Agent-Based Systems – Extensive Auction Games

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I. Introduction

Auction theory delves into the practical and theoretical applications of strategic approaches to understand how bidders behave in an auction environment. Auctions can be divided into four main types: English (open-cry) auctions, Dutch auctions, first-price sealed-bid (Vickrey) auctions, and second-price sealed-bid auctions [1]. Agent theory is concerned with the question of what an agent is and the use of mathematical formalisms for representing and reasoning about the properties of agents [2]. By using the strategies derived from auction theory, artificial intelligence can simulate decisions made (using agents) to apply practices commonly used in auctions, making strategical choices from algorithms and large amounts of data. This paper will focus on the implementation and strategies used in a first-price sealed bid auction, which involves bidders submitting a sealed bid and the highest bid determining the auction winner.

II. First Price Auctions

A. Background

First-price sealed bids are an auction format where each bidder submits a sealed bid, and the highest bidder wins the item. The payoff for the bidder can be described below [3]:

If b_i is not the winning bid, then the payoff to i is 0. If b_i is the winning bid, then the payoff to i is $v_i – b$ (where v is the payoff to bidder i with value v_i and bid b_i)

In this situation, the best strategy for player i is to bid less than the actual value of the item. However, it's important to consider how much lower the bid should be. Bidding too low may lead to a loss, while bidding too high may result in a lower payoff. This problem is complex to strategize as one cannot predict the bids of other players. Without knowing other players budget and priorities we are unable to deduce what items are going to have higher bids. The revenue equivalence theory (RET) states that under a specific set of economic conditions, the revenue an auctioneer can expect to earn and the profit any bidder can expect to make will be the same for a broad class of auctions [4]. In a first-priced auction the expected revenue, or bidding price is determined by the bidder's valuation and the strategies they choose to bid with. RET can only be considered on three conditions [4]:

1. The seller has a single item to sell, with no prospect of resale.
2. The bidders are risk neutral.
3. The bidders' valuations of the item are independent of each other.

While this may be a useful indicator of the value of an item, and what bidding strategy a player chooses, it is important to consider that each bidder also has a private valuation for an item. A private valuation can be affected by each bidder's knowledge and information about an item, having items that are of higher priority can cause players to change their bid for certain items, and this in turn makes the overall bidding process more complex.

The next section will detail the simulated environment for a first-price sealed bid auction featuring several paintings from different artists.

III. The Auction

In this paper, we will be implementing a first-price sealed bid auction. The auction will consist of several first-price sealed bids for several different items. Bidders have a budget to bid on four paintings by Picasso, Van Gogh, Rembrandt, and Da Vinci. Players will make their bid at the same time and the highest bid wins the item; the overall winner is determined by the paintings collected where a combination of paintings is met. The full specifications of this model are described below:

<u>Number of bidders:</u> n = 1...10

<u>Number of items to be sold</u>:n = 1…200

<u>Number of rounds:</u> n = 1…200 (where if the winning condition is met then the auction ends)

<u>Budget:</u> Each player is given a budget of 1001. A player must bid each round and their bid cannot exceed their budget.

<u>Winning condition:</u> A bidder wins if they own 3 paintings of any artist, 3 of another artists, 1 of another.
artist and 1 of another artists. For example, 3 Van Gogh, 3 Picasso, 1 Rembrandt, and 1 Da Vinci; or 3 Da Vinci, 3 Rembrandt, 1 Picasso, and 1 Van Gogh (or any other combination of 3, 3, 1, 1 paintings).

The auction will be set up with up to 10 bidders, where the number of bidders will not be known to anyone but the auctioneer. Each bidder's private valuation for an item can only be deduced from the information provided. This includes the paintings collected, the budget, and the score for each bot and the upcoming paintings in the auction.

It is important to note, that while we are provided information regarding the painting's value, we are not concerned about getting the paintings with the highest values. Winners are determined by the number of paintings collected and not by the overall value of the paintings.

IV. The Strategy

A. The Strategy we are playing

When coming up with a strategy to maximize the winnings, it is important to know that a pure Nash Equilibrium can only exist if all players bid their actual, true value. However, due to the variety of different strategies that may be played, achieving this pure Nash Equilibrium is unlikely. This leads us to use multiple strategies to adjust and prioritize our bids for different paintings throughout the auction.

For this auction the actual value of each painting is roughly the same for all bots, as we are aiming to get a combination of paintings to win within a certain budget, the value of each painting can be described below:

Value = Budget/Total Number of paintings to collect

The payoff for each auction as described in part I is:

$$u_i = \begin{cases} 0\text{ , where player } i \text{ loses a bid} \\ v_i - b_i\text{, where player } i \text{ loses a bid} \end{cases}$$

In order to maximize our overall profit, it is essential to adapt our bidding strategies based on the available information throughout all bidding rounds. One effective approach is to bid slightly less than our actual value. This technique is known as bid shading [5] and can help us to optimize our profit while reducing the chances of loss.

To get the best combination of paintings, we will prioritize them based on how many we need to meet the target winning condition rather than their value. For instance, we can assign priorities based on weights, which means that if an painting is of high priority, we can bid up to 90% of its true value, thereby ensuring that we're paying close to its actual value while still bidding below it to maximize our payoff.

For this strategy we have decided to assign the following priorities and values, where the value is the percentage of the true value that we are willing to pay for each priority:

Table 1: Priority vs % of value to bid

Priority	% of the true value that we will bid
High	90%
Medium	60%
Low	30%

When assigning these priorities, we will need to consider how close the count of each type of painting is to the target. (i.e., Do we own 3 paintings of any artist, 3 of another artists, 1 of another artists, and 1 of another artist in our collection.) The following procedure describes the strategy in which we assign a priority to assess how important it is to obtain the current painting for auction:

Table 2: Psuedocode for priority allocation procedure

Priority-Based Auctioning Strategy

```
Procedure check_priority_items(current_painting,my_paintings,priority,target_collection)
sorted_paintings ← np.array(sorted(my_paintings.items(), key=lambda x:x[1], reverse=True))
If sorted_paintings[current_painting] == 0 then
    Priority = HIGH
Else
    u_vals ← np.sort(np.unique(sorted_paintings[:, 1]))[::-1]
    highest_vals ← u_vals[0]
    high_val_paintings ← [x for x in sorted_paintings if x[1] == highest_vals]
    If len(u_vals) > 1
        highest_value_2 ← u_vals [1]
        high_val_2_paintings ← [y for y in sorted_paintings if y[1] == highest_value_2]
    Else
        highest_value_2 ← 0

    If highest_vals < 3:
        If current_painting in high_val_paintings
            Priority ← HIGH
        ELSE:
            Priority ← MEDIUM
    Elif highest_value_2 < 3:
        If the current painting in high_val_2_paintings
            Priority ← HIGH
        ELSE:
            Priority ←MEDIUM
    ELSE:
        Priority ← LOW
End Procedure
```

In the following pseudocode, if we do not have a painting the priority is assigned as high. If we have 3 of the two highest counts of paintings the priority is set as Low as we do not require more than 3 paintings. If we have less than 3 paintings for the two highest count paintings, we assess if the current painting has the highest or second highest count of paintings in our collection, if this is the case, we assign the painting to have a high priority. Using this method, we can bid in a way that maximizes our payoff but reduces the chance of loss for paintings that we need the most.

To improve our payoff, we will also be considering the priority of paintings for other bidders. This is important as we do not know the priority or strategies played by other bots. However, by deducing what paintings other players are collecting, we adjust our bid to be higher or lower, when we expect paintings to be in demand. Using the priority system described above, we evaluate the current painting for auction against the paintings collected by other players. If a painting is deemed to be of high priority, we bid higher to compensate for this. As this auction consists of multiple paintings, we can calculate what the average price for each painting type is and bid higher or lower depending on this. This ensures that we are not overbidding on paintings while remaining competitive for the paintings that we require.

Before making a bid we also ensure that we adjust our bid for upcoming paintings. If we are at the end of the 200 rounds and an upcoming painting is of medium to high priority, we make sure to secure the painting we need from the last 5 paintings of each type. Failing to obtain paintings for a collection would lead us to automatically lose an auction. This condition is only likely to occur when there is a larger number of bots playing different strategies. After we have obtained half of the paintings, we focus on only obtaining paintings that are of high priority by setting low-priority paintings to always have a bid of 0. Reducing the need to use the budget on paintings that are not as important, maximizing the amount we can bid for paintings that are of high priority.

V. Results and Testing

To test this, we have created bots using some of the methods above. When testing the final implementation against the bots created, we win the following percentage of games.

Table 3 Test bots and win percentage

Bot	Description	Games won (%)
Random-Bot	Produces Random Numbers from 0-Budget	97%
Flat-bot-10	Always bids 10	100%
Test-Bot-3	Always bids the allocated budget/number of items to get	75%
Test-Bot-4	Bids allocated budget*Priority	80%
Test-Bot-5	Bids using the same strategy as final implementation.	52 %

With a combination of 10 bots, consisting of the bots described above, the final implementation has a win rate of approximately 50%. Against the random bot and flat bot, the final implementation wins most of the games. When we compare this to bots that are playing the same strategy the overall win ratio is equal for each bot. This can be due to the paintings being quite similar, bots are also given the same information so when playing the same strategies, the paintings order, initial bids, and remaining budget can affect the overall winner for a game.

VI. Evaluation

Our bot considers the strategy of other players by analyzing the paintings they choose to collect. However, we cannot determine this until a certain number of paintings have been collected. Furthermore, if players bid low in the initial rounds, our bot may perceive a lower average and subsequently bid lower, even if it is more likely to win the game, we have mitigated this by using the last 3 prices for a painting, yet this is heavily dependent on the strategies played by other bots. In a real-life auction scenario, various factors such as the reputation of sellers, the value of paintings, different budgets, and priorities can affect the outcome of the auction. While our current bot is efficient in its current setting, it may not perform as well in a real-life scenario, where bidders are playing with different strategies and may have access to different information. A possible solution to improving payoff in this scenario is to bid on the paintings that have a higher occurrence early in the auction to meet the target early. The number of players can also impact our bot's performance, The average number of wins becomes the total amount of rounds divided by the number of players and each bot ends up winning roughly the same number of games.

VII. Conclusion

The agent developed in the following paper provides us with a simple solution to winning a first-price sealed bid auction that focuses on the collection of paintings by evaluating methods described in the research. Through applying bid shading methodology with a priority-based system. However, this method is limited to the knowledge and information provided, in the real-life scenario, the priority budget and background of the bidders and auctioneer all affect how an auction plays. The solution we have developed would require further testing and development to consistently win auctions.

Moving forward a larger test set bidding with different strategies would be required, if the auction becomes more value-based, we will need to adjust the priorities assigned to focus on the total value compared to the budget available.

References

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