Consistency Regularization with High-dimensional Non-adversarial Source-guided Perturbation for Unsupervised Domain Adaptation in Segmentation

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Abstract

Unsupervised domain adaptation for semantic segmentation has been intensively studied due to the low cost of the pixel-level annotation for synthetic data. The most common approaches try to generate images or features mimicking the distribution in the target domain while preserving the semantic contents in the source domain so that a model can be trained with annotations from the latter. However, such methods highly rely on an image translator or feature extractor trained in an elaborated mechanism including adversarial training, which brings in extra complexity and instability in the adaptation process. Furthermore, these methods mainly focus on taking advantage of the labeled source dataset, leaving the unlabeled target dataset not fully utilized. In this paper, we propose a bidirectional style-induced domain adaptation method, called BiSIDA, that employs consistency regularization to efficiently exploit information from the unlabeled target domain dataset, requiring only a simple neural style transfer model. BiSIDA aligns domains by not only transferring source images into the style of target images but also transferring target images into the style of source images to perform high-dimensional perturbation on the unlabeled target images, which is crucial to the success in applying consistency regularization in segmentation tasks. Extensive experiments show that our BiSIDA achieves new state-of-the-art on two commonly-used synthetic-to-real domain adaptation benchmarks: GTA5-to-CityScapes and SYNTHIA-to-CityScapes.

1. Introduction

Deep learning methods for semantic segmentation [21], the problem of dividing the pixels in an image into mutually exclusive and collectively exhaustive sets of class-labeled regions, have gained increasing attention. Research progress is hindered by the difficulty of creating large training datasets with accurate pixel-level annotations of these regions. As a consequence, the use of synthetic datasets has become popular because pixel-level ground truth annotations can be generated along with the images. Unfortunately, when deep models that were trained on synthetic data are used to segment real-world images, their performance is typically limited due to the domain gap between the training and testing data. Domain adaptation methods seek to bridge the gap between the source domain training data and the target domain testing data. We here focus on unsupervised domain adaptation (UDA), the problem of adapting a model that was trained with a labeled source domain dataset and optimizing its performance on the target domain.

To perform domain alignment on a pixel-level or feature-level basis, existing methods [29, 11, 32, 22, 18, 4] typically use adversarial training [9], and training with the aligned data is then supervised by a loss computed with the annotation of the source domain dataset. However, the use of adversarial training typically comes with extra complexity and instability in training. Alternative approaches [39, 22, 18, 4] seek to exploit information about the unlabeled target dataset by performing semi-supervised learning including entropy minimization [10], pseudo-labeling [16] and consistency regularization. However, these approaches either just play an auxiliary role in the training process besides supervised learning, or fail to take full advantage of the target dataset.

In this paper, we propose Bidirectional Style-induced Domain Adaptation (BiSIDA) that takes better advantage of the unlabeled dataset and optimizes the performance of a segmentation model on the target dataset. Our pipeline includes a supervised learning phase that provides supervision using annotations in the source dataset and an unsupervised phase for learning from the unlabeled target dataset without requiring its annotation. To perform domain adaptation, we construct a non-adversarial yet effective pre-trained style-induced image generator that translates images...
through style transfer. In the supervised learning phase, the style-induced image generator translates images with different styles to align the source domain to the direction of the target domain. In the unsupervised phase, it performs high-dimensional perturbations on target domain images with consistency regularization. Consequently, the unlabeled target dataset is utilized efficiently and the domain gap is reduced effectively from another direction at the same time through a self-supervised approach.

Our model performs image translation from the source to the target domain using an image generator in the supervised phase similar to existing methods. However, in order to facilitate generalization, our model synthesizes images with semantic content from the source domain, and with a style that is defined by a continuous parameter that represents a "mix" of source and target domain styles, instead of transferring the style directly to the target domain. Consequently, the stochasticity of the whole process facilitates not only the training on the original images but also the gradual adaptation towards the target domain. The resulting image is then sent along with its corresponding pixel-level annotation to compute a supervised cross-entropy loss to train the segmentation model.

BiSIDA employs consistency regularization in the unsupervised phase to yield consistent predictions on randomly perturbed inputs without requiring their annotations. We apply our style-induced image generator as an augmentation method and transfer each target domain image together with a number of randomly sampled source domain images, just as in the supervised phase, but in an opposite direction. A series of images with identical content but different styles from source domain images is generated. Given that supervised learning is performed on source images that are transferred with combined styles of source images and target images, our model will be more adapted and more likely to produce correct predictions when target domain images are transferred towards the direction of the source domain images. Meanwhile, our style-induced image generator provides a high-dimensional perturbation that keeps the semantic content as indicated in [7] for consistency regularization in a computational affordable way. To further improve the quality of predictions, the transferred images are passed through the self-ensemble of the trained segmentation models, which is the exponential moving average of itself, and gathered to get a pseudo-label for the unlabeled target domain image. The training of the segmentation model on the original target domain image augmented with only color space perturbations is guided by its pseudo-label. During the process, information and knowledge lied in the unlabeled target images can be learned through the consistency regularization framework and the model is finally adapted to the target domain.

Combined with our supervised and unsupervised learning methods, we are able to utilize annotation from the labeled source dataset, exploit knowledge from the unlabeled target dataset and perform gradual adaptation between the source and the target domain from both sides. In conclusion, our key contributions include:

1. A Bidirectional Style-induced Domain Adaptation (BiSIDA) framework that incorporates both target-guided supervised and source-guided unsupervised learning. We also show that domain adaptation is achievable in a bidirectional way through a continuous parameterization of the two domains, without requiring adversarial training;

2. A non-adversarial style-induced image generator that performs a high-dimensional source-guided perturbation on target images for consistency regularization.

3. Extensive experiments show that our BiSIDA achieves new state-of-the-art on two commonly-used synthetic-to-real domain adaptation benchmarks: GTA5-to-CityScapes and SYNTHIA-to-CityScapes.

2. Related Works

2.1. Image-to-image Translation

Recent progress in image-to-image translation that transfers the style of an image while preserving its semantic content has inspired research in various related areas, including image synthesis and reducing domain discrepancy. Typical image-to-image translation approaches include CycleGAN [38] and DualGAN [36], which keep cycle-consistency in adversarial training to preserve the semantic content of images when transferring the style of image. UNIT [20] and MUNIT [14] address the problem by mapping images into a common latent content space. Neural style transfer offers an alternative way to perform image-to-image translation [8], but its optimization process is computationally impractical. Several works [15,17,20,31,6] proposed improvements, but these methods are limited since the style to be transferred is either fixed or the number of styles is limited.

2.2. Semi-supervised Learning

When the gap between source and target domains becomes small, the problem of unsupervised domain adaptation intriguingly degenerates to semi-supervised learning. Pseudo-labeling [16], a commonly-used semi-supervised learning method, takes predictions on the unlabeled dataset with high confidence as one-hot labels guiding further training. Entropy minimization [10] can be seen as a soft assignment of the pseudo-label on the unlabeled dataset. Recently, consistency regularization has gained attention due to its outstanding performance as a semi-supervised learning method. The Mean-Teacher [28] approach minimizes
consistency loss on an unlabeled image between the output of a student network and the ensemble of itself, a teacher network. Fixmatch [27] further outperforms Mean-Teacher by performing pseudo-labeling and consistency regularization between images with different degree of perturbations and achieves state-of-the-art performance on several semi-supervised learning benchmarks.

2.3. UDA for Semantic Segmentation

Current methods in UDA for segmentation can be categorized into adversarial and non-adversarial methods. "FCN in the wild" [12] was the first to perform a segmentation task under UDA settings and align both global and local features between domains through adversarial training. Other works [11, 29, 32] tried to align features in one or multiple feature levels. The adversarial alignment process of each category between domains can be treated adaptively [22, 34]. [4] train an image translator in an adversarial way and take its output to perform consistency regularization. [13] applied bidirectional learning in which an image translator and a segmentation model guide each others training in a mutual way. Pseudo-labeling is also performed to enhance performance.

Non-adversarial methods include a variety of techniques. Curriculum DA [57] and PyCDA [19], for example, adopt the concept of curriculum learning and align label distribution over images, landmark superpixels, or regions. CBST [39] utilizes self-training to exploit information from the target domain images. DCAN [34] applies channel-wise alignment to merge the domain gap from both pixel-level and feature-level. Recently, [35] proposed to align pixel-level discrepancy by performing a Fourier transformation. Combined with entropy minimization, pseudo-labeling and model ensemble, their method achieves current state-of-the-art performance.

The work that maybe most resembles ours is by [4]. However, our methods does not rely on a strong image translator that needs to be trained in an adversarial way. Furthermore, our method of adopting consistency regularization is able to exploit information more efficiently from target images by virtue of our high-dimensional perturbation method.

3. Background

BiSIDA uses Adaptive Instance Normalization, or AdaIN [13], which consists of an encoder extracting a fea-
of a source and a target image controlled by a content-style in our framework, we control its output using content-style 

4.1. Continuous Style-induced Image Generator

The student network is denoted by $F$ and the teacher network is essentially the temporal ensemble of the student network so that a radical change in the architecture. The teacher network is formed prediction can be made. The weight of the teacher network can be alleviated and more information prediction can be made. The weight of the teacher network $F^t$ at the $i$th iteration $\theta^i_t$ is updated as the exponential moving average of the weight $\theta^t_i$ of the student network $F^s$, $\theta^i_t = \eta \theta^i_{t-1} + (1-\eta)\theta^t_i$ given an exponential moving average decay $\eta$.

4. Method

In the UDA setting, the dataset from the source domain $S$ includes images denoted by $X^S$ with their corresponding pixel-level annotations denoted by $Y^S$, and the dataset from the target domain $T$ contains images represented by $X^T$ without annotation. The task is to optimize a segmentation model using source dataset $\{(x^S_i, y^S_i)\}_{i=1,...,N^S}$ and target images $\{(x^T_i)\}_{i=1,...,N^T}$ with $C$ common categories. The student network is denoted by $F^s$, the teacher network by $F^t$. The architecture of our model is shown in Figure.

4.2. Target-guided Supervised Learning

Given a source domain dataset $\{(x^S_i, y^S_i)\}_{i=1,...,N^S}$ and a target domain dataset $\{x^t_i\}$, we at first perform a random color space perturbation $A$ on a source domain image $x_s$ to get $A(x_s)$ to enhance the randomness. Images with color space perturbation augmentation will then be passed through our style-induced image generator $G$ to perform style transfer as a stronger augmentation method using a target domain image $x_t$. In the process, a content-style trade-off parameter $\alpha$ is randomly sampled from an uniform distribution $U(0, 1)$ to control the style of the translated image $\hat{x}_s = G(A(x_s), x_t, \alpha)$. The translation process will be enabled with probability of $p_{s\rightarrow t}$ due to the loss of resolution in the translation process so the segmentation model can also be trained on details in images. For the rest of the probability, we simply assign $A(x_s)$ to $\hat{x}_s$. Finally, we compute the supervised loss $L_s$ through a cross entropy loss between the probability map $p_s = F^s(\hat{x}_s)$ and its pixel-level annotation $y_s$:

$$L_s = -\frac{1}{HW} \sum_{m=1}^{H \times W} \sum_{c=1}^{C} y^m_s \log(p^m_s)$$

Augmented by a strong and directed augmentation method, our framework facilitate generalization of model on images with different styles and further enable the adaptation towards the direction of the target domain.

4.3. Source-guided Unsupervised Learning

To start with, we introduce the generation of the pseudo-label that guides the self-learning on the target dataset. Given that our model is more adapted to the source domain where our supervised learning is performed, the quality of produced pseudo-label is generally higher. Consequently, pseudo-label will be computed from target images transferred to the direction of the appearance of the source domain in our framework. Similar to the supervised phase, we at first perform a random color space perturbation $A$ on a target domain image $x_t$ to get $A(x_t)$. Then we augment each augmented target image $A(x_t)$ using $k$ randomly sampled source images $\{x^S_i\}_{k=1}^k$ as style images through our style-induced image generator $G$ with probability of $p_{t\rightarrow s}$ for the consideration of the loss of resolution, and $x_t$ will be transferred to a set of images $\{\hat{x}^t_i\}_{i=1}^k$ generator $G$:

$$G(c, s, \alpha) = g(\alpha \hat{t} + (1-\alpha)t^c),$$

when $\alpha = 0$, the content image will be reconstructed with its own style kept, and when $\alpha = 1$, the output image will be the combination of the style of the style image $s$ and the content of the content image $c$. Finally, we rectify the output by clipping it in the range of $[0, 255]$. 

$$=\text{AdaIN}(t^c, t^s) = \sigma(t^s) \left( \frac{t^c - \mu(t^c)}{\sigma(t^c)} \right) + \mu(t^s),$$

where $\mu(t^s)$ and $\sigma(t^s)$ are the mean and variance of the feature maps.

A typical problem of training a model with pseudo-labels is the instability in the process caused by the uncertain quality of the pseudo-label. It may lead to oscillation in predictions or bias to some easier classes. To stabilize the generation of pseudo-labels, we employ self-ensembling which consists of a segmentation network as student network $F^s$ and a teacher network $F^t$ with the same architecture. The teacher network is essentially the temporal ensemble of the student network so that a radical change in the weight of the teacher network can be alleviated and more informed prediction can be made. The weight of the teacher network $F^t$ at the $i$th iteration $\theta^i_t$ is updated as the exponential moving average of the weight $\theta^t_i$ of the student network $F^s$, $\theta^i_t = \eta \theta^i_{t-1} + (1-\eta)\theta^t_i$ given an exponential moving average decay $\eta$.
$\hat{x}_i^k = G(A(x_i), x_i^k, \alpha)$. Otherwise it will simply be assigned to $\{\hat{x}_i^k\}_{k=1}^k = \{A(x_i)\}$ with $k = 1$. With the stochastic sampling of $k$ source images, our augmentation method performed on the target images will be stronger while their semantic meanings can also be preserved. After the augmentation process, transformed images $\{\hat{x}_i^k\}_{k=1}^k$ will be passed through the teacher model $F^T$ individually to acquire more stable predictions $\hat{y}^T = F^T(\hat{x}_i^k)$. We then average these predictions to get the probability map $p_t$ for the pseudo-label $p_t = \frac{1}{k} \sum_{i=1}^k \hat{y}^T$. Before the generation of pseudo-label, we employ a sharpening function which is widely adopted in various semi-supervised learning problems [1] to re-arrange the distribution of the probability map as follows, given temperature $T$:

$$\text{Sharpening}(p, T)_i := \frac{p_{i}^T}{\sum_{j=1}^{C} p_{j}^T}$$

Finally we can acquire the pseudo-label $q_t$ as $q = \text{argmax}(p_t)$, which can be used to compute the loss of our model on the target images in a supervised manner. Concretely, we augment the same target image $x_t$ using the random color space augmentation $A$ and pass it through the student network $F^s$ to get the probability map $p_t = F^s(A(x_t))$.

In practice, the imbalance and complexity among categories in training datasets will cause the model to bias to popular or easier categories, especially when they are trained in a semi-supervised manner that relies on pseudo-label. To address this problem, we employ a class-balanced reweighting mechanism which guide the unsupervised loss with a prior distribution of categories. We first compute the class prior distribution $d_c$ as the portion of number of pixels over all categories on the source training dataset. Then the reweighting factor $w$ for each class is computed as:

$$w_c = \frac{1}{\lambda d_c^\gamma},$$

where $\lambda$ and $\gamma$ are hyper-parameters. Thus, the final unsupervised loss is presented as:

$$L_u = -\frac{1}{HW} \sum_{m=1}^{H \times W} \mathbb{I}(\max(p_i^m) \geq \tau) \sum_{c=1}^{C} w_c q_i^m c \log(p_i^m c)$$

4.4. Optimization

To summarize, our framework comprises a supervised learning process performed on the labeled source dataset as well as an unsupervised learning process performed on the unlabeled target dataset via consistency regularization and pseudo-labeling. As a result, we can compute the final loss $L$, given the weight of the unsupervised loss $\lambda_u$ in a multi-task learning manner, as follows:

$$L = L_s + \lambda_u L_u.$$  (7)

During the training process, the weight of the student network $F_s$ is updated toward the direction of the gradient computed via back-propagation of the loss $L$, while the weight of the teacher network is updated as the exponential moving average of the student network.

5. Experiments

Extensive experiments are made on two commonly used synthetic-to-real segmentation benchmarks. Comparisons with other SOTA methods and ablation studies are presented to show the effectiveness of our BiSIDA framework. We visualize some segmentation results in Figure [2].

5.1. Datasets

We used two synthetic-to-real benchmarks, GTA5-to-CityScapes and SYNTHIA-to-CityScapes. The CityScapes dataset [5] consists of images of real street scenes of spatial resolution of $2048 \times 1024$ pixels. It includes 2,975 images for training, 500 images for validation, and 1,525 images for testing. In our experiments, we used the 500 validation images as a test set. The GTA5 dataset [23] includes 24,966 synthetic images with a resolution of $1914 \times 1052$ pixels that are obtained from the video game GTA5 along with pixel-level annotations that share all 19 common categories of CityScapes. For the SYNTHIA dataset [24], we used the SYNTHIA-RAND-CITYSCAPES subset, which contains 9,400 rendered images of size $1280 \times 760$ and shares 16 common categories with the CityScapes dataset.

5.2. Network Architecture

Image generator: To keep our continuous style-induced image generator light-weighted and computationally affordable, we adopted the first several layers up to relu4_1 of a fixed pre-trained VGG-19 network as the encoder in our experiments. For the decoder, we reversed the order of layers in the encoder and replaced the pooling layers by nearest up-sampling [13].

Segmentation network: We chose FCN-8s [21] with a VGG16 backbone network, pre-trained with ImageNet.

5.3. Training Protocol

The continuous style-induced image generator was trained using randomly-cropped $640 \times 320$ images, and a batch size of 4. The ADAM optimizer was used with a learning rate of $1 \times 10^{-5}$ and momentum of 0.9 and 0.999. To balance the reconstruction of the content image and the extraction from the style image, we optimized the generator loss in [13] and with style weight 0.1. The segmentation model was trained on images randomly cropped to
5.4. Comparisons with SOTA Methods

We first compare the performance of our BiSIDA on the GTA5-to-CityScapes benchmark with that of other methods using models with VGG-16 as backbone (Table 1). Our results reveal that our method outperforms most competitive methods, especially TGCF-DA+SE, which employs adversarial training as augmentation and achieves state-of-the-art performance by 1.6%.

We present the performance of our and other methods on the SYNTHIA-to-CityScapes benchmark using two metrics (Table 2). Due to the less realistic appearance and fewer training data, this task is more difficult than the previous one. However, our framework outperforms the current state-of-the-art method by a significant margin of 3.8%.

5.5. Ablation Studies

Style-induced image translation and unsupervised learning: We validate the effectiveness of our continuous style-induced image generator as well as our self-supervised learning modules through an ablation study, and explore how they contribute to achieve unsupervised domain adaptation. Results are presented in Table 3. Since our conclusions reveal that our method outperforms most competitive methods, especially TGCF-DA+SE, which employs adversarial training as augmentation and achieves state-of-the-art performance by 1.6%.

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Table 3: Ablation study on the style-induced image translation and unsupervised modules on SYNTHIA to CityScapes benchmark. S2T stands for source domain to target domain image translation, T2S stands for target to source domain image translation. PL stands for pseudo-labeling and SE stands for self-ensembling. GTA represents the mIoU (16 classes) from GTA5 to CityScapes benchmark while SYN represents the mIoU from SYNTHIA to CityScapes benchmark.

| S2T | T2S | PL | SE | GTA  | SYN  |
|-----|-----|----|----|------|------|
| ✓   | ✓   | ✓  | ✓  | 29.3 | 28.9 |
| ✓   | ✓   | ✓  | ✓  | 34.7 | 32.0 |
| ✓   | ✓   | ✓  | ✓  | 31.8 | 31.4 |
| ✓   | ✓   | ✓  | ✓  | 35.1 | 40.2 |
| ✓   | ✓   | ✓  | ✓  | 35.4 | 40.8 |
| ✓   | ✓   | ✓  | ✓  | 39.4 | 41.8 |
| ✓   | ✓   | ✓  | ✓  | 43.2 | 42.1 |

Table 4: Experiments on augmentation methods on SYNTHIA to CityScapes. cAUG represents color perturbation, T2S represents source-guided image translation performed on target domain. mIoU represents averaged mIoU over 16 classes and mIoU* represents that over 13 common classes.

| weight | 0.1 | 0.5 | 1.0 | 5.0 | 10.0 |
|--------|-----|-----|-----|-----|------|
| mIoU   | 37.8| 41.9| 42.1| 39.8| 38.6 |
| mIoU*  | 44.3| 48.1| 48.7| 46.3| 45.2 |

Table 5: Comparison with different unsupervised loss weights $\lambda_u$. mIoU represents averaged mIoU over 16 classes and mIoU* represents that over 13 common classes.

Unsupervised learning weight: In our BiSIDA, the unsupervised loss weight $\lambda_u$ is a crucial hyperparameter to balance the focus of our model between the supervised learning on the labeled source dataset and the self-supervised learning on the unlabeled target dataset. To investigate the effect of using different unsupervised loss weights $\lambda_u$, we conducted experiments on both of them respectively. Additionally, given that our self-supervised learning paradigm is based on the source-guided image translation, we deactivate the self-supervised learning when the source-guided image translation is suppressed in this experiment. As we can observe from the results, the target-guided and source-guided image translation improve the performance on both benchmarks when applied separately. It is also worth noting that the improvement brought by the target-guided image translation is slightly larger since the target domain images translated with styles from source domain cannot provide better self-guidance without having the source domain aligned to the intermediate continuous space. A more significant performance leap is shown when these two translations are performed simultaneously, especially on SYNTHIA-to-CityScapes benchmark where domain gap is larger, showing the advantage of our bidirectional style-induced image translation method.

As for the modules in unsupervised learning phase, we explore the capability of pseudo-labeling and self-ensembling. When pseudo-labeling is disabled, we use the probability maps to compute the self-supervised loss and the problem will be transformed to entropy minimization. Also, the probability maps will be generated by the segmentation model itself if self-ensembling is disabled. From the results, we can find that both pseudo-labeling and self-ensembling contribute to similar degree of enhancement in the performance. Additionally, we may also observe that most of the improvement on GTA5-to-CityScapes comes from the application of self-supervised learning modules while that on SYNTHIA-to-CityScapes, on the other hand, comes from the style-induced image translation process. Based on such observation, we can infer that the challenge in the GTA5-to-CityScapes benchmark is to perform feature-level alignment while for SYNTHIA-to-CityScapes is to perform pixel-level alignment.

Source-guided image translation: In the previous experiment, the unsupervised learning was suppressed when source-guided image translation was not performed. To learn more about the effectiveness of the color-space perturbation and source-guided image translation performed on target images in the unsupervised learning phase, we conducted an ablation study on the SYNTHIA-to-CityScapes benchmark, where pixel-level alignment plays a more important role. We tested these two perturbation methods with all other settings fixed. From the results, shown in Table 4, we find that the introduction of source-guided image translation significantly improves performance by a large margin. On the other hand, the color space perturbation only helps when the source-guided image translation is applied since it enhances the stochasticity in the high-dimensional perturbation process. Otherwise, the color space perturbation is not a sufficiently strong perturbation method for consistency regularization.

5.6. Discussion

Unsupervised learning weight: In our BiSIDA, the unsupervised loss weight $\lambda_u$ is a crucial hyperparameter to balance the focus of our model between the supervised learning on the labeled source dataset and the self-supervised learning on the unlabeled target dataset. To investigate the effect of using different unsupervised loss weights $\lambda_u$.
weights on our method, we conducted an experiment on the SYNTHIA-to-CityScapes benchmark with five different unsupervised loss weights. The results in Table 5 reveal that when the weight is too small, the benefit of unsupervised learning is limited and consistency regularization cannot be performed effectively. When the weight is too large, the model fails to achieve satisfying performance. A reason may be that the model becomes bias prone and prefers an easier category in the early stage of training. Our model reaches the peak of performance when the weight is set to 1.

**Number of style images used in source-guided image translation:** Since we gather the predictions over $k$ images translated from a target domain image with styles from $k$ different source domain style images, the number of images used in the image translation process is another important hyperparameter in our BiSIDA framework. We hereby conduct experiments on SYNTHIA-to-CityScapes benchmark with $k$ value of 1, 2, 4, 6 and 8 respectively. The results are presented in Table 6. As we can see from the table, when the number of style images is smaller, the model cannot achieve a good performance since the stochasticity in the perturbation process is undermined and the quality of the generated pseudo-label is limited. On the other hand, increasing the number of style images might not be a good idea as well since it does not necessarily improve the performance significantly when the performance starts to be saturated despite of the increase in the computational cost.

### 6. Conclusion

We proposed a Bidirectional Style-induced Domain Adaptation (BiSIDA) framework that optimizes a segmentation model via target-guided supervised learning and source-guided unsupervised learning. With the employment of our continuous style-induce image generator, we show the effectiveness of learning from the unlabeled target dataset by providing high-dimensional perturbations for consistency regularization. Furthermore, we also reveal that the alignment between the source and the target domain from both directions without requiring adversarial training is achievable.
References

[1] David Berthelot, Nicholas Carlini, Ian J. Goodfellow, Nicolas Papernot, Avital Oliver, and Colin Raffel. Mixmatch: A holistic approach to semi-supervised learning. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d’Alché-Buc, Emily B. Fox, and Roman Garnett, editors, Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, 8-14 December 2019, Vancouver, BC, Canada, pages 5050–5060, 2019.

[2] Yuhua Chen, Wen Li, Xiaoran Chen, and Luc Van Gool. Learning semantic segmentation from synthetic data: A geometrically guided input-output adaptation approach. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 1841–1850. Computer Vision Foundation / IEEE, 2019.

[3] Yuhua Chen, Wen Li, and Luc Van Gool. ROAD: reality oriented adaptation for semantic segmentation of urban scenes. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pages 7892–7901. IEEE Computer Society, 2018.

[4] Jaehoon Choi, Taekyung Kim, and Changick Kim. Self-ensembling with GAN-based data augmentation for domain adaptation in semantic segmentation. In 2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019, pages 6829–6839. IEEE, 2019.

[5] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The Cityscapes dataset for semantic urban scene understanding. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 3213–3223. IEEE Computer Society, 2016.

[6] Vincent Dumoulin, Jonathon Shlens, and Manjunath Kudlur. A learned representation for artistic style. In 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net, 2017.

[7] Geoff French, Timo Aila, Samuli Laine, Michal Mackiewicz, and Graham Finlayson. Semi-supervised semantic segmentation needs strong, high-dimensional perturbations. arXiv preprint arXiv:1906.01916, 2019.

[8] Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge. Image style transfer using convolutional neural networks. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 2414–2423. IEEE Computer Society, 2016.

[9] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. Generative adversarial networks. CoRR, abs/1406.2661, 2014.

[10] Yves Grandvalet and Yoshua Bengio. Semi-supervised learning by entropy minimization. In Advances in Neural Information Processing Systems 17 [Neural Information Processing Systems, NIPS 2004, December 13-18, 2004, Vancouver, British Columbia, Canada], pages 529–536, 2004.

[11] Judy Hoffman, Eric Tzeng, Taesung Park, Jun-Yan Zhu, Phillip Isola, Kate Saenko, Alexei A. Efros, and Trevor Darrell. CyCADA: Cycle-consistent adversarial domain adaptation. In Jennifer G. Dy and Andreas Krause, editors, Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018, volume 80 of Proceedings of Machine Learning Research, pages 1994–2003. PMLR, 2018.

[12] Judy Hoffman, Dequan Wang, Fisher Yu, and Trevor Darrell. FCNs in the Wild: Pixel-level adversarial and constraint-based adaptation. CoRR, abs/1612.02649, 2016.

[13] Xun Huang and Serge J. Belongie. Arbitrary style transfer in real-time with adaptive instance normalization. In IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, pages 1510–1519. IEEE Computer Society, 2017.

[14] Xun Huang, Ming-Yu Liu, Serge J. Belongie, and Jan Kautz. Multimodal unsupervised image-to-image translation. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss, editors, Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part III, volume 11207 of Lecture Notes in Computer Science, pages 179–196. Springer, 2018.

[15] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II, volume 9906 of Lecture Notes in Computer Science, pages 694–711. Springer, 2016.

[16] Dong-Hyun Lee. Pre-trained real-time texture model. CoRR abs/1406.2661, 2014.

[17] Chuan Li and Michael Wand. Precomputed real-time texture synthesis with Markovian generative adversarial networks. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part III, volume 9907 of Lecture Notes in Computer Science, pages 3213–3223. Springer, 2016.

[18] Yuncheng Li, Yu Lu, and Nuno Vasconcelos. Bidirectional learning for domain adaptation of semantic segmentation. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 6936–6945. Computer Vision Foundation / IEEE, 2019.

[19] Qing Liu, Lixin Duan, Fengmiao Lv, and Boqing Gong. Constructing self-motivated pyramid curriculums for cross-domain semantic segmentation: A non-adversarial approach. In 2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019, pages 6757–6766. IEEE, 2019.

[20] Ming-Yu Liu, Thomas Breuel, and Jan Kautz. Unsupervised image-to-image translation networks. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors,
Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA, pages 700–708, 2017.

[21] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015, pages 3431–3440. IEEE Computer Society, 2015.

[22] Yawei Luo, Liang Zheng, Tao Guan, Junqing Yu, and Yi Yang. Taking a closer look at domain shift: Category-level adversaries for semantics consistent domain adaptation. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 2507–2516. Computer Vision Foundation / IEEE, 2019.

[23] Stephan R. Richter, Vibhav Vineet, Stefan Roth, and Vladlen Koltun. Playing for data: Ground truth from computer games. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part II, volume 9906 of Lecture Notes in Computer Science, pages 102–118. Springer, 2016.

[24] Germán Ros, Laura Sellart, Joanna Materzynska, David Vázquez, and Antonio M. López. The SYNTHIA dataset: A large collection of synthetic images for semantic segmentation of urban scenes. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 3234–3243. IEEE Computer Society, 2016.

[25] Swami Sankaranarayanan, Yogesh Balaji, Arpit Jain, Ser-Nam Lim, and Rama Chellappa. Learning from synthetic data: Addressing domain shift for semantic segmentation. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pages 3752–3761. IEEE Computer Society, 2018.

[26] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. In Yoshua Bengio and Yann LeCun, editors, 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.

[27] Kihyuk Sohn, David Berthelot, Chun-Liang Li, Zizhao Zhang, Nicholas Carlini, Ekin D Cubuk, Alex Kurakin, Han Zhang, and Colin Raffel. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. arXiv preprint arXiv:2001.07685, 2020.

[28] Antti Tarvainen and Harri Valpola. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA, pages 1195–1204, 2017.

[29] Yi-Hsuan Tsai, Wei-Chih Hung, Samuel Schultet, Kihyuk Sohn, Ming-Hsuan Yang, and Manmohan Chandraker. Learning to adapt structured output space for semantic segmentation. In 2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018, pages 7472–7481. IEEE Computer Society, 2018.

[30] Dmitry Ulyanov, Vadim Lebedev, Andrea Vedaldi, and Victor S. Lempitsky. Texture networks: Feed-forward synthesis of textures and stylized images. In Maria-Florina Balcan and Kilian Q. Weinberger, editors, Proceedings of the 33rd International Conference on Machine Learning, ICML 2016, New York City, NY, USA, June 19-24, 2016, volume 48 of JMLR Workshop and Conference Proceedings, pages 1349–1357. JMLR.org, 2016.

[31] Dmitry Ulyanov, Andrea Vedaldi, and Victor S. Lempitsky. Improved texture networks: Maximizing quality and diversity in feed-forward stylization and texture synthesis. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 4105–4113. IEEE Computer Society, 2017.

[32] Tuan-Hung Vu, Himalaya Jain, Maxime Bucher, Matthieu Cord, and Patrick Pérez. ADVENT: Adversarial entropy minimization for domain adaptation in semantic segmentation. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pages 2517–2526. Computer Vision Foundation / IEEE, 2019.

[33] Zhonghao Wang, Mo Yu, Yunchoa Wei, Rogerio Feris, Jinxun Xiong, Wen-mei Hwu, Thomas S Huang, and Honghui Shi. Differential treatment for stuff and things: A simple unsupervised domain adaptation method for semantic segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12635–12644, 2020.

[34] Zuxuan Wu, Xintong Han, Yen-Liang Lin, Mustafa Gökhan Uzunbas, Tom Goldstein, Ser-Nam Lim, and Larry S. Davis. DCAN: dual channel-wise alignment networks for unsupervised scene adaptation. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss, editors, Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part V, volume 11209 of Lecture Notes in Computer Science, pages 535–552. Springer, 2018.

[35] Yanchao Yang and Stefano Soatto. FDA: Fourier domain adaptation for semantic segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4085–4095, 2020.

[36] Zili Yi, Hao (Richard) Zhang, Ping Tan, and Minglun Gong. DualGAN: Unsupervised dual learning for image-to-image translation. In IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, pages 2868–2876. IEEE Computer Society, 2017.

[37] Yang Zhang, Philip David, and Boqing Gong. Curricular data: Addressing domain shift for semantic segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 102–118. Springer, 2016.

[38] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. Unpaired image-to-image translation using cycle-
consistent adversarial networks. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 2242–2251. IEEE Computer Society, 2017.

[39] Yang Zou, Zhiding Yu, B. V. K. Vijaya Kumar, and Jinsong Wang. Unsupervised domain adaptation for semantic segmentation via class-balanced self-training. In Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss, editors, *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part III*, volume 11207 of *Lecture Notes in Computer Science*, pages 297–313. Springer, 2018.