The Impact of Environmental and Evolutionary Factors on the Emergence of Cooperation among Evolved Mobile Agents

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Abstract: This paper presents work investigating the influence of various environmental and evolutionary factors on the evolution of cooperation in a spatial game theoretical setting. These include agent mobility, population density, agent lifespan, and the placement mechanism. In the model considered, a population of agents inhabit a toroidal lattice grid, in which they participate in the Prisoner's Dilemma game. The agents have the ability to respond to, and learn from, environmental stimuli. In particular, agents learn movement strategies to compete with other agents in the game, which may result in improved payoffs by increasing the number of beneficial interactions. We compare the levels of cooperation and the corresponding movement strategies evolved under the various environmental and evolutionary settings. We present results indicating that, given suitable densities and evolutionary settings, cooperators in well-mixed populations develop a suitable movement strategy to promote the evolution of cooperation. Additionally, we show that cooperation may emerge without significant aid from mobile strategies given a placement mechanism conducive to the formation of cooperator clusters.

1 INTRODUCTION

The role of agent mobility has grown in recognition and importance as a factor in solving the puzzle of the evolution of cooperation. Mobility was originally perceived as a hindrance to cooperators by allowing highly mobile defectors go unpunished, leading to the 'free rider' effect (Enquist and Leimar, 1993). However, it has since been demonstrated that simple movement rules (Aktipis, 2004) and mobility rates (Vainstein et al., 2007) significantly curb this phenomenon allowing self-preserving, or evasive, cooperator clusters to form, which in turn allows for cooperation to proliferate. Mobile strategies now play a vital role as mechanisms for the emergence, promotion, and sustainability of cooperation. In this paper, we investigate the influence of some environmental and evolutionary factors on the evolution of these mobile strategies. We hypothesize that effective mobility strategies lead to the creation of evasive cooperator clusters, thereby facilitating the evolution of cooperation.

Contingent, or non-random, mobility has the capacity to be proactive, whereby individual agents deliberately seek out better environments. However, many of these models (Helbing and Yu, 2008; Buesser et al., 2013) suffer from incurring high memory requirements and complexity costs. In this paper, we present a reactive mobility model to imbue agents with a simple, yet expressive, range of actions: follow, flee, and stay still. The action to 'follow' enables an agent to maintain connections with others in their neighbourhood on the grid, conversely the action to 'flee' severs such connections. These actions are dependent on the strategies (cooperate or defect) and positions of an agent's neighbours, and are evolved through a process of selection and duplication. We encode each action into an 8-bit binary array, and include an option to move randomly. Agents determine where to move by ranking the free grid locations in their neighbourhood according to their chosen action. We hypothesize that mobility directly influences the evolution of cooperation by utilizing movement patterns, which allows for the formation of cooperative clusters which increase the number of beneficial interactions for cooperators.

Much of the contingent mobility strategies in the literature are heuristically guided and imbued to agents at the outset of a simulation. There has been less focus on the explicit evolution of these strategies by agents over the course a simulation. The use of evolutionary models may provide some insight into how mobility strategies may have originated in nature, and more generally allow for the investiga-

tion of the co-evolution of agent traits. In this sense, despite the possibility of adapting the traditional genetic algorithm-like approach, i.e. tournament selection, crossover, and mutation to be limited to the local interactions of each agent, it would add another layer of complexity to the model, which is not the aim of this work. In particular, considering this traditional evolutionary approach at a global level, i.e. building the next generation based on the best fittest agents of the entire population, which would negate the mechanism of network reciprocity (Nowak, 2006). Thus, this work adopts a simplified birth-death mechanism to keep the complexity of the procedures of selection and replacement at a minimum.

Agent mobility is not the only factor impacting the emergence of cooperation, population density and the specific settings of the evolutionary model also have considerable influence. These include: agent lifespan, generation length, and the means of placement of new agents. Population density has been shown to have a significant influence on the evolution of cooperation in spatial environments, particularly in a diluted lattice (Vainstein and Arenzon, 2001). On the other hand, fewer studies have focused on the effects of varying particular evolutionary settings, or on the impact that different placement mechanisms have on the outcome of a simulation. In this paper, we also investigate the influence of these factors on the emergence of cooperation using the proposed mobility model. We will begin by identifying the evolutionary and environmental settings conducive to the evolution of cooperation, and then attempt to accurately explain these phenomena through analysis of the evolved genotypes present in the final stage of a simulation. We hypothesize that the factors that influence cluster growth, and the number of interactions cooperators have with defectors, directly impact the evolution of cooperation.

The paper outline is as follows: we review the related work of mobility in the Spatial Prisoners Dilemma in the next section. Section 3 outlines our methodology, including a description of our agent representation, the evolutionary mechanism, and details of the movement function. In Section 4, we discuss a number of experiments and present results regarding the relative influence of factors on the emergence of cooperation, and the movement strategies evolved therein. Finally, we present our conclusions and suggest future avenues for this research.

2 RELATED WORK

Questions relating to cooperation and its emergence have been studied in a range of domains including economics, psychology, theoretical biology, and computer science. Researchers explore the conditions necessary for cooperation to emerge among groups using social dilemmas due to their usefulness in capturing the conflict between individual and collectively rational behaviours. Evolutionary game theory has been studied since the 1980s when John Maynard Smith incorporated ideas from evolutionary theory into game theory (Maynard Smith, 1982). However, these ideas become increasingly relevant as they expand into new fields, such as evolutionary robotics (André and Nolfi, 2016).

The Prisoner's Dilemma (Axelrod, 1984), and its extensions in the iterated form, is the game most often studied in this domain. It has attained such popularity due to its succinct representation of the conflict between individually rational choices and those made for the common good. It 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 players chose to defect, both receive P as a payoff such that: $T > R > P > S$.

Spatial models promote the evolution of cooperation by constraining agent interactions to a particular static topology. Previous work has investigated structures such as lattices (Nowak and May, 1992), small-world graphs (Santos et al., 2006), and scale-free graphs (Poncela et al., 2009). 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 (Nowak, 2006), which has been garnering increased attention in the literature due to its direct application in robotics (Floreano and Keller, 2010), and human behaviour (Antonioni et al., 2015). It 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 (Enquist and Leimar, 1993), allowing highly mobile defectors to go unpunished, using simple strategy rules (Aktipis, 2004; Ichinose et al., 2013) or using mobility rates (Meloni et al., 2009; Vainstein et al., 2007) significantly curbs the free-rider phenomenon allowing self-preserving cooperator clusters to form, and cooperation to proliferate.

Several mechanisms for the emergence of coope-

ration 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' definitions of mobility; all movement should be random (Meloni et al., 2009; Sicardi et al., 2009; Antonioni et al., 2014), or should be purposeful or strategically driven, but may indeed contain random elements (Cong et al., 2012; Droz et al., 2009; Jiang et al., 2010; Yang et al., 2010; Tomassini and Antonioni, 2015). Random mobility can be used to describe the minimal conditions for the evolution of cooperation. However, their expressiveness and applications to real-world problems are limited. Alternatively, contingent mobility has the capacity to be proactive. Agents can deliberately seek better environments, rather than simply react to stimuli and randomly relocate.

Aktipis (Aktipis, 2004) presents a simple contingent movement strategy, 'Walk Away'. In this set up, agents form pairs and repeatedly interact together when they meet in the spatial environment. The population evolves using a birth-death process, in which agents require certain energy levels to live and reproduce, and acquire this energy from interactions in the game. Following interaction, agents disconnect from defecting partners by relocating to a local random cell, and continue cooperative partnerships by staying still. The main strength of this strategy is its simplicity; agents are memoryless but cooperation can spread and dominate. However, one major criticism of this model is that it does not attempt to maintain those crucial mutually cooperative pairings.

The works by Helbing and Yu (Helbing and Yu, 2008; Helbing and Yu, 2009) describe a form of contingent movement called Success Driven Migration *SDM*, which forms one of the most influential models within the scope of mobility. In this model, agents can test potential sites for migration in order to discover neighbourhoods with the highest expected payoff. However, this model suffers from incurring high memory and information requirements; testing potential sites, regardless of a successful outcome, comes at a cost to an agent's payoff, and agents require complete knowledge of their environment. These requirements can prove to be cumbersome in instances where perfect global information may be incorrect or impossible to obtain. A small memory is a requirement that also comes from the robotics field, and has been well studied (Nguyen et al., 2018). Additionally, recent work has shown that cooperation can emerge from mobility models using only local information in both explicitly spatial (Burgess et al., 2017), and non-spatial (Joshi et al., 2017) environments.

There has been some research (Perc and Szolnoki, 2010; Joyce et al., 2006) indicating that evolutionary models may be used to evolve movement strategies that are conducive to the emergence of cooperation. Ichinose et al. (Ichinose et al., 2013) use an evolutionary model to investigates the co-evolution of migration and cooperation. Agents play an N-player Prisoner's Dilemma game after which they move locally according to an evolved probability vector. Agents evolve to move collectively in the same direction determined by cooperators. This model uses separate probability functions for the birth and death processes, which allows the population level to fluctuate. However, while this may be more realistic, it vastly complicates any investigation into the influence of population density. In previous work (Gibbons et al., 2016), we demonstrated that intelligent mobility strategies could be evolved for populations playing both the 2-Player and N-Player Prisoner's Dilemma to promote the evolution of cooperation in a wide range of sparse environments. However, the impact of varying the evolutionary setting of the genetic algorithm was not considered, and we were unable to demonstrate significant rates of cooperation using an unseeded population.

3 METHODOLOGY

This work considers a population of agents inhabiting 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 are determined using a Moore neighbourhood of radius one. This comprises the eight cells surrounding an agent in a cell on the lattice. The agents can only perceive and play with those within this radius.

A single simulation consists of a population of $N = 100$ agents placed randomly on a $L \times L$ torus. The population density is defined as $D = N/L^2$. A simulation consists of agents taking s steps per generation, using the replacement rate, r, over 5000 time steps. The game strategies (whether to cooperate or to defect) are assigned in equal proportion, and the movement strategies are assigned randomly. A total of 3000 simulations are performed for each configuration of density and evolutionary settings.

Each agent in the population is characterized by two different attributes: game strategy and a set of movement actions. The classical version of the Prisoner's Dilemma game is adopted as the interaction model for the agents in our population, in this way, an agent can either cooperate (*C*) or defect (*D*). Accordingly, an agent may receive a reward $R = 3$ for

mutual cooperation, $T = 5$ for successful defection, a punishment $P = 1$ for mutual defection or $S = 0$ for exploited cooperation.

At each time step, agents participate in a single round of the Prisoner's Dilemma game with each of their neighbours, if any. Agents play using pure strategies; either always cooperate or always defect. We implement pure strategies in order to reduce the strategy space allowing us to examine the effect of mobility in these experiments more clearly. Agents are aware of the actions taken by their neighbours in a single round, but these memories do not persist. This is done to allow agents to accurately identify the strategies of their neighbours when determining their next movement. The payoffs agents receive from playing the game are accumulated and used as their score. This fitness function used in this work is based on these accumulated payoffs within a generation, as we wish to capture both the payoffs and frequency of interaction for individual agents.

Following the interaction phase, agents then have the opportunity to respond to those interactions by moving to a position in their neighbourhood determined by their mobility strategy. In this model, each agent has an 8-bit genotype, which encodes the actions it can preform. Each action is represented by a 2-bit gene capturing the following four behaviours: remain where they are i.e. stay still (00), follow a neighbour (01), flee from a neighbour (10), and move randomly (11). Given the bit positions from left to right, the agents will perform one of these actions in each of the following scenarios, i.e. when it meets:

- only cooperator(s) (bit position 0 and 1);

- only defector(s) (bit position 2 and 3);

- cooperator(s) in a neighbourhood with defector(s) present (bit position 4 and 5);

- defector(s) in neighbourhoods with cooperator(s) present (bit position 6 and 7);

If an agent has no neighbours it explores by moving to an adjacent free location at random.

An agent's chosen action determines how each location in its neighbourhood is evaluated. Each location is assigned a score, based on the number and type of neighbouring agents, which in turn is used to rank those available locations. In this way, if the choice is:

- 'stay still' (00), the current cell location sums zero, while the other cell locations subtract one;

- 'follow' (01), the cell locations adjacent to each neighbour sum one, while the other cell locations sum zero;

- 'flee' (10), the cell locations adjacent to each neighbour sum zero, while the other cell locations sum

Table 1: An illustration of the calculation used to determine the move performed by an agent where: all neighbours are cooperators (left); all neighbours are defectors (middle) and neighbours are both cooperators and defectors (right).

C	1	0		1	1	1		C	2	1
1	**X** (1)	0		0	**X** (0)	0		1	**X** (1)	0
0	0	0		0	**D**	0		0	**D**	0

one;

- 'random' (11), all cell locations sum randomly;

based on the total score obtained for each cell, the agent moves to the highest ranking location and ties are broken by choosing a tied location at random.

For example, given an agent **X** with the genotype $\{0,1,1,0,0,1,1,0\}$, which translates to 'follow cooperators and flee from defectors', Table 1 outlines the results of agent **X**'s movement locations being scored in each of the non-trivial scenarios.

In Table 1(left), agent **X** sees a cooperator **C** and adjacent cells are rewarded. The current location is treated as an adjacent cell, thus staying still, or not moving, is a valid option. The opposite is true in Table 1(middle), where agent **X** sees a defector **D**, adjacent cells score nothing and distant cells are rewarded. In Table 1(right), agent **X** sees both **C** and **D**, multiple neighbours are handled by first calculating a score set for each individual and then combining them. Agent **X** will then move to the location represented by the highest scoring cell, and in the case of a tie, a location is chosen at random from the highest scoring cells.

At the end of each generation, s steps of interaction and movement, the population of agents is ranked according to their fitness score. The highest scoring agents duplicate themselves, and the lowest scoring agents die. In this way the population density remains constant throughout a simulation. The number of agents replaced in this way is controlled by the replacement rate, r. At the end of each generation, the fitness score of the whole population is reset. No other genetic operators are utilized. This evolutionary approach preserves the spatial structure of clusters present, in the population, across generations.

In this work, we consider two mechanisms for placing agent offspring in the environment. The first, 'random' placement, chooses a location at random from the available free spaces on the grid. Similar methodologies are present in other works (Aktipis, 2004; Burgess et al., 2017). The second placement mechanism investigated places offspring in the neighbourhood of their parent. In the case where the parent's neighbourhood is full, they are randomly placed on the grid instead. This 'nearby' placement approach should further strengthen the structure of clusters created between generations.
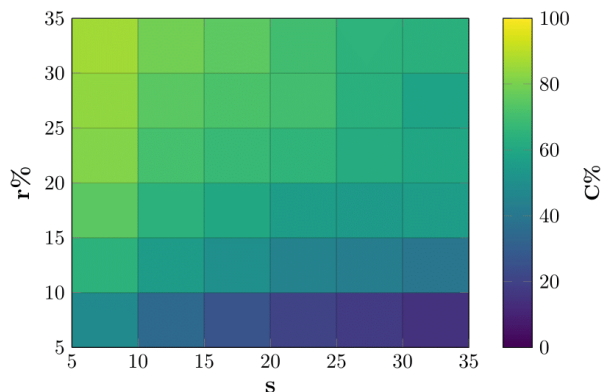
Figure 1: Average percentage of cooperators victories for grid size $L = 40$ as a function of replacement rate r, and the steps per generation s.

4 SIMULATION RESULTS

In this section, we present some of the relevant experimental results of the simulations of the Prisoner's Dilemma game on a diluted toroidal lattice grid. The first set of experiments comprise variations in the parameters r and s; the second set of experiments comprise variations in the parameters r and s at different density levels (varying L); the third set of experiments compare results across the two replacement mechanisms ('random' or 'nearby') and the fourth section presents an analysis of the genotypes of agents in a specific evolutionary setting with 'random' placement. The distribution of spatial strategies, level of cooperation, the time taken for the simulation to converge on cooperation (or defection), and the total number of interactions are recorded.

4.1 Varying the Evolutionary Settings

We start by investigating the scenarios in which a well-mixed population of agents playing the Prisoner's Dilemma game evolve movement behaviours conducive to the evolution of cooperation by identifying optimal evolutionary settings. The generation length s and replacement rate r, which constitute the lifespan of agents, are both varied from the values 5 to 35, while the population density remains fixed at $L = 40$. The 'random' placement mechanism is used.

In Figure 1, we see the percentage of simulations that end with total adoption of cooperation, this will be referred to henceforth as cooperator victories. Simulations always converge on either total cooperation or defection, 'draws' are very rare, and only occur when the convergence for a particular evolutionary setting is slow. We see that the settings that

lead to the most cooperative outcomes, on average, are hight replacement rates, r, coupled with low generation lengths, s. Using these settings, cooperators dominate the population in 93% of randomly initialized simulations. We note that the value of r has a bigger influence on the emergence of cooperation than s. In practice, this indicates that cooperation emerges more readily when fewer agents are replaced per generation, than when agents have longer to interact during a single generation and potentially be exploited by 'free riders' (Enquist and Leimar, 1993). However, the best results are achieved when these scenarios are combined. This suggests that the replacement process should be tuned in order for cooperation to emerge with the greatest probability.

Figure 2, shows a snapshot sequence of a population during a single, though typical, simulation. We observe the decline in the number of defectors over time as cooperator clusters form and expand.

4.2 Varying Environment Density

We investigate the influence of density on the evolution of cooperation by repeating the previous experiment across a range of grid sizes: $L = 20$ to $L = 60$.

In Figure 3, we observe the percentages of cooperator victories across a range of both evolutionary settings and density levels. In the high density graphs, Figure 3(a), we observe that extremely low levels of cooperation emerge despite the variation in evolutionary settings. These results are unsurprising as this environment is close to being fully connected. In this setting, we would expect defectors to easily invade cooperators as described by the 'free-rider' effect.

Figure 3(b)-(h) shows an increase in the level of cooperation emerging. We observe the evolutionary settings' growing effect on the emergence of cooperation. It becomes clear that as the population density decreases, the percentage of simulations resulting in a cooperative outcome increases, as agents have the space to learn and deploy their movement strategies.

In the low density environments, i.e. Figure 3(i), the trend becomes most pronounced. We see that cooperation is able to emerge in almost 100% of simulations for a wide range of evolutionary settings. In randomly initialized simulations, cooperators have enough time and space to learn the movement strategies capable of dominating the defectors.

Figure 4 more clearly demonstrates the impact of density on the evolution of cooperation. In the graph, the most extreme values for the evolutionary settings, r and s, are directly observed across the density values, from very low to very high. Again, it is clear that cooperation emerges most readily for high values
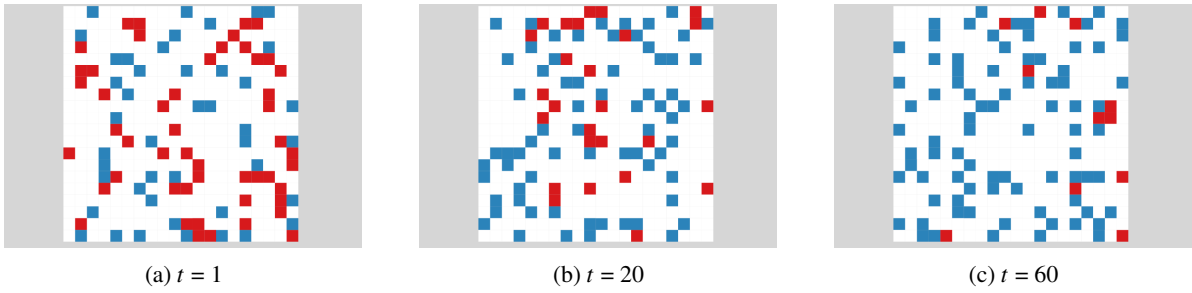
(a) $t = 1$　　　　　　　(b) $t = 20$　　　　　　　(c) $t = 60$

Figure 2: Typical distributions of agents, cooperators (blue) and defectors (red), at various timesteps (t) in a single simulation, using $r = 35$ and $s = 5$, on a $L = 20$ diluted lattice grid. Screenshots generated using Evolpex (Cardinot et al., 2018).
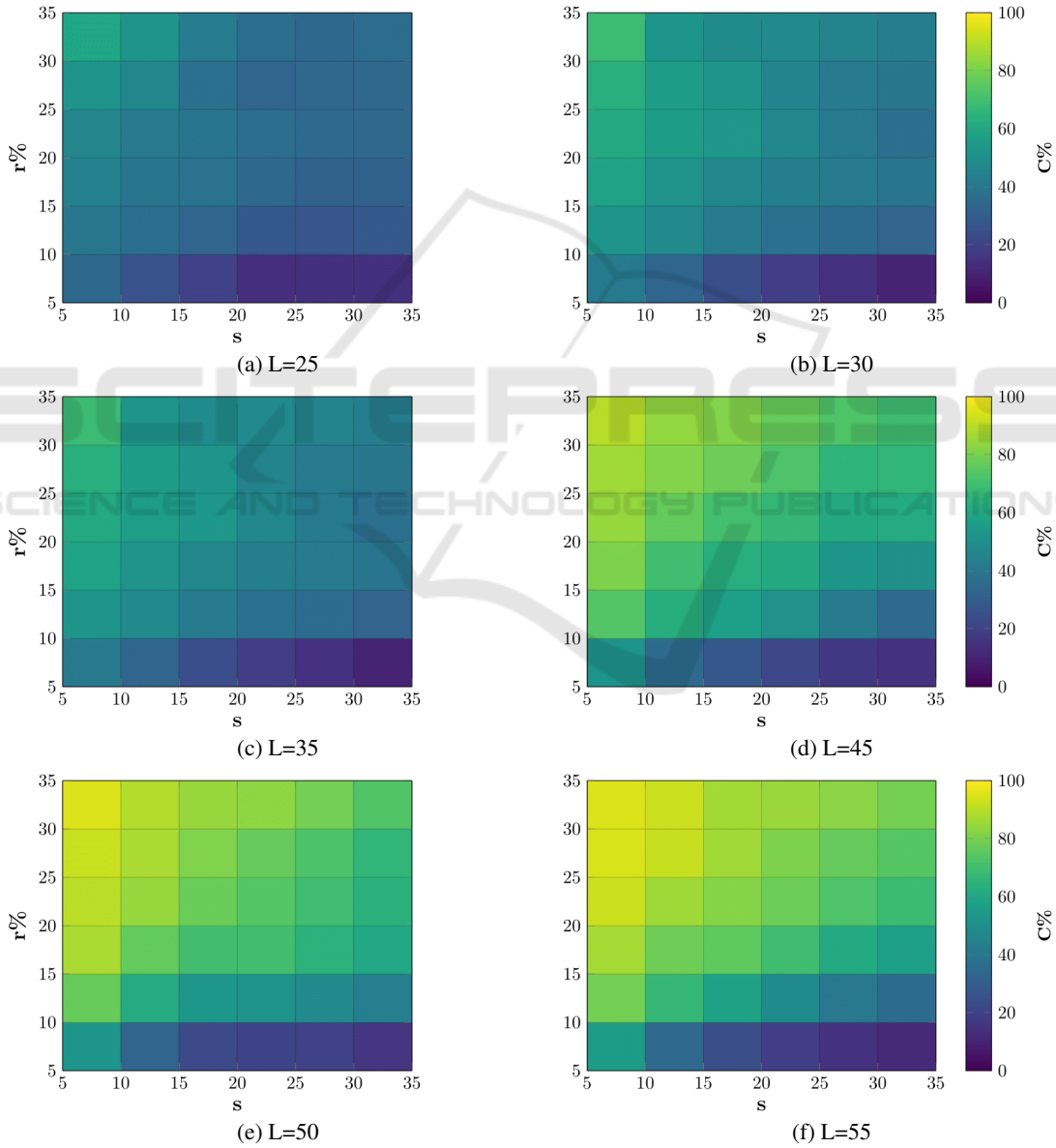

(a) L=25　　　　　　　(b) L=30

(c) L=35　　　　　　　(d) L=45

(e) L=50　　　　　　　(f) L=55

Figure 3: Average percentage of cooperator victories, C, for a variety of different values for the grid size L, as a function of replacement rate r, and the number of steps per generation s.
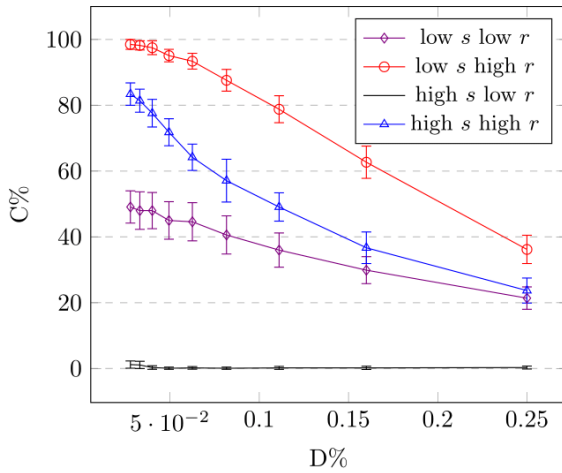
Figure 4: Average percentage of cooperator victories, C, for a number of evolutionary settings as a function of density, D. The low and high values are $r = 5, 35$ and $s = 5, 35$. The error bars show the standard deviation for each value of C.

of r and low values of s. However, it is also clear that for certain evolutionary settings, i.e. low r and high s, it is close to impossible for cooperation to emerge, regardless of any variation in density.

4.3 Comparing Placement Mechanisms

In this section, we repeat again our central experiment, co-evolving agent strategy and movement pattern, using the 'nearby' placement mechanism. In the previous two sets of experiments, new agents were placed in a 'random' free cell in the environment, without regard to the location of their parent, to the agent they were replacing, or to other agents. The 'nearby' placement mechanism locates new agents in the neighbourhood (i.e. the surrounding 8 cells) of their parent, if a free space exists, and otherwise places them randomly as before. This mechanism is more lifelike and realistic, and we hypothesise that it can promote cluster formation.

In Figure 5, we observe the percentages of cooperator victories across the range of evolutionary settings using the 'nearby' placement mechanism. Cooperation emerges in almost 100% of simulations for the vast majority of scenarios, and is only hindered in the most restrictive of evolutionary settings. These results are replicated across the density levels without significant variation, as seen in Figure 6.

4.4 Genotype Consistency

In order to better understand the reasons for obtaining higher levels of cooperation in specific evolutionary settings (the replacement rate r, the number of steps
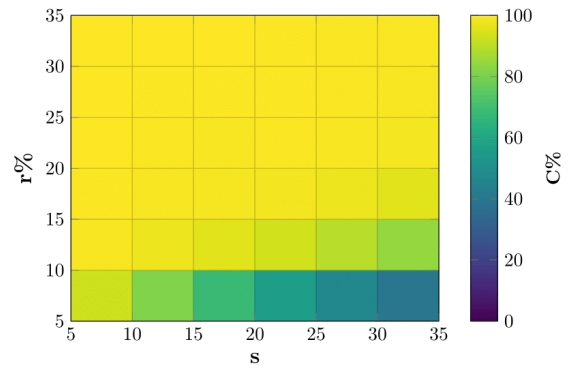

Figure 5: Average percentage of cooperator victories for grid size $L = 40$ as a function of replacement rate r, and the steps per generation s using the 'nearby' placement mechanism.
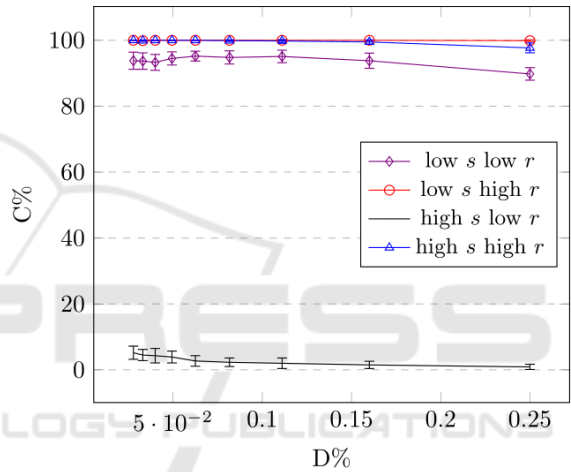

Figure 6: Average percentage of cooperators victories, C, for a number of evolutionary settings as a function of density, D, using 'nearby' placement. The low and high values are $r = 5, 35$ and $s = 5, 35$. The error bars show the standard deviation for each value of C.

in a generation s) and the grid size L (which determines the population density), we investigate the genotypic consistency across a number of simulations using 'random placement'. We only consider this placement mechanism as there is insufficient variation in agent behaviour when using 'nearby' placement (see Figure 5). Considering that all simulations are randomly initialised, in all scenarios, each agent could be assigned any combination of genes with equal probability. In other words, any of the 2^8 genotypes could be expressed in the population.

Thus, based on the outcomes generated in previous sections, we now are interested in looking specifically at the evolved movement behaviours of cooperative populations under the aforementioned evolutionary settings. To achieve this, at the end of each simulation, we record the game strategy and the most com-

(a) Evolved Cooperator Genotypes
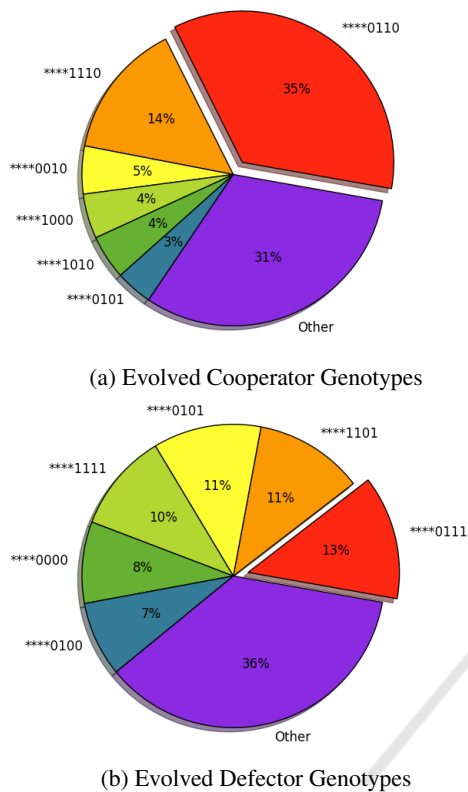

(b) Evolved Defector Genotypes

Figure 7: Percentage distribution of the most frequently evolved genotypes (the 8-bit set of actions) expressed in a population where (a) cooperation dominates and (b) defection dominates. The extruded segments represent the most commonly evolved genotypes. The 'Other' segment represents the combined total of the ten remaining set of genotypes that are less frequently evolved.

monly occurring genotypes that emerge in the population. The majority of simulations will result in convergence on either cooperation or defection. A small minority of simulations will result in a 'draw' using evolutionary settings with a slow convergence rate. The genotypes are recorded at the end of the simulations, despite the potential for genetic drift, because the convergence point can vary depending on many different factors including initialisation, the particular evolutionary settings, population density, and which strategy is undergoing convergence.

Figure 7 shows the percentage break down of the top ten most prevalent emergent genotypes (the 8-bit set of actions) from both (a) cooperator dominant and (b) defector dominant populations. It was observed that independently of the given evolutionary settings and population densities, the simulations resulting in widespread cooperation exhibit '01100110' as the most commonly evolved behaviour, with the critical segment, '****0110', being produced in 35% of all evolved behaviours, as shown in Figure 7 (a).

This genetic pattern corresponds to 'follow cooperators and flee defectors'. We focus our analysis on this gene section because it is critical both in terms of the evolutionary pressure it undergoes, and the major impact on the potential fitness it generates.

In other words, it is more important, from an evolutionary perspective, for an individual cooperator to move optimally in the scenario where both strategies are present than when just interacting with other cooperators. This is because there are fewer gene combinations that would lead to being punished in the latter scenario. For example, the 'stay still' behaviour, '00******', in the gene segment corresponding to 'only cooperators present', is almost functionally equivalent to the 'follow' behaviour, '01******', because both result in actions that lead to a continuation of the beneficial interactions with cooperators. However, the 'stay still' behaviour, '****00**', in the gene segment corresponding to 'cooperators with defectors present' is significantly worse than the 'follow' behaviour, '****01**', as it results in continual harmful interactions with defectors.

Additionally, we see in Figure 7 (a) that the second most frequently occurring set of genotypes in simulations resulting in the emergence of cooperation is '****1110'. These genotypes are genetically similar, and constitute a reasonable approximation of the optimal solution, because they often produce actions that are phenotypically identical. For example, the 'random' behaviour, '****11**', in the above genotype produces the more beneficial action, 'follow', in a significant percentage of interactions.

Moreover, due to the lack of genetic mutation in the evolutionary process, once a population reaches the point of convergence, meaning that agents are no longer subject to the same level of evolutionary pressure, it may settle on a sub-optimal solution. These results indicate that the 'follow-flee' pattern is usually the most beneficial mobility strategy for the creation of cooperative clusters which leads to the evolution of cooperation. These patterns are not found in the simulations resulting in defector dominance. As shown in Figure 7 (b), the 'follow-flee' movement pattern does not appear among the most commonly evolved genotypes. It is clear that defectors are subject to much less evolutionary pressure to optimise their mobility.

The genotypic consistency of populations using 'nearby' placement is also investigated. As shown in Figure 8, the results are largely similar, but one noteworthy deviation is that the 'follow-flee' movement pattern is less pronounced. It's clear that cooperators are under less pressure to be optimally mobile.
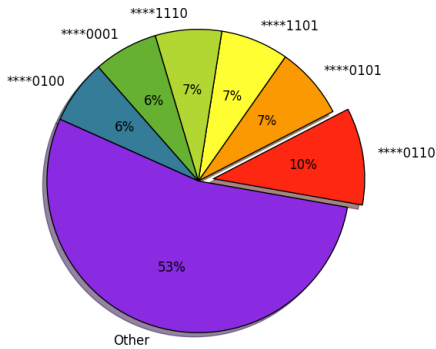
Figure 8: Percentage distribution of the most frequently evolved genotypes (the 8-bit set of actions) expressed in a population where cooperation dominates using the 'nearby' placement mechanism. The extruded segments represent the most commonly evolved genotypes. The 'Other' segment represents the combined total of the ten remaining set of genotypes that are less frequently evolved.

5 DISCUSSION

We have observed a number of environmental and evolutionary factors governing the emergence of cooperation within populations of mobile agents. Population density, agent lifespan, and the choice of placement mechanism all distinctly impact the formation of cooperator clusters, which is the most critical factor in the evolution of cooperation among agents using pure strategies. These clusters emerge as a consequence of the agents' evolved mobile strategies.

Agent lifespans consisting of short generations and high replacement rates favour, and often promote, the evolution of cooperation. These evolutionary settings curb the 'free rider' effect once the cooperators have learned good movement strategies, which form clusters, allowing agents to avoid repeated exploitation by defectors. If, in the initial generations of a simulation, cooperators have not learned to cluster by following neighbouring cooperators and fleeing from neighbouring defectors, defection will emerge. We have shown that in every simulation in which cooperation emerges some approximation of the 'follow-flee' movement strategy is evolved.

Population density has a major impact on the emergence of cooperation in spatial environments with a mobile population, because it directly impacts the interaction rate with defectors. Cooperation is most likely to emerge when clusters of cooperators, with appropriate genes, are formed and allowed to grow unimpeded in the initial timesteps of a simulation. The chance of this occurring is significantly higher in sparse environments. In dense environments, cooperators have a higher chance of being exploited by defectors, as a result neither the evolved movement strategies nor the evolutionary settings can ignite the evolution of cooperation, unless the initial conditions are particularly favourable. On the other hand, a sparse environment almost guarantees the emergence of cooperation. Clusters in sparse environments have a higher chance of avoiding exploitation, thus allowing its members to the learn beneficial movement patterns, and obtain a high fitness score.

There is a clear interplay between the population density and the evolutionary settings in this work. In general, the more time and space agents have to learn 'good' movement strategies, the more likely cooperation is to emerge. It is even possible to construct a set of parameters to ensure that cooperation emerges in the vast majority of simulations. However, unsympathetic agent lifespans will result in total defector domination, regardless of the population density. These aggressive evolutionary settings favour defectors because the movement strategies, which give cooperators the competitive edge over the defectors, are not learned in sufficient time to be effective.

The scenarios discussed thus far assume the use of the 'random' placement mechanism, however we observe a substantial decline in influence of both agent lifespan and population density when the 'nearby' placement mechanism is in effect. In fact, these factors become almost irrelevant (see Figure 5 and 6). Furthermore, the 'follow-flee' genotype doesn't occur with the same frequency in evolved cooperator populations as with 'random' placement. We hypothesise that this is due to there being significantly less pressure to learn clustering behaviours as 'nearby' placement ensures, where possible, that clusters grow.

6 CONCLUSION

In this paper, we presented a novel mobility model, in which agent proactively seek out better locations by moving in response to their local environment. We demonstrated the influence of several environmental and evolutionary factors on the emergence of cooperation among mobile agents using this mobility model.

We show that appropriately tuning the evolutionary process in conjunction with a favourable population density and sufficiently mobile agents can almost guarantee cooperation to emerge from a randomly initialized population. Additionally, we present results indicating that cooperation may emerge in a population with sub-optimal mobility strategies given a placement mechanism that promotes the growth of cooperator clusters.

Finally, we have shown that the impact of certain environmental and evolutionary settings can substantially diminish others. The 'nearby' placement mechanism creates cooperator clusters with such efficiency that the agents are under considerably less pressure to evolve the clustering behaviours.

Future work will involve modifying our agent representation to allow for the inclusion of noise in the model. A noise variable would be introduced that would cause agents to incorrectly identify interactions with their neighbours for some percentage of interactions. This would allow us to test the robustness of the evolved mobile strategies. In addition, we wish to investigate the impact on the evolution of cooperation when agents are given the ability to teleport, i.e. move to a location outside their neighbourhood, within their own lifespan. This ability would incur a cost to their fitness and allow them to randomly, or deterministically, jump to a distant location on the grid in a limited set of circumstances. Currently, both placement mechanisms allows for some amount of random relocation, however this only occurs with newborn agents. Additionally, other work has shown benefits of this type of mobility (Helbing and Yu, 2008). Finally, we may also consider other types of network topology to evaluate our proposed model in more realistic situations.

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