Stable Cooperation in the N-Player Prisoner's Dilemma: The Importance of Community Structure.

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2 authors:

Colm O' Riordan
National University of Ireland, Galway

Humphrey Sorensen
University College Cork

Stable Cooperation in the N-Player Prisoner's Dilemma: The Importance of Community Structure

Colm O'Riordan[1] and Humphrey Sorensen[2]

[1] Dept. of Information Technology, NUI, Galway, Ireland
colm.oriordan@nuigalway.ie
[2] Dept. of Computer Science, University College Cork, Ireland
h.sorensen@cs.ucc.ie

Abstract. N-player prisoner dilemma games have been adopted and studied as a representation of many social dilemmas. They capture a larger class of social dilemmas than the traditional two-player prisoner's dilemma. In N-player games, defection is the individually rational strategy and normally emerges as the dominant strategy in evolutionary simulations of agents playing the game.

In this paper, we discuss the effect of a specific type of spatial constraint on a population of learning agents by placing agents on a graph structure which exhibits a *community structure*. We show that, by organising agents on a graph with a community structure, cooperation can exist despite the presence of defectors. Furthermore, we show that, by allowing agents learn from agents in neighbouring communities, cooperation can actually spread and become the dominant robust strategy.

Moreover, we show that the spread of cooperation is robust to the introduction of noise into the system.

Keywords: Cooperation, N-Player Prisoner's dilemma, Community structure.

1 Introduction

The placing of constraints on agent interactions and the subsequent analysis of the resulting effect of these constraints on the society has been studied in a range of subdomains in multi-agent and artificial life societies. These include spatial constraints[8][6][13], tagging mechanisms[16] and trust and reputation systems[15]. Recently, there has been much interest in studying the emergent behaviour of agents playing in social dilemma games constrained by spatial constraints defined by some form of graph structure; these include small world graphs[24][22] and scale free graphs[23][19]. In these graphs constraints may exist on the clustering coefficient, the distribution of the node degree values and the average shortest path between two nodes.

A further interesting property of many real-world social networks is that of community structure. Given the existence of a community structure in many

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real-world social networks[11], questions arise regarding the effect of community structure on societies of agents playing in social dilemmas. Does the existence of community structure promote the emergence of cooperation?

This paper examines N-player social dilemmas. In the recent work on analysing the effect of various graph structures on agent interactions, the focus has been on the more widely studied two-player dilemma. In this work, we focus on the more general case, the N-player prisoner's dilemma. It has been argued that the N-player extension has greater generality and applicability to real-life situations [3].

In particular, we consider the effect of enforcing a community structure on a society of agents participating in N-player social dilemmas. We show that, by having a high degree of community structure, we can ensure that cooperative agents can insulate themselves from neighbouring non-cooperating strategies. By further adopting an update mechanism, whereby members of neighbouring communities can update their strategy to imitate that of a more successful strategy, we show that cooperation can actually spread throughout the society. We also show that, despite introducing considerable levels of noise to the learning process, cooperation can remain as the outcome.

Our simulations show that a high degree of community structure coupled with simple learning mechanisms can lead to the spread of cooperative behaviours, resulting in a robust stable cooperative society. In this paper we are interested in exploring the effect community structure has on the emergence of cooperation. It is plausible to propose that there is two-way relationship between these two features and that the emergence of cooperation and trust relationships can lead to the emergence of community structure. However, in this paper, we restrict our focus to one side of this relationship i.e. on the effect community structure can have on the emergence of cooperation.

2 Related Work

2.1 N-Player Social Dilemmas

An oft-studied game to model agent interaction is the N-player iterated prisoner's dilemma. N-player dilemmas are characterised by having many participants, each of whom may choose to cooperate or defect. These choices are made autonomously without any communication between participants. Any benefit or payoff is received by all participants; any cost is borne by the cooperators only. A well-known example is the *Tragedy of the Commons*[5]. In this dilemma, land (the commons) is freely available for farmers to use for grazing cattle. For any individual farmer, it is advantageous to use this resource rather than their own land. However, if all farmers adopt the same reasoning, the commons will be over-used and soon will be of no use to any of the participants, resulting in an outcome that is sub-optimal for all farmers.

In the N-player dilemma game there are N participants. Each player is confronted with a choice: to either cooperate (C) or defect(D). We will 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, i.e. for any individual, moving from cooperation to defection is beneficial for that player (they still receive a benefit without the cost):

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

$$C(i) > C(i-1) \quad 0 < i \leq N-1 \tag{2}$$

$$D(i) > C(i) \quad 0 < i \leq N-1 \tag{3}$$

However, if all participants adopt this dominant strategy, the resulting scenario is sub-optimal and, from a group point of view, an irrational outcome ensues:

$$C(N) > D(0) \tag{4}$$

If any player changes from defection to cooperation, the performance of the society improves, i.e. a society with $i+1$ cooperators attains a greater payoff than a society with i cooperators:

$$(i+1)C(i+1) + (N-i-1)D(i+1) > (i)C(i) + (N-i)D(i) \tag{5}$$

If we consider payoffs for this game, we can see that D dominates C and that total cooperation is better for participants than total defection.

The N-person game has greater generality and applicability to real life situations. In addition to the problems of energy conservation, ecology and over population, many other real-life problems can be represented by the N-player dilemma paradigm.

Several evolutionary simulations exist which study the performance of different strategy types playing the N-player game. This work has shown that, without placing specific constraints on the interactions, the number of participants or the strategies involved, the resulting outcome is that of defection[17][25].

2.2 Community Structure

In studying the two-player game, many researchers have explored the effect of placing spatial constraints on the population of interacting agents. These include, among others, experimentation with grid size and topology [12], graph structure in a choice/refusal framework [20], different learning mechanisms and topologies[10], small world[22], scale-free graphs[19] and graphs where the actual graph topology emerges over time [18].

In more recent work analysing small world and scale-free networks, researchers are often interested in key properties of these graphs. In this paper, we are interested in one key property of a graph: that of *community structure*. This property has also been explored in recent work[9]. A graph is said to have a community structure if collections of nodes are joined together in tightly knit groups between which there are only looser connections. This property has been shown to exist in many real-world social networks[11].

Our work differs from previous research exploring the emergence of cooperation in populations of agents organised according to a given graph topology in two ways. Firstly, we deal with the N-player dilemma where direct reciprocity towards, or punishment against, an agent is not possible (which is required in work that allows agents modify their connections towards other agents[18]) and secondly we utilise two update rules.

Many algorithms have been proposed to measure the degree of community structure in graphs. One such approach is that of hierarchical clustering. An alternative approach is that proposed by Girvan and Newman[11]. The *betweeness* of an edge is defined as the number of minimum paths connecting pairs of nodes that go through that edge. The algorithm repeatedly removes these edges. Donetti and Munoz[4] present another algorithm which involves extracting the eigenvectors of a laplacian matrix representing the graph. In this paper, we define graphs that have a predefined level of community structure. We systematically tune parameters to control the level of community structure present in the graph. Hence we do not need to utilise algorithms to measure the level of community structure as is necessitated when dealing with real-world data.

3 Model

3.1 Graph Structure

In the simulations described in this paper, agents are located on nodes of a graph. The graph is an undirected weighted graph. The weight associated with any edge between nodes represents the strength of the connection between the two agents located at the nodes. This determines the likelihood of these agents participating together in games.

The graph is static throughout the simulation: no nodes are added or removed and the edge weights remain constant.

We use a regular graph: all nodes have the same degree. In this paper, nodes have four neighbours. We use two different edge weight values in each graph: one (a higher value) associated with the edges within a community and another (a lower value) associated with the edges joining agents in adjacent communities. All weights used in the this work are in range [0,1].

The graph is depicted in Fig. 1, where the thicker lines represent intra-community links (larger value as edge weight) and the thinner lines indicate inter-community links between neighbouring communities. Each rectangle with thick lines represents a community of agents; the corners of these rectangles represent and agent.

3.2 Agents Interactions and Learning

Interaction Model. Agents in this model can have a strategy of either cooperation (C) or defection (D). Agents interact with their neighbours in a N-player prisoner's dilemma. The payoffs received by the agents are calculated according to the formula proposed by Boyd and Richerson [2], i.e. cooperators receive $(Bi/N) - c$ and defectors receive Bi/N, where B is a constant (in this paper, B is set to 5), i is the number of cooperators involved in the game, N is the

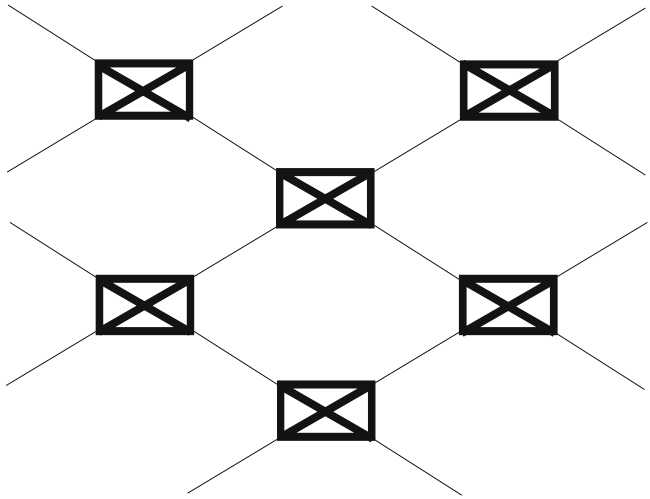

Fig. 1. Graph structure

number of participants and c is another constant (in this paper, c is set to 3). The values of B and c are chosen because they fulfill the requirements needed to ensure a dilemma.

Each agent may participate in several games. The algorithm proceeds as follows: for each agent a in the population, agents are selected from the immediate neighbourhood of agent a to participate in the game. Neighbouring agents are chosen to participate with a probability equal to the edge of the weight between the nodes. This means that, for a society with a high community structure, most games involve members of an agent's local community. This allows a high degree of insulation from agents in neighbouring communities. An agent's fitness is calculated as the average payoff received in the interactions during a generation.

3.3 Learning

Agents may change their behaviours by comparing their payoff to that of neighbouring agents. We adopt a simple update rule whereby an agent may update their strategy to that used by more successful strategies. Following each round of games, agents are allowed to learn from their neighbours. Again these neighbours are chosen stochastically; the neighbours are chosen according to the weight of the edge between agent and neighbour.

We incorporate a second update mechanism. The motivation for its inclusion is as follows: following several iterations of learning from local neighbours, each community is likely to be in a state of equilibrium—either total cooperation or total defection. Agents within these groups are receiving the same reward as their immediate neighbours. However, neighbouring communities may be receiving different payoffs. An agent that is equally fit as its immediate neighbours may look further afield to identify more successful strategies.

In the first update rule, agents consider other agents who are immediate neighbours. Let $s\_adj(x)$ denote the immediate neighbours of agents x chosen stochastically according to edge weight. The probability of an agent x updating their strategy to be that of a neighbouring agent y is given by:

$$\frac{w(x,y).f(y)}{\Sigma_{z \in s\_adj(x)} w(x,z).f(z)} \tag{6}$$

where $f(y)$ is the fitness of an agent y and $w(x,y)$ is the weight of the edge between x and y.

The second update rule allows agents to look further afield from their own location and consider the strategies and payoffs received by agents in this larger set, i.e. agents update to a strategy y according to:

$$\frac{w(x,y).f(y)}{\Sigma_{z \in adj(adj(x))} w(x,z).f(z)} \tag{7}$$

where again $f(y)$ is the fitness of agent y and now $w(x,z)$ refers to the weight of the path between x and z. We use the product of the edge weights as the path weight. Note that in the second rule, we don't choose the agents in proportion to their edge weight values; we instead consider the complete set of potential agents in the extended neighbourhood. In this way all agents in a community can be influenced by a neighbouring cooperative community.

Using the first update rule, agents can learn from their immediate neighbours and adopt a strategy of a more successful agent. Using the second rule, agents can look at their immediate neighbours and their neighbours' neighbours; this effectively gives them a larger set from which to learn. This is necessary in cases where a particular community has converged on some behaviour which is less successful than that adopted by a neighbouring community.

In our experiments we use a population of 800 agents; we allow simulations to run for 300 generations. In each generation, agents interact with their selected neighbours, update their scores based on these interactions and then learn from their immediate neighbours using the local update rule. Every four generations, agents also look to a larger community and learn from an agent in a larger set of agents. The motivation behind this is based on the notion that agents will learn from a wider set if their own neighbourhood has settled into an equilibrium state—which will be true following a set of local interactions. In our experiments, four generations is usually sufficient to allow a local community reach an equilibrium point.

4 Results and Discussion

In this section, we present the results of a number of simulations illustrating the effect of varying levels of community structure on cooperation in a population of agents playing an N-player prisoner's dilemma.

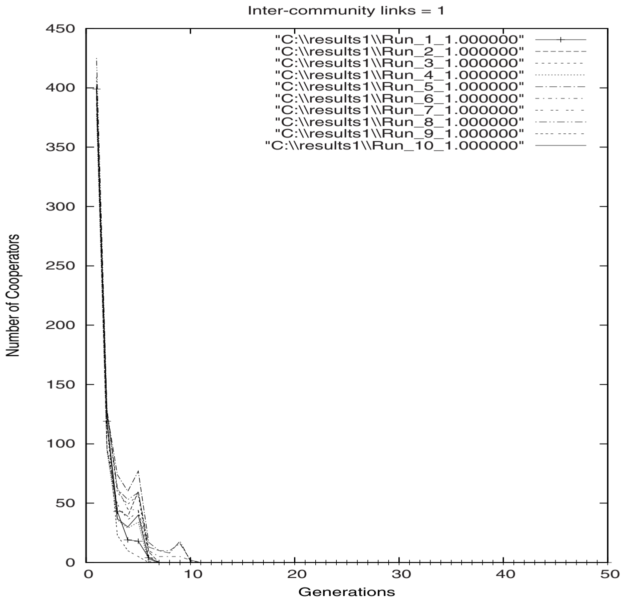

Fig. 2. Defection spreading in a regular graph

By setting the intra-community links to be high (1.0) and then varying the inter-community link weights from 0 to 1, we can model different levels of community structure. If we set the inter-community link weights to be 1, we have no community structure; we merely have a regular graph. If we set the inter-community links to zero then we have a population of separate isolated communities.

In any given N-player prisoner's dilemma game, a defector will score better than a cooperator. If we allow poorly performing strategies to imitate the behaviour of more successful strategies we see that there are two possible resultant equilibrium states—total defection and total cooperation. If any of the initial strategies are defectors, others will imitate that strategy and defection will emerge. If the initial state contains all cooperators, then cooperation will exist as an equilibrium state. Given n players, the probability of having a state of total cooperation is $1/2^n$; the probability of a non-cooperative equilibrium state is $1-(1/2^n)$. As n increases our chances of a cooperative equilibrium state decreases rapidly.

If we consider the scenario with no community structure, agents will have 5 players in every game. If any defector exists in the original population, defection will spread throughout. This is illustrated in Fig. 2, which depicts ten separate runs of the simulator resulting in a similar outcome—that of total defection.

By introducing a community structure, clusters of cooperators in a community can survive by participating in mutually beneficial cooperative games. By having inter-community links of weight zero, the local update rule will ensure that all groups will reach an equilibrium state and the population will then remain

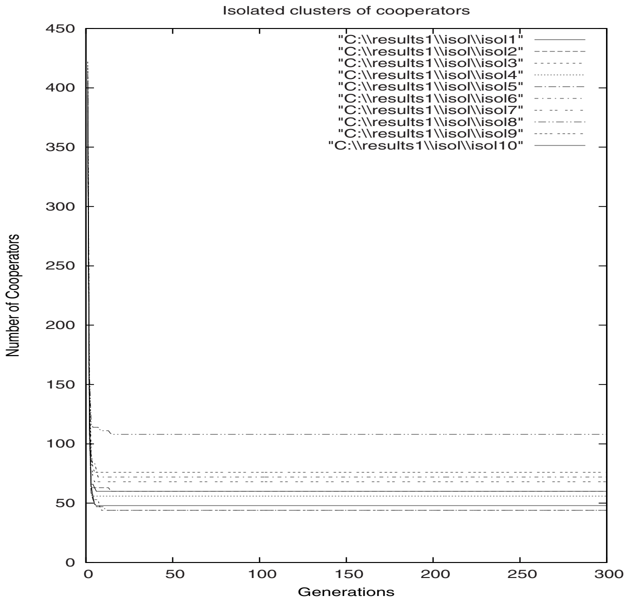

Fig. 3. Robust clusters of cooperators with local update rule and isolated communities

static with a minority of cooperative clusters existing in a large population of defectors. This allows robust groups of cooperators to exist in the environment but cooperation cannot spread throughout the population. We illustrate this for ten separate runs in Fig. 3.; in this simulation agents learn according to the local update rule only.

By allowing some interaction between neighbouring communities—i.e. having weights greater than zero with the update rules as described—we can have co-operation spreading through the population. If the relative difference between inter- and intra- community becomes too small, the community structure collapses, as does cooperation. The following graph (Fig. 4) shows a series of runs for differing values of inter-community links; these are the average of 20 runs.

As can be seen, for high levels of community structure (i.e. when the inter-community links are 0.1, 0.2), cooperation quickly emerges as a societal norm. As the community structure is decreased we see societies with both cooperation and defection co-existing. As the inter-community link weights reach higher values (0.7, 0.8, 0.9), we see defection spreading as the dominant behaviour.

We see sizable fluctuations among the runs with intermediate levels of community structure. These can be explained as follows: some members of communities of defectors neighbouring a cooperative community are likely to change their behaviour to cooperation following the second update rule. This occurs every four generations for all of the runs. Following this increase, we have a series of local updates, which leads to these cooperators being exploited and then adopting defection by updating their strategy according to the first update rule. This

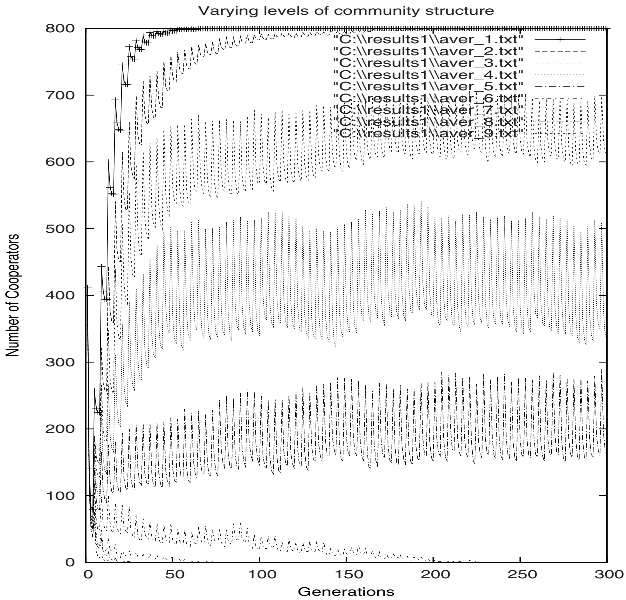

Fig. 4. Graph of number of cooperators over time for varying levels of community structure

leads to a subsequent dip in the cooperation; this occurs periodically throughout the simulation.

5 Robustness to Noise

The majority of work in multi-agent systems assumes a clean, noise-free environment i.e., moves are perfectly transmitted and received and agents learning a new strategy do so perfectly. There have been several efforts to model the effect of noise and to define strategies to deal with such effects [21],[7][14][1].

In much of the previous work, the emphasis has been placed on the effect of noise on reactive strategies. Previous research has promoted higher degrees of tolerance towards strategies whose moves may be mis-interpreted or mis-implemented[21]. Hence, strategies do not react as immediately or with the same degree of punishment.

In this work, agents with simple strategies participate in a one-shot N-player game; hence agents are not able to retaliate. Given this constraint, we implement noise in a different manner. Instead of allowing perfect imitation of more successful strategies, we introduce a probability of mis-imitation. The greater the level of noise, the more likely an agent is to fail to imitate a more successful strategy.

The effect of such noise on agents playing in these simulations is as follows: as strategies in a cluster of defectors attempt to imitate neighbouring cooperative

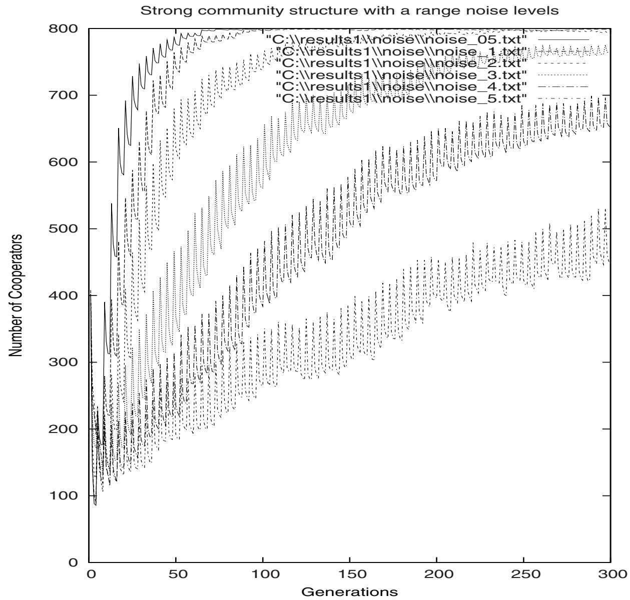

Fig. 5. Cooperation levels with noise

agents, there is an increased probability of not all agents successfully imitating their neighbours. The will lead to a cluster with mixed strategies which will quickly lead to an equilibrium of defection being reached. This slows down the spread of cooperation.

We run a number of simulations with the noise set to be the following the values (5%, 10%, 20%, 30%, 40% and 50%). For larger values, cooperation does not spread.

As can be seen in Fig. 5, cooperation can still emerge in the population as the dominant strategy despite the presence of noise in the agents' learning of strategies.

6 Conclusions and Future Work

Most investigations into the N-player social dilemma to date have shown the dominance of defection. In evolutionary simulations, defection often emerges. In our experiments, motivated by the recent work in identifying community structure in many real world social networks, we include different levels of community structure. We build graphs where we can tune the level of community structure.

In our experiments, we show that the presence of community structure can allow cooperation to be robust in the presence of defectors when using a simple learning rule whereby agents imitate nearby fitter agents. Furthermore, when allowing agents to periodically imitate from a larger set of nearby agents, we show that cooperation can emerge given the presence of a sufficiently strong community structure in the graph. We also show that cooperation will still spread even there is a relatively large level of noise in the learning of strategies by agents.

In this work, we examined how spatial constraints involving community structure can induce cooperation in a population of agents. Future work will also examine the role cooperation and cooperative relationships play in the emergence of community structure in societies of agents.

Future work will involve further exploration of several of the experimental parameters e.g. in this work we set the degree to be four for all nodes; it would be interesting to explore the effect of varying this value and also the effect of having variation in the degree throughout the graph. We will also involve further investigation into the effects resulting from community structure by considering the introduction of other types of noise, larger strategy sets and also on a wider range of graphs incorporating more features of real world social networks.

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