



Adaptive response-time-based category sequencing in perceptual learning



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ABSTRACT

Although much recent work in perceptual learning (PL) has focused on basic sensory discriminations, recent analyses suggest that PL in a variety of tasks depends on processes that discover and select information relevant to classifications being learned (Kellman & Garrigan, 2009; Petrov, Doshier, & Lu, 2005). In complex, real-world tasks, discovery involves finding structural invariants amidst task-irrelevant variation (Gibson, 1969), allowing learners to correctly classify new stimuli. The applicability of PL methods to such tasks offers important opportunities to improve learning. It also raises questions about how learning might be optimized in complex tasks and whether variables that influence other forms of learning also apply to PL. We investigated whether an adaptive, response-time-based, category sequencing algorithm implementing laws of spacing derived from memory research would also enhance perceptual category learning and transfer to novel cases. Participants learned to classify images of 12 different butterfly genera under conditions of: (1) random presentation, (2) adaptive category sequencing, and (3) adaptive category sequencing with 'mini-blocks' (grouping 3 successive category exemplars). We found significant effects on efficiency of learning for adaptive category sequencing, reliably better than for random presentation and mini-blocking (Experiment 1). Effects persisted across a 1-week delay and were enhanced for novel items. Experiment 2 showed even greater effects of adaptive learning for perceptual categories containing lower variability. These results suggest that adaptive category sequencing increases the efficiency of PL and enhances generalization of PL to novel stimuli, key components of high-level PL and fundamental requirements of learning in many domains.

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1. Introduction

Attaining expertise in many domains depends on changes in the way information is extracted – perceptual learning (Gibson, 1969; Kellman & Garrigan, 2009). In the last two decades, work in cognitive and neural sciences has witnessed a resurgence of interest in perceptual learning (PL). Most of this recent work has focused on simple sensory dimensions using a few specific stimulus values. In contrast, the focus of earlier PL research (Gibson, 1969) and the application of PL in virtually all real-world tasks involves discovery of invariance amidst variation.

These emphases relate to different scientific purposes. In the work of Eleanor Gibson, and in some recent work (e.g., Kellman & Massey, 2013; Kellman, Massey, & Son, 2010), the focus is on understanding how changes in information extraction advance performance in complex domains and real-world settings. The fo-

cus of many contemporary researchers on basic discriminations using a small set of simple stimuli relates to attempts to understand the neural bases of PL, especially receptive field changes in early cortical areas (e.g., Fahle & Poggio, 2002).

Much recent work suggests that learning effects in both so-called low-level and high-level PL tasks often involve common principles and mechanisms, specifically discovery of what information makes the difference in classifications being learned (Ahissar & Hochstein, 1997; Kellman & Garrigan, 2009; Petrov, Doshier, & Lu, 2005). In work on basic sensory discriminations, for example, data have tended to favor models emphasizing selective re-weighting of analyzers rather than receptive field changes (Petrov, Doshier, & Lu, 2005), and many PL results appear to be incompatible with explanation primarily in terms of changes in early receptive fields (Ahissar, 1999; Crist, Li, & Gilbert, 2001; Garrigan & Kellman, 2008; Ghose, Yang, & Maunsell, 2002; Liu, 1999; Wang et al., 2012; Xiao et al., 2008; for discussion, see Kellman & Garrigan, 2009).

The emphasis on discovery processes that lead to weighting of the most relevant analyzers strongly mirrors Gibson's (1969) emphasis on selection of relevant structure; in fact, Gibson often used "differentiation learning" as a synonym for PL. Contemporary

Abbreviation: PL, perceptual learning.

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models based on selection of analyzers place the focus within the nervous system, whereas selection of information or discovery of invariants in the world places the focus outside the organism and onto the environment, but clearly these are two sides of the same coin (assuming that analyzers pick up relevant information from the environment). Findings that PL appears to occur only for constancy-based information, rather than any arbitrary sensory invariant, also implicate learning processes focused on extracting functionally relevant environmental properties (Garrigan & Kellman, 2008).

Understanding that PL processes involve discovery and selection of information not only helps to unify various PL tasks and results but has direct practical implications. Recent work suggests that domain-specific changes in information extraction attained through PL comprise a much larger component of expertise than is often understood (Kellman & Garrigan, 2009). This is true even in high-level, symbolic domains, such as mathematics, chess, and reading (Chase & Simon, 1973; De Groot, 1965; Goldstone, Landy, & Son, 2008; Kellman & Massey, 2013; Kellman, Massey, & Son, 2010; Thai, Mettler, & Kellman, 2011), where PL functions synergistically with other aspects of cognition. Learning technology based on PL, in the form of perceptual learning modules (PLMs), has been shown to accelerate crucial and otherwise elusive aspects of learning, including pattern recognition, transfer, and fluency, in domains as diverse as aviation training (Kellman & Kaiser, 1994), mathematics learning (Kellman, Massey, & Son, 2010; Massey et al., 2011), and medical learning (Krasne et al., 2013; Guerlain et al., 2004; Kellman, 2013).

The realization of the importance of PL in diverse learning tasks and the emergence of PL interventions raise the question of whether PL shares principles that have been found to improve or optimize other kinds of learning. When we learn new perceptual classifications, what principles govern successful learning? Are there ways of organizing the order of presentation of material such that learning is enhanced? Such questions form the basis for the following studies, which investigate effective training strategies for enhancing perceptual learning – especially when learning concerns sets of categories or natural kinds.

1.1. Spacing and memory

One of the most robust and enduring findings in research on memory for factual items concerns the benefits of spaced practice relative to those of non-spaced practice. “Spaced” practice means repeated exposure of an item following delays or presentation of intervening items. In general, longer delays are more beneficial than shorter delays, up to some maximum after which the benefit to learning decreases (Benjamin & Tullis, 2010; Cepeda et al., 2008; Glenberg, 1976). Maximum benefit may occur when re-presentation of an item is just prior to – and no later than – the moment that its decaying memory trace becomes irretrievable; that is, items are best re-presented just before they are forgotten. Experimental evidence suggests that the value of a presentation of an item increases with the difficulty of successful retrieval (Benjamin, Bjork, & Schwartz, 1998; Pyc & Rawson, 2009). Pyc and Rawson (2009) labeled this idea the “retrieval effort hypothesis”: More difficult, but successful, retrievals are more beneficial.

Substantial data suggest that producing difficult but successful retrievals can be accomplished by expanding spacing during the course of learning. Expanding retrieval practice has been studied for nearly half a century (Cull, Shaughnessy, & Zechmeister, 1996; Landauer & Bjork, 1978; Pimsleur, 1967). Explanations of the value of expanded retrieval intervals usually invoke or assume an underlying notion of learning strength that increases with repeated presentations of an item. Learning strength can be thought of as a hypothetical construct related to probability of successful

recall on a future test. When a new item is presented, learning strength may be low, but it typically increases with additional learning trials.

Although a preset schedule of expanding spacing intervals across trials will tend to correlate with increasing learning strength, the match may be far from perfect. Even if learning strength increases monotonically, preset intervals may expand too much or not enough. Moreover, learning of particular items by particular individuals may produce different courses of improving learning strength, and learning strength may actually be a non-monotonic function of trials, depending on item difficulty and relations among items being learned. Ideal spacing intervals, from the standpoint of the retrieval difficulty hypothesis, might involve, not predetermined intervals, but flexible spacing that matches current learning strength. Arranging learning to approximate such an ideal would benefit from an ongoing indicator of learning strength, one which might vary for different learners, items, and their interactions.

1.2. The ARTS system

Evidence indicates that response time (RT) is a useful indicator of retrieval difficulty, and thus of an item's current learning strength (Karpicke & Bauernschmidt, 2011; Pyc & Rawson, 2009). This relationship offers a useful way of updating spacing to track underlying learning strength: Adaptive methods can use an individual's accuracy and RT performance data for learning items to dynamically schedule spacing intervals. Mettler, Massey, and Kellman (2011) showed that a system that determines spacing dynamically based on each learner's accuracy and speed in interactive learning trials (the Adaptive Response-Time-based Sequencing or ARTS system) produced highly efficient learning and compared favorably with a classic adaptive learning system (Atkinson, 1972).

ARTS uses a priority score system, in which the priority for an item to reappear on each learning trial is computed as a function of accuracy, response time, and trials since the last presentation. The system also implements mastery criteria based on both accuracy and speed. As learning strength increases, as reflected in performance, delay intervals automatically expand in this system. Because all items compete for presentation on any trial, through their priority scores, the system concurrently implements adaptive spacing for all learning items. (See the Method section for further detail on the ARTS system.)

ARTS was designed to test principles of learning and memorization of factual items (e.g., Mettler, Massey, & Kellman, 2011), but it can be applied to perceptual category learning as well, in cases where there are multiple categories to be learned. This situation occurs in many real world tasks, such as a dermatologist learning to identify different kinds of skin lesions, an air traffic controller learning to recognize different types of aircraft, or a chemist learning to recognize different types of molecular structures. In adaptive category sequencing, the ARTS system tracks learners' accuracies and response times in order to assess the learning strength of categories. Each category is given a dynamically updated priority score, reflecting the relative importance of an exemplar of that category appearing on the next learning trial.

1.3. Relationship between perceptual learning and factual learning

Although it is clear how adaptive spacing might be applied to PL, it is not clear whether the same principles of spacing and expanding the retrieval interval that improve item memory would enhance PL. There have not been many studies of PL in real-world learning domains, and there has been even less work exploring the conditions that optimize such learning. These two kinds of learning

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