Boosting Advertising Space: Designing Ad Auctions for Augment Advertising

Yangsu Liu
liu_yangsu@sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

Dagui Chen
dagui.cdg@alibaba-inc.com
Alibaba Group
Beijing, China

Zhenzhe Zheng*
zhengzhenzhe@sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

Zhilin Zhang
zhangzhilin.pt@alibaba-inc.com
Alibaba Group
Beijing, China

Chuan Yu
yuchuan@alibaba-inc.com
Alibaba Group
Beijing, China

Fan Wu
fwu@cs.sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

Guihai Chen
gchen@cs.sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

ABSTRACT

In online e-commerce platforms, sponsored ads are always mixed with non-sponsored organic content (recommended items). To guarantee user experience, online platforms always impose strict limitations on the number of ads displayed, becoming the bottleneck for advertising revenue. To boost advertising space, we introduce a novel advertising business paradigm called *Augment Advertising*, where once a user clicks on a *leading ad* on the main page, instead of being shown the corresponding products, a collection of *mini-detail ads* relevant to the clicked ad is displayed. A key component for augment advertising is to design ad auctions to jointly select leading ads on the main page and mini-detail ads on the augment ad page. In this work, we decouple the ad auction into a two-stage auction, including a leading ad auction and a mini-detail ad auction. We design the Potential Generalized Second Price (PGSP) auction with Symmetric Nash Equilibrium (SNE) for leading ads, and adopt GSP auction for mini-detail ads. We have deployed augment advertising on Taobao advertising platform, and conducted extensive offline evaluations and online A/B tests. The evaluation results show that augment advertising could guarantee user experience while improving the ad revenue and the PGSP auction outperforms baselines in terms of revenue and user experience in augment advertising.

CCS CONCEPTS

• Information systems → Computational advertising; **• Theory of computation** → Algorithmic mechanism design.

* Z.Zheng is the corresponding author.

WSDM '23, February 27-March 3, 2023, Singapore, Singapore

ACM ISBN 978-1-4503-9407-9/23/02…$15.00
https://doi.org/10.1145/3539597.3570381

KEYWORDS

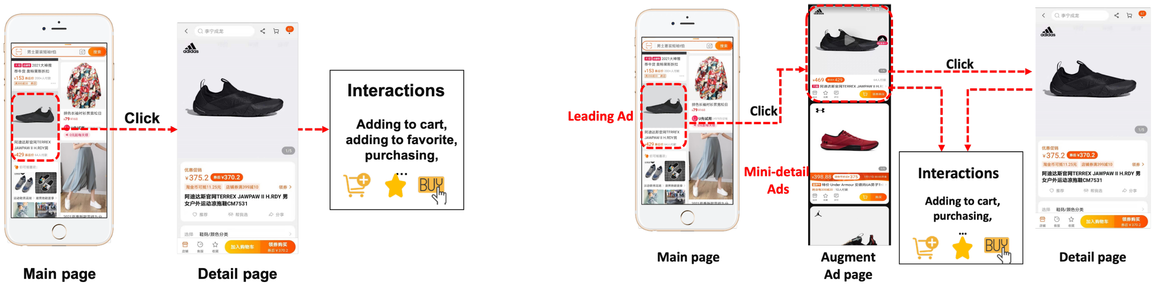
E-commerce Advertising, Ad Auction, Mechanism Design

ACM Reference Format:
Yangsu Liu, Dagui Chen, Zhenzhe Zheng*, Zhilin Zhang, Chuan Yu, Fan Wu, and Guihai Chen. 2023. Boosting Advertising Space: Designing Ad Auctions for Augment Advertising. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining (WSDM '23), February 27-March 3, 2023, Singapore, Singapore.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3539597.3570381

1 INTRODUCTION

With the rapid development of the Internet, e-commerce platforms, such as Amazon, Taobao and Rakuten, have become the primary venue for daily shopping. According to a report from UNCTAD [20], the gross merchandise value of e-commerce achieved 26.7 trillion dollars worldwide in 2020. The prosperity of e-commerce intensifies the increasing competition among sellers, which drives them to spend tens of millions of dollars every year on digital advertising for product marketing [26]. Digital advertising has become a significant source of revenue for online e-commerce platforms.

However, on online e-commerce platforms, ad items only occupy a small amount of display space due to the consideration of user experience, especially when ads are blended with organic content (*e.g.*, recommended items and search results). Organic content increases user stickiness and long-term engagement on the online e-commerce platform but generates less immediate revenue for the platform. Conversely, ads, that are not so relevant to the users' interests, may hurt user experience to some extent, but generate significant advertising revenue for the e-commerce platform. With the prevalence of mobile e-commerce applications, the small screens of mobile devices have further exacerbated the conflict between displaying organic content and ads, resulting in a further limitation on advertising space. As a result, scarce advertising space cannot meet advertisers' increasing demand for ad exposure, which has led to a bottleneck in revenue growth for online e-commerce platforms.



(a) Conventional advertising. (b) Augment advertising.

Figure 1: Examples of two types of advertising. (a) In conventional advertising, once a user clicks on a leading ad, she will be directed to the product detail page. (b) In augment advertising, when a user clicks on a leading ad, she will be guided to an augment ad page, which displays additional mini-detail ads relevant to the leading ad in a feed manner.

In addition, the limited advertising space further intensifies competitions among advertisers, thereby raising winning prices for ad auctions and reducing their willingness to increase ad expenditures.

To overcome issues from limited advertising space, we propose a novel advertising business, called *augment advertising*, to expand advertising space for e-commerce, and have deployed this new advertising format on Taobao advertising platform. We show the difference in users' interactions between conventional advertising and augment advertising in Figure 1. The augment advertising consists of three components: the main page, the *augment ad page* and the detail page. The main page displays both organic content and ads as usual, where these ads are called *leading ads*. When a user clicks a leading ad on the main page, she will be displayed with an augment ad page, containing a series of ads related to the clicked leading ad. We refer to these ads on the augment ad pages as *mini-detail ads*, as they exhibit brief product information such as prices, ratings, sale volumes, *etc.* In order to respect users' online browsing behaviors, the leading ad on the main page is placed at the top of the augment ad page.

Although augment advertising boosts advertising space, it also introduces new challenges to the problem of ad allocation and pricing. Since users behave differently on different augment ad pages generated by various leading ads, the potential social welfare of a leading ad is not only determined by its expected Cost Per Mille (eCPM) but also by the potential value of its augment ad page. Accordingly, the widely-used generalized second price (GSP) auction, which selects the top-K ads sorted by their eCPM and charges advertisers with the minimum bid required to retain their same position, is not effective in the augment advertising. We summarize three major challenges in designing ad auctions for augment advertising based on observations of our industrial deployment.

The first challenge comes from the asynchronous ad retrieval processes on the main page and the augment ad page. Due to the large volume of candidate ads and the limited response time in industrial ad systems, it is impractical for the online platform to retrieve leading ads and corresponding mini-detail ads together. For the sake of efficiency, the augment ad page with mini-detail ads is generated only when a user clicks on a leading ad. Therefore, the potential performance of the corresponding augment ad pages is unknown when we make ad allocation decisions on the main page, resulting in difficulties in optimizing the overall performance of augment advertising.

The second challenge comes from the potential "free-rider" problem in the pricing scheme of online advertising. The widely adopted Pay-Per-Click (PPC) scheme [4] is unfair to leading advertisers, which requires them to pay for both clicks on the main page and the augment ad page. Because users may be distracted from clicking on the leading ad again on the augment ad page, and pay more attention to other relevant mini-detail ads that usually come from the leading advertiser's competitors. In this situation, the leading advertiser pays for an invalid click on the main page, while other mini-detail advertisers benefit from the referral ad exposure opportunity paid by the leading advertiser. As we will show in Section 4, this situation is quite prevalent (accounts for 22.42% over 2 million instances) in our deployed augment advertising prototype. Therefore, we need to design a new ad pricing scheme to avoid this "free-rider" problem.

The last but not the least challenge is the unclear relation between auctions on the main page and the augment ad page. For overall efficiency, the decision for leading ads allocation is influenced by the potential value of their associated unknown mini-detail ads. However, traditional payment rules within GSP and VCG auctions, do not consider the relation between ads on these two pages. Inconsistency between the allocation scheme and the payment rule cannot guarantee the well-defined game-theoretical properties of auctions, resulting in advertisers' potential strategic behaviors and undermining the long-term prosperity of online advertising.

By jointly considering the above challenges, we make an in-depth study on the augment advertising, and design a new augment ad auction. To solve the first challenge, we decouple augment ad auction into two closely correlated auctions: a *leading ad auction* and a *mini-detail ad auction*, which select the optimal leading ads and mini-detail ads at different stages. To address the "free-rider" issue, we place the leading ad at the top of the augment ad page, and let the leading advertisers only pay for the click on the augment ad page. Then, we resort to a data-driven model to estimate the *virtual bid* of each leading advertiser, which represents the total potential social welfare of the leading ads together with mini-detail ads on the corresponding augment ad page. Finally, we propose the PGSP auction based on virtual bids to determine allocations and payments of leading ads. We demonstrate that the PGSP auction has a Symmetric Nash Equilibrium [21] for the utility-maximizing bidders, and is incentive-compatible [16] if all advertisers are value-maximizing bidders [27]. We still insist on using GSP auctions to determine the mini-detail ads for easy deployment. The main contributions of this work can be summarized as follows:

- We boost advertising spaces by introducing a novel ad business model called augment advertising, and have deployed the prototype on Taobao advertising platform. By considering challenges within this new advertising format, we formulate the problem of augment ad auction design with the goal of maximizing the overall social welfare across the main page and potential augment ad pages.
- For the augment ad auction design, we propose a new auction called PGSP auction based on a new concept of virtual bid, which estimates the potential social welfare of the leading ad associated with corresponding mini-detail ads by a data-driven model. Our theoretical results show that the Symmetric Nash equilibrium exists for the PGSP auction with utility-maximizing bidders, and the PGSP auction with reserve prices is incentive-compatible when advertisers are value-maximizing bidders.
- We conducted extensive offline evaluations on the dataset collected from the deployed augment advertising on Taobao display advertising platform. The evaluation results show that both the augment advertising business and the proposed PGSP auction with the virtual bid estimation model could improve both ad revenue and user experience, compared with baseline methods. Furthermore, we conducted online A/B tests on the deployed prototype, which demonstrates the same advantage of augment advertising in the industrial advertising environment.

2 PRELIMINARIES

In this section, we first illustrate the currently deployed augment advertising prototype on Taobao display advertising platform and then introduce the basic notation and concepts used in this paper. Finally, we formulate the augment ad auction problem as a two-stage auction design problem.

2.1 System Overview

To create abundant advertising spaces, Taobao display advertising platform has deployed a new business model: Augment Advertising. We illustrate the details of systems in this novel business model in Figure 2. Once a user visits the main page (Step ①), the platform retrieves candidate leading ads from the corpus. Then the platform sends an ad request to *Auction Module* to select leading ads displayed on the main page, by evoking an ad auction (leading ad auction) over the candidate leading ads. When the user clicks on a leading ad (Step ②), the platform will first retrieve candidate mini-detail ads, which are restricted to be relevant to the clicked leading ad. *i.e.*, their products have similar categories or similar brands to the leading ad. Then, the platform sends a request to the auction module to evoke a mini-detail ad auction to determine mini-detail ads displayed on the augment ad page. Thus, the user is displayed an augment ad page with mini-detail ads associated with more detailed product information. Moreover, the clicked leading ad will appear in the mini-detail format at the top of the augment ad page, without competing with other mini-detail ads in the mini-detail

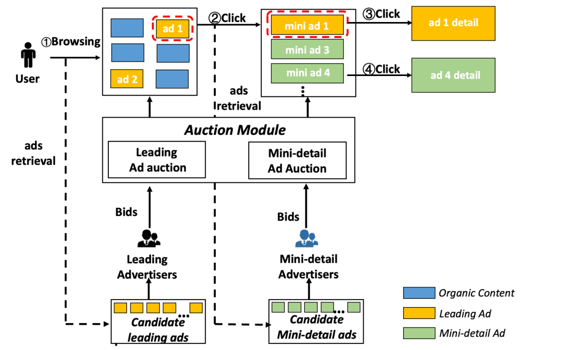


Figure 2: The overview of augment advertising system.

auction. If the user continues to click on the mini detail ad (Step ③ or ④), she will be displayed the detail page of the product.

2.2 Notations and Models

There are a set of candidate leading advertisers $N = \{1, \ldots, n\}$ competing for $K \leq n$ leading ad slots on the main page. We slightly abuse notation and use $i \in N$ referring to both the leading advertiser and her ad. A leading advertiser i has a private valuation v_i for her ad being clicked. She submits a bid b_i to the auction module, which is the maximum payment she is willing to pay for the click. Let vector $\boldsymbol{b} = (b_i, \boldsymbol{b}_{-i})$ denote all bids of n advertisers, where $\boldsymbol{b}_{-i} = (b_1, \ldots, b_{i-1}, b_{i+1}, \ldots, b_n)$. Without loss of generality, we let the ad i win the i-th leading ad slot if $i \leq K$, and lose the auction if $i > K$. The probability of a user clicking on the leading ad i is γ_i, and can be decomposed into $\gamma_i = \beta_j \times c_i$, where β_j, known as the slot effect, denotes the probability that an ad is noticed at the j-th slot. And c_i is the probability of the ad i being clicked once noticed, which is also known as the click-through rate (CTR). Let α_i denote the probability that a user clicks again on the leading ad i on the augment ad page. c_i and α_i could be estimated by CTR prediction models [32, 36]. We assume that β_j is non-increasing with the position, *i.e.*, $\beta_1 \geq \beta_2 \geq \cdots \geq \beta_K$. For a leading ad i, there exists a corresponding augment ad page, in which a set of relevant ads N_i competes for K_i ad slots. Similarly, a mini-detail ad $l \in N_i$ has a private value v_{il}, a bid b_{il}, and a probability γ_{il} of being clicked, respectively.

Allocations and prices of ads on the main page and the augment ad page are determined by an auction mechanism $\mathcal{M} = (\mathcal{X}, \mathcal{P})$. Specifically, the allocation scheme $\mathcal{X}$ is a function that takes all bids as input and outputs ad sequences $W \subseteq N$ and $W_i \subseteq N_i$, where W is the winning leading ad sequence to be displayed on the main page and W_i is the winning mini-detail ad sequence on i's augment ad page. The payment rule $\mathcal{P}$ calculates the payment p_i for the leading ad i as well as p_{il} for the mini-detail ad l. Thus, the utility of the winning leading advertiser i is denoted by $u_i = \gamma_i \alpha_i (v_i - p_i)$.

2.3 Problem Formulation

The objective of the platform is to design an augment ad auction mechanism $\mathcal{M}$ to maximize overall expected social welfare over the main page and augment ad pages with the game-theoretical equilibrium. Thus, the augment auction is to solve the following

Table 1: A toy example for the failure of GSP auction.

Ads	v_i	c_i	SW_i	Position	p_i^{GSP}	p_i^{PGSP}
A	3	0.5	4.1	1	4.8	1.5
B	6	0.4	1	2	4	4
C	4	0.4	1	-	-	-

optimization problem:

$$\max_{W,W_i} \sum_{i \in W} \gamma_i(\alpha_i v_i + \sum_{l \in W_i \subseteq N_i} \gamma_{il} v_{il}). \tag{1}$$

The objective in (1), *i.e.*, the overall expected social welfare, is the expected value of all winning leading advertisers and mini-detail advertisers. To keep the stability of the auction environment, we further require the augment ad auction to have a certain game-theoretical equilibrium, such as Symmetric Nash Equilibrium, which is widely used in digital advertising auctions.

Definition 2.1. [21] A bid profile $\boldsymbol{b}$ is a Symmetric Nash Equilibrium (SNE) if for any $i, j \leq N$, we have $\beta_i(v_i - p_i) \geq \beta_j(v_i - p_j)$.

Suppose that we simply adopt the widely-used GSP auction for leading ads. It selects the top-K ads according to their eCPM, *i.e.*, $c_i \times b_i$, and charges the advertiser with the minimum bid to retain her current position, *i.e.*, $p_i^{GSP} = \frac{b_{i+1} \times c_{i+1}}{c_i}$. However, the allocation of leading ads cannot maximize the expected social welfare in (1) by ignoring the potential value of the augment ad page. Furthermore, if we only change the allocation scheme but not the payment rule, even the basic game-theoretical property is not guaranteed. For example, suppose there are two ad slots competed by three leading ads A, B and C with their values v_i, CTRs c_i and expected social welfare SW_i of mini-detail ads on their augment ad pages, as shown in Table 1. Setting $\alpha_i = 1$, ads A and B will be displayed in the first two positions to optimize (1) by truthfully bidding (*i.e.*, $b_i = v_i$). However, the A's payment in GSP auction is $p_A^{GSP} = \frac{v_B \times c_B}{c_A} = 4.8$, resulting in a negative utility. Even if $b_A = 0$, A occupies the second slot with $p_A^{GSP} = 3.2$ and still gets a negative utility, which is unacceptable for advertisers. Therefore, the GSP auction fails to guarantee game-theoretical properties for the augment ad auction.

3 AUGMENT AD AUCTION DESIGN

We decouple the augment ad auction design into two closely correlated auctions: the *leading ad auction* $\mathcal{M}^L$ and the *mini-detail ad auction* $\mathcal{M}^M$. The goal of these two auctions is to jointly maximize the overall social welfare in (1) while ensuring the existence of SNE. We depict the auction processes in augment advertising in Figure 3. The online platform resorts to a data-driven model to estimate the virtual bids of candidate leading ads, which represents the expected social welfare of the leading ad together with mini-detail ads on the corresponding augment ad page. For the leading ad auction, we propose the Potential Generalized Second Price auction based on estimated virtual bids, and adopt a conventional GSP auction for the mini-detail ad auction.

In the following discussion, we first introduce the definition of the virtual bid, with which we design a PGSP auction for the leading ad auction on the main page. Then we prove the game-theoretical properties of the PGSP auction. Finally, to address the challenges in the practical system, we utilize a data-driven model to estimate the virtual bid.

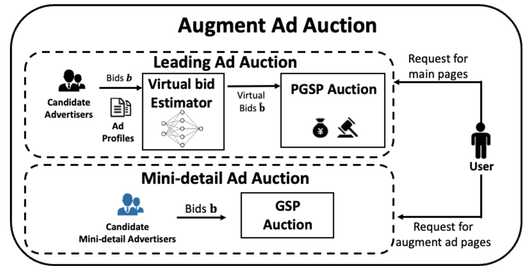


Figure 3: The auction processes for augment advertising. Leading ads are determined by the PGSP auction and mini-detail ads are determined by the GSP auction.

3.1 Leading Ad Auction

In the leading ad auction, we first assume that the augment ad page of each leading ad has been generated in advance, *i.e.*, W_i has been generated. We denote the overall social welfare of mini-detail ads of the leading ad i as g_i, *i.e.*, $g_i = \sum_{l \in W_i} \gamma_{il} v_{il}$. Thus, the objective of the leading ad auction is to select a set of leading ads W maximizing overall social welfare:

$$\max_{W} \sum_{i \in W} \gamma_i(\alpha_i v_i + g_i). \tag{2}$$

We define the virtual bid $\hat{b}_i$ of a leading advertiser $i \in N$ as the overall expected social welfare of the leading ad and mini-detail ads on the corresponding augment ad page, *i.e.*,

$$\hat{b}_i = \alpha_i b_i + g_i. \tag{3}$$

By leveraging the virtual bid, we follow the design rationale behind GSP auction, *i.e.*, selecting the top K ads by their expected social welfare and charging each winning advertiser the minimum bid required to maintain the current position. Thus, the PGSP auction $\mathcal{M}^L = (\mathcal{X}^L, \mathcal{P}^L)$ is designed as:

- **Allocation Scheme** $\mathcal{X}^L$: We sort leading ads in a non-increasing order by $c_i \times \hat{b}_i$, and select the first K leading ads as the winning ad sequence W, breaking ties arbitrarily.
- **Payment Rule** $\mathcal{P}^L$: When the user clicks the leading ad i again on the augment ad page, we charge the leading advertiser $i \in W$ the minimum bid required to keep her current position, *i.e.*,

$$p_i = \frac{(\alpha_{i+1} b_{i+1} + g_{i+1}) \times c_{i+1} - g_i c_i}{\alpha_i c_i}. \tag{4}$$

For the example in Table 1, where ads A and B still occupy the first two slots in the PGSP auction. The payment of A is $p_A^{PGSP} = \frac{(v_B + SW_B) c_B}{c_A} - SW_A = 1.5$, resulting in a positive utility. We claim that any leading advertiser has a non-negative utility in PGSP auction, which can be proved easily and is omitted. We next formally discuss the game-theoretical properties of PGSP auction.

Theorem 3.1. *There exists a non-empty set of SNE states in the PGSP auction.*

Proof. In the Symmetric Nash Equilibrium, the leading advertiser in the slot i would not prefer any other slot j, *i.e.*,

$$\beta_i c_i \alpha_i (v_i - p_i) \geq \beta_j c_i \alpha_i (v_i - p_i^j), \forall i, j \in N, \tag{5}$$

where p_i^j denotes the payment of ad i in the j-th slot under PGSP. Let $U_i = c_i(\alpha_i v_i + g_i)$ and $P_i = c_{i+1}(\alpha_{i+1} b_{i+1} + g_{i+1}) = c_{i+1} \hat{b}_{i+1}$.

Substituting (4) into (5), the condition of SNE is rewritten as:

$$(\beta_i - \beta_j)U_i \geq \beta_i P_i - \beta_j P_j, \forall i, j \in N. \quad (6)$$

If we set $j = i + 1$ and $j = i - 1$ respectively, we could obtain

$$\frac{\beta_{i-1}P_{i-1} - \beta_i P_i}{\beta_{i-1} - \beta_i} \geq U_i \geq \frac{\beta_i P_i - \beta_{i+1}P_{i+1}}{\beta_i - \beta_{i+1}}.$$

Thus, we can deduce recursively that

$$U_1 \geq \frac{\beta_1 P_1 - \beta_2 P_2}{\beta_1 - \beta_2} \geq U_2 \geq \frac{\beta_2 P_2 - \beta_3 P_3}{\beta_2 - \beta_3} \geq \cdots \geq U_K.$$

When $j = i + 1$, the condition (6) is rewritten as:

$$\beta_i(U_i - P_i) \geq \beta_{i+1}(U_i - P_{i+1}).$$

Similarly, the leading ad in slot $i + 1$ never prefer the slot i:

$$\beta_{i+1}(U_{i+1} - P_{i+1}) \geq \beta_i(U_{i+1} - P_i).$$

Thus, we can obtain the bound of P_i in a local SNE:

$$\frac{(\beta_i - \beta_{i+1})U_{i+1}}{\beta_i} + \frac{\beta_{i+1}P_{i+1}}{\beta_i} \leq P_i \leq \frac{(\beta_i - \beta_{i+1})U_i}{\beta_i} + \frac{\beta_{i+1}P_{i+1}}{\beta_i}. \quad (7)$$

According to the Fact 5 in [21], when all advertisers are in local SNE, *i.e.*, when they never prefer their adjacent slots, they are all in the global SNE. Thus, if all bids satisfy the inequality (7), all advertisers are in the SNE state. Thus, we have a lower bound $\hat{b}_i^L$ of the virtual bid of the advertiser i in the SNE state:

$$c_i \hat{b}_i^L = \frac{(\beta_{i-1} - \beta_i)U_i}{\beta_{i-1}} + \frac{\beta_i \hat{b}_{i+1}^L c_{i+1}}{\beta_{i-1}}, \forall i < K. \quad (8)$$

Since there are only K slots, we have $\beta_{K+1} = 0$. The lower bound for the virtual bid of the ad $K + 1$ is

$$c_{K+1}\hat{b}_{K+1}^L = U_{K+1}.$$

The lower bound of the virtual bid of the advertiser K is:

$$c_K \hat{b}_K^L = \frac{(\beta_{K-1} - \beta_K)U_K}{\beta_{K-1}} + \frac{\beta_K U_{K+1}}{\beta_{K-1}}.$$

Thus, we have

$$c_K \hat{b}_K^L - c_{K+1}\hat{b}_{K+1}^L = \frac{\beta_{K-1} - \beta_K}{\beta_{K-1}}(U_K - U_{K+1}), \quad (9)$$

$$c_{K-1}\hat{b}_{K-1}^L - c_K \hat{b}_K^L = \frac{\beta_{K-2} - \beta_{K-1}}{\beta_{K-2}}((U_{K-1} - U_K) + \frac{\beta_K}{\beta_{K-1}}(U_K - U_{K+1})). \quad (10)$$

Referring to (7), we have $U_{i-1} \geq U_i$ for any ad in slot i in the SNE state. Thus, $c_{K-1}\hat{b}_{K-1}^L \geq c_K \hat{b}_K^L \geq c_{K+1}\hat{b}_{K+1}^L$ and we could recursively deduce that $c_i \hat{b}_i^L \geq c_{i+1}\hat{b}_{i+1}^L, \forall i \leq K$, which is consistent with the allocation scheme of the PGSP auction. It indicates that there exists a set of bids $\{b_1^L, \ldots, b_N^L\}$ in the SNE state in the PGSP auction, where $b_i^L = \frac{1}{\alpha}(\hat{b}_i^L - g_i)$. □

When $g_i c_i > (\alpha_{i+1}b_{i+1} + g_{i+1}) \times c_{i+1}$, the payment p_i would be negative. For the example in Table 1, if $SW_A > 5.6$, then $p_A^{PGSP} < 0$. To address this issue, we add a sufficiently low reserve price $\epsilon \geq 0$ for all leading advertisers. Thus, the payment of i is corrected to $\hat{p}_i = max(p_i, \epsilon)$ under the PGSP auction with reserve prices. We figure out that the PGSP auction with reserve prices is incentive-compatible when all advertisers are *value-maximizing bidders* [6, 27]. We let $u_i(b_i, \boldsymbol{b}_{-i})$ denote the utility of i with bids $\boldsymbol{b} = (b_i, \boldsymbol{b}_{-i})$.

Definition 3.2. An advertiser a_i is a value-maximizing bidder if she aims to maximize her value v_i under the budget *i.e.*, $u_i(b_i, \boldsymbol{b}_{-i}) = v_i$ if $p_i \leq v_i$, otherwise, $u_i(b_i, \boldsymbol{b}_{-i}) = 0$.

Definition 3.3. [16] A mechanism is incentive-compatible if truthfully bidding is the dominant strategy for any advertiser i, *i.e.*, $u_i(v_i, \boldsymbol{b}_{-i}) \geq u_i(b_i, \boldsymbol{b}_{-i})$, for any $i \in N$ and any bid b_i.

Theorem 3.4. *The PGSP auction with reserve prices is incentive-compatible when all advertisers are value-maximizing bidders.*

Proof. Suppose that all advertisers truthfully report their values, *i.e.*, $b_i = v_i$. In the PGSP auction with a reserve price ϵ, the payment of the advertiser is

$$\hat{p}_i = \max\left(\frac{(\alpha_{i+1}b_{i+1} + g_{i+1}) \times c_{i+1} - g_i c_i}{\alpha_i c_i}, \epsilon\right). \quad (11)$$

First, we prove that the advertiser i never gets a higher utility by bidding $b_i' > v_i$ while others keep their bids $\boldsymbol{b}_{-i}$. According to the greedy allocation scheme of PGSP, there are two possible results for the advertiser i by bidding b_i'. The first is that she maintains the same position, and she obtains the same utility since her payment keeps the same. The second is that she gets a higher position j and the ad j gets the position $j + 1$. In this case, the payment of i is

$$\hat{p}_i' = \max\left(\frac{(\alpha_j b_j + g_j) \times c_j - g_i c_i}{\alpha_i c_i}, \epsilon\right).$$

Since the ad i is blow ad j by bidding truthfully, we have

$$(\alpha_j b_j + g_j) \times c_j > (\alpha_i v_i + g_i) \times c_i.$$

Thus, we can obtain

$$\max\left(\frac{(\alpha_j b_j + g_j) \times c_j - g_i c_i}{\alpha_i c_i}, \epsilon\right) > v_i.$$

Thus, $\hat{p}_i' > v_i$ and the utility $u_i(b_i', \boldsymbol{b}_{-i}) = 0$. Therefore, a value-maximizing advertiser cannot boost her utility by increasing her bid while others' bids $\boldsymbol{b}_{-i}$ keep the same.

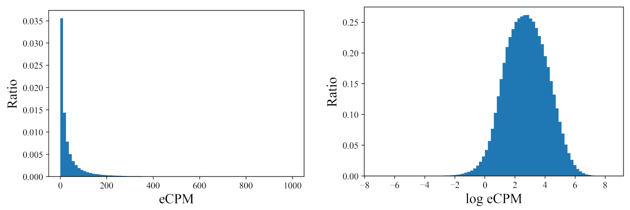
As for i reporting a bid $b_i' < v_i$, there are also two possible situations: The first is that she maintains the position getting the same utility. The second is that she gets a lower position or loses the auction, in which the value-maximizing advertiser gets a lower utility since the γ_i decreases. Therefore, a truth-telling advertiser cannot get a higher utility by decreasing her bid while others' bids $\boldsymbol{b}_{-i}$ keep the same.

Therefore, if all advertisers are value-maximizing bidders, the PGSP auction with reserve prices is incentive-compatible. □

3.2 Virtual Bid Estimation

In industrial systems, it is not possible to obtain accurate virtual bids of all leading ads in advance due to the large volume of candidate ads and the limited response time. Thus, we leverage a data-driven approach to estimate virtual bids.

To estimate the virtual bid $\hat{b}_i$, we need to estimate the expected overall social welfare g_i of mini-detail ads viewed by the user. Note that mini-detail ads on the augment ad page are closely related to the corresponding leading ad and the user entering the augment ad page always has a clear preference for the products related to the leading ad she clicks on. Therefore, it is reasonable to assume that g_i is strongly related to the characteristics of the user and the



(a) eCPM of exposed mini-detail ads. (b) log eCPM of exposed mini-detail ads.

Figure 4: Histograms of eCPM and log eCPM of exposed mini-detail ads.

leading ad. Furthermore, we illustrate histograms of overall eCPM of exposed mini-detail ads from the deployed augment advertising prototype in Figure 4. This figure shows that the expected social welfare g_i obeys a long-tail distribution while the log expected social welfare obeys nearly a Gaussian distribution.

With above observations, we adopt a deep learning model with embedding layers and a Multiple Layer Perception (MLP) paradigm to estimate $\log(g_i)$. The model consists of three components:

Features and Labels: We use log data of clicked leading ads from Taobao platform as the training set $\mathcal{S}$ of size M. We adopt three groups of features: ad profiles $\boldsymbol{x}^a$ (*e.g.*, brands, sales, prices of products, *etc.*), user profiles $\boldsymbol{x}^u$ (*e.g.*, user ids), and the prediction information $\boldsymbol{x}^p$ (*e.g.*, pCTR and pCVR) of leading ads from the off-the-shelf prediction models. Prediction information is considered to reflect the preference of the user for similar products. We emphasize that bids of leading advertisers are excluded from the ad profiles. Therefore, the prediction of g_i is independent of the advertiser's bid b_i to protect the game-theoretical properties of the PGSP auction discussed before. Furthermore, we record the overall social welfare of exposed mini-detail ads on the augment ad page of the leading ad i as g_i, which is the label of clicked leading ad i.

Multiple Layer Perception (MLP): Sparse features are embedded into low-dimensional dense representations, and are fed into a three-layer MLP with the ReLU activation function and 256 units in each layer. The output of the network is $\log(\hat{g}_i(\boldsymbol{x})+1)$, which is the estimated log social welfare of the mini-detail ads on the augment ad page with $\boldsymbol{x} = (\boldsymbol{x}^a, \boldsymbol{x}^u, \boldsymbol{x}^p)$ as the input features.

Loss function: Since the distribution of g_i is approximated by a logarithmic normal distribution, we update parameters of the network through a mean squared logarithmic loss function:

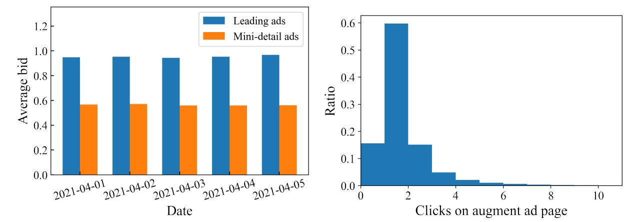
$$L = \frac{1}{M} \sum_{\boldsymbol{x}, g_i \in \mathcal{S}} (\log(\hat{g}_i(\boldsymbol{x}) + 1) - \log(g_i + 1))^2. \tag{12}$$

4 EVALUATION RESULTS

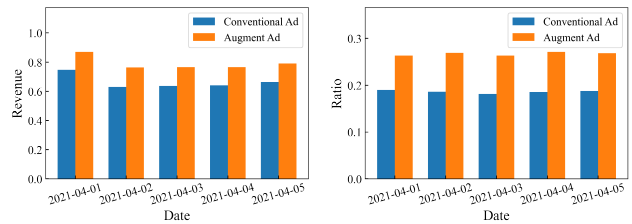
In this section, we conduct offline evaluations to evaluate the performance of augment advertising and PGSP auction. We also deploy the augment advertising on Taobao advertising platform, and present results of online evaluations with online A/B tests.

4.1 Offline Evaluations

To evaluate the performance of augment advertising under PGSP auction, we conduct offline evaluations to answer three questions:
• **RQ1**: Under GSP auction, could we increase the revenue by switching from conventional advertising to augment advertising?



(a) Average bid comparison. (b) Histogram of clicks on augment ad pages.



(c) Revenue Comparison. (d) Ratio of ad format with more revenue.

Figure 5: Evaluations on augment advertising.

• **RQ2**: Adopting augment advertising, could we further improve the revenue of the platform as well as user experience by replacing GSP auction with PGSP auction?
• **RQ3**: How does the performance of the virtual bid estimation model affect users' satisfaction and ad revenue under PGSP auction?

4.1.1 *Experimental Setup.*

We conduct offline evaluations on the dataset collected from the deployed augment advertising prototype on Taobao advertising platform. We refer to a complete browsing journey of a user on the main page and augment ad pages as a *session*, and an ad exposed to a user as an *impression*. The dataset records around 23 million impressions of users in almost 2 million sessions from April 1 to April 19, 2021, in the context of augment advertising. Payments of leading ads were determined by GSP auction and leading advertisers only paid for users' clicks on their ads on the augment ad page. The dataset consists of advertisers' bids, ad profiles, user profiles, prediction information and users' feedback. We randomly select 80% data of clicked leading ads as training data to train virtual bid estimation models, and the other data as testing data to validate the performance of the model. Due to the sensitivity of business data, all metrics in this section are scaled to the range $[0, 1]$, without loss of generality.

4.1.2 *Evaluations on Augment Advertising (RQ1).*

In conventional advertising (Figure 1(a)), clicks on leading ads on the main page are charged, which are free in augment advertising (Figure 1(b)). Due to the difference in charges for clicks on leading ads, even if the number of ad impressions increases, ad revenue does not necessarily grow by adopting augment advertising. Because users may not click on any ad or only click on mini-detail ads with relatively lower bids on augment ad pages. As Figure 5(a) shows, the average bid of mini-detail advertisers is almost half that of leading advertisers based on our observations from April 1 to April 5, 2021. We illustrate the histogram of users' clicks on the augment ad pages in Figure 5(b). While the majority of users (84.47%) clicked at least one ad, 16.23% users did not click on leading ads again on augment ad pages, and 15.53% users exited the page without any click, which may cause a loss of ad revenue.

In order to simulate the revenue generated by adopting conventional advertising, we charged only for the first click on leading ads on the main page. Because there is no difference in ad display formats on the main page between conventional advertising and augment advertising, users will have the same reactions (*i.e.*, click or not). Positions and payments for leading ads in conventional advertising are also determined by GSP auctions. Figure 5(c) illustrates that the ad revenue of the platform could be boosted by almost 14% on average by deploying augment advertising. Specifically, as shown in Figure 5(d), around 18.52% sessions get more revenue by adopting conventional advertising, while 26.22% sessions generate more revenue adopting augment advertising. The remaining 55.26% sessions generate the same revenue with two ad formats, because only leading ads are clicked on the augment ad page in these sessions.

4.1.3 *Evaluations on PGSP Auction (RQ2)*.

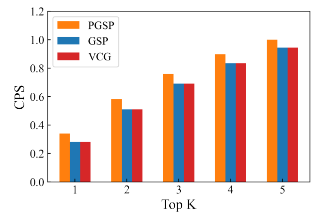
Given ad revenue is boosted by adopting augment advertising under GSP auction, we conduct evaluations to validate whether PGSP auction further improves ad revenue as well as user experience. The widely used GSP [7] and VCG auction [22] are selected as baselines.

- **Generalized Second Price auction (GSP).** In the GSP auction, ads are sorted by their eCPM. The payment for a bidder is the minimum bid required to retain the same position.
- **Vickrey–Clarke–Groves auction (VCG).** In the VCG auction, ads are also sorted by their eCPM. The payment for a bidder is the difference between the total social welfare of other bidders with and without her participation in the auction.

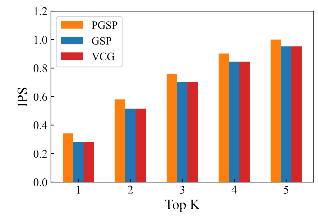
The VCG auction satisfies incentive compatibility, while the GSP auction and PGSP auction satisfy incentive compatibility when all advertisers are value-maximizing bidders [27]. Without loss of generality, we assume that advertisers' bids reflect their true value and keep the same bids in these three mechanisms. For comparing performances in different auctions, we use the following metrics:

- **Click Per Session (CPS)**: CPS $= \frac{\sum_m click + \sum_a click}{\sum session}$, where $\sum_m click$ and $\sum_a click$ are total clicks on main pages and augment ad pages, respectively. CPS reflects users' satisfaction with ads.
- **Impression Per Session (IPS)**: IPS $= \frac{\sum impression}{\sum session}$. IPS records the number of ads viewed by users on main pages and augment ad pages, and reflects the users' interest in the augment ad page.
- **Average Cost-per-click (Avg.CPC)**: The average Cost-per-click is the average price of ads at each position on the main page, and reflects the competitive intensity of the auction.
- **Revenue Per Session (RPS)**: RPS $= \frac{\sum_a click \times CPC}{\sum session}$.

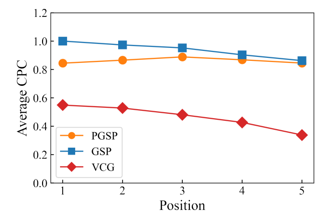
First, we compare user experience under these auctions. As proxies of user experience, the cumulative CPS and IPS of the top K slots, $K \in [1, 5]$, under three auctions are illustrated in Figure 6(a) and 6(b), respectively. It shows that leading ads selected by the PGSP auction could attract users to browse and click more ads on the augment ad page, implying that PGSP auction provides higher user experience. This is because PGSP auction prioritizes the leading ads with augment ad pages of higher quality. In addition, the CPS and IPS are the same under GSP and VCG auctions because their ad allocation schemes are the same.



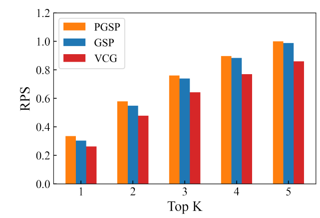
(a) CPS Comparison.



(b) IPS Comparison.



(c) Average CPC in each position.



(d) RPS Comparison.

Figure 6: Performance on the PGSP auction.

Table 2: Performance of Virtual Bid Estimation Models.

Metric	MEAN	LR	GBDT	MLP
NRMSE	0.881	0.879	0.850	**0.840**
CPS@5	–	+1.244%	+1.390%	**+1.730%**
IPS@5	–	+1.473%	+1.472%	**+2.012%**
RPS@5	–	+1.151%	+1.313%	**+1.681%**

Table 3: Online performance improvement of augment advertising compared with conventional advertising.

Metric	Week 1	Week 2	Week 3
PV	+3.077%	+3.128%	+3.591%
Clicks	+12.939%	+13.408%	+14.904%
GMV	+2.781%	+2.088%	+3.278%
REV	+0.876%	+0.540%	+0.690%
Avg.CPC	-9.639%	-9.091%	-9.412%

Second, we compare the average CPC in each ad position under three auctions in Figure 6(c). The average CPC of each position in GSP auction is higher than that in PGSP auction, which reflects that PGSP auction can mitigate the competition of leading advertisers. Moreover, the average CPC monotonically decreases with the position in VCG and GSP auctions, while it remains relatively stable in PGSP auction. Then, we plot the cumulative RPS of the top K slots in Figure 6(d). Although the average CPC in GSP auction is higher, PGSP auction actually generates more ad revenue than GSP auction, which comes from more clicks on the mini-detail ads on the augment ad pages.

Based on the discussion above, we conclude that the PGSP auction outperforms the GSP and VCG auctions in terms of user satisfaction and ad revenue in augment advertising.

4.1.4 *Evaluations on Estimation Models (RQ3)*.

In this part, we evaluate the impact of virtual bid estimation model performance on user satisfaction and ad revenue. Since there is no other specific learning model for estimating potential social welfare in auctions, we compare the performance of our estimation model (MLP) with the Linear Regression model (LR) and the Gradient Boosting Decision Tree model (GBDT) [9]. The Mean model, which estimates overall social welfare $\hat{g}$ by averaging historical data, serves as a benchmark for social welfare estimation. We use Normalized Root Mean Square Error (NRMSE) to evaluate the predictive performance of virtual bid estimation models. *i.e.*,

$$\mathrm{NRMSE}(g, \hat{g}) = \sqrt{\frac{\sum_{i=1}^{n}(g_i - \hat{g}_i)^2}{\sum_{i=1}^{n} g_i^2}}.$$

Furthermore, we compare the relative improvements in business performance under different estimation models with those under the MEAN model. We present, respectively, the cumulative CPS, IPS and RPS of the top 5 slots (*i.e.*, CPS@5, IPS@5 and RPS@5) under PGSP auction with different estimation models in Table 2. The MLP model shows a lower NRMSE and higher improvements in CPS@5, IPS@5 and RPS@5, indicating better predictive performance as well as higher business performance. Therefore, we conclude that the performance of the estimation model has a positive relationship with the business performance, *i.e.*, a model with better predictive performance might result in higher business performance.

4.2 Online Evaluations

We have deployed augment advertising on a feed product, named *Guess What You Like*, on the homepage of Taobao. We evaluate the online performance of augment advertising and compare it with conventional advertising, through online A/B tests from February 4 to February 25, 2021. We launched two online buckets serving 1% of production traffic. In the control bucket, advertisers can only participate in the conventional ad auction. In the treatment bucket, advertisers have the option to participate in either the conventional ad auction or the augment ad auction including both the leading ad auction and the mini-detail ad auction.

We consider five online metrics: Page Views (PV), Clicks, Gross Merchandise Volume (GMV), Ad Revenue (REV), and Avg.CPC of all ads. We present the improvements of the treatment bucket against the control bucket on these metrics for February 4-10 (Week 1), February 11-17 (Week 2), and February 18-25 (Week 3) in Table 3. We find that deploying augment advertising significantly improves user experience metrics (PV, Clicks, GMV), which mainly comes from users' interactions on augment ad pages. Besides, the AVG.CPC of advertisers is indeed decreasing as they have more advertising space available, which significantly reduces the competitive pressure of advertisers and may increase their ongoing investment in advertising. Even if the average CPC decreases, the ad revenue of the platform has slightly increased, which is consistent with our results in offline evaluations.

5 RELATED WORK

The ad auction design, one of the most concerning problems in e-commerce advertising, has been studied for a long time. The GSP auction [7] and VCG auction [22] have been extensively studied and adequately applied in the industry. Many methods have been proposed to boost the revenue of these auctions, such as reserve price [11, 19], squashing [12] and boosted second price auction [10]. To optimize multiple objectives of multiple stakeholders, Bachrach*et al.* [1] and Roberts *et al.* [17] proposed modified GSP auctions with a linear combination of social welfare, revenue and clicks. Chen *et al.* [3] proposed a two-stage framework, which consists of an ad auction module and a re-rank module, to optimize trade-offs among the platform, advertisers, and users. Wang *et al.* [25] proposed a two-stage auction to reduce the gap of the selected ad quality between the coarse ad retrieval and refined ad ranking module. In recent years, the machine learning based auction has received considerable attention. Some researchers [5, 13, 15, 18, 30, 31] leveraged the deep network to design the automated mechanism. Dütting *et al.* [5] proposed a deep learning model based on a regret network to design a revenue-maximizing auction with the incentive-compatible constraint. Shen *et al.* [18] designed a deep learning framework consisting of a mechanism network and a buyer network, which guarantees the incentive compatibility of the output mechanism. However, these auction mechanisms can only be applied to isolated ad auctions, ignoring effects from potential value of ads.

Another related topic is the blending ranking of ads and organic items [2, 8, 14, 23, 24, 28, 29, 33–35]. Wang *et al.* [23] proposed a learning model to predict the optimal number of displayed ads. Zhang *et al.* [29] investigated the whole-page optimization by solving a dynamic linear programming optimization problem. Feng *et al.* [8] proposed a multi-agent reinforcement learning model to collaboratively rank both organic content and ads over multi-scenarios. Yan *et al.* [28] and Chen *et al.* [2] proposed rule-based re-ranking methods to generate blend sequences, considering the trade-off between revenue and user experience. Zhao *et al.* [33, 35] has developed an ad agent based on reinforcement learning models to determine ad positions. However, these works only focused on determining the ad allocation in the context of blending, but none of them could break the limits of the advertising space as augment advertising.

6 CONCLUSION

In this paper, we have introduced a novel business model called augment advertising on online e-commerce platforms to boost advertising space. We have designed the augment ad auction by leveraging a two-stage auction, *i.e.*, the leading ad auction and the mini-detail ad auction. We have proposed a new auction called PGSP auction for the leading ad auction based on the virtual bid, which is estimated by a data-driven model. We have theoretically proved the game-theoretical properties of the PGSP auction. We have deployed augment advertising on Taobao advertising platform, and conducted extensive offline evaluations and online A/B tests. The evaluation results demonstrated the effectiveness of augment advertising and the proposed auction mechanisms.

ACKNOWLEDGMENTS

This work was supported in part by National Key R&D Program of China No. 2020YFB1707900, in part by China NSF grant No. 62132018, 61902248, 61972254, 61972252, 62025204, 62072303, in part by Shanghai Science and Technology fund 20PJ1407900, in part by Alibaba Group through Alibaba Innovative Research Program, and in part by Tencent Rhino Bird Key Research Project. 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.

REFERENCES

[1] Yoram Bachrach, Sofia Ceppi, Ian A. Kash, Peter B. Key, and David Kurokawa. 2014. Optimising trade-offs among stakeholders in ad auctions. In *Proceedings of EC*. 75–92.

[2] Dagui Chen, Qi Yan, Chunjie Chen, Zhenzhe Zheng, Yangsu Liu, Zhenjia Ma, Chuan Yu, Jian Xu, and Bo Zheng. 2022. Hierarchically Constrained Adaptive Ad Exposure in Feeds. In *Proceedings of CIKM*. 3003–3012.

[3] Xiang Chen, Bowei Chen, and Mohan Kankanhalli. 2017. Optimizing Trade-Offs Among Stakeholders in Real-Time Bidding by Incorporating Multimedia Metrics. In *Proceedings of SIGIR* (Shinjuku, Tokyo, Japan). 205–214.

[4] Nikhil R. Devanur and Sham M. Kakade. 2009. The price of truthfulness for pay-per-click auctions. In *Proceedings of EC*. 99–106.

[5] Paul Dütting, Zhe Feng, Harikrishna Narasimhan, David C. Parkes, and Sai Srivatsa Ravindranath. 2019. Optimal Auctions through Deep Learning. In *Proceedings of ICML*. 1706–1715.

[6] Paul Dütting, Felix A. Fischer, and David C. Parkes. 2016. Truthful Outcomes from Non-Truthful Position Auctions. In *Proceedings of EC*. 813.

[7] Benjamin Edelman, Michael Ostrovsky, and Michael Schwarz. 2007. Internet Advertising and the Generalized Second-Price Auction. *American Economic Review* 97, 1 (March 2007), 242–259.

[8] Jun Feng, Heng Li, Minlie Huang, Shichen Liu, Wenwu Ou, Zhirong Wang, and Xiaoyan Zhu. 2018. Learning to collaborate: Multi-scenario ranking via multi-agent reinforcement learning. In *Proceedings of WWW*. 1939–1948.

[9] Jerome H. Friedman. 2001. Greedy function approximation: a gradient boosting machine. *The Annals of Statistics* 29, 5 (2001).

[10] Negin Golrezaei, Max Lin, Vahab Mirrokni, and Hamid Nazerzadeh. 2021. Boosted Second Price Auctions: Revenue Optimization for Heterogeneous Bidders. In *Proceedings of SIGKDD*. 447–457.

[11] Jason D Hartline and Tim Roughgarden. 2009. Simple versus optimal mechanisms. In *Proceedings of EC*. 225–234.

[12] Sébastien Lahaie and R. Preston McAfee. 2011. Efficient ranking in sponsored search. In *Workshop on Internet and Network Economics (WINE)*. 254–265.

[13] Guogang Liao, Xuejian Li, Ze Wang, Fan Yang, Muzhi Guan, Bingqi Zhu, Yongkang Wang, Xingxing Wang, and Dong Wang. 2022. NMA: Neural Multi-slot Auctions with Externalities for Online Advertising. (2022). arXiv:2205.10018

[14] Guogang Liao, Ze Wang, Xiaoxu Wu, Xiaowen Shi, Chuheng Zhang, Yongkang Wang, Xingxing Wang, and Dong Wang. 2022. Cross DQN: Cross Deep Q Network for Ads Allocation in Feed. In *Proceedings of WWW*. 401–409.

[15] Xiangyu Liu, Chuan Yu, Zhilin Zhang, Zhenzhe Zheng, Yu Rong, Hongtao Lv, Da Huo, Yiqing Wang, Dagui Chen, Jian Xu, Fan Wu, Guihai Chen, and Xiaoqiang Zhu. 2021. Neural Auction: End-to-End Learning of Auction Mechanisms for E-Commerce Advertising. In *Proceedings of SIGKDD*. 3354–3364.

[16] Noam Nisan, Tim Roughgarden, Eva Tardos, and Vijay V. Vazirani. 2007. *Algorithmic Game Theory*. Cambridge University Press, Cambridge.

[17] Ben Roberts, Dinan Gunawardena, Ian A. Kash, and Peter B. Key. 2013. Ranking and tradeoffs in sponsored search auctions. In *Proceedings of EC*. 751–766.

[18] Weiran Shen, Pingzhong Tang, and Song Zuo. 2019. Automated Mechanism Design via Neural Networks. In *Proceedings of the AAMAS*. 215–223.

[19] David R.M. Thompson and Kevin Leyton-Brown. 2013. Revenue optimization in the generalized second-price auction. In *Proceedings of EC*. 837–852.

[20] UNCTAD. 2021. Global e-commerce jumps to $26.7 trillion. https://unctad.org/news/global-e-commerce-jumps-267-trillion-covid-19-boosts-online-sales. Accessed: 2022-11-01.

[21] Hal R Varian. 2007. Position auctions. *international Journal of industrial Organization* 25, 6 (2007), 1163–1178.

[22] Hal R. Varian and Christopher Harris. 2014. The VCG Auction in Theory and Practice. *American Economic Review* 104, 5 (May 2014), 442–45.

[23] Bo Wang, Zhaonan Li, Jie Tang, Kuo Zhang, Songcan Chen, and Liyun Ru. 2011. Learning to Advertise: How Many Ads Are Enough?. In *Proceedings of PAKDD*. 506–518.

[24] Weixun Wang, Junqi Jin, Jianye Hao, Chunjie Chen, Chuan Yu, Weinan Zhang, Jun Wang, Xiaotian Hao, Yixi Wang, Han Li, Jian Xu, and Kun Gai. 2019. Learning Adaptive Display Exposure for Real-Time Advertising. In *Proceedings of CIKM*. 2595–2603.

[25] Yiqing Wang, Xiangyu Liu, Zhenzhe Zheng, Zhilin Zhang, Miao Xu, Chuan Yu, and Fan Wu. 2022. On Designing a Two-Stage Auction for Online Advertising. In *Proceedings of WWW*. 90–99.

[26] WARC. 2020. Brands to spend $59bn on e-commerce ads this year. https://www.warc.cn/newsandopinion/news/brands-to-spend-59bn-on-e-commerce-ads-this-year/44139. Accessed: 2022-11-01.

[27] Christopher A. Wilkens, Ruggiero Cavallo, and Rad Niazadeh. 2017. GSP: The Cinderella of Mechanism Design. In *Proceedings of WWW*. 25–32.

[28] Jinyun Yan, Zhiyuan Xu, Birjodh Tiwana, and Shaunak Chatterjee. 2020. Ads Allocation in Feed via Constrained Optimization. In *Proceedings of SIGKDD*. 3386–3394.

[29] Weiru Zhang, Chao Wei, Xiaonan Meng, Yi Hu, and Hao Wang. 2018. The Whole-Page Optimization via Dynamic Ad Allocation. In *Proceeding of WWW*. 1407–1411.

[30] Yusi Zhang, Zhi Yang, Liang Wang, and Li He. 2019. Autor3: Automated Real-time Ranking with Reinforcement Learning in E-commerce Sponsored Search Advertising. In *Proceedings of CIKM*. 2499–2507.

[31] Zhilin Zhang, Xiangyu Liu, Zhenzhe Zheng, Chenrui Zhang, Miao Xu, Junwei Pan, Chuan Yu, Fan Wu, Jian Xu, and Kun Gai. 2021. Optimizing Multiple Performance Metrics with Deep GSP Auctions for E-commerce Advertising. In *Proceedings of WSDM*. 993–1001.

[32] Jun Zhao, Guang Qiu, Ziyu Guan, Wei Zhao, and Xiaofei He. 2018. Deep Reinforcement Learning for Sponsored Search Real-time Bidding. In *Proceedings of SIGKDD*. 1021–1030.

[33] Xiangyu Zhao, Changsheng Gu, Haoshenglun Zhang, Xiwang Yang, Xiaobing Liu, Jiliang Tang, and Hui Liu. 2021. DEAR: Deep Reinforcement Learning for Online Advertising Impression in Recommender Systems. In *Proceedings of AAAI 2021*. 750–758.

[34] Xiangyu Zhao, Long Xia, Lixin Zou, Hui Liu, Dawei Yin, and Jiliang Tang. 2020. Whole-Chain Recommendations. In *Proceedings of CIKM*. 1883–1891.

[35] Xiangyu Zhao, Xudong Zheng, Xiwang Yang, Xiaobing Liu, and Jiliang Tang. 2020. Jointly learning to recommend and advertise. In *Proceedings of SIGKDD*. 3319–3327.

[36] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Deep Interest Evolution Network for Click-Through Rate Prediction. In *Proceedings of AAAI*. 5941–5948.