Exploring XAI methods on Image Data

ECE 6960 Explainable ML

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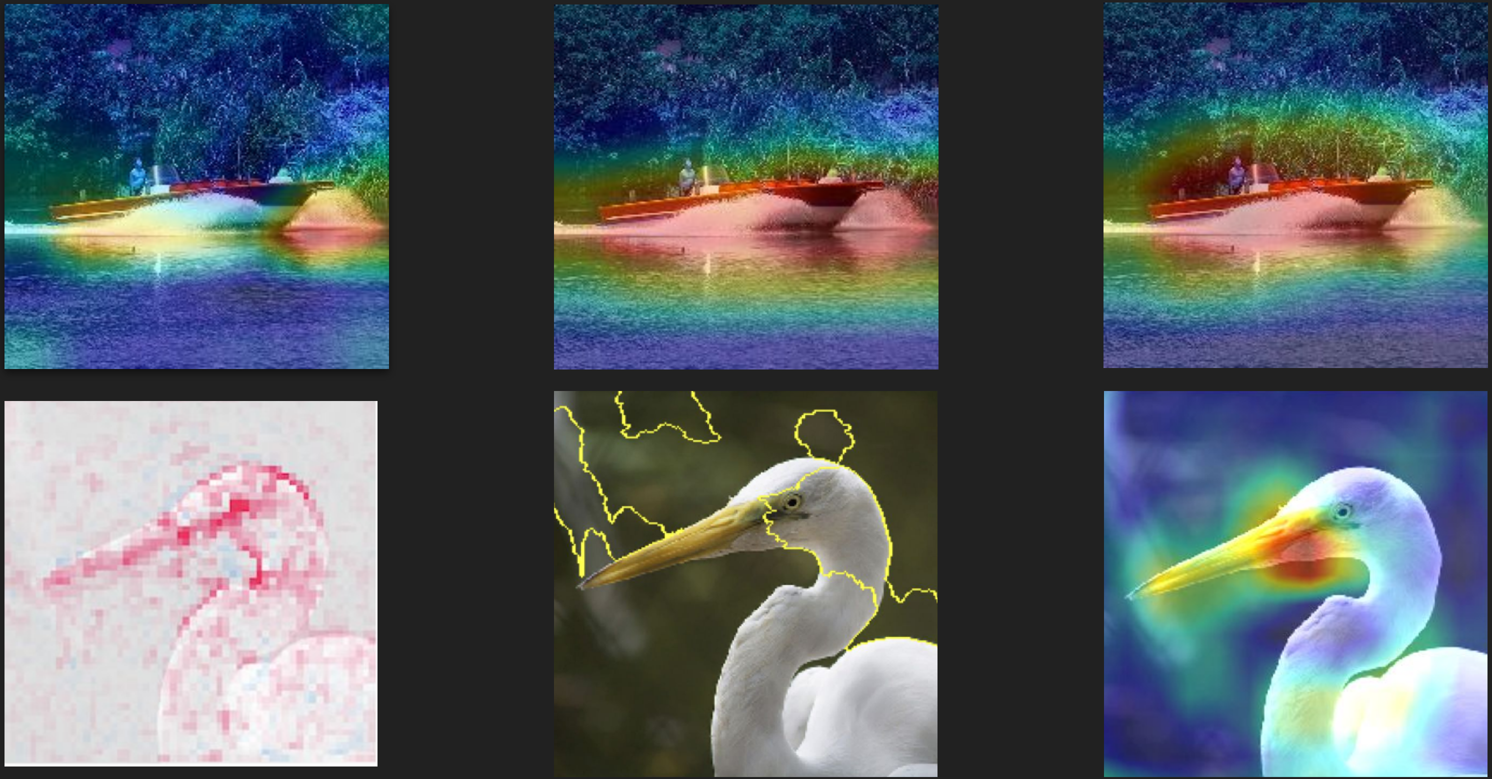
Motivation: Which explanation is better?



Data Description

Dataset: **Imagenet50**[1]

- Dataset of similar images to original ImageNet dataset but randomly collected through Google image search
- Pros:
  - Extremely diverse image dataset
  - Focus on explaining the models trained on ImageNet data while avoiding leakage
  - low computation overhead (compared to ImageNet test set 100,000 images)
- Cons
  - Small Image sizes
  - Ground truth labels are uncertain
- Preprocessed dataset to run in backbone, XAI methods

Example images

1. https://shap.readthedocs.io/en/latest/generated/shap.datasets.imagenet50.htm (Compiled by the authors of SHAP)

Exploration

Dataset

Imagenet50 (*n=50*)

Backbone Models

1. VGG 16
2. Resnet50
3. Densenet 121

**Used pretrained model weights (on Imagenet) for generating predictions on the dataset*

Explainable methods

1. SHAP (**gradient explainer**)
2. LIME
3. GradCAM

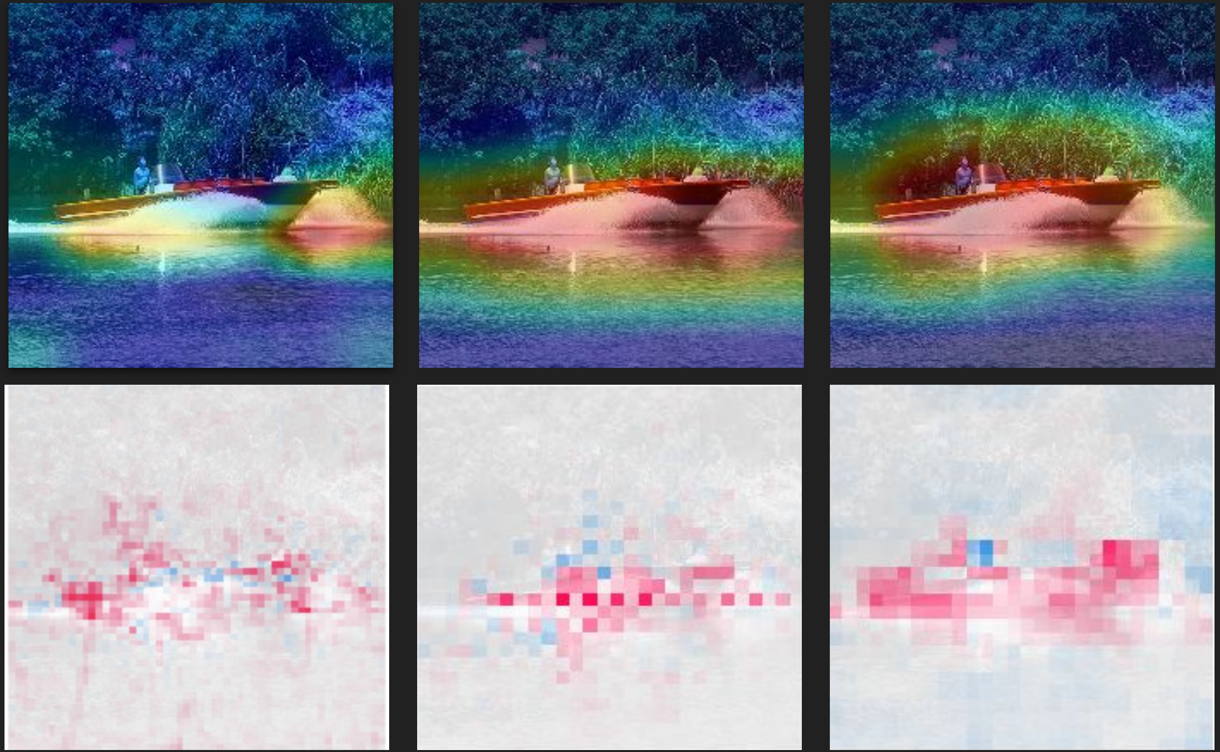
Qualitative Results

Original Image
“speedboat”

VGG16 Resnet50 Densenet121

GradCAM

SHAP

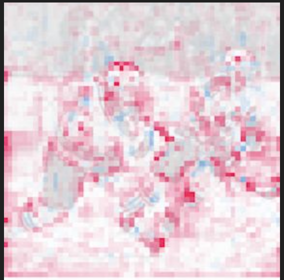


Qualitative Evaluation

SHAP

- Generally captured more helpful regions to understand the ground truth
- Sometimes the highly **relevant regions were scattered** & still identified even when the ground truth label was questionable

E.g. “puck”



GradCAM

- Smaller heatmaps were reshaped to overlap image, appearing blurry and distorted
- Most activated regions of the heatmap highlighted areas that were meaningful and helpful to understanding the ground truth

LIME

- Initially explored, but omitted
- Superpixels were often not captured for most images
- Experimented thresholds, but ultimately very low threshold resulted in **superpixel segmentation not particularly helpful/ accurate**

Quantitative Evaluation

1. % Increase in Confidence
2. % Drop in Confidence
3. % Increase in Confidence with ROAD
4. % Drop in Confidence with ROAD
5. IOU

$$\left(\sum_{i=1}^{N} \frac{\mathbb{1}_{Y_i^c < O_i^c}}{N}\right)100$$

% Increase in Confidence

$$\left(\sum_{i=1}^{N} \frac{max(0, Y_i^c - O_i^c)}{Y_i^c}\right)100$$

% Drop in Confidence

Quantitative Evaluation: Definitions

Original Image

Class: “speedboat”

Occluded “b”

(background is occluded)

Occluded “s”

(subject is occluded)

Quantitative Evaluation: GradCAM

Model \ Metric	**% ↑ in Confidence (Occlusion “b”)[a]**	**% ↓ in Confidence (Occlusion “b”)[b]**	**% ↑ in Confidence (Occlusion “s”)[b]**	**% ↓ in Confidence (Occlusion “s”)[a]**
VGG-16	16.00	36.08	8.00	33.11
ResNet-50	**26.00**	15.64	**2.00**	**56.72**
DenseNet-121	14.00	**15.13**	**2.00**	50.73

a. *Higher the better*
b. *Lower the better*

Quantitative Evaluation: SHAP

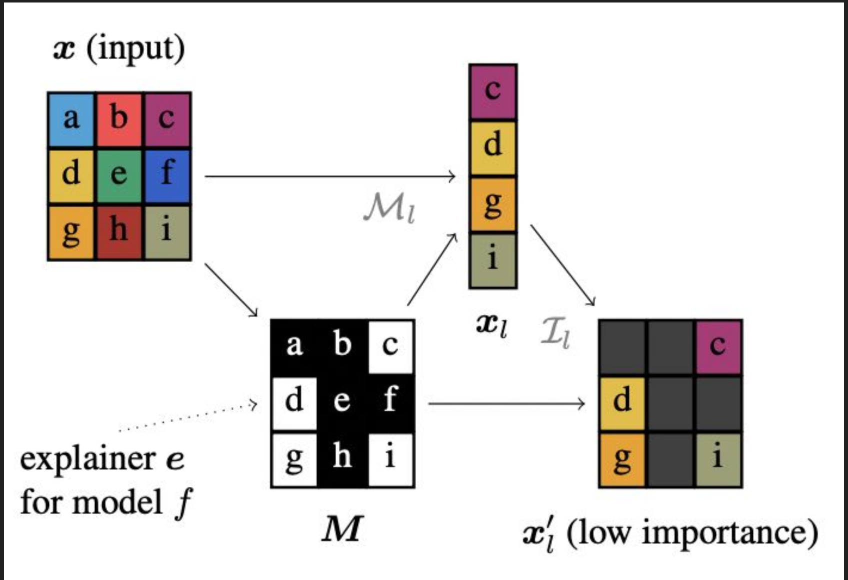
Model \ Metric	**% ↑ in Confidence (Occlusion “b”)[a]**	**% ↓ in Confidence (Occlusion “b”)[b]**	**% ↑ in Confidence (Occlusion “s”)[b]**	**% ↓ in Confidence (Occlusion “s”)[a]**
VGG-16	4.00	66.04	0.0	**86.62**
ResNet-50	**4.00**	64.66	**2.00**	85.47
DenseNet-121	2.00	**66.73**	**0.0**	75.98

a. *Higher the better*
b. *Lower the better*

Side track on evaluation methods: ROAD

- X = input image x (9 pixels a–i)
- M = mask produced by explanation method where important pixels are indicated in black
- Ml = masking operator that extracts remaining, less important pixel values xl and transforms to an imputed variant of the input x 0 l

Goal is to **separate the information** contained in the binary mask M



*Y. Rong, T. Leemann, V. Borisov, G. Kasneci, and E. Kasneci, "A consistent and efficient evaluation strategy for attribution methods."

Intuition: Remove and Debias (ROAD)

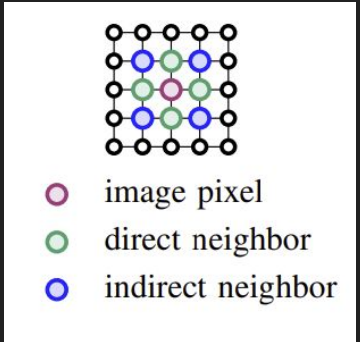
*“…classifier that **infers the class just from the location of the masked out pixels** and obtain high accuracy.”*

*Y. Rong, T. Leemann, V. Borisov, G. Kasneci, and E. Kasneci, “A consistent and efficient evaluation strategy for attribution methods.”

Intuition: ROAD (Continued)

Propose a *Noisy Linear Interpolation strategy* – approximate each pixel by a weighted mean of its neighboring pixels.

(perturbations are more difficult to detect) – still not ideal, but is an improvement



*Y. Rong, T. Leemann, V. Borisov, G. Kasneci, and E. Kasneci, “A consistent and efficient evaluation strategy for attribution methods.”

Quantitative Evaluation: ROAD-Definitions

Original Image

Class: “speedboat”

ROAD “b”

(background is hidden)

ROAD “s”

(subject is hidden)

Quantitative Evaluation: ROAD-GradCAM

Model \ Metric	**% ↑ in Confidence (ROAD "b")**[a]	**% ↑ in Confidence (ROAD "s")**[b]	**Mean ↑ in Confidence (Combined)**[a]
VGG-16	-13.33	-17.78	2.22
ResNet-50	-3.00	-26.10	11.55
DenseNet-121	**-2.97**	**-41.48**	**19.44**

a. *Higher the better*
b. *Lower the better*

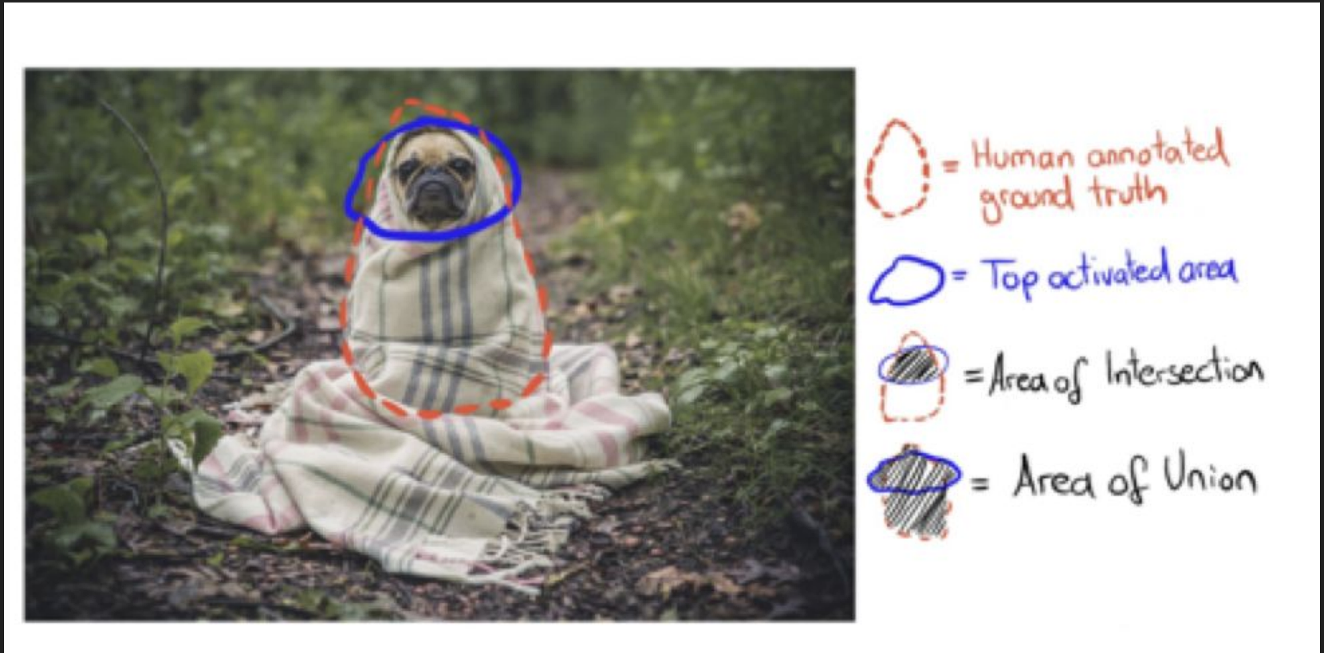
Quantitative Evaluation: ROAD-SHAP

Model \ Metric	**% ↑ in Confidence (ROAD "b")[a]**	**% ↑ in Confidence (ROAD "s")[b]**	**Mean ↑ in Confidence (Combined)[a]**
VGG-16	**-20.54**	-19.84	**-0.355**
ResNet-50	-32.39	-31.12	-0.636
DenseNet-121	-48.26	**-35.40**	-0.643

a. *Higher the better*
b. *Lower the better*

Quantitative Evaluation: IoU

Intersection Over Union (IoU) or Jaccard Index



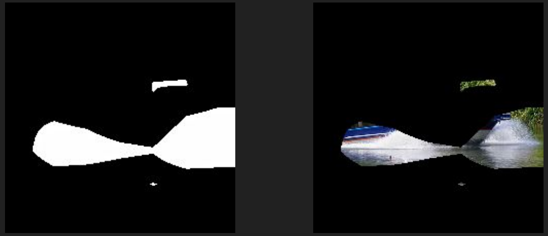
*Lecture Slides, C. Molnar

Quantitative Evaluation: IoU-GradCAM

Intersection Over Union (IoU) or Jaccard Index; Masks:

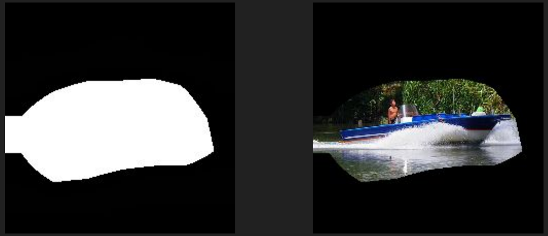
Original Image

Ground truth



VGG-16

ResNet-50



DenseNet-121

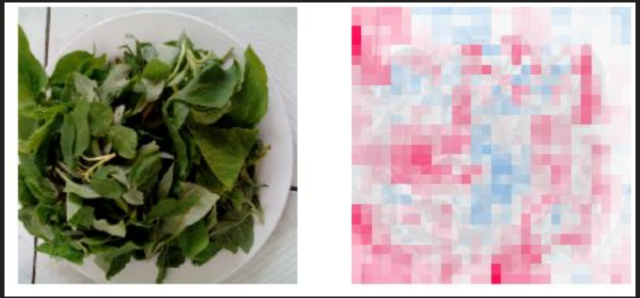
Quantitative Evaluation: IoU-Overview

XAI Method	Metric	VGG-16	ResNet-50	DenseNet-121
GradCAM	mIoU (%)	12.28	31.78	**38.75**
SHAP	mIoU (%)	19.48	26.24	27.65

Challenges

- Many images without meaningful masks (especially LIME)
- Consistency when comparing XAI methods
  - Gradient Explainer –results of course drastically change depending on the identified layer and architecture of backbone model
- Evaluation methods
  - How do we quantify “good” explanations?
  - Do quantified metrics fairly capture the explanation accuracy? Does it make sense to us, humans?
  - Technical challenges of just getting the explanation masks

“Picket fence”
LIME using VGG16



“Pot”
SHAP from Densenet121 (layer 7)

Practical Challenges

- Make segmentations by hand

“snow”

“flower”

“coast”

Conclusion

1. Both perturbation methods (occlusion, ROAD) and object localization metrics (IoU) have advantages and disadvantages, a good metric could be a combination of both
2. There is inherent subjectivity to explanations
3. There is scope to analyze more XAI methods and other evaluation metrics

References

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11. Imagenet50: https://shap.readthedocs.io/en/latest/generated/shap.datasets.imagenet50.htm

Thank you