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Miniature Artificial Language Learning as a Complement to Typological Data

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AS OBSERVED BY LINGUIST Joseph Greenberg (Greenberg 1963), languages across the world seem to share properties at all levels of linguistic organization. Some of these patterns are regularities in the cross-linguistic distribution of elements that hold across languages (*non-implicational universals*[1]). For example, sentential subjects almost always precede objects in declarative sentences (Greenberg 1963). Others, the so-called *implicational universals*, describe correlations between elements that vary together across languages: If a language has property A, then it most likely has property B. An example of such an implicational universal is the well-documented correlation between constituent order freedom and the presence of case-marking (Sapir 1921, Blake 2001): Languages with flexible constituent order often use morphological means, such as case, to mark grammatical function assignment (e.g., German, Japanese, and Russian), whereas

[1] Throughout this paper, we will assume the notion of language universals in the broadest sense, including both widespread features of natural languages such as recursion and compositionality (cf. Chomsky 1986, Hockett 1960) and more specific statistically recurring patterns (cf. Greenberg 1963).

languages with fixed constituent order typically lack case morphology (e.g., English, Mandarin, and Italian).

The existence of both types of cross-linguistically recurrent patterns points towards constraints on the space of structures that are possible or preferred in natural languages. The origins of such recurring patterns have been the subject of long-standing debate in linguistics and cognitive science. Most theories have argued that language universals originate from individual language users and suggest that language structures are shaped by biases and limitations on human cognitive systems (Chomsky 1965, Fodor 2001). Views differ, however, as to whether these biases are specific to language (Chomsky 1965, Fodor 2001) or stem from constraints on broader human cognitive mechanisms and pressures associated with language acquisition and use (Christiansen and Chater 2008, Bever 1970, Deacon 1997, Newport 1981, Slobin 1973, Hawkins 1994, Bates and MacWhinney 1982, Givón 1991).

Capturing language universals and understanding their causes has been one of the central objectives in modern linguistics. If language universals originate in human cognition, understanding their causes would give us insights into the nature of the constraints underlying language processing and representation in the human brain.

In this paper, we discuss an experimental approach that allows researchers to test hypotheses about the origin of cross-linguistically frequent patterns by studying patterns in the acquisition and use of miniature artificial languages in the laboratory. First, we briefly summarize the typological approach traditionally used to study language universals and outline two major limitations of this approach: one has to do with the structure of typological data itself; the other is the inability of this approach to address the causes of language universals. We then introduce a complementary approach that uses a miniature artificial learning paradigm to investigate typological distributions. Finally, we highlight some converging themes from studies of typological data, natural language acquisition, and miniature artificial language learning approaches and outline some outstanding issues concerning the application of miniature artificial language studies to typological questions.

Typological approach to linguistic universals

Traditionally, the study of linguistic universals has drawn evidence primarily from cross-linguistic and historical typological data. This approach has been extremely productive in identifying a large number of language universals (Dryer 1992, Greenberg 1963, Croft 2003) and in linking typological data to processing preferences (Hawkins 2004). The development of large data sets such as *The World Atlas of Linguistic Structures* (Dryer and Haspelmath 2011), a substantial increase in the number of languages on which we have documentation and some analysis, and developments in linguistic theory that originated within this approach (Dryer 1998, Croft 2003) have greatly enhanced our understanding of language universals and have added new views of language to the field. For example, this literature has prompted a shift away from categorical notions about universals (e.g., absolute linguistic universals or narrowly defined language types) towards a probabilistic view of language structure, in which common language patterns are viewed as tendencies or biases and language differences are viewed as typological distributions that are closely related to distributions of other factors such as human cognition, cultural underpinnings, and population movements.

However, relying solely on typological data for our understanding of universals of language structure has two serious limitations. The first is the sparsity of independent data points. Most languages are genetically related (that is, have evolved from common ancestors) and thus would be expected to share properties for this reason. Language contact can further diminish the independence of languages, since languages that remain in contact over long periods of time often come to share lexical and structural properties. A famous example of areal influences (language contact) is the Balkan Sprachbund, where geographically contiguous but genealogically unrelated languages (Macedonian, Bulgarian, Greek, Albanian, and Balkan Romance) have acquired a number of common features in phonology, morpho-syntax, and lexicon often referred to as *Balkanisms* (Friedman 2006).

Both genetic and areal influences drastically reduce the effective sample size of languages available for statistical tests of hypothesized universals – a challenge to typological approaches that has long been recognized (Dryer 1989) but has only recently begun to be addressed (Cysouw 2010, Dunn et al. 2011, Jaeger et al. 2011, Dryer 1989, Rafferty, Griffiths, and Klein 2014). Using advanced statistical methods, some of this recent work has called into question typological generalizations that have long been assumed to hold (e.g., Dunn et al. 2011).

Second, while the typological approach has been instrumental in documenting a large number of language universals and identifying their fine-grained structure, it cannot directly answer questions concerning the *origin* of linguistic universals. For example, if language universals are indeed shaped by constraints on the human cognitive system, how do these constraints enter the linguistic system and come to shape it over time? Do they originate during language acquisition, through constraints on learning, or through language use (e.g., fluency of comprehension and/or production) in mature users?

Both of these shortcomings of typological approaches can be addressed by complementing typological work on language universals with behavioral evidence from language learning experiments (for a similar perspective, see also Tily and Jaeger 2011)[2]. Hypotheses about underlying causes of language universals are often tested by studying outcomes of natural language acquisition. Evidence from natural language acquisition in normally developing children (Crain, Goro, and Thornton 2006, Slobin 1973, Bates et al. 1984, Hyams 1983) and studies of learners exposed to impoverished input (Senghas and Coppola 2001, Goldin-Meadow and Mylander 1998, Singleton and Newport 2004) suggest strong parallels between patterns observed in typology and learning and provide direct evidence for changes introduced by learners into linguistic systems that do not conform to typologically common patterns.

However, these approaches face the challenge of a lack of control over the input: It is almost impossible to have a complete picture of the amount of language exposure and the frequency of grammatical structures of interest that learners receive prior to

[2] Another methodology often used to complement typological data involves computational approaches that use multi-agent simulations to study how hypothesized language universals emerge and evolve over time (e.g., Kirby 1999, Niyogi 2006, Steels 1995, 2006). These approaches are beyond the scope of this paper, but see a comprehensive review by Steels (2011) for further details.

testing, which creates a potential confound that must be taken into consideration when interpreting the results.

Miniature artificial language learning approaches to linguistic universals

An addition to examining natural language acquisition in studying linguistic universals is presented by using a miniature artificial language learning paradigm, where participants (infants, children, or adults) are exposed to languages that are designed in the laboratory to have certain properties of interest, allowing researchers to obtain precise control over the stimuli and isolate the input dimensions of interest. Miniature languages are small enough to be acquired in the lab within a short period of time, with exposure typically ranging from several minutes for simpler languages (Saffran, Aslin, and Newport 1996) to several one-hour sessions distributed over several days for more complex languages that may involve reference and meaning (Amato and MacDonald 2010, Fedzechkina, Jaeger, and Newport 2012, Hudson Kam and Newport 2005, 2009, Wonnacott, Newport, and Tanenhaus 2008). In such experiments participants are exposed to written or, more commonly, auditory stimuli (e.g., a sentence in the artificial language), often accompanied by a picture or video representing the event described. After exposure to a set of sentences from the language, participants respond to questions about test items. For instance, participants might be asked to rate how familiar the stimuli are, to answer comprehension questions, and/or, increasingly more commonly, to describe new videos or pictures in the newly acquired language (see Figure 1 for an example of training and test items).

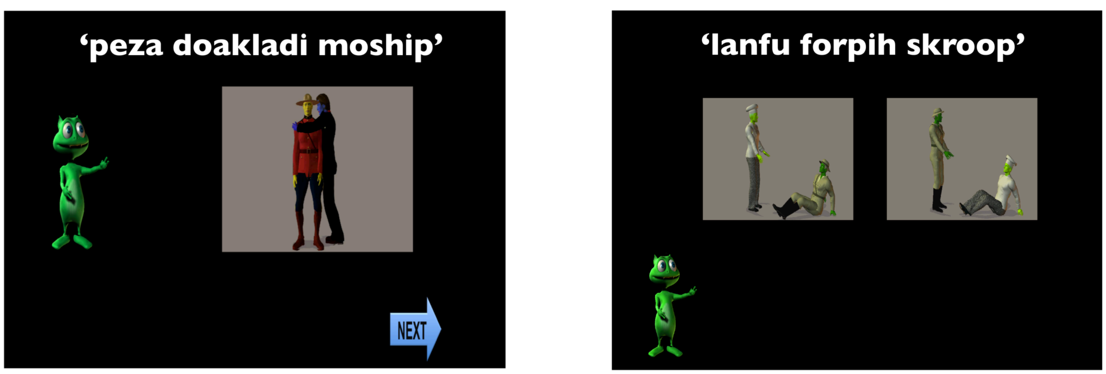

Figure 1: Example of a training item (left panel) and a comprehension test item (right panel) used in Fedzechkina, Jaeger, and Trueswell (2015). Pictures are still images of the videos accompanied by sentences in a miniature artificial language presented auditorily during the experiment (shown here in print for convenience).

Although the first miniature artificial language learning experiments were conducted many years ago (Cook 1988, MacWhinney 1983, Esper 1925, Morgan, Meier, and Newport 1987, Reber 1967), it was work in the late 1990s that established miniature artificial language learning as a widely used method in language acquisition research. Most of the work using this paradigm has focused on articulating the precise information that learners can extract from the input to acquire various aspects of the language and on revealing the biases that learners bring to the acquisition process. For example, Saffran, Aslin, and Newport (1996) exposed 8-month old infants to a stream of nonsense words (pibadubudaka….) that contained no information about word segmentation except transitional probabilities between the syllables (high within the word and low at word boundaries). After only 2 minutes of passive exposure to this sound stream, infants could successfully discriminate the nonsense words of which it was composed from other sound sequences that were present in the stream (across word boundaries), suggesting that learners were exquisitely sensitive to the statistical distribution of sounds in the input. Subsequent work has established that infants can also extract higher order regularities between items in the input and generalize to novel but similar examples (Marcus et al. 1999, Gerken 2006, Reeder, Newport, and Aslin 2013).

Researchers have expanded these paradigms to study increasingly more complex phenomena, such as acquisition of word order, verb subcategorization, phrase structure (Christiansen 2000, Thompson and Newport 2007, Wonnacott, Newport, and Tanenhaus 2008, Culbertson, Smolensky, and Legendre 2012, Tily, Frank, and Jaeger 2011) and morphology (Culbertson and Legendre 2010, Fedzechkina, Jaeger, and Newport 2012, Fedzechkina, Newport, and Jaeger in press, Hudson Kam and Newport 2005, 2009). Artificial language learning has also been combined with sentence processing methodologies such as eye-tracking (Magnuson et al. 2003, Wonnacott, Newport, and Tanenhaus 2008) and self-paced reading (Amato and MacDonald 2010, Karuza et al. 2014) to study how newly acquired distributional information is used in real time during incremental processing of novel languages.

The surprising appearance of many natural language learning phenomena in these artificial paradigms has suggested that miniature artificial language learning may also be well-suited to study syntactic and morphological universals, which have traditionally been of great interest in linguistic typology (Bickel 2011, Cysouw 2011, Dryer 1992). This has caused a rapid increase in studies applying this paradigm to cross-linguistic generalizations (e.g., to phonology: Finley and Badecker 2008, Wilson 2006; word formation: Newport and Aslin 2004; morphology: Fedzechkina, Jaeger, and Newport 2012, Hudson Kam and Newport 2005, 2009, Hupp, Sloutsky, and Culicover 2009, St Clair, Monaghan, and Ramscar 2009; syntax: Morgan, Meier, and Newport 1987, Tily, Frank, and Jaeger 2011, Thompson and Newport 2007). Miniature artificial language learning has two advantages over typological approaches, which makes it an exciting complement to traditional cross-linguistic investigations. First, unlike typological data, it does not suffer from data sparsity as new languages can be designed in the lab to have a variety of characteristics. Second, perhaps most importantly, studies using miniature artificial language learning paradigms can test specific hypotheses about the underlying causes of cross-linguistic universals, while approaches relying on typological data in most cases are necessarily correlational.

Studies of the relationship between language learning and language structure in miniature artificial language research typically use one of two somewhat different paradigms (see Figure 2). The most widely used approach compares the learnability of two or more artificial languages that each have consistent grammars but differ in certain crucial properties (for example, one language consistently uses cross-linguistically common structures such as subject-object-verb (SOV) word order while the other one consistently uses uncommon structures such as the much more rare object-subject-verb (OSV) word order). In these experiments, participants are trained on a subset of items generated by the underlying artificial grammar. Participants' performance is subsequently assessed by seeing how well they generalize the newly acquired artificial grammar to previously unseen data (Finley and Badecker, 2008; Tily, Frank, and Jaeger, 2011) or discriminate between familiar or novel grammatical items and highly similar but ungrammatical items (Reeder, Newport, and Aslin 2013). The logic behind this approach is as follows: If grammatical structures that mirror typologically frequent patterns are acquired more easily, then these patterns may have originated from biases or preferences in human cognitive mechanisms. Indeed, the recurrent finding from this paradigm is that typologically common properties and structures are acquired faster and more easily than less common ones at all levels of linguistic organization (e.g., phonology: Finley and Badecker 2008, Wilson, 2006; word formation: Newport & Aslin, 2004; morphology: Hupp, Sloutsky, & Culicover, 2009; St Clair, Monaghan, & Ramscar, 2009; syntax: Morgan, Meier, & Newport, 1987; Tily, Frank, & Jaeger, 2011).

The second and arguably more powerful miniature artificial language learning paradigm addresses questions about linguistic universals by investigating whether learners exposed to artificial languages that do not conform to cross-linguistically common patterns will introduce changes into the languages as they learn, making them more closely aligned with naturally observed types (Culbertson, Smolensky, and Legendre 2012, Culbertson and Newport 2015, Fedzechkina, Jaeger, and Newport 2012, Hudson Kam and Newport 2005, 2009). The key feature of this paradigm is that the input learners receive contains several grammatical structures that express the same meaning, thus creating a situation similar to language change or pidgin community variation in the laboratory. For instance, learners could receive an input language that inconsistently uses SOV and OSV word order variants. The reason to incorporate variability into input languages is two-fold. First, a large body of work in artificial language learning suggests that learners are not likely to introduce innovations into perfectly consistent languages, at least within the short amount of time spent in the laboratory (e.g., Christiansen, 2000; St Clair et al., 2009; Tily et al., 2011). Incorporating variability into artificial languages increases the likelihood of manifesting learning biases within a short period of time. Second, assessing learners' preferences for one of the two competing forms in learners' production allows researchers to gain insight into learners' synchronic preferences and also to see how these preferences may change the linguistic system over time.

The common finding from this paradigm is that children move languages quite substantially toward typologically common patterns (Culbertson and Newport 2015, Hudson Kam and Newport 2009, 2005). Adult learners are more likely to match or stay closer to the statistics of the input (Hudson Kam and Newport 2005, 2009). However, when adults do deviate from the input they receive, their changes tend to reflect typologically more common patterns (Culbertson, Smolensky, and Legendre 2012, Fedzechkina, Jaeger, and Newport 2011, Fedzechkina, Newport, and Jaeger in press).

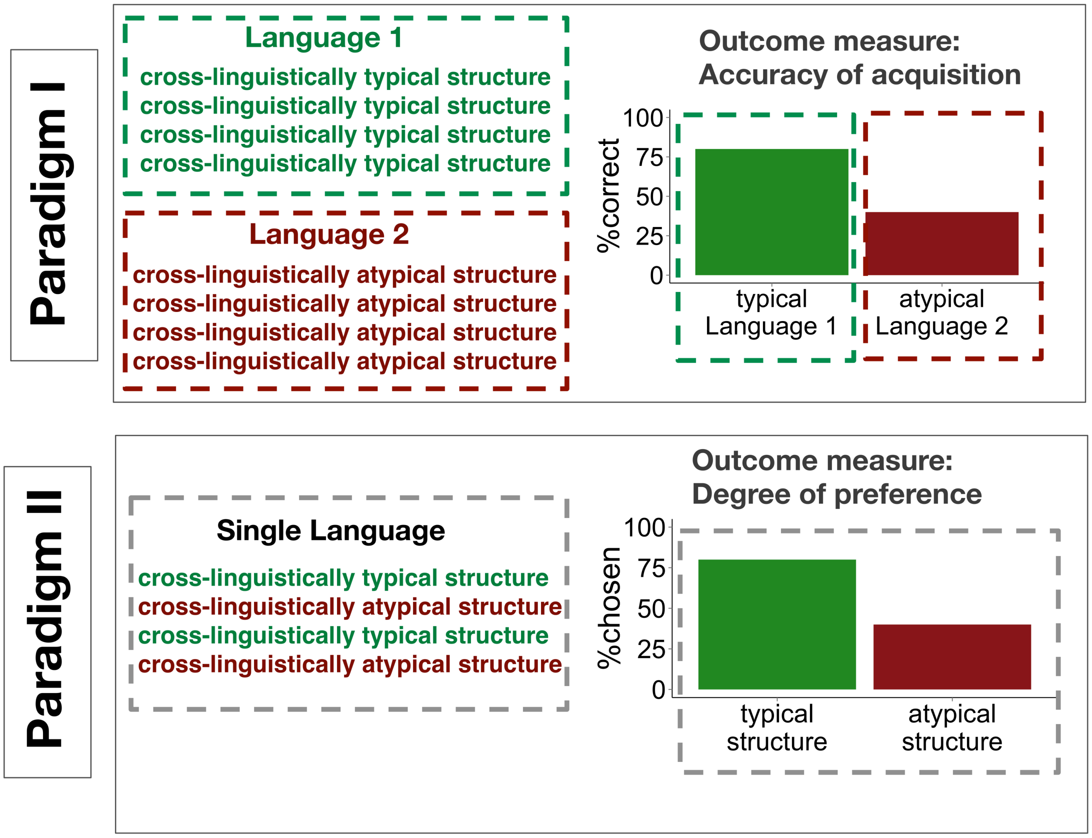

Figure 2: Two paradigms used in miniature artificial language learning research. In both paradigms, participants are exposed to different tokens of two or more structural types – a cross-linguistically frequent (typical) and a cross-linguistically infrequent (atypical) structure. Paradigm I uses a between-subject design where different groups of participants are consistently exposed to tokens of either typical or atypical structural type and assesses successful learning via accuracy measures. Paradigm II employs a within-subject design where the same group of participants is exposed to tokens of typical and typical type within the same language and successful learning is assessed through the degree of preference for tokens of either type in participants' productions.

In the next section, we highlight some of the converging themes that emerge from typological, natural language acquisition, and miniature artificial language learning approaches. Specifically, we review evidence for three linguistic universals that have received attention in both typology and language learning: cross-linguistic preferences for consistent headedness, predictable variation, and trade-offs between cues to sentence meaning.

Converging evidence for linguistic universals

Consistent headedness

Evidence from a large number of typological studies (Dryer 1992, Greenberg 1963, Hawkins 1983) and work in theoretical syntax (Chomsky 1988, Jackendoff 1977) suggests that languages tend to *consistently* order dependents with respect to their heads:

Word orders where heads either consistently precede or consistently follow their dependents are preferred cross-linguistically. A well-attested example of this preference is a correlation between the order of elements in the verb phrase, adpositional phrase, genitive phrase, and the position of the relative clause with respect to its head noun. Cross-linguistically, languages that have verb-final word order typically also have noun-postposition, genitive-noun, and relative clause-noun orders, while verb-initial languages tend to have preposition-noun, noun-genitive and noun-relative clause orders (Dryer 1992, Greenberg 1963). Recent work, however, has failed to provide support for these universals after the genetic dependencies between languages are appropriately accounted for (Dunn et al. 2011), thus calling into question the universality of these cross-linguistic patterns.

Early miniature artificial language learning studies conducted by Cook (1988) investigated whether learners exposed to one grammatical construction of interest would generalize it to another construction in line with the cross-linguistic preference for consistent headedness. For example, some learners were exposed exclusively to sentences with simple verb phrases (using SOV or VSO word order) and then tested on adpositional phrases (preposition-noun and noun-postposition). The results provide only partial support for the preference for consistent headedness. Cook found that learners of both verb-final and verb-initial orders generalized to noun-postposition order, which goes against typological data for the second group of learners. However, there was a significant difference in the *degree of preference* for the noun-postposition order: In line with typological data, learners exposed to the verb-final constituent order chose the noun-postposition order significantly more often. This somewhat mixed pattern of results might be due to the methodological shortcomings of the study. For instance, all artificial sentences were accompanied by English translations throughout the study, so it is possible that learners experienced interference from their native language, making the results less clear-cut.

More recently, Christiansen (2000) investigated the same bias for consistent head ordering using a somewhat different paradigm. In this experiment, two groups of participants were exposed to nonsense letter strings (e.g., VVQXQXS or VQQVXXS) that were generated by either a consistent head ordering grammar (where all phrases were head-final) or an inconsistent head ordering grammar (where some phrases were head-final and some head-initial). At test, participants were asked to classify previously unseen strings as grammatical or ungrammatical. In line with typological data, participants exposed to artificial languages that contained consistent head orderings performed significantly better than participants trained on languages with inconsistent headedness.

Culbertson, Smolensky, and Legendre (2012) further showed that learners exposed to miniature artificial languages with probabilistic inconsistencies in head ordering tend to make headedness more consistent as they learn these languages. Culbertson, Smolensky, and Legendre (2012)'s work examined Greenberg's Universal #18 (Greenberg 1963) concerning the ordering of numeral, adjective and noun. Prenominal adjectives (e.g., 'blue sky') and postnominal numerals (e.g., 'chapter two') in the same language tend to be dispreferred cross-linguistically, while other orders of adjective and numeral with respect to the noun are well-attested (e.g., adjectives and numerals preceding nouns as in English or following nouns as in Tibetan). In line with this universal, they found that learners tend to regularize typologically frequent patterns, strongly preferring 'harmonic' patterns (where the adjective and numeral both occur before or both occur after the noun). Learners also successfully learned a less common but still widely attested pattern where the numeral precedes the noun while the adjective follows it. In contrast, the typologically infrequent word order (adjective preceding the noun, numeral following) was not learned well and not favored in regularization. Culbertson and Newport (2015) conducted the same experiment with children rather than with adult learners. They found that children preferred the harmonic orders even more strongly, moving the numeral in all languages to become consistent with the position of the adjective.

Predictable variation

Another linguistic universal that is widely supported by typological and language acquisition data is a preference for consistent rule-based linguistic systems that have *predictable* variation. It is highly uncommon for a natural language to have several forms that carry the same meaning and are in free variation in the same context. Instead, languages tend to have predictable variation in which the use of competing forms is conditioned by semantic, pragmatic, phonological, and other factors (Givon 1985, Labov 1963).

Support for this cross-linguistic property of human language comes from developmental studies showing that children acquiring consistent systems in their native language typically find them easier to learn than systems with high idiosyncrasy. For example, Slobin (1973) found that Serbo-Croatian and Hungarian bilingual children first mastered the locative expressions in Hungarian, which involve consistent locative inflections, while Serbo-Croatian locatives that involve an inconsistent combination of prepositions and case inflections appeared later in their speech. Monolingual children acquiring Turkish (a language with free constituent order and rich morphology) have been shown to acquire the nominative/accusative case inflections before the basic word order (Slobin and Bever 1982). A possible explanation for this asymmetry is that the case system in Turkish is highly consistent and displays little case syncretism, whereas Turkish word order contains variability and allows scrambling (Kornfilt 2003). Learners' preference for consistency has also been shown in early productions of children learning free word order languages such as Russian: They typically start out using one word order variant, with other possible orders appearing later (Slobin 1973, 1977).

Even stronger evidence for a bias against linguistic systems with unpredictable variation is found in learners receiving atypical input. Singleton and Newport (2004) followed the language development of a deaf child named Simon. Simon's ASL input came exclusively from his parents, who were both late learners of ASL. Their speech contained a lot of inconsistencies as is typical for late learners. In contrast, however, Simon's performance on most tests was much more consistent than his parents' and comparable to peers who acquired ASL from native signers, suggesting that Simon restructured the input he received and introduced a more consistent system in his own productions.

Similar observations have been made by Goldin-Meadow and colleagues (Goldin-Meadow and Mylander 1983, 1998, Goldin-Meadow et al. 1984), who have studied the emergence of simple gestural systems used by deaf children to communicate with their hearing parents (called *home sign* systems). In a series of studies, they have found that profoundly deaf children who received no sign language input tended to develop *structured* gestural communication systems that had a number of characteristics of natural languages (e.g., relatively consistent word order and recursion). Importantly, the gesture order used by these children was not modeled after the caregivers', whose own gesture use was highly inconsistent and often less complex than the children's gestural systems. These findings suggest that greater word order consistency was introduced by the child learners.

These results are also supported by laboratory studies that directly tested this hypothesized causality with hearing participants (Hudson Kam and Newport 2009, 2005). Adult and child learners were exposed to a miniature artificial language that contained unpredictable variation: Nouns in the artificial language were probabilistically followed by determiners ('ka', 'po', or omitted). Young learners regularized the inconsistent input they received, using one of the determiners in almost all of their productions. Adult learners reproduced the unpredictable variation when the language had a fairly simple structure but also showed regularization when the complexity of the system was high.

Trade-offs between cues to grammatical function assignment

Cues to grammatical function assignment ('who is doing what to whom' in a sentence) appear to trade off cross-linguistically (Bates and MacWhinney 1982, Givón 1991, Sapir 1921). There are a number of typologically common devices that mark the distinction between the subject and direct object in a sentence: word order (e.g., English), case-marking (e.g., Korean or Latin), animacy (e.g., Japanese or Hindi), agreement (e.g., Russian), pragmatic information (e.g., Italian) to mention a few. However, it is uncommon for a single language to simultaneously employ all existing devices for marking grammatical function assignment (Van Everbroeck 2003), and it is also uncommon for languages not to differentiate between the subject and direct object in any way (Wasow 2015). This pattern suggests that there is a preference for relatively efficient linguistic systems – marking grammatical function using a fairly restricted set of cues – and a bias against linguistic systems that have either excessive uncertainty or excessive cue redundancy.

The order of acquisition of devices marking grammatical function assignment appears to follow this trade-off as well: Children do not acquire multiple redundant cues to grammatical function in their native language at the same time; instead, devices that are more informative about grammatical function assignment are acquired earlier cross-linguistically. For example, Bates et al. (1984) studied the development of sentence interpretation strategies in English and Italian. They found that the cues acquired by children markedly differed depending on their native language. English-speaking children initially relied on word order for sentence interpretation, while their sensitivity to animacy developed later (around 4 years of age). Italian-speaking children showed the opposite pattern: they first acquired animacy, with word order sensitivity appearing later in development. These learning outcomes reflect the relative informativity of word order and animacy in the two languages. While animacy is associated with agency in both languages, English has fairly rigid word order, with non-canonical word orders being exceptionally rare. Animacy thus adds little information above and beyond that already expressed by word order. In Italian, however, all possible word orders can and do occur in certain contexts, rendering animacy a more informative cue.

These observations are supported by a series of miniature artificial language learning experiments investigating trade-offs between word order, case-marking, and animacy as cues to grammatical function assignment. For example, Fedzechkina, Newport, and Jaeger (in press) explored the well-described correlation between word order freedom and the presence of case-marking in a language: Languages with flexible word order typically have a case system, while languages with fixed word order typically lack case (Sapir 1921, Blake 2001, Siewierska 1998). The researchers exposed different groups of learners to two miniature artificial languages that had the same degree of optional case-marking in the input but differed in the amount of word order variability (no variability in the fixed order language and maximal variability in the flexible order language). Thus grammatical function assignment could be successfully recovered based on word order alone in the fixed word order language, rendering case redundant. In the flexible word order language, however, case provided important information about sentence meaning since word order was less informative of grammatical function assignment. Fedzechkina, Newport, and Jaeger (in press) found that learning outcomes in their experiment closely mirrored the typological pattern of case and word order trade-off: Learners of the flexible word order language were more likely to maintain case-marking in their own productions, while learners of the fixed word order language tended to drop case-marking.

Fedzechkina, Jaeger, and Newport (2012) extended this line of research to show that learning outcomes could also explain cross-linguistically recurring properties of differential (e.g., Hebrew, Sinhalese) and optional case-marking systems (e.g., Japanese, Korean). In these languages, case-marking is present on some subjects and direct objects and omitted on others. However, the presence versus omission of morphological case is highly principled and is generally associated with certain semantic properties of the referent such as animacy, definiteness, and person (Silverstein 1976, Lee 2006, Mohanan 1994, Aissen 2003). Overt case-marking is typically used when semantic or other properties of the referent are likely to bias the listener away from the intended grammatical function assignment (Kurumada and Jaeger in press). Fedzechkina, Jaeger, and Newport (2012) presented learners with miniature artificial languages that had flexible word order and optional case-marking which was *not* conditioned on animacy or other properties of the referent in the input, unlike in natural languages. Importantly, learners did not reproduce such morphological systems veridically. Rather, in contrast to their input languages, learners used more case-marking for direct objects that were animate (i.e., unlikely patients) than for direct objects that were inanimate (i.e., likely patients), thus bringing the case systems in these languages more in line with typological data.

Current issues in miniature artificial language learning

As outlined above, the parallels between typological data and learning outcomes in miniature artificial language learning experiments are ample, suggesting the suitability of this paradigm as a complement to typological data.

The miniature artificial language learning approach is, however, not without its limitations. Miniature languages need to be simple enough to be learnable within one or several short visits to the lab and thus lack the complexity of natural languages on virtually every dimension. They usually contain very few words (typically between 4 and

15; but see Frank, Tenenbaum, & Gibson (2013) for a 'miniature language' with 1000 words); and the words usually have little variation in length and syllabic complexity and are often stripped of many natural language acoustic cues such as pitch changes and rhythmic patterns. Sentences or phrases in artificial language learning experiments generally express fairly simple meanings, such as describing simple transitive events or object locations. These factors are likely to affect learning. For example, Kurumada, Meylan, and Frank (2013) investigated how learning performance in word segmentation task varied based on vocabulary size as well as the distribution over word lengths and word frequencies. All of these factors are found to affect word segmentation. For instance, some aspects of learning were facilitated when word distributions in the artificial language followed the cross-linguistically observed Zipf-like distribution, rather than a uniform distribution (for large-scale cross-linguistic review of Zipf's Law, see Piantadosi, 2014). A frequent criticism of the miniature artificial language approach has to do with this simplicity: Given the vast complexity of natural languages, can learning outcomes observed in miniature artificial language learning be representative of natural language acquisition? While this question cannot be definitively answered without extensive further research, the striking parallels between patterns in child acquisition and miniature artificial language experiments suggest that this paradigm is indeed powerful enough to reveal learning biases that reflect natural language acquisition and to inform questions concerning the relationship between language learning and language structure.

There are, however, several important issues regarding the assumptions made by the miniature artificial language learning approach that must be considered before behavioral evidence from miniature artificial language learning can be used in arguments about language universals. The logic behind miniature language learning studies of typological questions is as follows: If the input does not bias learners in a certain direction, then learnability preferences (in paradigm I) or observed deviations from the input (in paradigm II) *that are not reducible to native language biases* must indicate learners' own biases about natural language structure. These biases can create a seed for language universals: even small biases that occur across the population and then spread over multiple generations of speakers can cause language change towards systems that encode learners' biases as part of grammar (see Figure 3 for a schematic representation of this scenario). Thus for miniature artificial language learning studies to provide relevant behavioral data regarding typological distributions, two assumptions must be met: a) deviations from the input or learnability biases *cannot* be due to transfer from the native language; b) these preferences *must* reliably spread to subsequent generations of learners. Below we consider some of the issues that stem from these assumptions.

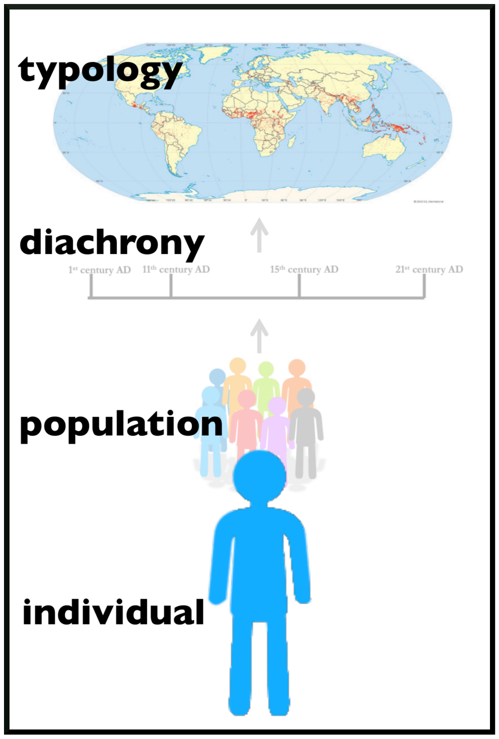

Figure 3: Hypothesized relationship between individual biases and language structures.

Native language influences
As artificial language learning methods are becoming increasingly more popular for studying the impact of learning biases on linguistic structures, understanding and controlling the influence of learners' native languages on the acquisition of artificial languages becomes more pressing. While many studies have considered the issue of native language influences (Tily, Frank, and Jaeger 2011, Culbertson, Smolensky, and Legendre 2012, Wonnacott, Newport, and Tanenhaus 2008, Fedzechkina, Jaeger, and Newport 2011), systematic investigations of this question have only recently begun in artificial language research. There is, however, a long tradition of using artificial language learning to investigate the role of native language background in second language learning (see, for instance, Pajak 2010) . It remains to be determined how much transfer from the native language takes place in these experiments and the exact circumstances leading to it, which will inevitably involve comparing the performances of speakers from different language backgrounds on the same artificial language learning tasks.

So far, studies linking learning biases to language structures have employed different types of controls. Most studies purposely select languages that are quite unlike the participants' native language in basic constituent order or in the type of syntactic or morphological devices employed, in order to avoid or reduce native language transfer. Some studies (e.g., Finley 2011, Christiansen 2000) have tried to assess the degree of structural preference stemming from native language biases by having a control group of learners who were tested on the artificial grammar without receiving any training in the language. Any preferences observed on the test materials in such a control group would stem from prior native language experience. It is important to note, however, that while this approach might work well for sound system biases, higher-level transfer (e.g., of constituent ordering) would not be visible until the participants learn the structure of the novel language. Other studies (e.g., Culbertson, Smolensky, and Legendre 2012) have exposed a control group of learners to languages in which multiple linguistic structures varied randomly to achieve the same goal. This technique may be more effective for revealing transfer effects that require learning, but learners' native language biases may be too weak to be visible in random or zero-exposure conditions while still affecting other conditions of interest (see Goldberg 2013 for similar and additional arguments).

Arguably, a more powerful way to mitigate native language biases as a potential confound is to test the acquisition of grammatical devices that are not present in learners' native language at all (Fedzechkina, Jaeger, and Newport 2012, 2013, Fedzechkina, Newport, and Jaeger in press). Studies of this type typically test monolingual native speakers, all with the same native language background, who are not fluent in other languages and have not been exposed to other languages in childhood. Under these circumstances, learners' preferences for typologically frequent patterns over typologically less frequent patterns can be taken as evidence for learning biases that cannot be reduced to transfer from the native language. This approach of course limits the scope of the phenomena that can be addressed within this paradigm, again underscoring the importance of more detailed investigations of the role of native language biases in miniature artificial language learning.

Converging on a cross-linguistically frequent pattern during language evolution

The second assumption underlying miniature artificial language applications to typological research concerns the causal link between the biases observed at the individual level and patterns in typology. It is commonly assumed that individual biases observed in miniature artificial language learning experiments are amplified as they percolate across multiple generations of learners during the process termed *cumulative cultural evolution*, gradually causing the linguistic system to express these biases in some form (Kirby 1999, Christiansen and Chater 2008, Kirby, Cornish, and Smith 2008).

Evidence in support of this view comes from studies using the iterative learning paradigm, which simulates cultural transmission of language by using the output of one learner as the input to another learner, either in laboratory settings (Kirby, Cornish, and Smith 2008, Smith and Wonnacott 2010) or in computational models (Kirby 1999, Reali and Griffiths 2009). Simulations in this paradigm show that even biases that are too weak to be detected within one generation can cause language change after they have been passed down across many generations of learners. For example, Smith and Wonnacott (2010) used this approach to study regularization of unpredictable variation in noun plural marking, similar to the type of probabilistic variation used in Hudson Kam and Newport's studies discussed above (Hudson Kam and Newport 2009, 2005). In this experiment, even though the first generation of learners showed significant unpredictable variation in their productions, this variation became conditioned on the noun, resulting in a regular linguistic system (characterized by zero conditional entropy of plural marking) only after five generations of learners.

Miniature language studies of learning biases have largely assumed that, over generations, iterative learning will make linguistic systems converge on grammars that explicitly encode learners' biases. Thus arguments about cross-linguistic universals are often based on learning outcomes in a single generation (Fedzechkina, Jaeger, and Newport 2012, Culbertson, Smolensky, and Legendre 2012, Christiansen 2000, Finley and Badecker 2008, Fedzechkina, Newport, and Jaeger in press). Recent work, however, has suggested that these conclusions need to be taken with some degree of caution, as not all biases observed in one generation reliably spread across subsequent ones (Rafferty, Griffiths, and Ettlinger 2013). In particular, this is true when the space of grammars is sufficiently large and the input includes a high proportion of instances that do not conform to the hypothesized bias.

Substantial between-participant variability is common in miniature artificial language learning experiments (Culbertson, Smolensky, and Legendre 2012, Fedzechkina, Jaeger, and Newport 2012, Fedzechkina, Newport, and Jaeger in press, Hudson Kam and Newport 2005, 2009). Consider Figure 4A, showing the performance of individual learners in the study conducted by Fedzechkina, Newport, and Jaeger (in press) discussed above. While *on average* learners of the fixed word order language produce case marking below the input and learners of the flexible word order language produce case marking above the input, there is dramatic variation among individual learners within the same condition. For example, some learners have categorically opposite preferences in case-marker use (100% vs. 0% case marking in production). However, viewing this variability from a functional perspective (namely, as a trade-off between production effort and uncertainty) suggests that the differing tendencies among learners may involve learners following the same trade-off principle in different ways (see Figure 4B). As Figure 4B shows, learners who tend to decrease uncertainty also tend to increase or maintain the input level of production effort, while learners who increase uncertainty tend to decrease production effort compared to the input. These data provide tentative evidence that at least for some universals, learners tend to entertain a constrained set of hypotheses.

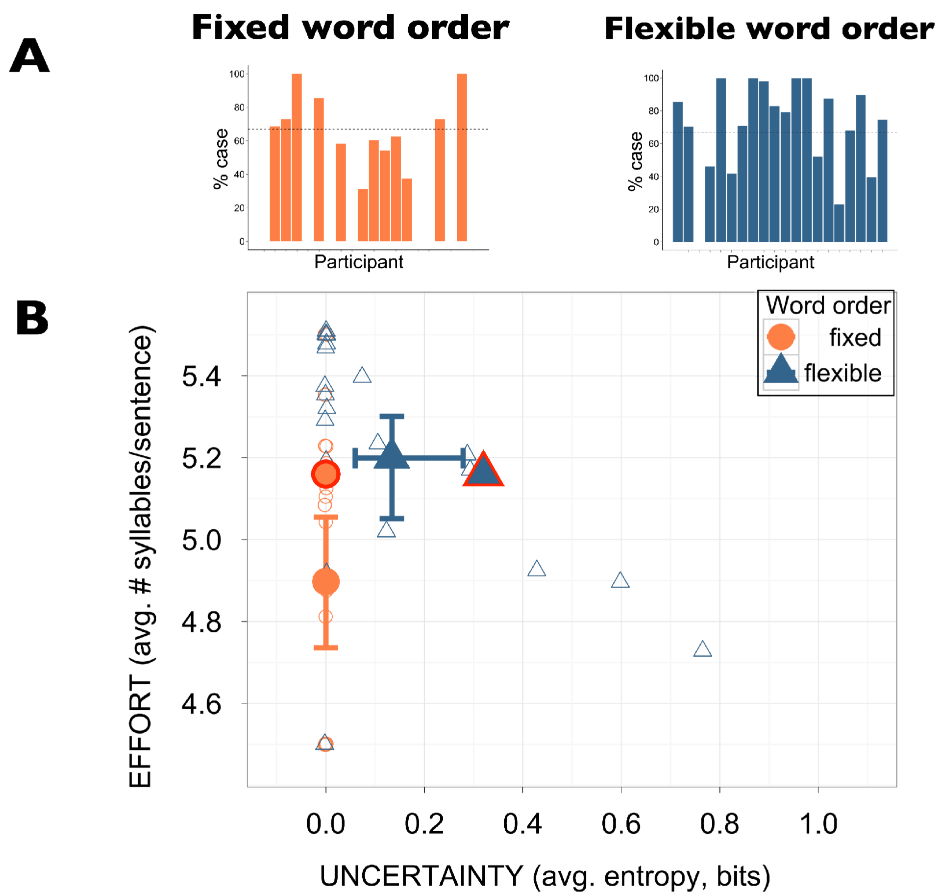

Figure 4: Between-participant variability on the final day of training in Fedzechkina et al. (in press). A: Case-marker preferences of individual learners in the fixed (left) and flexible (right) constituent order languages. B: Uncertainty vs. production effort trade-off. Red-border solid shapes represent input languages. Solid shapes without red borders represent mean output languages. Open shapes represent languages produced by individual learners. The error bars represent bootstrapped 95% confidence intervals.

Another open question concerns the role of child and adult learners in the process of language transmission over generations. Most studies exploring the relationship between language learning and language change using artificial languages have been conducted with adult participants. Only a few studies have explored whether young children acquiring a novel miniature language have similar preferences for typologically frequent patterns as adults (Culbertson and Newport 2015, Hudson Kam and Newport 2009, 2005). Importantly, all of these studies find that children show the same biases for cross-linguistically common structures and also restructure their input, bringing the acquired language closer to typologically common types. However, in children these biases are much more pronounced than in adults. For example, adults' bias to regularize unpredictable variation is fairly weak: within a single generation, only learners exposed to highly complex languages show a tendency to regularize (Hudson Kam and Newport 2009), and it typically takes several generations of learners before this bias becomes strong enough to cause substantial language change (Smith and Wonnacott 2010). Adults show a similarly weak tendency to shift word order patterns toward those that are common in languages of the world (Culbertson et al, 2012). In contrast, in children learners, a single generation can introduce almost-categorical systems into the newly acquired languages (Culbertson and Newport 2015, Hudson Kam and Newport 2009, 2005). As in adults, favored patterns can vary across child learners (for instance, while most children use the dominant pattern in their productions, some children regularize the minority pattern).

In sum, a single underlying bias can be manifested in somewhat different innovations that child and adult learners introduce into the linguistic system. Which innovations survive at the population level and become an enduring part of the grammar of the language community depends on various circumstances, perhaps including factors such as the social influence of the person creating the innovation (cf. Nettle 1999), the structure of the person's social network (Milroy 1980), or trends in the community (Heine and Kuteva 2006). The contributions of cognitive and social factors to the process of language change have so far been studied in largely separate literatures, necessitating further research to assess their interactions during cultural transmission. Since iterative learning studies to date have been conducted with adult participants, it also remains to be seen how the very strong cognitive biases of child learners contribute to long-term change and interact with social factors during language transmission.

Conclusion

The applications of miniature artificial language learning to questions in typology are still in their infancy, with a variety of issues and extensions that are still being explored. The parallels between typological data and learning outcomes in miniature artificial language learning are, however, numerous and striking. This suggests that miniature language learning can provide an independent source of evidence bearing on questions in typology and thus create an exciting collaboration between typological and behavioral research.

The similarity of patterns observed in natural and miniature language learning further suggests that this paradigm is powerful enough to uncover learners' biases during language acquisition and thus to investigate directly the origin of language universals. Recent developments in iterated language learning have allowed researchers to study how biases observed in one generation of learners can spread diachronically throughout the linguistic system, further underscoring the suitability of miniature language learning applications to typological research.

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