Learning Evolved Combinatorial Symbols with a Neuro-symbolic Generative Model

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Abstract

Humans have the ability to rapidly understand rich combinatorial concepts from limited data. Here we investigate this ability in the context of auditory signals, which have been evolved in a cultural transmission experiment to study the emergence of combinatorial structure in language. We propose a neuro-symbolic generative model which combines the strengths of previous approaches to concept learning. Our model performs fast inference drawing on neural network methods, while still retaining the interpretability and generalization from limited data seen in structured generative approaches. This model outperforms a purely neural network-based approach on classification as evaluated against both ground truth and human experimental classification preferences, and produces superior reproductions of observed signals as well. Our results demonstrate the power of flexible combined neural-symbolic architectures for human-like generalization in raw perceptual domains and offers a step towards developing precise computational models of inductive biases in language evolution.