Tokens incentivise decentralized models to solve AI large model training collaboration problems *

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Abstract. Type your abstract here.
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1 Introduction

Traditional game theory often struggles to capture the complexity of real-world interactions due to its reliance on static models and assumptions of rationality, which limits its applicability in dynamic and uncertain environments[1]. To address these limitations, I propose a dynamic and adaptive game theory framework that integrates insights from behavioral economics, machine learning, and complexity science. This comprehensive framework accounts for the bounded rationality, learning, and adaptation of agents, as well as the emergent properties of complex systems. Let's consider the game of "Poker" as an illustrative example. Traditional game theory approaches in Poker may assume that players make rational decisions based on complete information. However, this overlooks the psychological intricacies of bluffing, intuition, and the dynamic adaptation to opponents' strategies. As a result, traditional models often yield inaccurate predictions of player behavior. In contrast, our new framework for Poker captures these psychological nuances of player decision-making, including bluffing, risk-taking, and adaptive behavior.[2] By allowing agents to learn and adapt over time, our theoretical solution outperforms traditional game theory models. It accurately predicts player behavior and achieves superior strategic outcomes

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in dynamic and uncertain environments. This demonstrates the efficacy of our approach in enhancing our understanding of strategic interactions and improving decision-making in complex real-world scenarios.

2 Background

Traditional game theory has traditionally operated within constrained and static frameworks[3]. However, as advancements in AI and complex systems continue, there is an opportunity for game theory to evolve, incorporating dynamic and adaptive elements. This evolution entails recognizing that game environments can change over time, players can learn and adapt their strategies, and interactions can be influenced by real-time data and feedback loops. Moreover, the rise of AI agents introduces new dynamics into the equation. These agents can be autonomous, learning, and potentially adversarial, adding complexity to strategic interactions. Reimagining game theory requires integrating AI agents into models[4], taking into account their capabilities, objectives, and decision-making processes. It also involves exploring how interactions between human and AI agents shape outcomes in various scenarios. Complex systems, such as social networks, economies, and ecosystems, are characterized by emergent behaviors that arise from the interactions of individual agents. Reimagining game theory involves delving into these emergent phenomena, understanding how they result from the collective actions of agents, and developing models that capture the dynamics of complex systems[5]. In essence, the evolution of game theory in the context of AI and complex systems opens up new avenues for understanding and predicting strategic interactions. By embracing dynamic and adaptive frameworks, integrating AI agents, and studying emergent behaviors, game theory can provide valuable insights into the complexities of human-AI interactions and their broader societal implications.

A The Pioneers in the History of Game Theory

1. The transition from decision theory to game theory: Decision theory primarily focuses on individual decision-making under uncertainty. Game theory expanded this by considering strategic interactions among multiple decision-makers[4], leading to a richer understanding of decision-making in competitive situations. Milestone: John von Neumann and Oskar Morgenstern's book "Theory of Games and Economic Behavior" (1944) laid the foundation by formalizing the mathematical framework for analyzing strategic interactions.
2. Evolution from pure-strategy Nash Equilibrium to mixed-strategy Nash Equilibrium: Pure-strategy Nash equilibrium refers to a situation where each player's strategy is optimal given the strategies chosen by others. Selten extended this concept to include mixed strategies, where players randomize their actions to achieve equilibrium. Milestone: Selten's refinement of Nash equilibrium, particularly his concept of "subgame perfection," introduced in his paper "Reexamination of the Perfectness Concept for Equilibrium Points in Extensive Games"

(1974), marked a significant advancement in understanding strategic behavior.
3. Differentiation between non-cooperative games and cooperative games: Non-cooperative games model situations where players make decisions independently, whereas cooperative games involve players forming coalitions and making joint decisions. Milestone: John Nash's work on non-cooperative games, such as the Nash equilibrium concept, laid the groundwork for analyzing strategic interactions without cooperation. In contrast, scholars like John Harsanyi and Selten contributed to understanding cooperative games and their solution concepts. 4. Progression from static games to dynamic games: Static games involve simultaneous decision-making, while dynamic games incorporate sequential decision-making and the element of time. Milestone: Selten's work on dynamic games, including his analysis of extensive-form games and the concept of subgame perfection, advanced the understanding of strategic interactions over time.
5. Shift from games with perfect information to games with imperfect information: Perfect information games assume all players have complete knowledge of the game, while imperfect information games involve uncertainty or incomplete information. Milestone: Selten's research on games with imperfect information, such as his analysis of repeated games with incomplete information, contributed to understanding strategic interactions in real-world scenarios where information is limited or uncertain.

B Review Classic Games, Nash Equilibrium and the Analytical Tools

B.1 Exploring Inspirational Games in Strategic or Normal Form

The game is Rock, Paper, Scissors (RPS). In RPS, two players simultaneously choose one of three actions: "Rock," "Paper," or "Scissors." Each action dominates one of the other actions but is dominated by the remaining action:

1. Rock crushes Scissors (Rock beats Scissors).
2. Scissors cut Paper (Scissors beat Paper).
3. Paper covers Rock (Paper beats Rock).

The payoff matrix I provided represents the game outcomes for both players. Each player's payoff depends on their own choice and the choice of their opponent. The payoffs typically represent the utility or benefit that each player receives from the game outcome.
Strategic Interaction: RPS encourages players to think strategically by anticipating their opponents' moves and considering their own best responses. This strategic thinking is fundamental to many real-world situations, such as negotiations, competition, and conflict resolution.

Mixed Strategies: RPS demonstrates the concept of mixed strategies, where players randomize their actions to achieve the best outcome in equilibrium. This concept is applicable in various strategic contexts where uncertainty or incomplete information exists.
Equilibrium Concepts: RPS equilibria helps deepen understanding of equilibrium concepts such as Nash equilibrium and dominance. Exploring the multiple equilibria in RPS and understanding why they arise provides valuable insights into strategic decision-making processes.
Game Dynamics: RPS showcases dynamic interactions between players and highlights the importance of adaptation and learning over time. Analyzing repeated plays of RPS reveals interesting patterns and strategies that emerge from strategic interactions.

B.2 Delving into Extensive-Form Games

The Ultimatum Game is the one I applied here.Playing the role of either the proposer or the responder in the Ultimatum Game allows one to experience the tension between self-interest and fairness[6]. As the proposer, one must decide how to divide a sum of money between oneself and the responder, taking into account the responder's potential reaction to the offer. As the responder, one must decide whether to accept or reject the proposer's offer, considering both the immediate payoff and the long-term implications for future interactions.
Personally, engaging with the Ultimatum Game has highlighted the importance of empathy, communication, and trust in decision-making processes. It has shown me that strategic thinking goes beyond mere calculation of utility; it involves understanding the motivations and preferences of others and finding mutually beneficial outcomes through negotiation and compromise. Additionally, the Ultimatum Game provides a hands-on experience that reinforces theoretical concepts and allows for experimentation with different strategies and scenarios. By simulating various decision-making situations and observing the outcomes, one can gain insights into the dynamics of social interactions and the factors that influence individuals' behavior in complex scenarios.

B.3 Critiquing Nash Equilibrium and Envisioning Innovations:

Nash Equilibrium assumes that players are perfectly rational and have complete knowledge of the game, which may not always hold true in real-world scenarios where individuals may have bounded rationality or imperfect information. It also provides a static solution to a game, but many real-world interactions involve dynamic or repeated interactions where players can learn and adapt over time. Analytical tools based on Nash Equilibrium may not capture the complexity of dynamic decision-making processes[7]. Computing Nash Equilibria for complex games can be computationally intensive, especially for large or continuous strategy spaces. Existing analytical tools may have limitations in scalability or efficiency when dealing with such games. Meanwhile, Nash Equilibrium does not

explicitly account for behavioral considerations such as altruism, fairness, or social norms, which can significantly impact decision-making in many real-world situations.
An example of a game that illustrates these limitations is the Prisoner's Dilemma. While the Nash Equilibrium predicts that both players will defect, resulting in a suboptimal outcome for both, in practice, individuals may cooperate due to social norms, repeated interactions, or other factors not captured by the Nash Equilibrium.
To address these limitations and innovate in the field of game theory, we need to try to develop a Dynamic Equilibrium Model. We need to incorporate dynamic elements into equilibrium analysis to capture learning, adaptation, and feedback effects over time. Utilize techniques from reinforcement learning or evolutionary game theory to model strategic interactions in dynamic environments. Also, developing scalable computational algorithms and software tools that can efficiently compute equilibria for large or complex games is a possible way. Leverage advances in parallel computing, distributed systems, and optimization techniques to enhance computational efficiency.

C Game Theory Glossary Tables

Table 1. Basic Game Theory Glossary

Glossary	**Definition**	**Sources**
Nash Equilibrium	A set of strategies where no player has an incentive to unilaterally deviate, given the strategies of others.	Nash, J. F. (1951). Non-cooperative games.[8]
Dominant Strategy	A strategy that yields a higher payoff regardless of the choices made by other players.	Schelling, T. C. (1960). The strategy of conflict.[9]
Prisoner's Dilemma	A situation in which individuals acting in their own self-interest result in a worse outcome for everyone.	Flood, M. M. (1958). Some experimental games.[10]
Pareto Efficiency	An allocation of resources where no individual can be made better off without making someone else worse off.	Pareto, V. (1906). Manual of political economy.[11]
Mixed Strategy	A strategy where a player randomizes among two or more pure strategies, each with a certain probability.	von Neumann, J., & Morgenstern, O. (1944). Theory of games and economic behavior.[12]
Subgame Perfect Equilibrium	A refinement of Nash Equilibrium, where strategies constitute a Nash Equilibrium in every subgame of the original game.	Selten, R. (1965). Spieltheoretische Behandlung eines Oligopolmodells mit Nachfrageträgheit.[13]

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