



# Semi-Supervised Semantic Segmentation with Cross Pseudo Supervision

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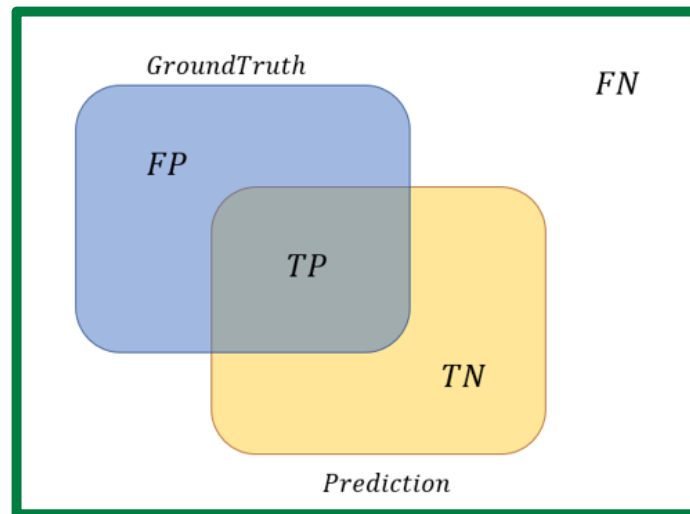
## Semantic Segmentation

- Category-label prediction for each pixel
- A pixel-wise classification
- mask

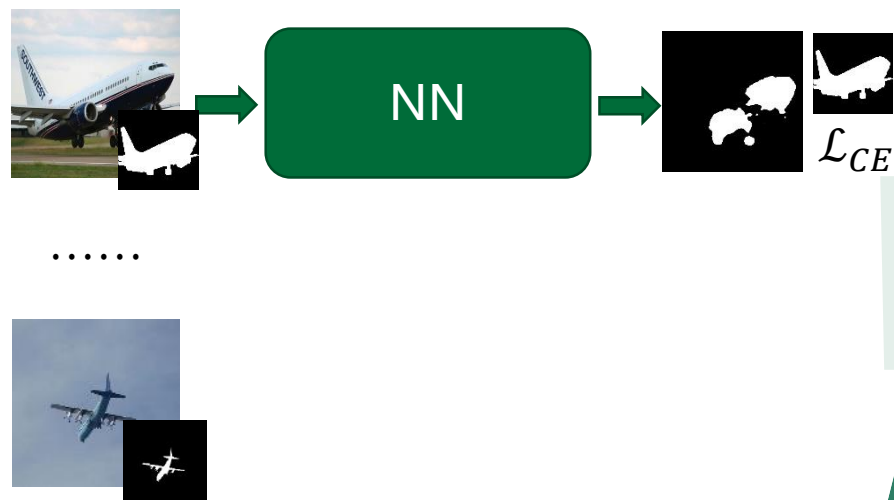


## IoU

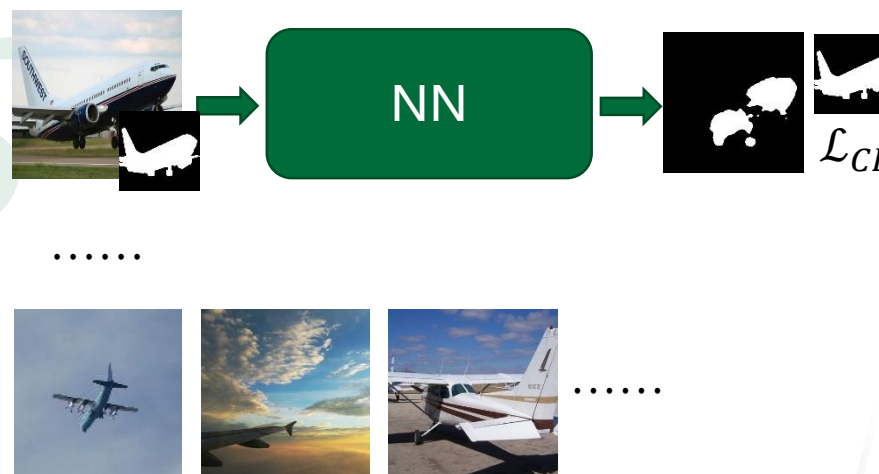
- $$\text{IoU} = \frac{\text{Prediction} \cap \text{GroundTruth}}{\text{Prediction} \cup \text{GroundTruth}}$$
$$= \frac{TP}{TP + TN + FP}$$



## Supervised-learning



## Semi-supervised learning



## Self-training

Predict label for unlabeled sample & enlarge train set

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### Algorithm 1 Self-training.

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1: **Initialize:**

2: Given  $(X_{train}, y_{train}) = (X_l, y_l)$

3: **while** stopping criteria not met **do**

4: Train classifier  $C_{int}$  from  $(X_{train}, y_{train})$

5: Use  $C_{int}$  to predict class label  $y_u$  of  $X_u$

6: Select confidence sample  $(X_{conf}, y_{conf})$ ;  $(X_{conf}, y_{conf}) \in (X_u, y_u)$

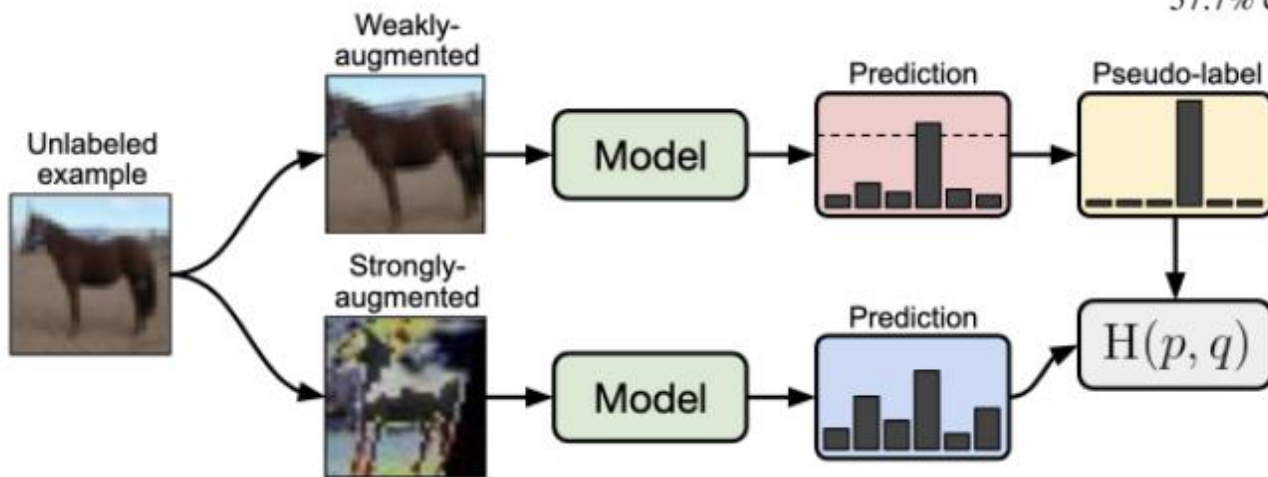
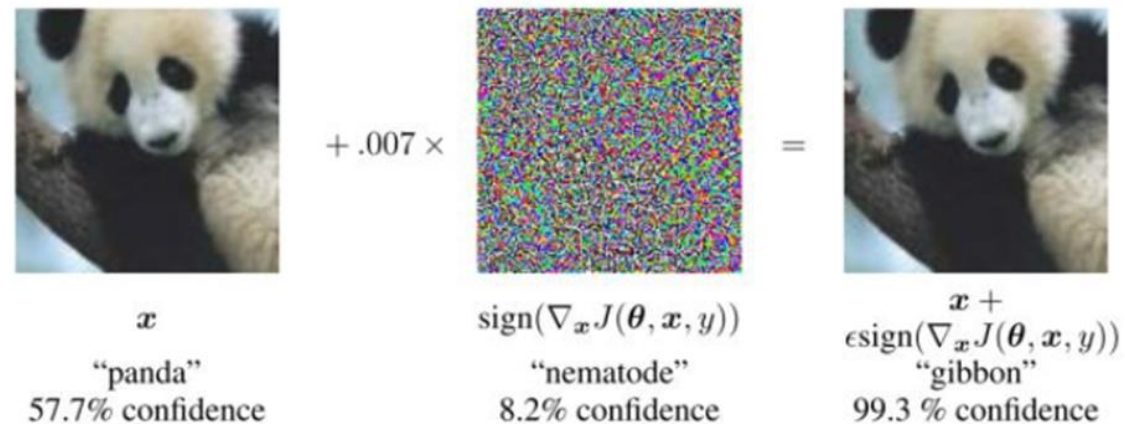
7: Remove selected unlabeled data  $X_u \leftarrow X_u - X_{conf}$

8: Combine newly labeled data  $(X_{train}, y_{train}) \leftarrow (X_l, y_l) \cup (X_{conf}, y_{conf})$

9: **end while**

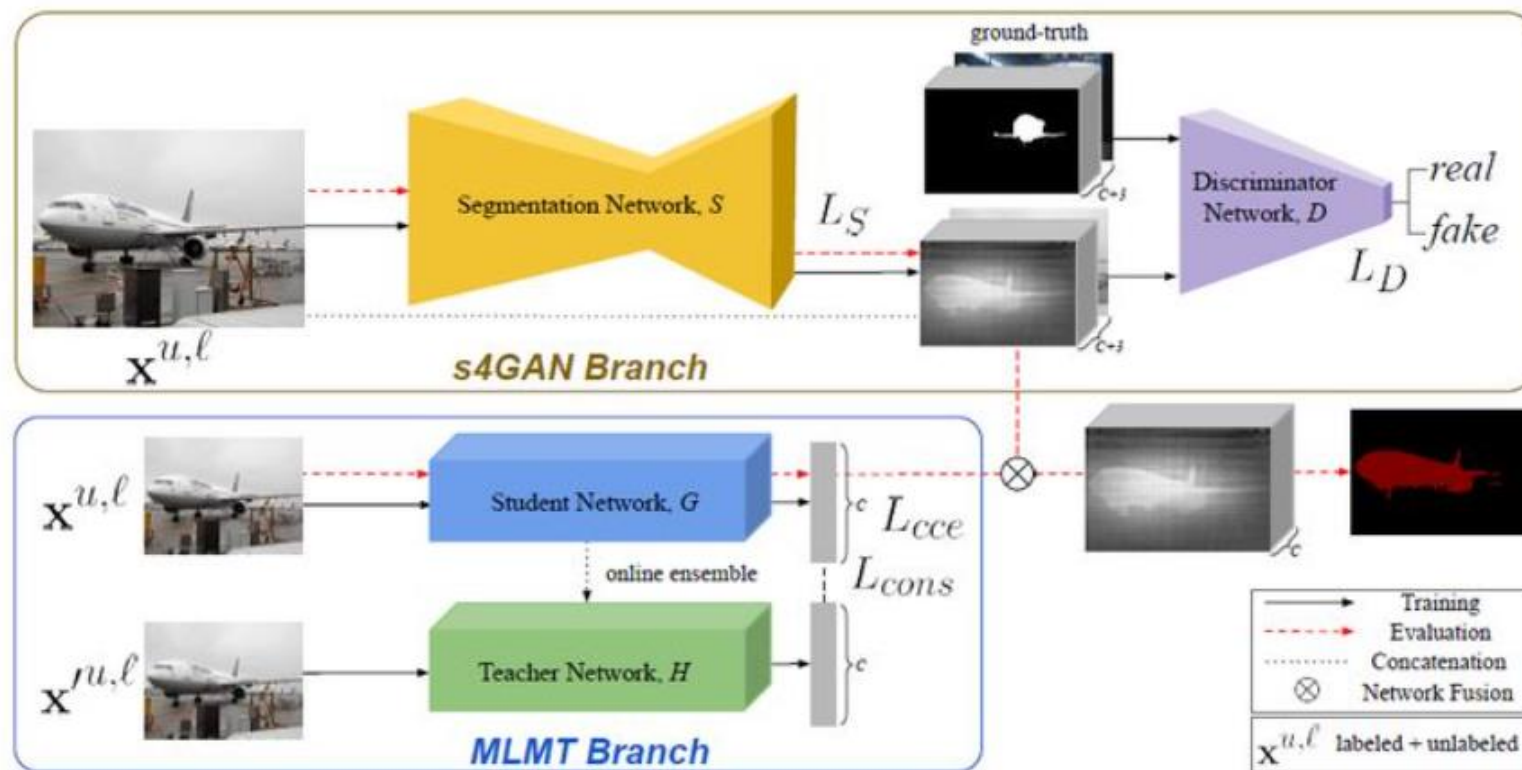
## Consistency Regularization

Enforce predictions consistency with various perturbations of input



- [1] Goodfellow I J, Shlens J, Szegedy C. Explaining and harnessing adversarial examples[J]. arXiv preprint arXiv:1412.6572, 2014.
- [2] Sohn K, Berthelot D, Li C L, et al. Fixmatch: Simplifying semi-supervised learning with consistency and confidence[J]. arXiv preprint arXiv:2001.07685, 2020.

## GAN-Based Methods



### Generator:

Input: image

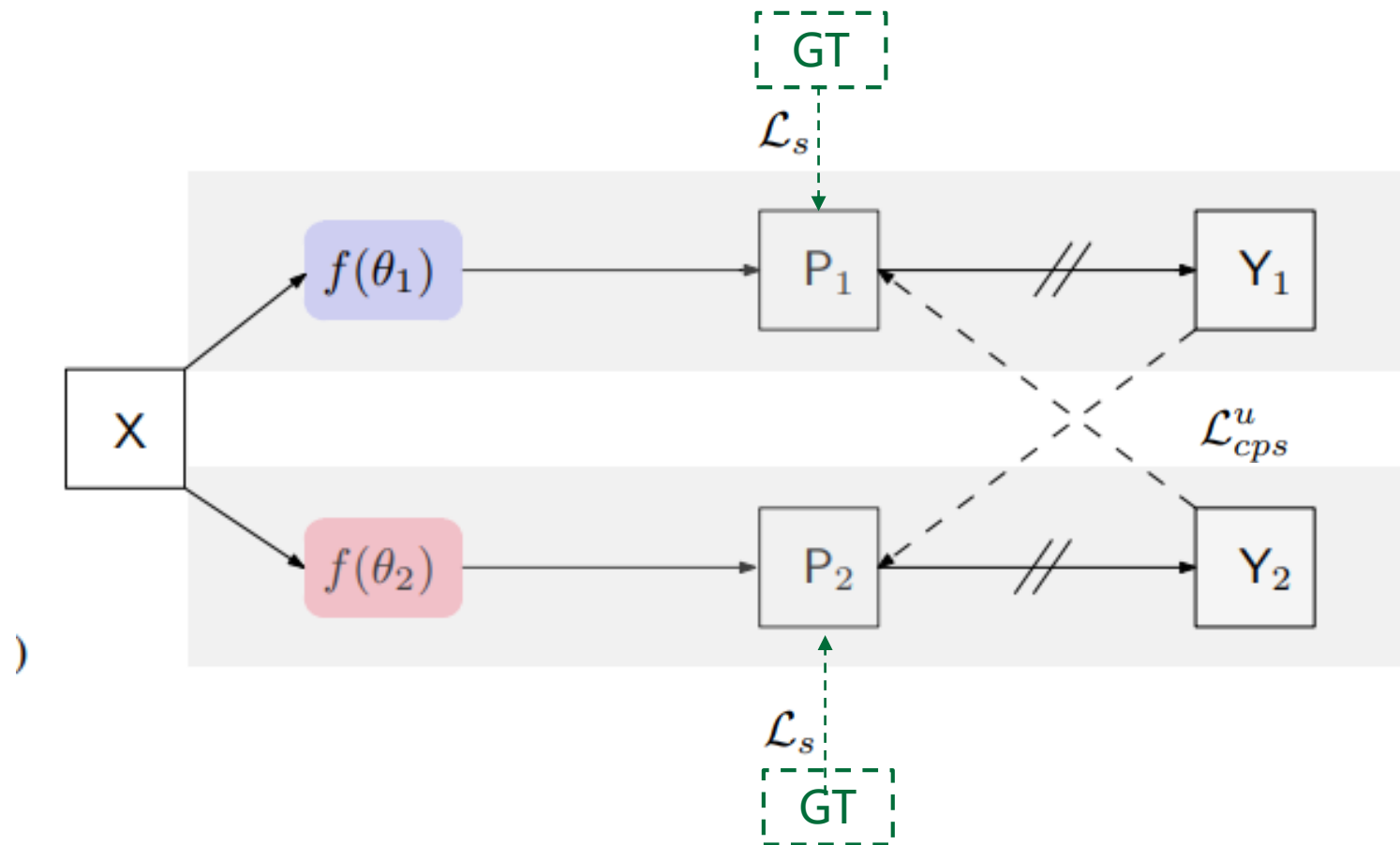
Output: C-channel mask

### Discriminator:

Input: C-channel mask  $\oplus$  Image

Output: real/fake

## Cross Pseudo Supervision







$f(\theta_1), f(\theta_2)$ :  
Same model  
architecture with  
different initialization  
// : stop gradient

$$\mathcal{L} = \mathcal{L}_s + \lambda \mathcal{L}_{cps}$$

**implement:**  
DeepLab v3+(ResNet)

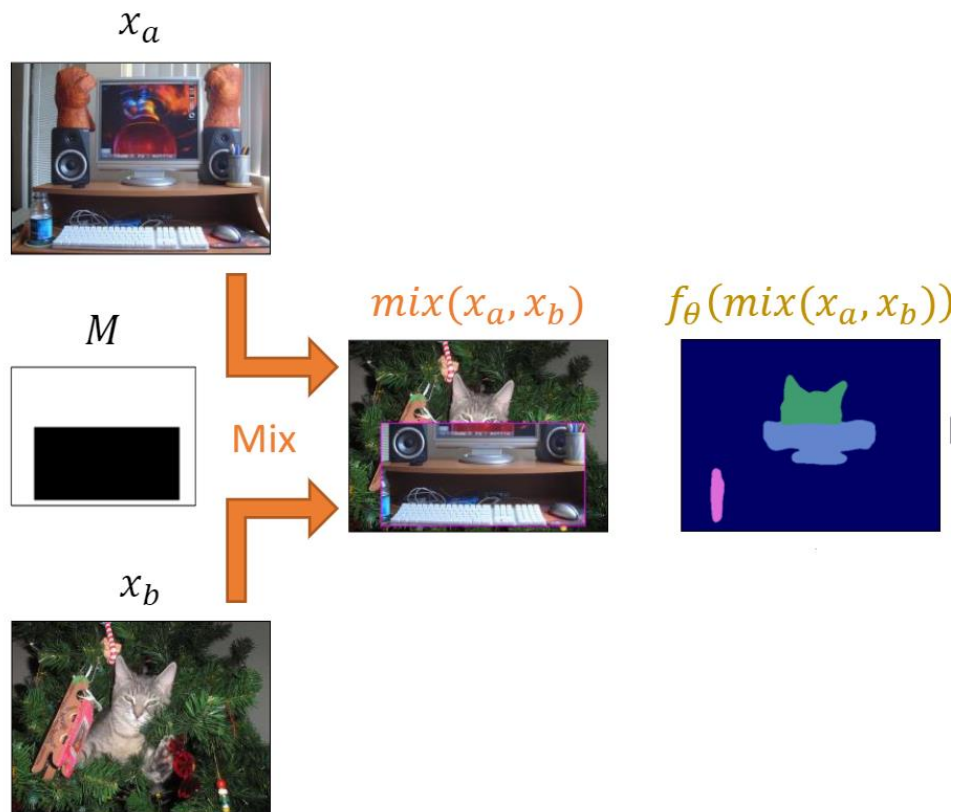


## Cutmix

	ResNet-50	Mixup [48]	Cutout [3]	CutMix
Image				
Label	Dog 1.0	Dog 0.5 Cat 0.5	Dog 1.0	Dog 0.6 Cat 0.4
ImageNet Cls (%)	76.3 (+0.0)	77.4 <b>(+1.1)</b>	77.1 <b>(+0.8)</b>	<b>78.6</b> <b>(+2.3)</b>
ImageNet Loc (%)	46.3 (+0.0)	45.8 <b>(-0.5)</b>	46.7 <b>(+0.4)</b>	<b>47.3</b> <b>(+1.0)</b>
Pascal VOC Det (mAP)	75.6 (+0.0)	73.9 <b>(-1.7)</b>	75.1 <b>(-0.5)</b>	<b>76.7</b> <b>(+1.1)</b>

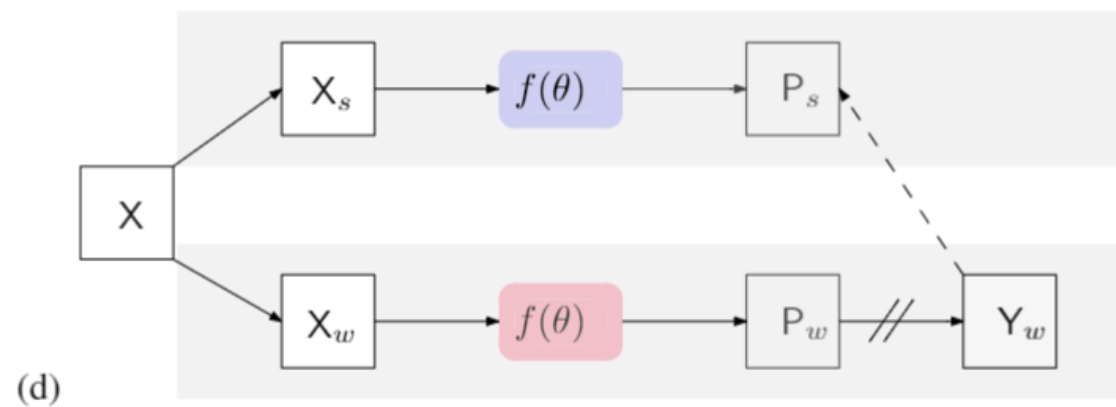
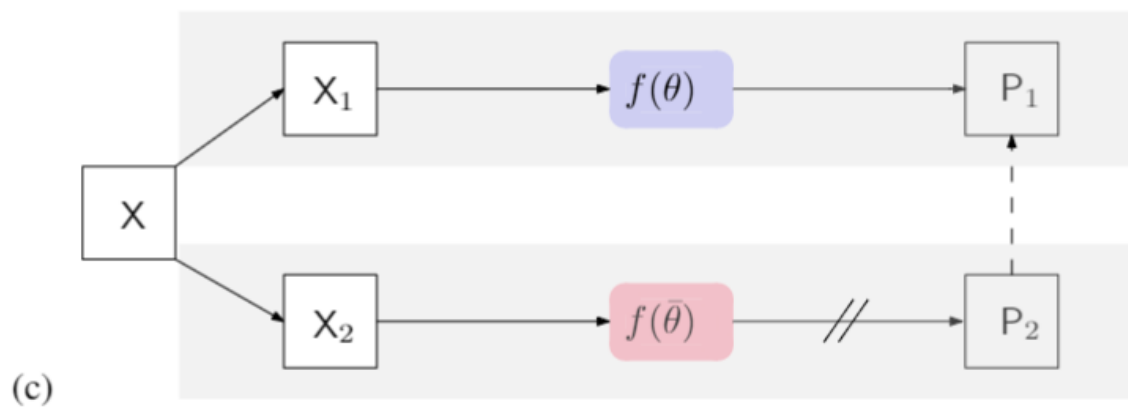
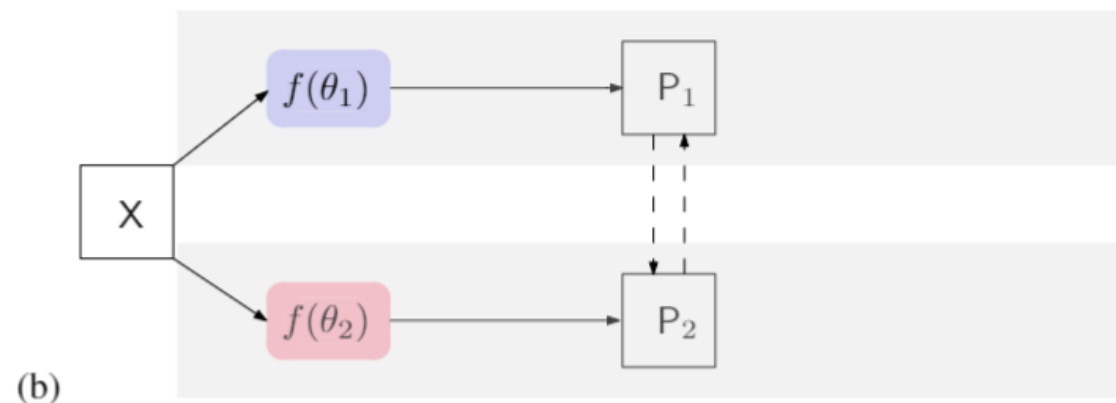
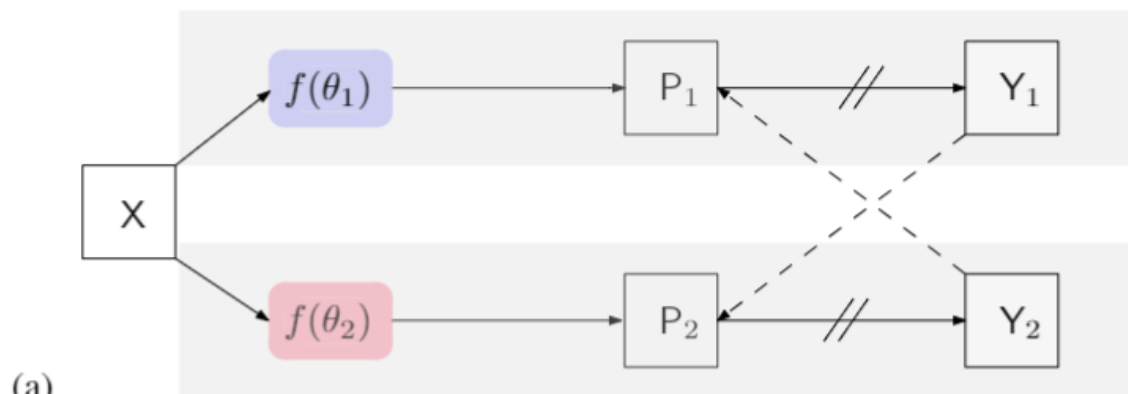


## Cutmix in Semi-supervised Segmentation



[3]French G, Laine S, Aila T, et al. Semi-supervised semantic segmentation needs strong, varied perturbations[C] //British Machine Vision Conference. 2020 (31).

## Comparison



## Overview

Table 1: **Comparison with state-of-the-arts** on the PASCAL VOC 2012 val set under different partition protocols. All the methods are based on DeepLabv3+.

Method	ResNet-50				ResNet-101			
	1/16 (662)	1/8 (1323)	1/4 (2646)	1/2 (5291)	1/16 (662)	1/8 (1323)	1/4 (2646)	1/2 (5291)
MT [32]	66.77	70.78	73.22	75.41	70.59	73.20	76.62	77.61
CCT [27]	65.22	70.87	73.43	74.75	67.94	73.00	76.17	77.56
CutMix-Seg [11]	68.90	70.70	72.46	74.49	72.56	72.69	74.25	75.89
GCT [17]	64.05	70.47	73.45	75.20	69.77	73.30	75.25	77.14
Ours (w/o CutMix Aug.)	68.21	73.20	74.24	75.91	72.18	75.83	77.55	78.64
Ours (w/ CutMix Aug.)	<b>71.98</b>	<b>73.67</b>	<b>74.90</b>	<b>76.15</b>	<b>74.48</b>	<b>76.44</b>	<b>77.68</b>	<b>78.64</b>

## Overview

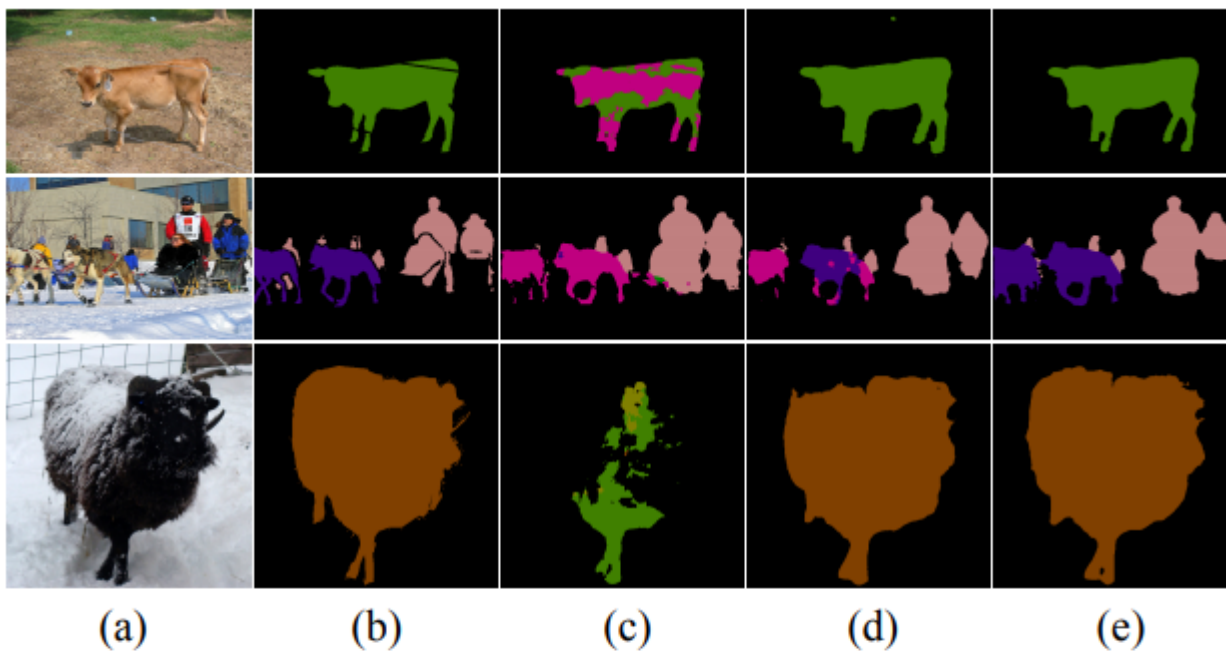


Figure 6: **Example qualitative results from PASCAL VOC 2012.** (a) input, (b) ground truth, (c) supervised only, (d) ours (w/o CutMix Aug.), and (e) ours (w/ CutMix Aug.). All the approaches use DeepLabv3+ with ResNet-101 as the segmentation network.

## Losses

Losses					PASCAL VOC 2012		Cityscapes	
$\mathcal{L}_s$	$\mathcal{L}_{cps}^l$	$\mathcal{L}_{cps}^u$	$\mathcal{L}_{cpc}^l$	$\mathcal{L}_{cpc}^u$	ResNet-50	ResNet-101	ResNet-50	ResNet-101
✓					69.43	72.21	70.32	72.19
✓	✓				69.99	72.98	71.73	73.08
✓		✓			73.00	75.83	73.97	75.28
✓	✓	✓			<b>73.20</b>	<b>75.85</b>	<b>74.39</b>	<b>75.71</b>
✓			✓	✓	71.23	74.01	72.03	73.77

## With single model(pseudo label)

Method	1/16	1/8	1/4	1/2
SPS (w/o CutMix Aug.)	59.54	69.05	72.55	75.17
Ours (w/o CutMix Aug.)	<b>68.21</b>	<b>73.20</b>	<b>74.24</b>	<b>75.91</b>
SPS (w/ CutMix Aug.)	65.62	71.27	73.70	74.87
Ours (w/ CutMix Aug.)	<b>71.98</b>	<b>73.67</b>	<b>74.90</b>	<b>76.15</b>

## With self-training

Method	ResNet-50		ResNet-101	
	1/4	1/2	1/4	1/2
<i>PASCAL VOC 2012</i>				
Ours	74.24	75.91	77.55	78.64
Self-Training	74.47	75.97	76.63	78.15
Ours + Self-Training	<b>74.96</b>	<b>76.60</b>	<b>77.60</b>	<b>78.76</b>