# DISCRIMINATIVE DOMAIN-INVARIANT ADVERSARIAL NETWORK FOR DEEP DOMAIN GENERALIZATION

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## **ABSTRACT**

Domain generalization approaches aim to learn a domain invariant prediction model for unknown target domains from multiple training source domains with different distributions. Significant efforts have recently been committed to broad domain generalization, which is a challenging and topical problem in machine learning and computer vision communities. Most previous domain generalization approaches assume that the conditional distribution across the domains remain the same across the source domains and learn a domain invariant model by minimizing the marginal distributions. However, the assumption of a stable conditional distribution of the training source domains does not really hold in practice. The hyperplane learned from the source domains will easily misclassify samples scattered at the boundary of clusters or far from their corresponding class centres. To address the above two drawbacks, we propose a discriminative domain-invariant adversarial network (DDIAN) for domain generalization. The discriminativeness of the features are guaranteed through a discriminative feature module and domain-invariant features are guaranteed through the global domain and local sub-domain alignment modules. Extensive experiments on several benchmarks show that DDIAN achieves better prediction on unseen target data during training compared to state-of-the-art domain generalization approaches.

**Keywords** Domain adaptation · Domain Generalization · Transfer learning · Computer vision · Machine learning

## 1 Introduction

Computer vision has attained remarkable progress with the developments in deep neural networks recently. Much of this progress has been achieved through the use of a supervised learning setting, which presumes that the training and testing samples follow an identical distribution. Nevertheless, this concept does not apply due to various shifting variables in many real-world situations, such as viewpoint changes, background noise and variance in lighting. These factors may induce bias in the collected datasets. Even powerful machine learning approaches such as deep learning may often decline quickly in performance due to dataset bias or if the training and test datasets have been collected from non-identical distributions. To resolve these problems, domain adaptation [1–9] and domain generalization [10–22] approcehes have been proposed. Domain generalization is intended to handle the situation where there is no way

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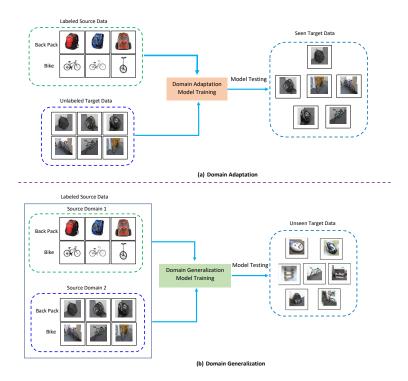


Figure 1: The comparison between the domain adaptation and domain generalization approaches. (a) Domain adaptation methods can access the unlabeled target data during training and the seen target data (seen in training phase) are evaluated in the test phase. (b) Domain generalization methods cannot access the target data during training and the unseen target data (unseen in training phase) are evaluated in the test phase.

to adapt to the target domain due to a lack of data. Compared to domain adaptation, domain generalization is a more challenging problem setting as explicit training on the target data is not allowed. Domain generalization learns domain-invariant feature representations from the given labeled data from multiple source domains and it generalizes well to unseen target domains without any further domain adaptation. Figure 1 shows the difference between domain adaptation and domain generalization.

Domain generalization is an active area of research which proposes a variety of approaches. Since there is no prior understanding of the target distribution, the crucial issue is how to lead the learning model to acquire discriminative representations for the particular task but is insensitive to domain-specific statistical shifts. Adversarial learning has recently been successfully integrated into deep networks to acquire transferable features to eliminate discrepancy in the distribution among the source domains to achieve domain invariant features that can be applied for the unseen target data. Recent advanced adversarial generalization methods [23–25] demonstrated promising outcomes in various domain transfer tasks in the context of domain generalization.

The capacity to generalize to unknown environments is critical when machine learning models are applied to real-world conditions because the training and testing data come from different distributions. Domain generalization seeks to learn from multiple source domains a classification model and to generalize it to target domains that are not seen before. A critical problem involves learning domain-invariant representations in the generalization of domains. Significant efforts have recently been committed to broad domain generalization (DG). We are therefore proposing in this work a simple but effective model for the application of domain generalization to exploit adversarial learning to align both marginal and conditional distribution.

Most previous research assumes that the conditional distribution among the source domains remains constant and that domain-invariant learning relies on the assurance of marginal distribution invariance. Most of these methods either align the global distributions across the source domains or align the conditional alignment. Li et al. [23] suggested a conditional invariant approach for deep-domain generalization to optimise deep learning for seeking domain-invariant features that uses class-specific domain identification mechanisms. Li et al. [24] utilize adversarial feature alignment via maximum mean discrepancy. Blanchard et al. [25] proposed a domain generalization method that predicts a classifier from the marginal distribution of the features. However, marginal and conditional distributions within domains

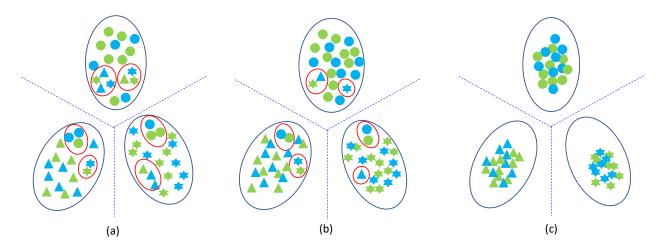


Figure 2: (Best viewed in color.) The importance of discriminative features learning for domain generalization. Green: samples from source domain 1; Blue: samples from source domain 2; Blue dot line: Hyperplane learned from the source domains during training; red circles indicate misalignment of the source samples; the Circle, Triangle and Star indicate three different categories, respectively. (a) Source Only (without using domain generalization), the hyperplane gained from the data of the source domains will be misaligned during training. (b) Domain alignment, the domain discrepancy has been reduced but not removed by the domain alignment. (c) Discriminative Feature Learning, the hyperplane gained from the data of the source domains can perfectly align the data according to their classes due to the discriminativeness of the domain invariant features.

sometimes lead to the adaptation in real applications differently. For instance, the marginal distribution is more important when the source domains are very dissimilar whereas the conditional distribution should be given more attention when the source domains are very similar. Most previous adversarial domain generalization approaches mostly adopt the discriminator which aligns the marginal distributions of the source domains. We introduce a framework for domain generalization that trains a shared embedding to align the marginal and conditional distributions and classes across the available source domains in order to obtain a domain agnostic model that can be applied for unseen target domains.

Moreover, most of the existing work on domain generalization focuses only on learning to reflect common features by reducing the distribution disparity across domains. The domain alignment methods can only minimise but not eradicate the domain shift. As a consequence, instances of a domain at the edge of clusters or far from their respective class centres are more probably to be incorrectly labeled by the hyperplane acquired from the source domains. A realistic way to alleviate this problem is to implement the samples with greater compactness in the intraclass. This will significantly reduce the number of samples that are far from the high density area and potentially misclassified. Likewise, by broadening the gap between different categories, another viable step is to remove the harmful effects of the domain disparity in aligned feature space. The effects of discrimnative features learning for domain generalization is shown in Figure 2. Fortunately, for the domain generalization task, the class information of the samples are available. In this regard, it is fair to render the source features more discriminatory in the matched feature space.

In this paper, we propose a novel Discriminative Domain-invariant Adversarial Network (DDIAN) for domain generalization. The proposed approach is capable of learning discriminative domain-invariant representations via end-to-end adversarial training. Stochastic Gradient Descent (SGD) will accomplish the adaptation with the gradients computed by backpropagation. The works's strengths include:

- This is the first attempt, as far as we know, to jointly learn the deep discriminative feature and domain-invariant representations for deep domain generalization.
- Besides the marginal distribution, we also align the conditional distributions across the source domains.
- The experimental results prove that integrating the discriminative representation will further reduce the domain disparity and aid the ultimate classification task, which would greatly improve the performance of the generalization task.

## 2 Related Work

Existing domain generalization methods for visual recognition can be divided into main two categories: shallow branch domain generalization and deep branch domain generalization.

## 2.1 Shallow Branch Domain Generalization

Shallow branch domain generalization approaches are built as a two stage formulation. The first stage is utilized for extracting the features and the second stage is used for domain alignment. The issue of domain generalization was articulately commenced by [26]. In [26], a kernel based classifier runs on multiple similar domains and the proposed approach is useful for solving automatic gating of flow cytometry. Specifically, [26] adds all the training samples together in one dataset and it trains a single SVM classifier. Muandet et al. [27] explored a kernel-based domain-invariant component analysis which is capable of learning a domain invariant transformation by decreasing the disparity across domains. It also preserves the operational correlation among the features and associated labels. A unified architecture for domain adaptation and domain generalization is proposed based on scatter component analysis in [28]. Khosla et al. [29] proposed a multi-task max-margin classifier that measures the dataset-specific disparity in the feature space by adjusting the weights of the classifier. In [30], a multi-task autoencoder approach taking into account the construction capability of an autoencoder to extract domain-invariant features is introduced. Xu et al. [31] add a nuclear norm-based regularizer which is capable of capturing the likelihoods of all positive samples to an exemplar-SVM for minimizing the domain discrepancy among source domains. Fang et al. [32] proposed unbiased metric learning by exploiting all information from the training source domains to train the classifier and produces a less biased distance metric that can be applied for object detection. Similarly, [33] also exploit all the information from the training data to minimize the discrepancy across domains. In [34] a robust classifier is learned reducing the domain bias among the training domains. These shallow domain generalization approaches require either hand crafted features or features extracted using pre-trained deep neural networks.

### 2.2 Deep Branch Domain Generalization

Deep branch domain generalization [11–13, 25, 35, 36, 36–39, 39, 39–41, 41–50] which is known as deep domain generalization incorporates the feature extraction and domain adaptation into a unified architecture. Deep domain generalization methods use a deep neural architecture to learn a model that can be applied to the target data. In these methods, the domain alignment module receives feedback from the feature extraction module and reinforces itself according to the feedback during training. Riccardo et al. [35] proposed a deep domain generalization method based on adversarial data augmentation aiming to synthesize hard data at each iteration which are used to train the model to enhance its generalization capability. In [13], Maximum Mean Discrepancy (MMD) constraints are applied within the representation learning of an autoencoder via adversarial learning. Li et al. [36] proposed an end-to-end low-rank parameterized convolutional neural network for domain generalization problem. In [37], an episodic training attempts to learn a domain agnostic model by alternating domain-invariant feature extractors and classifiers among domains. Yogesh et al. [38] proposed a regularization function for the classification layer that can be helpful to apply for unknown target data in future. The classifier's weights are trained to achieve a more general classification model.

In [39], a feature-critic network is proposed that learns an auxiliary meta loss depending on output of the feature extractor. Carlucci et al. [40] solve domain generalization problem by jigsaw puzzles using maximal hamming distance algorithm. Shankar et al. [41] generate domain-guided perturbations of input data that are utilised to train the model to obtain a robust model. [49,51,52] use semantic alignment that attempts to make latent representation given class label identical within source domains. Recently, Akuzawa et al. [44] proposed domain-invariant feature learning via adversarial learning as [52]. [44] needs one classifier whereas [52] needs the same number of classifiers as the source domains. [53] combines multiple latent domains and train the model without using the domain label. It solves domain generalization problem using clustering strategies with adversarial learning.

## 3 The Proposed Method

In this section, we illustrate the proposed DDIAN architecture in detail that is displayed in Figure 3. The whole architecture consists of a feature extraction network, a classification network, a discriminative feature network, global domain alignment network and local sub-domain alignment network. Our aim is to achieve discriminative domain-invariant features that will aid the generalization of the domain. We will be explaining how we achieve this in the following section.

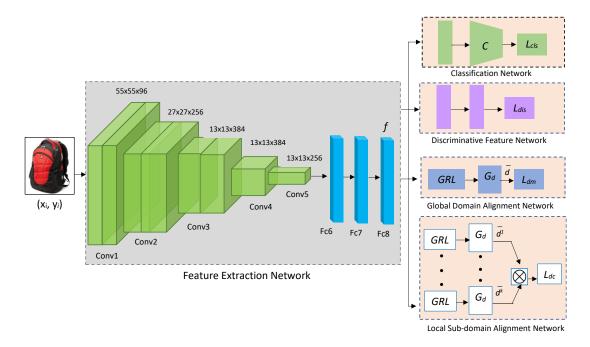


Figure 3: An overview of the proposed discriminative domain-invariant adversarial network. It consists of four subnetworks: feature extraction network, classification network, discriminative feature network and domain alignment network. Domain alignment network consists of two subnwtworks: global domain alignment network and local sub-domain alignment network. Either Alexnet or Resnet-18 pre-trained model is used to extract the features in the feature extraction network. Global and local sub-domain alignment networks are responsible to align the marginal and conditional distributions of the source domains during training. Discriminative feature network extracts discriminitive features which is helpful for final prediction by the classification network.

#### 3.1 Problem Definition

Suppose  $\mathcal{X}$  represents the feature space and  $\mathcal{Y}$  represents the label space. A domain  $\mathcal{D}$  is denoted by a joint distribution P(X,Y) defined on  $\mathcal{X} \times \mathcal{Y}$ . We assume that we have a set of N source domains such as  $\Omega = D_S^1; D_S^2; D_S^3; \ldots; D_S^N$  and target domain  $D_T^N$  where  $D_T^N \notin \Omega$ . The goal of DG is to gain a classifying function  $f: X \to Y$  able to classify  $\{x_i\}$  to the corresponding  $\{y_i\}$  given  $S_D^1; S_D^2; S_D^3; \ldots; S_D^N$  during training as the input, but  $T_D^N$  is unavailable during the training phase.

#### 3.2 Discriminative Domain-Invariant Adversarial Network (DDIAN)

## 3.2.1 Domain-invariant Feature Extraction

Domain adversarial learning leverages the GAN concept to support transferable learning functionality. This learning technique is a two-players game. The name of the first player is domain discriminator  $G_d$  which is trained to differentiate the source domains. On the other hand, the name of the second player is feature extractor F which attempts to mislead the domain discriminator by retrieving domain invariant representations. These two players are adversarially trained: the parameters of the feature extractor  $(\theta_f)$  and discriminator  $(\theta_d)$  are learned by maximising and minimising the loss of the domain discriminator respectively. Moreover, the classifier C loss is also decreased. We can formulate the loss function as,

$$L(\theta_f, \theta_c, \theta_d) = \frac{1}{n} \left( \sum_{x_i \in \Delta} L_y \left( C(F(x_i)), y_i \right) - \frac{\gamma}{n} \left( \sum_{x_i \in \Delta} L_d \left( G_d(F(x_i)), d_i \right), \right) \right), \tag{1}$$

where  $\gamma$  is a hyper-parameter, and  $L_y$  and  $L_d$  denote the classification loss and domain discriminator loss,  $\theta_c$  is the classifier's parameters.  $d_i$  denotes the domain label of the input instances. After the training converges, the parameters

 $\hat{\theta_f}$ ,  $\hat{\theta_c}$  and  $\hat{\theta_d}$  will deliver a saddle point of Eq. 1,

$$(\hat{\theta_f}, \hat{\theta_c}) = \underset{\theta_f, \theta_c}{\operatorname{arg\,min}} L(\theta_f, \theta_c, \theta_d)$$

$$(\hat{\theta_d}) = \underset{\theta_d}{\operatorname{arg\,max}} L(\theta_f, \theta_c, \theta_d).$$

$$(3)$$

$$(\hat{\theta_d}) = \underset{\theta_d}{\arg \max} L(\theta_f, \theta_c, \theta_d). \tag{3}$$

Previous adversarial domain generalization methods either align the marginal distributions or align conditional distributions. The alignment of these two distributions has been shown to help improve the efficiency because both distributions are useful for acquiring domain-invariant representations. In this work, we extract the domain-invariant features using both the global domain alignment network and local sub-domain alignment network. The global domain alignment network is responsible for aligning the marginal distributions across the domains whereas the local sub-domain alignment network is responsible for aligning the conditional distributions among the domains.

We will first present the classification network, global domain alignment network, local sub-domain alignment network and discriminative feature network in the next sections. Then, we demonstrate the DDIAN loss function and procedure for training the DDIAN.

#### 3.2.2 Classification Network

The category classifier (C, the green portion of Figure 3) is capable of classifying the categories of the input instances in the source domains. Hence the supervised or labeling information on the  $x_i$  can be used. The training objective of the classifier is a cross-entropy loss that can be defined as,

$$L_{cls} = -\frac{1}{n} \left( \sum_{x_i \in \Delta} \left( \sum_{c=1}^K \hat{P}_{x_i} \log C(F(x_i)) \right) \right), \tag{4}$$

where K is the number of classes of the source domains,  $\hat{P_{x_i}}$  is the probability of the input sample  $x_i$  belonging to category K, F denotes the feature extractor and C indicates the classifier.

## 3.2.3 Global Domain Alignment Network

The global domain discriminator is designed to eliminate the marginal distributions across the training source domains. The basic concept is to have the marginal domain discriminator accompanied by a domain-adversarial neural network [54]. In [54], the domain discriminator is designed to align the marginal distributions between the source domain and target domain whereas we designed the global domain discriminator among the n number of source domains. The loss of the marginal distribution which is achieved by the global domain discriminator can be formulated as,

$$L_{dm} = \frac{\gamma}{n} \left( \sum_{x_i \in \Delta} L_d(G_d(F(x_i))), d_i \right), \tag{5}$$

where  $L_d$  indicates the cross-entropy loss of the domain discriminator, F depicts the feature extractor, and  $d_i$  indicates the domain label of the input instances  $x_i$ .

## 3.2.4 Local Sub-domain Alignment Network

The discriminator in the local domain is structured to match the conditional distributions of the training source domains. The local domain discriminator is capable of coordinating the source distribution multi-mode structure with the global domain discriminator, allowing for more fine-grained domain adaptation. The local domain discriminator is divided into K class-wise domain discriminators  $G^K d$ , each one responsible for matching the K class-related details. The local-domain discriminator loss function can be formulated as,

$$L_{dc} = \frac{\beta}{n} \left( \sum_{k=1}^{K} \left( \sum_{x_i \in \Delta} L_d^K(G_d^K(y_i^K, F(x_i))), d_i \right) \right), \tag{6}$$

where  $L_d^K$  and  $G_d^K$  indicate cross-entropy loss associated with class K and domain discriminator respectively.  $y_i$  denotes the label of the input instances and  $d_i$  indicates the domain label of the input instances of  $x_i$ .

## **Algorithm 1: Training procedure of DDIAN**

Input: Source labeled samples  $\{X_i^s,Y_i^s\}$  from source source domains  $D_S^N$ , and target unlabeled data  $\{X_i^t\}$  from target domain  $D_T^N$ . Hyper-parameters  $\alpha$ ,  $\beta$  and  $\gamma$ 

Output: Classifier C

1 for iter from 1 to max-iter do

- Sample a mini-batch of source samples  $[X_i^s, Y_i^s]$  from source domains and target samples  $[X_i^t]$  from target domain;

Compute 
$$L_{cls}$$
 using  $L_{cls} = -\frac{1}{n} \left( \sum_{x_i \in \Delta} \left( \sum_{c=1}^K \hat{P_{x_i}} \log C(F(x_i)) \right) \right)$ .

- 4 Compute  $L_{dm}$  using  $L_{dm} = \frac{\gamma}{n} \left( \sum_{x_i \in \Delta} L_d(G_d(F(x_i))), d_i \right)$ .
- Compute  $L_{dc}$  using  $L_{dc} = \frac{\beta}{n} \left( \sum_{k=1}^{K} \left( \sum_{x_i \in \Delta} L_d^K(G_d^K(y_i^K, F(x_i))), d_i \right) \right)$ .
- 6 Compute  $L_{dis}$  using  $L_{dis} = \frac{1}{2} \sum_{i=1}^{m} \frac{\left\| F(x_i) c_{y_i} \right\|_2^2}{\sum_{j=1, j \neq y_i}^{K} \left\| F(x_i) c_{j} \right\|_2^2 + \phi}$ .
- Update feature extraction, classification, discriminative feature, global domain alignment and and local sub-domain alignment network using  $L = L_{cls} + \beta L_{dc} + \gamma L_{dm} + \alpha L_{dis}$ .
- 8 end

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#### 3.2.5 Discriminative Feature Network

In order to enforce the feature extraction network to learn even more discriminative features, we introduce a center based discriminative representation learning method for domain generalization. It should be noted that the entire training process concentrates on the SGD mini-batch. Hence the discriminative loss mentioned below is also dependent on the batch of instances. Since, the labels of the training samples are available for the source domain, the features of the source domains will be classified by the classifier. Furthermore, it is important to keep the discriminative power of feature representations during domain alignment. Although the distributions of the source domains are aligned, there may still be some samples falling into inter-class gaps, which proposes the requirement for learning more discriminative features.

There exists several methods for learning discriminative features [55–58], such as the triplet loss, the contrastive loss and the center loss. Both the triplet loss and the contrastive loss need to construct a lot of image pairs and compute the distance between images of each pair, which is computationally complicated. Therefore, in this study, we introduce the center loss, which can be flexibly combined with the above classification loss. The features derived from the deep neural network trained under softmax loss supervision are separable, but not as discriminatory because they show significant variations in intra-class distance. In [59], authors build an efficient loss function based on the hypothesis to increase the power of the deep features taken from deep neural networks. Center loss mitigates the intra-class distances, on the other hand the softmax loss is used to classify the features corresponding to their categories. Influenced by the center loss which penalises the distance of each sample to the corresponding class centre, we proposed the discriminative feature learning as below,

$$L_c = \frac{1}{2} \sum_{i=1}^{m} \|F(x_i) - c_{y_i}\|_2^2, \tag{7}$$

where  $L_c$  indicates the center loss, m indicates the number of the training instances in a mini-batch,  $x_i \in R_d$  indicates the ith training instances,  $y_i$  indicates the label of  $x_i$ .  $c_{y_i} \in R_d$  indicates the  $y_i$ th class of deep features and d indicates the deep feature dimension.

Discriminative representations should have greater separability within groups and intra-class compactness. Center loss utilizes the Equation 7 loss function to penalise large distances in the intra-class. Nevertheless, the lack of center loss is that it does not acknowledge the separability of the inter-class. As we know, if the distances of the different classes are far enough, the representations will be more discriminative for the greater separability of classes. Therefore, because the centre loss just penalises broad intra-class distances, and does not include inter-class distances, the inter-class adjustment is minimal, ensuring the class centre positions can change slightly throughout the training process. As a

consequence, if the network initialises the class centres using a relatively smaller variance, the smaller differences between the class centres would lead during training as the centre loss just penalises the wide intra-class distances without taking into account the inter-class distances. The center loss vulnerability is that it does not acknowledge the separability of the inter-class.

We are therefore proposing a new loss function to acknowledge inter-class separability and intra-class compactness concurrently by penalising the the sum of the distances of training samples to their non-related class centres and contrasting values between the distances of training data to their respective class centres as,

$$L_{dis} = \frac{1}{2} \sum_{i=1}^{m} \frac{\|F(x_i) - c_{y_i}\|_2^2}{\sum_{j=1, j \neq y_i}^{K} \|F(x_i) - c_j\|_2^2 + \phi},$$
(8)

where  $L_{dis}$  denotes the discriminative loss. m denotes the number of training samples in a mini-batch.  $F(x_i) \in R_d$  denotes the deep features of the ith training sample with dimension d.

#### 3.2.6 Overall Objective

The overall objective of the model can be formulated as:

$$L = L_{cls} + \beta L_{dc} + \gamma L_{dm} + \alpha L_{dis}, \tag{9}$$

where  $\gamma$ ,  $\beta$  and  $\alpha$  are weighted parameters.  $L_{cls}$  is the classification loss,  $L_{dm}$  is the marginal adversarial loss,  $L_{dc}$  is the conditional adversarial loss and  $L_{dis}$  is the discriminative loss. Algorithm 1 describes the overall training procedure of our proposed method.

## 4 Evaluation and Testing

$Source \rightarrow Target$	$P, C, S \rightarrow A$	$P, A, S \rightarrow C$	$A, C, S \rightarrow P$	$A, C, P \rightarrow S$	Ave.
Source only	64.9	64.3	86.7	55.1	67.2
MASF	70.4	72.5	90.7	67.3	75.2
CIDDG [60]	62.7	69.7	78.7	64.5	68.9
DBADG [36]	62.9	67.0	89.5	57.5	69.2
DSN [61]	61.1	66.5	83.3	58.6	67.4
MLDG [62]	66.2	66.9	88.0	59.0	70.0
CrossGrad [41]	61.0	67.2	87.6	55.9	70.0
MetaReg [38]	63.5	69.5	87.4	59.1	69.9
D-SAM [63]	63.9	70.7	64.7	85.6	71.2
JiGen [40]	67.6	71.7	89.0	65.2	73.4
Epi-FCR [37]	64.7	72.3	86.1	65.0	72.0
DDIAN (Ours)	67.8	69.6	89.2	66.2	73.2

Table 1: Recognition accuracies for DG on the PACS dataset [36] using pretrained AlexNet.

$Source \rightarrow Target$	$P, C, S \rightarrow A$	$P, A, S \rightarrow C$	$A, C, S \to P$	$A, C, P \rightarrow S$	Ave.
Source only	77.8	74.3	94.7	69.1	79.0
MASF	80.3	77.2	95.0	71.7	81.0
MLDG [62]	79.5	77.3	94.3	71.5	80.7
MAML [64]	78.3	76.5	95.1	72.6	80.6
CrossGrad [41]	78.7	73.3	94.0	65.1	77.8
MetaReg [38]	79.5	75.4	94.3	72.2	80.4
D-SAM [63]	77.3	72.4	77.8	95.3	80.7
JiGen [40]	79.4	75.3	96.0	71.4	80.5
Epi-FCR [37]	82.1	77.0	93.9	73.0	81.5
DDIAN (Ours)	83.4	76.7	95.3	74.1	82.4

Table 2: Recognition accuracies for DG on the PACS dataset [36] using pretrained ResNet-18.

In this section, we demonstrate the experiments we have conducted to evaluate our proposed approach and compare the proposed approach with state-of-the-art domain generalization methods.

### 4.1 Datasets

The proposed approach is evaluated on **PACS** [36], **Office-Home** [65] and VLCS benchmarks in the context of domain generalization.

$Source \rightarrow Target$	$L, P, S \rightarrow C$	$P, C, S \rightarrow L$	$C, L, S \rightarrow P$	$P, L, C \rightarrow S$	Ave.
Source only	85.7	61.3	62.7	59.3	67.3
CIDG [51]	88.8	63.1	64.4	62.1	69.6
CCSA	92.3	62.1	67.1	59.1	70.2
SLRC	92.8	62.3	65.3	63.5	71.0
DBADG	93.6	63.5	70.0	61.3	72.1
MMD-AAE	94.4	62.6	67.7	64.4	72.3
D-SAM	91.8	57.0	58.6	60.9	67.0
JiGen	96.9	60.9	70.6	64.3	73.2
DDIAN(Ours)	95.7	64.8	69.2	65.1	73.7

Table 3: Recognition accuracies for DG on the VLCS dataset using pretrained AlexNet.

Source $\rightarrow$ Target	$C, P, R \rightarrow A$	$A, P, R \rightarrow C$	$C, A, R \rightarrow P$	$C, P, A \rightarrow R$	Ave.
Source only	54.3	44.7	69.3	70.8	59.8
DBADG [36]	54.8	45.3	70.3	70.6	60.3
CIDG [51]	55.1	45.8	70.2	71.4	60.6
D-SAM	58.0	44.4	69.2	71.5	60.8
CIDDG [60]	55.3	46.2	70.9	71.9	61.1
JiGen [40]	53.0	47.5	71.5	72.8	61.2
DDIAN (Ours)	57.9	47.2	72.3	73.8	62.8

Table 4: Recognition accuracies for DG on the Office-Home dataset using pretrained ResNet-18.

$Source \rightarrow Target$	$P, C, S \rightarrow A$	$P, A, S \rightarrow C$	$A, C, S \rightarrow P$	$A, C, P \rightarrow S$	Ave.
Source only	77.8	74.3	94.7	69.1	79.0
DDIAN (Global Domain Alignment)	81.4	74.2	94.5	69.1	79.8
DDIAN (Local Domain Alignment)	79.6	74.0	94.6	70.8	79.8
DDIAN (Discriminative Feature)	80.2	75.5	94.9	71.3	80.5
DDIAN (Ours)	83.4	76.7	95.3	74.1	82.4

Table 5: Recognition accuracies for DG on the PACS dataset [36] using pretrained ResNet-18.

#### 4.1.1 PACS

The **PACS** [36] domain generalization dataset is built by taking the common categories among Caltech256, Sketchy, TU-Berlin and Google Images. It has 4 domains: Photo, Sketch, Cartoon and Painting. Each domain consists of 7 categories: dog, guitar, giraffe, elephant, person, horse, house. It contains total 9991 images. We evaluate our proposed method on four transfer tasks P, C, S  $\rightarrow$  A; P, A, S  $\rightarrow$  C; A, C, S  $\rightarrow$  P; and A, C, P  $\rightarrow$  P. The transfer task P, C, S  $\rightarrow$  A indicates three source domains Photo (P), Cartoon (C) and Sketch (S) and one target domain Art-Painting (A). We follow the standard protocol for domain generalization where during the training phase we access the labeled source data but not access the target data. The target data is used only in test phase only.

### 4.1.2 VLCS

VLCS is another cross-domain object benchmark that consists of the images from four popular datasets: PASCAL VOC2007 (V), LabelMe (L), Caltech-101 (C), and SUN09 (S). The are five common classes, i.e., 'bird', 'dog', 'car', 'chair' and 'person' across four domains. We follow the same setting in where each domain of VLCS is divided into a training set (70%) and a test set (30%) trough random selection. We evaluate our proposed method on four transfer tasks L, P, S  $\rightarrow$  C; P, C, S  $\rightarrow$  L; C, L, S  $\rightarrow$  P; and P, L, C  $\rightarrow$  S. The transfer task L, P, S  $\rightarrow$  C indicates there are three source domains LabelMe(L), PASCAL(P) and Sun09(S); and one target domain Caltech-101(C).

#### 4.1.3 Office-Home

Office-Home dataset contains four domains named Art (Ar), Real-World (Rw), Clipart (Cl) and Product (Pr) with 65 different object categories. It has around 15,500 images with 65 categories. To build the Art and Real-world domains, public domain images were collected from websites such as www.deviantart.com and www.flickr.com. Clipart images were taken from various clipart webpages. The Product domain images were obtained utilizing web-crawlers from www.amazon.com. We evaluate our proposed method on four transfer tasks C, P, R  $\rightarrow$  A; A, P, R  $\rightarrow$  C; C, A, R  $\rightarrow$  P; and C, P, A  $\rightarrow$  R. The transfer task C, P, R  $\rightarrow$  A indicates there are three source domains Clipart (C), Product (P) and Real-world (R); and one target domain Art (A).

#### 4.2 Comparison with state-of-the-art

We compare the performance of DDIAN against several recent domain generalization methods. **Source only** is the simple source domains aggregation approach for DG without any adaptive loss function. **CIDDG** [60] is a deep DG method based on adversarial networks where the discrepancy among source domains is minimized by using class prior normalized domain classification and class conditional domain classification loss. **MLDG** [62] is a meta-learning based DG method. **CIDG** [51] is DG framework where both marginal and conditional representations are considered to mitigate the DA problem. **DBADG** [36] is a DG framework based on low rank parameterized convolutional neural network. **CrossGrad** [41] is a recent approach of disrupting the input manifold for DG utilising Bayesian networks. **MetaReg** [38] is a recently proposed approach for DG that meta-learns the classifier regularizer. **MMAL** [64] is originally designed for domain adaptation and re-purposed for domain generalization. **MMD-AAE** [24] is a recent domain generalization approach that learns domain invariant features by aligning the features by MMD constraint. **CCSA** [49] uses semantic alignment to regularize the learned feature subspace. **DSN** [66] gains domain alignment by decomposing the source domains into private and shared spaces and learned them by reconstruction signal. **D-SAM** [63] is a domain generalization approach based on the utilization of domain-specific aggregation modules. **MASF** [47] regularizes the semantic features by a gradient-based meta-training procedure. **EPI-FCR** [37] achieves domain invariant features for domain generalization by episodic training which is based on the domain aggregation method.

## 4.3 Implementation Details

We implement our proposed method based on the PyTorch deep learning framework. We fine-tune the network using either AlexNet or ResNet-18 models pretrained on the ImageNet dataset. All the convolutional and pooling layers are fine-tuned during the training and the classifier layer is trained from scratch by backpropagation for all the transfer tasks. We set the learning rate of the classifier to be 10 times compared to other layers as it is trained from scratch. We use mini-batch Stochastic Gradient Descent (SGD) with momentum of 0.9 for optimization and we change the learning rate as [67]. We set  $\alpha=1,\,\beta=0.5,\,\gamma=0.5$ , batch size = 32. We follow standard evaluation for domain generalization and use all source examples with labels during training. It is noted that the target data is unavailable during training. To compute the average accuracy, the results are obtained by running each transfer task 5 times.

#### 4.4 Results

The classification accuracy on the four transfer tasks on the PACS dataset is reported in Table 1 using pre-trained AlxNet architecture on ImageNet. From Table 1, we can see that our discriminative domain-invariant approach achieved comparable results on each transfer task and our proposed approach outperforms most of the state-of-the-art approaches except MASF and JiGen methods. We also observe that DDIAN provides the highest overall efficiency, with just 6% progress on source only approach.

The classification performance on the four transfer tasks on PACS dataset using ResNet-18 is reported in Table 2, we can observe that with ResNet-18 architecture, the obtained results are enhanced as anticipated across the board. Our system nevertheless retains the highest overall efficiency, with a 3.4 percent increase on source only approach.

Table 3 presents the classification performance on the four transfer tasks on VLCS dataset in the context of domain generalization. For VLCS dataset, we follow the same protocol of [37] where each domain is split into train (70%) and test (30%) and do leave-one-out evaluation. From the results we observe that our method outperforms prior state-of-the-art approaches for domain generalization. We obtained 6.4% improvements over source only method in the four transfer domain generalization tasks.

The classification accuracy on the four transfer tasks on Office-Home dataset is shown in Table 4. From the results, we can see that our proposed approach has obtained the highest results on the P, C, S  $\rightarrow$  A; C, A, R  $\rightarrow$ P and C, P, A  $\rightarrow$  R transfer tasks and comparable performance on A, P, R  $\rightarrow$  C transfer task. DDIAN also provides the best performance overall, with 3% improvement on source only approach, and at least 1.6 % improvement on prior state-of-the-art methods CIDDG, D-SAM and JiGen.

## 4.5 Ablation study

In this section, we further conduct additional experiments using PACS dataset to investigate the contribution of each component of our proposed domain generalization network's performance. The average accuracies over five runs using individual components are shown in Table 5. We conduct experiments of three individual components: DDIAN (Global Domain Alignment), DDIAN (Local Domain Alignment) and DDIAN (Discriminative Feature). We remove two components and keep one component, DDIAN (Global Domain Alignment) means that we remove local domain alignment and discriminative feature components to see the contribution of global domain alignment component.

DDIAN (Local Domain Alignment) indicates that we remove global domain alignment and discriminative feature whereas DDIAN (Discriminative Feature) idicates that we remove both global and local domain alignment modules and keep only discriminative feature component with our baseline. From the ablation study, we observe that DDIAN with each individual component outperforms source only approach. It is also noted that DDIAN with all components outperform other approaches. From the results of the ablation study, we conclude that each component plays its own role for achieving domain-invariant features and gains generalization on unseen target data. We also found that the discriminative features are useful for generalization on the unknown target domain.

### 5 Conclusion

In this paper, we addressed the domain generalization issue where the discriminative features are extracted in an adversarial way. The adversarial module not only aligns the marginal distributions of the source domains but also aligns the conditional distributions of the domains. The approach of learning a discriminative feature is introduced to apply the feature space for better inter-class separability and intra-class compactness that can help both predicting the categories and domain compatibility. There are two factors that can contribute the deep-feature discriminativeness lead to achieve the domain agnostic model. On one side, since the deep representations are better clustered, it is much easier to perform the domain alignment. On the other side, there is a wide distance across the hyperplane and every cluster owing to the improved inter-class separability. Therefore, it is less probable to misclassify the samples scattered far from the middle of each cluster within a domain or close to the edge. We have demonstrated the effectiveness of the proposed approach on several benchmarks and have achieved the state-of-the-art performance in most of the transfer tasks.

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