A Rational Analysis of Cognitive Control
in a Speeded Discrimination Task

Michael C. Mozer++, Michael D. Colagrosso++, David E. Huber##
++ Department of Computer Science
## Department of Psychology
* Institute of Cognitive Science
University of Colorado
Boulder, CO 80309
{mozer, colagrom, dhuber}@colorado.edu

Abstract

We are interested in the mechanisms by which individuals monitor and adjust their performance of simple cognitive tasks. We model a speeded discrimination task in which individuals are asked to classify a sequence of stimuli (Jones & Braver, 2001). Response conflict arises when one stimulus class is infrequent relative to another, resulting in more errors and slower reaction times for the infrequent class. How do control processes modulate behavior based on the relative class frequencies? We explain performance from a rational perspective that casts the goal of individuals as minimizing a cost that depends both on error rate and reaction time. With two additional assumptions of rationality—that class prior probabilities are accurately estimated and that inference is optimal subject to limitations on rate of information transmission—we obtain a good fit to overall RT and error data, as well as trial-by-trial variations in performance.

Consider the following scenario: While driving, you approach an intersection at which the traffic light has already turned yellow, signaling that it is about to turn red. You also notice that a car is approaching you rapidly from behind, with no indication of slowing. Should you stop or speed through the intersection? The decision is difficult due to the presence of two conflicting signals. Such response conflict can be produced in a psychological laboratory as well. For example, Stroop (1935) asked individuals to name the color of ink on which a word is printed. When the words are color names incongruous with the ink color—e.g., “blue” printed in red—reaction times are slower and error rates are higher. We are interested in the control mechanisms underlying performance of high-conflict tasks. Conflict requires individuals to monitor and adjust their behavior, possibly responding more slowly if errors are too frequent.

In this paper, we model a speeded discrimination paradigm in which individuals are asked to classify a sequence of stimuli (Jones & Braver, 2001). The stimuli are letters of the alphabet, A–Z, presented in rapid succession. In a choice task, individuals are asked to press one response key if the letter is an X or another response key for any letter other than X (as a shorthand, we will refer to non-X stimuli as Y). In a go/no-go task, individuals
are asked to press a response key when \( X \) is presented and to make no response otherwise. We address both tasks because they elicit slightly different decision-making behavior. In both tasks, Jones and Braver (2001) manipulated the relative frequency of the \( X \) and \( Y \) stimuli; the ratio of presentation frequency was either 17:83, 50:50, or 83:17. Response conflict arises when the two stimulus classes are unbalanced in frequency, resulting in more errors and slower reaction times. For example, when \( X \)'s are frequent but \( Y \) is presented, individuals are predisposed toward producing the \( X \) response, and this predisposition must be overcome by the perceptual evidence from the \( Y \).

Jones and Braver (2001) also performed an fMRI study of this task and found that anterior cingulate cortex (ACC) becomes activated in situations involving response conflict. Specifically, when one stimulus occurs infrequently relative to the other, event-related fMRI response in the ACC is greater for the low frequency stimulus. Jones and Braver also extended a neural network model of Botvinick, Braver, Barch, Carter, and Cohen (2001) to account for human performance in the two discrimination tasks. The heart of the model is a mechanism that monitors conflict—the posited role of the ACC—and adjusts response biases accordingly. In this paper, we develop a parsimonious alternative account of the role of the ACC and of how control processes modulate behavior when response conflict arises.

1 A RATIONAL ANALYSIS

Our account is based on a rational analysis of human cognition, which views cognitive processes as being optimized with respect to certain task-related goals, and being adaptive to the structure of the environment (Anderson, 1990). We make three assumptions of rationality: (1) perceptual inference is optimal but is subject to rate limitations on information transmission, (2) response class prior probabilities are accurately estimated, and (3) the goal of individuals is to minimize a cost that depends both on error rate and reaction time.

The heart of our account is an existing probabilistic model that explains a variety of facilitation effects that arise from long-term repetition priming (Colagrosso, in preparation; Mozer, Colagrosso, & Huber, 2000), and more broadly, that addresses changes in the nature of information transmission in neocortex due to experience. We give a brief overview of this model; the details are not essential for the present work.

The model posits that neocortex can be characterized by a collection of information-processing pathways, and any act of cognition involves coordination among pathways. To model a simple discrimination task, we might suppose a perceptual pathway to map the visual input to a semantic representation, and a response pathway to map the semantic representation to a response. The choice and go/no-go tasks described earlier share a perceptual pathway, but require different response pathways. The model is framed in terms of probability theory: pathway inputs and outputs are random variables and microinference in a pathway is carried out by Bayesian belief revision.

To elaborate, consider a pathway whose input at time \( t \) is a discrete random variable, denoted \( X(t) \), which can assume values \( 1, 2, 3, \ldots n_x \) corresponding to alternative input states. Similarly, the output of the pathway at time \( t \) is a discrete random variable, denoted \( Y(t) \), which can assume values \( 1, 2, 3, \ldots n_y \). For example, the input to the perceptual pathway in the discrimination task is one of \( n_x = 26 \) visual patterns corresponding to the letters of the alphabet, and the output is one of \( n_y = 26 \) letter identities. (This model is highly abstract: the visual patterns are enumerated, but the actual pixel patterns are not explicitly represented in the model. Nonetheless, the similarity structure among inputs can be captured, but we skip a discussion of this issue because it is irrelevant for the current work.) To present a particular input alternative, \( i \), to the model for \( T \) time steps, we clamp \( X(t) = i \) for \( t = 1 \ldots T \). The model computes a probability distribution over \( Y \) given \( X \), i.e., \( P(Y(t) | X(1) \ldots X(t)) \).