Towards Source-free Domain Adaptive Semantic Segmentation via Importance-aware and Prototype-contrast Learning

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Abstract—Domain adaptive semantic segmentation enables robust pixel-wise understanding in real-world driving scenes. Source-free domain adaptation, as a more practical technique, addresses the concerns of data privacy and storage limitations in typical unsupervised domain adaptation methods. It utilizes a well-trained source model and unlabeled target data to achieve adaptation in the target domain. However, in the absence of source data and target labels, current solutions cannot sufficiently reduce the impact of domain shift and fully leverage the information from the target data. In this paper, we propose an end-to-end source-free domain adaptation semantic segmentation method via Importance-Aware and Prototype-Contrast (IAPC) learning. The proposed IAPC framework effectively extracts domain-invariant knowledge from the well-trained source model and learns domain-specific knowledge from the unlabeled target domain. Specifically, considering the problem of domain shift in the prediction of the target domain by the source model, we put forward an importance-aware mechanism for the biased target prediction probability distribution to extract domaininvariant knowledge from the source model. We further introduce a prototype-contrast strategy, which includes a prototypesymmetric cross-entropy loss and a prototype-enhanced crossentropy loss, to learn target intra-domain knowledge without relying on labels. A comprehensive variety of experiments on two domain adaptive semantic segmentation benchmarks demonstrates that the proposed end-to-end IAPC solution outperforms existing state-of-the-art methods. Code will be made publicly available at https://github.com/yihong-97/Source-free_IAPC.

Index Terms—Source-free domain adaptation, semantic segmentation, importance awareness, prototype contrast.

I. INTRODUCTION

A san important visual task, semantic segmentation has achieved excellent performance in recent years with

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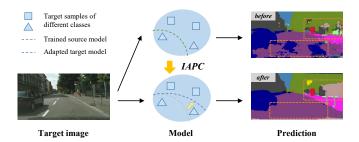


Fig. 1. The trained source model shows poor performance when directly making predictions on the target images. With the proposed IAPC framework, a significant improvement is achieved in road-driving scene segmentation.

deep convolution neural networks [1]–[3]. However, training a deep network requires a lot of time and labeled data, and it takes 90 minutes to finely annotate an image of semantic segmentation [4]. Furthermore, it is more challenging for a model trained in one certain scene (source domain) to achieve good performance in another scene (target domain) due to its low generalization ability. Unsupervised Domain Adaptation (UDA) is a solution to migrate knowledge from the source domain to the unlabeled target domain through aligned distribution.

Typical UDA methods [5]–[7] usually require accessing data from both the source and target domain simultaneously, which is restricted when encountering privacy security or storage problems. Specifically, the GTA5 datasets [8], commonly used for semantic segmentation, require 57GB of storage space. Moreover, it should be noted that due to data privacy concerns, some of the source domain data used for training may not be available for use in practice. To solve these problems, Source-Free Domain Adaptation (SFDA) techniques [9]–[13] are proposed. The data from the source domain is not accessible due to data privacy or storage limitations, and only the model trained on the source domain and unlabeled target domain data can be provided. Under this setting, the current UDA methods are not applicable. Specifically, adversarial Learning (AL) based UDA methods [14]–[16] require access to both the source and target domains in order to align their distributions, whereas self-training UDA methods [17]-[19] can be prone to catastrophic error growth without guidance from labeled data in the source domain.

Recently, several SFDA methods for semantic segmentation have been proposed, and they can be roughly categorized into two kinds: generative methods and self-training-based

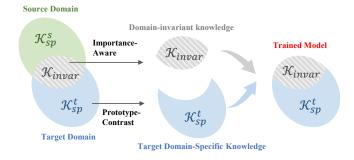


Fig. 2. Task of IAPC. The importance-aware mechanism is employed to extract domain-invariant information \mathcal{K}_{invar} . Furthermore, the prototype-contrast strategy is utilized to learn target domain-specific knowledge \mathcal{K}_{sp}^t . As a result, the trained segmentation model that performs excellently on the target data is obtained.

methods. Generative SFDA methods [20], [21] generate synthetic source-like data to fit the distribution of the source domain. Despite their impressive results, generating more reliable source-like data poses a new challenge and brings additional storage resources. Other SFDA methods [22], [23] utilize data augmentation techniques to generate more training samples for the target domain, aiming to address the issues of class imbalance and lack of reliable samples. The self-trainingbased SFDA methods [24]-[27] adopt a more practical and restrictive setting, wherein only the well-trained source model and unlabeled target data are used for adaptation. Due to the domain shift caused by the different data distributions between the source and target domains, directly using the well-trained source model to generate predictions on target data often results in noisy pseudo-labels. Some methods [24]– [26] attempt to improve the effectiveness of self-training by denoising or enhancing the quality of pseudo-labels. However, due to the limited quantity of labels, these approaches can only partially align the knowledge of the source model with the target domain. Other methods [27], [28] propose using the similarity between prototypes and features as a further measure of credibility for pseudo-labels. However, modeling the prototypes based on the target features still relies on the relevant knowledge extracted from the source model. Overall, these methods are unable to effectively address the impact of domain shift in the absence of source domain data and lack sufficient learning of information from the target data.

To address these issues, as shown in Fig. 2, we propose an IMPORTANCE-AWARE AND PROTOTYPE-CONTRAST (IAPC) framework. IAPC utilizes the proposed importance-aware mechanism to capture shared knowledge between the two domains in the presence of domain shift. Additionally, it enhances the learning of the specific knowledge in the target domain by incorporating the designed prototype-contrast strategy. As a result, a segmentation model that performs well in the target domain is achieved. Specifically, in the absence of source data and target labels, we address this goal from two aspects: (1) Extracting Domain-Invariant Knowledge (EDIK) from the trained source model, and (2) Learning Domain-Specific Knowledge (LDSK) from the unlabeled target domain. For EDIK, we observe that the impact of domain

shift is directly reflected in the predicted class probability distribution when the well-trained source model predicts the target data. The source model exhibits higher confidence in predicting data with minimal distribution differences between the source and target domains. Insufficient confidence leads to maximum prediction probability bias towards other categories. Therefore, we propose an importance-aware mechanism that effectively extracts domain-invariant knowledge from the biased target prediction probability distribution under the influence of domain shift. For LDSK, we introduce a prototypecontrast strategy to learn domain-specific knowledge in the absence of labeled target data. The prototypes, estimated by a delayed-updating memory network, serve as anchors and provide reference distribution probabilities and predictions for the target data. The prototype-symmetric cross-entropy loss and the prototype-enhanced cross-entropy loss are designed to enhance the model's fit to the target task at both the feature and output levels. Finally, through the synergy of EDIK and LDSK, our model achieves accurate segmentation in the target domain even in the absence of source data and target labels.

At a glance, our contributions are summarized as follows:

- (1) We propose the Importance-Aware and Prototype-Contrast (IAPC) framework, an end-to-end solution to source-free domain adaptive semantic segmentation, to adapt the capabilities of the well-trained source model to target domain data without accessing source data and target labels.
- (2) We design an importance-aware mechanism to extract domain-invariant knowledge from the well-trained source model and develop a prototype-contrast strategy to learn domain-specific knowledge from the unlabeled target domain.
- (3) We evaluate our method on two benchmarks, GTA5→Cityscapes and SYNTHIA→Cityscapes, and the results show that our method achieves state-of-the-art results compared to existing SFDA methods.

II. RELATED WORK

A. Domain Adaptive Semantic Segmentation

Domain Adaptive Semantic Segmentation (DASS) is a crucial task in computer vision that aligns the distribution of the source and target domains to improve the model's performance in the unlabeled target domain. It effectively solves the challenge of time-consuming annotation of training data in target domain scenes. Existing DASS methods can be roughly categorized into two types: adversarial learning (AL) based methods [16], [29], [30] and self-training (ST) based methods [31]-[33]. AL-based methods train one or multiple domain discriminators to distinguish whether the input comes from the source or target domain, thus prompting the segmentation model to generate domain-invariant features to counter the discriminator. AL can be applied at the feature level [15], [16] and output level [30], [34]. Although the introduction of AL can effectively align the data distribution of different domains to improve the performance in the target domain, accessibility to the source data is necessary.

ST-based methods generally leverage confident predictions as pseudo-labels to optimize the model. Considering that the pseudo-labels in the target domain may contain noises,

two common methods to address this issue are threshold-based filtering [32] and uncertainty-guided filtering [19], [33]. Traditional DASS methods require simultaneous access to data from both the source and target domains, which is impractical due to data privacy and storage limitations. Therefore, adapting the model to the target domain using only unlabeled target data without using source domain data is essential. To this end, we explore domain adaptation without source data and propose a source-free domain adaptive semantic segmentation method via importance-aware and prototype-contrast learning.

B. Source-free Domain Adaptation

In recent years, source-free domain adaptation techniques that use a well-trained model in the source domain instead of source domain data to adapt to the unlabeled target domain have received increasing attention. Due to the unavailability of source domain scene data, some generative SFDA methods have been proposed. Li *et al.* [35] develop a collaborative class conditional generative adversarial networks for producing target-style training samples to improve the prediction model. Liu *et al.* [20] leverage a generator to estimate the source domain and generate fake samples similar to the real source data in distribution, which can use the well-trained source model to transfer the source knowledge. Although this approach can improve the performance of model adaptation, the large amount of new data generated also brings storage capacity challenges.

Therefore, more self-training-based SFDA methods comply with the restriction of only using a well-trained model in the source domain and unlabeled training samples in the target domain. The pseudo-labels can be roughly divided into prediction-based and prototype-based. For prediction-based pseudo labeling methods, it is widely considered to filter out noise in predictions by setting a threshold [24], [36]. In addition to directly using a certain threshold for filtering, adopting the class-balanced threshold strategy to select a certain percentage of predictions based on the threshold set for each class is a more effective approach [24]. Prototype-based pseudo labeling methods [9], [37]–[39] estimate prototypes first and then calculate the similarity between prototypes and the features to obtain target pseudo-labels. Since the initial estimation of prototypes requires guidance from predictions, this approach is currently more suitable for image-level image classification tasks. During the training phase of using pseudolabels to train the model, introducing confidence weights as a measure of the reliability of pseudo-labels is an effective way to further avoid the influence of noisy predictions. Some methods [27], [28], [39] attempt to use the similarity between prototypes and features directly as the reliability. Huang et al. [27] adopt the classification entropy to estimate the reliability of each historical embedding. Other works [26], [40] also use predictive consistency to identify the reliability of the pseudo labels. Chen et al. [40] leverage the pixel-level uncertainty information from the model's predictions to indicate potentially unreliable pseudo labels. Furthermore, some methods explore the utilization of style transfer techniques to leverage the knowledge acquired by the source model. Paul et al. [41] decrease the shifted distribution between the source and target domains through update only the normalization parameters of the network with the unlabeled target data. Zhao *et al.* [12] propose a cross-patch style swap module to diversify samples with various patch styles at the feature level.

In this paper, we propose an importance-aware mechanism to extract domain-invariant knowledge from the pseudo-labels generated by the well-trained source model. Additionally, we introduce a prototype-contrast strategy to learn domain-specific knowledge from the target domain data.

III. IAPC: PROPOSED FRAMEWORK

In the setting of SFDA for semantic segmentation, the task is to adapt the well-trained source model S_s from the source domain $x_s \in \{\mathcal{X}_s\}$ to the unlabeled target domain $x_t \in \{\mathcal{X}_t\}$, where $x_s, x_t \in \mathbb{R}^{H \times W \times 3}$ and H, W represent the height and width of the images. As shown in Fig. 3, our proposed IAPC framework consists of two parts: EDIK and LDSK. As aligning the data distribution between the source and target domains is not feasible, we propose an Importance-Aware (IA) mechanism to enable the training target model S_t to realize domain-invariant knowledge extraction from S_s . Due to the lack of target data labels, we propose a Prototype-Contrast (PC) strategy to facilitate the S_t to complete domain-specific knowledge learning in the target domain.

A. Importance-Aware Learning in EDIK

For the SFDA task, the information related to the segmentation ability is the well-trained source model, which has excellent performance on the source domain data distribution. However, due to the domain shift, the performance of the non-adapted model will sharply decline on the target domain. Therefore, it is necessary to adapt the knowledge acquired by the source model to the target scenario. Commonly, the well-trained source model S_s is used to generate prediction probability distributions $\hat{p}_t \in \mathbb{R}^{H \times W \times C}$ and pseudo-labels $\hat{y}_t \in \mathbb{R}^{H \times W \times C}$ of the target domain for training, where C denotes the number of classification categories.

The pseudo-labels \hat{y}_t are one-hot vectors, which are obtained from

$$\hat{y}_t^{h,w} = onehot(\arg\max_{c} \hat{p}_t^{h,w,c}), \text{ where } \hat{p}_t = S_s(x_t), \quad (1)$$

where onehot represents the one-hot encoding operation and (h, w, c) represents the index of the position. However, incorrect predictions in noisy pseudo-labels can lead to poor adaptation performance. To address this issue, we first conduct a theoretical analysis and a practical observation.

As shown in Fig. 2, due to the difference in data distributions, only a portion of the data distributions between the source and target domains overlap. This overlapping portion represents domain-invariant knowledge \mathcal{K}_{invar} , while the distinct characteristics of each domain represent domain-specific knowledge \mathcal{K}_{sp} . When the source model S_s is trained on the source domain $\{\mathcal{X}_s\}$, it acquires knowledge that includes both domain-invariant knowledge \mathcal{K}_{invar} and source domain-specific knowledge \mathcal{K}_{sp}^s , represented as

$$\mathcal{F}(S_s) = \mathcal{K}_{invar} + \mathcal{K}_{sn}^s. \tag{2}$$

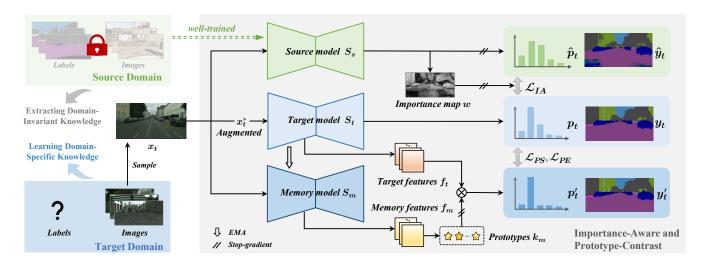


Fig. 3. The framework of our proposed IAPC. It effectively addresses the problem of model adaptation when the source domain is inaccessible and the target domain is unlabeled. The augmented image x_t^* is fed into the target model S_t , whereas the original image x_t is separately fed into the source model S_s and the memory model S_m . Guided by the importance map w, the predictions \hat{p}_t , \hat{y}_t from the source model and target predictions p_t , y_t are combined to extract domain-invariant knowledge under the constraint of \mathcal{L}_{IA} . The features f_m from the memory network are used to estimate prototypes, and combined with target features f_t are utilized together by using the prototype-contrast strategy to enable domain-specific knowledge learning within the target domain under the constraint of \mathcal{L}_{PS} and \mathcal{L}_{PE} .

When S_s is directly used to make predictions \hat{p}_t on a target image x_t , the shift between the source and target domains leads to expected prediction $p_t = S_t(x_t)$ biases, denoted as

$$\mathcal{F}(\hat{p}_t) = \mathcal{F}(S_s(x_t)) = \mathcal{K}_{invar}(x_t) + \mathcal{K}_{sp}^s(x_t)$$

$$= \mathcal{F}(S_t(x_t)) - \mathcal{K}_{sp}^t(x_t) + \mathcal{K}_{sp}^s(x_t)$$

$$\approx \mathcal{F}(p_t) + \varepsilon(\mathcal{K}_{sp}^s, \mathcal{K}_{sp}^t),$$
where $\mathcal{F}(S_t) = \mathcal{K}_{invar} + \mathcal{K}_{sp}^t$. (3)

The \mathcal{K}^t_{sp} denotes the target domain-specific knowledge. The $\varepsilon(\mathcal{K}^s_{sp},\mathcal{K}^t_{sp})$ represents the knowledge bias between the target and source domains, indicating the shift of knowledge between the two domains. This bias weakens the confidence of the source model in predicting the target domain and is reflected in the uncertainty of the final predicted class probability distribution \hat{p}_t . In Fig. 4, we randomly sample the predicted probability distribution of some pixel positions in a target image and visualize the top two largest probability values in the bar charts. As shown in Fig. 4(a), the source model exhibits greater confidence for correctly predicted pixels, i.e., the model assigns a very high probability to a certain category for that pixel compared to other categories. Conversely, as shown in Fig. 4(b), under the influence of domain-specific knowledge bias, the model tends to exhibit prediction biases for pixels with incorrect predictions, which is reflected by a relatively large value for the second-largest probability. That is, the difference between the probability values of the largest probability and the second-largest probability is positively correlated with the bias ε between the domains.

We first design a simple yet effective method to estimate the importance $w^{h,w}$ of each pixel position, denoted as

$$w^{h,w} = 1 - \frac{\max_{c \in C} \hat{p}_t^{h,w,c}}{\max_{c \in C, c \neq \hat{y}_t^{h,w}} \hat{p}_t^{h,w,c}}.$$
 (4)

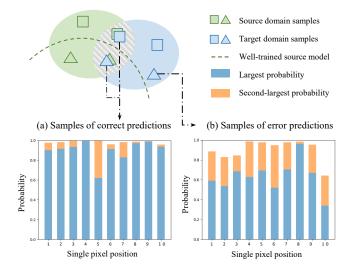


Fig. 4. We randomly sampled and visualized the top two probability values of the predictions made by the non-adapted source model directly on the target data. The left and right sides represent the probability values of correct predictions and incorrect predictions, respectively.

If the source model is confident about the prediction of the current position, the importance value will be close to 1. Conversely, the uncertainty of the model prediction will lead to a lower importance value. The IA-based pseudo-label loss \mathcal{L}_{IA} is given by

$$\mathcal{L}_{IA} = -\frac{1}{HW} \sum_{h,w} w^{h,w} \sum_{c} \hat{y}_{t}^{h,w,c} \log p_{t}^{h,w,c}.$$
 (5)

The \mathcal{L}_{IA} effectively knowledge of the small shift in the source model to the target model under the guidance of the importance map. Furthermore, we argue the target probability distribution should be close to a one-hot encoding. To achieve

this, we adopt the information maximization loss \mathcal{L}_{IM} to enhance the certainty and diversity of the target predictions.

$$\mathcal{L}_{IM} = -\frac{1}{HW} \sum_{h,w} \sum_{c} p_t^{h,w,c} \log p_t^{h,w,c}.$$
 (6)

The combination of \mathcal{L}_{IA} and \mathcal{L}_{IM} effectively enables the transfer of domain-invariant knowledge from the source domain to the target domain when only the well-trained source model is available for access.

B. Prototype-contrast Learning in LDSK

Extracting domain-invariant knowledge from the source model can only ensure that the model has the segmentation ability for common information (*i.e.*, similar distributions between the source and target domains). In order to further improve the model's segmentation ability for the target domain, we need to further excavate the proprietary information within the target domain.

Considering that feature prototypes are less sensitive to the minority outliers and irrelevant to the frequency of category occurrence, we propose a prototype contrast strategy to learn the target domain-specific knowledge. It utilizes a delayupdated memory model S_m to calculate feature prototypes k_m and further guide the model's self-adaptation. The memory model S_m uses the parameters of the target model S_t to update with the exponential moving average (EMA). The input image x_t and augmented image x_t^* are fed into the S_m and S_t respectively to obtain intermediate features f_m and f_t . Considering that calculated prototypes in the hidden feature space are prone to be suboptimal, we adopt a strategy that differs from existing methods [37]-[39] for prototype calculation. On the one hand, the features f_m used for prototype calculation are obtained by the delay-update memory model S_m . On the other hand, a separate prototype is estimated for each input image x_t , rather than using the features of a batch or all samples. Since semantic segmentation is a pixel-level classification task, we believe that using the feature from a single image is sufficient for prototype estimation. In addition, prototypes for different images differ slightly, and prototypes smoothed over more samples may not be conducive to local contrastive learning. Therefore, our prototype k_m^c of class c can be obtained via the following equation:

$$k_{m}^{c} = \frac{\sum_{h,w} y_{m}^{h,w,c} f_{m}^{h,w,c}}{\sum_{h,w} y_{m}^{h,w,c}}, c \in C.$$
 (7)

Then, we can calculate the similarity between the features f_t output by the target network and each prototype k_m^c to obtain the reference class probability distribution $p'_t^{h,w,c}$ for each position in the feature space:

$$p_t^{h,w,c} = \frac{f_t^{h,w} \cdot k_m^c}{\sum_{c} f_t^{h,w} \cdot k_m^c}.$$
 (8)

Specifically, by using the features f_m , f_t respectively from the memory model and the target model to calculate the class probability distribution p'_t of the current sample, we can

avoid the association between the prototype and individual features, and improve the accuracy of the prototype-based class probability distribution. To this end, we first design the following prototype-symmetric cross-entropy loss \mathcal{L}_{PS} to promote consistency in the probability distribution of model predictions at both the instance and category levels:

$$\mathcal{L}_{PS} = -\frac{1}{HW} \sum_{h,w} \sum_{c} (y'_{t}^{h,w,c} \log p_{t}^{h,w,c} + y_{t}^{h,w,c} \log p'_{t}^{h,w,c}), \tag{9}$$

where y'_t represents the reference labels in the form of one-hot vectors. Subsequently, we design a prototype-symmetric cross-entropy loss \mathcal{L}_{PE} , which leverages prototype-based reference predictions y'_t to enhance the target model's performance on hard classes:

$$\mathcal{L}_{PE} = -\frac{1}{HW} \sum_{h,w} \sum_{c} \mathbb{1}_{[y_t^{h,w,c} = y_t^{h,w,c}]} y_t^{h,w,c} \log p_t^{h,w,c}.$$
(10)

Compared to the \mathcal{L}_{IA} in EDIK, dynamically updated prototypes during the iteration process can better utilize information within the target domain to guide the model adaptation.

At this stage, we leverage a delayed update memory model to guide the estimation of the prototype, and then promote the compression of intra-class features and the separation of inter-class features through the proposed \mathcal{L}_{PS} and \mathcal{L}_{PE} . This effectively improves the target model's learning of domain-specific information, enhancing the adaptation.

IV. EXPERIMENTS

A. Datasets

To facilitate the evaluation and fair comparison of the effectiveness of our IAPC framework, we conduct evaluations on two widely-used cross-domain benchmarks in $GTA5 \rightarrow$ Cityscapes and SYNTHIA \rightarrow Cityscapes. GTA5 [8] contains 24,966 fully annotated urban scene synthetic images. The pixel-level ground truth labels are automatically generated by computer graphics and compatible with the format of Cityscapes [4]. We used the 19 common classes with Citysacpes for training. SYNTHIA [46] is another synthetic dataset, and commonly the SYNTHIA-RAND-CITYSCAPES subset is used, which contains 9, 400 images. The ground-truth labels are also compatible with Cityscapes and we select 16 common classes for training. Cityscapes [4] is a real-world dataset acquired while driving in European cities. It consists of 2,975 images from the training set and 500 images from the validation set. These images are precisely labeled for 19 semantic classes.

B. Implementation Details

We adopt the DeepLabV2 architecture [47] with ResNet-101 [48] as the segmentation network. The same architecture is used for the memory network. For the well-trained source model, following [43], [44], we adopt the stochastic gradient descent algorithm with momentum 0.9, weight decay 5e-4 and learning rate 2.5e-4. For the source-free target adaptation stage, the learning rate is set as 1e-4. For both stages, the

TABLE I EXPERIMENTAL RESULTS OF THE $GTA5 \rightarrow Cityscapes$ adaptation scene in terms of per-category IoU, mIoU. The **SF** column indicates whether the adaptive method is source-free. The best results are shown in bold.

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|------------------|----------|------|-------|---------|------|-------|------|---------------|------|--------|---------|------|--------|-------|------|-------|------|-------|-------|--------|------|
| Methods | SF | Road | Sidem | Buildin | Wall | Fence | Role | Lights | Sign | Jegeta | Terrain | SKA | Person | Rider | Cat | Truck | Bus | Train | Motor | Bicycr | mIoU |
| Source only | | 78.9 | 15.5 | 75.0 | 17.6 | 15.8 | 24.8 | 30.1 | 21.4 | 73.9 | 20.1 | 77.4 | 55.6 | 24.4 | 70.9 | 27.8 | 7.1 | 2.9 | 25.3 | 31.3 | 36.6 |
| AdaptSegNet [15] | | 86.5 | 36.0 | 79.9 | 23.4 | 23.3 | 23.7 | 35.2 | 14.8 | 83.4 | 33.3 | 75.6 | 58.5 | 27.6 | 73.7 | 32.5 | 35.4 | 3.9 | 30.1 | 28.1 | 42.4 |
| CBST | × | 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 |
| AdvEnt [42] | / | 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 |
| MaxSquare [43] | | 89.3 | 40.5 | 81.2 | 29.0 | 20.4 | 25.6 | 34.4 | 19.0 | 83.6 | 34.4 | 76.5 | 59.2 | 27.4 | 83.8 | 38.4 | 43.6 | 7.1 | 32.2 | 32.5 | 45.2 |
| UDAClu [44] | | 89.4 | 30.7 | 82.1 | 23.0 | 22.0 | 29.2 | 37.6 | 31.7 | 83.9 | 37.9 | 78.3 | 60.7 | 27.4 | 84.6 | 37.6 | 44.7 | 7.3 | 26.0 | 38.9 | 45.9 |
| UR [24] | | 92.3 | 55.2 | 81.6 | 30.8 | 18.8 | 37.1 | 17.7 | 12.1 | 84.2 | 35.9 | 83.8 | 57.7 | 24.1 | 81.7 | 27.5 | 44.3 | 6.9 | 24.1 | 40.4 | 45.1 |
| SFDA [20] | | 91.7 | 52.7 | 82.2 | 28.7 | 20.3 | 36.5 | 30.6 | 23.6 | 81.7 | 35.6 | 84.8 | 59.5 | 22.6 | 83.4 | 29.6 | 32.4 | 11.8 | 23.8 | 39.6 | 45.8 |
| LD [45] | / | 91.6 | 53.2 | 80.6 | 36.6 | 14.2 | 26.4 | 31.6 | 22.7 | 83.1 | 42.1 | 79.3 | 57.3 | 26.6 | 82.1 | 41.0 | 50.1 | 0.3 | 25.9 | 19.5 | 45.5 |
| HCL [27] | V | 92.0 | 55.0 | 84.0 | 33.5 | 24.6 | 37.1 | 35.1 | 28.8 | 83.0 | 37.6 | 82.3 | 59.4 | 27.6 | 83.6 | 32.3 | 36.6 | 14.1 | 28.7 | 43.0 | 48.1 |
| DTAC [25] | | 78.0 | 29.5 | 83.0 | 29.3 | 21.0 | 31.8 | 38.1 | 33.1 | 83.8 | 39.2 | 80.8 | 61.0 | 30.3 | 83.9 | 26.1 | 40.4 | 1.9 | 34.2 | 43.7 | 45.7 |
| IAPC | | 90.9 | 36.5 | 84.4 | 36.1 | 31.3 | 32.9 | 39.9 | 38.7 | 84.3 | 38.6 | 87.5 | 58.6 | 28.8 | 84.3 | 33.8 | 49.5 | 0.0 | 34.1 | 47.6 | 49.4 |

decrease in learning rate is set at a polynomial decay with a power of 0.9. The size of input images is resized to 1024×512 and cropped 512×256 patch randomly for training. We adopt the partial image augmentation in [49] to perform photometric noise on the input data of the target network. The memory network is updated with the parameters of the target network with the smoothing factor 1e-4. As for the hyper-parameters, the weights of the four losses $\mathcal{L}_{IA}, \mathcal{L}_{IM}, \mathcal{L}_{PS}, \mathcal{L}_{PE}$ are set to the same 0.2, 0.5, 0.01, and 2 in the two benchmarks, respectively. The batch size is set to 6. The proposed IAPC is implemented with the PyTorch toolbox on a single NVIDIA GeForce RTX 3090 GPU. The metric of segmentation performance is measured by the Intersection over Union (IoU) of each category. The mean IoU of all training categories is used to compare the overall performance of the methods. Following previous methods, mIoU* (13 common categories in SYNTHIA excluding wall, fence, and pole) is added in the benchmark of SYNTHIA \rightarrow Cityscapes.

C. Comparison against the State of the Art

In this part, we present the experimental results of the proposed IAPC on two benchmarks and compare it with other existing SFDA methods [20], [24], [25], [27], [45] for semantic segmentation. We also report results of source data accessible UDA methods [15], [17], [42], [43], [50]. For a fair comparison, all methods adopt the DeepLabV2 architecture [47] with a ResNet-101 backbone [48]. The results show that IAPC outperforms existing methods and achieves state-of-the-art performance on both benchmarks, demonstrating its effectiveness and progressiveness.

1) GTA5 → Cityscapes: Table I shows the comparison of the proposed IAPC's performance compared with other methods. IAPC achieves the best mIoU of 49.4 without accessing source domain data. With EDIK and LDSK, IAPC improves the performance of the "Source Only" by 35%. This indicates that our proposed strategy can effectively utilize the well-trained source model and unlabeled target domain data to achieve model adaptation in the target domain. Although the contrastive-learning-based HCL [27] also utilizes information

on feature level and prediction level, our IAPC exceeds it by a large gap of 2.7%. This confirms the effectiveness of our proposed IA mechanism for extracting domain-invariant knowledge. In addition, compared to the UDA methods [17], [42], [43], [50], IAPC achieves excellent segmentation performance even in the absence of source data, effectively addressing the concerns about data privacy and capacity limitations in domain adaptive semantic segmentation tasks. Fig. 5 visualizes the segmentation results of a set of representative samples. It can be clearly observed that IAPC effectively completes the adaptation of the source model to the target domain compared to the baseline of "Source Only" and achieves excellent segmentation results in the target scene.

2) SYNTHIA \rightarrow Cityscapes: Table II displays the comparison results in another scenario. Following the same evaluation protocols, we report the experimental results in two metrics: mIoU and mIoU*. IAPC surpasses existing methods by a significant margin, achieving a surprising mIoU of 45.3 and mIoU* of 52.6. This further confirms the effectiveness of IAPC. IAPC outperforms HCL [27] by 4.1%in mIoU and 4.7\% in mIoU*. Our approach also performs exceptionally well compared to source-accessible UDA methods. UDA-Clu [50] is a feature-level method that utilizes estimated prototypes for clustering and separation. In comparison, IAPC gains a 10.2% improvement in mIoU and a 9.1% improvement in mIoU* by employing the feature-level PC strategy. Unlike UDAClu, which can access source domain data to provide more accurate estimates of prototypes, IAPC's prototype estimation does not have access to any real labels. The outstanding performance confirms the effectiveness of the single image prototype dynamic estimation guided by the memory network in the PC strategy. We observe significant improvements in two categories: Bus and Motobiker, which are often easily confused and misclassified by the segmentation model. This indicates that utilizing the PC in the LDSK strategy can better guide the model to learn the features of these challenging less-frequent categories in the target domain.

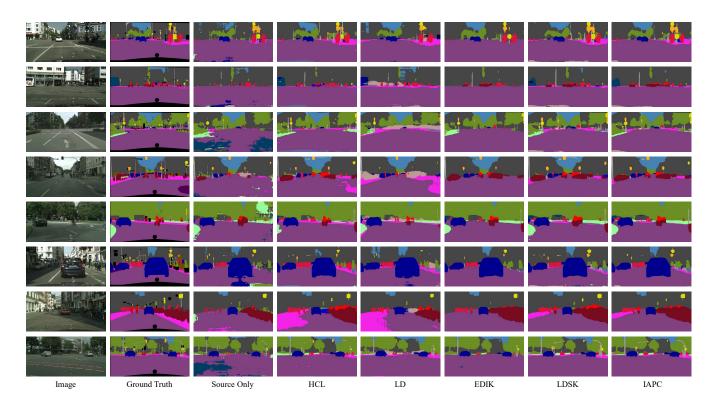


Fig. 5. Qualitative results of semantic segmentation adaptation on GTA5 \rightarrow Cityscapes. (From top to bottom: Image, Ground Truth, Source Only, HCL [27], LD [45], IAPC-EDIK, IAPC-LDSK, and IAPC results (best viewed in color).

TABLE II EXPERIMENTAL RESULTS OF THE SYNTHIA \rightarrow CITYSCAPES ADAPTATION SCENE IN TERMS OF PER-CATEGORY IOU, MIOU AND MIOU*. THE **SF** COLUMN INDICATES WHETHER THE ADAPTIVE METHOD IS SOURCE-FREE. THE BEST RESULTS ARE SHOWN IN BOLD.

| | | | á | × | 36 | | | ^ | | á | ion | ^ | | | | × | ike se | | |
|------------------|----------|------|--------|---------|------|-------|------|--------|------|----------|------|--------|-------|------|----------|-------|--------|------|-------|
| Methods | SF | Road | Şidemi | Buildin | Wall | Fence | Role | Lights | Sign | Vegetati | e)K) | Person | Rider | Cat | Bu^{S} | Motor | Bicycl | mIoU | mIoU* |
| Source only | | 39.5 | 18.1 | 75.5 | 10.5 | 0.1 | 26.3 | 9.0 | 11.7 | 78.6 | 81.6 | 57.7 | 21.0 | 59.9 | 30.1 | 15.7 | 28.2 | 35.2 | 40.5 |
| AdaptSegNet [15] | | 84.3 | 42.7 | 77.5 | - | - | - | 4.7 | 7.0 | 77.9 | 82.5 | 54.3 | 21.0 | 72.3 | 32.2 | 18.9 | 32.3 | - | 46.7 |
| CBST [17] | X | 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 | 48.9 |
| AdvEnt [42] | | 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 | 48.0 |
| MaxSquare [43] | | 78.5 | 34.7 | 76.3 | 6.5 | 0.1 | 30.4 | 12.4 | 12.2 | 82.2 | 84.3 | 59.9 | 17.9 | 80.6 | 24.1 | 15.2 | 31.2 | 40.4 | 46.9 |
| UDAClu [44] | | 88.3 | 42.2 | 79.1 | 7.1 | 0.2 | 24.4 | 16.8 | 16.5 | 80.0 | 84.3 | 56.2 | 15.0 | 83.5 | 27.2 | 6.3 | 30.7 | 41.1 | 48.2 |
| UR [24] | | 59.3 | 24.6 | 77.0 | 14.0 | 1.8 | 31.5 | 18.3 | 32.0 | 83.1 | 80.4 | 46.3 | 17.8 | 76.7 | 17.0 | 18.5 | 34.6 | 39.6 | 45.0 |
| SFDA [20] | | 67.8 | 31.9 | 77.1 | 8.3 | 1.1 | 35.9 | 21.2 | 26.7 | 79.8 | 79.4 | 58.8 | 27.3 | 80.4 | 25.3 | 19.5 | 37.4 | 42.4 | 48.7 |
| LD [45] | ✓ | 77.1 | 33.4 | 79.4 | 5.8 | 0.5 | 23.7 | 5.2 | 13.0 | 81.8 | 78.3 | 56.1 | 21.6 | 80.3 | 49.6 | 28.0 | 48.1 | 42.6 | 50.1 |
| HCL [27] | V | 80.9 | 34.9 | 76.7 | 6.6 | 0.2 | 36.1 | 20.1 | 28.2 | 79.1 | 83.1 | 55.6 | 25.6 | 78.8 | 32.7 | 24.1 | 32.7 | 43.5 | 50.2 |
| DTAC [25] | | 77.5 | 37.4 | 80.5 | 13.5 | 1.7 | 30.5 | 24.8 | 19.7 | 79.1 | 83.0 | 49.1 | 20.8 | 76.2 | 12.1 | 16.5 | 46.1 | 41.8 | 47.9 |
| IAPC | | 68.5 | 29.2 | 82.0 | 10.9 | 1.2 | 28.7 | 22.3 | 29.1 | 82.8 | 85.3 | 60.5 | 19.3 | 83.1 | 42.5 | 32.2 | 47.7 | 45.3 | 52.7 |

D. Ablation Study

To evaluate the effectiveness of each component in the proposed framework, we conduct a comprehensive set of ablation experiments, as presented in Table III. Precisely, we conduct our analysis in terms of EDIK and LDSK.

For the EDIK, we investigate the importance-aware-based pseudo-label loss \mathcal{L}_{IA} (P+IA) and information maximization loss \mathcal{L}_{IM} (IM). The "P" represents a regular pseudo-label loss. Specifically, IA extracts the domain-invariant knowledge between the source and target domains to improve the classification ability, improving by 31.2% in mIoU over the "Source Only". Compare with "P", IA effectively reduces the

domain shift by suppressing biased noise predictions under the guidance of the importance distribution map. We visualize the importance distribution map and the prediction mask of some representative examples after passing through the well-trained source model in Fig. 6. This mask is obtained by extracting the consistent regions of the ground truth and the prediction. These examples demonstrate the consistency of the importance distribution map and prediction mask. This indicates that our designed method for estimating the importance of each prediction effectively guides the model to mitigate the influence of domain shift during training. Additionally, the IA mechanism serves as an effective solution for addressing the lack of labels

TABLE III
ABLATION EXPERIMENTS FOR COMPONENTS. THE BEST RESULTS ARE SHOWN IN BOLD.

| | EDIK | | LD | SK | mIoU | | |
|--------------|--------------|--------------|----|--------------|------|--|--|
| P | P+IA | IM | PS | PE | | | |
| | | | | | 36.6 | | |
| \checkmark | | | | | 43.5 | | |
| | \checkmark | | | | 44.1 | | |
| | ✓ | \checkmark | | | 46.3 | | |
| | | | ✓ | | 42.2 | | |
| | | | | \checkmark | 47.7 | | |
| | | | ✓ | \checkmark | 48.1 | | |
| | \checkmark | \checkmark | ✓ | \checkmark | 49.4 | | |

in the target domain in SFDA. IM effectively improves the adaptation ability of the well-trained source model in the target domain by encouraging peak probability distribution of predictions.

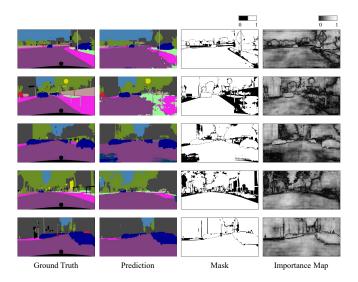


Fig. 6. Visualization results of representative examples using the proposed importance calculation strategy. The prediction in the second column is inferred from the well-trained source model (best viewed in color).

For LDSK, we evaluate the effectiveness of the prototypesymmetric cross-entropy loss \mathcal{L}_{PS} (PS) and the prototypeenhanced cross-entropy loss \mathcal{L}_{PE} (PE). They improve the selflearning ability within the target domain by fully utilizing the information of the target prototype. Compared with the source model, PS and PE show an improvement of 15.3% and 30.3\%, respectively. Especially for the improvement of PE, it demonstrates that our proposed PC strategy is better suited for completing the adaptation of the target model compared with the existing method that uses the source model for filtering. Furthermore, we use t-SNE [51] to obtain the feature distribution in low dimensions as shown in Fig. 7. IAPC can successfully guide features to form tight clusters, thereby improving the discriminativeness of the features. Particularly, the features of the "sign" class (represented in yellow) exhibit a tighter clustering under the guidance of the prototype-contrast strategy. As a result, accurate segmentation of this class is

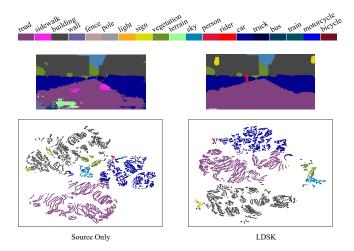


Fig. 7. When adapting from GTA5, visualize the feature distribution of a single image from Cityscapes by assigning labeled classes with corresponding colors and using t-SNE to plot the distribution (best viewed in color).

achieved in the actual prediction map.

These components complement each other, and their combination achieves the best performance.

E. Hyperparameter Analysis

Our proposed IAPC framework utilizes four hyperparameters as weights to control the strength of four losses $\mathcal{L}_{IA}, \mathcal{L}_{IM}, \mathcal{L}_{PS}, \mathcal{L}_{PE}$. In this part, we conduct a sensitivity analysis of these weights, as presented in Table IV. Each row in the table corresponds to a separate experiment in which we varied the value of a specific hyperparameter while keeping the others at their optimal values. Different weights of IM lead to some fluctuations in the segmentation performance. As the weight value increases, we observe a significant performance drop, which is attributed to the detrimental error growth caused by excessively large IM weight. Apart from the IM, the proposed IPAC solution is generally not sensitive to the other parameters, and the performance remains relatively stable across different weight values.

TABLE IV
HYPERPARAMETER SENSITIVITY ANALYSIS. THE BEST VALUES AND
RESULTS ARE SHOWN IN BOLD.

| IA | 0.1 | 0.2 | 0.3 | 0.4 | |
|------|----------|------|------|------|------|
| mIoU | 49.1 | 49.4 | 48.8 | 48.8 | |
| IM | 0.3 49.2 | 0.4 | 0.5 | 0.6 | 0.7 |
| mIoU | | 49.3 | 49.4 | 49.0 | 47.6 |
| PS | 0.02 | 0.03 | 0.04 | 0.05 | 0.06 |
| mIoU | 48.9 | 48.9 | 49.4 | 49.3 | 49.0 |
| PE | 1.0 48.5 | 1.5 | 2.0 | 2.5 | 3.0 |
| mIoU | | 48.9 | 49.4 | 49.1 | 49.2 |

F. Failure Case Analysis

For a more comprehensive analysis of the performance of our IPAC, we showcase several examples of prediction failures in Fig. 8. In the first row, a larger-sized car is incorrectly



Fig. 8. Examples of prediction failures. They are commonly caused by challenges in class discrimination, variations in lighting, and the presence of less-frequent objects. Best viewed in color and with zoom.

identified as a truck due to the similarity of its square model to a truck. In the second row, although the truck is correctly classified, the front bottom of the truck is affected by the lowlight environment and the steering of the wheels, causing the model to mistakenly assume that this part is the car in front of the truck. In the third row, we observe that the continuous shadows cover most of the road and the sidewalk, and the road in the middle-right section is not clearly visible. These lighting variations and road conditions that are difficult to distinguish for humans can confuse the model and result in incorrect predictions. In the last row, some infrequent signs fail to predict, whereas the common signs on the right side are correctly segmented. It is worth noting that these lessfrequent object categories often pose challenges for crossdomain semantic segmentation, and this problem becomes more prominent when the source domain is inaccessible. While simply incorporating a few specialized samples for learning within the model adaptation framework is a potential solution to this problem, we aim to formalize few-shot domain adaptation with selective category-level alignment to facilitate more effective cross-domain knowledge transfer.

V. CONCLUSION

In this work, we propose a Source-Free Domain Adaptation (SFDA) method for road-driving scene semantic segmentation, called IAPC. The proposed Importance-Aware Prototype-Contrast (IAPC) framework enables end-to-end adaptation from a source model to a target domain without accessing the source data and target labels. We introduce an Importance-Aware (IA) mechanism to extract domain-invariant knowledge from the source model. Additionally, we introduce a Prototype-Contrast (PC) strategy to learn domain-specific knowledge from unlabeled target domain data. As a result, we obtain a model with excellent segmentation performance on the target data. Experimental results on two benchmarks for domain adaptive semantic segmentation show that our

method achieves state-of-the-art performance and ablation studies verify the effectiveness of each component in IAPC.

In the future, we intend to explore source-free domain adaptation for panoramic semantic segmentation to enable 360° surrounding perception and the potential of our method in other vision tasks such as object detection, panoptic segmentation, 3D scene understanding, *etc*.

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