

Semantic Prompt Learning for Weakly-Supervised Semantic Segmentation

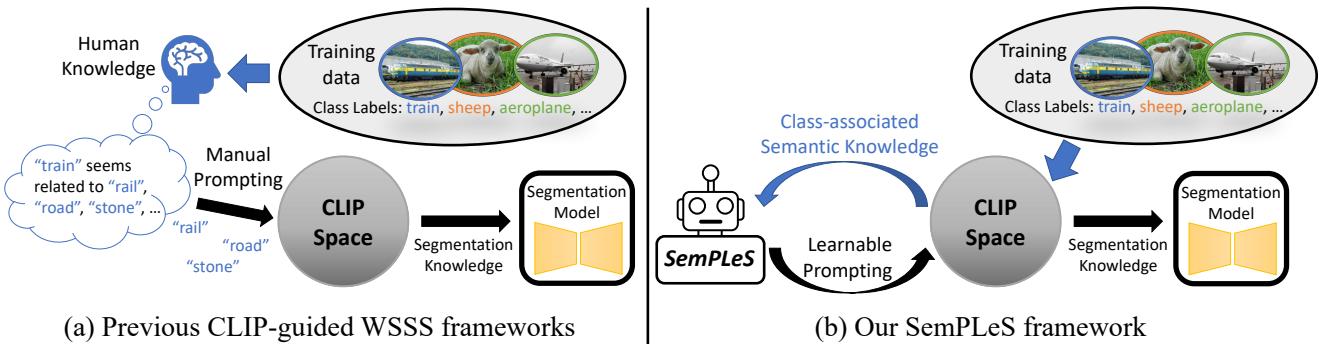
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Figure 1. (a) Previous CLIP-guided WSSS methods [42, 65] rely on manual prompt engineering involved with heuristic human knowledge, while (b) our proposed *SemPLeS* framework automatically discovers and learns prompts embedded with class-associated semantic knowledge from the CLIP latent space without any manual effort.

Abstract

*Weakly-Supervised Semantic Segmentation (WSSS) aims to train segmentation models using image data with only image-level supervision. Since precise pixel-level annotations are not accessible, existing methods typically focus on producing pseudo masks for training segmentation models by refining CAM-like heatmaps. However, the produced heatmaps may capture only the discriminative image regions of object categories or the associated co-occurring backgrounds. To address the issues, we propose a *Semantic Prompt Learning for WSSS (SemPLeS)* framework, which learns to effectively prompt the CLIP latent space to enhance the semantic alignment between the segmented regions and the target object categories. More specifically, we propose Contrastive Prompt Learning and Prompt-guided Semantic Refinement to learn the prompts that adequately describe and suppress the co-occurring backgrounds associated with each object category. In this way, SemPLeS can perform better semantic alignment between object regions and class labels, resulting in desired pseudo masks for training segmentation models. The proposed SemPLeS framework achieves competitive performance on standard WSSS benchmarks, PASCAL VOC 2012 and MS COCO 2014, and shows compatibility with other WSSS methods.*

1. Introduction

Semantic segmentation aims to classify every pixel in images to identify object categories and the associated regions, which can benefit various applications in the real world [48, 53, 75]. While promising results have been presented by fully-supervised approaches [6–8, 39, 45, 77, 78], collecting pixel-level annotations could be time-consuming and expensive, and therefore limits the scalability and practicality of fully-supervised methods. To address this issue, Weakly-Supervised Semantic Segmentation (WSSS) has emerged as an alternative approach to train segmentation models with only coarse or incomplete annotations such as bounding boxes [29], scribbles [40], points [3], or image-level labels. Among these annotation forms, *image-level labels* which indicate the presence or absence of certain object categories are commonly used due to the efficiency in data collection and the availability in various benchmark image datasets. Since precise annotations of object positions are *not* observed, learning to localize and segment object categories from image-level supervision is particularly challenging. Most existing methods [4, 28, 32, 55, 61, 68] focus on producing pseudo ground truth masks by learning CAM-like heatmaps [57, 80] with class labels as discriminative supervision. Despite the shown efficacy, the learned CAMs may still miss relevant regions of target object categories and fail to cover the entire object. Furthermore, co-

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occurring backgrounds associated with certain object categories may also be falsely activated (*e.g.*, rails in a photo of a train). Consequently, learning precise image regions that align with the semantics of target objects from weak supervision remains a challenging task.

With the rapid growth in the amount of image and text data in recent years, several vision-language models [11, 46, 51] have been proposed to bridge the underlying semantics between the two modalities. Given that both the images and the associated class labels (object names) are available in the setting of WSSS, the underlying image-text semantics from the CLIP [51] latent space can be leveraged to enhance the quality of CAMs and pseudo masks. Recent CLIP-based methods [42, 49, 65, 69, 72] mainly focus on designing text prompts or prompt learning techniques for the text encoder. Despite the effectiveness demonstrated, they either consider only the foreground class prompts, or rely on general background prompts (*e.g.*, “a photo of rail”, “a photo of road”, *etc.*) defined by additional manual efforts and heuristic human knowledge, as shown in Fig. 1 (a). Moreover, such manually-defined prompts may not fully exploit the knowledge in the CLIP latent space.

In this paper, we aim to fully exploit the CLIP latent space to benefit the weakly-supervised semantic segmentation problem without manual prompting. To achieve this goal, we propose a *Semantic Prompt Learning for WSSS (SemPLeS)* framework to learn prompts embedded with class-associated semantic knowledge *discovered* from the CLIP latent space, as shown in Fig. 1 (b), where the learned prompts can enhance the semantic alignment between the segmented regions and the target object categories with image-level labels. More specifically, we perform image-text contrastive learning under the guidance of CLIP and train a mask generator to generate class activation maps. Such produced object masks, however, might not be sufficiently precise, and the co-occurring backgrounds associated with the object categories may be falsely activated. To alleviate this problem, we uniquely present *Contrastive Prompt Learning* and *Prompt-guided Semantic Refinement* to suppress class-associated background regions. In *Contrastive Prompt Learning*, we learn prompts to capture co-occurring backgrounds from images and class labels. Without manually defining the background texts, our learned prompts would properly describe the backgrounds associated with each object category. Under the guidance of our learned class-associated background prompts, we further suppress co-occurring backgrounds from the activation maps via *Prompt-guided Semantic Refinement*. With the above-designed learning strategy, the semantic matching between object regions and the associated class labels will be enhanced, resulting in precise pseudo masks desired for training segmentation networks. The proposed *SemPLeS* framework achieves competitive performance on

standard WSSS benchmarks, PASCAL VOC 2012 and MS COCO 2014. Moreover, our proposed *SemPLeS* framework can integrate and improve other WSSS methods including CNN-, Transformer-, and foundation model-based ones, confirming its effectiveness and compatibility.

In summary, our contributions are three-fold:

- We propose a novel *Semantic Prompt Learning for WSSS (SemPLeS)* framework, which fully exploits the CLIP latent space to benefit the weakly-supervised semantic segmentation without manual prompting. Additionally, our *SemPLeS* framework shows compatibility with other WSSS methods, including CNN-, Transformer-, and foundation model-based ones.
- In *SemPLeS*, we present *Contrastive Prompt Learning* to learn prompts embedded with class-associated semantic knowledge. With no need to manually define background texts, our learned prompts would properly capture co-occurring backgrounds associated with distinct object categories.
- With the derived prompts, our *Prompt-guided Semantic Refinement* learns to suppress co-occurring backgrounds while enhancing the semantic alignment between object regions and the associated class labels, resulting in precise pseudo masks and competitive segmentation performance in WSSS.

2. Related Works

2.1. Weakly-Supervised Semantic Segmentation

Existing WSSS approaches typically follow a three-stage learning process. Firstly, the image-level labels are utilized as supervision to generate Class Activation Maps (CAMs) [57, 80]. Secondly, the CAMs are refined by using dense CRF [31] or pixel affinity-based methods [1, 2] to obtain pseudo masks. Lastly, the pseudo masks are further exploited to train segmentation networks. Among all the stages, producing precise CAMs (*i.e.*, the first stage) is the main focus of WSSS, and various approaches have been proposed to improve the quality of CAMs [9, 14, 19, 21, 27, 33, 35, 36, 63, 66, 73]. With the rapid development and the success of vision transformers [18], recent approaches [16, 50, 54–56, 68, 69, 84] generate finer activation maps based on the patch-level affinity learned from the attention layers. Very recently, several works [10, 13, 26, 59, 72] exploit foundation segmentation models (*e.g.*, SAM [30]) to enhance the quality of the pseudo masks. On the other hand, there are also end-to-end WSSS works [56, 62] which do not require multiple training stages, yet their performances are inferior to standard 3-stage methods. In general, most WSSS methods learn CAMs through object classification, overlooking the textual semantics of class labels. Instead, our

method exploits vision-language models to discover class-associated semantic knowledge, therefore producing high-quality CAMs for segmentation.

2.2. CLIP-based Semantic Segmentation

Recently, the Contrastive Language-Image Pretraining (CLIP) model [51] has been adopted in semantic segmentation tasks thanks to the generalized knowledge learned from a large corpus of image-text pairs. Given the generalization capability, a number of zero-shot/open-vocabulary approaches [17, 22, 34, 38, 47, 52, 67, 70, 71] exploit CLIP to segment the classes which are unseen during training. However, these methods still require mask annotations during training. To minimize the annotation effort, CLIP has also been adopted to improve unsupervised methods [24, 58, 81]. Nevertheless, the segmentation performance is still unsatisfactory and is not desired for further applications. On the other hand, CLIP has also been utilized to benefit WSSS [42, 49, 65, 69, 72]. These works mainly focus on designing text prompts or prompt learning techniques for the text encoder. However, they either consider only the foreground class prompts, or rely on general background prompts defined by additional manual efforts and heuristic human knowledge. Moreover, such manually-defined prompts may not fully exploit the knowledge in the CLIP latent space. In contrast, with no need for any manual efforts, our proposed *SemPLeS* framework *automatically* learns prompts embedded with class-associated semantic knowledge discovered from the CLIP latent space.

2.3. Prompt Learning

In natural language processing (NLP), prompting [43] involves giving a text-based input such as a sentence or phrase to obtain desired responses from language models. Driven by the recent success of pre-trained vision-language models (*e.g.*, CLIP [51]), there has been an increasing interest in identifying proper prompts for computer vision tasks. Early work relies on prompt engineering to identify text templates (*e.g.*, “a photo of ”) describing classes of interest to obtain underlying knowledge. However, such a trial and error approach generally takes a large amount of time and effort and also requires expertise about the task. To tackle the problem, prompt learning [25, 82, 83] is proposed to replace the manually-defined text templates with a set of learnable context vectors preceding the class names to automate the prompting process. Distinct from these prompt learning methods, our *SemPLeS* framework aims to capture class-associated semantic knowledge for *segmentation* purposes rather than replacing general text templates like “a photo of” in classification tasks.

3. Proposed Method

3.1. Problem Formulation and Model Overview

We first define the problem setting and notations used in this paper. In weakly-supervised semantic segmentation (WSSS), we assume that there is a set of N images X with the associated image-level labels y , where $X \in \mathbb{R}^{H \times W \times 3}$ and $y \in \{0, 1\}^K$ is a multi-hot vector indicating the presence or absence of K object categories. Without access to pixel-wise annotations, we propose a novel *Semantic Prompt Learning for WSSS (SemPLeS)* framework to exploit CLIP [51] to learn prompts that can enhance the semantic alignment between the segmented regions and the target object categories.

As shown in Fig. 2, we first introduce (a) *Segment-Label Matching* in our *SemPLeS* framework, which leverages image-text contrastive learning to produce initial object masks M from our mask generator S . To suppress falsely activated backgrounds in such masks (*e.g.*, X_k^f in the red box), we uniquely propose (b) *Contrastive Prompt Learning* and (c) *Prompt-guided Semantic Refinement*. The former learns class-associated prompts p_k to capture co-occurring backgrounds from images and labels, while the latter takes the derived prompts to disregard co-occurring backgrounds from the object masks (*e.g.*, $X_k^{f'}$ in the green box). By jointly enforcing vision-language matching and suppression objectives, our framework would enhance the semantic alignment between object regions and the associated text labels, resulting in precise segmentation results.

3.2. Semantic Prompt Learning for WSSS

3.2.1 Segment-Label Matching

Given an input image X , our mask generator S is designed to produce foreground masks $M = S(X)$ for target object categories. Since pixel-wise annotations are not available, we choose to leverage vision-language models to guide the learning of our mask generators from image-level supervision. To be more precise, we exploit the joint latent space for images and texts from CLIP to learn object regions aligned with the associated text labels. To achieve this, an image-text triplet (*i.e.*, foreground-background-text) would be formulated to perform contrastive learning, as illustrated in Fig. 2 (a). For the k th ground truth category which presents in the input image X (*i.e.*, $y_k = 1$), we derive the foreground image $X_k^f = M_k \cdot X$ by applying the k th predicted mask M_k to the original image X . Similarly, we reverse the predicted mask to obtain the background regions $X_k^b = (1 - M_k) \cdot X$. As for the text input t_k , we adopt the common prompt template “a photo of {}” filled with the k th class name to describe the category of interest. With the triplet $[X_k^f, X_k^b, t_k]$ serving as the input of the image encoder E_I and text encoder E_T pre-trained by CLIP, we per-

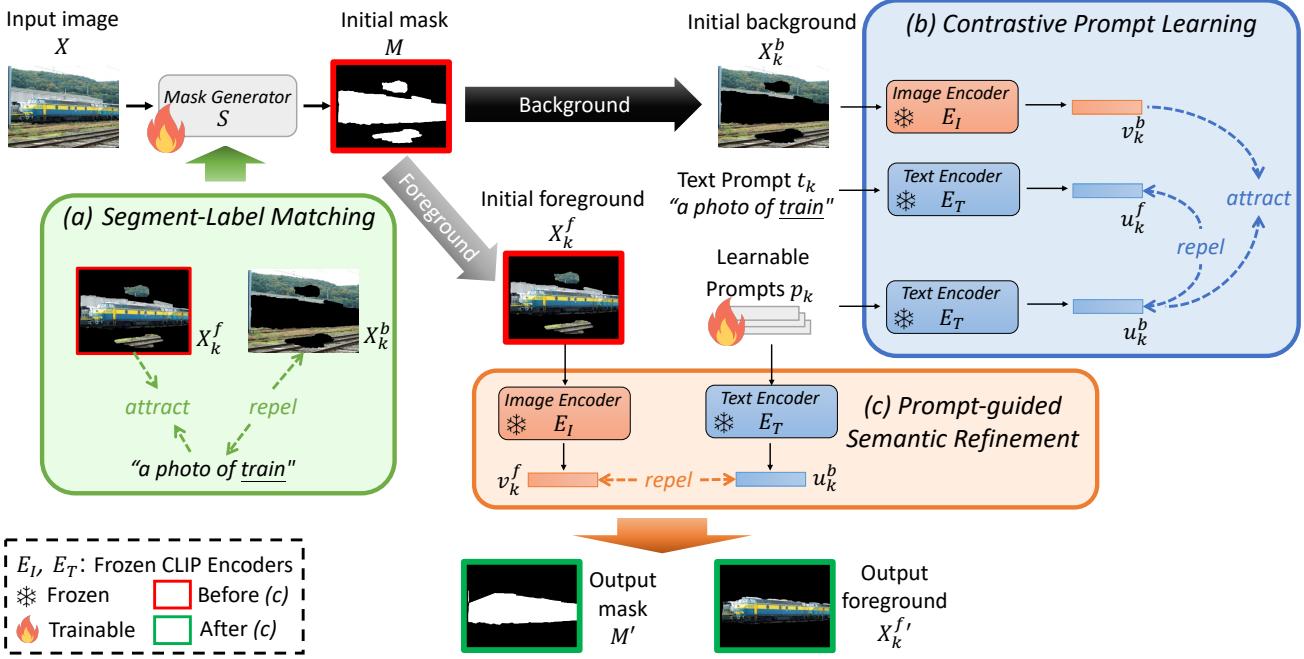


Figure 2. An overview of our proposed **SemPLeS** framework. We first introduce (a) *Segment-Label Matching*, which leverages image-text contrastive learning to train the mask generator S and produce initial object masks M . Such derived masks are still coarse and may falsely include co-occurring backgrounds. To achieve class-associated mask refinement and produce the refined mask M' , we propose (b) *Contrastive Prompt Learning* to automatically learn prompts p_k embedded with semantic knowledge from the CLIP latent space, followed by (c) *Prompt-guided Semantic Refinement* to suppress co-occurring backgrounds associated with each category k .

form image-text contrastive learning to maximize the cosine similarity between X_k^f and t_k for the foreground, while the similarity of X_k^b and t_k would be minimized to repel the background. Therefore, our matching loss L_{match} would be formulated as follows:

$$L_{match} = \mathbb{E}_X \left[-\log(\text{sim}(v_k^f, u_k^f)) \right] + \mathbb{E}_X \left[-\lambda_b \cdot \log(1 - \text{sim}(v_k^b, u_k^f)) \right], \quad (1)$$

where $v_k^f = E_I(X_k^f)$, $v_k^b = E_I(X_k^b)$, $u_k^f = E_T(t_k)$.

Here, λ_b is the loss weight for repelling backgrounds and sim refers to cosine similarity. Note that we keep the image encoder E_I and the text encoder E_T frozen during training and preserve the latent space learned from CLIP to avoid potential overfitting. With the above *Segment-Label Matching*, our mask generator S is encouraged to distinguish foregrounds and backgrounds with the associated text labels. However, as noted above, such masks learned from image-level supervision are still coarse, and may falsely include co-occurring backgrounds associated with certain object categories. Therefore, the above image-text matching is not sufficient to achieve precise segmentation.

3.2.2 Contrastive Prompt Learning

To address the coarse mask issues, the previous language-guided approach [65] exploits vision-language models to

refine the masks with manual prompting techniques. However, these methods require additional prompt engineering efforts with human knowledge involved. Moreover, manual prompting may not be able to fully exploit vision-language representation space. To tackle these problems, we propose *Contrastive Prompt Learning* (Fig. 2 (b)) to learn prompts embedded with semantic knowledge from vision-language models, facilitating the following object mask refinement. Different from the previous work, we employ a sequence of learnable prompts p_k as the input of the text encoder E_T to describe backgrounds for each distinct category k . Specifically, to align the prompts p_k with the background image X_k^b , we maximize the similarity of their representations in the latent space via L_{prompt}^I . On the other hand, to avoid describing the target object category, we encourage the feature similarity between p_k and t_k to be low with L_{prompt}^T . Thus, the prompt learning loss L_{prompt} is defined as below:

$$\begin{aligned} L_{prompt} &= L_{prompt}^I + \lambda_T \cdot L_{prompt}^T \\ &= \mathbb{E}_X \left[-\log(\text{sim}(u_k^b, v_k^b)) \right] + \mathbb{E}_X \left[-\lambda_T \cdot \log(1 - \text{sim}(u_k^b, u_k^f)) \right], \end{aligned} \quad (2)$$

where $u_k^b = E_T(p_k)$, $v_k^b = E_I(X_k^b)$, $u_k^f = E_T(t_k)$.

Here, the mask generator S is fixed and p_k is the only trainable part for loss L_{prompt} , and λ_T is the loss weight for minimizing the similarities to the text labels. Once

the above learning is complete, our prompts p_k would represent co-occurring backgrounds for each category k without requiring manually-defined background prompts, and is therefore preferable to existing CLIP-based methods [42, 49, 65, 69, 72]. In addition, our *Contrastive Prompt Learning* aims to capture class-associated backgrounds for segmentation purposes, rather than replacing general text templates like “a photo of {}” for classification tasks as previous prompt learning methods [25, 82, 83] do.

3.2.3 Prompt-guided Semantic Refinement

Finally, to suppress co-occurring background regions from the object mask M , our *SemPLES* framework exploits the previously derived background prompts p_k to perform *Prompt-guided Semantic Refinement* (Fig. 2 (c)). More specifically, we encourage our mask generator S to produce refined masks M' by excluding the semantic knowledge embedded in the background prompts p_k , while the objectives introduced in Eq. (1) are retained to match the class labels. Hence, the refinement loss L_{refine} and the total loss function L_{total} are defined as follows:

$$L_{total} = L_{match} + \lambda \cdot L_{refine}, \\ \text{where } L_{refine} = \mathbb{E}_X \left[-\log(1 - sim(v_k^f, u_k^b)) \right]. \quad (3)$$

Here, λ is the weight for the refinement loss. It can be seen that, with the derived background prompts p_k (fixed here) and the introduced refinement loss L_{refine} , the class-associated background regions would be suppressed from the foreground mask M , preventing possible false activation. More importantly, by jointly applying the matching and refinement objectives with image-level supervision, our *SemPLES* framework advances vision-language learning to enhance the semantic alignment between the segmented regions and the target object categories, resulting in compact and complete object masks M' desired for WSSS. It is worth noting that, the CLIP model and the learned prompts p_k are leveraged to guide the learning of the mask generator S in our framework, and hence only the mask generator S is needed for producing object masks M' in the WSSS pipeline when the training is complete.

4. Experiments

4.1. Datasets and Evaluation Metrics

We train and validate our proposed framework on the benchmark semantic segmentation datasets, PASCAL VOC 2012 [20] and MS COCO 2014 [41]. The PASCAL VOC 2012 dataset contains 20 object categories along with a background category. The original training, validation, and testing set consists of 1464, 1449, and 1456 images, respectively. Following the common protocol in previous WSSS

Method	CAM	Mask
MCTformer CVPR’22 [68]	61.7	69.1
CLIMS CVPR’22 [65]	57.5	72.8
WeakTr arXiv’23 [84]	65.9	74.2
CLIP-ES CVPR’23 [42]	58.6	75.0
FPR ICCV’23 [5]	63.8	66.4
D2CAM ICCV’23 [60]	58.0	71.4
USAGE ICCV’23 [50]	67.7	72.8
MCC WACV’24 [62]	-	73.0
POLE WACV’24 [49]	59.0	74.2
DuPL CVPR’24 [64]	-	76.0
SemPLES (Ours)	68.7	78.4

Table 1. Quantitative results of CAMs (CAM) and the resulting pseudo masks (Mask) on PASCAL VOC 2012 *train* set.

works, we use an augmented set of 10582 images for training. The testing set results are obtained from the official evaluation website. As for the MS COCO 2014 dataset, the training and validation set contains 82081 and 40137 images from 80 object categories, respectively. The mean Intersection over Union (mIoU) is used as the evaluation metric for all experiments.

4.2. Implementation Details

For CLIP [51], we use ViT-B/32 [18] as the image encoder. Following [65], we adopt the cosine feature similarity where non-positive scores are clamped to a small positive number. The learnable prompts are randomly initialized with the sequence length $K = 30$. The default batch size is 64. We set the initial learning rate to 5e-4 and 5e-6 and train our framework for 60 epochs on PASCAL VOC 2012 and MS COCO 2014, respectively. For loss weights, we set λ_b , λ_T and λ as 2.4, 0.02 and 0.05 for PASCAL VOC 2012 and 0.75, 0.01 and 0.2 for MS COCO 2014. The AdamW optimizer is adopted with the cosine scheduler. The proposed framework is implemented in PyTorch and trained with NVIDIA V100 GPUs.

4.3. Quantitative Comparisons

To evaluate our proposed *SemPLES* framework, we follow the standard WSSS pipeline and take our refined masks M' as CAMs to produce pseudo masks. In Table 1, we compare the quality of CAMs and also the resulting pseudo masks with previous works. From the results in this table, we see that our *SemPLES* achieves the best performance compared with previous weakly-supervised segmentation methods. Specifically, our CAMs achieve **68.7%** and the produced pseudo masks report **78.4%** in mIoU. This verifies that, by exploiting CLIP to perform vision-language learning plus the designed prompt learning, our proposed *SemPLES* framework successfully generates pixel-wise pre-

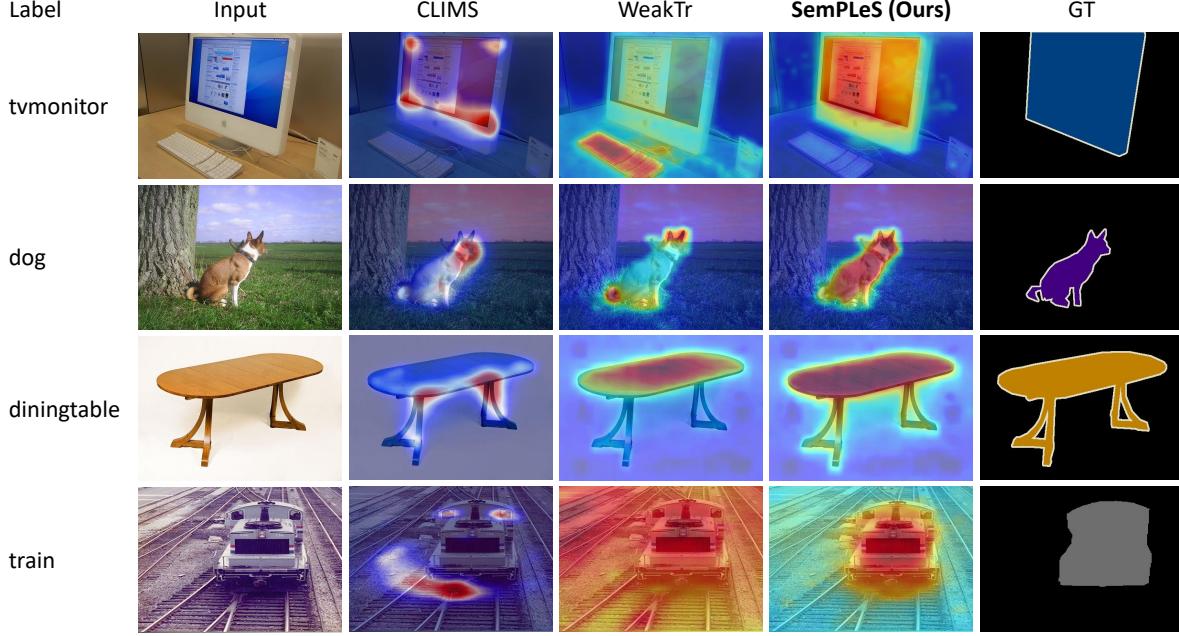


Figure 3. Qualitative results of CAMs. ‘‘GT’’ denotes the ground truth masks. We see that our proposed SemPLeS framework produces precise CAMs better aligned with the ground truth masks.

Method	Backbone	val	test
<i>CNN-/Transformer-based approaches</i>			
SIPE CVPR’22 [9]	DL2-Res101	68.8	69.7
CLIMS CVPR’22 [65]	DL2-Res101	70.4	70.0
MCTformer CVPR’22 [68]	DL1-WRes38	71.9	71.6
CLIP-ES CVPR’23 [42]	DL2-Res101	71.1	71.4
MMCST CVPR’23 [69]	DL1-WRes38	72.2	72.2
LPCMAM CVPR’23 [12]	DL1-WRes38	72.6	72.4
FPR ICCV’23 [5]	DL2-Res101	70.3	70.1
D2CAM ICCV’23 [60]	DL2-Res101	71.2	70.7
MCC WACV’24 [62]	DeiT-B	70.3	71.2
POLE WACV’24 [49]	DL2-Res101	71.5	71.4
SFC AAAI’24 [79]	DL2-Res101	71.2	72.5
DuPL CVPR’24 [64]	ViT-B	73.3	72.8
<i>SAM-based approaches</i>			
SEPL NeurIPS’23 [10]	DL2-Res101	71.1	-
SG-WSSS arXiv’23 [26]	DL2-Res101	71.1	72.2
FMA-WSSS WACV’24 [72]	M2F-Swin-L	82.6	81.6
SemPLeS (Ours)	DL2-Res101	73.9	73.8
SemPLeS (Ours)	M2F-Swin-L	83.4	82.9

Table 2. Quantitative results of segmentation masks on PASCAL VOC 2012 [20] val and test sets. ‘‘Backbone’’ denotes the segmentation network. ‘‘DL’’, ‘‘Res’’, ‘‘WRes’’, and ‘‘M2F’’ denote DeepLab [6], ResNet [23], WideResNet [74], and Mask2Former [15], respectively.

dictions from image-level supervision, which helps learn the following segmentation network.

In Table 2, by taking the derived pseudo masks to

Method	COCO val
MCC WACV’24 [62]	42.3
USAGE ICCV’23 [50]	42.7
LPCMAM CVPR’23 [12]	42.8
FPR ICCV’23 [5]	43.9
D2CAM ICCV’23 [60]	44.0
WeakTr arXiv’23 [84]	44.4
DuPL CVPR’24 [64]	44.6
G-RAM-SAM arXiv’23 [13]	54.6
FMA-WSSS WACV’24 [72]	55.4
SemPLeS (Ours)	56.1

Table 3. Quantitative results of the segmentation masks on MS COCO 2014 [41] val set.

train the segmentation networks, we see that our SemPLeS achieves the best performance on PASCAL VOC and reports 83.4% and 82.9% mIoU on the validation and testing sets, respectively. Our method outperforms the previous work, FMA-WSSS [72], by 0.8% and 1.3% mIoU on the validation and testing sets, respectively. In addition, our SemPLeS achieves the competitive performance of 56.1% mIoU on MS COCO in Table 3. The above results verify that our method is effective in performing semantic segmentation from image-level supervision.

Comparison with CLIP-based methods: In light of the constraint in WSSS (*i.e.*, training using only class labels), several approaches have leveraged CLIP to enhance the quality of the produced CAMs by prompting, such as

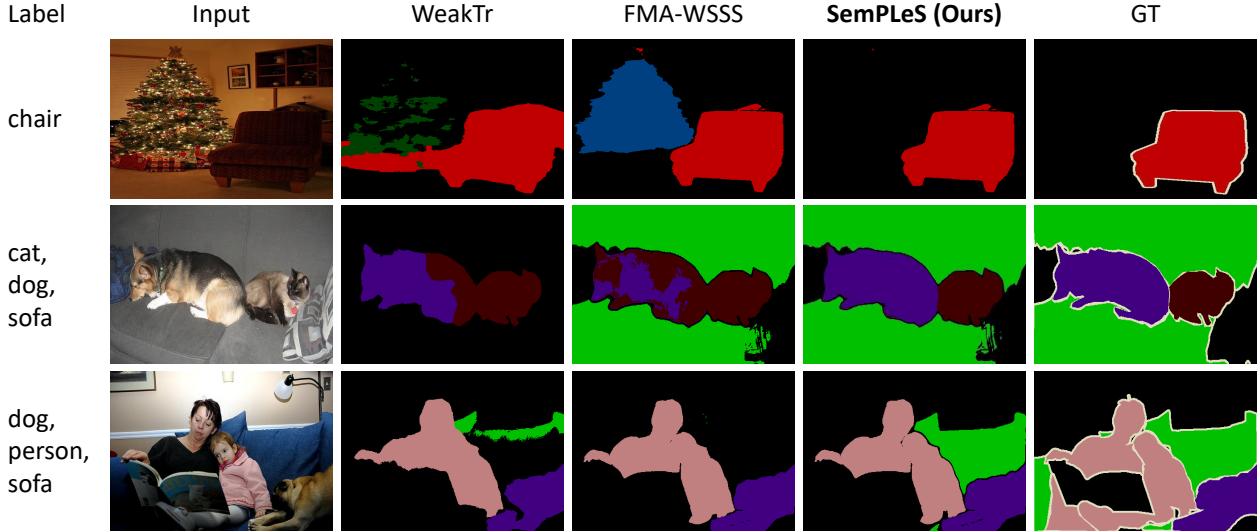


Figure 4. Qualitative results of segmentation maps. “GT” denotes the ground truth masks.

Method	val	test
CLIMS [65]	70.4	70.0
+SemPLeS (Ours)	71.0	71.5
WeakTr [84]	73.2	74.0
+SemPLeS (Ours)	74.2	74.8
FMA-WSSS [72]	82.6	81.6
+SemPLeS (Ours)	83.4	82.9

Table 4. Quantitative results of our proposed SemPLeS framework based on different WSSS methods, including CNN- (CLIMS), Transformer- (WeakTr), and SAM-based (FMA-WSSS) ones.

CLIMS [65], CLIP-ES [42], MMCST [69], and POLE [49]. However, they either consider only the foreground class prompts, or rely on general background prompts defined by additional manual efforts and human knowledge. Moreover, such manually-defined prompts may not fully exploit the knowledge learned in CLIP. In contrast, our method automatically learns prompts embedded with class-associated semantic knowledge from the CLIP latent space with no need of any manual efforts, resulting in better performance than these CLIP-based methods in Table 2.

Comparison with SAM-based methods: Recently, SAM has been proposed to produce high-quality class-agnostic masks with overwhelming generalizability. Several approaches [10, 13, 26, 59] have explored the potential of leveraging SAM for WSSS, and most of them require additional foundation models (*e.g.*, BLIP-2 [37], Grounding-DINO [44], and RAM [76]) to incorporate semantic information for semantic segmentation. Specifically, FMA-WSSS [72] exploits CLIP and achieves competitive performance among the above methods, and

we further outperform FMA-WSSS with the proposed SemPLeS framework, as shown in Table 2.

Compatibility with other WSSS methods: We evaluate the compatibility of our method by integrating the proposed SemPLeS framework with other WSSS methods, including CNN-based [65], Transformer-based [84], and SAM-based ones [72]. The quantitative results are presented in Table 4. From this table, we see that our SemPLeS improves all types of methods, demonstrating the compatibility and robustness of the proposed framework. It is worth noting that, even though CLIMS [65] already uses manually-defined prompts, our SemPLeS could still achieve further improvement with our learnable prompts. This shows that manually-defined prompts are limited and may not fully exploit the CLIP latent space, while our learnable prompts is able to automatically capture the semantic knowledge associated with target object categories to complement such pre-defined prompts, verifying the effectiveness of our designed prompt learning and proposed SemPLeS framework.

4.4. Qualitative Comparisons

For qualitative comparisons, our method shows more precise activation maps on various object categories and performs favorably compared with previous works, as shown in Fig. 3. In Fig. 4, we also show that our segmentation results are superior to other WSSS methods. This validates that, by advancing image-text contrastive learning with learnable prompts, our SemPLeS would enhance the alignment between the segment regions and the target object categories, resulting in precise CAMs and segmentation masks better aligned with the ground truth.

In addition, we also visualize the corresponding regions of our learned prompts by calculating the similari-

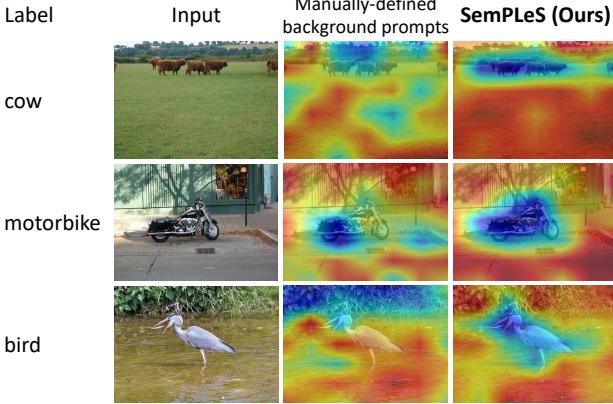


Figure 5. Visualization of the manually-defined background prompts [65] and our learned prompts.

L_{match}	L_{prompt}^T	L_{prompt}^I	L_{refine}	mIoU
✓				67.6
✓			✓	67.6
✓	✓		✓	67.7
✓		✓	✓	67.9
✓	✓	✓	✓	68.7

Table 5. Quantitative ablation studies of our loss functions. With both L_{prompt}^T and L_{prompt}^I applied (Eq. (2)), the derived prompts would be desired to guide the semantic refinement through loss L_{refine} , resulting in the best performance.

ties to image patches with the text and image encoders of CLIP. As shown in Fig. 5, the manually-defined background prompts [65] may falsely highlight the foreground objects (*e.g.*, the bird example in the third row) due to their high co-occurrence when pre-training CLIP. Also, such manual prompts are limited and may fail to cover the whole background in images (*e.g.*, the cow example in the first row). In contrast, our learned prompts highlight all the background regions associated with each object category, showing the effectiveness of our Contrastive Prompt Learning.

4.5. Ablation Studies

To analyze the importance of the introduced loss functions, we conduct both quantitative and qualitative ablation studies, as shown in Table 5 and Fig. 6. In Table 5, we see that applying only the matching loss L_{match} would result in 67.6% mIoU. If we directly add the refinement loss L_{refine} without prompt learning, the performance would be similar since the prompts are randomly initialized and are not learned. When prompt learning is further considered, applying only the L_{prompt}^T to repel the text labels may result in trivial solutions with little improvement. On the other hand, if only L_{prompt}^I is enforced to align with the background im-

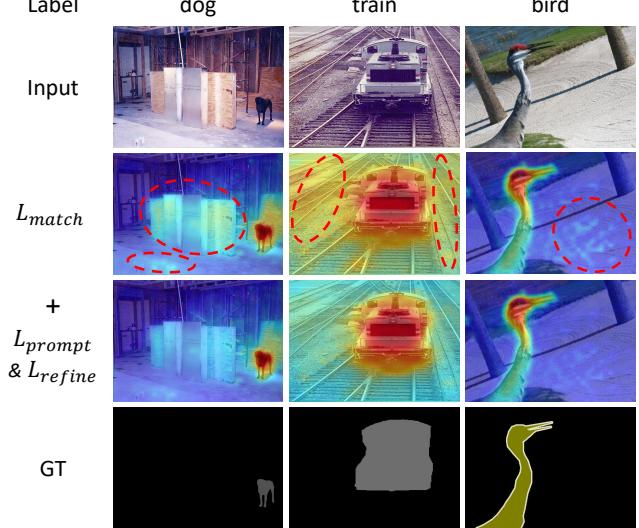


Figure 6. Qualitative ablation studies of loss functions. With both L_{prompt} and L_{refine} applied, the resulting CAMs are better aligned with the ground truth masks.

ages, the prompts are still likely to capture the semantics of the foreground object categories, resulting in 67.9% mIoU. Finally, when L_{prompt}^I and L_{prompt}^T are jointly applied to learn the background regions while avoiding describing the foreground object categories, the mIoU would improve to 68.7%. Together with the qualitative results in Fig. 6, we validate that our designed prompt learning and the proposed SemPLES framework would prevent false activation of co-occurring backgrounds and therefore benefit segmentation in a weakly-supervised fashion.

5. Conclusion

In this paper, we propose a *Semantic Prompt Learning for WSSS (SemPLES)* framework, which advances vision-language learning to achieve weakly-supervised semantic segmentation (WSSS). In addition to exploiting the pre-trained CLIP model to perform *Segment-Label Matching*, we further present *Contrastive Prompt Learning* and *Prompt-guided Semantic Refinement* in the proposed *SemPLES* framework to prevent false activation of image backgrounds. With no need to manually define background texts through prompt engineering, our learned prompts properly capture and suppress co-occurring backgrounds for each object category, resulting in precise activation maps for segmentation in a weakly-supervised fashion. Quantitative experiments on the segmentation benchmarks confirm the effectiveness of our proposed *SemPLES* framework, and visualization and ablation studies are conducted to demonstrate and verify the effectiveness of learned prompts. Our method achieves competitive performance on the standard WSSS benchmarks, PASCAL VOC 2012 and MS COCO 2014, and shows compatibility with other WSSS methods.

6. Appendix



Figure 7. Failure case analysis. From the first to the third row, we show failure cases where the objects are partially visible, of small size, and visually similar to the surroundings, respectively.

6.1. Failure Case Analysis

In Fig. 7, we show several types of failure cases. In the first row, the potted plant in the top right corner is only partially visible in the image and thus is not easily recognized. In the second row, the two people in the top left corner are far away from the camera. The reduced size of such distant objects result in the failure of segmentation. As for the third row, the potted plant on the left is visually similar to its surroundings and therefore may confuse the models. Note that our SemPLeS still outperforms the previous SOTA (FMA-WSSS) in these challenging cases.

6.2. Limitations and Potential Negative Impact

Limitations: In weakly-supervised semantic segmentation (WSSS), as only image-level labels are available for training, existing WSSS methods still struggle to segment the objects that are partially visible, of small size, or visually similar to the surroundings, as shown in Fig. 7.

Potential negative impact: No specific potential negative impact is identified in this work.

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