Evolution of Communication Using Symbol Combination in Populations of Neural Networks

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Abstract

This paper uses a model of neural networks and genetic algorithms to simulate the evolution of communication in populations of evolving neural networks. It focuses on the emergence of simple forms of syntax, i.e. the combination of two symbols. The simulation task resembles Savage-Rumbaugh & Rumbaugh's experiment [11] on ape language and symbol acquisition. The simulation results show the evolution and cultural transmission of languages based on combination of grounded symbols. The model is analyzed according to the issues of the symbol grounding and symbol acquisition problems.

1. Introduction

Computational models using genetic algorithms, neural networks, and robotics, have been used for studying the evolution of language and communication [13]. Some models [2,10] have used neural networks and genetic algorithms for simulating the emergence of single-word languages. For example, organisms controlled by neural networks evolve a shared lexicon of two signals for naming two different types of food sources [2]. In other studies [4,12], agents use signal-meaning matrices for communication games. At the beginning of evolution all signals are randomly associated to all possible meanings. During evolution adaptive pressure only strengthens associations between one signal and one meaning. Communication games have also been used for originating meanings and language in groups of real robots [14]. Other modeling approaches have focused on the dynamics of syntax evolution. For example, the role of the Language Acquisition Device for learning artificial grammars has been studied [8].

This paper focuses on the emergence of simple forms of syntax. It will describe the simulation of the early stages of the evolution of syntax with the combination of two symbols. In particular, the model studies the evolution of two-symbol combinatorial rules that resemble the "action-object" structure. The spontaneous production of this syntactic rule has been observed in ape language studies. Greenfield and Savage-Rumbaugh [6] report that the chimpanzee Kanzi, whilst learning to communicate with experimenters through a keyboard of visual symbols (lexigrams), incidentally "invented" the syntactic rule of "action-object". For example, Kanzi used symbol combinations to express messages such as "Hide-Peanut" or "Grab-Kanzi". This experimental evidence suggests a possible role of combinatorial syntax in the early stages of language evolution.

Modeling of the evolution of syntactic languages, and their reference to animal language studies, is related to the problem of symbol acquisition. Deacon [3] states that the main difference between animal communication and human language relies on the acquisition of symbolic references, and in particular on the fact that animals have problems acquiring symbolic associations. Animals only learn associations between meanings and words through conditional learning. Instead, symbolic associations in human languages have double references, one between the word (symbol) and the object, and the second between the symbol itself and other symbols. According to Deacon this difference explains why no form of "simple language" has been found in animals. The missing gap between human and animal languages can therefore be explained by the symbol acquisition problem. Our model addresses the evolution of early forms of syntactic languages that can be related to the simulation of the missing animals' "simple languages". Model analyses will establish whether the type of associations learned by organisms are symbolic.

2. Method

Genetic algorithms and neural networks are combined together for studying the evolution of communication. This simulation method, called ECONET (Ecological Neural Network), was proposed by Parisi *et. al.* [9] to model populations of virtual organisms that live in an environment. ECONET models are used to study the interaction of evolutionary, behavioral, social, and cognitive factors. In our simulation a population of 80 organisms have to perform a foraging task by collecting "edible mushrooms" and avoiding "toadstools". In the environment there are 6 types of mushrooms, three edible and three poisonous. Once an edible mushroom is approached, organisms have to identify its type in order to gain fitness. As toadstools must be avoided, no further classification of their type is required. These foraging stimuli resemble those in Savage-Rumbaugh & Rumbaugh's study on ape language [11]. In their experiment chimpanzees were fed through a vending machine that could "give" solid foods and "pour" drinks. Therefore animals had to learn not only the names (lexigrams) for the single foods/drinks but also a lexigram for the different types of solid foods to be "given" and another lexigram for different types of liquid to be "poured".

Organisms live in a 2D environment of 100 by 100 cells. At the beginning of each epoch there are 1200 randomly distributed mushrooms, 200 per category. During one epoch every organism performs 50 actions. Each organisms lives for 20 epochs, 1000 actions. A mushroom is characterized by a binary string of 18 features. These features will be used by the organism's neural network to identify the mushroom type and appropriate action. A set of 3 binary features always set to 1 identifies the mushroom category whilst the remaining bits are either 0 or 1. Therefore, the 200 mushrooms of each category share a common binary prototype. When this 18-bit string is input to the organism's neural network, the mushroom should be classified into one of the six categories.

Each time an organism collects an edible mushroom, its fitness is increased by one point if the correct category of mushroom is identified. Identification is based upon the level of activation of one output unit. When a toadstool is collected, the fitness decreases by one point. At the end of their lifetime the fittest 20 organisms are selected and reproduce 4 offspring each. The organism's genotype made up of the neural network's connection weights. Ten percent of each offspring's connection weights are randomly mutated.

A 3-layer feedforward neural network controls the behavior of the organism (Figure 1). In the input layer, 3 units encode the location of the closest mushroom and 18 units encode their binary features. Eight input units are used for the 8 symbols (words) used for naming mushrooms. The network has 5 hidden units. In the output layer, 3 units control the organism's behavior (movement and identification of mushroom category), and 8 units are used to encode the mushroom names. These symbolic output units are organized in two clusters of competitive winner-takes-all units (one cluster of 2 units, the other of 6 units). Since only one unit per cluster can be active, each mushroom will be named using two symbols.

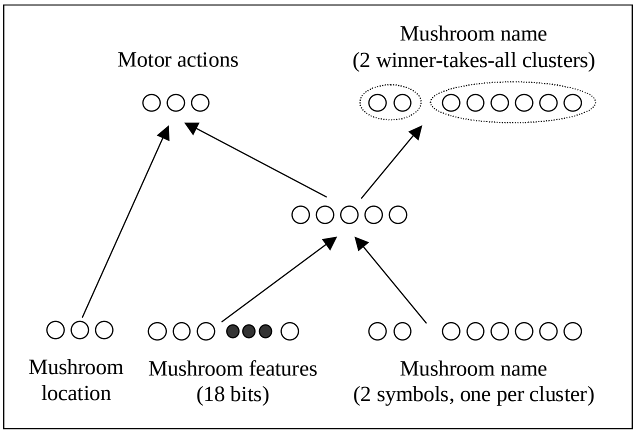

Figure 1: Neural network architecture

During the first 300 generations organisms evolve the ability to differentiate between the 6 types of mushrooms. Organisms do not communicate and do not use the 8 symbolic input and output units. Only the closest mushroom's location and the 18-bit feature string are available as input.

From generation 301 to 400 organisms can communicate by using the 8 linguistic input/output units. During these generations the new 80 organisms live together with their 20 parent organisms. Only the 80 offspring will forage and reproduce. The parents serve as speakers and teachers for naming the mushroom categories. During each action, the parent network receives the 18-bit feature as input and produces two output symbols describing the mushroom. These symbols are used as input to the child's neural network. Ten percent of the time the child receives the 18-bit string as input. This is to facilitate the evolution of good languages as the availability of the mushroom features is rare. Therefore, the parent's linguistic description becomes an important source for discriminating between mushroom categories. The child's network uses the parent's symbols not only to decide what action to perform but also to imitate the parent's description through backpropagation. The parent's two-symbol string is the teaching input. Some random noise is added to the error between the child's output symbols and the parent's output symbols to introduce variability in the process of cultural transmission [5].

3. Results

The simulation from generation 1 to 300 was repeated 10 times, using different initial random populations (i.e. neural networks with different random weights). At generation 300 the foraging task fitness in 9 out of 10 populations reached an optimal level. Indeed, analysis of the behavior of the best organisms shows that all toadstools were avoided and all edible mushrooms were approached and correctly identified.

The 9 successful populations are used in the second stage of simulation from generation 301 to 400. In this stage, communication is permitted and organisms can learn how to name mushrooms from their parents. Forty-five different simulations were performed (9 populations *5 initial random lexicons). In 20 of the 45 runs the evolution of communication was successful since each organism evolved a good language. In fact, they use at least 4 symbols, or 4 symbols-combinations, to distinguish the 4 functional categories of mushrooms (the toadstools + the three types of edible mushrooms). In the remaining 25 runs the evolved languages have signal mismatches. Some mushrooms are incorrectly labeled and classified due to the lack of a symbol for one of the 4 functional categories.

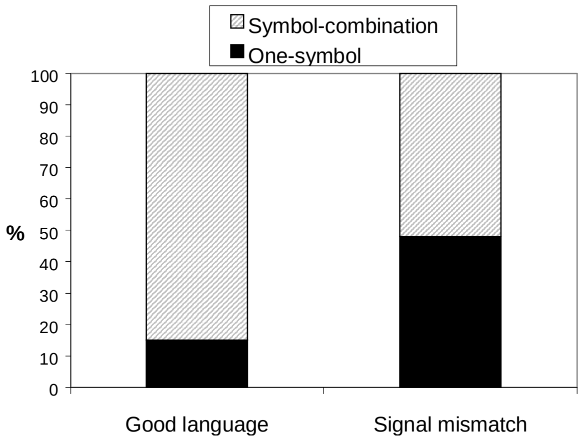

Figure 2: Percentages of the different types of languages in the 45 replications of the simulation at generation 400.

The distribution of the different types of evolved languages has been analyzed. Figure 2 shows that 85% (17 populations) of the 20 simulations with good languages evolved combinations of symbols. Ten of the 17 lexicons use an “action-object” structure. That is, two different “action” symbols ("verbs") are used for all toadstools and all edible mushrooms respectively. The second symbol is used for distinguishing the three edible categories. Only 15% of these good-language simulations use one-symbol languages. At least four different symbols are used to describe the general category of toadstools and the three types of edible mushroom. In the 25 simulations with language mismatch the distribution of one-symbol languages (48%) versus symbol-combination languages (52%) was approximately equal.

The evolution of optimal languages in the populations with good languages is also reflected by their fitness. The average fitness in the simulations with good languages is higher than that of the simulations with signal mismatch (Figure 3). The lower fitness is due to the fact that organisms incorrectly label some of the mushroom categories. They use the same symbol, or symbol combination, for two of the four functional categories.

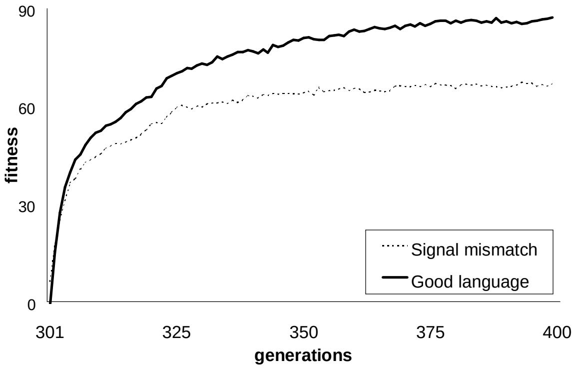

Figure 3: Average fitness of the best 20 organisms in the population with good language and with imperfect language.

4. Discussion

The results of this simulation show that the ecological setting (e.g., foraging task), the neural network architecture, the mechanisms of cultural transmission, and the evolution allow the emergence of language. Moreover, in the simulations with good languages there is a strong tendency to evolve the use symbol combinations. Some populations also evolve the "action-object" rule, i.e. one symbol is systematically used for distinguishing the two main actions ("avoid" all toadstools, "approach" all edible mushrooms) and the other symbol is used for distinguishing between the three categories of edible mushrooms.

In the introduction the problem of symbol acquisition in the evolution of animal communication and human languages was discussed [3]. Human languages are characterized by the fact that learned words (symbols) have double associations. One association is between the word and its semantic referent (which has a direct link to the world's object or event). The second type of association is between the symbol itself and other symbols, through the use of syntactic rules. Therefore, a system that is truly acquiring symbols will be able to use the potential of symbolic associations and of syntactic rules. Due to the possible combinatorial interrelationships between symbols, there can be an exponential growth of reference with each new added word.

It is possible to test for symbol acquisition and to establish if the learned syntactic rules are based on symbol-symbol associations. In the experiment by Savage-Rumbaugh & Rumbaugh [11], upon which the foraging task and stimuli were based, a test for symbol acquisition was used. In their experiment, chimpanzees initially learned to associate “pour” with the name of drinks (coke and juice) and "give" with the name of solid foods (banana and orange). Subsequently, they assessed animals with new names of drinks and foods. These results show that under certain language training conditions animals are able to learn real symbolic associations and make correct rule generalizations. Chimpanzees correctly associated the new drinks' name with the verb "pour", and the new foods' name with "give".

A similar symbol acquisition test was developed for the foraging task of the model presented in this paper. Organisms are first taught to associate the verb "avoid" with the names of two toadstools and "approach" with the names of two edible mushrooms. Subsequently, they are taught the name of a new toadstool and the name of a new edible mushroom. No direct feedback for the verb association is given during the learning of these new names. Finally neural networks are tested to establish whether they learned to use the "action-object" rule to associate the correct verb with the new names. The results show that in 70% of populations the learned language is actually based on symbolic associations between the mushrooms’ names and the two verbs [1]. Therefore, neural networks are able to use a symbolic strategy when learning linguistic symbols and the syntactic rules for combining them.

Neural networks have been proposed as a good model for the symbol grounding problem in cognitive modeling [7]. Every good cognitive model should use symbols that are "grounded" in the world so that this grounding can affect the way symbols are made available to the system and used by it. The communication systems evolved in this simulation use symbols, i.e. signals combined together to represent different meanings. Due to the fact that communicating organisms are controlling by neural networks, their symbols are “grounded” because they are intrinsically linked to their referents in the environment, through the input units.

The proposed model is able to simulate and study the emergence of communication and syntax. This model is an example of the use of neural networks and genetic algorithms for the evolution of syntax. It shows the emergence of the "action-object" syntactic rule starting with the complete absence of any form of communication. The results in this paper are consistent with experiments performed on animal communication (e.g. ape language studies [11]) and the symbol grounding and symbol acquisition problems. Further developments of this model, such as simulations in which ecological, social, and evolutionary variables are manipulated, will increase the understanding of the role of these factors in the origin and evolution of language.

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