An Egocentric Perspective on Active Vision and Visual Object Learning in Toddlers

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***Abstract*—Toddlers quickly learn to recognize thousands of everyday objects despite the seemingly suboptimal training conditions of a visually cluttered world. One reason for this success may be that toddlers do not just passively perceive visual information, but actively explore and manipulate objects around them. The work in this paper is based on the idea that active viewing and exploration creates "clean" egocentric scenes that serve as high-quality training data for the visual system. We tested this idea by collecting first-person video data of free toy play between toddler-parent pairs. We use the raw frames from this data, weakly annotated with toy object labels, to train state-of-the-art machine learning models for object recognition (Convolutional Neural Networks, or CNNs). We run several training simulations, varying quantity and quality of the training data. Our results show that scenes captured by parents and toddlers have different properties, and that toddler scenes lead to models that learn more robust visual representations of the toy objects in them.**

I. Introduction

Visual object recognition is a fundamental skill, and even infants as young as 3-4 months are able to extract perceptual cues that allow categorical differentiations of visual stimuli [1], [2]. Two-year-old toddlers are easily able to recognize a variety of everyday objects, allowing them to rapidly learn word-to-object mappings [3] that build the developmental basis for more complex skills such as language learning. But how do toddlers become such efficient learners despite relying on visual input from an inherently cluttered and referentially ambiguous environment, where objects are encountered under seemingly sub-optimal conditions? Recent studies started using head-mounted cameras to approximately capture a toddler's visual experience, finding that the structure of a toddler's egocentric scene is profoundly different from that of an adult, even within the same context [4]. Toddlers tend to actively seek out one object of interest to manipulate, and (due to their small visuomotor workspace) create scenes that are visually dominated by that object [5]. As the success of any learning system depends on the quality of the input that it is trained on, the overall hypothesis in the present study is that toddlers naturally create visually "clean" training data that facilitates learning to visually recognize objects.

To test this idea, we use video data collected from head-mounted cameras of toddlers and parents jointly playing with a set of toy objects to train and compare different object recognition models. More specifically, we train Convolutional Neural Networks (CNNs), which are the current state-of-the-art for object recognition in the computer vision community [6], and are also increasingly used as "proxy models" by researchers who study human vision [7]. Our recent related work [8] using a similar paradigm has shown that CNNs benefit from the visually diverse object viewpoints that toddlers create through active manipulation of toys. However, these experiments relied on fully-supervised training based on cropped-out close-up images of toy objects, ignoring the context of how and where objects actually occurred in the toddler's field of view.

In contrast, the current study draws inspiration from recent insights into weakly-supervised CNN training for object localization [9]. We directly feed the raw frames of the entire first-person scenes to the neural network model and only use weak supervision of objects, thus better approximating the actual visual input of the toddler. This new paradigm allows us to study differences in the first-person data from toddlers and parents at the scene level, and introduces referential

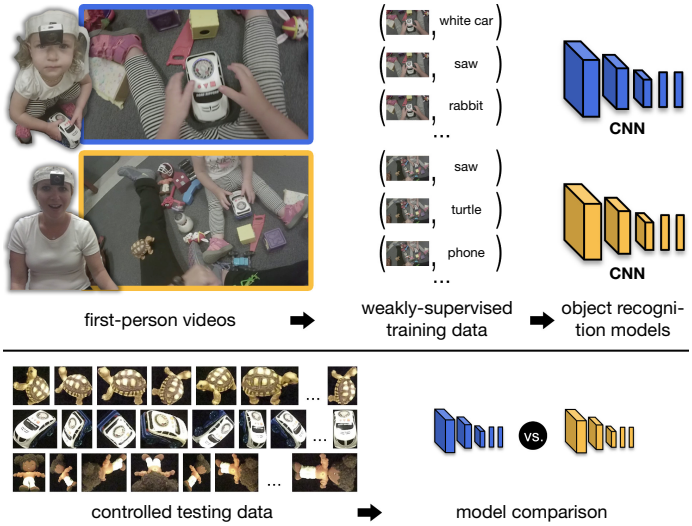


Fig. 1: *Overview of our experiments.* Using head-mounted cameras, we capture video data from toddlers and their parents during joint toy play. We use this data, weakly annotated with toy object labels, to train different object recognition models. We compare performance of models trained with toddlers versus parents using a separate, controlled test set.

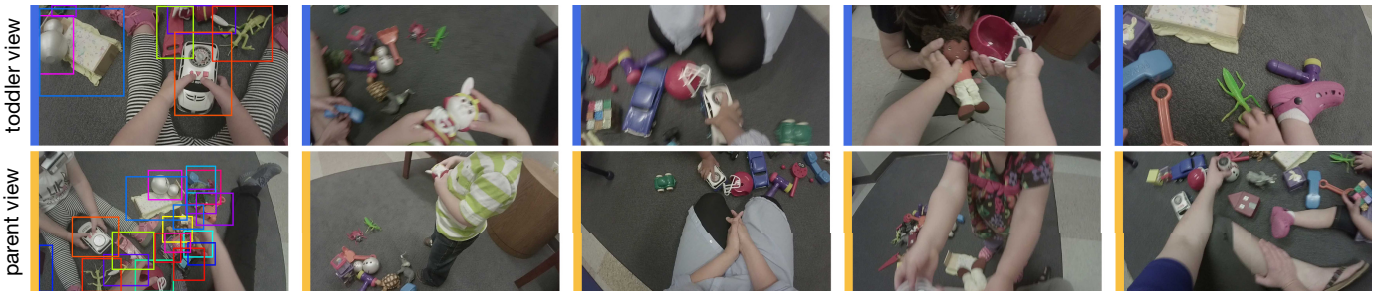


Fig. 2: *Sample first-person video frames* captured during joint toddler-parent toy play, contrasting toddler views (top) and parent views (bottom). Each column shows synchronized frames. The first column also depicts the bounding box annotations for each type of toy.

uncertainty between object labels and objects in view. Moreover, it allows us to investigate the trade-off between training data quantity (many relevant objects in the field-of-view) and quality (fewer, more dominant objects in view). Specifically, we manipulate quantity by annotating varying numbers of toys in view, and quality by annotating toys based on how large or how centered they appear in view. We compose a series of training simulations, finding that networks that were trained with toddler data sometimes drastically outperform their parent data counterparts, suggesting that toddlers create scenes that facilitate visual object recognition.

The rest of the paper is structured as follows: Section II introduces the datasets that were used in all of our experiments, and Section III reviews statistics of the first-person dataset that are relevant for visual object learning. In Sections IV to VI we describe different CNN training simulations and discuss their results. We summarize and conclude our findings in Section VII.

II. Datasets

We use an existing dataset collected by our past related study [8] to test our hypothesis. This dataset consists of videos from head-mounted cameras that capture the first-person viewpoints of toddlers and parents jointly playing with a set of toys in a natural environment. It also includes a set of controlled close-up photographs of the same set of toys. We use the first-person viewpoints to train our CNN object models, and the controlled viewpoints to test their performance on an independent dataset.

We briefly summarize the datasets here; see [8] for details. For the first-person dataset, ten toddler-parent dyads (mean child age 22.6 months) were invited to engage in free-flowing play with a set of 24 toys (Figure 3) in a small lab outfitted as a play room. Each dyad was simply encouraged to play together and with the toys as they pleased. Parent and toddler both wore head-mounted cameras to capture an approximation of their respective fields of view (Figure 2). About 8 minutes of video data were collected per dyad. One frame every five seconds was then extracted from each video, producing a set of 1,914 frames (957 each from toddlers and parents). Objects were manually annotated in each image with a bounding box (Figure 2, first column), yielding a total of 9,646 toy instances in the toddler data, and 11,313 instances in the parent data.

The controlled dataset (Figure 3) consists of 128 close-up photos of each of the same 24 objects, photographed on a turntable: 64 photos from each combination of the eight 45° orientations about the vertical axis and eight 45° orientations about the axis of the camera center, and a cropped and uncropped version of each image.

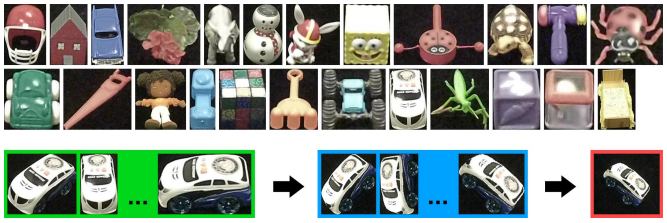


Fig. 3: *Sample images from the controlled test data.* To add viewpoint and scale variation, each toy was photographed from 8 different viewpoints (green), and then rotated 8 times (blue) and cropped at a lower zoom level (red).

III. Scene Statistics of the First-person Data

During joint play with a set of toys, toddlers and parents actively create many scenes within their self-selected fields of view. These scenes may contain toys in different quantities, scales, and levels of clutter (see Figure 2). From the perspective of a learning system that aims to build a stable visual representation of each type of toy, different scenes thus create different levels of ambiguity and difficulty. We are interested in whether the active viewing and visual exploration behavior of toddlers actually creates less ambiguous scenes and thus potentially higher quality data for visual object recognition. To substantiate this idea, we begin by studying different properties of toy objects in the fields of view (FOV) of toddlers and parents. While we already reported some of the scene-level properties in previous work [8], they are particularity important to review in the context of the current study.

A. Object Size

Scenes might be more informative if the objects of interest dominate. We approximate the actual size of a toy object with

the area of its bounding box, and measure the fraction of the field of view that is occupied by this box. Figure 4a contrasts the distributions of perceived object sizes between toddlers and parents. Toddlers create significantly larger object views with a mean size of 5.2% FOV versus 2.8% FOV for parents. For reference, the white car toy (orange bounding box) in the fist column of Figure 2 has a size of 13% FOV in the toddler view and 5% FOV in the parent view.

Even when only large objects are in view, there may be substantial referential ambiguity if all objects are roughly the same size. When toddlers actively select and manipulate toys, those toys should be visually dominant in comparison to the remaining toys in view. To examine this idea, we compute the fraction of the average size of the largest n toys in view over the average size of the remaining toys. As shown in Figure 4b, the relative size difference between large and small toys in view is consistently greater in the toddler data, suggesting that toddler scenes feature less ambiguity than parent scenes.

B. Object Centeredness

How centered an object appears within the field of view may also contribute to its visual importance considering the center-bias of eye gaze observed in head-mounted eye-tracking experiments [10]. To measure centeredness, we compute the distance from the center of an object bounding box to the center of the field of view. Figure 4c contrasts the distributions of object-to-center distances between toddlers and parents. We observe no significant difference (mean distance is 48.4% of the maximum possible distance for toddlers, 48.5% for parents), suggesting this is not actually a major differentiator between the views.

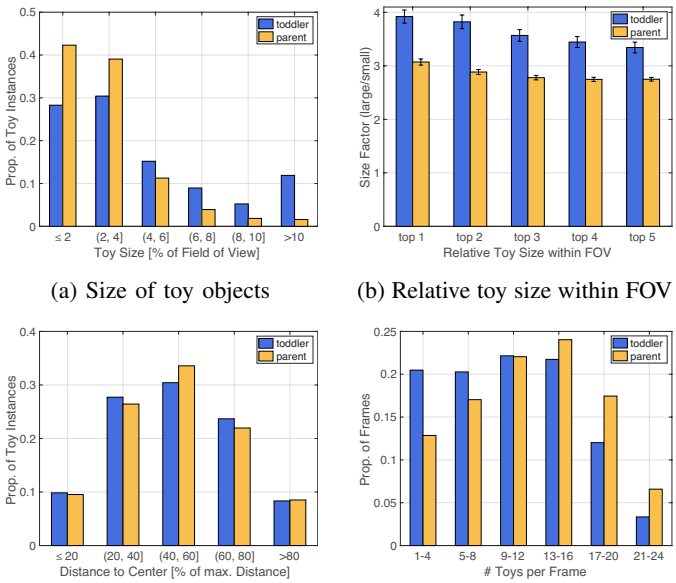
C. Number of Objects

Finally, the ambiguity of a scene also depends on how many objects appear in view at the same time. Figure 4d studies this, showing the number of objects that appear simultaneously in each frame. The results suggest that toddlers create scenes that contain significantly fewer toys in view compared to their parents (10.1 versus 11.8 on average). Moreover, the fraction of frames with a small number (fewer than 5) of objects is about 20% for toddlers but only 13% for parents. Conversely, parents are more likely to have almost all objects in view at once (24% with more than 16 objects for parents versus only 15% for infants).

IV. Object Recognition with Deep Networks

A. Fully-supervised Object Recognition with CNNs

In the computer vision literature, object recognition algorithms are usually trained and evaluated on datasets that contain a set of n predefined visual object classes [11]. As a result, most techniques use discriminative models that are trained to classify an image of an object into one of these (mutually exclusive) n classes, and each training image is assumed to contain an instance of exactly one class, and nothing else. State-of-the-art object recognition models like Convolutional Neural Networks (CNNs) explicitly encode this



(a) Size of toy objects

(b) Relative toy size within FOV

(c) Toy distance to FOV center

(d) Number of toys per frame

Fig. 4: *Toy object statistics of the first-person scenes.* A comparison of how toy objects appear in the fields of view of toddlers and parents, in terms of (a-b) object size, (c) object location in view, (d) number of objects in view.

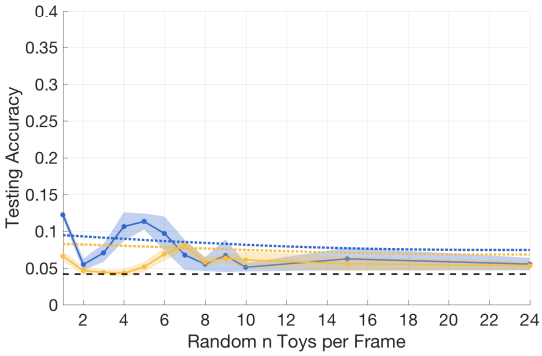
assumption into the loss function that is minimized during training. For example, the most common loss function for classification tasks is categorical cross-entropy, which encourages the network to output a probability distribution across classes that is very confident for exactly one class (low entropy) rather than multiple classes (high entropy).

B. Weakly-supervised Training with First-person Data

In the context of the naturalistic first-person data described in Sections II and III, the assumption that every scene contains exactly one object of one class is almost always violated: real-world scenes contain multiple objects, and the labeled object may not dominate the view. We are interested in studying (1) to what extend a standard CNN classifier (trained with crossentropy loss) can overcome these violations, and (2) differences between models that are trained with data collected by toddlers when compared to models trained on parent data.

Towards these goals, we run various simulations where we train multiple CNN models under different "weakly-supervised" conditions. In each condition we label a specific subset of the toys that are present in the field of view under the following paradigm: Starting from a frame f that contains k toy objects ($1 \leq k \leq 24$), we generate up to k training exemplars where each exemplar consists of a pair of the same (repeated) frame and the toy object label l, i.e. $(f, l_1), ..., (f, l_k)$. Only generating training exemplars based on a subset of the toys in each frame lets us manipulate the overall amount of training data, while choosing which of the toy objects to label potentially affects the quality of the training data.

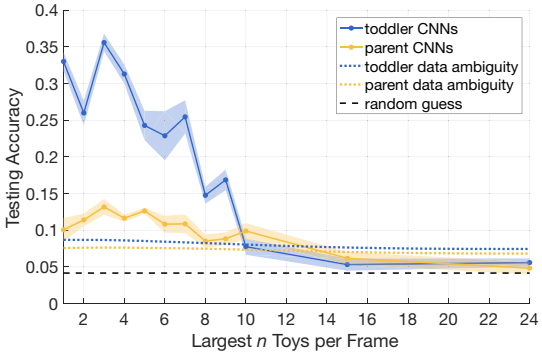
Since this paradigm creates simple image-label pairs, it



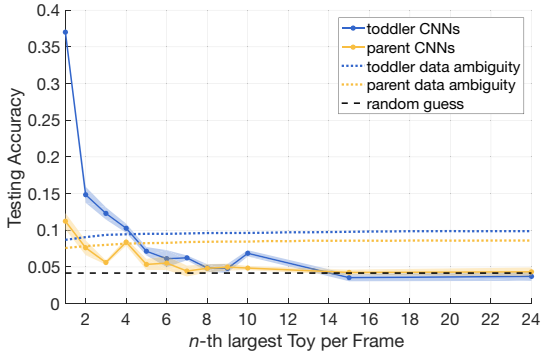
(a) Labeling n random objects per frame

top n	1	2	3	4	5	6	7	8	9	10	24
(a),(b),(c) # exemplars	917	1,794	2,632	3,430	4,191	4,905	5,582	6,207	6,774	7,285	9,646
	942	1,862	2,761	3,622	4,456	5,262	6,029	6,741	7,412	8,025	11,313
(b) avg. object size [%]	15.6	12.4	10.4	9.2	8.4	7.8	7.3	6.9	6.5	6.3	5.2
	7.1	5.9	5.2	4.7	4.4	4.1	3.9	3.7	3.5	3.4	2.8
(c) avg. object size [%]	10.2	8.7	7.8	7.3	6.9	6.6	6.3	6.1	6.0	5.8	5.2
	3.8	3.6	3.5	3.4	3.3	3.2	3.1	3.1	3.0	3.0	2.8
(b) avg. center distance [%]	38	41	43	44	45	46	47	47	47	48	48
	44	45	46	46	46	46	47	47	47	47	48
(c) avg. center distance [%]	20	25	29	32	34	37	38	40	42	43	48
	21	25	28	31	33	35	37	39	40	41	48

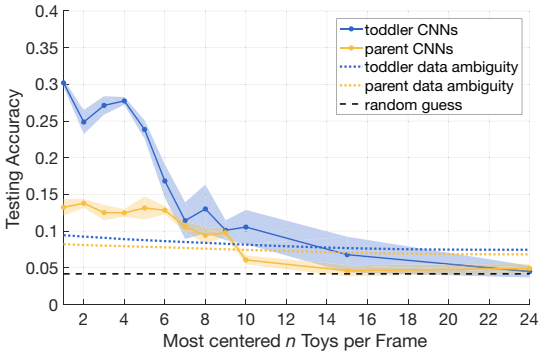
(d) Training data statistics



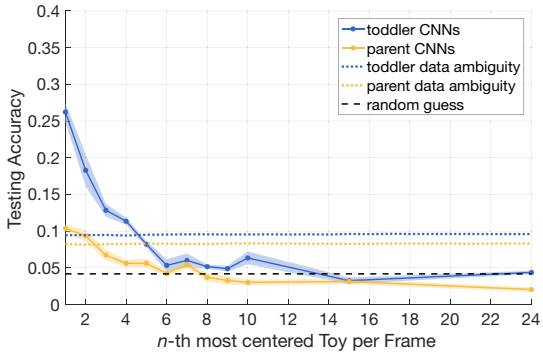
(b) Labeling the n largest toys per frame



(e) Labeling the n-th largest toy per frame



(c) Labeling the n most centered toys per frame



(f) Labeling the n-th most centered toy per frame

Fig. 5: *Object recognition accuracies for different training simulations.* (a-c, e-f) Solid lines depict the overall testing accuracy of CNN models based on the controlled test set of 24 toy objects. Every data point shows the average of five independently trained networks and the shaded areas depict the standard error. Dashed lines depict baselines. (d) Summary of the total number of training exemplars, the average size and average center distance of labeled objects across different training simulations.

allows us to train a discriminative CNN under the same conditions as described in Section IV-A. This is a difficult learning problem for two main reasons: (1) each training image shows the whole first-person view and is potentially referentially ambiguous with respect to the object label, and (2) part of the training data may even be contradictory since the model (falsely) assumes that each frame contains only one object.

Across all simulations, we train models using either the first-person data collected by toddlers, or the first-person data collected from parents, and compare their object classification accuracy on the controlled dataset of Section II.

C. Implementation Details

We use the well-established VGG16 [12] CNN architecture for all of our experiments. VGG16 has a fixed input layer of 224×224×3 neurons, which means we resize all frames to 224×224 pixels. This input layer is followed by 14 convolutional layers, 2 fully-connected layers, and the output layer. The convolutional layers are divided into 5 blocks and each

block is followed by a spatial max-pooling operation. All neurons have ReLU activation functions. A complete description of the architecture can be found in [12]. We adjust the output layer of the network to have 24 neurons to accommodate our 24-way object classification task. Following common protocol, we initialize the convolutional layers with weights pre-trained on the ImageNet dataset [11]. Each network is trained via backpropagation using batch-wise stochastic gradient descent and a categorical crossentropy loss function. The learning rate is 0.001, the momentum is 0.9, and the batch size is 64 images. We stop training each network after 20 epochs, after which the loss had converged consistently across different simulations.

V. Learning based on Frame-Specific Metrics

One basic question is whether CNNs can successfully learn object models from the first-person scenes at all. Since not all 24 toys occur simultaneously in every single frame, learning (in the sense of finding a mapping between toy objects and correct labels) should be possible in principle. Moreover, we expect the toddler data to be less ambiguous in that regard since the toddler scenes contain fewer toys on average. Recall that we create training data by generating up to k exemplars $((f, l_1), ..., (f, l_k))$ from a single frame f that contains k toys. Thus we can compute the probability that an exemplar is labeled as toy t given that it contains t, $P(l = t|t \in f)$ by simply computing the fraction of training images that are labeled as t over the training images that contain t. One can think of the average probability across all object classes as a measure that captures the referential ambiguity between labels and objects (assuming each object in a scene is equally likely to be labeled). This probability would be 1 for perfectly clean training data, and $\frac{1}{24}$ if the data is completely ambiguous. We report this measure in our results as an additional baseline.

A. Learning from random Toys in View

In our first simulation, we generate training data by simply labeling a random subset of the toys in each training frame. Figure 5a shows the testing accuracies (on the controlled dataset described in Section II) of different CNNs as a function of the number of annotated toys per frame. The blue solid line depicts accuracies based on CNNs trained only on the toddler data while the orange line is based on CNNs trained only on the parent data. As CNN training is non-deterministic, each data point shows the mean testing accuracy across five independently trained networks.

The results show that both parent and toddler networks can achieve above chance accuracies. Also in both cases, the accuracy tends to decrease as n is increased, i.e. as more toys per frame are labeled. This suggests that training with fewer overall training exemplars facilitates learning compared to training with more (but potentially contradictory) exemplars. Overall, the toddler networks indeed perform better than the parent networks. This difference may be caused by two different factors: (1) toddlers see fewer objects in view (as indicated by the different baselines), and (2) toddlers create larger views of objects. We further investigate the effect of object size in the next simulation.

B. Learning from the largest Toys in View

From a teaching perspective, labeling a random toy in view is perhaps not the most effective strategy. If the size of objects matters we should see better learning overall and better learning for toddler data in particular if we instead label the subset of the n largest toys in each scene. The results of this simulation are summarized in Figure 5b. Indeed, both parent and toddler networks now outperform their baselines, indicating that the models were more likely to associate object labels with larger objects in view.

Overall, the toddler networks now drastically outperform the parent networks (top accuracy of 36% versus 13%), which further supports the idea that larger objects facilitate learning. For reference, when labeling only the largest toy in each frame its average size is 15.6% FOV in the toddler data, but only 7.1% FOV in the parent data.

Since we generate labels based on object size, generating more training data does not only result in more contradictory exemplars, but also lower quality exemplars. Consequently, we observe a more drastic drop-off in accuracy as n increases.

C. Learning from the most centered Toys in View

A different reasonable teaching strategy is to label the n most centered toys in each scene. Figure 5c summarizes the results of this simulation. Again, both parent and toddler models outperform their baselines, indicating that they successfully learned that more centered toys in view are more likely to be labeled. There is a positive correlation between object size and centeredness (0.23 in the toddler data; 0.16 for parents), so object size may still have an effect. However, the most centered toy in each frame is on average much smaller than the largest toy (10.2% FOV for toddlers, 3.8% for parents), yet the networks achieve overall comparable accuracies.

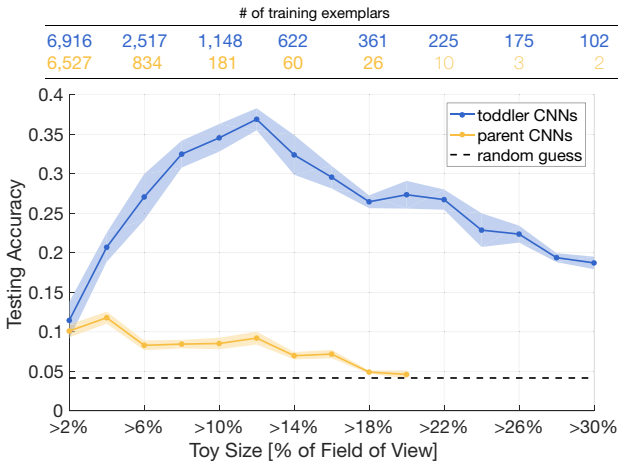


Fig. 6: *Object recognition accuracies* when only labeling toy objects with a minimum size. The table shows the total number of training exemplars for each condition.

Again, toddler networks drastically outperform parent networks. Since there is no significant difference in object centeredness across the datasets, this difference is still likely driven by the overall difference in object size.

D. Learning from Misleading Exemplars

Another insightful training approach is to only label the n-th largest (or most centered) toy object in each frame rather than the top n objects. This approach controls for the total number of training exemplars (as it is independent of n) and avoids contradictorily labeled exemplars. At the same time, if centeredness or size are important, then increasing n creates increasingly misleading exemplars.

Figures 5e and 5f show the simulation results of training with the n-th largest and n-th most centered objects respectively. In both cases, only toddler networks achieve results that are significantly above the baselines. Compared to the previous simulations, overall recognition accuracies decrease much more sharply as n increases, highlighting the effect of the misleading exemplars. This drop-off is most drastic for the toddler networks trained on the largest versus second-largest toys in view. This implies that having a very large "distractor object" in view is particularity detrimental for learning, further highlighting the importance of object size.

VI. Learning based on Absolute Metrics

The results presented in Section V suggest that toddlers create scenes that facilitate visual object learning primarily by bringing a few objects dominantly into the field of view. To measure the effect of object size more directly, we run another set of training simulations. This time, we only label objects of a certain minimum absolute size, regardless of their relative size to other objects in view. This creates another quality versus quantity trade-off since increasing the minimum object size results in fewer training exemplars.

Results are summarized in Figure 6. Object recognition accuracy increases with object size in the toddler data, reaching its peak when training with ~800 frames in which the target object covers at least 12% of the FOV. Interestingly, while there is a quality versus quantity trade-off, the overall accuracy remains relatively high, indicating that CNNs can build relatively robust object models from just a few high-quality exemplars. Parents on the other hand did not generate enough high-quality exemplars to learn robust object representations.

VII. Summary and Discussion

In this work we captured first-person video from toddlers and parents during free-flowing toy play, and used it to train CNN models to recognize those toys. This toy play paradigm was intentionally not designed to allow a well-controlled comparison of visual object learning between toddlers and parents (e.g. the toys are not novel and subjects are not instructed to learn to recognize them). Instead, our goal was to simulate a naturalistic scenario that captures how toddlers interact with objects in their day-to-day lives, with parents functioning as a reference. Our results show that toddlers, both as a result of their exploratory behavior and their small visuomotor workspace, naturally create visual scenes that are dominated by a small set of large objects. We believe that these naturally occurring statistics of the visual input are crucial towards toddlers' growing efficiency to recognize, distinguish, and ultimately learn to map words to objects. To support this idea, we demonstrated that a computational visual learning system (CNNs) can indeed benefit from such statistics.

Specifically, we showed that (1) CNNs could learn representations of the toy objects despite being trained only with raw frames from the first-person view, and (2) models trained with data from the toddlers' perspectives drastically outperformed parent-trained models in many conditions. These differences appear to be driven by toddlers centering objects dominantly in view and creating more diverse viewpoints of objects [8].

Acknowledgments

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