Chapter 4
An Associative Approach to Additivity and Maximality Effects on Blocking

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ABSTRACT

Schmajuk, Lam, and Gray (SLG, 1996) introduced an attentional-associative model able to describe a large number of classical paradigms. As other models, the SLG model describes blocking in terms of the competition between the blocker and the blocked conditioned stimulus (CS) to gain association with the unconditioned stimulus (US) or outcome. Recent data suggest, however, other factors together with competition might control the phenomenon. For instance, Beckers et al. (2005) reported that blocking and backward blocking are stronger when participants are informed that (a) the predicted US is submaximal than when it is maximal, and (b) the predictions of the US by the CSs are additive than when they are sub-additive. Submaximality refers to the evidence that the predicted US is weaker than its maximal possible value. Additivity denotes the fact that two CSs, each one independently predicting a given US, predict a stronger US when presented together. Beckers et al. suggested that their results are better explained by inferential accounts, which assume involvement of controlled and effortful reasoning, than by associative views. This chapter shows that a configural version of the SLG attentional-associative model is able to quantitatively approximate submaximality and additivity effects on blocking while providing a mechanistic explanation of the results. In general, the chapter illustrates the potential of associative models to account for newly discovered properties of known psychological phenomena.

INTRODUCTION

In the last four decades, powerful computational models of associative learning have been developed which are able to describe in great detail a large number of classical conditioning paradigms (Schmajuk, 1997, 2010). Many of these models assume that conditioned stimuli (CS) compete to gain association with the unconditioned stimulus (US). Recently, competition between cues to be-

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come accepted as the cause of certain outcome has become a major topic in the field of causal learning (De Houwer and Beckers, 2002; Shanks, 2007). Cue competition has been traditionally studied in forward blocking (Kamin, 1968), a classical conditioning paradigm that consists of presentations of CS A and CS X (the putative causes in causal learning) followed by the US (the outcome in causal learning), following A-US presentations. The procedure results in a weaker conditioned response to X than that attained when A-X-US presentations follow reinforced presentations of another conditioned stimulus, B.

According to traditional associative theories, forward blocking is the consequence of stimulus A winning the competition with X to predict the US, because the US is already predicted by A at the time of A-X-US presentations (e.g., Rescorla and Wagner, 1972), or because stimulus A is a better predictor than X of the US (e.g., Mackintosh, 1975). In contrast with these views, Beckers et al. (2006) proposed that blocking is the consequence of an inferential process which verifies that both additivity and submaximality assumptions are true. Additivity denotes the fact that two causes predict a stronger outcome when presented together than when presented independently. Submaximality refers to the evidence that a single cause does not predict the possible maximal outcome value. Therefore, according to the inferential process view, a relative weak response to X (blocking) is justified only when cause A by itself predicts an outcome that is smaller than the possible maximal outcome, thereby allowing a potential additive effect of X on the outcome to be detected. If no increment in the outcome is detected, X is said not to be a cause of that outcome.

Beckers et al. (2005) used a food allergy task in which participants were shown that the effect of stimuli other than A and X can be added (G and H additivity training) or the maximal possible value of the outcome (US maximality training) before blocking. They also tested the effect of G and H additivity training before backward blocking or recovery from overshadowing, and of G and H additivity training after blocking. Subsequently, participants were asked to rate how likely it is for a patient to develop an allergy after eating different food items. According to Beckers et al. (2005, 2006), their results can be explained in inferential terms (which might involve syllogistic logic, natural logic, inference schemes, or causal Bayes nets). Blocking is not present if either the submaximal premise (the predicted US is weaker than its maximal possible value) or the additivity premise (the predictions of the US by the CSs can be added) are not satisfied. In contrast, Beckers et al. (2005) applied the Rescorla-Wagner (1972) model to the description of outcome maximality and showed that, assuming a maximal outcome, the model incorrectly predicts more blocking with an intense than with a moderate outcome. Similar results to those reported by Beckers et al. (2005) were found both in humans (Lovibond et al., 2003) and rats (Beckers et al., 2006).

In this chapter, we show that a configural version of the Schmajuk, Lam, and Gray (1996) attentional-associative model (see also Schmajuk and Larrauri, 2006; Larrauri and Schmajuk, 2008) describes maximality effects on forward blocking, and additivity effects on forward and backward blocking.

AN ATTENTIONAL-ASSOCIATIVE MODEL OF CONDITIONING

Schmajuk, Lam, and Gray (SLG, 1996; Schmajuk and Larrauri, 2006) proposed a neural network model of classical conditioning. The network incorporates (a) an attentional mechanism regulated not only by Novelty (difference between the actual and the predicted magnitude) of the US as in the Pearce and Hall (1980) model, but also by Novelty of the conditioned stimuli (CSs) and the context (CX), (b) a network in which associations are controlled by a modified, moment-to-moment (vs. trial-to-trial) version of the Rescorla and

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