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Refining the Visual-Cortical Hypothesis in Category Learning

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Abstract

Participants produce steep typicality gradients and large prototype-enhancement effects in dot-distortion category tasks, showing that in these tasks to-be-categorized items are compared to a prototypical representation that is the central tendency of the participant's exemplar experience. These prototype-abstraction processes have been ascribed to low-level mechanisms in primary visual cortex. Here we asked whether higher-level mechanisms in visual cortex can also sometimes support prototype abstraction. To do so, we compared dot-distortion performance when the stimuli were size constant (allowing some low-level repetition-familiarity to develop for similar shapes) or size variable (defeating repetition-familiarity effects). If prototype formation is only mediated by low-level mechanisms, stimulus-size variability should lessen prototype effects and flatten typicality gradients. Yet prototype effects and typicality gradients were the same under both conditions, whether participants learned the categories explicitly or implicitly and whether they received trial-by-trial reinforcement during transfer tests. These results broaden out the visual-cortical hypothesis because low-level visual areas, featuring retinotopic perceptual representations, would not support robust category learning or prototype-enhancement effects in an environment of pronounced variability in stimulus size. Therefore, higher-level cortical mechanisms evidently can also support prototype formation during categorization.

Keywords

categorization; prototypes; typicality; perceptual representation system; visual cortex

Categorization—the formation and use of psychological equivalence classes—is a basic ability that is critical to all domains of cognition and to survival. For this reason, categorization is a sharp research focus (e.g., Ashby & Maddox, 1992; Homa, Sterling, & Trepel, 1981; Kruschke, 1992; Medin, 1975; Murphy, 2003; Rosch & Mervis, 1975; Smith & Minda, 1998).

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There is strong evidence that humans sometimes categorize objects using prototypes. That is, category learners average or blend the category members they experience to form a prototype, compare new to-be-categorized items to it, and accept these items as category members if they are similar enough to the prototype (e.g., Ashby & Maddox, 2005, Cook & Smith, 2006; Smith, 2002; Smith, Chapman, & Redford, 2010; Smith & Minda, 1998, 2001, 2002)¹.

Humans' capacity for prototype abstraction can be illustrated using the influential dot-distortion category task (e.g., Blair & Homa, 2001; Homa et al., 1981; Knowlton & Squire, 1993; Posner, Goldsmith, & Welton, 1967; Smith, Redford, & Haas, 2008; Smith et al., 2010). In this task, participants are trained on a family of shapes that are all distortions of an originating prototype, and they are then asked to endorse (or not) previously unseen probe items as belonging in the trained category. These probe items are copies of the prototype, low- and high-level distortions of it, and random items outside the trained category (Figure 1, Rows 1–4, respectively).

Humans in this task show strong endorsement of the prototype relative to other category members, as they would if they had abstracted with privilege that central category representation (e.g., Knowlton & Squire, 1993). They also produce a steep typicality gradient—that is, a large change in category-endorsement level from prototypes to low-level distortions to high-level distortions (Figure 2). This steepness also points to an underlying prototype representation because the prototype is the unitary, central point in psychological space, and as one creates higher-level distortions, one always moves directly away from it, producing more dissimilar stimuli and weaker category members (Smith & Minda, 2001, 2002). These results are fit distinctively well by a prototype model—in Figure 2, the model's predictions missed the actual observations by only 1.5% per data point². Thus, these results confirm that prototype abstraction is one component of humans' multifaceted categorization capacity (Ashby & Maddox, 2005).

It is possible now to grant humans' prototype-formation capacity greater phylogenetic depth. Smith et al. (2008) found that monkeys (*Macaca mulatta*) also showed steep typicality gradients that were distinctively well fit by a prototype model (Figure 3). In this case, the model's predictions missed the actual observations by only .2% per data point. Clearly, humans and animals share a capacity for prototype formation in the dot-distortion category task, suggesting that there may be basic mechanisms common to human and monkey perception that underlie prototype-enhancement effects. The dot-distortion task is the focus of the present research because it currently provides the strongest evidence for prototype-abstraction processes and because it is the dominant task within the cognitive-neuroscience literature that is reviewed shortly. In fact, though, a wide range of prototype and typicality effects have now been demonstrated in the comparative-cognition literature (e.g., Aydin & Pearce, 1994; Cook

¹That humans have prototype formation as one component of their category-learning capacity does not imply that humans learn only through prototypes or that their categorization is unitarily prototype based. It is not. A complete description of the categorization system of humans and possibly nonhumans would include, in addition to prototypes, rules, decision bounds, exemplar processes, and so forth. Indeed, a multiple-systems approach is an important part of the human categorization literature (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ell, 2001; Erickson & Kruschke, 1998; Homa et al., 1981; Minda & Smith, 2001, Rosseel, 2002; Smith & Minda, 1998) and the comparative categorization literature (Cook & Smith, 2006; Herbranson, Fremouw, & Shimp, 1999; Smith et al., 2010; Smith, Beran, Crossley, Boomer, & Ashby, 2010; Wasserman, Kiedinger, & Bhatt, 1988). Prototype formation is one important component of humans' overall categorization system that we emphasize in the present article simply because it is the article's empirical and theoretical focus.

²Detailed modeling procedures for the dot-distortion paradigm can be found in Smith (2002), Smith & Minda (2001, 2002), or Smith et al. (2008). Generally, the prototype models illustrated in Figures 2 and 3 of the present article begin with the stimulus distance between a to-be-categorized stimulus and the prototype of the category that is the presumed reference standard. Distance is transformed into psychological similarity using an exponential-decay function that incorporates a freely varying sensitivity parameters. Similarity is transformed into a category-endorsement level using a choice rule. Standard hill-climbing algorithms are used to maximize the fit between observed and predicted performance profiles and thus to find the configuration of the model that best reproduces the observed profile. The prototype models illustrated in Figures 2 and 3 are particularly constructive within the literature because they offer a direct comparison to exemplar models that take identical inputs, have identical parameters, and differ only in their underlying representational assumption.

& Smith, 2006; Huber & Lenz, 1993; Jitsumori, 1996; Smith et al., 2008, 2010, von Fersen & Lea, 1990; White, Alsop, & Williams, 1993)³.

Given the consensus about prototype abstraction as one aspect of category learning, theorists have begun to analyze the mechanism underlying prototype formation. The current hypothesis is that prototype formation is mediated by Schacter's (1990) Perceptual Representation System (PRS). The PRS was proposed to account for various repetition-familiarity-fluency effects in which prior exposure to a stimulus improves performance on subsequent presentations of that stimulus (Gazzaniga, Ivry, & Mangun, 2002). These repetition effects are long lasting (up to 48 weeks in Cave, 1997) and can occur after only a single stimulus repetition (e.g., Wiggs & Martin, 1998), even when participants have no conscious recollection of the degraded stimulus and even in patients with amnesia (Gabrieli et al., 1990; Knowlton & Squire, 1993). Though the type of learning mediated by the PRS is sometimes referred to as repetition priming, it is not so highly specific as to be limited to repetitions of identical stimuli. To the contrary, PRS effects can be induced when stimuli are different but perceptually similar (e.g., Biederman & Cooper, 1992; Cooper, Schacter, Ballesteros, & Moore, 1992; Seamon et al., 1997). This fact makes the PRS potentially highly relevant to the categorization literature. Regarding categorization and prototype formation, the idea is that the repeated presentation of perceptually similar shapes sensitizes the cognitive system (i.e., the PRS) to novel shapes belonging to the same general shape class or derived from the same underlying prototype.

Cognitive neuroscientists have postulated that PRS learning and consequently prototype formation occurs within visual cortex (Gabrieli et al., 1996; Raichle et al., 1994; Rolls, 2000). In fact, Reber, Stark, and Squire (1998a,b) provisionally identified the visual-cortical areas involved in prototype formation. They collected neuroimaging data when human participants were categorizing dot distortions. They observed changes in visual-cortical activity that were dependent on category (non)membership. When participants were endorsing category members, less activity was found in the early visual-cortical areas in posterior occipital cortex (i.e., primary visual-cortical areas V1 and V2). This suggests that the categorical patterns were processed more easily, quickly, or fluently. (Past studies in word repetition have also found that decreased activity in V1 and V2 were an indication of visual priming whereby repeated words were processed more fluently than new words—see Squire et al., 1992). At present, the pattern of reduced visual-cortical activation found by Reber et al. appears to be replicable, appearing also in Reber, Wong, and Buxton (2002) and Reber, Gitelman, Parrish, and Mesulam (2003).

Aizenstein et al. (2000) also observed reduced visual-cortical activity when humans in dot-distortion tasks were endorsing category members (compared to non-members). For unknown reasons, the locus of reduced activation in Aizenstein et al. was in the early visual area V3, a different locus from that found in Reber et al. (1998a,b) and one surprisingly more superior and dorsal in the brain (Udin, pers. commun. Dec. 4, 2008, Reber et al., 2003).

The finding by Aizenstein et al. (2000) underscores that there remain uncertainties in interpreting the present evidence. After all, discrepant brain loci for prototype formation were identified in the studies by Aizenstein and Reber et al. Moreover, Reber et al. also found some changes in frontal areas during categorization, a complicating factor suggesting that higher-

³An apparent exception to findings of prototype formation by humans and animals was reported by Sigala, Gabbiani, and Logothetis (2002). However, the reasons for this exception are clear. Humans and monkeys in these tasks were trained using only five exemplars in each category. The small size of these exemplar sets is well known to encourage exemplar memorization as a task strategy and to discourage abstraction or prototype formation (Homa et al., 1981; Smith et al., 1997, 1998, 2000). Moreover, the Sigala et al. categorization task was not linearly separable along two of its four dimensions, definitionally ruling out the adaptive use of abstraction or averaging along those dimensions. Finally, the tasks in Sigala et al. were essentially solvable by a single-dimensional rule, discouraging multi-dimensional prototype formation for yet another reason.

order cognitive mechanisms were also involved. In Aizenstein's study, the purpose of the training phase was withheld from participants in order to make the task implicit. This may also have changed participants' approach to the task and changed the underlying processes away from those sometimes seen in dot-distortion tasks. Finally, Reber et al. (1998a,b) presented alternating blocks of mostly category members and mostly non-members. The repetitive exposure to similar stimuli within blocks could also change participants' approach and the underlying processes used, and could even seem to place a heavy emphasis on immediate repetition and on the earliest stages of visual-cortical processing.

Consequently, Casale and Ashby (2008) stressed that it was premature to strongly link PRS effects and prototype formation to any particular regions of early visual processing. Sigala et al. (2002) issued the same caution. We share the sense of these researchers that further research is required in this area, and this was a primary empirical goal of the present research. We also share their sense that in this area behavioral evidence, not only neuroimaging evidence, has an important role to play in specifying the integration of prototype formation into the overall categorization system.

The purpose of the present study, therefore, was to use behavioral evidence to refine the hypothesis that category learning in prototype-formation tasks is primarily supported by early visual-cortical areas. To do this, we manipulated the size of the stimuli and asked whether categorization performance is robust to stimuli of different sizes. This manipulation and empirical approach had the following rationale. Neurons in the early areas of the visual cortex represent topographically, and thus they respond differently to differently sized stimuli. Selectivity for shape is not preserved over size change—similar stimuli that vary in size create different patterns of activity (Engel, Glover, & Wandell, 1997; Vuilleumier, Henson, Driver, & Dolan, 2002). Engel et al. differentiated retinotopic and nonretinotopic areas of the visual cortex in humans by using a stimulus that produced traveling wave responses and measuring these responses with functional magnetic resonance imaging (fMRI). Primary, secondary, and tertiary visual cortices (V1, V2, and V3) were determined to be organized retinotopically. Other researchers have found similar results in the visual cortex of monkeys (Zeki, 1969; Allman & Kaas, 1974; Van Essen & Zeki, 1978; Gattass, Sousa, & Gross, 1988). Vuilleumier et al. examined repetition-priming effects in visual cortex given repetitive exposure to stimuli of different sizes. Repeated exposures were accompanied by decreases in visual-cortical activity. But size variability disrupted these priming effects/activity decreases in early visual areas. Konen and Kastner (2008) also demonstrated that even intermediate visual-cortical areas (V3A, V4, V5, and V7) are size dependent. If category learning is occurring in early visual areas, size variability should weaken it and undermine the process of prototype formation.

Accordingly, we asked whether training with stimuli of different sizes would produce these weakening and undermining effects. To the extent these effects emerged, it would support the hypothesis that only early areas of visual cortex are supporting category learning and prototype formation. To the extent these effects did not emerge, it would suggest that higher-order cognitive areas can also support prototype formation. Note that this latter result, even while positively asserting a role for higher-level visual processes in prototype abstraction, would still allow a role for lower-level visual processes in prototype abstraction under other conditions as specified in previous studies.

Experiment 1

Experiment 1 evaluated the effect of varying stimulus size on category learning in a dot-distortion task. Cells in early areas of the visual cortex are known to be sensitive to size transformation (Engel et al., 1997; Vuilleumier et al., 2002; Konen & Kastner, 2008). Thus, if prototype formation is supported by early visual areas, variation of stimulus size will reduce

prototype-enhancement effects and typicality gradients will become less steep. Experiment 1 contrasts performance on two dot-distortion tasks in which the stimuli were size constant in one task and size variable in the other task. Experiment 1 evaluates whether high-level areas can contribute to prototype formation under conditions that would make it difficult for low-level areas to do so.

Method

Participants—Sixty undergraduates from SUNY Buffalo—in their late teens or early twenties with normal or corrected-to-normal vision—participated in a session lasting about an hour to fulfill a course requirement. Our participant pool contained more males and it had an approximate racial mix of 52% Caucasian, 38% Asian, 3% African-American, and 7% Other. Half the participants were randomly assigned to the size-constant and size-variable conditions.

Dot-pattern stimuli—The dot-distortion stimuli were created with a common method that creates families of dot patterns from prototypes. Nine random points—the prototype—are selected from within the central 30×30 area of a 50×50 grid. The distortions (the family members) are produced by applying probabilities that govern whether each dot will keep the position it had in the prototype or how far it will be moved. Different probabilities let one produce dot patterns that are low- or high-level distortions of the prototype and that form families of dot patterns that have strong or weak similarity to the prototype.

Specifically, distortions were built from prototypes by probabilistically moving each dot into one of five areas that covered the 20×20 grid of pixels that surrounded it. For Area 1, the dot kept its original position. For Area 2, the dot moved to one of the 8 pixel positions immediately around its original position. For Area 3, the dot moved to one of the 16 pixel positions in the second layer of pixels around it. For Area 4, the dot was moved into one of the 75 pixel positions in the third, fourth, and half of the fifth pixel layer around it. For Area 5, the dot was moved into one of the remaining 300 pixel positions in the surrounding 20×20 pixel grid (i.e., to the 5th, 6th, 7th, 8th, 9th, or 10th pixel layer around the dot's original position). Different levels of distortions were arranged by adjusting the probabilities that dots would make small or large movements. For Low-level distortions, the five probabilities were .2, .3, .4, .05, .05. For High-level distortions, the five probabilities were .0, .24, .16, .3, .3.

Random items, unrelated to the target category and to be excluded from it, were created as high-level distortions of random prototypes unrelated to the target prototype.

With the dot positions chosen for a pattern, the DrawPoly procedure within Turbo Pascal 7.0 connected successive dots by lines and filled the resulting polygon shape in red. This followed the common practice of presenting the dot distortions as random polygon shapes (Homa et al., 1979, 1981).

Stimulus sizes—The five stimulus sizes were created as follows. For each shape, we had 9 X–Y coordinates expressed relative to the 50×50 virtual space of the shape-distortion algorithm. On the monitor's screen, we mapped these coordinates to 50×50 single pixels (Tiny shapes), 50×50 4-pixel squares (Small shapes), 50×50 9-pixel squares (Medium), 50×50 16-pixel squares (Big), and 50×50 25-pixel squares (Huge). Thus, T, S, M, B, and H shapes, respectively, occupied at maximum a 50×50 , 100×100 , 150×150 , 200×200 , or 250×250 pixel area on the screen. Humans viewed these stimuli at a distance of about 20 inches, so that the T, S, M, B, and H sizes, respectively, subtended, 2.29, 4.58, 6.86, 9.15, and 11.42 degrees of visual angle. Stimuli were presented generally centered in the top half of the screen. Figure 4 shows low-level distortions of one underlying prototype at the five stimulus sizes.

Dot-distortion trials—Each trial consisted of one shape presented in the top half of an 11.5-in. computer screen against a black background. Below the shape was the letter “N.” Responses were made by moving the cursor to the shape (a category endorsement) or to the N (a category exclusion). These responses were made by pressing the keyboard’s arrow keys to move the cursor up or down. Participants heard an 0.5 s computer-generated reward whoop for each correct response and an 8 s computer-generated penalty sound for each wrong response. Following feedback, the next trial was presented.

Training phase—Participants were placed randomly into the size-variable (SV) or size-constant (SC) condition. They received these instructions: “You will now see 120 red polygon shapes that belong to the same category of shapes. Study each shape for 2 seconds, and then move the cursor to the shape to move on to the next member of the category. Your goal is to learn the shape category so that you will be able to recognize members of it when you are tested in a while. So watch the training shapes carefully and learn all you can about the category.” Participants were then given 120 training trials, divided into 24 5-trial blocks, in which all trials were high-level distortions of the prototype. For the SV condition, each block contained stimuli of 5 different sizes (T, S, M, B, H). For the SC condition, all shapes were size M. Participants had to move the cursor to the shape to proceed to the next trial. To ensure that participants attended to the training shape each time, the cursor appeared in different locations from trial to trial and it had to be aimed at the training shape. This ensured that some observation of the shape took place. Following 120 training trials, participants entered the test phase.

Test phase—Participants received the following instructions: “Now you will see new shapes. Some of them belong to the studied category and some do not. Decide whether each shape is a member of the studied category. Move the cursor to the shape if YES; move the cursor to the N if NO. You will hear a WHOOP if you are CORRECT and a BUZZ if you are INCORRECT.” There were 20 blocks of 18 trials, with each block containing one prototype, four low-, four high-level, and nine random items. For the SC condition, all stimuli were size M. For the SV condition, the size (T, S, M, B, H) of each stimulus was randomly determined, ensuring that prototypes, low-level and high-level distortions, and random items could all be presented at all stimulus sizes. Each shape was visible until the participant made a response.

Results

Typicality gradients—SC participants made .973, .913, and .659 correct category endorsements on prototype (P), low-level distortion (L), and high-level distortion (H) items, respectively. They made .211 incorrect category endorsements on random (R) items. SV participants made .952, .883, and .637 correct category endorsements on P, L, and H items, respectively. They made .263 incorrect category endorsements on R items. Thus, in both conditions, participants showed a steep endorsement or typicality gradient from P to H items (SC: .314, SV: .315). This suggests that the differences in the endorsement gradients were small across the SC or SV conditions. These typicality gradients also compare well to the typicality gradients that have been reported in other dot-distortion studies with humans as participants (e.g., Reber et al., 1998a, b; Smith & Minda, 2002). Figure 5A shows the typicality gradients for the five stimulus sizes (T, S, M, B, H) separately in the SV condition. The figure suggests that the differences in endorsement gradients were also small across the levels of stimulus size.

To explore this suggestion statistically, we entered participants’ proportion of category endorsements into SAS’s General Linear Model (GLM) procedure. This multivariate analysis accommodated the imbalance in the design caused by the homogeneously M-sized stimuli in one condition and the stimuli of varying size in the other condition. The analysis had Condition

(SC, SV) as a between-subjects variable and Item Type (P, L, H, R) and Size (T, S, M, B, H) as within-subject variables. This multivariate analysis produced the following results.

There was a strong effect of Item Type, $F(3, 174) = 454.76, p < .05; \eta^2 = .90$. Category endorsements fell sharply in both conditions as stimuli were more distorted and distant from the prototype. This confirmed Smith and Minda's (2001) result about the steep typicality gradients and large prototype-enhancement effects in the dot-distortion task. There was no Condition by Type interaction, $F(3, 174) = 0.42, ns, \eta^2 = .08$. This result emphasizes the similarity of the typicality gradients across conditions. There was a weak Size by Type interaction, $F(12, 348) = 2.23, p < .05; \eta^2 = .04$, (see Figure 5A). This result and Figure 5A emphasize the similarity of the typicality gradients across the five stimulus sizes in the SV condition.

Thus, across SC and SV conditions, there were nearly identical typicality gradients and performance levels. Within the resolution of this experiment, SC and SV category learning proceeded identically. Category learning was robust to size changes during training and testing.

Experiment 2

There was a residual concern about the previous experiment. Participants were trained on all five stimulus sizes, and then tested on the same five sizes. It was possible that participants had developed repetition-priming prototype responses for the prototypes of five categories (actually, the same category instantiated at five size scales)—that is, they might have learned categories at five size scales in parallel. We thought that this was unlikely, for it would have granted participants only 24 training trials in each category-learning task, a small number that should have produced poor performance from minimal training, yet participants were essentially as strong performers in the SV condition as they were in the SC condition in which they would have experienced five times the training. Nonetheless, we undertook an additional experiment to rule out this possible interpretation. Now, in the training phase, all stimuli were size M. Then, in the test phase, participants experienced size variation for the first time.

Method

Participants—Thirty students from the participant pool already described participated to fulfill a course requirement.

Procedure—All aspects of the procedure were the same as Experiment 1, except that size variation was eliminated during training and all the training stimuli were size M.

Results

Typicality gradients—Experiment 2's participants (all SV participants during the transfer phase) made .909, .868, and .602 correct category endorsements on P, L, and H items, respectively. They made .245 incorrect category endorsements on R items. Thus, once again, participants showed a steep endorsement or typicality gradient from P to H items (.307) that compared well to those found in Experiment 1 and in related studies as already described. Figure 5B shows the endorsement gradients for the five stimulus sizes separately. The figure suggests that the differences in endorsement gradients were small across stimulus sizes. This result, like that in Experiment 1, cannot appropriately be viewed as a null result in the traditional sense. Participants did not show equally poor, chance, or random performance across the size conditions. They showed equally sharp and sensitive performance and equally steep typicality gradients over five size conditions that in combination would have qualitatively ruled out retinotopic template matching or shape-similarity comparisons. Therefore, one can assert strongly and positively that they were not solely relying on those processes in this task.

To explore the similarity of the typicality gradients statistically, we entered participants' proportions of category endorsements into an Analysis of Variance (ANOVA) with Type and Size as within-subject variables. As before, there was a strong effect of Item Type, $F(3, 87) = 249.68, p < .05, \eta^2 = .87$. Category endorsements fell sharply as stimuli were more distant from the prototype. There was a weak Size by Type interaction, $F(12, 348) = 2.37, p < .05, \eta^2 = .08$, caused by a slight flattening of the endorsement gradients for Tiny and Small P and L items.

We also examined the endorsement gradient for the first transfer block that represented participants' first exposure to stimuli varying in size. Across these 18 trials, participants made .836, .796, and .603 correct category endorsements on P, L, and H items, respectively. They made .237 incorrect category endorsements on R items. This steep gradient, similar to that obtained analyzing all the transfer trials, confirms that participants experienced immediate transfer to the size-variable stimuli instead of slowly learning the different size scales over blocks during the transfer phase.

Experiment 3

Experiment 3 extends in two ways the demonstration that prototype abstraction in the dot-distortion task is robust to stimulus-size variability.

First, Reber et al. (1998) presented their dot-distortion task implicitly—that is, participants were exposed to training stimuli incidentally and only later asked to categorize additional stimuli. But Experiment 1,2 here presented the dot-distortion task explicitly—participants saw the training stimuli knowing that they should learn from them to discriminate category members and non-members. Possibly, the different levels of category effects in visual cortex sprang from the different levels of category awareness during training. Accordingly, in Experiment 3, we contrasted the effect of stimulus-size variability on categorization performance when participants were trained implicitly or explicitly.

Second, in Experiments 1,2 here, we gave participants trial-by-trial feedback during their category transfer test. Though this is a standard practice in category-learning studies, it left open the possibility that SV participants underwent a rapid learning of category prototypes at all five size scales when they moved into transfer tests with size variability and received feedback for each response. We thought this was unlikely, given that participants immediately expressed mature typicality gradients in the transfer phase of Experiment 2. Nonetheless, we evaluated this possibility in Experiment 3, using a method of deferred/rearranged feedback that has become prominent in the comparative-cognition literature (e.g., Couchman, Coutinho, & Smith, 2010; Smith, Beran, Redford & Washburn, 2006). This method prevents organisms from mapping outcomes back to particular stimuli or stimulus-response combinations, and therefore controls purely reinforcement-based influences on learning and behavior.

Method

Participants—Sixty students from the participant pool already described participated to fulfill a course requirement—30 in the Explicit Condition and 30 in the Implicit Condition.

Procedure—All aspects of the stimuli, stimulus presentation, and task structure were the same as in Experiment 2. Once again, size variation was eliminated during training—all the training stimuli were size M.

Explicit training instructions—Explicit participants received these instructions before viewing the training stimuli: “In Part I of this experiment you will see 120 red polygon shapes that belong to the same category of shapes. Study each shape for 2 seconds, then move the

white-cross cursor to touch the shape. You will receive a point for each shape you touch. Your goal is to learn the shape category so that you will be able to recognize members of it when you are tested in a while. So watch the training shapes carefully to learn all you can about the category.”

Implicit training instructions—Participants in the Implicit Condition received these instructions before viewing the training stimuli: “In Part I of this experiment you will see 120 red polygon shapes. All you have to do is move the white-cross cursor to touch each shape. You will receive a point for each shape you touch.”

Transfer instructions—Participants in both conditions received these instructions before viewing the transfer stimuli: “Now you will see new shapes. Some of them belong to the studied category and some do not. Decide whether each shape is a member of the studied category. Move the cursor to the shape if YES; move the cursor to the N if NO.”

Deferred feedback—Participants received no direct feedback for responses in either the training or transfer phases of the experiment. Instead, they performed without feedback for blocks of six trials. At that point, they received a computer-generated reward sound for each trial they had answered correctly in the block. Following that, they received sequentially all of their computer-generated penalty sounds, and brief timeout periods (4 s for each error) for all of the trials they had answered incorrectly in the block. The deferred feedback after 6 trials, rearranged by outcome, kept participants generally attentive to the transfer task and engaged with it, but it prevented them from knowing which trials they had gotten correct or incorrect. They could not assign credit for particular outcomes to particular stimuli or particular stimulus-response combinations. This made the transfer test more of a generalization test of category knowledge, and less a phase of ongoing category training supported by trial-by-trial feedback. Deferred, summary feedback is surprisingly common in formal educational settings, as when undergraduates received a single score after taking an examination without any item-by-item feedback. This approach to feedback has also figured prominently in recent cross-species studies of metacognition (Smith et al., 2006) and category learning (Couchman et al., 2010). We believe this approach also has constructive utility in studies of human category learning and we illustrate that utility here.

Results

Typicality gradients: explicit condition—Explicit participants made .832, .759, and .593 correct category endorsements on P, L, and H items, respectively. They made .395 incorrect category endorsements on R items. Here, too, humans showed a strong endorsement gradient from P to H items (.239), although deferred/rearranged feedback does seem to have produced somewhat less sharp category learning than was seen in Experiments 1,2 that provided trial-by-trial feedback. Figure 5C shows the endorsement gradient for the five stimulus sizes separately. The figure suggests that the differences in endorsement gradients were small across stimulus sizes. Once again, humans showed equally sharp performance and equally strong typicality gradients over five size conditions that in combination would have ruled out retinotopic template matching or shape-similarity comparisons. Therefore, one can assert positively that humans were not relying on those processes in this task.

To explore this assertion statistically, we entered explicit participants’ proportions of category endorsements into an Analysis of Variance (ANOVA) with Type and Size as within-subject variables. As before, there was a strong effect of Item Type, $F(3, 87) = 51.19$ $p < .05$, $\eta^2 = .76$. Category endorsements fell sharply as stimuli were more distant from the prototype. There was no Size by Type interaction, $F(12, 348) = 1.11$, ns , $\eta^2 = .04$ (Figure 5C).

Typicality gradients: Implicit Condition—Implicit participants made .727, .687, and .541 correct category endorsements on P, L, and H items, respectively. They made .412 incorrect category endorsements on R items. Here, too, humans showed a strong endorsement gradient from P to H items (.186). Figure 5D shows the endorsement gradient for the five stimulus sizes separately. The figure suggests that the differences in endorsement gradients were small across stimulus sizes. Even under implicit conditions, humans showed equivalent performance over five size conditions that in combination would have ruled out retinotopic template matching. They were not relying solely on those processes in the implicit task, either.

To explore this assertion statistically, we entered explicit participants' proportions of category endorsements into an Analysis of Variance (ANOVA) with Type and Size as within-subject variables. As before, there was an effect of Item Type, $F(3, 87) = 26.94, p < .05, \eta^2 = .54$. Category endorsements fell as stimuli were more distant from the prototype. There was no Size by Type interaction, $F(12, 348) = 0.85, ns, \eta^2 = .03$ (Figure 5B).

General Discussion

Participants performing dot-distortion category tasks showed strong prototype-enhancement effects and steep typicality gradients. These results join others showing that humans and animals have prototype abstraction as one component of their overall categorization competence (Aydin & Pearce, 1994; Cook & Smith, 2006; Homa et al., 1981; Huber & Lenz, 1993; Jitsumori, 1996; Knowlton & Squire, 1993; Reber et al., 1998a,b; Reed, 1972; Smith & Minda, 1998, 2001, 2002, Smith et al., 2008; von Fersen & Lea, 1990; White et al., 1993). That is, humans and animals sometimes (not always!) refer to-be-classified items to some representation that is near the center of the psychological space encompassing the category and that is the average of their exemplar experience. The existing evidence for this capacity extends across different kinds of stimuli and tasks. However, the dot-distortion task provides especially diagnostic evidence supporting prototype formation (Knowlton & Squire, 1993; Smith, 2002; Smith & Minda, 2001, 2002; Smith et al., 2008; Squire & Knowlton, 1995) and therefore it has been the dominant prototype-formation paradigm within the cognitive-neuroscience literature (Aizenstein et al., 2000; Ashby & Maddox, 2005; Casale & Ashby, 2008; Reber et al., 1998a,b; 2002a,b; 2003).

Reber et al (1998) and Aizenstein et al. (2000), exploring the neuroscience of prototype formation, found reduced activity in low-level areas of visual cortex when participants responded to category members. Based on this finding, Ashby and Maddox (2005) suggested that these changes in activation were a result of familiarity/fluency effects occurring in early visual cortex. Given the limited research on this issue, we sought to refine this low-level repetition-fluency hypothesis by challenging it empirically using stimuli varying in size over orders of magnitude to prevent the buildup of fluency effects and familiarity signals from repetitive stimulation. Even across dramatic variations in stimulus size, humans still showed large prototype-enhancement effects and strong typicality effects. Thus, categorization was robust to stimulus-size changes—sufficiently to suggest that low-level fluency-repetition effects cannot be the full explanation of what occurs during humans' prototype formation. To the contrary, our results confirm that prototype-abstraction processes also occur at higher and non-retinotopic visual-cortical levels.

We hasten to point out that our results are complementary to those in Reber et al., not directly opposed. In a sense, Reber et al. optimized their task and methodology to show visual-processing at lower cortical levels. They used an implicit-task manipulation that may not have engaged higher levels of deliberate, declarative, category-learning processes. They used a constant size scale for their stimuli, possibly allowing that size-specific and retinotopic prototype-formation processes might occur at the earliest levels of visual processing. They

used unconnected, constellation-type stimuli that may have activated lower-level, visual-pattern recognizers. We endorse that under these conditions Reber et al. validly showed prototype-averaging processes occurring at low levels of visual processing.

In a complementary sense, our methodology and task were optimized to show visual-processing at higher cortical levels. Crucially, we used a variable size scale for stimuli, this alone ensuring that size-specific and retinotopic prototype-formation processes would not be sufficient for prototype abstraction in our tasks. We used an explicit task manipulation that may have engaged higher levels of deliberate category-learning processes. We used bounded polygon shapes that may have activated higher-level shape-recognition processes, perhaps even extending into inferotemporal cortex. And finally, we used free-viewing conditions that might have allowed saccades. Remember that the principal goal of our research was to demonstrate that prototype-abstraction processes sometimes occur at higher visual-cortical levels. For that purpose, the free-viewing conditions (and even eye movements if they occur) are appropriate, the bounded-shape stimuli are a strong aspect of the design, and the size-variation manipulation is critical because it definitively rules out retinotopic priming effects and prototype-formation processes. Our results show clearly that the full description of humans' and animals' prototype-formation processes will include higher levels of the visual system, though it may include lower levels, too.

One resolution of the existing empirical picture would be to assume that our result demonstrates that there are also prototype-forming processes active at higher levels or later stages within the ventral stream of visual processing. It would be interesting to ask whether fMRI studies could trace the migration upwards of the locus of abstraction as the task of abstraction was made more sophisticated. That is, one might show Reber et al.'s region of interest replicated given minimally trained humans, fixed size scales, constellation stimuli, and passive/implicit viewing conditions. But the prototype-forming region of interest might migrate upwards through the visual system, perhaps to inferior temporal or even frontal cortex given explicit attempts to learn size-variable categories composed of bounded polygon shapes. Indeed, Reber et al. also observed increases in frontal areas when human participants were endorsing category members. Thus, frontal cortex provides another possible brain locus for abstraction.

Perhaps the present results and those of Reber et al. are expressions of a more basic point. Prototype abstraction is probably an important cognitive utility in many cognitive domains. It may be important and ubiquitous enough to receive diverse and multiple expression within the overall cognitive system. This idea is also supported in recent work by Zeithamova, Maddox, and Schnyer (2008). They examined the nature of the neural systems involved in prototype learning in two tasks—A/not A (in which Category A members must be discriminated from random non-members that have no similarity to one another) and A/B (in which mutually similar Category A members must be discriminated from mutually similar Category B members). Prototype-abstraction processes were mediated by different systems depending on the demands and structure of the task. A/not A learning was associated with activation in lateral occipital cortex and the striatum, areas generally acknowledged to be involved in implicit learning. A/B learning was associated with activity in the parahippocampus, inferior parietal cortex, and orbitofrontal cortex, areas generally acknowledged to be involved in explicit learning. This levels-of processing analysis, clearly grounded in neuroscientific evidence, reinforces the idea that prototype formation may migrate upwards when a task is too sophisticated for early visual-cortical regions to integrate successfully its information.

We add to this discussion an important intuition about ecological category learning, prototypes, and robustness to stimulus-size variability as category members are encountered in daily life. Size-specific category representations of food items, predators, or mates would be non-starters in coping with the fitness demands of living. Even the most basic behavioral reactions—for

example, approach (food-items; mates) and avoidance (predators)—would not be sustainable unless perceptual categories were substantially robust in the face of stimulus-size change and variability. Retinotopic object- or shape-recognition processes would be disrupted as stimulus distance changed retinal size, and this the organism could not afford. Therefore, in a sense it is pre-ordained that organisms cannot suffice with retinotopically represented categories that are defined at a particular size scale. (Again, we stress that these retinotopic processes could be available, and artificially enhanced and predominant, within the dot-distortion task as it has traditionally been given.) To the contrary, it would be a fundamental adaptation of category learning that category representations would be robust to stimulus-size changes, preserving the possibility of maintaining stimulus similarity and psychological/behavioral equivalence over profound changes in stimulus distance and retinal extent.

We close this discussion by pointing out a seldom appreciated reason why it is natural that prototype abstraction would be one component of humans' overall and multi-faceted category-learning capacity. Animals commonly encounter natural-kind categories in their habitats that have an underlying family-resemblance or prototype-based structure. In these cases, the prototype representation is well positioned—mathematically and geometrically—to provide the strongest and clearest category signal for discriminating category members from nonmembers. From an algebraic perspective, the prototype of the category is the least-squares solution to the category. From a geometric perspective, it is the stimulus (and category representation) closest to the most category exemplars. In particular, it is closer on average to the category exemplars than the category exemplars are to each other. Thus, humans' and animals' prototype-formation capability could be reflective of one class of ecological categories and expressive of a categorization affordance favoring prototypes that those categories offer. It is curious that such an intuitive idea was for so long so sharply controversial within the categorization literature. Fortunately, this controversy has eased substantially with the advent of new evidence (e.g., Smith et al., 2008), new analytic techniques (e.g., Smith & Minda, 2001), and new multiple-system theories of categorization (e.g., Ashby & Maddox, 2005). This discussion also illustrates well our belief that theoretical development in the categorization literature will be well served by a stronger grounding in the natural history and fitness context of various categorization capacities. Indeed, as just discussed, this grounding can play a constructive role in bridging divides in this area, as it does in helping build the consensus that prototype formation is a meaningful and adaptive part of humans' and animals' overall category-learning ability.

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Figure 1.

A dot-distortion category, with the originating prototype, low-level distortions, high-level distortions, and random-unrelated shapes in Rows 1 to 4, respectively.

Figure 2.

The composite observed profile (filled circles) of category endorsements (i.e., affirmations that shapes belong in the training category) produced by humans in four dot-distortion category-learning studies (controls and amnesics in Knowlton & Squire, 1993; participants in Reber et al. 1998a,b). Also shown (open circles) is the average of the four best-fitting predicted profiles when a prototype model fit the individual data sets. Prot: prototype; Low, High: low- and high-level distortions of the prototype; Rand: random shapes unrelated to the target category.

Figure 3.

The composite observed performance profile (filled circles) from 10 dot-distortion sessions by a rhesus macaque (*Macaca mulatta*) in Smith et al. (2008). Also shown (open circles) is the average of the 10 best-fitting predicted profiles when a prototype model fit the individual data sets. Prot: prototype; Low, High: low- and high-level distortions of the prototype; Rand: random shapes unrelated to the target category.

Figure 4.

A. Low-level distortions of a dot-distortion prototype shown at the five size scales used in the experiments.

Figure 5.

A–D. The endorsement profiles of humans for Tiny, Small, Medium, Big, and Huge stimuli in the Size-Variable condition of Experiment 1 (A), Experiment 2 (B), Experiment 3's Explicit Condition (C), and Experiment 3's Implicit Condition (D). Progressively darker color symbols denote performance with progressively larger stimuli (Tiny to Huge). Prot: prototype; Low, High: low- and high-level distortions of the prototype; Rand: random shapes unrelated to the target category.