

Social Cohesion and Cooperation for Public Goods

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Abstract

A cohesive network keeps groups together and enables members to communicate about and cooperate for public goods. For ongoing cooperation, group members have to know if their group members cooperate or defect, but this information—mostly through gossip—is threatened by noise and biases. If there are redundant information channels, however, errors in monitoring and transmission in one imperfect channel can, to some degree, be corrected by information through another imperfect channel, and may lead to higher levels of cooperation. An influential conceptualization of social cohesion based on redundancy is K-connectivity: the minimum number (K) of node-independent paths connecting pairs of nodes in a group's network. In a lab experiment, we tested if higher K-connectivity yields higher levels of cooperation for public goods, controlling for a number of other network effects such as density, size, and average distance. We do not find the hypothesized effect, which might be due to a not-earlier-found shortcoming of the concept, and we propose a solution.

Keywords

Public goods, Cooperation, Social cohesion, K-connectivity.

Public goods pose dilemmas of collective action, which require a mechanism (or combination of complementary mechanisms) to solve. Solutions usually come in the form of selective incentives: (promises of) rewards and (threats of) punishments (Olson, 1965). In order for incentives to have the intended effect, however, individuals have to be monitored, and gossip that establishes their reputations has to be passed through the group's network reliably (Panchanathan and Boyd, 2004; Hilbe et al., 2018). As a result of unreliable information, people who deliver selective incentives may confuse cooperators and defectors, or ostracize the former and invite the latter in. The challenge is, therefore, to establish accurate reputations, on the basis of which indirect reciprocity can become an effective mechanism. The challenge is more severe in larger groups where most people do not know one another directly (Sommerfeld et al., 2007). In contrast to smaller groups, in which people are more likely to be in direct contact and can easily monitor, and

communicate with, each other, information in larger groups has to be transmitted through longer network paths (concatenations of ties) where it deteriorates with distance, shown in chain experiments (Eriksson and Coultas, 2012). Another experiment showed that without indirect reciprocity, network topology (i.e., structure) has no effect on the contributions to public goods (Suri and Watts, 2011). In real life, however, networks are important for reputations, and in a recent study of indirect reciprocity, reliable transmission of gossip was said to be “an interesting direction for future research” (Hilbe et al., 2018). In this paper, we take up the challenge, theorize redundancy of information channels, and conduct a lab experiment to compare a low-redundancy network with a high-redundancy network.

Theory

A century ago, Georg Simmel (1908) noticed advantages of a triad over a dyad, where a third

person can mediate between two others in case of misunderstandings. In modern parlance, a direct tie between two actors is complemented by a second, indirect, connection that provides redundancy of monitoring and information transmission, such that noise and bias in one imperfect channel can, to some extent, be corrected by information through another imperfect channel. Whereas in a triad, everybody is connected by two node-independent paths to everybody else, this structural homogeneity does not hold in larger, typically clustered, groups where some people are better connected than others. How could we generalize path-redundancy to larger networks? Research on “complex contagions” (Centola and Macy, 2007; Guilbeault et al., 2018) has shown that multiple paths are important indeed, but has not measured the independence of these paths, which may overlap at some nodes before arriving at the recipient of a message. Douglas White and Frank Harary (2001) proposed to decompose the generalization challenge into the analysis of one pair of actors at a time. For each pair, one can count the number of node-independent paths between them. In inhomogeneous social networks with clusters, pairs embedded within a cluster will often turn out to be connected by more redundant paths than pairs across different clusters. A group of individuals can then be depicted as a “landscape” with mountains for more connective parts, usually dense clusters, separated by valleys in between the clusters (Moody and White, 2003). This way of looking at redundancy implies that for a given network and every sub-network therein, there is a minimum number of node-independent paths, K , instead of one value that ignores heterogeneity. By using a mathematical theorem by Menger (1927), White and Harary showed that the minimum number of redundant paths in a (sub)network is equivalent to the minimum number of people who would have to be removed to break up the (sub)network into parts. Because these numbers of people and paths are identical, they can be unified in the notion of K -connectivity, where values of K vary across subgroups in the network (White and Harary, 2001). This conceptualization of social cohesion was the first where redundancy on behalf of information transmission was explicated as a key property.

The prime reason why cohesive groups exist is that their members can realize public goods. To test if more node-independent paths yield higher levels of cooperation for a public good, we compare two networks in an experiment (Chaudhuri, 2011; Camerer, 2003), one with low ($K=1$) and the other with high ($K=3$) connectivity. When introducing some noise in the information that people get about one another, we

expect that in the network with higher K -connectivity, ensuing inconsistencies can be more easily resolved, leading to higher levels of cooperation. To show that the expected difference is due to K -connectivity, we have to control for other network effects. Figure 1 (a) shows two networks that can be distinguished on the basis of their K -connectivity, not on the basis of other widely used network notions (Bruggeman, 2018): both networks have the same size (7), number of ties hence density (0.57), average shortest path distance (1.43), degree distribution with one central node, and both networks are 3-cores. The wheel is less clustered (0.55) than the bow-tie (0.73) but has higher K -connectivity ($K=3$), whereas the bow-tie has a topological bottleneck and therefore lower K -connectivity ($K=1$). Another famous network concept, k -core (Seidman, 1983), cannot perceive topological bottlenecks, and is therefore unsuited to describe redundancy. The concept of cluster has the same shortcoming. Taken together, these two networks seem to be suitable to test our expectation.

An earlier experiment showed that when individuals receive inconsistent gossips about someone from different sources, they tend to believe the majority (Sommerfeld et al., 2008). If the level of noise is not extreme and people have no incentive to manipulate strategically, the majority view will usually be right. This implies for our experiment where people can either contribute or free ride that an error in one channel can be corrected by true information from two other channels, if there are. We, therefore, expect that the wheel network, where everyone has three independent channels, will help the participants to better reduce noise than the bow-tie network, and that therefore contributions to the public good will be significantly higher in the wheel. This expectation is the hypothesis we test experimentally.

Experimental design

The experiment took place at the ELSE lab at Utrecht University, the Netherlands. Subjects for the experiment were students recruited at the Utrecht University through the online recruitment system ORSEE (Greiner, 2015). Experimental sessions consisted of one, two or three groups (networks), depending on the availability of subjects. Upon arrival, subjects were randomly assigned to groups and seated behind computer screens with separators preventing them from looking at each other’s screens and at each other. They stayed in the same network topology for the entire session, and made all of their decisions via a computer interface that prevented them from identifying their fellow group members.

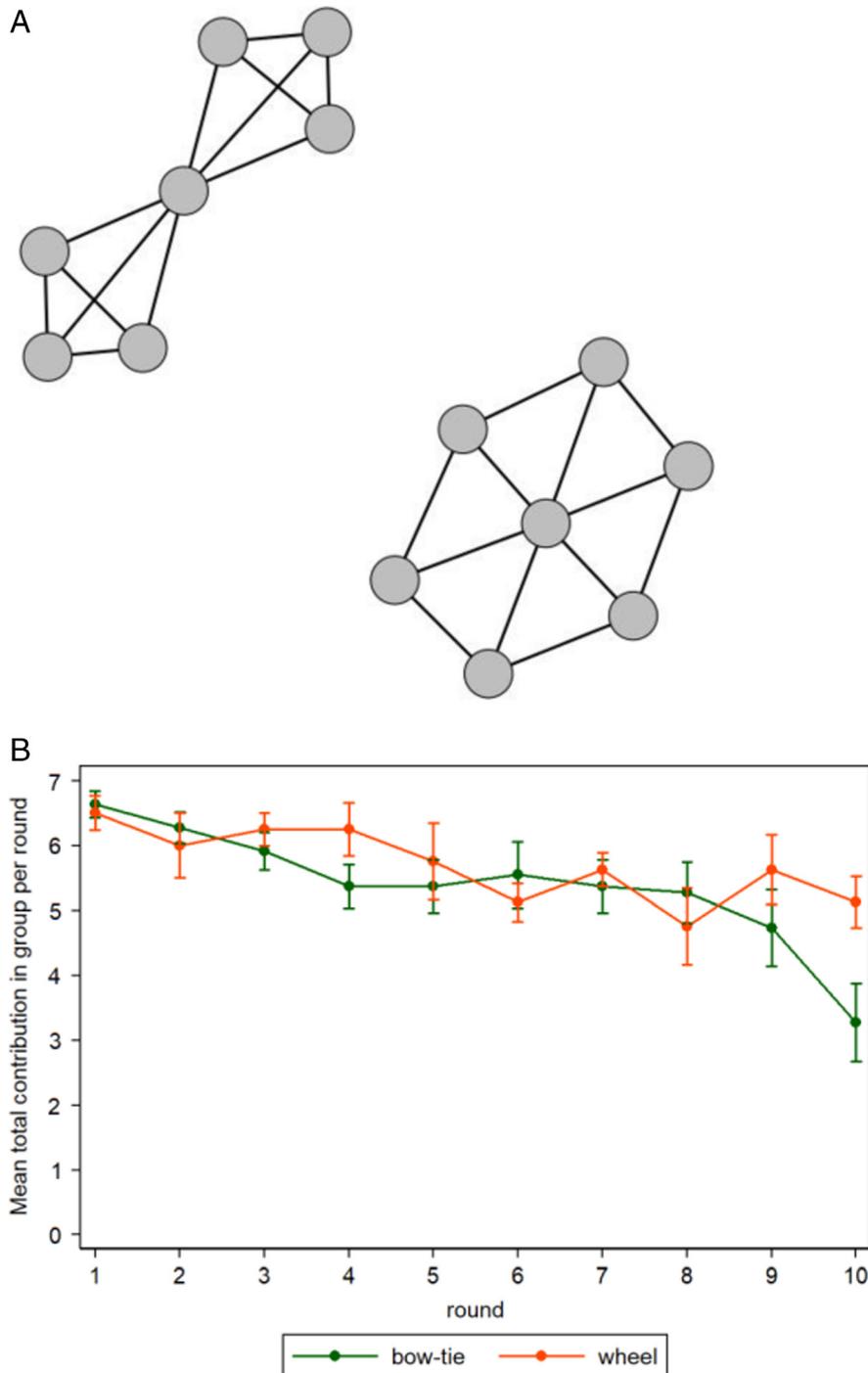


Figure 1: (a) Bow-tie and wheel networks, adapted from Bruggeman (2018). (b) Experimental outcomes over all groups (N=19). Error bars represent standard errors of the means.

There were 133 subjects in 11 bow-tie groups and 8 wheel groups, hence $N=19$ at the group level. Subjects were given instructions on paper that they applied in three practice rounds before the experiment started. After the three practice rounds,

groups were reshuffled, with the exception of two sessions that consisted of only one group each. Each round had three stages:

First, from an initial endowment of 10 points (at an exchange rate of 0.7 to the Euro) subjects could decide

to contribute 1 or 0 points, being informed that the sum total of contributions would be multiplied by $r = 1.6$ and then distributed equally among all seven group members. Formally, given $N = 7$ participants (Figure 1a) and $n < N$ contributors without the focal individual, the latter faces a choice to defect and get a payoff $P_D = rn/N$, or to cooperate and get $P_C = r(n+1)/N - 1$, at a cost of 1 unit. Consequently, only if there are at least $n = 4$ cooperators it makes sense for the focal individual to contribute herself.

Second, the subjects were shown the contributions of their network neighbors (direct contacts), being informed that there was a 1/12 chance (given 12 ties) that information about someone’s contribution was wrong—our implementation of noise. Subjects could then gossip about their neighbors’ (lack of) contributions by clicking thumb up or down, visible to their neighbors except the gossipees.

Third, they were shown the gossips from their neighbors, and could propose a monetary punishment of 1 point for one of them, being informed that the computer would implement it by majority vote at no cost. The reason for cost-free punishment is to avoid that costly punishment blurs the network effect we are after. Because gossip and punishment proposals were hidden for, respectively, gossipees and punished individuals, the confounding effect of revenge against particular individuals was precluded. Furthermore, the subjects were informed that their total payoff could never become negative. At the end of the experiment, the points earned by the subjects were converted to euros and paid out discretely in cash.

Results

Figure 1(b) shows the aggregate results of the contributions in each of the two network topologies. While contributions were overall slightly higher in the wheel, the overall difference is not significant. Only in the final round, contributions are significantly higher in the wheel than in the bow-tie (t -test with $N = 19$, difference = 1.85, $p = 0.016$), suggesting that the wheel network may be more robust against the end game-effect than the bow-tie network, although we did not hypothesize this to happen. Overall, however, we conclude that our hypothesis that cooperation is higher in the wheel than in the bow-tie network is not supported.

The main difference between the two networks is in the central node and others’ dependence on it. Rather than an overall network effect, as we hypothesized, it might be the case that the outcome is mainly due to the central node in each network, which we did not anticipate. We, therefore, also

examine whether contributions of the central actor differ between the wheel and the bow-tie network. We furthermore examine whether it is the case that the more often a subject observes consistently positive information about another subject, the more likely they will contribute in the next round, and the more often a subject observes inconsistent information about another subject (both positive and negative), the less likely they will contribute in the next round.

To these ends, we estimate a multilevel mixed-effects logistic regression model with individual contributions per round as the dependent variable. As independent variables, we include the network position of the subject (central or not); the network topology; the round number; the number of alters about whom the subject saw inconsistent gossips in the previous round; the number of alters about whom the subject saw two positive gossips in the previous round; and, the total proportion of contributions by network neighbors in the previous round. We furthermore include a coefficient for the cross-level interaction between network topology and network position, along with a random slope for network position.

The results of this analysis (Table 1) do not provide evidence that the network position, network topology, or the consistency of the information available to the

Table 1. Multilevel mixed-effects logistic regression model of individual contributions per round on network topology, network position, and information available to the subject. N(level 1) = 133; N(level 2) = 19.

	Coeff.	St. Err	z
Central	-0.050	0.479	-0.104
Topology: wheel	0.391	0.506	0.773
Central in wheel	0.472	0.783	0.602
Round nr.	-0.223*	0.093	-2.385
Inconsistent gossip	-0.167	0.195	-0.860
Two thumbs up	-0.200	0.369	-0.543
Tot. contrib.	0.373	1.012	0.369
Gossip tot. pos.	0.296	0.555	0.532
Gossip tot. neg.	0.150	0.402	0.374
Cons.	2.605	2.103	1.238

Note: * $p < 0.05$.

subject had any impact on her contributions. The only significant effect is that of the increasing round number.

Discussion

We tested the hypothesis that under noisy conditions, redundancy in the form of multiple node-independent network paths makes it possible to reduce noise and to cooperate at higher levels. This was not supported by the experiment. To control for other network effects, the two networks were similar, but thereby perhaps too similar to make their difference significant. It might also be the case that a higher level of noise would have shown their difference more clearly.

One could argue that on top of redundancy, a proper concept of cohesion should also take distance into account, but in our small networks, distances are small and the average distances are identical. One candidate for such an alternative concept that has, to our knowledge, not yet been described in the literature, relies on the notion of nexuses. On top of node-independent paths, there may be nexuses between these paths, which can re-enforce messages from a sender (S) to a recipient (R), illustrated in Figure 2 both networks have the same K-connectivity ($K=2$) but network (a) features nexuses, with significant positive effects on the reliability and accuracy of information transmission, shown in an experiment (Eriksson and Coultas, 2012).

There is a network measure that does take redundancy, distance, and nexuses into account: algebraic connectivity. To calculate this measure, one row-normalizes the adjacency matrix, as in models of social influence (Friedkin and Johnsen, 2011), and transforms it into a Laplacian matrix by putting 1 everywhere on the diagonal, provided that everyone has at least one tie, and a minus sign everywhere else (Chung, 1997). The second smallest eigenvalue of the Laplacian is called algebraic connectivity (Fiedler, 1973). It is higher if there are more node-independent paths ($\lambda_2 = 2/3$ wheel; $\lambda_2 = 1/3$ bow-tie), consistent with K-connectivity, hence it varies across sub-graphs, just like K-connectivity. Furthermore, it is lower for longer average distances, which neither K-connectivity nor k-core is responsive to. Information transmission deteriorates with distance, certainly off-line, and it's therefore important to have a measure that takes distance into account. Algebraic connectivity distinguishes nexuses, and equals $\lambda_2 = 2/3$ for the network with nexuses in Figure 2 and $\lambda_2 = 1/2$ for the other one. Last but not least, it predicts how quickly consensus is achieved (Olfati-Saber and Murray,

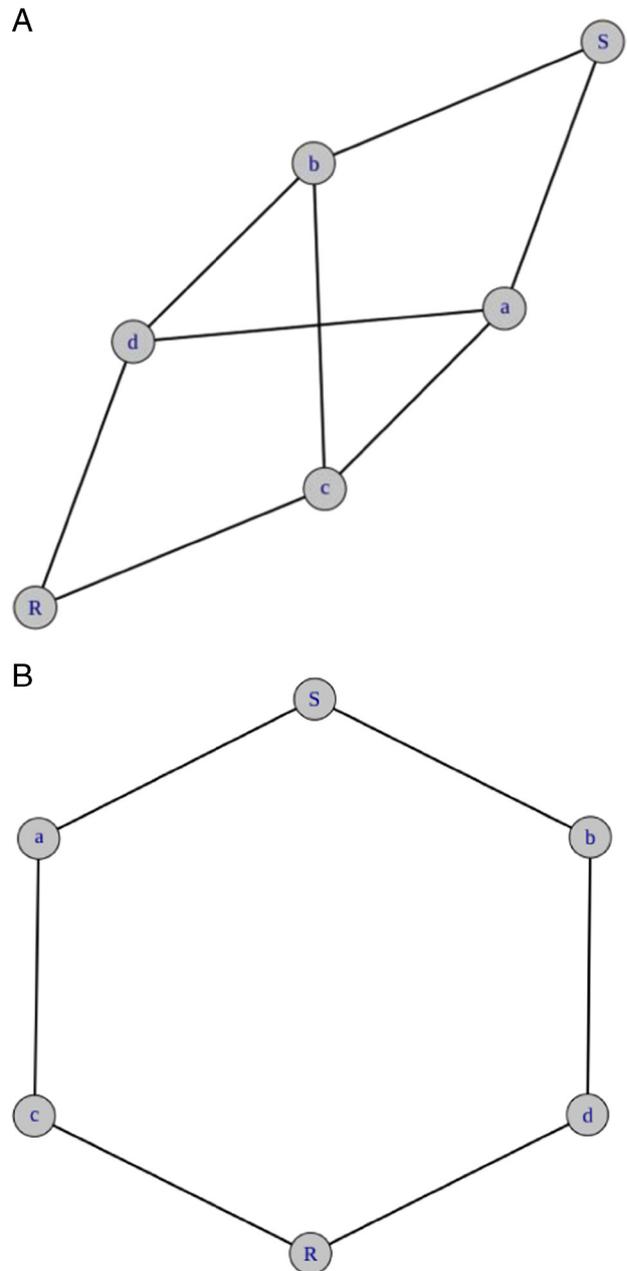


Figure 2: Two 2-connective networks, (a) with nexuses and (b) without nexuses.

2004), consistent with experimental outcomes (Judd et al., 2010). Consensus is important in groups to decide which public goods to realize and how.

In our experiment, the positive effect of the multiple paths in the wheel might have been nullified by the positive effect of the additional nexus in each sub-network of the bow-tie. If for social cohesion, algebraic connectivity is a significantly better measure than K-connectivity remains a question for future

research. Whereas in all likelihood, social cohesion, measured in one way or another, is important for cooperation, we note that the effect is nonmonotonic. High cohesion overburdens group members with social pressure, decreases innovation, and may strengthen rather than dampen false information (Burt, 2008). At too low cohesion, in contrast, groups fall apart. The sweet spot must be somewhere in between the extremes, which poses a challenge for future studies to discover.

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