FD-CAM: Improving Faithfulness and Discriminability of Visual Explanation for CNNs

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Abstract—Class activation map (CAM) has been widely studied for visual explanation of the internal working mechanism of convolutional neural networks. The key of existing CAM-based methods is to compute effective weights to combine activation maps in the target convolution layer. Existing gradient and score based weighting schemes have shown superiority in ensuring either the discriminability or faithfulness of the CAM, but they normally cannot excel in both properties. In this paper, we propose a novel CAM weighting scheme, named FD-CAM, to improve both the faithfulness and discriminability of the CAM-based CNN visual explanation. First, we improve the faithfulness and discriminability of the score-based weights by performing a grouped channel switching operation. Specifically, for each channel, we compute its similarity group and switch the group of channels on or off simultaneously to compute changes in the class prediction score as the weights. Then, we combine the improved score-based weights with the conventional gradient-based weights so that the discriminability of the final CAM can be further improved. We perform extensive comparisons with the state-of-the-art CAM algorithms. The quantitative and qualitative results show our FD-CAM can produce more faithful and more discriminative visual explanations of the CNNs. We also conduct experiments to verify the effectiveness of the proposed grouped channel switching and weight combination scheme on improving the results. Our code is available at https://github.com/crishhh1998/FD-CAM.

I. INTRODUCTION

In recent years, deep learning has achieved great breakthroughs in various fields. Especially in the domain of computer vision, Convolutional Neural Networks (CNNs) have produced remarkable results for image classification [1], [2], object detection [3], [4], semantic segmentation [4], [5] etc. However, most existing deep learning methods are data-driven and lack of an interpretable way to explain why the networks make a certain prediction. The interpretability of the deep neural networks or CNNs still needs to be developed so that they can be confidently applied to high-stakes domains such as healthcare, financial services and autonomous driving.

Visual interpretation or explanation of the internal working mechanism of the deep neural networks, particularly the CNNs, has drawn wide attention and various methods have been proposed. The early methods focus on interpreting the CNNs via the direct visualization of the gradients in the forms of the saliency map [2], [6]–[8]. Since the saliency maps generated by the gradient visualization are usually noisy and low quality, following works [9]–[11] attempt to improve the sensitivity and smoothness of the results. Meanwhile, visual explanation of the CNNs by the class activation map (CAM) is another popular technique that can produce more intuitive and high quality results than the gradient visualization.

CAM aims to compute a weighted linear combination of the activation maps in the target convolutional layer of a CNN model and the output is usually a heat map corresponding to the input image. Typically, the CAM visualization is often used in explaining the classification models so that one can easily get a sense of why the network has made a certain prediction. The key of CAM-based explanation is to compute effective weights to combine the activation maps w.r.t to the specified class. And the generated CAM is expected to be faithful and discriminative for explaining the network results.

The original CAM formulation proposed by Zhou et al. [12] requires a retraining step to compute the weights of the activation maps in the last convolutional layer. Later, various CAM weighting schemes that do not need to modify the network architecture or retraining have been proposed and they can mainly be categorized into gradient and score based

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methods. The gradient-based methods compute the gradients of the class prediction score w.r.t. each activation map and use the channel-wise global average pooled gradients as the weights. The gradient-based CAM such as Grad-CAM \cite{13} is discriminative for different class, but may not work faithfully for multiple targets due to the global average pooling operation (see Figure 1 left column). On the other hand, the score-based methods compute the weights by perturbing the input image or feature maps in the target layer and measuring the changes of the classification scores. While the score-based CAM such as Score-CAM \cite{14} can improve the faithfulness of the explanation for multiple targets, it is inferior in the discriminability for different class. The reason is for the class that has a low prediction score in the image (e.g., the “Cat” class in Figure 1), its score change may also be insignificant when the perturbation is applied. Hence, the score-based weights may not be discriminative in this case.

To improve both the faithfulness and discriminability of the CAM-based CNN visual explanation, we propose a novel activation map weighting scheme, named FD-CAM, by combining the merits of the gradient and score based CAM methods. First, we improve the faithfulness and discriminability of the score-based weights by performing a grouped channel switching operation. Specifically, for each channel (feature map) in the target layer, we compute its similarity group and switch the group of channels on or off simultaneously to compute changes in the class prediction score as the weights. Then, we combine the improved score-based weights with the conventional gradient-based weights from Grad-CAM so that the discriminability of the final FD-CAM can be further improved. We perform extensive comparisons with the state-of-the-art CAM algorithms. The quantitative and qualitative results show our FD-CAM can produce more faithful and more discriminative visual explanations of the CNNs. We also conduct experiments to verify the effectiveness of the proposed grouped channel switching and weight combination scheme on improving the results.

In summary, our contributions are as follows:

- We propose FD-CAM, a novel CAM weight scheme which combines the gradient and score based weights to improve the faithfulness and discriminability of visual explanation for CNNs.
- We introduce the grouped channel switching which perturbs groups of channels simultaneously to obtain more faithful and more discriminative score-based weights.
- We conduct extensive quantitative and qualitative comparisons with the state-of-the-art CAM algorithms and the results show our FD-CAM can achieve superior performance in explaining the prediction of CNNs.

II. RELATED WORK

In this section, we first summarize a generalized CAM formulation. Then, we briefly survey on the existing gradient and score based CAM methods with the focus on how they compute the activation map weights and their performance in the visual explanation of CNN classification models.

**Generalized CAM formulation.** Assume $f(X)$ is a CNN model which takes an input image $X$ and predicts the probabilities or scores of different classes. For the target convolutional layer in $f$ which contains $K$ feature maps or channels of spatial size $h \times w$, define $A_k^h \in H^{h \times w}$ as the $k$-th feature map. Normally, the generalized formulation of the class activation map of the CNN model $f$ w.r.t class $c$ can be defined as:

$$L^\text{Gen-CAM} = \Phi \left( \sum_{k \in K} \omega_c^k A_k^h \right),$$

where $\Phi(\cdot)$ is an activation function, $\omega_c^k$ are the weights to combine the activation maps $A_k^h$.

In the original CAM \cite{12}, $\Phi(\cdot)$ is defined as an identity function and $\omega_c^k$ is a set of retrained weights for classifying the features obtained by applying global average pooling on each channel of the last convolutional layer. Inspired by [12], numerous CAM variants have been proposed, in which $\Phi(\cdot)$ is usually defined as the ReLU function to focus on the features with positive influence. For $\omega_c^k$, various schemes including the gradient and score based methods have been investigated to find effective weights which can produce more discriminative CAMs with faithful visual explanation.

**Gradient-based CAM.** In contrast to \cite{12} which requires to retrain a modified model to obtain the weights, Selvaraju et al. propose Grad-CAM \cite{13}, the first gradient-based weighting scheme, to define $\omega_c^k$ as the channel-wise global average pooled gradients $\alpha_c^k$ of the model prediction $f_c(X)$ w.r.t the activation map $A_k^h(X)$ for class $c$:

$$\omega_c^k = \alpha_c^k = \frac{1}{h \times w} \sum_i \sum_j \frac{\partial f_c(X)}{\partial A_{ij}^k(X)}.$$  

Using the gradients as weights, Grad-CAM can be applied to different CNN involved tasks beyond the image classification in \cite{12}, such as image captioning \cite{15} and visual question answering \cite{16}. In addition, Grad-CAM computes per-pixel gradients of the activation map w.r.t the given class. Therefore, it is discriminative to different classes. On the other hand, because of the global average pooling, Grad-CAM may discard the spatial information which can make the CAM-based localization not faithful to multiple object targets.

To solve this issue, Chattopadhyay et al. propose Grad-CAM++ \cite{17} which employs weighted average of the positive gradients as $\alpha_c^k$, while the weights of the gradients are calculated by the higher-order derivatives of $f_c(X)$ w.r.t $A_k^h(X)$. With the weighted combination of the gradients, Grad-CAM++ has shown more faithful results on explaining images with multiple targets than Grad-CAM. Additionally, CAMERAS \cite{18} performs multi-scale accumulation and fusion of the activation maps and backpropagates gradients to compute high-fidelity saliency maps. In our FD-CAM, we aim to improve the faithfulness of Grad-CAM while keeping its discriminability. Different from using the higher-order derivatives which may be unstable to compute, we combine the score-based weights with the gradient-based weights so that the faithfulness of the CAM can be improved.
Score-based CAM. Perturbation is a way to generate the variants of the input or the model so that the change of the model’s prediction score can be used as an indicator for the importance of the perturbation operation. For example, in RISE [19], random binary masks are sampled to generate the perturbed masked input images and the output prediction scores are used as importance weights to combine the sampled predictions to get the visual explanation of the black-box model. In the score-based CAM methods, \( \omega^k \) is defined as the changes of the classification scores caused by perturbing the input image \([14], [20]–[22]\) or feature maps \([23]\) in the target layer, i.e.,

\[
\omega^k_{c} = s^k_{c}, \tag{3}
\]

where \( s^k_{c} \) is classification score change w.r.t class \( c \) and it will be used as the weight for activation map \( A^k \). Instead of performing backpropagation to compute the gradients in the gradient-based method, \( s^k_{c} \) is calculated by applying forward propagation and comparing the original classification score with the perturbation-induced score.

Score-CAM \([14]\) is one representative score-based method which performs the perturbation by multiplying the input image with each activation map in the target convolutional layer and then combines the activation maps using the change of the model’s confidence score as the weights. Meanwhile, Desai et al. propose Ablation-CAM \([23]\) that perturbs the feature maps in the target layer. Each feature map or unit \( A^k \) is disabled or switched off in turn to compute score changes as the weight for this unit. LIFT-CAM \([24]\) formulates the explanation model as a linear function of binary variables denoting the existence of the associated activation maps, while the weights of each activation map is derived from the SHAP \([25]\) values. These methods compute the weight \( \omega^k \) based on only manipulating the activation map \( A^k \). In contrast, we perform grouped channel (feature map) perturbation and introduce the group switch-off and switch-on operation to compute the score change. To further improve the discriminability of the score-based methods, we combine the scores obtained by the grouped switching and the gradient-based weights to compute the final weights for FD-CAM.

III. METHOD

In this section, we first discuss the motivation of channel grouping and introduce how to form the groups based on cosine similarity between different channels. Then, we apply the grouped channel switching operation to compute the change of class classification scores as the improved score-based weights. Finally, we propose a novel CAM weighting scheme by combining the gradient-based weights with score-based weights. Figure 2 shows the pipeline of our FD-CAM.

A. Channel Grouping

Motivation. Inspired by the Ablation-CAM \([23]\) which computes the score-based weights by switching off each individual channel and measuring the classification score changes, we perform grouped channel switching operation to find the importance of each channel in a more discriminative manner. The reason for using the grouped switching is, in a particular convolutional layer, the features in different channels may actually have high similarities (see Figure 3). If only one channel is switched off, the final classification score may not change much, since other channels may still have the similar features activated. Moreover, performing the grouped switching can be regarded as considering more context when computing the importance for each feature map \( A^k \). Hence, the score changes may better represent the importance of the interested channel if all of its similar channels are switched on or off together.

Channel similarity. Specifically, to determine the weight for each channel \( A^k \), we simultaneously switch on or off a group of channels which have high similarities to \( A^k \), and compute the score changes as \( s^k_{c} \). The similarity between channel \( A^k \) and another channel \( A^l \) is defined by the cosine similarity:

\[
\cos(A^k, A^l) = \frac{v^k \cdot v^l}{\|v^k\| \cdot \|v^l\|}, \tag{4}
\]
where \( \mathbf{v}^k \) and \( \mathbf{v}' \) are the vectors obtained by flattening the matrices \( A^k \) and \( A' \). Then, a cosine similarity matrix \( M \) is computed to store the similarities between each pair of channels in the target layer.

Next, the similarity group of \( A^k \) is defined as

\[
G(A^k) = \{ A | \cos(A^k, A^l) > \tau_k, l, k \in K \}.
\]

Here, \( \tau_k \) is a similarity threshold determined by the \( \theta \)-th percentile of the high-to-low sorted similarities for channels in \( G(A^k) \). Empirically, we use \( \theta = 5 \) to set top 5% similar channels to be in the same group. Note that, for each channel, we find its own group for the score change computation.

### B. Grouped Channel Switching

Similar to [23], for each \( A^k \), we first switch off all the channels in its similarity group \( G(A^k) \) and compute the score change as the switch-off score:

\[
s_k^c = f_c(X) - f_k^{c-}(X),
\]

where \( f_c(X) \) is the original classification score of input \( X \) w.r.t class \( c \) and \( f_k^{c-}(X) \) is the new classification score from the modified model with channels in \( G(A^k) \) switched off.

In addition to switching off or dropping the group of similar features for evaluating the importance of \( A^k \), we also propose a new grouped channel switch-on score:

\[
s_k^c = f_k^{c+}(X),
\]

where \( f_k^{c+}(X) \) is the classification score when only the channels in \( G(A^k) \) are switched on and other channels are switched off.

Finally, we define our grouped channel switching based score as

\[
s_k^c = \frac{1}{2}(s_k^{c-} + s_k^{c+}).
\]

By combining \( s_k^{c-} \) and \( s_k^{c+} \), we can evaluate the importance of each channel from two perspectives: switch off and on to deactivate and activate the influence, respectively. Moreover, the grouped channel switching treats the feature maps in a larger channel-wise context, while the influence of one channel is associated with all of its similar channels. Conceptually, when our channel group is set to be the interested channel itself, our grouped channel switching is reduced to the Ablation-CAM, while the only difference is how we compute the score \( s_k^c \).

### C. Combination of Gradient and Score based Weights

In our FD-CAM, we combine the gradient-based weights \( \alpha_k^c \) and score-based weights \( s_k^c \) to define \( \omega_k^c \) so that the merits of both methods can be highlighted:

\[
\omega_k^c = \rho(\alpha_k^c, s_k^c),
\]

where \( \rho(\cdot, \cdot) \) is a function that combines \( \alpha_k^c \) and \( s_k^c \).

Since the original gradient-based and score-based weights are in different scales, to combine them properly, we apply the standard min-max normalization to \( \alpha_k^c \) and \( s_k^c \) and obtain \( \tilde{\alpha}_k^c \) and \( \tilde{s}_k^c \) for which the values are linearly scaled to \([0,1]\). Next, we define

\[
\rho(\alpha_k^c, s_k^c) = \tilde{\alpha}_k^c \tilde{s}_k^c - b,
\]

where \( b \) is a bias parameter (empirically set to 0.5) to allow negative weights for combining the activation maps. Generally, there are multiple options to combine the two different types of weights. In our formulation, we treat the \( e^{s_k^c} \) as a special scaling weight for \( \tilde{\alpha}_k^c \), while the influence of \( \tilde{s}_k^c \) is incorporated in an exponential manner. In Section [IV-D], we show our proposed formulation outperforms other options by comparing the results of using different parameters \( b \) and different weight combination methods.

Finally, like other CAM methods, we define our FD-CAM for target convolutional layer \( \{ A^k | k \in K \} \) w.r.t class \( c \) as

\[
L_{FD-CAM} = \text{ReLU} \left( \sum_{k \in K} \rho(\alpha_k^c, s_k^c)A^k \right).
\]

### IV. Experiment

In this section, we first introduce the implementation details of FD-CAM. Then, we compare our results with SOTA methods on visual explanation of CNNs. In addition, we perform qualitative and quantitative evaluation on the faithfulness and discriminability of our method. Finally, we conduct ablation studies to show the effectiveness on the grouped channel switching and the weight combination scheme.

#### Implementation details

In the following, except for the quantitative evaluation on discriminability, we use 2,000 images randomly selected from the ILSVRC2015 validation set [26] for the qualitative and quantitative evaluation. For the discriminability evaluation, we experiment on the VOC2007 validation set [27] which contains more images with multiple categories. During the pre-processing, all the images are resized to \( 224 \times 224 \times 3 \). For the CNN model to be explained, we choose the pre-trained VGG16 [2] from the PyTorch model zoo. We implement FD-CAM in PyTorch and conduct all experiments on a desktop with 1 NVIDIA TITAN RTX GPU. For other methods, we adopt their open source implementation and test each method on our datasets.
| Methods       | Insertion | Deletion | Overall |
|---------------|-----------|----------|---------|
| Grad-CAM [13] | 0.5357    | 0.1117   | 0.4240  |
| Grad-CAM++ [17] | 0.5321   | 0.1088   | 0.4233  |
| XGrad-CAM [28] | 0.5464    | 0.1072   | 0.4392  |
| Score-CAM [14] | 0.5422    | 0.1059   | 0.4363  |
| Ablation-CAM [23] | 0.5502  | 0.1013   | 0.4489  |
| Layer-CAM [29] | 0.5389    | 0.1021   | 0.4368  |
| Group-CAM [22] | 0.5397    | **0.0921** | 0.4476  |
| FD-CAM        | **0.5534** | 0.1001   | **0.4533** |

A. Comparison with SOTA on Visual Explanation

In Figure 4, we show the heat map visualization of the results for some images in ILSVRC. We compare the FD-CAM with different types of CAM (or saliency map) methods, including the gradient-based visualization (Integrated Gradients [9], XRAI [11]), gradient-based CAM (Grad-CAM [13], Grad-CAM++ [17] and XGrad-CAM [28]) and score-based CAM (Score-CAM [14], Ablation-CAM [23]). It can be observed the IG and XRAI results are more noisy and less useful comparing to the CAM-based methods. In Grad-CAM, Grad-CAM++ and XGrad-CAM, the visualization may not highlight all related targets (e.g., the odometer on the right). Score-CAM and Ablation-CAM produce better results for multiple targets situation, but they may still include less focused regions. Our FD-CAM can faithfully and more accurately highlight all related regions w.r.t the specified class.

B. Evaluation on Faithfulness

One important characteristic to evaluate the visual explanation technique is the faithfulness, which measures how the results can accurately highlight the regions related to the model’s decision. To quantitatively evaluate the faithfulness, we adopt the metric proposed in [19]: the area under the deletion and insertion curve (AUC). The deletion curve shows the decrease of class prediction probability when gradually deleting the high-activated regions from the input image, while the insertion curve shows the increase of probability when inserting the regions to a zero-valued image or blurred version of input. A faithful explanation is expected to start with a sharp drop in predicted probability at the start of the deletion curve, which corresponds to a smaller AUC. At the start of the insertion curve, the predicted probability is expected to increase quickly which can result in a larger AUC.
We evaluate the faithfulness of the results from several CAMs and FD-CAM by deleting or inserting regions with a rate of 3.6% of the original image’s area at each step. The quantitative results are shown in Table I. We also show some CAM visualizations along with their deletion and insertion curves in Figure 5. It can be observed FD-CAM can generally outperform other methods on faithfulness.

C. Evaluation on Discriminability

Discriminability on different classes is another critical property for evaluating the performance of the visual explanation methods. Given an input image, it usually contains multiple classes with different prediction probabilities. For the non-dominant class in the image, even its probability may be low, an effective method is still expected to correctly visualize the regions corresponding to the model’s decision. Figure 6 shows the qualitative evaluation on the class discriminability for FD-CAM. It is clear that FD-CAM outperforms other gradient and score based methods in distinguishing different classes when explaining the model’s decision.

For quantitative evaluation, we employ the localization-based metric pointing game [30] to compute the point-based localization accuracy for different classes as the discriminability measure. Specifically, for each image in VOC2007 val, the saliency map of each class is computed and the point with max value is extracted. If the point falls into the annotated bounding box of the corresponding class, a hit is counted, otherwise a miss is counted. The final accuracy is defined by considering all images and all classes therein:

\[
\text{Acc}(\text{all classes in all images}) = \frac{\text{Hits}}{\text{Hits} + \text{Misses}}. \tag{12}
\]

Table II shows the results of representative CAM methods on discriminability evaluation. It can be seen the gradient-based methods are naturally more discriminative than score-based methods as the gradients may still be prominent even for the low probability classes. Our FD-CAM outperforms both kinds of methods by combining them in a proper manner.

| Methods                  | Insertion ↑ | Deletion ↓ | Overall ↑ |
|--------------------------|-------------|------------|-----------|
| Grad-CAM++               | 0.5260      | 0.1084     | 0.4176    |
| Score-CAM               | 0.5396      | 0.1020     | 0.4376    |
| FD-CAM                  | 0.5534      | 0.1001     | 0.4533    |

D. Ablation Studies

**Grouped channel switching.** In FD-CAM, we propose the grouped channel switching to perturb the channels with similar features and introduce the switch-on score to obtain the enhanced score \(s_{e}^{k}\). To verify the effectiveness of these two operations, we perform ablation studies and evaluate the AUC values for different versions of FD-CAM. From Table III, it can be seen the channel grouping and the switch-on score can both improve the performance and the full version FD-CAM can produce the best AUC values which means the explanation is more faithful. Note, when no channel grouping and only switch-off score is applied, the FD-CAM reduces to the similar formulation of Ablation-CAM [23].

**Weight combination schemes.** Similarly, we also compare different schemes for combining the gradient and score based weights and evaluate the effectiveness of the bias parameter \(b\). From Table IV the proposed weighting scheme can achieve the best performance. It should be noted that we only propose one possible solution for combining the gradient and score based weights to improve CAM-based visual explanation. We leave the investigation for better weight combination schemes to the future work.

### Table II: The evaluation on discriminability using the pointing games metric.

|                      | Grad-CAM [13] | Grad-CAM++ [17] | XGrad-CAM [28] | Layer-CAM [29] | Score-CAM [14] | Ablation-CAM [23] | FD-CAM     |
|----------------------|---------------|-----------------|----------------|----------------|----------------|--------------------|------------|
| Acc(%)               | 81.20         | 81.91           | 80.72          | 78.46          | 58.19          | 83.70              |            |

### Table III: Ablation study on grouped channel switching.

| Methods                           | Insertion ↑ | Deletion ↓ | Overall ↑ |
|-----------------------------------|-------------|------------|-----------|
| FD-CAM\(_{ng+off}\)              | 0.5465      | 0.1048     | 0.4417    |
| FD-CAM\(_{s+off}\)              | 0.5437      | 0.1044     | 0.4393    |
| FD-CAM\(_{r+off,s+off,0.5}\)    | 0.5534      | 0.1001     | 0.4533    |

### Table IV: Ablation study on weight combination schemes.

| Methods                           | Insertion ↑ | Deletion ↓ | Overall ↑ |
|-----------------------------------|-------------|------------|-----------|
| FD-CAM(\(\rho = \alpha_{b}c_{e}^{k}\)) | 0.5465      | 0.1048     | 0.4417    |
| FD-CAM(\(\rho = \hat{\alpha}_{b}c_{e}^{k}\)) | 0.5437      | 0.1044     | 0.4393    |
| FD-CAM(\(\rho = \hat{\alpha}_{b}c_{e}^{k} - 0.5\)) | 0.5534      | 0.1001     | 0.4533    |

**V. Conclusion**

In this paper, we propose the FD-CAM, a novel activation map weighting scheme that shares the advantages of both gradient and score based CAM methods in producing faithful and discriminative visual explanation of CNNs. Extensive qualitative and quantitative evaluations have shown superiority of FD-CAM and ablation studies also verify the effectiveness of the proposed modules. We believe our FD-CAM can inspire more follow-ups such as learning a weight combination scheme instead of current heuristic-based formulation and designing more sophisticated channel grouping and scoring functions for more effective feature perturbation.
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