Lenguas Modernas 40 (Segundo Semestre 2012), 11 - 27
Universidad de Chile

THE WORDS WE CAN ALL AGREE ON: A COMPUTER-GENERATED ENVIRONMENT TO TEST FOR EVOLUTION OF LEXICAL AGREEMENT

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Abstract: This paper reports on an experiment in which virtual agents in a computer simulated program were set up to assimilate the evolution of lexical agreement based on Complex Adaptive Systems theory (Lee & Schumann 2003, Waldrop, 1992), and Artificial Life (Kirby 2002). Prior studies (Matsen & Nowak 2004; Kirby 2001) have shown that, through iterated learning, computer agents can agree to map a sign to a single referent. In the current experiment, initially agents were randomly assigned to different letter signs. A simple rule based on cellular automata environment (Wolfram 2002) allowed agents to either converge with the sign of their neighbor or change the sign of their neighbor to one similar to theirs. Results of the experiment showed that only under certain conditions could a general consensus on meaning-signal mapping be achieved. If agents had a very loose rule that involved maximum degrees of freedom for agreeing with the neighboring agents, the environment became unstable and no consensus was reached. Similarly, a strict rule with few degrees of freedom produced clusterization with no overall agreement in the environment. The optimal situation for a consensus was achieved under the condition in which agents had more degrees of freedom to agree with a neighboring agent, as well as having less heterogeneity of signs. Furthermore, it is discussed that contrary to biological evolution, patterns of organization such as lexical agreement can emerge out of mere agents' interaction with one another without the need for the presence of an advantageous trait in the agent as required by Darwinian evolution through natural selection.

Key words: evolution of language, artificial life, complex systems, lexical agreement, evolution of lexicons.

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Las palabras con las que todos podemos concordar: un entorno generado computacionalmente para examinar la evolución del acuerdo sobre ítems léxicos

Resumen: Este artículo da cuenta de un experimento en el que se dispusieron agentes virtuales en un programa computacionalmente simulado para asimilar la evolución de acuerdos sobre léxico, basado en la teoría de sistemas complejos de adaptación (Lee y Schumann 2003, Waldrop 1992) y vida artificial (Kirby 2002). Estudios previos (Matsen y Nowak 2004; Kirby 2001) han demostrado que, a través del aprendizaje iterativo, agentes informáticos pueden ponerse de acuerdo para asignar un signo a un único referente. En el experimento descrito en este artículo, los agentes fueron inicialmente asignados al azar a diferentes signos que, en el presente caso, estaban representados por letras. Una regla simple basada en un entorno celular autómata (Wolfram 2002) permitió a los agentes converger con el signo del agente vecino, o bien, cambiar el signo de su vecino por uno similar al signo que cada uno representaba. Los resultados del experimento mostraron que solo bajo ciertas condiciones podía lograrse un consenso general sobre el mapeo del significado del signo. Si los agentes tenían una regla muy relajada que involucraba grados máximos de libertad para concordar con los agentes vecinos, el entorno se hacía inestable y no se llegaba a consenso. Del mismo modo, una regla estricta con pocos grados de libertad producía agrupamientos que no mostraban en general acuerdos en el ambiente. La situación óptima para lograr consenso se alcanzaba bajo la condición de que los agentes tuvieran más grados de libertad para ponerse de acuerdo con un agente vecino, así como también presentaran menos heterogeneidad entre los signos que representaban. Además, se discute que, contrariamente a la evolución biológica, los patrones de organización tales como el acuerdo léxico pueden surgir a partir de la mera interacción entre agentes sin la necesidad de la presencia de un rasgo ventajoso en un agente, como es requerido por la evolución darwiniana a través de la selección natural.

Palabras clave: evolución del lenguaje, vida artificial, sistemas complejos, acuerdo léxico, evolución del léxico, evolución de ítems léxicos.

Recibido: agosto de 2012 Aceptado: noviembre de 2012

1. Introduction

How did people come to agree on the same system of communication within a language? What mechanisms might have been at work that allowed people to agree on the same sign-to-referent in the vocabularies of human languages? This paper reports on an experiment in which virtual agents in a computer environment were set up to simulate the evolution of lexicon based on theories of language evolution according to Complex Adaptive Systems theory (Lee & Schumann 2003), and Artificial Life (Kirby, 2002). The simulation showed that patterns of organization such as lexical agreement can emerge out of agents' interaction with one another without the need for the presence of an advantageous trait in the agent.

Humans are the only species who have the ability to communicate in a structured symbolic system called language. The structure of language in linguistic terms is called *grammar*. Moreover, language consists of arbitrary signs which differ from one language to another. The history of all natural languages indicates a tendency toward dynamism and an ever-evolving complexity in the system of language. In almost all areas of physical sciences, scientists have been able to explain the mechanism of most organized systems. Darwin, for instance, provided us with a comprehensive theory to explain the mechanism of a pattern of organization we call life (Darwin 1859). However, language seems to be very unyielding with respects to its mechanism of organization. Chomsky's (1957) publication of *syntactical structure*, and his subsequent work (Chomsky 1965, 1966, 1972, 1975, 1986) partially tackled this question by showing that, at the deep level, all languages share common structure which he termed *Universal Grammar*, or UG. He argued that every infant must be borne with an innate biological system to acquire UG. He called this system *Language Acquisition Device*, or LAD. The biological source for this innate ability has yet to be found either in the genetic or the neural structure of humans.

Syntax is a system which allows words to combine in orderly and universally understood ways. Prior to syntax, however, there must have been a system which allowed humans to agree on the same lexical items and on their meaning referring to those items. For instance, the word 'table' in English refers to an object which usually has four legs, a flat surface, and most probably is used for holding objects at a certain vertical distance from the ground. However, there is nothing in the word 'table' itself that refers to these qualities other than the collective agreement of certain users to call it that way. As a result, the word 'table' for English speakers is referred to in different ways for other language speakers such as *mesa*, *tisch*, *miz*, etc. In this regard, one important question still remains to be answered: how did humans come to agree on this referential quality of language? In other words, what method or system allowed humans within a certain locality to unanimously refer to an object in the shape and function of a 'table' to be called a 'table?'

As languages do not leave physical remains, every theory about the evolution of language or emergence of early lexicon is, at best, just an educated guess. However, with the help of computers, now it is possible to simulate environments with different mechanisms to provisionally test some of these theories. This paper reports on an experiment in which virtual agents in a simulated environment were set to negotiate with one another on one of the properties of language, namely, lexical agreement. In the first part of this paper, a brief description on complex systems is introduced. The second part of this paper discusses how computer simulations can help us to test theoretical questions about the structure of language. And finally, the results of a computer simulation are reported to test for the evolution of lexical agreement in an artificial environment.

2. Literature review

2.1. Natural selection and the evolution of language

The organization and structure of human language cannot be readily explained through the theory of natural selection as theorized by Darwin (Christiansen & Kirby 2003). In natural selection, patterns of organization can only emerge within the framework of competition. Only species or functions that have a slight advantage over others will prevail in the succeeding generation. As such, natural selection only favors a divergent pattern of organization where agents or evolutionary functions tend to become increasingly dissimilar. In principle, natural selection does not favor cooperation or convergence. Of course, there are many similarities of behavior between and within species. For instance, many kinds of animal species, and of course all humans, digest food and process oxygen flow in the blood the same way. But there are specific and similar genes in animals and humans that code for such similar functions. Dissimilarities, such as different skin tones are also coded genetically. It is an absurd claim to say that people who speak language 'A' have a different language gene or other biological differences than those who speak language 'B.' All human babies from across the globe come to naturally learn any language spoken in their immediate environment. Hence, we need to find a theory that can explain the organization of language, such as its systematic and semiotic structure, without relying on the theory of evolution through the process of natural selection.

There is actually a new theory that bids to account for many forms of organization in nature without depending much on the theory of evolution. As a series of gradual development from *Connectionsim* (Rumelhart & McClelland 1986), to *Chaos theory* (Gleich 1987), to *Emergence* (Blitz 1992), and to *Artificial Life* (Langton 1992), *Complex Adaptive Systems* (Holland 1999) theory, or CAS, describes the possibility of spontaneous emergence of organization in natural agents or functions without much support on hardwired biological structures such as genetic coding or specific neural mechanism, that are the very necessary ingredients for the process of evolution through natural selection. By tapping into broad examples from ant colonies, to the V-shape fly pattern of Canadian geese, and to the immense complexities of modern cities, CAS explains that very often organization merely can emerge as mere random interaction between agents within a closed system that has been set to function with few simple predefined rules.

2.2. Emergence, Artificial Life, and Complex Adaptive Systems theories

The idea of emergence and self-organization was first introduced by the advent of powerful computers in the late 70s. Complex computer simulations were able to produce artificial environments in which networks could learn, use resources of their immediate environment, adapt, and eventually grow and become more complex, the very same functions we would expect to see only from living organisms. The computer simulations and many other parallel discoveries in molecular biology, economics, and modern physics encouraged scientists from across disciplines to rethink their definition of life as something only organic, but rather to extend it to artificially constructed structures a well, or as later called, *Artificial Life*.

Much of the work of emergence on computer simulations comes from 2-dimensional environments called cellular automata, or CA (Wolfram 2002). These programs usually consist of rectangular agents randomly spread over a computer simulated environment. Each agent can have an ‘ON’ or ‘OFF’ status depending on the status of its neighbor. Some initial rules are implemented in this environment. For instance, an initial rule may require that if two of the agents’ neighbors are ‘ON’, but not more than 4, the agent will be ‘ON’ on the next generation, otherwise it stays ‘OFF’. Experiments with different yet simple rules showed that very complex patterns can emerge in such environments which could have not been previously anticipated. These new findings and analyses both in artificial environment as well as actual biological organisms suggested that evolution in the way of natural selection may not be the only way to form patterns of organization in the world.

2.3. Complex systems and evolution of language

Recently, within the framework of Artificial Life and Complex Systems theories, there have been many attempts to explain the evolution of language and the emergence of symbolic cooperation (Lee & Schumann, 2003; Larson-Freeman, 2008). The basic idea behind such theories is that language is an artifact that can emerge through interaction alone and that no genetic or specific brain structure is needed to account for organization of human language. However, experimental supports for these theories are as rare as they are for theories that attempt to explain the evolution of language within the framework of natural selection. Evidence is hard to come by because oral language is just a symbolic artifact that does not leave physical remains for archeological investigation. To test for emergence in the evolution of language, researchers have usually resorted to two kinds of experiments; 1. longitudinal studies of the historical evolution of creolization and pidginzation (Andersen 1983), 2. computer programs that can simulate different aspect of language within the theories of Artificial Life or Complex Systems (Batali 1994, 1998; Kirby 1998, 2000, 2002).

2.4. Computer simulation as a tool to study the evolution of language

Despite their limitations, computer simulations can be very helpful in testing theories. Computers can simulate any behavior especially when manipulations of the variables are not possible in the real world. For instance, in order to see what factors affect language-change, one needs to vary those factors across many generations of humans, an impossible experiment especially when language-change occurs over many, many years. However, computers can show the evolution of any given environment in thousands of generations within a fraction of a second. Moreover, computer simulations allow testing for many ‘what-if’ scenarios. As mentioned before, life shows both a divergent as well as a convergent pattern. It is rather impossible to conceive of all the divergent paths that an artifact such as language must have gone through over millennia. However, computers allow us to intervene within each time interval and to test different paths within each evolutionary course. Computer programs have also many limitations. Computer simulations are not domain-specific. A rectangular shape assigned to be a human agent in a computer simulation can be assumed as a symbol or almost as anything else that a researcher argues that rectangle shape stands for. Moreover, computer agents are bodiless. This is a very important factor especially in regard to language because humans use many other non-verbal means to communicate with one another.

In order to create a computer program that meaningfully corresponds to one or some of the characteristics of language at least three conditions must be met (Steels, 2006): 1. It must be evident what emergent quality of language is being investigated. Many different features of language such as phonetics, grammar, and the lexicon can be assumed to have emergent qualities. All these features are furthermore confounded by cognitive and developmental characteristics. An informative program must concentrate only on one emergent quality at a time. 2. Agents must not be aware of effects of global properties in the environment. Artificial Life simulations, for the most part, operate based on bottom-up processes. Consequently, agents have only local control on their surroundings and are ignorant about the global outcomes of their actions. 3. It is important to consider non-working models as well as working models. Not every random and local interaction among agents gives rise to an emergent quality of language.

2.5. Previous computer simulations of evolution of language

There are three major techniques available to simulate the evolution of language (De Boer 2006). In the *optimization* model, based on a mathematical algorithm, individual properties of language such as sound, grammar, or lexicon are separately and gradually modified for the best possible solution. The *genetic algorithm* model creates an artificial environment that allows different properties of language to compete and evolve based on the characteristics of Darwinian natural selection. In the *agent-based* model, starting with some initial yet simple rules, robotic or computer simulated shapes act as agents that can interact with other agents in a given environment. For instance, a linguistic property is introduced in the environment and agents may exchange phonetic utterances, words, or grammatical structures with one another. Based on Artificial Life and Complex Adaptive System theories, it is assumed that such environments can give rise to more complex patterns which could have not been anticipated beforehand. *Agent-based* models are more frequently utilized for the investigation of the evolution of language as this model does not have a priori condition for optimization or enhancement which one must assume for the other models. Agent-based models are also more realistic as they correctly assume that humans must conform to a property of language rather than improve it.

Computer simulations have usually been utilized to investigate the syntactical and phonetic property of language (Batali 1998, 1994; Kirby 2007, 2000, 1998; Miranda, Kirby & Todd 2003). Lexical agreement is an understudied phenomenon. Simon Kirby introduced a model he called the *Iterated Learning Model*, or ILM, to explain the propagation of lexicon or grammatical structure from one generation to another (Kirby & Hurford 2002). ILM attempts to account for propagation of language according to Chomsky's notion of E-language, or language in terms of words and grammar which are transmitted from one generation to another. According to this model, a set of adults teach their language to a set of learners through interaction based on principles of *Game Theory* (von Neumann & Morgenstern 1947). After a learner has acquired the language, the adult leaves the environment and the learner replaces the adult. Kirby showed that a complex compositional meaning-mapping pattern emerges after many iterations, or generations between adults and learners (Kirby 2001). Niyogi and Nowak, both computational linguists, have also suggested that learning and change in language occur at two different levels; learning happens at the individual level, and language-change takes place over many generations (Niyogi 2006; Nowak 2006).

Based on Artificial Life and Game theories, Oliphant and Batali (1997) and Matsen and Nowak (2004) also proposed two new machine learning systems correspondingly called 'Imitate-Choose' and 'Win-stay, lose-shift' to account for linguistic coherence in artificial environments. In Matsen and Nowak's study, computer agents were simulated to jump around a 3-dimentional hypercube from one node to another to accept one of many languages offered to them on each node. There were finite number of nodes (or languages) and agents in this space. The goal of all agents was to find a common language by utilizing a strategy that was implemented in the simulation. The result of the study showed that if the number of languages was more than individuals in this environment, then the environment would finally stabilize with everyone speaking the same language, an interesting finding since each agent was required to speak to only three other agents. Moreover, this simulation showed that learners do not need to integrate their pervious experiences with another language into the new language and, very often, they only shifted to the most successful way of communication in the environment.

In a similar study (Steels 1995), a set of agents were able to develop a new vocabulary to identify each other through names and spatial descriptions. In this simulation, an agent called the 'initiator' referred to an object with a name, and another agent called the 'receiver' tried to identify the object using *language-games*. The language-game consisted of a series of dialogues between the initiator and the receiver until both agents reached an agreement as to which object was intended by the initiator or until they ended the dialogues because no agreement could be reached or the required common vocabulary was not available in the environment. The result of this simulation showed that more than 80% of the time communicative success was established between the initiator and the receiver after about 1000 conversations. By 3000 conversations a complete coherence was achieved between both agents. These findings are important because they indicate that by providing feedback loops and constant negotiation between interlocutors it is possible to construct meanings from a random set of linguistic signs.

3. Current research study

The current study intended to create an artificial environment to simulate the evolution of early lexical agreement. This program, however, had at least three assumptions for relating a synthetic environment to a natural environment in which lexical agreement could have possibly evolved. First, it was assumed that any word produced in a natural way is formed by attribution of an object, idea, or phenomenon to an arbitrary symbolic sign, and such attribution must be based on cooperation and shared interest rather than conflict of interest. Simply put, this assumption states that there is no "tableness" in the word 'table'. Any word is just an arbitrary sign and humans need, at some level, to agree with one another to attribute a sign to its referent. The second assumption expected that there must exist some level of proximity whether temporally, or more importantly, locally between human agents in which an agreement can emerge. That is, homo-sapiens who lived 40,000 years ago in northern Europe could have not possibly agreed with another group of homo-sapiens who lived in South Africa on assigning a sign to its referent as they did not have the opportunity to interact. It follows from this assumption that the spread of agreement must be proportionally related to spread of geographical location of human agents. In other words, the closer spatial proximity of a group of people to one another, there are better chances for them to reach an agreement, and the farther away they are from one another, the less likely they are able to cooperate and eventually reach a consensus on mapping a sign to its referent. The relative closeness in the topology of language dynamics has also been observed to be one of the conditions required for any convergence between languages (Lee, Collier, Taylor & Stabler 2007).

Based on the previous studies, two questions were asked in the current research investigation. First, it was asked whether some level of cooperation between agents could eventually lead to a consensus in which the entire population in the given environment would come to agree to attribute only one sign to one referent. This is a very important question to ask because there is no reason to believe that all cooperation between agents will necessarily lead to a ubiquitous consensus. The second question was intended to investigate the optimal conditions for local agreements and eventually a consensus in a given environment. As noted above, clusters of agreement have, if not greater, at least the same chance of actualization. However, it is not readily apparent what conditions or variables can support or hinder the formation of an agreement or a consensus in any given niche.

3.1. The program

The interface of the program consisted of a 200X200 grid, a set of buttons called *control*, and a set of trackbars called *rules* (figure 1). The matrix grid provided a visual display of the inner program operations. This matrix was initially set to a blank page. Upon hitting the *fill world* button, random letters would cover the entire grid. This grid acted to simulate 40,000 humans. Each cell represented one individual, and a letter could randomly be assigned to each cell as an initial tendency of an individual to associate one symbolic sign to a referent. As argued before, it was assumed that the human agents did not have any initial preference for symbolic attribution of objects because language is an arbitrary system for referring to objects or ideas. The *clear* button cleared the grid and provided a fresh page. The *control* group consisted of four buttons. The *fill world* button populated the grid with random letters assigned to agents. The *run* button executed the program by allowing the agents in the grid to interact with one another. Next to the *run* button, the *iteration* box displayed numerical value of executed generations until the *stop* or *step* buttons were hit. The *step* button allowed users to execute the program one generation at a time. The *stop* button terminated the execution of the program. When the *run* button was hit, each cell looked at the letter of their neighbor. At this point, each cell made certain adjustments based on the rules explained below. 'One generation' is a term used here to signify one observation and/or adjustment at a time. The *step* button allowed users to see each of these observations/ adjustments one generation at a time. However, the *run* button allowed the program to produce successive number of generations until the *stop* button was hit.

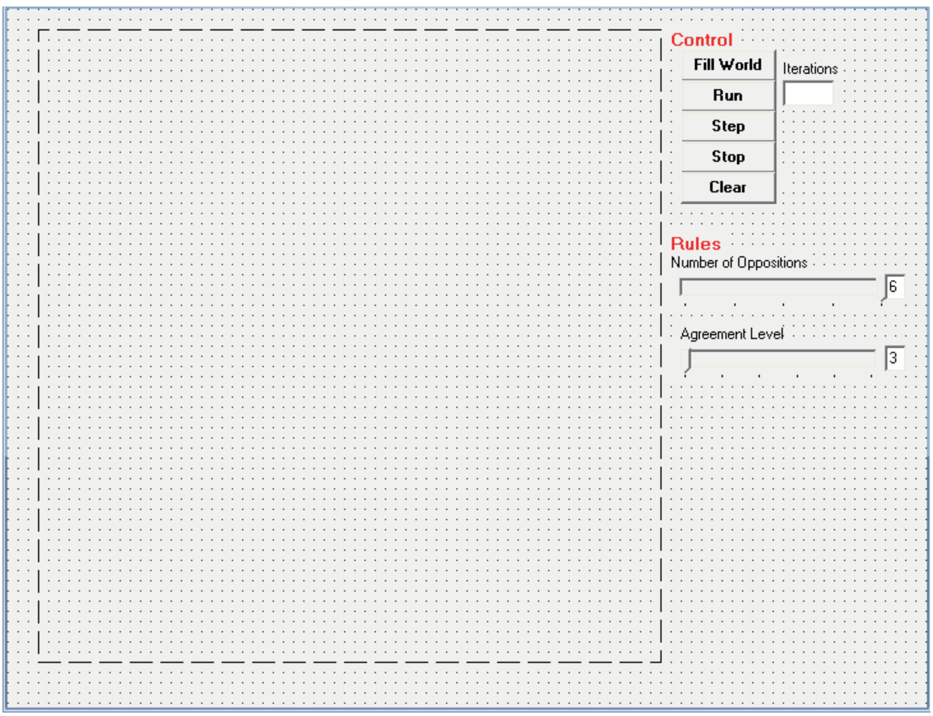

Figure 1. The interface of the program to simulate the evolution of lexical agreement

The *rules* buttons allowed users to set conditions of interaction among agents. The *number of opposition* (NO) trackbar allowed users to adjust the number of different letters which populated the grid. For instance, if a user selected 2 on the number of opposition trackbar, then, two different letters were randomly displayed within the grid (e.g., 'S' and 'V'). However, if a user selected 6 on the number of opposition trackbar, then, six different letters were randomly displayed on the grid (e.g., 'S', 'V','O', 'P', 'A' and 'U'). The trackbar had values from 2 to 6. The default value was set to 6 and changes in the values were displayed in a small value box next to the trackbar.

The *agreement level* (AL) trackbar allowed users to assign the degrees of freedom (df) for each agent. A 2-dimensional cellular automaton environment consists of a grid of agents in which each agent has eight neighbors (figure 2). Usually a rule or a set of rules are applied to a cellular automaton environment, and based on these rules each agent *looks* at its neighbors and consequently changes its state from one generation to another based on the state of its eight neighbors.

This program had two rules. Rule one stated that each agent initially checks for the number assigned by the users in the *agreement level* trackbar. The agent, then, agreed to change its state to the state of its neighbor in the next generation when there would be at least that many similar neighbors as selected by the user. For instance, if the user selected number 4 on the *agreement level* trackbar, the computer program directed the agent that it should have at least four neighbors with the similar sign for it to change its state to the state of its neighbors' in the next generation. Rule two asserted that the agent first must check the number selected by the user in the agreement level trackbar. If the agent had fewer numbers of neighbors with similar sign than those selected by the user, then, it kept its sign in the next generation. Note that the rule was based on the "at least" condition. That is, if the *agreement level* was set at 3 and an agent had, for instance, five neighbors with a similar sign, then, the agent changed its state to the state of its five neighbors in the next generation.

Figure 2. An example of a cellular automata (CA) neighborhood. Each cell in a 2-dimensional CA environment has usually eight neighbors. In this example, the letter 'P' has eight neighbors around it. Those eight letters, consequently, have another eight neighbors around them until the whole environment is populated.

3.2. The experiment

The purpose of this experiment was to answer these questions: 1. Will the environment ever reach a consensus to allocate one sign to only one referent? In other words, is it possible that the whole environment can be populated with only one letter? 2. What are the conditions in which such agreement is achieved? 3. What kinds of changes in the variables will facilitate or impede such consensus? To answer these questions a set of trials were run. There were two independent variables in this experiment; 1. Number of oppositions (NO), and; 2. Agreement level (AL). Two dependent variables were also analyzed, 1. Percentage of consensus under each set of trials, and 2. Number of iterations. Initially, NO and AL were set to their lowest level, 2, and 3 respectively. Twelve trials were run under this condition. The program came to an end position when either a consensus in the entire environment was achieved or no further changes in the environment were observed. These sets of 12 trials were executed under all different variations of NO, and AL. This precesdure intended to provide a statistical average from the collected data. Based on Kirby's (2001) *Iterated Learning Model*, an overall agreement was interpreted as total learning in the environment.

3.3. Results

Table 1 represents the percentage of an overall successful consensus under each experimentally varied condition. It is shown that the optimal conditions for consensus were achieved under two similar situations. In other words, 91 percent of the times a consensus in the environment was achieved when the number of oppositions was set to either 3 or 5, and the agreement level stayed unchanged at its lowest level, namely 3. There was decreasing consensus at NO3 and NO5 when agreement level stayed unchanged at AL3. This percentage was increased, however, at level NO6. In general, it appeared that consensuses fluctuated between low and high at level AL3, starting with %91 at NO2, then 64% at O3, 91% at O4, and 55% at O5, and finally 82% at level O6. At level AL4, the percentage of consensus was equally significant at levels NO3 and NO4 (73%). This, however, was changed with an increase at levels NO3 and NO4, with only 18% of consensus, and finally at zero consensus under NO6 condition. Agreement levels of 5 and 6 did not result any consensus, unaffected by different varying conditions of number of oppositions. Figure 3 shows a graphical view of these data with a line bar chart.

Table 1. The percentage of an overall successful consensus under each condition of different numbers of oppositions (NO) and different agreement level (AL)

Opp/Agr	AL3	AL4	AL5	AL6
NO2	91	73	0	0
NO3	64	73	0	0

NO4	91	18	0	0
NO5	55	18	0	0
NO6	82	0	0	0

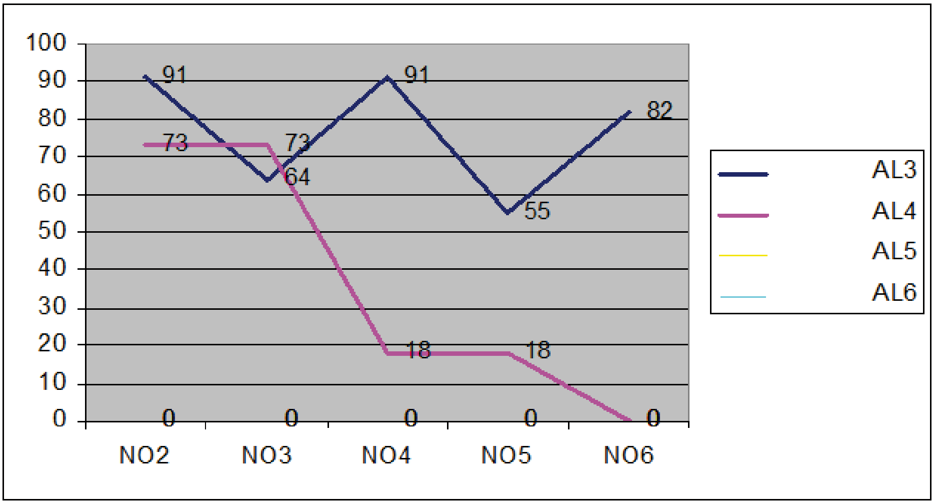

Figure 3. A line bar chart view of successful consensus within different experimentally varied conditions of the number of oppositions (NO) and agreement level (AL)

As mentioned before, another dependent variable considered for this study was the number of iterations for a successful consensus. In other words, it was important to know how many generations were needed so that the environment could successfully come to a consensus. It is assumed that an optimal learning environment can provide an overall consensus with the least possible number of iterations. Table 2 shows the results of this analysis. As there were no consensuses under levels AL5 and AL6, only the number of iterations for levels AL3 and AL4 are reflected here. The analysis showed that on average AL3 produced the least number of iterations to reach a consensus in the environment. Analogous fluctuations as observed in the percentage of consensus are similarly reflected within the level AL3. In this respect, under level AL3, NO2 produced an overall consensus in the environment over only 1000 generations. This consensus could only be reached over 2240 generations at level NO3, 1715 generations at level NO4, 3326 generations at level NO5, and 1984 generations at level NO6 respectively. Parallel results such as those observed in percentages of consensuses are similarly found at level AL4. At level A4, the number of iterations stood almost similar at around 1400 at levels NO2 and NO3. These iterations were significantly increased under levels NO4 and NO5 with exceeding more than 4200 iterations to reach a consensus in the environment. Figure 5 shows a graphical representation for these data.

Table 2. Number of iterations for a successful overall consensus in the environment under experimentally varied conditions of the number of AL and NO

Opp/Agr	AL3	AL4
NO2	1000	1450
NO3	2240	1341
NO4	1715	4258
NO5	3326	4293
NO6	1984	N/A

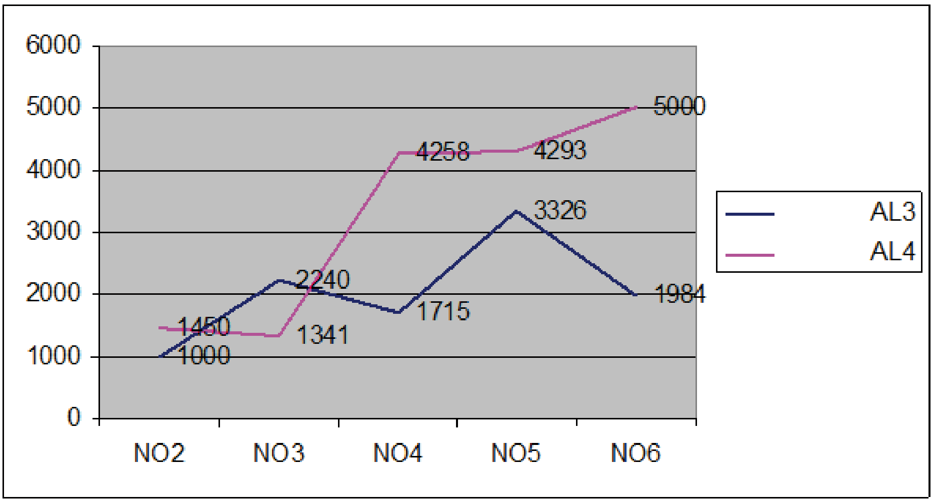

Figure 4. A line chart view of the number of iterations for a successful consensus under experimentally different conditions of NO and AL

3.4. Discussion

Results supported the hypothesis of the study that, under certain conditions, agents in a cellular automata environment are able to agree on assigning only one sign to one referent based on the Complex Systems theory. This result supports the idea that symbolic conventionalization can be achieved by mere interaction between agents. This finding is very important and could have not been readily obtained by other methodologies used in linear systems such as by calculations or inferences from similar organizations. Under initial conditions set for this simulation, agents had more opportunities to disagree with one another, or just to reach clusters of agreements in the environment. However, it was shown that very frequently the entire environment reached a consensus for a sign-to-referent mapping.

Moreover, it was shown that certain conditions in the environment facilitate and other conditions hamper reaching a consensus for a sign-to-referent mapping. For instance, it appeared that the environment was very sensitive to changes in the degrees of freedom at the level of agreement between agents. That is, the environment reached to lexical agreement much faster and more frequently when agents had less strict rules for sign exchange. An increase in the number of opposing signs, similarly, made it harder for the agents to reach an agreement. This effect was observed both in the frequency as well as the time of consensus-building in the environment. That is, the more diverse signs in the environment, the more time and generations it took to reach an overall consensus. The environment, however, showed more tolerance to an increase in the number of signs as to an increase in the levels of agreement. In other words, it only took more number of iterations to reach a consensus when the number of signs was increased. The higher ends in the levels of agreement, however, stopped any consensus-building in the environment altogether.

These results are also consistent with previous simulations. For instance, as discussed earlier, in Matsen and Nowak's study (2004), a ubiquitous language was achieved with each agent speaking to only three other people. In the current experiment, the environment also achieved the best overall consensus between sign-referent mapping when agents chose to *speak* to only three neighbors, namely level AL3 (table 1). Similarly, it was noted that Steels (1995) showed that, in similar environments, more than 80% of the time a communicative success can be established between the initiator and the receiver after about 1000 conversations. By 3000 conversations a complete coherence was achieved between both agents for almost all reference-to-object mappings. In the current experiment, the first onset of consensus was also achieved at precisely 1000 iterations (table 2). Additionally, on average, it also took more than 2400 iterations under all levels of AL3 and AL4 to reach a consensus, which is also close to Steels' findings.

It was also noted that at level AL3, there was a fluctuation in the rate and speed of learning when the number of opposing signs were linearly increased. At first, this may appear as an anomaly. These results are, however, consistent with many models of learning obtained from natural observations. Many developmental psychologists and cognitive scientists have observed that learning usually progresses, in children and adults alike, in a non-linear and U-shape form. For instance, Plunkett & Marchmann (1991) showed that 18-month old children initially can correctly recognize and pronounce irregular past tense verbs in English (e.g., "I went"). This is due to the fact that infants as young as 18 months have limited vocabulary and it is cost effective for them to learn language by en route memorization. However, when they are 24 months old, they have a wider lexicon and are able to understand certain regularities in the language such as by adding 'ed' at the end of verbs to form past tense. At this stage, infants make mistakes by spilling over the law of regular verbs onto irregular verbs (e.g., "I goed"). It is only when they reach 3 years of age that again they correctly differentiate and pronounce irregular past tense verbs from regular past tense verbs (e.g., "I talked, I went"). Similarly, Tomasello (2003) observed that one year old American children learn to correctly use unparsed expressions such as "I wanna see it" or “lemme do it” called *holophrases*. By the time, children pass 18 months of age, they adopt another strategy called *pivot schema* in which they make occasional mistakes by filling empty slots in a phrasal expressions with some content words of their own (e.g., “throw ball”; “throw can”). It is only by 24 months of age that children learn and are able to correctly produce the abstract syntactical structures found in adult language.

It can, however, be argued that this simulation did not adequately assimilate a natural environment and its inhabitants. For instance assuming that the purpose of language is to allow humans to communicate with one another, then, there are many more variables such as prosody and body language involved in communication which have been ignored in this simulation. Moreover, a computer agent is usually a disembodied dot, a rectangular representation, or a symbolic sign that can only deal with one or two variables at a time. The intention of this study was not to account for all aspects of language with its rich prosodic characteristics. Primarily, this study dealt with lexical conventionalization. The purpose of this research was to show that based on Complex Adaptive Systems theory, agents can agree to assign one sign to only one referent. As it was shown, contrary to Darwinian theories of natural selection, this agreement can be achieved under random interaction between agents. According to theories of natural selection, patterns of organization are manifested only when agents carry an advantageous trait and when there exists a selective pressure for that quality in the environment. This simulation showed that such selective pressure, at least in the case of lexical conventionalization, may not be needed. Other mechanisms such as cooperative strategies based on complexity theory present a better alternative to explain this phenomenon.

4. Conclusion

In this paper, languages in general and lexical conventionalization in particular are perceived as cultural artifacts that have emerged through interaction. The computer program in this study also supported the idea that sign to referent mapping such as those found in natural languages are also possible through the properties of emergence as described in Complex Adaptive Systems and Artificial Life theories. Agents in the simulated environment came to agree to assign only one sign to one referent without the need for an advantageous trait, or a central authority. Additionally, it was shown that a decrease in competing signs, and more importantly, a less strict rule of negotiation, may facilitate such consensus-building. In addition to lexical agreement, future studies may be able to study other dimensions of language, such as grammatical and phonological features.

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