Saliency Methods for Explaining Adversarial Attacks

Jindong Gu
The University of Munich
Siemens AG, Corporate Technology
jindong.gu@siemens.com

Volker Tresp
The University of Munich
Siemens AG, Corporate Technology
volker.tresp@siemens.com

Abstract

In this work, we aim to explain the classifications of adversary images using saliency methods. Saliency methods explain individual classification decisions of neural networks by creating saliency maps. All saliency methods were proposed for explaining correct predictions. Recent research shows that many proposed saliency methods fail to explain the predictions. Notably, the Guided Backpropagation (GuidedBP) is essentially doing (partial) image recovery. In our work, our numerical analysis shows the saliency maps created by GuidedBP do contain class-discriminative information. We propose a simple and efficient way to enhance the created saliency maps. The proposed enhanced GuidedBP is the state-of-the-art saliency method to explain adversary classifications.

1 Introduction

The explanations produced by saliency methods reveal the relationship between inputs and outputs of the underlying model. In image classifications, the explanations are generally visualized as saliency maps. A saliency map (SM) is defined by three components: an input $x \in \mathbb{R}^d$, a model $M$ corresponding to a function $f_x()$, and an output class $y_m$.

A saliency method can be formulated as a function $g()$. A saliency map $s^m \in \mathbb{R}^d$ for the classification of the $m$-th class is defined as

$$s^m = g(x, M, y_m)$$ (1)

where $s^m$ has the same dimensions as the input $x$. The value of an element $s^m_i$ in $s^m$ specifies the relevance of the input feature $x_i$ to the $m$-th class. To be noted that the $m$-th class could be neither the ground-truth class nor the predicted class.

In recent years, a large number of significant saliency methods have been proposed [1–14]. [15, 16] show that SMs created by Guided Backpropagation (GuidedBP [3]) are neither class-discriminative nor sensitive to model parameters. [17] proves that Guided Backpropagation is essentially doing (partial) image recovery, which is unrelated to the network decisions. Different from their conclusions, our numerical analysis shows that the SMs created by GuidedBP do contain class-relevant decisions.

Most of the existing saliency methods only consider the SM of the ground-truth class without considering the change of the class $y_m$ in Equation (1) [18] shows that meaningful explanations should be robust to small local perturbations of the input. However, the small perturbation can lead the misclassification of neural networks [19, 20]. We would not expect that the explanations stay unchanged in this case since the neural networks make totally different decisions. Hence, the saliency methods should be discriminative to adversary perturbation.

Our contributions can be summarise as follows: 1) We identify class-discriminative information in SMs created by GuidedBP and propose a simple and efficient way to enhance the created SMs; 2) We explain classifications of adversary images with the proposed enhanced Guided Backpropagation and the existing methods. The explanations created by them are compared with each other via qualitative and quantitative experiments.

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2 Enhanced Guided Backpropagation

Similar to raw gradient backpropagation, GuidedBP propagates gradients back to inputs and takes the received gradients as their saliency values. The two methods differ only in handling ReLU layers. In GuidedBP, \( G_l = G_{l+1} \cdot 1_{G_{l+1} > 0 \text{ and } X_l > 0} \) where \( G_l \) is the gradients of the \( l \)-th layer and the \( X_l \) are the activations before ReLU layer, and 1 is the indicator function. Since the indicator function filters out part of gradients, the gradients received by some input features can be zeros, which is called filtering effect (FE). The filtering effect of a SM is formally defined as \( s_l \cdot 1_{s_l > 0} \).

[18] provides a theoretical analysis of GuidedBP. They show that the created SMs of different classes have similar filtering effects, which means that GuidedBP is not class-discriminative. In the following, we show the SMs created by GuidedBP do contain class-discriminative information and propose a simple way to enhance the discriminative information in the corresponding saliency maps.

2.1 Identifying Discriminative Information

\( s^k \) and \( s^m \) are the two saliency maps created by GuidedBP for the \( k \)-th output class and the \( m \)-th output class. They have similar filtering effects, as theoretically analyzed in [18]. The difference between them can only be their saliency values, if existing. However, in all published work, SMs are visualized by normalizing saliency values in a SM and mapping them to a color map \([0, 255]\). The possible difference of their saliency values is hidden by the normalization.

We take pre-trained VGG16 [21] model and fine-tune it on the PASCAL VOC2012 [22] dataset. Each image in the dataset may have many objects belonging to more than one class. We select images with multiple labels from the validation dataset. For each image, we produce \( n \) SMs for \( n \) ground-truth classes and choose any two of \( n \) SMs to form a SM pair \((s^k, s^m)\), i.e., \( \binom{n}{2} \) SM pairs.

For each pair, we binarize the SMs and compute the similarity between two binarized ones, which is defined as the ratio of the number of pixels with the same value to the number of all pixels. The scores of all SM pairs in the validation images are shown in Figure 1a. All the scores are close to 1, which means the SMs of different classes have almost the same filtering effect.

Without normalizing values of SMs, we compute their average. For each SM pair, we compute the difference of saliency values of two SMs as \( \text{Avg-Diff} = \frac{\text{Avg}_1 - \text{Avg}_2}{\max(\text{Avg}_1, \text{Avg}_2)} \). The scores are visualized in Figure 1b. They vary from 0 to 0.8. In summary, given a classification, the two SMs \( s^k \) and \( s^m \) differ in saliency values instead of filtering effect.

2.2 Enhancing Discriminative Information of Saliency Maps

In this section, we propose a simple and efficient way to extract information about the difference. We argue that the relatively larger saliency values in SMs correspond to the input features that support a specific class. We extract such class-relevant information by normalize them and subtract them, which is visualized in Figure 2. Figure 1b shows the saliency values of two SMs where input features are ordered by the saliency values of a SM \( s^k \). The two SMs have zeros in the interval \([0, A]\) since
We propose the channel-wise energy-based normalization to circumvent the problem. We consider an alternative is the energy-based normalization. The individual SMs are normalized by the sum of its

The Basic Iterative Method (BIM) [23] extends FGSM by taking multiple small steps instead of one

Advantages of the saliency methods:

1. Since the existing saliency methods always create similar SMs for a clean image and its adversary versions, they cannot be applied to explain classifications misled by adversary perturbations. Our

Enhanced GuidedBP reacts the adversary attacks strongly. However, we argue that saliency methods should reflect the strong reaction of deep neural networks. The advantage of the saliency methods: they can still identify the object in the image even when attacked.

3 Explaining Classifications of Adversary Images

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enhanced GuidedBP can identify the relevant evidence of the decisions. For the classification of the original input (e.g., sheepland dog), the created SM shows the VGG16 focus on the important visual feature of the target object (the head), while it focuses on class-irrelevant features (background and body parts) when explaining the classifications of adversary inputs.

The saliency methods can identify the input features that contribute to the classification decision. We can apply saliency methods on misled classifications of adversary samples. If we perturb the pixels relevant to the misclassification according to the created SMs, the attack effectiveness will be decreased. The performance of the model on the perturbated samples can be recovered to some extent. Figure 4 shows the performance of the model on the adversary samples (C&W attack) when they are perturbated according to the SMs. We can observe that the perturbation with SMs of our enhanced GuidedBP can recovery the most score. Instead of claiming the SM-based perturbation is an effective defense method, we aim to show that SMs created by enhanced GuidedBP can better identify the pixels relevant to classifications. When too many images pixels are perturbated, the visual features of true target objects is lost, which can also lead to low performance of the model.

To further analyze the adversary-discriminativity of SMs created by enhanced GuidedBP, we categorize created adversary images into two categories: Adv_f, the ones that fail to attack the neural network and Adv_s, the ones that mislead the classification decisions successfully. For the clean images and the perturbed images in Adv_f, the created SMs should identify the class-discriminative parts. Contrarily, for the adversary images Adv_s, the parts identified in the SMs are irrelevant to the ground-truth label, which means the network focuses on the wrong parts of the adversary images when making decisions.

In Figure 5 the image in the first row contains a vulture. If the created adversary image fails to fool the neural network, the corresponding SM focuses on the head of the vulture (see 1st-3rd columns right of the image). If the attack is successful, the created SM for the misclassified class (i.e., kite) focuses on wings of the vulture. As a comparison, the GuidedBP always visualizes all the salient low-level features of all the images (e.g., the ski, the persons, and the alp in the image of the second row).

4 Discussion and Conclusion

Why enhanced GuidedBP is better? The pre-softmax scores (logits) are often taken as output scores to create SMs. The previous attribution methods show that the scores of different classes can be attributed to the same pixels. They explain where the scores themselves come from. Our approach explains where the difference between logits comes from, which is the exact reason why the network predicts a higher probability for a class than another. In the optimization of creating adversary images, the loss of the neural network is increased, which results in the change of the rank of logits. Our approach can find the evidence for the difference between the scores, i.e., the rank of logits. The change of the rank is the reason for misclassifications. That is why the enhanced GuidedBP can explain the classification decisions of adversary images better.

The generalization and limitation of the enhancing method As shown in Sec. 2.1, the important factor to support the success of enhanced GuidedBP is that s^k and s^m have similar Filtering effect. When generalizing the enhancing method to other methods, the effectiveness depends on the similarity of filtering effects. [25, 26] show that SMs can be manipulated due to vulnerability of DNNs. The limitation of the method is that we assume that artificial perturbation itself is not aware of our method.

In this work, we identify the class-discriminative information in SMs created by GuidedBP and propose a simple way to enhance it. The proposed enhanced GuidedBP can explain classification decisions of adversary images better. In future work, we will investigate how to regularize the deep neural networks using the captured discriminative information so that the rank of logits is not easily changed by adversary perturbations.
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