What Have Computational Models Ever Done for Us?  
A Case Study in Classical Conditioning

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ABSTRACT

The last 50 years have seen the progressive refinement of our understanding of the mechanisms of classical  
conditioning and this has resulted in the development of several influential theories that are able to explain  
with considerable precision a wide variety of experimental findings, and to make non-intuitive predictions  
that have been confirmed. This success has spurred the development of increasingly sophisticated models  
that encompass more complex phenomena. In such context, it is widely acknowledged that computational  
modeling plays a fundamental part. In this paper the authors analyze critically the role that computational  
models, as simulators and as psychological models by proxy, have played in this enterprise.

Keywords: Classical Conditioning, Computational Models, Psychological Models, Psychology, Simulators

INTRODUCTION

In natural environments organisms are compelled to constantly accommodate their behavior  
to dynamic surroundings. Learning to predict  
event regularities in such sensory rich conditions is vital for adaptive behavior and decision-making. Associative learning studies have mostly been conducted within the groundwork of classical conditioning—which is based on the principle that repeated pairings of two events will allow an individual to predict the occurrence of one of them upon presentation of the other, as consequence of the formation of an association between them (see Mackintosh, 1994; Wasserman & Miller, 1997; Pearce & Bouton, 2001). This simple mechanism is considered to underlie many learning phenomena and has proved to be relevant to human learning both theoretically (judgment of causality and categorization, e.g., (Shanks, 1995)) and practically, as the core of a large number of clinical models (Haselgrove & Hogarth, 2011; Schachtman & Reilly, 2011).

Hence, it is widely accepted that classical conditioning is at the basis of most learning phenomena and behavior and thus paramount that we develop accurate models of conditioning. In this endeavor, collaboration between psychologists and computer scientists has enjoyed considerable success (Schmajuk, 2010a; Schmajuk, 2010b; Alonso & Mondragón, 2011). This collaboration is sustained on well-known
arguments: Expressing models as sets of algorithms grants us formal ways of representing psychological intuitions and means of calculating their predictions accurately and quickly; from computational models we also borrow a view, the so-called computer metaphor, on how information is processed that has proved useful in understanding cognition; moreover, the architectures in which computational models are implemented, artificial neural networks for instance, resemble those of associative learning, both at conceptual and neural levels; finally, machine learning models, such as temporal difference learning and Bayesian learning, can be viewed as effective abstractions of how associations are formed and processed.

Despite the appeal in this line of argumentation, it is widely acknowledged that ANNs do not resemble natural neural networks in any fundamental way (Enquist & Ghirlanda, 2005); moreover, there is no strong evidence suggesting that neural activity and associative learning are indeed related (Morris, 1994)–or for that matter, that psychological processes can be uniquely localized in specific brain regions as recently shown in Vul, Harris, Winkielman, and Pashler (2009), and advanced in Uttal (2001).

Even if it did, a neural analysis would not necessarily shed light to the study of learning phenomena. In the words of B. F. Skinner “The analysis of behavior need not wait until brain science has done its part. The behavioral facts will not be changed (…) Brain science may discover other kinds of variables affecting behavior, but it will turn to a behavioral analysis for the clearest account of their effects” (Skinner, 1989, pp. 18). It should be noted that such a radical statement does not contradict a version of reductionism that most neuroscientists and cognitive psychologists would endorse, namely, Richard Dawkin’s hierarchical reductionism (Dawkins, 1986), according to which one should determine the proper low explanatory level for the system under study.

**COMPUTATIONAL MODELS AS MODELS OF LEARNING**

Computational models of learning have been considered as psychological models in themselves. This position, that constitutes a milestone in the annals of cognitive science and artificial intelligence, is in fact a misuse of the term. We are illustrating our contention by means of a paradigmatic example, the use of Artificial Neural Networks (ANNs) in conditioning theory. In what follows we discuss the inadequacy of such approach at different levels of analysis, namely, ontological, formal, representational, functional, and structural.

**The Ontological Level**

ANNs are considered the substratum of conditioning. The motivational rationale is that (a) ANNs model by analogy natural neural networks and that (b) psychological processes, including conditioning, are ultimately embedded in natural neural networks; consequently, ANNs stand as a model of conditioning.
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