Computational Exploration on Language Emergence and Cultural Dissemination

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Abstract- Evolutionary computation is used to explore the emergence of language, focusing particularly on the intrinsic relationship between the lexicon and syntax, and the exogenous relationship between language use and cultural development. A multi-agent model traces a coevolution of the lexicon and syntax, and demonstrates that linguistic and some distance constrain on communications can trigger and maintain cultural heterogeneity. This model also traces an optimization process using evolutionary mechanisms based on local information. Certain mechanisms in this model, such as recurrent pattern extraction, strength-based competition and indirect feedback, can be generalized to study robot learning, optimization and other evolutionary phenomena.

1 Introduction

The adoption of evolutionary computation in linguistics has grown rapidly as more computational models are proposed and their validity has more readily been accepted (e.g., Cangelosi and Parisi 2002; Wagner et al. 2003). Models based on evolutionary computation can assist linguistic research in several aspects. First, many linguistic phenomena are based on local actions without resorting to coordinating influence of certain centralized authority (Axelrod 1997). Therefore, self-organizing mechanisms in evolutionary computation are suitable for studying these phenomena. Second, these models provide an arena to test hypotheses based on linguistic data, to exemplify certain scenarios, and to suggest some research directions (Christiansen and Kirby 2003). Third, some general algorithms adopted in these models are derived from other domains (e.g., Genetic Algorithm (*GA*) (Holland 1975)) and they can be used to objectively study the dynamics of language evolution and compare it with other evolutionary processes, such as the evolution of music or social status. Finally, the model that we present here has only limited language-specific knowledge built in, so the mechanisms and conclusions of this model may instructively be applied to the study of other similar phenomena. In all, the recent frequent advances in computational techniques and the enormous availability of language resources have triggered a rapid development in computational linguistics (Huang and Lenders 2004).

This paper adopts a multi-agent model and uses evolutionary computation mechanisms to explore two open questions regarding the evolution of language, which is a resurgent interest in linguistics.

One essential question is how the lexicon (a set of mappings between semantic concepts and phonological structures) is gradually formed. The default dogma in linguistics states that it is the syntax that directs the semantics and phonology in forming lexicons and sentences, and this syntactic ability is unique to humans (Chomsky 1995). However, much evidence from anatomy (Schoenemann 2005), biology (Deacon 1997, 2003) and comparative study of the communication systems of humans and animals (Oller and Griebel 2004) suggests that syntax might have evolved gradually from some domain-general abilities (Knight et al. 2000). For example, the domain-general ability of detecting recurrent patterns and sequences is suggested to be necessary for language (Christiansen and Ellefson 2002). Research in both first and second language acquisition in children (e.g., Clark 1987) has attested a developmental process of syntax, which requires limited innate language-specific prerequisite and occurs in parallel to the acquisition of the lexicon.

Another open question concerns the mechanisms that, on the one hand, tend to increase the homogeneity among individuals but, on the other hand, tend to maintain the heterogeneity among cultures. Social scientists ascribe the durability of cultural differences to nonlinguistic factors, such as social differentiation or psychological factors like fads and fashions. However, linguistic factors like the mutual understanding and some restrictions on human communication system, such as different communication procedures or distance restrictions, are already sufficient to increase or decrease the chances for communications and adjust individual or group similarities (Nettle 1999). These linguistic factors may take place much earlier along with the emergence of language, and later, other nonlinguistic factors may cast their influences on cultural dissemination via these linguistic factors.

Evolutionary modeling provides a methodology with which to explore these questions. Our model exemplifies two processes: 1) domain-general abilities (e.g., sequencing ability, recurrent pattern extraction ability) and evolutionary mechanisms (e.g., rule competition, indirect feedback) can be used by a population of interacting agents to develop a simple language with a common lexicon and dominant word order; 2) communicational restrictions can gradually cause to emerge multiple speech communities, each community having a distinct language that is unintelligible to members of other communities.

Compared with previous models on language evolution (e.g., Kirby's Iterated Learning Model (*ILM*) 2002), our model implements a more realistic communication process with an indirect meaning transference, in which the comprehension of a perceived utterance is based on both linguistic and nonlinguistic information, and the feedback to the speaker is a variable of confidence, not a direct meaning check. The model is also inspired by some concepts in Learning Classifier Systems (*LCS*) (Holland 2001) (e.g., parallelism, learning through back-tracing) and modifies them by introducing a buffer, which extends the back-tracing mechanism.

In addition to the linguistic problem addressed, this model also explores some issues in evolutionary computation. The language emergence process in this model can be viewed as an optimization process whose aim is to develop a shared communication system. In this optimization task, it is difficult to define a global fitness function. The linguistic information is distributed into multiple linguistic rules, some of which come to be shared among agents. Our results show that certain evolutionary mechanisms (e.g., indirect feedback, strength-based competition) based on local information can still achieve the optimization, which extends the traditional view of optimization. These mechanisms, together with other general evolutionary mechanisms, can be adopted by other models on robot learning and optimization.

The remainder of the paper briefly describes the model (§ 2), summarizes the results of our experiments on language emergence and the formation of culture (§ 3), and discusses some of the mechanisms that we have adopted and introduces some future directions (§ 4).

2 Model Description

The major components of the model, like linguistic rules, agent's abilities and communication, are introduced here. A detailed description is given in Gong and Wang (2005).

2.1 Meaning, Utterance and Linguistic Rules

Language in this model is treated as a set of meaning-utterance mappings (*M-U* mappings). Agents (language users) express and comprehend 2 types of atomic sentence: "Predicate<Agent>", "Predicate<Agent, Patient>". For example, in the English sentence "dogs chase cats", "chase" is the predicate, "dogs" is the agent, and "cats" is the patient. Agents communicate with each other by exchanging utterances that encode atomic sentences. An utterance consists of a string of utterance syllables chosen from a signal space. Utterance syllables are combinable, and can be mapped to either a complete atomic sentence or to a partially specified atomic sentence with one or more variable elements (predicate, agent or patient).

The agent's linguistic knowledge includes bi-directional *M-U* mappings between atomic sentences and utterance syllables, and regulation methods for combining syllables that are mapped to atomic sentences with variable elements. This knowledge is represented by linguistic rules, which include *lexical rules* (*M-U* mappings + strength) and *word order rules* (sequencing orders + strength). The strength of each rule numerically indicates its fitness, i.e., the probability of successful use of that rule. Rule strengths are modified by self-organization mechanisms such as strength-based competition and usage-based avoidance (discussed in § 2.2, and § 2.3).

Lexical rules include *holistic* and *compositional* rules. Holistic rules map complete atomic sentences to complete utterances, e.g.,

"run<dog>" ↔ / a b c / (0.4)

where 0.4 is the rule strength. One holistic rule can only express one complete atomic sentence. Compositional rules map atomic sentences with variable elements to partial utterances, for example,

WORD RULES: "run<#>" ↔ / d e / (0.3)
"cat" ↔ / f / (0.5)
PHRASE RULE: "chase<dog, #>" ↔ / c * f / (0.4)

where "#" represents a variable argument in the atomic sentence, and "*" represents a variable syllable in the utterance. To construct a complete atomic sentence, several compositional rules must be combined so that all variable elements are specified, or a holistic rule that encodes the required atomic sentence must be used. For instance, the above 2 word rules can be combined to form an atomic sentence "run<cat>" ↔ / d e f /; furthermore, the second word rule can be combined with the phrase rule to form "chase<dog, cat>" ↔ / c f f /. The combination of a limited number of compositional rules allows many complete atomic sentences to be expressed.

The combination of utterance syllables is regulated by word order rules. To express the two types of atomic sentence, 8 word orders are required, VS, SV, VSO, VOS, OVS, SVO, SOV, OSV; here, S represents the utterance for Agent, V for Predicate and O for Patient. On the one hand, multiple word orders may be used to regulate some compositional utterances. For example, under VS order, the utterance for "run<cat>" is / d e f /; under SV order, the corresponding utterance might be / f d e /. On the other hand, the specific conditions of utterance syllables may restrict the permissible word orders. For example, based on the example word and phrase rules shown above, the utterance / c f f /, which encoded the atomic sentence "chase<dog, cat>", can only be formed under the regulation of SOV and VOS orders because the syllables that correspond to the patient "cat" must appear sentence medial. All these show that the lexicon and syntax (word order) are inter-related. In this model, all 8 orders evolve independently. When multiple orders are permissible, agents prefer the one having the higher fitness (rule strength).

The aim of this model is to determine that with some domain-general abilities and evolutionary mechanisms, whether a *compositional language* may emerge, after many iterative communications, from a *holistic signaling system*. A holistic signaling system is a system consisting of holistic rules only. Starting from such a system, following Wray's language emergence scenario (2002), all agents share a small set of holistic rules (6) to express a limited number of atomic sentences (6). These atomic sentences contain a total of 12 atomic sentence elements. In total, these elements can form 48 complete atomic sentences. Initially, there is no dominant word order in the holistic system, all 8 orders are treated equally (initialized with same strength). Such a holistic system, to a certain degree, represents the communication systems of some animals (Hauser 1996; Wray 2002). In a compositional language system, agents combine common compositional rules under the regulation of word order to express atomic sentences. Compositionality is one of the key features in human language (Hockett 1960).

2.2 Agent and His Linguistic Abilities

Agents in this model are autonomous entities with an internal memory system for storing linguistic rules, the ability to communicate with each other, and the ability to learn based on past experience.

The memory system (see Fig. 1) includes a buffer for storing "previous experience" — the *M-U* mappings comprehended in previous communications — and a rule list for storing lexical rules extracted from these mappings. These rules are used to express and comprehend complete atomic sentences in future communications. The buffer stores information obtained from not only the immediately previous step but also from several steps back, thereby extending the single-step back-tracing mechanism used in *LCS*.

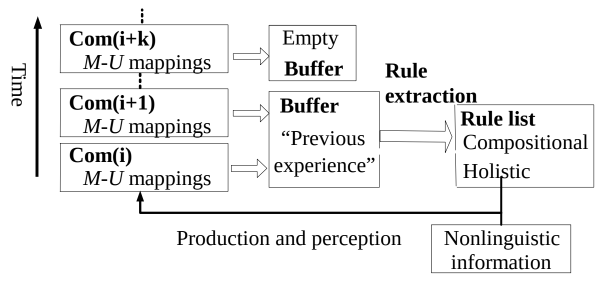


Fig. 1. Memory System

An agent's other abilities include rule acquisition and communication with other agents.

Agents have two mechanisms to acquire lexical rules, which are similar to the mechanisms used in *ILM* but different in detail:

- Random creation in production. When a speaker has insufficient rules with which to express a complete atomic sentence, he may, with certain probability, randomly select some syllables to map either the complete atomic sentence or the elements that his current rules cannot specify.
- Rule extraction through detecting recurrent patterns among *M-U* mappings in the buffer (see Fig. 2). Recurrent patterns are repeated elements that appear in 2 atomic sentences and their associated utterances, e.g., the repeated element ("dog") and the syllables (/ a b /) are repeated in the following two *M-U* mappings:

  "run<dog>" ↔ / a b c /

  "fight<dog, cat>" ↔ / a b d c a /

This pattern is mapped as a compositional rule with a default initial strength (0.5) and inserted into the listener's rule list: "dog" ↔ / a b / (0.5). A phrase rule, e.g., "chase<dog, #>" ↔ / c d * g/ (0.5), is created in a similar way. The detection of recurrent patterns that appear by chance triggers the segmentation of complete atomic sentences into atomic elements, and holistic utterance into compositional syllables. This internal mechanism results in the horizontal transmission of compositional language among agents.

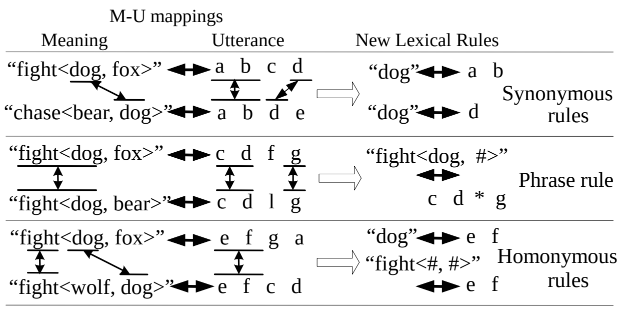


Fig. 2. Examples of Rule Extraction

In our model, rule extraction results in many synonymous (the same atomic element mapped to different syllables) and homonymous rules (the same syllable(s) mapped to different atomic element). For example, the presence in the buffer of multiple recurrent syllables but a single recurrent atomic element causes the emergence of synonymous rules in an agent's rule list (see Ex. 2 in Fig. 2). Synonymous rules increase the speaker's load for searching rules in production and occupy more space in the rule list; homonymous rules may cause ambiguity in the listener's comprehension. Some internal mechanisms for avoiding ambiguities caused by homonyms have been suggested based on some empirical research. For example, according to *the Principle of Contrast* (Clark 1987), children tend to avoid mapping syllables that are already mapped to an extant element to novel ones. In our model, a similar usage-based homonym-avoidance mechanism is adopted, i.e., if the chosen combination of rules helps the listener's comprehension then, besides the normal rule strength modification, an additional penalty is applied to the rule strengths of other rule combinations that are homonymous to the chosen one. The definition of successful or failed communication is given in § 2.3.

The memory system and rule acquisition abilities discussed above are not restricted to the linguistic domain. For example, the memory system makes possible a "learning from experience" strategy. The buffer can store useful information experienced by agents for future reference in the rule extraction. Such an information extraction mechanism based on temporary or historical inputs simulates a common way of learning in humans and some animals. In addition, the recurrent pattern extraction is similar to the general logic operation "AND", which can extract the common features among multiple instances. This extraction mechanism associates common semantic concepts with common phonological elements. Such cross-domain association is a general way to extract information and build up new knowledge, and is widely used in signal processing as well as other learning systems.

2.3 Communication

An indirect meaning transference is implemented in communications, which includes multi-source information processing and inexplicit feedback.

One type of nonlinguistic information, *cues*, is introduced in this model. Cues consist of complete atomic sentences, modeling an agent's perception of events that are ongoing or salient in his local environment, e.g., "chase<fox, dog>" (0.5), where 0.5 is the cue strength. Cues can assist the listener's comprehension in communications. In each communication, multiple cues comprising different atomic sentences are simultaneously available to the listener, all cues having the same strength. Cues, as semantic hints for comprehension, are sometimes ambiguous, and may be unreliable because there are situations where a speaker might not always describe an ongoing event in the listener's immediate environment or the listener may pay attention to the wrong event. To simulate this ambiguity, *reliability of cues* (*RC*) is used to manipulate the probability that one cue that is available to the listener corresponds to the speaker's atomic sentence.

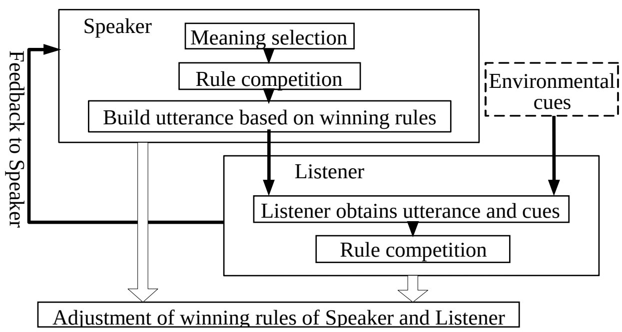


Fig. 3. Information exchange during communication

One information exchange in a communication event is summarized in Fig. 3. In production, the speaker selects a complete atomic sentence to produce. Among his related linguistic rules, the speaker determines his winning rules based on their combined rule strength, $CS_{Produce}$, and builds up an utterance accordingly. $CS_{Produce}$ is calculated based on both his lexical and syntactical information:

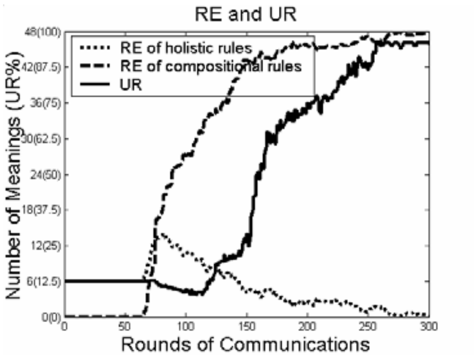
$$CS_{Produce} = \begin{cases} Str(\text{activated lexical rules}) \\ + Str(\text{applicable order rules}) \end{cases}$$

In comprehension, the listener receives the utterance produced by the speaker and, sometimes, some cues. Then, the lexical rules in the listener's rule list whose syllables partially or fully match the perceived utterance are activated. The rule competition in comprehension considers not only the strength of the listener's activated lexical and word order rules, but also the cues whose atomic sentences may assist the listener to comprehend the utterance. For example, a listener's linguistic rules might only allow an utterance to be comprehended as "eat<dog, #>". However, if the cue "eat<dog, meat>" were available, the strength of this cue would be included in the calculation of the combined strength, $CS_{Comprehend}$, of these linguistic rules. $CS_{Comprehend}$, is calculated based on both linguistic and nonlinguistic information:

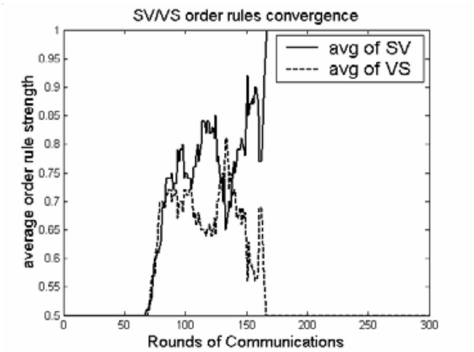
$$CS_{Comprehend} = \begin{cases} LanguageWeight \begin{cases} Str(\text{activated lexical rules}) \\ + Str(\text{applicable order rules}) \end{cases} \\ \quad + CueWeigh\{Str(\text{related cues})\} \end{cases}$$

After comprehension, the listener sends back a confidence feedback to the speaker. If the $CS_{Comprehend}$ of his winning rules exceeds a certain threshold (we use 0.5), the feedback is positive, indicating a strong confidence in the comprehension. Otherwise, the feedback is negative, meaning that the listener is either unable to comprehend the utterance or else is not confident of his comprehension (whether or not the listener comprehends the meaning intended by the speaker is not considered). Then, based on this confidence feedback, both the speaker and the listener adjust their rules. Under a positive feedback, both agents increase the strengths of their winning rules and decrease those of the losing rules; otherwise, the opposite operation is executed. Inexplicit feedback is common both in the primitive and modern stages of language use. For example, observing that another person nods their head might not give the speaker a strong confidence as to whether they clearly understand what he says. Based on the feedback after each information exchange, we can define *successful* (most of the feedbacks in one communication are positive) or *failed* communications, which can indirectly indicate the linguistic similarities among agents. Each communication event consists of an exchange of multiple (20) atomic sentences.

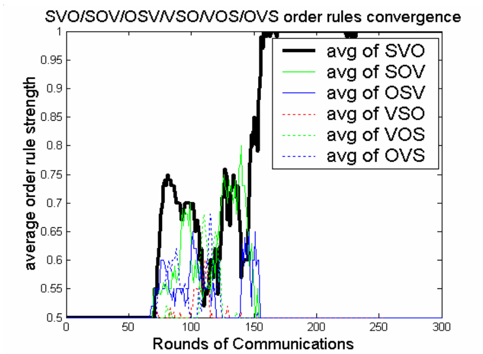
During the whole communication event, the speaker's production and the listener's comprehension are independent and the comprehension is based on the interaction of linguistic and nonlinguistic information. This communication process modifies the unrealistic assumption adopted in *ILM* that in every communication, the listener always acquires the meaning intended by the speaker. The speaker and the listener update their language based only on listener's feedback, which is not directly represented by linguistic information, but can nevertheless assist mutual understanding at a certain level. The multi-source information processing simulates the real comprehension process in the listener's mind during linguistic communication. The incorporation of multiple forms of feedback is important in robot learning tasks where the supervising information is usually indirect.



(a)



(b)



(c)

Fig. 4. Lexicon-syntax coevolution:
(a) Rule Expressivity (*RE*) and Understanding Rate (*UR*);
(b) Emergence of dominant order for "Predicate<Agent>" atomic sentences; (c) Emergence of dominant order for "Predicate<Agent, Patient>" atomic sentences.
The abscissa is N_{com}, the ordinate is $N_{atomic\ sentence}$ (and *UR* in brackets) in (a), and the rule strength in (b) and (c).

3 Simulation Results

Several parameters are defined to trace the emergence of language:

- Rule Expressivity (*RE*) — the average number of complete atomic sentences that each agent can express;
- Understanding Rate (*UR*) — the average proportion of complete atomic sentences understandable by each pair of agents based on linguistic information <u>only</u>. *UR* evaluates the real representation of the emergent language, which concerns not only the *RE*, but also whether such expressions are understandable by other agents using linguistic information only, even when those expressions do not refer to events that are on-going in the immediate environment, a property known as *displacement* (Hockett 1960). *UR* can also test similarities among the languages of different groups of agents.

$$UR = \frac{\sum_{i,j} \text{number of understandable meanings between agent i, j}}{\text{number of all possible paires of i, j}}$$

With these indices, the emergent process of language is traced. Moreover, heterogeneity within a community and, later, between linguistic communities can be traced by introducing communicational restrictions.

3.1 Language Emergence: Lexicon-Syntax Coevolution

The intrinsic relationship between the lexicon and syntax during language emergence is studied by analyzing the performance of the model for one set of parameter values (other reasonable parameters give qualitatively similar results): *P* (Population size) = 10, *RC* (Reliability of Cues) = 0.7, *BS* (Buffer size) = 40, *RS* (Rule list size) = 40, and N_{com} (Number of rounds of communication) = 300. A concurrent communication scenario is used in which, in each communication round, each agent communicates randomly with one other agent. In total, there are 1,500 ($N_{com} \times C_P^2$) communication events, or 30,000 (1,500 × 20) information exchanges.

The coevolution of the lexicon and syntax is traced by the Rule Expressivity (*RE*), Understanding Rate (*UR*) and the average rule strength of all 8 order rules after each round of communication (see Fig. 4). In Fig. 4(a), the decrease of the *RE* of holistic rules and the increase of the *RE* of compositional rules indicate a transition from the initial holistic signaling system to a compositional language. The *UR*-curve exhibits a sudden increase (at about 160 rounds of communication), which suggests that the understandability of the emergent compositional language undergoes a *phase transition* (Monasson et al. 1999). Figs. 4(b–c) trace the gradual forming of the preference for certain word orders. Two dominant orders, one for each type of atomic sentence, emerge from the 8 initial orders. No prior bias is conferred to any particular order; each order is *a priori* equally likely to be the dominant one. Combining Figs. 4(a–c), the sharp increase of *UR* is almost synchronized with the sharp increase of the strengths of the dominant orders. This suggests that the use of common compositional rules and the preference of the dominant orders boost each other; in other words, the lexicon and syntax coevolve during the emergence of language. This coevolution process weakens the traditional linguistics' claim of the predominance of innate syntax as a driving force for the emergence of the lexicon.

This lexicon-syntax coevolution is a self-organizing process, driven by mutual understanding and achieved by evolutionary computational mechanisms. At the beginning, agents can only communicate with each other using the initially shared holistic rules. Additional holistic rules are slowly introduced by random creation allowing agents to express more atomic sentences. This gradually increases the *RE* of holistic rules. As more holistic rules are added, so more recurrent patterns among the *M-U* mappings in the buffer are extracted, leading to an increase in the *RE* of compositional rules — the competition between holistic rules and compositional rules begins. In communications using compositional rules, mutual understanding can be achieved with the help of occasional accurate cues. The preference for compositional rules over holistic ones is then gradually formed by the usage-based avoidance and strength-based competition mechanisms.

A consistent word order is necessary for agents to be able to use compositional rules to produce and comprehend meanings — the competition of dominant order begins. With no prior bias conferred to any order, the rule strengths of all orders tend to be increased. Then, due to the strength-based competition (indicated by the drastic fluctuations of the average strength of the order rules in Fig. 4 (b–c)), certain orders gradually come to be preferred by all agents. Along with the acquisition of more compositional rules and the emergence of winning dominant order rules that are shared among agents, there is a sharp increase of the *UR*. Such sharing of the compositional lexicon and word order is gradually finalized. The *UR* approaches 100% in some simulations, indicating that the shared lexicon is sufficient to accurately produce and comprehend almost all 48 atomic sentences.

3.2 Cultural Dissemination: Global Polarization, Local Convergence (Axelrod 1997)

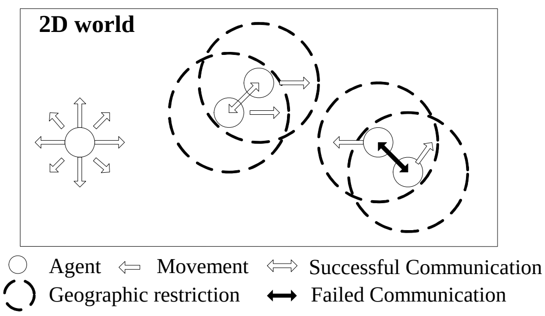
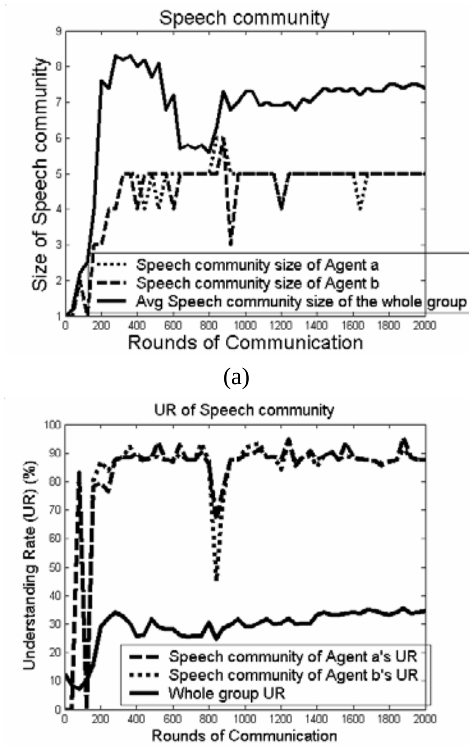


Fig. 5. Agent's movement tendencies in a 2D world

In this section, the influence of language use on the emergence and stability of cultural differences is studied. We put all agents in a 2D world in which they could freely move (see Fig. 5). Two communicational restrictions are introduced:

- a distance restriction — communication may only occur between agents separated by a limited Euclidian distance;
- mutual understanding — successful communication can link the speaker and the listener in a *speech community*, a subgroup of agents who can understand each other and whose members tend to move about the world together. A speech community can be broken in the future if communication fails repeatedly.

By tracing the *UR* of the each speech community that emerges and the *UR* of the whole population, the emergence and maintenance of cultural dissemination, indicated by the mutual intelligibility of each community's language, can be traced.



(a)

(b)

Fig. 6. Community sizes (a) and *UR*s (b) of the tagged agents (Agents a, b) and of the whole group. The abscissa is N_{com}, the ordinate is $N_{atomic\ sentence}$ (and *UR*).

In this simulation, we double the population size ($P = 20$), and increase the number of communication rounds accordingly ($N_{com} = 2{,}000$). The size of the world is set to 180×80 cells, the distance restriction is 5, and at each round of communication, each agent may move from its current position to one of its 9 neighboring positions. Two randomly chosen agents are set as tagged agents. Fig. 6(a) traces the community size of each of the tagged agents, and the average community size of the whole population. Fig. 6(b) traces the *UR* of each tagged agent community, and the average *UR* in the whole population. Multiple speech communities gradually emerge and attain stable states with fixed sizes after many rounds of communication. Within each community, a common language with high *UR* emerges. However, inter-community linguistic heterogeneity is maintained, indicated by the low *UR* of the whole population. After a common language emerges within each community, the community sizes of the tagged agents and the average community size of the whole population become stable, indicating that the further merging or splitting of speech communities is rare; in other words, the linguistic heterogeneity among speech communities is maintained.

This simulation traces the emergence and maintenance of inter-community heterogeneity during language emergence. Both the mutual understanding and the distance restriction contribute to the emergence and stability of community differences. On the one hand, they play the role of *intra-community cohesion*: agents within limited a Euclidian distance have more chances to communicate with each other. Once mutual understanding is built up, these agents tend to communicate more, and develop their own common language. On the other hand, these factors play the role of *inter-community repulsion*. The tendency for agents to move apart as a result of failed communication increase the distance between them, and reduces the chances for future communication, so allowing their linguistic difference to increase as each agents enters into speech communities with other agents. The interaction of these two contradictory effects triggers "global polarization, local convergence" during the language evolution, paving the way for the future emergence and stability of cultural heterogeneity.

4 Discussion, Conclusions and Future Directions

Computational simulation has gradually come to be accepted as a productive method for exploring evolutionary systems for which theoretical argumentations alone are not sufficiently reliable, or for which incomplete empirical data prevent a thorough understanding of the behavior of the system. In this paper, some evolutionary problems regarding the relationship between the lexicon and syntax, as well as between language use and cultural dissemination are studied in a multi-agent computational model. A lexicon-syntax coevolution process is traced, and, for particular communicational restrictions, a "global polarization, local convergence" phenomenon emerges during the emergence of speech communities. These results lead us to question the hypothesis of the intrinsic syntactic capability of humans proposed by Chomsky, and exemplify the influences of mutual understanding and distance restrictions on language emergence and the maintenance of cultural heterogeneity.

In addition to these linguistic conclusions, the model can be viewed as an optimization process, in which mutual understanding in communication is gradually achieved through the acquisition of common linguistic rules. In traditional optimization tasks, fitness is often assessed globally. However, many mechanisms adopted in this model are based on local information. It is difficult to develop an appropriate global fitness function for a linguistic communication system because the degree of mutual understanding between any pair of agents is determined by the local linguistic knowledge of each agent. Each linguistic rule has its own fitness value (its strength). The strength-based competition and usage-based avoidance mechanisms guide agents to choose winning rule combinations based on their combined strengths. These mechanisms act to gradually increase the strengths of rules that are used successfully. And these mechanisms are not explicitly oriented to increase mutual understanding; a successful communication does not necessarily mean that the listener understood the meaning intended by the speaker, just that the listener gave a positive feedback.

Regarding the communication aspect, agents are selected to communicate with each other randomly without any centralized guidance. The communicational restrictions act locally, cast their influence on the communications between specific pairs of agents. These mechanisms are not designed specifically to trigger cultural heterogeneity. Nevertheless, cultural heterogeneity emerges as an emergent property of the local interactions and restrictions among agents.

The model described here provides a method for optimization tasks that involve complex phenomena such as language, music, and personal preference (e.g., one may prefer communicate with others who share common interest with him or can understand him very well). In fact, approaches to optimization based on local, uncentralized mechanisms are already used in many popular methods, such as the Ant Colony Optimization (*ACO*) (Dorigo and Stützle 2004).

Based on this computational model, further discussions of the lexicon, syntax and culture are possible. First, although the current model weakens the claim that syntax regulates the development of the lexicon, exactly how syntax co-evolves with the semantic elements and phonological structures is not addressed. The predicates, agents and patients that combine to form atomic sentences are built into the model *a priori*. How the human cognitive system acquires these semantic concepts, and whether the acquisition process depends upon domain-general abilities, as the syntax might do (shown in our model), are not certain. Therefore, future models will necessitate adopting pragmatic mechanisms to acquire semantic concepts and studying the interactions between pragmatic and syntactic operations. If the pragmatic mechanisms might also be adapted from domain-general abilities, it will be reasonable to claim that syntax might not be language-specific, but a set of mechanisms that have developed from domain-general abilities to serve some linguistic functions.

Second, sociolinguists have observed dramatic variations in various linguistic abilities across speech communities, and studies on language acquisition have revealed various dichotomies in children's learning styles (Shore 1995). Agent-based modeling can be used to study such heterogeneity. Furthermore, the theory of complex networks (Newman 2003) can be introduced to study social structure and its influence on language evolution and use. Finally, in order to generalize and implement the evolutionary mechanisms adopted in this model to study other evolutionary phenomena or carry out other optimization tasks, an in-depth analysis and comparison with other popular optimization methods, such as *GA* and *ACO*, is required.

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Bibliography

Axelrod, R. (1997). "The Dissemination of Culture: A Model with Local Convergence and Global Polarization", *The Journal of Conflict Resolution*, vol. 41, no. 2, pp. 203-226.

Chomsky, N. (1995). *The Minimalism Program*. Cambridge, MA: MIT Press.

Cangelosi, A. and Parisi, D. Eds. (2002). *Simulating the Evolution of Language*. London, UK: Springer.

Christiansen, M. H. and Ellefson, M. H. (2002). "Linguistic Adaptation without Linguistic Constraints: The Role of Sequential Learning in Language Evolution", *The Transition to Language*, Wray, A. (Ed.), Oxford University Press, pp. 335-358.

Christiansen, M. and Kirby, S. (2003). "Language Evolution: Consensus and Controversies", *TRENDS in Cognitive Science*, vol. 7, no. 7, pp. 300-307.

Clark, E. (1987). "The Principle of Contrast: A Constraint on Language Acquisition", *Mechanisms of language acquisition*, MacWhinney, B. (Ed.), Lawrence Erlbaum Assoc, pp. 1-33.

Deacon, T. W. (1997). The Symbolic Species: the Coevolution of Language and the Brain. New York: W. W. Norton.

Deacon, T. W. (2003). "Multilevel Selection in a Complex Adaptive System: the Problem of Language Origins", *Evolution and Learning: the Baldwin Effect Reconsidered*, Weber, B. J. and Depew, D. J. (Eds.), MIT Press, pp. 81-106.

Dorigo, M. and Stützle, T. (2004). *Ant Colony Optimization*. Cambridge, CA: MIT Press.

Gong, T. and Wang, W. S-Y. (2005). "Computational Modeling on Language Emergence: A Coevolution Model of Lexicon, Syntax and Social Structure", *Language and Linguistics*, vol. 6, no. 1, pp. 1-41.

Hauser, M. D. (1996). *The Evolution of Communication*. Cambridge, MA: MIT Press.

Hockett, C. F. (1960). "The Origin of Speech", *Scientific American*, vol. 203, pp. 88-96.

Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*. Michigan, NM: University of Michigan Press.

Holland, J. H. (2001). "Exploring the Evolution of Complexity in Signaling Networks", Complexity, vol. 7, no. 2, pp. 34-45.

Huang, C. R. and Lenders, W. Eds. (2004). *Computational Linguistics and Beyond*. Taipei, Academia Sinica.

Kirby, S. (2002). "Learning, Bottlenecks and the Evolution of Recursive Syntax", *Linguistic Evolution through Language Acquisition: Formal and Computational Models*, Brisco, T. (Ed.): Cambridge University Press, pp. 173-205.

Knight, C., Studdert-Kennedy, M., Hurford, J. R. Eds. (2000). *The Evolutionary Emergence of Language: Social function and the origins of linguistic form*. Oxford: Oxford University Press.

Monasson, R., Zecchina, R., Kirkpatrick, S., Selman, B., Troyansky, L. (1999). "Determining Computational Complexity from Characteristic 'Phase Transitions'", *Nature*, vol. 400, no. 8, pp. 133-137.

Nettle, D. (1999). "Using Social Impact Theory to Simulate Language Change", *Lingua*, vol. 108, pp. 95-117.

Newman, M. E. J. (2003). "The Structure and Function of Complex Networks", *SIAM Review*, vol. 45, pp. 167–256.

Oller, D. K. and Griebel, U. (2004). *Evolution of Communication Systems: A Comparative Approach*. Cambridge, MA: MIT Press.

Shore, C. M. (1995). *Individual Differences in Language Development*, Thousand Oaks, CA: Sage Pub.

Wagner, K., Reggia, J. A., Uriagereka, J., Wilkinson, G. S. (2003). "Progress in the simulation of emergent communication and language", *Adaptive Behavior*, vol. 11, no. 1, pp. 37-69.

Wray, A. (2002). *Formulaic Language and the Lexicon*. New York: Cambridge University Press.