Evolving Bidding Strategies for Multiple Auctions

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Abstract. Due to the proliferation of online auctions, there is an increasing need to monitor and bid in multiple auctions in order to procure the best deal for the desired good. Against this background, this paper reports on the development of a heuristic decision making framework that an autonomous agent can exploit to tackle the problem of bidding across multiple auctions with varying protocols (including English, Dutch and Vickrey). The framework is flexible, configurable and enables the agent to adopt varying tactics and strategies that attempt to ensure the desired item is delivered in a manner consistent with the user's preferences. In this context, however, the best strategy for an agent to use is very much determined by the nature of the environment and by the user's preferences. Given this large space of possibilities, we employ a genetic algorithm to search (offline) for effective strategies in common classes of environment. The strategies that emerge from this evolution are then codified into the agent's reasoning behaviour so that it can select the most appropriate strategy to employ in its prevailing circumstances.

1 INTRODUCTION

Online auctions are a popular and effective medium for procuring goods and services. However, as the number of auction sites increases (there are currently more than 2000 [1]), consumers are faced with the problem of monitoring many sites, picking which auction to participate in, and making the right bid to ensure that they get the desired item under conditions that are consistent with their preferences. These processes of monitoring, selecting and making bids are both complex and time consuming. The task becomes even more complex when there are different start and end times and when the auctions employ different protocols (e.g. English, Dutch, Vickrey). To assist consumers in this task, simple bidding robots and auction search engines have been developed. However, they typically have the problem of only automating part of the process, or only being able to operate at a single auction site, or only operating with a single auction protocol.

To address these shortcomings, it is necessary to develop an autonomous agent that can participate in multiple heterogeneous auctions, that is empowered with trading capabilities and that can make purchases autonomously. In more detail, the agent should monitor and collect information from the ongoing auctions, and determine what price it should bid in each auction. Given the complexity, dynamism and time-constrained nature of this environment, the most practical basis for the agent's decision-making model is a heuristic one. To this end, [2] reports on the development of such a decision-making framework. In this model, the agent's behaviour is expressed as a series of tactics and strategies that vary the agent's bidding behaviour according to the user's objectives and the prevailing auction context. The empirical evaluation of this model showed the benefits of being able to act across multiple auctions, but also highlighted the high degree of dependence between the efficacy of an agent's strategy and the environment it was operating in. Given this observation, the aim of this paper is to determine what strategies are effective in a range of common environments. To achieve this, we decided to use genetic algorithms (GAs) since they are a well-proven method of searching large problem spaces [8]. Thus, we evolve agent strategies in an offline fashion and codify the result of this process into a meta-level reasoner that can select the strategy according to the agent's assessment of its prevailing context.

The remainder of the paper is structured as follows. Section 2 presents an overview of the decision-making framework. Section 3 describes how GAs were used to evolve bidding strategies according to the target environment. Section 4 reports on the outcomes of this evolution process. Section 5 discusses related work and Section 6 presents our conclusions and further work.

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2 BIDDING STRATEGY FRAMEWORK

Before describing the decision-making framework, it is necessary to detail our assumptions about the environment. Firstly, we consider three auction protocols: English, Dutch and Vickrey (three of the most common types). Secondly, all auctions have a known start time and English and Vickrey auctions have a known end time. Thirdly, our bidding agent is given a deadline (t_{max}) by when it must obtain the desired item and it is told the consumer's private valuation (p_r) for this item. Fourthly, the agent must not buy more than one instance of the desired item.

The agent's decision-making model works in the following manner (see [2] for a complete description). The bidder agent builds an active auction list (auctions that have started but not reached their end times, denoted as $L(t)$) and gathers relevant information (e.g. start and end times, current bid values) about them. It then calculates the *current maximum bid* it is willing to make at the *current time*. This current maximum bid, by definition, will always be less than or equal to the private valuation. To determine the current maximum bid, the agent considers several *bidding constraints* including the remaining time left, the remaining auctions left, the user's desire for a bargain and the user's level of desperateness. For each such bidding constraint, there is a corresponding function that suggests the value to bid based on that constraint at that time. These (polynomial) functions (based on [6]) are parameterized by two key values: k (range [0..1]) is a constant that determines the value of the starting bid and β (range [0.005 - 1000]) defines the shape of the curve (and so the rate of concession to p_r). As an example, when $k \geq 0.5$ and $\beta \geq 1$, the agent demonstrates a reasonable degree of desperateness and starts bidding close to p_r and quickly reaches p_r. At the other extreme, the agent can demonstrate hard bargaining behaviour ($k < 0.5$ and

$\beta < 1$), where it makes a low initial bid and only concedes up to p_r in a very slow fashion. All behaviours in between are also possible by setting the parameters appropriately. At any given time, the agent may consider any of the bidding constraints individually or it may combine them depending on the situation (what the agent sees as being important at that point in time). If the agent combines multiple bidding constraints, it allocates a weight to each of them to denote their relative importance. The set of functions is referred to as the *tactics* and the combination of these tactics are referred to as the *strategy*. Based on the value of the current maximum bid, the agent selects the potential auctions in which it can bid and calculates what it should bid at this time in each such auction. The auction and corresponding bid with the highest expected utility is then selected from the potential auctions as the target auction. Finally, the agent bids in the target auction.

A series of experiments were conducted in a controlled environment to test the efficiency (in terms of success rate and average payoff) of the agent's strategy (details can be found in [2]). The results of these experiments led to several conclusions. Firstly, p_r is one of the most important factors that needs to be considered when determining the strategy that should be employed by the agent. This is important, for example, since an agent with a very low p_r cannot practically look for a bargain and the agent should therefore consider this when accepting the user's preferences. The second observation is that the remaining time and auction tactics are the key determinants of successful behaviour. Thirdly, the strategies to be used by the agent need to be dynamic, since not all strategies work well in all situations. Thus, a successful strategy in one situation may perform badly in another. Nevertheless, it is possible to determine that certain classes of strategy are effective in environments that have particular characteristics. In this case, the key defining characteristics of an environment were found to be the number of auctions that are active before t_{max} and the time the agent has to purchase the item. Given this, it was decided to evolve strategies that are effective in these classes of environment.

3 EVOLVING STRATEGIES

The performance of the bidding agent is heavily influenced by the strategy employed, which, in turn, relates to the values of k and β in the given tactics and the weights for each tactic when these are combined. The number of strategies that can be employed is infinite, so, therefore, is the search space. Thus, handcrafting strategies as in [2], is not realistic in the long term. Thus, a means of automating the process of finding successful strategies is necessary. Here, we decided to use GAs to search offline for the most successful strategies in the predefined environments. Taking account of the above experimental observations, we defined four such environments. The first one (STLA) is where there is a short bidding time ($10 \leq t_{max} \leq 20$) and a small number of active auctions in the marketplace ($|L(t)| \leq 10$). The second environment (STMA) is where there is a short bidding time but the number of active auctions is large ($10 \leq |L(t)| \leq 45$). The third environment (LTLA) is where the allocated bidding time is long ($20 \leq t_{max} \leq 100$) and where the number of active auctions is small. Finally, the last environment (LTMA) is where there is a long bidding time with many active auctions. Naturally, finer subdivisions are possible but the focus here is in demonstrating that strategies can be successfully evolved for broad classes of environment. Evolving for these subcategories is left as future work at this point.

3.1 Encoding the Strategies

The individuals in the populations are the bidding agents and their genes consist of the parameters of the four different tactics and the relative weight for each tactic. The individuals are represented as an array of floating points values of:

- k and β for the remaining time left tactic (rt)
- k and β for the remaining auctions left tactic (ra)
- k and β for the desire for a bargain tactic (ba)
- k and β for the desperateness tactic (de)
- the relative weights for the four tactics ($w_{rt}, w_{ra}, w_{ba}, w_{de}$)

3.2 Computing the Fitness Function

The fitness function measures how well the individual performs against the others. Designing the fitness function is one of the key facets of GAs and so here we consider three plausible alternatives. These are the individual's success rate in obtaining the item (Fitness Equation I) and two variations based on the average utility. In the first case (Fitness Equation II), the agent gets a utility of 0 if it fails to obtain the item. If it is successful, the utility (U) of winning in an auction i with bid v is computed as $U_i(v) = ((p_r - v)/p_r) + c$, where c is an arbitrary constant ranging from 0.001 to 0.005 (these values were picked by empirical evaluation) to ensure that the agent does not get a utility of 0 when the winning bid is equivalent to the private valuation. The second utility function (Fitness Equation III) is similar to Fitness Equation II but the individual is penalised if it fails to get the item. In this case, the penalty incurred ranges from 0.001 to 0.005. These values were chosen to analyse how the population evolves with varying degrees of penalty. Intuitively, Fitness Equation I should be used if delivery of the item is of utmost important, Fitness Equation II should be used if the agent is looking for a bargain and Fitness Equation III should be used when delivery of the item and looking for bargain are equally important. The fitness score is then computed by taking the average utility from a total of 2000 runs. It is necessary to run these 2000 times to decrease the estimated standard error of the mean to a statistically significant level (when the number of runs is 500, the standard error of the mean is 5.0458, but this figure is reduced to 1.1559 when the number of runs is increased to 2000).

```
Randomly create initial bidder populations;
While not (Stopping Criterion) do
    Calculate fitness of each individual by running the
      marketplace 2000 times;
    Create new population
        Select the fittest individuals (HP);
        Create mating pool for the remaining
          population;
        Perform crossover and mutation in the
          mating pool to create new generation(SF);
        New generation is HP + SF;
End while
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Figure 1. The Search for Strategy Algorithm

3.3 Searching for Successful Strategies

The algorithm for searching for acceptable strategies in a given environment is shown in Figure 1 and is elaborated upon in the remainder of this subsection.

3.3.1 *Create Initial Bidder Population*

The initial bidder populations represent the starting point of the search and consist of $N = 50$ individuals that are generated randomly from the range of specified values. These values are based on the polynomial functions defined in [2]. For the remaining time and the remaining auctions left tactics, the values are $0 \leq k \leq 1$ and $0.005 \leq \beta \leq 1000$. In the desire for a bargain tactic, the values are $0.1 \leq k \leq 0.3$ and $0.005 \leq \beta \leq 0.5$. The values for k and β in the desperateness tactic are $0.7 \leq k \leq 0.9$ and $1.67 \leq \beta \leq 1000$.

3.3.2 *The Selection Process*

The purpose of the selection process is to ensure that the fitter individuals are chosen to populate the next generation in the hope that their offspring will in turn have higher fitness. "Elitism" is used here to force the GAs to retain some number of the best individuals at each generation [8], since such individuals can be lost if they are not chosen to reproduce or if they are destroyed by crossover and mutation. Ten percent of the best individuals are copied to the new population to ensure that a significant proportion of the fitter individuals make it to the next generation. The remaining ninety percent of the individuals in the population are then selected using Tournament Selection [4]. The selection is performed by choosing some number ψ (here 2) from the population and the best individual in this group is copied into the intermediate population (which is referred to as the mating pool). This process is repeated for 90% of N times. This selection technique is known to work well since it allows a diverse range of fit agents to populate the mating pool [4]. Once the mating pool is created, the individual with the highest fitness is selected and moved to the new generation. The remaining individuals go through the process of crossover and mutation before making it to the new population. The new population includes a group of the fittest individual and the offspring generated from the reproduction process.

3.3.3 *The Crossover Process*

This process exchanges the genes between the individual agents. Two individuals are randomly selected from the mating pool with crossover probability of $p_c = 0.6$, and the crossover point (c) is equal to 2. Crossover probability is the rate at which the population exchanges genetic materials [8]. More specifically, two individuals are picked from the population. Two crossover points are then randomly picked. These points are where the two individuals will exchange their genetic material. The exchanging of genetic material process is performed using an *extension combination operator* [3], which works by taking the difference between two values of the crossover point, adding this difference to the higher (giving the maximum range) and subtracting it from the lower (giving a minimum range). The new values are then generated between the minimum and maximum range.

3.3.4 *The Mutation Proces*

Mutation allows the population to explore the search space but at a slower rate. In this work, the individuals from the population are selected to mutate with a probability of $p_m = 0.02$. The gene from the chosen individual is picked randomly and a small value (0.05) is added or subtracted, depending on the range limitation for that particular gene. The mutation process is only applied to the values of k and β for each tactic. The weights are not considered here because adding a small value to the weight requires a renormalisation and will have very little effect on the agent's overall behaviour.

3.3.5 *The Stopping Criterion*

The process terminates when the population converges. This is the condition where the population evolves over successive generations such that the fitness of the best and the average individual in each generation increase toward a global optimum [8] (here defined as the highest peak in the search space [8]). In this case, the population always converges before 50 iterations (typically between 24 and 40).

4 EXPERIMENTAL EVALUATION

The aim of these experiments is to determine which strategies are effective in particular environments. The GAs are run in the four different environments (in which the agent's p_r is set to 75). For each environment, we use the three different fitness functions described in Section 3.2. Apart from determining the strategies that work well in a given context, these experiments also aim to evaluate the strategies in terms of their success rate (the number of times, as a percentage, the agent is successful in obtaining the item) and average payoff (in terms of utility) in a similar manner to [2]. However, the key difference is that, here, the performance of the agents is evaluated based on an environment that has a particular set of characteristics. The performance of the evolved strategies is then compared with that of a control model C. C's strategy is to bid in the auction that has the closest end time where the current bid is less than its p_r. This model was chosen because it performed well in the experiments reported in [2]. We also ran another set of experiments in the sub-environment of short time less auctions in which the value of p_r is varied between a low value of 68, a medium of 76 and a high value of 82. The purpose of this is to determine how the strategies evolve when varying p_r.

Turning to the first set of experiments (summarized in Table 1). These results show the best strategies that have evolved for the different classes of environment. Each column contains the resulting strategies for each environment using Fitness Equations I, II and III. The values for the tactics are expressed as a pair of k and β and the weights for the bidding constraints are expressed as $(w_{rt}, w_{ra}, w_{ba}, w_{de})$. When a particular tactic is not present in the evolved strategy, the column corresponding to it is blank. The utilisation of the different fitness functions reflects the varying behaviour that the agent can employ in a given situation. It can be observed that the agents that utilise Fitness Function I (where delivery is of utmost important) did indeed score a higher percentage in terms of success rate than the agents that used the other two fitness functions and the control model C, for all the environments. Agents that used Fitness Equation II achieved the highest utility in all the environments, whereas agents that used Fitness Equation III strike a balance between a high success rate and a high payoff. These results are all as expected (see Section 3.2).

In the STLA environment based on Fitness Equation I, the dominant strategy that emerged is the combination of remaining time and the desperateness tactics ($w_{rt} = 0.76, w_{de} = 0.24$). In this particular situation, the agent's initial bids in both tactics are high and the agent quickly reaches its p_r ($k_{rt} = 0.73, \beta_{rt} = 99.59, k_{de} =$

Table 1. Summary of Best Strategies with Private Valuation = 75

	Short Time Less Auctions (STLA)	Short Time Many Auctions (STMA)	Long Time Less Auctions (LTLA)	Long Time Many Auctions (LTMA)
Fitness Equation I				
Remaining Time Tactic	(0.73, 99.59)	(0.63, 515.67)	–	(0.23, 683.97)
Remaining Auctions Left Tactic	–	–	(1.00, 0.36)	–
Desire for Bargain Tactic	–	(0.28, 0.31)	–	–
Desperateness Tactic	(0.84, 56.04)	(0.73, 385.75)	(0.83, 67.38)	(0.78, 2.70)
Weights (w_{rt}, w_{ra}, w_{ba}, w_{de})	(0.76, 0.00, 0.00, 0.24)	(0.45, 0.00, 0.01, 0.54)	(0.00, 0.46, 0.00, 0.54)	(0.83, 0.00, 0.00, 0.17)
Success Rate, Payoff	**(77.90, 0.03818)**	**(96.55, 0.04893)**	**(81.95, 0.02621)**	**(99.70, 0.03688)**
Fitness Equation II				
Remaining Time Tactic	(0.89, 1.44)	(10.59, 507.92	(0.70, 8.28)	(0.81, 9.74)
Remaining Auctions Left Tactic	(0.94, 233.50)	(0.81, 6.31)	(0.40, 5.21)	(1.00, 0.83)
Desire for Bargain Tactic	(0.15, 0.40)	(0.23, 0.06	(0.25, 0.32)	(0.23, 0.04)
Desperateness Tactic	(0.71, 55.44)	(0.80, 68.07)	(0.83, 648.90)	(0.82, 575.00)
Weights (w_{rt}, w_{ra}, w_{ba}, w_{de})	(0.35, 0.16, 0.15, 0.34)	(0.17, 0.03, 0.25, 0.55	(0.65, 0.21, 0.02, 0.12)	(0.14, 0.49, 0.22, 0.15)
Success Rate, Payoff	**(62.30, 0.03930)**	**(86.20, 0.06842**	**(67.65, 0.03818)**	**(90.4, 0.07249)**
Fitness Equation III				
Remaining Time Tactic	–	(0.83, 52.00)	(0.41, 720.61)	(0.59, 0.33)
Remaining Auctions Left Tactic	(0.72, 25.56)	–	(0.27, 7.95)	(0.21, 654.55)
Desire for Bargain Tactic	–	(0.10, 0.29	–	(0.12, 0.03)
Desperateness Tactic	(0.87, 55.75)	–	(0.71, 9.12)	(0.89, 19.17)
Weights (w_{rt}, w_{ra}, w_{ba}, w_{de})	(0.00, 0.42, 0.00, 0.58)	(0.80, 0.00, 0.20, 0.00)	(0.57, 0.19, 0.00, 0.24)	(0.16, 0.05, 0.01, 0.78)
Success Rate, Payoff	**(74.05, 0.03730)**	**(88.95, 0.06666)**	**(76.55, 0.03519)**	**(92.30, 0.7097)**
Performance of Control Model	**(66.40, 0.026291)**	**(83.80, 0.03342)**	**(74.40, 0.02460)**	**(99.10,0.02865)**

$0.84, \beta_{de} = 56.04$). This behaviour is rational since an agent that is interested in delivering the item successfully in this context should bid aggressively from the beginning to maximise its chances of acquiring the item. When Fitness Equation II is used, the dominant strategy that emerged is one that utilises all the tactics, but that places more importance on the remaining time and desperateness tactics. This is because an agent that is looking for a high payoff should consider the bargain tactic as one of the tactics to ensure a higher payoff. The strategy that emerged based on Fitness Equation III is one that considers the remaining auctions left and the deperateness tactics where the agent's initial bids are high and quickly reach p_r. This strategy is similar to the one that emerged from Fitness Equation I, but the rate at which it reaches p_r is slower. The reason for this is that an agent that is looking to maximise the payoff, whilst ensuring delivery of the item, needs to maintain a balance between a low bid price and the rate at which it reaches p_r.

In the STMA environment, an effective strategy should consider the remaining time and desperateness tactic highly since the allocated bidding time is limited (as per STLA). This is true when delivery of the item is important (as reflected in Fitness Equation I's result), but also when payoff (refer to the result of Fitness Equation II) is the main consideration (here the agent combines all the tactics where heavier weights are placed on the desperateness and bargain tactics). This situation differs from STLA because here, the agent can afford to spend some time looking for a bargain since the number of active auctions is large. The dominant strategy that emerged based on Fitness Equation III is surprising because it combines the remaining time and the bargain tactics, instead of deploying a more aggressive behaviour of combining the remaining time, desperateness and the bargain tactics. In this case, the strategy is aware of the large number of active auctions so it tries to get a higher payoff, but at the same time it takes into account the length of time it has left to bid.

The strategy that evolved for the LTLA environment based on delivery is one that considers the remaining auctions and the desperateness tactics. This is because the strategy has to deliver the item successfully in an environment where there is a limited number of active auctions that the agent can participate in. As expected, when payoff is the main consideration, the strategy that evolved considers all tactics. The strategy that emerged based on Fitness Equation III considers the remaining time, remaining auctions and desperateness tactics. Bargain is not considered here, since the number of active auctions in the marketplace is small (as per STLA).

All the strategies that evolved in the LTMA environment, for all fitness functions, achieved more than 90% success rate, but they differ in terms of payoff. The reason for this high success is due to the long bidding time, as well as the large number of active auctions that the agents can participate in. Hence, the agent has many chances of winning. In this particular situation, the main consideration is the payoff. As can be seen, the strategies that utilise Fitness Equations II and III generate higher payoffs when compared to the strategy that evolved based on Fitness Equation I and the control model C. The reason for this is that both C and Fitness Equation I consider delivery as the most important criteria and payoff is not taken into account.

Turning now to the second class of experiments. Table 2 shows the strategies that evolve in the STLA environment based on Fitness Equation III. Fitness Equation III is used here since it offers a reasonably high success rate and payoff. For each agent's private valuation, there are three rows associated with it which correspond to the weights, tactics and its performance. As can be seen, the success rate and the payoff increase when p_r increases (as seen before). The high payoff that the agent receives when using the strategy evolved with p_r=82 indicates that the agent actively tries to look for bargain when its p_r is high (even though it does not have much time or many auctions). In contrast, when p_r is low, the agent evolves a strategy that combines the remaining time and desperateness tactic to take advantage of the limited time, limited number of active auctions and limited p_r. The strategy that emerged with $p_r = 76$ is similar to the one that evolved with $p_r = 68$, but, this time, it considers the remaining auctions left instead of the remaining time. With a higher private valuation, the agent has better chance of obtaining the item enabling it to switch to a strategy that focuses on the desperateness tactic and the remaining auctions left tactic. When p_r is high, the strategy that emerged considers all tactics as expected.

Table 2. Strategies for STLA with Varying Private Valuations

Reservation Price	Weights, Tactics and Performance
	(w_{rt}, w_{ra}, w_{ba}, w_{de})
	(k_{rt}, β_{rt}, k_{ra}, β_{ra}, k_{ba}, β_{ba}, k_{de}, β_{de})
	(success rate, utility)
68	(0.12, 0.00, 0.00, 0.88)
	(0.64, 5.44,0.57, 79.37,0.11, 0.15,0.75,466.24)
	(23.55, 0.00886)
76	(0.00, 0.17, 0.00, 0.83)
	(0.05,0.99, 0.58,508.59, 0.23,0.08, 0.90,86.53)
	(81.45, 0.04188)
82	(0.36, 0.35, 0.18, 0.11)
	(0.07,97.11, 0.06,12.37, 0.17,0.46, 0.75,4.74)
	(93.45, 0.09267)

Several conclusions can be drawn from these results. When selecting a strategy to bid in the multiple auctions environment, the agent needs to determine the current environment's type, as well as the user's preferences. Depending on these two, it can then decide which strategy to deploy. The results presented in Table 2 show that as the private valuation increases, the success rate increases, therefore allowing the strategy to deploy a bargaining behaviour to generate a higher payoff.

5 RELATED WORK

There have been several attempts to design sophisticated and efficient bidding strategies for agents participating in online auctions. The Recursive Modeling Method (RMM) uses a decision theoretic paradigm of rationality, where an agent makes decisions based on what it thinks the other agents are likely to do, what the other agents think about it and so on [10]. The downside of this approach is the computational complexity and the fact that not all the information in the recursive model is relevant in this context. Faratin et al's model is broadly similar to the one defined in this paper [6]. However, there are also several important differences between one-to-one negotiation and multiple auctions. Chief amongst these are the types of the tactics that are considered relevant and what aspects of the domain need to be reflected in these tactics. An extension to Faratin's model is [7] which analyses the evolution of negotiation strategies using GAs, and determines which of them are appropriate in which situations. The aim of this work was to perform an evaluation of the range of negotiation strategies by analysing their relative success, and how these strategies evolve over time to become a fitter population. This approach is somewhat similar to our work, but the main difference is in the domain that we are dealing with.

Preist proposed an algorithm design for agents that participate in multiple simultaneous English auctions [9]. The algorithm proposes a coordination mechanism to be used in an environment where all the auctions terminate simultaneously, and a learning method to tackle auctions that terminate at different times. Byde also considers this environment [5], but utilises stochastic dynamic programming to derive formal methods for optimal algorithm specification that can be used by an agent when participating in simultaneous auctions for a single private-value good. Both of these works are designed specifically for purchasing items in multiple English auctions and their algorithm are not applicable in a heterogeneous protocol context.

6 CONCLUSIONS AND FUTURE WORK

This paper has shown how GAs can be successfully employed to evolve effective bidding strategies for particular classes of environment. Its contribution to the state of the art is twofold. Firstly, we showed that GAs can be used to successfully evolve bidding strategies for different auction contexts. Secondly, we discovered effective reasoning strategies for the multiple, heterogeneous auctions context. By embedding these strategies into our agent, we now have an agent that can perform successfully across a wide range of auctions. For the future, we aim to finesse the categories of environment for which strategies need to be evolved so that the agent can better tune its bidding strategy to its prevailing circumstances. Also, we aim to extend our evaluation to cases where there are multiple such agents in the environment and to determine the effect of such a situation on the performance of the individual agents and the overall system.

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