**NETAJI SUBHAS UNIVERSITY OF TECHNOLOGY,**
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# Auction Simulator: Gauging Effect of Shilling in Ascending Second Price Dynamic Online Auctions

Shameek Pathak
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Tarush Bajaj
2019UCS2015

**Guided By:**
**Professor Preeti Kaur**

# INTRODUCTION

Auctions have been a common way to trade goods in human history with effective distribution and finding the right price.
There are numerous types of auctions but the most common auctions are English auctions, Dutch auctions, first-price sealed bid auctions, and second-price sealed-bid auctions(Vickery auction). Due to the effectiveness and widespread consistency of auction rules. English auctions have become synonymous with auctions.
English auctions are public and ascending bid auctions where participants compete with higher bids and the auction ends when the time runs out, or no one bids for a long time or if an upper limit price is reached(predetermined). The winner pays only one bid which can be the highest or second highest depending on the rules. Dutch auctions are decreasing bid auctions with a starting price which keeps decreasing until a buyer accepts that amount. English auctions take the lion’s share in auctions with 88% and the rest is taken by dutch and double auctions.

With the evolution of the internet, there have been major strides in capitalizing on this useful technology. Since the internet has developed a lot from the early days of just sharing local data to sharing and making high-level computations now, the auctions have developed too. Online auctions also known as e-auctions have connected millions of sellers to millions of buyers, across the globe, and in different time zones. This has significantly increased the revenue generated and moved from buyers to sellers. eBay (revenue $10.8 Billion) and Amazon are the two biggest websites for online auctions. They predominantly use second price-increasing bid English auctions.
eBay implements fixed-time auctions which end on closing time, and the winner with the highest bid wins and has to pay the second highest price. Amazon implements a soft-close strategy. An auction is closed when any bidder has not bid for a predefined time frame. We will focus on eBay in the rest of this report.

With the auctions and opportunities moving online, there is also a great increase in fraudulent behaviour. Online auction fraud can take various forms like a misrepresentation of items, shilling, counterfeiting, etc. The hardest one to detect among them is the shilling. Shilling is the practice often used by the sellers who plant a bidder in the set of potential buyers whose purpose is to drive up the profits of the sellers by racing up the bids. The shillers often employ a number of strategies which may seem perfectly innocent and harmless which makes it hard to detect them. They knowingly victimize genuine buyers. This practice puts other buyers at disadvantage and is prone to losses hence is banned by auction sites and is legally an offence. A few of the most commonly known shilling strategies include Reserve Price Shilling, the seller pre-decides a price for an auction item and the Shiller raises the bids until this reserve price is reached, Competitive Shilling, there is no target and the Shiller just goes on signalling and bidding aggressively.

Buy Back Shilling, When a seller is unhappy with the current highest bid and decides to buy the item back through shillers, the Shiller bids aggressively here because no one loses in this set-up except the auction fees are borne by the seller.
False Bidding, is most common in second-price auctions when the goal is placing a “bid destined to lose” and the final goal is to increase the second-highest bid. This targets the second-highest bid rather than the highest bid.

Here is how the shilling might look in real-world online settings. A devoted bidder who happens to need all kinds of different auction items at once. Which is highly unlikely in real life. Since the auction may or may not allow infinitesimal bid increments an absurd bid like 29.99 might be a perfect “false bid” which would increase the bids.

Before we start we define a few keywords so the reader can understand our work better.

1. Auction: a public sale in which goods or property are sold to the highest bidder.
2. Open Cry Auction: a method of trading on a financial market in which people shout out their bids and offers. That is, each bidder knows about the bids of every other bidder.
3. Sealed Bid Auction: A sealed-bid auction is a type of auction process in which all bidders simultaneously submit sealed bids to the auctioneer so that no bidder knows how much the other auction participants have bid. A sealed bid refers to a written bid placed in a sealed envelope.
4. Second Bid Auction Vickrey Auction: Bidders submit bids without knowing the bid of the other people in the auction. The highest bidder wins but the price paid is the second-highest bid.

5. Hard Close in timed auction: In this case, the bidders are allotted a time window in which they must place their bids and the auction ends when the window closes. The timed auctions with fixed end-time.
6. Early Bidder: A bidder who bids when the windows to bid start according to his/her evaluation of the item.
7. Sniper: Auction sniping is a technique where a user in a timed online auction waits until the time limit is nearly expired before entering a bid.
8. Shilling: Shilling is the act of a seller or seller agent bidding on his item in an effort to receive more for that item. This is very hard to find since the seller hides his/her identity and pretends to be a bidder in order to make money from real bidders. The shill pretends to have no association with the seller/group and gives onlookers the impression that he or she is an enthusiastic independent customer.

## PLAN & PROGRESS

- Environment

Online auctions where the highest bidder wins the auction and has to pay an amount equal to the value put up by the second highest bidder plus some fixed extra increment that is pre-decided. Thus bringing in the concept of the proxy bid. The second-highest bid is always flashed on the portal. Nobody except the highest bidder knows the value of the highest bid.

- Agents

Snipers and Early Bidders will be put in as rationality predicts. We will play with the distribution of the population and record the readings.

- Invariants

Shill bidding agents will be introduced and we will study the effects created by them. They will also affect the original bidder's willingness to bid/participate. We will also check if the sellers themselves are affected negatively by them.

## CONTRIBUTION

Shameek Pathak:

1. Developed the mathematical model and statistical log behind it.
2. Developed the next event-based time advance simulation in a .ipynb file.

Tarush Bajaj:

1. Did preliminary research in finalising the topic and including the history and evolution of auctions.
2. Developed the fixed-time advance simulation project.

Both the students held multiple discussions among themselves and several meetings with the guide and incorporated her suggestions into their research. In addition to developing the engine, they analysed the data from the simulator and have made multiple claims and suggestions.

The advice during mid sem evaluation guided us towards narrowing down our topic and motivate us in developing the data-generating simulator that we have developed.

## TECHNICAL WORKING

*Python 3.X* was used as the coding language for the research and project.
The presented model represents a sophisticated yet dynamic version of the Second Price Ascending Bid Auction, the most popular variant available on eBay. We have incorporated multiple biding agents; both ethical and unethical kinds as mentioned above. We are particularly interested in shilling affects these auctions. We have conducted both next-event time advance and fixed-increment time advance simulations.

The auction_house is used to create the common value auction environment— defining the rules, letting the bidders participate in the bidding process and maintaining order by setting a hard_close or closing time for the auction ***(varied from 500 to 1500)***. The current highest bid is kept hidden and only the second highest bid and the identity of the bidder who made the highest bid are flashed on the auction main page. Bid retraction is not allowed. Agents have been introduced below:

- Early Bidder: This bidder has an initial private ***valuation***, which is generally quite low, as they are not confident in their evaluation. It is mapped as a Lognormal random variable; as these distributions are highly favoured in asset pricing and valuation by economists. But, as the auction proceedings go on they update their evaluation by a factor determined by a Uniform random variable. If their, revised valuation is higher than the ***second_highest_bid*** they send in their bid with a probability of ***b.*** Their next watch timing is determined by an Erlang distribution. Lastly, each bidder has a willing-to-pay ***limit***, the upper cap that cannot be exceeded, due to several reasons such as personal income constraints, scepticism, etc. This ***limit*** is mapped, accordingly, as Mielke/Dagum random variable which has been used to understand income distribution, for a long time.

  ***revised_valuation = Uniform(1.2,2)*current_valution***

  ***bid_amount = minimum(revised_value, limit)***

- Sniper: These bidders are an entirely different breed from the early bidders. They do not possess any initial valuation. Rather, only a willing-to-pay ***limit***; is also derived from Mielke distribution but with a higher mean. It is taken so due to a strong practical argument. Various experimental results have shown that sniping increases the winning probability manifolds, putting snipers a step above their novice counterparts, the early bidders, as we assume they understand better what they have themselves into. They come in around just before the end of the auction (***hard_close-x***) and make a few aggressive bids. Also, be careful, while considering the last-second sniping— network traffic and delays might lead to the bid not being registered with the auctioneer.

***bid_amount = minimum(2*second_highest_bid, limit)***

- Special_Sniper: An experimental dummy agent that is used to determine when is it the best time to snipe. It will bid at t = 100, 150, 250, 350, 450, 495 in an auction with a hard_close set at 500.

  ***bid_amount = minimum(2*second_highest_bid, limit)***

- Reserve_Price_Shilling: This bidder or Shiller has a defined target price that the seller has set for them. It is a valuation thus pulled up from a lognormal distribution. As their aim is not to win but only to drive the bids higher. So they bid aggressively but stop well before the hard_close approaches (***hard_close-100***, independent of hard_close).
  We tweak the parameters of lognormal distribution to put the mean in three regions namely, around early bidders' general limit, snipers' general limit and finally, one in between the two.

  ***bid_amount = minimum(Uniform(1.5,2.5)*second_highest_bid, target)***

- Competitive_Shilling: Much like the reserve_bid_shiller but acts without any target in mind and keeps on shilling before ***stoppage_time***. There are two strategies that we developed.
  First, increasing the bids according to the weighted moving average of the last three bid increments($I_x$).

  $$I_i = (x * I_{i-1} + y * I_{i-2} + z * I_{i-3})/(x + y + z)$$

  $$bid\_amount = second\_highest\_bid + I_i$$

  Second, the agent's multiplication factor depends on the congestion or volume of bids recently, in direct proportion.

  If above congestion is above the threshold:

  ***bid_amount =Uniform(1,2)*second_highest_bid***

  Else:

  ***bid_amount =Uniform(2,3)*second_highest_bid***

- Buy_Back_Shilling: Due to reserve price being a paid feature sellers avoid setting an official reserve price and if made public affects negatively towards seller's profit, as shown by many researchers. This agent generates a ***target***, from a lognormal distribution and comes at ***hard_close-5*** to check if the ***second_highest_price*** is in the acceptable proximity of the ***target***; choosing not to bid when it satisfies otherwise raises an aggressive bid to buy back that item for the seller; to be sold later again.

  ***bid_amount = 2.5*second_highest_bid***

- False_bidding: This bidding attacks and tries to manipulate the ***second_highest_bid*** rather than ***highest_bid***. They come in as snipers on the seller's behalf raising the price that the winner ends up paying. They aim not to change the winner but rather the amount they would by paying.

  ***bid_amount = (highest_bid --)***

  When the data of ***highest_bid*** is not available they bid accordingly based on the past trends of ***highest_bid - second_highest_bid*** via doing a Maximum Likelihood Estimation fitting and generating the corresponding random variable.

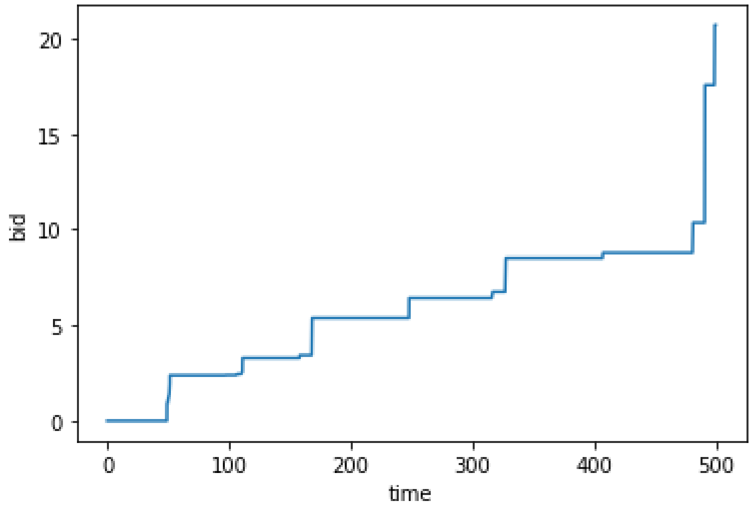
  ***I =*** <u>(random_variable)</u>

  ***bid_amount = (second_highest_bid + I)***

**NOTE: Though, it is commonplace we reiterate. None of the bidders mentioned above will outbid their own bid if they are the highest bidder.**

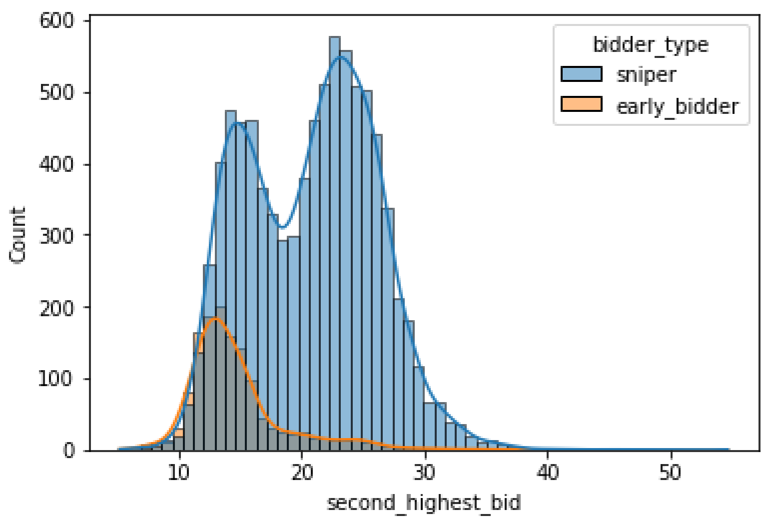
## RESULTS

1. This is general bidding progression during an auction.




Notice the sudden jump around near the end. Late sniping causes this.

2. When we pitted Early bidders vs Snipers:



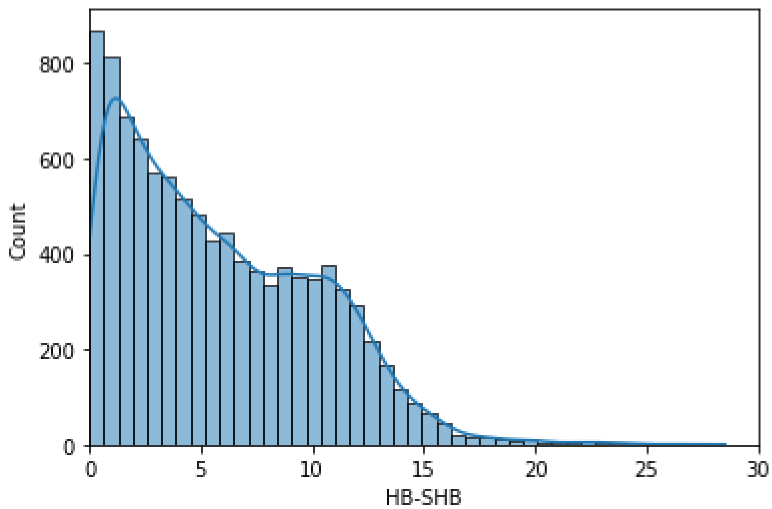

Notice the twin peaks in blue: The second peak represents a sniper outbidding another sniper. And the first peak is when the early bidder was outbid by the winning sniper.

3. When we set off a special sniper that bid at ***clock=100,150,250,350,450,495*** where ***hard_close = 500***:

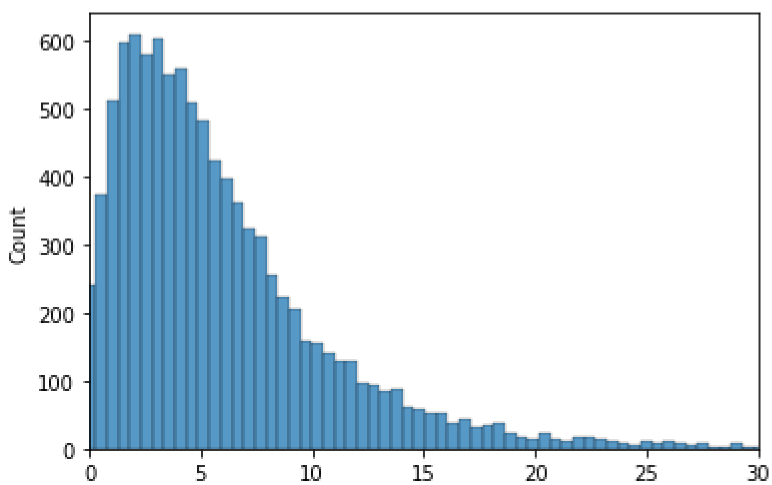
| Clock | 100 | 150 | 250 | 350 | 450 | 495 |
|---|---|---|---|---|---|---|
| P(winning) | 0.449% | 4.2% | 19.65% | 36.1% | 44.05% | 60.699% |

This tabulation shows the late you snipe the better probability of winning.

4. When we did a difference analysis of ***highest_bid*** and ***second_highest_bid***:



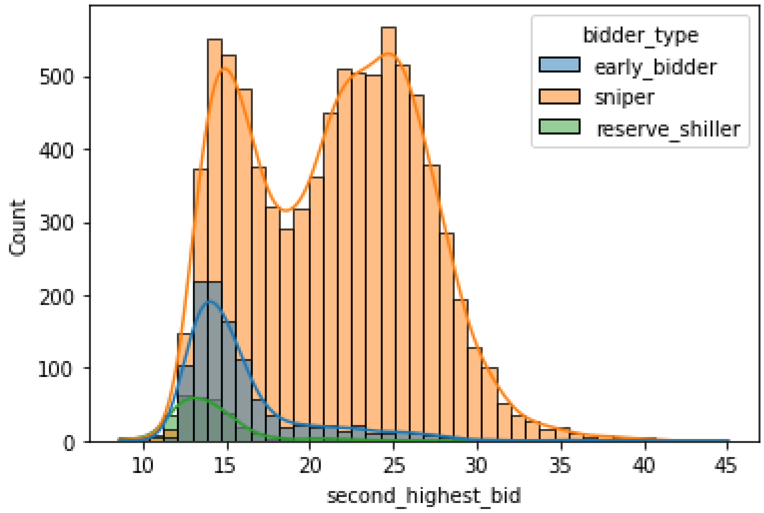

This is the histogram/kde plot of ***highest_bid-second_highest_bid.***

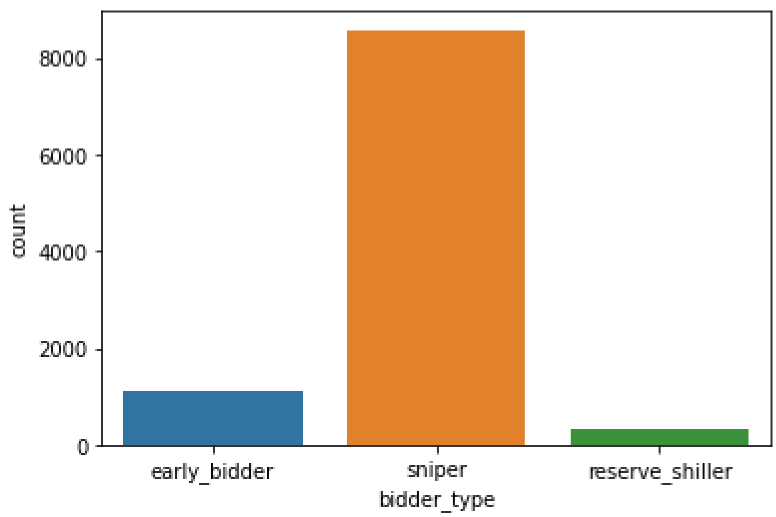



This is the histogram of output from MLE fitted lognormal random variable.

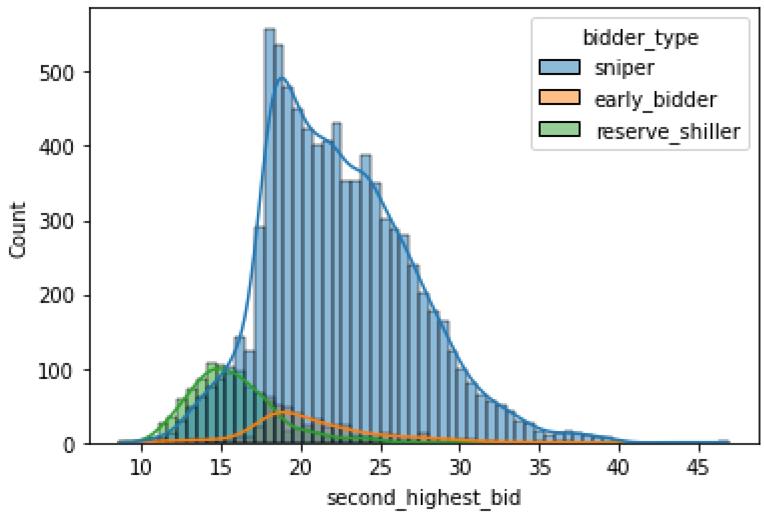
**Kaniadakis Weibull distribution would have fitted it much better but its random variable generator was not available.**

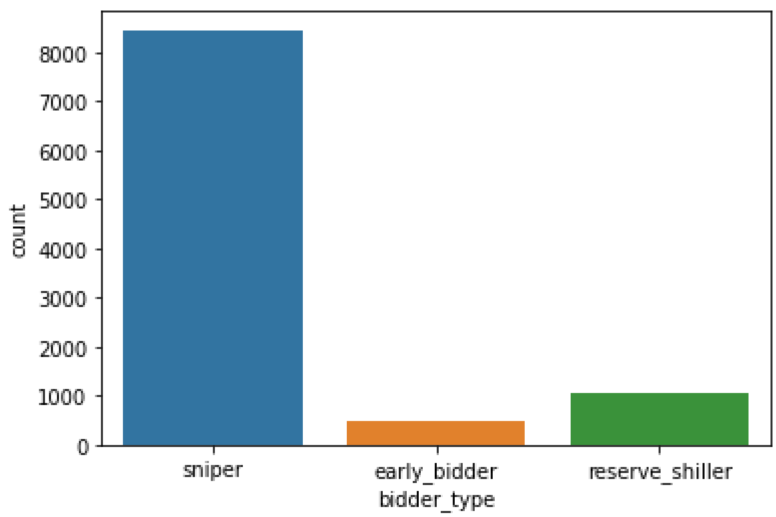
5. When we tested out reserve_shiller under three different conditions:



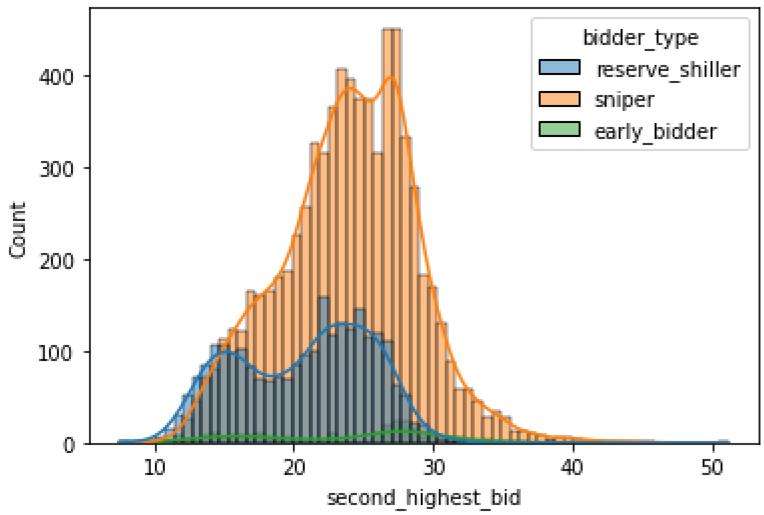



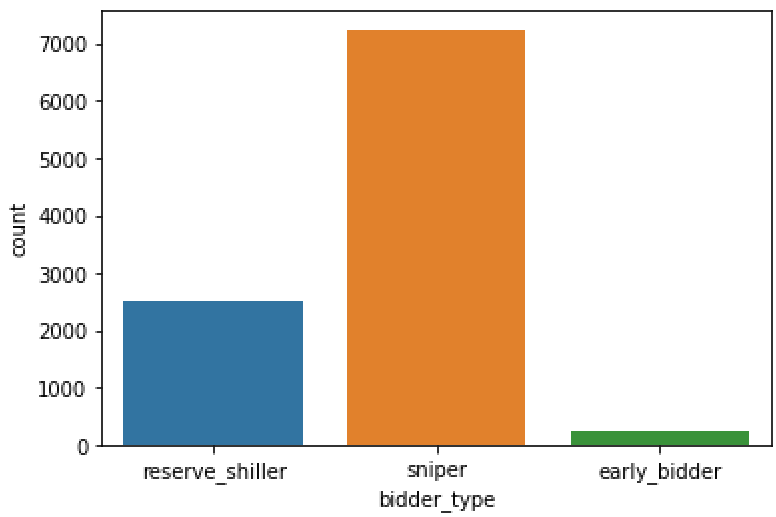

For ***Target ~ limit(EB)*** [Type 1]




For ***limit(EB) < Target < limit(Sn)*** [Type 2]

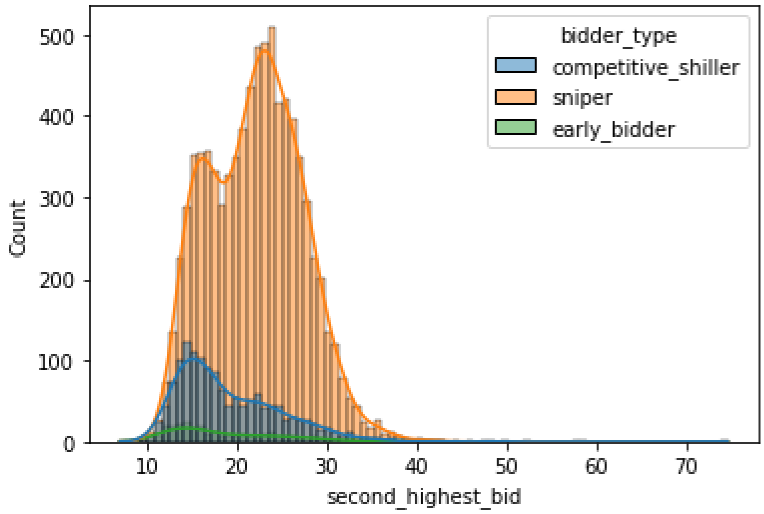


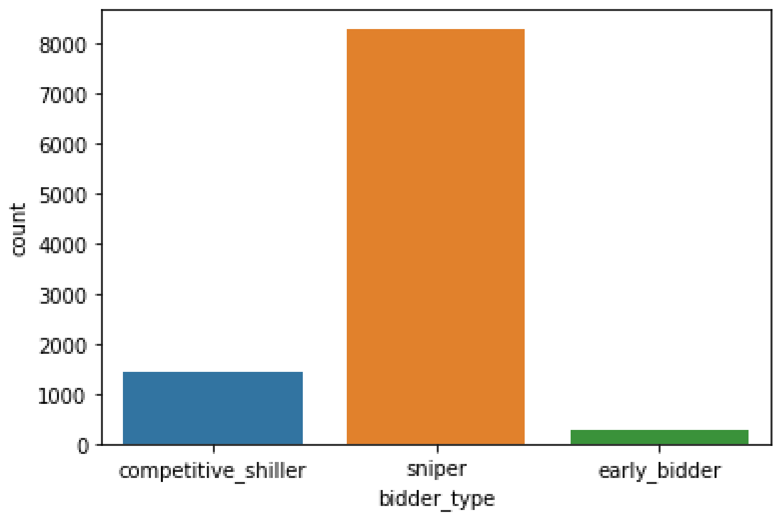




***Target ~ limit(Sn)*** [Type 3]

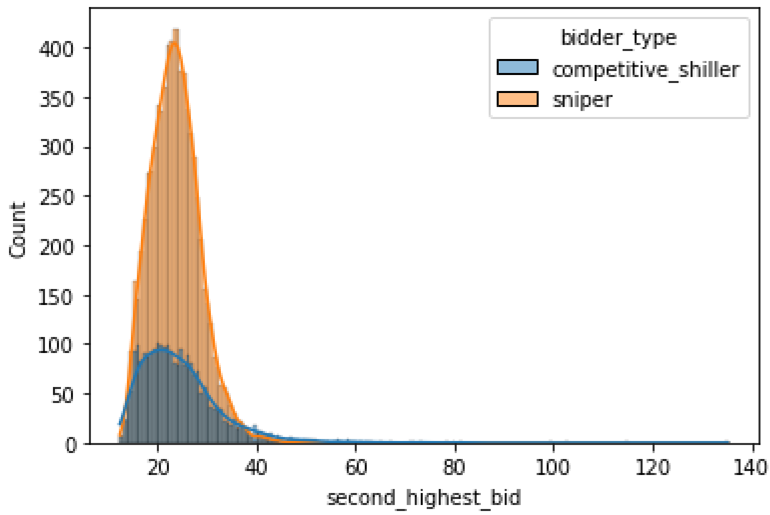
With the increment in target value, the chance of early bidder starts decreasing as well as the risk of winning increases. When the target of reserve_shiller reaches too high it ends up acting as a competitive Shiller.

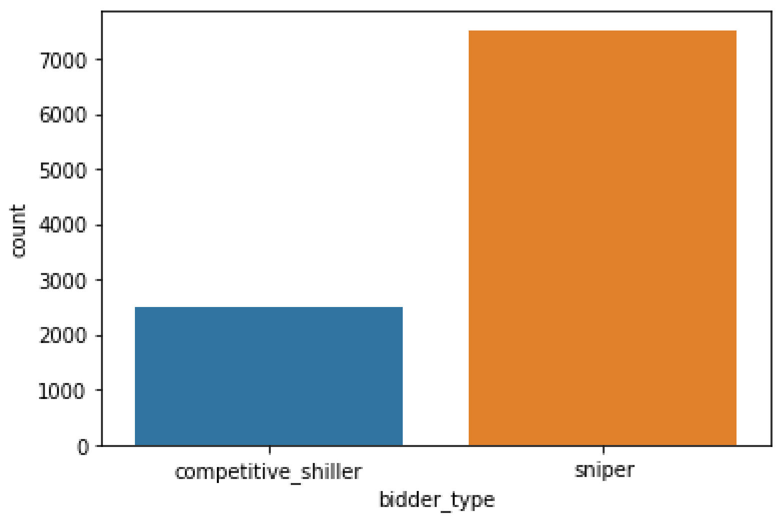
6. When we tested our Competitive Shiller (Type 1) (hard_close=500 and hard_close=1500) that used weighted moving averages to raise its increment:




For ***hard_close = 500***



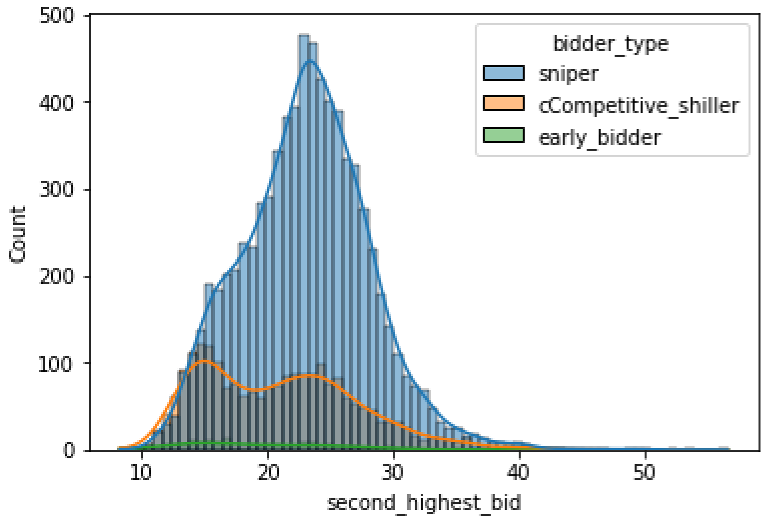



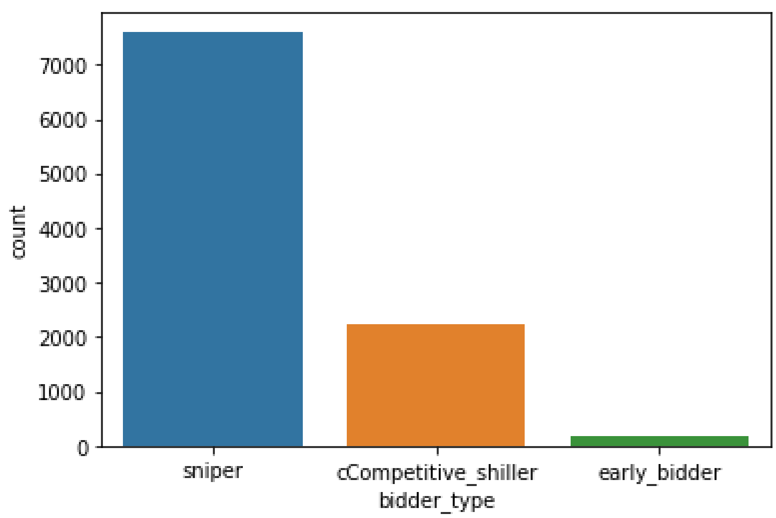

For ***hard_close = 1500***

Early bidders registered **ZERO** wins across 10000 iterations.

Competitive Shilling is a risky proposition but with the potential to make bidders reach for their limit to win the auction. But the longer it goes on the lesser the chance of early_bidder winning is.

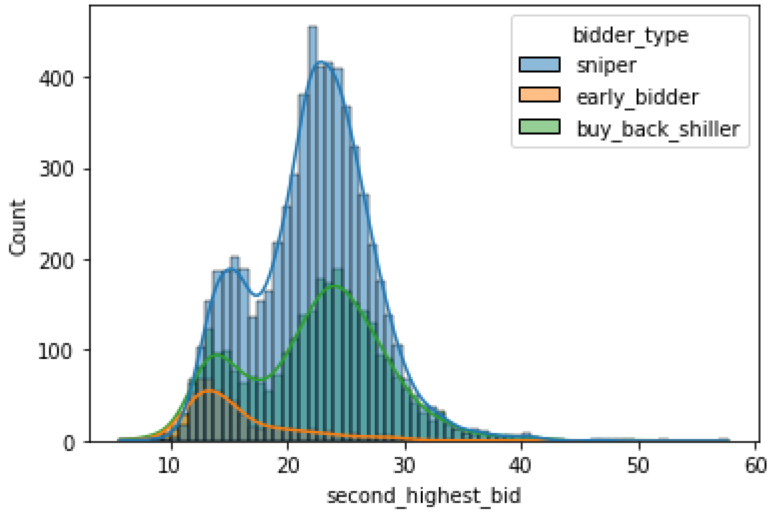
7. When the competitve_shiller (Type 2) was employed that used congestion-based bidding (for ***hard_close = 500***):

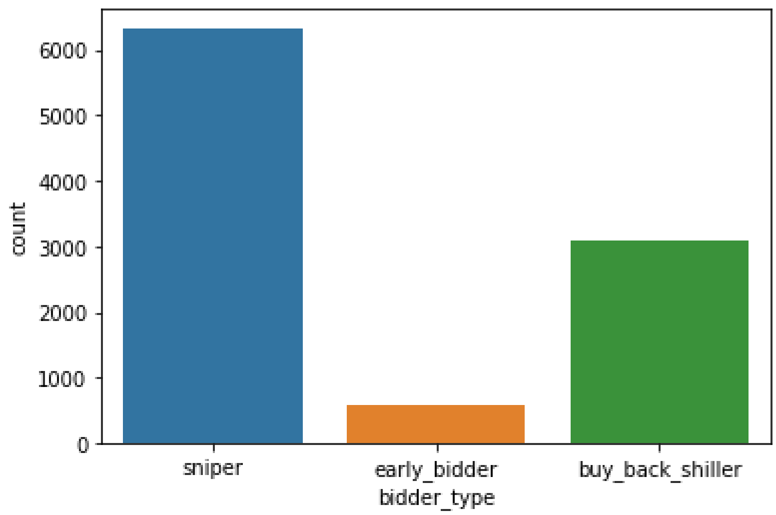



For the same ***hard_close = 500,*** it is clear congestion-driven competitive Shiller is more aggressive than competitive Shiller that uses a weighted moving average as it's bid incremental strategy.

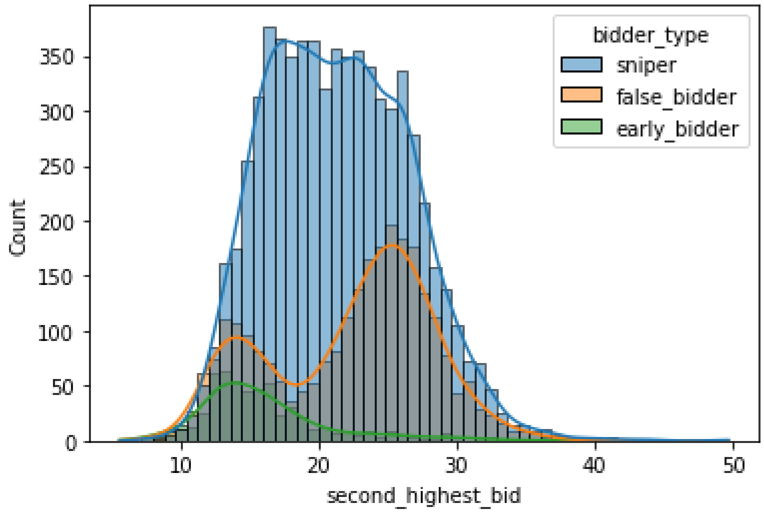
8. When buy_back_shiller was employed:

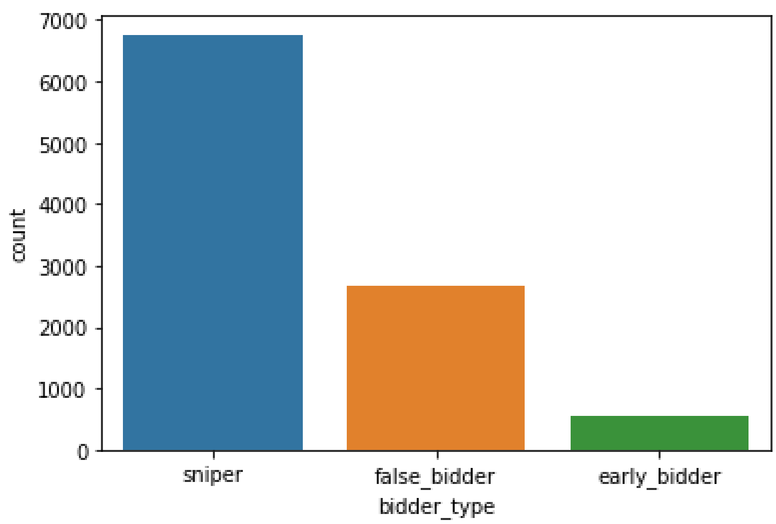



Buy_back_shiller is the only shiller that aims to win the auction and it shows how ultra-aggressive it can be.

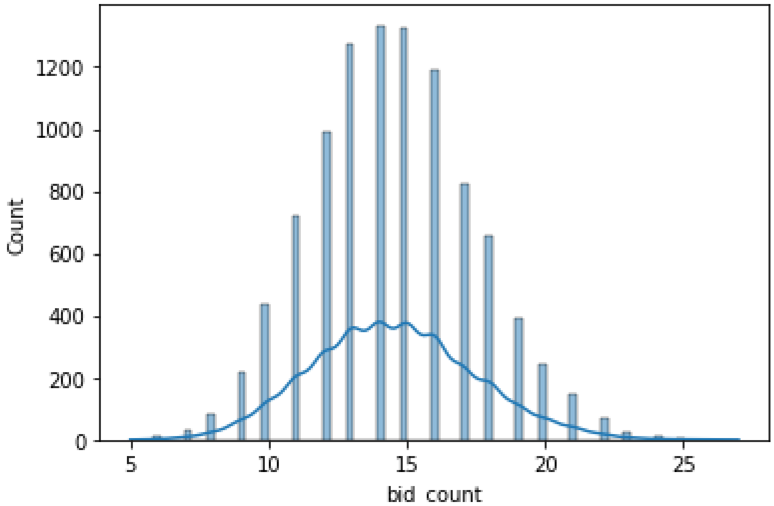
9. Finally, the false bidder was sent out:




As expected, the chances of false_bidder winning are much higher than any other shiller we have mentioned that does not aim to win, as false_bidder's core strategy relies upon bidding late. But, see, it was more successful in filling the gap between the twin blue peaks than we saw in (1).

10. When we did the bid_count analysis:




The trend resembles to some discrete version of normal distribution. The number of bids in an auction is one of the primitive yet imperative indicators of shilling. This analysis is used in building a congestion-driven competitive Shiller.

| S. No. | (6 Early Bidders + 3 Snipers) + 1 **Variable Bidder** | Avg Number of Bids |
|---|---|---|
| 1 | 7th Early Bidder | 14.53 |
| 2 | Reserve Price Shiller (Type 1) | 27.80 |
| 3 | Reserve Price Shiller (Type 2) | 18.04 |
| 4 | Reserve Price Shiller (Type 3) | 15.17 |
| 5 | Competitive Shiller (Type 1) | 21.03 |
| 6 | Competitive Shiller (Type 2) | 17.52 |
| 7 | Buy Back Shiller | 14.21 |
| 8 | False Bidder | 14.81 |

Buy Back Shiller and False bidder are not involved in signalling hence do not affect the average of 14 bids. You see 3 red/2 blue boxes in decreasing order which means that early bidders were kicked out early in the auction as they exhausted their limits. Reserve Price Shillers are very aggressive concerning their bid increments than the competitive bidder. An increment in Type # also leads to an increase in bid incremental aggressiveness.

## CONCLUSIONS

Sniping or the instinct of one shot kill is an evolved behaviour. Rational bidders that aim to maximize their utility and avoid the winner’s curse have found a dominant strategy in it. Sniper has no incentive to bid early and helps in signalling the bids to go higher. If they were to involve themselves in bidding throughout the auction the blue twin peaks we saw would have been just one. Both left and right peaks merged into the right— representing a decrement in utility. Which the false bidder was able to achieve by targeting the second-highest bid. It is concluded that the snipers who bid late have more chances of winning but at a cost of decreased utility.

All types of shillers in general were able to maximize the profits for sellers by around 6-10%. It is concerning because it is a multi-billion dollar industry and even if fractions of it are being lost that would take the amount in millions of dollars.

Better difference analysis (highest bid and second highest bid) in addition to helping in research would might also aid the false bidders to shoot up their profits.

Early bidders are new entrants or novice bidders. And shills eat up their winning chances; especially in longer auction formats. This would make them lose trust in this financial system and also might end up triggering a whole market collapse.

All the research material we went through, in their limitations, stated they could have developed better models to detect fraud and shilling if they had access to better data. Thus, building on previous works we have developed a comprehensive Auction Simulator that we hope would further the research in this domain and would also act as a data generator for existing models for them to check their accuracy and efficiency.

## FUTURE WORK

This model can be further extended to future more complex auction formats that are prevalent in the world. Namely, Ad Exchange Auctions through which tech giants like Google & Facebook make money.

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