A Computational Framework to Simulate the Co-evolution of Language and Social Structure

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Abstract

In this paper, a multi-agent computational model is proposed to simulate the co-evolution of compositional proto-language and social structure from a holistic signaling system through iterative interactions within a heterogeneous population. We implement an indirect meaning transference based on both linguistic and nonlinguistic information in communications, together with a feedback without direct meaning transfer. The emergent social structure, triggered by two locally selective strategies, *friendship* and *popularity*, has small-world (Watts 1999) characteristics. The influence of these selective strategies on the emergent language and the emergent social structure are discussed.

1. Introduction

Recently, computational modeling of language evolution has grown rapidly, as exemplified by many anthologies and reviews (Standish et al 2003; Cangelosi and Parisi 2001; Luc Steels 1999; Wagner et al. 2003). Many computational models, based on evolutionary or artificial life theories, have been reported, such as the neural network models (Batali 1998; Munroe and Cangelosi 2002), the vocabulary coherence model (Ke et al. 2002), and the iterative learning framework (Kirby et al. 2003). These "emergent" models (Schoenemann 1999) share several assumptions related to language development. However, there are still several limitations.

First, most of them assume *direct meaning transference* (not Munroe and Cangelosi (2002)) in the interactions among agents, i.e., the intended meanings encoded in linguistic utterances and sent by speakers are always accurately available to listeners. However, it is obvious that expression and interpretation are independent in speakers' and listeners' minds, and that there are at least no *direct* connections among them. Other channels, such as pointing while talking or primitive feedback, can only provide a certain degree of confirmation. Interpretation is a complex process requiring linguistic and nonlinguistic information. It is unrealistic to assume direct meaning transference.

Second, these models either fail to model syntax (e.g., Ke et al. 2002), build in the syntactic features (e.g., Munroe and Cangelosi 2002), or else do not adopt a co-evolutionary view of the emergence of syntax and the lexicon (e.g., Batali 1998; Kirby et al. 2003). However, syntax in language is likely to become conventionalized through language use, rather than as the result of an innate, grammar-specific module (Schoenemann 1999). The syntax is assumed to owe to a pre-adapted cognitive capacity reflected in other cognitive processes, i.e. the sequencing ability, which can be attested in other primates and pre-language infants (Christiansen 2000). The emergence of the lexicon and the convergence of syntax should be interwoven, i.e. they should co-evolve.

Third, these models often use random interactions, which disregard the influence of social structure. Although sociological research has studied structures that have emerged based on stable or global factors, very little research has touched upon the emergence of structure based on the evolution of language. Mutual understanding based on the evolving language can be a factor to trigger change in the social structure and so is worth studying.

Fourth, most current models are based on homogeneous populations. However, sociolinguists have shown there to be dramatic variations in the speech community and various dichotomies in the learning styles of children (Shore 1995). Heterogeneity of natural characteristics and linguistic behaviors among agents should therefore be considered in the computational models that are adopted.

Addressing these limitations and based on the "emergent" theory of Wray (2002), we present a computational model which uses an indirect meaning transference and simulates the co-evolution of lexicon and syntax (simple word order) during the transition from a holistic signaling system to a compositional language. Importing two locally selective strategies, this model also simulates the emergence of social structure based on the mutual understanding of the evolving language. In Section 2, we describe the model. Results and discussions are presented in Section 3. Finally, we draw some conclusions and point out some future directions in Section 4.

2. Description of the model

The model is basically a linguistic communication game among independent agents in a population. Agents express and interpret two types of meanings: "predicate<agent>", such as "run<tiger>", and "predicate<agent, patient>", such as "chase<tiger, wolf>" or "eat<tiger, meat>". Nonlinguistic information[1] is used to assist the meaning interpretation, especially meanings like "chase<tiger, wolf>". Without cues, it is not clear who is chasing whom, especially in the early stages of the language evolution.

This model uses a rule-based system to represent the language, including lexicon rules (meaning-utterance (M-U) mappings), such as holistic, phrase and word rules, and word order rules which cover all possible sequences to express the two types of meanings, such as "agent first, predicate last, patient in middle". A self-organizing strategy for rule competition adjusts the rule strengths, which indicate numerically the frequency of successful use of the rules. The presence of a common set of rules shared by all agents indicates the convergence of the language.

A memory system, inspired by a model (Holland 2001) based on the Classifier System, is used to handle M-U mappings. It includes a buffer (storing "previous experiences" — M-U mappings obtained in previous communications) and a rule list (storing rules generalized from M-U mappings in the buffer). Rules in the rule list are used to express meanings and interpret utterances in future communications.

Two mechanisms are used to acquire new rules: random creation in meaning expression (as in Kirby et al.'s model), and generalization, a flexible detection of recurrent patterns (recurrent meanings and utterances in two M-U mappings) without syntax or location restriction. Generalization happens when the buffer is full. Some examples of rule generalization are given in Fig. 1. By extracting recurrent patterns as new compositional rules, some holistic rules are decomposed.

Synonymic and homophonic rules emerge inevitably during the execution of these two mechanisms because there is no clear access to other agent's language, and rule generalization is flexible and doesn't consider the existent rules. Due to the lack of context (meanings expressed in communications are independent of each other) and the unreliability of cues (otherwise, it would still be *direct meaning transference*), homophone avoidance, in which the "successfully" used form is reinforced and others are weakened, is built in. As for synonyms, agents randomly learn one form from a set of synonymic rules based on the principle of contrast (Clark 1987).

This model implements an indirect meaning transfer-

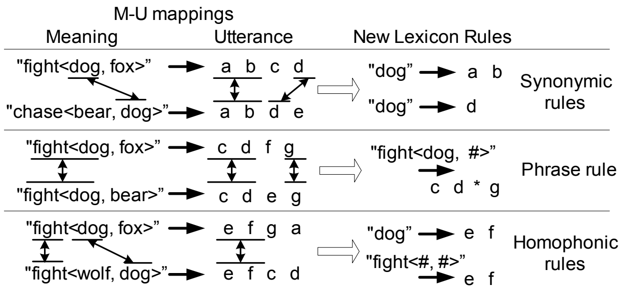


Figure 1: Examples of rule generalization. (#, *: matching pragmatic meaning items and syllable(s))

[1] Cues are pragmatic meanings available from the environment, and are all assigned the same strength, e.g., "fight<dog, cat>"/(0.5); 0.5 is the strength. Cue Reliability (*CR*) manipulates the probability that the intended meaning is one of the cues.

ence in communication. Communication proceeds as follows (summarized in Fig. 2). First, the speaker selects a meaning to express. The speaker expresses the selected meaning using the utterance that has the highest combined rule strength, CS_{speak}, calculated from the formula

$$CS_{speak} = \begin{matrix} \mathrm{Str}(\text{combinable activated rules}) \\ + \mathrm{Str}(\text{applicable word order rules}) \end{matrix} \quad (1)$$

The utterance, built up accordingly, is transferred to the listener, who attempts to interpret the utterance. The listener sometimes also receives cues from the environment. Interpretation involves a more complex process of rule competition in the listener's mind, based on the combined rule strength CS_{listen}:

$$CS_{listen} = \begin{matrix} LangWeight \left\{ \begin{matrix} \mathrm{Str}(\text{combinable activated rules}) \\ + \mathrm{Str}(\text{applicable word order rules}) \end{matrix} \right\} \\ + EnvWeight \left\{ \mathrm{Str}(\text{Environmental Cues}) \right\} \end{matrix} \quad (2)$$

The listener interprets the meaning based on the winning rules. If the listener's winning rules' CS_{listen} exceeds a threshold, a positive feedback is sent to the speaker indicating the listener's confidence in the interpretation. Otherwise, a negative feedback is sent, meaning that the listener was either unable to infer a meaning or else was not confident of inferring the intended meaning. Finally, based on this feedback rather than on a direct meaning check, both the speaker and the listener adjust their own rules, increasing the strengths of the winning ones and decreasing those of the losing ones.

Mutual understanding based on the evolving language can influence the possibility of future communication between these two agents. A fully-connected weighted network is used to indicate the social relationships among members; see Fig. 3. The connection weight, adjusted in both successful and failed communications, indicates the cumulative probability of successful communication between the two agents. Once the connection weight exceeds a threshold, a permanent edge is built. Agents permanently connected to each other are linguistic "friends", and have a higher chance to understand each other. The number of permanent edges of one agent indicates his linguistic "popularity", i.e., his propensity to communicate successfully with other agents. These factors are local factors focusing on individual agents.

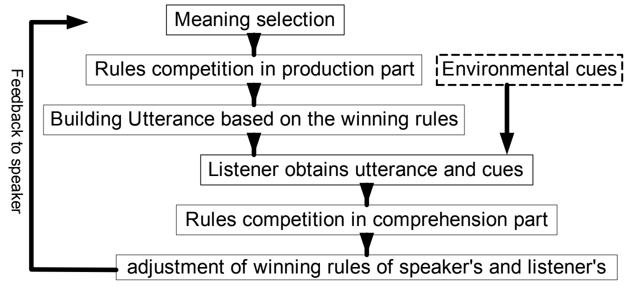


Figure 2: Indirect meaning transference.

To enhance the realism of the model, we introduce a *local-view* assumption, i.e., in one communication, one agent can only view several agents (local-view) instead of all group members and communicate with some of them.

We run two types of simulation. **Simulation 1:** Each generation, each agent selects the agents in his local-view, those to whom he is permanently connected having a higher chance to be chosen. Agents communicate with a subset of agents in their local-view, preferring to communicate with agents having higher popularity. A new generation begins after all agents have executed this process. **Simulation 2:** Each generation, agents randomly select the agents in their local-view and randomly attempt to communicate with some of them.

In this model, heterogeneities, such as different buffer or rule list size, different random creation and generalization rates (simulated by the Gaussian distribution), and different mechanisms to acquire new rules (simulated by random assignment), are allowed to make the model more realistic.

Finally, several major factors are used to study the performance: a) the *understanding rate* (*UR*), defined by

$$UR = \frac{\sum_{i,j} (\text{number of understandable meanings between agent } i, j)}{(\text{number of all possible pairs of } i, j)} \quad (3)$$

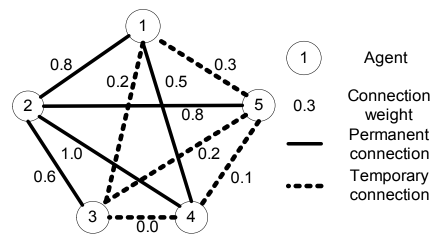


Figure 3: Social network used in this model.

indicates the average number of meanings understandable by every pair of agents in the population based on linguistic information only — this tests the real representation ability of the acquired language, considering not only the expressivity, but also the understandability of the emergent language; b) the *degree distribution* (P_k) indicates the distribution of the number of permanent connections (degree) versus the number of agents having such degree; c) the *number of sub-clusters* of connected agents, indicating the divergence within the population. Other parameters, such as the *rule expressivity* (*RE*), *convergence time* (*CT*) (the number of rounds of communication by which the highest *UR* is reached), the *average degree* (*AD*), the *clustering coefficient* (*C*), and the *average shortest path length* (*L*) are also considered.

3. Results[2] and Discussion

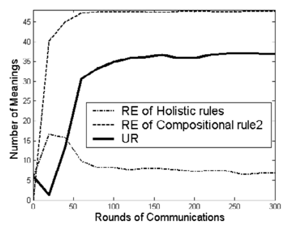
Co-evolution of lexicon and simple syntax

Co-evolution of the lexicon and syntax is simulated in this model, as shown in Fig. 4. Fig. 4(a) shows the *RE* of both holistic rules and compositional rules; the decrease of the former and the increase of the latter show the transition from initially holistic signals to a compositional language. The *UR* in Fig. 4(a) shows the convergence to a common lexicon. The *UR* undergoes an S-shaped evolution, matching the result of Ke et al.'s model (2002). The *RE* of compositional rules used in combination increases rapidly, but the use of compositional rules may cause some meanings understandable when expressed by holistic rules to be misunderstood, causing the *UR* to briefly drop slightly. However, the recurrence of these compositional rules in successive communications allows them to win the competition with the holistic rules, which finally makes possible the emergence of a common lexicon.

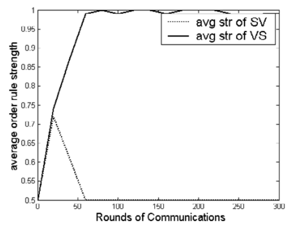
Figs. 4(b–c) show the convergence of the syntax from all possible sequential order rules; the curves trace the average strength of each of the eight order rules. Mutual understanding requires not only common lexicon rules but also a shared syntax to combine compositional rules. Two dominant word orders emerge from the initial state of no syntax, one for each of the two meaning types. There is no prior bias conferred to any particular word order; each is initially equally likely. Finally, combining Figs. 4(a–c), we observe the co-evolution of the lexicon and syntax: the use of compositional rules triggers the convergence of the syntax, which in turn boosts the convergence of the lexicon; the sharp increase of the *UR* and the dominant order's rule strengths are almost *synchronized*.

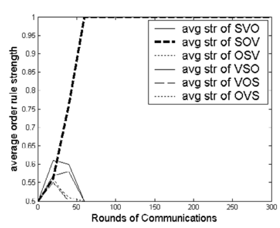
The emergence of social structure

During the emergence of language, the selective strategies trigger a global social structure based on the mutual understanding of the evolving language. The *AD* and *C*, also following an S-curve, trace the emergence of the social structure (see Figs. 5(a–b)). Due to the restriction of the selective strategies, the *AD* and *C* of Scenario 1 is smaller. Besides, these strategies have their own influences. For example, the local, "self-centered" strategy of friendship can trigger an earlier increase of *AD* and *C* compared with Simulation 2. It also triggers an earlier emergence of sub-clusters (see Fig. 5(c)). The high *C* and low *L* indicate the emergent social structures of both simulations have small-world characteristics. But their structure is different due to the influence of the friendship and popularity strategies (see Fig. 5(d)). In Simulation 2, a network that



(a)





(b) (c)

Figure 4: Co-evolution of Lexicon and Syntax (local-view=10, com. of each agent=5, Simulation 1 (Simulation 2 is similar)). (a) Lexicon convergence; (b) Syntax convergence for "predicate<agent>" meanings; (c) Syntax convergence for "predicate<agent, patient>" meanings.

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[2] Simulation conditions: 50 agents, 500 generations, *RC*=0.8.

is almost fully-connected emerges, with most agents having the same, high degree. However, in Simulation 1, the degree distribution is more uniform. Although almost all members can understand each other, some agents' degrees don't increase much. This is because friendship restricts the agents belonging to the local-view, and the popularity only triggers a local convergence inside the local-view. Agents within the local-view might have intensive connections with one another, but they don't connect to outsiders frequently. This local centralization prevents some agents' degrees from increasing greatly.

On the other hand, different local-view sizes in the selective strategies can influence the language that emerges. With the increase of the local-view size, the influence of friendship is gradually reduced, which breaks down the local convergence. Then, the degree of every agent increases gradually. This can be seen from the social structure that emerges (see Fig. 6(a)).

As for the language that emerges, with the increase of the local-view size, the centralization is more global; there seems to be an optimal centralization for peak *UR* (Fig. 6(b)) — too much "democracy" or too much "dictatorship" cannot achieve the best *UR*. Actually, centralization around some agent(s) has two effects. First, popular agents connects to many unpopular agents, like a network hub. Centralization around it can increase the chances for unpopular agents to exchange information, and then accelerate the convergence of linguistic rules. On the other hand, effective information transference between two agents (say, *Agent1* and *Agent2*) requires direct connection or connection through a "stable" intermediary (say, a popular agent, whose internal rules do not change much, so that the information received by *Agent2* via the popular agent does not change much from the original information sent by *Agent1*). However, with the increase of global centralization, other agents have higher chances to contact the popular agent and influence his rules. This makes the popular agent unstable, i.e., although the input information is the same, the output information differs greatly from time to time. It greatly affects the information transference and the convergence of linguistic rules between *Agent1* and *Agent2* through the popular agent. Compromising these two contradictory factors, the optimum performance happens at an intermediate level of centralization.

Finally, the structure of Simulation 1 is triggered by the social strategies which are based on the evolving language. The evolution of the language has its influence on the final result; these social strategies, if based on a non-evolving language, can trigger a local-world (Li and Chen 2003) (see Fig. 6(c)) or a scale-free (Barabási 1999) structure (if local-view is the whole group). However, the result of this model has no such structures. This shows that when using language-related factors to trigger structure, one should consider the evolution of language.

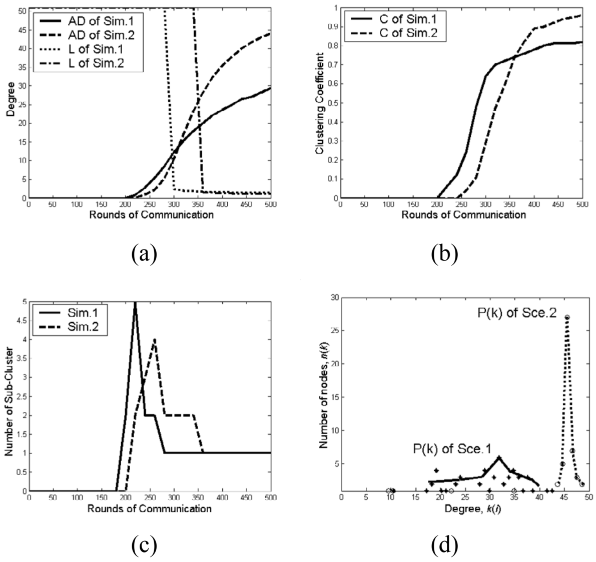

Figure 5: The emergent social structure. (a) *AD* and *L* of the two simulations; (b) *C* of the two simulations; (c) Sub-Clusters; (d) P_k.

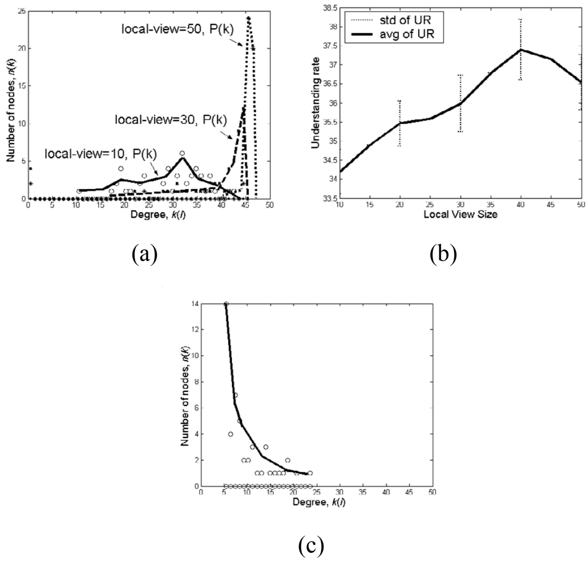

Figure 6: Local-view size effects. (a) P_k; (b) *UR*; (c) P_k of local world structure (based on Li and Chen (2003)'s model)

4. Conclusions and Future Directions

Considering the evolutionary point of view and real communication situations, the co-evolution and indirect meaning transference are more realistic. Social strategies (friendship and popularity), based on the mutual understanding of the evolving language, trigger a social structure showing small-world characteristics during the emergence of language. The results are different if the evolving property is not considered, which proves the influence of the evolving property on the emergent social structure.

This model has been introduced to study the emergence of social structure based on evolving factors. Artificial life modeling is an appropriate tool to simulate and study the influences of these evolving factors.

Several future directions are promising. First, the current model can be "situated" in an artificial world, and the Genetic Algorithm (GA) used to evaluate the fitness of using language or not. Second, it is worth comparing the structures triggered by linguistic communication with those triggered by other nonlinguistic communications.

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