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Differential impact of relevant and irrelevant dimension primes on rule-based and information-integration category learning☆

Lisa R. Grimm [a,*], W. Todd Maddox [b]

[a] Department of Psychology, The College of New Jersey, USA
[b] Department of Psychology, University of Texas at Austin, USA

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ABSTRACT

Research has identified multiple category-learning systems with each being "tuned" for learning categories with different task demands and each governed by different neurobiological systems. Rule-based (RB) classification involves testing verbalizable rules for category membership while information-integration (II) classification requires the implicit learning of stimulus–response mappings. In the first study to directly test rule priming with RB and II category learning, we investigated the influence of the availability of information presented at the beginning of the task. Participants viewed lines that varied in length, orientation, and position on the screen, and were primed to focus on stimulus dimensions that were relevant or irrelevant to the correct classification rule. In Experiment 1, we used an RB category structure, and in Experiment 2, we used an II category structure. Accuracy and model-based analyses suggested that a focus on relevant dimensions improves RB task performance later in learning while a focus on an irrelevant dimension improves II task performance early in learning.
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1. Introduction

Categorization is ubiquitous in human thinking, and as such, has been extensively studied by psychologists interested in a wide-variety of processes from language to object recognition to reasoning and decision-making. Some early work on basic categorization focused on the presence of a single categorization system (Nosofsky & Johansen, 2000) while other work demonstrated the existence of multiple memory systems (Ashby & Ell, 2001; Ashby & Maddox, 2005; Ashby & O'Brien, 2005). Specifically, researchers argued that there was an explicit-hypothesis testing system that was recruited to process rule-based (RB) classification and another implicit-procedural-based system that was recruited to process information-integration (II) classification. RB classification tasks are constructed to involve rules for category membership that are verbalizable (Ashby, Alfonso-Reese, Turken, & Waldron, 1998). Because the classification rule is verbalizable, the optimal strategy is to test and discard rules until the correct rule is discovered and classification accuracy improves. For example, if short, shallow-oriented lines are in category A and all others are in category B then this classification task might be solved by first trying a rule on length, and ultimately discarding this rule for a rule that makes a decision on length and a decision on orientation and then combines these decisions to generate the correct categorization response. In contrast, II classification tasks involve the predecisional integration of information across dimensions (Ashby & Gott, 1988) and therefore the optimal classification rules are not verbalizable (Ashby et al., 1998). For example, a possible II task rule could require that participants place lines that are longer than they are steep into a category. In this case the participant would rely on the implicit-learning system to incrementally learn the association between the stimulus and the appropriate response.

There is a huge literature on the dissociations between RB and II classification learning (e.g., Ashby, Ell, & Waldron, 2003; Ashby, Maddox, & Bohil, 2002; Ashby, Queller, & Berretty, 1999; Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005) and the different neurobiological systems that may be recruited for explicit hypothesis testing and implicit procedural-based learning (e.g., Filoteo, Maddox, Salmon, & Song, 2005; Filoteo et al., 2005; Maddox & Filoteo, 2001; Rao et al., 1997; Seger & Cincotta, 2002). Most relevant to the current studies is the literature that focuses specifically on the impact of working memory. RB classification is thought to recruit the explicit-hypothesis testing

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* Corresponding author at: Department of Psychology, The College of New Jersey, P.O. Box 7718, Ewing, NJ 08628-0718, USA. Tel.: +1 609 771 2787; fax: +1 609 637 5178.
E-mail address: grimm@tcnj.edu (L.R. Grimm).

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system and actively engage working memory to generate and apply candidate classification rules (Ashby et al., 1998). In contrast, II classification does not rely on working memory because learning occurs below the level of conscious awareness and is the result of stimulus–response association learning (Maddox, Ashby, Ing, & Pickering, 2004; Zeithamova & Maddox, 2007). Maddox et al. (2004) and Zeithamova and Maddox (2006, 2007) demonstrated that adding a verbal or visuospatial working memory load decreases RB but not II learning. In Maddox et al., participants viewed a classification stimulus, made a classification judgment, and received corrective feedback. Next, they completed a sequential verbal working memory task in which a digit memory set (set size 4) was presented and followed by a memory probe (i.e., "Was this item in the memory set?"). Zeithamova and Maddox (2007) adapted this working memory task by requiring that participants remember object locations instead of digits, which transformed the task from a verbal working memory task to a visuospatial task.

While tempting to assume that working memory loads will always show this dissociation between RB and II learning, there is an interesting set of predictions generated by the COmpetition between Verbal and Implicit Systems (COVIS) model (Ashby & Maddox, 2011; Ashby et al., 1998) argued to underlie RB and II learning. COVIS postulates that II tasks recruit visual cortical areas and the posterior caudate nucleus, while RB tasks use the prefrontal cortex, anterior caudate nucleus, and the anterior cingulate. It is believed that both the explicit and implicit systems are initially recruited to solve a classification problem (Ashby & Maddox, 2005; Zeithamova & Maddox, 2006). Each system generates a response and response selection is governed by the weight of the responses, determined by the past success of responses from that system. Moreover, participants are initially inclined to favor responses from the explicit system. Filoteo, Lauritzen, and Maddox (2010) tested the interesting prediction that adding a working memory task would engage working memory and make participants less likely to rely on rules which would also require working memory. This interference would result in participants disengaging from the explicit system, and allowing the implicit system to learn the classification task and operate without competition. Consistent with their prediction, they found that the working memory task impaired RB learning but improved II learning. This result is consistent with work by DeCaro, Thomas, and Beilock (2008) that examined the impact of working memory capacity. They found that individuals with a lower working memory capacity performed better on II learning tasks but worse on RB tasks relative to those with a higher working memory capacity.

All of the prior work examining working memory capacity has used traditional working memory dual tasks. Our studies ask a different question: Does the content of the verbal working memory store matter? Instead of relying on working memory tasks that are unrelated to the classification task, we used a method that allows us to directly compare content that is relevant and irrelevant to task performance. Our experiments are the first to consider the influence of dimension priming on the learning of RB and II category structures. In Experiment 1, we use a perceptual RB task, and in Experiment 2, we use a perceptual II task. For each task, participants viewed lines that varied in length, orientation, and position on the screen. A conjunctive RB rule (i.e., lines that are long and steep are in one category) could be used to perfectly classify the stimuli in Experiment 1, while in Experiment 2, an information-integration rule (i.e., lines that are longer than steep are in one category) could be used to perfectly classify the stimuli.

To examine the influence of dimension primes on each system, we varied the information available at the start of the experiment. Participants were told that a focus on the position, length, or orientation of the lines led to good performance in prior participants; control participants were told nothing. This simple manipulation allowed us to examine whether RB and II tasks would be differentially impacted when participants are told to focus on dimensions relevant or irrelevant to the classification rule.

Given the prior research on working memory, the predictions for Experiment 1 are fairly straightforward. We predicted that RB learning would benefit from a focus on relevant dimensions (i.e., length and orientation) but not from a focus on the irrelevant dimension (i.e., position). A focus on an irrelevant dimension is analogous to the prior work using unrelated working memory loads and therefore should hurt RB task performance. The participants should fill the verbal working memory store generating and testing rules that are not helpful to performance. In contrast, a focus on relevant task dimensions should help performance because the verbal store is being recruited for activities that directly benefit task performance.

There are two possible outcomes for Experiment 2 based on the prior literature. One possibility is that II learning will be unaffected by providing participants with a focus on relevant or irrelevant task dimensions. Simply, because II learning is thought to proceed without relying on working memory resources, the addition of content to working memory should not impact performance. This is consistent with several studies (Maddox et al., 2004; Zeithamova & Maddox, 2006, 2007) demonstrating that adding a verbal working memory load did not affect II learning. In contrast, the work by Filoteo et al. (2010) suggests that adding irrelevant content to working memory improves II learning and DeCaro et al. (2008) demonstrated that a larger working memory capacity resulted in worse II learning. If one assumes that individuals with a larger working memory capacity focused on content relevant to task performance, we should find a corresponding decrease in II performance when we ask participants to focus on relevant task dimensions. In contrast, consistent with Filoteo et al., asking participants to focus on the irrelevant task dimension of position would fill the verbal working memory store and allow for a disengagement of the explicit system, thereby permitting the II system to learn and generate the correct stimulus–response mappings that involve the task-relevant length and orientation dimensions. As such, we predicted that the opposite pattern would be true for II learning when compared to RB learning. II learning should benefit from a focus on an irrelevant dimension. This prediction is consistent with findings in Ashby and Crossley (2010) that using an RB explicit strategy may limit the use of the II system.

2. Experiment 1

2.1. Material and methods

2.1.1. Participants and design

One hundred forty-two undergraduate students at The College of New Jersey participated for course credit. Participants were randomly assigned to one of four dimension-prime conditions (Position, Length, Orientation, or Control) yielding a 4 Condition × 12 Block mixed-factorial design with Condition between participants and block within participants.

2.1.2. Materials

Dimensions were primed by manipulating the instructions participants read prior to completing the category learning task. All groups received basic instructions explaining the nature of the task (e.g., viewing lines that vary in length, orientation, or position) and the goal of the task (e.g., to learn how to correctly classify the stimuli into two categories). The Control group received no additional instructions. For the other 3 prime groups, participants received an additional hint to focus on a specific dimension. For example, for the Length group, participants were told that prior participants found that creating rules using the length of the line led to good task performance. Corresponding hints were presented to the Orientation and Position groups.

2.1.3. Stimuli and stimulus presentation

Participants viewed stimuli on a computer screen and were asked to classify a set of items into one of two categories. The stimuli to be categorized were lines that varied across items in their length, orientation,

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