Dynamics of Opinions and Social Structures

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Social groups with widely different music tastes, political convictions, and religious beliefs emerge and disappear on scales from extreme subcultures to mainstream mass-cultures. Both the underlying social structure and the formation of opinions are dynamic and changes in one affect the other. Several positive feedback mechanisms have been proposed to drive the diversity in social and economic systems (1, 2), but little effort has been devoted to pinpoint the interplay between a dynamically changing social network and the spread and gathering of information on the network. Here we analyze this phenomenon in terms of a social network model that explicitly simulates the feedback between information assembly and emergence of social structures: changing beliefs are coupled to changing relationships because agents self-organize a dynamic network to facilitate their hunter-gatherer behavior in information space. Our analysis demonstrates that tribal organizations and modular social networks can emerge as a result of contact-seeking agents that reinforce their beliefs among like-minded. We also find that prestigious persons can streamline the social network into hierarchical structures around themselves.

The competition between segregation and coherence in social systems has long been a subject of both practical and theoretical interest. T. Schelling proposed simple models to understand how segregation emerged in urban areas (3) and B. Arthur suggested that the emergence of industrial centers was a result of positive feedback between agencies that prefer to be close to similar agencies (1). In general, the goal of individuals to understand and agree with their closest associates (4, 5, 6) can be obtained by either merging opinions with friends or by creating new contacts. In this spirit, we will discuss a social network model where individuals can use their connections to communicate and update their views with friends or establish new contacts via friends to shortcut communication pathways. By modeling communication on the network and adaptive rewiring of the network together, we reveal strong reinforcement of opinions in emergent group structures.

A social system should be viewed as a network when links are long-lived and facilitate many communication events. If this was not the case, random people would share reliable information with anybody, and the whole society could be described by a simple “mean field” where nobody shows any preference for anybody. Realizing this, B. Skyrm modeled link formation between agents by using reinforcement associated to emergence of mutual trust (7). Trust-based networks have also been quantified and modeled for lobbyists (8) who are “experts in using experts” (9), and communication networks have been studied in a socio-economic setting with agents that trade off the costs versus rewards for forming strategic links (10).

FIG. 1 Interplay between network structure and the extent η to which gossiping influences the priority in social climbing. Varying η, the bottom pane illustrates cliquishness (C), diameter (D), and social horizon (E). Simulations based on C = 10 communication events per link for each rewiring event in the system with system size fixed to N = 100 and L = 150 links. The results are robust to a hundred-fold drop in the communication to rewiring ratio, but break down at an even lower communication rate when only small groups can be maintained by the communication. Panels C-E also illustrate the dependence of the rate of opinion adaptation, flexibility, with stubborn adaptation referring to a μ = 0.01% change of the interest elements per communication event, and flexible referring to μ = 1% change. We define the flexibility as μCL. Stubborn adaptation corresponds to a flexibility of 15% changes in all interest memory when all links are changed once whereas flexible adaptation corresponds to complete reallocation.

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In our analysis we instead let agents at nodes connected by links make decisions to improve their position in a dynamic network based on their own limited local perception of the system. To maintain this perception, they continuously communicate to obtain (1) a picture of where other agents are in the network and (2) an opinion about the importance of other agents. We incorporate information flows from distant parts of the social network into the model by letting two connected agents communicate and share information about any third agent in the network. This indirect information-gathering resembles the frequent gossiping in daily life and its consequences for non-local information assembly has been measured in static social networks (11).

Social networks are not static, but new links form and old links fade out (6). The information that people obtain by communication becomes outdated by time as well as their perception of the network. Therefore, when two agents communicate about a third agent, the third agent being the topic of the conversation chosen by one of the agents, they first decide which of them has the newest information (12). This information is considered the most reliable, and the agent with the older information updates its information and considers the agent with the newer information as a reliable source of information about the third agent.

To incorporate the above elements in a simple model, we give each agent an individual memory that includes three vectors with (1a) pointers associated to all agents in the system that show which friend provided information about the agent, (1b) the age of all this information to compare the quality of the information with friends, and (2) the names of other agents filling the memory to an extent that reflects the interest in these agents. The memory in (1a) and (1b) is a map and (2) is the priority.

The memory is updated through communication over links in the network, which in turn are rewired based on the locally obtained knowledge. We increment the age in (1b) after every communication event in the system. Because every agent always has information with age 0 about itself, the age of the information about an agent gets older the further away it is from the agent in the network.

The basic model, accessible as a Java applet with a detailed description (13), is defined in terms of $N$ agents with a fixed number of links. The network model is executed in time steps, each consisting of one of the two events:

- **Communication C**: Chose a random link and let the two agents it connects communicate about a third agent selected by one of them. The two agents also update their information about each other.
- **Social climbing R**: Let a random agent use the local information to form a link to a friend’s friend to shorten its distance to a selected third agent. Subsequently a random agent loses one of its links.

Communication or gossiping involves information sharing, and evaluation of its quality based on its age as described above. The social climbing, which corresponds to rewiring of the network, is a slow process compared to gossiping and the model is typically simulated with 10 communications per link for each rewiring event in the system. Links are formed to friends of friends similar to triadic closure (14) reflecting a gradual social climbing. Here friends refer to the particular agents that have provided the most recent information about the selected agent. The new links are therefore formed on basis of the memory rather than on basis of the present network.

The presented model does not specify the selection criterion for the third person in the communication and the social climbing event. Different selection mechanisms will result in the formation of widely different social networks. To illustrate this we in Fig. 1A and B show two networks. To generate the network in Fig. 1A, the agents selected the agent of interest randomly with equal chance for any agent. In contrast, agents preferentially selected agents that they recently had heard about in Fig. 1B (15, 16, 17).

We regulate the extent to which agents select the topic of conversation according to recent gossiping by the external parameter $\eta$, which may also be understood as the ratio of local to global interest. For each agent $j$, we model the interest memory in (2) above by $N\eta$ elements of which the first $N$ are static and fixed to each of the $N$ agents’ names corresponding to the global interest. The remaining memory can be changed by communication. When agent $j$ talks to, or hears about, another agent $i$, the name of $i$ will randomly replace a fraction $\mu$ of this memory. To illustrate the dependence, Fig. 1 shows two rates of this opinion adaptation.

In selecting communication topic or aim of social climbing, agent $i$ is chosen with probability $w_j(i) = n_j(i)/(N\eta)$ proportional to how many times the name of $i$ occurs in agent $j$’s interest memory, $n_j(i)$. The size of $\eta$ determines the degree of preferential allocation of memory. For $\eta = 1$ any topic is selected with equal chance, whereas larger $\eta$ increases the chance that the agents choose a topic proportionate to personal

![FIG. 2 Network structures where one agent, the prophet $P$, has increased prestigious power to capture an unusually large fraction of the memory of whoever she talks to. The results are based on a prophet with (A) weak prestige $P = 2$, and (B) high prestige $P = 10$. Note that when sub-networks separate entirely, as in panel A, the agents still maintain information about who they should contact in the social climbing step and separated clusters can reconnect. The $W_P$ values correspond to the fraction of global interest devoted to the prophet. Other parameters as in Fig. 1B.](image-url)
experience (15).

A dominant local interest and large $\eta$ predicts an evolving network with pronounced modular structure as in Fig. 1B. The emerging modular network does no longer develop large hubs, but instead shows large cliquishness quantified by the number of triangle motifs in units of the random expectation (18), $\Delta/\Delta_r$ (see Fig. 1C). Figure 1D shows that the diameter $d_{\text{max}}$ of the network easily doubles as $\eta$ increases, weakening the “small world effect” (19) and the global navigability of the network (20).

To quantify the locally acquired interest we counted the effective number of persons $n_{\text{local}}$, a typical agent has in the interest memory,

$$n_{\text{local}} = \langle 1/N(w_j^2(i)) \rangle_j.$$  \hfill (1)

Here $(w_j^2(i))$, averages over the weights allocated to different interests $i$ of agent $j$. Figure 1E shows this social horizon of the individual agent, $n_{\text{local}}$, as well as the global horizon where all memories are pooled together in $n_{\text{global}}$ (21). As $\eta$ increases, $n_{\text{local}}$ collapses while $n_{\text{global}}$ remains on the scale of $N$ — the development toward social cliques is democratic, with anyone getting a fair share of attention while still allowing people to focus locally on members of their particular “club”. The extent to which this club is maintained and closed for migration is controlled by the flexibility defined in the caption of Fig. 1: the modular structure breaks down when one changes opinion faster than one changes friends.

This idealized model-world consists of agents with equal properties. In spite of this equality, the model predicts segregation in the form of a social network with modular structure with widely different priorities and opinions. The local agreement and global divergence self-organize as a consequence of repeated recent communication and reinforced contacts to people one gossips about.

The model allows us to analyze how to manipulate the social structure by biased information spreading. By utilizing that the model goes beyond simple rumor spreading on fixed networks, we can analyze how the transmission of rumors or ideas reshape the space upon which they spread. We consider a simple directed strategy to influence public opinion aimed to increase the status of a particular agent:

- **Prophet** $P$: each time agent $P$ communicates, she imposes her personality on the agent $j$ she talks to by converting a fraction $P\mu$ of this agent’s interest memory to $P$.

The “prophet” uses the local network structure in analogy to the way the so called “heroes” or social leaders have influenced the society with their acquired prestige (22, 23, 24).

The spreading of information across the system is analogous to viral marketing (25), which makes it possible for the prophet to reinforce her position by gaining visibility and subsequently links from larger parts of the system. Moreover, higher connectivity makes the prophet preferentially more accessible to people, and the prestige-biased transmission of ideas (24) modeled by the interest memory connects the positive feedback. When $P = 1$ the prophet $P$ becomes a normal agent, and the overall network develops to resemble the one in Fig. 1B. Figure 2 shows that an increased ability of an agent to positively bias other persons’ interest memories drives the network topology toward a centralized structure. For example, a single prophet with strength $P = 2$ can generate a substantial group of followers (Fig. 2A). The figure also illustrates that separated social groups can emerge and collapse by temporally weaker interest in other agents. Figure 2B shows that a strong prophet drives the full system to a single hierarchical structure. In fact, by measuring the social horizons we find that a single $P$ with strength $P = 10$ drives both $n_{\text{local}}$ and $n_{\text{global}}$ to about 2 — a dominating prophet can efficiently initiate a totalitarian system to an extent that people barely think about anybody except the social leader. This facilitates social coherence and order, but obviously not the formation of diverse cultures or coexistence of small communities.

In general, the emerging structures are robust consequences of an interplay between the following positive feedback mechanisms:

- **Network centrality**: being central $\checkmark$ new information.
- **Positive assortment**: agent’s opinion $\checkmark$ neighbor’s opinion.
- **Segregation**: move toward opinion $\checkmark$ localization of opinion.

Without individuals with personal interests only the first feedback is active, but is in itself enough to give the network a broad degree-distribution (12). The two subsequent reinforcements generate interest groups and segregation manifesting itself in a modular network. Together these feedbacks make it very favorable to manipulate opinion spreading. Here we have provided a framework which can give insight into the mechanisms behind communication strategies used in historical as well as modern propaganda.

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### References

13. [http://cmol.nbi.dk/models/ibattle/ibattle.html](http://cmol.nbi.dk/models/ibattle/ibattle.html)
18. $\Delta$ is the number of triangles in the model network, whereas $\Delta_{\text{random}}$ is average number of triangles in a randomized network with exactly the same degree of each node as the model network.
21. Viewing memories of all agents as one common pool, we count the total weights of all memory slots allocated to agent $i$ as $W(i) = \sum_{j} w_{j}(i) \in [0; N]$ and define the global information measure for the effective agent diversity as $n_{global} = N/\langle W^{2}(i) \rangle$.