Cooperation and the Globalization-Localization Dilemmas

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Evolution of cooperation among self-interested agents is revisited in this paper in the context of globalization and localization. A globalized society is characterized by disentrenchment—or routine interactions between strangers across subcultures. Such interactions are rich in novelty, but also have high levels of distrust and insecurity. A localized society is comprised of clusters of subcultures where most social interactions happen. Each tightly knit subculture is rich in mutual familiarity and trust, but not conducive to the spread of novel ideas. A second dimension is that of utilitarian knowledge. Historically, social acquaintances were the primary (if not the only) source of utilitarian knowledge. With technologies like the internet, diffusion of utilitarian knowledge in a society is no longer modulated by acquaintance networks. This leads us to two different forms of (dis)entrenchment: (dis)entrenchment of knowledge and (dis)entrenchment of acquaintance, leading to four societal configurations. This paper asks how each of the configurations fares with respect to the evolution of cooperation. Entrenchment is represented using well-known network models from the literature, and evolution of cooperation is modeled by the evolutionary version of the iterated prisoners' dilemma game. Based on simulation runs, we note that acquaintance and knowledge are characteristically different aspects. We find that disentrenched knowledge is more conducive for evolution of cooperation in networks rather than disentrenched acquaintances.

Keywords: evolution of cooperation; entrenchment; prisoners' dilemma

1. Introduction

In the 1990s, the idea of globalization had caught the imagination of several leaders worldwide. This was catalyzed by the end of the Cold War and the emergence of the internet. Globalization was thought to dissolve artificial boundaries and create an interdependent world economy conducive for world peace.

However, less than a couple of decades later, there was increasing resentment against globalization, leading to the globalization-localization debate [1–4]. Many of these arguments pertain to economic

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matters involving intercurrency trade, arbitrage and capital flight. But the resentments are not just relegated to economic issues. Catalyzed by events like influx of refugees and impending demographic shifts, several countries, especially in Europe, witnessed social pushback against globalization and unfettered intermixing of cultures [5–7].

In general, the forces of globalization are feared to obliterate local cultures and practices, including regional languages. A globalized world also means that individuals would interact with strangers coming from different cultures and values on a daily basis. Such "disentrenched" interactions are characterized by distrust, requiring routine interactions to have high levels of defense mechanisms.

However, those in favor of globalization argue against the entrenched and insular nature of localized societies. A localized world is made up of several tightly knit communities within which many of the routine social interactions take place. Because localized worlds operate in familiar environments, trust and familiarity are high, leading to low transaction costs. But their insular nature leads them to favor conformance over novelty [8]. This leads to saturation and stagnation of ideas, making localized societies closed to novel ideas that may potentially hold solutions to their current problems. A localized world also has high levels of distrust across communities. People moving from one entrenched local community to another are often subject to prejudice, xenophobia and discrimination.

Given this dilemma, it is pertinent to ask which of the given configurations should be promoted for the world as a whole.

In this paper, we address this issue by building computational models of entrenchment and trust and explore how these two elements of social interaction are related. Entrenchment is modeled using two well-known social network models, and trust is modeled using the "evolution of cooperation" game.

One of the major initial insights we obtained is that entrenchment is of two types: *entrenched acquaintances* and *entrenched knowledge*.

Entrenched acquaintances simply means that many of the social interactions take place in largely familiar environments, while entrenched knowledge means that an agent obtains their utilitarian knowledge primarily from social acquaintances, rather than from independent sources like television or the internet.

Before technologies like the mass media and the internet, utilitarian knowledge largely diffused through social interactions. Even though books and other forms of knowledge diffusion existed, people looked into their network of acquaintances for knowledge about routine utilitarian decisions like which crop to grow, which company to invest in or which career to choose.

There was little difference between an entrenched-acquaintance society and an entrenched-knowledge society. And indeed even to this day, in several parts of the world that do not have easy access to information technology, utilitarian knowledge is largely diffused through social acquaintance networks.

With today's technologies, these two forms of entrenchment are getting decoupled. It is increasingly commonplace for people to make utilitarian decisions based on content found on the internet, rather than advice from acquaintances. But it is important to note that even on the internet, especially in online social media, acquaintance networks through which knowledge diffuses tend to be entrenched.

This decoupling of knowledge and acquaintance gives us four possible societal configurations:

- entrenched acquaintance entrenched knowledge (EAEK)
- entrenched acquaintance disentrenched knowledge (EADK)
- disentrenched acquaintance disentrenched knowledge (DADK)
- disentrenched acquaintance entrenched knowledge (DAEK)

Which of these configurations are most conducive to reducing distrust and the emergence of cooperation? To answer this, we use the well-known evolutionary version of the iterated prisoners' dilemma (EIPD) [9] as the underlying game. The different societal configurations are represented by well-known network models that are shown to possess the required characteristics. EIPD simulations are then performed on these network models to record the rate at which cooperative strategies prevail over distrustful strategies.

2. Related Literature

Axelrod and Hamilton's work [9] on the evolution of cooperation in a society of self-interested individuals is seen as a cornerstone in our understanding of how cooperation can be facilitated in societies of rational, autonomous agents.

The prisoners' dilemma (PD) represents commonly occurring social situations where there is a temptation for players to make choices that maximize their own self-interest, while severely impeding overall social gains. In its simplest form, PD requires players to choose between two options corresponding to "cooperate" and "defect." The payoffs are such that choosing to defect is the dominant strategy. This is true even in iterated versions of the game (IPD) where a purely uncooperative strategy can trivially overpower any other strategy. However, when an evolutionary version of the IPD is concerned

(EIPD), it can be shown that a population of uncooperative, self-interested individuals can be successfully "invaded" by a small number of players who have adopted a cooperative and reciprocative strategy (tit for tat). This causes an imbalance in fortunes across the players based on the strategy they have adopted, providing a rational incentive for uncooperative players to switch to the cooperative strategy.

Axelrod's primary work spawned a flurry of research interest into the emergence of cooperation. Further research [10–14] has addressed the impact of various factors like the number of agents, their possible choices, variation in payoff matrix, noise, shadow of the future and dynamics and structure of the population of agents. Natural selection can lead to emergence of cooperation using mechanisms such as kin selection, direct reciprocity, indirect reciprocity, network reciprocity and group selection.

Early models studying the evolution of cooperation have largely ignored the underlying network structure. Any player is assumed to be equally likely to interact with any other player.

However, social networks are known to evolve in specific patterns, which may affect the prospects for evolution of cooperation. The network structure has an effect on individual agents as well as on the resultant network [15]. One commonly occurring property in social networks is the closing of short acquaintance paths, which is popularly known as *triadic closure* [16, 17]. This property says that if a person is strongly acquainted with two other persons, then there is a high probability that the two other persons are also acquainted with each other.

A good way to model triadic closure along with random, intercluster weak ties is by the Watts–Strogatz (WS) model [18]. In this model, the network displays short average path lengths and a large clustering coefficient as observed in real-world social networks.

A WS graph is constructed as follows: An undirected graph is built with n nodes and $nk/2$ edges, with $k \ll n$, such that the n nodes are arranged in a ring lattice where each node has k neighbors, that is, with $k/2$ adjacent nodes on each side. All the edges of all the nodes are then rewired and connected randomly, with a probability $\beta (0 \leq \beta \leq 1)$, such that edges are not duplicated and there are no self loops.

In the WS graph, a given node in the network is said to be *entrenched* if most of its acquaintances are also acquaintances of one another. Formally, let $\Gamma(v)$ denote the set of neighbors of node v including v itself and let $|\Gamma(v)| = k$. Let $\psi(\Gamma(v))$ be the *induced subgraph* obtained $\Gamma(v)$. This is the graph formed by including all the edges from the graph between nodes that are present in $\Gamma(v)$. Let $\psi_e(\Gamma(v))$ be

the set of all edges in the induced subgraph. The *entrenchment factor* of v can be computed as

$$ef_{\mathrm{WS}}(v) = \frac{2\left|\psi_e(\Gamma(v))\right|}{k(k-1)}. \tag{1}$$

While the WS model captures an important element of social networks, it fails to display another important characteristic of real-world social networks—namely its scale-free nature [19]. A scale-free network is characterized by a power-law degree distribution where the probability of a node having degree k is approximated by the equation

$$\Pr[k] \propto \frac{1}{k^{\gamma}}, \quad \gamma > 0.$$

Scale-free networks can also be seen as hub and spoke graphs where a very small number of nodes (predominantly hubs) have a very large degree, and a very large number of nodes (predominantly spokes) have a very small degree. The presence of hubs at different levels ensures short paths and small diameters for such networks.

Scale-free graphs can also be seen in the light of entrenchment and disentrenchment. Spoke nodes that are connected to a very small number of other nodes can be seen as entrenched in their social acquaintances, as they have limited options for acquaintances and knowledge pathways. On the other hand, hub nodes that connect to a large number of other nodes can be seen as disentrenched in their social acquaintances.

Formally, the entrenchment factor of a given node v in a scale-free network can be computed as the inverse of its *degree centrality* based on its degree d_v:

$$\mathrm{ef}_{\mathrm{BA}}(v) = 1 - \frac{d_v}{\max_v d_v}. \tag{2}$$

A well-known generative model for scale-free networks is the preferential attachment or the BA model proposed by Barabasi and Albert [20]. This model starts with a small number of seed nodes that are randomly connected. Then, each incoming node connects to an existing node with a preferential probability that is proportional to the degree of the node. A control parameter γ, $0 \le \gamma \le 1$, is used to control the extent of preferential attachment. An incoming node connects preferentially with a probability $1-\gamma$, and randomly with a probability γ.

Evolution of cooperation on a square lattice is analyzed in [21]. Here, agents interact with their neighbors and decide to either

cooperate or defect based on the payoffs of their neighbors. However, a square lattice does not model realistic social acquaintance networks, and deciding a strategy based on a random neighbor may not be the best technique.

The topology of a network plays a major role in the evolution of cooperation. Graphs generated by growth and preferential attachment are shown to provide adequate conditions for cooperation to evolve [22]. When diverse agents in a set imitate each other in a scale-free network, it leads to complex emergent behavior at a systemic level [23]. However when payoffs of agents were normalized, it was found that the cooperative behavior deteriorated [24].

Research to study cooperation dynamics across multiple networks has been done with some interesting results. In random graphs, pure cooperators form multiple clusters; however, in scale-free graphs, pure cooperators form a single cluster consisting of hubs [25]. EIPD is simulated over a variety of networks, from lattice to scale-free to random networks [26]. Here, at every evolutionary change, agents know the strategy-wise payoffs of their neighbors and choose the strategy of the most successful neighbor, which resembles an entrenched knowledge society. They concluded that as the network becomes increasingly random, the fraction of unsatisfied agents that keep changing their strategies increases. The advantage of defectors over cooperators is studied for varying levels of average connectivity over variants of scale-free networks and growth and preferential attachment models [27]. However, there is no specific attention toward formally modeling entrenchment and studying its effects.

Cooperation is shown to evolve more easily in networks that have fewer connections [28] or where forming new connections is costly and local structure is absent, as compared to networks where friends of friends interact with high probability [29]. Evolution of cooperation has also been studied over different models of network heterogeneity, agent strategies, spatial structure and initial distribution of agents [30, 31]. Cooperation emerges and sustains much more easily in a heterogeneous network as compared to a homogeneous network [32, 33].

3. Problem Formulation

Formulation of the entrenchment problem is comprised of two parts: modeling the emergence of cooperation and modeling entrenchment. For the former, the EIPD game is chosen. A formal description of this game follows.

3.1 Modeling Evolution of Cooperation

PD is a game played between two players who can choose either to cooperate or defect. While there is an incentive to cooperate, there is a bigger incentive for one of the players to defect while the other is offering cooperation. Both players receive a reward R if they both cooperate and a penalty P if they both defect. In case one of them cooperates and the other defects, then the cooperating player receives a bigger penalty S and the defecting player receives a bigger reward T. These values are such that $T > R > P > S$.

		Agent 2	
		Cooperate	Defect
Agent 1	Cooperate	6,6	0,10
	Defect	10,0	1,1

Table 1. Payoff matrix of PD.

Table 1 shows the payoff matrix of the PD game used in our experiments. Choosing to defect is the dominant strategy of the PD game. As a result, the game state (Defect, Defect) forms the pure-strategy Nash equilibrium.

The PD is impervious to blind trust across players and retains its characteristics as long as the players are rational maximizers. For instance, if Agent 1 blindly trusts Agent 2 to offer cooperation, it would still be "rational" for Agent 1 to defect.

IPD is a variant of the PD game. In this variant, the PD game is played several times between two players. This brings an element of memory into the game. Strategies for the IPD have to contend not only with the current payoff, but also with future prospects of the game based on their current choices.

If an instance of the PD entered a state (Defect, Cooperate) where one player defects while the other offers to cooperate, the cooperating player is said to be a victim of exploitation. In the IPD, being subject to exploitation provides a rationale for a player to be inclined to defect in future interactions. This in turn affects the long-term prospects for the second player. Strategies for IPD have to address such future repercussions when making choices.

The impact of the future is modeled by a *discount parameter* δ, $0 \leq \delta \leq 1$. The greater the discount factor, the more important are future payoffs. If an IPD is played infinitely long and the state of the game in iteration k is given by a_k, then the strategic prospects for player i for a given strategy are modeled as:

$$U_i = \sum_{k=0}^{\infty} \delta^k u_i(a_k) \tag{3}$$

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where $u_i(a_k)$ is the payoff for player i in game state a_k, and a_k itself is the expected state of the game in iteration k.

Let the states of the PD game be represented as {CC, CD, DC, DD}, corresponding to (Cooperate, Cooperate), (Cooperate, Defect), (Defect, Cooperate) and (Defect, Defect), respectively. A strategy for the IPD that maximizes the occurrence of the state DC from the first player's perspective is said to be *exploitative* (of the gullibility of the other player). Similarly a strategy that minimizes the occurrences of state CD (i.e., prevents itself from being exploited) in a trace of an IPD game is said to be *stable*.

Several strategies have been proposed and explored for the IPD with different results. In this paper, we look into two specific strategies:

- *Always Defect*. The always defect (AD) strategy simply ignores the iterated nature of the game and chooses to defect in all iterations. Since this strategy never offers to cooperate, it is trivially exploitative and trivially stable.
- *Tit for Tat*. A strategy for an IPD is said to be *nontrivial* if it also cooperates sometimes. Several nontrivial strategies have been proposed, but it was shown that a strategy called tit for tat (TFT) is best when it comes to stability [10]. The TFT strategy proceeds as follows:
  1. To begin with, TFT offers cooperation in the first iteration.
  2. In the subsequent iterations, TFT mirrors what the other player chose in the previous iteration. That is, it responds to a defect with a defect, but is also quick to forgive and responds to a cooperate with a cooperate in the next iteration.

While TFT is a nontrivial strategy that is stable and cooperative, it is still not possible for a society comprised of uncooperative (AD) players in the IPD game to start trusting one another and cooperating. The trivial strategy of AD dominates over any nontrivial strategy that offers cooperation sometimes.

The EIPD is a third version of this game. In this game, players adopt some strategy to engage with other players in an IPD game. However, players are also allowed to change their strategies depending on how each strategy is paying off. This changing of strategies is called a *generational change* in the society, and the distribution of different strategies in the society is called its *demographics*. The overall gains for a strategy based on the individual payoffs of all players who have adopted that strategy is called its *demographic dividend*.

The EIPD brings the notion of *evolutionary stability*. A strategy s is said to be an evolutionarily stable strategy (ESS) if it cannot be successfully "invaded" or dominated over generational changes by another strategy t that was initially rare.

While the AD strategy was trivially stable and exploitative in the IPD, it can be shown that it is not an ESS in the EIPD game. A population of AD players can be dominated by an initially small population of TFT players over generational changes in an EIPD game. This can be shown as follows:

Assume an EIPD game over a population comprising a large number of AD players and a small proportion ρ of TFT players. When two AD players interact, they play an AD-AD game in which both players defect on each other all the time. Their game trace can be represented by the state sequence: DD, DD, DD, ...

With a discount parameter $\delta = 0.9$ representing the impact of the future, the payoff for an AD player for a sufficiently long iterated game is given by:

$$u^{\mathrm{AD}} = \frac{u(\mathrm{DD})}{1-\delta} = 10. \tag{4}$$

When two TFT players interact with each other, they play a TFT-TFT game. In this game, since neither of them would be the first to defect, the game trace can be given by the sequence: CC, CC, CC, ... and the overall payoff as:

$$u^{\mathrm{TFT}} = \frac{u(\mathrm{CC})}{1-\delta} = 60. \tag{5}$$

When an AD and a TFT player meet, they play an AD-TFT game, where in the first state, the TFT player offers cooperation and the AD player defects. Following this, both players defect on each other in all the subsequent iterations. The game trace would be the sequence: DC, DD, DD, DD, ...

The payoff for the AD player would be:

$$u_{\mathrm{AD}}^{\mathrm{ADT\ FT}} = u(\mathrm{DC}) + \frac{u(\mathrm{DD})}{1-\delta} = 10 + 10 = 20. \tag{6}$$

The payoff for the TFT player (who would have seen the game state as CD in the first iteration), would be:

$$u_{\mathrm{TFT}}^{\mathrm{ADT\ FT}} = u(\mathrm{CD}) + \frac{u(\mathrm{DD})}{1-\delta} = 0 + 10 = 10. \tag{7}$$

Given that the fraction of TFT players in the population is ρ, the expected demographic dividend for TFT and AD would be:

$$E(\mathrm{TFT}) = \rho u^{\mathrm{TFT}} + (1-\rho) u_{\mathrm{TFT}}^{\mathrm{ADT\ FT}} \tag{8}$$

$$E(\mathrm{AD}) = \rho u_{\mathrm{AD}}^{\mathrm{ADT\ FT}} + (1-\rho) u^{\mathrm{AD}}. \tag{9}$$

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With a relatively small value of $\rho = 0.1$, we get $E(\text{TFT}) = 15$ and $E(\text{AD}) = 11$. We can see that the TFT players are better off even when they constitute a small percentage of the population. At a generational change, an AD player will shift to a TFT strategy with a probability $\Pr[\text{AD} \to \text{TFT}]$ and a TFT player will adopt an AD strategy with a probability $\Pr[\text{TFT} \to \text{AD}]$, both of which are given by:

$$\Pr[\text{AD} \to \text{TFT}] = \frac{E(\text{TFT})}{E(\text{AD}) + E(\text{TFT})} \tag{10}$$

$$\Pr[\text{TFT} \to \text{AD}] = \frac{E(\text{AD})}{E(\text{AD}) + E(\text{TFT})}. \tag{11}$$

A transition from AD to TFT represents a player's *increasing trust* or *assurance* in the society, by adopting a more cooperative outlook from the previously uncooperative attitude toward social acquaintances. Similarly, a transition from TFT to AD represents a player's *disillusionment* with the system by prompting the player to fall back to the uncooperative outlook. Both transitions are important and we will be observing how these change for varying problem settings.

3.2 Modeling Entrenchment

In the EIPD game, there is an assumption that every player is equally likely to interact with every other player. The question of how evolution of cooperation changes if this assumption were to be relaxed forms the focus of this paper.

Entrenchment of both acquaintance and knowledge has been modeled in the system. This is done by representing the society as an acquaintance graph based on two well-known models for social networks. Players are assumed to play EIPD games only with their immediate acquaintances. Two different network models are used in our experiments. They are explained below.

3.2.1 Watts–Strogatz Model

As introduced in Section 2, the social network in a WS model is represented as a ring lattice where every player is initially connected to $2k$ other players, with k players on their left and with k players on their right. Then, with a probability β, $0 \le \beta \le 1$, each edge is rewired randomly, such that there are no multiple edges between nodes or self loops. An edge that is rewired is called a *bridge* and a non-rewired edge is called a *clustering edge*.

When $k \ge 2$, the clustering edges in the WS model represent *triadic closures* that are characteristic of social acquaintances. Bridges

connect disparate clusters that represent pathways for novel information to flow in the network.

An EIPD game over the WS model starts by each player choosing either AD or TFT strategy at random. Each player then plays the EIPD with all other players that are directly connected to them. These are also called the player's *1-hop neighbors*.

In an entrenched knowledge scenario, a node computes demographic dividends based purely on its knowledge of its neighbors' strategies and their payoffs. In a disentrenched knowledge scenario, a node computes demographic dividends based on the knowledge of strategies and payoffs over the entire network. Several forms of "*m*-partially entrenched" knowledge scenarios are also modeled, where a node computes demographic dividends based on knowledge of strategy and payoffs of up to its *m*-hop neighbors.

3.2.2 Barabasi–Albert Model

In the BA model, the social network is built by preferential attachment as introduced in Section 2. In this model too, there are two kinds of connections: *preferential* connections based on node degree and *random* connections.

The extent of preferential attachment is controlled by a rewiring parameter γ, $0 \leq \gamma \leq 1$. With a probability $1-\gamma$ an incoming node connects preferentially, and with a probability γ the incoming node connects randomly.

While both WS and BA networks model entrenchment, they are characteristically different. Figure 1 shows how the diameter of the network changes with increasing values of the corresponding rewiring probability (representing disentrenchment) for both the networks.

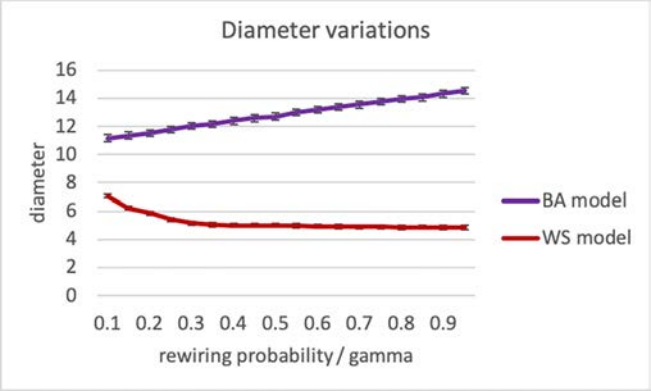

Figure 1. Changes in network diameter against rewiring probability.

In the BA model, preferential attachment creates densely connected hubs that reduce the overall diameter. Here, increasing rewiring probability makes the network larger in diameter. In contrast, the clustering edges in the WS model create short acquaintance links from one node to another, and the result is a network with a fairly large diameter. Increasing the rewiring parameter creates chords that form shortcuts to different parts of the network, thus reducing the overall diameter.

Rewiring and extent of entrenchment as defined in equations (1) and (2) were also observed to be negatively correlated. The Pearson correlation coefficient between rewiring and entrenchment in the BA model is -0.5011 and in the WS model is -0.9797. This means that increasing rewiring probability decreases entrenchment in both models. Based on this correlation, we use the rewiring probability as the baseline on which different parameters about the evolution of cooperation are plotted.

3.3 Controlled and Observed Parameters

The following parameters are the basic controlling factors of the simulation that were varied over simulation runs. These parameters address the extent of entrenchment of acquaintance and entrenchment of knowledge.

- *Rewiring Probability (β and γ)*. In the WS model, it is the probability with which an agent disconnects a clustering link and makes a random connection with any other agent in the network. In the BA model, this is the probability with which an incoming agent connects randomly in a network rather than preferentially.
- *Knowledge Expanse (m)*. This is the extent to which nodes query other nodes in the network for their overall payoff, while computing demographic dividends. For a given value of m, nodes query up to m-hop neighbors for their strategy and overall payoff, while computing demographic dividend at a generational change. Smaller values of m denote a highly entrenched knowledge society and large values of m denote a disentrenched knowledge society.

To measure the outcome regarding the evolution of cooperation, the following parameters are observed:

- *Demographic Reversal (RoS)*. We start with an initial population where a small fraction ρ has adopted TFT and the rest have adopted AD. Demographic reversal, also called reversal of strategies (RoS), refers to the smallest number of generations it takes in a game setup for the fraction of AD players to reduce to ρ or lower.
- *Individual Disillusionment (ID)*. This parameter captures the expected disillusionment of a randomly chosen player. Disillusionment is the number of times the player switches back to AD from TFT during the course of the game, before demographic reversal happens.

- *Collective Disillusionment (CD)*. CD refers to the expected proportion of disillusionment in the society in every generation, until demographic reversal.
- *Individual Assurance (IA)*. This parameter captures the expected assurance of a randomly chosen player. Assurance is the number of times a player switches back to TFT from AD during the course of the game, before demographic reversal happens.
- *Collective Assurance (CA)*. Collective assurance refers to the expected proportion of assurance in the society in every generation, until demographic reversal.

```
Generate a network of n agents using the WS or BA model with
    a rewiring probability β / γ and knowledge extent m
Agents in ρ proportion use TFT strategy and rest (1 – ρ) of the
    agents use AD strategy
genCount = 0
while TRUE do
    Agents play IPD with their neighbors
    genCount++
    Based on knowledge extent m, agents aggregate strategy-wise
        payoffs of m-hop neighbors
    Agents probabilistically decide whether to change their strategy
        or not
    if (TFTCount / (ADCount + TFTCount)) >= (1 - ρ) then
        System reached RoS
        Update all metrics and plots
        STOP
    end
end
```

Algorithm 1. Pseudocode of model.

4. Simulation Results

Simulation environments were set up for both WS and BA models with 100 agents using Netlogo (ccl.northwestern.edu/netlogo). Network models were generated by varying rewiring probabilities from 0.1 to 0.95 with a step size of 0.05. Knowledge expanse m depends

on the maximum diameter of the network and it varied between [1, 15] for the BA model and between [1, 5] for the WS model. On every network setup, simulation runs were performed where every node randomly chose TFT with a probability ρ and AD with a probability $1 - \rho$. Results were averaged over 100 simulation runs for every combination of controlling parameters (rewiring probability and knowledge expanse) in order to minimize biases introduced by specific runs. The initially rare distribution ρ of the TFT players was set to $\rho = 0.15$. Error bars in the line plots represent standard error.

In all the plots in this section, every parameter has an integer appended to it, representing knowledge expanse m—for example, *ID-5* or *RoS-3*. It denotes the extent of disentrenched knowledge, or the maximum number of hop link neighbors that were queried to compute demographic dividends.

4.1 Demographic Reversals

The first parameter we observe is how demographic reversal (RoS) changes with varying entrenchment levels. Figure 2 plots RoS values for the WS model against rewiring parameter β and different values of the knowledge expanse.

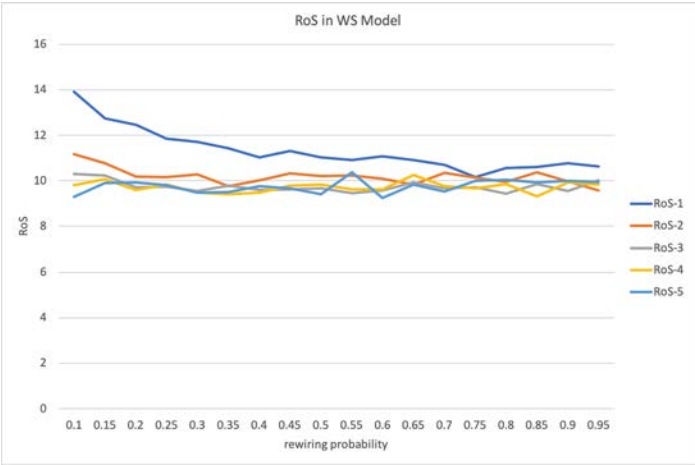

Figure 2. RoS in the WS model.

Some things are immediately apparent. We can see that demographic reversal takes much longer when knowledge expanse is lowest and entrenchment in acquaintances is highest. Clearly EAEK societies in the WS model are not conducive to the evolution of cooperation.

Increase in the value of knowledge expanse decreases the rate at which demographic reversal is achieved. Figure 3 plots the mean

value of RoS for a given value of knowledge expanse m aggregated across all values of the rewiring probability β.

We can also see a decreasing trend in the RoS with increasing values of β for any given value of knowledge expanse m. This trend also holds when we aggregate RoS to its expected value across all values of m. Figure 4 plots the mean value of RoS across different levels of entrenched knowledge against disentrenchment in acquaintance.

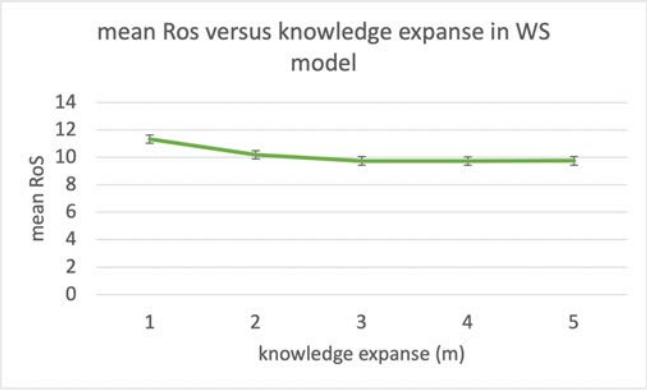

Figure 3. Expected value of RoS for a given value of knowledge expanse m in the WS model.

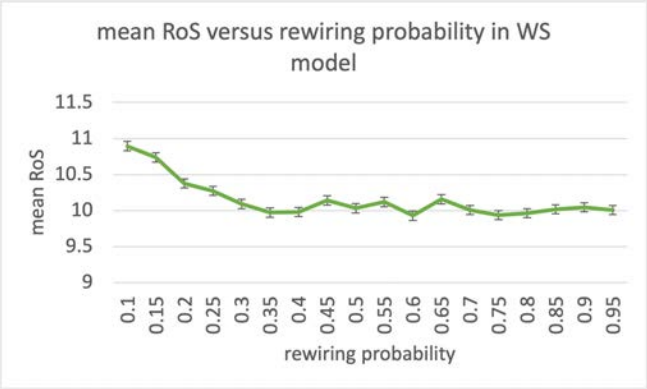

Figure 4. Expected value of RoS for a given value of β in the WS model.

Another observation we can make here is that disentrenched knowledge ($m = 5$) in an entrenched acquaintance network, or a EADK network ($\beta = 0.1$, $m = 5$), is just as conducive to the emergence of cooperation as are disentrenched acquaintance configurations.

Thus in the case of the WS model, both disentrenchment of interaction and disentrenchment of knowledge lead to attaining RoS sooner.

Figure 5 shows how demographic reversal happens in the BA model. The BA model is much more skewed in its degree distribution than the WS model. This skew also seems to affect the disparity in the rate of demographic reversal. For lower levels of knowledge ($m = 1, 2, 3$) we observe that it takes longer to reach RoS with increasing values of γ.

Figure 6 shows a sharp decreasing trend in the mean value of RoS for increasing values of the knowledge expanse m, aggregated across different values of γ.

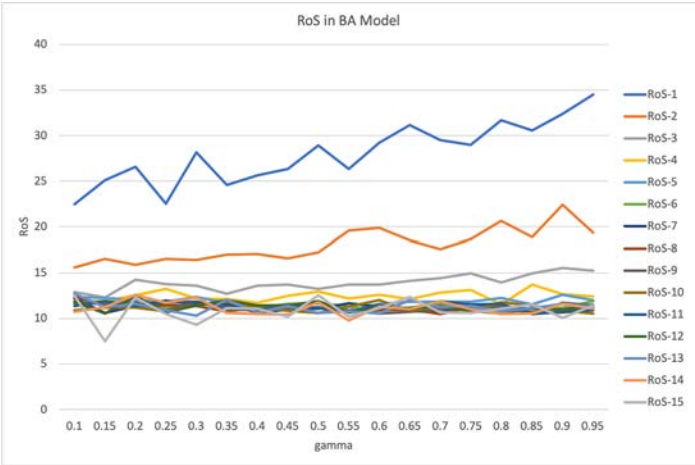

Figure 5. RoS in the BA model.

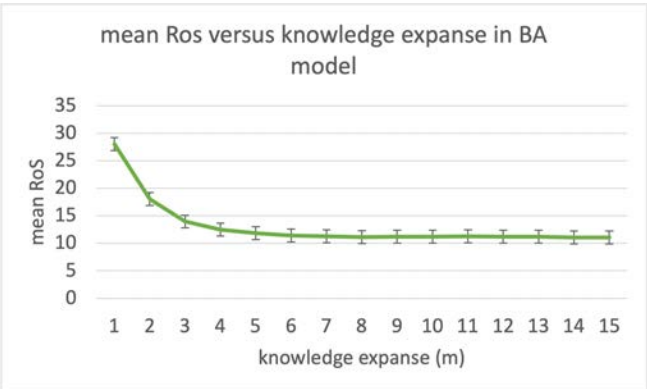

Figure 6. Expected value of RoS for a given value of knowledge expanse m in the BA model.

At an aggregate level with respect to interactions, Figure 7 shows an almost constant trend in the expected rate of demographic reversals for increasing values of γ.

Thus, disentrenched interactions do not seem to have a significant effect on the evolution of cooperation; however, increasing the knowledge expanse leads to a faster RoS in both WS and BA models.

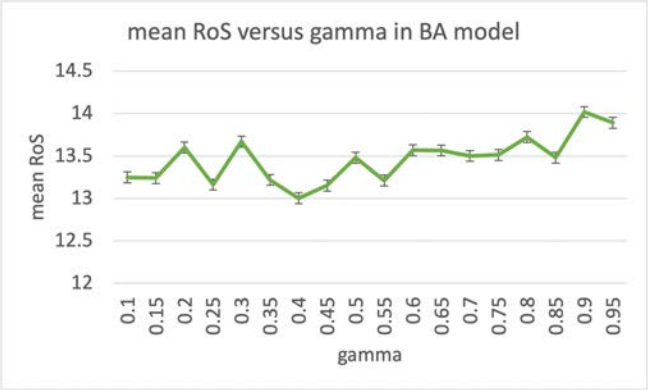

Figure 7. Expected value of RoS for a given value of γ in the BA model.

4.2 Effect of Acquaintance/Interaction

In this subsection, we look at the effect of varying levels of entrenchment of acquaintance on the observed parameters. Figure 8 shows the trends of collective metrics and Figure 9 shows the trends of individual metrics. Clearly, varying levels of entrenched acquaintances (by

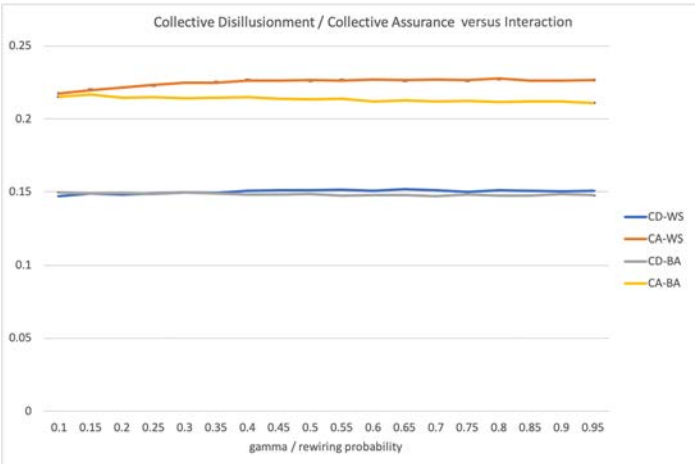

Figure 8. Effect of interactions on collective parameters.

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varying rewiring probability) does not have a significant effect on the observed parameters. Both collective and individual metrics remain almost constant with varying levels of entrenched acquaintances. Also in both cases of individual and collective metrics, it is interesting to note that the level of assurance is greater than the level of disillusionment.

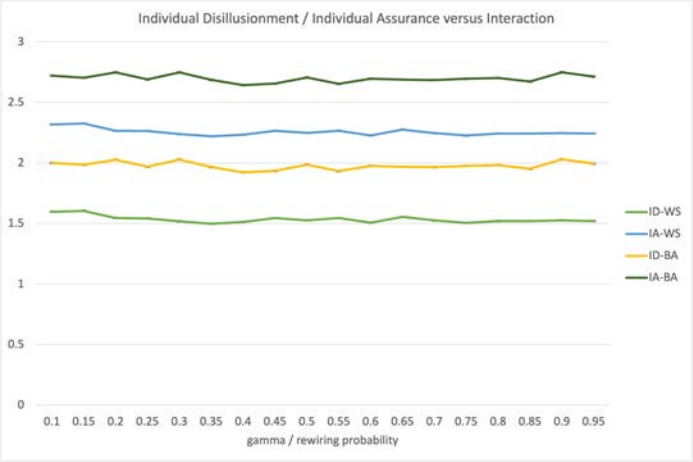

Figure 9. Effect of interactions on individual parameters.

4.3 Effect of Knowledge

Next we discuss the effect of knowledge on the parameters. Based on the level of the agent's knowledge of aggregate payoffs, they decide whether to switch their strategies or not.

Figure 10 shows that both collective disillusionment and collective assurance increase with increasing levels of knowledge in both the WS and BA models. An interesting observation is that although both parameters increase, assurance is always higher than disillusionment for both of the models.

Figure 11 shows that both individual disillusionment and individual assurance decrease with increasing levels of knowledge in both the WS and BA models. Similar to collective parameters, although both parameters decrease, assurance is always higher than disillusionment for both of the models.

Variation in the level of knowledge thus points to some intriguing outcomes. Even a small increase in the level of knowledge initially is sufficient to significantly change the parameters. This means that agents need not update their knowledge levels to a very large extent: even a small increase initially might improve their prospects. Second, increasing levels of knowledge lead to an increase in collective metrics

and a decrease in individual metrics. This implies that with increasing levels of knowledge, there is increased "confusion" at a collective level and surprisingly, reduced confusion at an individual level. As expected, for both collective and individual metrics, since assurance is higher than disillusionment, the ratio of TFT agents versus AD agents increases until RoS.

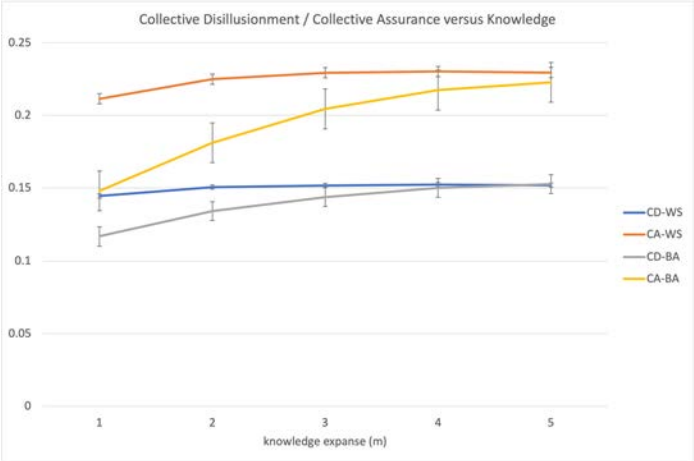

Figure 10. Effect of knowledge on collective parameters.

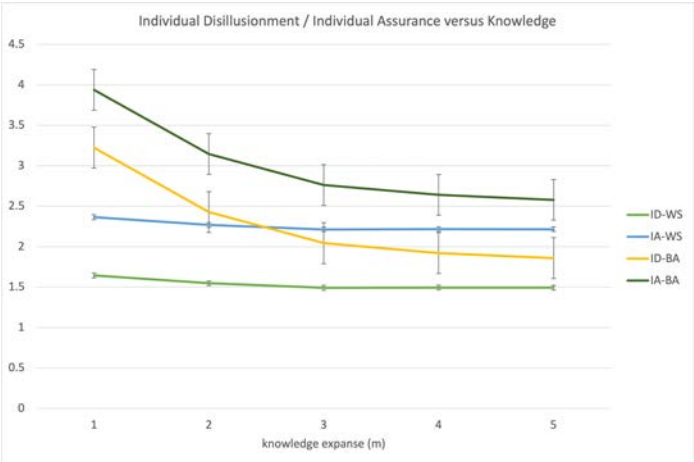

Figure 11. Effect of knowledge on individual parameters.

Thus we conclude that, while disentrenchment of both knowledge and acquaintances is beneficial in reaching RoS faster—disentrenchment of acquaintances does not affect RoS significantly due to large

variation in degree of agents in the BA model. On the other hand, varying levels of acquaintances does not have a significant effect on other output metrics. And finally, increasing levels of knowledge result in an increase in collective metrics and a decrease in individual metrics.

This can be a big lesson especially when designing cooperative societies or networks, where agents/people can be motivated to increase their levels of knowledge rather than making significant changes in their network. Until recently, disentrenchment of acquaintance was the only means to obtain disentrenched knowledge. But current technologies enable people to create knowledge networks that are very different from their acquaintance networks.

Globalization and localization, hence, are not two mutually exclusive social configurations. A globalized knowledge network with a localized acquaintance network can enable building trustful societies.

5. Real-World Examples

So far simulations were done on synthetic networks. Here we run simulations on real tribe networks to validate our conclusions. Some real examples of disentrenchment and its impact on society are also elaborated.

5.1 Simulation of New Guinea Tribe Network

We run the simulation on the New Guinea tribe network detailed in [34, 35]. This dataset shows data about a set of 16 tribal factions and the nature of relationships between them. The network dataset shows signed edges, representing allies and opposition tribes. We have considered only positive edges in this study, since the emergence of cooperation is defined over peaceful rather than belligerent interactions. The network is shown in Figure 12 and its network statistics are presented in Table 2. Here lcc-dia represents the diameter of the largest connected component, bet-cen is the mean betweenness centrality, eig-cen is the mean eigenvector centrality and clo-cen is the mean closeness centrality of all the nodes in the network.

We run simulations on this network. As observed in Figure 12, the network is split into two components. We vary knowledge expanse m between $[1, 4]$ and initially rare distribution ρ of the TFT players between $[0.25, 0.4]$, and the results are averaged over 100 simulation runs. For lower values of ρ, sometimes the network is not able to attain RoS, since it is split into two components.

Figure 13 shows the variation in mean RoS with varying levels of knowledge expanse. This is similar to the trends observed in the case of WS and BA networks as well. Figure 14 shows the line plots of

individual and collective trends of disillusionment and assurance for the tribe network. Even in this case, similar to the WS and BA networks, we observe that assurance values are higher than disillusionment values for both the individual and collective scenarios (i.e., IA > ID and CA > CD).

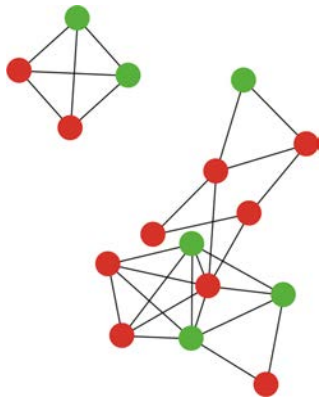

Figure 12. New Guinea tribe network.

num-nodes	num-edges	lcc-dia	bet-cen	eig-cen	clo-cen
16	29	4	4.125	0.649	0.637

Table 2. New Guinea tribe network statistics.

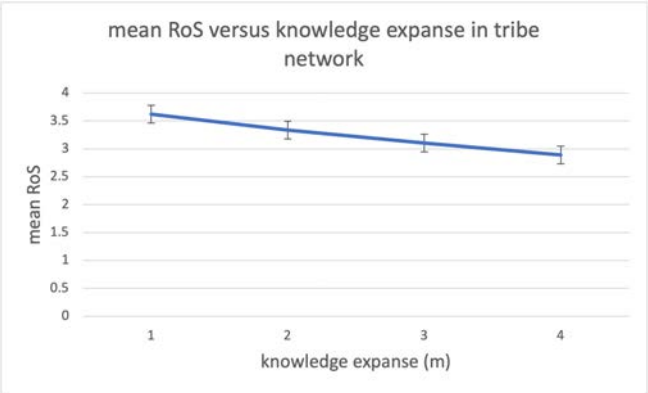

Figure 13. Mean RoS versus knowledge expanse in tribe network.

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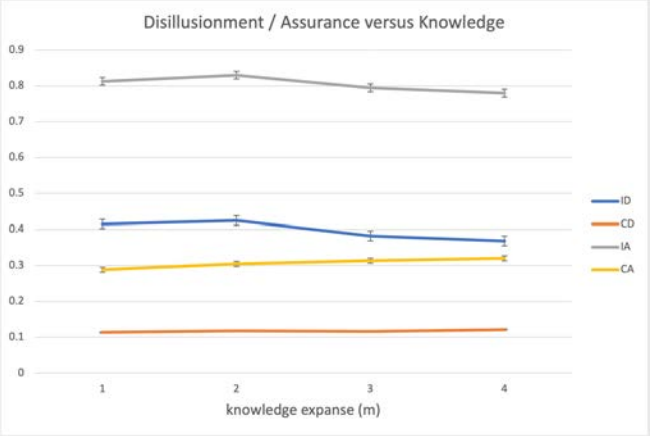

Figure 14. Disillusionment/assurance in tribe network.

The tribes of New Guinea are fragmented, with a strong relation within the tribe and friendly or opposing behavior across the tribes [34]. Also tribes are primarily dependent on interactions as a source of information. These interactions among the tribes and subgroups are limited by geographical constraints. The simulations on this network show the outcomes in the limited interaction context (knowledge expanse $m = 1$) and in a scenario where tribes are aware of other tribes on the island although they might not directly interact with those tribes (knowledge expanse $m > 1$).

5.2 Examples of Impact of Disentrenchment during Pandemic

In the second study on real-life datasets, we perform a qualitative analysis of information dissemination in the ongoing pandemic COVID-19 and the 1918 influenza pandemic. In the current day, knowledge is much more disentrenched as compared to 1918, due to the availability of the mainstream electronic and social media. During the 1918 influenza pandemic, newspapers were the main source of information for the public, and their attitudes were known to be mostly paternalistic. They censored the true scale of the impact of the pandemic in order to prevent triggering panic among the population, and believed that the public cannot be trusted with this kind of information [36]. Thus it was difficult for the public to be aware of the real causes of spread, prevention and impact of the pandemic. Entrenched information coming from limited and unreliable sources made it even more challenging for the people to verify the authenticity of the information.

On the other hand, information dissemination has been better during COVID-19 than before. Most people have multiple sources of

information, including detailed studies. For example, during the ongoing COVID-19 pandemic, researchers published genome sequences online [37] that were beneficial for other researchers around the world. Thousands of papers have been published related to COVID-19 and researchers have critically looked at the results, which has led to many papers being corrected or retracted [38, 39].

How then did the disentrenchment of information affect the impact and response to the two pandemics? In the 1918 pandemic, a total of 40 million lives were lost worldwide, which amounted to 2.1 percent of the then global population. A similar impact today would result in an estimated 150 million deaths! ("Social and Economic Impacts of the 1918 Influenza Epidemic," www.nber.org/digest/may20/social-and-economic-impacts-1918-influenza-epidemic.) This is despite the fact that the 1918 epidemic had an R0 estimate between 1.4 and 2.8, while the ongoing COVID pandemic has a median R0 value of 5.7! ("What Is R0? Gauging Contagious Infections," www.healthline.com/health/r-nought-reproduction-number.)

This leads us to conclude that the disentrenched knowledge networks today have been largely beneficial in disseminating best practices and eliciting cooperative behavior from populations across the world. There have, of course, been challenges related to fake news; however, easy accessibility to multiple credible news sources has made it easier to validate the authenticity of the information. Social media has been especially useful for real-time information sharing and collaboration during COVID-19 [40, 41].

6. Conclusion

Disentrenchment in general is shown to be conducive to the emergence of cooperation. However, cases like entrenched acquaintance and disentrenched knowledge, as shown in the Watts–Strogatz (WS) model, are just as conducive to the emergence of cooperation. In other words, operating in familiar environments while being connected to global knowledge sources is just as good (in terms of developing a cooperative outlook) as being widely traveled. Overall, disentrenched knowledge seems to be a better catalyst for cooperation than disentrenched acquaintance.

One of the implications of this is the importance of the so-called "digital divide." Digitally connecting entrenched societies with the rest of the world would likely be a peaceful and efficient way of expanding horizons and fostering collaboration. The alternative that would result in the same goal would be disentrenched acquaintances, which involves navigating through resultant distrust and upheavals.

The other interesting outcome of this experiment involves the contrasting forms of individual and collective confusion (denoted by

assurance/disillusionment) during the emergence of cooperation. It was found that with more knowledge, agents have lower individual confusion; however, a large number of agents experience some amount of confusion. On the other hand, with entrenched knowledge, there is lower collective confusion; but for some agents, individual confusion is high. Here is one interpretation for this:

Before the prevalence of the internet and mass media, the brunt of any issue or calamity was faced by a localized population, while the rest of the world was largely unaffected. However, today with the easy availability of information, every news event or issue has a global span. A calamity negatively affects a much larger number of people, although news of a calamity has much less impact than the calamity itself.

Disentrenchment of interaction and knowledge has been possible due to multiple advancements and it has had a great impact on society. For example, aviation and development of fast land transport made it easier for people to travel long distances. Mass media like newspapers, magazines, radio, television and films became a source for people to know about other people around the world who were earlier unknown. The internet further extended the capabilities such that people could not just know about others but could also interact with them online without traveling there. As compared to past pandemics, we observe that information dissemination has been better during COVID-19. Thus disentrenchment of acquaintance and knowledge has been instrumental in changing the overall structure of social networks. And the simulations show that if done right, it can lead to cooperative networks and societies.

Acknowledgments

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