

Modeling Social Learning of Language and Skills

Paul Vogt^{*,**}
Tilburg University

Evert Haasdijk[†]
Vrije Universiteit Amsterdam

Abstract We present a model of social learning of both language and skills, while assuming—insofar as possible—strict autonomy, virtual embodiment, and situatedness. This model is built by integrating various previous models of language development and social learning, and it is this integration that, under the mentioned assumptions, provides novel challenges. The aim of the article is to investigate what sociocognitive mechanisms agents should have in order to be able to transmit language from one generation to the next so that it can be used as a medium to transmit internalized rules that represent skill knowledge. We have performed experiments where this knowledge solves the familiar poisonous-food problem. Simulations reveal under what conditions, regarding population structure, agents can successfully solve this problem. In addition to issues relating to perspective taking and mutual exclusivity, we show that agents need to coordinate interactions so that they can establish joint attention in order to form a scaffold for language learning, which in turn forms a scaffold for the learning of rule-based skills. Based on these findings, we conclude by hypothesizing that social learning at one level forms a scaffold for the social learning at another, higher level, thus contributing to the accumulation of cultural knowledge.

Keywords

Social learning, language games, language evolution, agent-based modeling, population-based adaptive systems

1 Introduction

In the past decade, a lot of effort has been put into computational studies regarding the social learning of behaviors [1, 33, 41]. Simultaneously, many computational studies have investigated how languages can evolve in populations of autonomous agents (see, e.g., [11, 28, 59] for overviews). Drawing on such previous efforts, we present a model in which both skills and languages are transmitted from one generation to another by means of social learning.

Artificial models that implement the social learning of skills have been developed to allow individual agents to “blindly” copy the *overt* behavior displayed by other agents (possibly humans) by associating sensory information with motor actions (e.g., [35, 36]), often by having students receive the same sensory information as the teachers (e.g., [2, 24, 41]). Some other models work by trying to *emulate* the means-ends relations of observed behaviors and copying these [34]. Both types of social learning have been found among nonhuman primates (e.g., [55]) and other animal species (e.g., [19, 25]), as well as

* Contact author.

** Tilburg Centre for Cognition and Communication, Tilburg University, PO Box 90153, 5000 LE Tilburg, The Netherlands.
E-mail: p.a.vogt@uvt.nl

† Department of Computer Science, Vrije Universiteit Amsterdam, De Boelelaan 1081a, 1081 HV Amsterdam, The Netherlands.
E-mail: e.haasdijk@few.vu.nl

among human subjects (e.g., [21, 26]). Humans, however, also have the ability of learning through what Gergely and Csibra [20] have called *pedagogy learning*, in which opaque, or *covert*, knowledge (e.g., mental representations of how to achieve some goal) is communicated via some medium, such as language.

Although agent-based models provide an ideal tool for investigating the social learning of mental representations [15], relatively few such models have been developed so far (in most models, only visible behavior is copied or emulated). In some models the weights of neural networks or other internal knowledge are exchanged; see, for example, [3, 23]. Moreover, there are a number of approaches in distributed AI that resemble social learning, such as *rule sharing* in ensembles of learning classifier systems [8]. However, all these approaches are highly unrealistic from a biological point of view, because the internal representations are shared explicitly among the interacting agents. Clearly, biological systems do not explicitly share internal representations; these are communicated through other media, such as chemicals, physical postures, gestures, or language.

Similar approaches to social learning have been taken within the ALife community regarding simulating language evolution. Most models that simulate language evolution include individual agents who learn from other agents aspects of language, such as phonemic systems [16, 39], vocabularies [38, 47], syntax [5, 27], or grammar [49, 58]. Approaches to learning have included imitation [16], and copying behavior [38], as well as using socially provided corrective feedback [51]. Most approaches to developing shared vocabularies or syntax have allowed agents to exchange not only the public signals, but also the private mental representations (the meanings). As mentioned, such explicit meaning transfer is highly unrealistic from a biological point of view, but in addition, using such methods can affect the results substantially [58, 62].

Alternative approaches have assumed that individual agents were autonomous, embodied, and situated, and that they could not explicitly transfer internal representations, so that the language needed to be grounded in the environment, both physically and socially [64]. Grounded models come in two variants: those implemented on real physical robots and those using simulated robots. Those implemented on physical robots face many of the same consequences of embodiment and situatedness that humans do and thus form ideal platforms to verify models of human cognition [59]. However, scalability in population sizes and the long duration of experiments makes the use of physical robots very expensive and hard to achieve.

To overcome these problems of time and scalability, many grounded models have been developed and tested in simulations [6, 10, 44, 60]. The advantage of such models is that they are relatively straightforward to scale in population size, though still limited by the computational power required [60]. The downside of most simulations is that the environment is typically very simplistic, having relatively few types of objects described in terms of very few relevant features. For instance, the studies carried out with the Talking Heads simulation toolkit have used only four features: three RGB channels and one shape feature [60, 61].

Another aspect that is often absent in language evolution models is the functionality of language in relation to some life task for agents, which is required for language to become *really* meaningful to an agent [66]. For instance, language can have the function of assisting reproduction and mate choice [65], coordinating some survival task [32], or sharing knowledge about edible and inedible foods [9, 10]. Studies that have involved some functionality of language, however, typically have used evolutionary algorithms for the communication systems to emerge and have tended to ignore lifetime social learning.

The model we present in this article integrates a lot of previous work on modeling language evolution and social learning in a simulation in which the population needs to distinguish poisonous food from edible food as a *survival* task [37, 54]. The objective is not to present novel learning techniques or to study real behavior, nor to exceed already explored boundaries of (for example) population size or language complexity. Instead, the innovation here is the integration of various techniques into a model that comes closer to the real world than most previous models in autonomy, virtual embodiment, situatedness, population size, language functionality, skill learning, and social interactions. Clearly, there have been studies in which the scales of these factors have exceeded ours, but not in a combined fashion. The model has been developed in a framework to study the emergence of humanlike cultural societies. We have therefore based our development—as much as possible—on sociocognitive theories.

The primary purpose of this article is to investigate what sociocognitive mechanisms our *proto-human* agents require in order to distribute both language and skills over generations in simulations that assume—insofar as is possible—strict autonomy, embodiment, and situatedness. The article will focus less on the mechanisms for learning skills than on those required for transmitting language. The model integrates our earlier model of social learning of skills [23] (explained in Section 2.1) with an improved version of the language-game model presented in [64] (see Section 2.2). In Section 3 we show how the resulting model can lead to the effective sharing of survival skills among a population of knowers (i.e., agents who already have the skills) and students (i.e., those who have yet to acquire the skills). Sections 4 and 5 discuss and conclude the article.

2 The Model

The model was developed as part of the NEW TIES project,¹ which aimed to develop a simulation platform in which a cultural society could evolve through evolution, individual learning, and social learning [17, 22]. In the research presented here, we used the platform to set up a 2D grid-world environment containing both edible and inedible plants. When agents eat the edible plants, they gain a fixed amount of energy, and when they eat the inedible plants, they lose a fixed amount of energy.

Agents have a visual system with which they can detect their immediate surroundings with a total visual angle of 90° (45° left and 45° right) and a visual reach of 10 cells. Agents receive visual stimuli regarding the objects in their visual field and output actions that move them around, pick up or put down objects, eat, and communicate or interact otherwise with others (e.g., giving or taking objects to/from other agents). Obviously, agents cannot look through objects. Actions of agents are decided upon by their individual controllers, which are implemented as *decision Q-trees* (DQTs). These trees can adapt through evolution, individual learning, and/or social learning, but for the purpose of the current study, they only adapt through social learning.

A DQT is a decision tree that contains test nodes, bias nodes, and action nodes (Figure 1). The test nodes test whether the agent has categorized a concept from its current context, which includes visual stimuli, objects it may carry, and internal states. The concepts are formed from one or more categories that relate to some feature of an object, such as *shape*, *color*, *direction*, *sex*, or *action*. If the test on a test node succeeds, the agent traverses to the next node in the left branch; otherwise, it traverses to the next node in the right branch.

The bias nodes allow the agent to select from a multiple of branches based on a specific bias toward certain subtrees. The biases determine the probability with which a certain branch is visited in the tree. Note that a bias node can have more than two branches. These biases could be determined genetically through evolution, and ontogenetically through individual learning and social learning. In our model, the biases only change through social learning. When the learning process visits a certain bias node, the bias toward the learned subtree will increase, as explained in Section 2.1.

The leaves of the DQT are action nodes, which include simple actions, such as *move*, *turn-left*, or *turn-right*, first-order predicates such as *eat*(x), and second-order predicates such as *give*(a, o). The arguments can be any object, but if, for example, an agent attempts to eat a non-food item, this action will fail. The agent traverses the DQT until an action node is reached. The agent then performs the action at the cost of a certain amount of energy. When the agent's energy drops below zero or the agent reaches a certain age, the agent dies. However, in order to focus entirely on the social learning of language and skills, we maintained a constant population size by initializing all agents with sufficient energy and a maximum age to survive the entire simulation regardless of the energy intake and consumption.

The remainder of this section presents in more detail the implementation of the social learning of skills and of language. For convenience, we start explaining the social learning of skills as if the language

¹ NEW TIES stands for New Emerging World models through Individual, Evolutionary, and Social learning. For more details and software, consult <http://www.new-ties.eu>.

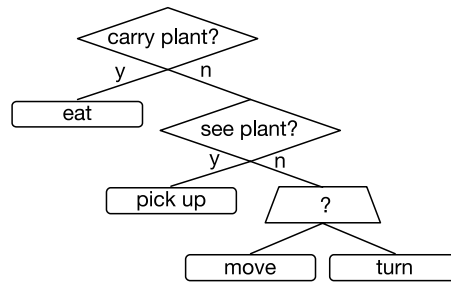


Figure 1. A simplified example of a decision Q-tree (DQT). The diamonds represent test nodes, the trapezoids bias nodes, and the rounded rectangles action nodes.

were already in place. We will then explain how the words in the language arise and become shared among the population.

2.1 Social Learning of Skills

The model implementing the social learning of skills is essentially the same as the one presented in [23], but in that study the language for all agents was predefined, so messages were always conveyed perfectly. A few changes have been made in order to accommodate language learning.

We have chosen for a push model, where teachers volunteer knowledge pieces that the students then may accept. Other options, such as a pull model where agents request knowledge from other agents, or a combined model where agents can advertise that they believe that they have useful knowledge to share and other agents can then request that knowledge (similar to the “plumage” concept in [46]) could be implemented as well. While this choice may seem improbably altruistic when considering the agents as participating in a competitive “struggle for life,” it allows us to focus our investigations on the feasibility and efficacy of social learning.

Social learning is implemented in the following sequence that every agent carries out at every time step:

1. An agent chooses to initiate teaching a skill with a probability proportional to its own estimation of communicative success c_s (see Section 3.2), provided the agent is not engaged in a language-learning interaction (see Section 2.2) and it sees one or more agents. The dependence on c_s is to prevent agents that are unskilled in language from teaching other agents too often.
2. Of all the agents in the visible range, the teacher then selects the one with the lowest energy as the *student*.
3. If the agent decides to send a message, the trace (or path) through its DQT that led to the current action (e.g., the rule `[not carry plant; see agent] ⇒ talk`) is chosen as the knowledge to be exchanged.
4. The teacher encodes a message using its lexicon (see next section). Only when *all* concepts that make up the DQT trace are encoded into words is the message actually sent. Thus we ensure that the relevant knowledge is transferred entirely (though possibly incorrectly) in order to reduce errors in transmitting knowledge. It is also another measure to prevent agents that are insufficiently skilled in language from teaching. The message is sent using a predefined syntax that marks negation and the separation of test nodes and action nodes.
5. When an agent receives such a message, it stochastically chooses to integrate or disregard it. It would have been more natural to allow agents to choose the adoption of knowledge according to other heuristics, such as the strength of social ties based on previous interactions, social

status, or perceived fitness of the sender. We have opted for a stochastic process in order to focus more on the ability of social learning. However, by setting the probability of adoption to $p = 0.2$, we provide that agents do not always adopt knowledge. Moreover, it is likely that if this probability is too high (e.g., $p = 1.0$), learning may suffer from overfitting or other biases.

6. When the agent accepts the message, it decodes all words into concepts in order to recreate the trace through the DQT, using the predefined syntax.
7. Only when all words in the message were decoded into existing concepts (agents that have not yet mastered the language to some degree may fail to do so, while others may do so inaccurately) will the agent actually incorporate the received knowledge. This way we promote the inclusion of complete rules and also allow agents to include rules only when they have achieved a reasonable level of language competence.
8. When an agent s chooses to incorporate a DQT path P it received from an agent t , agent s selects the most similar path P' in its own DQT according to the following criteria:
 - (a) The percentage of matching tests
 - (b) The number of tests in P but not in P'
 - (c) The number of tests in P' but not in P

If the percentage of matching elements in P' is 100%, the bias for the action that P' results in, as well as all other bias nodes above that action in the tree, is adapted by incrementing a frequency counter, which determines the probability that the bias node will be visited. Otherwise, the agent engages in a kind of dialectics, it inserts a bias node at the first point of divergence between P and P' . The remainder of P' is inserted as one option at that node; a subtree corresponding to the non-matching entries in P is inserted as the alternative. Figure 2 illustrates this procedure.

Steps 1–4 implement the sender (teacher or speaker) part of the model, while steps 5–8 implement the receiver (student or hearer) part. Agents can be both senders and receivers in the same time step, but only with different partners.

2.2 Social Learning of Language

Social learning of language is based on Steels' *language-game* model [47], in which a population of agents can develop (or evolve) a language from scratch. In such models, agents are given an interaction protocol (the language game) that allows them to exchange expressions, invent new expressions,

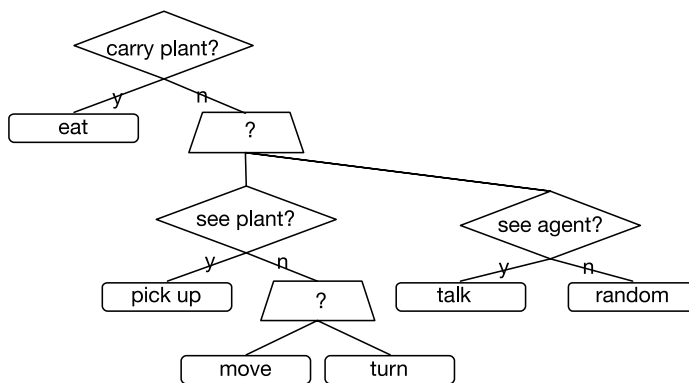


Figure 2. The result of integrating the path [not carry plant; see agent] ⇒ talk into the DQT from Figure 1.

and acquire them from other agents. As a result of the local interactions and learning mechanisms, a common language can emerge through self-organization, leading to a cultural evolution of language.

The current model is based on a previous implementation within the NEW TIES platform as described in [64], but is modified in crucial aspects to improve the performance and to make it compatible with the social learning of skills. In the previous model [64], agents could not communicate about actions, nor could they correctly learn to communicate about observer-dependent features such as directions and distances. Moreover, agents could previously only communicate about visible object features, whereas in this implementation agents are required to talk about paths through their DQTs to which the recipient has no access. However, in order to learn novel word-meaning mappings, receivers need to have (visual) access to those meanings. Emulation might work as well, but is more complicated, so we opted to distinguish between *language-learning interactions* and *skill-learning interactions*. In the former, agents communicate about visible objects and events, whereas in the latter, senders will communicate about what they are currently doing by transmitting the activated path through their DQTs, as explained in the previous section. The remainder of this section presents the language model in more detail.

2.2.1 The Lexicon

The lexicon is implemented as an association matrix that maintains co-occurrence frequencies f_{ij} of words w_i and meanings m_j (Table 1). Each time a word w_i is heard in a learning context C_L , the co-occurrence frequencies between this word and all meanings $m_j \in C_L$ are increased by one. The learning context is only constructed during language-learning interactions, as described later. Essentially, this implements *cross-situational learning* [42, 43, 56], where the meaning of a word is acquired by keeping track of which meanings co-occur with a word. A unique meaning tends to win the competition with other meanings as a result of the covariation between words and meanings across situations.

All words w_i for which an agent has unique interpretations in meanings m_j are stored in a separate, individual list of word-meaning mappings, $M = \{ \langle w_i, m_j \rangle \}$. Each time an agent has updated the co-occurrence frequencies of a word w_i , it will evaluate which meaning m_j has the highest co-occurrence frequency f_{ij} . If this yields a unique interpretation, the word-meaning mapping is added to M ; otherwise the mapping has not been learned yet. If, however, there is a tie with other meanings, the agent will apply the *mutual exclusivity* constraint [31, 45] by discarding those meanings that are already interpretations for other words. This may or may not yield a unique interpretation, but if it does, this interpretation is added to the list of mappings M .

When different situations in which a given word is heard relate to different learning contexts in which the word’s meaning always co-occurs, but not any other meaning, cross-situational learning (XSL) is sufficient for learning a consistent set of word-meaning mappings. However, in the current environment and setup, some concepts always coincide with other concepts. For instance, a female agent is always an agent, so each time the agent hears the word for female, both concepts *female* and *agent* are present in the learning context. Although it is possible to allow the agents to learn that the word “female” maps onto the conjunction of these concepts, we have decided to let the agents associate words with

Table 1. An illustration of the lexicon that agents construct and in which associations between concepts (columns) and words (rows) are stored based on their co-occurrence frequencies.

	agent	female	male	eat
“agent”	5	2	3	1
“female”	2	2	0	0
“male”	3	0	3	1
“eat”	1	0	1	1

single concepts. Now, because the concept `agent` sometimes coincides with the concept `male`, the word for `agent` can be learned through XSL alone (see Table 1). Once the word for `agent` is learned, an agent can infer that the word for `female` would not be used to denote `agent`; otherwise the word for `agent` would have been used. This constraint is similar to the mutual exclusivity constraint that children appear to use [31], and also relates to the *principle of contrast* [13]. Note that the implementation differs from the implementation of the principle of contrast described earlier in [64], where it was implemented by a specific update of the weights.

2.2.2 Production

To achieve social learning of skills, we have decided to let agents communicate about paths (or traces) through their DQT controllers. For language learning, however, agents need to construct a learning context that contains the meanings of the words expressed; but, as already mentioned, a recipient agent cannot determine the DQT traces without using language. So, learning language from this information alone would be infeasible. To facilitate the context construction, we let the agents engage in joint attentional activities by pointing to an object (more on this will follow in Section 2.2.5). However, a path through a DQT can relate to multiple objects; the rule `[not see agent; see plant] ⇒ eat` can relate to three different objects. Since pointing to three objects is likely to amplify the confusion, we have opted to separate language-learning interactions from skill-learning interactions.

- **Language-learning interactions (LLIs).** For these interactions, speaker agents select *one* object (called the *topic*), which is visible to both the speaker and the hearer. The hearer's attention is drawn to that object through a *pointing* gesture implemented as a signal that hands the object's identifier to the hearer. The object is categorized so that each feature maps onto one predefined concept.² This results in the *target* list of concepts for which the speaker will teach the hearer the words acquired by the speaker.
- **Skill-learning interactions (SLIs).** For these interactions, the target is set as the list of concepts that constitute the test labels and action from the DQT controller evaluated at that time step. The syntax of the DQT is adopted as the syntax of the speaker's expression, so the test labels (a test label may include several concepts) are separated from each other and are marked as being something visual, something carried, or internal to self; the test results (yes/no) are provided explicitly; and actions always occur at the end of the sentence.

Once the target is set, the speaker produces for each concept in the target the word it has acquired in its list of mappings, M . If a concept does not occur in this list, then the agent has not yet acquired this mapping unambiguously through XSL. In such cases, the speaker invents—with a low probability ($p = 0.01$)—a new word and adds the association both to the lexicon with usage frequency one and to the list of mappings. Words are invented as random strings containing one to three consonant-vowel pairs. The resulting set of words are transmitted to the hearer. In the case of an SLI, the expression is only transmitted if all concepts can be verbalized. This way, SLIs only tend to occur once the language is learned to some degree.

2.2.3 Interpretation

When an agent hears an expression, it will try to interpret this expression. Each word is interpreted according to the acquired mappings in M . If the expression concerns an LLI (i.e., the expression is accompanied by a pointing gesture), the interpreted meaning is only accepted if it is in the learning context C_L ; otherwise the interpretation fails.

² Although it is possible to have concepts constructed during an agent's lifetime by means of discrimination games [48], we have decided to predefine concepts in order to initiate agents with a DQT controller, as well as to reduce the learning complexity of the model.

In the case of LLIs, the co-occurrence frequencies and the mapping list are updated before interpretation proceeds, as described in Section 2.2.1. In addition, the co-occurrence frequency of a word and its interpreted meaning (if any) from the mapping list M is increased additionally to reduce the need to incorporate the mutual exclusivity step.³

If the expression concerns an SLI and *all* words are interpreted with an existing meaning (since there is no learning context, these meanings can be any meaning acquired in M), then—with the syntactic information attached to the expression—the interpretation is transformed into a DQT-compatible format that can be used for the social learning of skills as described earlier.

When a word cannot be interpreted in M , the interpretation fails. When it concerns an SLI, the agent will decide not to incorporate the knowledge. Failed interpretations can also be triggered following attention dialogues, as we will discuss later.

2.2.4 Perspective Taking

Since we assume full autonomy, (virtual) embodiment, and situatedness of the agents, the problems they face are similar to those faced by real robots (see, e.g., [59, 56] for discussions). In our model, concepts relate to properties of objects, such as shape, color, direction, distance, weight, sex, or actions (the last two only apply to agents). Due to our assumptions, it was found in [64] that although developing a shared lexicon regarding observer invariant properties, such as shape and color, is relatively straightforward, agents could not learn mappings of the observer-dependent concepts *front-left*, *front*, *front-right*, *reachable*, *near*, and *far*. The reason for this is that agents did not take each other's perspective, so that what was to the left of one agent could have been to the right of another agent, and what is reachable to one agent could have been far away to another.

To overcome this problem, we allowed the hearer to take the perspective of the speaker when constructing its learning context from the object pointed to in LLIs (a method that proved successful in robotic experiments [52]). Perspective taking is achieved by reconstructing the dialogue partner's visual view through straightforward triangulation by using the visual information concerning the distance and direction of both the pointed object and the speaker, as well as the speaker's orientation. Taking perspective in this way is necessary because the required autonomy and embodiment do not allow agents to have access to each other's stimuli, nor do the agents have a common absolute frame of reference.

Since the analysis of the model from [64] also revealed that agents were often communicating about objects that hearers could not see, we also used this perspective-taking mechanism to ensure that in LLIs speakers only communicated about (and hence pointed to) an object that the hearer could see.

2.2.5 Dialogue Control and Joint Attention

As mentioned, LLIs involve joint attention. In addition, LLIs require both agents to see each other in order to take each other's perspective, and both need to see the object that is the topic of the interaction. When—as in [64]—agents have no control of their actions dedicated to communication, situations in which these conditions occur tend to be rare. (Imagine communicating and learning language from each other while walking past each other in different directions without stopping and gesturing.) A dedicated dialogue controller was designed to implement dialogue-like LLIs that could override actions decided by the DQT. Since SLIs do not require that agents see each other, the dialogue controller did not coordinate such interactions. The main purpose of the dialogue controller is to coordinate the establishment of joint attention as described hereafter, whereby the conditions required to take perspective will be met implicitly. The dialogue controller is implemented as a *behavior-based cognitive architecture* [57], where two finite state automata implement the scripts of speaker and hearer. Transitions from one state to another are communicated with predefined gestures to the dialogue partner when turn-taking is required.

³ Children seem to use mutual exclusivity only for a small period. A mechanism like this could simulate this finding.

Two of the three joint attentional mechanisms proposed in [29] were implemented: *checking/sharing attention* and *following attention*.⁴ Checking/sharing attention is the most basic one and is initiated by the agent that becomes the speaker. If an agent is in its default state where it is not involved in any interaction and simply executes the actions decided by the DQT controller, then if it sees another agent, with a certain probability it will initiate a checking attention dialogue by sending a hardwired gesture to the visible agent. The initiator (or speaker) stops moving and waits for the other agent's response. The other agent, which becomes the hearer, will override its own DQT action and start turning left until it sees the speaker. Then it will stop and send the speaker a hardwired gesture indicating that it sees the other agent. (Note that such a gesture is not required, since the speaker could see this, but for computational efficiency it is thus implemented.) The speaker then selects an object visible to both agents as the topic (possibly one of the agents involved in the dialogue), and produces an expression containing a single word for each concept describing this topic and sends the resulting message accompanied by a pointing gesture to the hearer. In case the speaker itself is the topic, it will perform the action proposed by the DQT controller to show this to the hearer. The hearer then constructs the learning context C_L as the set of concepts describing the topic from the speaker's perspective. Using this learning context, the hearer adapts its lexicon and interprets the expression as described in Section 2.2.1.

Following attention dialogues are initiated by the hearer when—after interpretation—it wishes a clarification of one or more words. This can occur after interpreting either an LLI or an SLI for words that the hearer could not interpret or—with a low probability—for words it could interpret. If a following attention dialogue is initiated, the hearer sends a gesture to the speaker indicating for which words it requests clarification. In addition, the hearer starts turning to the left until it sees the speaker, which stops moving. Since the speaker already initiated the interaction earlier, it is safe to assume that the speaker sees the hearer.⁵ When the speaker is visible, the hearer sends a hardwired gesture to indicate it is ready. The speaker then searches for an object visible to both agents (using perspective taking) and whose concepts include one or more concepts that were expressed by the words that the hearer requests clarification for. If the hearer's request is a response to an LLI, then a preference is given to a different object than was pointed to in the first place. (If the speaker could not find a different object, the first object is taken.) If the new object does not cover all words that required a clarification, the non-covered words are discarded. The speaker then produces an expression containing the words it clarifies accompanied by a pointing gesture. If the clarification involves an action, the speaker performs that action. The hearer constructs the learning context as the set of concepts describing the object pointed to or—in case the following attention dialogue was a response to a previous LLI—as the cross section between that set and the learning context of the previous interaction. In the latter case, the learning context tends to be smaller than the original one, thus speeding up learning [29].

3 Experiments

3.1 Environment Specification

In the experiments we describe here, the agents are faced with the well-known poisonous-food problem [10, 37, 54]. They find themselves in an environment where there are two types of plants, both of which can be picked up and eaten. One type is nutritious and yields an energy increase; the other type is poisonous, and eating them actually drains energy. Agents can distinguish between the two types, but they do not know a priori that one kind—let alone which kind—is poisonous.

To measure the efficacy of social learning as a mechanism for the proliferation of knowledge pieces through a population, we ran a series of experiments where the population consists of two kinds of agents: knowers and students. The knowers have pre-built controllers that allow them to tackle

⁴ The three joint attentional mechanisms checking/sharing attention, following attention, and directing attention implemented in [29] were inspired by the three mechanisms that humans are assumed to use [12].

⁵ This assumption does not always hold, because the speaker may have moved either when it produced an SLI or when it had to show the action it was drawing the hearer's attention to.

the poisonous-food problem. The students have a partially randomly constructed controller—they know how to pick up and eat plants (regardless of their being poisonous or not), but the rest of their DQTs are constructed randomly. A varying proportion of the knowers are teachers, who can initiate, but not react to, SLIs. The remaining knowers do not engage in SLIs in any way (hence they neither teach nor learn skills); they are only there to ensure that the environment contains the same number of agents eating away at the edible plants across the experiments, so that the results are comparable. Students both initiate and react to SLIs. The teachers, but not the knowers or students, were initialized with a predefined lexicon where each concept is uniquely associated with a word form. Knowers do, however, engage in LLI, so they can contribute to (or frustrate) language development within the population.

We ran the experiment with varying numbers of teachers to compare the rate at which the population of students learns to differentiate between nutritious and poisonous food. In our simulations, the world was initialized with 5000 edible plants and 5000 poisonous plants distributed randomly on a 200×200 grid. Poisonous plants drain 1.5 times the energy that edible plants yield. Plants regrow practically immediately (within two time steps) after they have been picked, similar to food in SugarScape [18]. Thus, there is always food (and poison) available, and the ratio of poisonous to edible plants more or less remains at the initial value 0.5. The total number of agents was fixed to $N = 250$, of which 125 were knower agents and 125 were students, each of them positioned randomly at the start of the experiments. We varied the number of teachers, N_t , with the following values: $N_t = 0, 1, 25, 50, 75, 100, 125$. Agents were given sufficient energy to survive the entire simulations. So the population size remained constant throughout the simulations. All simulations were run for 50,000 time steps and were performed 10 times for statistical purposes.

3.2 Measures

We monitored the simulations using the measures of communicative success, communicative accuracy, and fitness.

3.2.1 Communicative Success

This is the average of the agents' *own* estimates for communicative success. An agent verifies, after the interpretation of each word in each LLI as a hearer, whether the interpretation yielded a valid meaning. If this was the case, the agent assumes the interpretation was successful. Each agent a_i keeps a measure cs_i , which is the proportion of the thus successful interpretations during the past 50 interactions where the agent acted as hearer. The communicative success (CS) is then the average cs_i :

$$CS = \frac{1}{N} \sum_{i=1}^N cs_i. \quad (1)$$

3.2.2 Communicative Accuracy

This measures the average of the agents' *accurate* interpretations. After each interpretation of each word in each utterance, the system verifies whether the interpreted concept is the same as that intended by the speaker. The communicative accuracy (CA) gives the proportion of accurate interpretations during a given number of time steps (500 in the experiments reported). Let $ca_{ij} = 1$ for each agent i that interpreted a word w_j accurately, and $ca_{ij} = 0$ for each word interpreted inaccurately. CA is then calculated as follows:

$$CA = \frac{1}{N} \sum_{i=1}^N \left(\frac{1}{W_i} \sum_{j=1}^{W_i} ca_{ij} \right), \quad (2)$$

where W_i is the number of words that agent i interpreted into some concept within the given time window. (Words that were not interpreted at all, i.e., those that did not yield a concept, were not included. This way, CA measures the accuracy of interpretations that agents themselves consider successful, so CA is relative to CS .) To investigate the dynamics of the learning in more detail, two different forms of CA were measured.

- CA_{all} , the overall communicative accuracy, is the accuracy measured over all interactions of all agents.
- CA_{sli} measures CA over all *students'* interpretations of *skill-learning interactions*.

3.2.3 Fitness

In order to measure the effectiveness of social learning of skills, we used a fitness function based on the proportions of the different types of food that the students eat:

$$F = \frac{E_c}{E_c + E_p} - \frac{P_c}{P_c + P_p},$$

where E_c and E_p are the numbers of edible and poisonous plants eaten by the population during a time frame of 500 time steps, and P_c and P_p are the numbers of edible and poisonous plants available in the environment. The second term is introduced to compensate for the sometimes skewed proportion of edible plants, which usually is around 0.5, but during the early stages tends to increase to 0.6. In this measure, random behavior will yield values around 0.0, whereas proper behavior will yield a fitness of 0.5, which occurs when all students have successfully learned the proper behavior.

Note that communicative success (CS) is calculated by individual agents to estimate their own language proficiency, which they use as a probabilistic indicator of whether or not to send or accept a skill-learning message. The number of words exchanged per time step depends on the frequency of contact and the proficiency in language as measured by CS . Communicative accuracy is processed by an external monitor that intercepts all received utterances, and it is calculated each 500 time steps.

3.3 Results and Discussion

Before presenting the results regarding the social learning of skills, we present those regarding the language development. Figure 3 shows that for each condition (i.e., number of teachers) communicative success rises toward values between 0.65 for $N_t = 25$ and 0.95 for $N_t = 125$, but CS remains well behind in speed of development and level for both $N_t = 0$ and $N_t = 1$. It is important to realize that CS is based on the agents' own perception and indicates the percentage of received words for which the agents succeeded in retrieving a concept by interpreting the utterances.

Since the agents themselves evaluate CS , there is no guarantee they do so correctly. We therefore also measure communicative accuracy, which checks, for each received word that agents interpreted successfully according to themselves, whether this interpretation matches the intended meaning. Considering all agents, the communicative accuracy rose rapidly to well above 0.8 in the cases where $N_t \geq 25$, and settled near 0.9 (Figure 4a). The speed with which CA increased, however, was lower for $N_t = 25$, and CA_{all} rose even more slowly in the cases where $N_t = 0$ and $N_t = 1$. The lower results when $N_t = 0$ or $N_t = 1$ is understood on realizing that in these conditions, the population had to develop their own language rather than adopting those the teachers were given. Even in the case where there was one teacher ($N_t = 1$), its language did not spread sufficiently over the population to become influential. Nevertheless, also in these cases, CA_{all} increased to a value of around 0.8, so the interpretation was quite accurate.

It is important to realize that CA_{all} was measured over LLIs and SLIs for all types of agents, including teachers that knew the language, as well as knowers and students, both of which had to acquire the

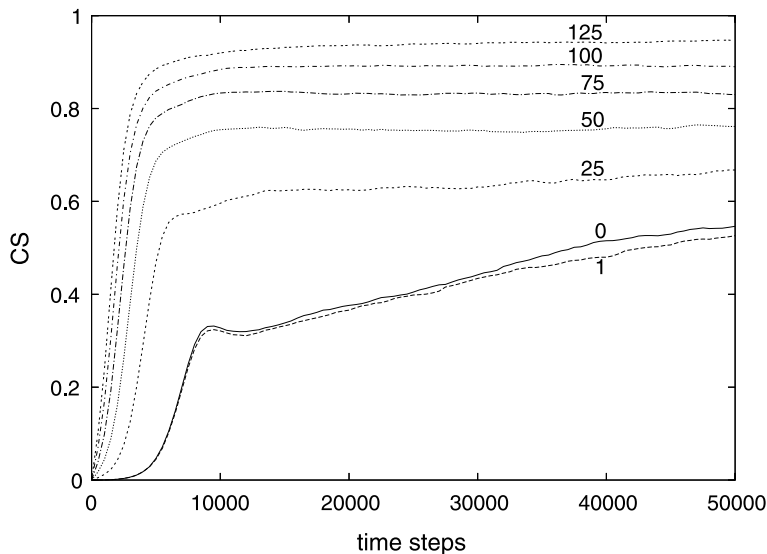


Figure 3. The development of communicative success. Each line relates to a different number of teachers, N_t , as indicated in the label, and is an average over 10 different runs.

language. To assess the adequacy of the acquired language to allow the social learning of skills, we also measured communicative accuracy only over SLI for students (Figure 4b). Here we see a similar result when the population contained 25 or more teachers, but when $N_t = 0$ or $N_t = 1$, CA_{sli} also increased early on to a value over 0.8. This high yield when $N_t = 0$ or $N_t = 1$ may seem odd, but it is important to realize that in SLIs an expression is sent or accepted by the agents participating in an interaction only if all concepts or words (each node in the DQT relates to one or more words) have a unique mapping for production or interpretation. This takes a while, because the language is (almost) nonexistent at first when $N_t = 0$ or $N_t = 1$ and only happens for one or possibly two branches of the DQT (e.g., [carry plant] \Rightarrow eat). Hence the late rise of CA_{sli} after approximately 4000 time steps. Shortly after CA_{sli} first increased, we see the curve drop again, after which it rises again, similar to the well-studied U curve observed in language learning (e.g., [30, 53]). (This also occurs for CS and to a lesser extent CA_{all} .)

To explain the occurrence of this U curve, it is important to stress that SLIs only lead to an actual utterance in the case where all concepts can be expressed. For teachers this always succeeds, but for students it only succeeds in the case where the language is sufficiently developed. Nevertheless, students can act as teachers and, in fact, form the majority of teachers when $N_t = 0$ or $N_t = 1$. So the first successfully expressed SLIs involve rules whose concepts are most straightforwardly learned through XSL, such as `plant` or `agent`. Since these words are by then already successfully established by the students, CA_{sli} rises sharply. However, when more complex rules are being expressed and interpreted, they involve concepts that the recipients may not have adequately disambiguated yet. For example, a word intended to mean `plant` by one agent may be inadequately interpreted as meaning `poisonous-plant` by another agent or vice versa. Consequently, CA_{sli} drops. However, over time, these problems are also solved through language learning, so CA_{sli} rises again. This, together with the low usage frequency of words when there are fewer teachers, explains the U curve.

Frequency is also an important factor regarding the effectiveness of language development. Figure 5 shows the number of words exchanged during a window of 500 time steps for the conditions $N_t = 0$ and $N_t = 125$. The lower lines show the number of words exchanged as part of language-learning interactions, which rises to about 3000 words per 500 time steps in both extreme cases. This means that each time step about six words are being expressed, which is slightly more than one LLI each time step (an LLI typically contains five words describing the object). The number of words exchanged in skill-learning interactions during each 500 time steps starts to rise later, but then rapidly exceeds the number of words expressed in LLIs. The main reasons for this difference are that the number of

SLIs is positively related to CS and that no dedicated physical coordination is required to carry out an SLI. Since the number of SLIs depends on the level of CS , it also depends on the number of teachers in the population, as they have a CS of 1. When there are no teachers, the number of words exchanged rises to about 18,000 (Figure 5a), whereas this number rises to around 76,000 when there are 125 teachers (Figure 5b). With more teachers in the population, the number of SLIs also exceeds the number of LLIs earlier in the simulations, because CS rises more rapidly.

The fitness measure F shows that the language needs to be shared among the population to a sufficient degree for skill learning to become successful (see Figure 6). F only increases when $N_t \geq 25$, but when $N_t = 25$, it remains substantially lower than when $N_t = 50$ and even more so than

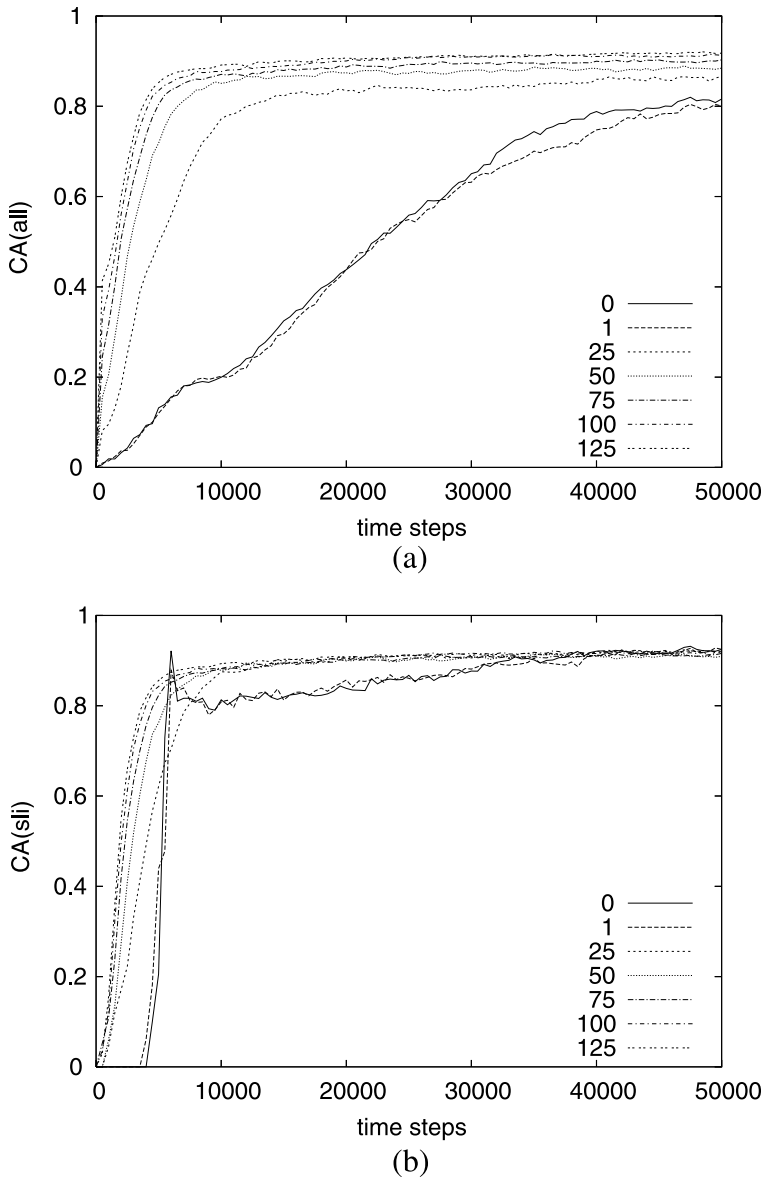


Figure 4. The results on average communicative accuracy for (a) all agents and all interactions, and (b) students' SLIs. Each line in CA_{all} and CA_{sli} shows averages over 10 different runs and relates to a different number of teachers, N_t , as indicated in the legends.

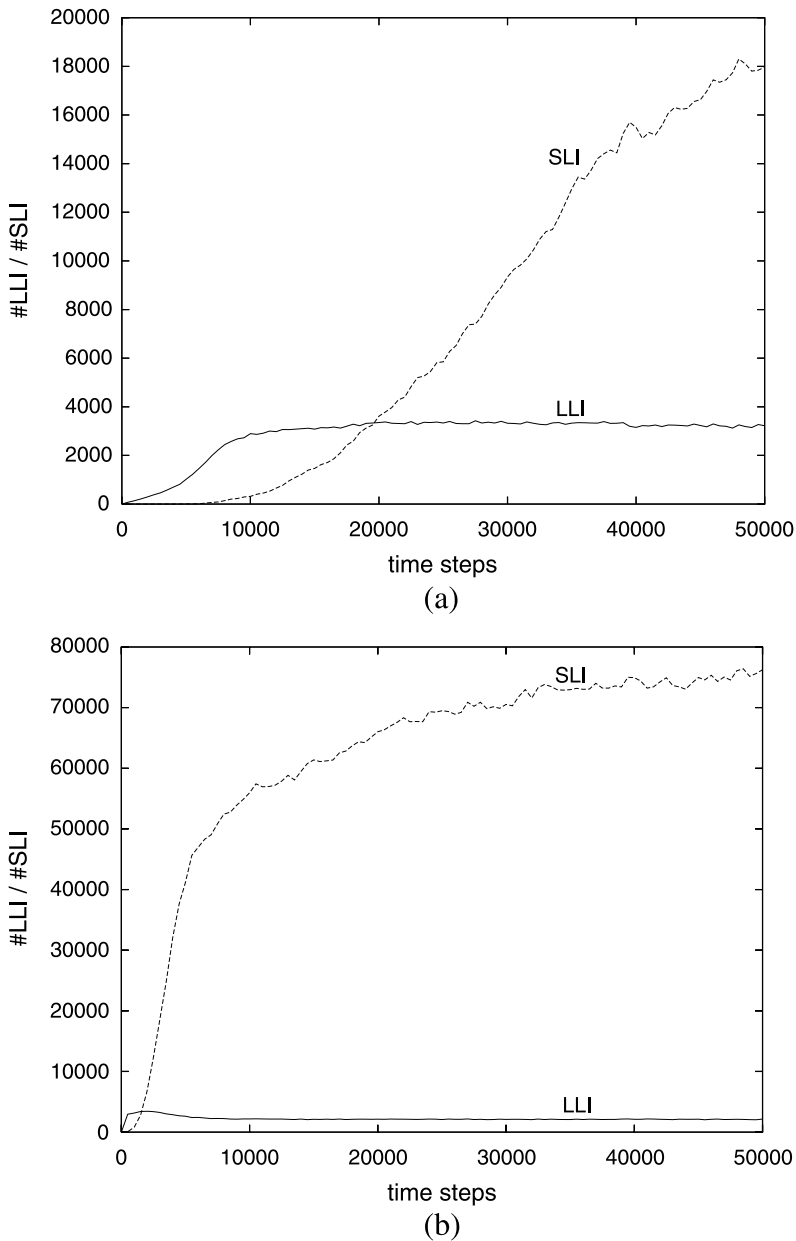


Figure 5. The number of LLIs (solid lines) and SLIs (dashed lines) played during 500 time steps for (a) $N_t = 0$ and (b) $N_t = 125$. All lines are averages over 10 different runs.

when $N_t \geq 75$. When $N_t = 0$ or $N_t = 1$, F remains practically 0. In these cases, the curve fluctuates greatly toward the end, because the students tend to eat less often. On average, when $N_t = 125$, the students ended up eating 35 times more often than the students when $N_t = 0$, in which case about one eating action is performed each 500 time steps. The reason for this low number of eating actions is that other (random) skills are being learned from other students, because the knowers do not engage in SLIs. Moreover, in the case that $N_t = 1$, the only teacher’s language fails to invade the population, so it cannot communicate its skills. This was despite the fact that the word creation probability (i.e., the chance an agent would invent a new word when it failed to produce an utterance) was kept low at 0.01,

so that existing words would have had enough time to propagate in the population. (In most language-game studies, this word creation probability is set to 1; e.g., [45, 51, 62].) Since learning from unskilled students is not beneficial, F remains low.

Basically, the above means that the mechanisms for the social learning of skills work well and also that the language appears to develop to a sufficient degree when $N_t = 0$ or $N_t = 1$, but then the agents learn skills from agents who are still students and have not (yet) mastered the proper behavior. A potential solution to this problem would be to use reputation (e.g., based on fitness) as a trigger to adopt socially transmitted skills, so students would tend to learn only from those agents who use the appropriate skills [40]. This worked well for $N_t = 1$ when the language was predefined [23], but during the model's development we discovered that this did not work when the language had to be acquired from scratch. Further studies are required to understand why reputation does not work well in the current model.

4 General Discussion

In this article we have related our model to what Gergely and Csibra have called *pedagogy learning* [20], that is, the learning of opaque knowledge through dedicated social transfer of skills. Both the rules representing the relevant skills and the meanings of words are opaque, because they are not directly accessible to other agents. In our model, the rules are transmitted through language, whose meanings—in turn—are transmitted by means of joint attention. Hence, one medium for communication (language) is acquired using another medium of communication (joint attention). So joint attention acts as a scaffold for learning language, which then forms a scaffold for learning rule-like skills. This shows that pedagogy learning can act at different levels of knowledge using different means of communication.

Our model goes beyond previous simulations in that the environment is more complex and demanding than most simulations in the *combination* of, among others, skill learning, language learning, the number of observable features, population size, embodiment, and situatedness. Various models have gone beyond the complexity of individual aspects of the model. For instance, the population size in [4] was much larger than in the current model, but the number of meanings was low and no embodiment was assumed. Likewise, the language and embodiment in Steels' robots implementing fluid construction grammars (e.g., [50]) exceeds the complexity of the current model, but there the population size was

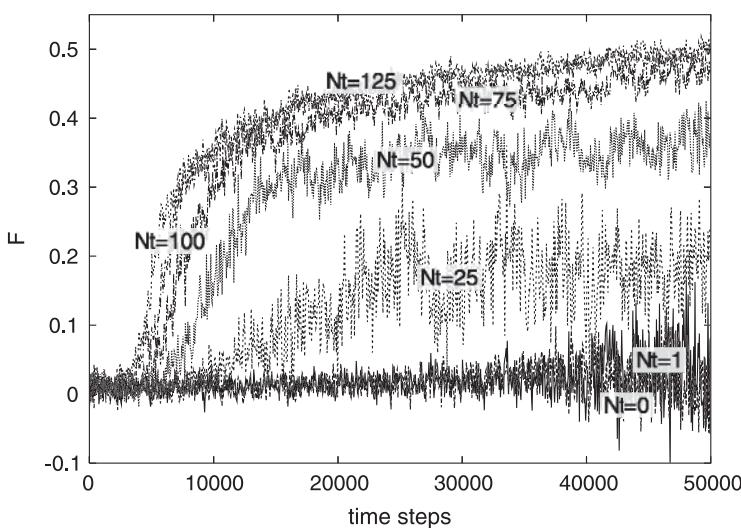


Figure 6. The development of the fitness F for the experiment with different numbers of teachers. Again the lines are averages over 10 different runs.

low and these robots did not use the language to transmit opaque rule-based skills. It is the combination of the various aspects we have implemented that makes the difference with other models.

The primary objective of this study has been to investigate what sociocognitive mechanisms are required for a population of agents to achieve this social learning at different levels in a model that assumes—insofar as is possible in a simulation—strict autonomy, embodiment, and situatedness. In particular, we have been interested in those mechanisms that become important when integrating various basic mechanisms, such as cross-situational learning of word-meaning mappings with skill-learning mechanisms, while being constrained by physical aspects of the real world (for instance, no explicit meaning transfer, different perspectives, etc.). As argued in [64], we believe that building such a model is highly instructive for understanding (some of) the sociocognitive mechanisms that our ancestors (protohumans) should and/or might have evolved as a prerequisite for the evolution of language and/or a complex culture.

Here we summarize the most crucial mechanisms we had to implement in order to deal with the problems agents in our environment face (mostly relating to language learning):

- We have distinguished between language-learning interactions and skill-learning interactions. As the SLIs involve agents communicating parts of their internal controllers, these communication acts could not be used directly to learn language. (Indirectly they could, by having agents request for clarifications of unknown words, after which the agents could engage in LLIs.) This is because agents need to construct a context of concrete objects in order to learn mappings between words and their meanings (concepts derived from visible objects or agents' own states and actions). So we expect that humans evolved different ways to interact with each other, depending on whether the interactions are aimed at learning language or other internal rules.
- On a related note, the language performance of agents has to be at a sufficient level to achieve an efficient transfer of skills. We devised heuristics for agents to evaluate their own competence, such as having agents measure their own communicative success, and transmit or incorporate skill knowledge only when the construction or interpretation of entire messages succeeds (whether correctly or not). We demonstrated that using these heuristics, communicative accuracy during SLIs tends to exceed 90%. We expect that humans have evolved (or otherwise acquired) the ability to self-assess language performance.
- The LLIs require coordinated interactions involving turn-taking and joint attention. Learning a referential language from each other in a complex world requires rather sophisticated and coordinated interactions, mostly in order to establish joint attention and perspective taking. Such interactions may be triggered by seeing another agent, but also by requesting clarifications for words that are not well understood. In order to show another agent a particular action, point to an object, or take perspective, both agents have to be able to see each other as well as the third object, and they have to stand still for an instant so that both agents can observe the situation well. To facilitate the turn-taking involved, agents have to signal to each other that they want to communicate, in what stage of an interaction they are, and what role they are taking. So, turn-taking and coordinated joint activity aimed to establish common ground [14] through joint attention appears to be a crucial prerequisite for human languages to have evolved.
- Although not surprising, perspective taking is pivotal to learning words relating to observer-dependent features such as directions and distances of objects with respect to agents. This requires agents to imagine what other agents see. To achieve this, an agent needs to see both the other agent and the target object. The dialogues are crucial in that respect. Perspective taking is not only crucial to learning observer-dependent word-meaning mappings, but can

also aid in preventing an agent from talking about something that is outside the visual field of another agent.

- The usefulness of mutual exclusivity is also not completely surprising, as it is a constraint that children appear to use [31] and has been incorporated successfully in previous models of cross-situational learning [45]. However, in the current model it has become clear why it could be a necessary constraint. As, for instance, the concept `female` always co-occurs with the concept `agent`, the word for female could not be learned through statistical cross-situational learning alone, unless we have allowed words to be associated with combinations of concepts such as `[female agent]`. For reasons of learning complexity (the search space would face a combinatorial explosion), however, we decided to opt for implementing the computationally cheap mutual exclusivity constraint. It is possible that mutual exclusivity arose to deal with exactly these types of problems.
- Syntax is required for covert complex rules to be transmitted such that agents can reconstruct the tree (rule) structure of the transmitted knowledge social learning. In this study, we have decided to predefine the syntax, as well as negation, but syntax is a prerequisite for social learning of complex opaque rules, and humans unquestionably have evolved it. The lack of syntax may be a reason why other species do not display the social learning of covert skills by means of pedagogy. It is also interesting to note that the structure of rules may be reflected in the syntax that humans have evolved; at least some components of rule-like knowledge occur in the grammar of natural languages (e.g., *if...then... constructions*).

We realize that the current analysis is far from complete and much more work needs to be done. For instance, additional research is required into the prerequisites required for syntax to evolve. Although various studies have already looked into that problem (e.g., [5, 27, 50]), we believe it is also important to investigate it in relatively complex platforms such as these. In addition, it is equally important to verify such formal models by comparing them with empirical findings on human behavior [63]. Also, more research is required into the sociocognitive mechanisms that underlie the social learning of rule-like skills. Quite a bit of research has already been done regarding, for instance, reputation-based social learning, but usually using explicit knowledge transfer [40]. However, the mechanisms developed in such models do not necessarily hold when transmitting covert rules using a language that needs to develop first. The reputation-based learning mechanism we implemented in our previous model that used explicit knowledge transfer [23], for example, did not work well in the current model when the language had to develop first.

5 Conclusions

We have investigated what sociocognitive mechanisms are required to design a model of social learning of both language and survival skills through pedagogy learning. Our design was constrained by our assumption of strict autonomy, virtual embodiment, and situatedness. We have demonstrated that the following sociocognitive mechanisms are crucial in our design, and we hypothesize that protohumans had to evolve (or otherwise learn) them:

1. Agents need to separate language learning from learning other skills (i.e., they cannot do both simultaneously).
2. Agents' ability to assess their own language performance aids the successful transmission of skill knowledge.
3. Learning word-meaning mappings requires agents to coordinate their interactions using turn-taking and joint attention.

4. Agents require taking each other's perspective when learning language.
5. Mutual exclusivity is advantageous for learning word meanings when words always coincide with multiple meanings.
6. Syntax is required to structure the rules so that they can be reconstructed by the recipient.

We have shown how pedagogy learning can work for different types of knowledge. Based on our findings, we hypothesize that—in general—“lower,” more primitive means of communication are required to facilitate the social (“pedagogy”) learning of the higher-level knowledge. In our model, the social learning of skills is facilitated by language, whose learning in turn is facilitated by joint attention. In a sense, one means of communication forms a scaffold for learning the next level. How this is generalizable across different levels of social learning is subject to further investigation. Research could be done to investigate what lower-level communication is required to facilitate the learning of joint attention, which—following our model—could be the communication that manages the turn-taking dialogues. One could also proceed in the other direction by investigating what the social learning of skills can contribute to advance social learning at the next levels. Perhaps the answer lies somewhere in the advancement of social learning among artificial agents. In any case, scaffolding social learning thus reduces the cost of learning opaque knowledge substantially and, following [7], could therefore contribute immensely to cumulative cultural evolution.

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