Empiric-rational Semantics of Agent Communication*

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Abstract

The missing of an appropriate semantics of agent communication languages is one of the most challenging issues of contemporary AI. Although several approaches to this problem exist, none of them is really suitable for dealing with agent autonomy, which is the decisive property of artificial agents. This work introduces a novel approach to the semantics of agent communication, which combines the benefits of the two most influential traditional approaches to agent communication semantics, namely the mentalistic *(agent-centric) and the* objectivist *(i.e., social commitment- or protocol-based) approach. Our approach makes use of the fact that the most general meaning of agent utterances lays in their expectable* consequences *in terms of agent actions, and that communications result from hidden but nevertheless rational and to some extend reliable agent intentions. In this work, we present a formal framework which enables the empirical derivation of communication meanings from the observation of rational agent utterances, and introduce thereby a probabilistic approach to social commitments.*

Keywords: Agent Communication Languages, Open Multiagent Systems, Artificial Sociality

1. Introduction

Currently, two major approaches to the meaning of agent communication in a broader sense, covering both traditional sentence semantics and pragmatics, exist. The *mentalistic* approach (e.g. [4, 5]) specifies the meaning of utterances by means of a description of the mental states of the respective agents (i.e., their beliefs and intentions, and thus indirectly their behavior), while the more recent *objectivist* approaches (e.g. [2, 3], also called *social semantics*) try to determine communication from an external point of view, focussing on public rules. The former approach has two well-known shortcomings, which eventually led to the development of the latter: At least in open multiagent systems, agents appear more or less as black boxes, which makes it in general impossible to impose and verify a semantic described in terms of cognition. Furthermore, they make simplifying but unrealistic assumptions to ensure mental homogeneity among the agents, for example that the interacting agents were benevolent and sincere. Objectivist semantics in contrast is fully verifiable, it achieves a big deal of complexity reduction through limiting itself to a small set of normative rules, and has therefore been a significant step ahead. But it oversimplifies social processes in favor of traditional sentence-level semantics, and it doesn't have a concept of meaning indefiniteness, and agent malevolence. In contrast to these approaches, we propose a semantics which is based on the pragmatic assumption that the meaning of utterances in open multiagent systems lies basically in their *expectable consequences* in terms of future agent actions which need to be continuously learned from already observed agent actions (the *context* of the utterances). These consequences are represented as probabilistic *Social Interaction Structures*, which are a variant of *Expectation Networks* [7], and they are learned by a *semantical observer*, which can be either an agent participating in the communication himself, or an external agent (e.g., a special middle agent or a supervision facility of the system designer). This learning task puts two general assumptions about agent communication into practice: i) observed agent interactions within a certain context are likely to reoccur in similar situations in the future (empirical stationarity assumption), and 2) agents act rational towards their communicated goals within a limited *sphere of communication* (limiting their trustability). From these assumptions, we retrieve the following "replacements" for traditional semantical concepts:

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- Verification of semantics according to normative rules as in social semantics → Verification regarding a learned model of concrete agent communication processes
- Assumption of mental agent rationality → revisable, probabilistic expectation of limited rational behavior (the so called *rational hulls* of communications)
- Social commitments and agent sincerity → revisable, probabilistic expectation of the limited maintenance of communicated goals by the uttering agents

For lack of space, we do not present the semantical model for a concrete, speech-act based ACL here. Instead, we propose the dynamic semantics of so-called *elementary communication acts* (ECAs) which obtain their meaning not from some given performative type ontology as usual, but entirely from their usage context. The theoretical assumption behind ECAs is that all kinds of speech acts can be translated into one or more demands to act in pragmatical conformance with a declared future course of behavior (e.g., an informational act would be the request to communicate in conformance with the expressed belief from now on, and a command would be the request to perform the described actions) [7], whereby each ECA can be contextualized with companion social structures resulting from other ECAs to clarify and get accepted the demand (e.g. sanctions).

The reminder of this paper is organized as follows: The next section defines *Expectation Networks* as the data structure used to describe agent interaction. Section 3 extends this definition with a formal learning and adaptation framework for social (i.e., communication) structures, and finally, section 4 draws some conclusions regarding current limitations of our approach and future work.

2. Expectation Networks

Expectation Networks (ENs) are the graphical data structures we will use for the stochastical modelling of Social Interaction Structures later. The formal EN definition we present in this work is an improved yet simplified version of the definition presented in [7].

The central assumption that is made in ENs is that observed events like agent actions (especially symbolic agent messages) may be categorized as expected continuations of other observed event sequences. An edge leading from event m to event m' is thought to reflect the probability of m and m' being correlated from the observer's point of view (the descriptive power of ENs is thus similar to Markov processes, but in contrast edges in ENs relate events, not states).

As for $\mathcal{M}$, this is a formal language that defines the events used for labelling nodes in expectation networks. Its syntax is given by the grammar in table 1. Agent actions observed in the system can be either "physical" actions of the format (a, ac) where a is the executing agent, and ac is an domain-dependent symbol used for a physical action, or symbolic elementary communication acts $ECA(a, c)$ sent from a to another agent with content c. We do not talk about "utterances" or "messages" here, because a single utterance might need to be decomposed into multiple ECAs. The symbols used in the $Agent$ and $PhysicalAction$ rules might be domain-dependent symbols the existence of which we take for granted. For convenience, $agent(eca)$ shall retrieve the acting agent of an ECA.

$$
\begin{array}{rcl}
\mathit{Expect} & \in & [0;1] \\
\mathit{Agent} & \rightarrow & \mathit{agent\_1} \quad | \quad \ldots \quad | \quad \mathit{agent\_n} \\
\mathit{PhysicalAction} & \rightarrow & \mathit{move\_object} \quad | \quad \mathit{touch\_agent} \quad | \quad \ldots \\
\mathit{Action} & \rightarrow & \mathit{ECA}(\mathit{Agent}, \mathit{Projection}) \\
 & & \quad | \quad \mathit{do}(\mathit{Agent}, \mathit{PhysicalAction}) \\
\mathit{ActionPattern} & \rightarrow & \mathit{Action} \quad | \quad ? \\
\mathit{Projections} & \rightarrow & (\mathit{Conditions}, \mathit{GoalStates}) \\
\mathit{Conditions} & \rightarrow & \mathit{SimplePath} \\
\mathit{GoalStates} & \rightarrow & \mathit{SimplePath} \\
\mathit{SimplePath} & \rightarrow & \mathit{Action}\ \mathit{SimplePath} \quad | \quad \varepsilon
\end{array}
$$

A grammar for event nodes of ENs, generating the language $\mathcal{M}$ (the language of concrete actions, starting with $Action$).

Table 1.

In addition to normal node labels, we use the symbol $(\triangleright_{EN})$ to denote the root node of an specific EN. The special symbol ? marks pseudo-nodes which are just graphical abbreviations for the so-called $completeEN$ which models the uniform distribution of all possible combinations and sequences of observable events (see below). A "node" labelled with ? thus stands for a branch with infinite depth.

The content c of a non-physical action, finally, is given by type $Projections$. The meaning of $Projections$ will be described later.

Syntactically, expectation networks are here represented as lists of edges (m, p, n) where m and n are actions, p is a transition probability (***expectability***) from m to n. We use functions $in : V \rightarrow 2^C$, $out : V \rightarrow 2^C$, $source : C \rightarrow V$ and $target : C \rightarrow V$ which return the ingoing and outgoing edges of a node and the source and target node of an edge, respectively, in the usual sense. $children : V \rightarrow 2^V$ returns the set of children of a node, with $children(v) = \emptyset$ in case v is a leaf. $\prec : V \times V \rightarrow \{true, false\}$ returns $true$ iff there is a path leading from the first argument node to the second and the event associated with the second node is expected to occur after the event of the first node.

C is the set of all edges, V the set of all nodes in the EN. Edges denote correlations in observed communication sequences. Each cognitive edge is associated with an

expectability (returned by $Expect : C \rightarrow [0;1]$) which reflects the probability of $target(e)$ occurring after $source(e)$ in the same communicative context (i.e. in spatial proximity, between the same agents, etc.).
For convenience, sometimes we denote paths in an EN leading from $v_0 \in V$ to $v_n \in V$ as strings of message labels (ECAs) $Label(v_0)...Label(v_n)$ in case this notation is unequivocal. $Node : SimplePath_{\mathcal{EN}} \rightarrow V$ results in the node corresponding to a certain path given as a string of labels. Nodes or corresponding messages along a path p will be denoted as p_i.
Having discussed the prerequisites, we can now define expectation networks formally:

Definition 1. An *expectation network* is a structure

$$EN = (V, C, \mathcal{M}, Label, Expect) \in \mathcal{EN}$$

where

- V with $|V| > 1$ is the set of nodes,
- $C \subseteq V \times V$ are the *cognitive* edges (or *edges* for short) of EN. (V, C) is a tree called *expectation tree*. (V, C) shall have a unique root node called $\triangleright_{\mathtt{EN}} \in V$ which corresponds to the first ever observed action. The condition

$$\forall v \sum_{e \in out(v)} Expect(e) = 1$$

  should hold.
- $\mathcal{M}$ is the *action language*. As defined in table 1, actions can be symbolic ($ECA(...)$) or physical actions ($do(...)$). While we take the existence and the meaning of the latter in terms of resulting observer expectations as granted and domain-depended, the former will be described in detail later.
- $Label : V \rightarrow \mathcal{M}$ is the *action label* function for nodes,
- $\forall v \in V : \forall e, f \in children(v) :$ $\neg unify(Label(e), Label(f))$ (where $unify$ shall be $true$ iff its arguments are syntactically unifiable, i.e., target node labels of outgoing links never match.
- $Expect : C \rightarrow [0;1]$ returns the edges' expectabilities. For convenience, we define $Expect(path|label) = Expect(in(v))$ if $Node(path \sqcup label) = v$.

Paths starting with $\triangleright$ are called the *states* of the EN.

3. Social Interaction Structures

Based on the definition of ENs, we can now define *Social Interaction Structures* as a special kind of communication structures. Social Interaction Structures capture the regularities of externally observed communication processes. The basic ideas behind this concept are that 1) agent sociality emerges from agent communication, and that 2) communications form a so-called *social system* which is closed in the sense that, to some degree, communication regularities come into being from communications themselves, such that the observer does not need to have to "look inside the agents' heads" to derive these structures. Because of that, communication structures can meaningfully be learned from observations. Nevertheless, this learning process needs to be continuously repeated to adopt the EN to new perceptions (since multiagent systems with truly autonomous agents with unknown life spans have no final state), and does always imply the possibility of failure of its prediction task (yet the term "expectation"). The Social Interaction Structures (respectively the probabilistic distribution it represents) triggered by a certain utterance (or an ECA which is part of this utterance, respectively) in the context of other utterances we call the *semantics* of this utterance.

3.1. Social Interaction Systems

In [7], we've introduced *Communication Systems* as a universal means for the description of social dynamics of open multiagent systems. The two main purposes of a Communication System are i) to capture the social expectations (represented as an EN) in the current state of a multiagent system under observation, and ii) to capture changes to these expectations. Whereas the EN models the meaning of communicative action sequences at a certain time (i.e., their expected, generalized continuations in a certain context of previous events), the communication system models the way the EN is build up, and, if necessary, adapted according to new observations of events. We introduce now *Social Interaction Systems* (SIS) as a concrete kind of general Communication Systems. The difference between Communication Systems in general and Social Interaction Systems is that the latter comes with a concrete EN learning algorithm, whereas for general Communication Systems we just demand unspecifically that the expectations within learned ENs shall reflect the expectation of the semantical observer regarding the future course of events [7], not taking into account agent rationality and social commitment. The term "interaction system" comes from social systems theory [1], where it denotes the most basic kind of communication (i.e. social) system.

Defintion 2. A *social interaction system* at time t is a structure

$$SIS_t = (\mathcal{M}, f, \varpi_t, \rho)$$

where

- $\mathcal{M}$ is the formal language used for agent actions (according to table 1),
- $f : \mathcal{EN}(\mathcal{M}) \times \mathcal{M} \rightarrow \mathcal{EN}(\mathcal{M})$ is the *expectations update function* that transforms any expectation network EN to a new network upon experience of an action $m \in \mathcal{M}$. $f(\perp, m)$ returns the so-called *initial EN*, transformed by the observation of m. This initial EN can be used for the pre-structuring of the social system using given social norms or other a-priori knowledge which can not be learned using f.
  Any ENs resulting from an application of f are called *Social Interaction Structures*.
  As a non-incremental variant we define $f : \mathcal{M}^+ \rightarrow \mathcal{EN}(\mathcal{M})$ to be
  $f(m_0 \sqcup m_1 ... \sqcup m_t) = f(...(f(f(\perp, m_0), m_1)...), m_t)$,
- $\varpi_t = m_0 \sqcup m_1 ... \sqcup m_t \in \mathcal{M}^*$ is the list of all actions observed until time t. The subindexes of the m_i impose a linear order on the actions corresponding to the times they have been observed[1],
- $\rho \in \mathbf{N}$ is a time greater of equal the expected life time of the SIS. We require this to calculate the so-called spheres of communication (see below). If the life time is unknown, we set $\rho = \infty$,

  and $\mathcal{EN}(\mathcal{M})$ is the set of all possible expectation networks over $\mathcal{M}$.

We refer to events and EN nodes as *past*, *current* or *future* depending on their timely position (or the timely position of their corresponding node, respectively) before, at or after t. We refer to $EN_t = f(\perp, \varpi_t)$ as the *current EN* from the semantical observer's point of view, if the semantical observer has observed exactly the sequence $m_0 m_1 ... m_t$ of events so far.
The intuition behind our definition of SIS_t is that a social interaction system can be characterized by how it would update an existing expectation network upon newly observed actions $m \in \mathcal{M}$. The EN within SIS_t can thus be computed through the sequential application of the structures update function f for each action within ϖ, starting with a given expectation network which models the observers' a-priori knowledge. ϖ_{t-1} is called the *context* or *precondition* of the action observed at time t.
To simplify the following formalism, we demand that this initial EN should be implicitly complete, i.e., to implicitly contain *all* possible paths, representing all possible action sequences (thus the EN within a social interaction system is always infinite). So, if the semantical observer has no a-priori knowledge about a certain branch, we assume this branch to represent uniform distribution and thus a very low probability for every future decision alternative ($\frac{1}{|M|}$), if the action language is not trivially small.
Note that any part of an EN of an SIS does describe exactly one time period, i.e., any node within the respective EN corresponds to exactly one moment on the time scale in the past or the future of observation or prediction, respectively, whereas this is not necessarily true for ENs in general. To express the definiteness of the past, we will later define the update function f such that the a-posteriori probabilities of past events (i.e., observations) become 1. There shall be exactly one path pc in the current EN leading from the start node $\triangleright_{en_t}$ leading to a node pc_t such that $|pc| = t$ and $\forall i, 0 \leq i \leq t : Label(pc_i) = m_i$. The node pc_i and the ECA m_i are called *corresponding*.
The *semantics* of ϖ_t (i.e. m_t within context ϖ_{t-1}) is defined as the probability distribution Δ_{EN_t,ϖ_t} represented by the branch starting with the node within EN_t which corresponds to ϖ_t:

$$\Delta_{EN_t,\varpi_t}(w') = \frac{\prod_{i,1 \leq i \leq |w'|} Expect(\varpi_t w'_1 ... w'_{i-1} | w'_i)}{\sum_{m \in (M)^+} \prod_{i,1 \leq i \leq |m|} Expect(\varpi_t m_1 ... m_{i-1} | m_i)}$$

for all $w' :\Leftrightarrow \varpi_t \sqcup w' \in M^+$ ($\sqcup$, which we omit sometimes for clarity, denotes the string concatenation. Labels with subindexes as in w_i denote single characters.)
Let's discuss the constituents of Social Interaction Systems in depth now:

3.2. Projections

As defined in table 1, ECAs consist of two parts: The uttering agent, and the ECA content (*projections*). The projections are a set of EN node pairs which are derived from the following two syntactical elements (cf. table 1), which by themselves need to be derived from the respective agent utterances (the latter task is not described in this work).

- *Conditions* chooses, using an EN path (without expectabilities), a possibly infinite set of EN states which have to become reality in order to make the uttering agent start to act towards its uttered goal (e.g. in "*If I deliver the goods*, you must pay me the money"). As shown in table 1, conditions are given as a linear list of node labels. This path must match with paths in the current EN, either absolutely beginning with $\triangleright$, or starting at nodes after the node which corresponds to the ECA. The end nodes of all matches in EN are called the *condition nodes* of the ECA projections. So, if the node list is empty, the only condition node is the node corresponding to the ECA. The path matching is

1 For simplicity, we assume a discrete time scale with $t \in \mathbb{N}$, and that no pair of actions can be performed at the same time, and that the *expected* action time corresponds with the depth of the respective node.

always successful, since in our model, an EN implicitly contains all possible paths, although with a probability near zero for most of them.

- *GoalStates* chooses, using an EN path (without expectabilities), the (possibly infinite) set of states of the expectation network the uttering agent is expected to aim for. The path must match with a set of paths within the EN such that the last node of each match lies within the branch having a condition node as its root (thus a condition, goal pair "$(do_a \sqcup do_b \sqcup do_c, do_x \sqcup do_y \sqcup, do_z)$" does either denote "I want you to do x first, then y, then z after a and b and c have been done" or "I want you to do c *if* a,b and c and somewhen after that also x and y have been achieved", depending from the position of do_x and do_y in relation to the condition do_c). In Conditions and GoalStates paths, wildcards "?" for single actions are allowed.
  For the purpose of this paper, we demand that the projections either refer to future interactions or be semantically inactive (i.e., they already failed or have been successful). Theoretically, we could also imagine projections regarding the past. In this case the respective ECA would express that the uttering agent will likely try to change the way other agents communicate about the past, but we do not consider this difficult and rather unusual case here for simplicity.
  Please note also that projected goal states possibly describe actions the uttering agent announces to perform *himself*, not just demands. In this case, the rational hull for this goal consists of behavior which increases the likeliness of support from other agents in order to make the goal state come true.

Every projection implicitly refers to previous or future projections which announce positive or negative *sanctions* the uttering agent would impose on the ECA receiver in case of a positive or negative response to the ECA. The projection of sanctions is an inevitable part of every elementary communication act, since among self-interested agents it would be unreasonable to make propositions without providing any reciprocative utility to the receiver. Sanctions can be either unspecified, to be specified later, or already be specified by means of previous events or predefined social structures like laws or other norms (which we do not consider in this work). Of course, as any other projections, projected sanctions need not to be honest, or put into action, or be effective.
Because the projections set can represent arbitrary probability distributions, it is possible for multiple ECAs to express disjunctive statements like "I want you to do either a *or* b", if *a* and *b* are inconsistent events (i.e., events which cannot occur both in the same context). Since consistent ECAs uttered by the same agent are interpreted as conjunctively related, and ECAs with redundant projections are allowed (which increases its impact of these projections on the social structures), one can project arbitrary probability distributions using multiple ECAs. The following functions returns the set of projections of a single ECA $ECA(condition, goal) \in M$:

$$projections_{\mathcal{EN}} : M \rightarrow V \times V$$
$$projections_{(V,C,M,Label,E)}(ECA(ce_1...ce_n, ge_1...ge_m)) =$$

$$\{(v_n, v_m) : \{(v_i, v_{i+1}) : 1 \leq i \leq n-1\} \subseteq C$$
$$\wedge\ unify(Label(v_i), ce_i)$$
$$\wedge\ \{(v_i, v_{i+1}) : n+1 \leq i \leq n+m-1\} \subseteq C$$
$$\wedge\ unify(Label(v_i), ge_i)$$
$$\wedge\ v_n \prec v_{n+m} \wedge unify(Label(v_n), ce_n)$$
$$\wedge\ unify(Label(v_{n+m}), ge_m)\}$$

$unify(?, l)$ and $unify(l, ?)$ shall always be true.
For convenience, we use $Goal((c, g)) = g$
and $Condition((c, g)) = c$.

3.3. Rational hulls

Per se, a projection has no power to make its goal states become true. In fact, projections don't have to be rational at all. But we consider it to be rational, that the uttering agent will act towards the projected events *at least for some significant amount of time* [2]. This time span and the event within, starting directly after the projecting utterance event, is called *sphere of communication*. Theoretically, each ECA could have its own sphere of communication. For simplicity, for this work we assume that the sphere of communication of any ECA eca is simply $\rho - time(eca)$, where the first operand is the expected time of the last observed utterance within the SIS, and the second is the utterance time of the projecting ECA. This setting is assumable realistic for small and simple interaction systems, where the interacting agents likely stick to their opinions and desires for the whole and usually short duration of the SIS (like chat rooms or auctions). For other domains we would have to determine the spheres of communication *a posteriori* from empirical observations.
The actions the uttering agents is expected to perform within the respective sphere of communication in order to make his projections come true is called the *rational hull* of the ECA. Thus, the determination of the rational hulls of observed ECAs constitutes the crucial part of the determination of ACL semantics. The rational hull can be seen as the actual pragmatics and meaning "behind" the more normative and idealistic concept of social commitments.
We assume the manifestation of the following agent in-

2 This time span of projection trustability can be very short though - think of *trick questions*.

tentions by means of ECAs *within the respective spheres of communication* and contextualized by means of other ECAs:

- *Information of other agents about desired states of communication* This information is given as projections as described above.
- *Support of other communicated goals* The supportive functionality communication has regarding other communications is defined by the rational hulls of the supported elementary communication acts, which will become implicitly more expectable too if supporting rational hulls increase their own expectabilities.
- *Manifestation of understanding* In case the agents "understand" each other, ECAs cannot express contradiction to the fact that other ECAs pursue the two previous intentions (i.e., Agent 1 does not need to believe Agent 2 is right, but she needs to believe at least that Agent 1 wants to be right). Since this is a meta-communicational issue, we do not consider misunderstanding in this work.

Capturing these intentions, and given the set of projections for each ECA eca uttered by an agent a, we calculate the rational hull of a certain ECA using the following two rules:

3.3.1. Rational choice After uttering eca, an agent a is expected to choose an action policy such that, within the respective sphere of communication, his actions maximize the probability of the projections of eca to occur. Let $p \in projections(eca, EN_t)$ be a projection. Then, considered that p would be a useful state for the uttering agent to be in, the rule of rational choice proposes that for every node v_d with $agent(v_d) = a$ along the path $v_t...p$ leading from the current node v_t to p, $Expect(in(v_d)) = 1$ for the incoming edge of v_d, and that the expectabilities of the reminding outgoing edges of the predecessor of v_d are reduced to 0 appropriately (if no other goals have to be considered). To reduce the complexity of applying this general rule on the possibly infinite projections set, and to observe the bounds of observer rationality, we propose the following constraints:

- expectabilities will be adopted within the respective sphere of communication of eca only, even if p is located beyond this sphere.
- expectabilities will be adopted only for parts of the current EN with a significant evidence regarding actions performed by other agents. Since we represent missing knowledge as uniform distribution, we put this rule into practice by demanding that at decision nodes of other agents (i.e., nodes with children representing actions of agents other than the agent which uttered eca) the *expectabilities entropy* $entropy_{EN} : V \to \mathbb{R}$ should be below some limit υ.

  $entropy_{EN}(v) = \sum_{v' \in children(v)} -Expect(in(v'))log_2 Expect(in(v'))$
- if multiple elements in $projections$ are identical despite their context, and the paths leading to these projections overlap, priority is given to those projections with a higher cumulative expectability. Finding the right paths is a markovian multiple-decision problem from the perspective of the uttering agent a (and thus from the perspective of the semantical observer which models the behavior of a also), which in general cannot simply be solved by pairwise comparison of paths leading from the current node to the competitive projections regarding their maximum expected utilities, if $projections(eca, EN_t) = \{p_1, ..., p_n\}$ contains more than two elements.
- The projections of previously uttered ECAs have to be maintained, so the rule of rational choice needs to do a weighting assessment of previously calculated rational hulls instead of simply outdating them.

We use the following function $u_{\mathcal{EN}(\mathcal{M})} : \mathcal{M} \times V \to [0;1]$ to calculate the *utility* regarding its supporting function for a specific elementary communication act eca of an arbitrary node v.

$$u_{EN}(eca, v) = \begin{cases} 0 \text{ if } \forall i, 1 \le i \le n : \\ \quad \neg v \prec Goal(p_i) \vee \neg Condition(p_i) \prec v \\ 1 \text{ if } \exists i : v = Goal(p_i) \\ 0 \text{ if } entropy_{en}(v) > \kappa \\ \dfrac{\sum\limits_{j, 1 \le j \le c} u(vc_j)}{c} \\ \quad \text{if } agent(Label(vc_j)) = agent(eca) \\ \dfrac{\sum\limits_{j, 1 \le j \le c} Expect(in(vc_j))u(vc_j)}{c} \text{ otherwise} \end{cases}$$

with $\{p_1, ..., p_n\} = projections(eca)$ and $\{vc_1, ..., vc_c\} = children(v)$, and κ is some predefined entropy maximum.

3.3.2. Empirical stationarity assumption If we would use the previous rule as the only EN updating mechanism, we would face at least three problems: 1) Predicting agent actions according to the rule of rational choice requires evidence about subsequent actions of other agents. In case this previous evidence is missing, the rule of rational choice would just "convert" uniform distribution into unform distribution. Therefore, we have to provide an initial probability distribution the previous rule can be ap-

plied on[3]. 2) the set of projections for a single ECA might be infinite. Most of the expectabilities along the paths leading from the current node to these EN branches sum up to very low probabilities for the respective projection. Thus, a preselection of likely paths will be necessary. And 3), the rule of rational choice treats all projections uniformly. If the uttering agent neglects to specify explicitly the order of preference of hier own projections, this order needs to be obtained from past agent practice.
For these reasons, we combine the application of the rule of rational choice with the assumption of some stationarity of event trajectories, i.e., the assumption that previously observed action sequences repeat themselves in the future in a similar context. We use this assumption to retrieve a probability distribution the rule of rational choice can be applied on subsequently .
In order to learn EN stationarity from previous observations, we follow the so-called *variable-memory approach* to higher-order Markov chains using *Probabilistic Suffix Automata* (PSA) introduced for *L-predictable* observation sequences [6]. This approach efficiently models Markov chains of order L (i.e., with a model memory size of L), allowing for rich stochastical models of observed sequences. The applicability of this approach to our scenario is based on the heuristical assumption that many Social Interaction Systems are *short-memory systems*, which allow the empirical prediction of social behavior from a relatively short preceding event sequence (assumedly pre-structuring using social norms , constraints from rational choice etc is done properly). The main advantage of the PSA-based approach over the more common *Hidden Markov Models* (HMM) is its easy learning method, with comparable expressiveness and prediction capabilities [6]. Nevertheless, other modelling techniques for temporal data are expected to be applicable here also.
For the calculation of the PSA from a set of sample agent action sequences, we use an algorithm introduced in [6], originally coming from *PAC-learning*, in a slightly modified version. It constructs a so-called *Prediction Suffix Tree* (PST) (sometimes called *Probabilistic Suffix Tree*) from the samples, which is roughly equivalent to the target PSA, but easier to build up. Its only disadvantage in comparison to the corresponding full PSA is that the time complexity for the predicting task is higher approximately by the factor L.

Defintion 3. A *Prediction Suffix Tree* with memory size L over the language of concrete agent actions M is a structure $PST_L(M) = (V, C, Label, \gamma)$ where

- (V, C) defines a tree graph consisting of a set of nodes $V, |V| > 0$ and a set of edges $C \subseteq V \times V$,
- $Label : V \rightarrow M^+$ returns for a node its label (with maximum length L),
- $\gamma : V \rightarrow \{(d_1, ..., d_{|M|}) : d_i \in \mathbb{R}\}$ returns for each node a vector which defines the probability distribution associated with this node. Each element $\gamma_\sigma(v)$ of the resulting vector corresponds to the conditional probability of the particular message σ in M.
  $\sum_{\sigma \in M} \gamma_\sigma(v) = 1$ should hold - nevertheless, vector elements with a very low probability are omitted.

A PST is able to predict the probability of sequences using a tree traversal up to the root, as γ returns for a specific message its conditional occurrence probability given that the largest *suffix* ν, $|\nu| \leq L$, of the message sequence observed before matches with the label of this node. L should depend from the available memory resources, the length of the samples and the expected spheres of communication.
In order to build up the PST from the empirical observations, we need to define the conditional empirical probability within a set of sample action sequences (where actions are either ECA utterances or physical actions). As input we us the set $samples_{SIS_t} = \{m_0 m_1 ..., m_t\} \cup \{r_1^1 ... r_1^{l_1}, ..., r_n^1 ... r_n^{l_n}\}$, where $m_0 m_1 ..., m_t$ is the sequence of events observed so far for SIS_t until time t, and the reminder of this set consists of additional samples to improve prediction accuracy. The $r_i^1 r_i^{l_i}$ are optional; we can omit these additional samples and learn the PSA from the single sequence $m_0 m_1 ..., m_t$ only. But as a rule of thumb, the lengths of the sample sequences should be at least polynomial in L[6]. If an initial EN is given for pre-structuring, the r_i could be obtained from a frequency sampling of sequences from this EN, which is straightforward and thus omitted here.
For lack of space, we omit the detailed PST-learning algorithm, which can be found in [6]. The probability for the PST-generation of a sequence $r = r_1 ... r_n \in (M)^n$ is

$$P_{PST}(r) = \prod_{i=1}^{n} \gamma_{r_i}(v^{i-1})$$

where v^0 is the (unlabelled) root node of the PST and for $1 \leq i \leq n-1$ v^i is the deepest node reachable by a tree traversal corresponding to a prefix of $r_i r_{i-1} ... r_1$, starting at the root node.
From the probability distribution obtained from P_{PST}, we derive the corresponding EN using the function $\delta : M^+ \rightarrow \mathcal{EN}(\mathcal{M})$:

$$\delta(m_0 m_1 ..., m_t) = (V, C, M, Label, Expect)$$

3 This probability distribution must also cover projected events and assign them a (however low) probability even if these events are beyond the spheres of communication, because otherwise it would be impossible to calculate the rational hull.

with
$V = \{\triangleright\} \cup \{v_p : p \in paths\}$,
$Label = \{(v_{p_1 ... p_n} \mapsto p_n) : p_1 \sqcup ... \sqcup p_n \in paths\}$,
$C = \{(\triangleright, v_p) : |p| = 1, v_p \in V\}$
$\cup \{(v_{p_1 ... p_{n-1}}, v_{p_1 ... p_n}) : v_{p_1 ... p_{n-1}} \in V \wedge v_{p_1 ... p_n} \in V\}$,
$Expect =$
$\{in(v_{p_1 ... p_n}) \mapsto \dfrac{P_{PST}(p_1 ... p_n)}{P_{PST}(p_1 ... p_{n-1})}, v_{p_1 ... p_n} \in V\}$, and
$paths = \{p : p \in M^+ \wedge P_{PST}(p) > P_{min}\}$, where P_{min} is a predefined lower bound for significant expectabilities.

3.3.3. Rationality-biased empirics Putting together the rule of rational choice and the assumption of empirical stationarity, we gain the following (non-iterative) definition for the Social Interaction Structures update function f of an SIS.

$$f(m_0 m_1 ... m_t) = \varrho(EN_{stat}, \triangleright_{EN_{stat}})$$

with $EN_{stat} =$
$(V_{EN_{stat}}, C_{EN_{stat}}, \mathcal{M}, Label_{EN_{stat}}, Expect_{EN_{stat}})$ such that
$V_{EN_{stat}} = V_\delta \cup \{v_{m_0}, ..., v_{m_t}\}$,
$C_{EN_{stat}} =$
$C_\delta \cup \{(\triangleright_{EN_{stat}} = v_{m_0}, v_{m_1}), ..., (v_{m_{t-1}}, v_{m_t}), (v_{m_t}, \triangleright_\delta)\}$
and $\forall i, 1 \leq i \leq t :$
$Expect(in(v_{m_i})) = 1$, $\forall i, 0 \leq i \leq t : Label(v_{m_i}) = m_i$,
with
$(V_\delta, C_\delta, \mathcal{M}, Label_\delta, Expect_\delta) = \delta(m_0 m_1 ... m_t)$.

$Expect(in(v_{m_i})) = 1$ reflects the definiteness of already observed events.

$\varrho : \mathcal{EN} \times SimplePath \rightarrow \mathcal{EN}$ applies the results of the calculation of single rational hulls to the entire EN by means of a recursive top-down tree traversal which is limited by the maximum search depth maxdepth (as an alternative, we could apply a entropy-based search limitation criterion similar to the criterion used for the limitation of *goal* calculations before).

$$\varrho((V, C, M, Label, Expect), path) =$$

$$\begin{cases} (V, C, M, Label, Expect) \text{ if } |path| > \text{maxdepth} \\ (V, C, M, Label, Expect_{|children(v)|}) \text{ otherwise} \end{cases}$$

using $v = Node(path)$, $\Delta U(v) = \{(v_j, u(Label(v), v_j)) : v_j \in V, agent(Label(v_j)) = agent(Label(v))\}$,

$\forall v_j \in V : Expect_0(in(v_j)) =$
$\begin{cases} \dfrac{Expect(in(v_j)) + \Delta U(v)[v_j]}{2} \text{ if } Time(v_j) < \rho \\ Expect(in(v_j)) \text{ otherwise} \end{cases}$ and
$\forall n, 1 \leq n \leq |children(v)| :$
$Expect_n :\Leftrightarrow (V, C, M, Label, Expect_n) =$
$\varrho((V, C, M, Label, Expect_{n-1}),$
$path \sqcup Label(children(v)_n))$.

Here, $\Delta U(v)$ assigns every node v_j its utility regarding the ECA $Label(v)$, if the acting agent is the same for v and v_j. $Expect_0(in(v_j))$ assigns the node its new expectability (equally weighted with its previous expectability, which might be already be utility biased from another ECA), and $Time(v_j) < \rho$ limits the application to nodes within the sphere of communication. $\Delta U(v)[v_j]$ denotes the utility for reaching v assigned to v_j.

4. Conclusions

We've introduced a novel approach to the semantics of agent communication languages, which combines features from traditional mentalistic and objectivist approaches. Our future work will be centered around the following issues: Expectation Networks currently do not have the power to model logical predicates, which would be required to allow an "ECA content language" similar to KIF instead of plain event projections. We propose the combination of situation calculus with Expectation Networks for this purpose, similar to the annotation of EN nodes with knowledge base states introduced in [7]. Another problem is that the EN learning algorithm does not consider agent roles, organizational structures and other types of generalization. And finally, our approach needs to be evaluated regarding its applicability for truly open multiagent systems and a heterogenous set of self-interested agents.

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