CAM-Based Methods Can See through Walls

Magamed Taimeskhanov^{1,3}, Ronan Sicre², Damien Garreau³

¹Université Côte d'Azur, Laboratoire J.A. Dieudonné, CNRS, Nice, France

²Centrale Méditerranée, Aix-Marseille Univ., CNRS, LIS, Marseille, France

³Julius-Maximilians Universität, CAIDAS, Würzburg, Germany





Introduction

- Setting: image classification using CNNs
- Explainable AI for image classification:
 - identifying key factors influencing predictions
 - post-hoc explanation: saliency maps



• This talk = pinpointing CAM-based method problem

Simple CNN description

$$f: \mathbb{R}^{V \times h \times w} \to \mathbb{R}$$



- **B** = activation maps
- look at one class score y_c

GradCAM in one slide

• Importance weights α :

$$\forall i \in \llbracket V \rrbracket, \qquad \alpha_i \coloneqq \operatorname{GAP}\left(\nabla_{\mathbf{B}^{(i)}} f\left(\mathbf{B}\right)\right) \in \mathbb{R}.$$

- Intuition: influence of a map $\mathbf{B}^{(i)}$ on prediction score
- GradCAM on previous simple CNN:



• then **upscale** to input size

Related work

• Other CAM-based methods:

- Seminal work: CAM [Zhou et al., 2015]
- Extensions:
 - GradCAM [Selvaraju et al., 2017]
 - GradCAM++ [Chattopadhay et al., 2018]
 - XGradCAM [Fu et al., 2020]
 - ScoreCAM [Wang et al., 2020]
 - AblationCAM [Desai et al., 2020]
 - EigenCAM [Muhammad et al., 2020]
 - HiResCAM [Draelos et al., 2020]
 - Opti-CAM [Zhang et al., 2024]
- Other limitations of saliency maps:
 - Adebayo et al., Sanity Checks for Saliency Maps, NeurIPS, 2018
 - ► Ghorbani et al., Interpretation of Neural Networks Is Fragile, AAAI, 2019
 - ▶ Kindermans et al., The (Un)reliability of saliency methods, Springer, 2019

A partially blind model

• CNN with zeroed out weights in the first fully-connected layer



The problem: GradCAM can see through walls



(a) CNN does not see the red area...



(b)...but GradCAM highlights inside

Theory on simple CNN

• Main result: GradCAM expected behavior

Theorem (Taimeskhanov, Sicre, and Garreau, 2024) Let $\mathbf{m} \coloneqq \boldsymbol{\xi}_{i:i+k-1,j:j+k-1}$ be a patch with (i, j) pixel and k filter size. Assume that $\mathbf{W}_{:,-\frac{h'}{2}:,:} = 0$ and the parameters are $\mathcal{N}(0, \tau^2)$ (i.i.d.). Then, $\mathbb{E}\left[[\mathbf{GC}]_{i,j}\right] = \mathbb{E}\left[\sigma\left(\sum_{v=1}^{V} \alpha_v \mathbf{B}_{i,j}^{(v)}\right)\right] \ge \frac{V-20}{\sqrt{V}}\sqrt{\frac{h'w'}{16\pi}}\frac{\tau^2}{hw}\|\mathbf{m}\|_2$.

• Consequence: GradCAM highlights an image area \mathbf{m} if $\|\mathbf{m}\|_2 > 0$

Training a VGG16

- Theory: does it hold in practice?
- masked-VGG16 trained to a reasonable accuracy
- Baseline v.s. masked: 71.5% v.s. 66.5% top-1





Two new datasets

• **Idea:** one animal at the top, the other at the bottom

• STACK-MIX:

- 100 animal images from ImageNet-1k
- created by mixing, à la cutmix^a

• STACK-GEN:

- 100 animal images generated by DALL·E 3
- post-processing

9 / 12





^aYun et al., *CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features*, ICCV, 2019

Qualitative results

$\mathsf{Grad}\mathsf{CAM}{++}$



ScoreCAM







HiResCAM



Quantitative results

• Metric (% of ℓ^2 -norm):



• Activation behind the wall for VGG16:

methods	STACK-MIX \downarrow	STACK-GEN \downarrow
GradCAM	22.7 ± 13.4	21.6 ± 11.6
GradCAM++	28.8 ± 8.1	28.5 ± 7.9
XGradCAM	23.8 ± 9.0	22.8 ± 9.0
ScoreCAM	19.9 ± 10.3	18.5 ± 10.6
Opti-CAM	32.7 ± 7.9	32.0 ± 7.8
AblationCAM	21.0 ± 9.9	20.8 ± 9.6
EigenCAM	51.7 ± 19.7	55.8 ± 21.6
HiResCAM	0.0 ± 0.0	0.0 ± 0.0

Conclusion

- Proceed with caution when using CAM-based methods
- Hope: possible sanity check for saliency maps using
 - our masked CNN
 - datasets STACK-MIX and STACK-GEN

• Future work:

- Extend size of datasets
- Theory and experiments on other models (ResNet, ...)
- Check other saliency map methods

Visit our poster (ID 98)!

code and datasets:

