Biomimetic Neural Networks

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The explosion of deep learning has made technologies such as OpenAI's ChatGPT and Google's Gemini household names. The excitement that follows such attention, however, engenders a narrow-minded focus, constraining what is possible only to what has become available. Despite their ability to learn to complete complex specialized tasks and mimic human written composition, such models can only give shallow understanding on how our minds operate. We may be able to infer some properties of low-level brain function from neural networks, but insight into higher cognition eludes us. These higher functions of cognition are what pique my curiosity. In particular, I wish to delve into the inner workings of motivation and long-term passions, but studying these things directly is untenable as the factors involved with any individual's motivations are not only intractably numerous, but also may not be feasibly measurable. My ultimate goal is to instead investigate and model biologically plausible neural networks as a proxy of brain function.

State-of-the-art deep learning algorithms today rely on mechanisms that are biologically implausible. They depend on gradient back-propagation, which computes the gradient of an objective function with respect to the weights of a neural network. Such back-propagation raises problematic issues that demonstrate the improbability of such a process in biology. First, back-propagation is a purely linear computation, while biological neurons apply both linear and non-linear operations. Credit assignment, which is the act of determining the influence that an action taken will have on future rewards, in such a paradigm, would require precise knowledge of the gradient in both directions and exact symmetry for the weights. Futhermore, artificial neurons communicate by continuous values, while their biological counterparts communicate through action potentials, which are binary in nature. Finally, most deep learning models have discrete training and prediction stages.

Although there has been research towards biologically plausible machine learning, this area of exploration is still in its infancy. There are many avenues of study in this field with a plethora of opportunities to expand upon already completed research. Much of the current research attempts to address one or more of the problems associated with gradient back-propagation. One such area that is of particular interest to me is continual learning, which is a hallmark of human intelligence. Recent work into continual learning combined multiple techniques to allow artificial neural networks to consolidate synapses to mitigate forgetting and strengthen connections between contextual information. Nevertheless, the research still relied on back-propagation of fully connected networks. Brain synapses are unidirectional with physically distinct feed-forward and feedback connections. It is also believed that the brain is capable of localized learning. Investigating neuron architectures with these features in continual learning is an exciting prospect of study for me.

Researching novel neural networks that more closely mimic biological systems could help uncover some of the mechanisms of higher cognition. Likewise, creating a model of cognition that closely simulates biological brains could unlock new insight into neurological diseases, mental illness and wellness, and learning. By pursuing a doctoral degree in Computational Cognitive Science, I will be among multidisciplinary experts that would be best equipped to assist me with my research interests. Although my long-term goals align more with affective science, affect is intimately linked with cognition and behavior. It is my hope that through my journey I will be making incremental discoveries towards unearthing a greater understanding of affect, cognition, and the interrelationship between both.