

A Situated, Embodied and Dynamical Systems Approach to Understanding Learning and Memory

Eduardo Izquierdo-Torres, Inman Harvey
Centre for Computational Neuroscience and Robotics
University of Sussex, Brighton, U.K.
e-mail: [e.j.izquierdo | inmanh]@sussex.ac.uk

In the days of traditional artificial intelligence cognition was seen as computation, memory was regarded simply as discrete storage space and learning would correspond then to the changing of the contents of this space. We are privileged enough to live in more interesting times, where cognition is now widely understood (but not universally) as arising from the real-time interaction between bodies, brains and environments (Thelen & Smith, 1994; Harvey, 1996; Beer, 1997; Pfeifer & Scheier, 2002).

Learning is a fundamental aspect of cognitive activity because it allows organisms to adapt to the ongoing changes in their environments. Despite much progress in the new artificial intelligence, learning continues to be one of the activities whose mechanisms are still understood as taking place ‘inside the brain’, with a particularly strong association to synaptic plasticity in neuronal networks (see for example Floreano & Urzelai, 2001). Although it is the case, in some organisms, where the dynamics of synaptic changes play a role in the adaptive modification of behavior, it is not necessarily the case that synaptic plasticity is either necessary or sufficient for learning behavior (see for example and review Phattanasri et al., submitted).

As cognitive activity in general, learning and memorization are behaviors that arise from the interaction between internal dynamics, body and environment. To be more precise, learning corresponds to a change of behavior that serves to adapt to the changing conditions of the environment. Under this perspective, an act of memorization corresponds to the organisms’ ability to make decisions in its current environment taking into account the history of its previous interactions with the world.

Interestingly enough, in situated, embodied and continuous-time dynamical system agents interacting with an environment changes in behavior according to past experiences are inevitable (Beer, 1997). This is because the different components that comprise the agent and environment interact in different time-scales; some at very fast time-scales such as neurons while others at much slower time-scales such as the growth of limbs, with the potential for interaction ranging over the continuum. In the extreme case of an agent with completely reactive internal dynamics (i.e. one that does not have internal state), the body’s intrinsic physical properties (e.g. inertia) in addition to its history of interactions with the environment (e.g. position in relation to other objects) allow it to be influenced by past experiences (Izquierdo-Torres & Di Paolo, 2005), and thus, to be able to learn. In the less extreme cases, where there are also internal states possible, then the potential for the modification of behavior is simply richer.

The question of interest then shifts from what is learning and what is not to how the different time-scales of the components throughout the brain, body and environment interact to produce a particular learning behavior and what the mechanisms are that allow the modification of behavior towards an improved adaptation to the current conditions under changing environments. Under this view, learning corresponds to a degree of interaction between varying time-scales in the brain, body and environment. The main question that our research asks is, then, how agents can use past experiences to influence their future behavior at several different time-scales. This, we

believe, corresponds to a fundamental challenge that a situated, embodied and dynamical systems approach to understanding cognition faces today.

In order to tackle these challenges we employ evolutionary robotics techniques (Harvey et al., 1997). The methodology is guided primarily by an attempt to make only the fewest possible assumptions about the sort of mechanisms an agent needs to perform learning and memorization behavior while at the same time allowing it to exploit its embodiment and situatedness as much as possible.

The study of learning has been impregnated by a computational view, where discrete tokens of presentation, recognition, reward are used in the experimental set ups. But not all studies of learning have been biased in this way, one particularly good example of a more ecological view of learning is the study of the development of social preferences in young animals for their parents or other stimuli ever since Konrad Lorenz's vivid descriptions of avian imprinting (Lorenz, 1981).

Our current efforts are directed towards evolving agents that can perform imprinting-like learning behaviors (Izquierdo-Torres & Harvey, in press). In particular our research seeks to understand, the necessary and sufficient dynamical systems mechanisms to 'record' a feature from the environment within a continuum and later 'make-use' of this 'stored-information' to make a decision, with particular emphasis in understanding the role that the agent's morphodynamics and situatedness play in the generation of such behavior. We are interested in these issues from an evolutionary perspective as well, so questions like: what sort of evolutionary pressure is needed to evolve agents with the capacity to retain a particular memory throughout its lifetime? This corresponds to certain aspects of learning irreversibility and the evolution of critical periods. But also, our research program is concerned with understanding how this learning can be made reversible. So, what sort of dynamical mechanisms does a system 'need' to be able to re-learn a feature in a continuum from the environment over and over?

References

1. Beer, R. D. (1995). A dynamical systems perspective on agent-environment interaction. In *Artificial Intelligence*, **72**:173-215.
2. Floreano, D. and Urzelai, J. (2001). Evolution of plastic control networks. In *Autonomous Robotics* 11:311-317.
3. Harvey, I. (1996) Untimed and misrepresented: connectionism and the computer metaphor. In *AISB Quarterly*, no. 96, pp. 20—27.
4. Harvey, I., Husbands, P., Cliff, D., Thompson, A. and Jakobi, N. (1997) Evolutionary Robotics: the Sussex Approach. In *Robotics and Autonomous Systems*, **20**:205--224.
5. Izquierdo-Torres, E. and Di Paolo, E. (2005) Is an Embodied System Ever Purely Reactive? In M. Capcarrere et al (Eds.) *Proc. of the 8th European Conf. on Artificial Life*. p252-261. Springer-Verlag.
6. Izquierdo-Torres, E. and Harvey, I. (in press). Learning on a continuum in evolved dynamical node networks. To appear in *Artificial Life X: Proc. of the Tenth Int. Conf. on the Simulation and Synthesis of Living Systems*. MIT Press.
7. Lorenz, K. (1981). *The Foundations of Ethology*. Springer-Verlag.
8. Pfeifer, R. & Scheier, C. (2002) *Understanding Intelligence*. MIT Press, Cambridge, MA.
9. Phattanasri, P., Chiel, H.J. and Beer, R.D. (submitted). The dynamics of associative learning in evolved model circuits. To appear in *Adaptive Behavior*.
10. Thelen, E. & Smith, L.B. (1994). *A Dynamic Systems Approach to the Development of Perception and Action*. Bradford Books/MIT Press, Cambridge, MA.