Visual Explainability in Machine Learning

Lecture 4: Visual Explanations II

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Short Course Materials

Accessible Online

SCAN ME

https://alregib.ece.gatech.edu/sps-education-short-course/

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IEEE Signal Processing Society

Title: Visual Explainability in Machine Learning

Presented by: ***Ghassan AlRegib, and Mohit Prabhushankar***

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

Short Course

Course Outline

Day 1: Define and Detail; Day 2: Evaluate; Day 3: Reassess

Day 1

- Lecture 1: Why Explainability?
- Lecture 2: What is Explainability?
- Lectures 3 and 4: Popular Methods of Explainability

Day 2

- Lecture 5: Evaluating Explainability
- Lecture 6: Robustness: A proxy for Explainability

Day 3

- Lectures 7 and 8: Reassessing Explainability via Uncertainty and Concept vectors
- Lectures 9 and 10: Causality and Generative AI

Outline

Lecture 4: Visual Explanations II

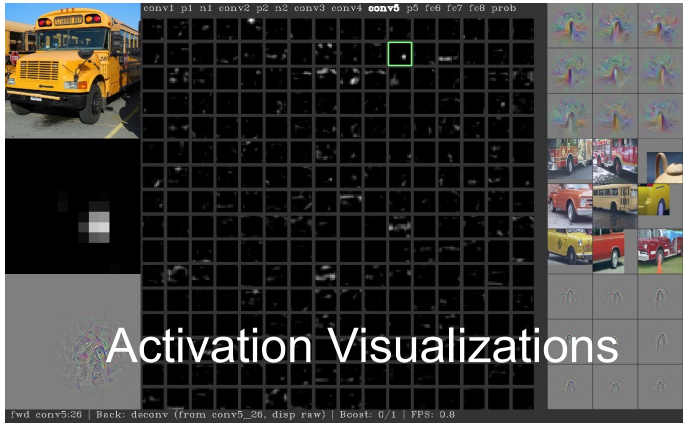
- Targeted Explanations
    - Role of Explainability
    - Definition
    - Contextual Questions
- GradCAM: Gradient weighted Class Activation Maps
    - Methodology
    - Results
- Explanatory Paradigms
    - CounterfactualCAM
    - ContrastCAM
    - Results
- Case Study: Image Quality Assessment
- Takeaways

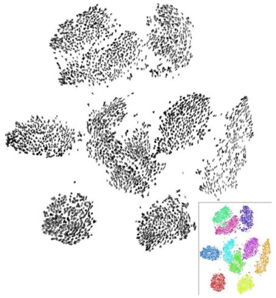
Explanations

Human-centric Explanations

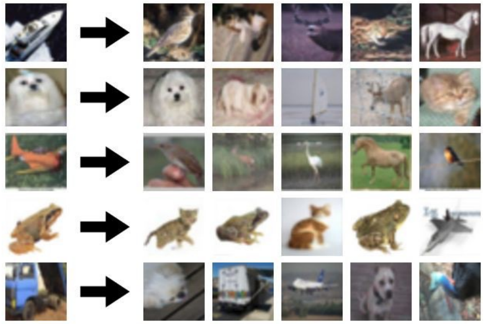
Explanations can be characterized based on the knowledge of the audience they cater to

Lecture 3: Indirect and Direct Explanations



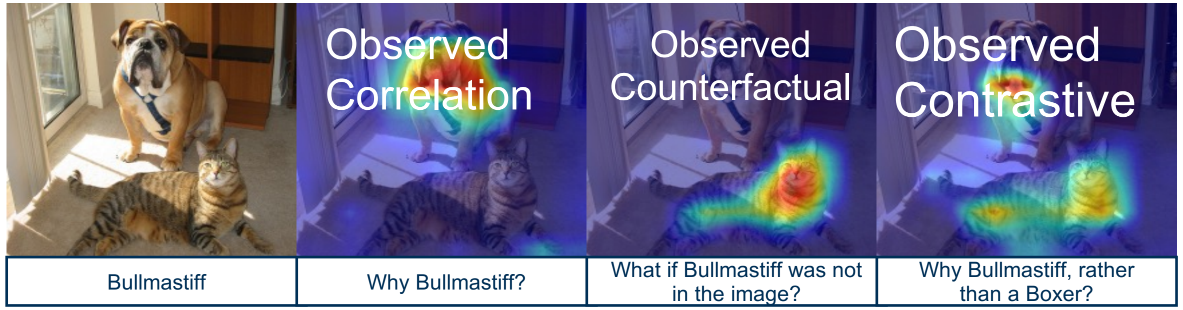


Dimensionality Reduction



Nearest Neighbor

Lecture 4: Targeted Explanations



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

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Explanations

Targeted Explanations

Targeted explanations highlight contextually relevant regions in an image

- **Required knowledge to understand explanations:** Knowledge about data and classes
- **Required knowledge to obtain explanations:** Models, model parameters, and training data
- **Explanations audience:** Researchers and Engineers, users, policymakers, and general public
- **Explanatory chronology:** Newer explanatory techniques are targeted

	Definition		
Methods	Indirect	Direct	Targeted
Deconvolution [21]	✓	–	–
Inverted Representations [22]	✓	–	–
Guided-Backpropagation [18]	–	✓	–
SmoothGrad [17]	–	✓	–
LIME [39]	–	✓	–
CAM [24]	–	✓	–
Graph-CNN [23]	✓	–	–
GradCAM [12]	–	–	✓
TCAV [40]	–	✓	–
GradCAM++ [16]	–	–	✓
RISE [35]	–	✓	–
Causal-CAM [15]	–	–	✓
Counterfactual-CAM [12]	–	–	✓
Goyal et al. [26]	–	–	✓
CEM [29]	–	–	✓
Contrast-CAM [13]	–	–	✓
Contrastive reasoning [14]	–	–	✓

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

Targeted Explanations

Role of Explainability

Targeted explanations enhance the role of Explainability

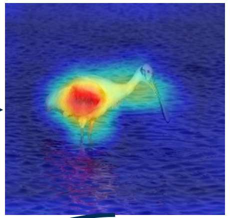
Neural Network, $f(\cdot)$

Spoonbill

Role of Explainability

Kid

Why Spoonbill?



Pink and round body, straight beak

The network taught me about spoonbills

Explain $f(\cdot)$'s decision

Direct Explanation

Kid does not have knowledge about Spoonbill!

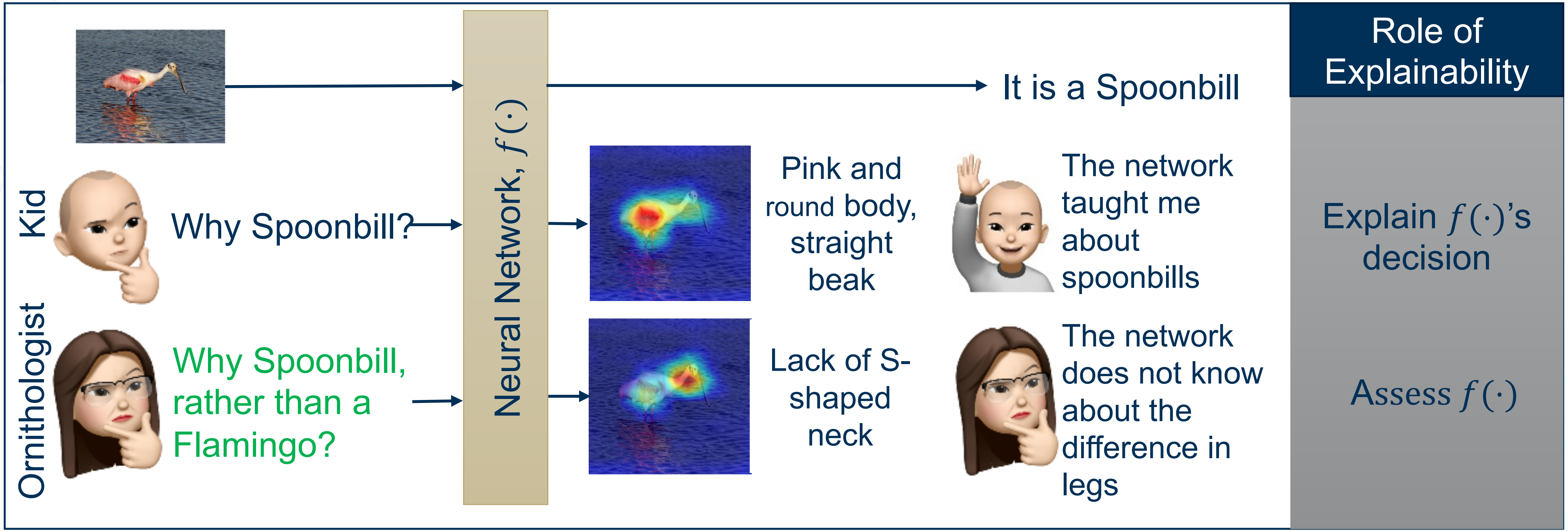
Direct Explanations: No network knowledge is required from the humans interpreting these explanations. No knowledge about the classes or data is required

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

Targeted Explanations

Role of Explainability

Targeted explanations enhance the role of Explainability



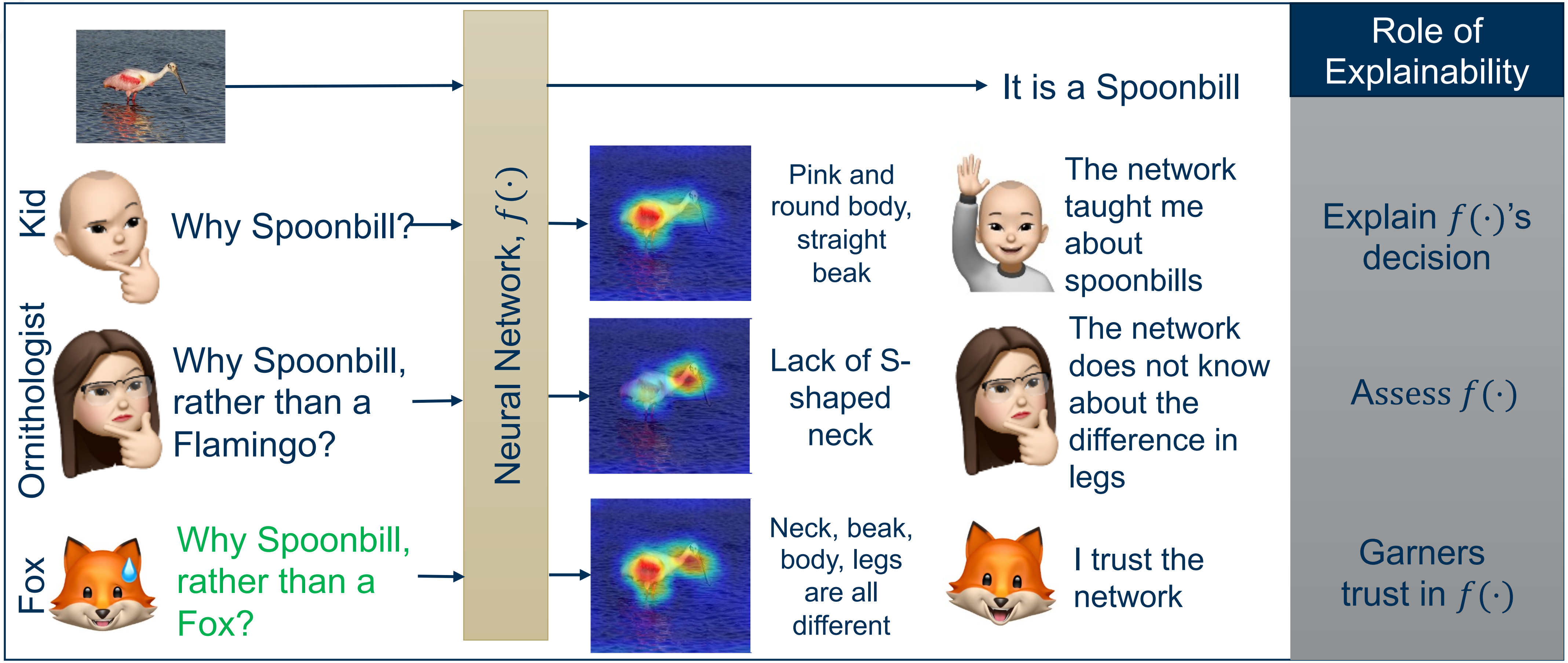
The ornithologist has knowledge of Spoonbills and Flamingos and uses this knowledge to ask **targeted** questions!

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

Targeted Explanations

Role of Explainability

More the interaction, more is the trust in the base network



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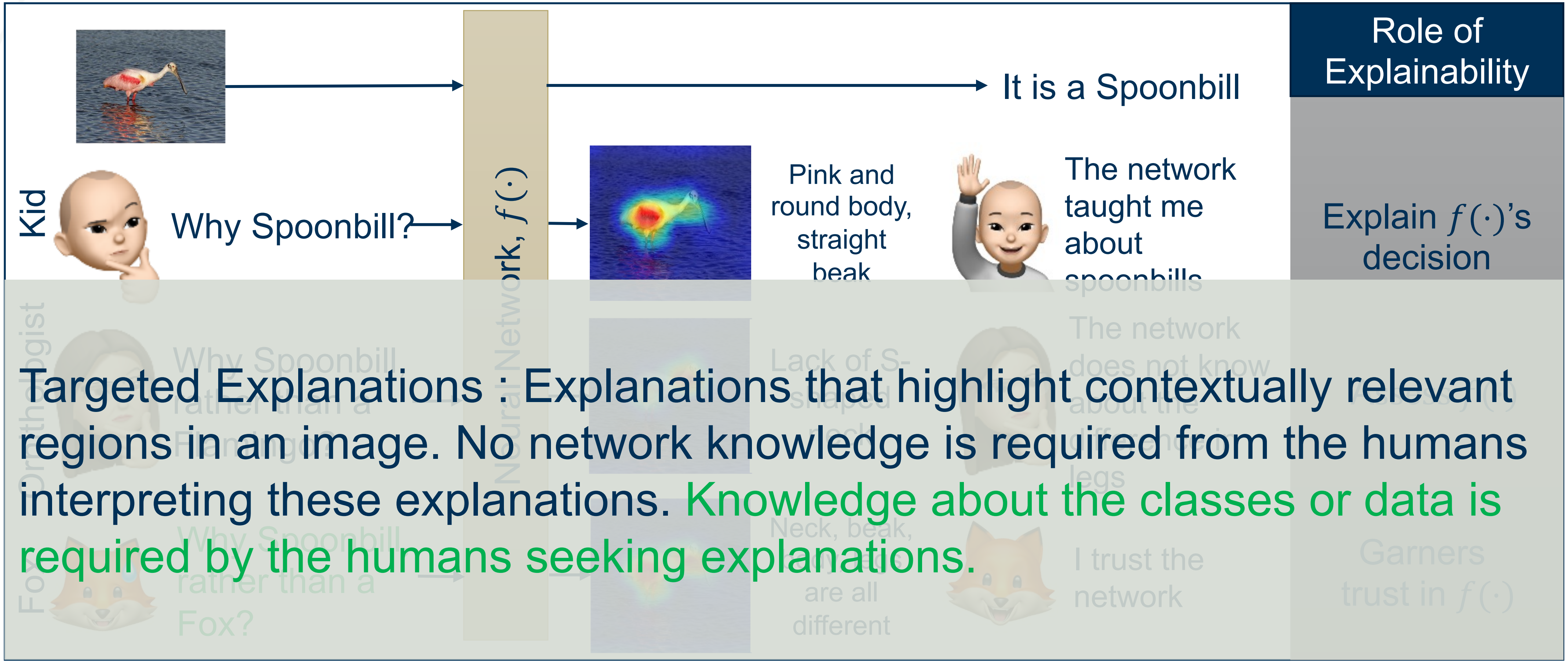
Targeted Explanations

Definition

Targeted Explanations highlight contextually relevant regions in an image



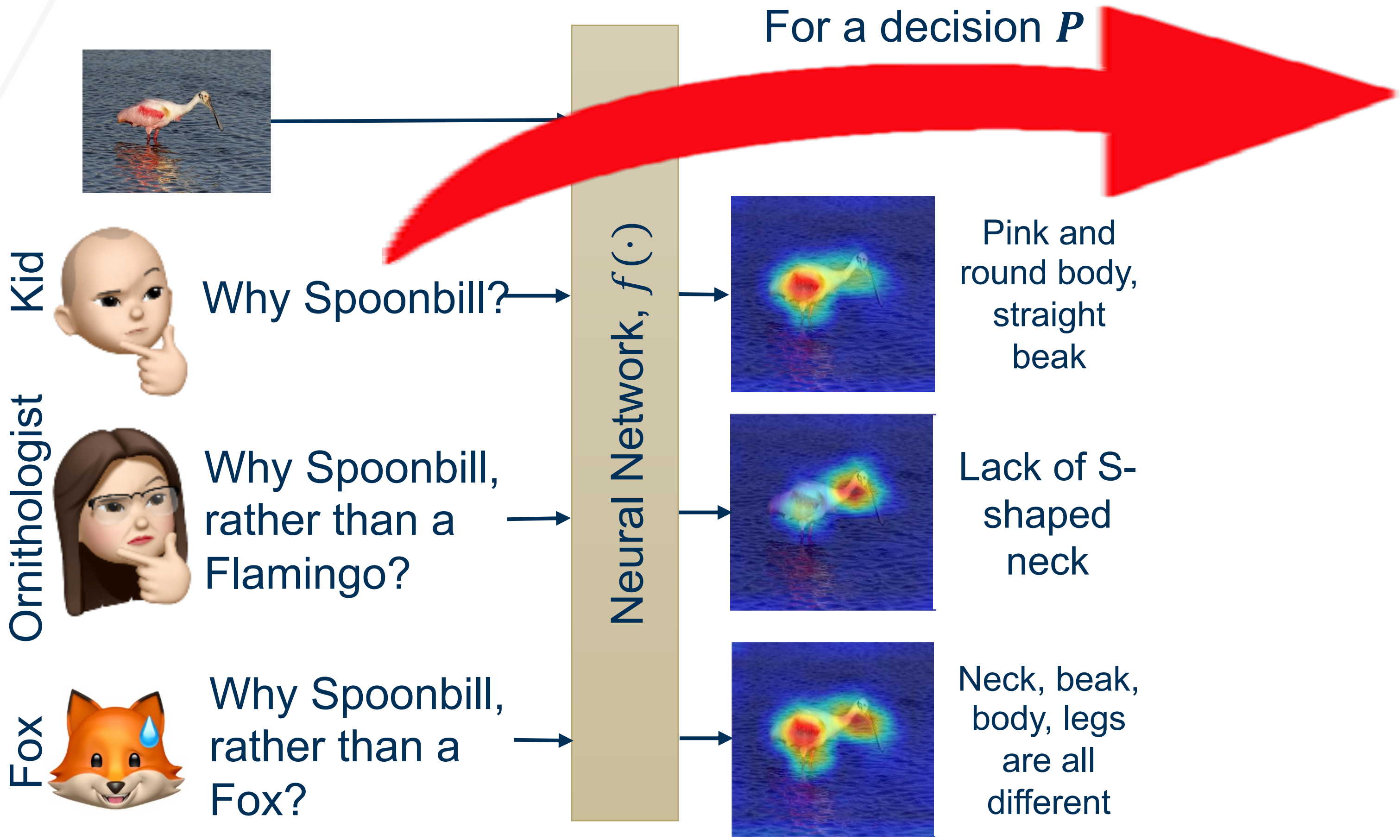
Targeted Explanations : Explanations that highlight contextually relevant regions in an image. No network knowledge is required from the humans interpreting these explanations. Knowledge about the classes or data is required by the humans seeking explanations.

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

Targeted Explanations

Contextually-relevant Questions

Targeted Explanations highlight contextually relevant regions in an image



3 forms of questions

- *`Why P?'* - Correlations
- *`What if?'*- Counterfactual
- *`Why P, rather than Q?'*- Contrastive

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

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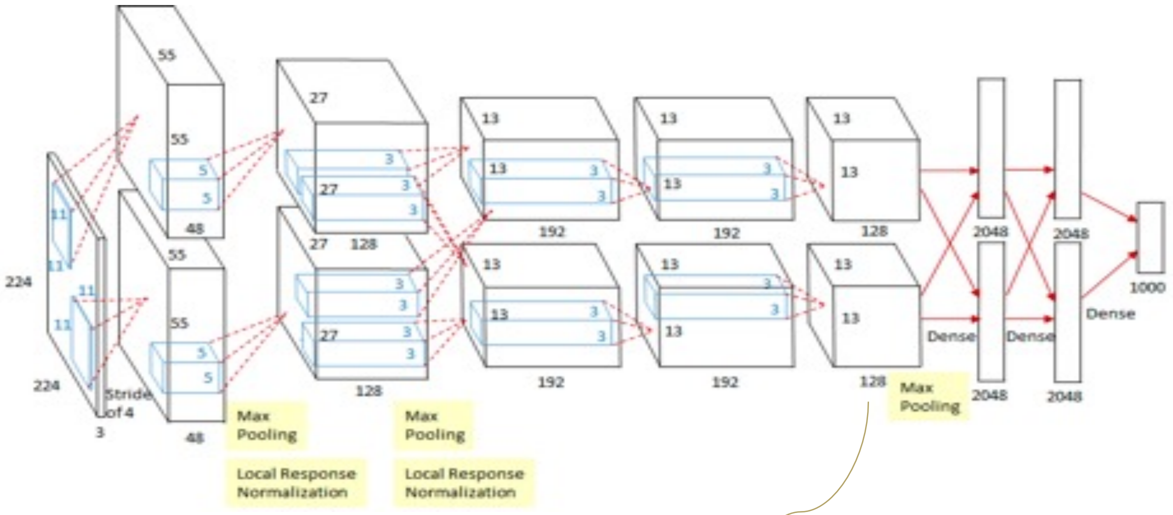
Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM

Gradients provide feature importance *for all* available features; Activations provide class-discriminative features

- GradCAM combines activations and gradients
- Which layer to extract activations:
  - **Higher layers** capture **class specific information**
  - **Spatial information** is **lost** in **fully-connected** layers
  - **Last convolutional layer** forms a best compromise between high-level semantics and detailed spatial resolution



Ideal layer for activation extraction

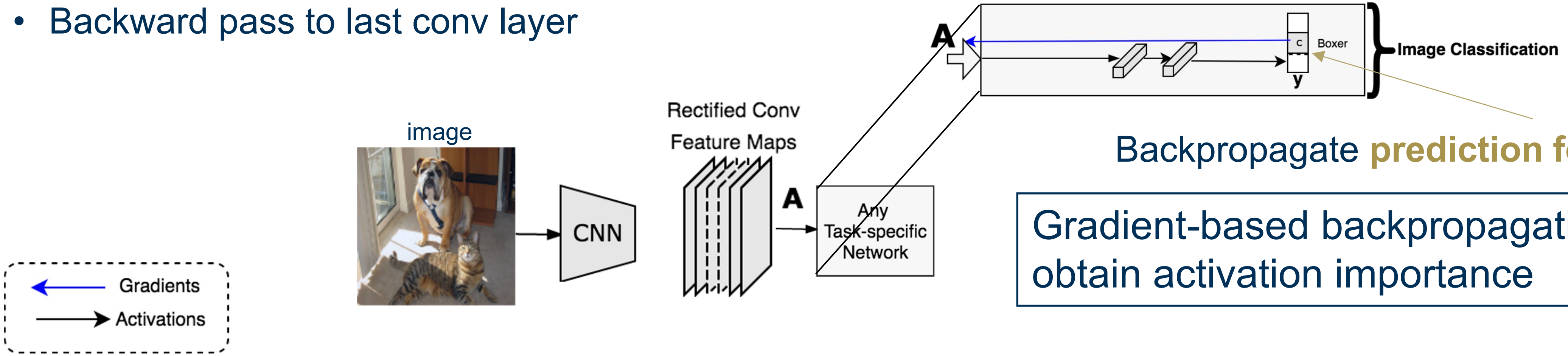
Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM Methodology

Gradients provide feature importance *for all* available features; Activations provide class-discriminative features

- Given an image, feed forward through CNN
- Final convolutional layer output feature maps for later task-specific layers, i.e., fc layer for classification
- Backward pass to last conv layer



Backpropagate **prediction for c-th class**

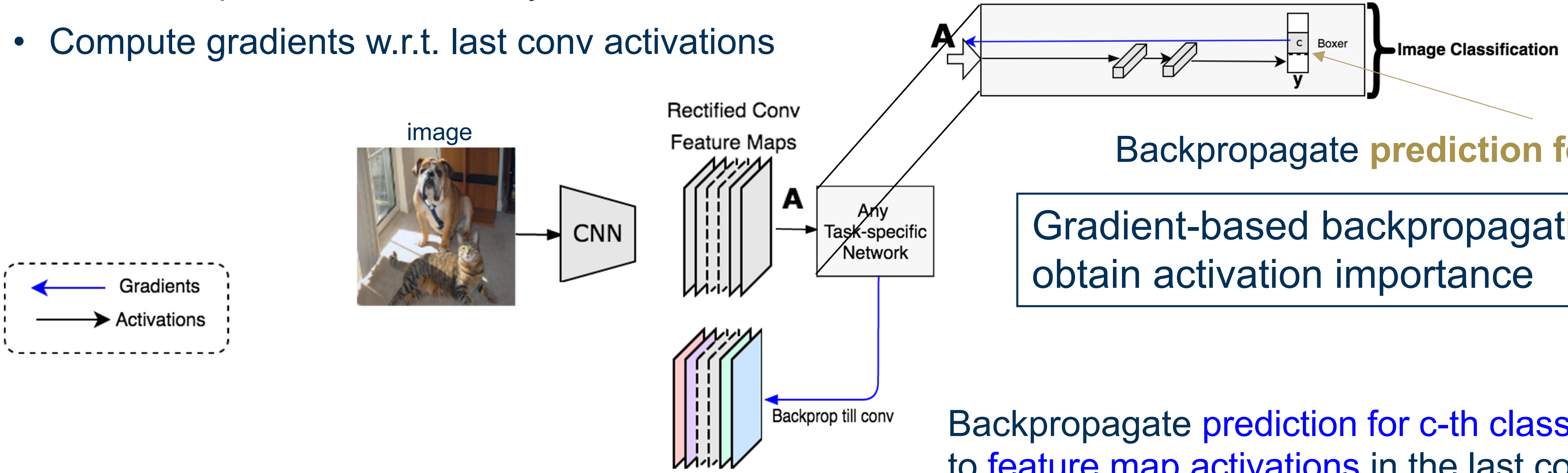
Gradient-based backpropagation to obtain activation importance

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-weighted Class Activation Mapping: GradCAM Methodology

Gradients provide feature importance *for all* available features; Activations provide class-discriminative features

- Given an image, feed forward through CNN
- Final convolutional layer output feature maps for later task-specific layers
- Backward pass to last conv layer
- Compute gradients w.r.t. last conv activations



Backpropagate **prediction for c-th class**

Gradient-based backpropagation to obtain activation importance

Backpropagate prediction for c-th class with respect to feature map activations in the last conv layer

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.

Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM Methodology

Gradients provide feature importance *for all* available features; Activations provide class-discriminative features

- Given an image, feed forward through CNN
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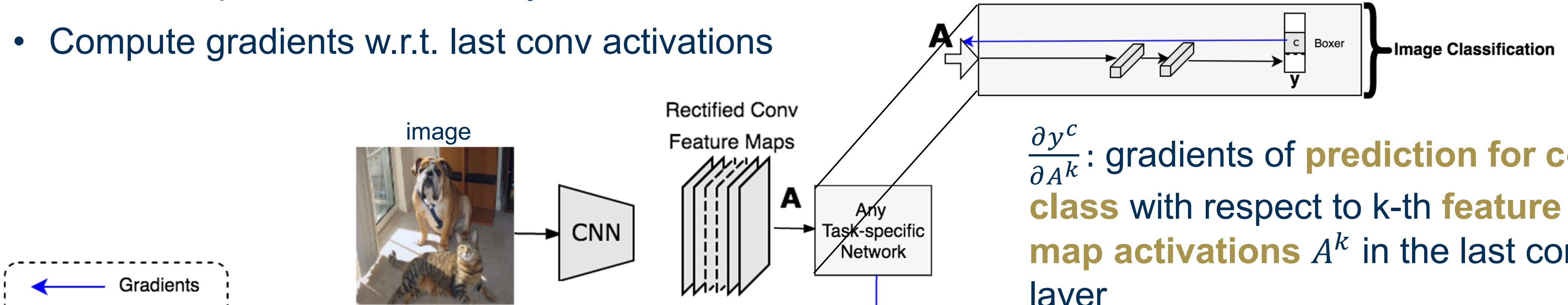
- Backward pass to last conv layer
- Compute gradients w.r.t. last conv activations



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

$\frac{\partial y^c}{\partial A^k}$: gradients of **prediction for c-th class** with respect to k-th **feature map activations** A^k in the last conv layer

α_k^c is the scalar **importance** of k-th **feature map** obtained by averaging $\frac{\partial y^c}{\partial A^k}$ spatially

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Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM Methodology

Gradients provide feature importance *for all* available features; Activations provide class-discriminative features

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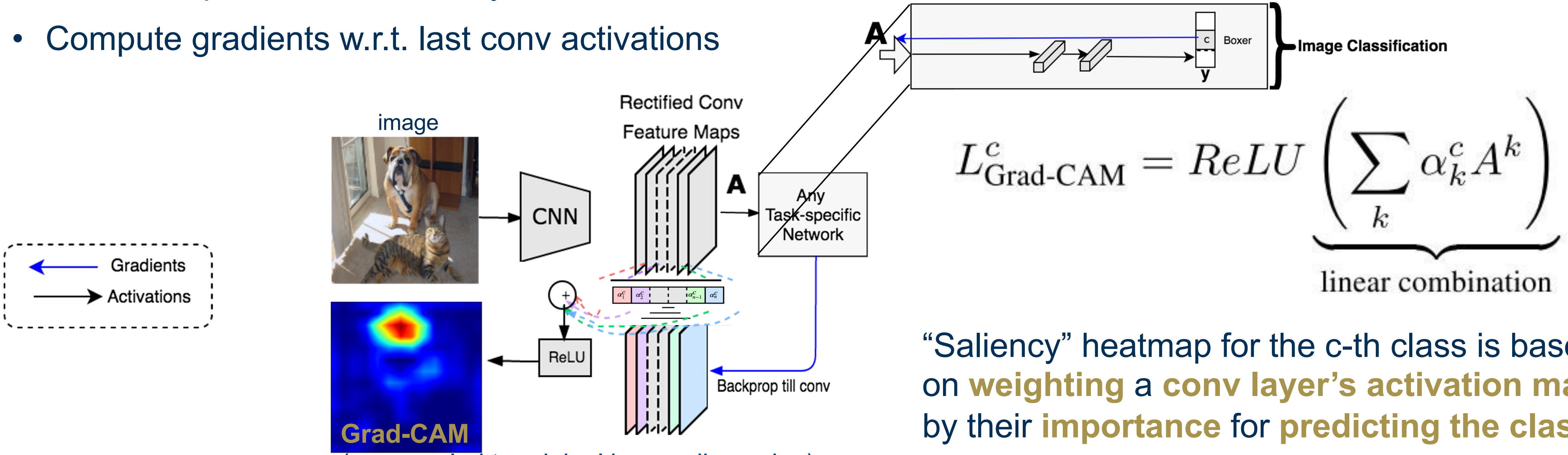


(up-sampled to original image dimension)

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

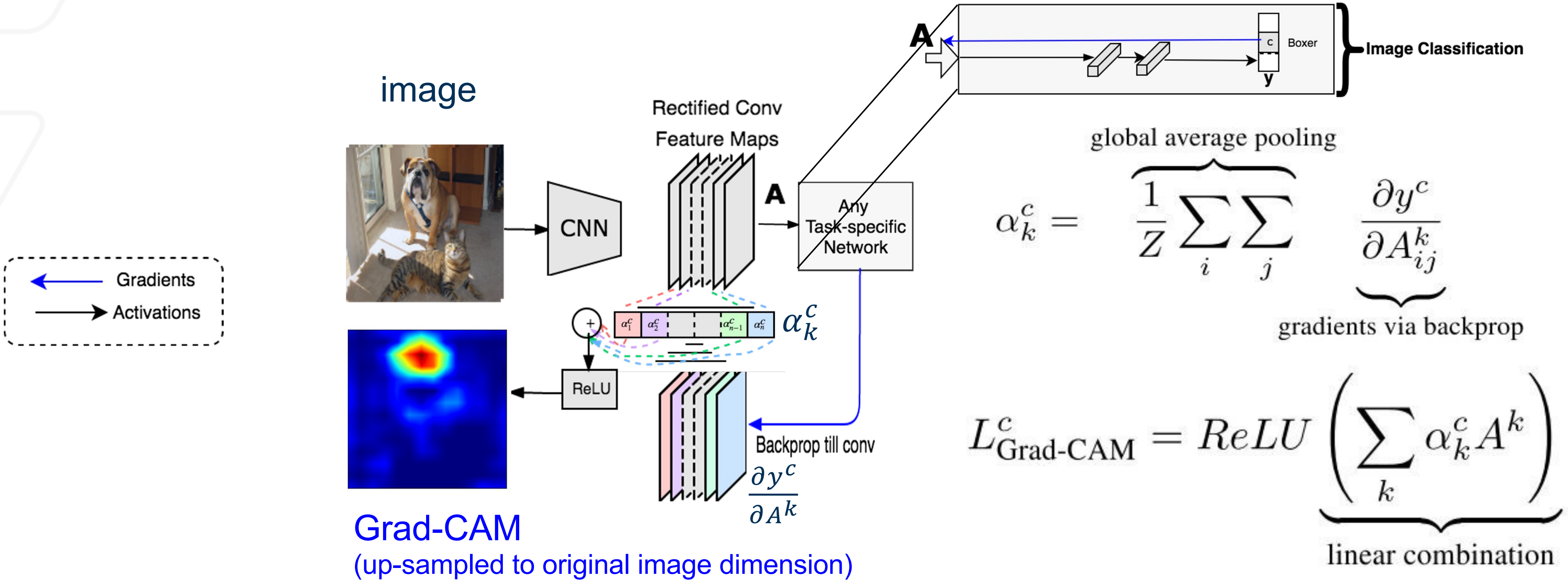
"Saliency" heatmap for the c-th class is based on **weighting** a **conv layer's activation maps** by their **importance** for **predicting the class**

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.

Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM Methodology

Grad-CAM uses the gradient information in the last convolutional layer of the CNN to assign importance values to each activation for any class c



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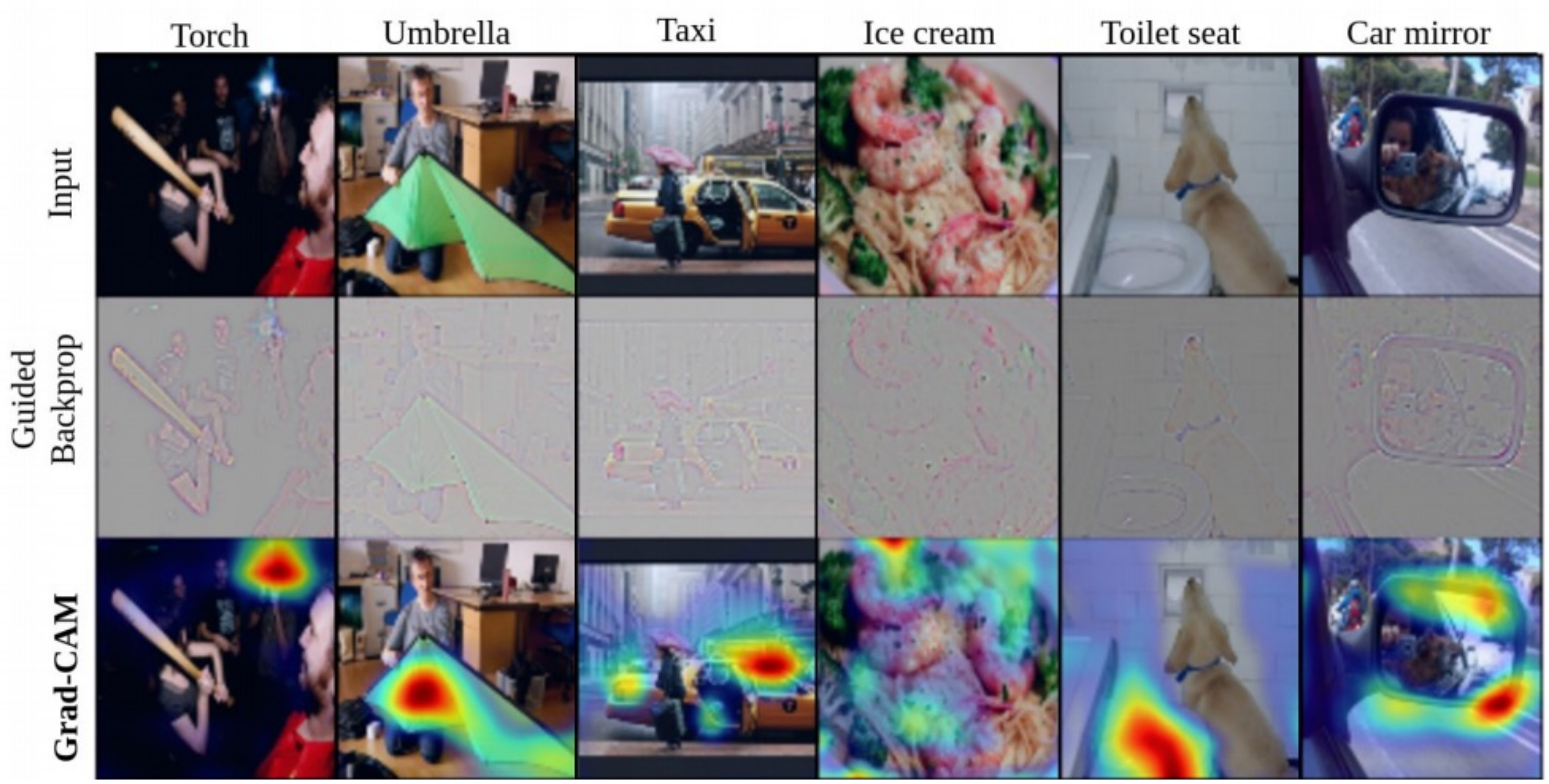
Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM Results

Results in image classification

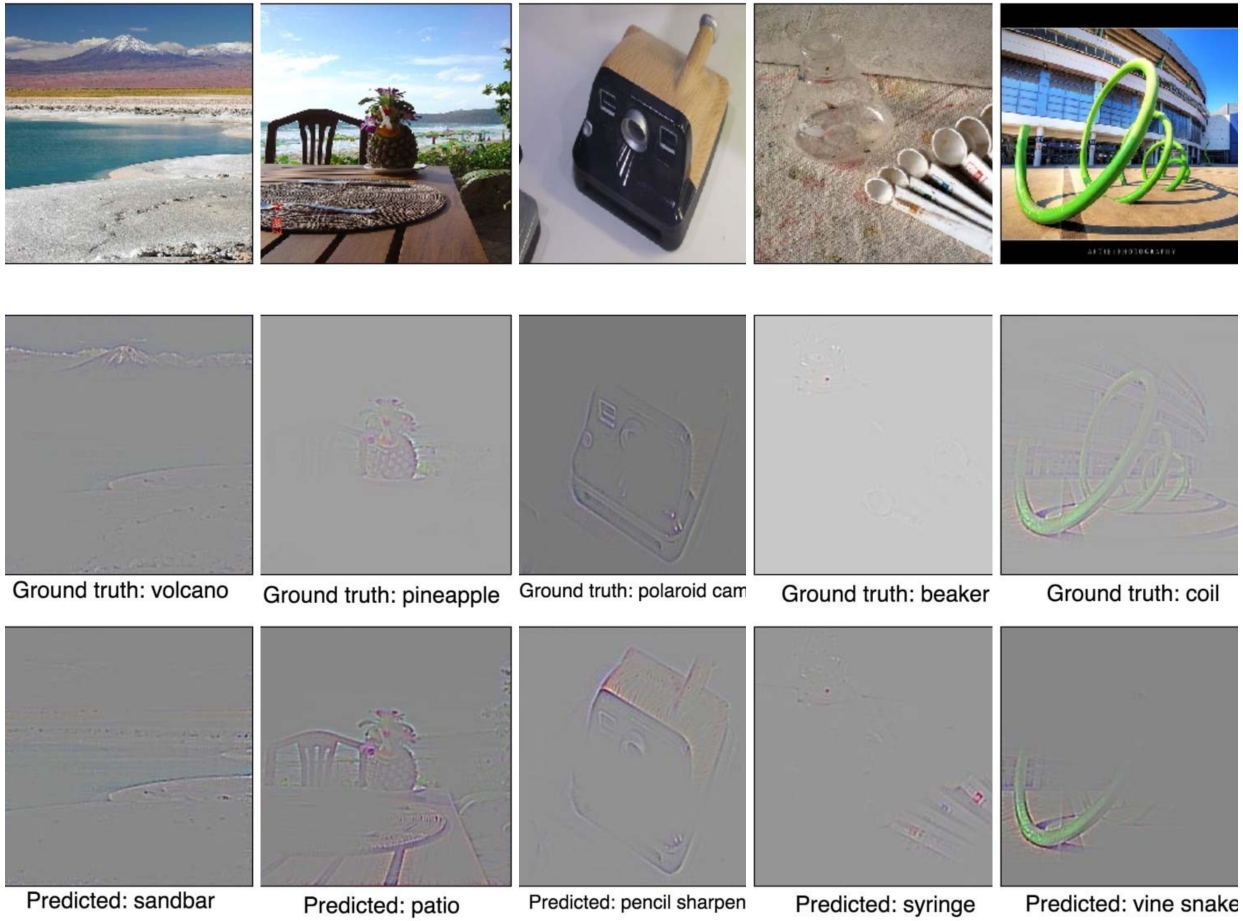


Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

Targeted Explanations

Gradient-weighted Class Activation Mapping: GradCAM Results

Results when the model has misclassified



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Gradient and Activation-based Explanations

Explanatory Paradigms

SCAN ME

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

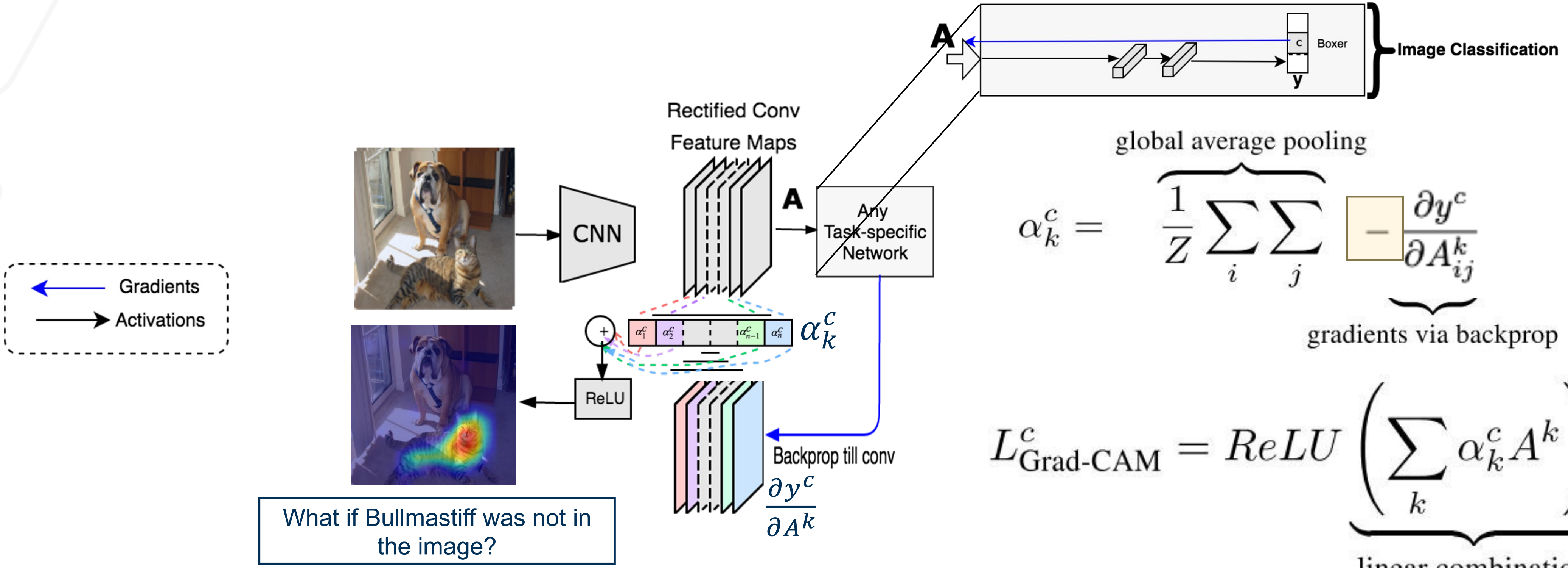
Bullmastiff	Why Bullmastiff?	What if Bullmastiff was not in the image?	Why Bullmastiff, rather than a Boxer?

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?

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



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

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

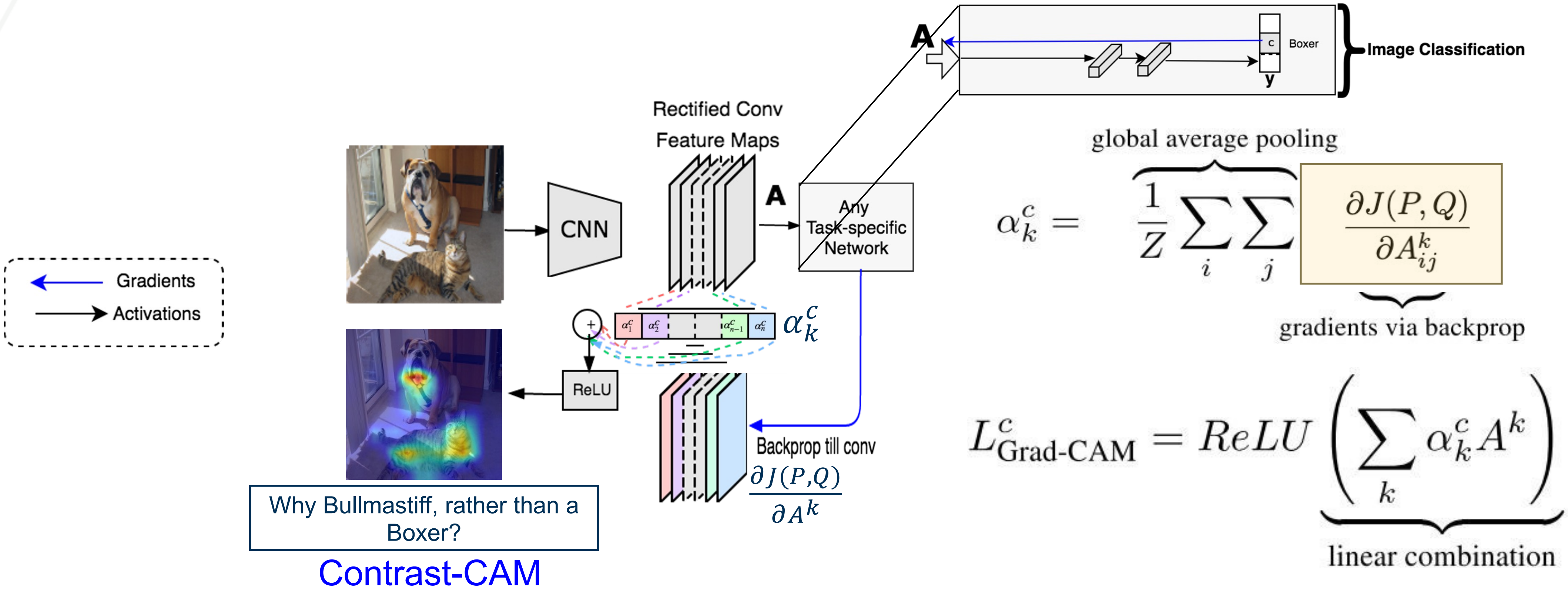
Negating the gradients effectively removes these regions from analysis

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



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

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

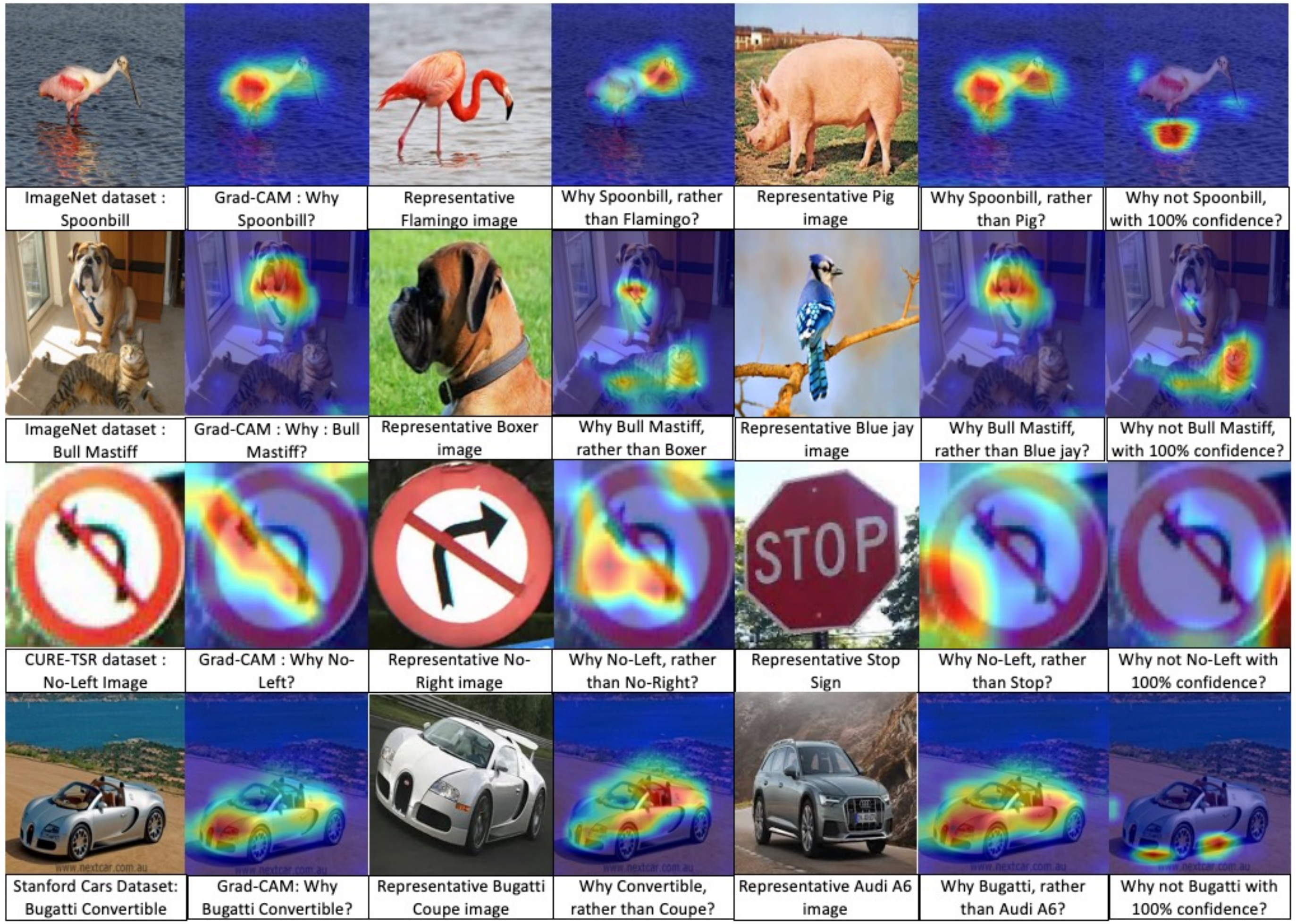
Backpropagating the loss highlights the differences between classes P and Q.

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

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



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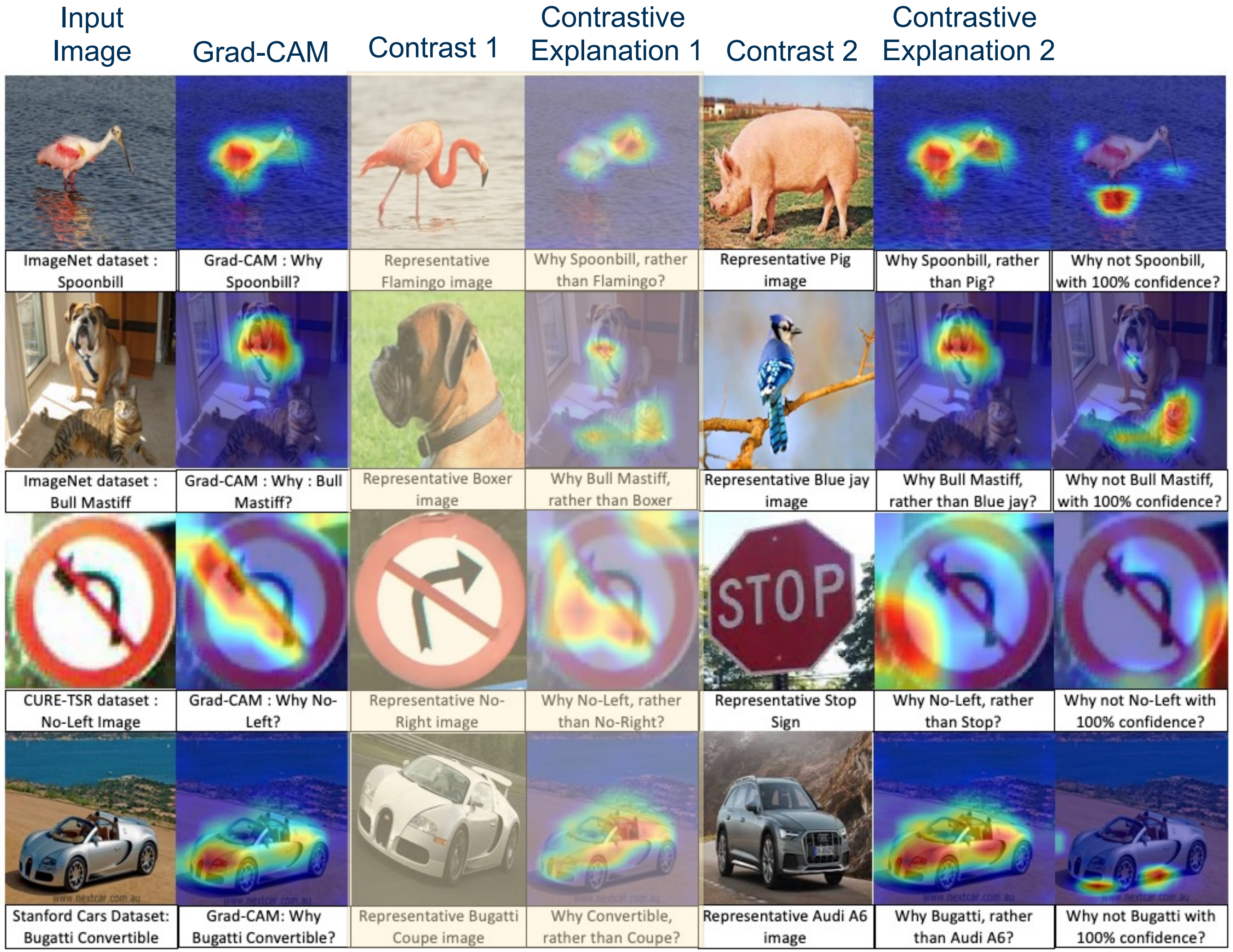

Human Interpretable

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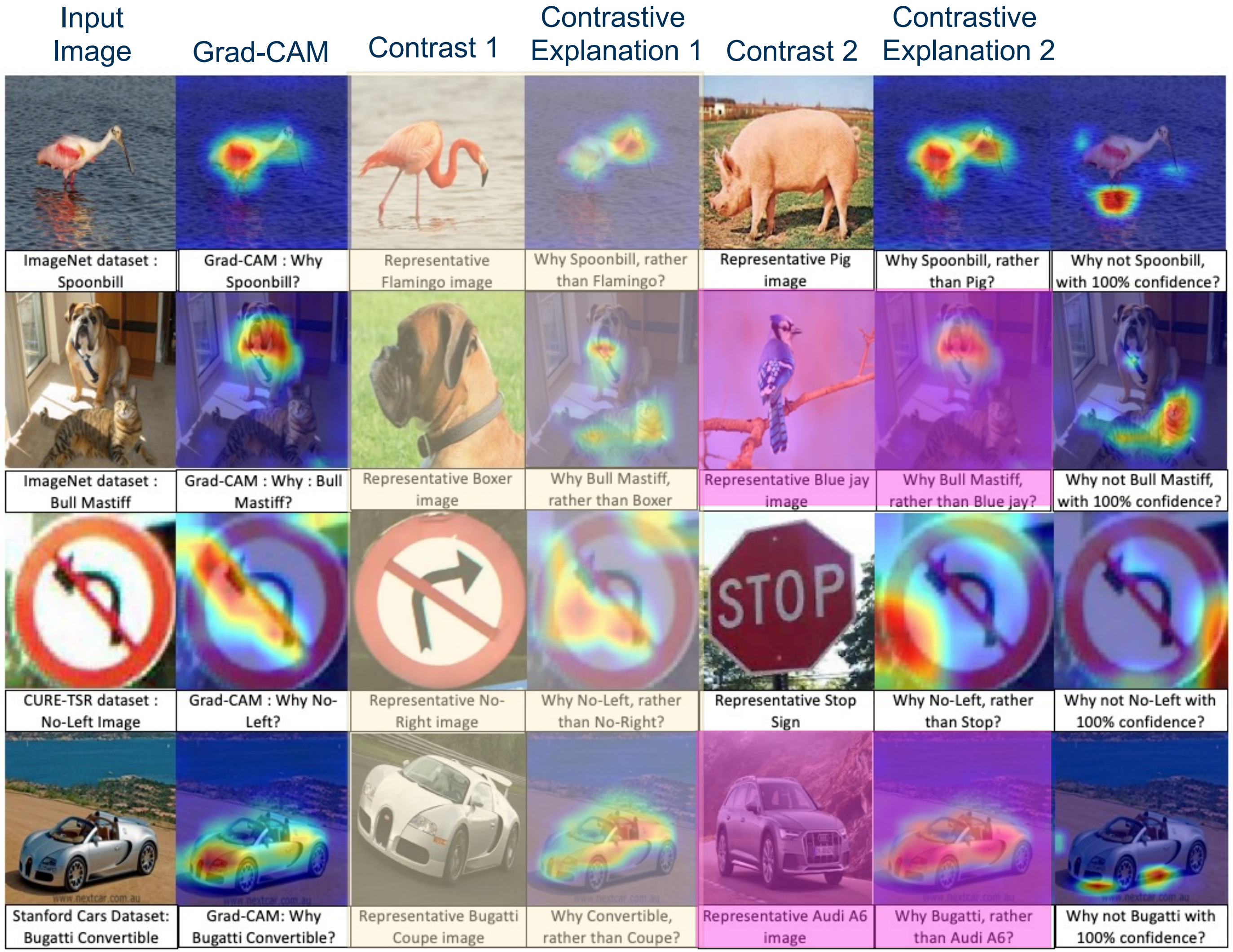

Human Interpretable

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.

Gradient and Activation-based Explanations

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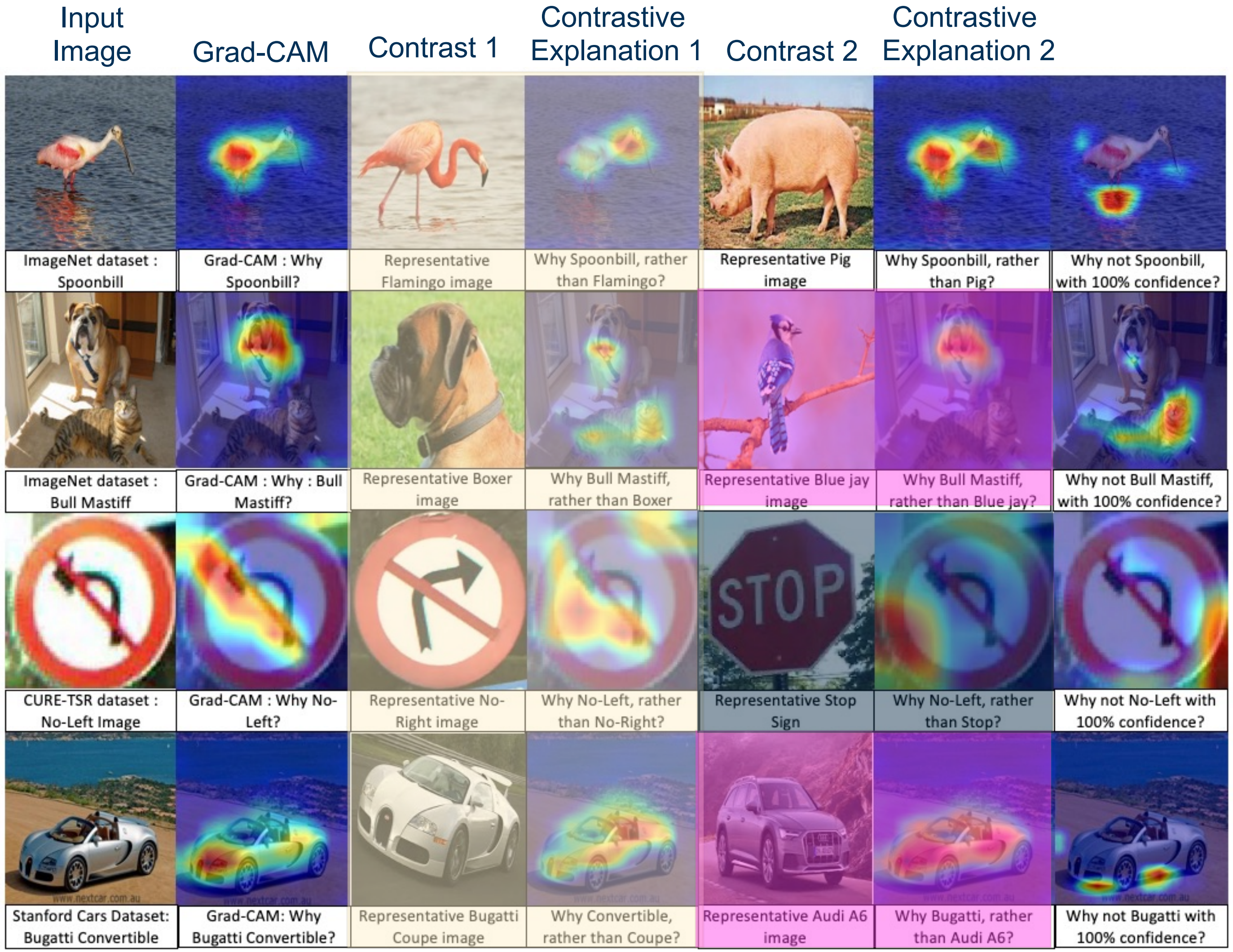

Human Interpretable

Same as Grad-CAM

Not Human Interpretable

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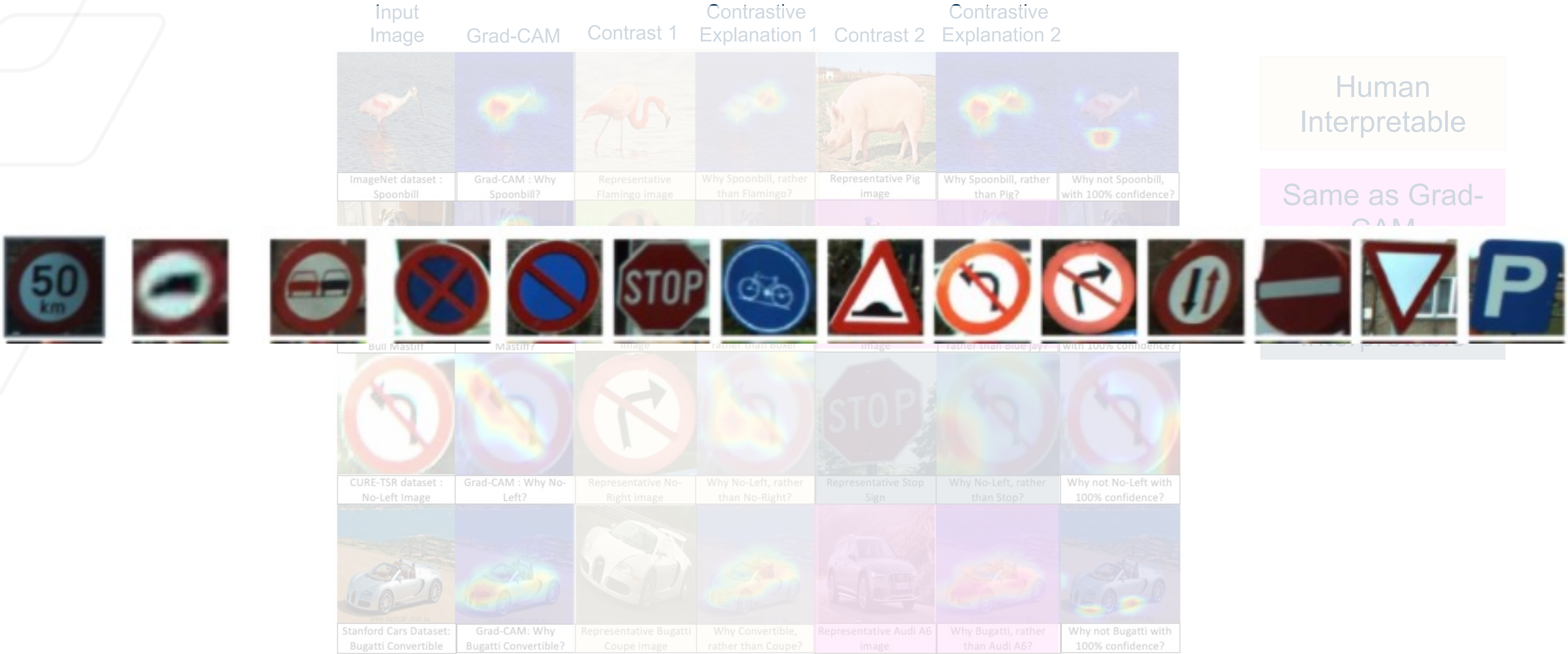

Human Interpretable

Same as Grad-

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Gradient and Activation-based Explanations

Results from GradCAM, CounterfactualCAM, and ContrastCAM

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

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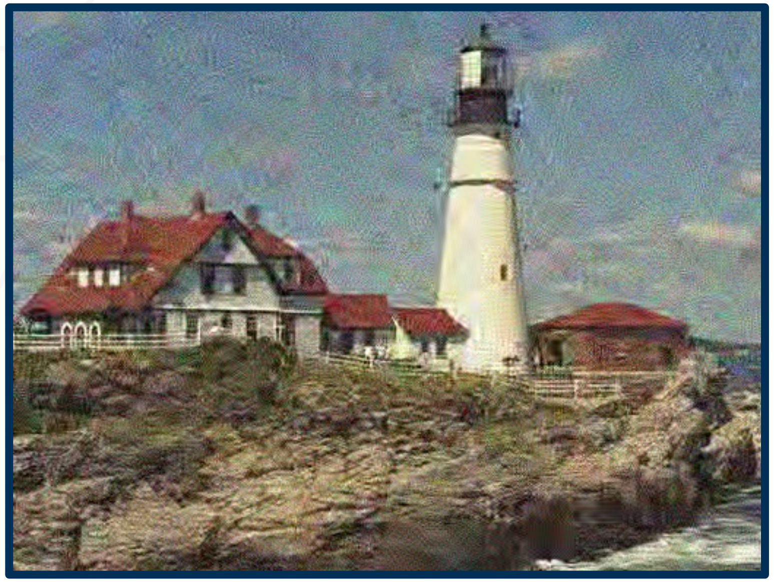
Case Study: Image Quality Assessment

What is IQA?

IQA is the objective Assessment of Subjective Quality



Lighthouse image with level 5 lossy compression from TID 2013 dataset

Image Quality Assessment Algorithm : DIQaM [1]

Score : 0.58

The given image is somewhat OK quality

Bad Quality

Good Quality

[1] Bosse S, Maniry D, Müller K R, et al. Deep neural networks for no-reference and full-reference image quality assessment. IEEE Transactions on Image Processing, 2018, 27(1): 206-219.

Case Study: Image Quality Assessment

Dataset Construction

Subjects make contrastive choices during Dataset Construction

- Subjects are shown a reference image in a controlled setting
- Based on the reference image, they are asked pick one of the images on the top that differs least from the reference image
- Reference image sets the expectancy
- The task of subjectively picking the least mis-matched image is IQA

This requires **Fine-grained** Analysis!

[1] Ponomarenko, Nikolay, et al. "Image database TID2013: Peculiarities, results and perspectives." *Signal processing: Image communication* 30 (2015): 57-77

Case Study: Image Quality Assessment

Expectancy-Mismatch in Dataset Construction

Subjects make contrastive choices during Dataset Construction

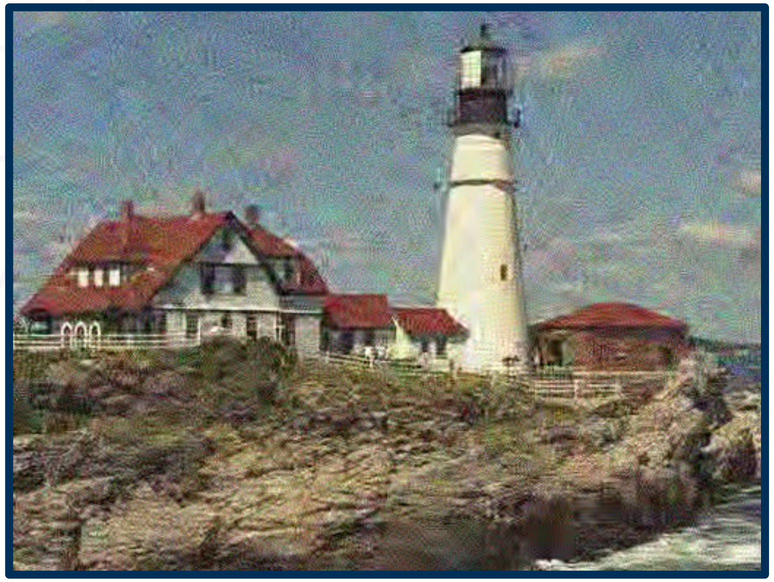
This requires **Fine-grained** Analysis on the part of the subjects!

Our Goal: To determine if a trained IQA detector understands the fine-grained nature of contrast in quality

[1] Ponomarenko, Nikolay, et al. "Image database TID2013: Peculiarities, results and perspectives." *Signal processing: Image communication* 30 (2015): 57-77

GradCAM in IQA

GradCAM explanation for Why 0.58?



Lighthouse image with level 5 lossy compression from TID 2013 dataset

The given image is somewhat OK quality

DIQaM : 0.58

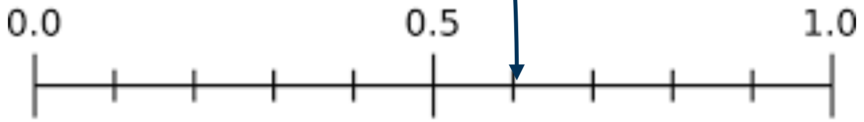
Grad-CAM

Why 0.58?

Add heatmap
Explain blue
Yellow, red, green

Bad Quality

Good Quality



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Case Study: Image Quality Assessment

GradCAM in IQA

GradCAM explanation may not be useful for fine-grained analysis

Grad-CAM explanation tells us that the quality score was decided based on all parts of the image and specifically based on the base of the lighthouse

Grad-CAM

Why 0.58?

Lighthouse image with level 5 lossy compression from TID 2013 dataset

Bad Quality

Good Quality

0.0 0.5 1.0

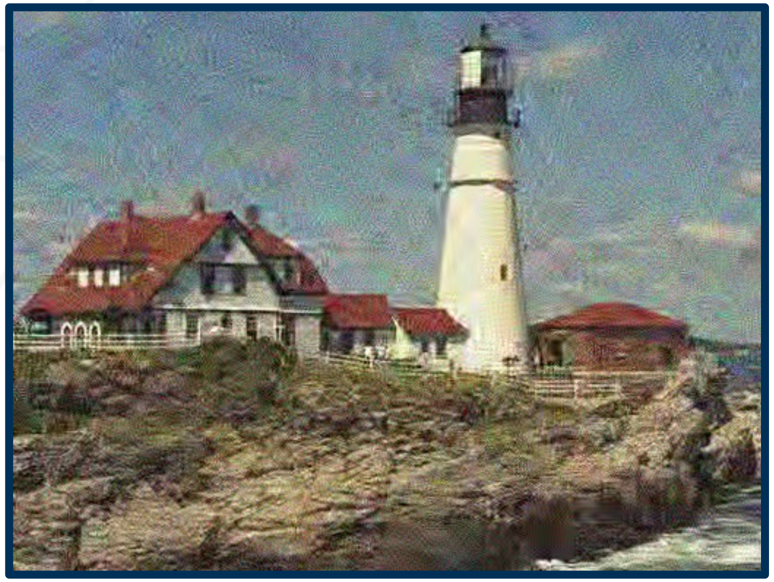
Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Georgia Tech

Case Study: Image Quality Assessment

ContrastCAM in IQA

All the distortions in the foreground prevent a quality score of 1



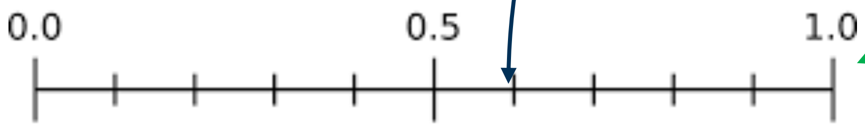
Lighthouse image with level 5 lossy compression from TID 2013 dataset

DIQaM : 0.58

Contrastive explanation

Why 0.58, rather than 1?

Bad Quality



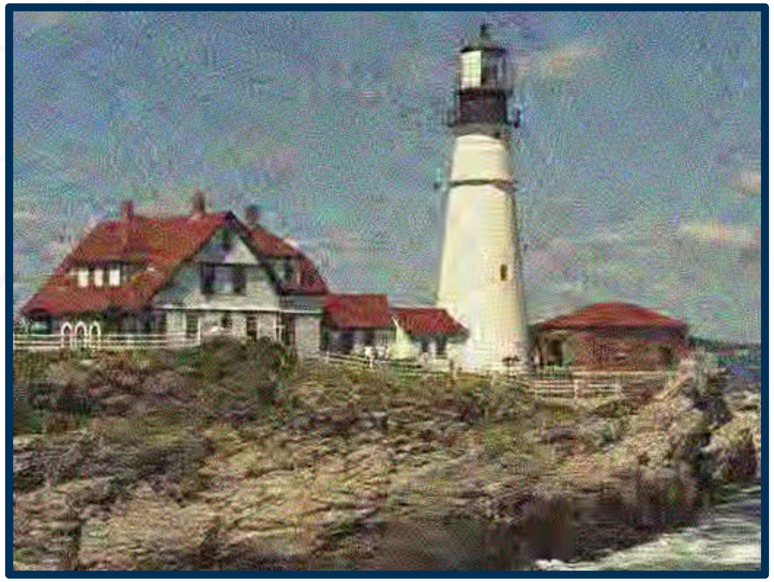
Good Quality

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.

Case Study: Image Quality Assessment

ContrastCAM in IQA

The distortions on the lighthouse and houses prevent a higher score of 0.75



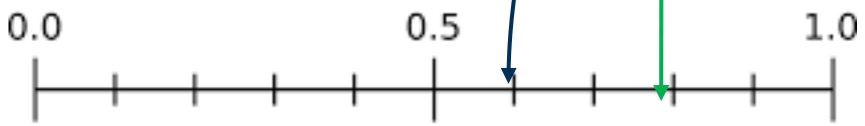
Lighthouse image with level 5 lossy compression from TID 2013 dataset

DIQaM : 0.58

Contrastive explanation

Why 0.58, rather than 0.75?

Bad Quality



Good Quality

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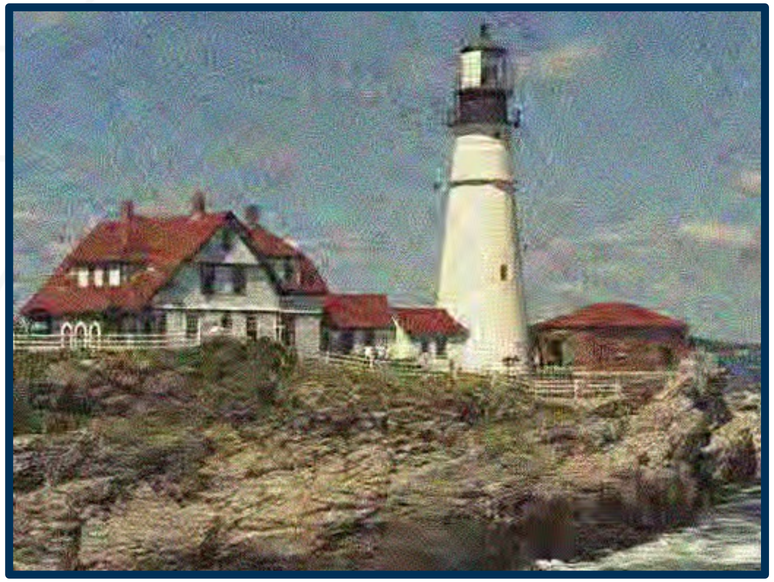
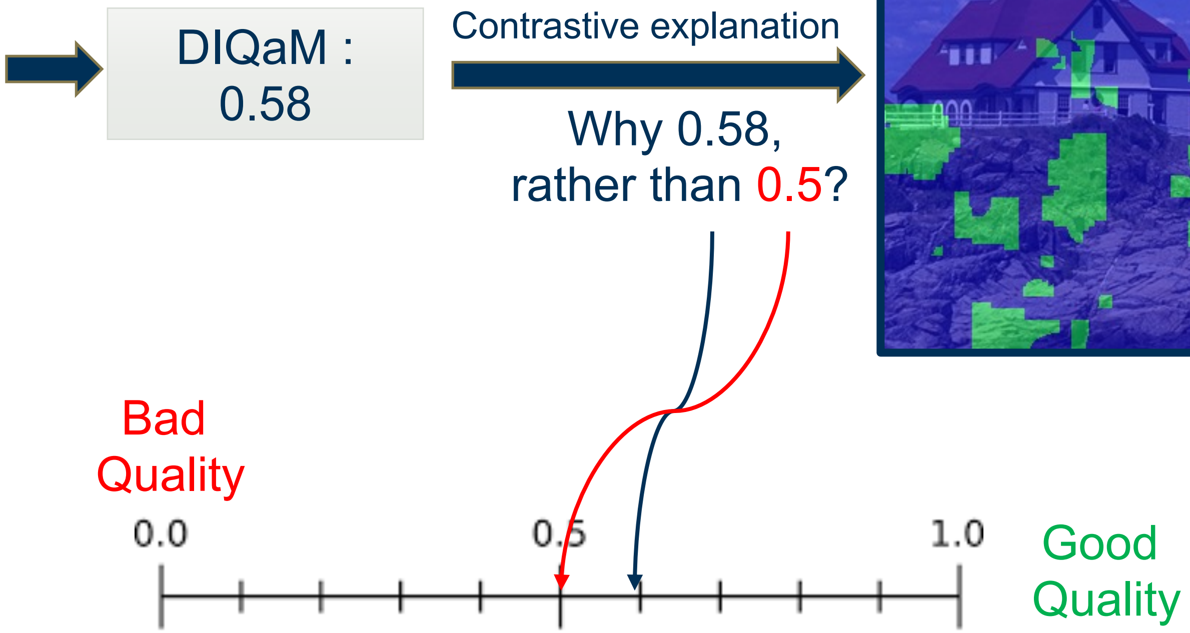
Case Study: Image Quality Assessment

ContrastCAM in IQA

The quality of the lighthouse and sky is better than a score of 0.5



Lighthouse image with level 5 lossy compression from TID 2013 dataset

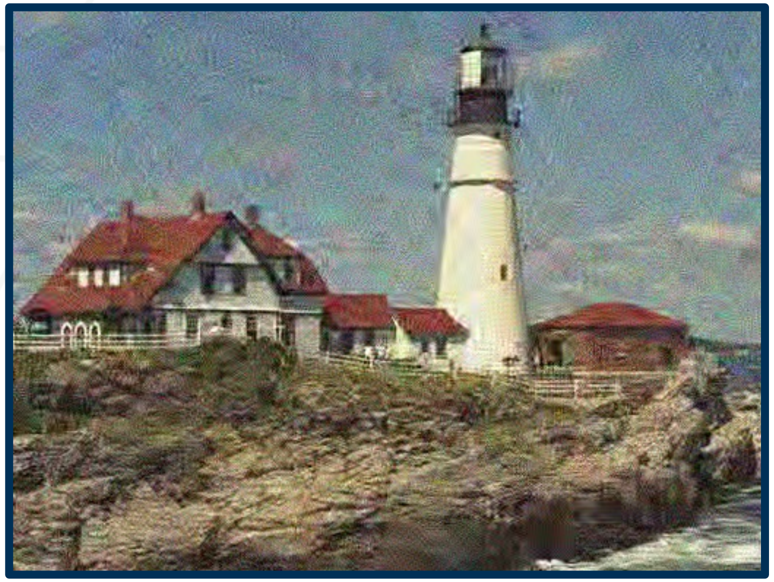


Prabhushankar, M., Kwon, G., Temel, D., & AlRegib, G. (2020, October). Contrastive explanations in neural networks. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 3289-3293). IEEE.

Case Study: Image Quality Assessment

ContrastCAM in IQA

The sky, lighthouse, and cliff merit a quality higher than 0.25



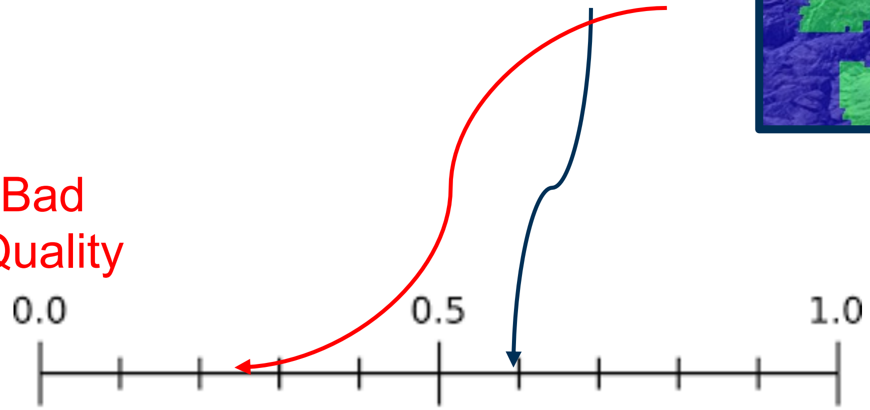
Lighthouse image with level 5 lossy compression from TID 2013 dataset

DIQaM : 0.58

Contrastive explanation

Why 0.58, rather than 0.25?

Bad Quality



Good Quality

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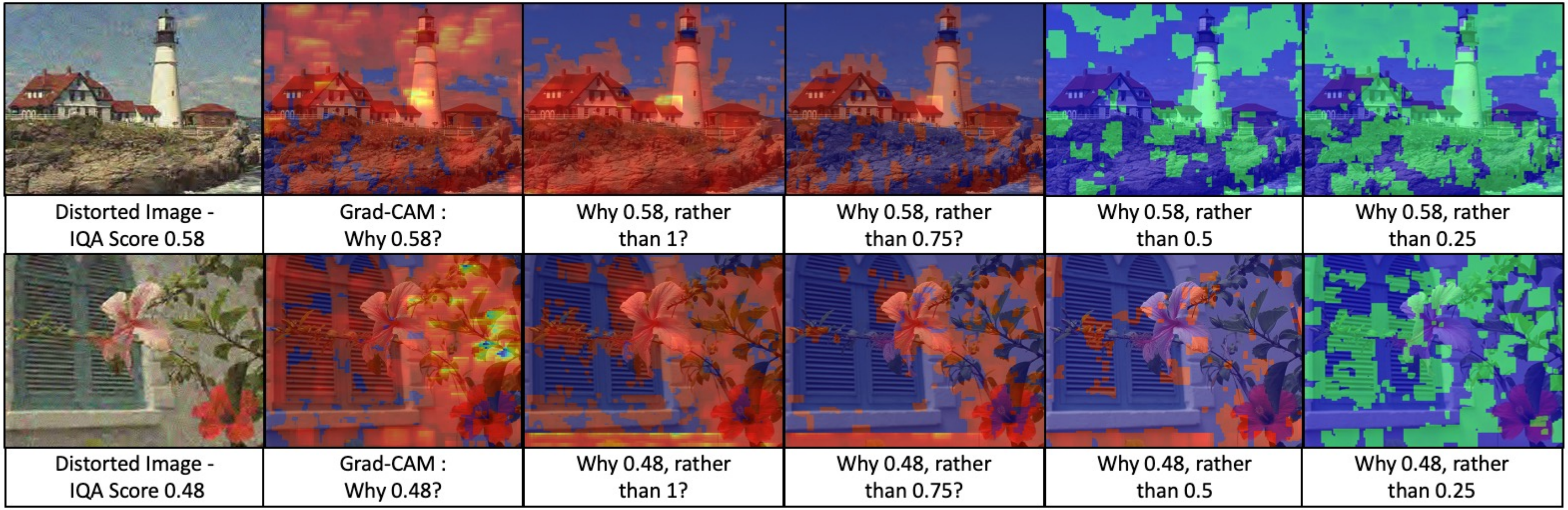
Case Study: Image Quality Assessment

ContrastCAM in IQA

Contrastive IQA elicits the fine-grained decisions made by the network



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Takeaways

Takeaways from Lecture 4

- There are **no "one size fits all" explanations** and techniques
- **Targeted explanations requires knowledge of data**
  - They are only accessible to most
- **GradCAM** uses **gradients and activations to highlight class-specific features**
  - **Logits are backpropagated** and the resulting gradients are used as feature weights
  - It's a single forward and backward pass explanatory method
- **CounterfactualCAM backpropagates the negative of the logit** and the resulting gradients are used as feature weights
- **ContrastCAM backpropagates a loss between predicted class and some contrast class** and the resulting gradients are used as feature weights
- Image Quality Assessment benefits from fine-grained analysis of explanations

References

Lecture 4: Visual Explanations II

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