

Estimation of Feedback Contingency Depends on Executive Function

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Abstract

Individuals in drug rehabilitation often experience relapse when returned to the original context of their drug use. Why do treatments generalize so poorly across different contexts? We recently addressed this question in the domain of procedural learning, which is thought to play an important role in forms of addiction, bad habits, and other maladaptive states (Crossley, Ashby, & Maddox, 2013). Our work suggests that feedback contingency, defined as the correlation between response confidence and outcome, plays a vital role in controlling a gate that normally prevents procedural knowledge from being modified during interventions. In particular, our results suggested that modification of procedural knowledge is possible only if feedback contingency is high. Here, we ask whether the estimation of feedback contingency depends on executive mechanisms (e.g., prefrontal networks involved in working memory and executive reasoning). Our rationale is as follows: If the estimation of feedback contingency requires executive function, then increasing cognitive load during intervention via the concurrent performance of an additional task should disrupt the accurate estimation of contingency, thereby keeping the gate on procedural learning open. We report the results from an experiment following this logic that suggests that feedback contingency estimation is indeed supported by executive function.

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Introduction

Relapse often occurs when an addict returns to the original context of their drug use (Higgins et al., 1995). This may occur because interventions given in clinics do not modify addiction-driving stimulus-response (SR) associations, but instead cause the learning of new clinic-specific associations. Returning to the original context of drug abuse then reactivates the preserved addiction-driving SR associations, causing relapse. If true, then this hypothesis means that the brain has a gating mechanism to protect learning obtained in old contexts from being modified. Our prior work, which was focused on understanding this gating mechanism (Crossley et al., 2013), found that feedback contingency – defined as the correlation between response confidence and outcome – is a principle driver of this gate. The present study is an extension of this earlier work, asking whether the estimation of feedback contingency depends on executive mechanisms. The rest of the introduction proceeds with a brief summary of the key findings reported by (Crossley et al., 2013), followed by the logic of the current study.

Crossley et al. (2013)

Crossley et al. (2013) attempted to understand why the SR associations underlying procedural learning, habits, and addiction are so remarkably resistant to modification. We developed a task that, after initial acquisition of SR associations, attempted to erase the just-formed engram. The results showed promising initial signs of true memory erasure.

Our experiments included three phases of equal duration: acquisition, intervention, and test. During acquisition, all participants were trained on the II categories shown in panel C of Figure 1. During intervention, the category structure was unchanged, but feedback about response accuracy was manipulated in an attempt to erase the learning that occurred during the initial acquisition. Our goal was to erase the initially acquired SR associations by overwriting them with random associations.

We investigated the effects of three different types of intervention. All used random feedback (RF) on some percentage of intervention trials. In the RF(.25) conditions, the intervention feedback was random on all trials. Since there are four categories, every intervention response was followed by positive feedback with probability .25 and negative feedback with probability .75. In the RF(.40) conditions, RF was also given on every trial, but the probability of positive feedback was .40 and the probability of negative feedback was .60. Finally, in the mixed feedback conditions, RF was given with probability .75 and true feedback was given with probability .25.

In all conditions, feedback returned to 100% veridical during the test phase. Half the participants in each condition relearned the original categories (the relearning conditions) and half learned new categories that used the same stimuli but permuted the category-response mappings. Thus the study included six conditions created from a 3×2 factorial design where three levels of intervention feedback [RF(.25), RF(.40), mixed feedback] were crossed with two levels of test (relearning, new learning).

Operationally, we require two conditions to conclude that unlearning is successful: (1) the behavior disappears during the intervention, (2) during test, both relearning and new learning occur at the same rate as initial learning. In contrast, if learning is preserved during the intervention, then relearning the original categories should be faster than initial acquisition and learning of new categories should be slower (because of interference).

Results are shown in Fig. 3. In the RF conditions (Fig. 3A and 3C), reacquisition is faster than initial learning, and new category learning is slower, suggesting that RF does not cause unlearning. In contrast, following mixed feedback intervention, reacquisition and new category learning both occur at approximately the same rate as initial learning. Thus, this intervention may have caused true unlearning.

The RF results are incompatible with classic models (see Figure 2A), which assume that procedural skills are learned at cortical-striatal synapses via DA-dependent synaptic plasticity, and that the DA signal is proportional to the reward prediction error ($RPE =$

Obtained Reward – Predicted Reward). Since RF is by definition unpredictable, it generates large RPEs, and therefore classic models predict that RF will cause new learning of random associations, which will overwrite the original category knowledge, causing true unlearning. In contrast, Figure 3A and 3C show that RF did not disrupt the previously acquired category knowledge.

Rapid relearning following RF suggests that **a gating mechanism protects procedural knowledge during RF**. We proposed striatal cholinergic interneurons called TANs (Tonically Active Neurons) as a candidate gate (Ashby & Crossley, 2011; Crossley et al., 2013). In their default state, TANs exert a tonic presynaptic inhibition of cortical inputs to the striatum (Figure 2) (Calabresi, Centonze, Gubellini, Pisani, & Bernardi, 2000). Thus, the default state of the gate is closed. However, TANs learn to pause in response to stimuli that predict reward (Kimura, Rajkowski, & Evarts, 1984), removing the presynaptic inhibition, and allowing striatal neurons to respond to cortical input and cortical-striatal learning to occur (i.e., the gate opens). The TANs are driven by centromedian and parafascicular (CM-Pf) intralaminar thalamic nuclei, which signal salient environmental cues and changes in context (Shimo & Hikosaka, 2001; Yamada, Matsumoto, & Kimura, 2004; Apicella, Legallet, & Trouche, 1997; Ravel, Sardo, Legallet, & Apicella, 2006). The TAN pause occurs only when the CM-Pf–TAN synapse is strong, and learning at both CM-Pf–TAN and cortical-striatal synapses is driven by DA-mediated reinforcement signals (Suzuki, Miura, Nishimura, & Aosaki, 2001; Setyono-Han, Henkelman, Foekens, & Klinj, 1982).

Our model that includes the TAN gating mechanism accounts for a variety of behavioral and physiological data from simple instrumental conditioning tasks (Ashby & Crossley, 2011; Crossley, Horvitz, Balsam, & Ashby, 2016), including rapid relearning following extinction. However, even this model failed to account for our RF results (Figure 3A and 3C). This is because we still modeled DA release as strictly proportional to RPE, which fluctuates widely during RF. This leads to random fluctuations in the CM-Pf–TAN

synaptic weight, preventing the TANs from reliably closing the gate.

For the TANs to close the gate and protect cortical-striatal plasticity during RF, two conditions must be met: (1) The model must detect RF. Since RF is non-contingent on behavior, the valence of feedback earned after each response is uncorrelated with the confidence that the response was correct (called *response confidence*). Contrast this with veridical feedback, in which negative feedback is typically accompanied by low response confidence. We recently showed that both RB and II learning are exquisitely sensitive to this feedback contingency (Ashby & Vucovich, in press). (2) The TANs must close the gate when RF is detected. This only occurs when CM-Pf-TAN synapses undergo consistent weakening. Crossley et al. (2013) modeled this by assuming that the DA response is attenuated and biased below baseline when feedback contingency is low.

With these modifications, the model not only accounts for savings in relearning after RF intervention, but also makes a novel prediction: **If true feedback is given on a small percentage of trials (e.g., 25%), then the correlation between feedback valence and response confidence could be high enough to cause the TANs to pause, allowing the RF on the other (75%) trials to induce true unlearning.** Results from our Mixed Feedback intervention (Figure 3B) are consistent with this prediction.

The Present Study

Crossley et al. (2013) hypothesized that the gate on procedural learning — and therefore the key to procedural modification — is controlled by the degree of feedback contingency, but we made no predictions about how feedback contingency is estimated by the nervous system. This article begins addressing this question — by asking whether the estimation of feedback contingency depends on executive function (e.g., prefrontal networks involved in working memory and executive reasoning). Our rationale is as follows: If feedback contingency is estimated by executive mechanisms, then increasing cognitive load during the intervention phase (by requiring participants to simultaneously perform a dual

task) should impair the ability of participants to detect random feedback. This should in turn cause the TANs gate to remain open, thereby allowing RF to modify the procedural knowledge that was acquired during initial learning.

With this goal in mind, we performed an experiment that mimicked the design of Crossley et al. (2013), except we added a concurrent numerical Stroop task during key classification trials. Previous research suggests that this dual task interferes with category learning that recruits executive function and declarative memory much more than with category learning that recruits procedural memory (Waldron & Ashby, 2001; Crossley, Paul, Roeder, & Ashby, 2016), and that the types of categories used here recruit procedural learning even when the dual task is being performed (Crossley, Paul, et al., 2016).

In conditions 1 – 3, the first dual-task trial was 50 trials before the onset of intervention, and continued for 100, 200, or 300 trials, respectively. In Condition 4, the first dual-task trial was 50 trials after the onset of intervention, and continued for 250 trials. Comparing conditions 1 through 3 allow us to look for a dose dependency. Condition 4 allows us to assess the importance of disrupting the estimation of feedback contingency during the transition from acquisition to intervention. Condition 5 was a control condition in which no concurrent Stroop task was ever performed.

If feedback contingency estimation depends on executive function then two behavioral markers are expected: (1) the dual task should slow the drop in categorization accuracy that occurs with the onset of RF; and (2) reacquisition of the original category learning should be slower in the dual task conditions than in the no dual-task control.

Methods

Design

There were four dual-task conditions (Condition 1 – 4) and one no dual-task control condition (Condition 5). The dual-task conditions differed on two dimensions, (1) the number of trials on which the dual task was applied, and (2) whether or not the onset of

the dual task preceded the onset of intervention.

Participants

163 participants were recruited from the University of Texas at Austin undergraduate population. There were 30 participants in Condition 1, 34 participants in Condition 2, 32 participants in Condition 3, 33 participants in Condition 4, and 34 participants in Condition 5. After exclusions (described in the next subsection), 119 participants were included in the reported analyses. Of these, there were 23 in Condition 1, 26 in Condition 2, 22 in Condition 3, 21 in Condition 4, and 27 in Condition 5. All participants completed the study and received course credit for their participation. All participants had normal or corrected-to-normal vision.

Exclusions

Of these 163 participants, 25 were excluded from the reported analyses for failing to reach a an average accuracy of 40% correct during the last 50 trials of the acquisition phase (described below). An additional 19 were excluded for failing to perform the concurrent numerical Stroop task with an average accuracy greater than or equal to 80%.

Stimuli and Categories

Stimuli were black lines that varied across trials only in length (pixels) and orientation (degrees counterclockwise rotation from horizontal). The stimuli are illustrated graphically in Figure 1, and were identical to those used by Crossley et al. (2013).

Procedure

Participants in all conditions were told that they were to categorize lines on the basis of their length and orientation, that there were four equally-likely categories, and that high levels of accuracy could be achieved. The experiment included three phases: acquisition (300 trials), intervention (400 trials), and reacquisition (150 trials). During acquisition and

reacquisition, feedback was based on the participant's response, whereas feedback was random during the intervention. Participants were given no prior instructions about the phases, and the transition from one phase to another occurred without any warning to the participant.

At the start of each non-Stroop trial, a fixation point was displayed for 1 second and then the stimulus appeared. The stimulus remained on the screen until the participant generated a response by pressing the "Z" key for category "A", the "W" key for category B, the "/" key for category C, or the "P" key for category D. Written instructions informed participants of the category label to button mappings. An "invalid key" message was displayed if any other button was pressed. The word "Correct" was presented for 1 second if the response was correct or the word "Wrong" was presented for 1 second if the response was incorrect (except during the intervention phase in which feedback was completely random).

Stroop trials began with a fixation point that was displayed for 1 second. The category stimulus and the Stroop stimuli (numbers flanking the category stimulus) were displayed simultaneously. After 200 ms the Stroop stimuli were replaced by white rectangles which remained on the screen until they made a category response. Responses emitted before the Stroop stimuli were replaced by white rectangles were not accepted. Feedback about the category response was given immediately in the same fashion as on non-Stroop trials. The word "value" or "size" then appeared on the screen prompting participants to indicate which side contained the numerically larger or the physically larger number. Participants pressed the "F" key to choose the number on the left or the "J" key to choose the number on the right. The word "Correct" was then again presented for 1 second if the response to the Stroop task was correct or the word "Wrong" was presented for 1 second if the response was incorrect. See Figure 1 for example trials both including and excluding the Stroop component. The Stroop task was included on trials 251-350 in condition 1, 251-450 in condition 2, 251-550 in condition 3 and 350-600 in condition 4.

Participants were instructed to try their hardest on both task components but to prioritize performance on the Stroop task. Both the category-learning task and the Stroop task were explained to participants prior to beginning the experiment, and on screen messages warned them when the Stroop component would begin, and again when it would end. These messages read, “You will now perform both the categorization task and the paired numbers task simultaneously. Keep trying your hardest!” and “You have now finished the section with the paired numbers task. You will now be shown only the line categorization task. Keep trying your hardest.” 85% of Stroop trials the numerically larger number was physically smaller. The proportion of Stroop trials that prompted “size” or “value” was split 50/50. Accuracy on the numerical Stroop task was indicated at the top of the screen when they received feedback regarding their performance on the concurrent task on each trial. This score was displayed in green if it was above 80% and red if it was below 80%. Note that when we refer to the “dual-task”, we are referring to the Stroop task just described.

Statistical Analyses

All t-tests comparing effects between conditions use the Welch-Satterthwaite approximation to the degrees of freedom to account for violations of homogeneity of variance.

Results

Numerical Stroop Accuracy

Figure 4 shows histograms characterizing mean dual-task performance separately for each condition. Overall, mean accuracy on the dual-task was very good, with mean proportion correct at 0.88 in Condition 1, 0.87 in Condition 2, 0.84 in Condition 3, and 0.82 in Condition 4. Participants that failed to perform the dual-task with an average accuracy greater than or equal to 80% were excluded from further analyses (see the

“Exclusions” section above).

Classification Accuracy

Figure 5 shows the mean accuracy in each block of 25 trials across the duration of the experiment. Recall that if feedback contingency is estimated via executive mechanisms, then (1) dual-task trials should slow the change in classification performance during intervention, and (2) dual-task conditions should show reduced savings relative to the no dual-task control. We see evidence for both features in our data.

Acquisition. Conditions 1 – 5 are identical for the first 250 trials (10 blocks) of acquisition (before dual-task onset), and so we expect performance during these blocks to be the same across conditions. However, Figure 5 shows modest differences between some of the conditions. A 5 Condition \times 10 Block repeated-measures ANOVA revealed a significant main effect of Condition $F(4, 1180) = 8.29, p < 0.01, \Omega = 0.02$, and a significant main effect of Block $F(1, 1180) = 250.83, p < 0.01, \Omega = 0.17$, but no significant interaction $F(4, 1180) = 1.95, p = 0.10, \Omega = 0.01$. Posthoc t-tests indicated that the main effect of Condition was driven by Condition 1 being significantly less than Condition 4 [$t(39) = -2.26, p < 0.05, d = 0.81$] and Condition 3 being significantly less than Condition 4 [$t(41) = 2.30, p < 0.05, d = 0.82$].

Intervention. If the estimation of feedback contingency depends on executive function, then we expect change in performance during intervention to be slowed during the simultaneous performance of the dual task. This is clearly seen in the first four blocks of the intervention phase, and is supported by the results of a 5 condition \times 4 block repeated-measures ANOVA. A significant effect of Condition [$F(4, 466) = 17.34, p < 0.001, \Omega = 0.11$] primarily reflected an overall difference in intervention performance in dual-task conditions relative to the no dual-task control. The effect of Block and the interaction between Condition and Block were also significant [Block: $F(1, 466) = 59.37, p < 0.001, \Omega = 0.10$; Condition:

$F(4, 466) = 2.41, p < 0.05, \Omega = 0.02]$. The directional interpretation of the omnibus test is supported by several planned comparisons on the overall mean accuracies during the first four blocks of the intervention phase. First, early intervention accuracy in all dual-task conditions in which the dual-task was introduced before the onset of the intervention phase was significantly different from intervention accuracy in the no dual-task control [condition 1 vs condition 5: $t(41) = 5.34, p < 0.01, d = 4.44$; condition 2 vs condition 5: $t(47) = 4.99, p < 0.01, d = 3.61$; condition 3 vs condition 5: $t(36) = 2.87, p < 0.05, d = 1.38$; condition 4 vs condition 5: $t(31) = 0.88, p = 0.38, d = 0.14$].

Savings. If the computation of feedback contingency depends on executive function, then we expect the dual-task conditions to exhibit less savings than the no dual-task control – that is, we expect reacquisition of the original categories to be slower under dual-task conditions. This is apparent via visual inspection of Figure 6, which shows the mean savings per condition.

There was no significant savings in any of the dual-task conditions [Condition 1: $t(22) = -0.27, p = 0.79, d = 0.02$; Condition 2: $t(25) = -0.95, p = 0.35, d = 0.18$; Condition 3: $t(21) = 0.39, p = 0.70, d = 0.03$; Condition 4: $t(20) = -0.49, p = 0.63, d = 0.05$;], but there was significant savings in the no dual-task control condition [Condition 5: $t(26) = 2.57, p < 0.05, d = 1.29$].

Moreover, the savings observed in Condition 5 was significantly greater than in all dual-task conditions except Condition 3 [Confition 1 < Condition 5: $t(43) = -1.78, p < 0.05, d = 0.48$; Confition 2 < Condition 5: $t(51) = -2.47, p < 0.05, d = 0.86$; Confition 3 < Condition 5: $t(45) = -1.45, p = 0.08, d = 0.31$; Confition 4 < Condition 5: $t(38) = -1.88, p < 0.05, d = 0.58$], and was significantly greater than the savings pooled across all dual-task conditions [$t(26) = 2.57, p < 0.05, d = 1.29$].

Recall that our design was constructed to allow for an examination of dose-dependency between conditions 1, 2, and 3. To answer this question, we performed a

1-way ANOVA asking if savings is different between Conditions 1 through 3. There was no significant difference between these conditions [$F(1, 69) = 0.22, p = .64, \Omega = 0.003$], indicating that we did not observe a dose-dependency.

We also designed our experiment to investigate the importance of placing the dual-task on the transition from acquisition to intervention. Since Condition 4 is significantly greater than Condition 1 and 3, we can only examine this question by comparing Condition 2 to Condition 4. A t-test revealed no significant difference [$t(41) = .18, p = .86, d = 0.06$], indicating that we found no evidence suggestion that the placement of the dual-task matters.

Discussion

Summary

Our results support our earlier conclusion (Crossley et al., 2013) that feedback contingency, defined as the correlation between response confidence and feedback valence, may be key to controlling a gate that prevents or permits the modification of procedural SR associations. To our knowledge, this article reports results from the first behavioral experiments that investigate the cognitive mechanisms that estimate feedback contingency. Specifically, our goal was to determine whether executive function and declarative memory mechanisms mediate contingency estimation. If they do, then a dual task that depends on working memory and executive function should make it more difficult for participants to recognize the sudden onset of random feedback. In our experiments, behavioral signatures of this difficulty would include (1) a slowed decrease in classification accuracy during intervention, and (2) decreased savings in relearning relative to a no dual-task control. Our results were consistent with both of these predictions.

Our design allowed us to ask not just whether contingency estimation relies on executive function, but also whether the effects of disrupted contingency estimation are dose dependent (i.e., whether effects increase with dual-task exposure), and also whether it

is important for the dual task to overlap with the transition from acquisition to intervention. We found no evidence for either of these possibilities.

Category Learning as a Procedural Skill

A natural question for readers unfamiliar with the category-learning literature is whether our behavioral paradigm is a good choice for studying procedural behaviors. In other words, how can a task with such simple motor demands (e.g., push a button) possibly recruit procedural networks that are strongly tied to motor processes? In fact, the empirical evidence is strong that performance improvements in the classification task used here are mediated via procedural learning and memory. A large database of evidence suggests that humans have multiple, qualitatively distinct category-learning systems (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Maddox, 2005; Erickson & Kruschke, 1998), and according to this view, procedural memory is used to form many-to-one stimulus-to-response mappings (S-R associations), whereas executive function and declarative memory are used to apply rules and test explicit hypotheses about category membership.

The majority of this evidence comes from prior research with rule-based (RB) and information-integration (II) category-learning tasks (Helie, Roeder, & Ashby, 2010; Nomura et al., 2007; Soto, Waldschmidt, Helie, & Ashby, 2013; Waldschmidt & Ashby, 2011). In RB tasks, the categories can be learned via an explicit hypothesis-testing procedure (Ashby et al., 1998). In the simplest variant, only one dimension is relevant (e.g., bar width), and the task is to discover this dimension and then map the different dimensional values to the relevant categories. In II tasks, accuracy is maximized only if information from two or more stimulus dimensions is integrated perceptually at a pre-decisional stage (Ashby & Gott, 1988). In most cases, the optimal strategy in II tasks is difficult or impossible to describe verbally (Ashby et al., 1998). Verbal rules may be (and sometimes are) applied, but they lead to suboptimal performance. The task used here (and

illustrated in Figure 1) was an II category-learning task.

At least 25 different behavioral dissociations tie II learning to procedural memory (and RB learning to executive function and declarative memory; for reviews, see Ashby & Maddox, 2005, 2010; Ashby & Valentin, in press). For example, one behavioral signature of procedural learning is that because of its motor component, switching the locations of the response keys interferes with performance (Willingham, Wells, Farrell, & Stemwedel, 2000). In agreement with this result, switching the locations of the response keys interferes with II categorization performance, even when the task only includes two categories¹ (Ashby, Ell, & Waldron, 2003; Maddox, Bohil, & Ing, 2004; Spiering & Ashby, 2008).

This hypothesis is further supported by a variety of investigations into the neural underpinnings of successful II and RB learning. Specifically, success in RB tasks depends on a broad neural network that includes the prefrontal cortex (PFC), anterior cingulate, the head of the caudate nucleus, and medial temporal lobe structures—regions that are also frequently associated with declarative memory and executive attention (Brown & Marsden, 1988; Filoteo, Maddox, Song, et al., 2007; Muhammad, Wallis, & Miller, 2006; Seger & Cincotta, 2006). Success in II tasks, on the other hand, depends on regions that have been implicated in procedural memory, including the striatum, premotor cortex, and the associated sensorimotor basal ganglia loop (Ashby & Ennis, 2006; Filoteo, Maddox, Salmon, & Song, 2005; Knowlton, Mangels, & Squire, 1996; Nomura et al., 2007). This network is consistent with the idea that S-R associations are built at cortical-striatal synapses via dopamine-dependent reinforcement learning (Ashby & Crossley, 2011; Houk, Adams, & Barto, 1995; Joel, Niv, & Ruppín, 2002).

Therapeutic Relevance

The old adage of “it’s like riding a bike” is a surprisingly accurate description of procedural knowledge, reflecting its remarkable retention over years without practice.

¹In contrast, the same button switch does not interfere with RB performance in tasks where the RB categories are created by simply rotating the II categories by 45°

Paradigms designed to study procedural learning in the lab have echoed this adage, reporting savings in learning up to a year after training (Romano, Howard, & Howard, 2010; Turner, 2012). However, the stability of procedural memory comes at the cost of remarkable inflexibility. For example, changing any stimulus or response parameter that was present during training can prove catastrophic to performance (Rozanov, Keren, & Karni, 2010; Dienes & Berry, 1997). While resilience and inflexibility are desirable traits when a useful skill has been sufficiently learned, they can also lead to persistent maladaptive behaviors that have serious negative consequences, and in some cases may prove detrimental to a person's health (e.g., drug abuse). Unfortunately, neither the potential for modification of procedural knowledge, nor a method to do so, are well understood.

Our previous research identified the interplay between striatal cholinergic interneurons and the midbrain dopamine system in controlling the eligibility of procedural knowledge for modification (Ashby & Crossley, 2011; Crossley et al., 2013). Directly targeting this network for improved interventions is unfortunately challenging, due to the difficulty of manipulating and measuring subcortical networks. Here, insofar as increasing cognitive load via a dual-task taps into prefrontal networks, we looked for more easily accessible cortical substrates that may control the striatal mechanism. Our results indicate that prefrontal networks likely do play an important role in controlling the estimation of feedback contingency, and therefore may provide an accessible cortical target for electrical or magnetic intervention.

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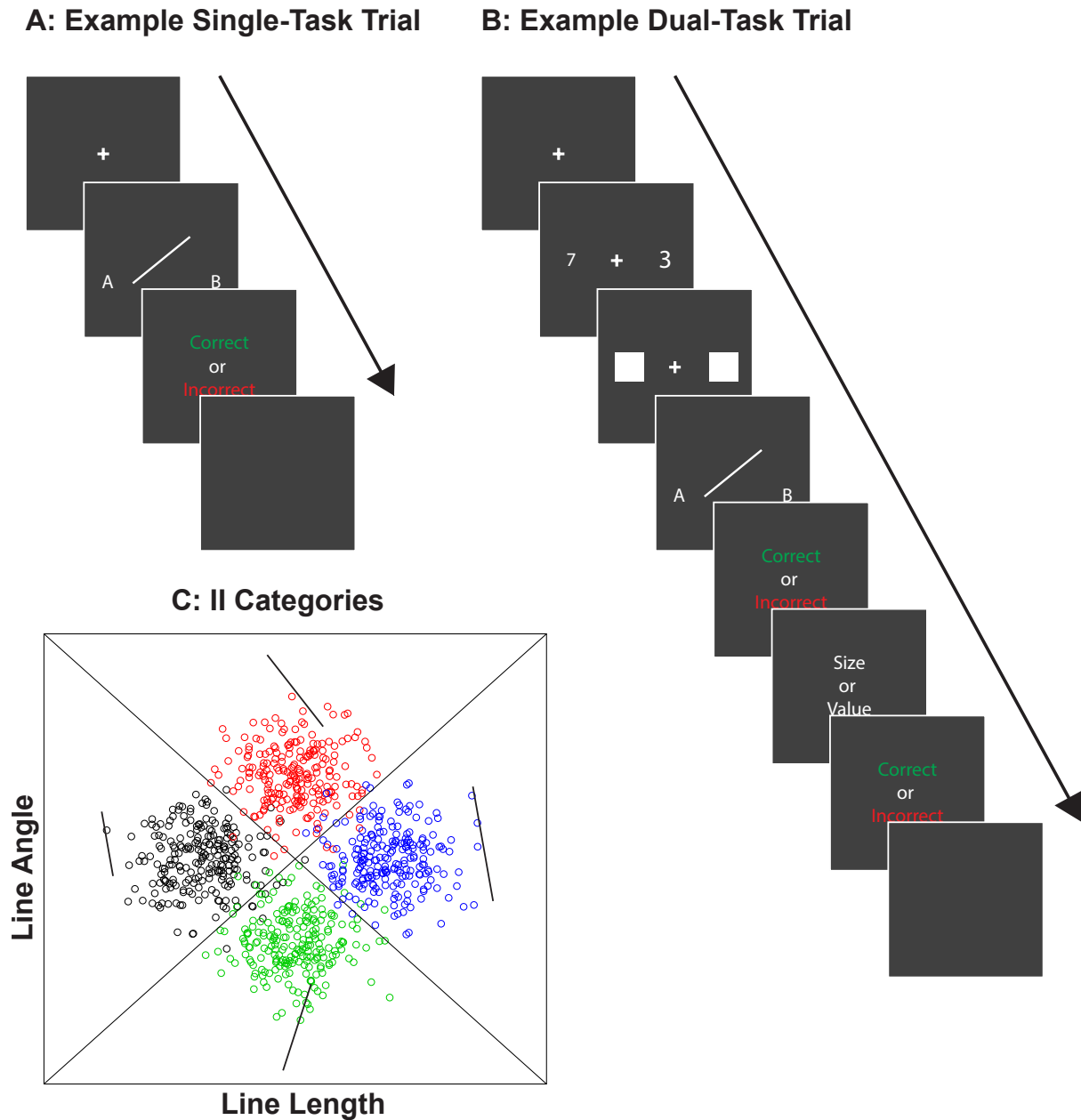


Figure 1. A: An Example trial during single-task conditions. *B:* An example trial during dual-task conditions. *C:* The II categories used during the acquisition phase of Crossley et al. (2013).

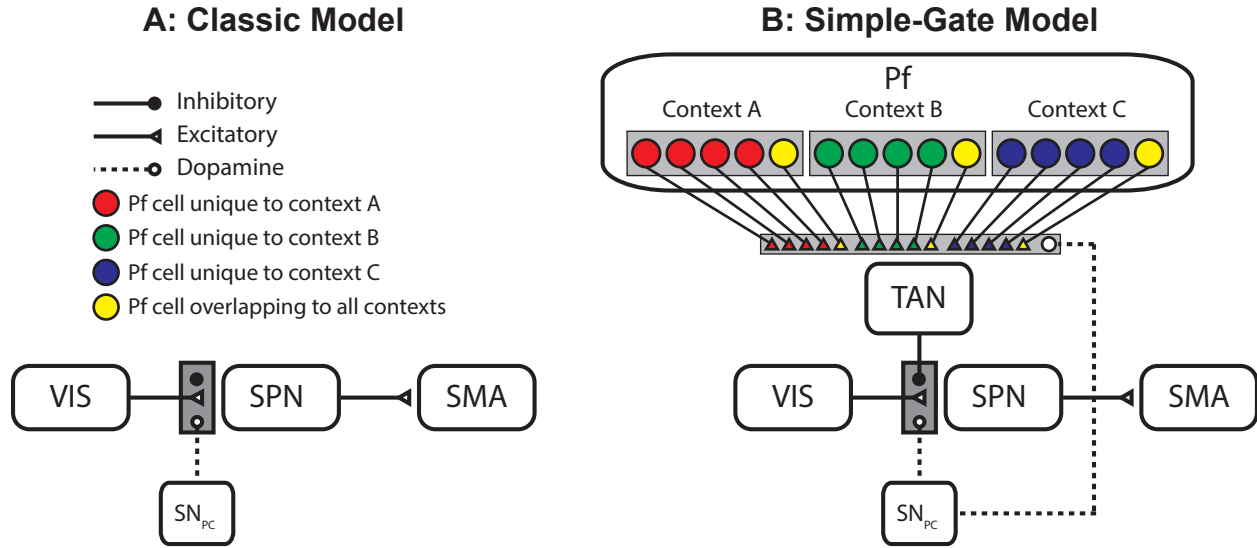


Figure 2. A: The Classic Model. A classic model of procedural learning based on a greatly simplified representation of the “direct pathway” through the basal ganglia. S-R associations are learned at cortical-striatal synapses, which are modified via dopamine-dependent reinforcement learning. The likelihood of repeating actions that lead to *unexpected* positive outcomes is gradually increased, and the likelihood of repeating actions that lead to *unexpected* negative outcomes is gradually decreased. **B: The TANs Model.** The classic model of procedural learning with the addition of a context-specific Pf-TAN pathway. This pathway acts as a gate on cortical-striatal synaptic plasticity, permitting or preventing the learning and expression of procedural knowledge. (SPN - spiny projection neuron of the striatum. D1 - Direct pathway SPN expressing the D1 DA receptor. D2 - Indirect pathway SPN expressing the D2 DA receptor. SMA - Supplementary Motor Area. SNpc - substantia nigra pars compacta. Pf - parafascicular nucleus of the thalamus. VIS - visual cortex)

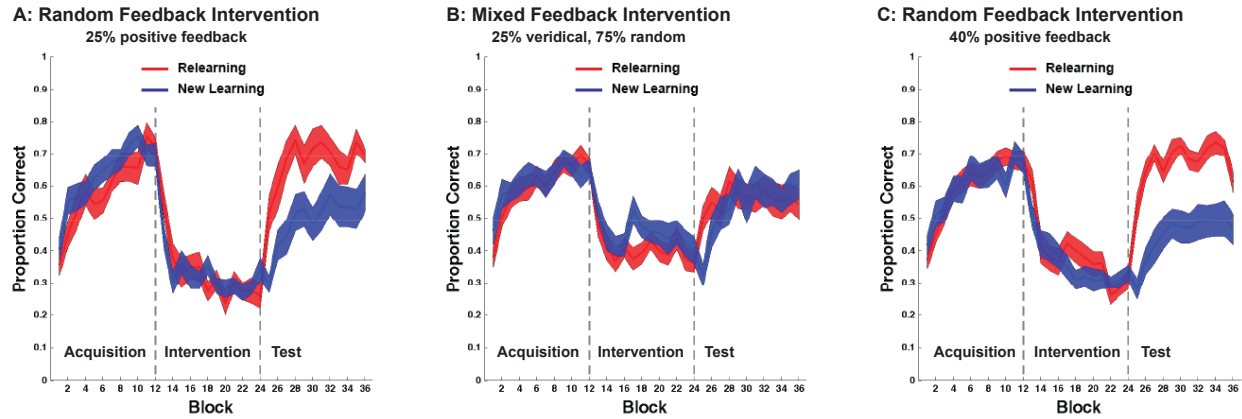


Figure 3. Crossley et al. (2013) behavioral results with different interventions. **A:** Random feedback intervention with 25% positive feedback. Accuracy drops to near chance during intervention, but is reacquired faster than original learning in the Relearning condition (red). In contrast, a lasting interference is observed in the New Learning condition (blue). Both results are consistent with the hypothesis that initial learning was not overwritten by random feedback. **B:** Mixed feedback intervention. Accuracy drops during intervention – though not to chance (i.e., 25%) – but subsequent learning proceeds at approximately the same rate and to the same extent as initial learning when either the original category-response mappings (red) or new category-response mappings (blue) are introduced. These results are consistent with the hypothesis that initial learning was overwritten during the intervention. **C:** Random feedback intervention with 40% positive feedback. Results are qualitatively identical to random feedback intervention with 25% positive feedback, implying that the mixed feedback results were driven by feedback contingency and not by positive feedback.

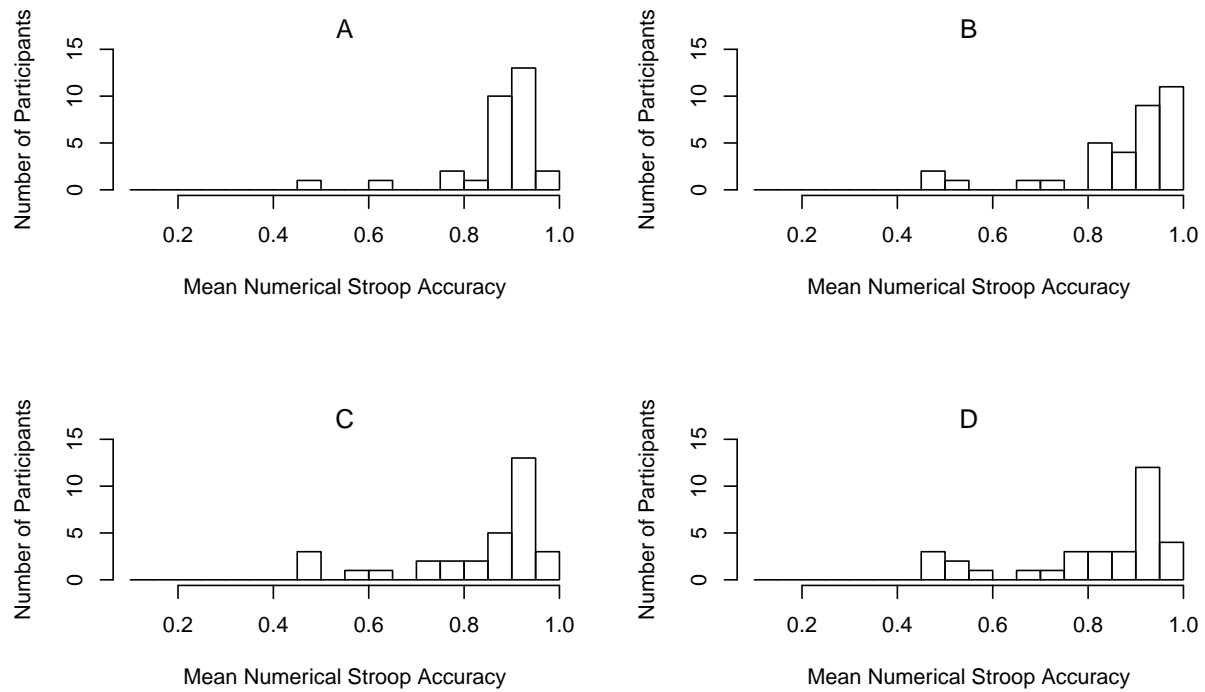


Figure 4. Histograms showing distribution of mean Numerical Stroop accuracy separately for each condition. **A:** Condition 1. **B:** Condition 2. **C:** Condition 3. **D:** Condition 4.

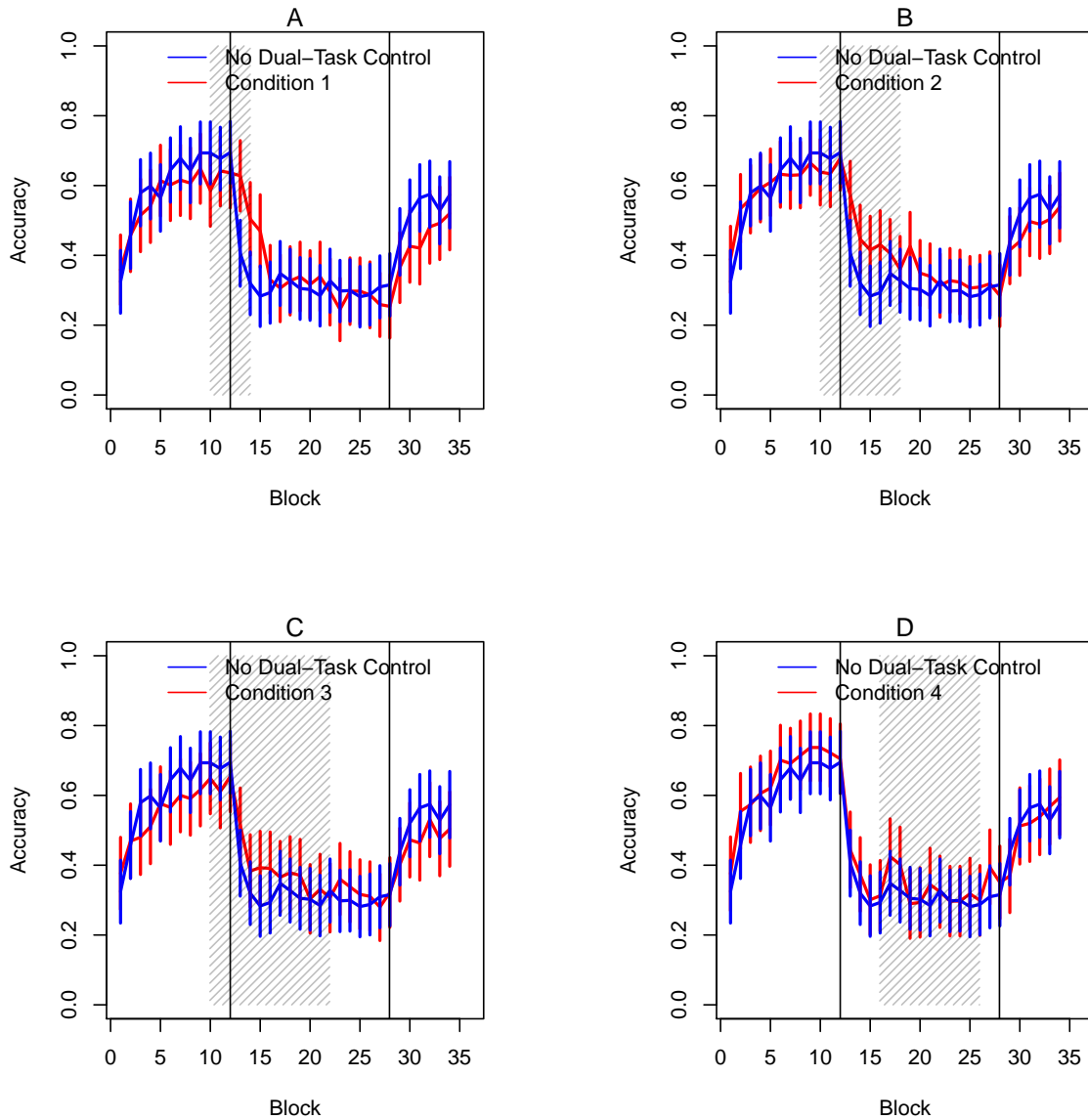


Figure 5. Mean accuracy per 25 trial block. The blue line in each panel is Condition 5 (no dual-task control). The hatch marks indicate dual-task trials. The key features are (1) dual-task slows the change in classification strategy (seen in this plot as “accuracy” decline), and (2) the dual-task conditions show less savings than the no dual-task control. There is no obvious dose-dependent effect of the dual task, nor is there an obvious difference between dual-task conditions. **A:** Condition 1 (dual-task applied on trial 251 through trial 350). **B:** Condition 2 (dual-task applied on trial 251 through trial 450). **C:** Condition 3 (dual-task applied on trial 251 through trial 550). **D:** Condition 4 (dual-task applied on trial 351 through trial 650). Error bars are SEM.

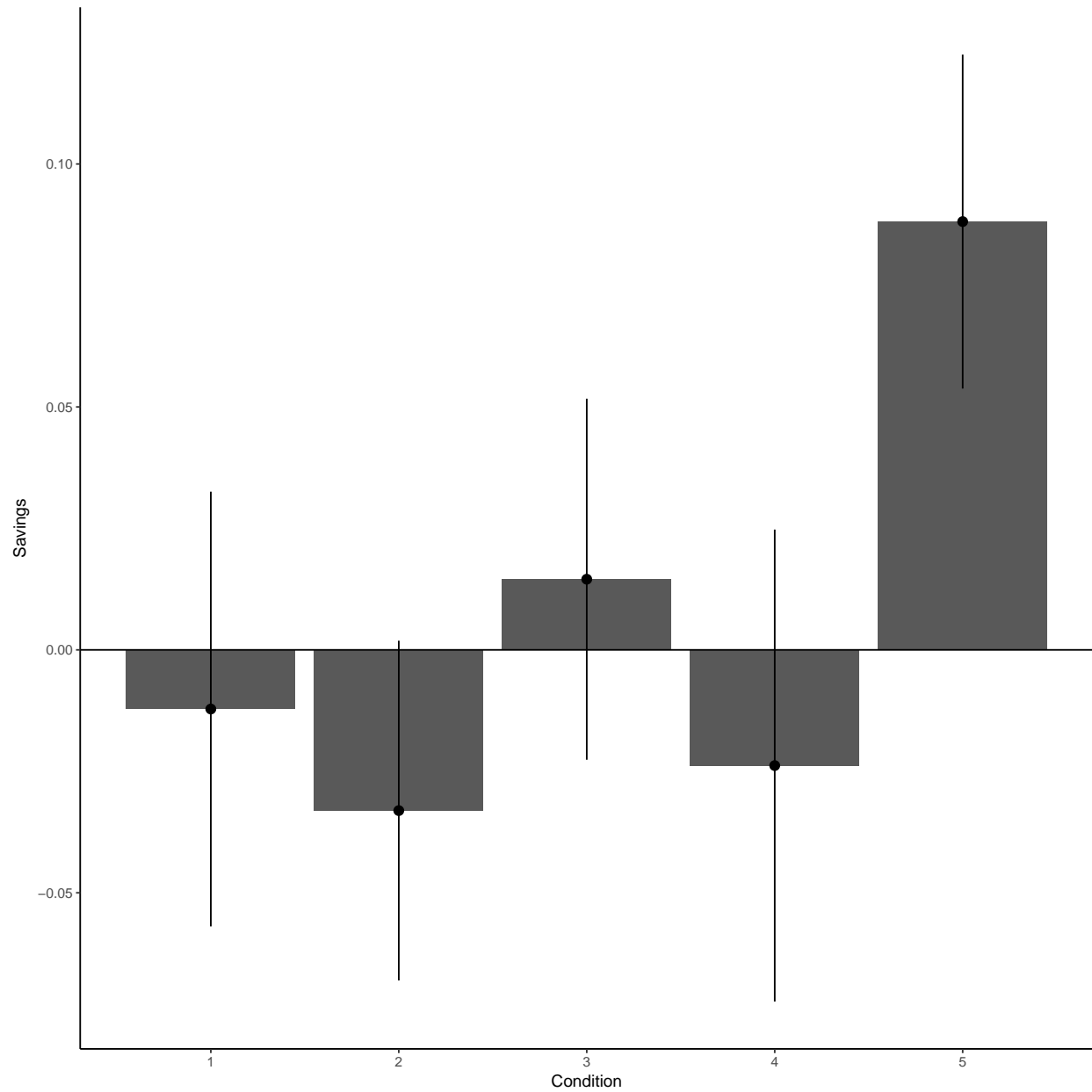


Figure 6. Savings (mean of the first 50 reacquisition trials - mean of the first 50 acquisition trials) in all conditions of the present experiment. Error bars are SEM.