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Post-error slowing predicts rule-based but not information-integration category learning

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Abstract

We examine whether error monitoring, operationalized as the degree to which individuals slow down after committing an error (i.e, post-error slowing), is differentially important in the learning of rule-based vs. information-integration category structures. Rule-based categories are most efficiently solved through the application of an explicit verbal strategy (e.g. sort by color). In contrast, information-integration categories are believed to be learned in a trial-by-trial associative manner. Results indicate that post-error slowing predicts enhanced rule-based but not information-integration category-learning. Implications for multiple category learning systems are discussed.

¹Introduction

The ability to learn new information and to adjust to changes in the environment is critically important at all stages of life. This skill is dependent upon the ability to utilize feedback to guide and shape future behavior (Holroyd & Coles, 2002; Ohlsson, 1996). Prominent theories of skill acquisition generally depict a multistep process that emphasizes an initial slow, declarative component to goal-oriented behavior (Anderson, 1982, 1987). Increased proficiency and automaticity are achieved via encoding an initial approximation of the desired behavior, gradually refining the behavior through error feedback, and finally compiling the multiple cognitive procedures into a single procedure (Anderson, 1987; Logan, 1988). Hallmark characteristics of these models include heavy reliance on executive functioning, such as rule shifting and information updating (Miyake et al., 2000), in the development of skilled performance (Anderson, 1982; Logan, 1988).

One of the most frequently employed behavioral proxies to index active error feedback processing is post error slowing (PES), which refers to an increase in response latency following an error. To control for individual differences in speed, PES has most frequently been quantified by taking the first correct reaction time after an error response and subtracting from it the average correct reaction time (Rabbitt, 1966, 1968).

Category Learning

Organizing objects into categories is a critical skill. Categorization reduces information load, assists in language acquisition, and influences the formulation of inferences, predictions, and decisions that affects human behavior (Farrar, Raney, & Boyer, 1992). The ability to accurately categorize environmental elements into simple groupings – ‘safe/dangerous,’

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‘same/different,’ ‘friend/foe’ – has been perpetuated throughout evolutionary history (Smith, Chapman, & Redford, 2010), and emerges early in development (Huang-Pollock, Maddox, & Karalunas, 2011; Quinn, Doran, Reiss, & Hoffman, 2010), emphasizing its relevance to survival and fitness. We focus on perceptual categorization learning and the associated COVIS model herein, providing a brief review of the model for those unfamiliar with it (for a more complete description, please see: Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby, Paul, & Maddox, 2011).

COVIS (COmpetition between Verbal and Implicit Systems), a neurobiologically-inspired multiple systems model of category learning, posits the presence of at least two distinctive systems of category learning: an (explicit) verbal rule-based (RB) system and an (implicit) information-integration (II) associative learning system (Ashby et al., 1998). Neuropsychological predictions based on COVIS have been validated in patients with Parkinson’s (Ashby, Noble, Filoteo, Waldron, & Ell, 2003), Huntington’s (Filoteo, Maddox, & Davis, 2001), Amnesia (Maddox & Filoteo, 2007), Anorexia Nervosa (Shott et al., 2012), and Attention Deficit Hyperactivity Disorder (ADHD) (Huang-Pollock, Tam, & Maddox, in review).

Verbal RB category learning is thought to be dependent on the anterior cingulate and prefrontal cortices. It operates via a hypothesis testing procedure where a verbalized rule is tested and updated until an optimal rule is identified (Ashby et al., 1998). Examples of verbalizable rules include single feature (if-then), conjunctive (if-and-then), disjunctive (if-or-then), and exceptions (if-then-except) (Minda, Desroches, & Church, 2008). Verbal skills, working memory, and attentional control facilities play important roles in RB category learning tasks (Ashby et al., 1998). In contrast, II categorization, mediated predominantly by the striatum, requires simultaneous assessment of multiple stimulus parameters to attain maximal accuracy and whose optimal “rule” is verbally difficult to express (Ashby et al., 1998). This system learns not by active hypothesis testing, but by automatically and gradually recognizing subtle covariations within the stimuli or environment, as well as which response or behavior to emit in response.

Both humans and non-human primates show a clear bias towards the RB system even when the optimal strategy requires an II approach (Smith et al., 2011). This is most likely because RB learning follows a rational hypothesis testing approach that leads to all-or-none mastery which is faster than the incremental trial-and-error associative process of II learning. The transition from a reliance on an RB to II approach in the course of an II task has been proposed to occur when the RB system ceases its inhibition of the II system (Ashby & Crossley, 2010).

If PES reflects the recruitment of effortful attentional control networks important in the acquisition of a new skill, then we might expect PES to differentially predict both accuracy and strategy use in RB vs. II category learning tasks. Specifically, in RB tasks, PES should be positively associated with the adoption of the correct strategy, which would in turn predict performance accuracy (*Hypothesis 1*). In II tasks, though the initial bias towards the RB system might result in observable PES, PES would either be unassociated with the adoption of the correct strategy or accuracy (or might be negatively associated) (*Hypothesis 2*). Correct strategy use would predict accuracy in both types of learning, however.

Methods

Participants

Thirty eight adults (15 males) between the ages of 18–25 (19.03 ± 1.44) with an average GPA of 3.32 ($SD = 0.45$) were recruited from the Department of Psychology Research

Participant pool at the Pennsylvania State University. Informed written consent was obtained for each subject. Course credit was granted for participation.

Procedures

Gabor patches were created using MATLAB routines to randomly sample from two bivariate normal distributions of spatial frequency and line orientation (Maddox, Ashby, & Bohil, 2003). Spatial orientation and frequency stimuli parameters ranged from -2.65° – 81.82° and 5.52–6.99 cycles/degree for the RB task, and from -14.62° – 89.16° and 2.52–8.52 cycles/degree for the II task (Figure 1). All participants received the same randomized order of stimuli appearance. Each task was divided into 5 blocks of 80 trials (40 Category A and 40 Category B). The task was self-paced; participants were allowed to view the stimulus for as long as they deemed necessary. After each response, visual feedback (“correct” or “wrong”) was presented for 500 ms. The next trial began immediately after the feedback period.

The conditions were (1) an RB task that could be solved using an explicit verbalizable rule along spatial frequency and (2) an II task in which both spatial orientation and frequency information were needed to achieve optimal performance. The order of administration was counterbalanced and spaced one week apart. Participants were asked whether the images presented on the screen belonged in category “A” or “B” (corresponding to the z and/keys, respectively). Stickers were placed over the appropriate keys. They were instructed that, although at first they might just be guessing, to try to be as accurate as possible, and to not be concerned with speed. Task length was ~20 minutes.

Data analysis

For each task, a univariate repeated measures ANOVA with Block (5) as a within-subjects condition was run for three continuous dependent variables (accuracy, mean correct reaction time, and post error slowing). A repeated measures logistic regression with Block as the within-subjects condition was run on type of model use as a categorical variable. All anticipatory reaction times (RT) <140 ms were excluded from analysis as they have occurred too quickly to represent active decision making behavior in response to a stimulus (Eppinger, Mock, & Kray, 2009). Less than 1% of the trials met this criterion. The mean correct reaction time (CRT) for each block was calculated by averaging the RT for correct trials that followed a correct trial. To correct for individual differences in mean RT (Leth-Steensen, King Elbaz, & Douglas, 2000), post-error slowdown (PES) for each participant was calculated as mean RT of the first correct response after an error minus the CRT of that block.

Because qualitatively different strategies can lead to identical accuracy rates, analysis of accuracy alone cannot fully explain individual differences in skill acquisition. A number of models were fit to each participant’s set of responses for each block to determine the type of strategy used. All models assumed that the participant partitioned the stimulus space into response regions (Ashby & Maddox, 1993; Maddox & Ashby, 1993) using either a rule-based or an information-integration strategy. Each response region was assigned to a category; and the decision bound parameters were estimated from each participant’s data.

Four models were applied to the RB data: (1) an RB unidimensional model along the correct frequency dimension, (2) an RB unidimensional model along the incorrect orientation dimension, (3) an II general linear classifier (GLC) model that partitions the stimulus space using a linear decision bound that includes both dimensions, and (4) a random responder model. Four models were applied to the II data: (1) an II GLC model, (2) an RB conjunctive (CJ) model that partitions the stimulus space into four perpendicular regions by frequency

and orientation, (3) an RB unidimensional model (along either dimension), and (4) a random responder model.

All models included a “noise” parameter which provides an estimate of the perceptual and criterial noise associated with classification. The model was fit using maximum likelihood procedures (Ashby & Maddox, 1992) and BIC (Bayesian Information Criterion). The BIC statistic penalizes models for each additional free parameter where $BIC=(2L)+n*\ln(80)$, where n equals the number of parameters and $\ln(80)$ is the natural log of the number of trials being fit; in this case 80 trials (Schwartz, 1978).

Regression analyses assessing sorting strategy (defined as fit to the correct RB or II model, depending on the task) as a mediator to explain the relationship between PES and accuracy were conducted. Indirect effects were calculated using bootstrap confidence intervals as per Preacher & Hayes (2008). Results did not differ by sex, and did not change when GPA (as a proxy for overall intellectual functioning) was used as a covariate. Results are reported without GPA as a covariate and without sex as a between subjects variable.

Results

Preliminary analyses

There was no evidence for speed-accuracy tradeoff effects (SATO) in either task. Correct and error RT for both tasks were positively correlated (all blocks $r>0.40$, all $p < 0.01$). RT was not correlated with error rate in the II task (all blocks $p > 0.13$) or in blocks 1–3 of the RB task (all $p > 0.63$); it was positively correlated with error rate in blocks 4 & 5 ($r>0.37$, $p<0.02$). We are therefore reassured that SATO effects were not present, and that RT and accuracy data can be validly interpreted.

Rule-Based Category Learning

As expected, a main effect of Block was found on Accuracy, $F(4,148)=34.05$, $p<0.001$, $\eta_p^2=0.48$, RT to correct responses, $F(4,148)=10.46$, $p<0.001$, $\eta_p^2=0.22$, and PES, $F(4,148)=2.38$, $p=0.05$, $\eta_p^2=0.06$. Over time, accuracy increased, and RT and PES decreased. The main effect of Block on the proportion of participants utilizing the correct RB strategy was not significant, Wald Chi-Square = 5.41, $p = 0.25$. Significant PES (i.e. >0) was only seen in Block 1, $t(37)=2.07$, $p=0.05$, as might be expected since that is presumably the period in which the greatest amount of learning occurs (Figure 2).

Block 1 PES was significantly and positively correlated with accuracy in that block, $R^2=0.12$, $\beta=0.09$, $p=0.03$. Adoption of the correct sorting strategy mediated the relationship between PES and accuracy in Block 1. Specifically, more PES was associated with better fit to the optimal rule, $R^2=0.11$, $\beta=-9.13$, $p=0.05$, which in turn was predictive of higher accuracy, $R^2=0.83$, $\beta=-0.01$, $p<0.001$. The unstandardized indirect effect of PES to accuracy through sorting strategy with bias corrected confidence intervals calculated using 5000 bootstrapping samples was 0.08 (95% CI 0.003–0.16). Results did not change when participants whose model fit showed 4 blocks of random responding ($N=4$) were excluded from analyses.

Information Integration Category Learning

A main effect of Block on Accuracy, $F(4,104)=14.19$, $p<0.001$, $\eta_p^2=0.35$, RT to correct p responses, $F(4,104)=5.16$, $p<0.001$, $\eta_p^2=0.17$, PES, $F(4,104)=5.74$, $p<0.001$, $\eta_p^2=0.18$, and model use, Wald Chi-Square = 10.43, $p = 0.03$, were seen. Specifically, accuracy and the proportion of participants using an II strategy increased, while RT and PES decreased over

time (Figure 2). Significant PES (i.e.>0) was only seen in Block 1, $t(26)=3.15$, $p=0.004$. However, Block 1 PES was not associated with accuracy, $R^2=0.07$, $\beta=0.08$, $p=0.17$, or with the adoption of an II strategy as measured by fit values to the II model, $R^2=0.03$, $\beta=-1.11$, $p=0.92$. Adoption of the correct II approach was predictive of accuracy as would be expected, $R^2=0.43$, $\beta=-0.003$, $p=0.002$.

Because similar levels of PES were found in the II and RB tasks, exploratory analyses were conducted to better understand the source of these similarities. Significant PES (i.e.>0) was only seen in Block 1 among participants who had not adopted an II sorting strategy in the final block, $t(10)=3.05$, $p=0.02$. For those participants, PES in Block 1 was neither associated with accuracy, $R^2=0.04$, $\beta=-0.05$, $p=0.53$, nor with the adoption of an II strategy as measured by fit to the optimal model, $R^2=0.01$, $\beta=4.5$, $p=0.83$. PES was not observed in any block among individuals who were not sorting according to an II strategy in block 5, $t(15)=0.11$, $p=0.11$. Results did not change when participants whose model fit showed 4 blocks of random responding ($N=4$) were excluded from analyses.

Discussion

We found significant main effects of Block for both the RB and II category learning tasks in which participants improved their performance over time over a range of indicators. PES was observed in the first block of trials for both tasks, but consistent with a multiple systems approach, it was only associated with performance in the RB task. Within the context of COVIS, unlike RB categorization, optimal performance in II category learning is an associative process that requires the simultaneous integration of multiple stimulus elements into a singular categorization decision (Ashby & Maddox, 2005). Thus, COVIS would predict that though the bias towards RB learning may lead to attempts at active hypothesis testing during the initial phase of skill acquisition in an II task, it would not be expected to result in improved performance for II category learning. This was in fact the pattern of results reported herein.

Other models of category learning could also account for the current pattern of data. For example, ATRIUM proposes the existence of a verbal rule-based system as well as a second exemplar-based system to account for performance for graded category structures and frequency effects (Erickson & Kruschke, 2002). Similarly, SUSTAIN is a network based model of category learning that represents categories as clusters of previously experienced stimuli and compares incoming stimuli to those clusters (Love, Medin, & Gureckis, 2004). If a simple rule-based cluster is not sufficient to solve the task, then new clusters are dynamically recruited to improve the representation. If the category structure is complex enough, the clusters ultimately come to resemble an exemplar-like storage system. Neither ATRIUM nor SUSTAIN explicitly suggest that the exemplar-based system or clusters are less dependent upon executive attention, but such a suggestion would not necessarily be incompatible with these theories, either. The logical extension of the COVIS model, however, would explicitly predict that post-error slowing, as a behavioral marker of the active recruitment of executive attentional processes, would be associated with performance on an RB but not II category learning paradigm.

Reinforcement learning theories propose that PES represents the behavioral manifestation of comparing outcomes to expectations (Holroyd, Yeung, Coles, & Cohen, 2005) whereas conflict control theories view PES as an increased response threshold triggered by the presence of consecutive, parallel, discrepant streams of information (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Carter & van Veen, 2007). Regardless, both suggest that PES reflects the activation of some level of executive attentional process in the service of achieving a particular goal. Within this context, an argument could have been made that

because PES indexes the triggering of the executive control system, we might have expected greater PES to be associated with worse RB performance due to the creation of a dual task conflict. However, we did not observe that pattern of data, and the directionality of this hypothesis was not compelling because any executive control exerted would be in the service of improving and solving the task, as opposed to distracting from it as in more typical dual task situations.

Though PES has historically been viewed as reflective of engagement of higher order executive processes (Botvinick et al., 2001; Carter & van Veen, 2007; Holroyd et al., 2005) others have more recently proposed that the phenomenon is a reflexive or automatic attentional orienting response to a rare event (i.e. an error) (Notebaert et al., 2009). Although it is difficult to completely rule out an orientating interpretation of PES, such an account seems unlikely here because PES predicted accuracy and model use, and because PES did not increase as error feedback event became increasingly less frequent for participants in later blocks.

Why PES decreased over time is unclear. A less interesting answer might simply be that it reflects the general decrease in RT that is typical of increased task mastery (Logan, 1988; Shiffrin & Schneider, 1977). A more interesting hypothesis would be that error reactivity decreases with increasing task mastery. There is, in fact, some neurophysiological evidence that ERP amplitudes associated with post-error processing decrease as participants become increasingly adapted to speeded reaction time tasks (Anguera, Seidler, & Gehring, 2009; Cavanagh, Frank, Klein, & Allen, 2010). COVIS also predicts that the explicit system only changes rules following negative feedback (Ashby & O'Brien, 2007) so PES would be expected to be greatest during early learning when rule changing is the most frequent. It is also possible that PES might have been observed beyond block 1 if a response deadline had been used, which could be evaluated in future studies. Similarly, we defined PES as the first correct response following an error because we were interested in understanding the cognitive processes involved in the successful resolution of conflict, and because it allows for comparison with the larger literature in error monitoring. However, other definitions of PES (e.g. first response following an error) may produce different insights and could be followed up in future studies.

Overall Summary

In summary, and consistent with a multiple systems model of category learning, we found evidence that PES reflects higher order processing that is related to improved future performance for RB but not II category learning. Our findings also support reinforcement learning (Holroyd et al., 2005) and conflict control theories (Botvinick et al., 2001) of PES as representative of the recruitment of effortful attentional processes recruited for goal directed behavior.

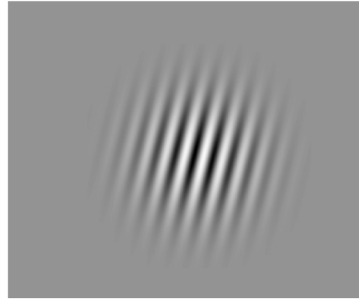
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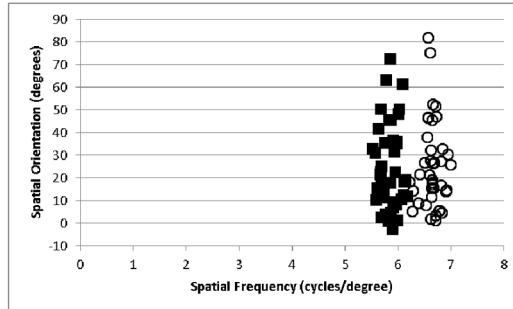
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A. Gabor Patch



B. Unidimensional Rule



C. Information-Integration

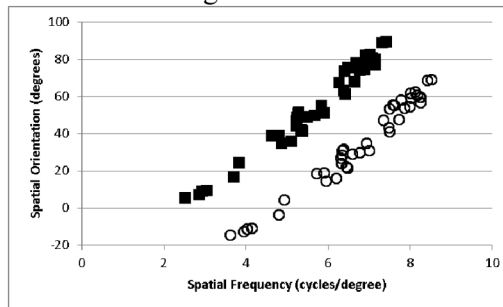


Figure 1.
Stimulus and stimulus plots.

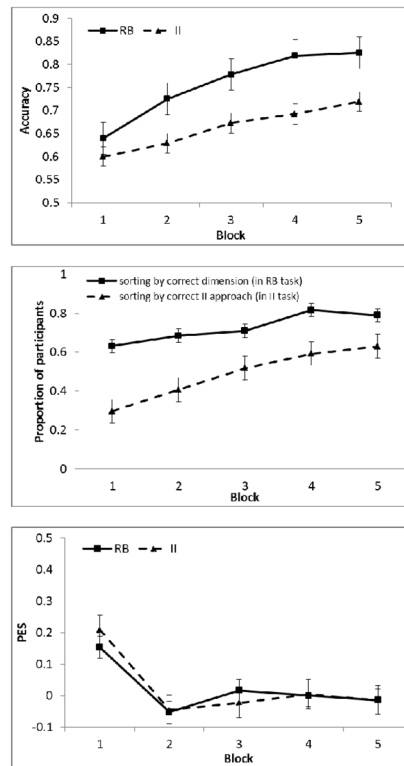


Figure 2. Accuracy, model use, and PES by Block for Rule-based and Information-Integration category learning tasks