Interlocutors preserve complexity in language

Anonymous CogSci submission

Abstract

Why do languages change? One possibility is they evolve in response to two competing pressures: (1) to be easily learned, and (2) to be effective for communication. In a number of domains (e.g. kinship categories, color terms), variation in the world's natural languages appears to be accounted for by different but near-optimal tradeoffs between these two pressures (Regier, Kemp, & Kay, 2015). Models of these evolutionary processes have used transmission chain paradigms in which errors of learning by one agent become the language input for the subsequent generation. However, a critical feature of human language is that children do not learn in isolation. Rather, they learn in communicative interactions with caregivers who can draw inferences from their errorful productions to their intended interests. In a set of iterated learning experiments, we show that this supportive context can have a powerful stabilizing role in the development of artificial languages, allowing them to achieve higher levels of asymptotic complexity than they would by vertical transmission alone.

Keywords: communication; language acquisition; language evolution; iterated learning

Introduction

How do you ask a group of people where they are going in Spanish? In Spain, the answer depends on the group: you might ask "Donde van ustedes?" of a group of work colleagues, but to address your friends, you use the informal "Donde váis vosotros?" instead. In Mexican Spanish, this distinction has disappeared, and the "ustedes" form is used exclusively. Why did Spanish change in this way, simplifying and shedding the formal second person plural? One working theory is that languages evolve to adapt to two dynamic competing pressures: (1) to be easily learned and transmitted, and (2) to be effective for communication (Lupyan & Dale, 2010).

Caregivers and children possess many different skills. While children are often the actors who drive language evolution (Senghas, 2003), they differ from adults in their cognitive capabilities (Kempe, Gauvrit, & Forsyth, 2015), interests and early vocabularies, and conversation partners. As early language learners who are inundated with new information each day, children may be particularly biased towards simplification (Hudson Kam & Newport, 2005; Senghas, 2003). Indeed, when children are learning language, they often make simplification errors (Bowerman, 1982). This reflects the influence of the transmissibility pressure – children may latch onto word-forms which are simpler, and easier to acquire. For example, if a child is asking for her bottle, she may be unable to produce the canonical label "bottle," and will produce "baba" instead. If this child grew up without competent speakers of the language, and failed to have multiple opportunities to acquire the correct label, it is possible that she would retain and reproduce "baba", even to her own children. In this way, her error is retained in the language and perpetuated over generations. But, with too many of these simplification errors, a language can lose the ability to be effective for communication (Kirby, Griffiths, & Smith, 2014). What enables languages to retain their communicative utility and expressivity in the face of these learnability pressures?

Children do not learn language in isolation, but they communicate with fluent speakers of the language: their parents and caregivers. Caregivers are able to combine their children's productions with both their own knowledge of the language as well as their knowledge of their children. This enables caregivers to be excellent interpreters of child utterances (Chouinard & Clark, 2003). Their interpretation skills may be a form of scaffolding for their children's language learning. Parents are able to successfully interpret a more simplified utterance, thus shouldering some of the complexity of the language – for a short time. Our hypothetical child may continue to call a bottle "baba" until she can handle the cognitive load of "bottle", and her caregivers will support this learning in multiple ways.

Caregivers, through their explicit interventions as well as their implicit modeling of correct language, may be scaffolding their children's language-learning, by providing a space for their children to simplify, as well as by re-introuding complexity into their communications. Adults can explicitly correct their children's language errors in various ways (e.g., by interruptions or repeating the correct word/grammatical form; Penner, 1987). Yet, children primarily learn language through listening to others talk, rather than explicit instruction (Romberg & Saffran, 2010). Thus, parents' modeling of accurate language constructions can have a powerful effect on reducing children's language errors: over time, children fix their own mistakes because they have had multiple opportunities to learn correct constructions from their caregivers (Hudson Kam & Newport, 2005). By way of this feedback, both implicit and explicit, children's simplification errors are corrected, and children are able to acquire adult-like speech. Eventually, when a child becomes an adult, they will not transmit the errors they previously had, but the correct forms they learned from their caregivers – as long as learning the correct forms is useful and necessary. Thus, over the course of a lifetime, the child language learner grows to become a parent language teacher, correcting their own children's errors. These error reconstructions may be a mechanism by which more complexity is retained in language over many lifetimes than children could sustain alone.

Using iterated learning to study language change

To model the impact of these competing pressures on language evolution in the laboratory, we use an iterated learning paradigm developed by Kirby et al. (2014). In this paradigm, one participant is trained on a randomly-generated language – e.g, a set of words created by arbitrarily pairing syllables together. The participant is later asked to recall the language, but inevitably makes some errors. Their errorful output becomes the training input for the subsequent participant, forming a transmission chain. This iterated learning process models the transmission of language over generations, with each participant unintentionally changing the language through their memory biases.

This paradigm has been used productively across a number of studies of cross-generational transmission in both adults (Christiansen & Kirby, 2003; Kirby, Dowman, & Griffiths, 2007; Kirby et al., 2014; e.g., Smith & Wonnacott, 2010; structure & signals, 2014), and children (Kempe et al., 2015; Raviv & Arnon, 2018). Various recent studies have also compared languages evolved over multiple generations (vertical transmission) to languages evolved by iterated use in the same conversational partners (horizontal transmission, Kirby, Tamariz, Cornish, & Smith, 2015). However, participants in horizontal transmission scenarios had similar levels of knowledge and similar cognitive constraints. This is different from children, who learn language in asymmetric knowledge situations, where their parent both knows more language and has an adult cognitive system (Figure 1). We predict that this asymmetry may have a unique role in the evolution of language, allowing it to resist some of the simplifying pressure of transmissibilty through adults' ability to maintain complexity while their children develop.

We adapted Kempe et al. (2015)'s non-linguistic iterated learning paradigm to model the effect of introducing a secondary, error-correcting participant on the evolution of language. We hypothesize that these error-correctors (analogous to caregivers and teachers) are pivotal not only to an individual's successful language acquisition, but also to the evolution of the language as a whole. This is because those who correct mistakes and provide feedback are able to protect against the strong transmissibility bias in early language learners by re-introducing and preserving complexity.

Experiment 1: Replicating Kempe et al. (2015)

We began by replication Kempe, Gauvrit, and Forsyth's (2015) experiment using a nonlinguistic stimulus to study the evolution of structure in an artifical language. Our motivations for using this paradigm were twofold. First, the stimuli lent themselves to algorithmic quantification of complexity. Second, Kempe et al. (2015) used this paradigm successfully with children, and our goal was to test our hypotheses not just in adult-adult chains, but also in child-child and child-adult chains (ongoing).

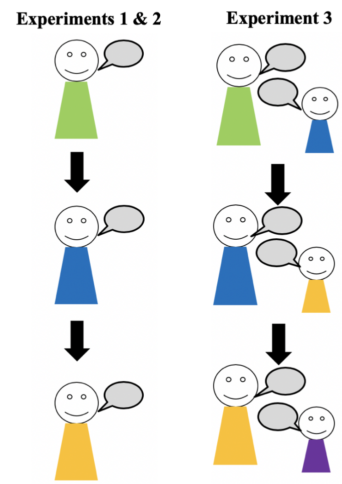

Figure 1: In Experiments 1 and 2 follow the conventional iterated learning paradigm, where a novel language is transmitted vertically through successive learning and recall. In Experiment 3, an element of horizontal transmission is added to the paradigm: novel language learners' reproductions are subject to feedback from a secondary participant, and this production is passed to the subsequent learner.

Method

Participants Participants were 125 adults recruited on Amazon Mechanical Turk. Because five users failed to meet inclusion criteria, a larger number of participants was required to obtain the planned sample of 120. These participants were members of one of twenty diffusion chains, each of which had six generations. Each participant gave informed consent. The task was approximately eight minutes long, and subjects were compensated $0.50 for their participation.

Design and Procedure Participants were asked to re-create patterns on a grid. Subjects were informed that they would see a target grid appear on their computer screen for ten seconds, followed by a picture (a visual mask) displayed for three seconds. After the visual mask, participants viewed a blank 8x8 grid where they were given one minute to re-create the target grid. Participants could click on any cell in the grid to change its color, and could also remove any color placed. A counter on the screen showed how many cells had been colored, and it varied dynamically with the participant's clicks. After placing 10 colors, participants could click a button to advance to the next trial (See Figure 5 for example grids). A timer was displayed on the screen, and participants were given an audio cue when they had fifteen seconds left.

After completing one training and three practice trials, each participant completed 6 experiment trials. Participants in the first generation of each chain received the same initial grid patterns. These initial 8x8 grids were generated by randomly selecting 10 of the 64 possible cells to be filled. Participants in subsequent generations received as their targets the outputs produced by the previous participant in their chain. All participants received the same training and practice trials. In the preliminary training trial, subjects viewed two 8x8 grids side-by-side and were instructed to make the blank grid on the right match the target grid on the left. Participants were unable to progress to the practice and experimental trials without reaching perfect accuracy on this first trial.

As mentioned above, participants were required to meet a set of attention criteria for their data to be included in the transmission chain. If the participant scored less than 75% accuracy on the last two practice trials, or if they failed to select 10 cells before time ran out, their outputs were not transmitted to the next generation.

Analysis

Our primary measures of interest were reproduction accuracy and pattern complexity. Reproduction accuracy served as a proxy for transmissibility – higher reproduction accuracies indicated that the language was easier to learn. Reproduction accuracy was computed as the proportion of targets out of 10 placed in the same location on the target and input grids.

Complexity served as a proxy for expressiveness. We followed Kempe et al. (2015) in using several measures of complexity: algorithmic complexity, chunking, and edge length. Algorithmic complexity was calculated using the Block Decomposition Method, a measure of Kolmogorov-Chaitin Complexity applied to 2-dimensional patterns (Zenil, Soler-Toscano, Dingle, & Louis, 2014). This measure computes the length of the shortest Turing machine program required to produce the observed pattern. The shorter the program, the simpler the pattern. Chunking is the number of groups of colored blocks which share an edge. The more groups of blocks, the easier the pattern is to transmit, and the lower its complexity. Edge length is the total perimeter of the colored blocks, and is similar to chunking. Implementation of these metrics was adapted from code provided by Gauvrit, Soler-Toscano, & Guida (2017).

Results and Discussion

If iterated learning captures the hypothesized pressures of transmissibility and expressiveness, we predict that reproduction accuracy should increase and complexity should decrease over generations. We tested these predictions with mixed-effects logistic regressions, predicting accuracy and all three measures of complexity separately from fixed effects of generation and trial number, and random intercepts for participant and initial grid (e.g. `accuracy ~ generation + trial + (1|subject) + (1|initialGrid)`.

Reproduction accuracy increased significantly over generations ($\beta = 0.033$, $t = 3.146$, $p = .002$). Figure 2 shows

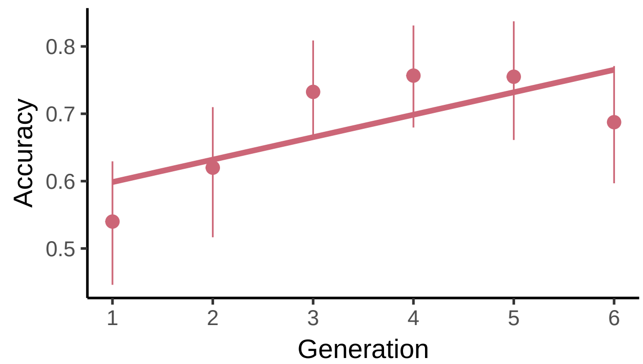

Figure 2: Experiment 1 shows increases in accuracy (measured by proportion of 10 targets placed correctly) across transmission generations.

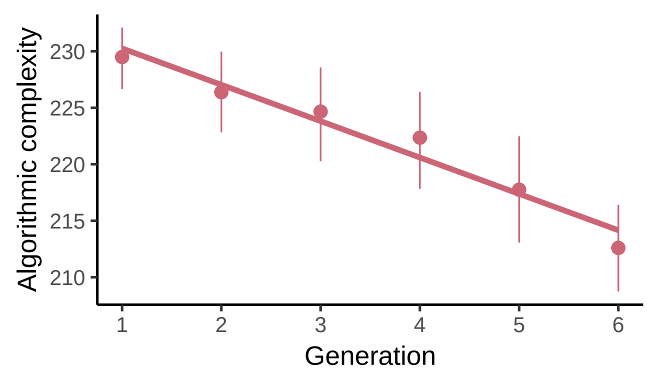

Figure 3: Experiment 1 shows decreases in algorithmic complexity (measured by the Block Decomposition Method) across transmission generations.

the results for accuracy. Complexity on all three measure decreased significantly over generations, as shown in Figure 3 ($\beta_{BDM} = -3.219$, $t = -6.696$, $p = < .001$; $\beta_{chunking} = -0.35$, $t = -6.499$, $p = < .001$; $\beta_{edge} = -0.763$, $t = -6.662$, $p = < .001$). Trial number, or how far along the subject was in the task, was not a significant predictor in any model.

In line with Kempe et al. (2015), we found that accuracy increased across generations and complexity decreased on all three measures. However, this change appeared to be non-linear, with later generations perhaps evolving less rapidly than earlier generations (Figure 2). We thus replicated this experiment again, and increased the number of generations from six to twelve to estimate the shape of the evolutionary functions.

Experiment 2: Replication and extension of Experiment 1

Experiment 2 replicated the task from Experiment 1 with the addition of twice as many chains and generations.

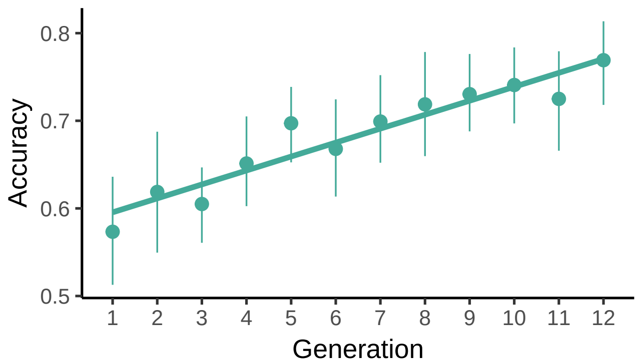

Figure 4: Experiment 2 shows increases in transmission accuracy over generations.

Method

Participants

Participants in Experiment 2 were 519 adults recruited on Amazon Mechanical Turk. Approximately 8% (n=39) of participants in Experiment 2 were excluded due to failure to meet accuracy requirements on the practice trials or failure to select the complete number of cells on one or more experimental trials. This resulted in a total of 480 participants included in the analysis. These participants were members of one of forty diffusion chains, each of which had twelve generations. Each participant gave informed consent and was compensated with $0.50 for their participation in this 8-minute task.

Design and Procedure

The task in Experiment 2 was identical to Experiment 1. Participants were told to reproduce patterns on a grid, and their responses were passed to the next subject in the transmission chain.

Results

The results of this experiment replicated those found in Experiment 1. Reproduction accuracy increased significantly over generations, as shown in Figure 4 ($\beta = 0.01$, $t = 6.029$, $p = < .001$).

Figure 5 shows the results for algorithmic complexity. Algorithmic complexity appeared to follow an exponential function of the form $y = e^{-x} + b$. We therefore fit an exponential mixed-effects regression model predicting complexity from fixed effects of generation and trial number, and random intercepts for participant and initial grid (e.g. `log(complexity) ~ log(generation+1) + trial + (1|subject) + (1|initial)`). Algorithmic complexity decreased and asymptoted over generations ($\beta_{BDM} = -7.307$, $t = -10.998$, $p = < .001$). Similar trends were also found with chunking and edge length, the alternate measures of complexity ($\beta_{chunking} = -0.693$, $t = -14.955$, $p = < .001$; $\beta_{edge} = -1.375$, $t = -13.11$, $p = < .001$). As in Experiment 1, trial number was not a significant predictor in any model.

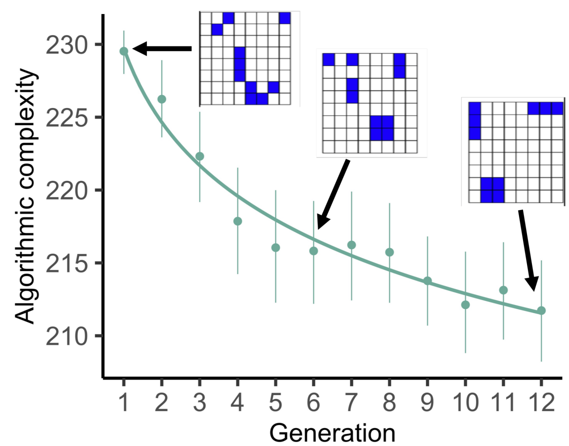

Figure 5: Experiment 2 shows a decrease in algorithmic complexity across generations. Examples of patterns produced by participants are shown for Generation 0 (the initial pattern), Generation 6, and Generation 12.

Experiment 3: Introducing an interlocutor

In order to add an element of feedback from a more experienced interlocutor to the iterated learning process, we adapted the task from Experiments 1 and 2 to include a secondary, "editing" participant. This participant was analogous to a caregiver who protects their child from acquiring and perpetuating incorrect linguistic forms.

Method

Participants

Participants in Experiment 3 were 1031 adults recruited on Amazon Mechanical Turk. Approximately 8% (n=71) of participants in Experiment 3 were excluded from analysis due to failure to meet accuracy requirements on the practice trials or failure to select the necessary number of targets on one or more experimental trials. This resulted in a total of 960 participants included in the analysis. These participants occupied one of forty diffusion chains and one of twelve generations. Each participant gave informed consent and was compensated with $0.50 for their participation in this 8-minute task.

Design and Procedure

A primary participant was designated as a "learner" and completed the same task as in Experiments 1 and 2. This participant was told to re-create patterns on a grid. After completing the experiment, a secondary, "fixer" participant was given an adapted task. Throughout the study, fixers were not told to re-create patterns, but to edit patterns to resemble a target grid exactly. Fixers in this experiment viewed the same target grid as learners, but instead of seeing an empty input grid, they were given a grid prepopulated with 10 elements. These were the elements the previous learner had generated. The fixing participant could then change the 10 items' positions. There

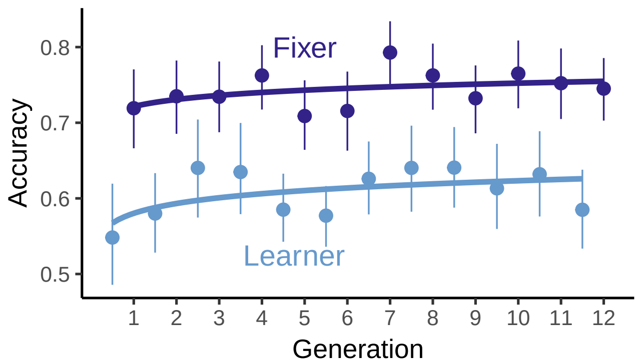

Figure 6: In Experiment 3, fixers show significantly higher reproduction accuracies than learners. Reproduction accuracies stay relatively constant, although the accuracies of the learners increase across generations.

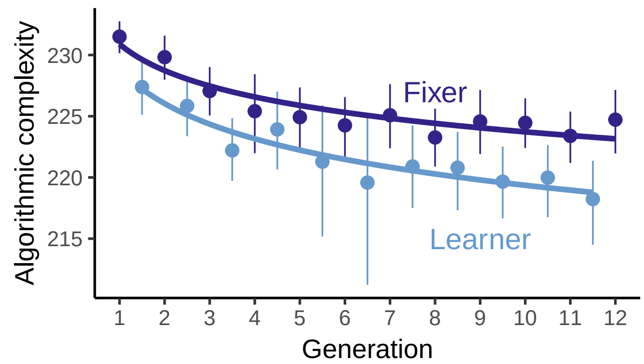

Figure 7: In Experiment 3, algorithmic complexity decreases and asymptotes for both Learners and Fixers. Learners have consistently lower complexity values compared to Fixers.

was no "reset" button during this task, so data reflected participants' initial instincts. In Experiment 3, a generation consisted of a learner, who re-created the target grid, and a fixer, who edited the learner's re-creation to match the same target grid. The fixer's edited pattern was used as the target grid for the subsequent generation.

Analysis and Results

As in Experiments 1 and 2, our primary measures of analysis were accuracy and complexity. These measures were computed using the same methods as in the previous experiments.

Fixers and learners had significantly different pattern reproduction accuracies (Figure 6). According to a linear mixed-effects model predicting group from generation and trial number and controlling for random effects of subject and initial grid, reproduction accuracies between groups were significantly different ($\beta_{condition-learner}$ = -0.086, t = -11.338, $p = < .001$). Neither the fixers' or learners' transmission accuracies increased significantly over generations (β_{fixers} = 0.007, t = 1.108, p = .269; $\beta_{learners}$ = 0.011, t = 1.706, p = .089).

Figure 7 shows the relationship between the complexity of fixers' and learners' patterns. In each generation, the learner decreased the complexity of the pattern, and the fixer was able to compensate for some of this loss by re-introducing complexity. As in Experiment 2, we fit an exponential model to the data. Both conditions show decreases in pattern complexity over generations ($\beta_{learners}$ = -0.021, t = -4.572, p = $< .001$; β_{fixers} = -0.014, t = -6.183, $p = < .001$), although the effect of generation is stronger for learners versus fixers ($\beta_{generation}$ = -3.648, t = -10.117, $p = < .001$). These results hold true for the measures of chunking and edge length.

Figure 8 shows the combined results of Experiments 2 and 3. The presence of a fixer into the task allowed a higher degree of complexity to be retained in the language over time ($\beta_{condition-learner}$ = -3.66, t = -6.296, $p = < .001$). Additionally, the patterns in the dyad condition appeared to asymptote earlier than in the baseline condition.

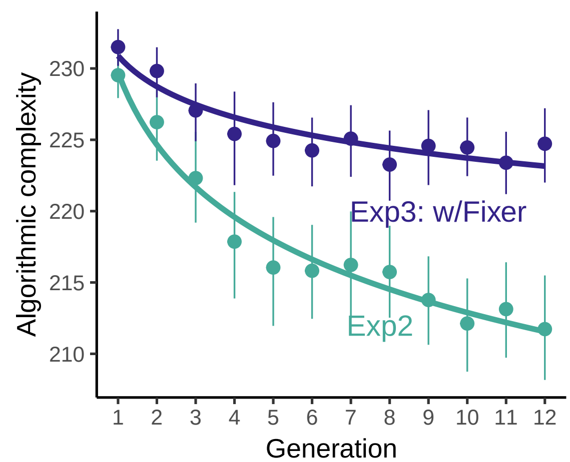

Figure 8: The fixer's reproductions from Experiment 3 show greater levels of algorithmic complexity across generations compared to the participants' reproductions from Experiment 2.

General Discussion

Despite the use of a non-linguistic task, we were able to measure change in a culturally-transmitted, learned symbol system. In Experiments 1 and 2, patterns simplified rapidly and dramatically, reflecting the strong transmissibility pressure in language learning. These findings replicated those of Kempe et al. (2015): when transmitting an artificial language, complexity was lost.

However, the results of Experiment 3 show that this loss is not cultural regression, as complexity can be reintroduced in the language by way of a secondary participant (Henrich, 2004). When the iterated-learning process begins to resemble the true process of language-learning, where children speak with and are subject to correction by those more competent in the language, a lesser amount of complexity was lost during transmission. Additionally, the stable level of complexity was much higher, and was reached earlier in the transmission chain, with the help of a fixing participant. This stability did not mean that the language was static, but that simplicity and expressiveness were in balance. Fixers in Experiment 3 represented caregivers – they were more accurate at reproducing the language, and could therefore be seen as more fluent speakers. The learners, on the other hand, had a more difficult task, which greater strained their working memories, similar to the strain on a child language learner who is exposed to many new words each day. The fixer's corrected language was passed to the next learner in the chain, representing a child who, after many years of being corrected by their own parent, becomes a parent, and, in turn, passes their language to the next generation. Due to the higher accuracies of fixers, and therefore greater knowledge of the language, the fixers were able to compensate for some (though not all) of the learners' losses in complexity.

When a caregiver prevents their child from growing up to believe that "baba" is the word for "bottle", they are not only helping their individual child become a competent speaker of the language, but they are also helping the language system as a whole from oversimplifying. Data collection is ongoing with children ages 6-8 at a local science museum in both the Experiment 1 and Experiment 3 tasks, in order to investigate whether these evolutionary pressures affect children similarly to how they affect adults in early language-learning conditions.

We do not learn language as passive listeners, who absorb a proportion of the linguistic input they hear. Therefore, we cannot measure language learning only through measuring input, nor through measuring only linguistic output. Language is both learned and changed through conversation to evolve to the needs of its users. Therefore, in order to understand how language adapts to and evolves with communicative interactions, we should study language learning in process.

All experiments were pre-registered on Open Science Framework, and all data and code will be made available through GitHub after de-anonymization.

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