

# Evolving Learning Ability in Cyclically Dynamic Environments: The Structuring Force of Environmental Heterogeneity

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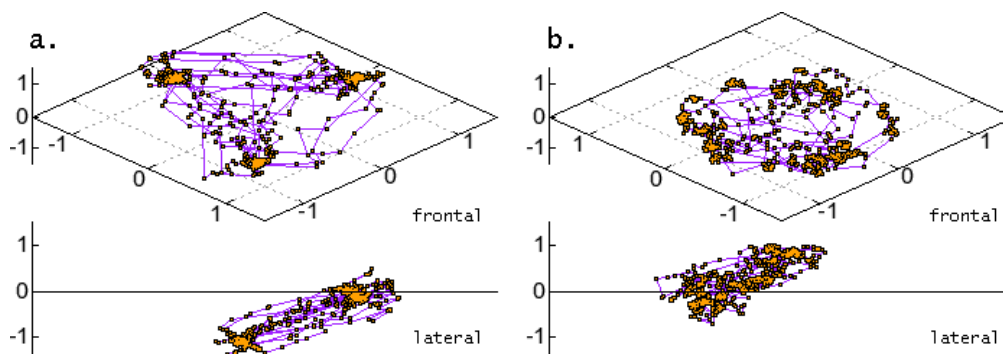
In nature, adaptation occurs at multiple levels (learning, multiple levels of evolution). Adaptation processes at different levels are known to interact in various ways. Especially the mechanism by which learning guides evolution (the Baldwin effect) has become a common theme in Artificial Life (see e.g. Suzuki and Arita, 2004, 2008). This research focuses on the opposite direction: how evolution facilitates learning by devising innate structures that guide learning processes.

In the computational model presented here, weight and plasticity structure of simple artificial neural networks are evolved in an environment with a cyclic dynamic, switching through 3 phases (or “seasons”), each requiring a distinct behaviour. To allow evolution to shape the networks’ weight dynamic, the genotype contains a separate plasticity (learning-rate) gene for every individual connection. It is shown that in response to the environmental dynamic, evolution devised a modular network structure, containing one rigid behaviour module for each phase, and a flexible module governing the switching between behaviours. The evolution process shows a pronounced Baldwin effect, indicating that the evolution of the innate structures guiding learning is itself guided by the presence of learning ability. The evolved networks show a highly structured plasticity differentiation. Comparison with networks using only a single global plasticity gene reveals that this differentiation facilitates learning by allowing the nets to learn without deteriorating their modular structure.

Both a functional and a mathematical interpretation of the evolved network structure are given. Mathematically, plasticity differentiation induced a large reduction in dimensionality of the networks’ active weight-space, and a high degree of consistency in weight-configuration between subsequent environmental cycles. Functionally, we find that through internalization of environmental structure, the networks gain an ability to improve their responses to unseen stimuli, in a way that similarity-based generalization alone cannot account for. The alignment of internal (network) structure with external (environmental) structure enables the nets to process a given piece of learning data as evidence for being in a particular environmental phase, and to adjust the whole of their behaviour accordingly. This feature might be understood as a primitive analogue of “latent learning” (see e.g. Gould and Gould, 1994) or the “poverty of the stimulus” phenomenon (Chomsky, 1980).

To further investigate the role of internalization, we compare performance of networks with varying numbers of hidden nodes. Reducing this number below the minimum necessary for successful internalization causes a marked drop in performance, while increasing the number beyond this minimum has virtually no effect. Next, as internalization should show as improved robustness against noise, we compare performance of networks with and without plasticity differentiation in a noisy environment. We find that the difference in performance is indeed increased in the noisy environment.

These findings are considered in the context of evolution of cognition, and linked to the idea that cognition is to be understood as adaptation to structured environmental heterogeneity (Spencer, 1855; Godfrey-Smith, 1994, 2002). Finally, extension to larger networks and more complex tasks is discussed.



Comparison of connection weight dynamics of top layer connections in networks with (a) and without (b) plasticity differentiation, over the course of 8 environmental cycles of 3 phases each. The clusters in (a) each correspond to one of the environmental phases, while in (b), subsequent occurrences of the same phase fail to produce identical weight configurations.

## References

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