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The Price is Right: A High Information Access Cost Facilitates Category Learning

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Abstract

Previous work in object categorization has shown that people tend to optimize their allocation of attention to object features, and suggests that attentional optimization may best be explained in terms of cost-benefit tradeoffs. In support of this idea, we found that implementing a cost for accessing information about object features in a category learning task facilitates both attentional optimization and category acquisition, contrary to the predictions of existing models.

Keywords: category learning; categorization; access cost; attentional learning; optimization.

An important component of proper psychological functioning is the adaptive usage of limited resources. In many situations, careful conservation of money, food, water, memory capacity, and time can be vital to survival. The choice of strategy for dealing with a particular issue depends largely on the relative availability of the various resources required – for instance, installing hardwood floors might be best accomplished by doing it oneself if money is tight and time is plentiful, while hiring a contractor might be a better idea if money is no object but the job must be done quickly. An optimal strategy for a given problem, then, balances situational priorities (urgency, desire for quality) with available resources (time, money).

This characterization of optimal strategy applies equally to psychological domains such as categorization. Fiske and Taylor (1984) characterized humans as cognitive misers, meaning we will attempt to solve problems using the smallest amount of mental resources possible. Indeed, a good deal of evidence suggests that in category learning, people learn to ignore irrelevant information, thereby optimizing their allocation of attention for the task at hand (Rehder & Hoffman, 2005; Blair, Watson, & Meier, 2009; Blair, Watson, Walshe, & Maj, 2009; Blair, Chen, et al., 2009). The process of selectively allocating attentional resources to task-relevant information is labeled *attentional optimization*.

One approach to characterizing the optimal usage of attentional resources takes the view that the benefits of attending to a piece of information must outweigh the costs. This view of attentional optimization as a process of cost-benefit tradeoffs parallels some of the decisions made in the domain of medical diagnosis. A doctor attempting to diagnose a patient will order only tests which are necessary, and even then will strike a balance between efficacy, cost, and safety. A doctor who suspects a particular condition may be more likely to order a cheap, safe blood test than expensive, dangerous exploratory surgery.

It is not yet clear which resources are conserved as a result of attentional optimization. One candidate is working memory capacity: unattended object features are unlikely to be stored in memory. There is, in fact, evidence that working memory shares a close relationship with category learning: those with low working memory spans are less able to suppress task-irrelevant information, creating a need for selective attention to fill the gap (Conway, Kane, & Engle, 2003). Another resource that may be conserved is time – attending only to what is necessary is likely to result in a reduction in the amount of time required to categorize something. In either view, attending to a particular feature of an object incurs a cost – whether temporal or mnemonic – and attentional optimization minimizes the cost incurred for a successful categorization.

Hayhoe and colleagues (Ballard, Hayhoe, & Pelz, 1995; Ballard, Hayhoe, Pook, & Rao, 1997; Droll & Hayhoe, 2007) provided empirical evidence of cost-benefit tradeoffs in visual perception. When performing a task along the lines of the Blocks World game (an interactive paradigm in which subjects must duplicate a target image by positioning a group of coloured boxes from a resource pool), participants generally gather information from the environment as they need it, minimizing the usage of short-term memory. However, increasing the predictability of the task encourages participants to save time by storing information in memory: time, rather than memory capacity, becomes the focus of their conservation efforts. Similar results were found in a series of studies by Gray and colleagues, many of which also employed the Blocks World paradigm (Gray & Fu, 2004; Gray, Sims, Fu, & Scholles, 2006; Fu & Gray, 2006). When the target window was occluded by a removable square, or participants were forced to make head movements in addition to eye movements in order to direct their gaze about the work area, there tended to be a switch to a memory-intensive strategy in order to save time and energy.

It appears that saving time is not the only advantage of adopting a memory-based strategy in tasks along the lines of Blocks World, although the evidence is not unequivocal. Gray et al. (2006) found that participants in a memory-intensive variation of the Blocks World task made fewer errors and mastered the task sooner than others performing a standard task. While this contradicted earlier results by Gray and Fu (2004), the results of Gray et al. (2006) are supported by the research of Waldron and colleagues on interface design (Waldron, Patrick, Howes, & Duggan, 2006; Waldron, Patrick, Morgan, & King, 2007; Morgan, Patrick, Waldron, King, & Patrick, 2009). As in the Blocks

World literature, Waldron and colleagues found that an increased information access cost leads to a change in information-gathering strategy in a variety of different paradigms. Implementing a time delay for accessing information on the target encourages the usage of memorization, in contrast to the default strategy of scanning back and forth (Waldron et al., 2006). This strategic shift was found to be beneficial to memory for particular system states, general understanding of the system, competence in the absence of available information (Waldron et al., 2007), and the ability to fluently resume a task after interruption (Patrick et al., 2009), though it has its costs in the form of increased response time (Waldron et al., 2006).

While the above research suggests that there are some benefits (and some penalties) resulting from a shift toward memory-based strategies in response to increased information access costs, it is not yet clear whether increased attentional optimization is one of them. None of the studies by Waldron and colleagues involved the presence of irrelevant information. This is not surprising, as interface design tends to avoid including irrelevant data in a display; however, in object categorization it is often vitally important to be able to divert one's attention away from unimportant information (e.g. Rehder & Hoffman, 2005).

In spite of the evidence regarding the importance of cost-benefit considerations in the allocation of attention, it is possible (and, until recently, routine) to develop a coherent model of attentional optimization without making any mention of costs. Computational models of category learning, such as ALCOVE (Kruschke, 1992), simply shift attention away from irrelevant information and towards relevant information. However, in a disease diagnosis paradigm, Matsuka and Corter (2008) found that participants appeared optimize attention in a way consistent with a sensitivity to cost-benefit considerations. When presented with stimuli with two different features which perfectly and redundantly predicted category membership, people attended to only one of them. The idea of attentional optimization as a cost-benefit tradeoff explains this result quite well: the benefit of viewing one feature far outweighs the cost of accessing it, while the second feature provides no additional information to offset its access cost and is thus ignored.

If attentional optimization is indeed based partially on cost-benefit considerations, then the degree to which people optimize their attention should depend on the additional cost incurred in attending to irrelevant features. A high information access cost should provide more motivation to avoid the waste of time or resources associated with attending to irrelevant information, increasing the rate of attentional optimization. In contrast, optimizing one's attention would provide only a minimal benefit in a situation in which accessing information is nearly or entirely free, and as such may be less of a priority for those who are able to master the task.

All other things being equal, then, a category learning task with a high information access cost should result in

more attentional optimization than a task with a low or nonexistent access cost. In addition, implementing a high access cost should encourage the use of a memory-based strategy, resulting in improved learning. The present experiment sought to test these hypotheses using the stimuli and category structure from Experiment 2 of Blair, Watson, Walshe, and Maj (2009). Since the stimuli involved three spatially separate features, we were able to manipulate access cost by obscuring the features with overlays and implementing a variable time cost to remove them.

Method

Participants

149 undergraduate students from Simon Fraser University students participated in exchange for course credit in introductory Psychology classes.

Apparatus

The computer program used in the present experiment was developed using E-Prime 1.1 (Psychology Software Tools), and was run on four Apple iMac computers running Windows XP. Responses were made using the computer mouse.

Design

The present experiment consisted of a supervised category learning task. Participants were shown computer-generated pictures of fictitious microorganisms (see Figure 1) and asked to categorize them as members of one of four different species. The microorganisms (following Blair, Watson, Walshe, and Maj, 2009), varied on three binary organelle-like features, each located in a distinct area of the cell. One organelle looked like either a muscle or a thin tube, another was a mitochondrion-like structure with either

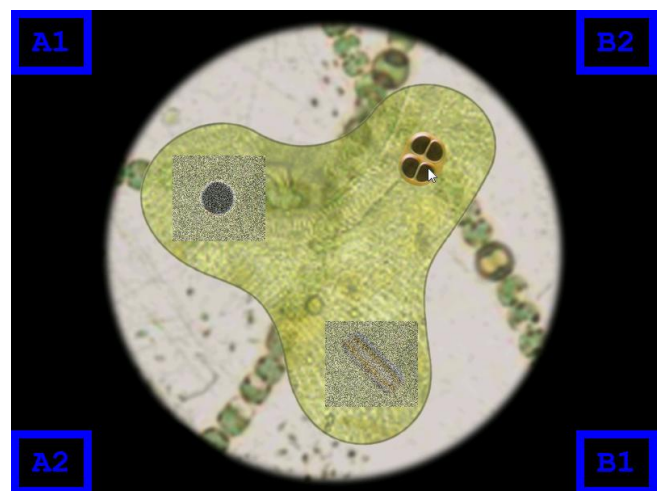


Figure 1: A sample microorganism stimulus with response buttons in the corners of the screen. The subject has revealed the top right feature by moving the mouse over it, while the other two are still occluded by overlays.

Table 1: Sample category structure.

Feature 1	Feature 2	Feature 3	Category
1	0	Irrelevant	A1
1	1	Irrelevant	A2
0	Irrelevant	0	B1
0	Irrelevant	1	B2

two or four internal compartments, and the third resembled an iris and pupil with either a green or a brownish coloration. Each feature occupied its own lobule of the cell, evenly distributed around the screen and counterbalanced across subjects.

There were four possible category labels for each stimulus: A1, A2, B1, and B2. One feature was always relevant, and determined whether the stimulus was a member of an A category or a B category. Of the two remaining features, one determined whether an A stimulus was A1 or A2, and the other determined whether a B stimulus was B1 or B2. Thus, only one of the two was relevant on any given trial, and the identity of the first feature informed the participant of which of the other features would be relevant (see Table 1). Feature relevance was counterbalanced across subjects, and category labels were assigned randomly according to the structure described above.

Procedure

Following a brief introduction to the experimental task, participants began a series of supervised categorization trials. A stimulus was presented, with its three variable features covered up by noisy square-like overlays. In order to remove an overlay and see the feature underneath, participants were required to hold the mouse on top of it for a predetermined period of time.

Participants were randomly assigned to a high-cost or low-cost condition. In the no-delay (low-cost) condition, the overlays disappeared instantly; in contrast, participants in the delay (high-cost) condition had to hold the mouse on top of an overlay for a full 3000ms before the feature was revealed. During this interval, the overlay was replaced by a black box marked “SCANNING...” In either condition, upon moving the mouse away from the revealed feature, the overlay would instantly reappear. The position of the mouse was tracked and recorded over the course of the experiment. Thus, at most one feature was available for viewing at one time. This allowed for a sensitive and dynamic measure of attentional allocation, similar to that of eye-tracking, and prevented participants in the delay condition from using the additional wait time to inspect other features.

Immediately after participants responded, they were presented with corrective feedback and were able to re-inspect stimulus features, with the same overlay restrictions as before, if they so desired.

By default the experiment lasted for 200 such categorization trials. An early learning criterion was implemented such that participants who learned the category

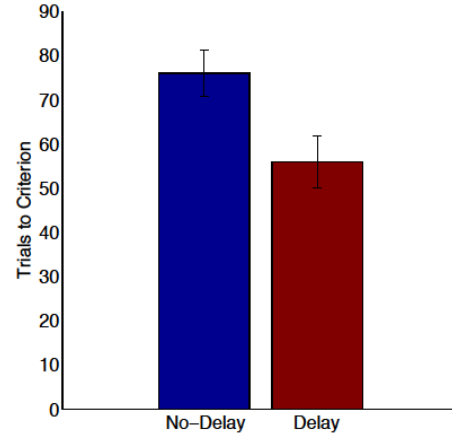


Figure 2: Mean number of trials taken to reach the learning criterion by condition. Error bars represent SEM.

structure well enough to provide 25 consecutive correct answers immediately proceeded to a 72-trial transfer phase where corrective feedback was not provided. Those who were unable to reach this criterion point by the 200th trial did not proceed to transfer. There was no time restriction on the experiment; participants were free to spend as long as desired on each trial. While there was some individual variation in completion times, the entire experiment took approximately 45 minutes to complete.

Results

20 participants were excluded due to computer errors or random responding, leaving 65 participants in the no-delay condition and 64 in the delay condition. The no-delay condition produced 45 learners and 20 non-learners, compared to 49 learners and 15 non-learners in the delay condition. This did not constitute a statistically significant difference, $\chi^2(1) = .877, p > .30$. Among those who were able to learn the category structure, however, participants in the delay condition reached criterion accuracy significantly earlier ($M = 57.5$ trials) than those in the no-delay condition ($M = 76.2$), $t(92) = 2.37, p < .05$ (see Figure 2).

We calculated attentional optimization scores for each trial following the formula used in the eye-tracking experiments of Blair, Watson, Walshe, and Maj (2009):

$$\frac{\bar{X}_{relevant} - \bar{X}_{irrelevant}}{\bar{X}_{relevant} + \bar{X}_{irrelevant}}$$

This amounts to a comparison of the average length of time spent attending to relevant versus irrelevant features, where $\bar{X}_{relevant}$ is the total time during which relevant features were visible divided by the number of relevant features and $\bar{X}_{irrelevant}$ is the total time during which irrelevant features were visible divided by the number of irrelevant features. Our measure of attentional optimization thus ranged from -1 (fixating only irrelevant features) to 0

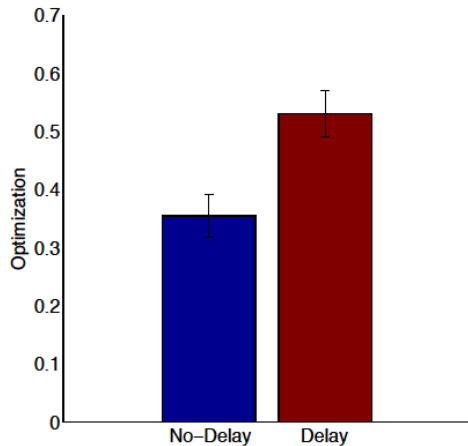


Figure 3: Mean optimization in the first 110 trials by condition. Error bars represent SEM.

(equal time spent fixating all features) to 1 (fixating only relevant features). Over the course of the experiment, subjects in the delay condition displayed significantly greater optimization ($M = 0.623$) than those in the no-delay condition ($M = 0.520$), $t(92) = 2.193$, $p < .05$.

Since the delay condition resulted in faster learning and thus an earlier end to the experiment, we elected to examine optimization between conditions over a set number of trials as an alternative comparison between conditions. We calculated the mean optimization over the first 110 trials (the approximate length of the shortest experimental run) for each successful learner. In this trial range, participants in the delay condition displayed a mean optimization score of .531 (SD .281), compared to .355 (SD .245) for the no-delay condition. This was a significant difference, $t(92) = 3.34$, $p < .01$ (see Figure 3).

As attentional optimization has been known to occur after categorization errors cease (Blair, Watson, & Meier, 2009), it is possible that the contribution of access cost to optimization in the first 110 trials was purely a product of the earlier learning criterion in the delay condition. With more error-free time to optimize, a greater degree of optimization would not be surprising. To examine whether access cost had an effect on optimization independent of its contribution to early accuracy, we performed a mediation analysis using the hierarchical multiple-regression techniques described by Baron and Kenny (1986). Having already demonstrated an association between access cost and criterion point (see Figure 2) and a connection between access cost and optimization in the first 110 trials (see Figure 3), we performed a hierarchical multiple regression analysis predicting early optimization from criterion point in the first step, and adding delay condition as a new predictor in the second. Criterion point proved to be a significant negative predictor of optimization, $\beta = -.777$, $t(92) = -11.85$, $p < .001$, as expected. Condition, when added to the model, contributed to optimization even after controlling for criterion point, $\beta = .140$, $t(91) = 2.11$, $p < .05$, indicating a

partial-mediation relationship. Access cost contributed to optimization both indirectly (via earlier learning) and directly.

Finally, we suspected that the time course of optimization may have differed between conditions – it is possible that a long delay encouraged earlier optimization, but participants in the no-delay condition may have caught up later on in the experiment. To investigate this possibility, we calculated each learner’s mean optimization scores before and after their criterion point. A 2 (pre-criterion/post-criterion) x 2 (delay/no-delay) mixed ANOVA revealed no interactive effect of stage and delay on optimization, $F(1,92) = .106$, $p > .70$, suggesting that attentional learning was uniform over the course of the experiment in both conditions.

Discussion

The results of the present work indicate that increasing the temporal cost of accessing information contributes not only to improved category learning, but also to more optimal allocation of attention. Learners in the high-cost delay condition reached the learning criterion earlier than those in the no-delay condition, and displayed greater attentional optimization over the course of the experiment. These findings support the counterintuitive idea that making information access more difficult improves multiple aspects of performance, extending earlier findings in disease-diagnosis (Matsuka & Corter, 2008) and interface design (Waldron et al., 2007). Taken together, this body of research provides compelling evidence for the validity of the conception of attentional optimization as a balancing act between costs and benefits.

In addition to cost-benefit considerations, one potential contributor to the improved learning in the presence of a high temporal access cost is the fact that such a cost encourages a strict sequential progression of attention. In recalling the positions of objects in space (Yamamoto & Shelton, 2009), as well as in recalling lists of words or letters (Frick, 1985; Goolkasian, Foos, & Krusemark, 2008), performance is significantly improved when information is presented sequentially rather than simultaneously. When access cost is low, participants are able to switch their attention back and forth as they please; in contrast, a high access cost discourages jumping back and forth between costly pieces of information and promotes a strategy of sequential attention.

Somewhat unexpectedly, in spite of the earlier criterion point among learners in the high-cost condition, there was not a concomitant difference in the number of learners. This may be an issue of motivation: while the increased access cost appears to facilitate learning by encouraging the use of memory-based strategies, participants in the delay condition may have become frustrated with the inconvenience of having to wait for features to become visible and applied less effort as a result. This possibility may be a fruitful topic for future research. Further investigation in this area may also benefit from some variance in the number of trials given to reach criterion; in the present study, participants in

both conditions were given 200, a number far in excess of the mean number of trials to criterion (58 for delay, 76 for no-delay).

The practical implications of the present research for training in interface design and related fields are obvious: implementing an access cost can in certain circumstances facilitate learning. However, caution should be taken, as a high temporal access cost can greatly reduce the temporal efficiency of a training period. While a subject might learn a particular system in fewer trials with a high access cost, the cost may make each trial so long that the net effect is ultimately more time spent on training. If it holds true that the learning advantage that comes with an increased access cost is largely the product of a shift toward memory-based strategies, there is probably a point beyond which increasing access cost confers no additional benefit. In addition, there may be more practical ways of encouraging the adoption of memorization strategies, such as only presenting information for a short period of time (Waldron et al., 2006) or implementing a non-temporal cost, such as money, tokens, or effort.

Within the field of category learning, researchers have long focused on tasks where all of the relevant information is immediately and simultaneously available to categorizers. Learning, according to the major models, is in most cases exclusively based on the accuracy of the response (e.g. ALCOVE; Kruschke, 1992). This is because they were designed around a specific event – the categorization trial – rather than around the dynamic unfolding of the task through time (though see Lamberts, 2002). While this has been a helpful simplification, it is becoming increasingly untenable in the face of dynamic measures of attention such as eye- and mouse-tracking (Rehder & Hoffman, 2005; Blair, Watson, Walshe, & Maj, 2009), as well as a number of results indicating a level of complexity untouched by the current generation of computational models. The time spent waiting for stimuli to appear can have implications for strategy selection and memory performance (Morgan et al., 2009), the information participants choose to access depends on which information was previously accessed during the trials (Blair, Watson, Walshe, & Maj, 2009), and the length of time spent viewing feedback impacts learning speed (Watson & Blair, 2008). Investigations of missing data (White & Koehler, 2004; Wood & Blair, 2010), tasks which present new sources of information (Blair & Homa, 2005), and studies of the speed of perceptual processing of features (Lamberts, 2003) are further evidence that the amount and order of known information exerts a considerable influence on the course of category learning.

These and other temporal effects on learning and performance are accumulating and will eventually force researchers to embed extant theoretical work in a dynamic, temporal framework in order to account for them.

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