Cultural Integration and Differentiation in Groups and Organizations

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Abstract. Experimental and field research has demonstrated a pervasive tendency toward pairwise conformity among individuals connected by positive social ties, and work using formal models has shown that connected influence networks should thus converge toward uniformity. Observing that diversity persists even in small scale groups and organizations, we investigate two empirically validated mechanisms of social differentiation that may account for this persistence: First, actors may dislike or disrespect peers who diverge too much from their own views, and may change their opinions or behaviors to distance themselves further from those negative referents. Second, when surrounded by similar others, actors may try to maintain a sufficient sense of uniqueness by exploring new opinions or behaviors. Using computational experiments, we demonstrate that these two forces lead to different patterns of polarization, radicalization, and factionalism and also investigate the conditions under which integration occurs.In closing, we discuss the implications for cultural dynamics in organizations.

Keywords: Social Influence, Social Differentiation, Opinion Dynamics, Polarization, Clustering, Organizational Culture

1 Introduction

Extensive research has documented the importance of organizational culture, but we are only beginning to understand the processes by which organizational cultures emerge, persist, and sometimes change or split into subcultures. Organizational cultures often prove to be remarkably stable, even despite substantial turnover in the membership, change of leaders, shifting networks of interaction among members, or disruptive external forces. Enriching our understanding of the basic dynamics of organizational culture will foster theoretical advances with important practical implications, especially in preparing for challenges such as organizational change, growth, or merger. To contribute to a rigorous microfoundation, we focus here on the dynamics of cultural influence in a simple, stylized model.

Most relevant research has employed formal theory to account for the emergence and persistence of cultural groups, showing how a population of agents with arbitrary opinions and social relations may over time develop a coherent collective culture. This work has overwhelmingly built on one of the starkest regularities in the social world: the tendency of social ties to connect individuals who are similar in attributes, attitudes, or behaviors. This observed lawlike regularity of homophily has inspired prominent "first principles" for models of local cultural emergence. First is the tendency for actors to build positive ties to interaction partners who are similar to themselves [1]. Second is the tendency for conformity to flow through social ties, engendering common attitudes or behaviors among friends and other close relations [2]. This combination of differential attraction and influence creates a self-reinforcing dynamic in which similarity increases conformity between interaction partners and conformity increases similarity of interaction partners. Such positive feedback generates a local homogenization that some have presented as an explanation for the emergence of "cultural norms" [3] in social networks.

These dynamics of attraction and conformity are the foundation for models of cultural diffusion and convergence in populations of agents, often arranged in particular network topologies. Such models have been used to understand the maintenance and stability of culture in social groups and organizations [4–6] as well as the integration of multiple cultures, such as following a merger of two organizations [7, 8]

Although the core dynamics of homophilous choice and conformity have received much theoretical attention and empirical support, and they provide a convincing account for cases of cultural integration and homogeneity, they leave us instead with the opposite puzzle of explaining cultural diversity in densely connected groups. If homophilous attraction and conformity are such general forces, how may we ever explain the maintenance of distinct cultural subgroups [9–12] in contact with one another? In fact, it has been proven for an important class of influence models [13, 14] that positive influence operating on a fully connected graph (where each actor is connected to each other by at least one influence path) will eventually result in a 'monoculture' where all individuals have the same opinions or attitudes. These models cannot explain why social groups and organizations often harbor a diversity of views, given that formal and informal networks are almost guaranteed to be connected and are often dense.

The most intuitive explanations for diversity have posited exogenous factors that may hamper cultural convergence or even create new diversity. These "top down" approaches assume, for instance, that class differences, social and political cleavages, boundaries between divisions or branches of an organization, or physical barriers somehow prevent social influence from flowing freely throughout the population [15]. In a similar way, it has been demonstrated that conflicting political parties or media may exert influence on individuals' cultural attributes and interfere with cultural convergence [16].

In contrast to approaches that rely on exogenous barriers or influences, research has also shown that cultural diversity can result from "bottom up" self-organization within a population of agents. Applying the principle of homophily to an extreme case, some scholars [17, 4, 12] assume that if two actors have disjoint cultures (share nothing in common), they then have zero propensity to interact with one another, creating a cultural boundary that operates like a geographic boundary. These models are then able to generate persistent diversity. In this case, the same local convergence that would lead to homogenization on a connected influence network can actually lead a network to disintegrate into disconnected components, where local influence paradoxically maintains cultural differences rather than erasing them. Once the members of two cultural subgroups have become too dissimilar to influence one another, their cultures evolve along divergent paths. This type of model thus incorporates both tendencies that are evident in cultural evolution - on the one hand, the drive toward uniformity within local relations, and on the other, the persistence of diversity in the greater population. While much of this work has modeled opinion scales as discrete, other studies combined homophily with continuous opinion scales [5, 18, 19]. These so called "bounded confidence models" showed that global diversity does not depend on the assumption that opinions are discrete, so long as influence can only occur between individuals who are sufficiently similar.

More recent extensions have pointed to the extreme fragility of the bottom-up theories of self-organized cultural diversity. Recent work [20, 21] relaxed the assumption that cultural traits are entirely determined by influence from neighbors and allowed instead a small probability of random perturbation of cultural traits. If this rate of perturbation is sufficiently low, occasional overlap between distinct cultures due to random distortions leads to the eventual collapse of cultural diversity. But if the rate of perturbation is sufficiently high, mutation is introduced faster than conformity can reduce it, leading to cultural turbulence that precludes the formation of stable subcultures. The window of conditions that allows cultural diversity in between these two regimes is exceedingly small and eventually all but vanishes in larger populations. A second problem with these explanations of self-organized cultural diversity is that they rely on the assumption that cultural influence is entirely precluded when interacting agents are too dissimilar. Even slight influence between agents who are highly dissimilar is sufficient to eliminate cultural diversity based on homophily and conformity alone, a result that has been obtained for models with discrete as well as with continuous opinion spaces [22, 23].

We focus on two solutions to the problem of self-organized cultural diversity, which were inspired by classical sociological theorizing [24–26] and prominent social psychological theories [27–29] on social differentiation dynamics.

The first approach invokes "distancing" as key driving force of social differentiation, drawing on balance theory [30] and cognitive consistency theories [31] from social psychology. Just as homophily suggests that actors form positive ties to similar actors and conformity suggests that actors change their opinions to better fit their friends, distancing theory posits that actors form negative ties toward peers that are very different (xenophobia) and then change their opinions to increase cultural differences toward those negative referents. Distancing has been incorporated in several formal modeling studies [32–34, 11, 35, 36], has been studied in extensive experimental research [37–39], and has been applied to social influence through networks in real-world organizations [40].

The second conceptualization of social differentiation postulates that individuals strive for a sufficient feeling of uniqueness [28, 23, 41]. Specifically, individuals who feel similar to too many others adjust their opinions and behavior such that they become more distinct, a notion that is also reflected by the theory of "optimal distinctiveness" [27] in social identity research.

While both approaches have been shown to generate "bottom-up" explanations of self-organized social and cultural diversity, it remains unclear to what extent these solutions are comparable and point to similar conditions under which diversity can arise and be maintained. To address this lacuna, we present in this paper a formal framework that incorporates both social distancing and striving for uniqueness and show how both conceptualizations of social differentiation can generate persistent and robust cultural diversity, even within a relatively small and fully-connected network where classical models would predict uniformity.

We further demonstrate that these two conceptualizations of differentiation lead to radically different patterns of cultural diversity. Populations of individuals that tend to dislike and thus distance themselves from dissimilar others tend to split into two factions with diametrically opposed opinions, so the entire group is polarized. This is because distancing implies that once sufficiently dissimilar subgroups have formed, members of subgroups strive to increase differences to the members of the other subgroup. Individuals, therefore, tend to develop increasingly extreme opinions. By contrast, differentiation conceptualized as striving for uniqueness leads subgroups to seek no more distance from each other than is sufficient to satisfy their desire for uniqueness. Striving for uniqueness creates subgroups with significantly different opinions. However, once these subgroups have formed, opinion differences remain relatively moderate.

Lastly, we demonstrate that the two conceptualizations of social differentiation imply different predictions about the conditions leading to cultural diversity and integration. On the one hand, social distancing increases social diversity only in populations where cultural variation is strong already at the outset of the process. In populations with small initial diversity, individuals perceive only very few others who are sufficiently dissimilar to generate negative ties and thus motivate distancing. As a consequence, the integrating force of social influence by similar others dominates and the population moves towards consensus. On the contrary, striving for uniqueness is strongest when many individuals hold similar opinions, implying that cultural diversification occurs mainly when there is low cultural diversity.

In closing, we discuss the implications for dynamics of cultural integration in organizations and point to future research aiming to test the boundary conditions under which the two kinds of social differentiations may shape cultural dynamics in organizations.

2 The Model of Social Differentiation

Our agent-based computational model builds on the key assumptions of classical social-influence models [13, 14, 42–47] supplemented with assumptions about social differentiation conceptualized as either distancing or striving for uniqueness. In the model, each member of the population is represented as an agent i that holds an opinion $o_{i,t}$ which varies continuously between zero and one $(0 \leq o_{i,t} \leq 1)$ and can change over time.

The social influence and differentiation process is modeled as a sequence of simulation events. At each event t the computer program randomly picks one of the N agents and updates this agent's (i) current opinion $o_{i,t}$ such that after the update a new opinion $o_{i,t+1} = o_{i,t} + \Delta o_{i,t}$, where the magnitude and direction of the opinion change $o_{i,t}$ is obtained as

$$\Delta o_{i,t} = \frac{\sum_{j=1}^{N} \left(o_{j,t} - o_{i,t}\right) w_{ij,t}}{\sum_{j=1}^{N} w_{ij,t}} + \xi_{i,t} \, . \tag{1}$$

Equation 1 integrates three key processes that previous models of cultural differentiation have considered: social influence, distancing and striving for uniqueness. The influence weight $w_{ij,t}$ represents the degree to which agent i is influenced by agent j and varies between -1 and +1 $(-1 \leq w_{ij,t} \leq 1)$. A positive weight implies that j has a positive influence on i, so i's opinion is "pulled" towards the opinion of j. This reflects the mechanism of social influence that has been central to early models of cultural consensus formation [13, 43, 44, 47]. However, weights can also have negative values, in which case the opinion of agent i is "pushed" away from j's opinion. With negative weights, equation (1) implements social distancing. Finally, equation (1) contains a noise term $\xi_{i,t}$ to implement "striving for uniqueness". Specifically, we assume that the less unique an agent's current opinion is in the overall opinion distribution, the larger is the perturbation $\xi_{i,t}$ that leads the agent away from her current opinion (in a random direction). The denominator in (1) normalizes incoming influence to ensure that all agents have a fixed capacity to be influenced, apportioned relatively among peers by the tie weights.

Equations 2 and 3 define the influence weights $w_{ij,t}$. Implementing homophily, we assume that the influence $w_{ij,t}$ that j has on i depends on their opinion distance $(dist_{ij,t} = |o_{i,t} - o_{j,t}|)$. To be more precise, equation 2 implies that the weights are more positive (or less negative) the more similar i and j are. Parameter c $(1 \leq c \leq 2)$ allows manipulating the balance of social influence, from positive-only to a mixture of positive and negative influence. If $c = 1$, then influence weights can have only positive values and thus only positive influence operates. If $c = 2$, social distancing is as strong as positive influence. If c is between those values then agents are influenced positively $(w_{ij,t} > 0)$ by similar others and (to a lesser extent) influenced negatively ($w_{i,j,t} < 0$) by dissimilar others. The value $1/c$ represents the critical opinion distance at which influence shifts from positive to negative.

$$w_{ij} = (1 - c \cdot dist_{ij,t})^a \quad if \quad dist_{ij,t} \leq \frac{1}{c} \tag{2}$$

$$w_{ij} = -1(c \cdot dist_{ij,t} - 1)^a \quad if \quad dist_{ij,t} > \frac{1}{c} \tag{3}$$

In the case of positive influence ($c = 1$), agents are strongly influenced ($w_{ij,t}$ approaches 1) by peers that are very similar to themselves, and influenced very little ($w_{ij,t}$ approaches 0) by dissimilar agents. When $c = 2$, agents are strongly influenced by very similar peers, strongly negatively influenced ($w_{ij,t}$ approaches -1) by very dissimilar peers, and influenced little ($w_{ij,t}$ approaches 0) by peers that are moderately distant. Parameter a ($a > 0$) allows us to vary the shape of this weight function. In the case of positive influence, high values of a imply that influence diminishes more rapidly with opinion distance, so agents are influenced predominantly by the most similar peers and pay little attention to other peers. In the case of equal positive and negative influence ($c = 2$), high values of a imply that agents are strongly influenced by very similar and also (negatively) by the most dissimilar peers, and pay little attention to the rest. Fig. 1 illustrates the value of $w_{ij,t}$ resulting from (2) and (3), under different values of a and c. For illustrative purposes, we have chosen here values of a that are different from those employed in the computational experiments reported further below[1].

Striving for uniqueness. The second conceptualization of social differentiation assumes that agents adjust their opinions or behavior when they feel indistinguishable from many other individuals. Whereas distancing implies opinion changes away from the opinions of dissimilar others, striving for uniqueness does not specify the direction of the opinion change. Accordingly, we follow the lead of earlier modeling work [23, 49] in including a stochastic perturbation $\xi_{i,t}$ in the updating of opinion.

Since opinion and behavioral adjustments always imply cognitive costs [31, 50], we assume that agents tend to make relatively small changes compared to their prior opinion. Specifically, the random perturbation is drawn from a normal distribution with an average of zero and a standard deviation specified in (4).

$$\xi_{i,t} = N\left(0, s\sum_{j=1}^{N} e^{-dist_{ij,}}\right) \tag{4}$$

[1] Digital computers may fail to distinguish very small numbers from zero [48], an error that would be consequential here in that it would erase the distinction between weak influence and no influence. To avoid such problems with floating point inaccuracy, we assign a minimum on positive weights at 10^{-5} and assign a maximum on negative weights at -10^{-5}. We thus conservatively ensure that weak ties are not mistakenly treated as null ties by the computer.

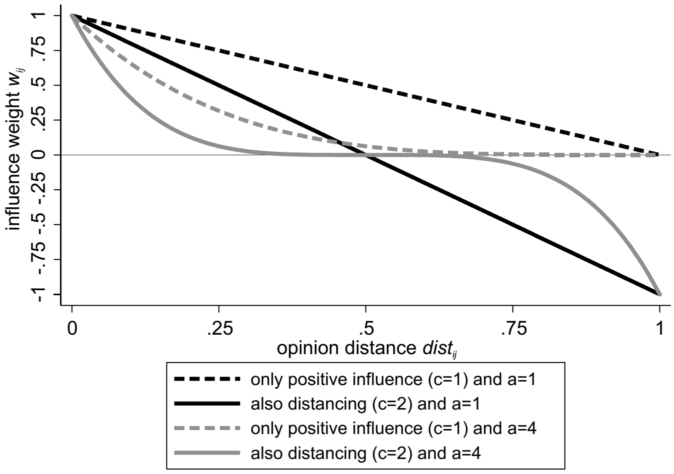

Fig. 1. Examples of weight functions for different values of parameters c and a.

Equation (4) thus determines the amount of randomness that is added to the agent's opinion, depending on how unique agent i is in the population. If agent i holds an opinion that is very similar to the opinion of many other agents then the standard deviation of the added noise is high. If, however, an agent holds an opinion very different from its peers, it is not driven to increase uniqueness and only a little noise is added.

We included a parameter s ($s \geq 0$) that determines the overall degree to which individuals value uniqueness. If $s = 0$, agents do not strive for uniqueness at all. The higher the value of s, however, the stronger is the striving for uniqueness in the population. Note that distancing may result in opinion values that are outside the defined range of the opinion scale ($0 \leq o_{i,t} \leq 1$). If an agent's opinion would otherwise exceed the range, we assign the extreme value of the range, 0 or 1.

Possible equilibria. Whether model dynamics can reach a state of equilibrium or not and also the number of possible equilibria depends critically on the values assigned to parameters c and s. The model has two possible equilibria if there is only positive influence ($c = 1$) and no striving for uniqueness ($s = 0$). The first equilibrium is characterized by perfect opinion consensus, a state where all agents hold exactly the same opinion[2]. In the second equilibrium, the population consists of two factions of maximally dissimilar extremists. Under this

[2] It is commonly believed that positive influence models invariably produce consensus on connected networks. Even as we add that the network must be *strongly* connected, this may not be strictly true in discrete time for certain networks. The lack of convergence is obvious if influence weights ($w_{ij,t}$) exceed 1.0, but the case of $w_{ij,t} = 1.0$ (i.e. opinions are strictly determined by network neighbors) may yield stable limit cycles that prevent convergence. See [6] for an explanation. Cycles cannot prevent convergence here because influence weights in our model are instaneously

condition, opinions cannot change because pairs of agents with nonzero influence hold identical opinions, which implies that opinions remain unaffected. Influence weights between maximally dissimilar agents take the value zero and do not result in opinion changes as well. This replicates the familiar pattern observed in the literature, where uniformity is a strong attractor of the influence dynamic, but distinct subcultures can exist if they are maximally different and have zero influence on one another. We do not further investigate this case here.

If there is negative influence ($c > 1$) and no striving for uniqueness ($s = 0$), then multiple equilibria are possible. As with the case of positive influence, global consensus is a locally stable equilibrium; that is, perturbations in the neighborhood of this equilibrium will be self-correcting, and the opinion distribution will return to consensus. Second, this version of the model also implies equilibrium when there are two maximally antagonistic subgroups of extremists. Each extremist is negatively influenced by the agents that adopt the opposite opinion and therefore sticks to the extreme opinion. Unlike in the positive influence case, this polarization equilibrium can be locally stable, and the model will return from small perturbations to the purely polarized state.

Third, the model with negative influence and no striving for uniqueness implies that multiplex equilibria can emerge. These equilibria are characterized by opinion distributions with two maximally extreme subgroups and at least one subgroup of moderate agents. In such constellations it is possible that the negative (distancing) and positive influences on the opinions of moderate agents neutralize each other. As a consequence, agents with moderate opinions do not adjust their opinions. For example, Fig. 2 shows a population that consists of six agents and is split up into four subgroups, with one agent on each pole of the opinion scale and two subgroups with moderate opinions. The arrows in Fig. 2 indicate the direction of influence that is exerted on the opinion of each agent. The two extremists are attracted by two moderate agents. However, this "pull" towards moderate opinions is overruled by the negative influence of those three agents with very different opinions. As a consequence, the extremists stick to their extreme opinion. Each of the moderate agents is positively influenced by one extremist and negatively influenced by the other. These two influences "pull" the opinion of each moderate towards the nearer extreme. In addition, each moderate agent is positively influenced by the two moderates who belong to the other moderate subgroup. These influences "pull" towards a more moderate opinion, but in the other direction than the pull of the extremist "friend". As a consequence, a multiplex equilibrium with more than two co-existing subgroups can arise with distancing, but in the absence of striving for uniqueness.

If there is striving for uniqueness ($s > 0$), then (4) implies that opinions are always exposed to random fluctuations. However, as has been demonstrated by Mäs et al. [23], the model can reach a dynamic equilibrium, where opinion distributions remain qualitatively similar over a long period of time. Furthermore, if opinion distributions happen to change due to random fluctuations, the system

determined by similarity. That is, if $w_{ij,t} = 1.0$ then agents' opinions are already identical and influence is impossible; if opinions are not identical then $w_{ij,t} < 1.0$.

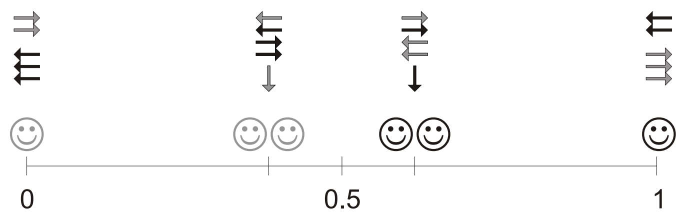

Fig. 2. Example of a multiplex equilibrium under negative influence.

tends to return to a similar state as before the disturbance. We demonstrate this in more detail in the results section (cf. Fig. 4)

3 Results

3.1 Ideal-typical Simulation Scenarios

To begin with, we show a number of scenarios that represent the most important qualitatively different outcomes that the model can generate. All of the models presented include a population of 100 agents subject to social influence and homophily, but the mechanisms of differentiation may be either distancing or striving for uniqueness. Fig. 3 shows an illustrative simulated trajectory for the model with distancing, but not striving for uniqueness ($c = 2$, $s = 0$). Fig. 4 shows the model with only striving for uniqueness ($c = 1$, $s = 0.00025$). In both scenarios, we compare initial opinion distributions that differ in the degree of initial variation in agent's opinions.

We know from previous work that both mechanisms can in principle generate persistent social diversity [11, 23]. Here, we are interested in how the variance of the initial opinion distribution affects the degree of social diversity that can be sustained under each of the two differentiation mechanisms. Therefore, we test conditions where diversity is possible under either mechanism of differentiation. Most importantly, we set a very steep influence function ($a = 100$) because earlier modeling studies [23] demonstrated that this is a critical condition for the formation of distinct subgroups in the uniqueness model. In the uniqueness model, much smaller values result in the formation of a single stable cluster of agents. On the other hand, for much higher a values, the model predicts highly fragmented opinion distributions without any stable cluster formation.

Each panel of Fig. 3 and 4 shows a line graph where the trajectory of the opinion of each agent is represented by one line. Under both model versions, the social influence process implies that often agents who hold relatively similar opinions from the outset quickly move to identical 'positions in the opinion space, and then their lines overlap. This is why the initially scattered opinions of agents quickly collapse into a much smaller set of opinions in both models.

Fig. 3 focuses on the distancing model ($c = 2$) without striving for uniqueness ($s = 0$) and compares influence dynamics that start with a low (panel A) or a high (panel B) initial opinion variance. For the simulation run shown in panel A, we started with a normal opinion distribution with an average of 0.5 and a relatively small standard deviation of 0.1. Accordingly, initial opinion differences in the population were very small, resulting in mainly positive influence weights in the population. Agents with moderate opinions were positively influenced by all members of the population. Only pairs of agents that held opinions near the opposite extremes of the initial opinion distribution had negative influence weights (distancing). However, even these relatively extreme agents were mainly influenced positively by agents with moderate opinions. These positive influences dominated distancing tendencies and the extreme agents then developed moderate opinions. Panel A shows that early in the influence process several subgroups of agents with similar opinions formed. Because of strong homophily, the social influence between agents that belonged to different clusters was weak but eventually led to a steady decrease in opinion differences between subgroups. The model reached a state of equilibrium when all agents converged to the same opinion.

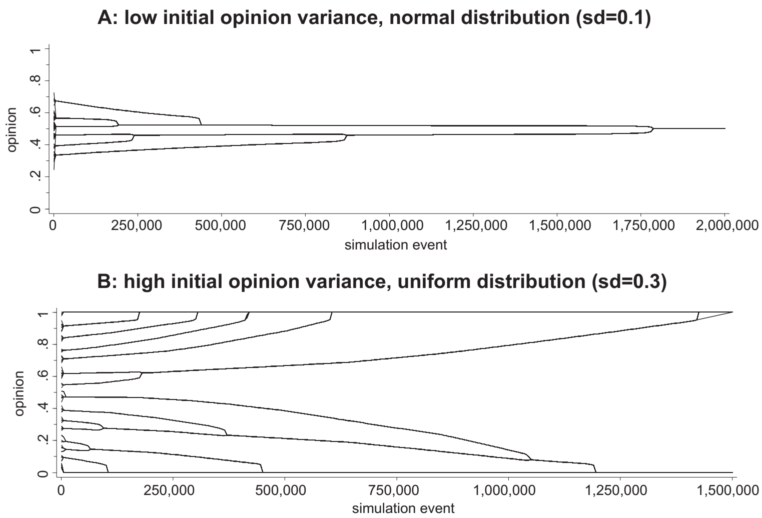

Fig. 3. Ideal typical simulation runs with distancing and without striving for uniqueness ($c = 2$, $s = 0$).

Panel B shows that the outcome of the influence process radically differs if there is initially more opinion variation. For this simulation run, we used the same parameter values as for the run shown in panel A. However, we assumed that the opinion was uniformly distributed in the range (0,1) at the outset, leading more agents to begin with very extreme opinions. In the run shown in panel B, several distinct subgroups formed very early in the influence process, butthe extreme agents developed even more extreme opinions over time. This happened because agents with extreme opinions were exposed to influences from multiple agents with very distinct opinions and tended to distance themselves from those with opposing opinions. Also agents with moderate opinions formed clusters in the early stages of the influence process. Once these subgroups had formed, moderates hardly adjusted opinions because they were exposed to positive influences from agents with both higher and lower opinion values. But as more agents adopted extreme opinions, the moderate agents were also increasingly exposed to negative influences. The figure shows that this resulted in shifts towards extreme opinions also for those who initially maintained moderate positions. Eventually, this process reached equilibrium with two maximally extreme and mutually dissimilar subgroups.

Fig. 4 depicts three ideal-typical influence scenarios of the model version with striving for uniqueness ($s = 0.00025$) but without distancing ($c = 1$). The scenario shown in panel A started from perfect consensus. Under this condition, positive social influence did not result in opinion adjustments. However, the opinions of the agents were minimally unique. Our implementation of the striving for uniqueness in (3) implies ongoing substantial perturbations from the initial consensus. Panel A in Fig. 4 shows that these individual opinion perturbations led to a strong increase in overall opinion variation and to the formation of two distinct clusters (e.g. after about $200,000$ simulation events).

Once distinct clusters had formed, the composition of each cluster remained temporarily stable. This was because members of each cluster were relatively unique, as there were sufficient opinion differences compared to the members of the other cluster(s). Nevertheless, there were still small individual perturbations from the subgroup consensus, according to (4). Because of the strong social influence between the members of an opinion cluster, these small individual perturbations could aggregate to substantial collective opinion changes of all cluster members. It was therefore possible that the members of distinct clusters happened to develop similar opinions and merged. Once this occurred, the uniqueness of the agents who belonged to the merged subgroup decreased, leading to an increased striving for uniqueness and to the development of new distinct subgroups.

The simulation scenario shown in panel A of Fig. 4 demonstrates that the interplay of social influence and striving for uniqueness can create a constant fusion and fission of subgroups. In other words, the system tends to develop opinion distributions that consist of several distinct subgroups. However, distributions with several subgroups are not stable because small individual opinion perturbations can lead to fusion of subgroups.

Obviously, the differentiation dynamics shown in panel A of Fig. 4 differ substantially from those shown in panel B of Fig. 3. Most importantly, the distancing mechanism (Fig. 3) implies that if dynamics do not end in perfect consensus, the population eventually includes two factions with extreme opinions[3].

[3] We show below that the model may generate multiplex equilibria, opinion distributions where two extreme factions are accompanied by moderate subgroups. While interesting, these outcomes are very rare and vanish in the presence of noise.

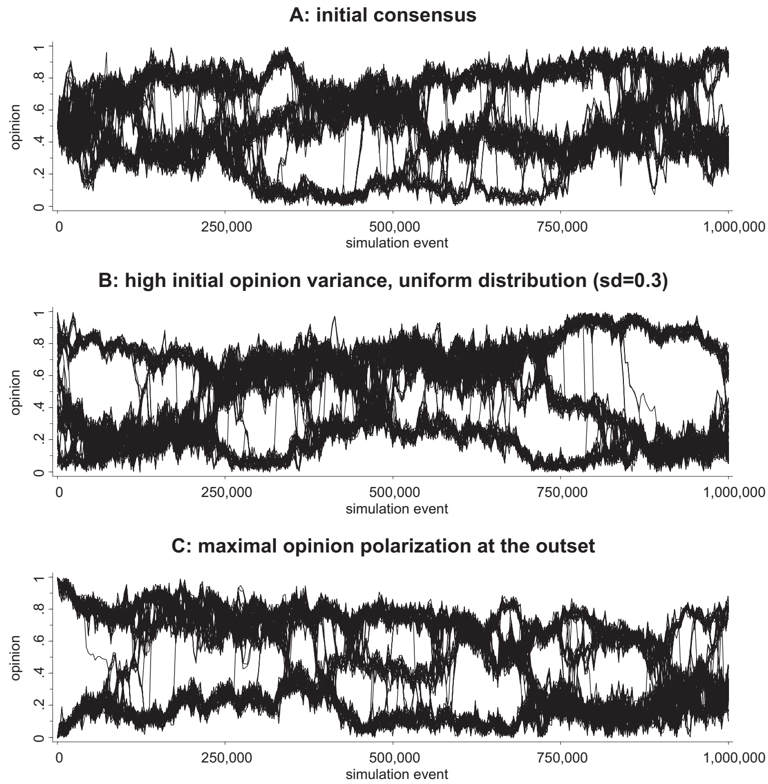

Fig. 4. Ideal-typical simulation runs with striving for uniqueness ($c = 1$, $s = 0.00025$).

However, Fig. 4 suggests that the striving for uniqueness mechanism generates clusters with nonextreme opinions.

Another crucial difference between the two conceptualizations of differentiation becomes obvious upon comparing the three simulation scenarios of Fig. 4. Panel B shows an ideal-typical simulation scenario that starts out with a uniform opinion distribution. In panel C the initial population consisted of two equally sized and maximally dissimilar subgroups. Even though the three simulation runs shown in Fig. 4 started with very different initial opinion distributions, the system produced eventually always the same fusion-and-fission dynamic with similar opinion distributions. This apparent robustness to initial conditions contrasts starkly with Fig. 3, which demonstrated that the initial distribution of opinions can have a substantial effect on outcomes under the distancing model. However, a comparison of ideal-typical scenarios does give us solid intuitions about the effect of the initial variation in opinions. Accordingly, we conduct a computational experiment in which we manipulate the initial distribution systematically across a wide range of possibilities.

3.2 The Computational Experiment

Design of the experiment. The ideal-typical simulation scenarios (Fig. 3 and 4) suggest that there are two substantial differences between the two conceptualizations of social differentiation. First, whereas the distancing mechanism appears to generate subgroups with maximally extreme opinions, we found subgroups with mainly moderate opinions in the uniqueness model. Second, the ideal-typical simulation scenarios suggested that the initial distribution of opinions was crucial for the distancing model but unimportant for the uniqueness model.

To investigate this conjecture more rigorously, we conducted a computational experiment which tested for both versions of the model whether the opinion distribution at the outset of the differentiation process has an impact on the opinion distributions that appear in equilibrium or, for the model with stochastic perturbations, after 25 Million simulation events.

We imposed for all experimental conditions that the initial opinion of each agent was randomly drawn from a normal distribution with a mean of 0.5 and manipulated the standard deviation of the normal distribution between zero and 0.5 in steps of 0.025. If the randomly drawn opinion value happened to be outside of the bounds of the opinion scale ($0 \leq o_{i,t} \leq 1$), a new random value was drawn until the value was inside the opinion scale. Fig. 5 depicts the opinion distributions that result from this procedure. The figure shows that with a standard deviation of zero there is an initial consensus of opinions. On the opposite extreme, an imposed standard deviation of 0.5 leads to an approximate uniform initial opinion distribution over the entire range of opinions.

For the distancing model ($c = 2$, $s = 0$) we conducted 100 independent replications per experimental condition. For the model version with striving for uniqueness ($c = 1$, $s = 0.00025$) we doubled the number of replications because

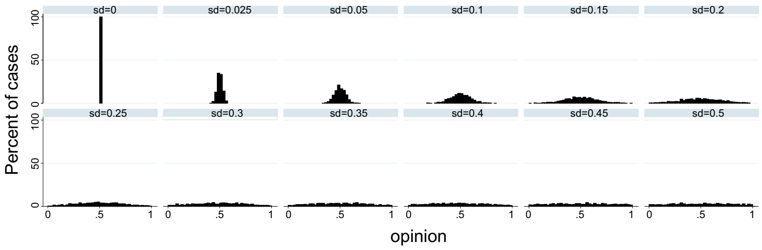

Fig. 5. Examples of initial opinion distributions.

in this model version dynamics depend to larger degree on random influences. Like in the ideal-typical simulation scenarios, we set $N = 100$ and $a = 100$.

We used three outcome measures to describe the opinion distributions in the computational experiment. First, we counted the number of subgroups in the population to express the degree of diversity in the distribution of opinions. In order to identify subgroups, we sorted the N agents in order according to their opinion and defined a subgroup as a set of agents in adjacent positions such that each member of that set was separated from the nearest other member of the set by at most 0.05 scale points. This allows us to identify subgroups of agents with very similar but not identical opinions, which is the appropriate approach for a system in which randomness precludes that two agents have fully identical opinions.

Second, we assessed for each opinion distribution the average extremeness, measured as the average distance between an agent's opinion and the mid point of the opinions scale. This is to test our expectation that differentiation under the distancing mechanism will lead to greater extremity of opinions than differentiation under the uniqueness mechanism. The minimal value of this outcome measure is zero, indicating that all agents hold an opinion of exactly 0.5. The maximal average extremeness of 0.5 obtains when all agents hold maximally extreme opinions (0 or 1).

Finally, we used a measure of polarization to quantify the degree to which the population splits into mutually distant but internally homogeneous subgroups. Polarization is measured as the standard deviation of the distribution of pairwise opinion distances. Obviously, this measure reaches its minimal value of zero when all agents adopt the same opinion. Its maximal value of 0.5 obtains if the population is evenly divided into two diametrically opposed subgroups. Thus, polarization implies extreme opinions, but extremism does not imply polarization.

Results of the computational experiment. Fig. 6 reports the effect of the initial opinion distribution on the result of each differentiation process. The solid lines represent the uniqueness model, and show that the initial opinion distribution does not have long term effects on the outcome of the differentiation process. Panel A shows that the model with striving for uniqueness generated about 2.2 subgroups on average, regardless of the initial opinion distribution. In addition, panel B shows that these subgroups held relatively moderate opinions on average, and panel C shows that opinion polarization is also relatively low.

The outcome of our experiment is radically different when the differentiation process is driven by distancing (see the dashed lines in Fig. 6). Panels A and B show that for initial opinion distributions with a low variance, distancing dynamics tend to generate consensus on moderate opinions. However, higher initial opinion variation resulted in higher extremeness and polarization of opinions. Panel A shows that the average number of subgroups reaches a maximum of about 2.4, indicating that several runs ended in a multiplex equilibrium. To examine this pattern in closer detail, Fig. 7 displays the exact distribution of the number of subgroups.

The size of the bubbles (see also the numbers below or above the bubbles) indicates how many simulation runs ended with the respective number of subgroups. As the figure shows, in conditions with a very low initial opinion variation, all 100 runs per condition ended with opinion consensus. However, as the initial opinion variance increases, more runs end with two distinct subgroups. If there was an intermediate level of opinion variance at the outset, several simulation runs ended in a multiplex equilibrium However, only very few runs ended in multiplex equilibria when the initial opinion variation was very high.

4 Summary and Discussion

Classical models of opinion dynamics show that the fundamental mechanism of social-influence - i.e. individuals' tendency to shift their opinions towards those of interaction partners - creates an inexorable march toward cultural homogeneity in connected networks. This contradicts the high degree of persistent diversity that we observe in many social settings, such as in relatively small scale organizations where formal and informal networks are almost guaranteed to be connected. This has led researchers to develop extensions of the classical models to explain emergence and persistence of diversity.

In this contribution, we focused on social differentiation, a recently proposed bottom-up explanation of persistent cultural diversity in strongly connected networks. In particular, we distinguished two alternative conceptualizations of social differentiation - distancing and striving for uniqueness - which operate together with social influence. Distancing implies that individuals tend to form negative ties to others that are very dissimilar, and then differentiate themselves from those negative referents. Striving for uniqueness holds that individuals tend to change their opinions when they perceive that they are not sufficiently different from others. We presented a formal model of social influence dynamics that incorporates both conceptualizations of social differentiation and studied differences in the implications of the two mechanisms.

Our computational experiment demonstrated that these two representations of social differentiation imply radically different patterns of cultural diversity. When individuals distance themselves from dissimilar others, the population may split into two factions with diametrically opposed opinions at the extreme

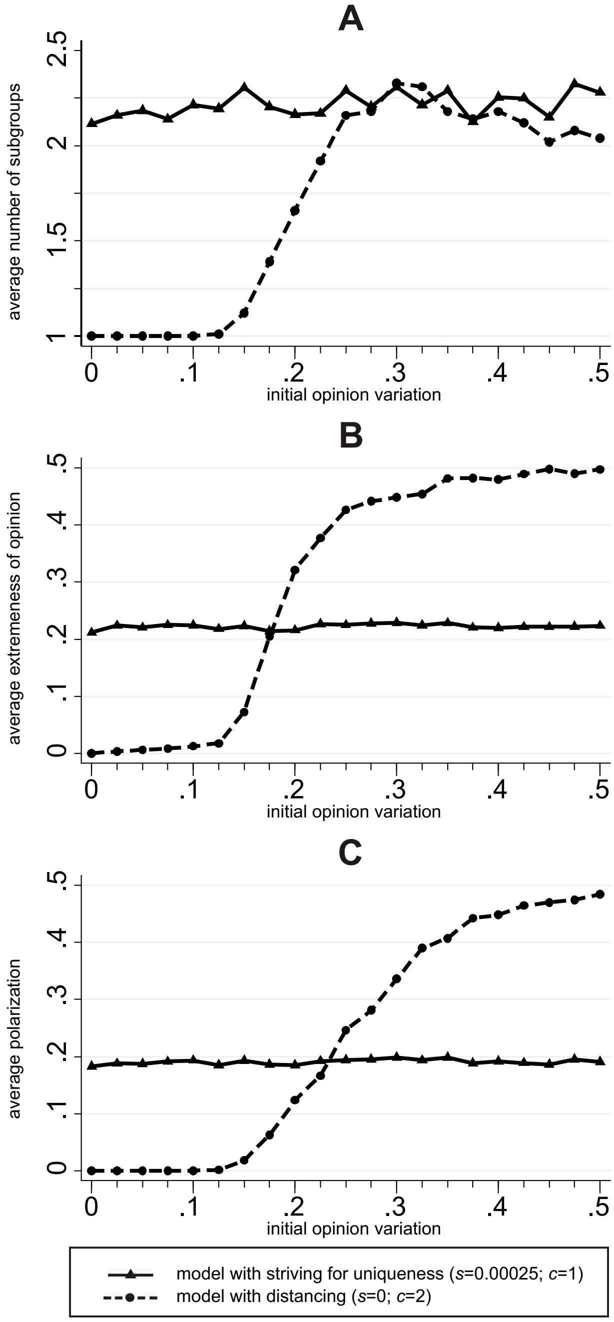

Fig. 6. Results of the simulation experiment.

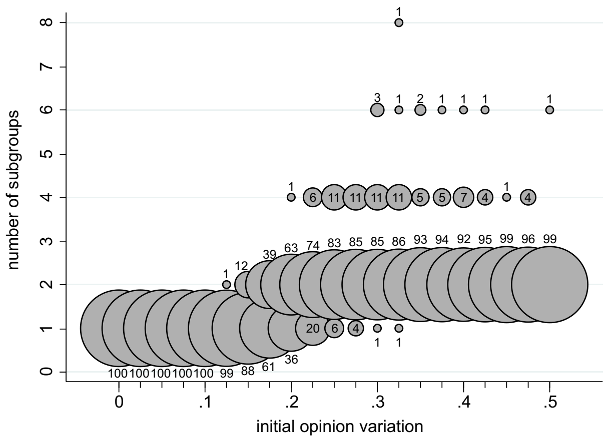

Fig. 7. Number of subgroups generated by the distancing model ($c = 2$, $s = 0$).

ends of the opinion spectrum. However, striving for uniqueness leads to multiple subgroups with moderate opinions.

In addition, we demonstrated that the two conceptualizations of differentiation imply opposing predictions about the boundary conditions of cultural diversity and integration. On the one hand, distancing increases social diversity only in groups where cultural variation is strong already at the outset of the process. In populations where initial diversity is too small to activate a cycle of distancing, positive influence prevails and the population approaches uniformity in the long run. On the contrary, striving for uniqueness implies that cultural diversity increases mainly when there is low cultural diversity. In the long run, the degree of cultural diversity in a population is unaffected by the initial distribution.

Both basic processes - distancing and striving for uniqueness - have been independently supported by empirical research. It may be that certain individuals are more driven by one force or the other, and it may be that certain situations lead one process or the other to exert a stronger influence. In order to identify different implications of the two conceptualizations of cultural differentiation, we use only a simple stylized model that allows us to examine each of these processes in isolation, and we otherwise hold the situation and the personality of agents constant in our experiments. We recommend that future research should examine both the individual-level and the group-level or situational factors that may moderate the processes that we investigate here.

Of course, distancing and striving for uniqueness may operate interactively in many cases. Our study suggests that this interaction may be quite complex. Remarkably, implications of an integrated model version are very difficult to intuit, as the two differentiation mechanisms have very different implications. For example, distancing implies the development of radicalized subgroups with highly homogeneous opinions and behavior. This, in turn, should motivate individuals who seek to achieve a high level of uniqueness to deviate from their subgroup's consensus and suggests that several individuals who belong to an extreme group will develop more moderate views. However, actors with relatively moderate opinions who are exposed to groups of extremists most likely seek to distance themselves from members of one of the extreme groups and will therefore tend to develop more extreme opinions and values again. Future modeling work is needed to understand the exact implications of the cultural differentiation based on both mechanisms acting in parallel, a research problem that can be tackled based on the formal model which we have presented here.

This paper offers insights into basic processes of cultural influence and differentiation in networks. Although we focus on general, abstract lessons here, a deeper understanding of structural conditions of consensus, clustering and polarization would be useful to managers or anyone with an interest in how people work together. Empirical research [51] has found that work teams with nonroutine tasks perform relatively poorly when there is no disagreement between team members, suggesting that social differentiation on task-related opinions might be beneficial for work teams as it might trigger inspiring discussions. However, our results suggest that social differentiation in the form of distancing leads to polarized opinions, which has been found to ignite conflicts on work related opinions and hinder team decision making [51–53]. We have demonstrated, on the other hand, that social differentiation based on striving for uniqueness can lead to moderate degrees of diversity. This might create sufficient opinion differences for stimulating discussions and, at the same time, implies enough opinion overlap for efficient team decision-making. Somewhat counter to intuition, this suggests that an organizational culture that supports individuals' striving for uniqueness might actually increase performance of work teams with nonroutine tasks.

Acknowledgments. The research of Andreas Flache and Michael Mäs has been supported by the Netherlands Organization for Scientific Research, NWO (VIDI Grant 452-04-351). James Kitts acknowledges support from the National Science Foundation (BCS-0433086 and IIS-0433637).

References

1. Homans, G. C.: The Human Group. Harcourt, Brace, and World, New York (1950)
2. Festinger, L., Schachter, S.,Back, K.: Social Pressures in Informal Groups. Stanford University Press, Stanford, CA (1950)
3. Latane, B.: Pressures to uniformity and the evolution of cultural norms. In: Ilgen, D. R., Hulin, C. L. (eds.) Computational Modeling of Behavior in Organizations: The Third Scientific Discipline, 189-215. American Psychological Association, Washington, DC (2000)
4. Carley, K.: A Theory of Group Stability. Am Sociol Rev. 56, 331-354 (1991)
5. Harrison, J. R.,Carroll, G.: The Dynamics of Cultural Influence Networks. Comput Math Organ Theory. 8, 5-30 (2002)
6. Kitts, J. A.,Trowbridge, P. T.: Shape Up Or Ship Out: Social Networks, Social Influence, and Organizational Demography. Comput Math Organ Theory. 13, 333-353 (2007)

7. Carroll, G. R., J. R. Harrison.: Come together? The Organizational Dynamics of Post-Merger Cultural Integration. Simulation Modelling Practice and Theory 10, 349-368 (2002)
8. Harrison, J. R.,Carroll, G. R.: Culture and Demography in Organizations. Princeton University Press, Princeton, NJ. (2006)
9. Bednar, J., A., Bramson, A., Jones-Rooy, A.,Page, S.: Emergent Cultural Signatures and Persistent Diversity: A Model of Conformity and Consistency. Ration Soc. 22, 407-444 (2010)
10. Centola, D., Gonzalez-Avella, J. C., Eguiluz, V. M.,Miguel, M. S.: Homophily, cultural drift and the co-evolution of cultural groups. J Conflict Res. 51, 905-929 (2007)
11. Macy, M. W., Kitts, J., Flache, A.,Benard, S.: Polarization and Dynamic Networks. A Hopfield Model of Emergent Structure. In: Breiger, R., Carley, K., Pattison, P. (eds.) Dynamic Social Network Modeling and Analysis: Workshop Summary and Papers, 162-173. The National Academies Press, Washington, DC (2003)
12. Mark, N. P.: Beyond individual differences: Social differentiation from first principles. Am Sociol Rev. 63, 309-330 (1998)
13. Abelson, R. P.: Mathematical Models of the Distribution of Attitudes Under Controversy. In: Frederiksen, N., Gulliksen, H. (eds.) Contributions to Mathematical Psychology, 142-160. Rinehart Winston, New York (1964)
14. Harary, F.: A criterion for unanimity in French's theory of social power. In: Cartwright, D. (eds.) Studies in social power, 168-182. Institute for Social Research, Ann Arbor (1959)
15. Parisi, D.,Cecconi, F.: Cultural Change in Spatial Environments. J Conflict Res. 47, 163-179 (2003)
16. Shibanai, Y., Yasuno, S.,Ishiguro, I.: Effects of Global Information Feedback Diversity. J Conflict Res. 45, 80-96 (2001)
17. Axelrod, R.: The dissemination of culture - A model with local convergence and global polarization. J Conflict Res. 41, 203-226 (1997)
18. Deffuant, G., Neau, D., Amblard, F.,Weisbuch, G.: Mixing beliefs among interacting agents. Advances in Complex Systems. 3, 87-98 (2000)
19. Hegselmann, R.,Krause, U.: Opinion Dynamics and Bounded Confidence Models, Analysis, and Simulation. JASSS-J ARTIF SOC S. 5, (2002)
20. Klemm, K., Eguiluz, V. M., Toral, R.,Miguel, M. S.: Global culture: A noise-induced transition in finite systems. Phys Rev E. 67, 045101(R) (2003)
21. De Sanctis, L.,Galla, T.: Effects of noise and confidence thresholds in nominal and metric Axelrod dynamics of social influence. Phys Rev E. 79, 046108 (2009)
22. Flache, A.,Macy, M.: Local Convergence and Global Diversity: The Robustness of Cultural Homophily. arXiv:0808.2710v1. (2008)
23. Ms, M., Flache, A.,Helbing, D.: Individualization as Driving Force of Clustering Phenomena in Humans. PLoS Computational Biology. 6, e1000959 (2010)
24. Bourdieu, P.: Distinction: A social critique of the Judgment of Taste. Harvard University Press, Cambridge, MA (1984[1979])
25. Durkheim, E.: The Division of Labor in Society. The Free Press, New York (1997 [1893])
26. Elias, N.: The Civilizing Process, Vol.I. The History of Manners. Blackwell, Oxford (1969[1939])
27. Brewer, M. B.: The Social Self - on Being the Same and Different at the Same Time. Pers Soc Psychol B. 17, 475-482 (1991)
28. Snyder, C. R.,Fromkin, H. L.: Uniqueness. The human Pursuit of Difference. Plenum Press, New York and London (1980)

29. Tajfel, H.,Turner, J. C.: The Social Identity Theory of Intergroup Behavior. In: Worchel, S., Austin, W. G. (eds.) Psychology of Intergroup Relations, 7-24. Nelson-Hall Publishers, Chicago (1986)
30. Heider, F.: Attitudes and Cognitive Organization. In: Fishbein, M. (eds.) Readings in Attitude Theory and Measurement, 39-41. John Wiley and Sons, Inc., New York, London, Sydney (1967)
31. Festinger, L.: A Theory of Cognitive Dissonance. Row, Petersen and Company, Evanston, White Plains (1957)
32. Baldassarri, D.,Bearman, P.: Dynamics of political polarization. Am Sociol Rev. 72, 784-811 (2007)
33. Durrett, R.,Levin, S. A.: Can Stable Social Groups be Maintained by Homophilous Imitation alone? J Econ Behav Organ. 57, 267-286 (2005)
34. Kitts, J.: Social Influence and the Emergence of Norms Amid Ties of Amity and Enmity. Simulation Modelling Practice and Theory. 14, 407-422 (2006)
35. Flache, A.,Ms, M.: How to get the timing right? A computational model of how demographic faultlines undermine team performance and how the right timing of contacts can solve the problem. Comput Math Organ Theory. 14, 23-51 (2008)
36. Mark, N. P.: Culture and Competition: Homophily and Distancing Explanations for Cultural Niches. Am Sociol Rev. 68, 319-345 (2003)
37. Berscheid, E.: Opinion Change and Communicator-Communicatee Similarity and Dissimilarity. J Pers Soc Psychol. 4, 670-680 (1966)
38. Sampson, E. E.,Insko, C. A.: Cognitive consistency and performance in the autokinetic situation. Journal of Abnormal and Social Psychology. 68, 184-192 (1964)
39. Schwartz, S. H.,Ames, R. E.: Positive and Negative Referent Others as Sources of Influence: A Case of Helping. Sociometry. 40, 12-21 (1977)
40. Kitts, J. A.: Mobilizing in Black Boxes: Social Networks and Participation in Social Movement Organizations. Mobilization. 5, 241-257 (2000)
41. Imhoff, R.,Erb, H. P.: What Motivates Nonconformity? Uniqueness Seeking Blocks Majority Influence. Pers Soc Psychol B. 35, 309-320 (2009)
42. Berger, R. L.: A Necessary and Sufficient Condition for Reaching a Consensus Using DeGroot's Method. J Am Stat Assoc. 76, 415-418 (1981)
43. DeGroot, M. H.: Reaching a Consensus. J Am Stat Assoc. 69, 118-121 (1974)
44. French, J. R. P.: A Formal Theory of Social Power. Psychol Rev. 63, 181-194 (1956)
45. Friedkin, N. E.,Johnsen, E. C.: Social-Influence and Opinions. J Math Sociol. 15, 193-205 (1990)
46. Latane, B.: The Psychology of Social Impact. Am Psychol. 36, 343-356 (1981)
47. Lehrer, K.: Social Consensus and rational agnoiology. Synthese. 31, 141-160 (1975)
48. Izquierdo, L. R.,Polhill, J. G.: Is Your Model Susceptible to Floating-Point Errors?. JASSS-J ARTIF SOC S. 9 (2006)
49. Pineda, M., Toral, R.,Hernandez-Garc?a, E.: Noisy continuous-opinion dynamics. Journal of Statistical Mechanics. P08001 (2009)
50. Aronson, E.: The social animal. Freeman Press, San Francisco (1994)
51. Jehn, K. A.: A Multimethod Examination of the Benefits and Detriments of Intragroup Conflict. Admin Sci Quart. 40, 256-282 (1995)
52. Jehn, K. A.: A Qualitative Analysis of Conflict Types and Dimensions of Organizational Groups. Admin Sci Quart. 42, 530-557 (1997)
53. Jehn, K. A.,Bendersky, C.: Intragroup conflict in organizations: A contingency perspective on the conflict-outcome relationship. Res Organ Behav. 25, 187-242 (2003)