The Impact of Category Type and Working Memory Span on Attentional Learning in Categorization

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Abstract

The present study investigated attentional optimization in participants learning rule-based (RB) and information integration (II) categories. Using an eye-tracker to measure the deployment of overt attention, we tracked participants' learning and optimization during a category learning experiment. We also measured working memory span. We found that participants in the RB condition optimized attention less than II participants before reaching the learning criterion, but more than II participants after criterion, and confirmed that this effect was not due to differences in speed of learning or accuracy. Working memory span was negatively related to pre-criterion optimization in both conditions, but was unrelated to post-criterion optimization. These results show that attentional optimization is influenced by the kind of task being learned or the types of strategies that these tasks elicit, and provide evidence that executive attentional factors influence overt attentional optimization.

Keywords: attention, category learning, categorization, rule-based, information-integration, eye-tracking, working memory.

Introduction

The ability to preferentially process relevant information is critical to achieving effective and efficient performance on virtually any task. Theories of category learning have long recognized the importance of incorporating selective attention into their frameworks, usually simulating selective attention with weights that modulate the importance of stimulus dimensions (e.g. Kruschke, 1992). However, the goal of modeling selective attention has been complicated by the fact that attention is difficult to measure.

Some studies have attempted to measure attention by using specially-chosen transfer stimuli to gauge the importance of each stimulus dimension on the categorization decision (e.g., Blair & Homa, 2005). One disadvantage of an indirect measure like this is that it may lead to improper inferences about attentional allocation – for instance, transfer and training may be treated differently by participants (Blair & Homa, 2003). Attentional allocation has also been investigated using a paradigm in which participants use a mouse click to reveal information that they wish to view (e.g., Matsuka & Corter, 2008). This method illuminates exactly which dimensions participants judge to be important, and the order in which they are accessed, but because information that is revealed remains available, no real-time information about which stimulus dimensions participants are considering is recorded.

A promising alternative is eye-tracking; it provides fine-grained temporal and spatial information, and is a precise and direct measure of one important aspect of attention: overt attention. Further, there is important overlap between the attentional biases suggested in computational models of attention and participants' real-life deployment of gaze (Rehder & Hoffman, 2005a). Rehder and Hoffman (2005b) have demonstrated a correspondence between the amount of time participants fixate stimulus features and the value of attention weights generated by model fits of the response data. Kruschke, Kappenman, and Hetrick (2005) showed that measures of eye-gaze were meaningful indicators of attentional flexibility and matched modeling analyses even at the level of individual participants.

Eye-tracking studies are beginning to elucidate the role of overt attention in categorization. For example, many important models of categorization assume that attentional weights are task-specific. Blair, Watson, Walshe, and Maj (2009) provided eye-tracking evidence that overt attention can be deployed differentially for different stimuli, supporting a more flexible implementation of attention, like those in recent models (e.g., Kruschke, 2001). In another example, Watson and Blair (2008) used eye-tracking to study participants' processing of feedback. They found that participants who successfully learned a categorization task spent far more time looking at the re-presented stimulus on incorrect trials than on correct trials, whereas non-learners showed no difference. In contrast, most current theories posit that the re-presented stimulus plays no role in the learning process.

Recent progress has also been made in understanding how the allocation of selective attention is optimized during rule-based category learning tasks. Many theories of category learning exclusively use error-minimization algorithms to shift attentional allocation. However, Matsuka and Corter (2008), using an information-board interface, showed that participants will flexibly optimize attention to contextual effort (cost) / accuracy (benefit) considerations, rather than error per se, a result that could not be predicted from algorithms of this sort. Similarly, in an eye-tracking experiment, Blair, Watson, and Meier (2009) found that neither performance error nor external feedback are necessary for attentional optimization, the opposite of what error-driven attention theories would predict. Participants in that study did not shift overt attention early, when performance errors were most common; instead, they optimized attention only after they had stopped making errors. Further, attentional optimization continued in the absence of performance error and external feedback until 72 trials later when the experiment ended.

The present study is a continuation of the line of research pursued by Blair, Watson, and Meier (2009) described above, which investigated the optimization of overt attention during a rule-based categorization task. We wish to illuminate how overt attentional allocations might differ when learning categories of different kinds.

For several decades, theories of categorization have assumed that selective attention operates under a single set of principles, regardless of the nature of the category being learned (e.g., Medin & Schaffer, 1978; Kruschke, 1992). Experiments have been conducted on many types of category structures; some of the more common ones used in research include rule-based (Maddox & Ashby, 2004), information integration (Ashby & Gott, 1988), prototype distortion (Blair & Homa, 2001; Posner & Keele, 1968), and prediction/probabilistic (Peterson, Hammond & Summers, 1965). However, there are some compelling reasons to believe that selective attention may not operate in the same way for all kinds of categories. One model of human categorization that predicts differences in how people learn categories based on structure is COVIS (Competition between Verbal and Implicit Systems; Ashby, Alfonso-Reese, Turken, & Waldron, 1998), a neuropsychologically-informed multiple-systems theory of category learning.

According to COVIS, categorization decisions are mediated by cortical-striatal-pallidal-thalamic circuits involved in two functionally separate systems: an explicit verbal system that attempts to learn a decision rule, and an implicit procedural system that attempts to learn a decision bound. Both systems are interdependently and actively involved during category learning, but through learning, the system more strongly associated with category membership responses will take over.

COVIS predicts that the explicit verbal system first dominates the learning of any new category structure. In psychological terms, this mean participants always begin a category learning task by creating and testing verbalizable rules. This verbal system involves a prefrontal network in the brain that attempts to learn the most efficient rule for making a correct categorization decision. In contrast, the implicit procedural system, which is also active at the beginning of a category learning task, mediates response selection by associating stimuli with motor responses rather than responding based on rule criteria.

The underlying mechanisms of COVIS predict a number of dissociations between learning two particular types of categories: rule-based structures, and information integration structures (Maddox & Ashby, 2004). The explicit system is assumed to govern the learning of rule-based categories. These structures are characterized by having dimensions with semantic labels that can be selectively attended and classified by using verbal rules (Ashby & Maddox, 2005). The implicit system, on the other hand, governs information integration categories because their dimensions are combined at a "predecisional" stage, and associated with correct procedural responses. Dissociations between the strategies used to solve the two tasks have been shown using behavioral measures (e.g., Ell & Ashby, 2006) and functional neuroimaging (Nomura et al., 2007). We seek to investigate if dissociations show up in the way participants learn to allocate attention during and after learning rule-based or information integration categories.

Blair, Watson, and Meier (2009) looked at overt attentional allocation during rule-based category learning, hypothesizing that participants' failure to optimize attention before mastering the categories may be due to rule construction and evaluation occupying executive attentional resources. While this explanation holds for rule-based categories, according to COVIS, information integration category learning strategies do not rely on the same executive attentional networks. COVIS predicts an initial rule-based approach to category learning, with a shift to the procedural system if rule construction proves unsuccessful (Ashby et al., 1998). Such a shift is expected when learning information integration categories, as candidate rules must be verbalized to be tested and rules delineating information integration categories are often difficult to verbalize. If this is true, then one might expect to see attentional optimization prior to category mastery when participants learn information integration tasks, unlike the rule-based tasks studies by Blair et al.. Testing this prediction is our main experimental goal.

The situation may be more complicated still, due to individual differences in executive attentional capacities. One study suggests that a high working memory span is actually negatively correlated with performance on information integration tasks (DeCaro, Thomas, & Beilock, 2008). This may be because working memory span is a measure of participants' ability to suppress unimportant or goal-incongruent conflicting information (Conway, Kane, & Engle, 2003), such that individuals with high working memory capacity may be more likely to persist in using rule-construction as a category learning strategy long after such an approach becomes counterproductive. Because working memory span has been implicated as an important factor in learning different category structures, we opted to include a computerized working memory span measure called the Aospan (automated operation span; see Unsworth, Heitz, Schrock, & Engle, 2005). Our secondary goal is to investigate possible relationships between working memory span and attentional allocation.

Method

Participants

84 undergraduate students with normal or corrected-to-normal vision from Simon Fraser University participated in this study for pay or course credit. 13 were excluded due to excessive eye-tracker errors or failing to complete all trials.

Stimuli and Categories

The stimuli participants learned to categorize were images of microorganisms containing three organelles (see Figure 1, top panel). In order to create these stimuli, we created a pool of 90 images for each of the three organelles representing the three category features, or dimensions. One feature was an organelle that varied along an orientation dimension, with each successive image changing by 1.5º of rotation. The second feature was a crescent-shaped elongated oval that differed along a curvature dimension, with each successive image altered by 1º of arc aptitude. The third feature was a circle filled with white that differed along a size dimension, with each successive image containing a slightly smaller white disc. Figure 1 (bottom panel) shows these features at the extreme and midpoint values.

The stimulus feature values for the two conditions were generated using bivariate distributions similar to those used by Ashby and Gott (1988) with parameter values shown in Table 1. Participants were randomly assigned to one of two possible category structures: rule-based (RB) or information integration (II) (Figure 2). Correct categorization of a stimulus in the RB condition required checking one relevant feature; two features were always irrelevant. Correct categorization of II structures required checking two relevant features; one feature was always irrelevant.

The selected features were superimposed onto the arms of the microorganism, which subtended 19º of visual angle on a display screen of 43.5 cm by 27 cm with a view distance of approximately 73 cm. The assigned location for each type of organelle remained constant for each participant, and was counterbalanced across participants. The three organelles were separated from each other by 11.2º of visual angle and equidistant from the centre of the microorganism.

Procedure

The experiment consisted of a working memory capacity evaluation task, followed by a categorization task. Participants were told they would first be doing a task that required remembering letters while performing simple math calculations, and then a categorization game that required them to sort images into two categories.

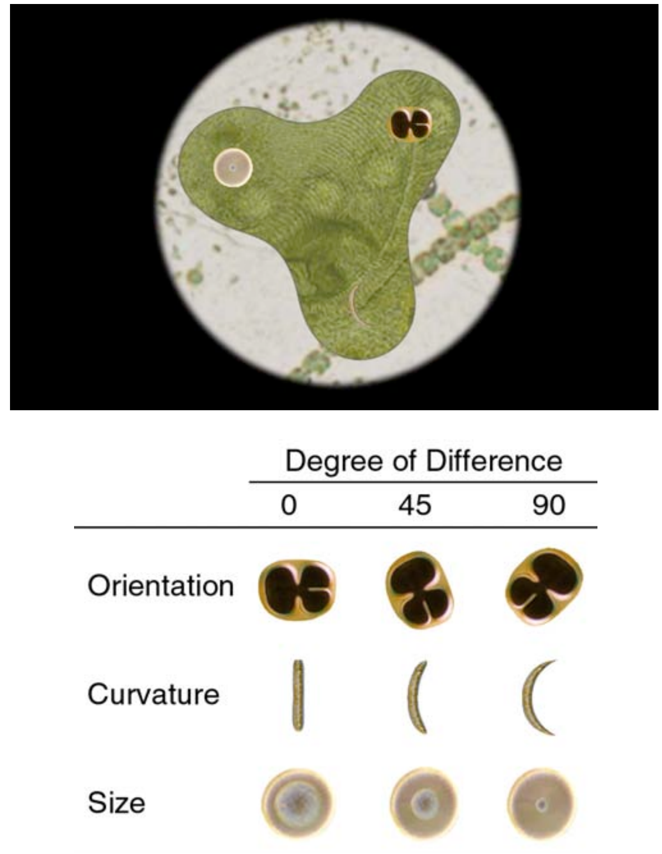

Figure 1. Stimuli used in the experiment. The top panel is an example of the stimulus that the participants learned to classify. The bottom panel shows the degree of variation on the three principle features.

Working memory capacity was evaluated using the Aospan task, which requires participants to recall strings of letters while performing a set of simple math operations. At the beginning of each trial, a simple math problem was presented. Participants judged whether the proposed solution was correct by clicking on the corresponding "true" or "false" box, received performance feedback, and were presented with a letter. After a set of three to seven math questions, participants were prompted with a letter recall display, where they were required to order the presented letters by clicking on the appropriate boxes. Participants were then shown a feedback screen, indicating both math and letter recall accuracy for that set. The Aospan task is designed to take 20-25 minutes, and concluded after 75

Table 1: Category Distribution Parameters for Information Integration and Rule-Based Structures

	Category A					Category B				
Condition	μ_x	μ_y	σ_x^2	σ_y^2	cov_{xy}	μ_x	μ_y	σ_x^2	σ_y^2	cov_{xy}
Information Integration	36	54	140	140	22.954	54	36	140	140	22.954
Rule-Based	30	45	12	120	0	60	45	120	12	0

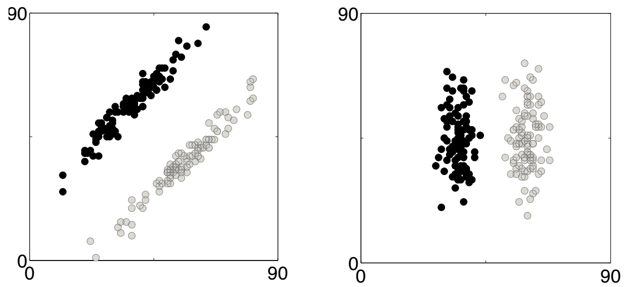

Figure 2. Categories similar to those used in the experiment. The left panel shows information integration (II) categories, and the right panel shows rule-based (RB) categories. Axes represent the stimulus feature values.

trials. The total number of correctly recalled letters reflected each participant's Aospan score.

The Aospan was followed by a categorization task. During this task, fine-grained spatial and temporal eye movement data were recorded using a Tobii X120 eye-tracker, sampling at a spatial resolution of 0.5º and temporal resolution of 60Hz. Using a modified dispersion threshold (Salvucci & Goldberg, 2000) with a spatial threshold of 28 pixels and a 75 ms minimum fixation duration, eye movements were counted as fixations to stimulus features if they fell within 100 pixels of the centre of an organelle. A trial began with the presentation of a black screen containing a red central fixation cross. Participants had to click on the cross to be presented with the image of a microorganism. After deciding whether the stimulus belonged to category A or category B, participants clicked to proceed to the response stage. The microorganism disappeared, and two response boxes appeared on the left and right sides of the screen. The location of each response box was constant for each participant, but counterbalanced across participants. After clicking on the appropriate box to indicate a response, participants received feedback on their performance and they were re-presented with the microorganism. The response box they clicked turned green if their response was correct. If their response was incorrect, the box turned red and the box containing the correct response turned green. Participants were given as much time as they wanted to examine the stimulus before clicking to begin the next trial. Participants completed a total of 200 trials in the category learning task.

Results

Five of the seventy-one participants, two from the RB condition and three from the II condition, had accuracies of less than 60% on the final 50 trials of the categorization task. The data from these participants were excluded from all remaining analyses. Aospan scores ranged from 33 to 75 (M = 61.20, SD = 10.4). A hierarchical multiple regression analysis was conducted to determine whether Aospan could predict performance on the categorization task. Aospan was not a significant predictor of total accuracy either on its own (β = .03, $t(63)$ = .44, p > .60) or in an interaction term with condition (β = -.11, $t(62)$ = -.24, p > .80). Category condition, however, was a significant predictor of accuracy (β = -.82, $t(63)$ = -11.17, p < .001), indicating that the RB condition (M = .94) was easier to learn than the II condition (M = .74).

Many studies use a learning criterion of a certain number of consecutive error-free trials to separate participants who learned the task from those who did not. Rather than selecting an arbitrary number, we ranked candidate criterion lengths from 1 to 40 according to three measures, each weighted equally: the inverse of the average pre-criterion accuracy across all participants, the average post-criterion accuracy, and the average difference between pre- and post-criterion accuracy. The best criterion for our data set was 13. Using this criterion there were 31 learners and no non-learners in the RB condition, and 23 learners and 12 non-learners in the II condition. The average number of trials it took to reach criterion was 20 for RB learners and 69 for II learners. Learners in the RB condition had a mean accuracy of 58% pre-criterion and 97% post-criterion, while II learners were 66% accurate before criterion and 83% accurate after. A 2 (RB/II) x 2 (pre-/post-criterion) mixed ANOVA revealed a significant interaction, $F(1,50)$ = 19.19, p < .001; in addition, post-criterion accuracy was significantly lower for II than for RB learners, $t(52)$ = 10.16, p < .001. Learning is an essentially dichotomous process in the RB task: participants have learned little or nothing about the categories before criterion, and are essentially perfect thereafter. In the II task, on the other hand, learning is a more gradual and continuous process, which accords with the results of previous studies using II categories (e.g., Ashby & Maddox, 2005).

Attentional optimization for each trial was defined as the difference between the mean total fixation time to relevant stimulus features and the mean total fixation time to irrelevant features, divided by the mean total fixation time to all features. Mean total fixation time to relevant features was defined as the time spent fixating relevant features divided by the number of relevant features; mean total fixation time to irrelevant features was analogously calculated. Attentional optimization thus ranges from -1, indicating that the participant spent the entire trial fixating irrelevant features only, to 1, indicating a trial in which the participant looked only at relevant features. On trials where the participant fixates only one of the two relevant features (23.5% of trials), we subtracted .5 from the optimization score.

We predicted that participants learning an II category would show a pattern of gradual optimization throughout the experiment, while RB participants would only optimize their attention after reaching the learning criterion. To examine this prediction, a 2x2 analysis of variance was conducted with stage of learning (before criterion, after criterion) as a within-subjects variable and condition (RB, II) as a between-subjects variable (see Figure 3). The results showed a significant stage-structure interaction, $F(1,47)$ = 62.89, p < .001. Compared to the RB participants, participants in the II condition showed more optimal attentional allocation before criterion (M = .31 versus M = .10) and less optimal allocation after criterion (M = .55 versus M = .87).

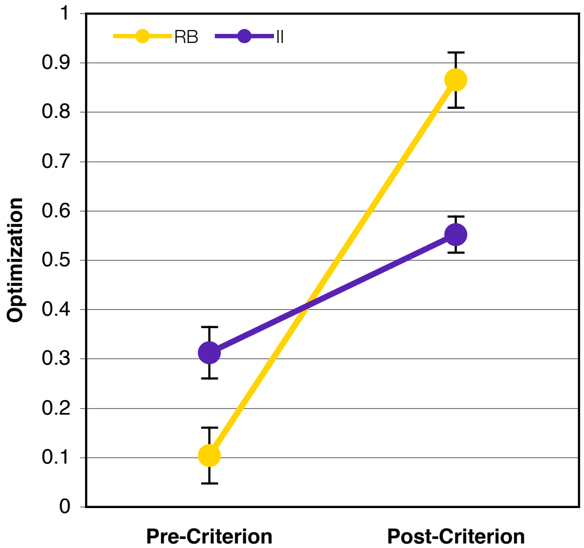

Figure 3. Pre-and post criterion optimization for rule-based and information integration conditions. Bars reflect standard errors.

In order to account for the possibility that the differences we found were due to the differences in learning speed and accuracy between conditions, we performed two multiple regression analyses. The difference between pre- and post-criterion optimization scores for each participant was regressed on total accuracy and condition. The same was performed for number of trials to criterion and condition. In both cases, the effect of condition remained significant.

A final analysis involved looking at the relationship between Aospan and optimization before and after participants reached criterion. We found a significant negative correlation between Aospan and pre-criterion optimization (r = -.35, p < .05) and no relationship with post-criterion optimization (r = -.10, p > .50). A larger working memory span seems to impair optimization during learning. There was no interaction between Aospan and condition in pre- or post-criterion stages (ps > .80), nor was there a significant correlation between Aospan scores and total optimization over the entire experiment (p > .20).

Discussion

Previous studies have found that learning is hampered in rule-based, but not information integration, category tasks if a working memory-demanding task is performed concurrently (e.g., Zeithmova & Maddox, 2006). According to the COVIS multiple-systems model, prefrontal networks involved in executive attention, which are not part of the implicit procedural system of category learning, are highly active when the verbal system is engaged in rule generation and evaluation. Recent work by DeCaro et al. (2008) suggests that high working memory capacity offers an advantage while learning rule-based categories, but hinders learning of information integration categories. We did not find the same result: working memory span did not predict accuracy for either rule-based or information integration categories. There are several differences between our procedure and theirs, however. We used a more stringent criterion of 13 (they used 8). In addition to the Aospan measure used in this study, DeCaro et al. used a measure of reading span and so may have had a more accurate measure of working memory span. Finally, DeCaro et al. used stimuli with four binary-valued dimensions, whereas our task required categorizing stimuli with three continuous dimensions. Nevertheless, if working memory span really is tightly connected to learning different types of categories, we might still expect to see a correlation between Aospan and performance. If increased working memory capacity really does help the learning of rule-based categories, while hindering learning of information integration categories, it does not seem likely to be a very large effect.

Although we found no evidence to suggest a relationship between working memory capacity and behavioural performance on our tasks, we did find an interesting relationship between working memory and attentional performance. Before categories are learned, participants with lower Aospan scores are able to allocate selective attention more optimally than those with higher scores. This effect was seen in both rule-based and information integration categories, but disappeared post-criterion. If, as COVIS predicts, all participants initially rely on a dominant verbal system regardless of the the kind of category they are learning, all participants begin by generating and evaluating possible rules. Regardless of condition, participants with higher working memory may be more likely to persist in using executive memory to test rules until they reach the learning criterion, while participants with lower working memory may give up on rule-testing and engage procedural learning systems before reaching criterion. This would lead to our finding: a negative relationship between participants' Aospan scores and their degree of attentional optimization. By the time all participants reached criterion, those with high Aospan scores quickly optimized attention, resulting in similar attentional optimization regardless of Aospan score. Future studies will be necessary to replicate and explore this finding.

Another result consistent with previous research on attentional optimization is that rule-based learners had very low optimization before reaching criterion, and optimized attention rapidly upon mastering the task (Blair, Watson, & Meier, 2009). When faced with categories that can be learned by forming perfectly predictive verbalizable rules, it appears that participants generally do not begin attentional learning until after these rules have been discovered. On the other hand, information integration learners optimization was higher prior to criterion, and lower subsequent to it. This suggests that for information integration tasks, response learning and attentional learning may be more tightly coupled than they are for rule-based tasks.

According to COVIS, the anterior cingulate and other areas important to executive function are in charge of selecting and switching between rules, and these areas are likely heavily involved in the learning of rule-based categories like ours. Since participants in our rule-based task are initially focused on attaining higher accuracy, executive attention may not work towards attentional learning until resources can be directed away from hypothesis-testing and towards speed or effort-related goals. In accordance with our predictions, participants learning information integration categories begin to optimize attention prior to reaching criterion, and proceed more gradually as performance slowly improved. If participants cannot predict category membership through rule-generation, executive attention is freer to work towards learning more efficient patterns of allocation as the procedural system begins to dominate the categorization task, even before the task is mastered. Our findings are consistent with multiple-systems view such as COVIS, and suggest that attentional optimization is another way in which rule-based and information integration categories are dissociated.

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