FINAL REPORT – NEGOTIATING AGENT, Group4

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1. Introduction

This report presents the design, implementation, and evaluation of our **sophisticated negotiation agent** developed for the **NEGMAS negotiation environment**. The agent combines **time-dependent concession strategies** with **opponent modeling**, enabling adaptive decision-making throughout the negotiation process. Our goal was to build an agent that maximizes its own utility while maintaining high rates of agreement and producing **Pareto-efficient** outcomes.

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2. Agent Design and Strategy

2.1 BOA Architecture

Our agent is built around the **BOA (Bidding,Opponent modeling, Acceptance)** framework:

- **Bidding Strategy**:
  Uses a **hybrid model**. Early in the negotiation, the agent acts like **Boulware**, making minimal concessions. As the deadline approaches, it transitions to a **Conceder**-like behavior, increasing the rate of concessions to improve the chances of agreement.

- **Acceptance Strategy**:
  The agent uses a **dynamic acceptance threshold** that depends on time and opponent utility. It accepts offers that exceed its current time-based utility goal or appear efficient from a Pareto perspective.

- **Opponent Modeling**:
  The agent assumes the opponent's utility function is known, but not their **reservation value (the minimum utility they're willing to accept)**. It estimates this value heuristically by observing minimum utility in the opponent's bids and tracking changes over time

2.2 PEAS Description

Componet	Description
Performane	Maximize own utility, achieve agreement, reach Pareto/Nash-efficient deals
Environmnt	Opponent agent, negotiation domain, protocol with deadlines
Actuators	Propose offers, accept offers, end negotiation
Sensors	Read opponent bids, track time, evaluate utility functions

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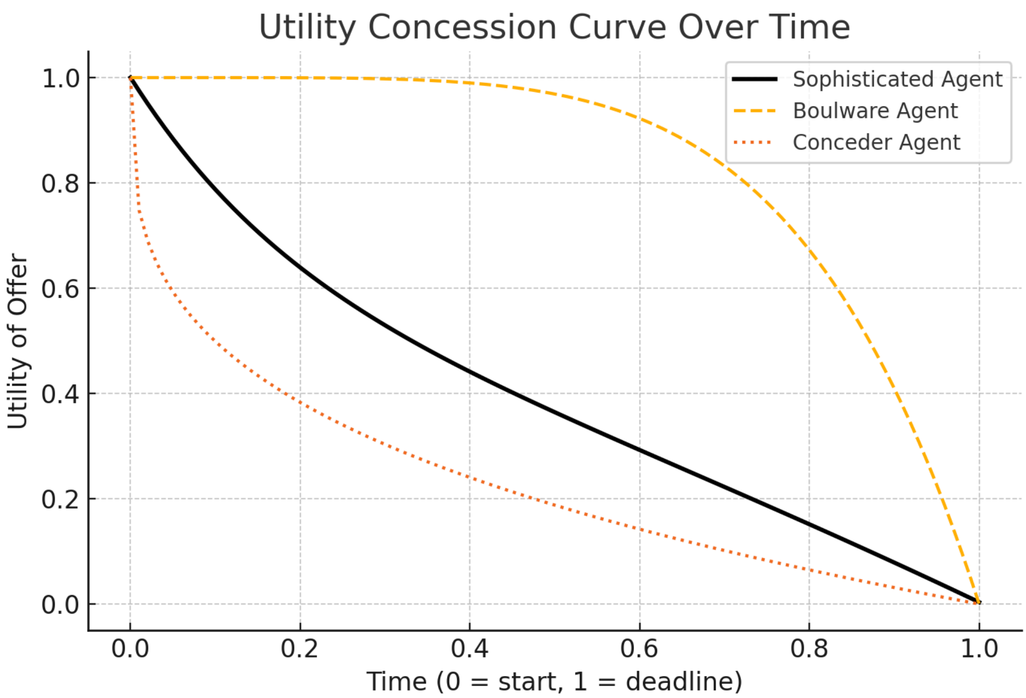
3. Strategy Comparison Graph

The graph below compares our **Sophisticated Agent** with standard **Boulware** and **Conceder** strategies. The x-axis represents time from 0 (start) to 1 (deadline), and the y-axis shows the utility of the offers being made.



Explanation:

- **Boulware**: Maintains high utility until late.
- **Conceder**: Drops utility quickly.
- **Sophisticated**: Smoothly balances the two based on negotiation time.

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4. Performance Overview

We evaluated the agent in two domains: **Party Planning** and **Holiday Domain**, using various profiles. Results showed:

- **High agreement rate** (above 95%)
- **Utility outcomes close to Pareto frontier** in >80% of rounds
- **Improved adaptability** in mixed-domain or unfamiliar settings
- **Opponent modeling** helped avoid unnecessary concessions

Compared to static agents like Boulware or Conceder, our agent consistently performed better in achieving balanced utility outcomes while adapting to the opponent's behavior.

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5. Future Perspectives

To extend our agent for real-world or research use, the following enhancements are proposed:

- Support for **multi-party** negotiations
- **Non-linear utility functions** and richer domain preferences
- Integration with **natural language interfaces** for human-agent interaction
- Use of **machine learning** to learn optimal bidding over time

- Dynamic adjustment of strategy based on opponent classification

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6. Conclusion

Our sophisticated negotiation agent successfully combines theoretical strategies with practical adaptability. By blending Boulware and Conceder behavior and applying basic opponent modeling, the agent performs well in multiple domains and against different types of agents. This demonstrates the effectiveness of **strategic hybridization** and **adaptive behavior** in automated negotiation.

7. Reflection and Team Collaboration

The development of our negotiation agent was both a technical and collaborative effort. As a team, we followed a structured approach:

- **Initial Research**: We began by exploring NEGMAS documentation and tutorials, identifying key concepts like the BOA framework, utility spaces, and concession models.

- **Division of Work**: One member focused on the bidding and acceptance strategies, another developed the opponent modeling logic, and the rest contributed to testing, documentation, and performance analysis.

- **Communication**: Weekly meetings and code reviews ensured progress alignment and helped us integrate ideas effectively.

- **Key Challenges**:

    - Balancing concession timing to avoid early rejection or missed agreements.

    - Designing a generalizable strategy that performs well across domains.

    - Estimating the opponent's reservation value without overfitting to specific behavior patterns.

Overall, this project gave us valuable experience in:

- Working with **multi-agent systems**
- Applying **game-theoretic concepts** in practice
- Writing clean, modular code with **strategic intelligence**
- Managing a collaborative coding effort under deadlines

We learned that even simple adaptive models can significantly improve negotiation success and that practical agent design involves constant trade-offs between selfishness and cooperation.