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The Effect of Gossip on Social Networks

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Technical 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, in both an analytic derivation and model simulations, that if gossip does not spread beyond simple triads, it destroys them but if gossip propagates through large dense clusters, it strengthens them. Additionally, our simulations show that the effect of gossip on network metrics (clustering coefficient, average-path-length, and sum-of-strengths) varies with network structure and average-node-degree.

Non-Technical Summary: 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, in both an analytic derivation and model simulations, that if gossip does not spread beyond simple triads, it destroys them but if gossip propagates through large dense clusters, it strengthens them. Additionally, our simulations show that the effect of gossip on network metrics varies with network structure and density of connections.

1 Introduction

Gossip is ubiquitous in human groups and has even been argued to be fundamental to human society [1]. 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 [2]. In [1], 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 private life of an individual. Gossip can essentially be defined as information passed from one individual (originator) to another (gossiper) about an absent third individual (victim) [3]. Therefore, any analysis of gossip must occur at the level of the triad or higher [4]. We assume, for the purpose of this paper, that gossip is negative and strengthens the relationship between gossipers while weakening 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 spread [3]. This work is closely related to the vast body of contagion literature [5] studying how cultural fads [6, 7], technological innovations [8] or contagious disease [9–12] 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 [4]. 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 through which it flows.

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 [13]. A similar type of path reinforcement has also been observed in ants [14], humans [15, 16], and even slime molds [17]. 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. We do this both analytically and in simulations.

2 Analysis

For a fully-connected network with m nodes (where $m \geq 3$ since we only consider interactions at the level of a triad or higher), there are $0.5\ m\ (m-1)$ links (relationships) in the network. We assume that spreading gossip results in a stronger relationship between all gossipers, and a weakened relationship between the victim and the gossipers, where the relationship strength is constrained to be between 0 and 1. Therefore for a single gossip event, $m-1$ of these links will be weakened and $0.5\ (m-1)\ (m-2)$ will be strengthened. For example, on a

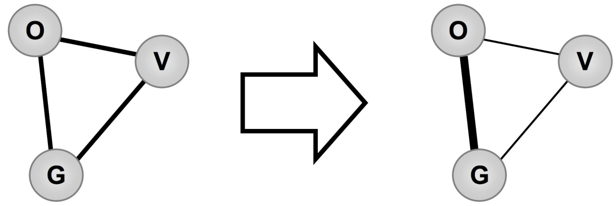

Figure 1: Schematic of a triad before and after a gossip event, showing the effect of gossip on the strength of relationships. Individuals are represented as nodes and the strength of each relationship is represented by the thickness of the line between two nodes. In a gossip event, an originator (O) 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.

network with 3 nodes, a single gossip event will cause 2 links to weaken and 1 to strengthen, and on a network with 5 nodes, a gossip event will cause 4 links to weaken and 6 to strengthen. For n independent gossip events, each link will weaken, on average (for very large n), $2n/m$ times and strengthen $n(1-2/m)$ times. We can use a power function to describe nonlinear changes in link strength so that the effect of gossip is strongest for relationship of medium strength and weakest for already very strong or very weak relationships. For example, let $w_{n+1} \leftarrow w_n^{1/L}$ be the function to strengthen a link and $w_{n+1} \leftarrow w_n^L$ the function to weaken a link, where w is the link (relationship) strength (defined as $0 < w < 1$), and L is an indicator of the magnitude of the effect of gossip with $L > 1$ so that 'strengthening' a relationship increases the w value and 'weakening' a relationship decreases it. Then, on average, over several gossip events, the strength of each link in the network will go to

$$w^{(1/L)^{n(1-2/m)}\ (L)^{2n/m}}$$

which simplifies to

$$w^{(L)^{-n(m-4)/m}} \quad . \tag{1}$$

This means that, after a very large number of gossip events (n) each link in a fully-connected network with m nodes should decrease to 0 if $m < 4$, stay constant if $m = 4$, and increase to 1 for $m > 4$. Note that the value of L, as long as $L > 1$, does not affect what value the link strength converges to, only the rate of convergence (faster convergence for bigger L). We can extrapolate this result and generate predictions for larger networks: we expect that gossip will strengthen relationships in a highly-clustered network, and weaken and break relationships in a network with low clustering. We use simulations, described below, to test these predictions and to further explore the effect of gossip on the clustering, average-path-length, and the sum of link strengths of a social network.

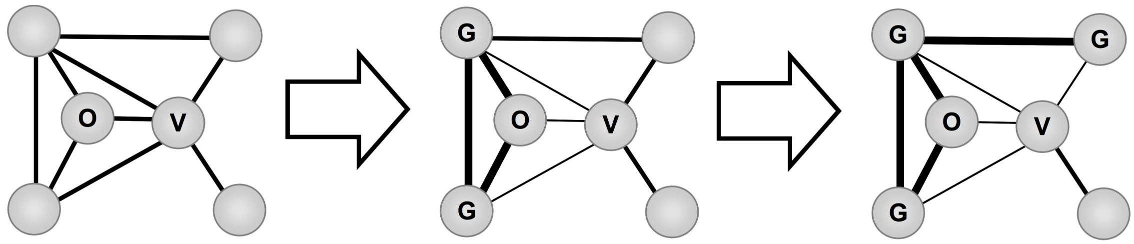

Figure 2: Schematic for how gossip spreads in a social network. A) We randomly choose a node to be the victim (V) and one of its neighbors to be the originator of the gossip (O). B) The originator spreads the gossip to all mutual friends with the victim, resulting in stronger relationships between all gossipers and weaker relationships between the victim and gossipers. C) This process continues until no more individuals can become gossipers.

3 Methods

We built a simple network model in NetLogo [18] to simulate how the spread of gossip influences social network structure. We ran each simulation for 10,000 gossip events, which was about the maximum length of time it took simulations to converge (as measured by the sum of all link strengths in the network). We ran simulations with 54 different parameter combinations (6 different networks and 9 average-node-degree values) for 20 repetitions each, for a total of 1,080 simulation runs.

3.1 Model

To simulate a single gossip event on a network, we first chose a random node in the network to be the 'victim' of the gossip event. Then, we randomly chose one of the victim's neighbors as the 'originator' of the gossip event (Fig. 2A). In the first wave of a gossip event, the gossip was 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 used the quadratic function to change the link strengths in our simulations (setting $L = 2$ in the power function described above) because of its nice convergence. All links were initially set to have a strength of 0.5 at the start of the simulations and those links whose strength dropped below 0.0005 during the course of the simulation were severed.

To test if any results we saw were due to just strengthening and weakening links between triads of nodes, we also ran simulations using a null-gossip algorithm, according to which each 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).

3.2 Networks

Real social networks vary greatly in their size, connectedness, and structure [19–21]. To capture this natural variation, we used a variety of networks in our simulations. In order to consider a range of network connection densities, we fixed the network size at 200 nodes and ran simulations with nine different average-node-degree values (4, 6, 8, 10, 12, 14, 16, 18 and 30). In terms of network structure, we used small-world networks. Small-world networks are generated by first creating a regular ring lattice where the number of neighbors to which each node is connected equals the average-node-degree and then, for each node, choosing every link and rewiring it to a randomly selected node with a certain probability (the rewiring probability) [21]. Networks with low rewiring probabilities look like regular ring lattices and have high clustering coefficients and long average-path-lengths. Networks with high rewiring probabilities look like random networks and have low clustering coefficient and short average-path-lengths. Thus, by generating small-world networks with different values of this single parameter, we can capture a large amount of the structural variation that exists in real social networks [20, 21]. For our simulations, we used networks with six different rewiring probabilities (0, 0.1, 0.15, 0.25, 0.4, and 0.6) in order to obtain a continuum from regular highly clustered networks to random-like networks. Since it is only possible to calculate average-path-length if all pairs of nodes in the network are connected by some path, we only ran simulations on networks that started as connected (which often required running the generative algorithm many times until we obtained a connected network).

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 ∃ mutual neighbors of the victim and a gossiper ∋ 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 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
```

3.3 Statistics

We quantified the effect of gossip on the networks using three characteristics: the average clustering coefficient, average-path-length, and sum-of-strengths. The first two metrics quantify two different aspects of cohesion and are metrics that are typically used to describe both actual social networks [19, 20] and model small-world networks [21]. The average clustering coefficient measures the cliquishness of a typical neighborhood and the average-path-length measures the average separation between two nodes in the network. Thus, while the first measure indicates the extent to which the network contains closely knit groups or cliques (a local property), the second one, in a certain sense, indicates the overlap between these dense groups and cliques (a global property). In other words, we capture both local clustering and overall connectedness.

More specifically, we calculated the average clustering coefficient of the network at the beginning and end of each simulation by estimating the local clustering of each node (how close the node's neighbors are to being a complete graph) and then averaging across all nodes [21]. We calculated the average-path-length as the number of steps in the shortest path between all pairs of nodes, averaged across the network. To compare our results more easily across network structures, we calculated the proportional change in both clustering coefficient and average-path-length over a simulation as the final value minus the initial value, all divided by the final value.

Finally, we calculated the sum-of-strengths, the sum of all link strengths in the network, over the course of the entire simulation. We use this as a metric for the dynamics of the system, in order to make sure we had run simulations for long enough, and to examine how long it took them to converge.

4 Results

4.1 Main Findings

In our model, although gossip both weakens and strengthens links, weak links break but no new links are created. Hence, a priori, we would expect that gossip decreases the network's average clustering and increases its average-path-length. This is generally what we found. In the simplest null-gossip model (when gossip was not allowed to spread beyond triads), the simulations quickly converged to have zero clustering, regardless of the properties of the initial network. In the full model (when gossip was allowed to spread beyond triads), the effect of gossip was still negative, but only for networks with low initial clustering (that is, with high rewiring probability). For example, the clustering coefficient after convergence in the 80 runs on networks with the highest rewiring probability (0.6) and small average-node-degree (10 or less) was effectively zero (mean = 0.0035, std. dev. = 0.0050). Nevertheless, in networks with sufficient initial clustering, the spread of gossip had exactly the opposite effect: it made certain triads more stable. As we showed in the analysis section, this occurs because when gossip originates in and spreads throughout a dense cluster, it strengthens more ties than those that it weakens. 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. 3).

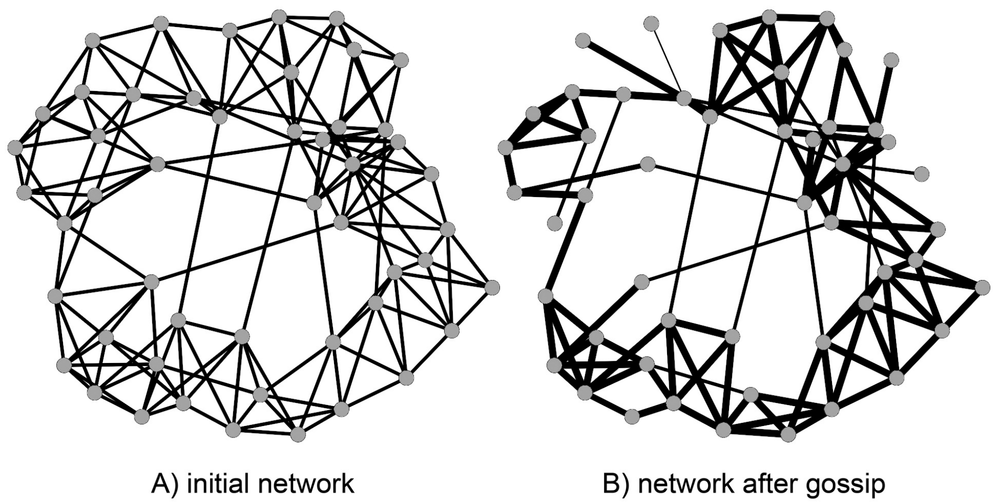

Figure 3: View of a small-world network with 50 nodes, average-node-degree of 6 and rewiring probability of 0.1, A) before and B) after 10,000 gossip events. Thicker links show stronger relationships.

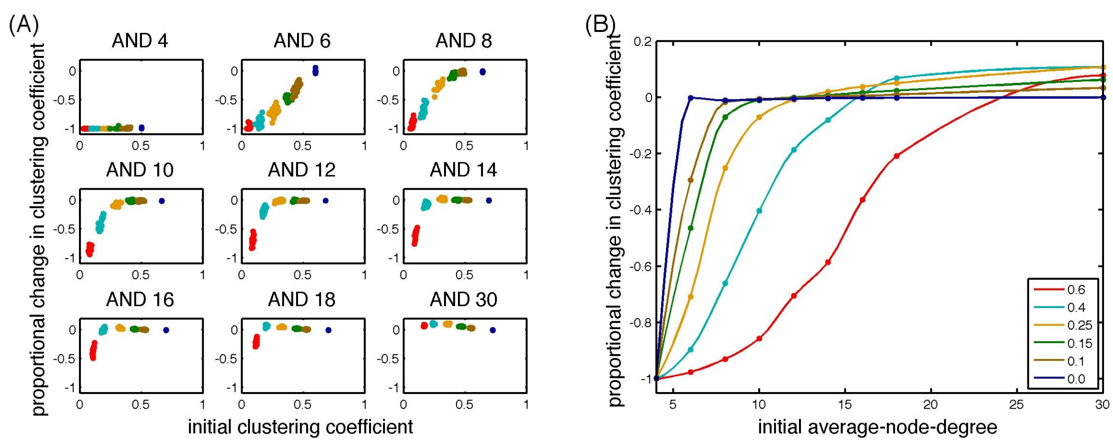

Figure 4: The effect of gossip on the clustering coefficient of a network: the proportional change in clustering coefficient (e.g. -1 means clustering coefficient decreased completely to zero) as a function of A) initial clustering coefficient, where different panels correspond to different initial average-node-degree (AND) values, and B) initial average-node-degree. Different colors correspond to different rewiring probabilities (0.0, 0.1, 0.15, 0.25, 0.4, 0.6) as shown in the legend in B).

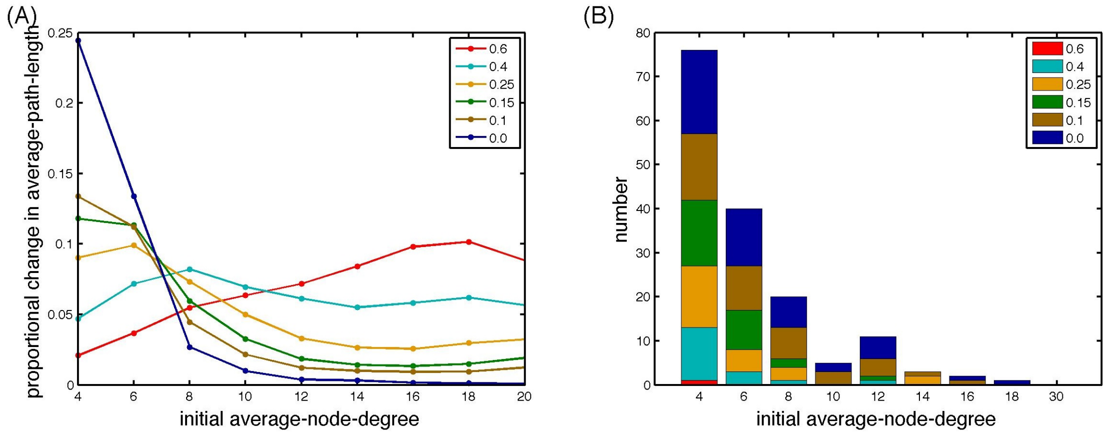

Figure 5: The effect of gossip on the average-path-length of a network. A) Proportional change in average-path-length for different networks as a function of initial average-node-degree. B) Number of cases where networks became disconnected over the course of a simulation for different values of initial average-node-degree. Colors are the same as in (Fig. 4).

The strength of gossip's effect on the network's clustering varied with both rewiring probability and average-node-degree (Fig. 4). For a given average-node-degree, gossip acted most negatively on networks with higher rewiring probabilities (more random-like networks) and had less of an effect on those with smaller rewiring probabilities (more ring-lattice-like networks) (Fig. 4A). Regardless of the rewiring probability of a network, increasing the average-node-degree tended to increase clustering. Thus, we found that the negative effect of gossip on clustering decreases with higher initial network average-node-degree. This trend, however, is non-linear (Fig. 4B). The decrease in the negative effect of gossip as average-node-degree increases was the steepest for networks with high initial clustering (low rewiring probability) and more gradual for networks with low initial clustering (high rewiring probability).

Regarding average-path-length, gossip generally affected clustered networks strongly at low average-node-degree and weakly at high average-node-degree, but it affected more random-like networks weakly at low average-node-degree and strongly at high average-node-degree (Fig. 5A). The reason is that at low densities, the regular networks have few bridges and these bridges are vulnerable to the negative effect of gossip. In contrast, at high densities, more links are broken in random networks than in regular networks because gossip is able to spread to a larger extent in them. These observations are based only on the networks that remain connected after gossip. If we look at the number of networks that get disconnected due to gossip (Fig. 5B), we see that the networks that are less likely to get disconnected are either denser or more random networks. In order for a network to break apart, two links in a triad must break simultaneously, which we expect to occur more often in random networks (since more links overall are broken in random networks). However, this is the opposite of what we see. We believe that this unintuitive result is due to the symmetry of network structure; gossip that originates randomly should affect links in more regular networks in

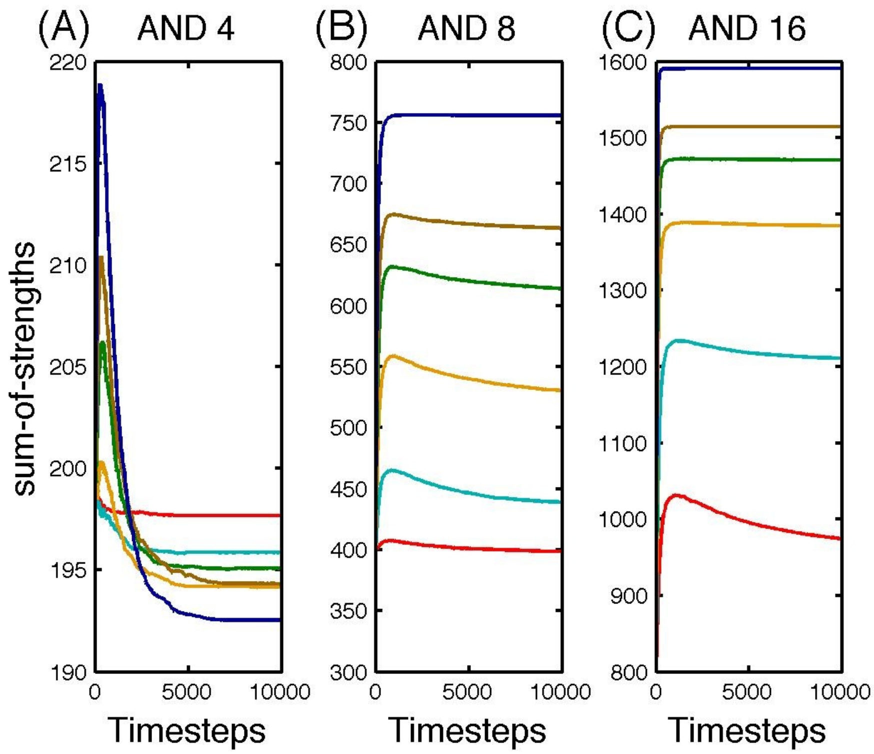

Figure 6: The effect of gossip on the sum-of-strengths in a network: the sum of all link strengths in the network as a function of timesteps during a simulation. Different lines correspond to different rewiring probabilities for average-node-degree (AND) values of A) 4, B) 8, and C) 16. Colors are the same as in (Fig. 4).

similar ways, thereby making it more likely that two links break simultaneously.

The sum-of-strengths (sum of the strengths of all links within the network) also varied with network structure and average-node-degree (Fig. 6). For a given average-node-degree, the sum-of-strengths was generally larger for the small-world networks with smaller rewiring probabilities than for those with larger rewiring probabilities. The sum-of-strengths was also larger for networks with higher average-node-degree values.

4.2 Dynamics

The dynamics of the network over the course of a simulation (as quantified by the sum-of-strengths) also varied with network structure (as determined by rewiring probability) and average-node-degree (Fig. 6). For small-world networks with high rewiring probability, for low average-node-degree values, the sum-of-strengths just dropped from the initial value over the course of the simulation (Fig. 6A). This is due to the fact that these networks consist mainly of triads, in which the link strength gradually decreases until a link breaks and no gossip can spread. In contrast, for higher average-node-degree values, the sum-of-strengths increased, peaked and then dropped (Fig. 6C). This pattern is the most striking in the small-world networks with low rewiring probability and low average-node-degree values (Fig. 6A). In both cases, the networks have relatively dense but incomplete clusters. Although the strength of links in these structures initially increases, the missing links leave some weak triads that trigger a domino effect resulting in the complete destruction of the clusters. Hence, the initial peak before the drop here. In contrast, for higher average-node-degree values, the sum-of-strengths increased to a peak and then leveled out instead of dropping. This is due to the fact that dense lattice-like networks consist of very dense clusters in which the strength of all links increases asymptotically towards the maximum value of 1.

4.3 Robustness of Results

Although we presented results in our analysis section for a general link-change function, we only used the quadratic ($L = 2$) rule for our main simulations. We ran additional simulations with different values for the exponent and found that, as predicted in the analytic section, the results were similar, apart from the fact that convergence was faster for larger values of L. In order to test whether our results depend on the shape of the power function, we tried using an alternative rule: a normalized link-change function. This function specifies $w_{n+1} \leftarrow w_n + \alpha(1 - w_n)$ for increasing and $w_{n+1} \leftarrow \beta w_n$ for decreasing the link strength, where $0 < \alpha < 1$ and $0 < \beta < 1$. The method has hysteresis, i.e. an increase and a decrease in succession do not necessarily cancel each other out. With this method, the negative effect of gossip on clustering was slightly weaker than under the quadratic rule. In addition, the normalized function produced oscillating sum-of-strengths and not as good convergence within 10,000 timesteps. The main intuition behind these differences is that while the quadratic rule causes most links to converge quickly to 0 or 1, the normalized link-changing method results in links that are more uniformly distributed in strength. Since links of intermediate strength tend to be more strongly influenced by gossip, the oscillation of the sum-of-strengths does not subside.

5 Discussion / Future Directions

In this paper, we developed a general model for the effect of gossip on the structure of social networks. We only considered negative gossip, which we defined as an exchange of information that strengthens the relationships between all gossipers but weakens the relationships between each 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 found these results both through analytic derivation and simulations.

Our findings provide a qualification to Dunbar's theory mentioned in the introduction [1]: negative gossip might help maintain relationships but only in groups that are already dense. Such highly clustered structures are ubiquitous in social life. They can be emergent (for example, friendship networks), but also exogenously determined: families, neighborhoods, university departments or company divisions. Our findings suggest that in such settings, bad-mouthing could paradoxically have a positive net effect on local cohesion, as long as everyone is equally likely to gossip and to be gossiped about. Thus, our study indicates a possible application in business management: under certain conditions, allowing gossiping

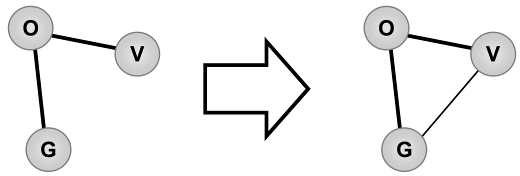

Figure 7: Schematic for the effect of positive gossip (as opposed to negative gossip as depicted in Fig. 1). The originator (O) tells a gossiper (G) good things about a friend V who G does not know, resulting in G connecting to V.

at the work place can strengthen team spirit.

As a pioneer study of the effect of gossip on social networks, our work also opens numerous avenues for further theoretical exploration. We made many simplifying assumptions in our model, several of which could be relaxed to make it more realistic. For example, in our model we assume the probability of becoming a victim or originator of gossip to be uniform across nodes. However, theoretical arguments and previous empirical findings suggest at least two additional algorithms for starting the gossip event. First, one can argue that more popular people are more likely to be subjects of gossip. This in fact is the working mechanism in the hypothesis that gossip serves to equalize the social status of individuals in a network [22]. This hypothesis could be tested with a model where the probability to become a victim increases with degree centrality. We would expect that such a gossip algorithm would not significantly affect our main results since they are based on networks with uniform degree distribution. However, we expect that if the algorithm is run on a network with a power-law degree distribution and a sufficiently high initial clustering, gossip will cause a more egalitarian distribution of popularity (as measured by degree). Second, we can also argue that one is unlikely to spread gossip about one's close friends. Indeed, it has been found that gossip tends to weaken already weak relations [4]. This situation can be modeled by increasing the probability for originating gossip for the agents with the weakest links with the victim. If this is the case, weaker links become more likely to be severed and we expect the effects of gossip on clustering and average-path-length to be even stronger compared to the case when the originator is randomly chosen from among the victim's links.

Gossip does not always have to be negative, and our model could be modified to allow positive gossip that is 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 victim. 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. Finally, the effect of gossip could differ not only in direction but also in strength. It might be more reasonable to assume that the credibility of gossip decreases as it moves 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 could also incorporate more heterogeneity among the agents, where 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 [23]. However, individuals succumb to peer pressure to different degrees. 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.

Ultimately, future theoretical elaborations will depend on whether the model's assumptions and predictions match empirical evidence. An adequate test of the model would require longitudinal data of the originators and targets of informal social communication over a complete network. One way such data can be obtained is through content analysis of digital communication: for example, e-mails or instant messages between office co-workers or text messages between school classmates.

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