

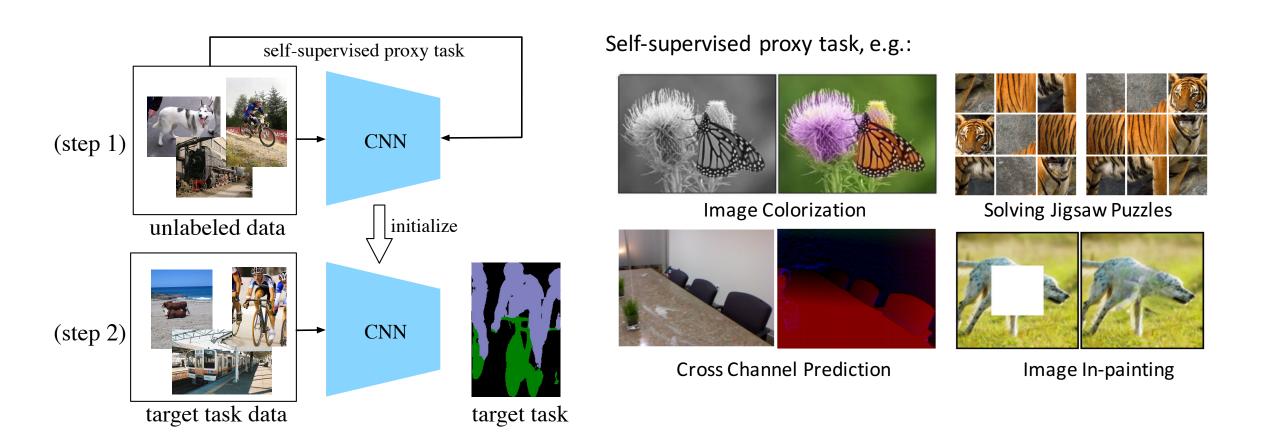
Mix-and-Match Tuning for Self-Supervised Semantic Segmentation

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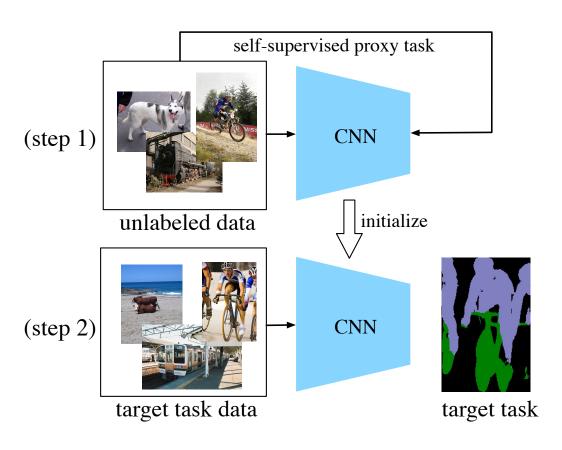
Self-supervised Learning









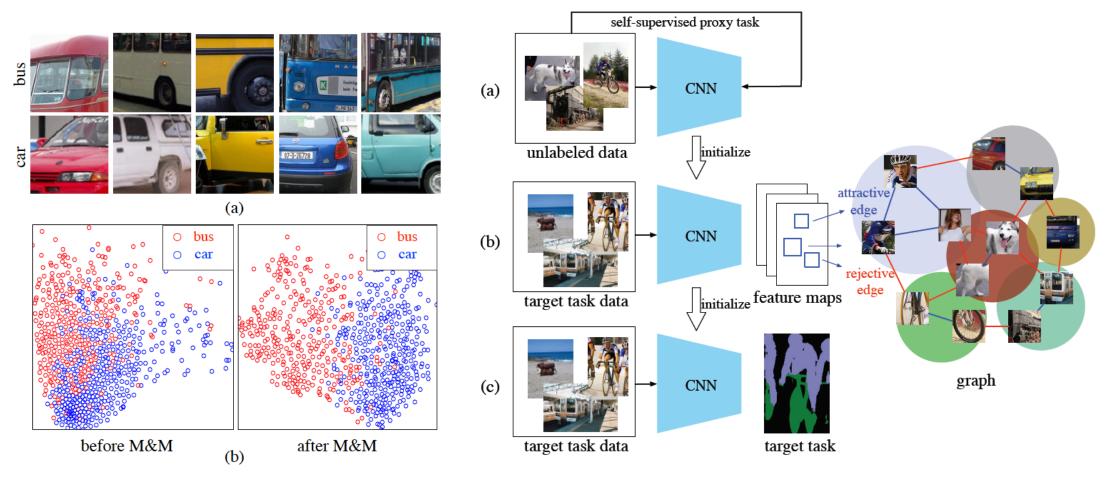


Method	Arch.	VOC12
		%mIoU.
ImageNet	VGG-16	64.2
Random	VGG-16	35.0
Larsson et al. (Larsson, Maire, and Shakhnarovich 2016)	VGG-16	50.2
Larsson et al. (Larsson, Maire, and Shakhnarovich 2017)	VGG-16	56.0
Ours (M&M + Graph, colorization pre-trained)	VGG-16	64.5
ImageNet	AlexNet	48.0
Random	AlexNet	23.5
k-means (Krähenbühl et al. 2015)	AlexNet	32.6
Pathak et al. (Pathak et al. 2016b)	AlexNet	29.7
Donahue et al. (Donahue, Krähenbühl, and Darrell 2016)	AlexNet	35.2 9.6%
Zhang et al. (Zhang, Isola, and Efros 2016a)	AlexNet	35.6
Zhang et al. (Zhang, Isola, and Efros 2016b)	AlexNet	36.0
Noroozi et al. (Noroozi and Favaro 2016)	AlexNet	37.6
Larsson et al. (Larsson, Maire, and Shakhnarovich 2017)	AlexNet	38.4
Ours (M&M + Random Triplets, colorization pre-trained)	AlexNet	40.9
Ours (M&M + Graph, colorization pre-trained)	AlexNet	42.8
Ours (M&M + Graph, randomly initialized)	AlexNet	43.6

Sematic Segmentation benchmark (PASCAL VOC 2012 validation set)

Task Gap





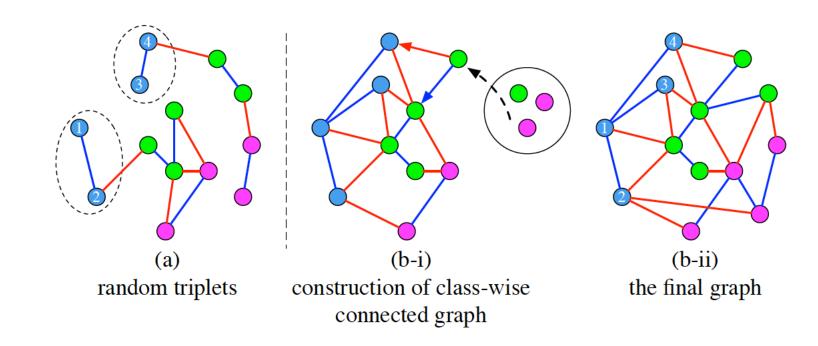
Self-supervised representations sensitive to the designed proxy task rather than the target task.

Mix-and-match tuning to narrow the gap.



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Class-wise Connected Graph

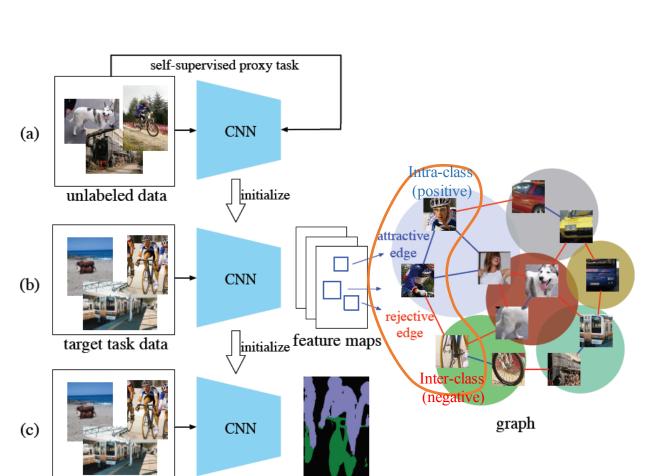


- (a) Randomly selected triplets
 - i. May form multiple centers for each class
 - ii. Some nodes will never be used

- (b) Our class-wise connected graph:
 - i. All nodes within the same class form a connected graph
 - ii. Each node can serve as an "anchor" node and to be used for optimization.

Training

target task data



target task



Formulate into triplet loss:

$$L = \frac{1}{N} \sum_{i}^{N} \max \left\{ D\left(P_a^i, P_p^i\right) - D\left(P_a^i, P_n^i\right) + \alpha, 0 \right\},\,$$

$$D(P_i, P_j) = \|(\mathbf{x}_i / \|\mathbf{x}_i\|_2 - \mathbf{x}_j / \|\mathbf{x}_j\|_2)\|^2,$$

For each node as an anchor (P_a) , and randomly selected positive (P_p) , randomly selected negative (P_n) . X_i : CNN representation on node i





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PASCAL VOC 2012 validation set



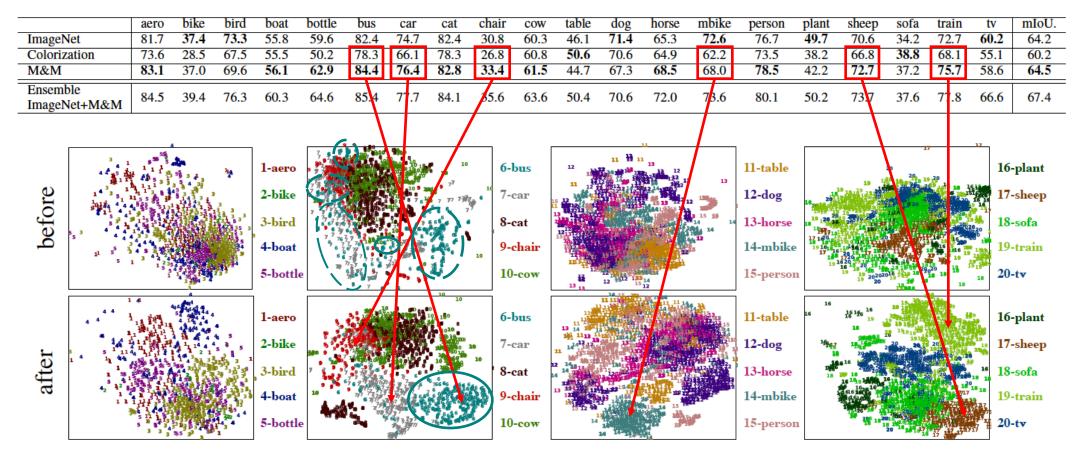


benchmark	PASCAL VOC2012				CityScapes		
pre-train	Random	Jigsaw	Colorize	Random	Colorize	Random	Colorize
backbone	AlexNet		VGG-16		VGG-16		
baseline	19.8	36.5	38.4	35.0	60.2	42.5	57.5
M&M	43.6	41.2	42.8	56.7	64.5 (64.3)	49.1	66.4 (65.6)
ImageNet	48.0		64.2		67.9		

Full results with different baselines and datasets

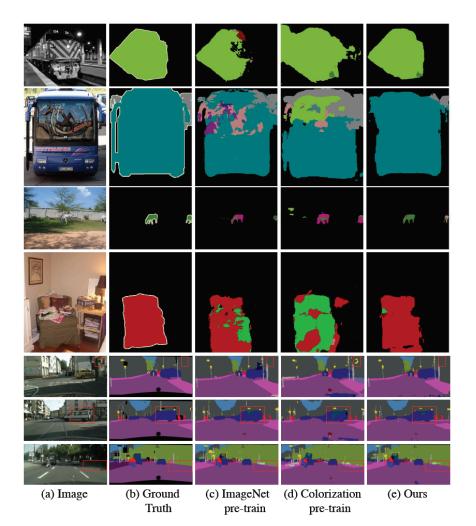




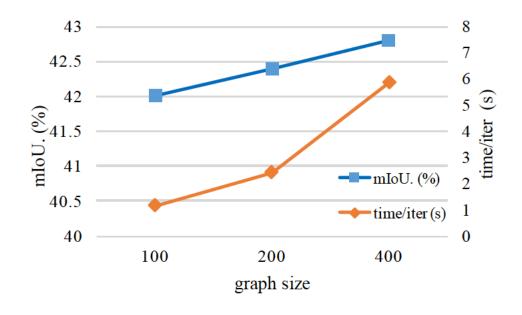


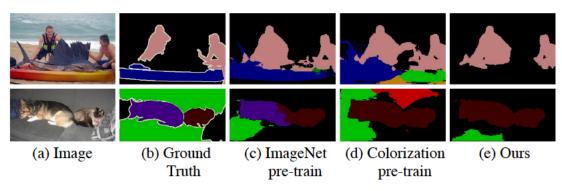
Per-class results and T-SNE feature visualization

Experiments



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Visualization results

Failure cases

Thank You!