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Who’s talking first? Consensus or lack thereof in coevolving opinion formation models

Cecilia Nardini,1,2 Balázs Kozma,1 and Alain Barrat1,3
1LPT, CNRS, UMR 8627, and Univ Paris-Sud, Orsay, F-91405 (France)
2Università di Padova, dipartimento di Fisica “G. Galilei” (Italy)
3Complex Networks Lagrange Laboratory, ISI Foundation, Turin, Italy
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We investigate different opinion formation models on adaptive network topologies. Depending on the dynamical process, rewiring can either (i) lead to the elimination of interactions between agents in different states, and accelerate the convergence to a consensus state or break the network in non-interacting groups or (ii) counter-intuitively, favor the existence of diverse interacting groups for exponentially long times. The mean-field analysis allows to elucidate the mechanisms at play. Strikingly, allowing the interacting agents to bear more than one opinion at the same time drastically changes the model’s behavior and leads to fast consensus.

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In the recent years, agent based models have been more and more used in the area of social sciences. Through a rather simple modeling approach for the individual processes of social influence, these models focus on the emergence of social behavior at the global population level. Statistical physics models and tools provide therefore a natural framework for such studies, and have been widely applied, leading to the appearance of the field called sociophysics (see [1] for a recent review on the application of statistical physics models to social dynamics).

The growing field of complex networks [2, 3, 4] has moreover allowed to obtain a better knowledge of social networks [1, 2], and in particular to show that the typical topology of the networks on which social agents interact is not regular. Many studies have therefore considered the evolution of models of interacting agents when agents are embedded on more realistic networks, and studied the influence of various complex topologies on the corresponding dynamical behavior [1]. An additional feature of networks, that may have a strong impact on the model’s behavior, lies in their dynamical nature. They may indeed evolve on various timescales, and the evolution of the topology and the dynamical processes can drive each other with complex feedback effects. Studies of this coevolution are more recent and still limited [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17], with many open issues.

In this Letter, we provide new insights into such feedback effects by an investigation of Voter-like models (VM), in which agents update their opinions by imitating their neighbors, and can also break and establish connections with other agents. More precisely, we show how slight modifications in the evolution rule, which have minor consequences if the topology of interactions is kept fixed, can change drastically the model’s behavior as soon as the topology can evolve on the same timescale as the agents’ opinions. On the other hand, the simple fact of allowing agents to have several opinions at the same time, in the spirit of the Naming Game [18] or of the AB model [19], leads to more robust behavior.

The Voter model [20] considers a population of size $N$ in which each individual $i$ has an opinion characterized by a binary variable $s_i = \pm 1$; only two opposite opinions are here allowed (for example a political choice between two parties) [20]. Starting from a random configuration of opinions, the dynamical evolution of the direct VM (d-VM) is the following: at each elementary step, an agent $(i)$ is randomly selected, chooses one of its neighbors $(j)$ at random and adopts its opinion, i.e. $s_i$ is set equal to $s_j$ (one timestep consists of $N$ such updates). In the reverse case (r-VM), the first agent $i$ instead convinces its neighbor $j$ ($s_i$ is set equal to $s_j$). The distinction between d- and r-VM is necessary since the two interacting nodes do not play the same role. Moreover, the degrees of the first and the second chosen nodes have different distributions, and the second is a large-degree node with larger probability [2]. The asymmetry in the opinion update between the two interacting nodes can then couple to the asymmetry between a randomly-chosen node and its randomly-chosen neighbor, leading to different dynamical properties. No important difference is expected on homogeneous networks but, on heterogeneous networks, the probability for a hub to update its state will vary strongly from one rule to the other. The basic imitation process of the VM mimics the homogenization of opinions but, since interactions are binary and random, do not guarantee the convergence to a uniform state. Since a consensus in which all individuals share the same opinion is an absorbing state of the dynamics, any finite population reaches a consensus, but the time needed $t_c(N)$ depends on its size $N$ and on the topology of interactions, and diverges as $N \to \infty$.

On static networks, $t_c(N)$ grows as a power-law of $N$, with an exponent depending on the degree distribution, and on the updating rule [21, 22, 23]. On homogeneous networks in particular, $t_c(N) \propto N$ for both d- and r-VM.

In this Letter, we consider the scenario in which agents can rewire their “unsatisfied” connections. More precisely, the initial configuration is given by a random homogeneous network of interacting agents, with average number of neighbors $\langle k \rangle$ and random opinions. At each timestep, an agent $i$ and one of its neighbors $j$ are cho-
opinions, i.e. of active links \( NL_{+} = NL_{-} \) (since the total number of links is preserved, \( k(2) = t_{+} + t_{+} - 1 \)). At the mean-field (MF) level, we can derive the evolution equation of these quantities. Let us first consider the magnetization: it changes of \(-2/N\) when an agent changes its states from \(+\) to \(-\), and of \(+2/N\) in the opposite case. For the d-VM, the probability of the first event is proportional to the density \( n_{+} \) of agents in the \(+\) state, times the probability that it chooses to interact with a neighbor that has \(-\) opinion, i.e. \( k_{+}/k_+ \) where \( k_+ \) is the average degree of a \(+\) node, and \( k_+/n_+ \) is the average number of \(-\) neighbors of a \(+\) node. The probability of the second event \((-\rightarrow +)\) is obtained in the same way, and finally

\[
\langle dm/dt \rangle_{dVM} = -2(1 - \Phi) \frac{N}{N} t_{++} \left( \frac{1}{k_+} - \frac{1}{k_-} \right) . \tag{1}
\]

In the case of the r-VM, the probabilities of the two processes are simply interchanged: \(\langle dm/dt \rangle_{rVM} = -\langle dm/dt \rangle_{dVM}\). On an adaptive network, it is essential to distinguish \(k_{+}/k_-\) as shown in Fig. 3. one has indeed \( k_+ > k_+ > k_+ \). In other words, the nodes of the majority opinion have more neighbors. This is a simple consequence of the rewiring dynamics: if \(m > 0\), any rewiring event \((i, j) \rightarrow (k, l)\) has a higher chance to randomly pick a \(+\) node as a new neighbor due to their larger number. Therefore, nodes of the larger group gain new links with larger probability. Equation (1) then immediately shows that for \(m > 0\), \(\langle dm/dt \rangle_{rVM} > 0\) and \(\langle dm/dt \rangle_{rVM} < 0\). In summary, the coevolution of opinions and topology generates a positive feedback for the d-VM driving the system to a consensus state, \(m_{stable} = \pm 1\), and a negative feedback for the r-VM resulting in \(m_{stable} = 0\). This readily explains the strong differences between these models. For the d-VM the adaptivity leads to an accelerated consensus, while it hinders the convergence for the r-VM and keeps the system in a dynamically evolving state with zero average magnetization.

It is moreover possible to write the evolution equations for the various types of links. It is easy to understand that, according to the model’s definition, the vector \(x = (m, t_{++}, t_{++})\) can evolve in 4 ways at each elementary update: \(x \rightarrow x + v^a, a = 1, \ldots, 4\), with respective probabilities \(w^a\). Let us start with the d-VM. The displacement vectors and the associated probabilities read then:

\[
N v^1 = (2, k_- - k_+, k_+), w_1 = (1 - \Phi) n_+ k_- / k_+;
N v^2 = (-2, k_+ - k_+, k_-), w_2 = (1 - \Phi) n_+ k_+ / k_+;
N v^3 = (0, -1, 0), w_3 = \Phi n_+^2 k_+ / k_-;
N v^4 = (0, -1, +1), w_4 = \Phi n_+^2 k_- / k_+.
\]

\(v^1\) and \(v^4\) correspond to opinion changes, for which the change in magnetization (+/2/N) is associated with changes in the densities of links. For example, when a \(-\) node is transformed to +, its \(-\) links become ++ and its \(+\) links become ++ ones (hence \(t_{++}\) varies of \((k_- - k_+) \)/N). The corresponding probabilities \(w_1\) and \(w_2\) are obtained as for Eq. (1). \(v^2\) and \(v^3\) correspond to rewiring events: when a \(+\) \(-\) link is rewired it can either be transformed...
to $-\pm$ ($v^3$) or to $+\pm$ ($v^4$). For the r-VM, the displacement vectors are exactly the same as for the d-VM, but the transition probabilities $w_3$ and $w_4$ are interchanged. $w_3$ and $w_4$ remain the same since the rewiring rules are the same for both models. Figure 2 shows the result of the numerical integration of the evolution equations $dx/dt = \sum_v v^a w^v$, compared with numerical simulations of the models. It is clear that these equations correctly account for the difference between $k_+$ and $k_-$ and for the system’s evolution in the phase space. Of course, the real systems are moreover submitted to fluctuations that are not taken into account in the MF description. In particular, looking at single runs (Fig. 2) shows clearly the difference between the d- and r-VM. For the d-VM, the density of active links decreases rapidly to 0 and the system is driven to one of the consensus states. For the r-VM on the contrary, the system performs a random walk in a sort of potential well around $r_\text{VM}$ and its neighbor is $r_\text{NG}$, and the update rules remain the same. When agents interact on a static topology, these dynamical rules lead to a global consensus. On homogeneous networks, we obtain $t_c(N) \sim \ln N$ (while $t_c(N) \sim N$ for the VM). The difference between the two models is due to the fact that in the VM, consensus is reached by a finite-size fluctuation of the average magnetization while in the NG, consensus is reached due to the surface-tension introduced by the 0 states, which tends to minimize the interface between the agents of different opinions and hence drive the system to a homogeneous consensus state.

For adaptive networks, Fig. 3 clearly shows that the convergence time remains logarithmic for both the direct and reverse version, even if the r-NG is slower. The MF analysis allows to understand this strong difference with the VM. We can indeed write the evolution equation for the magnetization $n_+ - n_-$, by introducing the average degree of 0 nodes $k_0$ and the density of $+0$ and $-0$ links, as

$$\langle dm/dt \rangle_\text{dNG} = \frac{1}{2} \langle dm/dt \rangle_\text{dVM} + \frac{1 - \Phi}{N} \left( \frac{l_{+0}}{k_0} - \frac{l_{-0}}{k_0} \right)$$

$$\langle dm/dt \rangle_\text{rNG} = \frac{1}{2} \langle dm/dt \rangle_\text{rVM} + \frac{1 - \Phi}{N} \left( \frac{l_{+0}}{k_+} - \frac{l_{-0}}{k_-} \right)$$

The first terms on the rhs represent the change in the magnetization mediated by the $l_{+}$ links. The factor 1/2 stems from the fact that $+$ and $-$ nodes are not transformed instantaneously to their opposite counterpart but to the intermediate state 0. The remaining terms correspond to the transformation of the 0 nodes to $\pm$ ones. For example, in the d-NG, the second term on the right-hand side is generated by the process when a 0 node is converted to...
FIG. 4: $\langle dm/dt \rangle$ vs $m$ (symbols) for the r-NG. According to Eq. (3), changes in the magnetization come from r-VM-like interactions (dashed line) and those mediated by the 0-links, $l_{+0}$ and $l_{-0}$ (dash-dotted line). The upper inset gives $l_{+0}$ and $l_{-0}$, the other $k_{+}/(k)$, $k_{-}/(k)$. $\Phi = 0.2$, $\langle k \rangle = 10$, $N = 10^4$.

+ by first picking a 0 node, with probability $n_0$, then one of its + neighbors, with probability $k_{+0}/k_0$, and so on. Even though the first terms in Eq.-s (2) and (3) change sign for the d- and the r- variants of the NG just as for the VM, this effect is suppressed by the remaining terms associated with the transitions ($0 \rightarrow \pm$) which will always generate a positive feedback to the change of magnetization. As shown in Fig. 4 indeed, $l_{+0} - l_{-0}$ is of the sign of $m$, which is expected since then $n_+ > n_-$. This effect overcomes the difference between $k_{+}$ and $k_{-}$; as a result, $\langle dm/dt \rangle$ remains of $m$’s sign even in the r-NG, leading to logarithmic convergence times. Very interestingly, the possibility for agents to remain in an intermediate state before updating their opinion strongly enhances the trend towards consensus.

In summary, we have shown how slight modifications of the interaction rules can have drastic consequences in the global behavior of opinion formation models in the case of dynamically evolving networks. In the case of the paradigmatic Voter model, adaptivity of the network can either accelerate the convergence to consensus, or on the contrary hinders it strongly, by maintaining the system in a dynamically evolving state for exponentially long times. A mean-field analysis allows to account for such differences, which are due to the coupling of the asymmetry between the interacting agents to the asymmetry in their degrees. Such coupling is known to change the scaling of the convergence time in heterogeneous static networks, which however remains a power-law of time and in fact does not have consequences in homogeneous networks. In strong contrast, and even if the adaptive network remains homogeneous, the fact that the majority has a slightly larger average degree suffices to change from a very fast convergence in logarithmic time for the d-VM to a dynamical state surviving for exponentially long times for the r-VM. Interestingly, if the agents cannot change opinion so easily, and have to go through an intermediate state, such as in the NG or AB models, convergence to consensus is enhanced also for adaptive networks, and irrespective of the order of interactions (d-NG vs. r-NG). The connections with nodes in the intermediate state determine then the dominant evolution of the magnetization, leading to a more robust behavior.

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[25] We have also investigated the case in which a finite number of opinions is allowed, with the same results.
Another possibility is that the rewired link becomes $(j,k)$; the same phenomenology is then observed.

Close to the transition $\Phi \sim \Phi_c$, $t_c(N) \sim N^a$, $a \approx 0.43$.

In the AB model, only $H$ changes its state; we have checked that this modification has no influence on the overall behavior of the system described below.