Emerging Insights from Eye-Movement Research on Category Learning

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Introduction

Attempts to develop an accurate measure of eye movements are over a century old (e.g., Delabarre, 1898; Huey, 1898; as cited in Karatekin, 2007), and predate the earliest studies of categorization (Hull, 1920). Given the long history of both categorization and eye-tracking, it is surprising that eye-tracking has only recently been added to the categorization researcher's toolbox (Rehder & Hoffman, 2005a).

Selective attention is an important component of theories of categorization and eye-tracking provides a measure of what features of a stimulus participants have selected to attend. There are alternatives to eye-tracking, such as inferring attention allocation based on model fits or carefully designed transfer tasks. However, these methods lack the directness of eye-tracking and provide only a coarse measure of how attention shifts over the course of learning. Moreover, they provide no account of how attention is allocated early in learning and within a single categorization trial (including after feedback is presented). This more fine-grained data can not only clarify our understanding of key phenomena, it broadens the range of experimental questions that can be asked to understand how humans learn categories (Blair, Watson & Meier, 2009; Blair, Watson, Walshe & Maj, 2009; Hoffman & Rehder; 2009; Kim & Rehder, 2009; Rehder, Colner & Hoffman, 2009; Rehder & Hoffman, 2005a; Rehder & Hoffman, 2005b; Watson & Blair, 2008)

This symposium brings together four talks on eye-tracking and categorization. Each talk focuses on a different aspect of categorization and demonstrates how using eye-tracking can extend our knowledge. One recent trend in category learning is the use of alternative training procedures. The inference learning task is the most popular of these procedures and in the first talk Aaron Hoffman presents eye-tracking data illuminating the differences between inference learning and categorization. Bob Rehder then presents his recent work on understanding the learning difficulties associated with Parkinson's disease. Marcus Watson discusses work using eye-tracking to inform our understanding of the basic issue in category learning: error. Finally, Mark Blair discusses the relationship between working memory, attention and performance in a category learning tasks.

Inference versus classification learning

It has been proposed that whereas feature inference learning promotes learning a category's internal structure (e.g., typical features and feature correlations), classification promotes the learning of diagnostic information (Markman & Ross, 2003). We tracked learners' eye movements and found that inference learners fixated features that were unnecessary for inferring a missing feature—consistent with their acquiring the categories' internal structure. However, those fixations were limited to features that needed to be predicted on future trials. Inference learning appeared to induce both supervised and unsupervised learning of category-to-feature associations, rather than any general motivation to learn the internal structure of categories.

In a second study, we compared how inference and classification learning support learners' ability to draw *novel contrasts*—category distinctions that were not part of training. We found that classification learners were at a disadvantage at making novel contrasts. Eye movement data indicated that this *conceptual inflexibility* was due to (a) a narrow attention profile that fails to encode many category features and (b) learned inattention that inhibits the reallocation of attention to newly relevant information. Implications of these costs of supervised classification learning for views of conceptual structure will be discussed.

Using eye-movements to understand Parkinson's patients learning difficulties

Those with Parkinson's disease (PD) exhibit not only motor difficulties such as tremors, rigidity, and postural instability but also a variety of cognitive deficits, including deficits in procedural learning and in switching to new tasks ("set shifting"). Out central hypothesis is that deficits in selective attention are central to many of PD patients' learning difficulties. Moreover, assessing how attentional deficits in PD affect learning is critical to understanding how other learning mechanisms are affected by the disease. A probabilistic category learning paradigm known as the weather prediction task (WPT) has played a central role in theorizing about learning in PD patients. We report eye movement data from both PD patients and controls while performing the WPT and discuss implications our results have for current theories of category learning.

Over and under-estimating the importance of error-processing in categorization

The category label (i.e., the correct answer) has a central role in most models of categorization. It supplies the information necessary to improve both categorization and attentional performance. But despite its theoretical importance, there has been little direct investigation of how errors are processed.

In this presentation we first evaluate the necessity and sufficiency of errors for optimizing attention. Error-driven models predict large shifts of attention when errors are most common and the absence of shifts when learners are not making mistakes. We review data that shows the opposite result. We next use eye-tracking to assess how participants process stimuli and category labels while receiving feedback on their errors. Results show that temporal aspects of this process that are not captured in extant models are consequential for learning.

Working memory, attention and category learning

Categorization is a core cognitive task that involves accessing information, remembering relationships, focusing on relevant aspects of the stimuli, etc. While long-term memory and selective attention have long been employed by theories of categorization, working memory has had nothing much to do. This is especially surprising given that working memory is described by some researchers as executive attention, and its influence has been demonstrated to be very broad. Intuitively, working memory capacity might influence categorization performance in a variety of ways. High working memory span might be associated with faster learning or improved accuracy. It also might influence how participants attend to stimulus features.

This presentation will describe work aimed at demystifying the effects of working memory capacity on categorization performance, including on attentional optimization. Studies reveal that, depending on the task, working memory span is related to both attentional optimization and learning speed. Working memory span (measured by the symmetry span task) is compared to measures of attentional network efficiency (measured by the Attention Network Test), and to several other aspects of attentional learning and categorization data.

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