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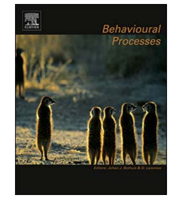

ECCO: An error correcting comparator theory

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ABSTRACT

Building on the work of Ralph Miller and coworkers (Miller and Matzel, 1988; Denniston et al., 2001; Stout and Miller, 2007), I propose a new formalization of the comparator hypothesis that seeks to overcome some shortcomings of existing formalizations. The new model, dubbed ECCO for “Error-Correcting COmparisons,” retains the comparator process and the learning of CS–CS associations based on contingency. ECCO assumes, however, that learning of CS–US associations is driven by total error correction, as first introduced by Rescorla and Wagner (1972). I explore ECCO's behavior in acquisition, compound conditioning, blocking, backward blocking, and unovershadowing. In these paradigms, ECCO appears capable of avoiding the problems of current comparator models, such as the inability to solve some discriminations and some paradoxical effects of stimulus salience. At the same time, ECCO exhibits the retrospective revaluation phenomena that are characteristic of comparator theory.

1. Introduction

The comparator theory of Pavlovian conditioning is Ralph Miller's best known contribution to associative learning theory—a continuing source of theoretical debate and an inspiration for many empirical investigations. At the time of writing, the three papers in which comparator theory is developed sum up to more than 1000 citations on Google Scholar (Miller and Matzel, 1988; Denniston et al., 2001; Stout and Miller, 2007). One reason for this enduring interest is the theory's tenet that many phenomena derive from information processing that occurs at the time of decision-making. This is in stark contrast with many other contemporary theories, which place most weight on how information is processed at the time of acquisition (Wagner, 1985, 2003; Pearce, 1987, 1994; Brandon et al., 2000; George and Pearce, 2012). Let me illustrate this central difference through an example.

Consider a conditioning experiment in which two conditioned stimuli (CSs) such as a tone and light can be paired with a meaningful unconditioned stimulus (US), such as food or shock. We may conduct such pairings with each stimulus separately, or with a compound of the two stimuli:

$$\begin{array}{ll} \text{Separate conditioning:} & \text{tone} \rightarrow \text{US},\ \text{light} \rightarrow \text{US} \\ \text{Compound conditioning:} & \text{tone} + \text{light} \rightarrow \text{US} \end{array}$$

It is commonly observed that compound conditioning results in weaker responding to the CSs, when these are tested alone after conditioning (overshadowing: Pavlov, 1927; Razran, 1965; Baker, 1968, 1969). Most theories interpret this finding as a deficit of acquisition, that is, as the tone and light acquiring smaller associative strength when conditioned in compound rather than separately (Pearce, 2008; Bouton, 2016). Comparator theory, in contrast, assumes that the tone and light (given equal salience) develop equally strong associations with the US in either training regime, but that in the case of compound conditioning these associations are not wholly expressed. That is, the theory assumes that at test a non-presented CS, say the tone, can interfere with responding to a presented CS, say the light, in proportion to the product of two associative strengths: a CS–CS association between light and tone, and a CS–US association between the tone and the US. Compound conditioning is assumed to result in a strong light-tone association, hence a significant interference, while separate conditioning results in no light-tone association, hence no interference. The mechanism whereby these interferences are computed is termed the “comparator process,” and will be discussed in more detail below.

Another reason why comparator theory has drawn attention is that it offered a relatively straightforward account of “retrospective revaluation” phenomena, at a time when these were hard to explain in terms of acquisition processes. For example, extinguishing the tone-US association after compound conditioning is predicted to render the comparator process ineffective and therefore increase responding to the light (unovershadowing, see below, and Miller and Witnauer, 2016 for review). Comparator theory remains of interest as an explanation of this and similar phenomena, although acquisition-based accounts now exist (Van Hamme and Wasserman, 1994; Aitken et al., 2001; Ghirlanda, 2005; Connor et al., 2014).

Comparator theory was initially formulated verbally rather than

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mathematically, and thus did not make quantitative predictions. Stout and Miller (2007) sought to remedy this shortcoming by proposing a formalization of comparator theory. They presented three formal models:

1 A model based on the original ideas of Miller and Matzel (1988), referred to here as "first-order" comparator theory.
2 A model of the "extended," or "second-order" comparator hypothesis proposed by Denniston et al. (2001).
3 A new model amending some aspects of the second-order theory, dubbed "sometimes competing retrieval" (SOCR).

Ghirlanda and Ibadullaiev (2015), however, showed that some predictions of these formalizations are paradoxical. In compound conditioning, for example, the Stout and Miller (2007) models predict that at asymptote the least salient CS should elicit either equal or greater responding than the most salient CS. Moreover, the models can fail to discriminate between stimuli with different consequences. For example, they predict that animals may respond equally to a CS conditioned in a given context and to the context itself (Ghirlanda and Ibadullaiev, 2015). This and other failures to discriminate stem from the (intentional) absence of what Stout and Miller (2007) termed *global error-correction*, often referred to simply as "error correction" by other authors. Error correction is a hallmark of acquisition-centered theories since the Rescorla and Wagner (1972) model, which assumes that the goal of learning is to use the presence or absence of CSs to correctly predict the US. In contrast, comparator theory assumes that the goal of learning is to estimate contingencies between stimuli. Even if these contingencies are learned correctly, however, the way they enter the comparator process does not guarantee that discriminations are solved (Ghirlanda and Ibadullaiev, 2015). Because contingency learning is also a form of error correction ("local" error correction in Stout and Miller, 2007), to avoid confusion I refer to error correction of behavioral responses as "total error correction," and I refer to contingency learning simply as such.

The purpose of this paper is to introduce and begin to explore a model that is as close as possible to the ideas of Ralph Miller and coworkers, while having a guaranteed capacity for solving discriminations. I dub the model ECCO for "Error-Correcting COmparisons." ECCO maintains both the comparator process as a performance rule and contingency learning of CS–CS associations (the latter is slightly modified, see Section 2.2). ECCO assumes, however, that CS–US associations are learned with the goal of reducing behavioral errors (or, equivalently, of predicting US occurrence). In what follows, I will describe ECCO and explore whether it can account for the following phenomena: acquisition, overshadowing in compound conditioning, blocking, backward blocking, and unovershadowing. This selection aims to show that ECCO may be able to remedy some of the shortcomings identified in existing comparator theories by Ghirlanda and Ibadullaiev (2015). A full evaluation of the theory will require further research.

In this paper I compare ECCO principally with comparator theory, but in a few cases I will also compare it with two acquisition-based theories: the classical Rescorla and Wagner (1972) model and its modification by Van Hamme and Wasserman (1994). The latter includes a mechanism for retrospective revaluation based on associative changes that take place during acquisition. Namely, it continues to use the Rescorla and Wagner (1972) learning rule, but it assumes that the associative strength of absent cues is also updated at each learning trial. The salience of absent cues is assumed to be negative, which results in changes for these cues that are in the opposite direction of changes for present cues. (An absent cue is recognized as relevant to a situation by virtue of shared associative history with the present cues.)

Lastly, I note that ECCO is a modification of first-order comparator theory, as formalized by Stout and Miller (2007). The second-order theory and SOCR can be modified similarly. These modifications are not pursued here for several reasons. A trivial reason is space: deriving and analyzing a second-order, error-correcting comparator model would more than double the length of the paper. A more substantial reason is that it is helpful to understand error correction in first-order comparator theory before turning to the more complex theories. In other words, my focus on first-order comparisons does not exclude that a number of phenomena may be analyzed by appealing to second-order comparisons (Stout and Miller, 2007; Wheeler and Miller, 2008).

2. Methods

In this section I introduce a comparator theory that uses total error correction. The theory is formulated in terms of three sets of variables:

- x_i indicates the presence and salience of CS *i* on a given trial. If the CS is absent, then $x_i = 0$. If it is present, then $x_i = \alpha_i$, where α_i is CS *i*'s salience.
- v_i is the associative strength between CS *i* and the US.
- U_{ij} is the associative strength from CS *i* to CS *j*. A stimulus cannot be associated with itself, i.e., $U_{ii} = 0$. As in current comparator theory, U_{ij} is not necessarily equal to U_{ji}.

I introduce first an equation to compute responding to stimuli, then a contingency-based learning rule for the $U'_{ij}s$, and finally an error-correction learning rule for the v_i's.

2.1. Response equation

With the notation introduced above, current comparator theory defines responding to CS *i* as

$$r_i = v_i - \gamma \sum_j U_{ij} v_j \tag{1}$$

The second term on the right-hand side is the comparator process. As anticipated informally in the Introduction, the effect of this term is to detract from responding to CS *i* in proportion to how much this CS is associated with other CSs (the U_{ij} terms) and how much the latter are associated with the US (the v_j terms). The parameter γ measures the strength of the comparator process. Stout and Miller (2007) suggest a value close to, but less than 1.

Eq. (1) calculates responding to one CS only. To achieve error-correction in the presence of multiple CSs, we need a response equation for compound stimuli (we cannot compute an error if we cannot compute a response). Here I simply assume that the response to a stimulus is the sum of the r_i responses to each component CS, each weighed by the CS's salience:

$$R(x) = \sum_i x_i r_i = \sum_i x_i \left(v_i - \gamma \sum_{i,j} U_{ij} v_j \right) \tag{2}$$

This equation replaces Eq. (1) wholly, even when a single CS is presented. The summation assumption is somewhat simplistic as in reality responses to stimuli rarely sum exactly (see Kehoe, 1994; Rescorla, 1997; Pearce et al., 2002; Pearce and George, 2002; Thein et al., 2008, for examples). A common solution is to assume that the representation of compound stimuli is not the exact sum of the representations of their components (Wagner, 2003; Ghirlanda, 2005). This strategy is possible in ECCO as well, but it is not pursued here for simplicity.

Two features of Eq. (2) are noteworthy. First, it assumes that high-salience CSs are more important in determining responding to a compound stimulus than low-salience CSs. This assumption is borrowed from connectionist models (Widrow and Stearns, 1985; Haykin, 2008) and is also consistent with the Rescorla and Wagner (1972) model, even though the latter's response equation is usually written simply as $\Sigma_i r_i$ with the present notation (see Ghirlanda, 2015, for details). Second, absent stimuli ($x_i = 0$) do not contribute to responding through their own CS–US associative strengths, but may do so through comparator