Semi-Supervised Domain Generalization in Real World: New Benchmark and Strong Baseline

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Abstract—Domain Generalization (DG) aims to learn domain invariant representation from multiple domains, which requires precise annotations. In realistic application scenarios, however, it is too cumbersome or even infeasible to collect and annotate the large mass of data. Yet, web data provides a free lunch to access a huge amount of unlabeled data with rich style information that can be harnessed to augment domain generalization ability. In this paper, we introduce a novel paradigm of DG, termed as semi-supervised domain generalization, to study how to interact the labeled and unlabeled domains, and establish two benchmarks including the close-set and open-set SSDG. The close-set SSDG is established on the basis of existing public DG datasets, and the open-set SSDG is close to real world that is built on a newly-collected web-crawled dataset, PACS-Webdata, which poses a novel yet realistic challenge to push the limits of existing technologies. To tackle these tasks, a straightforward solution is to propagate the class information from the labeled to the unlabeled domains via pseudo labeling in conjunction with domain generalization techniques. Considering narrowing domain gap can improve the quality of pseudo labels and further benefit domain invariant feature learning for generalization, we propose a cycle learning framework to encourage the positive feedback between label propagation and domain generalization, in favor of an evolving intermediate domain bridging the labeled and unlabeled domains in a curriculum learning manner. Experiments are conducted to validate the effectiveness of our framework. It is worth highlighting that web-crawled data benefits domain generalization as demonstrated in our results.

Index Terms—Domain generalization, unsupervised domain adaptation, semi-supervised learning, transfer learning.

I. INTRODUCTION

With the development of deep learning in recent years, an acute problem has been increasingly emerged: most of deep models are learnt under the i.i.d assumption that training data and testing data are identically and independently distributed, which, however, the performance of deep models will be degraded drastically when facing the real-world scenarios unsatisfied with i.i.d assumption. To address this problem, researchers concentrate on exploring domain generalization (DG) techniques that aims to obtain a domain-invariant model trained on multiple source domains to generalize to unknown target domains [1], [2], [3].

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Fig. 1: The paradigms of conventional domain generalization and semi-supervised domain generalization. We propose two settings of SSDG, including the close-set and open-set SSDG.

Most of DG tasks are formulated as a conventional supervised learning paradigm, where deep model is trained on the annotated data collected from multiple source domains [4], [5], [6], [7], [8]. As shown in Fig.1, we can see that the training data is composed of multiple styles, which can be explored to learn domain-invariant features and thus promote model generalization [9]. However, the conventional manner is not applicable in real world, since it is too cumbersome to collect sufficient annotated data from multiple domains. Nonetheless, there is a free lunch to obtain a large amount of unlabeled data, i.e., web data, from multiple domains in real world, which can be utilized to enhance model generalization ability.

To this end, we propose a new DG paradigm, namely Semi-Supervised Domain Generalization (SSDG). Unlike the existing semi-supervised learning regime, the labeled and unlabeled training data of SSDG are sampled from different data distributions (see Fig. 1). To meet the demand of SSDG, we develop two benchmarks, i.e., the close-set SSDG and open-set SSDG. The close-set SSDG is to exploit the existing public DG datasets, which are divided into homogeneous labeled and unlabeled source datasets for training, and the remaining domain served as agnostic target domain for testing. The open-set SSDG is established following more practical settings, where the unlabeled source domains are composed of stylized web data that inevitably contains unknown categories. For these two benchmarks, how to make full use of unlabeled data is the major challenge. Comparing to the existing DG methods that have not attempted to tackle unlabeled data, our task poses a novel yet realistic challenge and encourages to push the limits of the existing technology in the community.
A straightforward method of SSDG is to propagate the class information from the labeled source domains to the unlabeled source domains for pseudo labeling, and then learn DG model in conjunction with these pseudo labels. However, the pseudo labels tend to be noisy since there exist tremendous style gap between the labeled and unlabeled source domains, leading to performance degradation when the models are trained to fit the noisy labels, which confuses the model to disentangle label-related and domain-related features. In one word, the domain gap between source domains directly affects the quality of pseudo labels, while in turn the pseudo labels will affects learning domain invariant features for better generalization.

In this paper, we aim to build a cycle framework to encourage the processes of pseudo labeling and DG training to benefit mutually in a curriculum learning manner. For the former one, we introduce an Adversarial Pseudo Labeling (APL) method, borrowing the solution from unsupervised domain adaptation [10], [11]. The main difference lies in that the labeled source domains are updated by an Evolving Intermediate Domain (EID), bridging the labeled and unlabeled source domains, which is designed to reduce the domain gap so as to improve the quality of pseudo labels. For the latter one, despite the improvement of pseudo labels, they are inevitable to be noisy which will confuses the model to disentangle label-related and domain-related features during training. To this end, we propose a Dual Calibrative Generalization (DCG) method, which is designed to filter the clean samples (with correct labels) from unlabeled data to join DG training. In turn, we build EID by exploiting the labeled source domains and the clean set of unlabeled source domains, which benefits APL for better pseudo labeling. These processes are iterated cyclically in our framework (see in Fig.2). As the cycle goes on, EID gets evolved and both the performance of APL and EID will increase in a curriculum way.

Extensive ablation studies are carried out to validate the effectiveness of each component in our framework. To further evaluate our framework, we build extensive strong baselines by exploiting the solutions among unsupervised domain adaptation, domain generalization, as well as semi-supervised learning on multiple DG datasets. Compared with these strong baselines, our method outperforms them significantly. It is also worth emphasizing that we perform plenty of SSDG experiments in this paper, which can provide a strong benchmark to study SSDG in the future works. Overall, our contributions are summarized as follows:

- We propose a new domain generalization task, termed as Semi-Supervised Domain Generalization (SSDG), which is more practical and meaningful than conventional DG with fully supervised signals.
- We develop two different benchmarks for SSDG, including the close-set and open-set SSDG. Specifically, we build a web-crawled dataset, called PACS-Webdata, to assist the implementation of open-set SSDG.
- We provide extensive strong baselines for SSDG varying among unsupervised domain adaptation, domain generalization, as well as semi-supervised learning.
• We propose an Evolving Intermediate Domain to bridge the labeled and unlabeled source domains. With this assistance, we propose Adversarial Pseudo Labeling for label propagation driven by the annealing domain gap, and Dual Calibrative Generalization to disentangle domain invariant features driven by the clean labels selection. Extensive experiments validate the effectiveness of the proposed method. And the code and dataset have been already released.

II. RELATED WORKS

A. Domain Generalization (DG)

DG aims to train a model from multiple relevant style-variant source domains so as to generalize to the unseen target domain [12], [13], [14]. Early studies of DG focus on learning domain-invariant representation through domain adversarial training between domain classifier and feature extractor [12], [13], [14]. Recent researches developed from meta learning fields simulate domain shift in training, with the purpose of enforcing model robust to domain shift in testing [15], [16], [17]. Another line of solutions is based on the idea of data augmentation that aims to improve the style diversity in image-level [18], [5], [4], [19], or feature-level [7], [20]. Despite the promising results of DG methods, it still exists some weakness, e.g., most of them heavily depend on multiple labeled source domains, which are too cumbersome for annotation.

Compared with conventional DG, our SSDG is much closer to single DG, where only a single labeled source domain is available in training. Most of existing studies on single DG are based on adversarial domain augmentation that generates new training images to mimic virtual challenging domains in an adversarial way [21], [5], [22], [23], [24]. For example, a recent work [23] designs a style-complement module to generate images with diverse out-of-domain styles. Our work can serve as a complementary to existing single DG technologies by introducing unlabeled diversely-stylized images to enhance the performance of domain generalization.

B. Domain Adaptation (DA)

DA aims to mitigate the knowledge from labeled source domain to unlabeled target domain automatically, by training model on both domains jointly. Previous DA methods tend to explore discrepancy-based methods to align distributions between source and target domains, by using MMD distances and so on [25], [26], [27]. Subsequently, researchers discover pre-defined distance functions cannot well describe the real distance between source and target domains, and an adversarial training method is developed to automatically align these two domains, by adversarially training feature extractor and domain classifier [28] or task-specific classifier [11], [29]. Besides, generative adversarial networks are also utilized in DA field for domain mapping, by transferring source images to target styles, or in reverse [30], [31], [32]. Recently, some methods focus on generating precise pseudo labels that usually refines pseudo labels by self-supervised learning [33] or semi-supervised learning [34]. These DA methods can be implemented in our APL module to generate precise pseudo labels, and our domain-gap annealing strategy can further improve the performance of original DA methods.

C. Semi-Supervised Learning (SSL)

Semi-supervised learning paradigm is designed to leverage the knowledge from unlabeled data to improve the model performance. Pseudo labeling is an effective way for SSL that picks the confident prediction class as pseudo labels [35], where entropy minimization is usually used to promise the pseudo labels being confident enough [36]. Another popular SSL method, namely consistency regularization, is based on the assumption that the response of model should be retain consistent after perturbations being used on the input or the model. The perturbations on input data can be data augmentation [37] or adversarial transformation [38]. And it can be extended to perturb model, e.g., time ensembling of model in different time steps [39], an exponential moving average of model parameters [40], or adversarial perturbation on model parameters [38]. There are also some works combining pseudo labeling and consistency regularization for SSL, such as MixMatch [37],FeatMatch [41] and FixMatch [42], etc. SSDG can be viewed a special case of SSL where the labeled data and the unlabeled data are drawn from two different data distributions, equipping with the final purpose of domain generalization.

D. Noisy Label Learning (NLL)

When training with noisy labels, a memorization effect is discovered in deep networks that the model is prone to fit easy (clean) samples initially, and gradually over-fit hard (noisy) samples [43]. It indicates that samples with small-loss are likely to be easy or clean, which suggests to update networks on such samples to avoid overfitting on noise. Hence, researchers are inspired to design effective criterion to select small-loss (clean) samples, e.g., MentorNet [44] using mentornet to provide sample selection curriculum for student-net, and Meta-weight-net [45] constructing meta-net to assign larger weights for clean samples. Co-teaching [46] trains two networks mutually that each network is updated on the clean samples selected by its peer network per feed-forward. Under such inspirations, our DCG module is built to filter noisy pseudo labels provided by APL module. Besides, we not only focus on filtering noisy labels, but also concentrate on how to improve the generalization ability of deep model.

III. METHODOLOGY

A. Overview

We focus on $K$-way classification problem of SSDG in this paper. For simplicity, we only consider the situation that the labeled data is drawn from a single domain $D_{X} = \{(x_i, y_i)\}_{i=1}^{n_x}$, and the unlabeled data $D_{U} = \{u_i\}_{i=1}^{n_u}$ is drawn from multiple domains. As shown in Fig. 2, we treat SSDG as a progressive evolving two-stage task, including Adversarial Pseudo Labeling (APL) and Dual Calibrative Generalization (DCG), which are mutually benefited via an Evolving Intermediate Domain (EID) to bridge the labeled and unlabeled source domains.
Before introducing our framework, we have to emphasize that the motivations of APL and DCG are totally different, where the former one aims to learn accurate pseudo label for the unlabeled source domains, while the latter one aims to generalize well on the agnostic target domains. Actually, APL prefers a smaller domain gap so as to propagate the label information from the labeled source domain to the unlabeled source domains, while DCG prefers a larger domain gap so as to learn domain invariant features for better generalization.

Nonetheless, there still exist connections between these two stages. First, the performance of DCG heavily relies on the domain gap between the labeled and unlabeled source domains, which means we can improve the accuracy of the pseudo labels on the unlabeled source domains by narrowing the domain gap. Inspired by these two considerations, we develop EID to connect these two stages by promoting a cycle learning framework. Our method can be summarized as follows:

1) APL is designed to generate pseudo label for unlabeled source domains which can be implemented by any existing unsupervised domain adaptation (DA) methods;
2) Through exploiting the pseudo labels, DCG performs style confusion training and label diversity regularization for domain generalization. Besides, DCG can be further used to filter the noisy pseudo labels provided by APL module, when finishing training on each cycle;
3) EID builds an intermediate domain via fusing the labeled source domain and the clean set of the unlabeled source domains. Replacing the labeled source domain with the intermediate domain in APL, APL and DCG are promoted to drive next cycle optimization in a curriculum way, in order to benefit each other mutually.

B. Progressive Adversarial Pseudo Labeling

As shown in Fig. 2, our adversarial pseudo labeling (APL) module is designed to generate pseudo labels \( Q = \{ \tilde{q}_i \}_{i=1}^{n_u} \) for the unlabeled data \( D_u \) driven by the evolving intermediate domain \( \hat{D}_X \):  
\[
Q = \arg \max_{\phi} p_\phi(D_u), \\
\text{s.t. } \phi = \arg \min_{\hat{\phi}} L_{apl}(\hat{\phi}; \hat{D}_X, D_u),
\]
where \( p_\phi \) is the class probability predicted by the network parameterized by \( \phi \). The intermediate domain \( \hat{D}_X \) will be introduced in Sec.III-D. In the first cycle, we initialize \( \hat{D}_X \) with the labeled source domain \( D_X \). In Eq.1, we aim to propagate the label information from \( D_X \) to \( D_u \) by employing the supervision signals \( L_{apl} \) of any existing DA methods, such as MCD [11], which performs adversarial training between feature extractor and task-specific classifiers. Note that it can be replaced by any other DA methods. As the training goes on, \( \hat{D}_X \) is kept evolved to anneal domain gap between labeled and unlabeled domains, which advances the quality of pseudo label to promote the optimization of DCG.

C. Dual Calibrative Generalization

The pseudo labels provided by APL are inevitably to be noisy, which will confuse the model to disentangle label-related features and domain-related features. From this perspective, we construct DCG to calibrate pseudo labels when learning domain generalization, which is equipped with style confusion training and label diversity regularization jointly.

As shown in Fig.3, DCG consists of two identical subnetworks, parameterized with \( \theta_1 \) and \( \theta_2 \), respectively. Each subnetwork is calibrated by its peer network through updating the clean samples selected by each other. Specifically, each subnetwork is initialized randomly and fed with the same mini-batch. Suppose each mini-batch contains \( N \) labeled samples \( \mathcal{X} = \{(x_1, y_1), \ldots, (x_N, y_N)\} \) drawn from \( D_X \), and \( N \) pseudo-labeled samples \( \mathcal{U} = \{(u_1, q_1), \ldots, (u_N, q_N)\} \) drawn from \( D_U \).

It is worth to mention that DCG works on mini-batches, and thus, in this section, we present the equations in a mini-batch manner. In this way, the training objective of DCG in each iteration is composed of a labeled source part \( \mathcal{X}(\mathcal{X} \subseteq \mathcal{D}_X) \) and an unlabeled source part \( \mathcal{U}(\mathcal{U} \subseteq \mathcal{D}_U) \). For the \( \mathcal{X} \) part, the loss is defined as:

\[
\min_{\theta_1, \theta_2} L_{ce}(\theta_1; \mathcal{X}) + L_{ce}(\theta_2; \mathcal{X}),
\]
which can regularize the optimization of the unlabeled source part \( \mathcal{U} \). With the guidelines of \( \mathcal{X} \), the model is able to select the clean set of \( \mathcal{U} \) based on a small-loss strategy. It suggests that the samples with small classification loss tend to be clean and then can be used to update the model. In addition, we reduce the selection rate of small-loss samples as the training goes on, since the memorization effect reveals that models tend to learn easy (clean) samples before over-fitting to hard (noisy) samples [43]. Based on this sampling strategy, we can obtain two distinct clean sets, namely \( \mathcal{U}_1 \) and \( \mathcal{U}_2 \) (\( \mathcal{U}_1, \mathcal{U}_2 \subseteq \mathcal{U} \)), selected by the subnetworks \( \theta_1 \) and \( \theta_2 \), respectively. The two clean sets are swapped to update subnetworks by each other, where the loss of \( \mathcal{U} \) part can be defined as:

\[
\min_{\theta_1, \theta_2} L_{ce}(\theta_1; \mathcal{U}_2) + L_{ce}(\theta_2; \mathcal{U}_1).
\]

Fig. 3: Dual calibrative generalization (DCG) with style confusion training and label diversity regularization.

In this way, the two subnetworks will have different decision boundaries finally, which increases their noise-tolerant ability to avoid overfitting on the noisy samples.
1) **Style Confusion Training:** To improve the ability for domain generalization, a low-cost style confusion training method is employed via inserting style confusor layers into each subnetwork to augment the styles. These layers are developed from adaptive instance normalization [47] to confuse the styles between the labeled and unlabeled data in feature space. Specifically, the styles refer to the statistics of instance normalization [48], i.e., mean and variance, which can be represented as \( \mu = \{ \mu_x^1, \ldots, \mu_x^N, \mu_y^1, \ldots, \mu_y^N \} \) and \( \sigma = \{ \sigma_x^1, \ldots, \sigma_x^N, \sigma_y^1, \ldots, \sigma_y^N \} \) for each mini-batch \( \{ x_1, \ldots, x_N, u_1, \ldots, u_N \} \). The statistics are then randomly shuffled in the batch dimension to obtain \( \tilde{\mu} \) and \( \tilde{\sigma} \), respectively. Via a linear combination between \( \{ \mu, \sigma \} \) and \( \{ \tilde{\mu}, \tilde{\sigma} \} \), we can achieve new transformation parameters \( \{ \beta, \gamma \} \):

\[
\beta = \lambda \mu + (1 - \lambda) \tilde{\mu}, \quad \gamma = \lambda \sigma + (1 - \lambda) \tilde{\sigma},
\]

where \( \lambda \) is randomly sampled from a Beta distribution. By exploiting \( \{ \beta, \gamma \} \), we can augment the original features into new style spaces:

\[
\hat{F} = \gamma \cdot \frac{F - \mu}{\sigma + \epsilon} + \beta,
\]

where \( F = \{ F_x, F_u \} \) and \( \hat{F} = \{ \hat{F}_x, \hat{F}_u \} \) are the features in a mini-batch before and after style-confused transformation. Note that the style confusion is omitted during inference stage.

2) **Label Diversity Regularization:** Eq.3 indicates that only the clean part of the pseudo-labeled data is reserved to optimize the model, leading to inefficient utilization of the remaining unlabeled data. To remedy this issue, we employ a label diversity regularization on the whole unlabeled data part \( \mathcal{U} \) in each mini-batch. It is designed to minimize the instance entropy for instance discrimination and maximize the global entropy for label diversification:

\[
\mathcal{L}_{\text{div}}(\theta; \mathcal{U}) = \sum_{u_i \in \mathcal{U}} \log \mathcal{L}_{\text{ce}}(\theta_i; \mathcal{X}) - \mathcal{L}_{\text{div}}(\theta; \mathcal{U}),
\]

where \( \mathcal{L}_{\text{ce}}(\theta_i; \mathcal{X}) \) denotes the log of \( \mathcal{L}_{\text{ce}}(\theta_i; \mathcal{X}) = \sum_{x_j \in \mathcal{X}} \log p(x_j | \theta_i) \).

\[
\mathcal{L}_{\text{div}}(\theta; \mathcal{U}) = \sum_{u_i \in \mathcal{U}} p(u_i) \log p(u_i),
\]

where \( p(u_i) \) denotes the probability of the subnetwork parameterized with \( \theta \) (\( \theta \) can present \( \theta_1 \) or \( \theta_2 \) here). The first term expects for prediction diversification based on class balance assumption, while the second term requires instance discrimination based on entropy minimization theory. According to the aforementioned discussion, the final objective of DCG with each mini-batch \( \{ \mathcal{X}, \mathcal{U} \} \) is summarized as:

\[
\min_{\theta_1, \theta_2} \mathcal{L}_{\text{ce}}(\theta_1; \mathcal{X}) + \mathcal{L}_{\text{ce}}(\theta_2; \mathcal{X}) + \mathcal{L}_{\text{ce}}(\theta_1; \hat{\mathcal{U}}_2) + \mathcal{L}_{\text{ce}}(\theta_2; \hat{\mathcal{U}}_1) + \mathcal{L}_{\text{div}}(\theta_1; \mathcal{U}) + \mathcal{L}_{\text{div}}(\theta_2; \mathcal{U}).
\]

**D. Evolving Intermediate Domain**

As discussed above, the accurate pseudo labels of \( \mathcal{D}_U \) can promote the model to disentangle domain-invariant feature and generalize to the unseen target domain, while the existence of domain gap between \( \mathcal{D}_X \) and \( \mathcal{D}_U \) limits the performance of APL for pseudo labeling. Therefore, in order to reduce the domain gap, we propose evolving intermediate domain (EID) to synthesize an intermediate domain \( \mathcal{D}_Y \) to bridge \( \mathcal{D}_X \) and \( \mathcal{D}_U \). When training APL cyclically, we can replace \( \mathcal{D}_X \) by \( \mathcal{D}_Y \) to anneal domain gap.

Specifically, we design \( \mathcal{D}_Y \) by exploiting \( \mathcal{D}_X \) and the clean set of \( \mathcal{D}_U \) via data fusion. Upon the predictions of DCG, we adopt an agreement-based sampling strategy to obtain a clean set candidate \( \mathcal{D}_C \), which means only when the two subnetworks have identical prediction on the same sample can it be selected into \( \mathcal{D}_C \), which is formulated as:

\[
\mathcal{D}_C = \mathcal{D}_U \cup \{(u_i, q_i), \ s.t. \ \arg \max_{q \in \mathcal{D}_C} p_{\theta_1}(u_i) = \arg \max_{q \in \mathcal{D}_C} p_{\theta_2}(u_i), \quad \epsilon \}
\]

where \( p_{\theta_1}(u_i) \) and \( p_{\theta_2}(u_i) \) denote \( K \)-dimensional prediction probabilities from two subnetworks on the \( i \)-th unlabeled sample. Then, we select small-loss samples in \( \mathcal{D}_C \) with a clean rate of \( R \) to obtain the final clean set:

\[
\mathcal{D}_C = \arg \min_{D' \subset \mathcal{D}_C} \left( \mathcal{L}_{\text{ce}}(\theta_1; D') + \mathcal{L}_{\text{ce}}(\theta_2; D') \right) \quad \text{s.t.} \quad |D'| \geq R |D_C|
\]

The clean set \( \mathcal{D}_C \) is linearly mixed with labeled data \( \mathcal{D}_X \) to synthesize the intermediate domain \( \mathcal{D}_Y \):

\[
\hat{x}_i = \alpha x_i + (1 - \alpha) u_j, \\
\hat{y}_i = E(\alpha) y_i + (1 - E(\alpha)) q_j,
\]

where \( (x_i, y_i) \in \mathcal{D}_X, (u_j, q_j) \in \mathcal{D}_C \), and \( \alpha \) is a weighting map with the same spatial resolution as the input data to control the mixing mechanism. \( E(\alpha) \) denotes a scalar value, as well as the average of \( \alpha \). For simplicity, we only discuss three mixing mechanisms in this paper, including CutMix [49], MixUp [50], and our self-defined “X+U”, which can be extended to more mixing manners in the future works. (1) For CutMix, \( \alpha \) is filled with 1 pasted by a segment of 0 randomly. (2) For MixUp, \( \alpha \) shares the same value, which is randomly distributed in \( [0, 1] \) by sampling from a Beta distribution. (3) For “X+U”, \( \alpha \) shares the same value of 0 or 1, which means we directly combine \( \mathcal{D}_X \) and \( \mathcal{D}_C \) to form the intermediate domain \( \mathcal{D}_Y \). We can see that the replacement of \( \mathcal{D}_X \) by \( \mathcal{D}_Y \) will narrow the domain gap with \( \mathcal{D}_U \) for APL, which subsequently provides more accurate pseudo label for DCG to better generalize to unknown target domain.

In this way, APL and DCG are iterated alternatively driven by the EID. As the training goes on, the pseudo labels provided by APL will be more reliable, the clean set of the unlabeled
data provided by DCG will get enlarged and diversified, and the intermediate domain will get evolved to anneal the domain gap progressively. The entire pipeline is promoted in a curriculum manner as shown in Fig. 2, and the training procedure is illustrated in Algorithm 1.

IV. PACS-WEBDATA BENCHMARK DATASET

In real world, the web-crawled data is low-cost to obtain, which is encouraged to be applied in domain generalization due to its large variety of styles. To verify the viewpoint, we construct an open-set SSDG benchmark by collecting a new web-crawled dataset, namely PACS-Webdata, to serve as an auxiliary source domain for PACS [51]. As for the detailed setting of open-set SSDG, please refer to Sec. V-E.

| Amount/Class | Dog | Elephant | Giraffe | Guitar | Horse | House | Person | Avg. |
|--------------|-----|----------|---------|--------|-------|-------|--------|------|
| Total number | 1065| 1038     | 1591    | 1443   | 1104  | 852   | 1241   | 8334 |
| OOD number   | 431 | 545      | 751     | 636    | 516   | 348   | 703    | 3930 |
| OOD rate (%) | 40.67| 52.50    | 47.20   | 44.07  | 46.74 | 40.85 | 56.65  | 47.16 |

TABLE I: The OOD statistics of PACS-Webdata.

For PACS-Webdata, we collect more than 8k web-crawled images by using the class name as the query keywords of search engine, and crawling similar numbers of images per class. We show several searching results in Fig. 5, from which we can see that PACS-Webdata is rather different from the existing DG datasets since the images are filled with rich styles and unconstrained backgrounds, and we discover that

Fig. 5: Examples from PACS-Webdata benchmark, where the red box denotes the noisy samples with out-of-distribution classes (OOD), and the green box represents the noisy samples with inaccurate web-labels but in-distribution classes.
the query keywords can be regraded as an approximate to class labels of web-crawled images (termed as web-labels). However, the web-labels contain inevitable noise. As shown in Fig. 5, there exists two kinds of noisy web-labels: 1) the true labels of images are in-distribution classes but being inconsistent with the query keyword; 2) the true labels of images are out-of-distribution class, which are also termed as OOD for simplicity. We count the ratio of OOD per category in Table I, where we can see that the OOD occupies a large proportion, even nearly half of the total number of images. It seems that OOD is the main difference between close-set and open-set SSDG, which is also the major challenge to apply web-crawled data to enhance DG performance. Further analysis will be introduced in experiments.

V. EXPERIMENT

In this section, we first present experimental settings in detail, and then conduct plenty of ablation studies to explore the properties and performance of adversarial pseudo labeling (APL) module, dual calibrative generalization (DCG) module and evolving intermediate domain (EID), respectively. Next, the effectiveness of our method is demonstrated by comparing with related methods like domain adaptation (DA), domain generalization (DG) and semi-supervised learning (SSL) methods on different benchmark datasets. Further, we also build a more real-world benchmark of SSDG, namely open-set SSDG dataset, by applying PACS-Webdata as the unlabeled source domain for SSDG. Our method is evaluated on the open-set SSDG benchmark under multiple different settings of web-label. To sum up, our method is evaluated both on the close-set and open-set SSDG benchmarks, and the experimental results prove that our method is superior to other methods even under unconstrained real-world scenarios.

A. Datasets and Experimental Setup

1) Datasets: Our method is evaluated on three DG datasets:
- PACS [51] contains 7 categories from 4 domains: photo (P), art painting (A), cartoon (C), and sketch (S). We follow the train-test split strategy in the prior work [51] to split the training domains into 9:1 (train:val) where only the train split can be used to train model.
- Digits-DG [6] concentrates on digit recognition with 4 domains: Mnist (Mn), Mnist-m (Mm), SVHN (Sv), and Synthetic digits (Sy). Each domain contains 600 images per class sampled from Mnist [53], Mnist-m [10], SVHN [54] and Synthetic-digits [55] datasets, respectively. Following the prior work [6], we split the training domains into 8:2 (train:val).
- Office-Home [56] is a medium-size DG benchmark containing 15500 images with 65 categories from 4 distinct domains: Artistic images (Ar), Clip Art (Ci), Product images (Pr), and Real-world images (Rw). These domains are varied in background, viewpoint and image style.

2) Experimental Setup: For close-set SSDG, we conduct leave-one-domain-out strategy in each dataset that selects three source domains for training and leaves the remaining one for evaluation. Specifically, the three source domains consists of one labeled domain and two unlabeled domain, which forms 12 kinds of SSDG tasks. We evaluate our method on all the SSDG tasks for each dataset and report the average accuracy. Note that in each experiment we report the average accuracy of the last five epochs as the final result.

For open-set SSDG, we follow most of close-set SSDG settings, and the main difference is to use the web-crawled data as the unlabeled source domain, that means, the source domains contains two part: labeled source domain and web-crawled source domain. Since we have collected an auxiliary web-crawled dataset for PACS, the open-set SSDG is also evaluated on this benchmark.

B. Implementation Details

All the experiments are conducted on RTX 3090 GPU with PyTorch 1.7.1. For each SSDG task, we train domain-specific APL for each unlabeled domain, to avoid the disaster of performance degradation brought by training the labeled domain and multiple unlabeled domains simultaneously. Hence, there are two APL modules cooperated with a DCG module for each task in the following experiments. Without any specific statement, we implement APL by using MCD [11] and implement EID via MixUp. We use ResNet-18 [57] as the backbone for APL and DCG, which is initialized with the weights pretrained on ImageNet [58]. For DCG module, the style confusor layers are inserted into the feature maps after the $1^{th}$, $2^{rd}$, and $3^{rd}$ residual blocks of each subnetwork. The APL and DCG are trained with SGD, batch size of 128, initial learning rate of 1e-3, weight decay of 5e-4, momentum of 0.9, and maximum epochs of 30 and 15, respectively. The learning rate is fixed when training each module, while it is decreased globally as the EID cycles increased, as defined by: $\text{lr} = \text{lr}_{\text{initial}} / T^2$, where $T$ denotes the cycle number. Besides, the entire EID cycles is set as 3. The global clean-sample-selection rate in EID is set as 0.4, while the local clean rate in DCG is decreased from 1 to 0.5 linearly. As for the input, we resize each image to $224 \times 224$ and use random translation and random horizontal flipping to augment the data in PACS and Office-Home, while we do not use any augmentation on Digits-DG where each image is resized to $32 \times 32$.

C. Ablation Studies

Fig. 6: (a) Average accuracy of pseudo labels produced by APL module implemented with different DA methods during training. (b) Relationship between pseudo labeling ability of APL module and generalization ability of DCG module.

1) Ablation Studies on APL:
| Backbone       | PL Method                  | P→A | P→C | P→S | A→P | A→C | A→S | C→P | C→A | C→S | S→P | S→A | S→C | Avg. |
|---------------|---------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| ResNet-18     | Ours w/ DANN [10]         | 61.32 | 41.16 | 26.45 | 95.39 | 70.01 | 65.30 | 86.42 | 77.10 | 70.62 | 60.89 | 61.54 | 65.33 | 65.13 |
| ResNet-50     | Ours w/ MME [52]          | 75.94 | 68.11 | 63.50 | 94.94 | 68.37 | 68.46 | 84.94 | 76.40 | 71.47 | 64.48 | 67.33 | 69.46 | 72.78 |
| ResNet-101    | Ours w/ MCD [11]          | 75.52 | 70.98 | 64.01 | 94.94 | 71.82 | 67.18 | 86.44 | 77.39 | 72.24 | 67.21 | 66.86 | 72.83 | 73.80 |
| ResNet-18     | Ours w/ MME [52]          | 75.52 | 70.98 | 64.01 | 94.94 | 71.82 | 67.18 | 86.44 | 77.39 | 72.24 | 67.21 | 66.86 | 72.83 | 73.80 |
| ResNet-50     | Ours w/ MCD [11]          | 71.84 | 70.65 | 66.06 | 95.17 | 74.34 | 67.25 | 90.43 | 79.81 | 69.62 | 73.57 | 66.10 | 74.44 | 74.94 |
| ResNet-101    | Ours w/ MCD [11]          | 75.69 | 72.55 | 68.33 | 94.43 | 77.95 | 62.88 | 86.84 | 79.54 | 73.10 | 70.32 | 76.81 | 76.52 | 76.23 |

TABLE II: Ablation studies in terms of APL module with different pseudo labeling (PL) methods or different backbones on PACS dataset. “P→A” means P is the labeled source domain, A is the testing target domain, and the remaining domains are treated as the unlabeled source domains. Same representation in the following tables.

| Method              | P→A | P→C | P→S | A→P | A→C | A→S | C→P | C→A | C→S | S→P | S→A | S→C | Avg. |
|---------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| DCG w/o style conf. | 67.82 | 60.95 | 56.36 | 94.83 | 67.42 | 57.70 | 75.64 | 73.46 | 63.08 | 66.66 | 60.57 | 64.06 | 67.38 |
| DCG w/o div. reg.   | 71.45 | 63.46 | 63.78 | 95.81 | 66.14 | 64.31 | 90.86 | 78.58 | 71.50 | 50.48 | 50.21 | 55.40 | 68.50 |
| DCG w/o dual cal.   | 74.12 | 66.74 | 61.73 | 94.91 | 72.21 | 66.71 | 75.96 | 77.82 | 71.02 | 63.65 | 67.90 | 72.16 | 72.07 |
| Ours                | 75.52 | 70.98 | 64.01 | 94.94 | 71.82 | 67.18 | 84.64 | 77.39 | 72.24 | 67.21 | 66.86 | 72.83 | 73.80 |

TABLE III: Ablation studies in terms of different components in DCG module on PACS dataset.

- **Explore Different Pseudo Labeling Methods.** We study the impact of APL on SSDG by using different pseudo labeling (PL) techniques to implement APL, including DANN [10], MCD [11], and MME [52]. As shown in Fig.6(a), the accuracy of the pseudo labels is increased as the training goes on, since the domain gap in APL becomes smaller as EID evolves. The accuracy of the pseudo labels is comparable among MCD and MME, which are both better than DANN. Connecting Fig.6(b) to Table II, we can see that the accuracy of pseudo labels in APL is positively related with DG performance.

- **Explore Different Backbones of APL.** We also explore the influences of different backbones on APL module, by implementing APL module with different backbones (varying from ResNet-18, ResNet-50 to ResNet-101), whilst keeping the backbone of DCG module unchanged (ResNet-18). When using ResNet-101 as the backbone of APL module, the batch size is reduced to 64 due to the limitation of GPU memory. The experimental results are shown in Table II, from which we can see that the deeper network of APL module implemented, the better generalization performance of DCG module achieves. The reason is that the APL serves as a teacher model of DCG actually, and the deeper architecture obviously can teach more useful knowledge. Most importantly, in inference stage, the APL will be thrown away to reserve DCG merely, so that deepening the architecture of APL will improve the performance of DCG without increasing any inference cost. It suggests to employ deeper APL module to improve DG performance as long as the training resource allows.

- **Ablation Studies on EID:** We explore the effectiveness of different components in DCG, including dual-calibration, style confusion training, as well as label diversity regularization. The detailed ablation studies are shown in Table III, from which we can see that all the components play an important role for domain generalization.

- **Ablation Studies on EID:** We explore the properties of EID by conducting ablation studies with different EID cycles C, different clean rate R, and different EID manners (including MixUp, “X+U”, and CutMix). The comparison results are shown in Table IV, where we can see that:
  - **Explore Different EID Cycles C.** The performance is improved gradually as EID evolves, and achieves the best result when the EID cycles reaches 3. However, the performance is degraded when it continues enlarging, which can be imputed to the leakage of noisy samples in intermediate domain synthesis. Hence, we set C = 3 by default.
  - **Explore Different Clean Rates R.** The clean rate of the small-loss samples has positive impact on the generalization ability when it raises from 0.2 to 0.4, since the larger rate means more diverse clean set, which leads to the better evolution of intermediate domain. However, the result is
degraded when the clean rate raises to 0.6. Too large clean rate will induce the leakage of noisy samples that is harmful to intermediate domain synthesis. Hence, we set the clean rate as 0.4 by default in the following experiments.

- **Explore Different EID Manners.** We implement three manners to achieve intermediate domain, including CutMix, MixUp and “X+U”. We can see that EID with “X+U” achieves the best result on PACS benchmark, which is merely slightly better than MixUp. In fact, the intermediate domain synthesis is not limited to these manners, which encourages a further exploration in this direction for SSDG.

- **t-SNE Visualization.** To further explore the mechanism of EID, we visualize the feature distributions of APL and DCG modules in Fig. 7. The top row describes the feature distributions of APL on labeled source, unlabeled source, and intermediate domain, where we can see that the intermediate domain bridges the labeled and unlabeled source domains progressively as the training goes. The bottom row depicts the feature distributions of DCG on target domain, which shows the features are getting more discriminative to reduce outliers as EID evolves.

### D. Comparison with Other SOTA Methods

To stress the effectiveness of our method, we implement multiple strong baselines on the SSDG datasets:

- **DA:** Train the model on the labeled and unlabeled source domains simultaneously via different DA methods, whilst testing the performance on the agnostic target domain.
- **DG:** Train the model on single labeled source domain by using single DG methods.
- **DA+DG:** Train domain-specific pseudo labeling model for each unlabeled source domain via different DA methods, and the pseudo-labeled and true-labeled source domains are

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**TABLE V:** The generalization performance comparisons with DA, DG and SSL methods on PACS dataset.
used to train DG model with different DG methods.

- **SSL**: Train on the labeled and unlabeled source domains via different semi-supervised learning methods, whilst testing the performance on the agnostic target domains.

Our method is compared with these baseline methods on PACS, Digits-DG, and Office-Home benchmark datasets. The comparison results are reported in Table V, Table VI, and Table VII, respectively, where we can see that our method is not only superior to the existing DA, DG, SSL methods, but also outperforms the simple combination of DA and DG by a large margin, especially on PACS and Digits-DG datasets. The superiority of our method can be owned to the following parts: 1) the DCG module can facilitate to learn generalization from noisy labels via dual calibrated architecture, style confused training, and label diversity regularization; 2) the evolved intermediate domain (EID) promotes the interaction between APL and DCG module, by mixing the labeled and unlabeled source domains with different manners. As for which kind of EID manner to choose, there is still some room for exploration, since the experimental results shows that both MixUp and “X+U” have their own advantages on different benchmarks. It indicates that it is meaningful to explore more effective EID manners for SSDG, which can be studied in the future.

**E. Experiments on Open-Set SSDG**

We also conduct experiments on a more realistic and meaningful benchmark, namely open-set SSDG. The benchmark is built on the basis of our newly-constructed web-crawled dataset, namely PACS-Webdata, which serves as an auxiliary source domain to assist the labeled source domain $D_X$ for SSDG, where the details of experimental setup is referred to Sec. V-A. Besides, due to the existence of web-label in PACS-Webdata, we also develop different web-label processing manners, including:

- **Web-label ignored**: ignore web-label and treat web-crawled data as the unlabeled data $D_t$;

### Table V: The generalization performance comparisons with DA, DG and SSL method on Digis-DG dataset.

| Method               | Ar-Cl | Ar-Pt | Ar-Rw | Cl-Ar | Cl-Pr | Cl-Rw | Pr-Cl | Pr-Rw | Rw-Pr | Avg. |
|----------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Web-label ignored    | 51.36 | 59.29 | 55.30 | 79.12 | 58.90 | 88.00 | 96.73 | 60.89 | 87.51 | 89.21 |
| Ours w/ MixUp        | 52.00 | 59.01 | 59.53 | 79.45 | 56.87 | 71.08 | 81.95 | 58.80 | 86.52 | 88.68 |

### Table VI: The generalization performance comparisons with DA, DG and SSL method on Office-Home dataset.

| Method                  | P-A   | P-C   | P-S   | A-P   | A-C   | A-S   | C-P   | C-A   | C-S   | P-S   | A-S   | C-A   | C-S   | Avg.  |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Web-label ignored + MixMatch [37] | 52.77 | 46.20 | 41.99 | 78.15 | 68.30 | 59.69 | 77.85 | 60.47 | 73.80 | 64.90 | 70.85 | 65.47 | 70.73 | 69.37 |
| Web-label ignored + FixMatch [42] | 53.77 | 47.20 | 42.99 | 78.30 | 68.50 | 59.79 | 78.00 | 60.60 | 74.00 | 65.10 | 71.00 | 65.70 | 71.30 | 70.00 |

### Table VII: The generalization performance comparisons with DA, DG and SSL method on PACS-Webdata dataset.

| Method                  | P-A   | P-C   | P-S   | A-P   | A-C   | A-S   | C-P   | C-A   | C-S   | S-P   | S-A   | S-C   | Avg.  |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Web-label ignored       | 52.00 | 59.01 | 59.53 | 79.45 | 56.87 | 71.08 | 81.95 | 58.80 | 86.52 | 88.68 | 88.00 | 88.68 | 88.68 | 87.63 |
### Table IX: The adaptation performance comparisons with different DA methods based on Office-Home benchmark. “Ar→Cl” means that Ar is the labeled source domain, and Cl is the unlabeled target domain.

| Method                  | Backbone | Ar–Cl | Ar–Pr | Ar–Rw | Cl–Ar | Cl–Pr | Cl–Rw | Pr–Ar | Pr–Cl | Pr–Rw | Rw–Ar | Rw–Cl | Rw–Pr | Avg. |
|-------------------------|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Source only[57]         |          | 34.9  | 50.0  | 58.0  | 37.4  | 41.9  | 46.2  | 38.5  | 31.2  | 60.4  | 53.9  | 41.2  | 59.9  | 46.1  |
| DAN[62]                 |          | 43.6  | 57.0  | 67.9  | 45.8  | 56.5  | 60.4  | 44.0  | 43.6  | 67.7  | 63.1  | 51.5  | 74.3  | 56.3  |
| DANN[10]                |          | 45.6  | 59.3  | 70.1  | 47.0  | 58.5  | 60.9  | 46.1  | 43.7  | 68.5  | 63.2  | 51.8  | 76.8  | 57.6  |
| JAN[63]                 |          | 45.9  | 61.2  | 68.9  | 50.4  | 59.7  | 61.0  | 45.8  | 43.4  | 70.3  | 63.9  | 52.4  | 76.8  | 58.3  |
| CDAN[59]                | ResNet-50| 49.0  | 69.3  | 74.5  | 54.4  | 66.0  | 68.4  | 55.6  | 48.3  | 75.9  | 68.4  | 55.4  | 80.5  | 63.8  |
| CDAN+E[59]              |          | 50.7  | 70.6  | 76.0  | 57.6  | 70.0  | 70.0  | 57.4  | 50.9  | 77.3  | 70.9  | 56.7  | 81.6  | 65.8  |
| Ours w/ CDAN+E          |          | 60.9  | 72.4  | 74.3  | 56.9  | 73.8  | 69.3  | 53.5  | 57.6  | 75.5  | 65.9  | 66.7  | 83.9  | 67.6  |
| CDAN+E[59]              |          | 40.3  | 57.9  | 64.9  | 43.9  | 58.4  | 57.1  | 43.9  | 40.3  | 65.1  | 56.6  | 47.7  | 74.4  | 54.2  |
| Ours w/ CDAN+E          | ResNet-18| 55.6  | 67.4  | 69.2  | 49.6  | 65.5  | 63.6  | 46.7  | 53.9  | 70.0  | 60.6  | 62.2  | 78.8  | 61.9  |

- **Web-label retained**: treat web-label as the ground truth to train a DG model directly, without the need of DA method;
- **Web-label refined** (only implemented in our framework): use web-label to initialize pseudo labels which will be refined by APL module from the second EID cycle. Note that APL module is omitted in the first cycle.

Our method is compared with other methods under different web-label settings. It is worth noting that the APL module in our framework is implemented with the open-set DA method [64] when conducting “web-label ignored” or “web-label refined” settings. Specifically, the open-set APL module aims to classify the web-crawled data into K + 1 classes included by K classes from the labeled source domain and a new class for OOD. And the OOD recognized by APL module will be rejected to merely leave the “in-distribution” samples participating in training DCG module.

The comparison results of experiments are listed in Table VIII, from which we can see that: 1) Under the same web-label setting, our method always outperforms other methods like SSL method (MixMatch [37], etc) and DG method (RSC [5], Mixstyle [7], etc), which confirms the superiority of our method in open-set SSDG task. 2) Our method performs the best when in “Web-label retained” setting, which is superior to the “Web-label refined” and “Web-label ignored” settings. The reason is that web-label contains more knowledge provided by an extremely large teacher model, aka the search engine, which is difficult to be surpassed by the APL module. 3) Compared with the result of our method in close-set SSDG task (see in Table V), we can see that the open-set SSDG (in “Web-label retained” setting) achieves superior performance due to the arbitrarily diverse styles introduced by web-crawled data, which verifies the web-crawled data has positive effect on SSDG task, despite its out-of-distribution noise. We believe it is meaningful to explore better utilization of web-crawled data for SSDG, and we leave it as a future work.

#### F. Extension to Unsupervised Domain Adaptation

To stress the effectiveness of EID, our method is also extended to the unsupervised domain adaptation scenarios. The experiments are conducted on a popular DA benchmark, aka Office-Home dataset. There are a total of 12 task combinations in Office-Home, where we conduct experiments on each task and report the average accuracy of all tasks as the final result.

1) **Implementation Details**: We follow the standard DA protocols [59] by training models on labeled source and unlabeled target domains jointly. Different from SSDG task, the DCG module is thrown away to merely reserve APL module for evaluating on the testing set of target domain. We choose CDAN+E [59] as the baseline method to implement APL module. Besides, we utilize different backbones (ResNet-18 and ResNet-50) to implement APL module, whilst keeping the backbone of DCG module (ResNet-18) unchanged.

The training hyper-parameters of APL are mostly inherited from the baseline [59], where the models are trained with the SGD optimizer, learning rate of 0.01, batch size of 128, weight decay of 1e-3, momentum of 0.9, and maximum epochs of 50. Besides, the hyper-parameters of DCG and EID, e.g., the clean rate and cycle times, can be referred to the aforementioned SSDG setting. As for the input, the images are resized to 224 × 224, and then randomly cropped and flipped to be fed into the networks for training.

2) **Experimental Results and Analysis**: We compare the experimental results of our method with multiple DA methods, including DAN [62], DANN [10], JAN [63], CDAN [59] and CDAN+E (the baseline). As shown in Table IX, we can see that our method achieves significant performance improvements compared with the baseline, especially when using ResNet-18 as APL backbone. For CDAN+E, the performance of ResNet-18 is obviously less than that of ResNet-50, which shows the significant influence of network depths on DA task. Fortunately, our method can remedy the performance drop brought by shallower network (ResNet-18), since the performance of our method with ResNet-18 is close to the baseline with ResNet-50. The improvements brought by our method can be credited to the DCG module serving as a teacher model to teach useful target knowledge for APL module. In summarize, our method achieves significant success not only on SSDG benchmarks but also on DA tasks. It may be an interesting direction to further explore our method in DA tasks.

### VI. Conclusion

In this paper, we propose a new domain generalization paradigm, termed as Semi-Supervised Domain Generalization, which aims to exploit the rich style information of unlabeled data to cooperate with limited labeled source data for domain generalization. To this end, we propose a framework equipped with Adversarial Pseudo Labeling and Dual Calibrative Generalization modules for label propagation and learning generalization, respectively. To encourage the modules to benefit mutually, we propose an Evolving Intermediate Domain to
bridge the labeled and unlabeled source domains, which narrows the domain gap for label propagation and progressively enhance the ability to disentangle label-related features and domain-related features. Besides, we also investigate a more realistic setting of SSDG, aka open-set SSDG paradigm, by using low-cost and stylized web-crawled data to assist domain generalization. For this purpose, a PACS-Webdata dataset is constructed to implement open-set SSDG benchmark. We build extensive strong baselines in this paper to stress the effectiveness of our method, both on the close-set and open-set SSDG benchmarks. To sum up, our paper provides strong baseline and abundant benchmarks for SSDG, which can promote the development of DG community.

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