Automatic Negotiation using LCS-based Multi-Agent Systems

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ABSTRACT

Most of the time when someone wants to bargain over some good, service, or to negotiate over delicate matter, has a clear idea of what is wanted and not wanted as the negotiation outcome. There are deals that are totally unacceptable, some others that could be acceptable under some circumstances, and others that would be totally acceptable. Some times the most difficult part of a negotiation, is to ground the characteristics one wants as outcome.

The system presented in this paper extracts the information that the user is expecting to get, by stating the characteristics, quantity and preference of each characteristic. Upon the preferences, a game is designed so a rational set of agents can solve the problem replacing the humans.

A multi-agent system model that learns using learning classifier systems is shown to find negotiation solutions based on user preferences.

1. INTRODUCTION

Rationality is a characteristic that human beings lack when taking decisions [4]. Most of the time, very important things in a negotiation are at stake in order to leave them to the human irrational process of decision making. The aim of the work presented here is to extract the information that the user is expecting to get, by stating the characteristics, quantity and preference of each characteristic. Upon the preferences, a game is designed so a rational set of agents can solve the problem replacing the humans. It is well known that the extended classifier system (XCS) [13][2] can be used for multi-agent learning in games [7][6][9] and has been tested already in the "El Farol" Problem and the Minority Game [3][1]. This paper introduces a model based on a multi-agent system that learns using the extended classifier system (MAXCS)[6][7][5][9][8] which is able to solve a simple negotiation game: two parties bargaining for the best price. Learning classiffier systems, specially the Michigan-style have come to the spotlight in recent years to the multi-agent system simulation paradigm [6][7][5][9][8]. The versatility of representing each individual as a learning classifier system (LCS) and analyzing the dynamics of the population evolution are key aspects for using LCSs in simulation. Emergent behavior and adaptation have been observed when using MAXCS [6][7][5][9][8], even though these results were obtained for single step problems and at most 500 agents, it is expected that XCS that should be able to perform well in a multi-step environment. The rest of the paper is structured as follows: first, the automatic negotiation system is explained, then the test framework is presented, finally the results are presented and the conclusions and future work close the paper.

2. AUTOMATIC NEGOTIATION SYSTEM

Most of the time when someone wants to bargain over some good, service, or to negotiate over delicate matter, has a clear idea of what is wanted and not wanted as the negotiation outcome. There are deals that are totally unacceptable, some others that could be acceptable under some circumstances, and others that would be totally acceptable. However, you might ask yourself: "How can I achieve the deal I want?".

Some times the most difficult part of a negotiation, is to ground the characteristics one wants as outcome. For example: imagine you wanted to negotiate your work position. your work position. First of all there should be some minimum salary you expect, the maximum working hours, benefits or insurance or both. May be, the human resources department of the company that wants to hire you has other benefits or insurance or compensation features for your job that you never imagined. Due to these vast number of options and features to negotiate the solution space could be huge, specially if the characteristics have ranges, and the values aredistributed evenly on the range. During the design of the system, two ma jor points were found : *(i)* the user must be provided with the means to determine the characteristics that compose the key negotiation point; *(ii)* there must be a way to narrow down all the possible combinations that the categorization of the negotiation might yield. To solve the first issue, Ishikawas cause and effect diagram is used [10], in a very subtle way so the user never notices it. The use is as follows: the users input in the GUI the main negotiation topic, then they have to stablish the number of subcategories in which the negotiation will be divided. After structuring mentally the negotiation, the users must assign the features to the characteristics they have found useful to negotiate. Then, they must assign a priority to that characteristic, over the others (real numbers ranging between 0 and 1, but their sum is not always 1). For the second issue, there are two ways that are being currently tested: *(i)* the characteristics (with their priority and values) are used to develop an utility function of which the agents try to find the optimum according to their interests; *(ii)* using the Nash emergent equilibrium algorithm proposed by Rubinstein et al. [11] the characteristics for the negotiation are taken out of the preferences and then, the negotiation takes place. The GUI is used for the feature extraction in both cases find and the results are arranged in an XML which is then processed for either, generating the utility function or determining the emergent equilibrium negotiation.

3. TEST FRAMEWORK

Due to the complexity of the search space when contemplating several features and their ranges, the multi-agent system is tested with a simple negotiation (bargaining the price of a good), represented as a repeated game (Fig. 1). The game is stated as follows: there is a seller and a buyer; both of them have a certain expected profit value; the seller wants to get some margin between the price of the sale and the actual price of the goods (P_s), but will try to get the maximum out of the buyer. On the other hand, the buyer will try to get the cheaper price and have a margin between his very last price and all the money that possesses (P_b). Then, a reward (R) is assigned , depending on the number of times that the agents bargain. The game dynamic is in cycles: the buyer offers a price, then the seller either accepts or proposes a new price. This cycle is repeated 3 times, until the reward is 0 for both agents. Every time either of the agents proposes a price, the reward is multiplied by a discount factor (δ) of 0.1 (see Fig. 1).

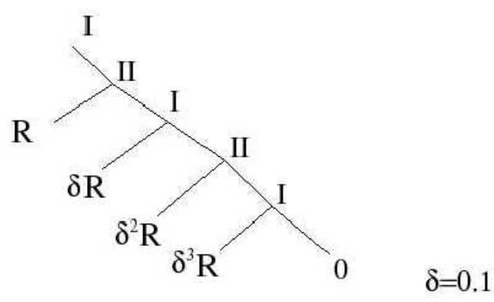

Figure 1: The bargaining game in which the agents must get the correct price at the first step to get the maximum reward. "I" is the buyer, and "II" is the seller

Because the XCS and in general reinforcement learning(RL) systems are based on the payoff, the design of the game stimulates an agreement on the first round. The classifier conditions are fully general, i.e. all # symbols, because there is no need to compare previous attempts, the only answer needed is the agreed price.

4. EXPERIMENTAL RESULTS

Each experiment consists of 210 games, i.e. sells, 100 games with a 0.5 exploration/exploitation regime, 100 with a simulated annealing decrease of the exploration rate and then 10 games are played in order to evaluate the multi-agent system, these final games are run in full exploitation mode (based on the experience obtained with MAXCS, this exploration regime seems to be effective [6][7][5][9][8]).

There are two types of games in which the system was tested with: the first kind of game is done with one seller and one buyer, the second one, with two buyers, therefore, the seller must adjust its strategies according to the buyer which he is dealing with. The game dynamics for the second game are quite similar to Fig. 1, the main difference is that instead of having a "II" agent, there are agents "II, III" for each turn of the game of agent "II" in Fig. 1.

The results are an average of 100 runs. The following parameters are used for XCS to run: # probability =0.333, explore/exploit rate =0.5, crossover rate(χ)=0.8, mutation rate(μ) =0.02, θ_{GA} =25, minimum error(ϵ_0)=0.01 and learning rate (β) =0.2.

5. RESULTS

For the first set of experiments, i.e. a single buyer, the system is run for 100 experiments. As Fig. 2 shows, the system converges to a satisfactory price negotiation for every experiment. Several ranges of overlapping values were tested, and for all of them the agents agree on a price. The agreement convergence is faster for larger value overlaps. For example, it is more difficult for the multi-agent system to converge when the seller has a [20, 35] interval and the buyer [10, 25], i.e. an overlap of 5 values for agreement (from 20 to 25); than the convergence for seller [10,35] and buyer [5, 25], i.e. 15 possible agreement values. For this experiment, only the actions are taken and the condition side of the classifiers are set to fully general.

For the first game the system converges very fast, as seen in Fig. 2. That is the reason for the design of the second game: to test the adaptivity of the agents to this new situation.

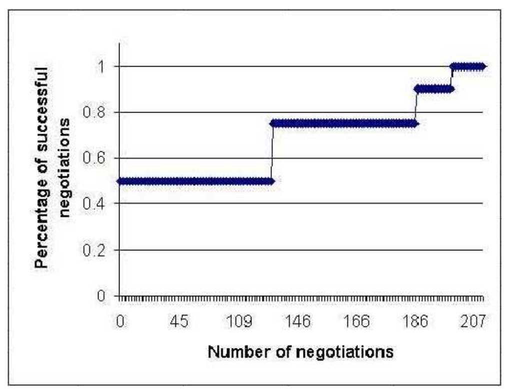

Figure 2: Bargaining results for one seller and one buyer. From step 200 to 210 are executed without exploration.

There must be an interval in which both buyers and the seller have common prices, otherwise it is impossible to reach an agreement, therefore the agents will never receive a reward greater than 0.

For the second set of experiments, i.e. two buyers, the seller has to associate the prices offered to each of the buyers. In this case, the conditions contain the number of the seller, but there is no restricted mating according to the conditions. Any classifier is allowed to exchange genetic information with any other. Restricted mating has not been tested, but it is not necessary due to the implicit niching of the application of the genetic algorithm in the action set. The second experiment sets a scenario where two people are buying the same product in a market, where prices can be bargained. That one who is better at bargaining will get a better price, based on the minimum price expected by the seller.

5.1 One buyer, one seller

As depicted in Fig. 2, the system adapts to all the problems tested, regardless the overlap size of the intervals. The adaptation happens before the fully exploitation games are run (i.e. before step 200). It has been observed in the agents' populations that there is a predominant classifier (or at most four) which fires its action all the time and has very high prediction and fitness values. This classifier (or set of classifiers) are the same in both agents.

The convergence after this classifier wins the action selection process makes the prediction value so high after few activations, that it wins from then on. In the case of many classifiers in both agents which satisfy the selling interval.

5.2 Two buyers, one seller

The agents adapt for all the experiments. To do this,the agents have been able to evolve the strategies needed to achieve an agreement at the first negotiation. XCS has not been tested before in multi-agent systems with multi-step environments, therefore it is very important to check if the single-step results also are valid for a multi-step environment.

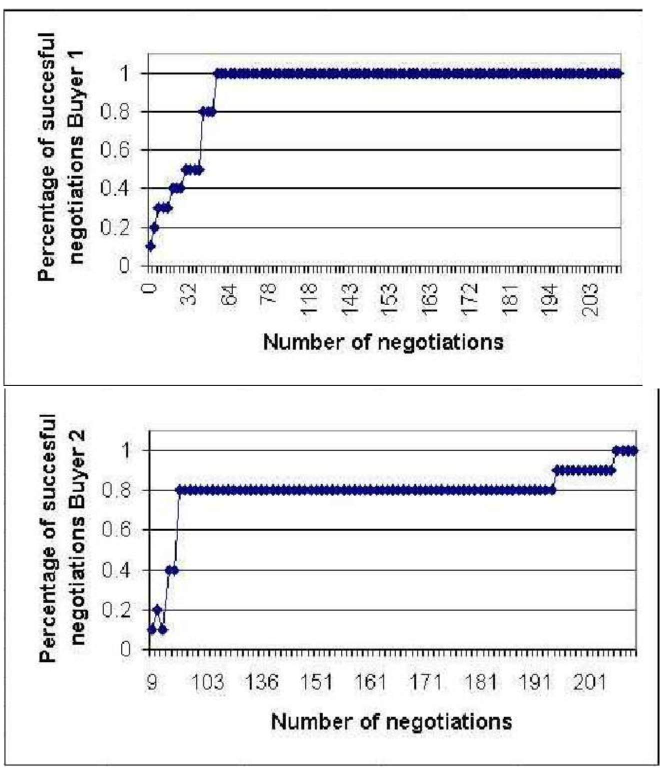

Figure 3: Bargaining results for one seller and two buyers. From step 200 to 210 are executed without exploration.

6. DISCUSSION

XCS has not been tested before in multi-agent systems in multi-step environments, therefore the experiments reported in this paper are important to show that MAXCS is also suitable for multi-step environments.

The discussion focuses in the experiments with two buyers and one seller. There are several distinctive features of the seller's behavior, when looking at the different prices that it bargains with both sellers. The stagnation of performance at 80% of successful negotiations for a longer period with the buyer 2 than with the buyer 1 has been observed throughout all the different experiments. The only conclusions that can be drawn from population analysis are that, despite using different seeds for the population initialization, the population tends to evolve toward the satisfaction of the bigger interval. In the case of the experiments reported here, the bigger interval is that between the buyer 1 and the seller. The key point is that the classifiers that post their action tend to get more reward due to the larger interval where the prices concur. Furthermore, it should not be overlooked that the successful negotiation is registered when both agents arrive to exactly the same price, i.e. if the seller offers 15, any of the buyers should also offer 15 in order to consider the negotiation as successful.

Therefore, reproduction biases the number of rules toward the bigger interval, because when there is a narrow interval, it is more difficult for the agents to agree on a price. It becomes like a needle in a haystack problem, where the needle is the interval which seller and buyer have in common.

Another interesting point is that both buyers start having successful negotiations toward the end of the exploration period (step 100). Results were very similar when increasing the exploration/exploitation period to 150 steps with a 0.5 exploration probability. More experiments are planned with shorter exploration/exploitation periods, in order to test the influence this factor.

7. CONCLUSIONS AND FUTURE WORK

The interval overlap is a key factor for a successful negotiation: the wider the overlap, the easier to achieve the negotiation successfully. It is interesting that MAXCS has been able to adapt to a multi-step environment. The use of XCS was helpful providing the population analysis.

The successful application of MAXCS to multi-step is encouraging and further experiments are planned.

One of these experiments includes the use of XCS with integer intervals and also real values [12]. This is thought to help to determine the XCS the different intervals.

Ideally, it would have been interesting to test XCS on the NKC landscape problems, as they are more complex than the problem tested here. However, this experiment was not possible, due to the hurry to get a prototype running. Skipping the theoretical test on the NKC landscapes is not so harmful for the current project. If XCS had not been able to adapt, then all the negotiations would have failed, therefore, there was no need for prior testing. Undoubtedly, it will be very interesting to test XCS in the NKC landscapes.

More experiments are planned with more than three agents and different negotiation environments.

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