GET AWAY FROM STYLE: CATEGORY-GUIDED
DOMAIN ADAPTATION FOR SEMANTIC SEGMENTATION

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ABSTRACT

Unsupervised domain adaptation (UDA) becomes more and more popular in tackling real-world problems without ground truth of the target domain. Though a mass of tedious annotation work is not needed, UDA unavoidably faces the problem how to narrow the domain discrepancy to boost the transfering performance. In this paper, we focus on UDA for semantic segmentation task. Firstly, we propose a style-independent content feature extraction mechanism to keep the style information of extracted features in the similar space, since the style information plays a extremely slight role for semantic segmentation compared with the content part. Secondly, to keep the balance of pseudo labels on each category, we propose a category-guided threshold mechanism to choose category-wise pseudo labels for self-supervised learning. The experiments are conducted using GTA5 as the source domain, Cityscapes as the target domain. The results show that our model outperforms the state-of-the-arts with a noticeable gain on cross-domain adaptation tasks.

Index Terms— unsupervised domain adaptation, semantic segmentation, self-supervised learning

1. INTRODUCTION

As a significant task in computer vision, semantic segmentation aims at producing pixel-wise labels for images, and has been widely applied to many different scenes such as auto driving and scene understanding [1, 2]. Despite the huge success, without enough labeled training samples, semantic segmentation usually yields unsatisfying performance. What’s more, it’s very difficult to apply supervised semantic segmentation to the emergence of diverse applications since preparing the pixel-wise annotation is time-consuming and expensive. Therefore, supervised learning based methods are unable to meet the requirements of current image segmentation tasks.

Recently, domain adaptation (DA) for semantic segmentation becomes more and more popular, which aims to eliminate the gap between two datasets. The main methods include adversarial learning and self-supervised learning (SSL). The former focuses on alleviating the discrepancy from input level, feature level and output level. While the core of self-supervised learning is pseudo labeling mechanism. For example, BDL [3] directly specifies a fixed confidence threshold for all categories and only those prediction with confidence scores above this threshold are chosen as available pseudo labels. However, the model’s performances on different categories are different because of the uneven prior distribution of different categories. Hence, the fixed threshold mechanism makes the number of pseudo labels for each category vary a lot, which unavoidably hurts the final segmentation performance.

In this paper, we firstly introduce a style-independent feature extraction mechanism that weakens style information for both domains to reduce the domain gap while maintains the content information invariant, based on the observation that the segmentation performance mainly depends on the content information. On the other hand, we propose a category-guided threshold method to construct pseudo labels for self-supervised learning, where the variable confidence threshold will be learned for different categories according to their respective contributions. The overall flowchart is displayed in Fig. 1.
The framework of our proposed model is shown in Fig. 2. Firstly, the model is trained on both domain data, where the style information between both domains is aligned as close as possible. It is worth noticing that data of the target domain are lack of pixel-wise domain annotations. Then pseudo labels are chosen based on the prediction of pretrained model on target domain (blue line). At last, self-supervised learning is conducted on the target domain by virtue of chosen pseudo labels (red line).

2.2. Pseudo labeling for target domain

Here we propose a category-guided threshold method for SSL. The idea is based on the hypothesis that the pretrained model’s performances on different categories are different because of the uneven prior distribution of different categories. For example, the category “road” accounts a lot while the category “train” is just the reverse. Therefore, the confidence threshold should vary among different categories. Based on the clustering method of [4] where the threshold is defined by the Euclidean distance between target features and category centroids, we consider that each intra-category feature makes different contributions to the category centroids because the prediction confidence varies. Consequently based on the given model’s output on the target domain $P_t \in \mathbb{R}^{H_t \times W_t \times C}$, we firstly define a confidence-weighted target domain-based category centroid $f^c \in \mathbb{R}^C$:

$$f^c = \frac{1}{|P^c|} \sum_{h=1}^{H_t} \sum_{w=1}^{W_t} \sum_{c=1}^{C} \hat{y}^h_w^c P^c_t$$

where $P^c$ denotes the collection of prediction confidence of all pixels which are decided as $th$ category, namely $P^c = \{p^h_w^c, c = \arg \max_p p^h_w^c\}$, $|P^c|$ denotes the number of pixels in $P^c$. $\hat{y}_c^h = 1_{c=\arg\max_c p^h_w^c}$, $1$ is the binary indicator function. Given $f^c$ in each category, our threshold is based on the entropy distance. The entropy of prediction vector at
the $h$th row and $w$th column $P_{h,w}^{t} \in \mathbb{R}^{C}$ is:

$$E(P_{h,w}^{t}) = - \sum_{i=1}^{C} P_{i}^{h,w} \log P_{i}^{h,w} \quad (2)$$

The entropy of category centroid $f_{c}$, namely $E(f_{c})$ is similar with Equation (2). Intuitively, $E(P_{h,w}^{t})$ decreases as the max confidence in $P_{h,w}^{t}$ increases, consequently we choose entropy-based threshold. Here we defined an indicator variable $m_{h,w}^{t}$ to decide whether the prediction on current position is chosen as available pseudo labels:

$$m_{h,w}^{t} = I[E(P_{h,w}^{t}) < E(f_{c}) - \Delta] \quad (3)$$

where $\Delta$ is a manually fixed hyperparameter to control the threshold for each category. When $\Delta$ increases, the number of available pseudo labels decreases while the model will have higher prediction confidence and vice versa.

### 2.3. Loss Functions

As mentioned above, the training process includes two phases: domain adaptation training and self-supervised learning. Domain adaptation training process utilizes the following three losses:

**Segmentation Loss.** Here cross entropy function is applied to penalize the error between prediction $\hat{y}_{s} \in \mathbb{R}^{H_{s} \times W_{s} \times C}$ and one-hot ground truth $y_{s} \in \mathbb{R}^{H_{s} \times W_{s} \times C}$:

$$\mathcal{L}_{\text{seg}} = - \frac{1}{H_{s} \times W_{s}} \sum_{h=1}^{H_{s}} \sum_{w=1}^{W_{s}} \sum_{c=1}^{C} y_{s}^{h,w} \log \hat{y}_{s}^{h,w} \quad (4)$$

**Output-based Domain Adaptation Loss.** Consistent with BDL [3], we also leverage the original GAN loss introduced by Goodfellow [5] as $\mathcal{L}_{\text{adv,seg}}$ to achieve domain adaptation on models’ output between the source domain and the target domain.

**Style Loss.** To help the encoder module $E_{c}$ extract style-independent features, $\mathcal{L}_{\text{style}}$ also utilizes the original loss to force the style information on the source domain $S_{sm}$ close that on the target domain $S_{tm}$.

During the self-supervised learning process, similar with $\mathcal{L}_{\text{seg}}$, **Self-supervised Loss** $\mathcal{L}_{\text{ssl}}$ also utilizes cross entropy function to make the prediction on the target domain $\hat{y}_{t} \in \mathbb{R}^{H_{t} \times W_{t} \times C}$ as close as possible to pseudo labels $y_{t} \in \mathbb{R}^{H_{t} \times W_{t} \times C}$:

$$\mathcal{L}_{\text{ssl}} = - \frac{1}{H_{t} \times W_{t}} \sum_{h=1}^{H_{t}} \sum_{w=1}^{W_{t}} \sum_{c=1}^{C} m_{h,w}^{t} y_{t}^{h,w} \log P_{t}^{h,w} \quad (5)$$

### 3. EXPERIMENTAL RESULTS

Here we evaluate our model on “GTA5 to Cityscapes” task. Both datasets are briefly introduced as follows:

#### 3.1. Datasets

GTA5 [6] includes 24966 synthetic images collected from the game engine. GTA5 have 19-category pixel-accurate annotations compatible with target domain Cityscapes [7].

Cityscapes [7] collected from streetscapes in 50 different Germany cities includes training set with 2975 images, validation set with 500 images, testing set with 1525 images. The former two sets contain pixel-wise semantic label maps, while the annotations of testing set are missing. To validate the performance of our model, during testing phase, we use validation set instead of testing set.

#### 3.2. Network Architectures

The whole framework of our model is shown in Fig. 2. The encoder module follows DeepLab V2 [16] using ResNet101 [8] as backbone. The parameters are tuned based on weights pretrained on ImageNet [17]. The discriminator $D_{c}$ for output-based domain adaptation applies PatchGAN [18] to output a 16x downsampled confidence probability map relative to the input semantic segmentation map. The style discriminator $D_{f}$ also utilizes PatchGAN [18], but it applies four 1-D convolutional layers with kernel size of 4. All modules are parameter-shared except style discriminator $D_{f}$ and segmentation discriminator $D_{c}$.

#### 3.3. Implementation Details

It is worth noticing that the all game-synthetic source domain images (GTA5 datasets) are firstly translated by CycleGAN [19] module of BDL model [3]. SGD optimizer with momentum $= 0.9$ is used to train encoder $E_{c}$ and decoder modules, where encoder $E_{c}$ adopts learning rate $lr = 2.5 \times 10^{-4}$, the decoder adopts $lr = 2.5 \times 10^{-3}$. For style discriminator $D_{f}$ and segmentation discriminator, Adam optimizer is utilized with $\beta = (0.9, 0.99)$ and $lr = 1 \times 10^{-4}$. In addition, “poly” policy for learning rate update with maxstep $= 250,000$ and power $= 0.9$ is introduced to encoder $E_{c}$ and decoder. Style discriminator $D_{f}$ and segmentation discriminator $D_{c}$ utilize exponential decay policy to update $lr$, where decay rate $= 0.1$, decay steps $= 50000$. Two rounds of SSL is applied in our experiments.

#### 3.4. Results

**Quantitative results:** The results of different related baselines are shown in Table 1. Consistent with previous work, mIoU metric on 19 specific categories is adopted, where the best result on each category is highlighted in bold. Our model has a gain of 1.7 in overall mIoU rather than the state-of-the-art BDL. Though AdaptSegNet [10] and CLAN [14] are also based on feature-aligned mechanism, however, they do not constrain the extracted features in the similar style space. In
addition, global reconstruction loss and adversarial loss increases the complexity and instability of these two models. In contrast, our style-independent encoder module introduces adversarial mechanism on style information, it is lightweight and easy to train. The results also demonstrate the effectiveness of our method.

Ablation Study: Our main contributions consists of a novel pseudo labeling mechanism for SSL and add style constrain to achieve feature-based style adaption. Table 2 illustrates the influence of each part, where “original” denotes the model without these two parts, “sc” implies style constrain and “SSL once” and “SSL twice” indicate using SSL once and twice, respectively. It can be seen that style constrain help improve the performance with a gain of 0.9. In addition, SSL is also helpful to boost performance since “SSL once” brings a gain of 3.0 and “SSL twice” achieves 50.2 which is 4.7% superior to that without SSL module.

Table 2: Ablation study on SSL and style constrain

| GTA5 → Cityscapes | model | mIoU |
|-------------------|-------|------|
| original          | 44.6  |
| original + sc     | 45.5  |
| original + sc + SSL once | 48.3  |
| original + sc + SSL twice | 50.2  |

Qualitative results: Some segmentation examples are shown in Fig. 3. It can be clearly observed that our method subjectively outperforms the state-of-the-art BDL, making less obvious prediction errors.

4. CONCLUSIONS

In this paper, we proposed a style-independent content encoder mechanism and category-guided threshold method for self-supervised learning on cross-domain semantic segmentation task, where the prior features on source domain are not needed. The former utilizes adversarial training to help the style distribution of extracted features become as close as possible. The latter makes the use of prior semantic distribution to dynamically choose threshold for self-supervised training on the target domain images rather than in a artificial threshold manner. A series of experiments have shown the effectiveness and superiority of our proposed model, which demonstrates the scientificity of our method.

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