Norm Emergence in Tag-Based Cooperation

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ABSTRACT

In multi-agent systems norms are an important influence that can engender cooperation by constraining actions and binding groups together. A key question is how to establish a suitable set of norms in a decentralised population of self-interested agents, especially where individual agents might not adhere to the rules of the system. In this paper we investigate the problem of norm emergence, and the related issue of group recognition, using tag-based cooperation as the interaction model. We explore characteristics that affect the longevity and adoption of norms in tag-based cooperation, and provide an empirical evaluation of existing techniques for supporting cooperation in the presence of cheaters.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence — *Multiagent systems*

General Terms

Experimentation, Algorithms, Reliability

Keywords

Cooperation, Tags, Rewiring, Norm Emergence

1. INTRODUCTION

Multi-agent systems often comprise multiple self-interested agents seeking to achieve tasks that they cannot, or not as easily, achieve alone. In a sense, however, this self-interest suggests that without some other constraining influence, cooperation is unlikely to emerge. Norms provide just one source of such influence on agent behaviour, by constraining actions and binding a group together so that cooperation naturally arises. In this view, one key question is how to establish a suitable set of norms. While formally established institutional rules offer a means of doing this in a centralised fashion, such centralised control is often not possible in large dynamic environments. Indeed, as has been recognised elsewhere [4, 23], *social norms* are not formal, prescriptive, centrally imposed rules, but emerge informally through decentralised agent interactions. In this paper, we explore the nature of such social norms and their impact on group formation through empirical analysis, and examine the impact of *cheating* agents: those that fail to comply with norms but seek to enjoy the benefits of the group.

In seeking to investigate these issues, we adopt the *tag-based* approach taken to the problem of *group recognition*, by Riolo, Cohen and Axelrod, who use observable tags as markings, traits or social cues attached to individuals [17]. Using this approach, Hales and Edmonds have achieved promising results in peer-to-peer settings [11], but these are not resilient when cheaters are introduced, and assume agents have complete control over their links to others. In particular, we need to support cooperation in dynamic environments in the presence of cheaters where individuals have limited control over their connections. Here, tags capture *social norms*: they are recognised by agents who form groups that share a tag (within their tolerance values). The tag can be seen as a norm that is adopted by the agents who share the tag, with the group itself being *governed* by that norm, which binds it together. In this paper, therefore, we examine the problem of supporting cooperation from the perspective of norm emergence, and evaluate the effect of alternative techniques on norm emergence. The key contributions are an evaluation of the characteristics affecting longevity and size of norm-governed groups in tag-based cooperation, and further understanding of mechanisms for coping with cheaters.

The paper begins with an introduction to tag-based cooperation, followed by the specifics of using *context assessment* and *rewiring* to improving group effectiveness in the presence of cheaters. Then, in Section 4, we present an analysis of our experimental findings, and finally we conclude with a discussion of our results and their more general significance.

2. BACKGROUND

It has been widely argued that *norms* provide a valuable mechanism for regulating behaviour in decentralised societies [2, 8, 23]. Through the ongoing behaviour of individuals, norms can emerge that provide coherence and stability, and support cooperation. A common view is that where a group of agents share a particular strategy, behaviour or characteristic, a norm is established [19]. In this paper we investigate factors influencing norm emergence in a population of agents, each of which has a set of neighbours with whom it interacts. This abstract environment reflects the form of many real-world settings, such as ad-hoc communication networks or P2P content sharing. We assume there is no direct reciprocity, and so adopt Riolo, Cohen and Axelrod's tag-based approach, introduced below.

Tag-based cooperation has been considered for many years by biologists and social scientists investigating how cooperative societies of selfish individuals might evolve through the recognition of cultural artefacts or traits [1, 5, 7, 12]. Simple observable traits, or *tags* [13], can be used as cultural artefacts to engender cooperation without relying reciprocity [3, 17, 22]. Existing work on tags, however, has given little consideration to the possibility that some members of the population may be *cheaters* who deviate from the rules of the system, by not cooperating when they should. In this paper, our investigation of norm emergence allows for the possibility of cheaters.

Riolo, Cohen and Axelrod (RCA) propose a tag-based approach to cooperation in which an individual's decision to cooperate is based on whether an arbitrary tag (i.e. observable trait) associated with it, is sufficiently similar to that associated with a potential recipient [17]. The approach is illustrated using a simple *donation scenario* in which each agent acts as a potential donor with a number of randomly selected neighbours. Should an agent opt to donate, it incurs a cost c, and the recipient gains a benefit b (it is assumed that $b > c$), otherwise both receive nothing. Each agent i is initially randomly assigned a tag τ_i and a tolerance threshold T_i with a uniform distribution from $[0, 1]$. An agent A will donate to a potential recipient B if B's tag is within A's tolerance threshold T_A, namely $|\tau_A - \tau_B| \leq T_A$. Agents are selected to act as potential donors in P interaction pairings, after which the population is reproduced proportionally to their relative scores, such that more successful agents produce more offspring. Each offspring is subject to mutation, so that with a small probability a new (random) tag is received or noise added to the tolerance. In relation to norms, the key aspect here is that donation rate is an assessment of the effectiveness of the society and the impact of norms: the greater the effectiveness, the higher the donation rate.

RCA have shown that a high cooperation rate can be achieved with this simple approach. They observe cycles in which a cooperative population is established, which is then invaded by a mutant whose tag is similar (and so receives donations) but has a low tolerance (and so does not donate). Such mutants initially do well, leading to them taking over the population subsequently lowering the overall rate of cooperation, but eventually the mutant tag and tolerance become the most common and cooperation again becomes the norm [17].

Hales and Edmonds (HE) apply RCA's approach in a P2P setting, with two main changes [11]. First, RCA's *learning interpretation* of reproduction is adopted, so that each agent compares itself to another at random and adopts the other's tag and tolerance if the other's score is higher (subject to potential mutations) [17]. Second, HE interpret a tag as being an agent's neighbours in the P2P network, i.e. an agent's links to others. In RCA's work each agent is connected to each other agent, with no corresponding notion of neighbourhood. In HE's model, the process of an agent adopting another's tag is equivalent to dropping all of its own connections, and copying the connections of the other agent (and adding a connection to the other agent itself) [11]. Importantly, in our view, this model reflects the formation of groups based on recognition of tags in group members.

Using simulations, HE have shown this approach to be promising in situations where agents are given free reign to rewire the network and replace all of their connections each reproduction. This rewiring is an *all-or-nothing* operation, in that although an agent can adopt a completely new set of neighbours (*replacing* its existing neighbourhood), it cannot *modify* its existing neighbourhood. Our view is that such extreme rewiring, where the neighbourhood topology might completely change with each new generation, is not practicable in all scenarios. For example, in a communication network this would imply that all existing routes become outdated and need to be re-established, while in a content sharing system an agent would lose all information about the content available in its neighbourhood. In this paper we consider a less extreme situation, in which agents are able to rewire a proportion of their neighbourhood.

Both RCA and HE assume that agents do not deviate from the rules of the system, i.e. they assume no cheaters. A *cheater* is an agent that accepts donations, but will not donate to others, even if the rules of the system dictate that it should. We assume that if a cheater reproduces, then its offspring will also cheat. In this paper we assume that the traits embodied by tags are observable to others, meaning that cheaters cannot falsify their tags. In standard tag-based cooperation, introducing even a small proportion of cheaters into the population causes cooperation to collapse [9].

Norm emergence has been considered in several other settings. For example, norms can emerge in a social dilemma game when individuals are repeatedly randomly paired [20], and in certain settings can emerge simply by individuals learning based on their own individual histories [21]. In this paper, however, our focus is on using the interpretation of a shared tag as representing a norm to further our understanding of tag-based cooperation.

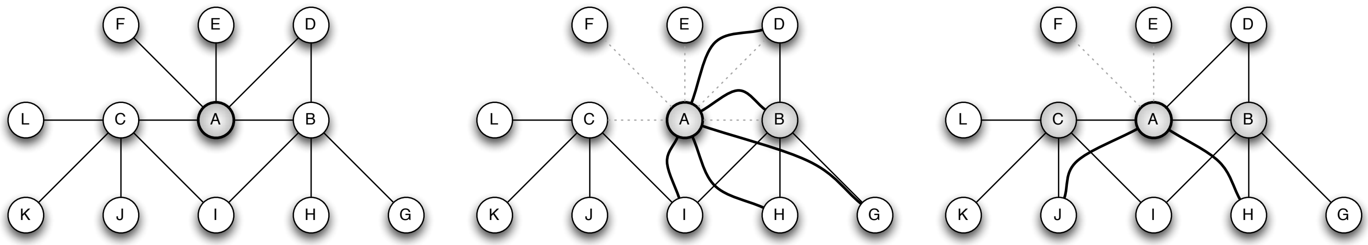
3. IMPROVING GROUP EFFECTIVENESS

In seeking to examine the impact of cheaters on group formation and norm emergence, we consider a population of agents, each of which has its own tag and a set of connections to n neighbours, such that agents can only interact with their neighbours (although for reproduction we consider the population as a whole). We assume that a proportion of agents are cheaters and will not cooperate with others even when their tags are within the tolerance threshold. The *donation scenario* and parameter values used by RCA are adopted, such that benefit $b = 1$ and cost $c = 0.1$ [17]. Each agent i is initially assigned an arbitrary tag τ_i and tolerance T_i with uniform distribution from $[0, 1]$[1]. We investigate norm emergence in relation to RCA's tag-based approach and two techniques that we have previously proposed for improving cooperation in the presence of cheaters: context assessment [9] and rewiring [10].

3.1 Context assessment

Our first technique, originally proposed in [9], enables agents to assess their neighbourhood, or group, in terms of how cooperative they perceive their neighbours to be. The donation decision is modified so that an agent's assessment of its neighbourhood context becomes a factor in the decision to donate. Agents are given a fixed length FIFO memory to record the last l donation behaviours observed for each neighbour. When the neighbour donates, an observation value of $+1$ is recorded, and when it does not -1 is recorded. This memory is fairly sparse, since the number of interactions is small compared to the number of agents, and so the overhead incurred is relatively small (2 bits per

[1]We actually use a lower bound on *tolerance* of -10^{-6} to address Roberts and Sherratt's concerns regarding agents with identical tags being forced to cooperate [18]. This also allows the population to contain non-cooperative agents of the form considered by Masuda and Ohtsuki [15].



(a) (b) (c)

Figure 1: Rewiring showing (a) the original neighbourhood rewired using (b) HE's method and (c) our rewiring approach.

observation for $n \times P$ observations, where n is the number of neighbours and P the number of pairings).

In order to assess its neighbourhood context, an agent considers each of its n neighbours in turn, and determines the contribution to the context assessment c_i of neighbour i, which is simply the proportion of observed interactions in which the neighbour donated, given by:

$$c_i = \begin{cases} \dfrac{\sum_{j=1}^{l_i} \begin{cases} o_i^j, & \text{if } o_i^j > 0 \\ 0, & \text{otherwise} \end{cases}}{l_i}, & \text{if } l_i > 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where o_i^j represents the j'th observation of neighbour i, and l_i is the number of observations recorded of i's donation behaviour ($l_i < l$). By considering each of its n neighbours, agent A's assessment of its current neighbourhood context C_A is given by:

$$C_A = \frac{\sum_{i=1}^{n} c_i}{n} \quad (2)$$

This context assessment can be used to influence the donation decision. The intuition is that agents 'expect' that by donating they are more likely to receive a future donation from some other (observing) agent, thus binding a group together. However, since the number of interactions is small compared to the number of agents, this is a *weak* notion of indirect reciprocity, and insufficient to support a typical notion of reputation. An agent's donation to another is unlikely to be directly repaid or directly observed by a third party, so there is little direct or indirect reciprocity. Instead, context assessment gives an impression of the donation behaviour in a neighbourhood, indicating the likelihood of receiving future donations. An agent's assessment of its neighbourhood context is incorporated into the model by adapting the decision to donate, such that both tolerance and neighbourhood context are considered. Thus, an agent A will donate to B if:

$$|\tau_A - \tau_B| \leq (1-\gamma).T_A + \gamma.C_A \quad (3)$$

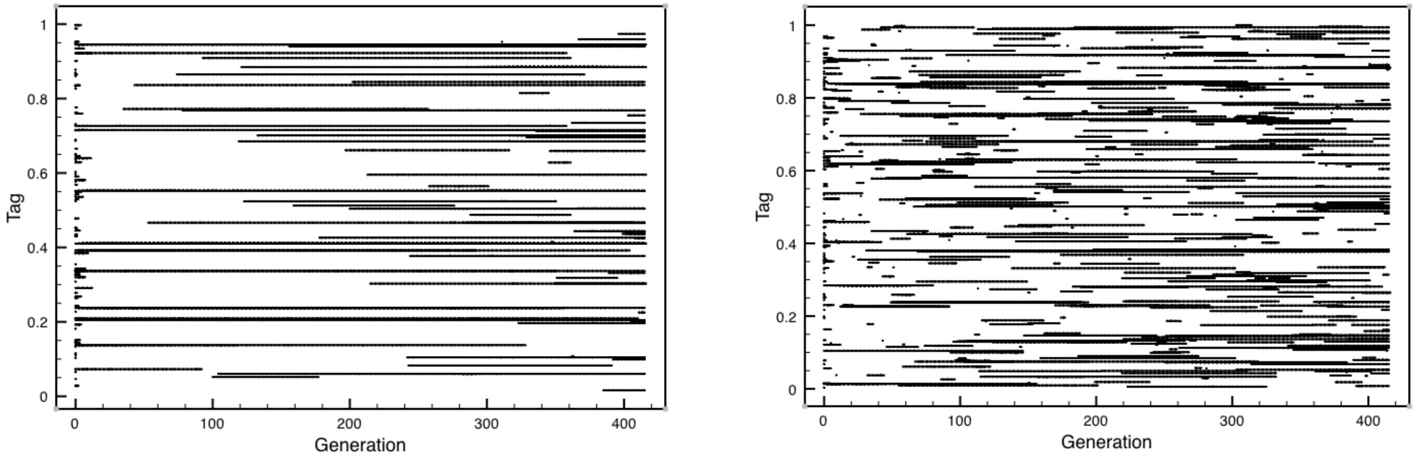
The parameter γ (the *context influence*) allows us to tune the technique. The context influence is in the range $[0, 1]$, with $\gamma = 0$ making the technique identical to RCA's method, while $\gamma = 1$ makes the donation decision determined solely by an agent's assessment of its neighbourhood context. We adopt RCA's learning interpretation of reproduction (as do HE), such that after a fixed number of interaction pairings P an agent compares itself to another, random selected from the population. If the other agent is more successful, then its tag and tolerance are copied (subject to a small probability of mutation), otherwise the tag and tolerance are unchanged.

3.2 Rewiring

Our second technique, proposed in [10], enables agents to *rewire* their network neighbourhoods, such that after reproduction an agent removes a proportion λ (the *rewire proportion*) of connections, and replaces them with connections to new neighbours. This approach is motivated by HE's results, but unlike HE we do not assume that agents can replace *all* of their connections since, as discussed above, this is likely to be impractical in real-world settings. In our mechanism, after reproduction, the $n \times \lambda$ worst neighbours are removed, and the best (non-duplicate) neighbour from each of the agent's $n \times \lambda$ best neighbours are added. The neighbours are considered in descending rank order and, for each, the best non-duplicate neighbour is added. Additional randomly selected neighbours are added if necessary to prevent the neighbourhood shrinking due to duplication (agents have at most one connection to another, and duplicate connections are meaningless).

Connections to remove are determined by ranking each neighbour i using the contribution to the context assessment c_i (defined in Equation 1), with agents having the lowest c_i values being removed. The contribution to the context assessment is also used to determine which connections to add, with an agent asking each of its $n \times \lambda$ best neighbours to recommend their best non-duplicate neighbour. If the c_i values of two or more agents are equal then one is selected arbitrarily. The *rewire proportion* determines the extent to which the network is rewired in each generation. Such rewiring can be thought of as a simplistic reputation mechanism, since agents update their connections based on the experiences and recommendations of others. However, unlike typical reputation mechanisms, the assessment is based on relatively little information, which is not predicated on a notion of (direct or indirect) reciprocity [14, 16].

Figure 1 illustrates the alternative rewiring approaches. Agent A's original neighbourhood is shown in (a). The results of applying HE's rewiring approach is shown in (b) where A drops all of its connections and adopts those of B. Our rewiring approach is illustrated in (c). If A's neighbours in order of preference are B, C, D, E, F, and 2 neighbours are to be replaced, then connections to E and F will be dropped. If B's neighbours, are D, H, I, G, A and C's neighbours are J, K, L, A, I in preference order, then A will add H from B's neighbourhood (D is already in A's neighbourhood and so



(a) low mutation

(b) high mutation

Figure 2: Tags with RCA's standard approach using low and high mutation rates.

not added) and J from C's neighbourhood.

4. EXPERIMENTAL ANALYSIS

Using the PeerSim P2P simulator[2], we have built a simulation that allows us to explore norm emergence using RCA's standard approach, context assessment, and rewiring. The quantitative results presented here are averaged over 10 runs using a population of 100 agents, a neighbourhood size of $n = 10$, with 10 pairings per agent per generation ($P = 10$), and a cheater proportion of 30%. Where context assessment is incorporated a *context influence* of $\gamma = 0.5$ is used, and similarly where rewiring is incorporated we use a *rewire proportion* of $\lambda = 0.5$. After reproduction there is a 0.001 probability of mutating the tolerance of each agent by adding Gaussian noise (with mean 0 and standard deviation 0.01), along with a probability of mutating each agent's tag by selecting a new random value. We consider two configurations for mutating tags: a *low mutation* rate of 0.001 and a *high mutation* rate of 0.01. The low mutation rate represents a generally stable population in which mutation is simply a small part of the evolutionary process. Conversely, the high mutation rate represents a more dynamic environment in which there is more significant fluctuation in tags present in the population (this is akin to a small proportion of the agents leaving and joining at the end of each generation).

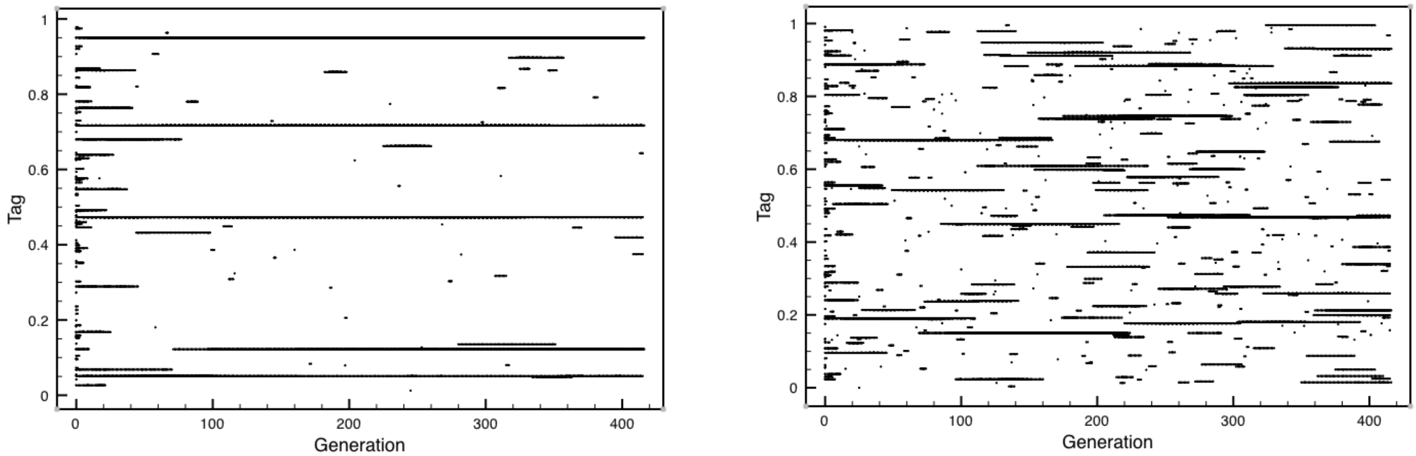
In this section we give an overview of the main findings from our simulations, focusing on two main characteristics. First, we consider the *donation rate* defined as the proportion of interactions resulting in a donation in the final generation of the simulation, averaged across the population. This indicates the effectiveness of the groups that emerge in complying with the norms that establish those groups and govern their maintenance. Second, we consider the *number of unique tags* present in the final generation, which indicates the number of norm-governed groups that have been established. Where a group of agents share a tag (and each others' tags are within their tolerance values) we interpret this as recognising a norm that is then established, since those agents will cooperate by donating to each other (provided that they are not cheaters). The number of unique tags indicates the number of such norm-governed groups that are formed, since each tag value corresponds to a tag group. However, it is important to note that some tags may be adopted only by a single agent in which case there is no norm, and so the number of tags is only an indicative metric.

Where there is a low number of unique tags, so that there are few groups, the average number of agents adopting each tag is high, and the groups are larger in size, with the respective norms being more widely adopted, and a reduced likelihood of a tag belonging to a single individual. Conversely, as the number of unique tags (and therefore groups) increases, the average number of agents having adopted each tag (and hence in each group) reduces, so that the corresponding norms are less widely adopted and there is an increased likelihood of a tag being ascribed to a single agent only. Thus, for lower numbers of unique tags there is more significance in them representing groups of agents having adopted those tags as norms. Note that this is an informal notion of norm establishment, in comparison to other approaches that have a group leader [6], or explict strategies emerging rather than simply shared tags [20].

4.1 Context assessment

The base case for our comparisons is RCA's approach which, with a low mutation rate gives a donation rate of 0.204, and with a high mutation rate gives a donation rate of 0.032. The increased dynamism of the environment, represented by the increased mutation rate, has a catastrophic effect on the donation rate, and in turn on group effectiveness. For a donation to occur, agents must share a tag (within their tolerance values). With a low mutation rate, RCA's approach gives an average of 35.8 tags, each shared by 2.8 agents on average. With a high mutation rate, there are 79.2 tags shared by 1.3 agents on average. Thus, with a high mutation rate a large number of tags are adopted by a single agent, as confirmed by the very low donation rate observed (0.032). In relation to norm emergence, this means that in the low mutation case the resulting norms are on average only adopted by 2.8 agents. In the high mutation case the tag groups do not, on average, correspond to norm emergence since less than two agents adopt each tag. It is not our concern in this paper to attempt to define the num-

[2] http://peersim.sourceforge.net/



(a) low mutation

(b) high mutation

Figure 3: Tags with context assessment using low and high mutation rates.

ber of agents needed for norm emergence, but clearly there must be at least two agents involved.

Figure 2 shows the evolution of tags in the population over the duration of a sample simulation run for both low and high mutation settings. Each point represents the presence of a tag in a particular generation, and where a tag persists for several generations the points form a line from the generation in which the tag group is created to the generation in which it collapses. Our numerical results are confirmed by Figure 2 which shows that many more tags are present in the high mutation setting than the low setting. This graphical representation also allows us to observe the formation of norm-based groups. In particular, in the low mutation setting norm-governed groups are established and maintained for many generations, while in the high mutation setting many such groups have very brief durations appearing as points or very short lines. (Note that since the number of unique tags is large in Figure 2(b), many of the points do not represent norm establishment, as discussed above.)

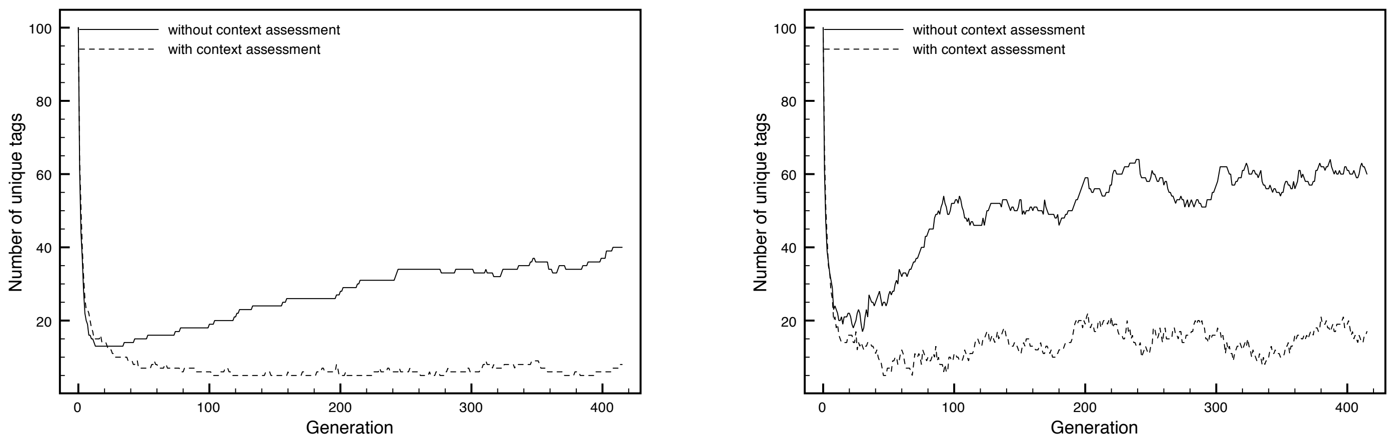
The evolution of tags in the population when using context assessment is shown in Figure 3. Comparing Figures 2 and 3 it is immediately apparent that there are significantly fewer tags present using context assessment than with RCA's approach. On average, context assessment in a low mutation setting results in only 3.7 tags (compared to 35.8 with RCA's approach) and 12.1 tags (compared to 79.2) for a high mutation rate. A donation rate of 0.475 and 0.429 is obtained for the low and high mutation settings respectively (compared to 0.204 and 0.032). The reduction in donation rate in the high mutation setting compared to the low mutation setting is less significant (approximately 10%) than with RCA's approach (where the reduction is approximately 85%). We see this as demonstration that context assessment is more stable in supporting cooperation in dynamic environments than RCA's approach. This tells us that norms resulting from context assessment are more widely adopted than with RCA's approach (by 27 and 8.3 agents on average for the low and high mutation rates respectively). Given that these norms are more widely adopted, we would expect an increase in the group effectiveness (as indicated by donation rate achieved), which is indeed the result we observe.

The evolution of the number of unique tags during a sample simulation run for low and high mutation rates is illustrated in Figure 4. In both settings the number of tags is initially very high and is (approximately) equal to the population size since agents are randomly allocated tags. During the first few generations the number of unique tags drops significantly as agents begin to copy tags from their more successful neighbours. As the simulation progresses the number of unique tags then stabilises. From Figure 4 we can see that in addition to context assessment resulting in significantly fewer tags than RCA's approach, the number of tags also stabilises more quickly. When the mutation rate is high the number of tags increases, as does the extent of the fluctuations over generations (with both approaches having similar fluctuation levels). It is clear that norm-governed groups emerge more quickly using context assessment than with RCA's approach, and on average norms are adopted by many more agents. Due to space constraints we do not discuss the effect of memory length in this paper, but in [10] we have shown that it is not a significant factor.

4.2 Rewiring

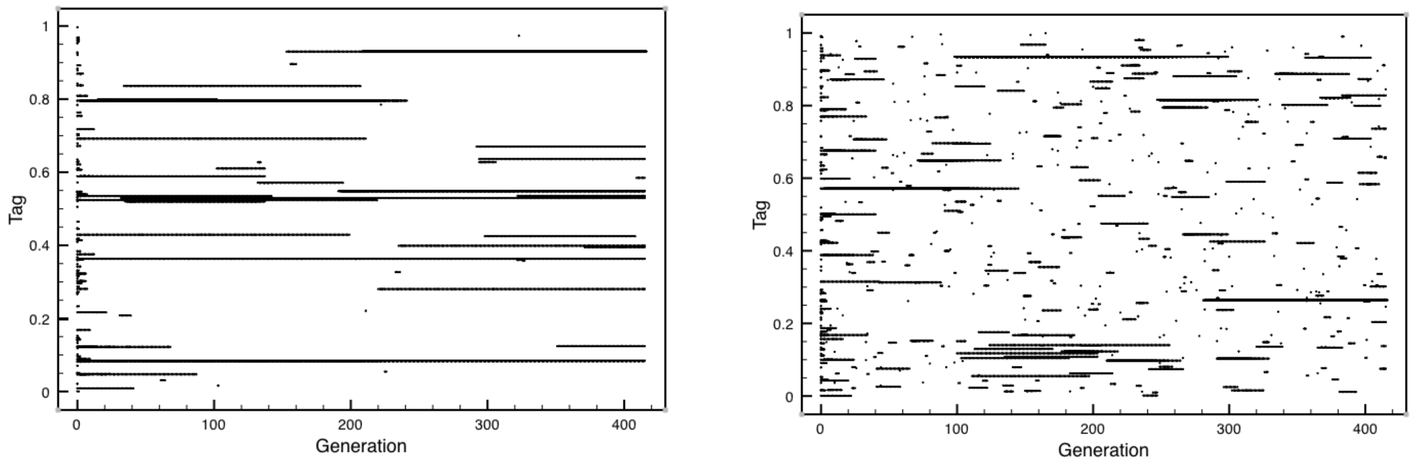
Rewiring gives similar improvements to context assessment, with donation rates of 0.57 and 0.498 for the low and high mutation settings respectively (both of which are higher than with context assessment). The average number of unique tags is higher than for context assessment, with 11.9 and 16.8 for low and high mutation rates, but is significantly lower than with RCA's approach. The norms that are established are adopted by fewer agents using rewiring than with context assessment, 8.4 (rather than 27) and 6.0 (rather than 8.3) for the low and high mutation rates, although by many more agents than with RCA's approach. This result is unexpected, since we intuitively expect that a higher donation rate (and therefore higher group effectiveness) would be achieved when norms are more widely adopted.

The discovery that a higher donation rate can be obtained with smaller groups is potentially very powerful, since in many situations we would like to balance the desire to have widely adopted norms (and few groups) with the desire to ensure that there are several established groups from which agents can select. The widest possible adoption of a norm is where a single norm is adopted by the population in a



(a) low mutation (b) high mutation

Figure 4: Number of unique tags with context assessment using low and high mutation rates.



(a) low mutation (b) high mutation

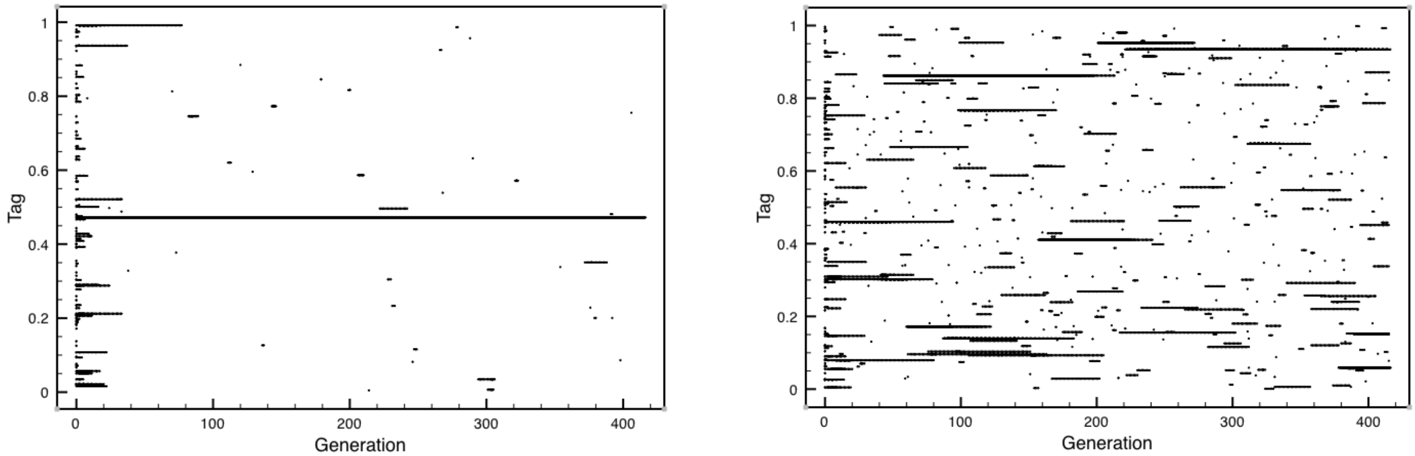
Figure 5: Evolution of tags in a population using rewiring with low and high mutation rates.

single group. Conversely, the largest set of norms is obtained where we have a minimum number of agents per tag for norm emergence, giving groups of that size. As mentioned above, we are not concerned with attempting to define a minimum membership, but clearly more than one agent is required, and so the upper bound of the number of norm-governed groups is half the population size. In the donation scenario the motivation behind balancing the level of adoption and number of norms established is that mutations can cause a norm to collapse at any point, and in such cases we would like agents to be able to adopt an alternative norm by joining another tag group. However, this balance is a general issue in many distributed systems, and corresponds to the general view that fostering competition and avoiding monopolies can be beneficial. The question of how many norms or groups is ideal in a particular setting is an open question, and we see this as a key area of future work.

The evolution of tags in the population using rewiring for sample simulation runs is shown in Figure 5. As is the case with context assessment (Figure 3) there are significantly fewer tags at any point in time than with RCA's approach (Figure 2). As noted above, rewiring results in slightly more tags than context assessment. Figure 5 also allows us to observe that the duration of a given tag group is generally slightly reduced using rewiring in comparison to context assessment, implying that the norms emerging are slightly less long-lived. In the donation scenario this is not a major concern, since there is little cost to changing tag groups, but more generally there may be a higher cost associated with such a change. It is desirable, in general, for norm-governed groups to be of longer duration as we observe with context assessment, but also for there to be a reasonable number of alternative groups as with rewiring.

4.3 Context assessment with rewiring

We have previously shown that combining context assessment and rewiring improves the donation rate [10]. We observe a donation rate of 0.686 and 0.631 for the low and high mutation settings respectively. In terms of norm emergence, a key question is which, if any, of the properties of context assessment (few norms of longer duration) and rewiring (more norms of shorter duration) the combined approach gives. We



(a) low mutation

(b) high mutation

Figure 6: Evolution of tags using context assessment and rewiring with low and high mutation rates.

find that the combined approach results in 4.4 and 10.4 tag groups in the low and high mutation setting, corresponding to adoption by 22.7 and 9.6 agents on average respectively. In the low mutation setting this is similar to context assessment, and we would prefer more norms given our desire to have alternative groups established in case of norm collapse. With a high mutation rate, the number of norms is similar to that obtained with rewiring, indicating that there are alternative groups in the event of a norm collapsing. However, the duration of norms and groups is also important in ensuring that alternatives are available.

Figure 6 shows the evolution of tags using the combination of context assessment and rewiring in sample runs, and we can make two important observations. First, the run for the low mutation rate represents a particularly low number of tag groups, with a single dominant group spanning all generations and a small number of short duration groups appearing. A similar situation can occur when using context assessment alone (although the run in Figure 3 shows an example where this does not occur). We would like to avoid this by ensuring that there are alternative established norms (i.e. tag groups) at any point in time, in case of norm collapse. Second, with a high mutation rate many of the groups established persist for only very short durations. Thus, although there are many groups, avoiding the problem from the low mutation case, we would like them to be of longer duration. It seems, therefore, that while combining context assessment with rewiring increases the donation rate, it does not result in groups that have the desired characteristics. In a low mutation rate we would prefer a higher number of norm-governed groups to ensure alternative groups are established in case of collapse, while with a high mutation rate we would prefer more persistence to avoid frequent collapses.

Context assessment appears to have a significant reduction on the number of norm-governed groups established, especially with a low mutation rate. Although this results in an increased donation rate (indeed, when combined with rewiring it gives the highest donation rate) suggesting group effectiveness, it also gives reduced diversity in the population. In many settings this is undesirable, since if there is collapse of cooperation in those groups due to the collapse of the respective norms, there are no alternative established groups for agents to join.

4.4 Summary of results

Our simulations show that both context assessment and rewiring improve group effectiveness (through donation rate) by the formation of groups of agents sharing a particular tag value, which we can interpret as norm establishment. A summary of the quantitative results is shown in Table 1. In both the low and high mutation settings the highest donation rate is achieved when combining context assessment and rewiring. Rewiring gives the second highest rate, followed by context assessment, and finally RCA's approach. In the low mutation setting context assessment, with and without rewiring, results in a low number of norm-governed groups being established. In the high mutation setting the number of groups established is reduced when context assessment is used in comparison to rewiring alone, but this difference is less significant. A visual analysis of the evolution of tags reveals that norm and group duration is potentially an issue, with each of the techniques discussed resulting in several short duration norm-governed groups being established.

5. DISCUSSION AND CONCLUSIONS

Interpreting the formation of groups of agents sharing a tag as the emergence of norms, allows us to view RCA's approach as facilitating norm emergence. Indeed, it is norm emergence that leads to donations, since only when two or more agents share a tag (within their tolerance) will a donation occur. Our previously proposed techniques of context assessment and rewiring to cope with cheaters [9, 10] also facilitate norm establishment, and this interpretation enables us to explore their operation. The norms and groups that are formed are more widely adopted (with fewer norms) than with RCA's approach. Using context assessment increases adoption, especially in the low mutation setting, however as a result there may not be alternative norm-governed groups available in the event of the collapse of an established norm.

An increase in mutation rate leads to less long lived and less widely adopted norms, so that there are more groups, with fewer members, persisting for less generations. Norms also emerge with many tag groups and few agents per tag, but only few such norms are widely adopted and long lived,

Approach	Mutation rate	Average donation rate	Average number of tags	Average size of tag group
RCA's mechanism	0.001	0.204	35.8	2.8
Context assessment	0.001	0.475	3.7	27
Rewiring	0.001	0.57	11.9	8.4
Context assessment and rewiring	0.001	0.686	4.4	22.7
RCA's mechanism	0.01	0.032	79.2	1.3
Context assessment	0.01	0.429	12.1	8.3
Rewiring	0.01	0.498	16.8	6.0
Context assessment and rewiring	0.01	0.631	10.4	9.6

Table 1: Summary of donation rate, number of tags and size of tag group (number of agents per tag).

as seen in Figures 3, 5 and 6, where there are few long duration groups. This is a key area of future investigation, namely to understand the factors that influence the number and duration of norms, and to investigate whether there is an optimal number of groups in a given configuration.

Using tag-based cooperation to investigate norm emergence allows us to observe the effects of various approaches. In particular, it is through norm establishment (i.e. reducing the number of tags) that context assessment and rewiring improve group effectiveness, and this interpretation may inform improvements to tag-based approaches. Since mutation can cause norm collapse it is important to ensure that there are alternative groups. Context assessment (with or without rewiring) is found to reduce the diversity of tags to a low level, and this suggests that further work is needed on coping with cheaters. There is a complex relationship between the evolution of tag groups, the number of tags, and donation rate, and we will investigate this in future work. In particular we aim to develop mechanisms to ensure norm diversity and prolong norm duration. We also aim to investigate the influence of connection topologies and population size to explore our techniques in more realistic settings.

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