Auction-based High Timeliness Data Pricing under Mobile and Wireless Networks

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***Abstract*—Data is the cornerstone of intelligent algorithms such as deep learning, and the explosive development of mobile and wireless networks has prompted more devices to share data in time via the Internet. Meanwhile, data is highly time sensitive. It has been found that the value of data is becoming more and more critical to any application areas, significantly highlighting the importance of data pricing mechanisms in data transactions. Although traditional auction mechanisms for ordinary commodities are gradually becoming matures, they fail in the high timeliness data pricing market due to the following key challenges: Firstly, the value and price of the high timeliness data is ever changing with time, making existing mechanisms with fixed prices expired. Secondly, the price changing of such data is uncertain and dynamic, requiring the auction mechanisms to work stably under different price variations of the high timeliness data. To address these challenges, we for the first time innovatively propose an efficient auction mechanism for High Timeliness Data Pricing, namely HTDP. The newly proposed HTDP can maximize the profit of auctioneer in the high timeliness data transactions. And the key factor for HTDP's success is the consideration of the price changing in the high timeliness data, which fills the blank of traditional auction mechanisms in this area. We further evaluate the newly proposed HTDP on the overall auction profit, and compare the results with the benchmark. Experimental results demonstrate that HTDP not only achieves high profit under proper settings, but also is stable and efficient.**

***Index Terms*—Data pricing, Auction, High timeliness**

I. INTRODUCTION

With the rapid development of data-dependent algorithms, such as deep learning [1], the information age has evolved into the data age. With valuable knowledge, data has the potential to create business value. Therefore, data transactions are attracting more and more attentions [2], and multiple new data application scenarios (*e.g.*, data markets and data banks) have begun to take shape. For example, Twitter licenses its data to Gnit for sale [3], and Inrix collects data directly through its network and sensors [4].

In recent years, mobile and wireless networks have experienced explosive growth [5], allowing more devices (*e.g.*, wearable devices and industrial IoT devices) to transmit data in a timely manner. As a special commodity, the key difference between data and other general commodities is that data has the high timeliness characteristics. In other words, the value of data changes over time, and may even change from valuable to worthless in an instant. For example, shared bicycles (*e.g.*, Mobike) are producing huge amounts of user mobility data every day. After removing private information, these real-time user mobility data is crucial to many services companies (*e.g.*, catering companies). This is because the company, which has the access to such real-time data, can quickly adjusts its market operation strategies by providing customized services to those bicycle users. But as time goes by, the bicycle usage data cannot provide any timely and valuable information.

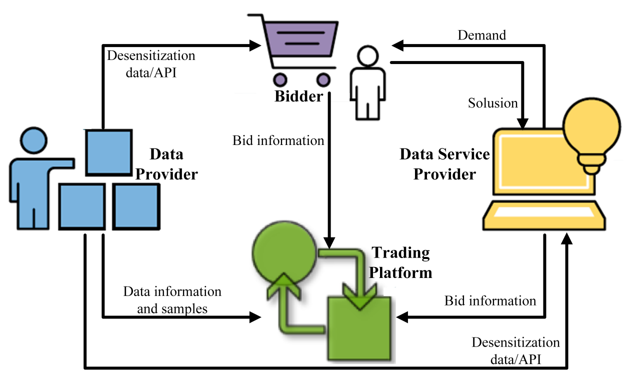

Fig. 1. An overview of programmatic data trading system.

Auction-based mechanisms [6], [7] have always been the classic solutions for data transactions and data pricing. However, existing auction mechanisms fail in the high timeliness data transactions due to the following two challenges. Firstly, the value of data changes with time, but the previous pricing strategies are designed for the price-fixed scenario. Thus, existing pricing strategies are not applicable to high timeliness commodities. Secondly, the price changing of such data is uncertain and dynamic, requiring the auction mechanisms to work stably under different price variations of the high timeliness data. In addition to auction mechanisms [8]–[10],

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traditional pricing strategies (*e.g.*, pay-per-time, pay-per-use, and freemium) also become invalidate in the high timeliness data transaction scenario.

To address above challenges, this paper for the first time innovatively proposes an efficient auction mechanism for High Timeliness Data Pricing, namely HTDP, which is a real-time one-by-one multi-price auction mechanism for maximizing the profit of auctioneer. In addition, we have designed a programmatic data trading system to run the auction-based pricing framework, as illustrated in Fig. 1. Regarding the newly proposed HTDP, we consider price changing in the data auction, and model the change of data value by different variations. To enable HTDP to work in different application scenarios, we give further analysis of HTDP in both *deterministic auctions* and *random auctions*.

The main contributions in this paper are as follows:

- A novel auction-based pricing mechanism for data is proposed, which for the first time integrates the high timeliness into data trading.
- Regardless of the pricing changing pattern, HTDP could work well with different price variations.
- Experiments have demonstrated that HTDP not only achieves high profit, but also is stable and efficient in the high timeliness data auctions.

II. RELATED WORK

With the rapid accumulation of data and data-dependent intelligent applications [11], the data market has attracted the attention of academia and industry. For example, Muschalle A. *et al.* [6] analyze the participant demands and the beneficiaries of the data market, as well as the major challenges of pricing strategies in different market conditions.

In terms of data pricing models, Heckman *et al.* [12] establish a universal pricing model for the data market. They have investigated the properties of data, classified the datasets and selected attributes which can be applied to determining the value of data. The candidate attributes contain value parameters of the data for consumers, the quality parameters of the data itself, and the parameters of fixed and marginal costs. A linear model is built to calculate the data value through the weighted summation of the cost and the value of relevant attributes. But it is a big challenge to estimate the value of each attribute. They propose to use Google AdWords's price to predict the data value and train the machine to learn the regression model to determine the impact of relevant attributes on the data value. This work gives the idea and suggestion of data pricing from the perspective of data valuation, but it does not propose specific, scientific algorithms or mechanisms to price data commodities in the data market.

In fact, there are many studies focusing on pricing problem, such as the network resources pricing [13], [14], time-based pricing [15], [16], auction performance analysis [7], [17], and digital commodity auctions [18]. Digital goods are similar to data, but there are essential differences, especially in terms of the high timeliness characteristics. In this article, we propose a novel auction-based mechanism for data pricing, which focuses on the high timeliness characteristics.

III. HTDP MODEL

Traditional digital commodity auctions have a deadline for bidding. These auction-based mechanisms receive the entire sequence of bidding information, and then decide who wins the auction and at what price. These commodities are auctioned once and delivered to all successful bidders. Bar-Yossef *et al.* [19] propose an online auction mechanism, where commodities can be auctioned continuously without an auction deadline. Based on this theory, we enrich it into HTDP. The bidder at different bidding time has to decide the outcome of the current target before the next bidding submission. The referred price s_i can be calculated from the bidding of the previous bidders. When a bidding b_i enters into the auction system, comparing the b_i with the referred price s_i. If the b_i is higher than or equal to the referred price s_i, the bidder wins. Otherwise, the bidder fails in the auction. Finally, the current auction results will return to the current bidders.

Regarding the newly proposed HTDP, each bidder i has a psychological valuation v_i of the auction data item, *i.e.*, the highest price that the bidder i is willing to pay. And its actual bidding is expressed in b_i. If the bidder will set v_i as its bidding (*i.e.*, $b_i = v_i$), the behavior of bidder i is *truthful*. In HTDP, *telling the truth* is the optimal strategy for bidders. When all users are telling the truth, the auction can reaches equilibrium. In other words, no one is willing to change his or her bidding decision. In HTDP, the profit of auctioneer is the sum of all prices paid by the winning bidders. If bidder wins in the auction, the utility equals the valuation minus payment price. Otherwise, the bidder fails to get the commodity, and the utility is zero. We assume that each bidder's target is to maximize his or her own utility. Meanwhile, all user are bidding-independent in HTDP, *i.e.*, the bidder's bidding only to determine whether he or she wins the auction or not, without determining its final price paid for the commodity.

The bidder's bidding is within the range of $[1, h]$, which is divided into $L = \lfloor \log_2 h \rfloor + 1$ subsets, *i.e.*, $I_0, I_1, \cdots, I_j, I_{j+1}, \cdots, I_{L-2}, I_{L-1}$, where $I_j = [2^j, 2^{j+1})$.

For different scenarios, we have proposed two pricing auction mechanisms with HTDP, *i.e.*, *HTDP-DA* and *HTDP-RA*. More specifically, in the proposed HTDP, different bidders submit the bid at different time. Before the next bid is submitted, the referred price has been determined from the bids of previous bidders. Therefore, the the referred price for user i can calculated based on the bids of previous bidders $b_1, \cdots, b_{i-1}$ and the time t, denoted by Eq. (1).

$$s_i = f(b_1, \cdots, b_{i-1}, t) \tag{1}$$

When f is a deterministic function, it is a *deterministic auction*, and we utilize the *HTDP-DA* mechanism. When f for the auctioneer to calculate the distribution and price is random, it is a *randomized auction*, and we have to utilize the *HTDP-RA* mechanism. Note that when b_i is greater than or equal to s_i, the bidder wins the auction, otherwise he or she fails in the data auction.

Before introducing the two newly proposed auction mechanisms, we first introduce two basic modules, *i.e.*, *optimal single-price auction* and *optimal multi-price auction*. More specifically, *optimal single-price auction* means that all the winning bidders are required to pay the same transaction price. F represents the profit of the *optimal single-price auction*. The number of bidders is denoted by n, and the bidding of bidder i is denoted by b_i. And then, the bidding set of all bidders in the auction can be denoted by $\mathcal{B} = \{b_1, \cdots, b_n\}$. Note that the elements in $\mathcal{B}$ are sorted in descending order. The target of *optimal single-price auction* is to determine the number of winners k, denoted by Eq. (2), so that the profit kh_k is the largest. And Bidders satisfying $b_i \geq h_k$ can become winners, and the transaction price is h_k.

$$F = \max_k kh_k \tag{2}$$

Therefore, the optimal transaction price is $\arg\max_k kh_k$. In the following content, we will use this price as a benchmark to analyze other auction mechanisms.

Different from the *optimal single-price auction*, the *optimal multi-price auction* means that the transaction price for different winning bidders can be different. In other words, all bidders can be winners. In this scenario, the optimal profit is the sum of the biddings of all bidders, denoted by Eq. (3)

$$M = \sum_{i=1}^{n} b_i \tag{3}$$

According to the Eq. (3), it can be found that M is the upper bound of the auction profit, because it charges the true valuation of each bidder.

We use R to represent the auction profit, *i.e.*, the sum of the prices paid by all winning bidders, where $E[R]$ is expected earnings for random auctions. $\bar{v}$ represents the bidder's valuation sequence for the pending data. And $F(\bar{v})$ represents that the optimal profit obtained from fixed pricing method (*i.e.*, the *optimal single-price auction*) based on the sequence $\bar{v}$. As defined above, $\mathcal{B}$ is the input of the trading system. And h is the maximum bidding in all bidders, while l is the minimum bidding in all bidders. In addition, we use Φ to represent the upper bound of R/M or R/F, and Ω is the lower bound of R/M or R/F.

A. HTDP-DA: HTDP to Deterministic Auctions

In this part, we describe the High Timeliness Data Pricing to Deterministic Auctions (*i.e.*, *HTDP-DA*) and the theory derived from the upper bound of its profit. For any b_i, if $b_i \geq s_i$, bidder i needs to pay s_i to get the commodity, otherwise the bidder fails in the auction. From Eq. (1), it can be found the s_i is related to the time t, which achieve the goal of taking into account the high timeliness of the data. Regarding the deterministic auction, the f in Eq. (1) is a deterministic function about time.

Theorem 1. *Compared to the optimal fixed pricing profit, any incentive-compatible HTDP-DA is $\Phi(h)$-competitive, even when $\bar{v}$ is limited to the following conditions: for any $\alpha \geq 1$, there are $F(\bar{v}) \geq \alpha h$.*

Proof of Theorem 1: The bidding price of any bidder, s_i, depends on $b_1, \cdots, b_{i-1}$ and time t. We construct a value sequence $\bar{v}$, which satisfy $R(\bar{v}) \leq F(\bar{v})/h$. Note that $\bar{v}$ is a biphasic sequence. In other words, the elements in this sequence contain only 1 and h. For such a sequence, we can, without loss of generality, assume that s_i is only taken from 1 and h, and the probability of 1 and h is related to t. This can indicate whether the submitted bid can win, and at what price, are time-dependent.

We assume any constant $\alpha \geq 1$. And the rules for constructing the value sequence $\bar{v}$ are as follows. If $s_i = 1$, then $v_i = h$. If $s_i = h$, then $v_i = 1$. Until the number of elements with the value of 1 in $\bar{v}$ is greater than αh, or the number of elements with the value of h is more than α. The winning bidder i needs to pay the transaction price s_i in the auction. Therefore, when $v_i = 1$, the profit earned by the auction from bidder i is 0. And when $v_i = h$, the profit is 1. We adopt n_h to represent the number of h in $\bar{v}$ and n_l represents the number of 1, then $R(\bar{v}) = n_h \cdot 1 + n_l \cdot 0 = n_h$. On the other hand, $F(\bar{v}) \geq \max\{hn_h, n_l\}$. Thus, when $F(\bar{v}) \geq \alpha h$, we have $R(\bar{v}) \leq F(\bar{v})/h$. ■

B. HTDP-RA: HTDP to Random Auctions

In addition to deterministic auctions, there may also be random auctions. Therefore, in this part, we describe the High Timeliness Data Pricing to Random Auctions (*i.e.*, *HTDP-RA*). And we have theoretically derived the lower bound on profit. And we assume that the bid scope of bidders is known. First, design an auction mechanism S. For the bidder i, we randomly select a j, so $j \in \{0, \cdots, \lfloor \log_2 h \rfloor\}$, $s_i = f(2^j, t)$. For example, as the time goes, if the price of data is reducing, then $s_i = 2^{j/t}$. And if the price of data is increasing, then $s_i = 2^j \cdot t$. Obviously, S the bid-independent.

Theorem 2. *Compared to the optimal fixed pricing profit, i.e., F, auction mechanism S is $\Omega(\log h)$-competitive.*

Proof of Theorem 2: First of all, we prove that the auction mechanism S is $\Omega(\log h)$-competitive compare to the *optimal single-price auction* M. Thus, the auction mechanism S is also $\Omega(\log h)$-competitive compared to F .

For each b_i, j_i represents the maximum integer j, which satisfies $2^{j_i t} \leq v_i$. Due to $v_i/2 \leq 2^{j_i t} \leq v_i$, if we have $s_i = 2^{j_i t}$ in the auction mechanism S, it is ensured that the auctioneer obtains at least $v_i/2$ revenue from the bidder i. Thus, we have Eq. (4).

$$E(R) \geq \sum_{i=1}^{n} \frac{v_i}{2} P_r[s_i = 2^{j_i t}] \tag{4}$$

Since j is uniformly and randomly selected, we can have Eq. (5).

$$E(R) \geq \sum_{i=1}^{n} \frac{v_i}{2} \frac{1}{(\log h + 1)} = \frac{1}{2(\log h + 1)} M \quad (5)$$

It has demonstrated that auction mechanism S is $\Omega(\log h)$-competitive compared to M. Since $M \geq F$, we have $E(R) \geq \frac{1}{2(\log h+1)} F$, *i.e.*, the auction mechanism S also is $\Omega(\log h)$-competitive compared to F. ■

C. Analysis of Truthful Auction

In this part, we prove that telling the truth is the best strategy for each user in the HDTP mechanism. As formally notified, each bidder i has a psychological valuation v_i on data, which represents the maximum price that the bidder i is willing to pay. However, the user's real bid is represented by b_i. The utility of user i is defined as Eq. (6)

$$u(i) = \begin{cases} v_i - \max\limits_{z \neq i} b_z, \; if \; b_i > \max\limits_{z \neq i} b_z \\ 0, \quad otherwise \end{cases} \quad (6)$$

To prove that telling the truth is the optimal strategy for each user, we consider three scenarios based on the relationship between v_i and b_i.

1) $v_i = b_i$: Obviously, this is telling the truth.

2) $b_i > v_i$: This is an overly competitive bidding strategy. When $v_i > \max\limits_{z \neq i} b_z$, whether it is telling the truth (v_i) or overly competitive bidding (b_i), the bidder will get data for auction. Overly competitive bidding strategy cannot change the profit, so the bidder will choose to tell the truth. When $b_i < \max\limits_{z \neq i} b_z$, the bidder cannot win regardless of the strategy. When $v_i < \max\limits_{z \neq i} b_z < b_i$, overly competitive bidding strategy bidding can enable users to obtain data, but the profit is negative. Considering individual rationality, users will still choose to tell the truth.

3) $b_i < v_i$: This is a conservative bidding strategy When $v_i < \max\limits_{z \neq i} b_z$, the bidder cannot win regardless of the strategy. When $b_i > \max\limits_{z \neq i} b_z$, both bidding strategies (*i.e.*, telling the truth and telling a lie) enable bidders to win with the same profit. Therefore, the bidder will tell the truth. When $b_i < \max\limits_{z \neq i} b_z < v_i$, if the bidder tells a lie, he or she cannot get the data and the profit is 0. Conversely, telling the truth enable the profit of bidder to be positive. Therefore, telling sthe truth is the optimal strategy.

In summary, HTDP has been proven to be a truthful auction.

IV. Experiments

In this section, we evaluate the profits of HTDP, where the biddings are subject to different distributions (*i.e.*, Bipolar distribution and Zipf distribution). As formally notified, the profit F of *optimal single-price auction* is used as the benchmark.

A. HTDP in Bipolar Distribution

First of all, we evaluate the profit, where the biddings are subject to the Bipolar distribution, *i.e.*, the bidding has only one or two inputs (1 or h). And we take *HTDP-DA* as an example for analysis, that is, the relationship between price (*i.e.*, value) and time is calculated based on the deterministic function in Eq. (1).

As illustrated in Fig. 2(a), regardless of whether the price s_i and time t are positively or negatively correlated, the profit of *HTDP-DA* will increase as the number of bidders participating in the auction increases. It can also be found that, when the number of bidders is less than 100, the auction performance is unstable. When the number of bidders gradually exceeds 100, the profit increases significantly, no matter how timeliness is related to value. Finally, when the number of bidders is large enough, the profit of *HTDP-DA* tends to be stable and is close to the maximum profit.

Fig. 2(b) shows how the ratio of the number of h to the quantity of 1 in bidding set $\mathcal{B}$ affects the profit. It can be found that, the profit is higher when the ratio of the number of h to the quantity of 1 tends to be 1. When the ratio of the number of h to the quantity of 1 deviates greatly from 1, the performance of *HTDP-DA* is less stable. And when the ratio of the number of h to the quantity of 1 tends to 1, the profit tends to be stable.

In Fig. 2(c), we can find that regardless of the relationship between price and time (*i.e.*, positively or negatively), as the number of winners increases, the auction profit increases. When the number of successful bidders is less than 100, the auction performance is unstable. And when the number of successful bidders is around 100, the efficiency of auction mechanism increases rapidly. Finally, when the number of successful bidders is large enough, the profit tends to be stable, as well as the maximum profit.

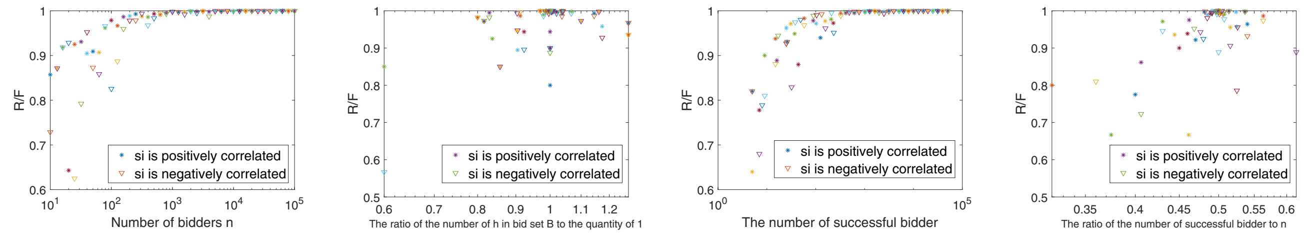
Fig. 2(d) shows how the ratio of the number of winners to the total number n affects the profit. It can be found that, the profit increases with the ratio. The auctioneer's profit is higher when the ratio of the number of successful bidders to the total number n tends to be 0.5. When the ratio deviates greatly from 0.5, the newly proposed *HTDP-DA* performance is less stable. And when the ratio tends to 0.5, the auctioneer's profit tends to be stable.

According to the results of Fig. 2(a) to Fig. 2(d), it can be found that, the newly proposed *HTDP-DA* is a profitable auction mechanism with Bipolar distribution.

B. HTDP-DA in Zipf Distribution

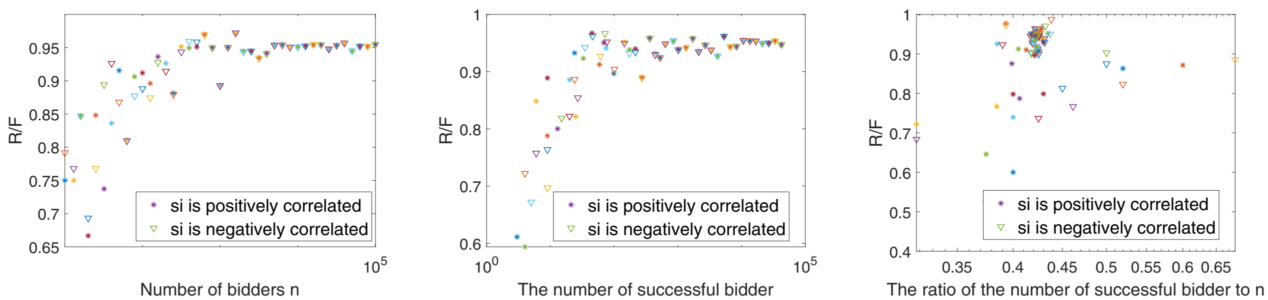
Here, we evaluate the profit of *HTDP-DA*, where the biddings are subject to the Zipf distribution, *i.e.*, the bidding ranges from 1 to h. And the referred price (*i.e.*, the winning price) is calculated based on the deterministic function. More specifically, regarding the Zipf distribution, 80% of the biddings are from 20% of the bidders.

Fig. 3(a) shows the impact of the number of bidders on profit. It can be found that regardless of the correlation between price and time, the profit will increase as the number



(a) Performance *vs.* Number of bidders. (b) Performance *vs.* Ratio of the number of h to the number of 1. (c) Performance *vs.* Number of winners. (d) Performance *vs.* Ratio of the number of winners to the total number of bidders.

Fig. 2. Analysis of *HTDP-DA* with Bipolar distribution.



(a) Performance *vs.* Number of bidders. (b) Performance *vs.* Number of winners. (c) Performance *vs.* Ratio of the number of winners to the total number of bidders.

Fig. 3. Analysis of *HTDP-DA* with Zipf distribution.

of users increases. Moreover, when the number of bidders is less than 100, the auction performance is unstable. When the number of bidders is large enough, the profit of *HTDP-DA* tends to be extremely stable, and achieve the maximum profit.

In terms of the number of successful bidders, we can see from Fig. 3(b) that, the profits are gradually increasing. And the difference in correlation between price and time (*i.e.*, positively or negatively) will not have a different effect.

Fig. 3(c) shows how the ratio of the number of winners to the total number n affects the profit. It can be found that, when the ratio of the number of successful bidders to the total number n gathers in the range of $[0.4, 0.45]$, the profits of *HTDP-DA* are maintained at a high level. When the ratio deviates greatly from $[0.4, 0.45]$, the *HTDP-DA* performance is less stable. In contrast, when the ratio tends to $[0.4, 0.45]$, the auctioneer's profit tends to be stable.

The above experimental results can demonstrate that the newly proposed *HTDP-DA* is a profitable auction mechanism with Zipf distribution.

C. *HTDP-RA in Zipf Distribution*

In this part, we further analyze the *HTDP-RA* in Zipf distribution. Similar to the configuration in Subsection IV-B, the biddings are also subject to the Zipf distribution, *i.e.*, the bidding ranges from 1 to h. The different is that the referred price is calculated from the random function, instead of the deterministic function.

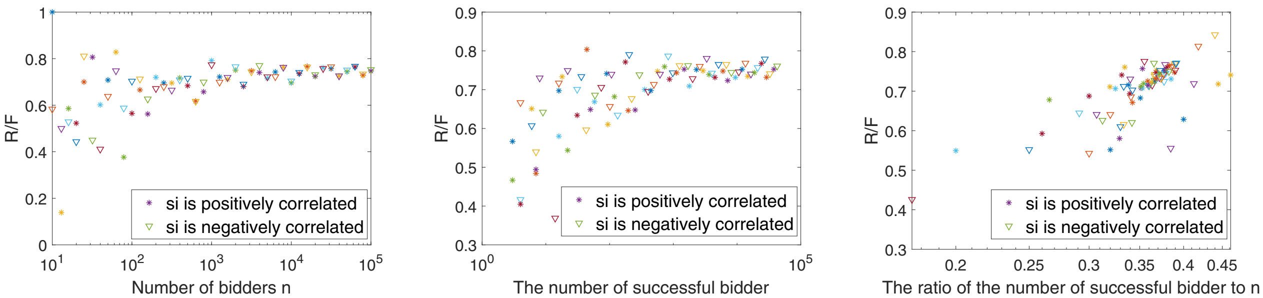
Fig. 4(a) describes the impact of the number of bidders. Similar to the phenomena in Subsection IV-A and Subsection IV-B, when the biddings are also subject to the Zipf distribution with the random function, the profit will still increase with the number of bidders. And it is not affected by the relevance of price to time. And when the number of bidders is less than 100, the performance of *HTDP-RA* is unstable. When the number of bidders increases sufficiently, the profits tend to stabilize and stay near the highest value.

Regarding Fig. 4(b), it shows the effect of the number of successful bidders. It can be found that, it is similar to the results of Fig. 4(a). This is because both the number of bidders and the number of successful bidders have a positive effect on the profit in *HTDP-RA*.

Fig. 4(c) shows how the ratio of the number of winners to the total number n affects the profit. It can be found that, when the ratio of the number of successful bidders to the total number n gathers in the range of $[0.35, 0.4]$, the profits of *HTDP-RA* are maintained at a high level. When the ratio deviates greatly from $[0.35, 0.4]$, the *HTDP-RA* performance is less stable, and the profits are scattered at a lower level. In contrast, when the ratio tends to $[0.35, 0.4]$, the auctioneer's profit tends to be stable.

Similarly, according to the results of Fig. 4(a) to Fig. 4(c), it can be found that, the newly proposed *HTDP-RA* is a profitable auction mechanism with Zipf distribution.

In summary, the number of bidders always has a positive effect on the profit. Whether it is a deterministic or random function in terms of the value function, or an Bipolar or Zipf distribution in terms of the bidding distribution, the profit



(a) Performance *vs.* Number of bidders.

(b) Performance *vs.* Number of winners.

(c) Performance *vs.* Ratio of the number of winners to the total number of bidders.

Fig. 4. Analysis of *HTDP-RA* with Zipf distribution.

always increases with the number of bidders, and eventually tends to a stable maximum profit. Meanwhile, the effect of the number of successful bidders is similar to that of the number of bidders. Regarding the ratio of the number of successful bidders to the total number n, the performance of profit is relatively stable and concentrated when the ratio gathers in a certain range. As the deviation from this range intensifies, the stability of profit performance deteriorates. In addition, this ratio range may differ for different mechanisms (*i.e.*, *HTDP-DA* and *HTDP-RA*) and distributions (*i.e.*, Bipolar and Zipf).

V. Conclusion

With the extensive accumulation of data, and the penetration of data-dependent intelligent applications in various scenarios, data trading has become an irreversible trend. Considering the value of data is closely related to timeliness, we propose a programmatic trading framework for the first time in this paper, which implements the auction-based pricing mechanisms and incorporates the high timeliness of data. In addition, in terms of the relationship between value and time, we consider the two scenarios of determinism and randomness separately, *i.e.*, *HTDP-DA* and *HTDP-RA*. And theoretical analysis and experimental results demonstrate that they are both truthful and profitable auction mechanisms. In the future, the development of data trading and pricing requires more considerations. For example, data can be used in multiple rounds, and how the multi-round auction mechanism can integrate the high timeliness of data remains to be solved.

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