Label-Driven Reconstruction for Domain Adaptation in Semantic Segmentation

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Abstract

Unsupervised domain adaptation enables to alleviate the need for pixel-wise annotation in the semantic segmentation. One of the most common strategies is to translate images from the source domain to the target domain and then align their marginal distributions in the feature space using adversarial learning. However, source-to-target translation enlarges the bias in translated images, owing to the dominant data size of the source domain. Furthermore, consistency of the joint distribution in source and target domains cannot be guaranteed through global feature alignment. Here, we present an innovative framework, designed to mitigate the image translation bias and align cross-domain features with the same category. This is achieved by 1) performing the target-to-source translation and 2) reconstructing both source and target images from their predicted labels. Extensive experiments on adapting from synthetic to real urban scene understanding demonstrate that our framework competes favorably against existing state-of-the-art methods.

1. Introduction

Deep Convolutional Neural Networks (DCNNs) have demonstrated impressive achievements in computer vision tasks, such as image recognition [20], object detection [17], and semantic segmentation [30]. As one of the most fundamental tasks, semantic segmentation predicts pixel-level semantic labels for given images. It plays an extremely important role in autonomous agent applications such as self-driving techniques.

Existing supervised semantic segmentation methods, however, largely rely on pixel-wise annotations which require tremendous time and labor efforts. To overcome this limitation, publicly available synthetic datasets (e.g., GTA [38] and SYNTHIA [39]) which are densely-annotated, have been considered recently. Nevertheless, the most obvious drawback of such a strategy is the poor knowledge generalization caused by domain shift issues (e.g., appearance and spatial layout differences), giving rise to dramatic performance degradation when directly applying models learned from synthetic data to real-world data of interest. In consequence, domain adaptation has been exploited in recent studies for cross-domain semantic segmentation, where the most common strategy is to learn domain-invariant representations by minimizing distribution discrepancy between source and target domains [50, 27], designing a new loss function [54], considering depth information [7, 46], or alternatively generating pseudo labels and re-training models with these labels through a self-training manner [55, 26]. Following the advances of Generative Adversarial Nets (GAN) [19], adversarial learning has been used to match cross-domain representations by minimizing an adversarial loss on the source and target representations [21, 32, 33, 13], or adapting structured output space across two domains [42, 26]. Recent studies further consider the pixel-level (e.g., texture and lighting) domain shift to enforce source and target images to be domain-invariant in terms of visual appearance [51, 1, 48, 34, 9]. This is achieved by translating images from the source domain to the target domain by using image-to-image translation models such as CycleGAN [53] and UNIT [28].

Despite these painstaking efforts, we are still far from being able to fully adapt cross-domain knowledge mainly stemming from two limitations. First, adversarial-based image-to-image translation introduces inevitable bias to the translated images, as we cannot fully guarantee that the translated source domain $\mathcal{F}(X_s)$ is identical to the target domain $X_t$ ($X_s$ and $X_t$ denote two domains, and $\mathcal{F}$ indicates an image-to-image translation model). This limitation is especially harmful to the source-to-target translation [51, 1, 48, 34, 26], since the data size of the source domain is much larger than the target domain in most of domain adaptation problems. Second, simply aligning cross-domain representations in the feature space [21, 1, 42] ignores the joint distribution shift (i.e., $\mathcal{P}(G(X_s), Y_s) \neq \mathcal{P}(G(X_t), Y_t)$, where $G$ is used for feature extraction, while $Y_s$ and $Y_t$ indicate ground truth labels). These limitations give rise to severe false positive and false negative issues in the target prediction. This problem can get even worse when there is a significant discrepancy in layout or structure between the source and target domains, such as adapting from synthetic to real urban traffic scenes.
In this paper, we propose an innovative domain adaptation framework for semantic segmentation. The key idea is to reduce the image translation bias and align cross-domain feature representations through image reconstruction. As opposed to performing source-to-target translation [1, 48, 26], for the first time, we conduct the target-to-source translation to make target images indistinguishable from source images. This enables to substantially reduce the bias in translated images and allows us to use original source images and their corresponding ground truth to train a segmentation network. Besides, a reconstruction network is designed to reconstruct both source and target images from their predicted labels. It is noteworthy that we reconstruct images directly from the label space, rather than the feature space as reported in previous studies. This is essential to guide the segmentation network by penalizing the reconstructed image that semantically deviates from the corresponding input image. Most importantly, this strategy enforces cross-domain features with the same category close to each other.

The performance of our method is evaluated on synthetic-to-real scenarios of urban scene understanding, i.e., GTA5 to Cityscapes and SYNTHIA to Cityscapes. Our results demonstrate that the proposed method achieves significant improvements compared with existing methods. Figure 1 demonstrates an example of our model in adapting cross-domain knowledge in semantic segmentation tasks and reconstructing the input image from its output label. We also carry out comprehensive ablation studies to analyze the effectiveness of each component in our framework.

The contribution of this paper is threefold.

- For the first time, we propose and investigate the target-to-source translation in domain adaptation. It enables the reduction of the image translation bias compared to the widely-used source-to-target translation.

- To enforce semantic consistency, we introduce a label-driven reconstruction module that reconstructs both source and target images from their predicted labels.

- Extensive experiments show that our method achieves the new state-of-the-art performance on adapting synthetic-to-real semantic segmentation.

2. Related Work

Semantic Segmentation  Recent achievements in semantic segmentation mainly benefit from the technical advances of DCNNs, especially the emergence of Fully Convolutional Network (FCN) [30]. By adapting and extending contemporary deep classification architectures fully convolutionally, FCN enables pixel-wise semantic prediction for any arbitrary-sized inputs and has been widely recognized as one of the benchmark methods in this field. Numerous methods inspired by FCN were then proposed to further enhance segmentation accuracy, which have exhibited distinct performance improvement on the well-known datasets (e.g., PASCAL VOC 2012 [14] and Cityscapes [11]) [5, 29, 52, 6, 4]. However, such methods heavily rely on human-annotated, pixel-level segmentation masks, which require extremely expensive labeling efforts [11]. In consequence, weakly-supervised methods, which are based on easily obtained annotations (e.g., bounding boxes and image-level tags), were proposed to alleviate the need for effort-consuming labeling [12, 37]. Another alternative is to resort to freely-available synthetic datasets (e.g., GTA5 [38] and SYNTHIA [39]) with pixel-level semantic annotations. However, models learned on synthetic datasets suffer from significant performance degradation when directly applied to the real datasets of interest, mainly owing to the domain shift issue.

Domain Adaptation  Domain adaptation aims to mitigate the domain discrepancy between a source and a target domain, which can be further divided into supervised adaptation, semi-supervised adaptation, and unsupervised adaptation, depending on the availability of labels in the target domain. The term unsupervised domain adaptation refers to the scenario where target labels are unavailable and have been extensively studied [31, 45, 15, 43, 44, 49]. Recent publications have highlighted the complementary role of pixel-level and representation-level adaptation in semantic segmentation [1, 35, 51, 48, 7], where the pixel-level adaptation is mainly achieved by translating images from the source domain to the target domain (source-to-target translation). Specifically, unpaired image-to-image translation is used in CyCADA [1] to achieve pixel-level adaptation by restricting cycle-consistency. Similarly, FCAN achieves
we propose the first-of-its-kind target-to-source image translation methods by a large margin. However, such a strategy undermines the side effect of pseudo labels that are incorrectly predicted. As a consequence, the segmentation model fails to increasingly improve itself using these wrong ground truth. Instead, our method reconstructs source and target input images from the label space to ensure these outputs are semantically correct. The image-to-image translation network in BDL uses a reconstruction loss and a perceptual loss to maintain the semantic consistency between the input image and the translated image. Different from BDL, we design a cycle-reconstruction loss in our reconstruction network to enforce the semantic consistency between the input image and the reconstructed image.

Reconstruction-based strategy for unsupervised domain adaptation has received considerable attention recently [16, 2]. The key idea is to reconstruct input images from their feature representations to ensure that the segmentation model can learn useful information. Chang et al. [3] follow a similar idea to first disentangle images into the domain-invariant structure and domain-specific texture representations, and then reconstruct input images. LSD-seg [40] first reconstructs images from the feature space, and then apply a discriminator to the reconstructed images. Rather than performing reconstruction from feature representations, we reconstruct both source and target images from their predicted labels.

3. Algorithm

3.1. Overview

The overall design of our framework is illustrated in Figure 2, mainly containing three complementary modules: a translation network \( F \), a segmentation network \( G \), and a reconstruction network \( M \). Given a set of source domain images \( X_s \) with labels \( Y_s \) and a set of target domain images \( X_t \) without any annotations. Our goal is to train \( G \) to predict accurate pixel-level labels for \( X_t \). To achieve this, we first use \( F \) to adapt pixel-level knowledge between \( X_t \) and \( X_s \) by translating \( X_t \) to source-like images \( X_{t\rightarrow s} \). This is different from existing prevalent methods that translate images from the source domain to the target domain. \( X_s \) and \( X_{t\rightarrow s} \) are then fed into \( G \) to predict their segmentation outputs \( G(X_s) \) and \( G(X_{t\rightarrow s}) \), respectively. To further enforce semantic consistency of both source and target domains, \( M \) is then applied to reconstruct \( X_s \) and \( X_{t\rightarrow s} \) from their predicted labels. Specifically, a cycle-reconstruction loss is proposed to measure the reconstruction error, which enforces the semantic consistency and further guides segmentation network to predict more accurate segmentation outputs.

3.2. Target-to-source Translation

We first perform the image-to-image translation to reduce the pixel-level discrepancy between source and target domains. As opposed to the source-to-target translation re-
Figure 3. Schematic overview of our framework which has three modules: (i) a translation network for pixel-level discrepancy reduction by translating target images to source-like images, where source-like images are indistinguishable from source images, (ii) a segmentation network that predicts segmentation outputs for source images and source-like images, and (iii) a reconstruction network for reconstructing source and source-like images from their corresponding label space.

Based on the trained model $F$, we first translate images from $X_t$ to source-like images $X_{t\rightarrow s} = F(X_t)$. Specifically, each image in $X_{t\rightarrow s}$ preserves the same content as the corresponding image in $X_t$ while demonstrating the common style (e.g., texture and lighting) as $X_s$. $X_s$ and $X_{t\rightarrow s}$ are then fed into a segmentation network for semantic label prediction.

Compared to translating images from the source domain to the target domain, the target-to-source translation has two benefits. First, it allows full supervision on the source domain by training the segmentation network with original source images and their corresponding labels. Second, it enables to reduce the bias in translated images, given that $|X_t| \ll |X_s|$.

3.3. Semantic Segmentation

Given that source-like images $X_{t\rightarrow s}$ preserves all semantic information from $X_t$, we apply a shared segmentation network $G$ to $X_s$ and $X_{t\rightarrow s}$ to predict their segmentation outputs with the loss function given by,

$$L_G = L_{seg}(G(X_s), Y_s) + L_{seg}(G(X_{t\rightarrow s}), Y_{t\rightarrow s}^{ssl}) + \lambda L_{adv}(G(X_s), G(X_{t\rightarrow s})),$$

where $L_{seg}$ indicates the typical segmentation objective, $Y_{t\rightarrow s}^{ssl}$ is pseudo labels of $X_{t\rightarrow s}$ which is derived from [26], $L_{adv}(G(X_s), G(X_{t\rightarrow s}))$ is an adversarial loss, and $\lambda$ leverages the importance of these losses. Specifically,
Table 1. A performance comparison of our method with other state-of-the-art models on "GTA5 to Cityscapes". The performance is measured by the intersection-over-union (IoU) for each class, mean IoU (mIoU), and mIoU gap between each model and the fully-supervised model (Oracle). Two base architectures, i.e., VGG16 (V) and ResNet101 (R) are used in our study.

GTA5 → Cityscapes

| Source only | Base | road | sidewalk | building | wall | fence | pole | traffic light | sign | terrace | sky | person | rider | car | truck | bus | train | motorcycle | bicycle | mIoU | mIoU Gap | Oracle |
|-------------|------|------|----------|----------|-----|-------|------|--------------|------|---------|-----|--------|------|-----|-------|-----|-------|-------------|---------|------|----------|--------|
| Source only | V    | 26.0 | 14.9     | 65.1     | 5.5 | 12.9  | 8.9  | 6.0          | 2.5  | 70.0    | 2.9 | 47.0   | 24.5 | 0.0 | 40.0   | 12.1| 1.5   | 0.0          | 0.0     | 17.9 | 46.7     | 64.6   |
| Source only | R    | 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          | 3.4     | 42.6 | -22.5    | 65.1   |
| CLAN [33]   | R    | 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    | 43.2 | -21.9    | 65.1   |
| DISE [3]    | V    | 91.5 | 47.5     | 82.5     | 31.3| 25.6  | 33.0 | 33.7         | 25.8| 82.7    | 28.8| 82.7  | 62.4 | 30.8| 85.2   | 27.7| 34.5  | 6.4          | 25.2    | 65.4 | -19.7    | 65.1   |
| BDL [26]    | V    | 91.0 | 44.7     | 84.2     | 34.6| 27.6  | 30.2 | 36.0         | 36.0| 85.0    | 43.6| 83.0  | 58.6 | 31.6| 83.3   | 35.3| 38.5  | 3.3          | 28.8    | 54.8 | -16.6    | 65.1   |

Ours | V | 90.8 | 41.4 | 84.7 | 35.1 | 27.5 | 31.2 | 38.0 | 32.8 | 85.6 | 42.1 | 84.9 | 59.6 | 34.4 | 85.0 | 42.8 | 52.7 | 3.4 | 30.9 | 38.1 | 49.5 | -15.6 | 65.1 |

\[
\mathcal{L}_{adv}(G(X_s), G(X_{t→s})) = \text{defined as,}
\]

\[
\begin{align*}
\mathcal{L}_{adv}(G(X_s), G(X_{t→s})) &= \mathbb{E}[\log D(G(X_s))] + \\
&\quad \mathbb{E}[\log(1 - D(G(X_{t→s}))],
\end{align*}
\]

\[\text{(2)}\]

which enforces \(G\) to learn domain-invariant features by confusing the discriminator \(D\). It is noteworthy that we regard the segmentation outputs \(G(X_s)\) and \(G(X_{t→s})\) as features in our study. This is based on the observation that \(X_s\) and \(X_{t→s}\) share significant similarities in terms of spatial layouts and structures [42].

3.4. Image Reconstruction from the Label Space

To encourage \(G\) to generate segmentation outputs that are semantic consistent, we introduce a reconstruction network \(\mathcal{M}\) to reconstruct \(X_\phi\) from \(G(X_\phi)\) in \(\mathbb{R}^{h_\phi \times w_\phi \times c}\), where \(h_\phi, w_\phi\) indicates image size, \(c\) represents the number of label classes, and the subscript \(\phi\) can be either \(s\) or \(t\) to denote the source or the target domain. However, directly reconstructing images from the feature space fails to provide semantic consistency constraint to \(G\). On the one hand, \(G(X_\phi)\) encodes rich information which makes the image reconstruction quite straightforward. As illustrated in Figure 4, in just a few epochs, the reconstructed images derived from \(\mathcal{M}\) are almost identical to the input images. On the other hand, to enforce cross-domain features with the same category close to each other, it is essential to perform the reconstruction based on the label space. Unfortunately, \(G(X_\phi)\) lies in the feature space instead. To overcome these limitations, the most clear-cut way is to convert \(G(X_\phi)\) to have zeros everywhere except where the index of each maximum value in the last dimension. Doing so formulates the categorical representation of the predicted label that corresponds to \(G(X_\phi)\). Nevertheless, such conversion is non-differentiable and cannot be trained using standard backpropagation.

Driven by the softmax action selection which is commonly used in the reinforcement learning, we apply Boltzmann distributed probabilities to approximate the semantic label map of \(G(X_\phi)\), which is defined as,

\[
\Omega_{\phi}^{h, w, i} = \frac{\exp(G(X_\phi)^{(h, w, i)}/\tau)}{\sum_{j=1}^{c} \exp(G(X_\phi)^{(h, w, j)}/\tau)},
\]

where \(\tau\) is a temperature parameter. This conversion is continuous and differentiable, therefore, we use \(\mathcal{M}\) to reconstruct input images \(X_\phi\) from \(\Omega_{\phi}\) (Figure 4).

To synthesize high-resolution images from the semantic label map, we use conditional GANs [22] to model the conditional distribution of \(X_\phi\) given \(\Omega_{\phi}\). To this end, we introduce \(\mathcal{M}\) and multi-scale domain discriminators \(D_k\) for \(k = 1, 2, 3\). \(M\) is designed to reconstruct \(X_\phi\) from \(\Omega_{\phi}\), and \(D_k\) aims to distinguish \(X_\phi\) from \(M(\Omega_{\phi})\). Specifically, \(\mathcal{M}\) follows the architecture proposed in [23], while \(D_k\) is based on PatchGAN [22] that penalizes structure at the scale of image patches. All \(D_k\) follow the same network architecture. Besides \(X_\phi\) and \(M(\Omega_{\phi})\) themselves, they are downsampled by a factor of 2 and 4 to obtain pyramid of 3 scales for \(D_1\), \(D_2\), and \(D_3\), respectively. It is worth mentioning that \(D_k\) is essential to differentiate real and reconstructed images with high resolution [47], owing to its ability in providing large
Table 2. A performance comparison of our method with other state-of-the-art models on "SYNTHIA to Cityscapes". The performance is measured by the IoU for each class, mIoU, and mIoU gap between each model and the fully-supervised model (Oracle). Two base architectures, i.e., VGG16 (V) and ResNet101 (R) are used in our study.

|                          | Base | roa | sidewalk | building | wall | fence | pole | traffic light | traffic sign | vegetation | sky | person | rider | car | bus | motorbike | bicycle | mIoU | mIoU Gap | Oracle |
|--------------------------|------|-----|----------|----------|------|-------|------|---------------|-------------|------------|-----|--------|-------|-----|-----|-----------|---------|------|---------|--------|
| Source only              | R    | 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 | —        | —      |
| AdaptSegNet [42]         | V    | 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 | -25.0    | 71.7   |
| DISE [3]                 | R    | 91.7| 53.5     | 77.1     | —    | —     | —    | 6.2           | 7.6         | 78.4       | 81.2| 55.8   | 19.2 | 82.3| 30.3| 17.1      | 34.3    | 48.8 | -22.9    | 71.7   |
| DADA [46]                | R    | 89.2| 44.8     | 81.4     | —    | —     | —    | 8.6           | 11.1        | 81.8       | 84.0| 54.7   | 19.3 | 79.7| 40.7| 14.0      | 38.8    | 49.8 | -21.9    | 71.7   |
| BDL [26]                 | R    | 86.0| 46.7     | 80.3     | —    | —     | —    | 14.1          | 11.6        | 79.2       | 81.3| 54.1   | 27.9 | 73.7| 42.2| 25.7      | 45.3    | 51.4 | -20.3    | 71.7   |
| Ours                     | R    | 85.1| 44.5     | 81.0     | —    | —     | —    | 16.4          | 15.2        | 80.1       | 84.8| 59.4   | 31.9 | 73.2| 41.0| 32.6      | 44.7    | 53.1 | -18.6    | 71.7   |
| ROAD-Net [8]             | V    | 77.7| 30.0     | 77.5     | 9.6  | 0.3   | 25.8 | 10.3          | 15.6        | 77.6       | 79.8| 44.5   | 16.6 | 67.8| 14.5| 7.0       | 23.8    | 36.2 | -27.6    | 64.1   |
| SPIGAN [25]              | V    | 71.1| 29.8     | 71.4     | 3.7  | 0.3   | 33.2 | 6.4           | 15.6        | 81.2       | 78.9| 52.7   | 13.1 | 75.9| 25.5| 10.0      | 20.5    | 36.8 | -22.7    | 59.5   |
| GIO-Ada [7]              | V    | 78.3| 29.2     | 76.9     | 11.4 | 0.3   | 26.5 | 10.8          | 17.2        | 81.7       | 25.8 | 81.9 | 45.8 | 68.0| 15.9| 7.5       | 30.4    | 37.3 | -26.8    | 64.1   |
| TGCF-DA [10]             | V    | 90.1| 48.6     | 80.7     | 2.2  | 0.2   | 27.2 | 3.2           | 14.3        | 82.1       | 78.4| 54.4   | 16.4 | 82.5 | 12.3| 1.7       | 21.8    | 38.5 | -25.6    | 64.1   |
| BDL [26]                 | V    | 72.0| 30.3     | 74.5     | 0.1  | 0.3   | 24.6 | 10.2          | 25.2        | 80.5       | 80.0| 54.7   | 23.2 | 72.7| 24.0| 7.5       | 44.9    | 39.0 | -20.5    | 59.5   |
| Ours                     | V    | 73.7| 29.6     | 77.6     | 1.0  | 0.4   | 26.0 | 14.7          | 26.6        | 80.6       | 81.8| 57.2   | 24.5 | 76.1| 27.6| 13.6      | 46.6    | 41.1 | -18.4    | 59.5   |

receptive field. The objective function is given by,

\[
L_{adv}^{\phi} = \sum_{k=1}^{3} [E[\log D_k(\Omega_{\phi}, X_{\phi})] + \log(1 - D_k(\Omega_{\phi}, M(\Omega_{\phi})))]
\] (4)

To further enforce semantic consistency between \(X_{\phi}\) and \(M(\Omega_{\phi})\), we introduce a cycle-reconstruction loss \(L_{rec}^{\phi}\) to match their feature representations, which is defined as,

\[
L_{rec}^{\phi} = \sum_{m=1}^{M} \sum_{n=1}^{N} \left[ || V^{(m)}(M(\Omega_{\phi})) - V^{(m)}(X_{\phi}) ||_1 \right] + \\
\sum_{k=1}^{3} \sum_{n=1}^{N} \left[ || D_k^{(n)}(\Omega_{\phi}, X_{\phi}) - D_k^{(n)}(\Omega_{\phi}, M(\Omega_{\phi})) ||_1 \right]
\] (5)

where \(V\) is a VGG19-based model for extracting high-level perceptual information [23], \(M\) and \(N\) represent the total number of layers in \(V\) and \(D_k\) for matching intermediate representations. Note that \(L_{rec}^{\phi}\) penalizes \(\Omega_{\phi}\) when it deviates from the corresponding image \(X_{\phi}\) in terms of semantic consistency. In this way, \(M\) enables to map features from \(X_{\phi}\) closer to the features from \(X_{\phi}\) with the same label.

Taken together, the training objective of our framework is formulated as,

\[
\min_{G, M, D_1, D_2, D_3} \max_{\phi, \beta} \left( L_G + \alpha (L_{adv}^{\phi} + L_{adv}^{\phi}) + \beta (L_{rec}^{\phi} + L_{rec}^{\phi}) \right)
\] (6)

where \(\alpha\) and \(\beta\) leverage the importance of losses above. Notably, our method is able to implicitly encourage \(G\) to generate semantic-consistent segmentation labels for the target domain.

4. Experiments

In this section, a comprehensive evaluation is performed on two domain adaptation tasks to assess our framework for semantic segmentation. Specifically, we consider the large distribution shift of adapting from synthetic (i.e., GTA5 [38] and SYNTHIA [39]) to the real images in Cityscapes [11]. A thorough comparison with the state-of-the-art methods and extensive ablation studies are also carried out to verify the effectiveness of each component in our framework.

4.1. Datasets

Cityscapes is one of the benchmarks for urban scene understanding, which is collected from 50 cities with varying scene layouts and weather conditions. The 5,000 finely-annotated images from this dataset are used in our study, which contains 2,975 training images, 500 validation images, and 1,525 test images. Each image with a resolution of 2048 \(\times\) 1024. The GTA5 dataset is synthesized from the game Grand Theft Auto V (GTAV), including a total of 24,966 labeled images whose annotations are compatible with Cityscapes. The resolution of each image is 1914 \(\times\) 1052. The SYNTHIA-RAND-CITYSCAPES (or SYNTHIA for short) contains 9,400 pixel-level annotated images (1280 \(\times\) 760), which are synthesized from a virtual city. Following the same setting reported in the previous studies, we use the labeled SYNTHIA or GTA5 dataset as the source domain, while using the unlabeled training dataset in the CITYSCAPES as the target domain. Only the 500 labeled validation images from CITYSCAPES are used as test data in all of our experiments.
Table 3. Ablation study on GTA5 → Cityscapes. S → T and T → S indicate source-to-target and target-to-source translation.

| Base | S → T | T → S | Reconstruction | mIoU |
|------|-------|-------|---------------|------|
| R    | ✔     |       |               | 48.5 |
| R    | ✔     | ✔     |               | 49.1 |
| R    | ✔     | ✔     |               | 49.5 |
| V    | ✔     |       |               | 41.3 |
| V    | ✔     | ✔     |               | 42.3 |
| V    | ✔     | ✔     |               | 43.6 |

Table 4. Ablation study on SYNTHIA → Cityscapes. S → T and T → S indicate source-to-target and target-to-source translation.

| Base | S → T | T → S | Reconstruction | mIoU |
|------|-------|-------|---------------|------|
| R    | ✔     |       |               | 51.4 |
| R    | ✔     | ✔     |               | 52.0 |
| R    | ✔     | ✔     |               | 53.1 |
| V    | ✔     |       |               | 39.0 |
| V    | ✔     | ✔     |               | 40.1 |
| V    | ✔     | ✔     |               | 41.1 |

4.2. Network Architecture

We use two segmentation baseline models, i.e., FCN-VGG16 and DeepLab-ResNet101 to investigate the effectiveness and generalizability of our framework. Specifically, FCN-VGG16 is the combination of FCN-8s [30] and VGG16 [41], while DeepLab-ResNet101 is obtained by integrating DeepLab-V2 [6] into ResNet101 [20]. These two segmentation models share the same discriminator which has 5 convolution layers with channel number 64, 128, 256, 512, 1. For each layer, a leaky ReLU parameterized by 0.2 is followed, except the last one. The kernel size and stride are set to 4×4 and 2, respectively. The reconstruction model follows the architecture in [23], containing 3 convolution layers (kernel 3×3 and stride 1), 9 ResNet blocks (kernel 3×3 and stride 2), and another 3 transposed convolution layers (kernel 3×3 and stride 2) for upsampling. The 3 multi-scale discriminators share the identical network, each of which follows the architecture of PatchGAN [22]. More details regarding the architecture of discriminators in both segmentation and reconstruction models can be found in the Supplementary.

4.3. Implementation Details

Our framework is implemented with PyTorch [36] on two TITAN Xp GPUs, each of which with 12GB memory. The batch size is set to one for training all the models discussed below. Limited by the GPU memory space, the translation network is first trained to perform target-to-source image translation by using Adam optimizer [24]. The initial learning rate is set to 0.0001, which is reduced by half after every 100,000 iterations. The maximum training iteration is 100k.

DeepLab-ResNet101 is trained using Stochastic Gradient Descent optimizer with initial learning rate $2.5 \times 10^{-4}$. The polynomial decay with power 0.9 is applied to the learning rate. The momentum and weight decay are set to 0.9 and $5 \times 10^{-4}$, respectively. For FCN-VGG16, the Adam optimizer with momentum $\{0.9, 0.99\}$ and initial learning rate $1 \times 10^{-5}$ is used for training. The learning rate is decreased using step decay with step size 50000 and drop factor 0.1. In equation 1, $\lambda$ is set to $1 \times 10^{-3}$ for DeepLab-ResNet101 and $1 \times 10^{-4}$ for FCN-VGG16.

The reconstruction network is first pre-trained by recon-
6.4% and 1.7% improvement than AdaptSegNet and BDL on ResNet101, respectively. Besides, our method narrows down the mIoU gap between the oracle model by a large margin.

4.6. Ablation Study

GTA5 → Cityscapes Compared to the baseline model, 0.6% improvement is achieved by considering target-to-source translation on ResNet101 (Table 3). By further enforce semantic consistency through a reconstruction network, our method achieves 49.5 mIoU. Similar improvements are also observed on VGG16, with 1.0% improvement over the baseline by performing target-to-source translation. The prediction power of our method is further boosted by combining translation and reconstruction, giving rise to another 1.3% mIoU improvement. The qualitative study of each module in our method is showcased in Figure 5.

SYNTHIA → Cityscapes We achieve a performance boost of 0.6% and 1.1% over the baseline by considering image translation on ResNet101 and VGG16, respectively (Table 4). The performance gain is 1.1% and 1.0% by incorporating the reconstruction network. Our results prove the effectiveness of target-to-source translation and reconstruction in adapting domain knowledge for semantic segmentation.

Parameter Analysis We investigate the sensitivity of temperature parameter $\tau$ in this section and find that $\tau = 0.001$ achieves the best performance (Table 5). Therefore, $\tau$ is set to 0.001 in all of our experiments to approximate semantic label maps.

5. Conclusion

We propose a novel framework that exploits cross-domain adaptation in the context of semantic segmentation. Specifically, we translate images from a target domain to a source domain to reduce image translation bias. To enforce cross-domain features with the same category close to each other, we reconstruct both source and target images directly from the label space. Experiments demonstrate that our method achieves significant improvement in adapting from GTA5 and SYNTHIA to Cityscapes.

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