A complex systems perspective on language evolution

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Language is acknowledged as a complex adaptive system, but its implications from a modeling perspective remain largely under-explored. This paper explores the application of complex systems theory, as formalized by Thurner, Hanel, and Klimek in their book, "Introduction to the Theory of Complex Systems" (2018), to the study of language evolution. Here we show that a simple agent-based model of language evolution that incorporates innovations, combinations, and the social transmission of cultural traits is sufficient to produce a rapid complexification of the linguistic systems in both evolutionary and developmental contexts. A key feature of this model, necessary for the emergence of complexity, is the ability to productively combine and selectively filter out traits. This highlights the importance of combinatorial interactions in the self-organization of linguistic systems. From a developmental perspective, it stresses the importance of acquiring a sufficient number of traits to bootstrap the complexity of natural language.

1. Introduction

As many scholars have observed, language is a complex adaptive system (Beckner et al., 2009; Ellis & Larsen-Freeman, 2009; Ellis, 2011; Schmid, 2020). Despite this recognition, the formalization of this complex nature remains an under-explored territory in the field of language evolution. One prevalent aspect of complex adaptive systems is that they self-organize. When it comes to language, self-organization occurs both at the individual level and at the population level (Schmid, 2020; de Boer, 2011). The Conventionalization-Entrenchment (CE) model of Schmid (Schmid, 2020) clearly points to the separation of the social dynamics, i.e. conventionalization, and the individual dynamics, i.e. entrenchment. In (de Boer, 2011), self-organizing processes are also categorized as individual or population processes. When it comes to modelling these self-organizing processes, most work have focused on self-organization at the population level using agent-based models (Hurford, 1987; Steels, 1995, 1997; Batali, 1998; Kirby, 2002). In contrast, self-organizing processes at the individual level have been given less attention and mostly focus on the self-organization of sound systems such as vowel systems (Lijencrants & Lindblom, 1972; Schwartz, Boë, Vallée,

& Abry, 1997; Ke, Ogura, & Wang, 2003) or syllable systems (Lindblom, MacNeilage, & Studdert-Kennedy, 1984). There is a need for modelling the self-organization of grammatical linguistic traits into systems to account for observed linguistic trait dependencies (Greenberg et al., 1963; Croft, 2002; Dunn, Greenhill, Levinson, & Gray, 2011; Skirgård et al., 2023; Enfield, 2017).

In this paper, we will use the theory of complex systems of Thurner et al. (2018), which relies on studying the joint dynamics of a number of entities and their interactions, to model the self-organization of linguistic traits into coherent linguistic systems. Models of cultural systems have recently been developed (Friedkin, Proskurnikov, Tempo, & Parsegov, 2016; Buskell, Enquist, & Jansson, 2019; Yeh, Fogarty, & Kandler, 2019; Goldberg & Stein, 2018), but have often fallen short in capturing the combinatorial nature of trait interactions. In contrast, the field of biology has explored combinatorial models of evolution extensively (Jain & Krishna, 2001; Solé & Manrubia, 1996; Kauffman, 1993). Notably, the open-ended co-evolving combinatorial critical model (CCC model) (Klimek, Thurner, & Hanel, 2010; Thurner et al., 2018) stands out in providing a simple model of evolution capturing many key properties of complex evolutionary systems and stressing the importance of both productive and destructive combinatorial interactions.

The main idea of this paper is to use the CCC model as an idealized model of a linguistic system in which traits represents linguistic features, such as word order or the presence of prepositions, and embed it into socially interacting individuals, thus providing a multi-agent version of the CCC model and capturing self-organizing processes both at the individual and at the population level. Our proposed model offers insights into the emergence and subsequent evolution of complex languages and displays punctuated equilibria in both evolutionary and developmental contexts. The non-linear dynamics of this model is highlighted by a phase transition from low to high diversity, potentially shedding light on the first emergence of complex languages. Additionally, we observe that the evolution of individual agents exhibits a pattern resembling human linguistic development, with a learning period followed by a phase of high diversity.

2. Complex systems

According to Thurner et al. (2018), complex systems can be conceptualized as co-evolving multilayer networks whose nodes represent various types of entities labeled by Latin indices i and links represents various types of interactions labeled by Greek indices α, with each interaction type defining a distinct layer of the network. Importantly, interactions are not static but dynamically evolve over time.

The strength of interaction α between elements $i, j, k, \ldots$ at time t is denoted as $M^{\alpha}_{ijk\ldots}(t)$. Interactions often involve more than two entities, encoding combinatorial interactions. Elements themselves are characterized by states denoted as $\sigma_i(t)$. In complex systems, states and interactions are not independent; rather, they mutually influence each other, resulting in a phenomenon known as *co-evolution*. This notion of co-evolution should not be confused with that of gene-culture co-evolution or other similar interpretation. Due to the discrete nature of interactions between interaction networks and states, complex systems are inherently *algorithmic*, making them challenging to describe analytically. Formally, co-evolving multiplex networks can be expressed as:

$$\begin{array}{c} \sigma_i(t+dt) \sim \sigma_i(t) + F(M^{\alpha}_{ijk\ldots}(t), \sigma_j(t)) \\ M^{\alpha}_{ijk\ldots}(t+dt) \sim M^{\alpha}_{ijk\ldots}(t) + G(M^{\alpha}_{ijk\ldots}(t), \sigma_j(t)) \end{array}, \tag{1}$$

where F and G are algorithms governing the computation of the next iteration.

The complexity that can arise from evolution is unlimited, but what is accessible from a given state of the system is usually much smaller. To account for that, Stuart Kauffman introduced the concept of the *adjacent possible* (Kauffman, 1969, 1993). The adjacent possible represents the set of all potential states of the world that could potentially exist in the subsequent time step and encapsulates the path-dependency inherent in evolutionary processes. In addition, most complex systems are both robust and adaptive, two properties that rarely occur together. In any dynamical system, the boundary separating the region of stability from that of chaotic behaviour in the phase space is termed the *edge of chaos* (Lewin, 1999). Evolutionary systems are often *self-organized critical systems* (Bak, Tang, & Wiesenfeld, 1987) meaning that their dynamics drives them toward the edge of chaos. At the edge of chaos, a system is metastable and alternates between stable and chaotic phases, leading to punctuated equilibria.

3. Modelling language as a complex evolutionary system

In language evolution, we study how large groups of speakers and their linguistic traits change over time. Therefore, we identify two principal categories of entities: (i) linguistic traits that collectively compose a language, and (ii) the speakers of the language, representing the individual and population levels respectively (de Boer, 2011; Schmid, 2020). We will use the CCC model (Klimek et al., 2010; Thurner et al., 2018) as a model of individual processes and use an agent-based approach to model transmission and conventionalization.

3.1. *The CCC model and self-organization at the individual level*

The CCC model captures complex evolutionary systems where entities, denoted by i, have binary states represented as $\sigma_i(t)$, where 1 indicates presence at time t, and 0 indicates absence. Entities interact through two types of interactions: constructive (M^{+}_{ijk}) and destructive (M^{-}_{ijk}) combinatorial interactions. When $M^{+}_{ijk} = 1$, it signifies that the joint presence of entities i and j supports the emergence of entity k, while $M^{-}_{ijk} = 1$ implies that their joint presence inhibits entity

k. For simplicity, we assume that an entity engages in r^+ constructive interactions and r^- destructive interactions on average. The fitness ($f_k(t)$) of entity k at time t is calculated as:

$$f_k(t) = \sum_{i,j} \left(M^+_{ijk} - M^-_{ijk} \right) \sigma_i(t)\sigma_j(t), \tag{2}$$

measuring the difference between constructive and destructive interactions. If $f_k(t) > 0$, entity k is present in the next time step; if $f_k(t) < 0$, it's absent. When $f_k(t) = 0$, the entity's state remains unchanged. Additionally, with a probability p, the state of entity k is randomly flipped, representing innovation. The CCC model exhibits common characteristics of evolutionary complex systems, including punctuated equilibria and a low-to-high diversity phase transition.

Here, entities represent linguistic features such as word order of the presence of prepositions. The elements $M^{\pm}_{ijk}$ represent their interactions and can be conceived as idealized version of Greenberg's universals (Greenberg et al., 1963). For example, if we consider the typological universal: *If a language has dominant SOV order and the genitive follows the governing noun, then the adjective likewise follows the noun* we could model such a situation by considering trait i to be a *SOV word order*, trait j to be that *the genetive follows the governing noun*, and trait k to be that *the adjective follows the noun*, then M^+_{ijk} encodes the fact that together traits i and j support trait k.

3.2. *Social learning and self-organization at the population level*

In order to model social learning, we assume that each agent is an instance of the CCC model. Trait ownership is now encoded as an interaction between agents and traits and denoted by $\sigma^{(i)}_k(t)$, where 1 indicates that agent i possesses trait k, and 0 indicates the absence of the trait. Interaction tensors between traits are defined as in the CCC model and we can define the fitness of an agent i as

$$f^{(i)}_k(t) = \sum_{l,m} \left(M^+_{lmk} - M^-_{lmk} \right) \sigma^{(i)}_l(t)\sigma^{(i)}_m(t)\,. \tag{3}$$

This fitness is different for every agents and is an example of a *subjective fitness*. The concept of subjective fitness in language dynamics is discussed in (Michaud, 2019, 2020). This models takes into account both evolution and self-organization of the linguistic system.

In addition, the age of an agent at time t is encoded as $a^{(i)}(t)$. The model is driven by social learning, i.e. copying a trait from another random agent (we assume homogeneous population for simplicity), which can formally be written as $\sigma^{(i)}_k(t+1) = \sigma^{(j)}_k(t)$. When acquiring a new trait, an agent performs n_C steps of the CCC model to stabilize their internal system. In addition, with probability

p, their will innovate a new trait. This model has two different timescales, that of social interactions and that of internal self-organization.

A simple population dynamics is added. Agents are initialized without any traits and gradually acquire them as they age. The population resides in an environment with a fixed carrying capacity. Agents face a constant probability of death, with new individuals replacing those who perish. Furthermore, agents cannot age beyond a predefined maximum age. Upon an agent's death, the corresponding elements of $\sigma^{(i)}(t)$ are reset to 0, modelling the birth of a new agent. Destructive interactions models filtering of traits not fitting within the system.

4. Results

We conducted simulations starting with a population devoid of any linguistic traits to model both language emergence and language evolution. Traits emerge through the innovation rule of the CCC dynamics. Once a trait has emerged, it can be adopted by other agents and combined with other traits, either supporting or inhibiting the emergence of additional traits.

Figure 1 depicts a typical simulation run with a population of approximately 100 agents, an expected lifespan of 50 time steps, and a maximum age of 100. For the CCC step, we considered 100 possible traits, with $r^+ = 3$, $r^- = 4$, and $n_C = 10$, and an innovation probability of $p = 3 \cdot 10^{-6}$. These parameters result in an innovation event, on average, every 3 time steps. In the top left panel, we observe the population's evolution, beginning with low trait diversity. After two plateaus, the average number of traits quickly increases and stabilizes at around 30. The top right panel illustrates ontogeny at the end of the simulation, showing a sharp rise in the number of traits followed by stabilization. To provide deeper insights into this process, the bottom left panel displays the learning history of a representative agent. It shows a period of low trait diversity transitioning to high diversity when a sufficient number of traits have been acquired. The curve in the top right panel doesn't exhibit a jump because the shift from low to high diversity occurs at different ages for different agents. Once agents enter the high diversity phase, we observe punctuated equilibria, a characteristic of the CCC model. The final panel presents the increase in diversity with r^+. It shows that below $r_+ = 1.5$ no diversity emerges in the population and then it is roughly proportional to r^+.

5. Discussion

One of the big question in language evolution is how complex language first appeared, and why only humans have it. In this paper, we suggest a vital part of the answer is our ability to combine linguistic traits and to organize them into systems. This combinatorial aspect of language is pervasive, extending from phonology (Lijencrants & Lindblom, 1972; Lindblom et al., 1984), to morpho-syntax (Greenberg et al., 1963; Croft, 2002; Enfield, 2017), to semantics (Wolfe, 1972;

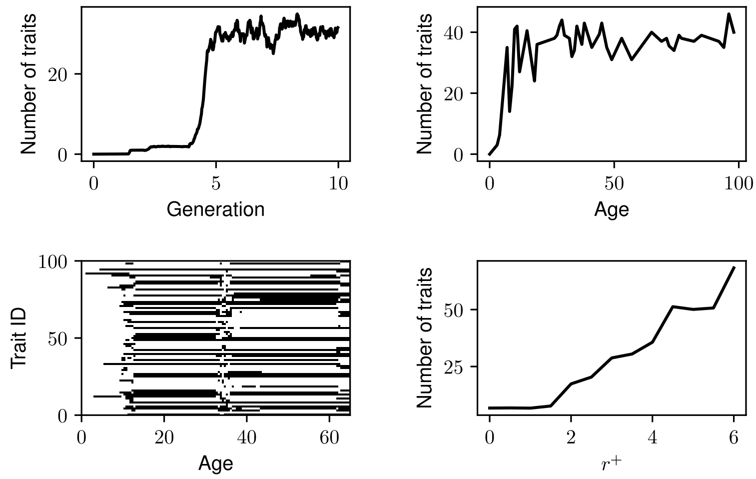

Figure 1. Top left panel illustrates the jump in diversity (average number of traits in the population) after about 5 generations. Top right panel shows the ontogeny of the number of traits at the end of the simulation. Bottom left panel shows the learning history of a typical agent (black indicates trait presence). Bottom right panel shows the averaged diversity achieved over 10 simulation runs when varying r^+ and keeping $r^- = 4$ constant.

de Boer, 2005; Wierzbicka, 2015). We argue that, for the emergence of complex language, speakers must possess the ability to productively combine linguistic traits as well as the ability to filter out traits not fitting into the system. We use Greenberg's implicational universals as an illustration of such processes. This leads to the hypothesis that humans may be better at productively combining traits than other animals and is compatible with the sequence hypothesis that states that only humans perceive order faithfully (Jon-And, Jonsson, Lind, Ghirlanda, & Enquist, 2023; Enquist, Ghirlanda, & Lind, 2023; Lind, Vinken, Jonsson, Ghirlanda, & Enquist, 2023; Ghirlanda, Lind, & Enquist, 2017).

From a developmental perspective, our model stresses the need for learners to acquire a critical mass of traits to bootstrap the complexity observed in later stages of life. This observation hints at the presence of "keystone traits" (Thurner et al., 2018) that initiate cascades toward complexity, marking the transition from childhood (a low diversity phase) to adulthood (a high diversity metastable phase) in linguistic development.

In conclusion, our exploration of language evolution using the multi-agent CCC model offers valuable insights into the joint dynamic between linguistic traits and language users. By simulating the emergence, evolution and self-organization of traits within a population, we provide a framework for understanding the complex, punctuated, and socially influenced nature of language evolution.

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