Drawings as a window into object representations in childhood

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Abstract

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Keywords: object representations; drawings; child development

Introduction

(Newell & Simon, 1972)

Consider what one has to do in order to draw "a phone" – one needs to access a the mental representation of "a phone", distill this into a pictoral format, and plan a sequence of motor actions to effectively convey this visual concept. Yet this is a trivial task for ordinary adults. How do we learn to so effectively produce recognizable drawings? And might drawings offer a window into how young children represent common object categories?

While drawing has been extensively studied in early childhood, a primary focus has been on when children come to treat drawings as symbols for object categories (Gardner, 1973). And a wealth of evidence now suggests that in fact young children attribute rich meanings to their drawings. For example, children will attribute different symbolic content (e.g., "a balloon", "a lollipop") to very similar drawings based on what they intended to draw (Bloom & Markson, 1998). Further, children will monitor whether their drawings are adequate symbols for the things they are trying to draw, and will improve their drawings when given feedback that their drawings are not effective at communicating the identity of object (Callagan, 1999).

Far less research, however, has examined how children's drawings reflect how children represent objects in the world around them. Indeed, drawings are a powerful way to tap internal representations of object categories, even in non-expert adults. For example, adults tend to draw objects that are small in the real-world at small visual sizes, and objects that are big in the real-world at big visual sizes (Konkle & Oliva, 2011). Further, to be recognizable, drawings have to depict the necessary features to express a given visual concept. This intuition is supported by recent computational work: deep neural network models of the ventral stream trained purely on photographs can also recognize drawings by non-expert adults, as drawings and photographs generated similar representations in higher-level layers of these models. In other words, drawings capture high-level similarity relationships between object categories (Fan, Yamins, & Turk-Browne, 2015).

Here, we explore how children draw common object categories across early childhood. First, we ask if children produce more recognizable drawings as they get older after factoring out low-level covariates (e.g., the number of strokes, ink used). Second, we examine the degree to which children's drawings contain the perceptual features characteristic of common object categories by comparing their representations in a deep convolutional neural network.

Part 1: How recognizable are drawings across childhood?

First, we examined how children across a wide range of ages produced drawings of 16 common object categories in a simple drawing game. Then, we asked nave adults to recognize these drawings using 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 and participated in this experiment. For the recognizability experiment, 14 adults with US IP addresses were recruited 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/museumdraw.

Drawing Game Procedure: On each trial, a text cue would appear (i.e., "Can you draw a [dog]?") that the experimenter would read out, ("What about a [dog]? Can you draw a [dog]?). Then, a drawing canvas appeared (600 x 600 pixels) and children were had 30 seconds to make a drawing before the game moved on to the next trial. After each trial, 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, (2) present in the Google QuickDraw database, (3) spanned the animate/inanimate distinction and (4) intuitively spanned a wide range of difficulty (for example, flowers seem easier to draw than couches).

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”). 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.

Load data and do basic preprocessing.

```
[1] TRUE
```

Number of drawings: 286
Number of drawers: 41
Average age of drawers: 6.9

Analysis

Low-level covariates. The use of a digital interface for drawing allowed us to quickly and easily assess the contribution of several low-level factors that may co-vary with drawing ability. For each drawing, we thus quantified the amount of time spend drawings, the number of strokes used, and the overall intensity (e.g., amount of ink). These factors were entered into the generalized logistic mixed-effect model referenced below.

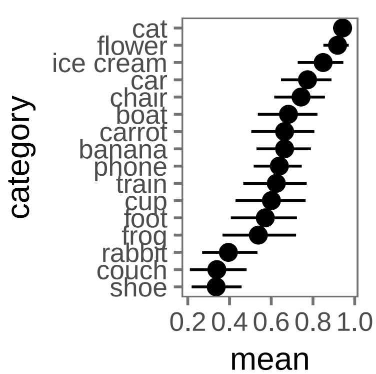

Figure 2: R plot

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 the following parameters:

Estimate Std. Error z value Pr(¿—z—) ———— ——— ———— ——— ——— (Intercept) -2.977 0.755 -3.941 0 age 0.538 0.099 5.427 0

Results

Overall, we found that the recognizability of children’s drawings increases with the age of the drawer. This can be seen qualitatively in a set of example drawings in Figure 2, is quantified in Figures 3 and 4. This relationship persisted even when we accounted for the influence of several low-level covariates, including the amount of time spent drawing, the number of strokes used, and the total “ink” used (“‘{r} stats). Interestingly, this relationship held despite the presence of some items in the dataset that were extremely easy for children to draw (e.g., flowers; see Figure XX) and some items that were quite difficult to depict (e.g., couch).

These results also suggest that the ability to produce visual concepts is highly developed by middle childhood. In under 30 seconds, even 6-year-olds produced drawings that were on average %% recognizable in our 21AFC task.

Part 2: Perceptual features of children’s drawings across childhood

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. Indeed, this trend was somewhat evident in the confusion matrices from beforehand: drawings of cats were most confused with frogs and bunnies (and not couches or chairs). Here, we turn to deep neural network models of object recognition to quantify the perceptual features in children’s drawings.

Here, we aimed to collect 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 broadly span superordinate category distinctions. With this broader sample of drawings, we asked the following questions

One-column images

Single column is the default option, but if you want set it explicitly, set `fig.env` to `figure`. Notice that the `num.cols` option for the caption width is set to `1`.

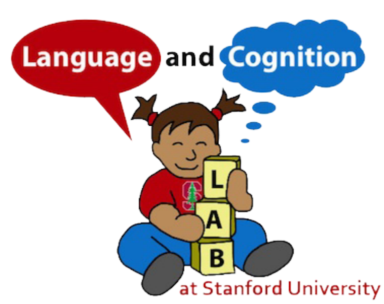

Figure 3: One column image.

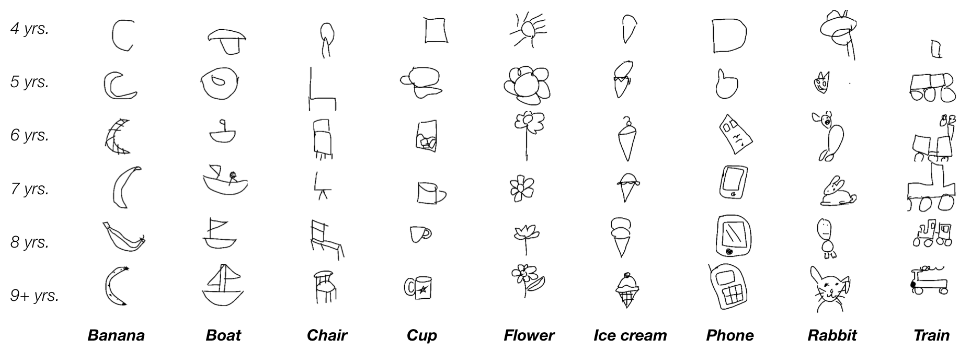

Figure 1: This image spans both columns. And the caption text is limited to 0.8 of the width of the document.

R Plots

You can use R chunks directly to plot graphs. And you can use latex floats in the fig.pos chunk option to have more control over the location of your plot on the page. For more information on latex placement specifiers see **here**

Tables

Number tables consecutively; place the table number and title (in 10 point) above the table with one line space above the caption and one line space below it, as in Table 1. You may float tables to the top or bottom of a column, set wide tables across both columns.

You can use the xtable function in the xtable package.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.04	0.10	0.4	0.66
x	1.95	0.11	18.4	0.00

Table 1: This table prints across one column.

Acknowledgements

Place acknowledgments (including funding information) in a section at the end of the paper.

References

Newell, A., & Simon, H. A. (1972). *Human problem solving*. Englewood Cliffs, NJ: Prentice-Hall.