





# Shape or Texture: Understanding Discriminative Features in CNNs

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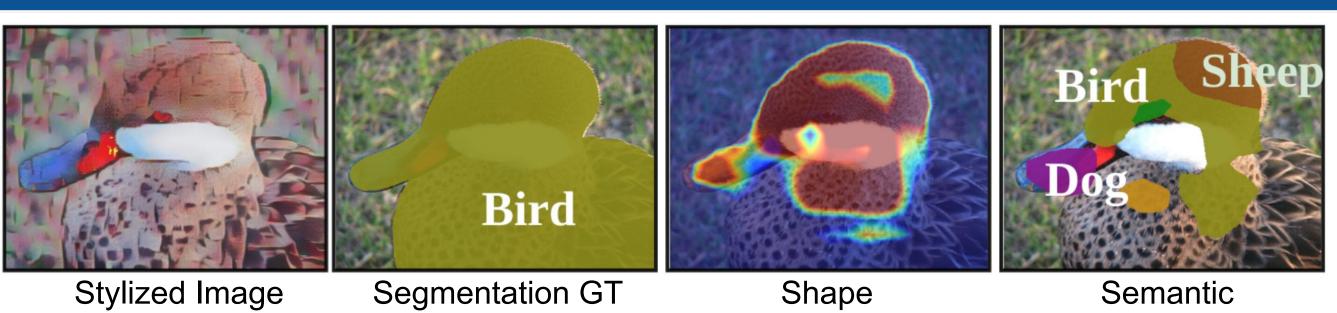
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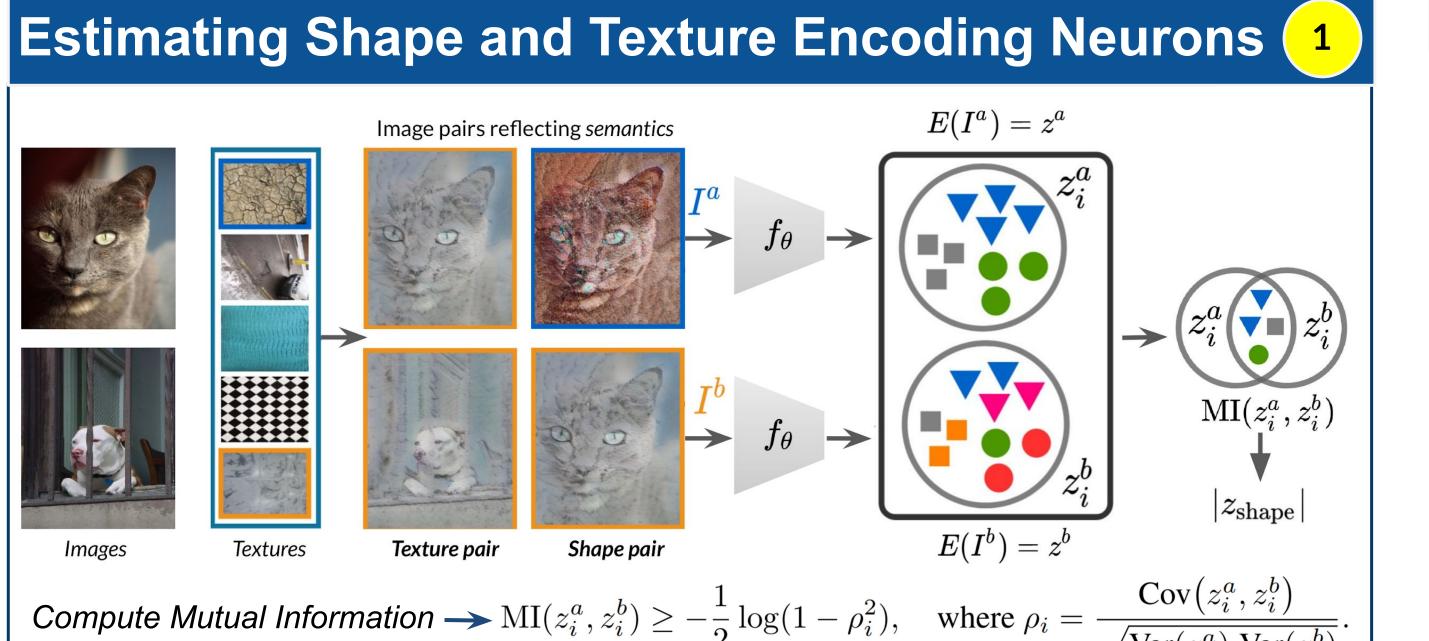
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### **Shape and Texture Bias IN CNNs**



- "Shape Bias models make predictions based on object's shape" -> Do they?
- We lack metrics for measuring the amount of shape encoded in CNNs.

## We propose the following **two new metrics**:



We calculate the mutual information between the latent representations to produce an estimate of which neurons encode shape.

## **Decoding Per-Pixel Shape Information**



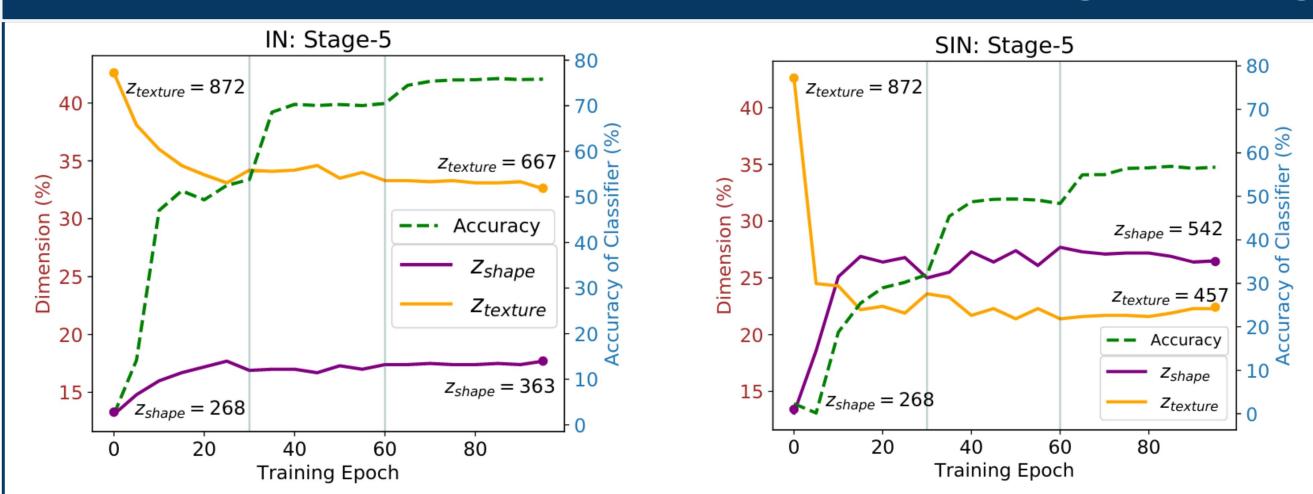
Quantifying per-pixel shape information in the latent representation of CNNs

#### Dimensionality Estimation of Shape and Texture

Model	Shape	Texture	Dataset*	Shape	Texture
ResNet50	349	692	ImageNet	349	692
BagNet33	284	825	Stylized ImageNet	536	477
BagNet9	276	841	IN + SIN	376	640

- BagNets have more neurons encoding texture than the shape
- Shape biased models have more shape encoding neurons than traditional ImageNet pretrained model

### When Does Shape Become Relevant During Training?



- Shape encoding neurons increase only marginally for IN but grows much larger and faster in case of SIN over the course of training.
- Texture factor decreases as the training progresses.

#### Decoding Per-pixel Shape from a Pretrained Network

Training Initialization	Shape	Semantic	Training Initialization	Shape	Semantic
Random	48.0	6.1	IN	79.8	61.6
IN-Freeze	80.2	62.7	SIN	76.4	53.7
IN	70.6	50.9	IN+SIN	77.8	58.0

Measure the amount of decodable shape from frozen CNN by training a one layer convolutional readout module.

#### Where is Shape Information Stored?

		Shape	Texture	
C42	IN	14.1	40.2	Bin
Stage2 (f2)	SIN	14.1	42.6	$egin{array}{cccccccccccccccccccccccccccccccccccc$
Stage5	IN	17.0	33.8	Image
(f5)	SIN	26.2	23.3	Sem GT $f_2$ $f_5$

- Examine if shape information is equally distributed across different stages
- CNNs encode a surprising amount of shape information at all stages

## **Targeting Shape and Texture Neurons** Binary Segmentation - SIN Semantic Segmentation - SIN Binary Segmentation - IN Semantic Segmentation - IN -- Texture

Validate if the most texture or shape-specific neurons can influence the shape decoding performance when keeping these specific neurons during training.

Percentage of Neurons Kept (%)

Shape biased model is *more reliant on shape neurons* than a texture biased model

#### Conclusions

- Introduced two new methods for quantifying shape information in the latent representation of CNNs in terms of **Neurons** and **Pixels**
- Shape is mostly learned during the first part of training
- Shape bias models do not encode global object shape
- Biasing a CNN towards shape predominantly changes the number of *shape* encoding neurons in the last feature encoding stage.