Journal of Experimental Psychology:
Animal Behavior Processes
2012, Vol. 38, No. 3, 322–328

0097-7403/12/$12.00 DOI: 10.1037/a0028803

BRIEF REPORT

A Category-Overshadowing Effect in Pigeons: Support for the Common Elements Model of Object Categorization Learning

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A model proposing error-driven learning of associations between representations of stimulus properties and responses can account for many findings in the literature on object categorization by nonhuman animals. Furthermore, the model generates predictions that have been confirmed in both pigeons and people, suggesting that these learning processes are widespread across distantly related species. The present work reports evidence of a category-overshadowing effect in pigeons' categorization of natural objects, a novel behavioral phenomenon predicted by the model. Object categorization learning was impaired when a second category of objects provided redundant information about correct responses. The same impairment was not observed when single objects provided redundant information, but the category to which they belonged was uninformative, suggesting that this effect is different from simple overshadowing, arising from competition among *stimulus categories* rather than *individual stimuli* during learning.

Keywords: object categorization, associative learning, prediction error, overshadowing, pigeon

Supplemental materials: http://dx.doi.org/10.1037/a0028803.supp

Visually recognizing objects in the environment confers a clear advantage for the survival and reproduction of any organism. Among many functions, it allows an animal to locate sources of food, conspecifics, and possible threats. Many animals, including humans, learn to respond similarly to nonidentical objects from the same category (categorization) as well as to respond differently to individual objects from the same category (identification).

We have recently proposed a model of object categorization based on basic mechanisms of associative learning and generalization (Soto & Wasserman, 2010a). The idea behind this model is simple: each image is represented as a collection of "elements" which vary in their level of specificity and invariance with respect to the stimuli they represent. Some elements tend to be activated by a single image—*stimulus-specific* properties. Other elements tend to be activated by several different images depicting objects from the same category—*category-specific* properties. These two kinds of elements are associated with responses in any categorization task depending on their ability to predict reward via an error-driven learning rule, in which any change in the strength of the association between a stimulus element and an action is proportional to the error in the prediction of reward for a given trial (e.g., Rescorla & Wagner, 1972). Reward prediction error equals the difference between the actual reward received and the prediction of reward estimated through the sum of the associative values of all active elements. Although this model is silent as to what the "elements" represent, it specifies which conditions lead to control by category-specific properties, yielding categorization learning and which conditions lead to control by stimulus-specific properties, yielding identification learning.

The idea of representing stimuli through common and distinctive elements has a long tradition in animal learning theory. The notion was first proposed by Konorski (1948) to explain generalization of learning in Pavlovian conditioning and later used by Estes and colleagues as a foundation for Stimulus Sampling Theory (Neimark & Estes, 1967). More recently, several authors have combined an elemental representation with an error-driven learning rule to explain associative learning phenomena (Harris, 2006; McLaren & Mackintosh, 2000, 2002), dimensional generalization phenomena (Blough, 1975), and prototype effects in categorization (Mackintosh, 1995; McLaren, Bennett, Guttmannahir, Kim, & Mackintosh, 1995). Our model (Soto & Wasserman, 2010a) is a natural extension of these ideas to explain object categorization learning.

The Common Elements Model can explain a large number of empirical results in the literature on object categorization by birds (reviewed in Soto & Wasserman, 2010a). More importantly, the model generates precise predictions about the conditions that should foster or hinder categorization learning. Because the model

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This research was supported by Sigma Xi Grant-in-Aid of Research grant G20101015155129 to Fabian A. Soto, by National Institute of Mental Health grant MH47313 to Edward A. Wasserman, and by National Eye Institute grant EY019781 to Edward A. Wasserman.

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proposes that associations between elements and actions are updated through an error-driven learning rule, different types of elements should "compete" with each other for a limited amount of available associative strength. For this reason, the model predicts that several "stimulus competition" effects discovered in associative learning research should have analogs in object categorization learning. We have already reported a categorization blocking effect in pigeons (Soto & Wasserman, 2010a) and people (Soto & Wasserman, 2010b) as well as an analog of the relative validity effect in pigeons (Soto & Wasserman, 2010a). Here, we studied an analog of the overshadowing effect (Pavlov, 1927).

In Pavlovian learning, the overshadowing effect occurs if conditioning to one stimulus is attenuated when it is presented in conjunction with a second equally reliable stimulus. The size of the effect depends on the relative salience of the two stimuli, with a more salient component strongly overshadowing a less salient component (Mackintosh, 1976).

An error-driven learning algorithm explains overshadowing as a result of both stimuli acquiring associative strength throughout training until, together, they perfectly predict the presentation of reinforcement. At that point, learning stops for both stimuli; thus, each conditioned stimulus (CS) only acquires part of the total response tendency that it would have acquired if it had been individually paired with reinforcement. The more salient component tends to acquire more associative strength because higher saliency supports a higher learning rate.

One factor that is particularly important for object categorization learning is that training with different objects from the same category should produce a "repetition advantage" effect for category-specific elements. In categorization training, category-specific elements are repeated across different training images and are frequently paired with the correct responses. This repetition gives them an advantage in controlling performance over stimulus-specific elements, which are not common to many images and therefore do not frequently get paired with the correct response. This effect explains why increasing the number of training exemplars improves categorization learning (Wasserman & Bhatt, 1992; Kendrick, Wright, & Cook, 1990) as well as why, when pigeons are trained to discriminate between objects from the same category, they learn to categorize the objects early in training and only later show correct discrimination performance (Cook & Smith, 2006; Soto & Wasserman, 2010a; Wasserman, Kiedinger, & Bhatt, 1989). This repetition advantage effect gives rise to an overshadowing effect at the level of whole categories, different from the overshadowing of single stimuli reported in past research.

A schematic of the training task that we used to investigate this category overshadowing effect is shown in Figure 1. The within-subjects design involved two conditions—Control and Overshadowing— each trained in a two-alternative forced-choice task. Each training trial involved the presentation of two objects over a gray background: one belonged to a Target category, whereas the other belonged to a Competing category. In both the Control and Overshadowing conditions, the Target Category was informative as to the correct responses; that is, all of the objects from the Target Category were associated with the same response. The main difference between conditions was in the information that was provided by the Competing Categories as to the correct responses. For the Control condition, half of the stimuli from each Competing Category were assigned to one response and the other half were assigned to the other response (left side of Figure 1); that is, although each individual stimulus from the Competing Categories was informative as to the correct response, the basic category to which the stimulus belonged was not. For the Overshadowing condition, all of the objects from the Competing Category were

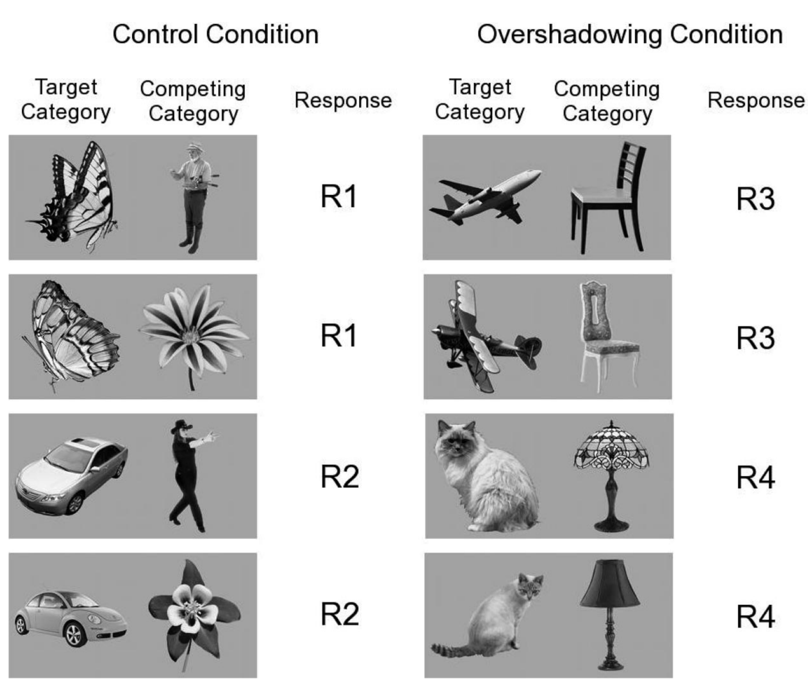

Figure 1. Examples of the different types of training stimuli used in this experiment and their associations with the different task responses in the Control and Overshadowing conditions. "R" stands for response.

associated with the same response (right side of Figure 1); thus, each individual stimulus as well as the category to which the stimulus belonged were informative as to the correct response.

These training conditions sought to determine whether learning about objects from the Target Categories could be influenced by whether or not the Competing Categories were also informative for making the correct response. According to the Common Elements Model, learning about the Target Categories should be impaired in the Overshadowing condition compared with the Control condition, because only in the former were there additional categories that were informative as to the correct responses. Note that this design tests for a phenomenon that differs from the standard overshadowing effect. Overshadowing is a *stimulus-competition effect*, in which the association of an individual stimulus with an event is impaired by the addition of another stimulus. The present design tests for a *category-competition effect*, in which both conditions involved presenting, on each trial, two competing stimuli that were each informative as to the correct response. Only at the category level did the two conditions differ.

After pigeons attained strong discrimination performance in the two training conditions, the presence of a category-overshadowing effect was tested in two different ways. In the Training Stimuli Test, each training stimulus was presented alone, without the stimulus that accompanied it during the Training Phase. This test measured whether a competing category could overshadow learning about the specific training objects from the Target Categories. In the Novel Stimuli Test, altogether new objects from all eight training categories were presented to the pigeons. This test measured whether a competing category could generally overshadow learning about the Target Categories beyond the specific stimuli that had been seen during training.

The predictions of the Common Elements Model for both tests are depicted in Figure 2A, with the simulated results for the Training Stimuli Test in the left panel and the simulated results for the Novel Stimuli Test in the right panel. A more detailed description of this simulation can be found in the Supplementary Online Material. The model's prediction is that performance to the Target Categories (gray columns in Figure 2A) should be lower in the Overshadowing condition than in the Control condition for both tests; that is, the model predicts a category overshadowing effect to the training stimuli that should generalize to new exemplars from the category.

The model also predicts discrimination performance that is near chance to stimuli from the Competing Categories in the Control condition. This prediction is not surprising in the case of the Novel Stimuli Test, because there are no grounds to generalize good discrimination performance to novel stimuli from the Competing Categories, which included objects from two categories that were randomly assigned to the two responses during training. In the case of the Training Stimuli Test, however, the prediction is rather surprising, because objects in the Competing Categories are individually informative as to the correct responses throughout training. Although the model is extensively trained with each of these individual objects, it learns practically nothing about the correct response associated with each object, focusing instead on category learning involving the Target Categories. The repetition advantage for category-specific elements in the Target Categories makes each individual stimulus in the Competing Categories a poor competitor for associative strength. In contrast, the prediction for the Overshadowing condition is that performance with stimuli from the Competing Categories should be similar to performance with stimuli from the Target Categories in both tests. In this case, the Competing Categories as a whole are informative as to the correct responses, and the repetition advantage effect in the Target Categories is nullified by the same effect in the Competing Categories. Finally, the model predicts that performance in the Novel Stimuli Test should be poorer than in the Training Stimuli Test across conditions, a result reflecting an overall generalization decrement effect with new stimuli.

Method

Subjects and Apparatus

The subjects were four feral pigeons (*Columba livia*) kept at 85% of their free-feeding weights. The birds had previously participated in unrelated research.

The experiment used eight 36- × 36- × 41-cm operant conditioning chambers (see Gibson, Wasserman, Frei, & Miller, 2004), located in a dark room with continuous white noise. The stimuli were presented on a 15-in LCD monitor located behind an AccuTouch resistive touchscreen (Elo TouchSystems, Fremont, CA), which was covered by a thin sheet of mylar for protection. A food cup was centered on the rear wall of the chamber. A food dispenser delivered 45-mg food pellets through a vinyl tube into the cup. A houselight on the rear wall of the chamber provided illumination during sessions. Each chamber was controlled by an Apple iMac computer, and the experimental procedure was programmed using Matlab Version 7.9 (The MathWorks, Inc.) with the Psychophysics Toolbox extensions (Brainard, 1997).

Stimuli

The stimuli were 192 images showing 24 objects from eight categories. Four of the categories were natural objects (butterflies, cats, people, flowers), and four were man-made objects (airplanes, cars, lamps, chairs). The stimuli were prepared using GIMP 2.6.8 (Spencer Kimball, Peter Mattis, and the GIMP Development Team; freely available at www.gimp.org). The objects were removed from their original photographs, rescaled so that their largest dimension (width or height) equaled 200 pixels, and centered over a 220 × 220 pixel gray background. The displayed size of each image was 6.5 × 6.5 cm.

Half of the stimuli in each category were used as training stimuli, and the other half were used as testing stimuli for the Novel Stimuli Test. The stimuli from each category were randomly assigned to these two sets.

Procedure

Each pigeon was concurrently trained on the Overshadowing and Control conditions. Four black-and-white icons were used as response keys, each positioned next to one corner of the photographs shown to the pigeons. Each condition was trained using a different pair of response keys in a two-alternative forced-choice task (either the two top response keys or the two bottom response keys). The assignment of conditions to pairs of response keys was counterbalanced across pigeons.

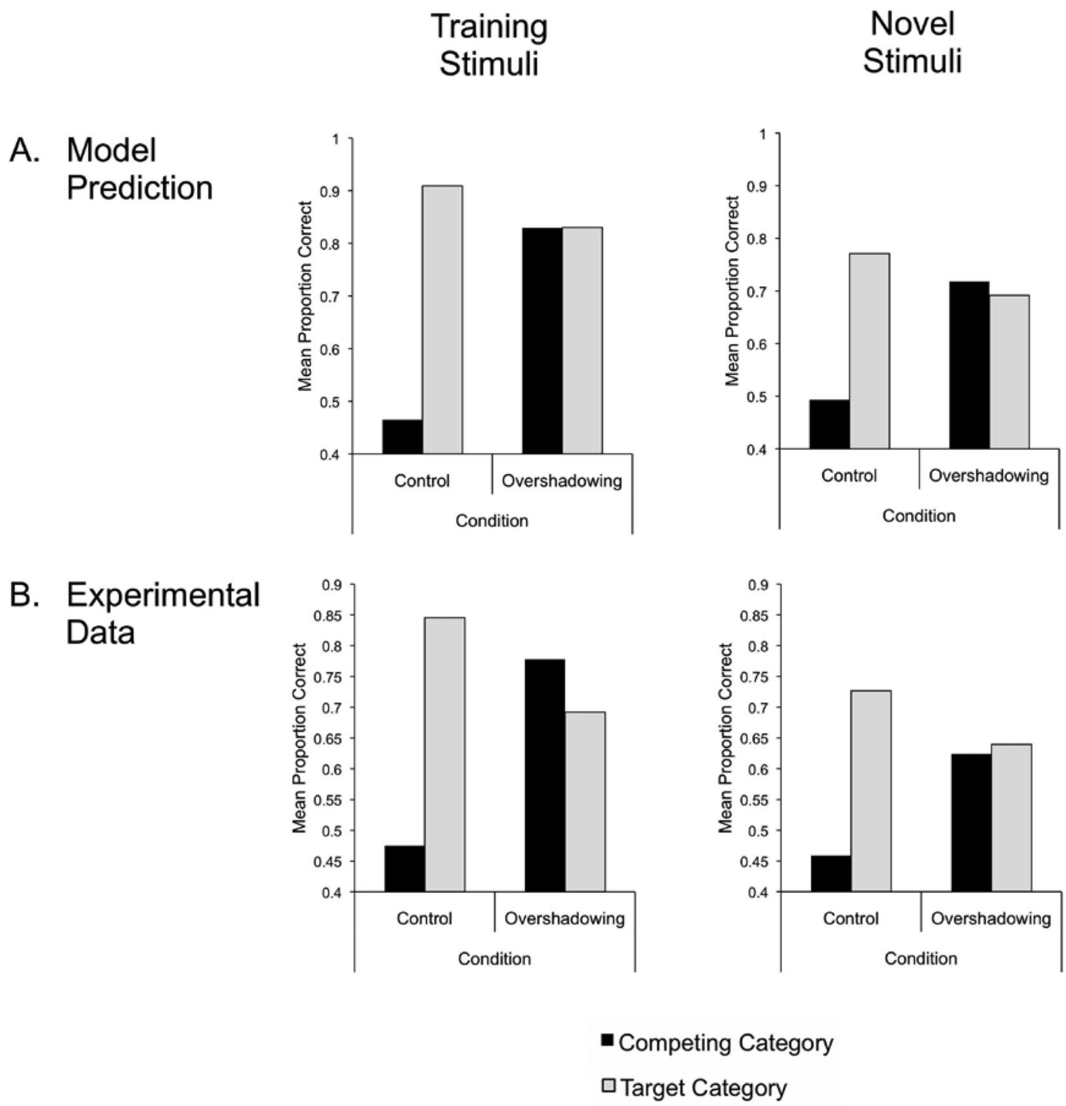

Figure 2. Predictions of the Common Elements Model (A) and results (B) of the reported experiment. The left part of each panel shows the predictions and results for the Training Stimuli Test, and the right part of each panel shows the predictions and results for the Novel Stimuli Test.

The assignment of each of the stimulus categories to the experimental conditions was done as follows. The eight categories were randomly assigned to two sets of four categories each. Set 1 included the categories: Cats, Butterflies, Cars, and Airplanes. Set 2 included the categories: Chairs, Flowers, People, and Lamps. For two randomly selected pigeons, the categories in Set 1 were assigned to the Control condition and the categories in Set 2 were assigned to the Overshadowing condition, whereas the opposite was true for the other two pigeons. Within each set, two categories were consistently assigned to be Target Categories and the other two were consistently assigned to be Competing Categories for all pigeons. This design allowed us to compare category learning across pigeons for the same target categories (either Chairs and Flowers or Cats and Butterflies) using the same training and testing stimuli to evaluate such category learning. The only variation between the conditions was in the way in which the Competing Categories (either People and Lamps or Cars and Airplanes) were related to each of their responses. Whereas in the Overshadowing condition these categories were good indicators of the correct response in the task, in the Control condition the categories themselves did not predict the correct response, although each individual stimulus did.

Stimuli were shown in pairs during the Training Phase. The stimuli were randomly assigned to pairs only once; these pairs were always presented together throughout training.

The stimuli were shown on a 6.5- × 13-cm rectangular screen positioned in the middle of a computer monitor. A trial began with the pigeon being shown a black cross in the center of a white screen. After one peck anywhere on the display, two training objects were shown side-by-side on the display screen. The side on which each image was presented (left or right) was randomly chosen on each trial. The bird had to peck the display screen a number of times (from 5 to 45, depending on performance); then, a pair of response keys was shown (either top-left and top-right or bottom-left and bottom-right) and the pigeon was required to peck one to advance the trial. If the pigeon's choice was correct, then food was delivered and an intertrial interval followed. If the pigeon's choice was incorrect, then the house light and the monitor screen darkened and a correction trial followed after a timeout ranging from 5 to 30 s (depending on performance). Correction trials continued to be given until the correct response was made. All of the report responses were recorded, but only the first report response of each trial was scored in data analysis. Reinforcement consisted of one to three food pellets, randomly chosen on each trial and made available only after a correct response.

During the Training Phase, a session consisted of four blocks of 48 trials, for a total of 192 trials. Each stimulus was presented once within each training block. Training continued until the pigeon met the criterion of 85% accuracy on each of the four response keys; then, the Novel Stimuli Test sessions followed.

Novel Stimuli Test sessions comprised one block of 16 warm-up training trials, randomly selected from the Training Phase contingencies, plus one testing block. The testing block included a single presentation of 12 novel stimuli from each of the eight training categories (96 test stimuli in total) and two presentations of each training trial (96 trials total), for a total of 208 trials. All of the trials involving novel test stimuli were nondifferentially reinforced and the left–right positions of the single stimuli were randomized. Pigeons continued to be tested as long as they met the criteria for the training trials. If a pigeon did not perform at 85% correct choices for the training trials, then it was put back on training until this criterion was met again. Pigeons continued to be tested until 15 Novel Stimuli Test sessions were completed; then, the Training Stimuli Test sessions followed. Training Stimuli Test sessions had the same structure as Novel Stimuli Test sessions, but with the novel test images replaced by the single training images.

Because tests involved nondifferential reinforcement, the behavioral pattern shown by pigeons during the first test was bound to be reinforced, perhaps fostering transfer of the same pattern to the second test. A test with stimuli that have been directly trained is arguably less prone to such generalization artifacts than is a test with novel stimuli; thus, pigeons were tested first with the novel test stimuli and later with the familiar training stimuli.

Across the entire experiment, trials within each session were randomized in blocks.

Results

It took the birds a mean of 20.75 training sessions to reach the learning criterion, with individual scores ranging from 13 to 25 sessions. The discrimination in the Overshadowing condition was learned slightly faster than in the Control condition early in training. A regression line was fit to the early training data (first nine sessions, when no pigeon had yet reached asymptote) for both conditions and each pigeon. The mean slope in the Overshadowing condition (M = 0.0483) was slightly higher than in the Control condition (M = 0.0344), a difference that was significant according to a paired-samples t test, $t(3) = 3.24$, $p < .05$. However, the difference disappeared with further training and the mean proportion of correct responses in the first training session in which the birds met criterion was similar for the Overshadowing (M = 0.9141) and Control (M = 0.9115) conditions, $t(3) = 0.22$, $p > .1$. Importantly, the Common Elements Model does predict this pattern of results, as shown in the Supplementary Online Material.

Figure 2B shows the mean proportion of correct choices to the test stimuli in the Control and Overshadowing conditions (x axis), for both the Competing Categories (black columns) and the Target Categories (gray columns). The left panel shows results for the Trained Stimuli Test, and the right panel shows results for the Novel Stimuli Test. The most important comparison is between the Target Categories in the Control and Overshadowing conditions (gray columns). The Common Elements Model predicts that performance in the Control condition should be higher than in the Overshadowing condition for both types of test (see Figure 2A).

As shown in the left panel of Figure 2B, during the test session involving training stimuli the proportion of correct responding to the Target Categories in the Control condition was higher than in the Overshadowing condition. That is, there was an overshadowing effect, as predicted by the Common Elements Model. It can also be seen that there was a substantial difference in the level to which each of the Competing Categories (black columns) acquired control over performance in the two conditions. In the Control condition, performance with the Competing Categories was near chance, despite the fact that each individual stimulus in these "pseudocategories" was informative as to the correct response. Thus, it seems that the Target Categories completely controlled performance in the Control condition, which is an extreme manifestation of the category advantage effect observed in previous studies (Soto & Wasserman, 2010a; Wasserman et al., 1988). On the other hand, when the same stimuli were grouped according to their basic categories in the Overshadowing condition, performance with the Competing Category was very high.

As shown in the right panel of Figure 2B, during the test sessions involving novel stimuli, the proportion of correct responding to the Target Categories in the Control condition was higher than in the Overshadowing condition. Thus, the overshadowing effect did generalize to new exemplars of the training categories, although the size of the effect was substantially smaller, because of an overall generalization decrement in both the Control and Overshadowing conditions. Also, as observed for the training stimuli, there was a difference in the level to which each of the Competing Categories acquired control over performance in the two conditions. In the Control condition, performance with the Competing Category was again near chance, whereas in the Overshadowing condition performance was higher and close to that observed for the Target Category. Thus, the difference between the Competing and Target Categories observed with training stimuli in the Overshadowing condition was not reproduced with the novel testing stimuli. Beyond this disparity, the overall pattern of results in the Novel Stimuli Test was essentially a scaled version of the pattern of results in the Trained Stimuli Test.

The data depicted in Figure 2B were entered in a 2 (Test Type) × 2 (Condition) × 2 (Category Type) repeated-measures ANOVA with the proportion of correct responses as the dependent variable. Given the goals of this study, two effects in this analysis were particularly important. First, the interaction between Condition and Category Type was significant, $F(1, 3) = 18.272$, MSE = 0.0137, $p < .05$, supporting the overall pattern of results in both panels of Figure 2B, with a difference between conditions in one direction with Target Categories and in the opposite direction with Competing Categories. Second, there was a significant Test Type × Condition × Category Type interaction, $F(1, 3) = 28.95$, $MSE = 0.0007$, $p < .05$, indicating that the pattern of results with Novel Stimuli differed reliably from that observed with Trained Stimuli.

There was also a main effect of Test Type, $F(1, 3) = 18.475$, $MSE = 0.0032$ $p < .05$, indicating that, as previously mentioned, the proportion of correct responses with Novel Stimuli was significantly lower than with Training Stimuli. Also significant were the main effect of Category Type, $F(1, 3) = 22.68$, $MSE = 0.0071$, $p < .05$, and the interaction between Condition and Test Type, $F(1, 3) = 21.173$, $MSE = 0.0001$, $p < .05$. Other effects were not significant.

Given that the interaction between Condition and Category Type was significant, a more direct test of an overshadowing effect was carried out by comparing performance with the Target Categories in the Control and Overshadowing conditions. Because we predicted that performance in the Control condition would be higher than in the Overshadowing condition, a one-tailed paired-samples *t* test was used. This planned comparison revealed a significant difference between the conditions, $t(3) = 2.91$, $p < .05$; that is, there was a reliable overshadowing effect in the data pooled across both tests.

On the other hand, the magnitude of this overshadowing effect varied depending on Test Type, as revealed by the significant Test Type × Condition × Category Type interaction, and by planned comparisons which tested the effect of Condition within Target Categories separately for the Trained Stimuli Test and the Novel Stimuli Test. These tests revealed that the overshadowing effect was significant in the Trained Stimuli Test, $t(3) = 4.13$, $p < .05$, but it was only marginally significant in the Novel Stimuli Test, $t(3) = 1.91$, $p = .076$. Thus, the overshadowing effect was robust with training stimuli, but it generalized less robustly to novel test stimuli.

In summary, the present results confirmed the prediction of the Common Elements Model of an overshadowing effect in natural object categorization by pigeons. The predicted (Figure 2A) and obtained (Figure 2B) patterns of results were quite similar. Although the overshadowing effect with test stimuli was only marginally significant, it was expected that, because of a generalization decrement, the pattern of results with novel test stimuli would be a scaled version of the pattern of results with training stimuli (see Figure 2A). This generalization decrement scales down the size of the overshadowing effect for novel stimuli, whereas the values of the corresponding standard errors are comparable to those of training stimuli. That is, the generalization decrement produces a smaller effect that is tested with the same statistical power. Thus, it is unsurprising that the overshadowing effect was stronger for training stimuli than for novel stimuli.

Discussion

This experiment found that categorization learning in pigeons can be impaired if another category of objects is informative as to the correct responses, but not if the individual objects themselves are informative as to the correct responses. The reliable category-overshadowing effect observed with training stimuli represents an unprecedented *category-competition effect* and was predicted by the Common Elements Model. The results also suggest that this overshadowing effect may generalize to novel exemplars of the relevant categories, albeit to a lesser degree.

The present results also underscore the importance of a repetition advantage effect for object categorization learning. Individual objects that were informative as to correct responses did not overshadow aggregate object categories that were also informative as to correct responses. The repetition advantage was so strong that pigeons did not learn anything about the informative value of individual objects, as indicated by the chance level of performance that pigeons exhibited when these stimuli were presented alone. On the other hand, when two object categories were each informative for solving the task, the repetition advantage of both categories was nullified and an overshadowing effect was observed.

Note that, although the results presented here were predicted by a model which uses the Rescorla-Wagner learning rule, a number of other models from the Pavlovian conditioning literature could be used to obtain the same prediction. As we have discussed elsewhere (Soto & Wasserman, 2010a), using Pearce's configural theory of associative learning (Pearce, 1987) together with a common-elements representation leads to similar predictions for object categorization experiments as does the Rescorla-Wagner model. In fact, any model which treats learning as an error correction process may produce similar results. However, the goal of the present study was not to compare models of associative learning but to test assumptions of the Common Elements Model that can be implemented through several of such models: namely, that categorization learning requires a repetition advantage for category-specific elements and that such learning is driven by prediction error.

On the other hand, our results might be difficult to explain by any model that does not incorporate such assumptions. For example, a model in which categorization is the result of similarity-based generalization, but that does not assume error-driven learning (e.g., Ashby, 1992; Astley & Wasserman, 1992; Nosofsky, 1986), would have trouble explaining why generalization to the target category exemplars is lower in the Overshadowing condition than in the Control condition. In both conditions, each object from the target category is equally informative about the correct response, the only difference being which object accompanied the target object during training. To explain this result, it seems necessary to appreciate that learning about the Competing category objects has an impact on how much an animal learns about the Overshadowing category objects.

The category-competition effect observed here was predicted by the error-driven learning mechanism implemented in the Common Elements Model. Together with previously presented evidence (Soto & Wasserman, 2010a), the category-overshadowing effect suggests that general associative learning mechanisms, which are known to operate in many different species and various forms of learning (e.g., Bitterman, 2000; Siegel & Allan, 1996), may also play an important role in object categorization learning.

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Received January 21, 2012
Revision received April 5, 2012
Accepted April 9, 2012 ■

A Category-Overshadowing Effect in Pigeons:

Support for the Common Elements Model of Object Categorization Learning

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Online Supplementary Material

1. Simulation Procedures

A detailed description of the Common Elements Model can be found in (Soto & Wasserman, 2010a). Here, we restrict ourselves to the description of our simulation of the category-overshadowing effect, the results of which are presented in Figure 2A of the main article.

The parameter values used in the simulation were the same as those used in all of the simulations presented in Soto and Wasserman (2010a). Stimulus representations in the Common Elements Model are generated probabilistically from what we have called a *specificity distribution*, which is modeled through a beta distribution with parameters *a* and *b*. The values in these parameters determine how likely it is that the elements representing an object are category-specific, stimulus-specific, or anything in between these extremes. The parameters *a* and *b* in the beta distribution were fixed to the values of 1.0 and 4.5, respectively, which produces a distribution in which stimuli activate a high number of exemplar-specific elements and a low number of category-specific elements. The stimulus representations tend to be highly sparse, meaning that each stimulus activates only a small proportion of all available elements. The total pool of elements that could be activated by any stimulus in this simulation was 100.

The learning rate parameter α was set to 0.1, and the learning rate parameter β was set to 0.02 for reinforced responses and 0.01 for nonreinforced responses. The value of the parameter θ, which determines the decisiveness of the model's choice rule, was set to 3.0.

The model was exposed to the same contingencies as were given to the birds throughout the simulation (see Procedure section in main article). Training and testing sessions had the same number of blocks and trials as for the pigeons, and they were structured and randomized in the same way as well. If the model achieved 85% correct responses to all four response keys during a training session, then it was run through a testing session. If the model did not achieve these criteria during a testing session, then it was returned to training. The simulation kept running until 15 test sessions of each kind were completed.

The simulation was run 5 times and the results presented in the article represent the average of all 5 runs.

2. Predicted and observed learning curves

As shown in the top panel of Figure S1, the Common Elements Model predicts a slightly higher learning rate early in training for the Overshadowing condition than for the Control condition. This learning rate difference is predicted because only in the Overshadowing condition are there *two* categories that are informative as to the correct response, which means a higher number of category-specific elements to accelerate learning through their repetitive presentation across training trials (i.e., what we have called a "repetition advantage").

The bottom panel of Figure S1 shows the average of the observed learning curves. Note that only data from the first 13 sessions are presented, which is when the first pigeon met the criteria for testing. The observed learning curves exhibit the pattern of performance predicted by the Common Elements Model: faster acquisition in the Overshadowing condition than in the Control condition, but a similar level of accuracy thereafter. The results of statistical tests on these data are presented in the main text of the article.

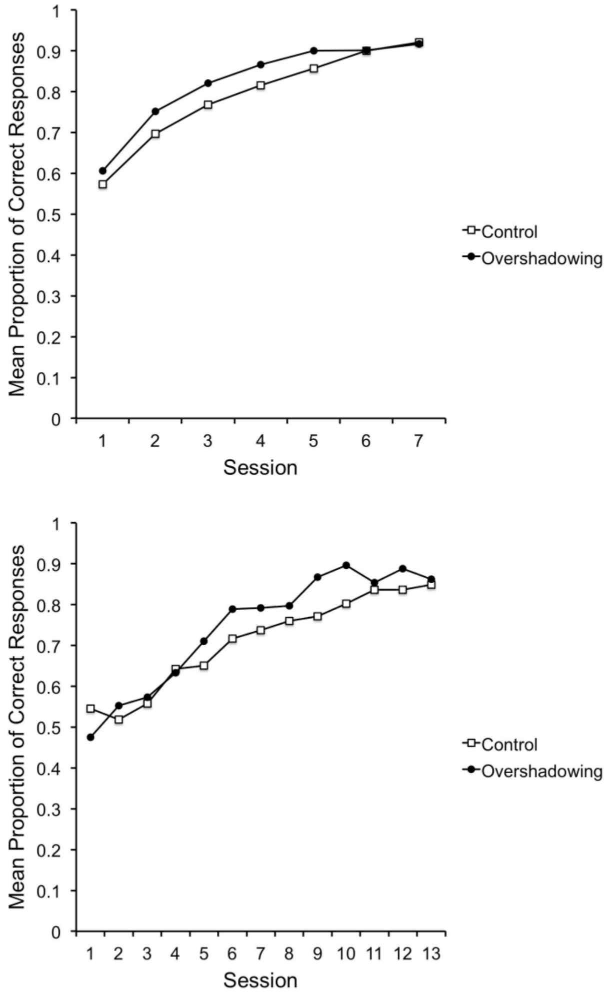

Figure S1: Learning curves for the Overshadowing and Control conditions predicted by the Common Elements Model (top) and observed in our experiment (bottom).