Self Adaptation of Cooperation in Multi-Agent Content Sharing Systems

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Abstract—This paper considers an adaptive data dissemination scenario that applies an autonomic trust protocol to a network of agents. The protocol uses social network structures to incentivize cooperation. Validation is conducted through a Prisoners Dilemma based simulation which uses similarity of interest between peers to define payoff. Positive correlation is observed between the number of social links placed and payoff received by single agents.

Content sharing allows calculation of similarity between agents within a system. Prior interaction history drives the formation of social links between nodes and allows estimation of an individuals cooperation by another. Agents may adaptively change their cooperation levels when forming social relationships by copying those of the most ‘popular’ members of their own social groups. Adaptation mechanisms can be prioritized within communities sharing similar interests.

Self-similarity of interest communities and their initial cooperation levels both have an effect on the self-adaptation of cooperation. The most divergent and least cooperative nodes have fewer opportunities to form new social links, increase their cooperation levels, and consequently increase their payoff.

Self-adaptation results in higher payoff for the population compared to the static scenario in which adaptation of agents cooperation does not occur.

I. INTRODUCTION

Trust and reputation models are widely recognised as effective drivers to incentivise cooperation within networks of agents in several emerging communication systems such as peer-to-peer and mobile ad hoc networks. Cooperative behaviours are then capable of producing the highest outcomes whenever the short-term benefits of selfish strategies are exceeded by the long terms costs and sanctions imposed by the protocols either externally or within the network. Frequent and repeated interaction has been often identified as a sufficient condition for the achievement of equilibrium status of stable cooperation [1].

This paper applies a trust model to a data dissemination scenario between agents sharing some level of interest. The protocol uses social network structures to incentivise cooperation in a network of mobile agents pushing and exchanging specifically tagged resources when they interact. Individuals are characterized by their behaviour (cooperation level) and their preference of interests (interest profiles). Social links of trust are formed to prioritize interaction according to the basic principle that ‘agents seek to interact with others at least as cooperative as themselves’ and they can be dynamically placed and removed based on the history of the payoffs received from other interacting agents (interactional dynamics). Simulation is conducted through a variation of the Prisoners Dilemma game in which payoffs and costs are re-defined according to the ‘similarity of interest’ between peers.

Given the positive correlation between the number of social links placed and utilities received by individuals a self-adaptive mechanism of cooperation is introduced in order to gain more utility and share and receive more resources. This is based on mimicking the behaviour of the most successful agents within a social group by copying the cooperation levels of those forming the highest number of social links (behavioural dynamics).

Self-adaptation results in higher payoff for the most altruistic individuals (and so to the whole population in average) in comparison with the static scenario in which levels of cooperation are fixed. However, the least similar and cooperative elements of the network appear unable to reach the highest levels of cooperation and so to maximise their payoffs when the system converges to a steady state in which the cooperation of each individual remains unchanged.

The rest of the paper is organized as follows. Section II presents an overview of the most significant related literature while Section III and IV describe respectively the static trust protocol and its adaptive mechanism. Section V shows and discusses the results of the experimental tests and, finally, Section VI summarizes the relevant contributions of this work.

II. RELATED WORK

Cooperative behaviours among agents are of fundamental importance in communication systems and lack of cooperation may have destructive effects on network performances [2]. Game Theory have shown that in absence of repeated interactions selfish strategies always outperforms altruistic behaviours [3].

When interactions between agents can be repeated in a period of time one possible way to encourage cooperation is by the introduction of economic models and incentive mechanisms. This is used for example in mobile ad-hoc networks routing schemes in which a cost-price model is used to reward nodes allowing transit through multi-hop paths [2], [4]; and in Peer-to-Peer resource sharing system with often the further addition of punishment mechanisms and sanctions imposed to uncooperative nodes by some
within networks of agents will be the main object of the rest of the model. The combined effects of social similarity can be considered as a further important driver for altruistic behaviors and it has been used as a successful criterion alternative to fitness evaluation for ‘copying’ peers strategies in adaptive mechanisms [13]. Similarity can be established on the basis of simple observable traits being displayed (tags) that in behavioural science literature have also been used to indicate dialects [14]. The combined effects of social similarity and reciprocal altruism on adaptive cooperation mechanisms within networks of agents will be the main object of the rest of this work.

III. STATIC TRUST PROTOCOL

The trust protocol to be applied in static conditions (without any adaptation of agents cooperation) is a variation of the one originally proposed in [15]. This model encourages cooperation between parties by prioritizing interactions within social group of trusts formed among agents of similar cooperation and interactions are modeled as instances of a Prisoners Dilemma (PD) game. The network is given a Graph representation where nodes $v_i$ are agents and edges social links between them. Nodes are characterised by their cooperation level $v_{coop}$ (uniformly randomly selected from the range $[0,1]$) defined as the probability that they chose to cooperate in each single PD session played. Costs and utilities of the original payoff matrix have been adapted to represent a data dissemination scenario in which at every interaction a pair of agents exchange each others specifically tagged resources. The key concepts of the model are outlined in the following, for an extended description of the model see [15].

- **Relationship formation**: The basis for forming relationships is that each individual seeks to interact with a peer that is at least as cooperative as itself. Nodes invite peer agents to form relationships basing on the average payoff $tp_{ij}$ they have received from each of the peers over a recent number of interactions. The invited node will accept the invitation if the corresponding average payoff per interaction is above some threshold, defined as $v_{accept} = v_{coop} \alpha$, where $\alpha \in [0,1]$ is a scaling factor representing how risk averse the node is. Nodes can drop a link whenever the average payoff per interaction (over some time window) falls beneath $v_{accept}$.

- **Peer selection**: A node $v_i$ chooses an opponent to invite using a roulette wheel selection weighted on the payoff that a node $v_j$ has received from his ‘social friends’ $v_{ij}$ over their recent interactions. The probability of selecting an opponent outside of this social group is weighted by the recent payoff produced by all nodes not belonging it. Note that this probability can become significant whenever nodes present social groups of very limited size.

- **Acceptance**: A node $v_i$ agrees to an invitation to play from $v_j$ if and only if $v_i$’s recent history of interaction with $v_j$ has yielded a non-negative payoff (with a small probability of forgiving a node giving negative payoff).

A. Interest Profiles and Communities

Each agent stores a set of $M$ ‘tags’ representing its preference of interests, defined as its own ‘interest profile’ $F_i^m$ (for $1 \leq m \leq M$). These are normalised so that $\sum_{m=1}^{M} F_i^m = 1$. Relative interest values are defined according to Zipf’s law [16], reflecting a global probability distribution of a real web application and individual agents are assigned a permutation of these values, thus partitioning them into a number of ‘interest communities’ $V_1, \ldots, V_N$. Hence all individuals belonging to a specific community share the same profile of interests.

$$F_i^m = F_i^m for i,j \in V_k, 1 \leq k \leq N$$

The relative interest value is used as a probability weighting that a particular interest (tag) is pushed to the currently connected agent during a pairwise interaction. Each interaction between nodes $i$ and $j$ is simulated by a PD session in which the payoff accrued is defined as:
Cooperate

A maximum payoff \( mp \) is calculated over all pairs of nodes and is used to normalise the payoff received. This allows comparison with previous experiments that applied the same model to an abstract Prisoner’s Dilemma simulation representing a pure resource sharing scenario in which all agents shared the same tags distribution as their own interest profiles (see [15]).

\[
mp = \max_{v_i, v_j \in V; i \neq j} U'_{ij} \\
U_{ij} = \frac{2U'_{ij}}{mp}
\]

The payoff table used in the PD game is given in Table I. If an agent chooses to cooperate it pushes one of its carried resources to the currently connected node and, consequently, a cost \( C \) is incurred. Again to allow direct equivalence with the original PD payoff matrix this cost is defined as \( C = \frac{mp}{2} \).

There is no cost incurred by a defecting agent who pushes no content. If the cost of cooperation is positive (\( C > 0 \)) then a node’s best strategy is to defect, as this maximises the payoff received regardless to the particular strategy chosen by its opponent. However, as long as individuals share sufficient common interests (\( U_{ij} - C > 0 \)), the total utility is maximised when they pairwise cooperate. Pseudocode of the model is shown in Algorithm 1.

**Algorithm 1** Simulation Pseudo-code for the model

```
Initialize parameters
for numIterations do
    for v_i = 1 to n_v do
        v_i removes any neighbour v_j s.that tpij/m < v_i^accept
        node v_i select a player, say v_j possibly from its social network
        node v_j decides whether to play with v_i
        if v_j decides to play then
            v_i and v_j select their PD strategy according to v^coop
            payoffs for v_i and v_j calculated according to the modified PD payoff matrix (Table I).
            tpij, tpij updated
        end if
        if (v_i^invite < tpij/m) ∧ (tpij/m > v_j^accept) then
            v_i and v_j form a relationship
        else
            if (v_j^invite < tpij/m) ∧ (tpij/m > v_i^accept) then
                v_i and v_j form a relationship
            end if
        end if
    end for
end for
```

**C. Model Performance**

In our simulations we adopt the parameter settings that in [15] showed the best performance. Namely we consider a population of 100 agents; a memoriespan \( m \) size of 10 for storing past payoffs received for each pairs of nodes; a ‘risk factor’ \( \alpha \) of 0.7; a forgiving probability of 0.05; and an initialization period of 50 time-steps before the protocol is actually applied.

In addition agents are now assigned a specific distribution of interests (tags) thus partitioning them into a number of ‘interest communities’ (five to ten in our experiments). Table II shows an example of the interest profiles for five ‘interest communities’, each having a different permutation of a global interest Zipf distribution with four tags, and Table III the corresponding divergence values between communities pairs.

<table>
<thead>
<tr>
<th>node s</th>
<th>node j</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooperate</td>
<td>0,0</td>
</tr>
<tr>
<td>Defect</td>
<td>0,0</td>
</tr>
</tbody>
</table>

Table I

PD PAYOFF TABLE

**B. Divergence Metric**

In common with other content dissemination studies (e.g. [17]), we quantify the similarity of the interests of node \( v_j \) to those of \( v_i \) using the Kullback Leibler divergence [18]:

\[
D_{i,j} = \sum_{m=1}^{M} F_{m}^{i} \log \frac{F_{m}^{i}}{F_{m}^{j}}
\]

Divergence of 0 means nodes \( v_i \) and \( v_j \) have identical interest distributions. A divergence of 1 means the interests are completely different.

<table>
<thead>
<tr>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1</td>
<td>0.48</td>
<td>0.24</td>
<td>0.16</td>
</tr>
<tr>
<td>V2</td>
<td>0.12</td>
<td>0.16</td>
<td>0.24</td>
</tr>
<tr>
<td>V3</td>
<td>0.12</td>
<td>0.16</td>
<td>0.48</td>
</tr>
<tr>
<td>V4</td>
<td>0.12</td>
<td>0.24</td>
<td>0.16</td>
</tr>
<tr>
<td>V5</td>
<td>0.12</td>
<td>0.24</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Table II

DISTRIBUTION OF INTERESTS FOR 4 INTERESTS AND 5 COMMUNITIES

When all nodes share a common set of interests and in the absence of a specific protocol during the IPD the selfish strategy is best, with the defective nodes gaining the highest utility at the expense of the most cooperative individuals. 
This is shown in the Enforced Cooperation curve in Figure 1 when the selection of pairs is conducted at random and nodes are enforced to play a game session at each interaction. When the PD sessions are played following the protocol described here, this tendency is reversed, with the most cooperative nodes receiving the highest payoffs, as shown in Figure 1, displaying the result for the network agents grouped by distinct communities: we can see for the most of the population a positive correlation between the payoff per iteration and the cooperation level.

However, for one community, which results to be the most 'divergent' (see Table III) the nodes have achieved much lower payoff per iteration. In fact, the partitioning of the network into distinct interest communities has an effect on the formation of the social links, which are used by the protocol as a driver for cooperative interactions. Interacting with a node with a significantly different interest profile (i.e. belonging to a 'divergent' interest community) produces far less benefit than interacting with those belonging to a node’s own community. Agents are therefore less willing to make social links with nodes from outside their community. This is shown in Figure 2, which shows the correlation between the number of links between each pair of communities (per iteration) against the divergence of them. The plot clearly shows that the more divergent a pair of communities, the fewer links are formed. This will also have a (negative) effect on the payoffs received during the simulation, as discussed in the next sections.

### Table III

<table>
<thead>
<tr>
<th>Interest Community 1</th>
<th>Interest Community 2</th>
<th>Interest Community 3</th>
<th>Interest Community 4</th>
<th>Interest Community 5</th>
<th>All Communities (Enforced Cooperation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1</td>
<td>0.531</td>
<td>0.483</td>
<td>0.499</td>
<td>0.431</td>
<td>0.5</td>
</tr>
<tr>
<td>V2</td>
<td>0.531</td>
<td>0.166</td>
<td>0.032</td>
<td>0.275</td>
<td>0.0001</td>
</tr>
<tr>
<td>V3</td>
<td>0.483</td>
<td>0.166</td>
<td>0.032</td>
<td>0.275</td>
<td>0.0001</td>
</tr>
<tr>
<td>V4</td>
<td>0.499</td>
<td>0.032</td>
<td>0.275</td>
<td>0.032</td>
<td>0.0001</td>
</tr>
<tr>
<td>V5</td>
<td>0.431</td>
<td>0.275</td>
<td>0.032</td>
<td>0.351</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

**Figure 1.** Cooperation against Payoff per Iteration with 5 Communities composed of 4 Interests

**Figure 2.** Average Number of Social Links between Interest Communities (per Iteration) against Communities Divergence

### IV. Estimating Cooperation and Similarity

The social popularity of an individual node can be used as a driver for self-adaptation of cooperation. A node *i* when interacting with another node *j* may see *j* as more successful if it has more neighbours in its social group. *i* may then copy the cooperation of *j* in order to increase its own popularity, and by doing so hope to increase the amount of payoff received per iteration.

Node *i* can obtain an estimate of the cooperation level of node *j* by retaining a memory of the last *n* interactions with node *j*. Counting the number of times *j* has cooperated with *i*, (*tc*<sub>j</sub>) and dividing by the number of interactions gives an approximate level for the cooperation of *j*, coop<sub>j</sub>:

\[
\text{coop}_j = \frac{tc_j}{n}
\]

The number of interactions stored in memory has an obvious effect on the accuracy of the cooperation estimate. By comparing one node’s estimates of cooperation for all other nodes with their actual cooperation values, we can obtain a variance figure over all nodes which gives a measure of the accuracy of each nodes cooperation estimates.

Figure 3 shows this variance over all nodes for different sizes of memory. Increasing the memory from 10 interactions to 20 interactions gives a large increase in accuracy. A further doubling of memory size does not result in a similar increase in accuracy. 20 interactions is therefore chosen as the value for the interaction memory for cooperation estimates, representing a tradeoff between cooperation estimate accuracy and memory use in each node.

The similarity of one nodes relative interest distribution to another can be estimated by recording the values received
from that node over multiple interactions. If node \(i\) chooses to cooperate during a PD game, it will push one of its interest tags with a probability based on the relative interest value \((F^R_{im})\) for that tag. Node \(j\), recording the frequency with which each tag is received from node \(i\), is therefore able to estimate the distribution of relative interests for that node.

Using this estimate of interest distribution allows node \(j\) to estimate the payoff \(U^*_{ij}\) received from interacting with node \(i\). A similarity estimate can then be calculated as

\[
S_{ij} = \left| 1 - \frac{U^*_{ij}}{U^*_{jj}} \right|
\]

A value close to 0 means that \(i\) and \(j\) are similar. As the nodes interests distributions become more divergent, \(S_{ij}\) gets larger. The number of received interests that are remembered by the node has an effect on the nodes ability to correctly estimate the similarity. Storing all interests received for every node would give a better similarity estimate, but require a larger memory usage.

If a population contains just 1 interest community, the similarity for all nodes should be 0, as they all share an interest distribution. Variance of a nodes similarity estimates for all other nodes gives us a measure of how accurate the similarity estimates are. The variance of the similarity estimates for different sizes of memory are shown in Figure 4. A value of 20 remembered interests is used for the interest memory based on the results shown.

The accuracy of the similarity estimate is also affected by the number of interest tags in an interest community. Figure 5 shows the similarity estimate variance for different numbers of tags; the fewer interests there are the easier it is to estimate correctly the interest distribution of another node. 4 interests presents a tradeoff between the accuracy of the similarity estimate and the number of permutations of relative interest values possible (and therefore the number of different interest communities that can be formed in one population).

V. EXPERIMENTAL RESULTS

For all experiments we carry out five simulations using the parameters in Section III with the same population of nodes, and present average results from the five simulations.

A. Copy from All

We first consider the case where a node may self-adapt its own cooperation level by copying the cooperation level of any other node with which it interacts that has a higher social popularity than itself; the 'Copy from All' scenario.

Observing the average cooperation level of a population at each iteration of the simulation gives an indication of the performance of the self-adaptation mechanism. As one node interacts with a peer with a higher social popularity, it estimates the peers cooperation level, and self-adapts to use this estimate as its own cooperation level. In general the
more socially popular nodes are those which are more co-operative, so this new cooperation will typically be a higher value than the current cooperation level. This raises the average cooperation of the population as a whole, as shown in Figure 6. It can be seen that the average cooperation of the population converges to a particular level within a few hundred iterations.

![Figure 6. Average Cooperation over all Nodes](image)

As the number of interest communities is increased, the level to which the average cooperation converges is reduced. An increased number of interest communities results in a decrease in the number of links between communities. Nodes within these communities will therefore have fewer social links, and so fewer opportunities to adapt their cooperation as they will only self-adapt when they interact with a node that is more socially popular. Nodes are unable to create large numbers of links between different interest communities so their social networks are restricted and fewer nodes are judged to be more popular. Populations converge on a lower average cooperation, as fewer nodes are able to self-adapt.

Examining the self-adaptation of nodes within each interest community reveals a link between the divergence of a community, its initial average cooperation, the rate at which it converges and the level to which it converges. Figure 7 shows the average cooperation for each of the five interest communities, and it is clear that the most divergent community, (Community 1) in which the nodes are not as able to self-adapt their cooperation to as high a level as the others, clearly cannot form as many social links, the average number of neighbours is far fewer than for the less divergent groups.

![Figure 7. Average Cooperation over all Nodes, 5 Interest Communities](image)

The effect the divergence of the communities and the adaptation of their cooperation has on the social links that can form between nodes can be seen by examining how the average number of neighbours changes as the simulation progresses in Figure 8. This shows the average number of neighbours for each interest community, sampled at intervals of 20 iterations. The most divergent community, (Community 1) in which the nodes are not as able to self-adapt their cooperation to as high a level as the others, clearly cannot form as many social links, the average number of neighbours is far fewer than for the less divergent groups.

![Figure 8. Average Neighbours over all Nodes, 5 Interest Communities](image)

These effects of divergence and self-adaptation result in a far lower average payoff per iteration for the population of nodes in interest community 1, as seen in Figure 9. The more similar groups have a high level of average payoff per iteration, as they are able to interact more freely between groups, with other nodes with higher cooperation levels and so have more chances of successful cooperative interactions.
As the nodes in community 1 are not able to make these social links, they have fewer opportunities to interact with highly cooperative nodes, so the communities average payoff per iteration is smaller.

However, examining the average number of neighbours against the average payoff received per iteration (Figure 10) for individual nodes at a particular iteration of the simulation (iteration 1000) shows that while the nodes in Community 1 are more divergent than those in communities 2-5 and fail to make as many social links, some are still able to achieve a fairly high payoff per iteration. This result is not seen in simulations with no adaptive cooperation (see Figure 1 where even the most cooperative nodes of interest community 1 still have a much lower payoff per iteration than nodes in the other communities), suggesting that the self-adaptation of cooperation has had a positive effect on the payoff per iteration for some of the nodes, even though the community has not raised its average cooperation as far as the others.

This result is shown in detail in Figure 11, showing payoff vs cooperation at iteration 1000, where the nodes of interest community 1 have been highlighted. This shows that those nodes in community 1 that have managed to self-adapt and raise their cooperation have a similar level of average payoff per iteration to their peers in other interest communities. The significant result for the group is that far fewer of the nodes within the community have managed to carry out this adaptation. Community 1 still has 11 nodes with a cooperation of less than 0.8, while the other communities have far fewer nodes less than this level (0-5 nodes per community).

B. Copy on Self-Similarity

When carrying out self-adaptation, a node may not wish to copy cooperation from every node it meets. Rather, it may only wish to copy those nodes that are more socially popular and similar to itself, the ‘copy on self-similarity’ scenario. In this scenario the probability that a node will copy the cooperation of a more popular peer is equal to 1 – \( S_{ij} \). So, when node \( j \) is estimated to have exactly the same interest distribution as node \( i \), the probability that node \( i \) will copy the cooperation of \( j \) is 1, as the similarity decreases so does the probability of copying the cooperation.

We see from the results in Figure 12 that the overall results have only been marginally affected by this new restriction on self-adaptation. The level of convergence for each population has shifted to a lower value than previously, but the same result is seen that more interest communities in the population results in a lower level of convergence for the population; due to the fact that fewer nodes are able to self-adapt to a high level of cooperation.

We can examine the effect on the separate communities in the case with 5 communities in Figure 13, and see that communities 2-5 converge to a lower level of average cooperation than previously, while community 1 converges...
to a slightly higher level. When copying cooperation from all other nodes is permitted, the nodes in communities 2-5 are able to copy cooperation across the (implied) boundaries of interest communities. In this scenario (copying only from similar nodes) there is a lower chance of this happening, as while the communities are similar they are not exactly the same, having some level of divergence. The probability of copying a cooperation level between interest communities in a given interaction is therefore less than 1. This results in individual nodes having fewer opportunities to self-adapt, lowering the level to which overall cooperation adaptation occurs.

Examining the average payoff per iteration in Figure 14 shows that this slight decrease in the average level of cooperation for communities 2-5 is accompanied by a slight decrease in the average payoff per iteration. The slight increase in average cooperation for community 1 is accompanied by a slight rise in the average payoff per iteration, as might be expected.

C. Initial Cooperation

In order to examine the effect of the initial values of cooperation on the results of the simulation, we now examine the same population of nodes but change the assignment of interest distributions to nodes. The community with the highest average cooperation at the beginning of the simulation is now assigned the most divergent interest distribution. This simulation is carried out using the ‘copy on self-similarity’ rule for adaptive cooperation.

Figure 15 shows the most divergent community (Interest Community 1) now has the highest average cooperation at the start of the simulation, and achieves a much higher level of average cooperation than previously. The lowest average cooperation at the beginning of the simulation is now found in Community 5. The divergence of this community from the others is fairly low, so even though the average cooperation of the group begins low, the nodes manage to self-adapt to a much higher level than when they had a very divergent interest profile. It is worth noting that the level of cooperation remains lower than the other interest communities and compared to Figure 13, most communities have reached a lower level of average cooperation than previously.

These results demonstrate that the initial cooperation level of the interest communities has a large effect on the ability of the nodes to self-adapt; especially so in the case of very divergent communities.

D. Divergence

The previous simulations involved interest communities that were similar, with the exception of one community which had a very divergent interest distribution from the others. These cases do not reveal what happens when the communities are all very divergent or all similar. It is clear that the divergence of interest communities has an
We define two sets of interest communities: \( L_1, \ldots, L_3 \) with relative interests as in Table IV, where the distributions are very divergent (Table V) and \( S_1, \ldots, S_3 \) with relative interests as in Table VI where the distributions have a small divergence (Table VII).

<table>
<thead>
<tr>
<th>( L_1 )</th>
<th>( L_2 )</th>
<th>( L_3 )</th>
<th>( F^1 )</th>
<th>( F^2 )</th>
<th>( F^3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.48</td>
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<td>0.16</td>
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<td>0.24</td>
<td>0.12</td>
<td>0.48</td>
<td>0.16</td>
<td>0.24</td>
</tr>
</tbody>
</table>

**Table IV**

3 GROUPS, 4 INTERESTS, LARGE DIVERGENCE

<table>
<thead>
<tr>
<th>( L_1 )</th>
<th>( L_2 )</th>
<th>( L_3 )</th>
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<tbody>
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<tr>
<td>0.431065</td>
<td>0.431065</td>
<td>0</td>
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</tbody>
</table>

**Table V**

LARGE DIVERGENCE

The effect this difference has on the average payoff received for each population is shown in Figure 17. A clear correlation is seen between the levels of cooperation to which the population self-adapts, and the average payoff received per iteration. Results are also included showing the average payoff per iteration for the whole population when no self-adaptation occurs, and it is clear to see that both self-adaptation methods (copy from all and copy from similar) result in a higher average payoff per iteration for the whole population. The overall pattern of greater divergence resulting in less payoff holds true for all cases.

**VI. CONCLUSION**

Self-adaptation mechanisms that promote modification of cooperation values based on social popularity allow the population as a whole to receive more payoff than in a system where no self-adaptation occurs. The trust protocol used in this work results in higher cooperation nodes obtaining more payoff; self-adaptation increases the average cooperation levels of a population by increasing the number of these high cooperation nodes, thus increasing the payoff obtained by the population as a whole.
The value of cooperation to which populations converge is affected by the initial cooperation values of nodes, the divergence of interest communities and the distribution of cooperative/uncoooperative nodes within those communities. Very divergent nodes are less able to make social links with other nodes and are less able to increase their cooperation as they are constrained to interacting within their interest community. A low average cooperation for a divergent community makes this effect worse, as there are fewer high cooperation peers for a low cooperation node to copy cooperation from.

However, some very divergent nodes are still able to adapt their cooperation enough to improve their average payoff above the value they would receive if no self-adaptation occurred. An increase in the number of high cooperation nodes within an interest community increases the chances of another high cooperation node being able to interact, form social links and receive payoff.

A ‘copy on self-similarity’ scenario restricts the ability of nodes to self-adapt, resulting in a lower level of average cooperation for a population than if nodes are able to ‘copy from all’. This lower level of average cooperation translates into a lower level of average payoff.

REFERENCES


