Learning Pixel-level Semantic Affinity with Image-level Supervision for Weakly Supervised Semantic Segmentation

CVPR’18

Junsoo Lee

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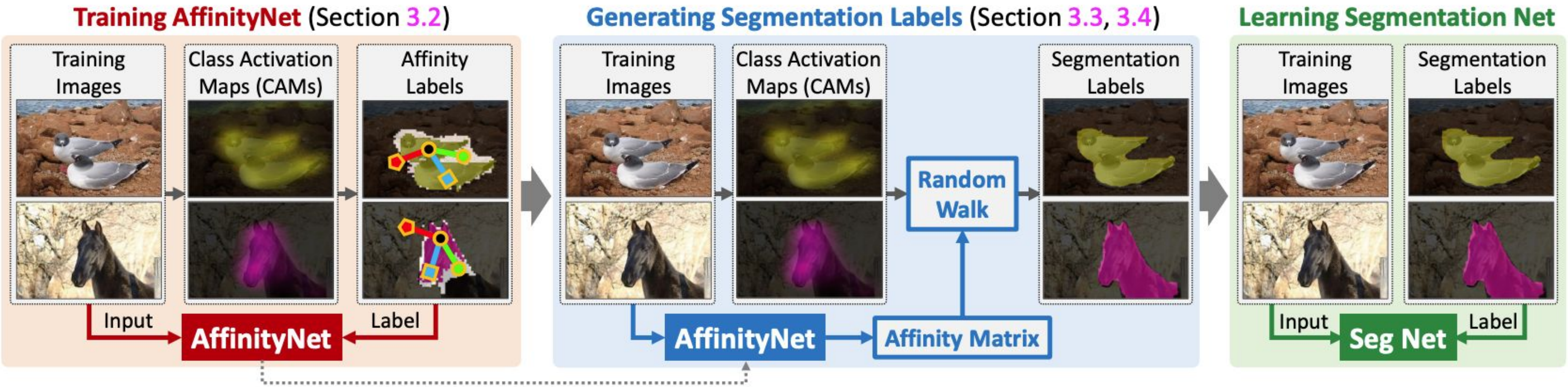

- Image-level label setting -> weakly supervised for semantic segmentation.
- Learning pixel-level affinities which encourage random work to propagate the activations to nearby and semantically identical areas, and penalize propagation to area of the other classes.

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1. Computing CAMs

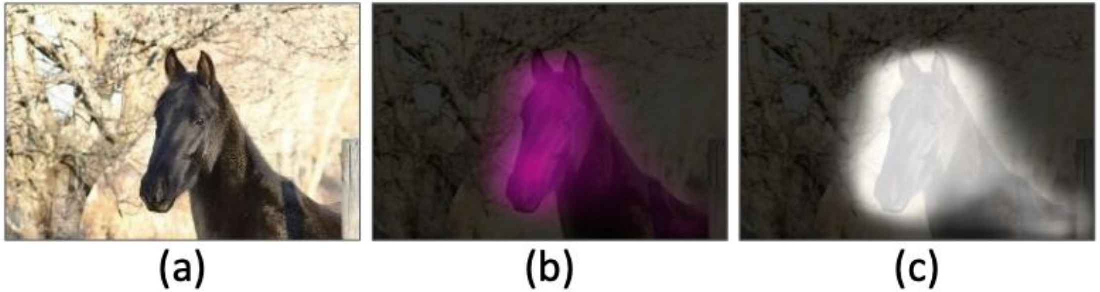

Figure 2. Visualization of CAMs obtained by our approach. (a) Input image. (b) CAMs of object classes: Brighter means more confident object region. (c) CAMs of background: Darker means more confident background region.

$$M_c(x, y) = \mathbf{w}_c^\top f^{\text{cam}}(x, y),$$

$$M_{\text{bg}}(x, y) = \left\{1 - \max_{c \in C} M_c(x, y)\right\}^\alpha$$

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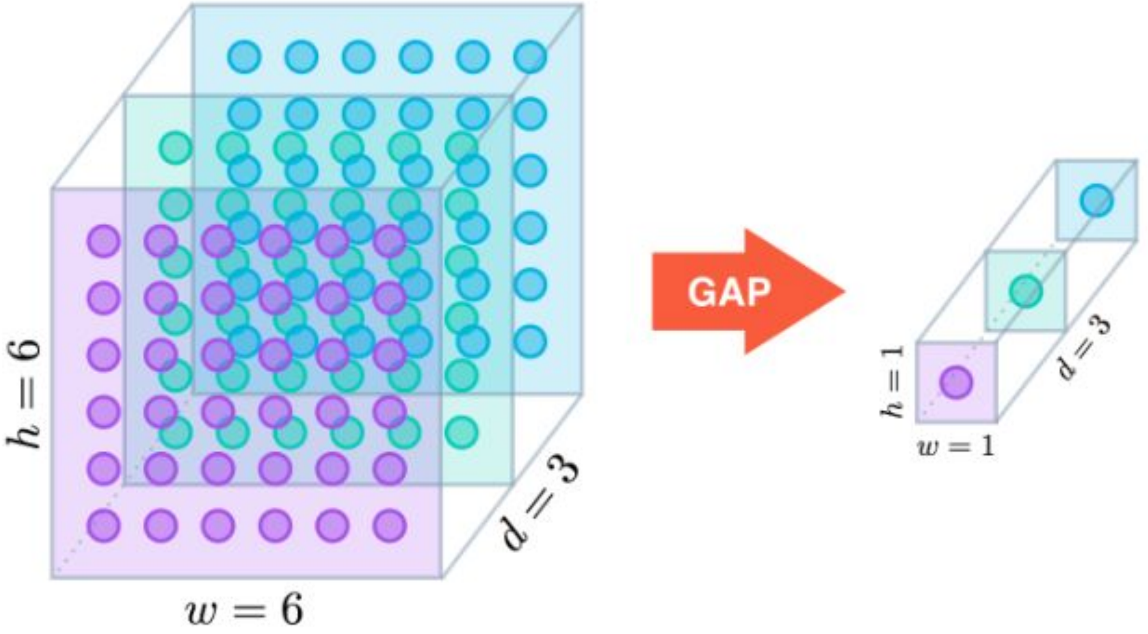
1. Computing CAMs



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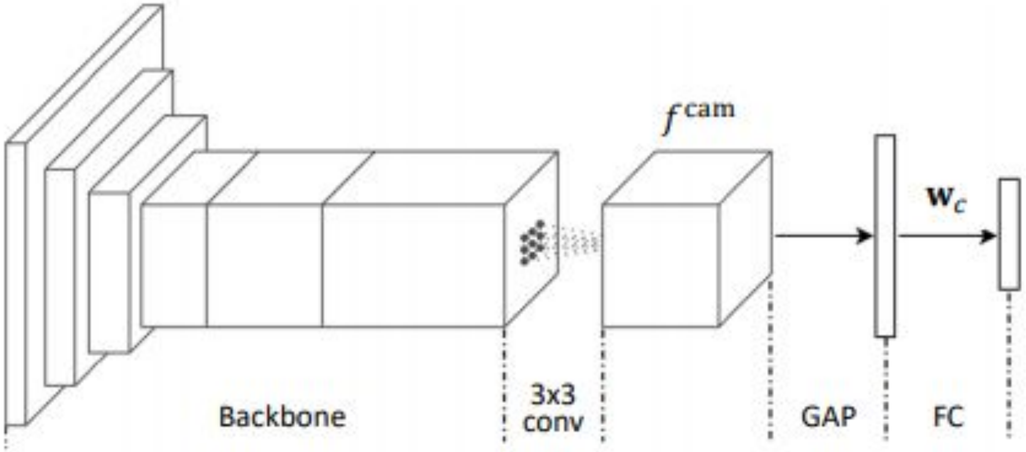
1. Computing CAMs



(c) Our network for computing CAMs

$$M_c(x, y) = \mathbf{w}_c^\top f^{\text{cam}}(x, y),$$

$$M_{\text{bg}}(x, y) = \left\{1 - \max_{c \in C} M_c(x, y)\right\}^\alpha$$

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2. Generating Semantic Affinity Labels

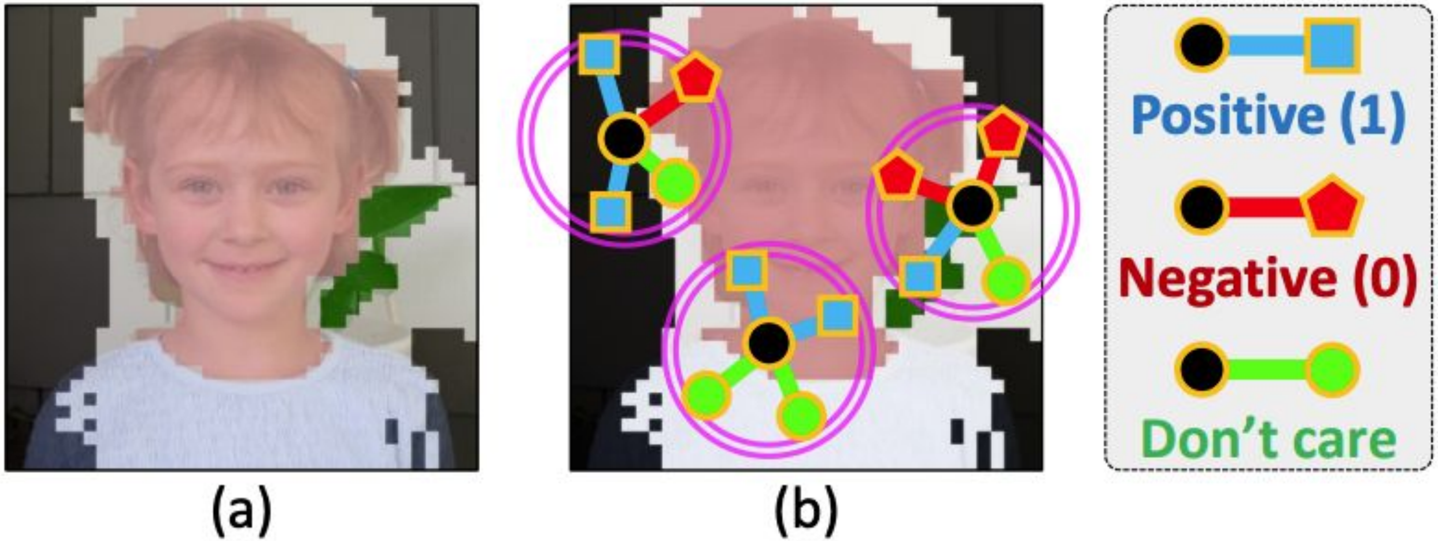

Figure 4. Conceptual illustration of generating semantic affinity labels. (a) Confident areas of object classes and background:

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3. AffinityNet Training

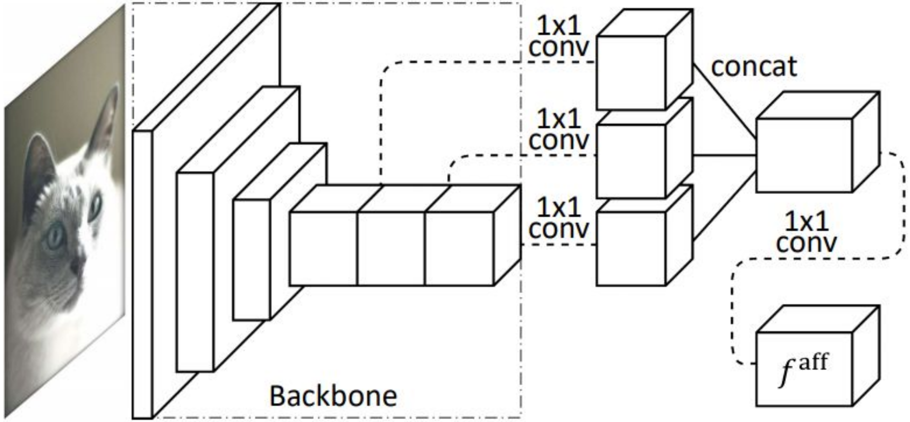

Figure 3. Overall architecture of AffinityNet. The output feature map f^{aff} is obtained by aggregating feature maps from multiple levels of a backbone network so that f^{aff} can take semantic information at various field-of-views. Specifically, we first apply 1×1

$$W_{ij} = \exp\Big\{ - \big\| f^{\text{aff}}(x_i, y_i) - f^{\text{aff}}(x_j, y_j) \big\|_1 \Big\},$$

$$\mathcal{P} = \big\{ (i,j) \mid \mathrm{d}\big((x_i, y_i), (x_j, y_j)\big) < \gamma, \forall i \neq j \big\}$$

$$\begin{aligned} \mathcal{P}^+ &= \big\{ (i,j) \mid (i,j) \in \mathcal{P}, W^*_{ij} = 1 \big\}, \\ \mathcal{P}^- &= \big\{ (i,j) \mid (i,j) \in \mathcal{P}, W^*_{ij} = 0 \big\}, \end{aligned}$$

her break $\mathcal{P}^+$ into $\mathcal{P}^+_{\text{fg}}$ and $\mathcal{P}^+_{\text{bg}}$ for objects a

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4. Revising CAMs using AffinityNet

$$T = D^{-1} W^{\circ\beta}, \;\; \text{where} \;\; D_{ii} = \sum_j W_{ij}^{\beta}.$$

$$\text{vec}(M_c^*) = T^t \cdot \text{vec}(M_c) \quad \forall c \in C \cup \{\text{bg}\},$$

ere $\text{vec}(\cdot)$ means vectorization of a matrix, and

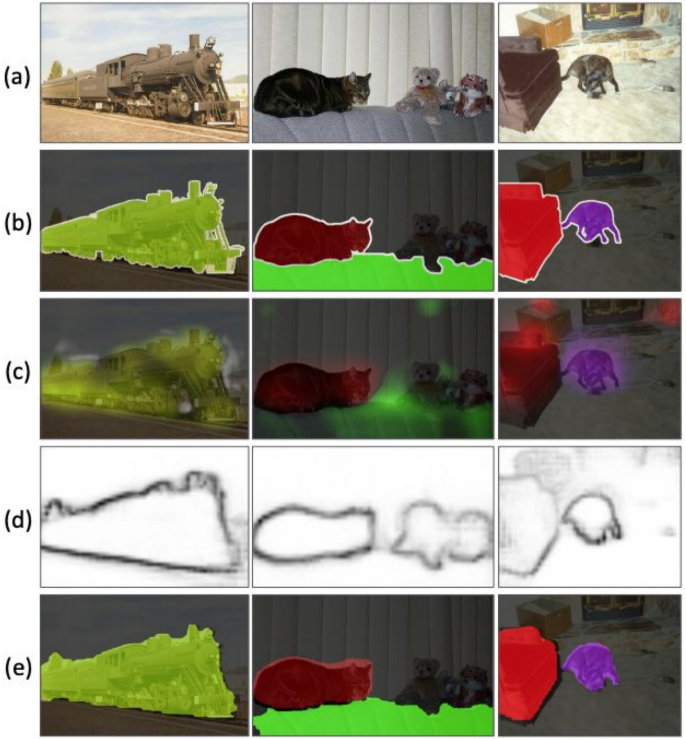

Figure 5. Qualitative examples of synthesized segmentation labels of training images in the PASCAL VOC 2012 benchmark. (a) Input images. (b) Groundtruth segmentation labels. (c) CAMs of object classes. (d) Visualization of the predicted semantic affinities. (e) Synthesized segmentation annotations.

- the Hadamard power of the original affinity matrix, ignores immaterial affinities in W.
- Using this technique makes out random walk propagation more conservative.

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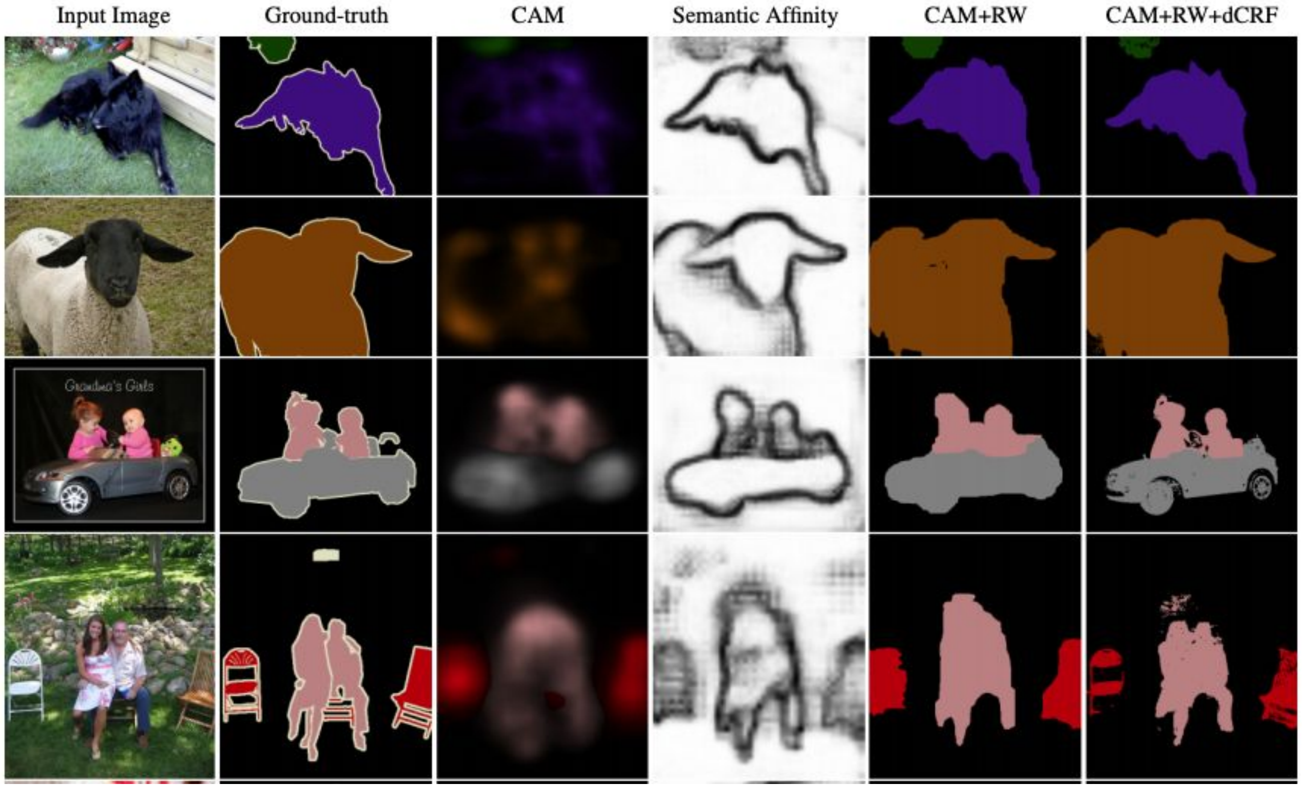
5. Qualitative Results



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6. Quantitative Results

Method	bkg	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbk	person	plant	sheep	sofa	train	tv	mean
EM-Adapt [28]	67.2	29.2	17.6	28.6	22.2	29.6	47.0	44.0	44.2	14.6	35.1	24.9	41.0	34.8	41.6	32.1	24.8	37.4	24.0	38.1	31.6	33.8
CCNN [29]	68.5	25.5	18.0	25.4	20.2	36.3	46.8	47.1	48.0	15.8	37.9	21.0	44.5	34.5	46.2	40.7	30.4	36.3	22.2	38.8	36.9	35.3
MIL+seg [30]	79.6	50.2	21.6	40.9	34.9	40.5	45.9	51.5	60.6	12.6	51.2	11.6	56.8	52.9	44.8	42.7	31.2	55.4	21.5	38.8	36.9	42.0
SEC [14]	82.4	62.9	26.4	61.6	27.6	38.1	66.6	62.7	**75.2**	22.1	53.5	28.3	65.8	57.8	62.3	52.5	32.5	62.6	32.1	45.4	45.3	50.7
AdvErasing [37]	83.4	**71.1**	30.5	72.9	41.6	55.9	63.1	60.2	74.0	18.0	**66.5**	32.4	71.7	56.3	64.8	52.4	37.4	69.1	31.4	58.9	43.9	55.0
Ours-DeepLab	87.2	57.4	25.6	69.8	45.7	53.3	76.6	**70.4**	74.1	28.3	63.2	**44.8**	75.6	**66.1**	65.1	71.1	40.5	66.7	37.2	58.4	49.1	58.4
Ours-ResNet38	**88.2**	68.2	**30.6**	**81.1**	**49.6**	**61.0**	**77.8**	66.1	75.1	**29.0**	66.0	40.2	**80.4**	62.0	**70.4**	**73.7**	**42.5**	**70.7**	**42.6**	**68.1**	**51.6**	**61.7**

Table 2. Performance on the PASCAL VOC 2012 *val* set, compared to weakly supervised approaches based only on image-level labels.

Method	bkg	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbk	person	plant	sheep	sofa	train	tv	mean
EM-Adapt [28]	76.3	37.1	21.9	41.6	26.1	38.5	50.8	44.9	48.9	16.7	40.8	29.4	47.1	45.8	54.8	28.2	30.0	44.0	29.2	34.3	46.0	39.6
CCNN [29]	70.1	24.2	19.9	26.3	18.6	38.1	51.7	42.9	48.2	15.6	37.2	18.3	43.0	38.2	52.2	40.0	33.8	36.0	21.6	33.4	38.3	35.6
MIL+seg [30]	78.7	48.0	21.2	31.1	28.4	35.1	51.4	55.5	52.8	7.8	56.2	19.9	53.8	50.3	40.0	38.6	27.8	51.8	24.7	33.3	46.3	40.6
SEC [14]	83.5	56.4	28.5	64.1	23.6	46.5	70.6	58.5	71.3	23.2	54.0	28.0	68.1	62.1	70.0	55.0	38.4	58.0	39.9	38.4	48.3	51.7
AdvErasing [37]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	55.7
Ours-DeepLab	88.0	61.1	29.2	73.0	40.5	54.1	75.2	**70.4**	**75.1**	27.8	62.5	51.4	78.4	**68.3**	76.2	71.8	40.7	**74.9**	**49.2**	55.0	48.3	60.5
Ours-ResNet38	**89.1**	**70.6**	**31.6**	**77.2**	**42.2**	**68.9**	**79.1**	66.5	74.9	**29.6**	**68.7**	**56.1**	**82.1**	64.8	**78.6**	**73.5**	**50.8**	70.7	47.7	**63.9**	**51.1**	**63.7**

Table 3. Performance on the PASCAL VOC 2012 *test* set, compared to weakly supervised approaches based only on image-level labels.

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6. Quantitative Results

Method	Sup.	Extra Data	*val*	*test*
TransferNet [10]	$\mathcal{I}$	MS-COCO [20]	52.1	51.2
Saliency [26]	$\mathcal{I}$	MSRA [21], BSDS [24]	55.7	56.7
MCNN [35]	$\mathcal{I}$	YouTube-Object [31]	38.1	39.8
CrawlSeg [11]	$\mathcal{I}$	YouTube Videos	58.1	58.7
What'sPoint [1]	$\mathcal{P}$	-	46.0	43.6
RAWK [36]	$\mathcal{S}$	-	61.4	-
ScribbleSup [18]	$\mathcal{S}$	-	63.1	-
WSSL [28]	$\mathcal{B}$	-	60.6	62.2
BoxSup [6]	$\mathcal{B}$	-	62.0	64.6
SDI [12]	$\mathcal{B}$	BSDS [24]	65.7	67.5
FCN [22]	$\mathcal{F}$	-	-	62.2
DeepLab [3]	$\mathcal{F}$	-	67.6	70.3
ResNet38 [38]	$\mathcal{F}$	-	80.8	82.5
Ours-DeepLab	$\mathcal{I}$	-	58.4	60.5
Ours-ResNet38	$\mathcal{I}$	-	61.7	63.7

Table 4. Performance on the PASCAL VOC 2012 *val* and *test* sets. The supervision types (Sup.) indicate: $\mathcal{P}$–point, $\mathcal{S}$–scribble, $\mathcal{B}$–bounding box, $\mathcal{I}$–image-level label, and $\mathcal{F}$–segmentation label.

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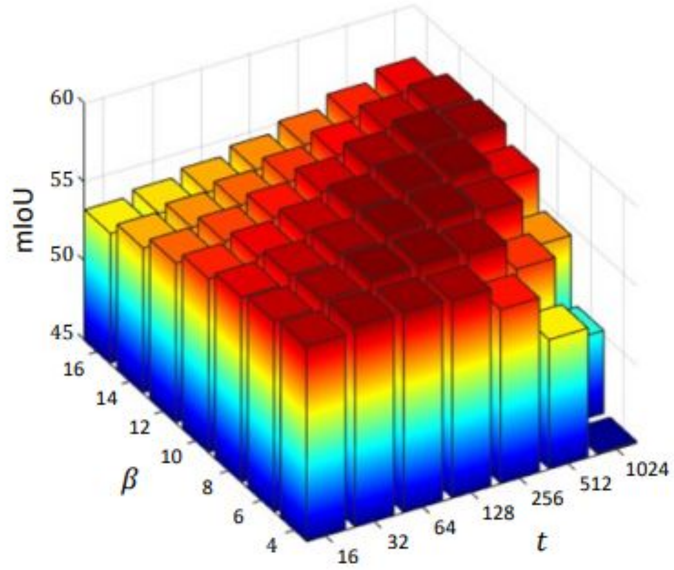
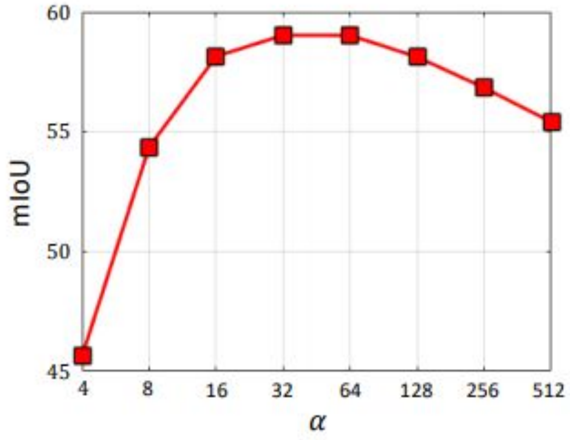
7. Analysis on Effects of the Hyper-parameters



(a) Accuracy versus β and t



(b) Accuracy versus α

Figure 8. Accuracy (mIoU) of segmentation labels synthesized by CAM+RW for different hyper-parameter values on the VOC 2012 *train*.