Progress in the Simulation of Emergent Communication and Language

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This article reviews recent progress made by computational studies investigating the emergence, via learning or evolutionary mechanisms, of communication among a collection of agents. This work spans issues related to animal communication and the origins and evolution of language. The studies reviewed show how population size, spatial constraints on agent interactions, and the tasks involved can all influence the nature of the communication systems and the ease with which they are learned and/or evolved. Although progress in this area has been substantial, we are able to identify some important areas for future research in the evolution of language, including the need for further computational investigation of key aspects of language such as open vocabulary and the more complex aspects of syntax.

Keywords multi-agent systems · evolution of communication · genetic algorithms · neural networks · animal communication · language

1 Introduction

How does an effective communication system arise among a collection of initially noncommunicating individuals? Answering this question is important for at least two reasons. First, scientifically, it is desirable to understand the evolution of animal communication, the origins of language, and how language has evolved and is culturally transmitted. Second, technologically, there is the potential that an understanding of the fundamental principles involved may lead to innovative communication methods for use by interacting software agents and in multi-robot systems. Support for this latter point of view comes from the successful development of other forms of biologically inspired computation (neural networks, genetic algorithms, ant

colony optimization algorithms, immunologically inspired computing, etc.) that have emerged during the last few decades.

As an example, consider understanding the origins of human language. Progress in this area has been slow, mainly due to scanty, ambiguous evidence and the difficulty in finding appropriate species and behaviors for comparative studies. After more than a century of intense study there are still many conflicting theories about the origins and evolution of language (see, for example, Dingwall, 1988; Wind, Pulleyblank, de Grolier, & Bichakjian, 1989; Donald, 1993; Pinker, 1994; Aitchison, 1996; Dunbar, 1996; Deacon, 1997; Bickerton, 1998; Dickins, 2001). Our understanding of this issue is impaired by the limitations of experimental investigative methods in analyz-

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ing a process (communication) that has not left a meaningful fossil record. In this context, there has been a recent surge of interest in using computer simulations to ask "what if" questions about specific scenarios. By building a computational model, the assumptions and implications of a theory about the evolution of animal communication or language can be made explicit and their implications examined. Although surely there will be unknowable details in the actual story of the origins of language, some general trends and features may be discovered through the convergence of simulation work and more traditional experimental approaches. For example, one would like to know (in principle, at least) any processes and behaviors necessary for, or facilitative to, the emergence of language (working memory, learning abilities, cognitive prerequisites, etc.), plausible intermediate stages on a path from simple signaling to language, social factors involved in the acquisition of language from a community, and so forth. Computer simulation experiments may suggest answers to many of these questions.

The goal of this article is to review and critique the recent rapid progress made, using computer simulations, in studying how shared communication systems can arise in a population of interacting agents (individuals) via learning or simulated evolution. Although many of these computer simulations have aimed to illuminate the emergence[1] of communication, the results in some cases apply to the special case of human language. While Parisi and Steels reviewed the progress of simulations investigating the evolution of language in 1997 (Steels, 1997; Parisi, 1997), much has happened since then that makes a new review timely. Another review by Kirby has been published that covers the emergence of language (Kirby, 2002). Kirby's review focuses on syntax, meaning (grounding), and one specific method of acquisition (the iterated learning method), whereas we take a broader view here, including not only work on language, but also on how animal communication (that may relate to human language) arises. We discuss various methods of acquisition/transmission, and we also focus on properties of communication systems in general, using a different framework (Hockett and Altmann's "design features"). Although our coverage is fairly complete, it is not exhaustive.[2] In addition, there is a very recent collection of articles on the evolution of language and communication (Cangelosi & Parisi, 2002) containing papers very similar to earlier versions that we have al-

ready reviewed here. Regardless, we have tried to be representative of the many issues examined and approaches taken.

Our analysis is organized as follows. Section 2 begins by briefly describing the kinds of simulations we will be considering and suggests a framework that places each simulation in one of four general categories. In each category, we first describe a few representative studies, and then we briefly summarize the results of many others. Section 3 analyzes the issue of which of the many aspects of language have actually been addressed by the simulations we reviewed. This could be done in a number of ways, but we chose to use the feature system of Hockett and Altmann (Hockett & Altmann, 1968) to organize the analysis. This well-known framework characterizes any communication system in terms of a collection of features or properties (repertoire, structure, groundedness, etc.) that applies both to animal and human communication. Hockett and Altmann's framework does not address many language-specific concerns (e.g., syntactic properties), but it is more amenable to the problem of communication in general. Since it antedates the computational studies we review and was developed independently of them, it provides a useful and objective context in which to assess the accomplishments and limitations of models of emergent communication. Section 4 concludes our analysis, summarizing the conclusions and suggesting important directions for future research.

2 Computational Models of Emergent Communication

In this section, we review a broad array of models of communication that emerges among initially noncommunicating agents via either learning or simulated evolution. Although a number of approaches might be taken to organizing this material, we find it intuitive and useful to divide past work into four main categories, based on whether the agents involved are situated in an artificial world, and whether the communication acts use single or several unstructured tokens versus structured utterances composed of multiple tokens. Situated agents should be able to develop a closer connection than nonsituated agents between each signal and its meaning, especially because each meaning will be related to some object or context in the world (e.g.,

as argued and demonstrated in Harnad, 1990). Studies of nonsituated agents sacrifice realism and grounded signals since they have no world or body to relate these signals to, but we have discovered that they are generally able to focus more closely on the dynamics of the emergence and use of a communication system. Structured utterances may be necessary for agents that operate within complex environments (and this is certainly a general trend in the studies we present in this review), whereas unstructured communication should suffice for agents that need to perform tasks with fewer nuances (e.g., finding food or avoiding predators). The approaches for each of these four categories tend to be similar: Most of the studies within a category tend to use the same adaptive process and similar tasks.

Situated simulations place agents in an environment or "artificial world" to which the agents have some causal connection.[3] Just being in an artificial world in which objects can be perceived is not enough for an agent to be classified as situated in this review. To be situated, an agent must also interact in noncommunicative ways with various entities such as food, predators, and other agents and must have outputs that can affect the environment and/or modify its own internal state. On the other hand, in *nonsituated simulations* an agent's actions consist solely of sending and receiving signals. Such nonembodied agents do not have noncommunicative interactions with objects or each other beyond being able perhaps to perceive objects or events.

Simulations can also be divided based on the kinds of communication employed by agents: *structured* versus *unstructured*. Structured utterances are composed of smaller units, such as the words forming a phrase. They can be emitted sequentially or simultaneously. Agents sending sequentially structured utterances produce each unit of the utterance over time, such as a string of symbols or a series of speech articulator commands. We include in this category agents that produce a structured utterance all at once, where hearers interpret the utterance as having parts (a bit like reading and parsing an entire sentence in a single moment). Other agents use unstructured utterances where the utterance is one unit. This includes agents whose utterances consist of single units on multiple channels, but the values on different channels have no relationship to each other and are not dependent on the other channels for their interpretation. Thus, if the

response to a multi-channel utterance depends on knowing the values of both channels, then we classify the utterance as structured. On the other hand, if the response to the utterance requires knowing the value of one channel and ignoring the other, then the utterance is unstructured. These divisions yield four basic types of simulations: nonsituated, unstructured; nonsituated, structured; situated, unstructured; and situated, structured. Accordingly, we organize our review of past work into these four categories below.

From a computational perspective, the simulations reviewed here are *multi-agent systems* (Ferber, 1999; Weiss, 1999), meaning that they simulate an entire population of individuals, or *agents*, allowing each agent a chance to act. Agent behavioral mechanisms include finite-state machines, neural networks of many kinds, lookup tables, production systems, and hybrid or novel mechanisms. Agents acquire a shared communication system either by using machine learning methods (e.g., backpropagation of errors in neural networks) or through a simulated evolutionary process (e.g., genetic algorithms). In nonsituated simulations, where agents typically interact with each other in the absence of a world or environment, the interactions are usually but not always between pairs of agents. An interaction within a pair of agents in general involves each member of the pair both "speaking" and "listening," possibly learning from their interactions. Nonsituated simulations typically treat agents as signal encoders/decoders, and the task is often to communicate as effectively as possible. In contrast, situated multi-agent simulations usually allow agents to interact with and affect multiple other agents in an artificial world, and multiple speakers may send signals simultaneously, requiring hearer agents to ignore all but one signal. Often there is a noncommunicative task to solve for which communication may be helpful (e.g., finding food or other items, avoiding predators, moving objects from one location to another).

2.1 Nonsituated, Unstructured Communication

In simulations involving nonsituated agents and unstructured signals, agents are typically paired randomly and given arbitrary meanings or internal states to communicate to each other. Usually, the agent's task is to encode an arbitrary meaning as a signal and send it to another agent, who decodes the signal back
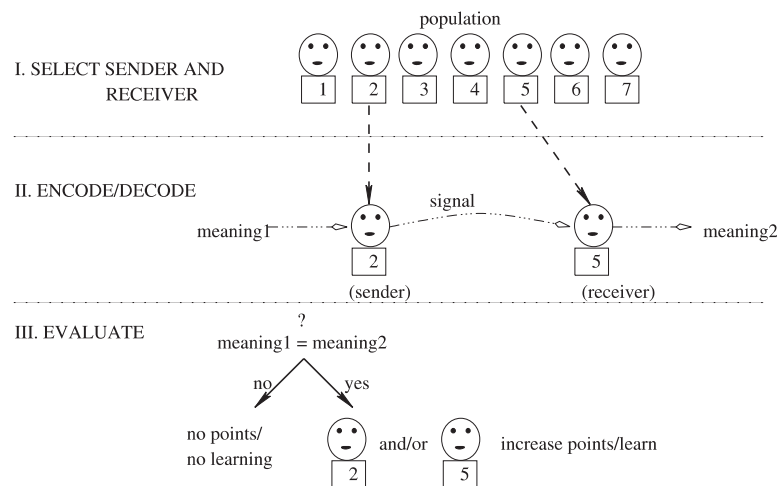
Figure 1   An encoder/decoder interaction between two agents in a typical nonsituated simulation. In step I, two agents are randomly chosen from the population. Here, agents 2 and 5 are chosen from a population of seven agents. In step II, agent 2 is designated to be the sender while agent 5 is designated as the receiver. Agent 2 is given a "meaning" (or state) to communicate to the receiver, and it encodes this meaning, *meaning1*, as a signal. Agent 5 decodes the signal to derive *meaning2*. In step III, the receiver's decoded *meaning2* is compared with the original *meaning1* given to the sender. If they match, then communication was successful. After successful communication has concluded, either the sender or receiver or both will be awarded fitness points (for evolutionary simulations), or they will learn from the interaction (for nonevolutionary simulations).

into a meaning (see Figure 1). We summarize the results of 24 such studies here that are mostly encoder/decoder games, although a few simulations involve mating calls and female preferences or visual discrimination (see Table 1). These simulations typically involve agents who are evolving or learning to communicate (rarely both). Simple feedforward neural networks, lookup tables, and similar associative memories are the mechanisms usually used for relating meanings or internal states to signals.

Overall, these simulations demonstrate several properties in the emergence of simple communication systems. They establish in the simplest of settings that a shared communication system can readily evolve or be learned by a population, and that the type of learning involved can be of different forms. Consensus among evolving signalers is best achieved when the signaler (at least) benefits from good communication, whereas agents who are endowed with observational learning can best achieve consensus when their population size is small. These simulations have also shown that spatial constraints encourage the emergence of signaling but can lead to local dialects and global variations. They show that while population flux can introduce variation into a communication system, it does not always disrupt the system. Finally,

genetic factors and female choice are found to play a role in the kinds of communication that can evolve.

2.1.1 Featured Examples   We consider two studies that are representative of work in this area: One focuses on the evolution of communication and the other looks at how a population could learn a system. Both use experimental designs to investigate the effects of specific factors on the resulting communication systems, and one (Levin, 1995) describes a set of highly controlled experiments. In the first of these, Levin (1995) studied various ecological and evolutionary factors in the evolution of communication. Populations of agents that had internal states and externally observable states (*observables*, represented as vectors of integers) were simulated. Encoders and decoders were matrices, specified in the agent's genome (see Figure 2). Each agent's goal was to guess another agent's internal states by paying attention to that agent's observables. During each generation, each agent A_i was randomly paired with members of a subset of the population (A_j). The size of this subset was determined by a parameter, *gregariousness*, defined as the fraction of the population with which an agent interacts. For each pairing, A_i was given a ran-

A $M_{enc} = \begin{bmatrix} 2 & -2 \\ -1 & 3 \end{bmatrix}$ $M_{dec} = \begin{bmatrix} 3 & -4 \\ 0 & 1 \end{bmatrix}$ genome: 2 -2 -1 3 3 -4 0 1

B $O = I \cdot M_{enc}$ $\begin{bmatrix} 2 & 1 \end{bmatrix} \cdot \begin{bmatrix} 2 & -2 \\ -1 & 3 \end{bmatrix} = \begin{bmatrix} 3 & -1 \end{bmatrix}$

C $I_2 = O \cdot M_{dec_2}$ $\begin{bmatrix} 3 & -1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 2 & 1 \end{bmatrix}$

Figure 2 (**A**) Example encoder and decoder matrices for two internal states and two observables as used in Levin's (1995) work, plus the genome that specifies them. (**B**) Example of using the M_{enc} matrix and a set of internal states I to produce a set of observables O. I is supplied by the program and has arbitrary values for each interaction. (**C**) Example of using another agent's M_{dec} matrix to decode the O in the previous example. In this case, the second agent's decoder perfectly decodes O so that I_2 is the same as I.
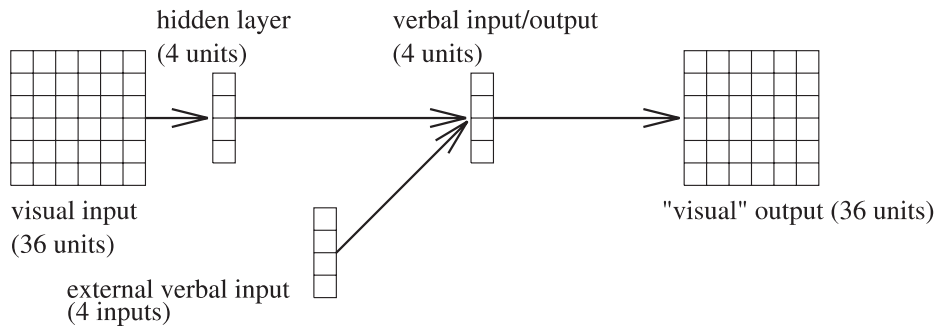

Figure 3 Three-layer feedforward neural network used by Hutchins and Hazlehurst's (1995) agents in the first experiment. A "visual scene" (this is a label of convenience only—there is nothing spatial about the inputs or how the net interprets them) is presented to the net's 36 input units. Activation propagates through the net to each layer of units. The goal is to make the output layer the same as the input layer (autoassociation). However, the crucial task for the agent is to discover and use the "verbal" layer as a description of the visual scenes. A scene is presented to the net, and the activations of the units in the verbal layer are interpreted as the agent's signal, describing the scene. This signal can be presented to another agent by setting its verbal units to the first agent's verbal layer activations. If the second agent produces a visual output consistent with the first agent's visual input, then effective communication has occurred.

dom internal state and encoded it as a signal (Levin's observables). A_i's partner, A_j, decoded this signal. A_i's fitness would increase proportionately to the similarity between its actual internal state and A_j's guess. A genetic algorithm was used to replace the least fit two-thirds of the population with offspring from the most-fit one third, creating new agents by applying multiple mutations and sometimes crossover to the agents with the highest fitness.

Levin manipulated the population size, selection method, mutation rate, use of crossover, number of states and signals, gregariousness, and number of interactions per agent. In most cases, the population converged to one mapping of states to signals (with four states and signals). Most manipulations had little overall effect on the evolution of consensus among the agents. However, larger population sizes caused the population to converge (achieve consensus) more

quickly than smaller ones, while more observables and internal states slowed convergence. Crossover with mutation speeded up evolution more than mutation alone, as would be expected since the signal systems were represented by matrices, so crossover could splice together good sections of matrices to create something better than the parents. Finally, gregariousness at around 40% (contact with around 120 agents) was optimal for consensus.

In another encoder/decoder study, Hutchins and Hazlehurst (1995) used agents with autoassociative two- and three-layer neural nets. The interactions were similar to Levin's above, except that these agents learned with backpropagation instead of evolving. In their first experiment, six agents with three layers of weights learned a set of associations between 12 "visual" input patterns and themselves. Visual patterns were 6×6 "scenes" representing phases of the moon,

Table 1 Studies involving nonsituated, unstructured communication

Simulation	Adaptive process[a]	Behavioral mechanism[b]	Type of communication/Task
Berrah and Laboissière 1999	L	Assoc?	Encoding/decoding
Bullock 1998	E	FNN	Visual discrimination
Bullock and Cliff 1997	E	FNN	Visual discrimination
De Boer and Vogt 1999	L	Assoc	Encoding/decoding
Dircks and Stoness 1999	L	FNN	Encoding/decoding
Enquist and Arak 1994	E	FNN	Visual discrimination
Hurd et al. 1995	E	FNN	Visual discrimination
Hurford 1989	E + L	Table	Encoding/decoding
Hutchins and Hazlehurst 1995	L	FNN	Encoding/decoding
Johnstone 1994	E	FNN	Visual discrimination
Kaplan 2000	L	Table	Encoding/decoding
Krakauer and Johnstone 1995	E	FNN	Encoding/decoding
Krakauer and Pagel 1995	CA	Fixed strategy	Encoding/decoding
Levin 1995	E	Table	Encoding/decoding
Livingstone and Fyfe 1999a, b	L	FNN	Encoding/decoding
Noble 1999a	E	Table	Mating advertisement
Noble 1999b	E	Params	Mating advertisement
Oliphant 1996	E	Table	Encoding/decoding
Oliphant 1999	L	FNN	Encoding/decoding
Ryan et al. 2001	E + L	RNN	mating call discrimination
Smith, K. 2002a	E + L	FNN	Encoding/decoding
Smith, K. 2002b	L	FNN	Encoding/decoding
Steels and Kaplan 1999	L	DT, Assoc, Rob	Object description
Wagner and Reggia 2002	E + L	FNN, Table	Encoding/decoding

[a] CA = cellular-automaton adaptation, E = evolution, L = learning

[b] Assoc = associative memory, DT = discrimination trees, FNN = feedforward neural net, Params = agent/contest parameters, RNN = recurrent neural net, Rob = robotic, Table = lookup table/matrix, ? = paper does not provide enough information

and each agent had to reproduce in its outputs the same scene that was given to its inputs (36 units for each input and output layer). Agents also developed two hidden-layer representations (note that while supervised learning was being used, these hidden units were free to develop any adequate hidden-layer representation). One of these layers was designated the "verbal layer" (see Figure 3). Pairs of agents—a *speaker* and a *listener*—were chosen at random and shown one of the 12 scenes. The listener used the speaker's verbal layer as a target during supervised learning (backpropagation). The listener also learned to autoassociate the scene, which helped ensure a unique verbal layer. In a first experiment, agents were able to develop a unique signal for each scene, and they were able to pass on their system to other agents. Eventually, the whole population achieved consensus (low variability between agents for each signal).

In a second experiment using simpler agents over thousands of interactions, each agent's verbal activation space showed distinct representations for each scene. Thus, consensus could be achieved through a supervised learning paradigm. Figure 4 shows how variability decreased over time among each agent's signal for a particular scene. This would be expected for the population to arrive at a consensus. Conversely, the same graph shows how each meaning's signals differed from the others, which is also crucial for distinguishing among different signals. However, as population size increased from 5 to 15, consensus
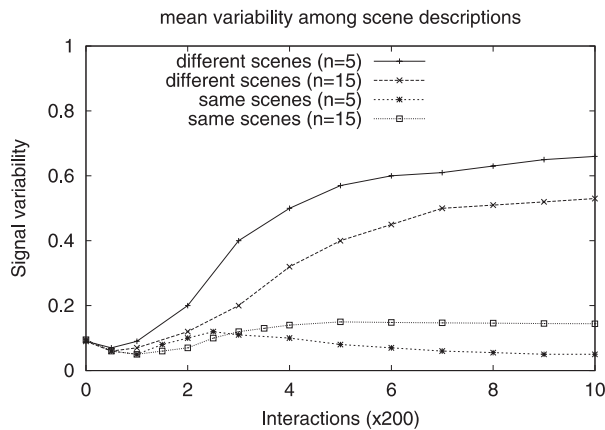
mean variability among scene descriptions

Figure 4 Summary of Hutchins and Hazlehurst's (1995) graphs of signal divergence versus agent interactions (time). Each signal emitted by an agent describes a visual scene (the "meaning" of the signal). Two different measures are shown for populations of size 5 and 15. One measure (*same scenes*) is the variability between different agents' signals for the same scene. Initially, agents will use different signals for the same scene and so exhibit higher variability. This variability continues to decrease slightly over time, indicating that the population closely agrees on a single signal for each meaning. The other measurement (*different scenes*) is variability between signals for different scenes. This increases over time, indicating that each meaning eventually gets a distinct signal. Smaller populations take less time to create unique and distinct signals than larger populations. Adapted from Hutchins & Hazlehurst (1995).

was harder to achieve (distinctions between agents' signals for the same meaning did not drop nearly as quickly when there were 15 as opposed to 5 agents). This study was limited both by the small population sizes in which communication would arise, and the unrealistic assumption,[4] fairly common among simulations incorporating learning, that agents could use supervised learning.

The effects of population size on convergence conflict with Levin's findings (above). This is almost certainly due to the different acquisition (transmission) mechanisms: Hutchins and Hazlehurst's agents used learning whereas Levin's agents used evolution. When agents teach each other their signals for various "meanings," then the more agents in the initial population, the more variation exists, and thus the more interactions will be needed before everyone settles into a stable set of associations. For genetically endowed signaling, initial population variation is important for natural selection to work and hastens the rate of evolution. Higher

initial population variation due to larger population sizes raises the probabilities for good initial signal–meaning mappings, which can become represented and modified in greater numbers in future populations. With a larger population, the chances are greater that at least a few agents will initially have partially compatible signaling systems. This would accelerate the process of evolving consensus.

2.1.2 Survey of Other Related Work Other work with nonsituated agents using unstructured communication has shown similar results to the simulations described above, demonstrating that either learning or evolution can account for the emergence of a shared communication system. Studies have begun to explore the effects of *what* is learned as well as *when* and *how* something is learned. For example, in one study agents focused on learning shared signal systems (Oliphant, 1999) and were able to achieve consensus when using a variant of Hebbian learning that employed lateral inhibition to encourage unique signals for different meanings (*how*). Just as with Hutchins and Hazlehurst's (1995) and Wagner and Reggia's (2002) simulations, increasing the number of signals and meanings, as well as increasing the population size, increased the time to convergence on one communication system. Wagner and Reggia's work further showed that larger population sizes allowed agents to achieve consensus more easily when agents evolved than when they learned (Wagner & Reggia, 2002). Furthermore, another study demonstrated that the stability of a learned communication system is enhanced when older agents cannot learn, that is, only young agents learn (de Boer & Vogt, 1999) (*when*). In perhaps the earliest encoder/decoder simulation, Hurford (1989) showed that the learning strategy (*what*) is very important to overall communicative success. *Saussurean* learners, who learn their encoder and decoder associations from others' decoder outputs (but not from others' encoder outputs) perform better than agents using more precise forms of imitation, where the agent uses others' encoder and decoder outputs to learn its own encoder and decoder associations.

Other work has examined how consensus is affected by various factors. Agents achieve consensus more readily when they have learning biases that favor one-to-one mappings between meanings and signals, and a genome can confer both learning biases and

learning rules in the aid of learning (Smith, 2002a, b). Benefits to the hearer and sender are also important factors in the emergence of communication. It has been found that consensus in a communication system could evolve when the sender and hearer both benefited from accurate communication, but that if only the hearer benefited, spatial constraints were needed (Oliphant, 1996). Specifically, when just hearers were rewarded, a population of agents could only achieve consensus if all agents could only signal and mate with other nearby agents (and offspring were placed nearby). Such spatial constraints have important implications concerning communication variation. When agents learn from each other, spatial constraints can lead to consensus, but local dialects will develop and there will be substantial global variation (Livingstone & Fyfe, 1999a, b). Population flux (migrants entering a population) also clearly adds variation to a communication system, although the system can still remain stable overall (de Boer & Vogt, 1999; Kaplan, 2000). Variation can also arise due to the noise and variability inherent in learning and in whom agents interact with (Dircks & Stoness, 1999).

Simulations have shown that populations of communicators can self-organize their communication systems, and some studies have found this even without direct pressure to do so. Kaplan found that the utterances developed by a population (in this case, sets of digits, for example, "25291") tended to move toward medium length (Kaplan, 2000).[5] Very short utterances could be interpreted as something entirely different if there were just one error among the utterance components (e.g., "12" instead of "17"), whereas long utterances were more susceptible to higher levels of noise. Medium-length utterances might still be understood with an error but would be less likely to have an error in the first place. Another useful feature of a self-organized communication system is openness, where new "words" can be added and "meanings" can change over time. A robotic simulation by Steels and Kaplan (1999) showed that agents could continually reshape their lexicon, adding new words and refining or modifying the meanings of old words in response to encountering new objects.[6] Robotic agents perceived objects as collections of features and used different "words" to describe a distinctive feature about a particular object. However, since each agent perceived different features of each object, ambiguities would arise as to what object was being referred to. Nevertheless, given enough time and with the added help of "pointing" to objects, agents could create a shared lexicon that could also be extended or modified when new objects were added to the group they had to describe (though pointing may not be necessary, as A. Smith's (2001) work suggests).

Somewhat different work has addressed how human vowel systems might self-organize. For example, one study showed that agents could create realistic vowel systems based on discrimination constraints and lookup "error" (when the wrong item is recalled from an associative memory due to a noisy cue; de Boer & Vogt, 1999). These agents learned by hearing the speaker's vowel, trying to reproduce it, and using feedback from the speaker to modify their own production. However, agents do not necessarily have to rely on the speaker for feedback, as shown by Berrah and Laboissière (1999). In this simulation, agents modified a vowel sound until it was close enough to the vowel sound they had heard. In both of these simulations, the agents' vowel systems were claimed to be similar to real, human vowel systems along certain featural dimensions.

In addition to population dynamics and learning methods, simulations have shown that details of the evolutionary and genetic processes themselves can play an important role in the emergence of a signaling system. Properties of "calls" can be affected by female preferences (Noble, 1999a; Ryan, Phelps, & Rand, 2001) and historical remnants of earlier evolutionary processes (Ryan et al., 2001). Preferences for symmetrical visual signals can arise in position- and orientation-invariant object recognition due to sensory biases (Enquist & Arak, 1994), biases for homogeneity (Bullock & Cliff, 1997), and mate recognition (Johnstone, 1994); distinct signals can arise from competition among signalers for receivers (Hurd, Wachtmeister, & Enquist, 1995); and honest signaling can arise under a variety of conditions (Bullock, 1998). Honesty in calls (mate advertisement) is usually necessary for them to carry information about the signaler, but honest signals require extra pressures, such as costly signals (Krakauer & Johnstone, 1995) or spatial constraints (Krakauer & Pagel, 1995) before they will emerge. Nevertheless, calls do not need to be honest (yield a fitness benefit for the hearer) in the face of certain genetic correlations (pleiotropy, hitchhiking[7]), mutational lag (when mutations are slower than environmental changes), or sensory biases (preferences for certain kinds of sounds due to other sensory needs such as predator vigilance).

Table 2   Studies involving nonsituated, structured communications

Simulation	Adaptive process[a]	Behavioral mechanism[b]	Type of communication/Task
Batali 1994	E + L	RNN	String recognition
Batali 1998	L	RNN	Encoding/decoding
Brighton 2002	L	FSMs	Encoding/decoding
Hare and Elman 1995	L	FNN	Encoding/decoding
Kirby 1998	L	Grammar	Encoding/decoding
Kirby 1999	L	DCG	Encoding/decoding
Kirby 2001	L	DCG	Encoding/decoding
Kirby and Hurford 1997	E + L	Table	Encoding/decoding
Kvasnicka and Pospichal 1999	E + L	RNN	Encoding/decoding
MacLennan and Burghardt 1993	E + L	FSM	Object names
Smith, A. 2001	L	Table	Object description
Steels 1998a	L	PS?	Object description
Steels 1998b	L	DT, Assoc, Rob	Object description
Steels and Oudeyer 2000	L	Assoc	Encoding/decoding
Werner and Todd 1997	E	Preference matrix	Mate choice

[a] E = evolution, L = learning
[b] Assoc = associative memory, DCG = definite clause grammar, DT = discrimination trees, FNN = feedforward neural net, FSM = finite-state machine(s), Grammar = production grammar, PS = production system, RNN = recurrent neural net, Rob = robotic, Table = lookup table, ? = paper does not provide enough information

In fact, if hearers have a negative payoff for responding to a call, they may still evolve to respond to signals due to mutational lag or sensory bias (Noble, 1999b).

2.2 Nonsituated, Structured Communication

A second class of simulations has given nonsituated agents the capacity for more complex communication and has studied how structured utterances can emerge. Some investigations have focused on the changes that occur to a complex communication system and what can bring about those changes. For the most part, the issues are similar to unstructured signals. However, structured signals require more complex mechanisms and a motivation for that complexity to be built and maintained. Just as with the nonsituated, unstructured simulations of Section 2.1, many of these simulations present agents with an abstract "meaning" (some vector, string, or number that does not correspond to anything in a world since there is no world) that the agent encodes as a structured utterance that another agent must decode. Agents typically do not have any internal states except for the purpose of producing a sequential stream of symbols. Since they are nonsituated, agents do not perform actions.

Not all of the simulations are of the encoder/decoder variety. Some simulations involve the description and naming of objects or the choosing of mates, and some deal with cooperation among a group of agents. Perhaps due to the more language-like nature of the signals, the tasks are a bit more language-like themselves. The majority are still encoder/decoder games, but object naming and description, as well as cooperation, are plausible tasks for linguistic behaviors.

We review 15 simulations here (see Table 2). A wide variety of mechanisms are used by the various agents, including recurrent neural networks, lookup tables, and associative memories. Learning (both supervised and reinforcement types) is the predominant form of adaptation, but a few simulations use evolution in conjunction with learning. These simulations demonstrate that structured communication can emerge under certain circumstances and that it is often related to the structure inherent in a task. Evolution and learning together are shown to be more effective than either alone. As with unstructured simulations, spatial constraints are again found to lead to local dialects. Linguistic variation may also be explainable by transmission errors (younger generations imperfectly learning from older ones) as well as by parsability and

production constraints (constructions that are difficult to transmit or understand might be eventually be replaced by easier constructions). Finally, phonological and grammatical classes have proven to be natural solutions to the problem of producing a large repertoire of utterances.

2.2.1 Featured Examples   We present two representative examples in detail. One example uses a common mechanism for both production and comprehension of signals that has become a popular tool in later work, and the other explores how agents could come to name objects without strong supervision. In the first of these, Batali (1998) showed how structured utterances might be created and acquired by agents by learning from each other (using backpropagation, a supervised learning algorithm). There were 100 meanings to convey, represented as pronoun–predicate tuples, with 10 pronouns and 10 predicates. Each agent used a recurrent neural network to produce a stream of tokens up to 20 long (there were 4 tokens, yielding $\sum_{i=1}^{20} 4^i$ possible utterances, an astronomical number). The agents were all initially given random weights in their neural nets. From the 30 agents in the population, a randomly chosen *learner* agent was paired with 10 randomly chosen *teacher* agents. For each teacher, the learner trained once on each of the teacher's utterances for all 100 meanings. After at least 15,000 rounds of training, agents learned to communicate about a number of situations ("meanings") using a small repertoire of tokens emitted in a temporal sequence.

Each agent used its neural network both to send and to receive signals. The network could take a sequence of tokens—one at a time—as input, and output a meaning vector, M′, with 10 values between 0 and 1. The sending agent's task was to send a string of tokens {a, b, c, d}, one token at a time, to a hearer/receiver agent that then had to decode what meaning M the sender was communicating. To decode an utterance, a hearer processed each token in the utterance (using its recurrent layer to remember the past tokens); the resulting M′ was the decoding of utterance U. To produce utterance U, an agent passed each token through its network and chose the token that would cause it to produce a meaning vector (M′) closest to the M it had to communicate. It then chose the next token in the same way, until M′ = M or 20 tokens had been sent (a "give up" limit).

Meaning vectors had some regularity. The first 4 bits of the vector were taken from a set of 10 arbitrary bit patterns (intended to correspond to pronoun referents such as "you" or "me"). The last 6 bits of the vector were taken from one of 10 arbitrary bit patterns intended to represent predicates such as "happy" or "sad." Batali found that agents initially developed a repertoire of token sequences that were different from each other, although error was still high and sequences were quite long. These differences were mainly attributable to the random weights with which each agent began. After the repertoire was distinguishable, error dropped and the average sequence length for each meaning fell from 20 to 4. The resulting token sequences exhibited some systematicity consistent with the structure found in the meaning vectors. Most of the predicates were represented by a common token sequence "root" (e.g., cd for "happy" and b for "sad") and the pronouns were often represented by a common suffix (e.g., ab for "you, singular"). Thus, an utterance representing "you-singular happy" would look like cdab and "you-singular sad" would look like bab. Agents also generalized their signaling system to new meanings fairly well. Kvasnicka and Pospichal (1999) extended this work by adding genetic and memetic components to agents (Kvasnicka & Pospichal, 1999). Agent genomes specified hidden-layer size and connectivity, and each child inherited some of the mappings that its parents had created (the memetic contribution), which is similar to having parents teach their children before sending them out into the world. The populations showed similar results to Batali's as well as demonstrating the Baldwin effect (learning affects the genome, for example, Baldwin, 1996) when memetic components were added.

In a second example, Steels (1998b) studied a variety of agents in experimental conditions similar to Batali's but used a different approach to learning. Agents played various "language games" with each other, usually involving the description of an object to another agent. Agents were located in a room, where they could "see" but not affect a set of objects. The objects could be perceived by low-level sensors and each agent first learned to build feature detectors for distinctive sensor readings. For example, if there were five objects in a room, and one object could be distinguished by its red color and its spherical shape, then an agent might develop a feature detector for red colors, spherical shapes, or perhaps both features.

Because every agent developed its own feature detectors, each agent might have different feature detectors, although most agents would be likely to share feature detectors for most colors, shapes, and so forth. Once each agent could distinguish each object from all of the others, the whole population was given a lexicon-creation task. This task involved agents that could expand their lexicons to describe new situations.

Initially, each agent began with an empty lexicon (a mapping from features to words). Two agents were paired and engaged in language games where the first agent (speaker) would "point" to and then attempt to describe one object (the topic) out of the set of objects to the other agent (the receiver). When a speaker could not describe one of the topic's features, it invented a new word for that feature. If the speaker's description failed to help the receiver pick out the object from the group, the receiver modified its lexicon. Receivers modified the associations between words and features or added a word when they did not know it. After thousands of interactions, agents achieved a high rate of communicative success, demonstrating that agents can develop a lexicon from simple object-description interactions despite having different internal representations of meanings (the objects' features). An extension to this work has shown that agents can still develop a shared lexicon without resorting to pointing (A. Smith, 2001).

Further work by Steels has shown that robotic agents using similar feature detectors and lexicon could develop a precursor to syntax: word order (Steels, 1998a). Agents were given the capability to create frames that held words in a certain order and the object features they related to. When objects with multiple, distinctive features were used, a group of words could be used to describe them, and from these common concatenated phrases a simple structure could arise. Sequential utterances are an important step in creating a syntactic communication system, although there are many other features (e.g., hierarchical utterances) that need to appear before syntax could be said to be present.

2.2.2 Survey of Other Related Work

Most other non-situated, structured simulations have focused on factors affecting structure features, the contributions of learning and evolution to the emergence of structured communication, or the role of grammatical and pho-nological classes in structured communication. Several studies have indicated that evolutionary processes and learning combined are more effective than either alone since evolution can lay a foundation from which learning can proceed (MacLennan & Burghardt, 1993; Batali, 1994; Kirby & Hurford, 1997).[8] Evolution seems to be able to provide a foundation from which learning can expand (Batali, 1994; Kirby & Hurford, 1997). There is also some evidence that structured signals used for cooperation can evolve when the number of situations to communicate is larger than the repertoire of signal components (MacLennan & Burghardt, 1993).

Communication systems can vary geographically (spatial variation), they can change over time (temporal variation), they can vary based on the relationship between speaker and hearer, and they can even vary within a single speaker. Spatial variation across speakers emerged in work by Kirby (1999; and also Livingstone and Fyfe, 1999a, from Section 2.1). In this model, spatial constraints prevented agents from communicating with others too far away, so local areas developed with one dialect while other areas farther away could retain a different dialect, both equally as efficient. The multi-agent work reviewed in this section has also explored temporal variation. Temporal variation might result from sexual selection. In one simulation, females chose mates on the basis of the relative novelty of each male's song (Werner & Todd, 1997). Female preferences and male songs were genetically fixed. Males who produced novel songs, while still adhering to a basic pattern, could gain more mating opportunities. Song variation between males was greatest when females could choose from fewer males and when females preferred "surprising" songs. But sexual selection is not the only mechanism responsible for temporal variation in a communication system. Studies have argued that *linguistic selection* could also account for how certain grammatical features could come to predominate in a language-using population: Parsability and ease of production could both play a role in generating more efficient grammars, while spatial constraints could account for variability among a multitude of equally efficient possibilities (Kirby & Hurford, 1997; Kirby, 1998). These results notwithstanding, linguistic variation does not always have to be based on optimality. Simulations have also demonstrated that transmission error, frequency of presentation, and ease of learning can explain some forms of linguistic variation (Hare & Elman, 1995), demonstrat-

ing that changes in regular and irregular verb inflections can occur over time as one agent learned from another, which then trained another, and so on. The kinds of variation that arose were similar in ways to those observed in modern languages (in this case, from Old English to modern English).

Finally, grammatical and phonological classes have been shown to be useful for agents communicating about a large number of meanings or things. Among several available sound production systems, the one that used phonological classes was much more efficient with respect to memory size (Steels & Oudeyer, 2000; also demonstrated mathematically in Nowak, Krakauer, & Dress, 1999). If a large repertoire of sounds (words in human languages) is necessary, rote memory of each sound becomes impractical. Phonological classes help both in the reduction of memory required to store and produce each distinct sound, as well as in the classification of each sound. Similarly, grammatical classes allow for a grammar with fewer and more general rules. One simulation showed that a simple grammar could be inductively learned to express a large number of meanings (in the form of propositions; Kirby, 1999). The meanings were in the form of propositions (e.g., p, p(a, b), p(q(a), b)). The agents evolved a grammar to reflect the forms of the meanings by creating classes for each kind of object and predicate atom, as well as using recursive rules to deal with higher-degree (embedded) propositions. In an extension to this work, Kirby showed that constraints on the frequencies of each meaning—a communication bottleneck—could give rise to irregular forms in the grammar (Kirby, 2001).

Using the same paradigm as Kirby, Brighton showed that when the communication bottleneck was small (i.e., agents were not able to communicate a large portion of their language when describing various objects to each other), compositional languages emerged and tended to be more stable than holistic (noncompositional) languages (Brighton, 2002). Because of its ability to generalize, a compositional system could capture more of a language given fewer interactions than a holistic system could. But generalization was only possible when objects had many features but few values for each feature (so that different objects were likely to share common features and values). In Kirby and Brighton's simulations, the population size was 2 (one agent training the other); larger populations may exhibit very different dynamics.

2.3 Situated, Unstructured Communication

The work we have considered so far, being nonsituated, is unrealistic in associating no external task with communication acts. To address this, many studies of the evolution of communication have examined situated agents using unstructured signals. As with nonsituated, unstructured simulations, agents send single atomic signals, but now agents exist and interact with the environment in an artificial world that is usually a two-dimensional landscape. In a few cases, agents send several atomic signals on multiple channels, but the signals are not related to each other. In other words, hearers choose to pay attention to only one channel, or use the information on each channel separately (e.g., an alarm call sent simultaneously with a mating call). Unlike with nonsituated simulations, agents are evaluated based on their performance on a task instead of being directly evaluated on their communication abilities.

Most past simulations involving the emergence of situated, unstructured communication have been directly or indirectly motivated by observations of animal communication rather than language. Animals communicate about many things: dominance, mate selection, food, predators, and so forth. For example, several species of tamarins and marmosets give one call type upon discovering food and another call type while consuming it (Elowson, Tannenbaum, & Snowdon, 1991; Benz, 1993; Caine, 1995). Vervet monkeys use four phonically different alarm calls to indicate the identity of terrestrial, aerial, arboreal or other predators (Cheney & Seyfarth, 1990). On the other hand, many alarm calls do not differentiate among predator types, although some alarm calls convey information about the urgency of the threat (Manser, 2001). A critical issue in the evolution of such communication acts is how they benefit signalers and receivers (and are therefore selected for). At present, close kinship provides one plausible explanation and has been an issue in some of the simulations described here.

We consider 17 studies involving situated agents and unstructured communication (see Table 3). These studies extend the results from nonsituated simulations by demonstrating that *grounded* signals can evolve or be learned. A grounded signal is one that is somehow related to the organism or its environment (see Harnad, 1990 for a discussion). Simulations using

Table 3 Studies involving situated, unstructured communication

Simulation	Adaptive process[a]	Behavioral mechanism[b]	Type of communication/Task
Ackley and Littman 1994	E	FNN	Food & alarm calls
Baray 1997	E	PS	Recruitment calls (food, predators)
Baray 1998	E	PS	Recruitment calls (food, predators)
Billard and Dautenhahn 1999	L	RNN	Object/location/orientation names
Cangelosi and Parisi 1998	E	FNN	Object description
de Bourcier and Wheeler 1995	E	Params	Aggression
Di Paolo 2000	E	DNN	Finding another agent
Grim et al. 1999	E	Fixed strategy	Food & alarm calls
Grim et al. 2000	CA	Fixed strategy	Food calls
Murciano and Millán 1997	L	Hybrid NN/PS	Object description
Noble 1998	E	RNN	Aggression
Oudeyer 1999	L	Assoc	Encoding/decoding
Quinn 2001	E	RNN	Movement coordination
Reggia et al. 2001	E	FSM	Food & alarm calls
Saunders and Pollack 1996	E	RNN + FSM	Food calls
Wagner 2000	E	Table	Food calls
Werner and Dyer 1991	E	RNN	Mate-finding

[a] CA = cellular-automaton adaptation, E = evolution, L = learning
[b] Assoc = associative memory, DNN = dynamic neural net, FNN = neural net, FSM = finite-state machine, Params = agent parameters, PS = production system, RNN = recurrent neural net, Table = lookup table

nonsituated agents cannot explore this kind of communication, and even the situated agent simulations described here only demonstrate a simple kind of grounding, tying signals directly to basic needs such as finding food. Nevertheless, these simple forms of concrete grounding serve as an important starting point for the study of meaning in communication.

In these simulations the agents typically have a task relevant to a real species such as finding food, finding a mate, or avoiding predators. Agents usually have a small repertoire of signals, but these signals are often initially unassociated with particular actions or situations. Through various adaptive processes, agents eventually come to associate each signal with a specific action or situation. Food, alarm and recruitment calls, mate-finding and other agent-finding signals, as well as object description/naming/location signals are utilized by agents to solve their various tasks. A few of these studies employ learning, but evolution is the most common adaptive process used. Agents are represented by neural nets, production systems, lookup tables, and a few less common kinds of mechanisms.

There are several implications of these simulations. They show that grounded signals can evolve in response to more realistic tasks, and they have assessed how environmental parameters such as the distribution of food sources or the density of predators influence the evolution of communication. Kin selection and spatial constraints are found to encourage the emergence of altruistic (selfless) food and alarm calls, while population size affects how useful food and alarm calls really are. Other findings are that signal cost ensures the sender's honesty, that continuous signals can evolve to be interpreted as having discrete meanings, and that the entrainment of signaling between two communicators can be useful.

2.3.1 Featured Examples We consider two illustrative examples of the types of artificial, multi-agent worlds that have been studied. These examples both highlight the typical kinds of tasks that situated agents face and demonstrate the power of controlled experimental design (which is somewhat rare among simulations of emergent communication). In the first of
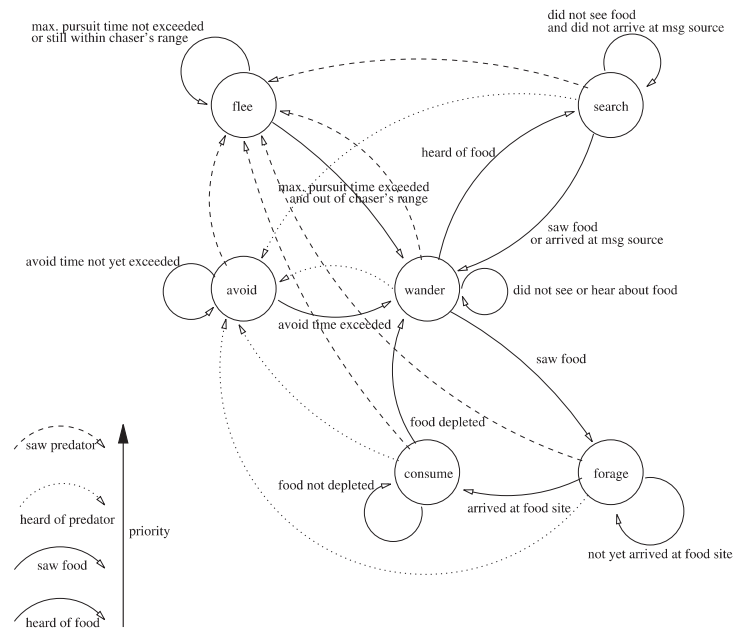
Figure 5 Automata model summarizing the behavioral states of agents in Reggia et al.'s (2001) simulations. States are indicated by labeled circles and transitions by oriented arcs. Built-in transition priorities are depicted at the lower left. Noncommunicating agents ignore signals, that is, their behavioral state changes could not follow "heard of…" links.

these, Reggia, Schulz, Wilkinson, and Uriagereka (2001) simulated a two-dimensional world with food, predators, and agents to determine environmental conditions under which food-call and alarm-call behaviors would evolve in a population of initially noncommunicating agents. Agents moved around their world, looking for food and avoiding predators, tasks that might be achieved nonoptimally in the absence of communication. If they found food, they could replenish their food stores. Agents would die if they reached old age, starved, or were caught by a predator. Each agent could only see what was immediately in front of it, and could move toward food or flee from predators if aware of these things (which they may not be due to the limited directionality and distance of their visual information). Each agent's genome specified the type of agent it was: a noncommunicator that could neither send nor hear calls, a food-caller that sent food calls when it was near food and moved toward food calls when it heard them, an alarm-caller that sent alarm calls when predators were near (and moved away from alarm calls it heard), and agents that could use both kinds of calls. In other words, this work assumes a communication system with a prespecified form. All noncommunicative behaviors were built into a finite state machine that determined the agent's movements,

whether or not it would eat food, flee predators, or react to signals (Figure 5). An agent's fitness was based on its food stores. New living agents replaced the dead and thereby maintained a constant population size. Simulations typically began with 50–100 noncommunicating agents (no other types of agents at the start) and were run for 100,000 iterations, after which the proportions of each type of agent were measured.

In this study, evolutionary and ecological factors were manipulated to explore their effects on the evolution of alarm calls and food calls among populations that initially consisted of only noncommunicating agents. Alarm calls evolved when population density was high enough (so that enough hearers could benefit). Only a few predators needed to be present for alarm calls to confer a benefit. Such altruistic signaling was able to evolve since any agent that could hear alarm calls would also send them (i.e., no cheating was possible, an important limitation of this study). Alarm calls did have an implicit cost, since any agent hearing an alarm call would flee and thus not be able to feed. Accordingly, alarm calls did not evolve in conditions where feeding was more important to producing offspring than surviving for a long time. Spatial constraints on mate selection had no effect on evolution of alarm calls.

Food calls evolved most often when food sites were rich but few in number. This was because food was harder to find but yielded a substantial fitness bonus if found; thus signals leading to food would greatly accelerate locating rare but rich food sites. Food sites with little food did not encourage food calls because they would be quickly depleted. Furthermore, spatial selection and the placement of offspring near parents tended to favor food calls. This is because a new cluster of food signalers near each other in a large population of noncommunicators could succeed, even if they made up a small portion of the population. In contrast, with offspring dispersal, signalers would become too far apart for their signals to reach other listeners. Without spatial selection, signalers might not reproduce with their nearby kin (who would also be signalers), so some of their offspring would be nonsignalers.

In a second example of situated, unstructured communication, Wagner (2000) placed agents in a similar two-dimensional cellular world, allowing them to move around and look for food. There were no predators. Several agents could occupy a cell simultaneously, and a food item might be present in some of the cells (based on a food abundance parameter). An agent could only acquire food when at least one other agent was in the same cell. Agents could only see other agents and any food in their current cell, but they could hear signals from several cells away. Agents used lookup tables that mapped their inputs (food and agents seen, signal heard) to a specific action (do nothing, signal, wander, move toward a signal). Sending a signal carried a fitness cost. Signal cost was necessary to achieve meaningful results because senders and receivers had different interests (cf. the handicap principle, Zahavi & Zahavi, 1997). When signals had no cost, agents evolved to emit signals constantly since they could only benefit from agents flocking toward them; as a consequence, receivers tended to ignore signals because they carried little information. Costly signals forced senders to have the same interests as receivers. This simulation was limited by the assumption of a direct cost to signaling as well as a narrowly defined task.

Population density, food abundance, and signal cost were varied to determine ecological effects on the evolution of food calls. Agents only evolved to send food calls under conditions in which population density was not too high. Otherwise, it was easy to find other agents by wandering around, and listening to

signals accrued no benefit to the hearer. In addition, food abundance had to be high enough so that the signaler could benefit from continuously signaling while waiting for another agent to follow its signal (otherwise, the signaler would be better off not signaling, since signaling had a cost). These results complement rather than contradict Reggia et al.'s results (above), showing that food calls are useful when population sizes are large enough to ensure agents are often within range of signalers. The benefit of high food abundance is much like the benefit from Reggia et al.'s rich food sites. High population densities eliminated the need for signals since agents could easily find each other by wandering around.

2.3.2 Survey of Other Related Work   Many other simulations have shown the evolution of food calls (Ackley & Littman, 1994; Saunders & Pollack, 1996; Baray, 1997, 1998; Grim, Kokalis, Tafti, & Kilb, 1999, 2000) and alarm calls (Ackley & Littman, 1994; Baray, 1997, 1998; Grim et al., 1999). Further, alarm calls tend to be more costly than food calls (Grim et al., 1999; Reggia et al., 2001), so predation pressure must be severe enough to outweigh the costs to foraging before they will evolve. A prominent finding is that spatially constrained mating and offspring placement (leading to kin selection) encourages the evolution of altruistic food and alarm calls (Ackley & Littman, 1994; Grim et al., 1999). Simulations have also showed the benefit of kin selection for food and alarm calls by using homogeneous populations of agents (Baray, 1997, 1998). As opposed to other kinds of alarm calls (resulting in flee responses), these latter agents evolved recruitment alarm calls, which caused other agents to flock to the signaler and confuse the predator (Baray, 1997). However, alarm calls were less useful when the population increased beyond a minimal size because agents would propagate the alarm call, eventually causing all agents in the world to respond to one agent in need (negating the specificity and usefulness of alarm calls). When population sizes were in a middle range (about 20–75), food calls were most useful (Baray, 1998). Overall, the combined results of simulations discussed in this section suggest that signals (particularly food calls) are generally useful in medium-density populations, since too few agents means that hearers are scarce and far away, and too many agents negates the need to signal at all.

A variety of other types of "artificial worlds" have been studied. For example, food and alarm calls also emerged in a cellular automaton world, but noise (small errors in action choice) was crucial to the stability of a signaling strategy (Grim et al., 1999, 2000). Agents needed to find food before they gave a food call, but they needed to "open their mouths" to find food (which costs energy). An ideal strategy for an agent is to wait for a food call before opening its mouth (preventing it from accruing huge costs by keeping its mouth open constantly). Without noise, neither signaling nor mouth opening would be initiated by these "ideal" agents, so they would never begin to eat or to signal (a sort of prisoner's dilemma).

Other kinds of grounded signals have also been learned or evolved by situated agents. Mate finding is important to many animal species (frogs, birds, and insects in particular). For example, in one study females and males were set in a two-dimensional world and had to try to find each other (Werner & Dyer, 1991). Females began by simply signaling their presence (only males could move). Eventually, females evolved to signal directions that males followed to find them (effectively, "turn left", "straight ahead", etc.). A later simulation with much greater realism pitted agents against several kinds of predators in an attempt to evolve food calls, mating calls, or predator-specific alarm calls (Werner & Dyer, 1994). It is interesting to note that, in this simulation, signaling did not evolve since another noncommunicative solution was evolved by the agents. Sometimes signals are not as useful as they might appear to be from an analytical standpoint. A similar finding occurred independently while attempting to evolve "intention signals," which are often used in displays of aggression to avoid a costly conflict (Noble, 1998). Intention displays did not evolve: agents instead evolved a non-signaling (but less efficient) strategy. A spatial version of this work, using a different agent representation and aggressive-interaction task, showed that reliable signals *would* evolve, but only when the signals were costly (and therefore honest) or if the signals were partially reliable and the only means of gaining information about a potential opponent (de Bourcier & Wheeler, 1995). Another spatial version of the evolution of intention signals demonstrated that agents trying to maintain a set distance away from each other could evolve a "signaling" protocol using proximity sensors and back-and-forth movements despite the absence of a dedicated communication channel (Quinn, 2001).

Given that communication about objects is so common among humans and found in a variety of other species (e.g., vervets: Cheney & Seyfarth, 1990; meerkats: Manser, 2001; prairie dogs: Slobodchikoff, Kiriazis, Fischer, & Creef, 1991; dolphins: Sayigh, Tyack, Wells, Scott, & Irvine, 1995), it is natural to explore how it might emerge. One study has shown that object descriptions and the proper approach to those objects can evolve even when only the hearer would benefit (Cangelosi & Parisi, 1998). Agents can also learn to describe objects when trying to collect them efficiently (Murciano & Millán, 1997). Learning of object names, locations and orientations has been found when agents can follow a teacher agent closely (so that the learner's position and orientation was similar to those of the teacher; Billard & Dautenhahn, 1999).

That discrete signals and meanings can emerge from continuous-valued signals was shown in two studies. In one simulation several agents in a small arena evolved to emit a food call by using two continuous channels (Saunders & Pollack, 1996). Agents evolved to emit oscillatory signals on one channel, but when near food they would change the phase of the oscillations. In another study two agents placed in a small arena and trying to find each other could emit a continuous-valued intensity on one channel (Di Paolo, 2000). Agents evolved to use cyclical intensity rhythms to *entrain* on each other, essentially synchronizing their signal oscillations as well as movements to find each other quickly.

As shown in nonsituated simulations, population flux can also lead to stable communication in a population of situated agents. Too much population flux will prevent consensus from developing. Encouraging agents to move toward those with similar signals can cause dialects to form, but even more interesting, when two groups come into contact, they can either "bounce" off of each other or they can merge, merging their lexicons as well (Oudeyer, 1999).

2.4 Situated, Structured Communication

The complexity of human language understandably makes it difficult to simulate, and accordingly only a few simulations involving situated agents using structured communication have been done (see Table 4). All

Table 4   Studies involving situated, structured communication

Simulation	Adaptive process[a]	Behavioral mechanism[b]	Type of communication/Task
Alterman and Garland 2001	L	CBR	Requests for help/replies
Cangelosi 1999	E + L	FNN	Object description
Cangelosi and Parisi 2001	E	FNN	Response to object/action commands
Moukas and Hayes 1996	L	Robots and NNs	Food information

[a] E = evolution, L = learning
[b] CBR = case-based reasoner, FNN = feedforward neural net

of them have dealt with built-in structure. For example, two studies have explicitly focused on the emergence of structured signals for facilitating simple, cooperative tasks (Cangelosi, 1999; Cangelosi & Parisi, 2001) involving actions related to several objects. This work has shown how signal structure might become related to the agents' ecology. Two other studies have shown how a given communication system might emerge to help coordinate a group of agents (Moukas & Hayes, 1996; Alterman & Garland, 2001). In all four of these studies, structure is mostly or completely built into the communication systems, so the *emergence* of communicative structure in the first place remains unstudied.

2.4.1 Featured Example   We now consider a situated example where, in contrast to the above, evolution of structured communication was the issue. In this study, Cangelosi (1999) simulated agents that had to approach properly three edible and three poisonous types of mushroom. Each of the three edible mushrooms differed in the proper approach toward it (a different way of eating each one), and all poisonous mushrooms were to be avoided. Each mushroom type had a pattern with some regularities that would indicate what type of mushroom the agent was looking at. Each agent's neural net (see Figure 6) could output an action concerning a mushroom (avoid, or eat in one of three ways) as well as produce a two-component output (two sets of competitive "linguistic" nodes, one set of six units and one set of two units). Agents were first evolved using a genetic algorithm to properly approach the different mushroom types. Then the population of agents was trained using backpropagation to name the mushroom types using their linguistic units (names for the three poisonous and three edible types). Evolution was used again to select for those agents that were best at approaching mushrooms.
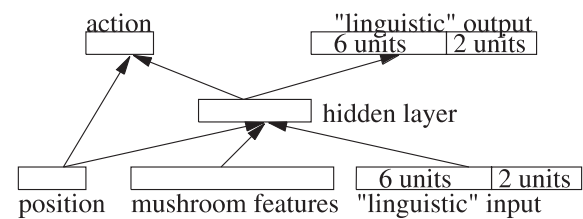

Figure 6   Neural networks used by agents in Cangelosi's (1999) study of structured communication. Position units detect if there is a mushroom at one of three 40° arcs in front of the agent. The first two action units code continuous values for the agent's movement (how much forward, how much turning left/right). The third action unit codes for which "approach" to take to a mushroom (three ranges, one for each edible mushroom type). Linguistic units are grouped into two competitive sets, one with six units and one with two units. Initially, agents were selected to output the appropriate actions given different kinds of mushrooms in different positions (using a genetic algorithm). Later, agents evolved and learned to use their linguistic units to refer to the different mushroom types.

Utterances were much like a multi-faceted signal with each component presented simultaneously (e.g., like the hand motion and hand shape of a manual sign). Over many experimental repetitions, each signal component often evolved to correspond to a distinct action toward a specific mushroom type. Furthermore, the two linguistic output sets were often specialized for distinct types of information: one output for object description (a "subject" or "noun") and the other output for the action toward the object (a "predicate" or "verb"). In 7 of the 18 experiments with initially random agent populations, the population evolved and learned to use its linguistic units in a structured manner closely reflecting its environment. Nevertheless, genetic drift may be responsible for these results—the relative contributions of evolution and learning are difficult to tease apart in

this set of experiments. In the populations that developed structured signals, the six-unit competitive linguistic units were used to name the specific type of mushroom while the two-unit group was used to name the general action associated with poisonous or edible mushrooms ("avoid" or "approach"). The neural nets were somewhat biased in favor of this result because of the competitive unit groupings (six and two). However, the structure that the network found was in some cases related to the task and not to explicit training for signal–input correlations. It remains to be seen if agents can build linguistic structure based—at least in part—on the structure in the environment (as Batali, 1998 has begun to explore using abstract meanings).

2.4.2 Survey of other related work   Another simulation also focused on the evolution of structured communication, this time involving two objects (A and B) and two actions (push and pull; Cangelosi & Parisi, 2001). Agents evolved one set of units ("verbs") associated with the actions push and pull, and another set of units ("nouns") associated with the objects A and B. Agents were better communicators when they were first selected for nonlinguistic tasks where they would see an object and always had to perform the same action with that object (push A, pull B). Something about the nonlinguistic task appears to have facilitated performance on the linguistic tasks, although many of the architectural assumptions would need to be examined to show the precise mechanisms involved, and the result would need to be scaled up to accommodate a more extensive communication system.

Two other studies did not focus on structured signals but used them as part of the task. One, a robotic study, showed that a complex visual language could be learned and associated with actions (Moukas & Hayes, 1996). Robots observed a teacher using a preprogrammed communication system whose components indicated a location, direction, and amount of power (like a food source for bees). Using a competitive learning approach, agents were able to associate each of three signal components with the three food variables (distance, angle, amount). A very different study of cooperation among several agents showed that offline learning could be used to acquire specific structured utterances that made a cooperative task more efficient (Alterman & Garland, 2001).

3   Language Features

It is important to point out that, with respect to human language, we are taking as a given that it evolved for communicative purposes. This is by no means a universally accepted view. There are many researchers, including one of us (JU), who believe that language emerged as part of a repertoire of cognitive abilities unrelated to communication (Chomsky, 1975). Many of these researchers would place syntactic concerns much more centrally to an investigation of language (Uriagereka, 1998; Saddy & Uriagereka, in press). For example, all languages can be viewed as falling into the Chomsky hierarchy of languages (Chomsky, 1956) based on their syntactic properties. Under this hierarchy are four classes of increasingly complex languages: regular (ordered strings), context-free (phrases: embedded/ordered sets of strings), contextsensitive (including transformations: ordered sets of phrases), and recursively enumerable (all computable functions). Each class contains the one before it and has fewer restrictions on the kinds of rules that can generate or recognize them than the preceding classes. A communication system for a regular language, for instance, would require less complex machinery than a system for a context-free language, which would require a more flexible memory. There are many critical issues in the development of syntax (many related to the Chomsky hierarchy) that have not been addressed by any multi-agent computational modeling to date, including phrase structures (e.g., parts of speech, connectives) and transformations (e.g., question formation: "Which article did you read?"; Saddy & Uriagereka, in press). Nevertheless, we are organizing this review in accordance with a framework by Charles Hockett both because these syntactic issues have generally not been addressed by multi-agent models and because we are addressing issues related to communication in general rather than those specific to human language.

The broad range of simulations described above have been successful in showing that communication can emerge via learning/evolution in multi-agent systems under a wide variety of interesting conditions. However, a key question remains: To what extent do these simulations shed light on the origins and evolution of language? We have chosen to answer this question within a well-known system of *communication features* originally proposed by Hockett in the late 1950s (Hockett, 1959, 1960; Demers, 1988) to under-

stand the origins of human speech. Hockett argued that all communication systems fall within a multi-dimensional feature space (see Figure 7). Hockett's original list of 13 features (Hockett, 1960) has been refined (Hockett & Altmann, 1968; Hockett, 1990) by classifying the features into groups [*frameworks* in Hockett and Altmann's (1968) terminology] and treating features not as binary properties but as dimensions along which any communication system can vary. We further refine the term "feature" to indicate either a dimension or a finite set of possible values. For example, the various possibilities for acquiring a communication system form an unordered set (e.g., various learning and evolutionary processes) and cannot be located along a continuum. Along more of a continuum is utterance structure. Human utterances are hierarchically structured and rule-like, whereas gibbon calls consist of sequences of units that appear in a somewhat rule-like order (Mitani & Marler, 1989; Ujhelyi, 1996), and vervet monkey alarm calls appear to be completely unstructured in the sense that each call is not used as a component in any other utterance (Cheney & Seyfarth, 1990). Within this continuum are several species of monkeys that use elements of syntax in their calls (Robinson, 1994; Zuberbuhler, 2002), and sac-winged bats (Davidson & Wilkinson, 2002) and humpback whales (Cerchio, Jacobsen, & Norris, 2001; Darling & Berube, 2001) that produce songs with recurring notes, although it is not clear if different orderings of these notes have any significance in these songs.

Hockett's features provide an objective "checklist" against which the computational work reviewed above can be assessed for completeness and significance. Even a casual comparison to these features indicates a number of limitations of the simulation studies we have reviewed. For example, no past work, to our knowledge, has substantially examined Hockett's features of duration, referents, and displacement, making these significant issues for further research. Table 5 provides a summary of Hockett's features that have been explored by simulations We group these features into three frameworks: form (structural), ecological and social. Structural features relate to the form of the utterances themselves (e.g., are the signals composed of smaller parts?), whereas ecological features relate somehow to the signaler's ecology (e.g., do signals relate to internal motivations or external events?) and social features relate to the social environment of
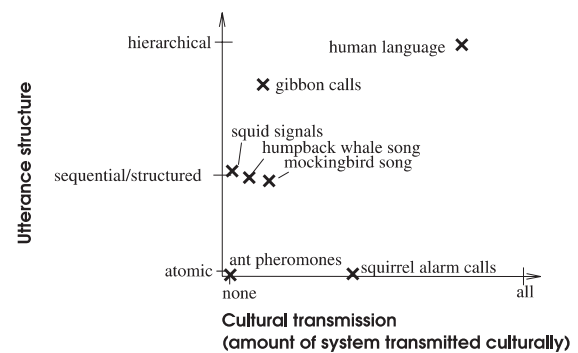

Figure 7 Communication systems can be viewed as points in a multi-dimensional space, where each dimension corresponds to one of Hockett and Altmann's (1968) features. This two-dimensional graph is only meant to illustrate how a multi-dimensional feature in a feature space might be filled by all known communication systems. In the figure, utterance structure acts mostly like an ordinal scale, roughly following the Chomsky hierarchy of languages (e.g., position indicates to some extent the relative structural complexity of a given system). Cultural transmission is represented as the proportion of the communication system that is transmitted culturally (as opposed to genetically).

the signaler (e.g., how are the signals acquired?). We find that, with a few exceptions, most of the features have received very limited attention.

3.1 Form and Structural Features

3.1.1 Realization The *realization* of utterances refers to how they are perceived in relation to how they are realized. Utterances or their components can be perceived as *continuous* values along some dimension (such as volume or pitch), or they can be *discrete*, meaning that they are perceived as units, rather than as the continuous signals that they are at the physical level. Thus, a letter p in a word spoken by a loud baritone or a quiet child will still be perceived by an English speaker as a discrete phoneme /p/. This is known as *categorical perception*. Alternatively, it is possible that a communication system could relate the continuous value of a signal to its meaning or response; this may be the case with some alarm cries, whose intensity may signal the degree of alarm (a continuous, rather than a discrete, relationship).

Among computational models, only a few studies have tackled the problem of discrete perception of continuous signals (Saunders & Pollack, 1996; Moukas & Hayes, 1996; Di Paolo, 2000), although some

Table 5 Features explored by multi-agent simulations

Category	Feature	Featural aspect	Relevant work
Form	Realization	Continuous→discrete	Saunders & Pollack 1996, Moukas & Hayes 1996, Steels & Oudeyer 2000, Ryan et al. 2001
	Utterance structure	Rule-like	Batali 1998, Kirby 1998, 1999, 2001
		Sequential	Batali 1998, 1994, MacLennan & Burghardt 1993, Steels 1998a, Brighton 2002
		Instantaneous/parallel	Cangelosi 1999
	Repertoire	Open, learned	Steels 1998; 1998a, Kirby 1999
Ecological relationships	Groundedness	Food calls	Ackley & Littman 1994, Reggia et al. 2001, Baray 1997, 1998, Wagner 2000, Grim et al. 2000, Saunders & Pollack 1996
		Alarm calls	Ackley & Littman 1994, Reggia et al. 2001, Baray 1997, 1998, Grim et al. 1999
		Mating	Werner & Dyer 1991, Werner & Todd 1997
		Navigation	Moukas & Hayes 1996, Billard & Dautenhahn 1999
		Object discrimination	Cangelosi & Parisi 1998, Cangelosi 1999, Murciano & Millán 1997, Steels 1998
		Group coordination	Grim et al. 2000, Murciano & Millán 1997, Baray 1997, Alterman & Garland 2001
	Signal elicitation	Internal, goal-driven	Alterman & Garland 2001
		Internal, aggression	Noble 1998, de Bourcier & Wheeler 1995
		External	Most situated simulations
Social relationships	Scope	Private	Most nonsituated simulations
		Public	Most situated simulations
	Variation	Mating	Werner & Dyer 1991, Werner & Todd 1997
		Spatial	Livingstone & Fyfe 1999, Kirby 1998
		Refinement	Alterman & Garland 2001, Steels 1998
		Parsability	Kirby & Hurford 1997, Kirby 1998
		Transmission error	Hare & Elman 1995, Kaplan 2000
	Acquisition	Genetic	Werner & Dyer 1991
		Teaching	Hutchins & Hazlehurst 1995
		Imitation/observation	Kirby & Hurford 1997, Kirby 1998

work has addressed continuous inputs and discrete behavior (Ryan et al., 2001). Since human utterances have hierarchical, discrete structures (morphemes/syllables composing words, words composing phrases) (Jannedy, Poletto, & Weldon, 1994), the problem is even more complex and this issue remains mostly untouched by simulations (but see de Boer & Vogt, 1999; Dircks & Stoness, 1999; Berrah & Laboissière, 1999; Steels & Oudeyer, 2000).

3.1.2 Utterance Structure Utterances may have no internal structure (as with most alarm and food calls), they may be composed of several units (as with mockingbird songs), or they may even have rule-like or hierarchical structures (as with language). Human language, as well as several other known animal communication systems [e.g., gibbons (Mitani & Marler, 1989), songbirds (Catchpole & Slater, 1995)], consists of utterances that exhibit a compositional or rule-

based *utterance structure*: Utterances are built out of smaller units that are ordered according to rule-like constraints. The origins of structured utterances is one of the biggest mysteries in the evolution of language.

Constraints on adaptation and creating a mapping from signals to meanings have been explored in mathematical modeling (Nowak et al., 1999; Nowak, Plotkin, & Jansen, 2000), but their ecological pressures have mostly been explored through multi-agent simulations. Nevertheless, the ecological motivation for structured utterances has only begun to be explored computationally. MacLennan and Burghardt (1993) set up a situation in which there were more "conversational topics" than signals. Thus, agents had to combine signals into longer utterances to communicate about every situation in their world. Hockett had suggested this as a possible motivation for the development of sequential signals (Hockett, 1960). Cangelosi's mushroom identification task was also structured by requiring different approaches to different mushroom types (Cangelosi, 1999). However, only one structure was available and the range of possibilities was limited. It remains an open question as to whether a sequential signaling system could then lead to syntactic rules and thematic roles for utterance components.

Batali's simulations demonstrated that recurrent neural networks can support the emergence of a structured, sequential communication (Batali, 1998). It is possible that rule-like utterances could emerge from the rule-like nature of conversational topics. However, this kind of structure is more complex than the sequential utterances created by Batali's agents. The story may involve not only the structure in the environment, but key nonlinguistic cognitive constraints (e.g., memory limitations, attention span, poverty of input) and production and comprehension constraints (e.g., Hare & Elman, 1995; Kirby & Hurford, 1997; Kirby, 1999; Kaplan, 2000; Brighton, 2002).

For example, Batali's agents were given "meanings" composed of a predicate and a referent (although meanings were not grounded in the agent's actions). The agents learned a communication system that often divided utterance components into a predicate part and a referent part. This is just the beginning; other external structures might be used by agents when structuring their communications, such as the relationships between objects and the structure of common events.

Other simulations have shown that if agents needed to communicate about embedded propositional meanings, a kind of grammar could arise to match this embedded structure (Kirby, 1999, 2001; Brighton, 2002). Also, the natural sequential naming of individual object features can serve as a starting point for compositional utterances (Steels, 1998a). Still others have indicated how learning and social interactions might play a role in the emergence of structured utterances (Batali, 1998; Steels, 1998b). Presumably other processes—especially exaptation[9]—endowed hominids with the ability to process sequences of input. Sequential processing of inputs might have arisen because of demands from noncommunicative tasks such as tool usage (Savage-Rumbaugh & Lewin, 1994) or attending to complex social events (e.g., as with vervet monkeys, Cheney & Seyfarth, 1990). Collectively these simulations indicate that the emergence of compositional or rule-based utterances may require the existence of some kind of working memory (a phonological loop[10] or the equivalent). However, at least some of the structure of utterances might be acquired through learning and without a mechanism specialized for that structure [as in Batali's work or Moukas and Hayes' (1996) work].

3.1.3 Repertoire   The *repertoire* of most communication systems is fixed or *closed*, but human language is mainly *open*. That is, most systems do not allow signalers to add new components or utterances to the system, but humans, mockingbirds, and possibly other species are able to add new components to their signal repertoires. This is not a claim that the systems are unbounded in size, but merely that new items can be added to the repertoire during the organism's lifetime. Human language is open through two processes: the construction of new sentences from existing words and phrases (open utterance repertoire), and the invention of new words (open lexicon).[11]

Only very limited work has used agents with an open utterance repertoire and the potential for a truly open lexicon (Steels, 1998b), and in it the utterance structure was fixed, effectively using *<property,value>* pairs that correspond to the properties of the objects being described. The mechanism used, only briefly described, is mostly symbolic, something like a production system. Another study also had an open lexicon and open utterances (Kirby, 1999), augmenting a simple grammar based on the structure of the meanings to be expressed.

3.2 Ecological Relationships

3.2.1 Groundedness In natural communication, signals exhibit what is referred to as *groundedness*: utterances relate to states and events in the world that are relevant to the sender and receiver. Grounding has been relatively well studied compared to other features (see sections above on situated simulations). Simulations have repeatedly shown that food finding, mate finding, and predator avoidance all seem able to give rise to simple (i.e., unstructured) communication systems. For example, food calls are given most often when food is difficult to find but highly rewarding when it is found, and alarm calls can be costly in some cases due to the lost foraging opportunities resulting from fleeing (Wagner, 2000; Reggia et al., 2001). Most of the usefulness of the signal lies in its being emitted and in its being distinct from other signals. As such, these kinds of pressures may not be the best foundations for a theory of language evolution. Object discrimination is a more demanding task requiring more complex signaling (Steels, 1998b; Cangelosi, 1999), but simulations showing this have not been truly grounded (agents had no actions other than communication), or involve rather artificial situations (one agent describing a mushroom to another). Future work on groundedness needs to place agents into more interesting worlds and set them to performing descriptive tasks under more natural circumstances.

3.2.2 Signal Elicitation Related to groundedness is *signal elicitation*, that is, what it is that causes the elicitation of signals. Signals can be internally or externally elicited. External elicitation of signals has been studied by virtually every situated simulation. The presence of food, predators, and other agents can cause agents to communicate about them. In addition, goal-driven signals have been employed to a small extent (Alterman & Garland, 2001), and motivations like aggression and mating have also been explored (de Bourcier & Wheeler, 1995; Noble, 1998, 1999b). Since human linguistic interactions might relate to motivations (hunger, sex, pain) and goals (finding a mate, hunting prey, escaping a trap, playing games), much more study needs to be made of these internal motivations to understand the evolution of human language. Deception is also important, as it implies theories of mind as well as internal goals and goal-driven

behavior. Much more needs to be studied in this vein, as only a start has been made (Krakauer & Johnstone, 1995; Noble, 1998).

3.3 Social Relationships

3.3.1 Scope Speakers may broadcast their message publicly for many to hear (e.g., sparrow food call, Ficken, 1989), or they may direct the message to a few individuals in private (e.g., bowerbird mating dance). *Scope* specifies the kind of audience to which a speaker directs an utterance. For human languages, this can be private or public or both. Public messages require the receiver to filter other messages out, since many senders can simultaneously broadcast in the same area (the cocktail party phenomenon; Sagi et al., 2001).

Most nonsituated simulations have used private scope, as they typically involve the pairwise interaction of encoder/decoder agents. Most situated simulations have used public scope since the agents are trying to solve tasks in which signals are used to find something (food: Ackley & Littman, 1994; Wagner, 2000; Grim et al., 2000; Reggia et al., 2001; a mate: Werner & Dyer, 1991) or avoid something (a predator: Ackley & Littman, 1994; Baray, 1997, 1998; Grim et al., 1999; Reggia et al., 2001). Even so, no simulation work has explicitly focused on the problems of scope, particularly publicly broadcast signals. Although some studies handle multiple, simultaneous signals by letting agents select which one(s) they will respond to and which they will ignore (e.g., Baray, 1999; Reggia et al., 2001), a systematic study of how this should be accomplished remains to be done. Others have shown how agents might ignore their own signals and pay attention to others through the use of rhythmic entrainment and cyclic movement (Di Paolo, 2000). Future work should address the mechanisms required to deal with public utterances, as well as the specific uses to which private and public communication are put.

3.3.2 Variation A communication system may exhibit a degree of *variation* from group to group or over time. Variation refers to how the existing system may be modified or acquire new parts. Variation can appear in form, form–meaning associations, responses to utterances, mode of transmission, or other features. It may

potentially be due to either genetic or cultural factors, and it can result from natural population dynamics or from external pressures for change.

Many aspects of variation have been studied via simulations. As described in Section 2.3, Werner and Dyer (1991) described *historical changes* in the mate-finding system their agents evolved. Their work suggests an outline for how human language could have evolved in a series of stages, from unstructured signals to sequential signals and eventually to our modern hierarchical structures. Several *causes* of variation have also been explored, most prominently the spatial constraints on communications. Spatial constraints on partners learning to communicate can create local dialects, each one slightly different from the others nearby (Kirby, 1998; Livingstone & Fyfe, 1999a). In addition, movement of agents within a spatial environment can reduce global stability of a language, but clusters of dialects can form and even merge when groups come into contact (Oudeyer, 1999). These kinds of geographical and temporal variation are similar in some ways to the variation exhibited by real neighboring language groups (e.g., Labov, 1972; Jannedy et al., 1994). Refinement of a system (making it more accurate or efficient) has been found to cause meanings to change or even new words to be coined (Steels, 1998b; Steels & Kaplan, 1999). Parsability and other cognitive constraints may also play a role (Kirby & Hurford, 1997; Kirby, 1998). Population flux is not necessary for large amounts of change to occur (Dircks & Stoness, 1999). Finally, simulations have shown how transmission and reception errors between speakers could influence changes in a communication system over generations (Hare & Elman, 1995; Kaplan, 2000), in addition to the accumulation of error through statistical sampling of the linguistic environment (Dircks & Stoness, 1999).

3.3.3 Acquisition   The *acquisition* via evolution or learning of a communication system can depend on its complexity, the cognitive abilities of the species in question, and other factors. Both *phylogenetic* (i.e., occurring over generations) and *ontogenetic* (i.e., occurring within the organism's lifetime) acquisition are possible. The form (phonological and morphological) and pragmatics (proper use) of all human languages are acquired partially by *cultural transmission*. Cultural transmission usually implies that some kind

of observational learning occurs. Its presence can allow for transmission of traits that are not necessarily the most fit from a biological standpoint (e.g., Neff, 2000). Cultural transmission plays a role in the communication systems of many nonhuman species such as vervet monkeys (Seyfarth & Cheney, 1997), Belding's ground squirrels (Mateo, 1996), bottlenose dolphins (Sayigh et al., 1995), and songbirds (Marler, 1991; Catchpole & Slater, 1995; Marler, 1997; Nelson, Khanna, & Marler, 2001). Which parts of human language are developmentally canalized and which are learned is an unresolved issue (Pinker & Bloom, 1990; Crain, 1991; Elman et al., 1996).

Most of the studies reviewed in this article involve the acquisition of a communication system, including the demonstration that an increasingly complex communication system can be acquired genetically by a population that had no such system to begin with (Werner & Dyer, 1991). On the other hand, a system could be entirely learned through explicit teaching (although there would need to be some "innate" ability to communicate; Hutchins & Hazlehurst, 1995; Moukas & Hayes, 1996; Billard & Dautenhahn, 1999). More relevant perhaps to human language and a few animal systems (e.g., Belding's ground squirrels, Mateo, 1996) are those simulations showing that acquisition can involve a genetically endowed system that is modified based on feedback from the world or other communicators (MacLennan & Burghardt, 1993; Batali, 1994). However, only one of these studies (Brighton, 2002) has begun to address the fundamental problem of the *poverty of the stimulus*, the claim that children do not get enough information in their linguistic environment to learn a language. This claim is a central component of human language acquisition. The poverty of the stimulus argument states that if children indeed fail to receive enough information to learn how to speak their language(s), then they must have some kind of specialized language-learning mechanism or even some innate knowledge of language. The implications of this claim and even the validity of the poverty of stimulus are hotly debated (Chomsky, 1975; Elman et al., 1996; Pullum & Scholz, 2002).

Many studies have revealed that population size, social structure, and linguistic constraints have important effects on the dynamics of acquiring a communication system through learning. Population size affects learning populations and evolved populations in opposite ways. Whereas consensus is easier to attain as

evolved populations increase in size (due to greater genetic variation; Wagner & Reggia, 2002), attaining consensus becomes more difficult for learning populations as they increase in size (Levin, 1995; Hutchins & Hazlehurst, 1995; Oliphant, 1999). Not only size, but social structure—the social networks within a population—can affect the transmission of a communication system. Tribal and other social structures can affect how broad the transmission of linguistic features will be (Steele, 1994), even if their contribution to fitness is zero or negative. Linguistic constraints, as opposed to ecological fitness, may affect the acquisition of certain features of a language (Kirby, 1998; Berrah & Laboissière, 1999). These constraints have been proposed to account for the acquisition of various grammatical features that may not have obvious fitness benefits (Kirby & Hurford, 1997; Kirby, 1998).

4 Discussion

As demonstrated by the studies reviewed above, very substantial progress has been made during recent years in developing computational models of emergent communication in multi-agent settings. The most fundamental result of this work has been the convincing demonstration that shared communication systems can readily appear among initially noncommunicating agents in a very wide range of contexts. This has been shown to be true for both structured and unstructured communication, when agents are situated versus when they are not, and when adaptation is brought about via learning, evolution, or both. The ease with which simulations have repeatedly led to simple shared communication systems suggests that the common occurrence of such systems in natural/biological settings is not surprising.

Each of the four general categories of simulation work have revealed different things about communication. Nonsituated simulations have the advantage of clearly illustrating general principles of communication systems (dynamics, effectiveness of various transmission techniques) whereas situated simulations are the only ones that can explore how utterances come to have meanings. Nonsituated simulations tend to use learning whereas situated ones have tended to use evolutionary adaptation; perhaps this trend should be reversed in the future, and more work should be done

with simulations combining both evolutionary and learning mechanisms. Because of their relative simplicity, unstructured simulations have been able to reveal how communication can emerge from initially silent agents as well as what kinds of ecological pressures might bring forth signals in the first place. Agents have tended to be simpler due to the complexity of their noncommunicative behaviors or due to the complexity of the experimental setup. On the other hand, structured simulations have shown how agents might come to use utterances with structure; these simulations have rarely been situated, so the ecological motivations are all but nonexistent. Some of the mechanisms used in these simulations (e.g., recurrent neural nets) are reasonable candidates to explore in situated simulations to attempt to ground signals. There seems to be a preponderance of encoder/decoder research; although this research has clearly produced important insights into the emergence of communication systems, future simulations should probably focus on deeper representations of meaning and grounded signals. Work is also evidently lacking in situated, structured simulations. This is likely to be a very fruitful area to explore in the future, although it is also the most difficult.

These simulations have also provided insight about a number of factors that influence the likelihood that a communication system will emerge, or its nature when it does. Introducing spatial relationships between agents with restricted communication ranges has repeatedly been shown to affect the learning or evolutionary process. For example, spatial restrictions can influence the likelihood that communication will develop and, when it does, encourage variability and the appearance of local dialects. In situated simulations where agents interact with an environment in a causal fashion, many other factors have been shown to affect communication, including agent density, food distribution, predator density, signal honesty, and sexual selection. Such results are directly relevant to many issues in the evolution of animal communication and may ultimately guide interpretation of the rapidly expanding experimental data in this area (Hauser, 1996; Bradbury & Vehrencamp, 1998). Furthermore, software agents and robotic systems may benefit from a better understanding of factors that encourage a shared communication system. It is difficult to design by hand a communication system or set of interaction protocols for a large group

of agents. Instead, simulated or robotic agents could be allowed to evolve and/or learn how to communicate (using the techniques from situated simulations) to increase their efficiency at performing their task. Spatial restrictions, agent density, and individual task assignment could be tailored to aid the agents, and the acquisition technique (evolutionary/learning algorithms) could be chosen to match the task: an "observational" learning algorithm could be used for small populations of homogeneous agents, while some kind of evolutionary algorithm might be more effective with large populations of agents with specialized tasks.

Although these results are encouraging for communication in general, less progress has been made in the quest to gain insight into the origins and evolution of the more complex linguistic features such as thematic roles, parts of speech, connectives, and transformations. On the positive side, many of the simulations reviewed in this article contribute to our understanding of specific features of communication that are widely recognized to be important in language (groundedness, variation, etc.). Some simulations, mostly nonsituated ones involving supervised learning, have gone so far as to demonstrate the appearance of structured communication, showing how sequential and rule-like utterances can arise, how their structure may be related to the agents' ecology or isomorphic to task structures, and how they depend on agent-to-agent interactions. Nonetheless, substantial gaps remain. For example, the origins of the open repertoire of human language has not been adequately explored, and the ecological validity of structured communication for situated agents has not been established. Such gaps are to be expected since the field is still quite young. As it matures, one hope is that future work will attempt to tackle existing hypotheses for the origins of communication/language and thoroughly test them. Currently, most researchers do not explicitly test exisiting biological, cognitive, or anthropological hypotheses for the origins of a communication system. Only a few computational works (Enquist & Arak, 1994; Bullock & Cliff, 1997; Noble, 1998, 1999b) take seriously several hypotheses on the origins of communication: the *handicap* hypothesis (Zahavi & Zahavi, 1997) and related hypotheses, although one simulation has begun to explore perceptual biases as one possible origin of mating calls (Ryan et al., 2001). Some related work in robotics has looked at cricket calls and female song preferences (Lund, Webb, & Hallam, 1998; Webb &

Hallam, 1996), taking mechanism and situatedness (especially embodiment) very seriously. Although computational modelers have only begun to enter this area, there is a large literature on mathematical approaches to biology, including a significant body of game-theoretic work that covers many issues directly and indirectly relevant to communicative hypotheses (e.g., Newman & Caraco, 1989; Caraco & Brown, 1986; Mesterton-Gibbons & Dugatkin, 1999). Unfortunately, coverage of this literature is beyond the scope of this article.

It is curious to note that most simulations have demonstrated that agents always succeed in developing a working communication system (except for Levin, 1995; Noble, 1998; Grim et al., 1999; Wagner, 2000; Reggia et al., 2001). There is a clear need for careful studies of when communication will *not* emerge. This leads into a second criticism of work in the field: Most of the work that we have reviewed has suffered from a lack of experimental controls (but see Levin, 1995; Noble, 1998; Baray, 1998; Grim et al., 1999; Wagner, 2000; Reggia et al., 2001). The use of controlled experiments would allow the discovery of specific factors responsible for the emergence of some communication system. For example, Wagner used agent and food density to demonstrate conditions under which communication would not be any more useful than remaining silent (Wagner, 2000).

Perhaps the greatest limitation of the work surveyed here with respect to language is that it has not yet shed substantial light on the origins and evolution of syntax. We have reviewed these simulations in the light of Hockett and Altmann's (1968) features, but there is an entire field of literature based on elements of Chomsky's language hierarchy as well as other theories that focus in more detail on language and syntax (e.g., Langacker, 1987; Uriagereka, 1998). The Chomsky hierarchy of formal languages incorporates levels of complexity involving sequential components, phrase structures and transformations (Saddy & Uriagereka, in press). So far, multi-agent work has revealed only sequential elements of syntax, with little investigation into phrase structure (only Batali, 1998; Kvasnicka & Pospichal, 1999; Kirby, 2001; Brighton, 2002 to a very limited degree) and no work (that we know of) on transformations. Progress with respect to language has been limited to dynamics (e.g., of language change) and simpler formal properties (e.g., lower regions of Chomsky's hierarchy of languages,

dealing with ordering of components and very simple phrase structures). Although progress has been made, it is relatively small compared to what has to be done to explore all aspects of language fully. Given that the field of multi-agent simulations in the evolution of communication is only about 10 years old and that the majority of work has been done in the past 7 years, it is not surprising that many explorations are still in their infancy.

Theories concerning the origins of language have often differed in their viewpoint on syntax. For the functionalist tradition (e.g., Haiman, 1985), syntax is viewed as a side effect of functional demands on effective communication. This approach has met with much skepticism from syntacticians, since it does little to account for actual conditions found by research. On the other hand, until recently no research within the generative tradition was devoted to language origins, as the question was deemed too obscure to pursue. That changed in the last decade, when two schools of thought emerged within generative grammarians. First, Bickerton (1990), Pinker and Bloom (1990), and Newmeyer (1991, 1992) tried to argue for different aspects of a neo-Darwinian approach to the evolution of syntax. Second, Chomsky (1980), Piatelli-Palmarini (1989), Lightfoot (1991), and Gould (1991) voiced a new kind of skepticism, based on punctuated equilibrium theories of evolution, showing that linguistic structure is not obviously adaptive [Christiansen (1994) summarizes the two positions]. The last few years have seen two new developments. Some researchers have argued that language is complex enough to demand a sophisticated explanation based on both kinds of theories (e.g., Kirby, 1996; Carstairs-McCarthy, 1999). In turn, developments in theories of "complexity" have resulted in both interdisciplinary teamwork and new models for the emergence of structure (Knight, Studdert-Kennedy, & Hurford, 1998). The reaction from syntacticians, however, remains skeptical (e.g., Uriagereka, 1998), primarily because the research in question still has little to say about the hallmarks of syntax, among these the locality and economy character of derivations and the recursive properties of syntax (but see Kirby, 1999). A combination of the multi-agent work reviewed in this article and mathematical modeling (Nowak, Komarova, & Niyogi, 2002) may eventually shed light on this difficult problem. Nevertheless, much more computational modeling work will be needed to address properly the many issues surrounding the evolution of syntax.

In more general terms, the multi-agent models we have reviewed here leave several areas largely unexamined, suggesting some important directions for future research. Even considering just Hockett and Altmann's feature set, it becomes evident that communication features such as utterance duration, arbitrary versos iconic referents, and displacement have basically been untouched by simulation work. Other features, such as discrete realization of continuous signals, open repertoires, internal signal elicitation, and scope have only begun to be studied with computational models. Future simulation work examining these features is likely to be fruitful, as is study of combinations of these features (e.g., studying repertoire and utterance structure interactions may reveal how open repertoires and hierarchical utterances interact).

With respect to language, as noted above the most critical issue needing further study is how syntactic processing can evolve. Although some mathematical modeling work has explored the general sorts of pressures and initial conditions required for signals to become structured (Nowak et al., 1999, 2000), this type of investigation cannot reveal why hominids in particular developed the communication system that they did, nor can it reveal how individual-level dynamics will affect the outcome. It seems probable that more realistic and complex neural network models may be able to investigate this. However, such research will be limited by the complexities involved in evolving neural nets, and by the large computational costs involved in combining evolutionary computation and neural network learning methods. Past research on emergent language has largely emphasized nonsituated agents and has primarily used supervised learning to examine cultural transmission. Although many researchers believe that this approach is justified, there are many who believe that these approaches are not biologically plausible in many language-learning situations (e.g., Elman et al., 1996). Future work that focuses on structured communication and syntax might benefit from focusing more on situated agents (e.g., so groundedness could be examined in this context) and by more emphasis on self-organizing communication systems based on unsupervised and reinforcement learning [see Dickins (2001) for a discussion of the kinds of learning processes that are likely to have played an important role].

There has been growth in each of the four subdivisions (on the situated/structured axes) of this field.

Little has yet been done with situated/structured simulations as noted earlier. Much of the work up to 1997 focused on more general aspects of the emergence of communication, asking questions about what mechanisms could make it happen (proof of concept) and what ecological pressures might bring it about. Later work has asked more detailed questions about mechanisms, dynamics, the relative contributions of learning and evolutionary processes, and the structure of signals. A few of the most recent simulations have employed controlled experiments, and the hope is that this is the primary improvement to occur in future work; controlled experimentation will bring this burgeoning field into maturity.

Notes

1   We use the term *emergence* in the sense that it is often used in artificial life and other fields (Cottrell, 1977; Ronald, Sipper, & Capcarrere, 1999), that is, to mean the appearance of a new global property of a complex system that derives from the local interactions of its numerous parts. In our case, interacting agents form the principal "parts," a multi-agent artificial world is the complex system, and a shared communication protocol arising via learning/evolution is the global property.

2   For example, we do not include work published in languages other than English, nor much work relevant to communication in social insects (ant pheromone trails, bee "dances," etc.), nor work on designing rather than learning/evolving inter-agent communication protocols (e.g., KQML) from the field of distributed artificial intelligence.

3   We combine the concepts of embodiment and situatedness under the single heading, *situated*. Although any communication occurring in the context of a population might be viewed as "situated," we do not adopt that view in this review.

4   Some have argued that supervised learning is not justified in learning language (e.g., Elman et al., 1996).

5   This is an example of indirect pressure for utterance length: Kaplan's agents were directly evaluated on the basis of communicative accuracy, not on the basis of the length of their utterances. Direct pressure would have been selecting agents based on the length of their utterances.

6   We classify this study as nonsituated according to our criteria, stated earlier, that the agents here have no effect on the world they are in.

7   Pleiotropy refers to a gene that is responsible for several traits, and hitchhiking refers to two genes that are very close on the same chromosome so that a relatively unrelated trait may be carried forward during evolution because its gene is located physically close to another gene that conveys fitness.

8   But see Noble and Cliff (1996) for a close replication of MacLennan and Burghardt (1993) that did not show an advantage for evolution and learning over evolution alone due to a slightly different population structure that did not allow agents to predict each other as accurately as MacLennan and Burghardt's agents could.

9   Exaptation is the process by which a trait emerges for one purpose and is later used by evolution to perform a different purpose. Archaeopteryx's feathers are one possible example: initially, feathers may have been used for heat radiation and only later became useful for short gliding and finally for flight.

10   A component of the working memory model (Baddeley, 1992), used to store and manipulate about 2 s of speech input.

11   For a critical perspective on this view, see Fodor (1998) and Fodor and Lepore (1998).

Acknowledgments

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