BBAM: Bounding Box Attribution Map for Weakly Supervised Semantic and Instance Segmentation

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Abstract

Weakly supervised segmentation methods using bounding box annotations focus on obtaining a pixel-level mask from each box containing an object. Existing methods typically depend on a class-agnostic mask generator, which operates on the low-level information intrinsic to an image. In this work, we utilize higher-level information from the behavior of a trained object detector, by seeking the smallest areas of the image from which the object detector produces almost the same result as it does from the whole image. These areas constitute a bounding-box attribution map (BBAM), which identifies the target object in its bounding box and thus serves as pseudo ground-truth for weakly supervised semantic and instance segmentation. This approach significantly outperforms recent comparable techniques on both the PASCAL VOC and MS COCO benchmarks in weakly supervised semantic and instance segmentation. In addition, we provide a detailed analysis of our method, offering deeper insight into the behavior of the BBAM. The code is available at: https://github.com/jbeomlee93/BBAM.

1. Introduction

Object segmentation is one of the most important steps in image recognition. Advances in deep learning have greatly improved the performance of semantic and instance segmentation [8, 23] through the use of huge amounts of pixel-level annotated training data. However, annotating with pixel-level masks requires a lot of effort. According to Bearman et al. [4], constructing a pixel-level mask for an image containing an average of 2.8 objects takes about 4 minutes. This is why weakly supervised methods have been proposed, in which segmentation networks are trained using annotations that are less detailed than pixel-level masks, such as bounding boxes [11, 31, 60], or image-level tags [1, 2, 36].

The most easily obtainable annotation is the class label. Labeling an image with class labels takes around 20 seconds [4], but it only indicates that objects of certain classes are depicted and gives no information about their locations in the image. Moreover, class labels provide no help in separating different objects of the same class, which is the goal of instance segmentation.

Bounding boxes provide information about individual objects and their locations. Bounding box annotations take about 38.1 seconds per image [5], which is much more attractive than constructing pixel-level masks. Many researchers have tackled semantic segmentation [11, 31, 34, 60] and instance segmentation [3, 27, 31, 40, 62] using bounding box annotations as a search space in which a class-agnostic object mask can be found by an off-the-shelf object mask generator. These are mostly based on GrabCut [53] or multiscale combinatorial grouping (MCG) [49]. Those mask generators operate on the low-level information of images, such as the color or brightness of pixels, and this limits the quality of the resulting mask. Thus, applying these mask generators to bounding box annotations requires additional steps such as estimating what proportion of the pixels in a bounding-box belong to the corresponding object [34, 60], iterative refinement of an estimated mask [11], and auxiliary attention modules [34].

We propose a pixel-level method of localizing a target object inside its bounding box using a trained object detector. We make use of attribution maps obtained from the trained object detector, which highlight the image regions that the detector focuses on in conducting object detection. Inspired by the perturbation methods used to explain the output of image classifiers [10, 17, 18], we introduce a bounding box attribution map (BBAM) which provides an indication of the smallest areas of an image that are sufficient to make an object detector produce almost the same result as that from the original image. The BBAM identifies the area occupied by the object in each bounding box predicted by the trained object detector. Since this localization takes place at the pixel level, it can be used as a pseudo ground truth for weakly supervised learning of semantic and instance segmentation.
The main contributions of this paper can be summarized as follows.

- We propose a bounding box attribution map (BBAM), which can draw on the rich semantics learned by an object detector to produce pseudo ground-truth for training semantic and instance segmentation networks.
- Our technique significantly outperforms previous state-of-the-art methods of weakly supervised semantic and instance segmentation, assessed on the PASCAL VOC 2012 and MS COCO 2017 benchmarks.
- We analyze our method from various viewpoints, providing deeper insights into the properties of the BBAM.

2. Related Work

Fully supervised semantic and instance segmentation based on pixel-level annotations is highly reliable, but the manual annotation process is laborious. This requirement is overcome by weakly supervised methods based on inexact, but easily obtainable, annotations such as scribbles [63], bounding boxes [31, 66], or class labels [1, 36, 61]. In this section, we briefly review some recently introduced weakly supervised approaches that use class labels (Section 2.1) or bounding boxes (Section 2.2). In addition, we describe some visual saliency methods related to our method (Section 2.3).

2.1. Learning with Class Labels

A class activation map (CAM) [69] is a widely adopted technique to obtain a localization map from class labels. However, a CAM only identifies the most discriminative regions of objects [36, 37], and hence the majority of existing methods that use class labels [2, 15, 24, 25, 28, 30, 36, 37, 38, 39, 58] are primarily concerned with expanding the area of the target object activated by a CAM. For instance, erasure methods [25, 64] iteratively find new regions of the target object by removing discriminative regions in an image. Other methods [15, 61] consider the information shared between several images by capturing cross-image semantic similarities and differences. Seed growing and refinement techniques [1, 2, 28] are typically used to expand the regions representing the target object imperfectly that are in the initial CAM, on the basis of relationships between pixels. Other methods construct CAMs that embody the multi-scale semantic context in an image [36, 38, 65]. Despite these efforts, the information available from class labels remains limited, so auxiliary information acquired from web images [56] or videos [24, 37] can be used together.

2.2. Learning with Bounding Boxes

Class labels have led to significant achievements in semantic segmentation, but they are inherently unhelpful in instance segmentation, which requires the separation of different objects of the same class. In contrast, bounding boxes do provide information about the location of individual objects in an image, and they are still much cheaper than constructing pixel-level masks [5]. Most existing methods utilized a bounding box as a search space to conduct low-level searches for object masks. They create a pseudo mask within a box using off-the-shelf methods of mask proposal such as MCG [49] or GrabCut [53]. These processes can be guided by specifying the proportion of the pixels in a bounding box that are likely to belong to the object [34, 60]. Iterative mask refinement techniques [11] can also be applied. However, these methods are largely based on low-level information in the image, and they ignore the semantics associated with the bounding boxes. A rare exception is the multiple-instance learning formulation with a bounding box tightness prior [27]: a crossing line within a box must contain at least one pixel of the target object. The drawback with this approach is that only a small number of pixels are contributing to the localization of the object.

2.3. Visual Saliency Methods

Various methods have been proposed to visually explain the predictions of deep neural networks (DNNs) [6, 17, 18, 54, 69] in a form of a saliency map. However, most studies have been concerned with classifiers, and only a few have looked at DNNs performing other tasks [26, 51]. In particular, there have been no attempts to explain the predictions of object detectors, except Wu et al. [66], who embedded interpretability inside the DNN, in this case Faster R-CNN [52]. However, the explanation produced by their modified DNN is not immediately understandable because it is given as a form of tree, and thus it is not appropriate to generate pseudo ground truth for weakly supervised segmentation. Gradient-based methods, such as SimpleGrad [68], SmoothGrad [59], and Grad-CAM [55], can provide visual saliency maps of the results from classifiers, but these methods are not easily extended to object detectors, because of the structural difference between classifiers and object detectors. Nevertheless, gradient-based methods have a significant bearing on our approach, and we look at them in more detail in Section 5.

3. Method

We first provide a brief description of the operation of object detectors in Section 3.1. In Section 3.2, we introduce the BBAM for localizing objects in the bounding box. We then utilize the BBAM for weakly supervised semantic and instance segmentation in Sections 3.3 and 3.4.

3.1. Revisiting Object Detectors

Modern object detectors can be divided into two categories: one-stage [41, 43, 50] and two-stage [20, 52] approaches. We focus on two-stage object detectors such as Faster R-CNN [52], in which the two stages are region proposal and box refinement. A region proposal network (RPN)
where \( M \) specifies a subset of the image in terms of the perturbation
unnecessary information reaching the detector. The mask
as the original image. A small
subset of the image that produces almost the same prediction
\( M \) to perform object detection. We find the smallest mask
respectively. We omit the proposal indices
bounding box annotations. We also have a set of object
3.2. Bounding Box Attribution Map
respectively.

Bounding box regression head. It adjusts the noisy
proposal to fit the object by computing the offsets \( t^c = (t^c_x, t^c_y, t^c_w, t^c_h) \) for each class \( c \in \{1, 2, \cdots, C\} \). The final
localization is obtained by shifting each coordinate of the
proposal using the offset \( t^c \). We refer to Ren et al. [52]
for the details of the parameterization of each coordinate.

For simplicity, we will abbreviate classification head and
bounding box regression head as cls head and box head,
respectively.

3.2. Bounding Box Attribution Map

Suppose we are given an image \( I \) and the corresponding
bounding box annotations. We also have a set of object
proposals \( O = \{o_k\}_{k=1}^K \), either given or obtained by RPN,
where \( K \) is the number of proposals. For each proposal \( o_k \),
the box head \( f^{box} \) and the cls head \( f^{cls} \) produce box offsets
\( t_k = f^{box}(I, o_k) \) and the class probability \( p_k = f^{cls}(I, o_k) \),
respectively. We omit the proposal indices \( k \) for brevity.

The bounding box attribution map (BBAM) identifies
the important region in the image that the detector needs
to perform object detection. We find the smallest mask
\( M : \Omega \rightarrow [0, 1] \) where \( \Omega \) is a set of pixels, which captures a
subset of the image that produces almost the same prediction
as the original image. A small \( M \) reduces the amount of
unnecessary information reaching the detector. The mask
specifies a subset of the image in terms of the perturbation
function \( \Phi(I, M) = I \circ M + \mu \circ (1 - M) \), where \( \circ \) denotes
pixel-wise multiplication, and \( \mu \) is the per-channel mean of
the training data with the same size as \( M \). For each proposal
\( o \), the best mask \( M^* \) is obtained by optimizing the following
function using gradient descent with respect to \( M \):

\[
M^* = \underset{M \in \{0,1\}^L}{\arg\min} \lambda \|M\|_1 + \mathcal{L}_{\text{perturb}},
\]

\[
\mathcal{L}_{\text{perturb}} = \mathbb{1}_{\text{box}} \left\| t^c - f^{box}(\Phi(I, M), o) \right\|_1 + \mathbb{1}_{\text{cls}} \left\| p^c - f^{cls}(\Phi(I, M), o) \right\|_1,
\]

where \( \mathbb{1}_{\text{box}} \) and \( \mathbb{1}_{\text{cls}} \) are logical variables that have a value of
0 or 1, to control which head is used to produce localizations,
and \( t^c = f^{box}(I, o) \) and \( p^c = f^{cls}(I, o) \) are the predictions
for the original image.

Previous studies show that using a mask of the same
spatial size as the input image incurs undesirable artifacts
due to the adversarial effect [21]: even a perturbation in a
tiny magnitude can significantly change the prediction of
a DNN. This problem can be addressed by introducing a
coarse mask downsampled by a stride \( s \) [10, 17, 18, 26], so
multiple image pixels are perturbed by a single element of
\( M \). We can then optimize \( M \in \mathbb{R}^{[w/s] \times [h/s]} \) for the image
\( I \in \mathbb{R}^{w \times h} \), using the perturbation function \( \Phi(I, M) = I \circ M + \mu \circ (1 - M) \), where \( M \in \mathbb{R}^{w \times h} \) is upsampled \( M \)
to a width of \( w \) pixels and a height of \( h \) pixels.

Existing methods of explaining the output of classifiers
[10, 17, 18] or semantic segmentation networks [26]
use a fixed value of \( s \) for all images, i.e., they fix the size of a
perturbation unit\(^1\). However, in the case of object detectors,
a perturbation unit of fixed size can result in perturbations of
different sizes to the RoI-pooled features, depending on the
size of the proposals, as shown in Figure 1(a). Figure 1(b)
shows how the size of a perturbation unit, after RoI pooling,
can fail to match the sizes of target objects: the perturbations
are too coarse for small objects and too fine for large objects.
Therefore, we use an adaptive stride \( s(a) \) where \( a \) is the
\footnote{The perturbation unit is a block of image pixels perturbed by a single element of \( M \).}
ratio of the area of the bounding box predicted by the object detector to that of the diversity of the predictions, we build a pseudo ground-truth from the BBAMs of multiple proposals. For each ground-truth box, we generate a set of object proposals $\mathcal{O}$ by randomly jittering each coordinate of the box by up to $\pm 30\%$. These proposals are sent to the $f^{\text{box}}$ and the $f^{\text{cls}}$. If the $f^{\text{cls}}$ correctly predicts the ground-truth class, and the intersection over union (IoU) value associated with the predicted box by $f^{\text{box}}$ is greater than 0.8, then the proposal is added to a set of positive proposals $\mathcal{O}^+ \subset \mathcal{O}$. We then use a modified version of $L_{\text{perturb}}$ in Eq. 1 to amalgamate all the positive proposals into a single localization map, as follows:

$$L_{\text{perturb}} = \mathbb{E}_{o \in \mathcal{O}^+} \left[ \| f^c - f^{\text{box}}(\Phi(I, M), o) \|_1 + \| f^c - f^{\text{cls}}(\Phi(I, M), o) \|_1 \right].$$

(3)

In this equation both $\mathbb{E}_{\text{box}}$ and $\mathbb{E}_{\text{cls}}$ are set to 1, since the BBAMs of $f^{\text{box}}$ and $f^{\text{cls}}$ provide complementary localization results (see Section 5 for details). A BBAM obtained in this way may partially cover the target object because not all pixels of the object are considered by $f^{\text{box}}$ and $f^{\text{cls}}$. Therefore we refine the BBAM using CRFs [35], following previous work [2, 31, 60]. Finally, we create pseudo instance-level ground-truth masks by considering the pixels in each BBAM with values greater than a threshold $\theta$ to be foreground. We denote such a mask as $T$.

The threshold $\theta$ controls the size of $T$. However, the proportion of pixels in each BBAM which correspond to the foreground will vary, so it may not be appropriate to use a fixed $\theta$. Therefore we introduce two thresholds $\theta_{\text{fg}}$ and $\theta_{\text{bg}}$: pixels whose attribution values are higher than $\theta_{\text{fg}}$ are considered to be part of the foreground, and pixels whose values are lower than $\theta_{\text{bg}}$ are considered to be part of the background. The remaining pixels are ignored in the loss computations during training segmentation networks.

Refine with MCG proposals. MCG [49] is an unsupervised mask proposal generator, which is commonly used in weakly supervised instance segmentation [3, 31, 44, 70, 71]. We can use mask proposals generated by MCG to refine a mask $T$. We first select the mask proposal that has the highest IoU with $T$. However, that proposal may partially cover the target object. Therefore we consider other proposals that are completely contained within $T$. More formally, given a set of MCG proposals $\{m_i\}_{i=1}^K$, the refined mask $T_r$ is derived as follows:

$$T_r = \bigcup_{i \in \mathcal{S}} m_i,$$

\begin{equation}
\mathcal{S} = \{ i | m_i \subset T \} \cup \{ \operatorname{argmax} \text{IoU}(m_i, T) \}.
\end{equation}

4. Experiments

4.1. Experimental Setup

Dataset and evaluation metrics. We conducted experiments on the PASCAL VOC [14] and the MS COCO datasets [42]. The PASCAL VOC dataset contains 20 object classes and one background class. Following the same protocol as other recent work on weakly supervised semantic and instance segmentation [1, 3, 27, 60], we used an augmented set of 10,582 training images produced by Hariharan et al. [22]. The MS COCO dataset has 118K training images containing 80 object classes. We report mean intersection-over-union (mIoU) values for semantic segmentation. For instance segmentation, we report average precision (AP) at IoU thresholds $\tau$: averaged AP over IoU thresholds from 0.5 to 0.95; and the average best overlap (ABO).

Reproducibility. We used the PyTorch [48] implementation of DeepLab-v2-ResNet101 [46]. We set $s(a)$ to $16 + 48\sqrt{a}$ and $\lambda$ to 0.007. We set $\theta_{\text{fg}}$ and $\theta_{\text{bg}}$ to 0.8 and 0.2 respectively. To find $M^*$ in Eq. 1, we used Adam optimizer [32] with a learning rate of 0.02 for 300 iterations. The experiments
were performed on NVIDIA Tesla V100 GPUs. For MCG mask proposals, we used the pre-computed proposals for PASCAL VOC and MS COCO images provided by Pont-Tuset et al. [49].

### 4.2. Weakly Supervised Instance Segmentation

#### Results on PASCAL VOC

Table 1 compares the performance of our method with that of other recent methods of weakly supervised instance segmentation which use image-level tags or bounding boxes. Our method significantly outperforms those methods. Specifically, the AP$_{50}$ and AP$_{70}$ values of our method are both 6.0% higher than those of the previous best performing method which uses bounding box annotation [3]. We include results from two fully supervised methods: MNC [12] and Mask R-CNN [23]. The performance of Mask R-CNN [23], which is fully supervised, can be viewed as an upper bound on the achievable performance of our method. We achieve 92.2% and 95.7% of the performance of fully supervised Mask R-CNN, in terms of AP$_{50}$ and ABO respectively. Figure 2 presents examples of instance masks produced by our method.

#### Results on MS COCO 2017

This is a challenging dataset containing more objects in an image on average than PASCAL VOC. The sizes of instances of objects are also more diverse. Table 2 compares the performance of our method with that of other weakly supervised instance segmentation methods with various levels of supervision on MS COCO. Our method achieves a 6.7% higher value of AP$_{75}$ than the previous best performing method which uses bounding box annotations. Since the labels for test-dev images are not publicly available, the results for the test-dev images were obtained from the MS COCO challenge website.

#### 4.3. Weakly Supervised Semantic Segmentation

Table 3 compares published mIoU values achieved by recent methods performing semantic segmentation on validation and test images from the PASCAL VOC 2012 dataset. Since the labels for test images are not publicly available, the results for the test images were obtained from the official PASCAL VOC evaluation server. Our method, using the BBAM, yields an mIoU value of 73.7 for both the validation and the test images in the PASCAL VOC 2012 semantic segmentation benchmark. Our method outperforms all the methods that use image-level tags or bounding boxes for supervision. This new state-of-the-art performance was achieved with vanilla DeepLab-v2 [8] without any modification.
samples to networks or additional training techniques, such as label refinement during training [11], recursive training [31], or fine-tuning with additional losses [60]. Figure 3 presents examples of semantic masks produced by our method.

The concurrent method, Box2Seg [34], achieved an mIoU of 76.4% on the PASCAL VOC validation images, but it is based on UperNet [67], which is a more powerful segmentation network than DeepLab-v2 [46]. For a fair comparison between Box2Seg [34] and our BBAM, we attempt to relieve the benefit of UperNet [67] over DeepLab-v2 [8] by comparing the relative performance of the weakly supervised model to the fully supervised model. Box2Seg achieves 88.4% of the performance of its fully supervised equivalent (76.4 vs. 86.4); but the corresponding figure for BBAM and its fully supervised equivalent is 96.7% (73.7 vs. 76.2).

### 4.4. Ablation Study

**MCG proposals.** Table 4 shows how mask refinement with MCG proposals improves the instance segmentation performance of our method on the PASCAL VOC and MS COCO datasets. Mask refinement with MCG proposals is particularly effective on masks for medium and large objects. The results obtained without MCG proposals offer the possibility of a fairer comparison with Hsu et al. [27], which do not use MCG proposals. Our method produces better results than that of Hsu et al. [27] for both the PASCAL VOC and MS COCO datasets, which are shown in Tables 1 and 2 respectively. Hereinafter, to observe the contribution of each component of our system, we report results without using MCG proposals.

**Box and cls heads.** BBAM can provide a separate attribution map for each head of the object detector by controlling the logical variables \(1_{\text{box}}\) and \(1_{\text{cls}}\) in Eq. 3. Figure 4 shows the effect of the BBAM obtained from each head on the
To determine which regions of an object are important to
cls head
and those by the
box head
ary of the object. We observed that high values attributed by
above 0.9 obtained from validation images of the PASCAL
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Parameter sensitivity analysis. Table 5 shows the effect
of the thresholds \( \theta_{fg} \) and \( \theta_{bg} \), and the seed growing technique
\( \mathcal{G} \). When \( \theta_{fg} \) equals to \( \theta_{bg} \), all pixels are assigned to either the
foreground or the background. We see that ignoring some
pixels can improve the AP values, and the seed growing
technique further improves performance. We then studied
the effect of \( \lambda \), which controls the sparsity of the BBAM,
on the performance of weakly supervised semantic and in-
stance segmentation. Using the BBAM obtained from either the
box head
or the
cls head
shows competent performance, but the best
performance is achieved when the two heads are used to-
gether. We attribute this to the complementary property of
the two heads, which is examined in more detail in Section 5.

5. Detailed Analysis of the BBAM

Examples of BBAMs. Figure 5 shows BBAMs for valida-
tion images from PASCAL VOC [14] and MS COCO [42].
The BBAMs have high values on the boundary and discriminative parts of each object, which are informative in con-
ducting object detection.

Complementary operation of the box and cls heads. To
determine which regions of an object are important to
each head, we investigated the distribution of high-value pix-
els in the BBAM produced by each head. In Figure 6(a), \( \mathcal{C} \)
is the set of points on the contour of the object mask, and \( \vec{x_c} \)is its centroid. For each pixel \( \vec{x} \), we determine
\( r_1 = \| \vec{x} - \vec{x_c} \|_2 \)
and
\( r_2 = \min_{\vec{c} \in \mathcal{C}} \| \vec{x} - \vec{c} \|_2 \). Letting the angle between
\( \vec{x} - \vec{x_c} \)
and the x-axis be \( \theta \), the position of the pixel \( \vec{x} \) relative to
\( \vec{x_c} \) is \( \vec{R} = (\frac{r_1}{r_1 + r_2} \cos \theta, \frac{r_1}{r_1 + r_2} \sin \theta) \). In Figure 6(b), we plot
the relative positions of all the pixels with attribution values
above 0.9 obtained from validation images of the PASCAL
VOC dataset. Pixels for which \( \| \vec{R} \|_2 \approx 1 \) are near the bound-
ary of the object. We observed that high values attributed by
the box head
mainly occur near the boundary of the object,
and those by the cls head
mainly occur in the interior.

Furthermore, we observed how much the prediction of
each head changes when either of \( \mathbb{1}_\text{box} \) and \( \mathbb{1}_\text{cls} \) is set to 1
during the optimization of Eq. 1. The extent of the change
in prediction of each head can be inferred from the corre-
sponding loss in Eq. 2. Figure 6(c) shows that applying the
optimization of Eq. 1 to one of the heads increases the loss
of the other head, implying that the discriminative area of
the image necessary for each head is not sufficient for the other
head to maintain the prediction. These two observations sug-
 gest that the BBAM of each head provides complementary
attributions. Examples of BBAMs obtained from each head
are presented in the Appendix.

Label noise in object detection. We also looked at the
robustness of our system against noisy box coordinate labels
in instance segmentation. Hsu et al. [27] considered the
effect of up to \( \pm 15\% \) of label noise: we extend this to \( \pm 20\% \).
The validity of the bounding box tightness priors used by
Hsu et al. [27] is seriously compromised by inaccurate box
coordinates, with a considerable effect on performance, as
shown in Figure 7(a). Our method shows better robustness
than that of Hsu et al. [27], whether the noise consists of
expanded or contracted bounding box annotations.
Figure 6: Complementary operation of the box head and the cls head. (a) The definition of relative position. (b) Relative positions of the highly activated pixels from each head. (c) Box and class loss curves.

Figure 7: (a) Robustness against noisy box coordinate labels. (b) Localization accuracy by different strides. (c) Localization accuracy by different attribution methods.

Effectiveness of an adaptive stride $s(a)$. As mentioned in Section 3.2, we use an adaptive stride $16 \leq s(a) \leq 64$ to cope with feature transformation due to RoI pooling. Figure 7(b) shows the IoU between the BBAM and ground truth mask on PASCAL VOC validation images, along with the results using fixed strides of 24 and 48. Figure 7(b) shows that a small fixed stride ($s=24$) is ineffective with large objects, as is a large fixed stride ($s=48$) with small objects. By contrast, an adaptive stride $s(a)$ can deal with objects of various sizes.

Comparison with gradient-based methods. Gradient-based attribution methods, such as SimpleGrad [68], SmoothGrad [59], and Grad-CAM [55] can also provide attributions for the output of an object detector. However, since only the subset of features associated with the imperfect proposal is delivered to the cls and box heads, the gradients with respect to pixels, which exist outside the proposal yet essential for prediction, can vanish (but not completely, due to the receptive field). We provide empirical results supporting this analysis on the PASCAL VOC validation images: (1) Figure 8 shows examples in which SimpleGrad [68] is applied to three similar predictions from different proposals. Pixels outside the proposal do indeed influence the predictions, but SimpleGrad’s attributions mainly appear inside the proposal. (2) We observed that the majority (87%) of pixels with attribution values above 0.9 appear inside the imperfect proposal; the mean IoU between the set of positive proposals and the corresponding predictions is low (i.e., 0.56). (3) Figure 7(c) shows that attribution maps from gradient-based attribution methods correlate poorly with ground truth masks.

6. Conclusions

We have introduced a bounding box attribution map (BBAM), which provides pixel-level localization of each target object in its bounding box by finding the smallest region that preserves the predictions of the object detector. Our formulation is built on two-stage object detectors, but applying our method to one-stage object detectors is straightforward as long as they have box and cls heads. Our experiments demonstrate that the BBAM achieves state-of-the-art performance on the PASCAL VOC and MS COCO benchmarks in weakly supervised semantic and instance segmentation. We have also analyzed BBAMs from various viewpoints, and compared our technique with other attribution methods, to provide a deeper understanding of our approach. We expect BBAMs to be a staple of future work on weakly supervised semantic and instance segmentation with bounding boxes, on a par with the CAM for class labels.

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We set the batch size to 8, the number of training iterations ξ where λ × 2. We followed the default settings provided by maskrcnn-benchmark repository [45].

Regarding the characteristics of the PASCAL VOC dataset, we adjusted the input image size and the anchor size accordingly. We set the max and min size of training images to 800 and 512, respectively, and anchor sizes for each FPN level to [21, 42, 84, 168, 332]. We trained Mask R-CNN [23] with a learning rate 8 × 10⁻³ for 2 × 10⁴ iterations.

Post-processing of semantic and instance segmentation. CRF [33] is a popular post-processing technique for semantic and instance segmentation [27, 28, 36, 37, 58]. We also used CRFs as a post-processing method for semantic and instance segmentation.

A.2. Additional Results

Comparison of per-class mIoU scores. Table A1 shows the per-class mIoU of our method and recently produced methods.

More examples of BBAMs. We present more examples of BBAMs for PASCAL VOC [14] validation images with Faster R-CNN [52] (Figure A1) and for MS COCO 2017 [42] validation images with Faster R-CNN [52] (Figure A2).

Additional mask examples on semantic segmentation. Figure A3 shows more examples of the semantic masks produced by DSRG [28], Shen et al. [56], FickleNet [36], Lee et al. [37], and our method.

More mask examples on instance segmentation. Figure A4 shows more examples of the instance masks on PASCAL VOC 2012 validation images obtained from IRNet [1], Hsu et al. [27], and our method. Figure A5 shows examples of instance masks on MS COCO 2017 validation images obtained by our method.

Table A1: Comparison of per-class mIoU scores.

| bkg  | aero | bike | bird | boat | bottle | bus | car | cat | chair | cow | table | dog | horse | motor | person | plant | sheep | sofa | train | tv  | mIoU%
|------|------|------|------|------|--------|-----|-----|-----|-------|-----|-------|-----|-------|-------|--------|-------|-------|-----|------|-----|------|
| 86.8 | 71.2 | 32.4 | 77.0 | 24.4 | 69.8   | 85.3| 71.9| 86.5| 27.6 | 78.9| 80.7  | 75.1| 72.7  | 73.1 | 49.6  | 74.8  | 36.1  | 48.1 | 59.2 | 63.0 |
| 88.5 | 79.5 | 32.6 | 75.7 | 56.8 | 72.1   | 85.3| 72.9| 81.7| 27.6 | 73.3 | 39.8  | 76.4| 77.0  | 74.9 | 66.8  | 46.6  | 81.0  | 29.1 | 60.4 | 53.3 | 64.3 |
| 89.5 | 76.6 | 32.6 | 74.6 | 51.5 | 71.1   | 83.4| 74.4| 83.6| 24.1 | 73.4 | 47.4  | 78.2| 74.0  | 68.8 | 73.2  | 47.8  | 79.9  | 37.0 | 57.3 | 64.9 | 64.9 |
| 89.0 | 62.5 | 28.9 | 83.7 | 52.9 | 59.5   | 77.6| 73.7| 87.0| 34.0 | 83.7 | 47.6  | 84.1| 77.0  | 73.9 | 69.6  | 29.8  | 84.0  | 43.2 | 68.0 | 53.4 | 64.9 |
| 90.8 | 82.2 | 35.1 | 82.4 | 72.2 | 71.4   | 82.7| 75.0| 86.9| 18.3 | 74.2 | 29.6  | 81.1| 76.6  | 81.8 | 76.4  | 44.2  | 78.6  | 35.4 | 72.8 | 63.0 | 66.5 |

Results on test images:

Shen et al. [56] 82.7 76.8 31.6 72.9 19.1 64.9 86.7 75.4 80.6 30.0 76.6 48.5 80.5 79.9 79.7 72.6 50.1 83.5 36.1 53.4
FickleNet [36] 90.3 77.0 35.2 76.0 54.2 64.3 76.6 71.0 80.2 25.7 68.6 50.2 74.6 71.8 78.3 69.5 53.8 76.4 74.0 65.0
SSDD [58] 90.0 62.5 28.9 83.7 52.9 59.5 77.6 73.7 87.0 34.0 83.7 47.6 84.1 77.0 73.9 69.6 29.8 84.0 43.2 68.0
Lee et al. [37] 91.2 84.2 37.9 82.4 72.2 71.4 82.7 75.0 86.9 18.3 74.2 29.6 81.1 79.2 74.7 76.4 44.2 78.6 35.4 67.4
BBAM (Ours) 92.8 83.5 33.4 83.7 64.9 75.5 91.3 80.4 88.3 37.0 83.3 62.5 84.6 80.8 74.7 80.0 61.6 84.5 48.6 71.8

References:

1. IRNet [1]
2. Faster R-CNN [52]
3. MS COCO 2017 [42]
4. PASCAL VOC 2012 [14]
5. SSDD [58]
6. FickleNet [36]
7. CIAN [15]
8. Mask R-CNN [23]
Figure A1: Examples of PASCAL VOC [14] validation images with the results of object detection and corresponding BBAMs, obtained from Faster R-CNN [52].
Figure A2: Examples of MS COCO 2017 [42] validation images with the results of object detection and corresponding BBAMs, obtained from Faster R-CNN [52].
| Image | Ground Truth | DSRG | Shen et al. | FickleNet | Lee et al. | Ours |
|-------|-------------|------|-------------|-----------|------------|------|

Figure A3: Examples of predicted semantic masks for PASCAL VOC validation images of DSRG [28], Shen et al. [56], FickleNet [36], Lee et al. [37], and our method.
Figure A4: Examples of predicted instance masks for PASCAL VOC validation images of our method.

Figure A5: Examples of predicted instance masks for MS COCO 2017 validation images of our method.