

Pigeon Category Learning: Revisiting the Shepard, Hovland, and Jenkins (1961) Tasks

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In a seminal study, Shepard, Hovland, and Jenkins (1961; henceforth SHJ) assessed potential mechanisms involved in categorization learning. To do so, they sequentially trained human participants with 6 different visual categorization tasks that varied in structural complexity. Humans' exceptionally strong performance on 1 of these tasks (Type 2, organized around exclusive-or relations) could not be solely explained by structural complexity, and has since been considered the hallmark of rule-use in these tasks. In the present project, we concurrently trained pigeons on all 6 SHJ tasks. Our results revealed that the structural complexity of the tasks was highly correlated with group-level performance. Nevertheless, we observed notable individual differences in performance. Two extensions of a prominent categorization model, ALCOVE (Kruschke, 1992), suggested that disparities in the discriminability of the dimensions used to construct the experimental stimuli could account for these differences. Overall, our pigeons' generally weak performance on the Type 2 task provides no evidence of rule-use on the SHJ tasks. Pigeons thus join monkeys in the contingent of species that solve these categorization tasks solely on the basis of the physical properties of the training stimuli.

Keywords: pigeon, categorization, rule use, ALCOVE, selective attention

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Categorization is an important cognitive function. With it, we sort the objects around us and recognize them as members of different classes (Murphy, 2002). For example, we treat high heels, sneakers, and flip flops as members of the same category (shoes), because they serve the same basic function, even though they have distinctly different physical properties.

In a seminal study, Shepard, Hovland, and Jenkins (1961; henceforth SHJ) assessed the psychological processes involved in human categorization. Specifically, SHJ evaluated whether participants' performance in a series of classification problems was based on simple associative principles (stimulus conditioning and generalization) and/or logical rules. In order to do so, SHJ trained participants to classify multidimensional stimuli that varied along three binary-valued, visual dimensions: shape, brightness, and size. When each of the eight stimuli resulting from the combination of these features (Figure 1A) is assigned to one of two categories, six distinct types of task emerge (Figure 1C).

In the Type 1 task, category membership is determined solely by the values along a single dimension. For example, in a color-

relevant Type 1 task, all black stimuli belong to one category, whereas all white stimuli belong to the other. Shape and size are irrelevant dimensions, as they do not convey any information regarding category membership. In the Type 2 task, category membership is determined by a two-dimensional, exclusive-or rule. For example, in a color/shape-relevant Type 2 task, all black triangles and white squares belong to one category, whereas all white triangles and black squares belong to the other. In this case, size is irrelevant for categorization. In task Types 3, 4, and 5, category membership is determined by rules and exceptions. For example, in a color-relevant Type 3 task, all black stimuli belong to one category except for one (the large black triangle in Figure 1A). Importantly, task Types 3, 4, and 5 differ mainly in the number of rules that can be used to determine category membership. The Type 4 task supports rules for all three dimensions, the Type 3 task supports rules for two dimensions, and, the Type 5 task supports rules for a single dimension. Of additional importance, Type 4 is a linearly separable task solvable by family resemblance. Lastly, in the Type 6 task, category membership cannot be determined by any simple rule. Therefore, it is often said that subjects learning this task must resort to rote memorization of each individual stimulus in order to solve this task. These six types of tasks also differ in structural complexity. When quantified with several different metrics (e.g., Alfonso-Reese, Ashby, & Brainard, 2002; Homa, Rhoads, & Chambliss, 1979; Kloos & Sloutsky, 2008), Type 1 is the least complex task, followed by task Types 4, 3, and 5. Finally, task Types 2 and 6 are—in that order—the two most complex, due to their nonlinear structures.

In order to test whether humans were classifying the training stimuli based on stimulus generalization alone, SHJ compared the

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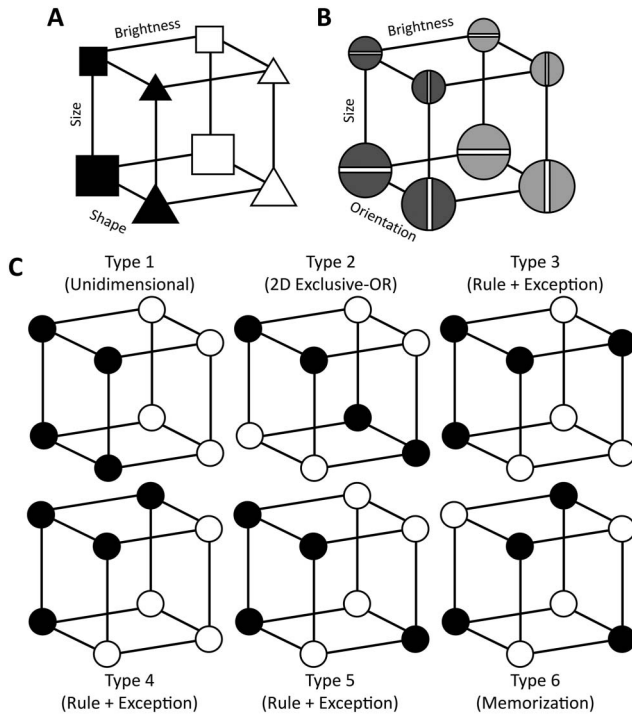


Figure 1. Stimuli and task types. (A) Shepard et al. (1961) originally used stimuli which were composed from three binary-valued dimensions: brightness, size, and shape. (B) The stimuli used in the present experiment were composed from three binary-valued dimensions: brightness, size, and line orientation. (C) The six types of tasks used by Shepard et al. (1961); see main text for details regarding the categorical structures of each type.

number of errors participants made while learning each of the tasks with those predicted by stimulus generalization. Under the assumption that classification is a product of between- and within-category discriminability, SHJ predicted the expected number of errors using different generalization gradients. Particularly, if subjects' generalization gradients are monotonic, decreasing, and convex (Shepard, 1987), the expected number of errors under stimulus generalization alone is directly related to the structural complexity of each task: Type 1 < Type 4 \approx Type 3 < Type 5 \approx Type 2 < Type 6.

Contrary to what was predicted by their stimulus generalization framework, SHJ observed that errors were ordered: Type 1 < Type 2 < Type 3 \approx Type 4 \approx Type 5 < Type 6. Notably, errors on the Type 2 task were lower than errors on the Type 4 task (a finding since known as the Type 2 advantage). The fact that performance on the Type 2 task did not fall in line with that predicted by stimulus generalization alone led SHJ to propose that humans learn the Type 2 task with the help of rules. That is, humans not only use stimulus generalization during categorization, but they also deploy rules to encode the regularities of some category structures.

The SHJ study elucidated the potential cognitive systems involved in human categorization learning, and has subsequently exerted a profound influence on the categorization literature. To this day, SHJ's results have served as a benchmark to evaluate most models of human categorization (e.g., Kruschke, 1992; Kurtz, 2007; Love, Medin, & Gureckis, 2004; Nosofsky, Gluck,

Palmeri, McKinley, & Glauthier, 1994). Importantly, these modeling efforts have demonstrated that the Type 2 advantage typically observed in humans can be reproduced by models that lack explicit rule-production systems, as long as they have dimensional representations of the stimuli and the ability to selectively attend to the relevant dimensions (see Nosofsky et al., 1994, for a review).

In one exceptional project, the SHJ tasks were given to nonhuman primates (Smith, Minda, & Washburn, 2004). In contrast to human participants, Smith, Minda, and Washburn (2004) found that the percentage of errors that their four rhesus macaques (*Macaca mulatta*) committed on the Type 2 task nicely aligned with that predicted by stimulus generalization theory (reproduced in Figure 2B). This finding suggests that the Type 2 advantage commonly observed in the SHJ tasks might be uniquely human, and depend on the availability of explicit rule-production systems or the opportunity to deploy selective attention to exploit category structure (Kurtz, Levering, Stanton, Romero, & Morris, 2013; Nosofsky & Palmeri, 1996).

To expand on the species generality of these intriguing findings, we developed a pigeon model of the SHJ tasks. Several anatomical disparities exist between mammalian and avian brains, although recent evidence suggests that the telencephalon of both taxonomic groups supports similar kinds of high-level cognition (Maler, 2018). Thus, comparing the categorization performance of nonhuman primates and birds is both especially timely and important.

Our pigeon model differed from Smith et al.'s (2004) primate model in two significant procedural respects. First, we *concurrently* trained our three pigeons on all six tasks instead of doing so *sequentially*. Such concurrent training avoids sequence effects, which could seriously contaminate categorization performance depending on the particular order of problem presentation given to individual subjects. Furthermore, because all of the problems were trained concurrently, monitoring the acquisition of individual subject performance on each of the six problem types was possible. Finally, concurrent training of the different problem types avoids the difficulty in deciding how long to continue training on challenging (or possibly unsolvable) problems before switching to other problems. We could thus train all of our subjects on all of the problems for the same number of sessions.

Notwithstanding the considerable merits of concurrent training, this method is not without potential pitfalls. In particular, concurrent training might hinder a subject's ability to learn one or more of the tasks because of interference between tasks. Therefore, in a final phase, we retrained all of our pigeons with four of the same problems they had been given concurrently, now one at a time, in a successive manner. In this way, we could determine if there was any crosstalk from one task to another as well as assess the replicability of the patterns of categorization performance that we had earlier observed.

Our design also differed from Smith et al.'s (2004) in that instead of using stimuli that varied in brightness, size, and shape (e.g., Smith et al., 2004), we used stimuli that varied in brightness, size, and line orientation (Figure 1B). Our research group has previously documented the discriminability and separability of these dimensions for pigeons (Teng, Vyazovska, & Wasserman, 2015; Vyazovska, Navarro, & Wasserman, 2016; Vyazovska, Teng, & Wasserman, 2014), thereby giving us confidence that they would be suitable for the present project.

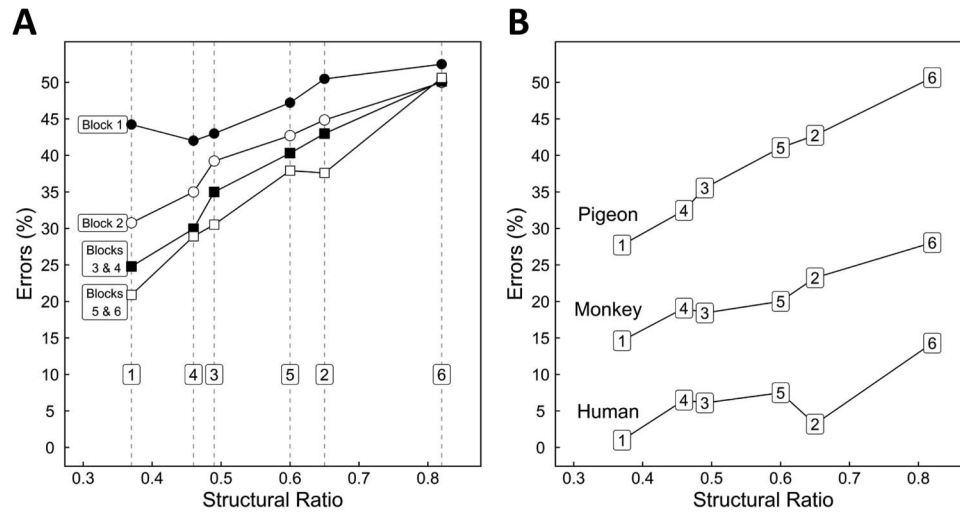


Figure 2. Percentage of errors in each of the Shepard et al. (1961) tasks, as a function of each task's structural ratio. (A) Pigeon performance in each task across blocks of the concurrent training phase. Each task is denoted by an annotated, dashed, vertical line. (B) Comparison of human (Nosofsky et al., 1994), monkey (Smith et al., 2004), and pigeon performance in the Shepard et al. (1961) tasks. Just as was the case for monkeys, the percentage of errors committed by pigeons was linearly related to the structural ratio of each task. In contrast, human performance in the Type 2 task was not linearly correlated with the task's structural ratio.

How did we expect our pigeons would learn the six SHJ tasks? Prior studies have suggested that pigeons lack the ability to exploit the structural regularities of rule-based categories (Berg & Grace, 2011; Smith et al., 2012). Furthermore, pigeons show feature-based, instead of rule-based generalization in the Shanks-Darby procedure (Maes et al., 2015; Shanks & Darby, 1998). Therefore, we predicted that our pigeons would perform just as did the monkeys in Smith et al.'s (2004) study (Figure 2B). Specifically, their performance on the Type 2 task should comport with the linear performance pattern predicted by the structural complexity of each task, instead of the nonlinear pattern of performance typically reported with human participants (Nosofsky et al., 1994).

Method

Subjects

Three captive-bred pigeons (*Columba livia*) were studied. Pigeons were kept at 85% of their free-feeding weights and had free access to grit and water. The animals had previously participated in unrelated studies of visual discrimination and categorization of real world images (Castro & Wasserman, 2014; Couto, Navarro, Smith, & Wasserman, 2016; Navarro & Wasserman, 2016). None of the subjects had any experience with the visual dimensions used to construct the stimuli used in this study. The institutional Animal Care and Use Committee at the University of Iowa approved the housing conditions and training procedures.

Apparatus

We used three 36 cm × 36 cm × 41 cm conditioning chambers (detailed in Gibson, Wasserman, Frei, & Miller, 2004), located in a dark room with continuous white noise. Each chamber was equipped with a 15-in. LCD monitor behind a resistive touch-

screen. The visible portion of the screen was 28.5 cm × 17 cm. Within it, a centered, 3.5 cm × 3.5 cm area was used to display the start stimulus, and two, equally spaced 3 cm × 3 cm areas were used to display the response buttons. The response buttons were positioned with a 2-cm and a 1-cm separation from the small and large stimuli, respectively. The stimuli to be categorized were presented centered, 8 cm above the wire mesh floor. A serial controller outside the chamber processed pecks to the touchscreen. A rotary dispenser delivered 45-mg food pellets through a vinyl tube into a plastic cup in the center of the rear wall opposite the touchscreen. Illumination during experimental sessions was provided by a houselight on the rear wall of the chamber. The pellet dispenser and houselight were controlled by a serial I/O interface. An iMac computer controlled each chamber, using programs developed in MATLAB with Psychtoolbox-3-extensions (Brainard, 1997; Pelli, 1997).

Stimuli

Two response buttons and a target stimulus were presented on the screen, over a colored background. The target stimuli were composed of features from three, binary-valued visual dimensions (Gottselig, Wasserman, & Young, 2001; see Figure 1B): the diameter of a circle (small or large), its brightness (bright or dark), and the orientation of a thin bar (horizontal or vertical) bisecting the circle. The small and large diameter circles were 4.1 cm and 6.6 cm, respectively. The bright and dark luminance values were RGB: 165, 165, 165, and RGB: 105, 105, 105, respectively. The background could be any of six different colors: red (RGB: 255, 0, 0); blue (RGB: 0, 0, 255); yellow (RGB: 240, 240, 40); pink (RGB: 240, 40, 240); orange (RGB: 255, 140, 0); and green (RGB: 25, 255, 0) depending on the task being given. The response buttons were 12 different multicolored patterns (see Supplemental Material 1 for examples of the different visual displays).

Procedure

Given the multiplicity of possible problems per task type, the particular problems that each subject received were carefully selected to balance the informational value of each of the three stimulus dimensions and the dyadic relationships they could form (Kloos & Sloutsky, 2008). Critically, this selection process required that the relevant dimension in Task 1 was the irrelevant dimension in Task 2. Conversely, the two relevant dimensions in Task 2 had to be the irrelevant dimensions in Task 1. Finally, our concurrent programming used different background colors and report buttons for each task type (assigned randomly on an individual pigeon basis). Both the background and button stimuli were available to serve as cues informing the pigeons as to which of the six different types of problems was in force on any given trial.

Concurrent training. Pigeons were given 180 daily sessions of training. Each session contained the 16 unique trials per task type (8 stimuli \times 2 randomly arranged locations of the correct and incorrect response buttons), for a total of 96 trials. Each trial began with a start stimulus. Once the pigeon pecked it, the stimulus to be categorized was presented in the center of the screen, over the colored background that corresponded to the task type. After the pigeon pecked the stimulus a fixed number of times (increased daily on the basis of each pigeon's performance, to a maximum of 25), the two response buttons—one correct and the other incorrect—appeared to the sides of the target stimulus. A final peck to either of the two response buttons determined the remainder of the trial. If the chosen button corresponded to the category of the stimulus being shown, then one to three food pellets were delivered randomly, followed by a 6-s to 10-s random intertrial interval. If the chosen button did not correspond to the category of the stimulus being shown, then no food pellets were delivered, and a correction trial with the same stimuli was given after the intertrial interval, under the same reinforcement contingencies. Correction trials continued to be given until the correct response was performed, but data from correction trials were excluded from analysis.

Successive training. As noted earlier, concurrent training might somehow have interfered with our pigeons' ability to learn each task by itself, possibly because the relevant dimensions in one task were irrelevant in another task, and vice versa. In order to assess such intertask interference, the same three pigeons were subsequently given four of the tasks they had received during the concurrent phase (Types 1, 2, 4, and 6), now one at a time, in a random order. The background colors and response button stimuli that distinguished the tasks in the concurrent training phase were carried forward to this phase. The pigeons received daily sessions of 96 trials until they reached 85% of correct responses in each of the two categories for 2 days in a row or until they had completed 30 sessions. When a new problem was first introduced, the number of pecks required for the observing response was reduced to 10 and then increased daily by one to a maximum of 25.

Results

To test whether our pigeons' behavior comported with the structural complexity of the categories in each task, we analyzed their choice performance as a function of the structural ratio of the tasks. The structural ratio is a measure of category structural complexity, based on the interstimulus distances along each dimension. This measure is expressed as the ratio of within-category

to between-category distances among category members (Homa et al., 1979; Smith et al., 2004); it is bounded between 0 and 1, with 0 indicating perfectly separated categories and 1 indicating perfectly overlapped categories. Type 1, the simplest task, has a structural ratio of .37 (there is no overlap between categories along the relevant dimension, but there is perfect overlap along the other two, irrelevant dimensions). Type 6, the hardest task, has a structural ratio of .82. Also worth noting, Type 2 has a structural ratio of .65. Finally, Types 3, 4, and 5 have structural ratios of .49, .46, and .60, respectively.

Concurrent Phase

The mean overall percentage of choice errors in task Types 1, 2, 3, 4, 5, and 6 were 27.7% ($SD = 11.21$), 42.8% ($SD = 11.02$), 35.5% ($SD = 4.71$), 32.5% ($SD = 3.11$), 41.1% ($SD = 7.32$), and 50.7% ($SD = 1.89$), respectively. Figure 2A shows the percentage of errors in each task across blocks of training, as a function of each task's structural ratio.

As illustrated in the figure, our pigeons' errors increased with the structural ratio of each task, and this relation steepened across blocks of training (cf. slopes of Block 1 and Blocks 5 and 6 in Figure 2A). Because we repeatedly measured each individual pigeon across time, we assessed our pigeons' errors using a logistic mixed-effects model. The model included structural ratio of each task and the logarithm of session as fixed effects (see Supplemental Material 2 for further details on mixed-effects models and model selection). As expected, the model revealed that the overall percentage of errors reliably decreased across sessions, $B = -0.20$, $SE = 0.03$, 95% CI $[-0.25, -0.15]$, $Z = -7.94$, $p < .001$. More importantly, the percentage of errors in each task was positively related to the structural ratio of the task, $B = 2.24$, $SE = 0.41$, 95% CI $[1.48, 3.00]$, $Z = 5.42$, $p < .001$. Furthermore, the reduction in the percentage of errors across training in each task was inversely related to the task's structural ratio, $B = 0.71$, $SE = 0.23$, 95% CI $[0.58, 0.84]$, $Z = 3.05$, $p < .01$. That is, the reduction in the pigeons' errors across sessions was larger for tasks with smaller structural ratios. Critically, pigeons made more errors in Type 2 than in Type 4 (42.8% vs. 32.5%, respectively); so, just like the monkeys in the Smith et al. (2004) study, our pigeons failed to show a Type 2 advantage (Figure 2B).

Finally, we asked whether the pigeons' errors fell reliably below chance in each task, during the last 10 sessions of concurrent training. As assessed by binomial tests, all pigeons were below chance in Type 1 (all $ps < .001$), 42Y and 81B were below chance in Type 2 (18% and 42%, respectively, $p < .001$ and $p < .05$, respectively), all pigeons were below chance in Types 3, 4, and 5 (all $ps < .01$), but no pigeon was below chance in Type 6 (all $ps > .10$).

Successive Phase

Recall that in this phase, each problem was given alone until the learning criterion was met or until 30 days of training had been completed. Therefore, in order to compare pigeons' performance across both phases, if bird met criterion on a given problem, we assumed that the remaining sessions would have had the same score as the session on which criterion was met (see Nosofsky et al., 1994 for a similar treatment of postcriterion performance in humans). Consequently, the mean percentages of errors observed

in task Types 1, 2, 4, and 6 were 15.9% ($SD = 8.15$), 35.2% ($SD = 15.75$), 21.1% ($SD = 4.91$), and 47.2% ($SD = 1.97$), respectively (see [Supplemental Material 3](#) for individual scores). Similar to the concurrent phase, the pigeons' errors were positively related to the structural ratio of the tasks. A mixed-effects logistic model including structural ratio and session as fixed effects (see [Supplemental Material 2](#) for details) again revealed that the overall percentage of errors reliably decreased across sessions, $B = -0.33$, $SE = 0.01$, 95% CI $[-0.35, -0.30]$, $Z = -22.87$, $p < .001$. Furthermore, the percentage of errors in each task and their decrease across sessions were again inversely related to the structural ratio of the task, $B = 3.59$, $SE = 0.31$, 95% CI $[2.98, 4.20]$, $Z = 11.48$, $p < .001$, and $B = 0.82$, $SE = 0.22$, 95% CI $[0.40, 1.26]$, $Z = 3.72$, $p < .001$, respectively. Most importantly and just as in the concurrent phase, our pigeons' errors in the Type 2 task (35.2%) exceeded those in the Type 4 task (21.1%).

A comparison of the overall percentage of errors across the two training phases suggests that concurrent presentation of the tasks might have made the tasks more difficult than successive presentation (see [Supplemental Material 3](#)). Assessing errors during the last two sessions of the successive phase (which approximates the number of trials per task we used to assess terminal performance in the concurrent phase) revealed that all of the pigeons' errors fell below chance in Type 2 (40%, 9%, and 31% for 17B, 42Y, and 81B, respectively; all $ps < .01$). Furthermore, errors for 42Y and 81B fell below chance in Type 6 as well (41% and 30%, respectively; both $ps < .05$).

More importantly, our results confirm that concurrent programming of the tasks did not materially alter the way our pigeons performed in each task. Indeed, the rank ordering of errors in each of the four tasks was conserved across the concurrent and successive training phases, for each bird; the correlation between the mean percentage of errors between phases by task type was high and significant (Pearson's $r = .98$, $p < .001$).

Strategy Analysis

We further assessed our pigeons' performance by measuring the extent to which the birds were using unidimensional strategies during the concurrent phase of the experiment. Recall that a unidimensional strategy is necessary to solve the Type 1 task, in which category membership depends on a single dimension. However, a variety of unidimensional strategies can also be applied to Types 3, 4, and 5. Under these *suboptimal* strategies, subjects will correctly categorize 75% of the stimuli. To measure the extent to which our pigeons adopted these strategies, we calculated the Phi coefficient to measure the relation between the dimensional values of the stimuli and the categorical choices our pigeons made in each task type (see [Minda, Desroches, & Church, 2008](#) for a similar analysis of human data in the SHJ tasks).

These analyses revealed that our pigeons' use of perfect unidimensional strategies (i.e., an absolute Phi coefficient of 1) was generally rare and varied substantially among individuals. We found perfect coefficients in four sessions for pigeon 17B, one session for pigeon 42Y, and 39 sessions for pigeon 81B (approximately 2%, 0.6%, and 22% of sessions, respectively). A closer look at these coefficients revealed that the single perfect coefficient for 42Y came from performance on the Type 3 task, whereas all of the perfect coefficients obtained for pigeons 17B and 81B

came from their Type 1 tasks, especially later in training. Despite perfect coefficients being rare, our pigeons' use of each dimension tended to match the availability of optimal or suboptimal unidimensional strategies (as denoted by the presence of high, but imperfect coefficients). For example, the relevant dimension in Type 1 yielded the largest coefficient value for all of our pigeons. Similarly, our pigeons adopted imperfect unidimensional strategies on those tasks that permitted them (Types 3, 4, and 5, in which perfect unidimensional strategies lead to 25% of errors), but did not do so in tasks on which individual dimensional values were orthogonal to category membership (Types 2 and 6). Overall, these results suggest that our pigeons' performance on the tasks was dimensionally oriented (see [Supplemental Material 4](#) for individual coefficients across the training blocks of both concurrent and successive phases).

Model-Based Analyses of Individual Pigeon Performance

As the previous analyses indicate, our pigeons' errors, as a group, increased as a linear function of each task's structural complexity ([Figure 2B](#)). However, individual pigeons' performances did vary considerably (see [Figure 3A](#), black circles). Specifically, although the errors of pigeons 17B and 81B increased monotonically as a function of the structural ratio of each task, the errors of pigeon 42Y did not. Notably, 42Y's errors for Type 2 (30.2%) were not only similar to that for Type 4 (28.9%), but also lower than for Type 1 (38.6%). In other words, the errors of pigeon 42Y were nonmonotonically related to the structural complexity of the tasks, much as is typically observed for human participants (cf. [Figure 2B](#)).

A potential explanation for this unusual pattern of performance lies at the junction between the discriminability of the dimensional values we used to construct the stimuli and their role in determining category membership. Recall that each pigeon received unique versions of each task; moreover, there was no overlap between the relevant dimensions in task Types 1 and 2. In the case of 42Y, this meant that brightness was the dimension determining category membership in task Type 1, whereas size and line orientation determined category membership in task Type 2. Thus, 42Y's performance may be at least partially explained by the brightness values having low discriminability and the size and line values having high discriminability. If so, then 42Y's ability to learn task Type 1 might have been hindered by low discriminability of the relevant dimension and high discriminability of the irrelevant dimensions. Similarly, 42Y's success in learning the substantially more complex task Type 2 might have been promoted by high discriminability of the relevant dimensions and low discriminability of the irrelevant dimension.

In order to test this idea, we fitted individual pigeon performance in each task, on a trial-by-trial basis, using the attention learning covering map model (ALCOVE; [Kruschke, 1992](#)). Briefly, ALCOVE is a three-layer, fully connected model for supervised category learning that uses exemplar-based representation and learns by gradient descent on error. Its exemplar-based representation allows ALCOVE to solve nonlinear learning problems (e.g., SHJ's Types 2 and 6), which models like that of [Rescorla and Wagner \(1972\)](#), without configural cues, fail to solve. More importantly, ALCOVE can learn to attend to (or to ignore) the portions of the input that lead to correct (or incorrect) categorization (i.e., attentional learning; [Mackintosh, 1975](#)).

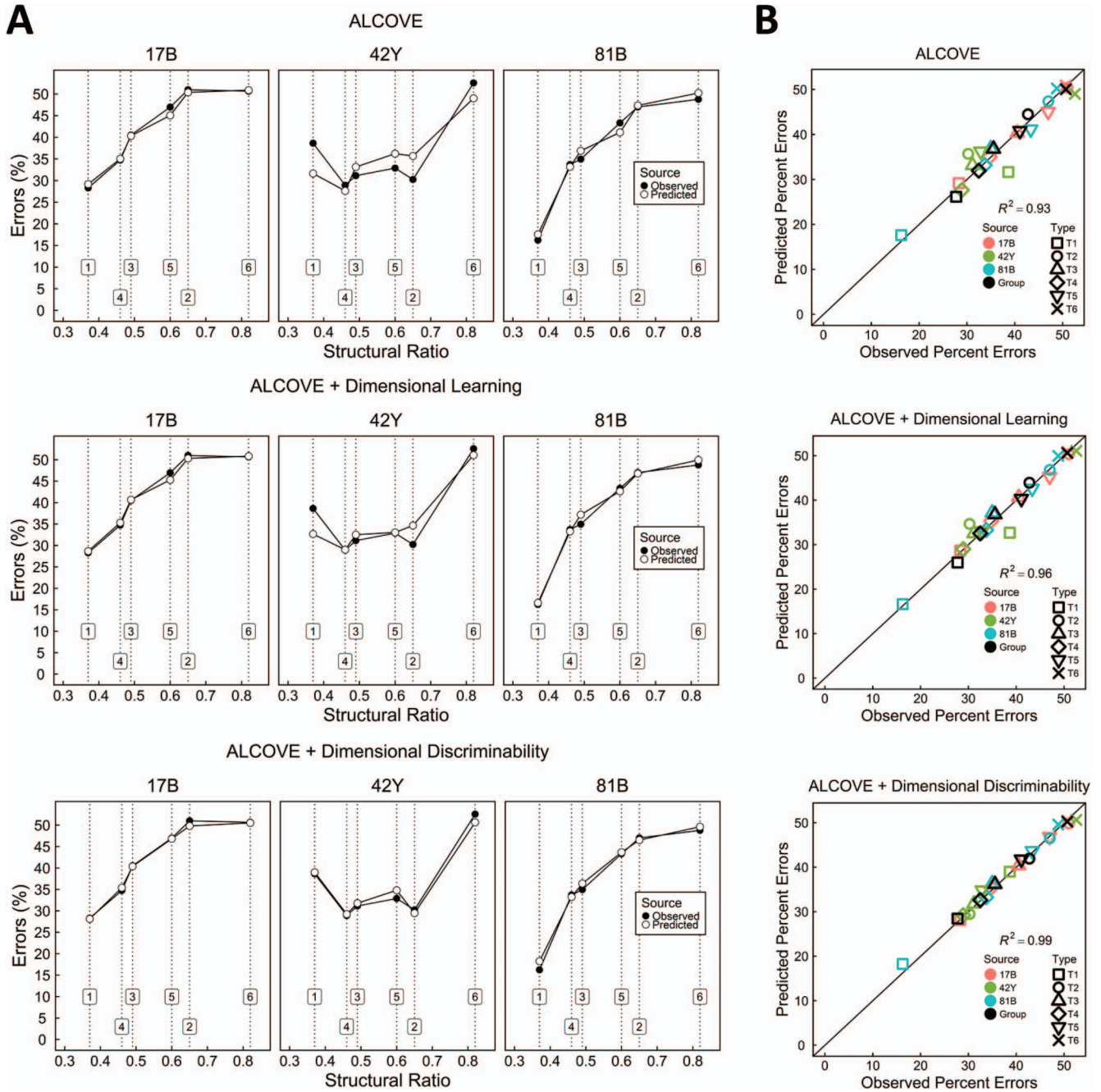


Figure 3. Model fits of our three pigeons' performance in the SHJ tasks. (A) Observed and predicted percentage of errors for the three pigeons in each of the SHJ tasks (1 to 6, annotated). The fits in the top row were obtained using [Kruschke's \(1992\)](#) original ALCOVE model. The fits in the middle row were obtained using a version of ALCOVE that allowed for differences in each dimension's attentional learning rate. The fits in the bottom row were obtained using a version of ALCOVE that allowed for differences in discriminability among the three dimensions (see text for details). (B) Observed-predicted plots assessing the quality of the fit provided by the original ALCOVE model (top) and its two expanded versions (middle and bottom), for the group and the three individual pigeons. Each model's annotated coefficient of determination (R^2) was calculated over individual scores only. See the online article for the color version of this figure.

ALCOVE's ability to learn which dimensions are relevant to the task at hand allows it to predict human performance in the SHJ tasks (see Pitt, Kim, Navarro, & Myung, 2006 for a comprehensive analysis of the behaviors that ALCOVE can exhibit in these tasks, and the model's falsifiability). Recall that the SHJ tasks vary in the number of dimensions that are necessary for categorization. Type 1 requires a single dimension; Type 2 requires two dimensions; and Types 3–6 require all three dimensions to different degrees (although the structural complexity of Type 6 is greater than that of Types 3, 4, and 5). Humans learn the six types of task in accord with this attentional ordering, and their performance can thus be reproduced by ALCOVE. Furthermore, the model is able to accommodate the performance of the monkeys in Smith et al. (2004) and the average performance of our three-pigeon cohort, by driving its attentional learning abilities toward zero. When unable to learn about the relevant and irrelevant dimensions of a task, the model's performance is entirely determined by the structural complexity of the tasks.

Despite its success in explaining our pigeons' group-level data, ALCOVE cannot faithfully reproduce 42Y's pattern of performance (Figure 3A, top row). This is because, although ALCOVE has dimensional attentional weights that control exemplar activation, the model does not have *dimension-specific* parameters that would regulate the subject's ability to learn to attend (or ignore) at different rates for each dimension or that would control the discriminability of the values along each dimension. If a dimensional discriminability account has merit, then such flexibility might be needed to explain the individual differences in performance that we observed. We thus created two extensions of ALCOVE that might have just this kind of flexibility.

We first explored whether our pigeons learned to attend to different dimensions at different rates. A single attentional learning rate parameter (λ_a) in ALCOVE controls how much the model

adjusts all of its dimensional attention weights after receiving feedback. Thus, our "ALCOVE + dimensional learning" model expanded ALCOVE's single attentional learning rate parameter into three dimension-specific attentional learning rates ($\lambda_{\text{brightness}}$, $\lambda_{\text{orientation}}$, λ_{size}), thereby allowing the model to learn to attend or ignore the three dimensions at differential rates, if necessary. (see Supplemental Material 5 for details on the fitting process.)

We then explored whether the dimensions we used to construct the stimuli varied in discriminability. A single sensitivity parameter (c) in ALCOVE scales the distance between the presented stimulus and the exemplar representations. Thus, our "ALCOVE + dimensional discriminability" model expanded ALCOVE's single sensitivity parameter into three dimension-specific sensitivity parameters ($c_{\text{brightness}}$, $c_{\text{orientation}}$, c_{size}), allowing the model to differentially weight the distances along each dimension, if necessary. In a sense, the inclusion of dimension-specific sensitivity parameters amounts to the estimation of interstimulus distances along each dimension using categorization data only (a process that would otherwise require gathering similarity-judgments; e.g., Lee & Navarro, 2002). The addition of these distance-scaling parameters is particularly relevant to the present stimuli, because they were constructed from binary-valued dimensions.

Figure 3 depicts the fits that were produced by each of the three models. Table 1 shows the parameters for each individual model and pigeon after optimization with a genetic algorithm over the negative log likelihood of the models. First, note in Figure 3A (top row) that the original ALCOVE model can predict the performance of 17B and 81B to close degree, by driving the attentional learning rate (λ_a) toward zero (see Table 1). However, the model does not closely reproduce 42Y's pattern of performance (e.g., the model's percentages of errors in Types 1 and 2 are similar, and its errors in Type 4 are less than in Type 2). Note, however, that because the performance of two out of our three pigeons was

Table 1
Best-Fitting Parameters and Akaike Information Criterion (AIC) for ALCOVE and Its Extensions

Model	Parameter	17B	42Y	81B	Mean
ALCOVE	c	.5788	.4253	.6206	.5416
	ϕ	.5786	.4288	.6211	.5429
	λ_w	.0111	.0223	.0098	.0144
	λ_a	.0008	.0022	.0004	.0011
	AIC	22,883	22,008	21,515	22,135
ALCOVE + Dimensional Learning Rates	c	.2204	.3972	.5281	.3819
	ϕ	.5498	.3714	1.0649	.6620
	λ_w	.0189	.0963	.0030	.0394
	$\lambda_{\text{brightness}}$.0000	.0000	.0000	.0000
	$\lambda_{\text{orientation}}$	1.0000	.1537	.0058	.3865
	λ_{size}	.0019	.0541	.0658	.0406
	AIC	22,885	21,966	21,504	22,118
	$c_{\text{brightness}}$.0950	.1223	.3383	.1852
ALCOVE + Dimensional Discriminability	$c_{\text{orientation}}$.5841	.6456	.6385	.6228
	c_{size}	.5040	.6165	.6606	.5937
	ϕ	.7761	1.1862	.9878	.9834
	λ_w	.0060	.0173	.0046	.0093
	λ_a	.0000	.0000	.0037	.0012
	AIC	22,878	21,829	21,530	22,079

Note. c = overall sensitivity parameter; ϕ = mapping constant for choice rule; λ_w = learning rate for output weights; λ_a = learning rate for attentional weights; $\lambda_{\text{brightness}}$, $\lambda_{\text{orientation}}$, and λ_{size} = attentional learning rates for the attentional weights of brightness, orientation, and size dimensions; $c_{\text{brightness}}$, $c_{\text{orientation}}$, and c_{size} = sensitivity to brightness, orientation, and size dimensions; AIC = Akaike Information Criterion.

directly related to the structural complexity of each task, the model did a good job in reproducing average group-level performance (Figure 3B, top panel, black symbols).

The fits of ALCOVE improved when we allowed for variations in the rate at which the model learned to attend to each dimension. Whereas the original ALCOVE's R^2 for individual performance was 0.93, the "ALCOVE + Dimensional Learning" R^2 was 0.96 (cf. top and middle rows of Figures 3A and 3B). As Table 1 illustrates, the "ALCOVE + Dimensional Learning" model converged on different learning rates for each dimension. In doing so, the expanded model more closely approximated the performance of 17B and 81B, and far more faithfully reproduced 42Y's peculiar pattern of errors. To test whether the improvement in model fit was substantial for each pigeon and not merely due to an increase in parameters, we calculated the Akaike Information Criterion (AICs; Akaike, 1974) for the ALCOVE and "ALCOVE + Dimensional Learning" fits of each pigeon's data. The AICs of the original ALCOVE fits were 22,883, 22,008, and 21,515, for pigeons 17B, 42Y, and 81B, respectively, whereas the AICs for the "ALCOVE + Dimensional Learning" for the same birds were 22,885, 21,966, 21,504, respectively. In other words, the additional parameters substantially improved the fits for both 42Y and 81B, but not for 17B. Note that "ALCOVE + Dimensional Learning" learned to attend to orientation faster than it learned to attend to size, but more critically, the model accounted for the performance of all three birds by being incapable of learning to modulate attention to brightness ($\lambda_{\text{brightness}} = 0$). The value for this parameter, however, does not imply that the pigeons could not learn to discriminate between brightness values. All birds showed control by brightness in the tasks that allowed it (see Supplemental Material 4). Furthermore, even 42Y managed to discriminate brightness to a decent degree during the last 10 sessions of concurrent training (28% errors in Type 1; see Supplemental Material 6). Instead of an inability to discriminate brightness, a low attentional learning rate for brightness suggests that the pigeons might have been unable to modulate their attention to brightness values when they were relevant or irrelevant for the categorization at hand.

ALCOVE's fits improved even more when we allowed for variations in the sensitivity to each dimension ($R^2 = 0.99$; Figure 3B, bottom row). Similar to the previous extension, "ALCOVE + Dimensional Discriminability" also improved upon ALCOVE's fits for 17B and 81B, and produced a remarkably close fit for 42Y's nonmonotonic pattern of performance. The AICs of "ALCOVE + Dimensional Discriminability" fits for pigeons 17B, 42Y, and 81B, were 22,878, 21,829, and 21,530, respectively. Therefore, this time around the additional parameters improved the fits for both 42Y and 17B, but not 81B. As Table 1 illustrates, the "ALCOVE + Dimensional Discriminability" model converged on different sensitivity parameters for each dimension, but most critically, the average sensitivity to brightness was the lowest ($c_{\text{brightness}} = 0.19$). Also worth noting is the fact that the model managed to obtain remarkably close fits to the pigeons' performance by driving the attentional learning rate parameter to 0.0037 for 81B and to 0.0 for both 17B and 42Y. These results prove that the performance exhibited by our pigeons, including 42Y, does not need to be explained by appealing to changes in attention across training. Indeed, a model with parameters to scale the distance between the presented stimulus and the exemplars stored in memory should suffice to capture our pigeons' performance with extremely high fidelity.

Discussion

The current experiment assessed pigeons' category learning with the highly influential Shepard et al. (1961) tasks. Although we observed notable individual differences, the performance of the pigeons as a group closely conformed to the structural complexity of the given tasks; pigeons committed more errors to the more structurally complex tasks (Figure 2B). Importantly, the percentage of errors the pigeons committed in the Type 2 task was not lower than the percentage of errors they committed in the Type 4 task. Thus, our pigeons did not show the Type 2 advantage that is often seen with human participants. This advantage is often considered to be a hallmark of rule use (Shepard, Hovland, & Jenkins, 1961) or a signature of selective attention to relevant dimensions (Nosofsky et al., 1994; Nosofsky & Palmeri, 1996).

Departing from traditional experimental designs, we concurrently programmed all of the problem types in each training session. Data from a subsequent training phase in which each of the problems was individually and successively presented suggest that concurrent programming might have increased the overall difficulty of the tasks. Nevertheless, the successive training data also suggest that concurrent programming might have not meaningfully affected the way our pigeons learned the tasks. Specifically, the rank order of difficulty of the tasks was the same across both training phases, for all pigeons. Do note that the order of the concurrent and successive phases was confounded in the present design; so, future studies will be needed to assess whether concurrent programming of the SHJ tasks limited our pigeons' ability to learn the tasks, even when they were later presented in isolation. To our knowledge, no concurrent programming of the SHJ tasks has been attempted with human participants.

Given the specific tasks that we assigned to each pigeon, we observed interesting individual differences (Figure 3A). Most notably, 42Y's errors on the Type 2 task were as low as the errors it committed on the Type 4 task. Although this low percentage of errors is impressive when compared with the other pigeons' performance, 42Y's performance still does not comport with human performance in the Type 2 task. For example, 42Y's learning curve shows no evidence of a sudden decrease in errors over tens of trials, often deemed to be a possible indicator of rule discovery (see Supplemental Material 6). Instead, it is likely that this pigeon's pattern of performance, as well as the other individual differences that we observed, resulted from disparities in the discriminability of the dimensions from which the stimuli were constructed.

In a sense, 42Y's exceptional pattern of errors helped us prove a more general point. By expanding a relatively simple, yet generally successful categorization model (ALCOVE; Kruschke, 1992), we showed that all of the birds' individual differences can be readily reproduced by incorporating either dimension-specific attentional learning rates or dimension-specific sensitivities. Both approaches suggested that brightness was the least discriminable dimension, not only for 42Y, but also for the other two pigeons. Moreover, this modeling process revealed that attentional learning is sufficient but not necessary to explain the individual differences that we documented. This is because in ALCOVE, both dimensional attentional weights and sensitivity parameters serve to scale interstimulus distances.

Do appreciate that we are not claiming that pigeons are unable to modulate their attention; evidence clearly indicates that they do learn to attend more to relevant than to irrelevant features in visual categorization tasks (e.g., Castro & Wasserman, 2017). Rather, we believe that the excellent fits that resulted from our expanded ALCOVE models underscore the complex relationship between the perceived psychological distance between different dimensional values (dimensional discriminability) and the ability to flexibly modulate the amount of attentional resources devoted to different dimensions (attentional learning). It is possible that organisms are unable to modulate the attention they pay to stimulus dimensions that are hard to discriminate. Conversely, organisms might have difficulty discriminating between dimensional values because they fail to increase the attention they pay to them. Future studies should aim to disentangle these two closely related possibilities.

The pigeons in our study had considerable difficulty learning the Type 6 task; all three of our pigeons' errors were at chance level by the end of the concurrent training phase, and the errors for only two of our pigeons fell below chance level by the end of the successive training phase. The Type 6 task is remarkably complex in structure, because the categories it contains are perfect pseudocategories. Although pigeons can learn pseudocategories comprised of natural stimuli (e.g., Navarro & Wasserman, 2016; Wasserman, Kiedinger, & Bhatt, 1988) where unique stimulus-specific physical features are available, in the present case, the stimuli assigned to each category contain no such features (Soto & Wasserman, 2010). Stimulus-specific features allow organisms to memorize the arbitrary mappings arranged in a pseudocategorization task. In the present case, however, the categories in Type 6 have the same average value along each dimension (e.g., for any of the categories, half of the exemplars are dark and the remaining half of the exemplars are bright), thus placing any single dimension orthogonal to category membership. Furthermore, the dyadic relations that can be formed with any two dimensions are also orthogonal to category membership. Effectively, in order to solve the Type 6 task, organisms need to combine all three dimensional values. The nonlinear combination of these dimensional values would allow them, for instance, to extract a configural cue and associate it with the correct categorization response. Previous studies have documented pigeons' ability to nonlinearly combine more than three dimensions at a time (e.g., Lea, Lohmann, & Ryan, 1993; Vyazovska, Navarro, & Wasserman, 2018), so it is unlikely that our pigeons were unable to do so with the current stimuli. Instead, it is possible that unidimensional control from the readily discriminable dimensions (and even the control exerted by dyadic relations) competed with configural control (Delamater, Sosa, & Katz, 1999; Redhead & Pearce, 1995). If discrimination along one or more dimensions overwhelms discrimination of configural cues, then failure to learn the Type 6 task is to be expected. Future studies should explore this possibility.

Our results further expand our general understanding of the category learning abilities of nonhuman animals (Lazareva & Wasserman, 2017). With particular regard to the SHJ tasks, both pigeons' and monkeys' errors can be seen to fall in line with the structural complexity of the tasks (Figure 2B). Importantly, for both species, Type 2 is the second hardest task to learn, whereas for humans, Type 2 is the second easiest task to learn. Our evidence thus further confirms that the Type 2 advantage may be

uniquely observed in humans and may require conditions in which more explicit categorization systems can help encode the nonlinear structure of the Type 2 task (Ashby, Alfonso-Reese, Turken, & Waldron, 1998).

Although evidence of a Type 2 advantage has not yet been obtained in nonhuman animals, there are several reports of humans behaving more like pigeons and monkeys. For example, Nosofsky and Palmeri (1996) showed that humans fail to show the Type 2 advantage when stimuli are composed from nonanalyzable dimensions, such as saturation, brightness, and hue (Shepard & Chang, 1963). Furthermore, Minda, Desroches, and Church (2008) found that humans' learning of the Type 2 task was impaired if they were performing a concurrent, verbal task. Finally, Kurtz et al. (2013) have reported that the likelihood of a Type 2 advantage decreases when participants are not given instructions that prompt them to decompose the stimuli into their constituent dimensions or to find rules for category membership.

The present findings thus inform a possible continuum of categorization learning abilities among different species (Smith et al., 2012). At one end of the continuum, human categorization learning can be—under proper conditions—both analytical and rule-based. Categorization is analytical in the sense that certain categories prompt human participants to encode those dimensions that are necessary to determine category membership and to ignore those dimensions that are not. As a result, humans learn rule-based tasks faster than information-integration tasks (Ashby & Gott, 1988; Smith, Beran, Crossley, Boomer, & Ashby, 2010). Rule-based tasks contain categories whose structures can be described with simple unidimensional, conjunctive, or disjunctive rules, whereas information-integration tasks involve categories whose structures cannot be so easily described. Consequently, humans can often produce verbal rules to encode representations of rule-based categories, thereby giving them an advantage when learning a category and inferring the membership of new category exemplars (Zakrzewski, Church, & Smith, 2018).

In the middle of the continuum, monkey categorization learning has been shown to be analytical (Smith et al., 2012), but apparently not rule-based. Although monkeys do learn rule-based tasks faster than information-integration tasks, they may have difficulty transferring such rules to novel exemplars (Zakrzewski et al., 2018).

Finally, at the other end of the continuum, we find that pigeon categorization learning is nonanalytical; pigeons appear to encode both relevant and irrelevant dimensions when learning the same tasks that encourage analytical category learning in humans and monkeys (Berg & Grace, 2011; Lea et al., 2018; Smith et al., 2011). Additionally, as the present study shows, the categorization learning of the pigeons we studied shows no sign of rule-use. We obtained no evidence to suggest that pigeons learn the SHJ tasks by relying on anything other than the physical properties of the stimuli.

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