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Review article

What do animals learn in artificial grammar studies?

Gabriël J.L. Beckers^{a,*}, Robert C. Berwick^{b,c}, Kazuo Okanoya^d, Johan J. Bolhuis^{e,f}

^a Cognitive Neurobiology and Helmholtz Institute, Department of Psychology, Utrecht University, Utrecht, The Netherlands

^b Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, MA, USA

^c Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA, USA

^d Department of Cognitive and Behavioral Sciences, The University of Tokyo, Tokyo, Japan

^e Cognitive Neurobiology and Helmholtz Institute, Departments of Psychology and Biology, Utrecht University, Utrecht, The Netherlands

^f Department of Zoology and St. Catharine's College, University of Cambridge, Cambridge, UK

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ABSTRACT

Artificial grammar learning is a popular paradigm to study syntactic ability in nonhuman animals. Subjects are first trained to recognize strings of tokens that are sequenced according to grammatical rules. Next, to test if recognition depends on grammaticality, subjects are presented with grammar-consistent and grammar-violating test strings, which they should discriminate between. However, simpler cues may underlie discrimination if they are available. Here, we review stimulus design in a sample of studies that use particular sounds as tokens, and that claim or suggest their results demonstrates a form of sequence rule learning. To assess the extent of acoustic similarity between training and test strings, we use four simple measures corresponding to cues that are likely salient. All stimulus sets contain biases in similarity measures such that grammatical test stimuli resemble training stimuli acoustically more than do non-grammatical test stimuli. These biases may contribute to response behaviour, reducing the strength of grammatical explanations. We conclude that acoustic confounds are a blind spot in artificial grammar learning studies in nonhuman animals.

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* Corresponding author at: Cognitive Neurobiology and Helmholtz Institute, Department of Psychology, Utrecht University, Padualaan 8, 3584 CH Utrecht, The Netherlands.

E-mail address: g.j.l.beckers@uu.nl (G.J.L. Beckers).

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1. Introduction

A key goal of the cognitive (neuro)sciences is to develop an account of the human language capacity, presumed to be an internal computational system. Since the latter part of the 20th century, a traditional approach to this problem, following Chomsky (1975) and much other work, is to characterize this capacity via generative grammars. Since grammars are part of neural computational systems, their activity is typically not directly observable, for example, in the sentences or language that comprise external behavior. The investigation of human, or “natural” generative grammars has thus proceeded by drawing on many kinds of experimental methods and data to indirectly infer the properties of human grammars—linguistic examples, sentence processing, language acquisition, brain imaging, and the like. An additional barrier is the lack of non-human model organisms, which impedes comparative work, since so far as it is known only humans possess full-fledged generative grammars (Berwick et al., 2013).

Artificial grammar learning (AGL) is one methodology that has been advanced in an attempt to overcome hurdles like these. Roughly, the idea is that one can construct deliberately simplified, hence artificial grammars (AGs) that focus on just a few syntactic properties, and then calculate what these simplified systems might yield in the way of observable external forms, what are sometimes called the grammar’s language, the set of strings defined (‘generated’) by that grammar, as described in the following section. Note that for an artificial generative grammar, the grammar itself is internal to the computational system, while some of the representations the grammar generates are “externalized,” like the sequence of sounds in speech. Since by design the experimenter knows both the internal form (the AG) and the observable, external forms the AG yields, the AG can be used in experimental paradigms where either humans or other animals can be tested to see whether the particular properties highlighted by the AG can be acquired, and so represented and used. This remains one of the few direct ways to ascertain whether nonhuman animals possess grammatical abilities, and if so, which level of complexity they can master.

2. Artificial grammar learning

2.1. What is an artificial grammar?

An artificial grammar is a particular subset of the full class of generative grammars. For our analysis in the remainder of this article, it is useful to define such grammars more carefully. In general, a generative grammar consists of a finite set of rules along with some computational (recursive) procedure to generate or derive possible sentences. Here for illustration we focus on one narrow type of generative grammar used most often in AGL studies, so-called *context-free* grammars. These consist of *production* or *rewrite* rules built out of a finite set of *nonterminal* and *terminal* tokens or symbols. Terminal tokens are analogous to externally observable words or sounds in a human language, like *the* or *apple*; nonterminals correspond to phrases like *Noun Phrase* or *Prepositional Phrase*. Each rewrite rule consists of two related parts, a lefthand side and a righthand side, where a specified symbol(s) on the lefthand side is to be replaced with the symbols on the righthand side. Additionally, given a set of rules, there is a set procedure to generate or derive possible sequences of terminal symbols, beginning with a designated nonterminal starting symbol, and successively replacing left-hand side symbols in rules with their right-hand sides until no more rules can apply. To illustrate, consider the following simplified grammar designed to reflect certain aspects of the syntactic structure of English Noun Phrases, which consists of five rewrite rules, each with a left- and right-hand sides separated by an arrow→, four

nonterminal symbols, which are capitalized, and three terminals, which are in lower case (the rules are numbered for convenience):

- (1) Start→ NounPhrase
- (2) NounPhrase→ Determiner Noun
- (3) Noun→ apple
- (4) Noun→ bird
- (5) Determiner→ the

Beginning with the nonterminal *Start* symbol, this miniature grammar can generate, for example, the sequence *the apple* via the successive replacement of symbols according to the grammar rules as follows: *Start*; *NounPhrase* (via Rule 1); *Determiner Noun* (via Rule 2); *the Noun* (via Rule 5); *the apple* (via Rule 3). (At this point no more rules apply since the last string has no symbols that appear on the left-hand side of any rule, so the generation halts, have produced the sequence noted.) This grammar will generate exactly one other form consisting of just terminal symbols, *the bird*.

Importantly, AGs are “artificial” and crucially different from natural grammars in at least two ways: (1) AG rule tokens are unlike those found in natural grammars, e.g., they use abstract symbols such as “B” or “Z” rather than, say, part of speech or phrase tokens like *Noun Phrase* or *Noun*; and (2) AG rules themselves are typically deliberately schematized and simplified as compared to those of natural human generative grammars. Note that despite the general claim under the so-called contemporary “Minimalist Program” that there is a single operation, Merge, that builds syntactic structure, Merge interacts with the features of lexical items and other linguistic principles to yield what amounts to a very large, complex set of equivalent context-free rules in any particular human language (Barton et al., 1987). However, AGs are often deliberately designed to reflect only certain key abstract properties of natural grammars as part of their methodological role in experimental manipulations. Even in this sense, however, the miniature example grammar just presented is “artificial” in that it does not fully reflect the properties of English Noun Phrases, for example, the fact that Noun Phrases may themselves be modified by sentence-like phrases, as in *the apple the bird ate*. One tenet of some current accounts of human generative grammar holds that the chief property of human language syntax is its arbitrarily deep hierarchical structure, rather than sequential left-to-right order (Everaert et al., 2015) but a glance at the miniature grammar above and most AGs shows that they typically do not partition syntactic information in this way, and embed sequential order directly into their rule systems along with hierarchical structure, which is nearly unavoidable (*the apple* but not *apple the*), while finding it challenging to focus on just hierarchical structure.

2.2. Learning tokens and sequence rules

An important consideration in the interpretation of AGL studies is that the learning of rules is implicit. That is, the only information available to the subjects is the auditory input itself, from which regularities should be spontaneously recognized and memorized. Subjects are not explicitly told what the grammar is, nor are they explicitly trained in a way that should promote the learning of grammatical rules. Indeed, an important motivation behind many studies is to test whether or not grammars can be acquired implicitly from exemplars of strings that are produced by them. Since non-human animals cannot explain *a posteriori* what strategy they apply to differentially respond to stimuli, and humans appear often not to be aware of their strategies (e.g. Knowlton and Squire, 1996), it is up to the researchers to provide a convincing case when they claim that subjects learned and apply grammatical rules.

What information do perceptual systems require to learn artificial grammars? A grammar not only consists of sequence rules but

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