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 to be 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. The 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 with 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 the 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.

1 INTRODUCTION
With the rapid development of the Internet, e-commerce platforms, such as Amazon [1], Taobao [3] and Rakuten [2], have become the primary venue for daily shopping. According to a report from UNC-TAD [21], 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 [27]. 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.
In addition, the limited advertising space further intensifies com-
petitions 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 pric-
ing. 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. Ac-
cordingly, the widely-used generalized second price (GSP) auction,
which selects the top-K ads sorted by their eCPM and charges adver-
tisers 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
are 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” prob-
lem in the pricing scheme of online advertising. The widely adopted
Pay-Per-Click (PPC) scheme [7] 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 oppor-
tunity 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. There-
fore, 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 be-
tween auctions on the main page and the augment ad page. For over-
all 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. In-
consistency 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

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.
payments of leading ads. We demonstrate that the PGSP auction has a Symmetric Nash Equilibrium [23] for the utility-maximizing bidders, and is incentive-compatible [17] if all advertisers are value-maximizing bidders [28]. 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 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 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 \( b = (b_1, b_{-1}) \) denote all bids of \( n \) advertisers, where \( b_{-1} = (b_1, \ldots, b_{i-1}, b_{i+1}, \ldots, b_n) \). 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 \( y_i \), and can be decomposed into \( y_i = \beta_j \times c_i \), where \( \beta_j \), 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 \( \alpha_i \) denote the probability that a user clicks again on the leading ad \( i \) on the augment ad page. \( c_i \) and \( \alpha_i \) could be estimated by CTR prediction models [33, 37]. We assume that \( \beta_j \) 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 \( N_i \) competing 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 \( y_{il} \) of being clicked, respectively.

Allocations and prices of ads on the main page and the augment ad page are determined by an auction mechanism \( M = (X, \mathcal{P}) \). Specifically, the allocation scheme \( X \) is a function which 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 \( W_i \) is the winning mini-detail ad sequence on \( i \)-th 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 \( u_i = y_i c_i (v_i - p_i) \).

2.3 Problem Formulation
The objective of the platform is to design an augment ad auction mechanism \( M \) 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
We depict the auction processes in augment advertising in Figure 3.

The online platform resorts to a data-driven model to estimate the welfare. The objective in (1), i.e.,
\[ \max_{W_i} \sum_{i \in W} y_i (a_i q_i + \sum_{l \in W_i \cup N_i} y_i q_i l). \]
The objective of (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 industry.

Definition 2.1. [23] A bid profile \( b \) is a Symmetric Nash equilibrium (SNE) if for any \( i, j \leq N \), we have \( b_i (v_i - p_i) \geq b_j (v_i - p_j) \).

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., \( p_i^{\text{GSP}} = \frac{\min(c_i \times b_i)}{c_i} \). 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 \( p_A^{\text{GSP}} = \frac{b_A \times v_A}{c_A} = 4.8 \), resulting in a negative utility. Even if \( b_A = 0 \), \( A \) occupies the second slot with \( p_A^{\text{GSP}} = 3.2 \) and still gets a negative utility, which is unacceptable to 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 \( \mathcal{A}^L \) and the mini-detail ad auction \( \mathcal{A}^M \). The goal of these two auctions is to jointly maximize the overall social welfare in (1) while ensuring the existence of SNE. We depicted 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.

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

<table>
<thead>
<tr>
<th>Ads</th>
<th>( c_i )</th>
<th>( SW_i )</th>
<th>Position</th>
<th>( p_i^{\text{GSP}} )</th>
<th>( p_i^{\text{PGSP}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3</td>
<td>0.5</td>
<td>4.1</td>
<td>1</td>
<td>4.8</td>
</tr>
<tr>
<td>B</td>
<td>6</td>
<td>0.4</td>
<td>1</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>C</td>
<td>4</td>
<td>0.4</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

### 3.1 Leading Ad Auction

In the leading ad auction, we first assume that the augment ad page of each leading ad have 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., \( g_i = \sum_{l \in W_i} y_i q_i l \). Thus, the objective of the leading ad auction is to select a set of leading ads \( W \) maximizing overall social welfare:
\[ \max_{W} \sum_{i \in W} y_i (a_i q_i + g_i). \]

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 its mini-detail ads on the augment ad page, i.e.,
\[ \hat{b}_i = a_i b_i + g_i. \]

By leveraging the virtual bid, we follow the design rationale behind GSP auction, i.e., to select the top \( K \) ads by their expected social welfare in descending order and charge each winning advertiser with the minimum bid required to maintain the allocated position. Thus, the PGSP auction \( \mathcal{M}^L = (\mathcal{X}^L, \mathcal{p}^L) \) is designed as:

- **Allocation Scheme** \( \mathcal{X}^L \): Leading ads are sorted in a non-increasing order by \( c_i \times \hat{b}_i \). We select the first \( K \) leading ads as the winning ad sequence \( W \), breaking the 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 \( i \in W \) with the minimum bid required to keep her allocated position, i.e.,
\[ p_i = \frac{(a_i+1) b_i + g_i+1 \times c_i+1 - g_i c_i}{a_i c_i}. \]

For the example in Table 1, where \( c_i \) and \( b_i \) of 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.

**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.,
\[ \beta_j c_i a_i (v_i - p_i) \geq \beta_j c_i a_i (v_i - p_j^i), \forall i, j \in N, \]

where \( p_j^i \) denotes the payment of ad \( i \) in the \( j \)-th slot under PGSP. Let \( U_i = c_i (a_i v_i + g_i) \) and \( P_i = c_i (a_i b_i + g_i) = c_i \hat{b}_i + g_i. \)
Substituting (4) into (5), the condition of SNE is rewritten as:
\[
(b_i - b_j) U_{ij} \geq b_i P_i - b_j P_j, \forall i, j \in N.
\] (6)

If we set \(j = i + 1\) and \(j = i - 1\) respectively, we could obtain
\[
\frac{b_i - P_i}{b_i - b_j} \geq U_{ij} \geq \frac{b_i P_i - b_j P_{i+1}}{b_i - b_j}.
\]
Thus, we can deduce recursively that
\[
U_1 \geq \frac{b_1 P_1 - b_2 P_2}{b_1 - b_2} \geq U_2 \geq \frac{b_2 P_2 - b_3 P_3}{b_2 - b_3} \geq \cdots \geq U_K.
\]

When \(j = i + 1\), the condition (6) is rewritten as:
\[
b_i(U_i - P_i) \geq b_{i+1}(U_i - P_{i+1}).
\]

Similarly, the leading ad in slot \(i + 1\) never prefer the slot \(i\):
\[
b_{i+1}(U_i + P_{i+1}) \geq b_i(U_i + P_i).
\]

Thus, we obtain the bound of \(P_i\) in a local SNE:
\[
\frac{b_i - b_{i+1} U_{i+1}}{b_i} + \frac{b_{i+1} P_{i+1}}{b_i} \leq P_i \leq \frac{b_i - b_{i+1} U_{i+1} + b_{i+1} P_{i+1}}{b_i}.
\] (7)

According to the Fact 5 in [23], when all advertisers are in local SNE, i.e., when they never prefer their adjacent slots, they are 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 \(b_i^L\) of the virtual bid of the advertiser \(i\) in the SNE state:
\[
c_i b_i^L = \frac{(b_i - b_{i+1}) U_i}{b_i} + \frac{b_{i+1} c_i}{b_i}, \forall i < K.
\] (8)

Since there are only \(K\) slots, we have \(b_{K+1} = 0\). The lower bound for the virtual bid of the ad \(K + 1\) is
\[
c_{K+1} b_{K+1}^L = U_{K+1}.
\]

The lower bound of the virtual bid of the advertiser \(K\) is:
\[
c_K b_K^L = \frac{(b_K - b_{K+1}) U_K}{b_K} + \frac{b_{K+1} U_{K+1}}{b_K}.
\]

Thus, we have
\[
c_K b_K^L - c_{K+1} b_{K+1}^L = \frac{b_K - b_{K+1}}{b_K - b_{K+1}} (U_K - U_{K+1}).
\] (9)
\[
c_{K-1} b_{K-1}^L - c_K b_K^L = \frac{b_K - b_{K-1}}{b_K - b_{K-1}} (U_K - U_{K-1}) + \frac{b_{K-1}}{b_{K-1}} (U_{K-1} - U_K).
\] (10)

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

When \(g_i c_i > (\alpha_i b_{i+1} + g_{i+1}) c_{i+1}\), the payment \(p_i\) would be negative. For the example in Table 1, if \(SW > 5.6\), then \(p_A^{PGSP} < 0\). To address this issue, we add a sufficiently low reserve price \(\varepsilon \geq 0\) for all leading advertisers. Thus, the payment of \(i\) is corrected to \(\hat{p}_i = \max (p_i, \varepsilon)\) 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 [8, 28]. We let \(u_i(b_i, b_{-i})\) denote the utility of \(i\) with bids \(b = (b_i, b_{-i})\).

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

**Definition 3.3.** [17] A mechanism is incentive-compatible if truthfully bidding is the dominant strategy for any advertiser \(i\), i.e., \(u_i(b_i, b_{-i}) \geq u_i(b_{-i}, b_{-i})\), \(\forall i \in N\).

**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 \(\varepsilon\), the payment of the advertiser is
\[
\hat{p}_i = \max \left(\frac{(\alpha_i b_{i+1} + g_{i+1}) c_{i+1} - g_i c_i}{\alpha_i c_i}, \varepsilon\right).
\] (11)

First, we prove that the advertiser never gets a higher utility by bidding \(b_i' > v_i\) while others keep their bids \(b_{-i}\). 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
\[
\hat{p}_i' = \max \left(\frac{(\alpha_j b_j + g_j) c_j - g_i c_i}{\alpha_i c_i}, \varepsilon\right).
\] (12)

Since the ad \(i\) is blow ad \(j\) by bidding truthfully, we have
\[
(\alpha_j b_j + g_j) c_j > (\alpha_i b_i + g_i) c_i.
\]

Thus, we can obtain
\[
\max \left(\frac{(\alpha_j b_j + g_j) c_j - g_i c_i}{\alpha_i c_i}, \varepsilon\right) > v_i.
\]

Thus, \(\hat{p}_i' > v_i\) and the utility \(u_i(b_i', b_{-i}) = 0\). Therefore, a value-maximizing advertiser cannot boost her utility by increasing her bid while others’ bids \(b_{-i}\) 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 \(r_j\) decreases. Therefore, a truth-telling advertiser cannot get a higher utility by decreasing her bid while others’ bids \(b_{-i}\) 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 the virtual bids.

To estimate the virtual bid \(b_i\), 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
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 \( S \) of size \( M \). We adopt three groups of features: ad profiles \( x^a \) (e.g., brands, sales, prices of products, etc.), user profiles \( x^u \) (e.g., user ids), and the prediction information \( x^p \) (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 \( \log(\hat{g}_i(x) + 1) \), which is the estimated log social welfare of the mini-detail ads on the augment ad page with \( x = (x^a, x^u, x^p) \) 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:

\[
L = \frac{1}{M} \sum_{x, g_i \in S} (\log(\hat{g}_i(x) + 1) - \log(g_i + 1))^2. \tag{13}
\]

\[\text{(a) eCPM of exposed mini-detail ads. (b) log eCPM of exposed mini-detail ads.}
\]

\[\text{Figure 4: Histograms of eCPM and log eCPM of exposed mini-detail ads.}
\]

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?
- **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 relative 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 [10] 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 [28]. 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 following metrics:

- **Click Per Session (CPS):** \[ CPS = \frac{\sum_{m} click_{m} + \sum_{a} click_{a}}{\sum_{session}} \]

- **Impression Per Session (IPS):** \[ IPS = \frac{\sum impression}{\sum session} \]

- **Average Cost-per-click (Avg.CPC):** The average Cost-per-click is the average price paid by users on main pages and augment ad pages, respectively. CPS reflects users’ satisfaction with ads.

- **Revenue Per Session (RPS):** \[ RPS = \frac{\sum clicks \times CPC}{\sum session} \]

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.

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) [12]. 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.,

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

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 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 [10] and VCG auction [22] has been extensively studied and adequately proposed in industry. Many methods have been proposed to boost the revenue of these auctions, such as reserve price [14, 20], squashing [15] and boosted second price auction [13]. To optimize multiple objectives of multiple stakeholders, Bachrachet al. [4] and Roberts et al. [18] proposed modified GSP auctions with a linear combination of social welfare, revenue and clicks. Chen et al. [5] 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. [26] 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 [9, 16, 19, 31, 32] leveraged the deep network to design the automated mechanism. Dütting et al. [9] proposed a deep learning model based on a regret network to design a revenue-maximizing auction with the incentive-compatible constraint. Shen et al. [19] 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 [6, 11, 24, 29, 30, 34–36]. Wang et al. [24] proposed a learning model to predict the optimal number of displayed ads. Zhang et al. [30] investigated the whole-page optimization by solving a dynamic linear programming optimization problem. Feng et al. [11] proposed a multi-agent reinforcement learning model to collaboratively rank both organic content and ads over multi-scenarios. Yan et al. [29] and Chen [6] proposed rule-based re-ranking methods to generate blend sequences, considering the trade-off between revenue and user experience. Zhao et al. [35, 36] 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.

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