Complex Communication – Investigating Communication Interaction as Complex Process

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Abstract:
Current applications of complexity theory in organization science focus primarily on the structure of the interactions and its evolvement over time. We contend that the interaction process realized by means of communication itself can be characterized as complex phenomenon. In order to provide informational value and simultaneously guarantee connectivity, communication interaction must be located between the two opposed extremes of order and randomness, a field of tension that is also characteristic for complex processes. The theoretical argument is supported by the empirical investigation. Applying the Grammar Complexity and the Shannon Entropy to negotiation timelines provides strong indication that the communication interaction processes can be considered complex phenomena. Furthermore, we show that the complexity of the communication interaction is a powerful predictor for determining whether negotiators reached an agreement or not.

Introduction

Since the 1960ies "complexity has been a central construct in the vocabulary of organization scientists" (Anderson 1999: 216) and "complexity caused self-organizing structures are now seen as ubiquitous natural phenomenon" (McKelvey 1999: 300). Scientists hold different perspectives about the definition of complexity in the context of organizational theory (for discussions see Anderson 1999; Cohen 1999; Morel and Ramanujam 1999), however, interacting and interdependent elements are considered as constituent for complex systems by the majority of the authors. This is not only reflected in conceptions of complex organizations put forward by early organizational scholars (e.g., Simon 1962; Thompson 1967; see Anderson 1999), but also central to more recent applications of complexity theories in organizational science. For example, the core in Kauffman's theory (1993) and its applications to organizational theory (Boisot and Child 1999; Levinthal and Warglien 1999; McKelvey 1999) is the density of interdependencies among the elements. Designing organizations under this paradigm "requires a tuning of the interdependencies" (Levinthal and Warglien 1999: 343). Similarly, in the conception of organization as complex adaptive systems the basic building blocks are interacting agents with schemata (Dooley 1997; Anderson 1999; Morel and Ramanujam 1999). Thus, interaction and interdependence is not only a key element in classical organization theory, but also crucial in the viewpoint of complexity theoretical approaches to organization.

The above named approaches focus primarily on the structure of the interactions and its evolvement over time another. A complementary approach in the realm of complexity theories can be applied to assess the very interaction process itself (Grassberger and Procaccia 1983; Rosenstein, Collins et al. 1993; Bandt and Pompe 2002). In social systems as opposed to natural systems this interaction process "is primarily informational rather than energetic" (Boisot and Child 1999, p. 238), thus realized by means of communication. Furthermore, Levinthal et al. (1999) consider communication as primary instrument for supporting coordination in rugged landscapes and Weick (1993) highlights its function for preventing social disintegration. Conceptions based on Luhmann's (1984) social system theory even see communication as the constituent element of organizations.

In our investigation, we focus on the analysis of communication interaction processes from a complexity theoretic point of view. First, we show that from an information theoretic perspective, communication interaction itself can be understood and characterized as complex process. Second, we further elaborate this conception on methods stemming from the field of complexity theory. Furthermore, the empirical application of these algorithms to analyze communication interaction processes will be exemplified. However, as Sterman and Wittenberg (1999: 323) point out, the "merely metaphorical use (…) while provocative, is not sufficient" and "(t)he full potential of these tools in the social sciences will be realized, we believe, only when they are used to develop and test formal models". In a final step, we hence present an empirical study analyzing 145 negotiations protocols (290 individual negotiators) using complexity measures. We decided for negotiations for the following reasons: First, negotiations are communicative in nature (Lewicki and Litterer 1985; Putnam and Roloff 1992) and an important form of organizational communication (Shea 1993). Second, in negotiations the actors are not socially isolated but influence each other in a mutual interdependent manner (Weingart, Prietula et al. 1999; Olekalns and Smith 2000). Thus, negations are interactions in the sense of Stogdill (1959; quoted in Frank and Fahrbach 1999, p. 257), i.e. "a system composed of two members, A reacts to B and B reacts to A in such a manner that the response of each is a reaction to the behavior of the other." Third, negotiations are processes (Zartman 1977; Bell 1988; Thompson and Hastie 1990), i.e. a dynamic that evolves over time. Hence, the temporal structure is as central in negotiations as in the majority of complexity theoretical approaches. Finally, negotiations have a clearly defined outcome, i.e. if an agreement was reached or not. Most studies in field of complexity theory and organizations or communication are theoretic in nature and the exceptions (e.g., Rapp, Jiménez-Montaño et al. 1991; Tschacher and Scheier 1995; Cheng and Van de Ven 1996; Snyder and Kurtze 1996; Haken and Schiepek 2006) do not relate the complexity measures to an outcome. Employing negotiations allows extending the analysis from a descriptive determination of the complexity to its impact on the result of the process.

Theoretical Background

Analyzing different conceptions of complexity Ebeling et al. (1998) conclude that qualitatively a complex phenomenon must be located between the two opposed extremes of complete order and complete randomness. This idea is highly compatible with an intuitive understanding of complexity: Neither a sine wave representing the periodic oscillations of a pendulum (complete order) nor a sequence of zeros and ones generated by tossing a coin (complete randomness) would be considered as being complex. The field of tension between order and randomness meets not only a qualitative, intuitive understanding of complexity, but can also be encountered in formal conceptualizations used to operationalize the complexity of a process.

For example, chaotic behaviour, often associated with complexity, is not random; however, despite being highly ordered, its structure is not identifiable with classical approaches nor can chaotic dynamics be forecasted in the long run (Tsonis 1992). Similarly, the Kolmogorov Entropy (*KE*) (Grassberger and Procaccia 1983; Frank, Blank et al. 1993), roughly spoken, defines the entropy of a dynamic by the possibility to predict the next event based on the knowledge about the previous state of the system. In a completely regular and ordered dynamic, an event n_{t+1} can be predicted with certainty from its predecessors n_t resulting in $KE = 0$. Contrary, the course of a random dynamic is unpredictable with $KE \to \infty$. A complex process is located between these two extremes with $0 < KE < \infty$: at the one hand it exhibits path-dependence as encountered in ordered dynamics; on the other hand it is not completely predictable as encountered in random dynamics. Likewise, a successful communication that possesses informational value and at the same time can be further processed by the counterpart should be located between these two extremes and exhibit the properties of a complex process.

Although the functions of human communication are manifold (e.g., Dance 1976) the transmission of information, or what Watzlawick et al. (1967) refer to as digital communication, can be considered as being central. However, when does information have an 'informational value'? From an information-theoretic perspective the 'informational value' can be defined by the self-information sometimes also referred as surprisal (Tribus 1961). The surprisal *S* of an event *i* represents the rate of additional information that the knowledge about (the occurrence of) one event, e.g. a communicative action within an interaction, adds to the overall knowledge. It is given by

$$S_i = \log_2\left(\frac{1}{p_i}\right) \qquad (1)$$

with p_i being the probability of occurrence of the event i given the current state of information. The more 'suprising' an event is, the more additional information is provided after its occurrence. Thus, in a completely ordered system in which an event i can be predicted with certainty from past events, the informational value added is zero as its occurrence was already known. Contrary, in a random system every next event is unpredictable based on the knowledge about previous events, thus providing maximal additional information after its occurrence.

Consider, for example, a negotiation process in which the two parties have at disposition the typology of bargaining steps suggested by Filzmoser and Vetschera (2008) consisting of concession, trade-off, insistence, and demand. Let's assume two scenarios: in scenario (a) one of the negotiators is stubborn and reacts to every offer with insistence; in scenario (b) one negotiator is capricious and reacts to an offer with one of the four options equiprobably. The two scenarios lead to the following informational value for a bargaining step:

$$S(a)_i = \log_2\left(\frac{1}{1}\right) = 0 \text{ bit}$$

$$S(b)_i = \log_2\left(\frac{1}{0{,}25}\right) = 2 \text{ bit}$$

Scenario (a) is a completely ordered process in which every offer is followed by insistence. Yet, although it might provide insights about the personality of the stubborn negotiator, the information value of his/her insistence is zero as the reaction was already known in advance (occurrence probability of 1) providing no additional, relevant information. Contrary, in scenario (b) the offer is followed by a random bargaining step, thus the reaction of the capricious negotiator provides on average maximal information.

However, a communication process is not concluded by the mere utterance of information but this information has also to be understood by the receiver: "communication emerges only to the extent that the sender's utterance is picked up and processed by a receiver" (Vanderstraeten 2000: 9). According to Luhmann (1984) the understanding and further processing is given by the degree the next communication connects to the previous: "Only in the process of connecting can one tell whether one has been understood" (Luhmann 1995: 143; quoted in Nassehi 2005: 182). In a completely ordered system, the knowledge about a successive event or communicative action is already contained in the previous events or communicative actions, thus exhibiting maximal connectivity. Contrary, a completely random communication process lacks connectivity leading to a breakdown of the communicative interaction. Thus, successful communication is not solely determined by conveying information but the information has to provide the possibility for the counterpart to connect its own information to it. With regard to the two negotiation scenarios introduced above, in scenario (a) the connectivity is maximal but no additional information is conveyed, whereas in scenario (b) every step provides maximal new information. However, due to the random nature of the reactions one step can not connect to the previous impeding the establishment or continuation of an interaction process.

Consequently, a completely ordered process contains no additional information necessary to be communicated. Contrary, in a completely random process every additional communicative event contains maximal information but lacks connectivity to be further processed by the receiver. A successful communicative interaction, however, should do both: convey information as well as allowing connectivity. Similarly, von Weizsäcker and von Weizsäcker

(1972) argued that effective information exchange among living systems should operate on a level between confirmation and newness. As a result, in communicative interaction one should encounter the same field of tension between order and randomness characteristic for complex processes.

This conception of communication interaction as complex process will be further elaborated based on two methods stemming from the field of complexity theories, namely the Shannon Entropy (Shannon 1948) and the Grammar Complexity (Ebeling and Jiménez-Montaño 1980; Jiménez-Montaño 1984), which are also employed in the empirical analysis.

Shannon Entropy

In 1948 based on works of Nyquist (1924; 1928) and Hartley (1928) Claude E. Shannon in an attempt to formalize and conceptualize the process of communication developed a measure H for the rate "of information, choice and uncertainty" (1948: 19) produced by such a process. The process is characterized by a discrete and finite probability distribution $p_1,...,p_i$ of events. In case of a communicative interaction, the *i* events over which the probabilities are distributed are represented by the different communicative enactments (e.g., making an offer, use a negotiation tactic, express negative emotions, etc.). These communicative enactments constitute the alphabet from which the interacting persons can choose to realize the communication. In communication research using quantitative content analysis, the alphabet is given by the coding scheme applied to the interaction. For instance, using the above mentioned classification by Filzmoser and Vetschera (2008) as coding scheme, the four possibilities represent the alphabet. One of the four possibilities is assigned to each negotiation step of an interaction.

According to Shannon (1948: 18f), a measure $H(p_1,...,p_i)$ to describe the rate of information, choice, and uncertainty of such a communication process should have the following properties:

- **(1)** *H* should be continuous in p_i, i.e. infinitesimal changes of p_i should only induce infinitesimal changes of *H*.
- **(2)** If $p_i = \frac{1}{n}$, then *H* should be a monotonic increasing function of *n* expressing that with a uniform probability distribution of the events there is more information, choice or uncertainty when the number of possible events increases.
- **(3)** If p_i of an event is split into two subsequent p_i, the initial *H* should be the weighted sum of the individual values of *H*.

Shannon showed that the only *H* satisfying the above assumption has to have the form

$$H = -K\sum_{i=1}^{n} p_i \log p_i \qquad (2)$$

with *K* being a positive constant referring to the chosen unit of measurement. Using the binary logarithm *H* is standardized to bit.

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i = \sum_{i=1}^{n} p_i \log_2\left(\frac{1}{p_i}\right). \tag{3}$$

It should be noted that *H* incorporates the aforementioned surprisal *S*. Hence, *H* can be considered the expectation value of the surprisal *S* of an event *i*

$$H = p_i \cdot S_i \text{, with } S_i = \log_2\left(\frac{1}{p_i}\right). \tag{4}$$

When applying the *H* to longer chains of behaviour or communication with multiple codings benchmarks derived from *H* can be helpful for interpretation. Let $N = |C|$ be the number of communicative enactments defined by the coding scheme in an interaction *I*. The maximal entropy $H_{\max}$ is obtained by $p_i = \frac{1}{|C|} \forall i$. It is given by

$$H_{\max}(I) = -\sum_i \frac{1}{N} \log_2 \frac{1}{N} = \log_2 N . \tag{4}$$

By relating $H_{\max}$ to the Shannon Entropy realized in a given interaction $H(I)$ one gets the relative Entropy H_{rel}

$$H_{rel}(I) = \frac{H(I)}{H_{\max}} = -\sum_{i=1}^{n} p_i \cdot \frac{\log_2 p_i}{\log_2 n} = -\sum p_i \cdot \log_n p_i \leq 1, \tag{5}$$

the redundancy $R(I)$

$$R_H(I) = 1 - H_{rel} \tag{6}$$

as well as the statistically minimal number of communicative or behavioural enactments $C_{\min}$ required for representing the interaction *I*

$$C_{\min}(I) = |C| \cdot H_{rel} . \tag{7}$$

However, as sound the mathematical derivation of *H* is, as ambiguous are its interpretations. The anecdote even goes, that John von Neumann suggested the term entropy for *H* to Claude E. Shannon as no one knows what entropy really is, thus, he would always have the advantage in a debate (Tribus and McIrvine 1971). Consequently, the interpretations of *H* range from disorder, positive information, lack of information, uncertainty, to freedom (of choice). The apparent contradictory interpretations can be resolved when considering the different perspectives (for an in depth discussion see Brissaud 2005). Let's reconsider the above mentioned example of the two negotiators. In the case of the capricious negotiator, the Shannon Entropy is maximal as during the negotiation process the four options are used uniformly distributed. Thus, the information contained in the process and gained after its conclusion is maximal. The capricious negotiator has exercised the maximal freedom of choice by not limiting himself to a specific step but using all of them uniformly. Changing the perspective, for the counterpart of the capricious negotiator the maximal *H* of the same negotiation process implies maximal uncertainty and lack of information about the behaviour of the capricious negotiator.

Although the Shannon Entropy incorporates the field of tension between order and randomness, it considers only the distribution of the events or communicative enactments. Changes in the sequence or temporal, dynamic structure do not affect *H*. Thus, shuffling a deck of cards, a common example for entropy increase (Lambert 1999), results in an increase of the Shannon Entropy of exactly zero. Accordingly, a chain of communicative or behavioural enactments as resulting from a coded interaction process exhibits the same *H* as its randomized pendant. Thus, the Shannon Entropy suffers the same shortcoming as common content analysis measures. It averages the results over the entire chain or proportions of the chain "which may wash out some important structural information" (Zimmerman, Eliezer et al. 1968: 192). Similarly, Rapp et al (1991: 210) state in the context of content analysis in psychotherapy that "the temporal sequence of material is lost. Given the sequence-dependent structure of language and interactional nature of psychotherapy, this is important information."

Grammar Complexity

A complexity measure which does not suffer such limitations and considers dynamical and structural properties of a communicative interaction is the Grammar Complexity introduced by Ebeling and Jimenez-Montaño (1980; 1984). It is rooted in the theory of algorithmic complexity introduced by Kolmogorov (1965) and Chaitin (1974). Accordingly, a sequence of communicative enactments $s = (C_1, C_2, ..., C_\upsilon) C_i \in (C_1, ..., C_N)$ can be considered random if there is no shorter program *t*

$$t = (C_1, C_2, ..., C_N),\ N < \upsilon \tag{8}$$

based on the same alphabet of enactments $C_i = (C_1, ..., C_N)$ able to reconstruct the sequence *s*. It possesses structure in terms of regularities if the length of *s* exceeds the length of *t*, $l(t) < l(s)$.

However, the theory doesn't provide a specific program. Therefore, a procedure to determine $\min l(t)^*$ which is not a reflection of the 'true' algorithmic complexity but a standardized and systematic approximation allowing comparisons of different sequences *s* generated with the same alphabet C_i is required. The Grammar Complexity now is a context free grammar in terms of the Chomsky-Hierarchy (Chomsky 1957) delivering an upper bound of $\min l(t)^*$ especially suitable for short sequences (for a comparison of different algorithms see Schürmann and Grassberger 1996).

In essence, the underlying algorithm of the Grammar Complexity follows the principle of common compression algorithms by looking for regularities (*c*) and replacing them in the string with a single symbol (σ). The replacement is recorded in a production rule $K(\sigma \rightarrow c)$. The process then continues by looking for other regularities (which might include newly generated symbols σ) and replacing them in the same way until no more regularities are found. The outcome of this process is a compressed string *t**. The grammar complexity $K_G(s)$ is then defined as the length of this optimal string and the generated production rules. For a comprehensive description and its implementation see Ebeling and Feistel (1982) or Rapp et al. (1991).

Two measures can be derived from K_G. Similarly to Shannon's redundancy, the grammar redundancy indicating the compression rate is given by

$$R_G = 1 - \frac{K_G(s)}{K_G^{\max}(s)} \tag{9}$$

whereby $K_G^{\max}(s)$ is the maximum value of complexity given with the original length of the sequence $l(s)$ or $\frac{1}{2}l(s) + 2N^2$ (N denoting the number of characters in the alphabet or codings used). A second measure S_G was suggested by Tschacher and Scheier (1995) testing the K_G of the original sequence against the mean K_G of n surrogate sequences created by randomizing the original sequence. Additionally to provide a direct test for order and randomness it is more invariant regarding the length of the sequences (Rapp, Cellucci et al. 2001).

For example, let us once again consider the case of the stubborn negotiator answering every offer (*O*) with insistence (*I*) and assume that the interaction is terminated after 18 exchanged communications. This would lead to the sequence:

O I O I O I O I O I O I O I O I O I.

As already apparent from this exemplary interaction sequence itself, the communication process is highly ordered, hence, reconstructable with a rather short algorithm compared to the original sequence. Specifically, the Grammar Complexity results in S_k = 3.53 (calculated with 50 surrogates) and R_g = 0.44 characterizing the process of being of very low complexity with high connectivity and low informational value. The opposite holds for two negotiators using all communicative options arbitrarily leading to S_k = 0.08 (calculated with 50 surrogates) and R_g = 0.05.

Research Questions

As shown, both measures assess the field of tension between order and randomness and quantify complexity as relation between these two extremes. If communicative interaction can be conceived as a complex phenomenon located between these two extremes, as theoretically argued above, the Shannon Entropy and the Grammar Complexity should be appropriate measures to characterize and describe negotiations. If this is the case, the following research questions investigated in the empirical study should be answered positively.

RQ1: On a descriptive level, do the two measures characterize the communication interaction as being located between order and randomness and consequently as complex process?

Furthermore, successful communication interaction should possess informational value as well as allow connectivity. These criteria are given in a complex process operating in the tension field between order and randomness. Thus, the complexity of the communication process should have predictive power whether a successful outcome was reached.

RQ2: Does the complexity of the communication interaction process have predictive power to determine whether the negotiators reach an agreement or not?

Classical negotiation content analysis explains the communication process as function of the frequency of the content items' usage. Similarly, the Shannon Entropy is derived from their distribution. Both therefore do not consider the dynamics in terms of the temporal structure, central to negotiations as well as the complexity of a process. Contrary, the Grammar Complexity is a measure that accounts also for dynamical features.

RQ3: Is the Grammar Complexity a better predictor for reaching an agreement in negotiation than the Shannon Entropy and the frequency of classical content items?

Empirical Study

Data and Description

For the empirical investigation we use data stemming from previous negotiation experiments (Koeszegi, Srnka et al. 2006; Pesendorfer and Koeszegi 2006). In total, the data set consists of 145 negotiations (290 individual negotiators), from which 107 (73.8 %) reached an agreement while 38 (26.2 %) failed to come to a mutual satisfactory conclusion of the negotiation.

Table 1 Descriptive Statistics

N=145		%
No Agreement	38	26,2
Agreement	107	73,8

N=145	Mean	s.d.	Bivariate Pearson Correlations									
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) S_G	1.89	2.26										
(2) H	2.67	0.28	-.21[a]									
(3) substantive negotiation communication	16.58	6.80	.27[a]	.15								
(4) task oriented communication	20.03	11.09	.31[a]	.17[b]	.45[a]							
(5) persuasive argumentation	9.12	8.57	.23[a]	.35[a]	.38[a]	.54[a]						
(6) tactical communication	8.09	7.99	-.10	.55[a]	.44[a]	.43[a]	.53[a]					
(7) affective communication	9.48	8.36	-.02	.45[a]	.33[a]	.29[a]	.36[a]	.61[a]				
(8) private communication	4.51	6.84	.10	.35[a]	.05	.22[a]	.16[b]	.21[b]	.35[a]			
(9) communication protocol	19.48	16.73	.66[a]	-.21[a]	.33[a]	.41[a]	.26[a]	.01	.18[b]	-.015		
(10) text specific communication	8.17	9.03	.038	.45[a]	.39[a]	.39[a]	.31[a]	.52[a]	.42[a]	.30[a]	-.01	
(11) procedural communication	5.07	4.65	.021	.52[a]	.26[a]	.40[a]	.30[a]	.42[a]	.38[a]	.22[a]	.20[b]	.38[a]

[a] denotes significance at the .01 level (2-tailed); [b] denotes significance at the 0.05 level (2-tailed).

The resulting negotiation transcripts have been coded based on an adapted version of the "Bargaining Process Analysis II"-category scheme (Waclcott and Hopmann 1978). For further information on the experimental design, coding procedure, and category scheme please see Pesendorfer and Koeszegi (2006) and Koeszegi et al. (2006). We reanalyzed the coded negotiation protocols using the Shannon-Entropy and the Grammar Complexity as described in the previous section. Table 1 provides an overview of the variables used in the further analysis.

Method

As the dependent variable is dichotomous we calculated logistic regressions. Since the main aim of this study is not to find the best prediction of whether negotiators reached an agreement or not, but to learn about the most important prognostic relationships (best predictors), we employed a stepwise procedure. Stepwise methods allow identifying a limited number of covariabels that may be considered the best predictors in a prognostic problem (Steyerberg, Eijkemans et al. 2000).

When using stepwise logistic regression for identifying best predictors, the exigencies are less restrictive than employing it to build the best predictive model, nevertheless, several drawback of this approach have to be taken into account (Derksen and Keselman 1992; Steyerberg, Eijkemans et al. 1999). Especially with small data sets, instability of the predictor selection and a bias in the estimation of regression coefficient can be encountered. In the present case, the number of observations can be considered high for coded communication protocols. Yet, the lower frequency of the dichotomous outcome variable in relation to the possible degrees of freedom (Harrell, Lee et al. 1996; Peduzzi, Concato et al. 1996) requires a careful selection and validation of the potential predictor variables.

Following Steyerberg et al. (2000) and Harrell et al. (1996) in a first step the number of possible predictors were reduced combining theoretical consideration as well as a data-driven approach. As the coding scheme included general negotiation communication not influencing the negotiation outcome, these variables can be removed in a pre-selection. Thus, „text specific communication" (e.g., redundancies, text structuring, and fillers), „communication protocol" (e.g., addresses and closures, business letter phrases), and „procedural communication"(e.g., technical and time coordination) can be eliminated a priori from the further analysis as there is no theoretical or empirical evidence that these variables have an impact on reaching an agreement or not. In a second step, the remaining variables were examined for their linear relation to the probability for reaching an agreement or not. For this purpose, we performed a graphical inspection of plots showing the relationship between the value of the predictor variables and the probability for reaching an agreement. Variables not exhibiting a linear relation were transformed accordingly. Finally, the potential predictors, both the transformed and original variable, were tested individually for their predictive power in logistic models. Only variables with $p \leq 0.1$ were included in the final model. Variables with $p > 0.1$ were eliminated as it can reasonably be assumed that they have no direct predictive power as single variable in a multivariate model. Including them in the analysis might enhance the overall model; however, as single variable their predictive value is negligible. The 'cost of data analysis' (Faraway 1992; Ye 1998) using such an approach appears justified to guarantee stability and accuracy of the further analyses, especially when the aim is to identify the best predictors and not the best predictions.

The most promising predictor variables were entered in a stepwise logistic regression model. The p-values for entering the stepwise model were set at 0.05 and for exclusion at 0.10. The model has been further validated using a bootstrap procedure (Efron and Gong 1983; Efron and Tibshirani 1993), which "provides nearly unbiased estimates of the predictive accuracy that are of relatively low variance" (Harrell, Lee et al. 1996, p. 372). Using the same entering and exclusion rules as for the original model, 500 bootstrap calculations were performed. The overall predictive accuracy of the models has been calculated by correlating the outcome variable with the predicted probability for reaching an agreement or not. Bootstrapping allows not only internally validating the model and correcting the predictive power of the model via the optimism, but the frequency with which a predictor is entered in the model during the bootstrap procedure can be used as indicator for the predictive power of a variable.

To further assess the significance of complexity measures, regression factor structure coefficients (FSC) (Cooley and Lohnes 1971) were calculated. Results from regression analyses constitute overall pictures and the role of single variables are not easy to interpret as the beta-weights are rather reflections of a predictor's role within the overall model than its single predictive power. Thus, Cooley and Lohnes (1971: 54f) suggest to use the quotient of the squared predictor-criterion correlation and the variance explanation (squared multiple correlation coefficient), the FSC, to evaluate the strength of an individual variable within the regression model. The FSC was calculated for all variables in the final model.

Altogether, three criteria to evaluate the role and significance of complexity and to compare it with classical content items within a communication interaction are applied: First, if and which complexity measures are entered in a stepwise logistic model; second, the frequency with which the complexity measures are entered in the model in competition with the classical content items during the bootstrap procedure; third, the individual predictive power of complexity measures compared to classical content items assessed via the FSC.

Results

On a descriptive level, both, the Shannon Entropy and the Grammar Complexity characterize the negotiation interactions as complex process in the tension field between order and randomness as represented by the respective redundancy values R_H=0.4 and R_G=0.19. On one hand, the communication processes are characterized by a considerable amount of 'newness', at the other hand they exhibit sufficient redundancy to guarantee connectivity.

In a second step, we assessed if the complexity of the communicative interaction has predictive power in determining whether negotiators reach an agreement or not by calculating logistic regressions including a bootstrap procedure. The overall model is highly significant with considerably high predictive power and only moderate optimism (see table 2). More interesting for the present purpose, the complexity measure ln(S_G) was included as first variable in the model (p=0.02) identifying it as important predictor for reaching an agreement or not. Contrary, the Shannon Entropy, although exhibiting a significant relation to reaching an agreement when entered in a model as single variable, was not included in the final model. In the model including only non-transformed variables the same predictors, except affective, were selected. Thus, the complexity of the negotiation communication process possesses predictive power for reaching an agreement or not. However, dynamic features, considered by the Grammar Complexity but not by the Shannon Entropy, appear to be essential.

Table 2: Best predictors for reaching an agreement or not

χ^2	df	p	Nagelkerke r^2	r	p	Mean Optimism
51.26	4	0.000	0.44	0.51	0.000	0.07

Predictors	B	S.E.	p	Odds Ratio	95% confidence interval	
ln(S_G)	0.94	0.39	0.015	2.57	1.10	5.51
1/(substantive)	-20.22	7.07	0.004	0.00	0.00	0.00
tactical	-0.12	0.03	0.000	0.88	0.83	0.95
ln(affective)	0.08	0.04	0.038	1.08	1.00	1.17

Additionally, the complexity of the communication process was not only identified as predictor in determining whether the negotiators reached an agreement or not but outperformed most of the negotiation content variables (see table 3 and 4). The Grammar Complexity measure was included in 84 % of the models during the bootstrap procedure; almost double of the average frequency of inclusion of the negotiation content variables (44.4 %) and second only to substantive negotiation communication (92.6 %). However, when calculating the FSC as indicator for the individual strength of a variable within the logistic regression model, the complexity of the negotiation process (FSC = 0.70) is identified as the most powerful variable in the model followed by substantive communication (FSC = 0.39).

Table 3: Frequency of predictors' inclusion in the model during bootstrap procedure

Predictors	% of Cases
1/(substantive)	92.6
ln(S_G)	84.0
tactical	56.3
ln(affective)	54.3
$(\text{tactical})^3$	42.5
substantive	21.8
S_G	10.7
H	6.9
ln(extra role)	8.7
$(H)^3$	3.4
sum	381.1

Table 4: Regression factor structure coefficients (FSC)

Predictors	bivariate correlation	FSC
ln(S_G)	0.42	0.70
1/(substantive)	0.32	0.39
tactical	0.24	0.22
ln(affective)	0.21	0.18
overall model	0.51	

Overall, the results provide strong indication that communication interaction can be characterized as being a complex process. Furthermore, the complexity of a process has proofed to have significant predictive power, also compared to classical negotiation content variables, in determining whether the negotiators reached an agreement or not.

Conclusion and Outlook

Complex phenomena qualitatively must be located between complete order and complete randomness (Ebeling, Freund et al. 1998), a conception compatible to an intuitive understanding of complexity as well as reflected in complexity measures. Likewise, successful communication interaction should be located between these two extremes in order to provide informational value as well as allow connectivity. Thus, it should exhibit the properties of a complex process. On a descriptive level, the analysis of 145 negotiation protocol provides strong indication for this conception. Consequently, not only organizations itself can be characterized as complex systems (Dooley 1997; Anderson 1999; Boisot and Child 1999; Levinthal and Warglien 1999; McKelvey 1999; Morel and Ramanujam 1999), but also the interaction process between the elements or agents of the system can be considered as being a complex phenomenon. Assuming linear relations between the agents might therefore be too restrictive.

Furthermore, extending the descriptive analysis by relating the complexity of the communication interaction to the outcome of the negotiations shows that the complexity of the process is a valuable predictor whether negotiators reached an agreement or not. Except substantive communication, possessing equal predictive strength, the complexity of the process outperforms classical negotiation content items in terms of predictive power. Complexity theories and corresponded measures allow capturing the field of tension between order and randomness, a property that appears to be essential for successful communicative interaction but is not captured by classical approaches.

Dynamical features, however, appear to be crucial. Contrary to the Grammar Complexity, the Shannon Entropy, a complexity measure only considering the frequency distribution and not the dynamic structure of the process, proofed to have only limited predictive strength. The importance of assessing a process' dynamics has been highlighted in organization literature (e.g., Langley 1999; Ancona, Okhuysen et al. 2001). Ancona et al. (2001: 647), pointing out the major obstacles to temporal research, even state that "some features of temporal research are inherently complex". Complexity theories do not only provide a theoretical framework but also empirical tools to investigate the dynamics of a process.

In the present study we consider only the digital component of communication interaction. But as stated by Watzlawick et al. (1967) and Schulz von Thun (1981), a message conveys more communicative layers simultaneously. To draw a complete picture of a communication process' complexity, the other layers should be considered as well with appropriate methods (e.g., Grassberger and Procaccia 1983; Rosenstein, Collins et al. 1993; Bandt and Pompe 2002). Furthermore, we focused on negotiations, a special form of communicative interaction and the role of complexity as predictor. Extending the analysis to other areas and integrate complexity in a full model would be necessary to externally validate the results. Especially relating the complexity of the process to outcome variables appears to be crucial for assessing the power of complexity measures.

References

Ancona, D. G., P. S. Goodman, et al. (2001). "Time: A New Research Lens." Academy of Management Review 26: 645-663.

Ancona, D. G., G. A. Okhuysen, et al. (2001). "Taking Time to Integrate Temporal Research." Academy of Management Review 26: 512-529.

Anderson, P. (1999). "Complexity theory and organization science." Organization Science 20: 216-232.

Bandt, C. and B. Pompe (2002). "Permutation Entropy: A Natural Complexity Measure for Time Series." Physical Review Letters 88: 174102/1-174102/4.

Bell, D. V. J. (1988). "Political Linguistics and International Negotiation." Negotiation Journal 4: 233-246.

Boisot, M. and J. Child (1999). "Organizations as Adaptive Systems in Complex Environments: The Case of China." Organization Science 10: 237-252.

Brissaud, J.-B. (2005). "The Meanings of Entropy." Entropy 7: 68-96.

Chaitin, G. J. (1974). "Information Theoretic Computational Complexity." IEEE Transactions on Information Theory 20: 10-15.

Cheng, Y.-T. and A. H. Van de Ven (1996). "Learning the Innovation Journey: Order out of Chaos?" Organization Science 7: 593-614.

Chomsky, N. A. (1957). Syntactic Structures. The Hague, Mouton.

Cohen, M. (1999). "Commentary on the Organization Science special issue on complexity." Organization Science 10: 373-376.

Cooley, W. W. and P. R. Lohnes (1971). Multivariate Data Analysis. New York, John Wiley & Sons.

Dance, F. E. X. (1976). The Functions of Human Communication. Information and Behavior. B. D. Ruben. New Brunswick, NJ, Transaction Publishers. 1: 62-75.

Derksen, S. and H. J. Keselman (1992). "Backward, Forward and Stepwise Automated Subset Algorithms: Frequency of Obtaining Authentic and Noise Variables." British Journal of Mathematical and Statistical Psychology 42: 265-282.

Dooley, K. J. (1997). "A Complex Adaptive Systems Model of Organization Change." Nonlinear Dynamics, Psychology, and Life Sciences 1: 69-97.

Ebeling, W. and R. Feistel (1982). Physik der Selbstorganisation und Evolution. Berlin, Akademie-Verlag.

Ebeling, W., J. Freund, et al. (1998). Komplexe Strukturen: Entropie und Information. Stuttgart, Teubner.

Ebeling, W. and M. A. Jiménez-Montaño (1980). "On Grammars, Complexity, and Information Measures of Biological Macromolecules." Mathematical Biosciences 52: 53-71.

Efron, B. and G. Gong (1983). "A Leisurely Look at the Bootstrap, the Jackknife, and Cross-Validation." American Statistician 37: 36-48.

Efron, B. and R. Tibshirani (1993). An Introduction to the Bootstrap. New York, Chapman and Hall.

Faraway, J. J. (1992). "On the Cost of Data Analysis." Journal of Computational and Graphical Statistics 1: 213-229.

Filzmoser, M. and R. Vetschera (forthcoming). "A Classification of Bargaining Steps and their Impact on Negotiation Outcomes." Group Decision and Negotiation.

Frank, K. A. and K. Fahrbach (1999). "Organization Culture as a Complex System: Balance and Information in Models of Influence and Selection." Organization Science 10: 253-277.

Frank, M., H.-R. Blank, et al. (1993). "Improvement of K2-Entropy Calculations by Means of Dimension Scaled Distances." Physica D 65: 359-364.

Grassberger, P. and I. Procaccia (1983). "Estimation of the Kolmogorov Entropy from a Chaotic Signal." Physical Review A 28: 2591-2593.

Grassberger, P. and I. Procaccia (1983). "Measuring the Strangeness of Strange Attractors." Physical Review D 9: 189-208.

Haken, H. and G. Schiepek (2006). Synergetik in der Psychologie: Selbstorganisation verstehen und gestalten. Göttingen, Hogrefe.

Harrell, F., K. Lee, et al. (1996). "Multivariable Prognostic Models: Issues in Developing Models, Evaluating Assumptions and Adequacy, and Measuring and Reducing Errors." Statistics in Medicine 15: 361-387.

Hartley, R. V. L. (1928). "Transmission of Information." Bell System Technical Journal 7: 535-563.
Jiménez-Montaño, M. A. (1984). "On the Syntactic Structure of Protein Sequences and the Concept of Grammar Complexity." Bulletin of Mathematical Biology 46: 641-659.
Kauffman, S. A. (1993). The Origins of Order: Self-Organization and Selection in Evolution. New York, Oxford University Press.
Koeszegi, S. T., K. J. Srnka, et al. (2006). "Electronic Negotiations: A Comparison of Different Support Systems." Die Betriebswirtschaft 66: 441-463.
Kolmogorov, A. N. (1965). "Three Approaches to the Definition of the Concept 'Quantity of Information'." Problems in Information Transmission 1: 1-7.
Lambert, F. L. (1999). "Shuffled Cards, Messy Desks, and Disorderly Dorm Rooms - Examples of Entropy Increase? Nonsense!" Journal of Chemical Education 76: 1385-1387.
Langley, A. (1999). "Strategies for Theorizing from Process Data." Academy of Management Review 24: 691-710.
Levinthal, D. A. and M. Warglien (1999). "Landscape Design: Designing for Local Action in Complex Worlds." Organization Science 10: 342 -357.
Lewicki, R. and J. Litterer (1985). Negotiation. Homewood, IL, Richard D. Irwin Inc.
Luhmann, N. (1984). Soziale Systeme: Grundriss einer allgemeinen Theorie. Frankfurt a.M., Suhrkamp.
Luhmann, N. (1995). Social Systems. Stanford, Stanford University Press.
McKelvey, B. (1999). "Avoiding Complexity Catastrophe in Coevolutionary Pockets: Strategies for Rugged Landscapes." Organization Science 10: 294-321.
Morel, B. and R. Ramanujam (1999). "Through the looking glass of complexity: The dynamics of organizations as adaptive and evolving systems." Organization Science 10: 278-293.
Nassehi, A. (2005). "Organizations as Decision Machines: Niklas Luhmann's Theory of Organized Social Systems." The Sociological Review 53: 178-191.
Nyquist, H. (1924). "Certain Factors Affecting Telegraph Speed." Bell System Technical Journal 3: 324-346.
Nyquist, H. (1928). "Certain Topics in Telegraph Transmission Theory." A.I.E.E. Transactions 47: 617-644.
Olekalns, M. and P. L. Smith (2000). "Negotiating Optimal Outcomes: The Role of Strategy Sequences in Competitive Negotiations." Human Communication Research 26: 527-557.
Peduzzi, P., J. Concato, et al. (1996). "A Simulation Study of the Number of Events Per Variable in Logistic Regression Analysis." Journal of Clinical Epidemiology 49: 1373-1379.
Pesendorfer, E.-M. and S. T. Koeszegi (2006). "Hot Versus Cool Behavioural Styles in Electronic Negotiations: The Impact of Communication Mode" Group Decision and Negotiation 15: 141-155.
Putnam, L. L. and M. E. Roloff, Eds. (1992). Communication and Negotiation. Newbury Park, Sage.
Rapp, P. E., C. J. Cellucci, et al. (2001). "Effective Normalization of Complexity Measurement for Epoch Length and Sampling Frequency." Physical Review E 64: 1-9.
Rapp, P. E., M. A. Jiménez-Montaño, et al. (1991). "Toward a Quantitative Characterization of Patient-Therapist Communication." Mathematical Biosciences 105: 207-227.
Rosenstein, M. T., J. J. Collins, et al. (1993). "A Practical Method for Calculating Largest Lyapunov Exponents from Small Data Sets." Physica D 65: 117-134.
Schulz von Thun, F. (1981). Miteinander reden: Störungen und Klärungen. Reinbeck bei Hamburg, Rowohlt.
Schürmann, T. and P. Grassberger (1996). "Entropy Estimation of Symbol Sequences." Chaos 6: 414-427.
Shannon, C. E. (1948). "A Mathematical Theory of Communication." The Bell System Technical Journal 27: 379-423 & 623-656.
Shea, G. F. (1993). Creative Negotiating. Boston, MA, CNI Publishing Co.
Snyder, H. and D. Kurtze (1996). "Chaotic Behavior in Computer Mediated Network Communication." Information Processing & Management 32: 555-562.
Sterman, J. D. and J. Wittenberg (1999). "Path Dependence, Competition, and Succession in the Dynamics of Scientific Revolution." Organization Science 10: 322-341.

Steyerberg, E. W., M. J. C. Eijkemans, et al. (1999). "Stepwise Selection in Small Data Sets: A Simulation Study of Bias in Logistic Regression Analysis." Journal of Clinical Epidemiology 52: 935-942.

Steyerberg, E. W., M. J. C. Eijkemans, et al. (2000). "Prognostic Modelling with Logistic Regression Analysis: A Comparison of Selection and Estimation Methods in Small Datasets." Statistics in Medicine 19: 1059-1079.

Stogdill, R. (1959). Individual Behavior and Group Achievement. New York, Oxford University Press.

Thompson, L. L. and R. M. Hastie (1990). Judgement Tasks and Biases in Negotiation. Research in Negotiations in Organizations. B. H. Sheppard, M. H. Bazerman and R. J. Lewicki. Greenwich, CT, JAI Press. 2: 31-54.

Tribus, M. (1961). Thermodynamics and Thermostatics. New York, Van Nostrand.

Tribus, M. and E. C. McIrvine (1971). "Energy and Information." Scientific American 225: 179-188.

Tschacher, W. and C. Scheier (1995). "Analyse komplexer psychologischer Systeme. II. Verlaufsmodelle und Komplexität einer Paartherapie." System Familie 8: 160-171.

Tsonis, A. A. (1992). Chaos: From Theory to Applications. New York, Plenum Press.

Vanderstraeten, R. (2000). "Luhmann on Socialization and Education." Educational Theory 50: 1-23.

von Weizsäcker, E.-U. and C. von Weizsäcker (1972). "Wiederaufnahme der begrifflichen Frage: Was ist Information." Nova Acta Leopoldina N.F. 37: 535-555.

Walcott, C. and P. T. Hopmann (1978). Interaction Analysis and Bargaining Behavior. The Small Group in Political Science: The Last Two Decades of Development. R. T. Golembiewski. Athens, University of Georgia Press: 251-261.

Watzlawick, P., J. Beavin Bavelas, et al. (1967). Pragmatics of Human Communication: A Study of Interactional Pattners, Pathologies, and Paradoxes. W. W. Norton, New York.

Weick, K. E. (1993). "The Collapse of Sensemaking in Organizations: The Mann Gulch Disaster." Administrative Science Quarterly 38: 628-652.

Weingart, L. R., M. J. Prietula, et al. (1999). "Knowledge and the Sequential Processes of Negotiation: A Markov Chain Analysis of Response-in-Kind." Journal of Experimental Social Psychology 35: 366-393.

Ye, J. (1998). "On Measuring and Correcting the Effects of Data Mining and Model Selection." Journal of the American Statistical Association 93: 120-131.

Zartman, W. I. (1977). "Negotiation as a Joint Decision-Making Process." Journal of Conflict Resolution 21: 619-638.

Zimmerman, J. M., N. Eliezer, et al. (1968). "The Characterization of Amino Acid Sequences in Proteins by Statistical Methods." Journal of Theoretical Biology 21: 170-201.