# Domain Adaptation: Consistency and Uncertainty

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# About Me

**Present**

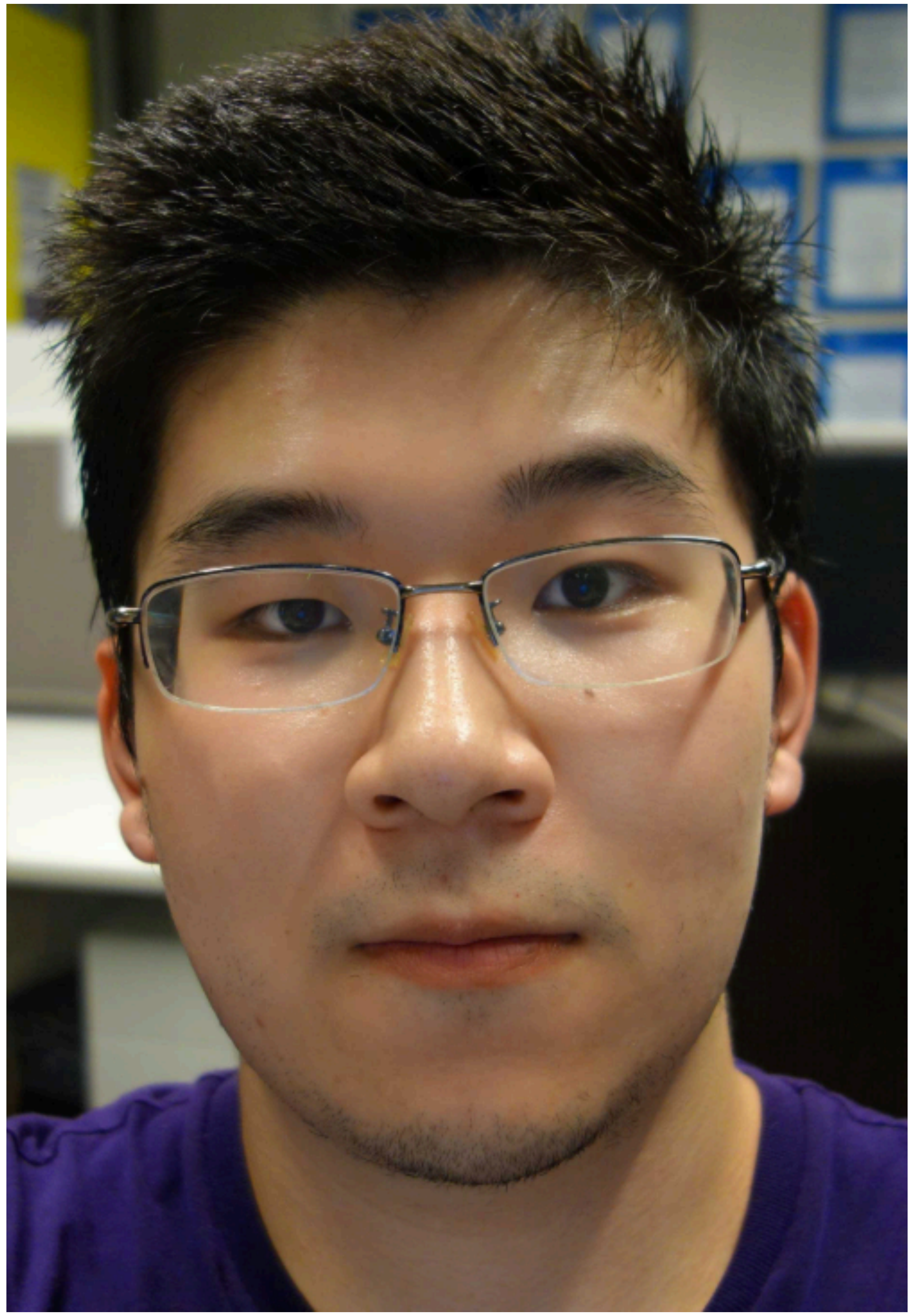
- **Postdoc at NUS with Prof. Tat Seng Chua (蔡达成)**
- Ph.D. Advised by Prof. Yi Yang 杨易 (UTS) and Dr. Liang Zheng 郑良 (ANU)
- Published 4 first-author conference papers and 5 first-author journal papers
- GoogleScholar 6000+ citations; Github 7000+ stars
- First-place winner in AICity Challenge CVPR 2020, CVPR 2021
- IEEE Circuits and Systems Society Outstanding Young Author Award 2021
- ( Thanks to my lab~ )

**Research Interests**

- **Image Retrieval**, Target Re-identification (Cross Cam)

- **Image Generation (GAN)**, Domain Adaptation

- Image-text Understanding, Adversarial Samples



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# Outline

- Task (Domain Adaptation for Segmentation)
- (IJCAI 2020) Unsupervised Scene Adaptation with Memory Regularization in vivo
- (IJCV 2021) Rectifying Pseudo Label Learning via Uncertainty Estimation for Domain Adaptive Semantic Segmentation
- Future Research Directions

# Domain Gap

Labeled Source-domain Data

GTA5 GAME

Unlabeled Target-domain Data

Real World

Pixel Level 的标注累啊！ 🥱

# Domain Adaptation

Labeled Source-domain Data

Training

Unlabeled Target-domain Data

Test

Target-domain Test Data

# Domain Adaptation

- **How to formulate this problem?**
  - Semi-supervised Learning
  - Inductive Learning

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- (TIP 2022) Adaptive Boosting for Domain Adaptation: Towards Robust Predictions in Scene Segmentation
- Future Research Directions

# Unsupervised Scene Adaptation with Memory Regularization in vivo

**Zhedong Zheng, Yi Yang**
University of Technology Sydney & Baidu Research

IJCAI-PRICAI YOKOHAMA 2020

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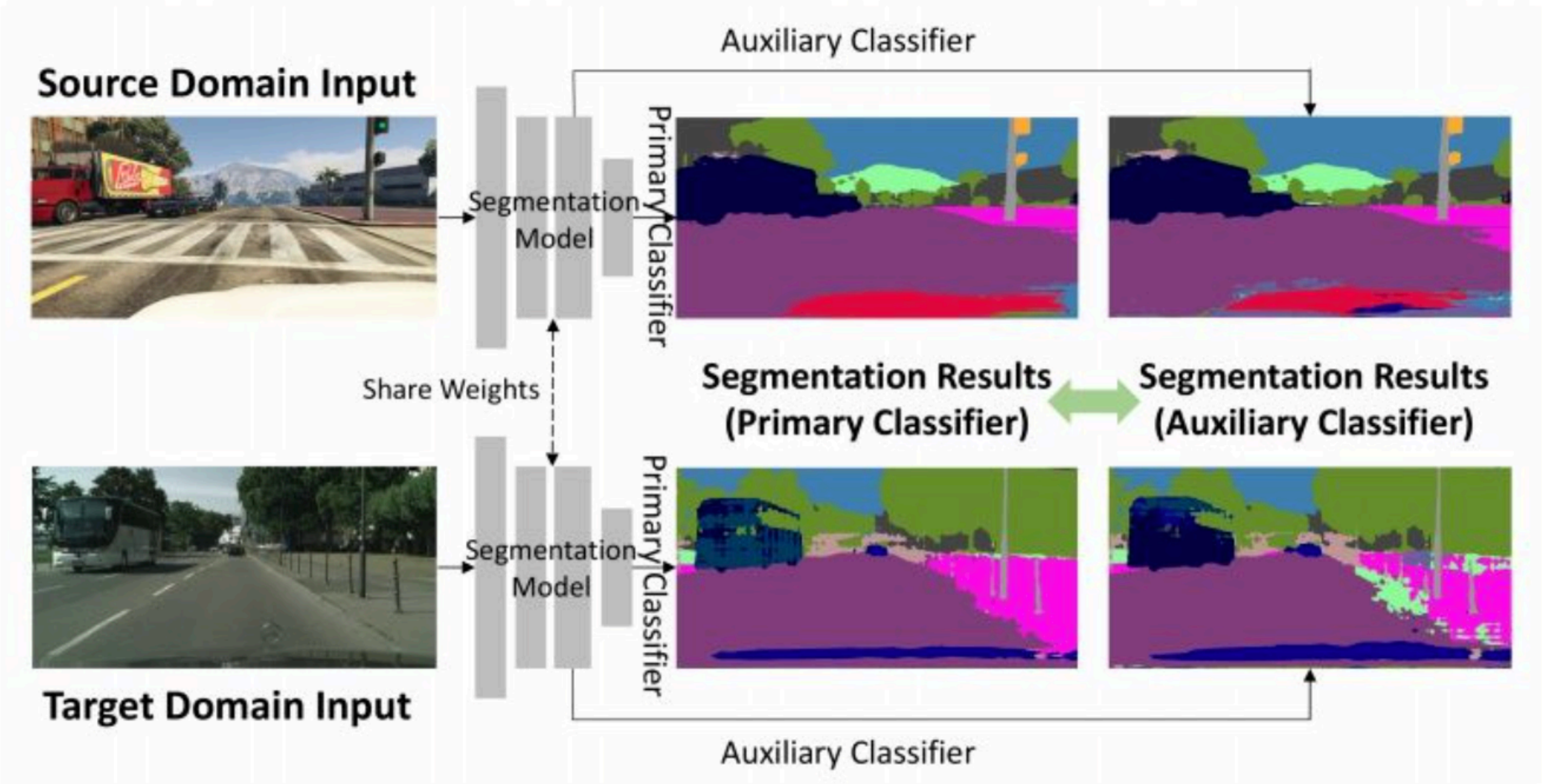
# Motivation： Inconsistency?



# Exisiting Semi-Supervised Methods (Memory)

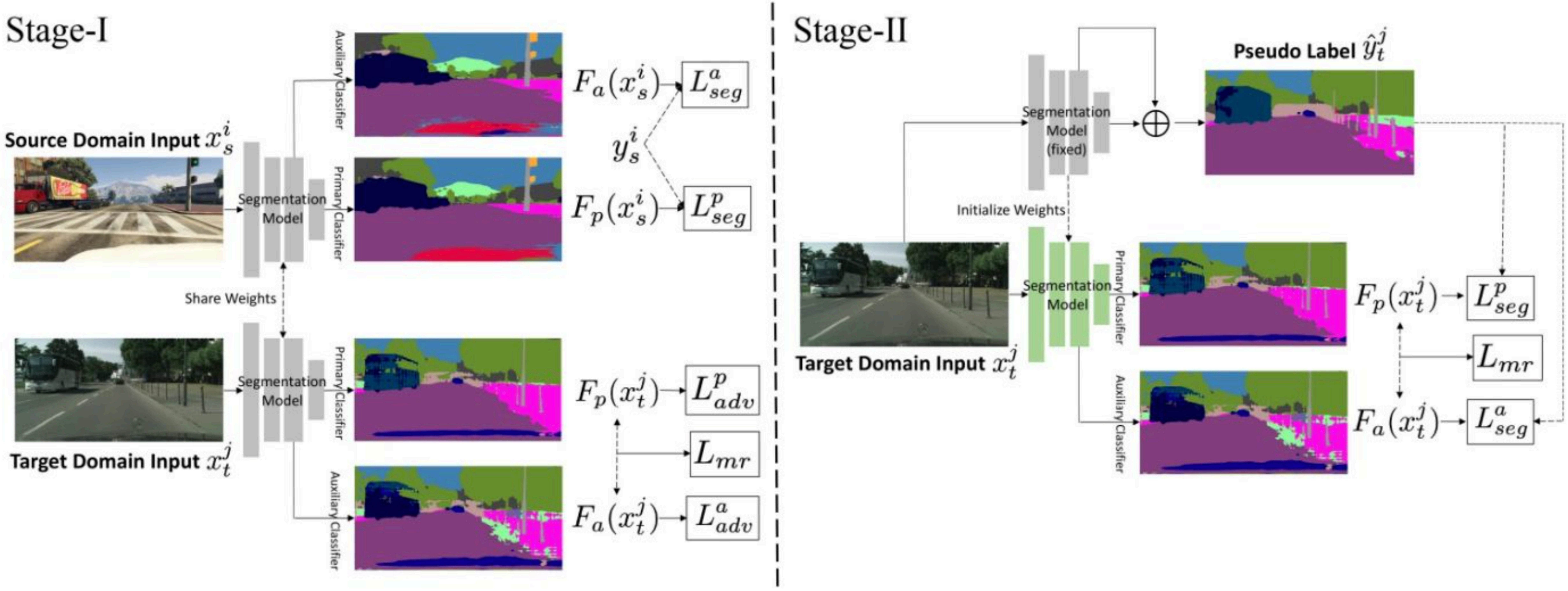

**Co-training is all your need !**

# What is advantages of Memory?

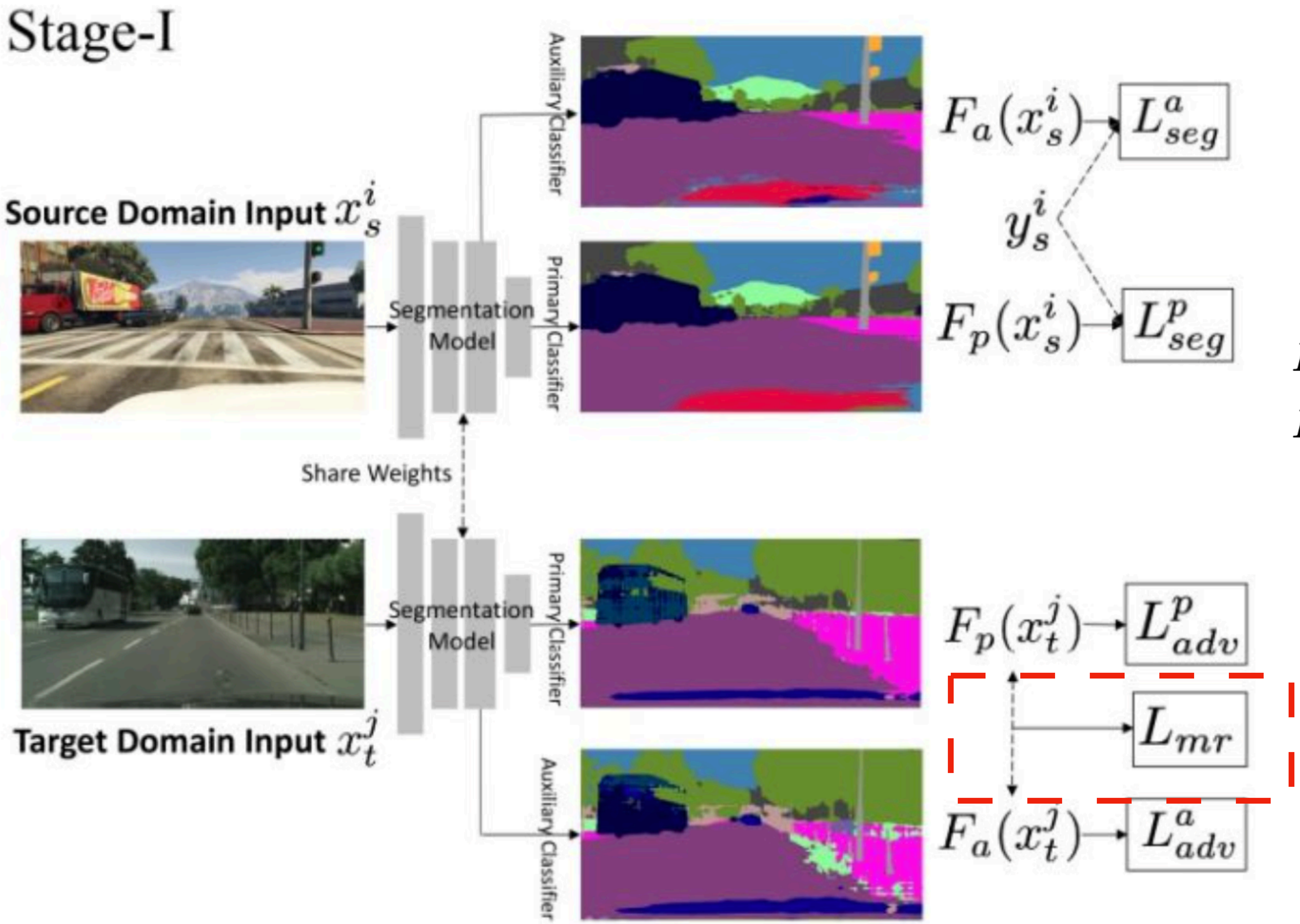
- One teacher model for unlabelled data;
- Save computation cost & Always up-to-the-date;
- Will the auxiliary classifier hurt the primary classifier? No.

# The Proposed Method

## Why two stage?



# The Proposed Method (Stage-I)



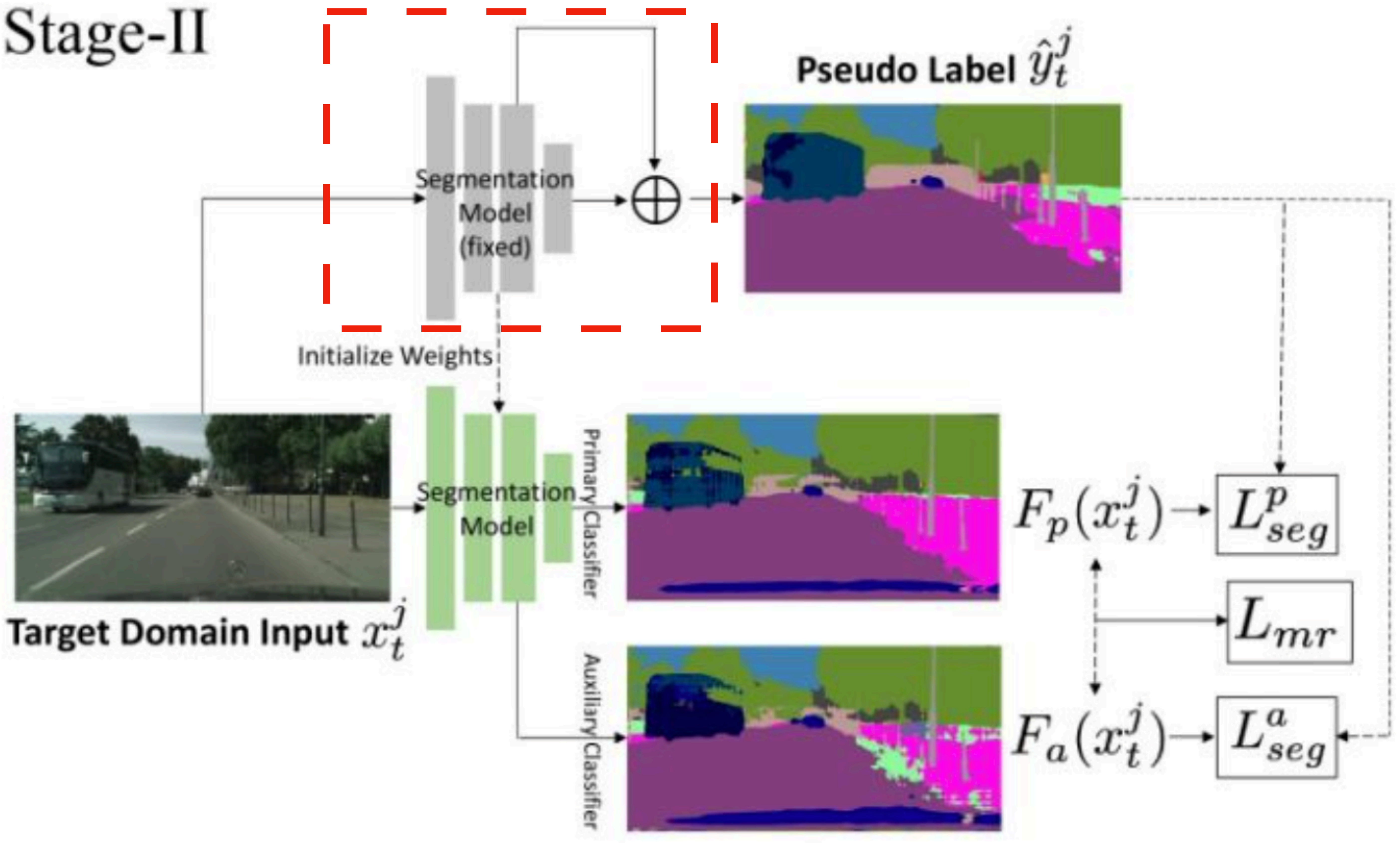

$$L^p_{seg} = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} y_s^i \log(F_p(x_s^i)),$$

$$L^a_{seg} = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} y_s^i \log(F_a(x_s^i)),$$

$$L^p_{adv} = \mathbb{E}[\log(D_p(F_p(x_s^i))) + \log(1 - D_p(F_p(x_t^j)))],$$
$$L^a_{adv} = \mathbb{E}[\log(D_a(F_a(x_s^i))) + \log(1 - D_a(F_a(x_t^j)))],$$

$$L_{mr} = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} F_a(x_t^i)\log\left(\frac{F_p(x_t^i)}{F_a(x_t^i)}\right) - \sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} F_p(x_t^i)\log\left(\frac{F_a(x_t^i)}{F_p(x_t^i)}\right).$$

# The Proposed Method (Stage-II)

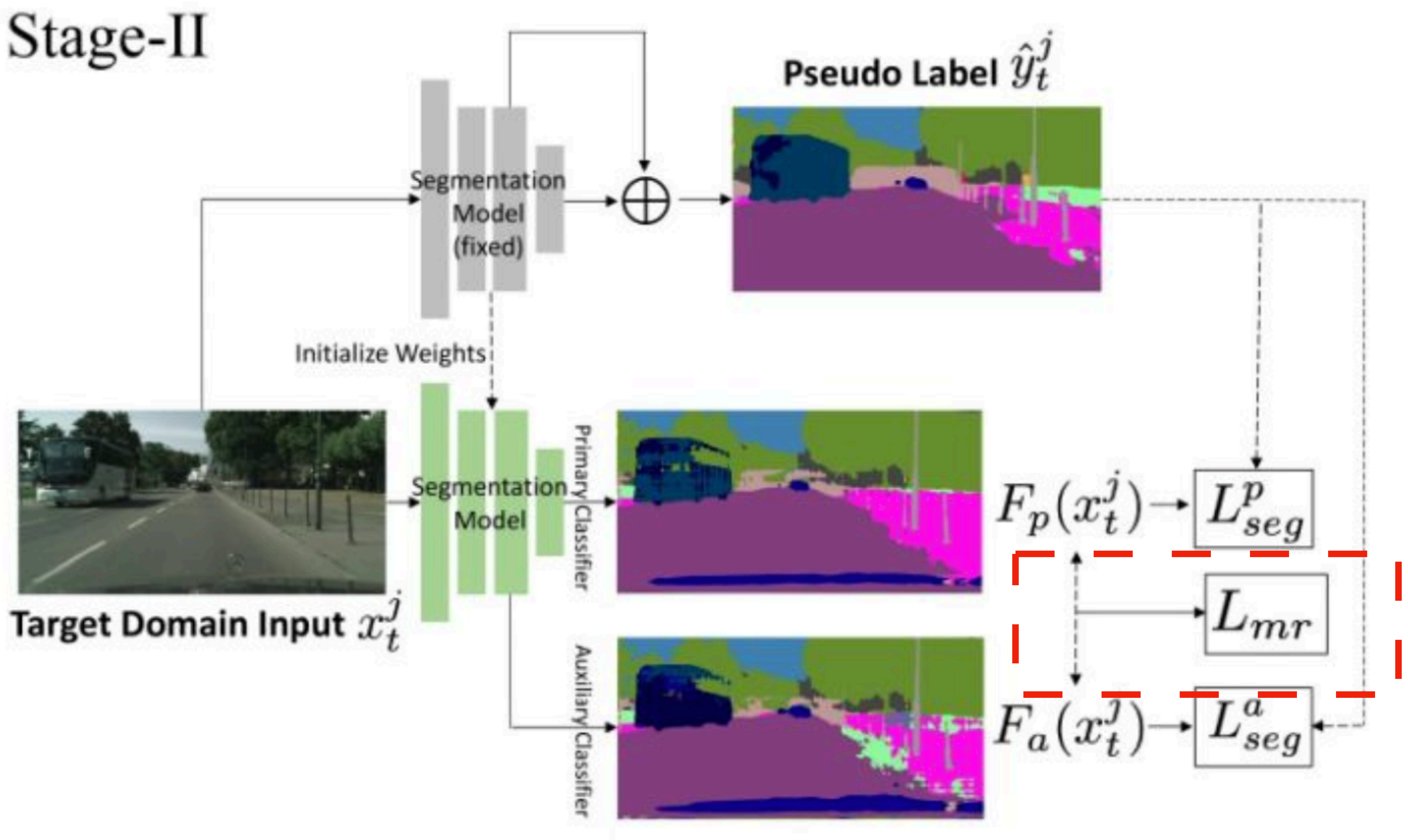



$$L_{pseg}^p = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} \hat{y}_t^j \log(F_p(x_t^j)),$$

$$L_{pseg}^a = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} \hat{y}_t^j \log(F_a(x_t^j)).$$

$$L_{mr} = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} F_a(x_t^i)\log\left(\frac{F_p(x_t^i)}{F_a(x_t^i)}\right) - \sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C} F_p(x_t^i)\log\left(\frac{F_a(x_t^i)}{F_p(x_t^i)}\right).$$

# The Proposed Method (Stage-II)




$$L_{pseg}^p = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C}\hat{y}_t^j \log(F_p(x_t^j)),$$

$$L_{pseg}^a = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C}\hat{y}_t^j \log(F_a(x_t^j)).$$

$$L_{mr} = -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C}F_a(x_t^i)\log(\frac{F_p(x_t^i)}{F_a(x_t^i)}) -\sum_{h=1}^{H}\sum_{w=1}^{W}\sum_{c=1}^{C}F_p(x_t^i)\log(\frac{F_a(x_t^i)}{F_p(x_t^i)}).$$

# Ablation Study

| Method | without $L_{mr}$ | with $L_{mr}$ |
|---|---|---|
| Auxiliary Classifier | 40.04 | 44.45 |
| Primary Classifier | 43.11 | 45.29 |
| Ours (Stage-I) | 42.73 | 45.46 |

Table 1: Ablation study of the memory regularization on both classifiers, *i.e.*, the auxiliary classifier and the primary classifier, in the Stage-I training. The result suggests that the memory regularization helps both classifiers, especially the auxiliary classifier. The final results of the full model combine the results of both classifiers, and therefore improve the performance further.

Stage-I

| Method | $L_{seg}$ | $L_{adv}$ | $L_{mr}$ | mIoU |
|---|---|---|---|---|
| Without Adaptation | ✓ | | | 37.23 |
| Adversarial Alignment | ✓ | ✓ | | 42.73 |
| Memory Regularization | ✓ | | ✓ | 43.75 |
| Ours (Stage-I) | ✓ | ✓ | ✓ | 45.46 |

Table 2: Ablation study of different losses in the Stage-I training. We gradually add the adversarial loss $L_{adv}$ and the memory regularization $L_{mr}$ into consideration.

Stage-II

| Method | $L_{pseg}$ | $L_{mr}$ | mIoU |
|---|---|---|---|
| Ours (Stage-I) | | | 45.46 |
| Pseudo Label | ✓ | | 47.90 |
| Ours (Stage-II) | ✓ | ✓ | 48.31 |

Table 3: Ablation study of different losses in the Stage-II training. The result suggests that the memory regularization could prevent the model from overfitting to the noise in the pseudo labels.

# Comparison with the State-of-the-art

| Method | Backbone | Road | SW | Build | Wall | Fence | Pole | TL | TS | Veg. | Terrain | Sky | PR | Rider | Car | Truck | Bus | Train | Motor | Bike | mIoU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Source | DRN-26 | 42.7 | 26.3 | 51.7 | 5.5 | 6.8 | 13.8 | 23.6 | 6.9 | 75.5 | 11.5 | 36.8 | 49.3 | 0.9 | 46.7 | 3.4 | 5.0 | 0.0 | 5.0 | 1.4 | 21.7 |
| CyCADA [Hoffman *et al.*, 2018] | | 79.1 | 33.1 | 77.9 | 23.4 | 17.3 | 32.1 | 33.3 | 31.8 | 81.5 | 26.7 | 69.0 | 62.8 | 14.7 | 74.5 | 20.9 | 25.6 | 6.9 | 18.8 | 20.4 | 39.5 |
| Source | DRN-105 | 36.4 | 14.2 | 67.4 | 16.4 | 12.0 | 20.1 | 8.7 | 0.7 | 69.8 | 13.3 | 56.9 | 37.0 | 0.4 | 53.6 | 10.6 | 3.2 | 0.2 | 0.9 | 0.0 | 22.2 |
| MCD [Saito *et al.*, 2018] | | 90.3 | 31.0 | 78.5 | 19.7 | 17.3 | 28.6 | 30.9 | 16.1 | 83.7 | 30.0 | 69.1 | 58.5 | 19.6 | 81.5 | 23.8 | 30.0 | 5.7 | 25.7 | 14.3 | 39.7 |
| Source | DeepLabv2 | 75.8 | 16.8 | 77.2 | 12.5 | 21.0 | 25.5 | 30.1 | 20.1 | 81.3 | 24.6 | 70.3 | 53.8 | 26.4 | 49.9 | 17.2 | 25.9 | 6.5 | 25.3 | 36.0 | 36.6 |
| AdaptSegNet [Tsai *et al.*, 2018] | | 86.5 | 36.0 | 79.9 | 23.4 | 23.3 | 23.9 | 35.2 | 14.8 | 83.4 | 33.3 | 75.6 | 58.5 | 27.6 | 73.7 | 32.5 | 35.4 | 3.9 | 30.1 | 28.1 | 42.4 |
| SIBAN [Luo *et al.*, 2019a] | | 88.5 | 35.4 | 79.5 | 26.3 | 24.3 | 28.5 | 32.5 | 18.3 | 81.2 | 40.0 | 76.5 | 58.1 | 25.8 | 82.6 | 30.3 | 34.4 | 3.4 | 21.6 | 21.5 | 42.6 |
| CLAN [Luo *et al.*, 2019b] | | 87.0 | 27.1 | 79.6 | 27.3 | 23.3 | 28.3 | 35.5 | 24.2 | 83.6 | 27.4 | 74.2 | 58.6 | 28.0 | 76.2 | 33.1 | 36.7 | 6.7 | 31.9 | 31.4 | 43.2 |
| APODA [Yang *et al.*, 2020] | | 85.6 | 32.8 | 79.0 | 29.5 | 25.5 | 26.8 | 34.6 | 19.9 | 83.7 | **40.6** | 77.9 | 59.2 | 28.3 | 84.6 | 34.6 | 49.2 | 8.0 | **32.6** | 39.6 | 45.9 |
| PatchAlign [Tsai *et al.*, 2019] | | **92.3** | 51.9 | 82.1 | 29.2 | 25.1 | 24.5 | 33.8 | 33.0 | 82.4 | 32.8 | 82.2 | 58.6 | 27.2 | 84.3 | 33.4 | **46.3** | 2.2 | 29.5 | 32.3 | 46.5 |
| AdvEnt [Vu *et al.*, 2019] | DeepLabv2 | 89.4 | 33.1 | 81.0 | 26.6 | **26.8** | 27.2 | 33.5 | 24.7 | 83.9 | 36.7 | 78.8 | 58.7 | 30.5 | 84.8 | **38.5** | 44.5 | 1.7 | 31.6 | 32.4 | 45.5 |
| Source | DeepLabv2 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 29.2 |
| FCAN [Zhang *et al.*, 2018a] | | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 46.6 |
| Source | DeepLabv2 | 71.3 | 19.2 | 69.1 | 18.4 | 10.0 | 35.7 | 27.3 | 6.8 | 79.6 | 24.8 | 72.1 | 57.6 | 19.5 | 55.5 | 15.5 | 15.1 | 11.7 | 21.1 | 12.0 | 33.8 |
| CBST [Zou *et al.*, 2018] | | 91.8 | 53.5 | 80.5 | 32.7 | 21.0 | 34.0 | 28.9 | 20.4 | 83.9 | 34.2 | 80.9 | 53.1 | 24.0 | 82.7 | 30.3 | 35.9 | 16.0 | 25.9 | **42.8** | 45.9 |
| MRKLD [Zou *et al.*, 2019] | | 91.0 | **55.4** | 80.0 | 33.7 | 21.4 | **37.3** | 32.9 | 24.5 | 85.0 | 34.1 | 80.8 | 57.7 | 24.6 | 84.1 | 27.8 | 30.1 | **26.9** | 26.0 | 42.3 | 47.1 |
| Source | DeepLabv2 | 51.1 | 18.3 | 75.8 | 18.8 | 16.8 | 34.7 | 36.3 | 27.2 | 80.0 | 23.3 | 64.9 | 59.2 | 19.3 | 74.6 | 26.7 | 13.8 | 0.1 | 32.4 | 34.0 | 37.2 |
| Our (Stage-I) | | 89.1 | 23.9 | 82.2 | 19.5 | 20.1 | 33.5 | 42.2 | 39.1 | **85.3** | 33.7 | 76.4 | 60.2 | 33.7 | **86.0** | 36.1 | 43.3 | 5.9 | 22.8 | 30.8 | 45.5 |
| Our (Stage-II) | | 90.5 | 35.0 | **84.6** | **34.3** | 24.0 | 36.8 | **44.1** | **42.7** | 84.5 | 33.6 | **82.5** | **63.1** | **34.4** | 85.8 | 32.9 | 38.2 | 2.0 | 27.1 | 41.8 | **48.3** |

Table 4: Quantitative results on GTA5 $\rightarrow$ Cityscapes. We present pre-class IoU and mIoU. The best accuracy in every column is in **bold**.

From 37.2% to 48.3%
On GTA5 -> CityScapes

| Method | Backbone | Road | SW | Build | Wall* | Fence* | Pole* | TL | TS | Veg. | Sky | PR | Rider | Car | Bus | Motor | Bike | mIoU* | mIoU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Source | DRN-105 | 14.9 | 11.4 | 58.7 | 1.9 | 0.0 | 24.1 | 1.2 | 6.0 | 68.8 | 76.0 | 54.3 | 7.1 | 34.2 | 15.0 | 0.8 | 0.0 | 26.8 | 23.4 |
| MCD [Saito *et al.*, 2018] | | 84.8 | **43.6** | 79.0 | 3.9 | 0.2 | 29.1 | 7.2 | 5.5 | 83.8 | 83.1 | 51.0 | 11.7 | 79.9 | 27.2 | 6.2 | 0.0 | 43.5 | 37.3 |
| Source | DeepLabv2 | 55.6 | 23.8 | 74.6 | – | – | – | 6.1 | 12.1 | 74.8 | 79.0 | 55.3 | 19.1 | 39.6 | 23.3 | 13.7 | 25.0 | 38.6 | – |
| SIBAN [Luo *et al.*, 2019a] | | 82.5 | 24.0 | 79.4 | – | – | – | 16.5 | 12.7 | 79.2 | 82.8 | 58.3 | 18.0 | 79.3 | 25.3 | 17.6 | 25.9 | 46.3 | – |
| PatchAlign [Tsai *et al.*, 2019] | | 82.4 | 38.0 | 78.6 | 8.7 | 0.6 | 26.0 | 3.9 | 11.1 | 75.5 | 84.6 | 53.5 | 21.6 | 71.4 | 32.6 | 19.3 | 31.7 | 46.5 | 40.0 |
| AdaptSegNet [Tsai *et al.*, 2018] | | 84.3 | 42.7 | 77.5 | – | – | – | 4.7 | 7.0 | 77.9 | 82.5 | 54.3 | 21.0 | 72.3 | 32.2 | 18.9 | 32.3 | 46.7 | – |
| CLAN [Luo *et al.*, 2019b] | | 81.3 | 37.0 | 80.1 | – | – | – | 16.1 | 13.7 | 78.2 | 81.5 | 53.4 | 21.2 | 73.0 | 32.9 | 22.6 | 30.7 | 47.8 | – |
| APODA [Yang *et al.*, 2020] | | **86.4** | 41.3 | 79.3 | – | – | – | 22.6 | 17.3 | 80.3 | 81.6 | 56.9 | 21.0 | 84.1 | **49.1** | **24.6** | 45.7 | 53.1 | – |
| AdvEnt [Vu *et al.*, 2019] | DeepLabv2 | 85.6 | 42.2 | 79.7 | 8.7 | 0.4 | 25.9 | 5.4 | 8.1 | 80.4 | **84.1** | 57.9 | 23.8 | 73.3 | 36.4 | 14.2 | 33.0 | 48.0 | 41.2 |
| Source | DeepLabv2 | 64.3 | 21.3 | 73.1 | 2.4 | 1.1 | 31.4 | 7.0 | 27.7 | 63.1 | 67.6 | 42.2 | 19.9 | 73.1 | 15.3 | 10.5 | 38.9 | 40.3 | 34.9 |
| CBST [Zou *et al.*, 2018] | | 68.0 | 29.9 | 76.3 | **10.8** | 1.4 | 33.9 | 22.8 | 29.5 | 77.6 | 78.3 | 60.6 | 28.3 | 81.6 | 23.5 | 18.8 | 39.8 | 48.9 | 42.6 |
| MRKLD [Zou *et al.*, 2019] | | 67.7 | 32.2 | 73.9 | 10.7 | **1.6** | **37.4** | 22.2 | **31.2** | 80.8 | 80.5 | 60.8 | **29.1** | 82.8 | 25.0 | 19.4 | 45.3 | 50.1 | 43.8 |
| Source | DeepLabv2 | 44.0 | 19.3 | 70.9 | 8.7 | 0.8 | 28.2 | 16.1 | 16.7 | 79.8 | 81.4 | 57.8 | 19.2 | 46.9 | 17.2 | 12.0 | 43.8 | 40.4 | 35.2 |
| Ours (Stage-I) | | 82.0 | 36.5 | 80.4 | 4.2 | 0.4 | 33.7 | 18.0 | 13.4 | 81.1 | 80.8 | 61.3 | 21.7 | 84.4 | 32.4 | 14.8 | 45.7 | 50.2 | 43.2 |
| Ours (Stage-II) | | 83.1 | 38.2 | **81.7** | 9.3 | 1.0 | 35.1 | **30.3** | 19.9 | **82.0** | 80.1 | **62.8** | 21.1 | **84.4** | 37.8 | 24.5 | **53.3** | **53.8** | **46.5** |

Table 5: Quantitative results on SYNTHIA $\rightarrow$ Cityscapes. We present pre-class IoU, mIoU and mIoU*. mIoU and mIoU* are averaged over 16 and 13 categories, respectively. The best accuracy in every column is in **bold**.

From 35.2% to 46.5%
On SYNTHIA -> CityScapes

# What is advantages of Memory?

- One teacher model for unlabelled data;
- Save computation cost & Always up-to-the-date;
- Will the auxiliary classifier hurt the primary classifier? No.

- **But pseudo labels are noisy.**

# Outline

- Task (Domain Adaptation for Segmentation)
- (IJCAI 2020) Unsupervised Scene Adaptation with Memory Regularization in vivo
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- Future Research Directions

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# Rectifying Pseudo Label Learning via Uncertainty Estimation for Domain Adaptive Semantic Segmentation

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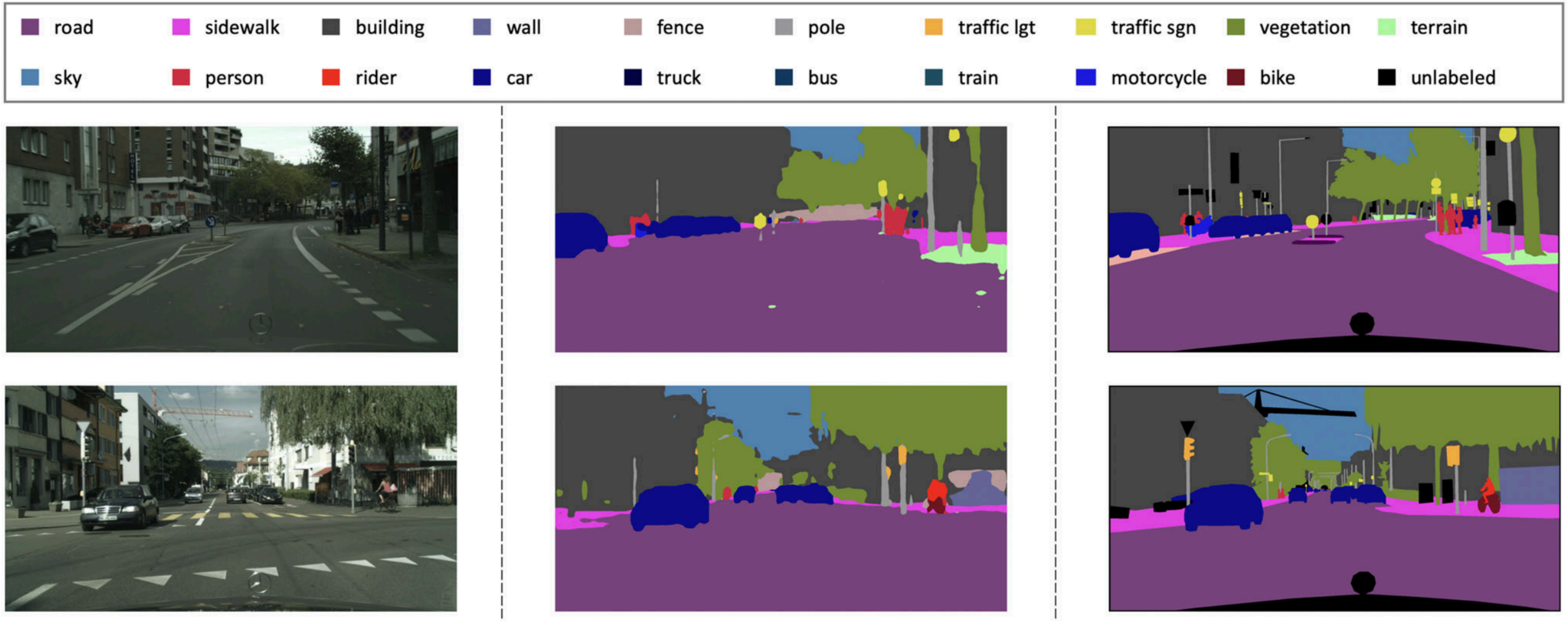
**Zhedong Zheng, Yi Yang**
University of Technology Sydney

# Motivation： Pseudo Labels contain lots of noise.




(a)unlabeled target-domain inputs (b) generated pseudo labels (c) ground-truth labels

# Motivation： Pseudo Labels contain lots of noise.

**Table 5** Variance Regularization vs. Handcrafted Threshold

| Methods | Threshold | mIoU |
|---|---|---|
| MRNet Zheng andYang (2020) | – | 45.5 |
| Pseudo Learning | $> 0.99$ | 45.5 |
| Pseudo Learning | $> 0.95$ | 47.2 |
| Pseudo Learning | $> 0.90$ | 48.4 |
| Pseudo Learning | $> 0.80$ | 48.1 |
| Pseudo Learning | $> 0.70$ | 48.2 |
| Pseudo Learning | $> 0.00$ | 48.3 |
| Ours | – | 50.3 |

The proposed method is free from hand-crafted threshold. '$> k$' denotes that we only utilize the label confidence $> k$ to train the model. We report the mIoU accuracy on GTA5 $\rightarrow$ Cityscapes

**Threshold??**

**Automatic Threshold.**

# Background： Uncertainty

1. **Epistemic Uncertainty - Model Uncertainty**
2. **Aleatoric Uncertainty - Data Uncertainty**

# Background： Uncertainty Reference

1. Robust Person Re-identification by Modelling Feature Uncertainty. ICCV 2019

2. 周志华 深度学习 贝叶斯网络

3. Training deep neural networks on noisy labels with bootstrapping. ICML workshop

4. **What uncertainties do we need in bayesian deep learning for computer vision?** NeurIPS, 2017.

5. (Reviewer 补充) Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In ICML.

# Background： Uncertainty

## Estimate Data Uncertainty in Regression

- Assume your target variable follows a Gaussian distribution
- Take the negative log likelihood to obtain the objective function

$$L = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2\sigma(x_i)^2}\|y_i - f(x_i)\|^2 + \frac{1}{2}\log\sigma(x_i)^2$$

Estimating **an *extra* output**

Original predictive output

- Another explanation: assume ground truth y follows Dirac delta function, then take KLdivergence

旷视上海研究院院长危夷晨：不确定性学习在视觉识别中的应用

https://www.bilibili.com/video/BV1RJ411D7QA

# Background：  High Certainty

1. 一般模糊的物体，在深度估计时会觉得很远（容易高估）。而清晰的物体，一般会觉得很近（容易低估）。
2. 一般消失线比较明显的物体，比如向远方延伸而消失的路啊，深度估计比较容易。而像没什么特别的强，就很难估计深度。

| Monoscopic Depth Cues | Examples | Appear Nearer | Appear Farther |
|---|---|---|---|
| Size of objects | Tree | Larger | Smaller |
| Texture | Grass patch | High quality texture | Low quality, blurry |
| Linear Perspective | Curb line | - | Converge to horizon |

Size

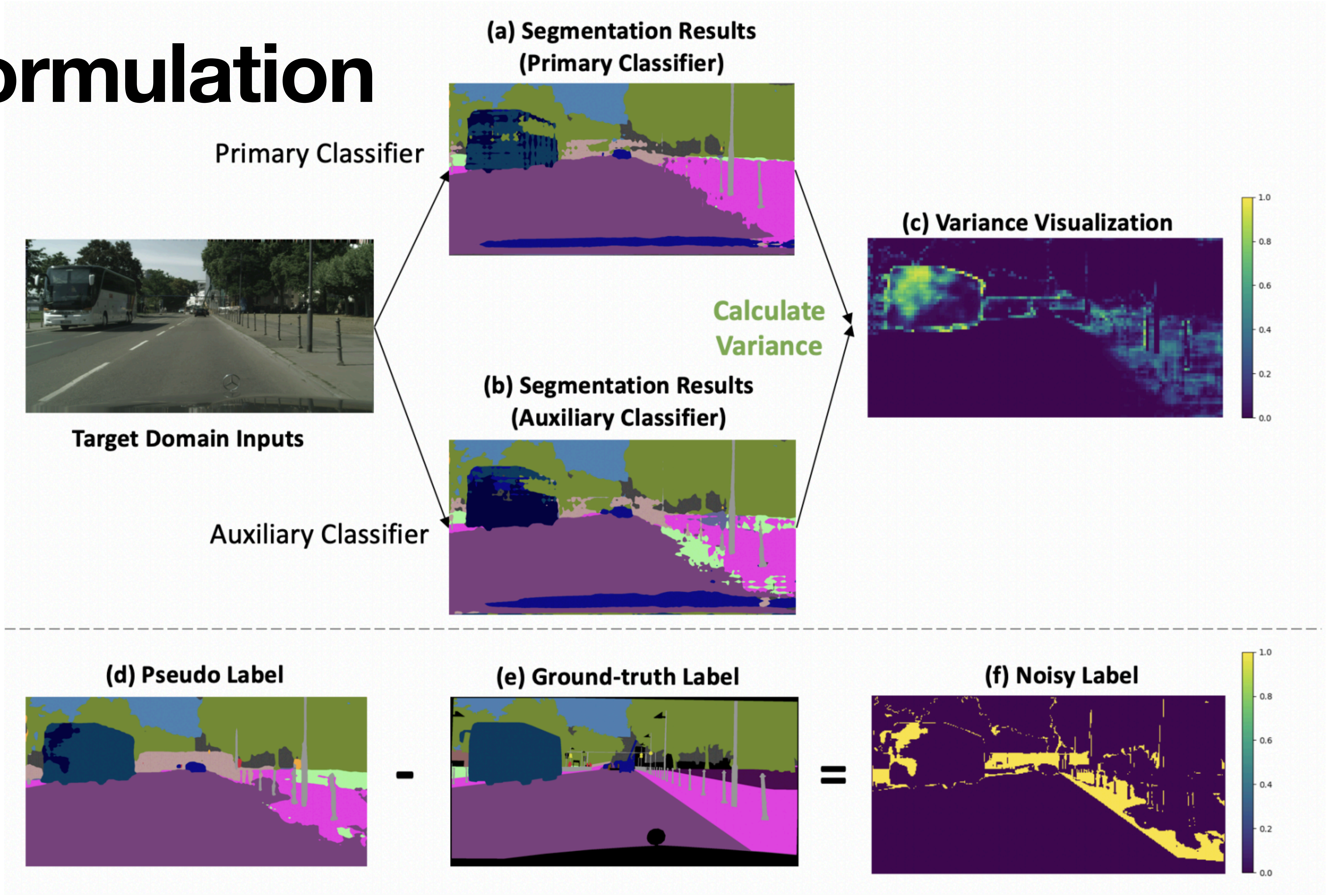
Rene Magritte, *The Listening Room*

# Background： Low Certainty

Interposition

Position, Probability, Size

# Uncertainty Formulation




Large Variance
= More Noise

# Uncertainty as **Automatic Threshold** to **Rectify**

Original loss

$$L_{rect} = \mathbb{E}[\frac{1}{Var(p_t)} Bias(p_t) + Var(p_t)]$$

Avoid large value.

Small weight for high uncertain label.

# Experiment

## Pseudo Label Quality

**Table 6** Ablation study of the impact of different pseudo labels

| Methods | Pseudo Label | mIoU |
|---|---|---|
| AdaptSegNet Tsai et al. (2018) | – | 42.4 |
| Pseudo Learning | AdaptSegNet | 46.8 |
| Ours | AdaptSegNet | 47.4 |
| MRNet Zheng andYang (2020) | – | 45.5 |
| Pseudo Learning | MRNet | 48.3 |
| Ours | MRNet | 50.3 |

The model name in the ‘Pseudo Label‘ column denotes that we deploy the pseudo label generated by the corresponding model

## Dropout

**Table 7** Ablation study of dropout rate on GTA5 → Cityscapes

| Dropout Rate | mIoU |
|---|---|
| Pseudo Learning | 48.3 |
| Droprate = 0 | 49.6 |
| Droprate = 0.1 | 50.3 |
| Droprate = 0.3 | 50.1 |
| Droprate = 0.5 | 50.1 |
| Droprate = 0.7 | 50.0 |

# Experiment

## Variance Vs Confidence Score

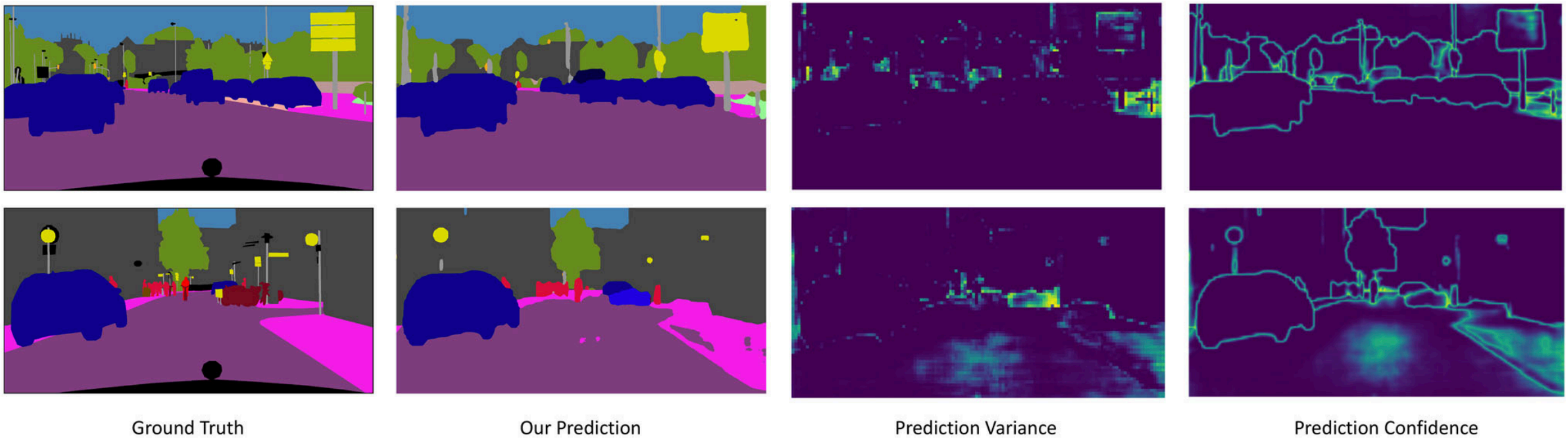



**Fig. 5** Qualitative results of the discrepancy between the prediction variance and the prediction confidence. We could observe that the prediction variance used in this work has more overlaps with the ambiguous predictions, while the prediction confidence usually focuses on the edge of the two different classes. (Best viewed in *color*)

IEEE TRANSACTIONS ON
IMAGE
PROCESSING

# Adaptive Boosting for Domain Adaptation: Towards Robust Predictions in Scene Segmentation

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Code

**Zhedong Zheng, Yi Yang**
University of Technology Sydney

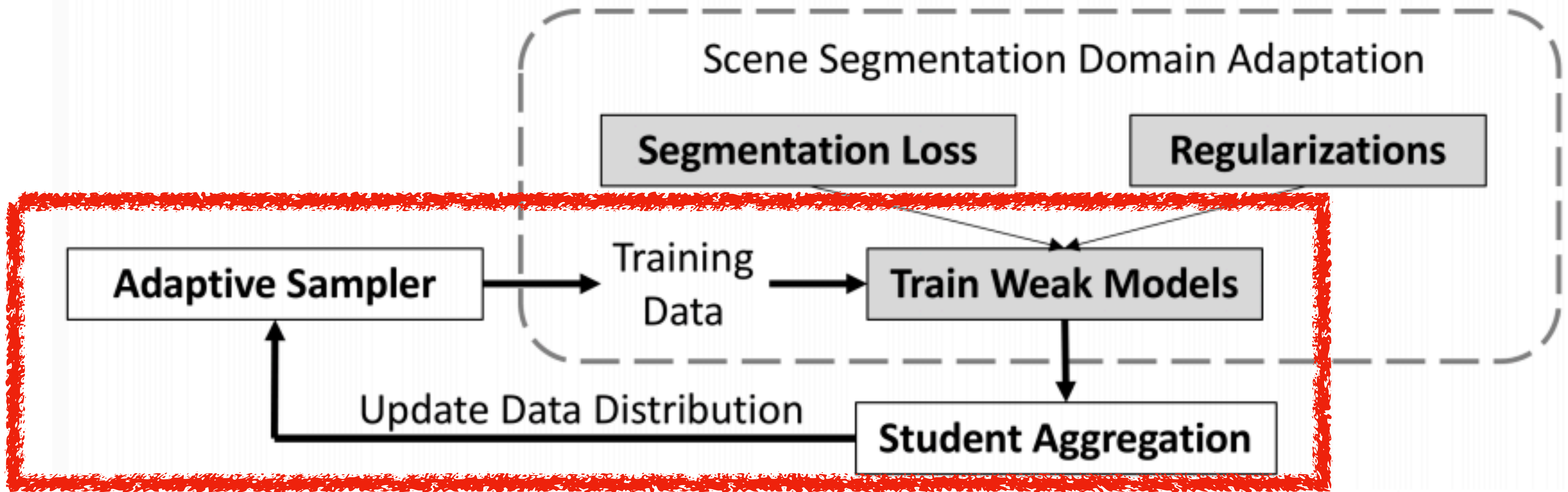


Figure 3. The brief pipeline of the proposed method. There are two main components, *i.e.*, Adaptive Sampler and Student Aggregation. We modify the training data distribution to learn complementary "weak" models, preventing the model from over-fitting. **Different from existing methods, the pipeline enables interactions between learned models and the data sampler.** The proposed method is orthogonal to most existing scene segmentation domain adaptation approaches (in the rounded rectangle).

https://arxiv.org/pdf/2103.15685.pdf

# Outline

- Task (Domain Adaptation for Segmentation)
- (IJCAI 2020) Unsupervised Scene Adaptation with Memory Regularization in vivo
- (IJCV 2021) Rectifying Pseudo Label Learning via Uncertainty Estimation for Domain Adaptive Semantic Segmentation
- (TIP 2022) Adaptive Boosting for Domain Adaptation: Towards Robust Predictions in Scene Segmentation
- Future Research Directions

# Future Research Directions

- Old-School Theory can Do Many Things. (Contrastive Learning? Ladder Network? Adaboost for Domain Adaptation.)
- Prior Knowledge always helps. (3D human structure etc.)

[1] Adaptive Boosting for Domain Adaptation: Towards Robust Predictions in Scene Segmentation
[2] Parameter-Efficient Person Re-identification in the 3D Space

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# Thanks a lot !

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