Modularization through the prism of shaping

Kai A Krueger and Peter Dayan

Gatsby Computational Neuroscience Unit, UCL

The only possible solution to the problem of acquiring temporally and structurally rich and complex cognitive capabilities is modularization, or divide and conquer. We, and indeed other species, are able to learn simple elements and recombine them in multifarious ways in order to address sophisticated challenges. However, despite some important suggestions[3], most computational models have focused on uniform, rather than modularized learning, that is, taking on the full complexity of tasks starting from a naive state. Not only does this make learning of a single problem more difficult, thus encouraging the development of architectural artifice, but it also fails to generate sub-solutions that can be used to solve future problems. Evidence for the nature and importance of modularity comes from the behavioral procedures used for training subjects to solve complex tasks. Subjects are shaped, ie are led step-by-step to acquire elemental sub-components before being presented with full tasks.

Previously, we used a computational model to elucidate shaping’s substantial beneficial effects on learning. We demonstrated this in a hierarchical, conditional one-back memory-based cognitive task called 12-AX [4], which we continue to employ here. However, in that study, we solved by hand one of the critical problems in making shaping work, namely the resource allocation mechanism that creates new network resources for each stage of shaping. This allowed our network to represent all the sub components of the task without interference. Here, we explore mechanisms that replace this homunculus with more principled algorithmic methods.

The basic approach has been clear since one of the earliest inventions in the probabilistic era of neural networks, namely mixture models[2]. These involve multiple modules, and allocate learning to each module for a particular input according to the responsibility that it is estimated to have for any error associated with that input. Different sorts of modules, and different ways of estimating responsibilities, lead to different architectures. We extend our earlier model for cognitive shaping into a mixture model, adapting the MOSAIC framework of Haruno et al. [1] for the responsibility estimation. MOSAIC uses a form of learned forward model for this; the sequential nature of tasks such as 12-AX, which are not Markovian in the input, impose extra demands on the forward model. We investigate solutions to this problem, and compare the ability of such an extended network to benefit from shaping, to that with the original, homuncular, resource allocation.

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References


