Brief article

Waiting and weighting: Information sampling is a balance between efficiency and error-reduction

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Abstract

The current study investigates the relative extent to which information utility and planning efficiency guide information-sampling strategies in a classification task. Prior research has pointed to the importance of probability gain, the degree to which sampling a feature reduces the chance of error, in contexts where participants are restricted to one sample. We monitored participants as they sampled information in an unrestricted context and recorded whether they began their search with a high gain feature or an efficient feature that ultimately allowed for fewer samples per trial. Participants preferred to sample the more efficient feature first, especially when feature information had a higher access cost (Experiment 1). When access costs were all but eliminated using eye-tracking (Experiment 2), participants’ fixations still emphasized efficiency over high probability gain, though probability gain was shown to influence access patterns.

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1. Introduction

One general feature of cognitive systems is that they turn information into action. Assessing information in the environment requires an investment of time and energy, and so these systems need ways of assessing which information sources to consult. A key factor determining how people gather information is how useful people believe these sources to be. Nelson, McKenzie, Cottrell, and Sejnowski (2010) conducted a study to elucidate how participants evaluate the utility of a category feature by training them on a probabilistic classification task before restricting their information-gathering strategies to a single mouse click. Under a number of conditions, participants preferred to select the feature with the highest probability gain, that is, the greatest increase in the probability of answering correctly. This finding parallels the claim in prominent theories of category learning that attentional learning serves to reduce error (e.g., Kruschke, 2001).

Error-reduction may not be the only important factor in determining information-access strategies, however. In some contexts, people attempt to reduce cognitive effort by adopting efficient strategies to achieve their goals. For example, participants adopt information-acquisition strategies in arithmetic tasks that minimize working memory demands and reaction times (Stevenson & Carlson, 2003). In demand-selection tasks, people use strategies that minimize effortful cognitive processing, independent of attempts to minimize errors (Kool, McGuire, Rosen, & Botvinick, 2010). In classification tasks, participants employ cost-effective strategies by optimizing attention when gathering information (Matsuka & Corter, 2008) and can apply these strategies dynamically, within a single decision (Blair, Watson, Walshe, & Maj, 2009). Efficiency underlies strategies in saccade planning (Araujo, Kowler, & Pavel, 2001) and visual search (Najemnik & Geisler, 2005).
Given that multiple factors seem likely to guide information-access, a critical question is the relative importance of these factors under various conditions. In the Nelson et al. (2010) study, participants could access only one of two features. While this is an effective design for evaluating how participants gauge feature informativeness, it gives no indication of how this information is incorporated into sampling behavior in an unrestricted context, nor does it speak to the importance of informativeness relative to concerns of efficiency when planning information-access strategies. This is a particularly pertinent question because daily life seems to present people with far more situations in which they have free access to multiple sources of information than situations wherein they must choose a single source.

The two experiments reported here compare the importance of informativeness and efficiency in a free-choice context. In both experiments, participants are asked to classify cells using three salient features. Participants are free to sample features in any order, and so there are many sampling paths one might take to learn the information necessary to make a correct classification – Feature 1 (F1) followed by Feature 2 (F2), or F3–F2–F1, or F2 only, for example. Participants seeking to maximize their gain at every step can be said to take a greedy path, whereas participants seeking to minimize total number of steps can be said to take an efficient path. We designed categories such that the first feature that participants should sample differs depending on whether they are guided by feature informativeness or planning efficiency, allowing for a comparison of these factors. Our general hypothesis is that participants are sensitive to effort-reduction, and will not always prefer to access high probability gain features first in free-access contexts.

Because feature values differ across trials, the exact sampling path a participant might take will also differ. To summarize the paths consistent with greedy and efficiency sampling goals, we created a sampling tree consistent with each goal (see Fig. 1). The greedy tree shows paths in which participants sample information based on their beliefs about how informative each feature will be (see Nelson, 2005; 2008 for background). Here, we define usefulness by a feature’s probability gain. In this tree, participants are driven to reduce error by sampling the feature with the highest expected gain, followed by the feature with the next highest expected gain, and so on. Step-by-step calculations of these expected gain values are described in the Supplementary material. The efficiency tree, on the other hand, shows paths which result from participants choosing to sample information in the order that requires the least effort. Here, we define effort as the average number of fixations necessary to make a correct decision. While a completely trained observer following the information-greedy path would take 2.17 samples per trial on average, the trained observer following the efficiency path would sample exactly 2 – a small, but perhaps notable, decrease in effort. The additive nature of probability gain (Nelson, 2008) dictates that a total probability gain of 0.58 is achieved for any correct answer given by participants following either path. It is important to note that three other prominent utility functions – information gain, Kullback–Leibler distance, and impact - predict a greedy tree identical to that of probability gain given the category structure used in this experiment. Greedy and efficient trees like those in Fig. 1 are provided for these alternative functions in the Supplementary material.

In Experiment 1, participants sampled information about a stimulus by clicking on masks obscuring stimulus features. To understand what guides information access in various conditions, we introduce a manipulation of access cost. Information access costs can change the way people interact with information: higher costs protect against performance deficits after interruptions in copy- (Morgan, Patrick, Waldron, King, & Patrick, 2009) and problem-solving (Morgan, Patrick, & Patrick, 2010) tasks, for example, and higher costs in the form of hard-to-read fonts promotes deeper processing (Diemand-Yauman, Oppenheimer, & Vaughan, 2011). In categorization tasks, high costs discourage people from sampling irrelevant features (Wood, Fry, & Blair, 2010), and so we predicted that participants faced with an access cost would be more likely to follow an efficient strategy. Our access cost manipulation required participants in a high-cost condition to wait three seconds before a feature was revealed. We used a hierarchical category structure previously shown to encourage participants to first sample a feature that allows for fewer overall samples to achieve perfect performance under free-viewing conditions (Blair, Watson, & Meier, 2009), and introduced a high probability gain feature by altering the relative frequency of category members. According to our general hypothesis, we expect participants in the high-cost condition will use the efficient strategy more often than participants in a low-cost condition. If probability gain guides information-gathering choices even in a free-access context, we expect participants will evaluate the high probability gain feature first more often.

Fig. 1. Two information-sampling path predictions. Each node shows the expected gain for sampling that feature, and each branch shows the actual gain for the obtained feature value. In the greedy tree (left), samples are ordered by the feature with the highest expected probability gain first. Expected gain calculated using other utility functions lead to the same predicted tree. In the efficiency tree (right), samples are ordered such that fewer samples are required overall, and the highest gain is obtained last. Note that the total gain for all possible paths in both trees is 0.58, and both trees result in gaining sufficient information to make an accurate classification. See in-text and supplementary materials for details.
2. Experiment 1

2.1. Methods

2.1.1. Participants

Participants were 104 undergraduates.

2.1.2. Stimuli and categories

Stimuli were images of fictitious cells with three features, each represented as an organelle (see Table 1). Organelle images and feature locations were counterbalanced across participants but remained constant for each participant. Features combined to form categories A1, A2, B1, and B2. As illustrated in Table 1, one feature (F1) distinguishes between group A and B; the second (F2) differentiates A1 from A2; and the third (F3) differentiates B1 from B2. This hierarchical category structure is designed such that consulting F1 first allows participants to make the fewest fixations to access all diagnostic features on a trial - one fixation to F1, followed by one fixation to F2 or F3. Categories were presented at an unequal frequency such that participants saw five group A category members for every one group B. Over each block of 24 trials, participants saw ten each of categories A1 and A2, and only two each of categories B1 and B2. This resulted in a high probability gain for F2 (see Fig. 1): evaluating this feature alone yields a 17% error rate (while all A-trials will be correct, all B-trials will be incorrect). The feature with the next-highest expected gain given knowledge of F2 was F1. Finally, F3 had to be sampled if they are viewing a B-trial, making this strategy less efficient overall. Note that category labels were counterbalanced such that half of participants saw more group B categories; for clarity, we collapse these common categories and refer to them all as group A.

2.1.3. Procedure

Participants classified cells into four categories for 240 trials using a mouse-driven interface. A trial began by presenting a stimulus with masked category features along with four response buttons (see Fig. 2). Participants revealed a feature by hovering the cursor over the mask. Participants in the high-cost condition viewed a three-second animation of the mask darkening before a feature was revealed, while participants in the low-cost condition revealed the feature immediately. Features were visible as long as the cursor remained over the feature location; when the cursor was moved away, the mask returned. The amount of time a feature was revealed for was recorded as a “fixation” to a feature. Participants had to reveal at least one feature before responding, and indicated responses by clicking the button corresponding to their category decision. The button with the correct category label turned green; if a participant was incorrect, their selection turned red. At the same time, all features were revealed. Participants clicked the mouse to advance to the next trial.

2.2. Results and discussion

We classified participants as learners if they reached at least 80% correct on common and 70% correct on rare categories during the last quarter of the experiment. We identified 45 of 51 participants in the low-cost condition and 37 of 53 participants in the high-cost condition as learners. Non-learner behavior and preferred sampling paths are described in the Supplementary material.

As an indicator of participants’ information-access strategies after categories are well-learned, we calculated the proportion of trials beginning with a fixation to each feature. A qualitative visualization of the full sequence of information-access patterns beyond the first fixation, and including F3, is presented in the Supplementary material. First-fixation proportions for features F1 and F2 over the last 60 trials are shown in Fig. 3. Over these trials, mean accuracy for low- and high-cost participants was near perfect at .99 (SDs = .01 and .03 respectively). For each participant, we computed the difference between their proportion of first fixations to F1 and F2. The obtained preference scores range from 1, where all trials began with F1,
...and −1, where all trials began with F2. A score of 0 indicates no preference.

In both conditions, participants showed a preference for sampling F1 first. The mean preference score for low-cost participants (0.45; 95% CI [0.20, 0.70]) and for high-cost participants (0.83; 95% CI [0.67, 0.99]) were both significantly greater than 0 (t(44) = 3.59, p < .001, and t(36) = 10.64, p < .001, respectively). In addition, the mean preference score for high-cost participants was significantly higher than low-cost participants, t(80) = 2.46, p = .016. These preference scores reflected fewer fixations on trials that began with a fixation to F1 than to F2. Over the entire experiment, fewer fixations were made during trials beginning with F1 (M = 2.9, SD = 1.0) than to F2 (M = 3.6, SD = 1.5), t(68) = 4.22, p < .001; participants with no F1- or no F2-first trials were excluded). Moreover, the high-cost participants made fewer fixations on trials beginning with F1 (M = 2.3, SD = 0.5) than low-cost participants (M = 3.4, SD = 1.2), t(78) = 5.13, p < .001, indicating high-cost participants adopted more efficient strategies for gathering information.

The results of Experiment 1 indicated that participants were motivated to rely on more efficient strategies when the cost of information was increased. We found that a three-second cost for accessing feature information encouraged more participants to use efficient F1-first strategies than when information was revealed instantly. This suggests that participants paying a cost for their information are more sensitive to the reduction in overall number of samples required by the efficient strategy. However, we were surprised to find that participants in the low-cost condition, though to a lesser degree than participants in the high-cost condition, also relied more often on efficient F1-first strategies than high probability gain F2-first strategies.

The magnitude of the efficiency preference found here is surprising given the preference for high probability gain features shown in Nelson et al. (2010). It may be that efficiency strongly influences performance, even with minimal access costs. Alternatively, the interface may have introduced access costs large enough to affect participants’ strategies, even in the low-cost condition. To disentangle these possibilities we further reduce access costs in Experiment 2.

3. Experiment 2

Instead of a mouse-driven display, we presented all features simultaneously and used an eye-tracker to record participants’ gaze. To further minimize motor demands, we collected responses with a gamepad rather than a mouse. If participants prefer efficiency to probability gain in this case, we can conclude that efficiency is a powerful, broadly applicable determinant of information access. Because of the strong preference for efficiency found in Experiment 1, we wanted a way to verify that participants were indeed sensitive to probability gain in the task we were using. To this end, we included a condition in which probability gain was equal for all three features. If participants are indeed influenced by probability gain, as suggested in Nelson et al. (2010), they should choose F2 more often in the high probability gain condition than in the equal gain condition.

3.1. Method

3.1.1. Participants

Participants were 128 undergraduates.

3.1.2. Stimuli and categories

Participants were presented with the same cells and categories as Experiment 1. In the 1:1 condition, participants saw group A and B stimuli at an equal frequency, and so all features had equal probability gain. In the 5:1 condition, as in Experiment 1, participants saw five group A stimuli for every one group B stimulus. As before, category labels were counterbalanced such that half of participants saw common group B categories; for clarity, we collapse common categories and refer to them as group A.

3.1.3. Procedure

The procedure was similar to Experiment 1. Here, features were always visible. Participants’ fixations were recorded with an eye-tracker, and responses were collected with a Logitech gamepad. Trials began with a centralized fixation cross. Participants pressed a button on the gamepad to reveal a stimulus (see Fig. 4). Feedback was presented as a 500 ms mask of green (correct) or red (incorrect), and the stimulus was re-presented with the response and correct answer centrally displayed. Because this task was much quicker to conduct, participants completed 480 trials. Instructions were identical to Experiment 1, except where procedural differences required different explanation.

3.1.4. Gaze collection and analysis

A Tobii X120 eye-tracker with a spatial resolution of 0.5° sampling at 120 Hz recorded participants’ gaze. Features subtended 1.3° of visual angle, and were located approximately 10.6° apart. Gaze coordinates were...
transformed into fixations using a modified dispersion threshold algorithm (Salvucci & Goldberg, 2000). Fixations to the centralized cross at the beginning of each trial were used to anchor fixation coordinates. Participants with excessive sampling failures, defined as more than 30% unregistered gaze coordinates, were discarded from analysis entirely. Gaze analyses are conducted only on trials with at least 75% registered coordinates.

3.2. Results and discussion

Data from 12 participants were discarded for excessive eyetracker sampling failures, and from four participants for responding randomly. Participants in the 1:1 condition were counted as learners for reaching at least 80% correct over the last quarter of the experiment. The criterion from Experiment 1 of at least 80% correct for common categories and 70% correct for rare categories was used for participants in the 5:1 condition. Forty-four of 54 and 45 of 58 participants were classified as learners in the 1:1 and 5:1 conditions, respectively.

As before, we calculated the proportion of trials beginning with a fixation to each feature during the last 60 trials (see Fig. 5) and computed a preference for each participant. Mean accuracy was nearly identical at .98 (SD = .02) for participants in both conditions. As expected, participants in the 1:1 condition had a mean preference score (.60; 95% CI [.45, .75]) significantly greater than 0, t(43) = 8.01, p < .001, indicating a preference for sampling F1 first. Participants in the 5:1 condition (.28; 95% CI [.07, .50]) also tended to sample F1 first, t(44) = 2.64, p = .01; but did this significantly less than 1:1 participants, t(87) = 2.41, p = .018. These findings show that probability gain manipulations indeed influence first-fixations, but participants still rely on the efficient feature more. Further evidence that participants attempted to engage in efficient strategies by fixating information covertly for small time savings is presented in the Supplementary material. Over the entire experiment, fewer fixations were made during trials beginning with a fixation to F1 than to F2 for the 1:1 condition (F1: M = 3.6, SD = 1.6; F2: M = 5.1, SD = 2.2; t(42) = 4.22, p < .001). There was no significant difference found for the 5:1 condition (F1: M = 3.0, SD = 1.1; F2: M = 3.3, SD = 1.7; t(44) = 1.05, p = .30).

4. General discussion

In two experiments, we monitored participants as they gathered information to see whether they first accessed a high probability gain feature, or a feature that allowed for ultimately more efficient information-seeking patterns. We found that a manipulation of access cost (Experiment 1) impacts performance: when information takes time to appear, participants use more efficient strategies than when information is revealed instantly. We also found that a manipulation of feature probability gain (Experiment 2) impacts performance: when a high probability gain feature is present, participants will use this feature to guide their information searches more often than when features have equal probability gain. Our most salient finding, however, was that under all circumstances tested we found participants value highly efficient strategies over highly informative features. In Experiment 2, information access costs were as low as we could make them. That people still show a preference for efficiency leads us to believe that efficiency is likely to strongly influence information access in real-world tasks.

Efficiency is not independent of utility, of course: people allocate attention to informative features and away from irrelevant ones (Rehder & Hoffman, 2005), even when information is sometimes useful but irrelevant for that decision (Blair, Watson, Walshe et al., 2009). It is remarkable, however, that participants first sampled information that was arguably only relevant on 16% of trials (F1), rather than information that would allow for 5 out of 6 correct classifications (F2), for such a small reduction in effort—a single sample on every sixth trial. Participants may be relying on strategies that do not require them to remember feature values: sampling F2 still requires an evaluation of F1, and the value of F2 must be recalled or discarded. This
may seem contrary to previous work showing higher information access costs in copying (Fu & Gray, 2000), planning (Waldron, Patrick, Howes, & Duggan, 2006), and problem-solving (Kibbe & Kowler, 2011) tasks encourage strategies that are memory-based, rather than perceptuo-motor-based. In such tasks, however, participants are motivated to use memory-based strategies because they are more efficient in the face of these access costs. Our study demonstrates a context in which constant memory updating is not considered efficient. In all cases, participants adopt whichever strategy is efficient given the task demands.

Researchers investigating fast and frugal heuristics in various kinds of decision-making (e.g., Bennis, Medin, & Bartels, 2010; Gigerenzer & Brighton, 2009) have argued that these strategies are not simply fast, they are fast and accurate. Similarly, in the present study participants prefer strategies which are efficient, but the majority were unwilling to use a more efficient strategy with lower accuracy (e.g., F2-only: just one participant in these studies clearly adopted this strategy; see Supplementary material). While the extent to which the current findings generalize to other tasks is unknown, it is clear that mouse- and eye-movement tasks, at least, produce similar findings.

Soliciting behavioral outcomes in restricted environments is key for understanding general principles of cognition. However, we must always examine behavior in richer contexts to see how our conclusions generalize. Nelson et al. (2010) demonstrated that participants reason differently about feature probabilities they experience, compared to those they only read about. This has significant implications for models of human reasoning. Our results take a further step by considering behavior in a free-choice paradigm, and show that while there is a tradeoff between probability gain and access cost, participants prioritize efficiency in all cases. We predict this will extend to decision-making behaviors that require planning, such that as costs increase, efficiency is valued higher. In some contexts, there may be a cost so great that efficiency is valued above accuracy. The extent of this tradeoff in more complex settings must still be determined, especially in the kinds of decisions we make about information-access in planning, copying, and problem-solving tasks more broadly. People may behave differently in response to time constraints, probabilistic rewards, uncertain environments, or in prolonged decision-making, for example. Models that incorporate information-seeking (e.g., Fu & Gray, 2006) must account for costs other than accuracy when modeling information-sampling strategies. The importance of efficiency in information-access becomes clearer when one considers the staggering number of complex but effortless ways in which we interact with our environment.

In quotidian tasks like making a sandwich or some tea, we access task-relevant information only just as we need it (Land & Hayhoe, 2001). Small savings achieved by making subtly more efficient decisions can rapidly add up.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2012.09.014.

References


