Comparing Different Modes of Horizontal Information Transmission in Stabilizing Cooperation in Different Complex Networks

Ivette C. Martínez
Universidad Simón Bolívar
Grupo de Inteligencia Artificial
Caracas, Venezuela
martinez@gia.usb.ve

Klaus Jaffe
Universidad Simón Bolívar
Laboratorio de Comportamiento
Caracas, Venezuela
kjaffe@usb.ve

ABSTRACT

An Agent Based Model was used to explore the effects of spatial social networks and of different means of horizontal information transmission over cooperation when groups provide protection against predation. We tested two ways to calculate transition probabilities governing the information diffusion of the majority's opinion: using fixed rates and using a rate proportional to group' sizes. This exploration was done by observing three fixed rates for the effectiveness of information diffusion of the majority's opinion. Our results show that spatial structures affect the cooperation dynamics. Particularly in Small World Networks, cooperation is more sensible to information transmission. The type of horizontal information transmission is less important as long as over 50% of individuals follow the majority rule.

Categories and Subject Descriptors

I.6 [**Simulation and Modeling**]: Applications

General Terms

Design, Experimentation

Keywords

Cooperation, Selfish Herd, Complex Networks, Spatial Effects, Horizontal Information Transmission

1. INTRODUCTION

Biologists, economists, computer scientists and physicists have all worked to further our understanding of human and animal cooperation. Yet different premises underlay these efforts. The main difference among them is the assumption that social behavior arrived through biological evolution among animals, and that culture and rational decision-making is a principal driver of the evolution of cooperation and sociality among humans [23]. Human cooperation seems to be molded by both, cultural and biological forces [13]. Using theories for biological evolution has provided a fertile ground to study the dynamics of processes governed by cultural evolution, such as human cooperation [8] and economics [17]

There exist important differences between the dynamics of cultural evolution [23] and biological evolution [19]. Although both processes are often mixed up and lumped together when studying the evolution of cooperation, as done in [20]. One important feature differentiating systems driven by biological (BE) and cultural evolution (CE) is the direction of information's transmission. The transmission of information in BE is vertical (heredity), and that in CE is horizontal (imitation of behavior). This feature affects the pattern and the speed of information transmission, and is sufficient to explain important differences in the dynamics between both types of evolution [12].

Several mechanisms have been proposed to explain the emergence and maintenance of cooperation in biological terms. Hamilton [6] explains cooperation between relatives through "kin selection"; in wich donor and recipient of a cooperative action are genetic relatives. Between the mechanisms that have been proposed to explain cooperation between unrelated individuals we have: Direct reciprocity [1, 24], indirect reciprocity [18], altruistic punishment [5] and direct economics forces favoring cooperative groups [14].

The study of the effects of spatiality over cooperation was introduced by Nowak and May [21]. They showed how cooperation could emerge in a population of strategies without memory when individual's relations conform a spatial structure. After Nowak and May's work, cooperation by individuals occupying spatial positions in lattices or networks that interact with their neighbors has been studied for the prisoner dilemma by several authors [9, 10, 16, 22]. They showed that structured populations help cooperation to evolve and maintain under certain conditions.

In this work we want to explore the effects of spatiality and the intensity of the horizontal information transmission over cooperation dynamics. To do so, we modify a one-dimensional spatial model proposed by Cipriani and Jaffe [3] in order to incorporate different spatial structures in the form of complex networks. Our model is based on the well-known "selfish herd" concept [7] and assume that cultural and biological dynamics are driven by natural selection of the phenotypes. This model allows us to study the differences between the dynamics of cooperative, group-forming individuals subject to a selective pressure (predation).

2. THE MODEL

We construct an agent-based model for the study of cooperation dynamics based on Hamilton's "selfish herd" [7]. The model simulates a population of interacting individuals with different social roles and different information transmission directions in environments with different spatial structure.

This model was initially proposed by Cipriani and Jaffe [3] using a cellular automaton. In this formulation, the "selfish herd" is implemented by means of the importance of group formation. In particular, group formation provides protection against predation.

Spatial structures (that represent spatial relations or contact between individuals) are modeled using graphs. The vertexes of these graphs can be occupied by individuals of any species or be empty. The phenotype of an individual determines its role: cooperators and non-cooperators. The neighbors of an individual in the graph form the group of this individual. These graphs are initially empty and are created at the beginning of the simulations, through the $createWorld()$ function, as shown in Algorithm 1. The structure of the graph remains fixed throughout the simulation execution.

Algorithm 1 Main simulation cycle

$createWorld(worldSize)$
$populateWorld()$
for $t = 0$ to $numIterations$ **do**
  for each $agent$ **do**
    $agentStep()$
  end for
  $reapDeadAgents()$
  $repopulateWorld()$
end for

Initial population is created using $populateWorld()$. This function fills each vertex with an agent, and the probability for each agent to belongs to each specie, cooperators or non-cooperators is given by the parameters $p_{co}Ini$ y $p_{nCo}Ini$ respectively.

The procedure $agentStep()$, see Algorithm 2, implements the main activities of the agents: horizontal information transmission (in the form of imitation), and selective pressures (in the form of predation). We will detailed this procedure on the next paragraphs.

The $reapAgents()$ procedure is in charge of removing dead agents from the world. Re-population, detailed in Algorithm 3, is done filling empty world' spaces (graph's vertexes) using the initial proportion of each individual's kind.

Algorithm 2 agentStep

$neigh \leftarrow getMyNeighbors()$
$nNeighs \leftarrow count(neights)$
$nNeighCoops \leftarrow countCooperators(neigh)$
$dead \leftarrow predate(nNeigCoops)$
if not dead **then**
  $naturalMortality()$
end if
if not dead and CT **then**
  $applyMajorityRule()$
end if

Now we will describe the $agentStep()$, Algorithm 2 procedure in more detail. The function $getMyNeighbors()$ obtains the direct neighbors of the agent, then we count the cooperators. When a cooperator agent is inside a group of cooperators (two or more of their neighbors are cooperators) it receive a protection against predations, i.e., its predation probability is set to pCo, while the predation probability for "isolated" cooperator agents ($pCo0n$) and no-cooperators agents ($pNCo$) are bigger.

Then, if the agent is still alive we checked if it should not be dead by natural reasons, as aging. This check is done for all kinds of agents but the $mortalityRate$ could be different between cooperators and non-cooperators. This difference allows establishing the "cooperation cost", by making the $mortalityRate$ of non-cooperators zero, and the giving to cooperators a $mortalityRate$ equals to the desired cooperation cost.

The majority rule is implemented here to simulate the horizontal information transmission (H). It assumes that individuals had a given probability pT of imitating the behavior of their neighbors. The majority rule used in our model uses the simple majority concept. If strictly more than half of the neighbors of an agent are of a different kind, this agent changes its behavior (cooperate or not) with probability pT.

Algorithm 3 World Repopulate

$p_{co} \leftarrow p_{co}Ini$ //initial proportion of cooperators
$p_{nCo} \leftarrow p_{nCo}Ini$ // initial proportion of non cooperators
for each empty $node$ **do**
  create a new $agent$ on $node$, cooperator with probability p_{co} or non cooperator with probability p_{nCo}
end for

3. EXPERIMENTS

We made the implementation of the proposed model in C++. This implementation allows structured environment for populations, in the form of complex networks, implemented as bi-bidirectional graphs. Simulations were done over populations of 10^4 individuals during 10^2 iterations.

At the beginning of simulations the graphs' vertexes were populated by cooperators and non-cooperator, using a probability of 0.5 for each. For non-cooperators and alone cooperators the rates for predation were $pNCo = 0.8$ and $pCo0n = 0.8$. For cooperators in groups the predation rate was $pGCo = 0.2$. The mortality rate, used modeling the cost of cooperation was 0 for non-cooperators and variable (into each experiment series) for cooperators. For all simulations the "fitness differential" was 0.6. The "Fitness differential" is the difference between the predation rate of isolated individuals and that for cooperators being part of a group of cooperators.

For each one of the spatial structures studied (Grids 2D, Random Graphs[4], Small-World Networks[25] and Scale Free Networks[2]) we considered two modes of horizontal information transmission: one using fixed rates (using three different rates: $pT \in \{0, 0.5, 1\}$) and one where transmission rate is proportional to the amount of neighbors of different kind. The three fixed rates plus the proportional rate gave us four scenarios of horizontal transmission.

In all scenarios production of new agents for was uniform (50/50), and the rate pT determined the probability an agent would imitate the behavior (cooperate or not) of the majority of its neighbors.

Our experiments consisted in 4 series of simulations, corresponding to the described scenarios, over each specific spatial structure. In each series (21 simulations) we varied the cost of cooperation (mortality rate of cooperators) in steps of 0.05, to cover the interval between 0 and 1. Each experiment was run 20 times to get the average of data.

For each network we set its parameters to get the same mean degree. We choose mean degree 4 in order to make a "fair" comparison between networks and with 2D grids. These parameters are presented in Table 1.

Graph	Parameter's names and values
Random Graph	size = 10000 edge probabilty = 0.0002
Small World Graph	size = 10000 connections by direction = 2 rewiring probability = 0.01
Scale Free Network	size = 10000 m = 2

Table 1: Networks' parameters.

Each network structure possess a set of statistical properties that allow explain their behavior. Even though significant properties are still been developed, the most studied are: the mean geodesic path, the clustering coefficient, the degree distribution, the network resilience, the mixing patterns, the degree correlations and the community structure[15].

Graph	mean degree	degree' SD	average path length
2D Grid	4	0	50
Random Graph	3.99	1.99	6.64
Small World Graph	4	0	1250
Scale Free Network	3.99	6.88	30615

Table 2: Grids and network properties' values.

In table 2 we present the values of some of these properties for studied networks. Degree related values were taken from our networks, while the average path length for complex networks was calculated using equations from [15]. We also checked that degree distributions correspond to theoretical predictions.

4. RESULTS

The results of our experiments are shown in Figure 1 and Figure 2, where each sub-figure summarizes the results from simulations of a particular complex network structure: Grid 2D (Fig.1), Random Graphs (Fig.2(a)), Small World Networks (Fig. 2(b)) and Scale Free Networks (figure 2(c)). These figures show the final proportion of cooperators for each scenario under various cooperation costs. In all the spatial structures and all the scenarios the proportion of cooperators decreases monotonically as cooperation cost (cc) increments. Also, cooperators are the majority of the population in most circumstances.

In Grids 2D (Fig. 1, used as control spatial structures, there is an small difference between $pT = 0$,$pT = 0.5$, and $pT = proportional$. In populations with $pT = 1$, with individuals that always change their behavior by imitation of the behavior of the majority of their neighbors, the final fraction of cooperators is up to 20% less than the proportion of cooperators for the other scenarios. As the cooperation cost increases, this tendency is reduced, changing to the opposite at the point $cc = 0.8$. This point is the predation rate for non-cooperators and isolated cooperators. In this spatial structure the $pT = proportional$ curve is stick to the $pT = 0.5$ curve for cooperation costs below 0.8, and it is stick to $pT = 1$ for cooperation costs above 0.8.

In Random Graphs (Fig. 2(a)) curves for $pT = 0.5$ and $pT = 0$ have the same shape that $pT = 0$, but there is a difference of at most 15% between $pT = 0$ and $pT = 1$, being $pT = 1$ below $pT = 0$. The $pT = 0.5$ curve have separation from the $pT = 0$ curve is less than a 3%.

For Small World Graphs (Fig. 2(b)) all curves have the same shape, but $pT = 1$ is up to 50% below the $pT = 0$ curve; and the $pT = 0.5$ curve up to 15% below the $pT = 0$ curve. This network shows the biggest differences between the different information transmission rates.

The Scale Free Networks curves follow the same shapes than the 2-D grids, with smaller differences between pTs values.

Is interesting to note that when $pT = 0$, the curves show no differences between all the spatial structures studied; and that when $pT = 0.5$ is very similar to $pT = proportional$. Large values of pT ($pT = 1$) provide the largest reduction of cooperators, especially in Small World Graphs.

5. DISCUSSION

The first feature that strikes us is that horizontal transmission of information has a negative effect on the amount of cooperators that survive the evolutionary dynamics unless the cost for cooperation is very high. This result is due to the fact that the cooperative strategy is more susceptible to invasion by the opposite strategy than the non-cooperative one. A lack of communication or horizontal transmission of information favors groups of cooperators, benefiting from each others neighborhood, who are then less likely to be disrupted by non-cooperators

The results show that some spatial networks but not all affect the effect of information transmission on cooperation dynamics. The largest effect was seen in Small World Graphs, which happen to be the networks with the lowest variance in the degree of connectivity of the nodes. The effect on the evolutionary dynamics of Random Graphs and Scale Free Networks was similar. This result makes us wonder what characteristic of Small World Graph produces this difference. As with the result discussed above, a more homogeneous network makes it less likely that isolated groups of cooperators benefit from each other neighborhood. Thus the low variance in connectivity of Small World Graphs makes them less prone to nurture groups of cooperators.

These results confirm that the spatial structure affects the cooperation dynamics under horizontal information transmission. Despite this susceptibility, however, it is curious

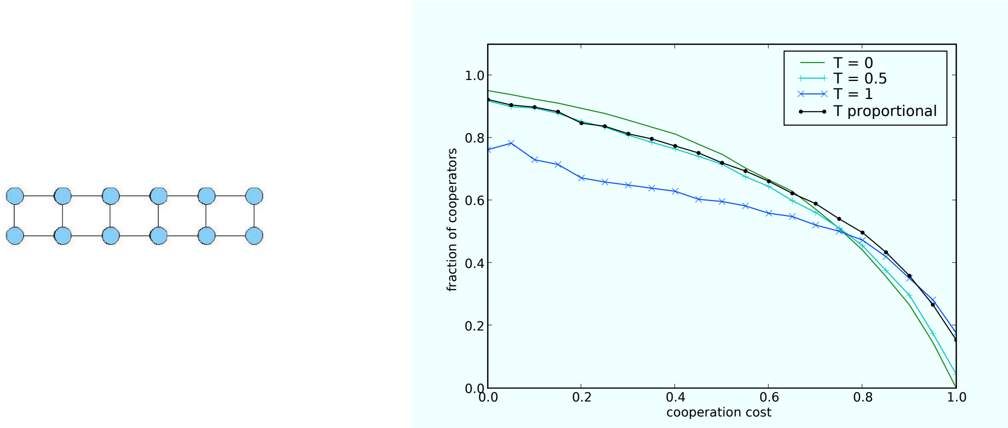


Figure 1: Effects of horizontal information transmission is stabilizing cooperation on grids 2D. Final fraction of cooperators in simulations with different costs for cooperation (x axis) and with different kinds of horizontal transmission of information (pT). On the left side of each sub-figure we present a graphical representation of the subjacent spatial structure.

to note that the type of transmission of information modeled did not seem to affect the outcome. That is, simulations with $pT = 0.5$ were undistinguishable from those with $pT = proportional$. This indicates that flexibility, or the lack of it, in implementing the majority rule has no effect on the evolutionary dynamics of cooperation. This result unveils an additional resilience for the evolution of cooperation.

6. REFERENCES

[1] R. Axelrod and W. Hamilton. The evolution of cooperation. *Science*, 211:1390–1396, 1981.

[2] A.-L. Barabási and R. Albert. Emergence of scaling in random networks. *Science*, 286:509–512, 1999.

[3] R. Cipriani and K. Jaffe. On the dynamics of grouping. In *Proceedings of the Fifth IASTED International Conference on Modelling, Simulation and Optimization*, pages 56–60. Acta Press, 2005.

[4] P. Erdös and A. Rényi. On random graphs. *Publicationes Mathematicae*, 6:290–297, 1959.

[5] E. Fehr and S. Gachter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

[6] W. Hamilton. The genetic evolution of social behaviour. papers i and ii. *Journal of Theoretical Biology*, 7:1–16, 17–52, 1964.

[7] W. Hamilton. Geometry for the selfish herd. *Journal of Theoretical Biology*, 31:295–311, 1971.

[8] P. Hammerstein, editor. *Genetic and cultural evolution of cooperation*. Dahlem Workshops Reports. MIT Press, 2003.

[9] C. Hauert. Fundamental clusters in spatial 2x2 games. *Proc. R. Soc. Lond. B*, 268:761–769, 2001.

[10] C. Hauert. Spatial effects in social dilemmas. *Journal of Theoretical Biology*, 240:627–636, 2005.

[11] K. Jaffe. An economic analysis of altruism: Who benefits from altruistic acts? *Journal of Artificial Societies and Social Simulation*, 5(3), 2002. Available from http://jasss.soc.surrey.ac.uk/5/5/3.html.

[12] K. Jaffe and R. Cipriani. Culture outsmarts nature in the evolution of cooperation. Available from http://jasss.soc.surrey.ac.uk/10/1/7.html, 2006.

[13] R. Kurzban and D. Houser. Experiments investigating cooperative types in humans: A complement to evolutionary theory and simulations. *PNAS*, 102:1803–1807, 2005.

[14] L. Lehmann and L. Keller. The evolution of cooperation and altruism – a general framework and a classification of models. *Journal of Evolutionary Biology*, 19(5):1365–1376, September 2006.

[15] M. E. J. "M. Newman. "the structure and function of complex networks". *SIAM Review*, 45(2):167–256, 2003.

[16] N. Masuda and K. Aihara. Spatial prisoner's dilemma optimally played in small-world networks. *Physics Letters A*, 313:55–61, 2003.

[17] R. Nelson and S. Winter. *Evolutionary theory of economic change*. Belknap Press, 1982.

[18] M. Nowak and K. Sigmund. The dynamics of indirect reciprocity. *Journal of Theoretical Biology*, 195:561–574, 1998.

[19] M. Nowak and K. Sigmund. Evolutionary dynamics of biological games. *Science*, 303:793–799, 2004.

[20] M. Nowak and K. Sigmund. Evolution of indirect reciprocity. *Nature*, 437:1291–1298, 2005.

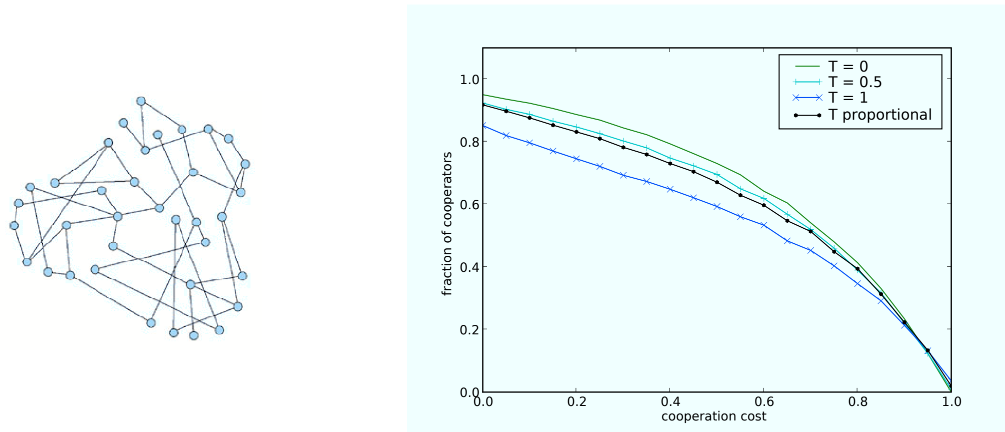
[21] M. A. Nowak and R. M. May. Evolutionary games and spatial chaos. *Nature*, 359:826–829, Oct. 1992.

[22] H. Ohtsuki, C. Hauert, E. Lieberman, and M. A. Nowak. A simple rule for the evolution of cooperation on graphs and social networks. *Nature*, 441:502–505, 2006.

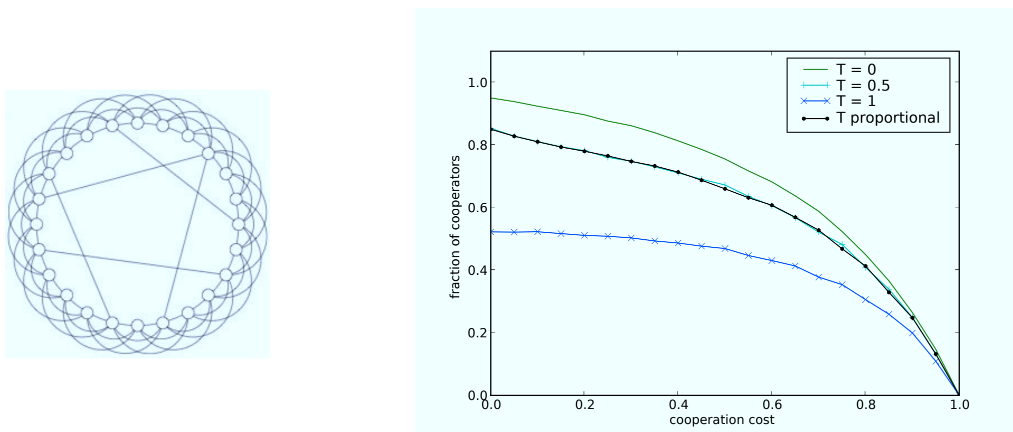
[23] P. Richardson, J. Strassmann, and C. Hughes. *Not by Genes Alone: How Culture Transformed Human Evolution*. Chicago Univ. Press, 2004.

[24] R. Trivers. The evolution of reciprocal altruism. *Quarterly Review of Biology*, 46:35–57, 1971.

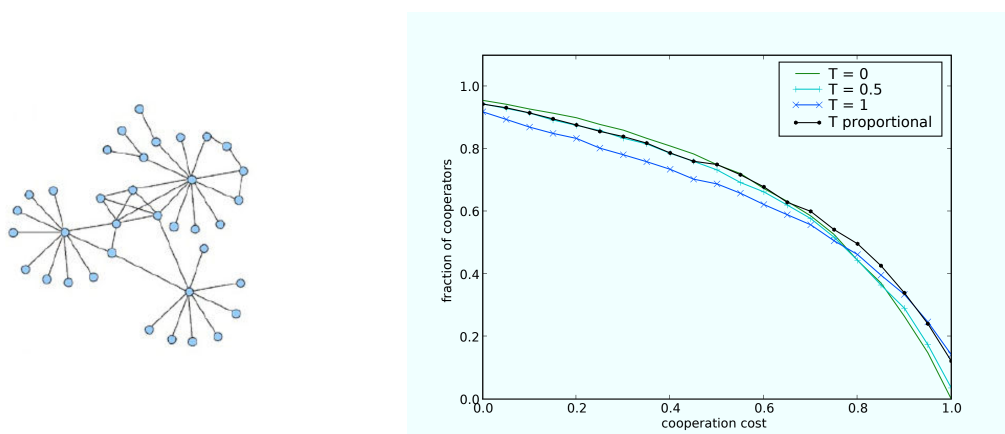
[25] D. Watts and S. Strogatz. Collective dynamics of 'small-world' networks. *Nature*, 393:440–442, 1998.



(a) Random Graph. Erdös-Renyi Model (G(10000, 0.0002)).



(b) Small World Graph. Newman-Watts model (G(10000, 2, 0.01)).



(c) Scale Free Networks. Barabasi-Albert model (G(10000,2)).

Figure 2: Effects of horizontal information transmission is stabilizing cooperation on complex networks spatial structures. Final fraction of cooperators in simulations with different costs for cooperation (x axis) and with different kinds of horizontal transmission of information (pT). On the left side of each sub-figure we present a graphical representation of the subjacent spatial structure.