

# Domain-Specific Bias Filtering for Single Labeled Domain Generalization

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**Abstract**—Domain generalization (DG) utilizes multiple labeled source datasets to train a generalizable model for unseen target domains. However, due to expensive annotation costs, the requirements of labeling all the source data are hard to be met in real-world applications. In this paper, we investigate a Single Labeled Domain Generalization (SLDG) task with only one source domain being labeled, which is more practical and challenging than the Conventional Domain Generalization (CDG). A major obstacle in the SLDG task is the discriminability-generalization bias: discriminative information in the labeled source dataset may contain domain-specific bias, constraining the generalization of the trained model. To tackle this challenging task, we propose a novel method called Domain-Specific Bias Filtering (DSBF), which initializes a discriminative model with the labeled source data and filters out its domain-specific bias with the unlabeled source data for generalization improvement. We divide the filtering process into: (1) Feature extractor debiasing using k-means clustering-based semantic feature re-extraction; and (2) Classifier calibrating using attention-guided semantic feature projection. DSBF unifies the exploration of the labeled and the unlabeled source data to enhance the discriminability and generalization of the trained model, resulting in a highly generalizable model. We further provide theoretical analysis to verify the proposed domain-specific bias filtering process. Extensive experiments on multiple datasets show the superior performance of DSBF in tackling both the challenging SLDG task and the CDG task.

**Index Terms**—Domain generalization, single labeled multi-source data, bias filtering, semantic feature projection.

## I. INTRODUCTION

DEEP learning based *supervised learning* (SL) and *semi-supervised learning* (SSL) have made great progress in recent years [23], [61]. However, their success heavily relies on the independent and identically distributed (i.i.d.) assumption [49], while the training (source) and test (target) datasets are usually sampled from different distributions in real-world applications, which is known as *dataset shift* [41]. To address this problem, *domain adaptation* (DA) [3] and *domain generalization* (DG) [4] are formulated and many effective methods [54], [31], [60], [57], [9] are proposed to improve the model out-of-distribution generalization ability.

Typical research fields of DA, such as *unsupervised domain adaptation* (UDA) [60], [68], [29], [28], [34], [67], *multi-source domain adaptation* (MSDA) [73], [39], [66], [69], [57], and *multi-target domain adaptation* (MTDA) [7], [32], [57],

[14], [63], [13] suppose both the source and the target datasets are available for model training. For each new target domain, they have to re-collect target data and use it to repeat the training process, which is expensive, time-consuming, or even infeasible. For example, an autonomous driving car can not know in advance which environment, i.e., domain, it will enter. DG is thus proposed to learn a generalizable model by incorporating the invariance across multiple labeled source domains without accessing any target data. However, labeling all the source data is laborious, and most of the previous DG methods [9], [2], [10], [55], [70], [38] do not make full use of the information contained in massive unlabeled data. Then a more practical problem arises: Is it possible to perform domain generalization with a single labeled source dataset as well as multiple unlabeled source datasets? For example, we may train a skin lesion classification model [27] by using a labeled skin lesion dataset from a central hospital. While we would like to further improve the model generalization by employing abundant data from other local hospitals, but these additional data are unlabeled due to the expensive annotation costs.

In this paper, in addition to the Conventional Domain Generalization (CDG) task, we further investigate a more practical DG task, namely Single Labeled Domain Generalization (SLDG), where only one of the multiple source domains is labeled (see Fig. 1). The single labeled multi-source data puts a serious obstacle in the path of domain generalization, which we call the *discriminability-generalization bias*: the discriminative information in the labeled source domain may contain domain-specific bias, constraining the generalization of the trained model. Therefore, how to train a discriminative model while removing its domain-specific bias for guaranteeing generalization is the key to solving this challenging task.

We propose a novel method called Domain-Specific Bias Filtering (DSBF) to tackle the discriminability-generalization bias problem for the challenging SLDG task. Our method presents to initialize a discriminative model with the labeled source data and filter out domain-specific bias in the initialized model with the unlabeled source data for generalization improvement, corresponding to a model initialization stage and a bias filtering stage, respectively. The bias filtering consists of: (1) Feature extractor debiasing using k-means clustering-based semantic feature re-extraction; and (2) Classifier calibrating using attention-guided semantic feature projection. Our method DSBF unifies the exploration of labeled and unlabeled source data to enhance discriminability and generalization of the trained model, resulting in a highly generalizable model, as verified by theoretical analysis and extensive experiments.

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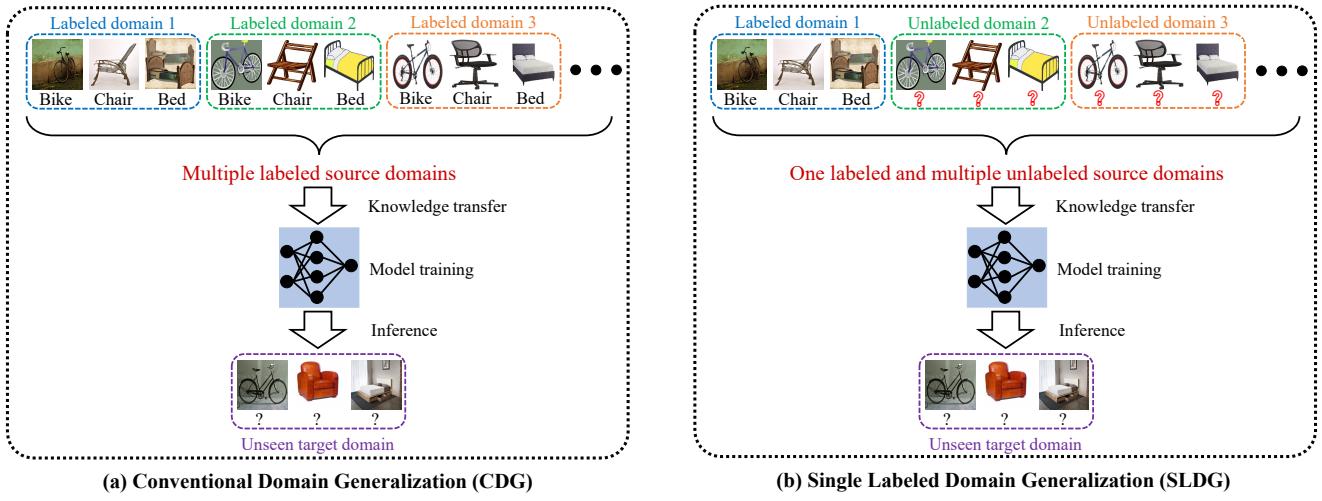


Fig. 1. We consider both the CDG and SLDG tasks. The latter is more practical for dealing with the high annotation costs problem in real-world applications, yet challenging, because only one of the multiple source datasets is labeled, which may lead to the serious discriminability-generalization bias problem.

Our contributions are summarized as: (1) We investigate a practical and challenging Single Labeled Domain Generalization (SLDG) task with only one source domain being labeled, which is significant for the real scenarios where massive unlabeled data is available and can be utilized for generalizable model training; (2) We propose a novel method called Domain-Specific Bias Filtering (DSBF) to tackle the SLDG task by unifying the exploration of the labeled and the unlabeled source data, which consists of model initialization and bias filtering for enhancing model discriminability and generalization, respectively; (3) We verify the proposed method DSBF with theoretical analysis, and extensive experiments on multiple datasets consistently show its superior performance in tackling the SLDG task. Besides, our method can be easily extended to the CDG task and also yields state-of-the-art results.

## II. RELATED WORK

### A. Supervised and Semi-Supervised Learning

In recent years, deep learning based supervised learning (SL) has been widely employed in a variety of applications [23]. It considers the principle of empirical risk minimization (ERM) [49] that a model with low empirical risk on a labeled training dataset is supposed to generalize well on a test dataset. Due to the expensive annotation costs, lots of recent works [47], [46], [62], [56] focus on semi-supervised learning (SSL) [61] that utilizes both the labeled and the unlabeled data for model training. For example, Tarvainen et al. [47] train a student model with a classification cost on the labeled data, and use a consistency cost to make the outputs of the student and a teacher be consistent on the unlabeled data for effectively capturing discriminative information. Although the general SSL methods make full use of both the labeled and unlabeled data for discriminative model training, they assume all the datasets are sampled from the same distributions, which may make the trained models suffer from significant performance degradation on the test (target) datasets in real scenarios. However, the SLDG task we investigate aims to train a

generalizable model using both the labeled and unlabeled data, for unknown target domains with different data distributions.

### B. Domain Adaptation

Unsupervised domain adaptation (UDA) [3] is a prevailing direction to DA that addresses dataset shift between a labeled source domain and an unlabeled target domain. Considerable progress has been made in UDA. A large proportion of them reduces divergence between the source and target domains via adversarial learning [68], [28], [12], [35], [34], [42], [67] or directly minimizing domain discrepancy with a metric like Maximum Mean Discrepancy (MMD) [29], [33], [35]. These methods may fail to take advantage of the available multi-source data, leading to an insufficiently generalizable model.

Increasing works [73], [39], [66], [69], [57] thus focus on multi-source domain adaptation (MSDA) [3] task, where multiple labeled source datasets from different domains are provided for model adaptation. For example, some works [73], [57] present an attention-based strategy to reduce domain divergence in the semantic feature space by using the multiple source datasets and an elaborate attention module. Multi-target domain adaptation (MTDA) is another research field of DA, which extends UDA to multiple [14], [13], [63], [57], [7], [63], continuous [16], [36], [58], and latent [19], [59], [37], [32] target domains. Among them, Chen et al. [7] introduce blending-target domain adaptation (BTDA) that aims to adapt the model to a mixed target distribution where the multi-target proportions are unobservable; and Liu et al. [32] assume the target domain is a compound of multiple homogeneous domains without domain labels and employ model predictions as pseudo labels of the unlabeled data to enable a curriculum learning process. Although annotation costs of the target dataset are avoided in the above DA researches, the requirements of re-collecting target data and training model for each new target domain still hinder their wide application. In contrast, we aim to train a generalizable model that can directly generalize to unseen target domains in the investigated SLDG task.

### C. Domain Generalization

Recently, domain generalization (DG) [4] attracts great interest, which learns to extract domain invariance from multiple labeled source datasets and trains a generalizable model for unseen target domains. Since the DG task is similar to meta-learning [43], some works [2], [10], [25] employ a meta-learning-based strategy that trains the model on a meta-train dataset and continues to improve the model generalization on a meta-test dataset, both the datasets are constructed from the available labeled multi-source data. Besides, lots of effort has gone into data augmentation techniques [5], [55]. The latent idea of these works is the augmented data generate various new domains, and the models trained on these generated domains could be more robust and generalizable. Similar to DA, some recent DG works [70], [38], [71] use adversarial learning to learn discriminative and domain-invariant semantic feature representations that can be applied to different domains. Some strategies like normalization [45], [72] and others [20], [40], [9] are also considered in the DG research fields. These methods may require fully labeled multi-source data, which can be hard to be satisfied due to the high annotation costs.

Qiao et al. [40] present to perform domain generalization with only one labeled source domain, and design a meta-learning scheme with an auto-encoder for model training. Besides, some data augmentation [52], [5], [55] and gradient-based [20] methods may also be extended to the one labeled source setting. However, they fail to utilize the abundant unlabeled data for learning a more generalizable model.

Therefore, in addition to the Conventional Domain Generalization (CDG) setting, we further investigate a more practical task called Single Labeled Domain Generalization (SLDG). The challenging SLDG task only assumes one source dataset to be labeled, and other unlabeled source datasets are provided for improving model generalization performance.

### D. Attention Mechanism

Attention [1] is first introduced in natural language processing for deciding which parts of a sentence should be paid more attention to, which is widely applied in various fields [53], [65], [11], [8]. Self-attention/intra-attention [50] is a specific form of the attention mechanism, which learns a representation of a sequence by reweighting its different positions according to their importance. A general process of the self-attention consists of three steps: (1) Getting the embeddings of *query*, *key*, and *value* from original sequence; (2) Obtaining normalized weights by calculating the similarity between the query and key; (3) Weighting the value. For example, Fu et al. [11] capture rich contextual dependencies in both spatial and channel dimensions by using a position attention module and a channel attention module to selectively aggregate spatial and channel features to obtain more effective representations. In the inter-domain attention module of our method DSBF, we let the key-value pairs be constructed from the semantic features of one source domain and the query be constructed from the semantic features of other source domains. In this way, the domain-invariant semantic information is automatically enhanced during the training process.

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### Algorithm 1 Domain-Specific Bias Filtering (DSBF)

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**Input:** A labeled source  $\mathcal{D}^1$ , unlabeled sources  $\{\mathcal{D}^j\}_{j=2}^K$ , a backbone  $g$  and a network  $b$  with parameter  $\theta_g$  and  $\theta_b$  of the feature extractor, a classifier  $c$  with parameter  $\theta_c$ , semantic feature projection networks  $\{v_j\}_{j=2}^K$  with parameters  $\{\theta_{v_j}\}_{j=2}^K$ , initialization/filtering epochs  $M/N$ ;

**Output:** Well-trained  $\hat{g}$ ,  $\hat{b}$ , and  $\hat{c}$  for inference;

- 1: Initialize SGD optimizers and parameters;
- 2: **for**  $epoch = 1$  to  $M$  **do** // model initialization stage
- 3:     Sample a batch data from  $\mathcal{D}^1$ ;
- 4:     Update  $\theta_g$ ,  $\theta_b$ ,  $\theta_c$  by minimizing  $\mathcal{L}_{CL}$  as Eq. (1);
- 5: **end for**
- 6: **for**  $epoch = 1$  to  $N$  **do** // bias filtering stage
- 7:     Sample a batch data from each  $\mathcal{D}^j$ ,  $j = 1, \dots, K$ ;
- 8:     Get pseudo labels by clustering as Eq. (2-4);
- 9:     Update  $\theta_g$ ,  $\theta_b$  by minimizing  $\mathcal{L}_{IM}$  as Eq. (5);
- 10:    Update  $\theta_g$ ,  $\theta_b$  by minimizing  $\mathcal{L}_{CU}$  as Eq. (6);
- 11:    Update  $\{\theta_{v_j}\}_{j=2}^K$  by minimizing  $\mathcal{L}_{FP}$  as Eq. (7);
- 12:    Update  $\theta_c$  by minimizing  $\mathcal{L}_{BF}$  as Eq. (8).
- 13: **end for**

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## III. PROBLEM SETUP

In the Conventional Domain Generalization (CDG) task, we assume that there are  $K$  labeled source datasets  $\{\mathcal{D}^j\}_{j=1}^K$  with  $n^j$  samples in the  $j$ -th dataset  $\mathcal{D}^j = \{(\mathbf{x}_i^j, y_i^j)\}_{i=1}^{n^j}$ . Any information of the target domain  $\mathcal{D}^{K+1}$  is not provided during model training. The source  $\mathcal{D}^1, \dots, \mathcal{D}^K$  and the target  $\mathcal{D}^{K+1}$  datasets are sampled from different distributions  $P(X^1, Y^1), \dots, P(X^K, Y^K), P(X^{K+1}, Y^{K+1})$ , respectively. The goal of the CDG task is to use the fully labeled source datasets  $\{\mathcal{D}^j\}_{j=1}^K$  to train a predictive model that can perform well on the unseen target dataset  $\mathcal{D}^{K+1}$ .

In this paper, we further introduce a more challenging task, i.e., Single Labeled Domain Generalization (SLDG). SLDG also aims to improve model generalization on the unseen target domain, but only the first source dataset  $\mathcal{D}^1 = \{(\mathbf{x}_i^1, y_i^1)\}_{i=1}^{n^1}$  is assumed to be labeled, the other source datasets  $\{\mathcal{D}^j = \{\mathbf{x}_i^j\}_{i=1}^{n^j}\}_{j=2}^K$  are supposed to be unlabeled.

The main challenge in SLDG task is the discriminability-generalization bias. That is, when we use the labeled source data to train a discriminative model for object recognition, the domain-specific bias in the labeled source data would mislead the model, constraining its generalization performance on other domains. Therefore, it is vital to train a discriminative model using the labeled source data while removing its domain-specific bias for generalization improvement.

## IV. METHODOLOGY

We address the SLDG task by proposing Domain-Specific Bias Filtering (DSBF). It initializes a discriminative model with the labeled source data and filter out domain-specific bias in the initialized model with the unlabeled source data for generalization improvement, corresponding to a *model initialization* stage and a *bias filtering* stage. The bias filtering consists of: (1) *Feature extractor debiasing* using the unlabeled data and its pseudo labels obtained via k-means clustering;

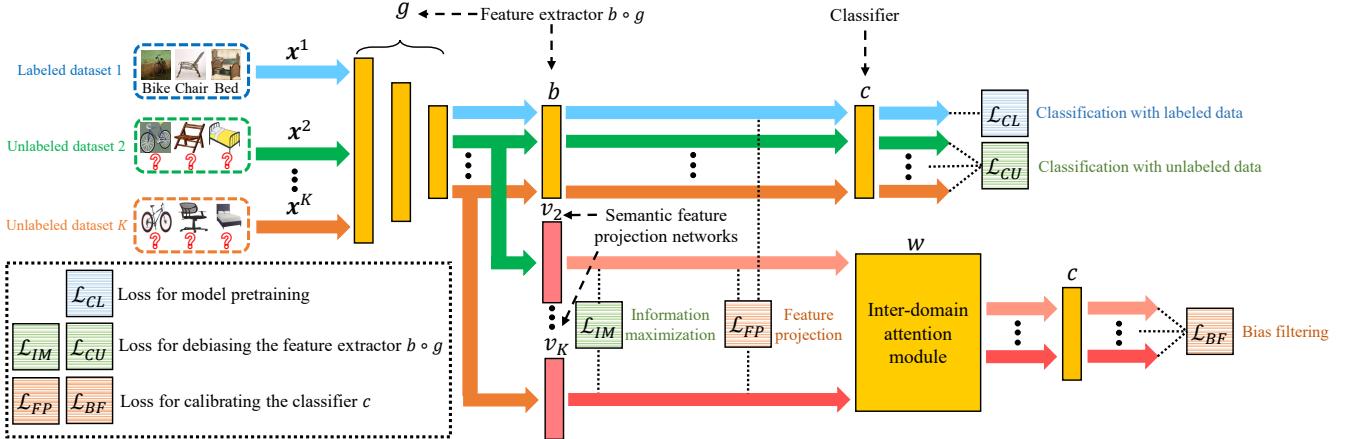


Fig. 2. Our proposed Domain-Specific Bias Filtering (DSBF) framework. The trained model consists of a feature extractor  $b \circ g$ , a classifier  $c$ ,  $K - 1$  semantic feature projection networks  $v_2, \dots, v_K$ , and an inter-domain attention module  $w$ . We only use the trained  $\hat{c} \circ \hat{b} \circ \hat{g}$  for inference after training.

and (2) *Classifier calibrating* using attention-guided semantic feature projection. Our framework and algorithm are shown in Fig. 2 and Alg. 1, respectively. We then introduce the details of the two stages of the proposed DSBF method in the following.

### A. Model Initialization

To initialize a discriminative model, we use the labeled source data  $\mathcal{D}^1$  to pretrain the feature extractor  $b \circ g$  and the classifier  $c$  for learning to extract semantic features of the data and classifying the extracted features to the corresponding categories, respectively. The cross-entropy classification loss of the labeled source data for initializing  $b \circ g$  and  $c$  is

$$\mathcal{L}_{CL} = -\mathbb{E}_{\mathbf{x}^1, \mathbf{y}^1} [\sum_{r=1}^C \mathbf{y}_r^1 \log f_r^b(\mathbf{x}^1)], \quad (1)$$

where  $f^b := c \circ b \circ g$  outputs softmax classification of the data, and  $f_r^b$  is the  $r$ th dimension output of  $f^b$ .  $\mathbf{y}_r^1$  is the  $r$ th dimension of one-hot encoding of the labels  $y^1 \in \{1, \dots, C\}$  of domain  $j$ , where the correct class is “1”, otherwise is “0”.

After model initialization, the feature extractor  $b \circ g$  and the classifier  $c$  are pretrained to extract semantic features of the data and use them for classification, respectively. However, they may be misled by the domain-specific bias of the labeled source data. Therefore, we then utilize the unlabeled data to filter out the domain-specific bias in the initialized model.

### B. Bias Filtering

We debias the feature extractor using k-means clustering-based semantic feature re-extraction, and calibrate the classifier with attention-guided semantic feature projection.

1) *Feature Extractor Debiasing*: We obtain pseudo labels of the unlabeled data to facilitate the following feature extractor debiasing and classifier calibrating processes. Inspired by recent works [21], [30] on deep clustering [6], we adopt k-means clustering to assign pseudo labels  $\{\hat{y}^j\}_{j=2}^K$  for the unlabeled source datasets  $\{\mathbf{x}^j\}_{j=2}^K$ . Specifically, we first get

a centroid  $\mathbf{a}_{(j,r)}^{(0)}$  of each class  $r$  for the semantic features of each unlabeled domain  $j$  via k-means clustering, that is

$$\mathbf{a}_{(j,r)}^{(0)} = \frac{\sum_{\mathbf{x}^j} f_r^b(\mathbf{x}^j) b \circ g(\mathbf{x}^j)}{\sum_{\mathbf{x}^j} f_r^b(\mathbf{x}^j)}. \quad (2)$$

The centroid  $\mathbf{a}_{(j,r)}^{(0)}$  represents the semantic feature distribution of each class  $r$  in domain  $j$ , which is used to assign the initial pseudo label  $d^j$  for samples  $\mathbf{x}^j$ , that is

$$d^j = \arg \min_r \text{dist}(b \circ g(\mathbf{x}^j), \mathbf{a}_{(j,r)}^{(0)}), \quad (3)$$

where  $\text{dist}(\cdot, \cdot)$  measures the cosine distance. Similarly, we then get updated centroid  $\mathbf{a}_{(j,r)}^{(1)}$  and final pseudo labels  $\hat{y}^j$  by

$$\begin{aligned} \mathbf{a}_{(j,r)}^{(1)} &= \frac{\sum_{\mathbf{x}^j} \mathbb{1}(d^j = r) b \circ g(\mathbf{x}^j)}{\sum_{\mathbf{x}^j} \mathbb{1}(d^j = r)}, \\ \hat{y}^j &= \arg \min_r \text{dist}(b \circ g(\mathbf{x}^j), \mathbf{a}_{(j,r)}^{(1)}). \end{aligned} \quad (4)$$

The pseudo labels  $\hat{y}^j$  can be transformed into one-hot encoding  $\hat{\mathbf{y}}^j$ . We consider the ideal form of the softmax outputs of  $c$  should be like one-hot encoding for each sample, and be distinct for samples from different classes. Therefore, we improve the clustering performance by optimizing  $g$ ,  $b$  with information maximization constraint [22], [30] loss:

$$\mathcal{L}_{IM} = \frac{1}{K-1} \sum_{j=2}^K \left( \underbrace{\sum_{r=1}^C t_r \log t_r}_{\text{class diversification}} - \underbrace{\mathbb{E}_{\mathbf{x}^j} [\sum_{r=1}^C u_r \log u_r]}_{\text{sample concentration}} \right), \quad (5)$$

where  $t_r = \mathbb{E}_{\mathbf{x}^j} [f_r^b(\mathbf{x}^j)]$  and  $u_r = f_r^b(\mathbf{x}^j)$ . The first term on the r.h.s. of Eq. (5), i.e., negative expected entropy of population, makes the outputs of  $c$  diverse at the class level; while the second term on the r.h.s. of Eq. (5), i.e., expected entropy of individual, makes the outputs of  $c$  be concentrated at the sample level. Through minimizing  $\mathcal{L}_{IM}$ , we encourage the unlabeled samples with closer distance group together while unlabeled samples far away are further separated, which improves the clustering performance and allows us to obtain more accurate pseudo labels for the bias filtering process.

After clustering, we obtain the pseudo labels of the unlabeled source data. To debias the feature extractor  $b \circ g$ , we present to retrain it with the average classification loss of all the unlabeled sources, thus re-extract the semantic feature of the source data, that is,

$$\mathcal{L}_{CU} = -\frac{1}{K-1} \sum_{j=2}^K \mathbb{E}_{\mathbf{x}^j, \hat{\mathbf{y}}^j} [\sum_{r=1}^C \hat{y}_r^j \log f_r^b(\mathbf{x}^j)]. \quad (6)$$

By minimizing classification loss of both the labeled and unlabeled data, i.e.,  $\mathcal{L}_{CL}$  and  $\mathcal{L}_{CU}$ , the feature extractor  $b \circ g$  is trained to filter out the domain-specific bias after initialization. It allows us obtain more effective domain-agnostic semantic features from multi-source data, facilitating the following classifier calibrating process with semantic feature projection.

2) *Classifier Calibrating*: As the feature extractor is debiased, we employ the generated semantic features of the unlabeled source to filter out the domain-specific bias in the classifier. Specifically, we first project the semantic features of the unlabeled sources, i.e.,  $g(\mathbf{x}^j)$ ,  $j = 2, \dots, K$ , to the semantic features of the labeled source, i.e.,  $b \circ g(\mathbf{x}^1)$ , with the semantic feature projection networks  $\{v_j\}_{j=2}^K$ . To improve the class-level domain invariance, we perform conditional projection, i.e., projecting the semantic features of the unlabeled sources to the semantic features of the labeled source which are in the same class via aligning the true labels  $y^1$  and the pseudo labels  $\{\hat{y}^j\}_{j=2}^K$ . We minimize a feature projection loss to optimize the semantic feature projection networks  $\{v_j\}_{j=2}^K$ :

$$\mathcal{L}_{FP} = \frac{1}{K-1} \sum_{j=2}^K \mathbb{E}_{\mathbf{x}^1, \mathbf{x}^j} [s^j (b \circ g(\mathbf{x}^1) - v_j \circ g(\mathbf{x}^j))^2], \quad (7)$$

where  $s^j = \mathbb{1}(y^1 = \hat{y}^j)$ , i.e., if  $y^1 = \hat{y}^j$ , then  $s^j = 1$ , else  $s^j = 0$ . Through semantic feature projection, the semantic invariance in data is contained in the projection semantic features  $v_j \circ g(\mathbf{x}^j)$ . Then we use it to calibrate/optimize the classifier  $c$  by minimizing the bias filtering loss, which is the average classification loss of the projections  $v_j \circ g(\mathbf{x}^j)$ :

$$\mathcal{L}_{BF} = \frac{1}{K-1} \sum_{j=2}^K \mathbb{E}_{\mathbf{x}^j, \mathbf{y}^j} [s^j \sum_{r=1}^C \hat{y}_r^j \log f_r^{v_j}(\mathbf{x}^j)], \quad (8)$$

where  $f^{v_j} := c \circ w \circ v_j \circ g$  outputs the softmax classification of the projections, and  $f_r^{v_j}$  is the  $r$ -th dimension output of  $f^{v_j}$ . An inter-domain attention module  $w$  is designed to enhance the domain-invariant semantic information during filtering, which will be introduced in the following. By minimizing Eq. (8), the classifier  $c$  uses the invariant semantic information contained in the projections to filter out the domain-specific bias and capture invariant correlation between the semantic features and the labels as verified by theoretical insights in Sec. IV-C.

**Attention-guided Semantic Invariance Enhancement.** To further enhance the domain-invariance with projection semantic features  $v_j \circ g(\mathbf{x}^j)$ , we put forward an inter-domain attention module as shown in Fig. 3. Let  $B$  be the batch-size and  $D$  be the semantic feature dimension, we feed the outputs of projection networks  $\{v_j\}_{j=2}^K$  with size  $B \times D$  to embedding networks  $\{a_j\}_{j=2}^K$  and get semantic feature

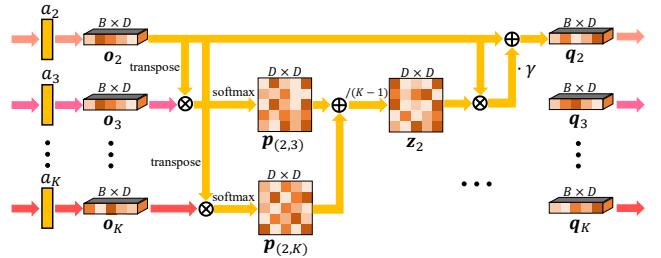


Fig. 3. The proposed inter-domain attention module. It first generates semantic feature embeddings  $\{\mathbf{o}_j\}_{j=2}^K$  with embedding networks  $\{a_j\}_{j=2}^K$ , then weights them according to the inter-domain similarities and obtain weighted semantic features  $\{\mathbf{q}_j\}_{j=2}^K$  for classifier calibrating. Domain invariance is enhanced automatically in this process during the classifier calibrating.

embeddings  $\{\mathbf{o}_j\}_{j=2}^K$  with size  $B \times D$ . Our goal is to obtain the re-weighted  $\{\mathbf{o}_j\}_{j=2}^K$ , i.e.,  $\{\mathbf{q}_j\}_{j=2}^K$ , based on the inter-domain similarities among  $\{\mathbf{o}_j\}_{j=2}^K$ , i.e.,  $\{v_j\}_{j=2}^K$ , for domain invariance enhancement.

We begin by taking domain  $i$  as an example. We first get the normalized inter-domain similarity matrices  $\{\mathbf{p}_{(i,j)}\}_{j=2}^K$  of  $\mathbf{o}_i$  by multiplying the transpose of  $\mathbf{o}_i$  with  $\{\mathbf{o}_j\}_{j=2}^K$  respectively:

$$\mathbf{p}_{(i,j)} = \frac{\exp((\mathbf{o}_i)^\top \mathbf{o}_j)}{\sum_{j=2}^K \exp((\mathbf{o}_i)^\top \mathbf{o}_j)}, j = 2, \dots, K, \quad (9)$$

where  $\mathbf{p}_{(i,j)}$  is the inter-domain similarity matrix of domain  $i$  and  $j$  with size  $D \times D$ . Each position of  $\mathbf{p}_{(i,j)}$  represents the similarities between the corresponding position of  $\mathbf{o}_i$  and  $\mathbf{o}_j$ . Since  $\{\mathbf{o}_j\}_{j=2}^K$  is learned from the projection of each unlabeled source to the labeled source, and  $\{\mathbf{p}_{(i,j)}\}_{j=2}^K$  extract the common semantic information between  $\mathbf{o}_i$  and  $\{\mathbf{o}_j\}_{j=2}^K$ , hence averaging  $\{\mathbf{p}_{(i,j)}\}_{j=2}^K$  encourages the invariant semantic information aggregation, which can be used to re-weight  $\mathbf{o}_i$ :

$$\mathbf{z}_i = \frac{1}{K-1} \sum_{j=2}^K \mathbf{p}_{(i,j)}. \quad (10)$$

Each position of  $\mathbf{z}_i$  represents the overall response of the projection of other domains to the projection of domain  $i$ , which also indicates the common/invariant semantic information of each position of them. Then we get the re-weighted semantic features  $\mathbf{q}_i$  by multiplying  $\mathbf{o}_i$  with  $\mathbf{z}_i$ , and perform an element-wise sum operation with  $\mathbf{o}_i$ , that is,

$$\mathbf{q}_i = \gamma \cdot \mathbf{o}_i \mathbf{z}_i + \mathbf{o}_i, \quad (11)$$

where  $\gamma$  is a parameter initialized as 0 and trained to provide suitable weight. In this way, through the calculation of all the embedding semantic features  $\{\mathbf{o}_j\}_{j=2}^K$ , we can obtain all the re-weighted semantic features  $\{\mathbf{q}_j\}_{j=2}^K$ , which is re-weighted by semantic similarities among the source domains. This inter-domain attention module encourages the domain invariance learning in an automatic manner, effectively assisting the bias filtering process as verified in the experiments.

**Remark.** Note that Fig. 3 is simplified. In our experiments, each network in  $\{a_j\}_{j=2}^K$  is composed of three sub-networks that output the embeddings of query  $\{\mathbf{o}_j^{query}\}_{j=2}^K$ , key  $\{\mathbf{o}_j^{key}\}_{j=2}^K$ , and value  $\{\mathbf{o}_j^{value}\}_{j=2}^K$ , respectively, from each projection semantic features. Eq. (9) is calculated with the key part of  $\mathbf{o}_i$  and query part of  $\mathbf{o}_j$ , i.e.,  $\mathbf{o}_i^{key}$  and  $\mathbf{o}_j^{query}$ . While Eq. (11) is calculated with the value part of  $\mathbf{o}_i$ , i.e.,  $\mathbf{o}_i^{value}$ .

3) *Optimization Details:* For simplicity, we merge the optimization losses to a loss for stage 1, i.e.  $\mathcal{L}_{S1}$ , and a loss for stage 2, i.e.  $\mathcal{L}_{S2}$ , that is,

$$\begin{aligned}\mathcal{L}_{S1} &= \mathcal{L}_{CL} \\ \mathcal{L}_{S2} &= \lambda(\mathcal{L}_{IM} + \mathcal{L}_{CU}) + \gamma(\mathcal{L}_{FP} + \mathcal{L}_{IF})\end{aligned}\quad (12)$$

In the first stage, we initialize the model with the classification loss on the labeled source data  $\mathcal{L}_{CL}$ ; in the second stage, we debias the feature extractor with the classification loss on the unlabeled source data  $\mathcal{L}_{CU}$  using the pseudo label obtained via k-means clustering with the information maximization loss  $\mathcal{L}_{IM}$ ; and calibrate the classifier with the feature projection loss  $\mathcal{L}_{FP}$  and the bias filtering loss  $\mathcal{L}_{BF}$ .  $\lambda$  and  $\gamma$  are the hyperparameters for obtaining the optimal feature extractor debiasing and classifier calibrating processes.

**The CDG task.** In the CDG task, since the ground-truth labels of all the source data are given, we directly employ them for training instead of obtaining them with the clustering.

### C. Theoretical Insights

In the SLDG task, since only one source dataset is labeled, we put forward to calibrate the classifier by using the semantic feature projection. For simplicity, we denote the semantic features extracted from data  $X^j$  as  $H^j \in \mathbb{R}^{d_h}$ , and let it be composed of domain-invariant factor  $U \in \mathbb{R}^{d_h}$  and domain-specific factor/bias  $L^j \in \mathbb{R}^{d_h}$ , that is,

$$H^j = (\boldsymbol{\lambda}^j)^\top U + (\boldsymbol{\eta}^j)^\top L^j, j = 1, \dots, K, \quad (13)$$

where  $\boldsymbol{\lambda}^j \in \mathbb{R}^{d_h \times d_h}$  and  $\boldsymbol{\eta}^j \in \mathbb{R}^{d_h \times d_h}$  are coefficient matrices, which may change across the domains.

Inspired by the ability of human in robust visual recognition that no matter how the domain/environment changes, human can always accurately identify the class of the recognized image [64]. We argue that there is an invariant correlation  $\beta$  between the semantic features  $H^j$  and the corresponding labels  $Y^j \in \mathbb{R}$ , meanwhile, the labels  $Y^j$  may also be biased by the domain-specific factor  $L^j$ , that is,

$$Y^j = \beta^\top H^j + (\psi^j)^\top L^j, j = 1, \dots, K, \quad (14)$$

where  $\beta \in \mathbb{R}^{d_h}$  and  $\psi^j \in \mathbb{R}^{d_h}$  are coefficient matrices, where  $\beta$  stays unchanged but  $\psi^j$  changes across the domains. Note that we let  $\mathbb{E}[L^j] = 0$  for  $j = 1, \dots, K$  (as we can project mean of  $L^j$  to  $U$  and  $H^j$  for satisfying this condition). We then give a data generation and invariance assumption in the following.

**Assumption 1.** The semantic features  $H^j$  and the labels  $Y^j$  in each domain  $j$  satisfy Eq. (13) and (14) respectively, where only the domain-invariant factor  $U$  and the correlation  $\beta$  stay

unchanged across domains. The domain-specific and domain-invariant factors are pairwise independent, i.e.,  $U \perp L^k$  and  $L^j \perp L^k$  for  $j, k \in \{1, \dots, K\}$  and  $j \neq k$ .

Our goal is to identify the true correlation  $\beta$  between the semantic features and the labels. Let  $m$  and  $n$  be an unlabeled and a labeled source domain, respectively. We first project the semantic features  $H^m$  of the unlabeled source to the semantic features  $H^n$  of the labeled source with mapping matrix  $\gamma \in \mathbb{R}^{d_h \times d_h}$ , i.e.,  $\hat{\gamma} = \mathbb{E}_{H^m}[H^m(H^m)^\top]^{-1}\mathbb{E}_{H^m, H^n}[H^m(H^n)^\top]$ . Then we use the projection semantic features, i.e.,  $\hat{H}^n = \hat{\gamma}^\top H^m$ , to fit the labels  $Y^n$  of the labeled source and estimate the correlation  $\hat{\beta} = \mathbb{E}_{\hat{H}^n}[\hat{H}^n(\hat{H}^n)^\top]^{-1}[\hat{H}^n(Y^n)^\top]$ , i.e., the classifier calibrating process. We have the following theorem.

**Theorem 1.** Suppose there are  $n$  samples from each domain, then  $\hat{\beta}$  is a consistent and unbiased estimator of the true correlation  $\beta$ , i.e.,  $\hat{\beta} = \beta + O_p\left(\frac{1}{\sqrt{n}}\right)$  and  $\mathbb{E}[\hat{\beta}] = \beta$ .

*Proof.* Assume that we sample  $n$  examples from each domain. Let  $\mathbf{H}^m \in \mathbb{R}^{n \times d_h}$  be the matrix where  $i$ th row is the observation  $\mathbf{h}_i^m \in \mathbb{R}^{d_h}$  of  $H^m$ , and other symbols are similarly defined. The first step is to regress  $\mathbf{H}^n$  on  $\mathbf{H}^m$ , i.e.,  $\hat{\gamma} = ((\mathbf{H}^m)^\top \mathbf{H}^m)^{-1}(\mathbf{H}^m)^\top \mathbf{H}^n$ . The second step is to regress  $\mathbf{Y}^n$  on  $\hat{\mathbf{H}}^n = \mathbf{H}^m \hat{\gamma}$ , i.e.,  $\hat{\beta} = ((\hat{\mathbf{H}}^n)^\top \hat{\mathbf{H}}^n)^{-1}(\hat{\mathbf{H}}^n)^\top \mathbf{Y}^n$ .

By Assumption 1, we have

$$\frac{1}{n}(\mathbf{H}^m)^\top \mathbf{L}^n = \frac{1}{n}((\mathbf{U}\boldsymbol{\lambda}^m + \mathbf{L}^m\boldsymbol{\eta}^m)^\top \mathbf{L}^n) = O_p\left(\frac{1}{\sqrt{n}}\right). \quad (15)$$

$$\begin{aligned}\frac{1}{n}(\mathbf{H}^n)^\top \mathbf{H}^m &= \frac{1}{n}((\mathbf{U}\boldsymbol{\lambda}^n + \mathbf{L}^n\boldsymbol{\eta}^n)^\top (\mathbf{U}\boldsymbol{\lambda}^m + \mathbf{L}^m\boldsymbol{\eta}^m)) \\ &= \frac{1}{n}(\boldsymbol{\lambda}^n)^\top \mathbf{U}^\top \mathbf{U}\boldsymbol{\lambda}^m + O_p\left(\frac{1}{\sqrt{n}}\right),\end{aligned}\quad (16)$$

$$\begin{aligned}&\frac{1}{n}(\mathbf{H}^m)^\top \mathbf{H}^m \\ &= \frac{1}{n}((\mathbf{U}\boldsymbol{\lambda}^m + \mathbf{L}^m\boldsymbol{\eta}^m)^\top \cdot (\mathbf{U}\boldsymbol{\lambda}^m + \mathbf{L}^m\boldsymbol{\eta}^m)) \\ &= \frac{1}{n}\left((\boldsymbol{\lambda}^m)^\top \mathbf{U}^\top \mathbf{U}\boldsymbol{\lambda}^m + (\mathbf{L}^m\boldsymbol{\eta}^m)^\top \mathbf{L}^m\boldsymbol{\eta}^m + O_p\left(\frac{1}{\sqrt{n}}\right)\right).\end{aligned}\quad (17)$$

Suppose the minimum eigenvalue of  $(\boldsymbol{\lambda}^m)^\top \cdot \mathbb{E}[UU^\top] \cdot \boldsymbol{\lambda}^m$  is bounded away from 0, we have

$$\begin{aligned}&\left(\frac{1}{n}(\boldsymbol{\lambda}^m)^\top \mathbf{U}^\top \mathbf{U}\boldsymbol{\lambda}^m + O_p\left(\frac{1}{\sqrt{n}}\right)\right)^{-1} \\ &= ((\boldsymbol{\lambda}^m)^\top \cdot \mathbb{E}[UU^\top] \cdot \boldsymbol{\lambda}^m)^{-1} + O_p\left(\frac{1}{\sqrt{n}}\right).\end{aligned}\quad (18)$$

Since  $(\boldsymbol{\eta}^m)^\top (\mathbf{L}^m)^\top \mathbf{L}^m \boldsymbol{\eta}^m/n$  is positive semidefinite matrices. Hence, the minimum eigenvalue of  $(\boldsymbol{\lambda}^m)^\top \cdot \mathbb{E}[U(U)^\top] \cdot \boldsymbol{\lambda}^m + (\boldsymbol{\eta}^m)^\top \cdot \mathbb{E}[L^m(L^m)^\top] \cdot \boldsymbol{\eta}^m$  is bounded away from 0, then

$$\begin{aligned}&\left(\frac{1}{n}\left((\boldsymbol{\lambda}^m)^\top \mathbf{U}^\top \mathbf{U}\boldsymbol{\lambda}^m + (\mathbf{L}^m\boldsymbol{\eta}^m)^\top \mathbf{L}^m\boldsymbol{\eta}^m + O_p\left(\frac{1}{\sqrt{n}}\right)\right)\right)^{-1} \\ &= ((\boldsymbol{\lambda}^m)^\top \cdot \mathbb{E}[UU^\top] \cdot \boldsymbol{\lambda}^m + (\boldsymbol{\eta}^m)^\top \cdot \mathbb{E}[L^m(L^m)^\top] \cdot \boldsymbol{\eta}^m)^{-1} \\ &\quad + O_p\left(\frac{1}{\sqrt{n}}\right).\end{aligned}\quad (19)$$

Therefore, by Eq. (15-19), we have

$$\begin{aligned}\hat{\beta} &= \left( \left( \hat{\mathbf{H}}^n \right)^\top \hat{\mathbf{H}}^n \right)^{-1} (\hat{\mathbf{H}}^n)^\top \mathbf{Y}^n \\ &= \left( (\mathbf{H}^n)^\top \mathbf{H}^m ((\mathbf{H}^m)^\top \mathbf{H}^m)^{-1} (\mathbf{H}^m)^\top \mathbf{H}^n \right)^{-1} \\ &\quad \cdot (\mathbf{H}^n)^\top \mathbf{H}^m ((\mathbf{H}^m)^\top \mathbf{H}^m)^{-1} (\mathbf{H}^m)^\top \cdot (\mathbf{H}^n \beta + \mathbf{L}^n \psi^n) \\ &= \beta + O_p \left( \frac{1}{\sqrt{n}} \right).\end{aligned}$$

We then have  $\mathbb{E}[\hat{\beta}] = \beta$ .

Theorem 1 indicates that we can use the semantic features of the unlabeled source to filter out the domain-specific factor/bias of the labeled source and capture the domain-invariant correlation  $\beta$  for more stable model generalization. Since the analysis are based on the linear setting, but the data and networks are non-linear, we then design the inter-domain attention module to further automatically enhance the domain invariance during domain-specific bias filtering process.

## V. EXPERIMENTS

We first implement experiments for the challenging task, i.e., Single Labeled Domain Generalization (SLDG). We compare our method DSBF with standard Supervised Learning (SL) algorithm as well as state-of-the-art methods of Semi-Supervised Learning (SSL), Unsupervised Domain Adaptation (UDA), Multi-Target Domain Adaptation (MTDA), and Domain Generalization (DG). To further testify the performance of our method DSBF in domain-specific bias filtering, we then include the comparison with the other DG methods for the Conventional Domain Generalization (CDG) task, where the labels of all the source datasets are available.

### A. Setup

**Benchmark datasets.** We first adopt two popular benchmark datasets. One is **PACS** [24] that contains 9,991 images from 7 classes in 4 domains, i.e., Artpaint (**Ar**), Cartoon (**Ca**), Sketch (**Sk**), and Photo (**Ph**). Another one is **Office-Home** [51] that consists about 15,500 images of 65 categories over 4 domains, i.e., Art (**Ar**), Clipart (**Cl**), Product (**Pr**), and Real-World (**Rw**). In order to further evaluate the performance under the scenarios of more unlabeled source datasets, we construct a new dataset **Office-Caltech-Home**. Specifically, we choose the common classes from Office-Caltech [15] and Office-Home [51] datasets, i.e., backpack, bike, calculator, keyboard, laptop (computer), monitor, mouse, mug, and merge the two datasets to be a new dataset Office-Caltech-Home that has 4,266 images of 8 classes in 8 domains, i.e., Amazon (**Am**), Webcam (**We**), DSLR (**Ds**), Caltech (**Ca**), Art (**Ar**), Clipart (**Cl**), Product (**Pr**), and Real-World (**Rw**). We discard DSLR since it only has few images, and use the rest 7 domains with 4,145 images. Example images are shown in Fig. 4.

**Baseline methods.** For the experiments in the SLDG task, multiple source datasets are used for model training while only one of them is labeled. The first baseline method is the standard Supervised Learning (SL), and ERM [49] is employed that minimizes the empirical risk, i.e., cross-entropy

loss of classification, on the labeled source dataset. For Semi-Supervised Learning (SSL), both the labeled source dataset and the mixture of the unlabeled source datasets are utilized. We conduct two state-of-the-art SSL methods, i.e., Mean Teacher [47] and FixMatch [46], their strategies are related to knowledge distillation [18] and data augmentation, respectively. We also compare DSBF with Unsupervised Domain Adaptation (UDA), where the labeled source dataset and the mixture of the unlabeled source datasets are used as the source dataset and the unlabeled target dataset in the UDA task, respectively. Several representative UDA methods are considered, i.e., DAN [33], MCD [42], and MDD [67]. Besides, Multi-Target Domain Adaptation (MTDA) is considered to use the labeled source dataset and multiple unlabeled source datasets as the labeled source dataset and multiple unlabeled target datasets, respectively. We employ the state-of-the-art MTDA methods, i.e., BTDA [7] and OCDA [32] as the baselines. Since only one labeled dataset can be utilized in the SLDG task, we compare DSBF with the DG methods which can be extended to this task, including data augmentation based methods JiGen [5] and GUD [52], a training heuristics method RSC [20], and a single domain generalization method M-ADA [40]. We have introduced them in the related work.

**Implementation details.** Following [5], [10], [20], we employ the pre-trained ResNet-18 [17] as the feature extractor  $bog$  for all the experiments. The architecture of each projection networks  $\{v_j\}_{j=2}^K$  is a fully-connected layer with 256 units. The classifier is a fully-connected layer with the same units as the image classes. For Alg. 1, we train the model by SGD optimizer with batchsize 64, learning rate 0.01, momentum 0.9, and weight decay 0.001. The epochs for pretraining (M) and filtering (N) are both set to 20, 30, 20 on PACS, Office-Home, Office-Caltech-Home datasets respectively. We split each dataset by 0.9/0.1 for training/validation. Note that we report the average classification accuracy of 3 runs with different random seeds for the experiments of the SLDG task. For the experiments of the CDG task, we cite the results of the baseline DG methods in the related papers. We directly use the groundtruth labels rather than the pseudo labels from clustering in the CDG task. Since all the source datasets are labeled in the CDG task, we are allowed to randomly choose one source dataset as the  $\mathcal{D}^1$ . In our experiments on PACS dataset, when target domain is Ar or Ph, we let Sk be the labeled source dataset  $\mathcal{D}^1$ ; and when target domain is Ca and Sk, we let Ph be the labeled source dataset  $\mathcal{D}^1$ . For Office-Home dataset, we let Pr be the labeled source dataset  $\mathcal{D}^1$  when target domain is Cl, and let Cl be  $\mathcal{D}^1$  otherwise. We use all the multi-source data for model initialization in the CDG task. We set the hyper-parameters  $\lambda$  and  $\gamma$  to 0.3 and 1, respectively, for the SLDG task, and both to 1 in the CDG task.

### B. Results for the SLDG Task

Table I and Table II report the results of the SLDG task on PACS and Office-Home datasets, respectively. We first note that the SSL methods, i.e., Mean Teacher and FixMatch, fail badly, which is probably because they rely on the i.i.d. assumption and severely overfit the labeled and unlabeled datasets that



Fig. 4. Example images from the adopted datasets. **Left:** PACS dataset [24] with four domains, i.e., Art Painting (Ar), Cartoon (Ca), Photo (Ph), and Sketch (Sk); **Middle:** Office-Home dataset [51] with four domains, i.e., Art (Ar), Clipart (Cl), Product (Pr), and Real World (Rw); **Right:** our Office-Caltech-Home dataset with eight domains, i.e., Amazon (Am), Art (Ar), Caltech (Ca), Clipart (Cl), Dslr (Ds), Product (Pr), Real World (Rw), and Webcam (We).

TABLE I  
CLASSIFICATION ACCURACY (%) FOR THE SINGLE LABELED DOMAIN GENERALIZATION (SLDG) TASK ON PACS DATASET. **A → B** REPRESENTS USING A, B, AND OTHER DOMAINS AS THE LABELED SOURCE, TARGET, AND UNLABELED SOURCE DOMAINS, RESPECTIVELY.

Methods	Type	Ca→Ar	Sk→Ar	Ph→Ar	Ar→Ca	Sk→Ca	Ph→Ca	Ar→Sk	Ca→Sk	Ph→Sk	Ar→Ph	Ca→Ph	Sk→Ph	Avg.
ERM [49]	SL	65.25	25.88	<b>66.65</b>	57.89	53.37	25.53	51.34	65.00	30.52	<b>97.01</b>	87.13	37.72	55.27
Mean Teacher [47] FixMatch [46]	SSL	30.66 30.03	17.43 14.45	28.61 22.85	33.36 31.66	21.50 24.79	28.16 25.64	25.78 19.64	38.20 39.07	29.07 29.68	42.04 25.87	37.07 14.31	16.71 26.00	29.05
DAN [33] MCD [42] MDD [67]	UDA	62.8 72.8 71.7	46.9 29.7 40.2	58.3 66.0 61.9	68.3 61.1 67.0	62.5 43.6 58.1	48.2 49.1 44.8	55.1 61.6 57.1	54.8 25.2 33.5	31.3 95.9 95.9	93.3 83.5 85.1	85.0 44.2 55.0	58.9 58.5 61.1	60.5
OCDA [32] BTDA [7]	MTDA	17.33 63.58	18.51 47.14	17.45 54.95	26.07 59.15	15.78 35.74	19.71 22.32	16.47 <b>70.90</b>	19.67 64.79	24.31 31.78	26.43 42.76	24.07 60.93	11.32 48.76	19.76 50.24
GUD [52] JiGen [5] RSC [20] M-ADA [40]	DG	68.12 66.60 64.79 55.18	22.75 23.68 53.03 24.41	66.06 64.36 66.50 55.71	68.17 53.91 67.15 62.33	34.68 33.45 26.58 58.36	26.11 50.24 55.46 35.92	64.27 62.76 73.96 51.95	68.44 28.58 44.06 72.28	52.48 95.75 94.79 31.15	82.75 84.31 82.10 84.43	36.53 30.24 61.86 71.98	57.16 51.71 61.86 53.22	
<b>DSBF</b>	SLDG	<b>74.99</b>	<b>68.67</b>	53.50	67.78	55.64	55.28	63.44	67.77	<b>59.79</b>	88.94	<b>90.17</b>	<b>76.55</b>	<b>68.54</b>

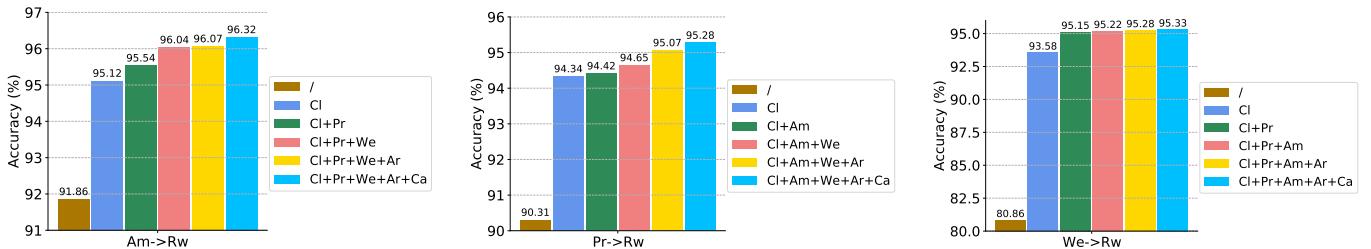


Fig. 5. Accuracy for the SLDG task on Office-Caltech-Home dataset. **A → B** represents using A, B, and other domains as the labeled source, target, and unlabeled source domains, respectively. We add one unlabeled source dataset each time from the unlabeled source domain set for each experiment. If no unlabeled source dataset is given (marked with “/”), the experiments are implemented in the supervised learning setting, i.e., using ERM [49] method.

sampled from completely different domains/distributions. The next observation is that the DG methods, i.e., GUD, JiGen, RSC, M-ADA, show comparable performance to the standard SL method ERM, which is probably because they can not identify the domain invariance by only utilizing one labeled source data. Since the UDA methods address the dataset shift by using both the labeled and the unlabeled data, they are allowed to learn more effective domain-invariant semantic information and hence perform obviously better. The reason for the worse performance of the MTDA methods, i.e. OCDA

and BTDA, may be that they need some strong assumptions. For example, OCDA [32] considers a more homogeneous setting that the domain divergence is indistinct, and it directly employs the model predictions of the unlabeled data as pseudo labels for the model training. In comparison, the proposed DSBF method performs the best on 5 and 7 sub-tasks on PACS and Office-Home datasets, respectively, and achieves the highest average accuracy which is much higher than other methods on both datasets. We argue that it is because DSBF method makes full use of the unlabeled source data to filter out

TABLE II

CLASSIFICATION ACCURACY (%) FOR THE SINGLE LABELED DOMAIN GENERALIZATION (SLDG) TASK ON OFFICE-HOME DATASET. **A** → **B** REPRESENTS USING A, B, AND OTHER DOMAINS AS THE LABELED SOURCE, TARGET, AND UNLABELED SOURCE DOMAINS, RESPECTIVELY.

Methods	Type	Cl→Ar	Pr→Ar	Rw→Ar	Ar→Cl	Pr→Cl	Rw→Cl	Ar→Pr	Cl→Pr	Rw→Pr	Ar→Rw	Cl→Rw	Pr→Rw	Avg.
ERM [49]	SL	44.39	42.65	<b>58.12</b>	38.83	33.96	40.92	58.14	56.84	<b>74.25</b>	67.84	59.61	65.43	53.42
Mean Teacher [47] FixMatch [46]	SSL	8.41 8.94	14.70 7.50	2.84 3.13	8.96 8.18	12.41 13.13	13.56 16.91	2.23 7.16	10.90 14.69	29.29 20.01	4.35 2.27	6.34 4.36	18.56 21.25	11.05 10.63
DAN [33] MCD [42] MDD [67]	UDA	46.6 42.3 45.9	43.8 42.6 47.4	58.1 58.1 56.7	38.3 35.7 39.4	33.8 32.3 34.6	41.9 39.1 42.9	58.8 56.3 59.6	57.9 53.7 59.1	73.0 72.6 72.8	66.6 65.5 68.1	59.5 55.4 61.3	65.2 64.8 65.5	53.6 51.5 54.4
OCDA [32] BTDA [7]	MTDA	13.26 39.27	11.58 <b>59.97</b>	20.60 50.57	13.57 42.37	25.40 <b>59.22</b>	12.69 <b>57.79</b>	11.04 43.95	24.10 48.39	11.97 51.84	13.34 40.14	18.46 47.74	11.76 58.50	15.65 49.98
GUD [52] JiGen [5] RSC [20] M-ADA [40]	DG	38.98 41.62 40.23 30.08	34.53 38.20 37.58 23.61	53.03 54.31 55.50 44.21	38.92 36.20 39.54 37.55	35.46 36.08 38.35 33.68	43.89 42.29 46.94 44.15	51.79 44.78 53.05 43.10	50.10 53.57 52.29 30.39	71.71 69.63 72.89 63.05	61.56 55.57 54.88 53.22	53.22 54.97 54.88 44.50	60.22 62.54 59.44 49.83	49.45 49.15 51.15 41.45
<b>DSBF</b>	SLDG	<b>51.45</b>	50.16	57.38	<b>43.28</b>	38.01	42.68	<b>60.90</b>	<b>61.76</b>	73.49	<b>68.73</b>	<b>65.01</b>	<b>68.36</b>	<b>56.77</b>

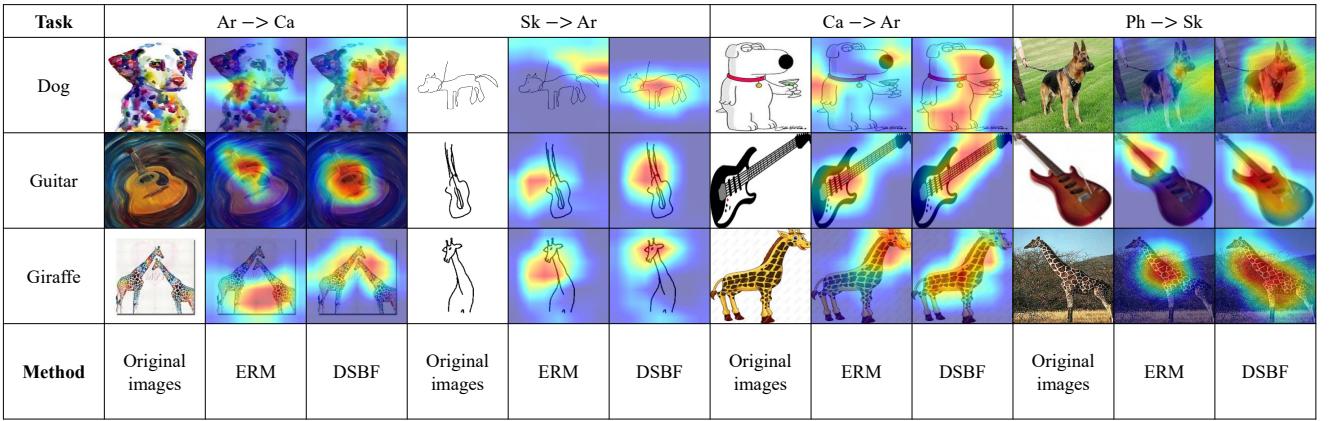


Fig. 6. Grad-CAM visualization [44] of the semantic information learned by the supervised learning method ERM [49] and the proposed method DSBF. The regions in the darker red are considered more important for the trained model to perform object classification.

the domain-specific bias and captures the invariant correlation between the semantic features and the labels, resulting in a highly generalizable model for out-of-distribution target data.

To further evaluate the generalization performance gain from the unlabeled source data, we consider the scenarios with more domains using Office-Caltech-Home dataset as shown in Fig. 5. We find that the performance improves obviously when only one unlabeled source dataset is used, especially in the third group (on the right of Fig. 5) where the labeled source domain is We and the target domain is Rw, the utilization of the unlabeled source domain Cl significantly improves the accuracy from 80.86% to 93.58%. Moreover, we observe a gradual improvement in performance when given more unlabeled source domains. It indicates that DSBF only needs one unlabeled source data to perform effective domain-specific bias filtering and domain invariance learning.

### C. Results for the CDG Task

We report the results for the CDG task on PACS and Office-Home datasets in Table III. We observe that DSBF method achieves the highest average classification accuracy on both PACS and Office-Home datasets, especially on Office-Home dataset. Besides, DSBF performs the best on more than half CDG sub-tasks. DSBF method has excellent performance in

effectively training a generalizable model not only in the challenging SLDG task but also in the CDG task, which illustrates the versatility of the proposed domain-specific bias filtering strategy that domain-specific bias of one domain can be filtered out by employing the data of other source domains.

### D. Analysis

1) *Semantic Invariance Learning*: Fig. 6 shows the semantic information learned by supervised learning method ERM [49] (using only the labeled source data) and our method DSBF (using both the labeled and unlabeled source data). We find that DSBF employs more effective regions of the images for visual recognition, but ERM fails to pay attention to the most effective regions. It demonstrates that DSBF makes full use of the unlabeled source data to filter out the domain-specific bias in the initialized model and capture the domain-invariant semantic information for object recognition.

2) *Semantic Feature Calibration*: We then exploit t-SNE [48] to analyze the semantic feature distributions after the model initialization stage and after the bias filtering stage as shown on the left and right of Fig. 7, respectively. It is evident that after bias filtering, DSBF extracts more discriminative semantic features of the source data by making the same-class samples gather together. It is probably because the filtering

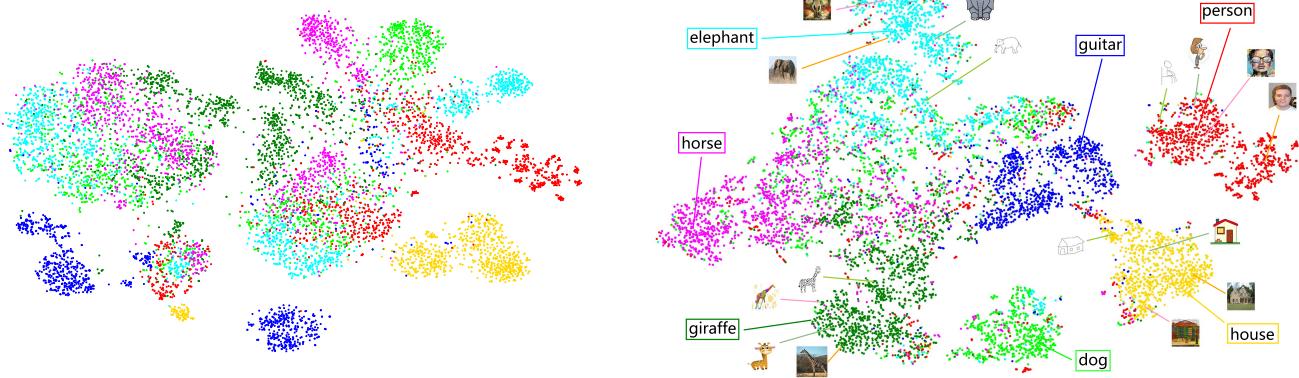


Fig. 7. T-SNE visualization of extracted semantic feature distributions on PACS dataset (the labeled source domain: Ph; the target domain: Sk; the unlabeled source domains: Ar and Ca), where each color represent a class. **Left:** After the model initialization stage; **Right:** After the bias filtering stage.

TABLE III

CLASSIFICATION ACCURACY (%) FOR THE CONVENTIONAL DOMAIN GENERALIZATION (CDG) TASK ON PACS AND OFFICE-HOME DATASETS.

Methods	PACS					Office-Home				
	Ar	Ca	Ph	Sk	Avg.	Ar	Cl	Pr	Rw	Avg.
DeepAll [5]	77.85	74.86	95.73	67.74	79.05	52.15	45.86	70.86	73.15	60.51
MMD-AAE [26]	75.2	72.7	96.0	64.2	77.0	56.5	47.3	72.1	74.8	62.7
RSC [20]	83.43	<b>80.31</b>	95.99	80.85	85.15	58.42	<b>47.90</b>	71.63	74.54	63.12
JiGen [5]	79.42	75.25	<b>96.03</b>	71.35	80.51	53.04	47.51	71.47	72.79	61.20
DSON [45]	<b>84.67</b>	77.65	95.87	<b>82.23</b>	85.11	59.37	44.70	71.84	74.68	62.90
<b>DSBF</b>	83.74	79.91	95.99	81.67	<b>85.33</b>	<b>59.62</b>	47.06	<b>73.62</b>	<b>75.33</b>	<b>63.91</b>

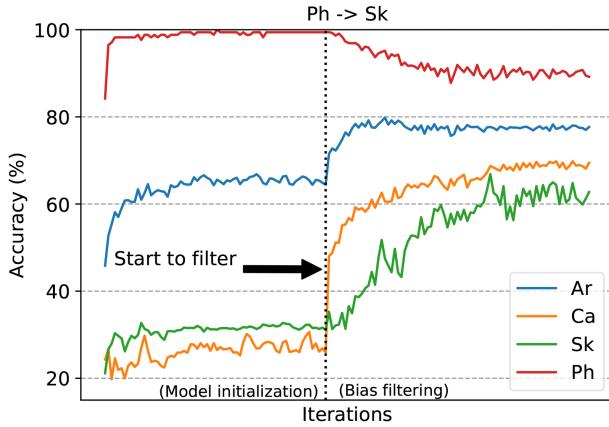


Fig. 8. Classification accuracy on PACS dataset during the model initialization stage and the bias filtering stage (the labeled source domain: Ph; the target domain: Sk; the unlabeled source domains: Ar and Ca).

process effectively tunes the initialized model for semantic bias calibration and leads to a more generalizable model.

3) *Learning Process Tracking*: We plot the learning process in Fig. 8. It is observed that: (1) In the model initialization stage, the trained model overfits the domain-specific bias of the labeled source data Ph (red line), and its classification accuracy rises rapidly; (2) In the bias filtering stage, the unlabeled data, i.e., Ar and Ca, are employed to filter out the domain-specific bias in both the feature extractor and classifier, the classification accuracy on the labeled source domain Ph thus drops slowly, while the performance on the

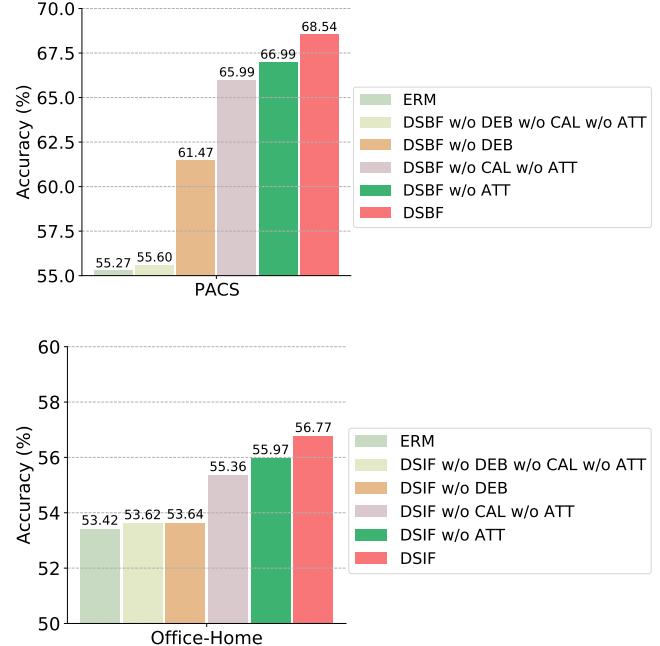


Fig. 9. Ablation study on PACS (**above**) and Office-Home (**below**) datasets. DEB: feature extractor debiasing; CAL: classifier calibrating; ATT: the inter-domain attention module in the classifier calibrating.

unlabeled source domains Ar (blue line) and Ca (orange line) domains, as well as the unseen target domain Sk (green line), improves significantly. It clearly illustrates the learning process of DSBF, which first uses the labeled source data to initialize

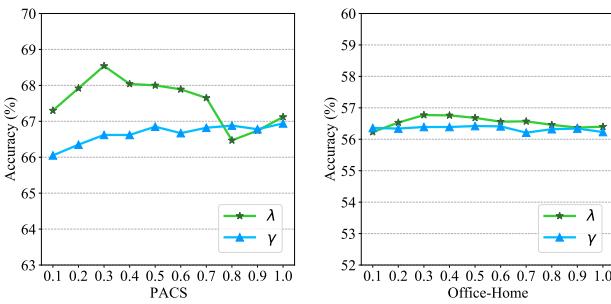


Fig. 10. Sensitivity analysis of the hyper-parameters  $\lambda$  and  $\gamma$ , which are used for the feature extractor debiasing and the classifier calibrating, respectively.

a discriminative model and then utilizes the unlabeled source data to filter out the domain-specific bias and calibrate the initialized model for generalization improvement.

4) *Ablation Study*: Fig. 9 shows the ablation results, where (1) **DEB** is feature extractor debiasing; (2) **CAL** is classifier calibrating; (3) **ATT** is the inter-domain attention module in the classifier calibrating. We note that all the three parts, i.e., DEB, CAL, and ATT, are important for DSBF to achieve superior performance. We then observe that feature extractor debiasing obviously improves the performance on both datasets. It is probably because feature extractor debiasing trains the ResNet-18 network that has much more parameters for tuning than the one fully-connected layer of the classifier trained in classifier calibrating process. The attention module shows invariance enhancement effect during classifier calibrating.

5) *Sensitivity Analysis*: We give sensitivity analysis by varying the hyper-parameters  $\lambda$  and  $\gamma$  in Fig. 10. It illustrates that the model performance is generally stable under different hyper-parameter settings, and our method can effectively perform domain-specific bias filtering and generalizable model training without carefully fine-tuning the hyper-parameters.

## VI. CONCLUSION

In this paper, we investigate a practical task to address the real-world high annotation costs problem for generalizable model learning, i.e., Single Labeled Domain Generalization (SLDG), where only one of the multiple source domains is labeled. To tackle this challenging task, we propose a novel method called Domain-Specific Bias Filtering (DSBF), which unifies the exploration of labeled and unlabeled source data, via a model initialization stage and a bias filtering stage, enhancing discriminability and generalization of the model. Extensive experiments on multiple datasets show the superior performance of DSBF in addressing both the challenging SLDG task and the CDG task. In future work, we may extend our work to other application scenarios like domain generalization with multi-model data.

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