Evolving Neural Networks to Exploit Problem Processing Regularities

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The field of machine learning was founded with the purpose of bridging the gap between machine and biological processing. However, as certain algorithms see more success—and more funding as a result—the field is increasingly leaving its founding purpose behind in favor of a more algorithmic approach. The field of neuroevolution offers an alternative approach that mimics biological phenomena to train neural networks. There are thousands of types of neurons in the human brain. This diversity of neurons enables the brain to efficiently process complex stimuli. Conversely, conventional artificial neural networks consist of a single type of neuron. Lacking neuron diversity, conventional approaches to machine learning struggle to process and solve complex problems like we do. This research proposes an extension to the neuroevolutionary algorithm HyperNEAT (ECS-HyperNEAT) that allows the algorithm to define its own types of neurons during training to process problems more efficiently. ECS-HyperNEAT was compared to a conventional implementation of HyperNEAT in the N-XOR problem environments. It was found that ECS-HyperNEAT outperformed HyperNEAT in all N-XOR environments. In a representative example in the 2-XOR environment, on average, ECS-HyperNEAT reached a solution in 2,000 generations vs. HyperNEAT, which required more than 150,000 generations. While ECS-HyperNEAT was proven to perform significantly better than HyperNEAT, the heuristic for classifying neuron types could benefit from further investigation and optimization.

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