Strategic Dynamics of Cooperation: Investigating Bots and Asymmetry Scenarios in Evolutionary Game Theory

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Strategic Dynamics of Cooperation: Investigating Bots and Asymmetry Scenarios in Evolutionary Game Theory

By

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Fukuoka, Japan

“I dedicate this thesis to my parents, whose love, guidance, and sacrifices have laid the foundation for my journey. Your unwavering support and belief in my dreams have been my greatest motivation. This achievement is as much yours as it is mine.”

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Declaration

I hereby declare that the thesis titled **“Strategic Dynamics of Cooperation: Investigating Bots and Asymmetry Scenarios in Evolutionary Game Theory”** is an original work composed and written by me. This thesis is a product of my independent research, conducted after my registration for the Doctor of Engineering (Ph.D.Eng) degree at the Interdisciplinary Graduate School of Engineering Sciences (Mechanical System Engineering Major), Kyushu University, Japan.

I confirm that this work has not been previously submitted, in whole or in part, for any other degree, diploma, or qualification at this or any other institution. Any work or text not my own has been duly referenced and acknowledged.

Signature: ______________________________

Name: Gopal Sharma

Date: November, 2024

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Abstract

The evolution and maintenance of cooperative behavior in diverse biological and social systems—from bacteria viruses to humans—are among the central puzzles in evolutionary biology and the behavioral sciences. Even when defection is the best strategy in a purely individual sense, cooperation is the leading behavior across many contexts. This thesis will apply EGT in mathematical modeling and strategic analysis so as to deduce the conditions whereby cooperation can thrive within a predominantly defective surroundings. Another further development from the basic modeling may be that of expressing strategy and environment in a coupled system, the latter of which environmental or common resources are impacted by the strategic behaviors of individuals and thereafter act upon further strategic decisions. This feedback is crucial in many real-life applications that concern resource utilization, management of common resources, as well as conservation of the environment. This will help in comprehension of the quantification of inefficiency arising from these systems. The subsequent parts of the thesis discuss the use of artificial agents or bots in driving cooperative behavior within optional Prisoner's Dilemma games. We use simulations to explore how different types of bots—always cooperate, always defect, opt-out, or random behavior—affect human players' strategies in one-shot, anonymous interactions. The outcomes all support the finding that cooperative bots can boost cooperation considerably under the weak imitation setting for both well-mixed populations and regular lattices. On the other hand, the addition of loner bots—withdraws from interactions—in structured populations has complex effects: while a moderate number of loner bots can stabilize cooperation under strong imitation, too much tends to break down cooperation. Finally, the last section develops cooperation on asymmetric populations with an imbalance in power and hierarchy. We consider an asymmetric model where weaker players are forced to cooperate, while stronger players receive always the temptation payoff with weaker opponents. Thus, the emerging interaction patterns and the resulting dynamics will differ substantially from their symmetric counterparts. In particular, in cases where network reciprocity mechanisms favor cooperation under traditional conditions, asymmetry destroys such support and cooperative networks disintegrate. Where reciprocity is inherently weak, on the other hand, asymmetry enables strong players to parasitize clusters of weak cooperators at an individual level but then promote cooperation more globally. However, as the scale of asymmetry grows, cooperation in the subgroups of weak players becomes undermined, with the whole system eventually becoming destabilized.

These results contribute to a better understanding of the detailed interplay between strategy revision mechanisms, environmental feedbacks, and population structures in the evolution

of cooperation. The results range beyond theoretical biology into possible applications in designing socio-economic policy, programming behavior in artificial intelligence, and public health strategies. Based on these poles, it further develops the analysis of cooperation by introducing new indices, and it also aims at extending traditional game settings to asymmetric interactions and optional participation. In short, the thesis will be able to present an overall framework to analyze cooperation across a wide array of systems. The insights gained can inform more effective interventions in promoting cooperative behaviors, particularly in scenarios characterized by complex social dilemmas or power asymmetries.

Preface

The research topics explored in this thesis focus on various evolutionary games, particularly involving human-machine interactions and asymmetric game. Chapters 2 and 3, where I am the primary (first) author, have been published in peer-reviewed journals. Each chapter is dedicated to a distinct research topic and is structured in a format suitable for publication.

Chapter 1 presents an introduction to the background of game theory, including an outline of the thesis.

Chapter 2 is published as:.
G. Sharma, H. Guo, C. Shen, and J. Tanimoto, "Small bots, big impact: Solving the conundrum of cooperation in optional prisoner's dilemma game through simple strategies," Journal of The Royal Society Interface, vol. 20, no. 204, p. 20230301, 2023 https://doi.org/10.1098/rsif.2023.0301

Chapter 3 is published as:
G. Sharma, Z. He, C. Shen, and J. Tanimoto, "Asymmetric population promotes and jeopardizes cooperation in spatial prisoner's dilemma game," Chaos, Solitons & Fractals, vol. 187, p. 115 399, 202 https://doi.org/10.1016/j.chaos.2024.115399

Chapter 4 summarizes the findings of the conducted research, the conclusions from the study, and discusses possible directions of future work in the area of cooperation dynamics.

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First and foremost, I would like to express my heartfelt gratitude to my supervisor, **Professor Dr. Jun Tanimoto**, for his invaluable guidance, unwavering support, and insightful feedback throughout my PhD journey. His profound wisdom and encouragement have been instrumental in shaping my research path and fostering my growth as a scholar. I am deeply indebted to him for his mentorship, which has been a beacon of inspiration and a guiding light in both my academic and personal development. Words cannot fully convey the depth of my appreciation for his contributions, which have profoundly influenced my life and future endeavors. I would also like to extend my heartfelt appreciation to **Professor Aya Hagishima** and **Professor Naoki Ikegaya** for their invaluable insights and constructive feedback. Their detailed critiques and suggestions have greatly enhanced the quality and depth of this research. My sincere appreciation go to **Research Associate Professor Dr. Shen Chen** for his invaluable advice and thoughtful suggestions. His constructive feedback and meticulous guidance were crucial in refining my research, especially during my all time in this research field of writing stages, which brought this work and to me to its final form. Additionally, I would like to express my sincere gratitude to my co-authors, **Dr. Hao Gao** from Tsinghua University, and **Zhixua He**, a PhD student from Yunnan University of Finance and Economics. Their collaboration and dedication have been instrumental in advancing our research. I truly appreciate their support and the opportunity to work together.

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dousan Scholarship for supporting me for two years, and to the **Lotte Foundation** for their crucial assistance during the final year of my PhD journey. Their generous support allowed me to focus entirely on my research without financial concerns. I am also thankful for the travel grants provided by **Kyushu University**, the **Yoshida Foundation for Science and Technology**, the **Kato Memorial Bioscience Foundation**, and the **Society for Promotion of Space Science Foundation**, which enabled me to present my research at global forums, significantly enriching my academic experience. The support from these institutions not only propelled my research forward but also instilled a sense of community and belonging that was vital during challenging times. I extend my heartfelt thanks to our lab secretary, **Yoshizuru-san**, for her dedication and for efficiently managing our daily activities in the laboratory. Her meticulous organizational support ensured a smooth research environment, allowing me to concentrate on my academic pursuits.

I am also profoundly grateful to my senior labmates: **Dr. Mamun, Dr. Soli, Dr. Wang** and Others, for their valuable guidance and mentorship throughout my research journey. Their wisdom and encouragement have been a constant source of motivation. I would also like to thank **Azhar-san, Zakir-san, Khadija-san, Ikeo-san, Utsumi-san, Haitham-san** and all lab-mates for their continuous support and camaraderie, which uplifted me during tough times.

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Finally, to all my friends and colleagues who have supported and encouraged me throughout this academic journey, I extend my deepest gratitude. Your faith in me has been a pillar of strength, and I am truly blessed to have you in my life. This thesis is a testament to the collective support and belief of all those who have contributed to my journey.

I would like to extend my heartfelt gratitude to everyone who has supported or even challenged me on this journey. Your guidance, encouragement, and unwavering belief in my potential have been instrumental in helping me reach this milestone. Thank you for being part of my path to success.

1 INTRODUCTION

1.1 Background

The study of cooperation and competition has long been a central theme in both social and biological sciences, where evolutionary game theory (EGT) provides a powerful framework for analyzing strategic interactions within evolving populations. Since its inception, EGT has been widely employed to understand how cooperative behavior can emerge and be sustained, even in situations where selfish strategies seem to offer a higher individual payoff. Early models, such as the Prisoner's Dilemma (PD), captured the fundamental social dilemma faced by individuals, yet recent research has extended these models to explore more complex scenarios involving optional participation, spatial structure, and asymmetric interactions.

In recent years, scholars have broadened the application of EGT by incorporating variations such as the Optional Prisoner's Dilemma (OPD) and asymmetric population structures. These adaptations address limitations in traditional models by considering realistic features like variable participation and unequal power dynamics, which are prevalent in real-world social systems. The literature on optional games highlights how voluntary participation can facilitate the coexistence of diverse strategies, thus stabilizing cooperation under certain conditions. Similarly, research on asymmetry has shed light on how power imbalances and differing capabilities impact strategic choices and long-term outcomes in structured populations.

The universally applied model of game theory, the Prisoner's Dilemma, has always brought out the fact that there might be an conflicting relationship between individual rationality and group benefit. All this model points out is those situations when the pursuit by individuals of their own self-interest leads them to a less-than-optimal joint outcome [1]. Variants of the PD are asymmetrical and optional prisoner dilemmas that could more accurately represent natural social and economic dynamics [2]. The development of simple bots-pre-programmed to play a certain strategy-furnishes new roads into understanding how strategic interventions may promote cooperation within these complex environments. This PhD research tries to understand, through the use of simple bots, the consequences of such an intervention in asymmetric and optional PD games. This is a fascinating branch of applied mathematics that delves into the strategic decision-making processes of individuals, whether they're humans, animals, or even computers.

1.1.1 What Is Game Theory?

Introduction Game theory seeks to help us understand scenarios where decision-makers behave strategically, taking the choices of others into account [3]. Where a ”game” in everyday life—think chess or sports—implies players competing against one another under predefined rules, the application of game theory is far broader. Game theory applies to any situation in which the payoffs for each one of them depend on what everyone else does, so it is a useful framework both for analyzing competition and cooperation and everything that lies in between.

1.1.2 Origins and Pioneers

This theory was not born in a game room but rather in the brains of brilliant mathematicians and economists. The work started by John von Neumann—a Hungarian-American mathematician—and Oskar Morgenstern—a German-American economist—they insisted in this influential book, The Theory of Games and Economic Behavior (1944) [4],[5], [6] that traditional mathematics generally copes with disinterested natural phenomena and cannot work out such a science as economics. Economics, they said [7], is a game—an intricate dance of strategic decisions. Thus, the term ”game theory” was coined; and a new science was born [8], [9].

1.1.3 Key Concepts

Players: These are the decision-makers—individuals, companies, or even nations.

Strategies: Each player has a set of possible actions or strategies they can choose from.

Payoffs: These represent the outcomes associated with different combinations of strategies. Payoffs can be rewards, penalties, or any measurable benefit.

Solution: Game theory aims to find optimal strategies for players, considering their interests and the potential outcomes. While the name game theory might sound fun and games, its applications are serious and all over the place. Some of the applications are:

Introduction

Economics: Understanding market behavior, pricing strategies, and negotiations comprise some of the key usages.

Political Science: Application in the analysis of voting systems, international relations, and conflict resolution.

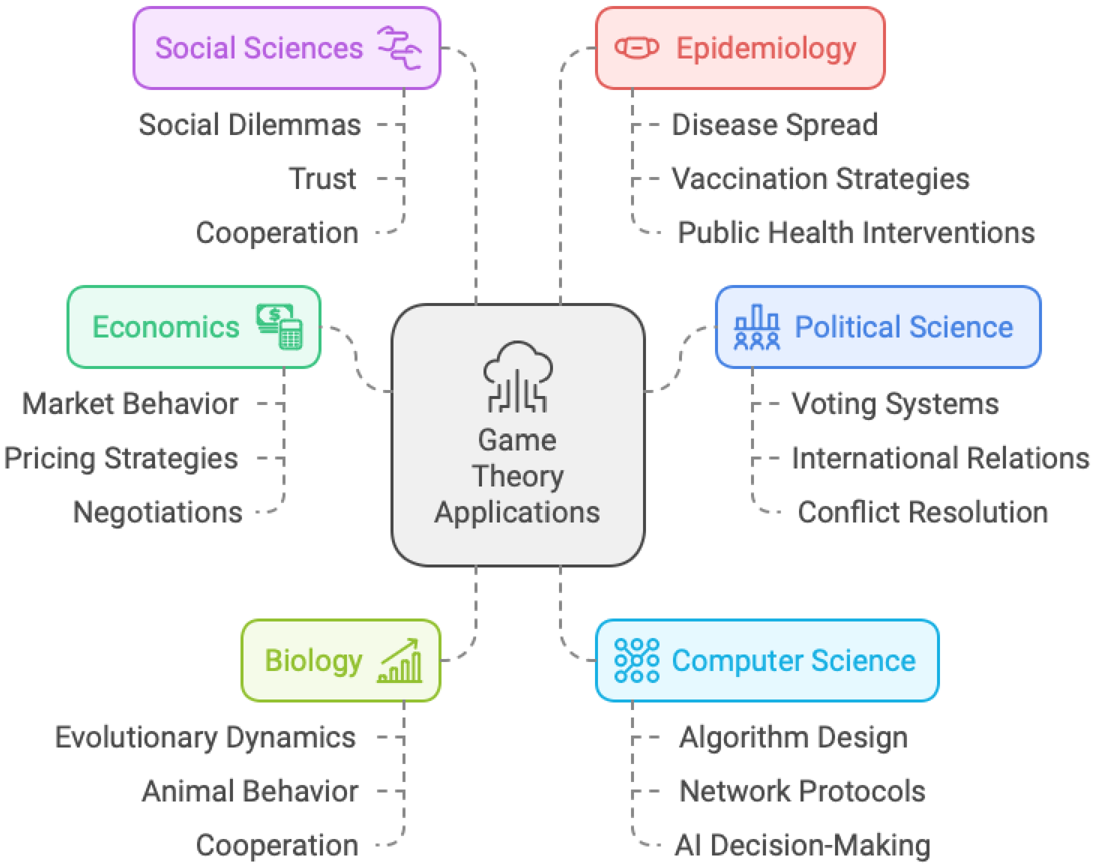

Figure 1: Overview of game theory applications across various disciplines

Biology: The use of evolutionary dynamics, animal behavior, and cooperation.

Computer Science: Algorithm design, network protocols, and decision-making in artificial intelligence. Social Sciences: Investigating social dilemmas, trust, and cooperation.

Epidemiology: Modeling the spread of diseases, understanding vaccination strategies, and optimizing public health interventions.

1.2 Optional Prisoner's Dilemma Game

The optional prisoner's dilemma is an extended form of the basic prisoner's dilemma, a well-known scenario that arises frequently when cooperation and conflict are analyzed within game theory [10]. The standard prisoner's dilemma involves two individuals who have to make a simple choice: whether to cooperate with their counterpart or defect. Their joint decision brings about the payoffs, as follows:

A. If both cooperate, then they get a moderate reward, denoted by R for reward.

B. If both defect, they both suffer a punishment.

C. If one cooperates while the other defects, the defector receives a higher payoff than the cooperator, who is left with the lowest payoff through being the sucker.

Now, let's introduce the twist in the OPD: players have a third option – they can abstain from playing altogether. This additional choice opens new possibilities beyond mere cooperation or defection.

The payoff matrix for the optional prisoner's dilemma game is shown here.

	Cooperate	Defect	Abstain
Cooperate	(R, R)	(S, T)	(L, L)
Defect	(T, S)	(P, P)	(L, L)
Abstain	(L, L)	(L, L)	(L, L)

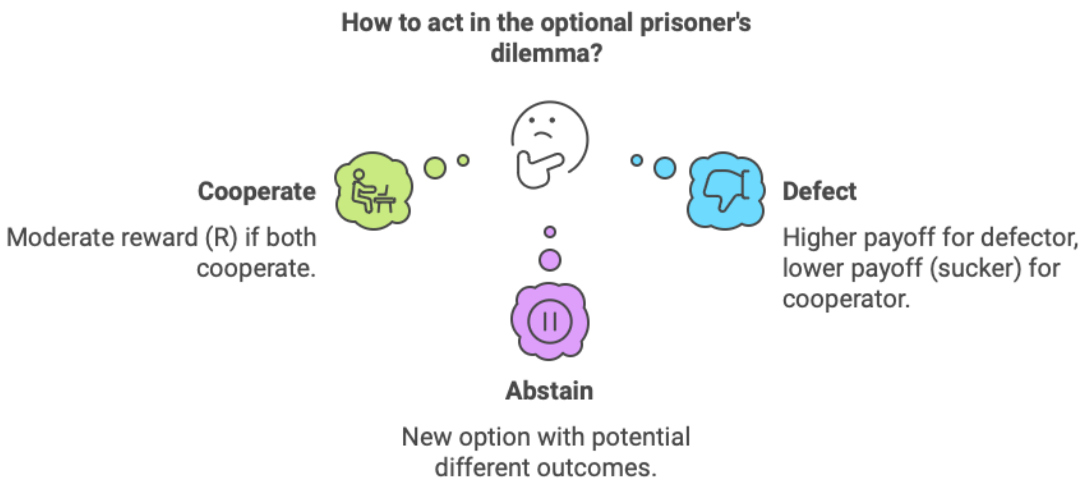

Figure 2: Decision-making in the optional prisoner's dilemma, illustrating the choices of Cooperate, Defect, and Abstain

If both players cooperate, they both receive the reward **R**. If both players defect, they both receive the punishment **P**. If one cooperates while the other defects, the defector gets **T**, and the cooperator gets **S**. If one or both players abstain, they both receive the loner's payoff **L**.

Realistic Example–The Job Offer Dilemma

Imagine two highly skilled software engineers, Anju and Gopal, who are presented with job offers from a prestigious tech company. If both accept the offer, they will benefit from a great work environment and high salaries, resulting in a mutually rewarding outcome (reward RR). However, if both decline the offer, they forfeit the opportunity and face a less favorable outcome (punishment PP). Now, here's an interesting twist: the company introduces an option for them to abstain from the decision. If either Anju or Gopal chooses to abstain, they won't work at the company, but they also won't face any penalties or consequences. This outcome is referred to as the loner's payoff (LL). This scenario highlights a variation of the classic game theory problem with an additional "abstain" option, creating new dynamics in decision-making.

If both accept the job (cooperate), they both thrive in their careers.

If both decline (defect), they miss out on a great opportunity.

If one accepts while the other declines, the acceptor enjoys the job (temptation payoff T), while the decliner avoids the risk (sucker's payoff S).

If either abstains, they avoid the risk and maintain their current situation (loner's payoff L).

This framework, known as the optional prisoner's dilemma (OPD), captures the nuances of decision-making when there is a third option beyond cooperation or defection. It reflects real-life scenarios where individuals can choose to opt out, even if doing so means forfeiting potential rewards.

Ultimately, the OPD is not merely about numerical payoffs but also offers deep insights into human behavior and strategic thinking. It highlights the delicate balance between self-interest and cooperation. Whether applied to job offers, environmental negotiations, or international diplomacy, the OPD sheds light on the art of navigating choices and the intricate dynamics of human decision-making.

1.2.1 2x2 Prisoner's Dilemma (PD) game

In a simplified strategic game involving two players, where each player has two choices—Cooperate (C) or Defect (D)—the outcomes are determined by the combination of choices made. The typical payoff matrix for this scenario is structured as follows:

	Cooperate	Defect
Cooperate	(R,R)	(S,T)
Defect	(T,S)	(P,P)

In this framework:

R (Reward): Occurs when both players choose to cooperate (C, C), resulting in a mutually beneficial outcome for both players. This is often seen as the optimal outcome for collective benefit.

T (Temptation): Happens when one player defects (D) while the other cooperates (C). The defector receives the highest possible payoff, exploiting the cooperative player's decision.

S (Sucker's Payoff): The payoff for a cooperating player when the other player defects (C, D). This is the lowest payoff because the cooperating player is taken advantage of by the defector.

P (Punishment): Occurs when both players defect (D, D), leading to a less desirable outcome for both, usually worse than mutual cooperation but sometimes better than being exploited as the sucker.

This structure often characterizes strategic decision-making scenarios, emphasizing the tension between individual incentives and collective outcomes.

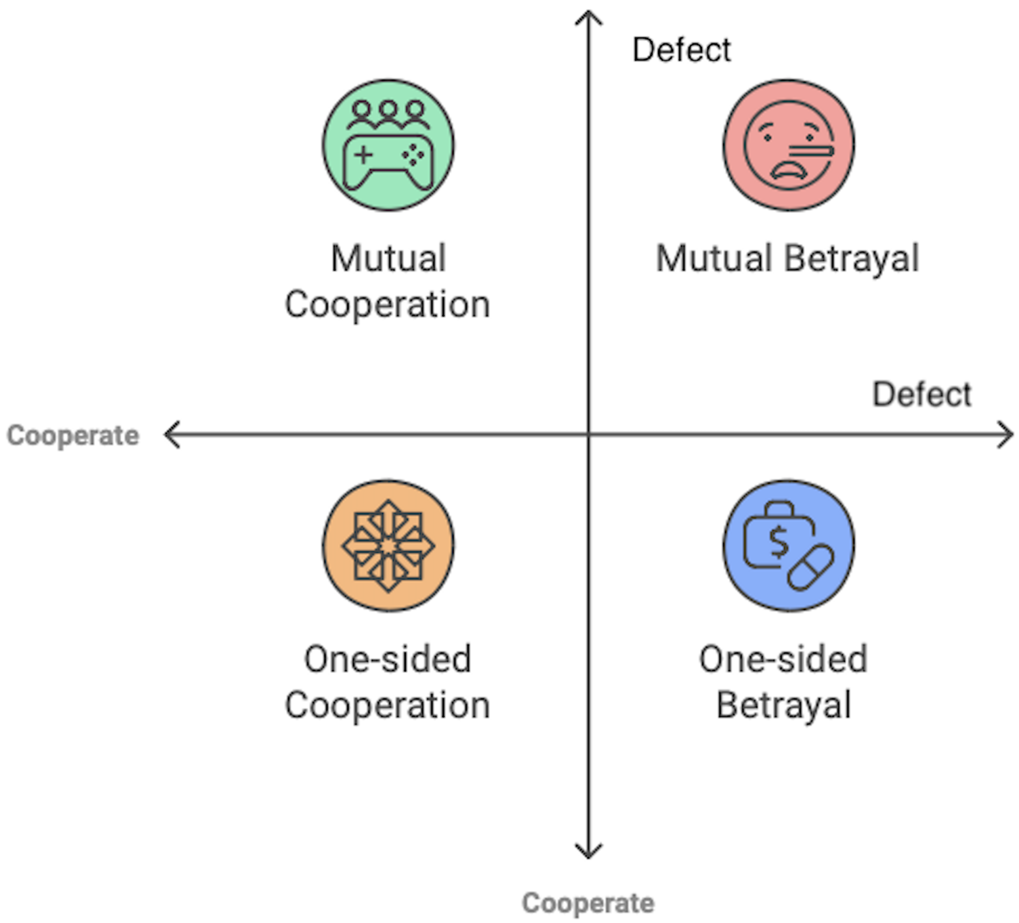

Figure 3: Illustration of the 2x2 Prisoner's Dilemma game

The typical ranking in a PD game is $T > R > P > S$, where each player is incentivize to defect, even though mutual cooperation would yield a better outcome than mutual defection.

1.2.2 3x3 Prisoner's Dilemma (PD) game

The 3x3 Prisoner's Dilemma extends the traditional game by introducing a third choice for each player—typically Cooperate (C), Defect (D), and Neutral (N). This added complexity allows for a broader range of strategies and outcomes. The payoff matrix expands to include nine possible outcomes, where each player's choice impacts the other's payoff.

Figure 4: Strategic Decision-Making in the 3x3 Prisoner's Dilemma Game: An interactive framework illustrating key dynamics of trust, cooperation, defection, and competition. Players' actions, whether collaborative or self-serving, influence the overall balance between mutual benefit and individual gain, highlighting the complex interplay of strategy and trust-building in decision-making scenarios.

Mutual cooperation (C, C) yields the highest collective reward (R, R), while mutual defection (D, D) results in punishment (P, P), a less desirable outcome for both. If one defects while the other cooperates, the defector gains the highest payoff (T), while the cooperator suffers the lowest (S). The Neutral option introduces moderate payoffs, such as a middle-ground reward when paired with cooperation or intermediate results when combined with defection. When both players choose Neutral (N, N), the outcome reflects compromise, often yielding balanced but suboptimal payoffs (W, W). This expanded model reflects real-world scenarios where individuals can choose strategies beyond binary decisions, incorporating nuanced interactions and risk management. It also increases the strategic depth, allowing for innovative approaches that balance cooperation, competition, and neutrality.

In a 3x3 PD game, players need to consider a wider range of strategic possibilities, and the temptation to defect may be weighed differently against the "Neutral" option, depending on the payoffs. The additional choice increases the complexity of the decision-making process and often provides new dynamics in exploring cooperation and conflict.

1.3 Spatial PD games

The Spatial Prisoner's Dilemma (SPD) modifies the classical Prisoner's Dilemma by placing players on a spatial structure, such as a grid or network, where they interact only with immediate neighbors rather than a well-mixed population. This localized interaction introduces complex patterns of cooperation and defection, influenced by spatial dynamics. In the classical version, two players choose to cooperate (C) or defect (D), with payoffs determined by their combined choices. Defecting while the other cooperates yields the highest payoff (T, Temptation), while mutual cooperation provides a reward (R) that benefits both. Mutual defection results in punishment (P), and cooperating while the other defects leads to the lowest payoff (S, Sucker's payoff). The payoff hierarchy $T > R > P > S$ makes defection the rational strategy in single rounds, yet mutual cooperation produces better collective outcomes. The SPD's spatial constraints challenge this dynamic by fostering clusters of cooperation or defection, driving emergent behaviors absent in the classical setup.

In the Spatial Prisoner's Dilemma (SPD), players are positioned within a spatial structure that determines their interactions. These structures can include lattices, where players are placed on square grids and interact with their neighbors; networks, where players are nodes connected by edges representing relationships; or continuous spaces, where interactions are based on physical proximity. Each player adopts a strategy—either to cooperate or defect—and engages in the game with their immediate neighbors, accumulating payoffs from these localized interactions. Unlike the classical model, where players interact with everyone in a well-mixed population, the SPD's spatial constraints create localized dynamics that can lead to the emergence of cooperation or defection patterns. These dynamics are heavily influenced by the structure of the spatial arrangement, fostering complex behaviors reflective of real-world systems. The Spatial Prisoner's Dilemma (SPD) operates through iterative processes involving four key steps as,

Initialization: assigns players initial strategies—either randomly or based on a defined distribution—while payoffs for cooperation and defection follow the classical Prisoner's Dilemma rules. During Interaction, each player plays the game with their immediate neighbors, accumulating a cumulative payoff based on these localized exchanges.

In the Strategy Update phase, players adjust their strategies over time, often using imitation, where a player adopts the strategy of their most successful neighbor with the highest payoff. Alternative update mechanisms include evolutionary dynamics like replicator rules or stochastic processes such as probabilistic strategy adoption. Finally, through Iterative Dynamics, the game unfolds over multiple iterations, allowing spatial structures to influence strategy formation. Cooperative players can form clusters that resist invasion by defectors, enabling cooperation to persist in ways that are impossible in well-mixed populations. This spatial clustering highlights the importance of local interactions in shaping long-term outcomes.

This method reveals several key insights. Spatial structures promote the emergence of cooperation by allowing cooperative clusters to form, which shield themselves from exploitation by defectors and remain robust against local invasions.

The role of network topology is crucial, as the arrangement of players—whether on grids, small-world networks, or scale-free networks—significantly influences the dynamics of cooperation.

Through evolutionary dynamics, the SPD examines how cooperation evolves in structured populations, offering insights into real-world phenomena like social norms, altruism, and trust.

Its applications span multiple disciplines: in biology, it aids in understanding cooperative behaviors in animal populations; in sociology, it helps analyze social trust and human collaboration; in economics, it sheds light on trade and alliances within structured markets; and in technology, it optimizes peer-to-peer networks and distributed systems, showcasing its versatility in addressing complex cooperative interactions.

1.4 Asymmetric games

In asymmetric games, contestants such as players, teams, or other entities start with differing capabilities, resources, or strategic options, adding variation and complexity compared to symmetric games where all participants begin on equal footing. A key feature of asymmetric games is **perceived differences**—contestants may vary in attributes such as size, age, special abilities, or resources, like a chess match where one player controls knights and the other commands dragons. These differences lead to **strategic choices** unique to each player, shaping distinct gameplay experiences, as seen in games like StarCraft, Magic: The Gathering, or Street Fighter, where characters or factions bring specific tactics and moves. Asymmetry also influences **rewards and payoffs**, as the outcomes depend on players' abilities and starting conditions, requiring careful balancing to maintain fairness [11]. In evolutionary biology, asymmetric games help study **evolutionarily stable strategies**—strategies that persist because they resist invasion by alternatives, exemplified by models like the hawk-dove game. This framework highlights how asymmetry can drive diverse and dynamic strategic interactions across gaming and real-world scenarios [12].

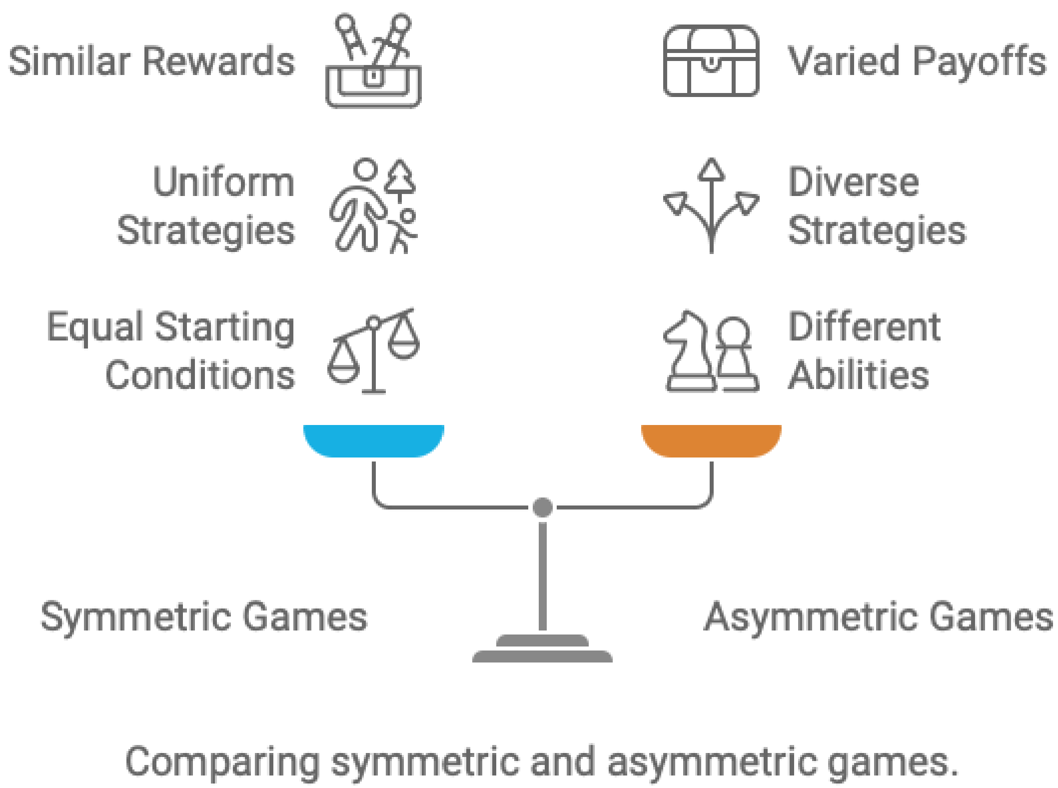

Figure 5: Balancing Dynamics: A visual comparison of symmetric and asymmetric games

1.5 Human Machine Interactions

The intersection of artificial intelligence (AI) and human gaming within the field of evolutionary game theory offers a powerful framework for studying adaptive strategies and behaviors [13]. By focusing on how strategies evolve over time based on their success, evolutionary game theory provides insights into the dynamics of competition and cooperation. AI systems, utilizing advanced techniques like reinforcement learning and neural networks, can replicate these evolutionary processes, simulating adaptive decision-making and optimizing strategies in dynamic game environments. This enables the modeling of complex interactions and the identification of evolutionarily stable strategies. Despite challenges in aligning AI behaviors with realistic evolutionary principles and ensuring adaptability to ever-changing conditions, the opportunities are immense. AI-driven models can shed light on real-world phenomena such as altruism, resource allocation, and the dynamics of social behaviors, while also advancing adaptive and evolving gaming scenarios. This integration enhances both the theoretical understanding of evolutionary processes and the practical development of innovative AI in interactive systems.

In the field of **Human-Machine Interactions** [14] within **evolutionary game theory**, unique challenges arise due to the integration of human decision-making processes with machine-driven strategies. One significant challenge is modeling human behavior, as humans often deviate from strictly rational decisions due to emotions, biases, and social influences. This unpredictability requires incorporating elements like bounded rationality, fairness, and trust into machine learning models. Additionally, machines must adapt their strategies dynamically to coexist with both rational and irrational human players in mixed populations, especially as human behavior evolves through learning or changing contexts. Building trust is another critical challenge, as machines must design strategies that encourage cooperation over repeated interactions while maintaining transparency to foster trust and accountability [15]. Furthermore, scaling interactions to multi-agent systems adds complexity, requiring machines to coordinate effectively and handle strategic uncertainty in noisy, dynamic environments. Ethical concerns also emerge, as complex machine strategies may result in opaque decisions, raising questions about fairness and accountability.

To address these challenges, several innovative techniques have been developed. Incorporating behavioral models from fields like behavioral game theory enables machines to simulate human tendencies, including loss aversion and bounded rationality. Reinforcement learning, particularly with human-in-the-loop or inverse reinforcement learning methods, allows machines to adapt their strategies by learning from human interactions.

Figure 6: Key Challenges in Human-Machine Interaction: Addressing ethical considerations, modeling human behavior, adapting strategies for unpredictability, building trust-based systems, and managing multi-agent complexity to enhance cooperation and decision-making in gaming and AI systems

Dynamic strategy adjustment using evolutionary algorithms and multi-agent deep learning provides adaptability in heterogeneous settings. Trust-building mechanisms, such as reputation systems and explainable AI models, enhance cooperation by making machine decisions transparent and understandable to humans. Additionally, designing asymmetric or optional games enables the study of realistic decision-making scenarios where humans can choose to participate or withdraw. Advanced simulation frameworks, such as agent-based models, facilitate testing machine strategies against diverse human behaviors, while fairness constraints ensure that machine algorithms remain ethical and non-exploitative. Emerging approaches like neuro-game theory, hybrid intelligence systems, and real-time feedback mechanisms further enhance the synergy between human intuition and machine rationality. By addressing these challenges through robust techniques, HMI in evolutionary game theory opens new possibilities for cooperation, strategy design, and decision-making in complex, interactive environments.

1.6 Problems and Objectives

Achieving cooperation in asymmetric and optional Prisoner's Dilemma (PD) games is a significant challenge due to the inherent differences in players' capabilities, payoffs, or strategies, as well as the ability of players to opt out of interactions. Asymmetry, whether in power, resources, or information, creates unequal dynamics that often discourage cooperation, while the optional nature of participation introduces further complexities by allowing players to disengage entirely [16]. Addressing these issues, this research focuses on the role of simple bots as strategic interventions to promote and stabilize cooperation in these challenging environments. Simple bots, due to their scalability and adaptability, offer a practical approach to influence game dynamics and foster cooperative behaviors. The study aims to explore how these bots, employing specific strategies, can effectively mitigate the adverse effects of asymmetry and optionality. The findings hold potential significance for addressing real-world issues, from social inequality and resource allocation to collective decision-making, and extend the applications of game theory to diverse domains such as economics, environmental policy, and social systems. By bridging complex theoretical models with simplified actionable strategies, this research contributes to a deeper understanding of cooperation in asymmetric and optional PD games and offers practical insights into enhancing coordination in social, economic, and political contexts.

1.7 Justification, Feasibility, Scope, and Delimitation

Promoting cooperation in asymmetric and optional Prisoner's Dilemma (PD) games is a critical step toward addressing real-world challenges such as social inequality, resource allocation, and collective decision-making. These games provide a powerful theoretical framework for understanding the dynamics of coordination under unequal conditions or when participation is voluntary. Simple bots, due to their scalability and adaptability, offer a novel approach to influence game dynamics, making them effective tools for fostering cooperation in such complex environments. By investigating the role of simple bots, this research has the potential to provide actionable insights with practical relevance in fields such as economics and environmental policy while simultaneously advancing the theoretical understanding of game theory. This work aims to distill complex dynamics, such as cascading effects in social systems, into simplified strategies for encouraging cooperative behavior.

The study is feasible due to the availability of advanced computational tools and established methodologies for simulating PD games. A strong foundation of existing literature on game theory, asymmetry, and cooperation ensures a robust theoretical basis for the research. The required academic resources, including access to simulation software and the opportunity to collaborate with experts in the field, are readily available. As a theoretical investigation, the research remains cost-effective and manageable within the constraints of a PhD project, requiring minimal material resources.

This research is scoped specifically within the context of asymmetric and optional PD game variations [17], focusing exclusively on external interventions through simple bots. It does not extend to exploring the psychological or emotional dimensions of human decision-making, as these factors lie outside the realm of game theory. Additionally, the study is conducted through simulations, which, while valuable for theoretical exploration, may limit direct applicability to real-world scenarios. However, the findings are expected to provide meaningful theoretical contributions, offering insights into the mechanisms that promote cooperation in diverse and asymmetric environments, with implications for broader applications in social, economic, and political systems.

1.8 Thesis Structure

This thesis is organized into four chapters, each contributing to the exploration of cooperation dynamics in evolutionary game theory, particularly in the context of Prisoner's Dilemma games. The first chapter provides a comprehensive introduction to the field of evolutionary game theory, outlining its foundational concepts, significance, and relevance to understanding cooperation in diverse and complex systems. It also establishes the motivation and scope of the research, highlighting the challenges posed by asymmetry and optional participation in social interactions.

The second chapter is based on the published article, **Small Bots, Big Impact: Solving the Conundrum of Cooperation in Optional Prisoner's Dilemma Game Through Simple Strategies** [18].This chapter investigates the role of simple bots in enhancing cooperative behavior in optional Prisoner's Dilemma games, demonstrating how these bots influence player decisions and stabilize cooperation under varying conditions.

The third chapter is derived from the published article, **Asymmetric Population Promotes and Jeopardizes Cooperation in Spatial Prisoner's Dilemma Game** [19]. This chapter examines the dual effects of population asymmetry on cooperation, revealing how disparities in power, resources, or strategic influence can both foster and hinder cooperative dynamics in spatially structured populations.

Finally, the fourth chapter provides a comprehensive conclusion and summary of the research findings, synthesizing insights from the preceding chapters. It highlights the contributions of this work to the field of evolutionary game theory and discusses its implications for future research and practical applications in fostering cooperation in asymmetric and optional interaction settings.

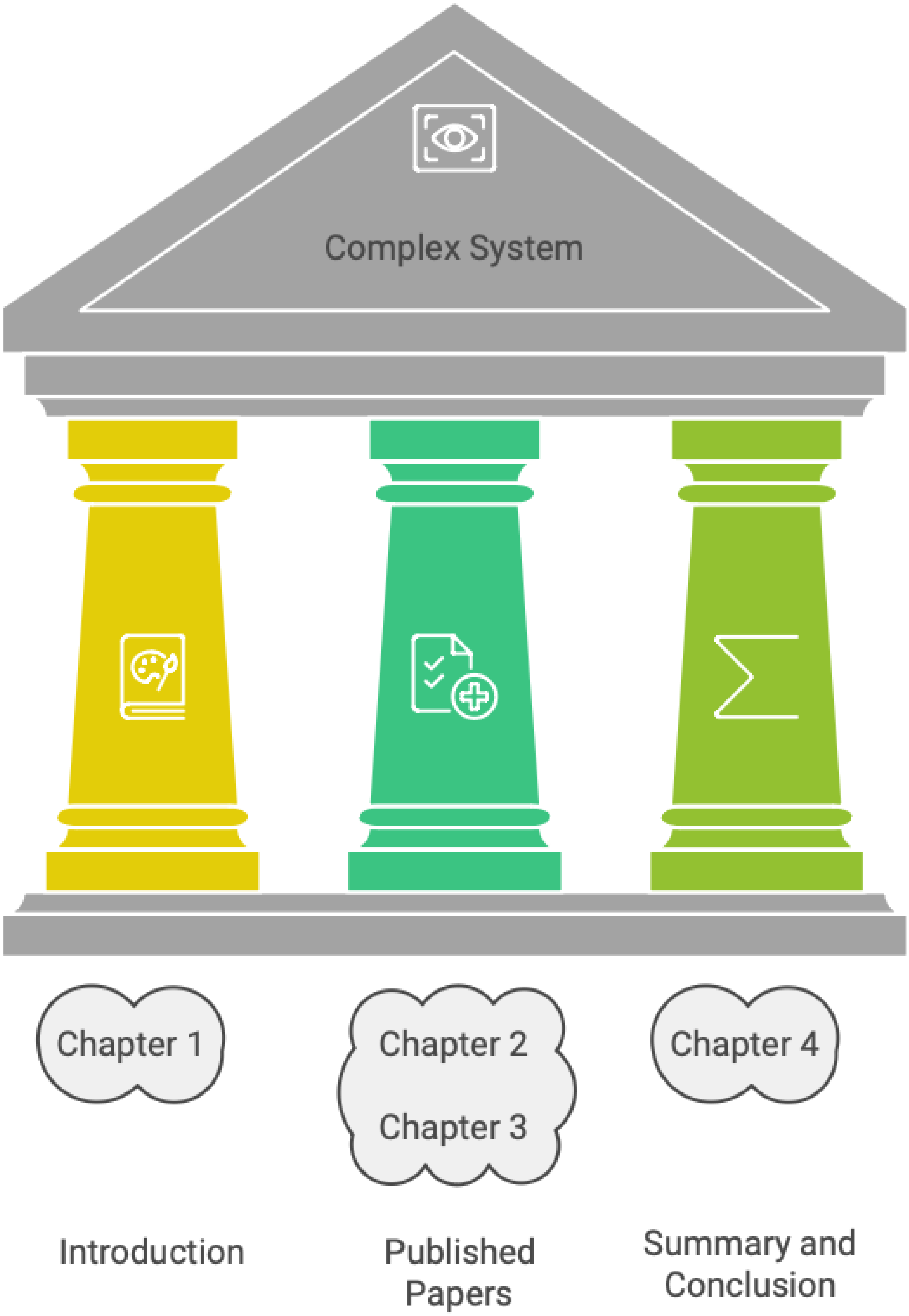

Figure 7: A structured representation of a thesis, Introduction (Chapter 1), Published Papers (Chapters 2 and 3), and Summary and Conclusion (Chapter 4).

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2 SMALL BOTS, BIG IMPACT: SOLVING THE CONUNDRUM OF COOPERATION IN OPTIONAL PRISONER'S DILEMMA GAME THROUGH SIMPLE STRATEGIES

Abstract Cooperation plays a crucial role in both nature and human society, and the conundrum of cooperation attracts the attention from interdisciplinary research. In this study, we investigated the evolution of cooperation in optional prisoner's dilemma games by introducing simple bots. We focused on one-shot and anonymous games, where the bots could be programmed to always cooperate, always defect, never participate, or choose each action with equal probability. Our results show that cooperative bots facilitate the emergence of cooperation among ordinary players in both well-mixed populations and a regular lattice under weak imitation scenarios. Introducing loner bots has no impact on the emergence of cooperation in well-mixed populations, but it facilitates the dominance of cooperation in regular lattices under strong imitation scenarios. However, too many loner bots on a regular lattice inhibit the spread of cooperation and can eventually result in a breakdown of cooperation. Our findings emphasize the significance of bot design in promoting cooperation and offer useful insights for encouraging cooperation in real-world scenarios.

Keywords: Evolutionary game theory; Simple bots; Optional prisoner's dilemma game; Cooperation

2.1 Introduction

Explaining the evolution of cooperation poses a scientific challenge because individuals who incur costs to benefit others may reduce their own fitness, which conflicts with the theory of "survival of the fittest" [1]. However, this prediction contrasts with the reality of ubiquitous altruistic behavior. Evolutionary game theory offers a powerful framework to address this issue [2]. Within this framework, the prisoner's dilemma game, in particular, has been extensively used to study the evolution of cooperation in the context of social dilemma games, as it highlights the conflict between individual and collective interests [3]. It has been shown that cooperation can survive through several reciprocity mechanisms, including group and kin selection [4, 5], direct and indirect reciprocity [3, 6], as well as network reciprocity [7, 8]. Although these reciprocity mechanisms may appear materially different, they share a common principle, which is the mutual recognition of cooperators, also referred to as positive assortativity [9]. If the game is one-shot and anonymous where the above reciprocity mechanisms are fully excluded, the problem of cooperation can still be addressed by enabling players to punish wrongdoers [10], reward altruists[11, 12], or exercise their freedom to choose whether to participate in the game or not [13, 14]. Several recent theoretical studies have shown that introducing committed cooperators can enable the survival of cooperation in well-mixed populations, even under unfavorable conditions such as one-shot and anonymous games without any reciprocity mechanisms [15, 16, 17].

In the context of social dilemma games, committed cooperators refer to individuals who hold strong beliefs about altruistic behavior and do not change their behavior over time. While committed cooperators may not alter the advantage of defection over cooperation, their presence does increase the likelihood of interactions between cooperators. This ultimately leads to a greater propensity for cooperation in well-mixed situations when frequency-dependent updating rules are applied [15, 17]. However, the cooperation-boosting effects of committed cooperators disappear when network reciprocity is considered [18]. Network reciprocity suggests that cooperators can survive by forming compact clusters to resist the invasion of defectors [7]. The establishment of network reciprocity can be better understood by examining how cooperative clusters can form during their enduring period and how they can expand their territories during the expanding period [19]. However, the presence of committed cooperators who consistently choose to cooperate can inhibit the formation of cooperative clusters and lower their spreading efficiency, resulting in a detrimental effect on cooperation rather than a beneficial one [18]. Committed minorities have also been studied in relation to various issues, including trust and trustworthiness [20], the development race in artificial intelligence [21], and opinion polarization in the voter model [22], among others [23].

Research has shown that committed minorities can play a crucial role in promoting cooperation, but in practical situations, such individuals are usually scarce. If a significant number of committed individuals are required to encourage cooperation, the impact of committed cooperators may be insignificant. With the advancement of artificial intelligence (AI), future populations will be more hybrid, consisting of both human and AI players. In the context of one-shot and anonymous games, where there are no reputation effects or repeated interactions, and where information is limited, bots can be designed using straightforward algorithms based on the concept of committed individuals [24]. These bots can be programmed to consistently choose one action and never change it over time. Although their strategy is simple, they can help solve complex problems that human players may find challenging. For example, they can aid in resolving cooperation problems [25, 24, 26], tackling the collective risk dilemma [27, 28], and addressing the conundrum of punishment [29], and others [30].

In this chapter, we investigate the evolution of cooperation among human players in human-machine interactions by examining the impact of four types of bots on an optional prisoner's dilemma game. The game involves three actions: cooperation to benefit others (C), defection for self-interest (D), and loner for risk aversion (L). The four types of pre-designed bots are: (i) always choosing to cooperate, (ii) always choosing to defect, (iii) always choosing loner, and (iv) choosing cooperation, defection, and loner with equal probability. Additionally, we consider two representative population structures: a well-mixed population where players have an equal probability of interacting with others, and a regular lattice where players can only interact with their nearest neighbors. This findings suggest that introducing cooperative bots can address the conundrum of cooperation under weak imitation scenarios in both well-mixed populations and regular lattices. Additionally, although introducing loner bots does not have any impact on the emergence of cooperation in well-mixed populations, it facilitates the dominance of cooperation under strong imitation scenarios in regular lattices. However, too many loner bots on a regular lattice inhibit the spread of cooperation and can eventually result in a breakdown of cooperation. This results, taken together, indicate that the level of cooperation can be maximized by managing the behavior of simple bots.

2.2 Model

This model involves four essential components, which are: (a) the payoff matrix, (b) population settings, (c) game dynamics, and (d) simulation settings. Each of these components is described in detail below.

2.2.1 Optional prisoner's dilemma game

In the optional prisoner's dilemma game, players choose between cooperation, defection, or acting as a loner simultaneously. Cooperators incur a cost of c but bring a benefit of b to their opponent, while defectors do nothing. Loners choose to quit the game and receive a small, but positive payoff of σ, generating the same payoff for their opponent. If two cooperators meet, they both receive a payoff of $R = b - c$. Two defectors receive a payoff of $P = 0$, while a cooperator meeting a defector incurs a cooperation cost of $S = -c$, and the defector receives a benefit of $T = b$. By rescaling the payoffs using $r = c/(b - c)$ and substituting, the payoffs become $T = 1 + r$, $R = 1$, $P = 0$, and $S = -r$. The resulting payoff matrix is shown in Table 1. We use the concept of universal dilemma strength [31] to quantify the dilemma extent, which is confirmed to be ${D_g}' = {D_r}' = r$ [32]. This particular prisoner's dilemma game exhibits characteristics of both chicken-type dilemmas (arising from greed) and stag-hunt-type dilemmas (arising from fear).

Table 1: Payoff matrix for the optional prisoner's dilemma game.

	C	D	L
C	1	$-r$	σ
D	$1+r$	0	σ
L	σ	σ	σ

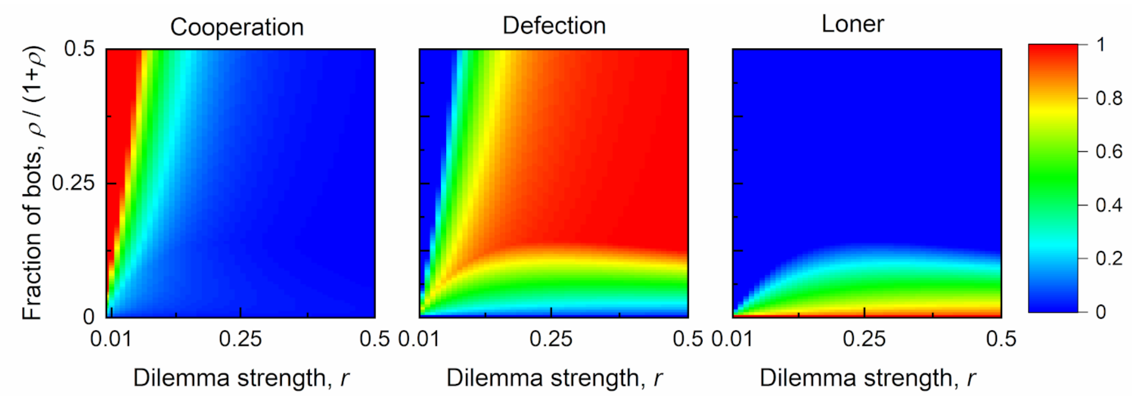

Figure 8: **In well-mixed populations, the introduction of cooperative bots can facilitate the emergence of cooperation among ordinary players, whereas in the absence of bots, loners tend to dominate the entire population.** Shown are the fraction of cooperation (left), defection (middle), and loner (right) at steady state, as a function of dilemma strength and density of bots in well-mixed situations. Here, bots were programmed to consistently choose cooperation and not change their action over time. The imitation strength was fixed at $\kappa^{-1} = 10$.

2.2.2 Population settings

There are typically two population structures considered in research: well-mixed and structured. In a well-mixed population, individuals can interact with any other individual. We represent the proportions of cooperators, defectors, and loners among normal players as x, y, and z respectively, where $x + y + z = 1$. We assume that the fraction of bots is ρ, and therefore the total population density is $1 + \rho$. In contrast, a structured population only allows for local interactions, where individuals can only interact with their immediate neighbors. We represent the structured population as a two-dimensional regular lattice with periodic conditions and a degree of four, indicating that each node has four closest neighbors in the up, down, left, and right directions. The regular lattice has a size of $L \times L$. The entire population is divided into two types at random in a regular lattice, with ρ proportion as bot players and the remaining proportion as normal players. In both well-mixed and regular lattice populations, normal players are presented with three options: cooperation, defection, and loner, each with an equal likelihood. Bot players are pre-programmed with four strategies: (i) always choosing cooperation, (ii) always choosing defection, (iii) always choosing loner, and (iv) choosing cooperation, defection, and loner with equal probability.

2.2.3 Game dynamics

The mean-field theory was utilized to analyze the human-machine game within an infinite and well-mixed population. We provide an example of the game dynamics for the cooperative bots, while additional details regarding the other three types of bots can be found in the Remark section. As described in the population settings section, the expected payoff for each actor can be represented by:

$$\begin{aligned} \Pi_C &= \frac{x-yr+z\sigma+\rho}{1+\rho} \\ \Pi_D &= \frac{(1+r)(x+\rho)+\sigma z}{1+\rho} \\ \Pi_L &= \sigma \end{aligned} \quad . \tag{1}$$

The expected payoff of cooperators in Equation 1 can be understood as follows: the probability of a cooperator interacting with another cooperator from the entire population is $(x + \rho)/(1 + \rho)$; similarly, the probability of a cooperator interacting with a defector from the entire population is $y/(1 + \rho)$, and the probability of a cooperator interacting with a loner from the entire population is $z/(1 + \rho)$. Thus, according to the payoff matrix defined in Table 1, the expected payoff of a cooperator should be $\frac{x-yr+z\sigma+\rho}{1+\rho}$. The expected payoff of defectors and loners can be similarly understood in the same way.

We adopt the pairwise comparison rule, where the imitation probability depends on the payoff difference between two randomly selected players. If the randomly selected players choose the same action, nothing happens. Otherwise, the probability that action i replaces action j is:

$$P_{j\to i} = 1/(1+e^{(\Pi_i-\Pi_j)/\kappa}) \ , \tag{2}$$

where $i \neq j \in \{C, D, L\}$, and $\kappa^{-1} > 0$ represents the imitation strength, indicating the degree to which players base their decisions on comparing payoffs [33]. This concept is similar to the widely used notion of selection strength in the literature on finite populations [34, 35, 36], which emphasizes the crucial role of selection strength in determining the evolutionary outcomes. For the sake of simplicity, we adopt a fixed value of $\kappa = 0.1$ throughout the main text. Additionally, in the Appendix, we explore the impact of varying levels of imitation strength on evolutionary outcomes. The evolutionary dynamics of the well-mixed and infinite population under the imitation rule are represented by:

$$\begin{aligned}
&\dot{x} = \tfrac{2}{1+\rho}((x+\rho)yP_{D\to C} + (x+\rho)zP_{L\to C} - xyP_{C\to D} \\
&-xzP_{C\to L}) \\
&\dot{y} = \tfrac{2}{1+\rho}(xyP_{C\to D} + yzP_{L\to D} - (x+\rho)yP_{D\to C} \\
&-yzP_{D\to L}) \\
&\dot{z} = \tfrac{2}{1+\rho}(xzP_{C\to L} + yzP_{D\to L} - (x+\rho)zP_{L\to C} \\
&-yzP_{L\to D})
\end{aligned} \ . \tag{3}$$

We utilize the Runge-Kutta method to generate numerical solutions for Equation 3.

To generate results for networked populations, we employed Monte Carlo simulations. These simulations involved the following steps: First, each node was designated as a bot with probability ρ, while the probability that each node was designated as a normal player was $1-\rho$. For the population of normal players, each player was randomly assigned as a cooperator (C), defector (D), or loner (L). Normal players and bots residing on networks received their payoffs by interacting with all direct neighbors. In each round of the game, a randomly selected normal player i updated its action by imitating the action of a randomly selected neighbor j, which could be either a bot or a normal player. The probability of imitation was determined by the pairwise Fermi function (PW-Fermi), as defined in Equation 2.

2.2.4 Simulation settings

The game dynamics for a single Monte Carlo step were executed $L * L$ times, allowing each player to modify their action at least once on average. We set the value of L at

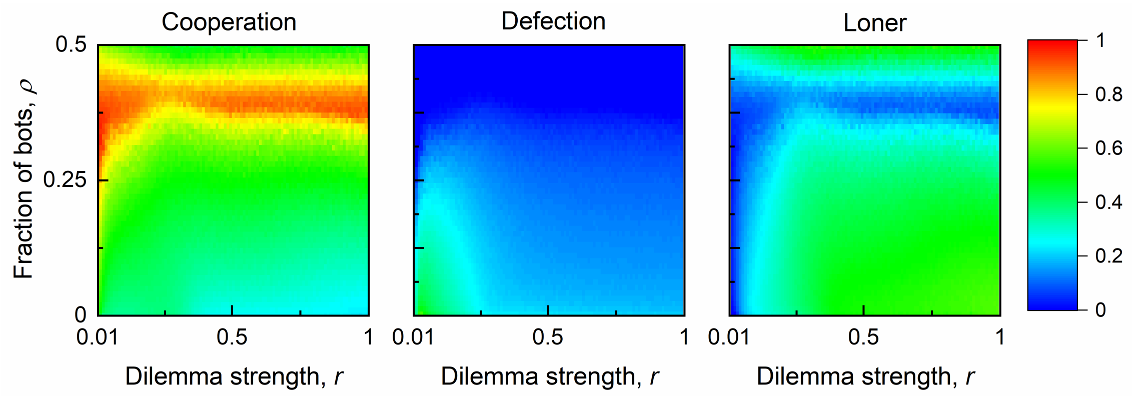

Figure 9: **In a regular lattice, the introduction of loner bots can facilitate the emergence of cooperation among ordinary players, whereas too dense of loner bots results in a breakdown of cooperation.** Shown are the fraction of cooperators, defectors, and loners among ordinary players as a function of dilemma strength and density of bots in a regular lattice. Here bots were programmed to consistently choose loner action and not change their action over time. The imitation strength was fixed at $\kappa^{-1} = 10$.

100 for the entire study. In order to achieve an equilibrium state, all simulations were typically conducted for 50,000 steps. This ensured that there was no obvious increasing or decreasing trend for the fractions of each actor. The proportion of each action was then calculated by averaging the results of the last 5000 steps, providing a more stable and accurate representation of the equilibrium state. To reduce the impact of initial conditions, we calculated the data by averaging the results of 20 independent runs. Our focus is solely on the impact of bots on the evolution of cooperation among normal players. Therefore, when calculating the fractions of each action in the population, we disregard the fraction of bot players.

2.3 Results

2.3.1 Well-mixed populations

Loners receive a small, but positive payoff by opting out and generate the same payoff for their opponent. This definition allows for the coexistence of cooperators, defectors, and loners through the effect of cyclic dominance in well-mixed populations [13]. However, the cooperation-sustaining effect by loners is only possible in the public goods game, and not in the prisoner's dilemma game [37]. In fact, the prisoner's dilemma game can lead to a pure loner state in well-mixed populations. Although the cyclic dominance pattern can still exist along the edges (i.e., C giving way to D, D giving way to L, who gives way to C), the invasion direction from L to C requires a certain level of cooperation [38]. The addition of simple bots to the optional prisoner's dilemma game can significantly alter the fate of cooperators. Rather than being entirely eliminated by defectors, cooperators can now thrive and even establish dominance over the entire population with the assistance of cooperative bots (Figure 8).

Introducing cooperative bots doesn't change the payoff scheme for human players, but it does increase the chances of human players encountering other cooperators. This higher likelihood of encountering cooperators helps to reduce the advantage that loners have over cooperators and defectors. However, it also creates an opportunity for free-riding defectors to exploit the system. If human players place less emphasis on material gains when updating their actions (in a weak imitation scenario), natural selection is likely to favor the dominance of cooperation (see Figure 12). Conversely, in a strong imitation scenario, where players tend to copy the behavior of those who are most successful, the entire population would be dominated by defectors (see Figure 12). The introduction of defective or loner bots cannot mitigate the advantage that loners hold over cooperators and defectors in the absence of bots. Consequently, these two types of bots do not affect the emergence of cooperation, as illustrated in the top and middle rows of Figure 13. If the actions of bot players were programmed to choose cooperation, defection, and loner with equal probability, then the diversity of bot actions reduces the cooperation-promoting effect by cooperative bots (refer to the bottom row of Figure 13).

While the pure loner state of the optional prisoner's dilemma game is observed in well-mixed populations, regular lattices facilitate the stable coexistence of cooperators, defectors, and loners through cyclic dominance, in which cooperation give ways to defection, who give ways to loner, who in turn give ways to cooperation [37]. This difference prompts further investigation into how the addition of simple bots influences the evolution of cooperation in structured populations.

2.3.2 Structured populations

Consistent with the cooperation-promoting effect by cooperative bots in well-mixed populations, introducing cooperative bots to the optional prisoner's dilemma game on a regular lattice still promotes cooperation among human players under the weak imitation scenarios (Figure 14). However, the required imitation strength threshold to achieve cooperation prosperity decreases. For example, introducing cooperative bots can decrease cooperation when the imitation strength equals $\kappa = 10^{-1}$ (as shown in the top row of Figure 15), whereas the same imitation strength value ensures increased cooperation in well-mixed populations. A similar cooperation-decreasing phenomenon can be also observed when using defective bots or when bots randomly choose among cooperation, defection, and

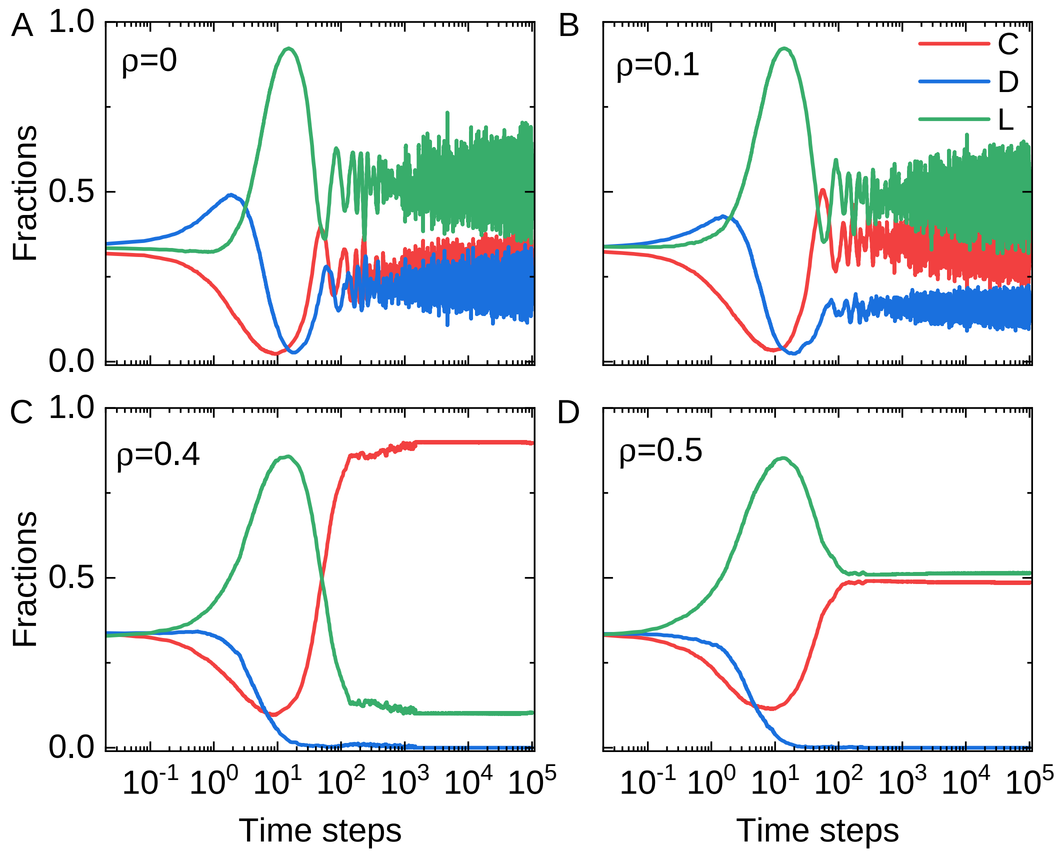

Figure 10: **The introduction of loner bots can disrupt the cyclic dominance that typically sustains cooperation among cooperators, defectors, and loners in a regular lattice. However, adding loner bots can improve the level of cooperation among human players by reducing the number of defectors.** Shown are the fractions of cooperators, defectors, and loners as a function of simulation steps under different values of density of bots. The dilemma strength was fixed at $r = 0.5$, while the values of ρ were set to 0, 0.1, 0.4, and 0.5 for panels A to D.

being a loner (as shown in the middle and bottom rows of Figure 15). In contrast with the results on well-mixed population in which introducing loner bots does not have any impact on the emergence of cooperation, the cooperation-promoting phenomenon can be observed if bots are programmed to always act as loners and not change their behavior over time, as demonstrated in Figure 9. This figure shows the fraction of cooperation (left panel), defection (middle panel), and loner (right panel) as a function of dilemma strength and the density of loner bots, obtained on a regular lattice using Monte Carlo simulations. Interestingly, introducing loner bots actually increases the level of cooperation over the entire range of dilemma strength. Moreover, there exists an optimal density of loner bots at which cooperation is maximized, and further increasing the density of loner bots results in the breakdown of cooperation. In addition, the cooperation-promoting effect by loner bots is restricted in strong imitation scenario, while loners tend to dominant the population in the weak imitation scenario (Figure 16). To reveal the potential mechanism behind the effect of loner bots on cooperation, we examine the overall evolution of actor abundance along the temporal dimension, as well as the spatial and temporal dimensions by analyzing the time-series of each actor and the evolutionary snapshots.

The dynamics of the three actors and their interactions can be seen in Figure 10, where the fractions of cooperators, defectors, and loners are plotted as a function of Monte Carlo steps for different values of ρ: 0, 0.1, 0.4, and 0.5. This figure illustrates how the behavior of one actor affects the others, and provides insight into the system's overall evolution. When $\rho = 0$, our model reduces to the traditional optional prisoner's dilemma game where cooperation coexists with defection and loner through cyclic dominance. As shown in Figure 10A, defectors initially reach their peak and then give way to loners, who in turn give way to cooperators. This process repeats until the system reaches its stable state, where the abundances of each actor fluctuate around their average value. Similar cyclic dominance occurs for a small density of loner bots (i.e., $\rho = 0.1$), but the stationary defection level decreases (Figure 10B). However, for a large density of bots (i.e., $\rho = 0.4$ and $\rho = 0.5$), the cyclic dominance phenomenon disappears, and loners initially reach their peak followed by cooperators, while defectors decrease and go extinct directly (Figure 10C and Figure 10D). The evolutionary dynamics at $\rho = 0.4$ and $\rho = 0.5$ are similar, but the survival periods of defection in the former situation are longer than those in the latter case.

Figure 11 shows the evolutionary snapshots under the same parameter values as Figure 10. In this figure, cooperators, defectors, and loners are represented by red, blue, and green, respectively. Bot players are represented by dark green. When $\rho = 0$, our model is reduced to the traditional optional prisoner's dilemma game, and we observe the expected traveling waves of cooperators, followed by defectors, then loners, and finally cooperators again

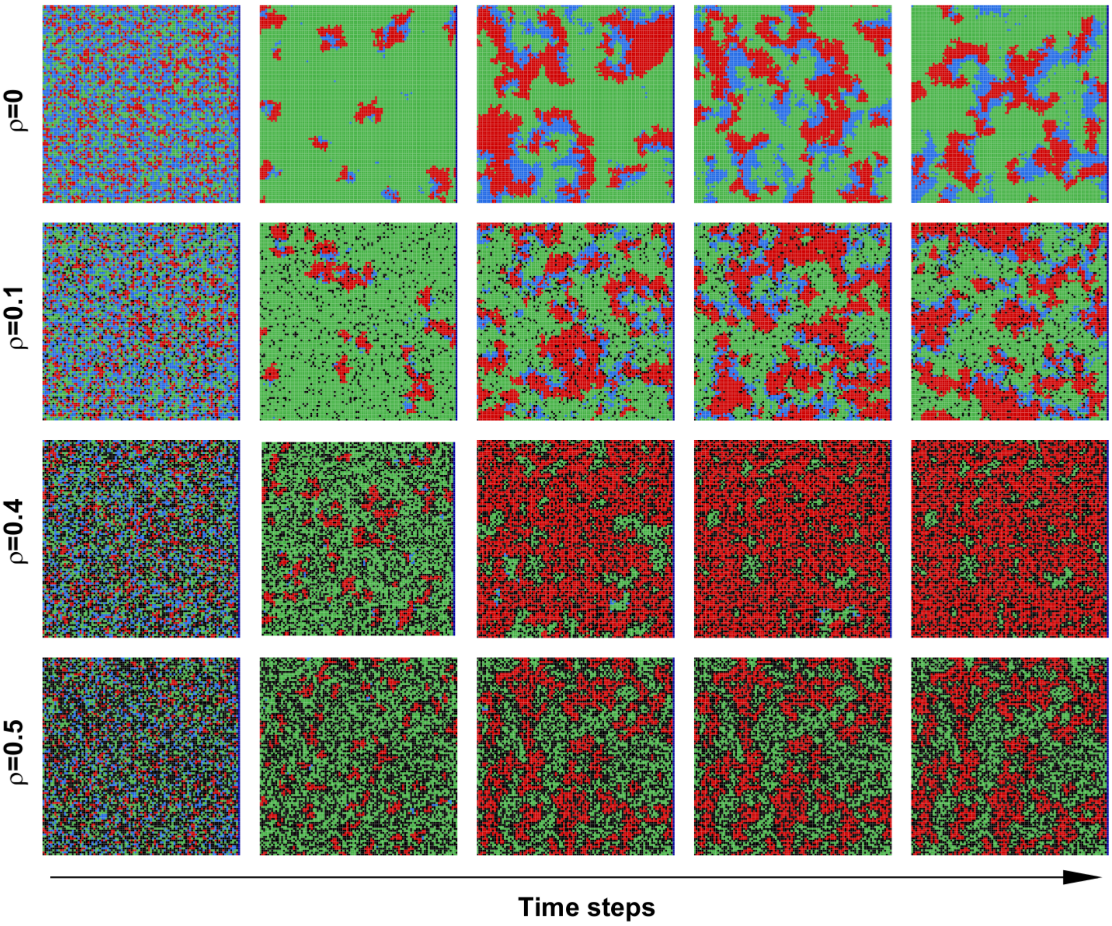

Figure 11: **Evolutionary snapshots reveal that a high density of loner bots can create a barrier for the spread of cooperation, leading to the breakdown of cooperative behavior.** Shown are the evolutionary snapshots taken at different values of bot intensity, with the dilemma strength fixed at $r = 0.5$ and the value of ρ fixed at 0, 0.1, 0.4, and 0.5 from top to bottom rows. The snapshots in the first column were taken at the initial step, where actions were distributed randomly for both human players and bot players. The snapshots in the remaining columns were taken at different time steps, making the figure as illustrative as possible.

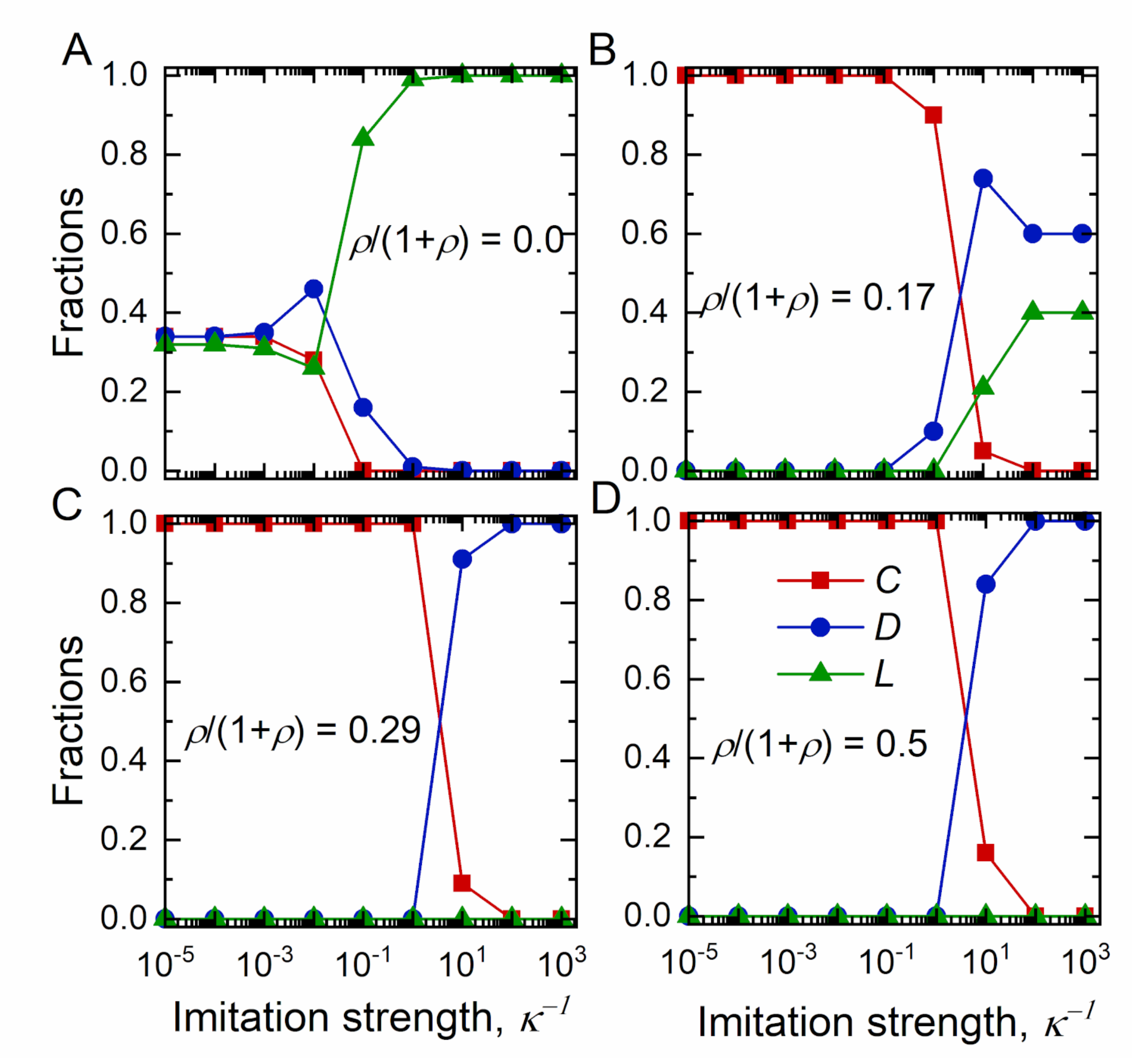

Figure 12: **The impact of cooperative bots on promoting cooperation in well-mixed populations depends on the strength of imitation. In weak imitation scenarios, cooperative bots can effectively increase cooperation rates, but in strong imitation scenarios, defection tends to dominate.** Shown are the proportions of cooperation, defection, and loners relative to imitation strength κ^{-1}, with fixed parameters of $r = 0.2$, and ρ values of 0 (panel A), 0.2 (panel B), 0.6 (panel C), and 1 (panel D).

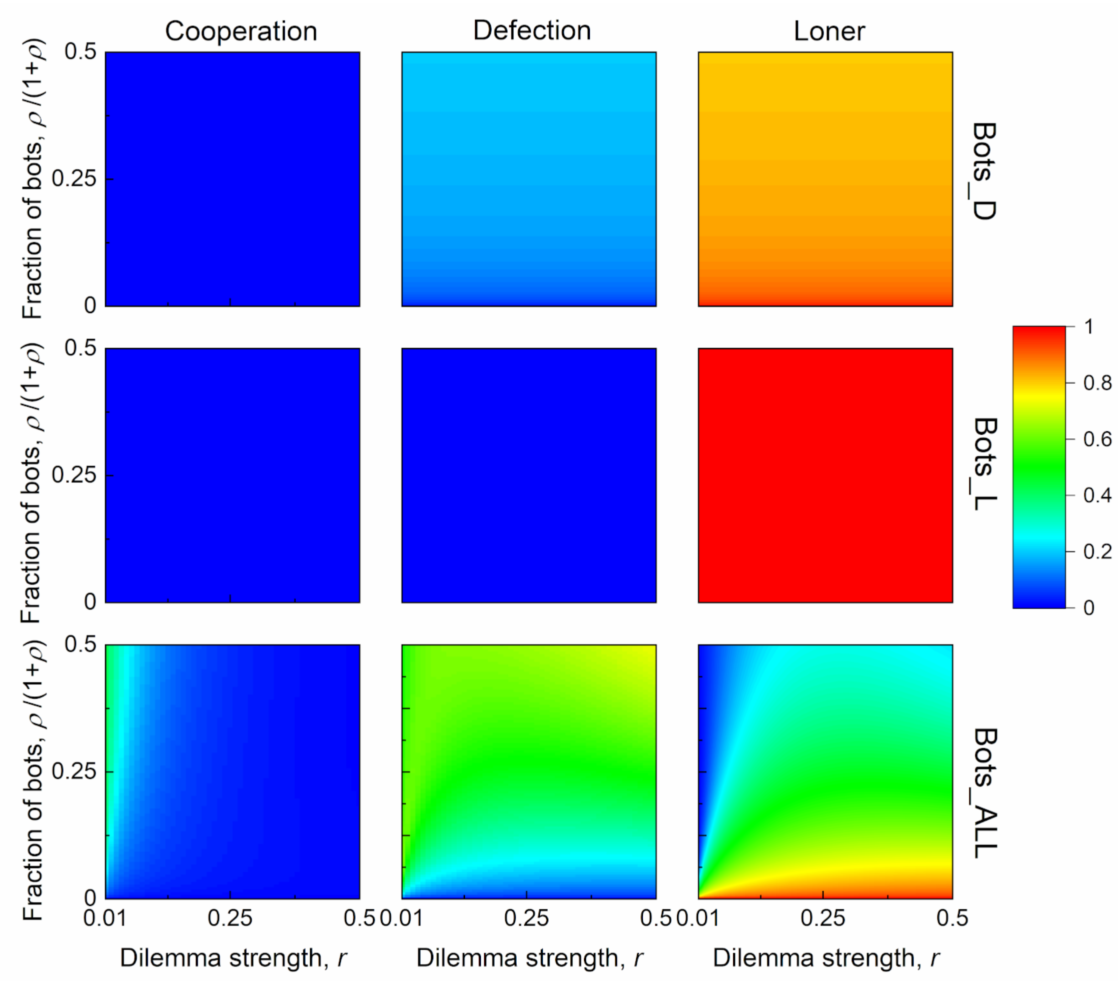

Figure 13: **Introducing defective or loner bots into the optional prisoner's dilemma game does not have any effect on the emergence of cooperative behavior in well-mixed populations, and the diversity of bot actions reduces the promotion effect of cooperation by cooperative bots.** The three panels from top to bottom correspond to different bot behaviors: (i) always defect (marked as $Bots\_D$), (ii) always loner (marked as $Bots\_L$), and (iii) random choice among cooperation, defection, and loner with equal probability (marked as $Bots\_ALL$). The imitation strength was fixed at $\kappa^{-1} = 10$.

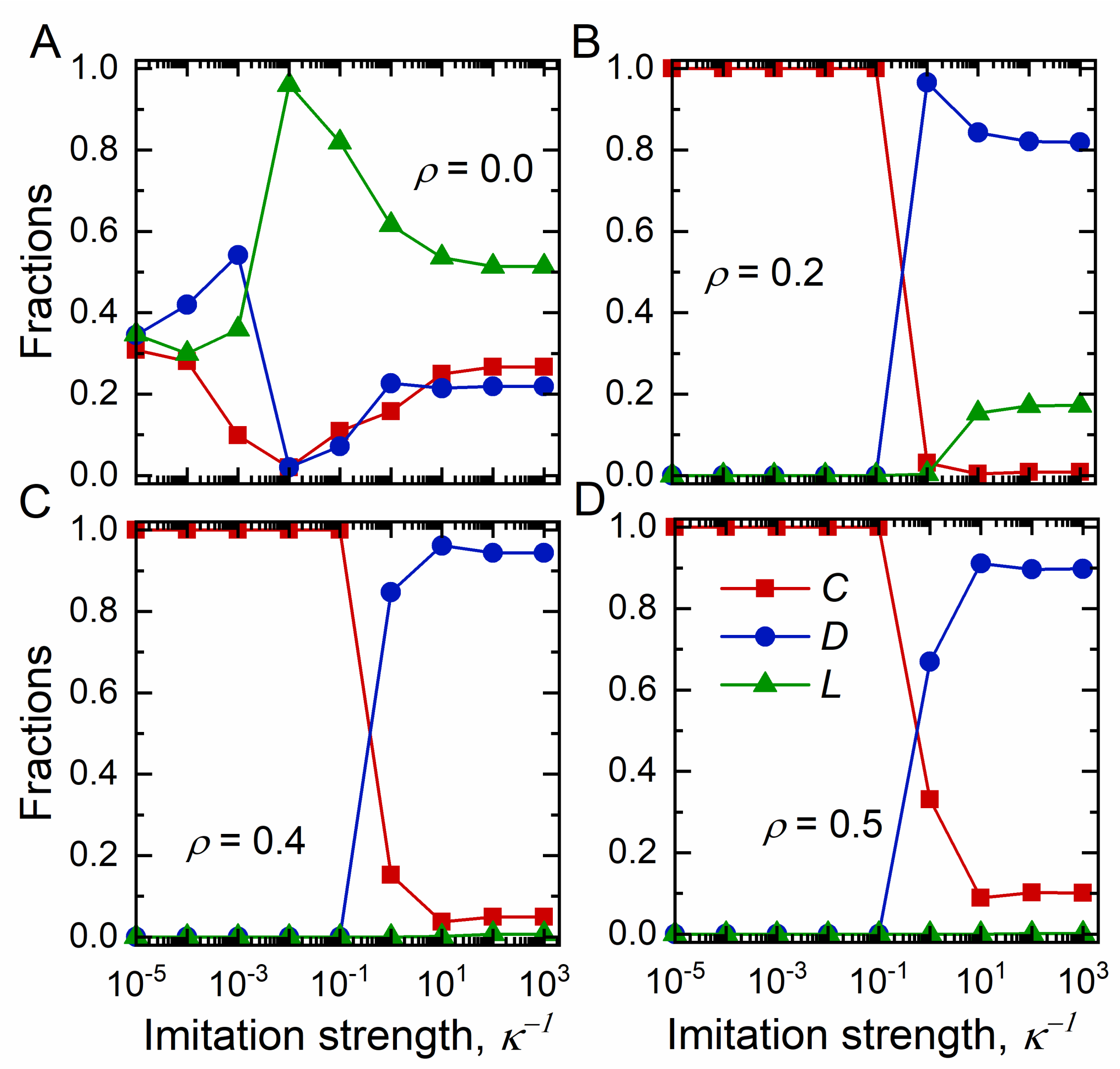

Figure 14: **The cooperation-promoting effect by cooperative bots in regular lattice still holds under weak imitation strength scenarios, while defectors tend to dominate the population under the strong imitation scenarios.** Shown are the proportions of cooperation, defection, and loners relative to imitation strength κ^{-1}, with fixed parameters of $r = 0.5$, and ρ values of 0 (panel A), 0.2 (panel B), 0.4 (panel C), and 0.5 (panel D).

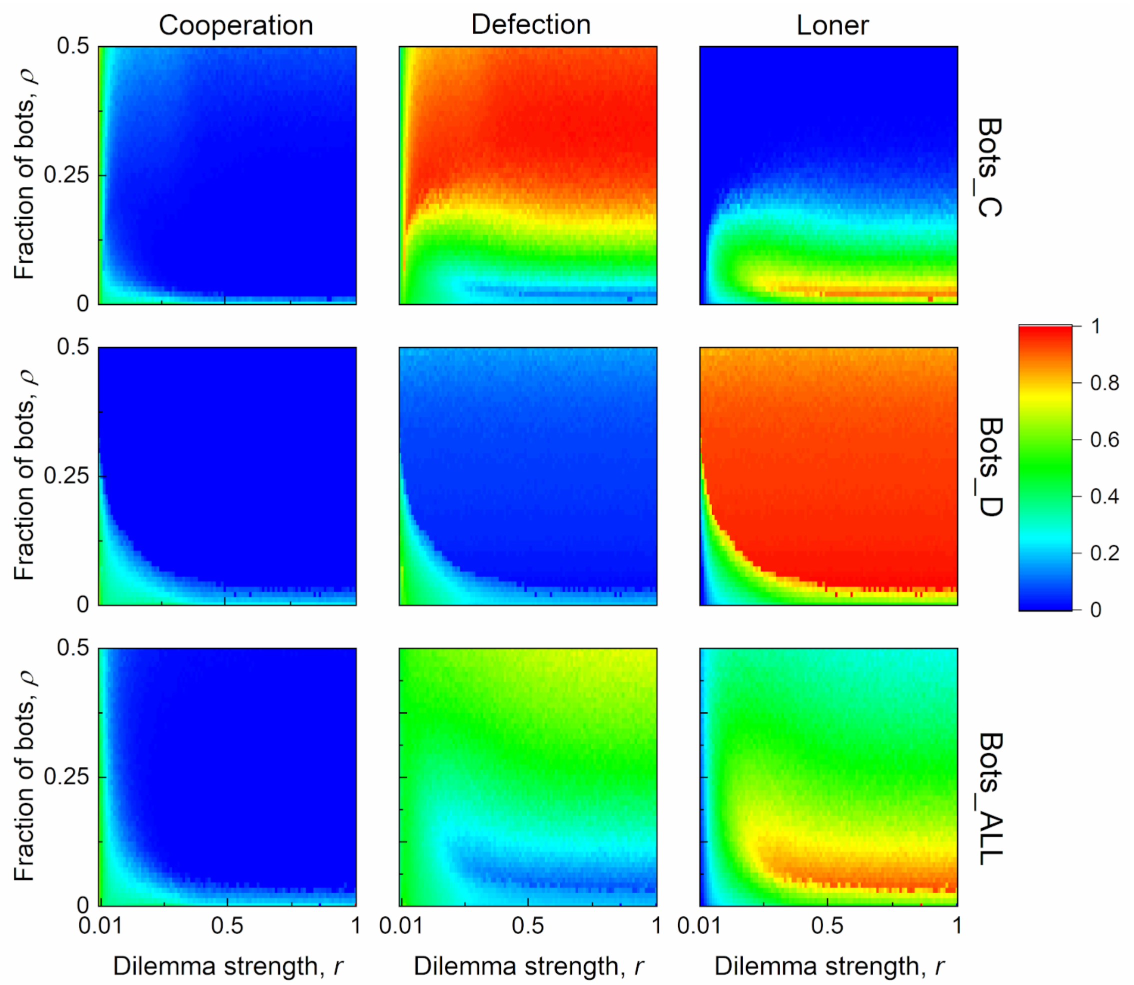

Figure 15: **Introducing cooperative or defective bots into the optional prisoner's dilemma game bring little impact on the emergence of cooperation in a regular lattice, and the diversity of bot actions reduces the promotion effect of cooperation by loner bots.** The three panels from top to bottom correspond to different bot behaviors: (i) always defect (marked as $Bots\_D$), (ii) always loner (marked as $Bots\_L$), and (iii) random choice among cooperation, defection, and loner with equal probability (marked as $Bots\_ALL$). The imitation strength was fixed at $\kappa^{-1} = 10$.

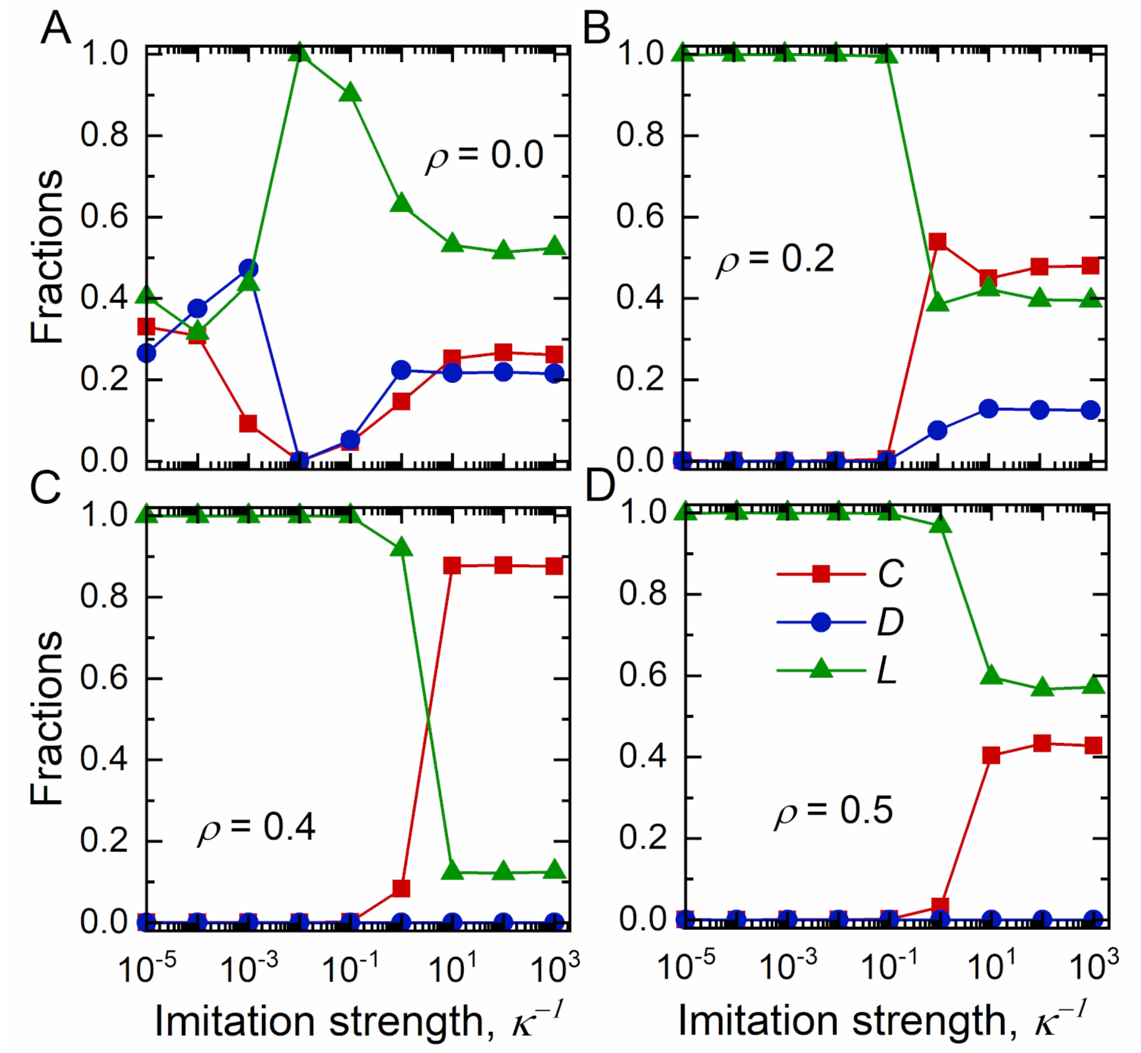

Figure 16: **The impact of loner bots on promoting cooperation in a regular lattice depends on the strength of imitation. In scenarios with weak imitation, loners tend to dominate the population, whereas in scenarios with strong imitation, loner bots can effectively increase cooperation rates.** Shown are the proportions of cooperation, defection, and loners relative to imitation strength κ^{-1}, with fixed parameters of $r = 0.5$, and ρ values of 0 (panel A), 0.2 (panel B), 0.4 (panel C), and 0.5 (panel D).

(top row of Figure 11). Introducing a small density of loner bots does not significantly affect the traveling waves of cooperators but reduces the chasing ability of defectors, as shown in the second row of Figure 11. Here, loner bots tend to be surrounded by compact cooperative clusters, and defective clusters are much smaller than those observed in the scenario without bots. However, when the density of loner bots is high (i.e., $\rho = 0.4$), defectors struggle to survive the invasion of loners (see the second column and third row of Figure 11) and gradually go extinct. Without the threat of defectors, cooperators take over the territory of loners until some lucky loners are surrounded by loner bots. If the density of loner bots is too large (i.e., $\rho = 0.5$), although defectors can still be eliminated by loners, cooperation cannot spread further in the population since cooperative clusters can easily be fully surrounded by loner bots (bottom row in Figure 11), leading to a decreased cooperation level compared to the situation with $\rho = 0.4$.

2.4 Discussion

To discuss, in this chapter, we investigated the impact of simple bots on the evolution of cooperation in the optional prisoner's dilemma game, using four types of bots and two representative populations. Despite their simplicity and lack of intelligent algorithms, these bots play a crucial role in determining the evolution of cooperation. Our findings demonstrate that the introduction of cooperative bots can enhance the emergence of cooperation among ordinary players in both well-mixed populations and regular lattices under weak imitation scenarios. However, regular lattices require a weaker imitation strength scenario to achieve the same level of cooperation. In contrast to the results on well-mixed populations, where adding loner bots does not impact the emergence of cooperation, we observed that introducing loner bots promotes cooperation on a regular lattice under a strong imitation scenario. Specifically, we found that an optimal density of loner bots exists, at which the highest level of cooperation is achieved; otherwise, cooperation levels decrease. Introducing defective bots does not significantly impact the evolution of cooperation in well-mixed populations, and diversity in bot actions reduces the cooperation-promoting effect by cooperative bots. Similar cooperation-devastating results can be observed for defective bots or considering the diversity of bot actions. Our results, taken together, indicate that the level of cooperation can be maximized by managing the behavior of simple bots.

Voluntary participation in public good games can be an effective way to promote cooperation in well-mixed populations, even in the absence of other reciprocity mechanisms like reputation, iterated interactions, or group selection. However, it's important to note that cooperation is only likely to emerge if the group size is larger than two; otherwise, pairwise interactions lead to the homogeneous loner state [39]. While we focused on the simplest form of the game with only two players and did not explore more complex multiplayer scenarios in this paper, the results on regular lattices may still hold as the cyclic dominance effect is valid for both pairwise and multiplayer games [14]. It's worth noting that the results on well-mixed populations may differ significantly as periodic oscillations can only be observed for multiplayer games [39]. Therefore, future research should investigate how the existence of simple bots affects period oscillations and which types of bots can promote cooperation in well-mixed populations, particularly in the context of public good games.

The critical assumptions in our human-machine framework are the one-shot game and anonymous interaction. It's important to clarify that a one-shot game differs from a strict one-round setting game. In a one-round game, the game can occur only once for all players, but it can still be played multiple times in a one-shot game setting as long as the opponents are strangers who have never met before. Unlike a strict one-round game, where players cannot revise their actions, players in a one-shot game can revise their actions based on their past experiences. This feature of the one-shot setting makes it possible for bot players to improve the cooperation level among human players, as experimental evidence shows that cooperative behavior can cascade among human players in social networks [40]. The existence of bots that always cooperate and do not change their actions over time may increase the probability that human players pass their obtained help to new strangers. This is possible under the weak imitation scenario, in which human players may still pass on this help even if they know they may endure some losses. However, our results are not limited to the weak imitation scenario since loner bots can realize high cooperation levels among human players in structured populations under the strong imitation scenario. These results indicate that cooperation can be improved through effective bot design management by considering specific population structures or the features of human learning moods.

The second anonymous interaction assumption posits that there are no reciprocity mechanisms such as indirect reciprocity, direct reciprocity, reputation, or costly signals [41, 3, 6, 42, 43]. This assumption implies that both human and bot players are unable to utilize information about their opponents in their decision-making process. Additionally, human players are unaware of the presence of bot players. These assumptions ensure that human players update their actions similarly when playing against either human or bot players. However, these assumptions also limit the intelligence of bot strategies as they lack access to information about their opponents. Although the past experiences of bot players are available in our framework, we deliberately disregarded them during the design of the bots' strategies. Our primary focus was to investigate the impact of simple bots on cooperation, and considering the past experiences of bots would have introduced unnecessary complexity to the analysis.

However, it is worth noting that future studies could explore the incorporation of reinforcement learning methods, as outlined in studies such as [44, 45], to leverage the past experiences of bots and develop more sophisticated strategies. Additionally, relaxing the strict anonymity of the game scenario while still focusing on the one-shot game scenario by allowing the presence of information sources, such as reputation [42], prior commitment [46], emotion [47], and intention [48, 49], would provide a more realistic and nuanced understanding of the role of bots in promoting cooperation.

While our assumptions may not hold in more complex and realistic game situations where human-machine interactions are not one-shot but repeated, or where the reputation of opponents is also available, our results offer valuable insights into the emergence of cooperation. Nonetheless, addressing these more complex scenarios would require the development of more intelligent machines. Our findings can serve as a valuable starting point for future studies in this direction.

Game Dynamics for Scenarios with Defective, Loner, and Randomized Bots

Remark 1: Defective bots. Let x, y, and z denote the fractions of cooperators (C), defectors (D), and loners (L) in a well-mixed and infinite population, such that $x+y+z = 1$. We assume the fraction of bots is ρ, and the bots are designed always to choose D and never change their action. The total population density is then $1 + \rho$, and the expected payoffs of each of the actors are as follows:

$$\begin{array}{l} \Pi_C = \frac{x-(y+\rho)r+z\sigma}{1+\rho} \\ \Pi_D = \frac{(1+r)x+z\sigma}{1+\rho} \\ \Pi_L = \sigma \end{array} . \tag{4}$$

We adopt the pairwise comparison rule, where the imitation probability depends on the payoff difference between two randomly selected players. If the randomly selected players choose the same action, nothing happens. Otherwise, the probability that action i replaces action j is:

$$P_{j\to i} = 1/(1 + e^{(\Pi_j - \Pi_i)/\kappa}) . \tag{5}$$

Where $i \neq j \in \{C, D, L\}$, and κ^{-1} is the imitation strength such that $\kappa^{-1} > 0$. The evolutionary dynamics of the well-mixed and infinite population under the imitation rule are represented by:

$$\begin{array}{l} \dot{x} = \frac{2}{1+\rho}(xyP_{D\to C} + xzP_{L\to C} - x(y+\rho)P_{C\to D} - xzP_{C\to L}) \\ \dot{y} = \frac{2}{1+\rho}(x(y+\rho)P_{C\to D} + (y+\rho)zP_{L\to D} - xyP_{D\to C} - yzP_{D\to L}) \\ \dot{z} = \frac{2}{1+\rho}(xzP_{C\to L} + yzP_{D\to L} - xzP_{L\to C} - (y+\rho)zP_{L\to D}) \end{array} . \tag{6}$$

Remark 2: loner bots Let x, y, and z denote the fractions of cooperators (C), defectors (D), and loners (L) in a well-mixed and infinite population, such that $x + y + z = 1$. We assume the fraction of bots is ρ, and the bots are designed always to choose L and never change their action. The total population density is then $1 + \rho$, and the expected payoffs of each of the actors are as follows:

$$\begin{array}{l} \Pi_C = \frac{x-yr+(z+\rho)\sigma}{1+\rho} \\ \Pi_D = \frac{(1+r)x+(z+\rho)\sigma}{1+\rho} \\ \Pi_L = \sigma \end{array} . \tag{7}$$

We adopt the pairwise comparison rule, where the imitation probability depends on the payoff difference between two randomly selected players. If the randomly selected players choose the same action, nothing happens. Otherwise, the probability that action i replaces action j is:

$$P_{j\to i} = 1/(1 + e^{(\Pi_j - \Pi_i)/\kappa}) \ . \tag{8}$$

Where $i \neq j \in \{C, D, L\}$, and κ^{-1} is the imitation strength such that $\kappa^{-1} > 0$. The evolutionary dynamics of the well-mixed and infinite population under the imitation rule are represented by:

$$\begin{array}{l} \dot{x} = \frac{2}{1+\rho}(xyP_{D\to C} + xzP_{L\to C} - xyP_{C\to D} - x(z+\rho)P_{C\to L}) \\ \dot{y} = \frac{2}{1+\rho}(xyP_{C\to D} + yzP_{L\to D} - xyP_{D\to C} - y(z+\rho)P_{D\to L}) \\ \dot{z} = \frac{2}{1+\rho}(x(z+\rho)P_{C\to L} + y(z+\rho)P_{D\to L} - xzP_{L\to C} - yzP_{L\to D}) \end{array} . \tag{9}$$

Remark 3: randomized bots Let x, y and z denote the fractions of cooperators (C), defectors (D), and loners (L) in a well-mixed and infinite population such that $x+y+z = 1$. We assume that bots have equal probabilities to be C, D, and L. Thus, the fractions of bots with action C, with action D, and with action L are all $\rho/3$. The total population density is $1 + \rho$. Therefore, the expected payoffs of each of the actors are as follows:

$$\begin{array}{l} \Pi_C = \frac{x+\frac{\rho}{3}-(y+\frac{\rho}{3})r+(z+\frac{\rho}{3})\sigma}{1+\rho} \\ \Pi_D = \frac{(1+r)(x+\frac{\rho}{3})+(z+\frac{\rho}{3})\sigma}{1+\rho} \\ \Pi_L = \sigma \end{array} . \tag{10}$$

We adopt the pairwise comparison rule, where the imitation probability depends on the payoff difference between two randomly selected players. If the randomly selected players choose the same action, nothing happens. Otherwise, the probability that action i replaces action j is:

$$P_{j\to i} = 1/(1 + e^{(\Pi_j - \Pi_i)/\kappa}) \ . \tag{11}$$

Where $i \neq j \in \{C, D, L\}$, and κ^{-1} is the imitation strength such that $\kappa^{-1} > 0$. The evolutionary dynamics for a well-mixed and infinite population under the imitation rule are represented by:

$$\begin{array}{l} \dot{x} = \frac{2}{1+\rho}((x+\frac{\rho}{3})yP_{D\to C} + (x+\frac{\rho}{3})zP_{L\to C} - x(y+\frac{\rho}{3})P_{C\to D} \\ -x(z+\frac{\rho}{3})P_{C\to L}) \\ \dot{y} = \frac{2}{1+\rho}(x(y+\frac{\rho}{3})P_{C\to D} + (y+\frac{\rho}{3})zP_{L\to D} - (x+\frac{\rho}{3})yP_{D\to C} \\ -y(z+\frac{\rho}{3})P_{D\to L}) \\ \dot{z} = \frac{2}{1+\rho}(x(z+\frac{\rho}{3})P_{C\to L} + y(z+\frac{\rho}{3})P_{D\to L} - (x+\frac{\rho}{3})zP_{L\to C} \\ -(y+\frac{\rho}{3})zP_{L\to D}) \end{array} . \tag{12}$$

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3 ASYMMETRIC POPULATION PROMOTES AND JEOPARDIZES COOPERATION IN SPATIAL PRISONER'S DILEMMA GAME

Abstract The evolution of cooperation in asymmetric populations has recently garnered widespread attention. In this study, we propose a new asymmetric model to explore the impact of asymmetric behavior on cooperation evolution. Our model assumes that weak players are always forced to cooperate when interacting with strong players, while strong players always receive the temptation payoff. When encountering peers from the same category, players engage in a prisoner's dilemma game, differing only in the intensity of the dilemma between population categories. Results suggest that in scenarios where traditional network reciprocity can support cooperation, asymmetric interactions between strong and weak players undermine this reciprocity and jeopardize the maintenance of cooperation. Conversely, in scenarios where traditional network reciprocity fails to support cooperation, asymmetric interactions enable strong players to leverage weak cooperative clusters to establish cooperation. However, as the prevalence of asymmetric interactions increases, it becomes detrimental to cooperation within the weak player subgroups, thus undermining overall cooperation. These findings contribute to a deeper understanding of how asymmetry impacts cooperation.

Keywords: Evolutionary game theory; Simple bots; Optional prisoner's dilemma game; Cooperation

3.1 Introduction

While cooperation forms the bedrock of modern society, it poses an evolutionary puzzle because benefiting others comes at a personal cost, which, according to the principle of "survival of the fittest," should lead to its extinction [1, 2, 3]. Evolutionary game theory [4], serving as a powerful mathematical framework, traditionally focuses on the evolution of cooperation under symmetric assumptions, where players derive equal benefits from cooperating and contribute equally to their associates. Reciprocity mechanisms developed from this symmetric framework [5]—such as direct, indirect, and network reciprocity, as well as group and kin selection—have demonstrated their effectiveness in enhancing cooperation through positive assortativity. This principle posits that actors are more likely to interact with their peers who use the same actions, a common principle behind these seemingly distinct reciprocity mechanisms [6].

Given the ubiquitous of inequality in both natural and human societies, the investigation of the conundrum of cooperation has gradually extended to the asymmetric populations nowadays [7, 8, 9, 10]. For example, in human societies, people differ in their wealthy [11], contributions [12], power[13], productivities [9], resource allocation[14, 15], information [16], the positions that they occupy in social hierarchies, and others [17, 18]. Asymmetries in social interactions result in disparities in action decisions, outcomes control, and influence among individuals. Current research often employs a simplified model, a binary sub-population games, involving strong and weak players. This exploration encompasses the effects of asymmetric interaction structures [19, 20, 21], payoff structures [22, 23, 24, 25] and asymmetric social dilemmas [26, 27, 28]. These research reveal that, compared to symmetric games, asymmetry in individual interactions alters the conditions under which cooperation exists, exerting a complex influence on the dynamics of cooperation. Specifically, the differences in costs and benefits of cooperation between strong and weak players stemming from the asymmetry, can maintain cooperation, contingent upon a high levels of payoff inequality or population abundance inequality [23]. When strong and weak participants face different types of social dilemmas, Guo et al.[27] proposes a paradigm model, revealing that weak players can protect cooperative clusters from exploitation, while at a moderate level of asymmetry, strong participants promote cooperation. These studies unveil the complex dynamics of cooperation shaped by social dilemmas in asymmetrical interactions between the strong and the weak.

In reality, we often see scenarios where employees (weak players) must comply with the demands of their bosses (strong players), while the bosses may not reciprocate this cooperation and may prioritize their own interests. On the other hand, interactions between management and employees frequently involve unequal dilemmas and varying magnitudes of benefits, indicating that the payoffs and costs are inconsistent between weaker and stronger players. Similar asymmetry is also prevalent in monopoly or oligopoly markets, where businesses have significantly more bargaining power than consumers. Consumers, being in a weaker decision-making position, have limited choices and are often forced to accept high prices or inferior services from dominant companies. Such asymmetry often gives strong side an advantage in interactions.

Inspired by these observations, we propose a novel asymmetric model where asymmetry allows strong players to always defect against weak players, who in turn always cooperate with strong players. When players interact with their peers from the same category, they engage in a standard prisoner's dilemma game, though the dilemma strength differs between the two categories. Our simulation results reveal that asymmetry has dual effects on cooperation, contingent upon the efficiency of network reciprocity. Under low dilemma strength conditions, as the frequency of interactions between strong and weak players increases, cooperation is suppressed. Conversely, under high dilemma strength conditions, asymmetric interactions can support the maintenance of cooperation among strong players due to the support from weak players. However, such cooperation can only be established when the proportion of strong participants is low. Asymmetric interactions always undermine cooperation within the weak player subgroup. Thus, our findings can deepen the understanding of how asymmetry affects cooperation in social dilemma.

3.2 Model

3.2.1 Game model and population setting

Our model builds on the prisoner's dilemma (PD) game. In a one-shot interaction, paired players can choose to either cooperate (C), incurring a cost c to provide a benefit b to the other player, or defect (D), doing nothing. Mutual cooperation yields a reward R, while mutual defection leads to a punishment P. If one player cooperates and the another defects, the cooperator receives the sucker's payoff S, and the defector receives the temptation payoff T. Following ref. [29, 30], we simplify the model by fixing $b - c = 1$ and adopting the concept of dilemma strength, defined as $r = c/(b - c)$, measuring the cost of cooperation relative to its benefit. Consequently, the payoff elements are scaled to $R = 1$, $P = 0$, $S = -r$, and $T = 1 + r$.

This study delve into a population with N players placed on a lattice network featuring periodic boundaries. Players can interact with their 8-nearest neighbors (i.e., Moore neighborhood). We specifically explore asymmetry population, comprising strong players with a proportion denoted by $\rho \in (0, 1)$, and weak players with a proportion of $1 - \rho$. The differences in social status and class among players lead to asymmetric interaction payoffs between strong and weak players. Specifically, the asymmetry in social status and class results in different cost of their cooperation and benefits providing to others, which creates varying dilemma strengths between interactions among weak players and those among strong players. We assume that the dilemma strength in interactions among strong players is denoted by r. For interactions among weak players, the dilemma strength is defined as rk, where $k \in (0, +\infty)$ represents the relative dilemma strength. For $k < 1$, the dilemma strength among weak players is lower than that among strong players. For $k = 1$, the model reverts to the traditional scenario, and when $k > 1$, the dilemma strength among weak players is higher than that among strong players. The interactions between strong and weak players are asymmetric. Due to dominant position of strong players, they can significantly influence the outcome of interactions, often exploiting weak players and gaining more benefits from these interactions. Therefore, whether strong players cooperate or not, they can always achieve the highest payoff T, acting like defectors in asymmetric interactions. In contrast, weak players, regardless of the strategy they adopt, are compelled to engage in “cooperation” and accept the minimum sucker’s payoff S.These interactions within an asymmetric population can be summarized using the payoff matrix outlined in Table. 2.

Table 2: Payoff matrix under asymmetric population

		Strong player		Weak player	
		C	D	C	D
Strong player	C	1	$-r$	$1+rk$	$1+rk$
	D	$1+r$	0	$1+rk$	$1+rk$
Weak player	C	$-rk$	$-rk$	1	$-rk$
	D	$-rk$	$-rk$	$1+rk$	0

3.2.2 Game dynamics

We conduct asynchronous Monte Carlo simulations (MCS) to obtain the evolutionary results. Initially, all players are randomly distributed on the lattice network and hold either the C strategy or the D strategy with equal probability. In each MCS time step, each player, on average, is selected once to update their strategy. The selected focal player, says i, interacts with each of their neighbors pairwise to obtain payoffs and then updates their strategy through social imitation. Player i imitates the strategy of a randomly selected neighbor, says j, with a probability of $w_{i\leftarrow j}$, which can be calculated using the Fermi rule:

$$w_{i\leftarrow j} = \frac{1}{1+\exp\{(\Pi_i - \Pi_j)\kappa\}}, \tag{13}$$

where Π_x is the total payoff that player x obtains from interacting with all neighbors in current MCS time step, and κ denotes the imitation strength. We typically set $\kappa = 10$ to explore a strong imitation scenario, where a player’s strategy updating is highly dependent

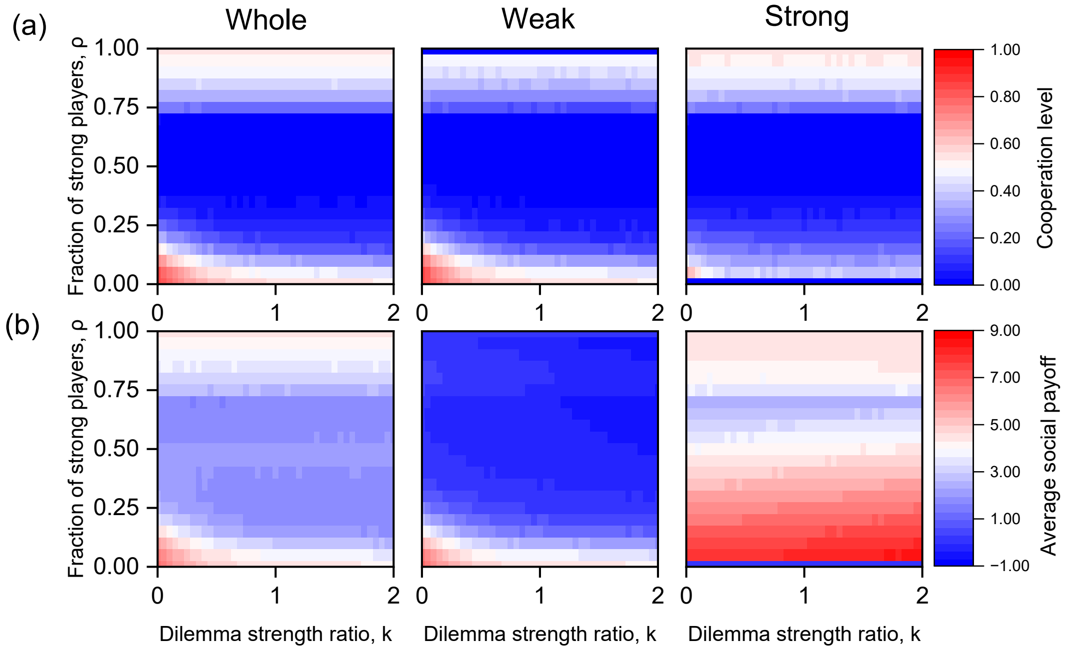

Figure 17: **Asymmetric interaction jeopardizes cooperation under low dilemma strength conditions.** Depicted are (a) the proportion of cooperation and (b) the average payoff as a function of relative dilemma strength k and proportion of strong player ρ within the whole population, the sub-population of weak players, and the sub-population of strong players. The parameter settings is $r = 0.05$.

on the payoff difference.

In simulations, we employ a network of size $N = 100^2$. To ensure stability, we obtain results from a single simulation by averaging the outcomes over the last 5000 MCS time steps out of a total of 10^6 MCS time steps. The final simulation results are derived from averaging over more than 100 independent simulations to exclude the influence of randomness.

3.3 Results

Previous studies on structured populations have shown that under low dilemma strength conditions [31, 30], network reciprocity mechanisms can sustain cooperation, with cooperators forming tight clusters to resist the invasion of defectors . However, under high dilemma strength conditions, network reciprocity fails to maintain cooperation. We investigate cooperation in asymmetric populations by selecting representative scenarios of both low ($r = 0.05$) and high ($r = 0.2$) dilemma strength.

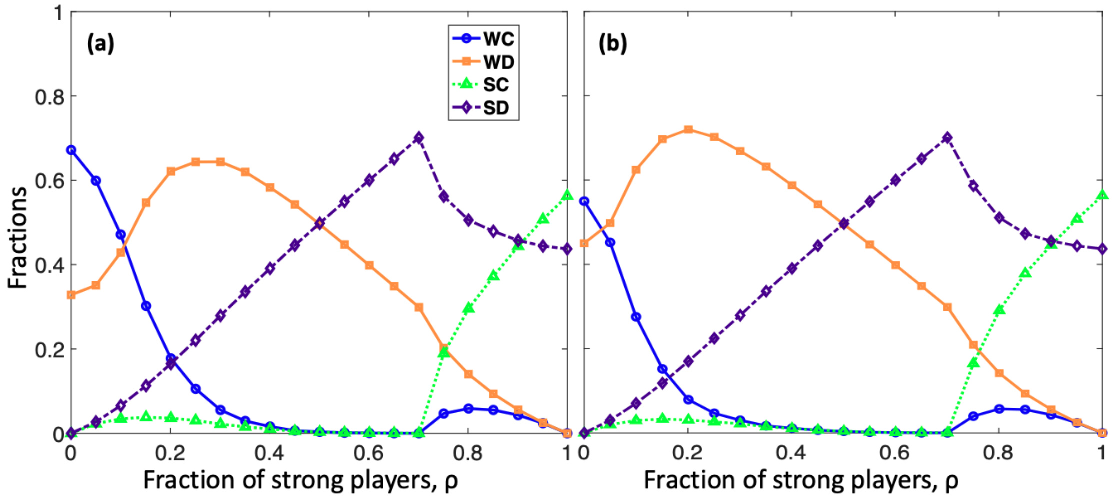

Figure 18: Depicted are the fraction of weak cooperator (WC), weak defector (WD), strong cooperator (SC) and strong defector (SD) in population as a function of proportion of strong player ρ for panel (a) $k = 0.3$ and panel (b) $k = 1.5$. The parameter settings is $r = 0.05$.

3.3.1 Results of low dilemma strength case

Figure 17 depicts the fraction of cooperation across the entire population C_{whole}, the subgroup of strong players C_{strong}, and the subgroup of weak players C_{weak}, as a function of proportion of strong players ρ and relative dilemma strength k. In the traditional PDG model (both $\rho = 0$ and $\rho = 1$), cooperation can be sustained at approximately 0.62 under low dilemma strength ($r = 0.05$), due to network reciprocity [31]. As ρ approaches 0.5, the proportion of strong to weak players becomes more balanced, increasing the likelihood of encounters between strong and weak players in the structured population. This also implies a higher probability of asymmetric interactions. The results shown in Figure 17 indicate that whether ρ decreases from 1 to 0.5 or increases from 0 to 0.5, the increase in asymmetric interactions suppresses cooperation, potentially leading to its complete disappearance. In populations with a lower proportion of strong players (i.e., $0 < \rho < 0.25$), when the relative dilemma intensity among weak players remains below 1, the overall level of cooperation increases due to the lower dilemma intensity faced by most weak players. However, when the relative dilemma intensity among weak players exceeds 1, the overall cooperation rate remains unchanged. Conversely, in populations with a higher proportion of strong players (i.e., $0.75 < \rho < 1$), variations in the relative dilemma intensity among a small number of weak players have little impact on the overall level of cooperation. Regarding social payoffs, the exploitation of weak players by strong players results in higher payoffs for the latter. The average payoff of strong players displays

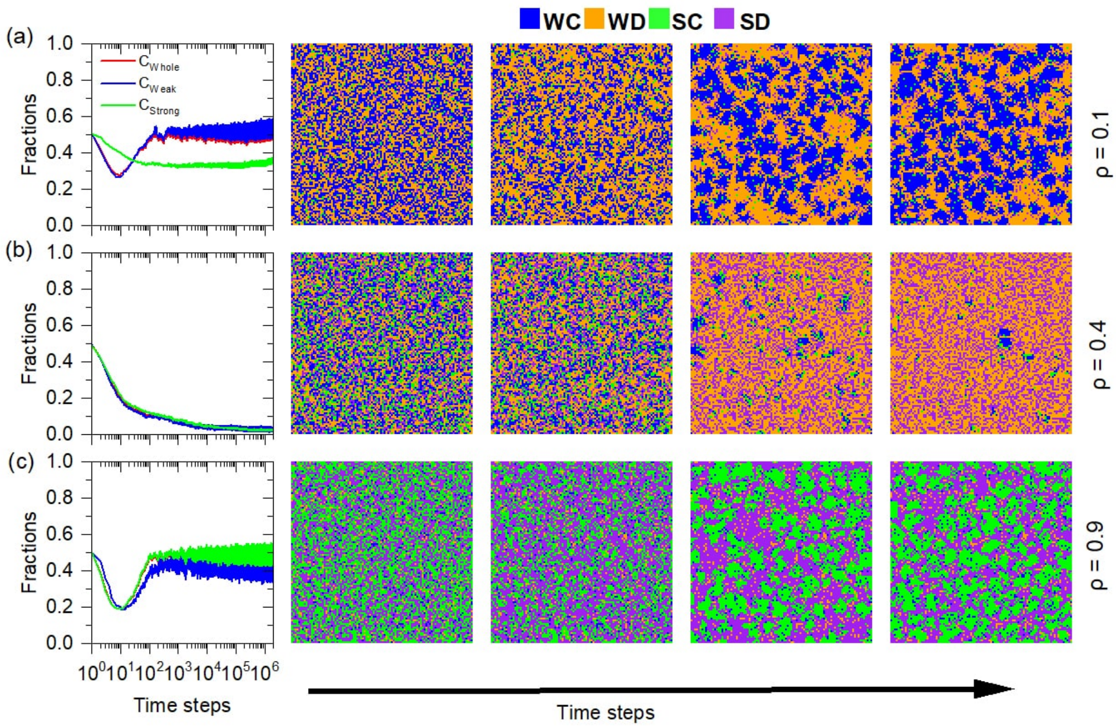

Figure 19: **Asymmetric interaction between strong and weak players weaken network reciprocity.** The leftmost panels show the fraction of cooperation within the whole population, the sub-population of weak players, and the sub-population of strong players as a function of time steps. Right panels show the typical evolutionary snapshots, where weak cooperator (WC), weak defector (WD), strong cooperator (SC) and strong defector (SD) are represented by blue, orange, green, and purple, respectively. For (a)-(c), the proportion of strong players is set as $\rho = 0.1$, 0.4 and 0.9, while other parameters are set as $r = 0.05$ and $k = 0.3$.

a “U-shaped” trend, initially decreasing and then increasing.

At a low dilemma strength of $r = 0.05$ network reciprocity can spontaneously sustain cooperation [31]. For $k = 0.2$, this indicates a lower dilemma strength among weak players. Conversely, at $k = 1.5$, there is a higher dilemma strength among weak players, but network reciprocity can still support cooperation. Asymmetric interactions allow strong players to exploit weak players, diminishing the payoff advantage of weak players. This negative impact intensifies as the proportion of strong players increases, regardless of the dilemma strength among weak players. Consequently, Figure 18(a) and (b) exhibit similar trends. As the proportion of strong players increases from 0 to 0.4, the population shifts from a state where cooperators and defectors coexist to one dominated by defectors. When the proportion ρ approaches 1, the impact of asymmetry diminishes, and the results for $k = 0.2$ and $k = 1.5$ converge, allowing cooperation to reemerge due to the low dilemma strength among strong players.

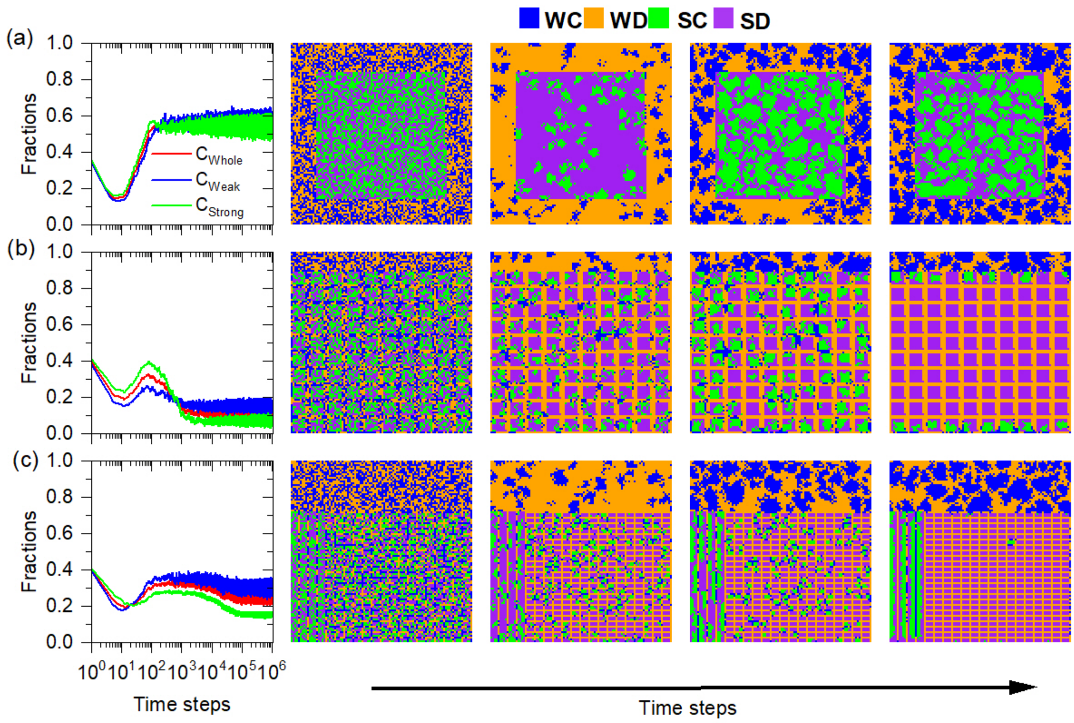

Figure 20: **Asymmetric interaction between strong and weak players suppresses the formation of clusters of weak cooperators, thereby weakening cooperation.** The leftmost panels show the fraction of cooperation within the whole population, the sub-population of weak players, and the sub-population of strong players as a function of time steps for (a) interaction probability $p = 0.04$, (b) $p = 0.35$ and (c) $p = 0.61$.The right panels show the typical evolutionary snapshots under a special spatial distribution. Other parameters are set as $r = 0.05$, $\rho = 0.5$ and $k = 0.3$.

To investigate the evolution of asymmetric population cooperation, we present represen-

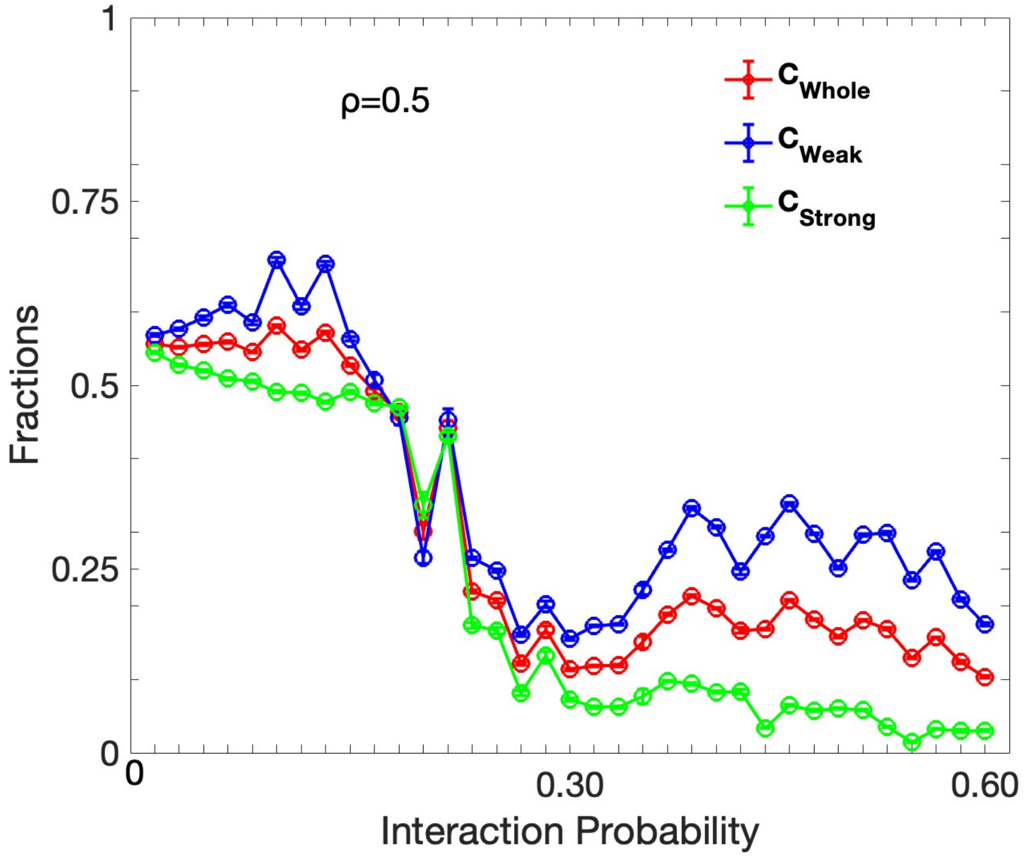

Figure 21: **High probability of interaction between strong and weak players inhibits cooperation.** Depicted are the fraction of cooperation within the whole population, the sub-population of weak players, and the sub-population of strong players as a function of interaction probability p. When fixing the proportion of strong players at $\rho = 0.5$, we control the interaction probability between strong and weak players by implementing a specific spatial distribution. The interaction probability is computed as $p = l_{s\text{-}w}/(l_{s\text{-}s} + l_{s\text{-}w})$, where $i, j \in \{(s)trong, (w)eak\}$ and $l_{i\text{-}j}$ represents the number of interactions between players of type i and j. Placing strong players in a single block yields the lowest interaction probability, as shown in subsequent Figure 20(a). Increasing the number of such blocks and reducing their size leads to higher interaction probabilities between strong and weak players, as illustrated in subsequent Figure 20(b)-(c). Other parameters are set as $r = 0.05$ and $k = 0.3$.

tative time evolutions and evolutionary snapshots in Figure 19. Initially, individuals are randomly distributed in a lattice network. Regardless of whether the population predominantly consists of strong or weak players, typical characteristics of cooperation evolution emerge. Defectors beat most of cooperators, and only a few cooperators surviving by forming tiny clusters, as shown in Figure 19(a) and (c). Subsequently, these cooperative clusters expand further. However, when the proportion of strong to weak players is balanced, increasing interactions between them fail to stabilize cooperative clusters; instead, it leads to their disintegration. Only a few small clusters remain in the population, indicating network reciprocity has been weakened.

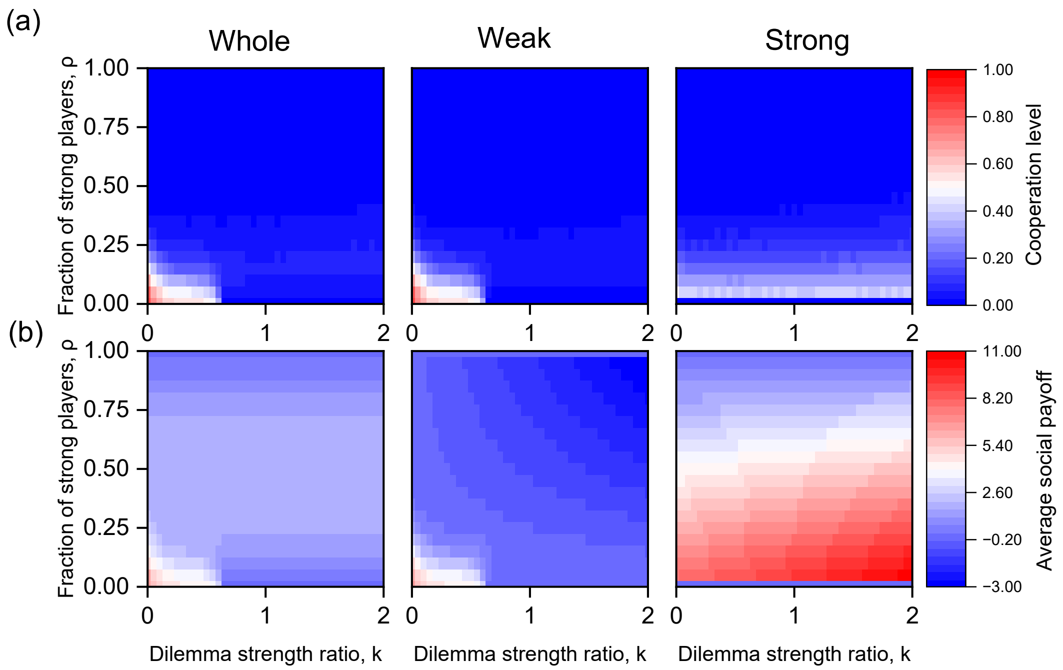

Figure 22: **Asymmetric interactions can sustain cooperation within the strong player subgroup in populations where strong players are in the minority, but undermine cooperation within the weak player subgroup.** Depicted are (a) the proportion of cooperation and (b) the average payoff as a function of relative dilemma strength k and proportion of strong player ρ within the whole population, the sub-population of weak players, and the sub-population of strong players. The parameter settings is $r = 0.2$.

To further explore the impact of interactions between strong and weak individuals on cooperation, we maintained a population composition with approximately $\rho \approx 0.5$ strong players and manipulated the likelihood of interaction between them using a specific spatial distribution. The interaction probability is defined as $p = l_{s\text{-}w}/(l_{s\text{-}s} + l_{s\text{-}w})$, where $i, j \in \{(s)trong, (w)eak\}$ and $l_{i\text{-}j}$ represents the number of interactions between players of types i and j, respectively. Initially, we concentrated all strong players within single chunk surrounded by weak players to create the scenario with the lowest probability of

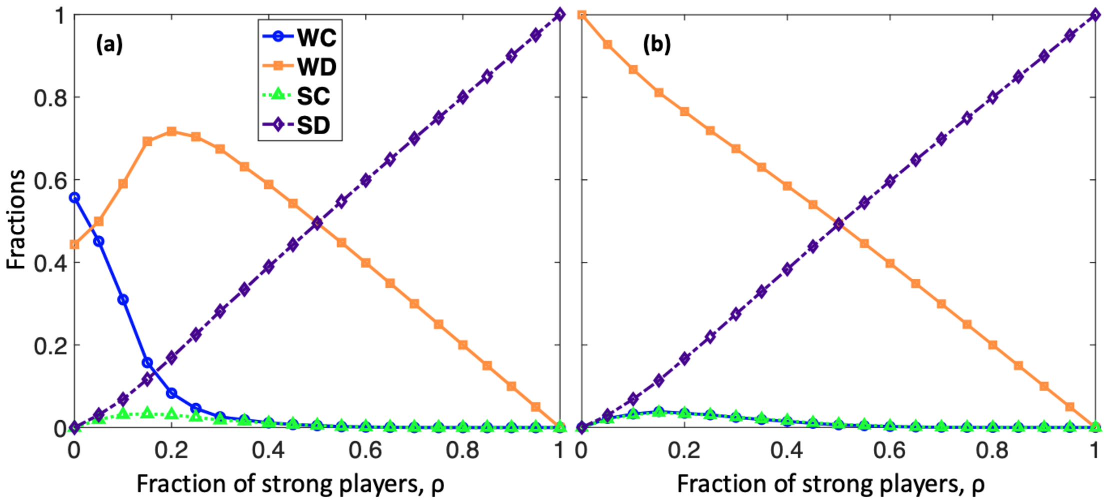

Figure 23: Depicted are the fraction of weak cooperator (WC), weak defector (WD), strong cooperator (SC) and strong defector (SD) in population as a function of proportion of strong player ρ for panel (a) $k = 0.3$ and panel (b) $k = 1.5$. The parameter settings is $r = 0.2$.

interaction (see Figure 20(a)). Subsequently, dividing the strong players into more distinct regions led to an increase in the interaction probability, as illustrated in Figure 20(b) and (c).

In the scenario with the lowest interaction probability ($p = 0.04$), stable cooperative clusters emerged within subgroups of both strong and weak players, as depicted in Figure 20(a). As the interaction probability increased, cooperative clusters persisted within the subgroup of weak players. However, interactions with weak players dismantled the cooperative clusters within the subgroup of strong players, as shown in Figure 20(b) and (c). This outcome arises from the capability of strong players to maximize individual gains through interactions with weak players, enhancing the advantage for strong defectors at the boundary and enabling them to invade cooperative clusters. The findings depicted in Figure 21 suggest that increasing the interaction probability between strong and weak players results in a decreased overall level of cooperation.

3.3.2 Results of high dilemma strength case

Unlike scenarios with low dilemma strength, network reciprocity cannot sustain cooperation in traditional models under high dilemma strength, as shown by the results for $\rho = 1$ in Figure 22. Interestingly, the results in Figure 22 reveal that in populations where strong players are a minority (e.g., $\rho < 0.25$), asymmetric interactions can help sustain cooperation within the strong player subgroup. Regardless of the value of k, asymmetric interactions can leverage the payoff advantage of some strong players (as seen in the right-most panel of Figure 22), thus supporting the presence of strong cooperators. Similar to scenarios with low dilemma intensity, an increase in k enhances the payoffs for the strong player subgroup. However, as the proportion of strong players increases, the reduction in their interactions with weak players diminishes their average payoff. Cooperation among weak players occurs only when the relative dilemma intensity is sufficiently low (i.e., $k < 0.5$). Asymmetric interactions, however, undermine cooperation within the weak player subgroup.

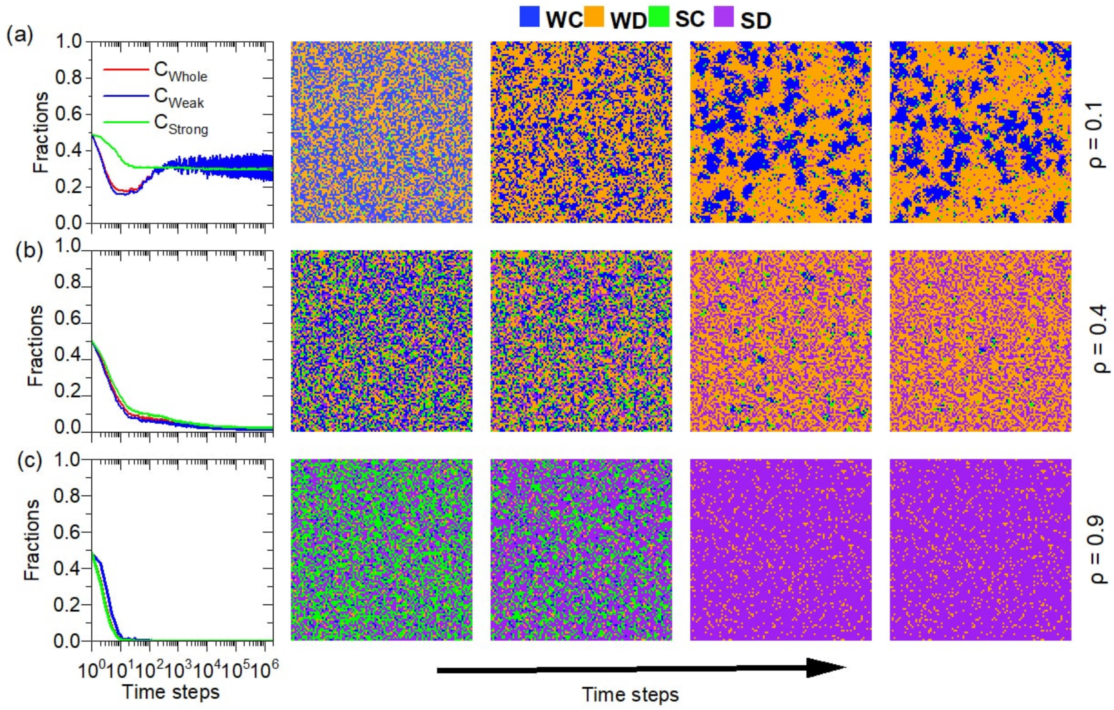

Figure 24: **Weak cooperative clusters can support the presence of strong cooperators, but asymmetric interactions suppress the formation of weak cooperator clusters.** The leftmost panels show the fraction of cooperation within the whole population, the sub-population of weak players, and the sub-population of strong players as a function of time steps. Right panels show the typical evolutionary snapshots. For (a)-(c), the proportion of strong players is set as $\rho = 0.1$, 0.4 and 0.9, while other parameters are set as $r = 0.2$ and $k = 0.3$.

The findings presented in Figure 23 show that the coexistence of four type of player occurs at low values of ρ. This suggests that interactions between strong and weak individuals support the presence of strong cooperators. However, as ρ increases, there is a noticeable shift towards the dominance of defectors. Specifically, at $k = 0.3$, the proportion of weak cooperators declines sharply with increasing ρ, while strong cooperators exhibit only a minor presence. In contrast, at a higher k value of 1.5, strong cooperators can only

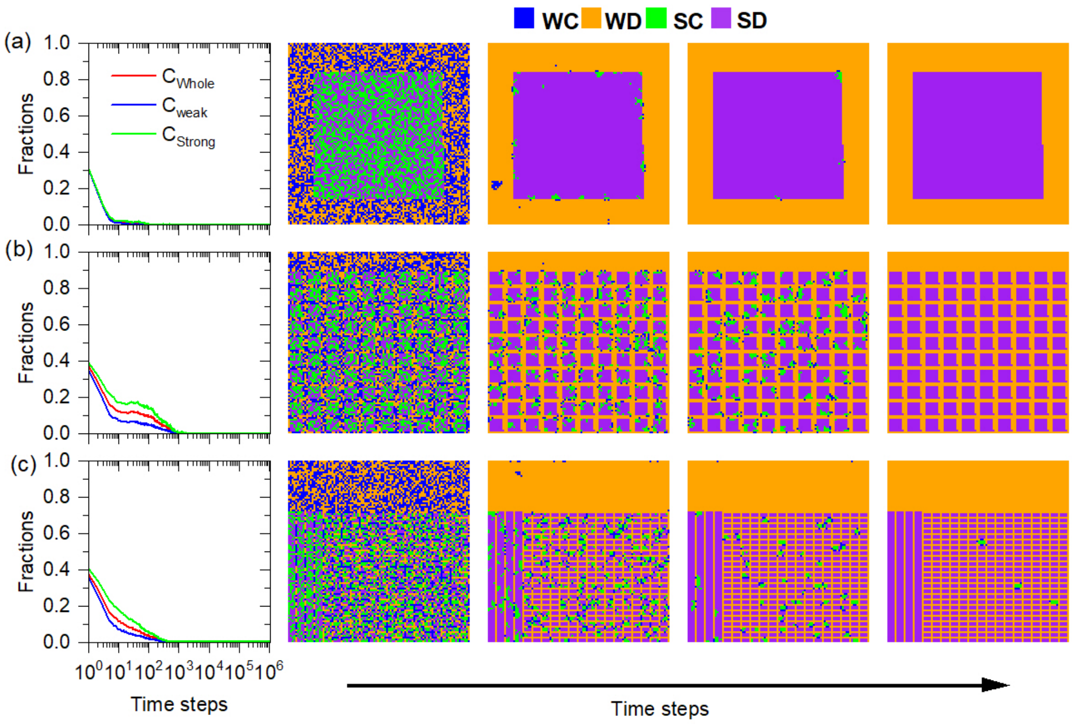

Figure 25: **Asymmetric interactions prevent the stable formation of cooperative clusters.** The leftmost panels show the fraction of cooperation within the whole population, the sub-population of weak players, and the sub-population of strong players as a function of time steps for (a) interaction probability $p = 0.04$, (b) $p = 0.35$ and (c) $p = 0.61$. The right panels show the typical evolutionary snapshots under a special spatial distribution. Other parameters are set as $r = 0.2$, $\rho = 0.5$ and $k = 0.3$.

maintain a very low fraction.

The analysis of the evolutionary dynamics depicted in Figure 24 reveals that the formation of cooperative clusters among weak players is crucial for sustaining cooperation within the entire population. However, an increase in the proportion of strong players impedes the formation of these cooperative clusters among weak players. To be specific, when k is low (see Figure 24(a)), it facilitates the formation of cooperative clusters among weak players. In this case, the presence of a few strong players does not inhibit the formation of most cooperative clusters. In contrast, these cooperative clusters among weak players can support the existence of strong cooperators around them. However, as the proportion of strong players increases to 0.4 (see Figure 24(b)), a large number of strong players hinders the formation of weak cooperative clusters. Finally, only a small number of clusters comprising both strong and weak cooperators can survive. It indicates network reciprocity is weakened by the asymmetric interaction between strong and weak players. Furthermore, when the majority of the population comprises strong players, neither clusters of weak cooperators nor clusters of strong cooperators can coexist, as shown in Figure 24(c).

Using the previously mentioned methodology, we examine the influence of interaction probabilities. The findings presented in Figure 25 demonstrate that the interaction between strong and weak players cannot promote cooperation. Irrespective of the specific levels of interaction probabilities, strong defectors consistently attain payoff advantages when interacting with weak counterparts. This advantage enables them to gradually infiltrate and disrupt cooperative clusters, even in scenarios characterized by low level of dilemma strength among weak players (e.g., $k = 0.3$). It means that asymmetric interactions make cooperative clusters unstable.

3.4 Discussion

The common asymmetry in social interactions stems from differences in power and social status, power imbalances affect the interaction outcomes between individuals. For instance, individuals in dominant status may exploit those with less power. Understanding how asymmetry affect cooperation is critical for addressing societal challenges.

To investigate how asymmetric populations affect cooperation in this context, we propose a novel model where the dilemma strength of interaction among weak players is different from that among strong players. The asymmetry is manifested that strong players can always act as defectors to exploit weak players, while weak players are forced to choose cooperation regardless of their strategy. Through Monte Carlo simulations, our study reveals the dual role of asymmetric interactions on cooperation. Under low dilemma strength, asymmetric interactions between strong and weak players undermine network reciprocity, making it detrimental to the maintenance of cooperation. Conversely, under high dilemma strength, asymmetric interactions benefit strong players by providing them with higher payoffs, enabling strong player subgroups to rely on weak cooperator clusters to establish cooperation. However, as the likelihood of asymmetric interactions increases, it hinders the establishment of cooperation within weak player subgroups, thereby undermining overall cooperation.

This findings indicate that increased interaction between strong and weak players undermines social cooperation. Asymmetric behavior enables strong players to accrue disproportionate benefits, potentially worsening societal inequality. This research underscores the conflict stemming from the asymmetric behavior. Interventions targeting asymmetric interactions and adjustments to the dynamics between strong and weak groups may reduce the occurrence of conflicts. It hold insights for addressing structural inequities and promoting social justice [9].

This model is built upon a strict assumption, where asymmetric interactions ensure that strong players always act as defectors, while compelling the weak players to cooperate. However, human behavior is nuanced. Influenced by social norms or social value orientation [32], some strong players may still cooperate [33], while weak ones may resist. This suggests that individuals do not always strictly adhere to these roles. Additionally, to intuitively explore the impact of asymmetry on cooperation, our model assumes that individuals do not exhibit biased behavior towards different types of others. In reality, individuals often have inconsistent attitudes towards various types of people [34]. Incorporating such complexities and biased preferences into model could better bridge the gap between our theoretical findings and real-world situations. On the other hand, to explore the effects of asymmetric behavior, our model overlooks the potential for individual mobility in social status [35], whereby the status of players remains constant. However, as interactions unfold in the real world, individuals may undergo changes in social status based on factors such as their educational attainment and accumulated resources. Thus, in future works, integrating the fluidity of social status will enhance our understanding of the dynamic impacts of asymmetric interactions.

In summary, our research contributes to advancing theoretical understanding of cooperation dynamics in asymmetric populations. By uncovering the dual role of asymmetry behaviors in promoting or inhibiting cooperation, thus enriching existing theoretical frameworks and deepen the understanding of how asymmetries shape cooperative behavior in complex systems.

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4 SUMMARY AND FUTURE WORK

This thesis weaves together into a collected volume of works various, yet connected studies within the complex systems approach of evolutionary game theory, with especial focus on so-called social dilemmas. Accordingly, each of the chapters provides insights from a different angle within the broader approach of how to understand and better facilitate cooperation in settings where cooperation is difficult.

4.1 Conclusive summary of Chapter 3

This chapter demonstrated the potential of simple bots to enhance cooperation even in those environments devoid of the so-called reciprocity mechanism. It demonstrated how cooperation could be induced by the careful design and management of bots in human-machine interactions without necessarily depending on complex algorithms. Gratitude is further extended to population structure and imitation strength for their determining role in the efficacy of cooperative strategies. Whereas the introduction of bots increased the chances of cooperation in well-mixed populations, their effect within structured populations was more subtle. In particular, loner bots played an ambivalent role: whereas their moderate presence favored cooperation, high density was detrimental to cooperation [1].

This work addresses these challenges by showing how the introduction of simple programmed bots can change the dynamics in social dilemma games. By analyzing the effects, the paper pinpoints strategies towards sustainable cooperation, even in environments where traditional mechanisms are deemed insufficient.

4.1.1 Key Findings

Adding cooperative bots strongly increased human cooperation within well-mixed populations, especially in the case of weak imitation. This was a result of the fact that under these conditions it is much more likely to play against cooperators than against defectors; therefore, cooperation paid off more often. On the other hand, loner bots did not raise cooperation among humans in well-mixed populations because loners dominate if only few clusters of cooperators exist. It turns out that the defection bots and randomized bots—those that randomly select between cooperation, defection, and opting out—seldom reached a critical threshold to impact the dynamics. Most often, their presence tended to act as an obstacle to the development of cooperation-enhancing dynamics.

In structured populations, the cooperative bots did continue to foster cooperation, but the effect was stronger under weak imitation. Under strong imitation, defection became the dominant strategy in a population. Somewhat surprisingly, loner bots tend to have a cooperation-promoting effect in structured populations. Cooperation was maximized at an optimal density of loner bots, but at too high a density, the loners broke down the cooperation. This effect was explained in terms of how loner bots disrupted the cyclic dominance characteristic of structured populations. Generally, defector bots and randomized bots impaired cooperation in structured populations by thwarting the emergence of cooperative clusters.

4.1.2 Implications

This study therefore has a number of implications, both theoretical and applied. The fact that bots can facilitate cooperation in anonymous one-shot games informs the design of artificial agents capable of usefully nudging human behavior in beneficial directions, be it encouraging prosocial behavior on digital platforms or solving collective action problems in the physical world.

4.1.3 Future work

Future work may investigate intelligent bot strategies further—such as via reinforcement learning—and explore whether these results generalize to multiplayer games, or to environments containing more complex social structures. Additionally, it could be of paramount importance to understand how, when reputations are at stake or in repeated games, bots interact with human players.

4.2 Conclusive summary of Chapter 4

The conclusions of this chapter give a more subtle understanding of how asymmetric social structures influence cooperation. While asymmetry can sometimes favor cooperation in subgroups, it tends to destroy cooperation in the general population, particularly when the number of strong players increases. The main role in this process is taken over by the exploitation of weak players by strong defectors; this underlines the dangers of inequality and injustices within social systems.

4.2.1 Key Findings

In the case of low dilemma strength, network reciprocity can maintain cooperation even in the traditional sense—wherein cooperators avoid exploitation by defectors by clustering together. However, such dynamics are disrupted in the presence of asymmetric interactions between strong and weak players. Cooperation is gradually suppressed as the population share of strong players increases, especially when interactions between strong and weak players become more frequent. As asymmetry increases, the exploitation of weak players by strong defectors intensifies, eventually leading to the breakdown of cooperation within the population. Nonetheless, when the proportion of strong players is low, the formation of cooperative clusters, particularly among weak players, can sustain some level of cooperation.

Under high dilemma strength—where cooperation is harder to maintain—network reciprocity alone cannot sustain cooperation in traditional models. However, asymmetric interactions can maintain cooperation among strong players, particularly when they are in the minority. Strong players exploit the presence of weak cooperators to preserve cooperation within their subgroup. Interestingly, as the fraction of strong players increases, this positive effect diminishes. The increasing prevalence of asymmetric interactions caused by strong players triggers the collapse of cooperative clusters among weak players, undermining overall cooperation [2].

This chapter also explores how the probability of interaction between strong and weak players influences cooperation. It demonstrates that as the interaction probability increases, strong players exploit weak players more intensely, further destabilizing cooperative clusters. Asymmetric interactions, therefore, inherently make cooperation more fragile, particularly when strong defectors have repeated opportunities to exploit weak cooperators.

4.2.2 Implications

The implications of this study also include insights into real-world dilemmas beyond mere theoretical modeling. For instance, in societies with highly concentrated use of power in the hands of a few, cooperation would be more difficult to maintain and would likely lead to more social conflict. Interventions that tackle these power imbalances and promote more equal interactions will help in fostering cooperation and reducing conflict in such systems.

4.2.3 Future work

It would also be interesting for further studies to synthesize models in which strong players may cooperate for reasons of social norms, cultural dynamics, or personal values, or in which weak players refuse to be exploited. Further evolution of models considering fluid social status—for example, changes driven by education, economic opportunities, or resource accumulation—can achieve greater realism with regard to real-world social mobility and its interaction with cooperation. Whereas broadening this to biases or uneven attitudes toward different kinds of players could capture the complexity of asymmetric interactions in far greater detail and provide a more realistic view of diverse populations, one might look into asymmetric games for insight into how the destabilizing effects of asymmetry in power can be ameliorated. The project could, for instance, include an investigation of policy-driven remedies that reduce inequality, advance principles of equity, and foster cooperative behavior at all levels of hierarchical social systems.

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Achievements During My PhD Studies at Kyushu University

During my doctoral studies at the Interdisciplinary Graduate School of Engineering Sciences, Kyushu University, I embarked on an academic journey that encompassed diverse fields of research. Initially, I have been worked eight months in the field of aerodynamics, conducting research in fluid dynamics. This work culminated in presentations at prestigious international conferences held in multiple countries, Japanese Society of Aeronautics and Astronautics Western Branch,Japan [1] including APISAT2023 in China [2] [3], ICAS2024 in Italy [4] [5], and APISAT2024 in Australia [6]. These conferences provided invaluable opportunities to disseminate my findings and engage with leading scientists and aerospace professionals worldwide.

Subsequently, I transitioned to game theory, the primary focus of my doctoral research, while continuing collaborative work in aerodynamics with international colleagues. This interdisciplinary approach enabled me to gain a holistic perspective on scientific inquiry, successfully bridging the domains of fluid dynamics and applied mathematics.

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