Cognitive Flexibility in Cognitive Architecture: Simulating using Contextual Learning in PRIMs

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Abstract

The universal flexibility of biological systems needs to be reflected in cognitive architecture. In PRIMs, we attempt to achieve flexibility through a bottom-up approach. Using contextual learning, randomly firing of a set of instantiated primitive operators are gradually organized into context-sensitive operator firing sequences (i.e., primordial "skills"). Based on this implementation, the preliminary results of the model simulated the averaged single-pattern processing latency that is consistent with infants' differential focusing time in three theoretically controversial artificial language studies, namely Saffran, Aslin, and Newport (1996), Marcus, Vijayan, Rao, and Vishton (1999), and Gomez (2002). In our ongoing work, we are analyzing (a) whether the model can arrive at primordial "skills" adaptive to the trained tasks, and (b) whether the learned chunks mirror the trained patterns.

Keywords: cognitive flexibility; contextual learning; language acquisition; processing efficiency; PRIMs architecture

Introduction

From epigenetics to behavioral appropriateness, adaptability is ubiquitously observed at each level of biological systems (see Bateson & Gluckman, 2011). Cognition, in particular, may well be the most flexible system of all, which contrasts the deterministic approach in cognitive theories and modeling. To show that cognitive flexibility is possible, we use a generally-implemented model to simulate the learning of three specific language tasks by infants (for a review, see Saffran & Kirkham, 2018). The reasons are as follows. Firstly, it agrees with the consensus that language is one of the most crucial aspects of cognition (Newell, 1990; Rumelhart & McClelland, 1986). More importantly, the acquisition of language highlights the pivotal role of flexibility and adaptability. Last but not least, young infants cannot be instructed as how to acquire a language, therefore motivating a hard-code free approach.

In the following sections, an introduction of the three representative tasks is provided, before describing the common mechanism that learns all three tasks. We then compare the models' predictions to empirical data.

Three Language Phenomena

Without being endowed *a priori* with a native language, very young infants are sensitive to speech sounds (e.g., Kuhl, Williams, Lacerda, Stevens, & Lindblom, 1992), and are already discovering word forms within their first year of life (e.g., Jusczyk & Aslin, 1995). Such pioneering findings

opened up a field focusing on infant language learning (see Saffran & Kirkham, 2018). However, it remains an open question as how infants can (a) identify atomic elements such as syllables (atomicity); and (b) compose atomic elements lexically and/or syntactically to form words or phrases (compositionality). This paper focuses on *compositionality* with the assumption of *atomicity*. In other words, it concerns the learning mechanism that connects lower-level syllables to higher-level words/phrases (Taatgen, 2017). This focus is discussed when the following tasks are introduced (see Figure 1).
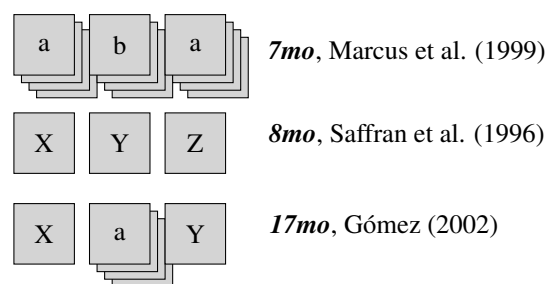

Figure 1: Three representative language tasks ordered based on developmental trajectory. Note: lowercase letter = variable token; uppercase letter = fixed token.

In Saffran et al.'s (1996) study, 8-month-olds are presented with an uninterrupted speech stream formed by randomly concatenating four fixed trisyllabic words in the form of *X-Y-Z* (see Figure 1). After the learning phase, infants are examined with a set of test words. Infants show more attention to novel non-word (e.g., "da-pi-ku") or part-words ("*tu*-da-ro") as compared to test words directly taken from the training phase (e.g., "da-ro-pi"). Saffran and colleagues (1996) interpreted their results from a connectionist perspective. They considered that infants' differentiation of speech streams is related to the acquirement of embedded transition probabilities between adjacent word-syllables (*statistical learning*). Nevertheless, the differentiation of speech streams at the global level does not fully explain whether word forms are learned/segmented. To verify this further, in a follow-up study, 17-month-old infants performed a label-object association task after listening to a continuous stream of words (Estes, Evans, Alibali, & Saffran, 2007). During

the habituation phase, shapes (i.e., objects) are either presented with words or other untrained non-words/part-words (i.e., labels) until a habituation criteria is reached. In the test phase, object-label pairings are switched to induce dishabituation. However, only when the labels are words versus nonword/part-words was the dishabituation detected, which implies that wordlike units are necessary for label-object association, and needs to be learned during the training phase. Similarly in modeling studies, previous simulated results were more in line with empirical findings when both token-level transitional probabilities and the generation of word-level patterns were taken into consideration (see Mareschal & French, 2017). These altogether support that infants are able to *compose* atomic elements into basic lexical units.

In contrast, Marcus et al. (1999) argued that pure connectionist learning account may not be applicable in all situations, and that syntactic structure is needed to recognize generalized pattern types. They showed that 7-month infants seem to be able to derive the more general *a-b-a* pattern, after being presented with a series of trisyllabic patterns of "le-we-le", "ga-ka-ga" and so on (see Figure 1). Infants focus distinctly more on the novel test patterns of *c-d-d* and *c-c-d*, as compared to the familiarized test pattern of *c-d-c*, even when the specific tokens are replaced. Marcus et al. (1999) therefore showed that infants are able to generalize even though there exist no transitional probabilities between the learned and test patterns (*algebraic learning*). However, their argument that infants possess innate ability of syntactic processing (e.g., knowing "the 1st token predicts the 3rd" in *a-b-a*) is not in line with empirical findings. In fact, infants generally needs to be more than 1-year-old to distinguish nonadjacent syntactic relations (e.g., Gómez & Maye, 2005). Alternatively, more recent studies have shown that younger infants (7-month-olds) are instead attuned to immediate repetitions without being able to acquire the full trisyllabic pattern (e.g., Wagner, Fox, Tager-Flusberg, & Nelson, 2011). Our previous model shows that the learning and transfer of algebraic patterns can be achieved in a bottom-up fashion when immediate repetition are rewarded (Ji, van Rij, & Taatgen, 2019). Therefore, the findings of Marcus et al. (1999) may only captures infants' ability to identify a particular element as it is (i.e., *atomicity*), rather than the capability to understand syntax fully. However, this is not to say that infants cannot learn syntactic structures. Research in syntactically-relevant non-adjacent dependency learning is championed by Gómez and colleagues. Taken non-adjacent pairs in the form of *X-a-Y* as an example (e.g., "pel-*a*-rud", see Figure 1), when variability of the middle token *a* (i.e., 24 variations) renders transitional probabilities unreliable to capture the regularity of that pattern, 17-month-old infants counterintuitively are better able to differentiate them by focusing more on novel non-adjacent pairs ("pel-*a*-jic") than learned ones (Gomez, 2002). Infants are therefore able to shift strategies (Saffran & Kirkham, 2018, p. 190), suggesting diverse form of language compositionality either by *lexicon* or *syntax*.

One Architecture that Learns

Although the theory of artificial language learning remains controversial, it is indisputable that infants have the ability to deal with all tasks. However, usually in the ACT-R model, stimulus-response production-rules related to task processing need to be artificially defined. Thus, the discovery and learning process of infants cannot be well simulated. For the problem of skill acquisition, Taatgen and Lee (2003) first proposed the learning strategy of production compilation and incorporating it into ACT-R. Through production compilation, general production-rules are combined into task-specific rules adapted to the task-demand. As early as 2002, Taatgen and Anderson (2002) boldly applied procedurally-related production compilation in children's language learning, and shows how regular past-tense rule can be learned as a specialization of more general rules. Until recently, the procedural hub of basal ganglia is viewed as relevant not only to motor learning, but also to many other skill domains including language (see Stocco, Lebiere, & Anderson, 2010, Kotz & Schmidt-Kassow, 2015). Nevertheless, the firing conditions (i.e., context or goal-state) and information processing flow of general-purpose production rules still need to be programmed manually. Moreover, production compilation is operated at the procedural level, but learned skills are often transformed as long-term declarative knowledge that can be transferred/reused in different scenarios (see Stocco et al., 2010).

For the same question of incorporating skill acquisition in a cognitive architecture, we propose a new bottom-up approach that seeks to organize primitive elements of procedural knowledge into context-sensitive stimulus-response rules through trial-and-error. These rules are maintained in declarative memory and can be transferred in other task contexts once necessary. The specific contextual learning mechanism to achieve this is inspired by the action selection process of basal ganglia and related cortical areas (see Stocco et al., 2010, Dehaene, Meyniel, Wacongne, Wang, & Pallier, 2015). The basal ganglia is a reinforcement learning hub that synthesizes contextual signals from multiple cortical areas and connects them with corresponding responses, and relays response outcomes gradually to the cortex to be maintained and integrated with contextual information. When a task-related reward state is reached, the cortex then fine-tunes the association between the contexts and specific primitive procedural elements to promote the rearrival at such task-relevant reward state. For infants' performance on artificial language tasks, Saffran and Kirkham (2018, p. 195) similarly suggests that reinforcement learning maybe a crucial candidate for language acquisition. It is possible that such reinforcement learning of language skills is supported by the cortico-basal ganglia mechanism (Kotz & Schmidt-Kassow, 2015).

In addition, the fine-tuning of contextual learning requires predefined reward states. Empirical evidence for these states are provided by Wagner et al. (2011). It is found that younger infants are more susceptible to the changing environment, especially the *exogenous* repetition of simple stimuli. For

slightly older infants, these simple environment-driven reactions are gradually replaced by the *endogenous* detection of more complex embedded regularities that are mirrored in memory. The learning from simple elements to more complex patterns is also reflected in animal studies. In one study, a saccade task with four targets is presented to the macaques. At the beginning of training, basal ganglia and related cortical areas respond to all single targets. However, cellular response in later stages is limited to only the sequential boundary made up of the four targets (see Dehaene et al., 2015, p. 5). These results support that the basal ganglia-inspired contextual learning mechanism may be the key to the transition from atomicity to compositionality.

The purpose of this article is to provide a proof of concept for the bottom-up learning approach. Through contextual learning, we investigate whether the model can provide a unified description on three theoretically controversial artificial language tasks, namely Saffran et al. (1996), Marcus et al. (1999), and Gomez (2002). In this article, our first task is to simulate and explain the experimental results, that is, focusing time differences. Currently, we are still analyzing the procedural and declarative knowledge acquired by the model under different task conditions.

Model

The model is implemented in the PRIMs architecture (see Taatgen, 2013). In PRIMs, operators are equivalent to production-rules, but with slightly different nature (van der Velde, 2018). Like ACT-R, operators are if-then rules that define how information are routed and compared between perceptual and memory buffers. Moreover, these operators can be further broken down into their smallest units (i.e., primitive operations). Contrary to ACT-R, in PRIMs operators share the properties of chunks, including base-level activation and spreading activation from the buffers. This is because procedural operations will eventually be stored in cortex to be used in future scenarios (Stocco et al., 2010, p. 548). Therefore, operators can be triggered based on its associations with the current buffer contents (i.e., the immediate contexts). For example, and operator can be triggered by a certain auditory input, or by a previously executed operator. Associations between the operators and the contexts are learned through reinforcement learning. This partially replaces goal-states that used to be explicitly defined for action selection with production-rules. The gradual acquisition of *context-sensitive operations* increases the flexibility of the architecture, and opens up a method of exploration-based learning.

Primitive Operations Primitive operations are the smallest units of production rules. They route and compare information between different buffers. In this model, environmental inputs can be encoded successively to the slots of the imaginal buffer. For example, the previous stimulus X fills the currently empty slot (e.g., slot-2, if slot-1 is filled) in the imaginal, the next stimulus Y can only fill the next free slot (e.g., slot-3). Encoding of the environmental stimulus in the
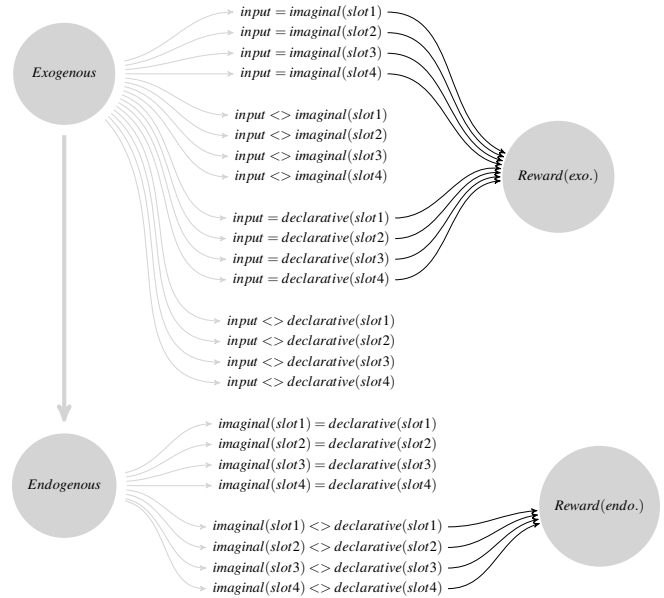

Figure 2: Comparison operations and reward preferences. Note: exogenous = comparisons with input; endogenous = comparisons with declarative unit; Reward(exo./endo.) = Exogenous/endogenous reward preferences.

imaginal also automatically starts the retrieval of the declarative memory chunk containing the stimulus, and the chunk with the highest activation and exceeding the retrieval threshold can be harvested. When the imaginal buffer is cleared (in PRIMs, this is achieved when "nil" is filled into imaginal slot-0), the chunk stored in the current imaginal will then be stored in the declarative memory as a whole.

When memory buffers and/or input buffers are not empty, another series of comparison operations can be fired to check whether there is match/mismatch between the buffer slots. Comparison operations in this model are categorized into *exogenous* and *endogenous* types (see Wagner et al., 2011). *Exogenous* operations check whether the immediately presented stimuli matches/mismatches the slot in the chunk currently stored in imaginal or retrieved from declarative memory. The reward state is to detect any immediate matches between input and the memory buffers (i.e., *Reward(exo.)*, Figure 2). *Endogenous* operations check whether the currently encoded pattern by slot mirrors the pattern as retrieved from declarative memory. The reward state is to find a mismatch that identifies the pattern boundary (i.e., *Reward(endo.)*, Figure 2).

A Walk-Through Example Here, we describe one possible processing solution to the specific pattern of "le-we-le". Suppose the model has already learned the bigram "le-we" in declarative memory. When the first input "le" is encoded into imaginal slot-1, the automatic retrieval process may harvest "le-we". Consequently, with the encoding of the second input "we", the model may find the syllable is now matched between slot-2 of the imaginal and the declarative chunk. How-

ever, after the encoding of the third input "le", a mismatch maybe found between slot-3 of the imaginal and declarative chunk (i.e., an empty slot), which suggest the current presented pattern are different from the memorized pattern at the global level. This time, the endogenous reward state is arrived. If there is sufficient time the model will strengthen associations between all fired operations and their corresponding contextual buffer states that lead to the reward.

On the other hand, the model may also process the pattern in an exogenous manner, and just find that the encoded first syllable "le" in imaginal slot-1 is repeated when the third "le" is presented. If the operations and related buffers states are reinforced after this reward state is reached, the model may alternatively oriented towards the detection of immediate repetition.

Learning Mechanism   The learning mechanism binds operations to their contexts in accordance with the reward preference. When a particular reward state is satisfied, the associations between operations and the contexts are strengthened:

$$\Delta S_{jik} = \beta \left(\textbf{payoff} - S_{jik} \right) \qquad (1)$$

where

$$\textbf{payoff}_{fired} = \frac{\max S_{jik} \times \left(\text{reward - timeToReward} \right)}{\text{reward}} \qquad (2)$$

At the same time, the bond between unused operations and the contexts are weakened by the payoff term:

$$\textbf{payoff}_{unfired} = \frac{\max S_{jik} \times \left(0 \text{ - timeToReward} \right)}{\text{reward}} \qquad (3)$$

In this function, association weight S_{jik} is updated every time when an reward is issued. Here, j denotes the specific operation fired, and ik denotes the associated context in buffer i and slot number k. The *beta* is a learning rate parameter, whereas the *payoff* term specifies how much context-operation association weights are updated each time. Specifically, *timeToReward* is the firing time of each used operation. *Reward* is the sum of the set reward parameter ($Reward_0 = 10.0$) and the "trial" duration (i.e., previous to current reward time). After the rewards are issued, the imaginal is cleared, and the next "trial" now starts afresh.

Timing Consideration   From birth to the age of 2 years, processing efficiency undergoes dramatic age-related changes without altering structure of the brain (see Dubois, Adibpour, Poupon, Hertz-Pannier, & Dehaene-Lambertz, 2016). This means that young infants are only able to fully process a stimulus when presentation is sufficiently long (see Chen, Peter, & Burnham, 2016). In the current model, the interaction between stimulus duration and the rate of operation firing is specifically considered. Operation firing takes time, and when the stimulus duration is short, the per-stimulus operation firing rate will be reduced accordingly. In addition, if the operator processes have not yet ended when the presentation of the current stimulus has ended, the processing time of

the operation would therefore exceed the presentation of the stimulus. In this case, the processes of the upcoming stimulus would be less sufficient as if its presentation time has been reduced. In this model, it is so far arbitrarily set that the stimulus would be completely ignored when the time window for processing a stimulus is reduced to less than 10% of the objective stimulus presentation time.

Object of Evaluation   Based on the general implementation, it is investigated whether infants' differential focusing time for different task conditions can be simulated by a single model. Our simulation and experimental results apply different time scales. The experimental results investigate the overall focusing time for all patterns in the test phase, whereas the simulation results focusing on the averaged time required to process a single pattern in the test phase. The reasons are as follows. First of all, we do assume that processing latency of a single pattern is related to the overall focusing time. When the infants need to spend more time to process a pattern, then the remaining task-irrelevant gap will be shortened accordingly. In this case, the probability of the infants deviating from the task is relatively small, so the overall focusing time will be relatively high. However, if the infants are now familiar with the pattern and can effectively process it, task-irrelevant gap will increase. At this time, the possibility that the infants deviate from the task will also increase, resulting in a decrease in the overall focusing time. However, for the current model, we do not know what the cause and duration when infants divert from the task. There are many possibilities, such as when an infant is captured by other interesting environment stimuli (external causes), or the needs for food or play (internal causes). It is much more difficult to reflect these factors in the current model. Therefore, we only consider the single-pattern processing latency of the learned and novel patterns after training, and assume the difference in processing latency would reflect the overall difference in focusing time. Specifically, duration from each stimulus onset to its last operation firing time are summed and averaged for each pattern. Note that when the operation/s cross the next stimulus boundary, the stimulus input onset will be delayed. In the next section, details of each task conditions are described, followed by the simulated results.

Experimental Details

Saffran et al. (1996)   In this task, infants are first presented with a training stream of continuous trisyllabic patterns. These trisyllabic patterns include four words in the form of *X-Y-Z* (i.e., "pa-bi-ku", "ti-bu-do", "da-ro-pi", and "go-la-tu"). These four words are concatenated randomly with no interval between them. After training, the experiments 1 and 2 further test whether infants exhibit a difference in the duration of focusing time on trained words versus untrained patterns during the test phase. The tested trained words are directly taken from two words presented during the training phase (i.e., "pa-bi-ku", and "ti-bu-do"), whereas the structure of untrained patterns and trained words have differ-

ent transitional probabilities to the trained words. In Experiment 1, the untrained non-words (i.e., "da-pi-ku", "ti-la-do") share no transitional probabilities ($p = 0$) with the trained words. In Experiment 2, the untrained part-words (i.e., "*tu*-da-ro", and "*pi*-go-la") share some transitional probabilities ($p = \frac{1}{3}$) with the trained words, as if the part-words are crossing over the word boundaries.

Marcus et al. (1999) The study investigated whether after training a certain type of trisyllabic patterns, infants show differential focusing time to the tested same and different pattern types with replaced tokens. In other words, the trained and tested patterns share no transitional probabilities. In the original experiment, the stimulus properties of experiments 2 and 3 are better-controlled. In Experiment 2, the training patterns are of the type *a-b-a* or *a-b-b*, and the test pattern types contain *c-d-c* and *c-d-d*. Similarly, in Experiment 3, the training patterns are of the type *a-b-b* or *a-a-b*, and the test pattern types are *c-d-d* and *c-c-d*. In this study, results regarding consistent and inconsistent type to the trained pattern are collapsed together. For all training patterns, there are four instantiations relates to the repeated syllables (**a**-*b*-**a**, a-**b**-**b**, or **a**-**a**-*b*; i.e., "le", "wi", "ji", and "de"); and two instantiations for non-repeated syllables (*a*-**b**-*a*, **a**-*b*-**b**, or *a*-*a*-**b**; i.e., "di", "je", "li", and "we"). For the patterns in the test phase, the instantiations of repeated (**c**-*d*-**c**, c-**d**-**d**, and **c**-**c**-*d*; i.e., "ba", "ko") and non-repeated syllable (*c*-**d**-*c*, **c**-*d*-**d**, and *c*-*c*-**d**; i.e., "po", "ga") are replaced.

Gómez (2002) The study investigated whether after training non-adjacent dependent *X-Y* patterns, infants show differential focusing time on the same *X-Y* pattern from other untrained *X'-Y'* non-adjacent dependent patterns. Here, the meaning of non-adjacent dependency is that the fixed tokens *X* and *Y* are not adjacent to each other, but separated by a variable token *a* in the form of *X-a-Y*. In the training phase, *X-Y* has two instantiations (i.e., "pel-rud", "vot-jic"). They are divided into three conditions based on the variability of the middle token *a*. In the first condition, *a* has only 3 variants, while in the second and third conditions, the variability of *a* increases to 12 and 24 variants. The instantiation of *a* includes "wadim", "kicey", "puser" and so on. During the test phase, it is then investigated whether infants can distinguish the same *X-Y* and different patterns *X'-Y'* after each of the three training conditions. The same test *X-Y* patterns are consistent with the training phase (i.e., "pel-rud", "vot-jic") and are separated by a variable token *a* that includes three variants. Similarly, the different test *X'-Y'* patterns uses the reverse of *X-Y* (i.e., "pel-jic", "vot-rud"), which also includes a 3-variant middle token *a*.

Task Lengths In the empirical studies, the presentation time of trisyllabic patterns in different tasks varies greatly. Specifically, in Saffran et al. (1996), the presentation time of each trisyllabic pattern is 750 ms (250 ms/syllable) without inter-pattern interval (note though that a 500 ms inter-pattern interval is added during the test phase). In Marcus

et al. (1999) and Gomez (2002), trisyllabic pattern are each presented for 1500 ms (500 ms/syllable) with an inter-pattern interval of 1000 ms and 500 ms respectively. In other words, the numbers of patterns trained in the Saffran et al. (1996) greatly exceeded the other two tasks. In the simulation study, in order to make the model fully acquire the patterns in each tasks, the simulation duration is set longer than it is in the empirical study. In detail, the total presentation lengths in the training phases are 500 patterns (6.25 min) for Saffran et al. (1996, 2 min), 100 patterns (4.17 min) for Marcus et al. (1999, 2 min), and 100 patterns (3.33 min) for Gomez (2002, 3 min). In addition, to better compare the operation firing patterns in the early and late training stages, the model divides the entire continuous presentation of patterns into streams. Each stream contains the continuous presentation of 10 patterns. On the other hand, in the test phase of the simulation, all task conditions consistently contains 10 patterns. This is done so because our model only focuses on how much time is spent on average to process a single trisyllabic pattern (along with the immediate inter-pattern interval that follows).

In addition, our model assumes that processing efficiency undergoes change during different months of age. Infants of 7-8 months are tested in Saffran et al. (1996) and Marcus et al. (1999), while 17-month-olds are tested in Gomez (2002). In our model, processing efficiency is differentiated by the firing duration of an individual operator, and operations that are not successfully fired also take time. To simulate younger infants in Saffran et al. (1996) and Marcus et al. (1999), the firing duration is set lower (70 ms) as compared to older infants (50 ms) in Gomez (2002).

Simulation results

Learning of Context-Sensitive Operation In here, we only show the difference between the operation firing responding to each single pattern of various task conditions during training (see Figure 3). For the specific firing pattern formed by these operations, we are currently conducting further analysis and will not be elaborated in this paper. Initial and later state describe the performance of the model in the first stream and the tenth stream respectively. Note that the number of streams applied here is only for demonstration purpose and do not represent the entire training length - for example, simulation of Saffran et al. (1996) consists of 50 streams (500 continuous patterns). We can see that in the initial state, the firing of the operation is without structure. However, in the later state, the operation seems to form some firing patterns. In addition, the efficiency of firing seems to have improved, so it can be seen that the transitional gaps between stimuli and/or pattern are also increased. However, for the simulation of Saffran et al. (1996), the increase in transitional gap is not as obvious. This is because in this experiment, the presentation time of each syllable stimulus is extremely short (250 ms) and there is no inter-pattern interval between patterns during the training phase.

initial state | later state

X-Y-Z
a-b-a
a-b-b
a-a-b
X-a-Y: 3 var.s
X-a-Y: 12 var.s
X-a-Y: 24 var.s

10 simulations per task condition
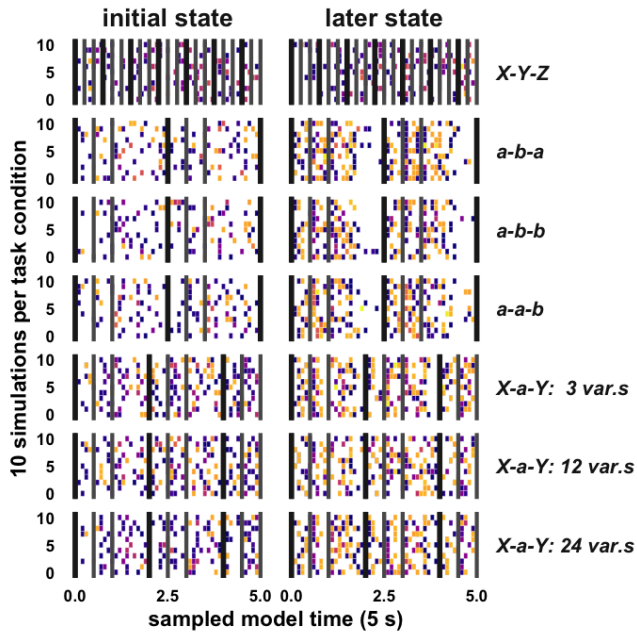
sampled model time (5 s)

Figure 3: Changes in operator firing for different tasks (grids represents different tasks; scales from 0 to 10 on the grid-Y-axis represents the 10 simulated subjects sampled) and different parts of the training (left blocks are onsets of training, right blocks are later stage in training). Each dot represents a fired operator, with varying colors for different operator types. The black vertical lines mark the onsets of sound patterns, the gray lines mark the onset of individual syllables.

Differentiating Acquired/Novel Patterns The empirical and the stimulated results are analyzed based on an unpaired two sample design. The reason for this is that (a) the experimental results leave only summarized data (such as mean, standard error, and sample size), therefore the original within-group difference cannot be reassessed; whereas (b) in the model, different task conditions are independently simulated. Moreover, Welch's t-test is performed to analyze the results, since (a) the original data is based on small samples, and (b) we do not assumed equal variance in experimental and simulated samples. For **Saffran et al. (1996)**, it was found that none of the experiments' focusing time difference on words/non-words (*mean difference* = 0.88 s, *p* = 0.16) and words/part-words (*mean difference* = 0.83 s, *p* = 0.17) reached statistical significance (see Figure 4A). Similarly in simulation, no difference was found between words/non-words (*mean difference* = 0.002 s, *p* = 0.61) and words/part-words (*mean difference* = 0.006 s, *p* = 0.12) for the single-pattern processing latency (see Figure 4B). Nevertheless, regardless of experimental and stimulated results, it is found, at face level, that the focusing time and processing latency for trained words is slightly longer than non-words/part-words. **Marcus et al. (1999)** investigated the focusing time difference between acquired/novel pattern types, and found that
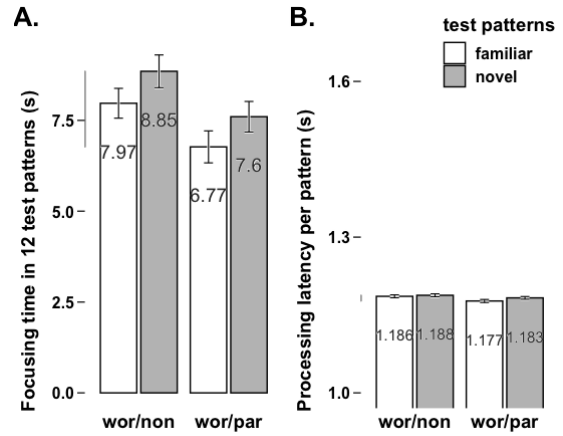

Figure 4: Simulation of Saffran et al., 1996. *A:* Data, average focusing time (±1SE) in 12 patterns. *B:* Simulation, processing latency *per pattern* (average of 200 runs, ±1SE). Note: wor = words; non = non-words; par = part-words.

there was significant differences between cdc/cdd (*mean difference* = 1.75 s, *p* = 0.04) and cdd/ccd (*mean difference* = 2.00 s, *p* = 0.003; see Figure 5A). Similarly in simulated results of single-pattern processing latency, we also found the difference between cdc/cdd (*mean difference* = 0.10 s, *p* = 2.63 × 10^{-9}, *Cohen's d* = 0.61) and cdd/ccd (*mean difference* = 0.07 s, *p* = 1.98 × 10^{-4}, *Cohen's d* = 0.38; see Figure 5B). Analysis of **Gomez (2002)** shows that the greater the variability of middle token *a* during the training phase, the larger the focusing time difference between acquired non-adjacent patterns and novel patterns. However, only when the variability contains 24 instantiations (*mean difference* = 0.05 s, *p* = 0.97), the focusing time difference reaches significance; whereas when the variability is with 3 (*mean difference* = 0.34
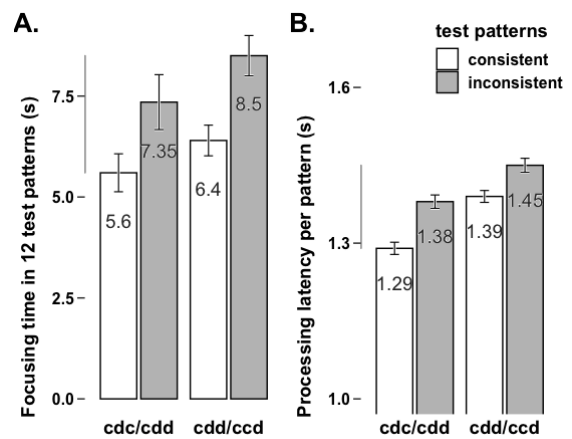

Figure 5: Simulation of Marcus et al., 1999. *A:* Data, average focusing time (±1SE) in 12 patterns. *B:* Simulation, processing latency *per pattern* (average of 200 runs, ±1SE).

s, $p = 0.73$) and 12 instantiations (*mean difference = 2.07 s, p = 0.003*), the differences are non-significant (see Figure 6A). In the simulated results due to the larger sample size, the differences in single-pattern processing latency among 3 (*mean difference = 0.04 s, p = 0.007*), 12 (*mean difference = 0.06 s, p = 6.79 × 10^{-5}*), and 24 instantiation conditions (*mean difference = 0.07 s, p = 8.30 × 10^{-7}*) have all reached significance. Further analysis of the simulated results shows that effect sizes increases as the number of instantiations increases from 3 (*Cohen's d = 0.27*), 12 (*Cohen's d = 0.40*) to 24 (*Cohen's d = 0.501*). Only the 24-variant condition shows substantive medium effect size latency difference (see Figure 6B).

Discussion

In this study, we use a single model to simulate three theoretically controversial infant artificial language tasks. The simulated results of different tasks are consistent with the original findings. Specifically, for Marcus et al. (1999), simulated difference in processing latency is found between consistent/inconsistent pattern types after training; and for Gomez (2002), as the variability of token *a* in non-adjacent dependent pattern *X-Y* increases, the difference in processing latency between trained/novel patterns gradually increases, showing substantive difference only when token is instantiated with 24 variants. These simulated results indirectly illustrate enhanced processing efficiency of the learned pattern. This is assumed to reserve longer task-irrelevant gap during pattern processing, thereby increasing the possibility of diversion and eventually leading to a reduction in focusing time for the trained pattern. Therefore, the simulated results are consistent with empirical findings and illustrates the learning ability of the model.

Nevertheless, for Saffran et al. (1996), further analysis suggests that the original data or the simulated results only revealed face level difference but neither reached statistical significance. This is the case even though the simulated length of this task is the longest. In Saffran et al. (1996), the presentation time of each syllable in the pattern is only 250 ms and without inter-pattern interval. Therefore, it is difficult for infants to sufficiently process the patterns. For example, for the trained pattern of "da-ro-pi", it is very likely that infants may only process "da" and "pi" but omit the middle syllable "ro". In addition, the model's reinforcement learning process also takes time, and the pattern presentation time is thus too short and prevents such reward process from occurring. These are among the reasons that the operation firing pattern are still sparse at the end of training (e.g., Figure 3). Our ongoing analysis did find that the operation firing patterns are differentiated for the trained/novel patterns. Though due to syllable omission, the model tends to acquire skip-grams rather than trigrams.

In general, our simulation shows that the model can gradually acquire the different task patterns through a cognitively constrained architecture, avoiding views that consider task-specific information processing as innate and deterministic.
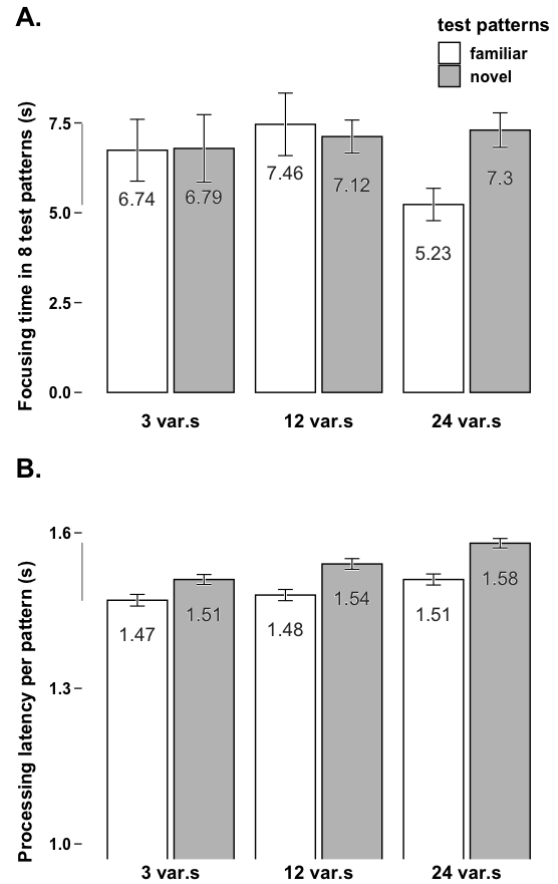

Figure 6: Simulation of Gómez, 2002, who tested the differentiation of *X-Y* and *X'-Y'* patterns after training *X-Y* with 3, 12, and 24 variations of middle token *a*. *A:* Data, average focusing time (±1SE) in 8 patterns. *B:* Simulation, processing latency *per pattern* (average of 200 runs, ±1SE).

Conclusion

The current simulation provides unified descriptions for the three artificial language tasks. The model can distinguish between task conditions at the level of processing latency, which implies its capabilities to acquire operation firing patterns or primordial "skills" related to the task conditions without explicit programming. Therefore, the PRIMs contextual learning mechanism contributes to the flexibility of cognitive architecture. However, to tackle the question of compositionality, this article has a few limitations and remains incomplete. The simulation has not considered the complex factors that lead to diversion, and the overall focusing time of the entire test phase has not been simulated. In addition, we are still analyzing the procedural and declarative knowledge acquired by the model. Only by answering this question can we better demonstrate the skill acquisition of PRIMs and the sure acquirement of language-related contents.

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