A Developmentally-Inspired Examination of Shape versus Texture Bias in Machines
Alexa R. Tartaglini, Wai Keen Vong, and Brenden M. Lake
{art481, waikeen.vong, brenden}@nyu.edu
New York University

Abstract

Early in development, children learn to extend novel category labels to objects with the same shape, a phenomenon known as the shape bias. Inspired by these findings, Geirhos et al. (2019) examined whether deep neural networks show a shape or texture bias by constructing images with conflicting shape and texture cues. They found that convolutional neural networks strongly preferred to classify familiar objects based on texture as opposed to shape, suggesting a texture bias. However, there are a number of differences between how the networks were tested in this study versus how children are typically tested. In this work, we re-examine the inductive biases of neural networks by adapting the stimuli and procedure from Geirhos et al. (2019) to more closely follow the developmental paradigm and test on a wide range of pre-trained neural networks. Across three experiments, we find that deep neural networks exhibit a preference for shape rather than texture when tested under conditions that more closely replicate the developmental procedure.

Keywords: shape bias, inductive bias, neural networks, word learning

Introduction

When presented with a new object and its label (e.g. “dax”), how do humans determine how to generalize the label to other objects? Starting around the age of two, children preferentially generalize novel category labels to solid objects of the same shape rather than the same size, color, or texture, a phenomenon known as the shape bias (Landau, Smith, & Jones, 1988). The standard experimental approach to measuring the shape bias in developmental psychology involves first presenting the participant with an anchor stimulus consisting of a novel shape and texture (see Figure 1(a) for an illustration). This is followed by the presentation of additional stimuli that match the anchor in shape, texture, size, or color (but not in any other dimension). Participants are asked which of the additional stimuli are the same category as the anchor; choosing the stimulus that matches along the shape dimension at levels above chance indicates a shape bias. The emergence of the shape bias indicates a crucial developmental shift in which children begin to recognize that shape information is a reliable indicator of object names, facilitating the acceleration of noun learning (Smith, Jones, Landau, Gershkoff-Stowe, & Samuelson, 2002; Diesendruck & Bloom, 2003; Gershkoff-Stowe & Smith, 2004). The shape bias strengthens as we grow older and gain more visual and linguistic experience; in fact, by the time we are adults, shape appears to serve as the primary predictor of our recognition of familiar categories (Biederman, 1995).

Due to its importance in understanding generalization and learning in humans, multiple computational accounts of the shape bias have been proposed, such as associative learning (Samuelson, 2002; Colunga & Smith, 2005) or hierarchical Bayesian models (Kemp, Perfors, & Tenenbaum, 2007). In the past decade, following the impressive achievements of deep neural networks (DNNs) on tasks such as image classification (Krizhevsky, Sutskever, & Hinton, 2012), there has been a push to better understand the ways in which machines encode and process images and whether they can be used as computational accounts of human vision (Yamins et al., 2014; Geirhos et al., 2021). In particular, this led to a renewed interest in the shape bias, with initial accounts demonstrating that DNNs did have a preference for shape. Ritter, Barrett, Santoro, and Botvinick (2017) showed that pre-trained convolutional neural networks (CNNs) prefer to categorize novel objects on the basis of shape rather than color, and Feinman and Lake (2018) found that simple neural networks can learn a shape bias from very few examples.

However, while this earlier work focused on comparing shape to color, more recent work has argued that deep neural networks actually rely on local texture information rather than global shape information for classification (Baker, Lu, Erlikhman, & Kellman, 2018; Brendel & Bethge, 2019; Geirhos et al., 2019). In particular, Geirhos et al. (2019) conducted a deeper examination by measuring shape versus texture bias.
Exp. 3: unaligned shapes, 40% and 80% size

![Example triplets from several experimental conditions](image)

Figure 2: Example triplets from several experimental conditions. Each row consists of two triplet-based trials, each with an anchor stimulus, a shape match, and a texture match. The first row demonstrates two triplets created from the original cue-conflict stimuli. For the second and third rows, the triplets on the left demonstrate the 40% size condition, while the triplets on the right demonstrate the 80% size condition. The textured silhouette stimuli in the second row also demonstrate the aligned shape condition, while the novel stimuli in the third row demonstrate the unaligned shape condition.

in ImageNet pre-trained deep neural networks. They created a set of novel cue-conflict stimuli by overlaying the shape information of one category with the texture information of another category via style transfer (Gatys, Ecker, & Bethge, 2016). Shape bias was then calculated as the proportion of trials in which a model classified a cue-conflict stimulus as its shape category divided by the total number of classifications to either its shape or texture category (and similarly for texture bias; see Figure 1(b) for procedure details). Using this procedure, they found that ImageNet pre-trained CNNs are actually strongly biased towards texture, while humans tested using the same stimuli showed a strong preference for shape, highlighting a large discrepancy between human and machine behavior. In light of this finding, additional research has framed the relevant problem as how to reduce the degree of texture bias in deep neural networks, such as work showing that shape bias can be increased via different kinds of data augmentations (Hermann, Chen, & Kornblith, 2020), or that vision transformers show less of a texture bias than CNNs (Tuli, Dasgupta, Grant, & Griffiths, 2021).

Despite the significant attention this finding has received, there are a number of important differences between the procedure used by Geirhos et al. (2019) and the procedure used in developmental psychology for assessing the shape bias, making it difficult to directly compare these recent findings with traditional findings. First, as shown in Figure 1, the style transfer method for creating the cue-conflict stimuli from Geirhos et al. (2019) produces stimuli where both the texture information may be inadvertently emphasized and the shape information de-emphasized, by covering the entire image—both the shape itself and the background—with the texture pattern. On the other hand, in developmental studies, the stimulus texture is always contained within the shape boundary, more closely reflecting how texture applies to objects in the real world: in fact, physical objects are often used rather than images of stimuli on a computer screen. Second, the procedure is limited to evaluating shape bias for 16 highly familiar categories (due to the use of a model’s output layer from the set of 1000 ImageNet categories), whereas developmental studies focus on testing shape bias via novel shapes. Finally, the use of model classification outputs to determine a shape or texture decision for each individual stimulus differs from the typical procedure showing an anchor against shape or texture matches. In fact, the procedure requires discarding a large proportion of trials that do not result in a correct shape or texture classification.

Motivated by these differences, we re-examine the texture bias claim and outline an alternative procedure for measuring shape bias in artificial neural networks that is more closely aligned with the developmental procedure. In Experiment 1, we adopt the cue-conflict stimuli from Geirhos et al. (2019) to parametrically reduce the saliency of the background texture. Our main result shows that across all models tested, removing the influence of background texture results in a preference for shape over texture, and that previous findings demonstrating a texture bias can be explained due to an aspect of this dataset, not from model behavior. In Experiment 2, we conduct additional tests to check the robustness of this finding by varying the size and positioning of the adapted stimuli, showing that this preference for shape over texture holds across different presentation conditions. Finally, in Experiment 3, we test the shape bias using a set of stimuli with novel shapes and textures, which most closely replicates the developmental procedure. We find that pre-trained models exhibit a higher rate of shape-based responses than their untrained counterparts, indicating that training increases shape bias. We will release our shape bias testing code to enable future benchmarking.

**Methods**

**Measuring Shape Bias.** In this section, we describe the procedure used in the following three experiments to measure shape bias in the models. Following the developmental procedure from Landau et al. (1988), a trial consists of a triplet of image stimuli: an anchor stimulus with a given shape and texture, a shape match stimulus that shares only its shape with the anchor, and a texture match stimulus that shares only its texture with the anchor. We assembled a large number of unique triplets for a given dataset by first considering each stimulus in the dataset as an anchor, then selected shape and texture matches for the anchor from other stimuli that have the same shape or texture class respectively.¹

¹Only shapes and textures from the same source image are considered to be a match; for example, if two stimuli both have the shape of a cat but use two different pictures of cats, they are not considered shape matches.
To process a trial, all three images in a triplet were passed individually to a given pre-trained model up to the penultimate layer to extract three embeddings of visual features. We then determined whether the model considered the shape or texture match to be more similar to the anchor by computing the cosine similarity between the anchor and the two matches.\(^2\) If the cosine similarity between the anchor and shape match is higher, the trial is considered a shape decision. Otherwise, it is considered a texture decision. The resulting shape bias of a model is computed as the proportion of the number of its shape decisions to the total number of trials. Because no trials are discarded with this method, texture bias of the models equals the remaining number of trials over the total number of trials.

**Models.** We measured shape bias for one convolutional neural network architecture, ResNet-50 (He, Zhang, Ren, & Sun, 2016), and one vision transformer architecture, ViT-B/16 (Dosovitskiy et al., 2021), across a wide range of learning objectives. As a baseline, we first ran all experiments with 10 randomly-initialized ResNet-50s and ViT-B/16s then computed the average shape bias for each across all 10 models. These models are referred to as random ResNet-50 and random ViT-B/16 respectively. We also tested supervised variants of ResNet-50 and ViT-B/16 that were pre-trained on ImageNet (Deng et al., 2009), as well as a self-supervised ResNet-50 trained via DINO (Caron et al., 2021), that did not require labels during pre-training. We also included CLIP ViT-B/16 (Radford et al., 2021), which was pre-trained on a dataset of 400 million image-caption pairs via contrastive learning, and was recently been shown to be most comparable to human vision on a range of benchmarks (Geirhos et al., 2021). Finally, we tested SAYCam-S model (Orhan, Gupta, & Lake, 2020), which uses a different convolutional neural network (ResNeXt-50, Xie et al., 2017) and was trained using a self-supervised objective on a longitudinal egocentric dataset of headcam footage filmed from the perspective of one child sampled regularly from the age of 6 months to 32 months. We included this final model because the footage is recorded during the developmental period and in the typical environment that English-speaking children tend to acquire a shape bias (although this model doesn’t get the labeled supervision thought to be important in acquiring the shape bias, Smith et al., 2002; Gershoff-Stowe & Smith, 2004).

**Experiment 1**

In this experiment, we examined the possibility that the texture bias observed in convolutional neural networks may be due to an over-emphasis of texture in the cue-conflict stimuli used in Geirhos et al. (2019). Specifically, the texture information in these test stimuli is highly salient, covering both the shape and background and obscuring some of the underlying shape information (see the top row of Figure 2). This is in contrast to the stimuli used in the developmental setup, in which the texture is contained within the shape of a stimulus and presented on a white or neutral background.

**Dataset.** In order to bridge these visual differences, we modified the original cue-conflict stimuli created by Geirhos et al. (2019) by parametrically decreasing the opacity of the background texture in varying degrees. This was achieved by making use of the separate “filled silhouette” dataset (Geirhos et al., 2019), which contained a silhouette of each shape instance used in the original cue-conflict stimuli. The silhouette of each shape instance was used to create a mask of the background for each matching cue-conflict stimulus. These masks were then superimposed onto the corresponding stimuli, obscuring the texture background with white pixels and highlighting the shape of the stimulus. We refer to these modified stimuli as the “textured silhouette” stimuli. The opacity of the white background mask was controlled by a variable \(\alpha \in [0, 1]\), where \(\alpha = 0\) is equivalent to the original cue-conflict stimuli, and \(\alpha = 1\) removes all background texture and replaces it with a white background. We created distinct datasets for 6 equally spaced \(\alpha\) values, as shown in Figure 3.

All possible (anchor, shape match, texture match) triplets of stimuli were generated as described in the Measuring Shape Bias section for each \(\alpha\)-valued textured silhouette dataset. In the original dataset used by Geirhos et al. (2019), stimuli with certain shapes and textures appeared more frequently than others, which resulted in a larger number of possible triplets with these anchor stimuli. To ensure that all shape and texture classes were equally represented in the final shape bias computation, we randomly selected 28 unique triplets for each of the 1,200 anchor stimuli, producing a total of 33,600 triplets used for evaluation. We repeated this procedure a total of 3 times, reporting the average measurements across replications.

**Results and Discussion.** When \(\alpha = 0\) and the background texture is fully salient, we predictably find a pattern of results that mirrors the observations made by Geirhos et al. (2019). Across the board, the models are highly texture biased, with the notable exception of random ResNet-50 and DINO ResNet-50, which are weakly shape biased (see Figure 3). Surprisingly, we observed an even stronger texture bias than Geirhos et al. (2019); for example, they observed about a 20% shape bias in ResNet-50 compared to the mere 2% shape bias we observed using the triplet-based procedure. As \(\alpha\) increases and background texture salience decreases, all models displayed a monotonic increase in shape bias, although at varying rates. The vision transformer models including the CLIP model and the SAYCam-S model showed a substantial increase in shape bias, and were between 70-80% shape biased when the background is completely white. On the other hand, the supervised ResNet-50 remained relatively texture biased throughout, only attaining a slight shape bias when \(\alpha = 1\). Still, this increase is surprising given the extremely strong texture bias observed for ResNet-50 when \(\alpha = 0\). DINO ResNet-50 is the most shape
objects vary in these factors, and thus, it is useful to understand how these properties influence model behavior.

**Dataset.** Starting with the subset of the textured silhouette stimuli with a white background ($\alpha = 1$), we created five different stimulus size conditions ranging from 20% to 100% of their original size, with each triplet being uniform in size. We also created two positional alignment conditions. In the aligned shape condition, all stimuli occupied the center of an image, resulting in perfect overlap between the anchor and shape match stimuli. In the unaligned shape condition, all stimuli were individually placed in random locations of the image; thus, in a given triplet, the three stimuli occupy different parts of the image. Figure 2 provides examples of both the size and alignment variations.\(^4\)

**Results and Discussion.** When the shapes of the stimuli are aligned, all models were highly shape biased across all stimulus sizes, although they were relatively more shape biased for smaller stimuli (Figure 4, top left). When the shapes were 20% of their original size, all models demonstrated a shape bias between 90% and 100% percent: for the largest stimuli, shape bias for the models ranged between 60% and 100%, with the ImageNet-trained ResNet-50 demonstrating the most significant decrease in shape bias. It is likely that shape bias decreased for larger shapes because a greater surface area allowed for a larger, more detailed patch of texture to be visible, thereby increasing the salience of the texture information. When the shapes were randomly positioned in the image and no longer overlap in the shape unaligned condition, the models displayed more variation in their degree of shape bias but were still above the chance level of shape bias for all stimulus sizes (Figure 4, top right).

These results show that a robust shape bias can be observed in all models by removing the background texture from the stimuli used by Geirhos et al. (2019), despite variations in size and positioning. This strengthens the findings in Experiment 1 by ruling out the hypothesis that pixel-overlap between the anchor and shape match are driving the preference for shape, but rather, the characteristics of the original cue-conflict stimuli are responsible for inducing the texture bias.

**Experiment 3**

The previous two experiments demonstrated that we could produce a robust shape bias response in a variety of artificial neural networks using stimuli from familiar categories. In this final experiment, we take one more step towards matching the developmental paradigm and measure shape bias using novel shapes and textures, differing from the categories the networks were trained on. This procedure is similar to that taken by Ritter et al. (2017) in which they also measured shape bias in DNNs using triplets of novel stimuli. However, while their work focused on testing shape versus color bias,

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\(^3\)We also ran Experiment 1 for all models besides the randomly initialized models using the original classification decision procedure from Geirhos et al. (2019) and found a very similar pattern of results.

\(^4\)Note that the 100% size condition in Experiment 2 is technically always aligned and is equivalent to the $\alpha = 1$ textured silhouette stimuli from Experiment 1, so the rightmost data points of Figure 3 are the same as the rightmost data points of the top two plots in Figure 4.
Figure 4: Results from Experiments 2 and 3. The rows indicate the experiment, while the columns represent the shape alignment condition with aligned shape results on the left and unaligned results on the right. Top row: using textured silhouette stimuli in Experiment 2, we find that all models are shape biased but respond differently to variations in shape size and alignment. Bottom row: using novel stimuli in Experiment 3, we find that all models are less shape-biased overall than Experiment 2. Unlike most of the models, DINO ResNet-50 increases in shape bias as shape size increases; also, for the unaligned shape condition, the random ResNet-50 hovers around chance levels of shape bias for all stimulus sizes with low variance.

our aim is to test shape versus texture bias.

Dataset. We created 256 unique novel stimuli using 16 high-quality textures (Brodatz, 1966) and 16 simple shapes (Parks, Griffith, Armstrong, & Stevenson, 2020) by overlaying random patches of each texture with a mask of each shape, resulting in misaligned textures between texture matches. As in Experiment 2, we varied the size and alignment of these novel stimuli, and generated all possible triplets as described in the Measuring Shape Bias section. Unlike Experiments 1 and 2, all anchor stimulus classes were equally represented in these datasets, so shape bias is measured once for a given condition using all 57,600 possible triplets. See Figure 1(a) and the bottom row of Figure 2 for examples of these stimuli.

Results and Discussion. When the novel stimuli are aligned in shape, all models were shape biased for the smallest size (see Figure 4, bottom-left). As shape size increased, most models showed a decrease in shape bias (whether aligned or not); DINO ResNet-50 is the exception and increased in shape bias as the shapes become larger.

When the stimuli were unaligned in shape, all models made fewer shape-based decisions when compared to the aligned stimuli (see Figure 4, bottom-right); the one exception was ResNet-50, which maintained the same pattern of behavior regardless of shape alignment. This drop may be due to the impoverished nature of the silhouettes compared to natural images, or the fact these stimuli are further out-of-distribution compared to pre-training. An advantage of this test setting is the neutral performance of the untrained random ResNet-50, which hovers around chance. Notably, ResNet-50, ViT-B/16, and CLIP ViT-B/16 all exhibited a shape bias relative to their untrained counterparts, indicating that they acquired more sensitivity to shape for novel stimuli during their training. This is consistent with the developmental picture, in which children acquire a shape bias as they learn more words (Smith et al., 2002; Gershkoff-Stowe & Smith, 2004).

Discussion

We outlined a more developmentally consistent procedure for testing shape bias in artificial neural networks. This procedure’s use of embedding similarity instead of model output allowed for the measurement of shape bias for pre-trained models, randomly-initialized models and for familiar and novel stimulus categories. We measured shape bias using this procedure and three different types of cue-conflict test stimuli for a range of architectures with varying pre-training data and learning objectives. In Experiment 1, we augmented the cue-conflict stimuli used by Geirhos et al. (2019) to demonstrate a texture bias in deep neural networks (DNNs) by removing the textured background in varying degrees. We found that shape bias in all models increased as background texture salience decreased, demonstrating that the sensitivity of shape bias measurements could be explained as test image characteristics. In Experiment 2, we tested whether the relatively strong shape bias observed in all models when the textured back-
ground was completely removed from the cue-conflict stimuli used by Geirhos et al. (2019) was robust to variations in shape size and position. We found that all models exhibited a shape bias above chance levels regardless of stimulus size or alignment. Finally, in Experiment 3, we generated triplets of stimuli with novel shapes and textures that varied in size and position over a white background. We found that the ImageNet pre-trained ResNet-50 and ViT-B/16 models exhibited a marked increase in shape bias over their randomly initialized variants, especially when the stimuli were randomly positioned, suggesting that these models had learned an inductive bias for shape that generalized to novel stimuli.

Our results suggest that the previously observed texture bias in DNNs may in part be an artifact of the cue-conflict stimuli from Geirhos et al. (2019). In fact, our results from Experiments 1 and 2 suggest a robust shape bias in all models using augmented versions of the same stimuli and a procedure that more aligns with the developmental setup. However, there is still one puzzling fact to explain. Geirhos et al. (2019) observed that humans tested using the original cue-conflict stimuli still showed a strong shape bias, despite the over-emphasized texture present in the stimuli. One possible explanation is that humans’ shape decisions were influenced by the specific testing procedure used. In their experiments, despite the neutral instructions to not bias judgments towards shape or texture, participants selected their classification decisions by clicking on one of 16 shape-based icons, which may have subtly encouraged them to classify on the basis of shape rather than texture (Geirhos et al., 2018).

The developmental account of the interrelationship between the shape bias and word learning in children seems to align with our observations that models with pre-training on labels or linguistic data exhibit a stronger shape bias than their untrained counterparts. However, the strong shape preference exhibited by the self-supervised models in some conditions is somewhat puzzling from the developmental point of view given their complete lack of language exposure. It remains unclear why a robust shape bias is observed in all models regardless of their pre-training objective. Moreover, it is uncertain why models are capable of displaying such high variations in shape bias while humans are relatively consistently shape biased.

As deep neural networks have continued to demonstrate impressive performance on visual tasks and have thus seen an expanding range of applications, it has become increasingly important to understand the nature of the biases they employ to classify objects and how these biases compare to those learned by humans. The recent explorations into the existence of a shape bias in DNNs have yielded a number of unexpected and significant results. In this paper, we add to this line of research by measuring shape versus texture bias in a range of DNN architectures using a procedure that more closely matches the developmental setup, highlighting that close attention needs to be paid to all aspects of the evaluation in order to conduct a “species-fair comparison” (Firestone, 2020). Ultimately, the shape bias is only one of many inductive biases employed by the human mind to understand and make sense of the world. Both machine learning and cognitive science stand to gain from further investigation into models that capture a range of inductive biases as well as methods that allow for fair comparisons between human and machine intelligence.

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