Indian Institute of Technology
Kanpur

ECO502A - Introduction to Game Theory
Case Study

A study on Sniping strategy in E-Bay auctions

Amlan Kar

Supervised by
Dr. Vimal Kumar

Contents

ECO502A Case Study
E-Bay Second Price Auctions
A study on Sniping strategy in E-Bay auctions

Amlan Kar
amlan@iitk.ac.in

Mentored By:
Prof. Vimal Kumar
vk@iitk.ac.in

Abstract

Ending second price auctions are second price auctions where bids can be submitted till a particular time limit. We develop a Recurrent Neural Network model of bidding price and bidding time in ending second-price auctions trained on E-bay auction data[Jank and Shmueli, 2010]. We use the results from the model and the data to provide concrete evidence of the prevalence of Sniping in E-bay auctions and provide theoretical arguments to justify its existence. We use the model predictions, theoretical arguments and survey data from [Roth et al., 2002] as our basis to justify the observed sniping behaviour.

1 Introduction

Auctions on the Internet have provided researchers with a new source of data on how bidding strategies are governed by the detailed rules of the auction. Here we study the second-price auctions run by eBay, in which a bidder can submit a maximum price he is willing to pay, which is kept private. This price is used to bid for him by automatically by proxy. That is, a bidder can submit his reservation price (called a proxy bid) early in the auction and have the E-bay engine register bids as the minimum increment above the previous high bid. As subsequent reservation prices are submitted, the bid rises by the minimum increment until the second-highest submitted reservation price is exceeded. Hence, an early bid with a reservation price higher than any other submitted during the auction will win the auction and pay only the minimum increment above the second-highest submitted reservation price by all other players.

The practice called "sniping" (or last minute bidding) is prevalent on E-bay despite advice from both auctioneers and sellers that a bidder should simply submit his/her true valuation (maximum amount that he/she wishes to pay) early in the auction as a reservation price. For example, eBay argues based on the logic of second-price auctions, using an example of a winning early bid. They discuss last-minute bids on a page explaining that they will not accept complaints about sniping, as follows: (the page is non-existent now and the link and text has been taken from [Roth et al., 2002]) [1]

> eBay always recommends bidding the absolute maximum that one is willing to pay for an item early in the auction. eBay uses a proxy bidding system: you may bid as high as you wish, but the current bid that is registered will only be a small

[1] http://pages.ebay.com/aw/notabase.html (1999)

> increment above the next lowest bid. The remainder of your Maximum Bid is held, by the system, to be used in the event someone bids against you ... Thus, if one is outbid, one should be at worst, ambivalent toward being outbid. After all, someone else was simply willing to pay more than you wanted to pay for it. If someone does outbid you toward the last minutes of an auction, it may feel unfair, but if you had bid your maximum amount up front and let the proxy bidding system work for you, the outcome would not be based on time.

Despite the advice by E-bay, sniping is prevalent and is seen in almost every auction on the website. One can find tons of blog posts describing the benefits of sniping and people have released open source software that enables automatic sniping on selected auctions based on a true price.

2 Theory

2.1 Recurrent Neural Network (LSTM)

We have used a LSTM (Long Short Term Memory) based Recurrent Neural Network trained on our dataset as a generative and predictive model of both, time of bid and the valuation of the bid (normalized by starting bid). *Recurrent Neural Networks have been a major part of the recent Deep Learning revolution that has taken over the field of Artificial Intelligence.* LSTM Recurrent Networks have been shown to give state-of-the-art results in time series regression and other temporal tasks such as speech recognition, Natural Language generation etc. These networks train a set of weights that help it decide what fraction of the history of the time series to remember, what fraction of the input to consider and what fraction to send forward. Since these models are recurrent, the input sent forward is fed back into the same unit and this is continued till the end of the input series is reached. Figure 1 shows a schematic of a single LSTM unit.

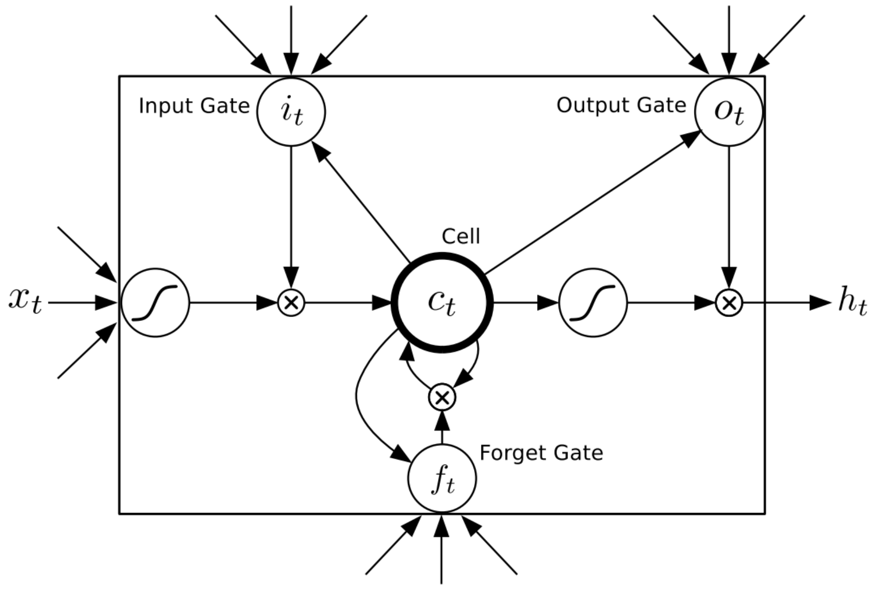


Figure 1: A Single LSTM Unit

2.2 Static vs Dynamic models of Auctions

Various auction mechanisms take place in a dynamic setting, while most of the theoretical models of auctions are static. In these dynamic auctions, bidders' valuations and strategies are likely to be affected by information that arrives during the auction; however, most of the literature has abstracted from this. Most literature on E-Bay auctions focus on the scenario where each bidders valuation of the item is constant. There exists recent work[Saeedi et al., 2015] where the authors model valuations and bids as a joint Markov process and treat the problem in a dynamic sense. Work done in [Groeger, 2014] models bidders as forward looking and looks at the inter-temporal connection of the strategies of a player based on independent auctions that are temporally close.

3 Observations and Inferences

3.1 Inexperienced Bidders

We believe that E-bay auctions are inherently dynamic and the assumption that a bidder has one and only one true valuation is not applicable in general as this means assuming that each bidder is an expert on the item being sold. Rather, on most E-bay auctions the bidders are relatively inexperienced. If we use the E-bay bidder ratings as a measure of experience/inexperience in auctions, the proposition above can be easily verified. Figure 2 shows the histogram of bidder ratings on our dataset. This plot has been created by taking bidder ratings from the Palm 7-Day auctions data. The same trend is seen in the XBox and the Cartier datasets as well.

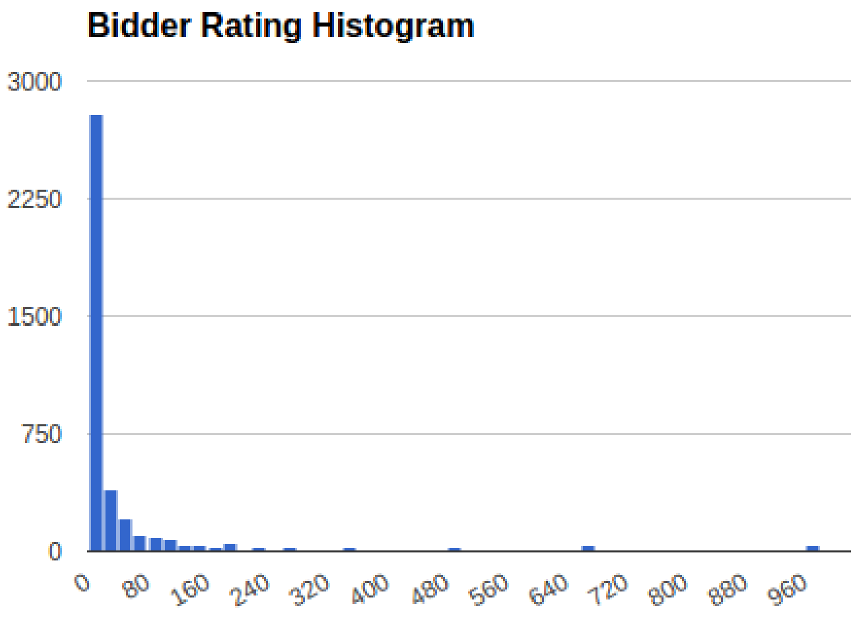


Figure 2: Histogram of Bidder Ratings on our dataset

3.2 Avoiding Signaling

Another way of explaining late bids without bringing in the inexperience of bidders in our case is the wish to avoid signaling one's intent and valuation to the other players[Roth et al., 2002]. Since E-bay auctions let people see the current highest bid, it can be thought of as a signal which let's other bidders know the current leaders valuation of the item. Thus, late bids can be rationalized as the bidder's wish to avoid giving information to others by placing an early bid of his valuation. If we bring in the study of experienced and inexperienced bidders into this inference, we can say that this might be a ploy to avoid giving inexperienced bidders enough information in time for them to update their own valuation of the object in question.

3.2.1 Rare Items

E-bay auctions very often result in the sale of rare and antique items. The real price of such items are in general debatable and are decided by the experts in the field. In such auctions, there might be an expert in the field amongst the bidders who could discern the true value of such an item. For him/her, the sniping strategy makes it possible to take advantange of prior knowledge of the true value of the object and helps him/her to avoid signaling this true value to the other competitors. Bidding just before the deadline, such that no other players gets enough time to bid back weakly dominates bidding his valuation before the deadline. This is because, due to the sniping, he will have to pay the maximum of the other bidder's bids (which might be much lesser than his knowledge of the true valuation and because his true valuation wouldn't be reached by bidding wars at the end due to the lack of time).

3.3 Sniping as a Best Response

Sniping can be a best response to a variety of real world strategies. For example, inexperienced bidders, in tune with First Price English Auctions, might continually raise their bids to remain the high bidder. Such strategies are very prominent in the dataset and the average rating of a bidder that engages in this kind of incremental bidding on our dataset is around 2. Sniping might be a best response to such incremental bidding strategies in our hard close auction setting as sniping late gives the incremental bidder very less time to submit a new bid and this gives the sniper an incentive to win the auction with a cost equal to the incremental bidder's last bid (given it is lesser than his valuation).

Sniping strategies can also be considered a best response against dishonest sellers on E-bay. A lot of sellers have been known to engage in shill bidding against a real bidder's proxy bid to increase the price of the object. Submitting the bid very close to the auction close doesn't give the seller an opportunity to resort to such a strategy.

3.4 Sniping as a Subgame Perfect Nash Equilibrium

In [Ockenfels and Roth, 2006] the authors show that two bidders simultaneously bidding their true values at t=1 (end-time) is a Nash Equilibrium strategy. Their proof is simple(shown for two players with the same valuation) and is based on the fact that a bid submitted at time t=1 has a finite probability p ($p < 1$) of reaching the website before the auction ends. They consider the strategy where if any player bids before t=1, the other player promptly bids his true value (Remember bidding true values is an equilibrium strategy). Else, both players bid their true values at t=1 and do not bid before t=1. This way, each player gets an expected payoff of $p(1-p) * (V - S)$, where S is the minimum bid and V is the valuation. In the subgame starting at t=1, given no other bids were registered before, this strategy is a Nash Equilibrium and if any player deviates and bids at any t¡1, then bidding true values is also a Nash Equilibrium in those subgames. Therefore, this strategy of Bidding-War/Sniping is a subgame perfect Nash Equilibrium.

4 Experimental Data

4.1 Bidding Time Histogram

The Bidding Time histogram (Figure 3 clearly shows how sniping occurs prevalently in E-bay auctions. [Roth et al., 2002] showed the prevalence of sniping in 2002 with a similar graph. Using data from 2010, we show that sniping is still a very widely used strategy. The persistence of this strategy for nearly a decade goes to show that if the population is to be considered rational, then there must be rationality in the sniping strategy. Else, the population would have learnt to avoid this strategy (or at least it would have been less dominant).

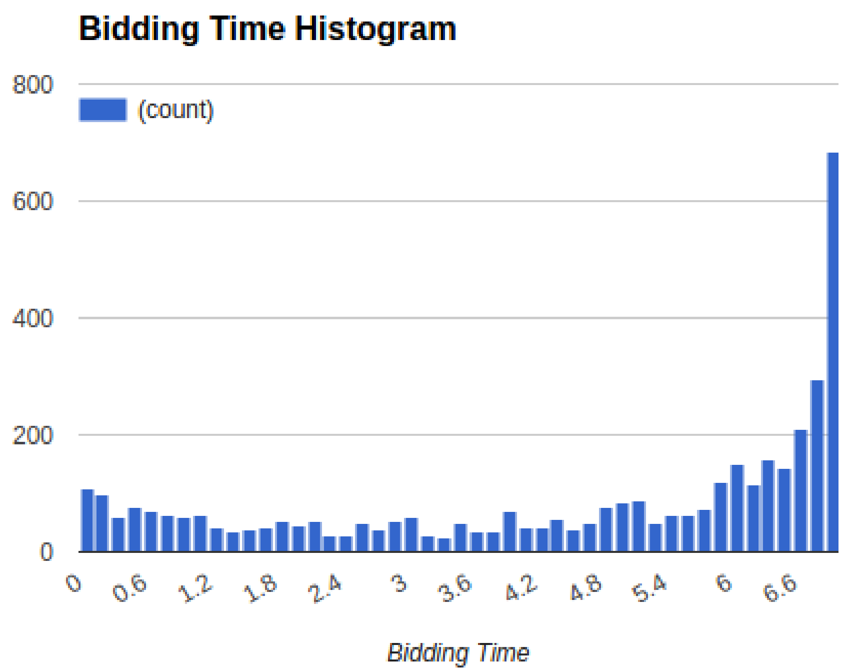


Figure 3: Histogram of Bid Times on our dataset

4.2 Recurrent Neural Network Performance

4.2.1 Bid Predicting LSTM

The Bid predicting LSTM architecture consists of a single LSTM layer that returns a sequence of encoded vectors. These encoded vectors are passed through a time distributed dense layer of 32 output neurons with linear activation which is then passed to the final regression layer[2]. The

[2]For the code, please contact amlan@iitk.ac.in

results of the bid predictions are shown in the following graphs:

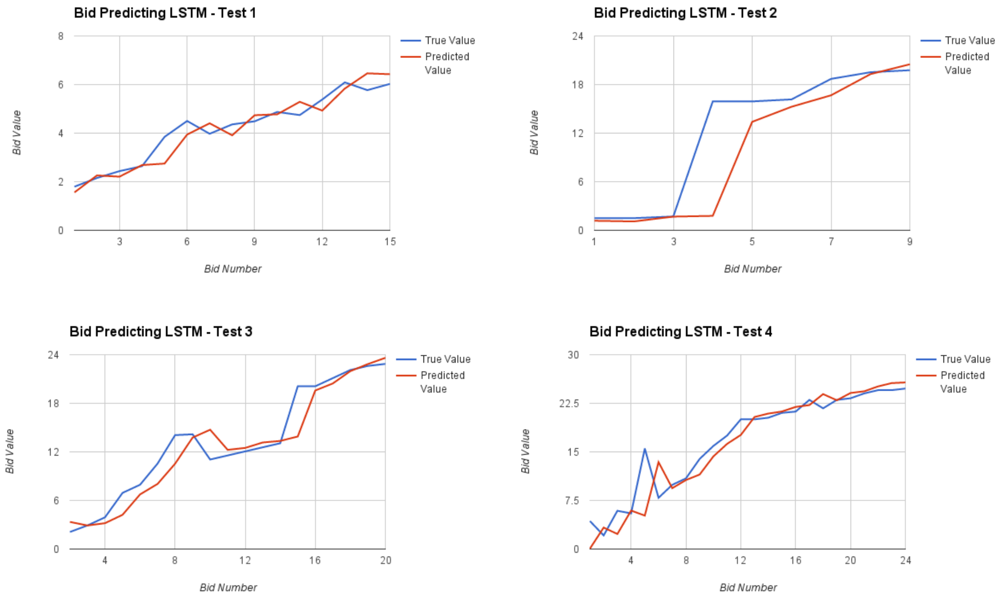
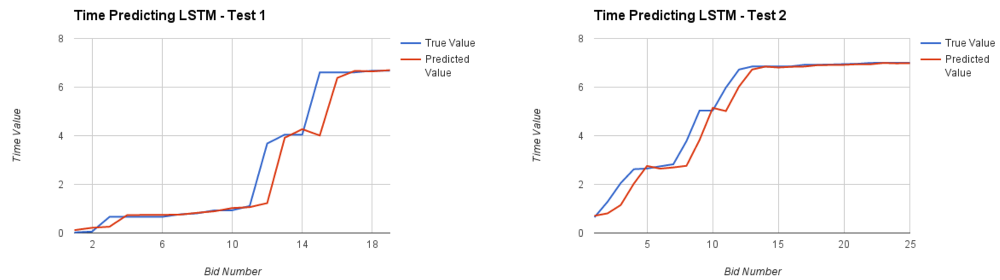


Figure 4: Comparison of LSTM performance with true data on bid prediction

From the figures, we can see that the network performs really well at predicting the next bid given the past time series input. This network can be used to dream up a time series of its own by just giving it a single input prior and letting it run on its own outputs along with the outputs of the Time Predicting network. Thus, this network is also capable of being a generative model of auctions.

4.2.2 Time Predicting LSTM

The Time predicting LSTM architecture also consists of a single LSTM layer that returns a sequence of encoded vectors. These encoded vectors are passed through a time distributed dense which also acts as the regression layer[3]. The results of the time predictions are shown in the following graphs:



[3]For the code, please contact amlan@iitk.ac.in

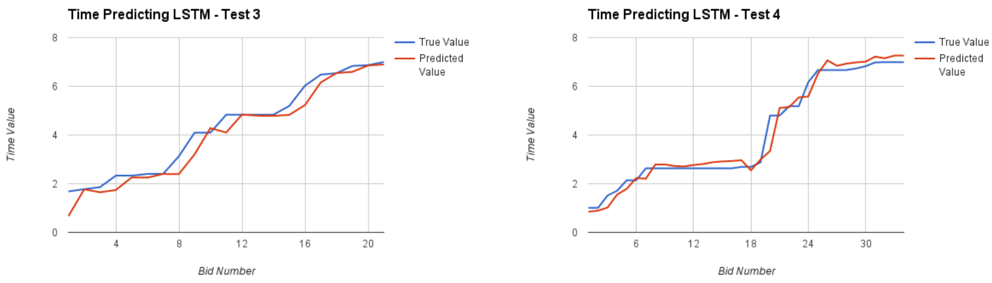


Figure 5: Comparison of LSTM performance with true data on time prediction

These graphs show the really satisfactory performance shown by the Time prediction network. Again, this can be used as a generative model for auction bid times. The distribution bias towards higher time values is again clear in most test cases.

4.2.3 Promise of these models

Currently, these models have been trained only on the previous bid amount and the previous bid time. [Munoz, 2014] provide a much bigger dataset with around 80 features per bidder. Using these features can improve prediction much more. Having a robust bid and time prediction model can be helpful to both bidders and sellers in planning their strategies based on what they have seen. Owing to the fact that the sequential data would probably be available to the seller, this might benefit the sellers more. It might be very interesting to study a situation where a seller predicts using such a model and plays his hand accordingly, where the fact that such a model exists is common knowledge.

5 Survey Data

[Roth et al., 2002] conducted a survey amongst three hundred and sixty eight E-bay bidders who had successfully won a lottery with a snipe bid. The survey complements the theoretical arguments by giving us an idea of the bidders' perspective of the advantages and disadvantages of sniping. A large majority of responders (91 percent) responded that late bidding is typically part of their early planned bidding strategy. Most of these bidders unambiguously explained that they snipe to avoid a "bidding war" or to keep the price down. This is very similar to the theoretical arguments provided above. The dataset does not provide list prices of the items (mostly because they were not available). It is left to be seen whether this strategy actually let's bidders keep the price down or not.

In addition, some experienced Antiques bidders (about 10 percent of all responders, mostly with high feedback numbers) very explicitly stated that late bidding enabled them to avoid sharing their valuable expert information with other bidders.

6 Other Interesting Work

Another interesting problem in E-Bay auctions is the selection of reserve price by a seller. [Mohri and Medina, 2013] cast the problem of selecting the reserve price to optimize revenue as a learning problem and present a full theoretical analysis dealing with the complex properties of the corresponding loss function. They also provide new algorithms to optimize the said loss function. The paper appeared in ICML 2014, which is a top conference in the field of Machine Learning.

7 Conclusion

We have seen through this case study the relevance of sniping behaviour in E-bay auctions, it's theoretical bases, experimental support and a bidders' point of view of why they prefer to bid late. Very interestingly, this kind of strategy has been seen only in E-bay styled auctions. Amazon performs very similar auctions but has a rule to extend the auction after the deadline until 10 minutes pass without a bid being submitted. Work done on Amazon auctions [Roth et al., 2002] suggest that last minute bids are as frequent as other bids in these auctions. Thus, the importance of the ending rule in an auction is paramount. It can lead to very different equilibrium strategies for the bidders and subsequently, different expected payoffs for the sellers as well as the bidders.

References

[Groeger, 2014] Groeger, J. R. (2014). A study of participation in dynamic auctions. *International Economic Review*, 55(4):1129–1154.

[Jank and Shmueli, 2010] Jank, W. and Shmueli, G. (2010). Modelling online auctions.

[Mohri and Medina, 2013] Mohri, M. and Medina, A. M. (2013). Learning theory and algorithms for revenue optimization in second-price auctions with reserve. *arXiv preprint arXiv:1310.5665*.

[Munoz, 2014] Munoz, A. (2014). Ebay auction dataset.

[Ockenfels and Roth, 2006] Ockenfels, A. and Roth, A. E. (2006). Late and multiple bidding in second price internet auctions: Theory and evidence concerning different rules for ending an auction. *Games and Economic behavior*, 55(2):297–320.

[Roth et al., 2002] Roth, A. E., Ockenfels, A., et al. (2002). Last minute bidding and the rules for ending second price auctions: evidence from ebay and amazon auctions on the internet. *American economic review*, 92(4):1093–1103.

[Saeedi et al., 2015] Saeedi, M., Hopenhayn, H. A., et al. (2015). Dynamic bidding in second price auction. In *2015 Meeting Papers*, number 1346. Society for Economic Dynamics.