Evolving Large-Scale Modular Neural Networks

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Modularity is a major feature of biological central nervous systems. For example, the human/primate cerebral cortex is composed of dozens of structurally and functionally identifiable regions that are interconnected in a hierarchical network [1]. Motivated by this, our research group is studying the evolution and self-organization of modular neural networks. We are interested both in explaining the origin of modularity in biological systems, and in understanding the fundamental principles that govern the emergence of modular neural networks in general. There has been a substantial amount of past research in this area during the last decade, examining how modularity in neural networks evolves (e.g., [2–4]). Our own group initially focused on using genetic algorithms and multi-objective evolutionary optimization methods to evolve module parameters that influence acquisition of functionality in predefined modules during learning [5, 6]. This past work was directed at explaining left-right asymmetries and hemispheric specialization in the brain.

In order to go beyond such issues and address the origin of neural modularity in a much more general fashion, we have recently introduced an encoding method that can represent neural networks as a hierarchy of layers (modules) [7]. In this framework, evolution (genetic programming) works at a very high level of abstraction on a tree structure that represents the top level architecture of modules and inter-modular connections forming a neural network. Modules consist of fairly uniform neurons with a set of shared properties (e.g., radius of projection into an adjacent layer) that are also evolved. Specialization of neurons, such as the specific weights on their connections, are not evolved but are acquired through a learning process that works synergistically with evolution (i.e., learning occurs prior to measuring phenotype fitness). Although we believe that this approach could serve as a general framework for evolving modular architectures when a large-scale target network is expected, practical considerations often require imposing network constraints to limit the size of otherwise enormous and complex search spaces, depending on the problem domain. For this reason, we have also created a human-readable, descriptive language that specifies the initial configuration of a problem and the desired search space. We will describe our top-down approach to evolving modular neural networks and summarize some of our initial experiments with it.

References

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