Parent Oriented Teacher Selection Causes Language Diversity

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An evolutionary model for emergence of diversity in language is developed. We investigated the effects of two real life observations, namely, people prefer people that they communicate with and people interact with people that are physically close to each other. Clearly these groups are relatively small compared to the entire population. We restrict selection of the teachers from such small groups, called imitation sets, around parents. Then child learns language from a teacher selected within the imitation set of her parent. As a result, there are subcommunities with their own languages developed. Within subcommunity comprehension is found to be high. The number of languages is related to relative size of imitation set by a power law.

Keywords: language diversity; evolution of language; language learning model

INTRODUCTION

Language remains mystery in many aspects including how it is emerged, how it is evolved, how it is learned [1–8]. This is partly due to no agreed definition of language. A group of scientist, including Chomsky, believe that “communication cannot be equated with language” [2]. Yet another group consider language as a means to transfer meanings between individuals through signalling structures [6, 9]. Assuming that language provides an evolutionary advantage, some evolutionary models are proposed [1, 10–17], some of which are game theoretical [18]. Information theoretical approaches predict that not only symbols but word formation is necessary in order to have efficient communication, which leads to basic grammatical rules [11, 14]. There are also empirical approaches to language evolution [4, 5, 19].

It is believed that language evolves within generation and while it is transferred from generation to generation. One of the critical issue, which includes rich discussions on universal grammar, is how language is learned by the new generation [1–5, 20, 21].

Individuals may imitate each other or prefer to imitate experienced members in population [22]. It may be the case that one learns language by means of imitation. If it is so, who should serve as teachers in community for the next generation? And which imitation strategies can be applied to the population that leads to emergence of language that is shared locally or across population?

Motivation

In this study, we use and extend the mathematical framework already established [11, 12, 23]. Our extension leads us to emergence of diversity in language. Language diversity is very popular indeed, it is even addressed in the well known story of the Tower of Babel. According to the story, the people who speaks the same language once scattered all around the world so that they could no longer understand each other.

One expects that a child can learn language from her neighbours in the society. The neighbourhood includes her parents, her kinship network, territoriality, labor roles [15]. Ref [12] considers language as a culturally transmitted entity where cultural transmission is defined to be a type of transmission where socially obtained information is passed on, in form of teaching. Three types of neighbourhoods, for child to learn language, are investigated. (i) In the parental learning, asexually produced child learns from her parent. An agent reproduces proportionally to its mutual comprehension, which will be define shortly, with the rest of the population. Therefore the agent who better fits to the population language-wise has better chances to transfer his language to agents of the next generation. (ii) The role model learning is based on repu-
tation. An agent with a higher reputation is imitated more. Therefore it is not important whose offspring it is, an child imitates agents who comprehend better. So the language of an agent with better mutual comprehension is transferred more. In this learning $K$ teachers are selected proportional to their mutual comprehension and child learns from them. It is observed that higher values of $K$ produce higher mutual comprehension although it take longer for system to settle down. (iii) In the random learning there is no structure. A child randomly selects an agent in the population as her teacher. That is, mutual comprehension has no role in teacher selection.

A child is born to her parent. So her teacher has to be related to her parent if not the parent itself. Considering the parent, there are two possible circle of friends. (i) We assume that one is surrounded by people that understand each other well. In the context of language, parent’s friends should be the ones that have high mutual comprehension. (ii) Since we all live in a physical environment, our friends should not be physically too far from us. If we assume that agents located on the nodes of 1D ring lattice, friends should be the ones close proximity to the parent. In the paper, we modify teacher selection to investigate these two cases.

BACKGROUND

We revisit the language model developed by Ref [11, 12, 23] with a slightly modified notation. Then we go over $k$-means nearest neighbors algorithm [24]. Finally we adapt $k$-means to language domain and use it to identify language subcommunities

Language Model

We model language communication in a very simple way, called proto-language, as follows: Suppose we have $M$ meanings and $S$ signals. Let $P$ be the set of $N$ agents. An agent $i$ thinks of a meaning $\mu$ and wants to pass it to agent $j$. Since she does not have means to pass a meaning in her mind directly to the mind of $j$, she has to use signals. She selects a signal $x$, which she thinks as a representation of $\mu$, and passes the signal to $j$. We assume that there is no noisy channel, i.e., one receives exactly what is sent. Receiving $x$, $j$ tries to interpret $x$ in his own way. Hopefully $j$ will interpret it as $\mu$.

Clearly mappings from $\mu$ to $x$ at $i$ and from $x$ back to $\mu$ at $j$ are very important for a successful communication. We need to specify how association of meaning and signal in sending and receiving ends are done. Suppose every agent has statistics $a_{\mu x}$ of how frequently she uses signal $x$ to mean meaning $\mu$. Then we have an $M \times S$ association matrix $A = [a_{\mu x}]$ from which we can derive encoding and decoding methods. Encoding matrix, $E = [e_{\mu x}]$, is an $M \times S$ matrix where $e_{\mu x}$ is the probability of using signal $x$ for meaning $\mu$. Decoding matrix, $D = [d_{x\mu}]$, on the other hand, is an $S \times M$ matrix where $d_{x\mu}$ is the probability of understanding meaning $\mu$ for given signal $x$.

The encoding and decoding matrices can be obtained from the association matrix as follows:

$$e_{\mu x} = \frac{a_{\mu x}}{\sum_{x'=1}^{S} a_{\mu x'}}, \quad d_{x\mu} = \frac{a_{\mu x}}{\sum_{\mu'=1}^{M} a_{\mu' x}}.$$  

We will focus on $A$ for language learning since $E$ and $D$ can be derived from $A$.

Comprehension

Suppose agent $i$ wants to pass meaning $\mu$ to agent $j$. Probability of doing this correctly is:

$$\sum_{x=1}^{S} e_{\mu x}^{(i)} d_{x\mu}^{(j)}$$

where $e_{\mu x}^{(i)}$ and $d_{x\mu}^{(j)}$ are encoding of $i$ and decoding of $j$, respectively. When we average that over all meanings, we obtain comprehension from $i$ to $j$, that is

$$F(i \rightarrow j) = \frac{1}{M} \sum_{\mu=1}^{M} \sum_{x=1}^{S} e_{\mu x}^{(i)} d_{x\mu}^{(j)}.$$
If we want them to communicate both ways, we consider \textit{mutual comprehension}

\[
F(i \leftrightarrow j) = \frac{F(i \to j) + F(j \to i)}{2}.
\]

Now, let’s consider comprehension within a community \(C \subseteq P\). \textit{Within community comprehension} is defined as the average comprehension in a community \(C\). Thus,

\[
W(C) = \frac{1}{|C|(|C| - 1)} \sum_{i \in C} \sum_{j \in C, j \neq i} F(i \leftrightarrow j).
\]

Within community comprehension of the entire population, i.e., \(W(P)\), is called \textit{overall comprehension}.

\textit{Learning Model}

The evolution of language can happen in two different ways. Language evolves either through agents interacting with each other within a generation, or as it is transferred from one generation to the next by means of learning. We follow the latter form as given in Ref \[12\].

At each generation, population is replaced with new set of \(N\) agents. Agents of new generation has no meaning signal associations initially. That is, the association matrices of agents are empty. For language to be transferred from the generation of parents to the generation of children, some agents are assumed to be chosen as \textit{teachers}.

In Ref \[12\], teacher selection is a result of fitness gains. Fitness of an agent is directly related to her ability to communicate with overall population. Specifically, the \textit{fitness} of agent \(i\) is defined as

\[
F_i = \sum_{j \in P} F(i \leftrightarrow j).
\]

For the next generation, offspring are produced proportional to the fitness of an agent: the chance that a particular agent arises from agent \(i\) is proportional to

\[
\frac{F_i}{\sum_{j \in P} F_j}.
\]

That is, each child agent selects her teacher according to this probability distribution. Thus, agents who have better fitness are picked more. In Ref \[12\], it is stated that more than one teacher could be assigned for each child agent. This case is examined as a form of cultural learning, where some elite group of agents is responsible for transition of language. It is reported that since the selection mechanism remains the same, total number of teachers assigned only effects how fast the language emerges in such populations \[12\].

After teachers of the next generation are assigned, language is transferred from teacher to child. The learning process between the child and her teacher is similar to a naming game \[25\]. Child learns the language of her teacher by sampling their responses to specific meanings. For each meaning, the teacher provides \(Q\) responses and the child uses these to populate her association matrix, where \(Q\) is called \textit{sampling size}.

\textit{K-means Nearest Neighbors Algorithm}

In this section, we will explain a method to detect sub-language groups. In order to do that we adapt \textit{k-means} clustering algorithm to the context of language.

For a given cluster count \(K\) and a distance metric defined on set of observations, \textit{k-means} clustering algorithm tries to find a partition with \(K\) clusters in such a way that average within cluster distance is optimised \[24\]. In this heuristic algorithm, one can find the best value of parameter \(K\) by trial and error.

\textit{k-means in language domain}

We adapt \textit{k-means} to language domain. In this adaptation, \textit{k-means} provides \(K\) communities in such a way that agents in the same community understand each other better. So the distance metric is mutual comprehension, and objective is maximization of within community comprehension in communities.

Our approach has two steps: first we find
the best partition for a given $K$, then we find the best $K$ for our purpose.

Let $\mathcal{P}_K = \{C_1, C_2, \ldots, C_K\}$ be some partition of set of agents $\mathcal{P}$ with $K$ clusters. We consider clusters as language communities. The average within community comprehension is defined as

$$W(\mathcal{P}_K) = \frac{1}{K} \sum_{i=1}^{K} W(C_i) \quad (1)$$

There are many partitions of $\mathcal{P}$ with $K$ clusters. We select the partition $\mathcal{P}_K$ with the maximum average within community comprehension for given $K$. That is,

$$\mathcal{P}_K^* = \arg \max_K W(\mathcal{P}_K).$$

Unfortunately, there are no algorithm to find the optimal community count. Therefore, we run the algorithm for $K \in \{K_{\text{min}}, \ldots, K_{\text{max}}\}$ and select the one with highest comprehension. Thus,

$$K^* = \arg \max_K \mathcal{P}_K^*$$

is the optimum community count. The corresponding partition $\mathcal{P}_K^*$ is the optimum partition with the optimum within community comprehension value of

$$W^* = W(\mathcal{P}_K^*). \quad (2)$$

**MODEL**

We propose an evolutionary model where every generation has $N$ agents. Every agent $i$ makes exactly one child $i'$. Each child learns her language from her teacher, donated by $t_i$. The teacher provides $Q$ samples for each meaning and the child fills her association matrix based on these samples. Note that there is only one teacher for a child.

For a given child, how to select a teacher is what we focus now. We use different ways to choose the teacher and investigate their effects to the language. Note that parent may not be the teacher but clearly effects the selection of it.

Selection of teacher is done in two steps. In the first step, a set of $R$ agents, called the imitation set, is selected. We consider three different ways to select $R$ candidates for the imitation set.

1. **Model-A.** Here, we are trying to construct a social structure that is similar to lifetime encounters. The most basic assumption is that agents make friends with whom they comprehend better. Therefore select $R$ agents that are closest to the parent language-wise.

2. **Model-B.** Another approach is that people physically close to each other interact more. We assume that agents are placed on an 1D ring lattice. Then we select $R$ agents that are physically closest to the parent.

3. **Model-C.** As a control group, we select $R$ agents uniformly at random.

In the second step, the teacher is selected within the imitation set. Let agent $l$ be in the imitation set of parent $i$. The agent $l$ is selected proportional to

$$F(i \leftrightarrow l) \left/ \sum_{j \text{ in the imitation set}} F(i \leftrightarrow j) \right.$$ 

as the teacher. That is, an agent who has better mutual comprehension with the parent has better chances to teach his language to the child.

**RESULTS AND DISCUSSION**

We investigate the effects of different selection strategies to global language. We compare our findings to the role model learning of [12], which we call it Base Model. In the Base Model, parent has no effect on teacher selection. The teacher is selected proportional to agent’s over all fitness from the entire population.

In Fig. 1 we shared the simulation results where overall comprehension $W(\mathcal{P})$ is a function of the relative size of the imitation set,
FIG. 1: Overall comprehension of selection strategies.

that is, \( r = R/N \). Since it is independent of \( r \), the Base Model is represented as straight line in our figures. There are \( N \) agents using \( S = 15 \) signals to communicate \( M = 8 \) meanings with sampling size \( Q = 4 \). We have results of \( N = 50, 100, 150 \) and \( 200 \) but we report only \( N = 100 \) in Fig. 1. Each data point is an average result of 100 realizations with corresponding \( r \) values. We run each realization for 500 generations. This number is sufficient since simulations rapidly converged even in 100 generations to a state where there is no longer a change in \( W(P) \), which indicates that the simulation has reached to steady state. We note that Model-B takes more time to settle than the other two models.

As one can observe in Fig. 1, Model-C resulted with the best overall comprehension, compared to Models A and B. This result can be explained by the fact that in Model-C agents are essentially free to select any agent. Thus, this results in a situation where every part of the population have a chance to transmit their languages. As a result, emerged language is a product of everyone, therefore it can be globally communicated with.

Models A and B fail to develop a global language, that provides successful communication among all members of population, unless the size of the imitation set is as large as half of the population, i.e., \( r > 0.5 \). In order to understand how bad the results of Models A and B for \( r < 0.5 \), we need a model that we can barely call a language. So lets develop one.

Let’s consider random comprehension within a population \( P \). Random community comprehension \( W_r(P) \) is defined as the average comprehension in a population where all meaning and signal associations are equally likely, that is, \( e_{\mu x} = 1/S \) and \( d_{x\mu} = 1/M \) for all possible \((\mu, x)\) meaning-signal pairs. In this case, the mutual comprehension between any two agents \( i \) and \( j \) is

\[
F(i \leftrightarrow j) = \frac{1}{M}.
\]

Thus,

\[
W_r(P) = \frac{1}{M}
\]  

(3)

which yields \( W_r(P) = 0.125 \) for \( M = 8 \). We expect that any reasonable language should provide much better mutual comprehension than random comprehension. Thus,

\[
W(P) > W_r(P)
\]

must hold in population.

In Fig. 1, comprehensions of both Models A and B are below the threshold of \( W_r(P) = 0.125 \) for \( r < 0.05 \). The comprehensions increase slowly. So clearly, the Models A and B are not good in terms of global language.

Subcommunities

This raises the question, why selection strategies that take into account either language-wise or spatial closeness to parent fail to provide a medium for emergence of global language. One possible explanation could be that rather than single language, that is used by the entire population, many languages, that are used by subcommunities, are emerged.

Testing the hypothesis above, we used \( k \)-means algorithm to see if there are such language subcommunities. On the very same data presented in Fig. 1, we apply \( k \)-means algorithm to obtain subcommunities. We obtained
within community comprehension $W^*$ of the subcommunities as defined in Eq. 2.

In Fig. 2a, a low $W^*$ value indicates that we could not find any suitable subcommunity structure, whereas when $W^*$ is high, there is such a clustering that agents of the same subcommunity comprehend each other quite well. Except the first data point around $r = 0.01$, all $W^*$ values are above the minimum language level of the random community comprehension, i.e., $W_r(P)$. We observe that $W^*$ curves for both Models A and B get close to that of Model-C even for as small values as $r = 0.1$. That indicates that multiple language communities emerge except for very low values of $r$.

Another observation is that $W^*$ value obtained in Model-A is greater than correspond-

The numbers of subcommunities

We now focus on the numbers of subcommunities. As we mentioned in the discussion on $k$-means, in order to find the optimal cluster count, one needs to try for different $K$ values. For $N = 100$, maximum possible value for $K$ is 100. We arbitrarily choose $K = 10$ as a maximum value. So, we tried $K = 1, 2, \ldots, 10$ and reported optimal $K^*$ value in Fig. 2b.

The curve in Fig. 2b starts around 9 and decreases to 1 as $r$ increases. Decrease to 1 is expected since when $r$ is large enough, system converges to a single global language as one concludes from Fig. 1.

The shape of the curve in Fig. 2b implies a power law relation between $K^*$ and $r$, that is,

$$K^* \propto r^{-\gamma}.$$  

We observe the same relation in Fig. 3, in which $K^*$ is plotted as a function of $r$ for not only $N = 100$ as in the case of Fig. 2b but values of $N = 50, 150$ and 200, too. We conclude that for Models A and B, the optimum community count $K^*$ is independent of the size of the population $N$ but dependents on $r$. Another way to put this observation is that the
number of sub-language communities in a population can be understood and controlled via the ratio of neighborhood size to population size.

**Future Work**

The models we used only cover very basic form of the process and far away from analyzing many complex details of language. Various additions could be made to the model.

First of all, we have assumed that each individual inherits their language from one teacher in a very specific way. Different types of learning processes has been reported in Ref [12]. For example, evolution of language can be perceived as a cultural process where some group of people are responsible for the transfer [11]. That is, more than one teacher could be assigned to each child.

Even though $k$-means is a widely used heuristics, we may need much more specialized form of community detection algorithms. First of all, $k$-means algorithm does not guarantee that the communities of the similar sizes. Indeed we encountered communities that are very small in size in our simulations. Alternative approaches that take into community sizes can be looked into.

In this work, we tried to model the fundamental forms of selection mechanisms. Specifically in Model-B we have discussed territorial differences and we use 1D ring lattice as a spatial organization. More meaningful networks other than our symmetric 1D ring lattice can be investigated. There are many other limitations that can effect selection of teachers in today's society such as division of labor, class structure, gender and racial differences. Networks, that imitate these asymmetric cases, are particularly interesting.

**CONCLUSION**

In this study we investigate two real life conditions to language evolution. (i) We prefer people, which we communicate well with, around us. (ii) We interact with people that are physically close to us. Clearly we cannot interact with all but a small percentage of the entire population. Given these, the children learn their language from teacher selected from such small group of people around their parents. Such restricted groups for transferring language result emergence of multi-language communities. Number of languages that emerged is related to the relative size of the imitation groups.

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