Improving Auction Mechanisms for Online Real-Time Bidding Advertising with a Two-stage Resale Model *

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Abstract: Real Time Bidding (RTB), widely publicized as one of the most promising big-data-driven business models for online computational advertising, has the potential of effectively monetizing user clicks and impressions via two-stage auctions with resale. Demand side platforms (DSPs) play a key role as intermediators in this auction process. Typically, the first-stage auctions will be conducted separately in each DSP to determine one winning advertiser registered on it, and in the second-stage auction, each DSP submits a bid based on its winning advertiser’s bid to the ad exchange platform (AdX). The highest-bid DSP wins the ad impression from AdX and resells it to its winning advertiser in pursuit of the intermediate fee. This two-stage resale auction is a critical component in maintaining the effectiveness and efficiency of RTB ecosystems. In this paper, we strive to identify and design potential improvements for this auction mechanism with the aim of enhancing the total revenue of both advertisers and DSPs. We also validated our proposed auction mechanisms using the computational experiment approach. The experimental results indicate that our proposed mechanisms can make both advertisers and DSPs better off. Our work represents the first step towards a new research area of optimal mechanism design for RTB auctions, and is expected to provide useful managerial insights in RTB market practice.

Keywords: real time bidding, demand side platform, two-stage resale model, auction mechanism, computational experiment

1. INTRODUCTION

With the rapid development of Internet and the ever-increasing popularization of big data analysis technology, Real Time Bidding (RTB) has in recent years emerged to be one of the most important online computational advertising formats (Cavallo et al., 2015). Besides its technical advantage of big-data-driven user profiling, RTB also outperforms other online advertising formats in the business aspect with its novel two-stage auction model with resale, which makes it possible for Demand Side Platforms (DSPs) to make profits of intermediation fees in the resale process (Qin et al., 2016).

Once receiving an ad request from the Ad Exchange (AdX), a technical trading platform linking both supply and demand sides of the RTB marketplace, the DSP will start an auction session immediately and determine the winner from all competing advertisers registered on it, and this is the first-stage auction. After that, each DSP will participate in the second-stage auction on the AdX based on the winning bid of its advertisers. The highest-bid DSP wins, and pays the AdX for the ad impression, and in turn resells it to its winning advertiser in pursuit of intermediate fees (Feldman et al., 2010). In this business model, DSPs have to make two key decisions on how to submit an optimal bid to the AdX in the second-stage auction (i.e., the bidding mechanism) as well as how to charge its winning advertiser in the resale process (i.e., the pricing mechanism). These decisions and the resulting revenues are largely determined by the auction mechanism. Therefore, designing a better RTB auction mechanism will not only significantly increase DSPs’ revenue, but also can help maintain the effectiveness and efficiency of the RTB ecosystems.

In current RTB practice, the commonly used pricing mechanism in DSPs is the Generalized Second Price (GSP) mechanism, i.e., charging the winning advertisers with the second-highest bids among all advertisers (Muthukrishnan, 2009). Meanwhile, the bidding mechanism commonly used by DSPs is thus to participate in the second-stage auction with this second-highest bid, so as to guarantee a nonnegative revenue from reselling each ad impression. However, these mechanisms have been proved to be non-

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optimal for DSPs (Stavrogiannis et al., 2014), and choosing a randomized reserve price may produce a higher revenue for DSPs (Feldman et al., 2010). In fact, such mechanisms may possibly cause DSPs’ potential loss of large numbers of ad impressions for their advertisers, especially in case when the highest bids of their advertisers are much higher than the second-highest bids. Therefore, there is a critical need for researchers to design and improve the pricing and bidding mechanisms for DSPs.

In this paper, we aim to identify key properties of the commonly used mechanisms by DSPs in RTB advertising, and design effective improvements on the pricing and bidding mechanisms in several typical cases, i.e., when the highest bids of all other DSPs satisfy uniform distributions in a given interval, which can be easily estimated by DSPs from the Web logs of their historical winning probabilities under different bids. Furthermore, we use the computational experiment approach to validate our proposed mechanisms, and the experimental results show that our proposed mechanisms can effectively increase the revenues for both the advertisers and DSPs.

The remainder of this paper is organized as follows. In Section 2, we introduce DSPs’ commonly used mechanisms in the two-stage resale auction model, identify its key properties, and then propose our improved auction mechanisms. In Section 3, we design computational experiments to validate our proposed mechanisms. Section 4 concludes our research efforts.

2. IMPROVEMENTS OF MECHANISMS IN RTB TWO-STAGE RESALE MODEL

2.1 Commonly Used Mechanisms

Typically in RTB markets, the first-stage auction will be conducted by each DSP among all competing advertisers registered on it, while the second-stage auction will be conducted by the AdX among all competing advertisers registered on it, in order to determine the highest and the second-highest bids of all other DSPs.

The highest bids for DSP usually charges the winning advertisers with the advertising effectiveness of RTB advertising.

As we can see, in this commonly used mechanisms, the DSP usually charges the winning advertisers with the second-highest bids from the advertisers according to the Generalized Second Price (GSP) mechanism, and bids $d_1 = b_2$ in the second-stage auction to guarantee a non-negative revenue from each ad impression. As such, the winning advertisers can only get the impressions in $D_1$, but all the impressions in $D_2$ will be lost, although their bids are higher than $b_2$, as can be seen in Fig. 2. This might significantly decrease the DSPs’ revenue, and also the advertising effectiveness of RTB advertising.

![Fig. 1. Commonly used mechanisms in RTB two-stage resale model](image1)

(1) Once an ad request arrives, the AdX will forward the information about this ad request to all DSPs connected with it, and start an auction session.

(2) After receiving the ad request from the AdX, each DSP runs the first-stage auction among all competing advertisers registered on it, in order to determine the highest and the second-highest bids $b_1$ and $b_2$ from the advertisers.

(3) The DSP bids $b_1 = b_2$ to the AdX to participate in the second-stage auction on the AdX, competing for the ad impression with other DSPs.

(4) The AdX runs the second-stage auction among all bidding DSPs, and the highest bids $b_1$ and the second-highest bids $b_2$ can be obtained. The DSP with the highest bids $b_1$ wins in the auction.

(5) The winning DSP receives, and then resells the ad impression to its winning advertiser, who should pay $c_1 = b_2$ to the DSP to get the ad impression, and get a revenue of $v_1 = b_1 - b_2$ from the impression.

(6) The winning DSP pays $c_2 = b_2$ to the AdX, and get a revenue of $v_2 = b_2 - b_2$.

More specifically, the commonly used mechanisms by the DSPs in the two-stage resale model of RTB advertising are shown in Fig. 1, and can be formally described as follows:

![Fig. 2. The winning impressions for the advertisers in commonly used mechanisms](image2)

In what follows, we present an numerical example to illustrate this problem faced by the DSPs in the two-stage resale model.
Example 1. Suppose the highest and the second-highest bids on the DSP are $b_1 = 10$ and $b_2 = 6$, respectively. Then according to the commonly used mechanisms in the two-stage resale model, the DSP will bid $d_1 = b_2 = 6$ in the second-stage auction, and charge $c_1 = b_2$ from its winning advertiser. Suppose the highest bid $d_2$ of all the other DSPs is a discrete random variable with the following probability distribution $Pr(d_2 = x_k) = p_k$, $k = 1, 2, \cdots, 10$, and the values of $x_k$ and the corresponding $p_k$ are given in Table 1.

Table 1. The random distribution of $d_2$

<table>
<thead>
<tr>
<th>$x_k$</th>
<th>2.5</th>
<th>3.5</th>
<th>4.5</th>
<th>5.5</th>
<th>6.5</th>
<th>7.5</th>
<th>8.5</th>
<th>9.5</th>
<th>10.5</th>
<th>11.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_k$</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Below, we compute the revenues of advertisers and the DSP. Obviously, the DSP wins only when $d_2 = 2.5, 3.5, 4.5, 5.5$, and needs to pay $d_2$ for the ad impression, and charges $c_1 = b_2 = 6$ from its winning advertiser. Thus, the expected revenues of the advertisers and the DSP can be given as

$$E[V_1] = (10 - 6)(0.1 + 0.1 + 0.1 + 0.1) = 1.6,$$
$$E[V_2] = 0.1(6 - 2.5)(6 - 3.5)(6 - 4.5)(6 - 5.5) = 0.8.$$ 

Obviously, although the highest bid of the advertisers on the DSP is higher than all the possible values of $d_2$ except for $d_2 = 10.5, 11.5$, the winning advertiser on the DSP cannot win the impression when $d_2 = 6.5, 7.5, 8.5, 9.5$ due to $d_1 < d_2$ in such cases. Thus, we can see that such mechanisms are not the optimal ones for the advertisers and DSPs. By randomly increasing the bids $d_1$ and the price $c_1$ charged from its winning advertiser, we provide the expected revenues of the advertisers ($E[V_1]$) and the DSP ($E[V_2]$) in Table 2, where “$\uparrow$” and “$\downarrow$” represent “increasing” and “decreasing”, respectively.

Table 2. Expected revenues of the advertisers and the DSP under different $d_1$ and $c_1$

<table>
<thead>
<tr>
<th>$c_1, d_1$</th>
<th>(6.6)</th>
<th>(6.7)</th>
<th>(7.6)</th>
<th>(7.7)</th>
<th>(7.8)</th>
<th>(8.7)</th>
<th>(8.8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[V_1]$</td>
<td>1.6</td>
<td>2.1</td>
<td>1.2</td>
<td>1.5</td>
<td>1.8</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>$E[V_2]$</td>
<td>0.8</td>
<td>0.75</td>
<td>1.25</td>
<td>1.25</td>
<td>1.75</td>
<td>1.65</td>
<td>1.85</td>
</tr>
</tbody>
</table>

From Table 2, it is obvious that $E[V_1'] > E[V_1]$ and $E[V_2'] > E[V_2]$ when $c_1 = 7$ and $d_1 = 8$, which illustrates that by increasing $c_1$ and $d_1$ properly, the expected revenues of the advertisers and the DSP can both be improved.

Example 1 indicates that the commonly used mechanisms are optimal for neither the advertisers nor the DSP. Thus, in the following sections, we will identify several key properties of the commonly used mechanisms and propose some improvements to these mechanisms.

### 2.2 Key Properties of Commonly Used Mechanisms

Suppose that the highest and the second-highest bids $b_1$ and $b_2$ on the DSP satisfy $b_1 > b_2 > \rho$, where $\rho$ is the reserve price of the ad impression, and the DSP bids $d_1$ in the second-stage auction. The highest bids of all the other DSPs in the second stage is denoted by $d_2$.

Generally, with the increasing of $d_1$, the winning probability of the DSP will also increase. In this paper, we consider the typical case that the winning probability increases linearly with $d_1$. In this case, $d_2$ can be assumed to be uniformly distributed in a given interval $[a_1, a_2]$, where $\rho < a_1 < b_2 < b_1 < a_2$ can be easily estimated by the DSP according to the Web logs of its historical winning probabilities under different bid prices.

With the probability distribution function

$$f(y) = \begin{cases} \frac{1}{a_2 - a_1}, & \text{if } a_1 \leq y \leq a_2 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

of $d_2$, we can obtain the expected revenues of the advertisers and the DSP with the following formulas

$$E[V_1] = \int_{a_1}^{a_2} \frac{1}{a_2 - a_1} (2b_1d_1 - a_1) \, da = \frac{b_1(1 - \frac{a_1}{a_2})}{2} \quad (2)$$
$$E[V_2] = \int_{a_1}^{a_2} \frac{1}{a_2 - a_1} (2b_2d_2 - a_1) \, da = \frac{b_2(1 - \frac{a_1}{a_2})}{2} \quad (3)$$

In the following, we study the properties of $E[V_1]$ and $E[V_2]$ when $d_1$ varies in $[b_2, b_1]$, which can be stated in the following theorem.

**Theorem 1.** Let the highest and the second-highest bid $b_1$ and $b_2$ on the DSP satisfy $b_1 > b_2 > \rho$. The highest bid of all the other DSPs in the second-stage auction is $d_2$, and it is uniformly distributed in the interval $[a_1, a_2]$, where $\rho < a_1 < b_2 < b_1 < a_2$. Then $E[V_1]$ increases with the increasing of $d_1$, while $E[V_2]$ decreases with the increasing of $d_1$. When $d_1 = b_2$, $E[V_2]$ reaches its maximum, and $E[V_1]$ reaches its minimum

$$E[V_1]_{\text{max}} = \frac{b_1(1 - \frac{a_1}{a_2})}{2}, \quad E[V_1]_{\text{min}} = \frac{b_2(1 - \frac{a_1}{a_2})}{2}. \quad (4)$$

**Proof.** Since

$$\frac{\partial E[V_1]}{\partial d_1} = \frac{b_1 - \frac{a_1}{a_2}b_2}{a_2 - a_1} > 0, \quad (5)$$

we can conclude that $E[V_1]$ increases with the increasing of $d_1$. Thus, $E[V_1]$ reaches its maximum at $d_1 = b_1$.

Since

$$\frac{\partial E[V_2]}{\partial d_1} = \frac{b_2 - b_1}{a_2 - a_1} \left(\frac{1 - \frac{a_1}{a_2}}{2}\right) \leq 0, \quad (6)$$

we can conclude that $E[V_2]$ decreases with the increasing of $d_1$. Thus, when $d_1 = b_2$, $E[V_2]$ will reach its maximum, and $E[V_1]$ will reach its minimum

$$E[V_2]_{\text{max}} = \frac{b_2(1 - \frac{a_1}{a_2})}{2}, \quad E[V_1]_{\text{min}} = \frac{b_1(1 - \frac{a_1}{a_2})}{2}. \quad (7)$$

From Theorem 1, it is obvious that there exists a principal-agent game between the advertisers and the DSP, in which setting $d_1 = b_1$ will lead to an optimal outcome to the advertisers, while $d_1 = b_2$ will be best for the DSP. As such, an equilibrium strategy is crucial for the advertisers and the DSP.

### 2.3 Improvements of the Bidding Mechanism

In this section, we explore the optimal bidding mechanism, with the aim of reaching the maximized revenues for both the advertisers and the DSP.

**Theorem 2.** Let the highest and the second-highest bids on the DSP satisfy $b_1 > b_2 > \rho$. The highest bid of all the other DSPs in the second-stage auction is $d_2$, and it is uniformly distributed in the interval $[a_1, a_2]$, where $\rho < a_1 < b_2 < b_1 < a_2$. Then the optimal bidding mechanism for the DSP is to set $d_1 = b_1$ in the second-stage auction.

**Proof.** Suppose the winning advertiser should pay $x$ to the DSP, then the total revenue of the advertisers and the DSP is

$$E[V] = E[V_1] + E[V_2] = \frac{(d_1 - a_1)(2b_1 - d_1 - a_1)}{2(a_2 - a_1)}. \quad (8)$$
Differentiate $E[V]$ with $d_1$, we have
\[ \frac{\partial E[V]}{\partial d_1} = \frac{(b_1 - a_1)d_1 - (d_1 - a_1)}{2(a_2 - a_1)} \geq 0. \] (9)
Thus, $E[V]$ increases with the increasing of $d_1$, and reaches its maximum at $d_1 = b_1$, and the corresponding maximum expected revenue is
\[ E[V]_{\text{max}} = \frac{(b_1 - a_1)^2}{2(a_2 - a_1)}. \] (10)

According to Theorem 2, we can conclude that setting $d_1 = b_1$ is optimal when taking the total revenues of the advertisers and the DSP into consideration. However, according to Theorem 1, bidding $d_1 = b_2$ is optimal for the DSP if the pricing mechanism is to charge $b_2$ from the winning advertisers. Therefore, a rational improvement of the pricing mechanism is of great importance.

### 2.4 Improvements of the Pricing Mechanism

In this section, we will analyze and improve the pricing mechanism of the DSP, aiming to increase the revenues of both the advertisers and the DSP under the improved bidding mechanism $d_1 = b_1$ comparing with that of $d_1 = b_2$.

**Theorem 3.** Let the highest and the second-highest bids on the DSP satisfy $b_1 > b_2 > \rho$, and the DSP bids $d_1 = b_1$ in the second-stage auction. The highest bid of all the other DSPs in the second-stage is $d_2$, and it is uniformly distributed in the interval $[a_1, a_2]$, where $\rho < a_1 < b_2 < b_1 < a_2$. Then the optimal pricing mechanism for the DSP in the two-stage resale model is to charge
\[ x^* = b_2 + \frac{(2-\lambda)(b_2 - \rho)^2}{2(b_1 - a_1)} \] (11)
from the winning advertisers, where $\lambda \in (0, 1)$. The corresponding revenues for the advertisers and the DSP are
\[ E[V_1(x^*)] = \frac{2(b_1 - b_2)(b_2 - \rho) + \lambda(b_1 - b_2)^2}{2(a_2 - a_1)}, \] (12)
\[ E[V_2(x^*)] = \frac{(b_2 - a_2)^2 + (1-\lambda)(b_2 - b_1)^2}{2(a_2 - a_1)}. \] (13)

Moreover, $E[V_1(x^*)]$ increases with the increasing of $\lambda$, while $E[V_2(x^*)]$ decreases with the increasing of $\lambda$.

**Proof.** Suppose the winning advertiser should pay $x$ to the DSP if he/she wins the ad impression, and the bidding mechanism for the DSP in the second-stage auction is $d_1 = b_1$. Then, $E[V_1]$ and $E[V_2]$ become
\[ E[V_1(x)] = \frac{(b_1 - a_1)2}{a_2 - a_1}, E[V_2(x)] = \frac{(b_1 - a_1)(2x - b_1 - a_1)}{2(a_2 - a_1)}. \] (14)

Since charging $x$ for the DSP from the winning advertiser can improve the revenues of both the advertisers and the DSP, we have $E[V_1(x)] > E[V_1]\text{min}$ and $E[V_2(x)] > E[V_2]\text{max}$, from which we can obtain that
\[ b_2 + \frac{(b_1 - b_2)^2}{2(b_1 - a_1)} < x < b_2 + \frac{(b_1 - b_2)^2}{b_1 - a_1}. \] (15)

Denote $x_1 = b_2 + \frac{(b_1 - b_2)^2}{b_1 - a_1}$ and $x_2 = b_2 + \frac{(b_1 - b_2)^2}{2(b_1 - a_1)}$. If we set
\[ x^* = \lambda x_1 + (1-\lambda)x_2 = b_2 + \frac{(2-\lambda)(b_1 - b_2)^2}{2(b_1 - a_1)}, \] (16)
where $\lambda \in (0, 1)$, then we have $x_1 < x^* < x_2$.

When $x = x^*$ and $d_1 = b_1$, the revenue of the advertisers and the DSP become
\[ E[V_1(x^*)] = \frac{(b_1 - a_1)2}{a_2 - a_1}, E[V_2(x^*)] = \frac{(b_1 - a_1)(2x^* - b_1 - a_1) - (b_2 - a_1)(b_2 - a_1)}{2(a_2 - a_1)}. \] (17)
\[ E[V_2(x^*)] = \frac{(b_1 - a_1)(2x^* - b_1 - a_1) - (b_2 - a_1)(b_2 - a_1)}{2(a_2 - a_1)}. \] (18)

Since
\[ \frac{\partial E[V_1(x^*)]}{\partial x} = \frac{(b_1 - a_1)2}{a_2 - a_1} > 0, \frac{\partial E[V_2(x^*)]}{\partial x} = \frac{(b_1 - a_1)(b_2 - a_1)}{2(a_2 - a_1)} < 0, \] (19)
we can conclude that $E[V_1(x^*)]$ increases and $E[V_2(x^*)]$ decreases with the increasing of $\lambda$.

According to Theorem 2 and Theorem 3, if the pricing mechanism of the DSP is to charge $x^*$ in the first stage, and then bid $d_1 = b_1$ in the second stage, both the revenues of the advertisers and the DSP can be improved.

### 2.5 Comparisons of Our Improved Mechanisms and the Commonly Used Mechanisms

As discussed in the above sections, the differences between our improved mechanisms and the commonly used mechanisms lie in the bidding and pricing mechanisms of DSP, which are illustrated in Fig. 3. Obviously, although the cost of the advertisers for each winning ad impression rises, the improved mechanism can get higher expected revenues for both the advertisers and the DSP.

![Fig. 3. Comparisons between the improved mechanism and the original mechanism](image)

In the following, we provide an example to illustrate the revenues of the advertisers and the DSPs under our improved mechanisms and the commonly used mechanisms.

**Example 2.** Suppose the highest and the second-highest bids of the advertisers on the DSP are $b_1 = 10$ and $b_2 = 6$, respectively, and the highest bid $d_2$ of the other DSPs in the second stage auction is uniformly distributed in $[2, 12]$, i.e., $a_1 = 2$ and $a_2 = 12$.

When using the commonly used mechanisms, the DSP bids $d_1 = b_2 = 6$, and charges the advertiser $b_2$. According to (4), the expected revenues of the advertisers and the DSP are $E[v_1] = 1.6$ and $E[v_2] = 0.8$, respectively.

When using our improved mechanisms, the DSP bids $d_1 = b_1 = 10$, and charges the advertiser $x^* = 8 - \lambda$, which can be obtained with formula (11). Then according to formulas (12) and (13), the expected revenues of the advertisers and the DSP can be computed as $E[v_1] = 1.6 + 0.8\lambda$ and $E[v_2] = 1.6 - 0.8\lambda$, respectively. With $\lambda$ varying, the corresponding values of $x^*$, $E[v_1]$ and $E[v_2]$ are given in Table 3.

From Table 3, we can see that $E[v_1'] > E[v_1]$, and $E[v_2'] > E[v_2]$ for any $\lambda \in (0, 1)$. 

Table 3. Values of $x^*$, $E[v_1']$ and $E[v_2']$ under different values of $\lambda$

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x^*$</td>
<td>7.9</td>
<td>7.8</td>
<td>7.7</td>
<td>7.6</td>
<td>7.5</td>
<td>7.4</td>
<td>7.3</td>
<td>7.2</td>
<td>7.1</td>
</tr>
<tr>
<td>$E[v_1']$</td>
<td>1.68</td>
<td>1.76</td>
<td>1.84</td>
<td>1.92</td>
<td>2.00</td>
<td>2.08</td>
<td>2.16</td>
<td>2.24</td>
<td>2.32</td>
</tr>
<tr>
<td>$E[v_2']$</td>
<td>1.52</td>
<td>1.44</td>
<td>1.36</td>
<td>1.28</td>
<td>1.20</td>
<td>1.12</td>
<td>1.04</td>
<td>0.96</td>
<td>0.88</td>
</tr>
</tbody>
</table>

3. COMPUTATIONAL EXPERIMENTS

As we analyzed in the above sections and illustrated in Example 2, our improved mechanism is more effective than the commonly used mechanism when there is only one ad impression. In this section, we aim to evaluate our proposed mechanism in case when there are multiple ad impressions in the RTB markets, with resort to computational experiments approach (Wang, 2004). For notational simplicity, we denote our proposed mechanism as “New Mechanism”, and denote the commonly used mechanism as “Baseline Mechanism”.

We design two experimental scenarios to validate the new mechanism. In both scenarios, the highest bid of the other DSPs for each ad impression in the second-stage auction is set to be uniformly distributed in a given interval, and their differences lie in the values of the highest and second-highest bids on the DSP. In the first scenario, both the highest and second-highest bids on the DSP are fixed, while in the second scenario they are randomly generated from two different intervals.

3.1 Computational Experiment I: Fixed Scenario

Without loss of generality, we randomly generate an experimental scenario that 2 DSPs exist in the RTB market, competing for 1000 ad impressions. For each ad impression, the highest bid ($b_1$) and the second-highest bid ($b_2$) on the DSP are fixed at $b_1 = 16$ and $b_2 = 6$, and the highest bid $d_2$ of the other DSP is uniformly distributed in [2, 20]. The winning impressions by the DSP under the two mechanisms are given in Fig. 4.

![Fig. 4. Comparisons of the winning impressions by the DSP under the two mechanisms](image)

The corresponding revenues of the DSP and its advertisers are given in Fig. 5 and Fig. 6, respectively. Moreover, the comparisons of the total revenues of the advertisers and the DSP under the two mechanisms are provided in Fig. 7.

From Fig. 4–Fig. 7, we can draw the following conclusions:

1. The DSP wins 533 out of 1000 ad impressions in our new mechanism, and only 245 in the baseline mechanism. This indicates that our new mechanism has the potential of obtaining more ad impressions for the DSP and advertisers.

2. Although the cost of each ad impression for the advertiser increases to the prices in the region $C_1 = (10.286, 12.571)$ in our new mechanism, which is higher than the cost $b_2$ in the baseline mechanism, our new mechanism proves to be able to bring higher revenues to both the advertisers and the DSP.

3. With the increasing of $\lambda$, the total revenue of the advertisers increases, while that of the DSP decreases.

3.2 Computational Experiment II: Random Scenario

The experimental setup in this experiment is the same with that in Section 3.1, except that the highest bid ($b_1$)
and the second-highest bid ($b_2$) on the DSP are randomly generated in $[12, 18]$ and $[6, 10]$, respectively.

We also run a computational experiment with randomly generated parameters of 2 DSPs and 1,000 ad impressions, and the value of $\lambda$ for each ad impression is randomly generated from $(0, 1)$. The winning impressions as well as the bidding and pricing for each ad impression by the DSP under the two mechanisms are given in Fig. 8 and Fig. 9. Moreover, the total revenues of the DSP and its advertisers are given in Fig. 10.

Moreover, the total revenues of the DSP and its advertisers under the two mechanisms are given in Fig. 8 and Fig. 9, the bidding and pricing for each ad impression by the DSP under the two mechanisms are given in Fig. 4–Fig. 10. We can obtain the following results:

(1) The DSP wins 741 ad impressions using our new mechanism, and only 353 using the baseline mechanism. This also indicates that our new mechanism outperforms the baseline mechanism in winning more ad impressions for the DSP and advertisers.

(2) The revenues for the advertisers and the DSP are 3081.458 and 1938.752 in our new mechanism, and 2400.480 and 1100.690 in the baseline mechanism. This illustrates that our new mechanism can improve the revenues for both the advertisers and the DSP (about 28.368% and 76.140%, respectively).

4. CONCLUSION

Mechanism design is a crucial issue faced by DSPs in RTB advertising markets. This paper presents a preliminary study of the properties of the commonly used two-stage resale auction mechanisms by the DSP, and analyzed the revenues of the DSP and the advertisers under these mechanisms. Under the assumption that the highest bid of the other DSPs is uniformly distributed in a given interval, we proposed an improved bidding and pricing mechanism for the two-stage resale model. Using the computational experiment approach, we validated our proposed mechanisms, and the experimental results showed that our new mechanisms can lead to an auction outcome with higher revenues for both the advertisers and the DSP in RTB advertising. Our work represents the first step towards a new research area of optimal mechanism design for RTB auctions, and is expected to offer useful managerial insights for DSPs’ mechanism design decisions in RTB advertising markets.

In our future work, we plan to extend our work from the following aspects: (a) Studying the improvement of the bidding and pricing mechanisms in case when the highest bids of the DSPs satisfy other types of random distributions; (b) Exploring DSPs’ optimal strategies (e.g., the market segmentation strategies) under these improved auction mechanisms.

REFERENCES


