The Effects of Learning on the Evolution of Saussurean Communication

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Abstract

This paper presents a computational framework for studying the influence of learning on the evolution of communication. In our model, an evolving population of learning agents is engaged in pairwise comunicative interactions. Simulation results show the genetic assimilation of trasmission behaviors as a consequence of saussurean learning.

Introduction

The evolution of communication is an excellent domain for studying fundamental questions of artificial life research. Previous work by Ackley and Littman (2), Arita and Taylor (3), Di Paolo (5), Hashimoto and Ikegami (8), and Steels (18), among others, have shown that we are able to explore important issues such as emergence, self-organization and cultural evolution within this framework.

The aim of this work is to study the influence of learning on the evolution of communication. We believe this is an instrumental aspect for understanding the origin and evolution of communication systems with the complexity of human languages.

In nature, learning seem to influence both the association of signaling behaviors to appropriate external referents and the development of responses to different signal types (10). However, there are several examples of innate underpinnings in transmission behaviors. For example, young vervet monkeys seem predisposed to alarm calling, dividing up the universe of predators into different ill-defined categories, leaving social experience to sharpeb the boundaries of exclusive predator categories and its corresponding association to particular call types (4). Moreover, there is indication of innate predispositions in human languages (16). On the other hand, there is a growing conviction that learning plays a substantial role in the development of how a receiver responds on hearing a signal (10).

A fundamental question that arises in the context of animal communication is whether a comunication system is likely to be symbolic. According to Marler, for an animal communication system to qualify as symbolic, information about external referents has to be both encoded by signalers and decoded by receivers (10). This definition is consistent with the nature of the saussurean linguistic sign (17).

In his seminal paper, Hurford proposed a model for studying the evolution of saussurean communication (9). In this model, an agent consists of two probabilistic matrices that provide a framework for semiotic interactions. Computational simulations were conducted to investigate the evolutionary potentials of different learning strategies. Further studies by Oliphant (14), Oliphant and Batali (15) and Nowak et al (13) have contributed to elucidate the fundamental properties of this model.

These studies have been largely conducted within the framework of Lamarkian evolution. In most cases, learned communicative behaviors are written back to the genetic description of agents and thus transmitted to offspring during reproduction. We believe that Darwinian evolution provides a more convenient framework for studying the evolution of communication. In their influential work, Hinton and Nowlan proposed a computational framework for conducting studies on the effects of learning on evolution in Darwinian evolution (7) (1). This holds much promise. For example, Turkel has shown that this computational framework can be used for exploring how the capacity of human language could have evolved via natural selection (19).

In this work, we conducted computational studies about the influence of learning on the evolution of communication. Experimental results show the genetic assimilation of transmission behaviors. This results are consistent with dominant theories on the evolution of communication (6).

The model

Agent architecture

The formal definition of the agent architecture presented below is based on considerations of the models proposed by Hurford (9) and Oliphant (14).

Agent Let $O = \{o_1, \ldots, o_n\}$ be a finite set of n objects and $S = \{s_1, \ldots, s_m\}$ be a finite set of m signals. A *learning communicative agent* is a triple (δ, ϕ, σ), where

1. $\delta : O \rightarrow S \cup \{s_\#\}$ is the transmission function, where $s_\#$ is the undetermined signal,
2. $\phi : S \rightarrow O \cup \{o_\#\}$ is the reception function, where $o_\#$ is the undetermined object, and
3. σ is the learning strategy.

Communication An agent $A_1 = (\delta_1, \phi_1, \sigma_1)$ comunicates to an agent $A_2 = (\delta_2, \phi_2, \sigma_2)$ as follows. Initially, A_1 perceives an object o_i and produces a signal s_j according to the mapping described by the transmission function δ_1, such that $\delta_1(o_i) = s_j$. Once A_1 produces the signal s_j, the agent A_2 interprets the signal s_j as the object o_k according to the mapping described by the reception function ϕ_2, such that $\phi_2(s_j) = o_k$. A communication event from A_1 to A_2 is successful if the following conditions are satisfied

1. $\delta_1(o_i) = s_j$,
2. $\phi_2(s_j) = o_k$, and
3. $o_i = o_k$

Homonymy An agent $A = (\delta, \phi, \sigma)$ is said to possess homonymy if there exist a signal $s_j \neq s_\#$ and a pair of objects o_i and o_k that satisfy the following conditions

1. $\delta(o_i) = s_j$,
2. $\delta(o_k) = s_j$, and
3. $o_i \neq o_k$

Synonymy An agent $A = (\delta, \phi, \sigma)$ is said to possess synonymy if there exist an object $o_i \neq o_\#$ and a pair of signals s_j and s_k that satisfy the following conditions

1. $\phi(s_j) = o_i$,
2. $\phi(s_k) = o_i$, and
3. $s_j \neq s_k$

Innate transmission Let $A = (\delta, \phi, \sigma)$ be an agent. A transmission from A for a given object o_i is said to be innate if $\delta(o_i) \neq s_\#$ and is said to be subject to learning if $\delta(o_i) = s_\#$.

Innate reception Let $A = (\delta, \phi, \sigma)$ be an agent. A reception of A for a given signal s_j is said to be innate if $\phi(s_j) \neq o_\#$ and is said to be subject to learning if $\phi(s_j) = o_\#$.

Learning In our model, both transmission and reception behaviors are partially learned. Before a communication event from A_1 to A_2 takes place, A_1 replaces the undetermined signals in δ_1 with signals in S using the learning strategy σ_1. Similarly, A_1 replaces the undetermined objects in ϕ_1 using the learning strategy σ_1. Agent A_2 proceeds similarly.

A fundamental aspect of our model is that learning is performed for communication purposes and does not permanently modify the actual description of an agent.

Learning strategies

We consider three different learning strategies: imitator, calculator and saussurean, after (9). In addition, we introduce a fourth learning strategy: random learner.

Imitator An imitator agent replaces the undetermined signals in his transmission function by the corresponding signals in the transmission function of another agent. Similarly, he replaces the undetermined objects in his reception function by the corresponding objects in the reception function of another agent.

Formally, an agent $A_1 = (\delta_1, \phi_1, \sigma_1)$ imitates an agent $A_2 = (\delta_2, \phi_2, \sigma_2)$ as follows.

1. $\delta_1(o_i)$ is set to $\delta_2(o_i)$ if $\delta_1(o_i) = s_\#$, $\delta_2(o_i) \neq s_\#$, for $i = 1, \ldots, n$, and
2. $\phi_1(s_j)$ is set to $\phi_2(s_j)$ if $\phi_1(s_j) = o_\#$, $\phi_2(s_j) \neq o_\#$, for $j = 1, \ldots, m$.

Calculator A calculator agent replaces the undetermined signals in his transmission function in such a way that a communication event to another agent would be successful. Similarly, he replaces the undetermined objects in his reception function in such a way that the communication event from another agent would be successful.

Formally, an agent $A_1 = (\delta_1, \phi_1, \sigma_1)$ calculates an agent $A_2 = (\delta_2, \phi_2, \sigma_2)$ as follows.

1. $\delta_1(o_i)$ is set to s_k if $\phi_2(s_k) = o_i$, $\delta_1(o_i) = s_\#$, for $i = 1, \ldots, n$, and

strategy	code
imitator	0
calculator	1
saussurean	2
random	3

Table 1: Codification of learning strategies

2. $\phi_1(s_j)$ is set to o_k if $\delta_2(o_k) = s_j$, $\phi_1(s_j) = o_\#$, for $j = 1, \ldots, m$.

Saussurean A saussurean agent replaces the undetermined signals in his transmission function by the corresponding signals in the transmission function of another agent. Similarly, he replaces the undetermined objects in his reception function in such a way that a communication event to himself would be successful.

Formally, an agent $A_1 = (\delta_1, \phi_1, \sigma_1)$ is saussurean with respect to and agent $A_2 = (\delta_2, \phi_2, \sigma_2)$ as follows.

1. $\delta_1(o_i)$ is set to $\delta_2(o_i)$ if $\delta_1(o_i) = s_\#$, $\delta_2(o_i) \neq s_\#$, for $i = 1, \ldots, n$, and
2. $\phi_1(s_j)$ is set to o_k if $\delta_1(o_k) = s_j$, $\phi_1(s_j) = o_\#$, for $j = 1, \ldots, m$.

Random A random agent can assume any of the strategies described above. Before a communication event takes place, a random agent randomly selects one of the following strategies: imitator, calculator or saussurean.

For convenience, we consider a codification of learning strategies as shown in table 1.

Evolution of communication

In our model, a population of learning communicative agents are intended to evolve successful communication at the population level. We use genetic algorithms for this purpose. The design decisions presented below are based on considerations of the performance of genetic algorithms in practical applications (12).

Genome representation A learning communicative agent $A = (\delta, \phi, \sigma)$ is represented linearly as follows

$$A = (\delta(o_1), \ldots, \delta(o_n), \phi(s_1), \ldots, \phi(s_m), \sigma)$$

For example, consider a set of objects $O = \{1, 2, 3\}$, a set of signals $S = \{a, b, c\}$ and a calculator agent $A_1 = (\delta_1, \phi_1, \sigma_1)$. In addition, consider the functions δ_1 and ϕ_2 described in table 2.

o_i	$\delta_1(o_i)$
1	b
2	$s_\#$
3	a

s_j	$\phi_1(s_j)$
a	$o_\#$
b	3
c	2

Table 2: Transmission and reception functions

The linear representation of agent A_1 is

$$(b, s_\#, a, o_\#, 3, 2, 1)$$

Genetic operators Agents produce a new offspring by means of genetic operators. Fitness proportional selection, one-point recombination and point mutation operate on the linear representation of agents described above.

Fitness function Fitness was defined as the communicative accuracy of learning communicative agents. The communicative accuracy is the ability of an agent to successfully communicate with a collection of other agents.

Let P be a finite population of agents, A be an agent in P, and $Q \subseteq P$ be a non empty collection of agents. The communicative accuracy of A with respect to Q given the set of objects $O = \{o_1, \ldots, o_n\}$ and the set of signals $S = \{s_1, \ldots, s_m\}$, $C(A, Q, O)$, is defined as

$$C(A, Q, O) = \frac{\sum_{o_i \in O} \sum_{A_k \in Q} c(A, A_k, o_i) + c(A_k, A, o_i)}{|Q|}$$

where $c(A, A_k, o_i) = 1$ if the communication event from A to A_k is successful given the object o_i, and 0 otherwise; $|Q|$ is the cardinality of Q. $c(A_k, A, o_i)$ is defined similarly.

Experiments and results

Experiments were conducted to investigate whether a population of learning communicative agents is likely to arrive to successful communication at the population level. In addition, we validated the evolutionary performance of competing learning strategies. Most importantly, we were interested in exploring the effects of learning on the genetic description of an evolving population of learning communicative agents. The simulation procedure is described in table 3.

Several simulations were conducted using different combinations of parameter values as shown in table 4. The following were the major results:

1. Create an initial random population P of agents
2. `Do until` number generations is met
   (a) `For each` individual $A_i = (\delta_i, \phi_i, \sigma_i) \in P$ `do`
      i. Perform the learning process of A_i according to the learning strategy σ_i with respect to a random agent $A_h \in P$
      ii. Select a random subpopulation of agents $Q \subseteq P$
      iii. Perform the learning process for all $A_j \in Q$ according to the learning strategy of A_j with respect to a random agent $A_k \in P$
      iv. Measure the communicative accuracy of A_i with respect to Q, $C(A_i, Q, O)$, given the set of objects O

      `End for`
   (b) Select two individuals $A_{mother} \in P$ and $A_{father} \in P$ for reproduction using fitness proportional selection
   (c) Produce an offspring A_{new} from A_{mother} and A_{father} using one-point recombination and point mutation
   (d) Select a random individual $A_{old} \in P$
   (e) Replace A_{old} by A_{new}

   `End do`

Table 3: Simulation procedure

Parameter	**Value**
generations	2000–3000
population P	128–512
subpopulation Q	4–16
signals	4–8
meanings	4–8
crossover probability	0.6–0.7
mutation probability	0.001–0.01

Table 4: Parameters for simulations

1. Agents arrived at highly successful communication at the population level. However, simulations showed that there exists a threshold condition on the number of interactions (size of set Q) required to achieve accuracy in communication. Figure 1 shows the results of the simulations for different number of interactions. Agents reached local minima in communication accuracy as the number of interactions is reduced.

2. Local minima were produced mostly by the presence of homonymy – i.e. when the same signal is used to describe two or more different objects. Synonymy – when two or more signals are interpreted as the same object, did not appear consistently.

3. In pairwise strategy contests, populations of calculators dominated a populations of imitators. However, populations of saussureans outcompeted both calculators and imitators.

4. In all strategy contests: imitators, calculators, saussureans and randoms, experimental results showed the superiority of the saussurean learning strategy. In most cases, saussureans took over the entire population. Only rarely, did imitators or calculators dominate such populations. Random learners never became dominant. Figure 2 shows the frequency of strategies in the population for a typical simulation where all strategies were initially present.

5. The undetermined signal trait disappeared in the population. All the signals produced for every object were genetically assimilated in the transmission gene segment of the genome for all agents. The frequency of undetermined signals in the population as evolution proceeded is shown in figure 3.

6. The undetermined objects trait prevailed in the population. Objects interpreted for every signal were not genetically assimilated in the reception gene segment of the genome. The frequency of undetermined objects in the population as evolution proceeded is shown in figure 3.

7. Most simulations considered a set of 4 objects and a set of 4 signals. Both homonymy and synonymy began to appear more consistently when both the number of objects and signals was increased. However, homonymy continued to be more common.

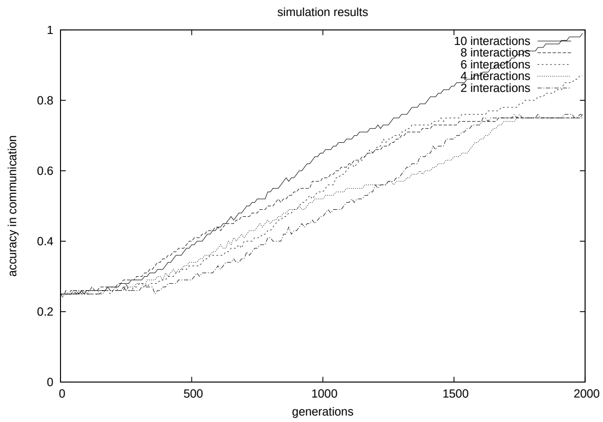

Figure 1: Threshold condition on interactions

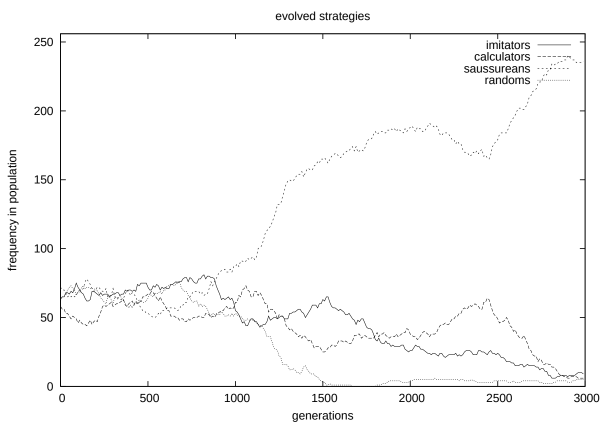

Figure 2: Evolved strategies

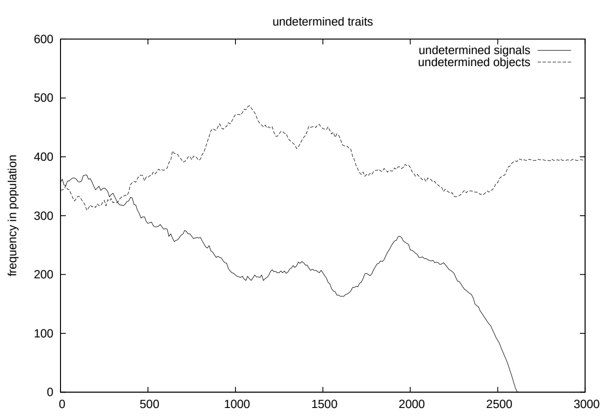

Figure 3: Genetically assimilated traits

Discussion

The overall experimental results indicate that given a sufficient number of interactions, a population of learning communicative agents is capable of arriving at highly successful communication. Surprisingly, transmission behaviors became innate as a consequence of the evolution saussurean learning. On the other hand, reception behaviors prevailed as characteristics that are subject to learning. Our results are consistent with several hypotheses formulated for the evolution of communication (10).

Why transmission was genetically assimilated

In general, experimental results showed that there is an evolutionary preference for saussurean agents. Saussurean learning implements a tight coupling between transmission and reception behaviors.

Why did signaling behaviors become innate? First, imitation of transmission in a static environment provides the opportunity for genetic assimilation of signaling behaviors. Second, a tight coupling between reception and innate transmission provide the oportunity for successful learning in reception behaviors.

Why saussureans prevailed

From the evolutionary perspective, how good is saussurean learning for evolving communication?. Could an alternative communicative strategy invade a population of saussurean learners?.

Maynard-Smith(11) has demostrated that game theory can be used as a framework to explain the evolution of most phenotypic traits in situation in which fitness of a trait depends on what others are doing. He has also provided the notion of evolutionary stable strategy (ESS). An ESS is a phenotype such that, if almost all individuals have that phenotype, no alternative phenotype can invade the population.

In our model, experimental results showed that saussurean learning is likely to be an ESS. However, further studies are required to formally demostrate what types of learning are evolutionary stable strategies.

In this study, we did not consider the cost of producing a signal. Previous studies suggest that honesty of communication become an issue when cost is considered (2).

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