Emergent grammar from a minimal cognitive architecture

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In this paper, we introduce a minimal cognitive architecture designed to explore the mechanisms underlying human language learning abilities. Our model inspired by research in artificial intelligence incorporates sequence memory, chunking and schematizing as key domain-general cognitive mechanisms. It combines an emergentist approach with the generativist theory of type systems. By modifying the type system to operationalize theories on usage-based learning and emergent grammar, we build a bridge between theoretical paradigms that are usually considered incompatible. Using a minimal error-correction reinforcement learning approach, we show that our model is able to extract functional grammatical systems from limited exposure to small artificial languages. Our results challenge the need for complex predispositions for language and offer a promising path for further development in understanding cognitive prerequisites for language and the emergence of grammar during learning.

1. Introduction

The question of what cognitive mechanisms underlie human language learning abilities is a long-standing controversy. Theories on inborn language organisation (Chomsky, 1957; Pinker & Jackendoff, 2005; Fodor, 1983) or learning biases (Nowak, Komarova, & Niyogi, 2002; Reali & Griffiths, 2009; Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010; Tenenbaum, Kemp, Griffiths, & Goodman, 2011) often disregard social aspects of human learning and the resulting variations in language structures. Furthermore, the claim that language learning requires predefined linguistic predispositions has been challenged by the achievements of modern language models (Piantadosi, 2023). In contrast, theories relying on domain-general learning with no specific predispositions for language (Bybee, 1985; Tomasello, 2003; Heyes, 2018) and culturally emergent structure (Kirby, Cornish, & Smith, 2008; Goldberg, 2007; Langacker, 1987; Croft, 2001) generally lack explicit suggestions on the machinery underlying such learning. Connectionist models have accounted for some aspects of language acquisition (Elman, 1996; Christiansen & Chater, 2001; McClelland et al., 2010; Piantasodi & Hill, 2022), but they are hard to interpret and face challenges in capturing symbolic representations.

Here, we suggest a simple formal operationalization of emergentist theories, grounded in cognitive architecture artificial intelligence research, where few general mechanisms should explain diverse and complex cognitive phenomena (Newell, 1994). To select relevant mechanisms, we start by considering minimal cognitive differences between humans and other animals. The empirically well supported sequence hypothesis postulates that faithful perception of order is uniquely human and a defining feature of human cognition (Grant, 1976; MacDonald, 1993; Ghirlanda, Lind, & Enquist, 2017; Read, Manrique, & Walker, 2021; Lind, Vinken, Jonsson, Ghirlanda, & Enquist, 2023; Enquist, Ghirlanda, & Lind, 2023; Jon-And, Jonsson, Lind, Ghirlanda, & Enquist, 2022). Processing of language or any sequential information also requires a capacity for chunking, i.e. considering a recurrent sequence of stimuli as a unit (Tomasello, 2003; Bybee, 2002; Servan-Schreiber & Anderson, 1990; McCauley & Christiansen, 2019; Christiansen & Chater, 2016; Miller, 1956; Cowan, 2001). The third feature of our model is schematizing, a fundamental aspect of learning in humans and other animals (Hull, 1943; Ghirlanda & Enquist, 2003), that is required for categories to emerge. With these three components, we build a minimal reinforcement learning model aiming at accounting for the emergence of grammatical categories from limited exposure to small artificial languages.

2. The learning task

During language learning words are perceived in a stream and the learner's task is to identify sentences. While research has focused on word segmentation (Saffran, Aslin, & Newport, 1996; Saffran, 2001), higher levels of segmentation are also necessary for language understanding. Here, we test the hypothesis that grammar emerges to facilitate language processing at the sentence level. Even though real life language learners receive support for segmentation from, for instance, prosodic cues (Kuhl, 2004), this support is absent in our model for reasons of simplicity and feasibility, and enables investigating how far the system can reach without it. We assume that the identification of meaningful units triggers internal or external rewards, as it contributes to understanding, even though no explicit instructions or feedback are present. Following Sutton & Barto (2018), we define the task as a Markov Decision Process (MDP): a framework for studying learning from interactions with an environment to achieve a goal. In our case, the goal is to identify sentences in a stream of words constituting the environment. Sentences are generated using probabilistic context free grammars. Words' frequency is inversely proportional to their rank, approximating distributions in natural languages (Zipf, 1932). Any hint as to the beginning of sentences, for example capital letters or punctuation are removed from the list of words. For example,

The cat chases the dog. The man loves his girlfriend. The sun shines.

will be transformed into

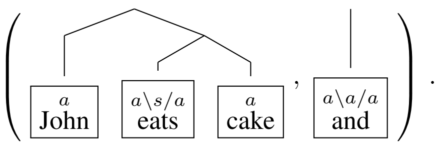
the cat chases the dog the man loves his girlfriend the sun shines

and the goal is to correctly identify sentences boundaries. The information about sentence boundaries is thus masked and used to drive the agent's learning. To assist the segmentation task, we implement schematizing using an adaptation of Lambek's syntactic type theory (Lambek, 1958), which provides the simplest mathematical framework for handling order, composition and abstraction of words (Heunen, Sadrzadeh, & Grefenstette, 2013). In this theory, every word is assigned a symbolic formula encoding how it can be grouped with other words. Primitive types are represented by one symbol, e.g. a or b, and compound types are represented as a/b or $b\backslash a$ and can be thought of as production rules encoding how types can be grouped to generate higher order types. For example, a/b followed by b or b followed by $b\backslash a$ both reduce to a. In the example

John	works	here
n	$n\backslash s$	$s\backslash s$

John is assigned the type n and *works* is assigned the compound type $n\backslash s$. Grouping them leads to typing the chunk *John works* as s for sentence. Furthermore, *here*, typed as $s\backslash s$, transforms the sentence *John works* into the longer sentence *John works here*. Our adaptation of the theory assumes no predefined categories.

In an MDP, the agent starts in a state, takes actions to move to a new state, and gets rewards (positive or negative) to drive the learning process. In our model, the possible states are encoded as pairs of structured *chunks*. A chunk refers to a sequence of potentially typed words and an associated binary tree with the words as leaves. By default, the second and most recently perceived chunk always consists of a single word. An example state is given by:



From a given state, and following an incremental processing of input akin to a chunk and pass mechanism (Christiansen & Chater, 2016), the learner needs to decide whether to insert the second element in the currently analyzed structure or to place a boundary between the two chunks. The possible resulting states corresponding to our example are displayed in Figure 1. Cases (1), (2), and (3) correspond to chunking actions in which the second element is inserted at different levels in the tree and case (4) corresponds to boundary placement, which triggers reinforcement. Positive rewards are given whenever the identified sentence is correct and negative rewards are given otherwise. We note that in this example, if previous types are correctly assigned, only case (1) is compatible with

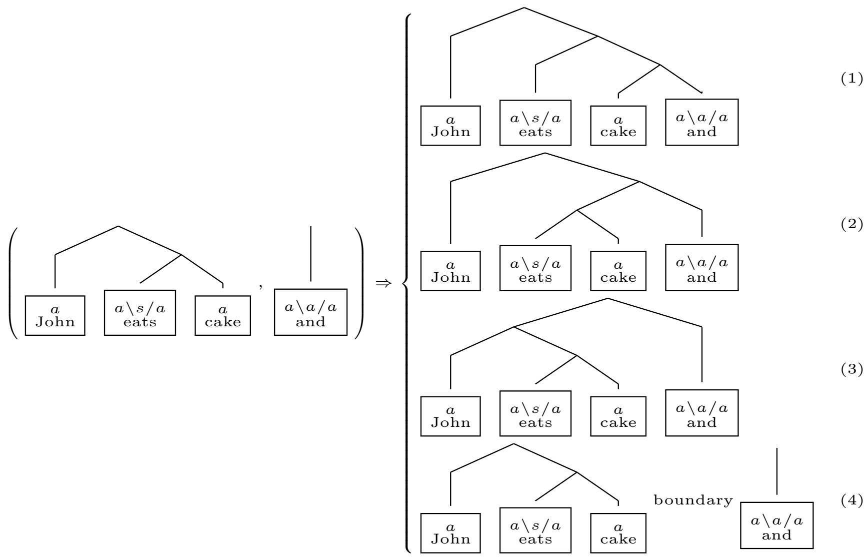


Figure 1. Possible decisions in a given state.

the assigned types since the list of types $[a, [a\backslash s/a, [a, a\backslash a/a]]]$ reduces to s/a. Placing a boundary is also incompatible with the assigned types because while the first element correctly reduces to a sentence, the second element expects to be preceded by a. The primary goal of the model is to successfully segment sentences and the secondary goal is to assign syntactic types to words to induce a grammatical representation of the input.

3. The cognitive architecture and learning mechanism

The cognitive architecture consists of a long term memory storing associations between states and actions as well as associations between words and types and a working memory used to process sentences, to invent types, and to update the long term memory through reinforcement learning.

Sentence processing works as follows. The learner initializes its state by reading the first two words in the stream and try to assign syntactic types to them. In the beginning of the learning process, no types are associated with words, but types will emerge during the learning process. If the words have compatible types, these types are chosen, otherwise, if only one word has a type, it assigns a compatible type to the other word. Once the typing process is done, actions are chosen based on both the state-action associations and the assigned types, if any. The process continues until the chosen action is a boundary placement. In that case, reinforcement is triggered. This is done using an error-correction algorithm (Rescorla

& Wagner, 1972; Sutton & Barto, 2018) that exploits the hierarchical structure of the states and takes into account whether type associations have informed the decision or not. Upon correct boundary placement, state-action associations and word-type associations are positively reinforced. If the words in the sentence were not typed, the recognized structure is typed s and compatible types are assigned to individual words constituting the sentence, randomly choosing among possible assignments. Initial types are always constructed minimalistically containing only the primitive s. Upon incorrect boundary placement, state-action associations and word-type associations are negatively reinforced. When all reinforcements have been performed, the working memory is emptied and a new sentence is processed.

During sentence processing, word-type associations that have decreased below a given threshold block type assignment and trigger the emergence of new primitive types, providing a mechanism to invent new types. Differently from the original theory of types and other categorial-based formalisms (Steedman & Baldridge, 2011; Kogkalidis, Moortgat, & Moot, 2020), we do not assume any predefined grammatical categories. Types are invented when needed, replicated through type assignment and selected based on their usefulness in sentence segmentation. These general processes of invention, replication and selection turn our type system into an evolutionary system following a broad definition of evolution (Hull, 2001). We call this modified framework an evolutionary type system.

4. Results and discussion

The evaluation of the cognitive architecture's ability to extract grammar from small artificial languages comprises two aspects: (i) do types emerge that make learning faster than learning without types (i.e. a model version without schematizing); (ii) do the types that emerge expose any resemblance with grammatical categories? If these two criteria are fulfilled, results support the hypothesis that grammar emerges because it makes learning more efficient.

We have implemented a pilot type system for two-word sentences, consisting of nouns and intransitive verbs. A more general type system that will encompass longer sentences like those previously exemplified is currently being developed.

Table 1. Stimulus-type associations (between -2 and 10) for a language with 4 nouns and 4 verbs.

	Noun 1	Noun 2	Noun 3	Noun 4	Verb 1	Verb 2	Verb 3	Verb 4
a	10	10	10	10				
s	-0.1	-0.5	-0.5	0.6				
$a\backslash s$					10	10	10	10
$s\backslash s$						1	1	
s/a					-0.38	-0.2	-0.4	

We see that functional types emerge. The left panel of Fig. 2 displays an example

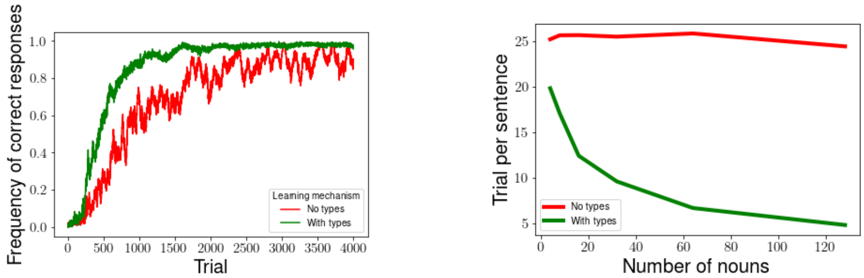


Figure 2. Left: Learning curves for a language with 16 nouns and 8 intransitive verbs with and without types. Right: Learning times for a varying number of nouns and a fixed number of verbs.

of a language with 16 nouns and 8 verbs, where learning to identify sentences is faster with types. The right panel shows that the difference in learning times increases with vocabulary size. For a learner without a type system, the number of trials it takes to identify each sentence is independent of vocabulary size, while for a learner with the evolutionary type system it decreases when the vocabulary grows, reflecting the productive assignment of types to novel words. This function is arguably similar to that of productive grammatical categories.

Table 1 shows final word-type association values. The strongest word-type associations correspond to nouns being typed as a and verbs being typed as $a\backslash s$. Note that the only type assigned to Verb 4 is $a\backslash s$, which indicates successful generalization. These emergent types are coherent with the original theory of syntactic types (Lambek, 1958) and indicate that the second element is analyzed as the predicate or head of the sentence and the first element as an argument or a dependent. The emergent types are parsimonious since they only use two primitives and all nouns and verbs have the same respective strongest type. Despite the fact that type invention and assignment are symmetric, the head second order is dominant. This is likely a consequence of the learning process and the fact that it is easier to generate blocking types for the first word of the sentence that for the second one, leading to a higher likelihood of nouns being assigned a new primitive type. This order bias is compatible with the fact that subject-verb is a more frequent word order in the world's languages than verb-subject .

Our pilot results support the hypothesis that accurate sequence perception combined with chunking and schematizing may suffice for learning grammar, which would imply that previously suggested more complex predispositions for language are unnecessary. The results also suggest that grammar can emerge as a self-organizing solution to the combinatorial problem of language learning. These results are promising for further development of the model, extending its capacity to process sentences of any length and structure, and applications to natural language corpora.

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