

SPECIAL SECTION

Beyond backprop: emerging trends in connectionist models of development: an introduction

Matthew Schlesinger¹ and Domenico Parisi²

1. Department of Psychology, Southern Illinois University Carbondale, USA

2. National Research Council, Rome, Italy

Introduction

Since the publication in 1986 of Rumelhart and McClelland's *Parallel distributed processing: Explorations in the microstructure of cognition*, neural network or connectionist models have become an increasingly common method for studying learning and development. A wide range of developmental domains have been investigated with connectionist models, including language acquisition, perceptual development, object permanence, developmental psychopathology and motor skill acquisition. Many of these models rely on the *backpropagation-of-error* learning algorithm, a form of supervised learning in which a 'teacher' shapes the output of the network by providing it with desired responses.

Why backprop?

There are many reasons, both historical and practical, for the popularity and success of 'backprop nets'. First, they are part of a well-studied class of mathematical techniques (i.e. nonlinear function approximation), which are widely used to estimate complex numerical functions (Bishop, 1999; Cybenko, 1989). Second, supervised learning algorithms such as backprop may be an ecologically plausible technique for simulating learning mechanisms that exploit a mismatch between expected and observed events (e.g. learning by prediction, or imitation of a model; see McClelland, 1995; Parisi, Cecconi & Nolfi, 1990). Third and most importantly, feed-forward nets trained by backprop also seem to capture several key features of development (e.g. qualitative shifts or transitions in behavior, adaptive internal representations, etc.; for recent reviews, see Mareschal, 2000; Schlesinger & Parisi, 2001).

Despite these strengths, there are several questions that backprop nets may not be well suited to address. For example, how do we simulate developmental processes that occur without explicit instruction or feedback? How can we incorporate principles of neural development into connectionist models, and more specifically, utilize learning mechanisms that are biologically plausible? Can we expand the scope of our models to investigate not only normative developmental processes, but also changes on a wider scale (e.g. individual differences, evolution or phylogenesis, etc.)?

Beyond backprop

In recent years, a number of novel connectionist paradigms, architectures and learning algorithms have been proposed to expand the reach of existing modeling techniques, while addressing these and other questions about development. The purpose of this special collection is to introduce and highlight four emerging connectionist approaches:¹ autoassociators, Hebbian learning, adaptive resonance theory and evolving agents. Each paper has three goals: (1) to offer a brief technical overview of a novel approach, (2) to highlight the features of the approach that are particularly relevant to developmental research and (3) to illustrate an application of the modeling approach to one or more specific developmental phenomena.

¹ In addition to the connectionist approaches introduced here, there are several other classes of models that are equally relevant for studying developmental processes. A few possibilities are dynamic field theory (Thelen, Schöner, Scheier & Smith, 2001), reinforcement learning (e.g. Schlesinger & Parisi, 2001), ACT-R (e.g. Jones, Ritter and Wood, 2000) and Bayesian nets (Tenenbaum & Xu, 2000).

In the first paper, Sylvain Sirois introduces the class of connectionist models known as autoassociators. The paper reviews the basic techniques for constructing and training an autoassociator network and discusses the relevance of this modeling approach for studies of habituation and novelty detection in infants. The paper describes several applications of autoassociator models, including a simulation of habituation processes in young infants.

Next, Yuko Munakata and Jason Pfaffly's paper illustrates the use of Hebbian learning in artificial neural networks. Hebbian learning is based on the idea that 'units that fire together wire together' and is a biologically plausible model of long-term potentiation and long-term depression. The authors apply the model to the explanation of critical period phenomena in development.

The third paper, by Maartje Raijmakers and Peter Molenaar, provides an overview of adaptive resonance theory (ART). Their tutorial highlights the relevance of ART for investigating the interaction between neural development and qualitative reorganizations in behavior during development. More specifically, they address the role of self-organization as a third causal factor in development in addition to environment and maturational factors which can explain the acquisition of more powerful structures without the addition of resources.

In the final paper, Matthew Schlesinger presents a metatheoretical approach inspired by Artificial Life research. Borrowing from evolutionary theory, Schlesinger proposes the notion of an evolving population of neural networks that are situated and embedded (i.e. embodied and living in a physical environment) as a metaphor for individual development. He focuses on trial-and-error processes during the development of reaching as an example of this approach.

A critical commentary is then offered by David Klahr, who provides both a philosophical and an historical

perspective from which these four approaches are evaluated. Highlighting both their strengths and weaknesses, he judges their prospects for contributing to future research in developmental science.

References

- Bishop, C.M. (1999). *Neural networks for pattern recognition*. New York: Oxford University Press.
- Cybenko, G. (1989). Approximation by superpositions of a sigmoidal function. *Mathematics of Control, Signals, and Systems*, **2**, 303–314.
- Jones, G., Ritter, F.E., & Wood, D.J. (2000). Using a cognitive architecture to examine what develops. *Psychological Science*, **11**, 93–100.
- McClelland, J.L. (1995). A connectionist perspective on knowledge and development. In T.J. Simon & G.S. Halford (Eds.), *Developing cognitive competence: New approaches to process modeling* (pp. 157–204). Hillsdale, NJ: Lawrence Erlbaum.
- Mareschal, D. (2000). Object knowledge in infancy: current controversies and approaches. *Trends in Cognitive Sciences*, **4**, 408–416.
- Parisi, D., Cecconi, F., & Nolfi, S. (1990). Econets: neural networks that learn in an environment. *Network*, **1**, 149–168.
- Rumelhart, D.E., & McClelland, J.L. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition*. Cambridge, MA: MIT Press.
- Schlesinger, M., & Parisi, D. (2001). The agent-based approach: a new direction for computational models of development. *Developmental Review*, **21**, 121–146.
- Tenenbaum, J.B., & Xu, F. (2000). Word learning as Bayesian inference. In L.R. Gleitman & A.K. Joshi (Eds.), *Proceedings of the 22nd Annual Conference of the Cognitive Science Society* (pp. 512–517). New Jersey: Erlbaum.
- Thelen, E., Schöner, G., Scheier, C., & Smith, L.B. (2001). The dynamics of embodiment: a field theory of infant perseverative reaching. *Behavioral and Brain Sciences*, **24**, 1–86.