Modeling the Emergence of Lexicons in Homesign Systems

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Abstract

Longitudinal data of conventionalization in emerging languages, combined with computational models explaining such data, are lacking in the literature on language emergence. In the present study we report on the emergence of gestural communication systems ("homesigns") invented by deaf individuals in Nicaragua. Analysis of longitudinal data from several families shows gradual convergence toward a gestural system with the essential characteristics of a shared lexicon. We propose a general computational framework to formalize the linguistic and social interactions among the individual signers such that a shared lexicon may arise. More specifically, a reinforcement learning process that adjusts the individual's probability of gesture use in response to others' actual gesture use provides a suitable account of the observed gestural convergence. Implications for language emergence are discussed.

Keywords: lexicon; homesign; conventionalization; language emergence; computational modeling; sign language; multi-agent reinforcement learning model

Introduction

How do languages emerge? What kinds of learners and environments, and particularly patterns of interaction among learners, give rise to language? The spontaneous emergence of gestural communication systems in deaf individuals not exposed to spoken or signed language (homesigners; Coppola & Newport, 2005; Brentari & Coppola, 2012) and of natural languages in deaf communities (Polich, 2005; Meir, Sandler, Padden & Aronoff, 2010) offer unique opportunities to study the process of natural language emergence. Computational models, in contrast, allow formalization and testing of theories of language emergence. These two approaches clearly complement each other, yet there have been no integrations of the two in the literature on language emergence. To begin to rectify this, in this paper we compare empirical data from emerging sign systems to computational models to investigate emergence of a fundamental component of language: the lexicon. In particular, we investigate the process of conventionalization of lexicons among small groups of individuals. We begin by reviewing extant literature on conventionalization.

Conventionalization of form-meaning mappings among interacting agents has been a major focus of language emergence research, mostly in experimental (see Galantucci, Garrod, & Roberts, 2012 for review) and computational (Hutchins & Hazlehurst, 1995; Barr, 2004; Steels & Loetzsch, 2012) investigations. Human adults are brought into the lab to develop novel communication systems under various conditions (Selten & Warglien, 2007), but in nearly all cases, conventionalization is observed among participants. In a related literature, researchers have investigated how language-learning biases shape communication systems as they are transmitted and learned across multiple generations (Kirby, Cornish, & Smith, 2008). The basic finding is that human learners exposed to unsystematic form-meaning mappings will restructure these form-meaning mappings to be more compositional and learnable.

Conventionalization in natural language emergence is far less studied—the opportunities to observe the process are of course few and far between, and, when researchers become aware of a case, it is often well after a basic lexicon has conventionalized (R. Senghas, 1997). In fact, we are not aware of any studies observing conventionalization over time in emerging natural languages. We are only aware of studies of emerging systems that examine either *inter*-user consistency at a single point in time (e.g., Osugi, Supalla & Webb, 1999), or *intra*-user consistency across a span of time (e.g., Goldin-Meadow, Butcher, Mylander & Dodge, 1994). Showing images of objects and eliciting gestures for them, Osugi et al. (1999) investigated consistency in form-meaning mappings of lexical items among 21 deaf and hearing individuals in the geographically and genetically isolated Koniya region of Amami Island south of Japan. They show that individuals either Deaf or hearing were consistent with each other to the extent that they interacted. Goldin-Meadow et al. (1994) investigated the consistency over time of form-meaning mappings of gestures produced in a naturalistic context by a child homesigner called David and his hearing mother. They found that David was more internally consistent than was his mother (and concluded that it was he who introduced into his system a noun-verb distinction, their primary object of interest).

In all, then, the two homesign studies, while shedding light on the *outcome* of conventionalization, reveal very little about the underlying *process*. The experimental research on conventionalization reviewed earlier, while suggestive, has not addressed conventionalization in natural linguistic settings. Computational modeling may provide explicit proposals of conventionalization mechanism, but it also suffers from the lack of connection with the empirical work. For instance, Barr (2004) investigated the effect of local vs. global information in conventionalization but the simulations are carried out on artificial data without making reference to experimental results or naturalistic case studies. The disconnect between experimental and computational approaches is a general concern for research on collective and cooperative behavior (see Goldstone & Gureckis, 2009 for review).

In this paper, we take a step toward unifying empirical and computational work. We first, present new longitudinal data on conventionalization from naturally emerging homesign systems. We compare this data to preexisting non-longitudinal data on lexical consistency in Nicaraguan Sign Language (NSL), a natural sign language emerging in a vibrant Deaf community (Senghas & Coppola, 2001; Senghas, 2003). We then present a general framework for studying conventionalization that incorporates elements of learning and social interactions. A specific implementation with reinforcement learning (Yang, 2002) appears to capture the observed trends of conventionalization. We conclude with a general discussion on the conditions for language emergence in a naturalistic setting.

Homesign lexicons

In the present study, we examine conventionalization over a 9-year period in form-meaning mappings for basic objects and concepts among deaf Nicaraguan homesigners and their family and friends.

Method

Participants Participants were four deaf Nicaraguan homesigners [3 male; aged 11 to 33 years (M=24) at various times of testing] and nine of their hearing family members and friends [4 male; aged 10 to 59 (M=30) at various times of testing; we henceforth refer to these family and friends as communication partners]. The homesigners have minimal or no interaction with other deaf individuals, including each other, and have minimal or no knowledge of Nicaraguan Sign Language or spoken or written Spanish, Instead, these homesigners have been using their respective invented gestural homesign systems all their lives. Despite their lack of linguistic input, they socialize with others, hold jobs, have families, and otherwise have typical lives. See Table 1 for relations between the homesigners and their family members.

Table 1: Homesigning groups

Family 1	Family 2	Family 3	Family 4
Homesigner	Homesigner	Homesigner	Homesigner
Mother	Mother	Mother	Younger brother
Older brother	Younger brother		Younger sister
Friend	Younger sister	*Hearing family and friends*	

Stimuli Stimuli were images of 22 basic objects and concepts. All items were familiar to participants. Nineteen of these objects and concepts were taken from Osugi et al. (1999), which itself was derived from Swadesh (1971). The stimulus items were: boy, cat, cold, cook, cow, dog, egg, fire, fish. flower, ice, girl, hot, moon, orange, palm tree, potato, rain, snake, stones, and sun.

Procedure In 2002, 2004, 2006, and 2011, M.C. showed participants images of the objects and concepts outlined above. Participants were tested individually. Using gesture and facial expressions, M.C. elicited participants' gestural responses to these images. Hearing participants were asked to use their hands to respond, and all were easily able to do the task. Participants responded to the camera, not to each other, and were not allowed to see each other's productions. All responses were videotaped for later analysis.

Coding Participants' responses were coded by a research assistant in consultation with R.R. A majority of responses contained more than one gesture (2 gestures: 40%, 3 gestures: 15%, 4 gestures: 4%, and 5 gestures: 2%), and so we coded every gesture individually for its *Conceptual Component* (CC), or aspect of the item's meaning that the gesture iconically represented. For example, a response to 'cow' might contain two gestures, one iconically representing horns (its CC is thus HORNS) and another iconically representing milking (its CC is thus MILKING)[1].

Results

Treating every CC as a dimension in a combinatorial space, every response can be represented as a binary-valued vector, with 1 representing the presence of a given CC and 0 the absence. The distance between two responses to the same object is thus a measure of conventionalization. We define distance here as the number of vector values by which two responses differ, and weight more heavily those vector values corresponding to CC's used more frequently (i.e. disagreement on the use of the CC ROUND will lead to a greater distance than disagreement on the infrequent CC

[1] We have also coded every gesture for its formal components (e.g., handshape, location, movement), but this coding does not bear on the current analysis, and so we do not discuss it further.

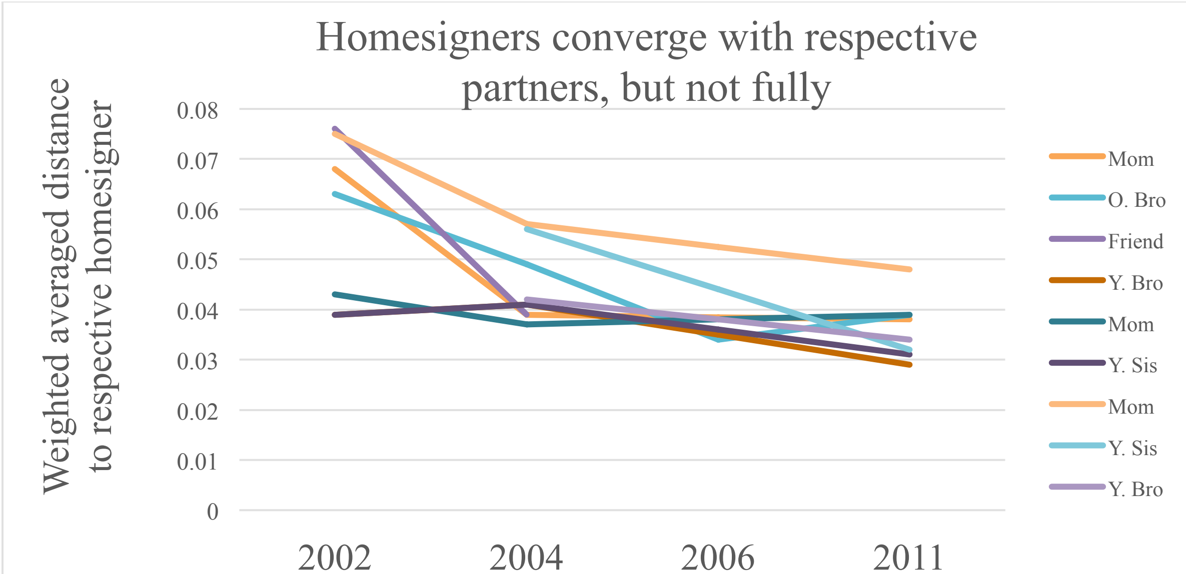

Figure 1: Average distances, across objects tested, between a partner's lexicon and his/her homesigner's lexicon, per year. Partners converge with their respective homesigners.

MILKING)[2]. For a given object in a given year, we calculated this distance between each homesigner's response and that of each homesigner's communication partner's responses. For example, we calculate the distance between Homesigner 1's 2011 response to 'cow' and his mother's 2011 response to 'cow', as well as their 2006, 2004, and 2002 responses to 'cow'. For each homesigner-partner pair and year, we average these distances across all tested objects, yielding an overall measure of lexicon distance or conventionalization between a pair. Results are summarized in Figure 1 which shows decreases in lexicon distance across partners. To give a sense of the scale of weighted distance, consider a partner that with probability P will agree with a homesigner in the usage of a CC. Simulations show that a partner agreeing with a homesigner 92.5% of the time gives a weighted distance of .069, and agreeing 96% of the time gives a weighted distance of 0.036 – a ~50% reduction in error. This is roughly the change a typical communication partner (CP13) undergoes from 2002 to 2011.

We ran two tests to establish that (1) communication partners gradually converge with their respective homesigners, but that (2) even in 2011, convergence was not complete (where distance would be zero). To investigate our first question, we first extracted, for every partner, slopes of the linear regressions predicting homesigner-partner distance from year of testing. A one-tailed, one-sample Wilcoxon Signed Rank test on the nine slopes indicated that the median of this sample was significantly below 0 ($W=0$, $p < .01$), confirming the gradual convergence between homesigners and partners. To investigate our second question, we ran a series of one-tailed, one-sample Wilcoxon Rank-Sum tests on the 2011 homesigner-communication partner distances. We found that these distances, despite decreasing over time, are still significantly greater than 0; all 9 of 9 such tests are highly significant ($W\text{'s} \geq 91$, $p\text{'s} \leq .001$).

Discussion

We showed above that deaf homesigners slowly converge on form-meaning mappings with their hearing communication partners, but that convergence is not complete, even in 2011, the latest year in which we collected data. This contrasts sharply with the state of convergence in Nicaraguan Sign Language. The Deaf community in Managua, Nicaragua initially formed in 1978 (Polich, 2005), and by 1993 was holding 'standardization seminars' in smaller cities and towns outside the capital of Managua to spread the signs developed in Managua to the rest of the country (R. Senghas, 1997; López Gómez, Perez Castellón, Rivera Rostrán, & Baltodano Baltodano, 1997). Thus, the NSL users in Managua must have converged on at least a basic lexicon in less than 15 years after coming together[3]. By 2011, all of the present homesigners had been using their respective systems for well more than 15 years, yet none of them had converged completely with any of their communication partners. What might explain this difference in rate of conventionalization between homesign and NSL? One possibility concerns the differences in patterns of interaction between users of homesign systems and users of NSL (and other Deaf community sign languages, Woll & Ladd, 2003). While the deaf user of a homesign system uses the system for all interactions, the

[2] CC's used more frequently offer more opportunities for convergence, and so should arguably be weighted more heavily in calculating distance.

[3] We are in the process of collecting data to verify convergence in NSL, though of course this data will be 20 years after the point of convergence we argue for.

hearing users only use the system to interact with that deaf user. In NSL and other deaf community sign languages, however, all users of the system interact with other users of the system *using the system*. In other words, the homesign interactive structure is one-to-many, while the NSL/deaf community structure is many-to-many. We now turn to our model, which replicates convergence, and allows us to test these predictions.

Modeling Conventionalization

What are the conditions for conventionalization, whereby a shared lexicon emerges through strictly local linguistic interactions among linguistic individuals? At least two elements of process suggest themselves. First, the individuals must be "lexicon ready". In the simplest case, they must be able to maintain a list of form-meaning pairings. Similar to our study of homesigns, the individuals must be capable of making combinatorial use of constitutive units as in our case of Conceptual Components. Second, the individuals must be capable of learning, or modifying their lexicon as the result of linguistic and social interactions. In this section, we first describe a general framework to study lexical conventionalization. We then study its dynamics through the use of reinforcement learning (Bush & Mosteller, 1951; Yang, 2002) as a model of learning and social interactions. Last, we use the model to test the hypothesis regarding the difference in conventionalization between homesign and NSL.

The Framework

Consider a population of N agents communicating a set of meanings through the combinatorial use of C binary signs that are analogous to Conceptual Components in the homesign data. For a specific meaning, agent i accesses a vector of probabilities $P_c = \{p^i_c\}$, defined over these signs ($j = 1, 2, \ldots, C$) such that with probability p^i_c, the cth sign is used by agent i and with probability $(1 - p^i_c)$, the cth sign is not used. This representation can also be used to encode atomic use of signs, i.e., each meaning is expressed by one sign, in which case the vector $\sum_c p^i_c = 1$ (i.e., agent i has a probabilistic distribution of the signs and only one of them is chosen at each instance of use).

The central premise of the conventionalization model is that individuals adjust their choices of linguistic encoding in attunement with their communicative partners. To communicate a meaning, agent i instantiates a vector U_i of 0's and 1's according to P_i. Agent j, the listener, generates a vector U_j for that meaning according to its own P_j. (Note that the instantiations $U_{i/j}$ are not deterministic since the values are probabilistically chosen.) For each sign, agent j compares U_j against U_i and makes adjustments to P_j to agree with agent i by the use of some learning algorithm. The changes in the distance between P_j and P_i over time represent the extent of convergence or conventionalization.

Linguistic communications among agents may also have a social component. Consider a matrix $S = [s_{i,j}]$, which defines the probabilities of communication between agents i and j such that $\forall i, \sum_j s_{i,j} = 1$. The social matrix provides a general platform to encode patterns of interactions among agents. A matrix with positive probabilities only among the neighboring agents, for instance, is a straightforward implementation of Schelling (1971)'s classic model of segregation. The matrix may be fixed or it may change as the result of communication. For instance, it seems reasonable that agents would modify their partner preferences based on past successes or failures of communication, which can be modeled as $s_{i,j}$ increasing if a successful communication has occurred between agent i and j and decreasing upon failure.

As the result of the communicative interactions, the probability vectors for agents $\{P_i\}^t$ change over time, which characterizes the evolution of the lexicons in the population. In general, the dynamics of $\{P_i\}^t$ can be analyzed as a Markov Chain, first used by Berwick & Niyogi (1997) to study language learning and change. Different choices of the learning algorithm (L), which may be discrete or probabilistic (including Bayesian inference), the social matrix S (and its own evolution), together with the current values in $\{P_i\}^t$ define the transition matrix T^t at time t, which can be multiplied with $\{P_i\}^t$ to produce the next state of lexicon $\{P_i\}^{t+1}$. Similar models have been developed in the iterated learning framework (e.g., Kirby, Dowman & Griffiths, 2007).

Conventionalization through Reinforcement Learning

In what follows, we propose a specific learning model and consider several variant implementations relevant to the present study of sign convergence. The learning model is an instance of reinforcement learning (Bush & Mosteller, 1951), a simple, efficient and domain general model of learning now with considerable behavioral and neurological support (see Niv, 2009 for review), and one which has been used in computational and empirical studies of language acquisition (Yang, 2002). Let agent j's current probability for sign c be p. Upon each communication, the listener j adjusts p to match agent i's choices, following the Linear-Reward-Penalty (L_{RP}) scheme of Bush & Mosteller (1995) where the magnitude of change is a linear function of the current value of p:

- Agent i chooses 1: $p' = p + \gamma (1 - p)$
- Agent i chooses 0: $p' = (1 - \gamma)p$

where the learning rate γ is typically a small real number. All probabilities are subsequently renormalized. Again, other models of learning can be studied in this fashion.

Social matrix: static vs dynamic We also consider the social communicative factors in conventionalization by manipulating the social matrix that defines the modes of individual interactions. As suggested above, we consider a case of adaptive social interactions where $s_{i,j}$ increases if listener j agrees with agent i in all the choices of signs and decreases otherwise. The update rules for S also follow the

LRP reinforcement learning scheme described above. Contrast this with static interactions where $s_{i,j}$'s remain constant.

Social matrix: homesign vs language An additional dimension of variation directly concerns the present study, for which we construct a homesign matrix in which one individual, the deaf signer (say agent 1), communicates with all other (hearing) individuals who do not use signs to communicate with each other. The matrix is initialized such that $s_{i,j} = 1 / (N - 1)$ where N is the total number of agents, $s_{i,1} = 1$ ($i \neq 1$) and $s_{i,j} = 0$ ($i, j \neq 1$). We also consider what can be referred as the language matrix, where all agents are deaf and use signs to communicate with each other ($s_{i,j} = 1 / (N - 1)$, $i \neq j$), which corresponds more closely to the sociolinguistic settings of typical sign language emergence (Woll & Ladd, 2003). In all, we have four different modes of social interaction, that is, (home sign, sign language) x (adaptive, static) and we explore their dynamical properties below.

Results In our simulations, we consider a population of $N = 5$ agents. For each sign, we initialize the values in P_i for each agent randomly between 0 and 1; they start out preferring either the use or the non-use of each sign with random probabilities. The learning rate γ is set to 0.01 and is used for the adjustment of both P_i's and S, the social matrix that encodes the probabilities of inter-agent communications. For each simulation, we run the simulations over 2 million instances of communications; in the case of convergence, i.e., all N agents in complete agreement with respect to sign usage (all P_i's at the value of 0 or 1), we record the number of iterations required for convergence. The main results are summarized in Table 2. Two things can be gleaned from these results: (1) there is no difference in convergence time between adaptive (p=0.412) and static (p=0.435) social structures and (2) there is a significant difference in convergence time between the homesign-type model and the language-type model ($p<10^{-12}$, for both social matrixes), indicating the importance of a mutually engaged community for the rapid emergence of a true linguistic system, and offering a potential explanation for the difference in rates of conventionalization between homesign and Nicaraguan Sign Language.

Table 2: Average number of iterations to convergence (percentage of simulations reaching convergence in 2 million iterations)

	Homesign	Language
Dynamic	757K (87%)	281K (100%)
Static	698K (80%)	260K (100%)

General Discussion

In the current work, we (1) presented longitudinal data showing conventionalization of lexicons among users of naturally emerging language-like systems (homesign gesture systems); (2) showed that conventionalization in these homesign systems is slower than in Nicaraguan Sign Language (NSL), a recently emerging sign language used by a Deaf community; (3) formulated a general framework and causal model of conventionalization, in the form of a multi-agent reinforcement learning model that obtains conventionalization; and (4) showed that an NSL-inspired model where all agents interact with each other converges significantly faster than a homesign-inspired model in which one agent (i.e. a deaf individual) interacts with every other agent (i.e. hearing individuals), but these other agents interact only with the first agent. We discuss implications our findings below, as well as open questions.

To the best of our knowledge, the present study is the first published observation of the lexicon, a fundamental component of language, emerging in natural human communication systems. Conventionalization has of course been obtained and studied numerous times in experimental settings (Galantucci et al., 2012), but our study is the first to connect the richness and complexity of real linguistic situations with well motivated models of learning. Surprisingly, variations in the dynamics of communications (the adaptive vs. static conditions in Table 1) led to little difference in the rate of convergence. The role of social/communicative factors in language emergence therefore deserves more careful consideration.

Our study is likewise, as far as we know, the first published paper to compare longitudinal or cross-sectional empirical data of naturally emerging languages to computational models of language emergence. As argued in the introduction, this synthesis is critical to a better understanding of language emergence. For example, many previous studies had established differences in linguistic complexity between homesign systems and natural sign languages (e.g., Coppola & Senghas, 2010 regarding incorporation of deictic forms into syntax; Flaherty & Senghas (2011) with respect to the existence of a count list), and had hypothesized about what differences between these systems' users affect language emergence (Senghas, 2005), but it has not been clear *how* exactly these differences influence language emergence. Our present data and model begin to answer this last question: more connected networks among users of the systems may accelerate conventionalization and language emergence.

Of course, alternative explanations of the different rates of conventionalization, and of complexity in general, in homesign systems and NSL do of course exist. For example, the hearing users of the homesign system have a spoken language to communicate with, and are thus under less pressure to use and conventionalize the homesign system. This contrasts with the situation faced by the deaf homesigner and users of NSL, who can only use their signed communication system and are thus behooved to conventionalize at a greater rate. Likewise, other learning models, e.g. Bayesian, can be studied in the general dynamic framework of language emergence. However, in the absence of more data to test the unique predictions of different models, we opt here for one of the simpler possible models. We speculate that the general effects of network structure on conventionalization do not differ by class of model. These and other possibilities are not mutually exclusive and can be subject to future research. To identify a set of empirically motivated and verified conditions under which emergence takes place, or fails to do so (in a timely fashion), is an important first step toward to understanding the emergence of language.

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