COMP6203: Intelligent Agents

(Group 46) Negotiation Agent Report

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Abstract

1 Introduction

Negotiation is a method of reaching a mutually beneficial agreement between mulitple, autonomous agents, in the presence of conflicting interests.
The problem to solve is creating a group agent (Agent46) that can successfully compete with other other self-interested agents and negotiate the best outcome possible given its own set of individual, weighted issues. To achieve this, the development of Agent46 will be inspired by previous winners, or top-performing agents, from the Automated Negotiating Agents Competition (ANAC) and built using the GENIUS Java framework which also defines the strict environment and protocols for the negotiation domain.
The success of every agent in the tournament is determined by a overall score calculated using the formula:

$$(1 - Distance) \times Utility \times \frac{Agreements}{Negotiations}$$

The best negotiating agents must therefore attempt to satisfy three objectives:

1. Minimise the distance between the final bid made by the agent and the Nash Point of the agreement space calculated between the agent and the opponent. (*Distance*)
2. Maximise the final utility of the agreed bid for the negotiation agent (*Utility*)
3. Maximise the chance of an agreement for each and every negotiation the agent takes part in. (*Agreements*)

The rest of this report documents the implementation of Agent46 and evaluating its attempt to meet these goals.

2 Implementation

The larger functionality of the agent is built from four main modules.

2.1 The Opponent Model

The first major challenge that will be faced by the agent, is the difficulty of having no knowledge of the opponent's own weighted preferences nor its negotiating strategy. The agent therefore utilises an opponent model to combat this uncertainty and improve the likelihood of pareto efficient agreements before the deadline expires.
The opponent model used by the agent is based largely on the opponent model used by the 'Johnny Black' agent that came third in the 2015 ANAC competition (*Yucel, Hoffman, Sen. 2017*). This technique is designed to accurately model the preferences of an opponent based on two assumptions:

1. Outcomes weighted highly by the opponent are more likely to be offered by the opponent.
2. The values of important issues to the opponent, within its bids, are unlikely to change much compared to less important issues the opponent would prefer to concede on.

The first assumption will be achieved by estimating the preference order of issues held by the opponent, calculated by counting the number of times the same issue is offered by the opponent using the following equation (*Yucel et al. 2017*):

$$V_0 = \frac{k - n_0 + 1}{k}$$

The most frequent option and, consequently, the most preferred option of the opponent, will have a value of k. The least preferred option will have a value of $\frac{1}{k}$.
The second assumption is fulfilled by working out the individual (un-normalized) weights of the opponent's issues using a Gini-impirity Score (*Yucel et al., 2017*):

$$\hat{w}_i = \sum_{o \in O_i} \frac{{f_o}^2}{t^2}$$

before normalising each of these weights by dividing each of them by the total sum of the un-normalized weights for every issue for the opponent.

$$w_i = \frac{\hat{w}_i}{\sum_{j \in I} \hat{w}_j}$$

The opponent model is dynamic and will be constantly updated and improved for every new bid sent by the opponent which will provide a better representation of the opponent's preference profile the longer the negotiation session lasts. Compared to other methods that learn from Bayesian inference or non-linear regression, this opponent model is simpler to implement and maintain, at the cost of a potentially less reliable estimation of the opponent's real preferences.

The opponent model is designed to accurately reflect the weighted issues of the opponent as best it can in order to make offers with a high chance of being accepted and achieving performance objectives (1) and (3).

2.2 Negotiating Strategy

The tournament will consist of many, separate bilateral negotiations following a Stacked Alternating Offers Protocol in which each agent in turn can decide to accept their opponents offer, make a counter offer or break off negotiations altogether and receive a utility of zero. Both agent are also pressured to complete the negotiation within a time limit of 90 seconds. After this period, the agents receive nothing unless an agreement is reached.
Agent46 does not follow a single negotiation strategy but follows three different strategies depending on the amount of time that has elapsed, t, since the start of the session. This is done to increase the robustness and resilience of the agent when placed in competition with a variery of adversaries. Since the negotiating stratergies of other agents within the tournament ar unknown, it was important that Agent46 was flexible to all kinds of opponent. This approach was inspired by the 'Gahboninho Strategy' and provides the best possible chance of the agent negotiating a high utility outcome regardless of the opponent or preference domain (*Ben Adar Bessos Mai., Sofy N., Elimelech A., 2013*).

2.2.1 Hardliner ($t \leq 45$)

The first of Agent46's three strategies is also its simpliest. Unlike the 'Johnny Black' agent, Agent46 chooses to act with the single, focused aim of maximising its own utility and not the social welfare of all other agents for the first half of the negotiation (*Yucel et al., 2017*). At this early stage, the agent prioritises objective (1) and offers random bids that guarantee itself a utility above an initial threshold of 0.85. During this first stage Agent46 makes no concessions at all. This first strategy was chosen for two main reasons.
Firstly, this hardheaded approach is extrememly effective against weak, time dependent strategies that are more likely to concede and more thus return a higher utility for the agent as a result (*Baarslag T., Fujita K., Gerding E. H., Hindriks K., Ito T., Jennings N. R., Jonker C. et al., 2013*). This approach also forces more adaptive opponents to eventually bend to its demands the longer the negotiation goes on.
Secondly, a hardliner strategy can tell us a lot about the type of opponent even if it fails at bullying this opponent into submission before the halfway point of the negotiation. Since a hardliner strategy is more likely to return a final utility of zero and break off negotiations with competitive opponents that are similar, the longer the negotiation lasts during this first stage, the more the agent is alerted to the fact that the opponent is likely to be just as selfish as itself. When $t = 45$, the agent should realise to change strategy. The purpose of this first stage is to exploit any weaker agents it faces quickly, while also giving it the opportunity to change tact if it makes more sense.

2.2.2 'Strong Nash Attack' ($45 < t \leq 75$)

The second strategy begins when $t > 45$. At this point the agent still refuses to compromise but begins to offer bids that are more likely to be accepted by the opponent by utilising its opponent model. The opponent model is already intialized at $t = 0$ and is improved on throughout the entire lifetime of the negotiation. When the agent enters into this second phase of the negotiation, it begins to compromise on objective (2) and offer more realistic bids to the opponent that continue to reward the agent with a high utility but that are also more likely to be accepted. The priority shifts to include objective (1) and focus on offering more pareto efficient bids, closer to the nash bargaining solution, when confronting an agent that is just as competitive.
The strengths of this second strategy are that agreements are now more likely than they were because Agent46 starts to predict what the opponents wants rather than simply offering randomly generated bids. The continuation of the hardliner strategy, from phase one, also enchances the performance of this opponent model from the start because it allows for the fast and constant communication of bids between both agents, which in turn, allows for a greater sampling of bids from the opponent that can be used to create a more faithful and accurate model of the opponent's actual values for each of its issues. This is important, as the closer the opponent model is as a representation of the opponent's real preference profile, the more likely that both agents can reach a deal that satisfies both of them (*Baarslag, T., Hindriks, K., Hendrikx, M., Dirkzwager, A., Jonker, C.,2014*).

2.2.3 'Weak Nash Attack' ($75 < t \leq 90$)

The final phase of Agent46's negotiating strategy occurs because the opponent has refused to compromise and time is running out to improve the opponent model much further.
In this scenario, Agent46 begins to prioritize an

agreement at any cost as the deadline approaches and the danger of ending up with no utility at all becomes more likely. The agent's behaviour suddenly becomes one of 'desperate concession' adapted from Agent Buyog - a finalist from the 2015 ANAC competition (*Sosale B., Satish S., An B., 2017*). As the value of t increases, the new minimum utility that Agent46 is prepared to accept is calculated using a small discount factor. The agent therefore favours objective (3) at any cost, even if it means agreeing to a much poorer utility for itself. At this point in the session, the agent must only ever be against a very strong oppoisition and must make concessions in order to perform well.
However, this minimum utility will never drop below the utility of the best bid offered by the opponent. The reasoning for this, is that an opponent will always accept a bid identical to one it has offered in the past if it is rational. Consequently, Agent46 would be irrational to offer any bid that awards itself with a utility less than this best opponent offer. The best offer made by the opponent, is constantly maintained throughout the entire negotiation and is the final insurance mechanism for Agent46 should all else fail.

2.3 Perference Uncertainty Model

There may be times that the agent has no exact knowledge about the utility of offers made by the opponent, only the ordinal information about these bids. This part of the agent attempts to ovecome this issue and derive a suitable utility function by experimenting with an orignal method baed upon the golden ratio.

Starting from the rear of the list, if there weren't too many issues, we could assume that the earlier a value changed, the smaller the weight of the value is among its issue because of the influence while changeing this issue is the slightest (contrast with the previous one). And subsequently we can get the ordered values lists to every issue by following this way, however, for most scenarios multiple issues will be changed one time, which is one of the biggest troubling points. We do not have a complete enough approach for covering this problem so far, and the strategy we currently use can be described as the pseudocode shown below.
The reason for involving the golden section is due to the idea that the ways of nature can be more smooth than other hidebound arrangement methods. Besides the way we speculate the Inner weights, the outer weights are arranged averagely in our strategy. Because although there are many approaches which guess the outer weights by calculating the repetition frequency and the changing regularity of specific values among different issues, the explainability of them isn't reliable enough.

2.4 Discount Factor

The discount factor used in the final stage of the negotiation strategy of the agent is discussed here. The discount factor (δ) was used to iteratively update the minimum utility that Agent46 was prepared to accept after each new bid it generated and sent to the opponent. This update rule is defined as

$$U_{min} = U_{min} \times (1 - \delta)$$

δ was kept constant at 0.05, in order to prevent the agent from conceding too much, too quickly and preventing a sub-optimal outcome. A high value for this constant would have risked a lower performance for this reason.
An explicit discount factor was chosen as the safest and most effective way to increase the percentage of agreements made by the agent, thereby contributing to a high overall performance score.
One negative aspect to this approach is that the concession rate is tied tightly to the number of bids sent by the agent. A more complex agent, with a higher number of calculations to perform as part of its strategy, would only ever send a fewer number of these bids over its lifetime and would concede slower as a result, potentially jeopardizing an agreement. For the purposes of Agent46, this approach seemed appropriate, however, it should be noted that this design element may be too inflexible for more specialized agents.

3 Results

The first tests made on Agent46 were established to assess the robustness of the agent against three opposing agents, each with its own unique negotiating strategy to see how he agent faired when challenged with a variety of opponents and how well it could adapt to their changing strategies.
These opponents included agents with a similarly competitive hardliner strategy, a linearly conceding strategy and an adaptive 'Tit-for-Tat' strategy. All three encounters were simulated using the same *party.xml* domain. The results of Agent46 for these negotiations are shown in the table in figure 1.

These initial results show that Agent46 was able to successfully end negotiations with every opponent regardless of the type of strategy they decided to use. Furthermore, Agent46 was able to behave in a way that helped it to achieve as high a final utility as possible for itself at the same time.

Opponent Strategy	Agreement?	Utility
HardLiner	Yes	0.679
Linear Conceder	Yes	1.00
Tit-for-Tat	Yes	0.743

Figure 1: Table to show the performance of Agent46 against other agents with varying negotiation strategies.

The next test was more rigurous and involved Agent46 competiting against 45 other agents within a negotiation tournment that included four different domains and either known or uncertain weights for each issue. This stage was the point at which the overall score for the agent was calculated.
Again figure 2 highlights the significant ratio between the agreements made by Agent compared to the total number of negotiations it was a part of. The agent was successful at walking away from 99% of negotiations with a positive outcome. These out-

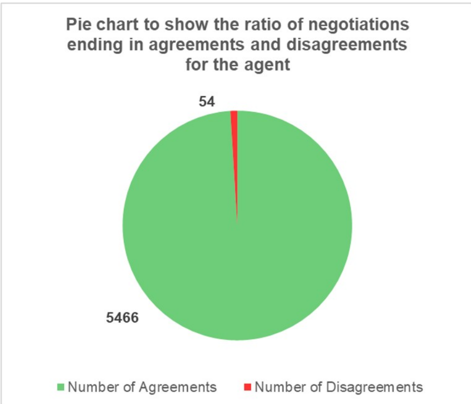

Figure 2: Pie chart to show the ratio of agreements and disagreements made by agent 46 during the negotiation tournament.

comes gained by the agent were also not trivial, as is illustrated in figure 3. The rewards made by Agent46 returned an average final utility of 0.83 over 5520 negotiations and placed the agent is in the top ten agents with the best utility score.
The agent also performance well in trying to minimise the average distance between the final agreed bid and the nash bargain solution across the complete set of negotiations it was a part of. The graph of figure 4 shows that the agent displayed a respectable effort at aiming for optimal bids that tried to maximise the product of utilities for each negotiating pair and performed in the top half of all agents based on this metric.
Both of these factors would have contributed to an immensely high overall performance score had Agent46 completed a similar number of negotaitions

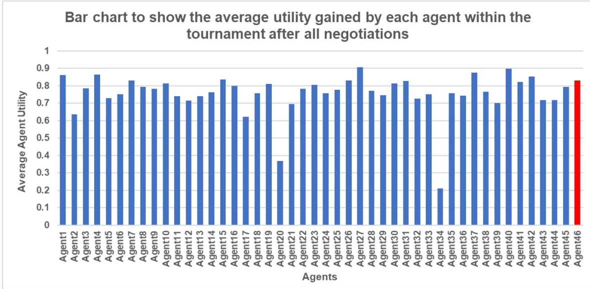

Figure 3: Bar chart to show the average utility gained by every agent within the tournament. Agent 46 is highlighted in red.

compared to the other tournament players it was up against. The percentage of total negotiations that

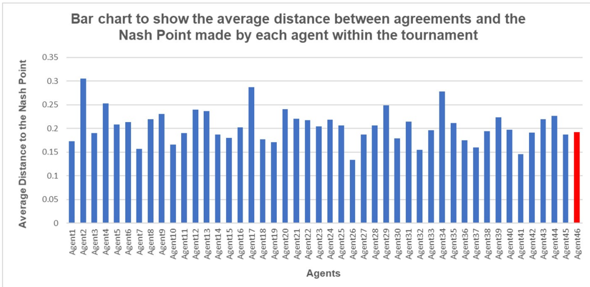

Figure 4: Bar chart to show the average distance between the final bid and Nash Point for every agent within the tournament. Agent 46 is highlighted in red.

the agent was able to finish was nearly 25% less than the average competitor.
It is for this reason why Agent46 was ultimately assigned an average overall performance score of 0.506, placing it below both the mean and the median performance for the set of all players, despite its above average performance in achieving a high average utility and low average distance to the Nash Point for each of its negotiations.
In the end, the success of Agent46 was undermined by number of negotiations it failed to complete.

4 Evaluation

The agent is evaulated using the three objectives highlighted in the intoduction.
Agent46 was able to adequately minimise the distance to the nash bargaining solution for each of the negotiations it was involved in, but this minimisation was negligible compared to most agents within the same tournement. The impact of this is that Agent46 could have improved the quality of

the final bids it agreed to, which would have been located closer to the 'pareto frontier' of the negotiation space. As such, the average distance to the Nash Point it received indicates the agent likely accepted a large number of sub-optimal bids. The reason for this is either the inadequacy of the opponent model or the inadequacy of the preference uncertainty model since these are used to estimate the weights of issues for the agent and opponent respectively.
In this case, the problem is unlikely to be due to the opponent model. Although it has already been established that better techniques to build it exist, the opponent model is the same one used by the 'Jonny Black' agent that has been proved to perform well at predicting the preferences of negotiating agents. The fault here, is instead much more likely to be the result of the experimental method that underpins the preference uncertainty model of the agent itself.
The user model currently obtained using the golden ratio method, could have been enormously improved using linear programming. In addition to being a more sophisticated technique, linear programming leads to a more accurate representation of issue domains similar in size to the ones used within the negotiation tournament explained above and a superior negotiation outcome (*Tsimpoukis D., Baarslag T., Kaisers M., Paterakis N., 2019*). The user model should have been rooted in more verifiable research and built using a more reliable method.

The biggest strength of Agent46 was in its ability to achieve a high final utility for itself and its capacity to avoid walking away from the table with nothing. Not only was the agent flexible and robust enough to return a high utiltiy against other agents with varying negotiating strategy, as seen in figure 1, the agent also receieved a higher utilty than the benchmarks set by these agents when they were placed in competition with each other. This demonstrates that the separation of Agent46's total negotiation strategy into three smaller components, each designed to deal with different types of opponent, is successful and adaptive enough to negotiate with any agent it may face.
Furthermore, the average utility made by the agent places it amongst the highest performers of the tournament as shown in figure 3. There is always the chance that the utility result could have been improved by trailing other, more complex, negotiation strategies used by other ANAC competitiors like 'K agent' or reducing the size of the discount factor and slowing the rate of concession. On the other hand, these results highlight how stunningly effective simply switching strategy can be for an agent when negotiating. The agent is proof, like the Gahboninho agent, that continiously pressuring an opponent into conceding before the agent concedes itself, at the last minute, can produce enviable results and contribute in satisfying the earlier objectives of (2) and (3).

The biggest weakness of the agent was that the total number of negotiations it completed, compared to other agents within the tournament, was significantly reduced because of a fatal error within its code when paired with the *energy.xml* domain. Figure 5 shows this disparity.
The fault in the this case has serious repercussions

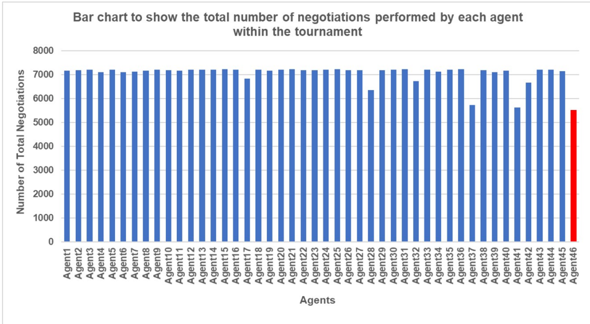

Figure 5: Bar chart to show the total number of complete negotiations performed by every agent within the tournament. Agent 46 is highlighted in red.

on the ratio of agreements made by the agent compared to the total number of negotiations. Agent 46 completes the fewest number of negotiations out of any other agent in the tournament because of this. Although figure 2 shows that the agent achieves a high percentage of agreements when it is working correctly and ignores these failed sessions, the overall performance score does not and therefore explains why the agent's final score (0.506) is below the average despite the agent doing well in relation to objectives (1) and (2). The fault in question appears to be a time out exception caused by the failed execution of Agent46's *chooseAction* function. What is strange about this bug, is that it is only presence for the *energy.xml* domain and not for the other domains the agent was ran with. The exact source of this bug still remains unknown.

5 Conclusion

The implementation of, as well as philospohy behind, the negotiation stratgies of Agent 46 were its main achievement and conclusively met the second of its objectives outlined at the very start.

Unfortunately, although close, the agent failed to minimise the average distance to the Nash Point for its final agreed bid because of a flawed preference uncertainty model and failed to maximise the ratio between the number of agreements and the number of total negotiations because of an exeception within its programming. The agent therefore came up short at trying to achieve the earlier objectives (1) and (3).
At the moment, the agent has only been tested in bilateral negotiations following a single protocol. Some future work and investigation could be done into how the agent operates and performs under multi-lateral negotiation and how its user and opponent models do at representating a more complicated negotiation domain. Other work could include assessing how much better the agent does, in the same scenario, with a more specialized uncertainty model that provides a more accurate prediction of its own preferences, thereby likely reducing the average distance to the Nash Bargaining Solution and leading to more optimal agreements. The potential for improvement of Agent46 is huge.

Individual Contributions

Negotiation Agent: Toby 35%, Laiyuan 55%, Siyuan 10%, Lei 0%
Toby - team co-ordinator, academic researcher, implemented negotiation strategies, planned and arranged team meetings, took meeting notes, completed some practical labs. **Laiyuan** - main developer, created opponent model, integrated other functional modules of the agent, completed all practical labs, supervised agent design, tested and submited agent. **Siyuan** - completed some practical labs, implemented the preference uncertainty model, helped with overall design and testing. **Lei** - development support

Report: Toby: 45%, Laiyuan 10%, Siyuan 15%, Lei 20%
Toby - academic researcher, negotaition strategies, abstract, results and graphs, evaluation and conclusion, individual contributions, opponent model, discount factor, overall proof-reading, managing team, formatting and submitting final document. **Laiyuan** - help support report, explained areas of the agent to aid writing. **Siyuan** - preference uncertainty model section of the report and research. **Lei** - contributions to the background, introduction and design objectives of the report.

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