The Effect of Gossip on Social Networks

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***Abstract*—In this paper we develop a simple model for the effect of gossip spread on social network structure. We define gossip as information passed between two individuals A and B about a third individual C which affects the strengths of all three relationships: it strengthens A-B and weakens both B-C and A-C. We find out that if gossip does not spread beyond simple triads, it destroys them but if gossip propagates through large dense clusters, it strengthens them. This work is novel in two respects. First, while past studies have looked at how network structure affects gossip spread, here we show how gossip spread affects network structure. And second, although there is previous theoretical work on how information or matter flowing through a network can change its structure, our contribution is to specifically model this process when the flow affects edges not necessarily along its direct path.**

***Index Terms*—Gossip, Social Networks, Network Dynamics**

I. Introduction

GOSSIP is ubiquitous in human groups and has even been argued to be fundamental to human society [7]. It usually has negative connotations: generally, no one wants to be thought of as a gossip, and gossiping has traditionally been viewed as an indirect form of aggressiveness. However, gossip also seems to have a variety of benefits, including helping individuals learn the cultural rules of their societal group [3]. In [7], the author even proposed that gossip is analogous to grooming in primates: it is essentially a tool to create and maintain relationships between individuals, with little importance given to the accuracy or quality of the actual information being passed.

Unlike rumors, which pertain to issues and events of public concern, gossip targets the behavior and life of a private individual. Gossip can essentially be defined as information passed from one individual (originator) to another (gossiper) about an absent third individual (victim) [13]. Therefore, any analysis of gossip must occur at the level of the triad or higher [20]. We assume, for the purpose of this paper, that gossip serves to strengthen the relationship between gossipers and weakens the relationship between the victim and each gossiper (Fig. 1).

Previous work has explored how social structure influences the flow of gossip and which network types best promote gossip [13]. This work is closely related to the vast body of contagion literature [6] studying how cultural fads [4], [9], technological innovations [1] or contagious disease [2], [12], [15], [18] spread on networks. Gossiping, however, has the potential to change the structure of the network on which it flows by damaging some relationships while strengthening others [20]. This suggests a flip side to the problem of the spread of gossip that has remained unaddressed to date. In this paper, we address exactly this problem, by investigating how gossip affects the structure of the social network it flows through.

The process of an information flow molding a network has been previously studied in the context of Hebbian learning, where the simultaneous activation of neurons leads to an increase in the strength of their synaptic connection [10]. A similar type of path reinforcement has also been observed in ants [8], humans [11], and even slime molds [16]. All of the above models, however, explicitly describe modification of the network only along the flow's direct path. Information or matter passed along one network edge only affects other edges indirectly, due to a "conservation" principle: for example, because there is a finite number of ants, by choosing one path more, the ants are indirectly choosing the other paths less. Our contribution is to model how information passed along one edge can directly affect the strengths of other edges in the network.

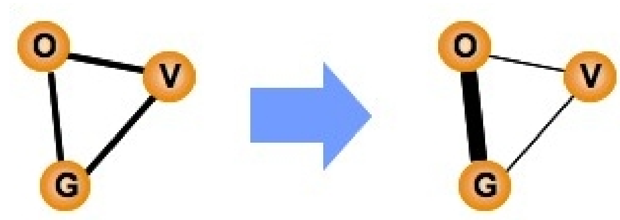

Fig. 1. Schematic for the effect of gossip on strengths of relationships of individuals in the triad. Individuals are represented as nodes and the strength of their relationship is represented by the thickness of the line between them. In a gossip event, an originator (O) spreads gossip about a victim (V) to a mutual friend, the gossiper (G). The result is a stronger relationship between the originator and the gossiper, and a weaker relationship between the victim and each the originator and the gossiper.

II. Methods

We built a simple network model in NetLogo [17] to simulate how the spread of gossip influences social network structure. In order to guarantee convergence, each simulation was run for 10,000 gossip events. We ran simulations with 48 different parameter combinations (3 network types, 2 network sizes, 2 methods of victim choice, 2 methods of originator choice, 2 methods of changing connection strength) for 10 repetitions each, for a total of 480 simulation runs.

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A. Model

To simulate a single gossip event on a network we first choose a random node in the network to be the 'victim' of the gossip event. Then we choose one of the victims neighbors as the 'originator' of the gossip event (Fig.2a). In the first wave of a gossip event, the gossip is spread to all the mutual neighbors, now gossipers, of the victim and originator (Fig.2b). In subsequent waves, each of these new gossipers then spreads the gossip to their mutual friends with the victim (Fig.2c). This process continues until no new individuals become gossipers (see Algorithm 1).

We assumed that spreading gossip results in a stronger relationship between all gossipers, and a weakened relationship between the victim and the gossipers. Allowing link weights to take values between 0 and 1, we used two functions describing this effect:

- **normalized**: For increasing, $w_{n+1} \leftarrow w_n + \alpha(1 - w_n)$ and for decreasing, $w_{n+1} \leftarrow \beta w_n$ in which $\alpha < 1$ and $\beta < 1$. This method has hysteresis, i.e. an increase followed by a decrease does not necessarily lead to the initial value of strength.
- **quadratic**: For increasing, $w_{n+1} \leftarrow \sqrt{w_n}$ and for decreasing, $w_{n+1} \leftarrow w_n^2$. Other powers can be used for extensions.

All edges were initially set to have a strength of 0.5 at the start of the simulations and those links whose weight dropped below 0.0005, during the course of the simulation, were severed.

Algorithm 1 Basic Model

for each gossip event **do**
  set all individuals as non-gossipers
  choose victim: pick a random individual
  choose originator: pick a random neighbor of victim
  set originator as a gossiper
  while $\exists$ mutual neighbors of the victim and a gossiper $\ni$ are non-gossipers **do**
    set all mutual neighbors of the victim and each gossiper as gossipers
  end while
  decrease the links between the victim and each gossiper
  increase the links between all pairs of gossipers
end for

To test if any results we saw were due to just strengthening and weakening connections between triads of nodes, we also ran simulations on a null-gossip network, where a single gossip event only occurred within a single triad of individuals. In other words, gossip was only allowed to spread from the originator to one other individual (see Algorithm 2).

B. Networks

We conducted simulations on several network types to see if the effect of gossip varied with network structure: random. We used random, small-world, and spatially clustered networks. These network types match observed patterns of social organization and provide sufficient variation in average path length and clustering. For the small-world networks, we used the original generative algorithm [19] with a rewiring probability of 0.15. The spatially clustered networks were generated by distributing the nodes randomly in space and then letting a randomly selected node establish a link with the closest node.

Algorithm 2 Null Model

for each gossip event **do**
  set all individuals as non-gossipers
  choose victim: pick a random individual
  choose originator: pick a random neighbor of victim
  set originator as a gossiper
  choose one random mutual neighbor of the victim and gossiper, and set as gossiper
  decrease the links between the victim and each gossiper
  increase the links between the pair of gossipers
end for

We also varied network size, comparing small (N=50) and large (N=200) networks, each with an average node degree of 6.

C. Alternative Gossip Algorithms

In the simplest case, the probability of becoming a gossip victim or originator is uniform across nodes. Following theoretical arguments and previous empirical findings, we also explored two additional algorithms for starting the gossip event:

- The probability to become a victim increases with degree centrality (see Algorithm 3). This algorithm models the situation where more popular people are more likely to be subjects of gossip, which is the working mechanism in the hypothesis that gossip serves to equalize the social status of individuals in a network [5].
- The probability to originate gossip is 1 for the agent with the weakest connection with the victim (see Algorithm 4). Here, we model the expectation that one is unlikely to pass gossip about one's close friends. Indeed, it has been found that gossip tends to weaken already weak relations [20].

We discuss further examples of alternative algorithms for spreading gossip in the 'Future Directions' section below.

D. Statistics

To quantify the results of our simulations, we looked at the average node degree and the clustering coefficient of the network at the end of each simulation. To measure the network clustering, we first estimate the local clustering of each node (how close the node's neighbors are to being a complete graph) and then average across all nodes [19].

We also looked at how final network structure, as defined by number of clusters and clustering coefficient, was related to connection strengths. We did this by including only links greater than 0.8 strength and calculating the number of clusters

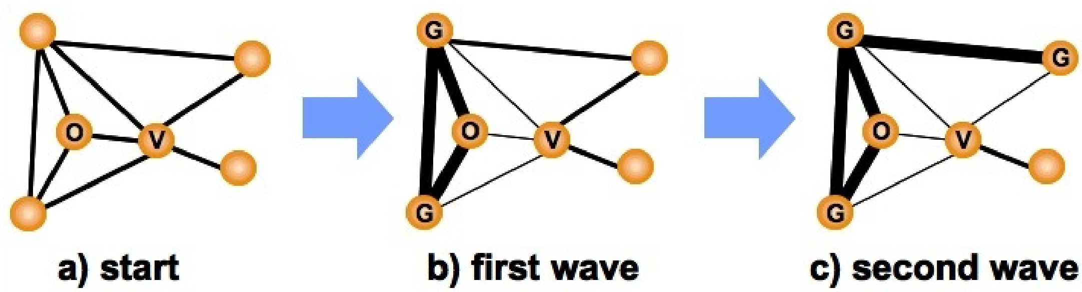

Fig. 2. Schematic for how gossip spreads in a social network. a) We randomly chose a node to be the victim (V) and one of its neighbors to be the originator of the gossip (O). b) The originator spreads the gossip to all mutual friends with the victim, strengthening connections between all gossipers and weakening all connections between the victim and gossipers. c) This process continues until no more individuals can become gossipers.

Algorithm 3 Model with Popular Agents More Likely as Victim

for each gossip event **do**
  set all individuals as non-gossipers
  choose victim: pick a random individual, chosen based on degree – individuals with higher degree more likely to be picked
  choose originator: pick a random neighbor of victim, chosen completely randomly
  set originator as a gossiper
  while $\exists$ mutual neighbors of the victim and a gossiper $\ni$ are non-gossipers **do**
    set all mutual neighbors of the victim and each gossiper as gossipers
  end while
  decrease the links between the victim and each gossiper
  increase the links between all pairs of gossipers
end for

Algorithm 4 Model with Victim's Weakest Link as Originator

for each gossip event **do**
  set all individuals as non-gossipers
  choose victim: pick a random individual, chosen completely randomly
  choose originator: pick neighbor of victim with the weakest connection to victim
  set originator as a gossiper
  while $\exists$ mutual neighbors of the victim and a gossiper $\ni$ are non-gossipers **do**
    set all mutual neighbors of the victim and each gossiper as gossipers
  end while
  decrease the links between the victim and each gossiper
  increase the links between all pairs of gossipers
end for

and clustering coefficient. Then we included links greater than 0.6 and recalculated the number of clusters and clustering coefficient. We repeated this for links greater than 0.5, 0.4 and 0.2 (see Results).

III. Analysis

A. Triads

For the simplest case, we assume that we have only three connected nodes and that links change according to the quadratic function. Without loss of generality, we assume that A gossips to B about C (see Fig.3).

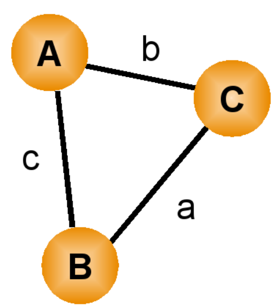

Fig. 3. A gossips to B about C

In this case, c is replaced with $c^{\frac{1}{2}}$, a is replaced with a^2 and b is replaced with b^2. After n steps of the same action, the new values are

$$a^{(2^n)}, b^{(2^n)}, c^{((\frac{1}{2})^n)} \tag{1}$$

If the victim is chosen at random for each step, after n steps the new values are (assuming that n is large enough)

$$a^{(1/2)^{(n/3)}\times(2)^{(2n/3)}} = a^{(2^{(n/3)})}, b^{(2^{(n/3)})}, c^{(2^{(n/3)})} \tag{2}$$

which means that when the victims are chosen at random, with further steps, the strengths of the connections weaken (until all of them tend to zero).

B. Complete Clusters

In a complete cluster we have n nodes $A_1 - A_n$ and there is a link between each pair of the nodes. The total link weights of node A_i is $\sum_{j=1}^{n} L_{ijk}$ (assuming that $A_{iik} = 0$). If

$$\sum_{j=1}^{n} L_{ijk} > \sum_{j=1}^{n} L_{ljk}$$

then node A_i has more probability than node A_l to become victim. So, considering the expected values regarding the probabilities, total link weights of A_i after change is[1]

$$\sum_{j=1}^{n} L_{ijk+1} = P_i \times NewValues + (1 - P_i) \times OldValues$$

Because of the dissipating effects of gossip on the victim, $NewValues < OldValues$. When P_i is small, $\sum_{j=1}^{n} L_{ijk+1}$ is close to $\sum_{j=1}^{n} L_{ijk}$ (as the second term, $(1 - P_i \times OldValues$, is dominant). But when P_i is a big enough number, $NewValues$ after being gossiped plays more role and decreases $\sum_{j=1}^{n} L_{ijk+1}$ compared to $\sum_{j=1}^{n} L_{ijk}$. This means that the proposed model of gossip moderates the network and brings the total weights of the nodes closer to each other.

IV. Results

In our model, although gossip both weakens and strengthens links, weak links break but no new links are created. Hence, a priori, we expect that gossip will decrease the networks clustering and average node degree.

The negative effect of gossip on clustering is most extreme in the null model: when gossip does not spread but occurs randomly in triads, the simulations quickly converge to networks with zero clustering, regardless of the properties of the initial network, the link-change function or the rules for selecting a gossip victim and a gossip originator. Furthermore, triads are unstable also when gossip spreads in networks with small initial clustering. For example, the average clustering coefficient after convergence in all 160 runs with random networks is effectively zero (mean = 0.0048, std. dev. = 0.0076). These results confirm the analytical prediction that gossip breaks triads.

Nevertheless, in networks with sufficient initial clustering, the spread of gossip can have exactly the opposite effect: it can make certain triads more stable. When gossip originates in and spreads throughout a dense cluster, it strengthens more ties than those that it weakens. For example, in a complete network of five agents, gossip weakens only four relations (between the victim and each of the gossipers), while it strengthens six (among all gossipers). Hence, although over the long run gossip destroys weakly triangulated links (i.e. "bridges"), it makes the links in dense clusters maximally strong. The result is a more fragmented and cliquish network (Fig. 6).

When we account for initial clustering, the effect of gossip does not appear to differ among network types (Table 1). We only find that gossip tends to destroy links and weaken clustering to a lesser degree in large networks. Furthermore, when the gossip originator is the victim's weakest link, average degree and clustering are lower compared to the case when the originator is randomly chosen from the victim's links. This is so because, as elaborated in the analysis, under this rule weaker links become more likely to be severed.

[1]This is disregarding the increase in value when A_i is selected by another originator to gossip.

We also looked at network structure as a function of minimum link strength (only including links stronger than this 'min link strength' value for the analysis). Clustering coefficient varies little with min link strength (Fig. 4, top panel). Network type influences clustering coefficient more than network size (lines are clustered by color in Fig. 4). In contrast, the fraction of clusters varies greatly with min link strength, and seems to be influenced more by network size than network type. (Fig. 4, bottom panel). Random networks become especially fractured as a function of min link strength. In most cases, both metrics show the largest jump in value between 0.4 and 0.5. We believe this is due to the fact that there are likely many links in the network that are never affected by gossip over the course of the simulations, and stay at their initial 0.5 strength.

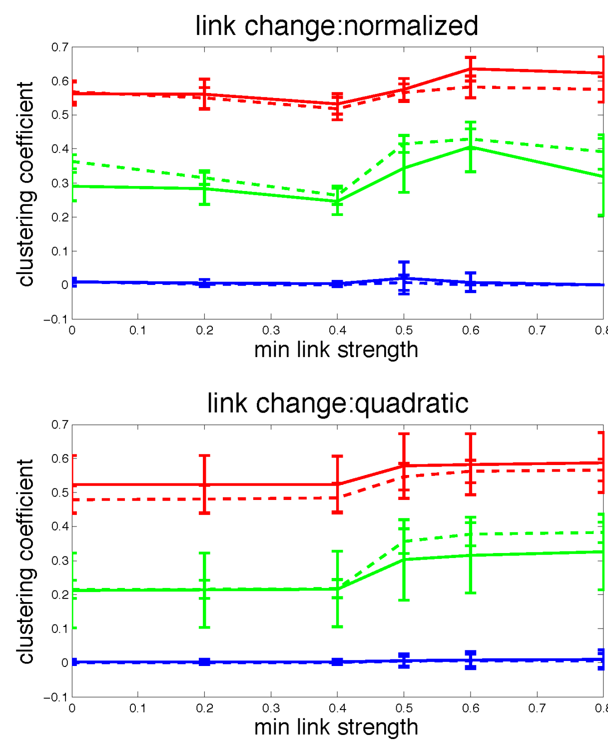

Fig. 4. Clustering coefficient as a function of what type of links are included in the network. (e.g. min link strength of 0.6 means that only links of 0.6 strength and higher are included). Results are shown by network type: blue is random network, green is small-world, and red is spatially clustered. Solid lines are for N=50 and dashed are N-200. In all cases victims and originators were chosen randomly. Panel 1 shows the result when the 'normalized' link change rule was used and Panel 2 shows the results when 'quadratic' is used.

The link change rule also influences both of these network metrics. With the quadratic method, most links converge quickly to 0 or 1, leaving few links of intermediate strength. This is demonstrated by the fact that the results for the quadratic method for both methods are flat as a function of min link strength (except the discontinuity at 0.5 mentioned above). In contrast, the normalized link change method results in links that are more uniformly distributed in strength. Hence,

TABLE I

LINEAR RREGRESSIONS OF FINAL NETWORK PROPERTIES ON SIMULATION PARAMETERS WITH STANDARD ERRORS ADAPTED FOR CLUSTERING WITHIN INITIAL CONDITION

	Clustering		**Average Node Degree**	
Variable	Coef.	Std. Err.	Coef.	Std. Err.
Large network	.0631**	.0167	.5085**	.0928
Quadratic effect	-.0699**	.0147	-.4006**	.0838
Spatially-clustered network	.0628	.0812	.6746	.4522
Small-world network	-.0698	.0499	-.3833	.2908
Victim: degree-central	.0081	.0147	.1131	.0841
Originator: weakest-link	-.0763**	.0147	-.4286**	.0843
Initial clustering	.8340**	.1539	-2.0728*	.8660
Constant	-.0221	.0242	5.5103**	.1241
R-squared	.9183		.7456	

* $p < 0.05$, ** $p < 0.001$

Number of observations = 480, Number of clusters = 48

the clustering coefficient is not flat as a function of min link strength (Fig. 4, top panel), and the fraction of possible clusters increases as a function of min link strength (Fig. 5, top panel).

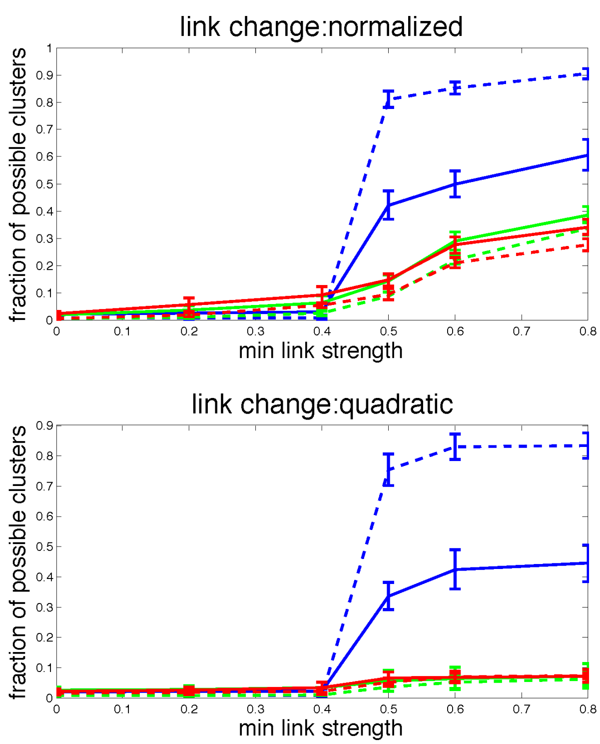

Fig. 5. Fraction of possible clusters (number of clusters / number of nodes) as a function of what type of links are included in the network. (e.g. min link strength of 0.6 means that only links of 0.6 strength and higher are included). Results are shown by network type: blue is random network, green is small-world, and red is spatially clustered. Solid lines are for N=50 and dashed are N-200. In all cases victims and originators were chosen randomly. Panel 1 shows the result when the 'normalized' link change rule was used and Panel 2 shows the results when 'quadratic' is used.

V. DISCUSSION / FUTURE DIRECTIONS

In this paper, we developed a general model for the effect of gossip on social structure. We only considered negative gossip, which we defined as an exchange of information that strengthens the relationships between those who gossip but weakens the relationships between any gossiper and the victim of gossip. We found that while gossip tends to dissolve isolated friendship triads, it strengthens them when they are embedded in dense clusters. Hence, gossip destroys clustering in weakly clustered networks and increases cliquishness in networks with already high clustering.

We made many simplifying assumptions in our model, several of which could be relaxed to make it more realistic. For example, gossip does not always have to be negative. Gossip could be positive and conductive to forming new relationships (Fig. 7). Furthermore, if O shares with G positive gossip about V, G may decide to divert time from her relationship with O and start hanging out with V. This time conservation principle implies a potential reverse mechanism where gossip could weaken the relationship between the gossipers and strengthen the relationship between each gossiper and the gossip target. Alternatively, this very effect could also occur when somebody who has lost credibility starts maligning a third actor, i.e. when negative gossip goes wrong. Schematic for positive gossip (as opposed to negative gossip as depicted in Fig. 1).

The effect of gossip could differ not only in direction but also in strength. It is reasonable to assume that the credibility of gossip decreases as you move away from its source. Consequently, a more realistic model would have the effect of gossip decreasing with each step away from the originator.

Future developments of the model should also incorporate more heterogeneity among the agents. Some individuals are more likely to originate gossip or to pass it along. People tend to exhibit conformist behavior because they pursue the fundamental sense of belonging to a group, as well as social approval from its members. Thus, being the one person in a network who does not gossip might lead to social isolation [14]. However, individuals succumb to peer pressure to different degree. Introducing individual variation in the tendency to originate or repeat gossip to the simulation model would lead to more realistic predictions about the effect of gossip on social structure.

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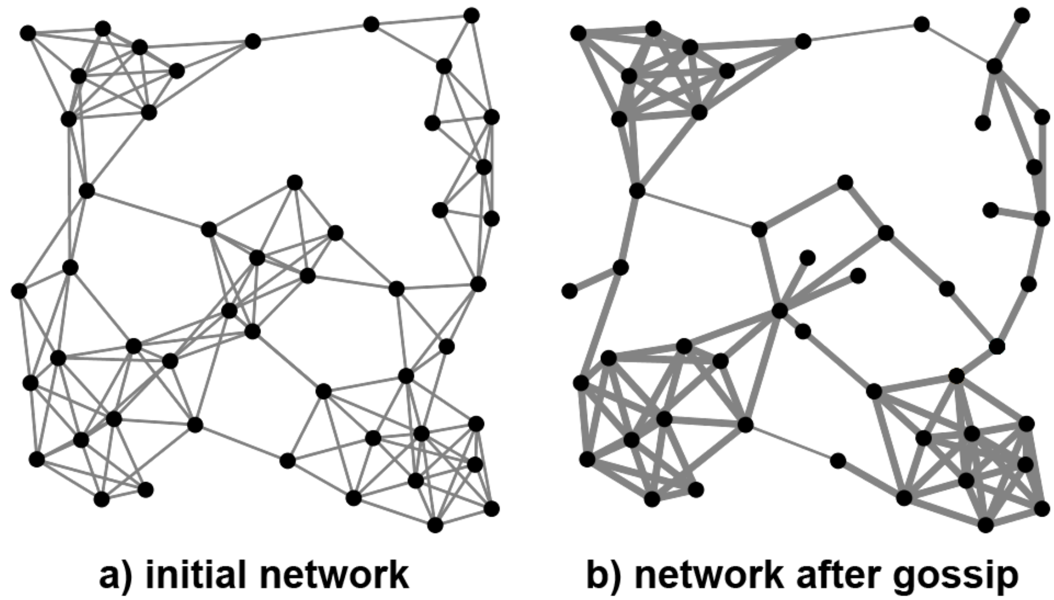

Fig. 6. View of a small spatially clustered network before and after 10,000 gossip events, where the gossip victim is likely to be with higher degree-centrality and the gossip originator is chosen to be the victim's weakest link. Thicker links show stronger connections.

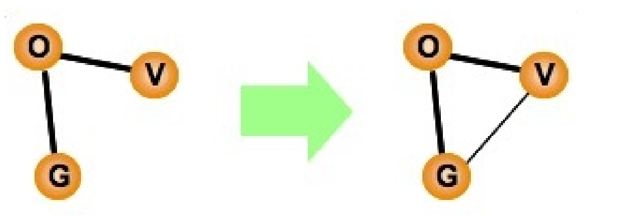

Fig. 7. Schematic for positive gossip (as opposed to negative gossip as depicted in Fig. 1). The originator (O) tells a gossiper (G) good things about a friend V who G does not know, resulting in G making a connection with V.

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REFERENCES

[1] Abrahamson, Eric, and Lori Rosenkopf. 1997. Social Network Effects on the Extent of Innovation Diffusion: A Computer Simulation. Organization Science 8(3):289-309.

[2] Barthélemy, Marc, Alain Barrat, Romualdo Pastor-Satorras, and Alessandro Vespignani. 2004. Velocity and Hierarchical Spread of Epidemic Outbreaks in Scale-Free Networks. Physical Review Letters 92, 178701.

[3] Baumeister, R.F., L. Zhang, and K.D. Vohs. 2004. Gossip as Cultural Learning. Review of General Psychology 8:111-121.

[4] Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. Journal of Political Economy 100(5):992-1026.

[5] Boehm, Christopher. 1999. Hierarchy in the Forest: The Evolution of Egalitarian Behavior. Harvard University Press.

[6] Dodds, Peter S., and Duncan J. Watts. 2004. Universal Behavior in a Generalized Model of Contagion. Physical Review Letters 92, 218701.

[7] Dunbar, R.I.M. 2004. Gossip in Evolutionary Perspective. Review of General Psychology 8(2):100110.

[8] Goss, S., Aron, S., Deneubourg, J. L. & Pasteels, J. M. 1989. Self-organized shortcuts in the Argentine ant. Naturwissenschaften. 76: 79-581.

[9] Grönlund, Andreas, and Petter Holme. 2005. A Network-Based Threshold Model for the Spreading of Fads in Society and Markets. Advances in Complex Systems 8(2/3):261-273.

[10] Hebb, D.O. 1949. The Organization of Behavior. New York: Wiley.

[11] Helbing, D., Keltsch, J. & Molnar, P. 1997. Modelling the evolution of human trail systems. Nature. 388: 47-50.

[12] Kuperman, Marcelo, and Guillermo Abramson. 2001. Small World Effect in an Epidemiological Model. Physical Review Letters 86, 2909 - 2912.

[13] Lind, Pedro G., Luciano R. da Silva, Jos S. Andrade Jr., and Hans J. Herrmann. 2007. Spreading Gossip in Social Networks. Physical Review E 76, 036117.

[14] McAndrew, Frank T. 2008. The Science of Gossip: Why We Can't Stop Ourselves. Scientific American Mind.

[15] Morris, Martina. 1993. Epidemiology and Social Networks: Modeling Structured Diffusion. Sociological Methods and Research 22(1):99-126.

[16] Nakagaki, T., Yamada, H. & Tth, . 2000. Intelligence: Maze-solving by an amoeboid organism. Nature. 407: 470.

[17] Wilensky, U. 1999. NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University. Evanston, IL.

[18] Newman, M.E.J. 2002. Spread of Epidemic Disease on Networks. Physical Review E 66, 016128.

[19] Watts, Duncan J., and Steven Strogatz. 1998. Collective Dynamics of 'Small-World' Networks. Nature 393(6684):440-443.

[20] Wittek, Rafael, and Rudi Wielers. 1998. Gossip in Organizations. Computational & Mathematical Organization Theory 4(2):189204.