



# Perturbed and Strict Mean Teachers for Semi-supervised Semantic Segmentation

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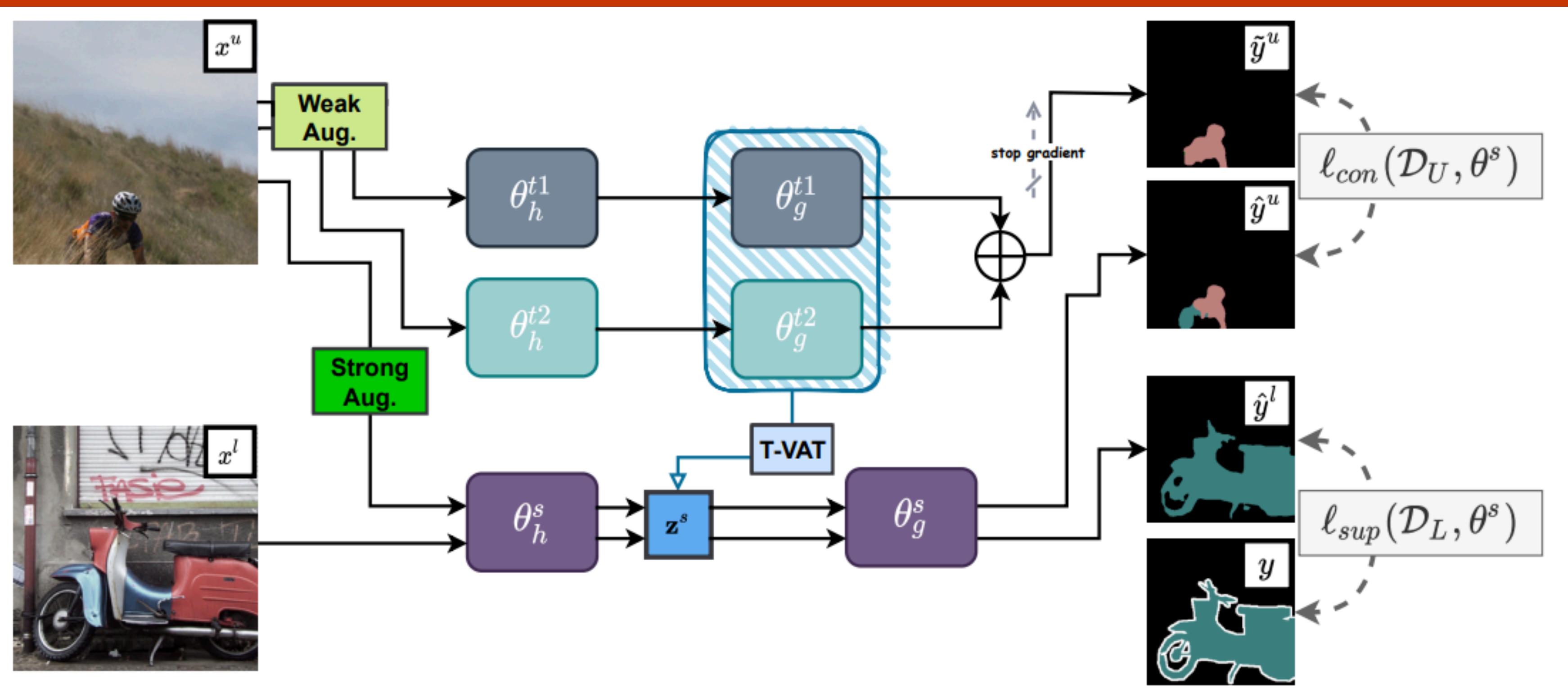
## Motivation

- ◆ Inaccurate pseudo-labels hinder the consistency regularisation.
- ◆ Vanilla Mean Teacher (MT) yields insufficient perturbation for semi-supervised segmentation.
- ◆ MSE loss leads the gradient to vanish, while CE easily overfits the noise signal (leads to confirmation bias).

## Contribution

- ◆ We include a new auxiliary teacher to improve the pseudo-label quality further.
- ◆ We introduce a novel teacher-based virtual adversarial training (T-VAT) noise to enhance consistency regularisation.
- ◆ We assign the teachers' ensemble confidence (conf-CE) to alleviate confirmation bias for learning the unlabelled data.
- ◆ Our model outperforms other SOTA approaches in both Pascal VOC12 and Cityscapes datasets.

## Methodology



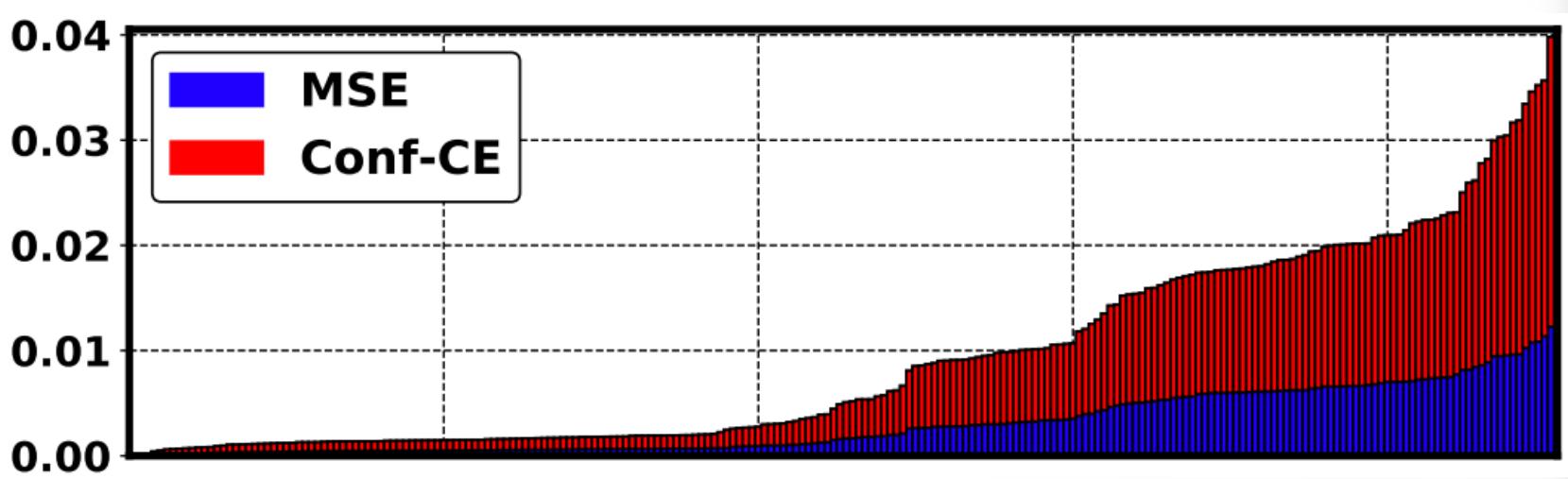
## Experiments

(measured by mIoU)

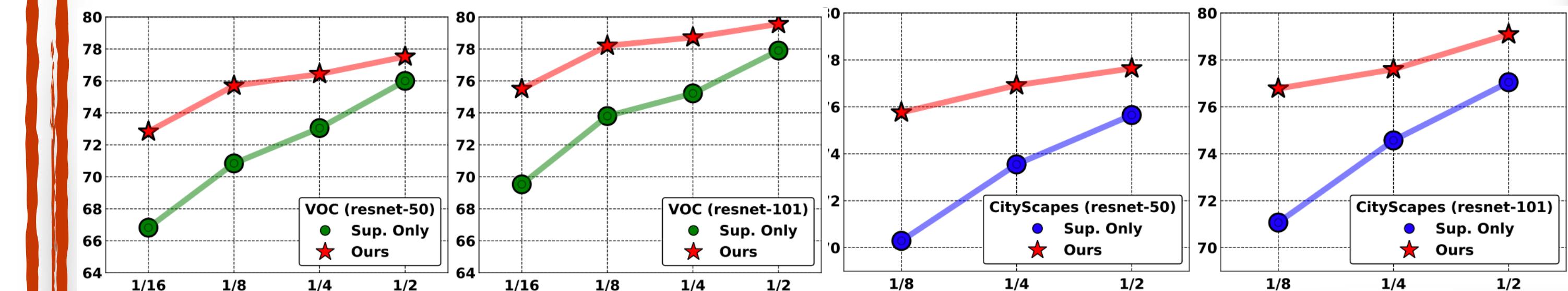
### a. ablation study

MT	conf-CE	T-VAT	AT	Backbone	
				ResNet-50	ResNet-101
✓				71.49	73.50
✓	✓			73.79	76.39
✓	✓	✓		74.87	77.36
✓	✓	✓	✓	74.92	77.47
✓	✓	✓	✓	75.70	78.20

### b. The different gradients from losses



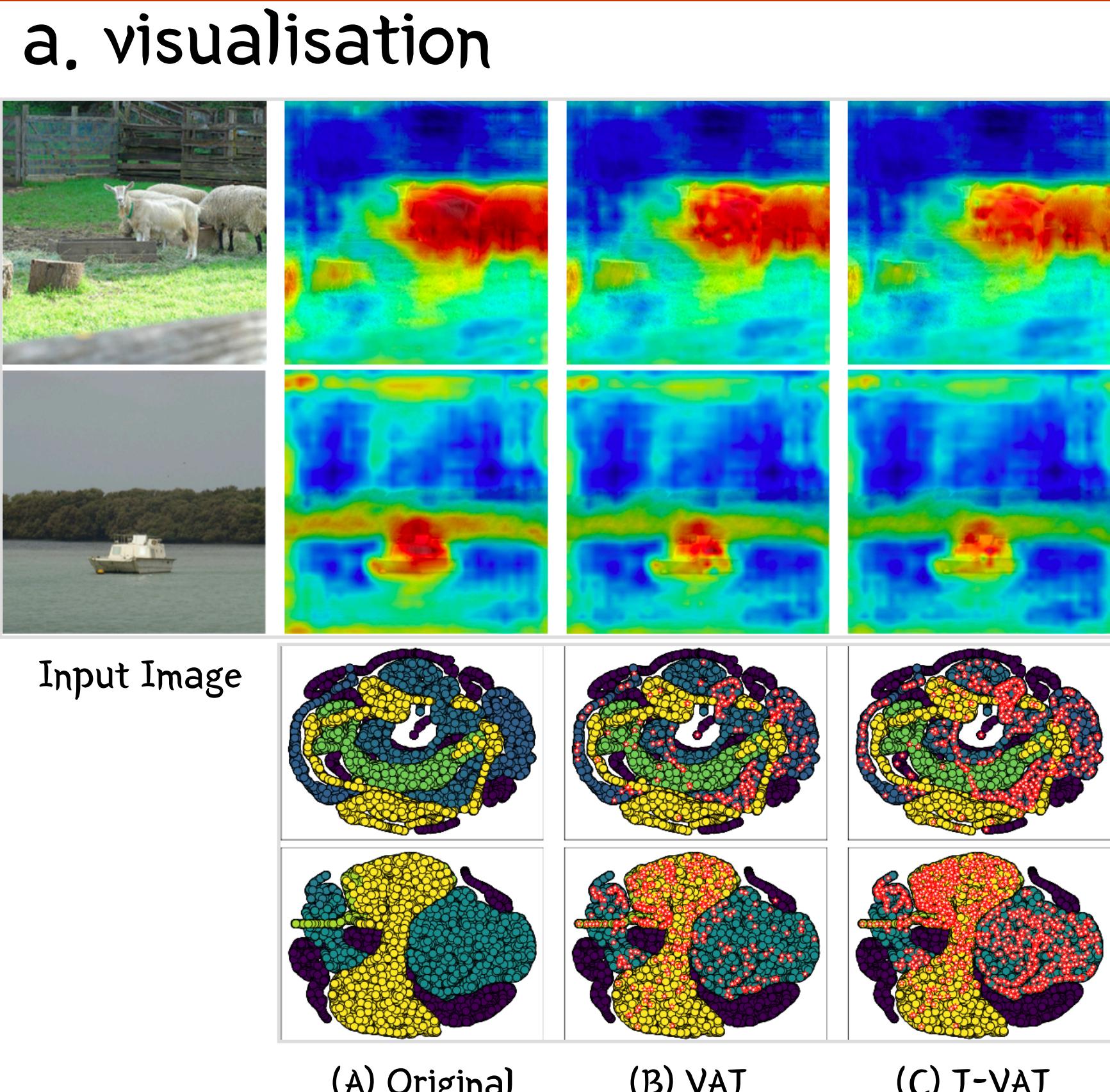
### c. comparing with sup. Baselines



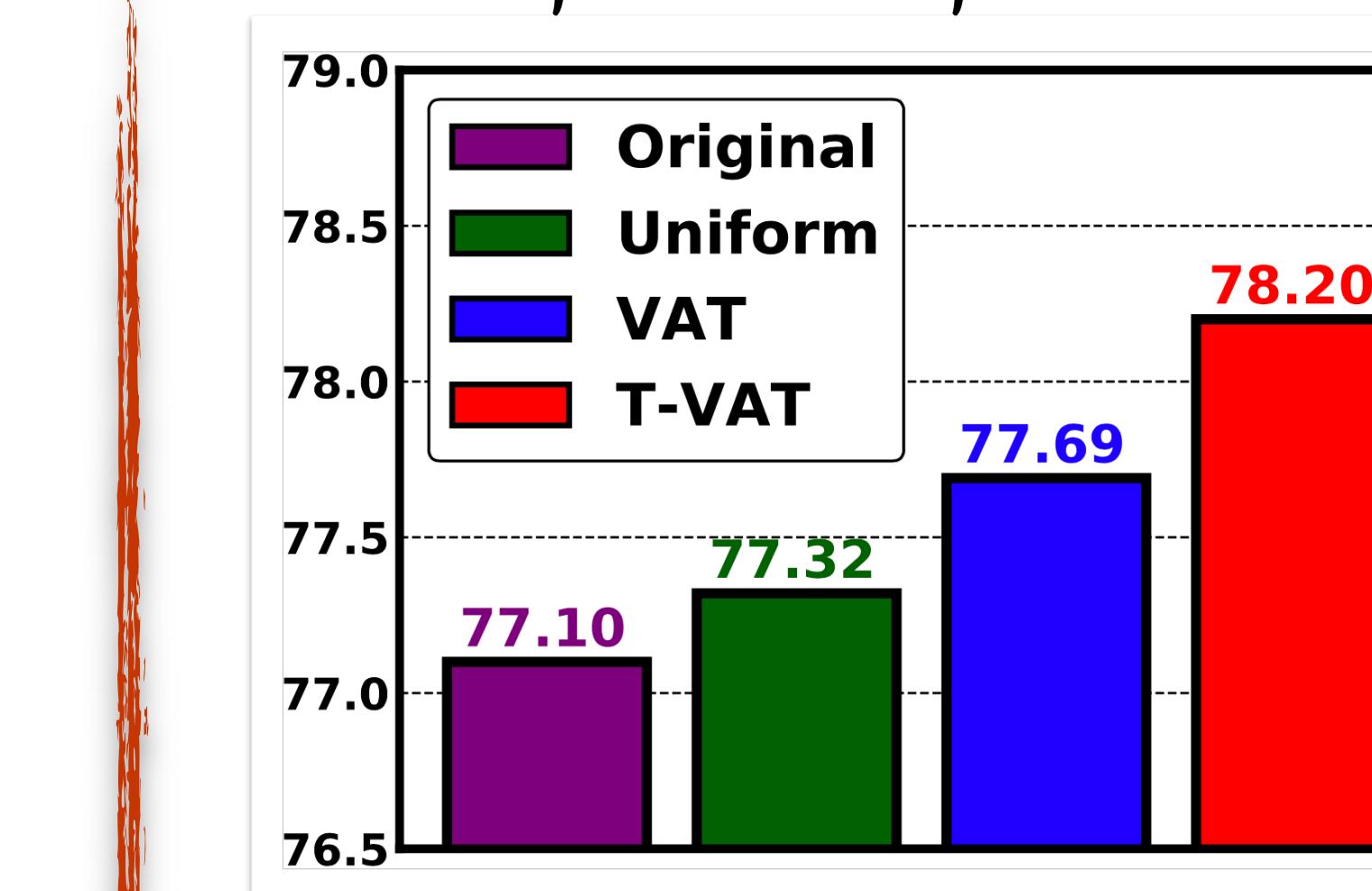
### d. comparing with other SOTA on VOC12

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* [37]	66.77	70.78	73.22	75.41	70.59	73.20	76.62	77.61
French et al.* [14]	68.90	70.70	72.46	74.49	72.56	72.69	74.25	75.89
CCT* [34]	65.22	70.87	73.43	74.75	67.94	73.00	76.17	77.56
GCT* [21]	64.05	70.47	73.45	75.20	69.77	73.30	75.25	77.14
ECS [31]	-	67.38	70.70	72.89	-	-	-	-
CPS [9]	71.98	73.67	74.90	76.15	74.48	76.44	77.68	78.64
CAC [22]	70.10	72.40	74.00	-	72.40	74.60	76.30	-
Ours	72.83	75.70	76.43	77.88	75.50	78.20	78.72	79.76

## Effectiveness of T-VAT



### b. Feature perturb. improvements



- ★ In Attention Visualisation, T-VAT confuses the student model the most.
- ★ In TSNE Visualisation, T-VAT leads to better consistency regularisation.

### e. comparing with other SOTA on City

Method	Backbone	1/8			1/4			1/2		
		1/8	1/4	1/2	1/8	1/4	1/2	1/8	1/4	1/2
ECS [31]	ResNet50	67.38	70.70	72.89	-	-	-	-	-	-
CAC [22]	ResNet50	69.70	72.70	-	-	-	-	-	-	-
Ours	ResNet50	74.37	75.15	76.02	-	-	-	-	-	-
Ours (sliding eval.)	ResNet50	75.76	76.92	77.64	76.89	77.60	79.09	-	-	-
GCT [21] <sup>†</sup>	ResNet50	71.33	75.30	77.09	-	-	-	-	-	-
CPS [9] <sup>†</sup>	ResNet50	76.61	77.83	78.77	77.12	78.38	79.22	-	-	-
Ours <sup>†</sup>	ResNet50	77.12	78.38	79.22	-	-	-	-	-	-

### f. additional data exp.

