Learning to Bid in Revenue Maximizing Auction

Extended Abstract

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ABSTRACT

We consider the problem of the optimization of bidding strategies in prior-dependent revenue-maximizing auctions, when the seller fixes the reserve prices based on the bid distributions. Our study is done in the setting where one bidder is strategic. Using a variational approach, we study the complexity of the original objective and we introduce a relaxation of the objective functional in order to use gradient descent methods. Our approach is simple, general and can be applied to various value distributions and revenue-maximizing mechanisms. The new strategies we derive yield massive uplifts compared to the traditional truthfully bidding strategy.

CCS CONCEPTS

• Computing methodologies → Machine learning; **• Applied computing → Online auctions**; **• Mathematics of computing** → Nonconvex optimization.

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INTRODUCTION

Modern marketplaces like Uber, Amazon or Ebay enable sellers to fine-tune their selling mechanism by reusing their large number of past interactions with consumers. In the online advertising or the electricity markets, billions of auctions are occurring everyday between the same bidders and sellers. Based on the data gathered, different approaches learn complex mechanisms maximizing the seller revenue [5, 9, 18, 19].

Most of the literature has focused on the auctioneer side [14]. Algorithms focused on the bidder's standpoint to enable them to be strategic against any smart data-driven selling mechanisms are lacking. These algorithms should ideally strengthen the balance of power driving the relationship between buyers and sellers. Our main objective is to exhibit simple robust algorithmic procedures that take advantage of various data-dependent revenue-maximizing mechanisms. This represents a big step forward in understanding possible strategic behaviors in revenue maximizing auctions. This is a new argument supporting the Wilson doctrine [22] claiming that data-dependent revenue maximizing algorithms are not robust to strategic bidders.

Framework

In the early stage of the market design literature (see, e.g., Myerson [17]), a typical underlying assumption is that the bidders' value distributions were commonly known to the seller and other bidders. This can be justified if different group of bidders with the same value distribution are interacting successively with one seller. In the aforementioned modern applications, the same bidders have billions of interactions everyday with the seller. Even if the latter does not know the value distribution beforehand, it might use in many cases the past bid distributions as proxies of value distribution.

Several mechanisms based on the value distribution of bidders have already been introduced. We will focus on the lazy second price auction with personalized reserve price [19], the Myerson auction [17], the eager version of the second price auction and the boosted second price auction [9]. When repeating these auctions (every day, or every milli-second, depending on the context) and if the bidder is *myopic*, i.e optimizing per stage and not long-term revenue, it is optimal to bid truthfully at each auction. So with myopic bidders, bids and values have the same distribution and the seller can design optimally the mechanism based on the former.

Non-myopic bidders optimize their *long-term expected utility* taking into account that their current strategy will imply a certain mechanism (for instance a specific reserve price) in the future. More precisely, we will consider the following steady state analysis. Assume the valuations of a bidder $v_i \in \mathbb{R}$ are drawn from a specific distribution F_i; a bidding strategy is a mapping β_i from $\mathbb{R}$ into $\mathbb{R}$ that indicates the actual bid $B_i = \beta_i(v_i)$ when the value is v_i. As a consequence, the distribution of bids F_{B_i} is the push-forward of F_i by β_i. In the steady state, the seller uses the distributions of bids F_{B_i} to choose a specific auction mechanism $\mathcal{M}(F_{B_i})$ among a given class of mechanisms $\mathcal{M}$. The objective of *a long-term strategic bidder* is to find her strategy β_i that maximizes her expected utility when $v_i \sim F_i$, she bids $\beta_i(v_i)$ and the induced mechanism is $\mathcal{M}(F_{B_i})$. This steady-state objective is particularly relevant in modern applications as most of the data-driven selling mechanisms are using large batches of bids as examples to update their mechanism.

In terms of game theory, these interactions are a game between the seller - whose strategy is to pick a mechanism design that maps bid distributions to reserve prices - and the bidders - who chose bidding strategies. Our overarching objective is to derive the best-response, for a given bidder i, to the strategy of the seller (i.e., a given mechanism) and the strategies of the other bidders (i.e., their bid distributions).

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Contributions

Our main contributions are the following. We first introduce the optimization problem that strategic bidders are facing when the seller is optimizing personalized reserve prices based on their bid distributions. A straightforward optimization can fail because the objective is discontinuous as a function of the bidding strategy.

To circumvent this issue, we introduce a new relaxation of the problem which is stable to local perturbations of the objective function and computationally tractable and efficient. We numerically optimize this new objective through a simple neural network and get very significant improvements in bidder utility compared to truthful bidding. We also provide a theoretical analysis of *thresholded strategies* and show their (local) optimality as improvements of bidding strategies with non-zero reserve value.

For the Myerson auction, the strategies learned by the model can be independently proved to be optimal. We apply the approach to other auction settings such as boosted second price or eager second price with monopoly price. We report massive uplifts compared to the traditional truthful strategy advocated in all these settings. Our simple approach can be plugged in any modern bidding algorithms learning distribution of the highest bid of the competition and we test it on other classes of mechanism without any known closed form optimal bidding strategies. We finally provide the code in PyTorch that has been used to run the different experiments. This approach opens avenues of research for designing good bidding strategies in many data-driven revenue-maximizing auctions.

Related work

Starting with the seminal work of Myerson [17], a rich line of work indicates the type of auctions that is revenue-maximizing for the seller. In the case of symmetric bidders [17], one revenue maximizing auction is a second price auction with a reserve price equal to the monopoly price, i.e, the price r that maximizes $r(1-F(r))$. However, in most applications, the symmetric assumption is not satisfied [9]. In the asymmetric case, the Myerson auction is optimal [17] but is difficult to implement in practice [16]. In this case, a second price auction with a well-chosen vector of reserve prices guarantees at least one-half of the optimal revenue [10].

In modern markets, some bidders are myopic simply because truthful bidding is a simple strategy to implement. Receiving truthful bid enables sellers to design various revenue maximizing auctions. [5] has therefore been interested in the automatic mechanism design that fine tunes mechanism based on some examples of bids. This work was extended recently in [7] with the use of deep learning. In [13, 18, 19], it is shown specifically how to learn the optimal reserve prices in the lazy second price auction. This practice was theoretically addressed by [4, 6, 11] looking at the sample complexity of a large class of auctions assuming an oracle offering iid examples of the value distribution.

However, it is quite intuitive that non-myopic bidders should not bid truthfully. Robustness to strategic bidders has been studied in [3, 8, 12]. A potential limitation of this type of approach is that it is either assumed that all bidders have the same value distribution (or up to ε for some specific metric on distributions) or that there is a very large number of bidders and a global mechanism designed so that any of them has no incentive to bid untruthfully. In [2], an involved mechanism was designed that keeps the incentive compatibility property even if the seller is learning on former bids.

None of these papers have exhibited optimal strategies that can be used when the seller is optimizing her mechanism based on past bids. This strategic behavior has been studied for posted price with one bidder and one seller [15]. An independent line of work has focused on learning to bid when the value is not known to the bidders [21, 23]. Some Bayes-Nash equilibria corresponding to games where bidders can choose their bid distribution were designed [1, 20] with some derivations of seller revenue and bidders utility at these equilibria. However, no strategies corresponding to these equilibria were provided in the general case. Our new optimization pipeline is very general and enables bidders to learn good bidding strategies in multiple settings and for any value distribution.

REFERENCES

[1] Marc Abeille, Clément Calauzènes, Noureddine El Karoui, Thomas Nedelec, and Vianney Perchet. 2018. Explicit shading strategies for repeated truthful auctions. *arXiv preprint arXiv:1805.00256.*

[2] Itai Ashlagi, Constantinos Daskalakis, and Nima Haghpanah. 2016. Sequential mechanisms with ex-post participation guarantees. In *Proceedings of EC 2016.*

[3] Santiago R Balseiro, Vahab S Mirrokni, and Renato Paes Leme. 2017. Dynamic mechanisms with martingale utilities. In *Management Science.*

[4] Richard Cole and Tim Roughgarden. 2014. The sample complexity of revenue maximization. In *Proceedings of Theory of computing.*

[5] Vincent Conitzer and Tuomas Sandholm. 2002. Complexity of mechanism design. In *Proceedings of UAI 2002.* Morgan Kaufmann Publishers Inc., 103–110.

[6] Nikhil R Devanur, Zhiyi Huang, and Christos-Alexandros Psomas. 2016. The sample complexity of auctions with side information. In *Proceedings of Theory of Computing.*

[7] Paul Dütting, Zhe Feng, Harikrishna Narasimhan, and David C Parkes. 2017. Optimal auctions through deep learning. *arXiv preprint arXiv:1706.03459* (2017).

[8] Alessandro Epasto, Mohammad Mahdian, Vahab Mirrokni, and Song Zuo. 2018. Incentive-aware learning for large markets. In *Proceedings of the 27th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee.*

[9] N. Golrezaei, M. Lin, V. Mirrokni, and H. Nazerzadeh. 2017. Boosted Second-price Auctions for Heterogeneous Bidders. In *Management Science.*

[10] Jason D Hartline and Tim Roughgarden. 2009. Simple versus optimal mechanisms. In *Proceedings of EC 2009.*

[11] Zhiyi Huang, Yishay Mansour, and Tim Roughgarden. 2018. Making the most of your samples. *SIAM J. Comput.*

[12] Yash Kanoria and Hamid Nazerzadeh. 2014. Dynamic Reserve Prices for Repeated Auctions: Learning from Bids. In *Proceedings of WINE 2014.*

[13] Andres M Medina and Mehryar Mohri. 2014. Learning theory and algorithms for revenue optimization in second price auctions with reserve. In *Proceedings of ICML 2014.*

[14] Paul R Milgrom and Steven Tadelis. 2018. *How Artificial Intelligence and Machine Learning Can Impact Market Design.* Technical Report. National Bureau of Economic Research.

[15] Mehryar Mohri and Andres Munoz. 2015. Revenue optimization against strategic buyers. In *Proceedings of NIPS 2015.*

[16] Jamie H Morgenstern and Tim Roughgarden. 2015. On the pseudo-dimension of nearly optimal auctions. In *Proceedings of NIPS 2015.*

[17] R. B. Myerson. 1981. Optimal Auction Design. *Math. Oper. Res.* 6, 1.

[18] M. Ostrovsky and M. Schwarz. 2011. Reserve prices in internet advertising auctions: A field experiment. In *Proceedings of EC 2011.*

[19] Renato Paes Leme, Martin Pal, and Sergei Vassilvitskii. 2016. A field guide to personalized reserve prices. In *Proceedings of WWW 2016.*

[20] Pingzhong Tang and Yulong Zeng. 2018. The price of prior dependence in auctions. In *Proceedings of EC 2018.*

[21] Jonathan Weed, Vianney Perchet, and Philippe Rigollet. 2016. Online learning in repeated auctions. In *Conference on Learning Theory.* 1562–1583.

[22] R. Wilson. 1987. Game-theoretic analyses of trading processes. In *Advances in Economic Theory.*

[23] Chara Podimata Zhe Feng and Vasilis Syrgkanis. 2018. Learning to bid without knowing your value. In *Proceedings of EC 2018.*