Social Influence and Bounded Rationality: Heuristic Decision Making in Complex Networks

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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 members' strategies for contacting fellow group members and integrating collected information, b) the steepness of status distributions in a network, and c) the clustering structure of the members' communication network. The results indicate that the contact and decision rules used by the members of the network affect group level outcomes and furthermore interact with both steepness of the group's status distribution and clustering of its communication network.

Keywords: Decision making; fast and frugal heuristics; social networks; small world networks; social influence; simulation; bounded rationality; dynamics.

Introduction

Research on group decision making indicates that group decisions often strongly depend on the distribution of individual group members' preferences (Davis, 1973; Kerr & Tindale, 2004). For example, a popular decision rule that is widely used when committees and teams do not reach unanimity is the majority rule (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 develop in a dynamic social environment.

Prior studies revealed that the preference distribution in groups depends on how the individual group members process their information when working on a choice task (Reimer & Hoffrage, 2006, 2003). 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 fraction of members who preferred the correct decision alternative and, consequently, improved group performance depended on the strategies they applied and on features of the information environment. Specifically, in environments in which validities were linearly distributed, groups using a compensatory strategy achieved the highest 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 each group member formed his or her decision separately, without influencing any other member. Here, we extend this approach to a dynamic context, in which group members are assumed to communicate with and to influence each other prior to the group decision process.

Overview

A major purpose of our simulation study was to investigate which impact group members' status and different communication networks have on social influence processes. We conceptualized social influence as the rate with which high status members in a network change their initial preferences. Analogous to research on cue-based group decision-making, we modeled member opinions as cue variables for individual decision making: Instead of processing information on cues, the agents in the network integrated 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.

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 it is common in the field of social network analysis (compare Wasserman & Faust 1994). While one could combine the facets of status and network structure, we are concentrating on a different aspect, namely network clustering. Previous research (Latané, 1996, Latané & L'Herrou, 1996) has shown that the way a communication network is clustered is a major predictor for 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.

In consequence, we focused on the following questions regarding global outcomes of social influence processes: Do members' preferences converge? Does the manipulation of decision strategies, status distributions in a network, and network structures affect faction sizes? And finally, under which conditions do high status group members change their initial decision?

Scenario: Partners in a Firm

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 with a pattern aligned to their formal work demands and informal preferences. At times, they also communicate 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.

Model Structure

In our thought experiment, we implemented this scenario in the following way: The lawyers of 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 (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 a 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 strategy. This decision strategy 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 to the extent to which they considered the preferences and status values of the agent and his/her neighbors in the network. Note that this environment is dynamic in that the simulation proceeds by repeated updates of all individual agents' preferences.

More formally, 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 s_i of an individual status variable S having continuous values in the range of $(0.5,\ldots, 1.0)$. 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 strategy f out of a set of decision strategies F. This function f consists of a contact rule r_c and a decision rule c_d and maps an agent's actual decision state d_{j_n} onto his/her subsequent state d_{i_n+1}. Iterated and sequential call of this decision rule f for all agents results in a dynamic evolution of the model.

In the next paragraph, we describe the three central features of our model in more detail: a) the contact and decision rules 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

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. According to a variation of the stopping criterion, decision strategies may be classified as *compensatory* or *non-compensatory*. Compensatory strategies utilize all available information: Any cue value can therefore be compensated by another one. This is not the case for the non-compensatory (or *fast-and-frugal*) strategies: here absorption of information is stopped according to a certain criterion. Empirical research indicates that decision makers use non-compensatory strategies in particular under time pressure or when information search is costly (Rieskamp & Hoffrage, 1999). We modeled the aspect of compensation in two ways: (1) Whether or not an agent contacted all possible neighbors or only a subset of neighbors; (2) and whether the opinions of the contacted neighbors were integrated on the basis of a compensatory or a non-compensatory decision rule.

In our simulation, we included two contact and four decision rules. According to the first contact rule, agents contact every direct neighbor in their network, regardless of their status. We call this rule the *"contact all"* or *ALL* rule. According to the second rule, agents contact only those neighbors, which have at least the same (or a higher) status value as the agents themselves. We name 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 expertise are at times more influential in the group decision process than members who have low expertise (e.g., Bonner, Baumann, Lehn, Pierce, & Wheeler, 2006). Note that both rules include the searching agent himself/herself as information source.

For the case of the decision component, we modeled an ensemble of four decision strategies (see Reimer & Hoffrage, 2006, 2003). The first strategy, the "*weighted additive model*" or *WADD*-rule, is a compensatory rule that integrates all available information. WADD chooses the alternative with the highest weighted sum, the weight being the cue's respective validity. The alternative with the highest weighted sum is then chosen. In the present application, WADD decides in favor of that alternative for which most contacted neighbors vote, each member's vote being weighted with his/her status value. The second rule is the "*unit weight model*" or *UWM*-rule, which is also compensatory and analogous to the WADD-rule with one significant difference: Status values are generally treated as being in unity, thus information on individual status is ignored. The UWM strategy therefore determines the number of neighbors who favor a specific alternative and adopts the one which is held most frequently. Consequently, it can be interpreted as a local majority vote over the different decision alternatives (Reimer & Hoffrage, in press). The third rule is a heuristic decision rule called the "*minimalist*" or *MIN*-rule. Here one of the decision values, which have been gathered during the contact phase, is chosen at random with uniform probability. Plainly spoken, the MIN-rule follows the opinion of a randomly chosen neighbor who has been contacted. The last decision rule employed, the "*follow the leader*" or *FTL*-rule, is also a non-compensatory one. The strategy follows the decision of the "leader"—the neighbor with the highest status among all contacted neighbors. The rule has been modeled in analogy to the "take the best" heuristic for cue-based decision making (Gigerenzer et al., 1999).

As can be seen in *Table 1*, we considered all possible combinations of contact and decision rules. The "follow the leader"-rule is listed only once, because it makes no difference, whether the "leader" is selected among *all* neighbors or only among 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)
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)
ALL (all neighbors)	MIN (minimalist)

Decision Environments

As further features 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 The first element of the decision environment (resp. the input variables of the set of agents´ decision rules) is the distribution *DS* of status values s_j.

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 than medium or low values. The last status distribution is a *steep J-shaped* one, which contains only few high status values and a majority of low status values (see Reimer & Hoffrage, 2006, for respective distributions of cue validities).

The status values of the respective 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.[1] We chose a range of (0.5,..,1.0), in line with prior studies in which we considered validities (Reimer & Hoffrage, 2006).

Network Structures The second feature of the decision environment is the structure of the communication network. Research on social influence processes in networks shows the eminence 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.

Contrary to the analyses of Latané and L'Herrou, who considered regular grid structures and regular grids of irregular (and highly clustered) substructures, we implemented random graphs, which allow for variation of clustering properties of a network in a more controlled manner.

Specifically, we concentrated on random graphs from the family of so called "*small world networks*" (compare Albert & Barábasi 2001, Newman 2003, and 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.

An intuitive illustration of the small world model can be given as follows: Suppose 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,

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

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.

We modeled this idea of clustering as follows. First, a regular ring network was created, 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 has the feature of high local clustering, thus representing a characteristic of spatial organization. Then, individual edges of the grid were rewired with a certain probability p_r with randomly chosen nodes. Introduction of these shortcuts, with a rewiring probability ranging approximately within the interval of $p_r = (0.001,\ldots0.2)$, leads to creation of a network with the mentioned *small world* effect: strong clustering, but no isolated highly clustered regions. A graphic example of a small world net is displayed in *Figure 1*.

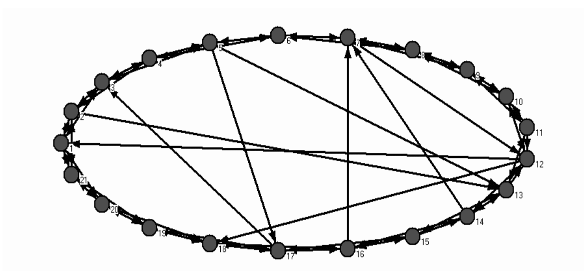

Figure 1: Small world network (*n=21, k=2, p=0.1*).

Note: 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.

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, 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, which jointly could be termed *isolated clustering*. Furthermore, we set the number of neighbors of the agents to approx. four ($k=2$) over all three variations.

In addition, we considered a *completely connected network* as a control condition in order to observe model behavior in the absence of structural effects. Furthermore, we assumed the network to have *loops*, which means that every agent was connected to himself/herself and, thus, had access to his/her own decision.

Initial Values and Setup Generally, initial values were set according to certain criteria. First, status values were randomly assigned to agents. Furthermore, the initial distribution of decision values d_j over the agents were assumed to be uniform, so that every alternative was assigned to exactly seven agents. Thus, we assumed no correlation of status values s_j and initial decision values d_j.

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

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

Every 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.

Simulation Results

The simulations revealed that the decision rules, network topology, and status distribution affected global outcomes. The reported effects were tested with Hotelling's T^2-tests and were significant at α=0.01 level.

Equilibrium, Faction Size, and Scaling

Equilibrium has been achieved in all variations of the model. While it took the groups employing a MIN decision rule an average of approximately 25 cycles to reach equilibrium, the remaining rules converged within two to seven cycles. The reached equilibrium was usually one of entrenched factions with unanimity only being present in the case of the complete network.

In cyclic regular networks, different faction sizes were observed for compensatory and non-compensatory rules. *Figure 2* shows the mean sizes of the three possible factions. Each faction refers to one of the three decision alternatives: The smallest faction refers to the alternative that was favored by the smallest number of members in a network and the largest faction refers to the alternative that was favored by most members in a network.

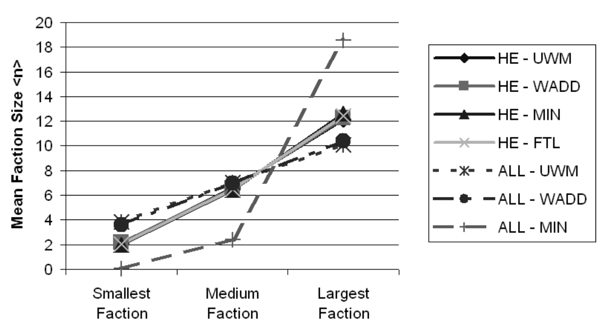

Figure 2: Mean faction sizes in a cyclic regular network (majority is reached at a count of eleven)

Non-compensatory rules accentuated contrasts in faction size, as can be seen from their steeper slope in *Figure 2*. These differences were smaller in small world and random regular networks, which typically yielded identical profiles for non-compensatory but a larger majority and smaller minorities for compensatory rules. For the case of compensatory rules, this finding is in coherence with the assumption that clustering stabilizes minority positions. Simulations, in which we included networks containing 9 and 31 agents revealed similar results.

Decision Change of High Status Partners

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

Network Structure Focusing on an aggregated view of network structures averaged across status distributions, as depicted in *Figure 3*, we identified the following results.

If status is important for contact behavior (as it is in case of the HE-rule), there is only a constantly low probability of a decision change in high status members, regardless of the decision rule employed.

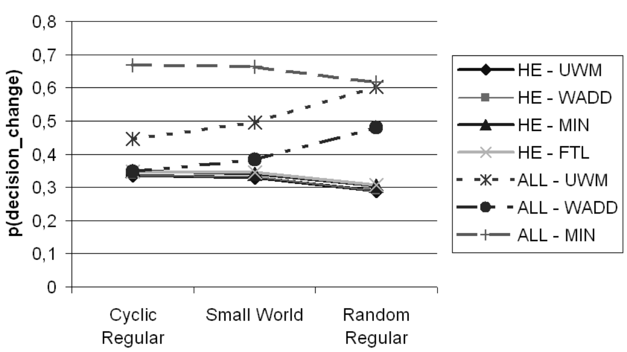

Figure 3: Probability of decision change of high status members over networks with decreasing isolated clustering (cyclic regular, small world, random regular)

If all neighbors are contacted, regardless of their status (as is the case for the ALL-rule), the clustering structure becomes important for the compensatory UWM and WADD decision rules. The lesser the degree of isolated clustering, the higher the probability of decision change of high status members, which increases in parallel by .15 for both decision rules. However, the status insensitive UWM-rule shows a respective probability which is constantly approx. 0.10 higher than for the WADD-rule. The MIN rule shows a maximal probability of decision change of high status members, which remains constant over all considered networks. In a completely connected network, the examined strategies showed only minor differences with regard to the probability of a change in the high status members' opinions. It ranges from 0.54 to 0.67.

The results for the different network types can be summarized as follows: Contrary to a completely connected network, the effectiveness of the rules varies considerably across the networks of the small world family. The rules which are status-sensitive with respect to their contact behavior (i.e. the HE contact rule) are *insensitive* to changes in the networks' clustering structure. In contrast, the status-insensitive rules, which consider all locally available information, regardless of status values, are *sensitive* to changes in the networks' clustering structure. The probability of high status initial decision change in this latter case increases with a decrease of isolated clustering. Highest probabilities can be found for the case of complete ignorance of status and of decision distributions, which is represented by the ALL-MIN rule. The latter finding is robust across all networks and status distributions.

Under a HE contact rule, the decision strategies yielded almost identical results. We checked whether the HE-contact rule yields insensitivity to network structure only because it 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 himself/herself). Therefore, we also simulated large networks with 31 agents and a structure with steeply varying connectivity from one to 15 neighbors, where elimination of all decision alternatives is implausible. However, we observed the same leveling effect of the HE-contact rule, concluding that this effect is not due to triviality of local decision environments.

Status Distributions Another interesting finding regarding the decision rules can be seen in *Figure 4*, which shows the results for the case of the small-world network; the same pattern was also observed in the other networks considered.

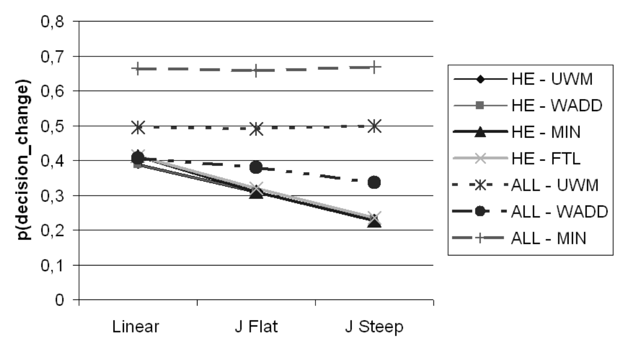

Figure 4: Probability of decision change of high status members in a small world network over status distributions of increasing steepness

Again, strategies with the hierarchy-oriented HE-contact rule showed virtually identical behavior. Furthermore, the HE-decision strategies are sensitive to variation of the shape of the status distribution. An increase of the steepness of hierarchy leads to a decrease of opinion changes in high status members.

To a smaller extent, this sensitivity is also true for the compensatory ALL-WADD strategy, which reacts to hierarchy in terms of information weighting. Because of their complete ignorance of the status distribution, ALL-UWM and ALL-MIN are insensitive to respective changes.

Conclusion

In summary, we were able to identify the following behavior of our virtual law firm: Although the influence process settles quickly, unanimity is unlikely and faction sizes are governed both by decision rules and by clustering of the network. Non-compensatory rules accentuate contrast in faction sizes, while decrease of clustering leads to marginalization of minority factions.

Furthermore, the change of high status partners' initial decisions is most probable under the following conditions: First, the status hierarchy is not relevant for the contact behavior of the partners. As soon as status becomes important for information search, the probabilities to exert influence on high status partners drops to minimum values, regardless of the network's clustering structure. Second, the status hierarchies are flat. Steep status distributions are especially hampering if partners consider status not only for information weighting but also for information search. Third, in the case of status insensitive (ALL-UWM) and weighted local majority (ALL-WADD) decisions, higher probabilities are obtained with decreasing isolated clustering. Finally, if individual partners decide at random, with complete ignorance of status distributions, high probabilities are obtained.

Altogether, our results show that the concept of heuristic decision making can be fruitfully applied to complex group processes. Under the model's premise that individual decisions are based on the status of fellow group members, we found an array of interesting results. In the present analysis, the interaction of group members' decision strategies and environment structures seems most important to us. We are able to show that a non-compensatory contact rule results in insensitivity of the influence process towards the network's degree of clustering.

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