STRUCTURED DYNAMICS: METHODOLOGY AND APPLICATIONS OF MODELS OF SOCIAL INTERACTION

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Introduction

Topic of this work is the explanation of collective behavior through its founding component, the behavior of the socially situated person. More specifically, I aim at developing methods and tools for this purpose, which are supposed to prove beneficial if applied to empirical, real world problems.

As it is clearly visible, the enterprize of explaining collective behavior is at the core of many, if not all, social sciences. Be it Sociology, Social Psychology, Economics or even Business Administration: all these have to deal with the causes and consequences of collective phenomena. Over the past centuries, a large body of approaches and concepts concerning this topic has evolved. However, there is a ubiquitous distinction, which is shared across scientific disciplines: It is the distinction between microscopic and macroscopic (or individualistic and collective) levels of explanation. So for instance, Durkheims´s (1973) social facts and his famous claim to explain social phenomena by social phenomena are a famous example for the collectivist position, while Webers´s (1984) also classical claim for methodological individualism locates itself on the opposite side of the spectrum. Of course, for individualists there is the need to acknowledge the existence of macroscopic properties, which is most prominently (but not sufficiently, as the reader will see later) reflected in Colemans´s (1990) work on the micro-macro link (c.f. Opp 2007).

However, I will not attempt to examine the different positions or their philosophical foundations in very detail at this point. (There will be reference especially to the ontological and methodological aspects in the later chapters.) What I want to do is to provide the reader with information which sets my enterprize in a proper frame. In order to demonstrate the challenges which one has to face in this subject, I now start by presenting an exemplary case.

Scenario

Consider the following situation which I adapted from Lazega (2001) and to which I will refer as blueprint - scenario in the later chapter on simulation of influence processes:

Suppose there is 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, thereby 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.

This scenario is obviously close to everyday experience, and with changed actors and topics, one might consider it a prototypical case of the ubiquitous processes of communication and influence. Therefore it is quite appealing as a starting point for discussion of the problems and approaches of explaining collective behavior. Of course reality can (and often will) be more complicated, but nevertheless this scenario contains all generic complexities of the problem on a small scale.

Terminology

In order to structure the problem, it should be helpful to introduce some basic notions, in line with the fundamental distinction of microscopic and macroscopic properties. A constructive terminology is provided by Bunge´s (1979) account on systemism. According to Bunge, a system is a set of interdependent components, nothing more and nothing less. It should be quite natural to identify the lawyers with the system´s components and their set of communications and opinion adjustments with the system´s structure of interdependence. Consequently, microscopic properties are those properties which belong to the systems components, the single lawyers. Macroscopic properties are furthermore those properties which belong to the system, i.e. the set of lawyers. (Of course it is possible to define macroscopic properties on some subsystem, that means a set of lawyers, which contains not all lawyers, but certainly more than one.) These macroscopic properties are by definition (or as a first conception as we will se later) relational properties, such like distributions of opinions or communication - or power relations. As the reader will certainly know, Bunge´s definition of a system is only one taken from a huge array of possible approaches to social phenomena. However, as its application to our scenario shows, it is an approach which is simple and can easily be applied to everyday problems. A further advantage is that it can be quite straightforwardly be used to reformulate concurring approaches, as will be shown subsequently.

Macroscopic Approach

A possible approach to explaining collective behavior is to restrict theorizing to the collective level, which means that only macroscopic properties are considered to be acceptable as explanatory factors. In our example, collective phenomena like for instance norms and culture would be such factors which could be used to explain the lawyers distribution of preferences.

A classical example is Parsons´ (1996) theory of structural functionalism with its famous AGIL paradigm. Here behavior of a social system is seen to be determined by functions the system is expected to fulfil in order to persist in the future. According to Parsons these functions are adaptation, goal-attainment, integration and latent pattern maintenance (AGIL). Without discussing this theory and its plausibility in too much detail, I want to point to the following fact: Since all relevant notions are defined on the collective, the flow of causality is confined to the system (i.e. macroscopic) level.

This restriction immediately results in the shortcoming that there is no way to explain how these macroscopic functions are related to the basic elements of a social system, the individual persons. Ironically, the confinement of theorizing to the macroscopic level ruins the theory´s explicit systemic character, as it is defined by Bunge (1979). Of course it is possible to propose other system components than persons, such as the "cultural subsystem" or the "economic subsystem". Taken to the extreme, this trick results in Luhmann´s (1984) conception of an "autopoietic social system", which only parasites on individuals without containing them. It is my strong conviction that restriction to qualitative reasoning may tempt oneself to such improper reductions of complexity. As Esser (1996) notes, Parson´s and Luhmann´s approaches are furthermore characterized best as terminological systems but as proper theories, which parallels our claim.

Microscopic Approach

Another approach is to base explanation of collective phenomena on assumptions about individual behavior. In our example this would mean that the lawyers distribution of preferences would be explained by individual characteristics like for instance utility functions or specific decision behavior.

As implied by these examples, rational choice theory can be considered a prominent microscopic approach. Its core is the assumption of maximization of subjective expected utility (SEU), which defines the concept of rational action of individuals. Rational choice theory is represented in two versions, either "hard" and microeconomics-oriented (c.f. Coleman 1991, Esser 1996, Diekmann / Preisendörfer 1993) or "soft", psychologically oriented (c.f. Ajzen 2005, Opp 2005). But regardless of the version considered, the main focus in empirical application lies in instantiation of the SEU-hypothesis, this is the determination of individual utility functions or attitudes. From this point, individual decisions can be derived, and it is possible to statistically aggregate a global distribution from these individual results.

In principle, rational choice theory provides a rationale for integration of macroscopic explanatory factors, as it has been developed by McClelland (1967) and has prominently been advocated by Coleman (1991) and Esser (1996). This schematic of micro-macro-explanation operates the following way. A collective state at some time point is supposed to form a decision environment for the individual actors. During a time step the individual actors assess their situation and update their decisions, whose aggregation can be considered the collective state at the next time point.

While this schematic appears convincing in principle, it is non-identified in a serious aspect. It makes no statements regarding how collective states are connected to individual decisions. Usually these connections are conceptualized as concrete and elementary hypotheses, analogous to behavioral hypotheses on the particular micro- or macro level. In this case hypotheses connecting the macro- to the micro level are called bridge hypotheses, following Nagel´s (1961) account on nomological reduction of theories, while hypotheses connecting the micro- to the macro-level are called aggregation rule. This rationale is advocated by Esser (1996) and Opp (2005). The critical (and in my view widely ignored) point is, that it is more than complicated to propose elementary hypotheses which connect a compound of objects to a single one. Coleman himself recognized this problem and wrote of these hypotheses as such which "could follow as deductions from a theory." (Coleman 1991, p.14) In his work, this theory was usually one of market mechanisms, which allows to determine some equilibrium point of the expected behavior of a set of market members. If one however lacks such a method of inference in a multi-agent situation, one may be tempted to mistake empirical instantiation of the SEU-hypothesis for building properly working bridge hypotheses, especially if usually only survey data on mutually unconnected persons is available. The discussion of Kelle and Lüdemann (1995) and Lindenberg (1996) is a lucid example for this. Another problem that arises before the background of proposing bridge-hypotheses is whether bridge hypotheses can be considered causal. The reason is that it is not self-evident how causal agency of a compound of objects refers to the causal agency of its elements. I will discuss this topic in detail in a later chapter on the philosophy of level transitory relations. I want to emphasize the most important result of above discussion. Properties of a compound of objects (or individuals) can not straightforwardly be connected to properties of its components, least in form of an elementary hypothesis. The reason is that such a projection needs to take account of the structure of interaction of the components, and for this specialized methods of inference need to be employed.

Structural Approach

The present work attempts to develop methods for the problem of inference on collectives based on individual behavior. The critical point is, that the structure of interdependence of persons has to be considered in order to make such inferences successful. Such a structure could be for example a homogenous market structure (as is usually assumed in microeconomics) or it could be the communication network of the lawyers in our introductive scenario.

In contrast to the previously presented approaches, there exists no closed theoretic paradigm of some "structural systemism" in the social sciences. However, and maybe due to the importance of inference tools, there exists a large body of research on methods for examining structured systems. I will now provide the reader with a short review of the most important concepts and approaches.

Coping with Complexity

Systems which show a structure of nonlinear and inhomogeneous interdependencies which make it difficult to predict its behavior from its components are often called complex systems. Adopting this term, the social systems in consideration can certainly be called complex. Important concepts linked to this notion are those of emergence and reduction. These deal with the nature and possible explanation of so called "novel properties", which are deemed to be characteristic for complex systems. Discussion of these terms is closely related to the previously mentioned task of inference of system behavior given structured interdependence of the system´s components. However, I will postpone detailed treatment to a later chapter on the philosophy of level transitory relations. There exist various methods which deal with the analysis of complex systems, which most often have their origin in the natural sciences. It should be noted that all approaches share a quantitative, resp. formal setup, which allows so to speak "automated" integration of exercised interdependencies.

The classical method of inference in systems is system theory, which is also called cybernetics (c.f. Bischof 1998 for an introduction for social scientists). Here the system´s components are represented by so called operator functions which transform some input into output. These operator functions are usually modeled as difference or integral equations, which describe the transformation rate behavior of the system´s components relative to time. Inference is either accomplished by specialized analytical methods or numeric simulation (c.f. Bischof 1998). This method has proven very useful over the last decades, but for the case of large and complex systems its application is limited, since in this case modeling easily becomes confusing.

Other methods, which allow the description of systems with a large population of components have been developed in the field of statistical physics. These deal with the development of distributions of element properties over time, prominently using stochastic differential equations. In the social sciences, such models are successfully applied to predict the movement behavior of crowds (c.f. Helbing 1996), but because they are much more strongly concerned with system size than structure of interdependence their success does not transfer to other fields.

At the time, one of the most active fields of research is on agent based modeling (c.f. Gilbert and Troitzsch 1999, Weiss 2000). This is a method for designing computer models, which simulate the interaction of (more or less) autonomous objects. Models which contain several software agents are called multi agent systems. The core concept of this method is that all functions a real world object can perform are bundled together to a software object by a specific programming technique, and that those software object is given maximum autonomy during program execution. The core advantage is that agent based modeling allows to keep the overview over the design of even huge and and heterogeneously structured models.

Of course, other promising ways to integrate the structured behavior of systems´ components are thinkable, as will be discussed in a later chapter on inference in microscopic models. At this point it is important to understand that theorizing in the domain of complex systems, as social systems are, is not only dependent on proper definition of concepts and consideration of empirical results. It is furthermore indispensable both to possess a method for integration of the systems components behavior and to put this method into the proper place of the theorizing endeavor. Social science theory has lacked recognition of this fact, which maybe supported its widespread drift towards informal accounts on complexity, which even have developed closed languages to disguise the emptiness of their statements. Luhmann´s (1984) work is the most drastic example for this.

Social Causality

So far my comments have shown the importance of consideration of the system´s structure of interdependence for the task of explaining collective phenomena. Of course the mere ability to integrate a set of dependence relations, as it may be provided by formal or computational methods, does not imply anything about the nature of these relations. Determining the nature of interdependence of social behavior is a task, which goes beyond both mathematics and what is usually considered to be social science methodology. Before proceeding to questions about measurement and testing of theories, (both being procedures which flow from epistemology), it is essential to elaborate the non-testable general structure, the ontology of the theory to be employed. Referring to a title of one of the works of Bunge (1979), ontology deals with what one considers to be the "furniture of the world", those concepts that are the objects of theorizing. Actually acknowledging the necessity to consider the nature of social interdependence appears to be a major accomplishment in contemporary sociology, as can be interpreted from the popularity of Esser´s (1996) and Hedström´s (c.f. Hedström 2005) apology of "social mechanisms" as opposed to some "sociology of variables", which originates in Hedström´s (. However, this is not enough. Most importantly, a fundamental decision has to be made whether social interdependence (as elementary building block of any social mechanism) can be interpreted as being causal or not. Exponents of rational choice theory may of course argue that purposiveness is the constituent element of human action as opposed to mere behavior. Without drifting off into a discussion on freedom of will, I want to emphasize that autonomy and goal directedness of a system does not necessarily conflict with its causal reconstruction. (This topic will be discussed in detail in the chapter on philosophy of level transitory relations.) Deciding for a causal account on social interdependence has an immediate important consequence, namely that analysis of a social system can proceed in terms of intervention, that is effects. Other consequences concern the methods which are employed for integrating a structure of interdependencies, but I will not elaborate on this point. As consequence of adopting a causal interpretation of social interdependence it is necessary to determine the actual position of the causal flow to be assumed. This point is crucial for the models realism and its applicability. Paralleling the claim of importance of purposive action, I will propose decision making (or more general, information processing) in a social environment to be the locus of causal flow in social systems. Recurring to the exemplary scenario of the lawfirm, causality is supposed to flow through individual processing of communicated information. In later chapters on measurement of cognitions of social influence and simulation of influence processes I will elaborate this point more deeply, in order to provide it with an appropriate treatment. In fact, with determination of the nature of social dependencies and an appropriate method for inference in an dependence structure, one has arrived at a position which seems a promising starting point for an actual modeling enterprize.

Successful modeling and feasible applications

The result from all above discussion is, that explanation of collective behavior is an endeavor which demands a large array of considerations to be made. Spanning from ontology and epistemology over social theory and mathematics to statistical measurement and testing, the complete spectrum of analytical social science is touched. This leads to the result that generalizable methods do not automatically follow once a certain aspect or an inference tool like agent-based modeling is mastered. In my opinion, it is essential to recognize that building successful models is not only a technical exercise, which can be dealt with according to some elaborate paradigm. I hope that such a successful paradigm may be available in future, but at present work in this area is still strongly demanding a scholars artistic abilities. Although I claim the important role of creativity for the process of modeling and theorizing, this does not mean that results are only subject to aesthetic judgement. On the contrary, the importance of immediate and mediate results in this field must not be underestimated. The immediate advances might be of most practical value. In the field of group research it becomes possible to derive group behavior from knowledge on individual attributes, which is of tremendous value for predicting and planning the effects of interventions. Returning to the initial example of the lawfirm, one could use such a model in order to understand the communication process among the lawyers. This knowledge could then be used to intervene into this process in order to yield desired group outcomes. Seen from a more abstract level, a successful modeling methodology adds value to structural analysis, as it is exemplified by social network analysis, by integrating the aspects of dynamics, systemicity and causality. In my view this might well lead to substantial theoretical progress since these fundamental aspects of social life are often ignored in social theory, which is generally not aligned with methodical progress.

Outline of the work

This dissertation aims at providing an integrated account on modeling collective behavior, dealing with a wide array of topics as it is discussed above. These topics

arch from ontology over modeling methodology and simulation modeling to measurement. Taking advantage of the liberties associated with the format of a cumulative dissertation it focuses on several central aspects of the task. Before presenting the exact topics of the individual chapters,
I will briefly explain the idea behind their structure.

As it has been discussed, the task of implementing models which can be used to actually explain collective behavior by processes on the individual level necessitates considerations on the ontology of level transitory relations. In a next step, it must be determined how such an ontological account can be turned into a methodology so that it can fruitfully be applied for research on real world problems. A further step towards practical application is the actual implementation of a model of collective behavior, together with the development of measurement instruments which allow its instantiation based on observed data.

The first chapter ("Interlevel relations and manipulative causality") deals with a philosophical approach to formulation of level-transitory relations. By this is meant if statements that connect the collective and individual levels can meaningfully be declared. As implied by the above discussion on the pitfalls of social theory and social causation, the nature (or better the adequacy) of level transitory relations is not easily determined. A core problem is that the individual levels appear to behave according to their own "logic" and that the causal character of inter-level relations seems unclear. While people generally assume some dependence between individual and collective states, there is both discussion why macroscopic entities could be considered as causal agents on their own, and where "unintended consequences of action" on the collective level could stem from.

My approach starts at the conception of a layered architecture of the world, which is clearly an ontological one. While ontology is often shunned in popperian science as being platonistic, this is clearly not the case. Even the notion of a cumulative growth of knowledge relies on some conception of reality, like the shape of a bolt is implied in the shape of a monkeywrench. This however does not imply that some conception of reality necessarily needs to be considered real itself. For this a nominalistic framework can of course be followed.

The basic argument on the identifiability of a level is concerned with the determination of identity of objects located on this specific level. Summarized, I claim that objects can be isolated from their environment by the set of causal mechanisms associated to them. So to speak, mechanism and object are being seen as being two sides of the same coin. A both crucial and problematic notion in this respect is the notion of causality, since it has a close relationship to the notion of action, which is made clear in the term of manipulative causality. This relation between object and agency makes it difficult to separate "reality" and "observer", to employ these well known terms. On the other hand, manipulative causality allows the recognition of multiple levels in a hierarchic structured world. This is the case, since manipulation is thinkable both on elementary objects and higher level objects which form an autonomous joint of lower level entities. To be more precise, autonomous structure is a prerequisite of higher level manipulation, since it forms higher level interfaces, viz. mechanisms.

Departing from these ontological assumptions, the first chapter discusses the relation of higher- and lower level causation and the ontological character of level transitory statements (whose importance has been stressed at the beginning of this introduction.) Further points of discussion are the concepts of reduction and emergence, together with methodological accounts on this subject. These are most importantly materialistic monism (or ontological reductionism), nomological reductionism and physical realizationism.

The second chapter ("Probabilistic inference for actor centered models") is build on the results of the first chapter. Its premier objective is to develop the already made philosophical advances into a productive modeling methodology. Therefore it discusses the representation of object identity as it is accomplished by different modeling frameworks, such as multi-agent-modeling, systems-theory and probabilistic graphical models. As it turns out, every modeling framework represents object identity in a certain way and furthermore allows to synthesize system behavior via a generic mode of inference. However, the individual frameworks differ in their focus on these two aspects. During the course of the chapter, special emphasis is given to the framework of probabilistic graphical models, which are interpreted in accordance to the already made philosophical considerations. In order to test the proposed methodology for representing systems and deriving level transitory statements, an exemplary application of probabilistic graphical modeling is presented. This example deals with interaction behavior in a dynamic context. The third chapter ("Simple Heuristics in Complex Networks") shifts the focus completely from methodology towards application. The central topic is the design and analysis of a simulation model of influence processes regarding opinion formation in social networks. Relating to the earlier discussion, such a model is important for the following reasons. First, as a simulation model, it allows for inferring collective level inferences from individual level assumptions. Second, as its representation of interdependencies between the elementary entities is based on the concept of social networks, it provides a very general and flexible framework for application. Third, with the concept of social influence, it proposes a general nexus for social causality on the individual level. Taken together, a model with these features can be considered a general framework for a wide class of models of social behavior and thus be very productive for development of theory. Of course the model also deals with more specific problems. When combined with social networks, the concept of social influence quite naturally provides a nexus for social causality. However, it does not immediately determine how the transfer of social causality is accomplished. This has been specified by using a cognitive approach to social influence. Here social influence is not seen as a kind of exerted force which is channeled through social relations, but as information which is processed by the receiving agent instead. A cognitive approach on social influence has the advantage that it precisely and plausibly defines an agent´s causal interface as compared to traditional relational model of power. Of course this does not mean that a relational model of power in which potential influence is based on resource control becomes useless. However, from the viewpoint of microscopic modeling a cognitive model is much more easily to handle since through its agent centered causal assumptions system level inference is facilitated. Aligned with recent developments in cognitive psychology (c.f. , social influence is modeled as a decision process based on social cues. More precisely, under the label of "fast and frugal heuristics" the simulation model considers several models of agent cognition with varying degree of cognitive effort required. Besides examining the effects of agent cognition, the simulation also considers the effects of clustering of the assumed communication network. This is important, since formation of cohesive subgroups may lead to situations in which minority positions can persist because cluster members shield each other against external influences. Based on these rather general setup of the simulation study, an array of interesting results concerning the behavior of social collectives is derived in the chapter. Furthermore, a case study based on empirical data from a New England lawfirm is presented. The fourth chapter ("Evaluating Social Influence Relations: an Item-Response-Modeling Approach") refers to operationalization of the cognitive model of social influence, which forms the central causal building block of the network model presented in the previous chapter. If this former model is about to be calibrated to real world data, appropriate measurements have to be obtained. Therefore this chapter´s aim is the development of scales for measuring perceptions of alter´s persuasiveness, authority and propensity towards coercive behavior. In order to fulfil this task questionnaires together with item-response-theory scales are developed in a survey setting. Furthermore these instruments are applied in a closed network setting in order to check their validity. The respective data deals with a group of scientists at two German universities and has been collected via an online survey. By combining these four chapters I want to present a coherent and stimulating work, which engages several topics that are important for the task of micro-macro-modeling in the social sciences. I hope that my effort had some success and provides the reader with a stimulating treatment of the subject.

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Chapter 1: Interlevel Relations and Manipulative Causality

SUMMARY. *Interlevel Relations and Manipulative Causality*. The topic of this article is the analysis of the relations between different levels of reality. The core argument is based on considerations of both an epistemology of action and manipulative causality as a criterion of object identity. The argumentation is extended towards the concepts of self-organization and self-regulation. Finally, several views on reduction and the problems of emergence and complexity are discussed.

Key words: interlevel relations, causality, action, epistemology, reduction, emergence, self-organization, self-regulation, complexity

Introduction

The conception of a layered architecture of the world has become a commonplace in today"s science. Its central difficulty, namely the question of the relation between the respective levels of existence, has gained significant interest. This is especially the case in scientific areas where reference to neighboring levels seem to promise significant new answers. One example is individualistic social science, my own field of research: Besides classical methodological considerations (compare McClelland 1967 and Coleman 1990) there is growing interest both in computational methods (compare Conte *et al.* 1997 and Gilbert/Troitzsch 1999) and results from Philosophy of Mind (compare Heintz 2004 and Sawyer 2002, 2003).

In accordance with these developments and due to its methodological importance, the question of interlevel relations will be the topic of this article. The discussion relates mainly to recent philosophical developments, namely advances in Philosophy of the Mind and in the study of causation. A central *epistemological* aspect for consideration is the connection between knowledge and action. *Manipulative causality* will be a key concept of my argumentation: I will be showing its contribution to the definition of objects and consequently levels. Furthermore I will be examining the effects of causality as a criterion of identity of objects on the analysis of interlevel relations. This leads to discussion of the concepts of *reduction* and *emergence*.

The provision of a coherent answer to the question of interlevel relations comes, unsurprisingly, at certain cost. This cost is the introduction of a *constructive* criterion of object identity via the concept of action. However, I support the viewpoint that observer-dependant knowledge is by no means arbitrary.

Object Identity and Structural Causality

Instead of enquiring the nature of interlevel relations directly, I will start by examining its constituents. Apparently these constituents are the objects found on the respective levels. Consequently, ignorance of interlevel relations leads to hierarchical properties of objects (such as „being emergent“, „being reducible“ or the like) becoming uninteresting. Nevertheless, what remains interesting in this case is the question regarding what properties or forces isolate these objects from their environment.

Structural Causality

If we want to analyze the relation between objects on different levels, we have to determine how an object can be *identified* as such. This necessary identification can be guaranteed by employment of the notion of *mechanism,* designating a stable and genetic relationship between properties. Determination of the set of mechanisms attached to an objects properties allows the isolation of it from its environment. This concept has been developed by Pearl (Pearl 2000) within the framework of his structural theory of causality. Within this theory local mechanisms are encoded by the set of edges of a *directed acyclic graph* which represents the composition of the system of interest[1] [2].

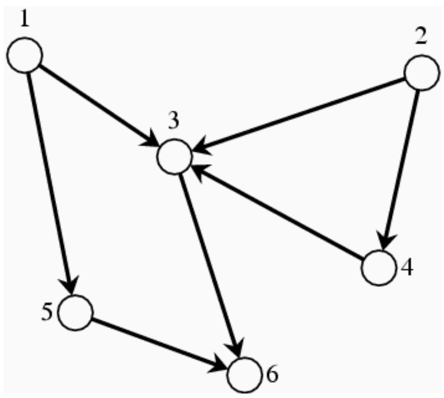

Figure 1: Illustration of a directed acyclic graph. (Arrows represent local causal mechanisms, circles represent properties.)

[1] The notion of „directed acyclic graph" is a central concept of the theory of *Bayesian Networks*, respectively *Probabilistic Graphical Models*, which provides the base calculus of the theory of structural causality. A fact of technical importance is that indirect probabilistic relationships are deleted out of a Bayesian network by application of the so-called criterion of *markov-parentship*. This criterion checks for conditional statistical independence in directed acyclic graphs. In any case, reasonably detailed introduction to this theory would go beyond the scope of this article. The reader is referred to (Baldi/Brunak 2001), (Jensen 2001) and (Pearl 1988, 2000).}

[2] A further point to note is the fact that although Pearl"s theory employs probabilistic methods, it contains a deterministic ontology. However, I will not make any concrete statements regarding the ontological part of this question and view probability as an epistemic concept.

Manipulative Action

The reader may well have noticed the catch that is inherent to this approach to *object identity*. Now we are able to isolate an object by its boundary of mechanisms, but the problem has only shifted towards the following question: How do we determine the existence of such a mechanism?

As is known, this question is associated with two fundamental aspects: the first is the problem of the identification of causality while the second is the problem of induction of lawful relations from experience[3]. First of all, I will follow the argumentation of scholars who view causation in close connection to *manipulation*. Manipulative action is necessary for the observer in order to isolate the mechanism of interest and to identify its conditions and consequences. Reasons for this is the necessity of elimination of background noise and identification of the mechanism"s genetic principle (compare Bischof 1998 and von Wright 1991). Furthermore, it is important to notice that the concept of manipulative causality is centered around the idea of an actor, with all the virtual limitations on his knowledge, decisions and actions. One consequence is its relative conservativeness with regard to the ontology of causation. Its integral concept of structural causality does not enforce different logical treatments of type and event causation (compare Kim 1993). Both facets of causality differ only with regard to the actors subjective scenario of information, namely what is known of a specific mechanism´s triggering- and side conditions (Pearl 2000 p.310).

Rationality

As mentioned before, the second aspect of the problem of identification of mechanisms is the problem of induction. It can be bypassed with certain elegance as

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[3] The problem of induction may be regarded as a sub-problem with respect to the identification of causality.

long one does not expect too much. Of course I will not argue against Falsificationism in its non-relativist facets (Popper 1994 and Lakatos in Lakatos/Musgrave 1970).

Although there can be no certainty regarding the correspondence of proposition and reality, there is of course the need for both decision and action. Shifting the focus of the problem of induction from *truth* towards *rationality* provides a viable solution: Now the question changes from „What is the correct relationship“ to „What is the best relation to propose, given the knowledge at hand?“. Since it includes its conditions, the second question can in principle always be answered. The tools for solving the problem of induction in its minor and pragmatic form have been delivered by the *bayesian* approach to probability theory (Jaynes 1974). Its constitutional Cox-Jaynes axioms reformulate probability theory as inductive logic [4].

Constructivity

It is important to note, that the problem of rationality can be viewed as the problem of induction, stripped of its *connection to reality*. This connection has to be established by other means, if one needs to arrive at adequate decisions. It can be provided by the concept of manipulative action which calls for experimentation as the basis of generation of knowledge, as introduced above.

The consequence of this argumentation is the establishment of an *epistemology of action*. Here the generation of knowledge can be viewed as a partially active process, depending on both action and experience. (compare Piaget 1981 and von Wright 1991). The (probably unavoidable) cost of the employment of action as my central

[4] In contrast to traditional opinion Bayesianism does not view probability theory as a means of rationalizing on the occurrence of events. Here probability is perceived as a logical value attached to propositions. One could say that classical interpretation of probability reasons a direct reality, while Bayesian interpretation focuses on knowledge, respectively belief. The question of correspondence does not necessarily enter into the semantics of the calculation.

concept is the infiltration of *constructivity* into the argumentation. This constructivity stems from the fact that what can be known is subject to the boundaries of action. Consequently, knowledge depends both on what one has done, is able to do, and, more fundamentally, *can imagine doing*. An important factor when considering these boundaries is the evolutionary development of human cognition (compare Vollmer 1981).

Let me complete this section with a short summary of the epistemological approach. In brief, I argue that a prerequisite of an analysis of interlevel relations is the analysis of object identity. In conclusion, objects can be identified via their boundary of associated mechanisms, which in turn can be identified by manipulative action, as considerations of the problems of causality and induction, respectively rationality show. The cost of employing of the concept of action is the introduction of a constructive element to the argumentation.

Object and Level

A further topic that is worthwhile to considering in the discussion of interlevel relations is the relationship between the *notions* of object and level. An elaborate concept of *level* is provided by Bunge (Bunge 1979, p.13). According to this view, levels are assumed to be relational concepts, whereby, roughly speaking, objects on a higher level are composed of objects on a lower level. As Bunge states, this approach to the definition of levels is purely conceptual and thus inert with respect to his proposed ontology. The critical point is, that levels are defined by a relation between objects, but the objects on the respective levels remain unidentified.

The conservativeness of the above mentioned definition lies in the fact that it avoids reliance on some mystical concept, like for instance entelechy, which could identify higher level objects in relation to lower level ones. Nevertheless, a notion of level which is inert with regard to the remaining concepts of a proposed ontology seems unsatisfactory.

Causal Affiliation

To provide a satisfactory account, the level needs to be defined with respect to its constituting objects. In accordance with the idea of structural causality, as introduced above, I will define level as follows: *A level is the set of all objects which can interact causally with a specific object (which forms the levels reference point), including this object.* A specific hierarchy of levels may be determined by the possibility of *aggregation of mechanisms*.

As the declaration of mechanisms ultimately depends on considerations of manipulative action, the declaration of a joint, respectively higher order mechanism depends on the intelligibility of joint, respectively higher order manipulation. One should note that it is a result of these considerations that the declaration of a specific level depends on both the reference object and the manipulations in focus. It is, so to speak, important „where to position the lever".

Autonomy

Certainly the choice of levels is not arbitrary. Reality determines how successfully joint mechanisms can be declared. The varying fit of descriptions of different granularity is often attributed to the existence of emergent properties[5]. Again, there exists a relational definition by Bunge (Bunge 1979 pp. 27), which states that emergent properties are properties which a system acquires during its process of assembly. In coherence to his previously mentioned definition of level, this definition lacks a statement of how these properties are constituted throughout the hierarchy. Again, this definition is proper, but nevertheless unsatisfactory.

Within a epistemology of action, a criterion of constitution is *ease* with which a higher level mechanism can be declared. The significance of this criterion stems from the fact that the declaration of a mechanism is dependant on the intelligibility or actual accomplishment of action.

I wish to remark, that it seems to be exactly this aspect of subjective ease which gives a concepts like entelechy its luring charms as constituting criterion of levels. However, there is the possibility of causal description of processes which seem to encourage teleological description at first glance (compare Stegmueller 1983). Thus, an easy aggregate description may be accomplished by means other than entelechy, but with similar results. Obviously, if a set of mechanisms has a structure which results in relative environmental *autonomy*, an aggregate description can easily be declared. Autonomous structures of mechanisms are known under the labels of *self-regulating* and *self-organizing*. Self-regulation is the case if a certain structure compensates for outside *disturbances* (Bischof 1998), while self-organization describes the tendency of certain structures to reach *steady-states* of relative environmental autonomy (Bertalanffy 1998). In accordance with these

[5] In a structural framework (emergent) „properties“ can be considered equivalent with (emergent) „mechanisms“, because the latter contain the former, and the former owe their significance to latter.

concepts, higher level properties could be identified with functions of the auto-functional subsets of the state space[6] unfolded by the component entities of the structure.

The significance of the concept of autonomy lies in the fact that it allows for intuitive identification of levels (and thus hierarchy) via its constituting autonomous objects. It is important to notice that it is only a secondary criterion of object identity, since it is defined on the notions of mechanism and thus action. Again, the result is rather an epistemological concept than an ontological one.

Logical Realization

Autonomous structures are per definition joints of mechanisms. Their aggregate descriptions can be generally considered many-to-one projections of the elementary level, since otherwise talk of autonomy would make no sense. In accordance with this bottom-up process of declaration of objects one could say that activity on the lower level of declaration *logically realizes* activity on the respective higher level.

However, within the framework of the proposed approach the relationship between levels is a conceptual one, as objects within a specific level are already *completely determined* by their defining mechanisms. This proposition is a result of the bottom-up approach to levels and seems to be the core argument of ontological reductionism (compare Schlick 1993). An ontologically contrary position needs to break this relation of constitution.

[6] According to my knowledge, this would be designated as an *attractor-structure* within the framework of dynamical systems.

The above considerations are closely related to the notion of *supervenience*. According to Kim (Kim 1998) in a layered model of the world supervenience can be defined via the notion of *microindiscernibility*: „For any *x* and *y*, belonging to level *L*..., if *x* and *y* are indiscernible in relation to properties at all levels lower than *L*..., then *x* and *y* are indiscernible with respect to all properties at level *L*.“ (Kim1998 p.17) Consequently, properties on level *L* supervene on properties on the lower levels. Regarding this definition to my own approach, higher level objects (as containers of properties) are apparently supervenient on the lower level objects. However, as Kim states, supervenience is a phenomenological theory which makes statements about „patterns of property covariance“ and not about „deeper dependence relations“ (Kim 1998 p.15).

Logical realization exceeds the relation of supervenience by the claim of its definitory necessity once a higher level object is identified. Admittedly, „realization“ is somehow misleading since within an epistemology of action the same status of reality is assumed on every level. It necessarily depends on experimentation.

Regardless of the proposed equivalence of higher level mechanisms with certain sets of lower level ones, the concept of level maintains its significance. Given that a hierarchy of several mechanisms has been declared, it is (among other things) a matter of *choice* which one will be triggered. As implied in the section on causal affiliation, action provides matter for the concept of level.

Reduction

There are two eminent concepts of interlevel relations, which have merely been touched upon in the above discussion, namely *reduction* and its counterpart, *emergence*.

Ontological Reductionism

The idea of reduction comes, so to speak, in two major shapes. The first could be called *ontological reductionism* (compare Smart 1987) and seems to be broad common sense in the sciences. It states that, if an object is composed out of smaller particles, these smaller particles obviously share a material reality, which is not owned by higher level objects. Consequently, the smallest particles make up for the substrate of the universe of which the higher level objects are only configurations.

I have two objections regarding this view: Firstly, it is merely a procedure to decrement the level, the character of reality of which is questioned. Secondly, one can never determine if the lowest level has been found, since the possibility of an unknown lower level can never be refuted as long as there is a single question left unanswered. However, it contains a very serious aspect, namely that the possibility of decomposition of an object allows for its description solely by its constituting components.

My opinion towards ontological the problems of reductionism is that it lacks an epistemological criterion for the assertion of status of reality. There is simply no tool available to stop the mentioned process of decrementation.

Nomological Reductionism

The second form of the idea of reduction is what could be called *nomological reductionism* and has been advocated by Nagel (Nagel 1961). Here the core idea is embodied in the attempt to convert one theory into another by employment of so-called *bridge hypotheses*. The reduction of theories belonging to different levels of existence is seen as only a special case of this general scheme. Several arguments have been advocated against nomological reductionism, the most prominent being the *multiple realization argument* (Fodor 1976; Putnam 1975). It states, that a proper bridge law might never be established because of the presumably huge and unsystematic array of microscopic realizers of higher level properties[7].

I wish to formulate another argument against nomological-reductionism. A weakness of this approach is that it operates within a universe of statements without explicit reference to a *model-ontology*, respectively *semantics*. As it turns out, the nomological reduction of theories which describe objects between which the composition-relation holds, violates the the respective definitions of *identity* of the objects. This leads to contradictions regarding the concepts of object and level, which can be regarded as semantic terms with respect to terms describing the actual instances in focus.

Since an object can be defined by its generic mechanisms and levels can consequently be defined by causal affiliation, the invocation of a bridge hypothesis would have two consequences: First, the notion of level would become paradoxical,

[7] This concept does not question the approach advocated here, as logical realization explicitly proposes a many-to-one map onto the higher level, and is furthermore only applicable where the decomposition of a higher level is known. This would be the case for processes of self-organization and -regulation. A further critical point is the availability of an appropriate structure calculus, as introduced below.

since the particular bridge mechanisms effecting object would become a higher- and lower level entity at the same time. Result is the violation of the respective objects criteria of identity. Secondly, it would result in causal overdetermination, since an object on a specific level is already defined by its set of generic mechanisms which would be exceeded by the declaration of an additional bridge mechanism.

Physical Realizationism

Apparently, nomological reductionism seems fairly inappropriate for treatment of the question of interlevel relations. Another reductionistic approach has been proposed within the framework of the mind-body problem (which is often considered as a subproblem with regard to interlevel relations). This is so-called *physical realizationism* (Kim 1998). It is in some respect similar to the approach advocated here, insofar as it identifies the higher (mental) level entities by reference to their causal (functional) roles. Nevertheless, the (physical) lower level entities, which realize the higher level ones, are identified by their material reality. As argued for the case of ontological reductionism this only makes sense if material reality does not fade during an infinite amount of level transitions.

Emergence

At this point I will briefly mention the concept of emergence which forms the counterpart of reduction. It is usually characterized by the proposal that decomposable objects on a certain level show novel properties which cannot be „reduced“ to their components. Usually it is unclear within the framework whether „reduction“ means „explanation“ or is understood in an ontologically stronger sense. If the latter is the case one faces the following problem. If there is no criterion for the assertion of reality (as is represented in epistemology of action), emergent properties can only be declared *per fiat*. Thus, ontological emergence is practically a transcendental statement.

An alternative is the statement of *weak emergence* which claims both the existence of higher level properties and the possibility of backtracking these to a lower level. Both physical realizationism (as a mind-body theory) and the claim of identification of higher level mechanisms with auto-functionality of autonomous structures, as introduced above, are both statements of weak emergence.

Both share criteria for the assertion of reality, the first by the intuitive identification of matter and function, and the second by the introduction of the epistemology of action.

Structure Calculuses and Complexity

The emergence of new properties is often said to be a feature of *complex systems*. If emergence is both understood as an epistemological concept and related to self-organization and -regulation, then this is true in some sense. A certain *behavioral plasticity*, and thus an accordingly complex composition, is a necessary prerequisite for an object in order to show these characteristics (compare Stegmueller 1983). Certainly this does not mean that complexity should be considered as a realm of strong concepts of emergence. Even hidden in a maze of mechanisms, a per fiat statement remains a per fiat statement. What is needed in order to cope with complexity (e.g. thedifficult decomposability of objects with respect to their mechanisms[8]) are methods of *system synthesis*. These provide the means for the declaration of joint mechanisms. I will call such methods which allow for computational treatment of systems synthesis „*structure calculuses*".

A classic example is the methods of control-theory, which allow the inference of the behavior of the system from the behavior of its components. *Probabilistic Graphical Models*, respectively *Bayesian Networks*, are a more modern approach. Today these are mainly employed in artificial intelligence, bioinformatics and epidemiology. As mentioned, the characteristic of this method is the decomposition of a joint probability distribution describing the behavior of global systems into a graph of local conditional distributions (compare Jensen 2001, Muehlenbein 2002 and Pearl 1988, 2000). The method easily integrates with empirical data, but application is limited by the size of the system in focus.

Conclusion

By declaring of an action-centered approach to epistemology I have tried to provide a basis for clarifying the concept of interlevel relations. This approach is insofar important as a critical discussion of the concept emergence with respect to observer-dependency has been long overdue. A further point worthwhile mentioning is that tools for coping with complexity

[8] It should be noted that the notion of complexity advocated here is ontologically stronger than the well known concept of computational complexity. It presumes representation of the mechanistic structure of the system, exceeding questions on prediction of data or procession of throughput.

exist, thus allowing assertions on specific processes of weak emergence to be made. I hope that I have presented a well founded, comprehensible and fruitful essay.

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Chapter two: Probabilistic Inference for Actor-Centered Models

Abstract

The analysis of relations between different levels of a system is a key issue in social science simulation. Here, I discuss the contribution of different modeling methodologies to this. Special emphasis is given to the formalism of "Probabilistic Graphical Models", resp. "Bayesian Networks", which is both advantageous for level transitory inference and integration of empirical data. Furthermore, issues of practicability and area of application are considered. The argumentation is exemplified by demonstration of a toy-application for which explicit level-transitory statements are inferred.

KEYWORDS: micro-macro-gap, agent based modeling, level transition, probability theory, graphical modeling, bayesian networks, complex systems

Were are we now? - Modeling across Levels

During the past years, Agent Based Modeling (compare Brassel *et al.* (1997) and Weiss (2000)) has become the key methodology in the field of social simulation. It's success has been far reaching; My colleagues who do not engage in computational methods tend to use the words Agent Based Modeling (ABM) and social simulation synonymously.

In this paper, I will be in tie with at least some of the reasons for this tremendous success. I usually do not forewarn the reader, but I will not discuss ABM’s possibilities of informal, qualitative modeling. Rather, I will focus on examining how models can be set up, which show emergent *global* behavior that is not coded in their *local* components.

Multi Agent Systems (MAS) certainly do belong to this class of models. However, the modeler`s toolbox can be stocked up with a method, which allows for more explicit theorizing in the micro-macro gap’s domain. With the theory of Probabilistic Graphical Models (compare Baldi and Brunak (2001), Lauritzen (1996) and Pearl (1988), (2000)), I will introduce formal calculus which may be employed to analyze the relation between the *component- and system levels* of conception. A more extensive account on the metatheoretical aspects of this approach can be found at Schwenk (2004b).

It should be noted, that acquaintance with the essential concepts of probabilistic micro-macro-modeling may be of considerable benefit for analysis of Multi Agent Systems, even if it’s formal apparatus is not employed.

The System´s Elements

As stated, the task is to find a formulation for the *relation of levels* of a given system. Now the first step to take is to define notions which allow to tackle the problem effectively. I have chosen the concept of *identity of objects* to be the basis of my argumentation. Instead of directly asking for the nature of emergent properties, I start by examining how an object is *isolated* from its environment and thus is *identified* [9] as such.

Isolation by Causation

Interestingly, but maybe not surprisingly, *structural isolation* is the core idea of Object-Oriented and Agent Based Modeling. (I will touch ABM's key aspect of autonomy shortly, after I have made the point on isolation clearer.) In both concepts, isolation of objects, as containers of properties, is accomplished by *information hiding*. As we know, this means that exogenously induced change of an object can only take place via a set of specific mechanisms, subsumed as its *interface*. With some refinement, this idea may serve as foundation of a general ontology which is able to solve our problem, at least for practical purposes. What needs to be examined in more detail is the concept of *isolating mechanisms*. For example, in Object Oriented Modeling, these mechanisms are allowed to be arbitrary functions, while in Agent Based Modeling the set of isolating mechanisms is explicitly requested to map the autonomy of the agent's (more or less strictly defined) preimage.

Relating to the general problem, my choice of characteristics of the mechanisms in question is based on the following considerations. Since the concept of autonomy reflects the isolation of an objects properties from a certain set of *causal influences*, I will propose the notion of *causation* to be the constituting aspect of isolating mechanisms. *Manipulation* will serve as means to identify a mechanism's existence and genetic principle, which accords to a, so to speak, pragmatic epistemological conviction.

[9] The reader may ask himself if this identi¯cation is meant tobe a feature of `perception' or of `reality'. This question can not be answered with certainty. Of course some of our beliefs may prove more valuable than others and possibly be closer to `reality'.

Because of the importance of these considerations, I will give a short summary: Objects are isolated from its environment by a bundle of primitive causal mechanisms, with causality being understood in a manipulative sense.

The Concepts of Level and Autonomy

Now having a definition of identity of objects, one can turn towards compounds of those. A first step is to decide on a definition of level. In accordance with the causal approach to identity I will understand a *level* as the *set of all objects which contain properties that are connected by causal mechanisms*.

To locate a levels position in a specific *hierarchy*, it becomes necessary to refine the above criterium of identity in order to cover *composite objects*. This is accomplished by invocation of the concept of *autonomy*: Given that a set of lower level objects has a structure which exhibits relative environmental autonomy, aggregated *joint mechanisms* may be declared on it. As a result, a higher level object may be identified by virtue of these higher level mechanisms. It should be noted, that within this scheme the *granularity* of mechanisms (and thus objects) is ultimately determined by what manipulations one is able to imagine and perform. Certainly a description of some granularity may perform better than another.

In most applications, autonomy is fed into the model *ex ante*. Normally, the modeler has predefined ideas about the preimages of both element and system levels.

However, subsets of the system may exhibit autonomy, which can be identified by analyzing the *functionality* of the subsystems state-space.[10]

Level-transitory statements are at the core of interest in analysis of complex systems. However, it is important to note that those statements *must not be considered as causal*, since in this case the notion of level would be rendered meaningless. It is a better understanding to say that certain local states result from the dynamics of the system, which can be summarized *phenomenologically* by a level-transitory formulation.

Due to the setting of this article, the treatment of above subjects can only be a sketchy one. For more elaborate philosophical discussion the reader is again referred to Schwenk (2006) and especially to Bischof (1998), Bunge (1979), Kim (1998), Pearl (2000), Sosa and Tooley (1993) and Stegmueller (1983).

Global Behavior in Local Terms

After having introduced the ontology of the approach, I will discuss how it can be implemented using formal calculus. As a first step, let's have a look on how *identity* and *aggregation* are handled in a selection of methods.

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[10] Undertaking parameter studies in order to examine its attractor structure would be an example.

Agent Based Modeling

As has been said, in ABM determination of identity, or in reverse formulation *system decomposition*, is achieved by both information hiding and bundling of properties; with the latter being aimed at devising self contained entities.

Aggregation, or *system synthesis*, is achieved by synchronized execution of the programm formed by the set of coupled agents. Naturally, program execution is the default mode of inference and thus system synthesis in computer simulation. Examination of the models trajectory, resp. it's behavior in state space is the standard mode of discussing system behavior.

System Theory

Another major paradigm is *System Theory* [11], which can be regarded as a variety of the theory of differential equations (compare Bischof (1998) for an introduction for social scientists). Here, the systems components are *operators*, functions which transform input-functions into output-functions.

System decomposition in System Theory takes place by formulating a system of equations. Usually, one ought to begin modeling the system by declaring a *black box*, with only gross input- and output-variables known. The black box is replaced by incrementally complex systems of explicit operator-functions until a satisfactory granularity is reached. It should be noted, that „object" is no genuine term of systems

[11] It seems that, depending on the scienti¯c community, `Cybernetics', `Control Theory' or `Signal Processing' would have also been good choices.

theory, nor is causality: This allows for coupling of variables regardless of considerations about their location within a hierarchy of levels. [12]

The key strength of Systems Theory is that it provides tools for systems synthesis. Certainly the systems trajectory as response to input can be computed by simulation. Moreover, the component operators can be aggregated algebraically in order to yield the system operator. Eventually, analytic propositions about system stability may be accessed by employing Laplace- or Z-transforms.

Probabilistic Graphical Models

The formalism I am most interested in, is those of *Probabilistic Graphical Models*, which is also known as *Bayesian Networks* [13]. It is a variety of Probability Theory (compare Jaynes (1974)), which enables decomposed formulation of joint probability distributions. Graphical Models are currently popular in Artificial Intelligence, Bioinformatics and Epidemiology. I will postpone more detailed treatment to the next section and continue the comparison.

In Graphical Models, component properties are isolated by their structure of *conditional statistical independence*, which is encoded in a special kind of network, an *directed acyclic graph*. Most important is that a *causal operators* for such

[12] If I remember correctly, this was something which astonished me when ¯rst looking at the design diagram of Jay Forresters well kown WORLD I model.

[13] I will use both terms interchangeably: I made contact with the topic over the AI-tradition of reasoning under uncertainty, in which the term "Bayesian Network" is common. "Graphical Model" is a rather statistical term which has grown faster in popularity.

independence structures exist, (compare Pearl (2000)), connecting above considerations on identity and level to formal inference.

The information stored in the components of the independence graph (the statistical associations between variables) can be considered al *local* and may be aggregated to yield a *global* joint probability distribution (which is accomplished by the so called *Chain Rule for Bayesian Networks*, as introduced below).

Perhaps the most significant logical aspect of Probability Theory is that it encodes *abductive* or *likelihood reasoning*. Abduction is the inversion of deduction: $A \Rightarrow B$, B is there, therefore A is more plausible; how plausible is coded in terms of probability. It can be interpreted that it is the possibility of *multiple causation* which corresponds with the use of probability in abduction. Thus, with joint probability distributions expressed by independence graphs, it is now feasible to employ abduction for reasoning about multicausality in structured systems.

One should note that a joint probability model represents the *local* dependence information *simultaneously*, and both abduction and deduction are employed to access the stored information in elementary or aggregated form.

A Sketch of Graphical Models

Now I want introduce the Graphical Model formalism in slightly more depth. Aim is to show how it can be used for level transitory inference in social science modeling. Starting point is a short description of the calculus.

Formalities

First, I will briefly review some basic concepts of Probability Theory. Then I will give an cursory introduction to the concepts necessary for building Bayesian Network models. For reasons of brevity I will spare many details and especially the treatment of inference algorithms.

Decomposition of Joint Probability Distributions

The first concept to introduce is the concept of *joint probability distribution*. This is a mathematical structure, where every joint occurrence a statement is attributed a probability. Presumably you are familiar with the *Fundamental Theorem of Probability Theory*, which shows the equivalence of the joint probability with a product of a conditional- and a marginal probability:

$$P(a,b) = P(a|b)P(b)$$

This formula can certainly be extended for a joint of more than two variables, which leads to the *Chain Rule*:

$$P(x_1, ..., x_n) = \prod_j P(x_j|x_1, ..., x_{j-1})$$

Applying the Chain Rule allows for the decomposition of a joint probability distribution into a product of conditional- and marginal distributions.

This immediately results in the following semantic advantage: Now the system of variables in scope can be described by their marginal distributions (as elementary properties) and their relationships in terms of conditional probabilities. *So to speak, global probabilistic propositions can be decomposed into local ones.*

Graphs and Conditional Independence

Within the Chain Rule, indirect relationships between variables are represented explicitly. This prohibits the design of a network model, of the system, since it would contain unnecessary connections between the marginal distributions. This can be avoided by accounting for *conditional independence* [14] of the considered variables: Two variables *X* and *Y* are said to be conditionally independent given *Z if*

$$P(x|y,z) = P(x|z) \text{ whenever } P(y,z) > 0$$

Given, that our network model should map the directions of the relations [15]and should furthermore contain no cycles (which is imperative since the elementary relations are to be represented simultaneously), we can find the set of prior variables in this network which makes a certain variable *xj* independent of all its other predecessors . This set is called *Parents of xj* or *paj* . To eliminate all indirect connections towards *xj* out of the directed and acyclic network, the *Parents of xj* need to satisfy the following condition:

[14] More implications of conditional independence can be found at Pearl (2000) p.11, Graphoid Axioms".

[15] Usually one has to decide on the ordering of the variables by causal intuition. Nevertheless there exist methods to extract causal orderings form data as is introduced at Pearl (2000).

$$P(x_j|pa_j) = P(x_j|x_1, ..., x_{j-1}) \text{ for all } x_1, ..., x_{j-1} \text{ prior to } x_j$$

This is the *Markov-Parentship-Criterion* for *directed acyclic graphs*. It is exactly this criterion which is employed to define the autonomy, resp. isolatability of an object with respect to certain, *a priori known* properties.

The Parentship-Criterion can easily be applied to the Chain Rule. This finally allows for the decomposition necessary for local representation of a joint probability distribution by a directed acyclic graph by invoking the *Chain Rule for Bayesian Networks*:

$$P(x_1, ..., x_n) = \prod_i P(x_i|pa(x_i))$$

This equation, together with the prerequisite of representation of the conditional independence-relations between the marginal distributions via a directed acyclic graph defines a bayesian network.

Inference in Graphical Models

Reasoning in Probability Calculus consists basically of *projecting* a joint probability distribution down to subsets of it: may that be joints, marginals or conditional probabilities.

So, the joint probability of two variables (*Y;X*) can be projected towards the probability of the occurrence of a certain value *yi* of the variable *Y* by summing over the values of *X*:

$$P(y_i) = \sum_{j=1}^{m} P(y_i, x_j)$$

This is also called *marginalization* and is denoted the following way, if applied to distributions:

$$P(Y) = \sum_{X} P(Y, X)$$

Conditional probabilities can be accessed by employing both fundamen- tal theorem and marginalization:

$$P(y|x) = \frac{\sum_s P(y, x, s)}{\sum_{y,s} P(y, x, s)}$$

As stretched before, the strength of Probability Calculus can be seen in the natural ability of performing *abductive* resp. *likelihood reasoning* e±ciently. The inversion of a conditional probability is accomplished by *Bayes' Theorem*:

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)} = L(x|y)$$

But as mentioned, a necessary prerequisite for all computations but for abductive reasoning is access to the joint probability distribution. This may only be the case in the most seldom cases, since it grows exponentially with the number of variable values. Consequently, the local representation by a Bayesian Network allows for the employment of local computations in order to gain results which may be intractable by common methods. This is accomplished by the various *inference algorithms*. For more information on this topic, the reader is referred to Baldi / Brunak (2001), Gilks *et.al.* (1995), Jensen (2001) and Pearl (1988, 2000).

System Interpretation

With respect to application, systemic interpretation of probability models represents the core of this approach. It consists in a classification of possible statements with respect to the methodological considerations made above.

In short, the systemic semantics associated with Graphical Models can be summarized as follows:

- *Objects* are mapped on sets of random variables.
- *Causal mechanisms* are mapped on conditional statements.
- Expressions (conditional statements included) which contain only marginal terms are defined al *local*.
- Expressions (conditional statements included) which contain joint terms are defined al *global*.

Application of this semantics to level transitory analysis will be demonstrated subsequently. It is noteworthy that such a semantic could be in principle be ported to a different calculus, with some function of *single variables* designating *local* statements and and some function of a *set of variables* designating *global* statements. What would need to be examined is the syntactical basis of the notion of

„causal mechanism“ (as it is connected to the notion of identity) and the according mechanism of inference.

I do not present such a porting at this point. However, the reader may consider the idea when he is analyzing a model of his own, which is not a probabilistic one. To me, the above methodological ideas seem possibly quite fertile, even if they are not implemented using the most powerful tool. [16]

Operationalization and Parameter Learning

It is inevitable to mention another core strength of probability theory, namely it's capability of modeling real world data. The reader may be familiar with the ubiquitous statistical methodology which is used for this task.

However, with *stochastic measurement theories* (compare van der Linden / Hambleton (1997)) there exist tools which are explicitly designed to parameterize social science models. A key aspect of those tools is the employment of maximum likelihood, resp. maximum *a posterori* methods for inference of hidden parameters. Obviously these tools go hand in hand with a probabilistic approach to system representation, resulting in the possibility of very sophisticated operationalizations, which is normally not paralleled in Agent Based Modeling.

[16] Admittedly, there may be pragmatic reasons to abstain from direct probability formulations, as lack of computing power or convenience of formulation.

A Toy Example

Now I will give a brief example in form of a reproduction of the so called *„Kirk-Coleman-Model“* (see Kirk / Coleman 1967 and Schwenk (2004b)), which is non-operational and simulates the dynamics of interaction and liking in a three-person group.

Brief Model Description

Theoretical basis of the original model are the „social behaviorist“ works of Homans (1961), while the actual version is modified in direction of Expected Utility-Theory and Social Impact Theory. The qualitative structure of the model is like this:

Within every „agent“ *Ai* there exist three types of (local) random variables:

- It’s *Attitudei*
- It’s *Trustij* to the other „agents”*Aj*
- The communicative *Actioni* it will chose

The structure of functional dependencies *BAi* attributed to the variables of a single „agent' *Ai* is the following:

$$\begin{aligned} \mathcal{B}_{Ai} = \{&(\Delta Attitude_{ij}, Trust_{ij} \rightarrow Action_i), \\ n(Neighbours) * &(Attitude_j, Action_j \rightarrow Attitude_i), \\ &(Action_j, Trust_{ji} \rightarrow Trust_{ji})\} \end{aligned}$$

For reasons of brevity, I will abstain from giving a detailed description of these functions, the reader may be referred to Schwenk (2004a) pp.45. However it should be noted, that these functions are implemented as discrete probability tables.[17] If those dependencies variables are coupled over the agents, the graph of a time slice of the model looks as depicted in *Figure 1*.

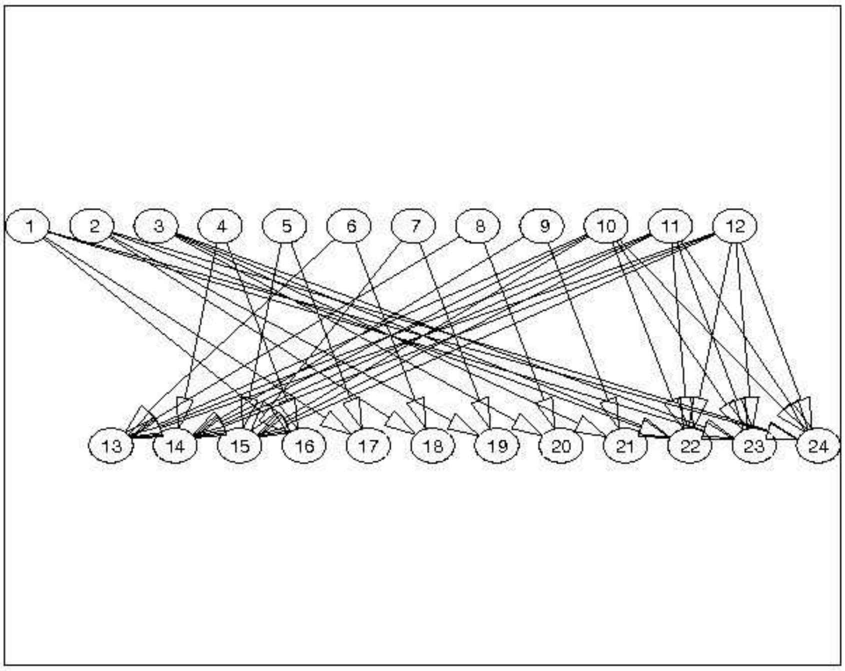

Figure 1: The top line of nodes represents the systems composition at time *t*, the bottom line at time *t + 1*. The first three nodes in a line represent the action variables of the respective „agents' (indexed $i = \{1; 2; 3\}$), the following six the trust variables for every possible interaction (indexed $ij = \{12; 13; 21; 23; 31; 32\}$) while the last three nodes in a line represent the "agents" attitude variables (indexed $i = \{1; 2; 3\}$).

[17] A major reason for this has been restrictions on the availability of inference engines (compare the previous section) in line with project schedule.

Higher Level

Subsequently I will demonstrate an instance of level-transitory analysis, with the levels being defined *a priori*. (Reason for this is that the model has only a single attractor which is actor's indifference, resp. a joint uniform distribution over all variables. Being a constant property, it cannot supply a meaningful partition of the systems state space.)

One possible definition of the systems global *property space* is given by Heider's (1958) *Theory of Structural Balance*. The theory can be summarized in metaphorical terms as follows. If within a three person group (a triad) [18] relations like „the friend of my friend is my friend" and „the enemy of my friend is my enemy" are fulfilled, the triad is said to be *balanced*. Otherwise, the triad is unbalanced, which leads to *cognitive dissonance* and consequently instability of the configuration. [19]

Within the model at hand, differences between „agents" attitudes have been mapped towards an evaluation variable. Is this difference lower than a certain threshold, the evaluation of the respective other agent is positive (+), otherwise it is negative (-). Thus the attitude space of the model has been mapped onto an evaluation space which is partitioned by Balance Theory into *balance states* and their *realizing configurations* (commonly called P-O-X triples), as depicted in *Figure 2 and Figure 3*.

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[18] Generalization to sets of triads is both feasible and common.

[19] A memory hook for this rule may be that it parallels multiplication of signs in elementary algebra. `The enemy of my enemy is my friend' can be modeled by (-) * (-) = (+)

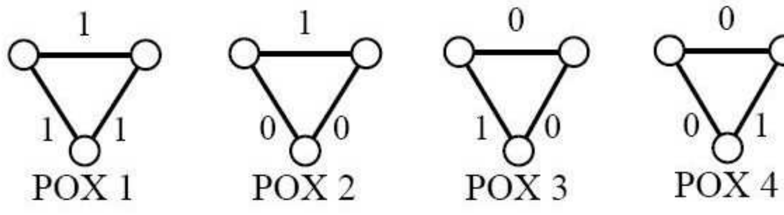

Figure 2: Balanced Triads (0 ≡ -, 1 ≡ +)

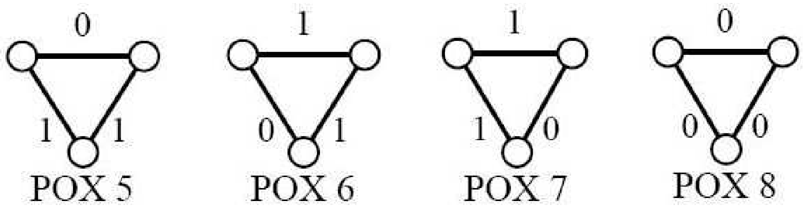

Figure 3: Balanced Triads (0 ≡ -, 1 ≡ +)

Level Transition

With this as starting point one could arbitrarily ask, how the immediate choice of an interaction partner (a *local* property) might depend on the balance state of the system, resp. on its realizing triad configuration (both being *global* properties).[20] As showcase, I choose agent 2 as target of „top-down influences". This results in computation of the following quantity over the possible configurations of its conditions:

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[20] As stated before, it is very important to note that such top-down-in°uences *must not* be called causal, since in this case the notion of level would be rendered meaningless. It is a better formulation, that the top-down formulation aggregates over the processes of the system. Compare Schwenk (2004b);

$$P(Action_{2,t+1} = x | Attitude_{1,t} = w, Attitude_{2,t} = y, Attitude_{3,t} = z)$$

The probability distributions have been aggregated to be mapped on balance states, according to their respective definition. This yields the following table, which describes the phenomenological top-down dependencies between balancedness and interaction choice of „agent" 2, which is now labeled „O" according to Balance Theory schematics.

Class	$P_{mu}(Action_O\text{=}P)$	$P_{mu}(Action_O\text{=}X)$	$SD_{Pmu}(Action_O)$
P-O-X 1	0.5000	0.5000	0.0490
P-O-X 2	0.7273	0.2727	0.1080
P-O-X 3	0.5000	0.5000	0.2031
P-O-X 4	0.2727	0.7273	0.1080
P-O-X 5	0.3954	0.6046	0.0344
P-O-X 6	0.5000	0.5000	0.0421
P-O-X 7	0.6046	0.3954	0.0344
P-O-X 8	0.5000	0.5000	0.3674
Balanced	0.5000	0.5000	0.1887
Unbalanced	0.5000	0.5000	0.0714

For interpretation the reader is referred to Schwenk (2004a) pp.68. Reason for sparing the interpretation is the arbitrariness in choice of the threshold of the mentioned evaluation variable. Large parts of the interpretation are determined by this, which is one of the reasons to call it a „toy model". However, what is important for this demonstration, is the *logical structure* of these level-transitory inferences.

Prospects – Employing the Methodology

I will conclude this article with a remark concerning advantages and handicaps of an probabilistic approach to actor-centered modeling. The key issue is the following:

Coherent higher level and level-transitory inference is no matter of course in the analysis of structured systems. However, this is necessary since *comprehension of complex processes is always accompanied by the introduction of functional higher levels*. As shown, Graphical Models can be supplied with a precise interpretation which allows exactly for this.

Returning to application, it may not be advantageous to em ploy a probabilistic approach under some circumstances. This may be the case if the model has a large number of components and/or has long range focus; Here probabilistic inference may be simply too time consuming. On the other hand, the project may heavily rely on intuitive model formulation, as for example a participatory modeling enterprize. In this case, a probability model may be harder to communicate than some alternative, e.g. rule-based model.

The most frequent case may simply be that component theories of a model are formulated in deterministic language. Maybe an effort to reformulate those probabilistically is feasible, or alternatively a *post hoc* probabilistic model can be set up on simulation data; Even if this is not the case, I still encourage the reader to keep above methodological considerations (and especially systemic semantics) in mind, while he is inferring conclusions from his own model.

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Chapter three: Simple Heuristics in Complex Networks: Models of Social Influence[21]

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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 the

[21] Part of the simulation study has been presented at the Annual Meeting of the Cognitive Science Society (see Schwenk & Reimer, 2007).

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

Research into group decision making indicates that group decisions often strongly 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 will 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 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 fraction 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 particular, 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 have extended 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 & Lin (1998), as well as Sun & Nahve (2004), we argue that it is important to consider agents' cognitive capabilities when examining information processing in a multi-agent environment. 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. To be more precise, agents contacted each other based on certain contact rules and updated their individual opinions based on certain decision strategies that integrated the opinions of their fellow neighbors who were contacted.

Overview

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 change 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).

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.

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 and conducted a systematic study of the model's behavior.

Background Scenario

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

We implemented the above scenario in the simulation model 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 (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 strategy. This 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 in the extent to which they considered the preferences and status values of the agent and his/her neighbors in the network. Note: this environment was dynamic in that the simulation proceeded by computing repeated updates of all preferences of individual agents.

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 s_i of an individual status variable S having continuous values in the range of $(0.5,\dots, 1.0)$. 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 r_d and maps an agent's actual decision state d_{j_n} onto his/her subsequent state d_{i_n+1}. The iterated and sequential call of this decision rule *f* for all agents results in a dynamic evolution of the model.

In the next 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

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. In our simulation we considered

$$Contacted = Neighbors$$

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 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 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 levels of expertise are at times more influential in the group decision process than members who have less expertise (e.g., Bonner, Baumann, Lehn, Pierce, & Wheeler, 2006). Note: both rules include the searching agent himself/herself as an information source.

Regarding the decision component, 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 strategy, the *“weighted additive model”* or *WADD*-rule, is a compensatory rule that integrates all of the available information. WADD chooses the alternative with the highest weighted sum; the weight being the cue’s respective validity. In the present application, 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. In more formal terms, 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.

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 about individual status is ignored. The UWM strategy therefore determines the number of neighbors who favor a specific alternative and adopts 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:

$$E_{Ai} = \sum_{j=1}^{k} o_{ji}$$
$$O_A = E_{Ai} \Rightarrow \max!$$

The third rule is a decision heuristic called the “*minimalist*” or *MIN*-rule. 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:

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

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 *j* with the highest status w_j 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) and can be expressed using the following equation.

$$O_A = O_j \mid j \rightarrow \sup(w_j)$$

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 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)
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 for 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 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.

We considered three shapes of status distribution, 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).

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.[22] 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, which we systematically varied in our simulation, was 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 & 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 analyses 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.

More specifically, we generated random graphs from the family of so called "*small world networks*" (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.

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

An intuitive illustration of the small world model can be given as follows: let us 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, 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 generated small world networks as suggested by Watts (1999). The implemented procedure has been 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 yields high local clustering, thus representing a characteristic of spatial organization. After this 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 $p_r = (0.001,\dots0.2)$, led to the creation of a network with the mentioned *small world* effect: strong clustering, but no isolated highly clustered regions. A graphic example of such a small world net is displayed in *Figure 1*.

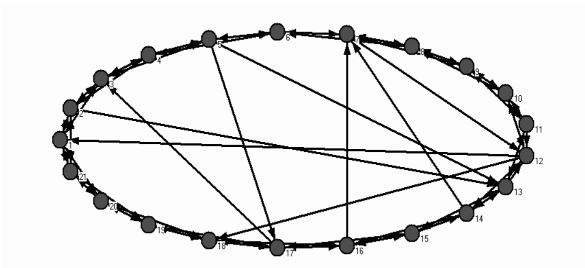

Figure 1: Small world network (*n=21, k=2, p=0.1*). Note: The network has been created by introducing shortcut ties to a regular ring network, where every node is connected to two neighbors on each side.

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, 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. Furthermore, we set the number of agent's neighbors to approx. four ($k=2$ on each side) over all three variations.

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

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

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

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

In the next step, 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

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 α=0.01 level.

Equilibrium and final distributions of individual opinions

Equilibrium has been achieved in all variations of the model at considerably fast rates. While it took groups employing a MIN decision rule approximately 25 cycles on average to reach a static equilibrium, 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.

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 this particular strategy does not defend any preference held at a certain step of the process. Exceptional cases are the ALL-UWM and ALL-WADD strategies in the random regular network, which showed substantial probabilities of unanimity of 18% and 6%

respectively. Typically, 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 equivalent distributions of faction size for all status distributions considered.

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 structure on the distribution of faction sizes, as can be seen from *Figure 2*. Here, results were sorted according to the size of the faction in an individual simulation run, regardless of the actual choice alternative favored.

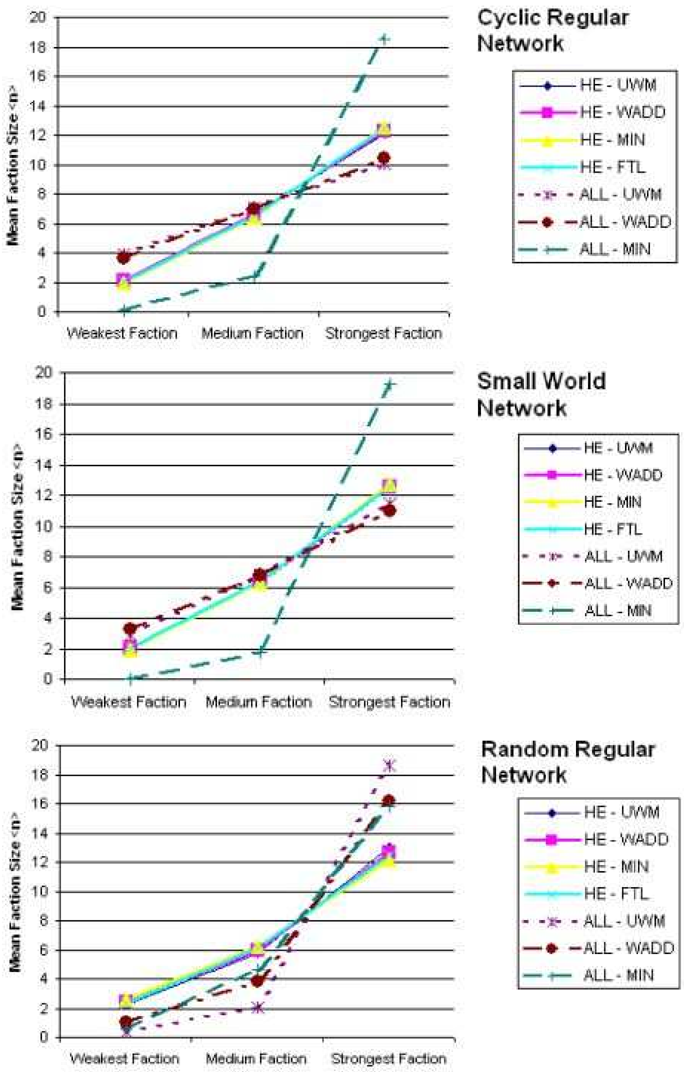

Figure 2: Mean faction sizes over networks with decreasing clustering. Results were sorted according to the size of the faction in an individual simulation run, regardless of the actual choice-alternative favored. A majority is reached at eleven.

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

Strategies containing the HE rule tend 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 unstructured random regular network. This is in coherence with Latane & L'Herrou's (1996) finding that clustering stabilizes minority positions.

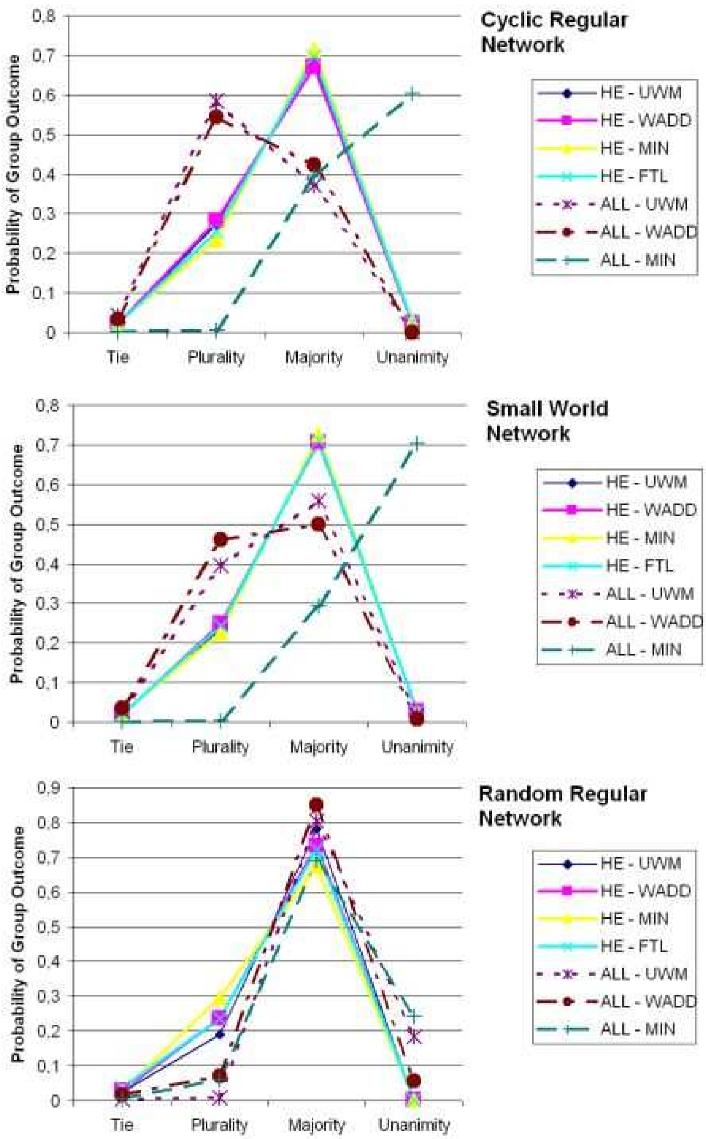

Figure 3: Group level outcomes over networks with decreasing clustering.

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 occurs 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 large 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 insensitivitizing effect of the HE- contact rule, concluding that this effect is not due to the triviality of local decision environments.

We presume that the HE-rule systematically modifies the network which is actually 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”. However, we lack a model to infer properties of this network in order to support our suggestion systematically.

Identically shaped distributions of expected faction size 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.

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

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

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

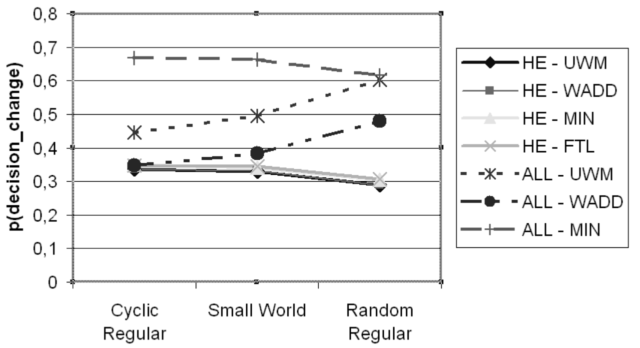

Figure 4: Probability of decision change of high status members over networks with decreasing clustering (cyclic regular, small world, random regular)

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

If all neighbors were contacted, regardless of their status, as was the case for the 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 change of high status members was, which increased in parallel about 15% for both decision rules. However, the completely status insensitive UWM-rule shows a respective probability which is constantly approx. 10% higher than for the WADD-rule. The MIN rule shows a maximum probability of decision change of high status members, which remains constant over all considered networks. For completeness, it should be mentioned that in a completely connected network, the examined strategies show only minor differences with regard to the probability of high status members' opinion change, which ranges from 54% to 67%.

The results for the different network types can be summarized as follows: contrary to the exception of a completely connected network, the rules' behavior varies considerably over the networks of the small world family. The rules which are status-sensitive with respect to their contact behavior (i.e. the rules containing an HE - component) are *insensitive* to changes in the networks' clustering structure. In contrast, the rules containing an ALL - component, 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 clustering.

Status Distributions

Another interesting finding regarding the decision rules can be seen in *Figure 5*. The figure displays the probability with which high status members changed their opinion separately for different status distributions. Here we consider the impact of the steepness of status distributions on the probability of decision change 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.

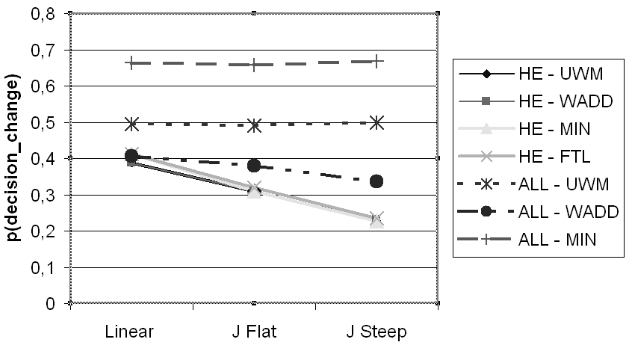

Figure 5: Probability of decision change in high status members in a small world network over status distributions of increasing steepness

Again, strategies based on the hierarchy-oriented HE-contact rule showed virtually identical behavior. However, the HE-decision strategies 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 can preserve their initial decision more effectively in environments with a steep hierarchy. To a lesser 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 less affected by variations in status distributions.

A Case Study

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.[23] 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 were interested in eventual sensitivity of the equilibrium distribution of the process towards variation of the decision strategies employed by the agents.

Empirical Data

The empirical setup of the case study is similar to our systematic simulation experiment, apart from the following differences: the employed data deals with the interaction of *n=36* partners and preferences on a binary policy variable, namely whether new cases in the law firm should in future 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 narrow majority in favor of preservation of the as – is policy.

[23] At this point, we would like to thank Dr. Lazega for his kind permission to use his data for the present study.

However, this situation might change due to influence processes occurring among the lawyers of the firm – which we tried to infer by simulation.

In order to model the influence process, partners were asked to say who they pay special attention to at partnership meetings. We transposed the reported adjacency matrix in order to convert “listening”- into proper “influence”- relations. The partner’s status was estimated via the reported individual hourly work fee, which they 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*.

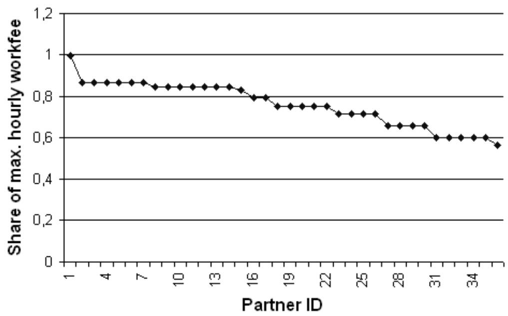

Figure 6: Status distribution of partners in an empirical network. Partners are numbered according to seniority.

Unlike in our systematic simulation experiment, the empirical data shows a certain dependence between higher status and preference of 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. In contrast, *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 original.

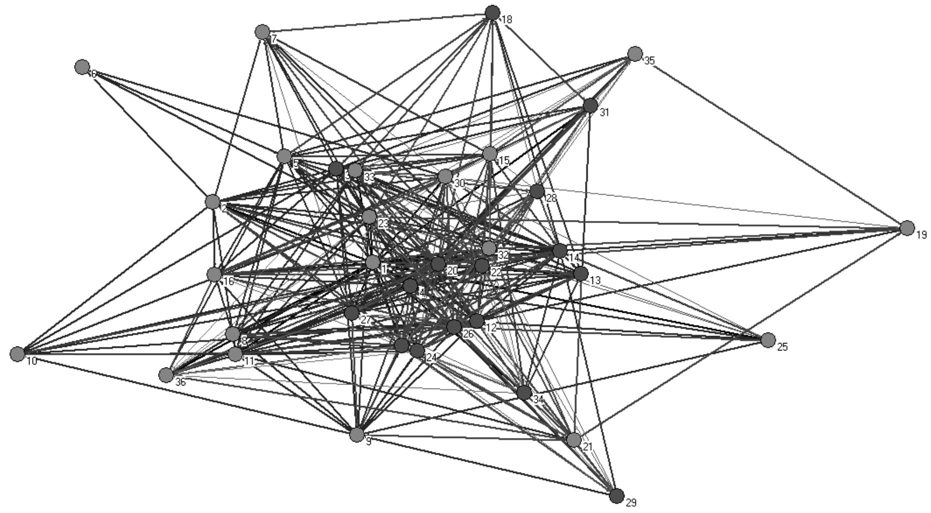

Figure 7: Empirical influence network. Highly connected partners are located in the center of the network. Dark and wide arrows represent high status relations. Green nodes represent an “as - is” and red nodes a “less flexible” policy opinion. Partners are numbered according to their seniority.

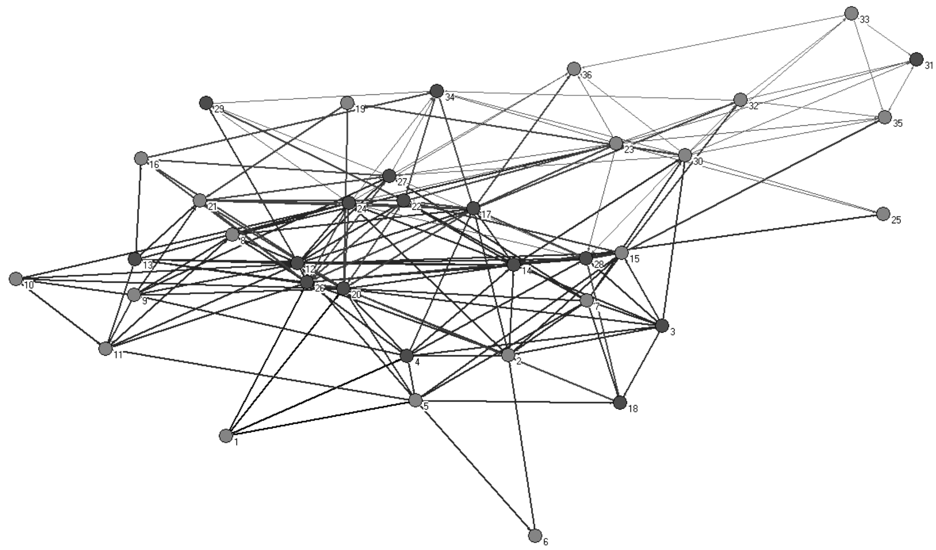

Figure 8: HE – relevant subnet of the empirical influence network: highly connected partners are located in the center of the network. Dark and wide arrows represent high status relations. Green nodes represent an “as - is” and red nodes a “less flexible” policy opinion. Partners are numbered according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

Inferences

The deductions taken from the simulation model for the empirical case are given in *Table 3.* 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: Equilibrium preference distributions for the considered strategies as inferred from empirical data. 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 equilibrium distributions depart considerably from the initial distribution. The results for strategies containing the MIN rule are stochastic, while the others are reached deterministically.

Strategy	n(as-is)	n(less flexible)	equilibrium cycle
HE - UWM	34	2	7
HE - WADD	34	2	5
HE - MIN	Majority	miniority	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	--

In general, the initial majority preference (which was preservation of the decentral case assignment policy) prevailed in the influence process and was able to suppress 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 from our systematic simulation experiment, the compensation characteristic of 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 summariy, 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.[24] 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 is dependent on the employed decision strategies, could bear the potential for discussion or even conflict in the future.

Conclusion

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 (cf. French 1956, Latané 1981, and Turner 1996). Following this rationale, we examined the interaction of decision strategies and features of the communication network.

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 the minority factions[25], which is in coherence to the results of Latané & L'Herrou (1996). However, when agents chose only higher status neighbors as information sources, the size of the minorities decreased. Of equal importance is the fact that in this case the distribution of equilibrium factions became independent from the clustering structure of the network. The steepness of the status distribution, which has no influence on

[24] In contrast to our procedure in the systematic simulation experiment, we abstain from presenting probabilities of decision change for high status partners. The reason is that in our experiment we assumed neither initial majorities nor correlation between preference and status, as is the case for our empirical data. The empirical circumstances result in in homogenous local neighbourhoods, which compromise the interpretation of a global probability of decision change in high status partners.

[25] In turn this certainly implies the decrease of size of majority factions.

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.

We also focused on the influence of low status agents on the preferences of high status agents. A change of preference of high status members was most probable when status played no role for contact behavior and hierarchies were flat. Given that the information of all neighbors was collected and integrated, a stronger influence of low status agents was obtained with a decreasing clustering, which again conforms to Latané & L'Herrou's (1996) findings.

Returning to our introductory considerations on 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. So does the consideration of high status for information search lead to a situation in which the formation of majorities becomes most probable, even if the communication network is clustered into cohesive subgroubs. These majorities still persist if committees, which are randomly selected from the group, are given the task of reaching a group decision.

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 superorganisms (cf. Seeley 2001) and by recognized results from the study of processes on complex networks (cf. Newman 2003). Finally, 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. With this knowledge at hand, it would, for instance, be conceivable to make expertise a salient category at the onset of some discussions. Given the situation of our specific example, this 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. We are convinced that our model may prove valuable for a wide range of organizational problems.

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Chapter four: Evaluating Social Influence Relations: an Item-Response-Modeling Approach

Abstract

Subject of this paper is the measurement of social influence in social networks. The theoretical point of departure is twofold. First, focus is on cognitive processing of perceived influence. Second, three distinct dimensions of social influence are considered: persuasion, authority and coercion. Combining these considerations with Item Response Theory methods, questionnaire-type measurement instruments are proposed. These instruments are employed in a closed network case study where applicability is checked by means of network autocorrelation models.

Introduction

Measurement of social influence in closed networks has a long tradition which can be traced back to French's "Formal Theory of Social Power" (French 1956). French & Raven's (1959) considerations on "The Bases of Social Power" in a follow-up paper have become classics in modern social psychology. The question of how to model influence weights was also put forward before the background of network autocorrelation modeling. In this case the answers were prominently based on considerations about structural features of the network in focus (cf. Friedkin 1998, Leenders 2002).

In this paper we want to contribute to answering this question. We will employ an approach, which is cognitively oriented and relies on item response theory for direct measurement. The latter methods are very popular in educational assessment and have already been successfully applied to the subject of social capital by (van der Gaag & Snijders 2005).

Social Influence and Cognition

It is a prominent conception to view social influence as being “power in action”. Central to this conception is the idea that power is a more or less persistent relation between individuals, whose potential may be realized in certain situations. In this framework, power is based on the capacity of the powerful person to control the powerless person’s outcomes. However, there is discussion regarding the nature of the outcomes which are relevant for power processes
(cf. Emerson 1981, Festinger 1950, French & Raven 1959, Turner 1991).

Despite the undoubted plausibility of this view, we want to conceptualize social influence in a different way. It seems to us that regardless of how strongly an influence relation is rooted in
certain “bases of power”, its appreciation by the target person is a necessary condition for it to be effective. Therefore we would like to understand social influence as an instance of
information processing rather than as an activity of “social forces”.

This approach promises several advantages, as compared to the relational model of power. The first advantage is that focusing on cognition allows us to build more elementary models of influence processes which highlight the causal assumptions held for the agents (viz. patients) of the influence system (cf. Schwenk 2006). The second advantage refers to the fact that attributes of elementary entities are often measured more easily than those of compound entities.

We have discussed a cognitive model of social influence which is based on the idea of ecological rationality (cf. Gigerenzer et al. 1999) in more detail elsewhere (see Schwenk & Reimer 2007), and only want to state a central assumption at this point. We assume that dyadic influence relations can be sensibly represented by a certain quantity which is attributed by the target person to the influence source. We expect such a quantity (it may be called the intensity of influence) to be key to the influence target's consideration of the
source, respectively for integration of influence-related information provided by several sources. In essence, we will frame social influence as a decision process, based on social cues and their perceived validities.

In this paper we want to discuss a way to provide these ideas with operational content. Summarized, we will focus on measuring subjective evaluations of neighbor attributes in the respondent's network.

Modes of Social Influence

Of course it is plausible to assume more than one dimension of influence to be effective. However, before the background of a cognitive model of social influence it might not suffice to just focus on the different bases of power as French & Raven (1959) do in their well-known paper of the same name. The reason is that, in addition to power, we can imagine further neighbor attributes to be relevant for consideration and processing of communicated information.

Concerning the qualities of social influence processes, we will start our attempt to the subject with Turner's (2005) Three Process Theory of Power. Although we hold some reservations regarding this theory, it should be possible to clear them up, resulting in a viable approach to measuring social influence on the basis of a cognitive model.

Turner's Three Process Theory of Social Power

(Turner 2005) names three core "processes" of social influence: *persuasion*, *authority* and *coercion*. In combination, these clearly exceed the concept of power, which can be related to the latter process of coercion. We want to add that Turner is not explicit with regard to the cognitive structure of those processes. On behalf of our purposes, we will proceed by identifying the capability to induce them with our mentioned dimensions of influence sources.

Interestingly, Turner's combination can be seen as joining major traditions of social psychology and sociology. We will discuss this after a short excursion to Turner's view on power, which presents his admitted motivation to pool the three mentioned "processes".

Power Over Both Volition and Action

Turner (2005: pp.5) argues that traditional research, which defined power as the *potential to exercise influence*, has neglected the fact that power is exerted "through people" and not

only "over people". Hereby is obviously meant that power is not only a feature of an exerting agent, but itself needs to be processed "through" compliant persons who, in the end, act upon a given environment. In order to account for varying degrees of voluntary compliance which may be present during the exercise of "power through others", Turner introduces the three mentioned modes of social influence. Obviously, coercion necessitates a lower amount of voluntary compliance, as compared to authority or even persuasion.

In our opinion, Turner's argumentation correctly refers to the aspect of processing of influence, but this could have been done more elegantly. The concept of "power through people" mixes the active and passive aspects of social influence. From the point of view of a cognitive approach, which focuses on consideration and the processing of influence, it is certainly possible to determine the receiving end respectively patient conditions under which an agent can exert influence. This renders a new concept of "power through people" unnecessary.

Furthermore, by replacing the phrase "power through others" with "power over volition and action", we might introduce a concept which also distinguishes between the three modes of influence on the basis of voluntary compliance. In our view, the attractiveness of such a concept would lie in the fact that it is both easily tractable and close to our personal experience.

Despite our criticism regarding the necessity of his new concept of power, we want to emphasize our position that Turner is convincingly right with his choice of what we like to call dimensions of social influence. We will sketch those subsequently with special attention to alternative derivations.

Persuasion

An obvious connection to Turner's previous work is made by referring *persuasion* to the self-categorization-theory of social influence (Turner 1987). Here, social influence is identified as some kind of informational dependence, which is called "social reality validation". A person is expected to be receptive to influence when she is unable to exert full control over a given task. In such a situation she will tend to socially validate the nature of the task. The degree of receptiveness is assumed to depend on the perceived similarity of the influence source to the person in focus. The linking assumption is that influence sources which are perceived as similar (belonging to the same "*category*") should bear useful information for the task at hand.

It should be noted, that by concentrating on mere individuals we deliberately depart from the standard use of this theory, which focuses directly on group behavior.

Authority

Turner (2005: p.11) defines *authority* analogous to what French & Raven (1959) call "legitimate power"; namely as "the power to control in-group members because they are persuaded that it is right for a certain person to control them in certain matters". As may be natural for a sociologist, the author would like to refer to Weber's (1984) classical and largely congruent concept of "legitimate order".

Coercion

Coercion is defined by Turner (2005: pp.12) as being "the attempt to control a target against their will and self-interest through the deployment of human and material resources to constrain and manipulate their behavior". Again following Weber (1984), we might extend "against the target's will" towards "regardless of the target's will".

As noted before, Turner (2005: pp.15) identifies coercion as being the "pragmatic power process in standard theory". We basically agree with Turner in this point, but want to note that the degree to which a person may be voluntarily involved obviously depends on the type of outcome controlled by the powerful person.

Item Wording

We attempted to express the above considerations in the form of a questionnaire-type instrument. A common idea underlying all item wordings is that they should reflect our cognitive interpretation of Turner's theory and be situationally unspecific, in order to indicate persistent traits and allow broad application.

Evaluation of a contact's ability to persuade the respondent, as understood by self-categorization theory, was handled as an exception. As mentioned above, persuasion has been decomposed into two separate concepts: informational dependence and perceived similarity. Unfortunately the former is strongly situation specific. We therefore developed an IRT-scale only for the situationally unspecific aspect of perceived similarity. In application, its measures can be used as weights for a specially tailored evaluation of task- or situation specific informational dependence. The resulting product should yield a viable estimate of the perceived potential to persuade in the respective situation. In summary, the instruments subscales can be listed as follows:

- *Persuasion* is measured by two subscales:
    - *Perceived similarity* focuses on the perceived helpfulness of a contact person regarding own problem coping.
    - *Informational dependence* is supposed to be measured tailor-made to the application, because of its situational specificity.

- *Authority* focuses on the perception of rational and accepted authority of a contact person.
- *Coercion* focuses on a contact person's use of coercive means in everyday interaction.

During the pretest, the respondents were presented 58 items in total, with approximately a third of them representing the item pool for an individual item set. Items were selected according to the results of a quantitative item analysis. Items were both expected to show an acceptable fit and to form an item set with easily intelligible semantics. The items selected for the three subscales considered are listed in *Table 1*. Responses were allowed to range on a five point agreement scale

Table 1: English translation of selected items (which were originally presented in German). The mean responses indicate the difficulty structure of the respective item set in the calibration sample. Agreement ranged on a 0-4 scale, with "0" representing "I do not agree." and "4" representing "I agree.".

Perceived Similarity		*Mean*	*Std. Dev.*
Item 1	This person has similar habits to me.	2.71	1.03
Item 2	This person is someone who often faces the same problems as me.	2.47	1.11
Item 3	This person knows many people who face the same problems as me.	1.80	1.10
Authority			
Item 1	This person has gained valuable experience.	2.77	1.08
Item 2	This person has accomplished much in her life, one should conform to her.	1.85	0.98
Item 3	I have often conformed to this person.	1.78	1.16
Item 4	It is normal to conform to this person.	1.08	1.03
Coercion			
Item 1	This person starts arguing if you have a different opinion.	1.97	1.30
Item 2	It may have consequences if you have a different opinion to this person.	1.14	1.22
Item 3	This person gets angry if you have a different opinion.	0.59	0.99
Item 4	This person will avoid me if I have a different opinion.	0.38	0.83

Measurement Model

Taken together, we were interested in measuring the strength of beliefs about another person's capability to induce influence over the above mentioned dimensions. We decided to employ an Item-Response-Theory (IRT) measurement model (cf. Embretson & Reise 2000, van der Linden & Hambleton 1997) for several reasons.

Firstly, IRT models allow the measurement of a latent trait on interval scale (as we assume by focusing on intensities), with only ordinal scaled observations given. This property is known as "conjoint measurement". Secondly, since the estimation of latent traits is explicitly related to response patterns, scale values can be given a rather “objective” interpretation, as compared to the standard procedure of assigning quantiles in a norm population. A third, and rather obvious advantage, as compared to factor analytic techniques, is that IRT models allow for skewed (and even dichotomous) response distributions.

The Rasch Model

The IRT’s fundamental principle is exemplified by the well known “Rasch Model” (cf. Embretson & Reise 2000: pp.65). Here both item and person are assumed to show differing degrees of intensity of the dimension to be measured. For example, some item could require a certain amount of perceived authority from a person in order to be agreed upon. Conversely, if the person fails to show this amount of authority, the item will not be agreed upon.

In practice, one expresses a probabilistic version of this idea. The Rasch-Model is a member of the logit-family and models a response probability via a logistic function, whose parameters are dependent on the difference in intensity between item and personal trait.

$$P(X_{ij}=1\,|\,\theta_j,\delta_i)=\frac{\exp(\theta_j)}{1+\exp(\theta_j-\delta_i)}$$

$P(X_{ij}=1\,|\,\theta_j,\delta_i)$ is the probability of a positive response $X_{ij}=1$ of person *j* to item *i*, given the latent person trait parameter θ_j and the latent item parameter δ_i. This probability is dependent on the logit θ_j, which is, as mentioned, simply the difference between those parameters. θ_j is often denoted as the “trait level” or “ability” and δ_i as „item difficulty“.

Essentially, the Rasch-Model has two fundamental assumptions. The first is obviously that the dependence between trait level and response probability can be described by a sigmoid-curve. The second assumption is about the local conditional independence of the items given the latent parameters. This implies that all correlation between the items must possibly be explained by the difference of the latent parameters θ_j and δ_i.

Since in the Rasch-Model the parameters of interest are latent, they have to be inferred abductively. This can be accomplished by the employment of several maximum-likelihood methods (cf. van der Linden/Hambleton 1996) or the MCMC-simulation of their a-posterori distribution (cf. Gilks *et al*. 1995).

Assessment of individual persons during application of a calibrated Rasch-Model (or one of it's derivates) is done by estimation of their trait level with fixed item difficulties. These fixed values of the item parameters have to be obtained beforehand by an appropriate calibration sample.

Employed Polytomous IRT-Models

Two models have been applied to data in the actual measurement task. Both are extensions of the Rasch-model for polytomous data and share its features and basic interpretation.

The Partial-Credit-Model (PCM)

The “Partial-Credit-Model” focuses on modeling the probability of a response to the particular higher of two adjacent categories. So to speak, an individual Rasch-Model is estimated for every threshold between the neighboring categories of a polytomous item. The Partial-Credit-Model can be written as follows.

$$P(X_{ij} = x \mid \theta_j, \delta_{i1}, ..., \delta_{im}) = \frac{\exp \sum_{k=0}^{x} (\theta_j - \delta_{ik})}{\sum_{h=0}^{m_i} \exp \sum_{k=0}^{h} (\theta_j - \delta_{ik})} \mid x = 0,1,...,m$$

The target quantity is now the probability $P(X_{ij} = x \mid \theta_j, \delta_{i1}, ..., \delta_{im})$ of person *j* scoring category *x* to item *i*, conditional on the person trait level θ_j and the difficulties δ_{ik} of the item *i*´s *m* category thresholds. For a more detailed explanation, we would like to refer the reader to Masters & Wright (1997).

The Rating-Scale-Model (RSM)

The Rating-Scale-Model is an important special case of the Partial-Credit-Model, which assumes the same structure of distances between the threshold difficulties δ_{ik} for all items $i \in [1,2,...,s]$. This is usually a reasonable assumption when the item set shares a common response format. The model can be written as follows.

$$P(X_{ij} = x \mid \theta_j, \lambda_i, \delta_1, ..., \delta_m) = \frac{\exp \sum_{j=0}^{x} [\theta_j - (\lambda_i + \delta_k)]}{\sum_{x=0}^{m} \exp \sum_{j=0}^{x} [\theta_j - (\lambda_i + \delta_k)]} \mid x = 0,1,...,m$$

Again, the target quantity is the probability $P(X_{ij} = x \mid \theta_j, \lambda_i, \delta_1, ..., \delta_m)$ of person *j* scoring category *x* on item *i*, but now it is conditional on both the person trait level θ_j, the *common* difficulties δ_k of the item *i*´s *m* category thresholds and an additional item-location parameter λ_i. This latter parameter adjusts the common threshold structure to the particular item. For detailed discussion, the reader is referred to (Anderson 1997).

Due to its restricted threshold structure, the Rating-Scale-Model is not as flexible as the Partial-Credit-Model. This may be a shortcoming if the data indicates considerable threshold variation. On the other hand, it should avoid over-fitting better than its more complex relative.

Instrument Development

It has been our aim to develop scales for assessment of social influence in closed social networks. It is plausible to assume the existence of nodes with a rather high degree in such a context. In order to facilitate economic data collection, we decided to develop scales which contain only a few items. These would need to be presented repeatedly to the respondents, once for every one of their neighbors.

The eventually small size of the networks in which the measurement instruments should be applied also posed a restriction to our task. It is not likely that such a small network would show enough variance in responses in order to allow the simultaneous estimation of both item- and person parameters. We therefore decided to prepare instruments which can be applied in a stepwise procedure. In a first step, we developed and calibrated the instruments in a survey setting, with an abundance of responses. In a second step, we employed the instruments, with now readily calibrated item parameters, for evaluation of individual responses in a closed network setting.

Survey Setting

Development and calibration of scales in a survey setting necessitated some considerations to allow application in a closed network setting. The critical point is that in a sampled survey, respondents can not be expected to be connected at all. We therefore decided to ask the respondents to evaluate a member of their personal network.

More precisely, the respondents were asked to complete a list with (up to) seven persons that they have contact with outside their family. Then one person from the list was drawn at random, employing a method similar to the familiar „Kish-Selection-Grid“ (Kish 1965). The items that were subsequently presented then referred to this randomly selected person, measuring in fact their perceived influence on the respondent.

Our consideration concerning the listing of contact persons and subsequent randomized selection, had been to avoid developing a scale of “best friends influence”. We assumed that persons, who are salient in memory are likely to be those assigned with strong and presumably positive emotions. By asking the respondents to name seven contacts, we hoped to trigger sufficient cognitive activity to overcome this tendency.

Samples

We collected data on two occasions, the first time for pretest and the second time for calibration from the student population at the social science department at a German university.

The pretest data was collected in an advanced statistics class and consisted of 63 cases: 68.3 % of the respondents were female and 31.7 % male.

Calibration data was collected at an inter-department lecture on introductory sociology, which is commonly attended by social science students and students who are studying to become teachers. On this occasion 352 cases were collected with the gender distribution being 73.6 % female and 26.4 % male.

Instrument Stability

The ordinality structure of selected items remained constant from the pretest to the calibration sample, together with the general structure of item fit.

The only major change was observed in the “coercion” item set. In the calibration sample, mean responses for all its items dropped approximately one agreement-category on a five category scale, indicating a lower total level of reported coercion. We have put this change down to environmental effects. The pretest had been collected after a rather unpopular evening lecture in statistics. However, the calibration sample was collected after the students had been told that the rest of the day's introductory lecture would be canceled. We believe that these different levels of experienced "coercion" are mirrored in the data.

Calibration

In this section, we will discuss the properties of our calibrated scales such as threshold structure and item fit. Our considerations will concentrate on the so called "infit mean squares". This value measures the proportion of observed to expected variance, with a value of *1* indicating perfect fit and complete local conditional independence. High infit-values *(> 1.33*) indicate that only an insufficient proportion of variance can be explained by the model. This may suggest that the assumption of local conditional independence is not met, implicating the presence of different data-generating processes. Low infit-values (< *0.66*) also indicate misfit of the model, namely that items show a higher discriminatory power than expected. Being certainly suboptimal, this kind of lack of fit may however be tolerable.

Furthermore, we computed both Partial-Credit and Rating-Scale models and decided for one alternative according to an analysis of Akaike's (*AIC*) and Schwartz' Information Criteria (*BIC*). Both are aimed at a comparison of nested models while controlling for a tendency of
overfitting, which is inherent in models of increasing complexity. This is accomplished by adding a complexity penalty term to the model's deviance, indicating that the model with the lower information criterion is preferable. The complexity penalty of Akaike's Criterion is higher than that of Schwartz' Criterion.

Scale I: Persuasion / Perceived Similarity

The scale on perceived similarity consists of the following items:

- Item 1: „This person has similar habits to me.“
- Item 2: „This person is someone who often faces the same problems as me.“
- Item 3: „This person knows many people who face the same problems as me.“

Model Selection

As shown in *Table 2*, the Likelihood Ratio-Test (*LR=14.21; df=3; α< 0.005*) indicates that the Partial Credit Model fits the perceived similarity item set significantly better than the Rating Scale Model. Akaike's Information Criterion (*AIC*) prefers the Partial Credit Model, while Schwartz' Information Criterion (*BIC*) prefers the Rating Scale Model. Since the recommendations of the information criteria are conflicting, we decided to err on the side of simplicity and chose the more parsimonious Rating Scale Model for this item set.

Table 2: Information criteria and Likelihood-Ratio-tests for the competing measurement models, based on calibration sample data. Two stars (**) indicate that the LR-Test is significant on a level (α < .005).

Item Set	*Model 1*	*Model 2*	*AIC(M1)*	*AIC(M2)*	*BIC(M1)*	*BIC(M2)*	*LR*
Perceived Similarity	Rating Scale	Partial Credit	2884.02	2875.82	2903.29	2906.66	14.24**
Authority	Rating Scale	Partial Credit	3742.09	3728.86	3765.10	3771.01	23.27**
Coercion	Rating Scale	Partial Credit	3253.32	3220.75	3276.41	3263.09	42.57**

Scale Properties

Table 3 shows the scales threshold structure, whose regularity stems from application of the Rating Scale Model. As can be seen from the infit-values in *Table 3*, a single item (item 2, “This person is someone who often faces the same problems as me.”) shows considerably higher discriminatory power (i.e. lower variance) than expected under the Rating Scale Model. However, for the sake of consistent semantics, we decided to leave the item in the set. The remaining two items show rather good infit values.

Table 3: Rating Scale Model for Perceived Similarity: Item Difficulties & Common Threshold Difficulties

Item	*Estimate*	*Error*	*Infit MnSq*
1	-0.530	0.045	1.21
2	-0.187	0.044	0.70
3	0.717	-	-
Threshold	*Estimate*	*Error*	*Infit MnSq*
1	-1.122	0.077	1.17
2	-1.158	0.069	1.11
3	0.677	0.072	0.97
4	1.603	-	-

Scale II: Authority

The scale for Authority consists of the following items:

- Item 1: “This person has gained valuable experience.”
- Item 2: “This person has accomplished much in her life, one should conform to her.”
- Item 3: “I have often conformed to this person.”
- Item 4: “It is normal to conform to this person.”

Model Selection

Again the Partial Credit Model fits significantly better than the Rating Scale Model, as indicated by a Likelihood Ratio-Test (*LR=23.27; df=5; α< 0.00*). However, consultation of the information criteria is again inconclusive, since *AIC* prefers the Partial Credit Model and *BIC* prefers the Rating Scale Model, as is shown in *Table 4*. For the sake of simplicity, we again decided to employ the Rating Scale Model for the Authority item set.

Scale Properties

Table 4 shows thresholds and item fit of the authority scale. The items of the scale can be regarded as well-fitting, since all infit values show only reasonable departure from a perfect fit.

Table 4: Rating Scale Model for Authority: Item Difficulties & Common Threshold Difficulties

Item	*Estimate*	*Error*	*Infit MnSq*
1	-1.093	0.045	1.22
2	0.012	0.043	0.84
3	0.095	0.043	0.96
4	0.987	-	-
Threshold	*Estimate*	*Error*	*Infit MnSq*
1	-1.307	0.065	1.14
2	-0.714	0.059	1.06
3	0.791	0.074	0.92
4	1.231	-	-

Scale III: Coercion

Coercion is measured by the following items:

- Item 1: “This person starts arguing, if you have a different opinion.”
- Item 2: “It may have some sort of consequence, if I have a different opinion to that person.”
- Item 3: “This person gets angry, if you have a different opinion.”
- Item 4: “This person will possibly avoid me, if I have a different opinion.”

Model Selection

As before, a Likelihood Ratio-Test (*LR=42.57; df=5;* $\alpha < 0.005$) shows that the Partial Credit Model fits significantly better than the Rating Scale Model (compare *Table 2*). Consultation of the information criteria indicates that the Partial Credit Model is indeed preferable, since both *AIC* and *BIC* show a minimum value for this model.

Scale Properties

The threshold structure and item fit of the Coercion scale is given in *Table 5*. It can be seen that the thresholds of the individual items are contracting with increasing mean difficulty. This decrease of discriminatory power can again be interpreted as corresponding with a decline in the respondent’s willingness (or ability) to provide unbiased responses. Again we assume that the extremity of the items is the reason for the observation of these response patterns in our calibration sample.

Item fit can be regarded as generally good for this scale. All but one of the infit values are in a reasonable range around 1. The third item ("This person gets angry, if you have a different opinion.") shows a rather low infit value, indicating that its discriminatory power has been underestimated. Being a tolerable feature, we decided to leave the item in the item set of the scale.

Table 5: Partial Credit Model for Coercion: Threshold Difficulties

Threshold	*Estimate*	*Error*	*Infit MnSq*
Item 1			
1.1	-1.921	0.121	1.05
1.2	-1.210	0.113	1.01
1.3	-0.338	0.144	0.99
1.4	-0.287	-	-
Item 2			
2.1	-0.826	0.114	1.01
2.2	-0.146	0.134	0.95
2.3	0.067	0.192	0.92
2.4	0.293	-	-
Item 3			
3.1	0.323	0.124	0.93
3.2	0.091	0.170	0.91
3.3	0.839	0.301	0.91
3.4	0.287	-	-
Item 4			
4.1	0.823	0.139	0.97
4.2	0.911	0.222	1.03
4.3	-0.005	0.305	1.00
4.4	1.099	-	-

Application in a Network Setting

Unfortunately rigorous validation of the scales in the sense of criterion validation of a survey instrument has been infeasible. The reason is that in the case of our subject of social influence, we cannot simply look for features that correlate with our measurements. Instead we need to look for the effects of a *composite* of influence measures and communication structures, because we assume that individuals employ evaluations of social influence in order to consider and integrate information from a possible array of sources. This clearly implies that the instruments cannot be validated by means other than a closed network study, where there is a known communication structure.

Network Autocorrelation Model

In order to get information about the joint effect of influences in a closed network setting, we decided to check our scales using a Network Autocorrelation Model (NACM). This class of regression models originates from spatial statistics (Anselin 1988) and has been discussed with regard to network application by Leenders (2002). For cross-sectional data the model can be written as follows.

$$Y = \rho WY + BX + e$$

Y indicates a dependent attribute vector and WY the so called "network autocorrelation term", where the vector of the dependent attribute Y is multiplied by a matrix of influence weights W. The scalar ρ and the elements of the vector B are the regression coefficients of the model which estimate the relative impact of the network autocorrelation term and the matrix of exogenous predictors X. e represents the stochastic error term of the model.

Applied to our problem, ρ indicates the effect of a social influence structure, as evaluated by our proposed measurement instruments, on a particular attitude variable. Analysis of such a model in a case study, with special attention to explained variance and fit, should lead to valuable conclusions regarding the applicability of our instruments.

Unfortunately we can not rule out a possible bias towards validity, namely that evaluations of communication partners are themselves subject to social influence. We abstained from constructing NACMs to explain neighbor evaluations, since this seemed unpromising in terms of the expected data base. It would have been necessary to set up a particular NACM for every person in the network, each based only on the probably small number of her direct neighbors.

Case Study

We collected data from a group of professors and assistants at two German universities who collaborated in order to apply for a grant from the German Science Foundation. The subject of their application was the field of “Evidence Based Policy”.

The core group, who both officially applied for the grant and actively participated in internal communication, consisted of 13 persons. Obvious features were distributed as follows over the group:

- Ten persons worked at one university (subsequently called “University A”) and three persons at the other (subsequently called “University B”).
- Eleven persons were male and two were female.
- Eleven persons were professors and two were assistants (including the project coordinator).

- Six persons were social scientists, five psychologists and two business economists.

In order to collect data from this group, we invited its members to participate in an online survey. In this survey, respondents were asked about their attitudes towards various aspects of the project, as well as their communication pattern and their evaluation of their contacts according to our social influence scales. After a field time of five weeks we were able to gather data from eleven of the 13 group members.

Measurements

We decided to employ the respondent's evaluation of qualitative methods (with regard to their utility for evidence-based policy) as the dependent variable (DV) of the model, since it showed considerable variance. We furthermore chose a single predictor variable (IV), the respondent's evaluation of structural equation modeling (again with regard to their utility for evidence-based policy). This variable had been chosen because of its good correlation (*r=0.308*) with the dependent variable. Both variables had been measured by a single item on a seven point scale ("1" representing "negative" and "7" representing "positive").

- DV item: "How do you evaluate *qualitative methods* with regard to their utility for evidence-based policy and practice?" ($\bar{x}$ *=5.73, sd=1.49, n=11*)
- IV item: „How do you evaluate *structural equation modeling* with regard to it"s utility for evidence based policy and practice?" ($\bar{x}$ *=5.73, sd=1.35, n=11*)

In order get a context specific measure of informational dependence, respondents were asked about their familiarity with qualitative methods, the attitude object of the dependent variable in focus. This variable was also measured by a single item on a seven point scale (“1” representing “I do not feel familiar.” and “7” representing “I do feel familiar.”).

- Informational dependence item: “How familiar do you feel with *qualitative methods*?” ($\bar{x}=4.27$, $sd=2.28$, $n=11$)

The evaluations of interaction partners was collected using our three proposed measurement instruments. The inferred trait parameters were allowed to vary between *-6* and *6* logits and were subsequently standardized for application. The values for persuasion were calculated by multiplication of the standardized trait parameters of perceived similarity with the standardized measurements of informational dependence. By this we tried to express the conditionality inherent to self categorization theory. (Perceived similarity only makes a difference if people need to depend on others in a task.) Altogether, the following measurements have been made on social influence.

- Persuasion scale ($\bar{x}=0.26$, $sd=0.03$, $n_{evaluations}=37$)
- Authority scale ($\bar{x}=0.62$, $sd=0.15$, $n_{evaluations}=37$)
- Coercion scale ($\bar{x}=0.36$, $sd=0.05$, $n_{evaluations}=37$)

Influence Networks

Our measurements of evaluation of interaction partners yielded the directed networks given in *Tables 6 – 9* and *Figure 1*). In order to provide the network autocorrelation model with appropriate input, the adjacency matrices have been transposed, thus converting subjective evaluations into properly directed influences. We furthermore set the diagonal of the adjacency matrices to unity in order to allow for maximum "self influence".

Table 6: Observed adjacency matrix, values set to unity

	1 Psychologist	*2 Sociologist (Uni B)*	*"3 Sociologist*	*4 Business Economist (Ass.)*	*5 Business Economist*	*6 Sociologist (Uni B)*	*7 Sociologist*	*8 Sociologist*	*9 Psychologist*	*10 Sociologist (Ass.)*	*11 Psychologist (Uni B)*
1 Psychologist	1	0	0	0	0	0	0	1	1	0	0
2 Sociologist (Uni B)	0	1	0	0	0	0	0	1	0	1	1
3 Sociologist	0	0	1	0	0	0	0	1	0	0	0
4 Business Economist (Ass.)	0	0	0	1	1	0	0	0	0	0	0
5 Business Economist	0	0	0	1	1	0	1	1	0	0	0
6 Sociologist (Uni B)	0	1	1	0	0	1	1	1	0	1	1
7 Sociologist	0	0	1	0	1	0	1	1	0	0	0
8 Sociologist	1	1	1	0	1	0	1	1	1	1	1
9 Psychologist	1	0	0	0	0	0	0	1	1	0	0
10 Sociologist (Ass.)	1	0	1	1	1	0	0	1	0	1	0
11 Psychologist (Uni B)	1	1	0	0	0	0	0	1	1	0	1

Table 7: Observed adjacency matrix, values as measured by persuasion instrument, receiving agent in columns

	1 Psychologist	*2 Sociologist (Uni B)*	*"3 Sociologist*	*4 Business Economist (Ass.)*	*5 Business Economist*	*6 Sociologist (Uni B)*	*7 Sociologist*	*8 Sociologist*	*9 Psychologist*	*10 Sociologist (Ass.)*	*11 Psychologist (Uni B)*
1 Psychologist	1	0	0	0	0	0	0	0.188	0.463	0	0
2 Sociologist (Uni B)	0	1	0	0	0	0	0	0.167	0	0.029	0.519
3 Sociologist	0	0	1	0	0	0	0	0.188	0	0	0
4 Business Economist (Ass.)	0	0	0	1	0.143	0	0	0	0	0	0
5 Business Economist	0	0	0	0.210	1	0	0.383	0.188	0	0	0
6 Sociologist (Uni B)	0	0.049	0.098	0	0	1	0.357	0.167	0	0.029	0.451
7 Sociologist	0	0	0.087	0	0.203	0	1	0.167	0	0	0
8 Sociologist	0.670	0.049	0.098	0	0.264	0	0.322	1	0.558	0.024	0.483
9 Psychologist	0.341	0	0	0	0	0	0	0.127	1	0	0
10 Sociologist (Ass.)	0.410	0	0.078	0.196	0.203	0	0	0.188	0	1	0
11 Psychologist (Uni B)	0.4103	0.049	0	0	0	0	0	0.208	0.524	0	1

Table 8: Observed adjacency matrix, values as measured by authority instrument, receiving agent in columns

	1 Psychologist	*2 Sociologist (Uni B)*	*"3 Sociologist*	*4 Business Economist (Ass.)*	*5 Business Economist*	*6 Sociologist (Uni B)*	*7 Sociologist*	*8 Sociologist*	*9 Psychologist*	*10 Sociologist (Ass.)*	*11 Psychologist (Uni B)*
1 Psychologist	1	0	0	0	0	0	0	0.653	0.440	0	0
2 Sociologist (Uni B)	0	1	0	0	0	0	0	0.653	0	0.999	0.882
3 Sociologist	0	0	1	0	0	0	0	0.653	0	0	0
4 Business Economist (Ass.)	0	0	0	1	0.403	0	0	0	0	0	0
5 Business Economist	0	0	0	0.488	1	0	0.0005	0.569	0	0	0
6 Sociologist (Uni B)	0	0.871	0.941	0	0	1	0.502	0.653	0	0.999	0.882
7 Sociologist	0	0	0.788	0	0.713	0	1	0.760	0	0	0
8 Sociologist	0.999	0.0005	0.941	0	0.784	0	0.219	1	0.765	0.999	0.991
9 Psychologist	0.536	0	0	0	0	0	0	0.653	1	0	0
10 Sociologist (Ass.)	0.0005	0	0.732	0.488	0.4957	0	0	0.760	0	1	0
11 Psychologist (Uni B)	0.536	0.0005	0	0	0	0	0	0.993	0.634	0	1

Table 9: Observed adjacency matrix, values as measured by coercion instrument, receiving agent in columns

	1 Psychologist	*2 Sociologist (Uni B)*	*"3 Sociologist*	*4 Business Economist (Ass.)*	*5 Business Economist*	*6 Sociologist (Uni B)*	*7 Sociologist*	*8 Sociologist*	*9 Psychologist*	*10 Sociologist (Ass.)*	*11 Psychologist (Uni B)*
1 Psychologist	1	0	0	0	0	0	0	0.442	0.309	0	0
2 Sociologist (Uni B)	0	1	0	0	0	0	0	0.419	0	0.217	0.0005
3 Sociologist	0	0	1	0	0	0	0	0.361	0	0	0
4 Business Economist (Ass.)	0	0	0	1	0.501	0	0	0	0	0	0
5 Business Economist	0	0	0	0.578	1	0	0.464	0.442	0	0	0
	0	0.368	0.557	0	0	1	0.501	0.442	0	0.310	0.0005
7 Sociologist	0	0	0.557	0	0.420	0	1	0.462	0	0	0
8 Sociologist	0.222	0.309	0.538	0	0.394	0	0.443	1	0.216	0.310	0.0005
9 Psychologist	0.465	0	0	0	0	0	0	0.419	1	0	0
10 Sociologist (Ass.)	0.501	0	0.519	0.395	0.361	0	0	0.394	0	1	0
11 Psychologist (Uni B)	0.366	0.217	0	0	0	0	0	0.419	0.216	0	1

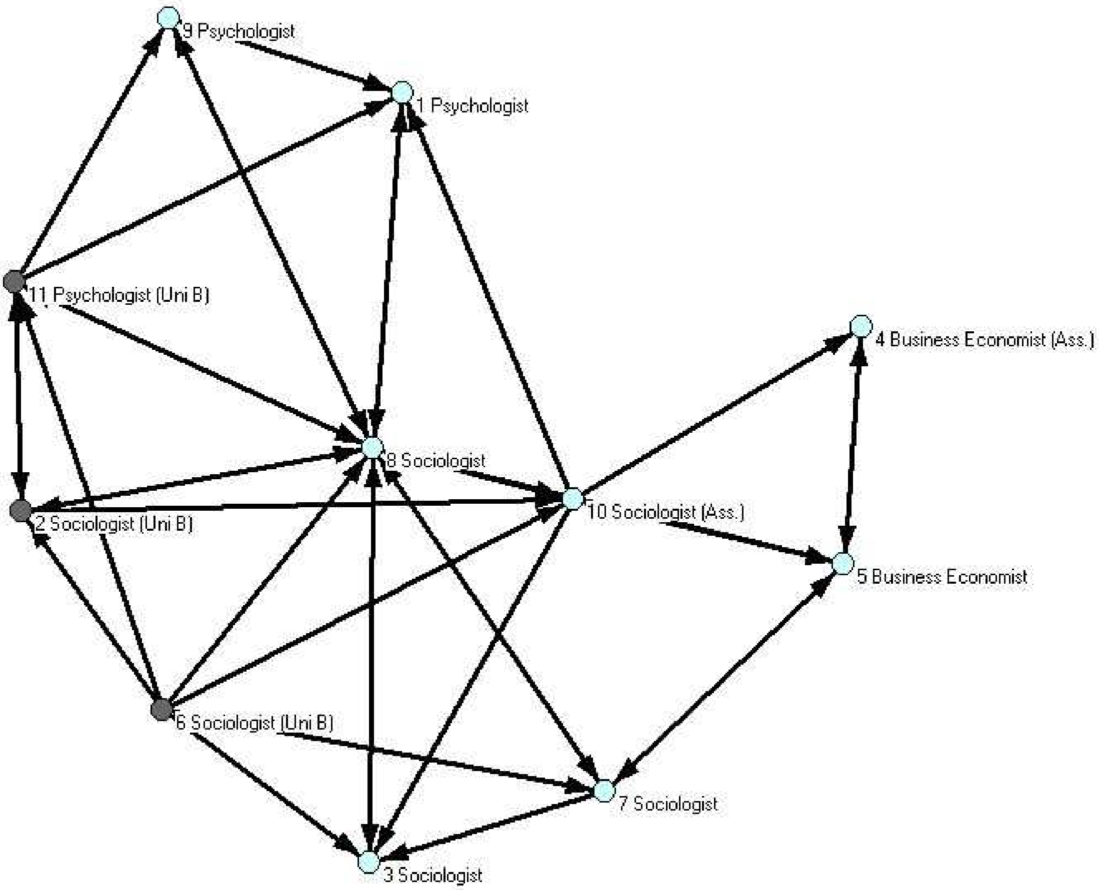

Figure 1 Unlabeled Influence Network

Model Results

We fitted several models to the data, using maximum likelihood estimation. All models had the evaluation of qualitative methods as their dependent variable. The baseline model was an ordinary bivariate regression model with the evaluation of structural equation modeling as its independent variable. Our extended models contained an additional network autocorrelation term, each model with a differently valued adjacency matrix. A first model contained the surveyed adjacency matrix with values set to unity. Three further models contained the surveyed adjacency matrix, each with values measured by the instruments on persuasion, authority, and coercion. A last model contained a complete adjacency matrix with values set to unity. Estimations are given in *Table 10*

Table 10: Fitted network autocorrelation models, dependent variable is evaluation of qualitative methods

Model	*IV*	*AC Matrix*	*Network Effect ρ*	*Sig. ρ*	*IV Effect β*	*Sig. β*	*R^2*	*LL*	*LR (to Basel.)*	*Sig LR*
Baseline	SEM	-	-	-	0.969	0.000	0.382	-20,67	-	-
Unity	SEM	Unity	0.068	0.012	0.676	0.000	0.454	-18.34	4.66	< 0.050
Persusasion	SEM	Persuasion	0.283	0.003	0.486	0.05	0.484	-17.46	6.42	< 0.010
Authority	SEM	Authority	0.097	0.006	0.681	0.000	0.468	-18.02	5.30	< 0.025
Coercion	SEM	Coercion	0.194	0.003	0.546	0.000	0.4147	-19.49	2.36	> 0.1

The baseline model shows a strong effect of evaluation of structural equation modeling on the evaluation of qualitative methods, and a considerable proportion of explained variance. When the surveyed adjacency matrix, with values set to unity, was entered into the equation, we observed a small effect of network autocorrelation. The effect of structural equation modeling dropped considerably, while the proportion of explained variance rose by over *0.08*.

When the surveyed adjacency matrix with values measured by the persuasion instrument was entered for the autocorrelation term, we observed a much stronger network effect, an even weaker effect of evaluation of structural equation modeling and a proportion of explained variance which exceeded the one of the baseline model by over *0.1*.

Compared to the model containing the observed adjacency matrix set to unity, the model containing the authority matrix showed similar behavior. The network autocorrelation effect was weak, the effect of the evaluation of the structural equation model was considerably lower and the proportion of explained variance was considerably higher than in the baseline model. However, knowledge of the distribution of perceived authority did not yield improved results, as compared to the case, when only the barren structure of communication was known.

The model containing measured evaluations of coercive behavior showed a considerable network effect and an accordingly lower effect of evaluation of structural equation modeling. Although its proportion of explained variance exceeded the baseline model by approx. 0.03, it was approx. 0.04 lower than in the model with the adjacency matrix values set to unity. Furthermore, a likelihood ratio test indicated no significantly improved fit as compared to the baseline model.

All other models containing a network autocorrelation term, but the coercion model, were superior compared to the baseline model, as indicated by likelihood ratio tests.

Implications for Validity

Summarized, our estimations show improved predictions for the case of the persuasion instrument. The instrument on authority did not improve predictive performance in our case study, while the coercion instrument yielded new predictions but did not fit well. This clearly suggests the validity of the persuasion instrument. However, the result does not necessarily strip the other two instruments of potential validity.

The reason is that in a setting of professors it is quite plausible to assume persuasion to be more important than authority and coercion not fitting well. Given the small size and specific culture of our network, the small effect and inferior fit of the latter measurements can not necessarily be generalized. It should make sense to expect different patterns under different circumstances.

Conclusion

In summary, we developed three instruments to measure the subjective evaluations of a communication partner's potential to induce influence. Following a cognitive reinterpretation of Turner's Three Process Theory of Power, we proposed persuasion, authority and coercion to be the relevant dimensions of social influence. We decided to employ IRT-methods in the form of partial-credit and rating-scale models as measurement rationale. In order to yield readily calibrated item parameters for application of the instruments in a closed network setting we developed scales in a survey setting. The calibrated models were then applied in a closed network study about communication and attitudes in an academic setting. The application of a network autocorrelation model to the case study's data showed a substantive predictive gain for the case of the persuasion measures, but only negligible predictive gain in the case of the authority measures and inferior fit in the case of the coercion measures. This supports our claim of validity for the persuasion scale. Although this claim has not been supported for the other scales, it can, however, not be refuted by the case study. It is plausible to assume that authority and coercion should have only minor effects in an academic setting. Investigation on these scales should therefore proceed using data from a different area.

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Conclusion

After presenting the core chapters of the work, I now want to provide the reader with a concluding summary, a discussion of the achievements made and an outlook towards possible follow-up research.

As stated in the introduction, the aim of this dissertation has been to develop methodological foundations and actual methods which enable explanation of collective behavior via individual behavior. As it has been exemplified in the core chapters of the present work, this is by no means a trivial task. The productivity of such an account depends on successful contributions in an array of related fields: ontology, modeling methodology, social psychology, computational inference and finally measurement models. In order to put the contributions made into a common frame, the individual chapters will be reviewed subsequently. The summaries of the individual chapters are varying in their amount of detail, depending on the complexity of the respective argumentation. The summary of chapter one will be most detailed, while the other, more technical chapters will be treated more cursory. This aims at sparing mathematical and technical detail in order to present the respective chapter´s argumentative structure.

Chapter one

Chapter one ("Interlevel relations and manipulative causality") dealt with the philosophy of level-transitory statements. Reaching beyond the practice of consulting philosophy only in its subfield of epistemology, it discussed primarily ontological questions. These questions were focused upon the relation between the concepts of causality and level and, derived from this, the concepts of reduction and emergence.

A focal point has been the identification of an object, since the proposal of a level depends on the identification of the levels respective elements. In order to avoid a materialistic account on the status of reality of level and object, causal structure has been introduced as criterion of identification. As a consequence it has been necessary to discuss the notion of causality, which is one of the most ambivalent concepts of philosophy. In this course a concept has been adopted, which defines a causal relation as a relation which is determined by a lawful and productive connection of properties. The two components, lawfulness and productivity, have immediate epistemological implications. Productivity can be associated with manipulative action, which is a primary means for an observer to isolate a mechanism of interest and identify its conditions and consequences. The concept of lawful connection however raises another serious problem, namely how some lawful relation can be induced from observation. In fashion similar to proposing the subject-centered concept of action as a means for identifying causal productivity, the problem of induction has been treated in a minor, subjective form. In particular it may suffice to concentrate on the most rational inferences on lawful relations, without necessarily proposing these inferences to be concordant to some hidden reality. Of course, this subject-centered, resp. constructive treatment lowers the degree of generality of the answers to be expected. Nevertheless it has been possible to show that such an approach provides productive results for the problem in focus.

In order to combine the aspects of an isolating structure of mechanisms and manipulative causality, we proposed the calculus of causal bayesian networks (Pearl

2000) as a both intuitive and productive means of representing the proposed ontology of structural causality.

Based on these considerations it has been possible to refine the relation between the concepts of object and level. The idea of structural causality implies that objects are defined by a network of causal relations. This in turn straightforwardly allows to identify a level by the set of all causally connected objects. Starting from this concept, a specific hierarchy of levels may be declared based on a possible aggregation of mechanisms. The latter proposal does not imply that the choice of the granularity of such an aggregation may be arbitrary. Again relying on a subject-centered argument, it has been stated that some aggregation of mechanisms may be more easily declared than others, depending on the effort needed to conceive or actually accomplish action. An aggregate mechanism may easily be declared if some joint of elementary mechanisms has a structure, wich results in its relative environmental autonomy. Self-regulating and self-organizing structures are joints of mechanisms of this type, on which an aggregate mechanism may easily be declared.

After discussion of the basic notions of the approach, chapter one concentrated on the formulation of relations between different levels of aggregation. The problem can be summarized by the term of logical realization. Hereby is meant that higher order objects are per definition joints of mechanisms, since without declaration of a fine granular micro-level, talk of aggregation and higher level properties would make no sense. A further proposal that activity on the lower level does not stop once a higher level is declared, leads to the proposition that lower level activity logically realizes activity on the higher level. However, this does not mean, that the lower level is "more real" than the higher one, since declaration could start with arbitrary granularity, provided manipulative causality applies to it. This has consequences in the following respect. Elements on some level are obviously completely determined by processes going on on this level, this conclusion being a tautology of the definition of level as the set of all causally affiliated objects. A result of this conclusion is, that relations between different levels are causally inert, since a causal claim for level transitory relations would immediately lead to causal over-determination of the lower level, which provides the most detailed description of a system. Furthermore, the closely related notion of supervenience has been discussed. According to Kim (1998), it can be defined by the concept of micro-indiscernibility: "For any x and y, belonging to level L . . ., if x and y are indiscernible in relation to properties at all levels lower than L . . ., then x and y are indiscernible with respect to all properties at level L." (Kim, 1998, p. 17) Consequently, properties on level L supervene on properties on lower levels. This concept is in accordance with the approach advocated above. However it is, as Kim states, only a phenomenological theory which is about patterns of covariance and not about "deeper dependence relations" (Kim, 1998, p. 15), as they are proposed in my own approach. After discussion of the detailed interlevel relations implied by my approach, chapter one dealt with the concepts of reduction and emergence and discussed some quite popular viewpoints. The first position to be mentioned has been those of ontological reductionism, which seems to be broad common sense in the natural sciences. Its basic claim is that the lower level objects obviously share a material reality, which is not owned by the higher level compounds, which can be described as structures of this lower level objects. A consequence of this view is that only the smallest particles conceivable are considered to be "real". The following objection has been risen against this approach. It seems that it is merely a method to decrement the level of explanation which does not include a criterion to stop this process of always referring to a lower level. The reason is that it is always possible to conceive a more detailed lower level for explanation, given that the answers provided on some levels are not completely satisfactory. A further position discussed has been that of nomological reductionism, which is prominent in the social sciences (c.f Esser 1996, Opp 2005). Here the idea is to convert different theories into each other via conjecturing so called bridge hypotheses. Theories operating on different levels are only seen as instances of this general scheme. The most important argument against this view has been the following. Since the implicit ontology of nomological reductionism does neither care about causality nor objects, it violates the conditions of identity of the latter ones, if applied to level transitory applications. Declaration of bridge hypotheses immediately results in causal over-determination of the lower level. Level transitory statements need to be inferred from the given levels and not be added to them, in order to prevent violation of the lower level objects identity. Finally, some remarks on the counterpart of reduction, emergence, have been made. Most prominently, the claim of the impossibility of explanation of emergent properties has been objected, since this is a per fiat statement. Weak emergentism, which allows backtracking higher level properties to lower levels is an alternative to this, which is advocated throughout chapter one.

Chapter two

The second chapter ("Probabilistic inference for actor centered models") dealt with application of the results yielded in chapter one. Its objective is to build a productive methodology based on the ontological system previously developed.

Starting point has been a short review of the ontological results made, which developed into a discussion of how objects and their separating set of mechanisms are represented in different modeling formalisms. The formalisms considered were agent based modeling, system theory and probabilistic graphical models. They have in common that they perform inference on global system behavior from a local formulation of element behavior and the elements´ structure of interdependence. Agent-based-modeling has been discussed first. Here elementary objects are separated from their environment by a technique which is called information hiding. An object is seen as a container of properties, the states of which are "hidden" from other objects. These other objects can access or alter the focal objects´ states only via a predefined interface. Recurring to the idea of isolation by a structure of mechanisms one can say that the interface provides the mechanistic relations between the focal object and its environment. The second formalism which has been discussed is system theory. It can be regarded as a variety of the theory of systems of differential equations. System elements are represented as operator functions, which transform some input into output over time and whose interconnections form the system´s structure of interdependence. The formalism of systems theory does not focus on the concept of object identity, except for the higher level object which is the system as a whole. This is identified by its boundary, namely the set of all modeled processes. Despite its focus on the macro object, systems theory is a powerful tool for inference of global behavior. The third formalism to be discussed was probability theory in form of bayesian networks. Here component behavior can be defined in terms of conditional probability statements, which as a whole define a joint probability distribution. From this joint distribution (or the equivalent graph of conditional statements) probability statements about subsets of the respective local variables can be projected. This amounts to deriving collective statements from individualistic formulation. An advantageous feature of probabilistic modeling is that it encodes abductive, i.e. reverse reasoning, under conditions of multiple causation. After presentation of the general features of the mentioned formalisms, the chapter presented bayesian networks in more detail, together with the systemic interpretation assigned to the calculus´ elements. Finally, a toy application has been presented, in which level transitory statements are derived from a bayesian network formulation. The toy application deals with contact choices in a network of three agents. Here a subjective expected utility approach which is adapted to consider homophily and reciprocity forms the agent model of the application. Recurring to Heider´s (1958) classical balance theory, decision distributions of a particular agent are derived for each of the possible balance states of a triad, thus instantiating level transitory statements.

Chapter three

Chapter three ("Simple Heuristics in Complex Networks") has been concerned with a multi-agent simulation study about social influence. It is connected to the previous chapters by presenting an application of the discussed methodology in the fields of sociology and social psychology.

The central topic of the chapter was the formation of attribute structures in social networks over time due to processes of social influence. Social influence has been conceptualized as result of cognitive activity on the side of the receiving agent in the influence relation. More precisely, the chapter dealt with the interaction of elaborateness (or effort) of agent cognition and the clustering structure of the agents´ social network.

Cognitive processing of social influence has been modeled as a decision process which is based on social cues. Given this framework, cognitive effort is identified with the amount of information which is considered during the decision process. Obviously, it may be possible that some agent may not use all the information which is available in her social environment, i.e. her local social network. This is important since such a situation implies that an agent would depart from perfect rationality. Choice of information sources may depend on some characteristic like the expected validity of information, a quantity which can be directly linked to the status of the agent in focus. We (that means my co-author and me) considered several strategies of contact selection and information integration, as suggested by work on heuristic decision making, each associated with a different amount of cognitive effort needed. It should be noted, that we purposively abstained from considering highly complex models of cognition, since we believe that simplistic modeling yields more rigorous and often more realistic analyses.

In particular, we distinguished a contact and an information integration phase in the employed decision models. Two different rules have been implemented for the contact phase: (1) the ALL-rule, where all locally available information is considered, regardless of the status of the agents who act as information source. (2) the better equal (BE) -rule, where only those agents are contacted, who have at least the same status as the contacting agent. For integration of collected information four different rules have been implemented: (1) the weighted additive model (WADD), which computes a weighted sum over the values of the feasible decision alternatives, the weight being the respective information sources´ status. The decision alternative with the maximum sum is then chosen. (2) the unit weight model (UWM) which proceeds in analogy to the WADD rule, with the difference that status remains unconsidered in the decision process. (3) the follow the leader (FTL) rule, which simply imitates the decision of the neighboring agent with the highest status. (4) the minimalist (MIN) rule, which randomly chooses one of the contacted agents for imitation.

The second important aspect that the simulation study focused on has been the clustering structure of the agents´ social network. More specifically, we focused on examining if the influence process going on in the interaction network is sensitive to the network´s clustering structure. Prior studies (c.f. Latané and L'Herrou 1996) have shown that clustering is a key variable for the persistence of minority factions, because agents who are embedded in highly cohesive clusters are effectively shielded against outside influences by their fellow cluster members.

In order to examine possible interaction between the decision strategies employed by the agents and the networks clustering structure, we attempted to vary the latter systematically. Therefore we decided to employ a stochastic network model which allows explicit variation of clustering. The so called small world model is such a network model. It starts by invoking a regular ring lattice in which each agent is connected to a certain number of neighbors on each side. Then randomly picked agents are reconnected to another randomly picked agent with a certain probability. The concept behind this procedure is the following. Regular lattices have the feature of high local clustering. An increasing probability of "rewiring" the regular network leads to first connecting and then breaking the highly clustered network. In our simulation study, we considered the three following configurations: (1) "cyclic regular" and not rewired networks, which are highly clustered, (2) "small world"-networks, which are rewired with a probability p=0.1 and represent a structure of interconnected clusters and (3) "random regular" networks which are rewired with a probability p=1.0 and which contain no regularity other than an equal expected number of neighbors.

Repeated simulations which aimed to explore systematically the model´s parameter space revealed very interesting results. I will only sketch the most important results at this point, a much more detailed treatment can be found in the respective chapter. As it turned out, the influence process settled quickly and both clustering structure and agents' contact strategies led to substantial differences in terms of outcomes of the process. In general, unanimity was unlikely and highly clustered networks increased the size of the minority factions , which is in coherence to the results of Latané & L'Herrou (1996). However, when agents chose only higher status neighbors as information sources, the size of the minorities decreased. In this case the distribution of equilibrium factions became furthermore independent from the clustering structure of the communication network. Taken together our results showed that there is a substantial impact of the employed decision strategy on the group decision to be made. So does the consideration of high status for information search lead to a situation in which the formation of majorities becomes most probable, even if the communication network is clustered into cohesive subgroups. Furthermore we found that interaction of agent cognition and communication structure is a central aspect for the course of social processes. Another significant (but of course expected) result is that even simplistic models of agent cognition can result in rich collective behavior. It may therefore not be necessary to assume agents with sophisticated mental capabilities in order to explain complex social processes. In addition to conducting a systematic parameter study we also employed our modeling framework in a case study based on empirical data. Our case data has been about work interaction in an American lawfirm, similar to the example given in the introduction of the dissertation. Using our simulation model, we computed equilibrium distributions for an interaction process about changing organizational policies. We inferred different possible outcomes of the process, where persistence of the minority position was ultimately governed by the decision strategy employed.

Chapter four

Chapter four ("Evaluating Social Influence Relations: an Item-Response-Modeling Approach") aimed at providing well founded measurement instruments in order to calibrate simulation models or to conduct closed-network studies in general. In doing so, it completes the topical arch of this dissertation, which ranges from philosophy and methodology to simulation modeling and measurement. Theoretical basis of the chapter has been the cognitive approach to social influence which has been advocated previously. This means that the instruments focused on measuring perceptions of the potential of contact persons to exercise social influence. Without exclusively relating to a model of heuristic decision making, the
chapter elaborated Turner´s (2005) theory of power with regard to cognitive processing of social influence. While being somewhat sloppy in formulation, Turner´s approach has the merit of joining important traditions in the study of social power. It proposes three processes (or, as I like to call them, dimensions) of social influence, which are persuasion, authority and coercion. The assumptions about persuasion stemmed from Turner´s self-categorization theory (cf. Turner 1991). Persuasion is defined as being the effect of a process of social reality validation, which means that given a person does not have full control over a given task, she will try to validate her conception of the task by means of social interaction. Put in different terms, this means that absence of control over some task is a prerequisite for being persuaded. A further assumption is that communication partners, which are perceived as similar will have a stronger persuasive impact, since those are expected to convey useful information. Authority is defined in analogy to Weber´s (1984) classical concept of legitimate order, namely by a person´s degree of conviction that it is right that she is controlled by another person in certain matters. Coercion finally captures the concept

that a person may comply to another person, because she is forced to do so since the other person controls the resources she needs.

Following the considerations summarized above, questionnaire items were presented, which had been developed as basis for a quantitative measurement instrument. The items on persuasion were intended to reflect perceived similarity, with emphasis on perceived helpfulness of a contact person for own problem coping, while operationalization of control of the task has been left open because of its situational specialty. The item set on authority were intended to capture the perception of rational and accepted authority of a contact person. Coercion was meant to be operationalized by items focusing on some contact person´s use of coercive means in everyday interaction. During the pretest 58 items in total had been presented to the pretest sample consisting of social science university students. In the end, 11 items from this pool had been selected for the final scales and were presented to a calibration sample also consisting of university students. All responses were allowed to range on a five-point agreement scale.

After discussion of theory and item wording, the mathematical apparatus of the instruments had been presented. Measurement models came from the class of item-response-theory models. Item response theory is a stochastic measurement theory which estimates strength of both person related unobserved attributes and item set related difficulty of questions from the response patterns provided. In particular, the binary-response Rasch-model and the polytomous response Partial-Credit- and Rating-Scale-models have been presented. The latter two have been employed for the scales developed and the results of calibration have been presented in the chapter. The choice of the employed measurement model had been based on comparison of the models´ fit to the respective item set´s responses.

Since the instruments had been developed and calibrated in a survey setting but were intended to be applied in a closed network setting, chapter four also presented a closed network study in which these instruments were applied. Data for the closed-network study had been collected via an online-survey in a group of researches which was jointly applying for a DFG-research grant. The researchers were asked to complete a questionnaire in which they were encouraged to provide information about specific project-related attitudes, their pattern of communication in the group and finally their evaluation of their respective communication partners in the group, using the proposed measurement instruments. From the gathered data, scale values had been inferred and were used to reconstruct networks of persuasion-, authority- and coercion-relations in the group. These networks were then employed to formulate network autocorrelation models (NACM), a special regression model which controlled for these network relations while explaining a particular attitude variable measured during data collection. In other words, it has been tested if knowledge of the inferred influence networks yields a better explanation of attitude variables. It had been demonstrated that inclusion of a network term always led to better performance of the regression model, as compared to a baseline model without any network information. However, only for one instrument prediction has been superior to the case where only the network of acquaintances, but not the perceptions of potential influences have been integrated. This has been the persuasion-network. However it has been stated that this does not lead to the conclusion that the other measurement instruments have no validity, since the data dealt only with the small and special case of a group of researchers, where both strong authority and openly coercive behavior seem less likely than in other contexts.

Achievements of the dissertation

After presenting a summary of the individual chapters it is now time to discuss the achievements made in this dissertation. The first chapter yielded important results in the field of philosophy of the social sciences, since it presents a systematic and coherent approach to modeling of social systems and inference of level transitory relations. The claim of importance is underlined by the fact that it relates to present discussions in social theory, namely the topics of bridge hypotheses, reduction and emergence and relation of social science and philosophy of mind. The second chapter contributes to scientific progress in terms that it combines a thoroughly elaborated philosophical approach with computational modeling methodologies and furthermore presents an actual application of the claims made. It therefore relates to actual methodology in the social sciences. The third chapter yielded interdisciplinary progress by combining the fields of social theory, computational modeling and cognitive science. Especially the analysis of the social effects of assumptions on agent cognition and their interaction with communication structures is noteworthy. With introduction of heuristic decision making to models of social influence, a recent concept of bounded rationality has been successfully applied. Chapter four contributed to progress in the social sciences by introducing parametric item response measurement to the study of social networks and elaborating social-psychological theory on social influence. A further achievement concerns the use of methods from spatial statistics to check the applicability of survey instruments in closed network settings. Taken together, the dissertation can be considered to be a very productive enterprize, at least in the eyes of the author and maybe also in the eyes of my supervisors.

Outlook

Although this dissertation has been a productive enterprize, it is certainly not the sorcerer´s stone. Work on the presented topics of course revealed limitations of the approaches considered and suggested both alternative approaches and follow up research. As in the previous section on the achievements made, I will discuss the implications of the individual chapters.

Dealing with the ontological foundations of level transitory modeling, chapter one has implications for modeling methodology and development of social theory. Perhaps the most important implication is that philosophical considerations should be integrated to a larger extend into actual theorizing and modeling. Although scientific work seems to be well defined in terms of standards and practices of a discipline, these are not as self-evident as it seems. On the contrary, only minor changes of the content of such elementary concepts as agency or the introduction of new modes of inference such as probability theory may lead to a completely different view on the world. Consideration of these foundations should therefore be more explicitly integrated into scientific work. Model structures should be defendable by coherent argument and not only by reference to a paradigm, which is often the case.

Of course, the methodology discussed in the first two chapters needs further development. With regard to the ontological part, it would be desirable to put it on firmer grounds, extending the subjectivist foundations to theory which is aligned to results in the special sciences. This might well be possible, especially since applicability has been an explicit intent of the project. With regard to productive application, further research on the implications of formalisms is necessary. A limitation of the probabilistic approach employed is, that it is very demanding in terms computation. However, it promises the integration of theoretical and statistical inference and therefore seems most promising.

The applied work presented in chapters three and four implies promising developments in the fields of agent cognition and social influence. Its primary objective has been to formulate a causally plausible model of social interdependence, which is an alternative to the frequently used rational choice assumption. Chapter three also implies empirical research on the interaction of agents decision behavior and organizational structure, variables that have shown to be important predictors of collective behavior. For this objective, instruments like the one presented in chapter four may be used. Here, future research may deepen our understanding of how to validate measurement instruments in structured, systemic settings.

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- “Evaluating Social Influence Relations: an Item-Response-Modeling Approach”: Eingereicht bei *Social Networks*

Erklärung**:** Hiermit versichere ich, daß ich diese Dissertation – mit Ausnahme des in Koautorenschaft verfaßten und dem Promotionsausschuß gegenüber genauer spezifizierten Teils – selbständig verfaßt, keine anderen als die angegebenen Quellen und Hilfsmittel verwendet und sämtliche Stellen, die den benutzten Werken im Wortlaut oder dem Sinne nach entnommen sind, mit Quellenangaben kenntlich gemacht habe.

Gießen, im Jahr 2007

Gero Schwenk