

Criterial Learning and Feedback Delay: Insights from Computational Models and Behavioral Experiments

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Abstract

The notion of a response criterion is ubiquitous in psychology, yet its cognitive and neural underpinnings remain poorly understood. To address this shortcoming, three computational models that capture different hypotheses about criterial learning were developed and tested. The time-dependent drift model assumes the criterion is stored in working memory and that its value drifts over time. The delay-sensitive learning model assumes that the magnitude of criterial learning is temporally discounted by feedback delay. The reinforcement-learning model assumes that criterial learning emerges from stimulus-response association learning without an explicit representation of the criterion, with learning rate also temporally discounted by feedback delay. The performance of these models was investigated under varying feedback delay and intertrial interval (ITI) durations. The time-dependent drift model predicted that long ITIs and feedback delays both impair criterial learning. In contrast, the delay-sensitive and reinforcement-learning models predicted impairments only with feedback delays. Two behavioral experiments tested these predictions. In Experiment 1, participants were explicitly instructed about the relevant dimension to isolate criterial learning, and short feedback delays impaired learning relative to immediate feedback. In Experiment 2, using binary-feature stimuli without instruction (isolating rule selection/switching), neither longer ITIs nor delayed feedback affected performance. These results support the delay-sensitive and reinforcement-learning models, and suggest that even in tasks that appear to rely on explicit, rule-based reasoning, criterial learning may have strong associative underpinnings.

Keywords: response criterion; criterial learning; associative learning; categorization; procedural learning

Introduction

The notion of a response criterion is ubiquitous in psychology. It is a key component of almost all decision models. For example, the hypothesis that even YES-NO detection decisions are determined by comparing the sensory magnitude to a response criterion that is under the observer’s control, rather than to a fixed absolute threshold, allowed signal detection theory to supplant classical threshold theory as the dominant model in psychophysics (Green & Swets, 1966). All models that include a response criterion assume its value is learned and can shift if changes are made to instructions or payoffs. So criterial learning is a fundamental component of almost all decision-making models. Despite its importance, however, the cognitive and neural mechanisms that underlie criterial learning remain poorly understood.

This article addresses this shortcoming through a combination of computational modeling and empirical data collection. Specifically, we develop and test three different computational models that make qualitatively different assumptions about how the criterion is learned. The models differ in the role they assign to working memory and in whether they treat the response criterion as a fundamental psychological construct, or instead assume that behavior is driven purely by stimulus-response associations without any criterion guiding responses. These models are then tested in two behavioral experiments. The modeling and empirical focus are on how feedback delays and the length of the intertrial interval (ITI) affect criterial learning. All criterial-learning models assume that updating (i.e., learning) of the criterion occurs during the time interval between feedback presentation and the stimulus presentation that defines the onset of the next trial. So feedback delay and the length of the ITI are the independent variables that most clearly differentiate the conflicting predictions of criterial-learning models. Furthermore, feedback delays are known to impair some forms of learning (i.e., procedural) much more than others (i.e., learning that relies on declarative memory), so feedback-delay manipulations offer a powerful method of disambiguating the nature of criterial learning (Ell et al., 2009; Maddox & Ing, 2005; Maddox et al., 2003).

Although the models could be tested in any task that depends on criterial learning, the two experiments we describe used a one-dimensional category-learning task. In such tasks, stimuli vary across trials on two or more dimensions – one relevant to categorization and one or more that are irrelevant. The observer’s goal is to identify the relevant dimension and learn the response criterion that maximizes accuracy. This task has been used in hundreds of studies, and all current models of performance in this task emphasize the role of criterial learning.

In the first behavioral experiment, participants were explicitly instructed about the relevant dimension, thereby isolating criterial learning from rule selection and switching processes. The results showed that short feedback delays impaired learning compared to immediate feedback. The second behavioural experiment used stimuli composed of binary features – where no criterial learning is needed – and did not instruct participants about the relevant dimension. Thus, this experiment isolated rule selection and switching from

criterial learning. The results found that increasing feedback delay or ITI did not affect performance. These findings suggest that feedback delays impact criterial learning but not the discovery of the relevant stimulus dimension. More broadly, they indicate that criterial learning may recruit procedural learning, even in tasks that seem to rely on explicit, rule-based processes.

New Computational Models of Criterial Learning

We developed computational models of criterial learning within two broad architectures and examined their sensitivity to ITI duration and feedback delay. The architectures differ in whether they assume that the response criterion is explicitly represented in memory. In the first architecture, the criterion is stored in memory, and responses are generated by comparing the current percept with this stored referent. The criterion is updated after errors using a gradient-descent rule. Models in this class can exhibit sensitivity to ITI and feedback delay in three distinct ways: (1) perceptual drift, where stimulus representations change over time, (2) criterial drift, where the stored criterion shifts over time, and (3) delay-sensitive updating, where the magnitude of criterion updates decreases with longer feedback delays. In the second architecture, no explicit criterion is stored. Instead, reinforcement learning forms direct stimulus–response associations that drive performance. Sensitivity to ITI and feedback delay arises from either perceptual drift or delay-sensitive updating, but criterial drift is not possible since no criterion is represented.

For each of these models, denote the time of stimulus presentation on the current trial by T_S , the response time by T_R , the time when feedback is displayed by T_F , and the time when the stimulus that begins the next trial is displayed by T_{S+} . Then note that the feedback delay equals $t_{FD} = T_F - T_R$ and the duration of the ITI equals $t_{ITI} = T_{S+} - T_F$.

Models that assume a stored criterion

These models assume that the observer constructs a response criterion, maintains it in working memory, and makes decisions by comparing the percept to this criterion. They may further posit that both the stored criterion and the perceived stimulus value drift over time, with the extent of drift increasing both within a trial and across consecutive trials. In addition, they may assume that the learning rate for updating the criterion decreases as the feedback delay increases.

Let $x_n(t)$ and $c_n(t)$ denote the values of the percept and the criterion, respectively, on trial n at time t . Then the decision rule on trial n is:

$$\text{Respond } R_n = \begin{cases} A, & \text{if } x_n(T_S) \leq c_n(T_S) \\ B, & \text{if } x_n(T_S) > c_n(T_S). \end{cases} \quad (1)$$

Note that this equation indicates that the response is made immediately upon stimulus presentation. We therefore are not explicitly modelling the time-extended cognitive processes that govern evidence accumulation and the corresponding response time.

If positive feedback is received, then the value of the criterion remains unchanged for the next trial (except for drift – see Equation 3). The rationale here is that if the response is correct, then the observer has effectively gained zero information about how their criterion

should be modified. If negative feedback is received, then the criterion is modified according to the standard model (Sutton & Barto, 1998):

$$c_n(T_F + \Delta_t) = c_n(T_F) + \frac{\alpha}{t_{FD}}[x_n(T_F) - c_n(T_F)], \quad (2)$$

where α is a learning-rate parameter, and Δ_t is the time it takes to complete the updating. It is straightforward to show that the iterative Equation 2 is equivalent to computing a weighted mean (weighted by recency) of the values of all percepts that occur on error trials (e.g., Ashby, 2017). This updating rule will gradually converge on the optimal criterion value (i.e., the true criterion value the observer is trying to learn).

The term $\frac{\alpha}{t_{FD}}$ captures the notion that the magnitude of the update decreases as the feedback delay increases. As a result, when feedback is delayed, the system becomes less responsive to errors, leading to slower learning compared to immediate feedback conditions. However, since this model is consistent with the idea that criterial learning relies on working memory – and the available evidence suggests that logical reasoning and working memory are unaffected by feedback delays of several seconds (e.g., in one-dimensional rule-based category learning tasks; Ell et al., 2009; Maddox & Ing, 2005; Maddox et al., 2003) – the learning process described in Equation 2 likewise be unaffected by feedback delay. In this case, the term $\frac{\alpha}{t_{FD}}$ is replaced by α , making the learning rate independent of feedback delay.

This model further assumes that both the stimulus and the criterion representations may drift randomly throughout the duration of time they are maintained in working memory. The representation of the criterion must always be maintained in working memory, whereas drift in the stimulus representation affects performance up until the feedback is presented, but not afterwards. We modeled the drift in both the criterion and the percept by adding white noise to their initial values. Specifically, we assumed that for all $t > T_S$

$$c_n(t) = c_n(T_S) + \eta_c \epsilon(t), \quad (3)$$

and

$$x_n(t) = x_n(T_S) + \eta_x \epsilon(t), \quad (4)$$

where $\epsilon(t)$ is white noise and η_c and η_x are parameters that determine the amount of drift over time. Note that these parameters are permitted to be equal to zero which is equivalent to assuming that the criterion and/or the percept do not drift over time at all.

This model predicts that at the time of feedback, the response criterion $c_n(T_F)$ will be normally distributed with mean $c_n(T_S)$ and variance $t_{FD}\eta_c^2$. Similarly, at the time when the stimulus that defines the next trial is presented, the criterion $c_n(T_{S+}) = c_{n+1}(T_S)$ is normally distributed with mean $c_n(T_S)$ and variance $(t_{FD} + t_{ITI})\eta_c^2$. The predictions for the percept are similar. Specifically, at the time when feedback is presented, the percept $x_n(T_F)$ is normally distributed with mean $x_n(T_S)$ and variance $(T_F - T_S)\eta_x^2$.

Reinforcement-learning models

The reinforcement-learning models gradually associate responses with stimuli, and therefore do not include an explicit representation of the response criterion. The models are based on an actor-critic architecture and use reinforcement learning to form stimulus-

response associations (Sutton & Barto, 1998). These models assumes that the perceptual representation of each stimulus is defined by the pattern of activation across 25 sensory units that are characterized by overlapping tuning curves. Each unit is maximally excited by one specific stimulus, which we call the unit’s preferred stimulus. Specifically, the activation of the i^{th} sensory unit on trial n is given by

$$A_i(n) = \exp\left(\frac{-[d_{i,S_n}]^2}{\sigma^2}\right) \quad (5)$$

where d_{i,S_n} is the (Euclidean) distance between the preferred stimulus value of the i^{th} sensory unit and the value of the stimulus that was presented on trial n , and σ is a constant that increases with perceptual noise.

The model includes two decision or actor units – one associated with each of the two possible responses. Initially, each sensory unit is connected to both actor units with some random connection strength. Let $\omega_{iJ}(n)$ denote the strength of the connection between sensory unit i and actor unit J (for $J = A$ or B) on trial n . Then the activation in actor unit J on trial n , denoted by $V_J(n)$, equals

$$V_J(n) = \sum_i \omega_{iJ}(n) A_i(n) \quad (6)$$

Responses are generated by the decision rule:

$$\text{Respond } R_n = \begin{cases} A, & \text{if } V_A(n) > V_B(n) \\ B, & \text{if } V_A(n) \leq V_B(n). \end{cases} \quad (7)$$

The connection strengths $\omega_{iA}(n)$ and $\omega_{iB}(n)$ are updated after feedback is received on each trial according to standard reinforcement learning rules (Sutton & Barto, 1998):

$$\omega_{iA}(n) = \omega_{iA}(n-1) + \frac{\alpha_{actor}}{t_{FD}} \delta(n-1) \quad (8)$$

$$\omega_{iB}(n) = \omega_{iB}(n-1) + \frac{\alpha_{actor}}{t_{FD}} \delta(n-1), \quad (9)$$

where α_{actor} is the learning-rate of the actor, and $\delta(n-1)$ is the reward prediction error on trial $n-1$. Note that as in Equation 2, the learning rate is scaled by the inverse of the feedback delay.

Much evidence suggests that this type of stimulus-response learning is mediated largely within the striatum, and is facilitated by a dopamine (DA) mediated reinforcement learning signal that is time dependent (e.g., Valentin et al., 2014). Specifically, the dopamine signal generated by positive feedback appears to peak at around 500 ms after feedback and then decay back to baseline levels within 2 or 3 s (Yagishita et al., 2014). As a result, synaptic plasticity at cortical-striatal synapses is attenuated with increasing feedback delays (Yagishita et al., 2014). The scaling of α_{actor} by $1/t_{FD}$ is one way to model this phenomenon. However, it is possible that criterial learning via stimulus-response associations is mediated by other brain systems that are less sensitive to feedback delay. In this case, the learning rate would be independent of feedback delay, and the term $\frac{\alpha_{actor}}{t_{FD}}$ would be replaced by

α_{actor} .

The reward prediction error on trial $n - 1$ is defined as the value of the obtained reward, denoted by $R(n - 1)$ minus the value of the predicted reward, denoted by $P(n - 1)$:

$$\delta(n - 1) = R(n - 1) - P(n - 1). \quad (10)$$

The predicted reward on trial n is determined by the critic via

$$P(n) = P(n - 1) + \frac{\alpha_{critic}}{t_{FD}} \delta(n - 1), \quad (11)$$

where α_{critic} is the learning rate of the critic. This learning rate may again be scaled by the inverse of the feedback delay. If sensitivity to feedback delay is not assumed in Equation 2, then the term $\frac{\alpha_{critic}}{t_{FD}}$ is replaced by α_{critic} .

Because this class of models does not store an explicit response criterion, it cannot incorporate criterial drift. It can, however, incorporate perceptual drift. In this case, the value of the current stimulus used to compute sensory unit activation (Equation 5) is assumed to drift over time according to

$$S_n(t) = S_n(T_S) + \eta_S \epsilon(t), \quad (12)$$

where η_c scales the magnitude of the drift and $\epsilon(t)$ is a noise process.

Simulation Results

We investigated how changing the duration of the feedback delay and ITI affect criterial learning for each class of model. More specifically, we simulated performance of each model in a categorization task that included two categories of stimuli that varied on a single stimulus dimension and that could be categorized perfectly by comparing each stimulus to an appropriate value of the response criterion (We used the same experimental design as in Experiment 1, so see those methods for more details). Our simulations included three experimental conditions: Delayed Feedback, Long ITI, and Control. The Delayed-Feedback condition included a long feedback delay (3.5 s) and a short ITI (0.5 s). The Long-ITI condition matched the total trial duration of the Delayed-Feedback condition but with a short feedback delay (0.5 s) and a long ITI (3.5 s). The Control condition included both a short feedback delay (0.5 s) and a short ITI (0.5 s). Each simulation continued for 200 trials or until the model responded correctly for 12 trials in a row. For each set of parameter values, we simulated the model 100 times and averaged the results, yielding one observed performance metric measured in trials-to-criterion for each condition.

Our approach was to generate predictions for each of the three experimental conditions across a wide range of parameter values. We then used parameter-space partitioning (PSP) to evaluate the performance of each model (PSP; Pitt et al., 2006). Classical PSP is defined for non-stochastic models and is often implemented by exploring the parameter space via MCMC. In contrast, we used brute force search over a grid of plausible parameter values. Because our models are stochastic, at each sampled parameter setting we generated multiple simulations and classified the expected qualitative pattern. PSP calculates the proportion of the parameter space where a model makes specific qualitative predictions. We

focused on four such predictions. The first was that learning under feedback delay would be slower than in the other two conditions. The second was that learning in the Long ITI condition would be slower than in the other two. The third was that learning in the control condition would be slower than in either of the other two conditions. The fourth was a catch-all category encompassing any other possible patterns of results. For each model, the PSP analysis quantified the proportions of the explored parameter space where the model made these qualitative predictions.

Models that assume a stored criterion

We investigated predictions of these models across a wide range of values for the parameters η_x , η_c , and α . Specifically, in the case of α , we stepped through every value in the interval $[0, 0.2]$, with a step size of .01. In the case of both η_x , and η_c , we searched over the interval $[0, 1]$, with a step size of 0.1. We also explored the binary case of whether or not the update rate α was scaled by the feedback delay. The results are shown in Figure 1.

Figure 1 shows that this class of models makes qualitatively different predictions depending on whether the update rule is sensitive to feedback delay. When delay sensitivity is assumed (panels A and B), the model consistently predicts that feedback delays impair criterion learning. When delay sensitivity is not assumed (panels C and D), the model instead predicts that long ITIs impair learning, except in cases with very small learning rates α (panel D).

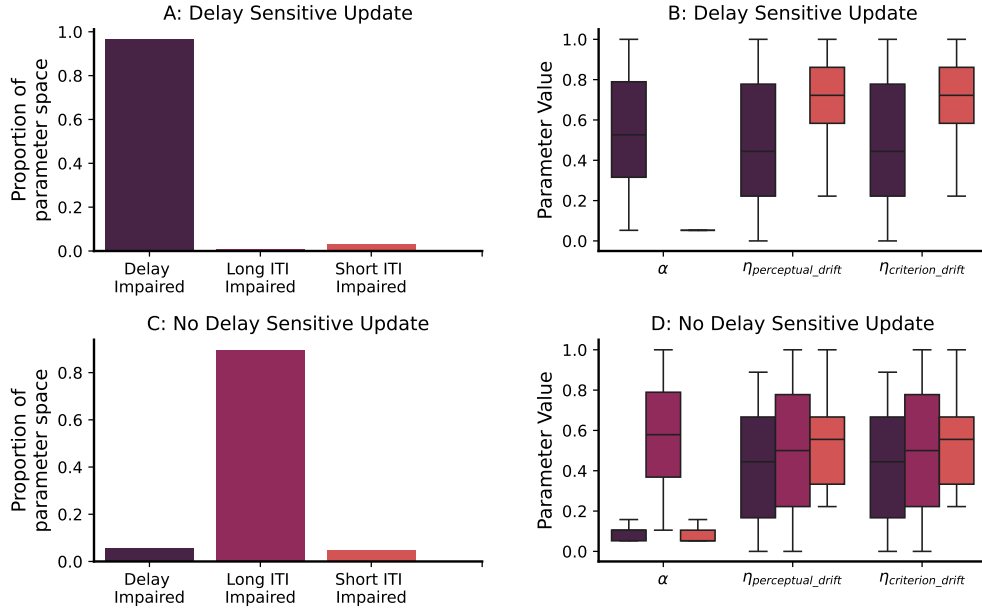
Reinforcement-learning models

We investigated the effects on performance predicted by the reinforcement-learning model of three parameters – the perceptual-noise variance σ^2 and the actor and critic learning rates (i.e., α_{actor} and α_{critic} , respectively). In the case of both α_{actor} and α_{critic} , we stepped through every value in the interval $[0, 0.2]$, with a step size of .02. We constrained our search over these parameters to this interval because reinforcement-learning models are prone to instability at very high learning rates (Sutton & Barto, 1998). As evidence of this, at higher learning rates, the model failed to learn with any consistency – that is, in most cases, it failed to reach the learning criterion (12 correct responses in a row) within the allowable 200 trials. In the case of σ , we searched over the interval $[1, 10]$, with a step size of 3. We also explored the binary case of whether or not the update rate α was scaled by the feedback delay. As with the other models, all scores were normalized by the largest observed value.

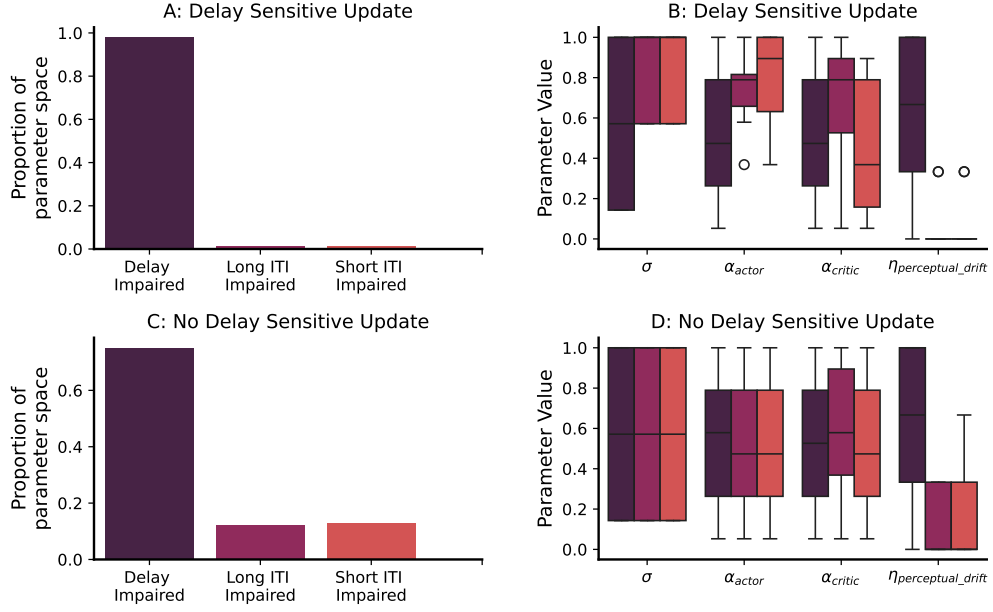
The results are described in Figure 2. Note this model predicts that delayed feedback impairs criterial learning more than a long ITI across the vast majority of parameters explored. As can be seen in Figure 2D, the few exceptions tend to occur when perceptual drift has relatively small values.

Summary of modeling results

We examined two classes of criterial-learning models that make different predictions about the effects of feedback delay and ITI. The first class assumes that the criterion is stored in memory and compared against incoming stimuli to generate responses. These models predict greater impairment from feedback delay only when the update rule is explicitly

**Figure 1**

A: Assuming a delay-sensitive update, the proportion of parameter space where the models that assume a stored criterion predicted each of four qualitative patterns: (1) slower learning under feedback delay, (2) slower learning in the Long-ITI condition, (3) slower learning in the control condition, and (4) any other pattern. **B:** Assuming a delay-sensitive update, Boxplot of the parameter ranges leading to each PSP pattern. All parameter values were normalized by the largest value in the search range, so the ordinate ranges from zero to one for all parameters. **C:** Assuming no delay-sensitive update, the proportion of parameter space where the models that assume a stored criterion predicted each of four qualitative patterns: (1) slower learning under feedback delay, (2) slower learning in the Long-ITI condition, (3) slower learning in the control condition, and (4) any other pattern. **D:** Assuming no delay-sensitive update, Boxplot of the parameter ranges leading to each PSP pattern. All parameter values were normalized by the largest value in the search range, so the ordinate ranges from zero to one for all parameters. Note: In all panels, color indicates the PSP pattern.

**Figure 2**

A: Assuming a delay-sensitive update, the proportion of parameter space where the models that assume a stored criterion predicted each of four qualitative patterns: (1) slower learning under feedback delay, (2) slower learning in the Long-ITI condition, (3) slower learning in the control condition, and (4) any other pattern. **B:** Assuming a delay-sensitive update, Boxplot of the parameter ranges leading to each PSP pattern. All parameter values were normalized by the largest value in the search range, so the ordinate ranges from zero to one for all parameters. **C:** Assuming no delay-sensitive update, the proportion of parameter space where the models that assume a stored criterion predicted each of four qualitative patterns: (1) slower learning under feedback delay, (2) slower learning in the Long-ITI condition, (3) slower learning in the control condition, and (4) any other pattern. **D:** Assuming no delay-sensitive update, Boxplot of the parameter ranges leading to each PSP pattern. All parameter values were normalized by the largest value in the search range, so the ordinate ranges from zero to one for all parameters. Note: In all panels, color indicates the PSP pattern.

delay-sensitive. Otherwise, they are generally more impaired by long ITIs than by feedback delay. The second class assumes no stored criterion, with responses driven instead by reinforcement learning through gradual tuning of stimulus–response associations. These models almost uniformly predict greater impairment from feedback delay than from long ITIs.

Experiment 1

Experiment 1 investigated how feedback delay and the length of the ITI affect criterial learning in humans. As a result, it also provides rigorous tests of the predictions of the time-dependent drift model, the delay-sensitive learning model, and the reinforcement-learning model.

The stimuli in Experiment 1 were circular sine-wave gratings that varied across trials in bar width and bar orientation. These stimuli were divided into two categories according to their value on one of the two dimensions. In other words, the optimal strategy was to set a response criterion on the single relevant dimension, and then choose a categorization response based on whether the value of the presented stimuli on this dimension was larger or smaller than the criterion value.

The experiment isolated criterial learning by (1) explicitly instructing participants on the relevant stimulus dimension and rule structure (e.g., thick bars are “A”, thin bars are “B”), and (2) eliminating variability along the irrelevant stimulus dimension. In other words, the instructions identified the relevant stimulus dimension, and as a result, the only learning required was criterial learning.

Method

Apparatus

All experiments were performed in a dimly lit room. Participants sat approximately 24” from a 17” \times 11” monitor running at a resolution of 1680 \times 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.

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. Each (x, y) pair from this arbitrary stimulus space was converted to a grating according to the nonlinear transformations defined by Treutwein et al. (1989), which roughly equate the salience of each dimension (for details, see also Crossley and Ashby (2015)).

The structure of the various criterial-learning tasks is illustrated in Figure 3. Each criterial-learning problem was created by first selecting a relevant dimension. This was spatial frequency for the problems 1 through 7 and orientation for problems 8 through 14. We then randomly selected one of the 7 bins defined on that dimension. Each bin was also

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

| Conditions | Stim | Mask | FB | ITI |
|------------------|------|------|-----|-----|
| Control | RT | 0.5 | 1.0 | 0.5 |
| Delayed Feedback | RT | 3.5 | 1.0 | 0.5 |
| Long ITI | RT | 0.5 | 1.0 | 3.5 |

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-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%. Note also that the relative location of the optimal response criterion varied across problems.

Procedure

There were three conditions (described in detail in Table 1). In the Delayed-Feedback condition, feedback was delayed 3.5 s after the response and the ITI was 0.5 s. In the Long-ITI condition, feedback was delayed 0.5 s after the response and the ITI was 3.5 s. Finally, in the Control condition, feedback was delayed 0.5 s after the response and the ITI was 0.5 s.

Each participant completed a series of one-dimensional category-learning tasks or problems, which are described in Figure 3. Each problem included stimuli in two distinct clusters that varied over a restricted range of the relevant dimension. Critically, the optimal criterion value varied from problem-to-problem with respect to its position within this range. For example, for some problems the optimal criterion was below the midpoint of the range and for other problems it was above the midpoint.

Participants were explicitly told the relevant dimension for each problem, as well as the generic response mapping (e.g., thick bars = “A”, thin bars = “B”). Figure 4 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.

Participants practiced each problem until they responded correctly on 9 of the previous 10 trials. At this point, the problem changed. Each participant completed as many problems as possible in 512 trials or until they had been in the lab for 60 minutes (including time to acquire consent and give instructions), at which point the session was terminated.

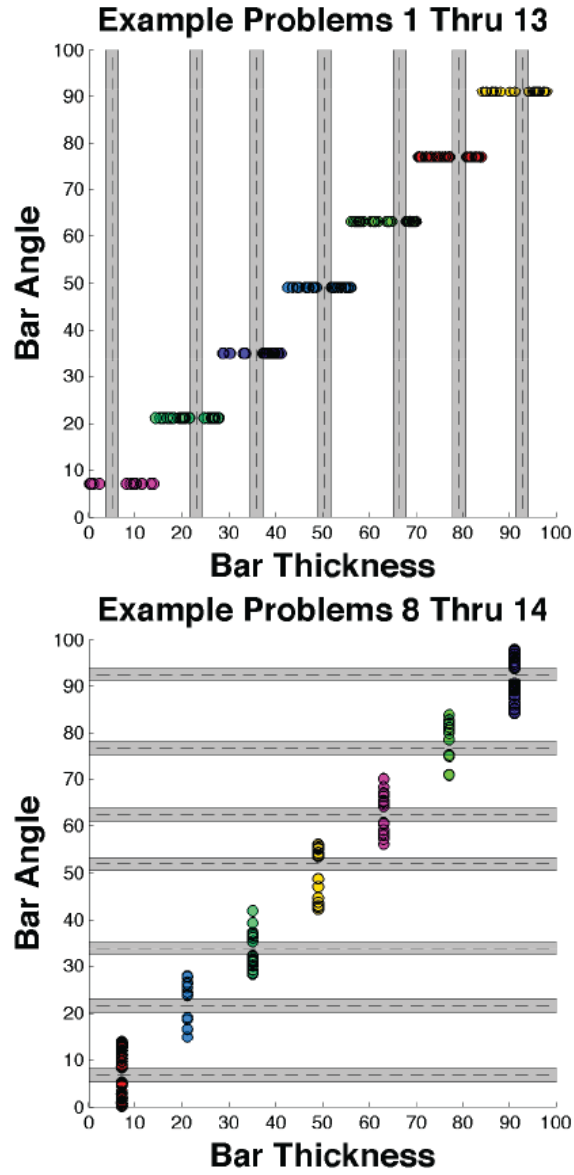
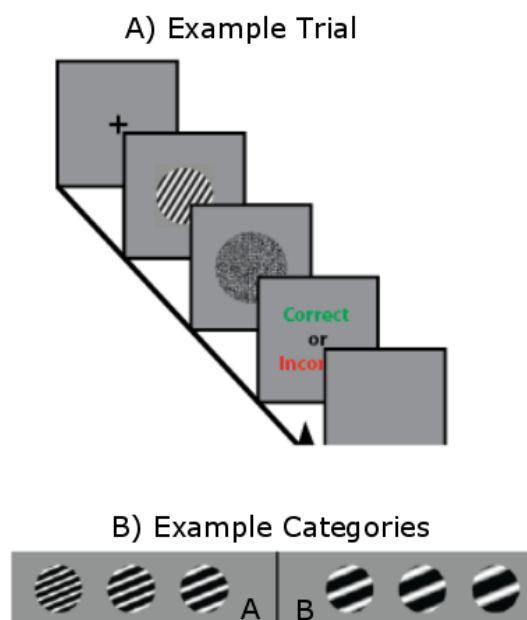


Figure 3

Category sample space. Different colors represent different category problems. Dashed lines are category boundaries (criterion) and the surrounding solid lines mark the no-stimulus region in which no stimuli were sampled.

**Figure 4**

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

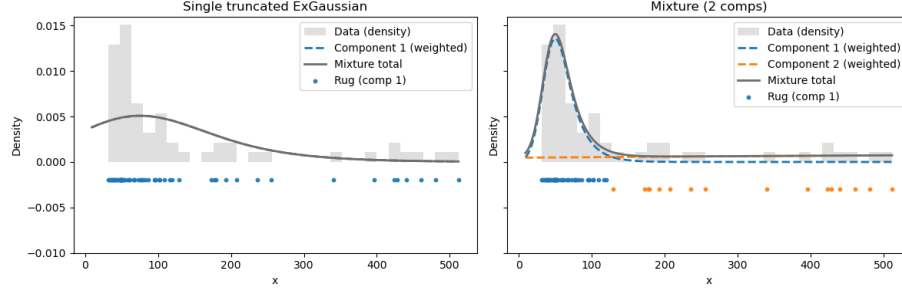
Participants

Fifty-nine participants participated in Experiment 1. All 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 ($N = 20$); Long ITI ($N = 21$), Control ($N = 17$). All participants gave written informed consent before participating in the study. All experimental protocols were approved by the University of California at Santa Barbara Human Subjects Committee in the Office of Research Development and Administration.

Results

Figure 5 shows a relative frequency histogram of the trials-to-criterion observed across all three conditions. The histogram shows that the majority of participants were able to learn each problem on average in less than 100 trials. However, this histogram also shows that a subset of participants required many more trials to learn each problem. Given that each problem is very simple and that the relevant dimension of each problem is explicitly instructed to participants, it is likely that the participants in the tails of this distribution did not pay attention to the instructions, were not motivated to learn the task, were distracted by other factors, or should be considered outliers for some other reason.

We modeled the distribution shown in Figure 5 using a mixture of Exponential-Gaussian distributions with two components, each truncated to the range of possible trials-

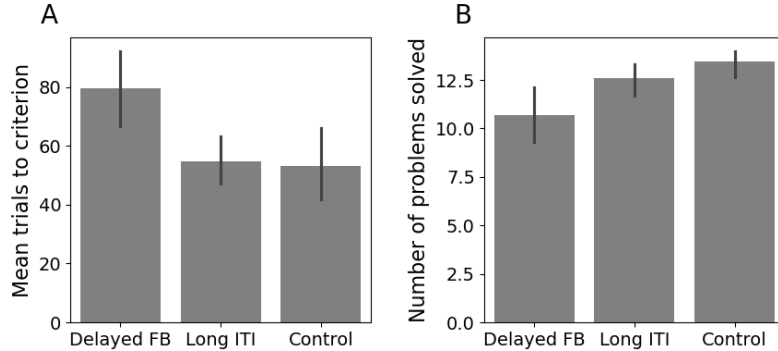
**Figure 5**

Relative frequency histogram of the trials-to-criterion observed across all three conditions in Experiment 1 and the fit of a single Exponential-Gaussian distribution (Left) and a two-component Exponential-Gaussian mixture model (Right). In the right panel, the blue dashed line is the first higher performance component, the orange dashed line is the second lower performance component. The gray solid line is the sum of the two components. Rug plots along the x-axes show the individual data colored by their assignment to either the higher or lower performance component. The two-component model provided a significantly better fit according to AIC, BIC, and a likelihood ratio test.

to-criterion values (i.e., [9,512]). The first component captured participants with a relatively low mean number of trials-to-criterion, while the second component identified outliers according to the above rationale. We estimated this model via MLE with proper normalization on the tasks bounded support and compared them via AIC, BIC, and a parametric bootstrap likelihood-ratio test (LRT). We compared the MLE fit of this two-component model to a single-component Exponential-Gaussian model using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), both of which indicated a better fit for the two-component model ($AIC_1 = 692.15$ vs. $AIC_2 = 652.81$; $BIC_1 = 698.33$ vs. $BIC_2 = 667.23$). Additionally, a bootstrap likelihood ratio test confirmed that the two-component model provided a significantly better fit than the one-component model ($D = 42.84$, $p_{boot} \approx 0.0099$) Participants that were deemed to most likely to belong in the low-performance Gaussian by this analysis were excluded from further analysis. After making these exclusions, we were left with the following sample sizes: Control condition ($N = 11$); Delayed-Feedback condition ($N = 14$); Long-ITI condition ($N = 17$).

Figure 6A shows the mean trials-to-criterion in each condition of Experiment 1. A one-way ANOVA revealed a significant effect of condition ($F(2, 39) = 6.17$, $p < .01$, $\eta^2 = .24$) and planned comparisons revealed that performance in the Delayed-Feedback condition was significantly worse than in either the Control condition ($t(23.00) = 2.70$, $p < .05$) or the Long-ITI condition ($t(20.96) = 2.94$, $p < .01$). Performance in the Control and Long-ITI conditions did not differ significantly from each other ($t(17.99) = 0.22$, $p = .83$).

Figure 6B shows the mean number of problems solved in each condition of Experiment 1. A one-way ANOVA revealed a significant effect of condition ($F(2, 39) = 5.77$, $p < .01$, $\eta^2 = .23$). Planned comparisons revealed that performance in the Delayed-Feedback condition was significantly worse than in the Control condition ($t(18.54) = -3.28$, $p < .01$) and worse than in the Long ITI condition ($t(21.60) = -2.14$, $p < .05$). Perfor-

**Figure 6**

A: Mean trials to criterion in each condition of Experiment 1. Error bars are standard errors of the mean. **B:** Mean number of problems solved in each condition of Experiment 1. Error bars are standard errors of the mean.

mance in the Control and Long-ITI conditions did not differ significantly from each other ($t(25.97) = -1.50$, $p = .15$).

Experiment 2

Experiment 2 was designed to reinforce the findings of Experiment 1 by using the same design but with stimuli that have binary-valued dimensions, thereby eliminating criterial learning. Unlike Experiment 1, we did not explicitly instruct participants on the relevant stimulus dimension in Experiment 2. While Experiment 1 isolated criterial learning from rule selection and rule switching, this experiment isolates rule selection and switching from criterial learning. Therefore, Experiment 2 was designed to test whether the impaired learning that we observed in Experiment 1 when the feedback was delayed can be attributed principally to criterial learning or whether it could be due to some more general category-learning process.

Method

Apparatus

The apparatus was the same as in Experiment 1.

Stimuli and Categories

The stimuli consisted of colored geometric figures presented on a colored background. These varied across six binary dimensions: the number of items (either one or two), the size of the items (small or large), the color of the items (yellow or blue), the shape of the items (circle or square), the texture of the background (smooth or rough), and the orientation of the background (horizontal or tilted by 20 degrees). This combination resulted in a total of 64 unique stimuli (2^6). An example trial and stimuli are shown in Figure 7. In all conditions, the order of stimulus presentation was fully randomized for each participant,

and the relevant dimension for each problem was selected randomly without replacement from the set of six dimensions.

Procedure

Participants received detailed instructions about the task. However, unlike in Experiment 1, they were not informed of the relevant dimension or the correct rule. The trial timing for the Delayed-Feedback and Long-ITI conditions in Experiment 2 were the same as in Experiment 1. Experiment 2 did not include a condition that was analogous to the Control condition of Experiment 1. Participants practiced each problem until they responded correctly on 12 consecutive trials. At this point, the problem changed. Each participant completed as many problems as possible in 600 trials or until they had been in the lab for 30 minutes (including time to acquire consent and give instructions), at which point the session was terminated.

Participants

Thirty-four participants participated in Experiment 2. All were Macquarie University undergraduates and received course credit for their participation. All had normal or corrected to normal vision. We randomly assigned each participant to one of two conditions: Delayed Feedback ($N = 17$) or Long ITI ($N = 17$). All participants gave written informed consent before participating in the study. All experimental protocols were approved by the Macquarie University Human Research Ethics Committee (protocol number: 52020339922086).

Results

Figure 8 shows a relative frequency histogram of the trials-to-criterion observed in both conditions. The histogram shows that the majority of participants were able to learn each problem on average in less than 100 trials. Unlike Experiment 1, there were no highly suspicious outliers in this data set. Nevertheless, for symmetry with Experiment 1, we performed the same Gaussian mixture model analysis as used there. The two-component model provided a slightly smaller AIC value (324.75 vs. 317.18), and a slightly larger BIC value (329.33 vs. 327.87). The bootstrap likelihood-ratio test was not significant ($D = 11.41, p_{\text{boot}} \approx 0.2277$). We therefore did not exclude any participants from further analysis in Experiment 1.

Figure 9A shows the mean trials-to-criterion in each condition of Experiment 2. An independent-samples t-test revealed no significant effect of condition ($t(32.0) = 0.69, p = .50, \eta^2 = .01$). The mean number of problems solved by each participant is shown in Figure 9B. An independent-samples t-test revealed no significant effect of condition ($t(32) = -0.49, p = .63, \eta^2 = .01$).

Discussion of Experiments 1 and 2

Experiment 1 clearly showed that a short feedback delay of 3.5 s slowed criterial learning. In contrast, increasing the ITI to this same value had no effect on learning. The task we used was one-dimensional category learning, but we isolated criterial learning by

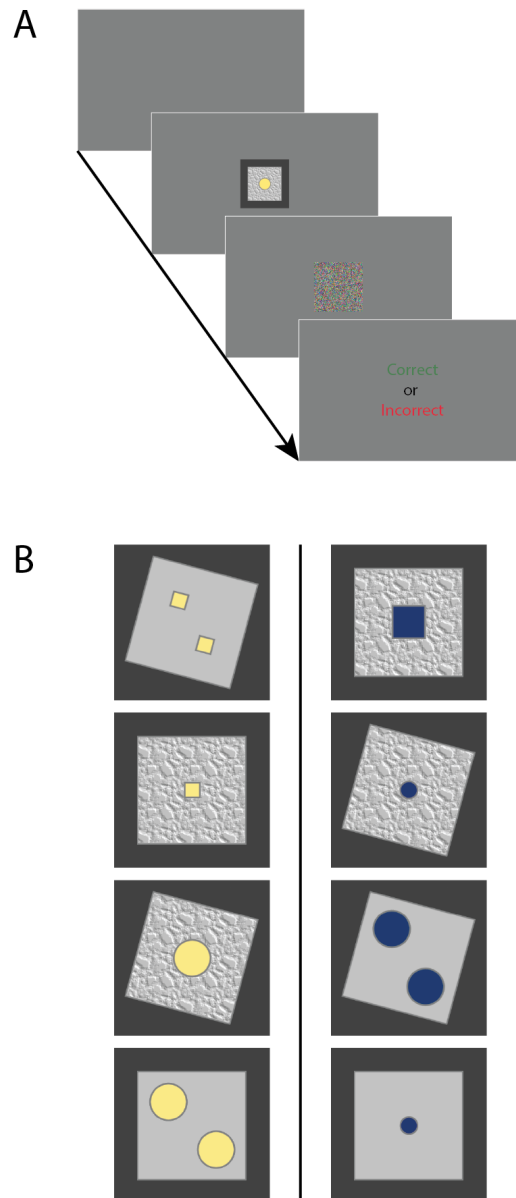
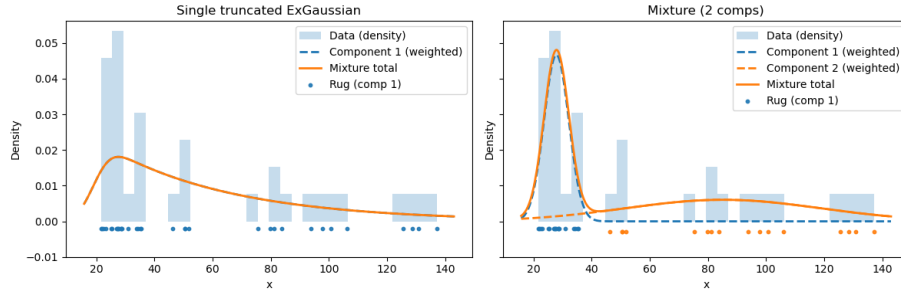
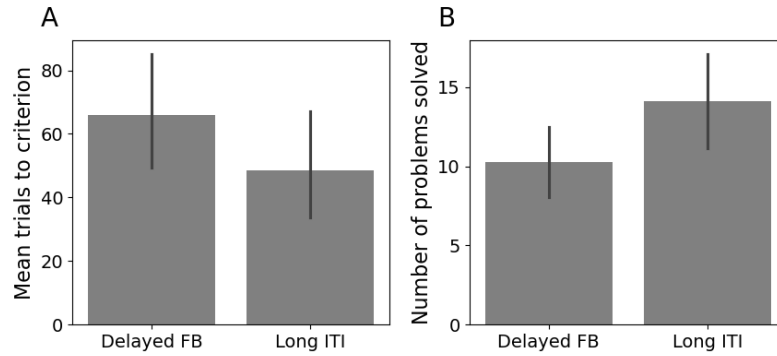


Figure 7

A: An example trial from Experiment 2. **B:** Eight example stimuli (out of 64 total stimuli) from a possible one-dimensional rule problem. In this case the correct rule is ‘A’ if the shape color is yellow and ‘B’ if the shape color is blue. The solid line represents the category boundary.

**Figure 8**

Relative frequency histogram of the trials-to-criterion observed across all three conditions in Experiment 2. The black line represents the best fit of the one-component Gaussian Mixture Model, and the red line represents the best fit of the two-component Gaussian Mixture Model.

**Figure 9**

A: Mean trials to criterion in each condition of Experiment 2. Error bars are standard errors of the mean. **B:** Mean number of problems solved in each condition of Experiment 2. Error bars are standard errors of the mean.

instructing participants about the optimal strategy. Specifically, we told them which stimulus dimension was relevant and that there was no trial-by-trial variability on the irrelevant dimension. Although these results strongly suggest that the feedback delay had its interfering effects on criterial learning, Experiment 2 was designed to confirm this inference. The goal here was to examine the effects of the same feedback delays and ITIs on performance in a one-dimensional category-learning task that did not require any criterial learning, but did require category-learning processes that are thought to mediate rule discovery (e.g., rule selection and switching). If the feedback delay effects observed in Experiment 1 were acting on some general category-learning skill then we should have seen the same interfering effects of feedback delay in Experiment 2. However, if the feedback-delay interference of Experiment 1 was operating selectively on criterial learning, then it should disappear in Experiment 2, since no criterial learning was required. Our results strongly supported this latter prediction. Therefore, Experiments 2 and 3 together strongly suggest that criterial

learning is impaired by feedback delays and is relatively unaffected by the length of the ITI.

Two prior studies investigated similar issues. First, Ell and colleagues reported that feedback delay and also a concurrent memory-scanning task each impaired rule-based category learning (Ell et al., 2009). Based on these results, they hypothesized that criterial learning may be tied to working-memory capacity and therefore to explicit cognitive mechanisms. However, criterial learning was confounded with rule selection and task difficulty in their design. Furthermore, Ell et al. (2009) found that feedback delay only impaired learning when working memory demand was high – that is, when participants had to learn more than one response criterion for optimal performance. In contrast, we found that feedback delay impairs learning even when working memory demands are trivial (participants never have to keep in mind more than one criterion).

Second, Bohil and Wismer (2014) reported that the effects of unequal base rates on criterion placement in rule-based category learning were diminished under delayed feedback and also under an observational training protocol that is also thought to selectively impair basal ganglia-dependent associative-learning mechanisms. These results are consistent with our findings. However, because they were obtained by manipulating base rates, it is difficult to conclude that the delay affected criterial learning, *per se*. For example, consider a simple two-stage model in which the first stage learns the base rates and the second stage uses what the first stage learned to adjust the response criterion appropriately. The Bohil and Wismer (2014) results are also consistent with the hypothesis that the feedback delay impaired the first of these stages but not the second. Our results strongly suggest that feedback delays impair criterial learning (and therefore the second of these hypothetical stages).

General Discussion

We developed novel models of criterial learning that were designed to explore how feedback delay and ITI duration affect criterial learning. One class of model assumed that decisions are made by comparing the current percept to a stored referent, or criterion, and that the remembered value of this criterion is updated following error feedback via a gradient-descent learning rule. This class of model generates sensitivity to feedback delay and ITI duration through (1) directly assuming that the update rule is inversely scaled by the feedback delay, (2) assuming that the representation of the percept drifts over time, or (3) assuming the representation of the criterion drifts over time. Simulations of these models in a task that was structurally identical to Experiment 1 revealed that this class of model typically predicts that feedback delay is more impairing than a long ITI only when the update rule is explicitly delay-sensitive. Otherwise, it typically predicts that long ITIs are more impairing than feedback delays.

The second model class, reinforcement-learning models, assumes that criterial learning arises through the gradual formation of stimulus-response associations, rather than via the construction of a response criterion. These models can generate sensitivity to feedback delay and ITI duration through the same two mechanisms as the first class of models. However, since these models do not explicitly represent a criterion, they do not assume that the representation of the criterion drifts over time. This class of model typically predicts that feedback delay is more impairing than a long ITI across wide ranges of parameter values.

The experiments were designed to test these predictions. Our results strongly suggested that human criterial learning is sensitive to feedback delay but not to the ITI du-

ration. These results shed important constraints on the new models of criterial learning developed here. In particular, the reinforcement-learning models are consistent with the observed behavioural data across wide ranges of their parameter spaces, regardless of whether or not the update rule is delay-sensitive. However, the models that assume a stored criterion are also consistent with the observed behavioral data, but only when the update rule is delay-sensitive.

One natural neural underpinning for models that assume a stored criterion is that the criterion is maintained in working memory. However, since it is widely accepted that working memory is largely insensitive to both feedback delay and ITI duration, this interpretation is difficult to reconcile with our results suggesting a delay-sensitive update rule is required for this class of model. An alternative possibility for where the criterion might be encoded in a more stable memory system. One appealing candidate for this function is the cerebellum, where synaptic plasticity has been shown to follow a gradient descent learning rule and also to be sensitive to feedback timing (Brudner et al., 2016; Held et al., 1966; Honda et al., 2012; Kitazawa et al., 1995; Kitazawa & Yin, 2002). Finally, the reinforcement-learning model draws on the idea that criterial learning could emerge through stimulus-response association learning driven by dopamine-dependent synaptic plasticity in the striatum. This process aligns with established theories of category learning that posit a key role to this learning process in the basal ganglia Ashby et al., 1998.

Our results do not strongly favor one model over another. The critical disagreement between these accounts is whether the criterion has any real psychological meaning. One class assumes the criterion is stored in memory and compared against incoming stimuli to generate responses. The reinforcement-learning model, in contrast, makes very different psychological assumptions. This model assumes that behaviors described as “criterial learning” are actually mediated by the learning of stimulus-response associations. According to this account, the criterion has no internal representation and therefore no psychological meaning. Testing between these two very different accounts of criterial learning should be a focus of future research.

We are not aware of any data that directly addresses the question of whether a response criterion is a fundamental psychological construct, or whether it is unnecessary. Even so, there are some results in the category-learning literature that support the interpretation of the reinforcement-learning model. In information-integration (II) category-learning tasks, the optimal strategy is similarity-based, and difficult or impossible to describe verbally (e.g., Ashby & Valentin, 2018). When the stimuli vary on two dimensions, the stimuli from contrasting categories can be partitioned by a decision bound that is conceptually similar to a response criterion. In both cases, all stimuli on one side are associated with one response, and all stimuli on the other side are associated with the contrasting response. Furthermore, in agreement with Experiment 1, II category learning is impaired by short feedback delays (Maddox & Ing, 2005; Maddox et al., 2003). The analogous question in II category learning is whether the decision bound is learned directly or whether it is simply the set of points that divide the perceptual space into contrasting response regions. In fact, the evidence strongly supports this latter interpretation (Ashby & Waldron, 1999; Casale et al., 2012). For example, if the decision bound is learned, then it should be possible to apply this bound to novel stimuli. With rule-based categories, this is easy for participants, but with II categories there is no evidence that the response strategy that participants learn

can be generalized to novel stimuli (Casale et al., 2012) – a result that strongly supports the hypothesis that the decision bound has no psychological meaning.

Our results clearly demonstrate that criterial learning is impaired by delayed feedback, and not by extending the intertrial interval. These results are consistent with the hypothesis that criterial learning is a form of basal-ganglia mediated associative learning, and are inconsistent with hypotheses that criterial learning is a working-memory-based process. Thus, our results provide a critical constraint on future models of rule-based classification and decision making, and possibly also on more general accounts of criterion setting, such as in signal detection theory.

Previous studies have failed to find that feedback delays impair rule-based category learning, and on the face of it, this seems to contradict our finding that feedback delays impair criterial learning. However, all earlier RB studies that looked for effects of a feedback delay, either used binary-valued stimulus dimension and so no criterial learning was needed, or else set the response criterion exactly midway between the category prototypes, which makes criterial learning trivial. For example, under these conditions, criterial learning might not even require feedback. The unsupervised category-learning experiments reported by Ashby et al. (1999) provide strong support for this because all of their rule-based participants learned the correct criterion (which was midway between the category means), even though the task was completely unsupervised. Moreover, all previous studies failed to isolate criterial learning, so even if there was an effect of feedback delay on criterial learning, it could have been masked by larger effects caused by other rule-learning processes.

Criterial learning is among the most classic and ubiquitous of all cognitive skills. For example, signal-detection theory teaches that it is the central form of learning in an enormous range of decision-making tasks – everything from simple YES-NO detection of a weak signal to assessing the guilt or innocence of a defendant in a jury trial. Our results suggest that even in simple rule-based tasks, criterial learning seems to be subserved, at least in part, by associative mechanisms. Most current theories tend to classify tasks as either executive function (e.g., rule-based category learning) or procedural (e.g., mirror tracing). Our results suggest that such classification schemes might oversimplify how humans perform these tasks, and therefore that much more work is needed to understand how different learning and memory systems interact.

Transparency and Openness

All data have been made publicly available in the following GitHub repository:
https://github.com/crossley/crit_learn_delay

Author Notes

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