Group 10

Final Project: Intelligent Negotiation Agent

Introduction:

In the project we implemented "Group10" intelligent autonomous negotiation agent. An SAO (stacked alternating offers) Based negotiation agent that negotiates against opponents with unknown reservation values in a stacked alternating offers protocol. The agent developed within the NegMas platform.

The agent's strategy is dynamic and adaptive to balance competitive elements. This strategy ensures it can negotiate efficiently across different scenarios while maintain a competitive driven approach, adapting its behavior to various opponent types while maintaining a strong utility-maximizing approach.

General phases of the strategy:

The Group10 negotiation agent follows a phase-based strategy, meaning that its behavior and decision-making dynamically change depending on the stage of the negotiation. The agent categorizes the negotiation into three key phases: Early, Middle and Final.

Each phase determines how the agent bids, concedes, and accepts offers. The transition between phases is based on relative time progress in the negotiation. In addition, the agent is time-sensitive, meaning it aware of the negotiation length in terms of the average step and total amount of steps, and provides a dynamic adjusted weight for each step during the negotiation.

Moreover, it contains behavioral classification strategies, for both long-term behavior and recent behavioral trends – such as Nash-seeking offers, a stubborn opponent, a randomized offer and a conceding approach. The behavioral classification is adjustable, and threshold based – to enhance flexibility.

Group 10 aims to learn and analyze the opponent during early to mid-phases, with a stubborn offering approach. Exploiting stochastic features, we aim to provide randomness and uniqueness to the agent to make it more profitable and optimal for the agent against the opponent.

Group10 seeks to reach a deal in the very late phases, in particular the last 3 round – and is using a reservation estimation mechanism to provide a beneficial offer that the opponent will likely agree to in the end.

A high-level overall description of the agent

Guidelines for the implemented strategy:

- It begins negotiations with an aggressive opening offer to secure the highest possible utility. As the negotiation progresses, it analyzes the opponent's behavior, adjusting its strategy based on whether the opponent is stubborn, conceding or unstable.
- The agent employs opponent modeling techniques to estimate the reservation value of the opponent, helping it determine the optimal level of concession. Using Pareto-optimal and Nash-equilibrium-oriented in the negotiation stages to achieve a fair and advantageous outcome (motivated by lesson 8).
- The acceptance strategy influenced by a time-dependent aspiration function, allowing the agent to adapt dynamically as the negotiation reaches its deadline (influenced by the material in lessons 5-6).

The core elements of the implemented strategy are:

Time and Opponent dependent Aspiration Function – The agent maintains a high-utility stance early in negotiations and gradually concedes as time progresses, ensuring a balance between firm bargaining and agreement likelihood.

Opponent Modeling – The agent tracks the opponent's offers, detects concession trends, and estimates the opponent's reservation value to adjust its bidding and acceptance strategies dynamically.

Bidding Strategy – Initially, the agent proposes its best possible offer and then adjusts its counter-offers based on:

- The opponent's behavior (e.g., conceding, stubborn, erratic).
- Nash equilibrium considerations (if beneficial for both parties).
- The time left in the negotiation.

Acceptance Strategy – The agent accepts offers only if they exceed a dynamically calculated aspiration threshold which decreases over time, while taking into consideration the ratio between opponent utility and our utility. If the deadline is near, it becomes more flexible to avoid a failed negotiation.

Final Stage Decision Making – The agent recognizes when the negotiation is in its final phase and prioritizes Pareto-optimal offers or Nash equilibrium solutions to ensure a favorable outcome.

Utility ratio – The agent aims to reach an agreement in the very final rounds of the negotiation. In this, he aims to learn the opponent behavior, the offering history and use the utility ration to secure an offer that will have a safeguard in a competition driven negotiation. Although the ration between utilities does will not always be the best agreement scenario for us, combining that with a good offering covers most of the cases in such tournament environment.

Stochasticity – The agent randomly selects offers from a beneficial offers pool we construct during middle to final phases, to introduce randomness and unpredictability to the negotiation.

Components Description:

The Group10 negotiation agent was designed with three core components:

Bidding Strategy `def bidding_strategy(self, state: SAOState) -> Outcome | None:`

- The function determines the counter-offer the agent will offer during a negotiation round (the agent's decision is based on the negotiation phase, the opponent's behavior and the remaining time).
- The bidding function Adapts its counter-offer based on the negotiation phase. At Early phase → Suggest the optimal offer of its own. At Middle stage → Adjusts based on opponent's behavior and Nash equilibrium. At Final stage → Prioritizes reaching an agreement while optimizing its final utility.
- Evaluates opponent behavior dynamically: detects whether the opponent is conceding, stubborn, or aiming for Nash equilibrium and adjusts its offers based on the trend of opponent utilities. In addition, the agent evaluates at every step the competitiveness of the negotiation.
- Use multi step process to determine the best counteroffer: if the opponent is conceding → Pushes for a higher utility deal. If the opponent is stubborn → Focuses on finding a balanced outcome. If time is running out → Moves towards a last-minute compromise.
- The counter-offer strategy is adaptive and considers the opponent's utility model while ensuring that the agent does not concede too early.

Acceptance Strategy `def acceptance_strategy(self, state: SAOState) -> bool:`

- The agent determines acceptance based on aspiration levels, which adjust dynamically based on the phase of negotiation. The acceptance strategy function determines whether the agent should accept the opponent's offer based on multiple factors: negotiation phase (Early, Middle, Final), opponent's concession trend, remaining time in the negotiation, agent's dynamic aspiration threshold. The goal is to maximize utility while ensuring an agreement when necessary.
- A deal is accepted if the received offer exceeds the calculated aspiration threshold. The agent considers time constraints, ensuring that offers closer to the deadline are evaluated with a more flexible threshold.
    - Early on, we can accept an offer that can reach 90% of our max utility.

Opponent Modeling & Reservation Value Estimation

- **Is Nash seeking –** Determines if the opponent is a Nash seeker by checking if their recent offers are close to the Nash. Bargaining solution for both parties. Using proximity and recent offers threshold
- **Is opponent conceding -** evaluates whether the opponent in a negotiation is conceding based on recent utility data. It first checks if there are enough utility values (defined by a window size) and then calculates the average decrease (trend) between consecutive moves. Additionally, it assesses the immediate drop in the last move. If either the average trend exceeds a specified threshold (min_trend) or the latest drop exceeds another threshold (min_drop), the method returns True, indicating that the opponent is conceding. Otherwise, it returns False.
- **Is opponent stubborn -** analyzes whether an opponent in a negotiation demonstrates stubborn behavior. It evaluates opponent offers after a predefined phase threshold, checking two main

criteria: (1) whether the opponent made a meaningful improvement (>= stubborness_threshold) since the start of this phase, and (2) whether the opponent's concession trend is sufficiently positive (concession_rate). If the opponent fails both checks—indicating minimal utility improvement and low concession rate—the method classifies the opponent as stubborn.

- **Estimate opponent reservation value** – Method that is used only in very final stages of the negotiation, to gain a better understanding of the opponent lower threshold. Estimates the opponent reservation value based on actual offers, avoiding reliance on behavior patterns alone. Able to adjust for risk handling when opponent utility is unclear.

Negotiation Strategy

A key component of the agent's intelligence is its opponent modeling and learning techniques. It tracks and analyzes the opponent's offers, detecting whether the opponent is conceding, stubborn, competitive, or Nash seeking. Using this data, it estimates the opponent's reservation value and adjusts its bidding and acceptance strategies accordingly. By incorporating these opponent-aware adjustments, the agent optimizes its decisions to maximize its final utility while ensuring an agreement is reached.

The Group10 agent follows a structured approach to negotiation:

0. At every step, the agent collects: the current state and step in the negotiation, opponent recent trends and the current negotiation phase. Out best possible offer is selected as the fallback outcome.
1. Initial Bidding Phase: Collect the best offer for us from the opponent outcome space and starts a filtering process. The process is diverged based on the opponent recent trends. An aspiration utility minimum is set, and it is very high at the beginning, which leads in most cases to our fallback selected outcome.
2. Mid-Negotiation Adaptation: The agent can now identify if the opponent is making strong concessions and maintains its position to extract maximum utility. If the opponent is rigid, the agent shifts towards Nash equilibrium offers to encourage agreement. We always set a minimal aspiration value, which is not lower than our reservation value.
3. Final Stage Strategy: The agent estimates the remaining time and adjusts its reservation threshold. In addition, it analyzes the opponent stubbornness further enhancing step 0 data re-collected at every step. For a stubborn opponent in the Final phases, we use a randomized approach, and build a beneficial outcome space, with offers that exceeds a target threshold, based on time left, current outcome space possibilities and safeguard minimal values.

The agent adapting its bidding and acceptance decisions based on time progression, opponent behavior, and utility maximization. The negotiation process is divided into three key phases: **Early→** the agent maintains a firm stance with minimal concessions; **Middle →** it strategically adjusts its offers based on opponent behavior; **Final →** prioritizes securing an agreement by lowering its aspiration threshold. This structured approach ensures that the agent remains competitive while increasing the likelihood of reaching a beneficial deal.

The agent's bidding strategy is designed to maximize utility while adapting dynamically. Initially, it proposes the best possible offer for itself, but as negotiations progress, it modifies its counter-offers based on factors such as opponent concessions, Nash equilibrium considerations, and time constraints. The agent also employs a final-step offer mechanism, ensuring that if no agreement has been reached, it selects a Pareto-optimal or Nash-equilibrium offer to finalize the deal efficiently.

The acceptance strategy is based on a dynamic aspiration function, which determines whether an offer is acceptable at any given moment. Early in the negotiation, the agent is highly selective, accepting only exceptionally high-utility offers. As the negotiation progresses, it gradually lowers its expectations and, in the final phase, becomes significantly more flexible to avoid negotiation failure. The strategy also accounts for time constraints, ensuring that offers closer to the deadline are evaluated with a more lenient acceptance threshold.

Quantifying the agent's performance

Testing and evaluating the agent:

Self-Testing

- The agent was tested against itself to observe its adaptability and self-competition behavior.

#Run	group10.Group10	_main_.Group10
1	0.169069	0.169069
2	0.358901	0.358901
3	0.356486	0.354923

Table 1: shows the scores the agent got against itself in 3 different tournaments runs each over 10 scenarios

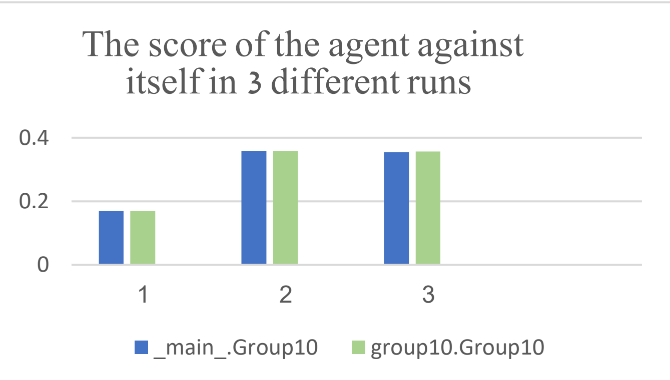


Diagram 1: presents the outcomes of agent got against itself in 3 different tournaments runs each over 10 scenarios

Table 1 and Diagram 1 representing the outcomes of 3 different runs of the agent against itself over 10 scenarios.

Analyzing and inferring the outcomes:

Across multiple runs, the agent achieved nearly identical scores on both sides of the negotiation. This suggests that the agent maintains a stable and symmetrical decision-making process, ensuring fairness in negotiations when facing itself. The relatively low average utility score, however, indicates that while the agent effectively reaches agreements, it may not be maximizing its own utility optimally and could be conceding too early in certain situations. Since both instances of the agent reached similar agreements, it suggests that its bidding and acceptance strategies are well-calibrated to maintain equilibrium. However, this also means that in competitive scenarios, the agent might be missing opportunities to leverage aggressive strategies against more concessionary opponents.

Tournament Testing

- The agent results against two of the default ANL competitor agents provided in anl2024_tournament:

#Run	Group10	Boulware	Conceder
1	0.477147	0.475764	0.24218
2	0.540386	0.42103	0.235174
3	0.238843	0.237606	0.097318

Table 2: shows the scores the agent got against 2 default agents in 3 different tournaments runs each over 7 scenarios

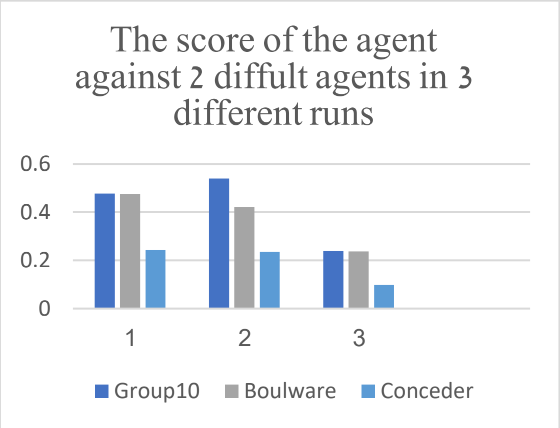


Diagram 2: presents the outcomes of agent got against 2 default agents in 3 different tournaments runs each over 7 scenarios

Analyzing and inferring the outcomes:

The Group10 agent consistently outperformed both Boulware and Conceder in multiple negotiation rounds, demonstrating its ability to balance competitiveness and adaptability. Against Boulware, Group10 successfully adapted its offers and secured higher utility, while against Conceder, it efficiently maximized its gains by taking advantage of the opponent's concessions.

The outcomes show Group10's ability to dynamically adjust its approach based on its opponent's behavior reinforces its effectiveness in strategic decision-making (each of the default agents has different strategy and Group 10 dealls good with it).

- The agent results against 4 ANL competitor agents provided in anl2024_tournament:

#Run	Group10	Boulware	NashSeeker	RVFitter	Conceder
1	0.424460	0.357763	0.306689	0.295985	0.199108
2	0.607122	0.465455	0.381479	0.423858	0.233401
3	0.428313	0.361713	0.309213	0.339529	0.215428

Table 3: shows the scores the agent got against 4 other agents in 3 different tournaments runs each over 3 scenarios

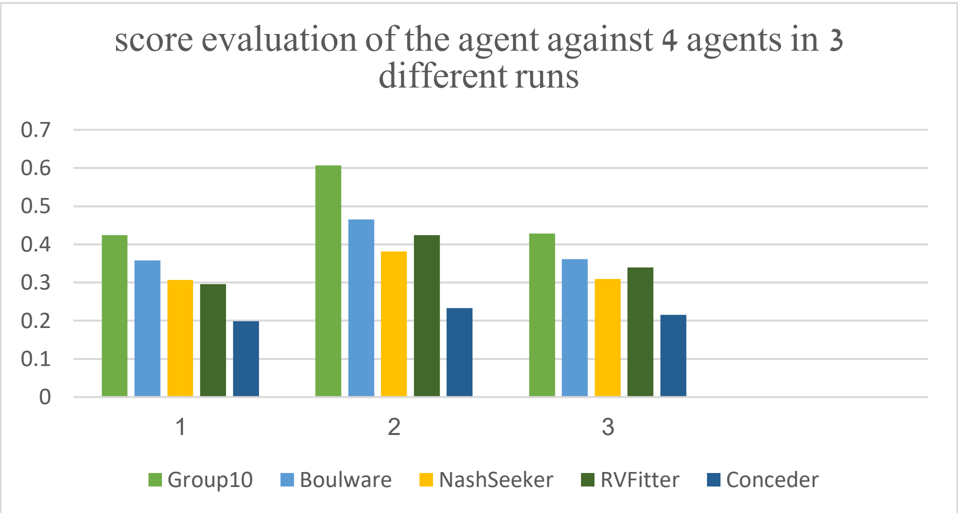


Diagram 3: presents the outcomes of agent got against 4 other agents in 3 different tournaments runs each over 3 scenarios

Analyzing and inferring the outcomes:

The Group10 agent demonstrated strong performance in competitions against different agents (Boulware, RVFitter, NashSeeker, and Conceder), consistently achieving the highest score across multiple runs. This indicates that the agent successfully balances competitive and cooperative negotiation strategies, adapting dynamically to different opponent types.

The results highlight Group10's adaptability, as it effectively handled both aggressive and cooperative negotiation styles, securing favorable agreements without over-conceding. The varying score margins between runs suggest that preference profiles and specific negotiation conditions influenced performance, but Group10 remained consistently dominant, reinforcing its robust and flexible strategy.

- The agent results against 2 hardest ANL competitor agents provided in anl2024_tournament:

#Run	Group10	Shochan	HardChaosNegotiator
1	0.203081	0.248555	0.270000
2	0.339740	0.478659	0.421217
3	0.210743	0.348562	0.200014

Table 4: shows the scores the agent got against 2 hardest agents in 3 different tournaments runs each over 3 scenarios

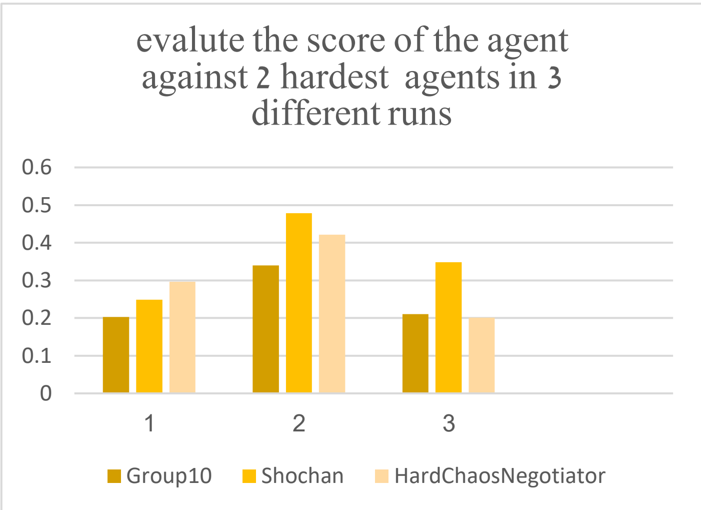


Diagram 4: presents the outcomes of agent got against 2 hardest agents in 3 different tournaments runs each over 3 scenarios

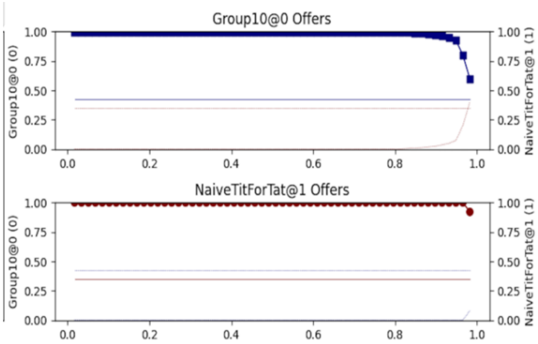
Analyzing and inferring the outcomes:

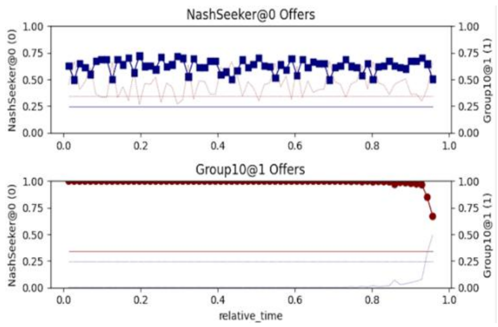
The Group10 agent faced two of the top ANL 2024 ranked agents, HardChaosNegotiator and Shochan, across multiple negotiation scenarios. The results indicate that Group10 consistently struggled to outperform these agents, often ranking last in the competitions. Group10's strategy appeared less effective in maximizing utility when faced with these agents' strategies. Despite of the fact that Group10 doesn't win it does get very close score to the opponent agent one place higher than him, it may indicate that with even with a minor change Group10 may win in more scenarios.

To improve performance, Group10 could benefit from enhancing its opponent modeling and adaptive strategies. By refining its ability to detect and counter extreme negotiation styles, it may achieve better results against both structured and unpredictable opponents. Strengthening these aspects would make the agent more resilient in competitive negotiation environments.

Agent Negotiation Analysis:

Throughout the development and implementation of our SAO negotiator agent, we experimented with several bidding techniques ranging from Pareto-driven offering strategies to zero-concession (stubborn) approaches. Our extensive testing revealed that Nash-seeking opponents can be strategically exploited in competitive environments emphasizing advantage-based scoring. Additionally, we explored a Smart Tit-for-Tat strategy (we discussed tit-for-tat in lesson4) integrated with stochastic offer generation. Although initially promising, we observed that this approach could be easily manipulated by intelligent agents and significantly reduced negotiation success rates against opponents employing stubborn or zero-concession tactics. To address these challenges, we developed a hybrid negotiation mechanism that dynamically evaluates the uniqueness and stubbornness of opponents, selectively activating Tit-for-Tat behavior only when strategically beneficial.



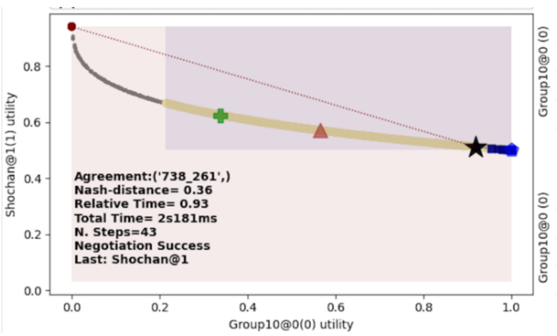


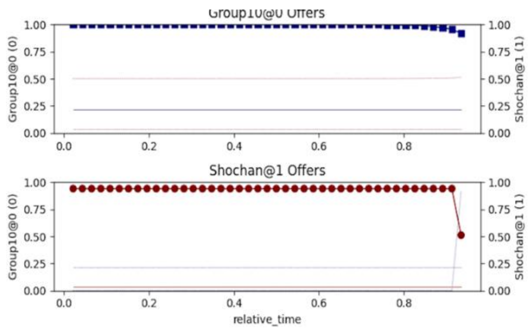
The Chosen tactic includes minimal compromises until the late stages of the negotiating, the rational is that in a tournament where social welfare Is not a major component in the score, we aim to get the best deal for us in expense of allowing the other agent getting a better deal for himself. We maintain a stochastic approach to help increase agreement rate in some negotiations out of the assumptions that in some part of the scenarios – we can get a deal that is better for our opponent – because it is a part of a calculated effort in the long run.

Last minute calling – During negotiation analysis and tracking, we have constructed a late-offer strategy approach, that include minimal concession before late stages. Late-stage definition include two parts: "Final stage" which is an adjustable normalized value that is compared to the relative time.

The objective of this metrics is to alert the agent that it is time to lower our aspirations a little bit more and introduce stochasticity to beneficial offers before the very final few rounds. This randomness approach was introduced to handle learning agents, such as Shochan and OUAgent from ANL 2024 Competition. It provided a 27% increase in average score rate across – from ~0.2 to 0.26, and in some scenarios – even beat the agent. In the illustration below, Shochan RV was set to 0.06 and Our agent RV was set to 0.25. We have leveraged Shochan big buffer into our advantage.

Last steps enhancement – A Shochan-inspired tactic directing negotiations toward strategic bidding in the final three steps, culminating in the most informed guess at the final stage. The objective is assessing the opponent's reservation value and behavior, thereby maximizing our own utility. This strategy was adopted after extensive exploration of methods to boost our overall negotiation scores.





Conclusion & Future Improvements

The Group10 agent successfully demonstrates an effective negotiation strategy by dynamically adapting to its opponent. It effectively balances competitive and cooperative negotiation styles.

The results indicate that the agent successfully balances competitive and cooperative negotiation styles, ensuring high-utility agreements in various scenarios. However, while the agent performs well in balanced and concession-based negotiations, it struggles against highly aggressive or unpredictable opponents. This suggests the need for further refinement in handling extreme negotiation styles.

Future Enhancements:

- **Introduce multi-agent learning to improve collaborative negotiation strategies.** Implementing a learning-based approach to refine negotiation tactics over multiple interactions, improving adaptability against different opponents. (Similar to the discussion in lesson 11).

- **Better Reservation Value estimation** – Using classification and perhaps reinforcement learning models, in order to identify agents' behavior and make a better estimation regarding the opponent next offer and reservation value was measure as an efficient approach in ANL agents. Reinforcement learning approach

- **Advanced Opponent Modeling:** Enhancing the agent's ability to predict opponent behavior more accurately, particularly against aggressive or chaotic strategies, to make better-informed concessions and counteroffers.

- **Optimize real-time decision-making to reduce response time in high-speed negotiations.** Reducing response time in high-speed negotiations by optimizing computational efficiency and refining decision heuristics.

- **Address Weaknesses** – Currently the agent performs poorly against Nash Bargaining agents (It can beat them, but some test runs showed flaws in the acceptance mechanism) and Learning agents such as Shochan. **Last steps acceptance strategy is not good enough,** as it sometimes makes a large concession that was exploited by Shochan and Nash seekers.

- **Parameters' adjustments** – The current agent setup offers a flexible thresholding approach in various components in the code. Fine tuning those metrics, based on a learning pattern of other agents' historical behavior would lead to a dramatic increase in the agent's performance (We have adjusted parameters based on historical runs and was able to improve our results).

Summary:

By combining real-time opponent adaptation, flexible bidding tactics, and a structured concession plan, the Group10 agent is capable of negotiating effectively against a wide range of adversaries while maintaining a robust utility-maximizing approach.

By integrating real-time opponent adaptation, flexible bidding tactics, and structured concession plans, the Group10 agent has proven to be highly competitive in automated negotiations. Its phase-based strategy, opponent modeling, and mathematically guided decision functions allow it to balance assertiveness and cooperation effectively. Future enhancements focusing on adaptive learning and real-time optimizations will further improve its performance against diverse negotiation strategies.

In summary, the Group10 agent utilizes a flexible, data-driven, and adaptive approach to negotiation. Its phase-based strategy, opponent modeling, and mathematically informed bidding and acceptance functions allow it to be very competitive and effective in automated negotiations. This ensures that the agent balances assertiveness and cooperation, achieving high-utility agreements across different negotiation scenario.