Learning Visual Words for Weakly-Supervised Semantic Segmentation

Lixiang Ru, Bo Du, Chen Wu

Institute of Artificial Intelligence, School of Computer Science, Wuhan University

{rulixiang,dubo,chen.wu}@whu.edu.cn

https://github.com/rulixiang/vwe

Abstract

Prevailing Weakly-Supervised Semantic Segmentation (WSSS) methods using image-level labels, *i.e.* predicting pixel-level labels with only image-level supervision, usually train a classification network and generate the Class Activation Maps (CAMs) from the network as the initial coarse labels. However, CAMs typically only consist of **partial discriminative object extents** and some **unexpected background regions**, which are attributed to the image-level supervision and the widely-used global average pooling (GAP), respectively.

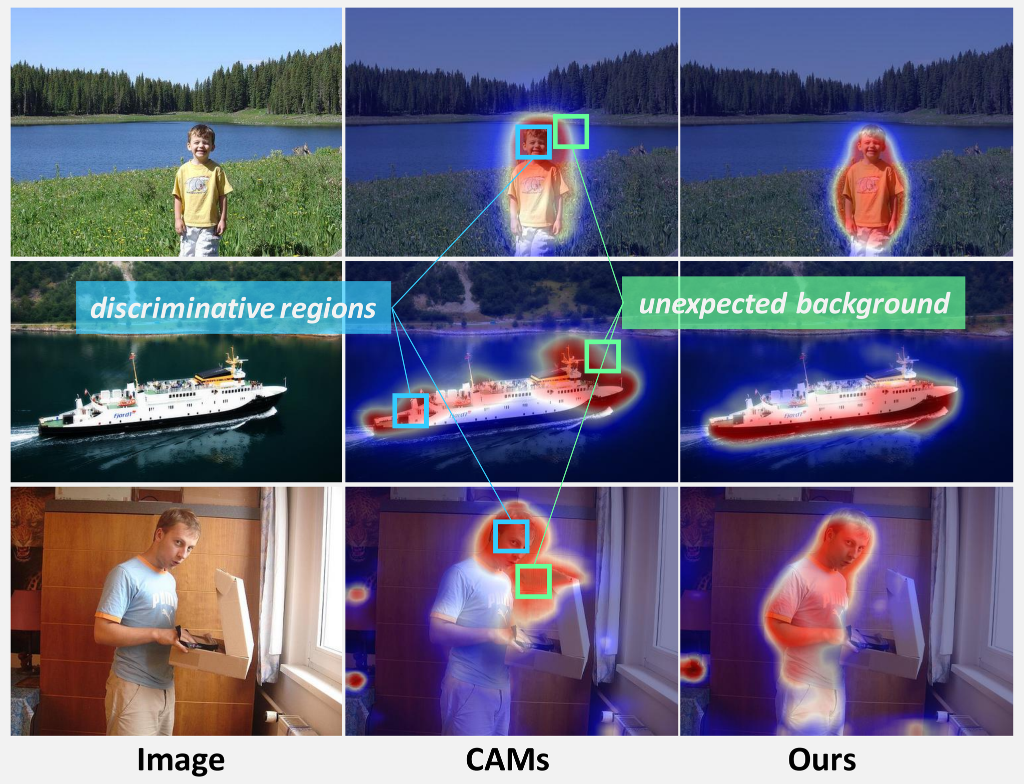


Figure: Illustration of the drawbacks of CAMs.

Contributions

The main contributions of this work are summarized as follows.

- We proposed to **learn and classify the local visual word labels**, which could enforce the network to discover more object extents and thus improve the quality of the generated pseudo pixel-level labels.
- We presented HSPP, a novel pooling method, which **averaged the local maximum and global average features** to alleviate the problem that the widely-used GAP and GMP can't estimate the objects accurately.
- We achieved **67.2%** and **67.3%** mIoU on the *val* and *test* set of the PASCAL VOC 2012 dataset, which is the new state-of-the-art performance.

Method Overview

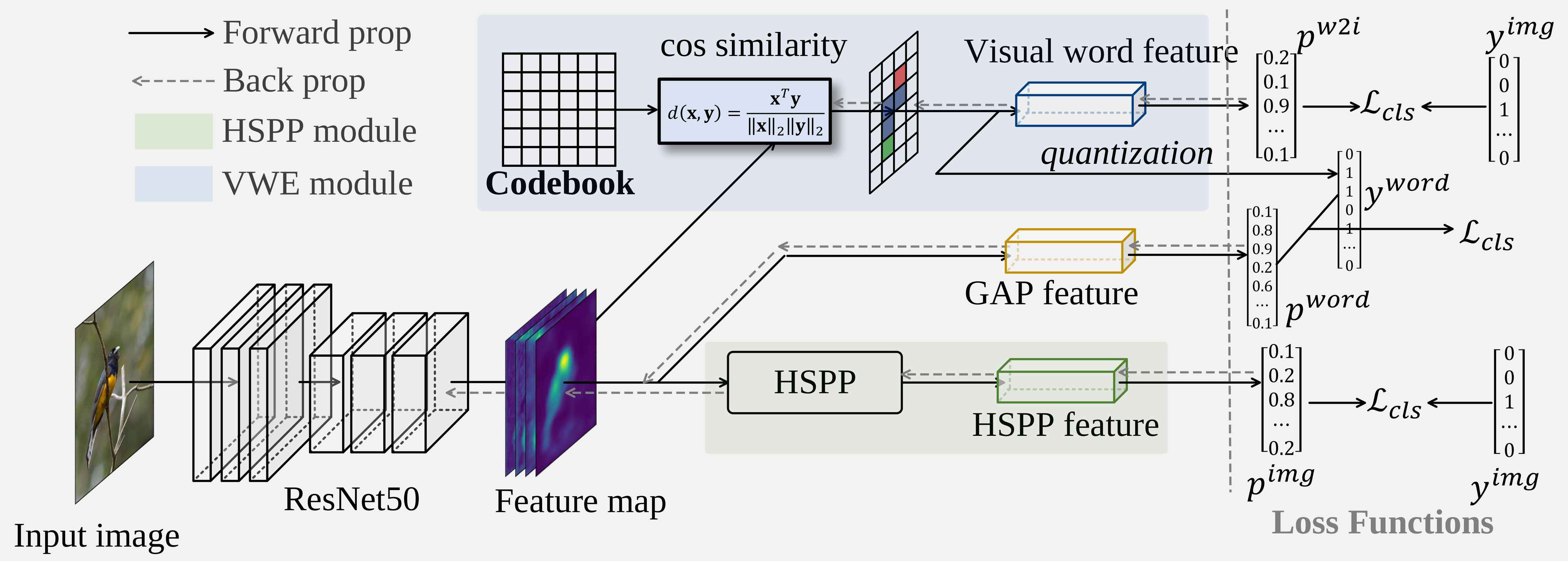


Figure: Overview of our proposed network.

To encourage the network to discover more object extents, we proposed an visual words learning module, which utilized a codebook to encode the feature maps extracted by CNN. The encoded visual word labels were then used to supervise the training process of the classification network. We also proposed a novel feature aggregation method, *i.e.* hybrid spatial pyramid pooling (HSPP) ,which incorporated GMP to reduce background information and GAP to ensure objetc completeness in the generated CAMs

Visual Words Learning

Given codebook $C \in \mathbb{R}^{k\times d}$ and feature map $F \in \mathbb{R}^{h\times w\times d}$, we use the $\cos$ distance to measure the their similarity:

$$S_{ij} = \frac{F_i^\top C_j}{||F_i||_2||C_j||_2}. \tag{1}$$

It's normalized row-wise using $softmax$ function:

$$P_{ij} = \frac{\exp(S_{ij})}{\sum_{n=1}^{k}\exp(S_{in})}. \tag{2}$$

The visual word label Y_i is the index of the maximum value in the i-th row of P_{ij}

$$Y_i = \arg\max_j P_{ij}\,. \tag{3}$$

The visual word labels are given as a k-dimensional vector y^{word}, where $y_j^{word} = 1$ if the j-th word is in Y, and $y_j^{word} = 0$ otherwise.

Hybrid Spatial Pyramid Pooling

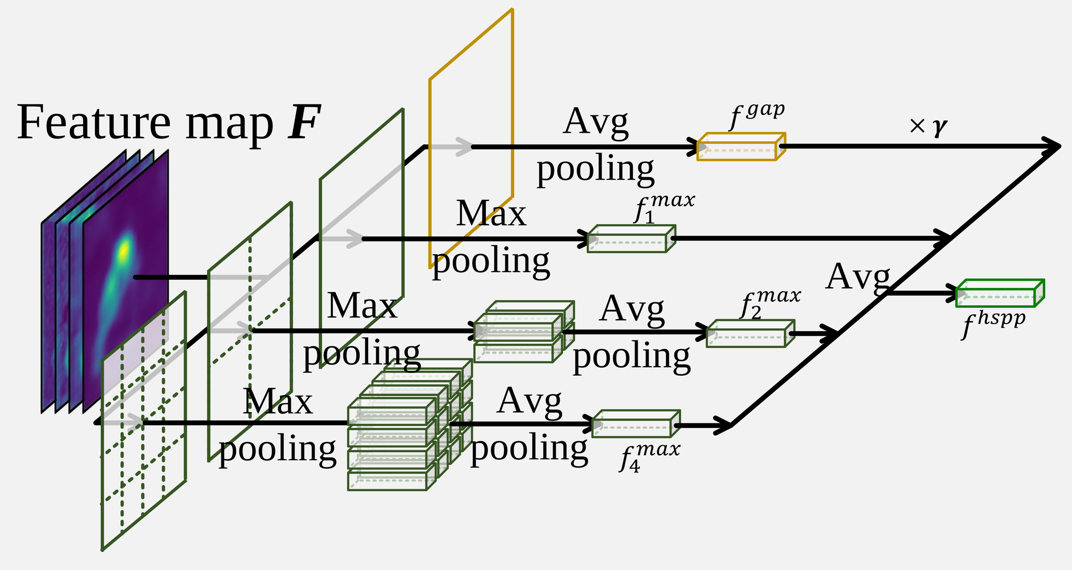


Figure: Illustration of the proposed HSPP.

The output of HSPP module is calculated by weighting the outputs of GAP and multi-scale max pooling,

$$f^{hspp} = \frac{1}{\gamma+3}\Big(\sum_{r\in\{1,2,4\}} f_r^{max} + \gamma f^{gap}\Big), \tag{4}$$

Loss Function

The overall loss of the proposed network is finally formulated as the sum of the aforementioned loss terms.

$$\mathcal{L} = \underbrace{\mathcal{L}_{cls}(p^{img}, y^{img})}_{\text{Learn Image label}} + \underbrace{\mathcal{L}_{cls}(p^{word}, y^{word})}_{\text{Learn visual word label}} + \underbrace{\mathcal{L}_{cls}(p^{w2i}, y^{img})}_{\text{Learn image label with visual words}} \tag{5}$$

Quantitative Results

Method	Refinement	*train*	*val*
PSA CVPR'2018	-	48.0	46.8
IRNet CVPR'2019		48.3	-
SC-CAM CVPR'2020		50.9	49.6
Ours		**52.9**	**52.0**
IRNet CVPR'2019	+ IRNet	66.5	-
1Stage CVPR'2020		66.9	65.3
Ours		**67.7**	**65.7**

(a) Evaluation and comparison of the generated CAMs in mIoU.

Baseline	VWE	HSPP	*train*	*val*
✓			48.3	47.0
✓	✓		51.1	50.2
✓		✓	50.6	50.0
✓	✓	✓	**52.9**	**52.0**

(b) Ablation studies of our proposed methods on PASCAL VOC *train* and *val* set.

	Sup	Backbone	*val*	*test*
WideResNet38	$\mathcal{F}$	WideResNet38	80.8	82.5
DeepLab		VGG16	69.8	-
DeepLabv2		ResNet101	76.3	77.6
AffinityNet CVPR'2018	$\mathcal{I}$	WideResNet38	61.7	63.7
IRNet CVPR'2019		ResNet50	63.5	64.8
SSDD ICCV'2019		WideResNet38	64.9	65.5
SC-CAM CVPR'2020		ResNet101	66.1	65.9
SEAM CVPR'2020		WideResNet38	64.5	65.7
BES ECCV'2020		ResNet101	65.7	66.6
MCIS ECCV'2020		ResNet101	66.2	66.9
Ours w/o CRF	$\mathcal{I}$	ResNet101	66.3	66.3
Ours w/ CRF		ResNet101	**67.2**	**67.3**

(c) Evaluation of the semantic segmentation results.

Qualitative Results

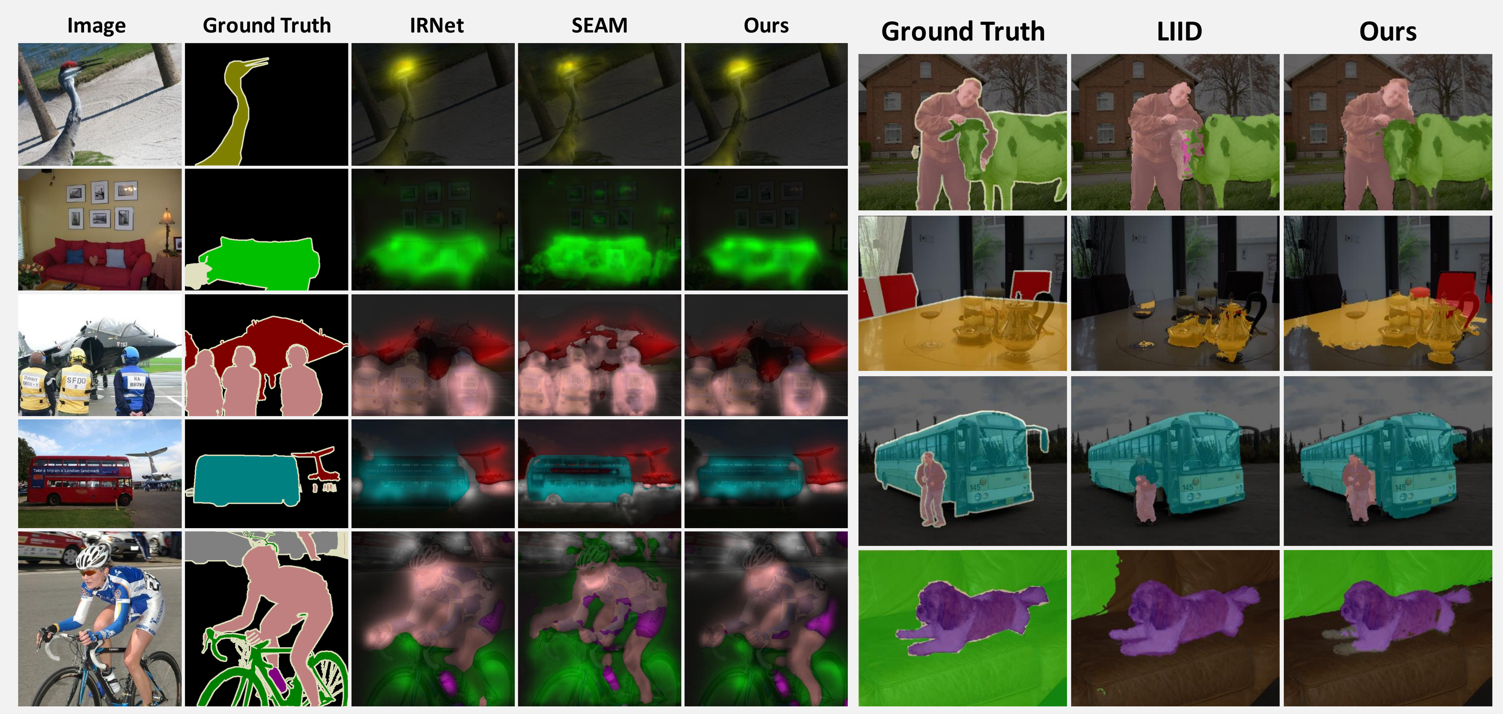
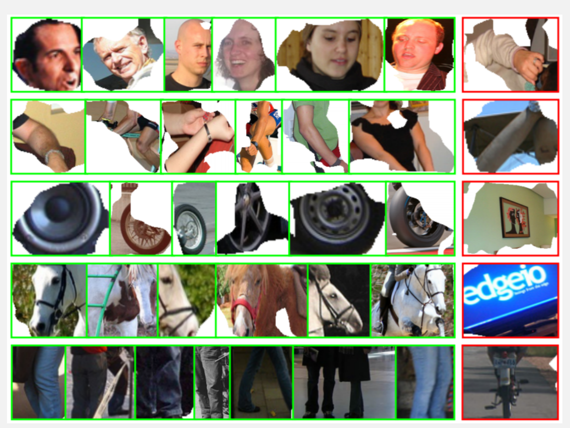


Figure: *Left*: Visualization results of the generated CAM. *Right*: The predicted semantic segmentation masks of the PASCAL VOC *val* dataset.

Visual Words in Codebook



This figure showed that the codebook could satisfactorily distinguish different visual words. We also observed that different parts of a visual object could be effectively encoded. For example, the visual words in Row 1, Row 2, and Row 5 could be roughly interpreted as *head*, *arm*, and *leg* of *person*, respectively.