Exploiting Negative Learning for Implicit Pseudo Label Rectification in Source-Free Domain Adaptive Semantic Segmentation

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Abstract

It is desirable to transfer the knowledge stored in a well-trained source model onto non-annotated target domain in the absence of source data. However, state-of-the-art methods for source free domain adaptation (SFDA) are subject to strict limits: 1) access to internal specifications of source models is a must; and 2) pseudo labels should be clean during self-training, making critical tasks relying on semantic segmentation unreliable. Aiming at these pitfalls, this study develops a domain adaptive solution to semantic segmentation with pseudo label rectification (namely PR-SFDA), which operates in two phases: 1) Confidence-regularized unsupervised learning: Maximum squares loss applies to regularize the target model to ensure the confidence in prediction; and 2) Noise-aware pseudo label learning: Negative learning enables tolerance to noisy pseudo labels in training, meanwhile positive learning achieves fast convergence. Extensive experiments have been performed on domain adaptive semantic segmentation benchmark, GTA5 $\rightarrow$ Cityscapes. Overall, PR-SFDA achieves a performance of $49.0$ mIoU, which is very close to that of the state-of-the-art counterparts. Note that the latter demand accesses to the source model’s internal specifications, whereas the PR-SFDA solution needs none as a sharp contrast.

Introduction

Unsupervised Domain Adaptation (UDA) aligns different domains and transfers the knowledge learned in well-annotated source domain onto non-annotated target domain. UDA plays an vital role in medical healthcare, autonomous driving and other scenarios where annotated data are far from sufficient for supervised learning. In UDA, the alignment between source and target data helps pre-trained source models to produce better predictions in target domain. The employment of UDA avoids supervised learning on target data, which can otherwise be obscured by the need of large amounts of data with fine-grained annotations.

Typical UDA methods map input data from both domains into the same feature space. Early methods achieve this via minimizing the statistical discrepancy between source and target features. Recently, with the success of Generative Adversarial Networks (Goodfellow et al. 2014), many methods utilize adversarial learning to match and align the distribution of features. However, since these methods inevitably require the coexistence of source and target data, they cannot be applied into some source-absent scenarios, i.e., medical healthcare and financial prediction. Under these circumstances, source data are not available due to privacy concerns. Source-Free Domain Adaptation (SFDA) is suitable for these scenarios: (1) SFDA methods are not dependent on source data; (2) source models are always available in these scenarios, from which SFDA methods can extract domain knowledge. The SFDA theory has proved powerful for source data absent transfer learning in many research hotspots, e.g., image classification, object detection and semantic segmentation etc., which forms the basis of this study.

Recent advances in SFDA have enabled the simulation of source distribution. These methods extract statistics of specific layers in source models and try to match target distribution with them. Some other methods divide source models into feature extractors and classifiers. They fix the parameters of classifiers and optimize extractors to adapt for target data. Typical SFDA methods have the access to a priori knowledge for source models. In this study, we further limit the availability of model specifications. Our approach is model-independent, which enables even black-box model’s adaptation.
data. However, all these methods require the detailed specification of source models. Practically, such a priori knowledge about source models is not always accessible. Some methods benefit from self-training to increase accuracy in target domain, but few of them explicitly deal with the inevitable noise in pseudo labels. In addition, since source models make main contributions to the quality of pseudo labels, source domains are supposed to provide models with strong capability of generalization. Nonetheless, most of existing SFDA methods focus on the adaptation, ignoring the importance of robust source models. In summary, an appropriate adaptation method is needed to take advantages of source models even without their specifications, and it should be robust enough to learn from noisy pseudo labels. To this end, there exists a pressing need for an approach to the pending problems:

- without any a priori knowledge about source models, it is non-trivial to adapt towards target domain by mimicking source distribution, or it will be prohibitively hard to selectively optimize part of the model. This problem has long been underestimated.
- the employment of self-training is already a common practice to enhance models on target non-annotated data. Due to the intrinsic noises in pseudo labels, enhancing the performance on target domain needs to bridge the gap between the latest self-training methods and an appropriate solution to rectifying noisy pseudo labels.

The strategy of this study is to first train a robust model in source domain then to adapt this model to target domain without the access to source data and source a priori. With style augmentation upon source data, source models are enhanced towards slight data variance. The detection and rectification of pseudo labels will benefit the adaptation on target data. This study develops a source-free domain adaptation solution with pseudo label rectification (PR-SFDA) operating in two phases:

- confidence-regularized unsupervised learning for adaptation without a priori knowledge of source models: the application of probability regularization benefits target outputs with higher prediction confidence. The adaptation is guided towards regions with higher predictive entropy, and the whole process does not need any explicit a priori knowledge about source domain.
- noise-aware pseudo label learning for enhanced self-training on target domain: collaborative learning on positive labels and negative labels extends naive self-training with noise rectification. The utilization of negative learning enables the tolerance to noisy pseudo labels, whereas classical positive learning promotes fast convergence and accurate supervision.

Experiments on domain adaptive semantic segmentation have been carried out to evaluate the performance of PR-SFDA. Experiments have also been performed to examine its effectiveness in pseudo label rectification and to investigate its sensibility to hyper-parameters.

The main contributions of this study are as follows:

- this study develops a training method for generating robust source models with class balance. This enhances performance on long-tailed classes and bridges the style gap between domains without access to target data.
- a complete solution has been fostered to adapt a well-trained source model towards non-annotated target data. It is noted that the adaptation is conducted in the absence of both source data and layer specifications of source models.
- a collaborative learning method has been developed to combine the advantages of positive and negative learning. This brings both fast model convergence and effective noise rectification of pseudo labels.

Related Work

Numerous attempts have been made to improve the performance of domain adaptive semantic segmentation, which transfer the segmentation knowledge learned from annotated source domain to non-annotated target domain. Studies undertaken for this purpose focus on (1) minimizing the distribution discrepancy between domains and/or (2) improving the performance with unsupervised or semi-supervised methods. The most salient works along this direction are introduced as the follows:

Adversarial Learning for Domain Adaptive Segmentation. FCNs (Hoffman et al. 2016) and ASN (Tsai et al. 2018) proposed frameworks to support cross-domain segmentation based on adversarial learning. By means of the game between feature extractor and domain discriminator, they achieved domain-invariant feature extraction. Upon these methods, ADVENT (Vu et al. 2019) proposed the concept of adversarial entropy minimization, which utilized entropy as certainty metric to regularize the model for domain-consistent confident predictions. Similarly, MSL (Chen, Xue, and Cai 2019) studied the imbalanced gradients of entropy loss between easy and hard samples. They proposed Maximum Squares Loss to prevent the training process being dominated by easy samples.

Self-training for Domain Adaptive Segmentation. CCM (Li et al. 2020) and CRST (Zou et al. 2019) proposed novel UDA frameworks based on self-training, i.e., optimization via alternatively updating pseudo labels and target model. Their studies employ class-balanced loss and confident constraints to further regularize self-training. Following them, FDA (Yang and Soatto 2020) employed the mean predictions of multiple models to regularize self-learning.

CCM (Li et al. 2020) evaluated the quality of pseudo labels via spatial contextual layout similarity, dropping noisy samples that have inconsistent contextual layouts. IntraDA (Pan et al. 2020) separated target domain into easy and hard splits and applied intra-domain adaptation to transfer hard samples. DAST (Yu et al. 2021) introduced discriminator attention to concentrate on potential noisy regions. MRNet (Zheng and Yang 2020, 2021) detected and rectified noisy
pseudo labels by means of scale variance in target predictions. Recently, ProDA (Zhang et al. 2021) exploited the feature distances from prototypes to enable online correction of pseudo labels, achieving tremendous performance advantage over previous methods.

Source-Free Domain Adaptive Segmentation. To adapt source knowledge in the absence of source data, UBNA (Klingner et al. 2020) studied the normalization layer statistics for adaptation. This enabled them to mix the statistics from both domains. Similarly, SFDA (Liu, Zhang, and Wang 2021) employed a generator to mimic the distribution of source features, which came from the adversary between fake-source and target batch normalization statistics.

This study aims at domain adaptive semantic segmentation and has the following major concerns: (1) to adapt and transfer source knowledge without access to any explicit source knowledge (neither source data/feature nor source model specification), and meanwhile (2) to detect and rectify noisy pseudo labels only with the predictions from black-box source models.

Preliminaries

This section clarifies: (1) the notations and operations of SFDA, which forms the basis of this study; (2) the basic concept of Negative Learning, which contributes to pseudo label rectification.

Source-Free Unsupervised Domain Adaptation

Under typical UDA settings, a labeled source dataset \( D_s = \{(x_s^i, y_s^i)\}_{i=1}^{N_s} \) an unlabeled target dataset \( D_t = \{x_t^i\}_{i=1}^{N_t} \) and a well-trained source model \( M_s \) work collaboratively to enhance model \( M \)'s performance on target domain, where \( x_s, x_t \) denote source and target images, \( y_s \) is source annotation and \( N_s, N_t \) denote the number of source and target samples, respectively.

Equation [1] formulates the basic optimization objective for source-present domain adaptation (SDA), where \( L_{SRC} \) is supervised loss in source domain, \( L_{DA} \) is the adaptation loss in both domain (which comes from adversarial learning or other training techniques) and \( L_{TGT} \) is regularization loss on target domain.

\[
L_{SDA} = L_{SRC} + L_{TGT} + L_{DA} \tag{1}
\]

In the absence of source data, i.e., \( D_s \), only a well-trained source model and non-annotated target data are available. Under this setting, source-free domain adaptation (SFDA) methods are applied.

For SFDA, source and target data are utilized separately in different domains. In source domain, the model is optimized with \( L_{SRC} \) to provide a well-trained source model \( M_s \). In target domain, the model is optimized with \( L_{TGT}(M_s, M_s, x_t) \), without the existence of source data.

Negative Learning

Given an input as well as its label, cross-entropy loss updates the model in a positive manner by maximizing the prediction probability towards the corresponding class. This is defined as positive learning. When labels are noisy, naive positive learning will lead to error accumulation. To alleviate this, negative learning updates models differently. Negative learning tries to minimizing the prediction probability that the given input does not belong to the corresponding label.

Figure 2 illustrates the concept of negative learning. The marked pixel has a less confident pseudo label, which is noisy (labeled as sidewalk instead of road). For simplicity, we assume that all the labels are subject to the uniform distribution. Thus, the probability that the pixel is labeled correctly is only \( \frac{1}{C} \). By contrast, negative learning uses its complementary label, whose probability of correctness is \( \frac{C-1}{C} \). In this way, negative learning can help avoid the impact of noisy labels via providing correct information even from wrong labels.

The loss calculation for positive and negative learning is defined in Equation[2] and Equation[3] respectively.

\[
L_{PL} = - \sum_{c=1}^{C} y_c \log p_c(x) \tag{2}
\]

\[
L_{NL} = - \sum_{c=1}^{C} \bar{y}_c \log(1 - p_c(x)) \tag{3}
\]

Based upon these preliminaries, this study proposes PR-SFDA, a domain adaptive solution for semantic segmentation, aiming at (1) adapting domain knowledge in the absence of source data and (2) rectifying intrinsic noises in pseudo labels without the help of source model a priori.

Method

This section first demonstrates how to generate a class-balanced robust source model for SFDA scenarios. Then, it details the design and operation of the PR-SFDA solution in two phases: (1) confidence-regularized unsupervised target adaptation, and (2) noise-rectified target self-training.

Architecture of PR-SFDA

Figure 3 gives an overview of the architecture and operation of PR-SFDA. The PR-SFDA solution operates in two phases: (1) confidence regularization helps improve the pre-trained source model for confident predictions. (2) the regularized model produces pseudo labels and confidence masks. Then, positive learning and negative learning work collaboratively to extend self-training with pseudo label rectification.
Class-Balanced Supervised Learning

SFDA methods cannot access source data for direct supervision. This requires robust source models to produce reliable segmentation results for target data. To alleviate class imbalance of source model, this study employs class-balanced cross-entropy loss for model optimization. Class-balanced cross-entropy (CBCE) loss uses class-aware weights to increase the contribution of those long-tailed rare classes, which helps improve the performance on them. CBCE loss is defined in Equation 4, where \( w_c \) is the weight for the \( c \)-th class. Each weight is calculated according to the pixels’ occurrence frequency among the whole dataset and their ratio in the image.

\[
L_{CBCE}(p(x), y) = - \sum_{c=1}^{C} w_c \cdot y_c \log p_c(x)
\]  

(4)

To bridge the style discrepancy between source images and unavailable target images, this study characterizes style variance between domains as noise perturbation. To this end, we apply color perturbation to augment source images. This enables abundant style variance and can slightly reduce the domain gap between source and target images.

The objective for source training can be formulated as Equation 5:

\[
L_{SRC} = \mathbb{E}_{(x_s,y_s) \sim (X_s \times Y_s)} L_{CBCE}(p(\tilde{x_s}), y_s)
\]  

(5)

Confidence-Regularized Unsupervised Learning

In this phase, PR-SFDA aims to adapt source model onto unlabeled target domain. Due to the significant discrepancy between source and target domains, source models are not guaranteed to generate accurate prediction for target images. Instead, the generated results often suffer from noisy regions, which have lower prediction confidence. Entropy minimization has been widely adopted to penalize regions with higher entropy (i.e., lower confidence). Since easy samples often come with higher entropy, PR-SFDA adopts maximum squares loss (MSL) (Chen, Xue, and Cai 2019) as certainty regularization to prevent the training process being dominated by easy samples. \( L_{MSL} \) is defined as in Equation 6 which has balanced gradients for each class and enables confident predictions for target data.

\[
L_{MSL} = - \mathbb{E}_{x_t \sim X_t} \frac{1}{2} \sum_{c=1}^{C} (p_c(x_t))^2
\]  

(6)

After confidence regularization, PR-SFDA is capable of predicting coarse-grained results in target domain. Previous studies employed self-training for further model optimization. These methods rely on either source representations or model specifications to rectify noises in pseudo labels. This limits their application in cloud-based environments and other scenarios where these a priori knowledge might be unavailable. As a consequence, there exists a technical barrier with noise rectification in the absence of architecture specification.

Noise-Aware Pseudo Label Learning

Current model in PR-SFDA has been capable of generating coarse-grained results in target domain (pseudo labels as well as confident maps). Based on confident maps, a predefined threshold (e.g., 0.6 in our experiments) is utilized to generate binary invalid masks, which indicates the distribution of potential noisy regions.

In this phase, PR-SFDA extends self-training with rectification in those noisy regions, which is achieved via the collaboration of positive learning and negative learning. As illustrated in Figure, negative learning assigns complementary labels for each prediction. This increases the probability...
that a supervision signal is correct. The generation of complementary labels is demonstrated as in Algorithm 1.

**Algorithm 1: Generation of Complementary Label.**

Input: Pseudo Label \( y \in [0, C]^{H \times W} \)

Output: Complementary Label \( \bar{y} \in [0, C]^{H \times W} \)

1. \( \bar{y} = y \cdot \text{copy}() \)
2. 
   \[ \text{foreach } \text{lab in } [0, C] \text{ do} \]
3.   \[ \text{tmpLab} = \text{random.randint}(0, C) \]
4.   \[ \text{while tmpLab} == \text{lab} \text{ do} \]
5.     \[ \text{tmpLab} = \text{random.randint}(0, C) \]
6.   \[ \bar{y}[y==\text{lab}]=\text{tmpLab} \]

For negative learning, PR-SFDA calculates the complementary prediction, pseudo label and invalid mask from the original outputs. After this, positive and negative learning collaborate with each other, which results in \( \mathcal{L}_{P, L, N, L} \). \( \mathcal{L}_{P, L, N, L} \) is defined in Equation (1), where \( M \) denotes invalid mask, \( y \) denotes pseudo label, \( \bar{y} \) denotes randomly shuffled pseudo label, \( p \) denotes soft prediction for input image \( x \) and \( \otimes \) is element-wise multiplication.

\[
\mathcal{L}_{P, L, N, L} = (1 - M) \odot \mathcal{L}_P + \lambda (M \odot \mathcal{L}_N) \quad (7)
\]

In summary, the PR-SFDA solution aims to detect noisy predictions with less confidence and to alleviate invalid supervision from noisy regions via negative learning.

**Experiments**

This section details experiments and results. Experimental studies were performed to examine the effectiveness of PR-SFDA. Specifically, we evaluated its performance in domain adaptive semantic segmentation, using two typical benchmarks, i.e., GTA5 \( \rightarrow \) Cityscapes and SYNTHIA \( \rightarrow \) Cityscapes.

**Dataset and Metric**

Specifically, GTA5 is a synthetic dataset rendered from video game engine. It contains 24,966 images with fine-grained semantic annotation. Cityscapes is a popular benchmark for urban-scene semantic segmentation, which collects street-view images from 50 cities. It contains a training split of 2,975 images, a validation split of 500 images and a testing split of 888 images. SYNTHIA is another synthetic dataset. This study employed one of its subsets, \( \text{viz. SYNTHIA-RAND-CITYSCAPES} \). It contains 9400 annotated synthetic images and its annotation is compatible with Cityscapes.

This study adopted the established evaluation protocol from previous work, calculating pre-class Intersection-over-Union (IoU) and mean IoU (mIoU) over all classes on the \text{val} split of Cityscapes. Equation (8) is the definition of mIoU, where \( p_{ij} \) denotes the number of pixels that belong to the \( i \)-th class and are classified as the \( j \)-th class.

\[
mIoU = \frac{1}{C} \sum_{i=1}^{C} \frac{p_{ii}}{\sum_{j=1}^{C} p_{ij} + (\sum_{j=1}^{C} p_{ji}) - p_{ii}} \quad (8)
\]

**Implementation Details**

Our method is implemented using the DeepLab framework with the ResNet-101 backbone. The model is implemented on the Pytorch platform and runs on a single RTX 6000 GPU with 24GB memory. We train the whole model through back-propagation. The decoding layers are trained with a learning rate 10 times that of the pre-trained encoding layers. During source training, the whole network is optimized with the stochastic gradient descent (SGD) algorithm, with a momentum of 0.9 and a weight decay factor of \( 5 \times 10^{-4} \). During target adaptation, the optimization is performed via AdamW optimizer, with \( \beta \) set as \( (0.9, 0.99) \) and a weight decay factor of \( 5 \times 10^{-4} \). The initial learning rate is \( 2.0^{-4} \) and is scheduled using the polynomial decay with a power of 0.9. For target regularization and self-training, the initial learning rate is initialized as \( 1.0^{-5} \). During training, we resize the images to \( 1280 \times 760, 1024 \times 512 \) for synthetic and realistic datasets, respectively. The batch size is 2 for all the experiments.

**Results of Adaptive Semantic Segmentation**

Figure 4 shows the qualitative results on GTA5 \( \rightarrow \) Cityscapes adaptation benchmark. It is obvious that our method can significantly improve the baseline source-only model. The introduced target regularization (i.e., Maximum Squares Loss, MSL) helps improve the confusing segmentation (e.g., road and sidewalk). By comparing the right-most two columns in Figure 4, it can be noticed that the prediction can be significantly improved with the proposed PR-SFDA solution, i.e., collaborative positive and negative learning.

Table 1 presents quantitative results, indicating that the proposed method achieves close performances to many state-of-the-art methods, in spite of the absence of source data and source \text{a priori}. The performance is even superior to some baseline source-dependent adaptation methods.

Furthermore, with weighted cross-entropy loss and collaborative positive and negative learning, PR-SFDA shows superior performance on those long-tailed categories (highlighted as \text{blue} in the table). The reason is two-fold. On the one hand, the weighted cross-entropy loss (in the “class-balanced supervised learning” phase) drives the source model to put emphasis on those hard classes during back-propagation, leading to increasing contribution of those classes. On the other hand, the prediction on those areas is generally less confident. In these regions, negative learning will be selectively applied (in the “noise-aware pseudo label learning” phase). This helps reduce the impact of false-prone pseudo labels in those regions and increase prediction confidence and accuracy.
Table 1: Performance on GTA5 → Cityscapes. The tail classes are highlighted in blue. The column SF denotes whether the adaptation method is source-free. For the listed methods, the results are taken from original papers.

| Method | SF | road | sidewalk | building | wall | fence | pole | traffic light | traffic sign | vegetation | N/A | terrain | sky | person | rider | car | truck | bus | train | motorcycle | bike | mIoU  |
|--------|----|------|----------|----------|------|-------|------|---------------|--------------|------------|-----|---------|----|--------|-------|-----|-------|-----|-------|-------------|------|-------|
| Source Only | / | 38.0 | 13.7 | 79.5 | 14.8 | 22.3 | 32.3 | 33.8 | 30.3 | 80.8 | 14.8 | 75.4 | 60.0 | 28.9 | 56.4 | 39.1 | 32.5 | 0.2 | 29.6 | 37.0 | 37.9 |
| ASN     | 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 |
| BDL     | 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 |
| CLAN    | 87.0 | 27.1 | 79.6 | 23.3 | 28.8 | 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 |
| ADVENT  | 89.9 | 36.5 | 81.6 | 29.2 | 25.2 | 28.5 | 32.3 | 22.4 | 83.9 | 34.0 | 77.1 | 57.4 | 27.9 | 83.7 | 29.4 | 39.1 | 1.5 | 28.4 | 23.3 | 43.8 |
| IntraDA | 90.6 | 37.1 | 82.6 | 30.1 | 19.1 | 29.5 | 32.4 | 20.6 | 85.7 | 40.5 | 79.7 | 58.7 | 31.1 | 86.3 | 31.5 | 48.3 | 0.0 | 30.2 | 35.8 | 46.3 |
| APODA   | 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 |
| FDA     | 92.1 | 51.5 | 82.3 | 26.3 | 26.8 | 32.6 | 36.9 | 39.6 | 81.7 | 40.7 | 78.2 | 57.8 | 29.1 | 82.8 | 36.1 | 49.0 | 13.9 | 24.5 | 43.9 | 48.8 |
| PR-SFDA | ✓   | 91.3 | 41.8 | 85.2 | 34.5 | 24.2 | 34.4 | 36.3 | 40.7 | 85.6 | 42.6 | 87.0 | 60.4 | 30.8 | 86.2 | 37.9 | 40.3 | 1.4 | 22.7 | 48.2 | 49.0 |

Ablation Study

To validate the contributions of different phases in PR-SFDA, we conduct some ablation experiments to compare performance under different settings. Table 2 shows the quantitative comparison amongst different phases.

Impact of Source Augmentation In Table 2, the difference between methods SO and SO(AUG) lies in the employment of data augmentation. For SO, the naive images are used without augmentation, and AUG denotes the employment of data augmentation (i.e., color perturbation in this study). The style variance between source and target images leads to domain shifts, which is the main cause of limited performance in target domain. Without the presence of both source and target images, it is non-trivial to bridge domain gaps via adversarial learning, style translation, etc. To this end, with color perturbation, PR-SFDA augments source images to increase their style diversity. This helps extend the range of source domain, and thus can help reduce the domain discrepancy between two domains, leading to $+6.3\%$ mIoU increase.

Impact of Target Regularization If source and target domains are subject to similar distributions, the pre-trained source model will perform well on target images. However, such assumption is not guaranteed during practice. This urges further optimization on target images. To regu-
Impact of Pseudo Label Rectification

Pseudo label learning can further regularize model in non-annotated target domain. As shown in Table 2 with the help of self-training (ST), SO(AUG)+ENT and SO(AUG)+MSL+ST can improve the performance on target domain. However, the employment of MSL brings more promotion, which can be explained by its balanced gradients towards each class.

Trade-off between Positive and Negative Learning

To make better trade-off between positive and negative learning, we also conduct ablation experiments to select the optimal coefficient for positive learning and negative learning. Table 3 shows the quantitative results of PR-SFDA with different coefficients for negative learning ($\lambda_{nl} = [0.1, 0.5, 1.0]$). The table implies that a higher weight of negative learning brings slight performance increases. However, the table also shows that PR-SFDA is generally not sensitive to the parameter $\lambda_{nl}$, with similar performances under different settings.

Conclusions

Aiming at the grand challenges for domain adaptive semantic segmentation in the absence of both source data and intermediate model specifications, this study developed a source free domain adaptation solution with pseudo label rectification (namely PR-SFDA) for domain agnostic learning, consisting of two phases: (1) confidence-regularized unsupervised learning, where different confidence regularizations have been investigated to enhance the predictive certainty over non-annotated target images, and (2) noise-aware pseudo label learning, where a collaborative learning method has been developed to detect and rectify the intrinsic noises in pseudo labels.

Experimental results indicated that: (1) confidence regularization could guide the optimization towards those less confident regions, leading to a performance improvement of +13.2% mIoU than the model trained with augmented source data; (2) without access to any explicit a priori knowledge on source domain, PR-SFDA could rectify pseudo labels for effective self-training, achieving a performance of 49.0 mIoU. It held potentials in domain agnostic learning and self-training with limited model/domain a priori knowledge.

References
