Neuronal Variation as a Cognitive Evolutionary Adaptation

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Abstract

Computational scientists studying cognition, robotics, and Artificial Intelligence have discovered that variation is beneficial for many applications of problem-solving. With the addition of variation to a simple algorithm, local attractors may be avoided (breaking out of poor behaviors), generalizations discovered (leading to robustness), and exploration of new state spaces made. But exactly how much variation and where it should be applied is still difficult to generalize between implementations and problems as there is no guiding theory or broad understanding for why variation should help cognitive systems and in what contexts. Historically, computational scientists could look to biology for insights, in this case to understand variation and its effect on cognition. However, neuroscientists also struggle with explaining the variation observed in neural circuitry (neuronal variation) so cannot offer strong insights whether it originates externally, internally, or is merely the result of an incomplete neural model. Here, we show preliminary data suggesting that a small amount of internal variation is preferentially selected through evolution for problem domains where a balance of cognitive strategies must be used. This finding suggests an evolutionary explanation for the existence of and reason for internal neuronal variation, and lays the groundwork for understanding when and why to apply variation in Artificial Intelligences.

Introduction

Neuroscientists often struggle with the removal of neuronal variation in multi-neuron recordings, highlighted in Mackevicius et al. (2018). Toward this end, many scientists seek to understand where this variation comes from, as it is hypothesized to originate from any number of sources: ion channels, within cells, within dendrites, between synapses, unobserved portions of the network, or as a result of the a chaotic network behavior. There is some evidence for these hypotheses. Matzner (2017) showed that evolution preferentially selects networks that exhibit behavior on the edge of chaos, suggesting that the bits of noise from dipping into the chaotic regime enhance evolvability. Nolte (2018) showed that dendritic noise is likely the dominant source of noise explaining neuronal variation. Jegminat (2018) showed a stochastic (variational) synapse model outperforms a deterministic synapse model for supervised learning. We explore a subset of hypotheses where computational units have a controllable amount of probabilistic variation, thereby testing cell, channel, dendrite, and synapse hypotheses in an evolutionary context. Milano and Nolfi (2016) showed that component noise improves evolvability of logic gate circuits, independently confirming our preliminary results; however, their study used only static networks and did not test the conditions under which noise accelerates adaptation. We investigate additional variation sources for input, internal, and output states.

Methods

To perform our experiments, we used the Modular Agent-Based Evolver (MABE) framework with probabilistic Markov Gates. These gates are arbitrary logic gates whose logic and networking are determined by evolution. For a full description of how MABE works, see (Bohm et al. (2017)). To allow controllable variation we created a new gate type called an Epsilon Gate with a parameter Epsilon from 0.0 to 1.0. Epsilon represents the probability for any logic operation of the gate to result in any of the outputs from the same logic table with equal probability.

In this preliminary work we surveyed a sweep of Epsilon values for evolving populations of networks across 3 previously published problems: Block Discrimination and Maze-Solving Edlund et al. (2011), and memory association Grabowski et al. (2010) (see 1). In the Block Discrimination task the agent could move only side to side and ideally decided if different shaped blocks falling toward it from above should be caught or avoided and proceed to do so. The Maze-Solving task was a binary maze with only one correct series of passages, and each passage was marked with a binary signal indicating direction of the next passage, which would ideally be seen and remembered to quickly solve the maze. The Memory Association task was a path-following task where the agent could not see ahead, except through environmental signals of upcoming turns. The difficulty was that the meaning of the signals changed for each new agent, disallowing evolution to genetically encode this information (Grabowski et al. (2010) proposed this as future work).

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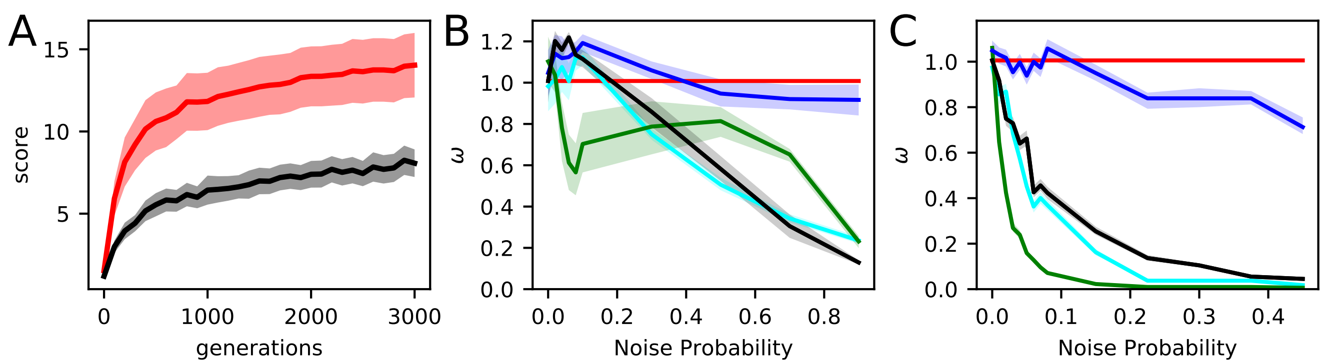

Figure 1: Comparison of Epsilon Gate effect for 3 different tasks. **A)** Score over evolutionary time in the Block Discrimination task. Epsilon Gates with $\epsilon = 0$ (deterministic) shown in Red. Average of 32 replicates. Epsilon Gates produce no enhancing effect for this task. **B)** Average end-of-evolution fitness in the Maze-Solving task after $50,000$ generations taken from 50 generations from the end of the line of descent across 48 replicates. Deterministic Gates shown in Red, Epsilon Gates shown in Black with ϵ equal to the x-axis, noise applied to input states shown in Cyan, noise applied to output states shown in Green, noise applied to hidden states shown in Blue. ϵ between 5% and 10% Epsilon Gates outperform deterministic and hidden state variation, resulting in increased efficiency of adaptation and final performance. **C)** Average end-of-evolution fitness in the Associative Memory task after $50,000$ generations take from 50 generations from the end of the line of descent across 48 replicates. Epsilon Gates produce no enhancing effect for this task. Same color legend as in panel B. Error bars on all panels are bootstrapped 95% confidence intervals of the mean.

Results

Agents evolved despite different types of noise (e.g., on inputs, outputs, hidden states, and component-level) show that the rate of adaptation – the speed of evolution – and final attained fitness depend greatly on the type of noise and the environment (cognitive-behavioral task) in which the agents evolve. Using component noise between 5% and 10% in the Maze-Solving environment has two distinctly different advantages: accelerating adaptation and improving performance of the final evolved solutions.

For Block Discrimination, variation is very detrimental. In the associative learning environment, at best the applied variation has no effect, and no form of noise allows for agents to evolve better performance at the end of evolution. At best, applied noise yields performance similar to adaptation without noise. This finding highlights the key problem we are beginning to investigate: Under which conditions do neural variation aid adaptation?

Conclusion

These preliminary results support our hypotheses that internal component-level variation can be beneficial and thus could be a product of evolution of cognitive structures and that this effect depends on the environment and the type and degree of variation. Whether or not this variation is truly noise or merely the product of another part of cognition is outside the scope of this investigation. There may exist a speed-accuracy trade-off between fast evolution and better final performance which would yield different possible applications. In future and ongoing work we will explore this phenomenon more systematically using a greater number of environments and other neurocomputational model systems, as well as investigate possible speed-accuracy trade-offs.

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