

Reverse-engineer the Distributional Structure of Infant Egocentric Views for Training Generalizable Image Classifiers

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Abstract

We analyze egocentric views of attended objects from infants. This paper shows 1) empirical evidence that children’s egocentric views have more diverse distributions compared to adults’ views, 2) we can computationally simulate the infants’ distribution, and 3) the distribution is beneficial for training more generalized image classifiers not only for infant egocentric vision but for third-person computer vision.

1. Introduction

Children are highly efficient learners, and better understanding how they succeed at visual learning could help build better machine learning and computer vision systems. Based on this ambitious motivation, we have a long-running project to apply egocentric vision for infants. The project has already provided many insights both for developmental psychology [4] and machine learning [1]. Other groups are also investigating similarly-motivated studies [2, 6], reflecting the increasing interest in the intersection of egocentric vision and infant learning.

To study infant visual learning in everyday environments, we have collected egocentric video and eye gaze tracking data from children and their parents as they freely play with 24 toy objects (Figure 1). The wearable cameras provides an approximation of the child’s field of view — the “training data” that they use to learn object models. We study the properties of this “training data,” for example using it to train CNNs. We find that deep networks trained from child views perform significantly better than parent counterparts recorded in exactly the same environment. We refer to our prior work [1] for more details.

This manuscript provides the latest findings from our project. 1) Egocentric images collected from children have a unique distributional property compared to adults. 2) We can computationally simulate image classification datasets with the child-like distributional property. 3) Image classification

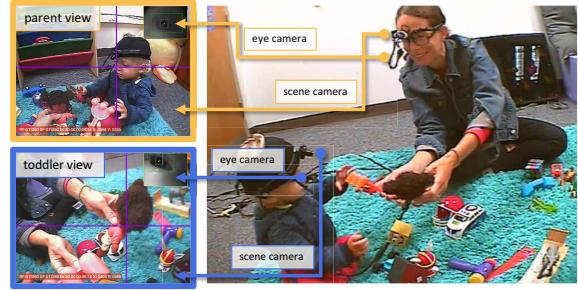


Figure 1: Our experimental setup. Child-parent dyads played together with a set of toys in a naturalistic environment, while each wore head-mounted cameras to collect egocentric video and eye gaze positions (left). A stationary camera recorded from a third-person perspective (right).

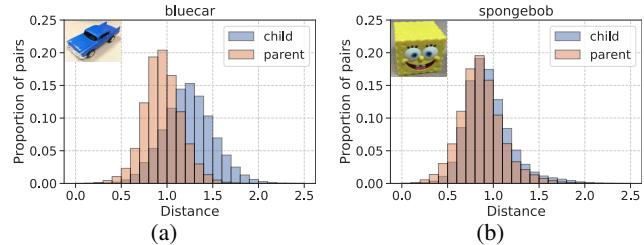


Figure 2: Histograms quantifying visual diversity of cropped instances for two specific objects: (a) the blue car and (b) the Sponge Bob toy.

datasets with the child-like property can train classifiers with higher generalization ability than those without it.

2. Findings

2.1. Children’s egocentric views indeed have a unique distributional property.

Our previous work [1, 5] suggests that views attended by children has more diverse distribution of object views with larger object size. In this section, we provide more empirical support for the previous findings.

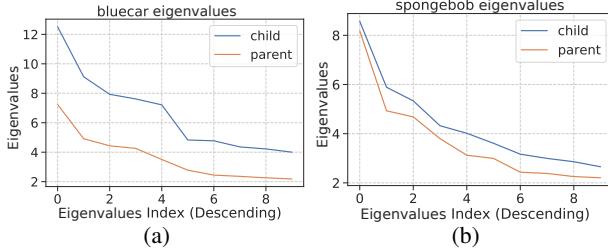


Figure 3: Another way of quantifying visual diversity is through eigenvalues of the principal components of PCA. Again, we see significantly greater variance for the child views for (a) the blue car and (b) the Sponge Bob toy.

Distribution of pairwise distances One way of quantifying the diversity of an image set is to compute the distance between all possible pairs of images, and investigate the distribution of the distances. We compute the Euclidean distances of all possible pairs of images for infants’ attended views and parents’ attended views for each toy. When computing a distance, we use GIST [3] feature as image representation. We chose GIST because it is a low-level feature (as opposed to more semantic deep features) that is sensitive to the spatial orientation of an object; we wanted a distance metric such that two instances of the same object viewed from similar angles would have a small distance, while different views of the same object would have a large distance. Figures 2a and 2b show the pairwise distribution plots of the two specific toy objects: the blue car and the Sponge Bob doll. We see that for both objects, the children’s data is more visually diverse than the parents’, but the difference is much more significant for the blue car. This indicates that the diversity of visual appearance is largely caused by greater diversity of viewing angles, since the car has more complex 3-D structure (e.g. body, tires, windows, etc) while the Sponge Bob is simpler and looks very similar from different views.

Variance from PCA Another of quantifying visual diversity is through Principal Component Analysis (PCA), which helps to interpret a high-dimensional space by decomposing it into orthogonal subspaces based on the variance of the data in the original space. We applied PCA for each object in the parent and child data and examine the top 10 eigenvectors, which indicate the degree of visual diversity along each of the principal components. We find that the eigenvalues of the child data are consistently higher than those of parent data; Figure 3 shows two examples for the blue car and the Sponge Bob doll. This means that the manifold of views attended by children is larger than the parent counterpart, which means children’s data has more diversity.

Visualizing visual diversity To visualize the diversity of visual data created by adults and children, we used Multidimensional Scaling (MDS) to embed the images into a 2D

space. Figure 4a presents an MDS visualization for the blue car, in which color indicates parent or child, and size of the point indicates the size of the cropped object bounding box compared to the viewer’s field-of-view. Figures 4b and 4c present the same MDS plots, but with the actual images superimposed on the points, and split across parent and child views. These plots confirm our previous findings. First, child data tends to have larger-sized objects, as the child data points (blue dots in Figure 4a) tend to be larger than the parent data points (orange dots). Second, child data has significantly greater diversity than parent data, as the child data points in Figure 4c are more spread out than the parent data points in Figure 4b. For both children and parents, there is a central “core” of highly-similar, typical, canonical views of the object, but the children also see “outlier” views, such as a cluster of images of the bottom of the car in the lower-right of Figure 4c that do not appear in the parent views.

2.2. Reverse-engineering the structure of child data

Having confirmed that children’s attended views have a unique diversity compared to the parent counterpart, we attempt to “reverse-engineer” the structure of the children’s data so that we can apply the findings to provide better insights for data collection for training image classifiers. We proceed by trying to synthetically generate a training dataset that works as well as the infant dataset, by artificially controlling the proportion of images that contribute to dataset diversity and those that do not. We approximate these sets as diverse set and similar set using pairwise GIST distances. (The definitions of diverse/similar images are provided in Sec. 4.3 of our previous work [1]). Specifically, we created new datasets consisting of a fraction p of randomly-sampled images from the similar subset, and fraction $1 - p$ of random images from the diverse subset. We used gaze-centered crops with 30° field of view, and employed the same setup as previous work [1] except that instead of producing a single set across all object categories, we select subsets for each class and then produce class-balanced datasets.

We train CNNs (VGG16) using these subsets and compute accuracy on the held-out test images of the same objects in the third-person canonical view for 24-way object classification (See our previous work [1] for details). Figure 5 presents accuracy for training datasets subsampled to have different numbers of exemplars per class (25, 50, 100, and 200) with different proportions of diverse and similar images. We see that training sets consisting only of diverse images lead to significantly better results than those consisting only of similar training sets (e.g., about 52% versus 32% for 25 images per class), until the number of images per class reaches 200. This is because when there are 200 images per class, the similar set is itself quite diverse.

More importantly, we see that for any number of exemplars per class, a mixture of diverse and similar sets always

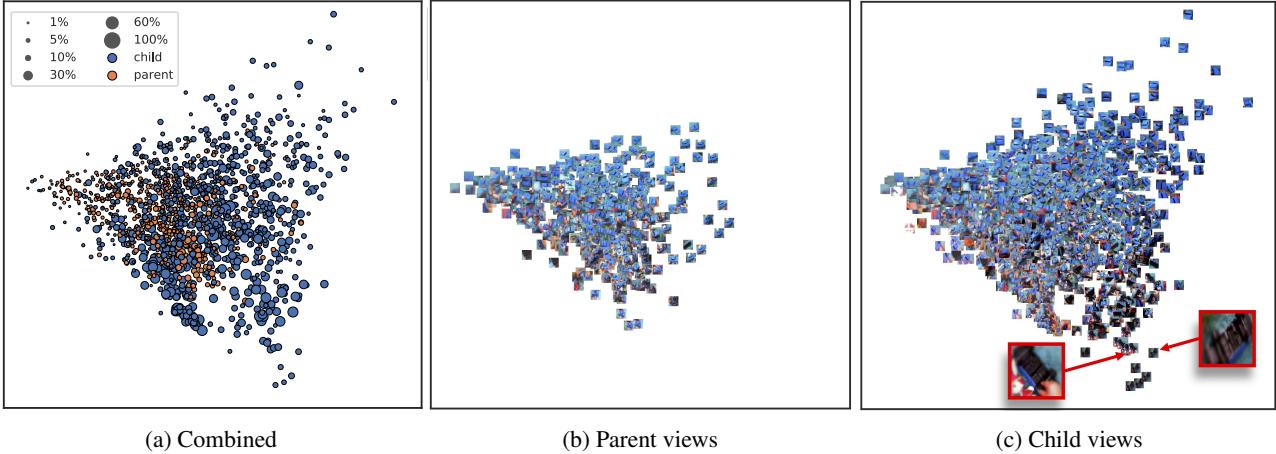


Figure 4: **Visualization of views of objects seen by parents and children** for one particular toy object, the blue car. The visualizations are 2D embeddings produced with Multidimensional Scaling (MDS) on GIST features of cropped images. (a): Each dot represents an image seen by parents (orange) or children (blue), and the size of the dot indicates the size of the object within the observer’s field of view. (b) and (c): The same MDS plot with actual images superimposed on the dots, and split across (b) parents and (c) children. The children see considerably greater diversity in both size and visual appearance.

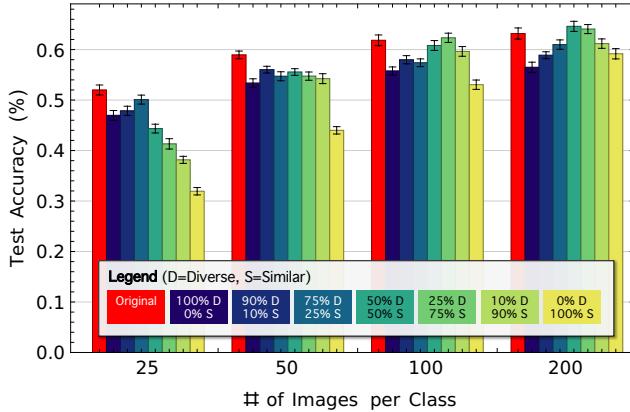


Figure 5: **Results of training on various mixtures of diverse and similar child egocentric data** while testing on independent third-person images, as a function of number of examples per class. Training on purely diverse (dark blue) or purely similar (yellow) subsets leads to significantly less accurate classifiers than the original child data (red), but a mixture of about 75% similar and 25% diverse leads to accuracy that is nearly as good.

performs significantly better than either set alone. This suggests that a high-quality training set needs both similar and diverse training instances. Moreover, for the dataset size of 100 and 200 examples per class, the subsets consisting of 75% similar images and 25% diverse images are as good as the original sets. This complements the finding in previous work [1] – the data created by toddlers, which consists of a mix of both similar and dissimilar instances, is a unique

combination of clustering and variability that may be optimal for object recognition. Indeed, we note that for the dataset size of 25 and 50, the original set outperforms the any combination of similar and diverse set. This suggests that the combination of similar and diverse sets is not the only characteristics that makes the child data better, and how toddlers collect data efficiently in the data-scarce situation is interesting future work.

2.3. Generalizing insights from child data

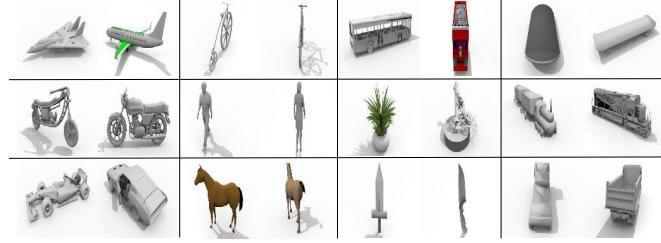
Inspired by the dataset from toddlers, the previous section shows a key factor that makes the toddler data better – combinations of similar and diverse images. Can this same insight be used to collect more generalizable training datasets in computer vision?

The vast majority of recognition datasets in computer vision include training and test splits that are sampled from the same dataset. In contrast, we need a dataset that can test our hypothesis that specific combinations of diverse and similar images in training could lead to better generalization in testing. This, of course, is the way in which children are able to generalize from, say, playing with toy firetrucks to recognizing real firetrucks as they drive by.

To do this, we constructed a dataset where the training data is from natural images while the test set is from canonical images of the objects. We collected training images from the MS COCO dataset, and test images from ShapeNet corresponding to the abstract representation of the objects. The dataset has 12 classes (aeroplane, bicycle, bus, car, horse, knife, motorcycle, person, plant, skateboard, train, and truck). Each class has 4,000 training images per class,



(a) Sample training images



(b) Sample test images

Figure 6: **Sample images from the dataset for object model generalization experiments**, consisting of (a) training images from COCO and (b) test images from ShapeNet. Each cell in the figure shows two randomly-selected images from one of the 12 object categories.

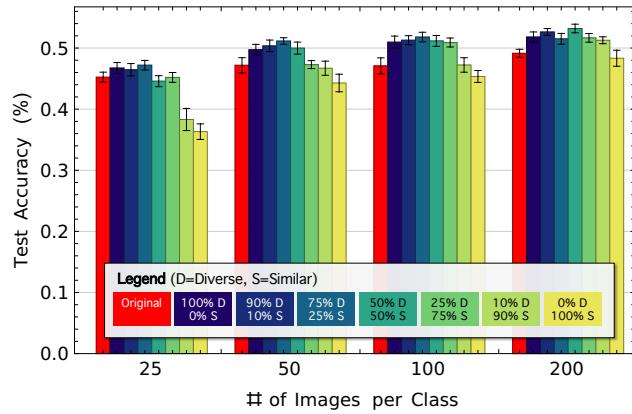


Figure 7: **Results of training on various mixtures of diverse and similar subsets of COCO** while testing on ShapeNet images. A mixture of similar and diverse subsets leads to better accuracy on ShapeNet than the original COCO distribution, suggesting that a training distribution like that of the child data leads to more generalizable classifiers.

totaling 48,000 images. We also have 1,500 test images and 1,500 validation images per class, totaling 18,000 images for each set. Figure 6 shows some sample images.

We note a key difference between this and the toyroom dataset task above: that task considered object instance recognition (identical objects for training and testing), but here we consider the more challenging and realistic problem of category recognition.

We performed similar experiments on this dataset as we did for child data, and show the results in Figure 7 as a function of number of images per class. As with the child data, the results on this dataset show that training datasets consisting only of diverse images lead to significantly better accuracy than those consisting only of similar images. In addition, the best accuracy is a combination of similar and diverse images, meaning that we need both similar images, which possibly help create a prototype representation, and

diverse images, which help to capture the representation of less typical cases. A notable difference from the child results is the accuracy of random subsets. Random subsets are inferior to the best combination of similar and diverse images. This suggests that random sampling, which is often used in computer vision work, is not always the best strategy.

3. Conclusion

We provided empirical observations that egocentric object views attended by infants are more diversely distributed than parent views. Then, we try to simulate the child-like distribution in a computational way both for the original egocentric dataset and an image classification dataset. Our ultimate goal is to generalize the insights that we found from the study of toddler’s visual development with egocentric vision into many computer vision problems, and we hope this paper shows the first step.

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