SLAMs: Semantic Learning based Activation Map for Weakly Supervised Semantic Segmentation

Junliang Chen, Xiaodong Zhao, Minmin Liu, Linlin Shen*
Shenzhen University
{chenjunliang2016,zhaoxiaodong2020,liuminmin2020}@email.szu.edu.cn
llshen@szu.edu.cn

November 11, 2022

Abstract

Recent mainstream weakly-supervised semantic segmentation (WSSS) approaches mainly rely on image-level classification learning, which has limited representation capacity. In this paper, we propose a novel semantic learning based framework, named SLAMs (Semantic Learning based Activation Map), for WSSS.

1 Introduction

Semantic segmentation is one of the fundamental tasks in computer vision, which aims to assign a category to each pixel of the image. Due to the development of the fully convolutional network (FCN), many fully-supervised semantic segmentation (FSSS) methods [15, 3, 4, 27, 29, 24] have achieved excellent performance and can be widely applied. However, FSSS is built upon the accurate pixel-level segmentation labels, which can be really time consuming and requires huge labour costs. To reduce the massive resources cost of pixel-level annotation, weakly-supervised semantic segmentation (WSSS) aims at achieving comparable performance with FSSS using weaker supervision, such as bounding boxes [8, 18], scribbles [13, 20], points [2], and image-level labels [22, 12, 28, 19]. These methods follow a two-stage paradigm: generating pseudo semantic segmentation labels based on these weak labels, and then training an FSSS network using the generated pseudo labels. Among these annotations, image-level labels are the most conveniently acquired ones and have been widely studied. Therefore, in this work, we focus on WSSS with image-level supervision.

*Corresponding Author
As the image-level annotations can not provide accurate location information, most of WSSS methods are built upon Class Activation Map (CAM) [30], which relies on image-level classification learning. The original CAM is simple and effective, but has an obvious weakness, i.e., under-activation. It only produces high response in the discriminative regions, leading to incompletely activated object regions. To address this issue, recent approaches have attempted to expand the area of CAM [23, 21] or adversarially erase the regions with high response and force the network to include less discriminative regions [22, 12, 10]. However, they still suffer from under-activation problem. Besides, they may sometimes falsely activate some background regions. The main reason for the failure of these approaches can be explained by the poor representation capacity of image-level classification learning. On one hand, the binary classification label can only tell whether a category exists or not in a given image, but fails to provide more details about where and what is the category in the given image. On the other hand, the image-level classification learning tends to build connections with the most relative regions. The most relative regions are mainly the most discriminative object regions of each category, and may include the closely related background regions which often co-occur, e.g., the railway in a train image.

In this paper, we make the following contributions:

- We propose a novel framework, SLAMs (Semantic Learning based Activation Map) for WSSS.

2 Related Work

The prosperity of WSSS benefits a lot from the development of Class Activation Map (CAM) proposed by Zhou et al. [30]. In this section, we introduce different manners to generate CAM, including image-level classification and recent approaches in new paradigm.

2.1 Image-level Classification Learning

Most recent WSSS methods built on CAM are trained with image-level classification learning, which suffers from under-activation of the less discriminative regions. To overcoming this problem, [9, 7, 17, 6, 1, 21] attempted to expand the initial CAM using boundary information or pixel-level relationship. However, they introduced additional complicated modules or training procedures. Recently, Li et al. proposed two-stage GAIN [12] consisting of CAM generation and classification stages with a shared classifier. The second stage minimizes the classification score of the masked image for each category using the thresholded CAM in the first stage. OC-CSE [10] improved GAIN [12] by using a pre-trained and fixed classifier in the second stage. However, Zhang et al. [28] indicated that the training phase of these methods is unstable as they will still lose some regions more or less, due to the randomness of the hiding process. Besides, they may suffer from over-activation problem, i.e. false activation in
background regions. It results in very small classification loss in the second stage which exacerbates the training instability.

2.2 Recent New Paradigm

Recently, some approaches explore new paradigms to generate CAM. CLIMS [25] introduces extra text knowledge with Contrastive Language-Image Pre-training (CLIP) [16] to conduct cross language image matching. With the open set knowledge available in the CLIP model trained with extra 400 million image text pairs, CLIMS can suppress the falsely activated background regions to a certain extent and thus makes the generated CAM more complete. AMN [11] proposes an activation manipulation with a per-pixel classification loss to penalize the most discriminative regions and promote the less discriminative regions using refined initial CAM, and thus generates more complete CAM. MCTFormer [26] introduces advanced transformer architecture to WSSS and achieves much higher performance than convolutional neural network (CNN) based approaches. For fair comparisons, we focus on CNN based approaches in this paper.

3 Experiments

3.1 Dataset and Evaluation Metric

We conduct our experiments on PASCAL VOC 2012 dataset [5] with 21 categories (20 object categories and one background category), and MSCOCO [14] with 81 categories (80 object categories and one background category). For PASCAL VOC 2012, as most approaches do, we use the augmented trainaug split (10528 images) with only image-level labels for training. The train split (1464 images) is used to validate our method. The val (1464 images) and test (1456 images) split are used to evaluate our WSSS approach and compare with other methods, respectively. We report all the experimental results in the standard mean Intersection over Union (mIoU) metric for semantic segmentation. For MSCOCO, we use train split with around 80K images for training, and val split with around 40K images for evaluation.

4 Conclusions

In this paper, we propose a novel framework, Semantic Learning based Activation Map (SLAMs), for weakly supervised semantic segmentation.

References

[1] Jiwoon Ahn and Suha Kwak. Learning pixel-level semantic affinity with image-level supervision for weakly supervised semantic segmentation. In CVPR, pages 4981–4990, 2018.

2
[2] Amy L. Bearman, Olga Russakovsky, Vittorio Ferrari, and Fei-Fei Li. What’s the point: Semantic segmentation with point supervision. In ECCV, pages 549–565, 2016. 1

[3] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Semantic image segmentation with deep convolutional nets and fully connected CRFs. ICLR, 2015. 1

[4] Chen, Liang-Chieh, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. TPAMI, 40(4):834–848, 2018. 1

[5] Mark Everingham, SM Ali Eslami, Luc Van Gool, Christopher KL Williams, John Winn, and Andrew Zisserman. The pascal visual object classes challenge: A retrospective. IJCV, 111(1):98–136, 2015. 3

[6] Junsong Fan, Zhaoxiang Zhang, Tieniu Tan, Chunfeng Song, and Jun Xiao. Cian: Cross-image affinity net for weakly supervised semantic segmentation. In AAAI, pages 10762–10769, 2020. 2

[7] Zilong Huang, Xinggang Wang, Jiasi Wang, Wenyu Liu, and Jingdong Wang. Weakly-supervised semantic segmentation network with deep seeded region growing. In CVPR, pages 7014–7023, 2018. 2

[8] Anna Khoreva, Rodrigo Benenson, Jan Hendrik Hosang, Matthias Hein, and Bernt Schiele. Simple does it: Weakly supervised instance and semantic segmentation. In CVPR, pages 1665–1674, 2017. 1

[9] Alexander Kolesnikov and Christoph H. Lampert. Seed, expand and constrain: Three principles for weakly-supervised image segmentation. In ECCV, pages 695–711, 2016. 2

[10] Hyeokjun Kweon, Sung-Hoon Yoon, Hyeonseong Kim, Dahee Park, and Kuk-Jin Yoon. Unlocking the potential of ordinary classifier: Class-specific adversarial erasing framework for weakly supervised semantic segmentation. In ICCV, pages 6994–7003, 2021. 2

[11] Minhyun Lee, Dongseob Kim, and Hyun Jung Shim. Threshold matters in WSSS: manipulating the activation for the robust and accurate segmentation model against thresholds. In CVPR, 2022. 3

[12] Kunpeng Li, Ziyan Wu, Kuan-Chuan Peng, Jan Ernst, and Yun Fu. Tell me where to look: Guided attention inference network. In CVPR, 2018. 1, 2

[13] Di Lin, Jifeng Dai, Jiaya Jia, Kaiming He, and Jian Sun. Scribblesup: Scribble-supervised convolutional networks for semantic segmentation. In CVPR, pages 3159–3167, 2016. 1

[14] Tsung-Yi Lin, Michael Maire, Serge J. Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. Microsoft COCO: common objects in context. In David J. Fleet, Tomás Pajdla, Bernt Schiele, and Tinne Tuytelaars, editors, ECCV, pages 740–755, 2014. 3

[15] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3431–3440, 2015. 1

[16] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In ICML, pages 8748–8763, 2021. 3
[17] Wataru Shimoda and Keiji Yanai. Self-supervised difference detection for weakly-supervised semantic segmentation. In *ICCV*, pages 5207–5216, 2019.

[18] Chunfeng Song, Yan Huang, Wanli Ouyang, and Liang Wang. Box-driven class-wise region masking and filling rate guided loss for weakly supervised semantic segmentation. In *CVPR*, pages 3136–3145, 2019.

[19] Kunyang Sun, Haoqing Shi, Zhengming Zhang, and Yongming Huang. Ecs-net: Improving weakly supervised semantic segmentation by using connections between class activation maps. In *IJCV*, pages 7283–7292, 2021.

[20] Paul Vernaza and Manmohan Chandraker. Learning random-walk label propagation for weakly-supervised semantic segmentation. In *CVPR*, 2017.

[21] Yude Wang, Jie Zhang, Meina Kan, Shiguang Shan, and Xilin Chen. Self-supervised equivariant attention mechanism for weakly supervised semantic segmentation. In *CVPR*, pages 12275–12284, 2020.

[22] Yunchao Wei, Jiashi Feng, Xiaodan Liang, Ming-Ming Cheng, Yao Zhao, and Shuicheng Yan. Object region mining with adversarial erasing: A simple classification to semantic segmentation approach. In *CVPR*, pages 1568–1576, 2017.

[23] Yunchao Wei, Huaxin Xiao, Honghui Shi, Zequn Jie, Jiashi Feng, and Thomas S. Huang. Revisiting dilated convolution: A simple approach for weakly- and semi-supervised semantic segmentation. In *CVPR*, pages 7268–7277, 2018.

[24] Enze Xie, Wenhai Wang, Zhiding Yu, Anima Anandkumar, Jose M Alvarez, and Ping Luo. Segformer: Simple and efficient design for semantic segmentation with transformers. *NeurIPS*, 34, 2021.

[25] Jinheng Xie, Xianxu Hou, Kai Ye, and Linlin Shen. Cross language image matching for weakly supervised semantic segmentation. In *CVPR*, 2022.

[26] Lian Xu, Wanli Ouyang, Mohammed Bennamoun, Farid Boussaid, and Dan Xu. Multi-class token transformer for weakly supervised semantic segmentation. In *CVPR*, 2022.

[27] Changqian Yu, Jingbo Wang, Chao Peng, Changxin Gao, Gang Yu, and Nong Sang. Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 325–341, 2018.

[28] Fei Zhang, Chaochen Gu, Chenyue Zhang, and Yuchao Dai. Complementary patch for weakly supervised semantic segmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 7242–7251, 2021.

[29] Sixiao Zheng, Jiachen Lu, Hengshuang Zhao, Xiatian Zhu, Zekun Luo, Yabiao Wang, Yanwei Fu, Jianfeng Feng, Tao Xiang, Philip HS Torr, et al. Rethinking semantic segmentation from a sequence-to-sequence perspective with transformers. In *CVPR*, pages 6881–6890, 2021.

[30] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning deep features for discriminative localization. In *CVPR*, pages 2921–2929, 2016.