Robustness at Inference: Towards Explainability, Uncertainty, and Intervenability

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Tutorial Materials

Accessible Online

SCAN ME

https://alregib.ece.gatech.edu/wacv-2024-tutorial/

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WACV 2024 Tutorial

Robustness at Inference: Towards Explainability, Uncertainty, and Intervenability

Presented by: *Ghassan AlRegib, and Mohit Prabhushankar*

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Georgia Institute of Technology, Atlanta, USA

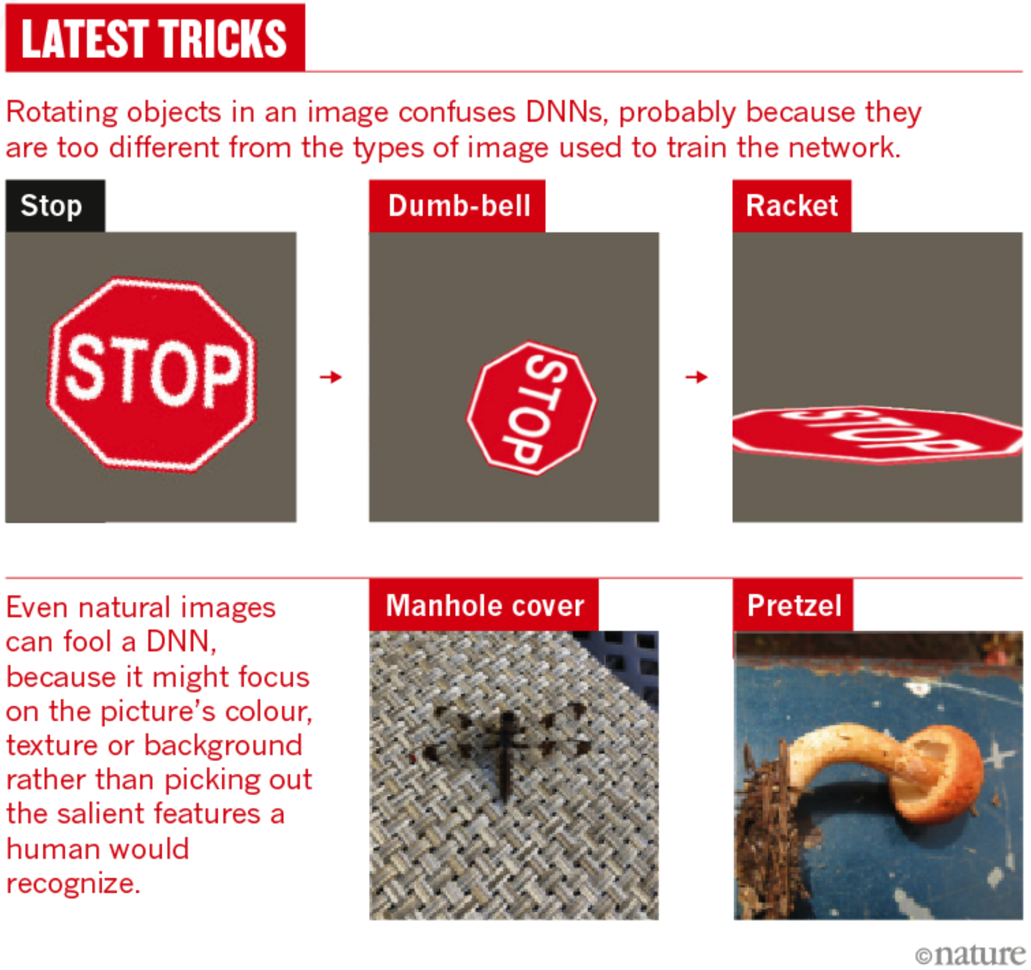
https://alregib.ece.gatech.edu/

Duration: Half-Day event

Expectation vs Reality of Deep Learning

Deep Learning

Expectation vs Reality



Deep Learning

Expectation vs Reality

“The best-laid plans of sensors and networks often go awry”

- Engineers, probably

Deep Learning

Requirements and Challenges

Requirements: Deep Learning-enabled systems must predict correctly on novel data

Novel data sources:

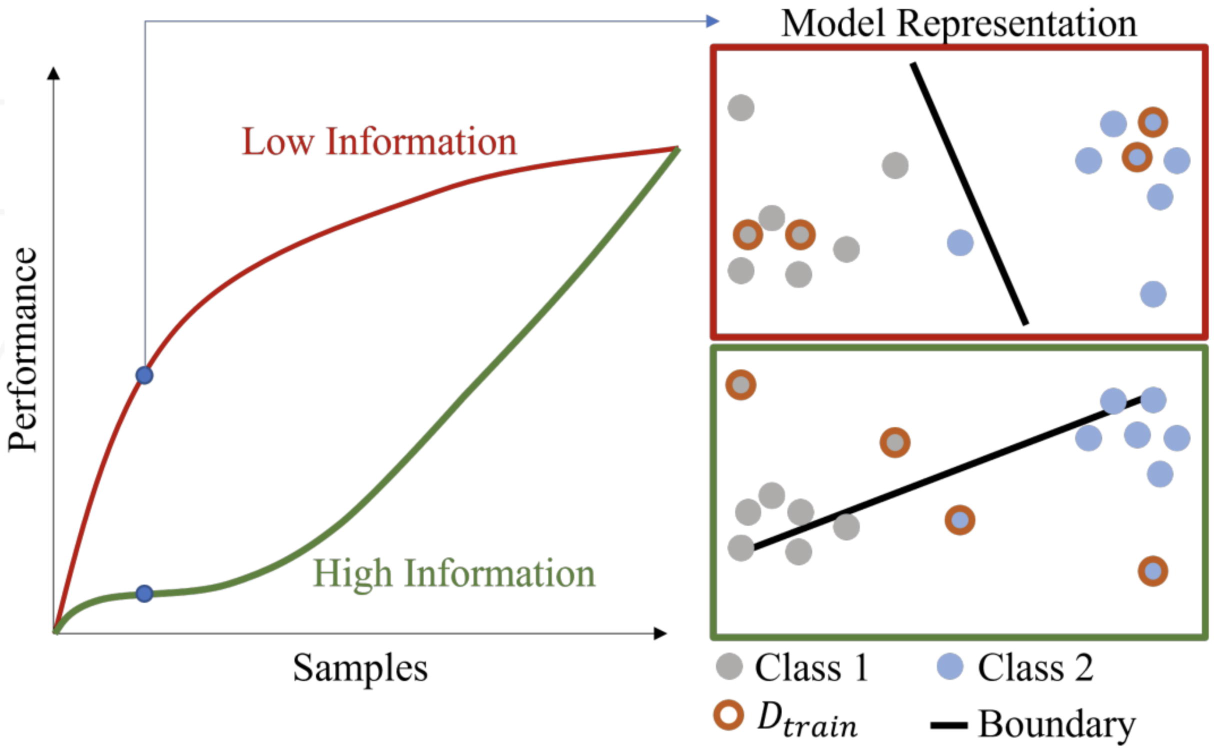
- Test distributions
- Anomalous data
- Out-Of-Distribution data
- Adversarial data
- Corrupted data
- Noisy data
- New classes
- …

Temel, Dogancan, et al. "Cure-tsd: Challenging unreal and real environments for traffic sign detection." *IEEE Transactions on Intelligent Transportation Systems* (2017).

Deep Learning at Training

Overcoming Challenges at Training: Part 1

The most novel/aberrant samples should <u>not</u> be used in early training

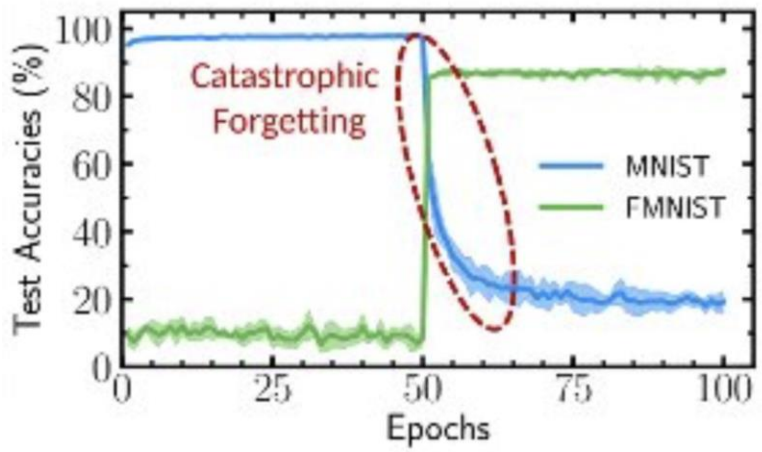


Novel samples = Most Informative

- The first instance of training must occur with less informative samples
- Ex: For autonomous vehicles, less informative means
  - Highway scenarios
  - Parking
  - No accidents
  - No aberrant events

Benkert, R., Prabushankar, M., AlRegib, G., Pacharmi, A., & Corona, E. (2023). Gaussian Switch Sampling: A Second Order Approach to Active Learning. *IEEE Transactions on Artificial Intelligence*.

Subsequent training must <u>not</u> focus only on novel data

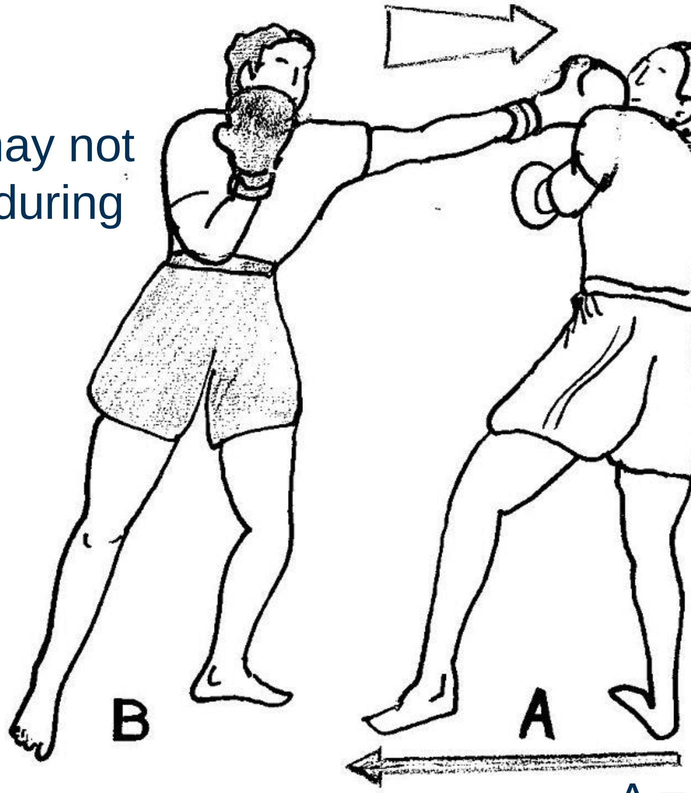


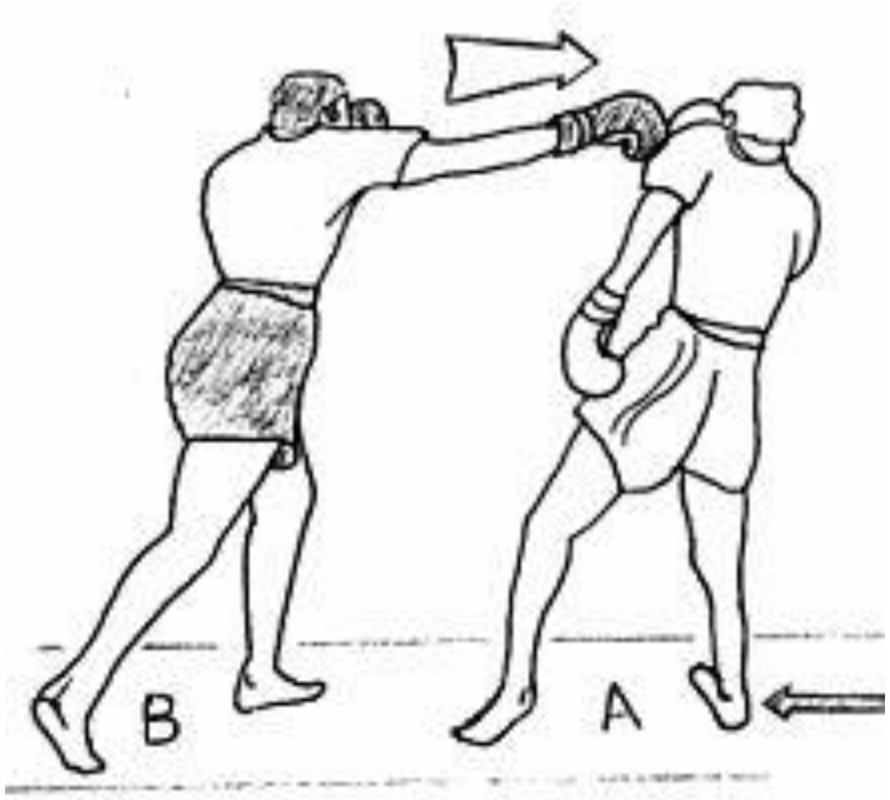
- The model performs well on the new scenarios, while forgetting the old scenarios
- A number of techniques exist to overcome this trend
- However, they affect the overall performance in large-scale settings
- It is not always clear **if and when** to incorporate novel scenarios in training

Laborieux, Axel, et al. "Synaptic metaplasticity in binarized neural networks." *Nature communications* 12.1 (2021): 2549.

Novel data packs a 1-2 punch!

Novel data may not be available during training





Even if available, novel data does not easily fit into either the earlier or later stages of training

A = Deep Neural Networks
B = Novel data

Deep Learning at Inference

Overcoming Challenges at Inference

We must handle novel data at Inference!!

Novel data sources:

- Test distributions
- Anomalous data
- Out-Of-Distribution data
- Adversarial data
- Corrupted data
- Noisy data
- New classes
- …

Model Train

At Inference

Objective

Objective of the Tutorial

To discuss methodologies that promote robustness in neural networks at inference

- Part 1: Inference in Neural Networks
- Part 2: Explainability at Inference
- Part 3: Uncertainty at Inference
- Part 4: Intervenability at Inference
- Part 5: Conclusions and Future Directions

Robust Neural Networks

Part I: Inference in Neural Networks

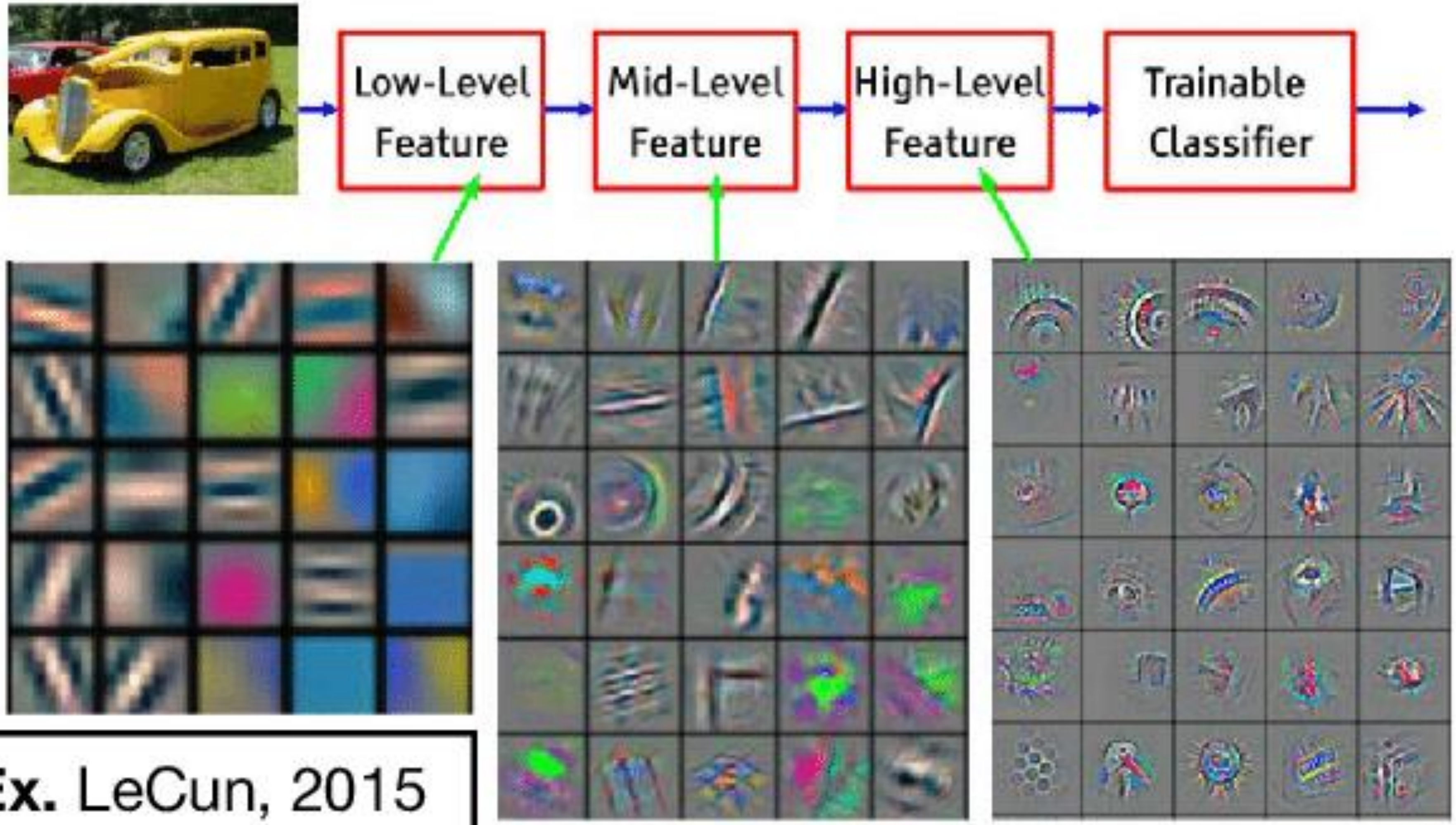
Objective

Objective of the Tutorial

To discuss methodologies that promote robustness in neural networks at inference

- **Part 1: Inference in Neural Networks**
  - Neural Network Basics
  - Robustness in Deep Learning
  - Information at Inference
  - Challenges at Inference
  - Gradients at Inference
- Part 2: Explainability at Inference
- Part 3: Uncertainty at Inference
- Part 4: Intervenability at Inference
- Part 5: Conclusions and Future Directions

Deep Learning
Overview

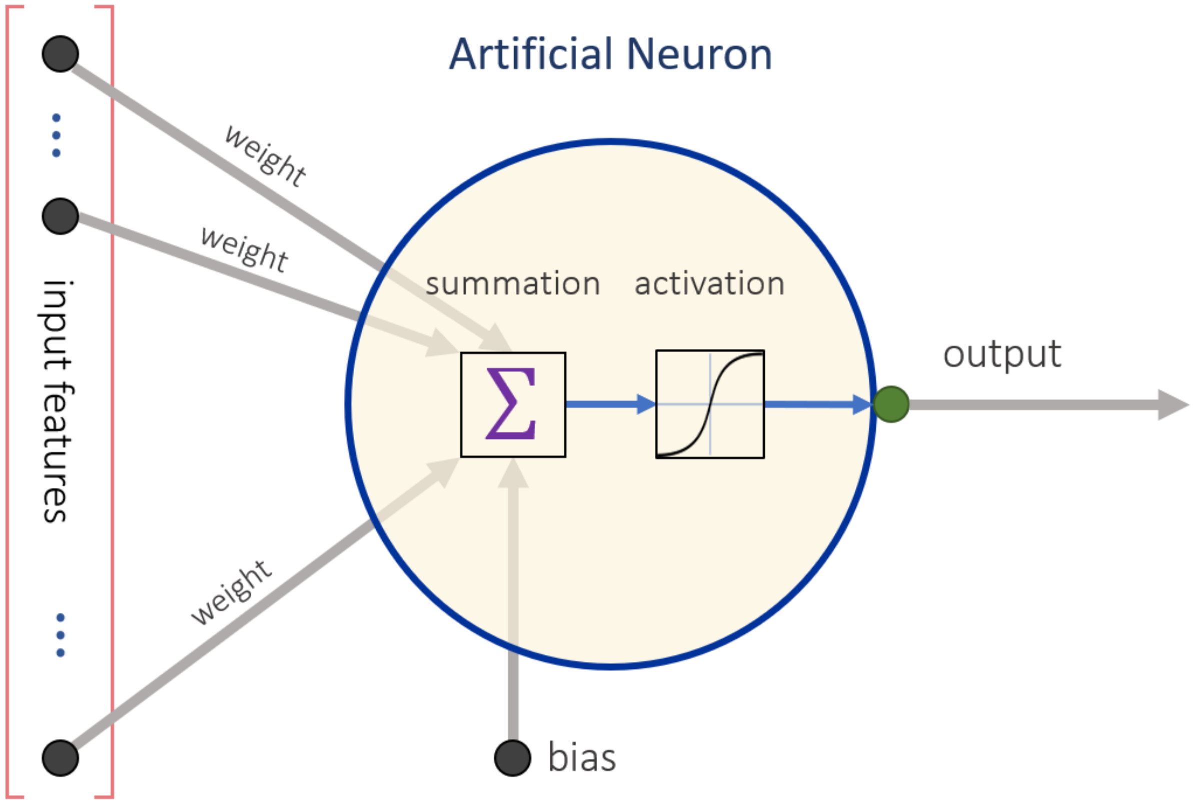


Ex. LeCun, 2015

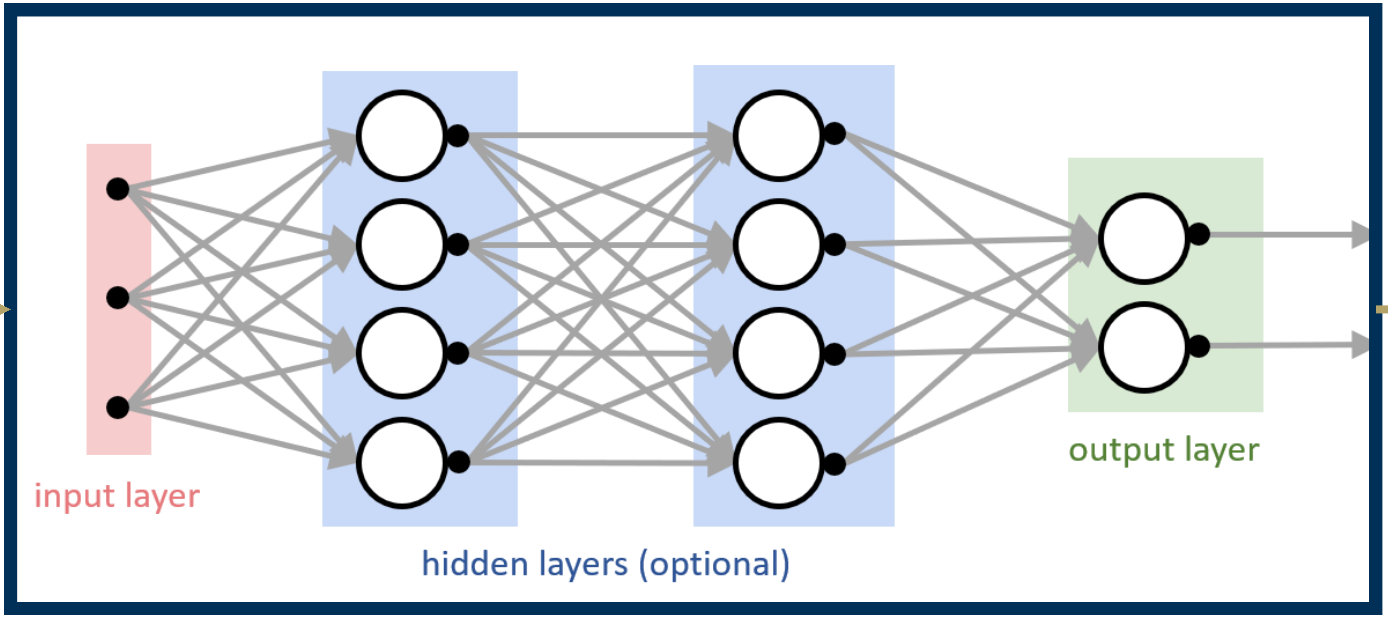
The underlying computation unit is the Neuron

Artificial neurons consist of:

- A single **output**
- Multiple **inputs**
- Input **weights**
- A **bias** input
- An **activation function**



Neurons are stacked and densely connected to construct ANNs



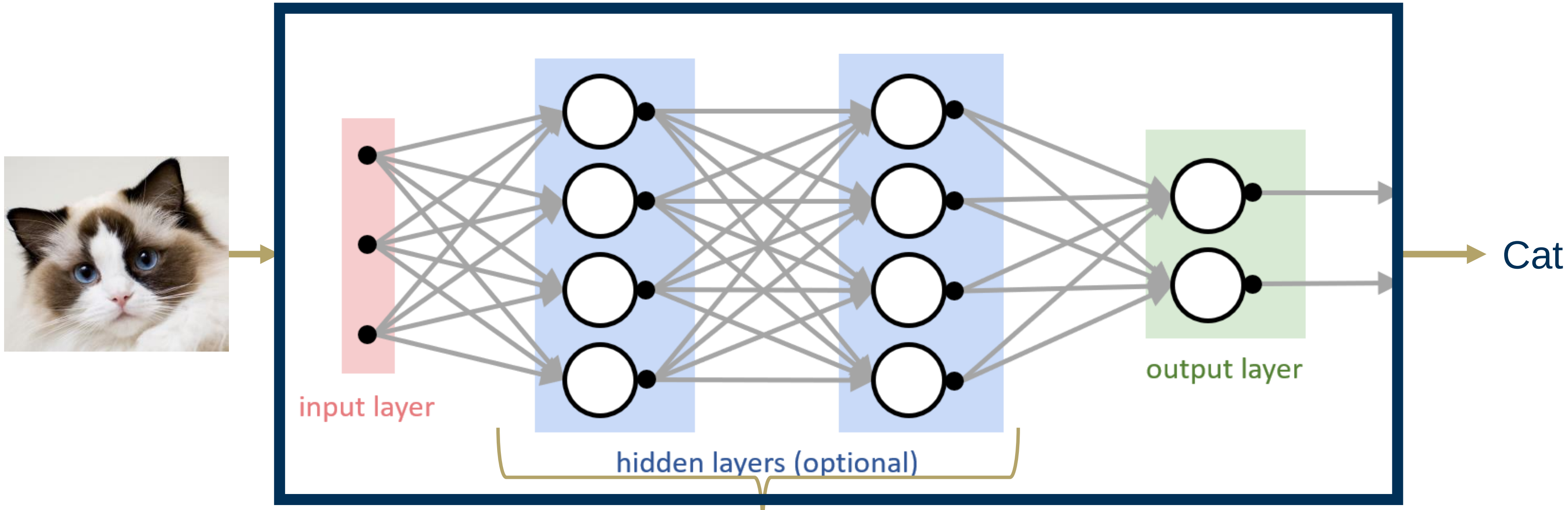
Cat

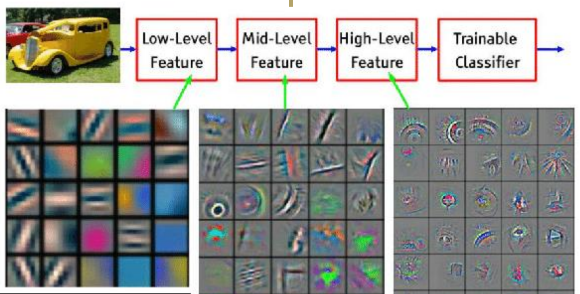
Typically, a neuron is part of a network organized in **layers**:

- An **input** layer (Layer 0)
- An **output** layer (Layer K)
- Zero or more **hidden** (middle) layers (Layers $1 \ldots K-1$)

Deep Learning
Convolutional Neural Networks

Stationary property of images allow for a small number of convolution kernels



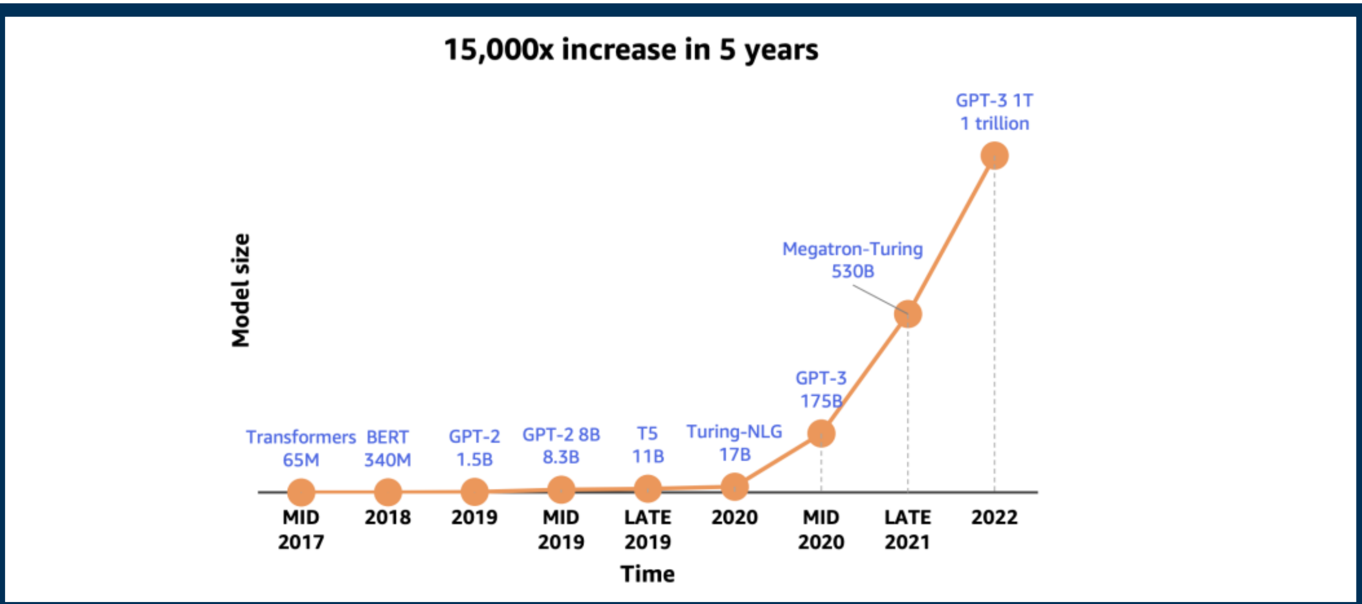


Ex. LeCun, 2015

Deep Deep Deep Deep Deep … Learning

Recent Advancements

Transformers, Large Language Models and Foundation Models



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Primary reasons for advancements:

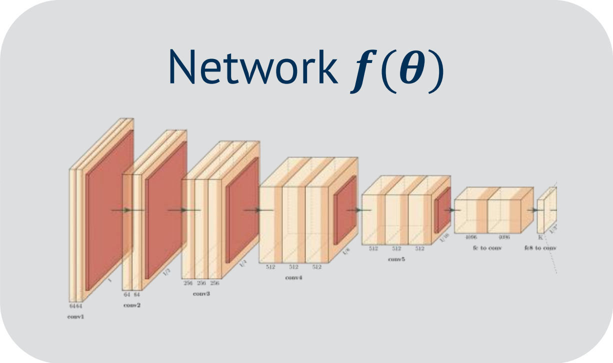
1. Expanded interests from the research community
2. Computational resources availability
3. **Big data availability**

Deep Learning at Inference

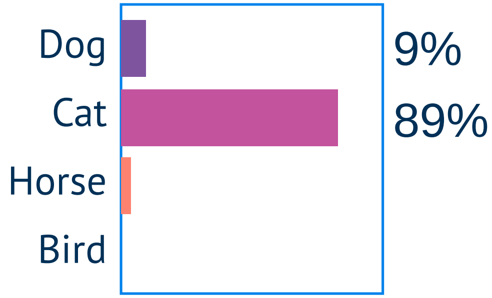
Classification

Given : One network, One image. Required: Class Prediction

x



Predicted
Class Probability



If $x \in \chi$, the data is **not novel**

$$\hat{y} = f(x)$$
$$y = argmax_i\ \hat{y}$$
$$p(\hat{y}) = T(f(x))$$

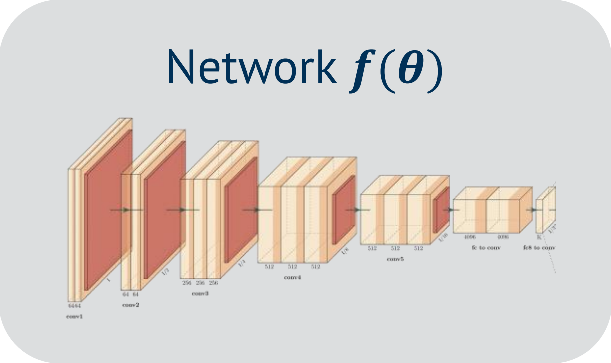
$\hat{y}$ = Logits
y = Predicted Class
$p(\hat{y})$ = Probabilities
$f(\cdot)$ = Trained Network
χ = Training data

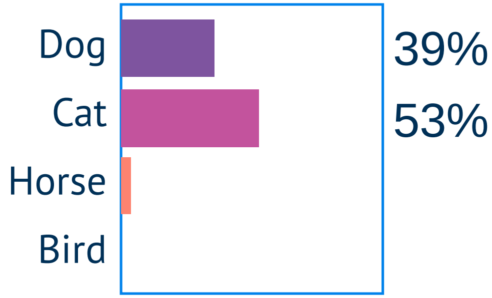
Deep Learning at Inference

Robust Classification in Deep Networks

Deep learning robustness: Correctly predict class even when data is <u>novel</u>

x'



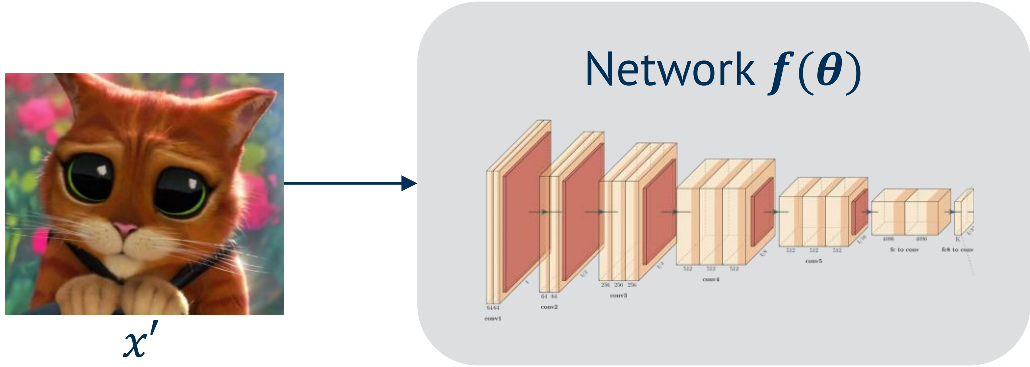


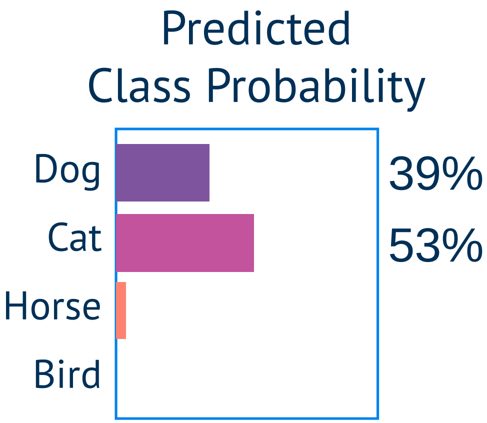
If $x \in \chi$, the data is **novel**

$$\hat{y} = f(x' + \epsilon)$$
$$y = argmax_i\ \hat{y}$$
$$p(\hat{y}) = T(f(x' + \epsilon))$$

$\hat{y}$ = Logits
y = Predicted Class
$p(\hat{y})$ = Probabilities
$f(\cdot)$ = Trained Network
χ = Training data
ϵ = Noise

Deep learning robustness: Correctly predict class even when data is <u>novel</u>





To achieve robustness at Inference, we need the following:

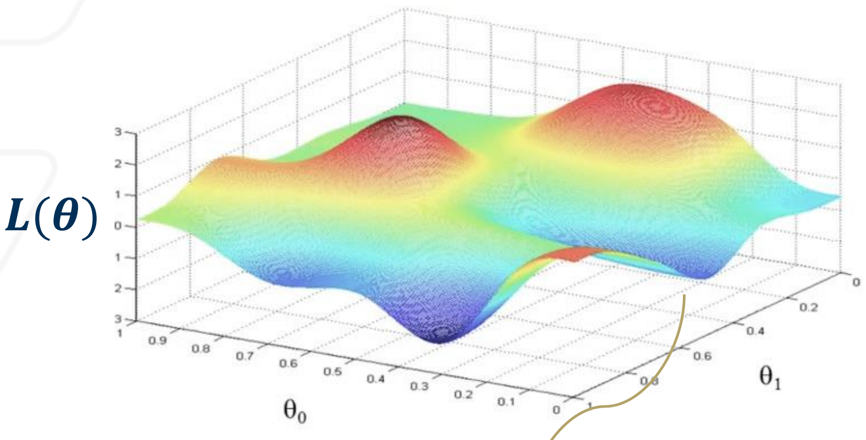
- **Information** provided by the novel data as **a function of training distribution**
- Methodology to **extract information** from novel data
- **Techniques** that utilize the information from novel data

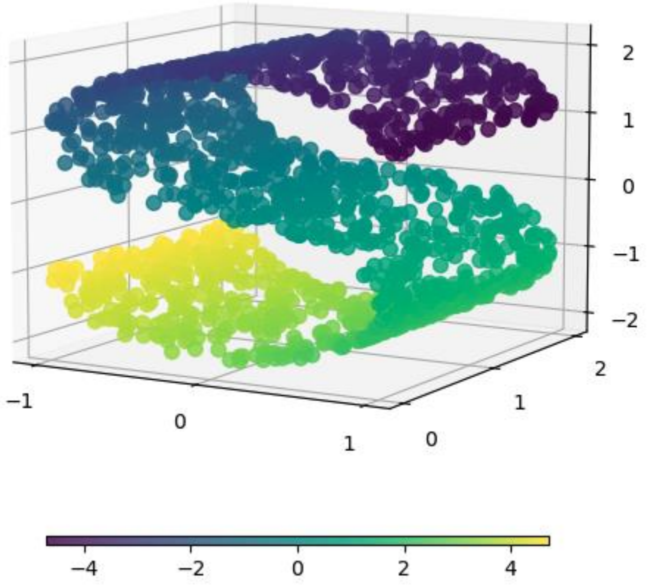
Why is this Challenging?

Challenges at Inference

A Quick note on Manifolds..

Manifolds are compact topological spaces that allow exact mathematical functions





Toy visualizations generated using functions (and thousands of generated data points)

Real data visualizations generated using dimensionality reduction algorithms (Isomap)

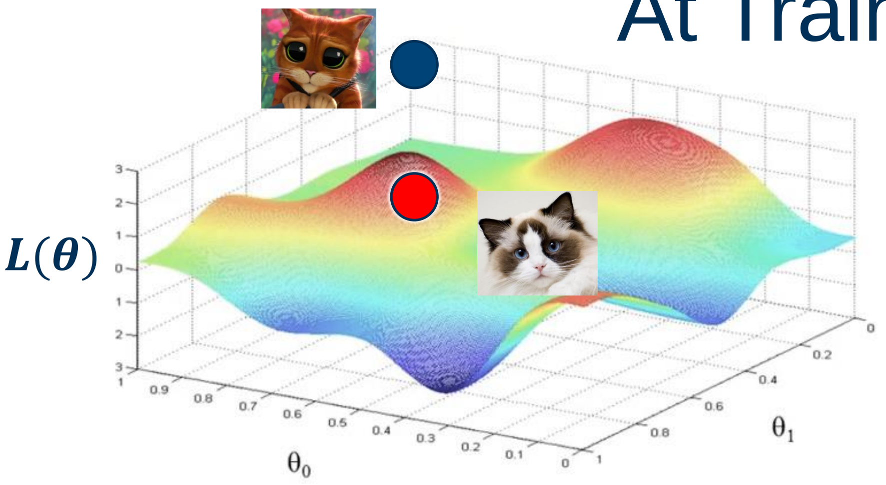
Challenges at Inference

Inference

However, at inference only the test data point is available and the underlying structure of the manifold is unknown

At Inference

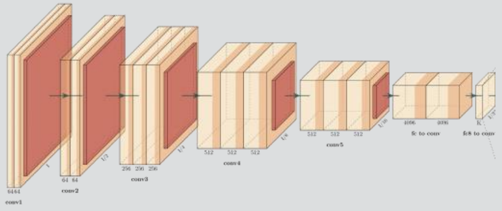
At Training



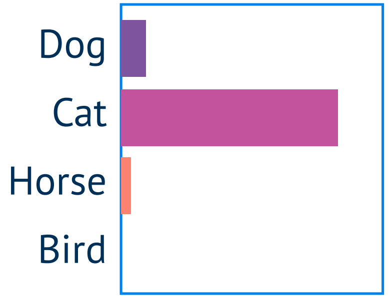
At training, we have access to all training data.

Colloquially, Fisher Information is the “surprise” in a system that observes an event

Network $\boldsymbol{f(\theta)}$



Predicted
Class Probability

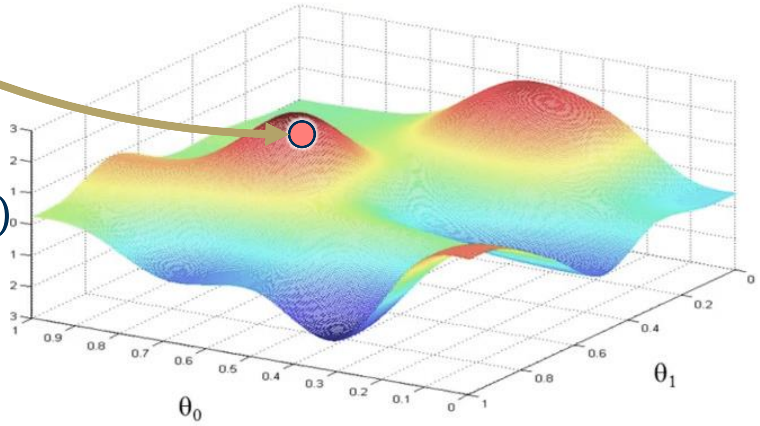


Fisher Information

$$I(\theta) = Var\left(\frac{\partial}{\partial\theta} l(\theta|x)\right)$$

θ = Statistic of distribution
$\ell(\theta \mid x)$ = Likelihood function

$\boldsymbol{l(\theta|x)}$

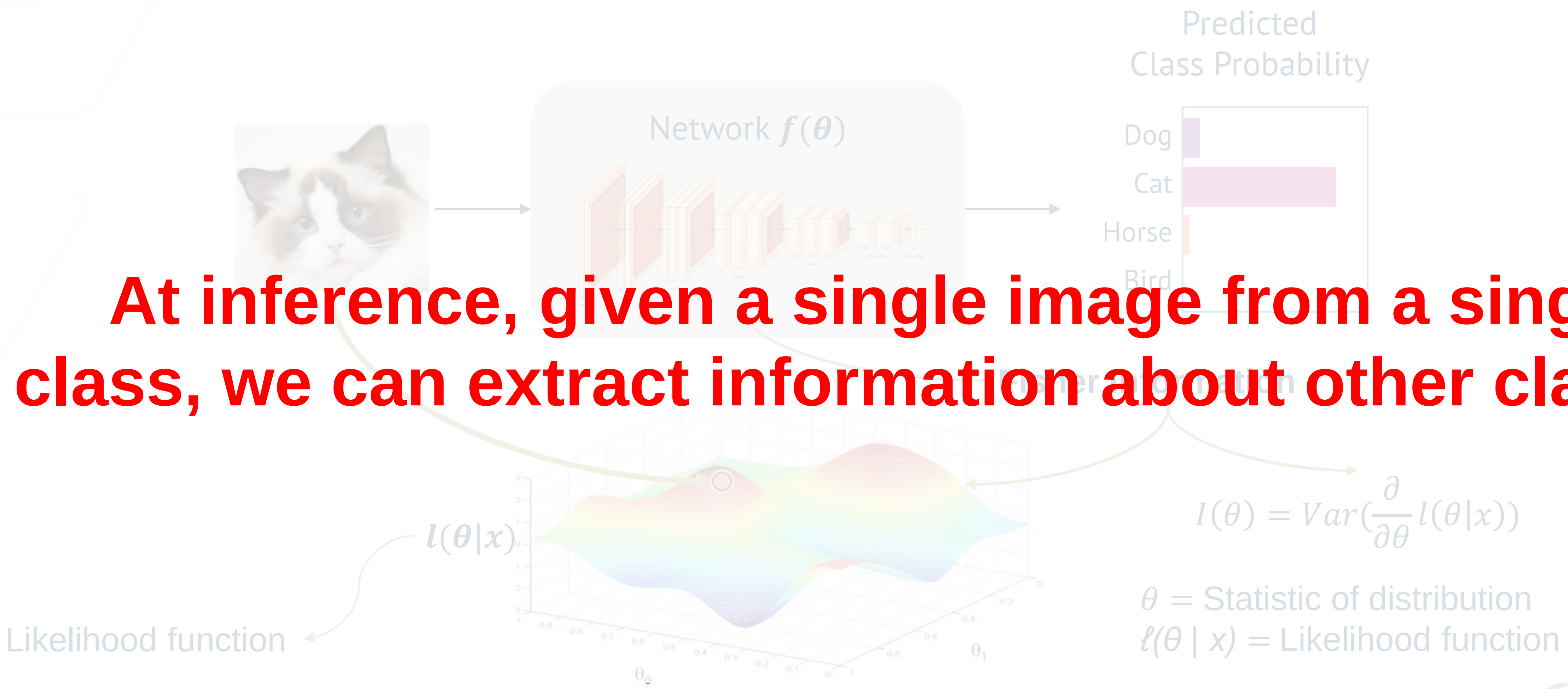


Likelihood function

[1] A good blogpost about Fisher Information: https://towardsdatascience.com/an-intuitive-look-at-fisher-information-2720c40867d8

Information at Inference

Information at Inference



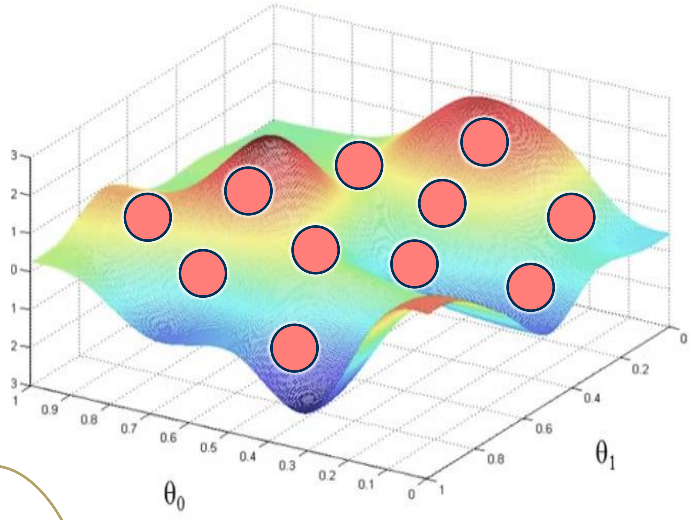
At inference, given a single image from a single class, we can extract information about other classes

Information at Inference

Gradients as Fisher Information

Gradients infer information about the statistics of underlying manifolds

$\boldsymbol{l(\theta|x)}$



Likelihood function instead of loss manifold

From before, $I(\theta) = Var(\frac{\partial}{\partial\theta} l(\theta|x))$

Using variance decomposition, $I(\theta)$ reduces to:

$I(\theta) = E[U_\theta U_\theta^T]$ where

$E[\cdot] = \text{Expectation}$
$U_\theta = \nabla_\theta l(\theta|x)$, Gradients w.r.t. the sample

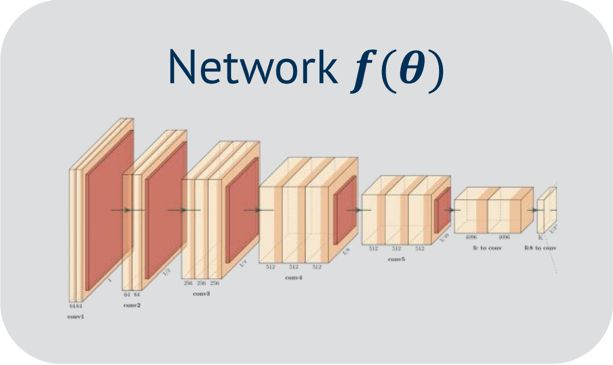
Hence, gradients draw information from the underlying distribution as learned by the network weights!

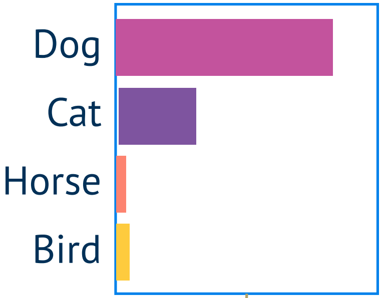
Kwon, Gukyeong, et al. "Backpropagated gradient representations for anomaly detection." *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXI 16*. Springer International Publishing, 2020.

Case Study: Gradients as Fisher Information in Explainability

Gradients infer information about the statistics of underlying manifolds

x

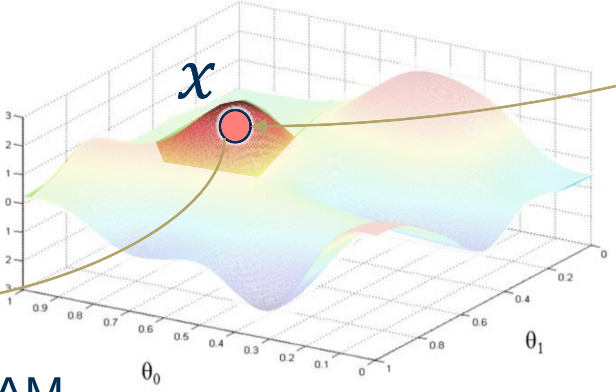




In this case, the image and its prediction extracts nose, mouth and jowl features.

Local information (specific to x) is sufficient!

$l(\theta|x)$



Feature attribution via GradCAM

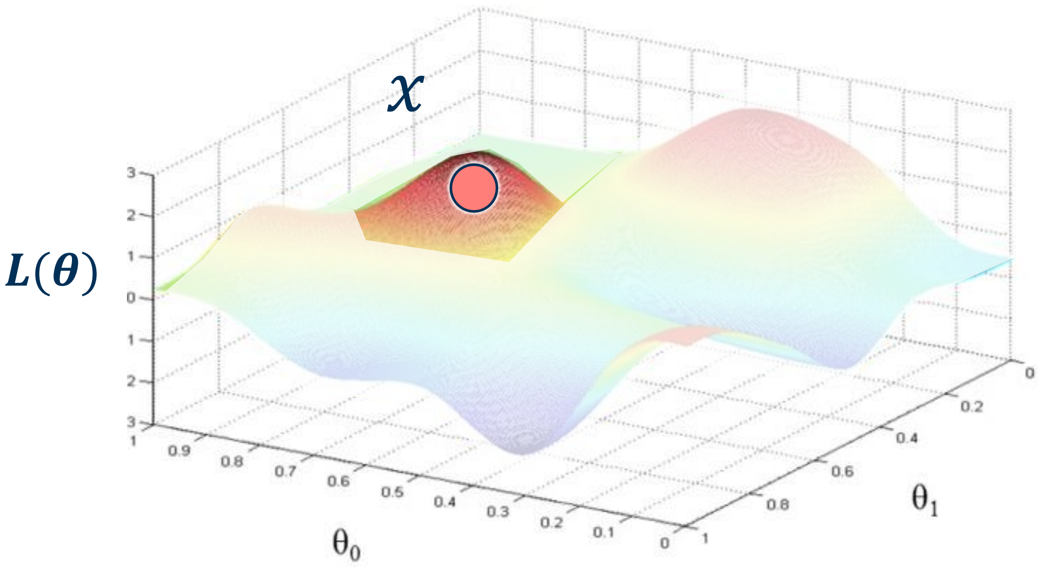
Hence, gradients draw information from the underlying distribution as learned by the network weights!

[1] A good blogpost about Fisher Information: https://towardsdatascience.com/an-intuitive-look-at-fisher-information-2720c40867d8

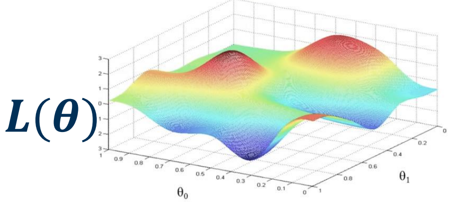
Gradients at Inference

Local Information

Gradients provide local information around the vicinity of x, even if x is novel. This is because x projects on the learned knowledge



Ideal

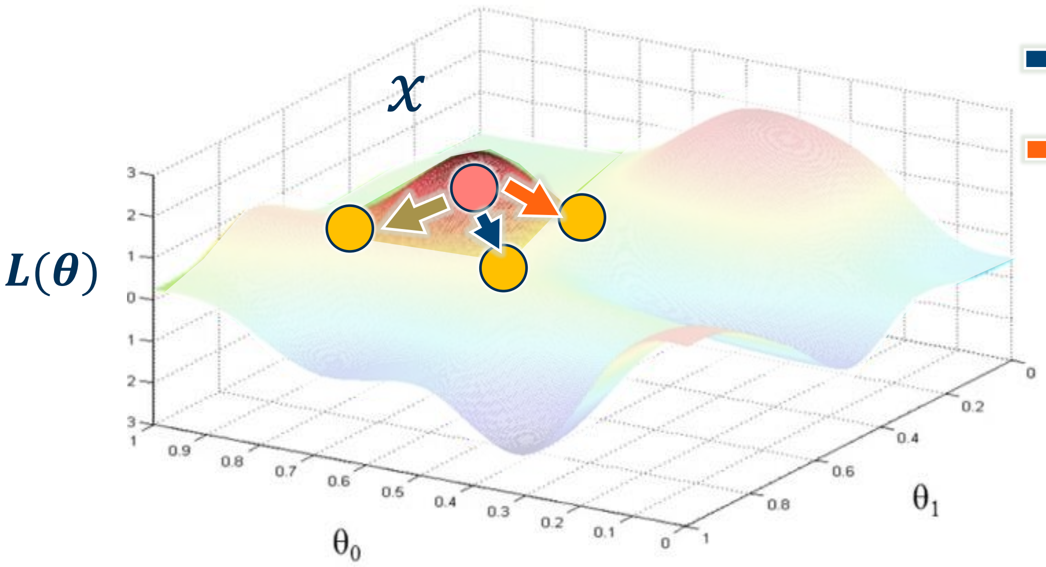


$\boldsymbol{\alpha} \, \nabla_{\boldsymbol{\theta}} \, \boldsymbol{L}(\boldsymbol{\theta})$ provides local information up to a small distance $\boldsymbol{\alpha}$ away from $\boldsymbol{x}$

Gradients at Inference

Direction of Steepest Descent

Gradients allow choosing the fastest direction of descent given a loss function $L(\theta)$



Path 1?

Path 2?

Path 3?

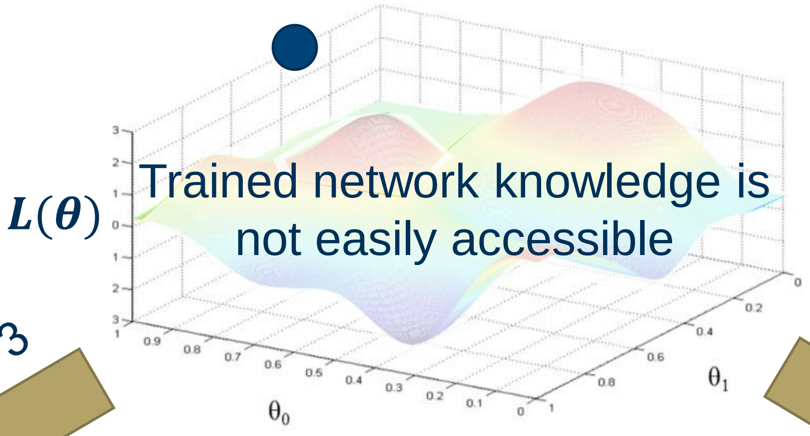
Which direction should we optimize towards (knowing only the local information)?

Negative of the gradient provides the **descent direction** towards the local minima, as measured by $L(\theta)$

Gradients at Inference

To Characterize the Novel Data at Inference

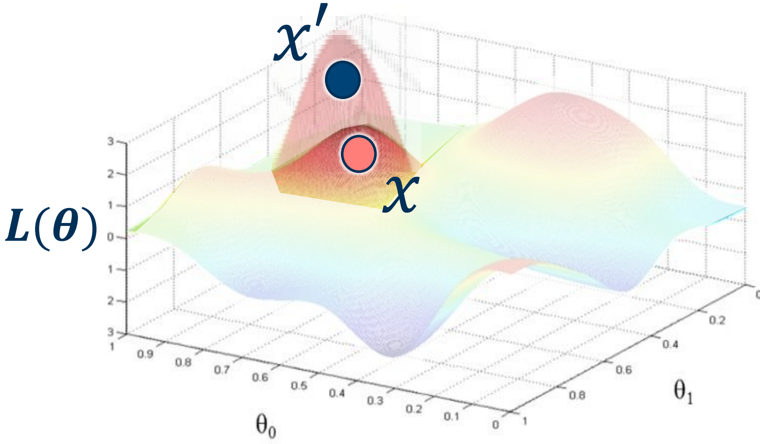
At Inference



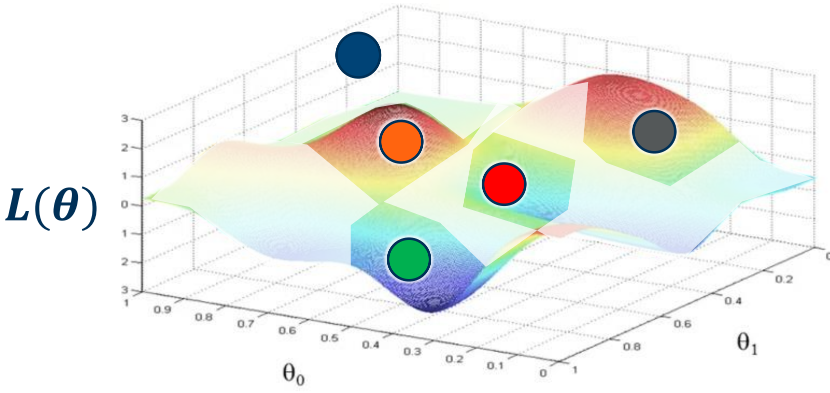
Part 2, 3

Part 4

Counterfactual and Contrastive Representations using Gradients



Representation Traversal using Interventions



Robust Neural Networks

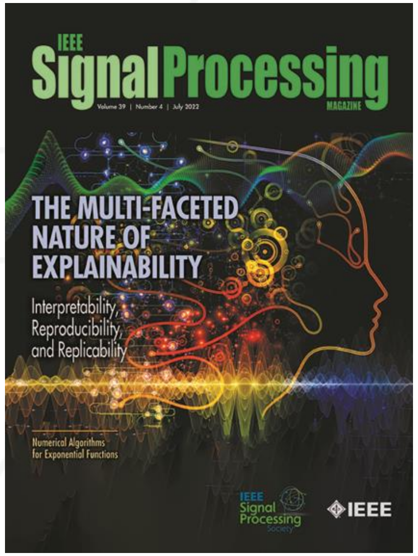
Part 2: Explainability at Inference

Objective

Objective of the Tutorial

To discuss methodologies that promote robustness in neural networks at inference

- Part 1: Inference in Neural Networks
- **Part 2: Explainability at Inference**
  - Visual Explanations
  - Gradient-based Explanations
  - GradCAM
  - CounterfactualCAM
  - ContrastCAM
- Part 3: Uncertainty at Inference
- Part 4: Intervenability at Inference
- Part 5: Conclusions and Future Directions



Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

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Postdoc

Ghassan AlRegib, PhD
Professor

SCAN ME

Explanations

Visual Explanations

Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

- **Explanations are defined as a set of rationales used to understand the reasons behind a decision**
- **If the decision is based on visual characteristics within the data, the decision-making reasons are visual explanations**

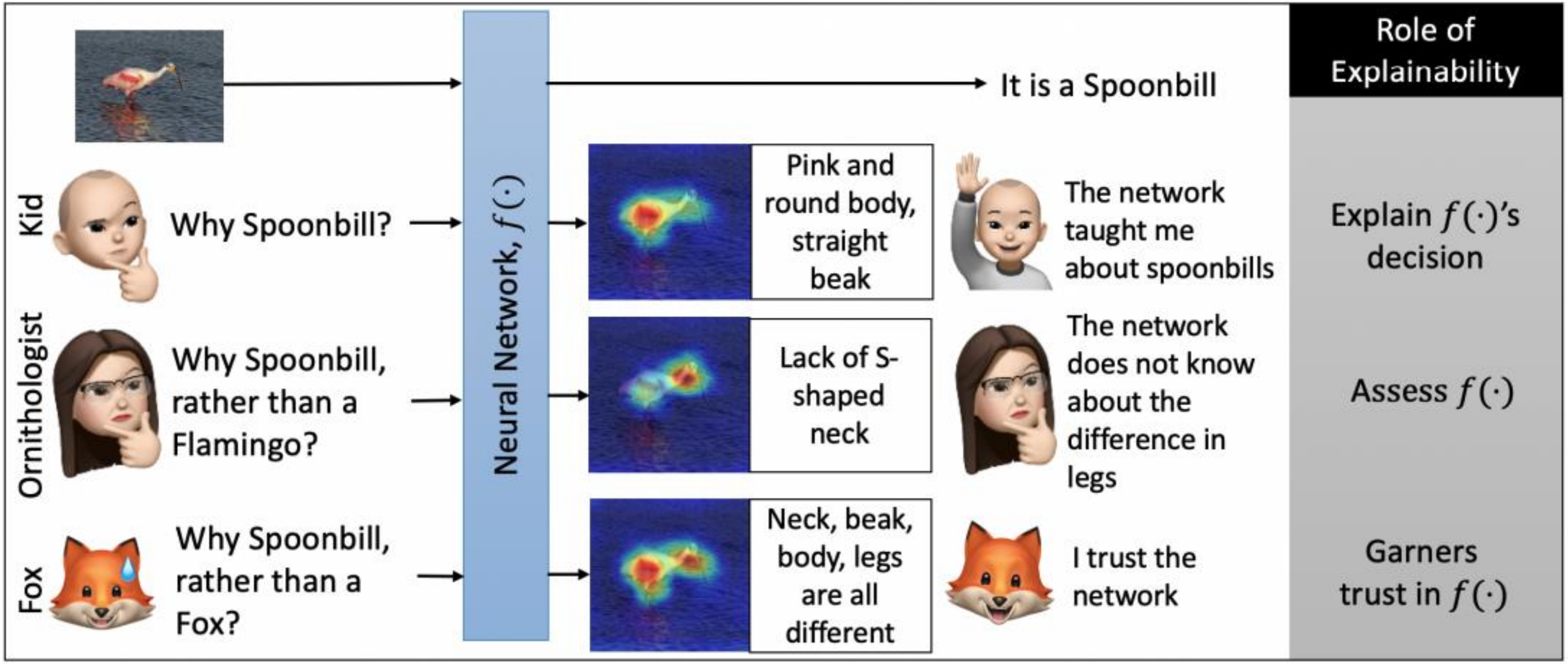
Bullmastiff	Why Bullmastiff?	What if Bullmastiff was not in the image?	Why Bullmastiff, rather than a Boxer?

AlRegib, G., & Prabhushankar, M. (2022). Explanatory Paradigms in Neural Networks: Towards relevant and contextual explanations. *IEEE Signal Processing Magazine*, *39*(4), 59-72.

Explanations

Role of Explanations – context and relevance

Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

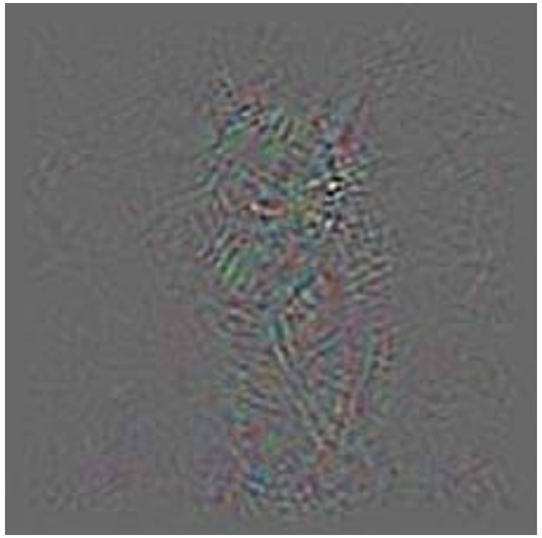


AlRegib, G., & Prabhushankar, M. (2022). Explanatory Paradigms in Neural Networks: Towards relevant and contextual explanations. *IEEE Signal Processing Magazine*, *39*(4), 59-72.

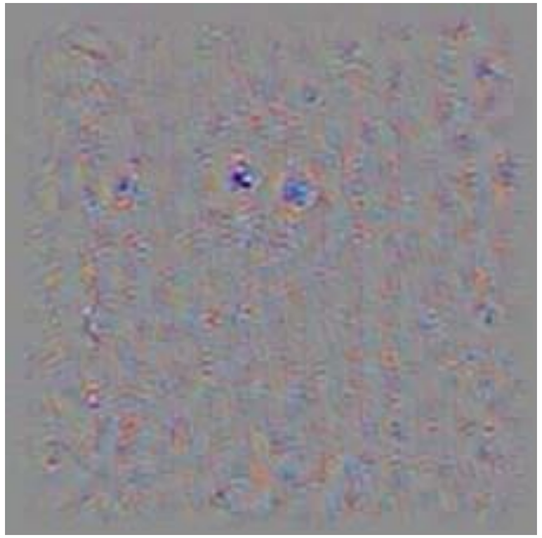
Gradients provide a one-shot means of perturbing the input that changes the output; They provide pixel-level importance scores

Input

Vanilla Gradients



Deconvolution Gradients



Guided Backpropagation

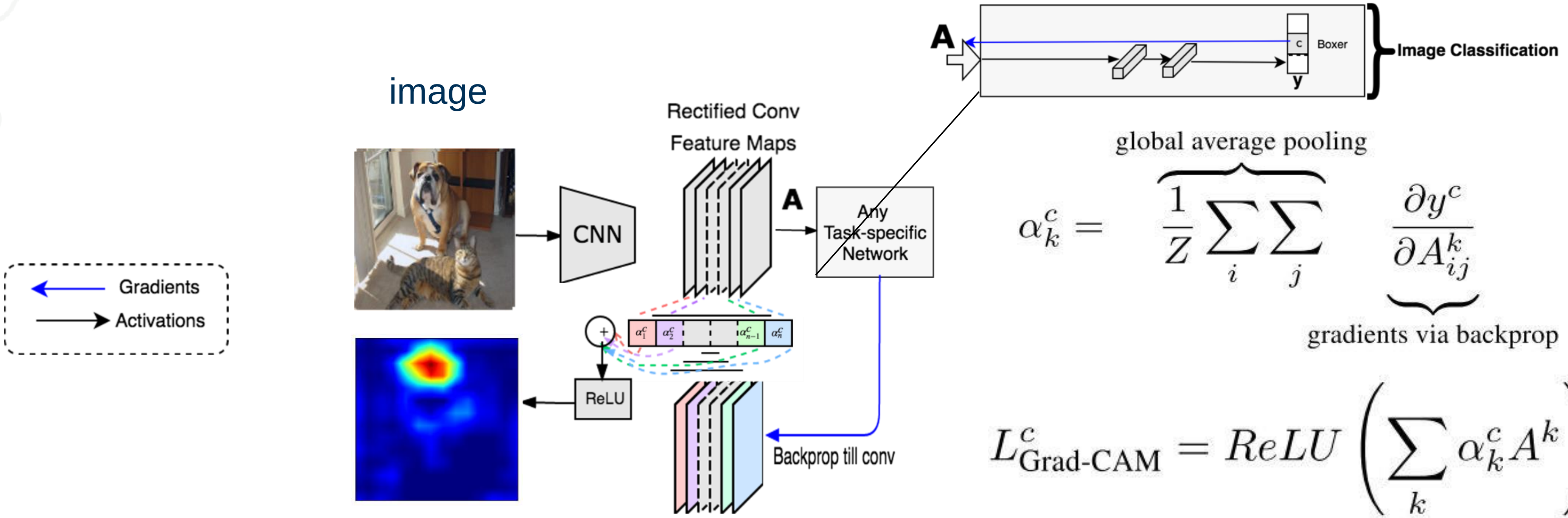
However, localization remains an issue

Springenberg, Dosovitskiy, et al., Striving for Simplicity: The all convolutional net, 2015

Gradient and Activation-based Explanations

GradCAM

Grad-CAM uses the gradient information flowing into the last convolutional layer of the CNN to assign importance values to each activation for a particular decision of interest.



$$\alpha_k^c = \overbrace{\frac{1}{Z}\sum_i \sum_j}^{\text{global average pooling}} \underbrace{\frac{\partial y^c}{\partial A_{ij}^k}}_{\text{gradients via backprop}}$$

$$L^c_{\text{Grad-CAM}} = ReLU \underbrace{\left(\sum_k \alpha_k^c A^k\right)}_{\text{linear combination}}$$

Grad-CAM (up-sampled to original image dimension)

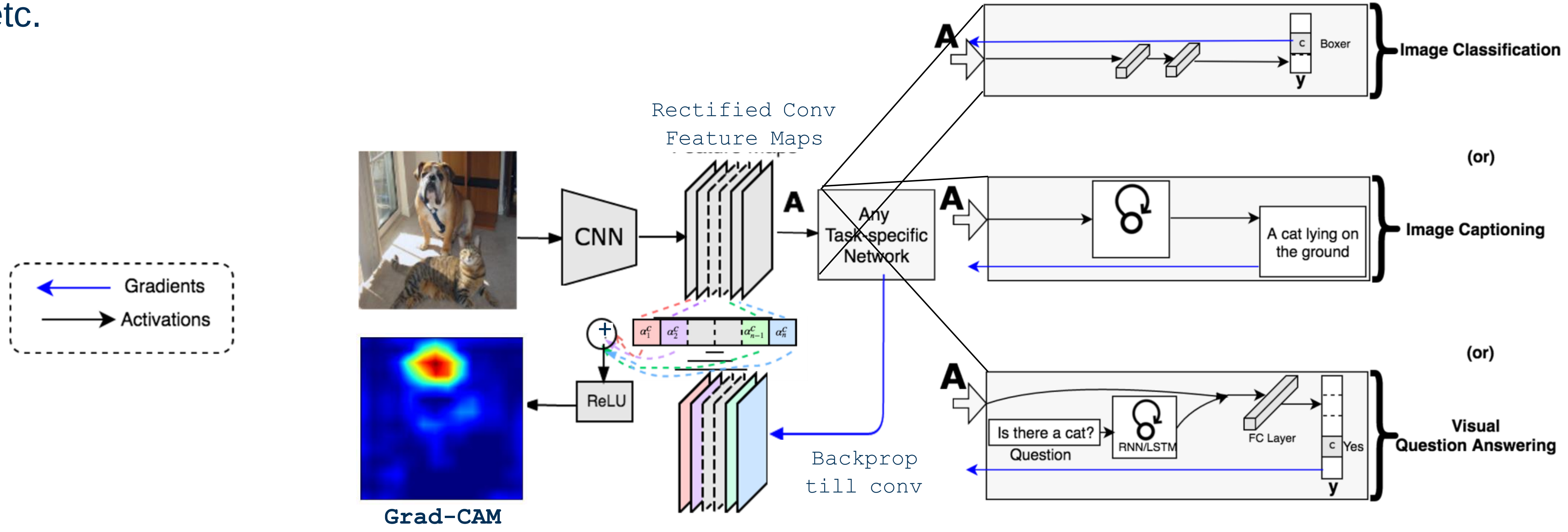
Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." *Proceedings of the IEEE international conference on computer vision*. 2017.

Gradient and Activation-based Explanations

GradCAM

Grad-CAM generalizes to any task:

- Image classification
- Image captioning
- Visual question answering
- etc.



Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." *Proceedings of the IEEE international conference on computer vision*. 2017.

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Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

GradCAM provides answers to *‘Why P?’* questions. But different stakeholders require relevant and contextual explanations

Bullmastiff	Why Bullmastiff?	What if Bullmastiff was not in the image?	Why Bullmastiff, rather than a Boxer?

AlRegib, G., & Prabhushankar, M. (2022). Explanatory Paradigms in Neural Networks: Towards relevant and contextual explanations. *IEEE Signal Processing Magazine*, *39*(4), 59-72.

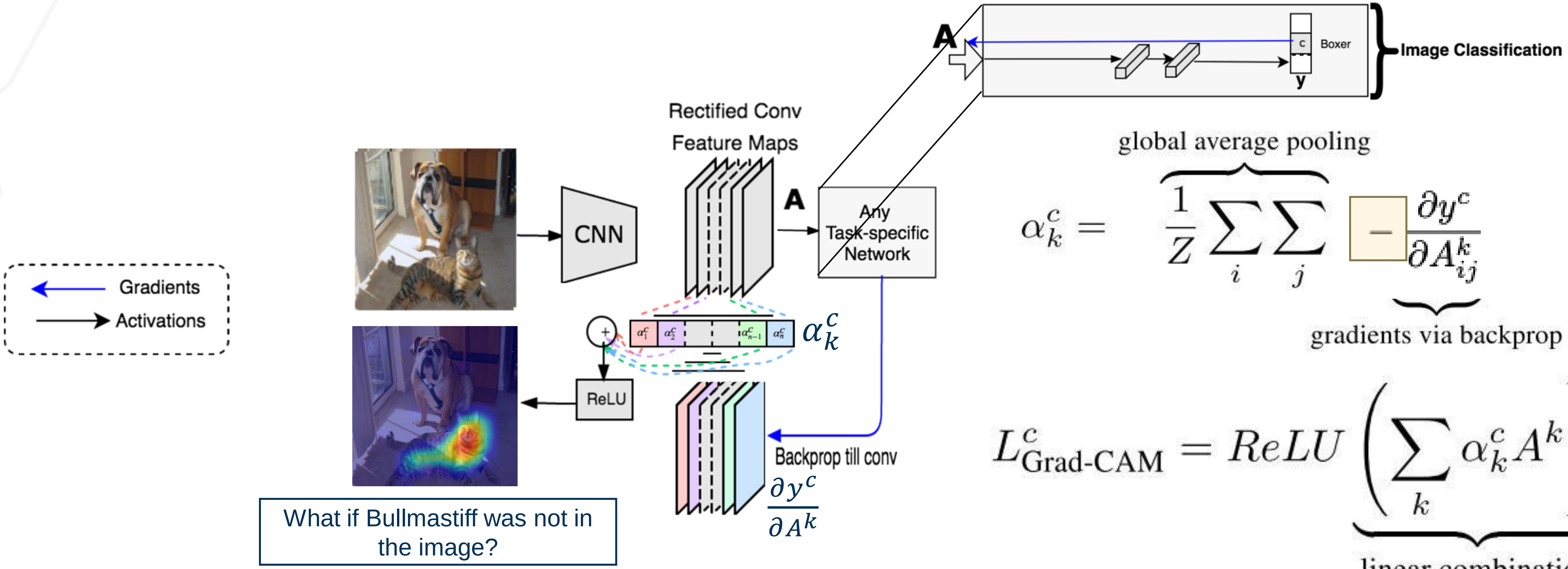
Gradient and Activation-based Explanations

CounterfactualCAM: What if this region were absent in the image?

Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

SCAN ME

In GradCAM, global average pool the negative of gradients to obtain α^c for each kernel k



$$\alpha_k^c = \overbrace{\frac{1}{Z}\sum_i \sum_j}^{\text{global average pooling}} \boxed{-} \underbrace{\frac{\partial y^c}{\partial A_{ij}^k}}_{\text{gradients via backprop}}$$

$$L^c_{\text{Grad-CAM}} = ReLU \underbrace{\left(\sum_k \alpha_k^c A^k\right)}_{\text{linear combination}}$$

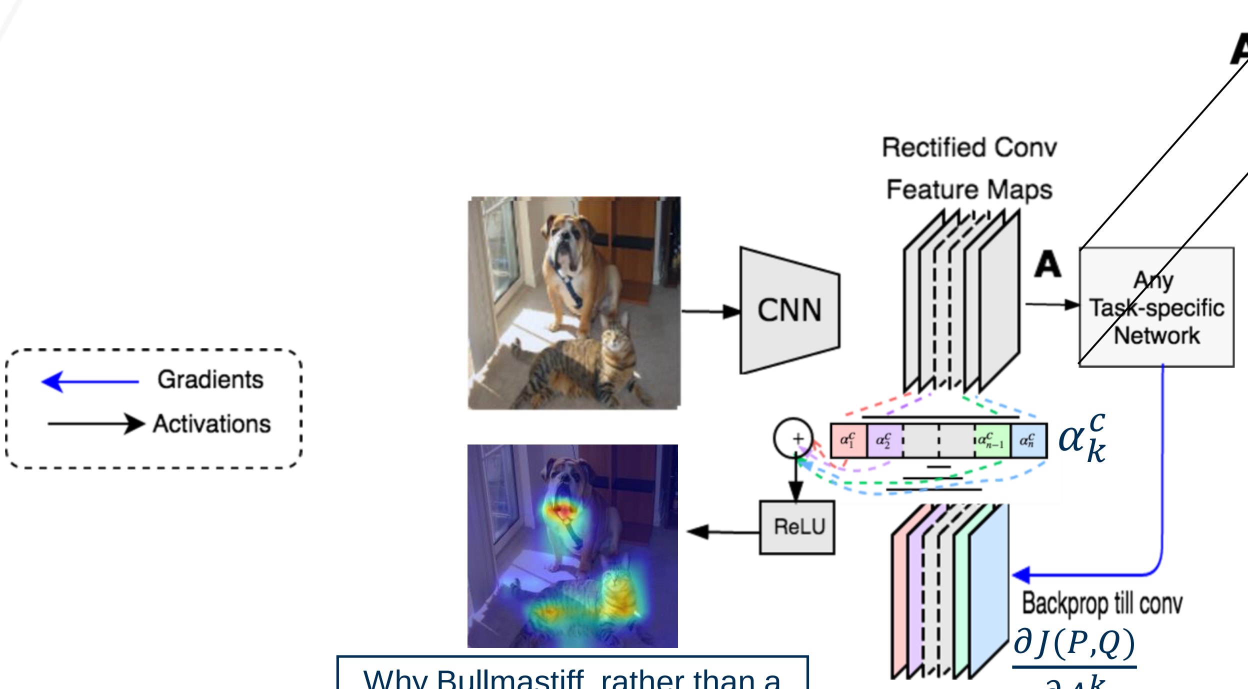
Negating the gradients effectively removes these regions from analysis

Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." *Proceedings of the IEEE international conference on computer vision*. 2017.

Gradient and Activation-based Explanations

ContrastCAM: Why P, rather than Q?

In GradCAM, backward pass the loss between predicted class P and some contrast class Q to last conv layer



Contrast-CAM

$$\alpha_k^c = \overbrace{\frac{1}{Z}\sum_i\sum_j}^{\text{global average pooling}} \underbrace{\boxed{\frac{\partial J(P,Q)}{\partial A_{ij}^k}}}_{\text{gradients via backprop}}$$

$$L^c_{\text{Grad-CAM}} = ReLU \underbrace{\left(\sum_k \alpha_k^c A^k\right)}_{\text{linear combination}}$$

Backpropagating the loss highlights the differences between classes P and Q.

Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Gradient and Activation-based Explanations

Results from GradCAM, CounterfactualCAM, and ContrastCAM

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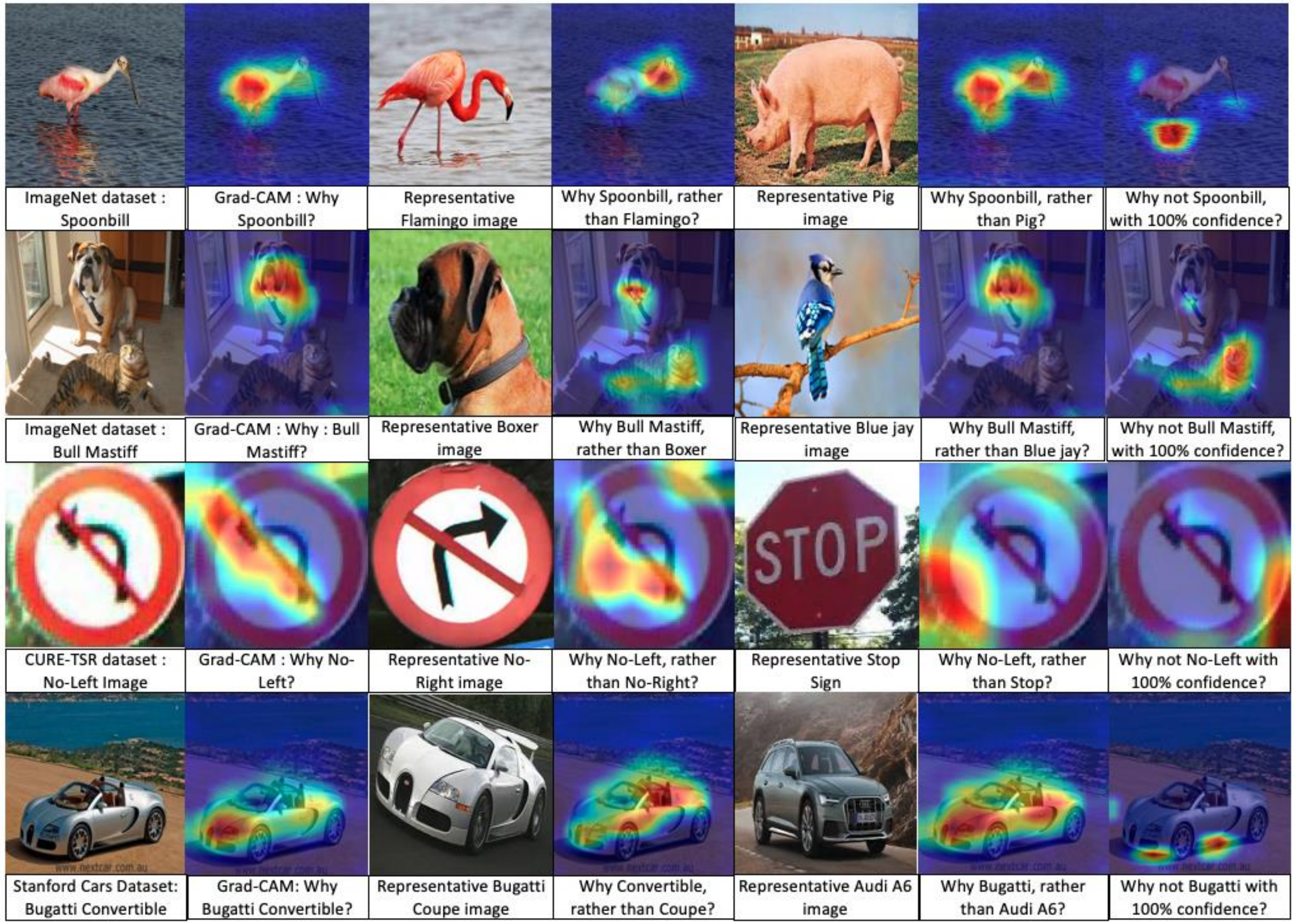
Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

Input Image | Grad-CAM | Contrast 1 | Contrastive Explanation 1 | Contrast 2 | Contrastive Explanation 2



Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Gradient and Activation-based Explanations

Results from GradCAM, CounterfactualCAM, and ContrastCAM

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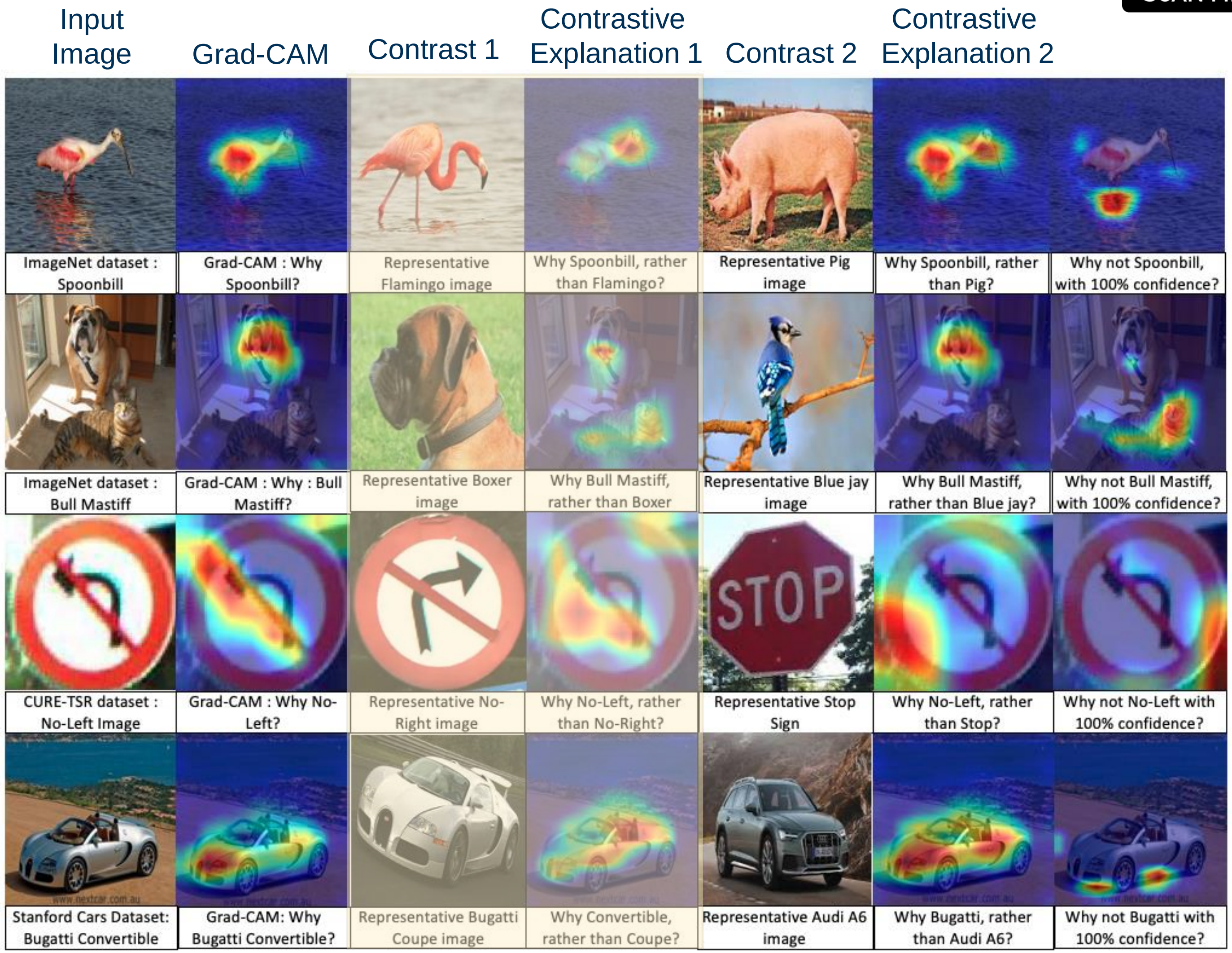

Human Interpretable

Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Gradient and Activation-based Explanations

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SCAN ME

Input Image | Grad-CAM | Contrast 1 | Contrastive Explanation 1 | Contrast 2 | Contrastive Explanation 2

Human Interpretable

Same as Grad-CAM

Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

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Gradient and Activation-based Explanations

Results from GradCAM, CounterfactualCAM, and ContrastCAM

Explanatory Paradigms in Neural Networks: Towards Relevant and Contextual Explanations

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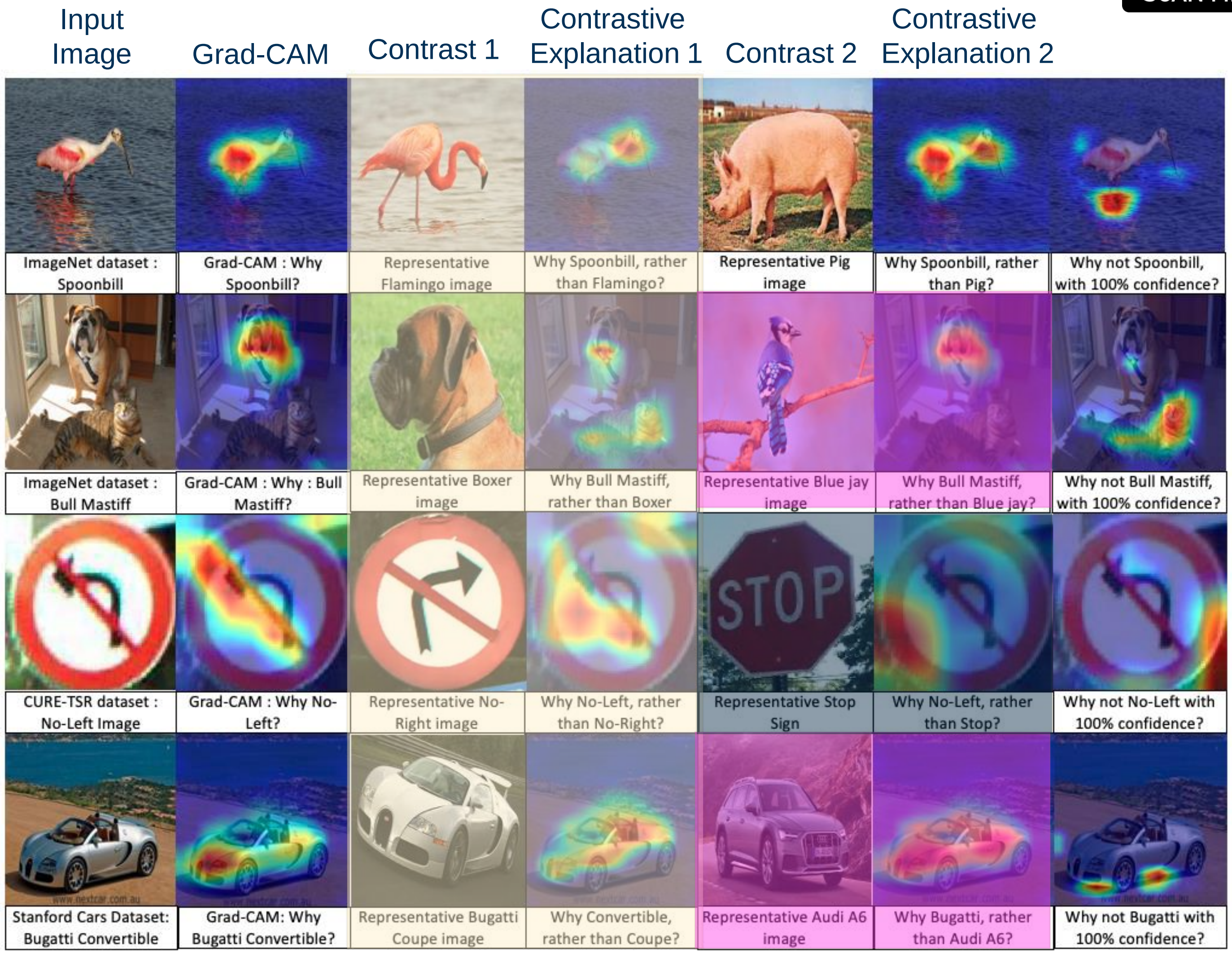

Human Interpretable

Same as Grad-CAM

Not Human Interpretable

Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Gradient and Activation-based Explanations

Results from GradCAM, CounterfactualCAM, and ContrastCAM

Input Image | Grad-CAM | Contrast 1 | Contrastive Explanation 1 | Contrast 2 | Contrastive Explanation 2

Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Gradient and Activation-based Explanations

Results from GradCAM, CounterfactualCAM, and ContrastCAM

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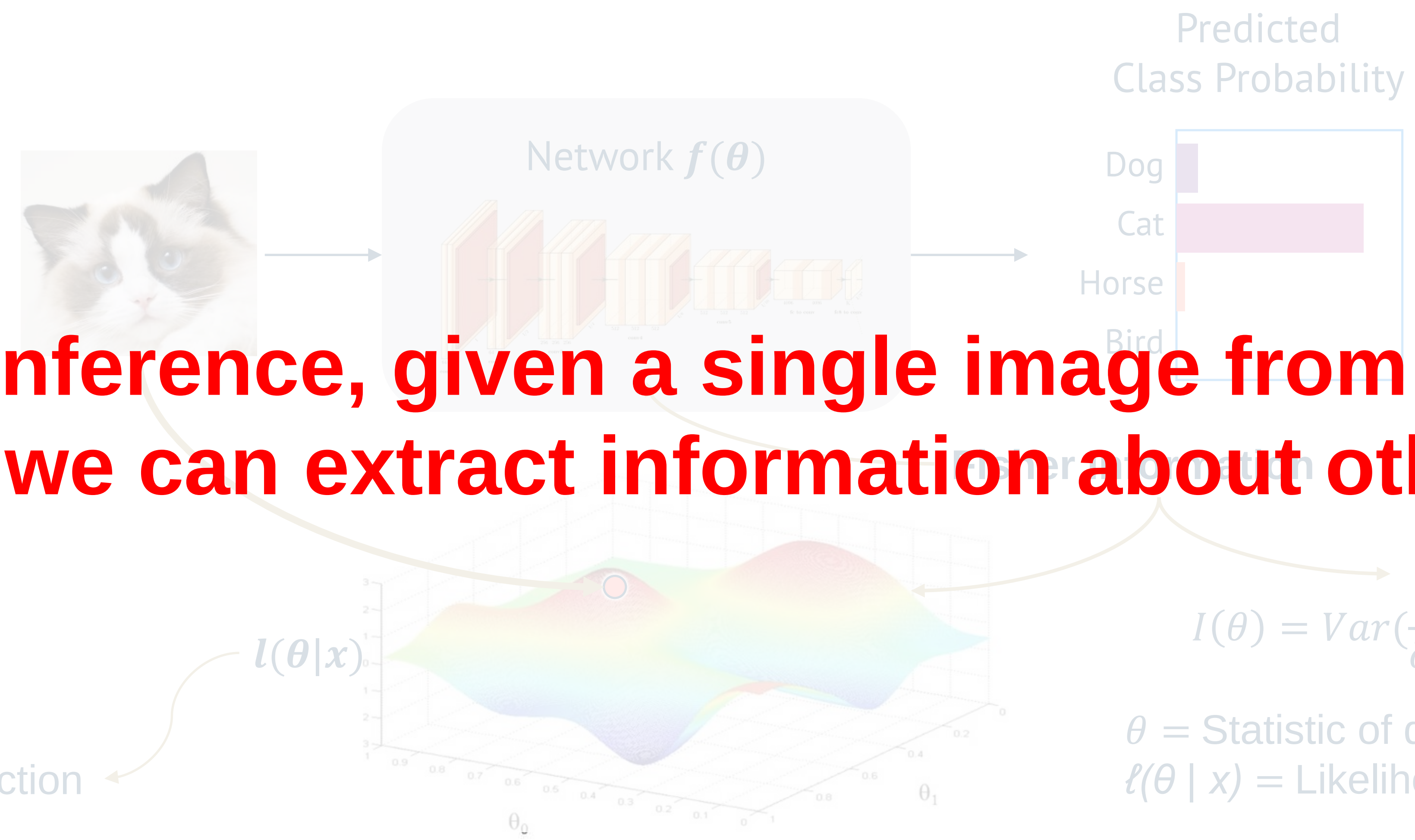
Only traffic sign with a straight bottom-left edge – enough to say `Not STOP Sign'

Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.



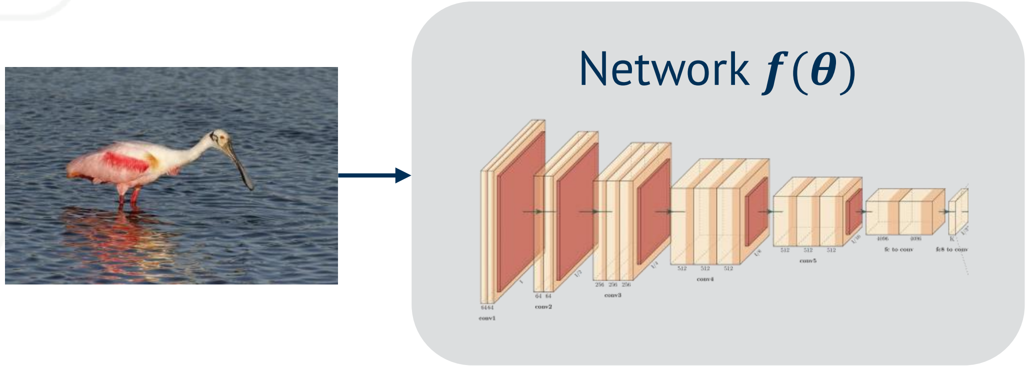
Likelihood function

$$I(\theta) = Var(\frac{\partial}{\partial\theta} l(\theta|x))$$

θ = Statistic of distribution
$\ell(\theta \mid x)$ = Likelihood function

At inference, given a single image from a single class, we can extract information about other classes

$\mathcal{T}$ is the set of all features learned by a trained network



Beak
Neck
Legs
Feathers
Water
Grass
Teeth
.
.

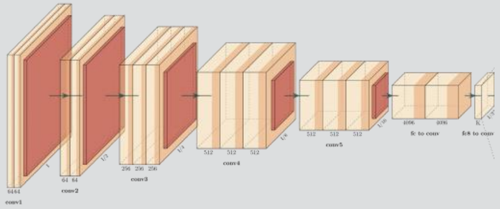
Features $\mathcal{T}$

Information at Inference

Case Study: Explainability

Given only an image of a spoonbill, we can extract information about a Flamingo

Network $\boldsymbol{f}(\boldsymbol{\theta})$



Beak
Neck
Legs
Feathers
Water
Grass
Teeth
.
.

Features $\mathcal{T}$

All the requisite Information is stored within $\boldsymbol{f}(\boldsymbol{\theta})$

Goal: To extract and quantify this information at inference

Robust Neural Networks

Part 3: Uncertainty at Inference

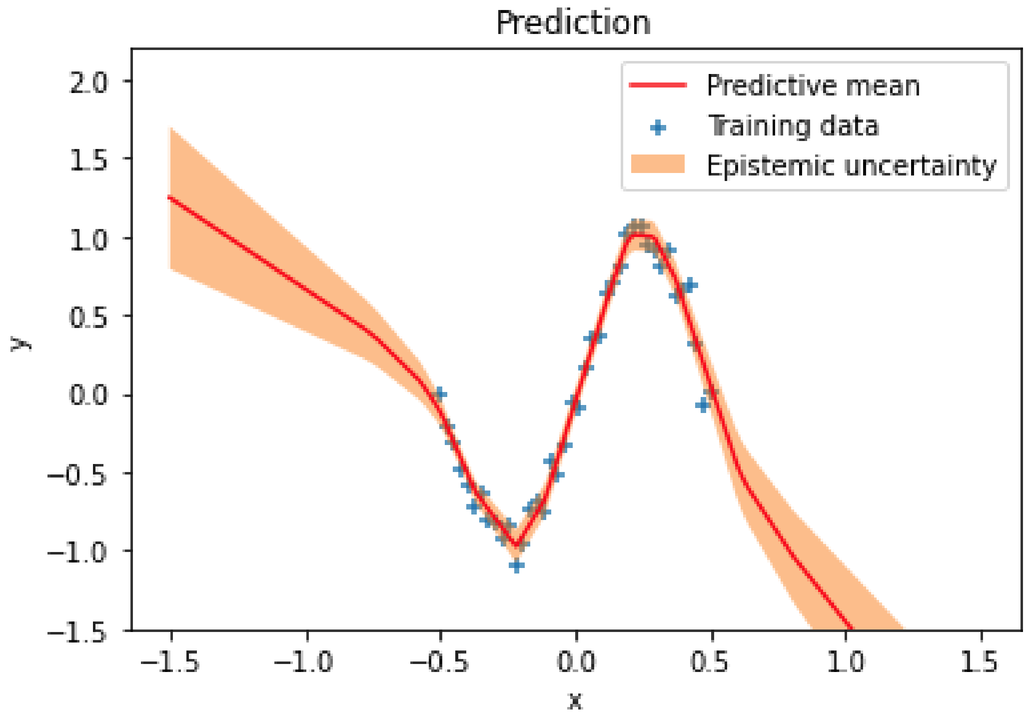
Objective

Objective of the Tutorial

To discuss methodologies that promote robustness in neural networks at inference

- Part 1: Inference in Neural Networks
- Part 2: Explainability at Inference
- **Part 3: Uncertainty at Inference**
    - Uncertainty Definition
    - Uncertainty Quantification
    - Gradient-based Uncertainty
    - Adversarial and Corruption Detection
- Part 4: Intervenability at Inference
- Part 5: Conclusions and Future Directions

Uncertainty is a model knowing that it does not know



A simple example:

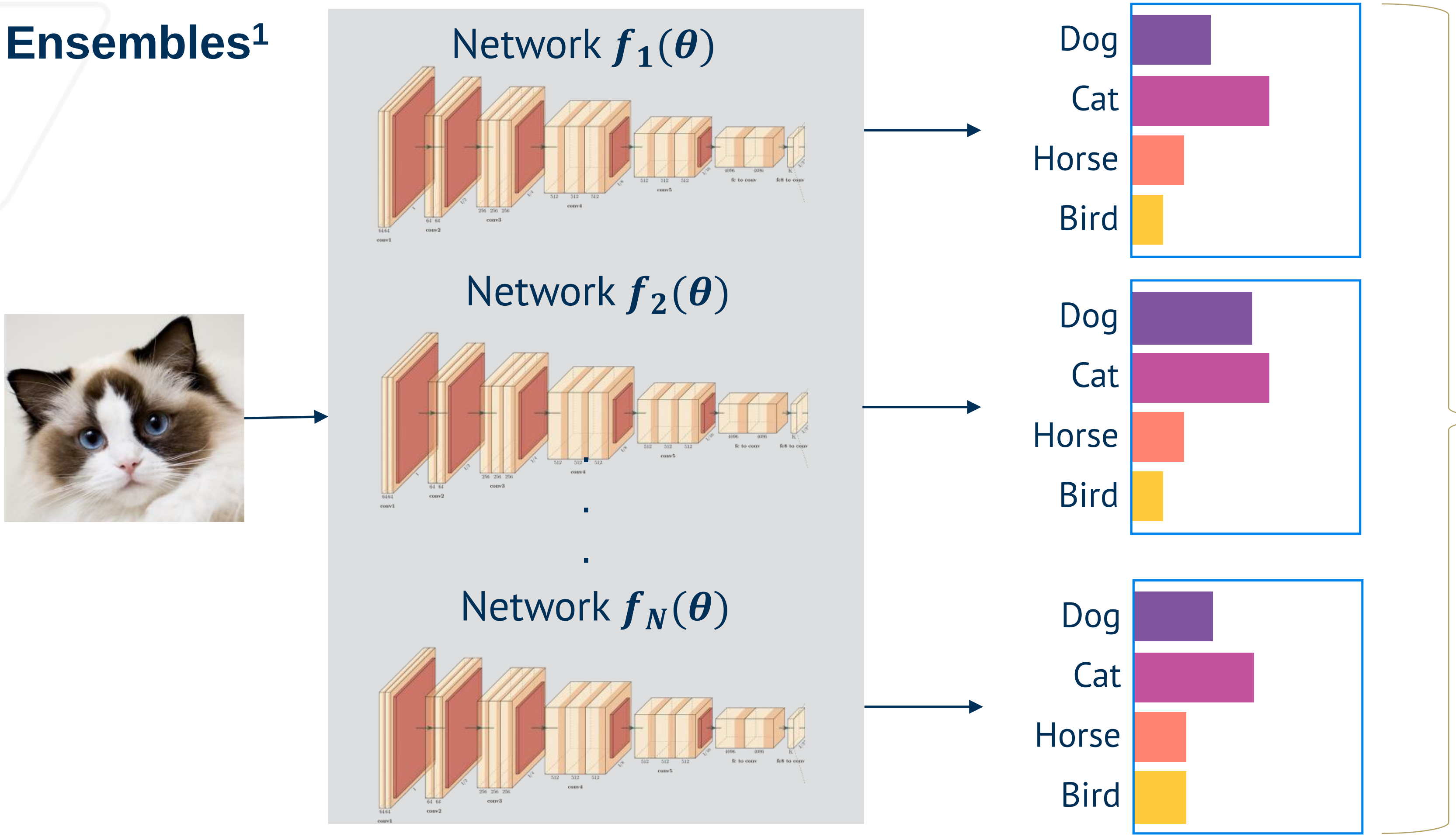
- When training data is **available: Less uncertainty**
- When training data is **unavailable: More uncertainty**

http://krasserm.github.io/2020/09/25/reliable-uncertainty-estimates/

Uncertainty

Uncertainty Quantification in Neural Networks

Via Ensembles[1]



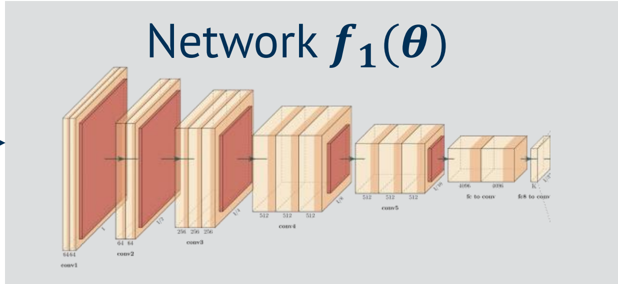
Variation within outputs $Var(y)$ is the uncertainty. Commonly referred to as **Prediction Uncertainty.**

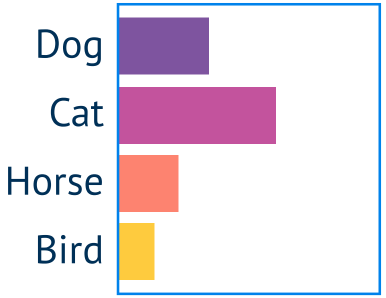
[1] Lakshminarayanan, Balaji, Alexander Pritzel, and Charles Blundell. "Simple and scalable predictive uncertainty estimation using deep ensembles." *Advances in neural information processing systems* 30 (2017).

Uncertainty

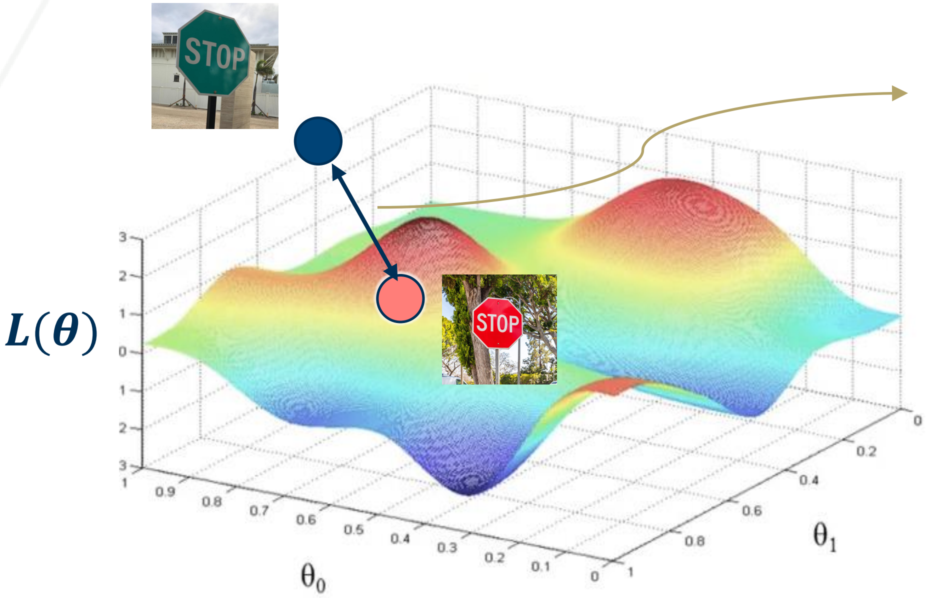
Uncertainty Quantification in Neural Networks

Via Single pass methods[1]





Uncertainty quantification using a single network and a single pass



Calculate distance from some trained clusters

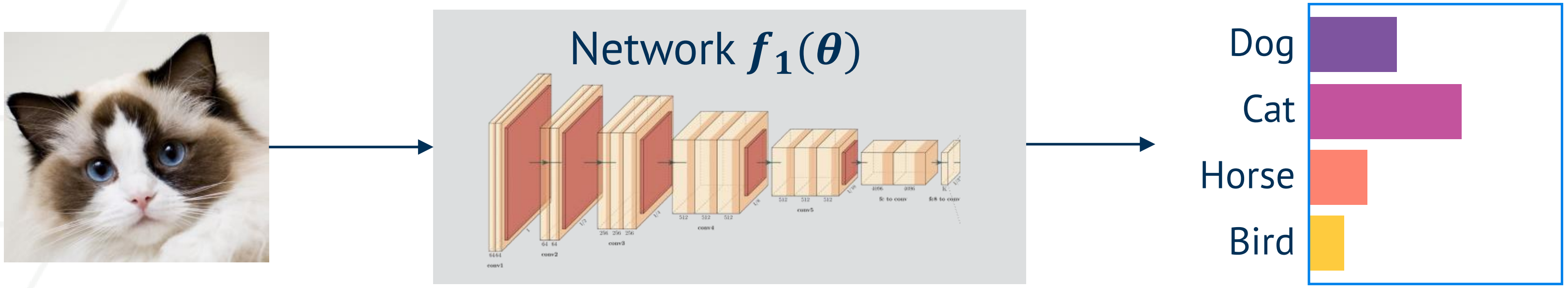
Does not require multiple networks!

[1Van Amersfoort, J., Smith, L., Teh, Y. W., & Gal, Y. (2020, November). Uncertainty estimation using a single deep deterministic neural network. In *International conference on machine learning* (pp. 9690-9700). PMLR.

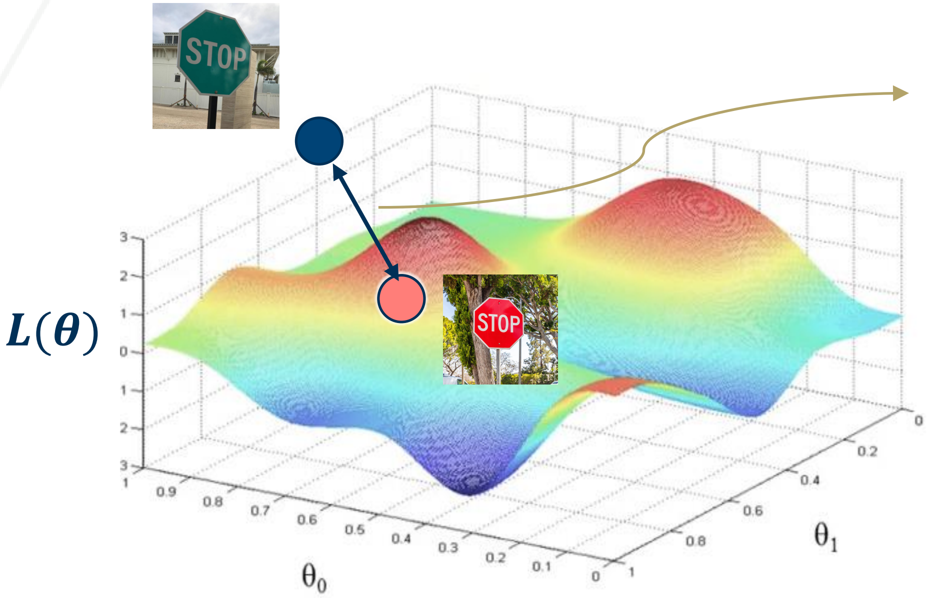
Uncertainty

Gradients as Single pass Features

Our Goal: Use gradients to characterize the novel data at Inference



Uncertainty quantification using a single network and a single pass



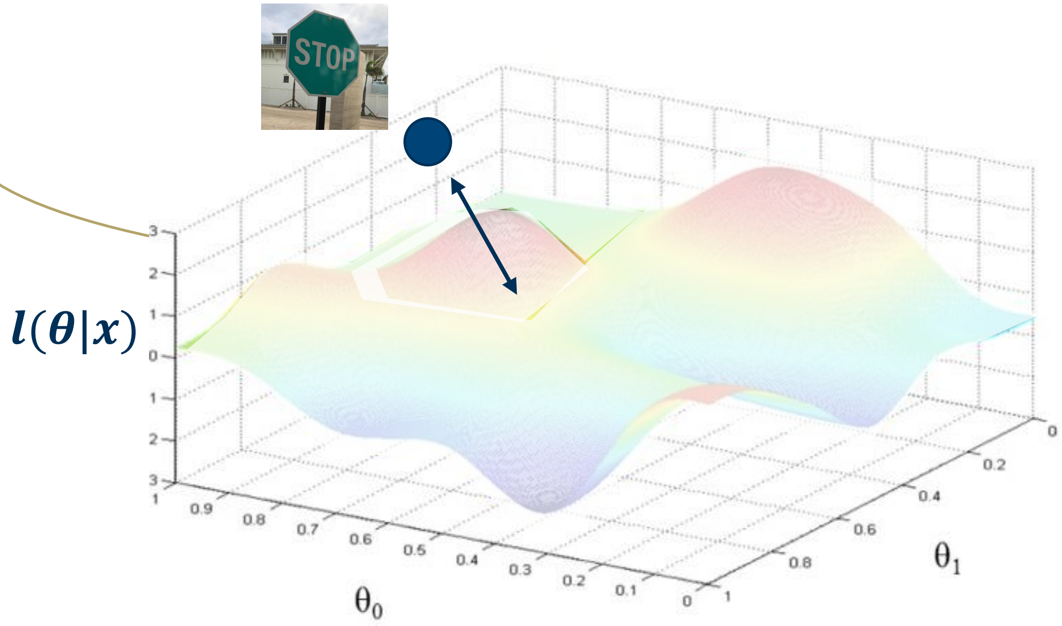
Calculate distance from some trained clusters

Does not require multiple networks!

Challenge: Class and prediction cannot be trusted!

Our Goal: Use gradients to characterize the novel data at Inference, without global information

Distance from unknown cluster



Two techniques:

1. **Gradient constraints during Training for Anomaly Detection**
2. Backpropagating Confounding labels for Out-of-Distribution Detection

ECCV'20 ONLINE
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Backpropagated Gradient Representations for Anomaly Detection

Gukyeong Kwon, PhD
Amazon AWS

Mohit Prabhushankar, PhD
Postdoc, Georgia Tech

Ghassan AlRegib, PhD
Professor, Georgia Tech

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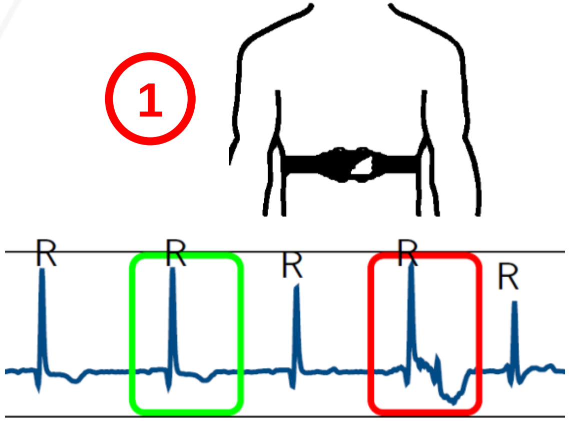
'Anomalies are patterns in data that do not conform to a well defined notion of normal behavior' [1]

1



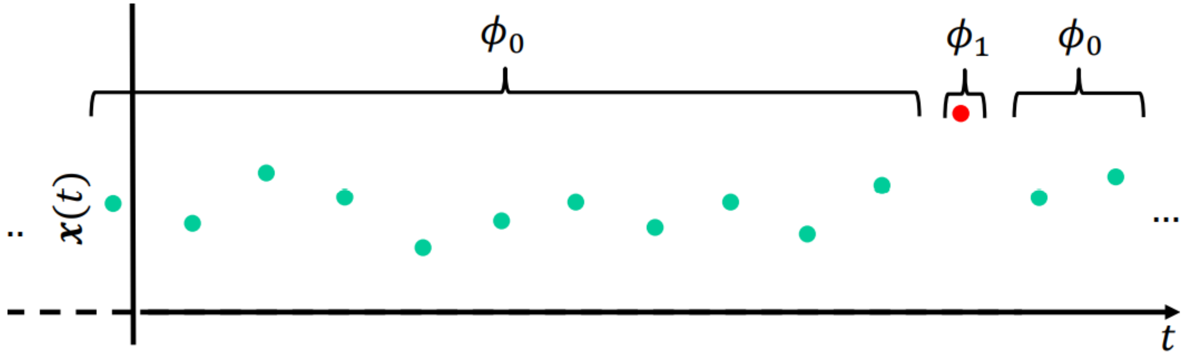
Statistical Definition:

- Normal data are generated from a stationary process P_N
- Anomalies are generated from a different process $P_A \neq P_N$

Goal: Detect ϕ_1

$$x(t) = \begin{cases} \phi_0 & \text{Normal data} \\ \phi_1 & \text{Anomalies} \end{cases}$$

2



[1] V. Chandola, A. Banerjee, V. Kumar. "Anomaly detection: A survey". ACM Comput. Surv. 41, 3, Article 15 (July 2009), 58 pages

Backpropagated Gradient Representations for Anomaly Detection

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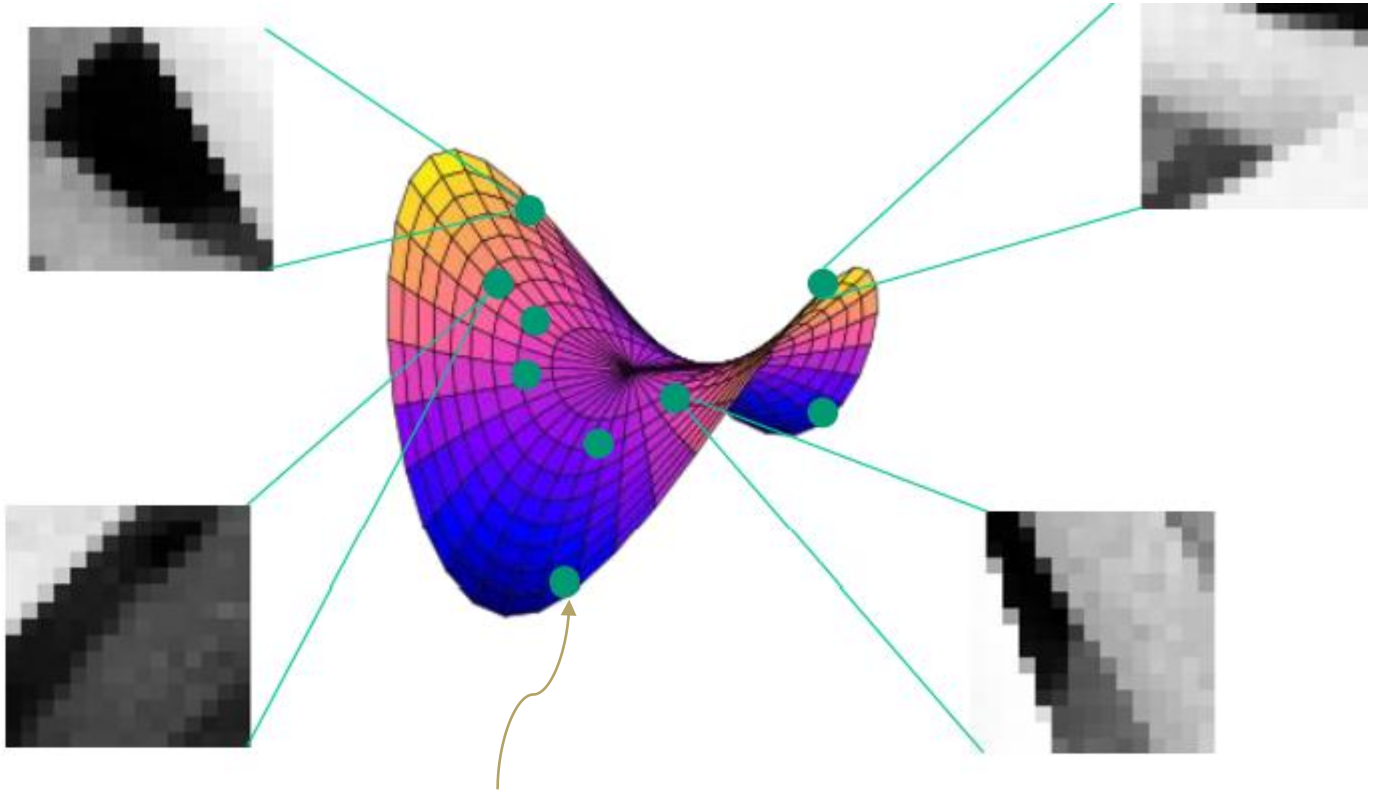
Step 1: Constrain manifolds, Step 2: Detect statistically implausible projections

- Step 1 ensures that patches from natural images live close to a low dimensional manifold
- Step 2 designs distance functions that detect *implausibility* based on constraints



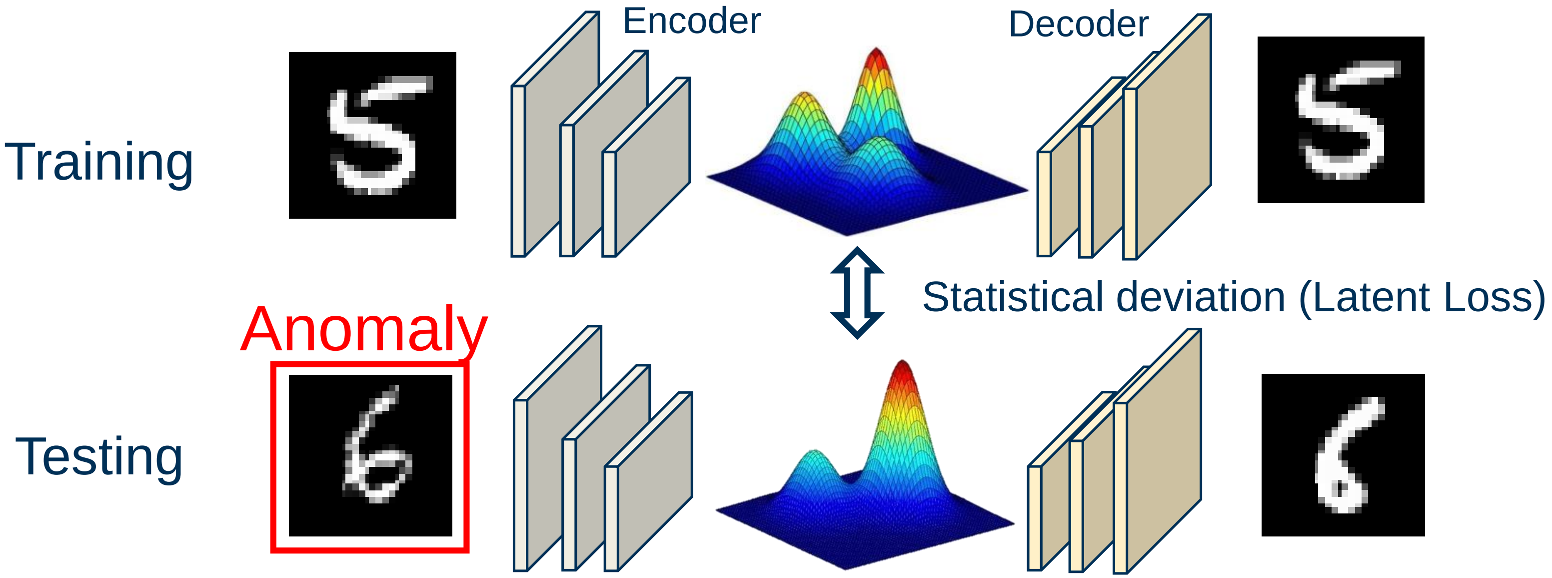
Constraining Manifolds
General Constraints

Backpropagated Gradient Representations for Anomaly Detection

Constrained Representation

2004 — Tax et.al [1]
2016 — Fan et.al [2]
2018 — Pidhorksyi et.al [3]
2019 — Abati et.al [4]

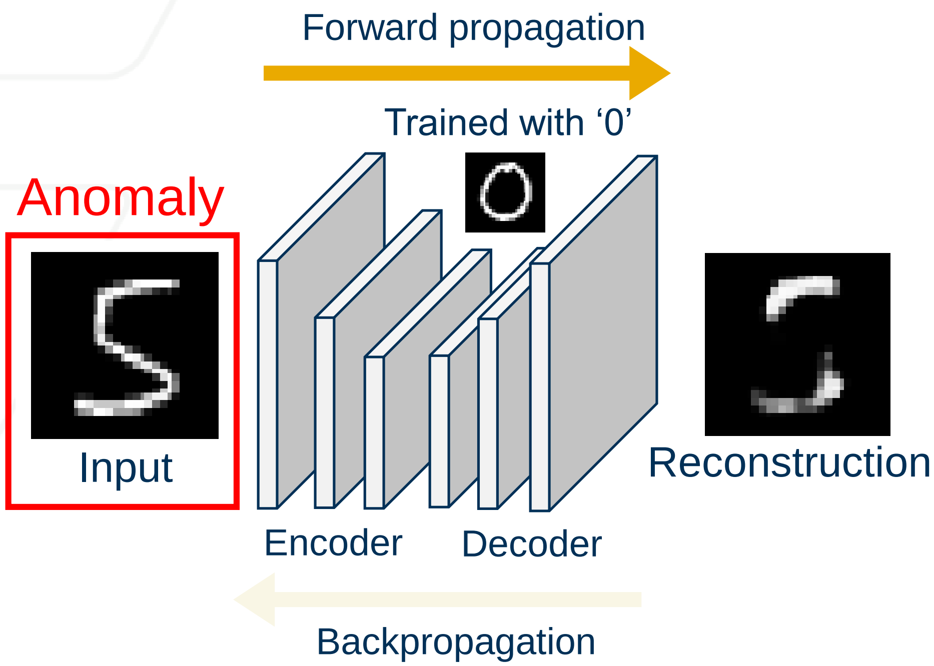
Activations are constrained using GANs, VAEs, etc.



[1] David MJ Tax and Robert PW Duin. Support vector data description. Machine learning, 54(1):45–66, 2004.
[2] Yaxiang Fan, Gongjian Wen, Deren Li, Shaohua Qiu, and Martin D Levine. Video anomaly detection and localization via gaussian mixture fully convolutional variational autoencoder. arXiv preprint arXiv:1805.11223, 2018. 1, 2
[3] S. Pidhorskyi, R. Almohsen, and G. Doretto, "Generative probabilistic novelty detection with adversarial autoencoders," in Advances in Neural Information Processing Systems, 2018, pp. 6822–6833.
[4] D. Abati, A. Porrello, S. Calderara, and R. Cucchiara, "Latent space autoregression for novelty detection," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 481–490.

Constraining Manifolds
Gradient-based Constraints

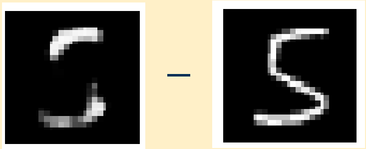
Backpropagated Gradient Representations for Anomaly Detection



Activation Constraints

Activation-based representation (Data perspective)

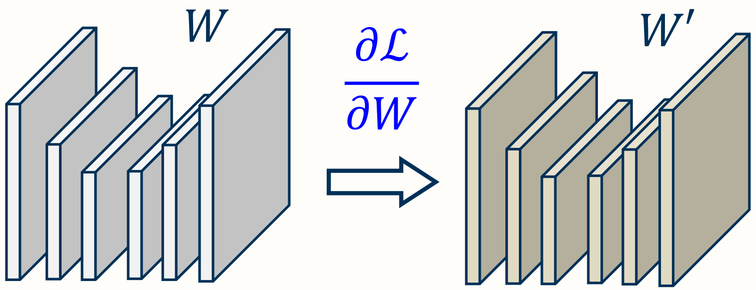
e.g. Reconstruction error ($\mathcal{L}$)



How much of the input does not correspond to the learned information?

Gradient Constraints

Gradient-based Representation
(**Model** perspective)



How much **model update** is required by the input?

G. Kwon, M. Prabhushankar, D. Temel, and G. AlRegib, "Backpropagated Gradient Representations for Anomaly Detection," 2020

Constraining Manifolds

Advantages of Gradient-based Constraints

Backpropagated Gradient Representations for Anomaly Detection

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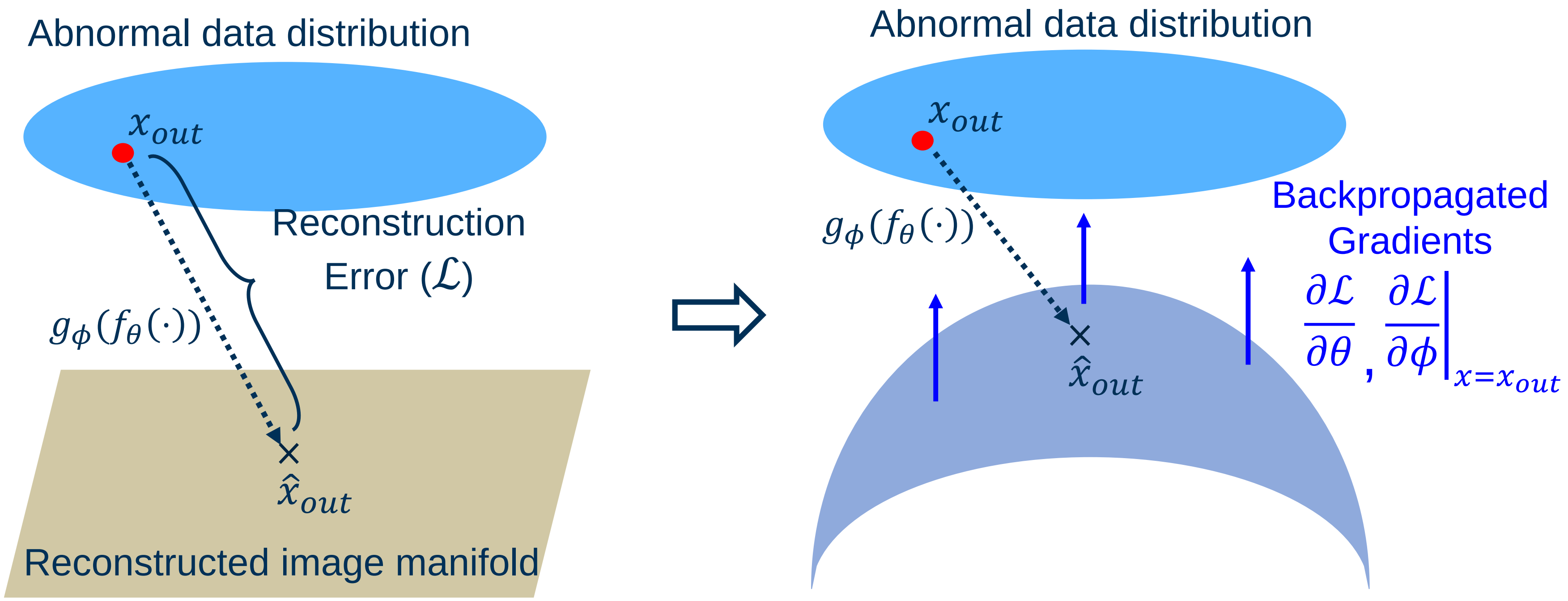
- **Gradients provide directional information to characterize anomalies**
- **Gradients from different layers capture abnormality at different levels of data abstraction**



G. Kwon, M. Prabhushankar, D. Temel, and G. AlRegib, "Backpropagated Gradient Representations for Anomaly Detection," 2020

GradCON: Gradient Constraint

Gradient-based Constraints

Backpropagated Gradient Representations for Anomaly Detection

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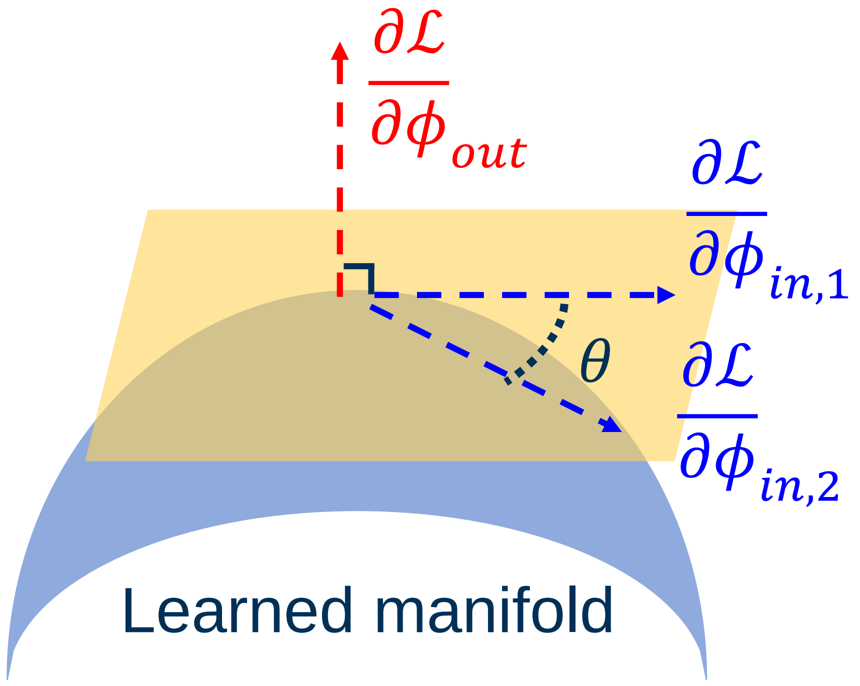
Constrain gradient-based representations during training to obtain clear separation between normal data and abnormal data



ϕ: Weights $\mathcal{L}$: Reconstruction error

At k-th step of training,

$$J = \mathcal{L} - \overbrace{\mathbb{E}_i\left[\mathrm{cosSIM}\left(\frac{\partial J}{\partial \phi_{i_{avg}}}^{k-1}, \frac{\partial \mathcal{L}}{\partial \phi_i}^{k}\right)\right]}^{\text{Gradient loss}}$$

Avg. training gradients until (k-1) th iter.

Gradients at k-th iter.

where $$\frac{\partial J}{\partial \phi_{i_{avg}}}^{k-1} = \sum_{t=1}^{k-1} \frac{\partial J}{\partial \phi_i}^{t}$$

G. Kwon, M. Prabhushankar, D. Temel, and G. AlRegib, "Backpropagated Gradient Representations for Anomaly Detection," 2020

GradCON: Gradient Constraint

Activations vs Gradients

Backpropagated Gradient Representations for Anomaly Detection

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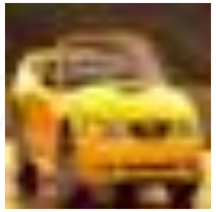
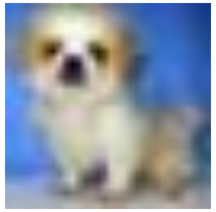
Abnormal "class" detection (CIFAR-10)

e.g.


Normal


Abnormal

AUROC Results

Model	Loss	Plane	Car	Bird	Cat	Deer	Dog	Frog	Horse	Ship	Truck	Average
CAE	Recon	0.682	0.353	0.638	0.587	0.669	**0.613**	0.495	0.498	0.711	0.390	0.564
CAE + Grad	Recon	0.659	0.356	**0.640**	0.555	0.695	0.554	0.549	0.478	0.695	0.357	0.554
	Grad	**0.752**	0.619	0.622	0.580	0.705	0.591	0.683	**0.576**	**0.774**	**0.709**	**0.661**
VAE	Recon	0.553	0.608	0.437	0.546	0.393	0.531	0.489	0.515	0.552	0.631	0.526
	Latent	0.634	0.442	**0.640**	0.497	**0.743**	0.515	**0.745**	0.527	0.674	0.416	0.583
VAE + Grad	Recon	0.556	0.606	0.438	0.548	0.392	0.543	0.496	0.518	0.552	0.631	0.528
	Latent	0.586	0.396	0.618	0.476	0.719	0.474	0.698	0.537	0.586	0.413	0.550
	Grad	0.736	**0.625**	0.591	**0.596**	0.707	0.570	0.740	0.543	0.738	0.629	0.647

Recon: Reconstruction error, Latent: Latent loss, Grad: Gradient loss

- (CAE vs. CAE + Grad) Effectiveness of the gradient constraint
- (CAE vs. VAE) Performance sacrifice from the latent constraint
- (VAE vs. VAE + Grad) Complementary features from the gradient constraint

G. Kwon, M. Prabhushankar, D. Temel, and G. AlRegib, "Backpropagated Gradient Representations for Anomaly Detection," 2020

GradCON: Gradient Constraint

Aberrant Condition Detection

Backpropagated Gradient Representations for Anomaly Detection

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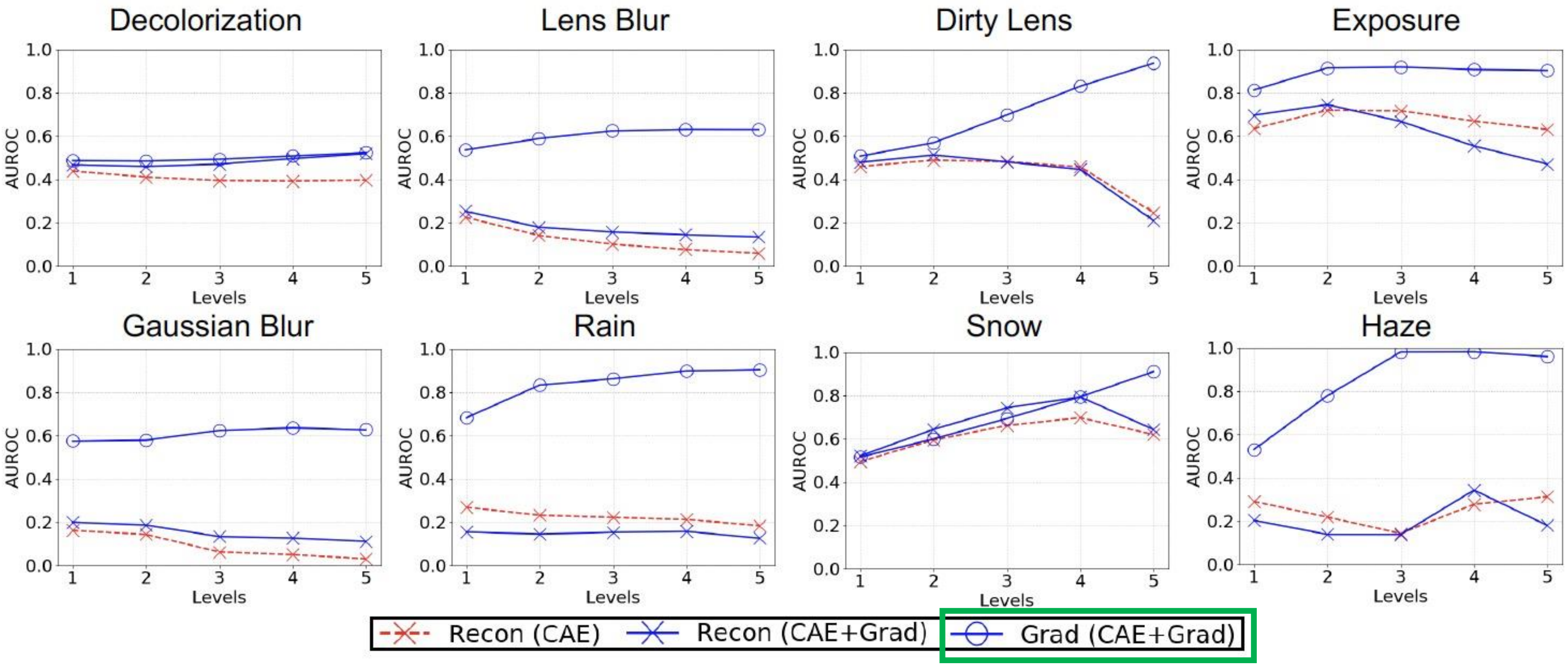
Abnormal “condition” detection (CURE-TSR)

Normal

Abnormal

AUROC Results

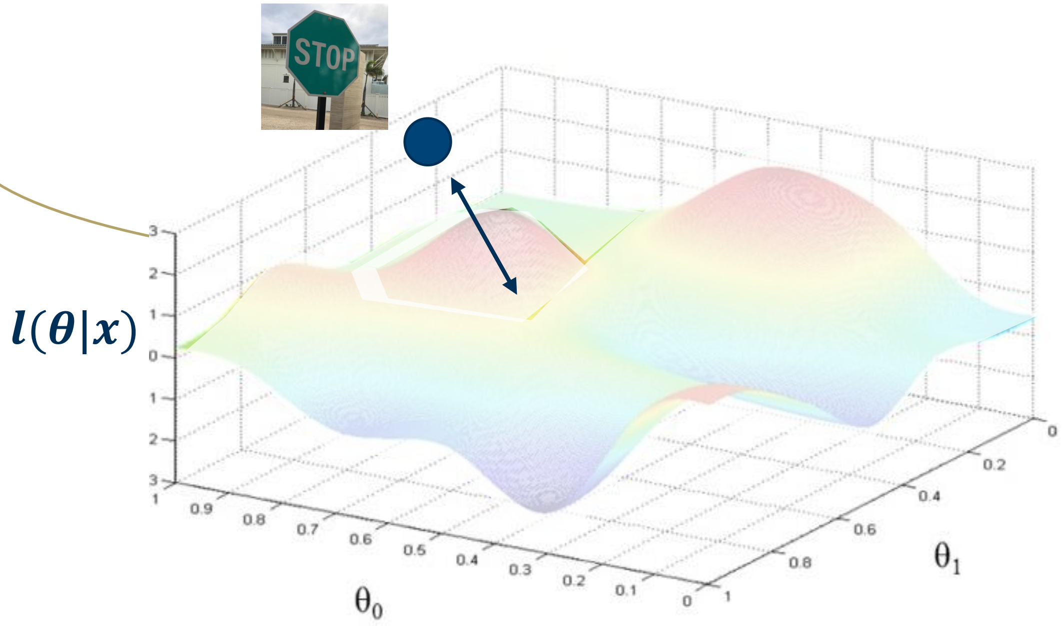


Recon: Reconstruction error, Grad: Gradient loss

G. Kwon, M. Prabhushankar, D. Temel, and G. AlRegib, "Backpropagated Gradient Representations for Anomaly Detection," 2020

Our Goal: Use gradients to characterize the novel data at Inference, without global information

Distance from unknown cluster



Two techniques:

1. Gradient constraints during Training for Anomaly Detection
2. **Backpropagating Confounding labels for Out-of-Distribution Detection**

Probing the Purview of Neural Networks via Gradient Analysis

Jinsol Lee,
PhD Candidate

Mohit Prabhushankar, PhD
Postdoc

Ghassan AlRegib, PhD
Professor

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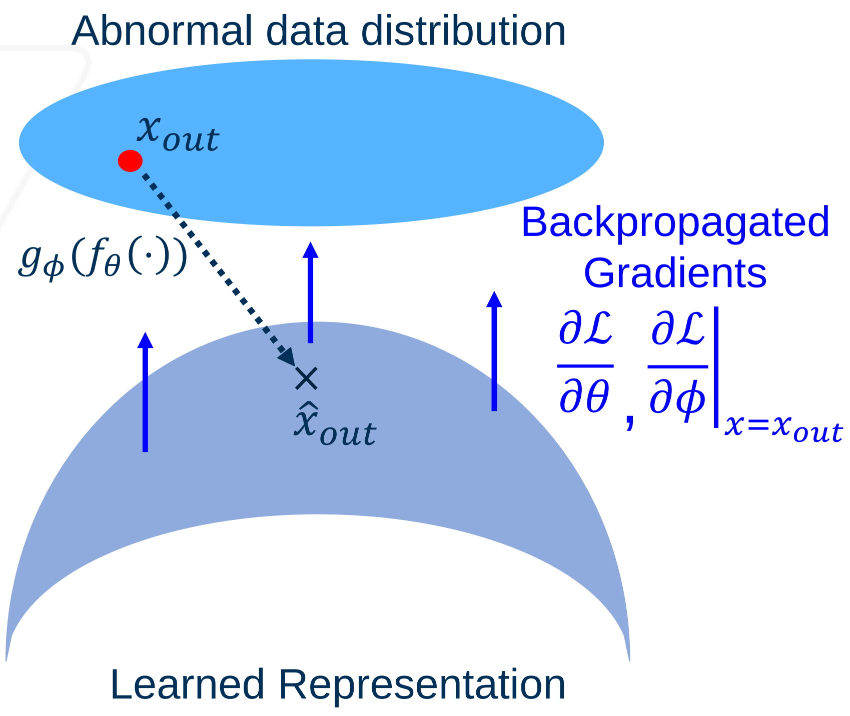
Principle: Gradients provide a distance measure between the learned representations space and novel data



However, what is $\mathcal{L}$?

- In anomaly detection, the loss was between the input and its reconstruction
- In prediction tasks, there is neither the reconstructed input nor ground truth

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Probing the Purview of Neural Networks via Gradient Analysis

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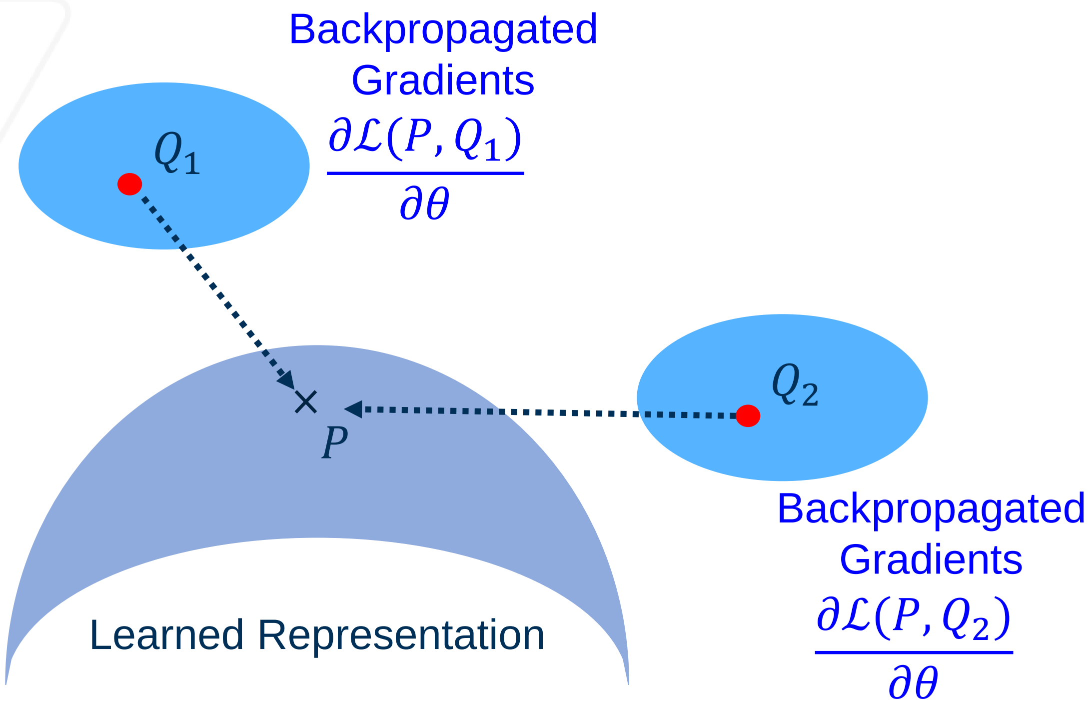
Principle: Gradients provide a distance measure between the learned representations space and novel data

P = Predicted class
Q_1 = Contrast class 1
Q_2 = Contrast class 2



However, what is $\mathcal{L}$?

- In anomaly detection, the loss was between the input and its reconstruction
- In prediction tasks, there is neither the reconstructed input nor ground truth

- **We backpropagate all contrast classes - $Q_1, Q_2 \ldots Q_N$ by backpropagating N one-hot vectors**
- Higher the distance, higher the uncertainty score

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Toy Manifold Example

What is uncertainty?

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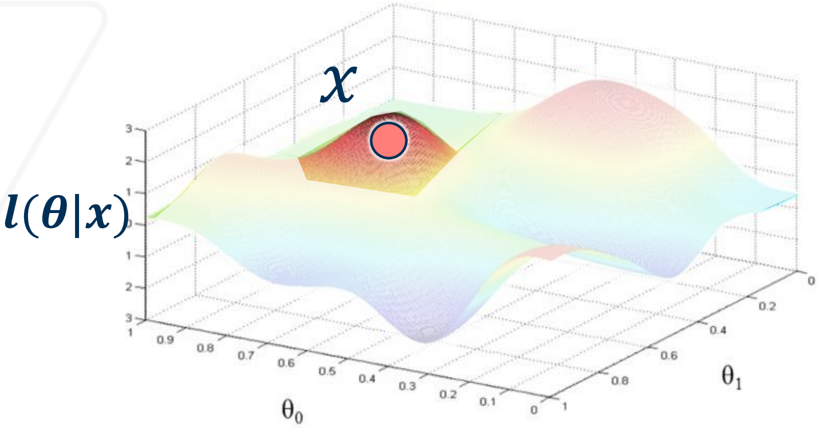
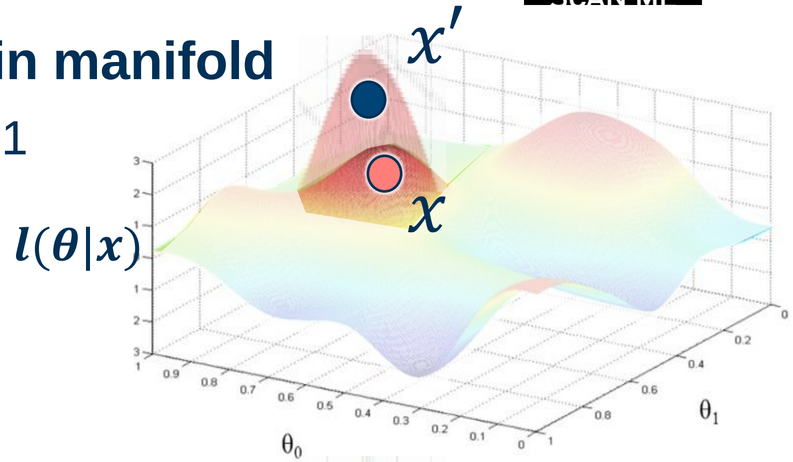
Gradients represent the local required change in manifold

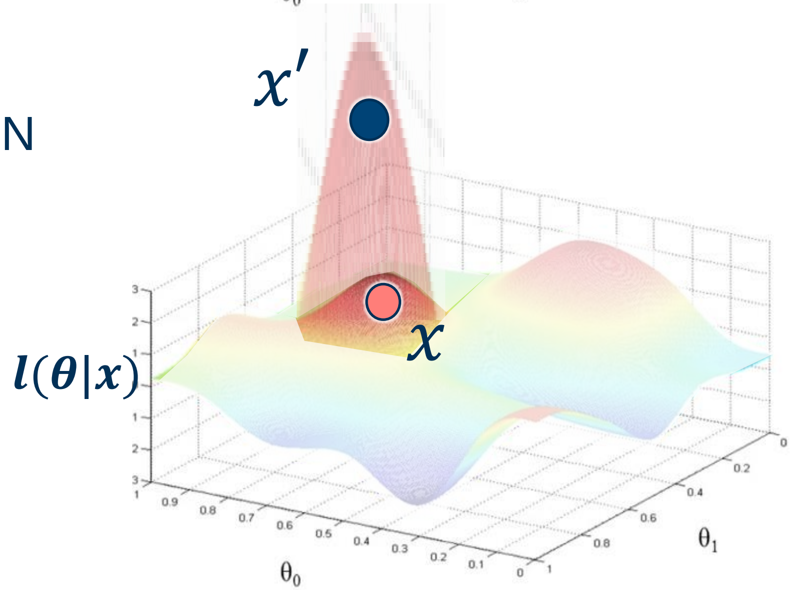
Similar to introspective learning!



Contrast class 1

Contrast class N





- Gradients provide the necessary change in manifold that would predict the novel data ‘correctly’.
- Correctly means contrastively (or incorrectly)!

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Toy Manifold Example

How is this different from Explainability?

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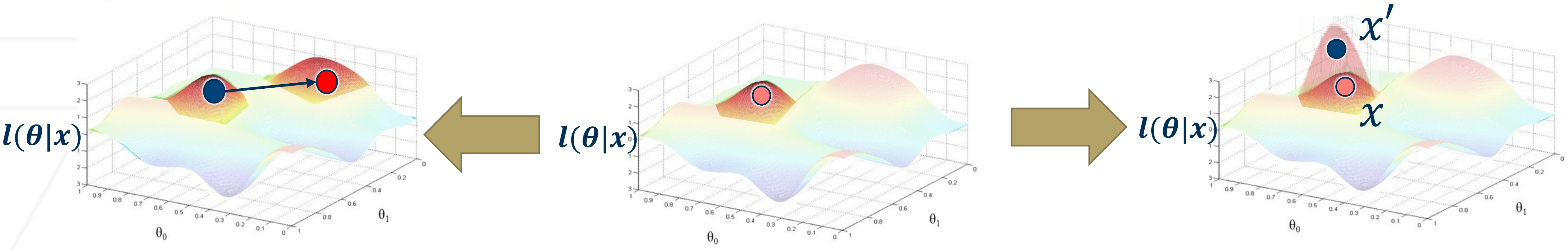
Part 3: Explainability

Part 4: Uncertainty



- In Part 3: Activations of learned manifold are weighted by gradients w.r.t. activations to extract information and provide explanations

- In Part 4: Statistics of gradients w.r.t. the weights (energy) will be directly used as features

Deriving Gradient Features

Probing the Purview of Neural Networks via Gradient Analysis

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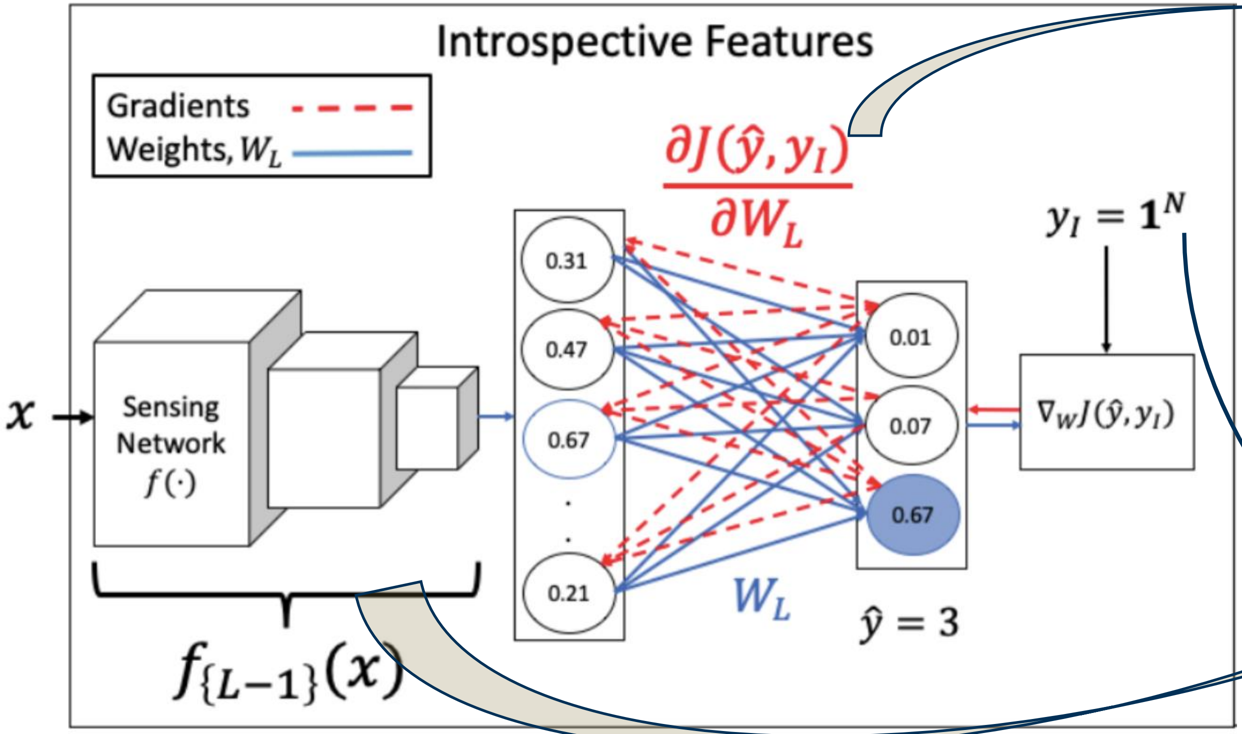
Step 1: Measure the loss between the prediction P and a vector of all ones and backpropagate to obtain the introspective features



Normalized and vectorized gradients are introspective features.

Why vector of all 1s? The theory is presented in [1]

[1] M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

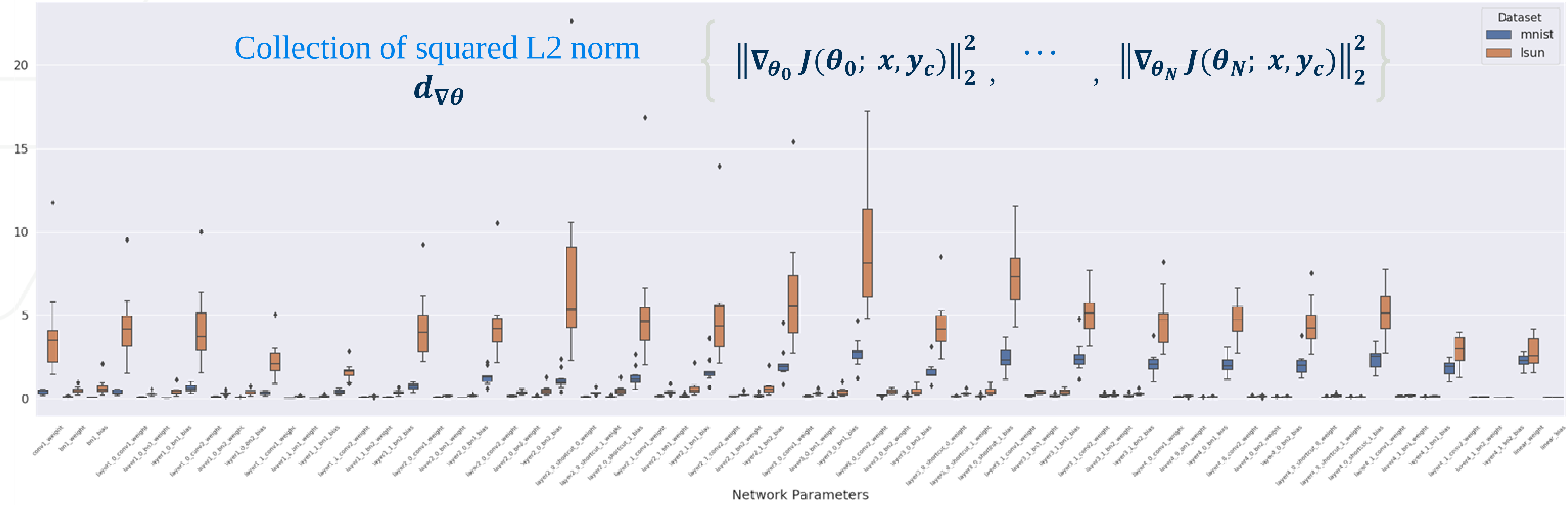
Uncertainty in Neural Networks

Utilizing Gradient Features

Probing the Purview of Neural Networks via Gradient Analysis

SCAN ME

Step 2: Take L2 norm of all generated gradients



MNIST: In-distribution, SUN: Out-of-Distribution

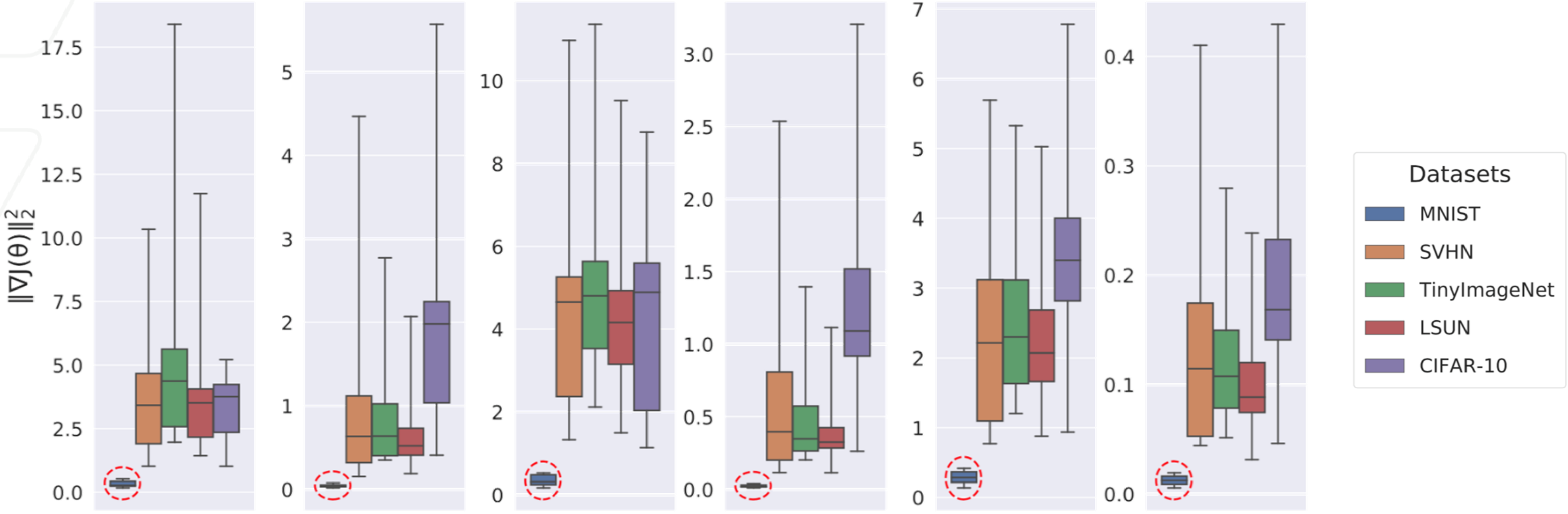
Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Gradient-based Uncertainty

Uncertainty in OOD Setting

SCAN ME

Squared L2 distances for different parameter sets



MNIST: Circled in red. Significantly lower uncertainty compared to OOD datasets

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

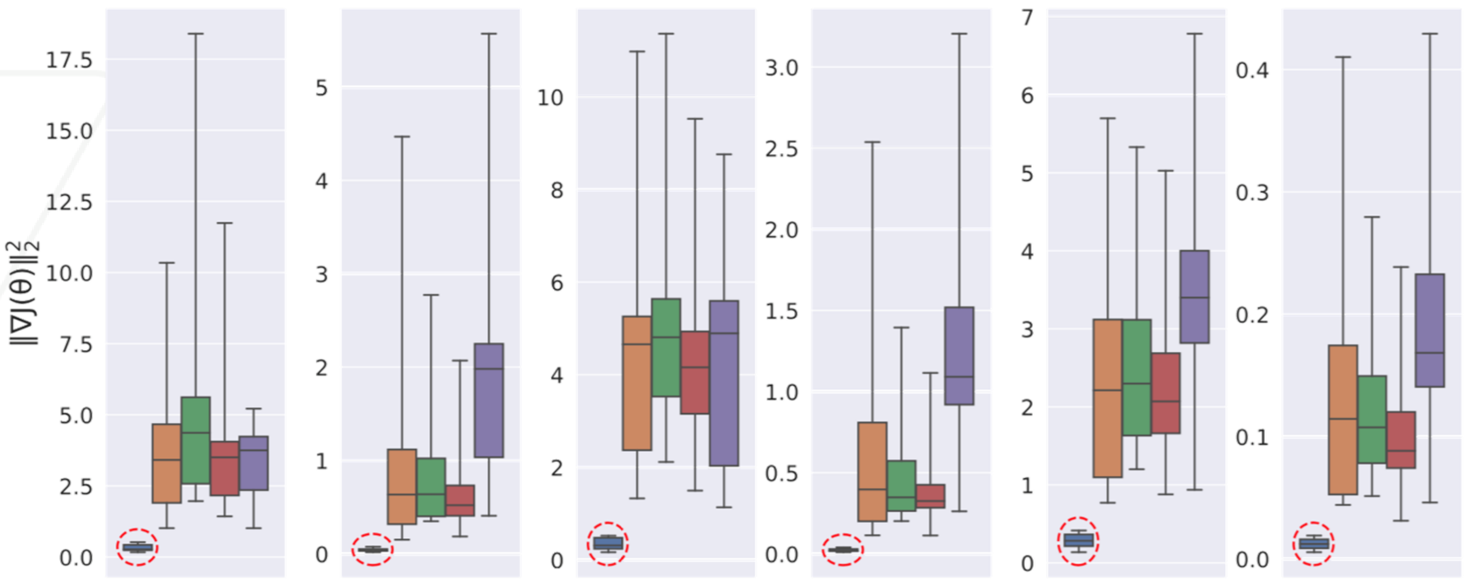
Gradient-based Uncertainty

Experimental Setup

Probing the Purview of Neural Networks via Gradient Analysis

SCAN ME

Utilize this discrepancy in trained vs untrained data gradient L2 distance to detect adversarial, noisy, and OOD data



Step 1: Train a deep network $f(\cdot)$ on some **training distribution**
Step 2: Introduce challenging (adversarial, noisy, OOD) data
Step 3: Derive **gradient uncertainty** on both trained and challenge data
Step 4: Train a classifier $H(\cdot)$ to **detect** challenging from trained data
Step 5: At test time, data is passed through $f(\cdot)$ and then $H(\cdot)$ to obtain a **Reliability classification**

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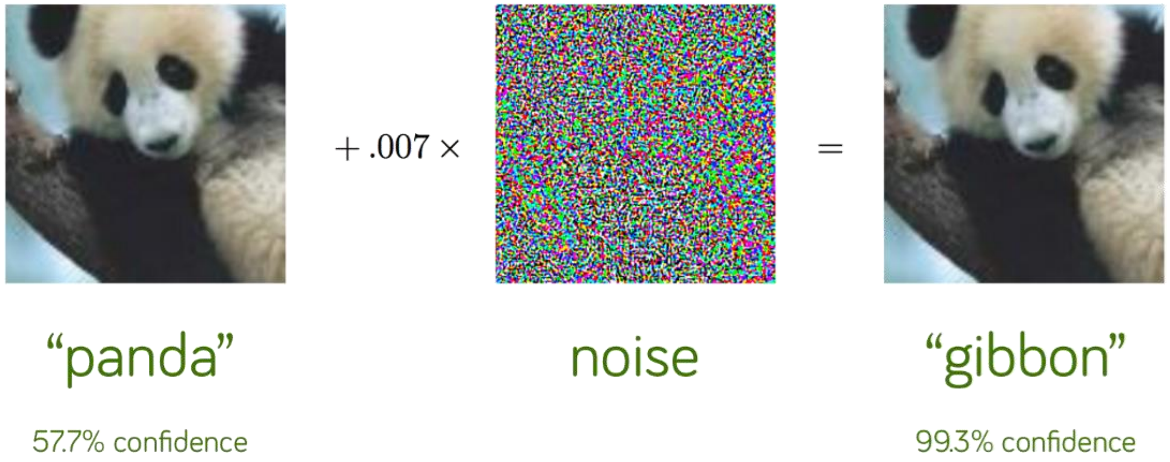
Vulnerable DNNs in the real world



Goal: to examine the ability of trained DNNs to handle adversarial inputs during inference

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Gradient-based Uncertainty

Uncertainty in Adversarial Setting

SCAN ME

Probing the Purview of Neural Networks via Gradient Analysis

MODEL	ATTACKS	BASELINE	LID	M(V)	M(P)	M(FE)	M(P+FE)	OURS
RESNET	FGSM	51.20	90.06	81.69	84.25	**99.95**	**99.95**	93.45
	BIM	49.94	99.21	87.09	89.20	**100.0**	**100.0**	96.19
	C&W	53.40	76.47	74.51	75.71	92.78	92.79	**97.07**
	PGD	50.03	67.48	56.27	57.57	65.23	75.98	**95.82**
	ITERLL	60.40	85.17	62.32	64.10	85.10	92.10	**98.17**
	SEMANTIC	52.29	86.25	64.18	65.79	83.95	84.38	**90.15**
DENSENET	FGSM	52.76	98.23	86.88	87.24	**99.98**	99.97	96.83
	BIM	49.67	**100.0**	89.19	89.17	**100.0**	**100.0**	96.85
	C&W	54.53	80.58	75.77	76.16	90.83	90.76	**97.05**
	PGD	49.87	83.01	70.39	66.52	86.94	83.61	**96.77**
	ITERLL	55.43	83.16	70.17	66.61	83.20	77.84	**98.53**
	SEMANTIC	53.54	81.41	62.16	62.15	67.98	67.29	**89.55**

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Gradient-based Uncertainty

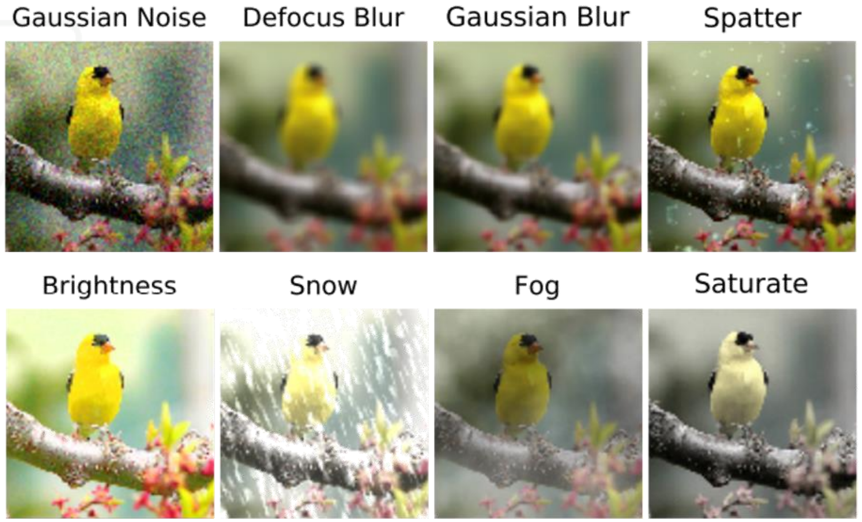
Uncertainty in Detecting Challenging Conditions

SCAN ME

Probing the Purview of Neural Networks via Gradient Analysis

Same application as Anomaly Detection, except there is no need for an additional AE network!

CIFAR-10-C



CURE-TSR

JAN 4-8 WACV 2024 WAIKOLOA HAWAII

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Georgia Tech

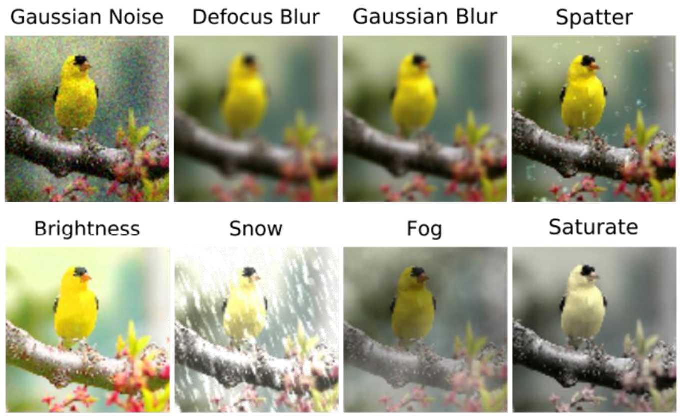
Gradient-based Uncertainty

Uncertainty in Detecting Challenging Conditions

Probing the Purview of Neural Networks via Gradient Analysis

SCAN ME

Dataset	Method	Mahalanobis [12] / Ours				
	Corruption	Level 1	Level 2	Level 3	Level 4	Level 5
CIFAR-10-C	Noise	96.63 / **99.95**	98.73 / **99.97**	99.46 / **99.99**	99.62 / **99.97**	99.71 / **99.99**
	LensBlur	94.22 / **99.95**	97.51 / **99.99**	99.26 / **100.0**	99.78 / **100.0**	99.89 / **100.0**
	GaussianBlur	94.19 / **99.94**	99.28 / **100.0**	99.76 / **100.0**	99.86 / **100.0**	99.80 / **100.0**
	DirtyLens	93.37 / **99.94**	95.31 / **99.93**	95.66 / **99.96**	95.37 / **99.92**	97.43 / **99.96**
	Exposure	91.39 / **99.87**	91.00 / **99.85**	90.71 / **99.88**	90.58 / **99.85**	90.68 / **99.87**
	Snow	93.64 / **99.94**	96.50 / **99.94**	94.44 / **99.95**	94.22 / **99.95**	95.25 / **99.92**
	Haze	95.52 / **99.95**	98.35 / **99.99**	99.28 / **100.0**	99.71 / **99.99**	99.94 / **100.0**
	Decolor	93.51 / **99.96**	93.55 / **99.96**	90.30 / **99.82**	89.86 / **99.75**	90.43 / **99.83**
CURE-TSR	Noise	25.46 / **50.20**	47.54 / **63.87**	47.32 / **81.20**	66.19 / **91.16**	83.14 / **94.81**
	LensBlur	48.06 / **72.63**	71.61 / **87.58**	86.59 / **92.56**	92.19 / **93.90**	94.90 / **95.65**
	GaussianBlur	66.44 / **83.07**	77.67 / **86.94**	93.15 / **94.35**	80.78 / **94.51**	**97.36** / 96.53
	DirtyLens	29.78 / **51.21**	29.28 / **59.10**	46.60 / **82.10**	73.36 / **91.87**	98.50 / **98.70**
	Exposure	74.90 / **88.13**	**99.96** / 96.78	**99.99** / 99.26	**100.0** / 99.80	**100.0** / 99.90
	Snow	28.11 / **61.34**	61.28 / **80.52**	89.89 / **91.30**	**99.34** / 96.13	**99.98** / 97.66
	Haze	66.51 / **95.83**	97.86 / **99.50**	**100.0** / 99.95	**100.0** / 99.87	**100.0** / 99.88
	Decolor	48.37 / **62.36**	60.55 / **81.30**	71.73 / **89.93**	87.29 / **95.42**	89.68 / **96.91**



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Gradient-based Uncertainty

Uncertainty in Detecting Challenging Conditions

Probing the Purview of Neural Networks via Gradient Analysis

SCAN ME

Dataset	Method	Mahalanobis [12] / Ours				
	Corruption	Level 1	Level 2	Level 3	Level 4	Level 5
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	LensBlur	94.22 / **99.95**	97.51 / **99.99**	99.26 / **100.0**	99.78 / **100.0**	99.89 / **100.0**
	GaussianBlur	94.19 / **99.94**	99.28 / **100.0**	99.76 / **100.0**	99.86 / **100.0**	99.80 / **100.0**
	DirtyLens	93.37 / **99.94**	95.31 / **99.93**	95.66 / **99.96**	95.37 / **99.92**	97.43 / **99.96**
	Exposure	91.39 / **99.87**	91.00 / **99.85**	90.71 / **99.88**	90.58 / **99.85**	90.68 / **99.87**
	Snow	93.64 / **99.94**	96.50 / **99.94**	94.44 / **99.95**	94.22 / **99.95**	95.25 / **99.92**
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CURE-TSR	Noise	25.46 / **50.20**	47.54 / **63.87**	47.32 / **81.20**	66.19 / **91.16**	83.14 / **94.81**
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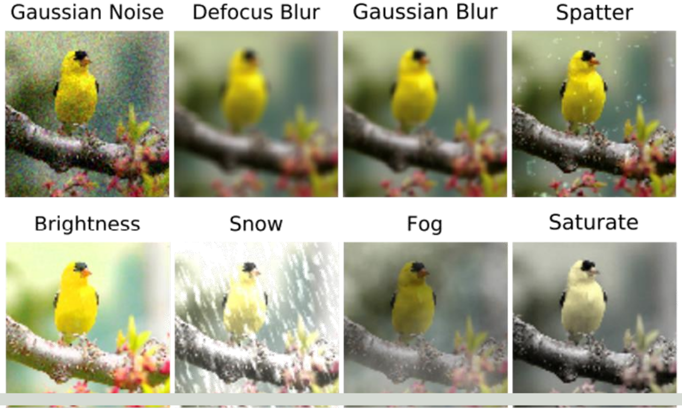
	Exposure	74.90 / **88.13**	**99.96** / 96.78	**99.99** / 99.26	**100.0** / 99.80	**100.0** / 99.90
	Snow	28.11 / **61.34**	61.28 / **80.52**	89.89 / **91.30**	**99.34** / 96.13	**99.98** / 97.66
	Haze	66.51 / **95.83**	97.86 / **99.50**	**100.0** / 99.95	**100.0** / 99.87	**100.0** / 99.88
	Decolor	48.37 / **62.36**	60.55 / **81.30**	71.73 / **89.93**	87.29 / **95.42**	89.68 / **96.91**



Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

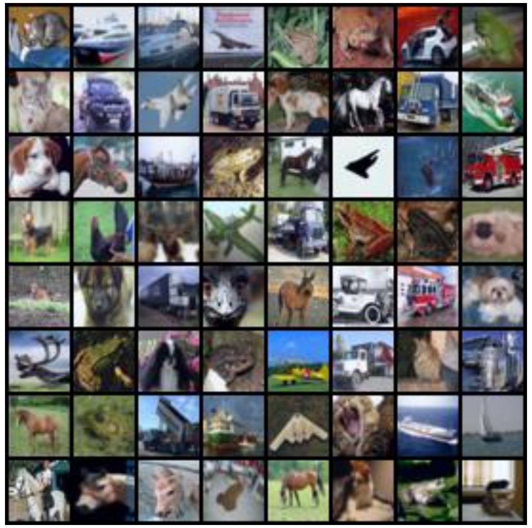
Out-of-Distribution Detection

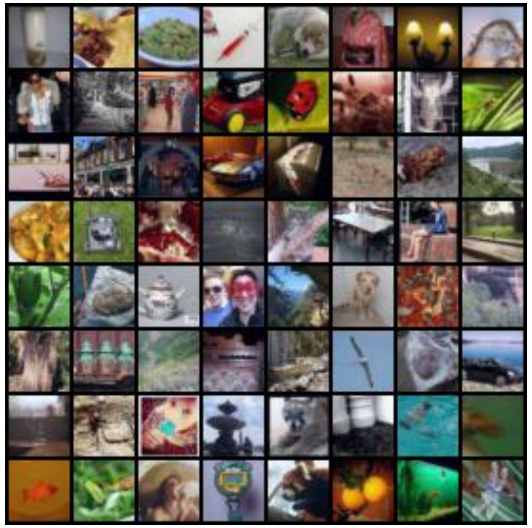
SCAN ME

Train set →  MNIST

Goal: To detect that these datasets are not part of training


SVHN


CIFAR10


TinyImageNet


LSUN

Lee, Jinsol, et al. "Probing the Purview of Neural Networks via Gradient Analysis." *IEEE Access* 11 (2023): 32716-32732.

Out-of-Distribution Detection

Probing the Purview of Neural Networks via Gradient Analysis

SCAN ME

Dataset Distribution		Detection Accuracy	AUROC	AUPR
In	Out	Baseline [5] / ODIN [6] / Mahalanobis (V) [7] / Mahalanobis (P+FE) [7] / Ours		
CIFAR-10	SVHN	83.36 / 88.81 / 79.39 / 91.95 / **98.04**	88.30 / 94.93 / 85.03 / 97.10 / **99.84**	88.26 / 95.45 / 86.15 / 96.12 / **99.98**
	TinyImageNet	84.01 / 85.21 / 83.60 / **97.45** / 86.17	90.06 / 91.86 / 88.93 / **99.68** / 93.18	89.26 / 91.60 / 88.59 / **99.60** / 92.66
	LSUN	87.34 / 88.42 / 85.02 / **98.60** / 98.37	92.79 / 94.48 / 90.11 / **99.86** / **99.86**	92.30 / 94.22 / 89.80 / 99.82 / **99.87**
SVHN	CIFAR-10	79.98 / 80.12 / 74.10 / 88.84 / **97.90**	81.50 / 81.49 / 79.31 / 95.05 / **99.79**	81.01 / 80.95 / 80.83 / 90.25 / **98.11**
	TinyImageNet	81.70 / 81.92 / 79.35 / 96.17 / **97.74**	83.69 / 83.82 / 83.85 / 99.23 / **99.77**	82.54 / 82.60 / 85.50 / **98.17** / 97.93
	LSUN	80.96 / 81.15 / 79.52 / 97.50 / **99.04**	82.85 / 82.98 / 83.02 / 99.54 / **99.93**	81.97 / 82.01 / 84.67 / 98.84 / **99.21**

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Out-of-Distribution Detection

Dataset Distribution		Detection Accuracy	AUROC	AUPR
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	TinyImageNet	84.01 / 85.21 / 83.60 / **97.45** / 86.17	90.06 / 91.86 / 88.93 / **99.68** / 93.18	89.26 / 91.60 / 88.59 / **99.60** / 92.66
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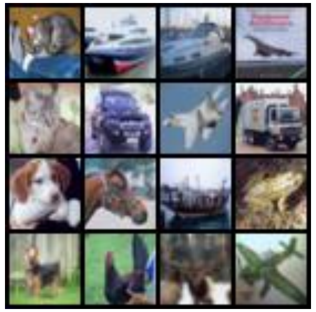
	LSUN	80.96 / 81.15 / 79.52 / 97.50 / **99.04**	82.85 / 82.98 / 83.02 / 99.54 / **99.93**	81.97 / 82.01 / 84.67 / 98.84 / **99.21**

Numbers

SVHN



CIFAR10

TinyImageNet

LSUN

Objects, natural scenes

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Out-of-Distribution Detection

Probing the Purview of Neural Networks via Gradient Analysis

SCAN ME

Dataset Distribution		Detection Accuracy	AUROC	AUPR
In	Out	Baseline [5] / ODIN [6] / Mahalanobis (V) [7] / Mahalanobis (P+FE) [7] / Ours		
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	TinyImageNet	84.01 / 85.21 / 83.60 / **97.45** / 86.17	90.06 / 91.86 / 88.93 / **99.68** / 93.18	89.26 / 91.60 / 88.59 / **99.60** / 92.66
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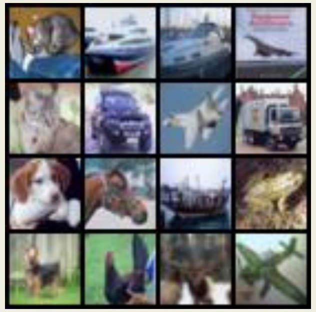
	LSUN	80.96 / 81.15 / 79.52 / 97.50 / **99.04**	82.85 / 82.98 / 83.02 / 99.54 / **99.93**	81.97 / 82.01 / 84.67 / 98.84 / **99.21**

More similar datasets (objects)

TinyImageNet



CIFAR10

LSUN

SVHN

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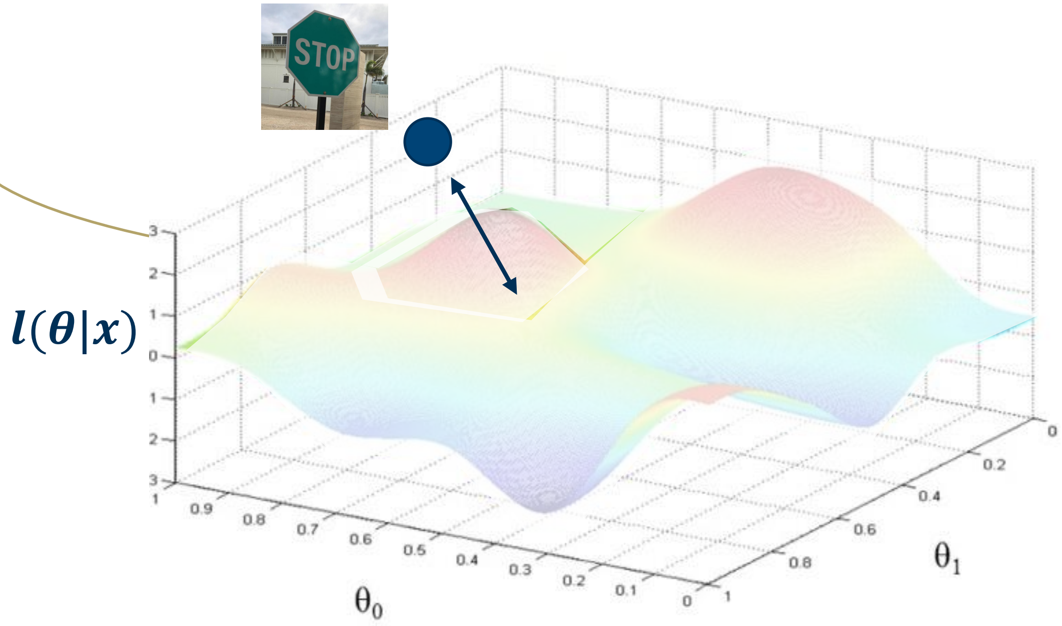
Case Study: Introspective Learning

Gradients as Single pass Features

Our Goal: Use gradients to characterize the novel data at Inference, without global information

Distance from unknown cluster



Two techniques:

1. Gradient constraints during Training for Anomaly Detection
2. **Backpropagating Confounding labels for Out-of-Distribution Detection**

NEURAL INFORMATION PROCESSING SYSTEMS

Introspective Learning: A Two-Stage Approach for Inference in Neural Networks

Mohit Prabhushankar, PhD
Postdoc

Ghassan AlRegib, PhD
Professor

SCAN ME

Robustness in Neural Networks

Why Robustness?

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

How would humans resolve this challenge?

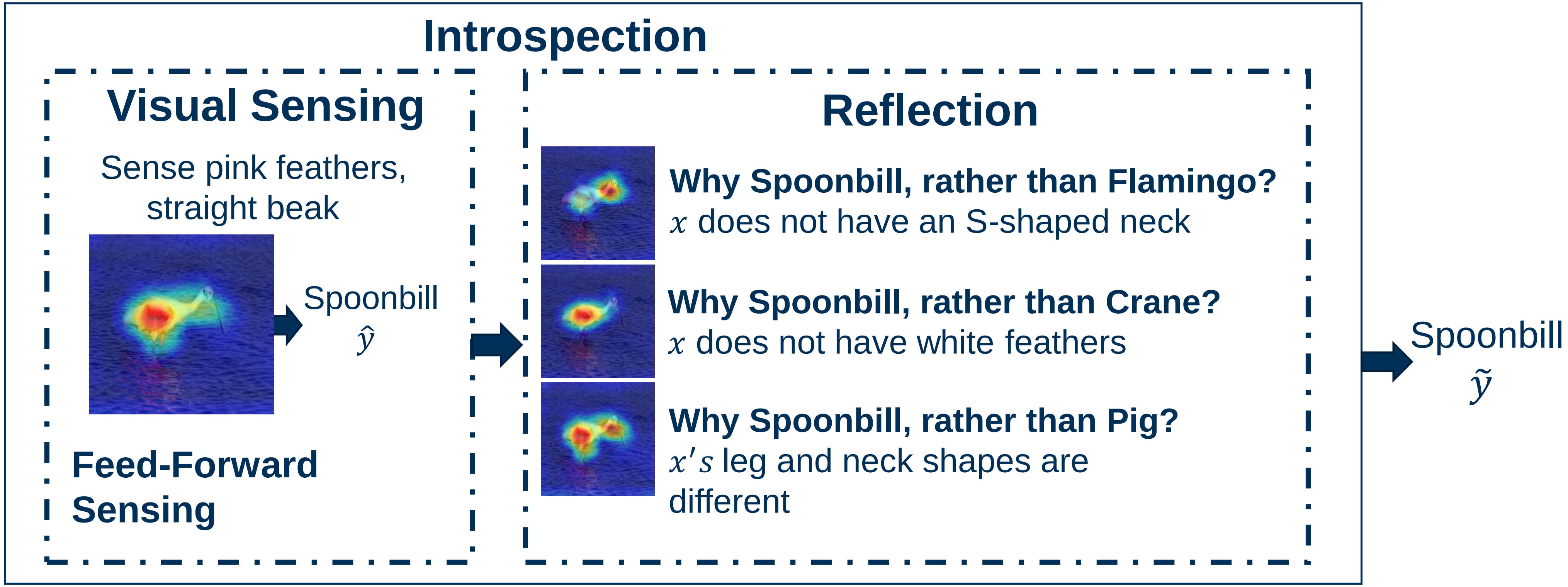
We Introspect!

- Why am I being shown this slide?
- Why images of muffins rather than pastries?
- What if the dog was a bull mastiff?

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Introspection Learning is a two-stage approach for Inference that combines visual sensing and reflection



M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

SCAN ME

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

Introspection Learning is a two-stage approach for Inference that combines visual sensing and reflection

Goal : To simulate Introspection in Neural Networks

Definition : *We define introspections as answers to logical and targeted questions.*

What are the possible targeted questions?

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Introspection

Introspection in Neural Networks

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Introspection Learning is a two-stage approach for Inference that combines visual sensing and reflection

Bullmastiff	Why Bullmastiff?	What if Bullmastiff was not in the image?	Why Bullmastiff, rather than a Boxer?

What are the possible targeted questions?

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Introspection Learning is a two-stage approach for Inference that combines visual sensing and reflection

Goal : To simulate Introspection in Neural Networks

Contrastive Definition : *Introspection answers questions of the form `Why P, rather than Q?' where P is a network prediction and Q is the introspective class.*

Technical Definition : *Given a network* $f(x)$, *a datum* x, *and the network's prediction* $f(x) = \hat{y}$, *introspection in* $f(\cdot)$ *is the measurement of change induced in the network parameters when a label* Q *is introduced as the label for* x..

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

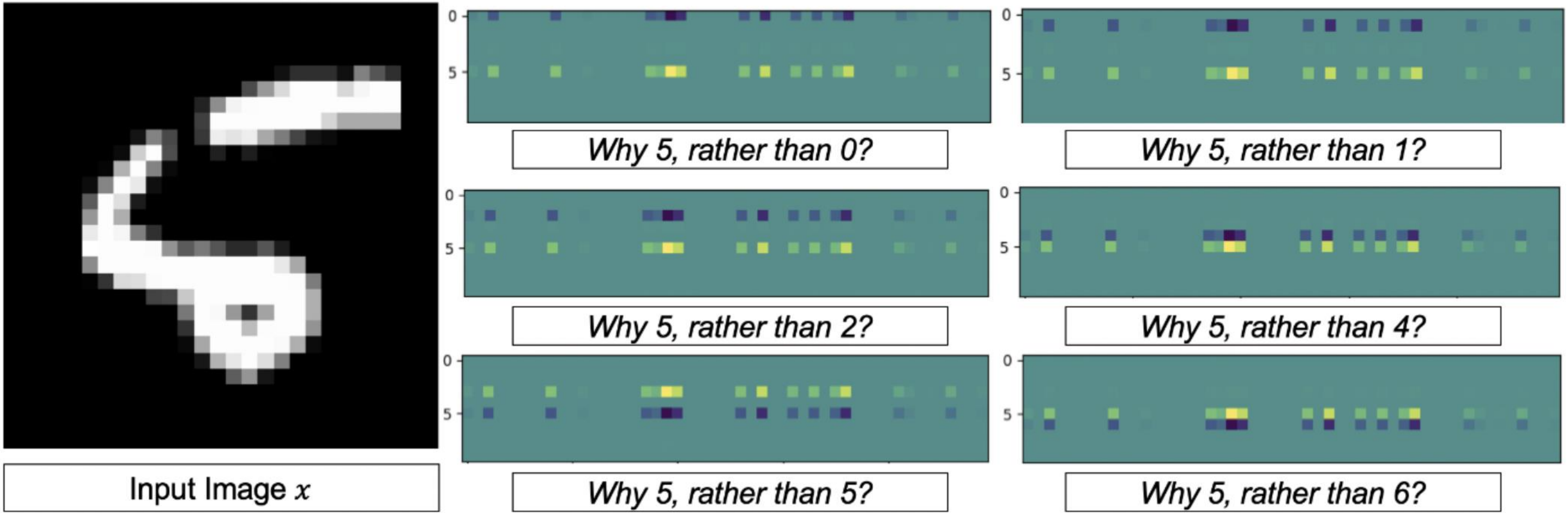
Introspection

Gradients as Features

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

For a well-trained network, the gradients are sparse and informative



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Introspective Learning: A Two-stage Approach for Inference in Neural Networks

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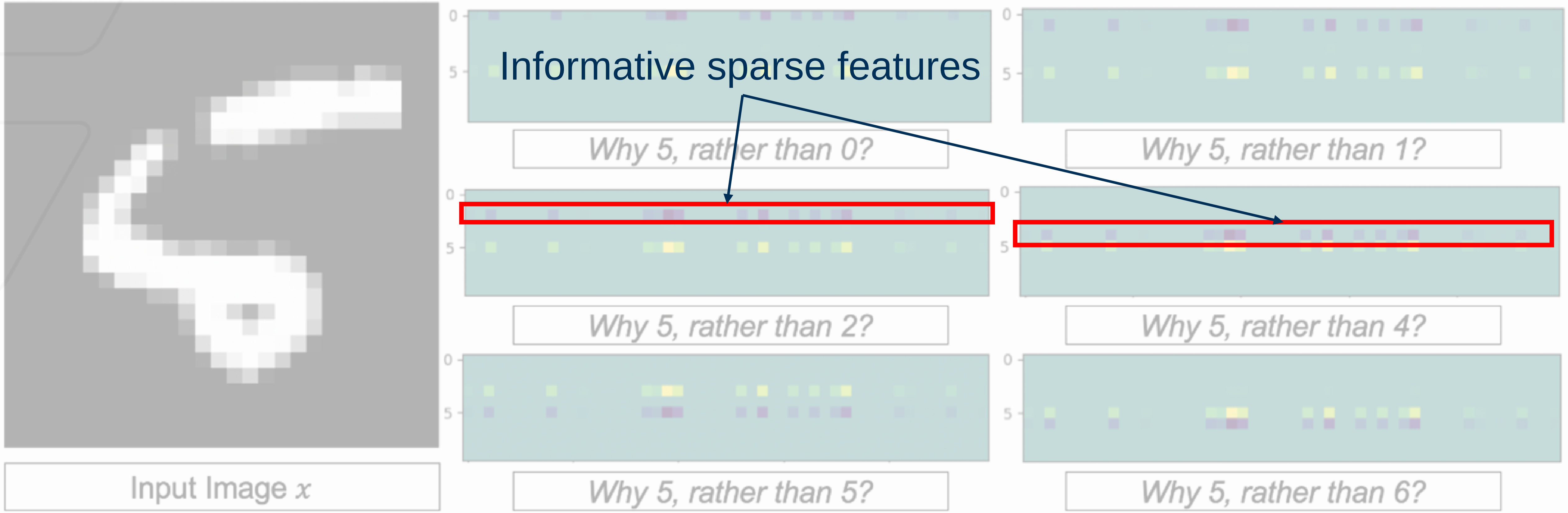

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Introspection

Gradients as Features

SCAN ME

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

For a well-trained network, the gradients are robust

∇_W = Gradients w.r.t. weights

J = Loss function

$\hat{y}$ = Prediction

$$\overbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \cdots \quad \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}}^{y_I}$$

Lemma1: $\nabla_W J(y_I, \hat{y}) = -\nabla_W y_I + \nabla_W \log\left(1 + \frac{y_I \hat{y}}{2}\right).$

Any change in class requires change in relationship between y_I and $\hat{y}$

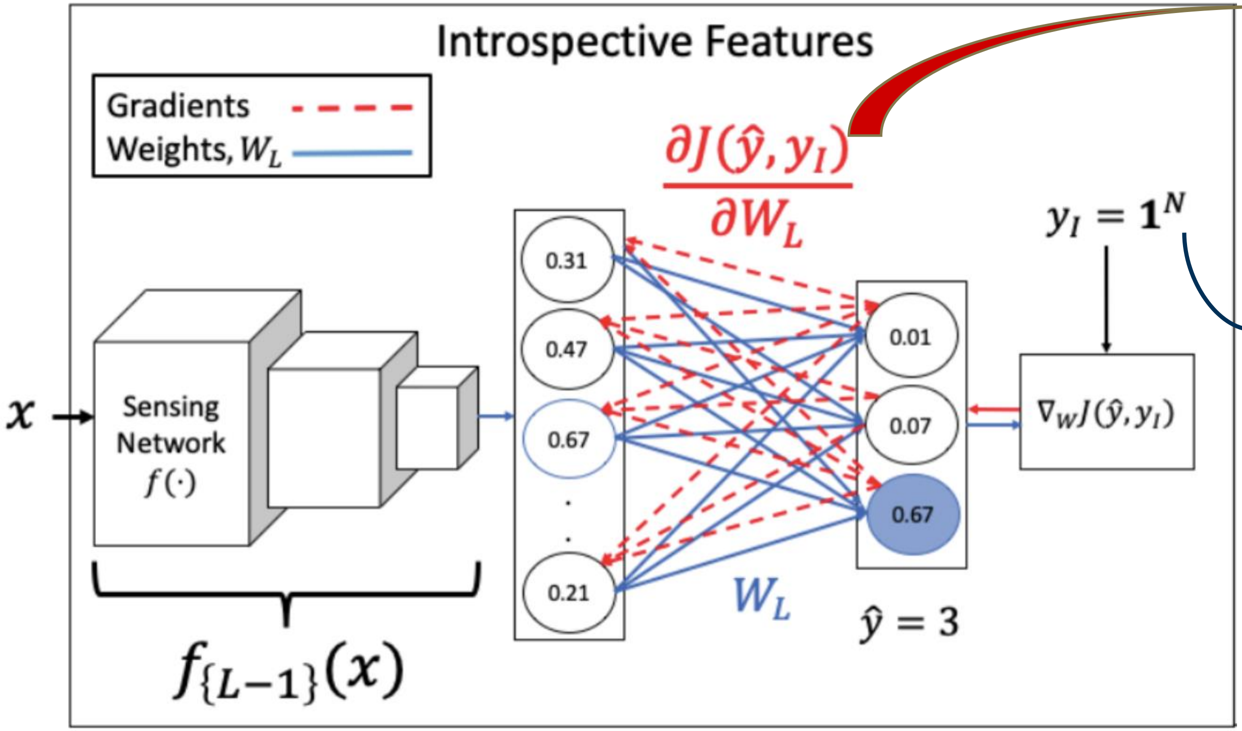
M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Introspection
Deriving Gradient Features

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Measure the loss between the prediction P and a vector of all ones and backpropagate to obtain the introspective features



Normalized and vectorized gradients are introspective features

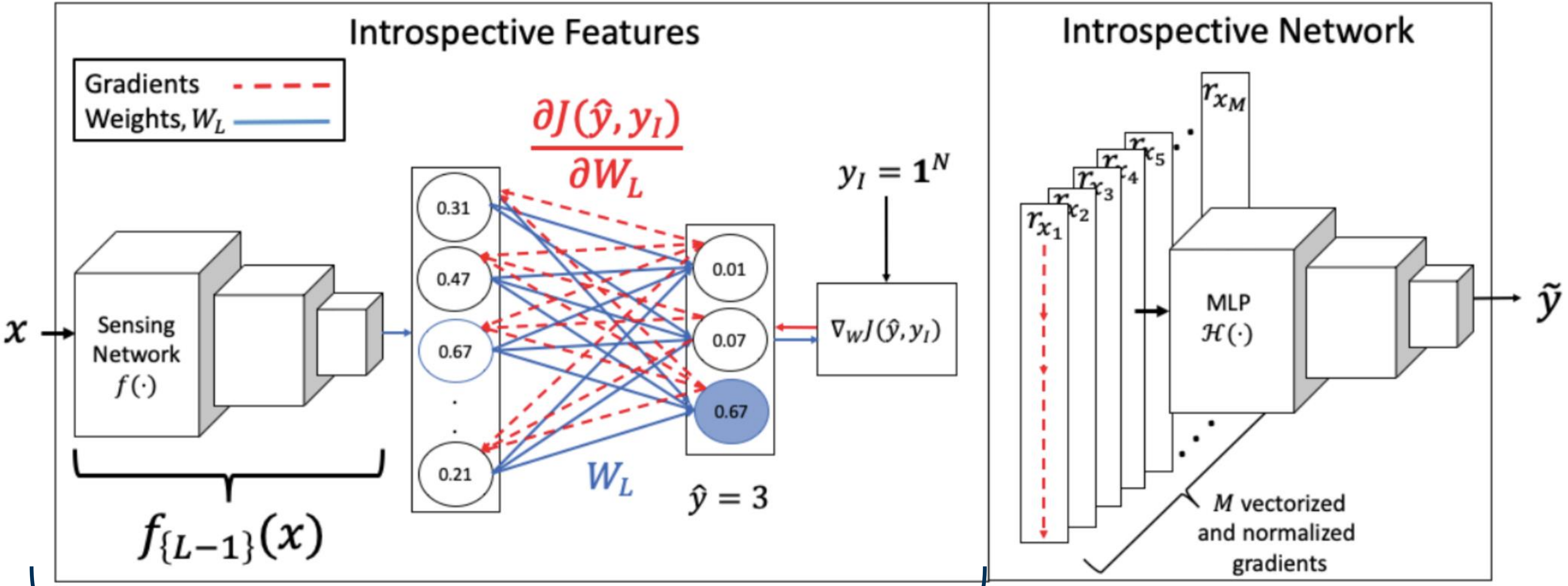
Vector of all ones: A confounding label!

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Introspection

Utilizing Gradient Features

Introspective Learning: A Two-stage Approach for Inference in Neural Networks



Introspective Features

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

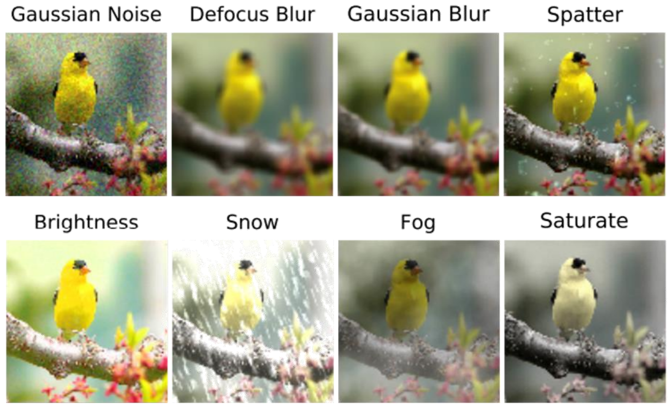
SCAN ME

Introspection provides robustness when the train and test distributions are different

We define robustness as being generalizable and calibrated to new testing data

Generalizable: Increased accuracy on OOD data

Calibrated: Reduces the difference between prediction accuracy and confidence



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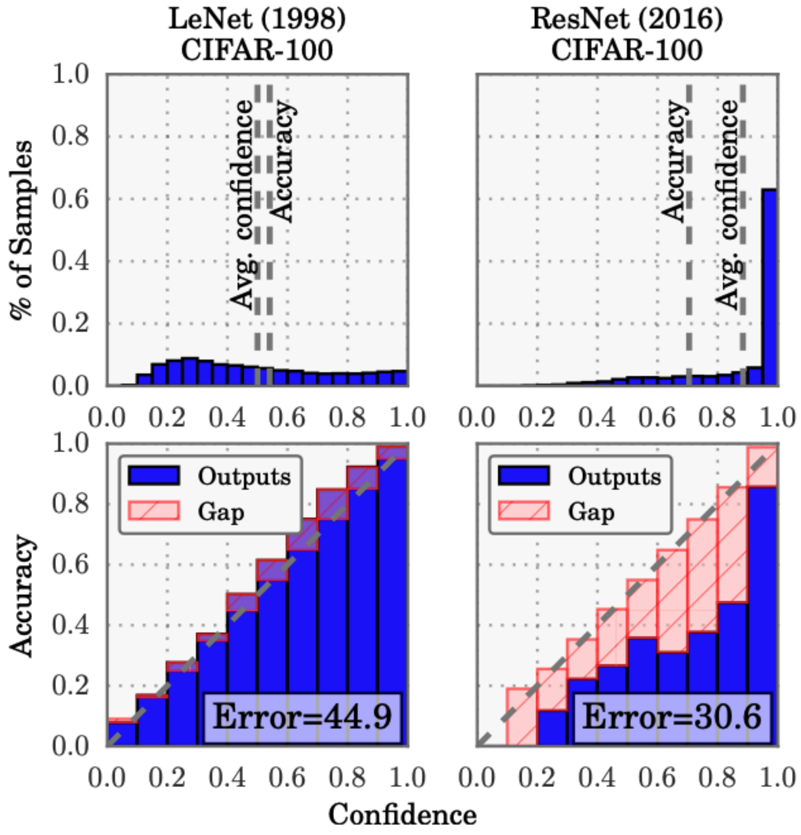
Calibration

A note on Calibration..

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Calibration occurs when there is mismatch between a network's confidence and its accuracy



- Larger the model, more misplaced is a network's confidence
- On ResNet, the gap between prediction accuracy and its corresponding confidence is significantly high

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Generalization and Calibration results

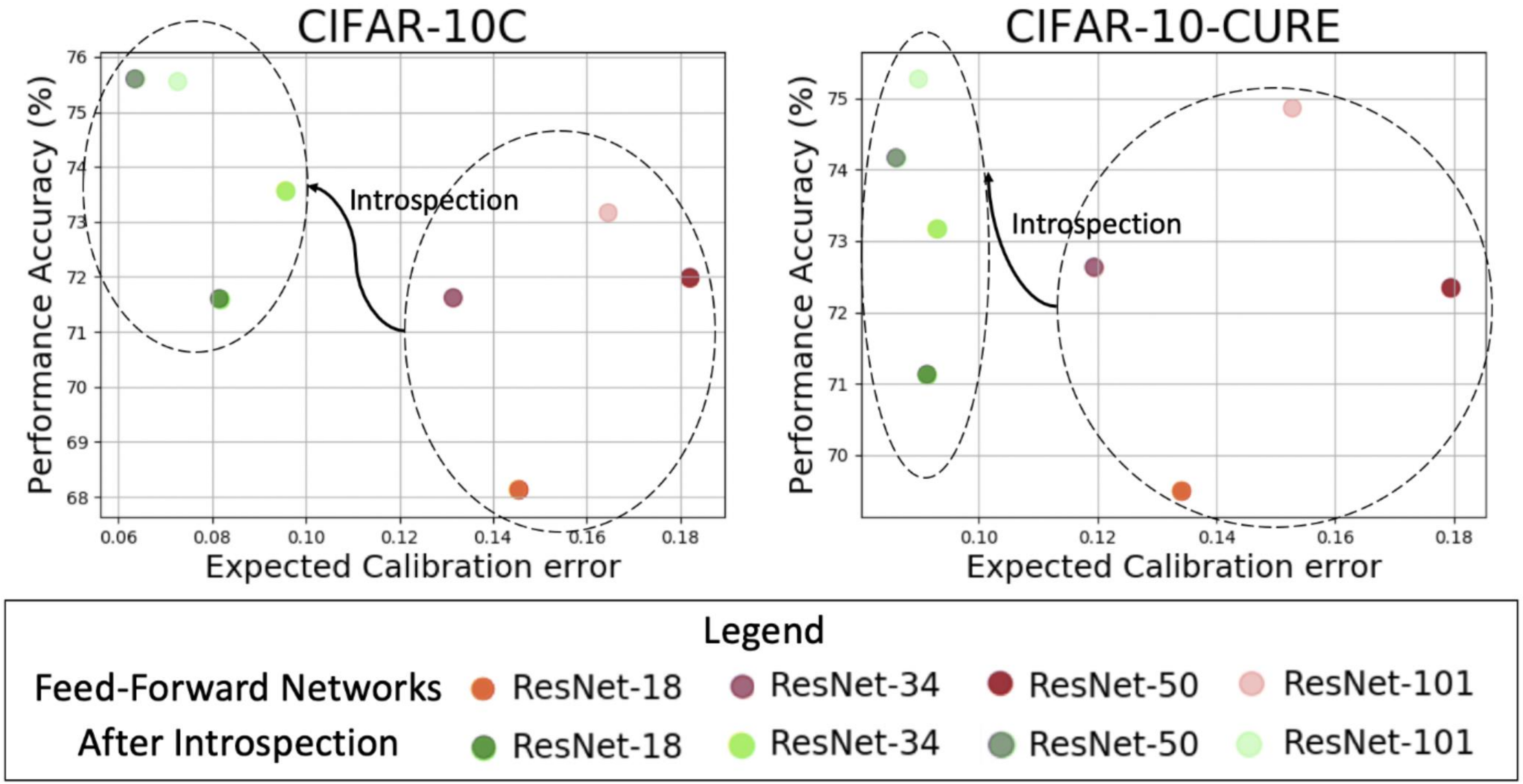
Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Ideal: Top-left corner

Y-Axis: Generalization

X-Axis: Calibration



M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Plug-in nature of Introspection

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Introspection is a light-weight option to resolve robustness issues

Table 1: Introspecting on top of existing robustness techniques.

Methods		Accuracy
ResNet-18	Feed-Forward	67.89%
	Introspective	**71.4%**
Denoising	Feed-Forward	65.02%
	Introspective	**68.86%**
Adversarial Train (27)	Feed-Forward	68.02%
	Introspective	**70.86%**
SimCLR (19)	Feed-Forward	70.28%
	Introspective	**73.32%**
Augment Noise (28)	Feed-Forward	76.86%
	Introspective	**77.98%**
Augmix (26)	Feed-Forward	89.85%
	Introspective	**89.89%**

Introspection is a **plug-in approach** that works on all networks and on any downstream task!

M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

Introspection in Neural Networks

Plug-in nature of Introspection

Introspective Learning: A Two-stage Approach for Inference in Neural Networks

SCAN ME

Plug-in nature of Introspection benefits downstream tasks like OOD detection, Active Learning, and Image Quality Assessment!

Table 13: Performance of Contrastive Features against Feed-Forward Features and other Image Quality Estimators. Top 2 results in each row are highlighted.

Database	PSNR HA	IW SSIM	SR SIM	FSIMc	Per SIM	CSV	SUM MER	Feed-Forward UNIQUE	Introspective UNIQUE
				Outlier Ratio (OR, ↓)					
MULTI	0.013	0.013	**0.000**	0.016	0.004	**0.000**	**0.000**	**0.000**	**0.000**
TID13	**0.615**	0.701	0.632	0.728	0.655	0.687	**0.620**	0.640	**0.620**
				Root Mean Square Error (RMSE, ↓)					
MULTI	11.320	10.049	8.686	10.794	9.898	9.895	**8.212**	9.258	**7.943**
TID13	0.652	0.688	0.619	0.687	0.643	0.647	0.630	**0.615**	**0.596**
				Pearson Linear Correlation Coefficient (PLCC, ↑)					
MULTI	0.801	0.847	0.888	0.821	0.852	0.852	**0.901**	0.872	**0.908**
	-1	-1	0	-1	-1	-1	-1	-1	
TID13	0.851	0.832	0.866	0.832	0.855	0.853	0.861	**0.869**	**0.877**
	-1	-1	0	-1	-1	-1	0	0	
				Spearman's Rank Correlation Coefficient (SRCC, ↑)					
MULTI	0.715	**0.884**	0.867	0.867	0.818	0.849	**0.884**	0.867	**0.887**
	-1	0	0	0	-1	-1	0	0	
TID13	0.847	0.778	0.807	0.851	0.854	0.846	0.856	**0.860**	**0.865**
	-1	-1	-1	-1	0	-1	0	0	
				Kendall's Rank Correlation Coefficient (KRCC)					
MULTI	0.532	**0.702**	0.678	0.677	0.624	0.655	0.698	0.679	**0.702**
	-1	0	0	0	-1	0	0	0	
TID13	0.666	0.598	0.641	0.667	**0.678**	0.654	0.667	0.667	**0.677**
	0	-1	-1	0	0	0	0	0	

Table 2: Recognition accuracy of Active Learning strategies.

Methods	Architecture	Original Testset		Gaussian Noise	
		R-18	R-34	R-18	R-34
Entropy (31)	Feed-Forward	0.365	0.358	0.244	0.249
	Introspective	0.365	0.359	**0.258**	**0.255**
Least (31)	Feed-Forward	0.371	0.359	0.252	0.25
	Introspective	0.373	0.362	**0.264**	**0.26**
Margin (32)	Feed-Forward	0.38	0.369	0.251	0.253
	Introspective	0.381	0.373	**0.265**	**0.263**
BALD (34)	Feed-Forward	0.393	0.368	0.26	0.253
	Introspective	0.396	0.375	**0.273**	**0.263**
BADGE (33)	Feed-Forward	0.388	0.37	0.25	0.247
	Introspective	0.39	0.37	**0.265**	0.260

Table 3: Out-of-distribution Detection of existing techniques compared between feed-forward and introspective networks.

Methods	OOD Datasets	FPR (95% at TPR) ↓	Detection Error ↓	AUROC ↑
		Feed-Forward/Introspective		
MSP (35)	Textures	58.74/**19.66**	18.04/**7.49**	88.56/**97.79**
	SVHN	61.41/**51.27**	16.92/**15.67**	89.39/**91.2**
	Places365	58.04/**54.43**	17.01/**15.07**	89.39/**91.3**
	LSUN-C	**27.95**/27.5	**9.42**/10.29	**96.07**/95.73
ODIN (36)	Textures	52.3/**9.31**	22.17/**6.12**	84.91/**91.9**
	SVHN	66.81/**48.52**	23.51/**15.86**	83.52/**91.07**
	Places365	**42.21**/51.87	16.23/**15.71**	**91.06**/90.95
	LSUN-C	**6.59**/23.66	**5.54**/10.2	**98.74**/ 95.87

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M. Prabhushankar, and G. AlRegib, "Introspective Learning : A Two-Stage Approach for Inference in Neural Networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, LA, Nov. 29 - Dec. 1 2022.

OLIVES @GeorgiaTech

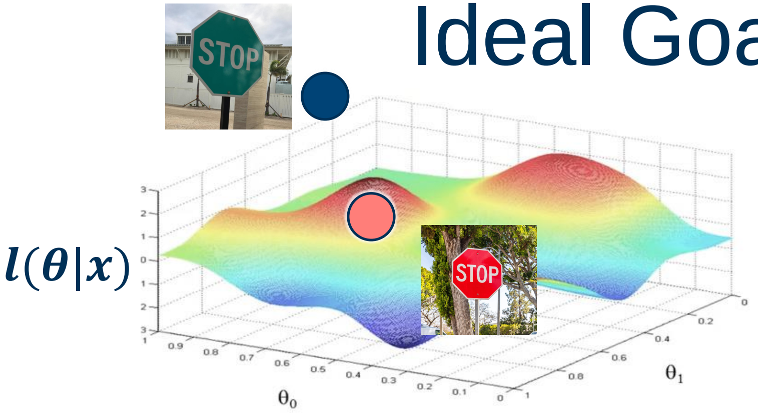
Georgia Tech

Part I, II and III

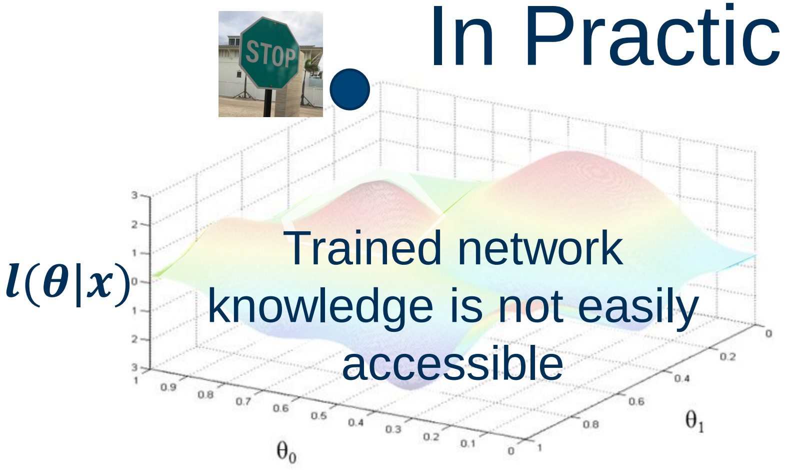
Tying it Back

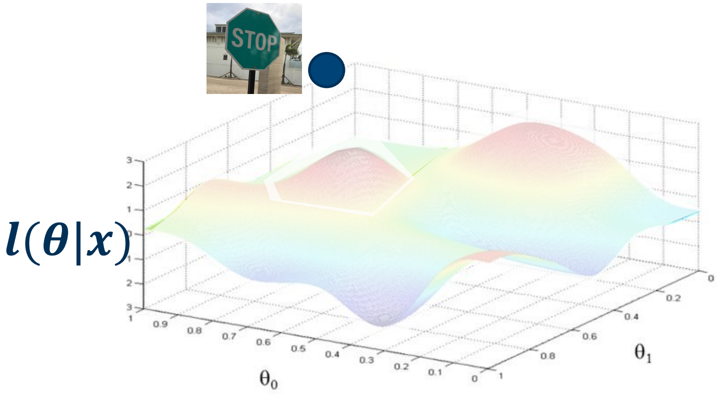
From Part I

Ideal Goal

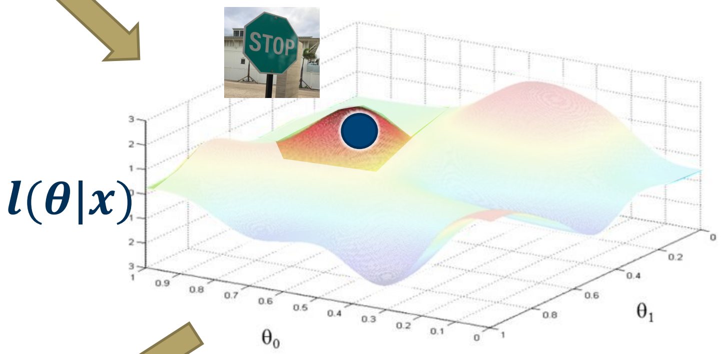


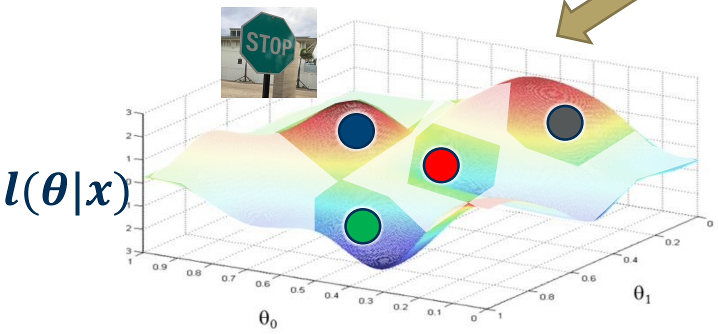
In Practice





Novel data projects onto the likelihood function (however incorrectly), and extracts fisher information around the projection





By backpropagating contrast classes (and not updating the network), the network finds the steepest descent towards other regions of likelihood function

Robust Neural Networks

Part 4: Intervenability at Inference

Objective

Objective of the Tutorial

To discuss methodologies that promote robustness in neural networks at inference

- Part 1: Inference in Neural Networks
- Part 2: Explainability at Inference
- Part 3: Uncertainty at Inference
- **Part 4: Intervenability at Inference**
    - Definitions of Intervenability
        - Causality
        - Privacy
        - Interpretability
        - Prompting
        - Benchmarking
    - Case Study: Intervenability in Interpretability
- Part 5: Conclusions and Future Directions

Intervenability

Through the Causal Glass

Assess: The amenability of neural network decisions to human interventions

*“**Interventions** in data are **manipulations** that are **designed** to test for causal factors”*

Schölkopf, B., Locatello, F., Bauer, S., Ke, N. R., Kalchbrenner, N., Goyal, A., & Bengio, Y. (2021). Toward causal representation learning. *Proceedings of the IEEE*, *109*(5), 612-634.

Intervenability

Through the Privacy Glass

Assure: The amenability of neural network decisions to human interventions

*"**Intervenability** aims at the possibility for parties involved in any **privacy-relevant** data processing to **interfere** with the **ongoing or planned data processing**"*

Hansen, M.: Top 10 mistakes in system design from a privacy perspective and privacy protection goals. In: Camenisch, J., Crispo, B., Fischer-Hübner, S., Leenes, R., Russello, G. (eds.) Privacy and Identity Management for Life. IFIP AICT, vol. 375, pp. 14–31. Springer, Heidelberg (2012)

Interpret: The amenability of neural network decisions to human interventions

*"The **post-hoc field** of explainability, that previously only justified decisions, becomes **active** by being involved in the decision making process and **providing limited, but relevant and contextual interventions**"*

AlRegib, Ghassan, and Mohit Prabhushankar. "Explanatory paradigms in neural networks: Towards relevant and contextual explanations." *IEEE Signal Processing Magazine* 39.4 (2022): 59-72.

Verify: The amenability of neural network decisions to human interventions

*"... new **benchmarks** were proposed to specifically **test generalization** of classification and detection methods with respect to **simple** algorithmically generated **interventions** like spatial shifts, blur, changes in brightness or contrast..."*

Schölkopf, B., Locatello, F., Bauer, S., Ke, N. R., Kalchbrenner, N., Goyal, A., & Bengio, Y. (2021). Toward causal representation learning. *Proceedings of the IEEE*, *109*(5), 612-634.

Intervenability

Through the Human Glass

The amenability of neural network decisions to human interventions

- **Assess: Causality**
- **Assure: Privacy**
- **Interpret: Interpretability**
- **Verify: Benchmarking**

Schölkopf, B., Locatello, F., Bauer, S., Ke, N. R., Kalchbrenner, N., Goyal, A., & Bengio, Y. (2021). Toward causal representation learning. *Proceedings of the IEEE*, *109*(5), 612-634.

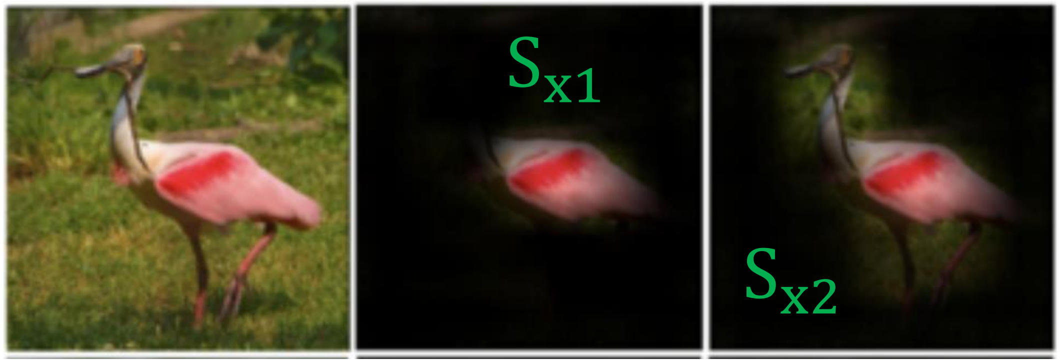
Case Study: Intervenability in Interpretability

Explanation Evaluation via Masking

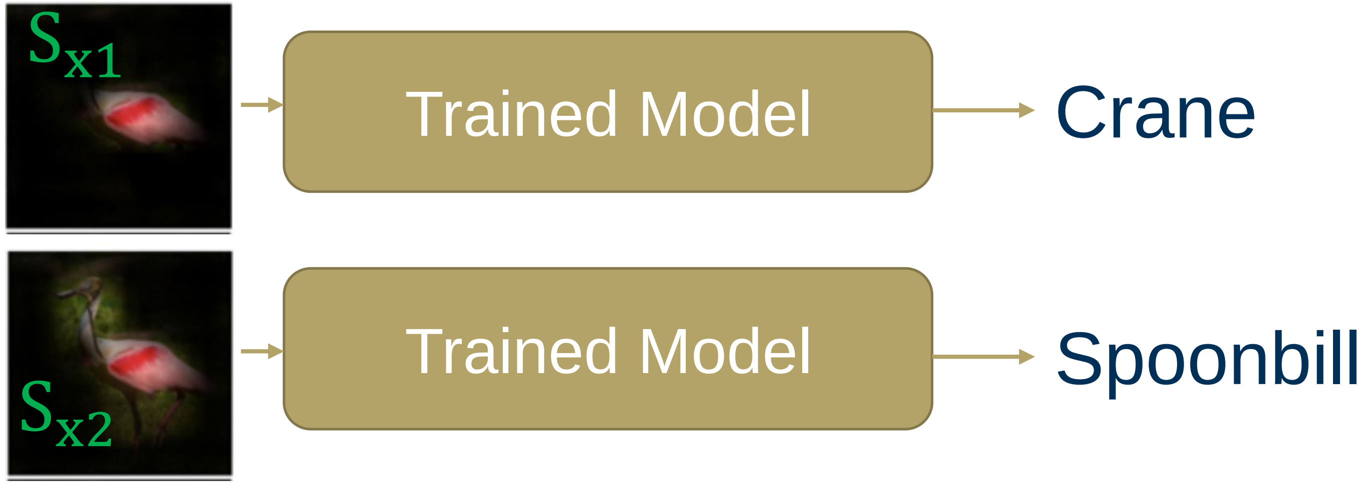
Common evaluation technique is masking the image and checking for prediction correctness

y = Prediction
S_x = Explanation masked data

$E(Y|S_x)$ = Expectation of class given S_x



If across N images, $\mathbf{E(Y|S_{x2}) > E(Y|S_{x1})}$, explanation technique 2 is better than explanation technique 1



Chattopadhay, Aditya, et al. "Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks." *2018 IEEE winter conference on applications of computer vision (WACV)*. IEEE, 2018.

VOICE: Variance of Contrastive Explanations for Quantifying Uncertainty in Interpretability

Mohit Prabhushankar, PhD
Postdoc

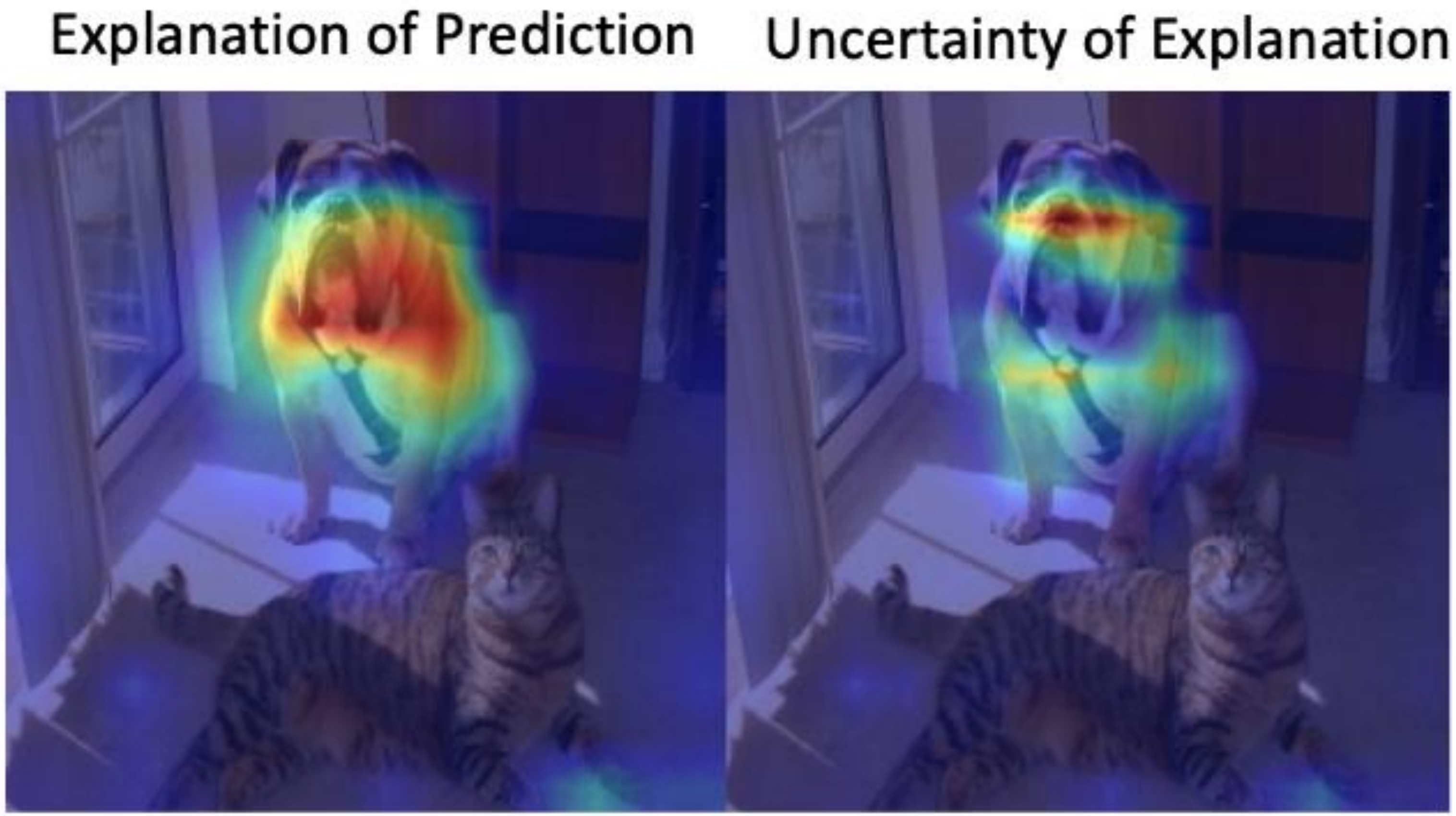
Ghassan AlRegib, PhD
Professor

Case Study: Intervenability in Interpretability

Predictive Uncertainty in Explanations

Explanatory techniques have predictive uncertainty

Why Bullmastiff?



Uncertainty in answering Why Bullmastiff?

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Predictive Uncertainty

Uncertainty due to variance in prediction when model is kept constant

x $\quad S_{x_1}$ $\quad S_{x_2}$

$$V[y|S_x] = V[E(y|S_x)] + E(V[y|S_x])$$

y = Prediction
$V[y]$ = Variance of prediction (Predictive Uncertainty)
S_x = Subset of data (Some intervention)
$E(Y|S_x)$ = Expectation of class given a subset
$V(Y|S_x)$ = Variance of class given all other residuals

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Visual Explanations (partially) reduce Predictive Uncertainty

A 'good' explanatory technique is evaluated to have zero $V[E(y|S_x)]$

x $\quad S_{x_1} \quad S_{x_2}$

$$V[y|S_x] = \underbrace{V[E(y|S_x)]}_{\text{zero}} + E(V[y|S_x])$$

y = Prediction
$V[y]$ = Variance of prediction (Predictive Uncertainty)
S_x = Subset of data (Some intervention)
$E(Y|S_x)$ = Expectation of class given a subset
$V(Y|S_x)$ = Variance of class given all other residuals

Key Observation 1: Visual Explanations are evaluated to partially reduce the predictive uncertainty in a neural network

Network evaluations have nothing to do with human Explainability!

[Tutorial@WACV'24] | [Ghassan AlRegib and Mohit Prabhushankar] | [Jan 07, 2024]

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Predictive Uncertainty in Explanations is the Residual

All other subsets 'not' chosen by the explanatory technique contributes to uncertainty

x $\quad S_{x_1}$ $\quad S_{x_2}$

$$V[y|S_x] = V[E(y|S_x)] + E(V[y|S_x])$$

y = Prediction
$V[y]$ = Variance of prediction (Predictive Uncertainty)
S_x = Subset of data (Some intervention)
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Key Observation 2: Uncertainty in Explainability occurs due to all combinations of features that the explanation did not attribute to the network's decision

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Predictive Uncertainty in Explanations is the Residual

All other subsets 'not' chosen by the explanatory technique contributes to uncertainty

$$V[y|S_x] = V[E(y|S_x)] + E(V[y|S_x])$$

The effect of a chosen Interventions can be measured based on *all the Interventions that were not chosen*

y = Prediction
$V[y]$ = Variance of prediction (Predictive Uncertainty)
S_x = Subset of data (Some intervention)
$E(Y|S_x)$ = Expectation of class given a subset
$V(Y|S_x)$ = Variance of class given all other residuals

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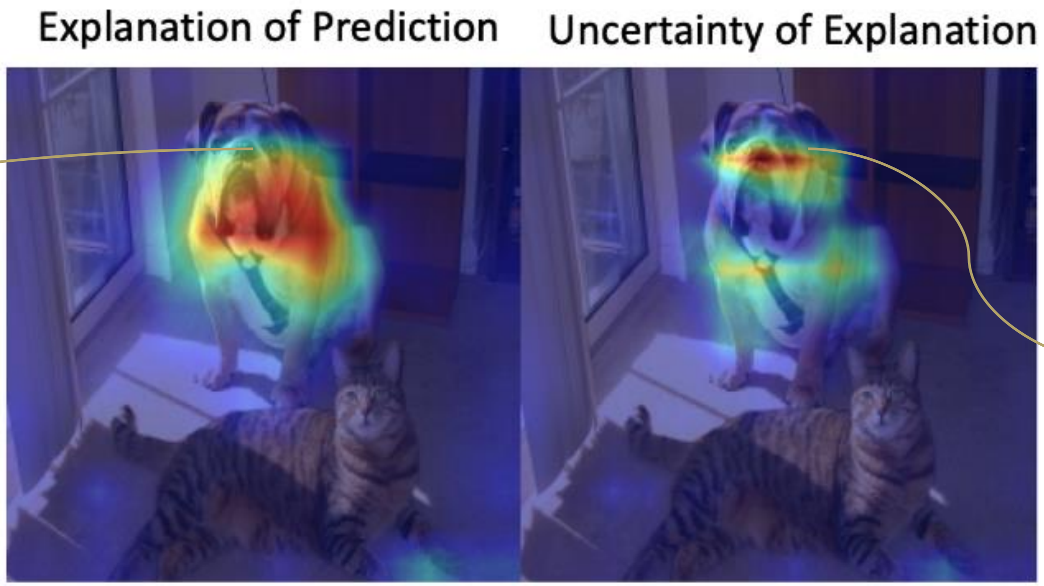
Case Study: Intervenability in Interpretability

Predictive Uncertainty in Explanations is the Residual

All other subsets 'not' chosen by the explanatory technique contributes to uncertainty



Snout is not as highlighted as the jowls in explanation (not as important for decision)

However, snout is an important characteristic that is used to differentiate against other dogs. Hence, there is uncertainty on why this feature is not included in the attribution

Key Observation 2: Uncertainty in Explainability occurs due to all combinations of features that the explanation did not attribute to the network's decision

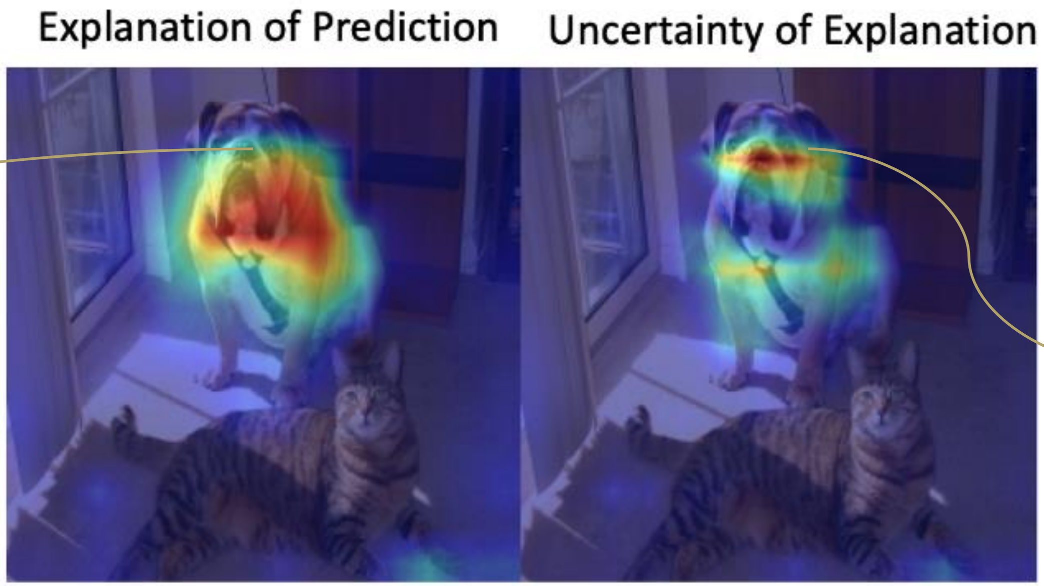
M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Predictive Uncertainty in Explanations is the Residual

All other subsets 'not' chosen by the explanatory technique contributes to uncertainty

Snout is not as highlighted as the jowls in explanation (not as important for decision)



However, snout is an important characteristic that is used to differentiate against other dogs. Hence, there is uncertainty on why this feature is not included in the attribution

Not chosen features are intractable!

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Quantifying Interventions in Explainability

Contrastive explanations are an intelligent way of obtaining other subsets

$$V[y|S_x] = V[E(y|S_x)] + E(V[y|S_x])$$

Make it finite by only considering the subsets that change y

S_{x_1}

S_{x_2}

....

S_{x_N}

$$\left.\begin{array}{c} Y_1|S_{x1} \\ Y_2|S_{x2} \\ Y_3|S_{x3} \\ Y_4|S_{x4} \\ Y_5|S_{x5} \\ . \\ . \\ Y_N|S_{xN} \end{array}\right\} \text{Variance}$$

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Quantifying Interventions in Explainability

Uncertainty in Explainability can be used to analyze Explanatory methods and Networks

- Is GradCAM better than GradCAM++?
- Is a SWIN transformer more reliable than VGG-16?

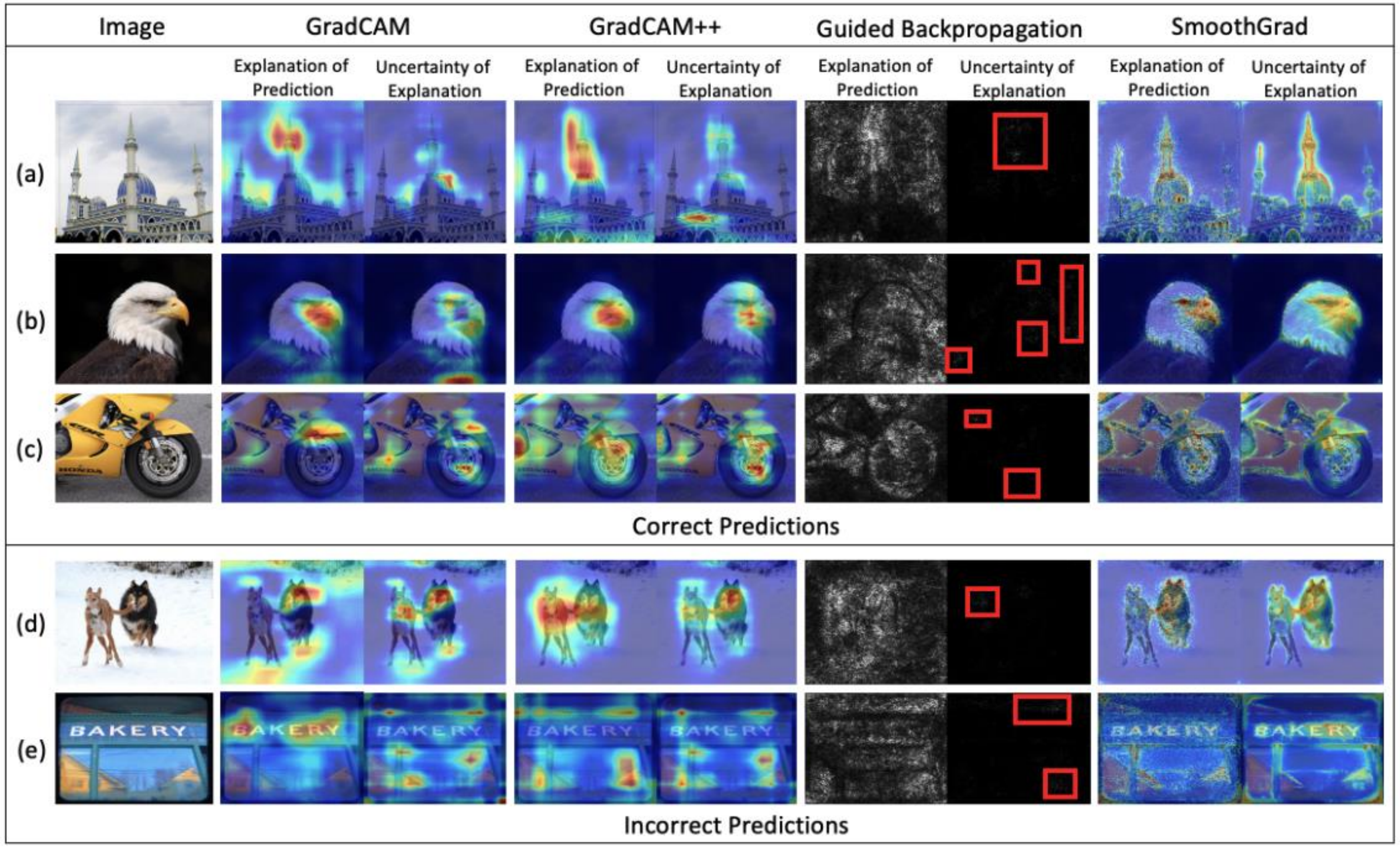
Need objective quantification of Intervention Residuals

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Quantifying Interventions in Explainability: mIOU

On incorrect predictions, the overlap of explanations and uncertainty is higher



Objective Metric: Intersection over Union (IoU) between explanation and Uncertainty

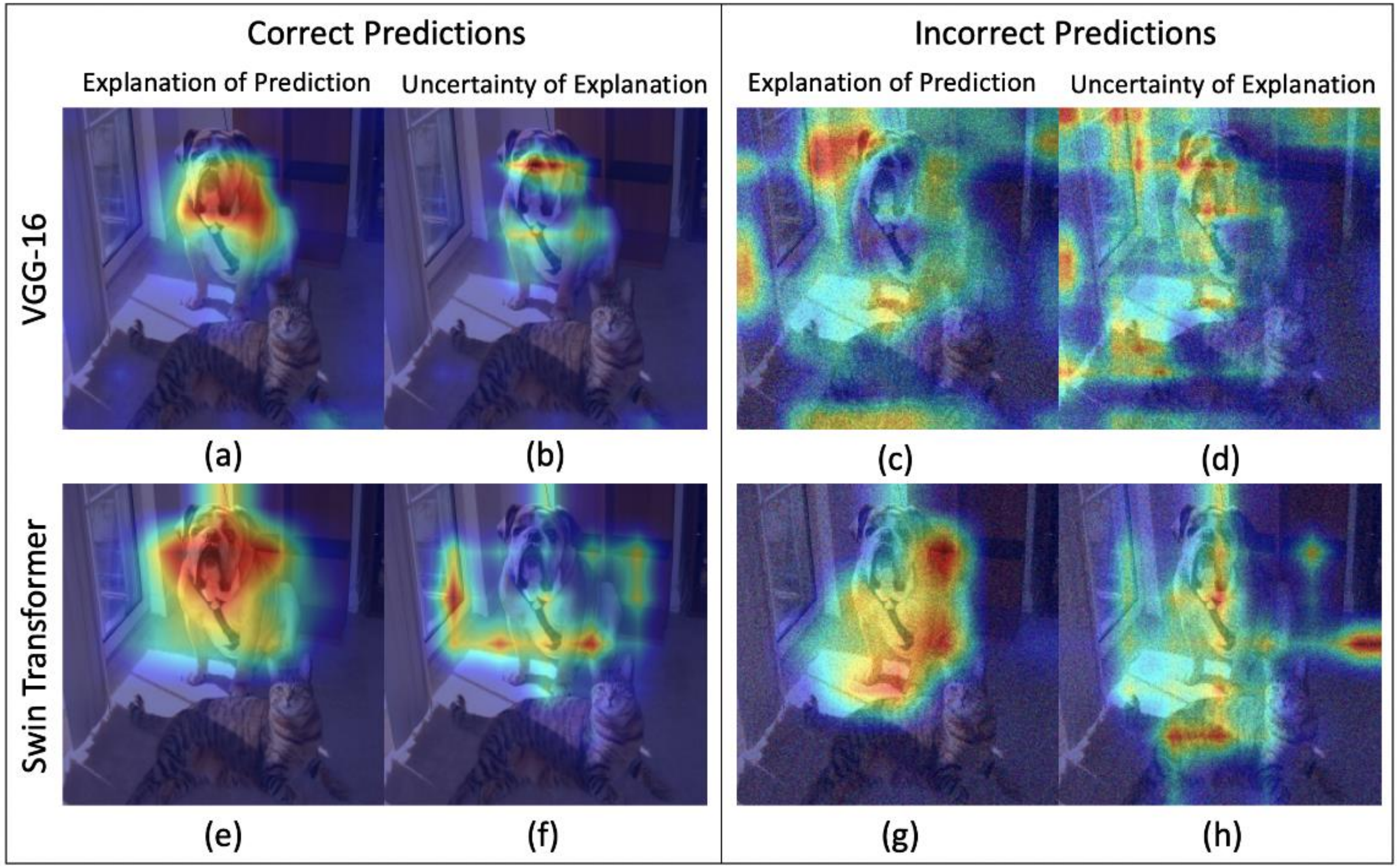
Higher the IoU, higher the uncertainty in explanation (or less trustworthy is the prediction)

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Quantifying Interventions in Explainability: SNR

Explanation and uncertainty are dispersed under noise (under low prediction confidence)



Objective Metric: Signal to Noise Ratio of the Uncertainty map

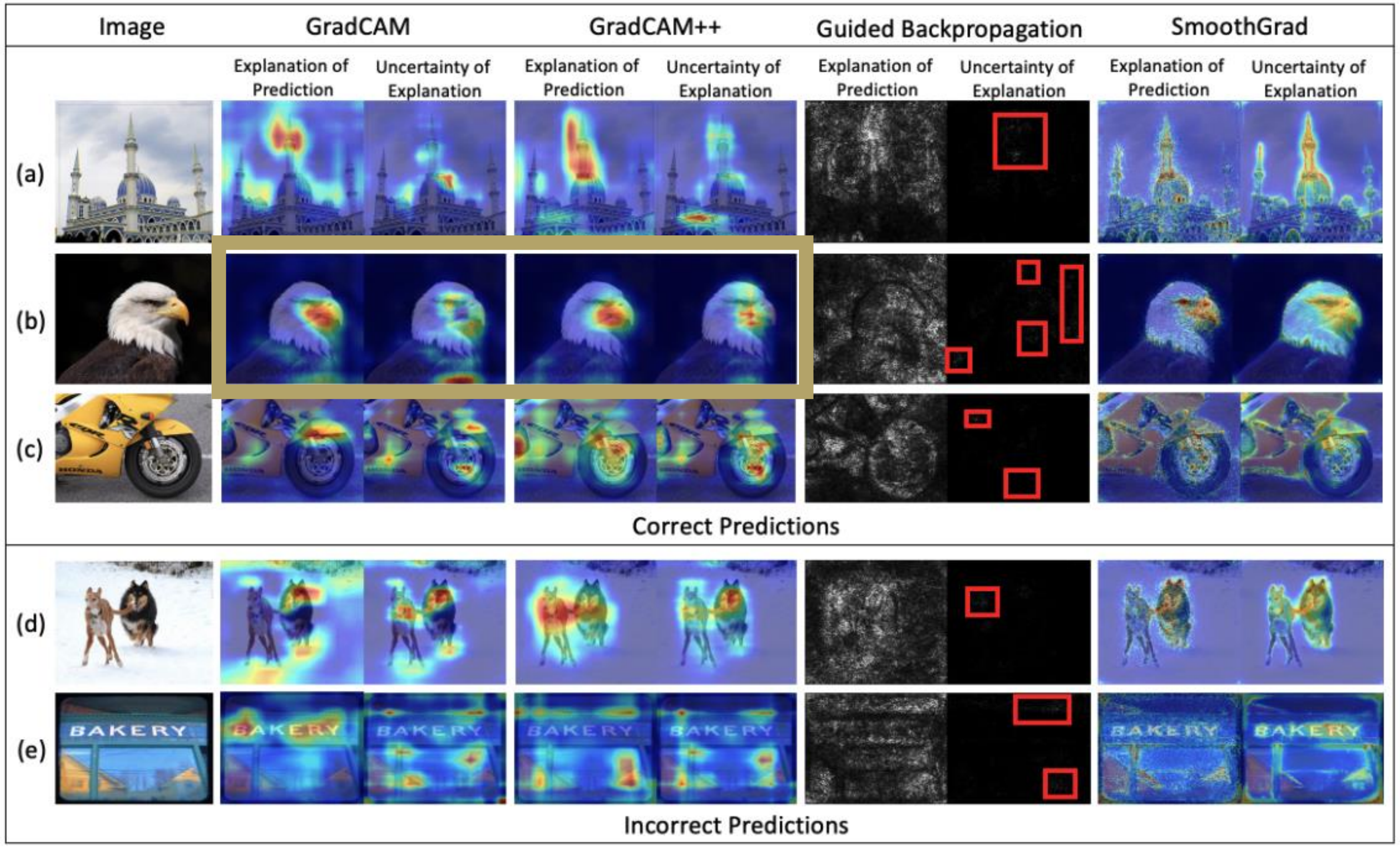
Higher the SNR of uncertainty, more is the dispersal (or less trustworthy is the prediction)

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Quantifying Interventions in Explainability: mIOU

On incorrect predictions, the overlap of explanations and uncertainty is higher



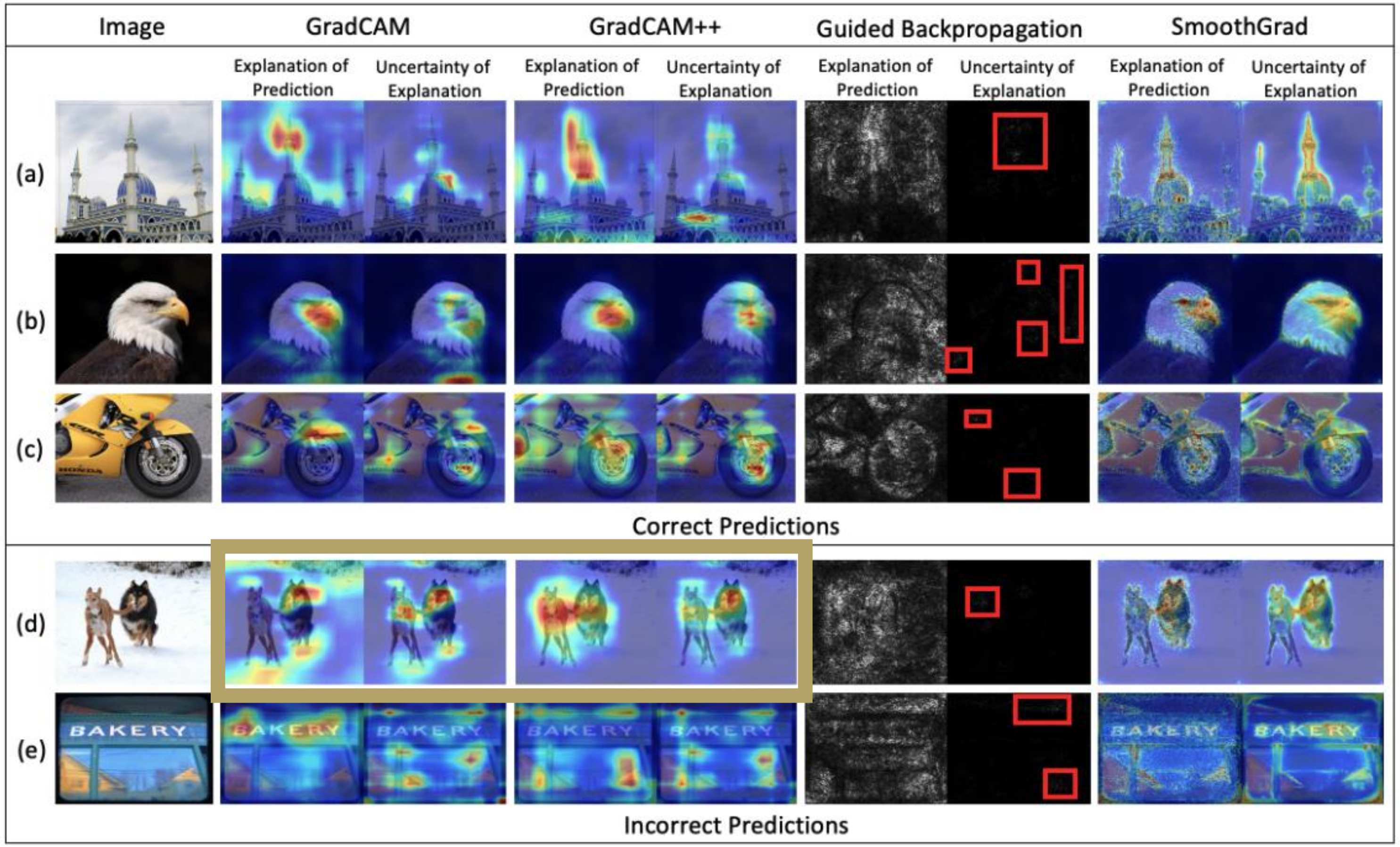
Objective Metric 1: Intersection over Union (IoU) between explanation and Uncertainty

Higher the IoU, higher the uncertainty in explanation (or less trustworthy is the prediction)

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Quantifying Interventions in Explainability: mIOU

On incorrect predictions, the overlap of explanations and uncertainty is higher



Objective Metric 1: Intersection over Union (IoU) between explanation and Uncertainty

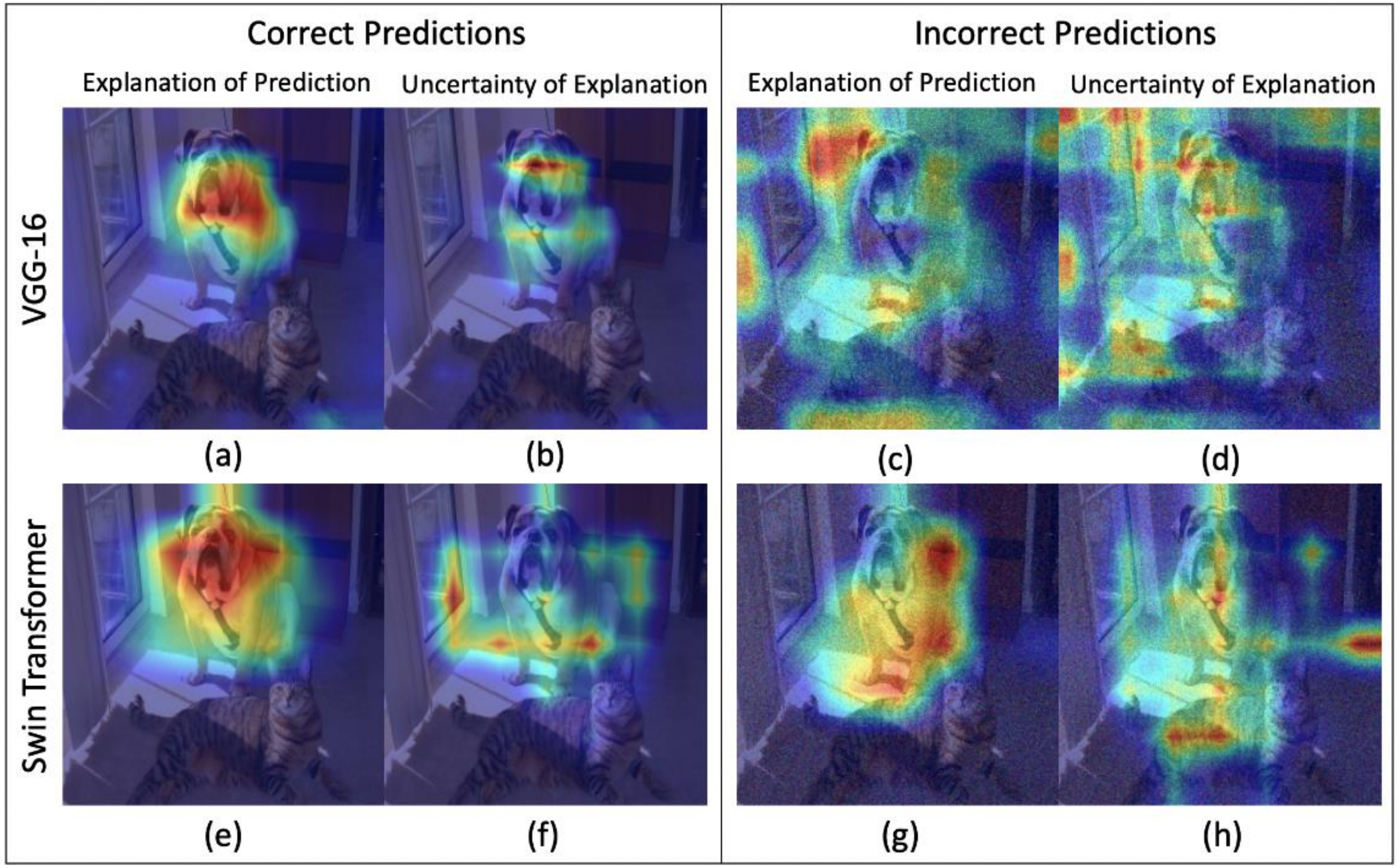
Higher the IoU, higher the uncertainty in explanation (or less trustworthy is the prediction)

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Case Study: Intervenability in Interpretability

Quantifying Interventions in Explainability: SNR

Explanation and uncertainty are dispersed under noise (under low prediction confidence)



Objective Metric 2: Signal to Noise Ratio of the Uncertainty map

Higher the SNR of uncertainty, more is the dispersal (or less trustworthy is the prediction)

M. Prabhushankar, and G. AlRegib, "VOICE: Variance of Induced Contrastive Explanations to Quantify Uncertainty in Neural Network Interpretability," *Journal of Selected Topics in Signal Processing*, submitted on Aug. 27, 2023.

Robust Neural Networks

Part 5: Conclusions and Future Directions

Key Takeaways

Role of Gradients

- **Robustness** under distributional shift in domains, environments, and adversaries are **challenges** for neural networks
  - **Gradients at Inference** provide a **holistic solution** to the above challenges
- **Gradients** can help **traverse** through a trained and unknown **manifold**
  - They approximate **Fisher Information** on the projection
  - They can be **manipulated** by providing **contrast** classes
  - They can be used to construct **localized contrastive** manifolds
  - They provide **implicit knowledge** about **all classes**, when only **one data** point is available at inference
- Gradients are useful in a number of **Image Understanding** applications
  - Highlighting features of the current prediction as well as **counterfactual** data and **contrastive** classes
  - Providing **directional information** in anomaly detection
  - **Quantifying uncertainty** for out-of-distribution, corruption, and adversarial detection
  - Providing **expectancy mismatch** for human vision related applications

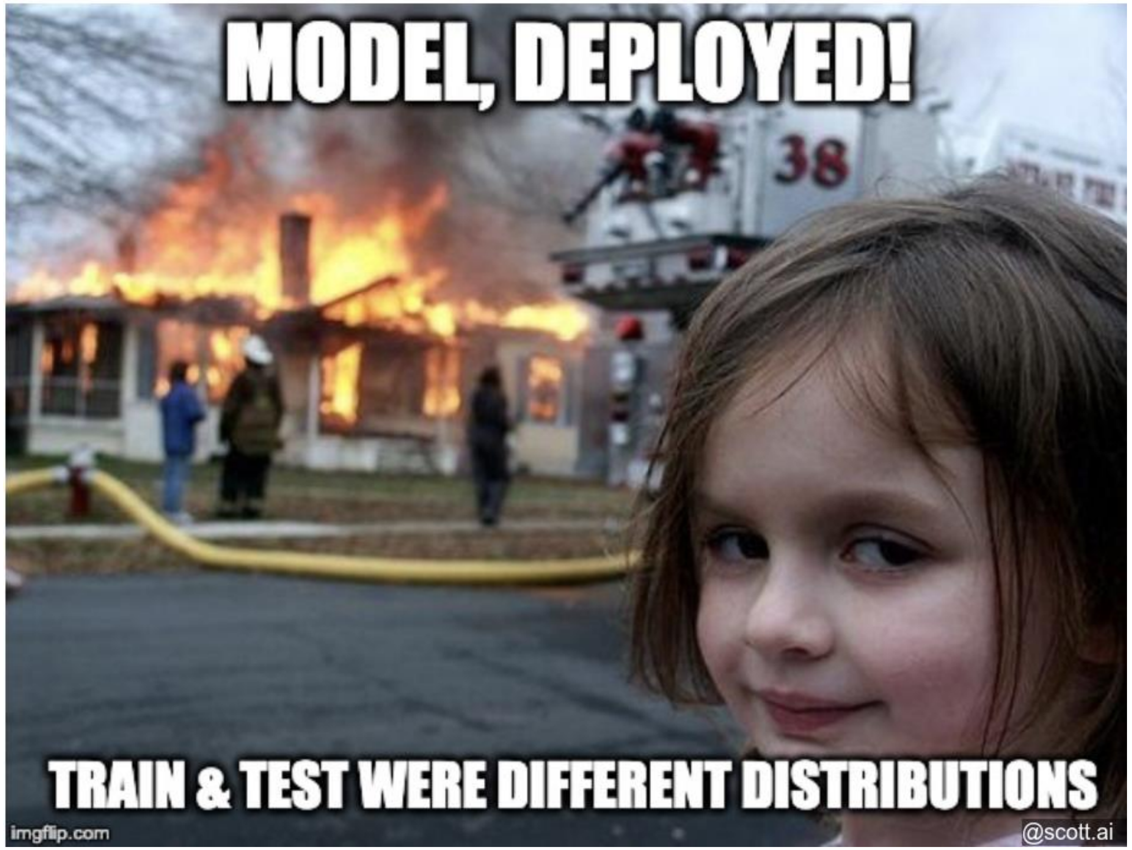
Future Directions

Research at Inference Stage

- **Test Time Augmentation (TTA) Research**
  - Multiple augmentations of data are passed through the network at inference
  - Research is in designing the best augmentations
- **Active Inference**
  - Utilize the knowledge in Neural Networks to ***ask it to ask us***
  - Neural networks ask for the best augmentation of the data point given that one data point at inference
- **Uncertainty in Explainability, Label Interpretation, and Trust quantification**
  - Uncertainty research has to expand beyond model and data uncertainty
  - In some applications within medical and seismic communities, there is no agreed upon label for data. Uncertainty in label interpretation is its own research
- **Test-time Interventions for AI alignment**
  - Human interventions at test time to alter the decision-making process is essential trustworthy AI
  - Further research in intelligently involving experts in a non end-to-end framework is required

Memes to Wrap it Up

Robustness at Inference



Cannot depend on training to construct robust models

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Tutorial Materials

Accessible Online

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https://alregib.ece.gatech.edu/wacv-2024-tutorial/

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WACV 2024 Tutorial

Robustness at Inference: Towards Explainability, Uncertainty, and Intervenability

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Georgia Institute of Technology, Atlanta, USA

https://alregib.ece.gatech.edu/

Duration: Half-Day event