Unsupervised Domain Adaptation for Semantic Segmentation with Symmetric Adaptation Consistency

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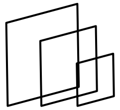
Background|Unsupervised domain adaptation (UDA)

Feature space

Domain A
(labeled)

Share the same
label space

Domain B
(unlabeled)



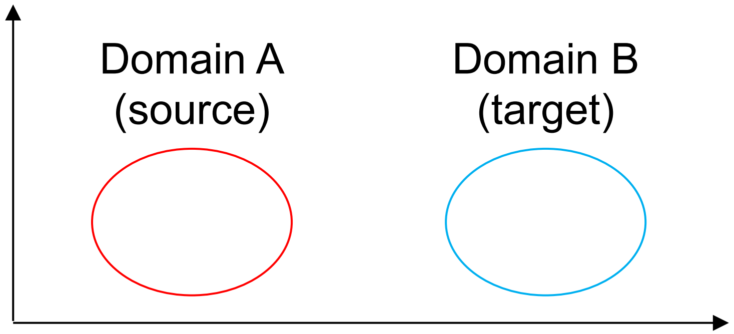
Model learned from domain A

Apply to domain B

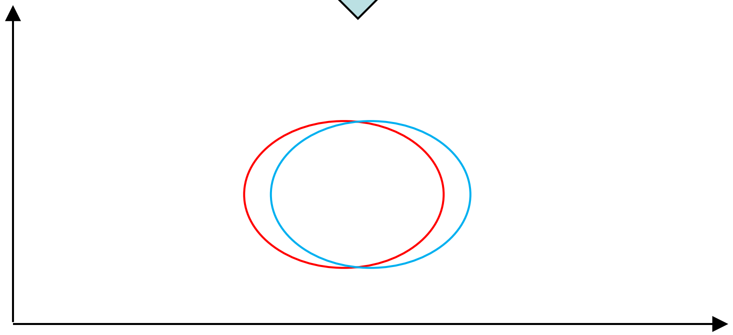
Performance drop
(cannot perform as well as in domain A)

Unsupervised domain adaptation problem

To solve this



adapt



Domains are aligned

Background|UDA for semantic segmentation

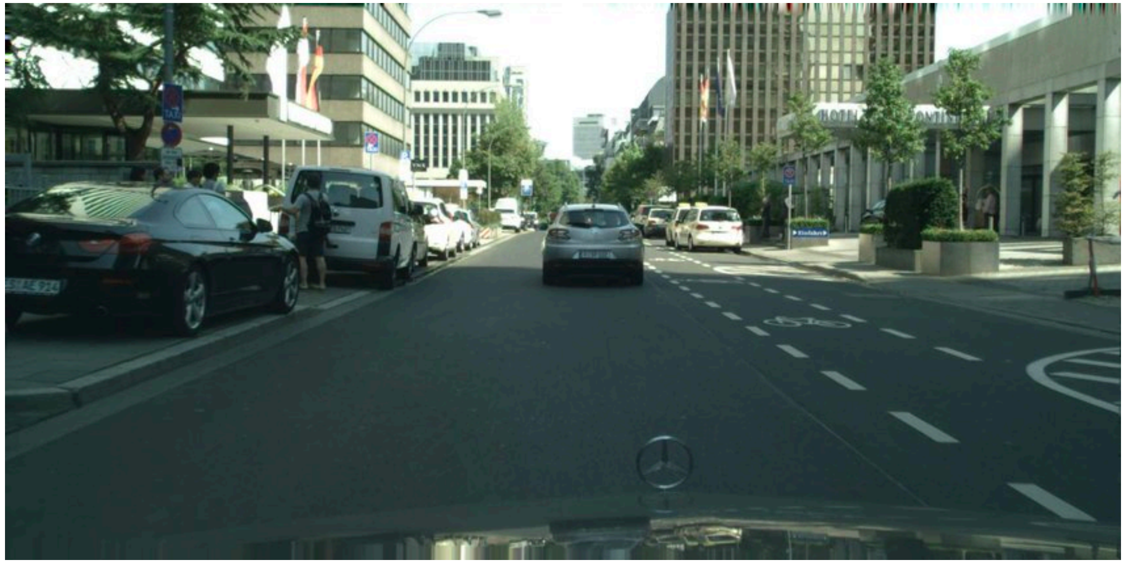
When applying semantic segmentation,
much more complex scenes
↓
much more complex feature space
↓
much more difficult

Example

GTA5 dataset[1] (source)

Adapt to →

CITYSCAPES[2] dataset (target)



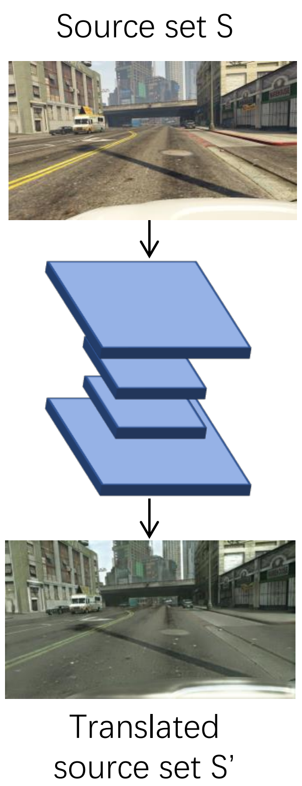
[1] Richter, Stephan R., et al. "Playing for data: Ground truth from computer games." *European conference on computer vision*. Springer, Cham, 2016.
[2] Cordts, Marius, et al. "The cityscapes dataset for semantic urban scene understanding." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Method|Overview

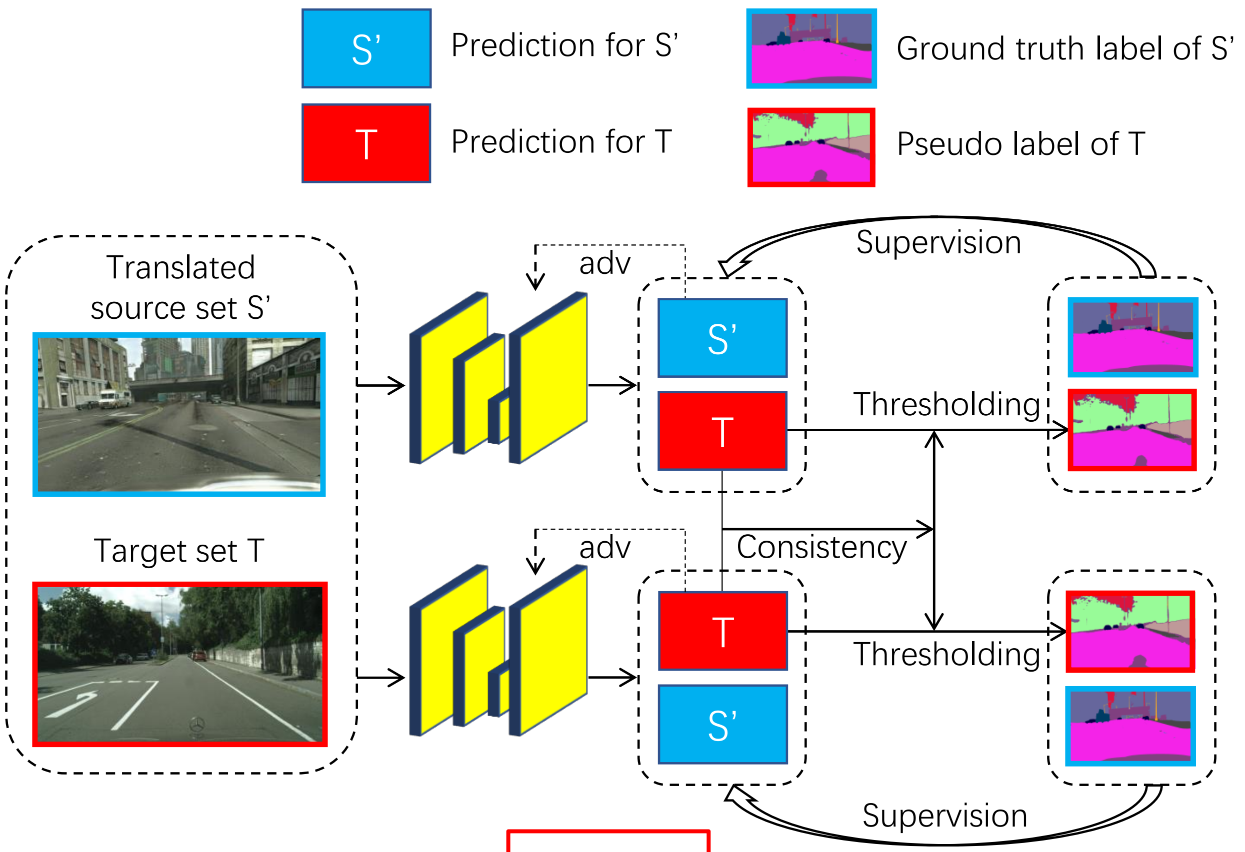
Stage 1 → Stage 2

Two stages:

Image-to-image translation



Feature-level domain adaptation



Novelty

Stage 1

Image-to-image translation:
(based on StarGAN[3])

- Translate source set S

to target domain (referred to as S') for reducing visual differences

Stage 2

Feature-level domain adaptation:

- Adversarial learning

for aligning features distributions

- Pseudo labels

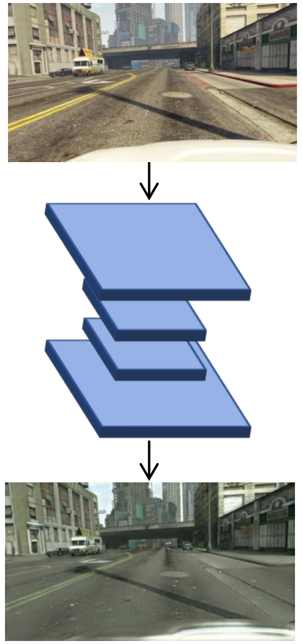
for further improvements

[3] Choi, Yunjey, et al. "Stargan: Unified generative adversarial networks for multi-domain image-to-image translation." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

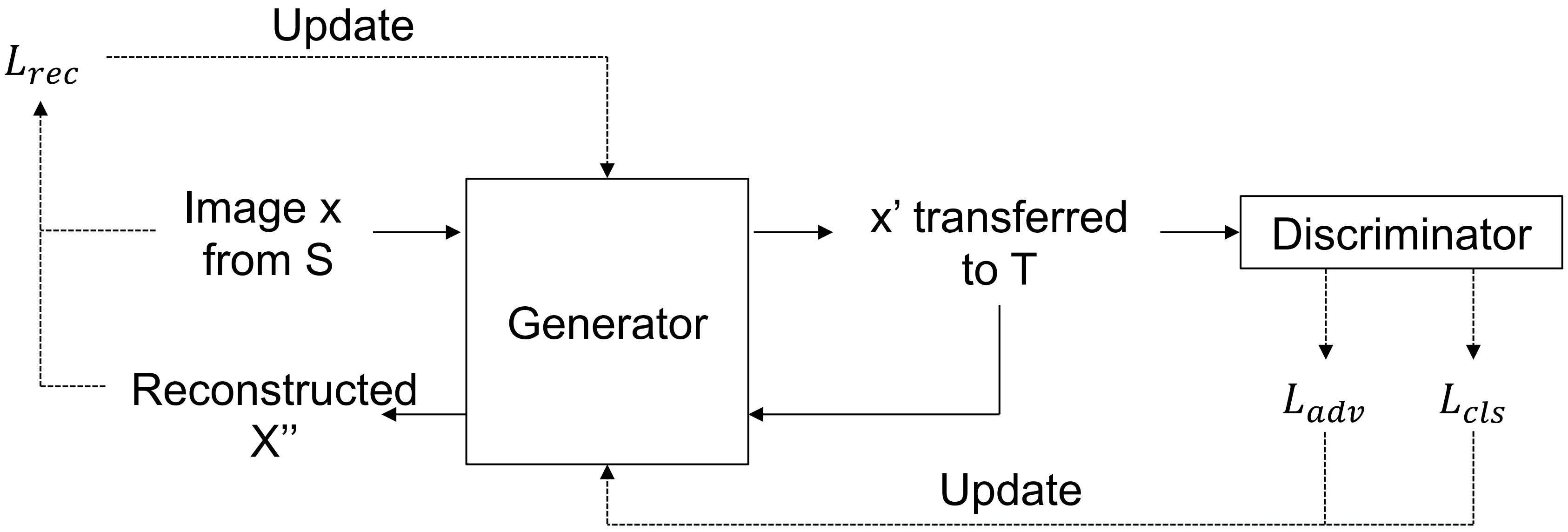
Method|Image-to-image translation

Image-to-image translation

Source set S

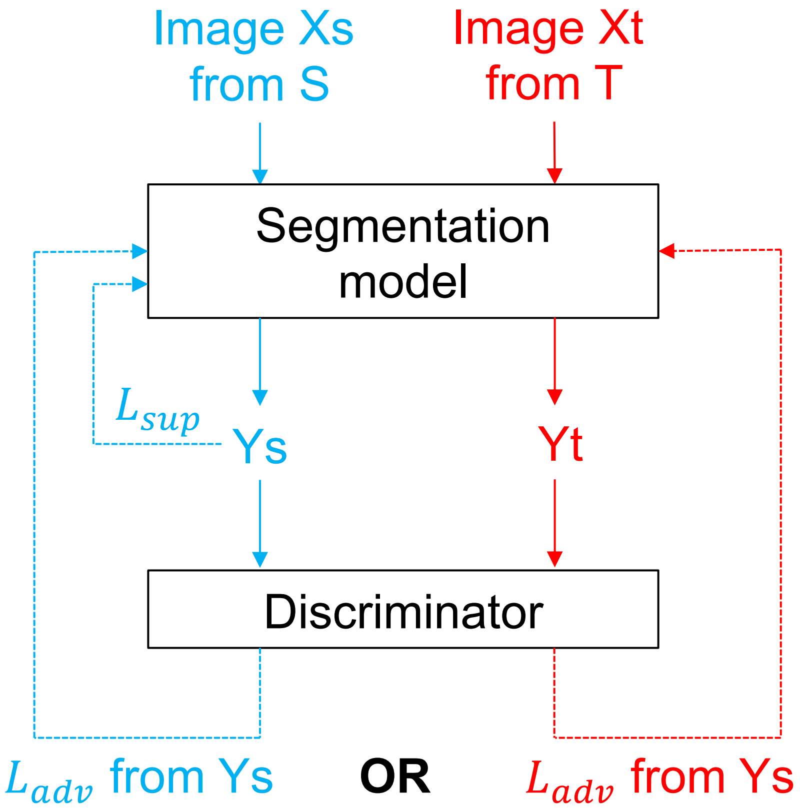


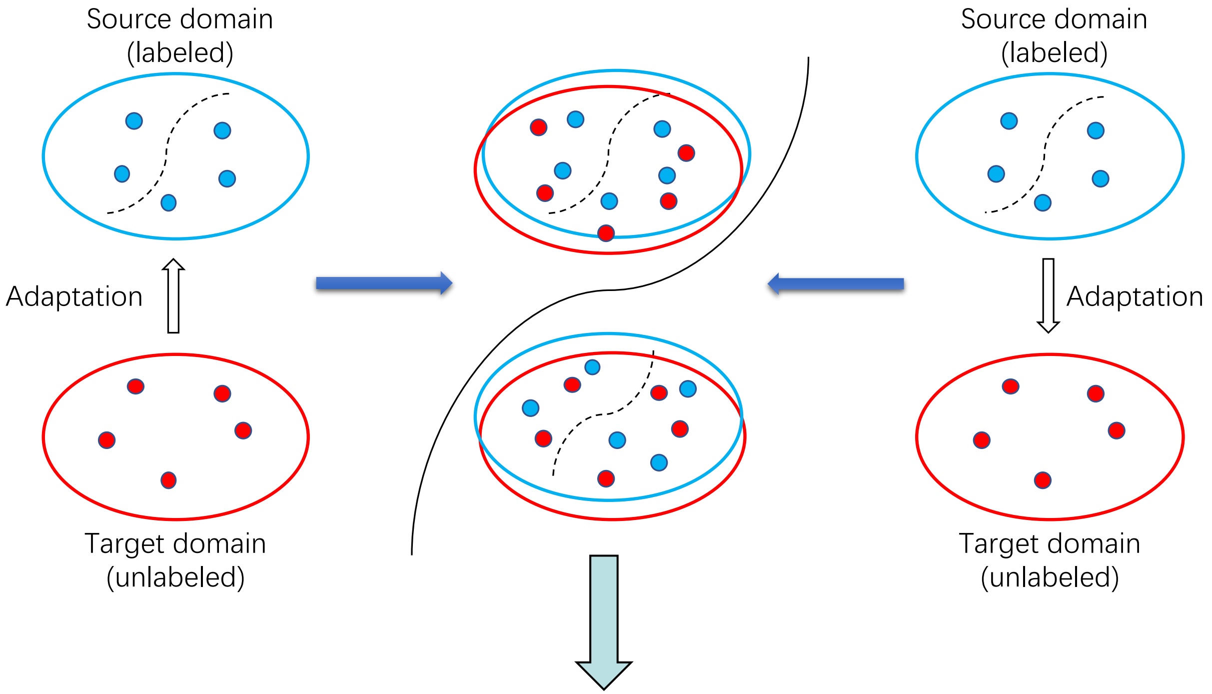
Translated source set S’



L_{rec}: reconstruction loss
L_{adv}: adversarial loss (real or fake)
L_{cls}: domain classification loss (S or T)

Method|Symmetric adaptation





More robust than single one

More accurate pseudo labels

Accuracy of pseudo labels has great impact on final performance.

Confidence map for selecting pixels:

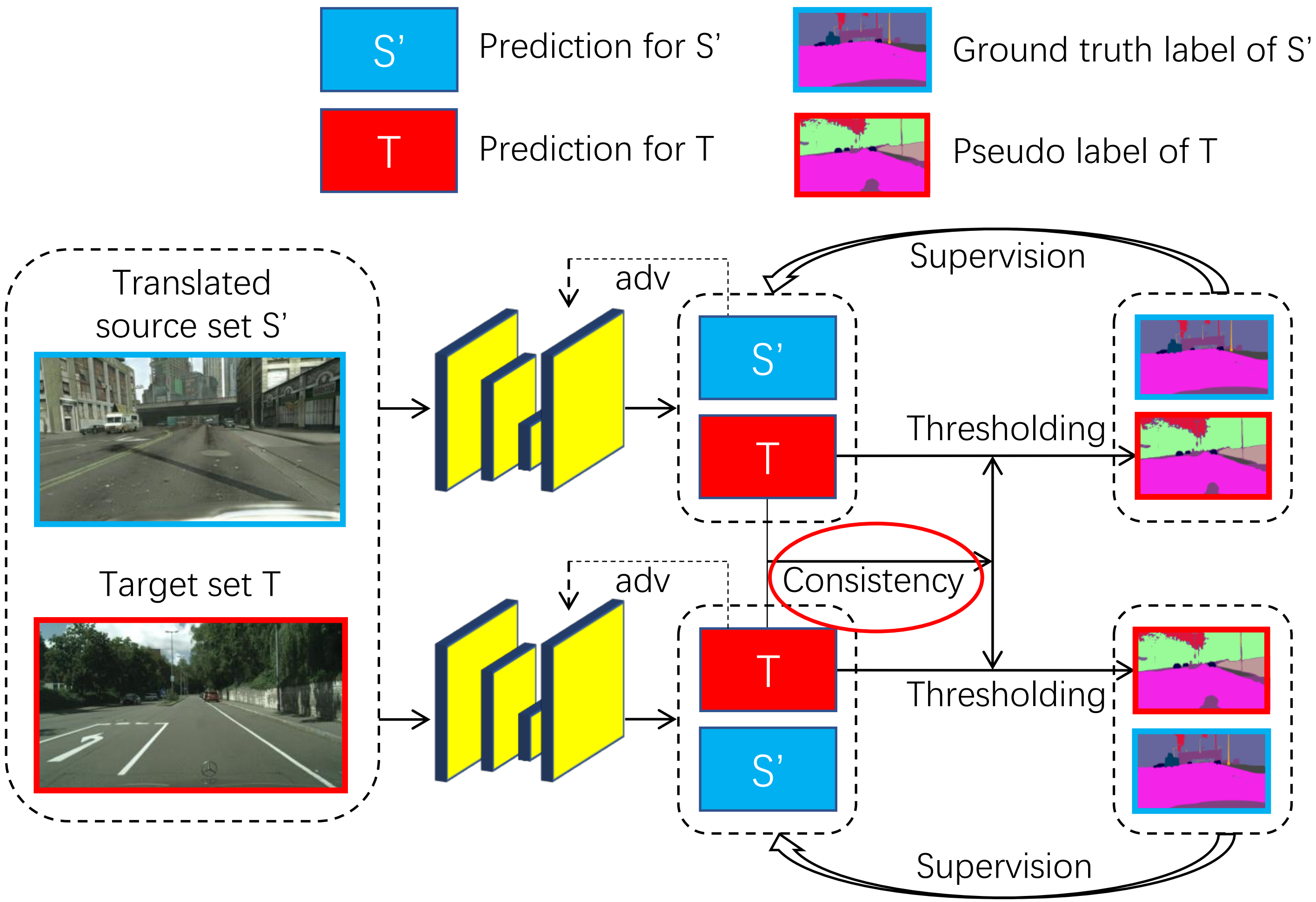
$$M_{confi} = \frac{M_{proba} + M_{consist}}{2}$$

M_{proba}: probability map

$M_{consist}$: consistency map

Consistency can help to produce more reliable pseudo labels.

Feature-level domain adaptation



Experiment|Datasets and implementation details

GTA5 dataset (used as source domain)

- Labeled synthesis data
- Including 24966 images of urban scenes
- 1914 x 1052 resolution

19 shared categories (road, sky, tree, car, building …)

CITYSCAPES dataset (used as target domain)

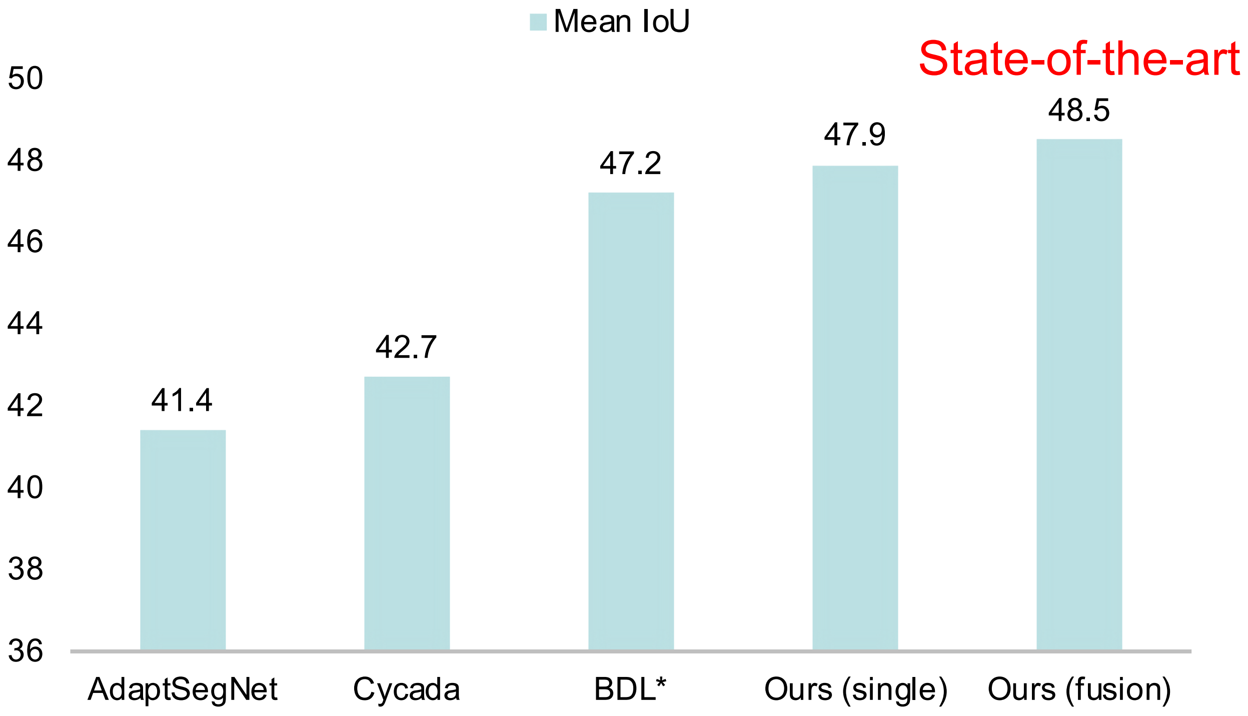
- Unlabeled real-world data
- Including 2975 images as training set and 500 images as test set
- 2048 x 1024 resolution

Implementation details

Implementation environment: Python3 + Pytorch1.1

Network architecture: DeepLab V2 with Resnet 101

Experiment|Experiment results



	Using consistency	Not using consistency
Accuracy of pseudo labels	72.6	70.6

AdaptSegNet[4]: adversarial learning

Cycada[5]: Image-to-image translation
+ adversarial learning

BDL[6]: Image-to-image translation
+ adversarial learning
+ pseudo label

Ours: Image-to-image translation
+ symmetric adversarial learning
+ pseudo label (using symmetric consistency)

Ours(single) – performance of single model

Ours(fusion) – performance fusing two models

*results when training image-to-image translation model once

[4] Tsai, Yi-Hsuan, et al. "Learning to adapt structured output space for semantic segmentation." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018.
[5] Hoffman, Judy, et al. "Cycada: Cycle-consistent adversarial domain adaptation." *arXiv preprint arXiv:1711.03213* (2017).
[6] Li, Yunsheng, Lu Yuan, and Nuno Vasconcelos. "Bidirectional learning for domain adaptation of semantic segmentation." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019.

Conclusion

We have proposed an unsupervised domain adaptation method for semantic segmentation.

Architecture of our method:

- Consisting of two stages, image-to-image translation and feature-level adaptation.
- In feature-level adaptation employing adversarial learning and pseudo labels.

Advantages of our method:

- Symmetric adaptation with adversarial learning is more robust.
- Pseudo labels produced using symmetric consistency are more reliable.

Achievement:

- Our method achieved state-of-the-art performance on GTA5-to-CITYSCAPES scenario.

Future work:

- The image-to-image translation method can still be improved for domain adaptation task.