Effective Label Propagation for Discriminative Semi-Supervised Domain Adaptation

Zhiyong Huang, Kekai Sheng, Weiming Dong, Member, IEEE, Xing Mei, Member, IEEE, Chongyang Ma, Member, IEEE, Feiyue Huang, Dengwen Zhou, Changsheng Xu, Fellow, IEEE

Abstract—Semi-supervised domain adaptation (SSDA) methods have demonstrated great potential in large-scale image classification tasks when massive labeled data are available in the source domain but very few labeled samples are provided in the target domain. Existing solutions usually focus on feature alignment between the two domains while paying little attention to the discrimination capability of learned representations in the target domain. In this paper, we present a novel and effective method, namely Effective Label Propagation (ELP), to tackle this problem by using effective inter-domain and intra-domain semantic information propagation. For inter-domain propagation, we propose a new cycle discrepancy loss to encourage consistency of semantic information between the two domains. For intra-domain propagation, we propose an effective self-training strategy to mitigate the noises in pseudo-labeled target domain data and improve the feature discriminability in the target domain. As a general method, our ELP can be easily applied to various domain adaptation approaches and can facilitate their feature discrimination in the target domain. Experiments on Office-Home and DomainNet benchmarks show that ELP consistently improves the classification accuracy of mainstream SSDA methods by $2\% \sim 3\%$. Additionally, ELP also improves the performance of UDA methods as well (81.5\% vs 86.1\%), based on UDA experiments on the VisDA-2017 benchmark. Our source code and pre-trained models will be released soon.

Index terms—Domain Adaptation; Semi-Supervised Learning; Self Supervised Learning; Deep Learning

I. INTRODUCTION

Deep convolutional neural networks (CNNs) have significantly advanced state-of-the-art in large-scale image classification on public datasets such as ImageNet [6] and Open Image [17]. Massive labeled training data are essential for the superior performance of CNNs, but they are not always available in a new domain practically. One popular approach to tackle this problem is *domain adaptation (DA)* [23], [4], [25], [33], [22]. The goal of DA is to leverage labeled data from a source domain to boost unsupervised learning (UDA) or semi-supervised learning (SSDA) in a new but related target domain. Over the past decades, DA has been successfully applied in many scenarios, such as image classification [4], [25], [21], [28], object detection [43], semantic segmentation [50], and person re-identification [7].

A central challenge of domain adaptation is the gap of the feature distributions between the two domains. Conventional UDA and SSDA methods focus on aligning these distributions with adversarial training [23], [4], [36]. More recent SSDA methods jointly minimize the task loss and the domain gap with subspace learning [47], consistency regularization [16], [9], [46], or entropy-based loss design [33]. These methods intend to learn transferable visual features for better classification accuracies on various DA datasets. Nevertheless, it is arguable that the feature transferability is not equal to the feature discriminability, and the classification accuracies on the target domain still remain unsatisfactory [3], [22]. We illustrate the problem with an example (Synthetic to Real) from the VisDA-2017 dataset [31], as illustrated in Fig. 1 the representations extracted by existing UDA (Fig. 1(b)) and...
SSDA methods (Fig. 1(c)) can fail to form clear decision boundaries in some target domain regions (marked with red rectangles). That is to say, one ideal DA method should take into consideration the transferability and the discriminability of learned representations at the same time.

There have been a few attempts in improving the discrimination of learned representations on the target domains. Representative methods are [46], [52], [22]. Despite their positive effects, the classification accuracies on large-scale datasets (e.g., for VisDA-2017 [31], please refer to Table V in Section IV) are still unsatisfactory, which might suffer from the noise of pseudo-labeled data on the target domain. In this paper, we introduce a new learning scheme with effective label propagation to propagate semantic-aware information from the source domain to the target domain, reinforce the feature discriminability on the target domain with an effective self-training strategy. In this way, we eventually promote the classification performance on the target domain.

Specifically, we propose a novel framework, namely Effective Label Propagation (ELP), to propagate label information both across the two domains and within the target domain. Fig. 2(b) shows the framework of our ELP. We first propose a cycle discrepancy loss (CDL) which requires the feature extractor to explain labeled samples in the source domain with unlabelled samples from the target domain and encourage label consistency between the two domains. With CDL, we encourage the label consistency in the representation space between the two domains. Besides, we conduct intra-domain propagation (i.e., an effective self-training scheme) to enhance the discrimination of features on the target domain. To combat against the noises in pseudo-labeled instances in the target domain, we propose some simple yet effective strategies: memory bank, dynamic threshold strategy, and balanced pseudo-label aggregation. We evaluate ELP on two domain adaptation benchmarks, including Office-Home [41] (small-scale), DomainNet [30] (large-scale), and the results in Section IV demonstrate the effectiveness of the proposed ELP. Besides, we also find that our ELP helps promote the classification accuracies of state-of-the-artUDA methods (e.g., DTA [19]) building on the UDA experiments on VisDA-2017 benchmark. These experimental results further verify the versatility of ELP in domain adaptation.

In summary, the technical contributions of our ELP are:

- To propagate semantic-aware information from the source domain and the target domain effectively, we propose a novel loss function based on cycle discrepancy.
- To improve feature discriminability in the target domain further, we propose an effective self-training strategy: memory bank, dynamic threshold strategy, and balanced pseudo-label aggregation.
- Extensive experiments and ablation studies on several domain adaptation benchmarks and two typical adaptation scenarios (SSDA + UDA) demonstrate the effectiveness and versatility of the proposed ELP.

II. RELATED WORK

A. Domain Adaptation.

Over the past decades, a number of domain adaptation (DA) methods have been proposed to minimize domain discrepancy and obtain domain-invariant features [9], [23], [25], [28], [43], [22]. A comprehensive survey of all DA methods is beyond the scope of this paper, and we mainly focus on recent semi-supervised domain adaptation (SSDA) methods that use a few labeled samples in the target domain. Yao et al. [47] proposed a subspace learning framework (SDASL) which projects samples from both domains into this subspace and learns classifiers with several regularization strategies. Xu et al. [46] used stochastic neighborhood embedding (d-SNE) to transform features into a common latent space for few-shot supervised learning and improve the feature discrimination on the target domain via metric learning. Recently, Saito et al. [33] proposed a minimax entropy approach (MME) which iterative updates the task classifier and the feature extractor in a min-max entropy training scheme.

Different from the aforementioned counterparts, the proposed method explicitly leverages semantic-aware information via
Fig. 3. The illustration of the proposed ELP. ELP extracts features with a CNN architecture \( F \), directs these features from different domains to different modules, calculates different losses \( \mathcal{L}_{cdl}, \mathcal{L}_{ce}, \mathcal{L}_{u}, \mathcal{L}_{uce} \) with a classifier \( G \) and minimizes the overall loss in the training process. The key contributions of ELP lie in two aspects. First, we introduce a new cycle discrepancy loss \( \mathcal{L}_{cdl} \) that conducts inter-domain propagation among the two domains. Second, we reinforce the feature discriminability on the target domain with self-training.

### TABLE I

| Methods   | Domain discrepancy | Feature subspace | Entropy or metric | Self-training on the target domain |
|-----------|--------------------|------------------|-------------------|-----------------------------------|
| SDASL [47] | √                  |                  |                   |                                   |
| MME [33]  |                    |                  |                   |                                   |
| CRST [52] |                    |                  |                   |                                   |
| dSNE [46] | √                  | √                | √                 | √                                 |
| SHOT [22] |                    |                  |                   |                                   |
| ELP (Ours) | √                  | √                | √                 | √                                 |

We will verify the effectiveness of the proposed novel learning scheme.

**B. Cycle Consistency.**

In this paper, we propose a new self-training scheme with memory bank, dynamic threshold strategy, and balanced pseudo-label aggregation. Different from the existing counterparts, the proposed method is simple to implement and turn out to be effective in eliminating the noise within the pseudo labeled data and facilitating the feature discriminability on the target domain. We provide an extensive comparison between ELP and representative methods (e.g. CRST and SHOT) in Section IV-E.

**III. EFFECTIVE LABEL PROPAGATION NETWORK.**

The framework of ELP is illustrated in Fig. 3. Our method extracts features from the labeled and unlabeled samples with a CNN architecture \( F \), directs these features to different modules, calculates different losses with a classifier \( G \), and minimizes the overall loss in the training process. The key components of ELP include inter-domain propagation (cycle discrepancy loss...
where \( h \) is a hypothesis of the ideal model, \( \mathcal{H} \) is the hypothesis space, \( \varepsilon_S(h), \varepsilon_T(h) \) are the expected errors of the hypothesis \( h \) in the source domain and in the target domain respectively, 
\[
d_{\mathcal{H}\mathcal{H}}(S, T) = \varepsilon_S(h) + \varepsilon_T(h),
\]
measures the domain discrepancy with the upper bound of the hypotheses disagreement in \( \mathcal{H}\mathcal{H} \), and \( \gamma = \min_h(\varepsilon_T(h) + \varepsilon_S(h)) \) is the minimum joint hypothesis error. 

Eq. (1) shows that the expected error in the target domain is upper bounded by both \( d_{\mathcal{H}\mathcal{H}}(S, T) \) and \( \gamma \). While most existing DA methods focus on reducing domain discrepancy \( d_{\mathcal{H}\mathcal{H}}(S, T) \) with better alignment of the feature distributions, our method tries to lower the joint classification errors \( \gamma \) with effective label propagation in the SSDA setting.

### B. Cycle Discrepancy Loss via Inter-domain Propagation

1) **Motivation:** As discussed previously, most domain adaptation methods attempt to learn a feature extractor for domain alignment, but well aligned features alone do not guarantee good classification performance on the target domain [3], [22]. On the other hand, the direct propagation of the label from the source domain to the target domain is not a good choice. See Fig. 5 for better understanding of the advantage of high-order propagation over direct label propagation. Inspired by recent work in cycle consistency [14], [8], we propose a new cycle discrepancy loss (CDL) to encourage samples with the same labels to stay close in the feature space through a cross-domain propagation process.

2) **Formulation:** Conceptually, CDL is computed for each sample in the source domain, as shown in Fig. 4, we approximate this sample from the source domain with unlabeled samples in the target domain, project this approximation back into the source domain and locate the nearest source sample. If the two source samples share the same label, we add the CDL loss to penalize the distance between them. In practice, we implement CDL on one mini-batch of labeled samples \( B^S \) from the source domain and one mini-batch of unlabeled

![CDL](image_url)
samples $B^{Tu}$ from the target domain. For a sample $\tilde{x}_i^S \in B^S$, we approximate $F(\tilde{x}_i^S)$ with a new feature vector $\tilde{v}_i$:

$$
\tilde{v}_i = \sum_{\tilde{x}_j^T \in B^{Tu}} \alpha_j F(\tilde{x}_j^T),
$$

where $\tilde{v}_i$ is a weighted average of the sample vectors from $B^{Tu}$, and the weights are determined by the pairwise $L^2$ distance in the feature space. We then use $\tilde{v}_i$ as an anchor point in the source domain and calculate a softmax-like score $\beta_j$ for each sample $\tilde{x}_j^T \in B^S$:

$$
\beta_j = \frac{e^{-||F(\tilde{x}_j^T) - F(\tilde{v}_i)||^2}}{\sum_{\tilde{x}_k^T \in B^S} e^{-||F(\tilde{x}_k^T) - F(\tilde{v}_i)||^2}}.
$$

We denote the sample with the highest score as $\tilde{x}_i^S = \arg\max_{\tilde{x}_j^T \in B^S} \beta_j$. If $\tilde{x}_i^S, \tilde{x}_j^S$ share the same class label, they should be close in the feature space to improve the decision boundaries of this class. The CDL on the mini-batch $B^S$ is finally formulated as:

$$
L_{cdl} = -\frac{1}{|B^S|} \sum_{\tilde{x}_i^T \in B^S} I(y_i, y_\hat{i}) \log(\beta_i),
$$

where $I(y_i, y_\hat{i})$ is a binary indicator function that is activated only when $y_i, y_\hat{i}$ are equal. As shown in Eqs. (4), minimizing $L_{cdl}$ will not only encourage the source samples within the same class to stay close to each other, but also drive unlabeled target samples towards nearest labeled source samples. In this way, the proposed $L_{cdl}$ helps propagate meaningful semantic-aware information between the two domains.

3) Theoretical insight: To further understand the rationale of $L_{cdl}$, we cast Eqs. (4) in another mathematical formulation as follows:

$$
L_{cdl} = -\frac{1}{|B^S|} \sum_{\tilde{x}_i^T \in B^S} I(y_i, y_\hat{i}) \log(\beta_i)
\begin{align*}
&= \lim_{I(y_i, y_\hat{i}) \to 0^+} I(y_i, y_\hat{i}) \log(I(y_i, y_\hat{i})) = 0, \\
&= \lim_{I(y_i, y_\hat{i}) \to 1^-} I(y_i, y_\hat{i}) \log(I(y_i, y_\hat{i})) = 0 \\
&= \frac{1}{|B^S|} \sum_{\tilde{x}_i^T \in B^S} [I(y_i, y_\hat{i}) \log(I(y_i, y_\hat{i})) - I(y_i, y_\hat{i}) \log(\beta_i)] \\
&= \frac{1}{|B^S|} \sum_{\tilde{x}_i^T \in B^S} I(y_i, y_\hat{i}) \log\left(\frac{I(y_i, y_\hat{i})}{\beta_i}\right)
\end{align*}
$$

It seems that there exists a strong connection between the CDL and the KL-divergence. Eqs. (5) indicates that, to minimize $L_{cdl}$ is equal to minimize the KL-divergence from $\beta_j$ to $I(y_i, y_\hat{i})$. $I(y_i, y_\hat{i})$ is the probability distribution based on label information from cycle consistency, and $\beta_j$ is the probability distribution based on the learned features from cycle consistency or mutual nearest neighbors. Consequently, the objective of $L_{cdl}$ is to propagate information from $I(y_i, y_\hat{i})$ to $\beta_j$, to learn to model $I(y_i, y_\hat{i})$ with $\beta_j$, and to make $\beta_j$ discriminative.

C. Intra-Domain Propagation via Self Training

Apart from the $L_{cdl}$ that encourages label consistency across the two domains, we also try to improve the feature discriminability on the target domain with an effective self-training strategy. Our strategy mainly consists of two steps, i.e., aggregation and propagation. In the aggregation, we record the discriminative information of each class with a set of memory banks (e.g., the centroids of the classes in the target domain) and leverage a dynamic threshold strategy to eliminate the noises within the pseudo labels. In the propagation, we apply a balanced pseudo-label aggregation to strengthen the meaningful training signal in the pseudo-labeled data.

1) Aggregation: We keep a memory bank $\tilde{m}_c$ for each class $c$ during the whole training process, which serves as the up-to-date centroid of the class in the target domain. At the start of each epoch, we update $\tilde{m}_c$ with all the samples in $X^{Tu} \cup X^{Tu}$ that have the label $c$ (denoted as $X^T_i$):

$$
\tilde{m}_c = \frac{1}{|X^T_i |} \sum_{\tilde{x}_i^T \in X^T_i} ||F(\tilde{x}_i^T)||_2.
$$

Note that we use both unlabeled samples and labeled samples in the target domain for this update. For unlabeled samples in $X^{Tu}$, we use the prediction results of the current classifier to determine their pseudo labels. For a given class $c$, we further use the median of the prediction probabilities of all the unlabelled samples as the threshold and select the half above this threshold to update $\tilde{m}_c$. We show in Section [V] that this dynamic threshold strategy generally outperforms a static score threshold in refining the pseudo labels. During each iteration of the SGD optimization process, we further smooth $\tilde{m}_c$ with the current mini-batch $B^{T}$ following [42]:

$$
\tilde{m}_c = (1 - w) \cdot \tilde{m}_c + w \cdot \tilde{m}_c^B,
$$

where $w$ is a linear weight in $[0,1]$ and $\tilde{m}_c^B$ is the local memory bank information we collect from this mini-batch.

2) Propagation: After updating the memory banks for all classes, we can generate pseudo labels for all unlabeled samples in the target domain. For a sample $\tilde{x}_i^{Tu} \in X^{Tu}$, its pseudo label $\hat{y}_i$ is determined with the small-loss criteria [12], [15]:

$$
\hat{y}_i = \arg\max_j F(\tilde{x}_i^{Tu}) \cdot \tilde{m}_j.
$$

Rather than using pseudo labels directly for training, we generate a new training sample $(\tilde{x}, y)$ by mixing up two pseudo-labeled instances $(\tilde{x}_i, \hat{y}_i), (\tilde{x}_j, \hat{y}_j)$ similar to [49]:

$$
\tilde{x} = (1 - \lambda) \tilde{x}_i + \lambda \tilde{x}_j, \\
\hat{y} = (1 - \lambda) \hat{y}_i + \lambda \hat{y}_j,
$$

where $\lambda$ is a hyper-parameter, and $(\tilde{x}_i, \hat{y}_i), (\tilde{x}_j, \hat{y}_j)$ are two samples randomly selected from two mini-batches. Different from the vanilla mixup in [49] where $\lambda$ randomly varies in $(0, 1)$, we set $\lambda = 0.5$ throughout our experiments. We show in Section [V] that this balanced aggregation achieves better performance than the vanilla mixup and one recent DA method based on domain mixup [44]. After generating new training samples with the balanced aggregation, we calculate the cross entropy loss on these samples and mark it as $L_{uce}$. 


Algorithm 1: The learning scheme of ELP

Data: \( \{X^S, Y^S\}, \{X^T, Y^T\} \)
Data: \( \text{Iter}_1, \text{Iter}_2, w_{cdl}, w_{uace}, w_{ce}, w_u \)
Result: \( \theta_F, \theta_G \)

begin
Initialize the model, \( \text{iter} = 1 \)
while \( \text{iter} \leq \text{Iter}_1 \) and \( \mathcal{L} \) doesn’t converge do
\( \text{iter} += 1 \), randomly sample mini-batches \( B^S, B^Tu, B^T \)
Train the model with \( \mathcal{L} = w_{cdl}\mathcal{L}_{cdl} + w_{uace}\mathcal{L}_{uace} + w_{ce}\mathcal{L}_{ce} + w_u\mathcal{L}_u \)
end

Get the best model in Stage one
Initialize the memory banks, \( \text{iter} = 1 \)
while \( \text{iter} \leq \text{Iter}_2 \) and \( \mathcal{L} \) doesn’t converge do
\( \text{iter} += 1 \), randomly sample mini-batches \( B^S, B^{Tu1}, B^{Tu2}, B^T \)
Calculate pseudo labels for \( B^{Tu1}, B^{Tu2} \) with the model
Update the memory banks
Refine the pseudo labels via the memory banks
Take \( B^{Tu1} \) and \( B^{Tu2} \) as input and perform balanced mixup
Train the model with \( \mathcal{L} = w_{cdl}\mathcal{L}_{cdl} + w_{uace}\mathcal{L}_{uace} + w_{ce}\mathcal{L}_{ce} + w_u\mathcal{L}_u \)
end
Return \( \theta_F, \theta_G \)

D. Overall Learning Scheme

Given one mini-batch of labeled samples \( B^S \) from the source domain, one mini-batch of unlabeled samples \( B^{Tu} \) and one mini-batch of labeled samples \( B^T \) in the target domain, the total loss \( \mathcal{L} \) is a weighted combination of four loss terms:

\[
\mathcal{L} = w_{cdl}\mathcal{L}_{cdl} + w_{uace}\mathcal{L}_{uace} + w_{ce}\mathcal{L}_{ce} + w_u\mathcal{L}_u,
\]

where \( \mathcal{L}_{ce} \) is the cross entropy loss for labeled samples in \( B^S \) and \( B^T \), \( \mathcal{L}_u \) is the entropy loss for unlabeled samples in \( B^{Tu} \), and \( w_{cdl}, w_{uace}, w_{ce}, w_u \) are the corresponding weights. In one practical implementation, ELP works in a two-stage manner, as described in Algorithm 1 in Stage One, we use \( \mathcal{L}_{cdl}, \mathcal{L}_{ce}, \mathcal{L}_u \) to transfer semantic information from the source domain to the target domain and learn an initial representation for the target domain. In Stage Two, we propose \( \mathcal{L}_{uace} \) and reinforce the feature discriminability with the self-training scheme. It should be noted that, the proposed ELP can be easily applied to various domain adaptation methods, including both UDA and SSDA settings, to promote their classification accuracies on the target domain.

E. Implementation Details

1) Training: Following the training practice in \cite{25, 33, 19}, we use different CNN architectures on different datasets: ResNet-34 \cite{13} on the DomainNet dataset \cite{30}, VGG-16 \cite{39} on the Office-Home dataset \cite{41}, and ResNet-101 \cite{13} on the VisDA-2017 dataset \cite{31}. All networks are pre-trained on ImageNet \cite{6}, and they serve as feature extractors by removing the last linear classification layer.

To verify the effectiveness of the ELP, we conduct most of our experiments in the SSDA settings and implement ELP based on MME \cite{33}. For all the experiments, we train the model using SGD with a momentum value of 0.9. The initial learning rates for the classifier and the feature extractor are 0.01 and 0.001 respectively. We use the learning rate annealing strategy as described in \cite{10}. We initialize the updating rate of the memory bank \( w \) to 0.01 and increase it linearly with the number of epochs, i.e., \( w = 0.01 \times \text{epochs} \). The weight parameters \( w_{cdl}, w_{uace}, w_{ce}, w_u \) are set to 0.1, 0.9, 0.1, 0.1, respectively, via cross-validation experiments.

To further verify the general effectiveness of the proposed ELP, we also conduct additional experiments in the UDA settings. In specific, we implement our ELP on DTA \cite{19} and analyze whether the ELP can help promote the performance of DTA. In the UDA experiments, we follow the same configurations as that of DTA. Specifically, we train the model with an initial learning rate of 0.001, and decay it by a factor of 0.1 after 10 training epochs. All networks are trained on one NVIDIA TESLA V100 GPU.

2) Inference: In the inference stage, we resize the shortest edge of input images to 256, crop 224 \times 224 patches from the center part, and report the classification accuracy based on the cropped patches, which is consistent with previous works \cite{25, 33, 36, 19}. For each adaptation scenario, we repeat the experiments three times and report the average accuracy.

IV. Experiments

In this section, we evaluate the performance of our ELP on multiple domain adaptation benchmarks and compare the results with several state-of-the-art DA approaches.

A. Datasets

We validate our method on three public DA benchmarks. For fair comparison, we randomly run our method for three times with different random seeds via Pytorch \cite{29} and report the average classification accuracies.

Office-Home \cite{41} contains approximately 15,500 images from 4 image domains (i.e., Real, Clipart, Art, and Product) with 65 classes. Follow the common practice, we conduct comparison experiments on 12 adaptation scenarios in total.

DomainNet \cite{30} contains 6 domains with 345 classes. It is usually used for testing large-scale domain adaptation. However, labels of some domains and classes are very noisy. Thus, by following the experimental configuration of \cite{33}, 4 domains (Real, Clipart, Painting, and Sketch) and 126 classes are selected. We conduct comparison experiments on the adaption scenarios where the target domains are different from real by picking up 7 scenarios from the domains, following the same configurations in MME \cite{33}.

VisDA-2017 \cite{31} contains approximately 280,000 images from 12 classes (see the first row in Table VI). It is a challenging

\footnote{From the authors: https://github.com/VisionLearningGroup/SSDA_MME}

\footnote{The official implementation: https://github.com/postBG/DTA.pytorch}
We choose multiple state-of-the-art DA approaches, including both typical methods and latest ones, as the baselines: S+T [32], entropy minimization (ENT) [11], domain adversarial neural network (DANN) [10], domain adaptation network (DAN) [24], adversarial dropout regularization (ADR) [35], conditional domain adaptation network (CDAN) [25], maximum classifier discrepancy (MCD) [36], CRST [52], batch spectral penalization (BSP) [3], adaptive feature normalization (AFN) [45], dSNE [46], drop to adapt (DTA) [19], MME [33], adversarial domain adaptation with domain mixup (DM-ADA) [44], gradually vanishing bridge (GVBG) [5], metalearning based framework (Meta-) [20], and SHOT [22].

We will demonstrate the effective of our method in improving classification accuracies of the aforementioned baselines on the target domain. For reliable results, we cited the performance of these baseline methods from [3], [19], [33].

C. SSDA Results on DomainNet.

We demonstrate the effectiveness of our ELP by comparing it with several existing counterparts on DomainNet benchmark. We apply ResNet-34 [13], the same backbone network in the previous work [36], [25], [19]. For the results of baselines, we directly reported their values from the original paper [33].

The classification accuracy per adaptation setting and the total average results on the DomainNet dataset are listed in Table II. We can observe that, among all the methods, the proposed ELP achieves the best classification accuracy of 69.0% (+2.6%) in one-shot SSDA and 71.5% (+2.7%) in three-shot SSDA, respectively. Besides, on all the 7 × 2 adaptation settings, our ELP consistently improves the classification accuracy on MME. Moreover, to demonstrate the versatility of our ELP, we randomly select 7 adaptation settings from Table II and conduct similar comparison experiments using VGG-16 [39]. The results indicate that on one different network backbone, the proposed ELP can also boost the classification accuracies of MME by 1 ~ 3%.

D. SSDA Results on Office-Home.

We also compare the proposed ELP with some state-of-the-art methods, including CDAN [25], ENT [11], and MME [33], on Office-Home benchmark. We apply VGG-16 [39] and ResNet-50 [13] as the backbone for fair comparisons.

The results are listed in Table III and Table IV as it can be observed that, our method achieves the best classification accuracy of 68.0% on average (three-shot SSDA with VGG-16), better than other SSDA counterparts. And on ResNet-50, the proposed ELP also helps improve the classification performance of MME. We also notice that: (1) asymmetric transferability generally exists, like 75.9% (Art → Product) ≠ 59.3% (Product → Art), and 73.3% (Clipart → Real) ≠ 57.1% (Real → Clipart). It necessitates the refinement of label propagation procedure between the source domain and the target domain. (2) For each sub-dataset pairs, the large amount of the source domain generally leads to the degradation in the classification accuracy on the target domain. These observations indicate the indispensable role of label information propagation in the target domain for improved feature discriminability and better classification performance.

For the results of Meta-MME [20], the authors only reported their three-shot SSDA accuracies in their paper.
TABLE III
Comparisons of different approaches on the three-shot SSDA scenarios from Office-Home with ResNet-50.

| Method  | A → C | A → P | A → R | C → A | C → R | C → P | P → A | P → C | MEAN |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Three-shot SSDA |
| MME    | 60.5  | 77.4  | 76.3  | 64.0  | 73.4  | 73.7  | 63.3  | 61.6  | 68.8 |
| MME + Ours | 62.0  | 78.3  | 77.5  | 64.9  | 75.3  | 79.0  | 64.4  | 63.1  | 70.6 |

TABLE IV
Comparisons of different methods on Office-Home dataset based on VGG-16. The results (%) include one-shot and three-shot on all possible adaptation scenarios. For details about number of runs, we mark the first / second with **bold** / **underline**.

| Method  | R / P / A → C | R / A / C → P | R / P / C → A | P / A / C → R | MEAN |
|---------|---------------|---------------|---------------|---------------|------|
| One-shot SSDA |
| S + T  | 39.5 / 37.0 / 37.5 | 75.3 / 63.6 / 65.9 | 61.2 / 32.0 / 51.4 | 71.6 / 69.5 / 64.5 | 57.4 |
| DANN [10] | 52.0 / 45.9 / 44.4 | 75.7 / 64.3 / 65.3 | 62.7 / 51.3 / 52.3 | 72.7 / 68.9 / 64.2 | 60.0 |
| ADR [35] | 39.7 / 37.2 / 39.0 | 76.2 / 63.9 / 65.2 | 60.2 / 51.4 / 50.0 | 71.8 / 68.7 / 64.8 | 57.4 |
| CDAN [25] | 43.3 / 37.4 / 39.8 | 75.7 / 67.7 / 66.2 | 60.9 / 44.5 / 41.6 | 69.6 / 64.8 / 58.7 | 55.8 |
| ENT [11] | 23.7 / 21.3 / 22.4 | 77.5 / 66.0 / 67.7 | 64.0 / 44.6 / 25.1 | 74.6 / 70.6 / 62.1 | 51.6 |
| MME    | 49.1 / 46.2 / 45.8 | 78.2 / 68.6 / 71.3 | 65.1 / 56.0 / 57.5 | 74.7 / 72.2 / 68.0 | 62.7 |
| MME + Ours | 49.2 / 46.7 / 46.1 | 79.7 / 69.0 / 71.6 | 65.5 / 56.3 / 57.4 | 75.3 / 72.4 / 68.2 | 63.1 |

| Three-shot SSDA |
| S + T  | 49.6 / 47.2 / 47.5 | 78.6 / 69.4 / 70.4 | 63.6 / 55.9 / 56.2 | 72.7 / 73.4 / 69.7 | 62.9 |
| DANN [10] | 56.1 / 52.4 / 50.0 | 77.9 / 69.5 / 69.8 | 63.7 / 56.3 / 56.4 | 73.6 / 72.3 / 68.7 | 63.9 |
| ADR [35] | 49.0 / 47.8 / 49.3 | 78.1 / 69.9 / 71.4 | 62.8 / 55.8 / 45.3 | 73.6 / 73.3 / 69.3 | 63.0 |
| CDAN [25] | 59.0 / 51.3 / 46.0 | 80.9 / 74.7 / 71.2 | 62.1 / 50.3 / 52.9 | 70.8 / 71.4 / 65.9 | 61.8 |
| ENT [11] | 48.3 / 46.8 / 44.8 | 81.6 / 73.0 / 77.0 | 65.5 / 56.9 / 59.1 | 76.6 / 75.3 / 72.9 | 64.8 |
| MME    | 56.9 / 53.6 / 54.9 | 82.9 / 75.7 / 76.3 | 65.7 / 59.2 / 61.1 | 76.7 / 75.3 / 72.9 | 67.6 |
| MME + Ours | 57.1 / 53.9 / 55.1 | 83.2 / 75.9 / 76.1 | 67.0 / 59.3 / 61.9 | 76.5 / 76.3 / 73.3 | 68.0 |

TABLE V
Classification accuracy (%) on the VisDA-2017 validation partition based on ResNet-101. S-only means training the model with the source domain alone. For details about number of runs, we mark the first / second with **bold** / **underline**.

| Method  | airplane | bicycle | bus | car | horse | knife | motorcycle | person | plant | skateboard | train | track | MEAN |
|---------|----------|---------|-----|-----|-------|-------|------------|--------|-------|------------|-------|-------|------|
| S-only  | 55.1     | 53.3    | 61.9| 59.1| 80.6  | 17.9  | 79.7       | 31.2   | 81.0  | 26.5       | 73.5  | 8.5   | 52.4 |
| DAN     | 68.1     | 15.4    | 76.5| 87.0| 71.1  | 48.9  | 82.3       | 51.5   | 88.7  | 33.2       | 88.9  | 42.2  | 62.8 |
| MCD     | 87.0     | 60.9    | 84.0| 64.0| 88.9  | 79.6  | 84.7       | 76.9   | 88.6  | 40.3       | 83.0  | 25.8  | 71.9 |
| ADR     | 87.8     | 79.5    | 83.7| 65.3| 92.3  | 61.8  | 88.9       | 73.2   | 87.8  | 60.0       | 85.5  | 32.3  | 74.8 |
| CDAN    | 85.2     | 66.9    | 83.0| 50.8| 84.2  | 74.9  | 88.1       | 74.5   | 83.4  | 76.0       | 81.9   | 38.0  | 73.7 |
| DM-ADA  | -        | -       | -   | -   | -     | -     | -          | -      | -     | -          | -     | -     | -    |
| CDAN+BSP| 92.4     | 61.0    | 81.0| 57.5| 89.0  | 80.6  | 90.1       | 77.9   | 84.2  | 77.9       | 82.8   | 38.4  | 73.6 |
| AFN     | 93.6     | 78.0    | 84.1| 70.6| 94.1  | 79.0  | 91.8       | 79.6   | 89.9  | 55.6       | 90.0   | 24.4  | 76.1 |
| CRST    | 88.0     | 79.2    | 61.0| 60.0| 87.5  | 81.4  | 86.3       | 78.8   | 85.6  | **86.6**   | 73.9   | 68.8  | 78.1 |
| SHOT    | 92.6     | 81.1    | 80.1| 58.5| 89.7  | **86.1**| 81.5       | 77.8   | 89.5  | 84.9       | 49.3   | 79.6  | **79.6** |
| dSNE    | -        | -       | -   | -   | -     | -     | -          | -      | -     | -          | -     | -     | -    |
| DTA     | 93.7     | 82.2    | **85.6**| 83.8| 93.0  | 81.0  | 90.7       | **82.1**| **95.1**| 78.1       | 86.4   | 32.1  | 81.5 |
| DTA + Ours | **98.0**| **88.4**| 74.3| 76.0| 92.6  | 81.1  | 87.5       | **83.1**| 93.3  | 86.0       | **87.3**| 84.4  | **86.1** |
Fig. 7. The visualizations of the confusion matrix from different methods on VisDA-2017 dataset. (a) BSP [3] (b) DTA [19] (c) DTA + ours.

Fig. 8. A t-SNE visualization [27] of the embedded features for the synthetic-to-real task from the VisDA-2017 dataset [31]. Features from classes 0 to 11 are marked with different colors. (Left) MME [33], (Middle) DTA [19], and (Right) DTA + the proposed ELP.

Fig. 9. Comparisons of using median and different fixed thresholds to separate the clean data and the noisy data. The results are generated by conducting three adaptation tasks on the DomainNet dataset. The horizontal axis represents different accuracy of the clean data, and the vertical axis represents the total number of categories in the corresponding interval.
| Setting                                | P → R | R → C | R → S | R → P | P → C | C → S | S → P | MEAN |
|---------------------------------------|-------|-------|-------|-------|-------|-------|-------|------|
| MME [33]                              | 78.5  | 72.2  | 61.9  | 69.7  | 71.7  | 61.8  | 66.8  | 68.9 |
| w/o stage two                         | 78.3  | 72.8  | 63.1  | 69.8  | 71.8  | 62.6  | 67.3  | 69.4 |
| Full model (ELP)                      | 81.0  | 74.1  | 64.9  | 72.1  | 74.4  | 64.4  | 69.7  | 71.5 |

### V. Further Investigation

To better understand the mechanism of the proposed ELP, we demonstrate the necessity of key components (i.e., the \( \lambda \) and the dynamic threshold strategy in self-training) of our model by conducting additional experiments.

#### A. Dynamic Threshold vs Pre-defined Threshold.

We compare two schemes of selecting clean data used in the aggregation phrase of intra-domain propagation with quantitative results. The experiments are conducted on the tasks of “painting to clipart”, “painting to real”, and “clipart to sketch” in the DomainNet dataset.

As shown in Fig. [9], our median scheme achieves the best performance in all tasks. Note that, for the clean classes obtained over 90\% accuracy, the proposed dynamic threshold strategy obtains the most numbers. When conducting the fixed threshold experiments, we observe that only two or three clean samples are obtained from some classes, and for some classes even no clean data is obtained. Apparently, using a fixed threshold cannot adapt to the complexity of classification task, the variance of the classes statistics, and additional domain shift in DA. The results indicate that using the dynamic threshold strategy does lay a better foundation for feature discriminability in the intra-domain propagation.

#### B. Ablation Study of Two-Stage Learning.

We omits the Stage Two (described in Sec. III-D) in the proposed ELP framework and compare the classification accuracy with baseline (MME [33]) and our full model.

As shown in Table [VI] we observe worse results on the classification accuracy than the results of full model but better results than the ones of baseline. This demonstrate the necessity of both stages: we need the Stage One to learn a good initial representation space and the Stage Two to finetune the representation for further improving discriminability on the target domain.

#### C. Value of \( \lambda \) in the intra-domain propagation.

We train the model using different values of \( \lambda \) in Eqs. (8) to investigate the effectiveness of our method in the intra-domain propagation stage.

As shown in Table [VII] the random row denotes that \( \lambda \) is randomly obtained from the beta distribution by setting the corresponding hyper-parameter to 0.4 [49]. When \( \lambda = 0 \), we use the generated pseudo labels directly without balanced mixup to calculate the entropy loss, i.e. ignoring the label information of another mini-batch. It is observed that the strategy of using random \( \lambda \) values generally works inferior than using the proposed balance mixup, but better than without stage two and zero \( \lambda \). Particularly, the model achieves the best performance when \( \lambda = 0.5 \), while the performance decreases with the decrease of \( \lambda (\lambda < 0.5) \). These results demonstrate our claim that the pair of randomly selected mini-batches images from the same labeled target domain should be treated in an equivalent way.

### VI. Conclusion

In this paper, we propose the ELP to reinforce the discriminability of learned representations in the target domain for semi-supervised domain adaptation. To this end, we carefully design one inter-domain propagation and one intra-domain propagation. First, ELP refines semantic-aware information propagation between two domains via a novel cycle discrepancy loss. Second, ELP facilitates the feature discriminability in the target domain via an effective self-training scheme. Through extensive experiments across three widely-used domain adaptation datasets and two typical adaptation cases, we demonstrate that the proposed ELP consistently helps promote the classification accuracy.
accuracies of state-of-the-art methods, in both semi-supervised domain adaptation and unsupervised domain adaptation.

For future work, we are interested in applying ELP in other usage scenarios, such as semantic segmentation and object detection. Besides, we plan to extend ELP to handle other important and practical adaptation tasks, such as multi-source domain adaptation.

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[49] Chongyang Ma received B.S. degree from the Fundamental Science Class (Mathematics and Physics) of Tsinghua University in 2007 and PhD degree in Computer Science from the Institute for Advanced Study of Tsinghua University in 2012. He is currently a Research Lead at Kwai Inc. His research interests include image processing, computer vision and computer graphics.

Zhiyong Huang is a master student at the School of Control and Computer Engineering, North China Electric Power University. He received his B.Eng. degree from North China Electric Power University in 2018. His research interest include single image super-resolution and domain adaptation.

Weiming Dong is a Professor in the Sino-European Lab in Computer Science, Automation and Applied Mathematics (LIAMA) and National Laboratory of Pattern Recognition (NLPR) at Institute of Automation, Chinese Academy of Sciences. He received his BSc and MSc degrees in Computer Science in 2001 and 2004, both from Tsinghua University, China. He received his PhD in Computer Science from the University of Lorraine, France, in 2007. His research interests include visual media synthesis and image recognition. Weiming Dong is a member of the ACM and IEEE.

Xing Mei received his PhD degree from Institute of Automation, Chinese Academy of Sciences in 2009. He is currently a software engineer at Bytedance Inc. His research interests include image processing, computer vision and computer graphics.

Feiyue Huang is the director of YouTu Lab, Tencent. He received his BSc and PhD degrees in Computer Science in 2001 and 2008, both from Tsinghua University, China. His research interests include image understanding and face recognition.

Chongyang Ma is the director of YouTu Lab, Tencent. He received his BSc and PhD degrees in Computer Science in 2001 and 2008, both from Tsinghua University, China. His research interests include image understanding and face recognition.

Dengwen Zhou is a Professor in the School of Control and Computer Engineering, North China Electric Power University, Beijing, China. He has long been engaged in research on image processing, including image denoising, image demosaicking, image interpolation and image super-resolution etc. Current research focuses on the applications based on neural networks and deep learning in image processing and computer vision.

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Kekai Sheng received his PhD degree from National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences in 2019. He received his B.Eng. degree in Telecommunication Engineering from University of Science and Technology Beijing in 2014. He is currently a researcher engineer at YouTu Lab, Tencent Inc. His research interests include image quality evaluation, domain adaptation, and AutoML.
Changsheng Xu (Fellow, IEEE) is currently a Professor with the National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, and the Executive Director of the China-Singapore Institute of Digital Media. His research interests include multimedia content analysis/indexing/retrieval, pattern recognition, and computer vision. He has hold 30 granted/pending patents and published over 200 refereed research papers in these areas. He is a fellow of IAPR and an ACM Distinguished Scientist. He received the Best Associate Editor Award of ACM Transactions on Multimedia Computing, Communications and Applications in 2012 and the Best Editorial Member Award of ACM/Springer Multimedia Systems Journal in 2008. He served as a Program Chair of ACM Multimedia 2009. He has served as an Associate Editor, a Guest Editor, a General Chair, a Program Chair, an Area/Track Chair, a Special Session Organizer, a Session Chair, and a TPC member for over 20 IEEE and ACM prestigious multimedia journals, conferences, and workshops. He is an Associate Editor of ACM Transactions on Multimedia Computing, Communications and Applications and ACM/Springer Multimedia Systems Journal.