PSYCHOLOGICAL SCIENCE

Research Article

Stages of Abstraction and Exemplar Memorization in Pigeon Category Learning

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ABSTRACT—*It has been proposed that human category learning consists of an early abstraction-based stage followed by a later exemplar-memorization stage. To investigate whether similar processing stages extend to category learning in a nonverbal species, we applied a prototype-exception paradigm to investigating pigeon category learning. Five birds and 8 humans learned six-dimensional perceptual categories constructed to include prototypes, typical items, and exceptions. We evaluated the birds' and humans' categorization strategies at different points during learning. Early on in both species, prototype performance improved rapidly as exception performance remained below chance, indicating an initial mastery of the categories' general structure. Later on, exception performance improved selectively and dramatically, indicating exception-item resolution and exemplar memorization. Abstraction- and exemplar-based formal models reinforced these interpretations. The results suggest a psychological transition in pigeon category learning from abstraction- to exemplar-based processing similar to that found in humans.*

Categorization is a crucial cognitive adaptation for humans and other animals. Not surprisingly, categorization is a sharp research focus in both human cognition (e.g., Ashby & Maddox, 1992; Brooks, 1978; Homa, Sterling, & Trepel, 1981; Murphy, 2003) and animal cognition (Chase & Heinemann, 2001; Herrnstein, Loveland, & Cable, 1976; Huber, 2001; Wasserman, Kiedinger, & Bhatt, 1988). From our perspective as categorization and comparative researchers (Cook, 2001; Smith, Minda, & Washburn, 2004), it is clear that these research traditions should share common theoretical ground, although this has frequently not been the case.

One important issue in both traditions concerns the contribution of abstraction-based and exemplar-based representations to categorization. Organisms might condense their experiences with exemplars of a category into a summary representation and use this derived abstraction to recognize and classify new category members. Or organisms might maintain the category exemplars they experience as separate, individuated memories and use this collection of exemplars to categorize new instances. The implications of these different processes are profound. Abstraction lets the organism transfer category knowledge to novel situations, with the possible cost that exemplar information is lost. Such an abstraction mechanism could also be neurally expensive and might evolve only with difficulty. In contrast, exemplar memorization retains faithfully the details of experience, with the possible costs that large exemplar stores could be expensive and reduce flexible transfer to novel situations. In this article, we argue that organisms bear the costs of having both processes because of the different advantages provided by each.

There is strong evidence for both processes in human categorization. Sometimes humans do abstract the central tendencies of categories (Smith & Minda, 2001). But human categorization is not exclusively dominated by abstraction. If it were, humans should fail to learn categories that have exception items. These exceptions should resist being assimilated into a category represented by a dissimilar prototype. Yet humans can learn such categories with difficulty (Medin & Schwanenflugel, 1981). Accordingly, researchers have come to the productive consensus that abstraction- and exemplar-based processes apply under different circumstances, so that a mixed theoretical perspective is preferable. Humans' overall categorization com-

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petence contains the potential for the two processes, and the balance between them shifts on the basis of category size, category structure, and stage of learning (Blair & Homa, 2001; Homa, Sterling, & Trepel, 1981; Minda & Smith, 2001; Smith & Minda, 1998).

There is also evidence for both processes in avian categorization. Pigeons can memorize large sets of specific exemplars (Cook, Levison, Gillet, & Blaisdell, 2005; Vaughan & Greene, 1984). This capacity is seen when birds remember visual exemplars and features (Aust & Huber, 2001; Edwards & Honig, 1987; Greene, 1983), auditory exemplars (Cynx, 1995; Stoddard, Beecher, Loesche, & Campbell, 1992), and stimulus relations (Carter & Werner, 1978; Wright, 1997). But pigeons also engage in abstract learning by forming perceptual categories (Herrnstein et al., 1976; Huber, 2001; Wasserman et al., 1988) and generalized relations (Cook, Katz, & Cavoto, 1997; Wasserman et al., 1988; Wright, 1997; Young & Wasserman, 2001). Although category size seems to be one factor determining the balance between these processes in animals (Kendrick, Wright, & Cook, 1990; Wright, Cook, & Kendrick, 1989), this balance is poorly understood in animals compared with humans (Minda & Smith, 2001; Smith & Minda, 1998). Are abstraction and exemplar memorization simply different aspects of the same process (Medin & Schaffer, 1978; Nosofsky, 1987), or are they separate and distinct processes—possibly drawing on different brain systems—as has been proposed for humans (Ashby, Alfonso-Reese, Turken, & Waldron, 1998)? Under what conditions is one process or the other employed?

For humans, Smith and Minda (1998) provided part of the answer to the last question. They showed that humans pass through an early stage of category learning consistent with abstraction- but not exemplar-based processing. To do so, Smith and Minda used categories that contained prototypes (defining each category's modal tendency), typical exemplars (similar to the prototypes), and exceptions (assigned to one category, but more similar to the opposing category). Early in learning, humans showed excellent prototype categorization but terrible exception-item categorization. The systematic misclassification of exceptions betrayed the participants' use of an abstraction-based categorization strategy. As a result, an abstraction-based model fit every aspect of early performance better than a comparable exemplar-based model. Later in learning, after the exceptions had been resolved and mastered, the opposite result emerged from the modeling—the exemplar model explained performance better than the abstraction model did. Apparently, secondary exemplar-memorization or exception-resolution processes had supplemented category-level knowledge to allow comprehensively good performance across the item types.

Smith and Minda (1998) suggested that their research could be extended to the study of animal categorization. For example, animals might have more primitive abstraction mechanisms than humans, especially if abstraction is based on explicit or verbal rules. If so, in Smith and Minda's prototype-exception paradigm, animals should exhibit less evidence of early abstraction than humans do, as animals rely predominantly on memorizing the exemplars (see Cook, Wright, & Kendrick, 1990). Alternatively, animals might lack the exception-resolution strategy that supplements human abstraction, especially if that strategy depends on episodic memories about specific problematic items. In this case, animals should have greater difficulty mastering exceptions than humans do. A third possibility is that mammals and birds have evolved similar categorization systems. If so, animals should show the same temporal stages of category learning as humans do. Any of these results would be interesting for establishing the continuities or discontinuities between humans' and animals' category learning. These contrasting scenarios are discernible, however, only if one studies the time course of category learning to reveal the trajectory of these processes and any strategy transitions that occur.

Accordingly, we trained pigeons on prototype-exception categories identical in structure to those of Smith and Minda (1998) but modified for pigeons. We examined the speed of acquisition of the prototypes, typical items, and exceptions to establish the existence of any transitions between strategies. We supported this search by using abstraction and exemplar models matched in mathematical complexity and fitting flexibility. Humans were tested with the same stimuli to replicate Smith and Minda's prior results. If the birds showed the same transition as humans, across millions of years of evolutionary divergence, this result would indicate that the progression from abstractions to exemplars is a fundamental principle of category learning extending across minds and species.

METHOD

Participants

Five experienced male Silver King pigeons (*Columba livia*) were tested. They had performed a motion discrimination unrelated to the current task. They were maintained at 80 to 85% of free-feeding weight, with free access to water and grit in their home cages in a colony room with a 12:12 light:dark cycle.

Nine Tufts University students also participated. One was dropped because of performance that never improved beyond chance.

Apparatus

Pigeons were tested in a black chamber (38 × 36 × 38 cm) controlled by a microcomputer. Stimuli were presented on a color monitor (NEC MultiSync C500; 800 × 600 resolution) visible through a window in the chamber's front panel. Pecks to the monitor were detected by an infrared LED touch screen (Elotouch Systems, Menlo Park, CA). A ceiling houselight was illuminated except during time-outs. Identical food hoppers (Coulbourn #E14–10) were located in the chamber's right and left walls, 3 cm from the front panel. Infrared LEDs mounted 2.5 cm in front of each hopper detected the bird's approach and indicated its choice of hopper. The right and left hoppers, respectively, contained mixed grain and safflower. Humans were tested individually using a microcomputer with a 17-in. monitor (Dell, 800 × 600 resolution).

Stimulus Materials

We instantiated Smith and Minda's (1998) category structure using six binary-color dimensions located in fixed sectors of a circular stimulus (Fig. 1). Pigeons and humans were randomly assigned to one of four prototype pairs that represented different randomizations of the colors to categories and to sectors within categories. Each category contained a *prototype*, an *exception* with five features in common with the opposing prototype, and five *typical* stimuli with five features in common with their prototype. This category structure defeats an abstraction-based strategy because it will lead to miscategorization of the exception stimuli, given their similarity to the opposing prototype. Further, each category contained complementary stimuli (Fig. 1, rows 5 and 7) sharing no common features. Any abstraction that allowed the correct classification of one of these stimuli guaranteed the incorrect classification of the other.

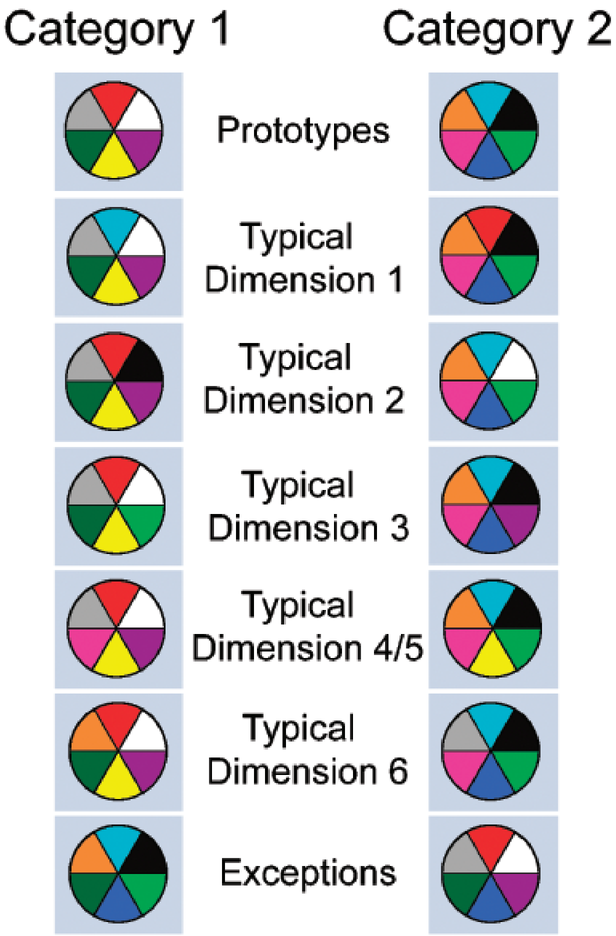

Fig. 1. Stimuli illustrating the category structure used to test pigeons and humans. The four sets of stimuli used had identical structure, but different combinations of contrasting colors defining each binary dimension. Each category contained a prototype (top row), an exception with five features in common with the opposing prototype (bottom row), and five typical stimuli with five features in common with their prototype (intervening rows). For each typical stimulus, the dimension that differed from the prototype is listed. Exemplars within and between categories shared 3.88 and 2.12 features, respectively, on average. Exemplars shared 4.57 and 1.43 features on average with their own and the opposing prototype, respectively. Stimuli took on the typical value for their category five, five, five, six, six, and five times for Dimensions 1 through 6 (clockwise from the top).

Pigeon Testing

A peck to a 2.5-cm white signal centrally presented on the monitor produced a to-be-categorized item (TBCI). After 10 pecks to that item, the lights inside the choice hoppers were illuminated. The pigeon then indicated its choice of Category 1 or 2 by entering its head into one of the hoppers. If the correct hopper was entered, it gave access to food for 2.3 s; if the incorrect hopper was entered, the hopper light went out, and the houselight turned off for 5 s. A 3-s intertrial interval followed either outcome.

Daily sessions contained 112 trials in eight 14-trial blocks (each block containing all 14 stimuli). A correction procedure was used in each session's first block to prevent the development of left/right biases. Correction trials were not analyzed. Training continued until each bird appeared to reach asymptotic performance.

Human Testing

Individual participants were tested using the same categories as for the pigeons. They pressed the "j" (Category 1) or "f" (Category 2) key of the computer keyboard to indicate their response on each trial. Feedback was provided by an 8- × 3-cm box that appeared for 3 s, replacing the categorization stimulus on the screen; the box was green after a correct response and red after an incorrect response. Participants received 392 trials in twenty-eight 14-trial blocks, all in a single session. Trials were separated by 1.5 s. Participants had unlimited time to view each stimulus before responding. No correction procedure was employed. The general instructions were the same as in Smith and Minda's (1998) study.

Formal Modeling

Our modeling procedures are described elsewhere (Minda & Smith, 2001; Smith & Minda, 2000). We used similarity-choice exemplar and abstraction models that are influential in the literature. They calculate similarity identically and incorporate it into the same ubiquitous choice rule. They instantiate transparently the commitments of exemplar- and abstraction-based processing so that they can be evaluated fairly. The influence, identical mathematics, and transparent representational assumptions of these models explain their use here.

These models take as inputs the distance between TBCIs and category representations (CRs). They transform distance into a TBCI-CR similarity and transform similarity into a category-endorsement level (i.e., how strongly would a TBCI that is similar to a CR be endorsed as a member of the category?).

Our measure of TBCI-CR distance incorporated attention that was presumed to be limited and distributed across the stimulus dimensions. For example, given an attentional distribution of .1, .1, .2, .2, .2, and .2, the stimuli 000000 and 001100 (0 and 1 representing different combinations of the six binary dimensions) would be 0.4 (0.2 + 0.2) apart. Our measure of TBCI-CR similarity came from mathematically inverting distance (more distance = less similarity) by making similarity an exponential-decay function of distance. A sensitivity parameter governed this inversion:

$$\text{similarity} = e^{-\text{sensitivity} \times \text{distance}}$$

Our measure of endorsement level came from entering similarity into a choice rule with this general form:

$$\text{endorsement level}_{\text{category1}} = \text{similarity}_{\text{category1}}/(\text{similarity}_{\text{category1}} + \text{similarity}_{\text{category2}}).$$

The exemplar and abstraction models had just one difference: In the exemplar model, the Category 1 and Category 2 similarities were found by comparing each TBCI with the seven Category 1 exemplars and the seven Category 2 exemplars; in the abstraction model, the similarities were found by comparing each TBCI to the Category 1 and Category 2 prototypes. Because pigeons can show response biases in discriminations, a bias parameter was added to both models so that the category choice rule became finally

$$\text{endorsement level}_{\text{category1}} = (\text{bias} \times \text{similarity}_{\text{category1}})/((\text{bias} \times \text{similarity}_{\text{category1}}) + ((1 - \text{bias}) \times \text{similarity}_{\text{category2}})).$$

We used standard hill-climbing methods to find the parameter settings that let each model reproduce as well as it could a categorization performance profile (i.e., the endorsement levels given to 14 stimuli). We used the sum of the squared deviations (*SSD*s) between the 14 observed and predicted endorsement levels to find the best fit of the models to the observations. In every case, we fit the models to the performance profiles of individual pigeons and humans to gain the clearest view possible of the models' fit to each subject's behavior.

RESULTS

Humans

The human participants replicated the crucial results of Smith and Minda (1998). Figure 2a shows their mean accuracy for prototypes, typical items, and exceptions over the 28 training blocks of their session. Their early performance (Blocks 1–4) showed strong differences among the prototypes (90.6%), typical items (71.2%), and exceptions (31.2%). This data pattern is consistent with the use of an abstraction that assimilates prototypes into their correct category but miscategorizes exceptions because of their similarity to the opposing prototype. Supporting this idea, formal modeling showed that the exemplar model fit early performance worse than the abstraction model, *SSD*s = 1.37 and 1.11, respectively, $t(31) = 3.95$, $p_{\text{rep}} = .991$, $\eta^2 = .02$. The upper left graph in Figure 3 shows the average observed performance levels and the average predicted performance levels for both models for prototypical, typical, and exception stimuli. The exemplar model underpredicted prototype accuracy by 6.7% and severely overpredicted exception

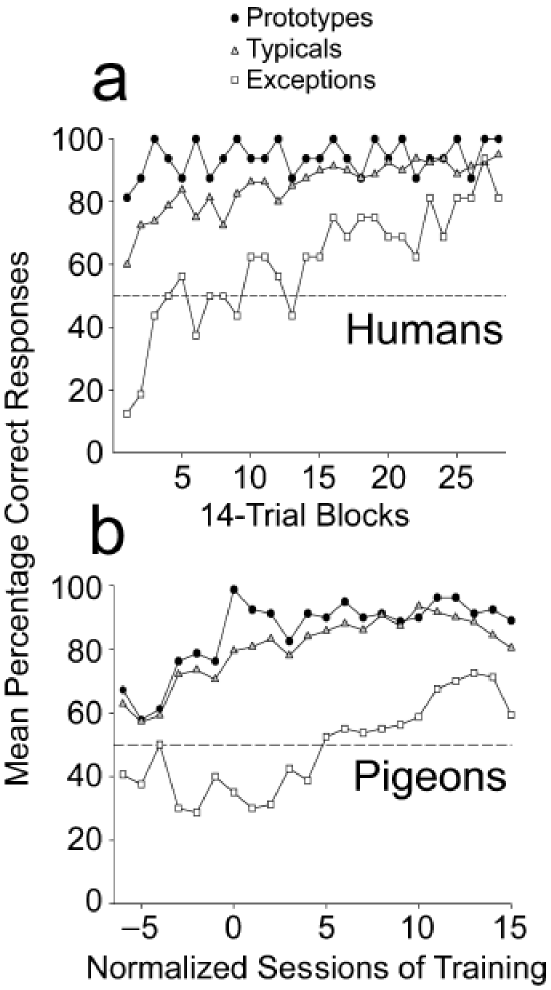

Fig. 2. Acquisition curves for the 8 humans (a) and 5 pigeons (b). Each graph shows the average percentage of correct responses for prototypes, typical items, and exceptions across blocks or sessions. The bottom panel (for pigeons) shows a backward learning curve; the individual acquisition curves were aligned at a comparable point of mastery, and then performance was averaged and plotted backward and forward from that point (see the text for details). The dotted line represents chance performance.

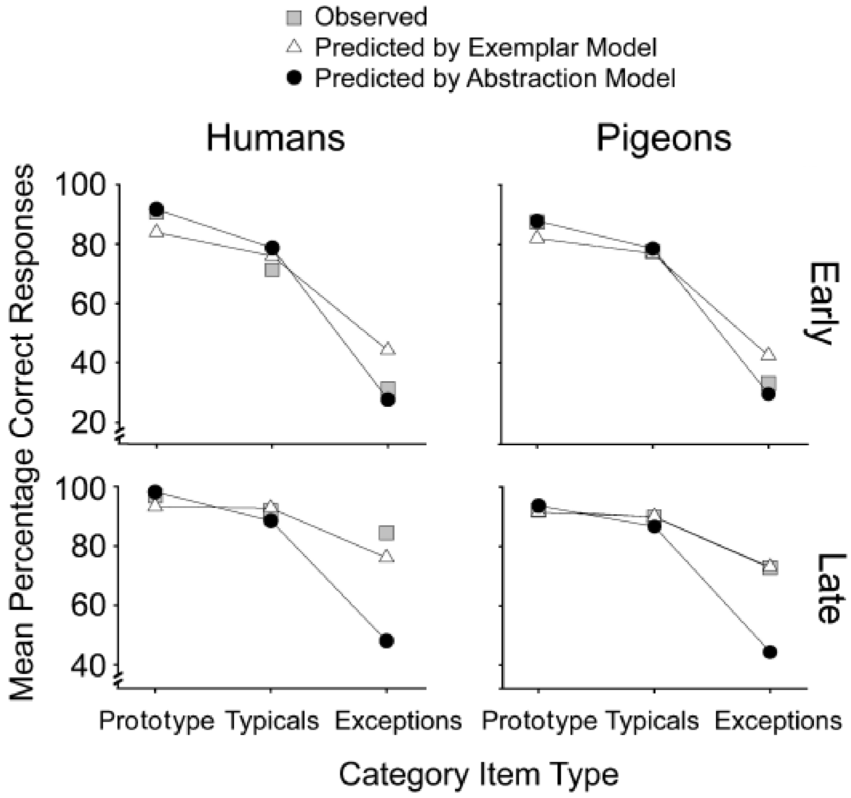

Fig. 3. Humans' and pigeons' observed and predicted accuracy for prototypes, typical items, and exceptions during the early (top panels) and late (bottom panels) stages of learning. The definitions of early and late differed between species (see the text for details). Predictions for the exemplar model and the abstraction model are shown.

accuracy by 13.0%. The character of this misfit springs from the exemplar model's representational assumption of storing all items in the same way. The more sensitively this model stores exemplars, the more sensitively it stores both prototypes and exceptions. This tends to produce a positive correlation between prototype and exception performance that acts against prototype-exception divergence. The abstraction model had smaller prediction errors that showed an opposite pattern reflecting the model's representational assumption. It overpredicted prototype accuracy by 1.0% and underpredicted exception accuracy by 3.7%. As this model enters configurations in which it stores category information more sensitively, it categorizes prototypes more accurately, but exceptions less so. This tends to produce a negative correlation between prototype and exception performance.

During the latter blocks of learning, as shown in Figure 2a, exception accuracy improved steadily for the humans. As a result, the lower left panel of Figure 3 shows a different pattern of fits for late in human category learning (Blocks 25–28). Participants were 96.9%, 91.9%, and 84.4% correct on the prototypes, typical items, and exceptions, respectively,. Exception accuracy had improved by 53%. This pattern is consistent with secondary exemplar-memorization or exception-resolution processes that treated exceptions appropriately despite their inconsistency with their categories' abstract structure. The exemplar model now performed better than the abstraction model, *SSD*s = 0.42 and 0.91, respectively, $t(31) = -5.11$, $p_{\text{rep}} = .998$, $\eta^2 = .14$. Moreover, the abstraction model's misfit had the expected character. It underpredicted exception accuracy by 36.3%. The abstraction mechanism in this model could not overcome the similarity of exceptions to the opposing prototype and categorize them as accurately as humans did.

Pigeons

The pigeons learned more slowly than the humans, requiring many sessions rather than one. Nevertheless, they showed an analogous pattern during acquisition. Although the individual birds differed in their learning rates, they all learned the prototypes most quickly, followed by the typical items, with the exceptions far behind. In an analysis of variance over the first 15 sessions of training, there was a significant Item Type × Session interaction, $F(28, 112) = 2.68$, $p_{\text{rep}} = .997$, $\eta^2 = .39$.

To accommodate the individual differences in learning rate among the pigeons, we generated backward learning curves (Byrne et al., 1991; Smith et al., 2004; Smith, Tracy, & Murray, 1993; Zeaman & House, 1963). This procedure let us align the acquisition curves at a comparable point of mastery and work backward and forward from there to determine the trajectory of learning. We defined the mastery point as the first session with 100% prototype accuracy (for 1 pigeon this criterion was relaxed to two consecutive sessions with 93.8% accuracy). Sessions were numbered backward and forward from this “Session 0.”

Figure 2b shows the pigeons’ average backward learning curves for prototypical, typical, and exception stimuli. Early in learning, accuracy on prototypes and typical items improved, while exception accuracy remained below chance. This produced strongly heterogeneous performance in the sessions surrounding Session 0 (Sessions −2 to +2). During this period, performance on prototypes, typical items, and exceptions averaged 87.5%, 77.5%, and 33.0% correct, respectively. As noted in the discussion of human performance, this pattern is consistent with the use of an abstraction that assimilates prototypes into categories but misclassifies exceptions because of their similarity to the opposing prototype.

Modeling supported this interpretation. The upper right panel of Figure 3 shows the average observed and predicted performance levels for prototypes, typical items, and exception items during these five sessions. The exemplar model performed worse than the abstraction model, *SSD*s = 0.1865 and 0.1280, respectively, $t(24) = 3.05$, $p_{\text{rep}} = .964$, $\eta^2 = .09$. The exemplar model underpredicted participants’ prototype accuracy (by 5.5%), but severely overpredicted participants’ exception accuracy (by 9.5%). The abstraction model had smaller errors and the opposite error regarding exceptions. It mispredicted prototype accuracy by only 0.3% and underpredicted exception accuracy by only 3.5%. Once again, the abstraction model was a better fit with divergent prototype-exception performance.

Figure 2b shows that subsequent to this period, exception accuracy improved selectively. Late in learning (each bird’s last five sessions), performance was generally more homogeneous across item types. The birds were 92.2%, 89.9%, and 72.8% correct on prototypes, typical items, and exceptions, respectively. Exception performance had improved 40% compared with the first five sessions. Now the exemplar model outperformed the abstraction model, *SSD*s = 0.060 and 0.485, respectively, $t(24) = -5.79$, $p_{\text{rep}} = .999$, $\eta^2 = .46$. The lower right panel of Figure 3 shows that the abstraction model underpredicted exception accuracy by 28.3% because it could not overcome the similarity of exceptions to the opposing prototype and categorize them accurately, as the pigeons generally did.

GENERAL DISCUSSION

These data show a striking similarity between pigeons and humans in the acquisition of a prototype-exception task. Both species learned the prototypes and typical items more quickly than the exceptions and were below chance with the exceptions early in learning. This pattern suggests the use of an abstraction-based representation during this stage. Later, exception accuracy improved in both species, a pattern consistent with the eventual deployment of a secondary exemplar-memorization process. The modeling of each species’ data strongly supported these conclusions.

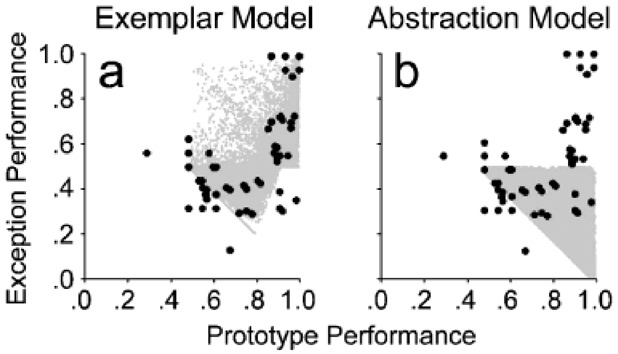

Fig. 4. Pigeons’ average prototype- and exception-item performance by aligned session, overlain on the results of 10,608 configurations of the exemplar model (a) and abstraction model (b). To make these configurations, the six attentional parameters were systematically varied from 0 to 1.0 in .05 steps (with the constraint that the six parameters sum to 1.0). Then, for each attentional profile, a random bias and sensitivity parameter were selected (from the ranges of 0–1.0 and 0–20.0, respectively), and the prototype and exception performance for that configuration of the model was calculated.

Figure 4 shows the pigeons’ prototype and exception performance across sessions, overlain on the universe of performances (gray areas) producible by the exemplar and abstraction models. Early on, as prototype and exception performance diverged, performance entered a region of performance space that no configuration of the exemplar model occupies. The exemplar model’s failure is qualitative at this point of learning near Session 0. It cannot predict such divergence between prototype and exception performance. The abstraction model can; because of its representational assumption, this divergence is just what it predicts.

The pigeons turned a corner at Session 0, and entered a region of performance space that is qualitatively denied the abstraction model. Clearly, some secondary strategy resolved the exceptions. Possibly the pigeons memorized the aberrant members or began to code multiple stimulus features more configurally. Exemplar storage and configural representations are two key features of the exemplar model.

Overall, these results suggest an important cross-species similarity in the time course of the basic processes serving category learning. The similarity across millions of years of evolutionary divergence is striking and contributes to the general and comparative categorization literature in several ways. First, it suggests that either these general processes are evolutionarily old or similar solutions to category learning have evolved independently in these distinct phylogenetic lineages.

Second, it shows the value of looking at the time course of acquisition in categorization studies. Much categorization research focuses only on asymptotic performance after learning is completed. This approach does not show the first principles or initial assumptions of category learning—extensive training paves these over. Moreover, looking only at terminal performance may unduly emphasize exemplar processes, because, as we have shown here, these will likely be strongest at the end of learning. Thus, analyzing the stages of category learning and the succession of strategies will be productive in comparative studies for the same reason it is productive in human studies.

Third, our results show the value of a mixed theoretical perspective that permits behavior to be determined by different categorization systems operating at different times. This perspective has enriched the human literature by moving it beyond forcing one process to explain all categorization behavior. In the comparative literature, too, some researchers have preferred a linear feature model allied to our abstraction model (Huber, 2001), whereas others have preferred a configural model allied to our exemplar model (Astley & Wasserman, 1992; Chase & Heinemann, 2001; Pearce, 1994). In our view, both perspectives will figure prominently in explaining fully animals' categorization behavior. Here we explored for the first time the changing balance of these processes across stages of learning. One could also explore the changing balance across category structures. For instance, categories that have few members or weak within-category similarity would probably shift animals toward exemplar processing, just as they shift humans (Blair & Homa, 2001; Homa et al., 1981; Smith & Minda, 1998).

Fourth, these results join Smith and Minda's (1998) to confer species generality on the claim that there is a progression in category learning from abstraction to exemplar-based processes. Although similar suggestions have been made in the human literature (Reed, 1978), this progression has not been as prominent in the animal literature. Cook et al. (1990) hypothesized that pigeons first memorize exemplars, then later derive abstractions from these items. This hypothesis was not supported by the present study. In a study more consistent with our results, Wasserman et al. (1988) tested pigeons' learning of subcategories of basic objects and found that learning moved from abstraction to exemplar memorization. The generality of this strategy transition has an important implication about how minds learn categories. Evidently, the basic approach or the initial stance is to first detect, recognize, and abstract the common features of a category. Evidently, the processes that focus on specific exemplars and master exceptions are secondary, subsequent, and possibly invoked only on demand of the error signals from recurrent problematic stimuli. We note, though, that different species could show variations on this general progression or particular biases more toward abstraction-based or exemplar-based processing. Such variations could produce important differences across species. For example, human language might quicken, sharpen, or strengthen the abstraction phase of category learning. Also, pigeons probably have important strengths in exemplar memorization that they may deploy quickly in some categorization tasks (Cook et al., 2005).

We should point out that to use abstractions, animals do not need a cognitively sophisticated abstraction device. This assumed sophistication is sometimes used as a philosophical objection to abstraction in animals. Any mechanism that accumulates cue or response strength in parallel over dimensions would yield the observed initial responses to the categories' central tendencies. Of course, such a simple abstraction mechanism would fail to learn exceptions, exactly as established here. Another point in favor of early abstraction is that the categories' abstractive tendencies are experienced and reinforced on almost every trial—far more frequently than are the category exceptions. Arguments like these explain why it could be the episodic memory for problematic exceptions and the behavioral solutions for them that need to be cognitively sophisticated. Perhaps this is why exemplar processes tend to be secondary and subsequent in categorization tasks.

Fifth, the initial stance toward abstraction may betray a default assumption that organisms use in processing collections of items. This assumption is that categories are perceptually coherent and well organized in family-resemblance terms. It is for these ubiquitous categories that abstraction works reliably and completely. The evolution of this processing assumption likely reflects the category structure that the natural ecology often presents to animals. Thinking as a pigeon for the moment, consider that the categories of mates, seeds, grit, hawks, snakes, trees, and so forth all have coherent perceptual organizations. As a result, an organism could safely use abstraction for these categories and gain cognitive economy from it by not needing to learn and retain potentially large numbers of exemplars. So we are interested in the possibility that the default abstractive stance in category learning stems from an affordance of the natural kinds that organisms have experienced during their cognitive evolution. Of course, organisms may also need an exception memorizer or resolver. But this perspective helps explain why this mechanism might be secondary to abstraction during learning.

Much remains to be discovered about the character of humans' and animals' categorization processes. In the human literature, these questions are being explored from the perspective of cognitive neuroscience and the brain systems underlying different processes (Ashby et al., 1998; Ashby & Ell, 2001). Similar characterizing and localizing questions could be asked about animals' abstraction and exemplar processes. Indeed, it will be interesting to consider the systems that let animals focus on different aspects of categories at different stages of learning and to ask whether there are structural analogies in the brain regions or architectures that support these different processes in animals and humans.

Acknowledgments—Preparation of this article was supported by Grant IOB 0316016 from the National Science Foundation (R.G.C.) and by Grant HD-38051 from the National Institute for Child Health and Human Development (J.D.S.).

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(RECEIVED 8/10/05; REVISION ACCEPTED 11/29/05;
FINAL MATERIALS RECEIVED 5/31/06)