Artificial Life and Higher Level Cognition

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Artificial Life is the study of biological phenomena through their reproduction in artificial systems. Cognition is a form of biological adaptation and it therefore falls within the province of Artificial Life. However, neural network models and Artificial Life simulations of entire ecosystems tend to address simple behaviors and elementary forms of cognition, while it is often thought that higher level (human) cognition is best accounted for using symbol manipulation models that ignore biology. This type of division of work is rejected and it is argued that Artificial Life should be able to simulate higher level cognition by showing how higher level cognition emerges evolutionarily, developmentally, and culturally/historically from lower level cognition. Three directions of research addressing the emergence of more complex forms of cognition are described using ''ecological'' neural networks that live in a (simulated) physical environment: (a) networks that learn to predict the consequences of their actions in the environment; (b) networks that are not passive receivers of input but control in various ways the input to which they respond; (c) populations of networks that evolve language to help classifying environmental inputs in useful categories. Other directions that should be explored are the evolution of modular network architectures that can support more sophisticated cognitive abilities and the role of man-made social, cultural, and technological environments in shaping the form of cognition typical of modern man. © 1997 Academic Press

1. INTRODUCTION

Artificial Intelligence and Artificial Life are two different approaches to an understanding of cognition through its reproduction in man-made systems. Artificial Intelligence views cognition as symbol manipulation and it considers the analysis of cognition without taking into account the physical machine—the brain, the entire body, the external environment—which underlies cognition in real organisms both possible and desirable. Artificial Life, on the other hand, views cognition as a biological phenomenon that must be simulated by using models such as neural networks which are inspired

by the nervous system and by embodying neural networks in (simulated) physical bodies existing in (simulated) physical environments. The theoretical language used by Artificial Life is not made up of symbols and explicit rules for manipulating symbols, as in the case of Artificial Intelligence, but it consists of quantities and changes in quantities (e.g., activation levels, connection weights, etc., in neural networks) as is appropriate for the study of all physical systems.

The difference in how to approach the study of artificial cognition is accompanied by a difference in what is considered cognition. Artificial Intelligence tends to be anthropocentric: cognition is equated with human cognition. Not only is cognition in nonhuman animals almost completely ignored, but Artificial Intelligence tends to concentrate on higher level human cognitive capacities such as language, reasoning, and deliberate planning. In contrast, research within Artificial Life (neural networks) takes the opposite stand of concentrating on elementary cognitive capacities in nonhuman animals and in humans: perception, motor behavior, simple memory and associative tasks.

This difference in current scientific practice is sometimes taken as justification for a sort of theoretical division of work. Higher level human capacities are thought to be best accounted for by symbol manipulation models, while lower level capacities, in both humans and animals, would lend themselves more easily to nonsymbolic, purely quantitative treatments. Organisms such as humans which exhibit both low level and high level cognitive capacities should be modeled as hybrid systems that include both purely quantitative components and symbol manipulation components.

This conclusion is unsatisfactory since it leaves unsolved the problem of what theoretical framework is appropriate for dealing with the various processes of change which lead to the emergence of higher level cognitive capacities from lower level ones. High level and low level cognitive capacities are not simply juxtaposed and coexistent. This is a purely synchronic perspective. In a diachronic perspective higher level capacities emerge evolutionarily, developmentally, and culturally (historically) from lower level capacities. Not only are these processes of change themselves phenomena that a complete science of cognition should be able to describe and explain, but it is not even clear that we can really understand higher level capacities without taking into account how they have emerged from lower level capacities.

Artificial Life is crucially concerned with change in all its forms as a basic biological phenomenon. Hence, its general strategy with respect to higher level cognition is to propose computer models of elementary cognitive capacities as the basis from which more advanced capacities can be shown to emerge through processes of evolution in genetic populations of artificial organisms, development in individual organisms, and cultural change in historical/cultural populations. The Artificial Life literature contains many

descriptions of simulations that try to capture at least some aspects of these various processes of change (Holland, 1975; Langton, Taylor, Farmer, & Rasmussen, 1992; Parisi, Nolfi, & Cecconi, 1992; Belew, 1993; Hare & Elman, 1994; Nolfi, Miglino, & Parisi, 1994; Hutchins & Hazelhurst, 1995; Nolfi & Parisi, 1995; Belew & Mitchell, 1996). Once the theoretical and methodological tools for simulating change at various levels have been mastered, the next step is to investigate in the simulations how higher level cognition can emerge from lower level cognition.

Although the general attitude of Artificial Life with respect to higher level cognitive capacities is sufficiently clear, the tendency has been to explore the lower end of the cognitive continuum rather than the higher, human, end. Artificial Life has offered interesting analyses claiming that cognition can be found in elementary biological phenomena and in systems other than the nervous system. For example, according to Stewart (1993), the immune system can be said to have basic cognitive capacities such as learning, memory, and recognition (cf. also Varela, Coutinho, Dupire, & Vaz, 1988). This tendency of Artificial Life to root cognition in biology and to find elementary forms of cognition in phenomena that we are not used to considering as cognitive appears to be a healthy one in consideration of the narrow, anthropocentric view of cognition that characterizes much research on cognition. However, cognition has a natural history of change and development. Even if the immune system can be said to possess some form of cognition, the evolutionary appearance of nervous systems, the evolution of animal species, and the evolution of human societies have all contributed to the emergence of new and more complex forms of cognition. A complete science of cognition must be able to give an account of all forms of cognition. In particular, an attempt at simulating cognition centered on change must be able to show how the most complex forms of cognition—which, as far as we know, are those exhibited by humans—can emerge through various processes of evolution, development, and historical/cultural change. (Piaget has been perhaps the only psychologist who has embraced this research program that consists of both looking for the biological roots of cognition and at the same time trying to describe how higher level cognition emerges from lower level cognition—although for him emergence was developmental, not evolutionary.)

Within Artificial Life, cognition and behavior tend to be studied by using neural network models. However, classical neural networks (Rumelhart & McClelland, 1986a) are not adequate as tools for studying the emergence of higher level cognition from lower level cognition. Since Artificial Life is the study of all kinds of biological phenomena through their reproduction in artificial systems, neural network models are by definition part of Artificial Life. However, explicitly viewing neural networks as a chapter of Artificial Life has important consequences that tend to make research on neural networks in an Artificial Life perspective rather different from research on clas-

sical neural networks. In this perspective organisms are not modeled simply as neural networks. Artificial organisms include an inherited genotype which maps into the phenotypical neural network through a complex process of biological development. They have a body with a given shape, size, spatial disposition of sensory and motor organs, etc. They live in and interact with a physical environment. They are members of biological and, in some cases, cultural populations. They have a life, i.e., they are born, develop, reproduce, and die.

One particularly important characteristic of neural networks viewed in an Artificial Life perspective is that the networks live and behave in an environment. Classical neural networks rely on an impoverished notion of environment, which tends to be identified with the input and teaching input patterns the researcher presents to the network. Neural networks as part of Artificial Life are ''ecological'' neural networks (Parisi, Cecconi, & Nolfi, 1990; cf. also Wilson's notion of ''animat'' in Wilson, 1991). Ecological neural networks live in a (simulated) physical environment. What is simulated not only is a neural network and what happens inside the network (for example, during learning), but also includes both a neural network and the physical environment in which the network lives and behaves and, especially, the interactions between the network and the environment. It is the environment (not the researcher) that decides what input is received by the network at any given time and, furthermore, the network can act on the environment and change it. We believe that viewing neural networks as ecological networks is a necessary step toward an understanding of higher level cognition.

In the present paper we describe some directions of research which view neural networks in the perspective of Artificial Life and try to identify ways in which more complex forms of cognition can arise in Artificial Life systems. In Section 2 we point out that ecological neural networks have an enlarged temporal perspective that can allow them to learn to predict the consequences of their actions. In Section 3 we show that neural networks are not necessarily passive receivers of input but they can control in various ways their own input—which is critical for the emergence of more complex forms of cognition. In Section 4 we outline how a crucial higher level cognitive capacity, i.e., language, should be tackled by using neural networks viewed as Artificial Life. In Section 5 we draw some conclusions and point out some further directions of research.

2. LEARNING TO PREDICT THE CONSEQUENCES OF ONE'S OWN ACTION

If cognition means to know reality, then neural networks can be said to know reality in a very basic sense since they are able to respond to inputs with outputs which are appropriate to each particular input. To generate the appropriate outputs, neural networks must construct internal (neural) repre-

sentations of the inputs. By progressively adjusting their connection weights through learning at the level of the individual or evolutionary processes at the level of the population, neural networks are able to generate patterns of activation levels on their hidden units which group the inputs in ways that help the network to produce the appropriate output in response to each particular input. Different inputs that must be responded to with the same output are classified together internally in that they evoke the same or similar pattern of activation on the hidden units, while inputs that must be responded to with different outputs tend to be classified in separate classes by evoking different patterns of activation on the hidden units. These patterns of activation can be considered as internal (neural) representations which capture important properties of the inputs (reality). Hence, in this basic sense all neural networks can be said to be cognitive systems.

However, the reality which is known by classical neural networks has almost no temporal depth. It is true that the connection weights that allow a network to construct useful (i.e., adapted to reality) internal representations are the result of past ''experiences'' (of the individual or of the population). This contrasts neural networks with the programmed symbol manipulation systems of Artificial Intelligence. Neural networks are systems that start with zero knowledge and learn or evolve whatever knowledge they possess. Hence, what they know is entirely a function of what has happened to them in the past. Symbol manipulation systems are what they are because some human being has programmed them. Even symbol manipulation systems that learn start from some knowledge which is wired into them by the programmer and they are restricted to changing this initial knowledge.

However, the past is important for classical neural networks only insofar as it has a causal role in determining what they are in the present, but there is no *present* role of the past (or of the future) in these networks. Each activation cycle (input/propagation of activation/output) is a temporal atom with no intrinsic relation to previous or subsequent cycles in that each new input to the network is arbitrarily decided by the researcher. (A partial exception are recurrent networks; cf. below.)

As we have said, unlike classical neural networks, neural networks viewed in an Artificial Life perspective live in an independent (simulated) physical environment. This has one important consequence. If the network's output encodes some movement on the part of the organism that either changes the physical environment or, by modifying the position of the organism or of some of its body parts in the environment, changes the relation of the organism to the environment, then the network can partially control its own input. By changing the external environment or its relation to the environment, the network has an influence on what the next input from the environment will be.

This gives a temporal depth to the behavior of an ecological network which is absent in classical networks. The current input to an ecological

network becomes a function of both the independent structure of the external environment *and* the network's past behavior (the preceding motor output). At the same time, what the network does now (its current output) will have an influence on future behavior (on the next input and on the corresponding output). We conclude that while classical neural networks live in the present only, ecological networks live not only in the present but also in the past and in the future. Hence, their knowledge of reality (their cognition) is richer than that of classical networks.

Classical neural networks can be made more sensitive to the past in their current behavior. Networks with recurrent connections are one way of realizing this sensitivity to the past. One type of recurrent networks are networks that store (copy) their past state (e.g., the activation pattern of their hidden units in the preceding cycle) in some special units (context or memory units) and use this trace of the past along with the current input to choose the appropriate output (Jordan, 1986; Elman, 1990). This clearly extends the temporal depth of their cognition. What they do now depends both on the current state of the environment and on past states (as reflected in the network's past states).

The greater temporal depth which is obtained is manifested in the network's ability to predict the future. If reality has some temporal structure (regularity), a network with recurrent units can incorporate this temporal structure in its connection weights and acquire the ability to predict the next input in a sequence of inputs. The network has some output units which encode a prediction of what the next input will be. The network responds both to the current input and to the stored trace of its own previous states. By using this knowledge of the past the network is able to discover the temporal structure in the succession of inputs as indicated by its ability to predict the next input given the preceding inputs. Clearly, networks with recurrent units have a temporally more extended cognition.

However, classical networks with recurrent connections can learn only about the independent temporal structure of reality. If reality contains temporal regularities these networks can discover these regularities. Recurrent networks demonstrate their acquired knowledge of the temporal structure of reality by predicting future inputs, but the ability to predict future inputs can become a much more powerful cognitive tool in the hands of an ecological neural network. Ecological networks live in an environment and, as we have seen, this allows them to at least partly determine their own input. Consider an ecological network that generates a motor output which changes the external environment or the relation of the network to the environment. This change has as its consequence that some particular input will arrive to the network's input units. For example, the network displaces an object with its ''hand'' and, as a consequence, the network perceives the object in a different position. Or the network rotates its ''eye'' and, as a consequence, some new visual input becomes accessible to the network.

Now, an ecological network can learn to predict the next input on the basis of the current input *and* some planned but not yet executed motor action on its part (Nolfi, Elman, & Parisi, 1994). The network generates a prediction in its output units and, after the action has been physically executed, the network uses the observed next input as teaching input to correct its connection weights and generate better predictions in the future (using the backpropagation learning procedure, cf. Rumelhart, Hinton, & Williams, 1986).

A network that learns to predict the consequences of its own actions has a considerably enlarged knowledge of the world. As suggested by Piaget, we know reality by knowing how reality reacts to our actions. For example, we know the weight of an object by lifting the object and recording the intensity of our effort. We know if an object is breakable by trying to break it. And we know the physical properties of our own body by generating movements that displace our sensors and by observing the resulting changes in sensory input. Therefore, the cognitive powers of a system that can act on the physical environment and can predict the sensory consequences of its own motor actions on the environment (including its own body) are greatly enhanced (Parisi & Cecconi, 1995).

This enlarged knowledge is practically demonstrated when the system must reach some goal, i.e., when it must act to realize some particular state of affairs. By knowing which consequences follow which actions, the system is able to select the particular action that is likely to cause some desired consequence. In other words, the following evolutionary or developmental sequence occurs: first, networks cause changes in the environment or in their relation to the environment (as all organisms do); second, the networks become able to predict the changes caused by their actions (as more advanced organisms can do); third, the networks select some action because they know that this action is likely to cause some desired consequence. This sequence may suggest how intentions may have evolved in organisms.

The beneficial role of the ability to predict the consequences of one's own actions on the ability to cause desired consequences with these actions has been demonstrated in simulations in which ecological networks that must approach some object (food) in the environment are shown to evolve this ability more easily if the networks learn to predict how the position of the object relative to themselves changes as a consequence of their displacements (Parisi et al., 1992; Nolfi, Elman, & Parisi, 1994; for simulations using other tasks, cf. Cecconi & Parisi, 1991; Parisi & Cecconi, 1995).

We believe that being able to predict the consequences of one's own actions is a crucial ability in the evolution of cognition, at least of primate cognition. Human beings possess a very sophisticated knowledge of their physical environment because they are very good at predicting which changes in the environment will be caused by which actions. And they use this sophisticated knowledge to radically change their environment to suit

their needs. Furthermore, human beings develop an ability to predict the consequences of their actions that are independent from the physical properties of both their actions and the objects to which they are applied, and this forms the basis of their logicomathematical knowledge of the world (Langer, 1980, 1986, in press; Antinucci, 1989). Finally, the ability to predict the consequences of one's own actions can be demonstrated not only with respect to the inanimate world but also with respect to the social world. Being able to predict how our conspecifics will react to our actions addressed to them is a critical step in the emergence of a more sophisticated social knowledge. We know other people's minds because we are able to predict their reactions to our actions or to the actions of other conspecifics.

In summary, human beings possess to a greater extent than other animals all sorts of prediction abilities with respect to the consequences of their own actions (although nonhuman primates may be rather sophisticated at least with respect to social actions). And this can explain much of their more complex cognition.

3. NEURAL NETWORKS ARE NOT NECESSARILY PASSIVE RECEIVERS OF INPUT

Classical neural networks are passive receivers of input. An activation pattern is imposed on the network's input units, activation propagates through the network, and the network responds to the input by generating an appropriate activation pattern on its output units. For the network the input is a given. There is no control of the input on the part of the network whose only task is to generate an appropriate output in response to the input. This passive view of cognition is inherited from symbol manipulation models that view cognition as information processing which maps inputs into outputs.

Organisms are not passive receivers of input. They determine in part or completely their own input, and cognition becomes more sophisticated as organisms increase their control over their input. Therefore, by doing simulations with neural networks that in various ways control their own input, we can extend the Artificial Life approach to cognition to more complex and sophisticated cognitive abilities.

We have already seen that ecological networks partly determine their own input by acting on the environment. They change the environment or their relation to the environment and, as a consequence, they influence the kind of inputs the environment sends to their input units.

It can be shown that ecological neural networks use the possibility open to them to control their own input by evolving a two-component strategy in acquiring the ability to respond to the input with the appropriate output. Instead of evolving the ability to respond equally well to all possible inputs (the only strategy available to classical neural networks), ecological net-

works (a) behave in such a way that they tend to restrict the range of inputs to a subset of all possible inputs (self-selection of input) and (b) acquire an ability to respond more appropriately to this subset of inputs (Nolfi & Parisi, 1993a). This can be a more economic strategy, which, among other things, implies that since different networks can self-select different inputs each individual network in some sense lives in its own environment.

Another consequence of being able to control one's own input is that one can generate output with the only purpose to be exposed to useful input. For example, networks can evolve an ability to rotate their (single) ''eye'' so that a previously unseen object becomes visible and the network can then reach the object with its ''hand'' (Di Sano, Cecconi, & Parisi, 1995; Parisi, 1996). Or, if their visual field has a more discriminative central portion (fovea) and two less discriminative lateral portions (periphery), they can generate fine rotation movements of their eye to be able to see an object with their fovea and discriminate good objects from bad object to approach the former while avoiding the latter (Mancuso, Cecconi, & Parisi, 1994; Parisi, 1994).

In other simulations networks have been shown to evolve a tendency to move in the environment in such a way that they are exposed to input which is useful for learning. For example, networks can learn by imitating other networks (Hutchins & Hazelhurst, 1995; Denaro & Parisi, in press). Both the learner and the teacher are exposed to the same input and the learner takes the output of the teacher as its teaching input to learn by using the backpropagation procedure. Networks that must learn by imitating other networks evolve a tendency to move in the environment in such a way that they tend to remain near their teacher if proximity to the teacher is necessary to be able to observe the output of the teacher and learn from it (Parisi, Piazzalunga, Cecconi, & Denaro, 1994).

Complex organisms can influence or control their input not only by physically moving in particular ways but also by selectively attending to different portions of the input. In selective attention an organism receives an input made up of various parts. The organism reacts to the input by generating an output that depends on some part of the input while the remaining part of the input is ignored; i.e., it has no role in determining the output.

Selective attention can be simulated in simple neural networks. For example, a network is given some input encoding both the form and the color of an object. The network is also given a command (another input) to generate some output describing either the form (e.g., circle or square) or the color of the object (e.g., red or blue). The network can learn to selectively attend to the input by making its output dependent on either the portion of the input which encodes the form of the object or the portion that encodes its color as a function of the particular attentional command. Hence, the network is not a purely passive receiver of the input but it plays an active role in selecting what part of the input is to be taken into consideration in choosing the

output (i.e., is to be attended to) and what part must be ignored (Campeti, 1994).

In these simulations the attentional command comes from outside and therefore the network can be said to be controlled from outside in its selective attention. In other simulations it has been demonstrated that ecological neural networks can selectively attend to either food or water as a function of their motivational (internal) state (hunger or thirst) (Cecconi & Parisi, 1993). The motivational state is encoded in a set of special internal units that send their connections to the hidden units and therefore control the motor output together with the environmental input. The network always perceives both food and water but it chooses to approach food and ignore water or vice versa depending on whether it is hungry or thirsty. The motivational state in turn depends on the network's behavior since hunger disappears with eating and thirst with drinking. Therefore, these networks possess a selective attention mechanism which is internally controlled.

A more sophisticated mechanism of active control of one's own input is the internal self-generation of input. The (sensory) input to ecological networks comes either from the external environment or from the network's own body (or from both). A crucial step in the evolution of cognition is when actions become internalized and inputs are self-generated inside the neural network. Normally, an organism acts on the environment by physically executing motor actions and these actions have sensory consequences for the organism. More sophisticated organisms, and especially human beings, appear to possess a capacity to internalize these actions, i.e., to self-generate sensory input without actually executing motor actions. This can be simulated by neural networks with output units that directly feed back their pattern of activation to the network's input units with no generation of physical movement and no intervention of the environment. These networks can be said to ''imagine'' some state of affairs.

For example, networks can evolve an ability to reach a particular food zone in their environment by regulating their movements on the basis of sensory input emanating from some fixed landmark present in the environment (landmark navigation) (Treves, Miglino, & Parisi, 1992). Let us hypothesize that in some occasions (i.e., in some input/output cycles) the landmark cannot be perceived. In these occasions the network lacks any external sensory input that can guide its navigation toward the food zone. However, in addition to the motor output units that control the network's movements in the environment the network possesses some additional *output* units which encode the changing position of the landmark. We can call these output units ''imaging'' or ''imagining'' units. They are very close to the ''prediction'' output units of the preceding section. When the landmark is normally visible, the input (sensory) units of the network use the information coming from the environment, i.e., from the physical landmark. However, when the land-

mark is not visible the input units receive the information self-generated by the network itself in its imaging units. It can be shown that neural networks can evolve an ability to generate useful imaging behavior. In other words, the position of the landmark is correctly monitored in the networks' imaging units and this internally self-generated information can be used by the networks to do landmark navigation even when the physical landmark is not visible (Miglino & Parisi, 1994).

It is interesting to speculate on what might happen when the ability to predict the consequences of one's own actions (cf. the preceding section) is found in the same networks that are also able to internally self-generate their own input. Given a present (perceived) state of affairs in the environment a network can plan some particular motor action. The motor action is encoded in the network's motor output units but is not physically executed. The planned action is then copied in the network's input units and the network generates a prediction about the state of affairs which would result if the planned motor action were physically executed. These predicted consequences (a pattern of activation of the prediction output units of the network: cf. the preceding section) are fed back to the network's sensory input units. Now the network lives in an imagined (or imaged) world. The network can plan a second action in this imagined world and predict the consequences of this second action. The process can be repeated for a certain number of cycles. This would be the beginning of simulating important human abilities such as reasoning and deliberate planning (Rumelhart, 1989)—although in humans these abilities may be accompanied by or require language (cf. the next section).

Another line of speculation (that could, it is hoped, become a line of simulation) concerns the ability of complex organisms, especially humans, to reason before acting. Ecological networks basically are systems that act. They respond to sensory input by executing motor actions. However, humans, at least on some occasions, appear to be able to respond to sensory input by first reasoning and then possibly acting. Can this ability to reason before acting be simulated using neural networks?

Since Thorndike's ''law of effect,'' psychologists have recognized that the probability that an organism will respond to some input with some motor output will change over time as a function of the perceived consequences of the motor output. The perceived consequences of some motor action can either increase or decrease the probability that the organism will respond with that motor action to that sensory input in the future. If the probability increases, the consequences are called ''reinforcement'' (or ''reward''). If the probability decreases, the perceived consequences of the motor output are called ''punishment''.

The neural network literature includes another type of supervised learning algorithm in addition to the better known backpropagation algorithm. This is the reinforcement learning algorithm. The network is given an input and

it reacts by generating probabilistically some output. The output is examined by the researcher, who, instead of providing the network with the correct output as in the backpropagation procedure, provides the network with a teaching input which is either 1 or 0. This number is the reinforcement signal. The reinforcement learning algorithm changes the network's connection weights in such a way that the same output is more likely to be produced in future occasions if the reinforcement signal is 1 and less likely if the reinforcement signal is 0. (For a recent review of reinforcement learning, cf. Kaelbling, Littman, & Moore, in press.)

The obvious question is: Where the reinforcement signal comes from? When the reinforcement learning algorithm is applied to classical neural networks, it is the researcher who decides which input/output pairs should be reinforced and which should be weakened (punished) and who provides the network with the corresponding reinforcement signals. However, real organisms do not usually depend on an external teacher when they learn using the reinforcement procedure (or the backpropagation procedure). They self-generate their own reinforcement signals. They respond to some sensory input with some motor output. The motor output has some consequences that are perceived by the organism. The organism is able to judge these perceived consequences of its own actions by self-generating a reinforcement signal that either increases or decreases the probability that the organism will respond to that sensory input with that motor output in future occasions.

How can we construct an artificial organism which will be able to self-generate its own reinforcement signals? Imagine that the organism's nervous system is modeled by a pair of neural networks. The first network is the usual network that receives sensory input from the environment and responds by generating motor actions. The second network is a special network. When the first network has responded to the current sensory input from the environment with some motor action and the action has been physically executed, the motor action will have some consequences that will result in some new sensory input for the organism. This new sensory input that results from the organism's motor action constitutes the input to the second network. The second network responds to this input by generating a number that can vary from 0 to 1. This number is a reinforcement signal. It is used by the first network to change its connection weights using the reinforcement learning algorithm.

How can we determine that the second network will be able to generate good reinforcement signals? We have done some simulations in which the second network takes as input the same sensory input from the environment which is the input for the first network and generates an encoding of a motor action (Nolfi & Parisi, 1993b). However, the motor action generated by the second network is not physically executed but is used by the first network as teaching input for learning using the backpropagation procedure. In our

simulations it has been shown that in a population of neural networks that reproduce as a function of the goodness of the motor actions generated by the first, not the second, network, the second network evolves connection weights that allow it to generate good teaching input for the first network. After a certain number of generations, while the first network is unable to find food already at birth, by using the teaching input generated by the second network the first network is able to learn this ability in the course of its life. In other words, we have been able to evolve networks that can self-generate the teaching input appropriate for backpropagation learning.

The same approach can be used to evolve neural networks that are able to self-generate the teaching input appropriate for reinforcement learning. The reproductive chances of an individual depend on the motor behavior generated by its first network but this motor behavior is not genetically inherited. The individual will not be able to exhibit a good food finding ability at birth. Instead, the connection weights of the second network which is also part of the nervous system of these individuals will evolve in such a way that the second network will increasingly be able to generate good reinforcement signals for the first network based on the observed consequences of the first network's behavior. By using these self-generated reinforcement signals to learn how to respond to sensory input and generate the appropriate motor actions, the individuals of the later generations will be able to look efficiently for food as their learning proceeds. On the basis of previous work by Ackley and Littman (1992), Batali and Grundy (submitted for publication) have been able to study the evolution of various network architectures that self-generate their own reinforcement signals.

Once we have evolved artificial organisms that can self-generate their reinforcement signals, we can put together this ability of self-generating one's reinforcement signals and the ability to predict the consequences of one's own actions to evolve organisms that are able to reason before acting. Imagine an organism that receives some sensory input from the environment. The organism responds by generating an encoding of some motor action. The motor action is not physically executed, however, but together with the environmental input it constitutes the planned motor action that the network uses to generate a prediction about the sensory input resulting from the action (cf. section 2). Then the predicted consequence of the planned motor action is given as input to the second network that self-generates reinforcement signals. The reinforcement signal generated by this network, however, is not used by the first network to learn, as it was in the preceding scenario, but it is used to decide whether the planned action should be physically executed or not. An organism such as this would be able to evaluate the consequences of its possible actions before actually executing these actions and it would execute only those planned actions that have received a good evaluation, i.e., that have elicited a reinforcement signal of 1 instead of 0. This organism could be said to be able to reason before acting.

4. LANGUAGE

Language is the prototypical human ability which is both ''advanced'' and certainly based on symbol manipulation. Furthermore, language has been rather successfully studied using the symbol manipulation paradigm by generative linguists, cognitive psychologists, and students of Artificial Intelligence. It represents therefore a great challenge for the alternative paradigm of neural networks and Artificial Life. In fact, many interesting simulations of the learning of linguistic abilities using neural networks have been done since the beginning of connectionism (or neoconnectionism) in the 80s (Rumelhart & McClelland, 1986b; Sejnowski & Rosenberg, 1987; Elman, 1990; cf. also Reilly & Sharkey, 1992). The results of these simulations suggest that some of the problems posed by symbol manipulation models of language can have different answers from those offered by these models. For example, some aspects of language can be acquired by systems such as neural networks that do not manipulate symbols but quantities at their basic level of functioning. Or complex linguistic abilities can be acquired on the only basis of experience by systems which begin their learning as a ''tabula rasa'' (cf. the initial randomly generated connection weights used in network learning), i.e., with no innate basis.

However, an Artificial Life approach to language should try not only to give alternative answers to the same research questions posed by symbol manipulation models but also to make an effort to pose different questions. In other words, Artificial Life should change the research agenda with regard to language (Parisi, in press-a).

A crucial difference between language simulations that use classical neural networks and Artificial Life simulations is that simulations with classical networks tend to simulate laboratory experiments using linguistic materials and tasks while Artificial Life simulations should simulate the real life conditions under which organisms evolve a language at the population level and acquire and use it at the individual level. Simulations with classical neural networks tend to reproduce the controlled situations of the experimental laboratory and to train networks with tasks that resemble artificial laboratory tasks. While the laboratory can be a necessity if one wants to obtain reliable and controlled results with real organisms, the situation is different if one is doing simulations and studying artificial organisms. Simulations necessarily simplify but one can choose to simulate whatever one is interested in. Unlike classical connectionist simulations, Artificial Life simulations with ecological neural networks tend to simulate not laboratory experiments but real, even if simplified, ecologies.

This issue is crucial with regard to language. Language evolves, is acquired, and used in a rich context which tends to be ignored in psycholinguistic experiments and in the elicitation of ''linguistic intuitions'' by linguists. Language results from complex evolutionary, developmental, and cultural/

historical processes that cannot be investigated in the experimental labora-
tory or in simulations such as those of classical connectionism that simulate
the experimental laboratory. It is this rich context and these complex pro-
cesses of change underlying language that must be the object of Artificial
Life simulations. This is especially critical if one is interested in how lan-
guage contributes to the type of higher level cognition that characterizes
humans. More specifically, language, and communication generally, is a kind
of behavior that typically tends to change the (social) environment in which
the language-producing individual lives and behaves. Hence, language can-
not be studied in artificial systems such as classical networks that do not
have an environment.

A first step in a program of Artificial Life simulations concerning language
is the study of the emergence of communication in populations of networks.
Communication is the generation of some motor output on the part of one
network which results in some sensory input for another network. This sen-
sory input (the ''signal'') is not simply a by-product of the motor behavior of
the first network. Networks must evolve a tendency to produce such signals
because the networks that produce the appropriate signals in the appropriate
circumstances tend to have more reproductive chances than noncommunicat-
ing networks. Furthermore, the behavior of producing signals must co-evolve
with the behavior of understanding the signals on the part of the receiving
network. Receiving networks must evolve a capacity to react to the received
signals with output which is appropriate to the particular signal (Werner &
Dyer, 1992). The two behaviors, producing the appropriate signals in the
appropriate circumstances and reacting to the received signals in the appro-
priate manner, co-evolve in the sense that neither behavior can increase the
reproductive chances of the individuals exhibiting it if the other individuals
do not exhibit the complementary behavior.

When a signal is produced and is received, it is likely that some other
input from the environment (including the producer's and receiver's bodies)
is also experienced by the networks involved, each particular signal having
the tendency to be accompanied by some particular input or class of inputs.
This additional input is the ''meaning'' of the signal. Or, more precisely,
the accompanying input or the aspect of the environment which has physi-
cally caused the accompanying input is the ''referent'' of the signal, and the
internal representation of the accompanying input (its neural representation
inside the network; cf. section 3 above) is the signal's ''meaning.''

Organisms may start producing and understanding signals when the ac-
companying sensory input is present but then they may become able to pro-
duce and understand the signals also when the accompanying sensory input
is absent. This property of signals of functioning as substitutes of aspects of
the experience is one of the reasons that explain why they tend to emerge
in a population of organisms (neural networks). For example, it has been
shown that if two different signals accompany the perception of various ob-

jects that must be classified in two different classes in order to respond differently to the two classes (say edible and poisonous mushrooms), the signals can elicit the appropriate behavior even when the objects are not perceived well enough for the organism to be able to discriminate between them based on their perceptual characteristics (Cangelosi & Parisi, submitted for publication).

However, signals can be important for the purpose of classifying reality appropriately even if they are used together with the accompanying sensory input to which they refer. As already noted at the beginning of section 2, neural networks tend to put different inputs in the same class, i.e., to generate a common internal (neural) representation in order to respond to all the inputs in a class with the same output. Language can have a crucial role in this type of classificatory behavior. Consider a population of networks that live in an environment containing both food elements (say, edible mushrooms) and dangerous elements (poisonous elements). The food elements cause an increase and the dangerous elements a decrease in reproductive chances when a neural network happens to step on them. The behavior which is likely to evolve in this environment is approaching the food elements and avoiding the dangerous elements.

However, if the food elements are not all identical and the same is true for the dangerous elements, the networks must evolve two abilities, not just one. They must be able to discriminate the food elements from the dangerous elements by classifying them in two separate classes and they must be able to respond with the appropriate behavior to each of the two classes of objects (approaching vs. avoiding). This more complex behavior will also evolve but, quite predictably, it will evolve with more difficulty than if the food elements are all identical and the dangerous elements are also identical, although different from the food elements. However, if the perception of some particular food element or dangerous element is accompanied by the simultaneous perception of a signal which is different for food and for danger but is the same for all food elements and for all dangerous elements, the evolutionary emergence of the more complex behavior will tend to be facilitated. The two signals stabilize the two classes and make it easier to recognize (discriminate or classify) foods and dangers in order to respond appropriately to each distinct class of objects (Floreano, Miglino, & Parisi, 1991).

It is interesting to ask where these signals perceived by the individual together with the environmental input come from. We can imagine that they are the result of the motor output of another network. The second network is able to produce the appropriate signal in the presence of the appropriate sensory input (the physical appearance of the perceived food or danger) and is also willing to help the first network to classify reality. However, while the advantages that cause the evolution of the capacity to respond to the signals appropriately (signal understanding) are sufficiently clear, one should ask what are the reproductive advantages that cause the evolution of the

behavior of producing the appropriate signals in the appropriate circumstances (signal production). One possible answer is in terms of inclusive fitness (Hamilton, 1964). Even if the behavior of producing the appropriate signals does not directly increase the reproductive chances of the signal-producing individual, this behavior may evolve in the population because it increases the reproductive chances of another individual who has the same genes as the signal-producing individual (Oliphant, 1994), or, in a population in which signals are exchanged among nongenetically related individuals, the behavior of responding to some input by producing the appropriate signal can be a by-product of the cognitive ability to classify the environmental inputs into appropriate classes (Cangelosi & Parisi, submitted for publication).

Of course, the production of the appropriate signals in the appropriate circumstances can be useful for the signal-producing individual for many other reasons, such as functioning as a means for obtaining some desired information or action on the part of the signal-receiving individual. These other reasons can also explain its evolutionary emergence. However, what is critical if we are interested in human language is that while a generic predisposition to learn a language may be genetically evolved and inherited in humans, each human language is culturally rather than genetically inherited. Hence, to deal with human language, we must first be able to simulate the cultural inheritance of behaviors in populations of neural networks.

Cultural inheritance can be interpreted as learning from others, from their behaviors, and from their artifacts. A neural network model of learning from the behavior of others is a neural network that learns by using as its teaching input the output of another network (the model or teacher) in response to some shared input (Hutchins & Hazelhurst, 1995; Denaro & Parisi, in press). By changing its connection weights to reduce the discrepancy between its own output and the output of the model (backpropagation learning), a neural network will progressively learn to approximate the model's behavior.

This model of learning from others can be applied to the learning of language. The linguistic signals are produced by an ''adult'' network which already knows the language. The signals are produced in presence of some input (the referent of the signal) which is shared with the ''young'' network, which must still learn the language. The young network learns to produce the same output (signal) as the adult network in response to the same input. Hutchins and Hazelhurst (1995) have shown how a system of shared labels for entities in the environment can emerge in a population of neural networks in which each individual functions as a teacher for all the other individuals.

If language can be transmitted culturally from one generation to the next, it can also evolve culturally if transmission (cultural reproduction) is selective and the language that an individual transmits to another is not identical to the language inherited by the first individual. In fact, it can be shown that population of networks can evolve new adaptive behaviors if only the best

individuals in each generation become the ''teachers'' or ''models'' for the next generation (selective cultural reproduction) and if some random variation is applied at the moment of the copying of the teacher's behavior on the part of the learner (Denaro & Parisi, in press). Hare and Elman (1994) have shown how language can change from one generation to the next due to accumulated variations in transgenerational transmission in ways that resemble actual historical changes.

Of course, cultural evolution happens not only because of the existence of random variation in the transmission process but also because the individuals of one generation innovate in a more goal-directed way and transmit their innovations to the next generation. Hence, culturally inheriting a language means to incorporate in one's behavior the accumulated experience of many preceding generations, which cannot but increase the complexity and the powerfulness of human cognition across time.

Notice that after a network has learned to produce the appropriate linguistic signals in the presence of the appropriate referents, it not only can teach the language to some other network but can also use the language for itself. This can be a most important function of language from the point of view of cognition. If classifying the world is helped by linguistic signals (cf. above) it might be useful for a network that must classify the world to first apply linguistic signals as labels to inputs and then to respond to labeled rather than unlabeled inputs. Labels can stabilize classes of inputs even if they are self-generated rather than received as signals from other networks.

The critical role of language for the development of higher level cognition becomes even more evident when one reflects that language can be much more complex than merely a system of one-to-one correspondences between signals and classes of inputs. The correspondences are likely to be many-to-many. The same signal can be associated with different classes of inputs in different occasions (the signal ''red'' associated with a red car and with a red ball) or two different signals can be associated with the same class of inputs (the two labels ''red'' and ''car'' associated with a red car). Other complexities may emerge if not a single signal but a sequence of signals (say, a sentence) is associated with the same ''referent'' (object, scene, or situation), and the individual signals that compose the sequence can be found in other sequences associated with partially different objects, scenes, and situations, in other occasions. Furthermore, the order in which the individual signals follow each other in a sequence may be critical for determining the referent with which a sequence is associated (syntax) and special signals may be found in these ordered sequences of signals that help the receiver associate the correct referent with the particular sequence (morphology).

If an Artificial Life approach to language is to be successful, it is crucial that neural networks be shown to have the ability to acquire these more complex signaling behaviors (on both the production and the understanding side) and to be able to generalize whatever behaviors they have acquired to

new situations to capture the ''generativity'' intrinsic to language. (Acquiring language in the ''real life'' ecologies of Artificial Life simulations may help overcome the limits of classical neural network simulations in capturing language's systematicity and compositionality since an ecological network can use various sources of information in addition to the information contained in the linguistic signal, i.e., referential, pragmatic, and social information, in dealing with the linguistic signal; cf. Hadley, 1994.)

A further step toward the complexity of human cognition can be represented by a merging of the ability to generate language for oneself with the ability to self-generate input without executing motor actions (cf. section 4). The production of linguistic signals normally results from motor (phono-articulatory) actions. Talking to oneself can become thinking if one can self-generate linguistic signals without actually executing the corresponding phono-articulatory motor actions. (Thinking, however, can include visual and other self-stimulation, not only self-generated language; cf. the ''imaging'' networks of section 3.) In any case, the adaptive importance of language for oneself—in either its physical or its purely internal form—becomes evident if one reflects that language may have evolved in the phylogeny of the human species not only for its adaptive value in internetwork communication but also for its adaptive value for the individual in dealing with a linguistically labeled rather than with a ''raw,'' unlabeled reality (cf. our comments above on self-generating linguistic labels for classificatory purposes).

4. CONCLUSION

Simulations using biologically inspired models have so far been concerned mostly with elementary cognitive abilities. Higher level cognition such as that which characterizes human beings tends to be considered as beyond the reach of neural network and Artificial Life models and to be more appropriately dealt with using symbol manipulation models that ignore the physical and biological underpinnings of cognition. This article has rejected this division of work between biologically inspired and symbol manipulation models. Artificial Life is an attempt at simulating all sorts of biological phenomena and this includes the forms of cognition typically found in humans. Therefore, Artificial Life simulations must simulate not only simple organisms and elementary behaviors but also complex organisms and higher level cognitive abilities.

Artificial Life approaches the study of cognition like that of other biological phenomena using a developmental framework which tries to simulate the processes of change that lead to the emergence of particular phenomena. It is therefore perfectly appropriate that neural network models and Artificial Life simulations of entire ecosystems begin by addressing simple behaviors of simple organisms in simple environments. However, it must then be shown that these simple models and systems can be gradually extended to cover more complex behaviors and forms of cognition.

To use neural networks as models of higher level cognition, it is crucial that neural networks be explicitly viewed in the perspective of Artificial Life. This paper has concentrated on one particular implication of this perspective, i.e., on the need to simulate both the organism (the neural network) and its environment and to study the two-way interactions between them. Classical connectionist networks live in a void or, at best, in a simulated laboratory completely controlled by the researcher. Ecological networks live in a (simulated) physical environment and they can in part control their environment. This is crucial since higher level cognition may have emerged as a form of adaptation which consists of changing the environment to which the organism must adapt rather than only adapting to the environment as it is (Pedone & Parisi, 1996).

The Artificial Life study of higher level cognition is still in its early stages. (Psychologists are perhaps the least represented subcommunity in the community of Artificial Life.) However, some work has been done. In this paper we have reviewed three directions of research that try to identify ways in which the behavior of neural networks can become more complex.

A first direction of research consists of trying to extend the temporal perspective through which neural networks view reality. Ecological networks respond to input which is in part determined by their past behavior and react to this input with output which will determine their future input and, therefore, their future behavior. Hence, unlike classical networks which live in the present only, ecological networks live also in the past and in the future. Since ecological networks determine their next input with their present output they may learn to predict the future consequences of their own actions. This may be the basis for the emergence of intentionality in that in order to reach some goal an ecological network may generate some behavior because it can predict its consequences (the goal).

A second direction of research focuses on neural networks as active determinants of their own input. Classical neural networks are passive receivers of input. What is expected from them is that they respond to some externally imposed input with the appropriate output. Neural networks viewed in an Artificial Life perspective control in various ways the input to which they must respond. As we have just seen, this is intrinsically true for ecological networks since ecological networks can at least in part determine their next input with their output. Selective attention is another mechanism for controlling the input to which one is responding. The network decides which part of the current input should be taken into consideration for selecting the output to be generated and which part of the same input should be ignored. The attentional command can come from outside but it can also be internally generated, for example, in the form of a motivational state.

A further degree of autonomy from the external environment is reached when a neural network self-generates internally its own input without any role of motor behavior and of the external environment. We have briefly described simulations in which neural networks generate their own sensory

input which turns out to be functional for the network's adaptation to the environment. This may represent a primitive form of imaginative behavior. If neural networks can predict the sensory consequences of their planned actions and they can imagine these consequences as self-generated activation patterns to be fed to their sensory input units, this may be the basis for further planning and reasoning about action prior to any physical action. Furthermore, networks that can evolve a capacity to self-generate their own reinforcement signals may be able to evaluate the predicted consequences of their actions on the basis of these self-generated reinforcement signals and decide whether to physically execute a planned action or not—a form of reasoning before acting that may characterize advanced cognition.

Third, we have turned our attention to language as an essential component of human-level cognition and we have tried to outline some steps of an Artificial Life approach to the simulation of language. (For a more detailed consideration of language in an Artificial Life perspective, cf. Parisi, in press-a.) An Artificial Life approach to language is rather different from the connectionist simulations of linguistic behavior that have been done since the renaissance of connectionism. The main difference is that while in classical connectionism language is simulated as a set of laboratory tasks with little reference to the actual functioning of linguistic behavior in real life, Artificial Life starts with simplified ecologies in which language plays a role in determining the adaptation of the organisms living in those ecologies.

The Artificial Life study of language begins with animal communication and the evolutionary emergence of the behaviors of producing and understanding signals in that these behaviors increase the reproductive chances of the individuals exhibiting them. The next step is to study the role of language in dealing with the environment and, more specifically, with classifying the environment in order to generate appropriate responses. Linguistic labels can help discriminate between stimuli that must receive different responses and recognize stimuli that must be responded to in the same way. Human languages are very complicated systems of labels with many-to-many correspondences between labels and classes of inputs, ordered sequences of labels, and an intrinsic generativity for dealing with new inputs. An important test of neural networks and Artificial Life models as models of higher level cognition is whether these models will be able to simulate the emergence of behavioral repertoires of this complexity.

Both the communicative and the cognitive/classificatory functions of language can explain why and how language has emerged evolutionarily. However, language has both biological–evolutionary components and cultural–evolutionary components. Artificial Life has sophisticated tools for simulating genetic transmission and biological evolution in populations of neural networks but it has only begun to approach cultural evolution. Cultural evolution requires a model of cultural transmission. Cultural transmission can be simulated by neural networks that learn by using the output of another

network as their teaching input. Given this model of cultural transmission, one can simulate how language is transmitted from one generation to the next, how it changes in successive generations, and how the accumulated changes due to the experience of past generations can empower how the individual cognizes and deals with reality.

The three research directions we have briefly reviewed in this paper do not exhaust the possibilities that must be explored by Artificial Life models to deal with higher level cognition. For example, neural networks tend to have very simple and homogeneous network architectures, while the strength of the human brain in supporting advanced cognitive abilities seems to reside not only in the sheer (large) number of neurons and synaptic connections but also in its complex modular architecture. However, the space of possible network architectures is so large that it is impossible to find interesting architectures by simply designing and trying them. Artificial Life suggests that we use genetic algorithms to evolve network architectures appropriate for organisms that must possess sophisticated cognitive abilities to survive and reproduce. For example, complex evolved modular architectures may be critical for facilitating selective attention and the learning of behavioral repertoires with properties of systematicity and compositionality.

Another important issue is whether human cognition can be explained entirely in biological terms, that is, by looking inside the body of the organism and by considering the interactions of the organism with the physical environment, or whether it is necessary to pay attention to extrasomatic but not purely physical factors such as the social, cultural, and technological environment. Artificial Life is the simulation of biological phenomena, but human cognition may have evolved via its interactions with structures and phenomena that are traditionally studied by the social sciences. Social organizations (e.g., for resource sharing) that go beyond the immediate kin group, the emergence of institutions for rule enforcement, cultural transmission through artifacts, the emergence of symbolic artifacts, etc., characterize the human environment at least since the Upper Paleolithic (Mellars, 1989). Human cognition as we know it is likely to have been shaped by this man-made environment as much as by the natural environment we share with the other animals. Even if these are not phenomena that fall within the province of biology, we expect Artificial Life simulations to be able to address the co-evolution of human cognition and these more complex environments. (For some Artificial Life simulations that address some aspects of human societies, cf. Cecconi & Parisi, in press; Parisi, in press-b.)

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