

## **I'm just talking with my generation:**

### **The crucial role of the first peer group in modeling initial lexical consensus**

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**Abstract:** This paper focuses on the role of peer-provided input to language learners as an essential ingredient in language development, and calls attention to the repeated oversight of this influence in artificial models of the process. Examining the case of Nicaraguan Sign Language, I show an instance of language creation that is both extremely quick—nearing completion after two half-generations of learners—and whose first growth is exclusively peer-to-peer. Studying the work of several authors, I explore productive proposals of modeling various aspects of language acquisition and linguistic change, but when compared to the speed of real language nascence, all of these attempts are lacking. Building from these simulations, and in light of the evidence from Nicaraguan Sign Language, I suggest a new model, focusing on the tools that must be given to learners in order for a single generation to create a simple system of language. In imitating the specialized learning methods of K. Smith (2002), I demonstrate the capacity of a single peer group to establish a lexicon that is communal though limited in size.

## **Introduction**

The process of language creation is linguistically compelling and yet difficult to study from empirical evidence; until fairly recently, the best tool in examining language genesis was the progression from incompatible language systems through pidgins to creoles. Several scholars in language change have recently attempted to add to our knowledge by simplifying aspects of transmission and internal representations of language into computational models of language creation and evolution, therein seeking to find the most essential components of this process. Additionally, extensive scholarship on Nicaraguan Sign Language (NSL), the signed language that emerged in the 1970s-1990s in a Managua school for deaf children, provides insight into the actual development of a new language. Using existing theoretical models and the details of NSL's genesis, I argue that the focus in language modeling must be on the two distinct steps in language creation. Based on this two-step hypothesis, I propose a new model that aims to complete the first step: creating a common lexicon in a single generation of language learners.

The models examined, though modeling the creation of small and syntactically simple languages, all require significantly more generations than NSL's creation did. Additionally, all assume a system wherein a set of agents learns language from the previous generation, and then becomes the new set of teachers, with no intervening period where they both receive and produce language. This design misrepresents the way in which all humans, but particularly those using emerging languages, learn from and speak to their peers. Linguistic systems are not a unidirectional information transfer but a network of parallel growth. I posit, in fact, that this reciprocal nature of language teaching is what enables such quick development as is seen in NSL. Thus, the models examined cannot

demonstrate the speed of language creation because they fail to incorporate the influence of the peer group on newly-forming languages. I will later propose a new model, based on the assumption that children forming a new communication system gain linguistic input not from adults but from peers who are learning the language from them in turn.

### **Foundation for modeling**

The basic assumption behind models of language change is that information about natural language development can be uncovered with the use of simplified structures. These structures contain data representing real-world language use, mental representations of language, and, sometimes, non-linguistic environmental input. Within these simplified structures, the transmission of linguistic items from speaker to listener is simulated, and the listener's preset framework is filled in with information about the language use she has seen or heard.

In working towards this basic representation, many simplify both the information that is transmitted when language is spoken and the frameworks that language speakers use to store their experience with and intuitions about this information (Kirby, Cornish & Smith; Kirby, Dowman & Griffiths; Oliphant; A.D.M. Smith; K. Smith (2002)). Many models, for instance, approach the question of how communities can come to a consensus on the meanings of signals that they use. In this case, signals are usually individual lexical items, and meanings come from unambiguous environmental input: one might see a fuzzy creature with pointy ears and assume that a heard signal "cat" represents that creature. In the simpler representations examined here, the 'gavagai' problem of identifying an intended

referent—the external meaning that a spoken symbol refers to (Quine, 1960)—is bypassed, with the exception of A.D.M. Smith’s model (2003). These models also ignore as outside their scope problems such as parsing meaning/signal pairings out of a longer sequence of utterances. In instances of this type of model, an agent—a user of the language—might be represented by a single matrix whose columns and rows denote meanings and signals and whose cells represent the frequency of co-occurrences. An invented example is seen in Figure 1.

	meaning	concept1	concept2	concept3
signal				
word1		49	100	17
word2		12	41	53
word3		132	38	30

Figure 1

When a new signal is heard, the listener’s matrix is adjusted according to a set of rules dictating what to do with new input: a simple example would be a rule to increment the cell in the row of the signal used and the column of the meaning perceived. If the agent hears word2 and sees concept2, for instance, he increments that cell to 42. Then when it comes time for this agent to communicate a meaning to another agent, he consults the column corresponding to the meaning he wants to convey and probabilistically selects a signal based on the weights in that column. If he wants to express concept3, he’ll pick word1 17% of the time, word2 53% of the time, and word3 30% of the time. Thus, an agent’s overall production of language depends entirely on the input it receives and the rules and structures it has for processing that input.

This bias in transmission is important to notice: a speaker's selection of forms for meanings is based on weights, but is not always the same; even though our example agent heard the second form the most, he still has a chance of picking the less-frequent alternatives. Other possibilities for production exist, such as always selecting the most commonly-heard form for a particular meaning. In some simulations of language transmission, that type of winner-takes-all model is actually necessary to provide the impetus away from ambiguity and to result in the production of a communicative system, but this model is less than realistic as compared to the way language is actually produced: humans clearly can and do keep track of synonyms and near-synonyms (Cruse 1985, p. 265), for instance, so a model would ideally allow multiple symbol possibilities for a single meaning. Similarly, the variance of meaning for individual lexical forms is well-acknowledged (Cruse 1985, p. 80), and thus a single symbol should have the potential to match with multiple meanings. My preference, along with that of some other authors (e.g. K. Smith 2002), is to use a probabilistic transmission model. This type of model biases itself towards creating an optimal communication system by assuming that input data may be noisy and even inconsistent, and so a form that an agent has heard less frequently still may be the 'correct' form—that is, the one more that's agreed-upon at present.

After individual learners are handled, it is necessary to examine how the language will be passed down over time, extending to entire generations the method a single learner uses in order to recreate the language of other speakers from a limited set of transmissions. In an iterated model, a certain group of agents receives inputs provided by another group for a specified period of time: each agent in the learning population will receive the same number of input items, though not necessarily from the same teachers. Then this generation

of learners—each with her own solidified language—becomes the new group of input producers, and a fresh batch of learning agents receives and stores their transmissions. Repeating this process over several, dozens, or hundreds of generations simulates an extended dissemination, and often evolution, of language. As I alluded to when discussing the way an agent picks a ‘winning’ signal for a given meaning, the rules learners use to process received inputs must be picked carefully, as they shape the structure of the language that the learner eventually adopts. When learners have intuitions about language learning that support one-to-one mappings between words and meanings—that is, when they have certain specially-designed algorithms for processing inputs into their internal matrices and producing outputs from these matrices—optimal languages will emerge, where an optimal language is defined to have exactly one signal for each meaning (K. Smith, 2002). Later I explore different potential groups of rules for input processing as proposed by Smith.

The type of model explained here uses what is termed ‘cultural transmission’ to pass down language: agents build their conception of the language based on inputs from the previous generation, and produce output to teach the next generation of learners. Another approach, which is used in the first model discussed below (Oliphant, 1996), is to build the language through reproductive selection: speakers who are successful communicators are allowed to reproduce, and hence to pass down their personal lexicon to their children. In this type of model, attempts at communication are not the means of linguistic transmission, but a fitness metric for determining which agents are successful enough communicators that they should be allowed to reproduce.

In comparison, the other models discussed use cultural transmission: they do not assume that communicative success is a factor in determining which agents can reproduce

(A.D.M. Smith 2003; K. Smith 2002; Kirby, Cornish & Smith). Thus, for the sake of simplicity, all agents generally begin with the same innate biases for dealing with input data; any relationships between agents, such as paternity, cannot affect these biases. They may, though, affect the routes of language transmission in that it is possible to build a model where agents have a higher percentage of communication with certain others. Agents could, for instance, be grouped by proximity in a circular list of agents or by clustered social groups and speak mostly with those close to them.

The general aim behind language modeling in this form is to simplify aspects of language transmission and reception that are difficult to simulate, while preserving the key information: each agent's individual conception of a changing linguistic system, the transmission of input data from other agents that forms this personal conception, and the way these communications are interpreted and produced.

### **Nicaraguan Sign Language and its relevance to language simulations**

In creating an accurate model of language development, it is crucial not only to examine theoretical hypotheses, but also to test the implications of the model against real instances of language genesis. To this end, I examine the case of the rapid emergence of Nicaraguan Sign Language, and particularly the way that the creation process seems to have been split into two distinct steps (Senghas, 1995). The initial step, coming to consensus on a common lexicon, is the focus of most of the models discussed and of the model proposed in this paper, and while NSL completed this step quickly, models of language learners struggle to quickly build this basis for language. The second step, the formation of a fully-fledged

language from this more rudimentary communication system, is seen in many aspects of NSL's development discussed below and is made possible only by the initial foundation.

NSL is a particularly pertinent case study for a few reasons: first, it began with almost no external language-like input; second, the rapidity of its nascence and maturation was recent and well-documented; and third, its development can be coherently partitioned into multiple steps. The language was created entirely by deaf children without previous linguistic knowledge, meaning it was built only from a conglomeration of simple home-signing systems. It moved from a collection of signs—the small vocabulary of home-signs that varied between speakers—to a fully-fledged language in a tiny space of time. Its progression can be traced through the language use of the successive groups, or “cohorts,” of deaf language learners who entered the community.

### **NSL's history, grammatical developments, and significance**

Nicaraguan Sign Language is a signed language which emerged in a pair of deaf schools near Managua in the 1970s, 1980s and 1990s. NSL evolved and evolves, as all languages do, from the patterns that become popular among groups of speakers, but is distinctive because of its entirely bottom-up (speaker-directed) beginnings: it had no superstrate language providing a basic lexicon and grammar, as a creole would, and no substrate language to help guide innovations. Also unusual are the records of its development made by linguists who interacted with many NSL speakers. The speakers had varied levels of mastery over increasingly complex versions of the language; NSL is thus well-documented enough to use as a case study for language emergence.



The development of the language was enabled by the creation of a special education center near Managua in 1977, where deaf students were placed together in classes and, more pertinently, breaks and bus rides—the first time Nicaragua had seen such numbers of deaf people brought together (Senghas, 2003). By 1979, more than 100 deaf children were learning and socializing together. The class environment itself was entirely uncondusive to sign language creation: the teachers actively discouraged the use of signing there, attempting to teach children to speak and lip-read Spanish, which was mostly unsuccessful. Yet outside the classroom, the children used their home-signing systems with each other rather than Spanish; in these interactions on the playground and on trips to and from school, the children had enough exposure to each other's signing systems that they came to develop a vocabulary and simple syntax in common. This initial stage of the language is called *Lenguaje de Signos Nicaragüense*, or LSN, and was derived from combinations of the children's homesigning systems; it is still in use by the original group which entered the school in its first few years (Senghas 1995, p. 39). In its complexity, LSN is analogous to a pidgin, incorporating a vocabulary with a basic syntax but lacking some elements of a full language, such as pronouns and complex morphological constructions.

In 1980 a related school was created to provide vocational training for deaf adolescents; additional adolescent and adult communication was enabled by the creation of a social group for deaf teens and adults in 1986, which later became the National Association of Deaf Nicaraguans (Senghas, 2003). The creation of this group allowed older deaf Nicaraguans to interact both with each other and with younger cohorts through classroom support and athletics: thus, the second cohort of NSL learners had contact with

older users of the language in a way that the original cohort, being the first group of speakers, did not.

In 1986, as the teachers continued to be unable to communicate with their students, either in Spanish or in NSL, linguists (led by J. Kegl) from the Massachusetts Institute of Technology were brought in to attempt to gain an understanding of the budding sign language. On recognizing the unique opportunity to document language birth in action, they conducted extensive studies on the use of the budding language through personal interviews, with a particular focus on the effect a speaker's age at entry and year of entry into the community had on her individual form of the language.

### **Morphological and lexical abstraction**

Senghas's dissertation (1996) illuminates the vast differences between earlier and later learners of the evolving NSL. She studies splits both by age of entry and by year of entry into the community, eventually determining that the most reasonable divide among the speakers is into cohorts based on year of entry into the school. The variations that she finds among speakers are both lexical and morphological. An example of the former is the changing use of mimetic signs over time—signs whose appearance is somehow linked with their meaning, frequently called iconic signs (Senghas 1995, p. 54). Speakers in this study were split by age: members of the first group were born between 1962 and 1969, while members of the second were born between 1970 and 1985. The group of younger speakers used only 28% mimetic signs, as opposed to 38% use by older speakers, who by and large learned the language earlier in its development; thus, the language became less iconic over time, as reflected in the increasing abstractness of the individual words used by its speakers.

One mark of the evolution of morphological complexity is in a simple count of the number of morphemes used per sign, again compared between the same two groups split by year of birth. Those signers who were born later used an average of 2.4 morphemes per lexeme, as opposed to only 1.5 in older speakers. The gap was largely caused by verbal inflection. Younger signers tended to use more verbs inflected with position and location, which were usually verbs of motion and location; older signers used this type of verb less. Additionally, the young signers had a much stronger “system of person inflection”: they averaged 0.418 person inflections per sign, almost five times’ increase from the older group, who used only 0.085 person inflections per sign. The younger group was also more likely to use number inflection rather than a separate sign to represent number, and their signing incorporated more classifiers, particularly object classifiers, which are “handshapes that are incorporated into signs to indicate semantic class” (Senghas 1995, p. 61). In all of these discontinuities, we see a general pattern of greater meaning density in the language of younger signers: the language markedly changed between the time the older and the younger signers were learning it.

The younger signers were able to learn such an advanced form of NSL only because they took input from older signers, who had developed a basic language off of which learners could build. As evidenced by the fact that the original group of learners had significantly more representational and less morphologically complex signing, it is apparently impossible to generate a fully-fledged language from no input. Just as a creole needs a pidgin from which to grow, so NSL needed its precursor, LSN.

### **The nominal point and why it shows the need for a quick, simple lexicon**

Coppola and Senghas (2011) describe a linguistic development between the first and second cohorts of NSL learners that reaffirms the importance of the initial form of the language created. Their study traces the development of a pointing gesture into an abstract grammatical sign in the language. Originally, the gesture was used to indicate relative locations of agents or events in one-off descriptions; later, it came to be used as a reference marker for previously established participants in a sentence or narrative, acting somewhat as a pronoun would in English. As the point developed into an abstract form in NSL, it lost the original connotation of location, which Coppola and Senghas assert is “a crucial step in the transformation of pointing gestures into forms that can be used as abstract, recombinable linguistic elements” (139). Thus, the loss of the sign’s original meaning enabled a rapid transformation of a simpler, representational gesture into an abstract linguistic element. Beyond the speed of this shift, the aspect of the progression that is most relevant to this study is the prerequisite condition for the transformation: widespread use of the sign with a concrete meaning.

Emphasizing the importance of a linguistic community in developing complex language, Coppola and Senghas document the increasing use of a nominal point without locative connotations among each subsequent cohort of speakers, with these cohorts being grouped by entry year. The authors note that the new community of deaf children was a unique breeding ground for the true evolution of language: “the fact that homesigners are not part of a larger signing community [...] seems to limit the complexity of homesign systems” (129). In order for a signer to develop more abstract meaning, there must be an external foundation based in a language community—a fundamental linguistic system

rooted in cultural transmission on top of which more complex ideas can be built. This foundation creates the potential for quick abstraction: in the case of NSL, “where much of the system was still very close to its holistic and unanalyzed gestural roots, the process of learning results in more than tweaks—it leads to the creation of linguistic structure” (Coppola and Senghas, 139). This gesture-to-structure transformation is an example of the type of semantic evolution that occurs after the emergence of an initial lexicon. Thus, the example of the nominal point’s development highlights the importance of quickly forming a lexical foundation for language evolution, which is the focus of the models discussed below.

### **The uniqueness of NSL’s example**

An important question about NSL’s genesis is how distinct its creation is from most instances of language acquisition: since it had to be peer-to-peer at its beginnings because no adults spoke the language, it is likely that the sheer amount learned from other children is not reproduced in many other languages. Whether or not school-based education is widespread, adult input forms the bulk of many children’s initial language exposure. Even in NSL, adult and adolescent input were important as conduits for a solidified linguistic foundation for the second cohort of children to build from. Yet the first stage of the language developed, by necessity, within a single peer group, and thus any accurate model of language creation must reflect this incredible potentiality for rapid growth: adults’ language is more of a storage mechanism of a basis for learning, while other children’s use is the root of innovation and development.

In creoles, where some form of the language is spoken by an older group, there is more potential for ambiguity—as in standard language acquisition—because while other children will have stronger grammatical structure and abstraction in their variants of the developing language, adults are still crucially present to provide the pidgin from which the more complex forms develop. I note that NSL's development is distinct from that of creoles because of its suboptimal initial input: pidgins, as Senghas notes, are “extracted from the framework” of a nativized language, while NSL's only input was from varying homesigns. Still, though, the speed of a creole grammar's development, or that of the nativized version of NSL from its simpler roots, requires that one of two things is happening (or some combination thereof). Either the children are collectively deciding—without conscious awareness, of course—on the form the language will take by influencing each other's speech as they learn, or else they are independently creating an identical grammar from different, certainly limited and perhaps inconsistent, sets of input.

The latter possibility would necessitate an exceptionally prescriptive version of the language acquisition device that seems very unlikely to exist, given the vast differences between human languages. Hence, I claim that the malleability of the teachers is an asset to quick language change: new speakers must be shaping the way that their peer group learns the language. As young speakers will tend to acquire a more structured, regularized version of the blossoming creole, their input is likely more valuable to other learners than an inconsistent or simpler version—while children are good at generalizing from limited and flawed or noisy data, they should learn more quickly with more regular input. If child A's teachers can react to a new morphosyntactic construction in the language fast enough that they can provide more consistent input to child A, A will be more likely to see this as a

probable, preferred rule in the language. Consequentially, he will acquire that construction in his own internal language, in turn providing consistency in input to his own interlocutors. Additionally, if the learners teach each other, one child's innovation in speech can immediately become the next regularized construction, which would allow for much greater speed in syntactical development. Therefore, the uncemented version of language which only children possess is a key ingredient in the swift abstracting of a developing language.

Presumably, this heavy bias towards using peers rather than older teachers will change as a language becomes more established—it seems likely that a language will begin to solidify after a generation or two precisely because more input comes from post-pubescent speakers who are less likely to shift their mental representations of the language's constructions. Adult input will also be more satisfactory when it is drawn from a nativized language, so young learners may put more stock in this fully-formed and consistent input than they would in adult input drawn from a pidgin language. In the case of NSL, a peer teaching group was the groundwork of the first generation's signing because other learners were the only ones with any knowledge of the language at all; later on, older speakers stored the solidified, pidgin-like LSN while the peer group was the epicenter of syntactic, morphological and lexical innovation.

### **Significance of NSL to language modeling**

As we see in the example of Nicaraguan Sign Language's creation and growth, there are two general steps of development which are equally crucial to the creation of a fully-fledged language. The second is the progression from a base lexicon into an abstracted, morphologically and syntactically complex linguistic system; the first is the invention—in

this case, almost from thin air—of a lexicon and simple syntax from which to build and innovate. The models below, and the proposal that follows, center themselves around replicating this first key step in population-based models of communication systems.

### **An early model of language creation**

One early model of iterated communication in a population is seen in Oliphant (1996), where selective pressure to accurately convey information is put on the sender and/or the receiver of a message. The goal of the paper is to demonstrate the development of Saussurean communication, which is a system that pairs a single word with a single meaning in a way that the majority of speakers agree on. For each agent, a potentially unique communication system is modeled by a pair of matrices with mappings between mental representations and sent or received signals. Unlike the models discussed above and below, Oliphant differentiates the transmission and reception matrices, meaning that an agent may end up interpreting input to mean something different than it would if she produced that same signal.

In the example represented by Table 1, taken directly from Oliphant's article, the agent will transmit environmental information 'o' with the symbol '1'; on receiving symbol '1', the agent would respond with 'o.' The left side of the table represents the transmitting agent's choice of symbol for a particular environment, while the right side shows the receiving agent's response to a particular symbol. (This response could denote the receiver's interpretation of the symbol transmitted, or an actual verbal response; the significant question here is how this interpretation or utterance compares to the environmental input given to the transmitter.) Thus, if two agents with matching matrices attempt to



communicate, a 'o' in the environmental input to one agent will result in a 'o' response from the other; Oliphant defines this as a successful communication instance.

Transmission Genes			Reception Genes		
Symbol			Response		
Env	0	1	Symbol	0	1
	1	0		1	0

Table 1

Which agents get to reproduce is based on a probabilistic selection of candidate reproducers by relative fitness, where the fitness test consists of many attempted communications and is scored by the percentage of successful transmissions. Each time a candidate is selected to reproduce, a pair of matrices is passed down to a child agent, with the potential for mutation. In this way, the development or maintenance of the matrices becomes representative of a population's language use changing or staying consistent through time.

Oliphant's study consists of three simulations. In the first, those agents on either side of a successful communication are rewarded with increased fitness, which does result in the eventual development of Saussurean communication. The second simulation fails to find such a system because it puts selective pressure only on receivers: that is, those agents who properly interpret others' communication are more likely to reproduce. However, because successful transmission is not selected for and because transmission and reception matrices are disjunct, fluctuations continue to persist in transmission. Thus, reception systems must constantly change to adapt to the latest chance trends in transmission, preventing the linguistic system from ever reaching equilibrium.

Oliphant's third simulation finds that even pressure solely on receivers effectively breeds communication under a certain set of conditions: when those who transmit also receive from the same agents, and when each agent has a single memory bit denoting whether or not the previous communication was successful. In this experiment speakers also have two potential communication matrices to use; when speakers are transmitting to an agent who previously transmitted successfully to them, they will use one matrix, and when the last transmission failed, they use the other. Here, a tit-for-tat strategy emerges, where transmitters cooperate with those who have cooperated with them in the past—by using a transmission matrix that conforms to standard reception expectations—and not with those who have misled them. This population will sometimes accidentally mutate into a failed-transmission matrix that matches the correct-transmission matrix, meaning that those speakers who do not cooperate with receivers will still be given accurate communications and will thus stand up to selective pressure for good communication in reproducing. Over time, though, the simulation shows that a communication system will evolve such that those speakers who cooperate with others will be rewarded, and a community-wide set of matrices will evolve to allow for Saussurean communication.

In the first simulation, it takes about forty generations to develop a full Saussurean system with the portion of the population using the same matrices wavering around a 92% (the lack of total adoption is due to mutation variation), and it takes twenty generations for even 80% of the population to come to an agreement on this system. In the third run, it takes about eighty generations for the communication system to stabilize.

Clearly, the agents in this model have none of the innate language capacities that humans do, besides a simple framework in which to fit their eventual communication

system, but its slow pace demonstrates the need for a stronger emphasis on cultural transmission of language. When a linguistic system can only pass from a single parent to each child through the genes, it will be difficult for a relatively successful system to become widely adopted: though speakers with one 'language' will be reproducing somewhat more than those with a less successful 'language,' it will take a long while for this system to become close to universal in the population.

Cultural transmission of language ameliorates this condition somewhat because input to a child flows not just from one or two parents but from a larger group, such that the trends of that group will be reflected more immediately in a learner—for instance, if 60% of a population uses symbol 1 for meaning 1, a child who is exposed to a representative sample of the population using that symbol will always interpret it as meaning 1. A large group of children all receiving fairly representative inputs will all adopt the same system. If, in contrast, each child were learning from only one parent, he would have a 40% chance of learning the less-common symbol for that meaning, forcing the group to spend several generations reaching consensus. (In addition to increased speed, the reproductive pressure on the development of communication that Oliphant assumes is necessary for language creation is shown to be optional by the later, culturally transmitted models.) Yet it will become clear these cultural transmission simulations are still quite slow compared to natural language genesis, with lexicon creation taking place over many generations rather than a single one.

All of the subsequent models discussed assume an identical reception and transmission system, such that speaker X producing symbol 'a' for meaning 'b' implies that X will also interpret symbol 'a' from another speaker to mean 'b'.

## The importance of a learner bias structure

A study by K. Smith (2002) approaches the subject of learner biases, specifically tackling how learners should be predisposed to manipulate linguistic input in order for a population to develop a new language. The model assumes a simple matrix representation of meaning-to-signal mappings, presuming as usual that input will be received in pairs, with one signal heard and one meaning seen in the environment. Smith's proposal focuses very specifically on the way each input pair that an agent receives will be incorporated into the agent's internal matrix. It splits this matrix into four types of cells, denoted by ( $\alpha$   $\beta$   $\gamma$   $\delta$ ). As seen in Table 2,  $\alpha$  represents the change to the single cell which is the cooccurrence of the meaning seen and signal heard.  $\beta$  is the change to the rest of the row for the same meaning, while  $\gamma$  is the change to the rest of the column for the signal.  $\delta$  contains the change to all the rest of the cells: those connected neither to the signal heard nor to the meaning seen.

	other signal	signal heard	other signal
meaning seen	$+\beta$	$+\alpha$	$+\beta$
other meaning	$+\delta$	$+\gamma$	$+\delta$
other meaning	$+\delta$	$+\gamma$	$+\delta$

Table 2

The purpose of distinguishing each of these types of cell is to create a simple system whose structure nonetheless allows for learners to seek or avoid meanings that correspond to the same signal, and vice versa. That is, if a learner's increment to the form-heard/meaning-seen cell,  $\alpha$ , is greater than her increment to the form-not-heard/meaning-seen cell,  $\beta$ , then she will be biased against synonyms: the meaning that she saw in the environment is more likely to correspond to the word that she heard than to any words she

didn't hear, and thus she'll be more likely to have a preference for a particular word for each meaning. Additionally, if her increment to a form-not-heard/meaning-not-seen cell,  $\delta$ , is greater than her increment to a form-heard/meaning-not-seen cell,  $\gamma$ , then she will be predisposed to avoid homonyms: words that she didn't hear are more likely to be linked to meanings that she didn't see than to ones that she did, leading her to assume that if a meaning is attached to one word, it is less likely to also be attached to others.

K. Smith points out several types of bias structure, and I will elaborate upon two of them here. The first is one called a [+maintainer] rule, and is characterized by the anti-synonymy bias,  $\alpha > \beta$ ; the system of incrementation described in Foundation for Modeling above follows this pattern. Smith claims that this rule for bias structure allows a group to maintain a currently functional language, but is not sufficient to come to a consensus from random input—no language will be created by maintainers. The second relevant bias rule structure is a [+constructor] rule, where  $\alpha > \beta$  and also  $\delta > \gamma$ , meaning that the learner is biased against both synonymy and homonymy. These learners—which are also [+maintainer], because they avoid synonymy—are the only ones that Smith says can create a language from scratch, not just preserve a currently working language. (Other rule structures can be clearly nonsensical, such as a +1 increment to all four of ( $\alpha \beta \gamma \delta$ ), or a structure that encourages synonymy.) In Smith's words, these constructors are "biased in favour of acquiring one-to-one mappings between meanings and signals" (79).

Overall, Smith's work clarifies the necessary criterion for complexifying poor input into a fuller communicative system: rule-based input processing. Such a cognitive setup must have existed for Nicaraguan Sign Language—or any other full language—to come into being. In my model proposal below, I address the utility of a constructor bias for language

learners' input processing; the distinction proves to be important. Still, Smith's model is still iterated over many generations; learners receive input from teachers whose language has already solidified, and begin to teach in turn only once their personal language representations have finished changing.

### **Attempting to trace the creation of morphology**

Another study attempts to shed light on later step of language creation: the development of a productive morphology from a basic lexicon. The article aims to illuminate the creation of morphology through human subjects' learning and teaching a simplified, artificial language of phrases in an iterated chain of reception and production (Kirby, Cornish and Smith, 2008). In their study, a subject is exposed to names for some, but not all, of a group of 27 items that vary along three features: color (red, blue or black), shape (circle, triangle or square) and motion (straight line, bouncing, or spiraling). She is then asked to provide names for a test set, some of whose items are ones she's seen named and some of which she hasn't. Then, these names are passed along to a new group of subjects for learning—simulating a generation of cultural transmission; this process is repeated through ten subjects. Ideally, the theory goes, the subjects will find and/or create a set of words that is split into morphemes referring to color, shape and motion, as well as a way to organize these morphemes into lexemes.

The first experiment failed to yield useful results, because the simplest answer to the problem is overgeneralization—one example language reused the same lexeme for all spiraling objects, another for all straight-line-moving objects, and one each for a bouncing square, circle and triangle. In response, for the second experiment the authors automatically

culled homonyms by eliminating all but one meaning for each word from the training set for the next participant. One of the four chains created a structured and somewhat consistent morphology: each color was denoted by a single-lettered prefix for each color, the types of motion had one or two suffixes each, and each shape had four to six (usually distinct) infixes. The system still required some amount of memorization, clearly, because motion had not entirely generalized and the morpheme provided by shape varied extensively: a learner attempting to exactly replicate the language would need exposure to almost every training item to have a chance at guessing the shape morpheme for any other object. For instance, if a subject is trying to name a spiraling red triangle, he might remember that a spiraling black triangle is *n-eki-pilu* (hyphens added for clarity), a spiraling blue triangle is *l-aki-pilu*, a bouncing red triangle is *r-aho-plo*, and a straight-moving red triangle is *r-ah-eki*; he will be able to conclude that the first morpheme should be *r* for ‘red’, the last morpheme should be *pilu* for ‘spiraling’, but that the internal morpheme could be either *ah* or *aho*. Perhaps this difficulty would be resolved over more iterations, but perhaps not; the other three chains of subjects in this experiment, whose example languages are not shown in the article, apparently made systems with less full morphologies.

Ultimately, this study demonstrates a reasonable capacity of this simplified model to nourish the development of morphology through iterated transmission. It ignores, however, the more central issue, which is that in our case study of actual language development, the morphology developed between the first and second cohorts of learners—within two generations, or only one if the counting begins after a basic lexicon is in place. Even these human learners could not create a morphology when they had no ability to create input for those who might also create input for them: without the back-and-forth communication of

true language acquisition, even our clearly adequate innate biases cannot create a productive morphology. Therefore, this study suggests that linguistic intuition is not the only important element in morphological development. It clearly demonstrates the necessity of peer group teaching in realistic models of language creation.

### **Creating meanings based on properties of objects in the world**

The final study I examine before suggesting a new model attempts to create different simple linguistic intuitions in order to allow a more natural formation of language. I include it because it raises a valid objection to the current standard of models, but do not implement its theories in my own proposal. The goal of A.D.M. Smith's paper (2003) is for agents to not be born with an innate set of meanings to map to new words, but rather to build up structures of meaning based on a multi-featured, publicly visible environment. The old models contain a preprogrammed structure—a list of forms, and a list of meanings—and find a clear mapping between them; Smith claims that these models are invalid because the innateness of the meanings gives the models an artificially pre-established structure. In his model, the meanings attached to words are not cleanly transferred between language users in a form-meaning pair during the learning process, but instead must be derived from information in the world around them. Having this more ambiguous “external world” is, he says, essential, because new language learners are not really passed form-meaning pairs by their teachers, but instead need to discover the referents of the words they hear. There must be, claims Smith, three full “levels of representation” of information: a public world which everyone experiences, an individual's conceptual understanding or “private semantic representation,” and the public communication via lexemes.



Thus, Smith's model adds an external, shared environment to attempted communications and agents' internal representations, and adds another type of internal structure to the traditional form-meaning map matrix. The environment consists of several objects, each of which varies along a continuum of values for each of several features. The agents then store a binary tree for each feature, or sensory channel, which contains a number of categories that are subsets of the range 0.0-1.0. The leaves of the tree are differentiated by a series of branchings, each cutting the parent node in half. The first branch split distinguishes range 0.0-0.5 from 0.5-1.0, the next might distinguish 0.0-0.25 and 0.25-0.5, the next 0.25-0.375 and 0.375-0.5, and so on. As these splits are made, each additional break is assumed to imply a possible distinction in meanings.

The feature range splits are made during a 'discrimination game,' where an agent is given multiple objects in the environment to distinguish between: the agent succeeds if each object can be distinguished by at least one feature from each other object—that is, if for each pair in question there is one feature where the agent has ranges distinguished finely enough that the two objects are in different range branches for that feature. If there is no such feature, the agent randomly adds another branch split to one of its features, allowing for more discriminatory categorization in that feature. Then, to test communication after sufficient discrimination games, one speaker takes a successful object result of the discrimination game, selects a winning signal from a slightly modified form-meaning matrix, and lets the hearer try to infer the referent of that signal in the environment using only her own modified matrix. In this way, though communication is much more difficult at the beginning, each agent in the population has a form-meaning matrix that holds meanings

she has inferred are relevant based on the environment, rather than ones which were somehow inborn.

In Smith's model, a greater focus on each individual generation's language creation is a strong point, and though his meaning-creation mechanism is too intricate to focus on below, it addresses as relevant and important a concern in language creation as it does in standard acquisition.

### **Analysis in the light of natural language development**

The consistent problem with the standard models of language birth is that they assume that the creation of a new language must occur over many generations. Since innovations in learners' representations of the language are not immediately reflected in speakers' output, any change will take several generations to spread throughout a majority of the population. While it is true that some changes in language take place over a long period of time, this assumption is flawed when examining the emergence of new languages. It is very clear from the example of NSL's birth that a working lexicon will be built in under a generation. Although the emergence of a true language from a pidgin-like form is the locus of a large amount of innovation, it hinges on the existence of a basic consensus on lexicon and simple syntax. Syntax's emergence is not addressed here, but most of the models discussed above do center around the question of a basic consensus on a lexicon, and thus it is appropriate to reject dependence on iteration over generations and to aim instead for a model where the first cohort of speakers can converge on a working vocabulary.

Studies of the age ranges in which language use is most innovative present further evidence that language will develop more quickly if learners provide the input for each

other. As evidenced by their greater use of novel formations and words, it is apparent that adolescents around seventeen years old use the newest linguistic forms (Tagliamonte and D'Arcy, 2009). Before this age, children's language use is closer to that of adults, and after this age, language use solidifies, such that the system continues changing but an individual speaker's lexicon and constructions are more constant. Since adolescents—people who are themselves just nearing the end of their language acquisition—lead the development of languages, exposure to the novel forms that these speakers make more often will make it more likely that a child also acquires this form. Thus, input from young speakers will expedite children's learning of the next variation of a language.

Additionally, by the “incrementation model,” changes in language follow the shape of an S-curve, such that new trends in language begin slowly, pick up speed as they reach the midpoint of adoption, and slow down as they approach universal use (Tagliamonte and D'Arcy). Based on this adoption curve, if the moment of highest spread is at the middle phase of adoption, then an innovation that hits this middle phase sooner will reach the majority of the language community more quickly. In a simulated population, therefore, if the group of producers is largely made up of learners then new changes will reach a critical mass more quickly.

Another point to consider is that a change which does not take hold with enough learners might be lost. This loss is much more likely when learners can't quickly pick up on new innovations that other learners are using: a development that would be adopted quickly if it constituted enough of a few learners' input could instead die out, lost because of its infrequent appearance in the utterances of older speakers. The need for innovation in order to spur the development of language also makes it clear that a learner cannot always pick

the most common construction in her language use and interpretation. Rather, she will occasionally use the less common forms—those that originate with single speakers—allowing others in the population the chance to pick up on those usages as well.

### **Creating a better model of language birth**

To address the common issue of a slow consensus on the first, more basic version of a language, I propose a model that examines the behavior of a single generation, studying how many interactions it will take for the community of language learners to come to a version of the language that results in almost entirely successful communications. The goal of this model is to demonstrate that a single generation can indeed develop a working communication system, given useful learner biases and enough opportunities for transmission.

#### **Factors to consider**

In directing my focus on the first generation, I must give greater weight to questions about the assumptions that a model makes, as the first cohort's behavior radically alters the shape of the future language: my simulation cannot depend upon consensus gradually being reached over the period of generations. One important aspect of my proposal is the inclusion of K. Smith's approach to learner biases, because the assumptions made by a child about the significance of each instance of language he hears determine the success or speed with which he learns.

Other variables to consider beyond learning biases are variables like lexicon size and population size: how many form-meaning mappings must the children come to agree on

and must thus be chosen for transmission enough times that they come into common use? How many agents are trying to communicate with each other, and how many must thus be exposed to a certain pairing in order for it to gain acceptance in the broader population?

A final consideration is the manner of selection of forms on each trial run. When an agent has a particular meaning to communicate, she could use either the winner-take-all method or a probabilistic method of choosing the form to use—that is, she could either always select the form with the highest value in her lexical matrix, or she could randomly pick among weighted candidates, such that the one with the highest count will be selected the most. Probabilistic word choice is strongly preferred, if it still allows for consensus to be reached (some models have claimed that it does not), since it much more closely simulates the behavior of real speakers, who may vacillate between two definitions of a word, or between multiple words for one concept.

In this model, I aim for the agents to converge on meanings for individual forms just by repeatedly transmitting tiny pieces of information about their own lexica, and using others' input to adjust these lexica.

### **Methods**

I propose that learning agents begin both hearing and using language as soon as they enter the community. For the sake of simplicity, all learners simultaneously enter this simulation (the code for which is included in the Appendix). Each agent begins with a set of potential words it can form, and an equally-sized set of potential meanings with which it will attempt to match those forms. Specifics of these forms and meanings are abstracted away, being represented simply by indices in the lists of possible forms and meanings.

Each learner is represented primarily by a square matrix—with meanings along one side, and forms along another—which holds information about the cooccurrences they have seen thus far; the functionality to pick winning forms for creation or interpretation and to learn according to input given is included in the Learner class. A Population holds many learners, and provides simple methods for creating training and test data between those learners. The main body of the code establishes a population and works through a loop, first giving one piece of training data (a signal-meaning pair) produced by another agent to each learner and then testing pairs of learners on their ability to successfully pass a meaning from one to the other; I run as many tests as there are learners. This loop repeats many times, attempting to allow learners enough data to come to individual and group decisions on word use.

The way a learner processed the training data depended on the way he processed a form-meaning pair to incorporate into his mental matrix—his learning bias, or his linguistic intuitions. His success on a test item depended both on his manner of picking winning meanings for a given form and on the teacher's manner of picking winning forms for a given meaning. I kept these manners consistent, such that the learner's method of choosing a meaning was always the same as a teacher's method of picking a winning form.

The items I varied were lexicon size (from 20-100), the manner of choosing form and meaning winners (winner-takes-all or probabilistic choice), the learning biases they used (a simple (1, 0, 0, 0) bias, or a (1, -1, -1, 0) bias), and the number of training and testing rounds (from 3,000 to 300,000, based on preliminary runs for each lexicon size I tried).

In approaching learning biases, I tried giving learners a constructor bias as defined by K Smith (2002): when hearing pair ( $f$ ,  $m$ ), they both increment the cell at the intersection

of the form and meaning, and decrement all other cells in the  $m$  row and  $f$  column.

Specifically, I used a (1, -1, -1, 0) structure of incrementing ( $m$ -and- $f$ ,  $m$ -not- $f$ ,  $f$ -not- $m$ , not- $m$ -not- $f$ ). As the this constructor bias was consistently more successful than the basic (1, 0, 0, 0) rule structure, I used it for the majority of the tests.

## Results

If an agent and his peers all adopt the constructor bias, which assumes that synonymy and homonymy are less likely to appear in the language, the group will be able to reach a consensus given no coherent starting language. Otherwise, no matter how many communicative instances there are, the language learners will not find a single lexicon in common. Of course, this simplification in learning biases represents a divergence from the way that language is actually used—since words can have multiple meanings and meanings multiple words—but for the time being it seems to be a necessary one.

The winner-take-all method for picking forms and meanings simply does not work here: if a learner is unable to consider even the possibility that another agent has a different strongest candidate for a particular form or meaning, he will have much more difficulty successfully communicating with other agents. In contrast, if different mappings are a possibility during the language-building process, much more communication is possible even without the completion of a full lexicon. This intermediate ability to communicate is what makes possible the eventual creation of this communal lexicon.

I first compared winner-take-all choice with probabilistic choice expecting that the winner-take-all method would actually be more effective; in a simpler simulation involving attempts to converge on a form for one meaning, the winner-take-all choice method was essential in allowing the population to agree on a form for the idea. In contrast, here, only

probabilistic form-selection allows a population to converge on mappings. As seen in Figures 2 and 3, when the winner-take-all method of selecting forms and meanings is used instead of a probabilistic, roulette-wheel style selection, the population fails to converge on any usable linguistic system—instead, they hover around the chance success rate (here, 2%, with a lexicon of meanings of size 50). Even on a lexicon of size 20, the group was unable to come to consensus, with the success rate hovering around 20%. Hence, probabilistic form- and meaning-selection is used for the remainder of the tests.

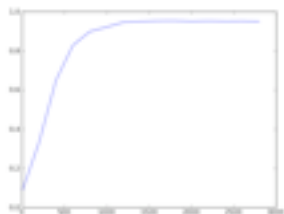
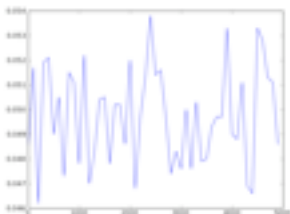


Figure 2: winner-take-all form and meaning choice    Figure 3: probabilistic form and meaning choice

The x-axis represents the number of training instances each learner has received, and the y-axis represents the recent success rate of communication attempts in the general population.

The second variable I studied was the effect of learner bias on the rate of successful transmissions in the learners over time. Here I confirmed K. Smith (2002)'s finding that the 'constructor bias' does, in fact, allow for the creation of a group lexicon, while a simple 'maintainer bias' gets its successes only by chance. With a lexicon of 60 items each in forms and meanings, the (1, 0, 0, 0) bias yielded only about a 17% success rate; in contrast, a (1, -1, -1, 0) bias resulted in about 88% success. Even on a lexicon of only 20 items in each



category, the maintainer bias only reached 20% success, as seen in Figure 4, as opposed to 95% success for the learner bias. This huge disparity in success rates demonstrates the failure of the maintainer bias—which does quite well when given a linguistic community with an already agreed-upon lexicon—to create language in a single generation, even over a large number of inputs, just as it does in iterated simulations.



Figure 4: maintainer bias, 20-item lexicon

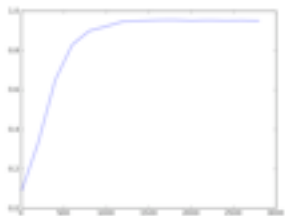


Figure 5: learner bias, 20-item lexicon

Again,  $x$  represents training items over time, and  $y$  the recent success rate, as throughout this section.

The final factor to be studied in this model is the effect of lexicon size on training time and—tentatively—the final success rate of a population. For a group of 100 agents, about 1200 training items for each learner are enough to bring the population to consensus 96% of the time on a lexicon of 20 forms and 20 meanings, as seen in Figure 6. In contrast, for the same population and a lexicon of 50 forms and 50 meanings, it takes about 6000 items for the group to come to consensus at about 94% success (Figure 7); for 65 forms and meanings, the summit of the curve begins around 20,000 items, and reaches a success rate

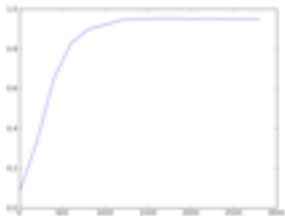


Figure 6: success with a 20-item lexicon

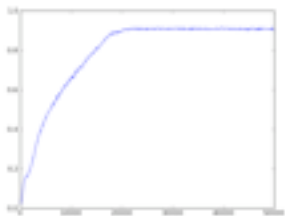


Figure 7: success with a 50-item lexicon

of just over 90%. For 70 or 75 forms and meanings, however, after hundreds of thousands of items the population still has not reached consensus, but stays fairly steady around 30% successful communications (Figures 8 and 9). From this data, it is clear that lexicon size has

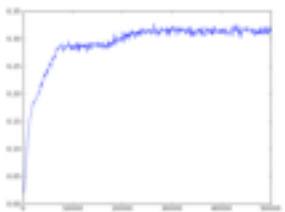


Figure 8: success rate with a 70-item lexicon



Figure 9: success rate with a 75-item lexicon

a measurable impact on the success of lexical consensus, as demonstrated by its effect on the success rate of communicative attempts between members of the population. For some

reason besides number of training instances, however, the population suddenly fails to reach as broad a consensus when the lexicon surpasses around 65 forms and 65 meanings to be paired.

Despite this inconsistency in larger lexica, my final result here is that over a few thousand inputs and trials, agents can create and learn small lexica (under 70 items) with and from each other. A constructor learning bias and a probabilistic selection of winning candidates for form and meaning are essential ingredients to this process of lexical consensus-building, too.

### **Conclusions**

The results from this model demonstrate that it is possible for a single generation of learners, modeled with lexical matrices and learning with constructor biases, to create a linguistic system that allows them very high communicative accuracy. Thus, a peer group of children, previously inexperienced in language, can with no adult input form a working lexicon together.

In order for a functional language to actually emerge, some linguistic intuition like the constructor biases as described by K. Smith must be innate in an agent's cognitive structure. Although Smith's proposed learning biases represent a simplification from the flexibility of word use in natural languages—namely, our abilities to use more than one word for identical or nearly-identical meanings and to attach more than one meaning to a single word—they are an elegant solution to the problem of language creation, and are as necessary in the birth of a single generation's self-taught lexicon as in an iterated population's development of a lexicon over time.

I claim that if the amount of inputs needed for groups to establish small communal vocabularies is unrealistic, this model is still a step in the right direction: it is necessary to simulate that first lexical consensus before studying language's evolution over time. No matter how well a model emulates gradual language shift, if it is inconsistent with our data on language genesis, it will not generalize to natural language development. Thus, any changes to the model from here should attempt to make children better at quickly mapping words to meanings—presumably by giving them more intuitions about language learning before they begin—but should not relinquish the requirement that a simple lexicon be agreed upon by the end of the first generation.

### **Potential extensions and next steps**

This model's results vary from NSL's creation in a couple of regards. First, those children clearly had a lexicon of more than 60 words, such that while the number of transmissions in the models converging on smaller vocabularies may be realistic, those necessary to create much larger lexica are less so—this discrepancy suggests a stronger or richer set of linguistic biases in human language learners than were given to the learning agents here. Additionally, I made no attempt to simulate a syntactical system; though NSL's first syntax was simpler than the one that later evolved, word order and some morphology were included with a common lexicon in the most basic forms, so this is an area that language-birth models need to explore.

An interesting extension could explore the effects of age: perhaps adjusting the weights given to a speaker's input based on his age would more closely simulate real children's language communities—learners might give more weight to others who were

slightly older, for instance. Under the current model, older speakers will have a more solidified language because they have heard more instances of form-meaning pairings already, so each additional one affects the running total less—but perhaps old speakers are also simply less impressionable, weighting new inputs less strongly than those they've heard before. (Or perhaps they give greater weight to new inputs, in order to allow recently-created lexemes some influence on already heavily populated lexicon matrices.)

Additionally, A.D.M. Smith's note about the importance of creating meaning based on exposure to the world, rather than being born with an innate set of potential forms and meanings, is crucial in bringing language simulations closer to reality. One way to address the issue of predetermined forms and meanings while building off of the current model might be to aim for consensus on a small set of forms and a small set of meanings, while allowing for a larger number of forms and meanings to potentially be drawn in to match them: this would evade the demand that there be one-to-one mappings between a preset group of forms and meanings. Because of the flexibility added by extra words and meanings, this addition could also allow the use of synonyms and homonyms, drawing a simulation closer to natural language use through greater fluidity of form and meaning selection.

Overall, the outlined models of language nascence (Oliphant; K. Smith; Kirby, Cornish & Smith; A.D.M. Smith) explicate useful ways of approaching language creation. All capture the essential nature of language as a socially transmitted system. Because they fail to accurately represent the peer-to-peer nature of transmissions during the initial stages of language development, however, they cannot simulate rapid development. As seen in real language birth and development in the case of Nicaraguan Sign Language—in the initial emergence of a communal lexicon and simple syntax, and in the later growth of productive

morphology and abstract grammatical forms—these first steps in language creation occur in single generations. Thus, a single-generational model for initial lexical consensus is the most accurate representation, and has a greater chance of extending well to realistic models of language progression over time. Additional linguistic intuitions in learners will be necessary to support generalization to larger lexica; however, my single-generation simulation demonstrates that, given certain learning biases, a certain amount of lexical consensus can indeed be reached in a limited period of time and within a single peer group.

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## Appendix

The following is the Python code for the model proposed above. The variables which I adjusted and tested over are:

- ▶ `length` in `def __init__(self, length = 50):` under the `Learner` class, which represents the number of forms and meanings in the lexical matrix
- ▶ `wta` in `def pickForm(self, ind1, lex = [], wta = False),` which determines whether the winner-take-all or probabilistic selection was used—`False` signifying probabilistic and `True` winner-take-all
- ▶ the `m_and_s, m_not_s, s_not_m, not_m_not_s` variables in `def learn(self, mInd, fInd):`, signifying the learner bias in input interpretation
- ▶ `trainings` under `def main():` at the bottom, denoting how many training instances each learner received.

Lines beginning with `#` are comments, and are not read by the computer.

To test the code, copy and paste the text below into a plaintext editor, save as `filename.py` into the home directory, then from a command line (like Terminal on a Mac) enter `python filename.py`.



```
#!/usr/bin/env python
"""
This code is part of Kristen C. Allen's Linguistics thesis at
Swarthmore College.
It models a population of vocabulary-learning agents who create
each other's input data.
It is not an iterated progression of generations, but a map of the
consensus progress
  of a single group of learnings over the amount of training input
  supplied.
Among other things, it uses K. Smith's idea of certain classes of
learner biases.
Date: 12/16/2011
"""

import random
import matplotlib.pyplot as plt

class Learner():
    """A class that represents one agent's internal language matrix,
    with two versions of
    the same information being stored in meaning-to-form and form-to-
    meaning matrices."""

    def __init__(self, length = 50):
        self.lexicon = [] # meanings will be rows, and signs columns
        self.lexiconFtM = [] # is kept identical to above, but with
        rows and columns swapped
        self.length = length # how many meanings are in the lexicon,
        and also how many forms.

        # set up the starting mental lexicon matrices
        for i in range(self.length):
            self.lexiconFtM.append([])
            for k in range(self.length):
                self.lexiconFtM[i].append([])

        # then start them off with small, random weights
        for i in range(self.length):
            self.lexicon.append([])
            for j in range(self.length):
                # self.lexicon[i].append(random.randint(-5,5))
                self.lexicon[i].append(0)
                self.lexiconFtM[j][i] = self.lexicon[i][j]
```

```
def pickForm(self, ind1, lex = [], wta = False): # uses roulette
wheel type function.
# if no lexicon fed in, ind1 is index of meaning, and ind2 is
form
# if lexiconFtM fed in, ind1 is index of form, and ind2 is
meaning
if lex == []:
lex = self.lexicon

if wta == True: # if we're using the winner-take-all method of
picking words
return lex.index(max(lex)) # return the word with the highest
count

minVal = min(lex[ind1])
maxVal = max(lex[ind1])
rng = maxVal - minVal
if rng == 0: # if values are all the same--most likely, all 0
return random.randrange(self.length)

# otherwise, some values are more likely than others; pick via
roulette wheel
spin = random.random()
partial = 0
for ind2 in range(self.length): # for each form, or meaning
if given lexiconFtM
chance = (lex[ind1][ind2] - minVal) / rng # must be 0 or
positive
partial += chance
if partial >= spin: # if the spin "landed" on this item
return ind2

def hearForm(self, fInd):
# calls pickForm using the form-to-meaning lexicon to return
interpreted meaning
return self.pickForm(fInd, self.lexiconFtM)

def learn(self, mInd, fInd):
# Given a form and a meaning, adjust the learner's lexicon
matrices,
# according to the rules provided by learner biases.
m_and_s = 1 # if cell's meaning and signal cooccurred
m_not_s = -1 # if cell's meaning seen, signal not heard
s_not_m = -1 # if cell's signal heard, meaning not seen
not_m_not_s = 0 # meaning not seen; signal not heard
```

```
self.lexicon[mInd][fInd] += m_and_s
self.lexiconFtM[fInd][mInd] += m_and_s

for i in range(len(self.lexicon[mInd])): # for the meaning seen
    if i != fInd: # if the form in question wasn't heard,
        adjust entries accordingly
        self.lexicon[mInd][i] += m_not_s
        self.lexiconFtM[i][mInd] += m_not_s

for j in range(len(self.lexiconFtM[fInd])): # for the form
    heard
    if j != mInd: # if the meaning in question wasn't seen,
        adjust entries
        self.lexiconFtM[fInd][j] += s_not_m
        self.lexicon[j][fInd] += s_not_m

if not_m_not_s != 0: # so we don't waste time on this loop if
    does nothing
    for m in range(len(self.lexicon)): # for each potential
        meaning
        if m != mInd: # if it wasn't the one
            seen
            for f in range(len(self.lexicon[m])): # for each form
                cell in that meaning row
                if f != fInd: # if the form wasn't
                    heard, adjust entries
                    self.lexicon[m][f] += not_m_not_s
                    self.lexiconFtM[f][m] += not_m_not_s

class Population():
    """A class that keeps track of a group of Learners. Includes
        methods to transmit
        between speakers, and to train and test the whole group."""

    def __init__(self, size = 100):
        self.learners = [] # create empty list of learners
        self.size = size
        for i in range(self.size):
            self.learners.append(Learner()) # fill the population with
            Learners

    def communicate(self, l1, l2):
```

```
# Given two learners, have the first pick a random meaning to
transmit to second.
# Use pickForm to select the form used, and hearForm to
receive.
# Return 1 for success and 0 for failure, as well as updating
pop's statistics.
meaning = random.randrange(len(l1.lexicon))
form = l1.pickForm(meaning)
interpretation = l2.hearForm(form)

if interpretation == meaning:
    return 1
return 0

def train(self):
    # Give each learner one training example from another learner.
    for learner in self.learners:
        teacher = learner
        while teacher == learner: # just to make sure a learner
            doesn't teach herself
            teacher =
self.learners[random.randrange(len(self.learners))]
        meaning = random.randrange(len(teacher.lexicon))
        form = teacher.pickForm(meaning)
        learner.learn(meaning, form)

def oneTest(self):
    # Pick two random learners and have them attempt to
communicate; return success
    l1 = self.learners[random.randrange(self.size)]
    l2 = l1
    while l2 == l1:
        l2 = self.learners[random.randrange(self.size)]
    return self.communicate(l1, l2) # failure is 0, success is 1

def main():
    myPop = Population()
    success_rates = [] # store intermediate success rates
    trainings = 10000 # how many times to train each learner
    interval_length = 100 # how frequently to update graph on recent
        success rate
    successes = 0 # successes counter within one interval
    t = 0 # counter for intervals

    for i in range(trainings):
```

```
t += 1
myPop.train()

for j in range(myPop.size): # do a bunch of test transmissions
    successes += myPop.oneTest()

if t == interval_length:
    # save average success in this interval, then reset counters
    success_rates.append(successes*1./myPop.size/t)
    successes = 0
    t = 0

plt.plot(range(0, trainings, interval_length), success_rates)
plt.show()

main()
```