

# WeakSAM: Segment Anything Meets Weakly-supervised Instance-level Recognition

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## Abstract

Weakly supervised visual recognition using inexact supervision is a critical yet challenging learning problem. It significantly reduces human labeling costs and traditionally relies on multi-instance learning and pseudo-labeling. This paper introduces WeakSAM and solves the weakly-supervised object detection (WSOD) and segmentation by utilizing the pre-learned world knowledge contained in a vision foundation model, i.e., the Segment Anything Model (SAM). WeakSAM addresses two critical limitations in traditional WSOD retraining, i.e., pseudo ground truth (PGT) incompleteness and noisy PGT instances, through adaptive PGT generation and Region of Interest (RoI) drop regularization. It also addresses the SAM’s problems of requiring prompts and category unawareness for automatic object detection and segmentation. Our results indicate that WeakSAM significantly surpasses previous state-of-the-art methods in WSOD and WSIS benchmarks with large margins, i.e. average improvements of 7.4% and 8.5%, respectively. Code is available at <https://github.com/hustvl/WeakSAM>.

## 1. Introduction

Weakly-supervised learning (WSL) (Zhou, 2018; Wang et al., 2013; Xu et al., 2014) is a crucial component of machine learning. It is particularly valuable in tasks where strong supervision is difficult to annotate due to the high cost of data labeling (Locatello et al., 2020; Schroeter et al., 2019; Fu et al., 2020). Due to the massive demand for annotated data in visual perception, WSL is essential in developing a label-efficient recognition system. In the standard weakly-supervised visual perception paradigm (Tang et al., 2018a; Sui et al., 2022), training commences with in-

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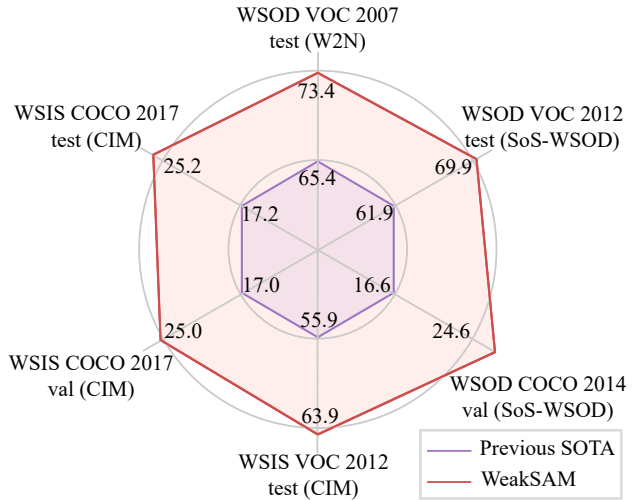


Figure 1. Quantitative comparisons between WeakSAM and previous SOTA methods under different tasks and benchmarks. The scale of each axis in the radar chart is normalized by the performance of the previous SOTA methods (marked in parentheses), and the stride of each axis is the same.

exact supervision, such as image-level labels. Subsequently, the trained WSL network is employed to generate pseudo ground truth (PGT), which serves as a form of refined, albeit still inaccurate supervision. Finally, the PGT is used as inaccurate supervision to launch WSL retraining. Although the iterative WSL process achieves significant progress, it is still limited by the lack of external knowledge, which restricts the performance of WSL and hinders it from matching fully-supervised learning (FSL).

Nowadays, foundation models are gaining increasing attention because of their transferable pre-learned world knowledge, which can be regarded as powerful external knowledge for WSL. As a vision foundation model, SAM (Kirillov et al., 2023) achieves outstanding performance in interactive, class-agnostic segmentation. SAM owes its success to promptable training on a large-scale dataset. However, there are two main drawbacks to SAM: First, SAM requires interactive operations as input, which means it cannot work automatically without human prompts. Second, SAM produces class-agnostic segments and cannot assign class labels. These drawbacks severely restrict the application of SAM

as a generic visual framework. As a strong complement, WSL is good at mining classification clues through inexact supervision, which can provide automatic prompts for SAM. Subsequently, WSL with SAM’s knowledge can further bring class-aware perception.

This motivates us to assimilate SAM within the WSL paradigm. The WeakSAM framework is designed to harness transferable knowledge from SAM, thereby enriching the WSL process. Simultaneously, it offers the capability to deliver automatic classification clues to SAM. This bidirectional enhancement constructs a promising foundation-model-based weakly-supervised visual perception framework. Specifically, in a weakly-supervised object detection (WSOD) setting, WeakSAM uses classification clues as SAM prompts to produce proposals automatically. These proposals are then used in WSOD training for class-aware perception.

Within the scope of the WeakSAM framework, our analysis identifies two prevailing limitations in the iterative WSOD retraining approach: the issue of pseudo ground truth (PGT) incompleteness and the presence of noisy PGT instances. The former, PGT incompleteness, refers to the tendency of WSOD-generated PGT to omit some objects or categories, leading to insufficient training for these categories. The latter, noisy PGT instances, pertain to the prevalent presence of noise within the PGT, which adversely impacts the retraining process. To effectively mitigate these challenges, we introduce two key strategies: adaptive PGT generation to address the PGT incompleteness problem, and Region of Interest (RoI) drop regularization to counteract the noise in PGT instances. Moreover, WeakSAM’s capability enables the extension in the realm of weakly-supervised instance segmentation (WSIS). In this context, SAM is employed to further refine WeakSAM-PGT, enabling the generation of pseudo instance segmentation labels. This approach exemplifies WeakSAM is promising to build a unified weakly-supervised instance-level recognition framework.

The main contributions of this paper can be summarized as follows:

- We propose a weakly-supervised instance-level recognition framework (WeakSAM), which automatically prompts SAM by classification clues for proposals. The WeakSAM-proposals improve both the effectiveness and efficiency of WSOD.
- We analyze the weaknesses in traditional WSOD retraining, and propose adaptive PGT generation and RoI drop regularization to address them, respectively. After the WeakSAM-WSOD is complete, the proposed WeakSAM can be easily applied to WSIS further.
- The proposed WeakSAM achieves state-of-the-art (SOTA) results on the WSOD and WSIS benchmarks,

significantly surpassing previous SOTA methods as shown in Fig. 1.

## 2. Related Work

### 2.1. Segment Anything Model

The recent Segment Anything Model (SAM) (Kirillov et al., 2023) draws great attention from researchers. The SAM is trained on SA-1B with over 1 billion masks, following the model-in-the-loop manner. Besides, SAM performs superior zero-shot transfer capabilities and is applied in many visual tasks, e.g., FGVP (Yang et al., 2023) incorporates SAM to achieve zero-shot fine-grained visual prompting, MedSAM (Ma & Wang, 2023) adapts SAM into a large scale medical dataset to build a medical foundation model, and some methods (Sun et al., 2023; Jiang & Yang, 2023; Chen et al., 2023) utilize SAM to deal with the weakly-supervised semantic segmentation problem. However, SAM is an interactive segmentation method, which heavily relies on human prompts.

In our approach, we innovatively propose to automatically prompt SAM using classification clues for extracting region proposals. This method results in high-recall proposals that surpass traditional methods like Selective Search in terms of both efficiency and effectiveness. This advancement represents a significant improvement in the domain of proposal generation within the WSOD framework.

### 2.2. Weakly-supervised Object Detection

Weakly-supervised object detection (WSOD) with image-level labels (Laptev et al.; Diba et al., 2017; Tang et al., 2018b; Gao et al., 2018; Wan et al., 2018; Zhang et al., 2018a; Liu et al., 2019; Li et al., 2019; Arun et al., 2019; Sun et al., 2020; Arun et al., 2020; Jia et al., 2021; Wan et al., 2019) is important for reducing the human annotation burden. The previous works, i.e., WSDDN (Bilen & Vedaldi, 2016b) and OICR (Tang et al., 2017), proposed the Multiple Instance Learning and online refinement paradigms. The later works aimed to improve the WSOD performance from different perspectives. Such as WSOD<sup>2</sup> (Zeng et al., 2019) introduced bottom-up object evidence, PCL (Tang et al., 2018a) proposed to cluster proposals, MIST (Ren et al., 2020) utilized a self-training algorithm, etc. Besides, some methods (Tang et al., 2018a; Jie et al., 2017; Li et al., 2016; Sui et al., 2022; Zhang et al., 2018b; Huang et al., 2022) also retrained a fully-supervised object detection network with generated pseudo ground truth (PGT). However, most of them used the proposals generated from low-level methods, i.e., Selective Search (Uijlings et al., 2013), EdgeBox (Zitnick & Dollár, 2014), and MCG (Pont-Tuset et al., 2016), which contain a great number of redundant proposals and bring an optimization challenge.

Different from previous methods, our WeakSAM-proposals

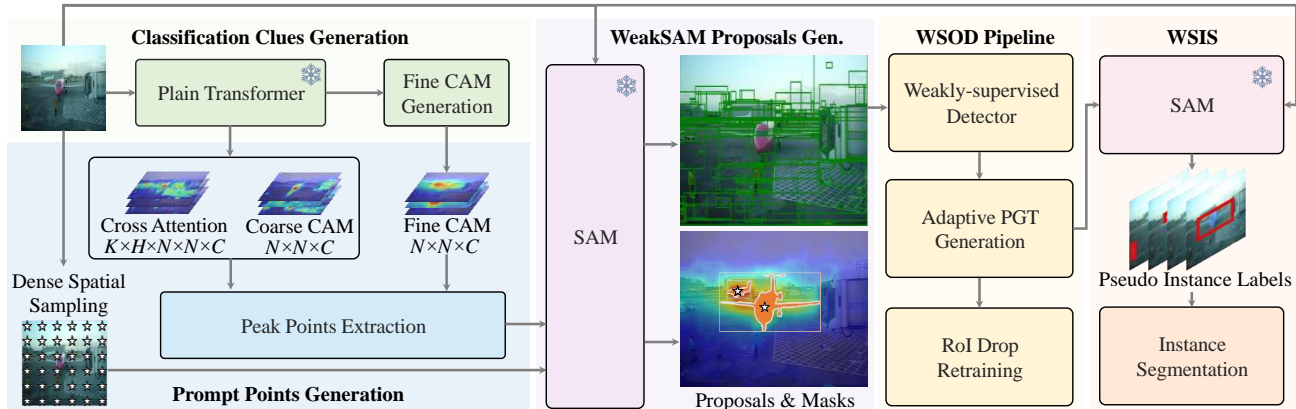


Figure 2. An overview of the proposed WeakSAM framework. We first introduce classification clues and spatial points as automatic SAM prompts, which address the problem of SAM requiring interactive prompts. Next, we use the WeakSAM-proposals in the WSOD pipeline, in which the weakly-supervised detector performs class-aware perception to annotate pseudo ground truth (PGT). Then, we analyze the incompleteness and noise problem existing in PGT and propose adaptive PGT generation, RoI drop regularization to address them, respectively. Finally, we use WeakSAM-PGT to prompt SAM for WSIS extension. The snowflake mark means the model is frozen.

have fewer numbers and higher recall, which reduces the difficulty of finding the correct proposals for WSOD methods. For the key problem of PGT incompleteness and noisy PGT instances, we propose adaptive PGT generation and Region of Interest (RoI) drop regularization to address them, respectively.

### 2.3. Weakly-supervised Instance Segmentation

Weakly-supervised instance segmentation (WSIS) aims to achieve instance segmentation through weak supervision, such as box-level supervision (Tian et al., 2021; Wang et al., 2021; Cheng et al., 2023; Hsu et al., 2019; Liao et al., 2019; Lee et al., 2021; Khoreva et al., 2017; Zhang et al., 2023; Zhu et al., 2023b; Li et al., 2022), and image-level supervision (Ge et al., 2019; Ou et al., 2021; Zhu et al., 2019; Liu et al., 2020; Hwang et al., 2021; Zhang et al., 2021; Hu et al., 2020; Hsieh et al., 2023; Laradji12 et al.). The WSIS with image-level supervision is challenging because it lacks accurate instance locations. Some image-level WSIS methods use CAM to extract coarse object locations, such as PRM (Zhou et al., 2018), IAM (Zhu et al., 2019), IR-Net (Ahn et al., 2019), BESTIE (Kim et al., 2022), etc. Some other image-level WSIS methods try to incorporate instance clues from extra priors, such as Fan et al. (Fan et al., 2018b), LIID (Liu et al., 2020), CIM (Li et al., 2023), etc. However, they always need complicated networks and lack high-quality instance segments.

Different from previous WSIS methods, the proposed WSIS extension using WeakSAM-PGT and SAM’s prediction is concise and effective. The generated pseudo instance labels can further be applied to any fully-supervised instance segmentation method.

## 3. Method

We present the WeakSAM framework as shown in Fig. 2. At first, WeakSAM automatically generates prompts from classification clues and spatial samples. Next, WeakSAM send the prompts to SAM for WeakSAM-proposals. Then, we launch the weakly-supervised object detection (WSOD) pipeline, which is enhanced by WeakSAM-proposals, adaptive pseudo ground truth (PGT) generation, and RoI drop regularization. Last, we use the PGT boxes generated by the WSOD pipeline to launch the weakly-supervised instance segmentation extension.

### 3.1. Classification Clues as Automatic Prompt

Previous WSOD methods face an optimization problem caused by the redundant proposals, e.g., Selective Search (Uijlings et al., 2013) and EdgeBox (Zitnick & Dollár, 2014), because these proposals are only based on low-level features. To address this problem, we propose to transfer knowledge in the foundation model, i.e., SAM, for proposal generation. We use classification clues to prompt SAM automatically, which also solves the shortcoming of SAM requiring interactive prompts

**Classification Clues Generation** As shown in Fig. 2, we extract classification clues from a classification ViT. Specifically, we choose the pre-trained weakly-supervised semantic segmentation network, WeakTr (Zhu et al., 2023a), to provide classification clues because of its superior localization ability. At first, we extract cross-attention maps  $CA \in \mathbb{R}^{K \times H \times N \times N \times C}$  from the self-attention maps, where  $K$  is the number of transformer encoding layers,  $H$  is the number of attention heads in each layer,  $N \times N$  is the spatial size of the visual tokens, and  $C$  represents the total

number of classification categories. Then, we obtain coarse CAM,  $\text{CAM}_{\text{coarse}} \in \mathbb{R}^{N \times N \times C}$ , from the convolutional CAM head, which takes visual tokens at the final transformer layer as input and produces coarse CAM. Last, we use WeakTr to produce fine CAM,  $\text{CAM}_{\text{fine}} \in \mathbb{R}^{N \times N \times C}$ .

**Prompt Points Generation** As shown in Fig. 2, we extract prompts from dense sampling points, cross-attention maps, and CAMs. At first, the dense sampling requires splitting the image into  $S \times S$  patches and taking the center points as prompts. Notably, the dense sampling points provide spatial-aware prompts but lack explicit reference to objects and semantics, which means increasing the  $S$  usually leads to a great number of invalid sampling points. Then, we get peak points from the cross-attention maps as prompts. We observe that these maps do not solely concentrate on objects from their corresponding categories but also give attention to objects from different categories. So, we mark these prompts as instance-aware ones. Last, we extract peak points from coarse CAM and fine CAM as semantic-aware prompts, which are more precise and focus on areas of foreground objects.

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#### Algorithm 1 Peak Points Extraction

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**Require:** maps  $M$  (either CA or CAM), kernel size  $k$ , activation threshold  $\tau$

**Ensure:** peak points coordinates list  $P = [p_0, p_1, \dots, p_{n-1}]$ , corresponding peak values list  $V = [v_0, v_1, \dots, v_{n-1}]$

- 1:  $M = M.\text{view}(-1, N, N)$  // reshape
- 2: Initialize  $P, V$  as empty list
- 3: Initialize Maxpool() operation with kernel size  $k$
- 4:  $P, V = \text{Maxpool}(M)$  // get coordinates and values
- 5: Sort  $V$  in descending order of numerical value, and rearrange  $P$  accordingly
- 6: Initialize list  $P_{\text{delete}}, V_{\text{delete}}$  to mark points for deletion
- 7: **for** each index  $i$  from 0 to  $\text{length}(P)$  **do**
- 8:   // skip further checks for points marked for deletion
- 9:   **if**  $p_i$  in  $P_{\text{delete}}$  **then**
- 10:     Continue
- 11:   **end if**
- 12:   // mark activation points with low score
- 13:   **if**  $v_i < \tau$  **then**
- 14:     Append  $p_i, v_i$  to  $P_{\text{delete}}, V_{\text{delete}}$
- 15:     Continue
- 16:   **end if**
- 17:   // mark lower-score points near the current point
- 18:   **for** each index  $j = i + 1$  to  $\text{length}(P)$  **do**
- 19:     **if**  $\|p_j - p_i\| \leq k/2$  **then**
- 20:       Append  $p_j, v_j$  to  $P_{\text{delete}}, V_{\text{delete}}$
- 21:     **end if**
- 22:   **end for**
- 23: **end for**
- 24: Remove all points in  $P_{\text{delete}}$  and  $V_{\text{delete}}$  from  $P$  and  $V$
- 25: **return**  $P, V$

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Specifically, we extract peak points from cross-attention maps and CAMs, as shown in Algorithm 1. Given cross-attention maps or CAMs as input, we first initialize the peak points list  $P$ , peak values list  $V$ , deleted lists  $P_{\text{delete}},$

$V_{\text{delete}}$ , and max pooling operation. Next, we reshape the input maps and ensure the last two dimensions correspond to the original image size and the others as the first dimension. Then, we apply max pooling on the input maps  $M$ , and sort  $V$  and  $P$  in descending order based on  $V$ . Last, we remove points with low activation values or close to high-score points.

**WeakSAM Proposals Generation** At the WeakSAM proposal generation stage, we use the three kinds of prompts to prompt SAM automatically. We directly add semantic-aware prompts and spatial-aware prompts to the prompt list, because they usually have clear localization to foreground objects and spatial positions, respectively. For the instance-aware prompts that have some redundancy, we cluster them to filter the duplicated ones and then add them to the prompt list. Finally, all prompts in the prompt list are used to prompt SAM for proposals.

### 3.2. WeakSAM WSOD Pipeline

To better describe the proposed weakly-supervised object detection (WSOD) pipeline, we first present the weakly-supervised detector training with WeakSAM-proposals. Then, we identify the PGT incompleteness problem and introduce the proposed adaptive PGT generation to address it. Last, we analyze the noise problem existing in the re-training phase, and propose Region of Interest (RoI) drop regularization to alleviate the effect of noise.

**Weakly-supervised Detector Training** A primary challenge in traditional WSOD methods is the low training efficiency, largely attributed to the redundancy of proposals. Traditional approaches often involve the Region of Interest pooling layer processing thousands of proposals per image, which impairs both effectiveness and efficiency. To address this issue, our WeakSAM-proposals adopt transferred knowledge from SAM and classification clues. The proposed method focuses on generating a smaller quantity of proposals while maintaining high recall, thereby enhancing the overall efficiency and efficacy of the detection process in a WSOD context. We mainly apply the proposed WeakSAM on some convincing WSOD methods, including OICR (Tang et al., 2017) and MIST (Ren et al., 2020), which receive significant improvements. As shown in Table 1, quantitative results show that WeakSAM-enhanced WSOD can annotate bounding boxes for objects more precisely.

**Adaptive PGT Generation** Generating high-quality pseudo ground truth (PGT) is the key to the WSOD paradigm. Traditional WSOD methods often encounter the issue of PGT incompleteness. This occurs because these methods typically select top-scoring proposals as PGT or apply a uniform threshold to filter proposals across all cate-

gories. Such approaches can lead to the omission of objects or entire categories, especially when proposals in certain categories score low. To address these problems, we propose an adaptive PGT generation method to normalize the score distribution of proposals, ensuring they fall within a similar range, as shown in Algorithm. 2.

For box list  $B \in \mathbb{R}^{N \times 5}$  and corresponding score list  $S \in \mathbb{R}^{N \times 1}$ , we first select them with a specific classification label and then normalize the scores. The  $N$  is the number of predicted boxes, and the second dimension of  $B$  is the combination of a category label and four coordinate values. Next, we keep boxes with scores higher than the threshold  $\tau_s$ . Please note that the normalization enables the threshold to work for all categories adaptively, so we would not lose a ground truth category even if all boxes in this category have low scores. Then, we select the boxes whose main parts are not contained in some bigger boxes. Because the boxes that have more *overlap* are often local components of some objects. Last, we return the box list  $B'$  as the final PGT.

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#### Algorithm 2 Adaptive Pseudo Ground Truth Generation

**Require:** boxes list  $B$  of an image, corresponding scores list  $S$ , corresponding classification labels  $Y$ , score threshold  $\tau_s$ , overlap threshold  $\tau_o$

**Ensure:** pseudo ground truth boxes  $B'$

- 1: initialize  $B'$  as empty list
- 2: **for** each  $y_i$  in  $Y$  **do**
- 3:    // get boxes' indices with label  $y_i$
- 4:     $idx_i = \text{where}(B[:, 0] == y_i)$
- 5:     $S_i = S[idx_i, :]$
- 6:     $B_i = B[idx_i, :]$
- 7:     $S_i^{norm} = \frac{S_i - \min(S_i)}{\max(S_i) - \min(S_i)}$  // normalize scores
- 8:    // keep boxes with high score
- 9:     $idx_{keep} = \{j \mid s_j \in S_i^{norm}, s_j > \tau_s\}$
- 10:     $B_i = B_i[idx_{keep}, :]$
- 11:     $S_i^{norm} = S_i^{norm}[idx_{keep}, :]$
- 12:    // select boxes with less overlap
- 13:    **for** each box  $b_j$  in  $B_i$  **do**
- 14:        $overlaps = \{\frac{|b_j \cap b_k|}{|b_j|} \mid b_k \in B_i, k \neq j\}$
- 15:       **if** all  $overlap < \tau_o$  in  $overlaps$  **then**
- 16:           Append  $b_j$  to  $B'$
- 17:       **end if**
- 18:    **end for**
- 19: **end for**
- 20: **return**  $B'$

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**RoI Drop Regularization** A recognized issue in the re-training phase of WSOD is noisy PGT instances. These noisy instances result in PGT acting as the inaccurate supervision. Alleviating this problem is critical for enhancing the performance of WSOD retraining. To analyze this problem in depth, we first divide the RoIs into different loss intervals. Then, we mark the RoIs whose corresponding PGTs do not have at least 70% IoU with the ground truth boxes as error ones. Last, we present the statistics as shown in Fig. 3, which demonstrates that the RoIs with larger losses are in a small amount and have a high error rate.

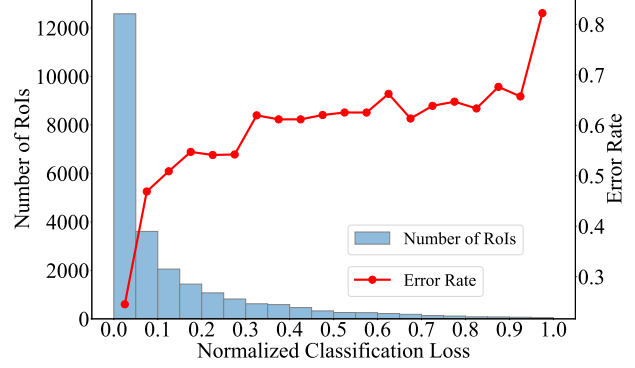


Figure 3. The relationship between the normalized classification loss, the corresponding number of RoIs, and the corresponding error rate. The results are obtained from training the Faster-RCNN using PGT in the preliminary training stage.

Intuitively, we propose a method, named RoI drop regularization, to adaptively drop the RoIs with larger losses. Notably, the proposed method is easy to implement and can further help the query-based detectors to alleviate the noisy PGT problem by its variant, query drop regularization. For anchor-based FSOD methods, e.g., Faster-RCNN (Ren et al., 2015), we first determine the thresholds  $\tau_{cls}$  and  $\tau_{reg}$  for classification loss and regression loss, respectively. Then, we compute the drop signal  $d_i$  for  $i$ -th RoI.

$$d_i = \begin{cases} 1, & l_i^{cls} \leq \tau_{cls}, \text{ and } l_i^{reg} \leq \tau_{reg} \\ 0, & \text{others} \end{cases}, \quad (1)$$

where the  $l_i^{cls}$  and  $l_i^{reg}$  represent the classification loss and regression loss for each RoI, respectively. When the two losses of a RoI are all below their thresholds, we set its drop signal  $d_i$  as 1. Finally, we integrate the  $d_i$  into the computation of final loss  $\mathcal{L}$ .

$$\mathcal{L} = \sum_i d_i l_i^{cls} + \lambda \sum_i p_i^* d_i l_i^{reg}, \quad (2)$$

where  $p_i^*$  is 1 if the box is positive, and 0 if the box is negative. The  $\lambda$  is a balancing weight.

For query-based FSOD methods, e.g., DINO (Zhang et al., 2022), since queries can be regarded as dynamic RoIs, we apply query drop regularization on them. Because only a few matched queries need to calculate box loss  $l^{box}$  and IoU loss  $l^{iou}$ , we only set a percentile threshold based on classification loss  $l^{cls}$ . Only when the  $i$ -th query's loss  $l_i^{cls}$  is less than the loss at  $\tau\%$  percentile, i.e.,  $l_\tau^{cls}$ , will its corresponding  $d_i$  be set to 1.

$$d_i = \begin{cases} 1, & l_i^{cls} \leq l_\tau^{cls} \\ 0, & \text{others} \end{cases}. \quad (3)$$

## WeakSAM: Segment Anything Meets Weakly-supervised Instance-level Recognition

Table 1. Comparisons of the WSOD performance in terms of AP metrics on three benchmarks: PASCAL VOC 2007, PASCAL VOC 2012, and COCO 2014. The *Sup.* column denotes the type of supervision used for training including full supervision ( $\mathcal{F}$ ), point-level labels ( $\mathcal{P}$ ), image-level labels ( $\mathcal{I}$ ). “\*” means the results rely on MCG (Pont-Tuset et al., 2016) proposals. “‡” means this method use the a heavy RN50-WS-MRRP (Shen et al., 2020) backbone ( $1.76 \times$  parameters than VGG16 and  $10.10 \times$  parameters than RN50). We mark the best WSOD results in bold.

Methods	Proposal	Sup.	Retrain	VOC 07	VOC 12	COCO 14		
				AP <sub>50</sub>	AP <sub>50</sub>	AP <sub>50:95</sub>	AP <sub>50</sub>	AP <sub>75</sub>
<b>Fully-supervised object detection methods.</b>								
Faster R-CNN (Ren et al., 2015)	RPN	$\mathcal{F}$	–	69.9	–	21.2	41.5	–
<b>WSOD methods with point supervision.</b>								
P2BNet (Chen et al., 2022)	RPN	$\mathcal{P}$	–	60.2	–	19.4	43.5	–
<b>WSOD methods with image-level supervision.</b>								
C-MIDN (Gao et al., 2019)	SS, MCG	–	–	52.6	50.2	9.6*	21.4*	–
WSOD <sup>2</sup> (Zeng et al., 2019)	SS	–	–	53.6	47.2	10.8	22.7	–
SLV (Chen et al., 2020)	SS	–	–	53.5	49.2	–	–	–
CASD (Huang et al., 2020)	SS	–	–	56.8	53.6	12.8	26.4	–
IM-CFB (Yin et al., 2021)	SS	$\mathcal{I}$	–	54.3	49.4	–	–	–
OD-WSCL (Seo et al., 2022)	SS, MCG	–	–	56.4	54.6	13.7*	27.7*	11.9*
WSOD-CBL (Yin et al., 2023)	SS	–	–	57.4	53.5	13.6	27.6	–
WSOVOD (Lin et al., 2024)	LO-WSRPN + SAM	–	–	59.1	59.8	18.8	27.1	19.7
WSOVOD‡	LO-WSRPN + SAM	–	–	63.4	62.1	20.5	29.1	21.4
<b>Baseline and ours.</b>								
OICR (Tang et al., 2017)	SS, MCG	$\mathcal{I}$	–	41.2	37.9	8.0*	18.9*	7.0*
WeakSAM (OICR)	WeakSAM	–	–	58.9+17.7	58.4+20.5	19.9+11.9	32.1+13.2	20.6+13.6
<b>Baseline and ours.</b>								
MIST (Ren et al., 2020)	SS, MCG	$\mathcal{I}$	–	54.9	52.1	11.4*	24.3*	9.4*
WeakSAM (MIST)	WeakSAM	–	–	67.4+12.5	66.9+14.8	22.9+11.5	35.2+10.9	24.6+15.2
<b>WSOD methods with image-level supervision. + Retrain</b>								
W2F (Zhang et al., 2018b)	RPN	–	Faster R-CNN	52.4	47.8	–	–	–
SoS-WSOD (Sui et al., 2022)	RPN	$\mathcal{I}$	Faster R-CNN	64.4	61.9	16.6	32.8	15.2
W2N (Huang et al., 2022)	RPN	–	Faster R-CNN	65.4	60.8	15.9	33.3	13.4
<b>Ours. + Retrain</b>								
WeakSAM (OICR)	RPN	–	Faster R-CNN	65.7	62.9	22.3	36.5	23.0
WeakSAM (MIST)	RPN	–	Faster R-CNN	71.8	69.2	23.8	38.5	25.1
WeakSAM (OICR)	–	$\mathcal{I}$	DINO	66.1	63.7	24.9	36.9	26.8
WeakSAM (MIST)	–	–	DINO	<b>73.4</b>	<b>70.2</b>	<b>26.6</b>	<b>39.3</b>	<b>29.0</b>

$$\mathcal{L}_{\text{Hungarian}} = \sum_i d_i[l_i^{cls} + p_i^*l_i^{box} + p_i^*l_i^{iou}]. \quad (4)$$

### 3.3. WeakSAM for WSIS

Thanks to the high-quality WeakSAM-PGT, we can directly use them to prompt SAM for precise segments as pseudo instance labels. Following the practices in the WeakSAM-WSOD pipeline, we evaluate the quality of WeakSAM-PGT using R-CNN-based and query-based instance segmentation methods, respectively. Notably, we do not introduce more techniques in the WeakSAM-WSIS, because the WeakSAM pseudo instance labels are accurate enough.

## 4. Experiment

### 4.1. Experimental Setup

**Datasets and Metrics** We evaluate the proposed WeakSAM on both weakly-supervised object detection (WSOD) and weakly-supervised instance segmentation (WSIS) benchmarks. Notably, the same datasets for different tasks

may have different settings. **For WSOD**, we use three datasets, i.e., PASCAL VOC 2007 (Everingham et al., 2015), PASCAL VOC 2012 (Everingham et al., 2015), and COCO 2014 (Lin et al., 2014). PASCAL VOC 2007 has 2501 images for training, 2510 images for evaluation, and 4592 images for testing. PASCAL VOC 2012 contains 5717 training images, 5823 validation images, and 10991 test images. COCO 2014 includes around 80,000 images for training and 40,000 images for validation. Following previous WSOD methods, we train WeakSAM on *train* and *val* sets and evaluate WeakSAM on the *test* set for PASCAL VOC 2007 and 2012. For COCO 2014, we use the *train* set for training and the *val* set for evaluating. PASCAL VOC 2007 and 2012 datasets comprise 20 object categories and COCO 2014 comprises 80 ones. We report the average precision AP metrics for these benchmarks. **For WSIS**, we use two datasets, i.e., PASCAL VOC 2012, and COCO 2017. The PASCAL VOC 2012 dataset includes 10582 images for training, and 1449 images for evaluation, comprising 20 object categories. The COCO 2017 dataset includes 115K training images, 5K validation images, and 20K testing images, comprising 80 object categories. Following previous

## WeakSAM: Segment Anything Meets Weakly-supervised Instance-level Recognition

Table 2. Comparisons of the WSIS performance in terms of AP metrics on PASCAL VOC 2012. The *Sup.* column denotes the type of supervision used for training including mask supervision ( $\mathcal{M}$ ), saliency maps ( $\mathcal{S}$ ), image-level labels ( $\mathcal{I}$ ), and SAM models ( $\mathcal{A}$ ). We mark the best WSIS results in bold.

Methods	Backbone	<i>Sup.</i>	Retrain	VOC 12			
				AP <sub>25</sub>	AP <sub>50</sub>	AP <sub>70</sub>	AP <sub>75</sub>
<i>Fully-supervised instance segmentation methods.</i>							
Mask R-CNN (He et al., 2017)	ResNet-101	$\mathcal{M}$	–	76.7	67.9	52.5	44.9
<i>WSIS methods with image-level supervision. + Retrain</i>							
WISE (Laradji et al., 2019)	ResNet-50	$\mathcal{I}$	Mask R-CNN	49.2	41.7	–	23.7
IRNet (Ahn et al., 2019)	ResNet-50	$\mathcal{I}$	Mask R-CNN	–	46.7	23.5	–
LIID (Liu et al., 2020)	ResNet-50	$\mathcal{I} + \mathcal{S}$	Mask R-CNN	–	48.4	–	24.9
Arun et al. (Arun et al., 2020)	ResNet-50	$\mathcal{I}$	Mask R-CNN	59.7	50.9	30.2	28.5
WS-RCNN (Ou et al., 2021)	VGG-16	$\mathcal{I}$	Mask R-CNN	62.2	47.3	–	19.8
BESTIE (Kim et al., 2022)	HRNet-W48	$\mathcal{I}$	Mask R-CNN	61.2	51.0	31.9	26.6
CIM (Li et al., 2023)	ResNet-50	$\mathcal{I}$	Mask R-CNN	68.7	55.9	37.1	30.9
<i>Ours.</i>							
WeakSAM	ResNet-50	$\mathcal{I} + \mathcal{A}$	Mask R-CNN	70.3	59.6	43.1	36.2
WeakSAM	ResNet-50	$\mathcal{I} + \mathcal{A}$	Mask2Former	<b>73.4</b>	<b>64.4</b>	<b>49.7</b>	<b>45.3</b>

Table 3. Comparisons of the WSIS performance in terms of AP metrics on COCO 2017. The *Sup.* column denotes the type of supervision used for training including mask supervision ( $\mathcal{M}$ ), saliency maps ( $\mathcal{S}$ ), image-level labels ( $\mathcal{I}$ ), and SAM models ( $\mathcal{A}$ ). We mark the best WSIS results in bold.

Methods	Backbone	<i>Sup.</i>	Retrain	COCO val 2017			COCO test-dev		
				AP <sub>50:95</sub>	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>50:95</sub>	AP <sub>50</sub>	AP <sub>75</sub>
<i>Fully-supervised instance segmentation methods.</i>									
Mask R-CNN (He et al., 2017)	ResNet-50	$\mathcal{M}$	–	34.4	55.1	36.7	33.6	55.2	35.3
<i>WSIS methods with image-level supervision.</i>									
WS-JDS (Shen et al., 2019)	VGG-16	$\mathcal{I}$	–	6.1	11.7	5.5	–	–	–
PDSL (Shen et al., 2021)	ResNet18-WS	$\mathcal{I}$	–	6.3	13.1	5.0	–	–	–
Fan et al. (Fan et al., 2018a)	ResNet-101	$\mathcal{I} + \mathcal{S}$	Mask R-CNN	–	–	–	13.7	25.5	13.5
LIID (Liu et al., 2020)	ResNet-50	$\mathcal{I} + \mathcal{S}$	Mask R-CNN	–	–	–	16.0	27.1	16.5
BESTIE (Kim et al., 2022)	HRNet-W48	$\mathcal{I}$	Mask R-CNN	14.3	28.0	13.2	14.4	28.0	13.5
CIM (Li et al., 2023)	ResNet-50	$\mathcal{I}$	Mask R-CNN	17.0	29.4	17.0	17.2	29.7	17.3
<i>Ours.</i>									
WeakSAM	ResNet-50	$\mathcal{I} + \mathcal{A}$	Mask R-CNN	20.6	33.9	22.0	21.0	34.5	22.2
WeakSAM	ResNet-50	$\mathcal{I} + \mathcal{A}$	Mask2Former	<b>25.2</b>	<b>38.4</b>	<b>27.0</b>	<b>25.9</b>	<b>39.9</b>	<b>27.9</b>

methods, we report the average precision AP metrics with different Intersection-over-Union (IoU) thresholds.

**Implementation Details** For WeakSAM proposals generation, we adopt the WeakTr (Zhu et al., 2023a) with DeiT-S (Touvron et al., 2021) model for generating classification clues, the SAM (Kirillov et al., 2023) with ViT-H (Dosovitskiy et al., 2020) model to generate proposals. For WeakSAM WSOD pipeline, we use the WSOD networks, i.e., OICR (Tang et al., 2017), and MIST (Ren et al., 2020), with the VGG-16 (Han et al., 2021) backbone to generate pseudo ground truth (PGT), and FSOD networks, i.e., Faster R-CNN (Ren et al., 2015) and DINO (Zhang et al., 2022), with the ResNet-50 (He et al., 2016) backbone to retrain. As for the WeakSAM-WSIS, we use SAM-ViT-H to generate pseudo instance labels and train the R-CNN-based and query-based methods, i.e., Mask R-CNN (He et al., 2017) and Mask2former (Cheng et al., 2022), respectively. All hyper-parameters in Alg. 1 and Alg. 2 are following the default manners as Zhu et al. (2023a) and Sui et al. (2022).

## 4.2. Comparisons with State-of-the-art Methods

**Weakly-supervised object detection** We present the quantitative WSOD results in Table. 1. Compared with our WSOD baseline methods, i.e., OICR and MIST, the proposed WeakSAM achieves over 10% improvements on all metrics. The results of WeakSAM (MIST) surpass all WSOD methods on all metrics, which demonstrate the effectiveness of WeakSAM-proposals. Compared with WSOD methods retrained by pseudo ground truth (PGT), the WeakSAM (MIST) with Faster R-CNN retraining still outperforms the SoS-WSOD (Sui et al., 2022) and W2N (Huang et al., 2022) on all metrics, and the WeakSAM (MIST) with DINO retraining even has comparable performance with fully-supervised Faster R-CNN. The retraining results demonstrate the effectiveness of the proposed WSOD pipeline, which includes the adaptive PGT generation and RoI drop retraining. Compared with concurrent work, WSOVOD (Lin et al., 2024), which also incorporates SAM,

Table 4. Ablation studies for WeakSAM prompts on PASCAL VOC 2007. We evaluate the average number of proposals, recall, and WSOD performance by MIST (Ren et al., 2020).

SS	Dense Sample	CAM <sub>fine</sub>	CAM <sub>coarse</sub>	Cross Attn.	Num.	Recall			AP <sub>50</sub>
						IoU=0.50	IoU=0.75	IoU=0.90	
✓					2001	92.6	57.7	19.2	54.9
	✓				129	79.6	50.7	24.3	45.2
	✓	✓			151	88.9	67.0	37.2	63.3+18.1
	✓	✓	✓		174	90.6	70.1	40.1	65.5+20.3
	✓	✓	✓	✓	213	95.6	75.0	42.1	67.4+22.2

Table 5. Ablation studies for adaptive PGT generation and RoI drop regularization. We present the results on the PASCAL VOC 2007 test set.

(a) Ablation studies for the anchor-based detector, i.e., Faster R-CNN (Ren et al., 2015).

Top-1 PGT	Adaptive PGT	RoI Drop	AP <sub>50</sub>
✓			68.4
	✓		70.7+2.3
	✓	✓	71.8+3.4

(b) Ablation studies for the query-based detector, i.e., DINO (Zhang et al., 2022).

Top-1 PGT	Adaptive PGT	Query Drop	AP <sub>50</sub>
✓			71.1
	✓		72.8+1.7
	✓	✓	73.4+2.3

our WeakSAM (MIST) also achieves better performance.

**Weakly-supervised instance segmentation** We first present the quantitative WSIS results of the PASCAL VOC 2012 *val* set in Table 2. The proposed WeakSAM with Mask R-CNN retraining achieves the best performance, which demonstrates the WeakSAM can benefit WSIS effectively. Furthermore, the pseudo instance labels generated by WeakSAM can also be used by the modern query-based methods, e.g., Mask2Former (Cheng et al., 2022), which achieves the best results.

We then show the quantitative WSIS results on COCO 2017 *val* and *test* sets. On these more challenging benchmarks, WeakSAM with Mask R-CNN retraining achieves better results than CIM (Li et al., 2023). Besides, the WeakSAM with Mask2Former also presents the best results.

### 4.3. Ablation Studies

In this section, we present the ablation studies to evaluate the improvements brought by the proposed methods, i.e., WeakSAM prompts, adaptive PGT generation, and RoI drop retraining.

Due to the limitation of pages, we leave more ablation studies in the supplementary material, including efficiency analysis, sensitivity analysis, qualitative analysis, etc.

**Improvements of WeakSAM Prompts** To further analyze the improvements brought by the proposed WeakSAM prompts, we conduct ablation experiments for different prompts in Table 4. Here, we use the Selective Search (Uijlings et al., 2013) as the baseline method. When only using the densely sampled points, the generated proposals can achieve 5.1% higher Recall (IoU=0.90), and 9.7% lower AP<sub>50</sub> for MIST. After adding peak CAM points and peak cross attention points as prompts, we can achieve higher recall and AP<sub>50</sub> through only 213 proposals on average.

**Improvements of WSOD Pipeline** To further analyze the improvements brought by the proposed WeakSAM-WSOD pipeline, we conduct ablation experiments for adaptive PGT generation and RoI drop regularization in Table 5. Here, we set a baseline that uses the predicted boxes with the top-1 score as PGT and plain Faster R-CNN as the retraining network. It shows that adaptive PGT generation and RoI drop can both improve the retraining results of Faster R-CNN (Ren et al., 2015) and DINO (Zhang et al., 2022), respectively.

## 5. Conclusion

In this paper, we introduce WeakSAM, a novel framework utilizing the Segment Anything Model (SAM) for weakly-supervised instance-level recognition, demonstrating leading performance in WSOD and WSIS benchmarks. Different from the original SAM, which requires interaction and can not be aware of categories, WeakSAM represents an innovative fusion of SAM with weakly-supervised learning (WSL), overcoming the redundancy problem of WSOD proposals. To further address WSOD issues such as pseudo ground truth (PGT) incompleteness and noisy PGT instances, our approach includes adaptive PGT generation and a Region of Interest (RoI) drop regularization. The adaptability of WeakSAM is further showcased through its extension to weakly-supervised instance segmentation (WSIS). Our work aims to inspire further research with SAM and WSL, contributing significantly to the develop-



ment of a universal framework for weakly-supervised recognition.

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## A. More Details of WeakSAM Proposals

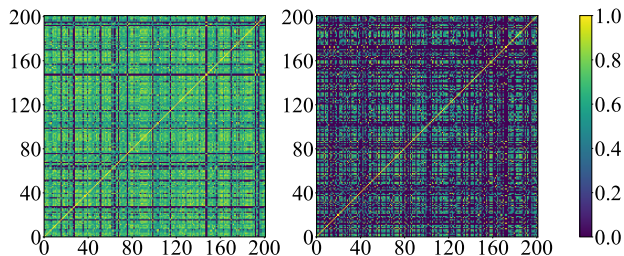


Figure 4. The cosine similarity among the features of proposals, i.e., Left for Selective Search proposals and Right for WeakSAM-proposals. For a single image from PASCAL VOC 2007, we randomly sampled 200 proposal features to calculate their similarity.

We further analyze the proposal similarity in the different weakly-supervised object detection (WSOD) proposals, as shown in Fig. 4. We randomly sample 200 proposal features each from Selective Search (Uijlings et al., 2013) proposals and WeakSAM-proposals, and then compute their cosine similarity, respectively. Please note that all the features are output by the RoI pooling layer. It can be seen that the features from Selective Search tend to have higher similarity with other ones. In contrast, the features from WeakSAM-proposals show lower similarity, which usually means it has less overlap and redundancy.

## B. More Details of RoI Drop Regularization

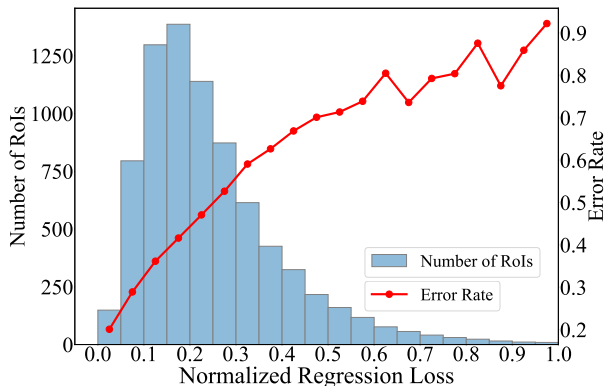


Figure 5. The relationship between the normalized regression loss, the corresponding number of RoIs, and the corresponding error rate. The results are obtained from training the Faster-RCNN (Ren et al., 2015) using PASCAL VOC 2007 pseudo ground truth (PGT) in the preliminary training stage.

We further present the relationship between the normalized regression loss, the corresponding number of RoIs, and the corresponding error rate in Fig. 5. It shows that the

regression losses of RoIs have different number distributions compared to the classification losses. However, they exhibit similar error rate curves. This observation further demonstrates the necessity of RoI drop regularization with a regression threshold  $\tau_{reg}$ .

## C. More Details of Query Drop Regularization

Because DINO (Zhang et al., 2022) employs Focal loss (Lin et al., 2017) as the classification loss, queries associated with background classes tend to have higher predicted probabilities and lower losses. This results in the inadvertent omission of most foreground category queries when directly dropping queries. To mitigate this issue, our first step involves normalizing the unweighted Focal loss, which is essentially the binary cross-entropy loss, for both foreground and background queries within each training batch. Normalizing at the batch level broadens the sampling scope from a single image to the size of the batch. In the second step, queries are dropped based on their loss ranking post-normalization. This approach avoids making the model converge slowly due to the dropping of the most foreground queries.

## D. Efficiency Comparison

To further analyze the efficiency improvement brought by the WeakSAM, we present the efficiency comparison between Selective Search (Uijlings et al., 2013) and our WeakSAM on a machine with 4 GPU cards, as shown in Table 6. Our WeakSAM reduces the number of proposals by 89.4%, the proposal generation time by 65.5%, the WSOD network training time by 43.8%, and the GPU memory cost by 68.2%. The results demonstrate the significant efficiency improvement brought by the proposed WeakSAM.

## E. Additional Quantitative Results

We present the comparison on PASCAL VOC 2007 *trainval* set in terms of CorLoc, as shown in Table 7. It can be seen that the WeakSAM achieves the 13.9% and 14.1% CorLoc improvements on OICR and MIST, respectively. The WeakSAM (OICR) outperforms the WSOD-CBL (Yin et al., 2023) by 11.1% CorLoc. The results demonstrate the significant effectiveness improvement brought by our WeakSAM.

## F. Additional Ablation Studies

### F.1. Improvements of Classification Methods

To further analyze the impact of methods that generate classification clues, we replaced WeakTr in WeakSAM with MCTformer and CLIP-ES. As indicated in Table 8, Weak-

Table 6. Efficiency comparison between Selective Search and our WeakSAM during the training on the PASCAL VOC 2007. ‘Num.’ is the number of proposals, ‘ $T_{\text{Proposals}}$ ’ is the time consumption for generating proposals, ‘ $T_{\text{WSOD}}$ ’ is the time consumption for training the WSOD network, i.e., MIST (Ren et al., 2020), and ‘ $M_{\text{WSOD}}$ ’ is the GPU memory cost for each GPU card.

	Num.	$T_{\text{Proposals}}$	$T_{\text{WSOD}}$	$M_{\text{WSOD}}$
SS (Uijlings et al., 2013)	2001	11.6 hrs	16 hrs	17810 MiB
Ours	213-89.4%	4 hrs-65.5%	9 hrs-43.8%	5667 MiB-68.2%

Table 7. Comparison on PASCAL VOC 2007 trainval set in terms of CorLoc(%) with multi-scale testing.

Methods	Sup.	Proposal	CorLoc
WSDN (Bilen & Vedaldi, 2016a)		EB (Zitnick & Dollár, 2014)	53.5
Yang et al. (Yang et al., 2019)		SS (Uijlings et al., 2013)	68.0
C-MIL (Wan et al., 2019)		SS	65.0
C-MIDN (Gao et al., 2019)		SS	53.5
WSOD2 (Zeng et al., 2019)	$\mathcal{I}$	SS	69.5
CASD (Huang et al., 2020)		SS	70.4
OD-WSCL (Seo et al., 2022)		SS	69.8
WSOD-CBL (Yin et al., 2023)		SS	71.8
WSOVOD (Lin et al., 2024)		LO-WSRPN+SAM	77.2
WSOVOD $\ddagger$		LO-WSRPN+SAM	80.1
OICR (Tang et al., 2017)	$\mathcal{I}$	SS	60.6
WeakSAM (OICR)		WeakSAM	74.5+13.9
MIST (Ren et al., 2020)	$\mathcal{I}$	SS	68.8
WeakSAM (MIST)		WeakSAM	82.9+14.1

SAM (MCTformer) achieves a 1.6% higher Recall (IoU=90) than WeakSAM (WeakTr). Furthermore, WeakSAM (CLIPES) records increases of 0.6% and 2.4% in Recall over WeakSAM (WeakTr) at IoU thresholds of 75 and 90, respectively. These results demonstrate the versatility of the WeakSAM proposal-generating method across different classification methods. Please note that all classification methods employed in this study are CAM networks from weakly-supervised semantic segmentation (WSSS) methods. Since these networks are typically well-tuned on specific datasets, such as PASCAL VOC 2012 and COCO 2014, they are adept at providing rich classification clues.

## F.2. Ablation Studies for RoI Drop Regularization

To further analyze the impact of the regression threshold and classification threshold in RoI drop regularization, we conduct experiments as shown in Table 9. It is observed that the best regression threshold  $\tau_{reg}$  and classification threshold  $\tau_{cls}$  for RoI drop regularization is 1.0 and 4.0, respectively.

## F.3. Ablation Studies for Query Drop Regularization

To analyze the impact of dropping queries corresponding to foreground categories  $\text{Query}_{\text{things}}$  and background categories  $\text{Query}_{\text{bkg}}$ , we conduct ablations as shown in Table 10. Experimental results indicate that dropping only the foreground queries ( $\text{Query}_{\text{things}}$ ) leads to the best perfor-

mance, whereas dropping both types of queries results in a slight decrease in performance. We maintain the viewpoint that dropping more background queries may also lead to slower convergence. Consequently, we choose to drop only  $\text{Query}_{\text{things}}$  to achieve better performance.

We further analyze the impact of classification threshold  $\tau$  in query drop regularization, as shown in Table 11. Quantitative results demonstrate that 90 is the best percentile classification threshold.

## G. Additional Visualization Results

Fig.6 compares the Selective Search proposals with those generated by WeakSAM. The WeakSAM-proposals exhibit less redundancy than Selective Search proposals. Fig.7 contrasts the Top-1 PGT with adaptive PGT, demonstrating that adaptive PGT generation captures a greater number of objects, which might be missed by the Top-1 approach. Additionally, adaptive PGT can be seamlessly integrated to generate pseudo instance labels. Fig.8 presents the object detection results using WeakSAM (MIST), showing its capability to accurately capture entire objects without generating excessive noisy bounding boxes. In Fig.9, the instance segmentation results of WeakSAM-Mask2Former retraining are showcased. The results indicate effective segmentation of entire instances with a notable reduction in overlapping segments.

## WeakSAM: Segment Anything Meets Weakly-supervised Instance-level Recognition

Table 8. Ablation studies for classification methods that generate WeakSAM queries on PASCAL VOC 2007 *trainval* set. We evaluate the average number of proposals and Recall. We present the results of Selective Search (Uijlings et al., 2013) at the first row as a baseline.

CLS Methods	Num.	Recall		
		IoU=0.50	IoU=0.75	IoU=0.90
None	2001	92.6	57.7	19.2
WeakTr (Zhu et al., 2023a)	213	95.6	75.0	42.1
MCTformer (Xu et al., 2022)	173	93.2	74.8	43.7
CLIP-ES (Lin et al., 2023)	205	93.8	75.6	44.5

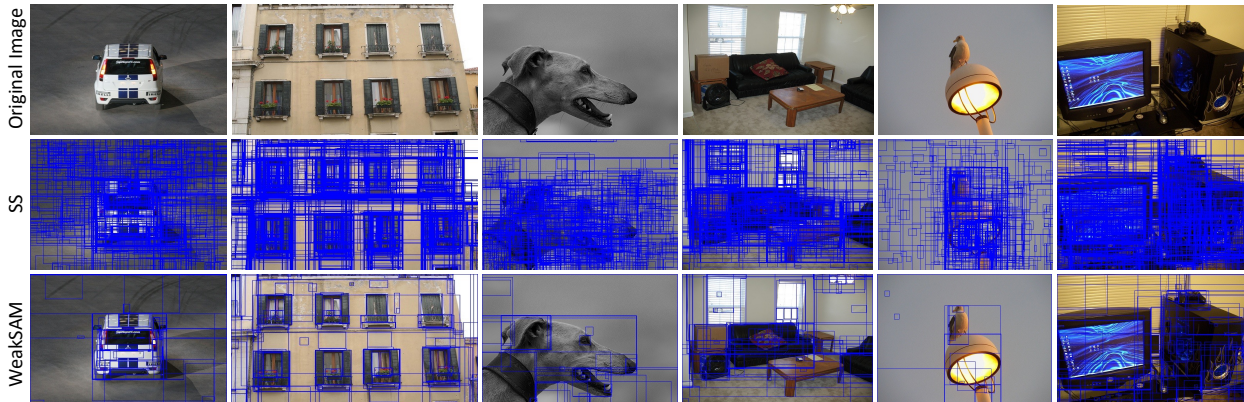


Figure 6. Visualization of the proposals boxes on the PASCAL VOC 2007 *trainval* set.

Table 9. Ablation study for the regression threshold and classification threshold in RoI drop regularization in terms of AP<sub>50</sub> on the PASCAL VOC 2007 *test* set.

(a) Ablation study for the regression threshold.

$\tau_{reg}$	0.8	1.0	1.2
AP <sub>50</sub>	71.0	71.8	71.3

(b) Ablation study for the classification threshold.

$\tau_{cls}$	3.0	4.0	5.0
AP <sub>50</sub>	71.2	71.8	71.1

Table 10. Ablation studies for query drop regularization on the PASCAL VOC 2007 *test* set.

Baseline	Query <sub>things</sub>	Query <sub>bkg</sub>	AP <sub>50</sub>
✓			72.8
	✓		73.4+0.6
	✓	✓	73.3+0.5

Table 11. Ablation study for the classification threshold in query drop regularization in terms of AP<sub>50</sub> on the PASCAL VOC 2007 *test* set.

$\tau$ (%)	100	90	80
AP <sub>50</sub>	72.8	73.4	71.8

## H. More Implementation Details

For Algorithm 1, we set the kernel size  $k$  to 128 and activation threshold  $\tau$  to 0.9 following default parameters from WeakTr (Zhu et al., 2023a). And for Algorithm 2, we follow the default manners similar to SoS-WSOD (Sui et al., 2022), in which score threshold  $\tau_s$  is set to 0.3, and overlap threshold  $\tau_o$  is set to 0.85.

For Faster R-CNN (Ren et al., 2015) retraining, we adopt the same training strategy and hyper-parameters as the Fully-supervised ones. For DINO (Zhang et al., 2022) retraining, we use a learning rate of 9e-5 with the AdamW (Loshchilov & Hutter, 2017) optimizer, and a max epoch of 14. Moreover, we apply multi-scale augmentation and horizontal flips in both training and testing.

For implementations of Mask R-CNN (He et al., 2017) and Mask2Former (Cheng et al., 2022), we follow their default hyper-parameters.





Figure 7. Visualization of the pseudo ground truth boxes and pseudo instance labels on the PASCAL VOC 2012 *trainaug* set.



Figure 8. Visualization of the weakly-supervised object detection on the PASCAL VOC 2007 *test* set.

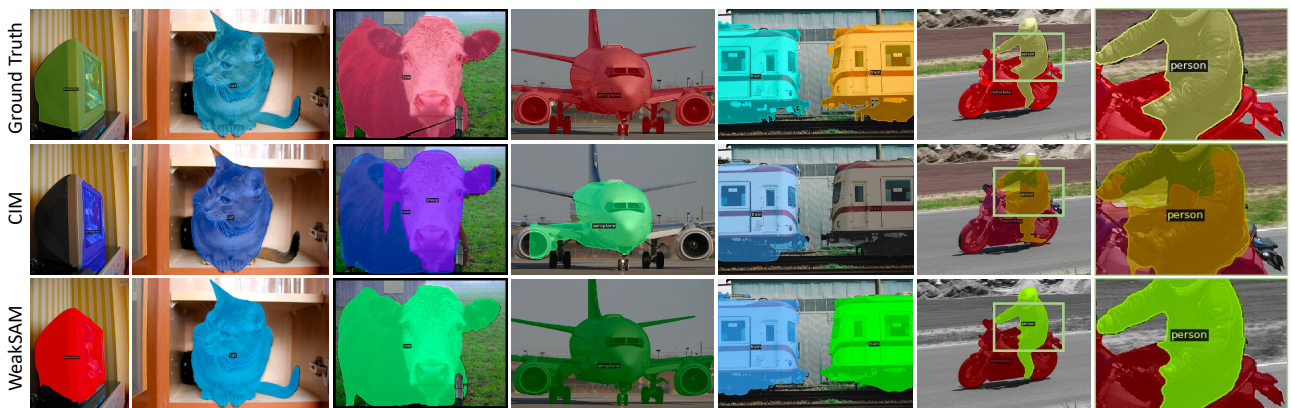


Figure 9. Visualization of the weakly-supervised instance segmentation on the PASCAL VOC 2012 *val* set.