Normative behavior based on emergent invariant expectations

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Abstract

In this paper we suggest a strictly evolutionary approach of establishing normative behavior and norms in agent systems. Our approach is strongly inspired by macro-sociological systems theory and is especially based on symbolically generalized media of communication. By means of expectation structures we avoid well-known problems of logic based methods, which usually arise around the notion of commitments. Our concept of norms is, due to the chosen background of systems theory, an observer based notion.

Keywords
Systems Theory, Normative Behavior, Evolution, Symbolically Generalized Media

1 Introduction

Although norms are represented in some way in individuals it is a difficult matter to set up norms in multi-agent systems in a sociologically reasonable way by means of logic based approaches. A predominant role in such approaches play commitments (e. g. [3]), e. g., embedded in a BDI-architecture [12]. However, it is generally assumed that norms came into existence by evolution [15]. There are approaches that code a normative behavior directly into the agent architecture ([13]), in order to look at the dynamics of the system. Also, the evolutionary dynamics of a population of normative agents and of strategic agents is considered ([9]) and the proportion of survived agents in relation to their type (normative vs. strategic) is evaluated.

In this paper we focus on the evolution of a behavior that may be regarded as normative from the point of view of an observer. In our simulations, the behavior of agents is not determined in advance, thus no norm can be assumed to exist at the beginning of a simulation. A normative behavior can only evolve, based on expectation structures, which play a crucial role in our agent architecture.

In Section 2 we present a short overview about a sociological theory which serves as a basis of our research. The benefits of symbolically generalized media, introduced in Section 2, are discussed in Section 3 in relation to multi-agent systems. We describe the framework of our simulation in Section 4, and the agent architecture in Section 5 together with the achieved simulation results. Section 6 concludes the paper.

2 Norms in the Context of Autonomous Social Systems

In the research project we present here, we focus on individual cognitive autonomy and the function of communication in processes of individual acquisition of social competence. We analyze the conditions which allow the emergence of symbol systems that are used by interacting agents to coordinate their behavior. The "semantics" of the symbols is expected to evolve during the simulation; each agent is supposed to learn how to react on communication in order to gain cooperational benefits. Therefore, we refer to norms not as prescriptive behavioral rules that represent concepts of social reality, but as effects of coordinated behavioral selectivities, individually learned in communicational interaction with others.

The central characteristics of this modeling approach are inspired by the theoretical work of the German sociologist Niklas Luhmann, who formulated a macro-theoretical position that introduces social systems as emergent autopoietic systems, based on self-referential communication [6, 7]. Due to the fact that in autopoietic theory systems are defined by the organization and effects of *self-referential* processes, a strong analytical distinction of individual cognitive systems and communication-based systems is necessary: While cognitive systems can be characterized by the operationally closed self-referential selection of neuronal modes (perceptible as thoughts, meaning and expectations), communication-based systems refer to self-referential selection of communicative behavior in the interaction of individuals. Luhmann explains the emergence of autonomous communication-based systems as a result of *structural couplings*, constituted by interacting individuals that perceive each-other as "black boxes". They have to learn to generate information by observing each others, to build expectations and to select communicative reactions in order to manipulate others according to these expectations. As a consequence of this situation of *double contingency* – based on recurrent expectations of communicative reactions – structures of self-referred communication may emerge if they lead to the manipulation of individual behavioral selectivities (including communication and perception) in a way that allows their own reproduction and, simultaneously, the reproduction of the involved cognitive systems. Concerning the type of system-constituting self-referential processes, communication-based social systems have to be located as autonomous and autopoietic in the environment of individual cognitive systems.

The constructivistic roots of Luhmann's approach have strong consequences on the analysis of norms: The identification of "a norm" can only be made by an observer; in any case, it is an *individual cognitive phenomenon*, based on expectations about the social behavior of others in an iterated "prediction-and-error"-analysis. If the so constructed model of the *complexity-reduced* social environment allows predictions that match the observed facts, this gain of social competence may allow coordinated behavior and results in social integration. Thus, any social phenomenon is based on inter-related cognitive expectations and behavioral selectivities. The relevant question in the context of normative analysis is: which expectation needs to be perceived as being normative? Luhmann's answer refers to the way how expectations are build and changed [7, pp. 319]:

1. Normative expectations are defined as expectations, which are not modified if they are disappointed.
2. Additionally, in the case of disappointment, there exist pre-dispositions what to do then.

The first mentioned characteristic of normative expectations – as being defined as not objected to modifications if disappointed – has implications on the behavioral disposition of others, as far as further interactions with the deviant individual are intended: The renunciation of expectational adaptation is only possible, if the individual member of a society *can rely on the support of others* in the case of a conflict [8, p. 638]. Thus, the concept of norms is strongly related to the ability of being able to mobilize cooperational networks in order to apply an aggregation of sanctions, that has to be avoided in any case by the one who breaks the rules. The possibility to do so presupposes the existence of special forms of symbolic communication, which can be used to symbolize the dominant ability and willingness to enforce, if necessary, the adaptation of deviant behavior to the own normative expectations. This form of symbolized treatment only works, if the symbols, their meaning and the constraints of using them are known by all members of the society. Additionally, everybody has to know that the other members are also aware of the meaning of these symbols.

2.1 Generalized Media

The concept of gaining influence on behavioral selectivities by symbolizing the potential to engage others, is defined by Luhmann as *symbolically generalized media of communication*. It is strongly influenced by the concept of *generalized media of interchange*, formulated by Talcott Parsons [11]. In the context of sociological systems theory, these concepts are used to explain the functional differentiation of social structures and cooperation in modern society. Therefore, the analysis of the evolutionary mechanisms of generalized media in multi-agent societies is one of the central interests of our research project.

Generalized media may be coded in different ways: For functional differentiation and evolution of norms, the codings of *power* and *money* are of upmost importance. The main benefit of using generalized media in processes of functional differentiation is the possibility to avoid ponderous procedures of committing others to cooperation: By means of generalized media – regardless of the situation they are used in – others can effectively be convinced to cooperate by generating expectations (about sanctions or rewards) that directly influence their motivational basis of behavioral selectivity. Therefore, generalized media are coded in a simple binary way: If based on the symbolization of *power*, it uses the distinction of *right/false* in the second-order-coding mechanism of law. In a similar way, the media of *money*-based communication uses the distinction of *having/not-having* to symbolize social claims of opportunities of action (cf. [4]).

In any case, symbolically generalized media has an *autocatalytic* function in processes of structural differentiation: If generalized media is involved, networks of cooperation can use its mechanism to symbolize the aggregated sanctioning/reward-potential – resulting from cooperational benefits – to motivate others to cooperate too. In this context, the media itself is only a universal mechanism to motivate cooperation: it is independent of the specific functional communication of differentiated subsystems, but grants the integration of the system itself. This dynamic reinforces the symbolizing mechanism of generalized media, as long as sanctions or rewards can effectively be applied if needed. Usually, this is an exception, as most people cooperate without trying to test if they really get applied to sanctions if they do not comply with normative rules. Nevertheless, if sanctions or rewards cannot be applied as expected (and this situation is observed by others), the symbolizing mechanism of generalized media collapses inflationary (the most prominent examples of these kind of phenomena are rebellions, civil wars and money-inflation).

2.2 Predispositions

According to Luhmann, there's another important characteristic of normative expectations we want to integrate in our simulation model: As already mentioned in point two of the definition above, normative expectations include predispositions if they are disappointed. In the context of human society, this feature is important to be not regarded as being naive or socially incompetent. Luhmann emphasized the importance to refer to this predisposition when normative expectations are expressed to others ([7, 437]) One way of doing so is to symbolize the readiness to apply sanctions as described above. Additionally, this concept of behavioral predispositions in case of disappointment has to be modeled on the cognitive level of agents. Our approach is to model some – as we expect – central characteristics of *cognitive framing processes* as far as behavioral selectivities are concerned. We want to emphasize, that no *representational* implications (e.g. those of "norms" or "interests") are intended. Our strategy is to draw a distinction between two classes of possible reactions, depending on the situational context:

- On the one hand, there are communicational and other behavioral reactions, that are performed by the majority of others in a comparable situation. In the context of cooperation, they coordinate the individual contributions and are perceived as being the "usual" behavior as defined by social norms. The range of possible normative reactions that are expectable in a given situation can be represented as organized in a cognitive "frame". We define this frame as a set of selectivities, that relate expectable observations and normative reactions in the context of a given situation.
- Other observations, that are not expected in the context of this situation, have to trigger a specialized procedures in order to clarify the reason for the unexpected reaction. If the unexpected reaction is identified as intended (other possibilities like misunderstandings etc. have to be excluded) normative conformity may be enforced by using the mechanism of generalized media as described above.

3 Benefits of Media in Agent Systems

But apart from these functions on the level of the social system, what is the function of such a medium on the interactional level? As Luhmann states, symbolically generalized media of communication reduce complexity, especially complexity outside an individual. A very complex situation may collapse into a simple yes-or-no question. By means of these media, a lot of information and therefore complexity is excluded from interest, and an interaction just focuses on a yes or on a no, or in other words, accepting something or not accepting something. For example, if one individual offers something to buy, another individual just thinks about buying it or not, but it does not think about the reason why the other individual may sell it, or what product it wants to get for it later. A buyer has no reason to care about the money when it is once spent, and a seller does not care about where the money comes from. Luhmann points out that symbolically generalized media are based on their "embodiness". They are related to physical entities, e. g. *money* is related to needs, or *power* is related to physical force and pain

Why do media reduce complexity during an interaction? They serve as structures of expectation, they order and structure with respect to what should be expected in which situation. On the one hand, media reduce possibilities, and, on the other hand, they open possibilities for further communication or the prospect of further communication. Thus, media reduce external complexity to expectable internal complexity.

Some concepts related to symbolic media are already dealt with on a large scale in multi-agent research, especially norms (see e. g. [9] or [2]) and market based coordination mechanisms (see e. g. [10] or [1]). All the mechanisms based on these concepts, first of all norms, have the goal of enabling interactions between agents which do not know much about each other, but do know something in general. Norms are condensed expectation structures. A population wide norm makes actions of agents expectable.

It is obvious that mechanisms like symbolically generalized media of communication may play an important role in scaling huge agent systems. The largest utility of media is concerned with their knowledge reducing effect for agent interactions. Interactions, controlled by a medium, are structured in a straightforward way. They do not ensure that an interaction always succeeds, but they ensure that

- agents know in advance on what aspect(s) negotiation should be limited,
- agents need not to know each other,
- agents can be black boxes to each other (they cannot look inside their head), but coordination may still succeed, and

- agents know in what stage an interaction currently is, and when it should be stopped.

Every agent is only concerned with its own beliefs or goals, there is no need to take into account elaborated reasoning mechanisms about beliefs or goals of other agents, since they become immediately apparent to each other during an interaction to some extent. Whatever an agent wants or believes it will be canalized by a medium to another agent. A medium does not reveal an agent's goal or its beliefs, but it offers a way to achieve a goal or to verify or to strengthen its own beliefs.

Different media are based on different techniques to support inter-agent coordination. *Power* may an agent force to do something which is not in its own best interest, but may serve someone else. Especially the symbolized power by many agents may another agent force to confirm and to comply with population wide norms. Symbolizing power does not necessarily mean to apply power, it just symbolizes the potential application of power. However, in the case power is applied the receiver suffers in some way.

The medium *money* is related to resources, especially to the shortage of one or more resources. Because *money* is the second coding of assets (of resources) (see [7]) it serves as an exchange medium for all kinds of resources. Therefore, an agent without a direct access to a certain resource but with a need for it may get it by spending money. That is, if two agents negotiate about the access to a resource they do it by negotiating the value for it. As a result they do not negotiate on the basis of who has a more urgent need for the resource, or which agent has a greater impact on the hole population.

4 The Model

A simulation consists of a large number of trials of a cooperation game which we called the "Planter-and-Harvester-Game" for simplicity. We introduce two different types of agents, with respect to their ability to change the environment. There are also two types of actions that change the state of the environment in an effective way, namely "planting" and "harvesting" complementing each other. Plant agents, called *Planter* (or agent type 0) can perform only plant actions effectively, harvest agents, called *Harvester* (or agent type 1) can perform only harvest actions effectively. At the beginning of a game the environment U is always in state $U_s = 0$. A plant action $Plant_I$ – performed by a *Planter* – transforms the environment into state $U_t = 1$, a harvest action $Harvest_I$ – performed by a *Harvester* – transforms it into the final state $U_e = 2$. In more complicated games the final state may be $U_e > 2$ assuming action sequences $Plant_I$, $Harvest_I$, $Plant_{II}$, and so on. Action $Plant_I$ in state $U = 1$ has no effect with regard to the state of the environment, similarly action $Harvest_I$ in state $U = 0$. In general, the transformation of the environment state U_t at time t that a plant agent may perform by action a_t is defined by

$$[(U_t = i) \wedge ((i \bmod 2 = 0) \wedge (type = 0)) \wedge (a_t = i)] \Longrightarrow U_{t+1} := i + 1$$

and for harvest agents by

$$[(U_t = i) \wedge ((i \bmod 2 = 1) \wedge (type = 1)) \wedge (a_t = i)] \Longrightarrow U_{t+1} := i + 1 \,.$$

In any other situation the environment remains in state i ($U_{t+1} = i$).

At the beginning of a game two agents are randomly selected from the population, and one of them is chosen as the start agent. This agent begins by sending a message M_0. The other agent receives this message and does both, it – the first time – performs an action a_1 and sends another message M_1 to the start agent. Then, the first agent performs an action a_2 and sends a message M_2 to the second agent, and so on. A round is defined by a successive sequence of performing one action and generating a message for each of the two agents. Both types of agents have the same repertoire of actions regardless of the efficiency: apart from plant and harvest actions they have a *Null*-action without any effect, a sanctioning action *Bite*, an action *Exit*, and an action

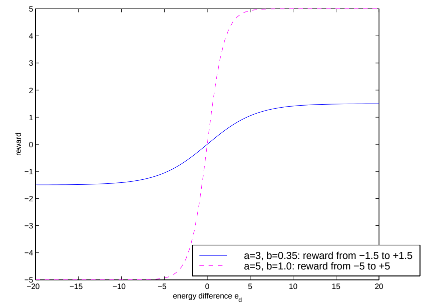

Figure 1: Two examples of the reward generating function.

Replace. The later action affects the opponent agent in the way that it gets replaced by a other agent, randomly selected from the population. This may increase the general possibility for a successful coordination. A game may end with three different outcomes: an agent performed the *Exit* action, the environment reached the final state U_e, or the number of rounds in the games exceeded the defined threshold *rounds*.

There is a predefined set of symbols $\mathcal{S} = \{0, 1, 2, ..., S_{max}\}$. A message consists exactly of one of these symbols. A symbol itself has no meaning to an agent, there is no predefined semantics at all.

A game ends successfully if the environment was transformed into the final state. In this case, the last two agents participating in the game get a certain amount $E^{\star}$ of "energy". In other cases there is no energy payoff. Every action that an agent performs consumes a specified amount of energy of the agent. There are low cost actions (*Null*, *Exit*, and *Replace*) and high cost actions ($Plant_x$, $Harvest_x$). For a low cost action the agent consumes energy $E_l > 0$, for a high cost action $E_l + E_h$, $E_h > 0$. The cost of the action *Bite* is $E_l + E_b$, $E_b > 0$. This action affects the other agent in the way that the "bitten" agent looses pain energy $E_p > 0$. At the beginning of an agent's life time its energy is set to $E = E_s > 0$, its start energy. If E ever falls below 0, the agent dies, i. e., the agent is removed from the population.

An agent does not know its own type nor perceives the type of another agent. They are black-boxes to each other. An agent perceives the message of another agent and – perhaps – some sensory input like the state of the environment or the fact of being bitten. In any case not all relevant aspects of the environment are known in the same way to all the participants. Agents must test different actions at different times and the only hint to whether an action or message was appropriate or not is given by a reward signal. This signal is always generated by the agent itself, based on the energy difference between two consecutive actions. A sigmoid function f_r (see Equation (1)) generates the reward signal r based on the energy difference e_d; a positive energy difference results in a positive reward, a negative difference results in a negative reward. The reward generating function f_r is parametrized by two values, a and b:

$$f_r = 2 * a * \frac{1}{1 + exp(-b * e_d)} - a \ . \tag{1}$$

Figure 1 shows two examples of the function. Thus, the individual learning of an agent is of reinforcement-learning type. This definition of a reward signal is a weak one, since it does not assume any intelligent observer (outside the agent) who generates a reward signal based on its knowledge about to correct actions.

Beside an energy value agents have an age A, which at the beginning of an agent's life time is set to 0. Any time an agent is selected to play the game, its age will be incremented by 1. If the age reaches an individual maximum, A_{max}, the agent will be removed immediately from the population. At the start of the simulation, the population P consists of a certain number of agents P_s. The number of agents during the simulation may shrink or grow, depending on the fitness of the agents. An agent may enter the population if there are at least two agents, whose age is above a value A_{sex} and whose energy value is above a value E_{sex}. The two "parents" are selected by a "Roulette wheel" [5] from all possible parent agents based on their energy values. Once a successful breeding occurred, the two parent agents are prevented from reproduction for a certain period of time t_{pause}. The amount of gene material parents pass on to their child is described in the next section. The general schedule of the simulation is:

1. initialize start population P_s
2. do forever
   - select randomly two agents, $Agent_1$ and $Agent_2$, and $t := 0$, $U_0 := 0$
   - $Agent_1$ generates and sends a start message M_0
   - do
     - $t := t + 1$
     - $Agent_2$ receives previous message M_{t-1} and generates action a_t and message M_t
     - $t := t + 1$
     - $Agent_1$ receives previous message M_{t-1} and generates action a_t and message M_t

     until $U_t = U_s$ or $a_t = Exit$ or $t = 2 + rounds$
   - remove from or add agents to the population

Whenever the number of agents in the population P_t falls below P_s, agents are randomly added to the population until $P_t = P_s$. If this situation happens it can be interpreted as restarting a simulation.

5 Evolution of Frame-like Structures

As mentioned in the Introduction, expectations in choosing an appropriate answer to a received message are the main feature of the proposed agent architecture. Using only previously sent messages in order to define an internal state on which an agent bases its reply and action does not capture the entire situation. Thus, we combine an internal state with the expectation of a received message. This results in a frame-like structure which will be executed on two levels. In a first step a set F_i of frames is chosen based on the state of the environment. This step will be performed without any learning by the agent and is totally determined by the environment. In a second step the agent chooses one frame from the previously chosen set F_i. The selected frame will be executed resulting in an action a_{t+1} and a new message M_{t+1}. A frame F is defined with respect to a received message $M_r = M_t$ in the following way:

$$\begin{array}{llllll} \text{if} & M_r = M_{e1} & \text{then} & a := act_1 & \text{and} & M := mes_1 \\ \text{elseif} & M_r = M_{e2} & \text{then} & a := act_2 & \text{and} & M := mes_2 \\ \text{else} & & \multicolumn{4}{l}{\text{execute trouble frame} \quad F^T ,} \end{array}$$

where $a_{t+1} = a$ and $M_{t+1} = M$. The "trouble frame" F^T will be executed in the case that the received message was neither M_{e1} nor M_{e2}. This frame has a special structure, because it does not check the occurrence of a certain message, rather it checks whether the agent was bitten or not in order to determine the new action and message:

$$\begin{array}{llllll} \text{if} & bitten = true & \text{then} & a := act_{T1} & \text{and} & M := mes_{T1} \\ \text{else} & & \text{then} & a := act_{T2} & \text{and} & M := mes_{T2} \, . \end{array}$$

For every state of the environment the agent has $n_f \geq 1$ frames. The selection of a frame at time t will be guided by a Q-value Q_F, i. e., reinforcement learning ([14]) takes place in order to choose an appropriate frame in a given (environmental) situation. The entire collection of frames for an agent by a given final state U_e of the environment is:

state (depends on U)	frame set $F_i = \{F_{(i,0)}, \ldots, F_{i,n_f-1}\}$
0: $U^\star$	$F_{(0,0)}, \ldots, F_{(0,n_f-1)}$
1: $U = 0$	$F_{(1,0)}, \ldots, F_{(1,n_f-1)}$
2: $U = 1$	$F_{(2,0)}, \ldots, F_{(2,n_f-1)}$
$\vdots$	$\vdots$
U_e: $U = U_e - 1$	$F_{(U_e,0)}, \ldots, F_{(U_e,n_f-1)}$
U^T	$F_0^T, \ldots, F_{n_f-1}$

$U^\star$ is the frame set for an agent when it starts the communication by generating just a message M_0, and U^T is the frame set for the trouble state.

Evolution is based on frames, agents do not change frames during their life time, they are just able to change the Q-value of a frame with respect to other frames inside the same frame set. At the beginning of the simulation, all frames of all agents are initialized randomly. In particular, variables M_{e1}, M_{e2}, mes_1, mes_2, mes_{T1}, and mes_{T-2} are randomly chosen values from $\mathcal{S} = \{0, 1, 2, \ldots, S_{max}\}$, and variables act_1, act_2, act_{T1}, and act_{T2} are randomly chosen values from $\mathcal{A} = \{Null, Bite, Exit, Replace, Plant_I, Harvest_I, Plant_{II}, \ldots\}$. Inheritance happens on the frame level, i. e., cross-over takes place *between* frames, not inside a frame (but inside a frame set). Individual parts of a frame are subjected to mutation. Therefore, e. g. part M_{e1} or act_2 may get a new random value during a mutation process. Q-values are not passed on to offspring, and are set to small random values at the beginning of an agents life time.

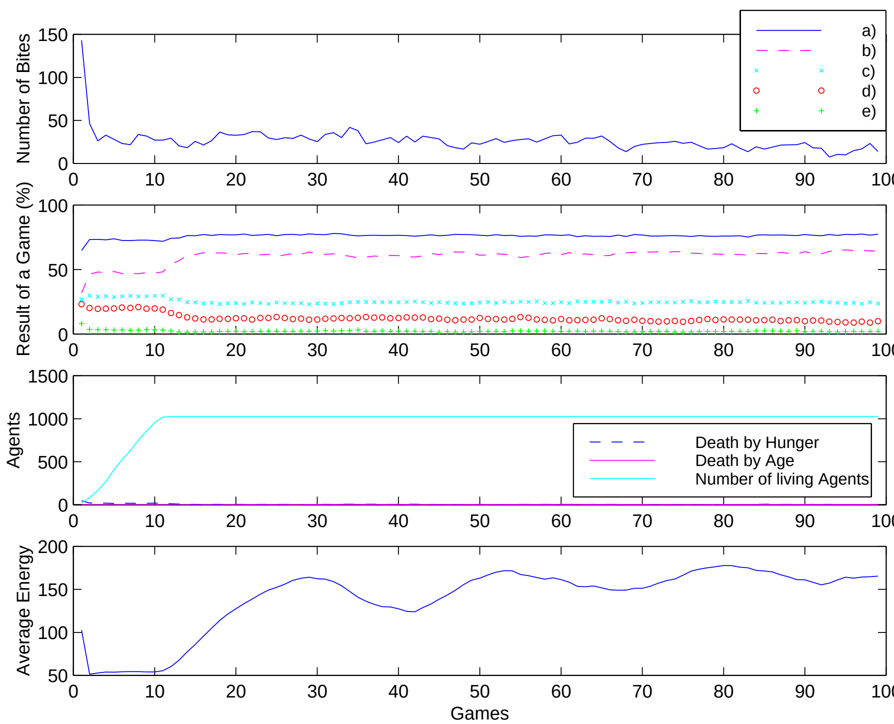

Figure 2: Results averages 1000 games, apart from the *Bites*-graph, which shows the total number of bites in 1000 games. Result of the game (legend for the second graph is shown on top): a : maximum possible success (counting the occurrence of a "correct" pairing of the agents); b : the actually achieved success; c : correctly performed *Exit*; d : *Exit* in wrong situation; e : stopped, because maximum rounds exceeded. $U_e = 4$, $S_{max} = 3$, $rounds = 10$, $E^\star = 10.0$, $E_l = 0.5$, $E_h = 2.5$, $E_b = E_p = 0.1$, $E_s = 50.0$, $A_{max} \in \{550, \ldots, 800\}$, $A_{sex} = 20$, $t_{pause} = 20$, $a = 5.0$, $b = 1.0$, $n_f = 2$.

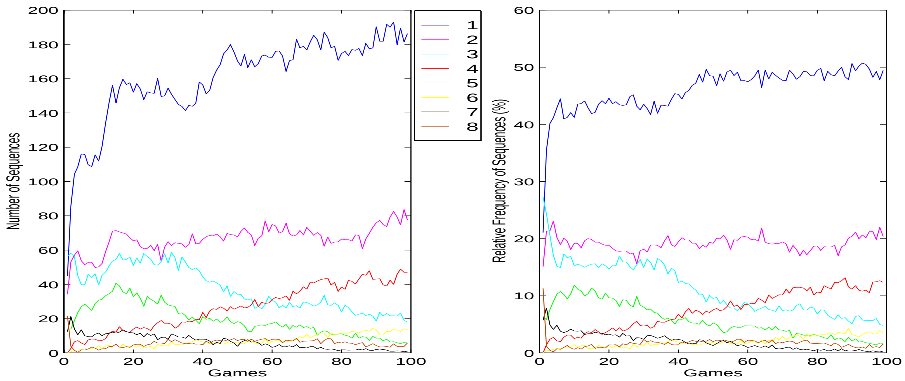

Figure 3: The eight main sequences. Left: Absolute occurrence of sequences, right: relative occurrence of the sequences (in relation to 346727 successful sequences). The eight sequences occur 329895 times. See text for further explanations.

Figure 2 shows the general outcome of a simulation based on frame type agents. The maximum number of agents was set to 1024. The simulation started with 3 agents and as long as the number of agents was below 15 a higher energy pay off $E^{\star}$ was given for success than indicated in the figure (to support an onset of evolution). The number of agents grows rapidly until the limit is reached. Later, evolution still takes place optimizing the frame structures. This may result for example in changing cooperation sequences, or in a "competition" of different sequences (cf. Figure 3). Figure 3 shows the eight most frequent sequences of the entire simulation. In detail, they are:

number (cf. Fig. 3)	number of occurrence	sequence M_0 M_1 a_1 M_2 a_2 ...
1	160877	1 0 4 0 5 1 6 2 7
2	66551	2 0 4 0 4 0 5 1 6 2 7
3	37402	0 0 4 0 5 1 6 2 7
4	26721	0 1 5 0 4 0 5 1 6 2 7
5	19039	2 1 5 0 4 0 5 1 6 2 7
6	7118	0 0 4 0 4 0 5 1 6 2 7
7	6453	2 0 5 0 4 0 5 1 6 2 7
8	5734	2 1 7 0 4 0 5 1 6 2 7

The first sequence occurs 160877 times, out of 346727 successful sequences, without a *Replace*-action. In contrast to the previous simulation, frame agents were able to select the start message M_0.

The communicative behavior of agents becomes more and more regular. Because we have chosen $n_f = 2$ it is obvious that a frame set is assumed to contain exactly one appropriate frame for $Planters$ and one for $Harvester$. An individual only has to explore which one is better suited. A detailed analysis of the communicative behavior reveals indeed that communication controls the behavior of agents. Thus, agents realize the type of the other agent and choose a useful action in the case that the other agent is of its own type (see Figure 4). Furthermore, we regard the question of which action is performed on the basis of a received message (see the analysis in Figure 5), and indeed, agents act in a foreseeable way, i. e., one agent may control by communication the action of the other agent. Further investigations could be done, especially a more detailed analysis with respect to a combination of two or more dimensions of interest. For example, in which situation (state of the environment) a $Planter$ reacts with which action after receiving message 0 (cf. left graph on top of Figure 5)?

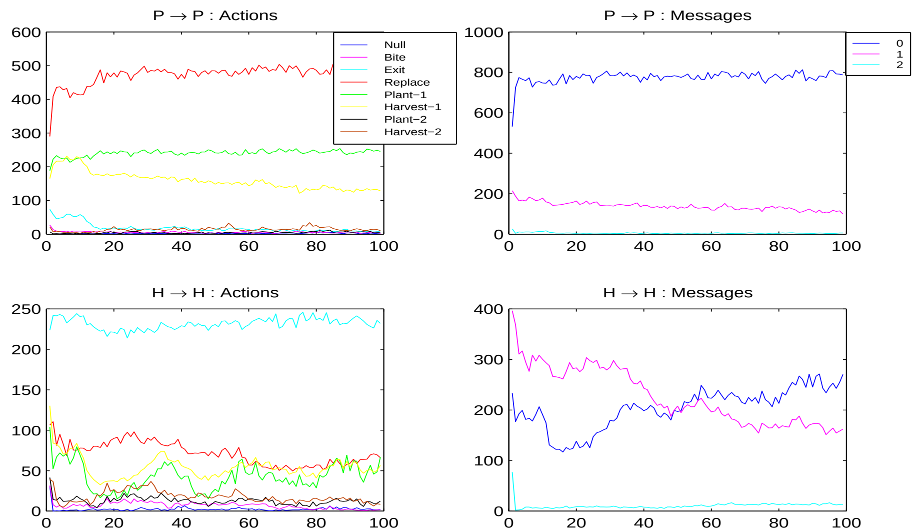

Figure 4: Performed actions and sent messages of *Plant* agents and *Harvester* agents with respect to unfavorable agent grouping. *Planters* (top row) prefer the *Replaces* action, *Harvester* (bottom row) prefer the *Exit* action. Both types of agents realized that the other agent was not a "correct" partner and that without having any direct access to the type of an agent (neither to the own nor to the type of another agent).

6 Conclusion

In this paper we argued that a strict evolutionary approach to norms may prevent traditional problems of logic based methods, especially in the case, no norms are pregiven to agents' disposal. The macro-sociological systems theory of Niklas Luhmann offers an elegant way the anchor normative behavior on structures of expectation. Although we have not modeled all aspects of generalized media up to now, a normative behavior of agents, playing a coordination game, in simulation experiments emerged.

In interesting feature of symbolically generalized media is the emergent establishment of functional social substructures [7]. Although still a speculative matter, we expect media to play also a crucial role in artificial agent societies with respect to functional structuring of large scaled systems. Our approach has to be further evaluated and extended. Thus, in the next period of our project we will extent the described frame structure with respect to the selection of a frame set 6, which is so far determined solely by the environment. Furthermore, individual learning capabilities will be increased.

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References

[1] G. Ballot and E. Taymaz. Technological change, learning and macro-economic coordination: An evolutionary model. *Journal of Artificial Societies and Social Simulation ¡http://www.soc.surrey.ac.uk/JASSS/2/2/3.html¿*, 2(2), 1999.

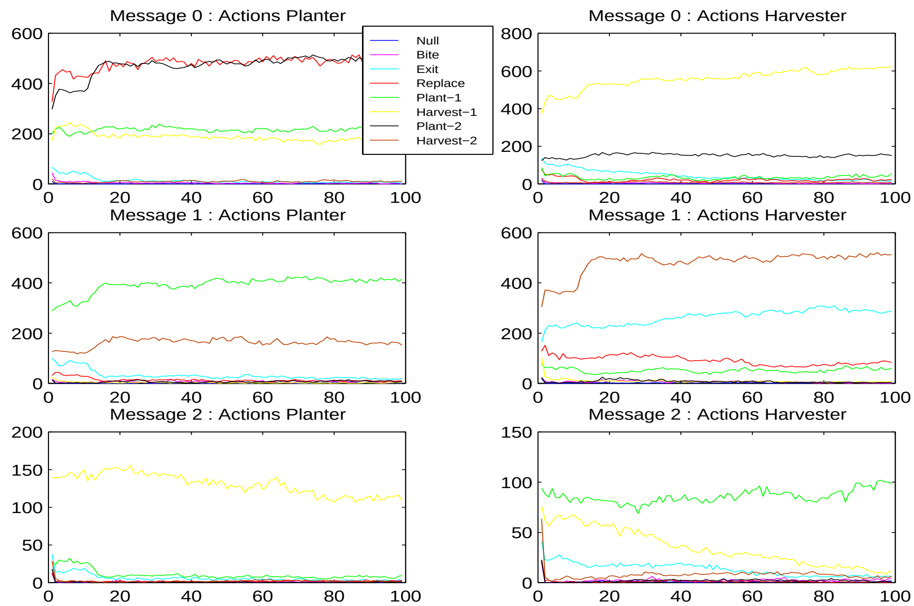

Figure 5: Frame agents. The actions of *Plant* agents and *Harvest* agents which follow a certain message.

[2] K. Binmore. *Game Theory and the social contract*, volume 1: Playing fair. Cambridge, Mass.: MIT Press, 1994.

[3] L. Gasser. Social conceptions of knowledge and action: DAI foundations and open systems semantics. *Artificial Intelligence*, 47:107–138, 1991.

[4] B. Giesen. Media and markets. In M. Schmid and M. Wuketits, editors, *Evolutionary Theory in Social Science*, pages 171–194. Reidel Publishing Company, 1987.

[5] D. E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Publishing Company, Inc., Reading, Mass., 1989.

[6] N. Luhmann. The Autopoiesis of Social Systems. In F. Geyer and J. van der Zouwen, editors, *Sociocybernetic Paradoxes*, page 172ff., London, 1986. Sage.

[7] N. Luhmann. *Social Systems*. Stanford University Press, Stanford, Ca., 1995.

[8] N. Luhmann. *Die Gesellschaft der Gesellschaft*. Frankfurt/M.:Suhrkamp, 1 edition, 1997.

[9] M. Paolucci and R. Conte. Reproduction of Normative Agents: A Simulation Study. *Adaptive Behavior*, 7(3/4):307–322, 1999.

[10] S. Park, E. H. Durfee, and W. P. Birmingham. Emergent Properties of a Market-based Digital Library with Strategic Agents. In Y. Demazeau, editor, *Third International Conference on Multi-Agent Systems (ICMAS98)*, pages 230 – 237, Los Alamitos, Cal., 1998. IEEE Computer Society.

[11] T. Parsons. *The Structure of Social Action*. Free Press, New York, 1968.

[12] A. S. Rao and M. P. Georgeff. Modeling Rational Agents within a BDI-Archtiecture. In *Proceedings of the Second International Conference on Principles of Knowledge Representation and Reasoning*, pages 473–484, Cambridge, Mass., 1991.

[13] Y. Shoam and M. Tennenholtz. Social Laws for Artificial Agent Socities: Off-line Design. *Artificial Intelligence*, 73, 1995.

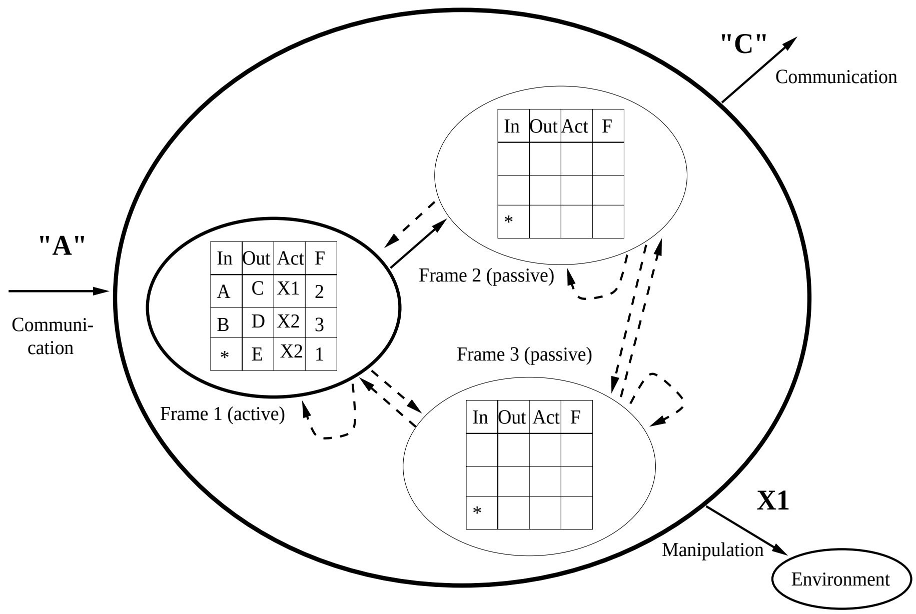

Figure 6: The general outline of the frame concept in further simulations (here, a frame set is supposed to contain only one frame). This figure shows an simplified example, how behavioral selectivity is related to the framing-concept: In a given situation, the agent is able to observe communication in the context of frame 1 (active frame). In this frame, he "expects" the symbols "A" or "B". In case of "A", he would select his answer "C", perform the activity X1 and select frame 2 as the next active frame. In any other case (e.g. the symbols "C" to "Z"), he would answer with the symbol "E", perform the activity X2 and remain processing communication using frame 1.

[14] R. S. Sutton and A. G. Barto. *Reinforcement Learning: An Introduction.* The MIT Press, Cambridge, Mass., 1998.

[15] E. Ullman-Margalit. *The emergence of norms.* Oxford University Press, Oxford, 1977.