Weakly-Supervised Semantic Segmentation Network with Deep Seeded Region Growing

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Weakly-supervised visual learning (WSVL)

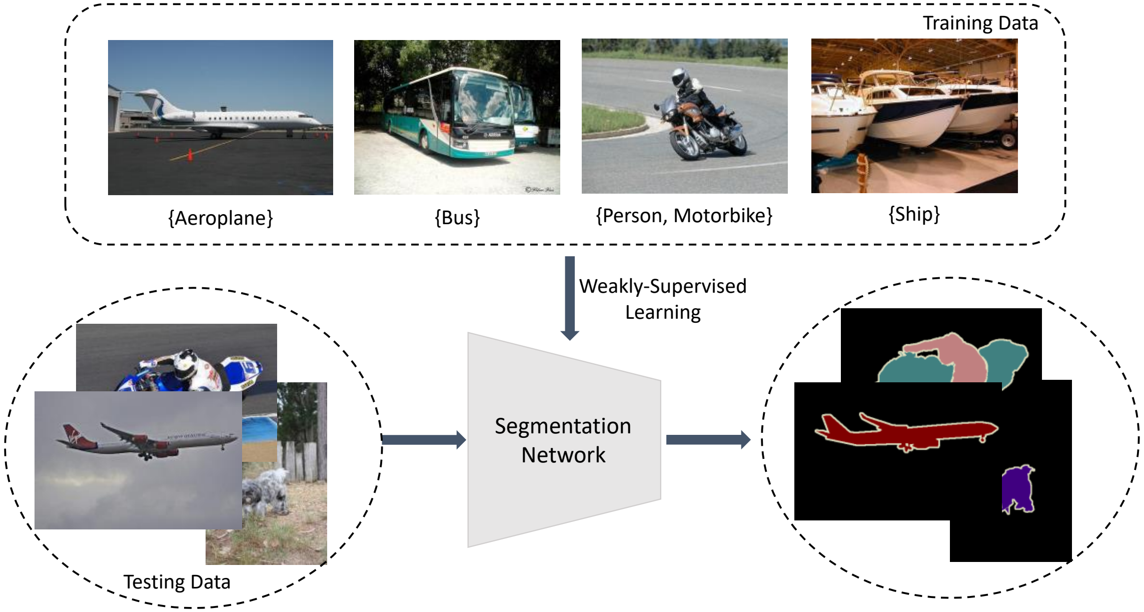
- Weakly-supervised visual learning is a new trend in CVPR

Search keyword "weakly supervised" and "weakly-supervised" in CVPR 17&18

Keyword	Weakly supervised	Weakly-supervised	In total
cvpr17	14	5	19/783
cvpr18	19	10	29/979

Weakly supervised semantic segmentation

The task of WSSS



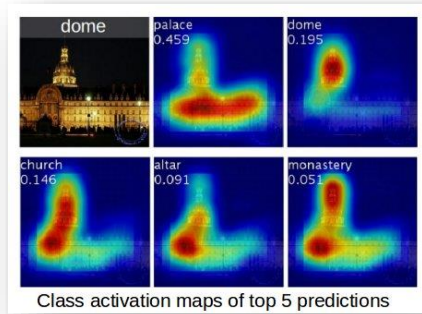
WSSS overcomes the deficiency problem in semantic segmentation labelling.

The development of WSSS

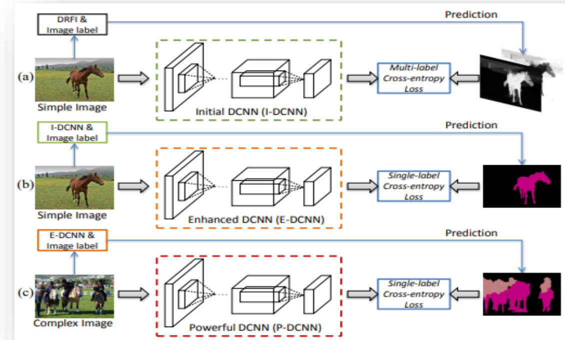
$$(x_l, y_l) = \arg\max_{\forall (x,y)} \hat{p}_l(x,y) \qquad \forall l \in \mathcal{L}_I$$

$$\text{MIL LOSS} = \frac{-1}{|\mathcal{L}_I|} \sum_{l \in \mathcal{L}_I} \log \hat{p}_l(x_l, y_l)$$

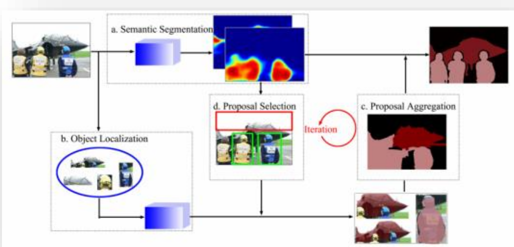
MIL-FCN, Pathak et al, Arxiv 14, ICLRW 15



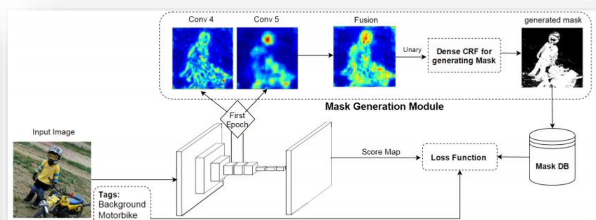
CAM, Zhou et al, CVPR 16



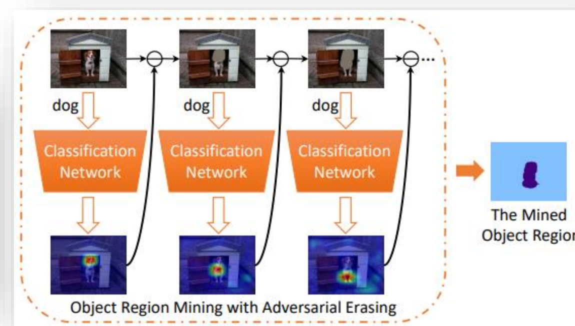
STC, Wei et al, TPAMI 15



Proposal classification, Qi et al, ECCV 16



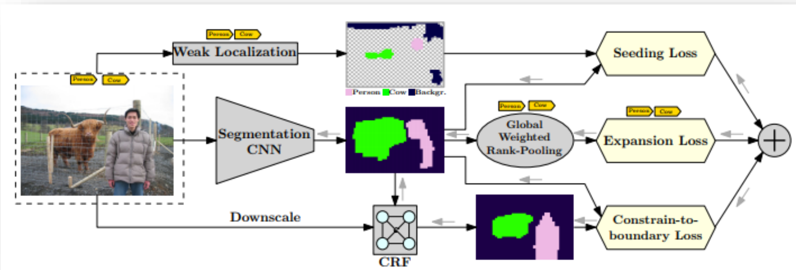
Built-in FG/BG Model
Saleh et al, ECCV 16



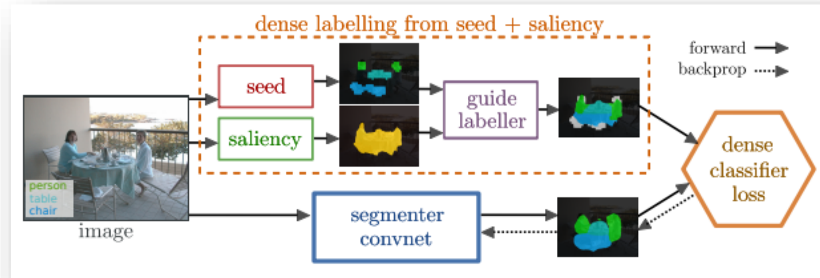
Adversarial erasing, Wei et al, CVPR 17

Figures are from the original papers

The development of WSSS



Seeding loss,
Kolesnikov et al, ECCV 17



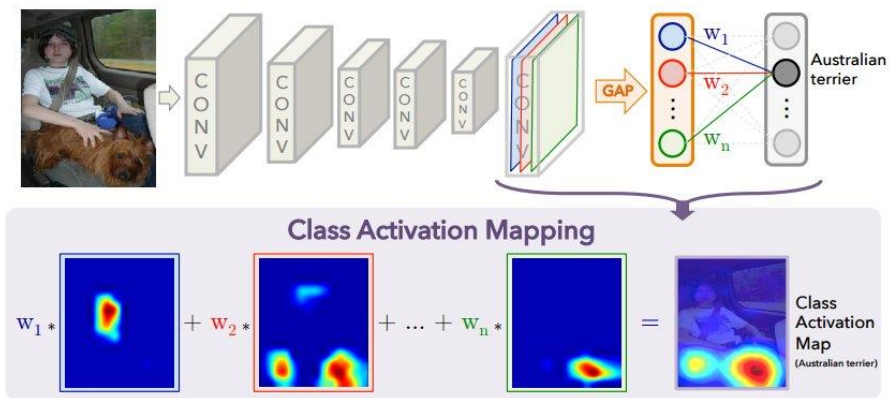
Saliency guided labler,
Oh et al, CVPR 17

1. **Multi-instance learning**
2. **Saliency guided**
3. **Built-in network information**
4. **Adversarial learning**
5. **Seeding loss**

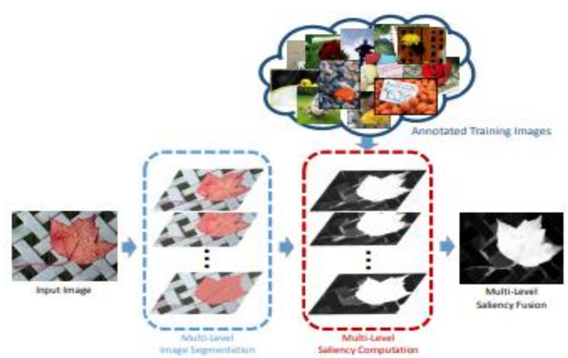
Figures are from the original papers

The basic framework in our paper

Step 1： Foreground seeds from CAM



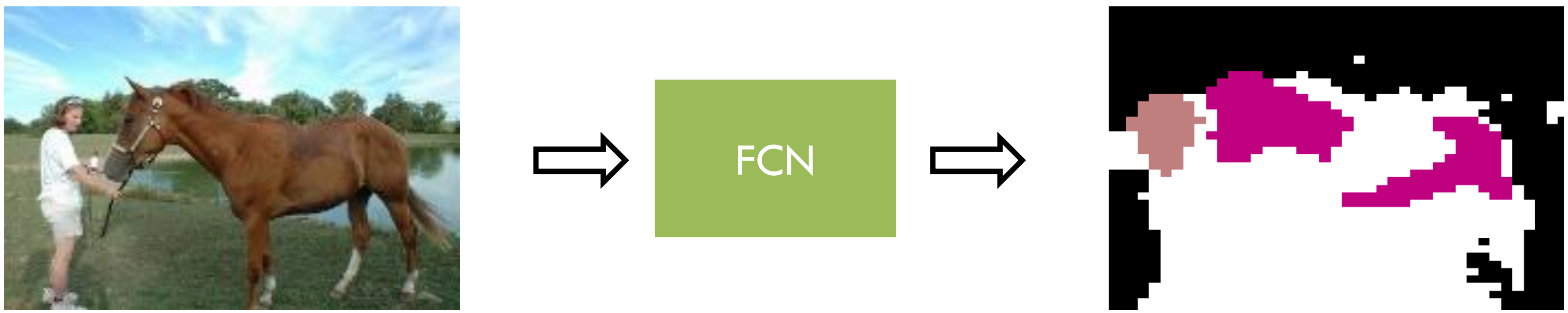
Step 2： Background seeds derived salient region detection [Jiang et al, CVPR13]



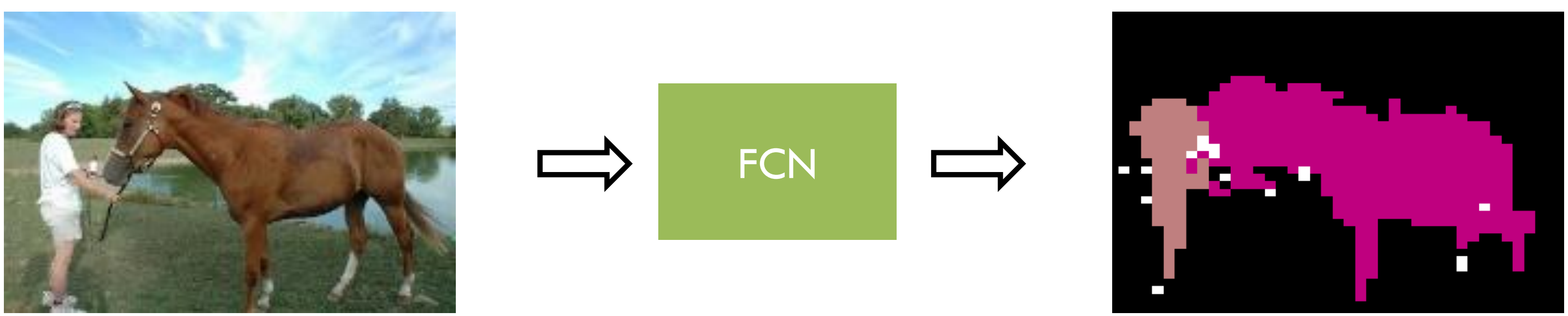
Figures are from the original papers

The basic framework in our paper

Step 3： FCN with seeding loss



Step 4： Retrain with FCN

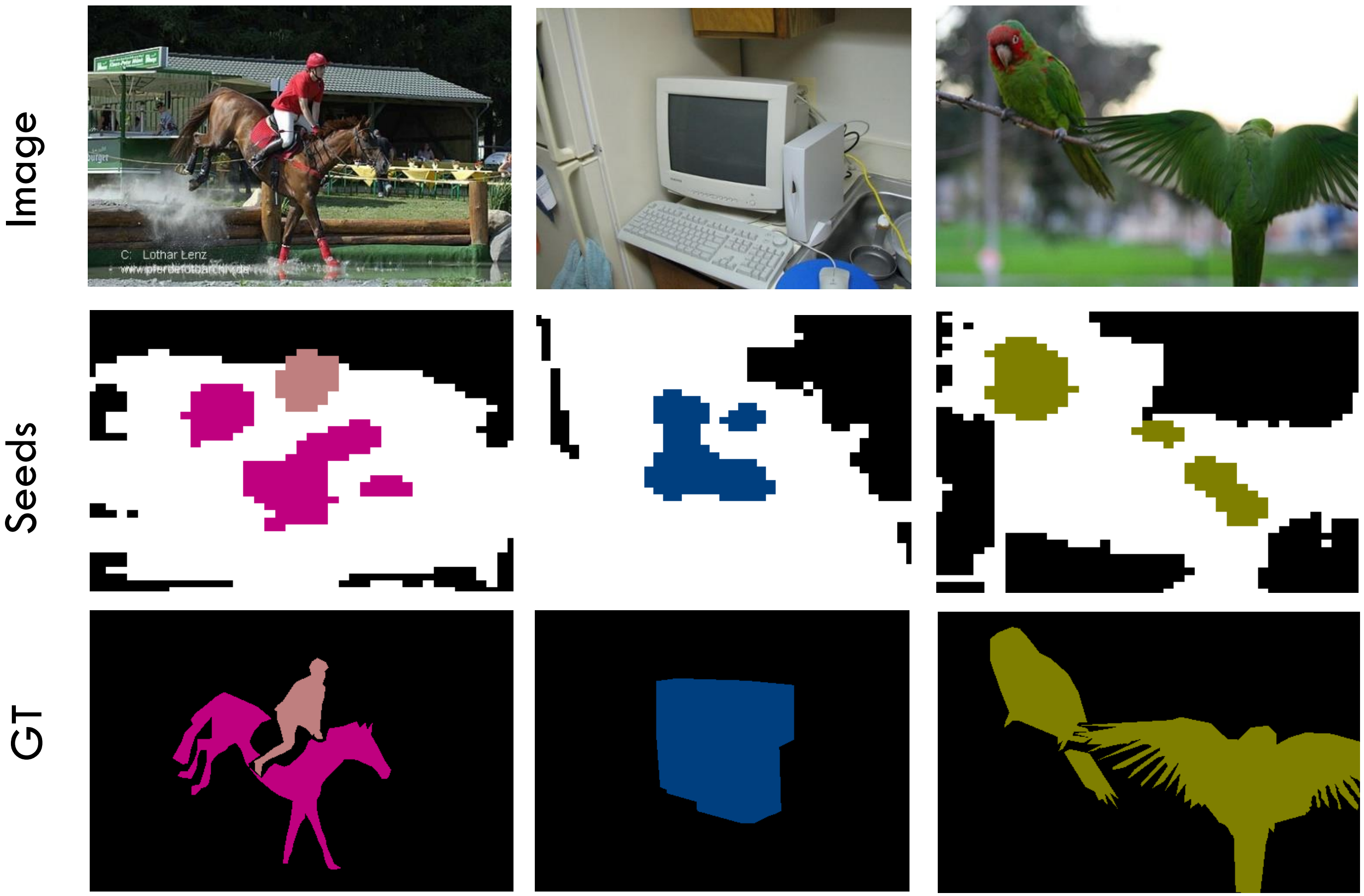


A small trick: balanced seeding loss

Balance the weights between foreground and background

$$\ell_{seed} = -\frac{1}{\sum\limits_{c \in \mathcal{C}} |S_c|} \sum_{c \in \mathcal{C}} \sum_{u \in S_c} \log H_{u,c} - \frac{1}{\sum\limits_{c \in \bar{\mathcal{C}}} |S_c|} \sum_{c \in \bar{\mathcal{C}}} \sum_{u \in S_c} \log H_{u,c},$$

However, the seeds are sparse



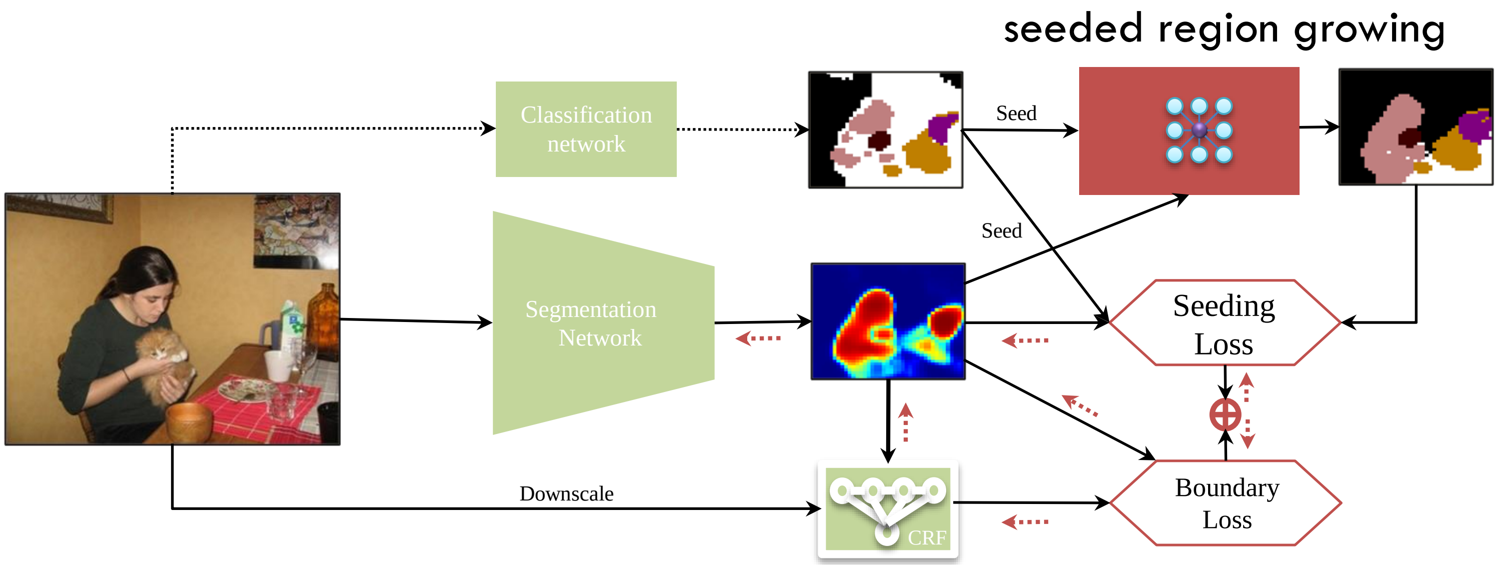
In practice, to retain the precision of seeds, there are about 40% pixels have labels.

How to improve the quality and quantity of seeds

- Better “CAM” network
- Saliency guidance
- Adversarial erasing
- …

- Online seeded region growing

Deep seeded region growing



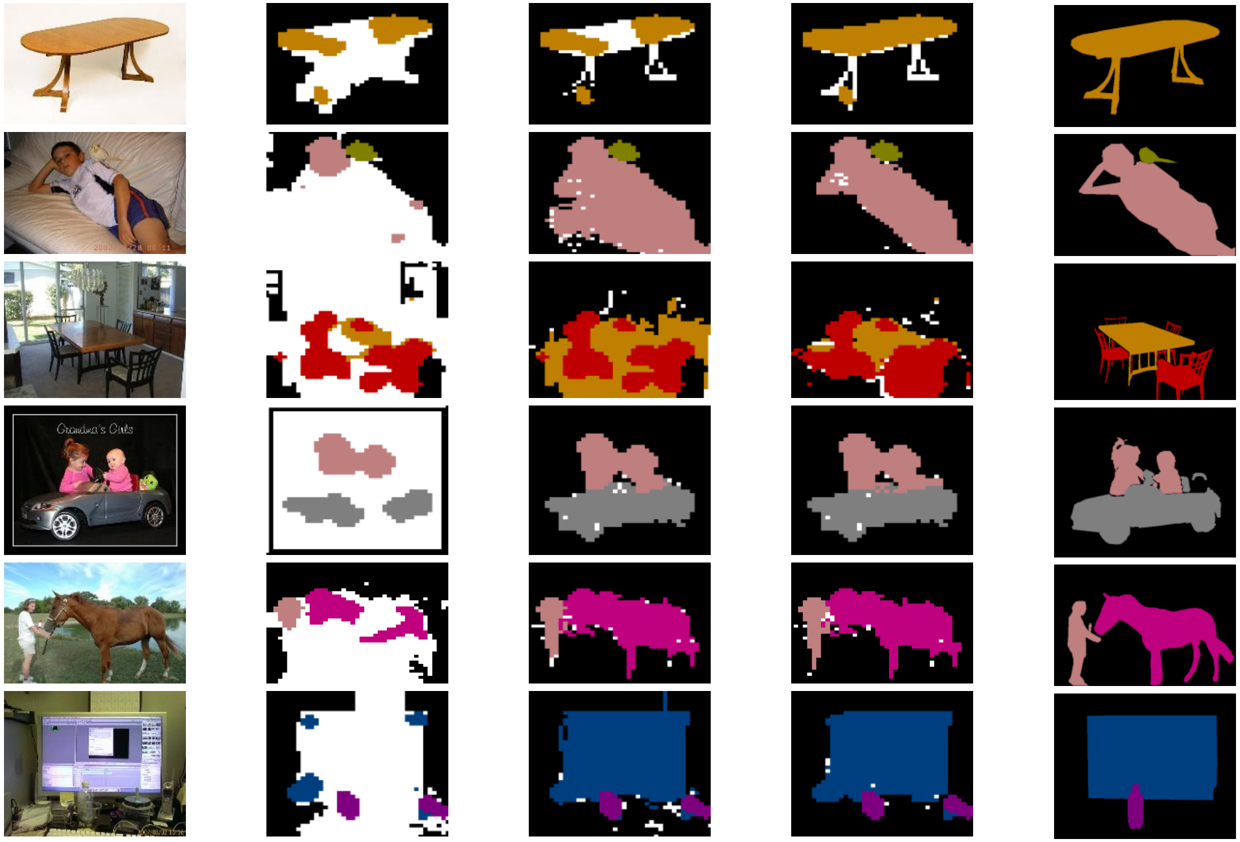
Region growing criteria:

$$P(H_{u,c}, \theta_c) = \begin{cases} \text{TRUE} & H_{u,c} \geq \theta_c \text{ and} \\ & c = \arg\max_{c'} H_{u,c'}, \\ \text{FALSE} & \text{otherwise.} \end{cases}$$

1. Directly use deep prob features
2. Cheap to compute
3. Online supervision updating

Progressively check the neighborhood pixels

Deep seeded region growing



Training Image | Seed Cues | Epoch #1 | Epoch #12 | Ground Truth

Deep seeded region growing

Algorithm 2 Deep Seeded Region Growing Training

1: **Input:** Training data $D = \{(I_i, S_i)\}_{i=1}^{N}$.
2: **Initialize:** initialize M_0, $t = 1$.
3: **while** $(t \leq max\_iter)$ **do**
4: Select a sample $\{I_i, S_i\}$ from input data randomly;
5: $H_i = M_{t-1}(I_i)$;
6: Perform $G_i = DSRG(S_i, H_i)$ for seed expansion
7: Compute the $loss = \ell(G_i, , H_i)$
8: back propagate the error and update model from M_{t-1} to M_t
9: **end while**
10: **Output:** M

Experiments

- Datasets
  - **PASCAL VOC 2012**, 10582 train, 1449 val, 1456 test
  - **COCO**, 80k train, 40 val

- mIoU criterion

- Classification network: VGG-16
- Segmentation network: DeepLab-ASPP

Main Results

PASCAL VOC

Method	Training	Val	Test
DCSM[2]	10k	44.1	45.1
BFBP[3]	10k	46.6	48.0
STC [4]	50k	49.8	51.2
SEC [5]	10k	50.7	51.7
AF-SS [6]	10k	52.6	52.7
Combining Cues [7]	10k	52.8	53.7
AE-PSL [8]	10k	55.0	55.7
DCSP [9]	10k	58.6	59.2
DSRG (VGG16)	10k	**59.0**	**60.4**
DSRG (Resnet101)	10k	**61.4**	**63.2**

COCO

Method	Val
BFBP[3]	20.4
SEC [5]	22.4
DSRG (Ours)	**26.0**

Ablation studies

The contributions of **Balanced seeding loss, DSRG & Retrain**

Table 2. Comparison of mIoU using different settings of our approach on VOC 2012 val set

Method	bkg	plane	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	motor	person	plant	sheep	sofa	train	tv	mIoU
baseline	82.5	67.5	23.2	65.7	29.7	47.5	71.8	66.8	76.7	23.3	51.7	26.2	69.7	54.2	63.2	57.2	33.7	64.5	33.5	48.7	46.1	52.5
+BSL	82.4	71.9	29.1	67.7	32.4	49.8	75.5	67.9	74.7	22.8	54.9	26.6	64.3	55.7	64.7	56.0	35.0	67.7	32.7	50.2	45.8	53.6
+DSRG	86.6	70.5	28.8	70.6	34.7	55.7	74.9	70.1	80.2	24.1	63.6	24.8	76.6	64.1	64.9	72.3	38.5	68.7	35.8	51.8	51.9	57.6
+Retrain	87.5	73.1	28.4	75.4	39.5	54.5	78.2	71.3	80.6	25.0	63.3	25.4	77.8	65.4	65.2	72.8	41.2	74.3	34.1	52.1	53.0	59.0

Ablation studies

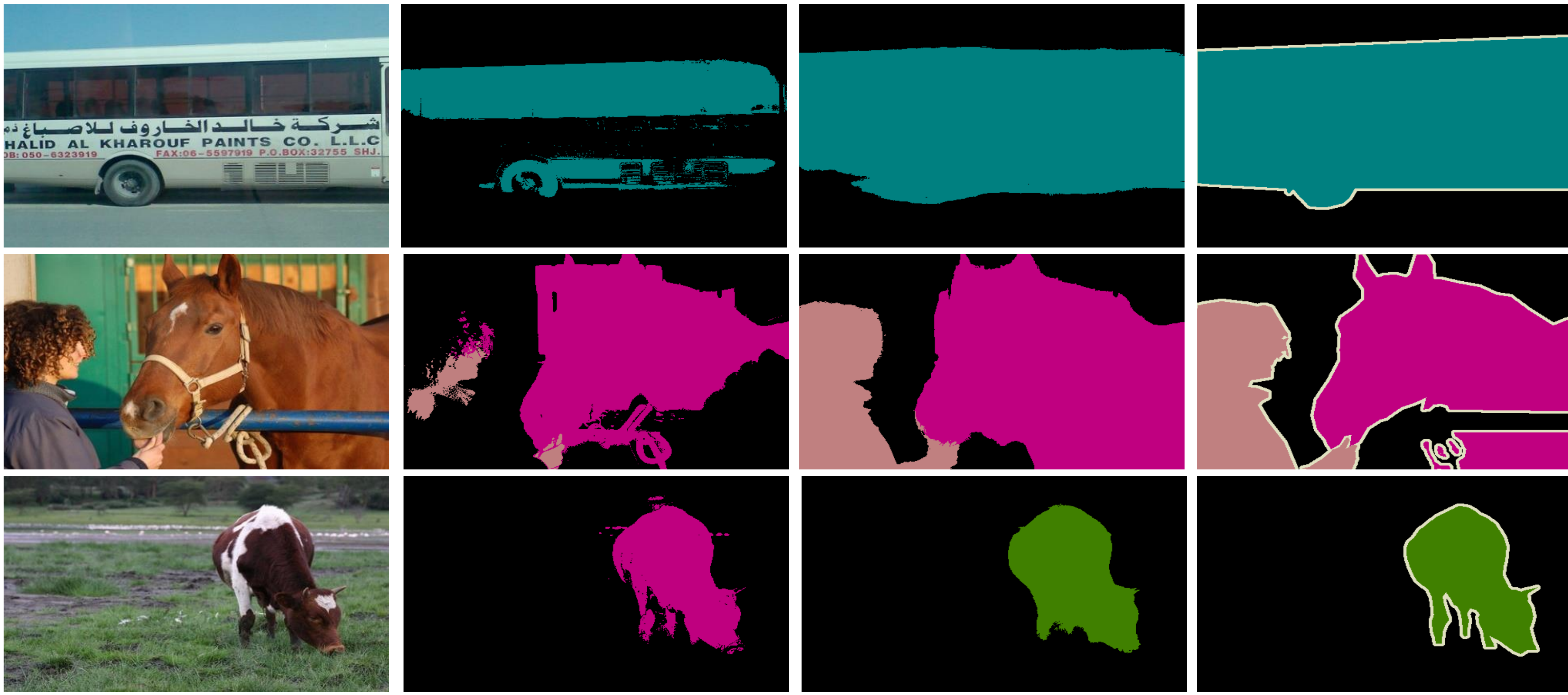
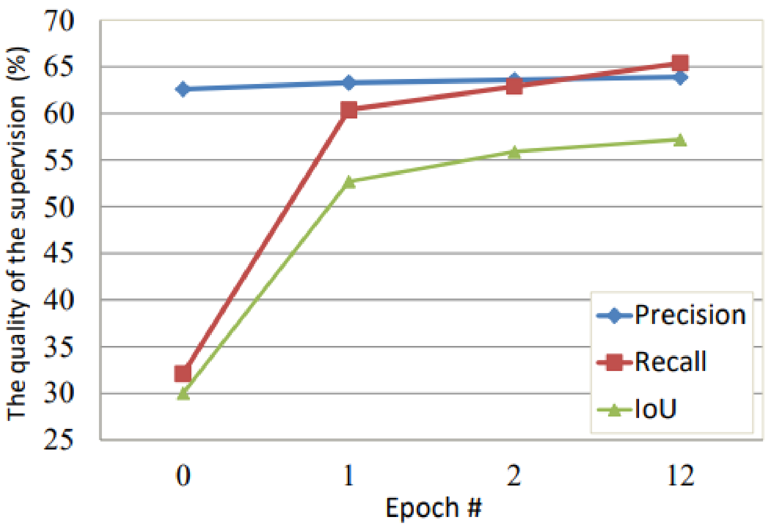


Image | w/o DSRG | +DSRG | Ground Truth

Ablation studies

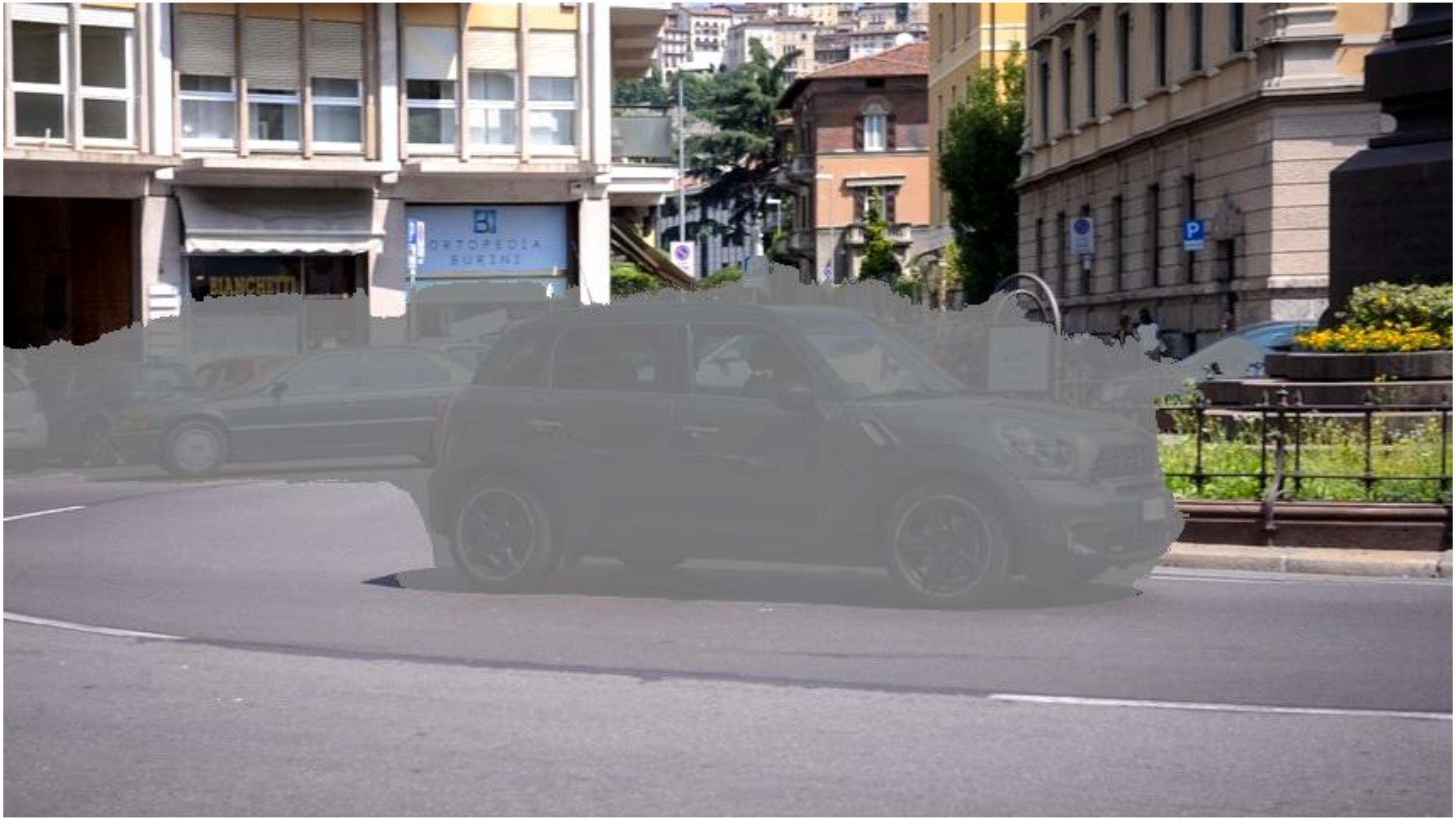


The quality of the dynamic supervision (%) with respect to the epochs.

θ_b \ θ_f	0.99	0.95	0.90	0.85	0.80
0.99	57.45	57.59	57.63	**57.69**	57.66
0.95	57.43	57.56	57.64	57.67	57.63
0.90	57.23	57.35	57.40	57.44	57.45

Performance on PASCAL val dataset for different θ

Video demo



Discussion

- How to interpret DSRG
  - A Neural network generates new label by itself.
  - The inner structure of image/video helps, e.g., [Ahn & Kwak, CVPR 18].
  - From the perspective of SSL, pseudo label/supervision [Lee, ICMLw 13, Wang et al, MM 16] works.

Discussion

- Current limitations of WSSS
  - Hard to obtain precise boundaries
  - Does not work well in complex dataset, e.g., COCO & Kitti

- Let deep networks know what is an object, e.g., unsupervised learning from video.
- Weakly and semi-supervised (WASS) visual learning.

- The paper is available at http://www.xinggangw.info/pubs/cvpr18-dsrg.pdf

- Codes will be available at https://github.com/speedinghzl/DSRG

Thanks for your attention!