

# Semantic Segmentation and Adversarial Domain Adaptation

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## Introduction

**Image Segmentation:** Deep learning-based image segmentation models, like **deeplab family**, often achieving the highest accuracy, have received a lot of attention.



Figure1: Examples of Image Segmentation.

**Domain Adaptation:** To reduce the labeling cost, unsupervised domain adaptation (UDA) approaches are proposed to transfer knowledge from labeled synthesized datasets to unlabeled real-world datasets.

## Datasets

**Cityscapes:** It includes 5,000 annotated images with 2048 × 1024 resolution, grouped into 8 categories.

**SYNTHIA:** We use the SYNTHIA-RANDCITYSCAPES subset consisting of 9,400 1280×760 synthetic images.

## Metrics

**Intersection over Union (IoU)** is defined as

$$IoU = \frac{Intersection}{Union} = \frac{TP}{TP + FP + FN}$$

where TP (true positive) represents a pixel that is correctly predicted to belong to the given class. Similar as FP and FN.

**Mean-IoU (mIoU) is defined as the average IoU over all classes.**

$$mIoU == \frac{\sum_n IoU_i}{n}$$

where  $n$  is the number of classes and  $IoU_i$  is the IoU metric for the  $i$ -th class

## Model Framework

**AdaptSegNet:** Figure2 shows that AdaptSegNet consists of two parts: one is the **segmentation network**, the other is the **domain adaptation module**. We use DeepLabV2 and DeepLabV3+ as the segmentation network separately

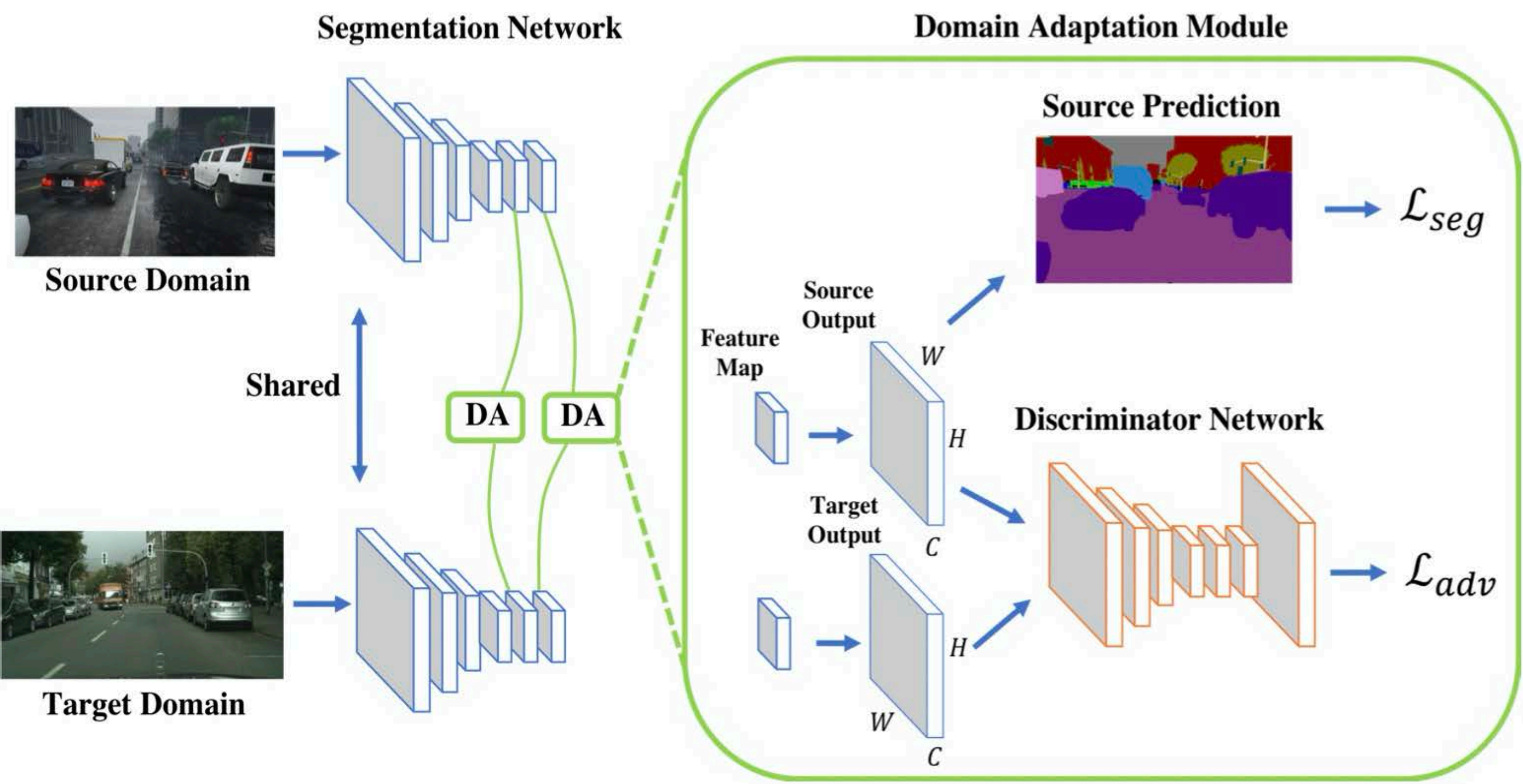


Figure2: AdaptSegnet Architecture .

## Qualitative and Quantitative Results

Figure3 shows the training results of DeeplabV2 model on SYNTHIA dataset.

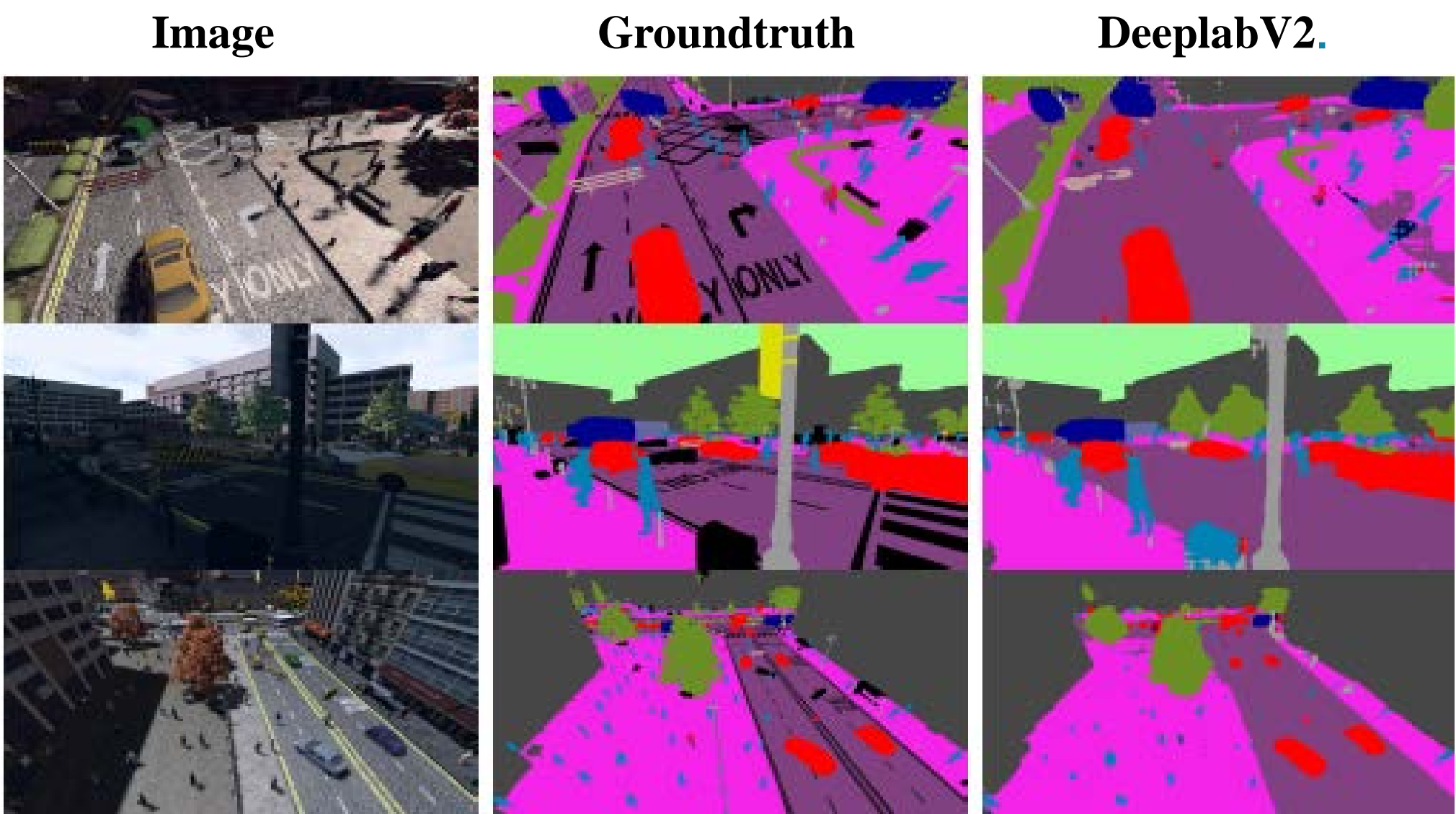


Figure3: Segmentation Result of DeeplabV2 on SYNTHIA.

## Qualitative and Quantitative Results (Cond)

Figure4 compares the segmentation results with and without domain adaptation. We can see that adversarial training along with DeeplabV3+ achieves the best visual results on target domain.

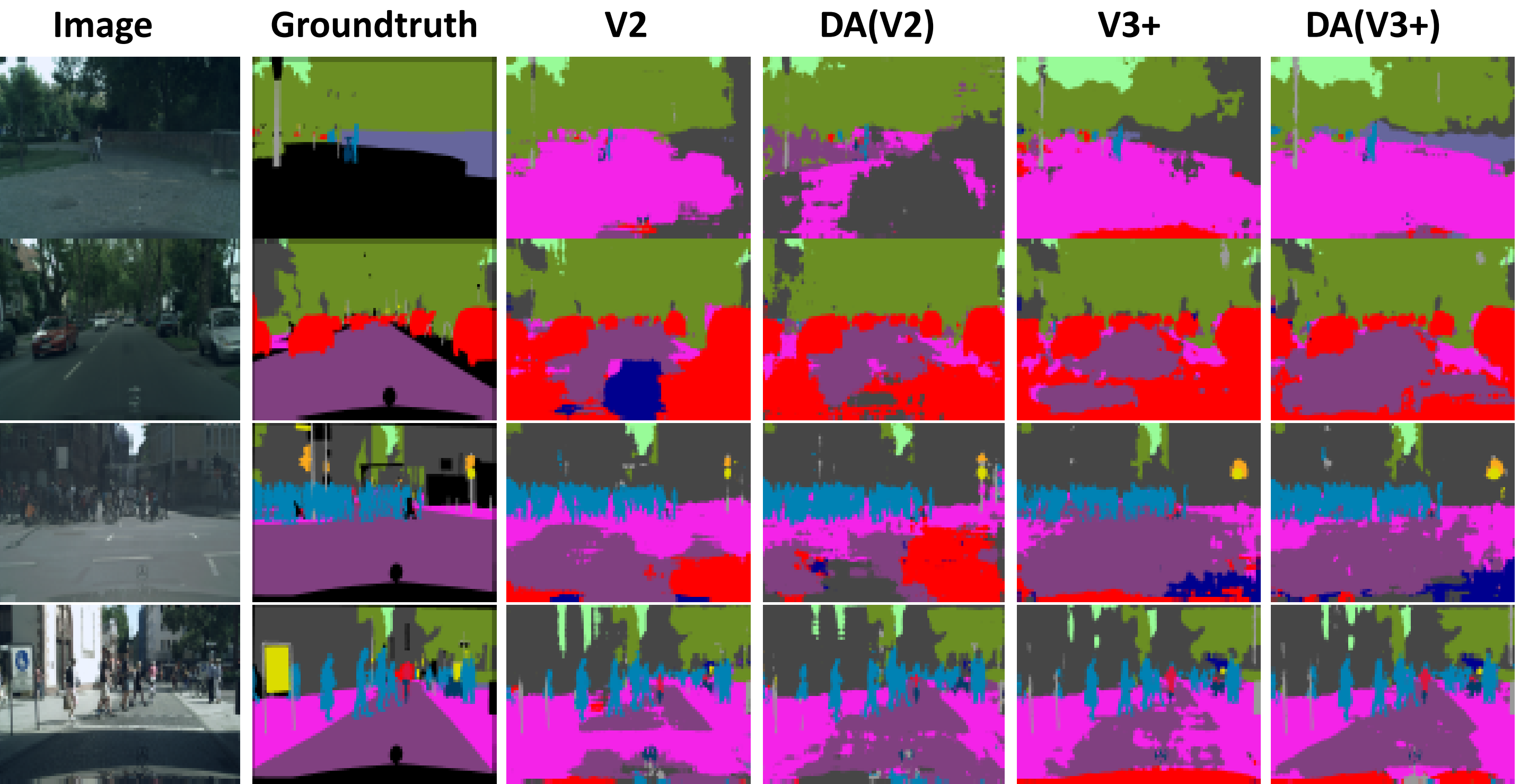


Figure4: Qualitative Image Segmentation Results on the Cityscapes Dataset.

Table1 is our quantitative results. As expected, the adaptation model along with DeeplabV3+ have the best mIoU(mean intersection over union) results.

Table1: Quantitative Results for SYNTHIA-to-Cityscapes experiments

| Method      | Seg Model  | building    |             |             |             |             |             |             |             | mIoU (%)    | mIoU* (%) |
|-------------|------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-----------|
|             |            | walls*      | veg         | sky         | person      | motor       | bike        |             |             |             |           |
| Source only | DeeplabV2  | 75.8        | 6.4         | <b>79.0</b> | <b>81.1</b> | <b>57.6</b> | <b>20.8</b> | 28.2        | 34.1        | 39.4        |           |
| Source only | DeeplabV3+ | 74.8        | 5.3         | 74.0        | 71.9        | 52.0        | 10.0        | 22.5        | 33.2        | 38.6        |           |
| AdaptSegNet | DeeplabV2  | 64.9        | 4.7         | 76.9        | 76.3        | 52.8        | 16.0        | <b>34.7</b> | 35.3        | 41.1        |           |
| AdaptSegNet | DeeplabV3+ | <b>76.8</b> | <b>10.1</b> | 75.7        | 73.4        | 53.1        | 19.1        | 29.9        | <b>37.0</b> | <b>42.8</b> |           |

## Conclusion

- For segmentation before adaptation, DeeplabV2 performs better due to our limited time for fine-tuning DeeplabV3+ model.
- Results show that domain adaptation with DeeplabV3+ model performs favorably against DeeplabV2(which is used in the original paper) even it is less accurate before adaptation.
- The adversarial domain adaptation works well on big datasets with relatively big domain discrepancy.