Score-CAM: Score-Weighted Visual Explanations for CNNs

Oriol Miró López-Feliu
Marc Gonzalez Vidal

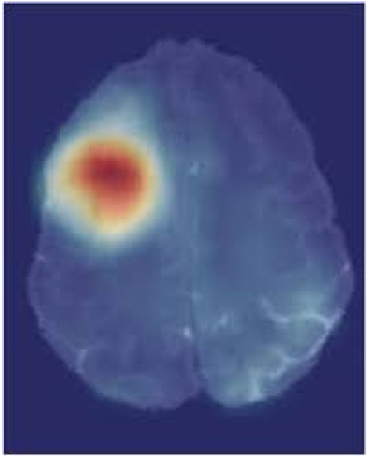
Computational Vision
Master in Artificial Intelligence (MAI)

December 18, 2024

Outline

Motivation

- CNNs achieve high performance but are often "black boxes" [2].
- Understanding model decisions enhances trust and transparency.
- Visual explanations help interpret CNN predictions, essential in critical applications (e.g., medical diagnosis).



[15]

Challenges with Existing Methods

- **Gradient-based Methods** [2, 3, 4]
  - Sensitive to gradient issues (vanishing/exploding).
  - Often produce noisy explanations.
- **Perturbation-based Methods** [5, 6]
  - Computationally expensive (many forward passes).
- **CAM-based Methods** [7, 8, 9]
  - Depend on network architecture.
  - Still rely on gradients.

Need: A method that is architecture-independent and gradient-free.

Gradient Issue

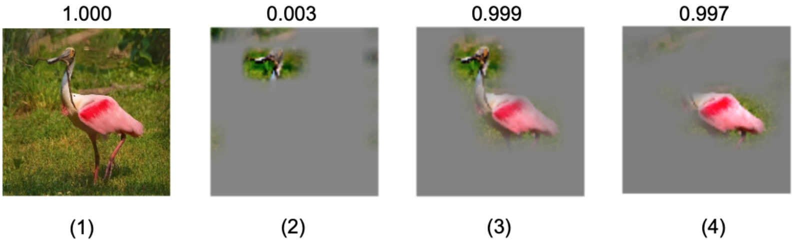


Figure: Higher activation weights do not always result in higher score increases.

- Example:
  - Activation weights: (2) $= 0.035$, (3) $= 0.027$, (4) $= 0.021$.
  - Score increases: (3) $>$ (2), despite its lower weight.
- **Cause:** Gradient saturation.

Objective

Goal: Develop a visual explanation method that:

- Is independent of gradients.
- Works with various CNN architectures.
- Provides accurate and interpretable saliency maps.

Solution: *Score-CAM* [1] (2019)

Score-CAM Overview

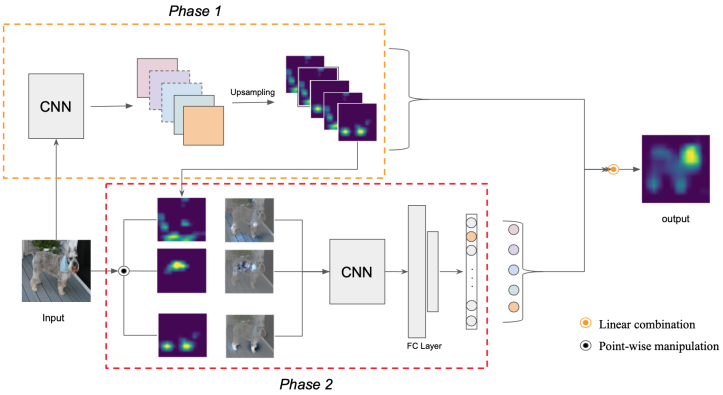


Figure: Score-CAM Pipeline [1]

Key Steps in Score-CAM

1. **Activation Map Extraction:**
   - Extract activation maps A^k from a convolutional layer.
2. **Mask Generation:**
   - Upsample and normalize A^k to create masks M^k.
   - $M^k = \text{Normalize}(\text{Upsample}(A^k))$
3. **Masked Inputs:**
   - Create masked inputs $\tilde{X}^k = X \odot M^k$.

Key Steps in Score-CAM (cont.)

4. **Forward Passes:**
   - Feed $\tilde{X}^k$ into the model to get class scores S_k^c.
5. **Weight Computation:**
   - Compute weights:

$$\alpha_k^c = \frac{\exp(S_k^c)}{\sum_j \exp(S_k^c)}$$

6. **Saliency Map Generation:**
   - Combine activation maps:

$$L^c_{\text{Score-CAM}} = \mathrm{ReLU}\left(\sum_k \alpha_k^c A_l^k\right)$$

Qualitative Results

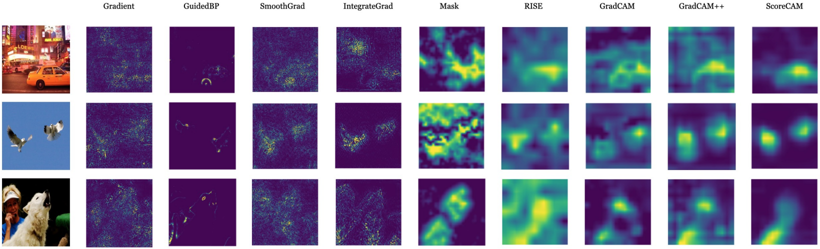


Figure: Comparison of Saliency Maps [1]

Quantitative Evaluation

Evaluation Metrics [9, 6]:

- **Average Drop (%)**: Lower is better.
- **Average Increase (%)**: Higher is better.
- **Localization Accuracy (%)**: Higher is better.

Method	**Avg. Drop** $\downarrow$	**Avg. Increase** $\uparrow$	**Loc. Acc.** $\uparrow$
Grad-CAM [8]	47.8%	19.6%	48.1%
Grad-CAM++ [9]	45.5%	18.9%	49.3%
Score-CAM [1]	**31.5%**	**30.6%**	**63.7%**

Limitations and Connection to Course Topics

Limitations

- **High Compute Cost:** Requires a forward pass per activation map.
- **Low Resolution:** Deep-layer maps are less detailed.
- **CNN-specific:** Limited applicability to non-convolutional models.

Connection to Course Topics:

- **Convolutional Neural Networks:**
  - Utilizes activation maps to interpret features.
- **Attention Mechanisms:**
  - Similar to focusing on important input regions.
- **Object Detection**
  - Proposes explanation for detected objects.

Conclusion

- Score-CAM provides effective, gradient-free visual explanations.
- Overcomes limitations of previous methods.
- Enhances model interpretability and reliability.

Current Relevancy:

- Dec. 2024: Cited by **1107**.
- SOTA Advances:
  - **Grad++ScoreCAM (2023) [12]:** Integrates gradients and scores for accurate multi-object localization and efficiency.
  - **CNNC (2022) [13]:** Visual tool combining explanation methods for interpretable CNN comparison.
  - **Score-CAM++ (2023) [14]:** Enhances Score-CAM with better visual outputs and precise quantitative metrics.

Thank You!

Questions?

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