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BRIEF REPORT

Brief Report: Simulations Suggest Heterogeneous Category Learning and Generalization in Children with Autism is a Result of Idiosyncratic Perceptual Transformations

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Abstract Children with autism spectrum disorder (ASD) sometimes have difficulties learning categories. Past computational work suggests that such deficits may result from atypical representations in cortical maps. Here we use neural networks to show that idiosyncratic transformations of inputs can result in the formation of feature maps that impair category learning for some inputs, but not for other closely related inputs. These simulations suggest that large inter- and intra-individual variations in learning capacities shown by children with ASD across similar categorization tasks may similarly result from idiosyncratic perceptual encoding that is resistant to experience-dependent changes. If so, then both feedback- and exposure-based category learning should lead to heterogeneous, stimulus-dependent deficits in children with ASD.

Keywords Connectionist · Heterogeneity · Perceptual learning · Random projection · Self-organizing map

Introduction

Individuals with autism spectrum disorders (ASD) sometimes have difficulty learning to categorize faces (Gastgeb et al. 2009, 2011; Newell et al. 2010), complex objects (Gastgeb et al. 2006; Klinger and Dawson 2001; Klinger et al. 2007; Plaisted 2000), and abstract patterns (Church et al. 2010; Froehlich et al. 2012; Gastgeb et al. 2012; Vladusich et al. 2010). In particular, some individuals take much longer to learn such categories than typically developing (TD) individuals (Bott et al. 2006; Schipul and Just 2016; Soulières et al. 2011), especially for challenging categorization tasks (Vladusich et al. 2010). When high-functioning adults with ASD were tested on their ability to form categorical prototypes of abstract dot patterns, half failed to form prototypes (Gastgeb et al. 2012; see also Vladusich et al. 2010). The remaining participants performed like TD adults. Dichotomous category learning capacities have also been observed in high-functioning (HF) children with ASD (Church et al. 2010, 2015; Mercado et al. 2015), with some children showing typical patterns of generalization and others showing large performance deficits.

Explanations for why individuals with ASD find some category learning tasks difficult have focused on systematic biases in perceptual or representational processing (Gastgeb et al. 2009; Newell et al. 2010; Rump et al. 2009). For instance, attention to specific details of images (Gastgeb et al. 2009; Vladusich et al. 2010) or atypical subsets of features (Behrmann et al. 2006; Dawson et al. 2005; Plaisted et al. 1998), could interfere with category learning. Current perceptually-focused theories of ASD (e.g., weak central coherence, enhanced perceptual function) suggest that ASD is associated with increased salience of local/discrete features relative to more global/configural features (Happe and Frith 2006; Mottron et al. 2006), which could negatively affect some category learning tasks. More general deficits in the processing of complex information could also disrupt category learning (Minshew and Goldstein 1998; Minshew et al. 2002; Williams et al. 2015). None of these explanations predicts that category learning should only be negatively affected in a subset of

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individuals with ASD. The mixed findings from past studies have thus usually been attributed to other factors, such as within-group variations in: (1) IQ subtests (Gastgeb et al. 2012); (2) symptoms of autism (Gastgeb et al. 2011); or (3) language abilities/mental age (Molesworth et al. 2008).

A recent study by Mercado et al. (2015) found that some children with ASD tested on multiple category learning tasks showed both intact and impaired performance, calling into question past trait-based accounts of heterogeneity in category-learning deficits. Children (ages 7–13) learned to classify complex shapes (Fig. 1) as being either a particular kind of "ghost" or not through computer-guided training. On every trial, a unique shape was shown and the child had to indicate if that shape was one of the target ghosts. Target ghost shapes were designed to be perceptually similar to a prototype shape, whereas non-target shapes were dissimilar both to target ghost shapes and to each other. Children were successively trained to classify four different kinds of ghosts; training and testing for one ghost category was completed before progressing to training and testing with the next ghost category, using unique shapes for each task. In each of the four tasks, TD children typically identified the prototype shape as a member of the learned category in later generalization tests, as did about half of the HF children with ASD (Fig. 2a). Surprisingly, the children with ASD that performed similarly to TD children varied across tasks, with about half showing both good and poor performance (Fig. 2b).

Existing theories of perceptual and conceptual processing associated with ASD uniformly propose that individuals with ASD should be systematically atypical in their processing or integration of inputs. Consequently, these theories neither predict nor account for large differences in category learning capacities either within or between individuals with ASD. The current approach builds instead on the computational work of Gustafsson and Paplinski (2004), who proposed that distortions to cortical feature maps formed during development might contribute to atypical categorization abilities (see also Noriega 2007). Atypical cortical organization in individuals with ASD leads to idiosyncratic activation patterns (Hahamy et al. 2015), which potentially could contribute to the heterogeneity of category learning abilities seen within and across studies (Schipul and Just 2016). To investigate the possible effects of such atypical cortical processing on the learning and generalization of novel categories, we developed a connectionist model in which abstract shapes were represented either by sets of features that efficiently coded the properties of shapes (simulating processing by TD individuals), or by sets of features that were idiosyncratically transformed (simulating processing by individuals with ASD). The basic assumption underlying this approach is that cortical processing of sensory inputs can vary substantially across individuals with ASD.

The current simulations were developed in an attempt to simultaneously account for intra-group and intra-individual differences in the category learning performances of children with ASD, as well as group-level deficits relative to TD individuals. The specific question addressed by these simulations was whether systematic differences in the transformations of inputs might contribute to instability in category learning abilities. We predicted that individual-specific transformations of shape representations would lead to idiosyncratic, stimulus-dependent capacities to form new categories, similar to what has been observed in children with ASD. The current simulations provide a computational test of the hypothesis that idiosyncratic visual cortical processing resulting from deficits in cortical map formation in children with ASD can make it more difficult for these children to learn novel categories.

Methods

Simulations

Forty self-organizing maps (SOMs), a type of neural network, were trained using inputs representing each of four different shape categories, for a total of 160 simulations. In SOM simulations, the spatial arrangement of nodes within the network becomes organized through training such that neighboring nodes respond to similar inputs (Gustafsson and Paplinski 2004; Kohonen 2013). The performance of each SOM can be viewed as analogous to the performance of an individual participant. Half of the SOMs were trained

Fig. 1 Examples of prototype abstract shapes used to generate each of the four categories of target "ghosts" used in the current simulations. Prototype shapes were systematically distorted to create a set of unique, but similarly shaped, ghosts

with idiosyncratically transformed inputs (described below) simulating category learning by children with ASD, and the remaining SOMs were trained with more systematically transformed inputs, simulating learning by TD children. Trained SOMs were analyzed to determine how often map nodes activated by shapes from a particular category of ghost were also activated by shapes that were not members of the category. Simulations were conducted using Mathworks Neural Network toolbox running in the Matlab R2010b environment.

Materials and Design

Quantitative descriptions of shapes that children learned to categorize in the study by Mercado et al. (2015) were used as model inputs. In each simulation, an SOM learned to sort inputs based on their similarity (i.e., grouping similar inputs together while simultaneously separating them from dissimilar inputs). The set of shapes used for training each category corresponded to fifteen distorted versions of a prototype shape. Random shapes that were dissimilar from shapes in each category were used as examples of non-targets. Shape-describing inputs (vectors containing 18 coordinate values) were transformed into simpler representations that were then used to train the SOMs. Shape processing by TD children was grossly approximated by transforming inputs into 3-element vectors using principal-components analysis (PCA). PCA-based encoding of inputs is often used in neural networks to reduce their dimensionality while preserving relevant variations across stimuli, and was not intended to replicate the specific representational processes TD children use when perceiving visual shapes. How individuals with ASD process visual inputs is poorly understood, making it difficult to quantitatively reproduce the specific transformations they employ. It is possible to simulate unpredictable, individual-specific variations in the efficiency with which inputs are transformed, however. To simulate these hypothesized properties of shape processing by children with ASD, shape representations were transformed into 3-element vectors using a technique called *random projection* in which inputs are represented in terms of a subspace created from randomly selected dimensions (Fern and Brodley 2003; Kaski 1998). Surprisingly, such representations often provide a robust foundation for forming categories (Arriaga and Vempala 2006). The use of random projection made it possible to present each SOM with a unique set of idiosyncratic features extracted from the shape-describing inputs. These transformations were not intended to replicate visual processing by individuals with ASD, but rather to simulate heterogeneous, atypical processing across individuals.

Procedure

PCA-based transformations were implemented with the Matlab function *princomp*, and random projection-based transformations were implemented by multiplying a matrix of shape-describing inputs by a smaller weight matrix of random values. Once the shape-describing inputs were transformed using either PCA or random projection, they were then used to train sets of 2 × 2 SOMs. Each 2 × 2 SOM provided four nodes for sorting inputs, more than needed to distinguish distorted prototypes from random shapes. Nodes acquired selectivity to input features by competing to match each input; the winner node and its neighbors were automatically adjusted to increase their responsiveness to matching inputs during training (i.e., using exposure-based learning rather than feedback-based learning). Different sets of non-target shapes were contrasted with inputs representing each of the four target ghost categories (as in past behavioral experiments), and different random projections were used for each ASD simulation. After training, each SOM was evaluated on its ability to classify shapes by tallying the number of times each node was activated by either a random shape or by a shape within a category. Map nodes showing a preference for category members were used to calculate the percentage of appropriately sorted shapes. For example, if all category members were associated with a single map node and that node also responded to three random shapes, then this would correspond to 100 % endorsement of category members and 20 % endorsement of random shapes. How well each SOM distinguished category members from random shapes was assessed within and across different simulations. The goal of these simulations was to clarify possible mechanisms that could account for the heterogeneity of category learning shown by individuals with ASD rather than to reconstruct specific performance profiles previously observed in individuals.

Results

SOMs easily sorted PCA-based representations of shapes, showing near perfect differentiation of distorted prototypes from random shapes (Fig. 2c), performing as well as, or better than, TD children in all four tasks. SOMs were also able to successfully sort patterns transformed using random projection, although less reliably and with much more variability across simulations (Fig. 2c). Importantly, for a subset of maps trained with inputs transformed by random projection, some categories of ghosts were successfully sorted, but others were not (Fig. 2d). Furthermore, the categories of ghosts that were successfully categorized varied across maps. In other words, whether a particular

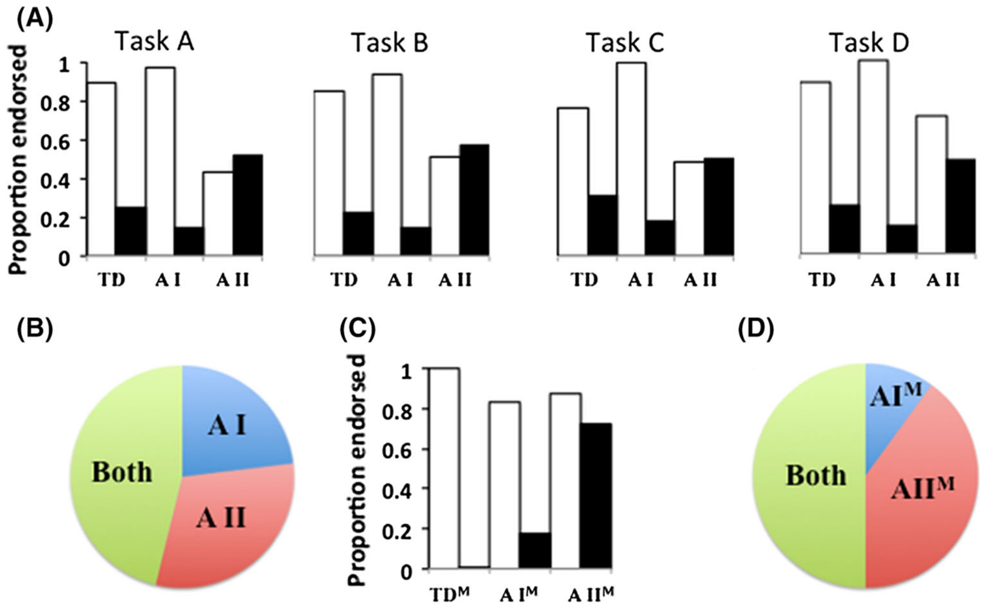

Fig. 2 **a** Average endorsement proportions for prototypical within-category ghosts (*white bars*) and random non-category ghosts (*black bars*) by children in four similar categorization tasks (data from Mercado et al. 2015). In each task, typically developing children (TD) easily identified the prototype after training, as did approximately half of the children with ASD (A I). The remaining children with ASD (A II) showed little recognition of the prototype. **b** About half of the children with ASD showed both good and poor performance across the four tasks. **c** Self-organizing maps that received inputs reduced in dimensionality based on principle components (TD^M) easily distinguished category members from non-members in all four tasks. Some maps that received randomly projected inputs successfully categorized ghosts in a subset of tasks (AI^M), but failed in others (AII^M); *bars* show averages across the four tasks. **d** Like children with ASD, about half of the maps showed task-dependent abilities to learn shape categories

SOM was able to successfully learn to classify randomly projected target ghost shapes as being different from other ghost shapes depended on both the specific transformation and the specific shape category being learned. The simulations with SOMs involving random projection of abstract shape-describing inputs thus showed unstable, dichotomous performance profiles similar to those observed both within and across children with ASD. This was true despite the fact that the SOMs did not use any form of error correction to learn new categories, in contrast to the children with ASD tested by Mercado et al. (2015), who were given feedback on their performance after each training trial. SOMs trained with randomly projected inputs differed from children with ASD in that they were less likely to successfully learn to categorize shapes and were generally more likely to endorse any shape as being a ghost. The superior performance of children with ASD at learning shape categories suggests that their representations of shapes may be more refined or flexible than those constructed through random projections.

Discussion

Our modeling results show that idiosyncratic perceptual transformations can disrupt the formation of some abstract categories while preserving the capacity for rapidly learning other similar categories. This finding suggests that the mixed results reported by researchers studying category learning by individuals with ASD (Gastgeb et al. 2012; Molesworth et al. 2008), as well as the large intra-individual variations in category learning and generalization seen in children with ASD (Mercado et al. 2015), may be a consequence of idiosyncratic perceptual transformations. Our simulations also indirectly support earlier suggestions that deficits in cortical plasticity during early development may contribute to later cognitive deficits associated with ASD (Gustafsson 1997; Gustafsson and Paplinski 2004; LeBlanc and Fagiolini 2011; Markram and Markram 2010; Thomas et al. 2011, 2015). Whereas TD children learn in ways that lead to convergent representational frameworks, children with ASD may acquire atypical perceptual maps that emphasize idiosyncratic dimensions, causing some "random" features to be atypically salient. Use of idiosyncratic dimensions during category learning would also be consistent with past reports of atypical category use and category preferences by individuals with ASD (e.g., Alderson-Day and McGonigle-Chalmers 2011; Bowler et al. 2008; Ropar and Peebles 2007).

As in weak central coherence (Happe and Frith 2006), and enhanced perceptual function theories (Mottron et al. 2009), the basic idea underlying the current simulation results is that individuals with autism encode perceptual events using stimulus dimensions that may differ from those used by TD individuals (see also Bowler et al. 2008). Our simulations lead to similar group-level predictions as these perceptual theories, because SOMs trained with random projection-based inputs may show greater sensitivity to atypical details. However, our findings suggest that rather than being systematically biased to attend to an atypical subset of features (e.g., low-level details), people with ASD may be "stuck" using individual-specific dimensions that are not easily customized to more effectively encode novel inputs (Schipul and Just 2016). In this respect, the idea that idiosyncratic perceptual transformations might contribute to atypical category learning by individuals with ASD differs significantly from all other current proposals.

Individual-specific perceptual transformations can potentially give rise to both "intact" and atypical category learning depending on the match between the transformation and the specific inputs. Similarly, in the current simulations, some SOMs trained with randomly projected inputs performed well in all four category-learning tasks, whereas others failed in all the tasks. The success of any given SOM on a particular task depended on whether the specific dimensions emphasized by its idiosyncratic transformation differentiated category members from other shapes. Although individuals with ASD are likely not representing complex inputs in terms of randomly selected dimensions, they could easily be representing inputs in ways that differ substantially across individuals (Leekam et al. 2007). In the last decade, several researchers have proposed that differences in cortical connectivity (reviewed by Just et al. 2012; Thomas et al. 2015; Wass 2011), inhibition (Rubenstein and Merzenich 2003; Yizhar et al. 2011), and plasticity (Auerbach et al. 2011; Dovgopoly and Mercado 2013; LeBlanc and Fagiolini 2011), may contribute to the atypical learning, categorization, and perception seen in individuals with ASD. If the neural connections between sensory representations and later perceptual processing networks in children with autism are resistant to experience-dependent changes (Dovgopoly and Mercado 2013; Schipul and Just 2016), then the representational distortions associated with autism may differ across individuals due to variations in initial connectivity or early sensory experiences. A recent report of idiosyncratic distortions in spontaneous functional connectivity patterns across the cortical networks of adults with ASD is consistent with this possibility (Hahamy et al. 2015). Plasticity-resistant, idiosyncratic perceptual transformations would force individuals with ASD to make do with whatever pre-existing representational processes they bring to a task when learning new categories.

An alternative explanation for why children with ASD might show intermittent difficulties in learning categories is that they may fail to choose an appropriate strategy early in training, defaulting instead to a guessing strategy, or they may have dysfunctional executive functions that lead to fixation on inappropriate stimulus dimensions (Soulières et al. 2011). Gustafsson and Paplinski (2004) simulated the latter possibility and found that reduced attentional shifting had only small effects on the structure of SOMs. Soulières et al. (2011) also reported that category-learning deficits were present in individuals with ASD who showed no measurable executive dysfunction. Extended guessing could contribute to variability in performance across different category learning tasks. However, this interpretation simply emphasizes a possible atypical aspect of performance rather than identifying any mechanisms that might drive such tendencies. Individuals with ASD might engage in extended guessing when they are unable to rapidly identify, or learn to recognize, relevant category-distinguishing information.

If children with ASD learn categories in ways that depend on idiosyncratic perceptual transformations, then this should be experimentally detectable. For instance, our simulations predict that subtle variations in how stimuli are presented could lead to rapid increases in category learning rate for some individuals. The current simulations also predict that only a subset of categories formed by TD children will match those formed by children with ASD, and that children with ASD will form and categorize percepts in unique ways. Consequently, children with ASD should show higher than typical within-task variability and the relative difficulty of different category learning tasks should also vary greatly across children with ASD. Finally, our simulations predict that atypical category learning in children with ASD should occur not only when these children are explicitly trained to categorize items, but also when they are merely exposed to images that vary systematically in similarity (e.g., Froehlich et al. 2012; Schipul and Just 2016). This possibility is particularly relevant with regards to understanding how one might avoid or counteract category-learning-related deficits in children with ASD, because most of the communicative and social skills that are problematic for these children depend heavily on categories (e.g., categories of speech sounds, facial expressions, social situations) that are commonly learned through repeated exposure rather than through explicit training.

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Authors' Contributions BC designed and analyzed data from the behavioral experiments simulated in this study and assisted in formulating theoretical mechanisms capable of explaining the performances of children with autism. EM developed and analyzed the described computer simulations and contributed to developing the theoretical framework instantiated by these simulations.

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