Semantic Data Augmentation based Distance Metric Learning for Domain Generalization

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ABSTRACT
Domain generalization (DG) aims to learn a model on one or more different but related source domains that could be generalized into an unseen target domain. Existing DG methods try to prompt the diversity of source domains for the model’s generalization ability, while they may have to introduce auxiliary networks or striking computational costs. On the contrary, this work applies the implicit semantic augmentation in feature space to capture the diversity of source domains. Concretely, an additional loss function of distance metric learning (DML) is included to optimize the local geometry of data distribution. Besides, the logits from cross entropy loss with infinite augmentations are adopted as input features for the DML loss in lieu of the deep features. We also provide a theoretical analysis to show that the logits can approximate the distances defined on original features well. Further, we provide an in-depth analysis of the mechanism and rational behind our approach, which gives us a better understanding of why leverage logits in lieu of features can help domain generalization. The proposed DML loss with the implicit augmentation is incorporated into a recent DG method, that is, Fourier Augmented Co-Teacher framework (FACT). Meanwhile, our method also can be easily plugged into various DG methods. Extensive experiments on three benchmarks (Digits-DG, PACS and Office-Home) have demonstrated that the proposed method is able to achieve the state-of-the-art performance.

CCS CONCEPTS
• Networks → Network architectures; Network design principles.

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1 INTRODUCTION
With the rapid development of deep neural networks [25, 42, 58], the performance of many essential tasks in multimedia [56, 57, 59, 60] has been dramatically improved. However, the domain shift problem [49, 51], where the training (source domain) and test (target domain) datasets follow different distributions, is still challenging for deep learning. It is due to the fact that deep learning is easy to fit the training set with an over-parameterization neural network. The overfitting phenomenon makes the generalization to the test set from a different distribution intractable. For example, a model trained on a dataset collected from clear weather may perform poorly and unexpectedly on another dataset collected from foggy or snowy weather.

To address the domain shift problem, domain adaptation [6, 31, 41, 46] commits to bridging the difference between the source domain and target domain with the assistance of labeled source samples but unlabeled target ones. However, in many practical applications, the unlabeled target samples are unavailable or unseen. A more realistic research topic, domain generalization (DG), is therefore intensively studied [19, 22, 47, 65]. DG aims to leverage one or more different but related source domains to obtain an applicable model that could be generalized into an unseen target domain.

Recent studies on DG [29, 36, 54] indicate that the performance mainly depends on the number of diverse source samples. To this end, existing DG approaches usually utilize generative adversarial networks (GANs) [65] or adaptive instance normalization (AdaIN) [65] to synthesize unseen samples and improve the diversity of source domains accordingly. However, GANs-based DG models are difficult to be optimized. Besides, the discrimination...
Figure 1: (a) Data distribution by CE loss; (b) Our method, where the dashed samples represent our augmented samples.

ability of augmented samples generated by AdaIN-based DG methods is poor for instance normalization procedure throws away discriminative information.

Besides, many DG methods have variants of cross entropy (CE) loss for optimization, which is hard to capture the intra-class variance [34]. Therefore, some method proposes to include an additional loss from distance metric learning (DML) to learn fine-grained patterns within each class [9]. Compared with the CE loss, that of DML focuses on optimizing the local geometry of data distribution, which can obtain informative representations to model the variance in each class. The DML loss can improve the performance of DG substantially [9] while the augmentation strategy has less been investigated for DML in DG.

Inspired by recent study on data augmentation [50], this paper utilizes the semantic direction based data augmentation in feature space for DG to improve the diversity of source domains. Specifically, there are many semantic directions in the deep feature space based on the intriguing observation that the features are usually linearized [20, 50]. Therefore, we translate a sample in source domain (s) along these semantic directions to produce more augmented samples with the same class label but different semantics as in ISDA [50]. For example, we use the semantic direction corresponding to the semantic translation of “lipstick”, to realize data augmentation for the feature of a person without “lipstick”, then the produced samples belong to the same person but with lipstick. Compared with the conventional augmentation in input space, the semantic augmentation in feature space is more effective to generate diverse examples with the large variance for DG.

However, feature augmentation strategy of ISDA [50] is only for CE loss on classification. It perturbs the logits defined by deep features and a decoupled fully-connected (FC) layer with the semantic directions from the corresponding covariance matrix. Considering that the distance in DML is defined on pairs of original examples, the coupled variables make applying the semantic augmentation for a DML loss in DG challenging. By further investigating the structure of CE loss, our analysis shows that the distance between pairs of examples with deep features can be approximated well by that with logits from CE loss. Therefore, we propose to apply the logits with semantic augmentation as input features for an arbitrary DML loss in DG. This strategy is simple yet effective to augment deep features sufficiently with semantic direction for DML and improve the generalization of DG accordingly. Fig. 1 (b) illustrates the proposed method. With the implicit augmentation for DML, the learned model can capture the intra-class variance better.

To verify the effectiveness of the proposed method, we apply a recent work Fourier Augmented Co-Teacher (FACT) [53] as a baseline DG method and include an additional DML loss with the proposed semantic augmentation strategy for it. Our experimental results demonstrate that DML with semantic augmentation can effectively improve the domain generalization ability. In a nutshell, our main contributions are summarized as follows:

- A novel implicit semantic augmentation strategy is proposed for DML in DG. Concretely, the logits with semantic augmentation is applied as input features for the DML loss in lieu of the original deep features. The theoretical analysis shows that the logits can approximate the distances defined on original features well but is much easier to be augmented by infinite augmentations in feature space.
- Notably, our method introduces no extra network modules over the backbone network, making it simple to implement and computationally efficient. As a light-weight and general technique, our method can be easily plugged into various DG methods to significantly boost their performance.
- Extensive empirical evaluations on several competitive benchmarks including Digits-DG, PACS and Office-Home demonstrate that our method improves the baseline model by significant margins. Even on the single-source domain generalization task, our method shows delightful performance improvements over the baseline.

2 RELATED WORK
2.1 Domain Adaptation

Domain adaptation aims to transfer the learned knowledge from the source domain to the target domain. In this setting, the source domain is usually a labeled large-scale dataset, while the target domain is either partially labeled or completely unlabeled. They are usually called semi-supervised domain adaptation (SUDA) [1, 8, 37, 61] and unsupervised domain adaptation (UDA) [4, 5, 7, 13, 41, 43, 62].

Semi-supervised domain adaptation methods work by imposing constraints on unlabeled or lightly labeled target domains. For instance, Ao et al. [1] align source and target domains by generating pseudo-labels on the unlabeled data of the target domain. Donahue et al. [8] transferred knowledge by establishing similarity graph constraints on partial data of unlabeled target domain and using a projected model transfer method. Satio et al. [37] estimated class-specific prototypes with sparsely labeled examples of the target domain through an adversarial learning method. Yao et al. [61] combine subspace learning and semi-supervised learning into the domain adaptation problem to learn a subspace so that the data distribution of different domains is basically matched after mapping to this subspace.

In unsupervised domain adaptation, most methods perform feature alignment between source and target domains. To this end,
PFAN [4] aligns discriminative features across domains by exploiting the intra-class discriminative feature of the target domain efficiently. CORAL [41] minimizes the distance between the two domains by the covariance matrices. CyCADA [13] adapts the domains by specifying the transfer between domains through a specific discriminative training task and avoiding divergence by enforcing coherence of relevant semantics before and after adaptation, resulting in spatial alignment of generated images and spatial alignment of latent representations. Recently, data augmentation [15, 21] is another generative stream that can enhance the diversity of the source domain. Inspired by data augmentation, TSA [21] augment source features with random directions sampled from the distribution class-wisely. LTIR [15] uses a style transfer algorithm to diversity the textures of the synthesized images. Our method is related to domain randomization which tries to generate diverse source domains. However, they are not suitable for domain generalization as the target domain is not available. On contrary, our method is able to leverage domain randomization to solve the problem of DML and improve the diversity of the features.

2.2 Domain Generalization

Domain Generalization (DG) [11, 22, 27, 35, 39, 65] aims to extract knowledge from multiple source domains so that it can generalize well to unseen target domains. Unlike UDA, target domain data is not accessible during training, which makes the task more challenging than UDA. Moreover, the conditional distributions of multiple source domains are not the same. Early DG research mainly exploits the idea of distribution alignment in domain adaptation to learn domain-invariant features through kernel methods [11, 27] or domain adversarial learning [19, 22, 39]. Later on, most DG methods try to learn the domain invariant representation and leverage data augmentation to expand the diversity of the source domain. The key idea behind the former category is to learn a domain-invariant feature by reducing the difference between representations from multiple source domains. For example, L2A-OT [65] leverages a data generator to synthesize data from pseudo-novel domains to enhance the source domain. This explicitly increases the diversity of available training domains and leads to more general models. Qiao et al [36] leverage the adversarial perturbations on the source images to augment the source domains. MTAE [12] proposes to learn the latent invariant representation by jointly considering the domain reconstruction tasks. DIAC [27] proposes a kernel-based optimization algorithm that learns an invariant transformation by minimizing the dissimilarity across domains. Based on the Fourier method, FACT [53] proposes to leverage the Fourier-based data augmentation strategy to mix the amplitude of the two images to generate augmented images. Different from these methods, we strive to explore the class distribution as a composite representation to expand the diversity of the class. We propose to leverage the implicit semantic augmentation strategy for DML in DG.

3 THE PROPOSED METHOD

3.1 Domain Generalization with Distance Metric Learning

For the domain generalization (DG) task, there are multiple datasets of $K$ source domains $\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_K\}$ for training. Each dataset $\mathcal{D}_i$ contains a set of images $X^i = \{x_1^i, x_2^i, \ldots, x_{n_i}^i\}$ with the corresponding set of class labels $Y^i = \{y_1^i, y_2^i, \ldots, y_{n_i}^i\}$, where $n_i$ is the number of images in the $i^{th}$ dataset, and $y_{n_i}^i \in \{1, \ldots, C\}$, where all the datasets share the same label space. DG aims to train a network that can generalize to the unseen target domain well. Many sophisticated methods [53] have been developed for DG task and the optimization problem can be written as

$$\min_{\theta} \sum_i L_{DG}(X^i, Y^i; \theta)$$

(1)
Cross entropy (CE) loss is widely applied in $\mathcal{L}_{DG}$ to obtain discriminative models as

$$L_{CE}(W, b) = -\log e^{w^T_y f_i + b_y} \sum_{j=1}^C e^{w^T_j f_i + b_j}$$  \hspace{1cm} (2)

where $b = [b_1, \ldots, b_C]^T \in \mathbb{R}^C$ and $W = [w_1, \ldots, w_C]^T \in \mathbb{R}^{C \times d}$ are the biases and weight matrix corresponding to the final connected layer, respectively.

However, cross entropy loss is hard to capture the intra-class variance [34], which is important for generalizing learned models to the unseen domain. To preserve the diversity within each class, a loss function for distance metric learning (DML) can be included for DG [9] and the problem can be cast as

$$\min_{\theta} \sum_i \mathcal{L}_{DG}(X^i, Y^i, \theta) + \alpha \mathcal{L}_{DML}(X^i, Y^i; \theta)$$  \hspace{1cm} (3)

Unlike cross entropy loss which pulls all examples from the same class together, DML optimizes the distribution of nearest neighbors for an anchor example, which is flexible to model the intra-class variance.

Despite the success of DML in DG, augmentation, especially the augmentation in semantic space, has been less investigated for DML. Different from cross entropy loss, many DML losses are defined on triples consisting of original examples, which makes the semantic augmentation challenging. Inspired by the augmentation for classification, we develop a novel strategy for implicit data augmentation in DML to improve the performance of DG.

3.2 Semantic Data Augmentation for Classification

First, we briefly review the semantic augmentation for classification [50]. Compared with augmentation in the original input space, that in feature space can be more effective. The main challenge is to obtain appropriate translation directions in the feature space. To alleviate the challenge, ISDA [50] proposes to sample random vectors from a multivariate normal distribution, with the eigenvalues of the source domain as the mean and the class-conditioned covariance as the covariance matrix for each class. By doing so, a rich set of meaningful semantic translation directions can be discovered.

Concretely, we begin the analysis by explicitly augmenting each $f_i$ at $M$ times to form an augmented feature set $\{(f^1_i, y_i), \ldots, (f^M_i, y_i)\}$ of size $MN$, where $f^m_i$ is the $m$-th sample of augmented features for sample $x_i$. With the multi-augmentation, the network for discrimination can be optimized by minimizing the cross-entropy loss as

$$\mathcal{L}_M(\theta) = \frac{1}{N} \sum_{i=1}^N \frac{1}{M} \sum_{m=1}^M -\log \left( \sum_{j=1}^C e^{w^T_j f^m_i + b_j} \right)$$  \hspace{1cm} (4)

Then, when $M \to \infty$, the CE loss under all possible augmented features can be obtained by the following formulation:

$$\mathcal{L}_{CE}(\theta | \Sigma) = \frac{1}{N} \sum_{i=1}^N \log \left( \sum_{j=1}^C e^{w^T_j f_i + b_j} \right)$$  \hspace{1cm} (5)

Then, according to the Jensen’s inequality $E[\log X] \leq \log E[X]$, as the logarithmic function $\log()$, the Eqn. 5 can be written as

$$\mathcal{L}_{CE}(\theta | \Sigma) = \frac{1}{N} \sum_{i=1}^N \log \left( \sum_{j=1}^C e^{\frac{\sigma^2_j y_i f_i + (b_y - b_j)}{\sigma^2_j}} \right)$$

where $\sigma^2_j y_i f_i = w^T_j f_i + b_j - b_y \sim N(0, \sigma^2_j y_i f_i + b_j - b_y, \sum_{y_i v_i}$).

3.3 Semantic Data Augmentation for DML

According to the analysis above, the decoupled FC layer makes the semantic augmentation from infinite augmentations feasible. However, many DML losses optimize triplets that only retain original examples. Given a triplet $(x_i, x_j, x_k)$, where $x_i$ and $x_j$ share the same label and $x_k$ is from a different class, DML aims to refine representations such that

$$\|f(x_i) - f(x_j)\|_2^2 - \|f(x_i) - f(x_k)\|_2^2 \geq \delta$$  \hspace{1cm} (7)

where $\delta$ is a pre-defined margin. Given a set of triplets $\{ (x_i', x_j', x_k') \}$, the corresponding loss can be written as

$$\mathcal{L}_{DML}(\theta) = \frac{1}{N} \sum_{i} \left[ \|f(x_i') - f(x_j')\|_2^2 - \|f(x_i') - f(x_k')\|_2^2 + \delta \right]_+$$  \hspace{1cm} (8)

where $[.]_+$ denotes the hinge loss.

Compared with the cross entropy loss in Eqn. 5, the coupled features of examples make it hard to apply ISDA for DML directly. To incorporate the semantic augmentation for DML, we first analyze the structure of CE loss. Given the representation of the $i$-th example, the similarity to the $j$-th class is computed as logits in CE loss

$$s_{i,j} = w^T_j f_i + b_j$$  \hspace{1cm} (9)

and the vector $s_i = [s_{i,1}, \ldots, s_{i,C}]^T$ denotes the similarity to different classes. According to the analysis in [33], the similarity vector also demonstrates a good approximation for the full pairwise similarity matrix from the perspective of Nyström method [52]. Inspired by the previous work, we propose to apply logits as features for DML. The distance between pairs of examples can be well bounded by logits as illustrated in the following theorem.

**Theorem 1.** Let $f_i$ and $s_i$ denote the deep features and similarity vector generated from deep features as in Eqn. 9 for the $i$-th example, respectively. Assuming the norm of representations is bounded as $\|f_i\|_2 \leq c$, we have

$$\|s_i - s_j\|_2^2 - 4c^2\|UU^T - WW^T\|_2 \leq \|f_i - f_j\|_2^2 \leq \|s_i - s_j\|_2^2 + 4c^2\|UU^T - WW^T\|_2$$  \hspace{1cm} (10)

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where $U \in \mathbb{R}^{d \times k}$ denotes the SVD decomposition for the feature matrix $[f_1, \ldots, f_n] = U\Sigma V^T$.

Proof. We omit the bias term for brevity. First, with the definition of SVD decomposition, we have

$$
\|f_i - f_j\|^2 = f_i^T (U U^T - WW^T) f_i - 2 f_i^T (U U^T - WW^T) f_j + f_j^T (U U^T - WW^T) f_j
$$

$\quad + f_i^T (U U^T - WW^T) f_j + f_j^T (U U^T - WW^T) f_j - 2 f_i^T (U U^T - WW^T) f_j$

$\quad = \|s_i - s_j\|^2 + f_i^T (U U^T - WW^T) f_i - 2 f_i^T (U U^T - WW^T) f_j + f_j^T (U U^T - WW^T) f_j$

$\quad + f_j^T (U U^T - WW^T) f_j$

With the bounded norm for $f_i$ and $f_j$, the desired result can be obtained by Cauchy–Schwarz inequality

$$
\|f_i - f_j\|^2 \geq \|s_i - s_j\|^2 - 4\epsilon^2 \|UU^T - WW^T\|_2
$$

and

$$
\|f_i - f_j\|^2 \leq \|s_i - s_j\|^2 + 4\epsilon^2 \|UU^T - WW^T\|_2
$$

Remark: Note that $W$ denotes the FC layer and contains proxies for different classes. Therefore, an ideal network can have orthogonal class proxies and representations of examples such as the rank $k = C$ and $\|UU^T - WW^T\|_2 = 0$ when $w_j$ has the unit norm. Theorem 1 implies that the logits $s_i$ can be a good substitute for deep features if the model is optimized appropriately.

With the logits as features, the loss function for DML can be defined as

$$
L_{DML}(\theta) = \sum_t [\|s_i^t - s_j^t\|_2^2 - \|s_i^t - s_k^t\|_2^2 + \delta]_+
$$

Now, we investigate the cross entropy loss with ISDA. By augmenting examples in feature space, CE loss with ISDA can be written as

$$
L_{CE}^{ISDA} = -\log \frac{e^{w_{i,j}^T f_i + b_{y_i}}}{\sum_{j=1}^C e^{w_{i,j}^T f_i + b_{y_j} + \sigma_j y_{y_i}^t \Sigma y_t^c a_{y_{y_i}^t}}}.
$$

Compared with the conventional CE loss, the logits for the negative class is augmented in the feature space with the covariance matrix. Hence, we have the logits as

$$
\begin{align*}
\hat{s}_{i,j}^{ISDA} = \begin{cases} 
  w_{i,j}^T f_i + b_{y_i} & j = i \\
  w_{i,j}^T f_i + b_{y_i} + \sigma_j y_{y_i}^t \Sigma y_t^c a_{y_{y_i}^t} & o.w.
\end{cases}
\end{align*}
$$

By applying the logits $s_{i,j}^{ISDA} = [\hat{s}_{i,j}^{ISDA}, \ldots, \hat{s}_{i,C}^{ISDA}]^T$ as input features for a DML loss, the examples are augmented with semantic directions for DML implicitly.

### 3.4 Final Objective

With the augmented features, we can define our final objective for effective domain generalization. First, a recent work of Fourier Augmented Co-Teacher (FACT) [53], which leverages fourier phase information and amplitude spectrums to improve the generalization ability, is adapted for the DG loss. FACT consists of three-loss including classification loss, Fourier augmented loss and co-teacher regularization loss. Combining all these losses function together, we can get the objective of FACT as

$$
L_{FACT} = L_{cls}^{ori} + L_{cls}^{aug} + \beta \left( L_{col} + L_{aol} \right)
$$

where $\beta$ is a trade-off parameter and we set $\beta = 2$ for Digits-DG and PACS, and 200 for Office-Home which is the same as the original paper FACT.

Then, the lifted structure loss [30] is applied for DML. Given logits with ISDA $\{s_i\}$ as features, it can be defined as

$$
\mathcal{J}_f = \sum_{y_{ij} = 0} \left[ \|s_i - s_j\|^2 + \log \left( \sum_{y_{ik} = 0} \exp(m - \|s_i - s_k\|^2) \right) + \log \left( \sum_{y_{kj} = 0} \exp(m - \|s_j - s_l\|^2) \right) \right]_+
$$

$$
L_{DML} = \frac{1}{2|F|} \sum_{(i,j) \in F} \mathcal{J}_{ij}^2
$$

where $y_{ij} = 1$ denotes $s_i$ and $s_j$ are from the same class while $y_{ik} = 0$ shows that $s_k$ has a different label.

By combining the classification loss and DML loss, our final objective becomes

$$
\min_{\theta} L_{FACT} + \alpha L_{DML}
$$

where $\alpha$ is a constant controlling the strength of corresponding loss. Note that the logits for DML are defined with a FC layer and we have an additional FC layer for $L_{DML}$ to model intra-class variance better. By optimizing Eqn. 20, clusters of samples belonging to the same category are pulled together in the feature space while synchronously pushing apart from other categories. In this way, our method can simultaneously minimize the domain gap across domains as well as enhance the intra-class compactness and inter-class separability in a unified framework as can be seen in Fig. 2.

### 4 EXPERIMENTS

In this section, we demonstrate the superiority of our method on three DG benchmarks. We also carry out detailed ablution studies about the impact of different components.

#### 4.1 Data Description

Digits-DG is a digit recognition benchmark which consists of four digit datasets: MNIST [16], MNIST-M [10], SVHN [28] and SYN [10]. The four datasets mainly contain four different image quality, font style and background. MNIST [16] contains 10 categories of handwritten digits dataset. MNIST-M [10] is a variant of MNIST [16] by blending the image with random color patches. SVHN [28] contains street view house number images. SYN [10] consists of synthetic digital images with different fonts, backgrounds and stroke colors.
PACS [17] is consisted of four domains, namely Photo (1,670 images), Art(2,048 images) Cartoon(2,344 images) and Sketch(3,929 images). Each domain contains seven categories. Following the previous work [17], we choose one domain as the test domain and use the remaining three domains as the source domains. For a fair comparison with the published methods, our model is trained using only data from the training split.

Office-Home [45] is a more complex dataset than PACS [17] , which contains a total of 15,500 images in 65 categories . There exist four extremely different domains in the Office-Home dataset: Artistic images, Product images, Clipart images and Real-World images. Following [3], we randomly split each domain into 90% for training and 10% for validation.

4.2 Implementation Details

For all benchmarks, we performed a leave-one-domain-out evaluation. We train our model on training splits and select the best model on validation splits for all source domains. For testing, we evaluate the selected model on all images that preserve the target domain. All results are reported in terms of classification accuracy and averaged over three experiments. We leverage a popular model (FACT) as our baseline to test the effectiveness of our method. We also compare our proposed method with a variety of state-of-the-art domain generalization methods, including DeepAll [64], Jigen [3], CCSA [26], MMD-AAE [19] , CrossGrad [38], DDAIG [65], L2A-OT [64], ATSRL [55], MetaReg [2] , Epi-FCR [18], MMLD [24], CSD [32], InfoDrop [40], MASF [9], Mixstyle [66], EISNet [48], MDGH [25], RSC [14] and FACT [53]. The results of baselines are cited from the original papers.

We implemented our method with Pytorch and Nvidia Tesla v100 32GB. For Digits-DG, we use the same backbone as FACT [53], we train the network from scratch using SGD, batch size of 128 and weight decay of 5e-4 for 50 epochs. The initial learning rate is set to 0.005 and decayed by 0.1 every 20 epochs. For PACS and Office-Home, we use ImageNet pretrained ResNet as our backbone. We train the network with SGD, batch size of 16 and weight decay of 5e-4 for 50 epochs. The initial learning rate is 0.001 and decayed by 0.1 at 80% of the total epochs. The weight β of the consistency loss is set to 2 for Digits-DG and PACS, and 200 for Office-Home. We also set α = 1 for all three benchmarks. We empirically set the hyper-parameter λ from the set {0.5, 1.0, 1.5, 2.0} according to the performance on the validation set. All the other set is the same as FACT [53].

4.3 Results on Digits-DG

We present the results in Table 1. Among all the competitors, our method achieves the best performance, exceeding the second-best method FACT [53] by 2% on average. Specifically, on the hardest target domains SVHN and SYN, where involve cluttered digits and low image qualities, our method outperforms FACT with a large margin of 1.9% and 2.2% respectively. The success of our method indicates that the logits with semantic augmentation applied as the input features for the DML loss to replace the original deep features can significantly promote its performance on leave-one-domain-out images.

| Methods       | MNIST | MNIST-M | SVHN | SYN | Avg.  |
|---------------|-------|---------|------|-----|-------|
| DeepAll [64]  | 95.8  | 58.8    | 61.7 | 78.6| 73.7  |
| Jigen [3]     | 96.5  | 61.4    | 63.7 | 74.0| 73.9  |
| CCSA [26]     | 95.2  | 58.2    | 65.5 | 79.1| 74.5  |
| MMD-AAE [19]  | 96.5  | 58.4    | 65.0 | 78.4| 74.6  |
| CrossGrad [38]| 96.7  | 61.1    | 65.3 | 80.2| 75.8  |
| DDAIG [65]    | 96.6  | 64.1    | 68.6 | 81.0| 77.6  |
| L2A-OT [64]   | 96.7  | 63.9    | 68.6 | 83.2| 78.1  |
| ATSRL [55]    | 97.9  | 62.7    | 69.3 | 83.7| 78.4  |
| FACT (baseline) [53] | 97.9  | 65.6    | 72.4 | 90.3| 81.5  |
| Ours          | 98.9  | 68.2    | 74.3 | 92.5| 83.5  |

Table 1: Leave-one-domain-out results on Digits-DG. The best and second-best results are bolded and underlined respectively.

| Methods       | Art  | Cartoon | Photo | Sketch | Avg.  |
|---------------|------|---------|-------|--------|-------|
| DeepAll [64]  | 77.63| 76.77   | 95.85 | 69.50  | 79.94 |
| MetaReg [2]   | 83.70| 77.20   | 95.50 | 70.30  | 81.70 |
| CrossGrad [38]| 79.81| 76.8    | 96.0  | 70.2   | 80.70 |
| Jigen [3]     | 79.42| 75.25   | 96.03 | 71.35  | 80.51 |
| Epif-FCR [18] | 82.10| 77.00   | 93.90 | 73.00  | 81.50 |
| MMLD [24]     | 81.28| 77.16   | 96.09 | 72.29  | 81.83 |
| DDAIG [65]    | 84.20| 78.10   | 95.30 | 74.70  | 83.10 |
| CSD [32]      | 78.90| 75.80   | 94.10 | 76.70  | 81.40 |
| InfoDrop [40] | 80.27| 76.54   | 96.11 | 76.38  | 82.33 |
| MASF [9]      | 80.29| 77.17   | 94.99 | 71.69  | 81.04 |
| L2A-OT [64]   | 83.30| 78.20   | 96.20 | 73.60  | 82.80 |
| MixStyle [66] | 84.1 | 78.8    | 96.1  | 75.9   | 83.7  |
| EISNet [48]   | 81.89| 76.44   | 95.93 | 74.33  | 82.15 |
| FACT (baseline) [53] | 85.37| 78.38   | 95.15 | 79.15  | 84.51 |
| Ours          | 87.96| 82.41   | 98.85 | 83.21  | 88.08 |

Table 2: Leave-one-domain-out results on PACS. The best and second-best results are bolded and underlined respectively.
Table 3: Leave-one-domain-out results on Office-Home. The best and second-best results are bolded and underlined respectively.

| Methods          | Art   | Clipart | Product | Real   | Avg.  |
|------------------|-------|---------|---------|--------|-------|
| DeepAll [64]     | 57.88 | 52.72   | 73.50   | 74.80  | 64.72 |
| CCSA [26]        | 59.90 | 49.90   | 74.10   | 75.70  | 64.90 |
| MMD-AAE [19]     | 56.50 | 47.30   | 72.10   | 74.80  | 62.70 |
| CrossGrad [38]   | 58.40 | 49.40   | 73.90   | 75.80  | 64.40 |
| DDAIG [65]       | 59.20 | 52.30   | 74.60   | 76.00  | 65.50 |
| L2A-OT [64]      | 60.60 | 50.10   | 74.80   | 77.00  | 65.60 |
| JiGen [3]        | 53.04 | 47.51   | 71.47   | 72.79  | 61.20 |
| RSC [14]         | 58.42 | 47.90   | 71.63   | 74.54  | 63.12 |
| FACT (baseline) [53] | 60.34 | 54.85   | 74.48   | 76.55  | 66.56 |
| Ours             | 68.29 | 57.63   | 76.21   | 80.69  | 70.71 |

4.4 Results on PACS

The results of PACS are shown in Table 2. It can be seen that our method achieves the best results and outperforms the existing methods by a large margin. Meanwhile, we notice that our method also performs well on the large domain discrepancy task cartoon and sketch domains. We also notice that our method lifts a tremendous margin of 4.06% on ResNet-18 and 3.83% on ResNet-50, respectively. Meanwhile, the performance of our method on the photo domain improved performance is also better than other domains. This is reasonable since domains like Photo contain redundant and complicated details, and our method may capture meaningful information. Compared with the state-of-the-art methods, our method clearly beats the methods based on the GAN-based data augmentation and meta-learning methods, such as the latest L2A-OT [64], MDGH [23] and ATSRL [55]. Our method also enjoys an efficient training process without any additional adversarial training. All the above comparisons reveal the effectiveness of our method and further demonstrate that our method not only leads to lower generalization error, but it is simpler and more efficient.

4.5 Results on Office-Home

We report the results of Office-Home in Table 3. Due to a relatively smaller domain discrepancy and the similarity to the pretrained dataset ImageNet, our method acts as a strong baseline for Office-Home. Many previous DG methods, such as CCSA [26], MMD-AAE [19], CrossGrad [38] and JiGen [64], can not improve much over the tasks. Nevertheless, our method achieves a consistent improvement over all the leave-one-domain-out domains. Moreover, our method also surpasses the latest RSC [14] and L2A-OT [64] in terms of average performance. This again justifies the superiority of our method.

5. ANALYSIS

Ablation Study. We conduct an extensive ablation study to investigate the role of each component in out our method in Table 4. FACT (baseline) denotes that we only use FACT without any other strategy. Based on FACT (baseline), we add a DML loss [30] to obtain FACT (+DML) [30] (here we leverage original features and logits as the inputs, which denotes FACT (+ DML (features)) and FACT (+DML (logits)), which improves over FACT (baseline) slightly. Further incorporating the implicit semantic data augmentation (ISDA), which perform better than FACT (+DML) [30]. This indicates that leverage logits to replace features can provide better domain generalization ability.

Table 4: Ablation studies on different components of our method on the Office-Home dataset.

| Methods          | Art   | Clipart | Product | Real   | Avg.  |
|------------------|-------|---------|---------|--------|-------|
| FACT (baseline) [53] | 60.34 | 54.85   | 74.48   | 76.55  | 66.56 |
| FACT (+DML (features)) [30] | 63.58 | 55.61   | 74.73   | 78.02  | 67.99 |
| FACT (+DML (logits)) [30] | 64.28 | 56.21   | 75.39   | 78.94  | 68.71 |
| FACT (+ISDA) [50] | 63.27 | 55.31   | 75.67   | 77.77  | 68.00 |
| Ours             | 68.29 | 57.63   | 76.21   | 80.69  | 70.71 |

Effectiveness of our method. To verify the effectiveness of our proposed method, we tested it on three other baselines including DG_via_ER [63], JiGen [3] and EISNet [48] in Table. 5, we find that JiGen+Ours, DG_via_ER+Ours, EISNet+Ours improve the baseline 2.13%, 2.58% and 1.57%, respectively. This not only demonstrates the effectiveness of our proposed method, but also shows that our method is a plug-and-play method.

Visualization of augmented images. To demonstrate that our method is able to generate meaningful semantically augmented samples, we introduce an approach to map the augmented features back to show semantic changes of the images. Figure 3 show the visualization results. The first column represents the original images. The other columns present the images augmented by our method. It can be observed that our method is able to alter the semantics of images, e.g., backgrounds, visual angles, actions of dogs and color of skins, which is not possible for traditional data augmentation techniques. For a clear comparison, we also present the randomly generated images of the same class.

Visualization of Deep Features. We visualize the learned deep features on PACS using the t-SNE algorithm [44] in Fig. 4. We use “Photo” as the target domain and “Art-Cartoon-Sketch” as the source domain. From the t-SNE [44] analysis, we can observe that previous FACT category alignment method could produce separated features, yet it may be hard for dense prediction since the margins between different category features are not obvious and the distribution is
Figure 3: Visualization of the semantically augmented images. Our method is able to alter the semantics of images that are unrelated to the class identity, like backgrounds, actions of animals, visual angles, etc.

Figure 4: Visualization of deep features learned by FACT and Ours on PACS. (Target: Photo)

still dispersed. When we use our method, features among different categories are better separated, demonstrating that the semantic distributions can provide correct supervision signal for unknown target domain. In comparison, the embedded representations of our method exhibit the clearest clusters compared with other state-of-the-arts, revealing the discriminative capability of the domain generalization.

Parameter Sensitivity. To study how the hyper-parameter $\alpha$ affects the performance of our method, sensitivity tests are conducted for PACS on task Photo and Sketch. The results are shown in Fig.5. When $\alpha = 0$, there is only the baseline of FACT. From Fig.5, we can see that when $\alpha = 1$, the results for the datasets of PACS are the best.

6 CONCLUSION

In this paper, we propose a semantic data augmentation based distance metric learning for domain generalization. We leverage a novel implicit semantic augmentation strategy for DML loss in domain generalization. We find that the logits with the semantic augmentation to replace the input features for DML loss is more suitable for domain generalization. We also provide a theoretical analysis to show that the logits can approximate the distances defined on original features well. Further, we provide an in-depth analysis of the mechanism and rational behind our approach, which gives us a better understanding of why leverage logits in lieu of features can help domain generalization. Extensive experiments on three benchmarks demonstrate that our method achieves state-of-the-art performance in domain generalization. Considering that the mainstream of related work is still domain-adversarial learning, we hope that our work can bring some inspiration to the community.
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