Agent Based Systems - Auctions

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***Abstract*—This project investigates the different strategies that can be used in different auctions ranging from getting five-of-a-kind to sealed-bid first and second price auctions.**

I. Introduction

The assignment for this module focuses on creating bots for bidding in virtual auctions to buy paintings. In total, there are four different kinds of auctions, which have different sets of rules for declaring a winner ranging from the first bot to buy 5 paintings from an artist to the bot with the most valuable art collection. In the auction environment, each bot is aware of the other bidders, their assets which include the paintings they have won as well as their left-over budget. In some auctions, the order of paintings that are going to be sold are known whilst in some, its unknown. Furthermore, in most auction, the highest bidder wins the round and they pay their bid amount; whilst in another, the highest bidder wins but pays the 2nd highest amount. The left-over budget at the end of the auction is useless and has no utilitarian value. That is the primary reason why this auction cannot be compared to most auctions as the profitability cannot be maximised by bidding for lower prices.

II. Extensive game modelling

The four types of auctions for this task are strategic incomplete information with perfect recall games which can be modelled in their extensive forms. Although in all of the games we know the assets of the bidders and the money paid by the winners; we do not know the bids of all the players. The notion of perfect recall can be seen as we know the price paid by each winner in each round of the auction. Itâs not possible to determine the utility function of the other players as we do not know the bids of all the players. It is complex to estimate the values of the bids of the bots as they have different approaches to risk [1]. However, due to budget constraints affecting all bots, it is possible to apply a ceiling amount to the bids of all the players which is their entire left-over budget.

III. Reinforcement learning

The game can be modelled in a Markov decision process (MDP) [2]. The states can be modelled as the paintings owned by each of the bots, the next up-coming painting, the paintings remaining to be auctioned and the money of each player. The transition from one state to another is stochastic as its only possible to estimate the bids of the enemy bots. The number of states available for this game is huge. As a result, it is impractical to use reinforcement learning in viable time without simplifying the problem so much that it becomes useless.

IV. Strategies

The four auctions have different rules for declaring winners in the game but all of them have the same starting budget of 1000 currency points for each player, the highest bidder wins the bid. In the case where there are multiple high bidders, the tie breaking is done by choosing the winner randomly. The approaches taken for this task has been to start off with creating a strategy which is able to beat the random-bid strategy for each of the games. Once the initial strategy is able to beat the random bids, its iteratively improved by creating other strategies which are able to best respond to the initial strategy.

A. Auction 1

The aim of the first auction game is to collect five paintings as quickly as possible from the same artist. Given the order of paintings by all the artists, it is possible to find out which artist will have a completed set of five paintings first. Then, bid was budget divided equally for each painting; that is 200 currency points for each of the five paintings by the artist to complete the set first. The problem arises when the first painting is lost to another bot with a higher bid, it is challenging to recover and win the auction. Other bots, with their budgets untouched are able to outbid the initial bot to reach a nash equilibria where all the bots end up with one painting each by that given artist. Only when all the bots have attained a painting each, their budgets / aggressiveness are low enough to allow for the bots to gain their second paintings. However, in 1 v 1 scenarios with just two bots are playing, the bot which bids 200 at every single round will always win. Even when outbid in any of the paintings by the second bot, the higher remaining budget of the first bot allows it to outbid the second bot in the remaining rounds to be the first one to win all 5 paintings. The strategy being submitted works well in 1 v 1 situations where the opponent is trying to complete their set as quickly as possible. It involves working out the first and second artists who complete the set of 5 paintings first. Assuming that opponent is bidding an average of 200 for the paintings (it could be 230 for the first, 210 for the second, 200 for the third, 190 for the fourth and 170 for the fifth) or anything similar to that. In these bids, the strategy can be defeated if the second bot aims to get the second set of completing of paintings whilst blocking the first bot from completing itâs set. By bidding an average value of 300 up to a total of 900 until it wins 3 paintings of the first-completing artist, 100 is left over to be used for bidding on the second-completing artist. An average bid of 20 is used for completing the 5 paintings of the second set. As there are no other bidders bidding for the second painting, this bot wins.

```
first_artist = first_n_artists(1)
second_artist = first_n_artists(2)

if current_artist == first_artist and block_first_count <= 2:
    block_first_count = block_first_count + 1
    return ceil((max_budget - 150) / 3)

if current_artist == second_artist:
    return ceil(25)

return 0
```

Fig. 1. Pseudo-code for auction 1

This strategy will work given that 8 paintings by the first-completing artist do not get auctioned before 5 paintings by the second-completing artist. However, since almost all of the artists have a similar amount of paintings being auctioned and the order being chosen randomly, this is unlikely to occur in practise.

B. Auction 2

This winner of the second auction is the person to complete the acquiring five paintings by the same artist. However, the order in which the paintings will be auctioned is unknown. As a result, the strategy of targeting certain artists that will complete their sets first is not deterministically not possible. Therefore, the most obvious strategy here is to bid 200 for the first painting that arrives. After that, stick to that artist and bid 200 for every painting by that artist. The best response to this is to bid an amount greater than 200, for example 300. This will mean that the enemy will lose out on the first painting. By bidding 300 for every single painting by the first artist whilst the budget allows so and buying the second artist at a lower price will allow for the player to win. A further improvement on this strategy is to big low amounts such as 2 currency points on paintings that are not being currently targeted by the bot. If just by luck, a set of paintings are at 4 (1 below the required amount of completion), then when the next painting by the same artist comes, the entire budget is used to bid on that painting in the hope of winning. The policy of bidding low amounts for paintings that are not being targeted has made this a dominant strategy in 1 v 1 auctions.

```
if round == 0:
    first_painting = itemsinauction[0]
    return 865

if round >= 1 and second_painting == "" \
        and first_painting != itemsinauction[round]:

    if first_painting != itemsinauction[round]:
        second_painting = itemsinauction[round]

if second_painting == itemsinauction[round]:
    return 23

if almost_complete_set(my_assets) != False:
    artist = almost_complete_set(assets)
    if itemsinauction[rd] == artist:
        return budget

return 2
```

Fig. 2. Pseudo-code for auction 2

C. Auction 3

The winner of the third auction is the bot with the highest total value of all their paintings. The value of each painting ranges; 4, 6, 8 12 current points. Unlike the first and second auction where aggression and speed is preferred, experiments have shown that patience helps in this auction as the other bots battle each other for paintings at the start with higher bids; winning towards the end becomes easier as a higher budget left compared to opponents who have depleted budgets. In a two-player scenario, the bot aims to achieve 55% of the total value of the paintings available. By buying paintings worth more than 50% of the total value, the player is a winner. 55% has been used as it might not be possible to win paintings worth exactly 50% of the points. In situations with a greater number of n players, the strategy is to aim to achieve total value of paintings given by the formula shown below:

$$\frac{totalvalueallofpaintings}{n} + \epsilon \tag{1}$$

Here the epsilon is value between 0.05 and 0.5. As the number of players, n increase, the bot bids higher amounts for the paintings. In the case where the bot makes a bid for a painting but is lost; the money that was going to be paid for the painting is saved. As a result, the future bids for the same painting will be proportionally higher. The valuations with the amount of money left and the target value of paintings are dynamic as bids are made and paintings are bought. Therefore, the highest amount that should be bid for a painting is calculated at every round of the auction. A way to beat this strategy in 1 v 1 situation would be to bid slightly more aggressively (for example, aiming for 52% of the total value of paintings). However, in most cases, given the limited budget, the bids would be the same resulting in the tie-breaking process of randomly selecting a winner. Another associated risk is looking at the last painting which would exceed the given percentage target so the painting would get completely ignored. As a result, targeting 55% of the total value is a good number according to the experiments carried out.

D. Auction 4

The fourth and the final auction has similar rules to the third action where the over-all winner is the bot with the highest

```
AIM_DECIMAL = 1 / numberbidders + 0.1
if (numberbidders > 10):
    AIM_DECIMAL = 1 / numberbidders + 0.05
elif numberbidders > 15:
    AIM_DECIMAL = 1 / numberbidders + 0.02
else:
    AIM_DECIMAL = 1 / numberbidders + 0.1

total_value_left = total_value_of_paintings
if total_value_of_paintings < total_value_left:
    total_value_of_paintings = total_value_left

target_valuation = total_value_of_paintings * AIM_DECIMAL
current_valuation = total_value_of_my_paintings()

value_until_target = target_valuation - current_valuation

overall_cost_per_point = maxbudget / target_valuation
cost_per_target_remaining = (budget) / (value_until_target)

points_for_current_artist = value_of_current_artist \
                            * cost_per_target_remaining

return ceil(points_for_current_artist)
```

Fig. 3. Pseudo-code for auction 3

total value of paintings. In each round of bidding, the winner is the highest bidder. However, the bidder only pays the second highest bid. This auction should be a Vickrey auction [3] which would imply the auction is incentive-compatible and truth-telling is the dominant strategy. However, in Vickrey auctions, the utility function for the bidder would include the cost of the item that is saved at the end of the auction. However, in this case, the value of money left over at the auction does not have any utility. As a result, this is not a Vickrey auction and truth-telling is not a dominant strategy. The strategy used for this auction is very similar to the strategy used in the 3rd auction. However, a difference is a constant is added on to each calculated bid before it is submitted. The optimal price of payment in this auction is approximately the same price paid by the bots in the third auction. This payment price paid should be the second-highest submitted bid. As a result, the best strategy would be to bid slightly higher than the estimated second highest price. The extra added value can be considered as a variable alpha. The equation used for calculating the bidding price is

$$\frac{totalvalueofpaintings}{n} + \epsilon + \alpha \tag{2}$$

. In order to win the bids of this strategy would be for the enemy to increase their own bid. Should the enemy have the highest bid, the price paid will the best bidding price plus alpha. Due to the addition of alpha to the bidding price, the

```
episilon = 2

optimal_bid = get_optimal_bid()

return optimal_bid + episilon
```

Fig. 4. Pseudo-code for auction 4

enemy will run out of money before the required, winning amount of paintings can be purchased. As a result, as the budget of the enemy is depleted, this strategy will bid higher amounts and pay lower amounts leading to a winning strategy.

V. Evaluation

All the bots for the four types of auctions were tested in both environments with 10 to 20 bots created by the author and other students as well as 1 v 1 environments against my own strategies. The group tests were carried out with the permission of the authors of the bots who had submitted the source code in a minified format. In most of the cases, the bots are tested more rigorously against the authorâs own bots in an one versus one compared to the group tests.

A. Auction 1

The initial versions of the strategy of bidding a constant value of 200 was tested in a group environment where it was performing to a decent standard although the number of outright wins remained few. The further improvements which is submitted as part of this paper has not been tested in a group environment but tested in small scenarios against the authorâs own bots. In this case, this strategy was performing well consistently as the other strategies focused on getting the set as quickly as possible.

B. Auction 2

This strategy was tested in both large group and small situations. In one versus one situation, the bot performed outstandingly well against bots which were using calculating the highest probability of the paintings and just focusing on those artists. Furthermore, this strategy performed well against bots which were aggressive for the first painting by outbidding with an extremely high amount to delay their win. The victory for this bot came from targeting the second complete set which could be purchased at a significant discount. Additionally, often purchasing non-sought after paintings at low prices allowed the strategy to win where non-targeted paintings were arriving quickly. The results completely reversed when tested in a large group environment. Many strategies by other students were being much more consistent with their bids. As a result, they were able to strategically bid higher amounts for paintings targeted by authorâs own strategies even though they were not seeking those paintings to win. As the money was depleted for the authorâs own bot due to the high bidding at the start, the authorâs bot performed poorly in this group environment.

C. Auction 3

This strategy was tested in both large group and one versus one situation. As the strategy had varied aggressiveness with the bids it was able to perform well in both small and large environments. As the aggressiveness had been manually tuned and tested in one versus one situation, it proved victorious in all tested small situations. When being tested in large groups, the strategy came consistently third in the auctions. As the bot aimed for a certain number of points in the game, other bots which aimed higher number of points and waited till later on in the game were able to purchase higher values of paintings at a discounted rate due to depleted money. A way to update this would be further tune the hyper parameter of aggressiveness as a function of the number of bidders that are taking part.

D. Auction 4

This strategy was tested only in one versus one situations. In the test conditions with just another bot to compete with, this strategy proved to be dominant. However, this might change in an environment with a large number of bot as there will always be some bots bidding unexpectedly high amounts and winning those bids but paying only a small amount. Although not supported by this strategy, âanti-trollingâ features such as estimating how high enemies are bidding and then bidding slightly below that amount to drain them of money would prove as an effective counter measure.

VI. Conclusion

The strategies used for these auctions do not follow the theory from traditional auctions due to the lack of utility in the left-over money at the end of auctions. As a result, the strategies used in this paper have been developed with the aim of being bankrupt by the end of the auction sessions. As a general observation, auctions 1 & 2 requires high bidding strategies. On the other hand, the optimal strategy for game 3 & 4 focuses on trying to win a certain point worth of paintings. This requires steady bidding generally. However, when losing bids to opponents at the start of both 3 and 4, it is worth it to be patient and wait for the opponents to run out of cash and try bidding higher values.

References

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[3] P. Turrini, "Algorithmic game theory - auctions." 2019.