Drawings as a window into developmental changes in object representations

Bria Long
bria@stanford.edu
Department of Psychology
Stanford University

Judith E. Fan
jefan@stanford.edu
Department of Psychology
Stanford University

Michael C. Frank
mcfrank@stanford.edu
Department of Psychology
Stanford University

Abstract

How do children's representations of object categories change as they grow older? As they learn about the world around them, they also express what they know in the drawings they make. Here, we examine drawings as a window into how children represent familiar object categories, and how this changes across childhood. We asked children (age 3-10 years) to draw objects on an iPad, and analyzed their semantic properties. Across this age range, we found dramatic and consistent gains in how well children could produce drawings that are recognizable to adults. We hypothesized that this improvement reflects increasing convergence between children's representation of object categories and that of adults. To measure this, we extracted features of drawings made by children and adults using a pre-trained deep convolutional neural network, allowing us to visualize the representational layout of object categories across age groups using a common feature basis. We found that the organization of object categories in older children's drawings were more similar to that of adults than younger children's drawings. This correspondence was especially strong for higher layers of the neural network, showing that older children's drawings tend to capture high-level perceptual features critical for adult recognition. Broadly, these findings point to drawing as a rich source of insight into how children represent object concepts.

Keywords: object representations; drawings; child development

Introduction

As humans, we have a variety of powerful tools to externalize what we know, including language and gesture. One tool that has been particularly transformative for human cognition and culture is graphical representation, which allows people to encode their thoughts in a visible, durable format. Drawing is an important case study in graphical representation, being a technique that dates back at least 40,000 years (Pike et al., 2012; Valladas et al., 1992), well before the emergence of symbolic writing systems (Clottes, 2008), and practiced in many cultures (Gombrich, 1989).

In modern times, drawings are produced prolifically by children from an early age (Kellogg, 1969), providing a rich source of potential insight into their understanding of the visual world. On the one hand, children quickly reach a remarkable degree of sophistication in forming abstract perceptual representations of the objects they frequently encounter, leveraging shape information (in conjunction with linguistic cues) to learn the composition of object categories (best citation here? (Landau, Smith, & Jones, 1988)). When presented with a target object to draw in which a prominent feature is occluded (e.g., the handle of a mug is turned away), children as young as 5 years of age frequently include the occluded object part in their drawing anyway, demonstrating the robustness of their internal representation to variation in viewpoint (Davis, 1983).

Meanwhile, important developmental changes in perceptual processing continue throughout childhood (for reviews, see Nishimura, Scherf, & Behrmann (2009); Juttner, Wakui, Petters, & Davidoff (2016)). The ability to process the relationship between objects' parts has a protracted developmental trajectory: For example, young children have a bias to categorize novel objects on the basis of part-specific information, older children rely more on the relationship between the object parts (Mash, 2006); and even older children have difficulty detecting changes in the proportions of an object's parts in familiar categories (i.e., animals; (Davidoff & Roberson, 2002; Juttner, Petters, Wakui, & Davidoff, 2014; Juttner, Wakui, Petters, Kaur, & Davidoff, 2013)). This is resonant with evidence from the drawings they make: drawings by children between 4-8 years of age reveal rapid changes in how they encode semantically relevant information in their drawings: younger children tend to include fewer cues in their drawings to differentiate between target concepts (e.g., adult vs. child) than older children, who enrich their drawings with more diagnostic part (Sitton & Light, 1992) or relational (Light & Simmons, 1983) information, especially when they know their goal is to make their drawings recognizable to someone else.

Figurative drawing tasks have long provided inspiration for scientists investigating the representation of object concepts in early life (Minsky & Papert, 1972). However, a major barrier to understanding has been the lack of principled, quantitative measures of high-level semantic information in drawings. As such, previous studies employing drawing tasks have typically relied on qualitative assessments (Karmiloff-Smith, 1990; Kosslyn, Heldmeyer, & Locklear, 1977), ad hoc quantitative criteria (Davis, 1983), and/or quantitative measures of low-level visual properties, such as pixel distance and area (Perdreau & Cavanagh, 2014; Tchalenko, 2009).

Recent work leveraging recent advances in computational vision has validated the use of deep convolutional neural network models, pre-optimized to recognize objects in natural images, to quantitatively measure semantic information in adult drawings (Fan, Yamins, & Turk-Browne, 2015). This work found that these models, despite never having been trained explicitly on drawings, succeeded in recognizing them, suggesting that a common feature basis may serve both the formation of robust object recognition based on natural visual inputs and the production of recognizable drawings. Moreover, higher layers of these models capture adult perceptual judgments of shape similarity (Kubilius, Bracci, & Beeck, 2016), providing further evidence that features learned by these models provide a strong high-level perceptual feature basis for extracting semantic information, including object identity.

Here we examine children's drawings as a window into how they represent familiar visual object categories, and how this representation changes across childhood. We ask children to draw a variety of object categories on a digital tablet. Then, we examine if children produce more recognizable drawings as they get older, after factoring out low-level covariates related to motor production, such as how long they spend drawing and how many strokes they use. Second, we compare the perceptual features of child and adult drawings by comparing their representations in a pre-trained deep convolutional neural network model, allowing us to visualize the representational layout of object categories across age groups using a common feature basis.

Part 1: Adult recognition of children's drawings

How do children's ability to convey semantic information in their drawings change across childhood? First, children (ages 3-10 years) produced drawings of 16 common object categories in a simple drawing game. Then, other participants (nave adults) attempted to recognize these drawings in a forced-choice recognition task.

Methods

Participants For the drawing task, children (N = 41, M = 6.9 years, range 4-10 years) were recruited at the San Jose Children's Discovery Museum. Children or their parents told the experimenter their age (in years) and this information was saved with their drawings. For the recognizability experiment, 14 adults with US IP addresses were recruited from Amazon Mechanical Turk and rated all of the 268 drawings.

Materials We implemented a simple drawing game in HTML/Javascript using the paper.js library; this web-based experiment was run on an iPad on the floor of the museum. All code is available at www.github.com/brialorelle/kiddraw.

Drawing Game Procedure On each trial, a text cue would appear (i.e., "Can you draw a [flower]?") that the experimenter would read out, ("What about a [flower]? Can you draw a [flower]?). Then, a drawing canvas appeared (600 x 600 pixels) and children had 30 seconds to make a drawing before the game moved on to the next trial; pilot testing suggested that 30 seconds was enough for many children to complete their drawings, and we aimed to collect a large number of drawings of object categories (rather than expert drawings of only a few object categories). Afterwards, the experimenter asked the child whether they wanted to keep drawing or whether they were all done. On the first two trials of the experiment, every child was prompted to draw the same two common shapes—-a circle and a triangle. These trials served to familiarize children with the drawing task and to practice using their fingers to draw.

Stimuli Stimuli were words referring to 16 common object categories (banana, boat, car, carrot, cat, chair, couch, cup, flower, foot, frog, ice cream, phone, rabbit, shoe, train). These categories were chosen such that they were (1) likely to be familiar to children, and (2) spanned the animate/inanimate distinction and (4) intuitively spanned a wide range of difficulty (for example, flowers seem easier to draw than couches). We also choose items that were present in the Google QuickDraw database (a large database of adults drawings made in under 20 seconds) so that we could eventually compare children and adult drawings.

Recognizability Task 14 nave adults assessed the recognizability of all of the 286 drawings produced by these children. On each trial, participants saw a drawing, and were asked "What does this look like?", and responded by typing into a text box; participants could then choose between 21 possible answers. 16 of these possible answers were the original object categories; however, we also included five additional foil items (bean, arm, person, rock, and "cannot tell at all"). These additional foils were designed to be relatively general (e.g., rock, person, and cannot tell) and somewhat similar in shape to some of the original items (e.g., bean and bananas have similar shapes). All drawings were presented in a random order, and participants were not informed that these drawings were produced by children or the context in which they were produced. An answer was scored as "correct" if adults were able to correctly guess the object category that children were cued with.

Low-level covariates related to motor production. Our goal is to measure semantic information in children's drawings, but we anticipated that drawings may also vary along other dimensions more directly related to the motor production demands of the task, such as the amount of time spent drawing, the number of strokes used, and amount of ink (i.e., mean pixel intensity of sketch). See Figure 3.

GLMM procedure. We aimed to assess whether children's ability to produce recognizable drawings increased with age, independent of low-level covariates. To do so, we used a generalized logistic mixed effect model, with age (specified in years), drawing duration, amount of ink used, and number of strokes as fixed effects, and with random intercepts for each individual child drawer and object category. The dependent variable was whether the proportion of adults that recognized a given drawing. This was specified in the lme4 r package as: glmer(correct ~ scale(age) + scale(draw_duration) + scale(mean_intensity) + scale(num_strokes) +(1|session_id) + (1|category), family = "binomial").

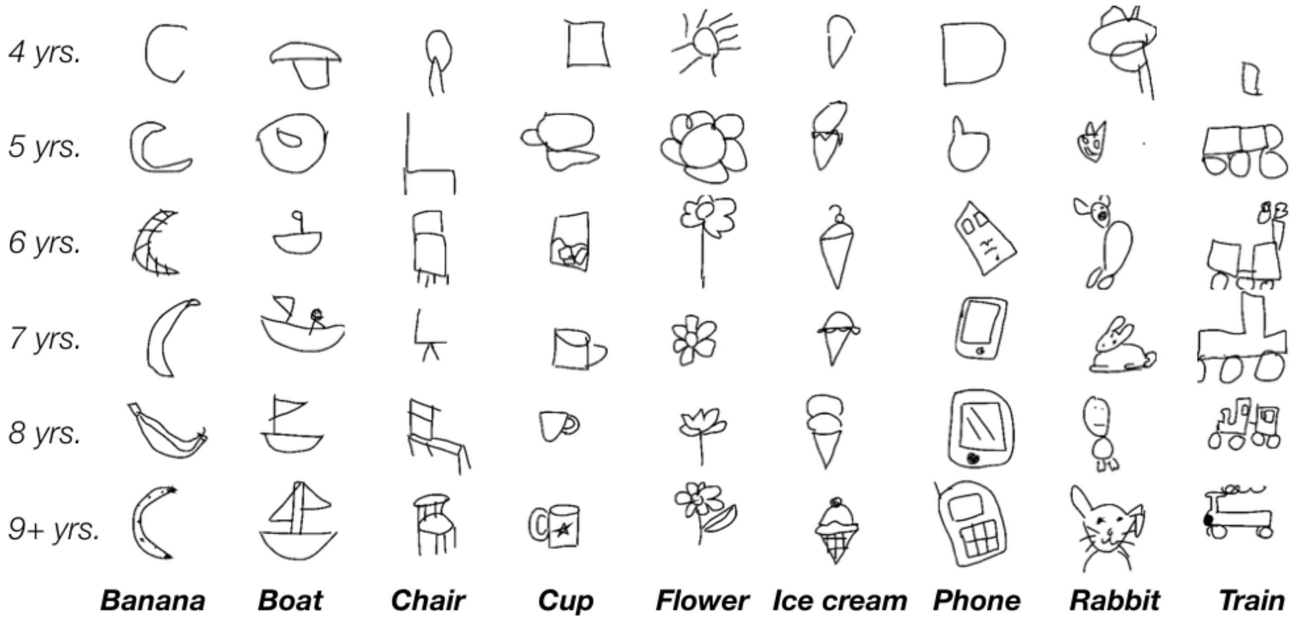

Figure 1: Example drawings made by children ages 4-10 of several object categories.

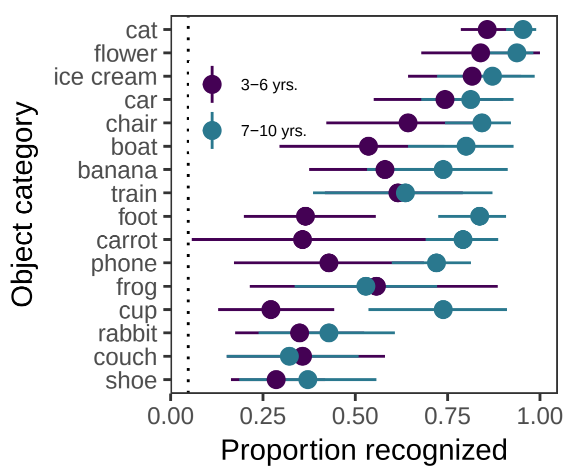

Figure 2: Proportion of drawings recognized in each object category. The dashed line represents chance performance. Error bars represent non-parametric 95 percent confidence intervals, estimated using the langcog r package.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.861	0.321	2.680	0.007
Age	0.956	0.174	5.497	0.000
Drawing time	0.338	0.109	3.105	0.002
Amount of ink	0.014	0.080	0.179	0.858
Num. strokes	-0.289	0.098	-2.959	0.003

Table 1: Model coefficients of a GLMM predicting the recognizability of each drawing.

Results

First, we observed that some items were much easier to draw than others. For example, children of all ages produced drawings of cats that were readily recognizable as “cats”, but few children of any age produced drawings that were recognizable as “shoes” (see Figure 2). However, almost all items also saw an increase in recognizability with the age of the drawer. Across all items, the proportion of drawings recognized increased steadily with age (see Figure 3).

Next, we asked whether this relationship persisted when we controlled for low-level covariates: the number of strokes, amount of ink used, and the time spent drawing. In other words, is this increase in recognizability due to an increase in expressive power, or simply due to the fact that older children may have put more effort into their drawings? Our generalized logistic mixed-effect model revealed that the recognizability of drawings increased reliably when controlling for these low-level covariates — the amount of time spent drawing, the number of strokes, and total ink used ($b = 0.96$, $SE = 0.17$, $Z = 5.5$), and accounting for variation across object categories and individual children. All model coefficients can be seen in Table 1. Adding interaction terms between age and these low-level covariates did little to decrease the effect of age on recognizability ($b = 0.94$, $SE = 0.18$, $Z = 5.4$).

Thus, these results suggest that the ability to quickly produce graphical representations of object categories increases with age, controlling for low-level covariates related to motor production.

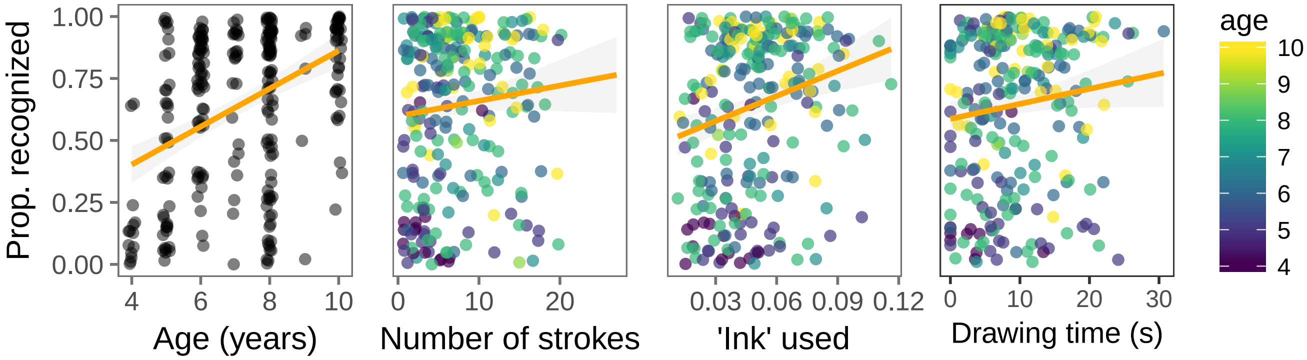

Figure 3: The proportion of adults who recognized each drawing is plotted as a function of child's age, the number of strokes, amount of ink used, and the time spent creating each drawing. Each dot represents an individual drawing; dots in the right three plots are colored by the age of the drawer.

Part 2: Model-based feature analyses of children's drawings

While younger children often produced drawings that were unrecognizable at the basic-level, these recognizability ratings may underestimate the perceptual content depicted in children's drawings. For example, children may not be able to depict the visual differences between a bunny and a frog, but they still may capture many of the essential perceptual features needed to depict an animal. Here, we turn to deep neural network models of object recognition to quantify the similarities between children's and adults drawings. While the earliest layers of this network tend to capture similarities in low-level features (e.g., spatial frequency, edges), intermediate and higher layers tend to capture similarities in mid- to high-level visual features, including overall object shape and the presence of diagnostic object parts (e.g., legs, handles) (Gucclu & Gerven, 2015) and predict neural responses in object-selective cortex (Gucclu & Gerven, 2015; Yamins et al., 2014).

We thus examine the feature similarity between children and adult's drawings at each layer of a deep convolutional neural network optimized for object recognition–called VGG-19 (Simonyan & Zisserman, 2014). Prior work has found that adults drawings of objects tend to be the most similar to photos of these objects in terms of higher-level layers of deep CNNs (Fan et al., 2015). Thus, if children's drawings also exhibit high-level perceptual similarities to adults' drawings, then we should expect feature similarity to reach a peak in later, higher layers of the network. However, if children's drawings do not contain these more diagnostic features, then we might expect similarity to peak in earlier convolutional layers. We perform these analyses separately for two age groups, roughly "young children" (ages 3-6) and "older children" (ages 7-10).

Methods

Stimuli For this analyses, we collected a larger sample of drawings using the same methodology, this time sampling from both the previously used categories as well as a new selection of 22 categories (see Stimuli) allowing us to span superordinate category distinctions and to include equal numbers of vehicles, furniture, small objects, food items, mammals, and non-mammals (new items: airplane, bus, bike, piano, table, door, bed, fork, keys, hat, apple, cookie, mushroom, horse, dog, sheep, bear, fish, bird, spider, shark, duck); this wider category structure has often be used to compare object category representations using deep convolutional neural networks (Kriegeskorte, Mur, & Bandettini, 2008; Yamins et al., 2014).

Participants Participants included those who participated in the first round of data collection, used in Experiment 1, as well as an additional 37 children, again recruited from the floor of the San Jose Children's Discovery Museum. Overall, this yielded an additional 98 drawings (excluding practice trials) for a total of 387 drawings. For the subsequent analyses, we binned children's age coarsely into "younger children" (aged 3-6 years) and "older" children (aged 7-10 years) and restricted analyses to categories where we had at least 3 drawings per age group (16 categories); this allowed us to analyze approximately the same number of drawings in each age group (younger children, N=118 drawings; older children, N=161 drawings). By including a minimum number of drawings per class and age category, we ensured robust estimates in the following analyses.

Adult drawings We obtained a sample of adult drawings from the Google QuickDraw database. Specifically, we randomly sampled 100 drawings from each object category, irrespective of any information about the adult drawer or the quality of the drawing. See `https://quickdraw.withgoogle.com/data` for visualizations of this dataset.

Convolutional Neural Network (CNN) Features We used a standard, pre-trained implementation of VGG-19 (Simonyan & Zisserman, 2014) to extract features in response to all sketches at each layer of the network, including the first five convolutional layers (C1-C5) as well as the two fully-connected layers (FC6 and FC7). Features were normalized within each layer across all sketches and then averaged within each category (e.g., "cat", "rabbit"). This yielded a vector corresponding to the number of features in each layer for all 38 of the drawn categories in younger children, older children, and adults.

Representational Similarity Analyses Representational similarity analysis treats each feature in VGG-19 as a dimension in a high-dimensional space and uses these values to compute the representational distances between images. Separately for drawings from younger children, older children, and adults, we averaged the feature vectors within each object class for a given layer of VGG and then computed a layer-specific matrix of the Pearson correlation distances between these average vectors across classes (Kriegeskorte et al., 2008). Formally, this entailed computing:

$$RDM(R)_{ij} = 1 - \frac{cov(\vec{r}_i, \vec{r}_j)}{\sqrt{var(\vec{r}_i) \cdot var(\vec{r}_j)}}$$

, where $\vec{r}_i$ and $\vec{r}_j$ are the mean feature vectors for the ith and jth object classes, respectively, where R represents the correlation betwen two classes (e.g., rabbits and shoes). Each of these 16x16 representational dissimilarity matrices (RDMs, shown in Figure 4) provides a compact description of the layout of objects in the high-dimensional feature space inherent to each layer of the model. Following Kriegeskorte et al. (2008), we measured the similarity between object representations in different layers by computing the Spearman rank correlations between the RDMs for those corresponding layers. Finally, we computed a noise ceiling by performed the above similarity computations between two randomly sampled subsets of adult drawings that matched the number of drawings children made in each object category; this allowed us to estimate the maximum correlations we expect to observe given the number of drawings we analyze.

Estimates of standard error for the Spearman correlation between RDMs (i.e., between domains or between layers) were generated by jackknife resampling of the 16 object classes. This estimate of standard error allows us to construct 95% confidence intervals and compute two-sided p-values for specific comparisons (Efron, 1979; Tukey, 1958). This entails iterating through each of the 16 subsamples that exclude a single class, computing the correlation on each iteration, then aggregating these values. Specifically, the jackknife estimate of the standard error can be computed as: $s.e._{(jackknife)} = \sqrt{\frac{n-1}{n}\sum_{i=1}^{n}(\bar{x}_i - \bar{x}_{(.)})^2}$, where $\bar{x}_i$ is the correlation based on leaving out the ith object class and $\bar{x}_{(.)} = \frac{1}{n}\sum_i^n \bar{x}_i$, the mean correlation across all subsamples (of size 15).

Category classification analyses Model features were also used to train softmax classifiers (`http://scikit-learn.org/`) with L2 regularization to evaluate the degree to which category information was linearly accessible from sketches made by each group of participants. Predictions are then made for images held out from the training set, and accuracy is assessed on these held-out images. The robustness of classifier accuracy scores was determined using stratified 5-fold cross validation on 80% train/20% test class-balanced splits.

Results

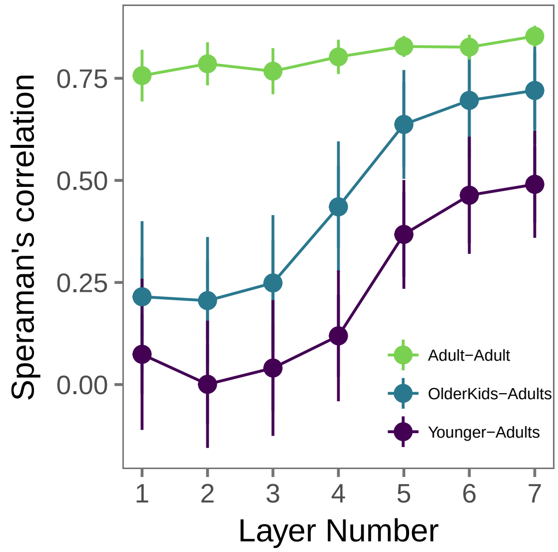

Figure 5: Spearman's correlation between representational dissimilarity matrices (RDMs) of drawings produced by adults vs. other adults, adults vs. older children, and between adults vs. younger children at each layer of VGG-19. Error bars represent standard error of the mean obtained by a jacknife re-sampling procedure (see Methods).

Layer-wise feature similarity We first examined the featural similarities between sketches produced by adults and children at each layer of VGG-19. Overall, we found that the similarity between older children and adults' drawings increased in each subsequent layer of the network, reaching a peak in the final layers of the network (see Figure 5). For younger children, we found a similar pattern of results, though similarity to adult drawings was overall lower. The RDMs for the final layer of the network (where similarity was the highest; FC7) are shown in Figure 4 for younger children, older children, and adults. Similarity between adult and children's drawings was lowest in the lower layers of the network, while adults drawings were quite similar across even in lower layers of the network. We speculate that this may be because children's drawings are more variable that adult drawings, leading to dissimilar low-level perceptual representations.

Classification results We examined the degree to which these featural representations could be used to classify these sketches at the basic-level. We found that sketches made by younger children were classifiable 35% of the time (SD=5%), while those made by older children (7-10 years) were classifiable 51% of the time (SD=6%). While the overall performance of the classified is relatively low compared to the human performance seen in Part 1, we still observed a relative increase in recognizability between younger and older chil-

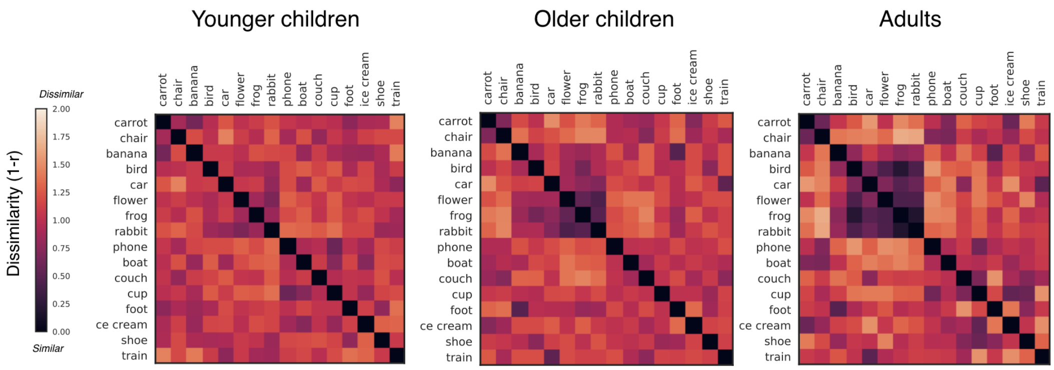

Figure 4: Representational dissimilarity matrices (RDMs) in the highest layer of VGG-19 (FC7) for drawings made by younger children (3-6 years of age), older children (7-10 years of age), and adults (Google QuickDraw database). Each square in one of these matrices represents the correlation distance between two categories (e.g., chair and couch) in this layer of the network; lighter colors indicate pairs of categories that generated dissimilar feature representations; darker colors indicate pairs of categories that generated more similar feature representations. Categories are grouped to reveal the inherent similarity structure.

dren. Thus, these results suggest that the difference in recognizability of the sketches stems directly from a differences in perceptual features that can be detected by a deep convolutional neural network trained to recognize objects. Taken together, these results suggest that children and adults are accessing somewhat similar category representations when asked to "draw a chair", and that these representations manifest in perceptual similarities in children and adults' drawings.

General Discussion

How do children's drawings change throughout childhood? We found that the capacity to quickly produce drawings that communicate object category information improves with age. Older children (and children who took longer to draw) produced drawings that were more recognizable to adults. Further, children's drawings were most similar to adult drawings in the higher-level layers of a deep convolutional neural network trained to recognize objects, suggesting that children and adults drawings share some the perceptual features useful for object recognition.

These findings are a first step towards a larger project. Ultimately, we seek to understand how changes in children's drawings reflect changes in internal representations of object categories. Throughout childhood, children continually experience different object categories, and this experience likely helps build more detailed internal representations of the categories. Thus, one possibility is that children's internal representations of objects are becoming more detailed as they grow older. A second possibility is that the similarity structure of children's internal object representations is changing. As children learn about the hierarchical structure of object categories (i.e., living thing–animal–mammal–dog) and their typical properties (e.g., all mammals have four legs) this might differentially change which visual features take precedence in their internal representations. Future work that links childrens' categorization abilities with drawing behaviors will help to adjudicate between these possibilities.

However, a first obvious future direction concerns how children's fine motor control influences their drawings. Here, we found that recognizability still increased with age even controlling for the overall time spent drawing and the number of strokes children used. Nonetheless, these measures only partially estimate children's motor control abilities. In future work, we will also measure children's ability to perform orthogonal fine motor tasks (e.g., tracing a complex shape) to further explore the contribution of motoric development to drawing behaviors.

Together, this work integrates novel methods to investigate children's internal representations of object categories and how they are linked to their developing perceptual, cognitive, and motor abilities. We propose that a full understanding of how we come to produce visual abstractions will help uncover the primary factors that shape how we represent our adult object representations.

Acknowledgements

We thank Jacqueline Quirke for help with piloting and data collection. We thank members of Stanford Language and Cognition lab. This work was partially funded by an NSF SPRF-FR (1714726) grant to BLL. We also gratefully acknowledge those who made the Google QuickDraw database avaliable.

References

Clottes, J. (2008). *Cave art*. Phaidon London.

Davidoff, J., & Roberson, D. (2002). Development of animal recognition: A difference between parts and wholes. *Journal of Experimental Child Psychology*, *81*(3), 217–234.

Davis, A. M. (1983). Contextual sensitivity in young children's drawings. *Journal of Experimental Child Psychology*, *35*(3), 478–486.

Efron, B. (1979). 1977 Rietz Lecture - Bootstrap Methods - Another Look at the Jackknife. *Annals of Statistics*, *7*(1), 1–26.

Fan, J. E., Yamins, D., & Turk-Browne, N. B. (2015). Common object representations for visual recognition and production. In *CogSci*.

Gombrich, E. (1989). *The story of art*. Phaidon Press, Ltd.

Gucclu, U., & Gerven, M. A. van. (2015). Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. *Journal of Neuroscience*, *35*(27), 10005–10014.

Juttner, M., Petters, D., Wakui, E., & Davidoff, J. (2014). Late development of metric part-relational processing in object recognition. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(4), 1718.

Juttner, M., Wakui, E., Petters, D., & Davidoff, J. (2016). Developmental commonalities between object and face recognition in adolescence. *Frontiers in Psychology*, *7*.

Juttner, M., Wakui, E., Petters, D., Kaur, S., & Davidoff, J. (2013). Developmental trajectories of part-based and configural object recognition in adolescence. *Developmental Psychology*, *49*(1), 161.

Karmiloff-Smith, A. (1990). Constraints on representational change: Evidence from children's drawing. *Cognition*, *34*(1), 57–83.

Kellogg, R. (1969). *Analyzing children's art*. National Press Books Palo Alto, CA.

Kosslyn, S. M., Heldmeyer, K. H., & Locklear, E. P. (1977). Children's drawings as data about internal representations. *Journal of Experimental Child Psychology*, *23*(2), 191–211.

Kriegeskorte, N., Mur, M., & Bandettini, P. (2008). Representational similarity analysis–connecting the branches of systems neuroscience. *Frontiers in Systems Neuroscience*, *2*.

Kubilius, J., Bracci, S., & Beeck, H. P. O. de. (2016). Deep neural networks as a computational model for human shape sensitivity. *PLoS Computational Biology*, *12*(4), e1004896.

Landau, B., Smith, L. B., & Jones, S. S. (1988). The importance of shape in early lexical learning. *Cognitive Development*, *3*(3), 299–321.

Light, P., & Simmons, B. (1983). The effects of a communication task upon the representation of depth relationships in young children's drawings. *Journal of Experimental Child Psychology*, *35*(1), 81–92.

Mash, C. (2006). Multidimensional shape similarity in the development of visual object classification. *Journal of Experimental Child Psychology*, *95*(2), 128–152.

Minsky, M., & Papert, S. A. (1972). Artificial intelligence progress report.

Nishimura, M., Scherf, S., & Behrmann, M. (2009). Development of object recognition in humans. *F1000 Biology Reports*, *1*.

Perdreau, F., & Cavanagh, P. (2014). Drawing skill is related to the efficiency of encoding object structure. *I-Perception*.

Pike, A. W., Hoffmann, D. L., Garcia-Diez, M., Pettitt, P. B., Alcolea, J., De Balbin, R., … others. (2012). U-series dating of paleolithic art in 11 caves in spain. *Science*, *336*(6087), 1409–1413.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *ArXiv Preprint ArXiv:1409.1556*.

Sitton, R., & Light, P. (1992). Drawing to differentiate: Flexibility in young children's human figure drawings. *British Journal of Developmental Psychology*, *10*(1), 25–33.

Tchalenko, J. (2009). Segmentation and accuracy in copying and drawing: Experts and beginners. *Vision Research*.

Tukey, J. W. (1958). Bias and confidence in not-quite large samples. *Annals of Mathematical Statistics*.

Valladas, H., Cachier, H., Maurice, P., Quirost, F. B. de, Clottes, J., Valdes, V. C., … Arnold, M. (1992). Direct radiocarbon dates for prehistoric paintings at the altamira, el castillo and niaux caves. *Nature*, *357*(6373), 68.

Yamins, D., Hong, H., Cadieu, C. F., Solomon, E. A., Seibert, D., & DiCarlo, J. J. (2014). Performance-optimized hierarchical models predict neural responses in higher visual cortex. *Proceedings of the National Academy of Sciences*, *111*(23), 8619–8624.