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Prior work has demonstrated that neural networks can induce both concatenative and non-concatenative morphological patterns, including infixation and reduplication (e.g., Kann & Schütze, 2017; Nelson et al. 2020)

#### **Research questions**

1. Can the networks learn *unattested* non-concatenative patterns that are formally simple but unlike those found in natural languages?

2. Do the networks have *inductive biases* that favor natural (or unnatural!) non-concatenative morphology?

We studied learning and generalization by LSTM and GRU encoder-decoder networks for a variety of natural and unnatural infixation and reduplication patterns under various low-resource conditions



## Read the full paper here.

This research was supported by NSF grant BCS-1844780 to Colin Wilson.

# **Deep neural networks easily learn** unnatural infixation and reduplication **Datterns.** Society for Computation in Linguistics, 2021

#### Which patterns were learned most easily?

Unattested counting patterns (e.g., place the infix before the third segment), were learned reliably in even low-data contexts. Overall, unattested patterns were learned at least as robustly as attested patterns.

### Which patterns were most difficult to learn?

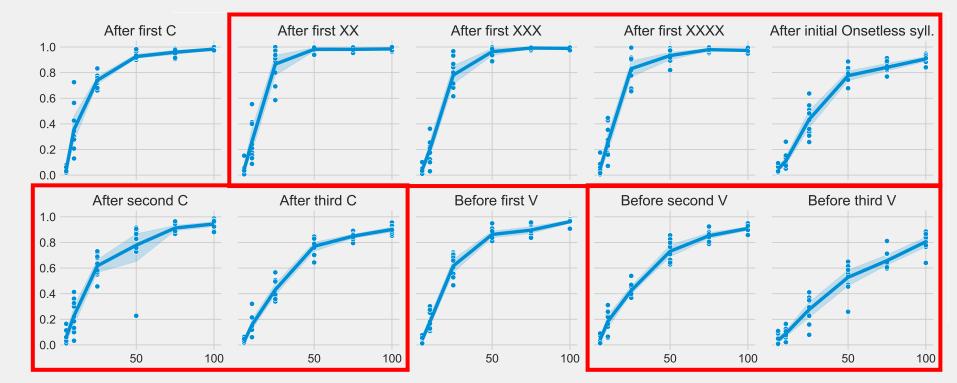
Unattested patterns that involve both counting and distinguishing consonants and vowels (e.g., place infix before the third vowel) required the most training data.

### **Do LSTM and GRU networks** differ?

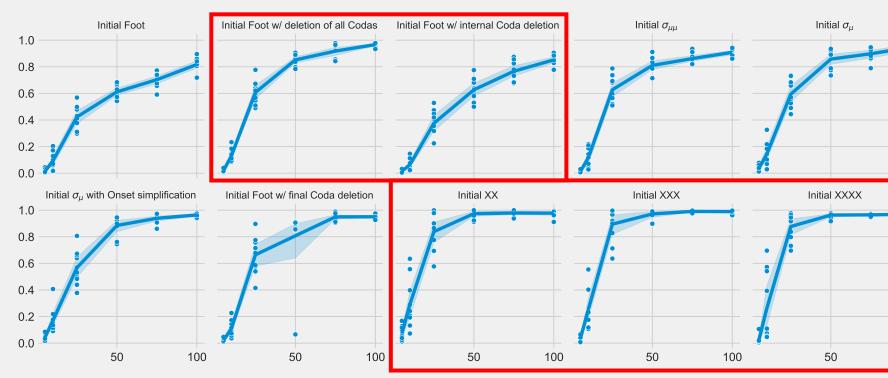
Despite the limited counting ability of the GRU unit, it showed the same patterns as LSTM models, including easily learning unattested counting patterns.

Infixation pattern	LSTM	GRU
Initial 2 segments $X_{\underline{1}}X_{\underline{2}}X_{1}X_{2}$	.99	1.0
Initial 3 segments $X_{\underline{1}}X_{\underline{2}}X_{\underline{3}}X_{1}X_{2}X_{3}$	1.0	1.0
Initial 4 segments $\underline{X}_{\underline{1}}\underline{X}_{\underline{2}}\underline{X}_{\underline{3}}\underline{X}_{\underline{4}}X_{1}X_{2}X_{3}X_{4}$	.98	.97

Table: Average test set performance for LSTM and GRU networks for 50 training examples.



(a) *Infixation* test accuracy as a function of training size (red = unnatural pattern)



(b) *Reduplication* test accuracy as a function of training size (red = unnatural pattern)

#### How many examples are required to learn the patterns?

Unattested segment-counting patterns were learned from as few as 25 examples, other patterns required at least 50-100+ training examples

