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Simple Heuristics in Complex Networks: Models of Social Influence

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Abstract

The concept of heuristic decision making is adapted to dynamic influence processes in social networks. We report results of a set of simulations, in which we systematically varied: a) the agents' strategies for contacting fellow group members and integrating collected information, and (b) features of their social environment — the distribution of members' status, and the degree of clustering in their network. As major outcome variables, we measured the speed with which the process settled, the distributions of agents' final preferences, and the rate with which high-status members changed their initial preferences. The impact of the agents' decision strategies on the dynamics and outcomes of the influence process depended on features of their social environment. This held in particular true when agents contacted all of the neighbors with whom they were connected. When agents focused on high-status members and did not contact low-status neighbors, the process typically settled more quickly, yielded larger majority factions and fewer preference changes. A case study exemplifies the empirical application of the model.

Keywords:
Decision Making; Cognition; Heuristics; Small World Networks; Social Influence; Bounded Rationality

Introduction

1.1

Research into group decision-making indicates that group decisions often depend on the distribution of individual group members' preferences (Davis 1973; Kerr & Tindale 2004). A popular example is the majority rule that committees and teams often employ when they do not reach unanimity (Hastie & Kameda 2005; Sorkin, West, & Robinson 1998). When groups integrate their members' opinions on the basis of a majority rule, the group decision is determined by the distribution of individual votes. In the present paper, we address the question of how the distribution of individual group members' preferences as a central input to group processes develops in a dynamic social environment.

1.2

Prior studies revealed that the distribution of preferences and opinions in groups depends on how the individual group members process their information when working on a choice task (Reimer & Hoffrage 2006; 2005). For example, in one set of simulation studies we compared the performance of groups whose members used either a compensatory decision strategy (a Weighted Additive Model or a Unit Weight Model) or a non-compensatory heuristic (Take the Best or the Minimalist Heuristic; see Gigerenzer, Todd, & the ABC Research Group 1999). All groups integrated the individual members' decisions on the basis of a majority rule. The proportion of members who preferred the correct decision alternative, and consequently, the performance of the groups, depended on the strategies the individual group members applied and on features of the information environment. In environments in which validities were linearly distributed, groups using a compensatory strategy achieved the highest degree of accuracy. Conversely, when the distribution of cue validities was skewed, groups using a simple lexicographic heuristic performed best. In these prior studies, we considered only static environments, in which group members formed their decisions separately without influencing each other. Here, we extend this approach to a dynamic context, in which agents are assumed to communicate with and influence each other prior to the group decision process. In line with Carley, Prietula, and Lin (1998), as well as Sun and Nahve (2004), we argue that it is important to consider agents' cognitive capabilities when examining information processing in a multi-agent environment (also see Kearns et al. 2006; Sun 2006). Following the view of Gigerenzer et al. (1999), we consider it plausible that agents use simple cognitive processes for a possible wide array of contexts, including decision making in complex social networks. In the current study, we applied some of these fast and frugal heuristics to a dynamic context: We explored social influence processes in various social networks, in which the individual agents used, either fast and frugal heuristics to form their opinions, or compensatory decision strategies that demand greater cognitive resources. Agents contacted each other according to a specified contact rule and updated their individual opinions according to a specified decision strategy that integrated the opinions of their fellow neighbors who were contacted.

Overview

2.1

The thought experiment allowed us to explore the extent to which influence processes in social networks depend on the decision strategies that are used by the networks' agents. As in the case of group decision-making, it is reasonable to assume that potential effects of decision strategies on global outcomes of a network depend on features of the social environment. We focused on the following two features that we systematically manipulated: the distribution of the agents' status, and the structure of the communication networks. The strength of social influence was measured as the rate with which high status members in a network changed their initial preferences. Analogous to research on cue-based group decision-making, we modeled member's opinions as cue variables for individual decision making: instead of processing information on cues, the agents in the network integrated the opinions of other agents into an individual decision. While this framework departs from the prominent understanding of social influence, which sees social influence as an activity of "social forces" (cf. French 1956; Latané 1981; and Turner 1996) rather than as an instance of information processing, to us, it seems to be a very plausible approach to conceptualize social influence processes within an information-processing framework (see Latané & L'Herrou 1996; and Mason, Conrey, & Smith 2007).

2.2

In addition to status hierarchies we considered different network structures as an environmental feature that can affect and moderate social influence processes (see Festinger et al. 1950; French 1956; Friedkin 1998; Latané 1996; and Latané & L'Herrou 1996). We considered networks of stable contacts, as is common in the field of social network analysis (Wasserman & Faust 1994), and varied the degree of clustering in the networks. Previous research (Latané 1996; Latané & L'Herrou 1996) has shown that the way a communication network is clustered is a major factor in the prediction of the persistence of minority groups and, therefore, also a factor that may determine the extent to which high status members may be influenced by social interactions.

2.3

We focused on the following questions, taken together, regarding global outcomes of social influence processes: Under which conditions do members' preferences converge in a dynamic environment, in which agents communicate with each other and update their individual opinions? Are the faction sizes in the agents' network affected by the agents' decision strategies, the distribution of their status, and the structure of their network? More specifically, under which conditions do high status group members change their initial opinions? To shed light on these questions we constructed a simulation model[1] and conducted a systematic study of the model's behavior.

Background Scenario

3.1

Our simulation model can be exemplified by the following scenario which we adapted from Lazega (2001): consider a group of lawyers who are partners in a law firm. In regular intervals these partners gather in a partnership meeting in order to decide about topics concerning the firm, for instance, the branch of business in which the firm should further expand. In the time between those meetings, the partners communicate among each other, of course, in a pattern aligned with their formal work demands and informal preferences. At times, they also communicate with each other about the forthcoming meeting. During the course of their communication, the partners may possibly alter their views and opinions on the topic to be discussed, therefore, changing the communication environment of their fellow partners. Eventually, this repeated process either converges to unanimous views on the mentioned topics or leads to entrenchment of factions in the forthcoming partnership meeting.

General Model Structure

4.1

We implemented the above scenario in the simulation model in the following way: the lawyers in our example were represented by a set of 21 agents, each having a certain preference for a branch of business into which the firm should expand (let us say corporate law, litigation, or public law). Each lawyer was assigned a certain status value, which determined whether this agent was considered a high or low status member of the network, which neighbors were contacted by the lawyer, and how much influence the lawyer had on the preferences of other lawyers who might contact him/her. Furthermore, a directed network connected the agents and represented their persistent communication channels. Every agent was assumed to update his/her preference according to some decision procedure. This procedure consisted of a contact rule, which selected communication partners from the agents' local network neighborhood, and a decision rule, which integrated the absorbed information. The decision strategies we implemented differed in the extent to which they considered the preferences and status values of the agent and his/her neighbors in the network. The environment was dynamic in that the simulation proceeded by computing repeated updates of all preferences of individual agents.

4.2

In more formal terms, the model structure can be declared as follows: let the lawyers be represented by a set L of N_l =21 agents. Each agent l_i is associated with both a value d_i of a decision variable D, which contains three discrete values *D=:{corporate law, litigation, public law}* and a value w_i of an individual status variable W having continuous values in the range of (0.5,..., 1.0). Furthermore, a directed graph G, describes a network of directed communication channels c_{ji} between the agents *L: G:={L,C}*. Finally, each agent l_i is assigned a decision procedure f out of a set of decision procedures F. This function f consists of a contact rule r_c and a decision rule r_d and maps an agent's actual decision state d_{j_n} onto his/her subsequent state d_{j_n+1}. The iterated and sequential call of this decision rule f for all agents results in dynamic evolution of the model.

4.3

In the following paragraphs, we describe the three central features of our model in more detail: a) the contact and decision rules, r_c and r_d, used by the individual agents; b) how the members' status was distributed in a network; and c) the clustering structure of the communication network.

Contact Rules and Decision Rules

5.1

Decision strategies can be conceptualized on the basis of the following building blocks (Gigerenzer et al. 1999): a) a search rule, b) a stopping rule, and c) a decision rule. In order to tailor the decision strategies to our task of decision making in a dynamic network, including ongoing interactions between agents, we added an additional building block by including a contact rule that specifies the neighbors that are contacted by an agent. The contact rule considers agents' status as selection criterion. In our simulation, we considered two contact and four decision rules. According to the first contact rule, agents contact every direct neighbor in their network, regardless of their status.

$$Contacted = Neighbors$$

We call this rule the " *Contact All* " or *ALL* rule. According to the second rule, agents contact only those neighbors who have at least the same (or a higher) status value w_j as the agents themselves.

$$Contacted = Neighbors \mid w_j \geq w_{self}$$

We call this rule the " *Higher Equal* " or *HE* rule. Its inclusion is based on observations in research on collective choice, which indicate that group members who have high levels of expertise or status are, at times, more influential in the group decision process than members who have low levels (e.g., Bonner, Baumann, Lehn, Pierce, & Wheeler 2006). Both rules include the searching agent himself/herself as an information source.

5.2

In addition, we modeled an ensemble of four decision strategies (see Reimer & Hoffrage 2006). These decision strategies describe how decision makers integrate cue-based information when choosing an alternative in a choice task. The first procedure, the " *Weighted Additive Model* " or *WADD* -rule, is a compensatory rule that integrates all information on the choice alternatives a decision maker has available. *WADD* chooses the alternative with the highest weighted sum, the weight being the cue's respective validity. In the present context, in which a decision maker integrates opinions of other agents instead of cue values, *WADD* decides in favor of the alternative for which most contacted neighbors vote, each member's vote being weighted with his/her status value. The *WADD* -rule can be expressed using the following equations:

$$I_{Ai} = \sum_{j=1}^{k} w_j o_{ji}$$

$$O_A = I_{Ai} \Rightarrow \max$$

I_{Ai} designates the inference of agent A made on a specific alternative i. This inference I_{Ai} is computed in two steps. Firstly, the available opinion o_{ji} of neighbor j on alternative i is weighted with the latter neighbor's status w_j. Secondly, all k neighbors' weighted opinions $w_j o_{ji}$ are summed up. Agent A chooses the inference I_{Ai} with maximal value as her preference O_A.

5.3

The second rule is the " *Unit Weight Model* " or *UWM* -rule, which is also compensatory and works similar to the WADD-rule with one significant difference: Status values are generally treated as being in unity, thus information about individual status is ignored. The *UWM* procedure counts the number of neighbors who favor each alternative and chooses the one which is favored most frequently. Consequently, it can be interpreted as a local majority vote over the different decision alternatives (Reimer & Hoffrage, in press). The *UWM* -rule can be expressed using the following equations, with symbols as introduced above:

$$E_{Ai} = \sum_{j=1}^{k} o_{ji}$$

$$O_A = E_{Ai} \Rightarrow \max!$$

5.4

The third rule is the " *Minimalist* " or *MIN* -heuristic (Gigerenzer et al. 1999; Reimer & Hoffrage 2005). Here, one of the *k* neighbors' opinions O_j , which have been gathered during the contact phase, is chosen at random with uniform probability. In other words, the *MIN* -rule follows the opinion of a randomly chosen neighbor *j* who has been contacted. The rule can be formally expressed as follows:

$$O_A \approx unif(O_j) \mid j \in Contacted$$

5.5

The last decision rule employed, the " *Follow the Leader* " or *FTL* -heuristic, is also a non-compensatory one. The strategy follows the decision of the "leader" - the neighbor *j* with the highest status w_j among all contacted neighbors. The rule has been modeled in analogy to the "Take the Best" heuristic in the domain of cue-based decision making (Gigerenzer et al. 1999) and can be expressed using the following equation:

$$O_A \approx unif(O_j) \mid j \in Contacted$$

As can be seen in Table 1, we have considered all possible combinations of contact and decision rules. The *FTL* -rule is listed only once, because it makes no difference whether the leader (by definition, the member with the highest status) is selected from amongst all neighbors or only from amongst the subset of higher status neighbors.

Table 1: Contact and Decision Rules Considered

Contact Rule	Decision Rule
HE (Higher Equal)	UWM (Unit Weight Model)
HE (Higher Equal)	WADD (Weighted Additive Model)
HE (Higher Equal)	MIN (Minimalist)
HE (Higher Equal)	FTL (Follow the Leader)
ALL (All Neighbors)	UWM (Unit Weight Model)
ALL (All Neighbors)	WADD (Weighted Additive Model)
ALL (All Neighbors)	MIN (Minimalist)

Decision Environments

6.1

Research involving group decision-making indicates that group choices and the performance of decision strategies depend on features of the information environment (Reimer & Hoffrage 2006; Reimer & Katsikopoulos 2004). In our simulation, we varied two dimensions of the decision environment: the distribution of the agents' status in a network, and the structure of the communication network.

Status Distributions

6.2

The first feature of the decision environment (respectively the input variables of the set of agents' decision rules) was the distribution *DS* of status values s_j.

6.3

We considered three shapes of status distributions, each with increasing steepness. The first is a *linear* distribution which contains equal proportions of values over its entire range. The second is a *flat J-shaped* distribution which contains considerably more high values than medium or low values. The last status distribution is a *steep J-shaped* distribution which contains only few high status values and a majority of low status values (see Reimer & Hoffrage 2006, for respective distributions of cue validities).

6.4

The status values of the distributions were randomly assigned to the agents, because in our model we had no external criterion with which status was correlated. For the same reason, the absolute range of the distributions was effectively arbitrary.[i] We chose a range of (0.5, …,1.0), in line with previous studies in which we considered validities (Reimer & Hoffrage 2006).

Network Structures

6.5

The second feature of the decision environment, which we systematically varied in our simulation, was the structure of the communication network. Research on social influence processes in networks shows the importance of the degree of clustering of a communication network. For example, Latané and L'Herrou (1996) found that high local clustering contributes to the emergence of stable clusters of opinions, because it allows members to shield each other against external influence. The study of Latané and L'Herrou considered regular grid structures and regular grids of irregular (and highly clustered) substructures. We implemented a type of random graph, which allows for variation of the clustering properties of a network in a more controlled manner.

6.6

More specifically, we generated random graphs from the family of so called small world networks (Albert & Barábasi 2002; Newman 2003; Watts 1999). This type of network has attracted considerable interest, because it plausibly captures characteristics of real-world social networks, namely the joint occurrence of both high local clustering coefficients and short average path lengths. This is also known as the small-world effect. Both the model, as well as its name have their roots in the observation that seemingly unrelated persons often have mutual acquaintances and are therefore reachable via only a few intermediaries.

6.7

An intuitive illustration of the small world model can be given as follows: let us consider individuals are situated in spatial units, such as an office hall in a company building or a neighborhood of a town. Then, it should be plausible to expect strong connectivity within such a unit. Furthermore, one could expect that some member of a unit also knows some members of another, different unit who are also strongly connected locally. Related to our example, the spatial units could correspond to different office halls in the law firm's building.

6.8

We generated small world networks as suggested by Watts (1999). The implemented procedure was as follows. In a first step, we created a regular ring network in which each of the n nodes was connected to k neighbors on each side. This structure is called *cyclic substrate,* and as a regular grid it yields high local clustering, thus, representing a characteristic of spatial organization. In a second step, we rewired individual edges of the grid with a certain probability p_r with randomly chosen nodes. Introduction of these shortcuts, with a rewiring probability ranging approximately within the interval of p_r = (0.001,... 0.2), led to the creation of a network with the mentioned small world effect: strong clustering, but no isolated highly clustered regions. An example of such a small world net is displayed in Figure 1.

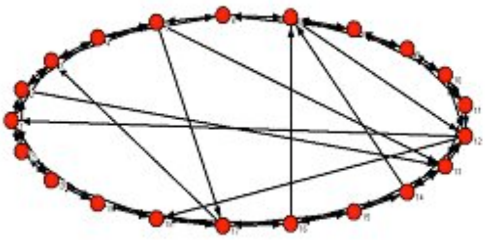

Figure 1. Small world network (n =21, k =2, p_r =0.1). The network has been created by introducing shortcut ties to a regular ring network, where every node is connected to two neighbors on each side

6.9

Of special interest for our question is the fact that by varying the rewiring probability p_r, we are able to produce an array of differently clustered networks. A parameter of $p_r=0$ results in a completely regular and highly clustered network, whereas a parameter of $p_r=0.1$ results in a small-world network, and a parameter of $p_r=1$ results in a random and unclustered network, the so called *random regular graph* (see Table 2.) We employed these three parameter settings as variations of the agents' network environments, thus, controlling for the effects of clustering and average path length. The number of agents' neighbors was held constant and was set to approx. four (k=2 on each side) in each of the three variations.

Table 2: Employed Variations of the Small-World Model (n =21, k =2).

Rewiring Probability	Network Characteristic
$p_r=0$	Cyclic Regular, high clustering
$p_r=0.1$	Small-world
$p_r=1$	Random regular, no clustering

6.10

Additionally, we considered a *completely connected network* as a control condition in order to observe the model's behavior in the absence of structural effects. In general, we assumed the networks to have loops—every agent was connected to himself/herself and, thus, had access to his/her own decisions.

Initial Values and Setup of the Simulation Experiment

7.1

Initial values were set according to the following criteria: The initial distribution of decision values d_j over the agents was assumed to be uniform, so that each of the three alternatives was initially preferred by exactly seven agents. Status values were randomly assigned to agents. Thus, we assumed no correlation of status values w_j and initial decision values d_j.

7.2

In the experiment, every possible combination of decision rule, status distribution, and network structure was simulated 1000 times, each with a newly sampled network and a process length of 50 cycles.

Results of the Simulation Experiment

8.1

The manipulation of decision rules, network topologies, and status distributions had several effects on global outcomes of the influence process. In the following, we will report results regarding equilibrium and the final distributions of the agents' opinions, and the ratio with which high-status agents changed their initial opinions. All reported differences were tested with Hotelling's T^2-tests and were significant at a α=0.01 level.

Equilibrium and Final Distributions of Individual Opinions

8.2

Equilibrium has been achieved in all variations of the model at considerably fast rates. While it took the agents employing a MIN decision rule approximately 25 cycles on average to reach a static equilibrium in their network, the remaining rules converged within two to seven cycles. Without exception, strategies containing the HE-rule showed the fastest rates of convergence: Overall, networks reached a state of equilibrium faster when agents contacted only higher-status members than when agents contacted all members with which they were connected.

8.3

However, the reached equilibrium was usually one of entrenched factions including stable subsets of agents favoring a minority position. In general, unanimity could only be achieved in the case of the complete network or when agents applied the ALL-MIN strategy. The latter finding appears straightforward since the ALL-MIN strategy does not defend any preference held at a certain step of the process. The ALL-UWM and ALL-WADD strategies in the random regular network reached unanimity in an exceptionally high percentage of cases—in 18% and 6% of the networks, respectively. Most often, an equilibrium state was reached in which each of the three possible choice alternatives was favored by some members. Surprisingly, variation of the steepness of the employed status distribution had no effect on the model's equilibrium behavior. We observed similar distributions of faction sizes for all status distributions considered.

8.4

Even though each of the three choice alternatives was favored by at least one agent in the vast majority of cases, the sizes of the respective factions varied substantially. Our results show considerable impact of decision rules and network structures on the distributions of faction sizes, as can be seen in Figure 2. In a first step, we sorted the three factions in each network according to their sizes—the faction with the fewest members was categorized as the "weakest faction" and the faction with the most members was categorized as the "strongest faction." In a second step, we averaged across the weak, medium-size, and strong factions across all networks.

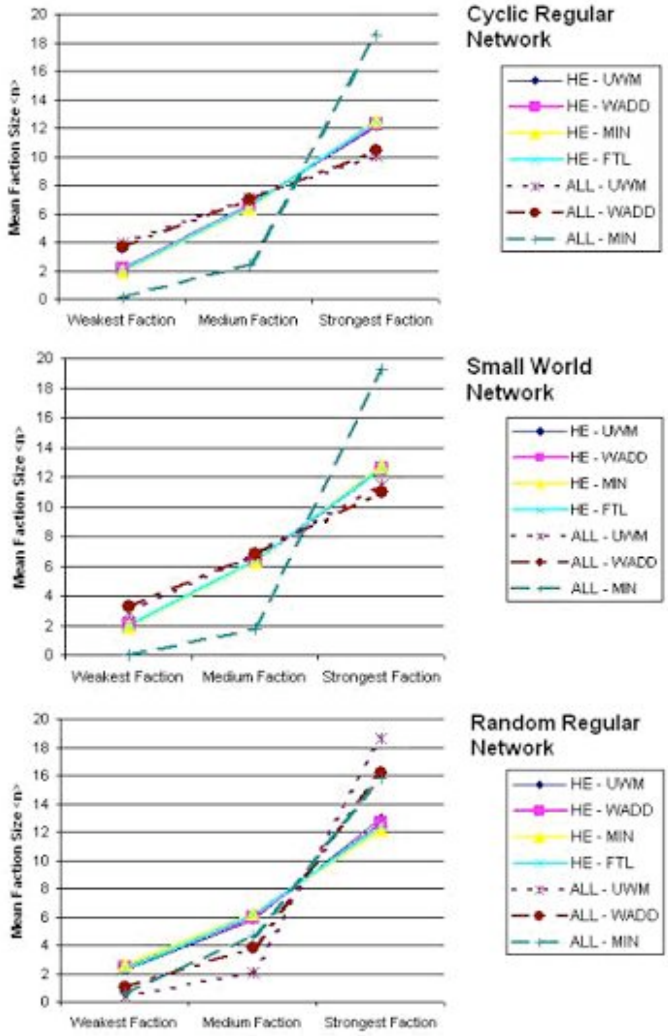

Figure 2. Mean faction sizes over networks with decreasing clustering. Results were sorted according to the size of the faction in an individual simulation run, regardless of the actual choice-alternative favored. A majority is reached at eleven.

Different patterns of faction sizes were observed for strategies containing an HE- or ALL contact rule. As expected, the decrease of network clustering generally led to smaller sizes of minority factions.

8.5

Strategies containing the HE rule tended to accentuate contrasts in faction size, as can be seen from their steeper slope in the first two sections of Figure 2. While the absolute differences are small in numbers, they may however be crucial since they decide between plurality and majority, making the majority the stable modal outcome for non-compensatory rules, as can be seen from Figure 3. The profile of the ALL-MIN heuristic can be considered an outlier, due to its unique opportunism in the literal sense of the word. The aforementioned patterns blur together with decreasing clustering, making a majority state commonly the most probable outcome in the case of the random regular network. This is in coherence with Latané and L'Herrou's (1996) finding that clustering stabilizes minority positions.

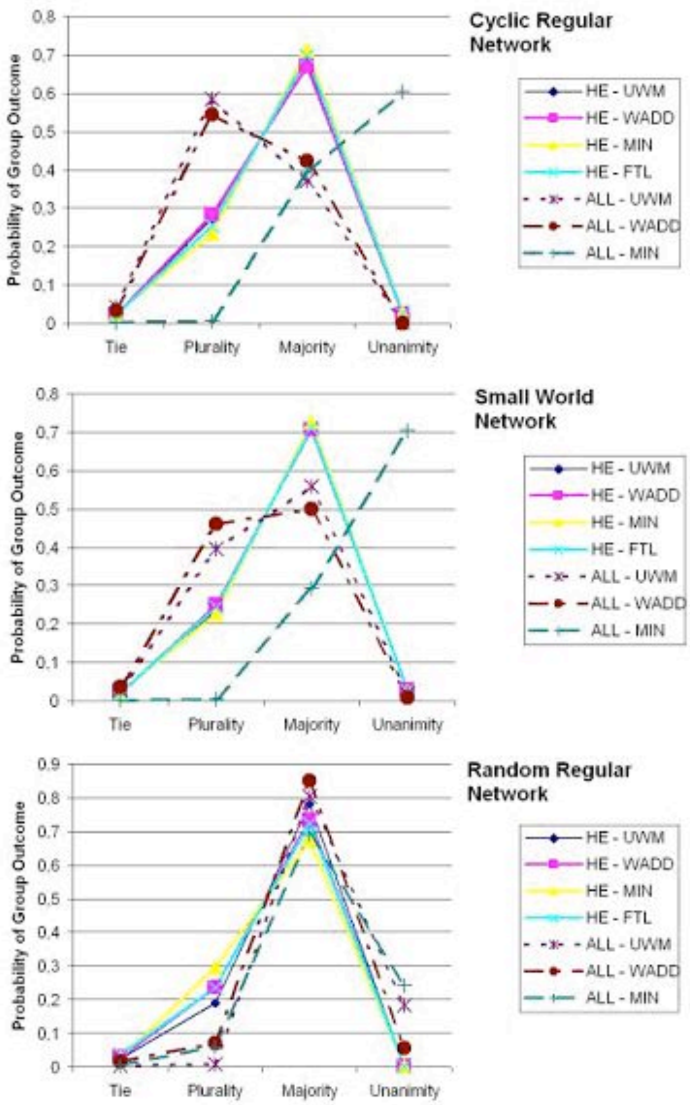

Figure 3. Group level outcomes over networks with decreasing clustering.

8.6

An important observation is that the profile of faction sizes for strategies containing the HE contact rule is not affected by network clustering. These always behave like the strategies containing the ALL rule in absence of clustering. Under the regime of the HE contact rule, the decision strategies yielded almost identical results, regardless of the employed network structure. We checked whether this effect occurred only because the HE contact rule eliminates all individual decision scenarios except the trivial one, where only a single alternative is left. This had been considered possible because every agent in the non-complete networks had, on average, only five neighbors (including him-/herself). Therefore, we also simulated larger networks with 31 agents and a structure with steeply varying connectivity from one to fifteen neighbors, where elimination of all decision alternatives is implausible. Here, we observed the same desensitivitizing effect of the HE- contact rule, concluding that this effect is not due to the triviality of local decision environments.

8.7

We presume that the HE-rule systematically modifies the network, which is relevant for the transmission of information. We suggest that the exclusion of lower status neighbors from the communication process leads to the creation of a closed discourse of the agent population's "elite." Identically shaped distributions of expected faction sizes could be reproduced for three- and five-person committees, which were sampled randomly from the agent population. This indicates the relevance of the above effects for situations in which group level decisions are based on preferences of only a subset of the group members. In order to check for scaling effects, we subsequently repeated the simulations for networks containing 9 and 31 agents, in which we observed comparable results.

8.8

Taken together, the networks typically reached equilibrium. The contact rule had a major impact on the speed with which the network settled and the size of the final factions. More specifically, when agents used the HE-rule, equilibrium was reached fastest, differences in faction sizes were larger, and the influence of network clustering was minimized.

Decision Change of High Status Partners

9.1

There is substantial variation of the propensity of the different decision rules to induce an opinion change in high status members, which we defined as the subset of agents having above average status. The manipulation of network structures and status distributions had an effect on opinion changes in high status members.

Network Structure

9.2

Focusing on an aggregated view of network structures averaged across status distributions, as depicted in Figure 4, we identified the following results.

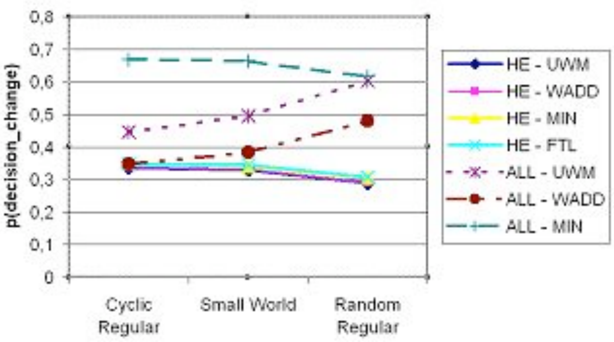

Figure 4. Probability of decision change of high status members over networks with decreasing clustering (cyclic regular, small world, random regular).

9.3

When status was important for contact behavior (HE rule), the probability of a decision change in high status members was constantly low, regardless of the decision rule employed. When all neighbors were contacted (ALL rule), the clustering structure became important for the compensatory UWM and WADD decision rules. The lower the degree of isolated clustering, the higher the probability of decision changes in high status members was, which increased in parallel about 15% for both decision rules. The completely status insensitive UWM-rule showed a respective probability which was constantly approx. 10% higher than for the WADD-rule. The MIN rule showed a maximum probability of decision change of high status members, which remained constant over all considered networks. For completeness, it should be mentioned that in a completely connected network, the examined strategies showed only minor differences with regard to the probability of high status members' opinion changes, which ranged from 54% to 67%.

9.4

The results for the different network types can be summarized as follows: with the exception of a completely connected network, the rules' behaviors varied considerably over the networks of the small world family. The rules which were status-sensitive with respect to their contact behavior (i.e. the rules containing an HE - component) were insensitive to changes in the networks' clustering structure. Conversely, the rules containing an ALL - component were sensitive to changes in the networks' clustering structure. When all members were contacted (All-rule), the probability of decision changes in high-status members increased with a decrease of clustering.

Status Distributions

9.5

Another interesting finding regarding the decision rules is depicted in Figure 5. The figure displays the probability with which high status members changed their opinions separately for different status distributions. Here, we consider the impact of the steepness of status distributions on the probabilities of decision changes in high status members. In order to avoid redundancy, we will only present the results for the case of the small-world network; however, the same pattern can be found in all networks considered.

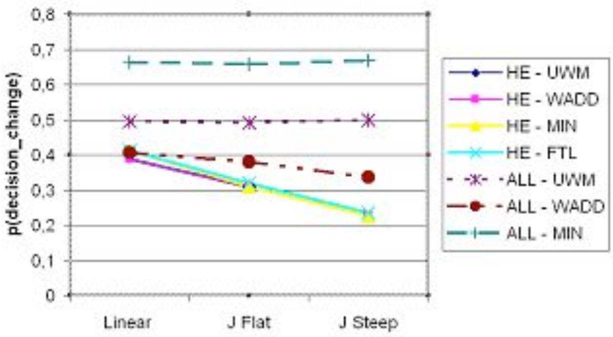

Figure 5. Probability of decision change in high status members in a small world network over status distributions of increasing steepness.

9.6

Again, strategies based on the HE-contact rule showed virtually identical behaviors. However, they were sensitive to variation in the shape of the status distribution. An increase in the steepness of the hierarchy leads to a decrease in the opinion changes in high-status members. These members can preserve their initial decisions more effectively in environments with a steep hierarchy. To a lesser extent, this sensitivity did also hold for the compensatory ALL-WADD strategy. Because of their complete ignorance of the status distribution, ALL-UWM and ALL-MIN were not affected by variations in status distributions.

A Case Study

10.1

To see how the different decision strategies might work and potentially affect the social influence process and equilibrium in a real world scenario, we applied our model to the study by Lazega (2001), who collected data between January and February of 1991 in a New England law firm. [2] We used the available empirical data as initial values for the simulation model. Combining our model and empirical data, we inferred outcomes of a hypothetical influence process. In particular, we explored to what extent the social influence processes in the law firm would be affected by the decision strategies employed by the agents.

Empirical Data

10.2

The empirical setup of the case study is similar to our systematic simulation experiment, apart from the following differences: the employed data deal with the interaction of n =36 partners. The agents' preferences referred to a binary policy variable, namely, whether new cases in the law firm should be distributed via a central authority or kept to being the personal responsibility of the individual lawyers who acquired them. Preservation of the status quo was preferred by 20 partners (56%) while a change of the case assignment policy was advocated by 16 partners (44%). This indicates a majority in favor of preservation of the as-is policy. This initial distribution of opinions might change due to influence processes occurring among the lawyers of the firm—which we tried to infer on the basis of a simulation. Consider the lawyers discuss the case and influence each other. How would the contact rules, decision strategies, and communication networks influence the distribution of opinions in their law firm?

10.3

Lazega (2001) asked the partners in the law firm who they pay special attention to at partnership meetings. We used these data to infer the partners' network of influence-relations. The partners' status was estimated via the reported individual hourly work fee, which the partners granted each other in the partnership assembly. In our case study, status values correspond to a certain partner's share of the maximal possible hourly work fee. Based on this criterion, we determined the empirical status distribution of the law firm, which is depicted in Figure 6. It should be noted that this setup measures a fairly general concept of status, which is not restricted to actual expertise with regard to the problem. However, to us it seemed to be nevertheless a viable approach, since the findings of Littlepage et al. (1995) suggest that people themselves are not very accurate in inferring the actual expertise of their communication partners.

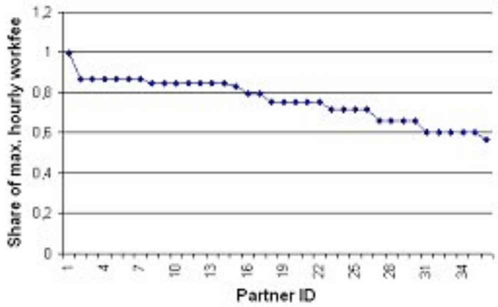

Figure 6. Status distribution of partners in an empirical network. Partners are numbered according to seniority.

10.4

Unlike in our systematic simulation experiment, the empirical data show a systematic relationship between members' status and their preferences. High status members tended to prefer the preservation of the current workflow policy. This is indicated by a correlation r_{xy} = -0.123 and the odds *exp(b)* = 0.093 obtained by a logistic regression analysis. However, these parameters are not statistically significant. As can be seen in the illustration of the influence network in *Figure 7*, the network shows formidable complexity. Figure 8 shows the subnetwork which is relevant according to the HE contact rule. It contains only links to neighbors of sufficiently high status and appears much less complex than the network in Figure 7.

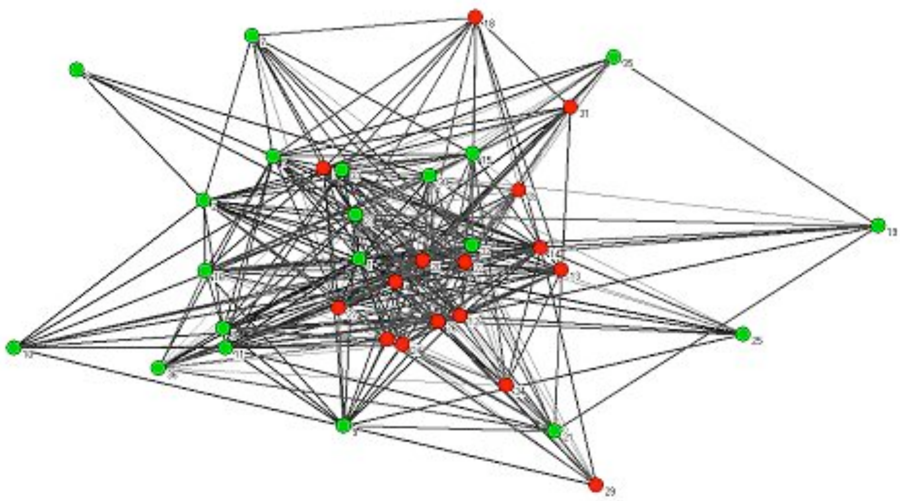

Figure 7. Empirical influence network. Highly connected partners are located in the center of the network. Dark and wide arrows represent high status relations. Green nodes represent an "as - is" and red nodes a "less flexible" policy opinion. Partners are numbered according

to their seniority.

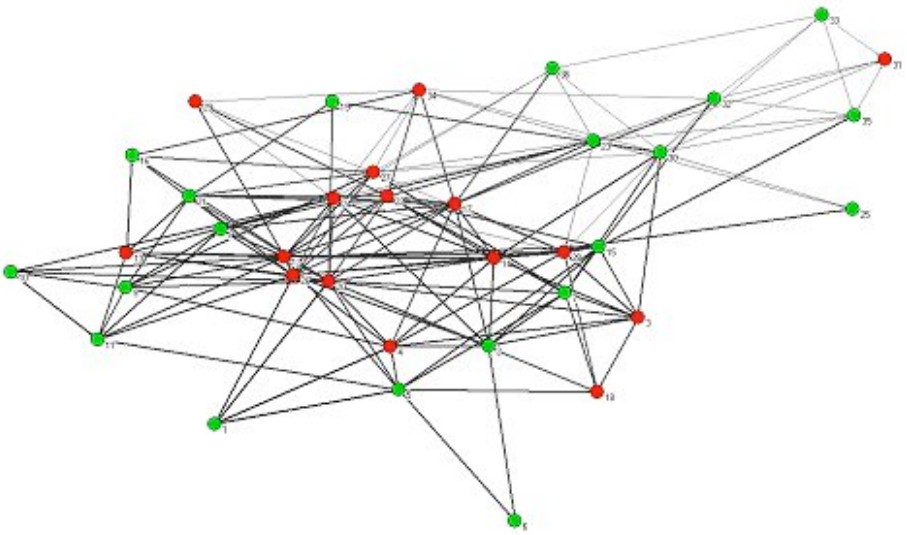

Figure 8. HE - relevant subnet of the empirical influence network: highly connected partners are located in the center of the network. Dark and wide arrows represent high status relations. Green nodes represent an "as - is" and red nodes a "less flexible" policy opinion. Partners are numbered according to their seniority.

Social Influence Processes

10.5

Table 3 displays the main results of the simulation. In line with the results of our systematic simulation experiment, unanimity could not be achieved under the regime of the HE-contact rule.

Table 3: Preference distributions for the considered strategies in the network. The two possible preferences were "keep case assignment as it is" and "organize case assignment less flexible via a central authority." As can bee seen, the final distributions of opinions depart considerably from the initial distributions.

Strategy	**n(as-is)**	**n(less flexible)**	**Equilibrium cycle**
HE - UWM	34	2	7
HE - WADD	34	2	5
HE - MIN	Majority	Minority	Fluctuating
HE - FTL	26	10	3
ALL - UWM	*36*	*0*	4
ALL - WADD	*36*	*0*	4
ALL - MIN	*36* (p=0.77)	*36* (p=0.23)	Mean=17.8
Initial distribution	20	16	--

10.6

In general, the initial preference of the majority of partners in favor of the preservation of the decentralized case assignment policy prevailed in the influence process and suppressed the initial minority position to a large extent. In the case of the ALL - MIN strategy, the process converged to unanimous acceptance of the initial majority preference in the majority of simulation runs. When the HE contact rule was active, a few agents were able to defend their minority position and did not join the majority. As we expected based on our systematic simulation experiment, the decision strategies played a major role in determining features of the inferred equilibrium distribution of preferences. Their proportion was largest for the case of the FTL decision-rule. In summary, we may expect substantive variation of the outcome of the influence process, depending on the strategies employed by the agents. Again, employment of the HE contact rule has the largest impact, deciding over extinction of minority positions. In the case of our law firm, this could be decisive in whether there is faction regarding the vote for the new company policy. The size of the minority faction, as it depends on the employed decision strategies, could bear the potential for discussion or even conflict in the future.

Conclusion

11.1

In this article, we applied the concept of recurrent decision making to processes of social influence. Hereby we are filling a gap in the literature, which has analyzed social influence primarily as an exercise of a power relationship rather than an instance of information processing (French 1956; Latané 1981; and Turner 1996). Following this rationale, we examined the interaction of decision strategies and features of the communication network.

11.2

As it turned out, the influence process settled quickly and both, the clustering structure of the network and the agents' contact strategies, made a substantial difference in terms of the outcomes of the process. In general, unanimity was unlikely. Furthermore, highly clustered networks increased the size of minority factions, which is in coherence to the results of Latané and L'Herrou (1996)—clustering stabilized minority factions. When agents chose only higher status neighbors as information sources (HE rule), the size of the minorities decreased. Of equal importance is the fact that in this case the distribution of equilibrium factions was not affected by the clustering structure of the network. The steepness of the status distributions, which had no influence on the contact behavior of the agents due to the contact rules we examined, played only a minor role with regard to the final distribution of preferences of the process.

11.3

In our analysis, we focused on the influence of low status agents on the preferences of high status agents. A change of preferences in high status members was most probable when status played no role for contact behavior and when hierarchies were flat. Given that the agents used the ALL-rule, a stronger influence of low status agents was obtained with a decreasing clustering, which again conforms to Latané and L'Herrou's (1996) findings.

11.4

Returning to our introductory considerations regarding member preferences as a basis for group decisions, our results imply a substantial impact of the information processing strategy on the group decision to be made. Specifically, when information search is based on status (HE rule), the formation of majorities becomes most probable, even if the communication network is clustered into cohesive subgroups. These majorities still persist if committees, which are randomly selected from the group, are given the task of reaching a group decision.

11.5

In line with the findings of Carley et al. (1998), we conclude that the interaction of agent cognition and structure of the multi-agent environment is an aspect which is central for the course of social processes. Furthermore, our work suggests that assuming parsimonious agent cognition is not only psychologically plausible, but in a multi-agent setting with a complex structure of interactions also has the prospect of resulting in rich collective behavior. This claim is well supported by research into the behavior of super-organisms (Seeley 2001) and by studies into processes operating on complex networks (Newman 2003). Our case study showed the model's potential to guide and inform interventions on concrete real-world processes. By variation of the assumed decision strategies we were able to produce an array of scenarios in which persistence of the minority faction was more or less likely. Our simulation suggests that the priming of status might well activate status sensitive information search. This in turn might eventually result in the otherwise unlikely persistence of the minority faction.

11.6

The simulation model can be applied to a wide range of organizational contexts and network structures. One promising extension may be to incorporate different random-network structures like the prominent preferential attachment network (Albert & Barabasi 2002; Newman 2003) or structures that evolve according to behavioral assumptions (cf.Guimera et al. 2007; Masuda & Konno 2006). A second branch of future research could be concerned with a more detailed analysis of the contribution of microstructure to global outcomes. An example would be to include less productive, 'weak' ties (Csermely 2006) in the networks considered. Such a variation might allow the evaluation of specifically targeted interventions.

Notes

[1] Part of the simulation study has been presented at the Annual Meeting of the Cognitive Science Society (see Schwenk & Reimer 2007). A set of files for running the simulation using Matlab may be downloaded as a ZIP archive here.

[2] Originally, we employed both high and low valued linear status distributions. As expected, both induced exactly the same process behavior.

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