Angular Visual Hardness

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PART 0

Motivation

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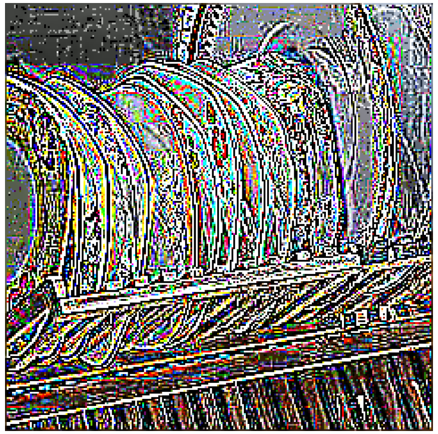
Human Visual Hardness

plate rack

sharpness



contrast

blur

Image Degradation

dishwasher

saltshaker

nail

oil filter

Semantic Ambiguity

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Gap between human visual system and CNNs

Hard for Human and **Easy** for CNNs

Easy for Human and **Hard** for CNNs

Class Name

Softmax Score

Nail	Oil Filter	Golf Ball	Radio
0.93	0.998	0.001	0.001
0.2	0.2	1.0	1.0

Human Selection Frequency

Agenda

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PART 01

Background

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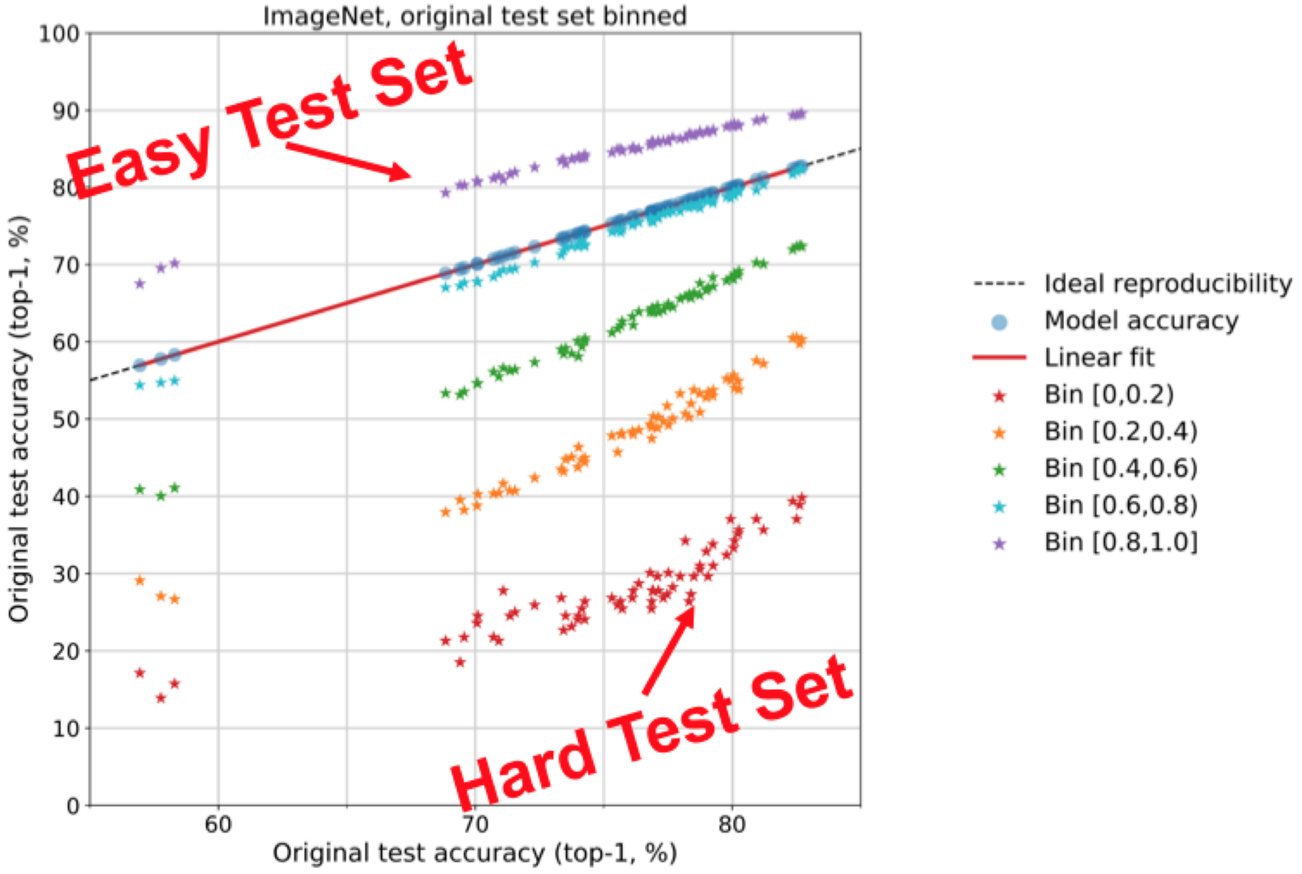
Do ImageNet Classifiers Generalize to ImageNet?

Human Labeling Interface



Recht et al. “Do ImageNet Classifiers Generalize to ImageNet?” ICML 2019

Loss function of CNNs in visual recognition

Softmax cross-entropy loss

$$L = \frac{1}{N}\sum_i L_i = \frac{1}{N}\sum_i -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)$$

$$L_i = -\log\left(\boxed{\frac{e^{\boxed{\|\boldsymbol{W}_{y_i}\|\|\boldsymbol{x}_i\|}\boxed{\cos(\theta_{y_i})}}}{\sum_j e^{\|\boldsymbol{W}_j\|\|\boldsymbol{x}_i\|\cos(\theta_j)}}}\right)$$

The magnitude information

The angle between feature and classifier

Model Confidence

PART 02

Discoveries

Proposal: Angular Visual Hardness (AVH)

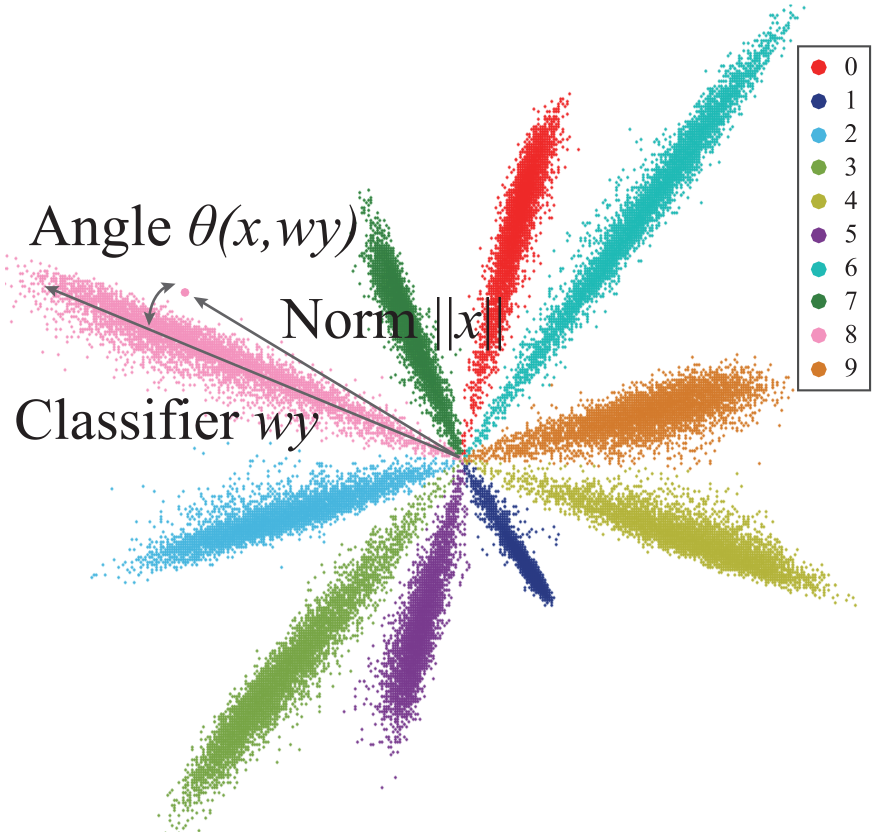
Given a sample *x* with label *y*:

$$\boldsymbol{AVH}(x) = \frac{\mathcal{A}(x, w_y)}{\sum_{i=1}^{C} \mathcal{A}(x, w_i)}$$

where,

$$\mathcal{A}(\boldsymbol{u}, \boldsymbol{v}) = \arccos\left(\frac{\langle \boldsymbol{u}, \boldsymbol{v} \rangle}{\|\boldsymbol{u}\| \|\boldsymbol{v}\|}\right)$$

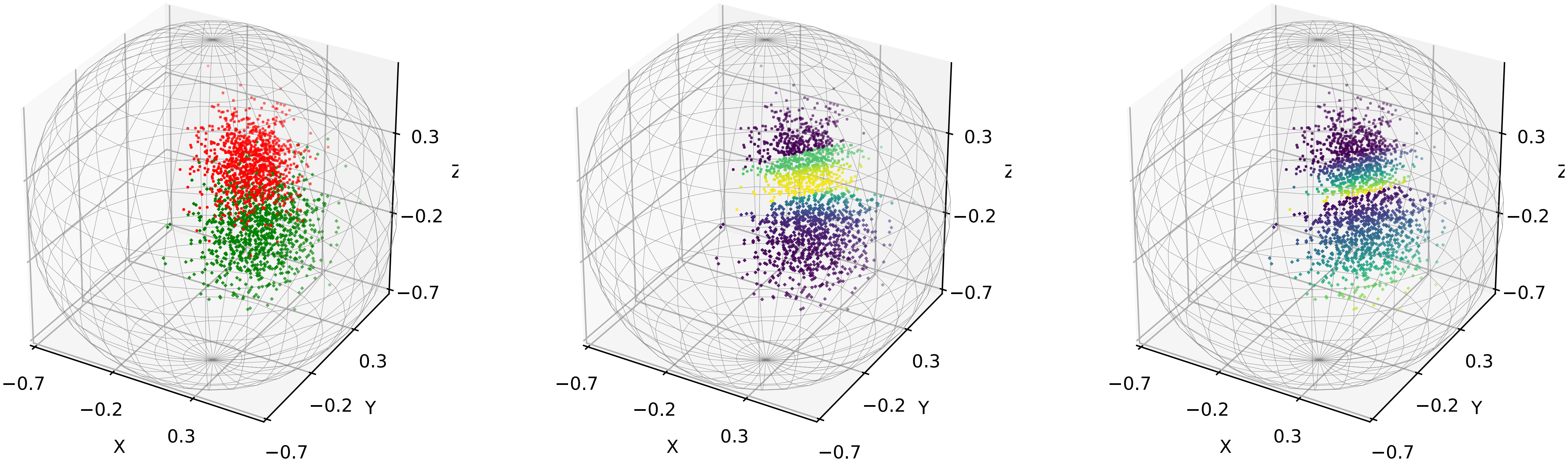
wi is the classifier for the i-th class.



Theoretical Foundation:

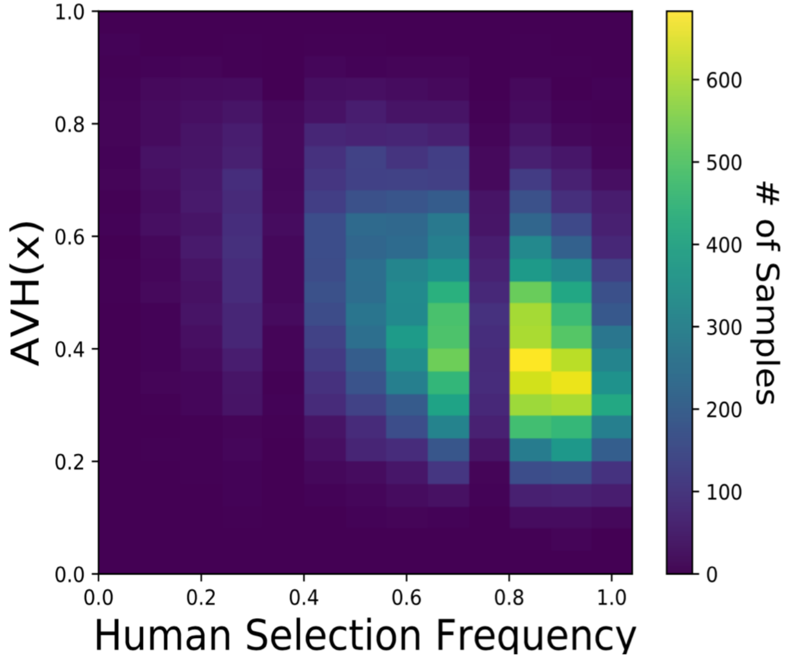
Soudry et al. “The Implicit Bias of Gradient Descent on Separable Data” ICLR 2018

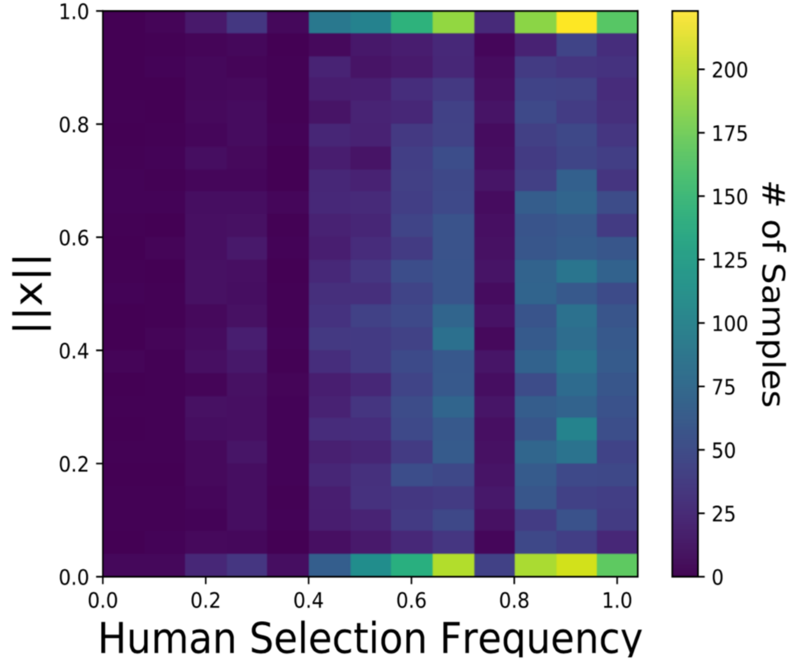
Simple Example: AVH vs. $||\mathrm{x}||$

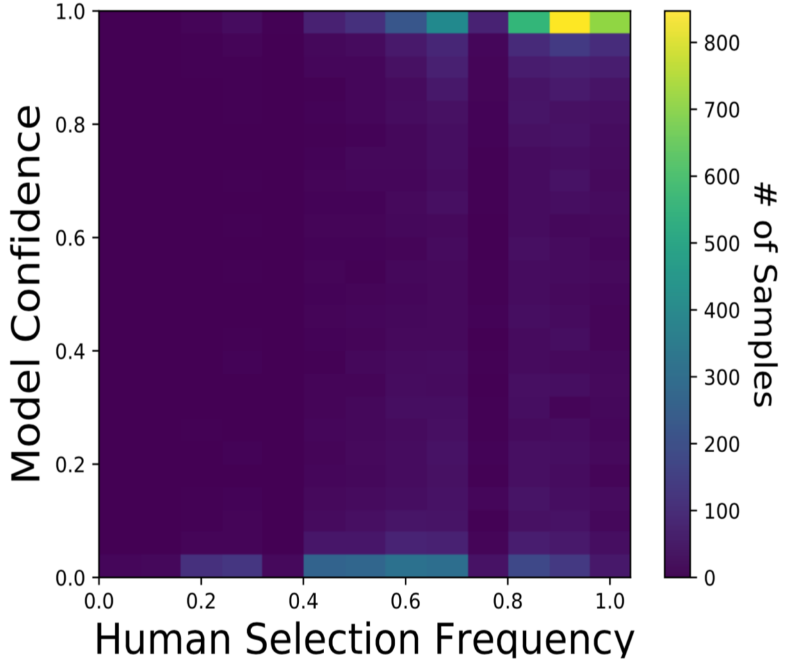


Raw data **Color map of AVH** **Color map of $||\mathrm{x}||$**

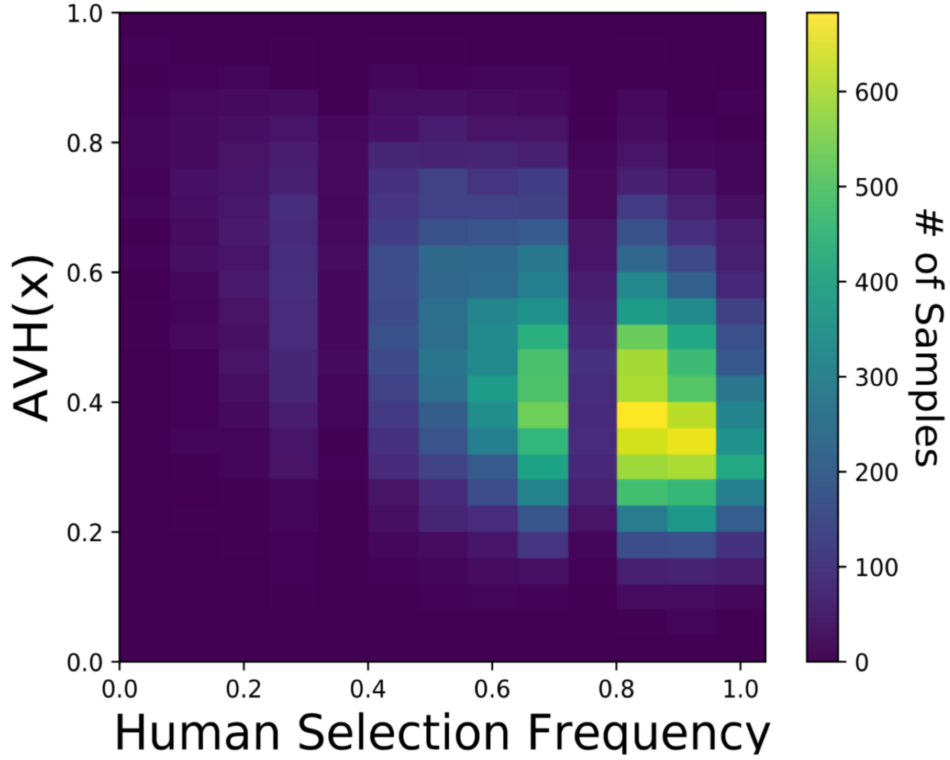
CNN characteristics vs. human selection frequency







AVH is well aligned with human frequency

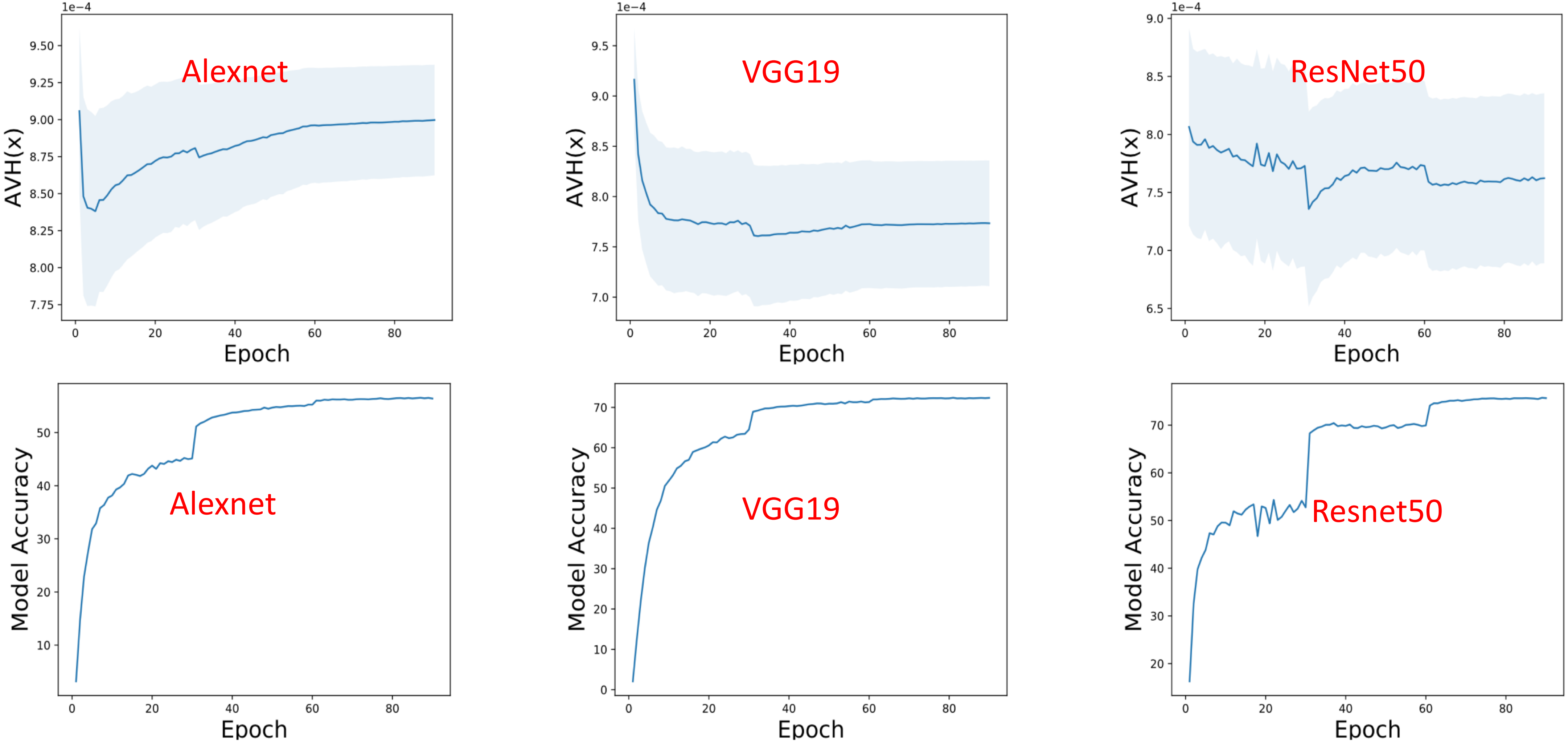


Spearman rank correlations

	z-score	Total Coef	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Number of Samples	-	29987	837	2732	6541	11066	8811
AVH	0.377	0.36	0.228	0.125	0.124	0.103	0.094
Model Confidence	0.337	0.325	0.192	0.122	0.102	0.078	0.056
$\|\mathbf{x}\|_2$	-	0.0017	0.0013	0.0007	0.0005	0.0004	0.0003

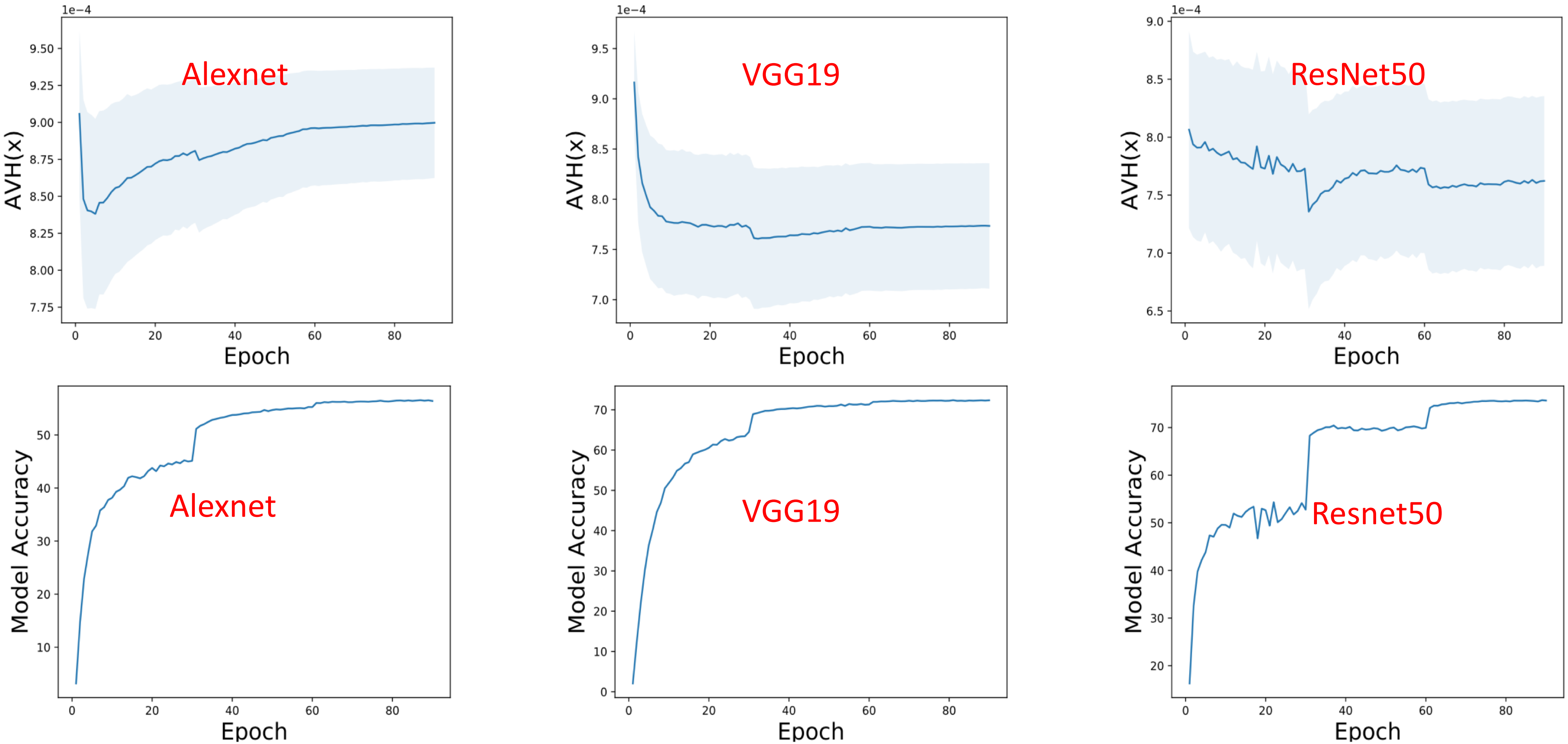
Discovery 1

AVH hits a plateau very early even when the accuracy or loss is still improving



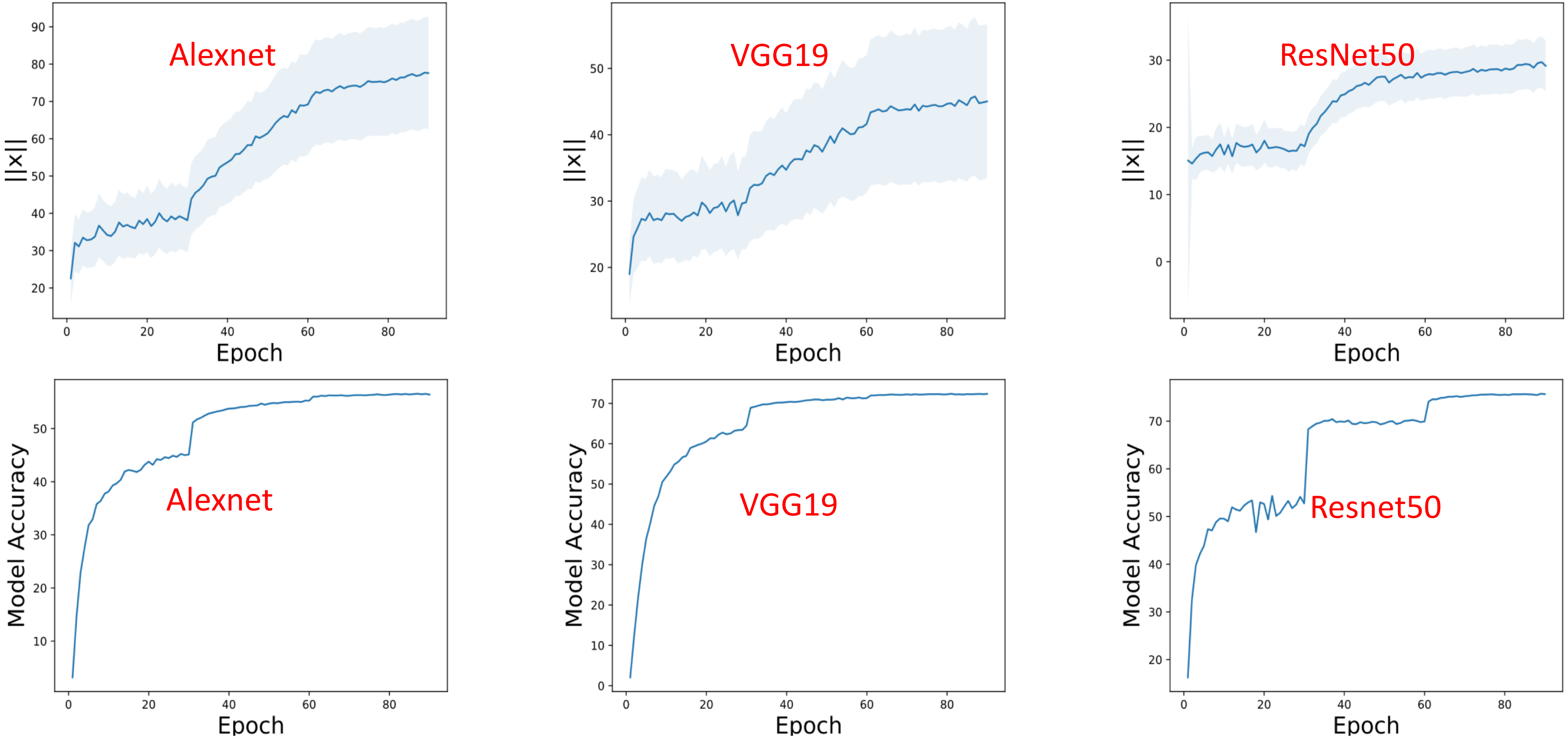
Discovery 2

AVH is an indicator of model's generalization ability



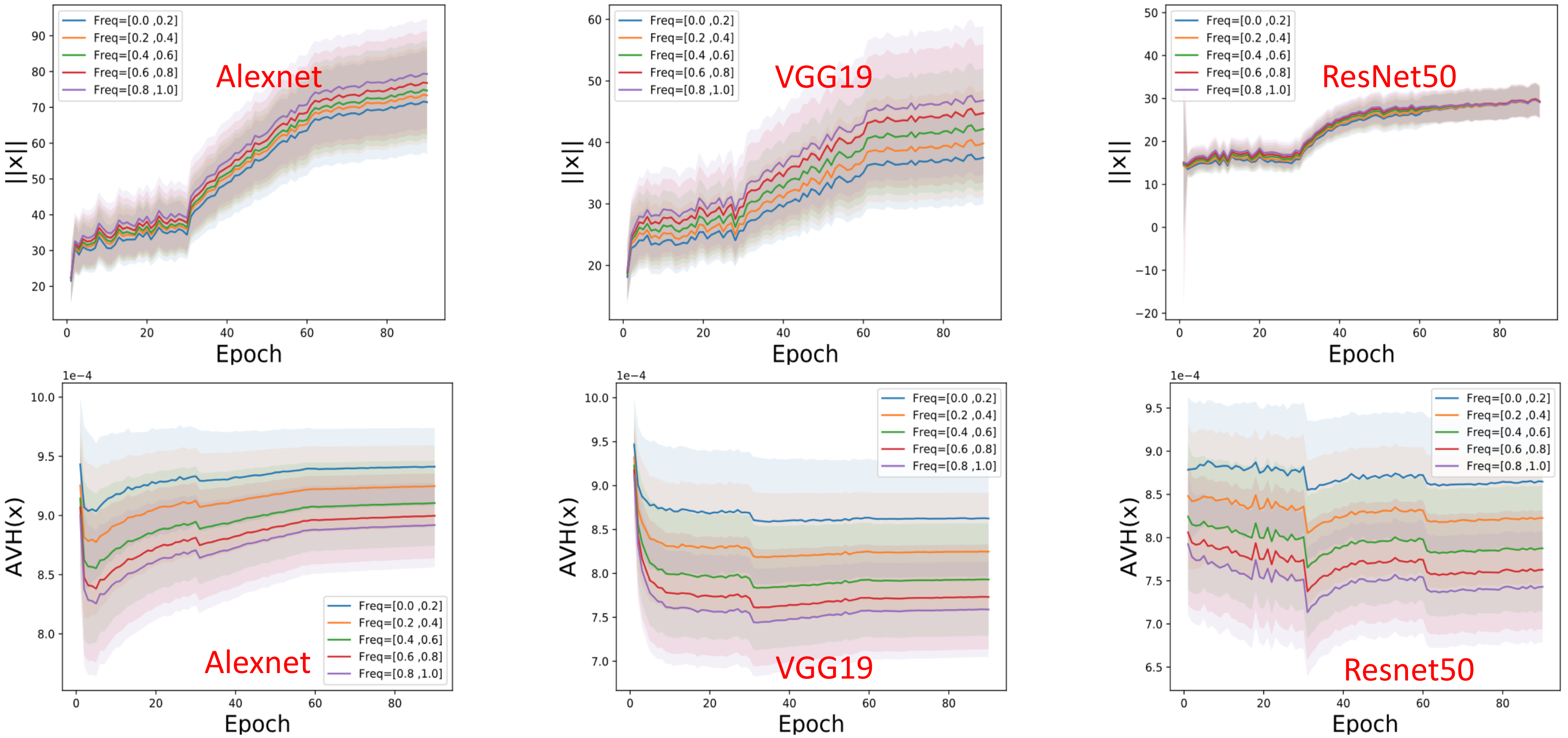
Discovery 3

The norm of feature embeddings keeps increasing during training



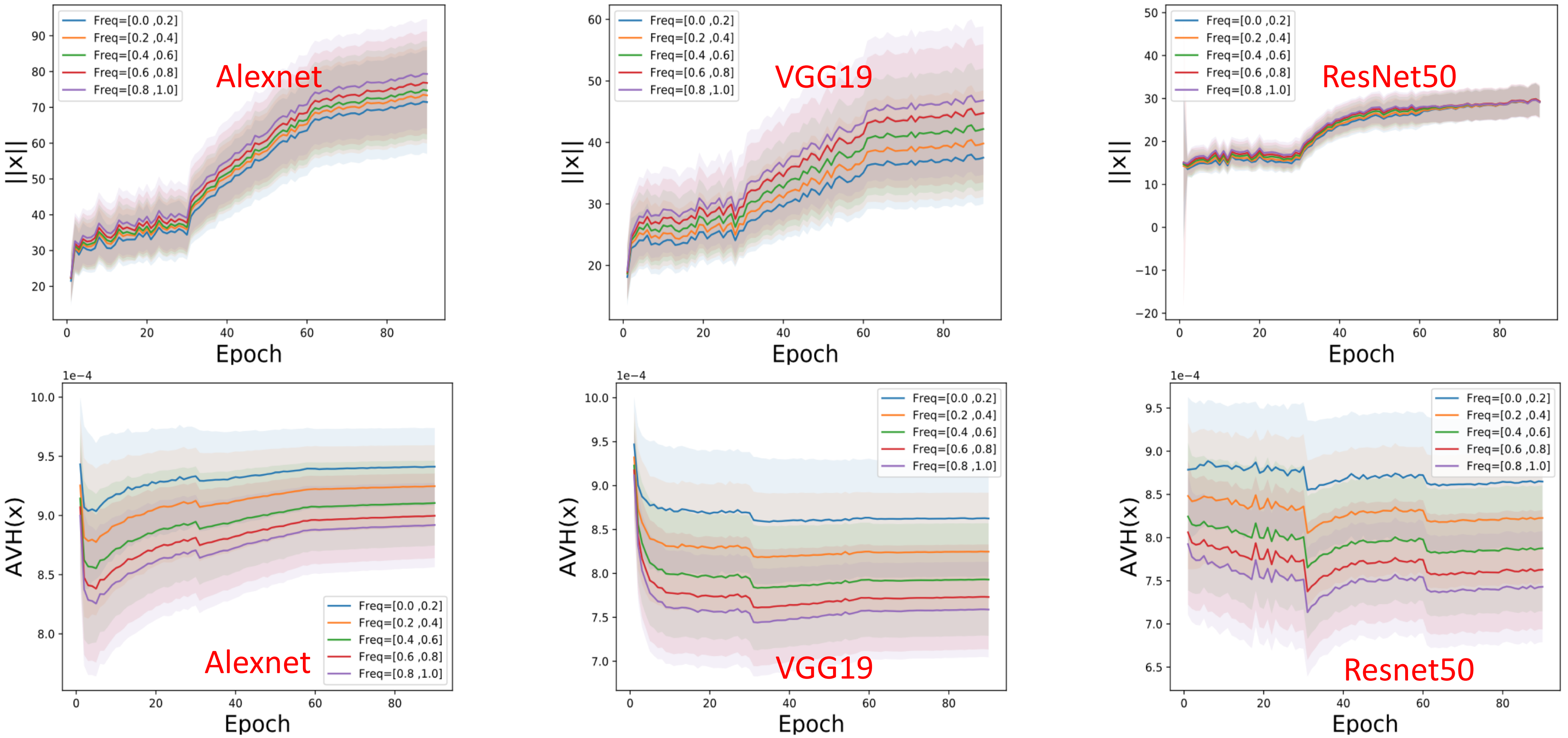
Discovery 4

AVH’s correlation with human selection frequency holds across models throughout training



Discovery 5

The norm’s correlation with human selection frequency is not consistent



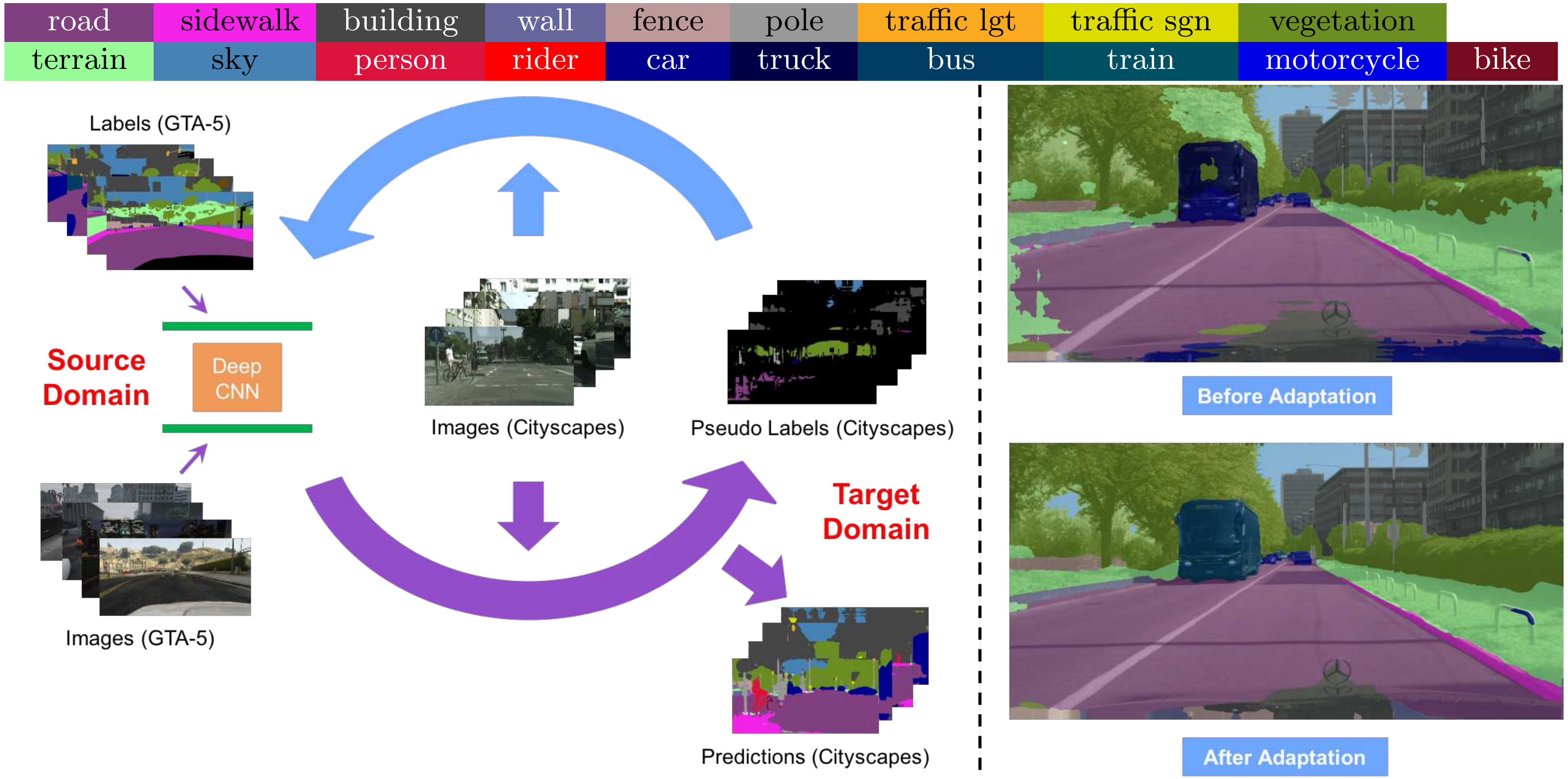
Conjecture on training dynamic of CNNs

- Softmax cross-entropy loss will first optimize the angles among different classes while the norm will fluctuate and increase very slowly.
- The angles become more stable and change very slowly while the norm increases rapidly.
- Easy examples: the angles get decreased enough for correct classification, the softmax cross-entropy loss can be well minimized by increasing the norm.
- Hard examples: the plateau is cause by unable to decrease the angle to correctly classify examples or increase the norms otherwise hurting loss.

PART 03

Applications

Self-training and Domain Adaptation



Zou et al. "Unsupervised domain adaptation for semantic segmentation via class-balanced self-training" ECCV

AVH for Self-training and Domain Adaptation

Replace Softmax-based confidence with AVH-based one during sample selection:

$$\mathcal{AVC}(c|\mathbf{x};\mathbf{w}) = \frac{\pi - \mathcal{A}(\mathbf{x}, \mathbf{w}_c)}{\sum_{k=1}^{K}(\pi - \mathcal{A}(\mathbf{x}, \mathbf{w}_k))}$$

Similarly, AVH-based pseudo label

$$\hat{y}_t^{(k)*} = \begin{cases} 1, \text{ if } k = \arg\max_k \{\frac{\mathcal{AVC}(k|\mathbf{x}_t;\mathbf{w})}{\lambda_k}\} \\ \quad \text{and } \mathcal{AVC}(k|\mathbf{x}_t;\mathbf{w}) > \lambda_k \\ 0, \text{ otherwise} \end{cases}$$

Main Results

Method	Aero	Bike	Bus	Car	Horse	Knife	Motor	Person	Plant	Skateboard	Train	Truck	Mean
Source [51]	55.1	53.3	61.9	59.1	80.6	17.9	79.7	31.2	81.0	26.5	73.5	8.5	52.4
MMD [42]	87.1	63.0	76.5	42.0	90.3	42.9	85.9	53.1	49.7	36.3	**85.8**	20.7	61.1
DANN [16]	81.9	77.7	82.8	44.3	81.2	29.5	65.1	28.6	51.9	54.6	82.8	7.8	57.4
ENT [19]	80.3	75.5	75.8	48.3	77.9	27.3	69.7	40.2	46.5	46.6	79.3	16.0	57.0
MCD [50]	87.0	60.9	**83.7**	64.0	88.9	79.6	84.7	76.9	88.6	40.3	83.0	25.8	71.9
ADR [51]	87.8	79.5	**83.7**	65.3	**92.3**	61.8	**88.9**	73.2	87.8	60.0	85.5	32.3	74.8
Source [65]	68.7	36.7	61.3	**70.4**	67.9	5.9	82.6	25.5	75.6	29.4	83.8	10.9	51.6
CBST [65]	87.2	78.8	56.5	55.4	85.1	79.2	83.8	77.7	82.8	**88.8**	69.0	**72.0**	76.4
CRST [65]	88.0	79.2	61.0	60.0	87.5	81.4	86.3	78.8	85.6	86.6	73.9	68.8	78.1
Proposed	**93.3**	**80.2**	78.9	60.9	88.4	**89.7**	**88.9**	**79.6**	**89.5**	86.8	81.5	60.0	**81.5**

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Inner Metric

	TP Rate	AVH (avg)	Model Confidence	Norm $\|\|x\|\|$
CBST+AVH	0.844	0.118	0.961	20.84
CBST/CRST	0.848	0.117	0.976	21.28

Examples chosen by AVH but not Softmax

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AVH-based loss for Domain Generalization

AVH-based Loss:

$$\mathcal{L}_{AVH} = \sum_i \frac{\exp\left(s(\pi - \mathcal{A}(\mathbf{x}_i, \mathbf{w}_{y_i}))\right)}{\sum_{k=1}^{K} \exp\left(s(\pi - \mathcal{A}(\mathbf{x}_i, \mathbf{w}_k))\right)}$$

Method	Painting	Cartoon	Photo	Sketch	Avg
AlexNet (Li et al., 2017)	62.86	66.97	89.50	57.51	69.21
MLDG (Li et al., 2018)	66.23	66.88	88.00	58.96	70.01
MetaReg (Balaji et al., 2018)	**69.82**	70.35	**91.07**	59.26	**72.62**
Feature-critic (Li et al., 2019)	64.89	**71.72**	89.94	**61.85**	72.10
Baseline CNN-9	66.46	67.88	89.70	51.72	68.94
CNN-9 + AVH	**71.56**	**69.25**	**89.93**	**60.86**	**72.90**

PART

04

Conclusion

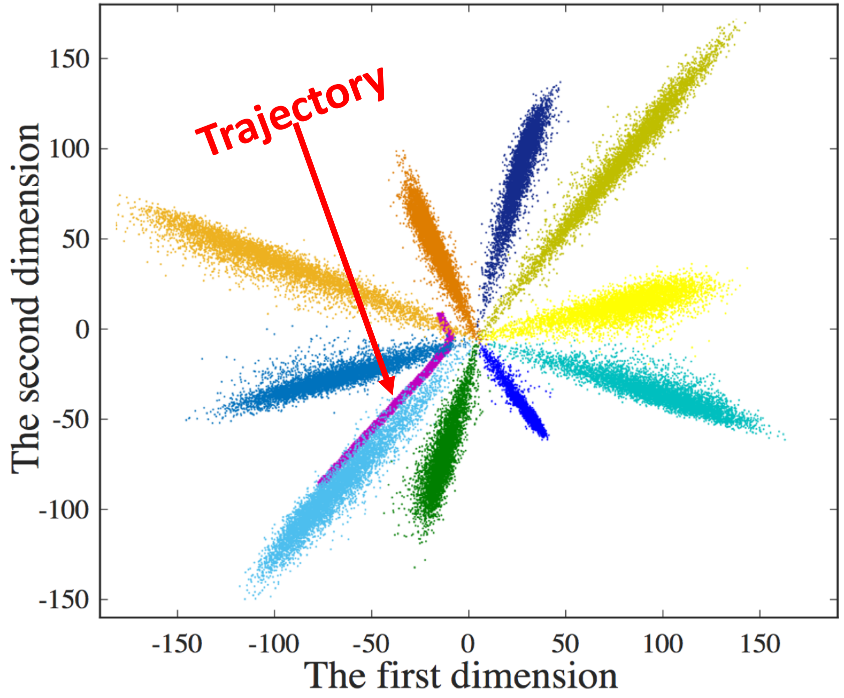
Summary

- Propose AVH as a measure for visual hardness
- Validate that AVH has a statistically significant stronger correlation with human selection frequency
- Make observations on the dynamic evolution of AVH scores during ImageNet training
- Show the superiority of AVH with its application to self-training for unsupervised domain adaptation and domain generalization

Discussions

- Connection to deep metric learning
- Connection to fairness in machine learning
- Connection to knowledge transfer and curriculum learning
- Uncertainty estimation (Aleatoric and Epistemic)
- Adversarial Example: A Counter Example?

Trajectory of an adversarial example switching from one class to another



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THANKS

Paper URL

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