Better Pseudo-label: Joint Domain-aware Label and Dual-classifier for Semi-supervised Domain Generalization

Ruiqi Wang*, Lei Qi*, Yinghuan Shi†, Yang Gao

Abstract—With the goal of directly generalizing trained models to unseen target domains, domain generalization (DG), a newly proposed learning paradigm, has attracted considerable attention. Previous DG models usually require a sufficient quantity of annotated samples from observed source domains during training. In this paper, we relax this requirement about full annotation and investigate semi-supervised domain generalization (SSDG) where only one source domain is fully annotated along with the other domains totally unlabeled in the training process. With the challenges of tackling the domain gap between observed source domains and predicting unseen target domains, we propose a novel deep framework via joint domain-aware labels and dual-classifier to produce high-quality pseudo-labels. Concretely, to predict accurate pseudo-labels under domain shift, a domain-aware pseudo-labeling module is developed. Also, considering inconsistent goals between generalization and pseudo-labeling: former prevents overfitting on all source domains while latter might overfit the unlabeled source domains for high accuracy, we employ a dual-classifier to independently perform pseudo-labeling and domain generalization in the training process. Extensive results on publicly available DG benchmark datasets show the efficacy of our proposed SSDG method compared to the well-designed baselines and the state-of-the-art semi-supervised learning methods.

Index Terms—semi-supervised learning, domain generalization, image recognition, image representation.

I. INTRODUCTION

NOWADAYS, with the development of data acquisition, current data are frequently captured from multiple sources (e.g., video, image, text), generated from various contributors (e.g., different artists), or collected from multiple sites (e.g., different data centers), making the distribution shift between different modalities or sites usually occurs. Therefore, due to the distribution shift, the model trained on training data or source domains could perform poorly on test data or target domains. To address this limitation, a new setting namely domain generalization (DG), aiming to train the model on observed source domains for directly generalizing to arbitrary unseen target domains, is becoming a hot topic with increasing interests.

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According to our investigation, unfortunately, most current DG models belong to the supervised setting where multiple fully labeled source domains are the prerequisite before training DG models. As we known, high-quality labels are often expensive and laborious to obtain, which drives us to alleviate the label requirement in the observed source domains.

Formally, we here name our setting—first training the model with both labeled source domains and unlabeled source domains and then performing prediction on unseen target domains—as semi-supervised domain generalization (SSDG in short). We show this setting in Figure [1] Particularly, in this paper we merely consider the case that only one source domain is fully labeled (along with several unlabeled source domains) in the training stage.

In our setting, since unlabeled samples in source domains are abundant and each unlabeled sample actually belongs to a specific yet unknown class, this inspires us to utilize pseudo-labeling technique [1] to unlabeled domains, which has shown its effectiveness in conventional semi-supervised learning (SSL) problems by iteratively using higher confident samples to aid subsequent learning on lower confident samples. Intuitively, the accuracy of pseudo-labels largely affects the final results. However, compared with conventional SSL, producing high-quality pseudo-labels in SSDG is much more challenging due to the following two reasons:

1) The domain shift between observed labeled and unlabeled source domains is definitely a negative factor to accurate pseudo-labels, which might cause a drastic performance degeneration.

2) Since the unseen target domain also suffers unpredictable domain discrepancy with observed source do-
mains, to perform satisfactory predictions on both unlabeled source domains and target domains by only using a common classifier is nontrivial.

Considering these two issues, we develop two improvements for accurate pseudo-label prediction.

Firstly, we propose domain-aware pseudo-labeling method to improve the quality of pseudo-labels under domain shift. As aforementioned, the domain shift between labeled and unlabeled source domains deteriorates the accuracy of pseudo-labels. In Figure 2 we visualize the feature distribution of the DANN [2] model trained via fully supervised learning on PACS. As observed, the experimental result shows that samples have been well mapped to their categories, whereas inside a typical class, features from different domains intra a class are separated. Therefore, to obtain more accurate pseudo-labels, we iteratively maintain the average feature of the top-k confident unlabeled samples for each class of each domain in the memory, which is used as domain-aware class representation. Afterward, when assigning pseudo-labels to unlabeled samples, we combine the output probability of the classifier with the similarity to its class representation to decide which class it belongs to.

Secondly, in SSDG, the generalization ability of the network is essential, but it is intuitive that a generalizable model could underfit the unlabeled training domains, thus the accuracy of pseudo-labels could decrease. Considering inconsistent goals between generalization and pseudo-labeling—former prevents to overfit source domains while latter might overfit specific domain for high accuracy, we propose to use a dual-classifier to avoid the possible accuracy degradation of pseudo-labels, which leverages the independent classifiers for joint pseudo-label assignment and domain generalization. In our dual-classifier network, the two branches are trained with different objective functions but a shared feature extractor.

Our contributions can be summarized as follows:

- We develop the domain-aware pseudo-labeling module to handle the domain shift during generating pseudo-labels. Also, the dual-classifier is proposed to mitigate the conflict between the DG task and the pseudo-label generation.
- Extensive experiments on benchmark datasets, i.e., PACS, OfficeHome and miniDomainNet show that our effectiveness for SSDG compared with several baselines and the SOTA semi-supervised methods.

The rest of this paper is organized as follows. We review some related work in Section II. The proposed framework is introduced in Section III. Experimental results, analysis and visualizations are presented in Section IV and the conclusion is given in Section V.

II. RELATED WORK

We review the recent work about domain generalization, semi-supervised learning and semi-supervised domain generalization.

A. Domain Generalization

Domain generalization methods can be substantially categorized into data-based methods, feature-based methods and learning strategy-based methods [3]. The data-based methods aim to generate virtual training data for a more generalizable model, e.g., the methods in [4], [5], [6], [7] enlarge the training set by image generation techniques and data augmentation. Feature-based solutions [8], [9], [10], [11] extract domain-agnostic representations on multi-source domains. Another promising technique for domain generalization is meta-learning, such as [12], [13]. Besides, some methods based on other learning strategies (e.g., self-supervision, Ensemble learning) are proposed to obtain the generalizable model, including [14], [15].

B. Semi-supervised Learning

Current semi-supervised learning methods can be roughly classified into three categories, i.e., entropy regularization based methods, pseudo-label based methods and consistency regularization based methods. The essence of all these three categories is to force a low-density distribution between different classes [16]. Entropy regularization [17] encourages a confident prediction on unlabeled data by minimizing the entropy of the predictions of unlabeled data. Pseudo-label method [1] is a simple method, which outputs approximate classes on unlabeled samples by the inference of the model trained on labeled samples. Consistency regularization shows great success more recently, which includes π-Model [18], Temporal Ensembling [19] and Mean Teacher [20], etc. Besides, a series of holistic approaches to semi-supervised learning have obtained state-of-the-art performance on commonly-studied SSL benchmarks recently. Unsupervised Data Augmentation (UDA) [20] improves consistency loss by substituting simple noising operations with advanced data augmentation, such as RandAugment [21], MixMatch [22] unifies the existing
data augmentation, pseudo-labeling and mixup to achieve both consistency regularization and entropy regularization. ReMixMatch [23] further improves MixMatch [22]. FeatMatch [24] applies learned feature-based augmentation to consistency loss. FixMatch [25] inherits UDA and ReMixMatch, and combines pseudo-labeling and consistency regularization, finally obtains good performance on SSL benchmarks. Differently, in our SSDG, there is data-distribution discrepancy between labeled and unlabeled training data, thus these typical SSL methods could not effectively handle the issue.

C. Semi-supervised DG

To the best of our knowledge, only very a few works have been proposed for the semi-supervised domain generalization problem. DGSML [26] and StyleMatch [27] tackle a new setting in domain generalization problem, where the labeled samples in each domain are not fully labeled. Although we both assign pseudo-labels to unlabeled data, we solve two different scenarios and the challenges we face are totally different. DSDGN [28] solves a semi-supervised domain generalization problem that is similar to us. It applies a Wasserstein generative adversarial network with gradient penalty based adversarial training framework to align feature embedding, and simply adopts the original pseudo-labeling method for unlabeled data. However, this method does not consider the domain shift during pseudo-labeling.

III. METHOD

Unlike the supervised domain generalization (DG) setting, as aforementioned, semi-supervised DG further alleviates the fully-labeled requirement and allows several source domains to be totally unlabeled during training. Formally, we now provide the notations used in our setting. In SSDG, assume we have one labeled source domain in the labeled domain set $S_l = \{D_l\}$, and $n$ unlabeled source domains in the unlabeled domain set $S_u = \{D_u^1, \ldots, D_u^n\}$, and one target domain $D_t$. Note that, $D_t$ is not used in the training process. A training sample in the labeled source domain can be represented as a raw input $x$, a semantic label $y$ and a domain label $z$. Assuming that the number of the training samples in the labeled source domain is $n_l$, it can be denoted as $D_l = \{(x_i^l, y_i^l, z_i^l) = 0\}_{i=1}^{n_l}$. And an unlabeled domain $D_u$ can be represented as $D_u = \{(x_i^u, z_i^u = j)\}_{i=1}^{n_u}$, when the number of the training samples in $D_u$ is $n_u$, $C$ stands for the number of categories in the classification dataset. The shared feature extractor, the predictive classifier, the generalizable classifier and the domain classifier are denoted by $F_g, F_c, F_m$ and $F_d$, respectively. The overview of our method is illustrated in Figure 3.

In the following, domain-aware pseudo-labeling is firstly presented in Section III-A. Secondly, in III-B the dual-classifier architecture is introduced. Then, in III-C the confident samples with pseudo labels and the ambiguous unlabeled samples with prediction probabilities are recognized, then domain mixup and consistency regularization are applied to them respectively. Finally, the training process of our framework is described in Section III-D.

A. Domain-aware Pseudo-labeling

In the cross-domain scenario, a mixture of samples from all domains are fed into a shared classifier together. However, the appearances of different domains could have an extremely large variation. Accordingly, for different domains, the discriminative characteristics that are critical to classification could be different. For instance, on the PACS dataset, images in photo domain are color-specified, while images in cartoon domain are not. In sketch domain, the color information is totally erased, which makes samples in this domain even harder to distinguish. Thus, even we have applied a discriminator to align features from different domains, the features haven’t been perfectly aligned yet. Being aware of this large and unpredictable domain gap, the classifier which well fits the labeled domain could cause a bias when applying to unlabeled domains for generating pseudo-labels.

In order to alleviate the bias caused by the aforementioned domain gap, we propose a domain-aware pseudo-labeling module in our framework. In particular, we first yield the
domain-aware class representation for each class of each unlabeled domain, which indicates the mean feature of the most highly confident samples for each class in each domain. Then, when generating the pseudo-label for each unlabeled sample by integrating 1) its predicted probability from the shared predictive classifier and 2) its largest similarity to the class representation from its domain, we can obtain the modified probability for the more reliable pseudo-label.

For an unlabeled sample \((x^u, z^u)\), if the domain label \(z^u\) is equal to \(d\), it means that this sample is from the \(d^{th}\) domain. Using \(M^d \in \mathbb{R}^{C \times D}\) to denote the matrix by gathering the \(D\)-dimensional class representation from total \(C\) classes in the \(d^{th}\) Domain. \(\psi(x^u)\) is used as the \(C\)-dimension similarity vector for \(x_u\) and \(\text{sim}(\cdot, \cdot)\) is a similarity measurement function. And in our experiments, we use cosine similarity for measuring similarity. Then we modify the predicted probability by a correction term to form \(s(x^u)\). This above process can be formulated as follows:

\[
s(x^u) = \gamma q(x^u) + (1 - \gamma)\psi(x^u),
\]

where \(q(x^u) = F_c(F_g(x^u))\), \(\psi(x^u) = \text{sim}(F_g(x^u), M^d)\).

Now the pseudo-label \(y_i^u\) is assigned by \(s(x^u)\) as same as the conventional pseudo-labeling way:

\[
\hat{y}_i^u = \begin{cases} 1 & \text{if } i = \arg\max_{s_i^u} \text{ and } s_i^u > \delta \\ 0 & \text{otherwise,} \end{cases}
\]

where \(\delta\) is a threshold. If the final confidence of one sample is larger than the threshold, the pseudo-label is reliable, otherwise, it is ambiguous.

The group of representation is updated at each epoch and used at the next epoch. We propose two policies for domain-aware class representation production. The simplest way is to select the sample with the highest confidence predicted by the classifier as class representation at each epoch. However, the mislabeled sample could arise an accumulation of prediction error at the next epoch [29]. Furthermore, we propose to calculate an ensemble representation with some reliable samples of each class in each unlabeled domain. The comparison of the two schemes will be shown in our experiment.

### B. Dual-classifier

As known, overfitting empirically occurs when a model begins to fit the domain-specific characteristic in the training data rather than learning to generalize from a trend [30]. Consequently, the overfitting issue finally causes performance degradation on unseen test data. This empirical knowledge inspires us that a generalizable model which works well in domain generalization could be non-overfitting for the source training domains.

We train a model with domain mixup [31] and without domain mixup in a supervised way and draw the comparison of both test and validation accuracy. As shown in Figure 4 by domain mixup, the model performs more accurate in test domain, indicating that the model is more generalizable. However, the accuracy in the training domains drops, which is displayed by the validation accuracy.

In our approach, we apply cross-domain mixup towards a more generalizable classifier. However, we observe that the generalizable DG classifier is not good at pseudo-labeling. Thus, we apply an auxiliary classifier to achieve the pseudo-labeling, and the classifier for giving the pseudo-labels is trained only by pure samples from source domains. Therefore, we utilize dual-classifier architecture to reduce the conflict between the DG task and the pseudo-label production.

### C. Mining the Knowledge of Unlabeled Domains

When accurate pseudo-labels on unlabeled samples are generated, domain mixup is applied to confident samples with their pseudo-labels and the raw labeled data. For ambiguous samples, since pseudo-labels are not be assigned, the entropy loss is applied to make full use of these samples.

**Confident unlabeled samples.** As inspired by [31], we innovatively interpolate between a labeled domain and unlabeled domains to achieve inter-domain data augmentation. Our intuition is that the inter-domain samples generated by domain mixup can boost the generalization of networks by introducing additional training domains, which has been verified as an important technique in domain generalization [7], [5], [6]. Assuming that we have already assigned a pseudo-label for an unlabeled sample \((x^u, z^u)\), forming \((x^u, \hat{y}^u, z^u)\). And we have a sample from a labeled domain \((x^l, y^l, z^l)\). \(\hat{y}^u\) and \(z^u\), and \(z^l\) are all one-hot vectors. Then the operation is formulated as below:

\[
\hat{x} = \lambda x^l + (1 - \lambda)x^u, \quad (3)
\]

\[
\hat{y} = \lambda y^l + (1 - \lambda)\hat{y}^u, \quad (4)
\]

where \(\lambda \sim \text{Beta} (\alpha, \alpha)\), for \(\alpha > 0\), and \(\lambda \in [0, 1]\). The hyper-parameter \(\alpha\) controls the strength of interpolation. Additionally, to further enhance the generalization ability, we also apply mixup to domain labels of labeled and unlabeled samples for training domain discriminator as follows:

\[
\tilde{z} = \lambda z^l + (1 - \lambda)z^u, \quad (5)
\]

where \(\lambda\) is same with that used in Eqn. (3) and Eqn. (4). According to these steps, we could finally generate a virtual sample \((\hat{x}, \hat{y}, \tilde{z})\).

**Ambiguous unlabeled samples.** For the unlabeled samples with low-confidence prediction, since we are unclear about their real labels, it is hard to generate mixed samples by them. In order to further improve the generalization ability...
of our method by fully leveraging these unlabeled samples, we employ entropy loss:

\[ L_{\text{cent}} = \frac{1}{N_u} \sum_{i=1}^{N_u} H(F_c(F_g(x_u^i))), \]  

(6)

where \( H(\cdot) \) is the entropy function.

D. Training Procedure

Formally, as aforementioned, we denote \( S_i \) as the set of all labeled samples, \( S_u \) as the set of all unlabeled samples. During training, once we select the reliable unlabeled samples with high confident pseudo-labels, forming \( S_{u'} \), we move them to the set of samples with pseudo-labels which is denoted as \( S_p \). At each training epoch, we assume, \(|S_i| = N_i| \), \(|S_u| = N_u| \) and \(|S_p| = N_p| \). The total number of all training samples is denoted as \( N = N_i + N_u + N_p \) (refer to Algorithm 1).

For training our network, we apply 1) a classification loss \( L_{\text{cls}} \) to \( S_i \) and \( S_p \) since they are with labels or predicted pseudo-labels, and 2) an adversarial loss \( L_{\text{adv}} \) to all sets of samples, i.e., \( S_i \), \( S_p \), and \( S_u \).

Algorithm 1: Training Process

Input: Labeled source \( S_i \), unlabeled source \( S_u \)  
Output: Generalizable model \( F_g \) and \( F_m \)

1. Initialize Networks, Pseudo-label Set \( S_p = \emptyset \), Class representation list \( L = \{\text{none}\} \times C \) for each domain;
2. while not end of epoch do
3. \( S_m \leftarrow \) Perform domain mixup on \( S_i \) and \( S_u \);
4. Training the model using Eqns. (11) and (12);
5. Inference the model on \( S_u \), and obtain \( q(x) \);
6. if no none in \( L \) then
7. \( s(x_u^i) \leftarrow \) Calculated by Eqn. (1);
8. Update class representation by \( q(x_u^i) \);
9. Assign pseudo-labels by \( s(x_u^i) \);
10. Recognize confident and ambiguous samples by Eqn. (2), and the confident set is denoted as \( S_{u'} \);
11. Update \( S_u \leftarrow S_u - S_{u'} \), \( S_p \leftarrow S_p \cup S_{u'} \);
end

\[ L_{\text{cls}} = \frac{1}{N_i} \sum_{i=1}^{N_i} \ell(F_c(F_g(x_i^i)), y_i^l) + \frac{1}{N_p} \sum_{i=1}^{N_p} \ell(F_c(F_g(x_p^i)), y_p^l), \]  

(7)

\[ L_{\text{adv}} = \frac{1}{N} \left( \sum_{i=1}^{N_i} \ell(F_d(F_g(x_i^i)), z_i^l) + \sum_{i=1}^{N_u} \ell(F_d(F_g(x_u^i)), z_u^l) \right) + \sum_{i=1}^{N_p} \ell(F_d(F_g(x_p^i)), z_p^l), \]  

(8)

where \( \ell(\cdot, \cdot) \) is the cross-entropy loss. The loss on samples mixed up by \( S_p \) and \( S_i \) is defined as:

\[ L_{\text{cls, mix}} = \frac{1}{N_l} \sum_{i=1}^{N_l} \sum_{j=1}^{N_p} \ell(F_m(F_g(\tilde{x})), \tilde{y}), \]  

(9)

The training objective of our semi-supervised DG model can be described as follows:

\[ \min_{F_g, F_c, F_m} \ L_{\text{cls}} + L_{\text{cls, mix}} + w^t(-L_{\text{ado}} - L_{\text{adv, mix}} + L_{\text{cent}}), \]  

\[ \min_{F_g} L_{\text{ado}} + L_{\text{adv, mix}}, \]  

(10)

where the weight function \( w^t \) ramps up from zero to one during the training procedure. The whole training procedure is described in Algorithm 1.

IV. EXPERIMENTS

In this part, we firstly introduce the datasets and implementation details in Section IV-A. Then we compare our method with SSDG baselines and the state-of-the-art semi-supervised methods in Section IV-B. Furthermore, we conduct ablation studies in Section IV-C. Lastly, in Section IV-D we conduct sensitivity analysis, compare different schemes for class representation and visualize our feature distribution.

A. Experimental Setting

Datasets. To evaluate the effectiveness of our method for the semi-supervised domain generalization, we conduct several experiments on three benchmark datasets. PACS [32] contains 7 categories of images from 4 domains (Photo, Art painting, Cartoon, and Sketch). OfficeHome [33] consists of images from 4 different domains (Artistic, Clip art, Product and Real-World). For each domain, this dataset involves 65 object categories found typically in office and home. To verify that our method also has promotion when data is abundant, we validate our method on miniDomainNet. It is a subset of DomainNet aggregated by [34], which contains 140,006 images from 4 domains (Clipart, Painting, Real and Sketch), covering 126 classes in the raw dataset. For each dataset, we select two domains as the unlabeled source domains, one domain as the labeled source domain, and leave the remaining one for test. We test all 12 combinations of domains on each dataset and report the average accuracy. To ensure a fair comparison with other methods, all experiments utilize the same scheme of data division.

Implementation Details. In all experiments, we use ResNet50 [35] as the backbone, and we start with a pre-trained model and fine-tune on source domains with the batch size of 128. Since the test domain is unavailable during training. For PACS and OfficeHome, we train 120 epochs and select the model obtained in the final epoch for test. For miniDomainNet, the network converges at an earlier epoch due to the huge amount of data. So we just train 60 epochs and save the final model. We apply a SGD optimizer with momentum 0.9 and an initial learning rate 0.01 when training our network. The learning rate is divided by 10 at the 30-th and the 50-th epochs. All experiments are implemented in Pytorch with 4 × 11 GB RTX 2080Ti GPUs.
### TABLE I

Experimental results on PACS based on ResNet-18 and ResNet-50. The title in the first row indicates the name of the target domain and the title in the second row is the name of the labeled domain in training source. P, A, C, S are Photo, Art painting, Cartoon, Sketch, respectively. Note that the best performance is **bold**.

| Method      | Photo | Art Painting | Cartoon | Sketch | Avg. |
|-------------|-------|--------------|---------|--------|------|
|             | A     | C            | P       | A      | S    |       | A      | P       | A      | C    |       | Avg.  |
| SupOne      | 95.69 | 86.17        | 40.66   | 64.60 | 68.75 | 25.93 | 25.90  | 58.53   | 38.10  | 32.55 | 49.05 | 61.29 | 53.94 |
| DSDGN [23]  | **96.29** | 88.38       | 36.94   | 66.46 | 70.36 | 26.12 | 47.27  | 67.96   | 50.64  | 46.35 | 59.35 | 61.77 | 59.82 |
| FixMatch [25] | 95.39 | 85.63        | 59.40   | 65.38 | 68.41 | 51.37 | 45.22  | 62.20   | 55.55  | 53.32 | 61.52 | **76.94** | 65.03 |
| FeatMatch [24] | 95.33 | 82.57        | 56.89   | 66.06 | 72.02 | 58.69 | 47.10  | 65.57   | 57.30  | 64.39 | 72.59 | 74.40 | 67.74 |
| Ours        | 94.37 | **91.02**    | **66.53** | **69.92** | **75.68** | **55.37** | **54.22** | **71.46** | **57.94** | **65.69** | **71.27** | **71.06** | **70.38** |

### TABLE II

Experimental results on OfficeHome. The title in the first row indicates the name of the target domain and the title in the second row is the name of the labeled domain in training source. **A, C, P, R** stand for **Art, Clipart, Product, Real**, respectively. The best performance is **bold**.

| Method      | Art    | Clipart        | Product | Real  | Avg. |
|-------------|--------|----------------|---------|-------|------|
|             | C      | P              | R       | A     | C    |       | A      | C      | P    |       | Avg.  |
| SupOne      | 43.63  | 38.20          | 54.84   | 38.95 | 37.34 | 44.10 | 54.88  | 54.02  | 70.94 | 64.08 | 57.54 | 62.98 | 51.79 |
| DSDGN [23]  | 45.49  | 41.57          | 56.49   | 38.40 | 37.46 | 43.98 | 55.37  | 54.99  | 72.11 | 64.56 | 59.93 | 63.44 | 52.47 |
| Ours        | 47.55  | **46.07**      | **58.01** | **44.33** | **42.34** | **47.90** | **57.56** | **57.83** | **72.43** | **65.48** | **59.74** | **65.09** | **55.36** |

### TABLE III

Experimental results on miniDomainNet. The title in the first row indicates the name of the target domain and the title in the second row is the name of the labeled domain in training source. **C, P, R, S** stand for **Clipart, Painting, Real, Sketch**, respectively. The best performance is **bold**.

| Method      | Clipart | Painting       | Real    | Sketch | Avg. |
|-------------|---------|----------------|---------|--------|------|
|             | P      | R              | S       | C      | P    | S    | C     | P    | S    | C    | P    | S    | Avg.  |
| SupOne      | 47.77  | 47.80          | 53.36   | 37.93  | 48.71 | 42.41 | 47.50  | **61.74** | 47.67  | 43.69 | 42.38 | 42.06 | 46.92 |
| DSDGN [23]  | 47.09  | 48.14          | 53.71   | 39.61  | 50.36 | 46.21 | 45.52  | 61.32  | 50.14  | 42.06 | 44.97 | 42.74 | 47.66 |
| Ours        | **52.73** | **52.93**   | **57.72** | **42.18** | **56.41** | **52.12** | **50.27** | **61.72** | **54.95** | **48.42** | **48.76** | **48.35** | **52.21** |

### TABLE IV

Accuracy (%) of ablation study on PACS. **P, A, C, S** stand for **Photo, Art painting, Cartoon, Sketch**, respectively. **Baseline** represents our method without both DAPL and DC. The best performance is **bold**.

| Method      | Photo | Art Painting | Cartoon | Sketch | Avg. |
|-------------|-------|--------------|---------|--------|------|
|             | A     | C            | S       | A      | P    | S    | A     | P    | A    | C    |       | Avg.  |
| Baseline    | 92.52 | 87.49        | 48.80   | 66.80  | 72.51 | 45.51 | 51.07  | 67.53  | 51.83 | **52.07** | **53.47** | **59.36** | **62.41** |
| Ours w/o DAPL | 92.64 | 88.38        | 49.40   | 69.24  | 69.14 | 45.02 | 54.10  | 68.94  | 53.41 | **58.77** | **64.01** | **65.20** | **64.85** |
| Ours w/o DC | 93.29  | 85.69        | 60.96   | 66.31  | 73.68 | 46.83 | **56.83** | **68.13** | **52.30** | **54.26** | **56.05** | **63.32** | **64.80** |
| Ours        | **94.37** | **91.02** | **66.53** | **69.92** | **75.68** | **55.37** | **54.22** | **71.46** | **57.94** | **65.69** | **71.27** | **71.06** | **70.38** |

### B. Comparison with Other Methods

On PACS, we compare our method with the following baselines and the state-of-the-art semi-supervised learning approaches (i.e., FixMatch [25] and FeatMatch [24]) on the classification accuracy of the target domain using ResNet-18 and ResNet-50. And we also report our performance and baseline results on OfficeHome and miniDomainNet datasets using ResNet-18.

- **SupOne**: Train a plain model on one labeled source domain in a supervised way and the other unlabeled source domains are not used.
- **DSDGN**: Implement the semi-supervised DG method proposed in [23] using the same network structure as our framework.

Table II displays the results on PACS. Compared with the baseline, our method achieves outstanding performance by significant margins with both smaller and larger network architectures. Specifically, our method improves the performance of the simplest baseline by 16.44% with ResNet-18. Compared with the recent SOTA semi-supervised methods, ours also shows priority in the SDDG task.

Experimental results on OfficeHome and miniDomainNet are shown in Tables II and III. We effectively utilize unlabeled data compared with DSDGN. As seen, our method still shows priority, which thanks to the accurate pseudo-labels using domain-aware class representation and dual-classifier. For example, our method achieves 4.55% gain compared with DSDGN on miniDomainNet.
Fig. 5. Pseudo-label accuracy (%) on PACS.

**TABLE V**

Experimental results with different modules on PACS. The titles indicate the target domains and each column is the average accuracy of three combinations of the source domains as in Table IV (e.g., A, C, S under Photo).

| Target          | Photo | Art  | Cartoon | Sketch | Avg.  |
|-----------------|-------|------|---------|--------|-------|
| w/o Mixup       | 80.48 | 63.48| 62.88   | 60.03  | 66.72 |
| MixupAll        | 79.50 | 63.51| 59.24   | 63.16  | 66.35 |
| w/o Entropy     | 82.69 | 62.44| 59.43   | 67.15  | 67.93 |
| w/o AdvMix      | 81.66 | 67.58| 61.96   | 64.87  | 69.02 |
| Ours            | 83.97 | 66.99| 61.21   | 69.34  | 70.38 |

**C. Ablation Study**

In order to verify the contributions of domain-aware pseudo-labeling (DAPL) and dual-classifier (DC), we conduct an ablation study on PACS, as reported in Table V. "Ours w/o DAPL" replaces DAPL by naive pseudo-labeling, and "Ours w/o DC" conducts prediction and generalization by the same classifier in the training stage. Without DAPL or DC, the generalization ability of our method dramatically drops. The results show that our modules are crucial to improve the accuracy of the classification on unseen target domains. Besides, we show the pseudo-label accuracy in Figure 5. As seen, our method can obtain more accurate pseudo-labels for unseen target domains.

As mentioned above, domain mixup is applied to promote the generalization ability of our model on unseen target domain. And we only choose confident unlabeled samples to mix up with the labeled ones. To demonstrate the effectiveness, we conduct experiments on mixup. Table VI shows the evaluation results. As seen, our method shows better performance compared with "w/o mixup" and the model that mixes up all unlabeled samples. Besides, if we do not use the ambiguous unlabeled samples during training (i.e., "w/o Entropy"), the performance of our method also drops. Moreover, we validate that using mixed samples in adversarial learning can bring slight improvement of performance (i.e., "w/o AdvMix").

**D. Further Analysis**

**Sensitivity of Hyper-parameters.** Here we discuss the sensitivity to hyper-parameters of our method on PACS, including $\alpha$ in mixup and $(\gamma, \delta)$ in domain-aware pseudo-labeling. To simplify the analysis, we select 4 combinations. To be specific, "Photo(Sketch)", "Art(Photo)", "Cartoon(Art)" and "Sketch(Cartoon)" are chosen, where "Photo(Sketch)" represents the case that Sketch is labeled for training and Photo is the target. We train our model with $\alpha$ in $[0, 0.2, 0.4, 0.8, 1.0]$. With the increase of $\alpha$, mixup is more likely to generate more confusing samples. The results are reported in Figure 6. The effect of hyperparameter $\alpha$ on testing accuracy does not show similar trends in each experiment. Photo(Sketch) and Sketch(Cartoon) show large variance. And an optimal value for all experiments is between 0.2 and 0.8. As for $\gamma$, we set four appropriate value pairs for the weight $\gamma$ and the threshold $\delta$ in domain-aware pseudo-labeling, specifically, (0.05, 0.2), (0.1, 0.24), (0.2, 0.3) and (0.3, 0.36). It can be observed that the performance is not sensitive to $\gamma$ and the smaller value is slightly better. We set $\alpha$ and $\gamma$ as 0.2 and 0.1 for all combinations in our experiments.

**Different Schemes for Class Representation.** We propose two policies of selecting class representation for domain-aware pseudo-labeling in our framework. The results are shown in Table VI. "One" stands for picking up the most confident one unlabeled sample from each class as class representation at every epoch, and "Ensemble" means calculating the average of several samples as domain-aware class representation. When applying "Ensemble" policy, we choose one sample only if its confidence is higher than the existing highest confidence in the same class. We hold all chosen samples and calculate the average at every epoch. This experiment shows that "Ensemble" policy is more fault-tolerant and its performance is better.

**TABLE VI**

Compare different policies of selecting class representation in domain-aware pseudo-labeling.

| Target          | Photo | Art  | Cartoon | Sketch | Avg.  |
|-----------------|-------|------|---------|--------|-------|
| One             | 83.06 | 66.57| 61.11   | 67.95  | 69.67 |
| Ensemble        | 83.97 | 66.99| 61.21   | 69.34  | 70.38 |

**Visualization of Feature Distributions.** Figure 7 visualizes the feature distributions of three source domains on PACS, including one labeled domain and two unlabeled domains. As seen, the selected domain-aware class representations...
are accurate according to the corresponding original images. Meanwhile, it can be observed that there are still some misclassified unlabeled samples, especially in Sketch, due to the large domain gap.

V. Conclusion

In this paper, we address the problem of semi-supervised domain generalization via producing better pseudo-labels for unlabeled data. Firstly, we propose domain-aware pseudo-labeling for picking up more accurate pseudo labels for unlabeled data by domain-based modification. Then, a dual-classifier network structure is employed for promoting generalization and predicting pseudo-labels separately. Finally, utilizing the accurate pseudo-labels in unlabeled domains, we apply domain mixup to them and enforce entropy regularization on ambiguous samples. Extensive experiments on benchmark datasets validate the efficacy of our framework.

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