

Chapter 13

Computational Models of Learning and Beyond: Symmetries of Associative Learning

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ABSTRACT

The authors propose in this chapter to use abstract algebra to unify different models of theories of associative learning -- as complementary to current psychological, mathematical and computational models of associative learning phenomena and data. The idea is to compare recent research in associative learning to identify the symmetries of behaviour. This approach, a common practice in Physics and Biology, would help us understand the structure of conditioning as opposed to the study of specific linguistic (either natural or formal) expressions that are inherently incomplete and often contradictory.

1. INTRODUCTION

The ability of animals to recognize and link different patterns of stimuli to adapt to dynamic environments is essential for their survival. Associative learning studies how animals *learn* by connecting the relevant events in their environment (that is, how they acquire causal information) and *behave* (that is, how what has been learned is expressed in their behavior) and is, therefore, of paramount importance in Psychology. Indeed, models of associative learning have proved to be relevant to human learning both theoretically (judgment of

causality and categorization, *e.g.*, Shanks, 1995) and in practice (in such diverse areas as behavioral therapy, drug addiction rehabilitation, or anticipatory nausea in cancer treatment to name just a few).

Of course, associative learning is not the only type of learning. There are learning phenomena such as habituation or sensitization that are traditionally considered as non-associative. Others such as spatial learning, perceptual learning and some forms of social learning seem to admit an associative account but such an interpretation is debatable. Besides, behavior – not even adaptive behavior – cannot be reduced to learned behavior. Some reflexes such sucking in babes or sexual

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patterns of behavior are indeed adaptive but not learned (although this is also controversial, see, *e.g.*, Dickinson & Balleine, 2002). Finally, it must be stressed the difference between learning, the hypothetical psychological and physical changes in the brain (memory), and performance, the manifestation of such change in behavior (see, *e.g.*, Bouton & Moody, 2004).

All this taken into account, it is commonly accepted that *associative learning is at the basis of most learning phenomena and behavior*.

2. PSYCHOLOGICAL MODELS OF ASSOCIATIVE LEARNING

The study of associative learning in Psychology has specialized in two sub-fields: Classical (Pavlovian) conditioning focuses on how “mental” representations of stimuli are linked whereas instrumental conditioning deals with response-outcome associations. It is agreed though that, at the most general level, their *associative structures* are isomorphic (Hall, 2002). In both procedures, changes in behavior are considered the result of an association between two concurrent events and explained in terms of operations of a (conceptual) system that consists of nodes among which links can be formed. Since research in associative learning has predominantly focused on classical conditioning, we will use it as our leading example.

At the risk of over-simplification, we can identify the main trends in classical conditioning according to two dimensions, namely, the mechanisms of the learning process and the way in which the stimuli are represented by the learning system. The former fuels the debate between stimulus-processing theories *vs.* connectionist models, exemplified in the competitive model of (Rescorla & Wagner, 1972) and the Standard Operating Procedures (SOP) theory (Wagner, 1981) respectively; the latter illustrates the distinction between elemental models (for instance, both

Rescorla and Wagner’s and SOP) and configural approaches (*e.g.*, Pearce, 1987).

Rescorla and Wagner’s model rests on a sum error term. The idea that all stimuli present in a trial compete for associative strength is at the heart of the model. It is precisely this characterizing feature that differentiates it from earlier models such as Hull’s (Hull, 1943). This assumption allows the model to explain phenomena such as blocking and conditioned inhibition, that is, phenomena that result from the interaction among different stimuli. Other assumptions of the model are path-independence (*i.e.*, that the associative strength of a stimulus does not depend on its previous learning history), monotonicity (*i.e.*, that learning and behavior are one and the same thing), that acquisition and extinction are opposite processes, and that the associability of the conditioned stimulus (CS) is fixed.

It has been argued, quite rightly, that Rescorla and Wagner made such assumptions not to reflect strong psychological principles but, rather, to express their main discovery (competitiveness among stimuli) in a general, abstract model. It should not come as a surprise, therefore, that many phenomena cannot be accounted for by their model (latent inhibition being, perhaps, the most paradigmatic) and that myriads of extensions and truly innovative variants regarding the underlying psychological processes involved have been proposed (*e.g.*, attentional approaches like Mackintosh, 1975 and Pearce & Hall, 1980). It remains the case however, that Rescorla and Wagner’s model is still the most influential theory of associative learning.

SOP, on the other hand, is a broader theoretical framework of stimulus processing and memory. Unlike Rescorla and Wagner’s model, SOP is not based on familiar theories of conditioning (although stochastic approaches used in SOP can be traced back to Estes, 1950) but instead borrows ideas from both information-processing theories and connectionism. It is beyond this proposal to give a detailed account of SOP. Suffice it to say

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