arg \max_{\pi_s} \left[ v(s|\pi) - \rho_{\text{THRES}} \times w(s|\pi) \right],$$

where we define knapsack value increment of $s$ as:

$$\Delta v(s|\pi) = v(s|\pi) - \rho_{\text{THRES}} \times w(s|\pi).$$

Combining with formulas (9) and (11), we can express the final exposure strategy for each request as:

$$\pi_s = \begin{cases} 
\pi^*_s, & \text{if } \rho(s|\pi^*_s) > \rho_{\text{THRES}}; \\
\pi^0, & \text{otherwise}.
\end{cases}$$

The detailed optimization methods of $\pi$ and $\rho_{\text{THRES}}$ will be described in Section 4.4 and Section 4.5 respectively.

### 4.3 Rank-Preserving Principle

Next, we aim to guarantee the optimization of $\pi$ under the ad auction mechanism. In this work, we focus on the two major game-theoretical properties: Incentive Compatibility (IC) and Individual Rationality (IR). Formally, if every participant advertiser bids truthfully (i.e., bids the maximum willing-to-pay price $[12]$), IR will guarantee their non-negative profits, and IC can further ensure that they earn the best outcomes. According to Myerson’s theorem [13], to satisfy these properties, the charge price of an ad should be related to its ranking in the ad list. However, most of the existing works blend ads and recommended items without considering the fact that changed orders of ads should affect the charge prices. These methods might lead to the advertisers’ misreporting, which is against the long-term stable performance of the advertising system.

To this end, **Rank-Preserving Principle** (RPP) is introduced: 1) the relative orders of items/ads in MS should be consistent with the prior orders from RS/AS [23], and 2) the final charge price for each exposed ad should be consistent with the price determined in AS.

More than acting as a guardrail for ad auctions, RPP contains some other benefits:

1. RPP allows RS and AS to run independently. Both RS and AS can have quite complex structures and are driven by respective optimization objectives, different groups are responsible for RS and AS in a large-scale feed application. Thus, RPP makes a clear boundary between the two subsystems and thus facilitates rapid technological upgrading within each subsystem.

2. RPP can effectively reduce the optimization complexity of request-level exposure strategy $\pi$. Under RPP, optimizing $\pi$ only needs to determine each slot for an ad or a recommended item, and then place the items/ads into the slots in their prior orders. Thus, $\pi$ can be represented by an exposure template, defined as an one-hot vector $\phi = [i_1, i_2, \ldots, i_L]$ to label the request’s slots, where $i_j = 1$ indicates that the $l$-th slot is for an ad and $i_j = 0$ otherwise, and we assume that there are $L$ slots on a request. Specifically, we denote the no-ad template by $\phi^0$ (corresponding to $\pi^0$ described in Section 3), i.e., $\phi^0 = [0, 0, \ldots]$.

We use $K$ to denote the number of candidate items (including recommended candidates and ad candidates) for each request. The exposure results without RPP are respectively $K^1/(K-L)$ and $2^L$, where $K^1/(K-L) \gg 2^L$ since the number of candidates is usually much larger than the number of slots. Thus, the complexity of optimizing $\pi$ is reduced.

### 4.4 Request-level Optimization with Exposure Template Search

Based on RPP, we optimize $\pi$ by searching the optimal exposure template $\phi^*$ on each request. We denote the set of all possible templates by $\Phi$. The length of each template is $L$.

#### 4.4.1 Template Evaluation

Given a request $s$, the optimal exposure strategy follows the equation (11), and thus any template $\phi \in \Phi$ should be evaluated by:

$$\Delta v(s|\phi) = v(s|\phi) - \rho_{\text{THRES}} \times w(s|\phi).$$
represents a sub-template (denoted by $\kappa$) whose length is equal to the depth of the corresponding layer (Line 4 to Line 11 in Algorithm 1). With the growth of the tree, we will iteratively prune some nodes to control the tree size (Line 12 to Line 14 in Algorithm 1). The pruning rule consists of the following two parts:

- **Eliminating unqualified nodes**: removing the nodes violating the request-level constraints;
- **Retaining top-$B$ nodes**: ranking the nodes by descending $\Delta v$ and only retaining the top-$B$ nodes.

At each layer, the number of remaining nodes is controlled by a beam size $B$, i.e., the top-$B$ nodes are reserved until the tree depth reaches the request length $L$. The complexity of exposure template search is $O(L \times B)$, which is further significantly reduced compared with the previous $O(2^L)$.

Within the final set of the well-chosen templates, denoted by $\Phi_L$, the optimal exposure template $\phi_s^*$ for $s$ is determined according to the formula (11), i.e., $\phi_s^* = \arg\max_{\phi_s, \Phi_L} \Delta v(s|\phi)$. Then the final exposure template

$$\phi_s = \begin{cases} 
\phi_s^*, & \text{if } \rho(s|\phi_s^*) > \rho_{\text{THRES}}; \\
\phi_s^0, & \text{otherwise},
\end{cases} \quad (15)$$

where $\rho(s|\phi)$ is according to (8). The ETS algorithm can flexibly balance the optimality (by selecting top-$B$ nodes) and computational complexity (by adjusting the beam size $B$).

### 4.5 Application-level Optimization with Real-time Feedback Control

However, the estimated $\rho_{\text{THRES}}$ might be different from the optimal $\rho^*_{\text{THRES}}$. When $\rho_{\text{THRES}} < \rho^*_{\text{THRES}}$, superfluous undesired ads are exposed and thus violate the application-level constraint (i.e., $m > m^*$). When $\rho_{\text{THRES}} > \rho^*_{\text{THRES}}$, it leads to the loss of application revenue due to a reduced supply of ads exposures (i.e., $m < m^*$). Thus, we should dynamically adjust $\rho_{\text{THRES}}$ to make actual monetization rate $m$ close to the target $m^*$.

We introduce a feedback control method [7] to timely adjust $\rho_{\text{THRES}}$, keeping it close to the optimal $\rho^*_{\text{THRES}}$ and adapting to the fluctuating online environment. In detail, we assume that $\Delta t$ is a time interval to update $\rho_{\text{THRES}}$. At time step $t$, we will calculate the monetization rate (denoted by $m(t-\Delta t)$) over the requests within $t-\Delta t$ to $t$. Accordingly, $\rho_{\text{THRES}}$ is updated as follows:

$$\rho_{\text{THRES}}(t) \leftarrow \rho_{\text{THRES}}(t-\Delta t) \times \left[ 1 + \gamma \times \left( \frac{m(t-\Delta t) - m^*}{m^*} - 1 \right) \right], \quad (16)$$

where $\gamma$ is the learning rate. Thus, when the actual $m$ exceeds (or is less than) $m^*$, $\rho_{\text{THRES}}$ will be increased (or decreased) towards $\rho^*_{\text{THRES}}$ to reduce the difference between $m$ and $m^*$. In online experiments, we demonstrate that the real-time $\rho_{\text{THRES}}$ adjustment greatly enhances the stability of monetization rate $m$.

### 4.6 Online Deployment

HCA2E can reliably be deployed for online services, as shown in Figure 6. The key ingredients are described as follows:

- In the online exposure service, once a user request arrives, RS and AS respectively process it as described in Section 2. Then MS
merges the two ranked lists (with predicted indicators) according to Algorithm 1. Exposure results will be recorded in logs.

- Every period of $\Delta t$, the real-time controller will calculate the latest monetization rate $m^t(t-\Delta t)+i$ and adjust $\rho_{\text{RIES}}$ according to Formula (16).

The initial threshold of VPW could be estimated by offline simulation with historical log data. HCA2E has been deployed on a leading e-commerce application Taobao to serve users daily.

5 EXPERIMENTS

In this work, we conduct offline and online experiments based on the feed platform of Taobao. We also claim that HCA2E can be applied in other types of feed applications.

5.1 Experiment Settings

5.1.1 Simulation Settings. In offline experiments, we set up a feed simulator that replays real log data to simulate users’ activities and application responses. Each data point corresponds to a user request and contains the information on recommendation candidates and ad candidates from RS and AS. The information mainly includes predicted indicators and homologous ranking scores. Based on the candidate lists and input information, MS generates a blended list following the embedded exposure strategy. Further, we leverage a temporal data buffer to store requests within the updating interval of $\rho_{\text{RIES}}$ (i.e. $\Delta t$). Every period of $\Delta t$, $\rho_{\text{RIES}}$ is updated according to (2) and the data buffer is initialized. In the implementation, we collected about 10 million requests totally and set the updating time window with $\Delta t = 10k$. For each request, we set the number of exposure slots as 50, i.e. $L = 50$. The top ad slot and minimum ad gap are set as 5 and 4 respectively.

5.1.2 Baseline Methods. We compare HCA2E with three baseline methods applied in industries. To make fair comparisons, we will guarantee the baselines to satisfy the same constraints of monetization rate, top ad slot, and minimum ad gap as the HCA2E. The baselines are briefly described as follows:

- Fixed represents the fixed-position strategy, where the positions of recommended items and ads are manually pre-determined for every request. The positions will be designed under the aforementioned different constraints.

- $\beta$-WPO is based on the Whole-Page Optimization (WPO) [24]. WPO ranks recommended and ad candidates jointly according to the predefined ranking scores. To satisfy the $m^t$-constraint, we introduce an adjustable variable $\beta$ to control the ad proportion.

- $\beta$-GEA is based on the Gap Effect Algorithm (GEA) [23], which also employs a joint ranking score. In addition, it takes the impact of adjacent ads’ gap into account. Similar to $\beta$-WPO, an adjustable variable $\beta$ is introduced to control the ad proportion under $m^t$.

5.1.3 Performance Metrics. We mainly focus on the following key performance indicators in the e-commerce feed:

- Revenue (REV) is the revenue produced by all exposed ads.
- Gross Merchandise Volume (GMV) is the merchandise volume of all purchased items (both recommendations and ads).
- Click (CLK) is the total number of clicked items by users.
- Click-Through Rate (CTR) is the ratio of clicks to exposures.

5.2 Offline Experiments

Within a specific simulation period, we observe the accumulative performances of the HCA2E and the three baseline methods.

5.2.1 Performance Evaluation. Under different target values of monetization rate ($m^t = 8\%, 10\%, 12\%$), we evaluate the offline performance with REV and GMV jointly, respectively as the advertising-side and recommendation-side key indicators. In this work, we measure the performance indicators with an advantage formula, calculated by the relative metric increment between an algorithm and a baseline, as follows:

$$\Delta\text{REV}_\% = \frac{\text{REV} - \text{REV}_{\text{Fixed}}}{\text{REV}_{\text{Fixed}}} \times 100\%.$$  \hspace{1cm} (17)

Given a trade-off parameter $\alpha$, we can obtain a corresponding tuple of $\Delta\text{REV}_\%$ and $\Delta\text{GMV}_\%$. Table 2 records the performances of different algorithms with $\alpha = 0.5$. For adaptive exposure strategies, varying the value of $\alpha$ can produce different performance tuples ($\Delta\text{REV}_\%, \Delta\text{GMV}_\%$), known as Pareto-optimal solutions [11]. We select several values of $\alpha$ to obtain a set of solutions and draw the Pareto-optimal trade-off curve as shown in Figure 7, where $\alpha$ is varied within $[0.1, 0.2, 0.3, \ldots, 1.0]$, and $\Delta\text{REV}_\%/\Delta\text{GMV}_\%$ is corresponding to y-axis/x-axis. From Table 2 and Figure 7, we can make the following observations:

1) As $\alpha$ varies, HCA2E algorithms with four values of beam size (i.e., $B = 1, 3, 5, 7$) could have better Pareto-optimal curves, i.e., when reaching the same GMV (or REV), HCA2E can achieve higher REV (or GMV) than $\beta$-WPO and $\beta$-GEA. The Pareto-optimal curves verify that HCA2E achieves the overall performance improvement compared with the baseline methods due to the optimization towards the application-level performance.

2) Within a certain range, the increase of beam size $B$ could boost the performance of HCA2E. A larger $B$ could provide more possible candidate templates, and thereby some better solutions are taken into account. However, such improvement by increasing $B$ is limited. For example, HCA2E($B = 5$) and HCA2E($B = 7$) achieve closed performances corresponding to the almost overlapping curves. This is because the request value is mostly determined by several top
Table 2: The offline performance ($\alpha = 0.5$).

| Method        | $m^* = 8\%$ |          |          |          | $m^* = 10\%$ |          |          |          | $m^* = 12\%$ |          |          |
|---------------|--------------|----------|----------|----------|--------------|----------|----------|----------|--------------|----------|----------|
|               | $m$ | $\Delta$REV | $\Delta$GMV |          | $m$ | $\Delta$REV | $\Delta$GMV |          | $m$ | $\Delta$REV | $\Delta$GMV |          |
| Fixed         | 8.23% | -- | -- |          | 10.36% | -- | -- |          | 12.29% | -- | -- |          |
| $\beta$-WPO   | 7.84% | 6.82% | 2.18% |          | 10.15% | 4.62% | 1.92% |          | 12.19% | 3.41% | 1.69% |          |
| $\beta$-GEA   | 8.13% | 8.57% | 2.47% |          | 10.18% | 6.58% | 2.21% |          | 11.78% | 4.62% | 1.82% |          |
| HCA2E(B=1)    | 7.97% | 13.58% | 2.68% |          | 10.01% | 10.45% | 2.64% |          | 12.01% | 7.78% | 2.03% |          |
| HCA2E(B=3)    | 8.03% | 15.18% | 2.67% |          | 9.96% | 12.32% | 2.70% |          | 12.04% | 8.78% | 2.07% |          |
| HCA2E(B=5)    | 8.01% | 18.04% | 2.78% |          | 9.99% | 13.42% | 2.78% |          | 11.96% | 9.61% | 2.10% |          |
| HCA2E(B=7)    | 7.99% | 18.45% | 2.79% |          | 10.02% | 13.68% | 2.81% |          | 12.03% | 9.81% | 2.09% |          |

Figure 7: The Pareto curves under different $m^*$.

5.2.2 Ad-exposure Distribution Analysis. Generally, ads at top slots will be viewed/clicked more probably and thus obtain more revenue. It is usually desirable to achieve higher revenue but expose ads at lower slots due to the cost of GMV. Thus, we analyzed the ad-exposure distribution, measured by the percentage of ad exposures on each slot within total ad exposures, to account for whether the performance improvements of HCA2E owe to that more ads are placed at front positions.

We select that $m^* = 10\%$ and $\alpha = 0.5$. For $\beta$-WPO, $\beta$-GEA, and HCA2E($B = 5$), the ad-exposure distributions are shown in Figure 8. We calculate the percentage of ad exposures for every 4 (equal to the minimum ad gap) slots. The result shows that HCA2E has a more even ad exposure distribution than the others. Within top-12 slots, HCA2E exposes much fewer ads than $\beta$-WPO and $\beta$-GEA. Below the 29-th slot, HCA2E still exposes a certain number of ads, but there are nearly none for $\beta$-WPO or $\beta$-GEA. Further, we calculate the average ad positions for each approach (corresponding to the dotted lines drawn in Figure 8). We can find that, despite achieving higher REV, the average ad position of HCA2E is lower than the others. Thus, we demonstrate that the higher REV of HCA2E does not rely on placing more ads at top slots, and HCA2E indeed achieves higher efficiency for ad exposure.

5.3 Online A/B Testing

In online experiments, we successfully deploy HCA2E on a feed product of Taobao, named Guess What You Like. Here we select the results from six major scenarios, located on various pages of the
| Scenario      | ΔREV%  | ΔCTR% | ΔGMV%  | ΔCLK% | #Slot$_{ad}^{avg}$ | Δ Diff% |
|---------------|--------|-------|--------|-------|-------------------|----------|
| Homepage      | 9.24%  | 6.24% | 1.09%  | 0.22% | 33 → 120          | 3.89%    |
| Collection    | 6.20%  | 4.63% | 3.89%  | 1.25% | 27 → 76           | 1.25%    |
| Cart          | 6.57%  | 6.19% | 4.96%  | 0.46% | 27 → 71           | 1.01%    |
| Payment       | 5.91%  | 4.33% | 1.01%  | 1.03% | 22 → 47           | 1.03%    |
| Order List    | 11.64% | 12.33%| 8.65%  | 1.01% | 26 → 53           | 1.01%    |
| Logistics     | 3.58%  | 1.79% | 5.88%  | 0.62% | 23 → 53           | 1.09%    |

The online performance in six feed scenarios of Taobao. The arrow "→" is from Fixed to HCA2E.

Figure 9: The fluctuations of $m$ within two weeks. The $y$-axis represents the relative difference of $m$ to $m^\star$. We can find that the stability of $m$ is enhanced by introducing the feedback control method.

Table 3: The online performance in six feed scenarios of Taobao. The arrow "→" is from Fixed to HCA2E.

6 RELATED WORKS

Earlier studies for adaptive ad exposure only focus on one of the following problems: whether to expose ads [2], how many ads to expose [20] and where to expose ads [24]. Recently, adaptive ad exposure has been studied integrally. Rule-based algorithms usually blend items according to the preset re-ranking rules. For example, the Whole-Page Optimization (WPO) method calculates a unified ranking score for both recommended and ad items, and then it ranks items in the order of descending ranking scores [24]. The Gap Effect Algorithm (GEA) [23] is proposed to maximize the ad revenue of each request under a user engagement constraint. The GEA also re-ranks mixed items through mapping ad-utility into a comparable metric with rec-utility. Different from WPO, GEA would consider the gap effect between consecutive ads. More complex learning-based methods mostly attempt to formulate adaptive ad exposure as a Markov Decision Process (MDP) [18] and learn the strategy with effective reinforcement learning approaches [10, 21, 26, 27]. In the MDP, a state is represented by contextual features of candidate items; an action corresponds to an exposure result; the reward function could be calculated by the feedback of a user request. Such methods allow the strategy optimization under an end-to-end learning pattern, where deep networks are usually utilized. Despite enjoying good performances in offline simulations, learning-based methods usually suffer from 1) a large action space, 2) massive model parameters, and 3) inflexible objective transitions. Thus, they are hardly deployed in large-scale applications.

5.3.1 Performance Evaluation. In response to the different characteristics of these scenarios, we will adjust the trade-off parameter $\alpha$ of HCA2E to guarantee positive performance. Here, mainly concerned indicators include REV, advertising CTR ($CTR^{ad}$), GMV, and CLK. Similar to the metric (17), they are expressed as the indicator advantage to Fixed. For all of these scenarios, the online results within a week, recorded in Table 3, also show the effectiveness and superiority of HCA2E compared with the Fixed. Due to the differences among these scenarios (e.g. traffic difference, user preference, and different target monetization rates), the performance indicators are improved to different degrees. In addition, we compare the average ad positions ($\#Slot_{ad}^{avg}$) of HCA2E and Fixed, as shown in the last column of Table 3. We find that $\#Slot_{ad}^{avg}$ of HCA2E is much lower than Fixed, further demonstrating higher ad exposure efficiency of HCA2E.

5.3.2 Robustness Analysis of monetization rate. Furthermore, for HCA2E and Fixed, we observe the fluctuations of the monetization rate in Homepage. We aim to demonstrate the effectiveness of introducing the feedback control method to stabilize the monetization rate. Figure 9 shows the monetization rate fluctuation results of HCA2E and Fixed within two weeks, where the $y$-axis corresponds to the relative difference between actual $m$ and target $m^\star$. We find that $m$ of the Fixed strategy has a larger variation margin. Though the ad positions are predetermined in Fixed, $m$ within different periods could be varying due to the differences in users’ exploring depth on different requests. Within all 14 days, the curve of HCA2E is consistently close to the zero-line (i.e., $m$ is close to $m^\star$). Thus, HCA2E enhances a accumulative stability of $m$ via the real-time $\rho_{THRES}$-control.

7 CONCLUSION

In this paper, we formulate the adaptive ad exposure problem in feeds as a Dynamic Knapsack Problem (DKP), towards application-level performance optimization under hierarchical constraints. We propose a new approach, Hierarchically Constrained Adaptive Ad Exposure (HCA2E), which possesses the desirable game-theoretical properties, computational efficiency, and performance robustness. The offline and online evaluations demonstrate the performance superiority of HCA2E. HCA2E has been deployed on Taobao to serve millions of users daily and achieved significant performance improvements.

ACKNOWLEDGMENTS

This work was supported in part by Science and Technology Innovation 2030 –“New Generation Artificial Intelligence” Major Project No. 2018AAA0100905, in part by Alibaba Group through Alibaba Innovation Research Program, in part by China NSF grant No. 62132018, 61902248, 62025204, in part by Shanghai Science and Technology fund 20PJ1407900. The opinions, findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies or the government.
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