Artificial Intelligence Techniques
Practical assignment 2: Automated Negotiation
Part 2: Final Analysis

Group 7

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Automated Negotation is the second assignment for the course Artificial Intelligence Techniques given at TU Delft. The assignment is to create a BOA agent using Genius, a tool to simulate negotiations between agents. This report presents an analysis of our agents performance compared to agents created by other groups.

1 Analysis of the agent's performance

We ran negotiation tournaments with 9 agents. Group 1 - 11 excluding 9 and 10. Group 9 was defective and group 10 too slow.

The bar charts below depict agents 1, 11, 2, 3, 4, 5, 6, 7 and 8 in that order. Our agent is at index 8.

We ran each match-up 10 times and computed the mean and standard deviation.

1.1 Utility

Figures 1, 2 and 3 represent the utility gained in easy, medium and hard scenarios.

Our agent has the highest average and one of the smaller variances.

1.2 Number of Rounds

Figures 4, 5 and 6 show the number of rounds that the negotiations lasted. Our agent is the slowest when compared to the others.

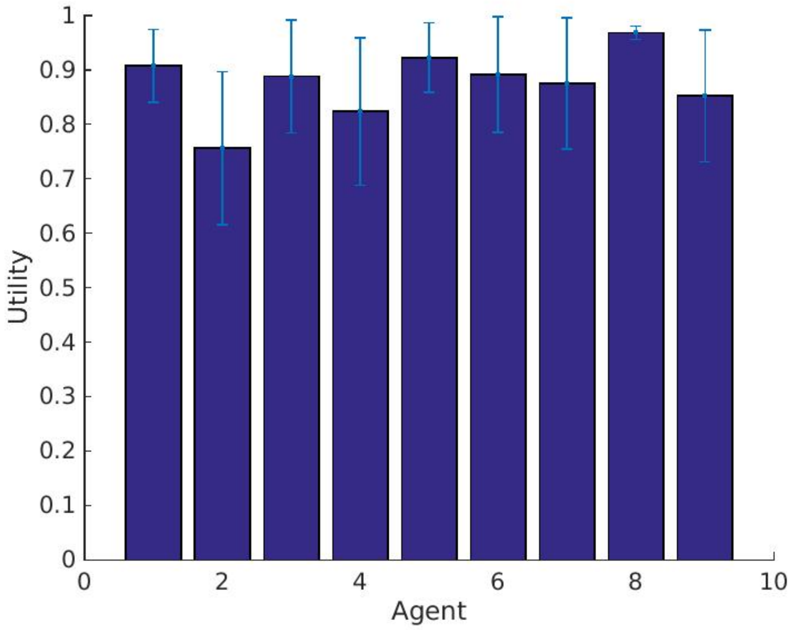

Figure 1: 1v1v1, 180 rounds, easy scenario, Utility

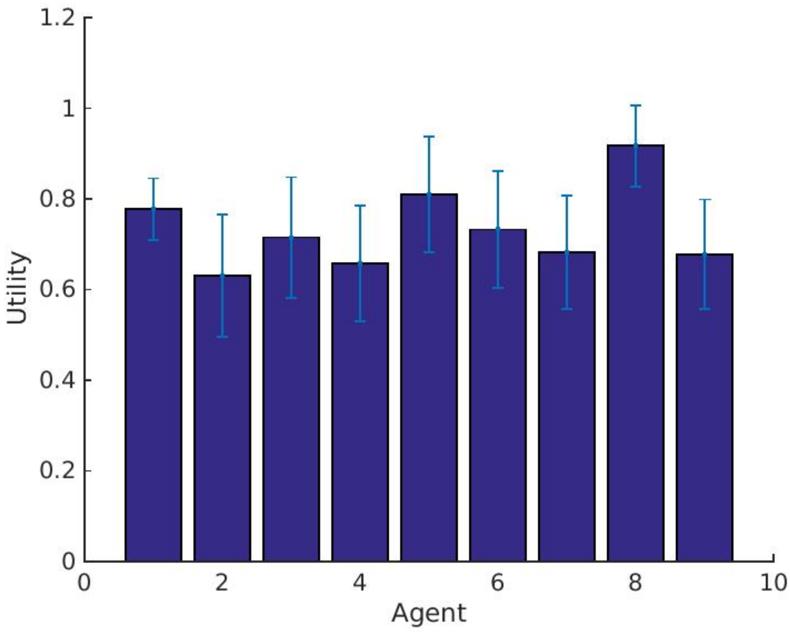

Figure 2: 1v1v1, 180 rounds, medium scenario, Utility

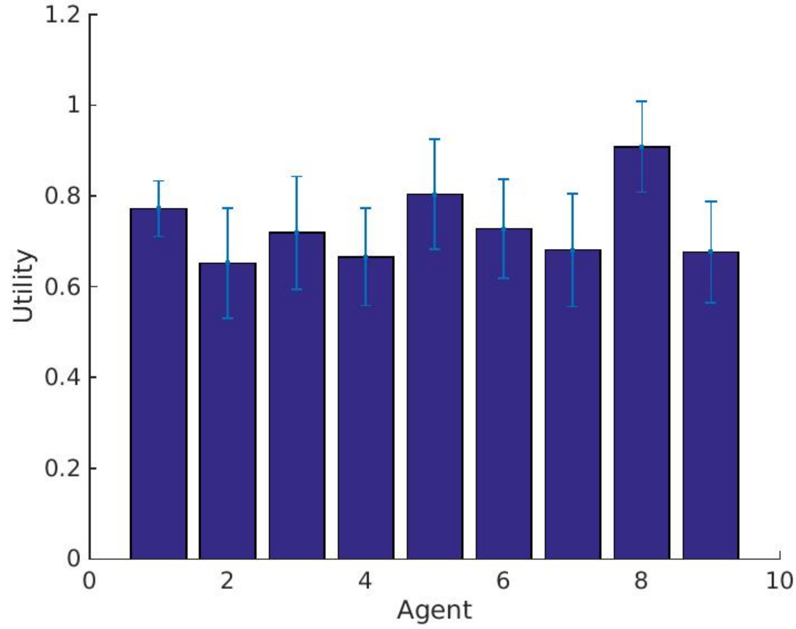

Figure 3: 1v1v1, 180 rounds, hard scenario, Utility

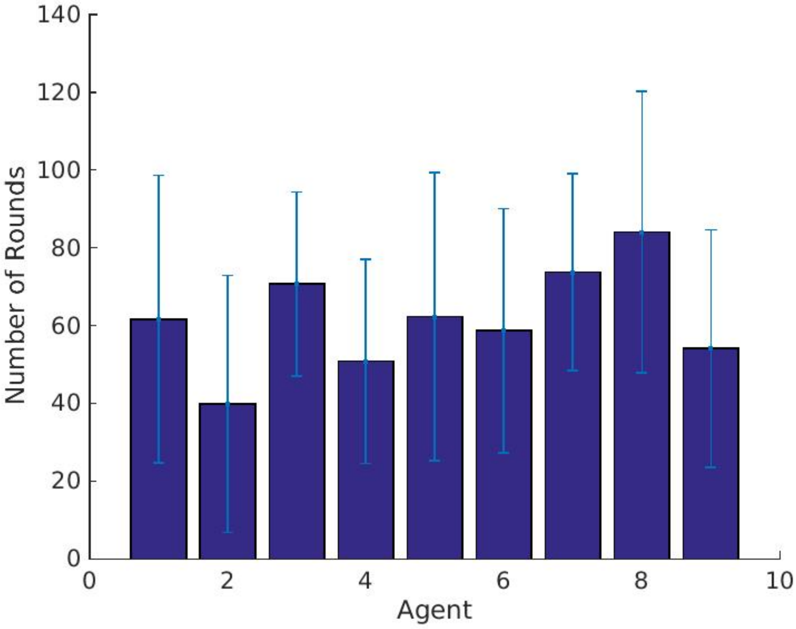

Figure 4: 1v1v1, 180 rounds, easy scenario, Number of Rounds

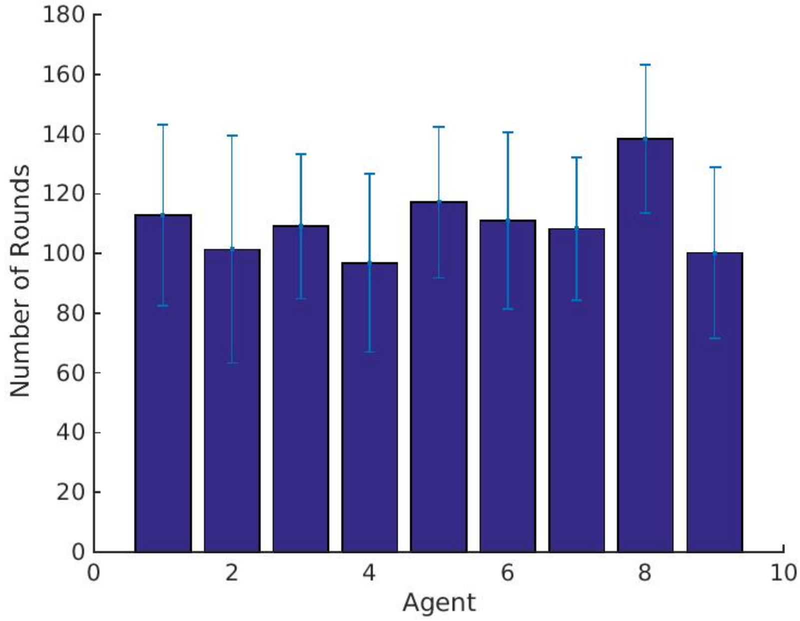

Figure 5: 1v1v1, 180 rounds, medium scenario, Number of Rounds

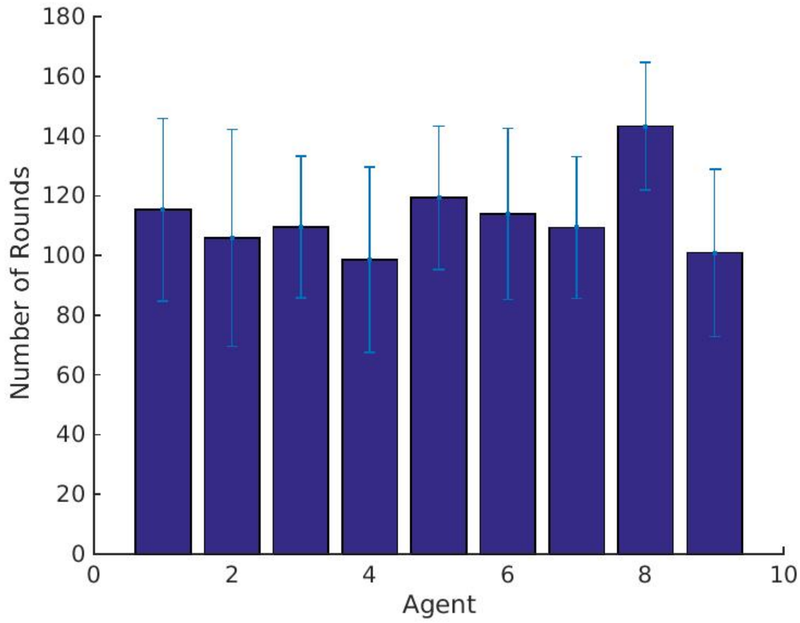

Figure 6: 1v1v1, 180 rounds, hard scenario, Number of Rounds

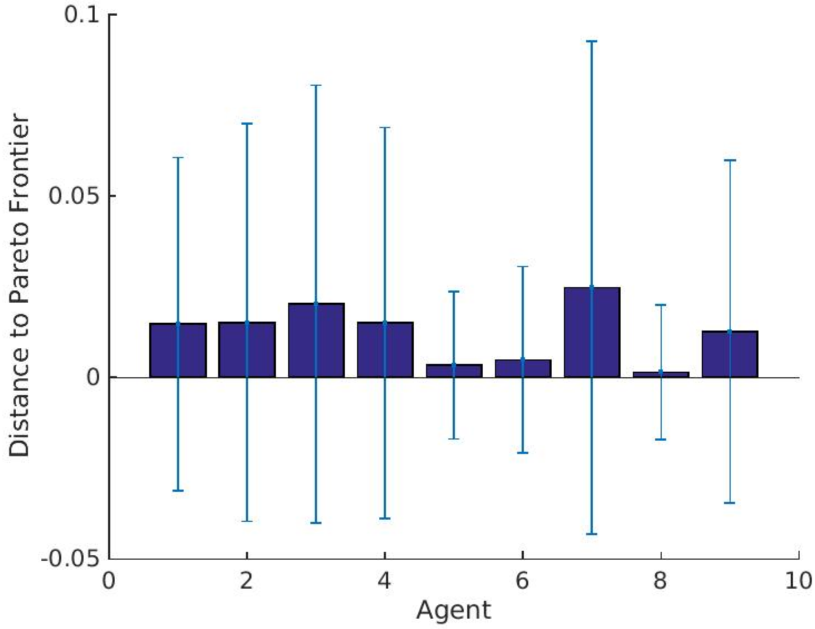

Figure 7: 1v1v1, 180 rounds, easy scenario, Distance to Pareto

1.3 Distance to Pareto

Figures 7, 8 and 9 show the average distance to Pareto for all agreements made in which the agent participated.

Our agent ensures a very optimal bid in easy scenarios. This is still noticable in the medium and hard scenarios but not as heavily.

1.4 Distance to Nash

Figures 10, 11 and 12 show the distance to Nash.

Our agent does not strive for a fair agreement and this is clearly visible in the plots.

1.5 Social Welfare

Figures 13, 14 and 15 show the average social welfare of the agreements in which the agent participated.

It looks like there is a correlation between the distance to nash and the social welfare. The average social welfares are pretty low overall.

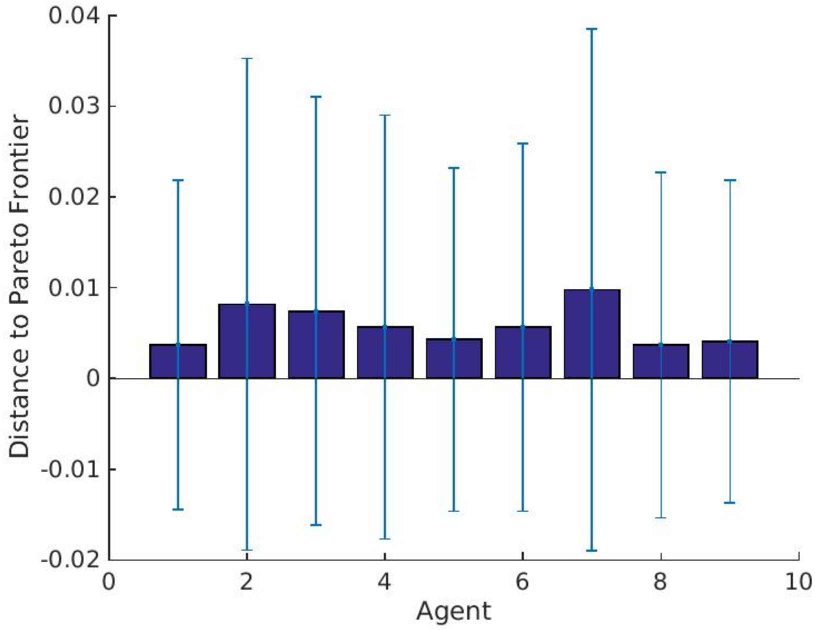

Figure 8: 1v1v1, 180 rounds, medium scenario, Distance to Pareto

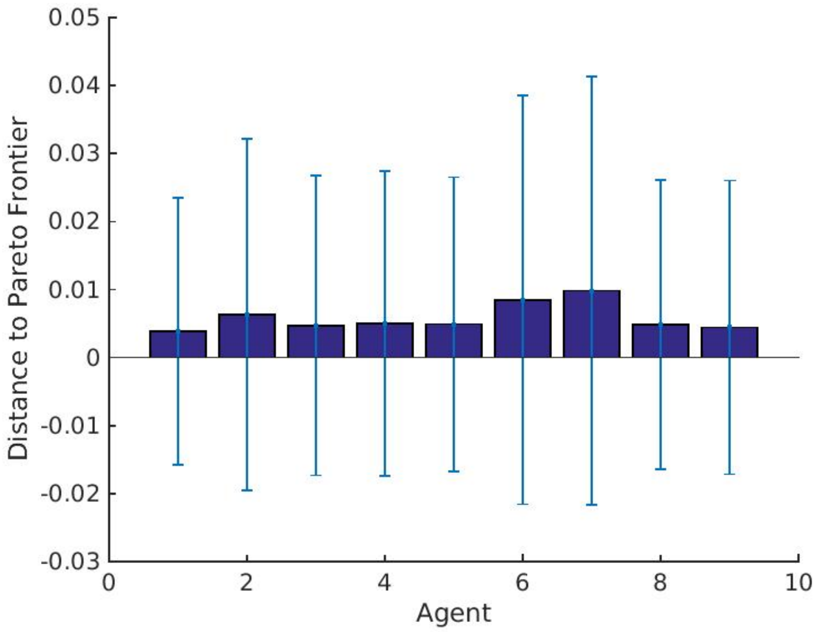

Figure 9: 1v1v1, 180 rounds, hard scenario, Distance to Pareto

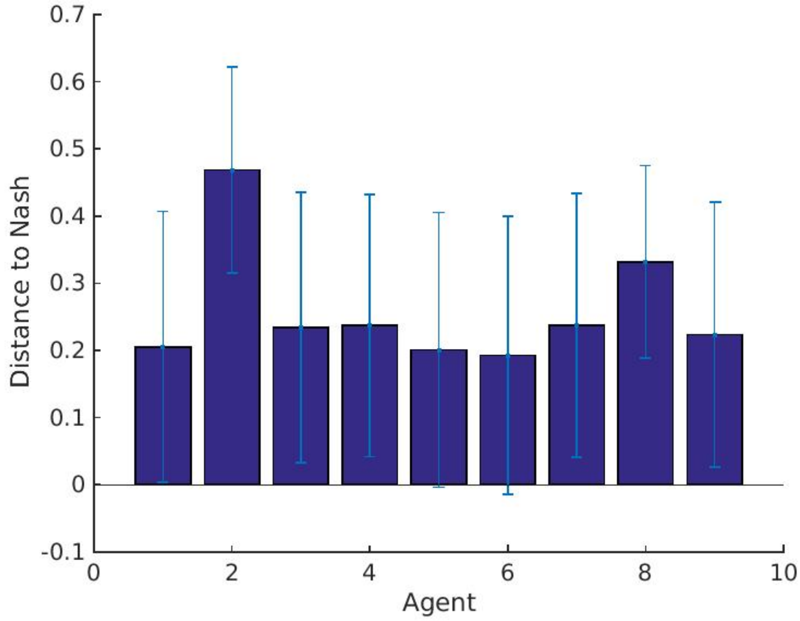

Figure 10: 1v1v1, 180 rounds, easy scenario, Distance to Nash

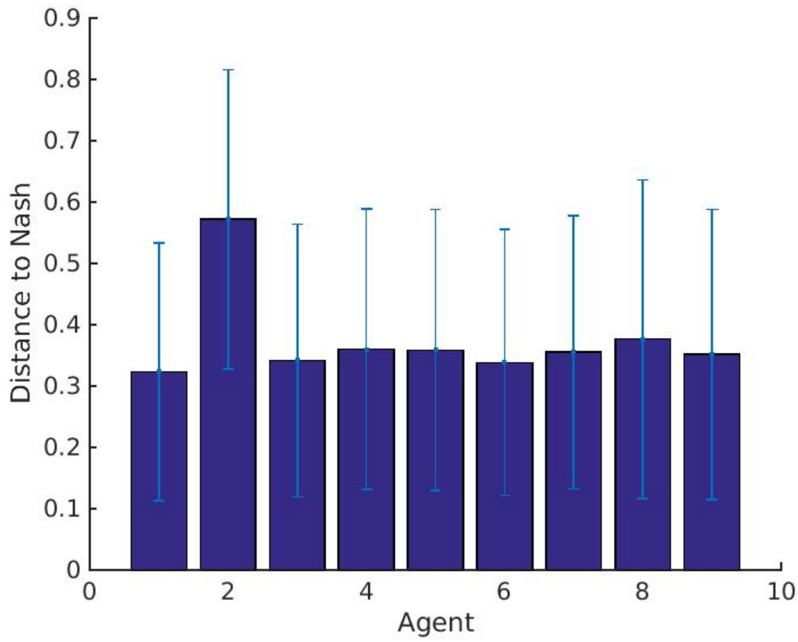

Figure 11: 1v1v1, 180 rounds, 180rounds scenario, Distance to Nash

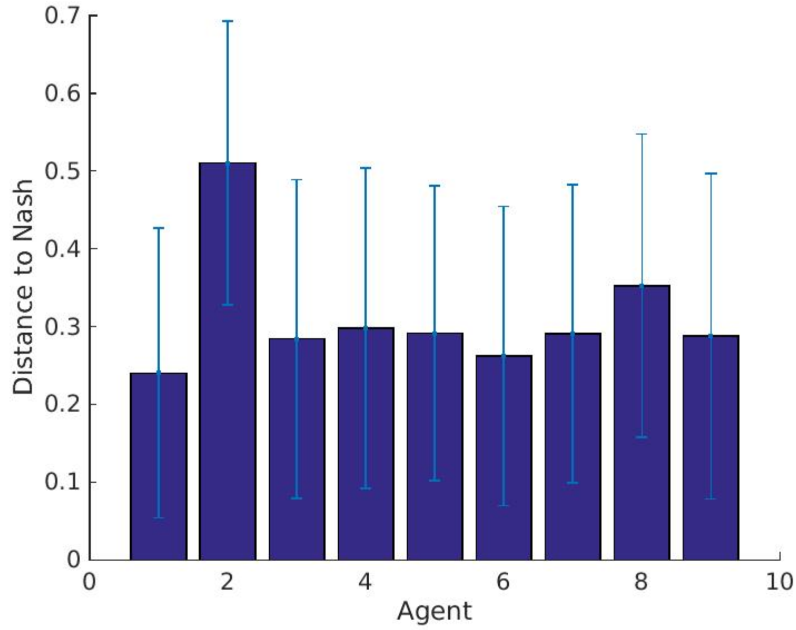

Figure 12: 1v1v1, 180 rounds, hard scenario, Distance to Nash

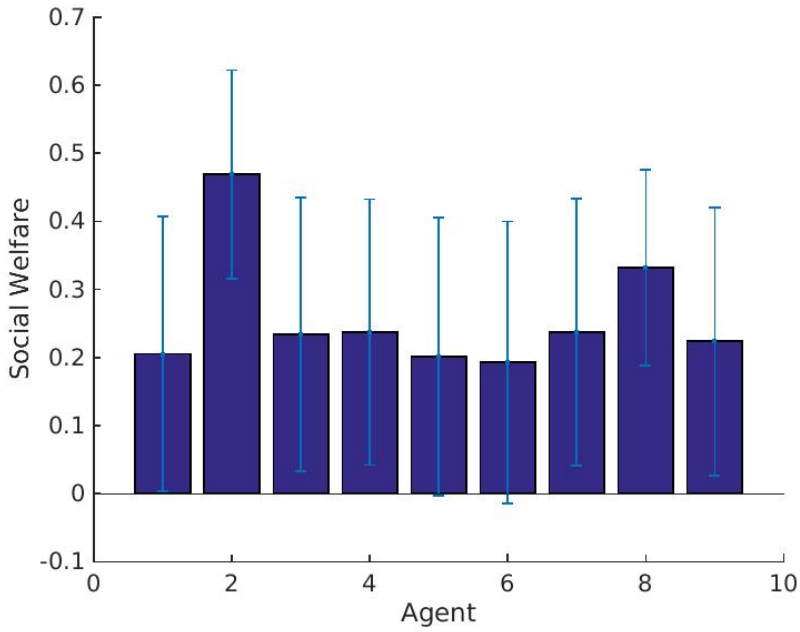

Figure 13: 1v1v1, 180 rounds, easy scenario, welfare

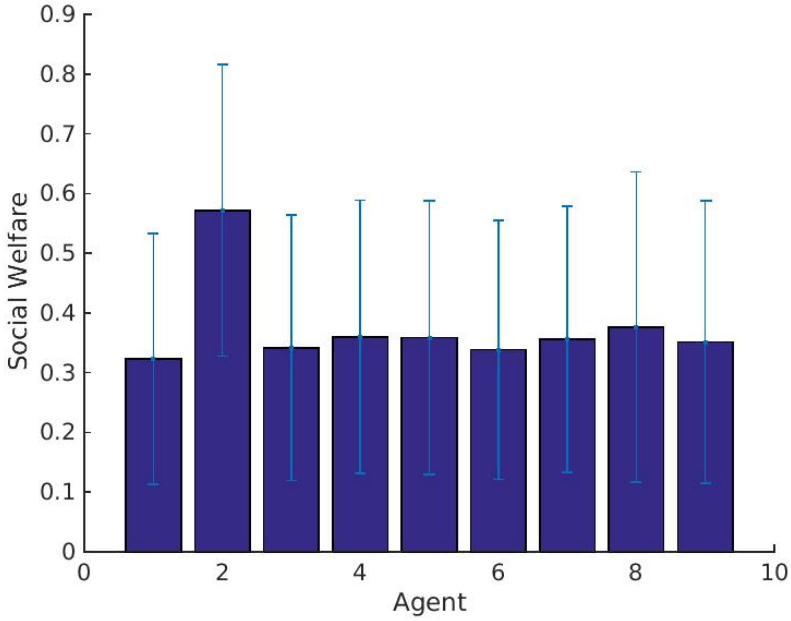

Figure 14: 1v1v1, 180 rounds, medium scenario, welfare

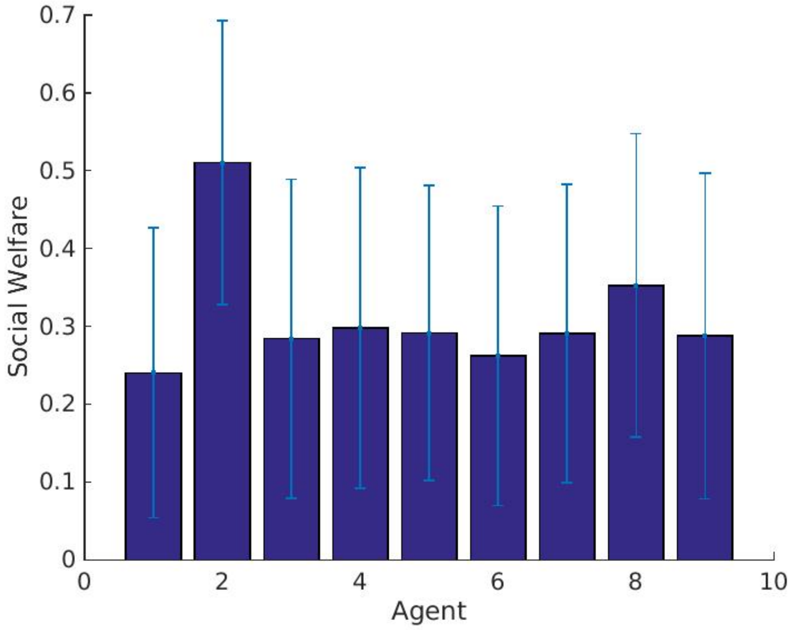

Figure 15: 1v1v1, 180 rounds, hard scenario, welfare

2 Improvements

To not get a low average utility the agent cannot make concessions too early. Of course the meaning of early is relative, it depends on how well we know the other agent (for the most of the cases). If we don't know the other agent very well even after lots of rounds can be early because we can still be very far from meeting the other agent preferences, so we start conceding without even know if we could have found a better option for both sides. That has an affect in the optimality as well. In conclusion, by having an idea about the other agent preferences we can decrease the number of rounds which decrease the probability of making concessions too early and by only making concessions when needed we have a higher chance to obtain agreements with optimal values for the utilities.

3 Conclusion

Looking at the numbers we see that our agent has the highest average utility and it's also consistent for many trials. So we conclude that in general our agent performs efficiently against other non-human agents. However that result is obtained by being greedy and not using opponent modeling. Using this kind of agent in a real life negotiation can be dangerous. When we deal with humans we have to take in to account feelings and emotions. By ignoring them and trying to exploit the other agents we may reach no agreement at all. So it's not the perfect agent to take over a real life negotiation. However it can be used as support to simulate the negotiation once it generally finds good outcomes.