# Does Criterial Learning Depend on Procedural Mechanisms?

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Learning a response criterion is a critical requirement in many categorization and decision-making tasks. Despite its importance, little is known about the cognitive and neural processes that mediate criterial learning. One possibility is that criterial learning relies exclusively on executive attention and declarative memory-based mechanisms, and another is that criterial learning is a form of simple associative learning that depends on procedural memory. Much evidence suggests that short feedback delays interfere with procedural learning, but not with learning that depends on explicit, declarative-memory systems. An experiment is described in which we investigated whether or not short feedback delays impaired criterial learning, relative to conditions where the feedback immediately followed the response.

*Keywords:* associative learning, categorization

## Introduction

A huge literature suggests that the learning of one-dimensional categorization rules is primarily an explicit process that depends on a large neural network that includes the prefrontal cortex (PFC) (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Bunge & Wallis, 2007; Erickson & Kruschke, 1998). Several different cognitive processes are thought to underlie rule learning of this nature. For example, the COVIS theory of category learning (Ashby et al., 1998) hypothesizes that rule learning includes subprocesses that select or construct an appropriate rule, maintain the selected rule in working memory, switch attention from a discredited rule to a new candidate rule, and learn the appropriate criterion on the relevant stimulus dimension that separates the two category responses. This latter criterial-learning process is thought to be ubiquitous in many different decision-making tasks. For example, it is the only form of learning assumed by signal detection theory (Macmillan & Creelman, 2005).

Despite the prevalence of criterial learning, and its key role in explicit tasks such as rule-based category learning, very little is known about its mediating cognitive and neural processes. An obvious hypothesis might be that criterial learning depends on explicit processes, such as executive attention and working memory. However, unlike the all-or-none nature of other rule-learning processes such as rule selection, criterial learning seems incremental, in the same way as category-learning tasks thought to depend on implicit, procedural-learning systems (Smith & Ell, 2015).

Thus, there are at least two qualitatively distinct possibilities. One is that criterial learning relies exclusively on PFC-based mechanisms associated with working memory and executive attention. For example, the criterion might be learned by holding a representation of a stimulus that has the criterion value on the relevant dimension in working memory and comparing new stimuli to this remembered referent. A quite different possibility is that criterial learning is a form of procedural learning. For example, the criterion might be learned by initial guessing followed by the gradual formation of stimulus-response associations.

This article describes the first known direct test of whether criterial learning is mediated by implicit, procedural-learning processes, or by explicit, declarative memory-based processes. To test between these two possibilities, we examined criterial learning when feedback was delayed by several seconds. A number of studies have reported that short feedback delays interfere with procedural learning, but even relatively long delays have no effect on learning that depends on explicit, declarative-memory systems (Dunn, Newell, & Kalish, 2012; Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005).

Much evidence suggests that procedural learning is mediated within the basal ganglia, and especially at cortical-striatal synapses, where synaptic plasticity seems to follow reinforcement learning rules (Ashby & Ennis, 2006; Houk, Adams, & Barto, 1995; Mishkin, Malamut, & Bachevalier, 1984; Willingham, 1998). Delayed feedback is thought to impair striatal-mediated procedural learning by interfering with the basic biochemical processes that mediate cortical-striatal synaptic plasticity. Synaptic plasticity in the striatum is strongest when the intracellular signaling cascades driven by NMDA receptor activation and dopamine (DA) D1 receptor activation coincide (Lisman, Schulman, & Cline, 2002; Rudy, 2014). The further apart in time these two cascades

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peak, the less effect DA will have on synaptic plasticity. For example, Yagishita et al. (2014) reported that synaptic plasticity was best [i.e., greatest increase in spine volume on striatal medium spiny neurons (MSNs)] when DA neurons were stimulated 600 ms after MSNs. When the DA neurons were stimulated before the MSNs or 5 s after the MSNs, then no evidence of any plasticity was observed. Similar results have been reported in information-integration category learning – which is thought to depend on procedural learning. First, Worthy, Markman, and Maddox (2013) reported that information-integration learning is best with feedback delays of 500ms and slightly worse with delays of 0 or 1000ms. Second, several studies have reported that feedback delays of 2.5 s or longer impair information-integration learning, whereas delays as long as 10 secs have no effect on the learning of explicit categorization rules (Dunn et al., 2012; Maddox et al., 2003; Maddox & Ing, 2005).

Thus, the critical question addressed in this article is whether criterial learning is impaired in the presence of feedback delays.

## Materials & Methods

### Participants & Conditions

Fifty-nine participants were UCSB undergraduates and received course credit for their participation. All had normal or corrected to normal vision. We randomly assigned each participant to one of three conditions (target $N > 16$ per condition based on similar previous research): delayed feedback (Delay: $N = 21$); immediate feedback with a short intertrial interval (ITI) (Short ITI:$N = 21$); or immediate feedback with a long ITI (Long ITI: $N = 17$). Participants were excluded from subsequent analyses if they solved fewer than 4 problems over the course of the entire experiment. This criterion was chosen from inspection of Figure **??**, which shows the number of problems solved by each participant in each condition displayed as histograms. Note that all conditions – especially the Short ITI and Long ITI condition – appear bimodal. The lower mode corresponds to participants that performed very poorly and were most likely poorly motivated. The number of participants excluded was not significantly different among groups [$\chi^2(2) = 0.56, p = .76$], indicating that exclusion was likely not driven by experiment-specific factors. Forty-five participants survived this exclusion (Delay: $N = 16$, Short ITI: $N = 17$, Long ITI: $N = 12$).

### Apparatus

All experiments were performed in a dimly lit room. Participants sat approximately 24” from a 17” × 11” monitor running at a resolution of 1680 × 1050 pixels. Participants made category judgments by pressing the ‘d’ or ‘k’ keys on a standard computer keyboard for ‘A’ or ‘B’ choices, respectively. Stickers with bold print ‘A’ or ‘B’ were placed on the appropriate keys.

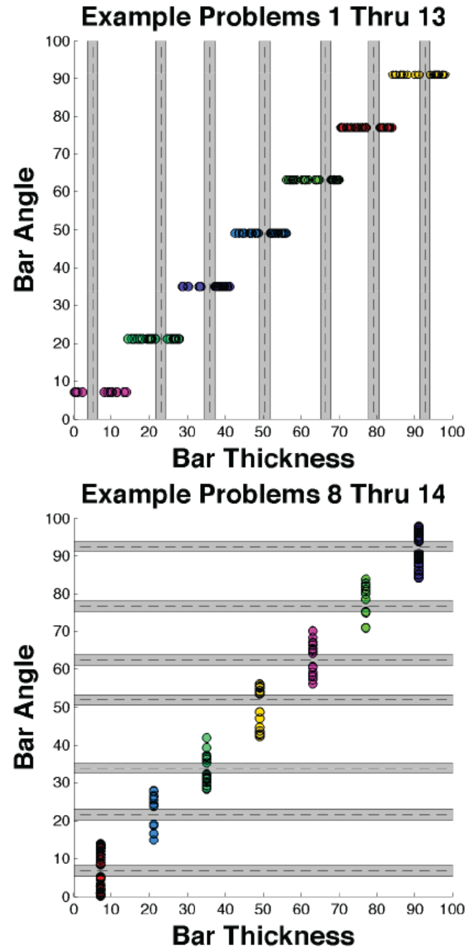


*Figure 1.* Category sample space. Different colors represent different category problems. Dashed lines are category boundaries (criterion) and the surrounding solid lines mark a no-man’s land in which no stimuli were sampled.

### Stimuli and Categories

Stimuli were circular sine-wave gratings that varied in bar width and bar orientation, drawn from various 1-dimensional uniform distributions specific to the current category problem. We first defined an arbitrary 2-dimensional $[0-100, 0-100]$ stimulus space, and then split each dimension of this space into 7 bins of width 14 units each. The structure of the various criterial-learning tasks is illustrated in Figure 1. Each criterial-learning problem was created by first randomly selecting a relevant dimension, and then randomly selecting one of the 7 bins defined on that dimension. Each bin was also associated with a corresponding unique value on the irrelevant dimension. We buffered the to-be-learned response criterion by 10% of total bin width on either side with a no-

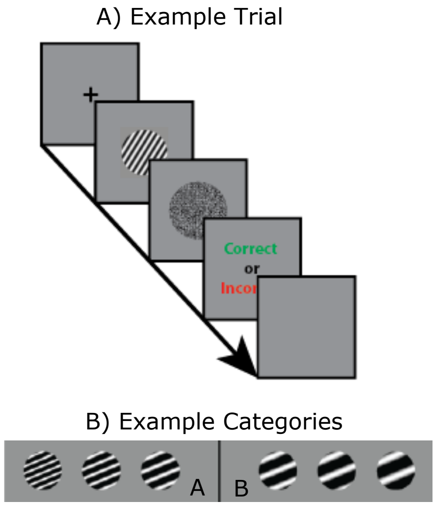


*Figure 2*. Example trial and category problem. A) Events that occurred on each trial. B) An example of a typical category structure.

stimulus region. Random uniform samples from the remaining eligible region of each bin were then selected and presented to the participant until 9 correct responses out of any 10 responses in a row advanced the participant to the next problem. Note that every category problem was a simple one-dimensional rule in which optimal accuracy was 100%. Each $(x, y)$ pair from this arbitrary stimulus space was converted to a grating according to the nonlinear transformations defined by Treutwein, Rentschler, and Caelli (1989) which roughly equate the salience of each dimension (for details, see also Crossley & Ashby, in press).

### Procedure

Participants were explicitly told the relevant dimension, as well as the generic response mapping (e.g., thick bars = 'A', thin bars = 'B'). Figure 2 shows the structure of an example trial, along with an example of a typical category structure. All trials in every condition included a 500 ms fixation cross, a response-terminated stimulus, a circular white-noise mask, corrective feedback, and an inter-trial interval (ITI) that varied according to condition. The text 'Correct' was displayed in centered, large green font after correct responses, and the text 'Incorrect' was displayed in centered, large red font after incorrect responses.

The three conditions are described in Table 1. In the Delay condition, feedback was delayed 3.5 s after the response and the ITI was 0.5 s. There were two immediate feedback control conditions in which feedback was given 0.5 s after the response. The Short ITI had the same ITI as the Delay condition and the Long ITI had the same trial duration as the Delay condition (i.e., the same inter-stimulus interval).

Table 1
*Durations (in s) of Trial Events in each Condition*

| Conditions | Stim | Mask | FB | ITI |
|---|---|---|---|---|
| Delay | RT | 3.5 | 1.0 | 0.5 |
| Immediate/Short ITI | RT | 0.5 | 1.0 | 0.5 |
| Immediate/Long ITI | RT | 0.5 | 1.0 | 3.5 |

## Results

INSERT FINAL PROJECT RESULTS HERE.

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## Author Notes

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