GETAM: Gradient-weighted Element-wise Transformer Attention Map for Weakly-supervised Semantic Segmentation

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Abstract

Weakly-supervised semantic segmentation (WSSS) is challenging, particularly when image-level labels are used to supervise pixel-level prediction. To bridge their gap, a Class Activation Map (CAM) is usually generated to provide pixel-level pseudo labels. CAMs in Convolutional Neural Networks suffer from partial activation i.e. only the discriminative regions are activated. Transformer networks, on the other hand, are highly effective at exploring global context, potentially alleviating the partial activation issue. In this paper, we introduce the Gradient-weighted Element-wise Transformer Attention Map (GETAM) and propose the first transformer-based WSSS approach. GETAM can show fine scale class-wise activation, revealing different parts of the object across transformer layers. Further, we propose an activation-aware label-completion module to generate high-quality pseudo labels. Finally, we incorporate the proposed methods into an end-to-end framework for WSSS using double-backward propagation. Extensive experiments on PASCAL VOC and COCO dataset demonstrate that our results outperform not only the state-of-the-art end-to-end approaches by a significant margin, but also most of the multi-stage methods.

1. Introduction

Recent work on 2D image semantic segmentation has achieved great progress via deep fully convolutional neural networks (FCNs) \cite{long2015fully}. The success of these models \cite{zhou2014dual, zhang2016context,liu2017pspnet} comes from large training datasets with pixel-wise labels, which are laborious and expensive to obtain. To relieve the labeling burden, multiple types of weak labels have been explored, including image-level labels \cite{zhou2014dual, leiva2014crowdsource, shin2017cascaded}, points \cite{chen2015semantic}, scribbles \cite{yuan2016end, nair2015scribblesup} and bounding boxes \cite{long2016fully, yu2016multi, luo2016multi, zou2017scale}. In this paper, we focus on weakly-supervised semantic segmentation (WSSS) with image-level labels.

To bridge the gap between pixel-level classification and image-level annotation, it is essential to localize object classes in the image from image-level labels. Most WSSS methods rely on the Class Activation Map (CAM) \cite{zhou2014dual} as initial seeds from the image-level label to learn pixel-level labeling. Typical multi-stage image-level WSSS methods usually adopt progressive steps \cite{zhou2014dual, shin2017cascaded, lee2016iterative, liu2017pspnet, li2018enriching, liu2018fusionseg, liu2018multilevel}: 1) training a CNN classifier to obtain object activation maps \cite{zhou2014dual, shin2017cascaded, lee2016iterative, liu2017pspnet}; 2) refining the maps with non-learning \cite{liu2018fusionseg} or learning based methods \cite{lee2016iterative, shin2017cascaded} to obtain pseudo labels; and 3) using these pseudo labels for fully-supervised training of an off-the-shelf semantic segmentation network, such as Deeplab \cite{chen2018deeplab}. Alternatively, recently end-to-end WSSS methods have become more prevalent \cite{chen2018parsing, liu2018fusionseg, liu2018multilevel}. In both cases, the quality of the initial response map plays a key role in WSSS. However, it is recognized by many approaches \cite{zhou2014dual, shin2017cascaded, lee2016iterative, chen2018parsing, chen2018hybrid, liu2018fusionseg, liu2018multilevel, li2018enriching} that CAMs suffer from two issues: 1) CAMs tend to only activate the discriminative regions of objects; 2) the rough object activation of CAMs loses accurate object shapes. The main causes of above issues are limited receptive fields and the progressively down-sampled CNN feature maps.

Transformers \cite{vaswani2017attention} have achieved great success in various
computer vision tasks, but transformer-based WSSS is yet to be well studied. We argue that transformers have several appealing mechanisms for WSSS. First, transformers are highly effective at exploring global context with long-range dependency modelling. Hence, one would expect they could address issues regarding the limited visual field of CNNs. Also, after computing the initial embedding, vision transformers have a constant global receptive field at every layer with constant dimensionality, which could retain more accurate structure information [45, 49]. Further, transformers use self-attention to spread activation across the entire feature map rather than just discriminative regions, leading to more uniform activation. We show that these properties are beneficial for generating object activation maps, as well for other dense prediction tasks [5, 42, 49, 54, 63].

Unfortunately, we observe extensive noise if we simply transplant the conventional CAM [81] into vision transformers (Fig. 2). Such noise leads to poor performance and is believed to arise along with the global context of the transformer architecture [79]. To address this, we closely study activation and propagation of the feature maps through transformer layers. Particularly, we explore element-wise weighting to couple the attention map (i.e. $Q \times K$) with its squared gradient to place greater emphasis on the gradient. Further, as attention is progressively propagated and refined through the transformer layers, it reveals different parts of the object. We sum the attention maps through transformer layers, leading to more uniformly activated object maps, as shown in Fig. 1. We refer to this as the Gradient-weighted Element-wise Transformer Attention Map (GETAM). After obtaining class-wise attention maps, we propose activation-aware label completion, combining the obtained object activation with off-the-shelf saliency maps to generate pseudo segmentation labels. In this way, we refine foreground object masks and actively discover objects in the background, leading to high-quality pseudo labels.

Finally, we propose a double-backward propagation mechanism to implement our framework in an end-to-end manner. Most WSSS methods require multiple stages, involving multiple models with different pipelines and tweaks, making them hard to train and implement. Although the existing end-to-end approaches [3, 47, 48, 73, 74, 78] are elegant, they show substantially inferior performance to multi-stage methods. Our method is easy to implement and extensive experiments on the PASCAL VOC [18] and COCO [41] datasets verify its effectiveness.

Our contributions can be summarised as: 1) We introduce the first weakly-supervised semantic segmentation framework based on vision transformer networks. The key to its performance is the Gradient-weighted Element-wise Transformer Attention Map (GETAM), capturing better object shapes than traditional CAMs. 2) We present activation-aware label completion guided by saliency maps to generate high-quality pseudo labels. 3) We propose a double-backward propagation mechanism to integrate our method in an end-to-end manner. Despite its simplicity, our method greatly boosts the performance of single-stage WSSS, and it is the first one to be competitive with multi-stage methods.

2. Related Work

2.1. Weakly Supervised Semantic Segmentation

To save labeling cost, various WSSS methods have been proposed, including those using image-level labels [2, 8, 37, 47, 66, 72, 74], scribbles [40], points [6], and bounding boxes [15, 36, 46, 57]. We mainly focus on image-level models. They can be grouped into two families: multi-step, and one-step methods.

2.1.1 Multi-step methods

[2, 7, 8, 23, 30, 37, 66, 72, 74, 77] refine one or multiple sub-modules within the multi-model framework. Among them, [2] predicts semantic affinity between a pair of adjacent image coordinates supervised by initial activation, the network is then used to guide a random walk to generate pseudo labels. [7, 23] utilize Mixup data augmentation to calibrate uncertainty in prediction. They randomly mix an image pair to force the model to pay attention to extra regions in the image. [37] directly uses saliency maps to constrain object activation during classification training, so the CAMs can better follow object shapes.

2.1.2 One-step methods

[47] adopts an expectation-maximisation mechanism, where intermediate predictions are used as segmentation labels. [74] presents an end-to-end framework to train classification and segmentation simultaneously, and integrates a method to obtain reliable segmentation pseudo labels. [3] introduces normalised Global Weighted Pooling (nGWP) to obtain better CAMs for segmentation, and adopts a Stochastic gate to encourage information sharing between deep features and shallow representations to deal with complex scenes. With all above solutions, end-to-end WSSS is still far from being well-studied, and has clear performance gaps from multi-step methods.

2.2. Network Visualization

Various works have been proposed for network visualization and are leveraged for tasks like weak semantic segmentation and weak object localization. CAM [81] replaces the first fully-connected layer in image classifiers with a global average pooling layer to calculate class activation
3. Revisiting CAM in ViT

In this section, we revisit conventional CAMs [2] used in most WSSS methods. We present a pilot experiment to investigate different activation mechanisms in convolutional and transformer backbones, demonstrating that the conventional CAM [81] and Grad-CAM [52] methods used in existing WSSS methods cannot be trivially transplanted to transformer-based approaches.

To generate a CAM in a CNN network, [81] feeds convolutional feature maps \( f \) into global average pooling (GAP) followed by a fully-connected layer to produce a categorical output. For an image \( I \), activation maps for category \( c \) are defined as: \( A^c(x, y) = \theta^c_p f(I(x, y)) \), where \( \theta^c_p \) is the classifier’s weight for class \( c \) and \( f(I(x, y)) \) is the extracted feature at location \((x, y)\). Then, we copy the same CAM structure to the transformer. Given the extracted feature maps \( O \in \mathbb{R}^{n \times d'} \), we obtain \( O[1:] \in \mathbb{R}^{n \times d} \), where \( n = h \times w \) is the input image patch size, and \( d \) is the feature embedding dimension. The first row \( O_{CLS} \in \mathbb{R}^{1 \times d} \) is the \([\text{class}]\) token. We explore two strategies to manipulate \( O_{CLS} \) and generate a feature map \( O \in \mathbb{R}^{n \times d} \). First, we add \( O_{CLS} \in \mathbb{R}^{1 \times d} \) to every location of \( O[1:] \in \mathbb{R}^{n \times d} \), we denote this method as \( \text{CAM}(\text{add}) \) in Fig. 2. Second, we ignore \( O_{CLS} \in \mathbb{R}^{1 \times d} \), and simply feed \( O[1:] \) into linear classifier, we denote this method as \( \text{CAM}(\text{ignore}) \) in Fig. 2.

As shown in Fig. 2, if we simply follow the conventional method, the transformer CAMs are flawed, i.e., the activation is not correctly located on targeted objects and cannot be used to generate pseudo segmentation labels. Due to the self-attention mechanism, every feature map location encodes information from the entire image in a fully connected manner. However, classification loss is indifferent to extensive activation across objects, requiring only a sufficient pooled global average value. So per-location features may not contribute to local classification predictions, and activation shows noise across the image, or can be completely wrong. Reliable CAMs are crucial for WSSS, but CNN-based CAMs cannot be naively migrated into vision transformers, i.e., changing backbones of current WSSS methods to transformers is non-trivial.

4. Approach

We show the overview of our framework in Fig. 3. Firstly, we introduce GETAM (Gradient-weighted Element-wise Transformer Attention Map), which generates better class-wise attention maps with image-level labels. Then, we introduce activation aware-label completion, which uses saliency information to produce high-quality pseudo segmentation labels. Finally, we present our double-backward propagation approach to implement our method into a single-stage framework.

4.1. GETAM

As discussed in Sec. 3, conventional CAM generation methods used in CNN backbones fail to generate reliable CAMs in transformers. Thus, inspired by Grad-CAM [52], we design a gradient-based method to obtain class-wise attention maps for vision transformers. Note that our method is substantially different to Grad-CAM [52], albeit also based on gradients. In Grad-CAM [52], classification predictions are back propagated to the output feature maps of the final convolutional layer. The obtained gradients are global average pooled, and used to weigh neuron importance of the feature maps.

However, transformer networks use different structures for predictions. A transformer network consists of several successive transformer blocks, each composed of multi-head self-attention modules and feed-forward connections. The \( i^{th} \) self-attention module on one of the multiple heads in a transformer block is defined as:

\[
\text{Attention}(Q^i, K^i, V^i) = \text{softmax} \left( \frac{Q^i K^i V^T}{\sqrt{d}} \right) V^i = A^i V^i, \tag{1}
\]

where \( Q^i, K^i, V^i \) are query, key and value matrices \( \in \mathbb{R}^{(n+1) \times d} \), \( n \) is number of patches \((n = w \times h)\) and \( d \) is...
feature dimensions. The \([\text{class}]\) is an extra learnable token in the first row of these matrices [17]. As shown in Fig. 5, \(A^i \in \mathbb{R}^{n \times n}\) is the attention matrix which encodes the attention coefficient between any two positions in input images, i.e., every image token has contextual information from all other tokens. Consequently, the \([\text{class}]\) token attends to all token information across the image. However, it is not affected by itself as it does not represent an image location. We define \(A^i[0,1:] = A^i_{\text{CLS}} \in \mathbb{R}^n\). We can reshape \(A^i_{\text{CLS}}\) back to the image shape \(A_{\text{CLS}} \in \mathbb{R}^{h \times w}\), and obtain a class-agnostic attention map, where every position in the map denotes its contribution to classification. In every transformer block with multiple self-attention heads, we define \(A^i_{\text{CLS}}\) as the average across all heads for simplicity. As empirically verified in [22], \(A^i_{\text{CLS}}\) aggregates attention from all heads to display the object extent that possibly contributes to classification predictions (see the leftmost column of Fig 4).

As \(A^i_{\text{CLS}}\) is class agnostic, we couple it with its gradients \(\nabla A^i\) to obtain the class-wise attention map. We back-propagate the classification score \(y^c\) for each class \(c\). The graph is differentiated using the chain rule through the transformer network. In the \(i^{th}\) block, the gradient map \(\nabla A^{i,c}\) is obtained with respect to the attention matrix \(A^i\). Referring to Fig. 5, we extract the corresponding gradient map \(\nabla A^{i,c}_{\text{CLS}} \in \mathbb{R}^n\) of \(A^i_{\text{CLS}}\) with respect to class \(c\). As discussed in [9, 29, 52], a positive gradient corresponding to a location in the feature map indicates that it has a positive influence on the prediction score of the target class. We find that this assertion still holds in vision transformers. Each position in \(\nabla A^{i,c}_{\text{CLS}}\) indicates the contribution of this token to the classification output of class \(c\).

Figure 3. Overview of the proposed end-to-end WSSS framework. We back-propagate classification predictions, and compute the sum of class-wise attention maps from cascaded transformer blocks. Then we generate high-quality pixel-wise pseudo labels guided by saliency maps. We mainly use the pseudo segmentation labels to supervise the segmentation branch of our vision transformer in an end-to-end manner. However, it can also be used to train a separate semantic segmentation network, as a conventional multi-stage method (see Section 5.2.3).

Figure 4. Visualizations of class-agnostic attention maps (leftmost column) and class-wise gradient maps (rightmost column). Class-agnostic attention maps show the regions that possibly contribute to the classification predictions. Class-wise gradient maps display class specific regions and retain clear object shapes. Recommend viewing digitally.

Figure 5. GETAM generation in a transformer block. \(A^i_{\text{CLS}}\): the class-agnostic attention map. \(\nabla A_{\text{CLS}}\): the class-wise gradient map.
4.1.1 Attention Gradient Coupling

We observe that $A_{CLS}^i$ shows class-agnostic areas with possibly targeted objects and relatively clean background. Further, we find $\nabla A_{CLS}^i$ is noisy but retains more complete and clear object shapes in comparison (see rightmost column of Fig. 4).

Based on the above observations, we propose to combine the attention map and its gradient inside every transformer block to generate reliable class-wise attention as shown in Fig. 5. Formally, the class-wise attention map of block $i$ for class $c$ is defined as:

$$\text{GETAM}_{c}^i = \text{ReLU} \left( \nabla A_{CLS}^i \odot A_{CLS}^i \right) \odot \text{ReLU}(\nabla A_{CLS}^i)$$

We first use an element-wise multiplication $\odot$ to couple the attention map $A_{CLS}^i$ with its gradient map $\nabla A_{CLS}^i$. Then, we perform another element-wise multiplication with $\text{ReLU}(\nabla A_{CLS}^i)$. Different from Grad_CAM which uses a Global Average Pool of the Gradients, our attention map is weighted element-wise by the square of the gradient, and negative responses of attention and gradients are eliminated by the ReLUs. Our Attention-Gradient coupling can better harvest spatial locations that have positive contributions to the targeted class, while suppressing noisy regions. Squaring places greater emphasis on the gradient as it shows more complete object shapes than the CAMs.

4.1.2 Successive Attention Aggregation

After obtaining the class-wise attention map in a single transformer block, here we present an analysis on how to aggregate class attention maps from cascaded transformer blocks. As commonly recognized by existing WSSS methods [56,56,58,66,76], the attention maps should not respond too sparsely (i.e., only highlighting discriminative regions), nor be overly smoothed. Based on the above requirements, we first visualize the class-wise attention maps from different transformer blocks in Fig. 6. Unlike CNNs where low-level features contain too much noise that buries useful information [29,67], we observe that the cascaded maps in vision transformers tend to focus on discriminative regions. For instance, in Fig. 6 (bottom), attention maps from different layers reveal different regions of the cat (e.g., cheek, nose, chin, body and hand). Thus, it is crucial to choose an appropriate fusion method to combine different class-wise attention maps.

In this view, we present a numerical analysis of different fusion approaches (Fig. 7). On the PASCAL VOC [18] training set, we apply three commonly adopted operations (element-wise multiplication, summation and matrix multiplication) to fuse the successive maps, and then visualize the distributions of the fused results after normalization. As illustrated in Fig. 7, element-wise multiplication will concentrate the values and most areas are suppressed, since the

![Figure 6. Sample attention maps from successive transformer blocks of our trained model in one forward pass. The cascaded maps focus on different object regions without low-level noise. In the first row, the network focuses on different people in the foreground and background separately at different layers. Recommend viewing digitally.](image)

![Figure 7. Distributions of class-wise attention maps using different fusion methods. Element-wise multiplication concentrates the distribution, but suppresses most areas. Matrix multiplication (dot production) smooths the attention, leading to additional noises.](image)

activation is canceled if the value is low in any level of the transformer. Contrarily, matrix multiplication (dot production) will smooth the attention, leading to additional noise in non-object regions. Based on the above analysis, we propose summation aggregation across cascaded attention maps, which encourages the final class-wise attention maps to cover accurate object areas and does not over-smooth them. Formally, the attention maps are added through $L$ layers of the vision transformer:

$$\text{GETAM}_{c} = \sum_{i=1}^{L} (\text{GETAM}_{c}^i)$$

Fig. 6 shows that GETAM from the cascaded blocks (Eq. 3) captures reliable object shapes and suppresses noise. See supplementary material for qualitative comparison.

4.2. Activation Aware Label Completion

GETAM generates reliable class-wise attention maps. However, the activation maps require refinement, so they can be served as pseudo segmentation labels. To achieve this, we first adopt pixel adaptive mask refinement (PAMR) [3], a parameter-free recurrent module that efficiently refines pixel labels using local information. Then, we pro-
pose saliency constrained object masking and high activation object mining to obtain high-quality pseudo labels. The two solutions work collaboratively to support accurate segmentation of salient objects, but do not suppress non-salient objects.

4.2.1 Saliency Constrained Object Masking

We observe that due to the global context of self-attention, candidate regions that may contribute to classification are activated, leading to high recall of our activation maps for targeted objects. Saliency maps from off-the-shelf models can provide precise foreground object shapes and have been used as background cues to many WSSS approaches [19, 28, 34, 37, 55, 65, 71]. Using a novel approach, we leverage the saliency mask to constrain activated object regions, which is particularly necessary in our case for GETAM to combat additional activation on object boundaries.

First, based on object activation maps $M_{fg} = \text{GETAM} \in \mathbb{R}^{C \times h \times w}$ which have $C$ foreground classes, we calculate an arbitrary background channel in a similar way to [2]:

$$M_{bg} = \left[1 - \max_{c \in C_{fg}} \left(M_{fg}^c(i)\right)\right]^{-\gamma},$$

where $\gamma > 1$ is a parameter to adjust background labels and $i$ is the pixel position. Then we concatenate $M_{bg}$ onto $M_{fg}$ to form activation maps $M$, and use $\text{argmax}(M)$ to find the per-pixel highest activation. After that, we can locate all possible objects in both salient and non-salient regions with rough boundaries, as shown in Fig. 8 (a). Then we adopt saliency maps to refine object boundaries of $M$, where the current temporary background (0) is set to unknown (255) and all non-salient regions are set to background (0). This is based on the observation that the saliency maps normally provide accurate object boundaries [37, 64, 71]. Formally, consider activation maps $M$ with saliency map $S$, then pixel $i$ of our pseudo label $P_{seg}$ is:

$$P_{seg}(i) = \begin{cases} 
  c & \text{argmax}(M) = c, S(i) = 1 \\
  255 & \text{argmax}(M) = 0, S(i) = 1 \\
  0 & S(i) = 0 
\end{cases}.$$  

4.2.2 High Activation Object Mining

With saliency constrained object masking, we obtain $P_{seg}$, where the structure of the instances that are consistent with salient objects is refined. However, recall that existing salient object detection models are trained with class-agnostic objects and center bias, and so non-salient objects may masked as background. As shown in Fig. 8(b), the TV monitor and potted plant are mislabeled as background. We then propose a high activation object mining strategy to solve this issue.

GETAM can correctly locate all desired objects in both salient and non-salient regions as shown in Fig. 8(a). For class $c$, we find high confidence regions by searching for pixels with activation greater than a threshold $\alpha$ in non-salient regions. We treat these as pseudo labels of class $c$ in the background (see Fig. 8(c)). In addition, we maintain another high-confidence conflict mask $M_{\text{conflict}}$ to register conflict areas in non-salient regions. That is, if a pixel is highly activated by more than one class in the background, we regard it as conflict and label it as unknown (255) to avoid introducing incorrect labels. Formally, high activation object mining is defined:

$$P_{seg}(i) = \begin{cases} 
  c & M(i) > \alpha, M_{\text{conflict}}(i) = 1, S(i) = 0 \\
  255 & M(i) > \alpha, M_{\text{conflict}}(i) > 1, S(i) = 0 \\
  0 & M(i) < \alpha, S(i) = 0 
\end{cases}.$$  

Figure 8. Activation aware label completion module. (a) First locate all objects with activation maps. (b) With the saliency constraint, we obtain accurate shape for salient objects, however, non-salient objects are suppressed. (c) High activation mining correctly locates suppressed background objects. Enlarge the figure by 3 times for best viewing.

We give a quantitative comparison of our pseudo labels to other methods in Table 3. Our high-quality pseudo labels can be directly used to supervise an off-the-shelf semantic segmentation model. They can also supervise a segmentation branch of the same vision transformer backbone in an end-to-end manner (detailed below).

4.3. Single-stage Double-backward Propagation

Most current WSSS methods [8, 23, 30, 66, 72, 74, 77] require multiple steps, generally involving training multiple models with different pipelines and tweaks. Interdependencies between the steps can easily influence final performance. However, the vision transformer shows properties that are especially advantageous for dense prediction
tasks like semantic segmentation [5, 42, 49, 63]. Hence, we propose an unified framework to train our WSSS method in an end-to-end manner. As shown in Fig. 3, the framework has two parallel branches, i.e., a classification and a semantic segmentation branch. Both branches share the same vision transformer backbone, and update the entire network simultaneously during training.

As illustrated in Fig. 9, the core of our approach is double-backward propagation. That is, the network back propagates to compute GETAM without updating to obtain pseudo labels, then back propagates again to optimize the network supervised by these pseudo labels. Each iteration consists of two back propagation operations but the network is only updated once. Specifically, we first perform a forward pass to produce classification predictions $Y$ without calculating the classification loss. Then, for the target class $c$, we back propagate its output $y^c$ to obtain GETAM. We iterate to obtain class-wise attention maps for every class appearing in the image, and use them to generate pseudo segmentation labels. In the second back propagation step, we clear the gradients and perform another forward pass to generate classification and semantic segmentation predictions. With the pixel level pseudo labels and image level labels, we train our network with classification and segmentation predictions from the second back propagation. Back propagating GETAM leads to improved localization of objects and segmentation performance. The proposed double-backward propagation does not rely on multi-step WSSS training, and shows competitive performance (see Table 5).

5. Experiments
5.1. Setup and Implementation Details

Our method is evaluated on the PASCAL VOC [18] and MS-COCO datasets [41]. PASCAL VOC [18] has one background and 20 foreground classes. The official dataset consists of 1,446 training, 1,449 validation and 1,456 test images. We follow common practice [24], augmenting the training set to form a total of 10,582 images. MS-COCO 2014 [41] contains 81 classes including the background class with 80k train and 40k val images and more complex scenes, which is more difficult for WSSS. In addition, we adopt [45] as our saliency detection model by re-implementing it to generate saliency maps on both datasets. The backbone network of our end-to-end framework is ViT [17]. We also test our method on other backbones including ViT-Hybrid [17], Deit [60] and Distilled Deit [60].

Our end-to-end framework has two branches, i.e., classification branch and segmentation branch, and they share the same vision transformer backbone. For the segmentation branch, we adopt the decoder from [49]. We train our network for 20 epochs, separated into two stages. In the first 10 epochs we only update the classification branch in order to generate reliable class attention maps. In the remaining 10 epochs we switch on the segmentation branch and simultaneously optimize two branches. Further, our generated pseudo labels can also be used in a multi-stage fashion, we use the pseudo labels to train Deeplab v2 [13] with the ResNet-101 backbone. Our model is implemented with PyTorch, with reproduction details in the supplementary material.

5.2. Ablation Studies

5.2.1 Effectiveness of GETAM

The proposed GETAM is a class-wise activation visualization method for vision transformers. We explore different ways of generating CAMs on transformer backbones and report their performances on PASCAL VOC as shown in Table 1. First, we directly leverage CAM [81] and Grad,CAM [53] on vision transformers as baselines. The proposed GETAM achieves significant improvements over CAM and Grad,CAM (+16.4 mIoU and +9.2 mIoU), demonstrating that it is non-trivial to directly use existing visualization methods on the transformer networks. TS,CAM [22] is a transformer based localization method, we follow its implementation and report the segmentation result. Furthermore, in GETAM we propose to couple the attention maps with the square of corresponding gradients, we implement a variation that we directly compute the element-wise product of the attention maps and gradient maps, we denote this method as \( \text{Att} \odot \text{Gradients} \). Our GETAM achieves a 2.6 mIoU improvement over this variation. It verifies the effectiveness of the coupling strategy of GETAM.

5.2.2 Effectiveness of Activation Aware Label Completion

We propose activation aware label completion to generate pseudo labels from CAMs. In Table 2, we demonstrate that the proposed Activation Aware Label Completion brings improvements over the CRF-based method under two settings. For the CNN network it improves the baseline [74] by 2.1 mIoU, for the ViT network the improvement is 7.7
Figure 10. Visualization examples of activation maps from different methods. (a) Image; (b) CNN-based CAM [81]; (c) ViT-based Grad-CAM [53]; (d) GETAM. GETAM can better capture object shapes and suppress noise than regular CAMs.

| Method       | Backbone | CAM generation | mIoU(val) |
|--------------|----------|----------------|-----------|
| CNN          | CAM      |                | 64.7      |
| ViT          | TS_CAM   [22] |              | 49.7      |
| ViT          | CAM      |                | 55.3      |
| ViT          | Grad_CAM |                | 62.5      |
| Ours         | ViT      | GETAM          | 71.7      |

Table 1. Ablation of different CAM generation methods. \textit{Att} $\odot$ \textit{Gradients} denotes directly computing the element-wise production of the attention maps and gradients.

| Model | Backbone | CAM generation | Pseudo generation | mIoU(val) |
|-------|----------|----------------|------------------|-----------|
| RRM   | CNN      | CAM            | CRF              | 62.6      |
|       | CNN      | CAM            | AA               | 64.7      |
| Ours  | ViT      | GETAM          | CRF              | 64.0      |
|       | ViT      | GETAM          | AA               | 71.7      |

Table 2. Ablation of pseudo label generation methods. We use bold to indicate our proposed components. AA: activation aware label completion module. It shows that activation aware label completion improves results on both CNN and ViT backbones.

mIoU. This validates that our activation aware label completion helps generate better pseudo labels from the activation maps on both CNN and transformer backbones.

5.2.3 Pseudo Label Quality

Pseudo label quality is crucial to segmentation performance for WSSS. We extract the generated pseudo labels in our end-to-end training process and evaluate them for quality with the PASCAL VOC ground-truth. The results in Table 3 show that the pseudo segmentation labels of GETAM outperform all end-to-end methods. Further, recent state-of-the-art multi-step approaches focus on obtaining pseudo labels using sophisticated pipelines and training multiple networks, our pseudo labels are still comparable to the best of these. In addition, we trained deeplabv2 [13] using our pseudo labels in an multi-stage manner and achieve a 70.6 mIoU on the PASCAL validation set. We report single-stage methods in Table 5.

5.2.4 Results with Different Vision Transformer Backbones

We investigate different vision transformer backbones including ViT, ViT-Hybrid [49], Deit and Deit-Distilled [60] in our end-to-end WSSS framework, where all networks have 12 transformer layers. In ViT_Hybrid, we aggregate attention maps from last 6 layers so as to decrease low-level noise from convolution, while in other backbones we aggregate attention from all 12 layers \(^1\). As reported in Table 4, our method performs consistently better than the previous state-of-the-art single-stage method AALR [78], validating the effectiveness of our approach. The efficiency of the proposed GETAM on various backbones also makes it a visualization tool for transformer networks(Fig. 10). It is widely recognized that convolutional structures in transformers

\(^1\)We refer the reader to the supplementary material for ablation.

Table 1. Ablation of different CAM generation methods.

Table 2. Ablation of pseudo label generation methods.

Table 3. Pseudo label mIoU on PASCAL VOC \textit{train} and \textit{val} set. Our results are obtained on ViT-Hybrid [17].

Table 4. Performances on different vision transformers. Our method performs consistently better.
provide performance gains in vision tasks [16, 17, 68]. Here we can see that ViT-Hybrid achieves the best performances among these backbones.

### 5.3. Comparison to the State-of-the-art Methods

#### 5.3.1 PASCAL VOC

In Table 5, we give a detailed comparison of our proposed approach with other WSSS methods. In the single-stage section, we achieve significantly improved performance over all existing end-to-end methods. Comparing to previous state-of-the-art method AALR [78], we have an impressive 7.8% mIoU increase. Compared to multi-stage methods, our result based on ViT_Hybrid (71.7 mIoU on val and 72.3 mIoU on test) achieves new state-of-the-art on PASCAL VOC. And our single-stage performances with other transformers including ViT, Deit, and Deit_Distilled are also significantly ahead of existing single-stage approaches, and competitive with multi-stage ones, showing the robustness of GETAM to transformer backbones. Notably, our approach is the first single-stage method that outperforms the multi-stage methods, which employ sophisticated pipelines and train multiple networks. For example, the previous state-of-the-art URN [38] requires three stages with many inter-dependencies, our single-stage method still outperforms it by 0.5 mIoU on val and 0.8 mIoU on test.

#### 5.3.2 MS-COCO

To further demonstrate the proposed method's effectiveness across different datasets, we evaluate it on the challenging MS-COCO dataset [41]. As shown in Table 6, our method achieves 36.4% mIoU on val and 36.7% mIoU on test. GETAM is the first end-to-end method evaluated on MS-COCO that performs on par with existing methods.
on PASCAL VOC (Table 5), which demonstrates promising ability when trained over different datasets. Notably, our method is the first end-to-end WSSS method that has reported a result on MS-COCO which saves on training complexity.

6. Conclusion

In this paper, we propose a vision transformer based WSSS framework by exploring the activation mechanism for transformers. Specifically, we propose a new transformer-based activation visualisation approach, GETAM. It generates class-wise attention maps that can better capture the object shape compared to previous methods. Based on GETAM, we introduce an activation aware label completion module to generate high-quality pseudo labels, it adopts saliency information to refine foreground object masks without suppressing background objects. Finally, we present a novel double-backward propagation scheme to integrate the proposed modules into an end-to-end training framework. We validate GETAM on weakly supervised semantic segmentation task, extensive experimental results on both multi-stage and single-stage training show the effectiveness of our method with different transformer backbones. The proposed method offers a new perspective for WSSS using vision transformers, and we believe that it can further facilitate related research areas.

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