

# Prototypical Pseudo Label Denoising and Target Structure Learning for Domain Adaptive Semantic Segmentation

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## Abstract

*Self-training is a competitive approach in domain adaptive segmentation, which trains the network with the pseudo labels on the target domain. However inevitably, the pseudo labels are noisy and the target features are dispersed due to the discrepancy between source and target domains. In this paper, we rely on representative prototypes, the feature centroids of classes, to address the two issues for unsupervised domain adaptation. In particular, we take one step further and exploit the feature distances from prototypes that provide richer information than mere prototypes. Specifically, we use it to estimate the likelihood of pseudo labels to facilitate online correction in the course of training. Meanwhile, we align the prototypical assignments based on relative feature distances for two different views of the same target, producing a more compact target feature space. Moreover, we find that distilling the already learned knowledge to a self-supervised pretrained model further boosts the performance. Our method shows tremendous performance advantage over state-of-the-art methods. The code is available at <https://github.com/microsoft/ProDA>.*

## 1. Introduction

Despite the remarkable success of deep learning in computer vision, attaining high performance requires vast quantities of data. It is usually expensive to obtain labels for dense prediction tasks, *e.g.*, semantic segmentation. Therefore, people think of leveraging abundant photo-realistic synthetic images with freely generated labels [44, 45]. However, deep neural networks are notoriously sensitive to the domain misalignment that any nuanced unrealism in rendered images will induce poor generalization to real data. To address this issue, domain adaptation techniques aim to transfer the knowledge learned from the synthetic images (source domain) to real ones (target domain) with minimal performance loss. In this work, we focus on the challenging

case, *unsupervised domain adaptation* (UDA), where there are no accessible labels in the target domain. Specifically, we solve the UDA problem for semantic segmentation.

Rather than explicitly aligning the distributions of the source and target domains as most predominant solutions [6, 27, 48, 54, 58], self-training [34, 69, 75, 76] has recently emerged as a simple yet competitive approach in the UDA task. This is achieved by iteratively generating a set of pseudo labels based on the most confident predictions on the target data and then relying on these pseudo labels to retrain the network. In this way, the network gradually learns the adaptation in the self-paced curriculum learning. However, the performance still lags far behind the supervised learning or semi-supervised learning using a few labeled samples, making unsupervised domain adaptation impractical in real scenarios.

After dissecting the self-training, we find two key ingredients are lacking in previous works. First, typical practice [75, 76] suggests selecting the pseudo labels according to a strict confidence threshold, while high scores are not necessarily correct, making the network fail to learn reliable knowledge in the target domain. Second, due to the domain gap, the network is prone to produce dispersed features in the target domain. It is likely that for target data, the closer to the source distribution, the higher the confidence score. As a result, data lying far from the source distribution (*i.e.* low scores) will never be considered during the training.

In this paper, we propose to online denoise the pseudo labels and learn a compact target structure to address the above two issues respectively. We resort to prototypes, *i.e.*, the class-wise feature centroids, to accomplish the two tasks. (1) We rectify the pseudo labels by estimating the class-wise likelihoods according to its relative feature distances to all class prototypes. This depends on a practical assumption that the prototype lies closer to the true centroid of the underlying cluster, implying that false pseudo labels are in the minority. It is worth noting that the prototypes are computed on-the-fly, and thus the pseudo labels are progressively corrected throughout the training. (2) We draw inspiration from the Deepcluster [4] to learn the intrinsic structure of the target domain. Instead of directly learning

\*This work is done during the first author's internship at Microsoft Research Asia.

from the cluster assignment, we propose to align soft prototypical assignments for different views of the same target, which produces a more compact target feature space. We refer to our method *ProDA* as we heavily rely on prototypes for domain adaption.

Supercharged with the above techniques, our ProDA can demonstrate clear superiority over prior works. Moreover, we find that the domain adaptation can also benefit from the task-agnostic pretraining — distilling the knowledge to a self-supervised model [10, 23] further boosts the performance to a record high. Our contributions can be summarized as follows:

- We propose to online correct the soft pseudo labels according to the relative feature distances to the prototypes, whereas the prototypes are also updated on-the-fly. The network thereby learns from denoised pseudo labels throughout the training.
- We propose to rely on the soft prototypical assignment to teach the learning of an augmented view so that a compact target feature space can be obtained.
- We show that distilling the already-learned knowledge to a self-supervised pretrained model further improves the performance significantly.
- The proposed ProDA substantially outperforms state-of-the-art. With the Deeplabv2 [8] network, our method achieves the Cityscapes [13] segmentation mIOU by 57.5 and 55.5 when adapting from the GTA5 [44] and SYNTHIA [45] datasets, improving the adaption gain<sup>1</sup> by 52.6% and 58.5% respectively over the prior leading approach.

## 2. Related Work

**Unsupervised domain adaptation.** As suggested by the theoretical analysis [3], domain alignment methods focus on reducing the distribution mismatch by optimizing some divergence [30, 35] or adopting adversarial training [20, 40] at either the image level [1, 12, 19, 26, 49, 63, 68], the intermediate feature level [6, 27, 48, 58] or the output level [54]. However, aligning global distribution cannot guarantee a small expected error on the target domain [7, 28, 72]. Recent approaches [17, 36, 59] attempt to align distribution in a class-wise manner, aiming to promote fine-grained feature alignment. In fact, it is unnecessary to rigorously align the distribution as long as the features are well-separated.

On the other hand, techniques originated from semi-supervised learning (SSL) offer competitive performance. Entropy minimization and its variants [9, 46, 57] encourage the network to make sharp predictions on the unlabeled target data, and the resulting network is prone to be over-confident on false predictions. To address this, self-training [75] that leverages iteratively generated pseudo la-

els has been proposed. However, the pseudo labels are inevitably noisy. Hence, [76] adds confidence regularization terms to the network, while [73] explicitly estimates a prediction confidence map to reduce the side-effect of unreliable labels. In [34], self-training and image translation are found mutually beneficial. A recent work [69] generates pseudo labels based on categorical centroids and enforces feature alignment in category level. However, these self-training approaches are optimized in an alternative manner — labels are fixed over the course of representation learning, and only get updated after the entire training stage. In contrast, we propose an online pseudo label updating scheme where the false predictions are rectified according to the prototypical context estimated in the target domain.

**Unsupervised representation learning.** A surge of research interest has been recently attracted to unsupervised learning [42]. Early efforts dedicate to designing pretext tasks [16, 18, 29, 70], which are proven beneficial for UDA when utilized as auxiliary tasks on target data [47, 53, 66]. The gap with supervised learning is considerably closed by a few prominent works [10, 23] that build on contrastive learning. A series of recent works [2, 5, 21, 39] find that the network is able to learn rich semantic features as long as they are consistent under different augmented views. Yet these methods assume image-wise discrimination [64], making them unsuitable for learning pixel-level semantics for segmentation tasks. In this work, we find the marriage of consistent learning and cluster-based representation learning fits remarkably well with the UDA problem and learn a compact target feature space inspired from Deepcluster [4]. Differently, we align relative feature distances rather than cluster assignments for different augmented views.

**Learning from noisy labels.** Self-training even with careful thresholding still gives noisy pseudo labels. Therefore, this work is also motivated by emerging techniques [52] of learning from noisy labels. A straightforward way is to design robust losses [62, 71], but these methods fail to handle real-world noisy data. Self-label correction [51, 61, 73, 74] is a more appealing approach. A typical manner [31, 38] under this category is to train two or multiple learners simultaneously and exploit their agreement of predictions to measure the label reliability. Our proposed pseudo label denoising is more close to [22] which online corrects the incorrect labels according to the prototypes determined by some complex heuristics. In contrast, we are able to compute prototypes on-the-fly. On the other hand, knowledge distillation (KD) [25, 32, 33, 65] is proven effective to transfer clean knowledge from the teacher model to the student even when the network learns from itself [10, 32]. In this work, we demonstrate that the knowledge distillation to a self-supervised pretrained model further pushes the performance limit in our task.

<sup>1</sup>The mIoU gain relative to the model without domain adaption.

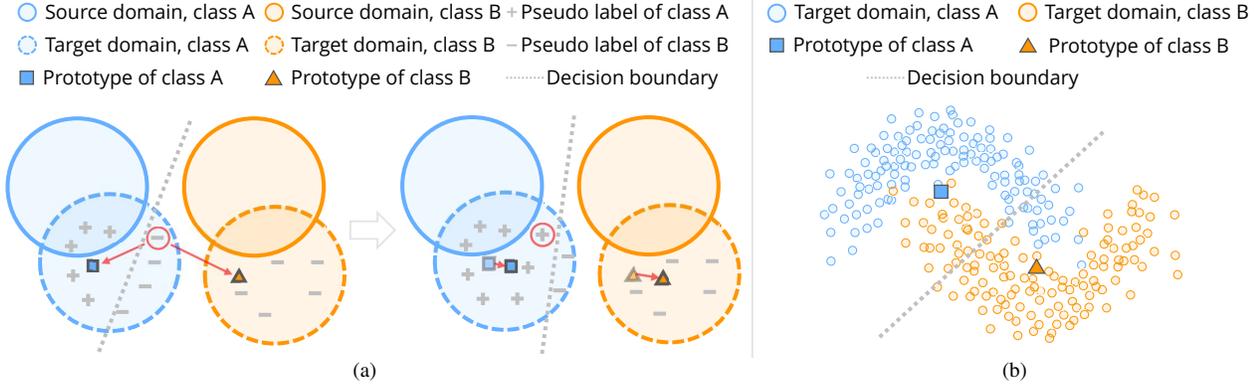


Figure 1: **We illustrate the existing issues of self-training by visualizing the feature space.** (a) The decision boundary (dashed line) crosses the distribution of the target data and induces incorrect pseudo label predictions. This is because the network is unaware of the target distribution when generating pseudo labels. To solve this, we calculate the prototypes of each class on-the-fly and rely on these prototypes to online correct the false pseudo labels. (b) The network may induce dispersed feature distribution in the target domain which is hardly differentiated by a linear classifier.

### 3. Preliminary

Given the source dataset  $\mathcal{X}_s = \{x_s\}_{j=1}^{n_s}$  with segmentation labels  $\mathcal{Y}_s = \{y_s\}_{j=1}^{n_s}$ , we aim to train a segmentation network that learns the knowledge from the source and is expected to achieve low risk on the target dataset  $\mathcal{X}_t = \{x_t\}_{j=1}^{n_t}$  without accessing its ground truth labels  $\mathcal{Y}_t$ , where  $\mathcal{Y}_s$  and  $\mathcal{Y}_t$  share the same  $K$  classes. Generally, the network  $h = g \circ f$  can be regarded as a composite of a feature extractor  $f$  and a classifier  $g$ .

Typically, the networks trained on the source data, *i.e.*, the source model, cannot generalize well to the target data due to the domain gap. To transfer the knowledge, traditional self-training techniques [75, 76] optimize the categorical cross-entropy (CE) with pseudo labels  $\hat{y}_t$ :

$$\ell_{ce}^t = - \sum_{i=1}^{H \times W} \sum_{k=1}^K \hat{y}_t^{(i,k)} \log(p_t^{(i,k)}), \quad (1)$$

where  $p_t = h(x_t)$  and  $p_t^{(i,k)}$  represents the softmax probability of pixel  $x_t^{(i)}$  belonging to the  $k$ th class. Typically, one can use the most probable class predicted by the source network as pseudo labels:

$$\hat{y}_t^{(i,k)} = \begin{cases} 1, & \text{if } k = \arg \max_{k'} p_t^{(i,k')} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Here we denote this conversion from the soft predictions to hard labels by  $\hat{y}_t = \xi(p_t)$ . In practice, since the pseudo labels are noisy, only the pixels whose prediction confidence is higher than a given threshold are accounted for the pseudo label retraining. In this way, the network in the target domain is bootstrapped by learning from pseudo labels that only get update till convergence, and then the updated labels are employed for the next training stage.

### 4. Method

#### 4.1. Prototypical pseudo label denoising

We conjecture that updating the pseudo label after one training stage is too late as the network has already overfitted the noisy labels. While simultaneously updating the pseudo labels and the network weights, on the other hand, is prone to give trivial solutions.

In this work, we propose a simple yet effective approach to online update the pseudo labels while avoiding trivial solutions. The key is to fix the soft pseudo labels and progressively weight them by class-wise probabilities, with the update in accordance with the freshly learned knowledge. Formally, we propose to use the weighted pseudo labels for self-training:

$$\hat{y}_t^{(i,k)} = \xi(\omega_t^{(i,k)} p_{t,0}^{(i,k)}), \quad (3)$$

where  $\omega_t^{(i,k)}$  is the weight we propose for modulating the probability and changes as the training proceeds. The  $p_{t,0}^{(i,k)}$  is initialized by the source model and remains fixed throughout the learning process, thus serving as a boilerplate for the subsequent refinement.

We exploit the distances from the prototypes to gradually rectify the pseudo labels. Let  $f(x_t)^{(i)}$  represent the feature of  $x_t$  at index  $i$ . If it is far from the prototype  $\eta^{(k)}$ , the feature centroids of class  $k$ , it is more probable that the learned feature is an outlier, hence we downweight its probability of being classified into  $k$ th category. Concretely, we define the modulation weight in Equation 3 as the softmax over feature distances to prototypes:

$$\omega_t^{(i,k)} = \frac{\exp(-\|f(x_t)^{(i)} - \eta^{(k)}\|/\tau)}{\sum_{k'} \exp(-\|f(x_t)^{(i)} - \eta^{(k')}\|/\tau)}, \quad (4)$$

where  $\tilde{f}$  denotes the momentum encoder [23] of the feature extractor  $f$ , as we desire a reliable feature estimation for  $x_t$ , and  $\tau$  is the softmax temperature empirically set to  $\tau = 1$ . In this equation,  $\omega_t^{(i,k)}$  actually approximates the trust confidence of  $x_t^{(i)}$  belonging to the  $k$ th class. Note that this equation has a close formulation in [43, 50] that shows promise in few-shot learning. Instead of relying on the prototypes for classifying new samples, we attempt to correct the mistakes in the pre-generated pseudo labels according to this prototypical context.

**Prototype computation.** The proposed label updating scheme requires to compute the prototypes on-the-fly. At first, prototypes are initialized according to the predicted pseudo labels  $\hat{y}_t$  for target domain images, which is

$$\eta^{(k)} = \frac{\sum_{x_t \in \mathcal{X}_t} \sum_i f(x_t)^{(i)} * \mathbb{1}(\hat{y}_t^{(i,k)} == 1)}{\sum_{x_t \in \mathcal{X}_t} \sum_i \mathbb{1}(\hat{y}_t^{(i,k)} == 1)}, \quad (5)$$

where  $\mathbb{1}$  is the indicator function. However, such prototype calculation is computational-intensive during training. To address this, we estimate the prototypes as the moving average of the cluster centroids in mini-batches, so that we can track the prototypes that slowly move. Specifically, in each iteration, the prototype is estimated as,

$$\eta^{(k)} \leftarrow \lambda \eta^{(k)} + (1 - \lambda) \eta'^{(k)}, \quad (6)$$

where  $\eta'^{(k)}$  is the mean feature of class  $k$  calculated within the current training batch from the momentum encoder, and  $\lambda$  is the momentum coefficient which we set to 0.9999.

**Pseudo label training loss.** With the online refined pseudo labels, we are able to train the network for target domain segmentation. Instead of using a standard cross-entropy, we adopt a more robust variant, symmetric cross-entropy (SCE) loss [62], to further enhance the noise-tolerance to stabilize the early training phase. Specifically, we enforce

$$\ell_{sce}^t = \alpha \ell_{ce}(p_t, \hat{y}_t) + \beta \ell_{ce}(\hat{y}_t, p_t), \quad (7)$$

where  $\alpha$  and  $\beta$  are balancing coefficients and set to 0.1 and 1 respectively. Following [62], we clamp the one-hot label  $\hat{y}_t$  to  $[1e-4, 1]$ , so as to avoid the numerical issue of  $\log 0$ .

**Why are prototypes useful for label denoising?** First, the prototypes are less sensitive to the outliers that are assumed to be the minority. Second, prototypes treat different classes equally regardless of their occurrence frequency, which is particularly useful to semantic segmentation as class imbalance poses a challenging issue. Experiments show that the proposed label denoising considerably improves the performance for hard classes. More importantly, prototypes help to gradually rectify the incorrect pseudo labels, which we illustrate using a toy example. As shown in Figure 1(a), the classifier  $g$ , may still give a decision boundary crossing the target clusters and yields false pseudo labels. Training

against them cannot further improve the classifier. The prototypes, on the other hand, downweight the false pseudo labels near the decision boundary of  $g$  as they are far from the prototypes. In this way, the network improves, and in turn, makes the prototypes closer to the true cluster centroid.

## 4.2. Structure learning by enforcing consistency

Pseudo labels can be denoised when the feature extractor  $f$  generates compact target features. However, due to the domain gap, the generated target distribution is more likely to be dispersed, as shown in Figure 1(b). In this case, the prototypes fail to rectify the labels of the data whose features lie in the far end of the cluster even when the target features from the source model are well-separated. A recent work [41] has identified this issue in semi-supervised learning, but the issue becomes worse in domain adaptation since a few pseudo labeled data cannot cover the entire distribution in the target domain.

To this end, we aim to learn the underlying structure of target domain, and hope to obtain more compact features that are friendly to the pseudo label refinement. Motivated by the recent success of unsupervised learning, we perform simultaneously clustering and representation learning. As opposed to learning against the prototypical assignment, we use the prototypical assignment under weak augmentation to guide the learning for the strong augmented view. Specifically, let  $\mathcal{T}(x_t)$  and  $\mathcal{T}'(x_t)$  respectively denote the weak and strong augmented views for  $x_t$ . We make use of the momentum encoder  $\tilde{f}$  to generate a reliable prototypical assignment for  $\mathcal{T}(x_t)$  which is,

$$z_{\mathcal{T}}^{(i,k)} = \frac{\exp(-\|\tilde{f}(\mathcal{T}(x_t))^{(i)} - \eta^{(k)}\|/\tau)}{\sum_{k'} \exp(-\|\tilde{f}(\mathcal{T}(x_t))^{(i)} - \eta^{(k')}\|/\tau)}, \quad (8)$$

where  $\tau = 1$  by default. Likewise, the soft assignment  $z_{\mathcal{T}'}$  for  $\mathcal{T}'(x_t)$  can be obtained in the same manner except that we use the original trainable feature extractor  $f$ . Since  $z_{\mathcal{T}}$  is more reliable as the feature is given by a momentum encoder  $\tilde{f}$  and the input  $x_t$  suffers from less distortion, we use it to teach  $f$  to produce consistent assignments for  $\mathcal{T}(x_t)$ . Hence, we minimize the Kullback–Leibler (KL) divergence between the prototypical assignments under two views:

$$\ell_{kl}^t = \text{KL}(z_{\mathcal{T}} \| z_{\mathcal{T}'}). \quad (9)$$

Intuitively, this equation enforces the network to give consistent prototypical labeling for the adjacent feature points, which results in more compact feature space in the target domain.

Similar to the previous works that simultaneously learn the clustering and representation, the proposed prototypical consistent learning may suffer from degeneration issue, *i.e.*, one cluster becomes empty. To amend this, we use a regularization term from [76], which encourages the output to

be evenly distributed to different classes,

$$\ell_{reg}^t = - \sum_{i=1}^{H \times W} \sum_{j=1}^K \log p_t^{(i,k)}. \quad (10)$$

Now equipped with the online label correction and the prototypical consistent learning, we train the domain adaptation network with the following total loss:

$$\ell_{total} = \ell_{ce}^s + \ell_{sce}^t + \gamma_1 \ell_{kl}^t + \gamma_2 \ell_{reg}^t. \quad (11)$$

By default, the weighting coefficients  $\gamma_1$  and  $\gamma_2$  are set to 10, 0.1 respectively.

### 4.3. Distillation to self-supervised model

After the training with Equation 11 converges, we further transfer knowledge from the learned target model to a student model with the same architecture but pretrained in a self-supervised manner. To be concrete, we initialize the feature extractor of the student model  $h^\dagger$  with SimCLRv2 [11] pretrained weights, and we apply a knowledge distillation (KD) loss, which lets the student mimic the teacher by minimizing the KL divergence of their predictions on the unlabeled target images. Besides, following the self-training paradigm, we rely on the teacher model  $h$  to generate one-hot pseudo labels  $\xi(p_t)$  so as to teach the student model. To prevent the model from forgetting the source domain, the source images are also utilized. Altogether, we train the student model using the following loss,

$$\ell_{KD} = \ell_{ce}^s(p_s, y_s) + \ell_{ce}^t(p_t^\dagger, \xi(p_t)) + \beta \text{KL}(p_t \| p_t^\dagger), \quad (12)$$

where  $p_t^\dagger = h^\dagger(x_t)$  is the output of the student model, and we set  $\beta = 1$ . In practice, such self-distillation can be applied multiple times once the model converges, which helps the domain adaptation to achieve even higher performance.

## 5. Experiments

### 5.1. Implementation

**Training.** We use the DeepLabv2 [8] for segmentation with the backbone ResNet-101 [24]. Following [69, 73], we utilize [55] that applies adversarial training at the segmentation output as a warm-up. We apply the SGD solver with the initial learning rate as 1e-4 which is decayed by 0.9 every training epoch, and the training lasts 80 epochs. During the structure learning, the augmentation is composed of random crop, RandAugment [14] and Cutout [15]. For knowledge distillation, we utilize the pretrained SimCLRv2 model with the ResNet-101 backbone as well. An extra batch normalization (BN) layer is introduced after its feature extraction layer so as to accommodate the activation magnitude for our task, with the learning rate set to 6e-4 and 6e-3 respectively before and after this BN layer. During the

distillation stage, we use hard pseudo labels with the selection threshold 0.95. Readers can refer to the supplementary material for more training details and algorithm flow. We conduct all the experiments on 4 Tesla V100 GPUs with PyTorch implementation.

**Dataset.** For evaluation, we adapt the segmentation from game scenes, GTA5 [44] and SYNTHIA [45] datasets, to real scene, the Cityscapes [13] dataset. GTA5 contains 24,966 training images with the resolution of 1914×1052 and we use its 19 categories shared with Cityscapes. SYNTHIA dataset contains 9,400 1280×760 images and we use its 16 common categories with Cityscapes. We also report the results on 13 common categories on this dataset following the protocol of some methods. The Cityscapes dataset contains 2,975 training images and 500 images for validation with the resolution of 2048×1024. Since its testing set does not provide ground truth labeling, we conduct evaluations on its validation set.

### 5.2. Comparisons with state-of-the-art methods

We comprehensively compare our proposed method with the recent leading approaches. These methods could be divided into two categories: 1) domain alignment methods that align the distribution through adversarial training, which include AdaptSeg [54], CyCADA [26], CLAN [36], APODA [67], PatchAlign [56], ADVENT [57], BDL [34] and FADA [60]; 2) self-training approaches, including CBST [75], MRKLD [76], Seg-Uncertainty [73], CAG\_UDA [69].

Table 1 shows the comparisons of GTA5 → Cityscapes adaptation. our ProDA arrives at the state-of-the-art mIoU score 57.5, outperforming existing methods by a large margin. Among all the 19 categories, we achieve the best scores on 15 categories. ProDA shows evident advantage in hard classes, *e.g.*, fence, terrace, motor, that cannot be well handled in previous works. Indeed, the performance improvement of ProDA mostly comes from these challenging cases, the small or rare objects, as we regard different categories equally thanks to the prototypes. Note that this is achieved without any heuristic class-balance strategies as [75]. Compared with the non-adapted baseline (*i.e.*, the model purely trained on the source), ProDA offers the mIoU gain by 20.9, outperforming the second-best method by 52.6%.

In Table 2, we show the adaptation results on SYNTHIA → Cityscapes, where ProDA also shows tremendous improvement. The proposed ProDA achieves the mIoU score by 55.5 and 62.0 over the 16 and 13 categories respectively. To be specific, we arrive at the best on 11 out of 16 categories, mostly the hard classes. Relative to the non-adaptive model, the segmentation model after our adaption sees the gain by 20.6, surpassing that of the prior leading approach by 58.4%. While the adaptation from SYNTHIA is more challenging than that from GTA5, our ProDA per-

	road	sideway	building	wall	fence	pole	light	sign	vege.	terrace	sky	person	rider	car	truck	bus	train	motor	bike	mIoU	gain
Source	75.8	16.8	77.2	12.5	21.0	25.5	30.1	20.1	81.3	24.6	70.3	53.8	26.4	49.9	17.2	25.9	6.5	25.3	36.0	36.6	+0.0
AdaptSeg [54]	86.5	25.9	79.8	22.1	20.0	23.6	33.1	21.8	81.8	25.9	75.9	57.3	26.2	76.3	29.8	32.1	7.2	29.5	32.5	41.4	+4.8
CyCADA [26]	86.7	35.6	80.1	19.8	17.5	38.0	39.9	41.5	82.7	27.9	73.6	64.9	19.0	65.0	12.0	28.6	4.5	31.1	42.0	42.7	+6.1
CLAN [36]	87.0	27.1	79.6	27.3	23.3	28.3	35.5	24.2	83.6	27.4	74.2	58.6	28.0	76.2	33.1	36.7	6.7	31.9	31.4	43.2	+6.6
APODA [67]	85.6	32.8	79.0	29.5	25.5	26.8	34.6	19.9	83.7	40.6	77.9	59.2	28.3	84.6	34.6	49.2	8.0	32.6	39.6	45.9	+9.3
PatchAlign [56]	<b>92.3</b>	51.9	82.1	29.2	25.1	24.5	33.8	33.0	82.4	32.8	82.2	58.6	27.2	84.3	33.4	46.3	2.2	29.5	32.3	46.5	+9.9
ADVENT [57]	89.4	33.1	81.0	26.6	26.8	27.2	33.5	24.7	83.9	36.7	78.8	58.7	30.5	84.8	38.5	44.5	1.7	31.6	32.4	45.5	+8.9
BDL [34]	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	49.7	3.3	28.8	35.6	48.5	+11.9
FADA [60]	91.0	50.6	<b>86.0</b>	43.4	29.8	36.8	43.4	25.0	86.8	38.3	<b>87.4</b>	64.0	38.0	85.2	31.6	46.1	6.5	25.4	37.1	50.1	+13.5
CBST [75]	91.8	53.5	80.5	32.7	21.0	34.0	28.9	20.4	83.9	34.2	80.9	53.1	24.0	82.7	30.3	35.9	16.0	25.9	42.8	45.9	+9.3
MRKLD [76]	91.0	55.4	80.0	33.7	21.4	37.3	32.9	24.5	85.0	34.1	80.8	57.7	24.6	84.1	27.8	30.1	26.9	26.0	42.3	47.1	+10.5
CAG-UDA [69]	90.4	51.6	83.8	34.2	27.8	38.4	25.3	48.4	85.4	38.2	78.1	58.6	34.6	84.7	21.9	42.7	<b>41.1</b>	29.3	37.2	50.2	+13.6
Seg-Uncertainty [73]	90.4	31.2	85.1	36.9	25.6	37.5	48.8	48.5	85.3	34.8	81.1	64.4	36.8	86.3	34.9	52.2	1.7	29.0	44.6	50.3	+13.7
<i>ProDA</i>	87.8	<b>56.0</b>	79.7	<b>46.3</b>	<b>44.8</b>	<b>45.6</b>	<b>53.5</b>	<b>53.5</b>	<b>88.6</b>	<b>45.2</b>	82.1	<b>70.7</b>	<b>39.2</b>	<b>88.8</b>	<b>45.5</b>	<b>59.4</b>	1.0	<b>48.9</b>	<b>56.4</b>	<b>57.5</b>	<b>+20.9</b>

Table 1: Comparison results of GTA5→Cityscapes adaptation in terms of mIoU. The best score for each column is highlighted.

	road	sideway	building	wall*	fence*	pole*	light	sign	vege.	sky	person	rider	car	bus	motor	bike	mIoU	gain	mIoU*	gain*
Source	64.3	21.3	73.1	2.4	1.1	31.4	7.0	27.7	63.1	67.6	42.2	19.9	73.1	15.3	10.5	38.9	34.9	+0.0	40.3	+0.0
AdaptSeg [54]	79.2	37.2	78.8	-	-	-	9.9	10.5	78.2	80.5	53.5	19.6	67.0	29.5	21.6	31.3	-	-	45.9	+5.6
PatchAlign [56]	82.4	38.0	78.6	8.7	0.6	26.0	3.9	11.1	75.5	<b>84.6</b>	53.5	21.6	71.4	32.6	19.3	31.7	40.0	+5.1	46.5	+6.2
CLAN [36]	81.3	37.0	80.1	-	-	-	16.1	13.7	78.2	81.5	53.4	21.2	73.0	32.9	22.6	30.7	-	-	47.8	+7.5
APODA [67]	86.4	41.3	79.3	-	-	-	22.6	17.3	80.3	81.6	56.9	21.0	84.1	49.1	24.6	45.7	-	-	53.1	+12.8
ADVENT [57]	85.6	42.2	79.7	8.7	0.4	25.9	5.4	8.1	80.4	84.1	57.9	23.8	73.3	36.4	14.2	33.0	41.2	+6.3	48.0	+7.7
BDL [34]	86.0	<b>46.7</b>	80.3	-	-	-	14.1	11.6	79.2	81.3	54.1	27.9	73.7	42.2	25.7	45.3	-	-	51.4	+11.1
FADA [60]	84.5	40.1	83.1	4.8	0.0	34.3	20.1	27.2	84.8	84.0	53.5	22.6	85.4	43.7	26.8	27.8	45.2	+10.3	52.5	+12.2
CBST [75]	68.0	29.9	76.3	10.8	1.4	33.9	22.8	29.5	77.6	78.3	60.6	28.3	81.6	23.5	18.8	39.8	42.6	+7.7	48.9	+8.6
MRKLD [76]	67.7	32.2	73.9	10.7	1.6	37.4	22.2	31.2	80.8	80.5	60.8	<b>29.1</b>	82.8	25.0	19.4	45.3	43.8	+8.9	50.1	+9.8
CAG-UDA [69]	84.7	40.8	81.7	7.8	0.0	35.1	13.3	22.7	84.5	77.6	64.2	27.8	80.9	19.7	22.7	48.3	44.5	+9.6	51.5	+11.2
Seg-Uncertainty [73]	87.6	41.9	83.1	14.7	<b>1.7</b>	36.2	31.3	19.9	81.6	80.6	63.0	21.8	86.2	40.7	23.6	<b>53.1</b>	47.9	+13.0	54.9	+14.6
<i>ProDA</i>	<b>87.8</b>	45.7	<b>84.6</b>	<b>37.1</b>	0.6	<b>44.0</b>	<b>54.6</b>	<b>37.0</b>	<b>88.1</b>	84.4	<b>74.2</b>	24.3	<b>88.2</b>	<b>51.1</b>	<b>40.5</b>	45.6	<b>55.5</b>	<b>+20.6</b>	<b>62.0</b>	<b>+21.7</b>

Table 2: Comparison results of SYNTHIA→Cityscapes adaptation in terms of mIoU. The best score for each column is highlighted. mIoU and mIoU\* denote the averaged scores across 16 and 13 categories respectively.

forms equally well on both datasets.

### 5.3. Discussion

**The effectiveness of pseudo label denoising.** In Table 3, the non-adapted source model only gives 36.6 mIoU on the target domain. After the model warm-up, we get a 5.0 mIoU increase. Initialized with the warm-up, the baseline model, *i.e.*, the vanilla self-training, which is trained using the offline pseudo labels, improves the mIoU to 45.2. Adding symmetric cross-entropy (SCE) brings +0.4 mIoU gain. By contrast, we are able to update the pseudo labels on-the-fly and the training with the denoised pseudo labels significantly boosts the performance to 52.3. The model with this component alone sets the state-of-the-art, outperforming the

prior best score by 2.0.

Figure 2 illustrates how the pseudo labels progress as the training proceeds. In the early phase, false pseudo labels are likely to occur and fail to recognize the tiny objects, *e.g.*, the poles and traffic signs. As the training goes on, pseudo labels get denoised by virtue of the prototypes, and tiny objects can be gradually identified in the refined pseudo labels. The training after 40k iterations can already correct most of the incorrect labels. In Figure 3, we further quantify the mIoU score of the pseudo labels during the whole training process. While convention self-training only updates the pseudo labels after each stage and leads to step-wise mIoU increase, the pseudo labels given by ProDA can quickly attain a high quality, showing a distinct advantage over the

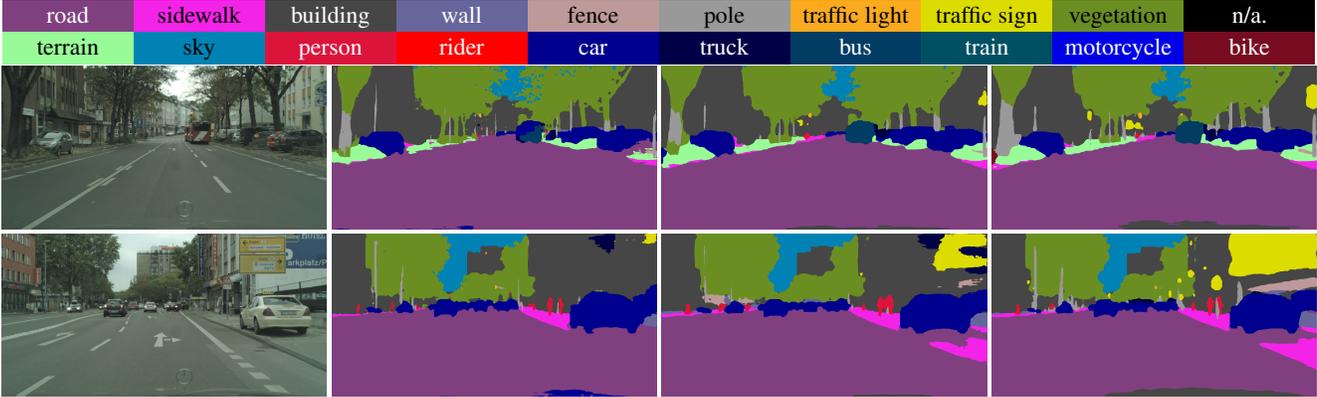


Figure 2: ProDA online refines the pseudo labels throughout the training. The first column is the segmentation input. The 2nd to 4th columns illustrate the pseudo labels after 1k, 10k, and 40k iterations.

		components				mIoU gain
initialization		source				36.6
		warm up				41.6 +5.0
stage 1		self training	sce	prototypical denoising	structure learning	mIoU gain
	✓					45.2 +8.6
	✓	✓				45.6 +9.0
	✓	✓	✓			52.3 +15.7
	✓	✓	✓	✓		47.6 +11.0
✓	✓	✓	✓	✓	53.7 +17.1	
stage 2		self distill.	stage 1 init.	supervised init.	self-supervised init.	mIoU gain
	✓				✓	55.8 +19.2
	✓	✓				56.3 +19.7
	✓		✓			55.7 +19.1
✓				✓	56.9 +20.3	
stage 3	✓				✓	57.5 +20.9

Table 3: Ablation study of each proposed component. The whole training involves three stages, where knowledge distillation can be applied in the last two stages.

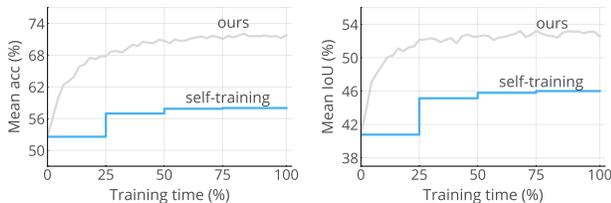


Figure 3: The mean accuracy and mean IoU score of the pseudo labels throughout the training. Comparing to the conventional self-training that updates pseudo labels only after the training stage, the pseudo labels in our method steadily improves as the training proceeds.

vanilla self-training of multiple training stages.

**How to prevent degenerate solution?** Simultaneously

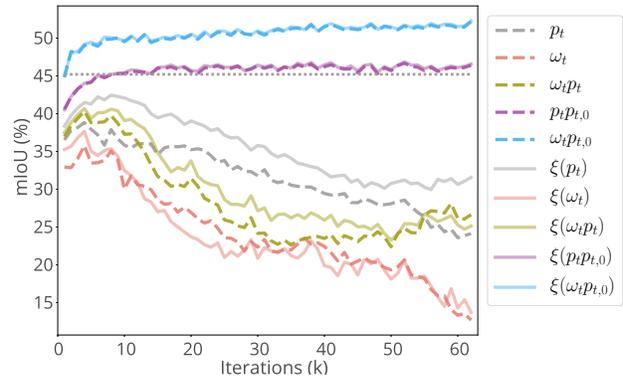


Figure 4: The training curves of different label reweighting schemes when online updating the labels. Adopting fixed  $p_{t,0}$  labels avoid the trivial solutions that plague the training with non-fixed pseudo labels  $p_t$ . The dotted line denotes the performance of conventional self-training.

learning the feature and updating the labels during self-training derives degenerate solutions. The key to avoiding such degeneration is to adopt a fixed soft label  $p_{t,0}$  as the boilerplate upon which we apply the weight  $w_t$  for rectification (Equation 3). To explain this, we investigate different variants for the online label updating in Figure 4, where the labels for self-training can be dynamic  $p_t$  or fixed  $p_{t,0}$ , and the modulation weight can be the network prediction  $p_t$  or the confidence  $w_t$  estimated according to prototypes. In addition, we investigate the benefit of using hard labels ( $\xi(\cdot)$ ). Figure 4 shows that the performance climbs up for a while and then starts to drop significantly when using non-fixed soft predictions ( $p_t$  and its variants), whereas the learning with the fixed ones ( $p_{t,0}$  and its variants) steadily improves throughout the training and surpasses the conventional self-training. We conjecture that fixing  $p_{t,0}$  makes the refined pseudo labels hardly deviate from this initial prediction, thus avoiding the trivial solution. Moreover, in contrast to using  $p_t$  for reweighting, prototypical reweighting improves

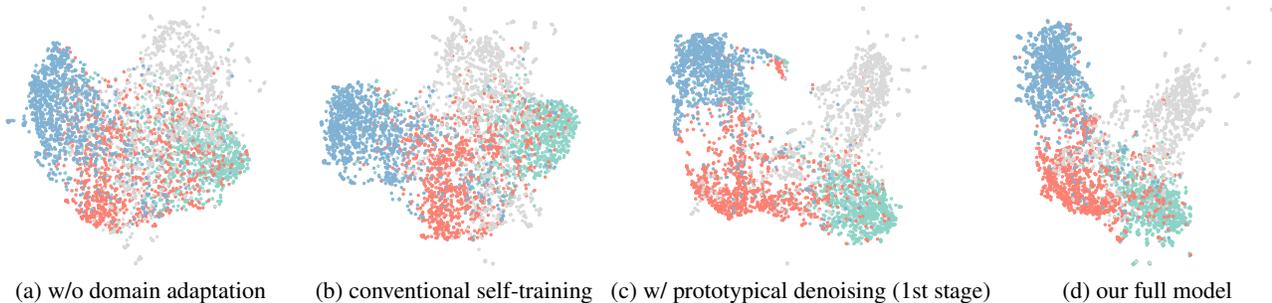


Figure 5: The visualization of feature space, where we map features to 2D space with UMAP [37]. For a clear illustration, we only show four categories, *i.e.*, blue for building, gray for traffic sign, orange for pole, and green for vegetation.

the mIoU by more than 5.0, corroborating the importance of using prototypes for label denoising. Besides, we observe slight improvement ( $\sim 0.2$ ) using hard labels over the soft ones.

**The effectiveness of target structure learning.** We propose to cultivate the intrinsic knowledge for the target domain and learns its underlying structure. As shown in Table 3, without the label denoising, the structure learning improves the performance from 45.6 to 47.6. Note that this is also competitive among self-training approaches, but we do not need to carefully choose the threshold for selecting the confident pseudo labels. The target structure learning assists the pseudo label denoising by forming compact feature clusters and brings the performance gain by 1.4.

**The effectiveness of distilling to self-supervised model.** At the second training stage, we apply knowledge distillation and transfer the dark knowledge of the 1st stage model to the current phase. Table 3 also compares different initialization strategies for this stage. Compared to resuming the last stage training, the initialization from a self-supervised pretrained model (*i.e.*, SimCLRv2) improves the mIoU by 0.6, whereas the initialization with the supervised pretraining degrades the performance. This is because the self-supervised pretraining possesses stronger transferability and can benefit a broad of downstream tasks. The initialization in this way helps the model escape from the local optima in the last stage. Table 3 also proves the effectiveness of the knowledge distillation: ablating this component drops the mIoU by 1.1. It is surprising to see that the third stage with the knowledge distillation further improves the performance by 0.6, attaining the 20.9 mIoU improvement relative to the model without domain adaptation.

**The UMAP visualization of target features.** To better develop intuition, we visualize the learned features for ProDA in Figure 5. The model before the domain adaptation mixes the features of the same class. The conventional self-training could produce more separated feature space, yet it is still hard for linear classification. When we apply prototypical pseudo label denoising, features among differ-

threshold	0.0	0.2	0.4	0.6	0.8	0.9	0.95
mIoU	53.7	53.8	53.7	53.7	53.8	53.7	53.3

Table 4: The effect of threshold in pseudo label selection during the prototypical label denoising.

momentum	0.99	0.999	0.9999	0.99999
mIoU	53.5	53.6	53.7	52.3

Table 5: The effect of prototype momentum during the prototype online update.

ent classes are better separated, though the distribution is still dispersed. In comparison, the full model gives the most compact feature clusters that are amenable to classification.

#### 5.4. Parameter sensitivity analysis.

To showcase that ProDA is robust to the hyper-parameter selection, we analyze the impact of parameters. In Table 4, we use different threshold values to select the pseudo labels and the performance is not sensitive to this threshold as opposed to the conventional self-training. Hence, ProDA does not apply thresholding for convenient usage. We also study the effect of momentum value when online computing the prototypes, and ProDA is robust to a wide numerical range as shown in Table 5.

## 6. Conclusions

In this paper, we propose ProDA which resorts to prototypes to online denoise the pseudo labels and learn the compact feature space for the target domain. Knowledge distillation to a self-supervised pretrained model further boosts the performance. The proposed method outperforms state-of-the-art methods by a large margin, greatly reducing the gap with supervised learning. We will make the code publicly available. We believe the proposed method is a general amelioration to the self-training and we hope to explore its capability in other tasks in the future.

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