How time spent on feedback influences learning and gaze in categorization training

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Abstract

Feedback is essential for many kinds of learning, but the cognitive processes involved in learning from feedback are unclear. In models of category learning, feedback is typically treated as an error signal without a temporal component. We conducted two simple category learning experiments that manipulated the duration of feedback (1s vs. 9s) and investigated the effect on learning and gaze. In two different category structures, participants in the longer feedback condition learned faster. The analysis of gaze data showed several findings. Participants in the 9s condition had longer fixations, and in both conditions and experiments, participants spent far more time looking at stimulus features than the feedback. Overall, our findings provide empirical support for the idea that feedback processes, and temporal factors more generally, have much to tell us about how people learn categories.

Keywords: Eye-tracking; Categorization; Learning; Attention; Feedback

Introduction

Research into the cognitive processes that enable a human to classify objects into categories has a long history within psychology (e.g., Hull, 1920). Work in this field has coalesced into a variety of computational models that describe how attention, combined with mental representations of various kinds (e.g., prototypes (Blair & Homa, 2003; Rosch & Mervis, 1975; Smith & Minda, 2000), stimulus exemplars (Medin & Schaffer, 1978; Nosofsky, 1986), or stimulus clusters (Love, Medin, & Gureckis, 2004)), can be used to predict how someone might classify a particular stimulus. Early models were aimed at capturing asymptotic performance, and thus might be called categorization models. Later models focused more on capturing the learning process. These category learning models use learning algorithms such as backpropagation to adjust connections between representations of stimuli, or stimulus features, and categories (Kruschke, 1992), and also to weigh (or attend to) various stimulus dimensions (Kruschke & Johansen, 1999). Telling the model which category is correct is a critical aspect of the learning process because, in most cases, these learning algorithms are supervised.

For a human participant in a category learning experiment, feedback can come in a variety of forms. In a task with just two categories, feedback can be simply confirmative—correct or incorrect—using a tone, or a red or green light for example. In a task with more categories, the correct category is typically specified more directly. It is common in category learning tasks that the stimulus be re-presented along with the feedback. The timing of feedback can also be different across tasks, and likewise in different naturalistic situations. While feedback might be presented for a set amount of time, many researchers use self-paced feedback, wherein participants themselves dictate when to move to the next trial (e.g., Meier and Blair, 2013).

Though feedback is obviously critical for category learning models, they are not really intended to capture the various processes through which feedback is seen and understood by participants. In a categorization experiment the primary unit of measure is the trial, so these models are usually trial-based. In a trial of a category learning experiment, the participants are shown a stimulus and asked to classify the stimulus into one of multiple categories. They are then given corrective feedback on their choice. After viewing the feedback they proceed to the next trial, wherein everything is repeated with a new stimulus. Many trials later, often hundreds, the experiment is completed. The models, very sensibly, are built to account for these data, and so also proceed in this trial-based manner. A stimulus is presented, the model makes a classification, feedback is given to the model, which adjusts its connection weights, and then the next trial begins. The particulars of the feedback are not important to such models—if the participant gets feedback, the model will treat it as a teaching signal, and the associative weights will be adjusted according to the learning algorithm.

There is some evidence to suggest that the details of how feedback is experienced affect learning. Consequently, there is some reason to think that category learning models might be extended to account for feedback processing, and that additional research concerning feedback is warranted. Bourne, Guy, Dodd, and Justesen (1965) showed that increasing the inter-trial interval gave the participants more time to process feedback, which impacted learning. In addition to suggesting that time spent on feedback matters, this research also showed that stimulus re-presentation during feedback influenced learning. More recently, Watson and Blair (2008), in an effort to understand what participants do during the presentation of feedback, used eye-tracking to investigate participants’ gaze while processing feedback. In two experiments,
participants learned complex categories with self-paced feedback. They found that participants spent more of their time looking at the stimulus features than the feedback signal itself. Further, they found that the time spent looking at stimulus features during feedback on incorrect trials was greater for those participants who were able to meet the learning criterion than for those who were not.

Findings involving within-trial temporal manipulations, such as manipulating feedback duration, are beyond the scope of what well-established learning models can predict. This is starting to change—for example, modern dynamical models of attention and gaze during category learning provide theoretical motivation for continuing such investigations (e.g., Barnes, Blair, Tupper, and Walshe, 2015). LAG-1 is a hybrid model that combines a simple category learning system with a spatial attention system and a saccade control system. It was built using the dynamic neural field theory framework, allowing it to simulate cognitive processes continuously in space (for eye-movement control, for example) and time. Because the model runs continuously in time, manipulations like changing the time available on feedback can directly influence its Hebbian learning. The model allocates attention and programs saccades to specific locations of the stimulus, also continuously in time, producing a stream of fixations to stimulus features during both stimulus and feedback presentation.

In LAG-1, learning occurs via Hebbian changes to the connections between stimulus feature detectors, activated by serial fixations to the stimulus, and category representation units. This learning occurs due to co-activation during presentation of feedback and happens incrementally at each timestep. This results in a straightforward prediction: if feedback lasts longer, there is additional time for the associations to strengthen. This model also predicts that investigating a represented stimulus’s features during feedback will allow for stronger and more selective associations between those features and the category. While receiving feedback, the model shifts its gaze among the feedback buttons and the various stimulus features, reactivating them as the feedback signal also boosts the correct category.

In the present paper, we conduct two experiments to investigate the influence of feedback presentation time on learning and on the allocation of attention, as assessed using eye-tracking. Each experiment investigates a different category structure, and both manipulate the time allotted to feedback in a 1s and 9s condition.

### Experiment 1

**Method**

**Participants.** Participants were 147 undergraduate students at Simon Fraser University who received course credit for their participation. Each had normal or corrected-to-normal vision. Some participants were dropped before the data were analyzed. Seven experienced computer or eye tracker failure and 31 participants were eliminated for poor gaze quality. Finally, 50 participants failed to meet the learning criterion (24 correct trials in a row). The 59 remaining participants broke down into 29 for the 9s feedback condition, and 30 in the 1s feedback condition. Though the present case is an extreme example, it is not unusual for a significant number of participants to fail to meet the learning criterion when learning complex categories such as the ones in the experiment (e.g., Blair, Watson, and Meier, 2009; McColeman et al., 2014).

**Stimuli and Categories.** Stimuli consisted of images resembling micro-organisms with three distinctive organelle-like features. There were two possible versions of each feature, leading to eight possible feature combinations. An example stimulus is shown in Fig.1.

The full micro-organism subtended 16.3° of visual angle. The features contained within the micro-organism were located centrally in each of its “arms”. Each feature subtended 1.3° and they were separated by 10.6° of visual angle. These stimuli have been used effectively several previous studies (e.g., Blair, Watson, and Meier, 2009; Meier and Blair, 2013).

The features used to classify the stimuli varied in relevance: the value of feature 1 determined which of feature 2 or feature 3 was relevant (see Fig. 2). This created an opportunity to employ a more complex attentional strategy. This category structure has been used before in our lab and it has

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**Figure 1:** The three phases of the experiment. First, there is the fixation cross. Second is the response phase, in which the participant chooses one of four categories for the stimulus. Finally, there is the feedback phase, in which the correct response is highlighted and the stimulus remains onscreen.

**Figure 2:** Category structures for Experiment 1 (L), and 2 (R). For both structures there were two relevant and one irrelevant feature. For the structure used in Experiment 1, the irrelevant feature was different for each pair of categories, requiring (and eliciting) a more difficult attentional strategy. Unlike in Experiment 1, for the structure used in Experiment 2, the relevance of a feature did not depend on the category to which it belonged.
produced effective attentional optimization (e.g., Blair, Watson, and Meier, 2009; Meier and Blair, 2013). Having used this structure before, we have well-supported expectations for learning and attention. The locations of particular features, and which features were relevant and irrelevant, were varied across participants.

**Procedure.** Participants were seated in a comfortable chair 60 cm from a 17 inch computer screen in a quiet experiment booth. They were given on-screen instructions explaining the goal of the task and which buttons to press on a game controller to indicate the possible categories.

Each experiment included several hundred learning trials. Each trial proceeded as follows. First, a fixation appeared in the center of the screen for 1 second. Next, a stimulus was presented for the participant to classify. Once the participant chose a category for the stimulus, they were given feedback: if they answered correctly, their answer turned green, and if they answered incorrectly, their answer turned red and the correct answer turned green. Fig. 1 shows this screen. Feedback remained onscreen for either 1 second or 9 seconds depending on the condition to which the participant was assigned. Each of the eight possible stimulus configurations was shown three times in each block of 24 trials, with the order randomized by block. As a result, we set learning criterion a little higher than usual, at 24 correct trials in a row.

Though the study was designed to run for a maximum of 264 trials, very few participants in the 9s condition seem to show a learning advantage, though peak performance is similar for the two conditions. This is confirmed by our analysis, using accuracy binned to 24 trials, in which we find a significant effect of condition ($\chi^2(1) = 21.62, p < 0.01$).

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**Analyses.** We use linear mixed effects modeling to determine the statistical significance of all effects reported. We predict accuracy, attentional optimization, and fixation duration from the fixed effects of condition and trial, as well as random intercepts and slopes for trial number estimated for each participant. All significance tests were done by performing a likelihood ratio test given the presence or absence of the factor in the model.

**Results and Discussion**

Fig. 3 shows the learning curves for each condition. Participants in the 9s condition seem to show a learning advantage, though peak performance is similar for the two conditions. This is confirmed by our analysis, using accuracy binned to 24 trials, in which we find a significant effect of condition ($\chi^2(1) = 21.62, p < 0.01$).

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use the definition of attentional optimization from Blair, Watson, and Meier (2009): the proportion of the average total fixation duration to relevant features, minus the same for irrelevant features. This produces a measure which is 1 if all the time spent is on relevant features, and zero if the time spent (per feature) was equal for relevant and irrelevant stimulus features. Increasing optimization was evident across trials in both conditions. However, feedback condition had no main effect on optimization, and there was no condition by trial interaction.

As discussed in Bourne et al. (1965), changing the duration of feedback also changes the inter-trial interval. Recent work looking at the effect of intertrial interval on eye movement vigour prompted us to consider how individual eye movements were affected by the feedback manipulation (Haith, Reppert, & Shadmehr, 2012). With fewer opportunities to maximize accuracy (a proxy for reward), participants in the 9s feedback condition are expected to make less vigorous eye movements, as they try to maximize their overall reward rate by behaving more cautiously. Fig. 4 shows the mean fixation duration during the feedback phase of the experiment, split by condition. A shorter feedback phase leads to shorter fixations during feedback presentation. Our analysis confirms a trial by condition interaction ($\chi^2(1) = 3.84, p = 0.05$), as well as a main effect of condition ($\chi^2(1) = 7.61, p < 0.01$).

Participants in the 9s condition learn faster, so it is important to consider what participants are doing during the additional time. Fig. 5 shows that participants in both conditions spend significantly longer viewing stimulus features than feedback buttons (by a factor of 10.54 in the 1s condition and 17.53 in the 9s condition). It would seem that the learning advantage afforded by the increase in time available to view the feedback derives largely from continued inspection of the stimulus.

Experiment 2

Experiment 2 sought to replicate the findings of Experiment 1 with a category structure where attentional optimization was less difficult.

Method

Participants. Participants were 105 undergraduate students at Simon Fraser University who received course credit for their participation. All participants had normal or corrected-to-normal vision. There were 58 participants excluded from the analysis: six experienced computer or eye tracker failure, 16 were eliminated for poor gaze quality, and 36 failed to meet the learning criterion. A total of 47 participants were included in the final analysis: 26 in the 1s condition, and 21 in the 9s condition.

Stimuli, procedure & analyses. The stimuli, procedure and analyses for Experiment 2 were identical to those in Experiment 1, with the exception of the category structure. Fig. 2 shows the categories used. Unlike Experiment 1, where two of the features were sometimes relevant and sometimes irrelevant, in Experiment 2, the same two features were relevant for all categories. This category structure has also been used in previous work in our lab, and has been shown to be easier to learn, and elicit somewhat stronger attentional optimization (McColeman et al., 2014).

Results and Discussion

Overall, the findings of Experiment 2 mirrored Experiment 1 in nearly every respect. The learning curves for Experiment 2, by condition, are shown in Fig. 6. The impact of feedback duration reproduces the same general trend seen in Experiment 1, and we find the same interaction between condition and trial ($\chi^2(1) = 6.65, p < 0.01$).

As in Experiment 1, we found increasing attentional optimization across trials in both conditions, but saw effects of feedback condition. If the extra time on feedback was being spent on improved attentional learning, we would expect some difference in this measure between feedback conditions.

Fixation duration differences by condition also replicate Experiment 1, with a significant interaction between feedback duration and trial ($\chi^2(1) = 9.23, p < 0.01$), and again, a main effect of condition ($\chi^2(1) = 11.44, p < 0.01$). Again, giving participants extra time on feedback seems to increase fixation durations on the order of 100ms, which is substantial.

Finally, participants spent far more time looking at stimulus features than they did feedback buttons. The ratios of time on stimuli to time on feedback buttons are roughly in line with the previous experiment (8.04, for 1s; 15.62 for 9s).

General Discussion

In the present study we looked at the influence of feedback time on learning during category learning. Most models of category learning are event-based, not time-based, so they treat feedback processing as a single event that causes learning; as such, they would not predict any impact of feedback duration on learning. We also explored the impact of feed-

Figure 6: Average accuracy of learners in Experiment 2. Each trial bin along the x axis is an average over 24 trials, and error bar shading represents STD.
The evidence that feedback duration influences fixation duration, with fixations during feedback in both experiments about 100ms longer in the 9s condition than the 1s condition, warrants further attention. This finding is interesting, as it exposes a link between strategic considerations—how do I look at everything in 1 second?—with what are commonly thought of as low-level processes of sensorimotor control. While the speed/accuracy trade-off in maximizing reward rate predicts such a finding, most models would not straightforwardly predict this. Accounting for the full range of human behaviour in category learning is a much broader agenda than simply elucidating category representation, and must address the complex interactions that produce findings that range from learning differences across an experiment to small, but reliable, differences in the timing of fixations.

We find that participants spend far more time looking at the stimulus features than the category feedback buttons in both conditions and in both experiments. Given that even the participants in the 1 second condition chose to spend the majority of their time looking at stimulus features, it seems performance is not being limited by lack of time to inspect the feedback itself. Further study is needed to understand this finding. One plausible explanation for preferring to spend time on the stimulus over the feedback relates to memory. In the present studies, the stimulus features are complex novel images, whereas the feedback consists of simple alphanumeric characters. We can imagine a new experiment where the stimulus features are simple alphanumeric features (e.g., 0 and 1, + and -, A and B) and the categories are complex perceptual features. In such a scenario, we might expect attentional allocation during feedback to shift toward the category labels, as participants need more time on the harder to remember portions of the experiment.

One measure that did not seem influenced by our manipulation of feedback duration was attentional optimization. One hypothesis on why feedback time might influence learning is that it allows for additional attentional learning, which in turn would allow learners to focus their time on only relevant features. Our findings argue against this hypothesis as we found no differences in this particular measure of attentional optimization between conditions in either experiment. There is also some evidence from similar experiments that attentional learning is delayed relative to performance (Blair, Watson, Walshe, & Maj, 2009), further undermining this possibility.

The present study is one of few that is focused on understanding the temporal dimension of feedback processing during category learning (Newell, Moore, Wills, & Milton, 2013). The paucity of research in this area is not completely unreasonable—if a given category learning researcher is more interested in the nature of category representation than in the connection between sensorimotor operations and learning, that is legitimate; certainly the structure and history of extant models emphasizes this focus. Nevertheless, feedback processing is an important aspect of a category learning experiment, and if we are to make better use of participant data,
it would be helpful to understand effective ways to communicate feedback.

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References


