

In the paper, we propose a novel framework for WSOL problem by augmenting CAM that is generated from traditional recognition networks. The performance of our model on ILSVRC [1] and CUB-200 [4] both outperform previous methods, becoming the new state-of-the-art.

In the supplementary material, we first show the detail structure of our backbone network for appending multiple classifiers to generate CAMs. In addition, we generate more visualization results to demonstrate that the combined CAM from our framework is more complete and precise compared with each individual CAM. Furthermore, we compare our method with SPG [6], a previous method which also utilizes background parts of CAM but sets fixed thresholds in an one-size-fit-all manner. The better localization results of our method indicates that the learned sample-adapted thresholds during training perform much better than the unique value predefined.

## A. Network Structure

We show the backbone networks used for our framework in Fig. 1, which are based on VGGnet [2] and GoogLeNet [3], respectively.

For VGGnet, we remove the last fully connected layer and append our two classifiers,  $\mathcal{W}_{\mathcal{L}}$  and  $\mathcal{W}_{\mathcal{F}}$  after fourth and last pooling layer. In addition, we change the last two pooling layers to keep the resolution of the feature map, which follows the configure in [6]. For GoogLeNet, we remove the convolutional blocks after *Mixed\_6e* and append two classifiers after *Mixed\_6b* and *Mixed\_6e*, respectively. For more details about our two classifiers, please refer to our paper.

## B. Visualization Result

We show more powerful visualization results in Fig. 3 and Fig. 4. In most cases, the combined CAM can generate more complete and precise localization results compared with each individual CAM. Besides, we also generate more visualizations to compare our framework with SPG [6] in Fig. 2. We can see the CAM augmented by our framework can cover more precise foreground object rather than only a small discriminative part, which demonstrate the advantages of our proposed method.

## References

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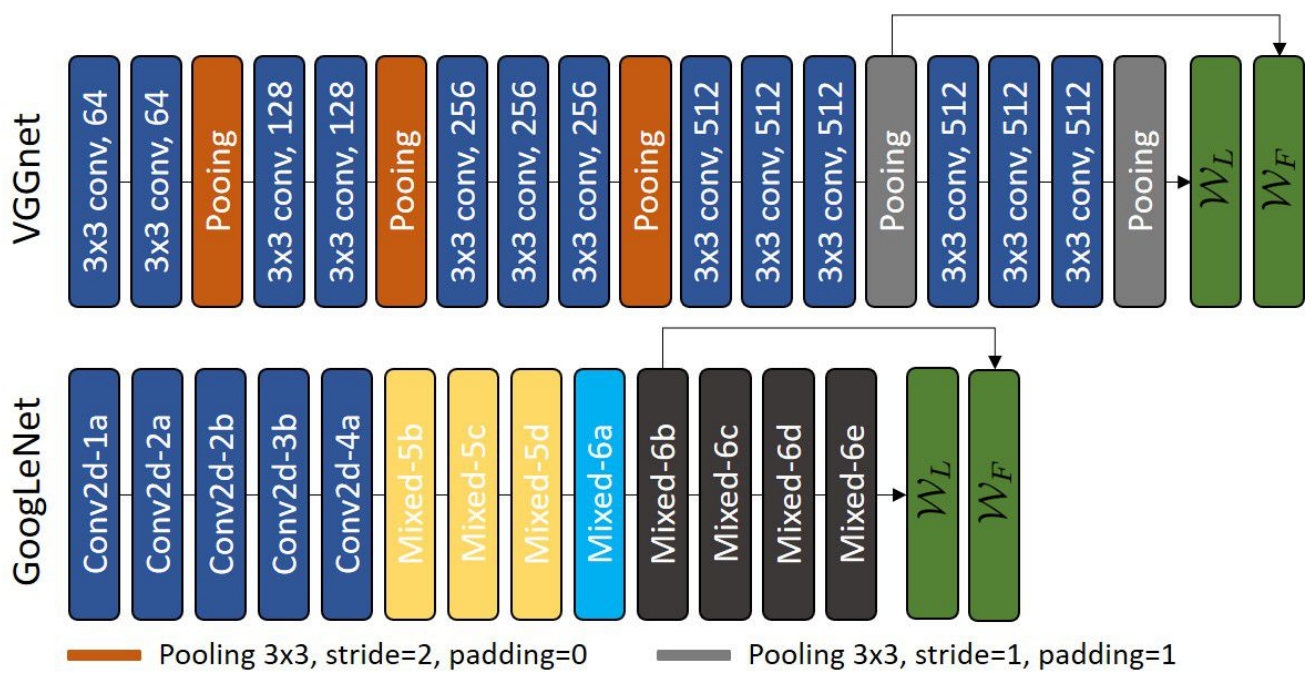
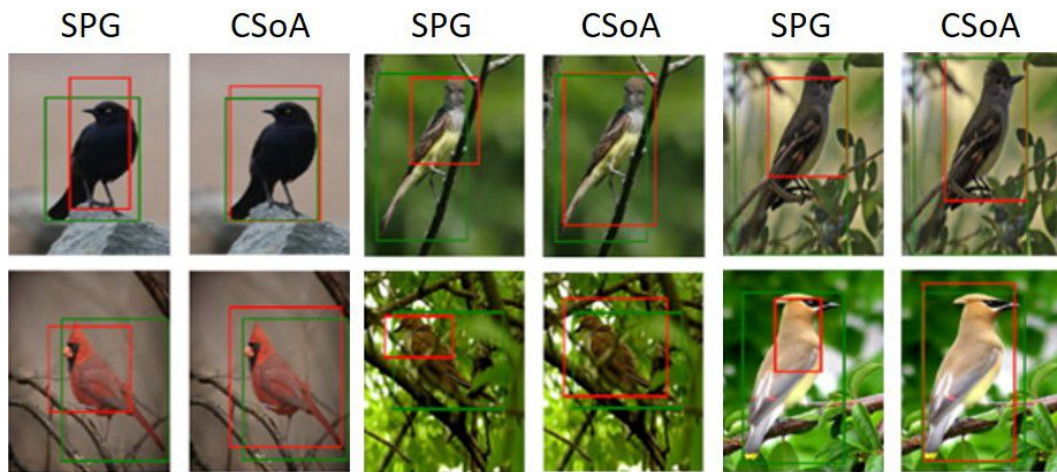
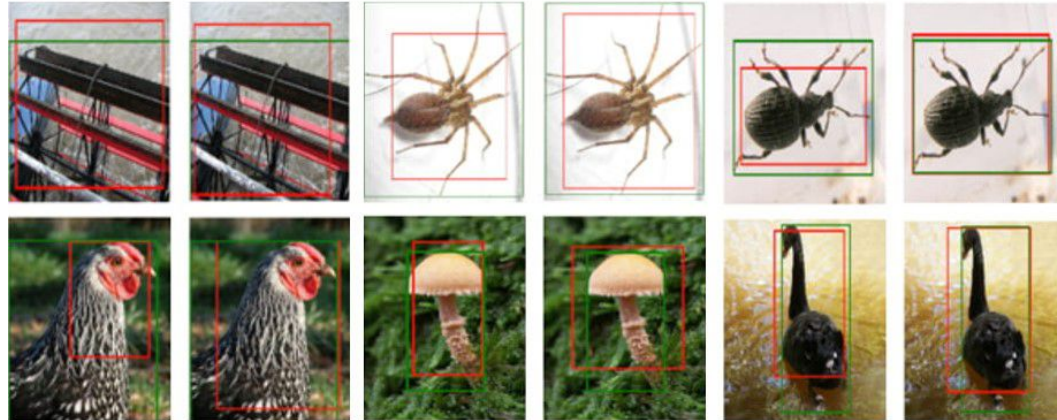


Figure 1. The structure of our backbone networks. We keep them same with SPG [6] and ACoL [5] to make a fair comparison.



(a) CUB-200-2011



(b) ILSVRC

Figure 2. Comparison between our model and SPG [6]. We keep the backbone network and related configures same.

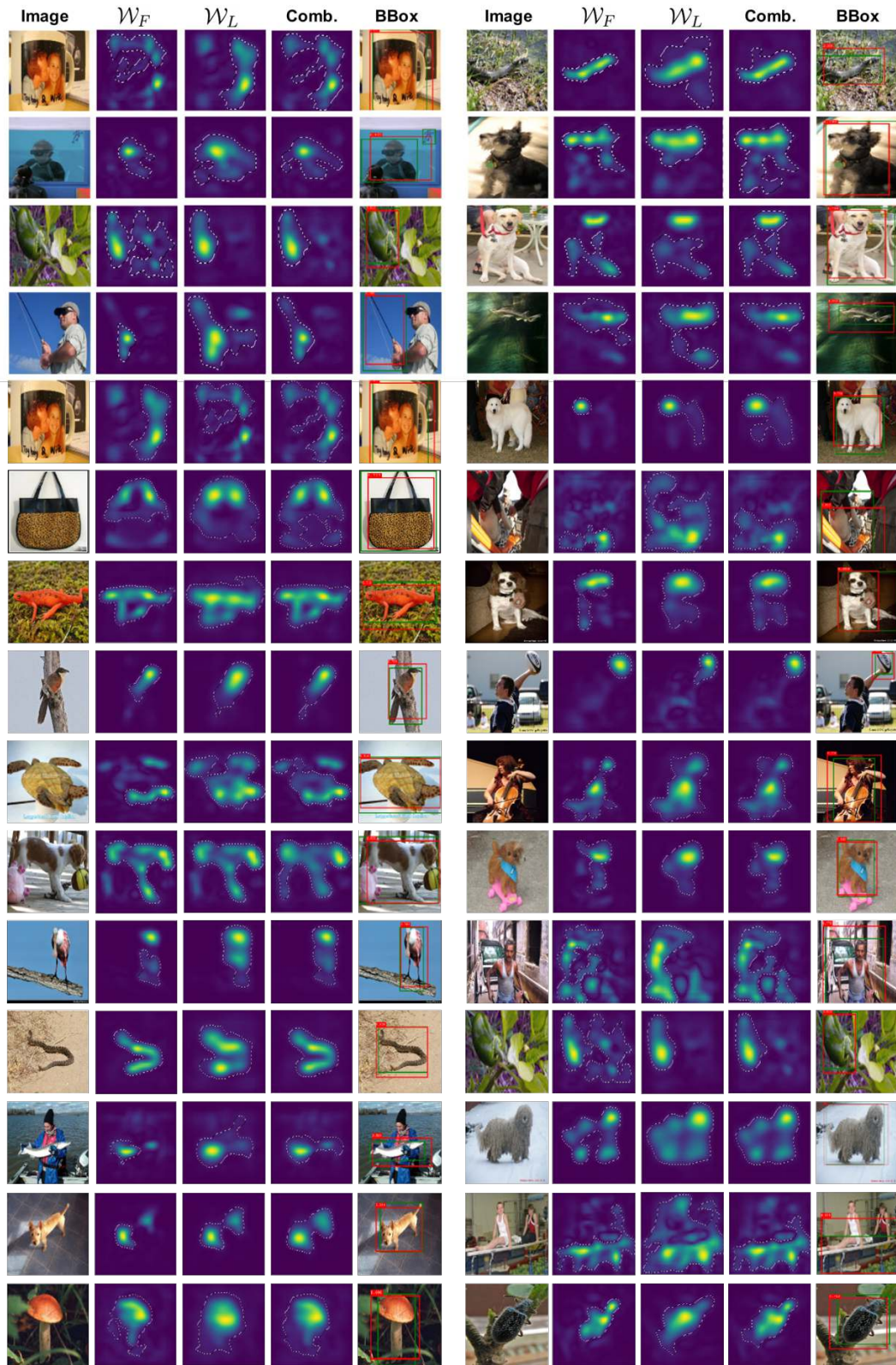


Figure 3. Visual examples from our CSoA framework on ILSVRC [1] dataset. The red box is predicted results while the green ones are ground truth labels.

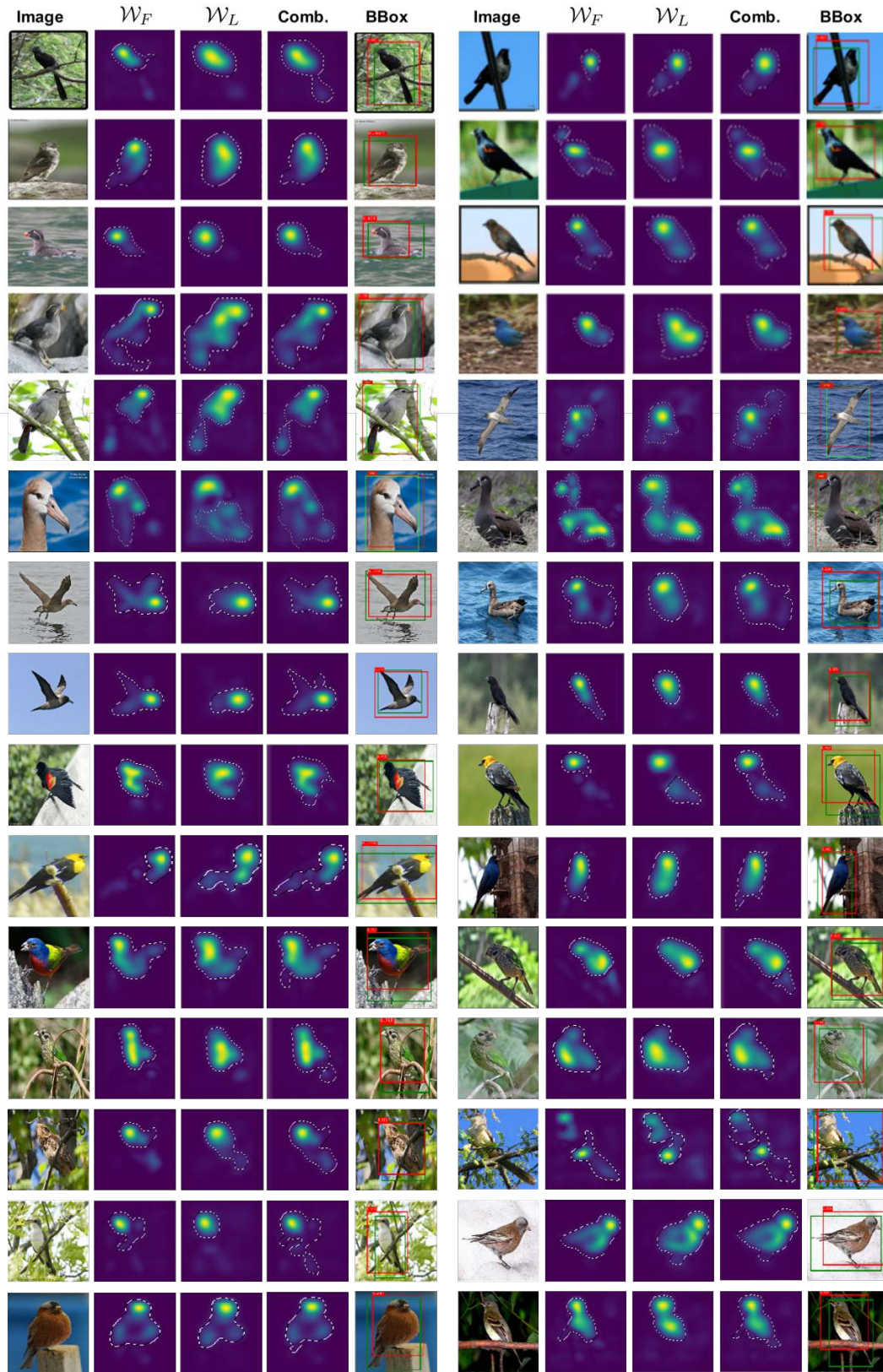


Figure 4. Visual examples from our CSoA framework on CUB-200 [4] dataset. The red box is predicted results while the green ones are ground truth labels.