A Simulation Model of Cultural Consensus and Persistent Conflict

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Abstract

In this study we develop a highly simplified simulation of diffusion through a structured society. By testing diffusion of a single arbitrary trait through different social network structures we show that the type of social network can significantly extend the time required for a population to reach consensus. This is especially true of small-world networks where conflict may persist far longer than in other network structures. In addition, we demonstrate that with simple dynamic linking rules, a network may evolve in such a way that consensus is inhibited altogether and ideological diversity becomes entrenched. To assess simulation results and inform future versions of the model we describe results from a real-world case study in which networked actors experience persistent conflict. While results of the case study align with simulation output, they also reveal areas for substantial improvement to the model.

Introduction

In a world of frequently violent clashes, disputes over natural resources, and seemingly insurmountable cultural conflict it is important to understand how and why adversarial norms and opinions can persist in a society. Many researchers have examined how ideas (Buskens and Yamaguchi 1999), norms (Axelrod 1986), innovations (Mahajan and Muller 1979), social values (Bikhchandani, Hirshleifer, and Welch 1992), and even diseases (Santos, Rodrigues, and Pacheco 2005) may diffuse through a society and how the structure of that society influences the rate, dynamics, and efficacy of diffusion (Abrahamson and Rosenkopf 1997, Cowan and Jonard 2004, Pacheco and Santos 2005, Santos, Rodrigues and Pacheco 2006, Delre 2007). However, it is also important to explore how social structures and cultural mechanisms may inhibit ideological diffusion. A better understanding of barriers to consensus-building may give policy makers new insight into conflicts centered on seemingly immutable differences.

Case studies of consensus and conflict within social networks often find that densely connected networks develop a “group think” (Friedkin and Johnson 1990, Borgatti and Foster 2003). While this may be a limitation in early stages of collaboration (Krackhardt and Stern 1988), this form of consensus may become useful when taking measurable action becomes desirable or necessary, especially since a desire to acquire resources, enhance legitimacy and attain collective goals often motivates attempts to structure cooperative arrangements (Galaskiewicz 1985, Brass et al 2004). In these cases, the efficiency in knowledge transmission, coordinated action, and conflict avoidance might outweigh the consequent reduction in creative potential and/or the potential to create and reinforce “us versus them” thinking patterns (Krackhardt and Stern 1988, Borgatti and Foster 2003).

In this paper we describe a straightforward simulation model of the societal diffusion of an arbitrary trait. One may consider this trait a social norm, an innovation, a moral value, or any other sociocultural factor that spreads through a society. We use the model to explore parameters under which a society may reach consensus with respect to its members’ arbitrary trait. We define consensus in this case as a convergence of the members of the society so that every member has the same value for its arbitrary trait. Furthermore, we examine social structures that may greatly extend the time required for a society to reach consensus. More importantly, we explore attributes of social dynamics that may allow perpetual conflict in a society despite high connectivity among the society’s members. Finally, we briefly describe a case study in which institutional actors embedded in a social network continue to experience conflict years after the network was created to resolve conflict.

It should be noted that the authors make no value judgment regarding the desirability of cultural consensus or diversity but simply offer insights into mechanisms that may promote each phenomenon.

Network Structure and Time to Consensus

In our first simulation experiment we explored the effect that different social network structures have on the time required for a population to reach consensus. We

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effectively extend the formal algorithm developed by Boyd et al (2006), in which a single arbitrary trait always converges to a value equal to the population mean of the initial trait values. However, while Boyd explored the consensus time on random networks, here we explore a number of other of network types (Table 1) through the use of computer simulations Scale-free networks were generated using a Barabási-Albert algorithm of preferential growth (Barabási and Albert 1999) with no nodal limit on links and in which each new node was connected to the existing network by two links. Small-world networks were generated using the Watts-Strogatz algorithm (Watts and Strogatz 1998) in which each node in a ring substrate is linked to the two neighbors on either side and in which initial edges are randomly rewired with a probability p = 0.005 when population size was 400 and p = 0.05 when population size was 64. Random networks were generated so that average degree = 4. Regular networks in this simulation refer to regular, torroidal lattices employing a Moore neighborhood (each node has eight adjacent neighbors – up, down, left, right and four diagonals).

Simulation description

The simulation initiates by placing N agents at the N nodes of one of several different social network structures (Table 1). Each agent is given a single arbitrary trait that is assigned an initial random value, with uniform probability, on [0,1]. Agents are not based on empirical input to the model but simply represent the most basic starting point for the purpose of studying trait convergence.

The model then proceeds through a number of sequential, pairwise interactions until the population either reaches consensus (every agent has the same value for its arbitrary trait) or the simulation reaches the maximum allowable number of iterations.

During a single iteration, one member of the population is chosen at random and then paired randomly with one its immediate neighbors as defined by the network type. Letting a_0 and b_0 represent the initial trait values of two interacting nodes and letting the initial difference between the trait values of the two nodes equal T then

$$T = |a_0 - b_0| . \qquad (1)$$

The interacting agents compare and then update their trait values to a_1 and b_2 by

$$\begin{aligned} a_0 \geq b_0; \quad a_1 = a_0 - i\frac{T}{2}, \quad b_1 = b_0 + i\frac{T}{2} \\ a_0 < b_0; \quad a_1 = a_0 + i\frac{T}{2}, \quad b_1 = b_0 - i\frac{T}{2} \end{aligned} \qquad (2)$$

where $i \in (0,1]$ is the degree to which each agent is induced to revalue its trait towards a consensus with its interaction partner. In other words, i is simply a measure of the strength of influence that each population member has on other members. When $i = 1$, both interaction partners move to the same new trait value – the mean of their original trait values:

$$a_1 = b_1 = \frac{a_0 + b_0}{2} \qquad (3)$$

As the simulation proceeds, the number of iterations required for the entire population to reach a consensus value of the arbitrary trait was tabulated and compared across various network structures.

Table 1 Network types used in the simulations

Network type	Description of neighbors
Regular	left, right, up, down, diagonals
Scale-free	determined by preferential attachment
Small-world	determined by random rewiring of a ring substrate
Random	determined by random attachment
Complete	every other agent

Because the small-world, scale-free, and random networks were generated through a stochastic algorithm and because the sequence of interacting partners was determined randomly, 100 replications of each parameter set was simulated to generate a distribution of outcomes. In other words, 100 different simulations were run, each with a different randomly generated network in the case of small-world, scale-free, and random networks. A list of all simulation parameter values for this experiment presented in Table 2.

Table 2 Model parameters and values for simulation 1

Parameter	Values
The population size (N)	64 & 400
The range for the arbitrary trait value	[0,1]
The interaction influence (i)	1.0
The network type	see Table 1

Results: Time to Consensus

In all network types the population eventually converged to a consensus value – every member eventually reached the same value for its arbitrary trait (Table 3). However, the number of iterations required to achieve this consensus differed significantly among network types both when using population size N = 64 (ANOVA, F = 582.83, p < 0.01) and when N = 400 (ANOVA, F = 966.1, p < 0.01).

While consensus occurred relatively rapidly in complete, random, scale-free and regular networks, consensus time in small-world networks was dramatically higher, requiring up to 50 times as many iterations as those simulations run on complete networks (Figure 1).

Discussion

Results from this experiment become meaningful when we consider that small-world networks are the primary interaction pattern within human societies (Watts and Strogatz 1998). These results demonstrate one possible reason why policy conventions intended to build multi-cultural consensus may appear to have little effect – sufficient time may simply not have elapsed for the policy to be effective. Furthermore, if a policy requires timely consensus in order to be effective, the nature of the target population's social structure may lead to that policy's ultimate failure.

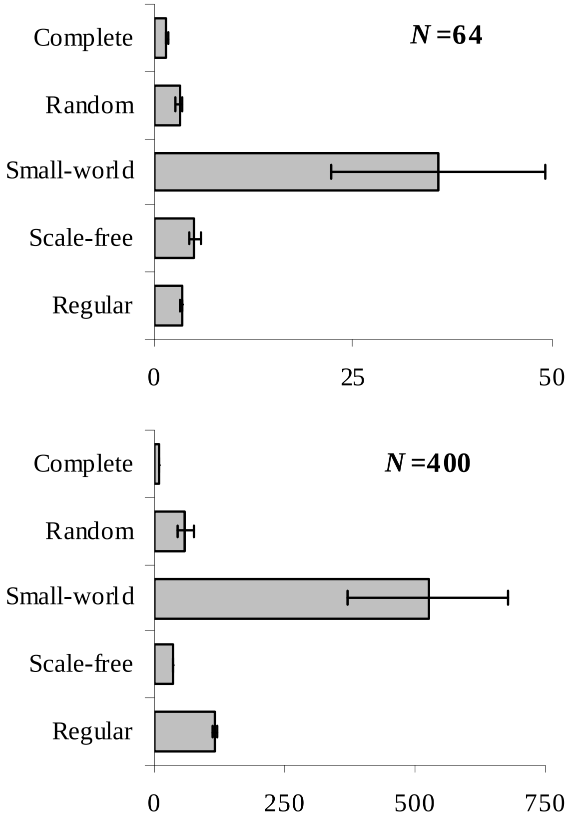

Figure 1 *Effect of network type on the number of iterations required to reach consensus under two different population sizes (N). Bars represent the mean number of iterations required over 100 replications. Error bars represent ±1 standard deviation of the mean.*

Table 3 Consensus time under different networks and population sizes (*N*)

	Mean (SD) iterations until consensus (in thousands)	
Network type	***N* = 400**	***N* = 64**
Regular	118.0 (3.9)	3.6 (0.2)
Scale-free	36.6 (1.9)	5.1 (0.7)
Small-world	525.7 (152.7)	35.7 (13.4)
Random	61.0 (16.5)	3.1 (0.6)
Complete	10.5 (0.2)	1.6 (0.1)

One possible remedy to such pitfalls is that preliminary policy evaluation may include an assessment of the social network governing interactions of a target society. If a policy is crafted to alleviate social upheaval in society A through consensus-building, finding that interactions among society A's members correspond to a small-world network may dictate that policy makers rethink their strategies.

Dynamic Networks and Persistent Conflict

Another explanation for long-standing cultural clashes, racial tension, value divergence and other ideological conflicts may be that there exists a dynamic polarizing mechanism that inhibits consensus altogether. In this experiment we extend the previous simulation by incorporating interaction rules that not only alter each agent's arbitrary trait value, but also alter the network structure itself. In other words, the network is no longer static but is dynamic and co-evolving with the individuals' arbitrary traits.

This is accomplished through an assessment of the difference between the initial arbitrary trait values of two interacting agents. Qualitatively speaking, if the difference is sufficiently low the agents sense that there is some hope of compromise and will attempt to come to some consensus (just as in the first experiment). However, if the difference is too great, the agents sense that they are simply too dissimilar to hope for a consensus and forgo future social interactions by severing the link between them (Zafonte and Sabatier 1998, Weible 2005). Each agent then compensates for the lost neighbor by reconnecting randomly to so some other agent in the population to which it is not already connected.

While it is true that an agent may subsequently connect to a second agent even more different that one from which it has severed a link, the connecting agent cannot make such an assessment without first connecting and interacting with second agent.

Simulation Description

Beginning with the simulation described in above we add the parameter D, a threshold of trait difference above which two interacting agents end the interaction without changes to their trait values and sever the link between them:

$$T < D;\ (a_1, b_1) = \begin{Bmatrix} a_0 \geq b_0; & a_1 = a_0 - i\dfrac{T}{2}, & b_1 = b_0 + i\dfrac{T}{2} \\ a_0 < b_0; & a_1 = a_0 + i\dfrac{T}{2}, & b_1 = b_0 - i\dfrac{T}{2} \end{Bmatrix}$$

$$T \geq D;\ (a_1, b_1) = (a_0, b_0) \qquad (4)$$

In the case that two interacting agents are too dissimilar ($T \geq D$) one link is severed and two new links are created – a net increase of one link in the network. This rule eventually leads to a nearly maximal densification of links in the network regardless of the type of starting network. Therefore, for the sake of brevity only regular networks were used as starting structures in this second experiment.

Unlike the previous simulation, there was no test after each iteration that determined whether the population had reached consensus. Instead the simulation ran for a fixed number of iterations after which the distribution of trait values was examined. Table 4 lists all simulation parameter values for this second experiment.

Table 4 Model parameters and values for simulation 2

Parameter	Values
The population size (N)	64 & 400
The number of iterations in a single simulation run	1,000,000
The range for the arbitrary trait value	[0,1]
The interaction influence (i)	1.0
The trait difference threshold (D)	0.3
The network type	regular

Results: Persistent Conflict

Like the first experiment, populations in some runs of the second simulation converged to a consensus value for the arbitrary trait. However, in other runs, the population failed to reach consensus but instead became partitioned into two groups, each of which had converged to a different common value. Results presented in Table 5 show examples of such runs. In each case, an analysis of the distribution of trait values after 10^6 iterations revealed that two different trait values were present in the population. Since in each case the difference between the two fixed values was greater than the threshold for attempting a compromise, the population was fixed with respect to each member's trait. Conflict was perpetuated – the initial population diverged over time into two permanently dissimilar camps.

Table 5 Final trait distribution after 10^6 iterations

Network	N	Trait value	Frequency
Regular	64	0.7776	25
		0.2397	39
Regular	400	0.6523	251
		0.2422	149

In addition, because of the network dynamics described above, the network evolved to become essentially complete; each agent was, or nearly was, connected to every other member of the network. So while two divergent trait values emerged, they coexist within a single well-connected group. This arises because the algorithm forces two dissimilar nodes to make connections to nodes to which they are not already connected. As members of each separate trait group become densely connected to each other, agents are eventually forced to link to a member of the opposing group so that a true partition of the groups never takes place.

Discussion

As pointed out above, the dynamic network rules added here evolve an essentially complete network. In the first experiment this was the network type that most rapidly facilitated consensus within a population (Table 2). However, it is clear that conflict, defined as differing arbitrary trait values, persists permanently in this second population despite its nearly complete network structure. The only method for ending this conflict and achieving consensus is for the threshold parameter D to increase so that dissimilar members stop ignoring each other and begin to move towards each other with respect to their trait values.

Policy makers facing such a persistent conflict in a real-world situation might then wish to focus on policies that increase the willingness of the members of a target society to accept dissimilar viewpoints or cultural values. Researchers have suggested that this may be accomplished through increased education and democratic reforms, among other methods (Klak and Martin 2003). Others have demonstrated that a crisis created by a threat from outside the conflicted society will drastically increase the willingness of dissimilar members to come to some consensus – the so-called "closing the ranks" phenomenon (Mullen and Hu 1989).

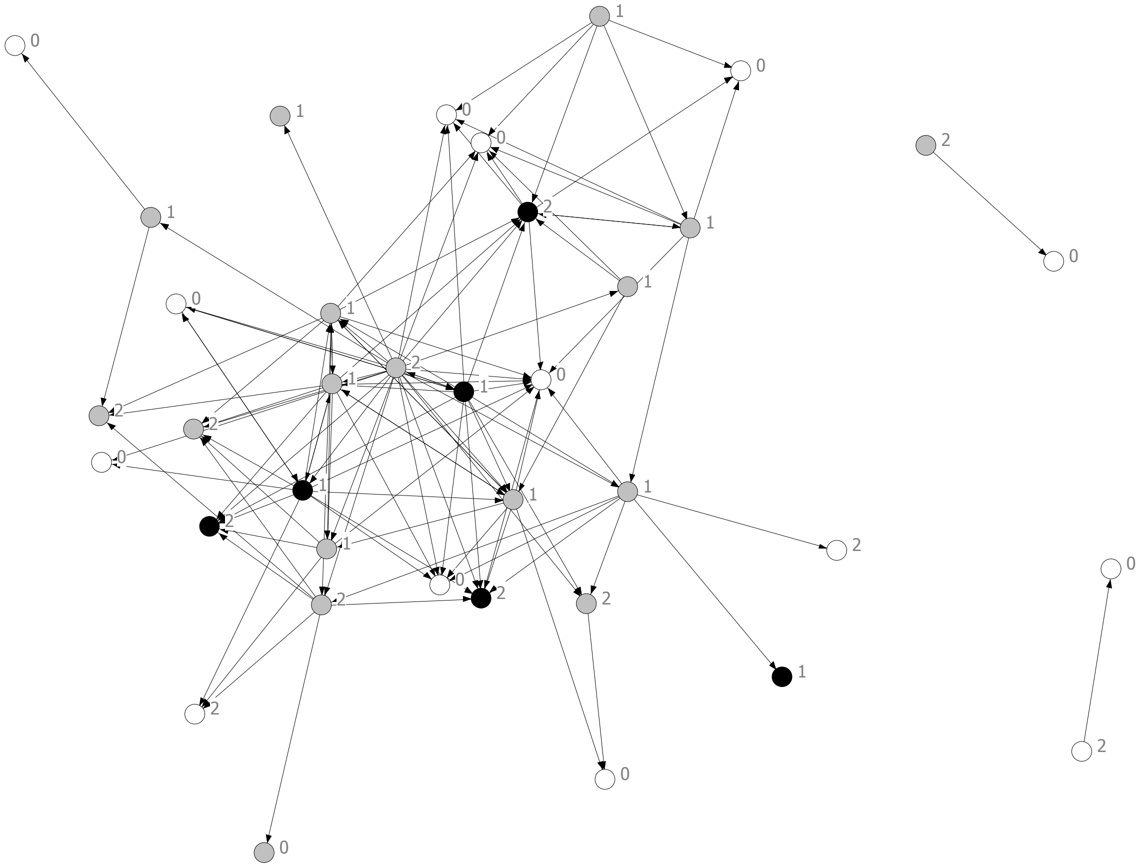

Figure 2 *The social network within the VRBP. Highlighted are links based on political ideologies (node label: 0 = no response 1 = more liberal, 2 = more conservative) and environmental values (node shade: white = no response, gray = pro-environmental, black = business as usual) are not distributed randomly.*

The Verde River Basin, Arizona – a Case Study of Persistent Conflict

Following the simulations we conducted a brief survey of local policy issues which might concur with simulation results and which might further inform future simulation designs. One applicable case study was undertaken by the Social Networks and Water Conflict Workshop[1] held at Arizona State University in the fall of 2007. The workshop studied a partnership of several entities in central Arizona concerned with groundwater pumping policies. Its network of actors was found to fit the description of a small-world network, yet conflict persists about how best to address the directive of the partnership.

The simulation described in this paper was in no way informed by findings of this case study. Instead, future extensions of this simulation will benefit from incorporating the workshop's empirical results.

Case Study Background

In 2003 U.S. Senator John McCain introduced a bill[2] to create the Verde River Basin Partnership (VRBP), a network of municipalities and community groups charged with addressing concerns about water withdrawal from the Big Chino aquifer (Bolin, Collins, and Darby 2008). Through the commissioning of scientific reports, the VRBP was to resolve concerns about how excess withdrawals would affect stream flow in the nearby Verde River and the ecological and economic impacts it would have downstream. Conflict, however, has prevented the partnership from reaching consensus regarding what science is needed, what existing science is valid, and how

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[1] Members included Bob Bolin, Bethany Cutts, Kate Darby, Tischa Muñoz-Erickson, Elisabeth Larson, Mark Neff, and Amber Wutich, all of Arizona State University.

[2] Bill S. 849, Northern Arizona National Forest Land Exchange Act.

Table 6 Tests for attricute correlation with tie frequency among the VRBP members

	Joint Count Contingency Analysis		Structural Block Model	
Variable	X^2	p	R^2 probability	No. of Comparisons (Significant)
Environmental Values	**42.33**	**0.05**	**0.13**	**9(1)**
Science Attitudes	20.96	0.19	0.48	9(0)
Scientist Attitudes	13.07	0.47	0.73	9(0)
Political Ideology	**43.45**	**0.05**	**0.11**	**9(0)**
Barrier	86.97	0.10	0.09	49(0)

Table 7 Network autocorrelation with categorical attributes - structural block model for environmental values

Independent Variable	Std. Coefficent	p	Higher (+) or Lower (-) than Expected
Non-response to Non-response	0.001	0.09	+
Non-response to Business as Usual	-0.03	0.07	+
Non-response to Pro-environmental	-0.02	0.09	+
Business as Usual to Non-response	0.06	0.10	-
Business as Usual to Business as Usual	0.04	0.31	-
Business as Usual to Pro-environmental	0.12	0.14	-
Pro-environmental to Non-response	-0.01	0.13	+
Pro-environmental to Business as Usual	**-0.09**	**0.02**	**+**
Pro-environmental to Pro-environmental (Intercept)	0.00	0.10	+

science should be used to aid decision making (Neff et al. 2008). The ability to make these types of decisions has been further hindered by the refusal of some upstream communities to participate in the process.

A survey was conducted to assess conflict within the VRPB network and to uncover the existence of barriers to achieving consensus. Several ideological and positional qualities of network members were examined including environmental values, political views, opinions about barriers to decision-making, views on science as a decision tool, and opinions about the role of scientists as policy developers (see Muñoz-Erickson et al. 2008 for further details).

Workshop Findings

Defining a link as an act of information sharing occurring at least monthly, the survey showed that the network contained three components representing ideological clusters similar to that which evolved in the second simulation experiment. The first component consisted of 33 actors and the second and third consisted of two actors each. Nine actors were isolated. The network density = 0.056, in-degree centralization = 0.193, and the clustering coefficient = 0.23. Overall, the network exhibited signs of power differences among actors, relatively high clustering, and short path lengths (Figure 2), matching the qualitative properties of a small world network (Watts and Strogatz 1998, Buchanan 2002).

Despite the clusters of divergent ideologies, we found that most ideological boundaries were being spanned. Individuals with divergent views about the biggest barriers to decision making, views about the role of science in providing objective facts, and views about the role of science in developing policy were all equally likely to interact with one another. However, connection frequency within and between groups diverged significantly from random in one case - environmental views. Using a relational contingency analysis statistical test, we found that links between members with divergent environmental values were not randomly distributed (Table 6). A structural block model ANOVA revealed no significant difference between the frequency of links within or between political ideologies (liberal, conservative, and non-respondents) or between environmental values (pro-environmental, “business as usual”, and non-respondents (Table 7). Individuals with pro-environmental views were most likely to connect to others with environmental views that advocated a “business as usual” perspective, although the overall model is not significant (p = 0.13). There were no differences in the prevalence of links between any other two groups.

The tendency for links to span across ideological boundaries rather than within them was contrary to the expectations for issues that create and perpetuate conflict. However, this finding did concur with results of the second simulation above in which actors of one trait value cluster became highly linked to actors of the opposing trait value cluster.

Informing Future Simulations

Although this case study aligns with simulation results by presenting an example of persistent conflict in a small-world network and demonstrating significant linkage between actors in divergent ideological camps, it should not be construed as a validation of the simulation model. On the contrary, the case study provides valuable insights regarding how to extend and improve the simulation.

Most importantly the case study reveals the importance of heterogeneity among actors in a network with regard to power and influence. The current simulation uses population level parameters for the influence that actors have on one another and for the threshold governing how actors behave towards one another given the magnitude of their difference. The case study suggests that both of these population level parameters should be moved to the agent level and that heterogeneity of the values held by agents should be allowed.

Furthermore, the case study reveals that another possible dynamic linking rule might be that certain agents intentionally seek out those most different from themselves in an intentional act of conciliation.

Conclusion and Future Directions

In this short study we have created a very simple model, stripped of much of the complexity found in actual societies. Our purpose was to create a foundation for future simulations in which cultural factors can be carefully added and their effects examined. We have intentionally crafted our agents to be abstract social entities.

Even in its simplicity, our findings demonstrate at least one potential mechanism to explain persistent conflict in real-world social networks. The qualitative attributes of the network structure may greatly extend the time required for a group to reach consensus or, under certain connection rules, may inhibit consensus altogether.

The case study revealed that other attributes of networked actors are also important and should be addressed in future iterations of the simulation. Furthermore, the simulation was written with parameter *i* for power of influence, but its parameter space was not explored in this set of simulations. Future versions of this simulation should include a parameter sweep of *i*.

Areas for improvement of the current simulation include its reliance on a uniform distribution of initial trait values. Future iterations of this simulation should explore not only alternate initial distributions but should also strive to use initial distributions grounded empirically. It is also worthwhile to develop simulations that explore the potential influence of traits on one another.

Finally, our model relies on a nominal classification scheme for the various networks with which we experimented. While useful, this scheme is far from the more desirable case in which an array of numeric attributes are generated for each stochastically created network used in the simulation. This would allow an array of simple regressions to be conducted against the simulated networks. Currently, there is no readily available software solution capable of the voluminous computational requirements needed to generate timely network statistics for tens of thousands of generated networks. For the field of evolutionary simulations on networks to progress it is imperative that a solution be developed that can address such large processing needs.

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