LEARNING OF CONTINGENT RELATIONSHIPS

Introduction

It has been four decades since Jenkins and Ward (1965; Ward & Jenkins, 1965) published their seminal papers concerned with judgments by human observers of the relationship between two binary events. In the intervening 40 years, research efforts in many laboratories have been directed at issues concerned with predictive and causal judgments, and the number of published papers has been increasing exponentially. This exploding interest has been revealed in a series of integrative articles (e.g., Allan, 1993; De Houwer & Beckers, 2002; Dickinson, 2001; Shanks, 1993; Young, 1995), an edited volume (Shanks, Holyoak, & Medin, 1996), the inclusion of symposia at conferences (e.g., Psychonomic Society, Vancouver 2003), and the appearance of focal meetings (e.g., Human Contingency Learning, Le Ligney, Belgium, 2004).

Although many different scenarios have been used to describe the binary judgment task to the observer, they have a basic common structure. One event either is presented or is not presented, and then another event either occurs or does not occur. In a *predictive* scenario, the antecedent event is described as a cue and the subsequent event is described as an outcome; in the *causal* scenario, the antecedent cue is usually described as a cause and the subsequent outcome is usually described as an effect. After observing a number of episodes in which each of the four cue–outcome combinations is presented with a predefined probability, the observer is asked to rate the strength of the relationship between the events.

Research and theorizing concerned with predictive and causal judgments are especially well suited to the mandate of *Learning & Behavior* to publish experimental and theoretical contributions and critical reviews concerning fundamental processes of learning and behavior in nonhuman and human animals. Although the papers in this special issue deal primarily with human data, the questions being asked and the theoretical perspectives invoked are very much influenced by data and models from nonhuman laboratories.

It was Dickinson, Shanks, and Evenden (1984) who first suggested an associative analysis of predictive judgments. Since then, there have been tremendous developments attesting to the value of applying simple, well-formulated models of learning, typically obtained from studies of the acquisition of conditional responses in nonhuman animals, to understanding the behavior of humans asked to make predictive and causal judgments. These models trace their paternity to the Rescorla–Wagner (RW) formulation of learning (Rescorla & Wagner, 1972; Wagner & Rescorla, 1972). A number of the contributed articles examine the current status of associative models with regard to providing adequate accounts of predictive and causal judgments. One important feature of these associative models is competition. There is a limit to the amount of predictive strength that an outcome can support which is allocated among all cues present—if one cue acquires more of the predictive strength available, then all other cues must get less. Thus, the attribution of an outcome to a target cue depends on the predictive value of other potential cues.

Human observers do not typically rate multiple cues independently. This observation of cue interaction led Dickinson et al. (1984) to propose an associative interpretation of their human judgment data. If Cues A and B result in a common outcome, the usual finding is that ratings of the relationship between A and the outcome depend on the strength of the relationship between B and the outcome. However, cue interaction has also provided some of the major challenges for associative accounts. Early associative models, like RW, focused on presented cues and did not allow the predictive strength of an absent cue to change. These models are unable to account for phenomena that appear to require the retrospective revaluation of absent but expected cues.

Van Hamme and Wasserman (1994) provided the first modification to RW to allow for the influence of absent but expected cues. Their revised RW model was able to explain otherwise vexing empirical findings such as backward blocking, recovery from overshadowing, and backward conditioned inhibition. In their contribution to this special issue, Wasserman and Castro emphasize the important role for absent cues. They explore new predictions of the revised RW model and provide new data for the evaluation of these predictions. Dickinson and Burke (1996), like Van Hamme and Wasserman (1994), were concerned with providing an account for retrospective revaluation effects, and they proposed a modified version of Wagner's (1981) SOP associative model (MSOP). In their contribution to the special issue, Aitken and Dickinson present a formalization of MSOP, along with simulation evidence to verify the earlier claims made by Dickinson and Burke on the basis of a descriptive analysis. Given the influence that MSOP has had on stimulating research in retrospective effects in human causal learning, a formalization of this model is most welcome.

Baetu, Baker, Darredeau, and Murphy present human and nonhuman data from a new version of the relative cue validity task, which, unlike the original task introduced by Wagner, Logan, Haberlandt, and Price (1968), does not require a priori assumptions about the effectiveness of the outcome. They conclude that their data cannot be accounted for by associative models such as RW and SOP, which attribute cue interaction to a failure to learn. They discuss the application of their *computational comparator* model to their data. According to this model, decisions about cues or causes are made by comparing the independently learned associative strength of a cue with the strength of comparator stimuli.

The dependent measure in most judgment studies is a rating about the strength of the relationship between the two binary variables. In the early literature, little attention was focused on the structure of the scenario (predictive or causal) or the exact wording or meaning of the rating question. The contributions by Vadillo, Miller, and Matute and by Pineño, Denniston, Beckers, Matute, and Miller demonstrate that these variables are indeed important. Vadillo et al. show that the pattern of ratings is different for causal, predictive-value, and predictive questions: Causal and predictive-value ratings depend on cue–outcome contingency, whereas predictive ratings depend on the probability of the outcome. Pineño et al. report that there is greater cue interaction with the causal scenario than with the predictive scenario; that is, causes interact more than predictors do. Both papers discuss the applicability of the comparator hypothesis (Miller & Matzel, 1988), as well as other models, to their data.

Associative models were introduced as an alternative to simple rule-based models, which were unable to encompass cue interaction. However, rule-based models that incorporate conditionalization have been more successful. Specifically, when assessing the contingency between Cue A and the outcome, observers must consider alternative causes; that is, they must conditionalize on the presence and on the absence of Cue B. Somewhat surprisingly, conditional rule-based accounts and associative accounts often make the same predictions, at least at asymptote. In their contribution, Goedert and Spellman present new data indicating that under certain conditions, cue interaction is observed even when it is not predicted by the conditionalization account. These results lead them to distinguish between two types of cue interaction: the process of controlling for alternative causes (i.e., conditionalization), and nonnormative discounting.

In recent years, a number of nonassociative models have been proposed that provide a “cognitive” account of cue interaction. Waldmann and his collaborators (e.g., Waldmann, 2000; Waldmann & Holyoak, 1992) have argued that judgments depend on the set of assumptions about the nature of the cues and outcomes—the causal model—adopted by the observer. One such model stipulates that multiple causes interact both when they precede and when they follow a common effect. Some researchers have reported that this is the case, but others have not obtained this result. Rather, they have found that antecedent events (whether labeled as causes or as effects) interact and that subsequent events do not. In their contribution, Waldmann and Walker present new data that shed light on this debate by delineating conditions under which the different patterns of results are found. A cognitive approach is also seen in the knowledge-based account proposed in the contribution by Buehner, who is interested in the role of temporal contiguity. Buehner suggests that the typical laboratory task oversimplifies the real-world causal structure, and discusses the important role of event parsing on causal judgments. De Houwer, Beckers, and Vandorpe favor an inferential reasoning account of cue interaction effects. They suggest that observers in causal

judgment tasks generate inferences about cues in the same way as they solve other deductive reasoning tasks. De Houwer et al. review data that are problematic for an associative account, and they discuss how these data can be encompassed by an account that incorporates higher order reasoning processes.

A novel approach is described in the contribution by Allan, Siegel, and Tangen. They note the similarity between contingency judgment tasks and signal detection tasks, and they apply a signal detection analysis to contingency judgment data. They demonstrate that the signal detection analysis provides a novel interpretation of a well-established but poorly understood phenomenon of contingency judgments—the outcome density effect.

When this journal was established (as *Animal Learning & Behavior*) in 1973, its first editor, Abram Amsel, stated the editorial policy on page 1 of the first volume. He referred to the “ecumenical spirit” that would prevail in the research published in the journal. This special issue attests to the success of such an ecumenical approach.

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