CS404 Agent Based Systems Auction Coursework

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INTRODUCTION

In this assignment, four strategies have been designed for various auctions and their win scenarios. There are a few assumptions that need to be made going into the design and development of the proposed solutions. Since this is a competitive scenario where bots are made by multiple people who have not coordinated or collaborated on the theory behind each individual strategy, there can be no assumption about opposing agents risk attitudes[3], meaning that a pure risk-neutral rational approach is not going to be optimal in all cases. There is also the assumption that winning has the best valuation, with a draw coming second and losing having a negative valuation.

THREE OF A KIND - KNOWN ORDER

In this auction the aim is to obtain three paintings of the same type before any other buyer. Since everyone has the same budget, it can be extremely challenging to perform better than another agent as valuations for a single item is only a component of the valuation for the winning combination of items.

The valuation for the sequence of items (that are won in the bidding) which results in a win should be equal to the budget since money is not import once the auction is complete.

$\sum_{i=1}^{n} valuation_i = budget$ for the sequence of bought items $[1..n]$

Since these bids are competitive, the individual bids should also be as large as possible, suggesting that the best case scenario will have as few bids as necessary to win the auction. This led to the design aims:

1) Minimize the amount of total bids
2) Find a sequence of items which will let this agent win first
3) Maximize the per item bid, so that this agent can win

As the winning bid is the highest in each round, bidding higher in one round and lower in a future round can easily result in not being able to successfully win a given item. As such, bids which equally distribute the budget are the best case scenario as each round will have an equal chance of success. There is a small exception to this in that the budget of 1000 can not be equally broken down into three. Therefore, one of three rounds can be budgeted higher.

Supposing that only three bids for a single item type are made, this suggests the values $(333, 333, 334)$ will be bidded for the items. Since there will be other rational agents acting in the game, there will eventually be a situation where two or more agents both bid the same value, which will result in the item being randomly allocated between the agents with the same bid. Unfortunately, this situation can not be improved upon because all agents work with the same budget and have the same goal.

Bidding High Early/Late

By making the larger bid early, other parties can be dissuaded from bidding on a given item, however there are several problems with this approach.

- May unknowingly lock into a popular item
- Can not bid high at a later stage
- Could be outbidded at a critical final stage

Bidding later has the benefit of making the final bid harder to beat (representing it's slightly higher valuation) and also leaves as much budget left in the rare occassion when switching to another item type is the optimal outcome. This is implemented as a scaled down bid which is made for other items. Winning an alternate item shows that few or no other agents are aiming for the object and it will

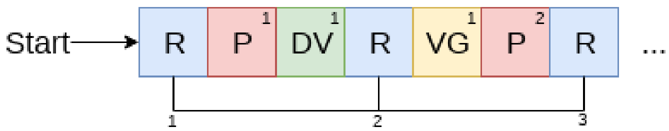

Fig. 1. Looking ahead in the auction shows which item can result in a win first. In this case, it is Rembrandts.

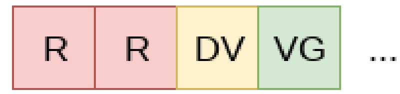

Fig. 2. Shows how Van Gogh painting will have a higher valuation in round 4 since there is more of that item type available for the rest of the auction

be easier to acquire in most cases, however it is extremely rare for this to occur.

Fortunately, this auction allows for the ordering of the items to be seen ahead of time, so some predictions on the best bidding order can be made. This implementation looks ahead to find the item type which can be completed first (as shown in Figure 1), with a degree of leniency which scales with the number of previously failed bids. Using this strategy, the agent can pass on an earlier item to collect three paintings which allow for an earlier auction completion.

In order to track bids from previous rounds, the agent needs to either recalculate it's previous bids, repeating work which has been previously done, or by storing the information in memory just before the bid is made. While recalculation was used in an earlier version of the agent implementation, this was replaced with memory storage as it was inefficient to recalculate values for the entire auction at every round. These values were essential since only non-zero bids were considered true attempts that the bot was trying to acquire.

Loss Prevention

For the most part, investing in preventing a loss will not be worth it in this auction as stopping one agent from winning will only be a delaying tactic at best. An attempt to prevent other agents winning has been implementing in the final stages when winning is no longer possible. At this point halting any other player is valued at the same level as winning the game, as a draw is better than losing.

Three of a Kind - Unknown Order

While the order of items is not known for this auction, the primary goals of the agent remain the same. As such, a strategy of $\frac{1}{3}$ budgeting per painting is implemented once again, with the ordering prediction being replaced with a valuation system which estimates the items most likely to appear next. This is possible due to the information stored in the $artists$ array, which informs the agent how many of each painting type exist in a given auction as shown in Figure 2. Combining this information with previous auction rounds, a valuation of a given item type can be generated, with the agents current ownership of an object being factored in as a multiplier.

Switching to another item after a successful bid has been placed is done only weakly, as there is far less of a guarantee of success when the order of items is not known.

Loss prevention can be implemented in much the same way as the last auction, as winning being possible can be ascertained at any point by checking the amount of remaining items of each type. The remaining budget of other agents can be used to decide what value should be bidded to prevent them from winning.

Three of a Kind - Conclusion

The three of a kind auction has few approaches which are optimal meaning that many bids are in a similar range, resulting in the winning strategy still producing a relatively random effect on which agent wins the auction. Overbidding is not rewarded, however being aggressive in the pursuit of the earliest paintings is essential to an optimum strategy. A possible extension to these bots would be to expand the leniency feature to scale with the amount that an item is valued when it is won or lost in a given round of bidding.

Another possible extension is the incorporation of cooperative bots. While paintings can not be shared, these cooperative bots could help one base bot win through preventing other agents from finishing their set of three paintings. This would require analysis of the remaining budget and goals of other bots, however this can be enacted in the same way as is displayed in the the first and second bidding strategies of this agent (bidding one more than the maximum budget of the agent who is about to win).

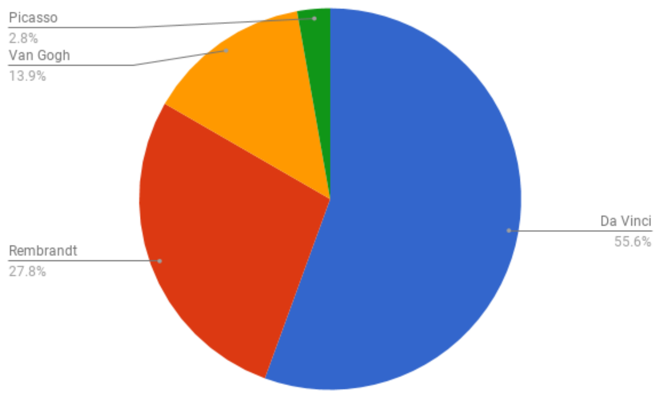

Fig. 3. Shows the breakdown of value across the four painting types in the default auction

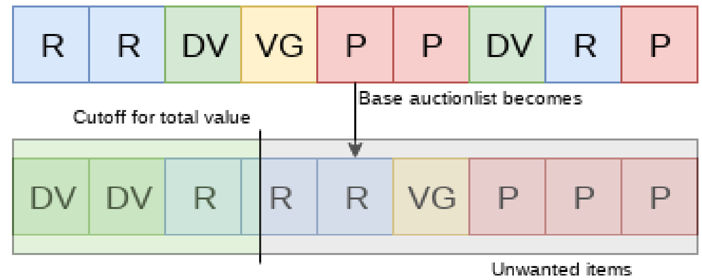

Fig. 4. The list of auction items can be reordered into a minimum cardinality set that has values summing to the target. In the case of a cutoff occurring between items, the next largest item is bought, as it is still likely that one item will be lost during bidding.

Highest Value - First Place Bid Cost

With this auction, it is far more common for bidding to last for every single round, with the total budget being expended relatively equally across the entire auction. The aim is, of course, to have the largest valuation of items by the end of the auction. As such, it is sufficient to have a target value of

$$\frac{\sum_{i=1}^{n} item\_value_i}{2} + 1$$

for all n items in the auction, since this is the lowest value which guarantees majority. However, this is not necessarily the best target to aim for, as this can result in bids being much lower than other agents which are more aggressively pursuing items. Some other considerations are:

- In the case that all agents are rational, the minimum value required to win is
$$\frac{\sum_{i=1}^{n} item\_value_i}{number\_of\_players} + 1$$
- The agent wants to minimize the number of lost bids, as this reduces the effectiveness of the bidding predictions. As such, the higher value items should be prioritized.
- Since rational agents can't be guaranteed, need to have the capability to scale between the rational case and the majority.
- If the agent isn't succeeding, need to aggressively pursue a new target value which places this agent in the lead.
- Need to decide on a round by round basis whether to bid on a given item.

These specification points create minimum and maximum target values to be aimed for, which the budget can be distributed over when buying items. Since the agent needed to be adaptable to different levels of aggression, a method of scaling up and down in this range needed to be devised. By testing which values were best in $CrescentAuction.py$ it was proved that aggressively reducing the target value when a bid failed to acquire an item was the best method to ensure that the agent won as many bids as possible. This target value could then conservatively raise back up over the course of successful bids, in a form of Adaptive Quality[2] which aims to maximize performance at any given round, working on the assumption that any win or loss acts as a prediction for future rounds.

One of the early test bots for this auction type only bidded on Da_Vinci's, since their value was higher than any of the other item types . Interestingly, this was a highly effective strategy because the sum of Da_Vinci's values was greater than all other item's values combined (as shown in Figure 3), despite only being 25% of the items on auction. This is also effective because of how it minimizes the chances of losing a given bid.

Suppose that n agents all come to the same valuation set $[v_1..v_k]$, resulting in the chance of getting any 1 item in the valuated item set as $\frac{1}{n}$. As this is true for each of the items that are bidded on, the average value will become

$$\left(\sum_{i=1}^{k} v_i\right) \times \left(\frac{1}{n}\right)^k$$

As such, the best way to maximize the achieved utility is to minimize the size of the set $[v_1..v_k]$ that achieves the target value, meaning that k must be as small as possible. Algorithmically, the best way to do this is to greedily claim the largest valued objects first as shown in Figure 4.

As the cutoff shows, this may well result in some items being eliminated from what is required and they will therefore not be bidded on.

Highest Value - Second Place Bid Cost

The Vickrey auction requires the highest bidding agent to pay the second highest bid. Previously it has been shown that being truthful with an agent's valuation is dominant[1], but only in the case that all agents are risk neutral, which the introduction noted will not always be the case for all possible submitted agents. However, it is useful to start from the valuation and scale up the aggressiveness of a given bid, since a higher bid is more likely to win. It is unlikely it will need to bid as much as the selected value, however this may become more of a problem as other aggressive bots come into play.

Since the fourth bidding strategy already includes the scaling which was implemented in the third strategy, the aggressiveness multiplier drops back down to the base level if any bid is won. This prevents other agents from exploiting the high bidding strategy to make the agent lose most of their budget. A internal multiplier based on wins and losses was used instead of comparing the agents' earned value since the latter solution could grow uncontrollably or barely change bidding at all dependent on the scenario.

Evaluation and Conclusion

The strategies detailed in this document draw upon game theory and mechanism design to provide solutions which should hold up against both risk averse rational agents and agents with different risk attitudes. While the first two auctions converge to all agents aiming to spend a third of their budget on 3 consecutive paintings of the same type, this is the optimal and dominant strategy despite the fact that this results in the winner being somewhat random. The later two auctions both aim to distribute the budget equally over a set of items which have a summed value of a calculated target, one which the agent estimates will provide a majority of the points.

Of the various strategies that were tested for this assignment, some performed better in very particular circumstances, however the final submitted agent is designed to perform well in all identified scenarios. Defining utility in this area can be challenging, as utility is usually described in the sense of a single games outcome. There are plenty of scenarios which the agent doesn't consider, like a world where the number of players isn't known, or where the third, fourth, fifth, etc. bid is payed by the highest bidder. Treating the value of an item as a factor of the total target goal seems to be an effective and concise method of implementation which is for the most part auction design independent.

References

[1] Paolo Turrini. Agent based systems: Auctions, 2018.

[2] Alex Vlachos. Performance based adaptive quality - advanced vr rendering, 2016.

[3] Kevin Leyton-Brown Yoav Shoham. *Multi-Agent Systems: Logical, Algorithmic and Game Theoretic foundations*. Cambridge University Press, 2009.