Prototypical Category Learning in High-Functioning Autism

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Lay Abstract

Do individuals with autism learn object categories in a typical manner? An example of prototypical category learning is the ability to classify coffee cups of varying shape, size and color into a single object-level representation that we know as 'cup'. Here we investigate this question with a classical psychological paradigm. In two experiments, we find evidence that a group of young autistic men learn visual prototypes typically, relative to a control group matched for age and IQ. We conclude that high-functioning autistic individuals do not experience severely compromised mechanisms of prototypical category learning.

Scientific Abstract

An ongoing debate in developmental cognitive neuroscience is whether individuals with autism are able to learn prototypical category representations from multiple exemplars. Prototype learning and memory were examined in a group of high-functioning autistic boys and young men, using a classic paradigm in which participants learned to classify novel dot patterns into one of two categories. Participants were trained on distorted versions of category prototypes until they reached a criterion level of performance. During transfer testing, participants were shown the training items together with three (3) novel stimulus sets manifesting variable levels of physical distortion (low, medium, or high distortion) relative to the unseen prototypes. Two experiments were conducted, differing only in the manner in which the physical distortions were defined. In the first experiment, a subset of autistic individuals learned categories more slowly than controls, accompanied by an *overall* diminution in transfer-testing performance. The autism group did, however, manifest a typical *pattern* of performance across the testing conditions, relative to controls. In the second experiment, group means did not differ statistically in either the training or testing phases. Taken together, these data indicate that high-functioning autistic individuals do not manifest gross deficits in prototypical category learning. A possible theoretical interpretation of these data is given in terms of underlying brain mechanisms.

Keywords: autism; category; learning; prototype; exemplar; memory; attention; vigilance; adaptive resonance theory

Prototypical Category Learning in High-Functioning Autism

Autism is characterized by atypical social interactions, delayed or impaired language acquisition and repetitive-stereotyped behaviors (American Psychiatric Association, 2000). An important issue in developmental cognitive neuroscience is whether such diagnostic symptoms arise from a breakdown in more fundamental cognitive processes (Frith, 2003). One putative cognitive process that may develop atypically in autism is the ability to learn prototypical category representations (Grossberg & Seidman, 2006; Pellicano et al., 2007; Tager-Flusberg, 1985). An example of prototypical category learning is the ability to classify coffee cups of varying shape, size and color into a single object-level representation that we know as 'cup'. According to a recent neural theory of atypical cognitive development in autism (Grossberg & Seidman, 2006), "hypervigilant" category learning in some autistic individuals may cause an impaired ability to learn prototypes for abstract general categories, with consequences for deficits in attention and related behavioral symptoms of autism. The current experiments were designed to provide more information about category learning by autistic individuals, with a view towards enabling a more sensitive test of this hypothesis.

At least one study has found evidence of atypical learning of visual object prototypes in autism (Klinger & Dawson, 2001; see also Molesworth et al., 2008), and several other studies have found evidence of impaired learning, recognition and memory processes, albeit not specifically related to prototype learning (Gastgeb et al., 2006; Mottron et al., 2006; Pellicano et al., 2007; Plaisted et al., 1998; Soulières et al., 2007). Klinger and Dawson (2001) trained a group of low-functioning autistic participants to correctly label category exemplars. During the transfer test, participants had to chose between (a) familiar or prototypical exemplars, on the one hand, and (b) novel non-prototypical exemplars, on the other. The authors found evidence that, relative to the control group, the autism group (and a group of children with Down's syndrome) did not categorize the prototypical exemplars better than the novel non-prototypical exemplars. It is important to bear in mind, however, that the Klinger and Dawson (2001) study tested low-functioning autistic participants, and so their findings cannot easily be extrapolated to high-functioning autistic individuals (Molesworth et al., 2005); their findings may be more related to intellectual disability than to autism *per se*.

Several studies have, however, failed to find specific evidence for atypical prototype learning in autism (Bott et al., 2006; Molesworth et al., 2005; Tager-Flusberg, 1985). Bott et al. (2006), for example, trained high-functioning autistic and control participants to categorize rectangle patterns into one of two categories, based on arbitrary criteria unrelated to the manipulated perceptual dimensions (rectangle width and height). They found that, while the autistic participants learned more slowly than control participants, generalization of the learned rules to novel exemplars during a transfer test was intact. Molesworth et al. (2005) had participants categorize cartoon-like drawings of fictional animals into one of two categories, based on differential visual appearance. During the testing phase, participants performed a recognition task on (a) the training items, (b) novel exemplars of various levels of distortion and (c) the unseen prototypes. The authors concluded that no overall differences in recognition performance could be found between the high-functioning autism and control groups. Molesworth et al. (2008) found evidence that a subset of high-functioning autistic participants—chosen based on their atypical performance in a task requiring identification of 'ideal' shapes—failed to show a typical prototype effect.

The present study aims to better characterize the putative impairment of category learning and/or generalization in autism. Our paradigm is closely based on the stimuli and protocols used in classical studies of prototype formation (e.g., Posner & Keele, 1968). In these experiments, participants learned to classify patterns composed of random dots into one of two categories during an *n*-alternative forced choice training session. Each exemplar dot pattern was produced by manipulating one of two original prototype patterns: the positions of the dots comprising each prototype were randomly displaced by a small factor to produce two sets of exemplars. Even though participants only learned to classify the distorted versions of the prototype (exemplars), rather than the prototypes themselves, categorization performance during a subsequent transfer test was better for the unseen prototypes than for the exemplars learned during training. Posner and Keele (1968) concluded that participants learned *prototypical category representations* from the distorted exemplars contained in the training set (cf., Zaki & Nosofsky, 2004, 2007). According to this hypothesis, when presented with the actual prototypes during the testing session, prototype memory representations—being an amalgam of the many slightly different exemplars—matched the prototypical items better than the exemplars.

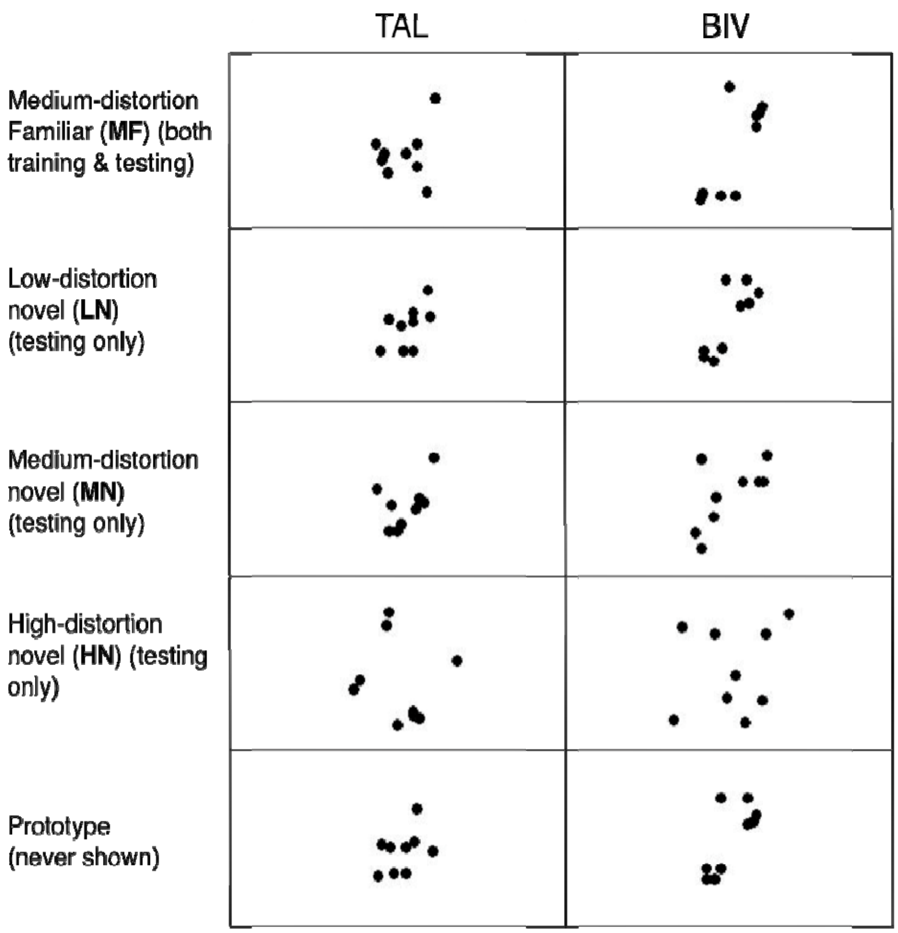

Fig. 1. Stimuli used in experiment one. Stimuli consisted of exemplar dot patterns generated from one of two prototype patterns. The categories generated from these prototypes were dubbed TAL and BIV for the purposes of the experiment. Subjects were trained on the MF items and tested on the MF, LN, MN and HN items.

By employing classical stimuli and protocols, our behavioral experiment overcomes several limitations in previous studies of prototype formation in autism. Firstly, we use unfamiliar dot patterns—similar to those employed in classic studies of prototype memory in health and disease (Knowlton & Squire, 1993; Posner & Keele, 1968; Reber et al., 1998; Squire & Knowlton, 1995; Zaki & Nosofsky, 2004, 2007)—to mitigate against the potentially-confounding influences of stored category memories acquired during everyday life. Unlike previous studies of category learning in autism, our exemplar patterns thus do not resemble familiar objects or patterns, such as animal cartoons (Bott et al., 2006; Gastgeb et al., 2006; Molesworth et al., 2005, 2008; Mottron et al., 2006; Plaisted et al., 1998; Soulières et al., 2007). Secondly, we tracked participants' learning performance over a prescribed number of training blocks in the training session. This allowed us to assess whether all participants learned the training patterns equally well. Once participants attained a criterion performance level in the training session, we proceeded to initiate the transfer-testing phase. Thirdly, the training and testing tasks were the same, ensuring that participants were well trained with respect to the relevant task constraints. Previous studies of prototype learning in autism have not always required participants to attain a specific performance criterion during training, nor have the training and testing tasks always been the same (Bott et al., 2006; Molesworth et al., 2005, 2008; Mottron et al., 2006; Plaisted et al., 1998; Soulières et al., 2007). Finally, we used many more exemplars in our category sets (32) than previous studies (2-8). As the proportions of correct and incorrect categorization trials are the dependent variables of interest, small exemplar numbers can often lead to distorted results, simply due to incidental errors, such as unintentionally pressing the wrong button.

We conducted two experiments differing only in the manner in which distorted dot patterns were generated. In experiment one, patterns were created in the same manner as in the classical Posner and Keele (1968) paradigm, by randomly jittering the positions of the *all* dots comprising each prototype by *different amounts* (Fig. 1). The items generated from the jittering process were named according to their level of distortion (i.e. amount of jittering) and familiarity (i.e. whether the items were seen by participants during training or not): medium-distortion familiar (MF), low-distortion novel (LN), medium-distortion novel (MN) and high-distortion novel (HF). In experiment two, the amount of jittering was kept constant and we instead varied the *number of dots* that were jittered. In both experiments, we expect the order of classification performance (percentage correct responses) to be LN > MF = MN > HN. In particular, we expect that LN items will be better categorized than the MF items, even though the LN items have never been seen.

Experiment One

Method

Participants

Nineteen (19) autistic and twenty-one (21) control subjects participated in experiment one (Table 1). All subjects were male. Signed consent was obtained from all participants in accordance with the IRB procedures of the Boston University School of Medicine.

All participants were tested with the Kaufman Brief Intelligence Test (KBIT) to obtain estimates of non-verbal IQ and verbal IQ. Participants in the autism group met clinical diagnostic criteria for autism (ADI-R). These participants were also assessed on the Autism Diagnostic Observation Schedule-Revised (ADOS-R) to quantify measures of current symptom severity. According to a two-sample t-test, the control group was significantly older [$t(38) = 2.94$, $p = 0.006$][1] than the autism group, although the two groups did not differ on KBIT measures of verbal IQ [$t(38) = -1.17$, $p = 0.25$] and non-verbal IQ [$t(38) = -1.16$, $p = 0.25$].

Table. 1. Participant characteristics for experiment one.

	Autism (n = 19)	*Control (n = 21)*
	Mean (SD), Range	Mean (SD), Range
Age	18.4 (2.95), 15.3-27.7	21.0 (2.7), 16.3-25.8
Kaufman Brief Intelligence Test (KBIT) Scores		
Full IQ	106.5 (17.5), 79-134	113.9 (13.3), 91-137
Verbal IQ	106.6 (14.3), 75-125	111.6 (12.6), 89-130
Non-Verbal IQ	104.1 (23.6), 65-139	111.9 (18.6), 69-141
Autism Diagnostic Interview – Revised (ADI-R) Scores		
Communication	21.4 (3.9), 15-28	-
Social	17.6 (3.8), 5-22	-
Repetitive Behaviors	6.1 (2.2), 2-11	-[1]

Stimuli

Before the experiment began, two patterns (prototypes) consisting of nine (9) black dots on a white background were randomly generated (Posner & Keele, 1968). For each prototype, low-, medium- and high-level distortions were generated using a distortion algorithm. Specifically, a random direction of displacement was selected for each dot in the pattern. The magnitude of displacement was determined by a Poisson noise generator. The parameter controlling the mean (= variance) of the noise was varied across testing conditions.

For each prototype, the 16 medium-level distortions for each category were used for training, giving a total of 32 training exemplars. Similarly, transfer-test items consisted of the 32 exemplars (termed medium-familiar, or MF, items), 32 medium-distortion novel items (medium-novel, or MN, items), 32 low-distortion novel items (low-novel, or LN, items), and 32 high-distortion novel items (high-novel, or HN, items). This gave a total of 128 testing items. Before the experiment proper, every subject performed a practice experiment based on two prototype dot patterns that differed from the prototypes used in the main experiment. The practice experiment consisted of fewer items: the same 8 items were used for both training and testing. The practice experiment allowed participants to become familiar with the stimuli and task. The level of difficulty of the practice experiment was much lower than the difficulty level of the main experiment. This manipulation was achieved in two ways. First, the prototypes selected by the experimenters for the practice experiment were perceptually very dissimilar, enabling easy learning of the training exemplars. Second, the overall amount of distortion applied to the exemplars was low, as determined by the values of the Poisson noise parameters. In the practice experiment, this value was 2. In the experiment proper, the noise values were 1, 10 and 15 for low, medium and high distortion levels.

Equipment

The experiment was conducted on a 17-inch Apple MacBook Pro laptop computer. The presentation software was written in Matlab 7.4 and displayed using Psychtoolbox Version 3.08. Responses were made by pressing buttons on a GamePad Pro USB controller.

[1] Control subjects were not systematically assessed.

Procedure

Participants were shown into the experimental room and explained the procedure carefully. The lights were left on during the experiment and the experimenter remained with the subject the entire time. Participants first undertook a practice experiment, followed by the main experiment. At the start of the practice experiment, the participants scrolled through a series of programmed instruction screens at their own pace, by pushing a button on a game pad controller. Each screen introduced a new piece of information concerning the experiment. Participants were encouraged to ask questions if they did not understand an instruction. This procedure took about 5 minutes to complete.

The first part of the process introduced the participants to an imaginary 'planet', where they would be shown 'creatures' of two types (Lupyan et al., 2007). The participants were told that their task was to learn which type of creature belonged to the two given labels denoted by non-sense words (LAC and ZIB for the practice experiment, TAL and BIV for the main experiment). These words appeared on the screen on either side of the item. Participants were first shown examples from each category. They were then given examples of the auditory feedback signals corresponding to correct and incorrect choices: A high pitch tone to denote a correct answer, and a low pitch tone to denote an incorrect answer.

Participants were then asked to press one of two buttons on the game pad controller, corresponding to the two options seen on the screen. The buttons and category names appearing on the screen corresponded in color and relative horizontal position (left or right), in order to facilitate the association. Both the items and names remained on the screen until participants responded. Following each response, participants received a feedback tone.

Participants were first given four (4) practice trials involving the examples shown to them earlier. To begin each trial, participants pressed a yellow button on the game pad controller. Participants rarely made any incorrect choices at this stage. Each block in the training session consisted of 8 items/trials in the practice experiment and 32 items/trials in the main experiment. Items were presented in random order within one of 10 training blocks. After a block of trials, participants were notified of their percentage correct for each category, relative to an arbitrary criterion, by means of a color-coded bar graph.

Training continued until participants reached the criterion. In the practice experiment, the criterion was 100% (8/8) correct. This strict criterion ensured that participants were very familiar with the task before the main experiment began. We did not analyze the data from the practice experiment, though we observed that subjects usually learned the categories quickly. In the main experiment, participants were required to score 75% correct, or more, for *both* categories before proceeding to the transfer testing (i.e. 12/16 for each category). The choice of 75% correct ensured that participants were unlikely to attain criterion simply by chance alone ($p \approx 10^{-6}$), while ensuring that a ceiling effect would not be observed in the testing phase. All participants were tested after a maximum of 10 training blocks, even if they did not meet criterion.

Following training, participants were instructed to take a short break. They then completed the testing portion immediately following the break. In the practice experiment, the testing session consisted only of the eight (8) training items. In the main experiment, testing consisted of 128 trials presented in random order (32 items in each of the four testing conditions: MF, MN, LN, and HN). Participants performed the same categorization task as during training, except that no feedback was provided after each trial.

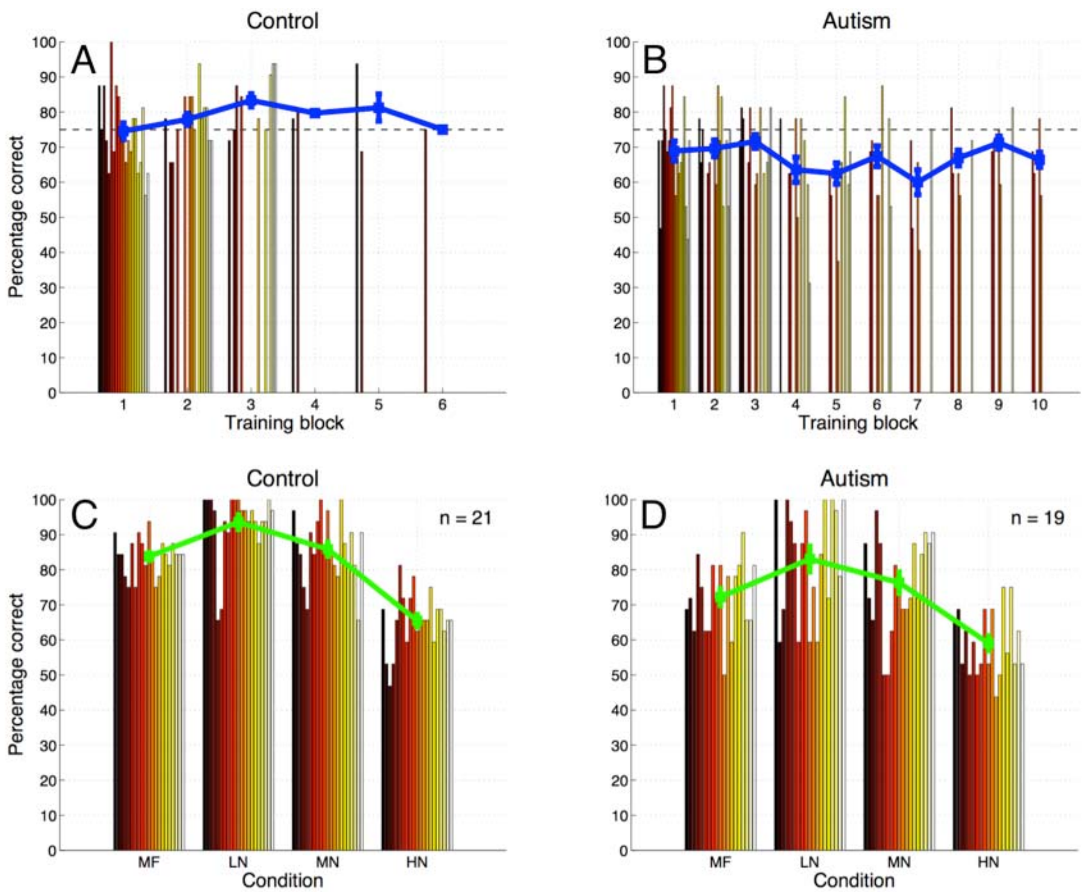

Fig. 2. Results of experiment one. Mean percentage correct scores during training (A, B) and testing (C, D), pooled over the two categories. The data show that the control group outperformed the autism group in both the training and testing phases. Each participants' data is represented by a colored bar. The blue lines with error bars indicate the group *running* means during training (i.e. means over subjects participating in each given training block). The dotted horizontal lines indicate the criterion level, recalling that participants had to reach criterion for *both* categories independently (thus the mean scores may fall under the dotted line on any given block). The green lines with error bars indicate the group means in the testing conditions.

Results

Data from the training phase are plotted in Fig. (2A, B). We found that the autism group required significantly more training blocks than the control group to reach criterion [control group mean (SD) = 2.33 (1.35), autism group mean (SD) = 4.63 (3.55), $t(38) = -3.88$, $p = 0.0004$]. Whereas only two (2) participants in the control group required more than three (3) training blocks to reach criterion, nine (9) of 19 participants in the autism group required more than three (3) training blocks, and four (4) of these participants did not reach criterion within the full 10 training blocks.

The *pattern* of performance across conditions in the testing phase appears similar for autism and control groups (Fig. 2C, D). A two-way analysis of variance (ANOVA), incorporating both testing condition and group as factors, revealed a significant effect of condition [$F(3) = 43.6$, $p < 0.00001$] and group [$F(1) = 32.7$, $p < 0.00001$], but no significant condition × group interaction [$F(3) = 0.45$, $p = 0.72$][2]. To test our *a priori* hypotheses (LN > MF = MN > HN), we conducted two-sample t-tests between conditions within each group. These tests revealed that both groups manifested the typical prototype effect, with percentage correct being higher in the LN condition than in the MF condition [control group: $t(20) = 4.16$, $p = 0.0001$, autism group: $t(18) = 2.48$, $p = 0.009$] and percentage correct in the MF condition being higher than in the HN condition [control group: $t(20) = 8.57$, $p < 0.00001$, autism group: $t(18) = 4.14$, $p = 0.0001$]. Both groups therefore showed evidence of a robust prototype effect.

To simply the next stage of our analysis, we computed the mean percentage of correct responses across all testing conditions for each group (Fig. 3). Consistent with the significant effect of group in the ANOVA, the mean percentage correct was significantly lower for the autism group [control group mean (SD) = 87.7 (6.18), autism group mean (SD) = 77.2 (10.65), $t(38) = 2.76$, $p = 0.009$][3]. We then computed correlations between the mean percentage scores with the number of training blocks completed and IQ scores. We found a significant correlation between training and testing performance for both the autism group ($r^2 = 0.39$, df = 18, $p = 0.004$) and control group ($r^2 = 0.2$, df = 20, $p = 0.04$). We also found evidence for a correlation between the non-verbal IQ scores of the autism group and the percentage of correct responses in the testing phase ($r^2 = 0.21$, df = 18, $p = 0.05$). No other correlations involving task performance and IQ scores or subject age were significant. We also found no evidence for significant correlations between either test or training performance and symptom severity in the autism group, as assayed by ADOS ($p > 0.2$ in all cases).

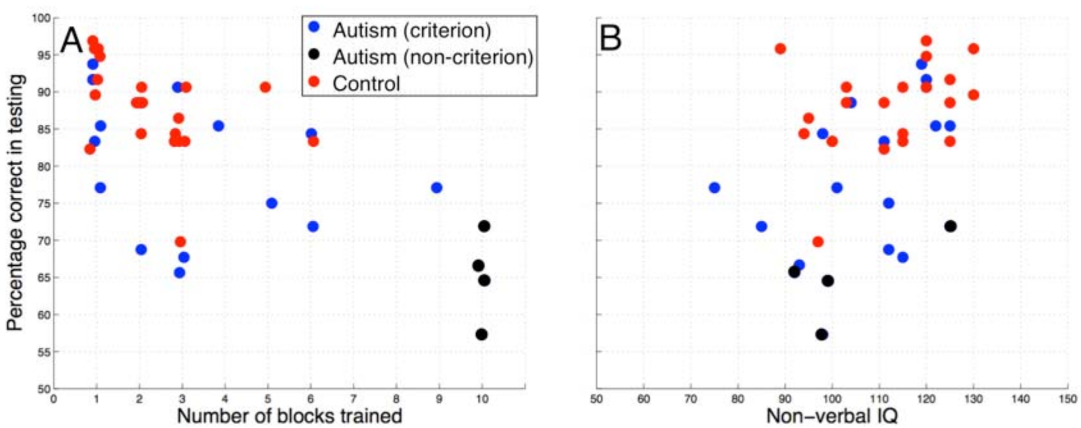

Fig. 3. Scatter plots of percentage correct scores in the testing phase against two variables of interest. (A) For the control group (red dots), we find weak evidence for a non-zero correlation between number of training blocks and testing performance ($r^2 = 0.2$, df = 20, $p = 0.04$). For the autism group (blue dots = autistic participants reaching criterion within 10 training blocks; black dots = autistic participants completing all 10 training blocks), we find relatively strong evidence for a correlation ($r^2 = 0.39$, df = 18, $p = 0.004$). Note: horizontal dot positions have been jittered slightly to prevent occlusion. (B) We find weak evidence for a correlation between non-verbal IQ and testing performance in the case of the autism group ($r^2 = 0.21$, df = 18, $p = 0.05$) but no evidence for a correlation between these variables in the case of the control group ($r^2 = 0.13$, df = 20, $p = 0.11$).

Experiment Two

Method

Participants

Thirteen (13) autistic, nine (9) of whom also participated in experiment one, and eighteen (18) new control subjects participated in experiment two (Table 2). All subjects were male. Signed consent was obtained from all participants in accordance with the IRB procedures of the Boston University Medical School.

KBIT, ADI-R and ADOS-R testing were conducted as in experiment one. We found no statistical difference in the ages of the control and autism groups [$t(29) = -0.1$, $p = 0.91$]. The two groups did not differ on KBIT measures of verbal IQ [$t(29) = 1.17$, $p = 0.25$] and non-verbal IQ [$t(29) = 0.76$, $p = 0.45$].

Table. 2. Participant characteristics for experiment two.

	Autism (n = 13)	*Control (n = 18)*
	Mean (STD), Range	Mean (STD), Range
Age	19.2 (3.3), 15.2-28.1	19.1 (2.1), 14.9-22.7
Kaufman Brief Intelligence Test (KBIT) Scores		
Full IQ	113.1 (17.6), 83-136	106.9 (10.3), 91-129
Verbal IQ	110.9 (21.8), 73-138	103.6 (12.8), 85-126
Non-Verbal IQ	111.4 (12.2), 85-125	107.7 (14.0), 80-130
Autism Diagnostic Interview – Revised (ADI-R) Scores		
Communication	21.4 (3.9), 15-28	-
Social	16.7 (4.8), 5-22	-
Repetitive Behaviors	6.8 (1.7), 4-10	-

Stimuli

Stimuli were similar to those used in experiment one, except for the following details. For each prototype, exemplars were generated by varying the number of dots jittered, while keeping the amount of jitter constant: for low-distortion items, one dot was jittered; for medium-distortion items, five dots were jittered; for high- distortion items, all nine dots jittered.

Equipment

The equipment was the same as in experiment one.

Procedure

The procedure was identical to that in experiment one, except the category names were changed to DAC and RAB in the practice experiment and VIM and LAN in the experiment proper.

Results

Data from the training phase are plotted in Fig. (4A, B). Group means of the number of training blocks required to reach criterion was not significantly different [control group mean (SD) = 1.83 (1.62), autism group mean (SD) = 3.17 (3.22), $t(28) = 1.5$, $p = 0.14$][4]. Unlike experiment one, autism and control groups manifested indistinguishable results in the testing phase (Fig. 4C, D). A two-way ANOVA (factors: condition and group) revealed a significant effect of condition [$F(3) = 12.3$, $p < 0.0001$] but not group [$F(1) = 0.1$, $p = 0.92$], and no significant condition × group interaction [$F(3) = 0.11$, $p = 0.96$]. Two-sample t-tests between conditions revealed that both groups manifested the typical prototype effect, with LN significantly greater than MN for the control group [t(17) = 3.14, p = 0.002] and borderline-significantly greater for the autism group [t(11) = 1.461, p = 0.06]. Furthermore, MF was significantly greater than HN for both the control group [t(17) = 2.1, p < 0.02] and the autism group [t(11) = 1.76, p = 0.05]. Thus, as in experiment one, both groups manifested a robust prototype effect.

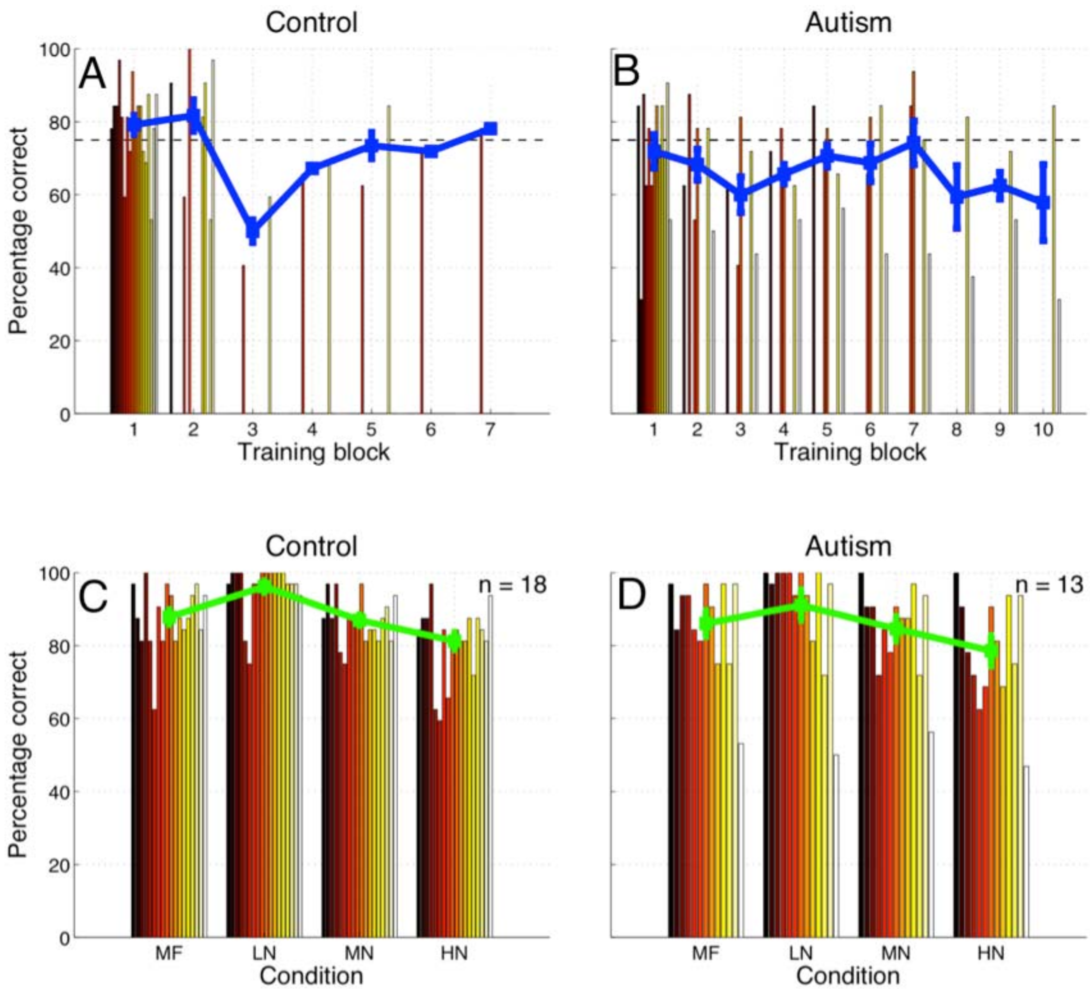

Fig. 4. Results of experiment two. Mean percentage correct for each training block and testing condition, pooled over the two categories. The results were similar to those of experiment one.

As in experiment one, further analysis was conducted on the mean scores computed over testing conditions. Consistent with the ANOVA, these scores did not differ between groups [control group mean (SD) = 88.1 (7.1), autism group mean (SD) = 87.9 (8.1), t(28) = 0.06, p = 0.95]. We found a significant correlation between training blocks completed and testing scores for the control group (r^2 = 0.32, df = 17, p = 0.01) but not the autism group (r^2 = 0.2, df = 11, p = 0.15). The only other significant correlation we found was between non-verbal IQ of the autism group and testing performance (r^2 = 0.53, df = 11, p = 0.007).

General Discussion

The results presented here provide a new twist to the tale of category learning and memory in autism (Bott et al., 2006; Klinger & Dawson, 2001; Molesworth et al., 2005, 2008; Mottron et al., 2006; Plaisted et al., 1998; Tager-Flusberg, 1985; Soulières et al., 2007). While some evidence for atypical prototype learning in low-functioning autism has emerged (Klinger & Dawson, 2001), similar evidence in high-functioning autistic individuals is relatively sparse (Bott et al., 2006; Molesworth et al., 2005; Tager-Flusberg, 1985). Consistent with these latter results, we found in both experiments that autistic individuals manifested a robust prototype effect (i.e. exhibited the expected *pattern* of performance across testing conditions).

We used only relatively high-functioning autistic participants in our study in order to avoid the potential confounding effects of low IQ (see Klinger & Dawson, 2001; Molesworth et al., 2005, 2008). Interestingly, in both experiments, we found a significant positive correlation between testing performance and non-verbal IQ, but not verbal IQ, for the autism group. This suggests that non-verbal IQ may be an important factor in determining performance of autistic individuals in prototype learning tasks. Molesworth et al. (2005, 2008) questioned the role of low verbal IQ in the prototype learning deficit observed in the Klinger and Dawson (2001) study, proposing that subjects may not have understood the instructions correctly. Our results suggest that non-verbal IQ should also be considered a limiting factor on performance in prototype learning tasks. Furthermore, both our experiments were preceded by shorter 'practice' experiments to ensure that subjects understood instructions correctly.

Molesworth et al. (2008) found that a subset of high-functioning autistic boys failed to learn prototypes in a typical manner. This subset was identified by atypical performance on a control task requiring subjects to identity 'best category members' from a selection of shapes. The authors found that the atypically performing subset of boys had lower mean chronological and verbal-mental ages than the typically performing subset. The results of Molesworth et al. (2008) resemble those of our experiment one, in which a subset of autistic individuals learned prototypes more slowly than others and scored lower in the testing phase. The mean age of autistic subjects in our study was, however, substantially higher than that of Molesworth et al. (2008). As indicate above, furthermore, we found a correlation between non-verbal IQ, not verbal IQ, and task performance. We also failed to find any evidence of atypical performance in experiment two. The conditions under which a subset of autistic individuals perform atypically, and the cognitive variables underlying this atypical performance, therefore remain to be identified.

In this study, we attempted to eliminate other potentially confounding factors inherent to previous studies of prototype learning in autism; namely, through use of (a) unfamiliar visual patterns, (b) large stimulus set sizes, (c) similar training and testing tasks (albeit without feedback during testing), and (d) close tracking of performance during the training phase and application of a learning criterion. We discuss each of these issues in turn below.

Unfamiliar patterns

A critical feature of the present study was our use of unfamiliar stimulus patterns; namely, random dot patterns. This contrasts with previous studies of category learning in autism, which have relied on the use of patterns that were either globally familiar or contained familiar visual features, such as rectangles (Bott et al., 2006), cartoons of fictional animals (Klinger & Dawson, 2001; Molesworth et al., 2005, 2008), filled disks (Plaisted et al., 1998), pictures of familiar objects (Tager-Flusberg, 1985) and elliptical line-drawings (Soulières et al., 2007). The principal utility of random-dot patterns, then, is that neither control nor autistic subjects are likely to be biased by previous categorical learning of the patterns resembling the prototype or parts of the prototype. Indeed, novelty was the original motivation for the use of dot patterns in the Posner and Keele (1968) study. A secondary reason for the use of unfamiliar patterns was that it allowed us to track category learning from the first exposure to the patterns, as discussed in detail below.

Large stimulus sets

We did not use prototype patterns themselves in the testing phase for the reason that the LN condition allowed us to present a set of 32 slightly different items that diverge marginally from the 'theoretical limits' of the prototypes (i.e. these items were pseudo-replicates). The use of this large stimulus set gives our study greater sensitivity, as spurious trials tend to get washed out. It is noteworthy, in this respect, to point out that although Molesworth et al. (2005) failed to find evidence of atypical generalization in their prototype condition, autistic participants performed slightly (though not significantly) below the level of the control group for the equivalent of our HN, MN, and MF conditions. As the prototype condition in Molesworth et al. (2005) contained only two (2) items, and the remaining conditions four (4) items, it seems likely that the sensitivity of the authors experimental design was insufficient to detect the deficiency we observed in our testing phase.

Similar training and testing tasks

Previous studies of prototype learning in autism have often employed different training and testing tasks. In Molesworth et al. (2005), for example, subjects classified patterns into one of two categories during training but performed a recognition memory task during testing. One might therefore argue that subjects may not have learned the category members in a manner effectively germane to the testing task. As subjects in our study performed exactly the same training and testing tasks, we may be reasonably confident that we were tapping into the same cognitive processes in the two phases of the experiment (see also Klinger & Dawson, 2001). In support of this claim, we found significant correlations between training and testing performance for the control group in both experiments and for the autism group in experiment one.

Tracking learning and applying a learning criterion

The tracking of learning performance in the training phase allowed us to collect important data on the relative learning rates of autistic and control participants. The results of experiment one suggest that a subset of autistic individuals do, in fact, learn prototypes more slowly than control participants. We further reasoned that the application of an unbiased learning criterion (i.e. one in which subjects were required to reach criterion for *both* categories) would ensure that autistic and control subjects had learned prototypes equally well prior to testing (see also Klinger & Dawson, 2001). We found instead that the autism group manifested a strong negative correlation between number of training blocks required to reach criterion and mean percentage of correct responses in the testing phase, implying that faster learners are also better learners (this correlation was weaker, though also significant, for the control group). In experiment two, however, we found no overall decrease in testing performance, nor did we find strong evidence to conclude that the autism group required more training blocks to reach criterion than the control group. This minor discrepancy between the results of experiment one and two therefore awaits further systematic study.

Theoretical considerations

The current experiments were designed to better test a hypothesis about how certain autistic individuals may learn to categorize objects and events in the world, and how category learning may influence related processes, such as how attention may be allocated during learning and performance. The iSTART model of Grossberg & Seidman (2006) proposed that some autistic individuals may be "hypervigilant" learners. This proposal was based on the Adaptive Resonance Theory, or ART, model of how the brain may learn recognition categories. ART predicts how this is done in a way that solves the *stability-plasticity dilemma*; namely, how fast learning can occur without forcing catastrophic forgetting. All the main ART predictions about how recognition learning occurs under normal conditions have received support from neurobiological and psychological experiments; see Grossberg (2003) for a review.

ART models the process whereby bottom-up features that represent an experience are matched with a learned top-down expectation that is read out by an active recognition category. If the match is good enough, then it focuses attention upon a prototype of critical features. This attended feature pattern "resonates" with the active category through bottom-up/top-down feedback signaling. Such a resonant state triggers fast learning of the adaptive weights, or long-term memory traces, within the resonating network. Restricting fast learning to resonating cells that embody the focus of attention solves the stability-plasticity dilemma and clarifies the link between fast learning and attention.

ART predicts how the "vigilance" of a learner may vary between low and high values in response to changing task demands. Low vigilance enables learning of abstract and general recognition categories, whereas high vigilance enables learning of concrete and specific recognition categories. iSTART proposed that some autistic individuals may have their vigilance stuck at high levels, therefore forcing hyperspecific learning in all situations. High vigilance does not prevent category learning by autistic individuals, but it would tend to induce learning of concrete and specific categories, and would thereby narrow the focus of attention upon specific details of objects and events. Do the current experiments support or contradict this prediction?

Despite the greater control over prototype learning and recognition that the current experiments provide, questions remain if only because several types of brain processes interact while learning recognition categories. For example, before category learning mechanisms in inferotemporal cortex and beyond are activated by visual stimuli, they are preprocessed by visual cortical areas V1 through V4. These cortical areas filter visual cues through multiple spatial scales to generate boundary groupings and surface representations that input to higher-order category learning mechanisms. Many perceptual and brain data about 3-D vision have been explained and predicted by neural models of how these boundaries and surfaces form; e.g., Cao & Grossberg (2005), Fang & Grossberg (2009), Grossberg (1994), Grossberg & Yazdanbakhsh (2005). In particular, multiple-scale processing is needed to convert scenic contour, texture, and shading information into object boundary and surface representations that are stable enough under the vagaries of the seeing process to enable behaviorally effective categories to be learned. For example, the "gist" of a natural scene can be computed as a large-scale coarse texture that is categorized to predict scene type, after which spatial attention shifts to smaller textures in the scene and accumulates additional evidence from them in the form of multiple-scale texture categories (Grossberg & Huang, 2008).

Inspection of the TAL prototype and low-distortion novel exemplar of experiment one (Fig. 1) shows that TAL dots may perceptually group into one cluster, with a possible individual dot outlier above the main cluster and somewhat to its right. In contrast, the BIV prototype and low-distortion novel exemplar may group into two distinct clusters, one above and slightly to the right of the other, with the cluster above including five dots and the cluster below including four dots. It is well known that human subjects often form perceptual groupings of individual features during visual search and related perceptual tasks, and these groupings, rather than the individual features themselves, are the functional units that control learning and performance (Bacon & Egeth, 1991; Banks & Prinzmetal, 1976; Bravo & Blake, 1990; Dukette & Stiles, 1996, 2001; Enns & Rensink, 1990; He & Nakayama, 1992; Humphreys, Quinlan, & Riddoch, 1989; Kimchi, 1998; Kimchi et al., 2005; Plaisted et al., 2006).

In experiment one, subjects are trained on MF stimuli in which the locations of all the individual dots are perturbed by a moderate amount, and there is a prototype effect in which LN is recognized better than the other conditions, with the autistic group learning generally less well than the normal controls (Fig. 2). The fact that there is a prototype effect at all with autistic subjects, given that all the dots move in each stimulus, could be viewed as challenging the hypothesis of hypervigilant learning about *individual* dots. However, given that all the dots move from their prototypical locations on each learning and performance trial, all subjects may be biased to process dot groupings, or clusters, to the best of their ability, since the cluster differences may be more stable than differences in the individual dots across trials. Both control and autistic participants could hereby be induced to classify the different clusters as perceptual units, similar to the way in which the gist of a scene may be classified. If this occurs, then the lower performance of autistic participants is consistent with hypervigilant learning, since these subjects would not be as good at recognizing variations of these clusters due to their known hypersensitivity to local elements in an input (Caron et al., 2006; Mottron et al., 2003) and to their tendency to detect local targets in visual search tasks (Plaisted, O'Riordan, & Baron-Cohen, 1998).

In experiment two, a subset of the dots did not vary across items in a category. Autistic participants, due to hypervigilance, may be sensitive to the specific locations of these dots, which may improve their performance in this task relative to that of controls, thereby overcoming the relative disadvantage that occurs in experiment one (Fig. 4). This interpretation is consistent with evidence showing a preference for local vs. global grouping in high functioning autistic children (Scherf et al., 2008).

The current results are thus weakly compatible with the hypervigilant learning hypothesis. Additional studies are, however, needed to further support or disconfirm this tentative conclusion. As in the current study, these additional studies should enable category learning of stimuli whose fixed and variable parts may alter processing of individual stimulus features vs. global feature groupings. Experimental designs in which the global groupings that could form are even more directly controlled should shed more light on how and whether autistic individuals learn in a hypervigilant state.

Concluding remarks

This study provides further evidence supporting the notion that autistic individuals manifest relatively intact prototypical category learning mechanisms. While we find evidence in experiment one that some autistic individuals learn prototypes more slowly than normal, leading to an overall decrement in testing performance, the pattern of performance across testing conditions is consistent with typical prototype learning. A second experiment confirmed this basic finding. Experiments that even more directly control the global groupings that can form in response to stimulus materials may further clarify how autistic individuals attend, group, and learn combinations of scenic features.

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Footnotes

1. Equal variances were not assumed for all t-tests throughout this paper.
2. We also conducted this analysis excluding the four (4) autistic subjects who did not reach criterion within the 10 training blocks, with similar results.
3. We also performed an analysis of covariance (ANCOVA), including subject age as a covariate and mean percentage correct as the dependent variable, to adjust for the different mean ages of the two groups, with similar results [adjusted control group mean = 87.4, adjusted autism group mean = 77.6, $F(1) = 10.52$, $p = 0.0025$].
4. For this analysis, we omitted the data of one autistic subject who did not reach criterion and who did not perform above chance in any training block or in any testing condition.