Evolution of Mobile Strategies in Social Dilemma Games: An Analysis of Cooperative Cluster Formation

Maud D. Gibbons, Colm O'Riordan and Josephine Griffith

Abstract This paper analyses the formation of cooperative clusters toward the emergence of cooperative clusters in evolutionary spatial game theory. In the model considered, agents inhabit a toroidal lattice grid, in which they participate in a social dilemma games, and have the ability to move in response to environmental stimuli. In particular, using the classical 2-player prisoner's dilemma and a generalised N-player prisoner's dilemma, we compare and contrast the evolved movement strategies, and the cooperative clusters formed therein. Additionally, we explore the effect of varying agent density on the evolution of cooperation, cluster formation, and the movement strategies that are evolved for both cooperative and non-cooperative strategies.

1 Introduction

Questions relating to cooperation and its emergence have been studied in a range of domains including economics, psychology, theoretical biology, and computer science. Researchers have explored the conditions necessary for cooperation to emerge among groups or societies of self-interested agents. Social dilemma games, such as the Prisoner's Dilemma [1], have been adopted as a succinct representation of the conflict between individually selfish behaviours and collectively rational behaviours. Evolutionary game theory has been studied since the 1980s when ideas from evolutionary theory were incorporated into game theory [2].

A variety of social dilemmas have been studied with the majority of attention afforded to the 2-player prisoner's dilemma. Many variations of this game exist, which allow researchers to explore questions regarding cooperation in the presence

M. D. Gibbons (✉) · C. O'Riordan · J. Griffith
National University of Ireland, Galway, Ireland
e-mail: m.gibbons11@nuigalway.ie

C. O'Riordan
e-mail: colm.oriordan@nuigalway.ie

J. Griffith
e-mail: josephine.griffith@nuigalway.ie

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of noise, trust, spatial mechanisms and other extensions. One interesting extension that has been explored in the literature is that of N-player social dilemmas [3] where N agents participate simultaneously in the interaction. Each agent can cooperate or defect, and receives a reward based on the number of cooperators present. Additionally, cooperators incur a cost to interact while defectors do not.

In this work, we consider populations of agents participating in both the 2-player and N-player versions of the prisoner's dilemma, and the clusters of cooperators formed therein. We adopt a spatial model where agents' interactions are defined by some topological constraints. Much recent work has focused on the effect of such constraints [4–6]. We use a toroidal lattice where agents may interact with their immediate eight neighbours, if any. We further imbue the agents with the ability to move based on environmental stimuli. The role of mobility in the evolution of cooperation has grown in importance and recognition in recent decades with several researchers demonstrating its use in the promotion of cooperation in artificial life simulations [7, 8]. We adopt an evolutionary framework where successive populations are evolved; the strategy for interacting in the games and the mobility strategy are both subject to evolution. Finally, we define a set of metrics to both qualitatively and quantitatively evaluate the formation of cooperative clusters.

The N-player prisoner's dilemma has not been widely studied in evolutionary models where agents are spatially situated with the inclusion of mobility. In previous work [9], we investigated the significant differences prevalent between the 2-player and N-player dilemmas in this context. In this work, we wish to further explore these differences in the context of cooperative cluster formation, and in addition, examine the effect of varying the density of the agents in the environment. Finally we wish to analyse the movement strategies evolved in these conditions.

In this paper, we show through simulation that there is in fact a substantial difference between the 2-player and the N-player scenarios in terms of the likelihood of cooperation emerging for varying density levels. We demonstrate that for a range of density levels, cooperation emerges in the N-player case. Finally, we analyse the formation and proliferation of cooperative clusters in simulations where cooperation emerges.

The paper outline is as follows: the next section discusses some related work in the field, Sect. 3 outlines our model and approach, and Sect. 4 presents and discusses our results. Finally conclusions and some potential future directions are presented.

2 Related Work

In this section we review some of the relevant research in the literature; we introduce some concepts pertaining to social dilemmas and discuss some work on spatial and evolutionary game theory and the role of mobility.

2.1 Social Dilemma Games

Social dilemma games (most famously the prisoner's dilemma and its variants) have been studied in a wide range of domains due to their usefulness in capturing the conflict between individual and collectively rational behaviours. The prisoner's dilemma in the classical game is described as follows: two players make a choice simultaneously to either cooperate or defect. Mutual cooperation yields a reward R for both participants. However, unilateral defection results in a greater payoff, T, for the defector and a worse payoff, S, for the cooperator (the sucker's payoff). If both defect, both receive P as a payoff such that: $T > R > P > S$.

It has been argued that the N-player variant captures a wider set of dilemmas (e.g. donating to charity organisations, environmental issues etc.). In the N-player dilemma game there are N participants, and again, each player is confronted with a choice: to either cooperate or defect. In one formalism of the game [10], all players receive a benefit based on the number of cooperators present. Cooperators have to pay a cost. No such cost is borne by defecting players. For instance, let B represent some fixed benefit, N the number of players, c the cost and i the number of cooperators. Participants receive $(B \times i)/N$. Cooperators must pay c and thus receive a net reward of $((B \times i)/N) - c$. This, or similar, formulas have been adopted in several other works [3, 11, 12].

We represent the payoff obtained by a strategy which defects given i cooperators as $D(i)$ and the payoff obtained by a cooperative strategy given i cooperators as $C(i)$. Defection represents a dominant strategy, that is, for any individual, moving from cooperation to defection is beneficial for that player in that they still receive a benefit without the cost:

$$D(i) > C(i) \qquad 0 < i \leq N - 1 \tag{1}$$

However, if all participants adopted this dominant strategy, the resulting scenario would be a sub-optimal, and from a group point of view, irrational outcome:

$$C(N) > D(0) \tag{2}$$

If any player changes from defection to cooperation, the society performs better:

$$(i + 1)C(i + 1) + (N - i - 1)D(i + 1) > (i)C(i) + (N - i)D(i)$$

In multi-person games, the problem of avoiding exploitation, or free riders, is more difficult, and cooperation may be harder to achieve. In 2-player games, reciprocity has been explored as a means to engender cooperation [13]. However, in N-person games reciprocity may be less advantageous. In order for an agent to punish a defector by defecting in retaliation, the agent must also punish all those that did cooperate.

2.2 Evolutionary N-Player Games

There have been several other notable approaches to exploring the N-player prisoner's dilemma using the tools and approaches in evolutionary game theory. Yao and Darwen [3] explore the effect of group size in the evolution of cooperation. Strategies are represented using a generalised form of the representation employed by Axelrod and Dion [14]. In their experiments, it is shown that cooperation can be evolved in groups but that it becomes more difficult with increasing group size.

The effects of spatial influences on the evolution of cooperation among strategies participating in the N-players prisoner's dilemma is explored by Suzuki and Arita [12]. The two spatial factors under investigation are on the *scale of interaction* (determines which neighbours to play with) and *scale of influence* (specifies which neighbouring candidates to choose for offspring). Results for simulations involving a *tit-for-tat* like strategy showed that cooperation becomes most wide-spread for a modest value of scale of interaction and that, as the cost of cooperation increases, the levels of cooperation decrease and a higher value of the scale of interaction is found. Results also indicate that higher cooperation levels are achieved for higher values of the *scale of influence*.

2.3 Mobility

Traditional spatial models promote the evolution of cooperation by constraining agent interactions to a particular static topology. Previous work has investigated structures such as lattices [15], small-world graphs [16], and scale-free graphs [17]. However, the inclusion of movement creates a more realistic model by allowing agents to respond to their current neighbourhood by moving within their environment.

Mobility is a form of network reciprocity [13], which has gone from being perceived as a hindrance to the emergence of cooperation to a key concept in its promotion. While unrestrained movement can, and does, lead to the 'free-rider' effect [18], allowing highly mobile defectors to go unpunished, using simple strategy rules [7, 19] or using mobility rates [8, 20] significantly curb the free-rider phenomenon allowing self-preserving cooperator clusters to form, and cooperation to proliferate.

Several mechanisms for the emergence of cooperation exist, but all essentially express a need for cooperators to either avoid interactions with defectors or increase and sustain interactions with other cooperators. Research in this domain is largely divided into two categories based on authors' definition of mobility; all movement should be random [8, 20–22], or should be purposeful or strategically driven, but may indeed contain random elements [7, 23–27]. Random mobility can be used to describe the minimal conditions for the evolution of cooperation. Alternatively, contingent mobility has the capacity to be proactive. This is where individuals deliberately seek better neighbourhoods, rather than simply reacting to stimuli and randomly relocating.

The majority of the contingent mobility strategies in the literature are hand crafted or guided by heuristics. However, there has been some research [28–30] using evolutionary models to evolve movement strategies that are conducive to the emergence of cooperation. Ichinose et al. [19] also use an evolutionary model and investigates the coevolution of migration and cooperation. Agents play an N-player Prisoner's Dilemma game after which they move locally according to an evolved probability vector. All agents are evolved to collectively follow or chase cooperators. The authors highlight the importance of flexibility in the direction of migration for the evolution of cooperation.

Chiong et al. [31] describe a random mobility model where a population of agents interact in an N-player Prisoner's Dilemma set in a fully occupied regular lattice. Pairs of agents move by exchanging grid positions. Mobility in this environment is a probability function based on the time an agent has spent in a location, and the relative fitness of the agent at the destination. The agents have a limited memory of past interactions, and past cooperator and defector levels. Cooperation is shown to be promoted under a limited small set of parameters including the cost to benefit ratio of cooperation and the movement radius.

Most recently, Suarez et al. [32] present a contingent mobility model, using the N-Player game, in which agents move toward locations with higher potential payoff. While cooperation does emerge, the authors do not elaborate on the specific effects of mobility, focusing more on the impact of the neighbourhood size.

3 Methodology

3.1 Environment and Agent Representation

The population of agents A inhabits a toroidal shaped diluted lattice with $L \times L$ cells, each of which can be occupied by up to one agent. The interaction and movement radii of agents is determined using the Moore neighbourhood of radius one. This comprises the eight cells surrounding an individual in a cell on the lattice. The agents can only perceive and play with those within this limited radius.

Each agent is represented by a genotype, which determines their strategy to interact with other agents and to move in the environment. The first section of the gene describes their strategy for playing the game: that is to cooperate or defect and the remaining sections determine how an agent will move. The remainder of the genotype encodes actions for a range of scenarios that may arise within the environment, including: encountering a cooperator, encountering a defector, or encountering both at once. If an agent meets a cooperator, they have a set of potential actions. These actions are as follows: remain where they are, move randomly, follow the cooperator or flee from it. Similarly these potential actions are mirrored when an agent meets a defector. The final section is used to determine actions when an agent meets both a defector and a cooperator. The actions are: flee from both cooperator and defector;

follow both cooperator and defector; follow the cooperator and flee from the defector and the converse action (flee from the cooperator and follow the defector). During a simulation run, each potential action of an agent is determined by its genotype.

At each time step, agents participate in a single round of the Prisoner's Dilemma with each of their neighbours, if any. The strategy with which agents play is fixed; either always cooperate or always defect. We choose to implement pure strategies in order to reduce the strategy space allowing us to more clearly examine the effect of mobility in these experiments. Agents are aware of the actions taken by their neighbours in a single round, but these memories do not persist. Following this interaction phase, agents have the opportunity to take one step into an adjacent free cell according to their movement strategy. Movement will not occur if there is no adjacent free space, or if their strategy dictates that they remain in their current location. Isolated agents will take one step in a random direction.

3.2 Evolutionary Dynamics

The movement strategies adopted by the population are explored by using an ALife inspired evolutionary model. In a single generation, agents accumulate their payoffs received from playing the Prisoner's Dilemma with their neighbours. This is used as a measure of fitness, and at the end of each generation, the agents are ranked according to this score. The bottom 20% are replaced with copies of the top 20%. This replacement strategy was chosen as it has been previously shown to produce a fair sampling of the population's fitness while still allowing for convergence in a reasonable time frame. No other genetic operators are utilized. These offspring are randomly placed on the grid, and the other agents remain in the same place, thus maintaining any spatial clustering between generations. Following reproduction, the fitness score of the whole population is reset and a new generation begins.

3.3 Interaction Model

In keeping with previous work, we adopt a well known formalism for the N-player prisoner's dilemma. Letting B be a constant representing social benefit, c be the cost of cooperation and i the number of cooperators from a group of N agents, the following payoffs are used:

$$C(i) = \frac{B \times i}{N} - c$$

$$D(i) = \frac{B \times i}{N}$$

Table 1 Prisoner's dilemma game matrix

	C	D
C	2,2	$-\frac{1}{2}$,$2\frac{1}{2}$
D	$2\frac{1}{2}$,$-\frac{1}{2}$	0,0

The following constraints hold: $B > c$ and both B and c are positive values.

Considering the N-player dilemma, when N = 2 and attempting to align with the classical interpretation of the 2-player prisoner's dilemma, we also require that $B < 2c$. Values chosen in this research that are in keeping with previous studies in the field are: $B = 5$, $c = 3$. For example, in mapping this back to the two player games, we use the payoff matrix as described in Table 1.

In our simulations, we contrast scenarios with 2-player interactions and N-player interactions. In the N-player case, an agent particpates in the dilemma with all of its immediate neighbours; the number of such neighbours determines the number of participants. In the 2-player case, an agent participates in individual 2-player games with each of its immediate neighbours.

3.4 Cluster Analysis

The aim of this work is to definitively determine that the clustering of cooperators is the primary cause for the proliferation of cooperation throughout a population. It is important to establish a metric for clusters as the concept is oftentimes ill-defined. Much previous research asserts the existence and formation of clusters without explicit measures of the number and type of clusters formed. We define a cooperative cluster as a set, with cardinality greater than one, of spatially contiguous cooperative agents. We also define three cluster metrics which we use to compare cluster formation across experiments. These are: (1) the number of clusters in the population, (2) the average size of clusters, and (3) the mean average neighbourhood size of individuals in each cluster. This value is obtained by first counting the number of neighbours of each agent in a cluster, calculating the average neighbourhood size for that cluster, and then calculating the average across all clusters in the population. This metric shall be referred to as cluster quality from this point onward.

4 Simulation Results

4.1 Experimental Setup

In these experiments, we run two sets of similar simulations, one with *2-Player* interactions the other with *N-Player* interactions, comparing the respective outcomes. It is generally accepted that when comparing the two interaction models inducing cooperation in the N-Player games is considerably harder.

Table 2 2-Player versus N-Player: % cooperator wins. extracted from [9]

	Avg	Std dev
2-player	33.2%	4.2%
N-player	25.8%	4.7%

The population of $A = 100$ agents is placed randomly on the $L \times L$ torus with $L = 30$, the strategies (whether to cooperate or to defect) are assigned in equal proportion, and the movement strategies are assigned randomly. A single simulation lasts 1,250 time-steps, in which the agents take 25 steps in each of 50 generations. The distribution of spatial strategies, level of cooperation, time taken for the simulation to converge on cooperation (or defection), and the total number of interactions will all be recorded. Each simulation will be run over a 1000 times to generate statistically valid results.

In order to perform the cluster analysis, a snapshot of the population calculating the cluster analysis metrics, number of clusters, average cluster size and quality, are recorded every 5 steps.

4.2 2-Player Versus N-Player

Cooperative Outcomes. On average in these environmental settings, the 2-Player interaction model is more effective at inducing the spread of cooperation in a larger percentage of simulations. Table 2 shows that in roughly one third of evolutionary simulations using 2-player interaction, cooperation emerges as the outcome, whereas when agents participate in an N-player interaction, cooperation emerges in roughly one quarter of the simulations. On average, simulations using the 2-Player interaction model tend to converge more quickly, and with less variance. The simulations resulting in the emergence of defectors exhibit a faster convergence and less variability in convergence speed regardless of the interaction model.

These results are in keeping with the general consensus that evolving cooperation in the N-player prisoner's dilemma can be more difficult. This previous research did not allow movement of agents, but still captured the difficulty with N-player dilemmas where an agent can exploit multiple participants and achieve a considerable gain in payoff per interaction.

Evolved Movement Strategies. Tables 3, 4 and 5 show the movement behaviours that are evolved for 2-player and N-player situations respectively in those runs when cooperation emerges. One hundred simulation runs resulting in cooperative outcomes are considered.

Upon seeing a cooperator in their neighbourhood, agents evolve to either stay where they are or to follow the cooperator; this occurs in both 2-player and N-player scenarios. When a defector is encountered, agents have evolved to flee or adopt a random movement in 75% of cases in the 2-player game and 97% of cases in the N-player game. For the scenarios where agents see both cooperators and defectors

Table 3 On seeing cooperator : % genes evolved. extracted from [9]

	2-player	N-player
Random	0%	0%
Follow	15%	27%
Flee	0%	0%
Stay	**85%**	**73%**

Table 4 On seeing defector : % genes evolved. extracted from [9]

	2-player	N-player
Random	34%	22%
Follow	16%	2%
Flee	**41%**	**75%**
Stay	9%	1%

Table 5 On seeing cooperator & defector : % genes evolved. extracted from [9]

	2-player	N-player
FollowCFollowD	27%	3%
FollowCFleeD	**44%**	**52%**
FleeCFollowD	9%	11%
FleeCFleeD	20%	34%

we see similar behaviours being evolved. Movement behaviours that promote cooperation and avoid exploitation are selected. We can see that cooperators who interact using the N-Player interaction model have a greater evolutionary incentive to be adverse to defectors.

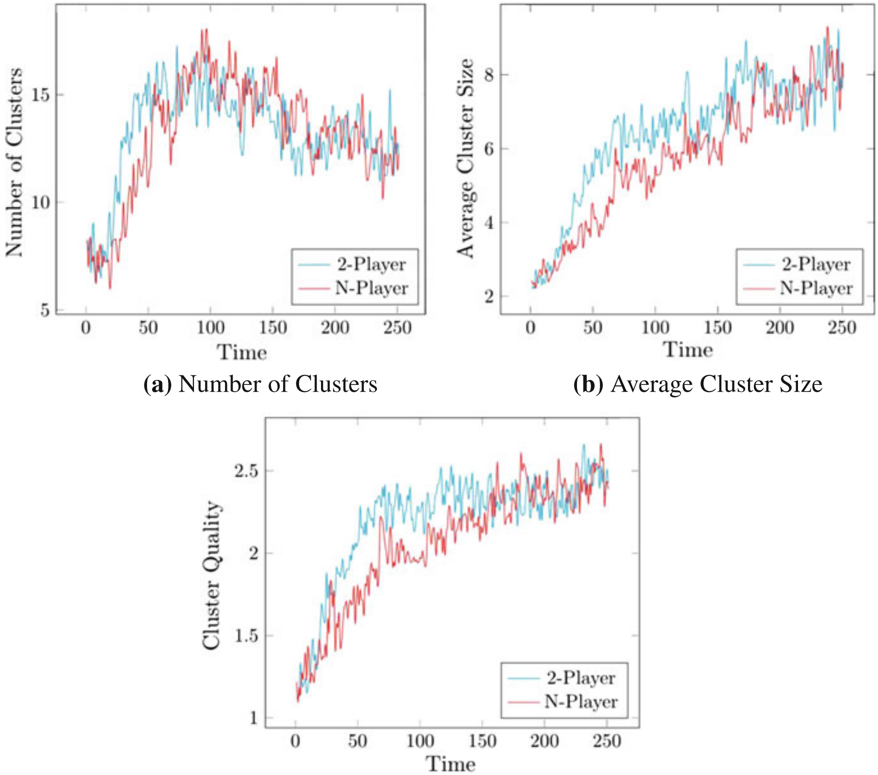
In all cases agents learn movement behaviours that allow them to continue cooperative interactions and, to a lesser extent, to avoid interactions with defectors. Behaviours that continue defector interactions die off, although at a slower rate. Following cooperators is selected more quickly than fleeing from defectors.

It is important to note that the selective pressure to avoid defectors is removed when the defectors are replaced in the population with cooperators and hence we do not see convergence to 100% for the genes that promote avoiding defector interactions. Adopting a random movement can also often have the same effect as fleeing from or indeed following an individual.

The population did not always evolve a single strategy; random fluctuation and lack of relevant stimuli resulted in simulations in which agents converged on several strategies that were genotypically different, but phenotypically similar.

In non-cooperative runs, defectors learned to (1) follow cooperators, (2) flee from defectors, and to (3) follow both cooperators and defectors.

Cluster Analysis. We can observe in Fig. 1a that the number of clusters, in both 2-player and N-player simulations, initially increases rapidly, then reaches a plateau, and eventually decreases. At the beginning of the simulation, the population is randomly dispersed with many small clusters forming as cooperators move and interact



(a) Number of Clusters

(b) Average Cluster Size

(c) Cluster Quality

Fig. 1 2-Player versus N-Player: The mean average number of clusters, size, and quality of clusters from a number of simulations resulting in cooperative victories

according to their strategy. As the defectors start to reduce in numbers, the cooperator clusters have the space and freedom to merge and grow larger, thus reducing the overall cluster count. This is backed up by Fig. 1b where we see that the average cluster size, in both cases, increases over time. The cluster quality quantifies the potential fitness of one cluster over another. Figure 1c demonstrates that in both 2-player and N-player simulations cooperator clusters are improving over time, facilitating the further spread of cooperation.

In Fig. 1 we see populations using the 2-player interaction model form a greater number, larger, and high quality cooperator clusters more quickly than those using the N-player version. We see variability in theses graphs because clusters can both be divided and broken up by defectors, and the evolutionary process.

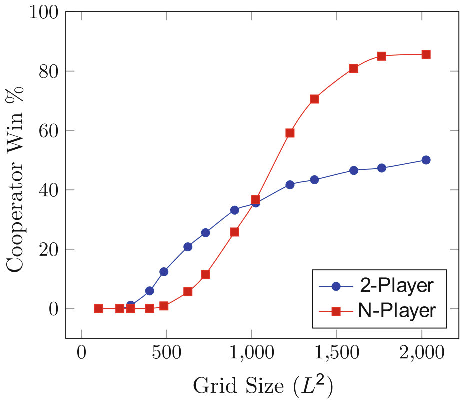


Fig. 2 2-Player versus N-Player: The percentage of simulations resulting in cooperative victories as we vary the grid density starting from random initialization. Extracted from [9]

4.3 Variation in Density

In the previous experiments, the percentage of cooperative outcomes and the evolution of movement strategies was a function of the agent interactions. The ratio of cooperative interactions to other types of interactions influences the evolutionary trajectories.

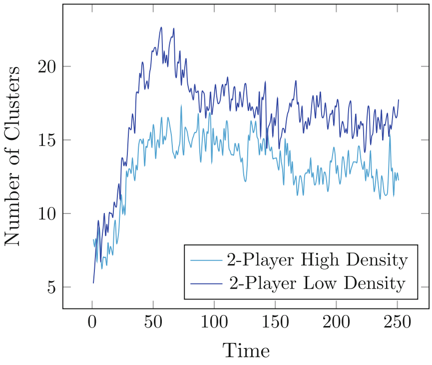
In this experiment we aim to investigate the impact of the density of agents in the environment. We define the density as $D = A/L^2$ where A is the size of the population, and L is the length of the lattice grid. Density is a function of the population size and the size of the grid. We keep the population size constant and vary the size of the grid as a means to vary the density.

The movement strategies of agents are randomly initialized, the strategies for game interactions are assigned in equal proportions and both the movement and interaction strategies are subject to evolution. In one set of simulations, the population interacts using the 2-player interaction model, and the other uses the N-player model.

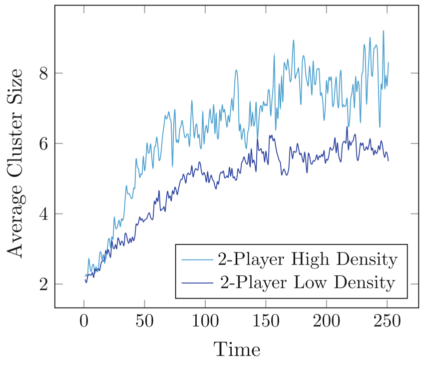
As shown in Fig. 2, at the highest density level, there is not enough space within the grid for agents to move freely and so defection dominates in the vast majority of simulations. These conditions echo the traditional spatial models with an agent located in every cell where no movement is possible. These findings mirror those results with defection spreading and dominating the population.

As the density is reduced, we see that the evolutionary runs using the 2-Player interaction model are more readily able to induce higher levels of cooperation. However, using the 2-Player interaction model, random initialization in low densities can only achieve cooperation in just above 50% of simulations. With these same settings the N-Player interaction model can induce cooperation in a far greater percentage (80%) of runs.

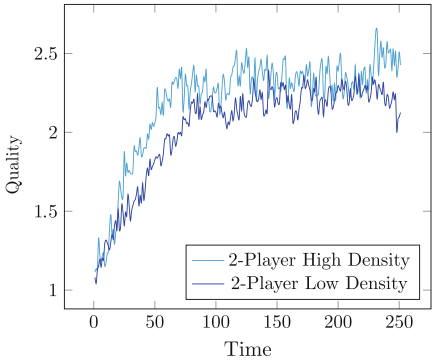
For a grid size of 32×32 (1024 cells), the N-player interactions overtake the 2-player interaction model in their ability to induce cooperation. This result demonstrates that despite the difficulty of inducing cooperation, cooperation emerges in



(a) 2-Player: Number of Clusters



(b) 2-Player: Cluster Size



(c) 2-Player: Quality

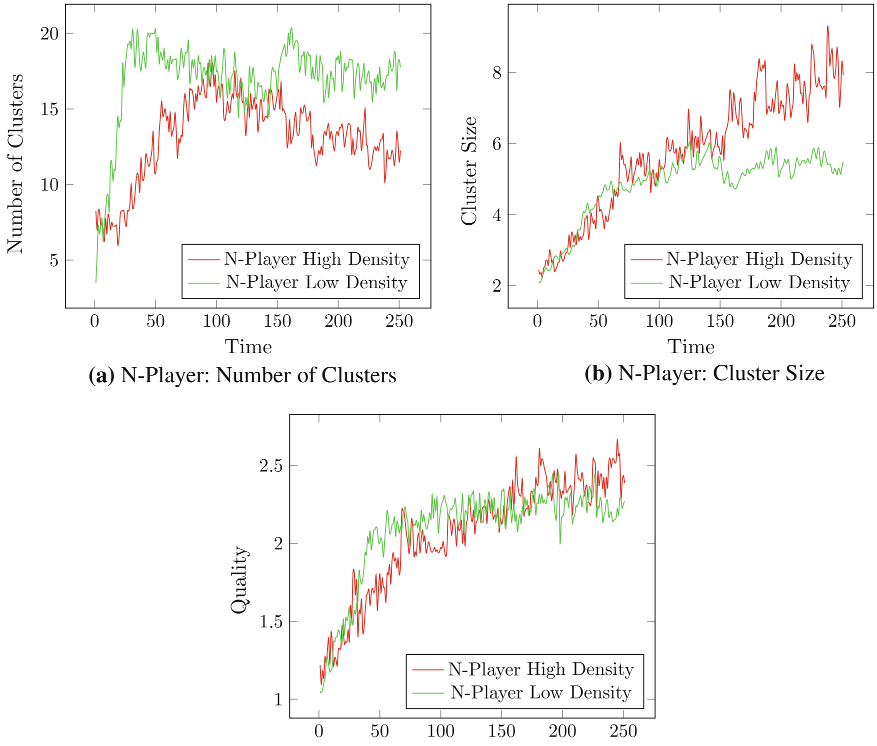
Fig. 3 N-Player High Density versus Low Density: The mean average number of clusters, size, and quality of clusters from a number of simulations resulting in cooperative victories

N-player games, the addition of movement capabilities can support the emergence of cooperation in these conditions.

Cluster Analysis. In low densities, for both 2-player (Fig. 3) and N-player (Fig. 4), cooperators, on average, form greater numbers of smaller clusters. In the lower densities, the population is more dispersed throughout the environment; thus cooperators, on average, meet fewer agents and do not form larger clusters. However, for both density levels, in terms of quality, similar clusters are formed.

4.4 Seeding the Evolved Strategies

In our final experiment, the evolved movement strategies for both cooperators and defectors are seeded in the population and we repeat the density experiment. In the previous experiment both movement strategies were randomly assigned and it took



(a) N-Player: Number of Clusters

(b) N-Player: Cluster Size

(c) NP: Quality

Fig. 4 N-Player High Density versus Low Density: The mean average number of clusters, size, and quality of clusters from a number of simulations resulting in cooperative victories

several generations for movement strategies to emerge. A number of these strategies. were identified as being favorable to the emergence of cooperation. The aim of this experiment is to explore the effect of these *good* strategies when they are present in the first generation. If these strategies help cooperators to follow each other and form cooperative clusters, then higher levels of cooperation are expected across the various density levels.

Results show in both sets of simulations that the evolved cooperator movement strategies are able to induce cooperation for a much wider range of densities, as illustrated in Fig. 5. There is a far greater level of cooperation than that which was achieved by either interaction model in the experiment with random initialization. For the N-player interaction model, once the grid size reaches 1024 (density roughly equal to 10%), cooperation is achieved 100% of the time. For the 2-player interaction model, this level of cooperation is also maintained for higher density levels. The agents using the N-player model are more hindered by the exploitative nature of defectors, who are also using a previously evolved movement strategy.

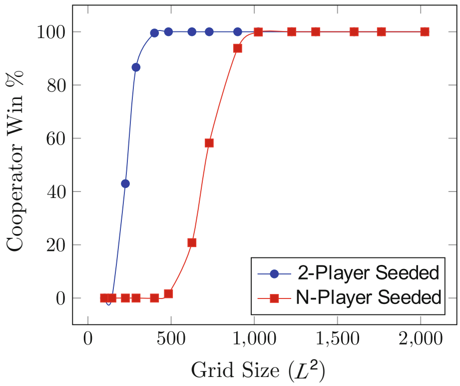
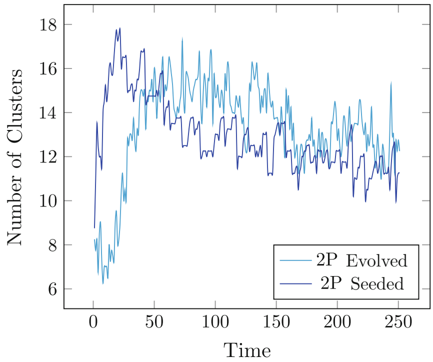
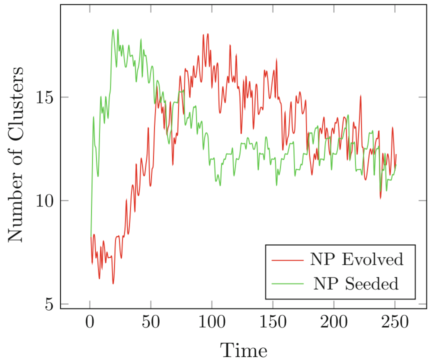


Fig. 5 2-Player versus N-Player: The percentage of cooperative victories, as we vary the grid density, seeding the most prevalent evolved strategies for cooperators and defectors. Extracted from [9]



(a) 2-Player:Number of Clusters



(b) N-Player: Number of Clusters

Fig. 6 Evolved versus Seeded: The mean average number of clusters from a number of simulations, using both 2-Player and N-Player interaction models, resulting in cooperative victories

Cluster Analysis. In both the 2-player and N-player scenarios (Fig. 6), the seeded strategies are able to generate a significantly greater number of clusters in the early generations than in the previous experiments where the strategies were unseeded. This difference is due to the fact that in the previous experiments the evolved population hadn't yet learned the optimum movement strategy and hence quick clustering of cooperators was hampered. However, other than the time to reach a level of clustering, there are no significant differences in the level of quality of the clusters.

5 Discussion

Traditionally, it has been difficult to induce cooperation using the N-player Prisoner's Dilemma. However, in our model we observe high levels of cooperation in a range of settings. The incorporation of a contingent mobility allows cooperators to cluster together, and avoid repeated defector interactions. In forming these clusters, these agents can increase their number of mutually cooperative interactions, thereby boosting their score. However, these cooperative clusters can be exploited by defectors unless they employ strategies that can avoid repeated exploitative encounters. We observe high levels of cooperation coupled with evolved movement strategies that encourage the formation of these larger self-preserving clusters free from the influence of defectors.

As expected, the 2-Player interaction model was more successful at inducing cooperation in the higher grid densities when we evolved from random strategies. This is due to the fact that while the chances of encountering a defector are higher, they have less of an exploitative impact on individuals or clusters of cooperators. Surprisingly, the N-player interaction model was significantly more successful at inducing cooperation when the grid density was very low. We attribute this success to the reduced chances of encountering a defector, and increased gains made by mutually cooperative interactions in clusters. Additionally, single defectors benefit by being in the neighbourhood of cooperators but this benefit is reduced in the presence of other defectors.

6 Conclusion

In this paper, we have shown that simple mobile strategies, which use both the 2-Player and N-Player interaction models, are extremely adept at spreading cooperation throughout agent populations by forming cooperator clusters.

Clusters form, and proliferate, when cooperators learn movement strategies that allow them to maintain beneficial cooperator interactions and avoid repeated, exploitative interactions with defectors, which leads to the evolution of cooperation. Over the course of the simulations that result in widespread cooperation, we observe, for all cluster metrics used (the number of clusters, the cluster size, and the cluster quality) increasing evidence of clustering of strategies. Furthermore, when a population is seeded with the movement strategies that promote cluster formation, in a suitable environment (medium to low agent density), it is possible to guarantee the evolution of cooperation. This is achieved using only local information and without the need for complex computation or costly memories.

Through experimentation, we show that the presence of contingent mobility strategies induces cooperation in the N-player Prisoner's Dilemma. Despite the inherent disadvantages of this interaction model, we demonstrate that it is possible to generate very high levels of cooperation from both seeded and, surprisingly, randomly initialised populations. It is clear that density plays a significant role, particularly in the N-Player model, as it possesses the greatest influence over cluster formation.

Future work will involve a more thorough investigation of the nature of the cooperative clusters that form throughout the evolutionary runs. We wish to explore a larger set of N-player social dilemmas and explore more expressive spatial topologies. We also intend to determine the conditions under which cooperative clusters fail to form, and investigate means to encourage their formation.

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