Investigating social interaction strategies for bootstrapping lexicon development

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Abstract
This paper investigates how different modes of social interactions influence the bootstrapping and evolution of lexicons. This is done by comparing three language game models that differ in the type of social interactions they use. The simulations show that the language games, which use either joint attention or corrective feedback as a source of contextual input are better capable of bootstrapping a lexicon than the game without such directed interactions. The simulation of the latter game, however, does show that it is possible to develop a lexicon without using directed input when the lexicon is transmitted from generation to generation.

1. Introduction

One important question in the scientific field of language evolution and acquisition is: how do language learners acquire the meaning of novel words? A famous example that perfectly illustrates one of the hardest problems these learners face was introduced in (Quine 1960).[1] Suppose a linguist is out in the field with a native speaker of a language that is unknown to the linguist when suddenly a rabbit passes by. Apparently in response the native speaker says ‘gavagai’. A natural reaction of the linguist would be to assume that ‘gavagai’ means <*rabbit*>. The native, however, could have referred to a specific rabbit, a part of the rabbit, a mammal or even to the sunny weather. The linguist’s assumption is therefore uncertain and he requires further social interactions to understand what the native really meant.

When learning a language, agents may engage in a variety of social interactions that guide the process of learning the language’s meanings. For instance, agents may establish joint attention on the subject of communication prior to the exchange of linguistic knowledge such as words. Thus learners may have certain pragmatic contextual cues to verify the meaning of words. For young language learners the input usually includes a context that is present in the ‘here and now’. Often the agents establish joint attention and sometimes learners receive corrective feedback on their language use. Many psycholinguists assume that directed contextual input such as joint attention or

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[1] The original example of Quine was introduced in relation to the radical translation problem (the problem that arises when two people try to learn each other’s language without knowing a common language). Although placed in a different context here, the example clearly identifies the problem that all language learners face.

corrective feedback is necessary to learn word-meanings, but there is some evidence that children do not need such directed cues to learn the meaning of their first words (Lieven 1994). There is much debate in the literature on the nature of input that language users, and children in particular, use to learn the meaning of words, see, e.g., (Bloom 2000) for a discussion. Similar debates are also prominent in the field of language evolution (Dessalles 2000; Kirby and Hurford 2002; Tomasello 1999).

Recent computational studies on the evolution of language have shown how agents can learn word-meanings successfully, for an overview see, e.g., (Cangelosi and Parisi 2002; Kirby 2002). In most of these studies it has been assumed that either joint attention was established, cf. (Oliphant 1999) or that agents receive corrective feedback, cf. (Steels and Kaplan 2002). These two interaction strategies have been modelled on real robots using variants of the language game model originally introduced in (Steels 1996a). The joint attention condition has been modelled with *observational games* (Vogt 2000a) and the corrective feedback condition with *guessing games* (Steels and Kaplan 2002; Vogt 2002a, 2002b).

Few studies have investigated whether interactions to establish joint attention and corrective feedback are really necessary. Smith has shown in simulations how two agents can develop a shared lexicon without any of the mentioned cues, as long as the objects to which words refer are present in some observable context (Smith 2001). Robotic experiments that use such principles (modelled by the type of language games called *selfish games*), however, have revealed results equal to chance (Vogt 2000a, 2000b). But these results were obtained with an experimental set-up that was very minimal in terms of the environmental complexity and the robots' architecture. In Smith's simulations the environment was more complex, because for every interaction a context of randomly generated objects was constructed. It is therefore likely that Smith's results are more realistic.

In this paper three research questions are addressed:

1. How do the three language game models relate to each other?
2. Can the selfish game deal with, or perhaps benefit from a population dynamics?
3. Are the models scalable in terms of population size?

The first question is investigated by comparing the three language game models with each other under the different conditions that are used to answer the other questions. The second question is investigated by modelling a flow of agents using the *iterated learning model* (Kirby and Hurford 2002). The final question is addressed in simulations with varying population sizes. As the last two questions have already been answered in the affirmative for the observational and guessing games (Oliphant 1999; Steels and Kaplan 2002), the focus for these questions will be on the selfish games for which these questions have not been addressed before. This study is based on the study that was previously presented in (Vogt and Coumans 2002). The current paper, however, is more detailed and additionally presents some new results and analysis.

The remainder of this paper is organised as follows: The next section presents a psycholinguistic background and surveys relevant computational studies relating to the problem statement. The three language game models are explained in Section 3. Section 4 presents the results of the simulations, which are discussed in Section 5. Section 6 presents conclusions.

2. Learning the meaning of words

When children learn the meaning of words, they tend to learn some types of words earlier than other types. Children usually acquire the meaning of basic-level categories such as *dog* before they acquire superordinate and subordinate categories such as *animal* and *terrier*. This can be explained by the observation that basic-level names occur more frequently in the input (Brown 1958) and because children "find it more natural to categorise a novel object as an instance of a basic-level kind than as an instance of a superordinate kind. As a result, children (and adults) find it easier to learn novel basic-level names than novel superordinates" (Bloom 2000, p. 90).

It is widely assumed that most words are learnt by associative learning, i.e. words are associated with the meaning of referents that are simultaneously presented. This requires a form of joint attention on the referent that can be established, e.g., by checking, following or directing an adult's attention toward an object of interest (Tomasello 1999). Many parents, for instance, teach their children novel words by holding something in front of the child and giving it a name ('look, it's an apple'). In some Eastern cultures, however, adults in a child's environment do not speak directly to their children until they used at least a few words meaningfully (Lieven 1994). These adults only speak with each other in front of children, who start speaking at some moment and therefore must grasp the meaning of words by observing adult speech without receiving explicit cues concerning its meaning. These children learn their first words somewhat slower than those raised in Western cultures (Lieven 1994), which is consistent with the finding that children who use joint attention learn faster than those who do not (Tomasello and Todd 1983).

An alternative for associative learning is reinforcement learning, in which children receive (corrective) feedback on their language use. This means that when a child uses a word for the first time (or perhaps somewhat later), it receives positive feedback when it uses the word properly. Otherwise it may receive negative feedback, while being corrected with the proper use. There is much dispute on the existence of such feedback, but consider, for example, the following situation: Suppose a parent requests a child to pass the salt. If the child in response hands over the pepper, the parent may say while pointing at the salt "no this is pepper, that's the salt". In this case, the child receives corrective feedback. One could also imagine that a parent does not present the feedback explicitly, but that the child itself is able to discover the correctness of its word use. In our study, we do not investigate how the feedback is presented, but we assume that a language learner can somehow receive feedback. As a result of the reinforcement learning strategy, word-meanings that have received positive rewards tend to be used more often on future occasions than those that have received negative feedback. Again such learning strategies are observed in Western cultures (mainly in middle class families), but less so in some Eastern cultures (Bloom 2000; Lieven 1994).

It is important to notice that from the moment that children raised in Eastern cultures start to speak, their caregivers start to use directed interactions as intensively as in Western cultures. This might put a question mark on the actual presence of such 'selfish' interaction policies.[2] However, the selfish learning strategy must sometimes be present when joint attention is established. For instance, when someone points at a rabbit and says 'gavagai', it is not necessarily clear what exactly is meant by the word 'gavagai', because it may not be clear what is pointed at. In such cases, the meaning of words may be uncertain and a language learner remains on its own in hypothesising the word's meaning.

[2] We can call this 'selfish' learning, because as the agents in this game do not explicitly 'care' whether they communicate about the same meaning, they behave more or less 'selfishly'.

Most computational studies on the origins or development of word-meanings use the Western strategies. Associative learning, for instance, is used by (Billard and Dautenhahn 1999; Oliphant 1999), while reinforcement learning is used by, e.g., (Steels and Kaplan 2002; Yanco and Stein 1993). Both learning types have also been implemented on real mobile robots as observational games and as guessing games, see (Vogt 2000b, 2001) for a comparison study. The first type of game models associative learning and the second reinforcement learning. The experimental results showed that agents using either strategy could develop a coherent lexicon rather well. Comparing the two games revealed small differences in the development of a grounded lexicon. The success rate of the observational games increased and stabilised faster than for the guessing games, although for both experiments the level of success approached approximately the same level. The amount of polysemy and synonymy[3] emerging from the guessing games, however, was substantially lower than from the observational games. Thus the lexicons developed with the guessing games are more informative. For a detailed discussion of this comparison consult (Vogt 2000b, 2001).

Models that try to explain the origins of language - or language acquisition - must also be able to explain learning word-meanings using the non-Western strategy. To study this, the *selfish game* has been developed (Vogt 2000a, 2000b). In the selfish game, neither joint attention nor corrective feedback is used. Agents in a selfish game observe a context of several objects (or meanings). The speaker of the game selects a topic from this context and tries to name it. The hearer guesses what the name refers to, but has no means to verify whether it was successful. When agents are exposed to different contexts in which one object always re-occurs together with a particular name, they may infer that the name refers to this re-occurring object. Learning such knowledge has been modelled with a *Bayesian learning* technique (Mitchell 1997). In a way this learning mechanism is similar to associative learning, but deals better with the uncertain relations that are present in the selfish games.

Robotic experiments with the selfish game were disappointing as they revealed results equal to chance (Vogt 2000a, 2000b). The reason for this has to do with the use of robots that were minimal in terms of their physical architecture. These robots revealed poor sensorimotor skills and operated in a limited environment containing only three to four objects. In the selfish game, the robots calculated within the context of a game the probability of the occurrence of a meaning, given the occurrence of some word, based on previous games. The association that had the highest probability determined the meaning of the word. So if all contexts would have the same meaning, the distribution of this probability would be flat making a word’s meaning highly uncertain. When the context would vary sufficiently, the distribution would bring forward word-meaning associations that co-occurred most frequently. In the robotic experiments removing and adding one of the four objects dynamically forced some variation, but this appeared to be insufficient. Nevertheless, the viability of the selfish game has been shown in simulations (Smith 2001), so the negative results of the robotic experiments are perhaps only valid for the minimal set-up. While a large number of experiments have been done with the guessing games and the observational games or similar models, the selfish game is rather unexplored. Both Smith and Vogt have only reported on one or two experiments with a population size of two, so more experiments are required to test, for instance, the scalability and population dynamics of the selfish game.

One important question that is investigated in this paper is how the three different language games compare to each other. The simulations will be compared in terms of communicative success and in

[3] Polysemy is the association of one word with several meanings and synonymy is the association of one meaning with several words.

terms of information, i.e. which game performs better in communication and which one reveals the most informative lexicon?

3. Language games

The simulations reported in this paper are all primarily based on the language game model introduced in (Steels 1996a). In the language game model, a population of agents develop a shared lexicon of word-meaning associations from scratch by means of cultural interactions, individual adaptation and self-organisation. Many successful experiments have been conducted both in simulations, e.g., (De Jong 2000; Steels 1996a) and on physical robots such as the Talking Heads (Steels and Kaplan 2002) and small LEGO vehicles (Steels and Vogt 1997; Vogt 2000a, 2002b).

Each agent in the population has a private lexicon. A lexicon is a set of word-meaning associations where each entry has a score σ indicating the effectiveness of the association. The words are constructed from arbitrary strings of consonants and vowels. The meanings are given and represented by integers in the simulations. The association scores σ are real values between 0 and 1. As the research is embedded in our aim at modelling aspects of language origins, at the start of each experiment, the agents have empty lexicons. In contrast to previous experiments, e.g., (Vogt 2000a, 2001, 2002b), we do not investigate how the agents develop ontologies containing the meaning of their observed environment. Therefore we assume the meanings given as was the case in, e.g., (Oliphant 1999; Steels 1996a). These meanings are stored in the agents' ontologies. During the simulations, the agents construct the lexicon by inventing and adopting words they associate with one or more meanings from the ontology. A word may be associated with more than one meaning and vice-versa. The system is open in the sense that the number of words is unlimited, and, in principle, new meanings and agents may be added and old ones may be removed.

The remainder of this section explains the three different types of language games. The iterated learning model is explained in the final part of this section and applies to all types of language games.

3.1 The observational game

The observational game uses joint attention to enable associative Hebbian learning. The game is organised as follows:

1. Two agents are randomly selected from the population. Arbitrarily, one agent is assigned the role of speaker and the other becomes hearer.
2. The speaker selects randomly one meaning as the *topic* from the ontology and informs the hearer what the topic is, thus establishing joint attention.
3. The speaker searches its lexicon for words that are associated with this topic and selects the association that has the highest score σ. If the speaker fails to find a matching association, it invents a new word and adds the word-meaning association to the lexicon with an initial association score of σ=0.01. The word is communicated to the hearer.
4. The hearer searches its own lexicon for an association of which the word matches the received word *and* of which the meaning corresponds to the topic.
5. If the hearer succeeds in finding a proper association, the observational game is a success. Otherwise it fails. Both agents know the outcome.
6. Depending on the outcome, the lexicon is adapted as follows:
    a. If the game is a failure, the hearer adopts the word and adds the word-meaning association to its lexicon with an initial association score of σ=0.01. The speaker

lowers the used association score by $\sigma=\eta\cdot\sigma$, where $\eta=0.9$ is a constant learning parameter.

b. If the game is a success, both robots increase the association score of the used association by $\sigma=\eta\cdot\sigma+1-\eta$ and they laterally inhibit all *competing associations* by $\sigma=\eta\cdot\sigma$. (An association is competing when either its meaning is the same as the topic, but its word differs from the uttered word, or when the word is the same, but not its meaning.)

3.2 The guessing game

In the guessing game, the contextual cue is given by evaluating the correctness of the game and the lexicon is learnt by a kind of reinforcement learner. This game differs slightly from the observational game and works as follows:

1. Two agents are randomly selected from the population. One is assigned the role of speaker and the other becomes hearer.
2. Both agents establish a context of a limited size that contains randomly selected meanings from the ontology. Both agents share the same context.
3. The speaker selects one meaning from the context as the topic, but it does not inform the hearer about this.
4. The speaker searches its lexicon for words that are associated with this topic and selects the association with the highest score σ. If the speaker fails to find a matching association, it creates a new word and adds its association with the topic to the lexicon, again with $\sigma=0.01$. The word is communicated to the hearer.
5. The hearer searches its lexicon for an association of which the word matches the received word *and* of which the meaning corresponds to one of the meanings in its context. If there are one or more matching associations, the hearer selects the association that has the highest score σ. The corresponding meaning becomes the hearer's topic.
6. If the hearer succeeds in finding an association, the guessing game is a success when its topic matches the speaker's topic. Otherwise it fails because either there is a mismatch in the topic or the hearer does not know the uttered word in relation to the context. The verification of the outcome implements the corrective feedback, which is known to both agents.
7. Depending on the outcome of the game, the lexicon is adapted as follows:
    a. If there is a mismatch in the topic and if the hearer does not already has the association of the uttered word and the topic[4], the hearer adopts the word in association with the topic ($\sigma=0.01$). In addition, both agents lower the association score by $\sigma=\eta\cdot\sigma$.
    b. If the hearer does not know the word, it adopts the word and associates it with the topic as in the observational game. The speaker lowers the used association score as above.
    c. If the game is a success, both agents increase the association score of the used association and they laterally inhibit all competing associations as in the observational game.

[4] Note that when the hearer has an association of the topic and the uttered word, it may select a different association when that one has a higher association score and its meaning is in the context.

3.3 The selfish game

In the selfish game there is no non-verbal input to indicate exactly the topic of a game. The only input to the hearer is a context that contains a number of meanings and the speaker's utterance. As in the selfish game the agents have no means to verify whether their communication was successful, they cannot use the association score as an indication of the effectiveness of a lexical element. The only information the hearers have with respect to the meaning of an utterance is the meanings present in the context. Hence, the meaning of an utterance may be uncertain for the hearer, because the context may consist of more than one meaning[5]. When the contexts vary sufficiently from game to game, the cross-section of these contexts in co-occurrence with a particular word indicates the meaning of this word. Learning this relation can be done using a *Bayesian learner*. For this the association score is now given by the following equation:

$$\sigma = P(m \mid w) = \frac{P(w \mid m)P(m)}{P(w)} = \frac{P(m \wedge w)}{P(w)}$$

In this equation $P(m|w)$ is the conditional probability that given a word w, the meaning m can be expected. Using Bayes' law, this can be translated into the quotient between the probability $P(m \wedge w)$ that m co-occurs with w and the probability $P(w)$ of w. This quotient can be transformed into the following equation, which is the same as the *confidence probability* used in (Smith 2001):

$$\sigma = \frac{U(w \wedge m)}{U(w)}$$

Here $U(w \wedge m)$ is the co-occurrence frequency of w with m, and $U(w)$ is the occurrence frequency of w.

Applying this new association score to the selfish game leads to the following algorithm:

1. to 5. are identical to the guessing game.[6]
6. Instead of evaluating the game's success, the agents adapt their lexicon immediately as follows:
    a. The hearer first makes sure that the word is associated with all meanings in the context. I.e., the hearer adds new word-meaning associations for each meaning in the context that has no existing association with the word. In addition the hearer increments the co-occurrence frequency $U(w \wedge m)$ by 1 for all meanings in the context and increases the occurrence frequency $U(w)$ with the context size, i.e. it increments $U(w)$ by 1 for all meanings in the context.
    b. The speaker increments both $U(w \wedge m)$ and $U(w)$ by 1 for the topic.

The selfish game implemented here is very similar to the implementation of (Smith 2001), except that his agents use discrimination games (Steels 1996b) to acquire meanings and that his agents use

[5] In the simulations of this paper, the context size was always set to five.

[6] When the speaker invents a new association (point 4), $U(w \wedge m)$ and $U(w)$ are initialised with 0; the association score is initially set to σ=1.

obverter learning (Oliphant and Batali 1997). The use of discrimination games causes the agents to acquire meanings that may not be shared. This increases the difficulty of arriving at a shared lexicon. We opted for a given meaning space, so we could focus our study at the differences between the different games and on the emergence of a shared lexicon.

Although we did not implement obverter learning in the way proposed by (Oliphant and Batali 1997), its underlying principle is adopted by the Bayesian learner. In obverter learning, the speaker selects a word-meaning by pretending it is a hearer. The speaker first searches all words that are associated with the meaning, and then tries to interpret these words in a similar way as point 5 of the algorithm. If there are one or more interpreted associations that match the topic, the speaker selects the word that it is most confident on. If, however, none of the interpreted associations match the topic, no utterance is produced in obverter learning and a new word must be invented to cover the topic, see also Smith (2001) for a discussion on obverter learning. With the Bayesian learner, the speaker selects an association based on the probability that given a word, the meaning occurs. This simulates – in a way – that the speaker selects the word it would best understand if it was a hearer. However, the speaker will always select an association matching the topic, even if the word would be better understood with a different hearer. We opted for this distinction, because we found that true obverter learning induced more ambiguity in the lexicon, as more words were created, causing a decrease in performance. This is an interesting observation, because (Oliphant and Batali 1997) have found that among the different algorithms they studied, obverter learning performed best.

3.4 The iterated learning model

The iterated learning model (ILM) implements a population dynamics and the transmission of linguistic knowledge over generations (Kirby and Hurford 2002). It can be applied to all kinds of language games. In the ILM the population contains two types of agents: adults and learners. Adults have passed the stage of learners and are assumed to have mastered the language. Learners enter the population as novices (i.e., they have empty lexicons) and learn the language from the adults.

Assuming that the sets of learners and adults each initially contain N agents[7] with empty lexicons, the ILM iterates the following steps:

1. A series of X language games are played.
2. Remove all adults, replace them by the set of learners and add N new 'empty' agents to the set of learners.

In the current simulations adults only take the role of speakers, while learners only take the role of hearers. This means that the adults do not communicate amongst each other, nor do the learners. As a consequence, the adults are the only agents that can invent new symbols, while the learners are the only ones that can adopt words expressed by the adults. In addition, once adults have established a way of naming a meaning, they will not invent new words, nor will they adopt existing ones. In general the adults will tend to produce the same word to express a meaning throughout their lifetime, unless the games are considered unsuccessful, which can only happen in the observational and guessing games. If a game is considered unsuccessful, the score of the used association decreases. When the lexicon contains an alternative to express the same meaning, the association score of this alternative may come to exceed the previously used one and will be used

[7] This means that the population constantly contains $2N$ agents.

henceforth. This does not happen in the selfish game, because in that game no success is evaluated and the highest association score will always remain highest. Hence, adults in the selfish game will always use the same word to express a meaning.

4. Experimental results

With the three models, three series of simulations were done. In each series we investigated all three models. Each simulation was repeated 10 times with different random seeds. In all simulations the world contained 100 meanings. The context size in each game was fixed at 5, except for the observational games where the context size was fixed at 1. In two series the population size was kept fixed at 10 agents. In the first series iterated learning was not applied, which is in accordance with the previous studies of Smith (2001) and Vogt (2000). In the second series iterated learning was applied. In the third series, the population size was varied between 2 and 20 in different simulations to investigate the scalability of the systems in terms of population size. In the remainder of this section, the results of the three series are presented, which are discussed in Section 5.

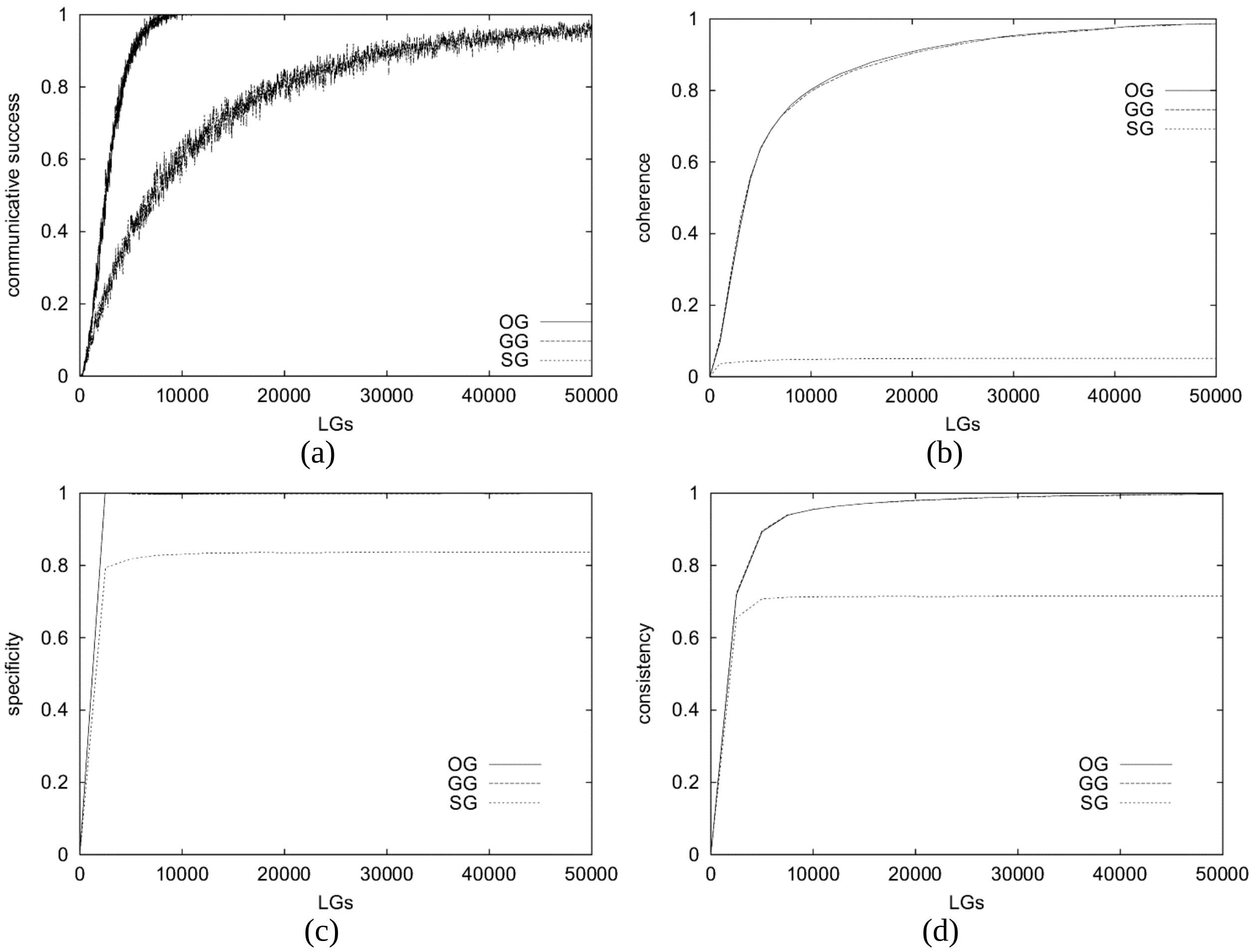


Figure 1. The results of the simulations without the ILM show (a) the communicative success, (b) the coherence, (c) the specificity and (d) the consistency of the observational games (OG), guessing games (GG) and selfish games (SG) as a function of the number of language games played (x-axis).

4.1 No iterated learning

In the first series of simulations the three language game models were investigated without applying the ILM. The population size was fixed at 10 agents, and each simulation was run for 50,000 language games.

Figure 1 (a) shows the *communicative success* for these simulations. The communicative success is the number of correctly played games averaged over the past 100 games or less when no 100 games have been played yet. The figure shows almost no difference between the guessing and the observational game: both reached a communicative success of 100% after about 10,000 language games. The selfish game, however, did not yet reach 100% after 50,000 games, although it would be reached when more games would have been played.

Figure 1 (b) shows the evolution of the *coherence* of the game. The coherence is the average rate in which each agent would produce the same word to express a meaning, based on their private lexicons and it was calculated every 1,000 games. As the figure shows, the coherence for the guessing and observational game increased to a value of 1.00 over the 50,000 language games. The coherence for the selfish game converged to a value near 0.05 within 10,000 games, which it remained over time. This means that with the selfish games a great deal of synonymy emerged in the global lexicon, which the agents nevertheless learnt to understand from each other.

Figure 1 also shows (c) the *specificity* and (d) the *consistency*, which are calculated from the mutual information of co-occurring meanings and words relative to the uncertainty of meanings in case of specificity and relative to the uncertainty of words for the consistency. These uncertainties, like the mutual information are calculated using the entropy measures introduced by (Shannon 1948). The two measures were developed by (De Jong 2000) to indicate how specific or consistent the agents' lexicons are used. A lexicon is specific if each word use predicts its meaning perfectly; it is consistent when each meaning is named with one word. Thus the specificity indicates the amount of polysemy in the lexicon and the consistency the amount of synonymy. For details how to calculate the specificity and consistency consult, e.g., (De Jong 2000; Vogt 2000b, 2002b). Although the measures were originally developed to be calculated from the agents' viewpoint, for this paper it was calculated for the global lexicon use. They were calculated over each 2,500 games.

The specificity of the observational and guessing games both increased to a value of 1.00 within 2,500 language games, see figure 1 (c). For the selfish game, however, the specificity did not exceed 0.84 after the 50,000 games. Figure 1 (d) shows that the consistency of the observational and guessing games increased toward a value very near to 1.00 after 50,000 games. But the selfish games remained below a consistency of 0.72. Hence, the selfish game model yielded a much less informative lexicon than the two other models, which seem to be indistinguishable from each other.

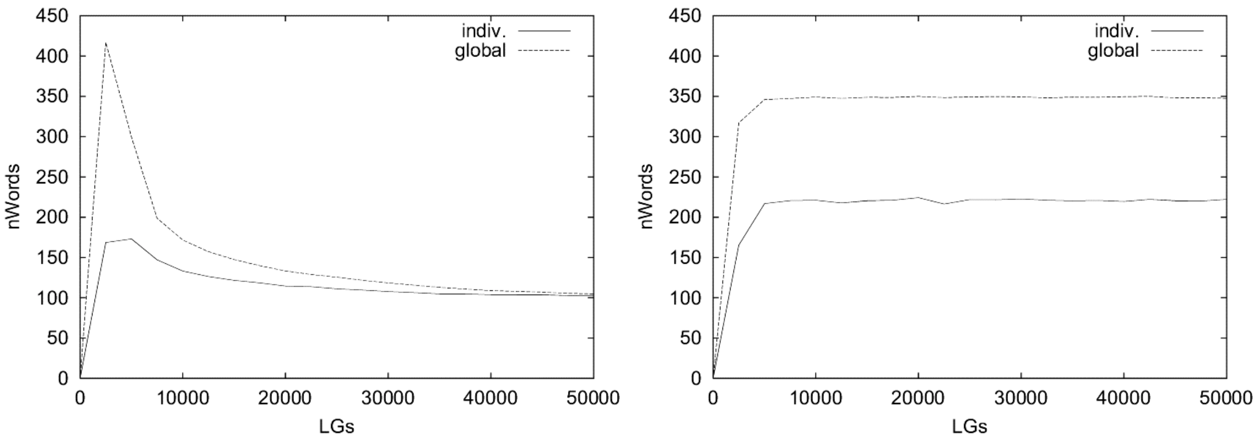


Figure 2. These figures show the evolution of word use by the *global* population and an *individual* agent of (a, left) the guessing games and (b, right) the selfish games for the first simulation series. The x-axis shows the number of language games played and the y-axis shows the number of words used in each window of 2,500 games.

Figure 2 shows how many words agents had used in each time frame of 2,500 language games, averaged over the 10 runs. Figure 2 (a) shows the word usage for the guessing games, which is similar to the evolution for the observational games (not shown). The upper line shows the number of words used by the entire population, and the lower line shows the number of words used by a typical individual agent. The graph clearly shows that after an initial period where the global population use more words than the 100 meanings, the entire population ends up using approximately 100 words to express the different meanings. The figure also shows that each individual agent used slightly over 100 words from 20,000 games onward. This means that initially the lexicons differ, but after approximately 4,500 games, each agent converges to more or less the same lexicon, which confirms the results shown in Figures 1 (b) and (d).

Figure 2 (b) shows the word usage for the selfish games. This figure shows that the global word use increased toward 350 words, while the individual agent used about 220 words within each time frame of 2,500 games. Assuming that each agent will play about 250 selfish games during each 2,500 games, each agent used more or less a different word in each game.

4.2 With iterated learning

For the second simulation series, the iterated learning model was applied to the three language game models. In each simulation 10 iterations of 10,000 games were processed. The population size was fixed at 10 individuals and each simulation was run 10 times with different random seeds.

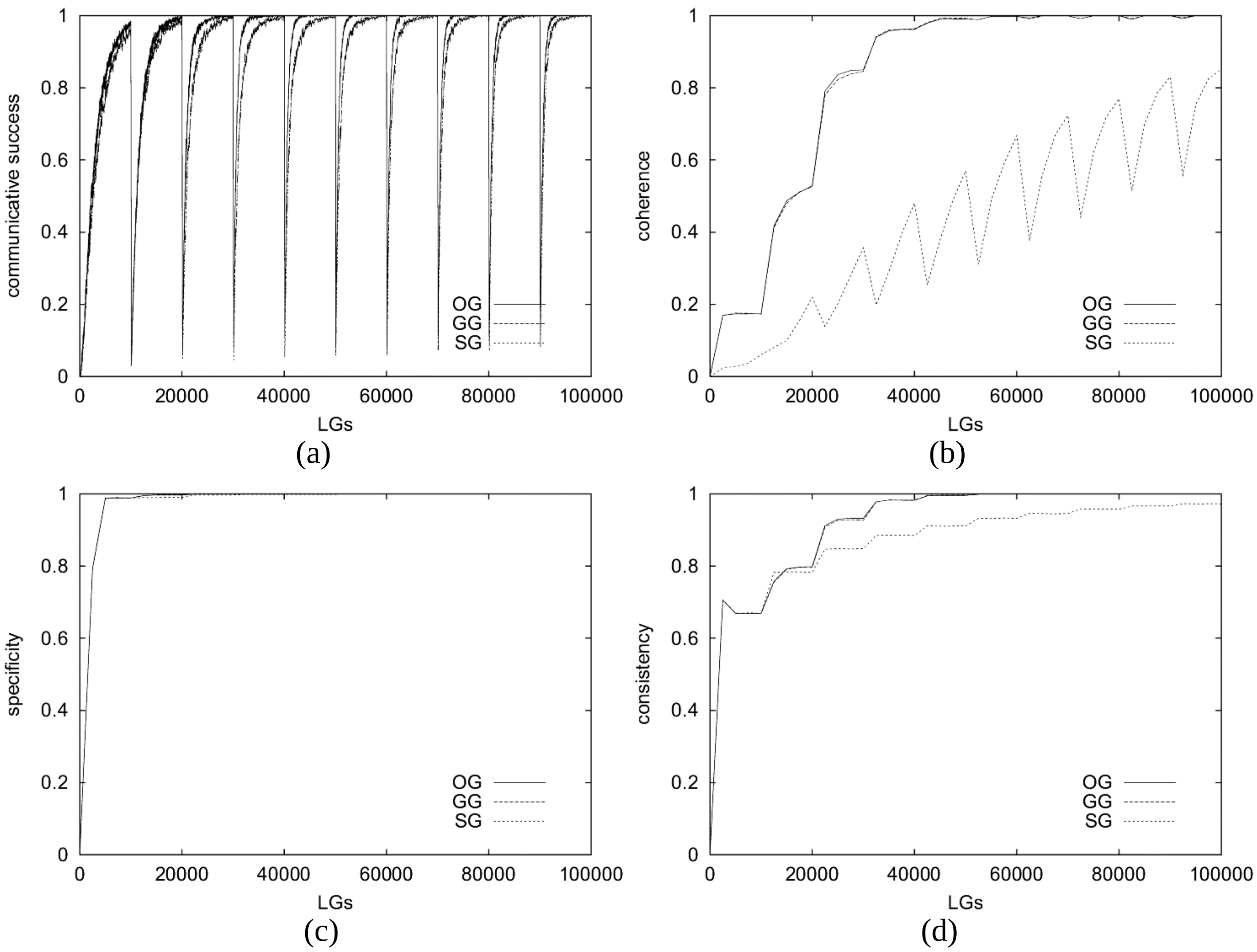
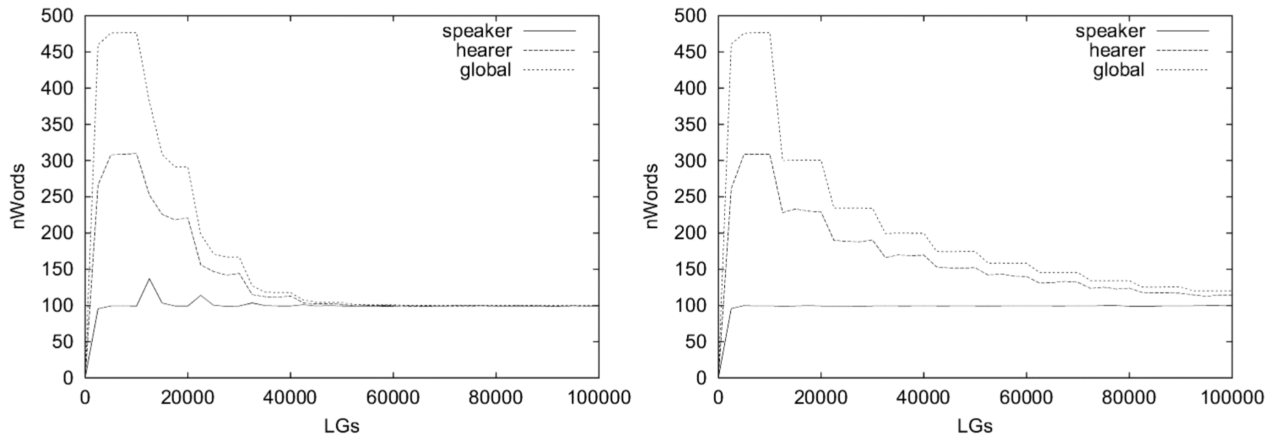


Figure 3. The results of simulations with the ILM show (a) the communicative success, (b) the coherence, (c) the specificity and (d) the consistency.

Figure 3 shows the averaged results of the experiments with applying the ILM to the language games. As Figure 3 (a) shows, the communicative success of all three games increased toward a value near 100% within the first iteration of 10,000 games. The speed of convergence in the communicative success increased in the successive iterations, while marking a clear distinction between the observational and guessing game on the one hand and the selfish game on the other. The latter revealed a slower convergence, but the improvement against the simulations that did not incorporate the ILM is significant.

Figure 3 (b) shows that the coherence increased more or less step-wise along with the iterations. It reached 1.00 for both the observational and the guessing game in the 6th iteration. The coherence of the selfish game did not increase to that high a value, but it increased to approximately 0.85 after 10 iterations. This is a similar result obtained for a population size of 2 without using the ILM (Smith 2001).

The specificity of all games increased toward 1.00 very fast, see figure 3 (c). Already after 2 iterations, it became 1.00 for all three games. Figure 3 (d) shows that the consistency of the three games also increased toward 1.00, although somewhat slower than the specificity. The consistency of the observational and guessing games reached 1.00 in the 6th iteration. The consistency of the selfish game only approached 1.00 and was approximately 0.98 in the 10th iteration.



(a) (b)

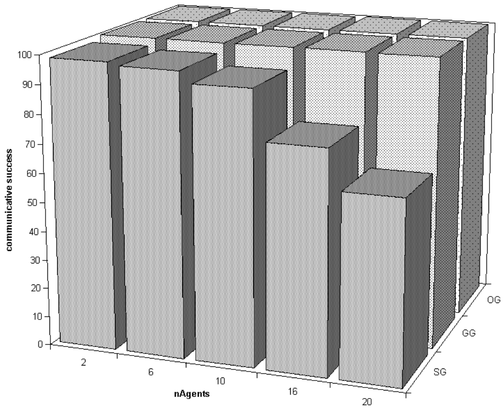
Figure 4. These figures show the evolution of word use by the *global* population and a typical *speaker* and *hearer* of (a) the guessing games and (b) the selfish games for the second simulation series. The x-axis shows the number of language games played and the y-axis shows the number of words used in each window of 2,500 games.

Figure 4 shows the averaged word use of the (a) guessing game and (b) selfish game models over each period of 2,500 games. As in the case where no iterated learning was used, the guessing game model reveals a fast convergence for the global word use toward the individual word use. Although the global word use for the selfish game scenario decreases significantly toward a number of approximately 120 words, no true convergence is found. However, as the global word use keeps decreasing and the coherence increases toward 1 (Fig. 3), it might be expected that the word use will converge to 100 words. It is interesting to see that the speakers tend to use approximately 100 words each, while the hearers tend to use about 300 words in the beginning and 115 words in the end.

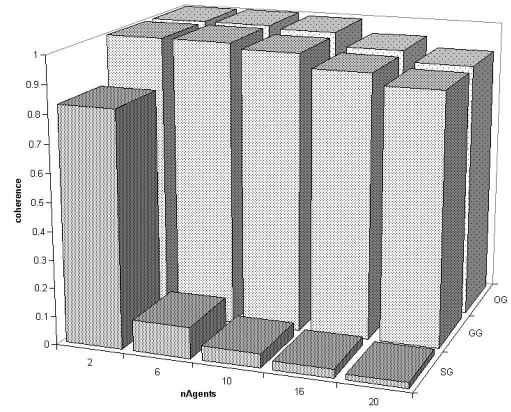
4.3 Varying population sizes

In the final series of simulations, we processed the above-mentioned simulations with different population sizes. We investigated the results of the simulations with population sizes of 2, 6, 10, 16 and 20 agents, both without and with applying iterated learning. Except for the population size, all parameters were the same as in the previous simulations.

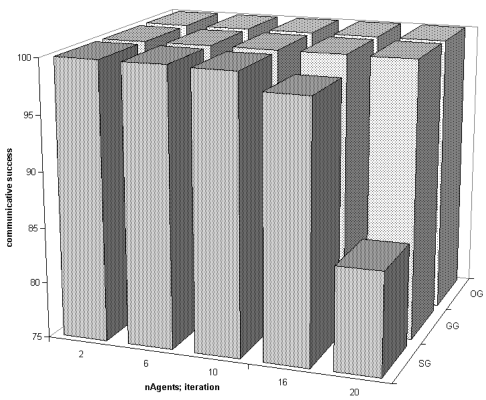
Figure 5 shows the results of these simulations. Figure 5 (a) shows the communicative success during the final 2,500 language games for the simulations without applying the ILM. As this figure shows, the communicative success for the guessing and observational games converges to 100% in the final period of 2,500 games for all population sizes. For the selfish game, the communicative success ranges from 98.5% for 2 agents to 62.7% for 20 agents. The communicative success remains high (≥ 93.4%) for population sizes up 10 agents, but then decreases significantly. Not shown in these figures is the speed with which the communicative success converged. We observed that the communicative success converged slower with increasing population sizes, as would be expected. The coherence tells another story (Fig. 5 (b)). The coherence for the guessing and observational games converges to 1.00 for population sizes 2 and 6, and then starts decreasing slowly to a value around 0.90 for 20 agents. It is to be expected, however, that the coherence will converge to 1.00 in these simulations when they are run for a longer period of time. The coherence for the selfish games reveals a different behaviour. Although the coherence for 2 agents is fair – 0.83 is in accordance with the results obtained by (Smith 2001), when the population size increases, the coherence drops dramatically. It is 0.11 for 6 agents after 50,000 games and decreases toward 0.02 for 20 agents. These levels were reached early in the simulations, and henceforth remained at that level, see Fig. 1(b) for a typical evolution. Such a dramatic decrease has been observed already from a population size of 3 agents (Coumans 2002).



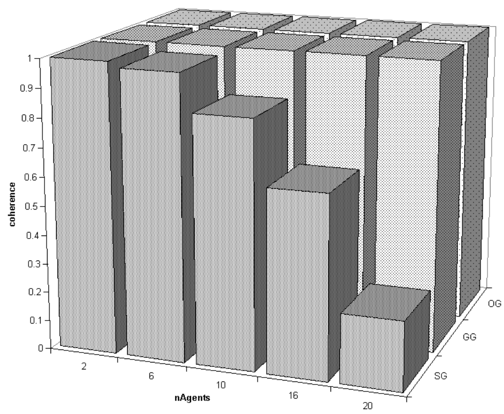
(a)



(b)



(c)



(d)

Figure 5. Plots (a) and (c) show the average communicative success (z-axis) during the final 2,500 games as a function of the population size (x-axis) for the observational games (OG), guessing games (GG) and selfish games (SG). The final values of the coherence are presented in Figures (b) and (d). Figures (a) and (b) are from the simulations without the ILM, and Figures (c) and (b) are from those with the ILM.

Figures 5 (c) and (d) show the results of different population sizes when iterated learning is applied. Where the communicative success for the guessing and observational games converge to 100%, this does not occur for the selfish games from population sizes higher than 10 (98.3% for 16 agents and 84.3% for 20 agents). The coherence drops below a point that may be considered fair from population sizes larger than 10. We assume that a coherence of around 0.80 is fair, as this is in accordance with Smith's (2001) results.

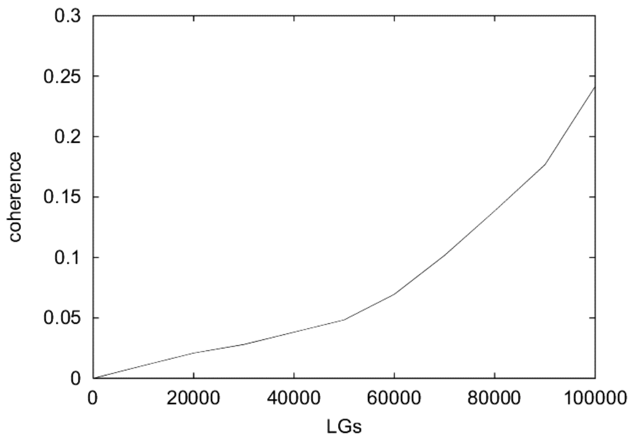


Figure 6. This figure shows the coherence at the end of each iteration (y-axis) for the selfish game with the ILM and a population size of 20. (Note the different scale on the y-axis.)

Figure 6 shows the coherence at the end of each iteration for the simulation of the selfish games with iterated learning and a population of 20 agents. The figure clearly shows that the coherence increases exponentially during the first 10 iterations. Hence it is to be expected that eventually the coherence would converge to 1.00 if the simulation had run longer. If this indeed happens has not been investigated yet.

5. Discussion

This paper investigates the effect of various interaction schemes on the origins of a symbolic communication system. The interaction schemes that are under consideration differ in how the meanings of words are transmitted from the speaker to the hearer. Three different types of language games modelled three interaction schemes: the observational game, the guessing game and the selfish game. In the observational game, the meaning is transmitted non-verbally by establishing joint attention. In the guessing game, this is done by verifying whether the agents communicate the same meaning by evaluating corrective feedback. The selfish game does not use such non-verbal strategies to transmit the meaning of words. The hearer of a selfish game has no other means to know the meaning of a word other than a co-occurrence of the word with a number of meanings that are present within the context of a game.

The investigation is based on the three research questions raised in the introduction. The first question involves a comparison between the three different language games. The second question focuses on the scalability of the selfish game. And the last question investigates if the selfish game can deal with or even benefit from a population dynamics as modelled with the iterated learning model. In the remainder of this paper, the results of the simulations are discussed in relation to these research questions and in light of some psycholinguistic data. In addition, some general aspects of the investigated models are discussed.

5.1 Comparison of the three language games

The simulations of this paper showed that the guessing and observational game models appear indifferent from each other, which differs from the results obtained with robots (Vogt 2000b, 2001), where the two models did reveal small differences. The indifference has most likely to do with the ‘perfect’ conditions of simulations that were not met in the robotic experiments. Where, for instance, the establishment of joint attention and corrective feedback was subject to much noise in the robotic experiments, this was simulated without noise in the current investigation. In addition, the internal meanings of the robots were not shared as a result of their experience-based development by means of the discrimination games, as was also the case in Smith's (2001) work. In the current research all agents shared the same ontology, which made the learning of a lexicon easier, compare, for instance, the results obtained in (Vogt 2000a, 2001, 2002b).

It is interesting to see that the communicative success of the selfish games converged much slower than with the other two games, if it converged at all. This has to do with the uncertain nature of the pragmatic input. The hearers had to guess what the speaker referred to, while they could not verify whether they guessed right. It took a large number of interactions before the hearers had enough information to make the right decisions. This slower convergence is consistent with the observation that children learn their first words slower in the Eastern cultures (Lieven 1994).

The more rapid convergence of the observational and guessing games is consistent with the finding that children learn word-meanings faster when joint attention is established than when not (Tomasello and Todd 1983). This result may have a consequence in relation to the *fast mapping phenomenon*, which is the observation that the meanings of many novel words are learnt within one or two exposures (Carey 1978). The results of the simulations suggest that fast mapping can only occur when joint attention or corrective feedback is used, because learning in the selfish game model is too slow.

The simulations also showed that even though in the selfish game the communicative success rose toward a value near one, the other measures remained well behind, with the exception of the specificity in the simulation with the iterated learning model, which did converge to one. This means that the selfish game results in less informative lexicons than the other two games; a finding that especially holds for the games played with static populations. This can be explained by the fact that the agents adopt word-meanings from every other agent they communicate with. As there is no strong pressure to disambiguate the word-meaning by means of joint attention or corrective feedback, the agents allow these different word-meanings to remain more or less equally strong. Each agent presumably has its own lexicon that, to a certain extent, differs from the other agents' lexicons, thus explaining the low level of coherence. When an agent uses some word in a certain context, another agent can understand this word if it previously adopted the word in a similar context, thus making the selfish game successful, which explains the high level of communicative success.

It should be stressed that the way we modelled joint attention and corrective feedback is not very realistic for at least two reasons. First, the speaker explicitly transfers the meaning to the hearer. It would be more plausible if the speaker indicates what the reference of an utterance is, for instance by means of pointing at an object as was done in the robotic experiments reported in, e.g., (Vogt 2000a, 2002b). Second, joint attention is a more complicated phenomenon than just indicating the reference of an utterance. It has to do with establishing a triadic relation between a speaker, hearer and an object, and with the understanding of each other's intentions (Tomasello 1999). In our study, understanding each other's intentions has been modelled as a kind of implicit knowledge. In a way, one could argue that the guessing game uses joint attention as the speaker directs the hearer's attention to the topic using a linguistic signal. We have opted for our methods of sharing meanings and disregard the way they are shared, so we could focus on lexicon creation, while having non-verbal means to indicate the meaning of an expression.

As one reviewer noted, the guessing game seems a bit unrealistic, as, in case of a failure, the hearer somehow automatically knows the right topic. However, the idea of the game is that in case of a failure, the speaker draws the attention of the hearer toward the topic non-verbally, for instance, by means of pointing as in the case of the parent requesting for salt (see Section 2). An alternative mentioned by this reviewer is a game halfway between the guessing game and the selfish game where the speaker – in case of a failure – does not indicate what the topic was and the hearer would only lower the association score of the used association. This kind of game has been investigated with real robots (Vogt 2000b). The results of this experiment were significantly worse than the guessing game as it is in its current form, and it was concluded that the hearer must somehow understand that the speaker meant something else in order to learn the lexicon successfully. In (Vogt 2000b) yet another alternative where the hearer adopted the word in relation to an arbitrarily selected object had proven to be equally good as the case where it adopted the word in relation to the topic that was ‘pointed’ at. However, the robotic experiments were done in a very minimal set-up and we did not expect the adoption of the word with an arbitrary meaning would reveal similar results as the results presented in this paper. It would be interesting to investigate this in more detail with the current simulation framework.

As for humans all three studied strategies are potential candidates to explain what input infants use to learn word-meanings, it might be the case that humans use a mixed strategy to learn words. Consider Quine’s (1960) example in which a linguist has to decide what the word ‘gavagai’ means: is it the rabbit, a part of the rabbit or something completely different? The (joint) attention of the linguist is focused on the passing rabbit, because the speaker might have looked at the rabbit and the linguist followed the speaker’s eye gaze. As there is a tendency that novel words are first associated with whole-objects and most naturally with basic-level categories (Bloom 2000), the linguist associates ‘gavagai’ with <*rabbit*>. But now suppose that ‘gavagai’ means <*large ears*>. If the linguist does not ask the speaker about the meaning of ‘gavagai’, he can only find out when he hears the word ‘gavagai’ in a different context where large ears are present. In that case negative feedback may lower his certainty about ‘gavagai’ meaning <*rabbit*>. The linguist may form new hypotheses about its meaning. If his attention is not completely focused on the large ears, i.e. the context may still be uncertain, the linguist can only make uncertain assumptions. When he is exposed more often with the word in a context where large ears are present, he may finally learn the meaning of ‘gavagai’. Computationally, this might be accomplished by designing agents that can use one of the three language game models in an appropriate situation. Such a model is currently under investigation.

5.2 Iterated learning

The results clearly showed that convergence of the lexicon did occur when the iterated learning model was applied to the selfish game. So, the selfish game is not only capable of dealing with a population dynamics, it even benefits from such a dynamics. As in the ILM there are only adult speakers, the results suggest that the selfish game only works when the learners learn from experienced speakers. The learners are only exposed to the lexicon use of adult speakers and do not invent parts of the lexicon themselves. Because the speakers do not communicate with each other, but each of them invent words for the hundred meanings when necessary, their lexicons differ from each other in the first iteration.[8] As a consequence, the hearers of the first iteration learn to understand each speaker, but their lexicons do not reveal any coherence with each other, nor with those of the speakers.

[8] It is important to realise that speakers only invent novel words in the first iteration, because the speakers in the successive iterations have already learnt at least one word for each meaning.

It seems odd that the selfish game already during the first iteration outperforms the simulations where iterated learning was not used, as was also the case for the observational and guessing games. To understand this, one has to realise that in the ILM, adults do not communicate amongst each other, nor do the learners. Each adult communicates only to five learners and the learners learn to understand the language use of the five adults. Although the learners learn from five different adults, the input they receive is rather consistent, as the adults do not tend to change their lexicons (except for increasing and/or decreasing association scores). This is an easier learning problem than when the ten agents communicate with each other agent, while having the ability to both invent and adopt parts of the lexicon. Naturally, it is an unrealistic aspect of the ILM that neither speakers nor hearers communicate amongst each other; humans have much more complex interaction patterns. It is currently investigated what the effect is when adults and learners do communicate amongst each other within the ILM.

From the second iteration, the coherence increases to a higher value than in the previous iteration. This can be explained by realising that the lexicons of the novel adults in the second iteration must be very similar, although the level of coherence may be very low. These novel adults have learned the lexicon of the five adults from the first iteration and observed word-meaning patterns with a more or less flat distribution, although some word-meaning associations may have occurred more frequently. In addition one must realise that the adults do not alter their preferences in selecting a word for a particular meaning, because when a word-meaning association is used, its score increases while competing ones decrease. So, when during a few interactions one or two words start to become dominant, these become even more dominant and the learners hear these words more consistently. When the learners of some iteration become adults themselves, they will spread the dominant words more frequently and may introduce new dominant associations. This process repeats itself over the different iterations, thus explaining the success of the iterated learning model.

Although the selfish game may explain some psycholinguistic phenomena, it may not be a likely mechanism for explaining the origins of symbolic language use. The results of the first simulations *might* indicate one amongst many reasons why non-human primates have not evolved symbolic communication to the same extent humans have. As chimpanzees do not seem to understand social interaction strategies and intentions of others[9] in a cooperative setting[10] (Hare et al. 2001), they seem to be constrained to use the selfish game strategy. This strategy is slow and if chimpanzees would try to develop symbolic communication using this strategy, they will be very ineffective and their utterances are therefore less likely to be picked up by conspecifics. When non-human primates do engage in joint attention behaviour, which occurs especially in experimental settings controlled by humans, they may indeed acquire symbolic communication. Moreover, it has been observed that an infant bonobo (or pygmy chimpanzee) learnt symbolic communication from observing its mother being trained for communication (Savage-Rumbaugh et al. 1986), which may be quite well possible given the selfish game learning strategy.

5.3 Increasing the population size

Our ‘control’ studies with a population size of two, see Section 4.3, revealed results that confirm the findings reported by (Oliphant 1999; Smith 2001; Steels and Kaplan 2002). The same holds for the guessing and observational games when the population size increases. The simulations with varying population sizes between two and twenty agents without applying the ILM revealed good results for the observational and guessing games, although the time of convergence increased with

[9] Understanding each other’s intention is required to establish joint attention (Tomasello 1999).
[10] Cooperation is required to develop language.

increasing population sizes. The results for the selfish game clearly decreased when the population size increased. Although the results showed that the communicative success always rose toward a high value, the level of coherence always stabilised at significant lower values. It seems that each agent developed more or less its own language, which the other agents understood, although they did not converge in their production.

When applying the ILM, the selfish game was better at dealing with higher population sizes, although the results dropped dramatically from population sizes larger than ten agents. Nevertheless, with a population size of twenty agents, the coherence was rapidly increasing over different iterations. So good results may be expected when the simulations are run for a longer period. This, however, has not been investigated, nor have we increased the population to sizes larger than twenty.

5.4 Other aspects

To investigate whether we were able to improve the selfish game without using iterated learning, we have tested the effect of varying the number of meanings and the probability with which speakers may create new words (Coumans 2002). Although the results benefit from increasing the number of meanings in the world, the quality of the lexicon in the selfish game remained poor. When speakers have no word to express a meaning, they invent a new word with a certain word-creation probability. This probability thus regulates the rate with which new words enter the population. If the population is large and/or there are many meanings, a high word-creation probability yields a lot of ambiguity which has to be disambiguated. In the simulations of this paper, this probability was set to 1. Lowering this probability, again, resulted in qualitatively better lexicons, but the coherence still remained low. Another reason why the selfish game did not yield a coherent lexicon might be explained by the lack of competition between the different lexical elements.

Various investigations have shown that the lateral inhibition of competing elements is crucial in establishing a coherent lexicon (De Jong 2000; De Lara and Alfonseca 2002; Oliphant 1999; Steels and Kaplan 2002). Lateral inhibition models the mechanism that one word-meaning association is strengthened, while others are inhibited, and thus implicitly implements the notion of *lexical contrast* (Clark 1993). Lateral inhibition, however, only works when an agent has precise knowledge about the topic, which requires interactions that establish joint attention or corrective feedback. Because the meaning of a word within a context of a selfish game is uncertain, it is impossible to inhibit the competing elements that are present in that context. And although there is some inhibition of competing elements that are not present in a game's context, this competition is weak. Perhaps the latter competition can be made stronger by using a different method for adapting the association scores such that they are similar to the updates made in the two other games.

Alternatively, it may be useful to include a forgetting mechanism as used in (De Lara and Alfonseca 2002). De Lara and Alfonseca have shown that the results of the language game improve when the agents forget word-meaning associations that have low association scores. Although their simulations involve a language game that is similar to the observational game, the results may apply to the selfish game as well.

6. Conclusion

The three types of language games that are investigated in this paper all work rather well, although the observational and guessing games that use precise contextual input converge faster than the selfish game which does not use such precise cues. The selfish game is only effective when a population dynamics is incorporated, as modelled with the iterated learning model (Kirby and Hurford 2002). In that case, agents can develop a highly informative lexicon after a few generations, even with relative large populations.

The results suggest that it is not unlikely that all types of input can be used to learn language, which conforms empirical data from the psycholinguistic literature. The use of joint attention or corrective feedback appears to be necessary to explain the phenomenon of fast mapping (Carey 1978). In addition, learning word-meanings from adult speakers under the absence of such input, which emerges as an observable pattern in some Eastern cultures (Lieven 1994), can be explained by the selfish game. The results additionally suggest that joint attention or corrective feedback are necessary to bootstrap symbolic communication, which is in accordance with (Dessalles 2000; Tomasello 1999).

To investigate whether the selfish game really is not a likely candidate for bootstrapping symbolic communication, further research is required. In such research, one may investigate what the effect is of using forgetting such as used in (De Lara and Alfonseca 2002), or of using a stronger competition between elements. In addition, future research on language evolution and acquisition - both in simulations or robotic experiments - should take a mixture of the investigated, and possibly more strategies into account. One possibility would be to use the same update or learning function used by either the observational and guessing games for the selfish game and regulate the certainty of the contextual cues, where joint attention and corrective feedback may induce precise or imprecise topic knowledge. It is interesting to verify whether the investigated results also hold in grounded experiments. Furthermore, research is required to investigate how joint attention and corrective feedback can emerge in grounded experiments and to scale up the selfish games even further.

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