Title
Development of selective attention in category learning

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 37(0)

Authors
Rivera, Samuel
Sloutsky, Vladimir M

Publication Date
2015

Peer reviewed

Development of selective attention in category learning

Samuel Rivera (rivera.162@osu.edu)
Department of Psychology, 1835 Neil Avenue
Columbus, OH 43210 USA

Vladimir M. Sloutsky (sloutsky.1@osu.edu)
Department of Psychology, 1835 Neil Avenue
Columbus, OH 43210 USA

Abstract

Categorization, the process of grouping distinguishable entities into equivalence classes, is an essential component of human cognition. Although it has been often argued that selective attention is an important component of categorization, organism with immature selective attention (such as human infants or young children) exhibit the ability to learn categories. This research addresses this apparent paradox by examining attention allocation in the course of category learning across development. Results suggest that while some young children are able to attend selectively, adults more flexibly deploy selective attention according to task demands.

Keywords: cognitive development; attention optimization; category learning; categorization; conceptual development

Introduction

Categorization, the ability to group distinguishable objects and ideas that share some important commonalities, is an essential component of cognition that supports the expansion of knowledge through generalization, inference, and communication. Given the importance of this ability, it is important to understand the mechanisms that support it and the way these mechanisms develop. Mechanisms of categorization involve an interesting paradox. On the one hand, the ability to learn categories exhibits early onset (i.e., infants as young as three months of age exhibit the ability to learn categories (Oakes, Madole, & Cohen, 1991; Quinn, Eimas, & Tarr, 2001). On the other hand, many models of categorization posit that selective attention plays a central role in category learning (Kruschke, 1992). If this is the case, how do organisms whose selective attention is immature (such as human infants or young children) learn categories?

Adult-like categorization is thought to rely on selective attention, focusing on some aspects of the stimuli (presumably the category-relevant ones) and ignoring others (presumably irrelevant ones). At the same time, selective attention exhibits protracted development (Plude, Enns, & Brodeur, 1994), which perhaps is related to the slow development of the brain structures sub-serving selective attention (Huttenlocher & Dabholkar, 1997; Bunge & Zelazo, 2006). The slower development of those structures coupled with childrens ability to learn categories, suggests that early category learning may not depend on selective attention: children learn category statistics as long as there is enough statistical structure in the input and fail otherwise. This implies that during infancy and childhood, the types of categories that can be learned will be limited by the maturity of selective attention and by category structure.

One hallmark of selective attention as a mechanism of mature categorization that is central to this investigation is attention optimization. Namely, as adults learn categories having a distinguishing characteristic, they will direct their attention more toward that feature and ignore the other features (Hoffman & Rehder, 2010). In contrast, if young children do not attend selectively when learning categories, then they should exhibit reduced attention optimization compared to adults. We tested this hypothesis with a supervised category learning task, in which children and adults learned categories while their gaze was tracked with an eye tracker. Since gaze is linked to visual attention, eye tracking allowed us to measure attention while participants learned novel visual categories.

A key issue alluded to above is that learning and attention may be affected by category structure. For example, the category of *living things* contains quite varied members, and classifying something as living or non-living requires looking beyond one or two highly varying surface features (such as color and shape) and focusing on key characteristics (reproduction, energy consumption). In contrast, the category of *dogs* contains members with many strongly correlated features. Therefore, it may be the case that attention optimization will depend on the category structure. To address this question, we systematically manipulated the category structure in our task to investigate what role, if any, category structure plays in modulating attention.

In summary, a growing body of literature has implicated selective attention as a key mechanism of human categorization. We hypothesize that early categorization does not rely strongly on selective attention, since executive function continues maturing through childhood. To foreshadow, our results suggest that while some children do exhibit selective attention, adults show a greater reliance on selective attention for more difficult categorization tasks.

Method

Participants

Fifty-seven five-year-olds (twenty-four female and thirty-three male, M = 5.26 years, SD = .44 years) participated in this study. Children completed either the standard (N = 31) or gaze contingent (N = 26) condition. Children were recruited through local daycares or preschools located in Columbus, Ohio, and public birth records. Ninety-nine adults (48 female and 51 male) participated in the study for course credit through The Ohio State University research experience pro-

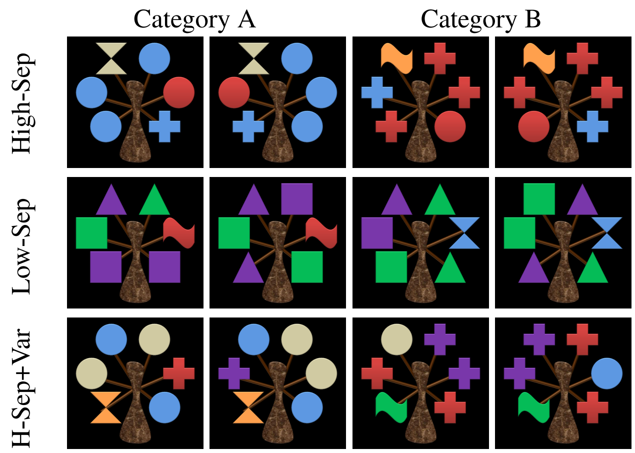

Figure 1: Some exemplars used in the study. The top-left feature corresponds to position one, with positions increasing clockwise. Deterministic features for the High-Sep, Low-Sep, and High-Sep+Var categories were distinct in color and shape, and located at the top-left, right, and bottom-left positions, respectively.

gram. Adults completed either the standard (N = 69) or gaze contingent (N = 30) condition. The majority of child and adult participants were Caucasian.

Stimuli

Categories were artificial *tree-like* objects with six spatially separated branches that differed along the dimensions of color and shape, as shown in Figure 1. This resulted in twelve features over 6 locations. We varied the feature values to construct six category types that were grouped into three pairs having category structures that complemented each other. The pairs were (1) highly separable (HS), (2) less separable (LS), or (3) highly separable with high variance (HS+V).

Every category had a deterministic color and shape at a single position that perfectly determined category membership, and ten less informative probabilistic color and shape features over five positions. The position of the deterministic feature varied between blocks so that participants would have to relearn the deterministic feature on subsequent blocks. In the HS conditions, 2 of the 10 probabilistic features took values from the contrasting category. In the LS condition, 4 of the 10 probabilistic features took values from the contrasting categories. In the high variance condition, probabilistic features could take 2 possible values within each category, increasing within category variance. Some example structures are shown in Table 1.

Experimental Paradigm

Non Gaze Contingent (Non-GC) Experiment Adult participants conducted a classification procedure while their gaze was monitored with an EyeLink 1000 hydraulic-arm eye-tracker at 500Hz (SR research, Ontario, Canada). Adult and

Table 1: Example category structures used in the study. H-Sep, L-Sep, and Var correspond to highly separable, less separable, and high variance categories, respectively. C1 and S1 correspond to color and shape at position one, respectively. In the highly and less separable conditions, each feature could take on one of two values, denoted by 0 or 1. Category A was primarily associated with feature 0, while category B was associated with feature 1. For variable categories, all features except the deterministic took on four values, denoted by 0,1,2 or 3. Category A was primarily associated features 0 and 1, while category B was associated with features 2 and 3. Deterministic features are in bold.

	C1	S1	C2	S2	C3	S3	C4	S4	C5	S5	C6	S6
H-Sep (A)	**0**	**0**	0	0	0	0	0	0	1	0	0	1
	0	**0**	0	0	0	0	1	0	0	1	0	0
	0	**0**	0	0	1	0	0	1	0	0	0	0
H-Sep (B)	**1**	**1**	1	1	1	1	1	1	0	1	1	0
	1	**1**	1	1	1	1	0	1	1	0	1	1
	1	**1**	1	1	0	1	1	0	1	1	1	1
L-Sep (A)	1	0	1	0	**0**	**0**	0	0	0	1	0	1
	0	1	0	1	**0**	**0**	0	0	1	0	1	0
	0	0	1	0	**0**	**0**	1	1	0	1	0	0
L-Sep (B)	0	1	0	1	**1**	**1**	1	1	1	0	1	0
	1	0	1	0	**1**	**1**	1	1	0	1	0	1
	1	1	0	1	**1**	**1**	0	0	1	0	1	1
H-Sep + Var (A)	2	2	1	0	1	0	0	0	**0**	**0**	0	0
	1	0	2	2	1	0	0	0	**0**	**0**	0	0
	0	0	0	0	2	2	1	0	**0**	**0**	1	0
H-Sep + Var (B)	0	0	3	2	3	2	2	2	**2**	**2**	2	2
	3	2	0	0	3	2	2	2	**2**	**2**	2	2
	2	2	2	2	0	0	3	2	**2**	**2**	3	2

child participants sat approximately 60cm from the 17" display within a quiet testing room. Adults sat alone, with an experimenter in an adjacent room controlling the experiment and communicating with the participant via microphone. Children had an additional experimenter sit beside them in the testing room to keep them on task and encourage them throughout the study.

On each block, participants were told that they would see a sequence of objects from two new categories. They were asked to look at the object, then categorize it as fast and accurately as possible to obtain the most points. The categories were associated with a target (small light or dark house) on either the left or right side of the display. Each trial began with a central fixation point. Once that orienting target was fixated, an experimenter initiated the presentation of a central category exemplar from one of the two groups that subtended approximately 19 $\times$ 19 degrees of visual angle, and two targets on either side of the target. Participants had no time limit, and made their classification decision by looking at the target on the left or right side of the display that was associated with the category. Corrective feedback was immediately given in the form of a centrally displayed smiling face for correct answers, and a neutral face for incorrect answers. Participants could look at the feedback screen as long as they wanted to, and engaged the next trial by fixating the bottom of the display. There were 50 trials in each of the three blocks.

Children conducted a similar procedure, with slight modifications for their age. Namely, they were told that the two different types of creatures needed help finding their home (either the light house or dark house). Instead of making their decision by looking at the corresponding target, they were asked to yell out "light house" or "dark house" to indicate where the stimulus went, and the experimenter recorded the response. In addition, the feedback screen for incorrect trials showed the exemplar beside the correct target without a neutral face. Correct trials ended with the exemplar near the correct target in addition to a central smiling face. There were 20 trials in each of the three blocks.

Gaze Contingent (GC) Experiment Although eye-tracking offers a measure of attention over learning, it has drawbacks. Namely, it is possible for participants to attend covertly during a task. Indeed, as we will show, adults in the standard task performed expertly without fixating any category defining features on about half of the trials. This demonstrates that adults were, at least sometimes, attending peripherally. To address this, we created a gaze contingent version of the study where features were occluded until fixated.

On each trial for adult participants, the six areas containing the category features were covered in black except for central white dots. Participants were told that the objects were occluded, and that they could look at the white dots to uncover the objects. During the experiment, a 300ms fixation within a box bounding a feature caused the feature to appear and remain visible for the remainder of the trail.

In the child version, the features were occluded by blue clouds that disappeared to show the covered feature when fixated. In addition, we increased the number of trials from twenty to thirty and eliminated the HS+V categorization block for children. As we will show in the next section, children had a difficult time learning the high variance categories. Eliminating that structure reduced fuss-out in children, and increased the proportion of participants who achieved the learning criterion.

Results

It was important to ensure that participants were engaged in and understood the task, so we only analyzed data for participants who reached a learning criterion of 10 correct trials within 11 consecutive trials within a block. For 20 trials (the child condition), this corresponds to $p = 0.054$ ($\text{binomial}(10, N = 11, \theta = 0.5) * 10$). Since each block contained different category structures, we considered each block separately according to the category type. We break down the number of participants who achieved the criterion out of the number that completed the minimum trials required to achieve the learning criterion by category and age group in Table 2. Mean trials to criterion are summarized in Table 3. We show the percentage of trials with no fixations at the category features (missing gaze trials) in Table 4.

Table 2: Number who obtained learning criterion over the number who completed minimum trials to achieve criterion.

	H-Sep	L-Sep	H-Sep+Var
Adult (Non GC)	65/68	63/69	66/68
Child (Non GC)	11/26	10/21	5/17
Adult (GC)	27/29	26/30	26/29
Child (GC)	17/26	15/25	

Accuracy

We first consider overall trends in accuracy and learning rates as a function of category type. We plot the normalized distributions of trials to learning criterion, and the mean participant accuracy for the first 20 trials in Figures 2 A and B, respectively. The first 20 trials are considered since this was the maximum trials encountered by children for each category type in the Non-GC condition. Figure 2 shows that while most participants who learned did so within the first five trials, some children (and adults) required at least 19 trials to achieve the learning criterion. Therefore, more children in the GC versus Non-GC condition met the learning criterion because of the additional 10 trials in that condition.

We then investigated whether there were systematic differences in accuracy, as a function of age group, category type, and experiment condition. Given the amount of participants who did not achieve the learning criterion for all category types, analysis was conducted using mixed-effect modeling which has the advantage of dealing with missing values, as opposed to repeated measures ANOVA. Accuracies were exponential transformed to be closer to Normally distributed. We first considered overall differences in accuracy between the age groups. Specifically, we modeled transformed accuracy as having a main factor of age group (Adult/Child) and a random factor of participant, and found no significant difference ($B = 0.016, SE = 0.046, t(165.74) = 0.36, p = 0.72$).

We then looked within age groups to find differences in accuracy as a function of category type. We modeled the transformed adult accuracy as having main factors and interactions of category type (HS/LS/HS+V) and condition (Non-GC/GC) and a random factor of participant. We found no significant main effect of condition, but a significant interaction between condition and the category type. We compared this model (BIC: 165.49) to a simpler model (BIC: 154.41) with only a main factor of category type and random factor of participant, and found no improvement with the more complex model ($\chi^2 = 5.75(3), p = 0.12$). Therefore we used the simpler model in the analysis. We found a significant difference for HS versus LS ($B = -0.098, SE = .044, t(172.51) = -2.25, p = .026$), indicating a reduced accuracy for the LS category versus the HS. We found no other significant differences (all $ps > 0.14$).

We modeled child transformed accuracies similarly to adults, with main factors and interactions for category type

Table 3: Trials to learning criterion (M ± SD).

	H-Sep	L-Sep	H-Sep+Var
Adult (Non GC)	5.4 ± 6.7	5.8 ± 6.5	6.9 ± 7.7
Child (Non GC)	4.4 ± 3.6	3.0 ± 3.2	2.8 ± 1.1
Adult (GC)	4.8 ± 7.4	9.0 ± 9.2	6.8 ± 6.8
Child (GC)	7.1 ± 6.8	4.6 ± 5.2	

Table 4: Percentage of trials with no fixations at AOIs.

	H-Sep	L-Sep	H-Sep+Var
Adult (non GC)	56.98%	48.95%	47.45%
Child (non GC)	5.91%	3.59%	3.00%
Adult (GC)	5.19%	2.15%	4.62%
Child (GC)	1.43%	0%	

and condition, and a random factor for participant. We found no significant main effect or interaction with condition (all $ps > .07$), so we used a simpler model that included category as a main factor and participant as a random factor. We found a significant main effect of HS versus LS ($B = 0.14, SE = .062, t(21.31) = 2.20, p = .039$), indicating an increased accuracy for the LS versus HS category. We found no other significant differences (all $ps > 0.31$).

Overall, children and adults performed equally well. However, there was an interesting developmental difference, where adults were more accurate for the HS categories versus the LS categories while children showed the reverse trend. Adults had the expected trend, given the the relative ease of categorizing the HS categories with either the deterministic or probabilistic features. We propose two possibilities for the unexpected child result. First, it is possible that there was a sampling bias, where more children completed and learned the HS categories, but a smaller set of skilled category learners completed the LS task. The results of Table 2 do not give much support for this, since there were equal proportions of children who learned HS and LS categories ($\chi^2 = 0.0011(1), p = 0.97$). Another possibility is that children may have learned the LS categories faster. We ruled this out by finding no significant effect of category type when modeling the trial to learning criterion with main factor of category type and random factor of participant (all $ps > .14$). We will return to this issue after considering attention during learning.

Attention Optimization

Recall that our goals are to investigate (1) whether children would optimize attention in the course of category learning, and (2) if category structure modulates attention. Categories were defined by the twelve feature values at the six positions, so our areas of interest (AOI) were six circular non-overlapping regions centered at the feature positions that completely contained the category defining features. Given a

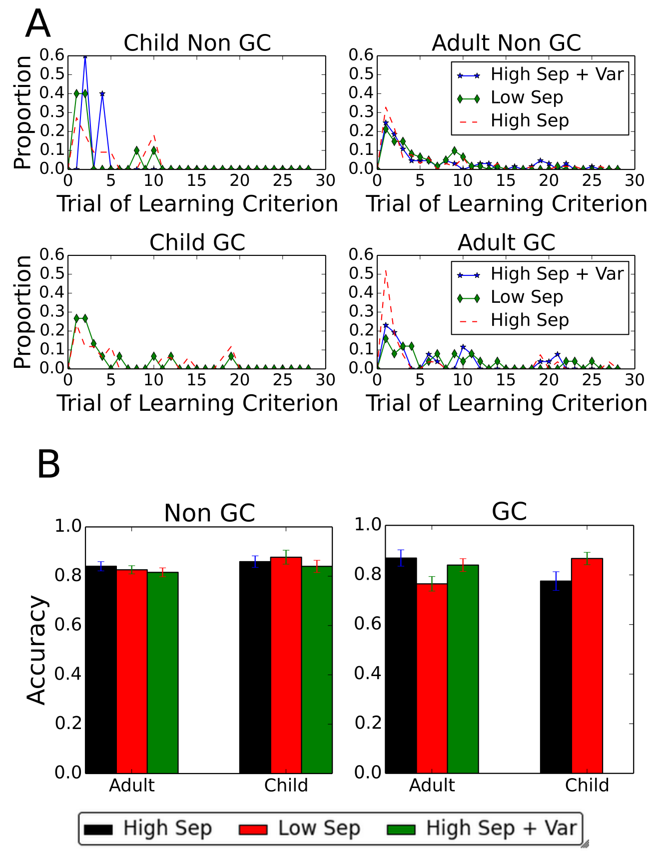

Figure 2: Figure A shows normalized histograms of the trials to learning criterion. The y-axis denotes the proportion of participants who learned by a given number of trials, while the x-axis denotes the number of trials required to achieve the learning criterion. Figure B shows the mean proportion correct trials (accuracy) for the first 20 trials.

category structure with two deterministic features at a single AOI that are perfectly associated with the category type, the optimal strategy is to look at just the deterministic features in order to categorize the object perfectly on every trial. Thus, our measure of attention optimization was the proportion of fixations to the deterministic features as a function of trial number.

Fixation positions were recorded online by the EyeLink system, then processed offline using custom MATLAB and Python software. Proportion of fixations to the deterministic feature was calculated as the number of fixations within the deterministic AOI divided by the total number of fixations within all AOIs. Fixations outside of the six AOIs were omitted from all analyses, trials without fixations at any AOIs were treated as missing data for the optimization analyses, and only accuracy information on those trials was used.

To determine the extent of attention optimization for each category type as a function of trial number, it was crucial to align participants with respect to the trial in which they learned the categories. This accounts for differences in learning rates and allows us a better measure of group optimization behavior. We denote the first trial in the sequence where participants reach the learning criterion as $T0$, and aligned participants with respect to this trial to create optimization curves. Optimization curves are shown in Figure 3.

For the Non-GC condition, the interpolated mean plot shows some increase in the proportion of fixations at the deterministic feature for the LS and HS categories for both children and adults. Recall that the LS categories contain less reliable probabilistic features, so more looks toward the deterministic feature would be advantageous. The HS categories, on the other hand, show a slight decrease from the initial proportion of deterministic fixations by the end of the task.

For the GC condition, the interpolated mean plots show an increasing proportion of fixations at the deterministic AOI, beginning slightly before $T0$ and persisting for several trials, for all category types and age groups. This means that on average, participants more frequently fixated the deterministic features than probabilistic features as they gained experience categorizing the objects - an indicator of attention optimization. The peak in deterministic looks occurred several trials after $T0$, indicating that attention optimization occurs after participants learn the category and replicating a trend found in another eye tracking categorization study (Rehder & Hoffman, 2005). These results, taken together, suggest that at least some adults and children optimized attention during the task. Of interest, however, is: (1) whether there are developmental differences in the proportion who optimize, and (2) the role of category structure.

To analyze individual differences in attention optimization behavior, for each participant we determined the change in the average proportion of deterministic AOI looks before to after $T0$. Positive values denote an average increase in the proportion of looking at the deterministic feature after $T0$, indicating attention optimization. We plot those results in Figure 4 to compare trends across age groups and category types.

For adults in Non-GC condition, trends shows increased attention optimization for the two more difficult categories (LS and HS+V), and there was a marginally significant effect of category type on the proportion who increased deterministic looks ($\chi^2 = 5.75(2), p = 0.056$). Further investigation showed that the effect was driven by difference between the HS and other groups: HS versus LS ($\chi^2 = 4.76(1), p = 0.029$), HS versus HS+V ($\chi^2 = 5.31(1), p = 0.021$), LS versus HS+V ($\chi^2 = 0.026(1), p = 0.87$). For the children in Non-GC condition, there was no significant difference in the proportion or participants who increased deterministic looks between categories ($\chi^2 = 0.098(2), p = 0.95$). For adults in the GC condition, Figure 4 shows an advantage for the LS categories, but we found no significant differences between the proportion who increased deterministic looking ($\chi^2 = 2.72(2), p = 0.26$). For children in the GC condition, there was no significant difference between HS and LS groups ($\chi^2 = 0.11(1), p = 0.74$).

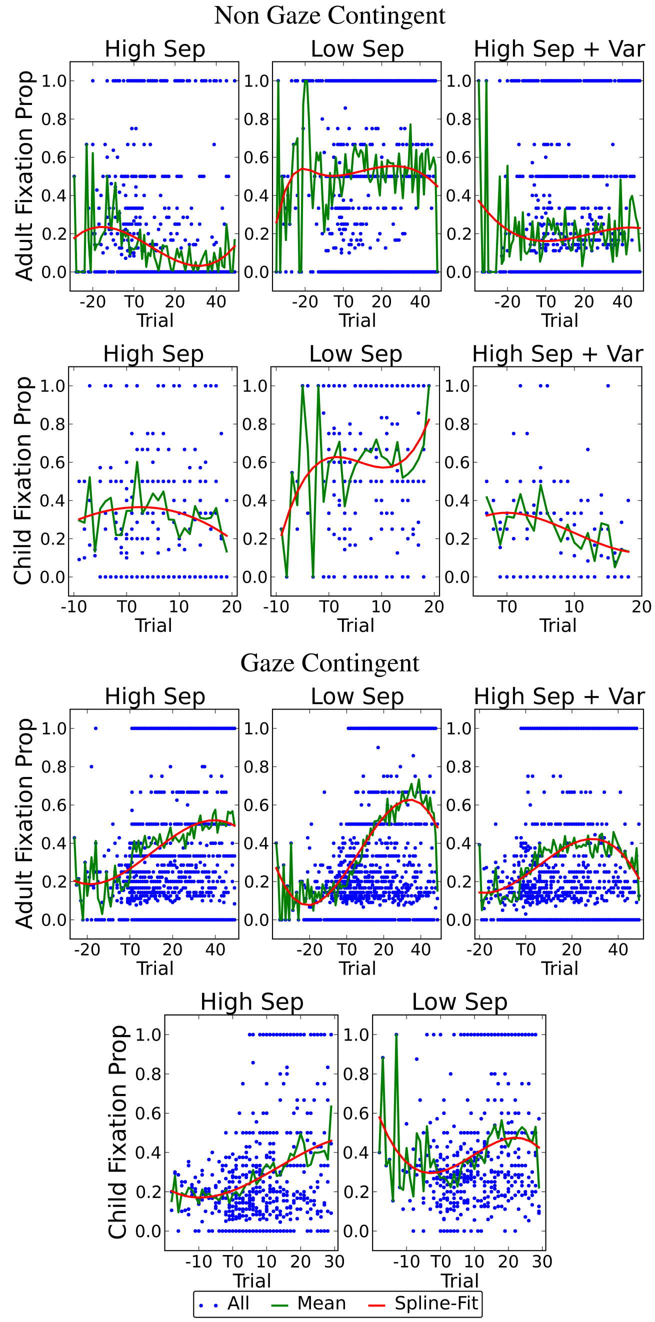

Figure 3: Optimization curves with respect to $T0$. The y-axis denotes the proportion of fixations at the deterministic area on each trial. The trials have been aligned with respect to $T0$, the first correct trial in a sequence where the learning criterion occurred. Blue dots indicate individual participants, while the green line shows the average, and the red line shows a cubic spline interpolation of the average.

We checked for developmental differences, and did not find significant differences between adults and children within any of the category groups when considering the experiment conditions separately. To increase power, we pooled the GC

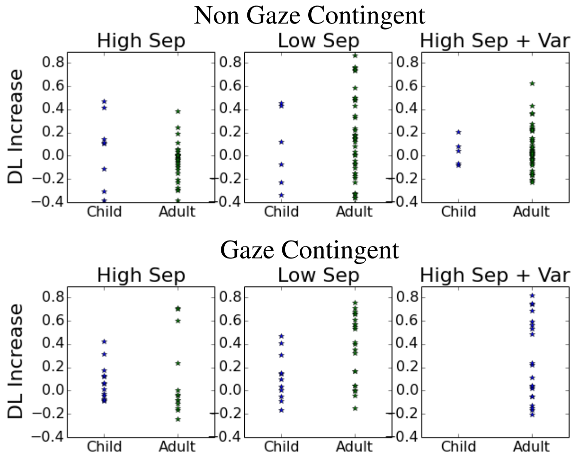

Figure 4: Change in deterministic looks (DL) before to after learning criterion, $T0$. Individual points denote individual participants, and positive values denote an increase in proportion of fixations to the deterministic area following $T0$. Participants with $T0$ at the first trial of the block were not considered.

and Non-GC conditions, then compared the proportion who increased deterministic fixations in the adult versus child groups. For the HS category, there was a significantly larger proportion in the child group who increased deterministic fixations ($\chi^2 = 4.45(1), p = 0.035$). We found no significant difference for the LS category.

Taken together, these results suggest that when probabilistic features were less reliable (LS/HS+V), adults optimized attention to a greater extent. When a time cost was introduced for viewing features (GC), the differential effect diminished and adults optimized attention across category type. Children also exhibited attention optimization that exceeded that of adults for the easily separable categories - perhaps explaining their improved accuracy for the LS versus HS categories. However, the proportion of optimizers was not affected by category structure or by the experiment condition.

General Discussion

From these results we can point to two key findings. First, adults are excellent at attending covertly, and did not fixate any AOIs on about half of trials in the Non-GC condition. Children, on the other hand, were much more consistent in fixating AOIs in the Non-GC condition, but the reason is unclear. More importantly, we found a developmental change in selective attention, where children about 5 years old did not optimize attention according to the category structure - instead exhibiting a kind of baseline attentional pattern. Unlike with children, adult attention optimization depended on category structure. Namely, shifting to perfectly deterministic category features increased as other probabilistic features became less reliable. These results taken together imply a clear reliance on selective attention in adult categorization - especially when category structure consists of few deterministic dimensions. Children, although sometimes attending like adults, did not optimize attention with respect to category structure.

Conclusion

Categorization exhibits early onset, and is central to intelligent behavior. However, it is not clear whether the mechanisms of category learning undergo developmental change. Specific to our investigation was whether children rely on selective attention when learning categories, and how attention is modulated by category structure. We found evidence that selective attention plays a diminished role in child category learning versus adults. Specifically, while children learned categories as well as adults (no difference in accuracy), unlike adults, children showed no change in attention profiles as probabilistic category features became less reliable for specifying category membership - instead showing a baseline level of attention optimization. We hypothesize that these differences stem from immature executive functioning in children. Overall, the study gives new insight into category learning and discrimination in childhood, and the role of selective attention in early categorization.

Acknowledgments

Research supported by NSF grant BCS-1323963 to Vladimir Sloutsky.

References

Bunge, S. A., & Zelazo, P. D. (2006). A brain-based account of the development of rule use in childhood. *Current Directions in Psychological Science*, *15*, 118–121.

Hoffman, A. B., & Rehder, B. (2010). The costs of supervised classification: The effect of learning task on conceptual flexibility. *Journal of Experimental Psychology: General*, *139*, 319–340.

Huttenlocher, P. R., & Dabholkar, A. S. (1997). Regional differences in synaptogenesis in human cerebral cortex. *Journal of Comparative Neurology*, *387*, 167–178.

Kruschke, J. K. (1992). Alcove: An exemplar-based connectionist model of category learning. *Psychological Review*, *99*, 22-44.

Oakes, L. M., Madole, K. L., & Cohen, L. B. (1991). Infants' object examining: Habituation and categorization. *Cognitive Development*, *6*, 377–392.

Plude, D. J., Enns, J. T., & Brodeur, D. (1994). The development of selective attention: a life-span overview. *Acta Psychologica*, *86*(2-3), 227-272.

Quinn, P. C., Eimas, P. D., & Tarr, M. J. (2001). Perceptual categorization of cat and dog silhouettes by 3- to 4-month-old infants. *Journal of Experimental Child Psychology*, *79*, 78–94.

Rehder, B., & Hoffman, A. B. (2005). Eyetracking and selective attention in category learning. *Cognitive Psychology*, *51*(1), 1 - 41.