



Exploring Blind Spots of Vision Models



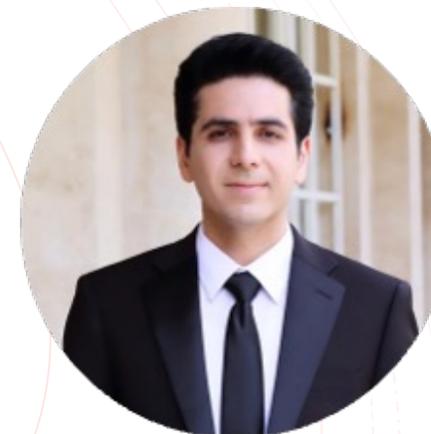
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Introduction

- Input *over-sensitivity* well studied in adversarial literature



Prediction: **Hamster**
Confidence = 99.99%

+ 0.02 *



50-step PGD targeted attack
with $\epsilon = \frac{8}{255}$ scaled by 50x

=



Prediction: **Banjo**
Confidence = 100%

Introduction

- Input ***over-sensitivity*** well studied in adversarial literature
- We study input ***under-sensitivity*** for general models
- Uncover extent of excessive invariance in common vision models?

Over-Sensitivity

$$\|f(x) - f(x')\| \uparrow$$

$$x \approx x'$$

Under-Sensitivity

$$f(x) \approx f(x')$$

$$\|x - x'\| \uparrow$$

Mathematical Preliminaries

- For $g : \mathbb{R}^d \rightarrow \mathbb{R}$, $L_g(c) = \{x \in \mathcal{X} : g(x) = c\}$ is called the Level Set
- Important Property: For any curve in the Level Set $\gamma(t) : [0, 1] \rightarrow L_g(c)$

$$\frac{d}{dt}(g(\gamma(t))) = 0 = \langle \nabla g(\gamma(t)), \gamma'(t) \rangle$$

Lemma 1. *If $g : \mathbb{R}^d \rightarrow \mathbb{R}$ is a continuously differentiable function, then each of its regular level sets is an $(d - 1)$ dimensional submanifold of \mathbb{R}^d .*

- How expansive are these submanifolds for common ML models?

Can we Traverse along Level Sets?

goose



Source Image \mathbf{x}_s

Confidence for class "goose" = 0.997
Confidence for class "Scottish Terrier" = 0

Scottish Terrier



Target Image \mathbf{x}_t

Confidence for class "goose" = 0
Confidence for class "Scottish Terrier" = 1.0

Level Set Traversal (LST) Algorithm

Compute Input Gradient

$$\Delta \mathbf{x} = \mathbf{x}_t - \mathbf{x}$$
$$\mathbf{g} = \nabla_{\mathbf{x}} CE(f(\mathbf{x}), y)$$

Compute Orthogonal Projection

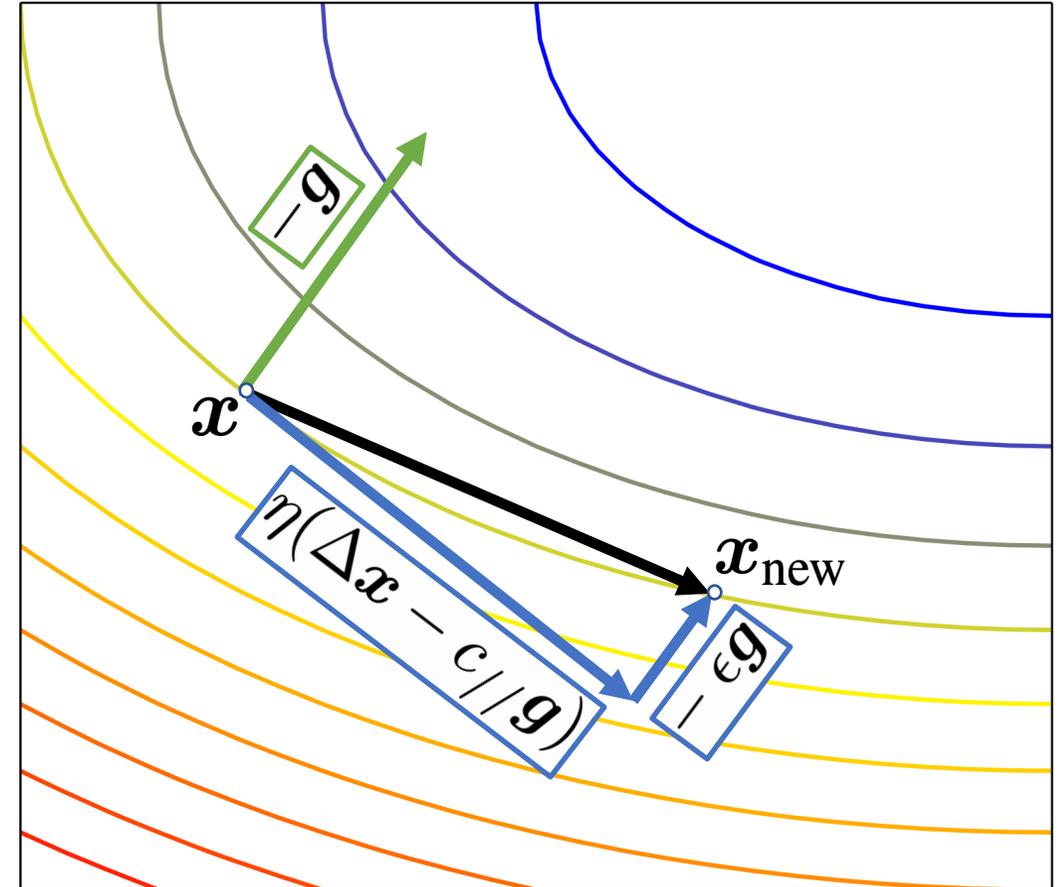
$$c_{//} = (\mathbf{g} \cdot \Delta \mathbf{x}) / \|\mathbf{g}\|^2$$
$$\Delta \mathbf{x}_{\perp} = \eta(\Delta \mathbf{x} - c_{//} \mathbf{g})$$

Update Image

$$\mathbf{x}_{||} = \Pi_{\infty}(\mathbf{x}_{||} - \epsilon \mathbf{g}, -\epsilon, \epsilon)$$
$$\mathbf{x}_{\text{new}} = \mathbf{x} + \Delta \mathbf{x}_{\perp} + \mathbf{x}_{||}$$

Verify Model Confidence

if $f(\mathbf{x}_s)[j] - f(\mathbf{x}_{\text{new}})[j] > \delta$ **then**
 return \mathbf{x}
 $\mathbf{x} = \mathbf{x}_{\text{new}}$



Repeat until Max Iterations

LST Path in Input Space for ResNet-50

goose



Source Image \mathcal{X}_s

Confidence for class "goose" = 0.997
Confidence for class "Scottish Terrier" = 0

Scottish Terrier



Target Image \mathcal{X}_t

Confidence for class "goose" = 0
Confidence for class "Scottish Terrier" = 1.0

Step: 0



Confidence: 0.997

Step: 10



Confidence: 0.998

Step: 20



Confidence: 0.999

Step: 40



Confidence: 0.999

Step: 60



Confidence: 1.0

Step: 80



Confidence: 1.0

Step: 120



Confidence: 1.0

Step: 160



Confidence: 1.0

Step: 200



Confidence: 1.0

Step: 300



Confidence: 1.0

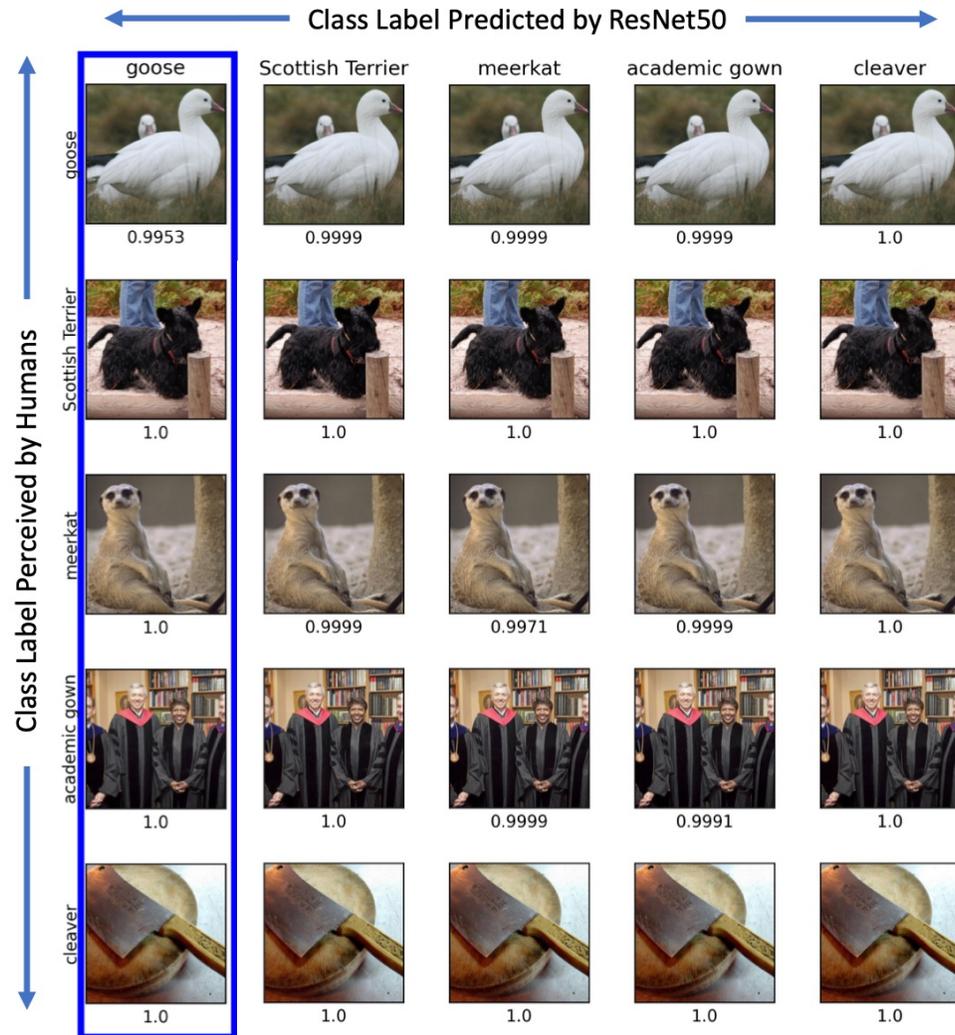
Step: 400



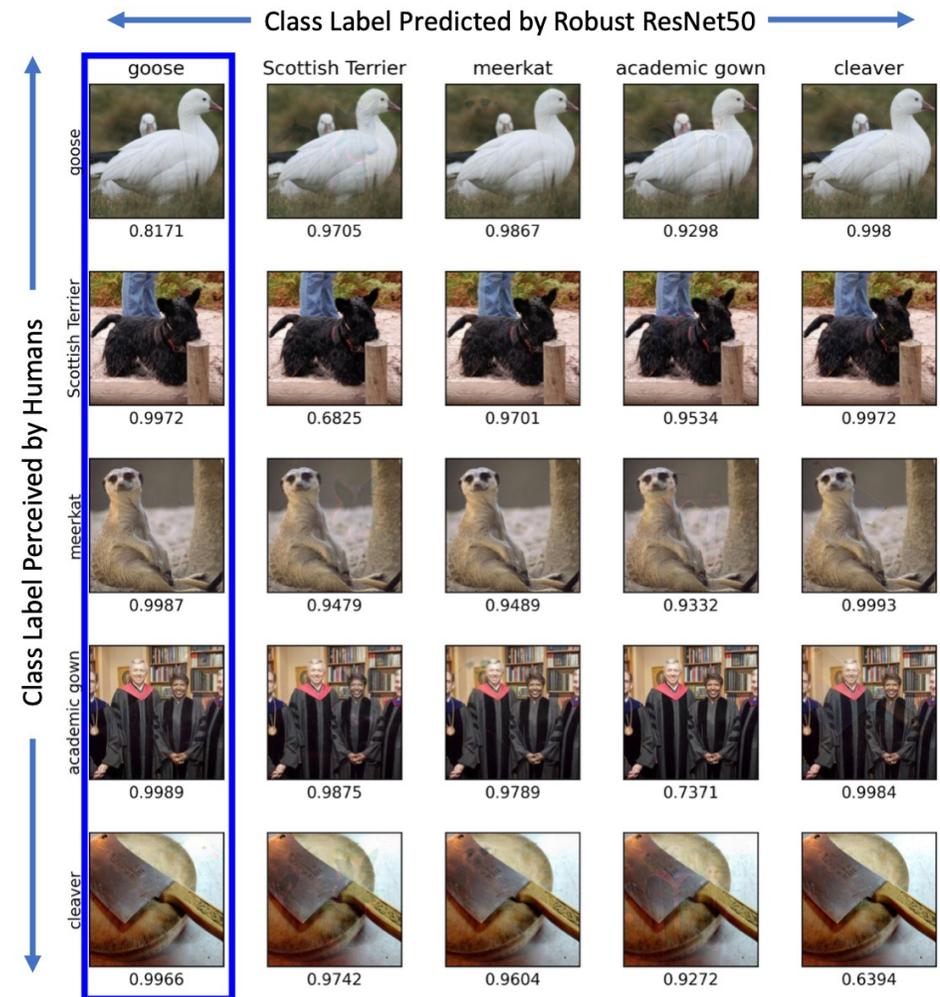
Confidence: 1.0

LST Blind Spots

LST over arbitrary Source-Target pairs



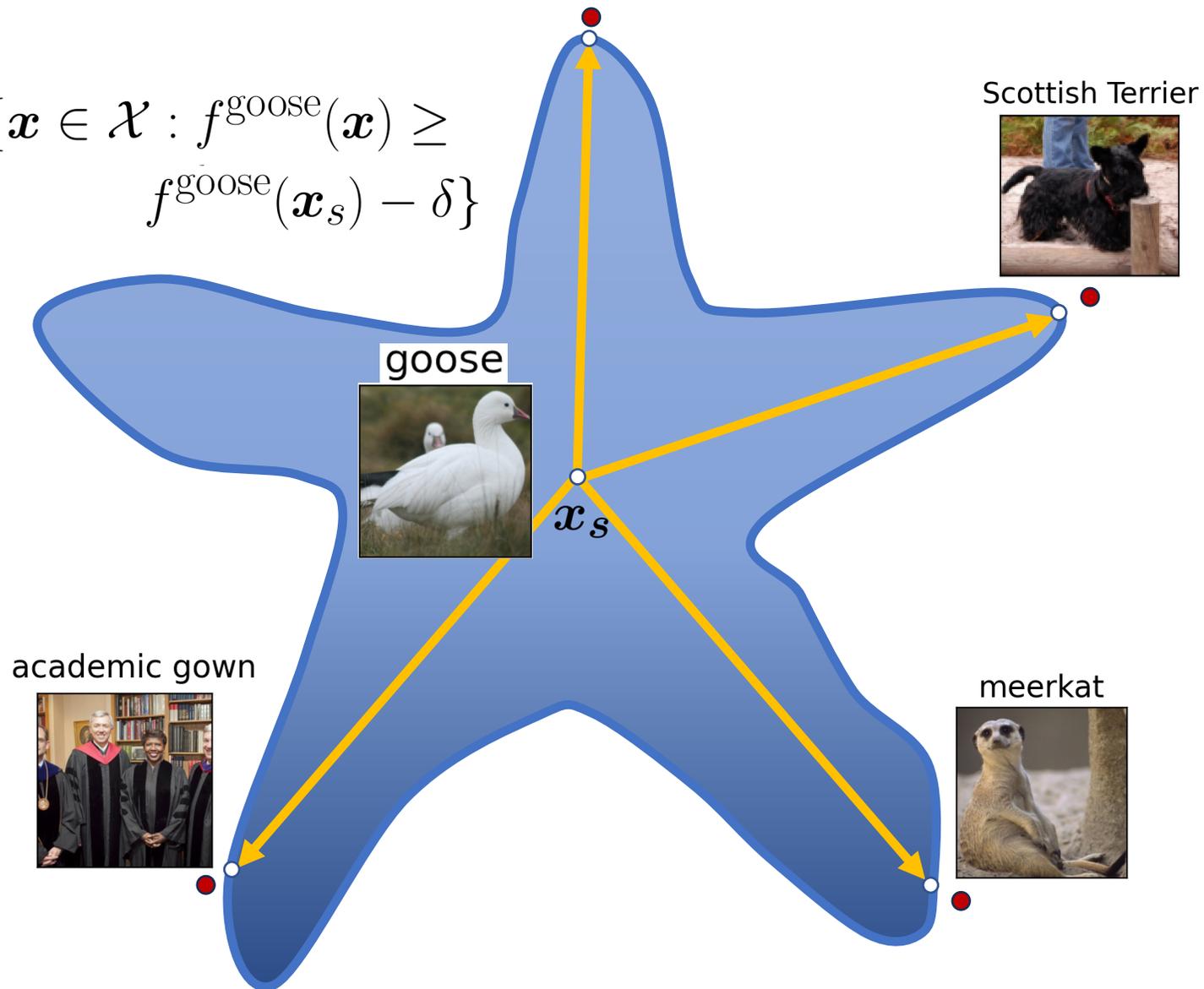
Normally Trained ResNet-50



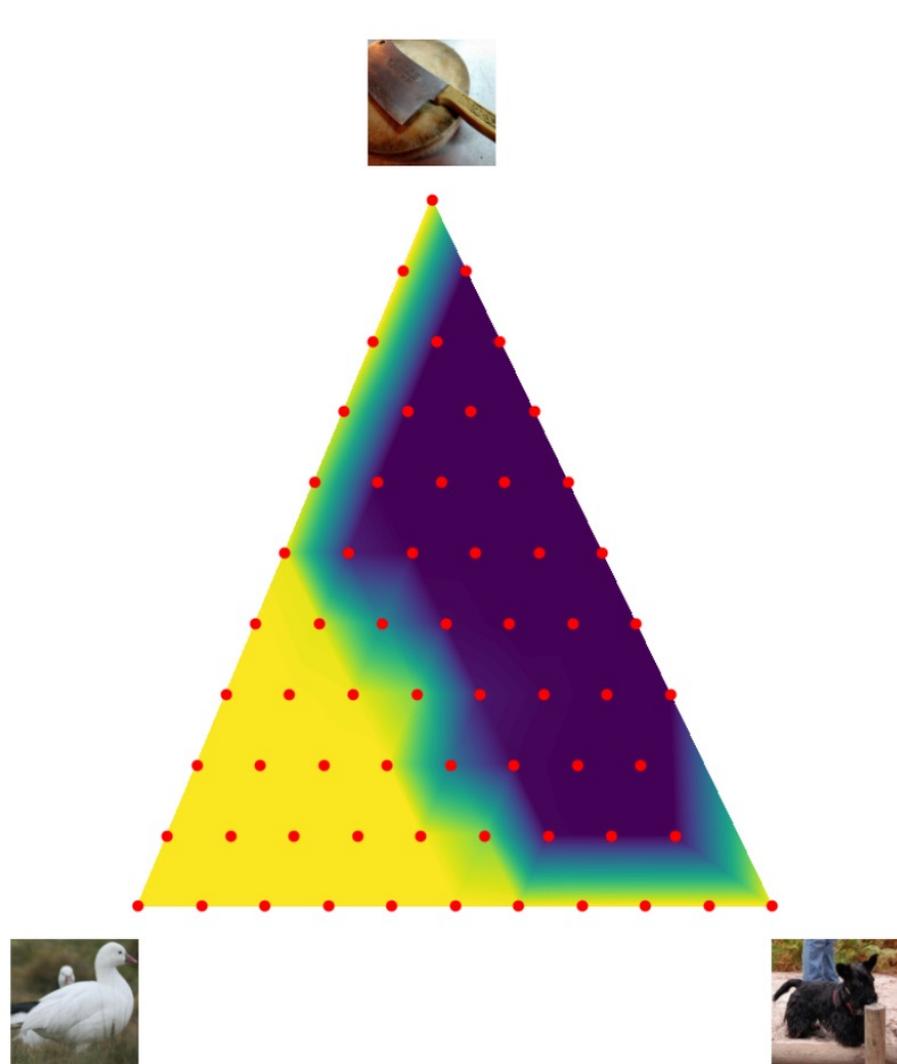
Adversarially Trained ResNet-50

Star-like Substructure of Level Sets

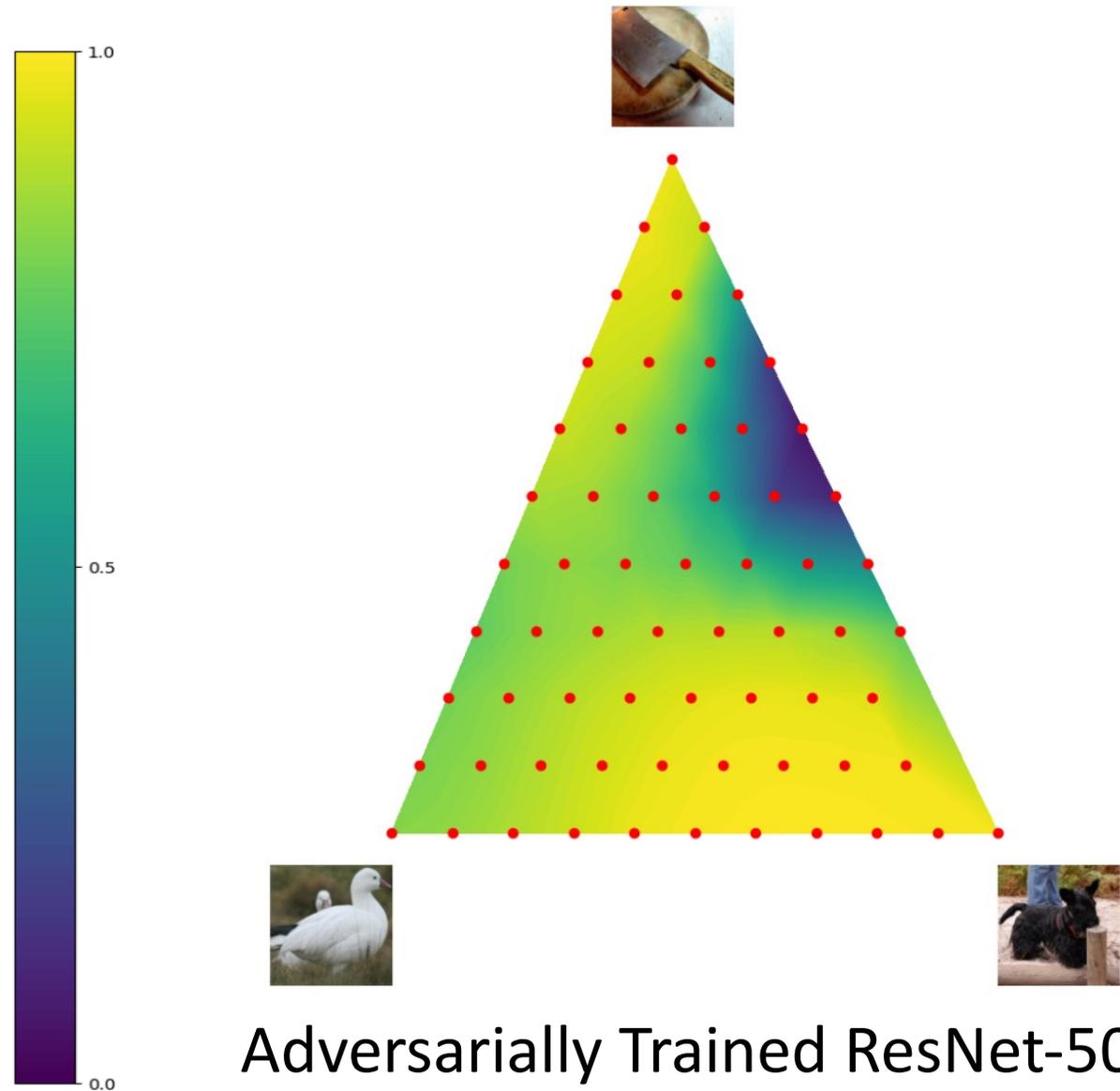
$$\{\mathbf{x} \in \mathcal{X} : f^{\text{goose}}(\mathbf{x}) \geq f^{\text{goose}}(\mathbf{x}_s) - \delta\}$$



Star-like Substructure of Level Sets



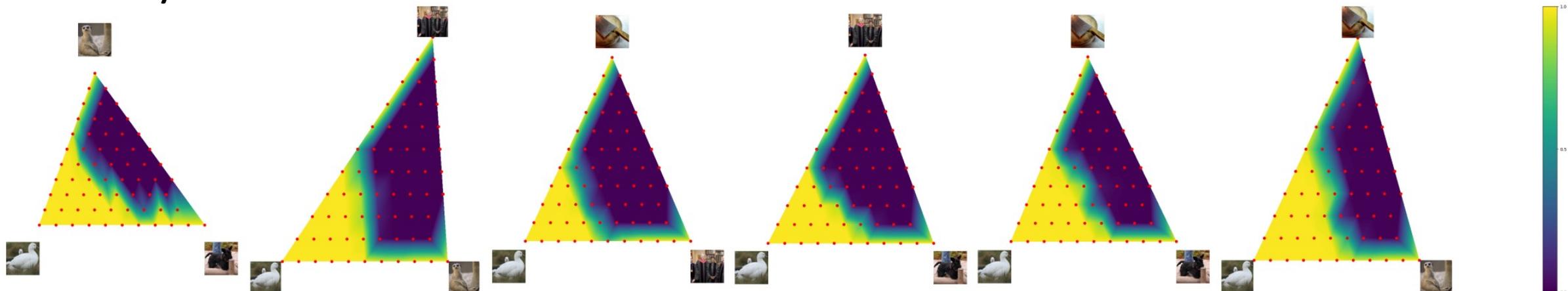
Normally Trained ResNet-50



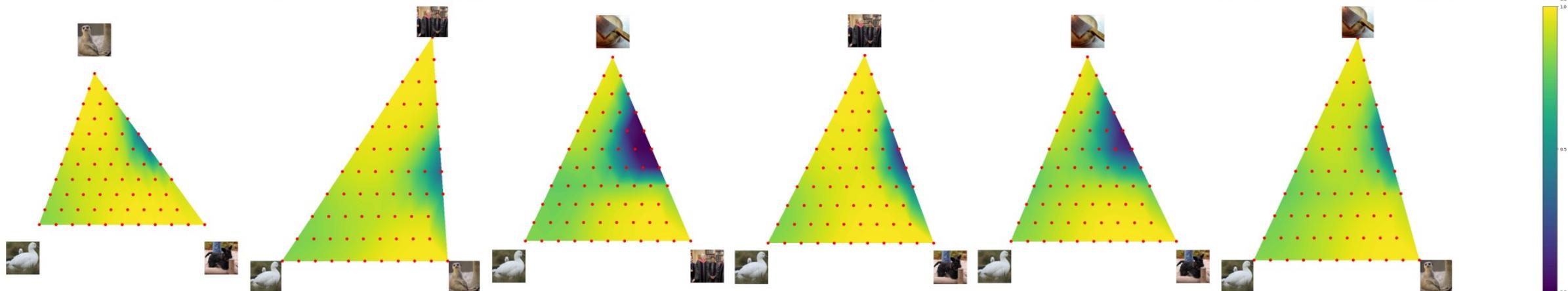
Adversarially Trained ResNet-50

Star-like Substructure of Level Sets

Normally Trained ResNet-50:



Adversarially Trained ResNet-50:



Quantitative Analysis of Blind Spot Invariance

Distance metrics:

1. RMSE:
Root mean squared error
2. Max norm (ℓ_∞):
Maximum absolute difference
3. SSIM:
Structural Similarity Index
4. LPIPS:
Perceptual Image Similarity

Confidence metrics:

1. Source confidence (p_{src}):
Confidence of the model for the source image
2. Average path confidence
Mean confidence over the linear paths connecting the source image to LST outputs
3. Average Δ confidence:
Mean confidence over the enclosed triangle
4. Average Δ fraction for a given δ :
Fraction of triangle over which confidence is at least $p_{src} - \delta$

Quantitative Analysis of Blind Spot Invariance

Table 1: Quantitative image distance metrics between output of Level Set Traversal and target images.

Models	RMSE : $\mu \pm \sigma$	ℓ_∞ dist: $\mu \pm \sigma$	SSIM: $\mu \pm \sigma$	LPIPS dist: $\mu \pm \sigma$
ResNet-50 (Normal)	0.008 ± 0.001	0.046 ± 0.020	0.990 ± 0.021	0.002 ± 0.004
ResNet-50 (AT)	0.029 ± 0.008	0.746 ± 0.124	0.915 ± 0.041	0.057 ± 0.037
DeiT-S (Normal)	0.011 ± 0.002	0.116 ± 0.030	0.973 ± 0.024	0.024 ± 0.017
DeiT-S (AT)	0.046 ± 0.010	0.821 ± 0.117	0.898 ± 0.041	0.219 ± 0.068

Table 2: Quantitative confidence metrics over the triangular convex hull (Δ) of a given source image and two target LST blindspot image-pairs and over linear interpolant paths between source and blindspot images. (For reference, a random classifier would have confidence of 0.001)

Models	p_{src} ($\mu \pm \sigma$)	Avg Δ Conf. ($\mu \pm \sigma$)	Avg Δ Frac. ($\mu \pm \sigma$)				Avg Path Conf. ($\mu \pm \sigma$)
			$\delta = 0.0$	$\delta = 0.1$	$\delta = 0.2$	$\delta = 0.3$	
ResNet-50 (Normal)	0.99 ± 0.02	0.56 ± 0.10	0.13 ± 0.15	0.51 ± 0.11	0.53 ± 0.1	0.54 ± 0.10	0.96 ± 0.05
ResNet-50 (AT)	0.88 ± 0.11	0.83 ± 0.09	0.49 ± 0.29	0.79 ± 0.13	0.85 ± 0.1	0.88 ± 0.09	0.93 ± 0.06
DeiT-S (Normal)	0.85 ± 0.06	0.68 ± 0.05	0.54 ± 0.11	0.67 ± 0.06	0.71 ± 0.06	0.73 ± 0.06	0.94 ± 0.02
DeiT-S (AT)	0.76 ± 0.08	0.59 ± 0.07	0.20 ± 0.09	0.43 ± 0.14	0.63 ± 0.15	0.76 ± 0.12	0.73 ± 0.06

Conclusions

- Using LST, we find that the level sets of common vision models is **remarkably expansive**
- The **linear** path from any given source image to LST blind spot outputs retain **high model confidence** throughout for arbitrary targets
- This unveils a **star-like substructure** for the equi-confidence level sets of common models
- Adversarially trained models are significantly more **under-sensitive**, over inputs **well beyond** the original threat model

Thank You!



NEURAL INFORMATION
PROCESSING SYSTEMS