

# The Effect of Intergroup Competition on Intragroup Cooperation

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## Abstract

This review aims to introduce several theories of how cooperation may have evolved in the biological world, and how such theories can be tested using agent-based simulations. An overview of machine-learning techniques necessary for agent-based simulations is provided, ultimately informing decisions for an implementation. This implementation will be used to test two different theories of how cooperation can evolve, one a game-theoretic model, the other more concrete and inspired by the biological phenomenon of stigmergy.

## 1 Introduction

In nature, a super-organism is defined as an organism consisting of many organisms: a collection of agents that behave, not for the benefit of themselves, but for the benefit of the collective (Kelly 1995). This designation is most commonly reserved for eusocial animals – where cooperation occurs to the extent that division of labour is so specialized that a colony is divided into reproductive and non-reproductive groups (Wilson et al. 1971). Ants are the most widely recognized example. Because individuals in such societies cannot survive for long on their own, and because each agent needs to perform its own designated tasks to ensure the survival of the group, cooperation is absolutely essential.

Several different theories and models exist that attempt to explain how cooperation (and consequently, eusociality) may have evolved. Reeve & Hölldobler (2007) present a game-theoretic model that emphasises the importance of intergroup competition facilitated by resource availability. Their model is analogous to a nested tug-of-war, where intragroup competition takes place within the larger context of intergroup competition. The goal of this model, and others, is to find a set of circumstances such that agents within a group, even though they have the capacity for selfishness, choose to act selflessly, for the good of their own group.

These theories are commonly evaluated in agent-based simulations, combinations of techniques with their roots in artificial intelligence. The purpose of this research is to assess the model proposed by Reeve and Hölldobler by implementing such an agent-based system. The tug-of-war model relies on an implicit definition of cooperation. A second implementation using a far more concrete notion of cooperation (stigmergy) will also be created, and the results of two implementations will be compared.

Research in this field is important for a number of reasons. It provides valuable insight into how group cooperation can be forced. This has implications for machine-learning

tasks where collaborative behaviour is required of the agents that are being trained (which in turn has implications for collaborative robotic control tasks). Furthermore, it will afford insights into the biological evolution of cooperative behaviour, not only in eusocial creatures, but perhaps in humans as well.

## 2 Eusociality

Eusociality is cooperation on an unprecedented scale. Organisms within a superorganism are incapable of surviving as individuals, lose the ability to perform certain tasks (such as breeding), and act in concert to achieve goals governed by the collective. In Darwinian terms individual selection no longer applies, as a large portion of a population cannot share its genetic material. Instead, selection for such organisms happens at a group level.

Research has identified four key organizational trends in eusocial societies (Hölldobler 1990). (i) Cooperation is more likely to occur between agents with similar genetics. (ii) Large colony sizes lead to higher levels of cooperation. (iii) As colony size increases, brood output decreases. (iv) Resource patchiness and intergroup competition are strongly associated with cooperation.

Reeve & Hölldobler (2007) claim that their game-theoretic model gives rise to all four of these organizational trends. If this is the case, the model serves as a strong explanation of how such behaviour may have evolved in the biological world.

This research is primarily concerned with cooperation in agent-based systems, and particularly with the fourth organizational trend mentioned above. That is, the effect of intergroup competition (facilitated by resource availability) on intragroup cooperation. The fewer resources available, the fiercer the competition between rival colonies will be. Agents in each colony will have to evolve to cooperate with each other in order to survive in such an environment. Reeve & Hölldobler (2007) themselves emphasize these conditions as being crucial for the development of cooperation, a sentiment echoed by others as well (Wilson & Hölldobler 2005).

## 3 Cooperation

There are several theories regarding how cooperation may have evolved in the natural world. Many researchers in the field of evolutionary biology feel that the classical model of natural selection, which operates on a purely individual and competitive basis, can not possibly account for altruistic behaviour as is observed in so many species (Hamilton 1963). How could natural selection be favouring individuals who would willingly sacrifice themselves for others? The following subsections briefly introduce several theories of how cooperation could have evolved, and cover approaches to replicating cooperation in agent-based and evolutionary robotics systems.

### 3.1 Kin Selection

Kin selection (Hamilton 1963) is an evolutionary strategy that promotes acts of altruism as long as they are directed at close relatives. If you were to sacrifice yourself to save another, it makes sense if the person being saved is as closely related to you as possible. The more closely related to you they are, the more genes you have in common, and

therefore the more of your own genetic material is being propagated forward if they survive. In simplest mathematical terms, genes should increase in frequency when:

$$rB > C \tag{1}$$

where  $r$  is the level of genetic relatedness between two agents,  $B$  is the reproductive benefit gained by the recipient of the altruistic act, and  $C$  is the reproductive cost to the agent performing the altruistic act. This relationship has been proven to hold in the real world, with organisms only exhibiting altruistic cooperation with one another when genetic relatedness is sufficiently high (Gorrell et al. 2010).

Floreano et al. (2007) conducted experimental trials on robots that were able to cooperate by communicating information about resource locations. They found that cooperation readily evolved when agents in a group had similar genetic material, affirming the theory of Kin Selection.

Floreano & Keller (2010), in another robotic foraging experiment, again found that genetic relatedness led to cooperation. In an environment with both small cubes (which could be collected by a robot on its own), and large ones (which required two robots to cooperate), cooperation only evolved when there was genetic similarity between the agents. Genetically identical agents showed the most cooperation. Importantly, it was also found that an environment containing only large cubes led to the evolution of cooperative behaviour, whether the agents were genetically related or not. This suggests that environmental factors also play a crucial role in the evolution of cooperation, as predicted by Reeve & Hölldobler (2007).

### 3.2 Levels of Genetic Selection

As is briefly mentioned in the introduction to this section, natural selection at the level of the individual does not seem to properly account for the evolution of cooperative behaviour between agents. Darwin himself mused that perhaps his natural selection, at some point, starts to apply to groups of entities (such as a superorganism as a whole), rather than the individuals of which they are comprised. Researchers have postulated that selection does not happen at one, or even two, levels, but at every level from that of the individual gene, right up to ecosystems in its entirety (Lewontin 1970). This view is known as the Levels of Selection model. For our purposes, the entire spectrum of selection is out of scope. Focussing on two levels, individual and group selection, will suffice. Selection at the level of the individual is straightforward Darwinism. An agent that is stronger, faster, or smarter (fitter) is more likely to survive and pass on its genes to future generations. Group selection occurs when a collection of agents, due to their interactions or division of labour, has a fitness level that is higher or lower than the mean fitness of its constituent individuals, and will succeed or fail based on the fitness level of competing groups. It is important to note that group fitness and individual fitness cannot be treated as totally separate, and that there is a complex interplay between the two. Individual fitness, in all but eusocial societies, is still operational, and selection happens at both an individual and a group level (Lewontin 1970). The parallels between this model, and the nested tug-of-war model proposed by Reeve & Hölldobler (2007), where competition takes place between individuals in a group (because agents have their own fitness, and therefore reason to be selfish), and between the groups, is hard to ignore.

Waibel et al. (2009) uses a simulated foraging task as a test bed for various combinations of group and individual selection in order to investigate the evolution of cooperative

teams of agents. Different combinations of team composition (heterogeneous vs homogeneous) and level of selection (group vs individual), were used to create teams of agents. The performance of these agents was then measured on a variety of foraging tasks, some where cooperation was required, and others where it was not. In all tasks where cooperation was required (whether or not it was altruistic), homogeneous teams trained with group selection outperformed all other combinations – once again stressing the importance of environmental demands and genetic similarity in the evolution of cooperation, as suggested by Reeve & Hölldobler (2007). Additionally, the results point to the potential of group selection as a means of instigating the evolution of cooperation. Waibel et al. (2009) found that there were scenarios where individual selection and heterogeneous team composition lead to more performant agents, indicating that the level of selection chosen for a team must be informed by the particular problem that must be solved. Even if the goal is simply to force the evolution of cooperation, the choice of whether group or individual selection should be used must be based on whether or not the environment strictly requires cooperation.

### 3.3 Stigmergy

Cooperation in insects may have evolved through the mechanism of stigmergy. Stigmergy is a method of indirect communication between agents. Agents leave traces (in the form of pheromone trails in the biological world) in the environment which other agents are capable of detecting (Marsh & Onof 2008). If an agent finds a path between its colony and a resource, it will move between them repeatedly. Each time, the ‘path’ to the resource will be reinforced. As it builds in strength, other agents will be more likely to follow it, adding their own traces. Stigmergy is a simple way of facilitating complex cooperation between incredibly simplistic agents such as ants, or indeed simple simulated agents (Marsh & Onof 2008). Stigmergy allows another way of evaluating cooperation: agents that are more likely to follow the trails left by others (hopefully to resources), are more cooperative than those that simply wander about.

Cazangi et al. (2005) tested the theory of stigmergic cooperation in a simulated navigation task. The automatic navigation system itself was not intelligent. Agents had to learn incrementally through exposure to the simulated environment. It was found that the addition of a stigmergic mechanism to the agents (the ability to detect and ‘excrete’ a pheromone trail), dramatically improved the agents’ ability to find resources in the environment. The author suggests that the method holds promise in tasks where more collaborative behaviour is required (such as the collaborative box pushing task used by Waibel et al. (2009)).

### 3.4 Tug-of-war

In the model proposed by Reeve & Hölldobler (2007), individual agents each have their own limited supply of energy. Agents have to make the decision to either remain within the bounds of their own colony, conserving energy, or to forage for resources, which costs energy. Resources gathered are shared by all agents in the colony. In this case, an agent that chooses to conserve energy is competing within its own group for the shared resources. An agent that chooses to forage is cooperating, helping to contribute to the pool of shared resources. This simple game-theoretic model encapsulates ideas that are present in both the Kin Selection model, and the Levels of Genetic Selection model.

The model predicts that cooperation within a group will increase as genetic relatedness increases, as in Kin Selection. Despite the fact that selection occurs on an individual level, certain environmental demands are expected to see this individual selection give rise to implicit group selection, with agents altruistically sacrificing their energy for the good of the group when conditions are harsh enough. An addition that this model makes is competition, and its expected effects on intragroup cooperation. By adding additional competing groups to the simulation, experimenting with resource availability, colony size, and a genetic threshold in which breeding can occur, it will be possible to explore which factors can be used to force the evolution of cooperative behaviour.

## 4 Controller Design

There are many computational methods for constructing agent/robot controllers.

Inspired by behaviourist psychology, Reinforcement Learning (RL) is an area of machine learning concerned with how an agent ought to act so as to maximise some or other reward (Barto 1998). By estimating a value function based on previously received rewards, RL aims to map certain states to certain actions. In effect, an agent, being faced with a set of environmental circumstances, ‘remembers’ that it was highly rewarded for performing action  $x$  in this situation in the past, and is likely to perform action  $x$  again. This mapping from state space to action space becomes problematic for multi-agent systems, where the complex interactions between agents themselves, and between agents and the environment, creates a state space too large for traditional RL methods to easily handle.

Fuzzy Logic (Zadeh 1988), in contrast to classical logic, underlies approximate rather than exact modes of reasoning. Fuzzy control systems, given some input, are able to provide an approximate output based on a store of knowledge that may be imprecise, incomplete, or partially unreliable (Zadeh 1988). Fuzzy controllers perform very well at tasks such as temperature control, where concepts such as ‘hot’ and ‘cold’ are not as clearly defined as traditional binary input and output. Fuzzy controllers have also shown promise for robot and agent control systems (Lee 1990), where the limited experience of the world afforded by an agent’s sensors has to be used as the basis for decision making.

Rule-based systems work by codifying behaviour into a group of situation-action rules (Hayes-Roth 1985). Behaviour comes about by following a pre-defined set of rules, which can be thought of as a collection of ‘if this, then that’ statements. Human experts explain their problem solving techniques as a process of situation-action rules, so it is perhaps unsurprising that rule-based systems excel as expert systems (Hayes-Roth 1985). As with Fuzzy Logic, rule-based systems also have applications in a variety of control tasks (Hayes-Roth 1985). Pradhan et al. (2006) had success using a rule-based system to control robot navigation with a collection of rules such as ‘if the object is less than 5cm away, turn left 30 degrees’.

Evolutionary Computation (EC) (Eiben & Smith 2003), is a sub-field of artificial intelligence that is concerned with Evolutionary Algorithms (EAs), and is a promising approach to the design of cooperative teams of agents (Waibel et al. 2009). EAs are based on Darwinian principles, using selection to find the ‘fittest’ of a group of randomized candidate solutions to a given problem. EC is renowned for its applicability to investigating cooperation between multiple agents (Eiben & Smith 2003), and an effective way of generating control systems for agents that must demonstrate collective behaviour

(Baldassarre et al. 2003). Neuro-Evolution (NE) (Miikkulainen 2010), carries the biological metaphor a step further, each candidate solution being described by rudimentary ‘DNA’, which is then crossed over, mutated, and selected from to refine the candidate population. Neuro-Evolution is one of the most popular approaches in agent-based systems/evolutionary robotics, and has proven an excellent choice for implementations that seek to evolve complex behaviour in simple agents (Miikkulainen 2010). Because of this, NE will now be considered in greater detail, after a brief overview of Artificial Neural Networks (ANNs) and Evolutionary Algorithms (EAs), constructs upon which NE relies.

## 4.1 Evolutionary Algorithms and ANNs

NE works by applying EAs to ANNs.

EAs are a subset of EC, algorithms that use a population of candidate solutions to provide the answer to an optimization problem. EAs use mechanisms inspired by biological evolution: recombination, mutation, and selection. How exactly these mechanisms function depends on how the candidate solutions are represented. This combination of mechanisms iteratively refines a pool of candidate solutions, until the solution criteria are satisfied. A fitness function is used to determine the quality of a candidate solution, and provides the basis for selection. The most popular type of EA is the Genetic Algorithm (GA) Holland (1975). GAs typically represent individual candidate solutions as bit-strings which are then manipulated using the evolutionary mechanisms noted above. The general structure for all EAs is as follows (Yao 1999): A population of random candidate solutions is initialized. Each candidate is evaluated. Then, the following steps are repeated until a termination condition is met - 1) Select parents. 2) Recombine pairs of parents. 3) Mutate the resulting offspring. 4) Evaluate the new candidates. 5) Select individuals for the next generation.

ANNs McCulloch & Pitts (1943) are a basic model of how biological brains function. Artificial neurons (nodes) are sorted into layers and connected to each other to form a neural network. Each neuron is a basic computational unit, with a number of inputs, and one output. Based on the input a node receives, and some activation function, the neuron will either ‘fire’, releasing an output that can be used as input to a connected node, or not. Nodes in the input layer receive stimuli directly from the outside world, and the output of the final layer of nodes in the network can be used to drive behaviour. All connections between neurons are given a weight. The input signal from a poorly weighted connection will have less of an effect on whether a neuron fires or not. By altering these connection weights, the output of a neuron, and therefore a neural network, can be changed, even with the same input. This is one way that ANNs can ‘learn’ – by having their connection weights adjusted. It has been shown that an ANN with one layer of input nodes, one intermediate or ‘hidden’ layer (a layer of nodes between the input and output layers), and one layer of output nodes, is a universal function approximator (Cybenko 1989). This means that an ANN of this type is capable of approximating any continuous function. This is very important for complex control tasks, as a relatively simple representation is capable of giving rise to complicated behavioural output.

## 4.2 Neuro-Evolution

As briefly mentioned above, NE works by refining a pool of candidate solutions that are represented as ANNs using an EA. This is done by modifying the connection weights in

the ANN, by modifying the connections between the nodes in the ANN, or by the addition or subtraction of nodes in the ANN. Modifications to the ANNs result in changes to agent behaviour, and therefore fitness. This fitness is then used to select the genotypes which led to the fittest phenotypes, so that they may be recombined, mutated, and selected for the next generation. In this way, the behaviour of agents evolves over time. There are two approaches to encoding the genotype for each ANN, indirect encoding, and direct encoding.

Indirect encoding is only concerned with the most important parameters of the genotype architecture, the number of hidden layers and the number of nodes in each layer Yao (1999). Other parameters, such as connectedness and connection weights, are left up to the training process to determine. Direct encoding allows the specification of every node, connection, and connection weight at the level of the ‘DNA’ from which ANNs are assembled. Direct encoding (the method of choice for this research) can be divided into several different techniques.

Conventional Neuro-Evolution (CNE) encodes a genotype architecture by concatenating all of the connection weights in an ANN Yao (1999). Evolution in the CNE approach works by optimizing only these connection weights, while the architecture of the network remains fixed. CNE is relatively simple to implement, and has a wide variety of practical applications. CNE suffers from several problems: Since the topology of the network remains unchanged, great care has to be taken to choose the appropriate topology; Using CNE, it is possible that a sub-optimal solution will be converged upon (the algorithm finds a local optimum in the search space, rather than a global optimum); Difficult problems present a challenge because the number of parameters in the network scales quadratically (in the worst case) to the size of the network.

Symbiotic Adaptive Neuro-Evolution (SANE) (Moriarty & Miikkulainen 1996), attempts to solve the problem of early convergence that CNE suffers. Rather than treating each network as an individual, as in CNE, SANE treats each node in the hidden layer of a three layer network as an individual to be evolved. This allows greater population diversity, which helps to mitigate chances of the conversion on a suboptimal solution. SANE, although it shows great success for simple tasks (finding the solution is just a few generations), is exceeded by CNE in tasks that require high precision Moriarty & Miikkulainen (1998).

The Enforced Sub-Populations (ESP) method is an extension of SANE that also aims to address the problem of early convergence (Gomez & Miikkulainen 1999). SANE allows networks to evolve recurrent connections which, in effect, gives the network a ‘memory’ that allows them to use information about passed experience. ESP is able to solve problems faster than CNE, and is able to solve far harder problems as well (Gomez & Miikkulainen 1999). The relatively high implementation difficulty is a drawback.

Because choosing the perfect ANN topology for CNE is a difficult and imprecise task, Stanley & Miikkulainen (2002) developed a method that allows the topology of the ANN to be evolved: Neuro-evolution of Augmenting Topologies (NEAT). By allowing the algorithm to control network topology, NEAT optimizes the NE search process by eliminating unnecessary nodes from the ANN, therefore decreasing the dimensionality of the weight space. This allows NEAT to evolve optimized networks to problems that are too complex for CNE to realistically handle.

### 4.3 Agent-Based Systems

Agent-Based Systems (or agent-based modelling) (Gilbert 2008) is a computational method that facilitates simulation of the actions/interactions of agents in an environment. Although related to Multi-Agent Systems (MAS), Agent-Based Systems (ABS) are distinct in a number of ways. ABS are used in a variety of non-computing fields, most notably the field of biology, where they are used to investigate questions pertaining to epidemiology, population dynamics, and many others (Niazi & Hussain 2011). ABS are also used extensively to test theories of evolution and interaction among ‘biological’ agents, glean- ing explanatory insight into collective behaviour between agents that follow simple rules. MAS, on the other hand, are usually used in the creation of systems designed to solve specific practical or engineering problems (Niazi & Hussain 2011). ABS are therefore the most applicable method for the purposes of this research, which aims to measure the emergence of complex behaviour (cooperation) from interactions between simple agents.

There are two major components to an ABS: the agent, and the environment.

#### 4.3.1 The Agent

Agents are a distinct part of the simulation (the entities driven by ANNs, in our case) that interact with, and within, an environment (Gilbert 2008). They are used to represent real entities, such as insects. Within the realm of NE, their behaviour, how exactly they react to the environment and each other, is dictated by the ANN that controls them.

#### 4.3.2 The Environment

The environment is the virtual world in which the agents act Gilbert (2008). This environment can be changed in any number of ways, and made as neutral or interactive as is desired. Biological applications of ABS tend to try to emulate an ecosystem in which agents can ‘live’, with life sustaining resources and/or obstacles to be avoided.

#### 4.3.3 Experimentation in Agent-Based Systems

NE works on the agents themselves, changing their driving ANNs (and consequently, their behaviour), from generation to generation. A set of parameters can be used to alter the environment in a number of ways. For the purposes of this research, the most pertinent changes will be to the number and richness of resource patches that appear in the world.

Manipulating the mechanisms of NE and the EA responsible for it, and making changes to environmental factors such as resource availability, will have a measurable effect on the behaviour of the agents. This will allow for the establishment and analysis of correlations between environmental and behavioural factors during the course of agent evolution.

## 5 Conclusions

To test the game-theoretic model proposed by Reeve & Hölldobler (2007), a ABS will be created where the effects of environmental factors on the evolution of cooperation can be measured. As a point of comparison, a second implementation using the more concrete definition of cooperation provided by stigmergy will also be created. The simulation will require agents to perform a simple foraging task.



Evolutionary Computation methods, particularly Evolutionary Algorithms, have proven to be a good approach to investigating biologically inspired phenomena. Cooperation, the measurement of which relies on behaviours exhibited by agents in response to environmental factors, requires the evolution of agent controllers. ANNs have seen broad use in control tasks, and Neuro-evolution will therefore be used to evolve the ANNs responsible for agent behaviour. Although there are several sophisticated encoding approaches for ANNs, their use may not be warranted in simple tasks such as the foraging task proposed. A CNE will be used to evolve the agent controllers. Agent behaviour will be measured in response to various environmental changes such as level of competition (facilitated by resource availability).

If the simulation reveals that the game-theoretic model proves to have the predictive power that the authors claim, it should be considered good evidence that a sufficiently high level of competition is one of the key factors required for the evolution of eusociality.

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