# Computational Neuroscience for Advancing Artificial Intelligence:

## Models, Methods and Applications

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# 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 that, in SOP stimuli activate memory nodes for which transitional probabilities are dictated by decay functions (traces); that learning rules separately account for excitatory and inhibitory links depending on the particular level of activation of the stimulus traces; and that behavior is explicitly dealt with through weighted response-generation rules. Regardless of its merits, it is difficult to assess the explanatory and predictive power of SOP due to its representational and algorithmic complexity.

Both Rescorla and Wagner's model and SOP share the assumption that when two or more stimuli are presented at the same time of conditioning, each element may enter into an association with the reinforcer that follows (an unconditioned stimulus, US). In general, such elemental theories further assume that responding in the presence of the compound is determined by the sum of the associative strengths of the constituents. As an alternative, configural theories are based on the assumption that conditioning with a compound results in a unitary representation of the compound entering into a single association with the reinforcer. Responding in the presence of the compound is then determined by its own associative strength, together with any associative strength that generalizes to it from similar compounds that have also taken part in conditioning. Configural models have proved to be particularly useful when studying conditional associations where a stimulus comes to control responding to a CS in a manner that is independent of its direct association with the US (Honey and Watt, 1998) or forming a configural cue that becomes associated with the US (Wilson and Pearce, 1989, 1990). Contrarily, elemental accounts tend to focus on the modulatory properties of the conditional cue over the CS-US association (Holland, 1983, Bonardi, 1991) or over the US representation (Rescorla, 1985).

Regardless of the individual merits of each model, research in associative learning suffers from various fundamental problems, namely:

1. **Incomplete theories:** There is no model that satisfactorily accounts for all the phenomena under study. Each theory explains a set of particular phenomena. Latent inhibition, that the Pearce-Hall model predicts, cannot be explained in Rescorla and Wagner's whereas over-expectation, on the other hand, can be explained by the latter but not by the former. Similarly, configural theories can account for feature discrimination effects but cannot predict summation effects, exactly the opposite of what elemental theories are able to account for;
2. **Inconsistent theories:** Different models make contradictory predictions under the same conditions. Mackintosh's and Pearce and Hall's models predict opposite changes in the associability of a stimulus as a consequence of the very same procedure. Likewise, elemental models predict that when two compounds (AB, CD) are trained their associative strength will be the same that the one observed when novel compounds (AC, BD) are tested. Contrarily, configural theories predict that the associative strengths of trained and novel compounds will differ. The problem is that evidence is not conclusive in neither of these cases;
3. **Excluding paradigms:** Certain theories are based on *a priori* excluding assumptions. For instance, although all stimulus processing models are cue competition models, Rescorla and Wagner's refers to competition for US processing whereas Mackintosh's model invokes competition between conditioned stimuli for a limited CS processing capacity. As another example, in configural theories like Pearce's a compound AB is viewed as a unique configuration, distinct from its component parts and from other stimuli. Each configuration develops associative strength through its own pairing with an US and also receives generalized associative strength from other configurations based on its simi-

larity. Elemental theories, on the other hand, simply assume that the associative strength of an AB compound can be viewed as the sum of the strengths of the elements;

4. **Unaccounted phenomena:** There are phenomena that are still waiting for a model to be dealt with. For example, it is not obvious (at least not without making use of *ad hoc* arguments) how to explain spontaneous recovery.

## 3. MATHEMATICAL MODELS OF ASSOCIATIVE LEARNING

Associative theories of associative learning have been mathematically expressed as quantitative models in the form of (sets of) equations. In the traditional syntactic view of mathematical models, equations are taken as formal models in which variables and their relations explicitly denote the phenomena under study.

In particular, Rescorla and Wagner use a simple difference equation (the well-known delta rule) to express the change in associative strength across discrete trials. On the other hand, continuous (a.k.a. real-time) models like SOP are, at least in theory, useful when it comes to making accurate predictions about inter-stimulus intervals effects. Finally, Pearce's model just adds a similarity function specified in terms of the proportion of elements that the stimuli share.

All in all, mathematical models of associative learning have so far been used as a means to make calculations through elementary algebra or differential analysis. The problem with adopting this narrow version of mathematical model is that it does not provide us with tools to address the above-mentioned limitations. For example, if the meaning of a mathematical model is in the linguistic expression it takes (that is, if there is a unique isomorphism between phenomena and algorithms) then either (a) we cannot explain how a theory can be expressed in different sets of equations or (b) we will not be sure about the effect the addition or the removal of a simple parameter may have. Paraphrasing (Chakravartty, 2001), theories and models can be given linguistic formulations but theories and models should not be identified with such formulations.

## 4. COMPUTATIONAL MODELS OF ASSOCIATIVE LEARNING[1]

The use of computational models of associative learning has followed the connectionist trend and borrowed from computer science several techniques, mainly Artificial Neural Networks (ANNs, for a review, Volge *et al*., 2004, and Balkenius & Morén, 1998). It is claimed that such models are adequate models of associative phenomena for four main reasons:

Firstly, computational models are considered material and/or formal analogue models of associative learning. The underlying reasoning is that (a) ANNs model by analogy natural neural networks and that (b) psychological processes, including associative learning, are ultimately embedded in natural neural networks; hence, indirectly, ANNs model associative learning.

However appealing this line of argumentation may be, it is widely acknowledged that ANNs do not resemble natural neural networks in any fundamental way (Enquist & Ghirlanda, 2005); besides, there is no strong evidence suggesting that electrical or chemical neural activity and associative learning are related (Morris, 1994) –or for that matter, that psychological processes can be localized in specific brain regions as recently exposed in (Vul *et al.*, 2009), but already advanced in (Uttal, 2001). That a version of Dirac's rule can be taken as a model of both neural plasticity and long-term potentiation effects –the Hebbian rule (Hebb, 1949) – and association formation –for example, Rescorla and Wagner's rule– cannot be considered as proof of any common underlying structure and should not be used as an argument to reduce psychological phenomena to their alleged neural substratum[2]. Likewise, that Rescorla and Wagner's rule is essentially identical to the Widrow-Hoff rule (Widrow & Hoff, 1960) for training *Adeline* units and that, in turn, such a rule can be seen as a primitive form of the generalized delta rule for backpropagation only tells us that, computationally speaking, associative learning follows an error-correction algorithm. What a computational model does not tell us, however, is which underlying psychological processes (attention, motivation, etc.) intervene in associative learning or how the physical characteristics of the units involved (*e.g.*, the salience of the stimuli) affect such processes.

Clearly, sharing a common mathematical expression does not imply that the phenomena it describes are of the same nature: For instance, power functions can be used to express the relationship between (1) the magnitude of a stimulus and its perceived intensity (Stevens' law), (2) the metabolic rate of a species and their body mass (Kleiber's law), and (3) the orbital period of a planet and its orbital semi-major axis (Kepler's third law).

Secondly, ANNs are connectionist models according to which information is not stored explicitly in symbols and rules but rather in the weights (strengths) of the connections; learning would consist of changes in such weights. It is claimed, rightly, that these are precisely the assumptions associative learning models are based upon and hence, wrongly, that ANNs are an ideal candidate to model associative learning. This quite straightforward argument is, in fact, a fallacy: As connectionists (at least implementational connectionists) themselves concede the way we represent learning, either as continuous changes of weighted connections or as the result of discrete symbolic processing, is *a matter of convenience* and therefore irrelevant to the study of the structures involved.

This brings us to the third argument. ANNs can be used, of course, not as models of phenomena but to solve problems that cannot be solved analytically –or when *in silico* experiments are needed. After all, ANNs are powerful statistical tools (with a misleading name) implemented in architectures that take advantage of massive computational parallelism – not surprisingly, Rumelhart's et al. *new connectionism* landmark paper introduced the Parallel Distributed Processing paradigm in cognition (Rumelhart *et al*., 1986). Although they are certainly not the simplest, fastest or most efficient data mining techniques (see, *e.g*., Mitchie *et al*., 1994), ANNs have proved useful when analytical methods fail and a bottom-up, data-driven approach is needed. Indeed, it is a common practice to use sheer computational power to simulate the dynamics of non-linear (chaotic or not) systems such as population growth or the weather. The point is, however, that associative learning does not seem to be one of such systems. In fact, the analytical solution of Rescorla and Wagner's equation represents a linear discrete dynamical system of the 1st order; besides, associative learning is not so data intensive as other areas like genetics where there is an obvious need for statistical tools (see, for example, Hastings & Palmer, 2003). Of course, we could study associative learning from a behavioral regulation approach according to which animals adjust their long-term behavior so as to reach an optimal (bliss or equilibrium) point (Timberlake, 1980). However interesting this point of view may be, it does not by itself oblige us to adopt numerical tools as (Dank, 2003) and (Yamaguchi, 2006) have proved.

Relatedly, ANNs typically approximate solutions by iteratively minimizing an error function. This can be understood as a type of learning that resembles learning by "trial and error" of which associative learning (and reinforcement learning) is an example. However, it is worth emphasizing that ANNs implement numerical *methods* whereas associative learning models such as Rescorla and Wagner's express dynamic *laws*. Against public opinion, animals do not make predictions and iteratively update an associative value through error minimization towards an optimal one. The associative value at a given time is the right associative value –that exactly describes to which extend the CS has become associated to the US. Let's put it another way: There is nothing to indicate that the system is compelled to gain a maximum value. That the system described by Rescorla and Wagner's rule is limited by an asymptote (λ, the reinforcing value of the US) does not confer any special status to such value –rather it just defines a constraint (limited capacity) of the system.

A final more general reason to explain the appeal of computational models in psychology rests on the idea that both computers and the brain are information processing systems, instantiations of a universal Turing machine or any other model of computation. But this alone does not justify the support the "computer metaphor" enjoys. After all, any phenomena can be expressed in terms of some sort of computation[3]. If this is such a powerful metaphor is because it is deeply rooted in Western philosophy and the mechanization of (formal) reasoning, reformulated in the twentieth century in terms of computation. That computation has been effectively embedded in computers has reinforced the idea that so it is in the brain, that the study of the former will help understand the latter and, in a *tour the force*, that computers may be capable of displaying intelligence. Indeed, every scientific theory is shaped in the context of its age's achievements and prejudices: Like Newton's laws of mechanics strengthened the view of the Universe as a deterministic machine that worked as the sophisticated clocks so popular at the time our conception of the mind as an information processing machine has certainly been influenced by the development of computing technology.

To sum it up, although the need to get influx from 'outsiders' is recognized within the psychology community (see Townsend, 2008) computational models of associative learning should be taken with caution. Computational models may provide us with complementary idealized models of psychological phenomena and with powerful statistical tools to construct models of psychological data but they alone are not the appropriate instruments to answer psychological questions. This is an obvious, hardly original, conclusion –and yet more often than not we read flamboyant news about robots that learn, think and experience emotions or ANNs that can do anything psychological models do only better.

Our contention is that what we are lacking in the field of associative learning and behavior is the identification of invariant structures that underlie specific (psychological, mathematical and computational) models. That is, we need to study psychological symmetries. Crucially, symmetries can be formalized mathematically as operations satisfying the conditions for forming various algebraic structures –typically groups. We propose to employ abstract algebra to explore models of psychological theories from a non-syntactical view (as Physics and Biology have done).

## 5. SYMMETRIES

Generally speaking, symmetries define *invariance*, that is, impunity to possible alterations. They refer to the fact that parts of a whole are equivalent (interchangeable) under a group of operations. Interestingly, the fact that the parts that are related by means of an equivalence relation corresponds to the fact that the family of operations transforming the parts into each other while leaving the whole invariant satisfies the conditions for constituting a group (*i.e.*, the existence of the identity and inverse operations, associativity and the closure of the product). Consequently, it has traditionally been assumed that *group theory is the language of symmetries.*

What is more important, in group theory the objects do not need to be mathematical objects or physical, biological or psychological objects. Objects and their elements can be any abstraction (shapes, phrases, laws, mathematical equations and even theories). And the transformations or operations under which the whole remains invariant can be any operation (from a rotation over an axis to a specific conditioning procedure). This is because groups act on operations not on elements or objects. This feature makes groups a powerful tool to study symmetries independently of a particular theory or expression.

The study of symmetries flourished in the XIX century, originally as an instrument to solve algebraic equations: It was the young E. Galois who first understood that groups opened a new general way of finding the (invariant) structures that underlie the number and form of the solutions for equations of arbitrary degrees. This had an immediate effect in Physics: C. G. Jacobi developed a procedure for transforming step by step the Hamiltonian formulation of the dynamical equations of mechanics into new ones that are simpler but perfectly equivalent. In geometry, F. Klein (Klein, 1872) proposed the *Erlangen Program* to classify various geometries (Euclidean, affine, and projective) with respect to geometrical properties that are left invariant under rotations and reflections. It was also in Göttingen where E. Noether proved the connection between symmetries and conservation laws (Noether, 1918).

In fact, we can view the history of the theories of modern Physics in terms of their symmetries and groups. Newtonian classical mechanics was based on Galilei transformations formalized in the Galilei group; the special theory of relativity unified seemingly contradictory mechanical and electromagnetic phenomena of the hand of Lorentz transformations and their corresponding Lorentz groups; and the general theory of relativity explained gravity, the most symmetrical of field theories so far, under the group of all diffeomorphisms of a space-time.

It has been, however, with quantum mechanics when symmetry groups have become an indispensable tool in Physics (see Weyl, 1928, for a starter). Internal symmetries (*i.e.*, those which act on fields while at the nuclear level and cannot be reduced to "classical" spatiotemporal symmetries), both global and gauge, can only be fully understood when studied through the groups their representations form. In particular, the Standard Model classifies all elementary particles and their interactions according to their flavor, charge and color symmetries (the SU(3) □ SU(2) □ U(1) group), and, in so doing, unifies electromagnetism, QED and QCD and explains electroweak interactions through spontaneous symmetry breaking.

Why is it that symmetries take such a prominent part in Natural Sciences? As argued in (Brading & Castellani, 2003):

1. First, we attribute symmetry properties to *theories and laws* (symmetry principles). It is natural to derive the laws of nature and to test their validity by means of the laws of invariance, rather than to derive the laws of invariance from what we believe to be the laws of nature;
2. At the same time, we may derive specific consequences with regard to particular *phenomena* on the basis of their symmetry properties (symmetry arguments). Pierre Curie (Curie, 1894) postulated a necessary condition for a given phenomenon to happen, namely, that it is compatible with the symmetry conditions established by a principle.

More specifically, symmetries play several inter-related roles that we illustrate with an example of the use of (point) groups in molecular biology (see *e.g*., Atkins & Friedman, 2005):

- *Normative role:* One the one hand, symmetries furnish a kind of selection rule. Given an initial situation with a specified symmetry, only certain phenomena are allowed to happen; on the other side, it offers a falsification criterion for (physical) theories: A violation of Curie's principle may indicate that something is wrong with the (physical) description. That is, symmetries can be viewed as normative tools, as constraints on theories –the requirement of invariance with respect to a transformation group imposes several restrictions on the form the theory may take, limiting the types of quantities that may appear in the theory as well as the form of its fundamental equations. For instance, the rule that determines whether or not two atomic orbitals can form a chemical bond (*i.e*., a molecule) is that they must belong to the same symmetry species within the point group of the molecule. The same applies to bonding in polyatomics;

- *Unification role:* Symmetries can be used as a heuristic to compare and unify theories, resulting from the possibility of unifying different types of symmetries by means of a unification of the corresponding transformation groups. Likewise, we can use symmetries to analyze whether or not different theories are, in fact, equivalent; and even if theories turn out to be incomparable (it seems, after all, that Rescorla and Wagner's model and SOP correspond to different algebraic structures –Rescorla and Wagner's model to groups, SOP to Lie groups) we will at least have a tool to formally show that they are so. Following our example in molecular biology, the analysis of symmetries and their corresponding groups provides us with a unifying approach to complex molecular behaviour such as molecular vibrations and vibrational spectroscopy;
- *Classificatory role:* Classifications can be used to identify gaps in the theories but also to predict the existence of new phenomena. This applies when new phenomena can be predicted exclusively in terms of symmetry and when the predictions so postulated are coherent with those of existing models. All possible molecules can be classified according to symmetry operations on five symmetry elements: the identity operation (doing nothing) on the identity element (the entire molecule); rotation on the proper rotation axis; rotation on the improper rotation axis; reflection in the plane of symmetry; and inversion on the centre of symmetry. We can group together molecules that posses the same symmetry elements and classify molecules according to their symmetry: For example, water belongs to the $C_{2v}$ group which contains the identity, a 2-fold axis of rotation and 2 vertical mirror planes. Interestingly, Dymethyl ether also belongs to such group no matter how different its composition and that of water's may look – $O(CH_3)_2$ and $H_2O$ respectively;
- *Explanatory role:* Symmetries are also explanatory in that phenomena can be explained as consequences of symmetry arguments. We know that the symmetry elements of the causes must be found in their effects and that the converse is not true. That is, the effects can be (and often are) more symmetric than their causes. In group-theoretic terms this means that the initial symmetry conditions are lowered into (more constrained) sub-groups: The symmetry has been broken. In biology, we know that for a molecule to have a permanent dipole moment it must have an asymmetric charge distribution. The point group of the molecule not only determines whether a molecule may have a dipole moment but also in which direction(s) it may point. The only groups compatible with a dipole moment are $C_n$, $C_{nv}$ and $C_s$. Besides, in molecules belonging to $C_n$ or $C_{nv}$ the dipole must lie along the axis of rotation. Now, we can explain and predict, at least partially, how a molecule of water behaves;

Of course, organizing our knowledge using symmetries does not prove anything. Symmetries (and group theory) provide us with very powerful abstract tools to analyze the structure of psychological models. But they are just abstract tools after all. In any empirical science, the ultimate proof rests on experimental evidence. Nonetheless, perhaps paradoxically, here it is precisely where the full strength of symmetries shows: Not from the models of theories built on symmetry principles but from the intimate connection (through symmetry arguments) between such models and observed phenomena.

If we look back to the problems faced by psychological models of associative learning as listed in section 2, we find that they relate to deficiencies that symmetry could be used to resolve. The first shortcoming, that no model accounts for all associative learning phenomena, refers to a lack of explanatory power in such models; the second one, that contradictory rules explain the same phenomena, claims for a normative approach; the third one, that models are partial, relates to the need for unifying principles where different theories that cover disjoint phenomena find common grounds and are made compatible; and the fourth one, that some phenomena remain unaccounted for, identifies a classification problem. It seems, therefore, that symmetries may be useful in solving such problems. First we must find the psychological symmetries. This is the purpose of our research.

## 6. IN SEARCH OF PSYCHOLOGICAL SYMMETRIES

Although there is not a universally accepted 'law of learning', all psychological models coincide in assuming that learning takes place when a (relatively permanent) change in behavior happens as a consequence of some experience. Now, we need to know whether such law establishes *sufficient* symmetry conditions for the occurrence of the observed phenomena –or, in other words, we have to investigate whether the observed phenomena describe *necessary* conditions for the law to hold (invariantly) true. Unfortunately, a glimpse at the literature suggests it does not:

1. That the sensory and motivational features of the stimuli as well as their novelty and relevance affect learning are well documented facts (Kamin and Schaub, 1963; Pavlov, 1927; Jenkins and Moore, 1973; Randich and LoLordo, 1979; Lubow, 1989; Garcia and Koelling, 1966);
2. Procedurally, the idea that learning is context-specific is also gaining ground (Bouton, 1993; Bouton and Swartzentruber, 1986; Hall and Mondragón, 1998); also, different results emerge depending on the order in which stimuli are presented during training and on the number (single or compound) and representation (elemental or configural) of the cues themselves (see, *e.g.*, Pearce and Bouton, 2001 for a survey).

This first setback may not challenge our search for psychological symmetries though. It could we argued that, after all, we should expect that the parameters in (a) affected the pace of learning (accelerating or decelerating the learning process, *i.e.*, strengthening or weakening the links between nodes/stimuli as time goes), defining, in the extreme, explicit symmetry breaks. Unfortunately, the study of complex phenomena in (b) does not only tell us that the learning rate changes in different experimental conditions. What these results tell us is that the *rules* of learning themselves fluctuate depending on such factors and, consequently, that they do not reflect any genuine object of invariance.

Not surprisingly, a mathematical analysis of the above-mentioned issues reveals that each of them violates one of the conditions for group formation: Associativity. This is rather worrying since associativity is *the* key condition for symmetry. It tells us that the concatenation of two different operations gives the same result, and *that* gives us much more information and reflects much more structure than commutativity[4].

Let us illustrate this point with an example: Both elemental models and configural models of stimulus encoding anticipate that after conditioning is given to two compounds (say, AB and CD) responding to them will be greater than responding to the constituent elements. However, they differ in their expectations for responding to different compounds formed with the same elements (for example, AD and BC); elemental theories expect it to be as large as that to the trained compounds whereas Pearce's configural theory expects some generalization decrement and, as a consequence, responding should be as small as that to the elements. That is, elemental theories assume associative invariance under different compounds; Pearce's theory, on the other hand, assumes invariance under elements *per se* and new configurations. Unfortunately, evidence suggests (see, *e.g*., Rescorla, 2003) that neither interpretation is complete: In agreement to Pearce's theory, novel compounds perform less than original compounds but, in agreement to elemental theories, novel compounds perform better than their separate elements. Symmetries, therefore, are elusive.

Should we conclude, on this basis, that there are no symmetries in associative learning? Perhaps we can try a different approach and investigate this issue through a representative case study, a model that embodies the fundamental laws of associative learning. Few would disagree that Rescorla and Wagner's model is such a model. Now, Rescorla and Wagner's model is based on five basic assumptions (see Miller *et al.*, 1995), namely:

1. The associative strength of a stimulus depends on the summed associative value of all the CSs present on a given trial;
2. Excitation and inhibition are represented by opposite signs on a single dimension of associative strength and, consequently, are assumed to be mutually exclusive;
3. Associability of a given stimulus ($\alpha$) is constant, that is, associability is not subject to changes as function of experience;
4. New learning is invariant to any prior associative history (path independence). Past associative status of a cue, *per se*, is assumed to influence neither behavior nor future changes in associative status;
5. Differences in behavior reflect differences in associative strength, that is, there is a monotonically positive relationship between associative value and a relevant response.

A simple analysis of these five premises tells us that only the first one is *a*symmetric. It states that the associative strength of each CS present on a specific trial does not independently gravitate toward the asymptotic value of the US ($\lambda$). If it were so, then the associative strength of each CS would be invariant to the presence of other stimuli. This assumption (that is at the heart of cue competition) has proven to be the most innovative feature of Rescorla and Wagner's model.

The rest of assumptions are, in fact, symmetry postulates: Symmetry between excitation and inhibition (2), invariance of associativity to experience (3) and to learning history (4), and symmetry between learning and performance (5). Sadly, countless observations refute in a consistent manner such assumptions[5]. The important point is that such failures do not come from Rescorla and Wagner's disregard for parametric features. The disproving phenomena do not refer to specific values that the context, time/schedule or stimulus characteristics may take but rather are the result of fundamental assumptions on the structure of conditioning.

We can attribute this unsuccessful search for symmetries in associative learning to alternative causes:

- Is it that the laws of associative learning are simply wrong? This does not seem to be the case. Despite the problems referred to in section 2, psychological models of associative learning have been confirmed experimentally so as not to doubt their general validity. As stated by S. Spreat and S.R. Spreat "*much like the law of gravity, the laws of learning are always in effect*" (from Bouton, 2006, pp. 3);
- Or is it that associative learning phenomena (and the theories in which they are modeled) do not show any underlying structure, at least not in the form of symmetries? Again, this is dubious. As we have seen in the previous section, symmetry has proved to be just too powerful a principle in the study of Nature as not to be found in Psychology;
- Or is it that the formalization of symmetries in the notion of group is too constraining and that associative learning shows, to some extent, symmetries that should be expressed with a subtler concept? Is there any notion in abstract algebra that provides us with the required flexibility to represent associative learning phenomena and theories, and, at the same time, preserves the properties that have made groups so popular in Physics, Chemistry and Biology? Yes, there is: The notion of groupoid.

Indeed, it seems that groups do not provide us with the right ontology to deal with the type of symmetries that associative learning may show. Each associative learning theory could perhaps be modeled as a unidimensional single-object category, in other words, as a group. Yet, the problem is that groups (and the theories so modeled) are not expressive or flexible enough and, consequently, are prompt to generate inherently limited classifications and contradictory explanations. Besides, as groups are independent from each other and do not form more general structures there seems to be no need for a meta-syntax that would regulate the relations between different theories and, potentially, unify them.

## 7. CONCLUSION: GROUPOIDS?

We have seen that mathematicians (and physicists) tend to think of the notion of symmetry as being virtually synonymous with the theory of groups (symmetry groups). In fact, though groups are indeed sufficient to characterize homogeneous structures, there are plenty of objects which exhibit what we clearly recognize as symmetry, but which admit few or no nontrivial automorphisms. It turns out that the symmetry, and hence much of the structure, of such objects can be characterized algebraically (and categorically) if we use groupoids and not just groups (see Brown, 1987, and Weinstein, 1996, for two formal introductions to groupoids).

Intuitively, a groupoid should be thought of as a group with many objects, or with many identities. A groupoid with an object is essentially just a group. So, the notion of groupoid is an extension of that of group. This apparently innocuous distinction between one-object structures (groups) and many-objects structures (groupoids) is actually crucial. The homomorphisms defined in groups are always automorphisms (homomorphisms of the object to itself). In other words, as groups are one-object categories, *all* morphisms can be composed with all other morphisms. From this, the algebraic conditions for the formation of groups (closure, unique identity, unique total inverse, and *total* associativity) follow directly. On the other hand, groupoids, can only compose morphisms (isomorphisms in their case) with the appropriate domains and co-domains. Algebraically, a groupoid is a set with a *partially* defined binary operation (that *is* associative *where* defined) and a total inverse function.

What is important to get from this mathematical mumbo-jumbo is (a) that in groupoids associativity is partially defined, allowing us to investigate *variable symmetries* (symmetry groupoids) and (b) that in groupoids isomorphisms are defined over sets of base points (fundamental groupoids), permitting us to study *more symmetries*. Indeed, groupoids show new structures that do not show at a group level –more specifically, in groupoids, the inverse relation, although total, is defined over paths; besides, groupoids lead to higher dimensional algebras and help us move between n-categories through natural transformations, limits and co-limits.

Summarizing, groupoids present three very useful properties: (1) Partial associativity, (2) path reversibility, and (3) hierarchism. How does this relate to our study of symmetries in associative learning?

1. To start with, the very idea of associative learning can be nicely expressed as morphisms (associations) defined over objects (stimuli or nodes), that is, as categories;
2. Building iteratively up categories may allow us to gain knowledge about hierarchical processes –associative processes between associative processes (Bonardi, 2001; Mondragón, Bonardi and Hall, 2003), in particular, about the role of context and occasion setters (Bouton, 1994);
3. Also, the isomorphisms that define groupoids (unlike all or nothing equivalence relations that define groups) permit us to introduce partial symmetries that may explain results where novel compounds seem to elicit less response than the original trained compounds but more than each separate element;
4. Finally, the ability to look at intermediate processes may be very useful in determining the causes for non-responding: Failure to express or failure to acquire (or to retrieve) information?

More generally, the theory of groupoids does not differ widely in spirit and aims from the theory of groups. The recognition of the utility of groupoids gives gains over the corresponding groups without any consequent loss. Our contention is that the above-described characteristics make groupoids an ideal candidate to fill in the symmetry roles that, we have argued, would help solve the problems outlined in section 2: Groupoids provide us with a multi-object language defined over paths along with rules of variance and rules of transformation with which to study both internal and external symmetries. In other words, the language of groupoids gives us the required expressiveness and flexibility to attack classification and explanation problems; and its syntax would allow us to solve normative and unification problems.

Admittedly, the debate over whether groupoids are useful or unmotivated abstractions is still going on (Corfield, 2003). Nevertheless, since they were introduced by H. Brandt in 1926 groupoids have been used in a wide area of mathematics as well as in theoretical physics, neurosciences, biodynamics and networks, and logic and computer science (see, *e.g*., Ramsay & Renault, 1999).

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## KEY TERMS AND DEFINITIONS

**Associative Learning:** An account of learning and the process by which animals learn by associating or linking experienced events: stimuli and/or responses, and adjust their behavior accordingly.

**Symmetries:** Symmetries define invariance: that is, impunity to transformations. They refer to the fact that parts of a whole are equivalent (interchangeable) under a group of operations.

**Groups:** An algebraic structure consisting of a set together with an operation that satisfy the existence of the identity and inverse operations: associativity and the closure of the product. Groups have been traditionally used to represent symmetries.

**Groupoids:** A groupoid should be thought of as a group with many objects: or with many identities. A groupoid with an object is essentially just a group. So the notion of groupoid is an extension of that of group. Algebraically, a groupoid is a set with a partially defined binary operation (that is associative where defined) and a total inverse function.

## ENDNOTES

1 The very concept of computational model is controversial. If we refer to David Marr's levels of analysis of information processing systems (Marr, 1982) then models such as Rescorla and Wagner's are both computational and algorithmic --but allegedly not implementational, in that they analyse what the system does and how it does it. What we refer to as a computational model of (associative) learning however is the more mundane exercise of taking architectures

and techniques from machine learning and applying them to the modelling of psychological phenomena and data.

2 Even if it did, a neural analysis would not necessarily be the right level to study associative learning phenomena. In the words of Burruhs F. Skinner "The analysis of behaviour need not wait until brain science has done its part. The behavioural facts will not be changed (…). Brain science may discover other kinds of variables affecting behaviour, but it will turn to a behavioural analysis for the clearest account of their effects" (Skinner, 1989, emphasis ours). Regardless of the antipathy that Skinner's radical behaviorism provokes among neuroscientists such an statement does not contradict a version of reductionism that most of them would endorse, namely, Richard Dawkin's hierarchical reductionism (Dawkins, 1986).

3 And precisely because of its generality the information processing model is not necessary or sufficient: Working physicists do not model electrons, atoms or galaxies as information processing entities –be it in the form of a cellular automaton as envisaged in (Zuse, 1969) or as a participatory universe (Wheeler, 1990); on the other hand, neither (computational) physicists nor the public would presume that the simulation of a nuclear reaction generates real energy or that a flight simulator really flies. Of course, this does not preclude physicists from theorizing about what type of information is contained in a physical system (see, for example, literature on quantum entanglement or black holes) or about exploring the physical limits of computers (pioneered by Richard Feynman (Hey & Allen, 2000) and followed up to contemporary theories of quantum computing (e.g., Vedral, 2006)).

4 Incidentally, associative learning has shown to be stubbornly non-Abelian: 'Associative symmetry' phenomena and the basic distinction between latent inhibition and extinction are just two examples of non-commutativity.

5 In defence of Rescorla and Wagner, it must be said that they themselves expressed their doubts about these four assumptions. For instance, it is hard to believe that Rescorla and Wagner really mistook extinction for unlearning or that they were ignorant of silent learning phenomena. It should also be noted that alternative models based on contingencies do not seem to improve the landscape. Although it has been proved that the non-pairings of CS and US influence behaviour as do pairing of CS and US we know that the four inter-event combinations do not contribute equally to the acquired behaviour (*i.e.*, they have equal normative weights but not equal psychological weights, Wasserman & Miller, 1997).