DISCRIMINATIVE DOMAIN-INVARIANT ADVERSARIAL NETWORK FOR DEEP DOMAIN GENERALIZATION

用于深度领域泛化的判别域不变对抗网络

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ABSTRACT

摘要

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.

域泛化方法旨在从多个具有不同分布的训练源域中学习一个对未知目标域不变的预测模型。最近，广泛的域泛化问题得到了显著的关注，这是机器学习和计算机视觉领域中的一个具有挑战性和前沿性的问题。大多数先前的域泛化方法假设源域之间的条件分布保持不变，并通过最小化边际分布来学习一个域不变模型。然而，训练源域的稳定条件分布的假设在实践中并不成立。从源域学习到的超平面很容易错误分类散布在聚类边界或远离其对应类别中心的样本。为了解决上述两个缺点，我们提出了一种用于域

泛化的区分性域不变对抗网络 (DDIAN)。通过区分性特征模块保证特征的区分性，通过全局域和局部子域对齐模块保证域不变特征。在多个基准上的广泛实验表明，与最先进的域泛化方法相比，DDIAN 在训练期间对未见目标数据的预测表现更佳。

Keywords Domain adaptation - Domain Generalization - Transfer learning - Computer vision - Machine learning

关键词域适应 - 域泛化 - 迁移学习 - 计算机视觉 - 机器学习

1 Introduction

1 引言

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

计算机视觉在深度神经网络的最新发展中取得了显著进展。这一进展主要通过使用监督学习设置实现，该设置假定训练和测试样本遵循相同的分布。然而，由于许多现实世界情况中的各种变化变量，例如视角变化、背景噪声和光照变化，这一概念并不适用。这些因素可能会在收集的数据集中引入偏差。即使是强大的机器学习方法，如深度学习，通常也会因数据集偏差或训练和测试数据集来自不同分布而迅速下降性能。为了解决这些问题，提出了领域适应 [1-9] 和领域泛化 [10-22] 方法。领域泛化旨在处理由于缺乏数据而无法适应目标领域的情况。

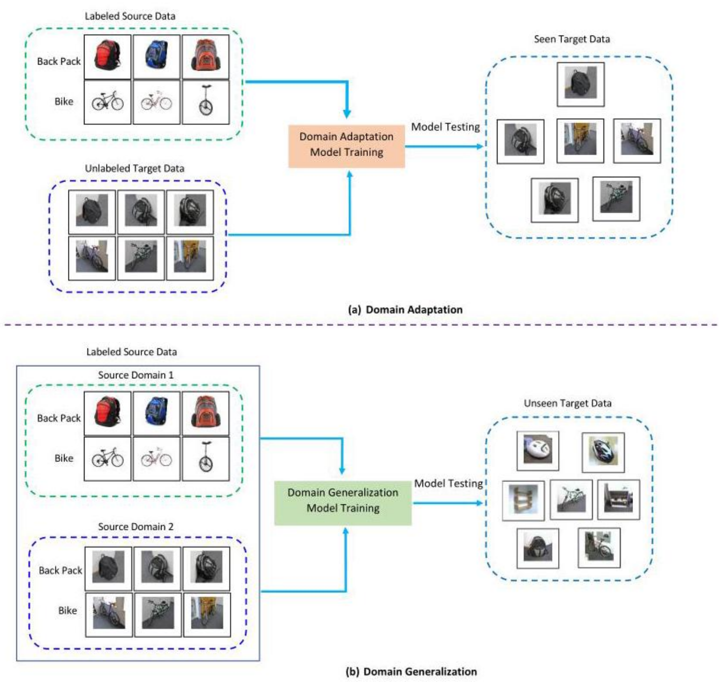

Figure 1: The comparison between the domain adaptation and domain generalization approaches. (a) Domain adaptation methods can access the unlabeled target data during training and the seen target data (seen in training phase) are evaluated in the test phase. (b) Domain generalization methods cannot

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access the target data during training and the unseen target data (unseen in training phase) are evaluated in the test phase.

图 1: 领域适应与领域泛化方法的比较。(a) 领域适应方法在训练期间可以访问未标记的目标数据，并且在测试阶段评估已在训练阶段看到的目标数据。(b) 领域泛化方法在训练期间无法访问目标数据，并且在测试阶段评估未在训练阶段看到的目标数据。

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.

由于缺乏数据，领域泛化相较于领域适应是一个更具挑战性的问题设置，因为不允许对目标数据进行明确的训练。领域泛化从多个源领域提供的标记数据中学习领域不变的特征表示，并且能够很好地泛化到未见过的目标领域，而无需进一步的领域适应。图 1 显示了领域适应与领域泛化之间的区别。

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.

域泛化是一个活跃的研究领域，提出了多种方法。由于对目标分布没有先前的理解，关键问题在于如何引导学习模型获取特定任务的区分性表示，同时对领域特定的统计变化不敏感。最近，adversarial 学习成功地集成到深度网络中，以获取可转移的特征，从而消除源领域之间分布的差异，以实现可以应用于未见目标数据的领域不变特征。最近的先进对抗泛化方法 [23-25] 在域泛化背景下的各种域迁移任务中展示了良好的结果。

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.

当机器学习模型应用于现实世界条件时，能够推广到未知环境的能力至关重要，因为训练和测试数据来自不同的分布。域泛化旨在从多个源领域学习分类模型，并将其推广到之前未见过的目标领域。一个关键问题涉及在域的泛化中学习领域不变的表示。最近在广域域泛化 (DG) 上投入了大量努力。因此，我们在本工作中提出了一个简单但有效的模型，以应用域泛化，利用对抗学习来对齐边际和条件分布。

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 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.

大多数先前的研究假设源领域之间的条件分布保持不变，并且领域不变学习依赖于边际分布不变性的保证。这些方法大多数要么对齐源领域之间的全局分布，要么对齐条件分布。Li 等人 [23] 提出了一个条件不变的方法，用于深度领域泛化，以优化深度学习以寻求使用类特定领域识别机制的领域不变特征。Li 等人 [24] 通过最大均值差异利用对抗特征对齐。Blanchard 等人 [25] 提出了一种领域泛化方法，该方法从特征的边际分布预测分类器。然而，领域内的边际和条件分布在实际应用中有时会导致不同的适应。

例如，当源领域非常不相似时，边际分布更为重要，而当源领域非常相似时，条件分布应给予更多关注。大多数先前的对抗领域泛化方法主要采用对齐源领域边际分布的鉴别器。我们引入了一个领域泛化框架，训练一个共享嵌入，以对齐可用源领域之间的边际和条件分布及类别，从而获得一个可以应用于未见目标领域的领域无关模型。

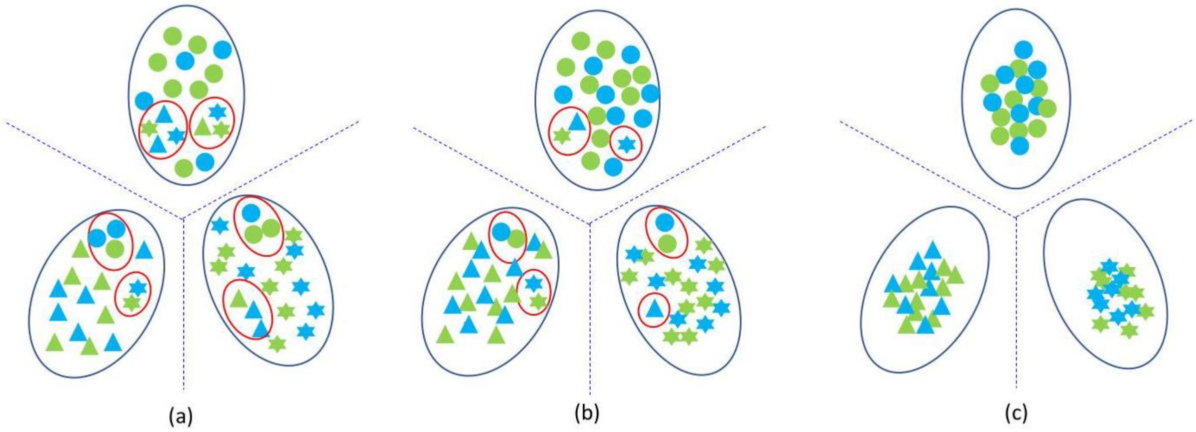

Figure 2: (Best viewed in color.) The importance of discriminative features learning for domain generalization. Green: samples from source domain 1; Blue: samples from source domain 2; Blue dot line: Hyperplane learned from the source domains during training; red circles indicate misalignment of the 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.

图 2:(最佳彩色查看。) 判别特征学习在领域泛化中的重要性。绿色: 来自源领域 1 的样本；蓝色: 来自源领域 2 的样本；蓝色虚线: 在训练期间从源领域学习到的超平面；红色圆圈表示源样本的错位；圆形、三角形和星形分别表示三种不同的类别。(a) 仅源 (未使用领域泛化)，从源领域数据获得的超平面在训练期间将会错位。(b) 领域对齐，领域差异已被减少但未被消除。(c) 判别特征学习，由于领域不变特征的判别性，从源领域数据获得的超平面可以根据其类别完美对齐数据。

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.

此外，现有的大多数领域泛化研究仅关注通过减少领域间的分布差异来学习反映共同特征。领域对齐方法只能最小化而不能消除领域偏移。因此，位于聚类边缘或远离各自类别中心的领域实例更可能被从源领域获得的超平面错误标记。缓解此问题的现实方法是实现类内样本的更大紧凑性。这将显著减少远离高密度区域且可能被错误分类的样本数量。同样，通过扩大不同类别之间的间隔，另一个可行的步骤是消除在对齐特征空间中领域差异的有害影响。判别特征学习对领域泛化的影响如图 2 所示。幸运的是，对于领域泛化任务，样本的类别信息是可用的。在这方面，将源特征在匹配特征空间中变得更加判别是合理的。

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:

在本文中，我们提出了一种新颖的判别域不变对抗网络 (DDIAN) 用于域泛化。所提出的方法能够通过端到端的对抗训练学习判别域不变表示。随机梯度下降 (SGD) 将通过反向传播计算的梯度完成适应。该工作的优势包括:

- 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.
- 据我们所知，这是首次尝试联合学习深度判别特征和域不变表示以实现深度域泛化。
- Besides the marginal distribution, we also align the conditional distributions across the source domains.
- 除了边际分布外，我们还对源域之间的条件分布进行了对齐。
- 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.
- 实验结果证明，整合判别表示将进一步减少域差异，并有助于最终的分类任务，这将大大提高泛化任务的性能。

2 Related Work

2 相关工作

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

现有的视觉识别域泛化方法可以分为两大类: 浅层分支域泛化和深层分支域泛化。

2.1 Shallow Branch Domain Generalization

2.1 浅层分支域泛化

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.

浅层分支领域泛化方法构建为两阶段的形式。第一阶段用于提取特征，第二阶段用于领域对齐。领域泛化的问题由 [26] 清晰地提出。在 [26] 中，一个基于核的分类器在多个相似领域上运行，所提出的方法对于解决流式细胞术的自动门控非常有用。具体而言，[26] 将所有训练样本合并到一个数据集中，并训练一个单一的支持向量机 (SVM) 分类器。Muandet 等人 [27] 探索了一种基于核的领域不变成分分析，能够通过减少领域之间的差异来学习领域不变的变换。它还保留了特征和相关标签之间的操作相关性。在

[28] 中，基于散布成分分析提出了一种用于领域适应和领域泛化的统一架构。Khosla 等人 [29] 提出了一个多任务最大边际分类器，通过调整分类器的权重来衡量特定于数据集的特征空间差异。在 [30] 中，介绍了一种多任务自编码器方法，考虑到自编码器提取领域不变特征的构建能力。Xu 等人 [31] 添加了一种基于核范数的正则化器，能够捕捉所有正样本的可能性，以最小化源领域之间的领域差异。Fang 等人 [32] 通过利用来自训练源领域的所有信息来训练分类器，提出了无偏度度量学习，生成一种较少偏倚的距离度量，可用于物体检测。类似地，[33] 也利用训练数据中的所有信息来最小化领域之间的差异。在 [34] 中，学习到了一种稳健的分类器，以减少训练领域之间的领域偏差。这些浅层领域泛化方法需要手工制作的特征或使用预训练深度神经网络提取的特征。

2.2 Deep Branch Domain Generalization

2.2 深层分支领域泛化

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.

深度分支领域泛化 [11-13, 25, 35, 36, 36-39, 39, 39-41, 41-50]，也称为深度领域泛化，将特征提取和领域适应整合到一个统一的架构中。深度领域泛化方法使用深度神经网络架构来学习一个可以应用于目标数据的模型。在这些方法中，领域对齐模块接收来自特征提取模块的反馈，并在训练过程中根据反馈进行自我强化。Riccardo 等人 [35] 提出了基于对抗数据增强的深度领域泛化方法，旨在每次迭代中合成困难数据，以用于训练模型以增强其泛化能力。在 [13] 中，最大均值差异 (MMD) 约束在自编码器的表示学习中通过对抗学习应用。Li 等人 [36] 提出了一个端到端的低秩参数化卷积神经网络，用于领域泛化问题。在 [37] 中，情节训练试图通过在不同领域之间交替领域不变特征提取器和分类器来学习一个领域无关的模型。Yogesh 等人 [38] 提出了一个分类层的正则化函数，这对于未来应用于未知目标数据可能是有帮助的。分类器的权重经过训练，以实现更通用的分类模型。

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.

在 [39] 中，提出了一种特征-评论网络，该网络根据特征提取器的输出学习辅助元损失。Carlucci 等人 [40] 通过拼图使用最大汉明距离算法解决了领域泛化问题。Shankar 等人 [41] 生成输入数据的领域引导扰动，这些扰动用于训练模型以获得稳健的模型。[49, 51, 52] 使用语义对齐，试图使给定类别标签的潜在表示在源领域内相同。最近，Akuzawa 等人 [44] 提出了通过对抗学习实现领域不变特征学习，如 [52] 所示。[44] 需要一个分类器，而 [52] 需要与源领域相同数量的分类器。[53] 结合多个潜在领域，并在不使用领域标签的情况下训练模型。它通过对抗学习结合聚类策略解决领域泛化问题。

3 The Proposed Method

3 提出的方法

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.

在本节中，我们详细说明了所提出的 DDIAN 架构，如图 3 所示。整个架构由特征提取网络、分类网络、区分特征网络、全局领域对齐网络和局部子领域对齐网络组成。我们的目标是实现区分性的领域不变特征，以帮助领域的泛化。我们将在接下来的部分中解释我们如何实现这一目标。

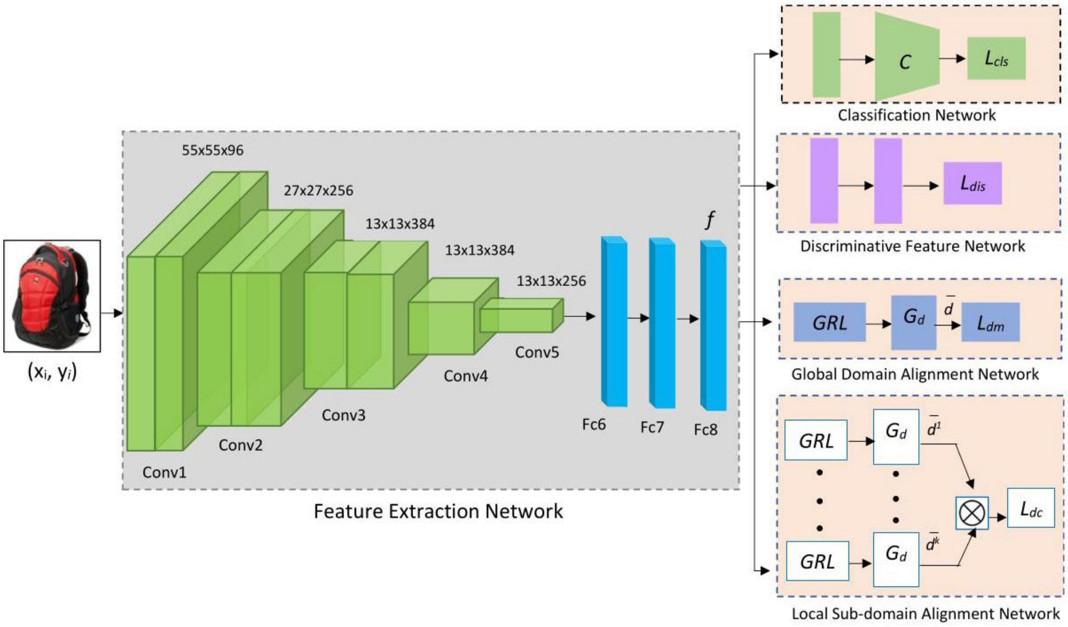

Figure 3: An overview of the proposed discriminative domain-invariant adversarial network. It consists of four subnetworks: feature extraction network, classification network, discriminative feature network and domain alignment network. Domain alignment network consists of two subnwtworks: global domain 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 discrminitive features which is helpful for final prediction by the classification network.

图 3: 所提议的区分性域不变对抗网络的概述。它由四个子网络组成: 特征提取网络、分类网络、区分特征网络和域对齐网络。域对齐网络由两个子网络组成: 全局域对齐网络和局部子域对齐网络。在特征提取网络中使用 Alexnet 或 Resnet-18 预训练模型来提取特征。全局和局部子域对齐网络负责在训练过程中对源域的边际和条件分布进行对齐。区分特征网络提取有助于分类网络最终预测的区分特征。

3.1 Problem Definition

3.1 问题定义

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.

假设 $\mathcal{X}$ 表示特征空间，$\mathcal{Y}$ 表示标签空间。一个域 $\mathcal{D}$ 由定义在 $\mathcal{X}\times\mathcal{Y}$ 上的联合分布 $P(X,Y)$ 表示。我们假设我们有一组 N 源域，如 $\Omega=D_S^1;D_S^2;D_S^3;\ldots;D_S^N$ 和目标域 D_T^N ，其中 $D_T^N\notin\Omega$ 。DG 的目标是获得一个分类函数 $f:X\rightarrow Y$ ，能够在训练期间将 $\{x_i\}$ 分类到相应的 $\{y_i\}$ ，给定 $S_D^1;S_D^2;S_D^3;\ldots;S_D^N$ 作为输入，但在训练阶段 T_D^N 是不可用的。

3.2 Discriminative Domain-Invariant Adversarial Network (DDIAN)

3.2 区分性域不变对抗网络 (DDIAN)

3.2.1 Domain-invariant Feature Extraction

3.2.1 域不变特征提取

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 (θ_f) and discriminator (θ_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,

域对抗学习利用 GAN 概念来支持可转移学习功能。这种学习技术是一个双人游戏。第一个参与者的名称是域判别器 G_d ，它被训练以区分源域。另一方面，第二个参与者的名称是特征提取器 F ，它试图通过提取域不变表示来误导域判别器。这两个参与者是对抗性训练的: 特征提取器 (θ_f) 和判别器 (θ_d) 的参数分别通过最大化和最小化域判别器的损失来学习。此外，分类器 C 的损失也会减少。我们可以将损失函数表述为，

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

where γ is a hyper-parameter, and L_y and L_d denote the classification loss and domain discriminator loss, θ_c is the classifier’s parameters. d_i denotes the domain label of the input instances. After the training converges, the parameters

其中 γ 是一个超参数，L_y 和 L_d 分别表示分类损失和域判别器损失，θ_c 是分类器的参数。d_i 表示输入实例的域标签。在训练收敛后，参数

$\widehat{\theta}_f,\widehat{\theta}_c$ and $\widehat{\theta}_d$ will deliver a saddle point of Eq. 1

$\widehat{\theta}_f,\widehat{\theta}_c$ 和 $\widehat{\theta}_d$ 将提供方程 1 的鞍点

$$\left(\widehat{\theta}_f,\widehat{\theta}_c\right)=\underset{\theta_f,\theta_c}{\arg\min}L\left(\theta_f,\theta_c,\theta_d\right) \tag{2}$$

$$\left(\widehat{\theta}_d\right)=\underset{\theta_d}{\arg\max}L\left(\theta_f,\theta_c,\theta_d\right). \tag{3}$$

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.

以前的对抗域泛化方法要么对齐边际分布，要么对齐条件分布。这两种分布的对齐已被证明有助于提高效率，因为这两种分布对于获取域不变表示都是有用的。在本研究中，我们使用全局域对齐网络和局部子域对齐网络提取域不变特征。全局域对齐网络负责对齐跨域的边际分布，而局部子域对齐网络负责对齐域之间的条件分布。

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.

我们将在接下来的部分中首先介绍分类网络、全局域对齐网络、局部子域对齐网络和区分特征网络。然后，我们演示 DDIAN 损失函数和训练 DDIAN 的过程。

3.2.2 Classification Network

3.2.2 分类网络

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,

类别分类器 (C ，图 3 的绿色部分) 能够对源域中的输入实例进行类别分类。因此，可以使用关于 x_i 的监督或标记信息。分类器的训练目标是一个交叉熵损失，可以定义为，

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

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

其中 K 是源域的类别数量，$\widehat{P_{x_i}}$ 是输入样本 x_i 属于类别 K, F 的概率，K, F 表示特征提取器，C 表示分类器。

3.2.3 Global Domain Alignment Network

3.2.3 全局域对齐网络

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,

全局域判别器旨在消除训练源域之间的边际分布。基本概念是将边际域判别器与域对抗神经网络 [54] 结合。在 [54] 中，域判别器旨在对齐源域和目标域之间的边际分布，而我们设计了在 n 个源域之间的全局域判别器。通过全局域判别器实现的边际分布损失可以表述为，

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

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 .

其中 L_d 表示域判别器的交叉熵损失，F 描绘了特征提取器，而 d_i 表示输入实例的域标签 x_i 。

3.2.4 Local Sub-domain Alignment Network

3.2.4 局部子域对齐网络

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,

局部域中的判别器结构旨在匹配训练源域的条件分布。局部域判别器能够协调源分布的多模态结构与全局域判别器，从而实现更细粒度的域适应。局部域判别器被划分为 K 个类别相关的域判别器 $G^K d$ ，每个判别器负责匹配 K 类别相关的细节。局部域判别器的损失函数可以表述为，

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

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 .

其中 L_d^K 和 G_d^K 分别表示与类别 K 和领域判别器相关的交叉熵损失。y_i 表示输入实例的标签，而 d_i 表示 x_i 的输入实例的领域标签。

Algorithm 1: Training procedure of DDIAN

算法 1:DDIAN 的训练过程

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 α, β and γ

输入: 来自源领域 D_S^N 的源标记样本 $\{X_i^s, Y_i^s\}$ 和来自目标领域 D_T^N 的目标未标记数据 $\{X_i^t\}$ 。超参数 α, β 和 γ

Output: Classifier C

输出: 分类器 C

1 for iter from 1 to max-iter do

1 对于 iter 从 1 到 max-iter 执行

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 ;

从源领域抽取一小批源样本 $[X_i^s, Y_i^s]$ 和从目标领域抽取目标样本 $[X_i^t]$ ；

/* Update feature extraction, classification, discriminative feature, global domain alignment and and local sub-domain alignment network

/* 更新特征提取、分类、判别特征、全局领域对齐和局部子领域对齐网络

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

使用 $L_{cls} = -\frac{1}{n}\left(\sum_{x_i \in \Delta}\left(\sum_{c=1}^{K} \widehat{P_{x_i}} \log C\left(F\left(x_i\right)\right)\right)\right)$ 计算 L_{cls} 。

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

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

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

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

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

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

Update feature extraction, classification, discriminative feature, global domain alignment and and local

更新特征提取、分类、判别特征、全局领域对齐和局部

sub-domain alignment network using $L = L_{cls} + \beta L_{dc} + \gamma L_{dm} + \alpha L_{dis}$.

子领域对齐网络使用 $L = L_{cls} + \beta L_{dc} + \gamma L_{dm} + \alpha L_{dis}$ 。

8 end

8 结束

3.2.5 Discriminative Feature Network

3.2.5 判别特征网络

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.

为了强制特征提取网络学习更具判别性的特征，我们引入了一种基于中心的判别表示学习方法用于领域泛化。需要注意的是，整个训练过程集中在 SGD 小批量上。因此，下面提到的判别损失也依赖于实例的批量。由于训练样本的标签对于源领域是可用的，源领域的特征将由分类器进行分类。此外，在领域对齐过程中保持特征表示的判别能力是重要的。尽管源领域的分布已对齐，但仍可能有一些样本落入类间间隙，这提出了学习更多判别特征的需求。

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,

存在几种学习判别特征的方法 [55-58]，例如三元组损失、对比损失和中心损失。三元组损失和对比损失都需要构建大量的图像对并计算每对图像之间的距离，这在计算上是复杂的。因此，在本研究中，我们引入了中心损失，它可以灵活地与上述分类损失结合。根据软最大损失监督下训练的深度神经网络所得到的特征是可分的，但由于在类内距离上显示出显著的变化，因此并不具备很强的判别性。在 [59] 中，作者基于假设构建了一种高效的损失函数，以增强从深度神经网络提取的深度特征的能力。中心损失减轻了类内距离，另一方面，软最大损失用于对特征进行分类，确保其对应的类别。受中心损失的影响，该损失惩罚每个样本与对应类别中心的距离，我们提出了如下的判别特征学习，

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

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 i th 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.

其中 L_c 表示中心损失，m 表示小批量中的训练实例数量，$x_i \in R_d$ 表示第 i 个训练实例，y_i 表示 $x_i.c_{y_i} \in R_d$ 的标签，d 表示深度特征的维度。

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.

判别表示应该在组内具有更大的可分性和类内紧凑性。中心损失利用公式 7 的损失函数来惩罚类内的大距离。然而，中心损失的缺陷在于它不承认类间的可分性。众所周知，如果不同类别之间的距离足够远，表示将更具判别性，从而增强类别的可分性。因此，由于中心损失仅惩罚宽广的类内距离，而不包括类间距离，类间的调整是最小的，确保类别中心位置在训练过程中可以稍微改变。因此，如果网络使用相对较小的方差初始化类别中心，类别中心之间的较小差异将在训练过程中导致，因为中心损失仅惩罚宽广的类内距离，而没有考虑类间距离。中心损失的脆弱性在于它不承认类间的可分性。

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,

因此，我们提出了一种新的损失函数，以同时承认类间可分性和类内紧凑性，通过惩罚训练样本到其无关类别中心的距离之和，以及训练数据到其各自类别中心的距离之间的对比值，如下所示，

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

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

其中 L_{dis} 表示判别损失。m 表示小批量中的训练样本数量。$F\left(x_i\right) \in R_d$ 表示第 i 个训练样本的深度特征，维度为 d 。

3.2.6 Overall Objective

3.2.6 总体目标

The overall objective of the model can be formulated as:

模型的总体目标可以表述为:

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

where γ, β and α 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.

其中 γ, β 和 α 是加权参数。L_{cls} 是分类损失，L_{dm} 是边际对抗损失，L_{dc} 是条件对抗损失，而 L_{dis} 是判别损失。算法 1 描述了我们提出的方法的整体训练过程。

4 Evaluation and Testing

4 评估与测试

Source → Target	P, C, S → A	P, A, S → C	A, C, S → P	A, C, P → 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

源 → 目标	P, C, S → A	P, A, S → C	A, C, S → P	A, C, P → S	平均值
仅源	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 (我们的)	67.8	69.6	89.2	66.2	73.2

Table 1: Recognition accuracies for DG on the PACS dataset [36] using pretrained AlexNet.
表 1: 使用预训练的 AlexNet 在 PACS 数据集 [36] 上的识别准确率。

Source → Target	P, C, S → A	P, A, S → C	A, C, S → P	A, C, P → 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 164	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

源 → 目标	P, C, S → A	P, A, S → C	A, C, S → P	A, C, P → S	平均
仅源	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 164	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 (我们的)	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.
表 2: 使用预训练的 ResNet-18 在 PACS 数据集 [36] 上的识别准确率。

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.

在本节中，我们展示了为评估我们提出的方法而进行的实验，并将该方法与最先进的领域泛化方法进行比较。

4.1 Datasets

4.1 数据集

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

在领域泛化的背景下，我们在 PACS [36]、Office-Home [65] 和 VLCS 基准上评估了所提出的方法。

Source → Target	L, P, S → C	P, C, S → L	C, L, S → P	P, L, C → 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

来源 → 目标	L, P, S → C	P, C, S → L	C, L, S → P	P, L, C → S	平均
仅来源	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(我们的)	95.7	64.8	69.2	65.1	73.7

Table 3: Recognition accuracies for DG on the VLCS dataset using pretrained AlexNet.
表 3: 使用预训练的 AlexNet 在 VLCS 数据集上的识别准确率。

Source → Target	C, P, R → A	A, P, R → C	C, A, R → P	C, P, A → 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

源 → 目标	C, P, R → A	A, P, R → C	C, A, R → P	C, P, A → R	平均
仅源	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 (我们的方法)	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.
表 4: 使用预训练的 ResNet-18 在 Office-Home 数据集上的识别准确率。

Source → Target	P, C, S → A	P, A, S → C	A, C, S → P	A, C, P → 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

源 → 目标	P, C, S → A	P, A, S → C	A, C, S → P	A, C, P → S	平均
仅源	77.8	74.3	94.7	69.1	79.0
DDIAN (全局领域对齐)	81.4	74.2	94.5	69.1	79.8
DDIAN (局部领域对齐)	79.6	74.0	94.6	70.8	79.8
DDIAN (判别特征)	80.2	75.5	94.9	71.3	80.5
DDIAN (我们的)	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.
表 5: 使用预训练的 ResNet-18 在 PACS 数据集 [36] 上的识别准确率。

4.1.1 PACS

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 $\mathrm{P,C,S} \rightarrow \mathrm{A}; \mathrm{P,A,S} \rightarrow \mathrm{C}; \mathrm{A,C,S} \rightarrow \mathrm{P}$; and $\mathrm{A,C,P} \rightarrow \mathrm{P}$. The transfer task $\mathrm{P,C,S} \rightarrow \mathrm{A}$ 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.

PACS [36] 领域泛化数据集是通过提取 Caltech256、Sketchy、TU-Berlin 和 Google Images 之间的共同类别构建的。它包含 4 个领域: 照片、素描、卡通和绘画。每个领域由 7 个类别组成: 狗、吉他、长颈鹿、大象、人物、马、房子。总共有 9991 张图像。我们在四个迁移任务 $\mathrm{P,C,S} \rightarrow \mathrm{A}; \mathrm{P,A,S} \rightarrow \mathrm{C}; \mathrm{A,C,S} \rightarrow \mathrm{P}$ 和 $\mathrm{A,C,P} \rightarrow \mathrm{P}$ 上评估我们提出的方法。迁移任务 $\mathrm{P,C,S} \rightarrow \mathrm{A}$ 表示三个源领域: 照片 (P)、卡通 (C) 和素描 (S)，以及一个目标领域: 艺术-绘画 (A)。我们遵循领域泛化的标准协议，在训练阶段访问标记的源数据，但不访问目标数据。目标数据仅在测试阶段使用。

4.1.2 VLCS

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 $\mathrm{L,P,S} \rightarrow \mathrm{C}; \mathrm{P,C,S} \rightarrow \mathrm{L}; \mathrm{C,L,S} \rightarrow \mathrm{P}$; and $\mathrm{P,L,C} \rightarrow \mathrm{S}$. The transfer task $\mathrm{L,P,S} \rightarrow \mathrm{C}$ indicates there are three source domains LabelMe(L), PASCAL(P) and Sun09(S); and one target domain Caltech-101(C).

VLCS 是另一个跨领域对象基准，包含来自四个流行数据集的图像:PASCAL VOC2007 (V)、LabelMe (L)、Caltech-101 (C) 和 SUN09 (S)。这四个领域中有五个共同类别，即“鸟”、“狗”、“汽车”、“椅子”和“人物”。我们遵循相同的设置，其中 VLCS 的每个领域通过随机选择分为训练集 (70%) 和测试集 (30%) 。我们在四个迁移任务 $\mathrm{L,P,S} \rightarrow \mathrm{C}; \mathrm{P,C,S} \rightarrow \mathrm{L}; \mathrm{C,L,S} \rightarrow \mathrm{P}$ 和 $\mathrm{P,L,C} \rightarrow \mathrm{S}$ 上评估我们提出的方法。迁移任务 $\mathrm{L,P,S} \rightarrow \mathrm{C}$ 表示有三个源领域:LabelMe (L)、PASCAL (P) 和 Sun09 (S)；以及一个目标领域:Caltech-101 (C)。

4.1.3 Office-Home

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 $\mathrm{C,P,R} \rightarrow \mathrm{A}; \mathrm{A,P,R} \rightarrow \mathrm{C}; \mathrm{C,A,R} \rightarrow \mathrm{P}$; and $\mathrm{C,P,A} \rightarrow \mathrm{R}$. The transfer task $\mathrm{C,P,R} \rightarrow \mathrm{A}$ indicates there are three source domains Clipart (C), Product (P) and Real-world (R); and one target domain Art (A).

Office-Home 数据集包含四个领域，分别是艺术 (Ar)、现实世界 (Rw)、剪贴画 (Cl) 和产品 (Pr)，共 65 个不同的物体类别。它包含大约 15,500 张图像，涵盖 65 个类别。为了构建艺术和现实世界领域，从 www.deviantart.com 和 www.flickr.com 等网站收集了公共领域的图像。剪贴画图像来自各种剪贴画网页。产品领域的图像是通过网络爬虫从 www.amazon.com 获取的。我们在四个迁移任务 $\mathrm{C,P,R} \rightarrow \mathrm{A}; \mathrm{A,P,R} \rightarrow \mathrm{C}; \mathrm{C,A,R} \rightarrow \mathrm{P}$; 和 $\mathrm{C,P,A} \rightarrow \mathrm{R}$ 上评估我们提出的方法。迁移任务 $\mathrm{C,P,R} \rightarrow \mathrm{A}$ 表示有三个源领域: 剪贴画 (C)、产品 (P) 和现实世界 (R)；以及一个目标领域: 艺术 (A)。

4.2 Comparison with state-of-the-art

4.2 与最先进技术的比较

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.

我们将 DDIAN 的性能与几种最近的领域泛化方法进行了比较。仅源是没有任何自适应损失函数的简单源域聚合方法。CIDDG [60] 是一种基于对抗网络的深度 DG 方法，通过使用类先验归一化域分类和类条件域分类损失来最小化源域之间的差异。MLDG [62] 是一种基于元学习的 DG 方法。CIDG [51] 是一个 DG 框架，其中考虑了边际和条件表示，以减轻 DA 问题。DBADG [36] 是一个基于低秩参数化卷积神经网络的 DG 框架。CrossGrad [41] 是一种利用贝叶斯网络扰动输入流形以实现 DG 的新方法。MetaReg [38] 是一种最近提出的 DG 方法，通过元学习分类器正则化器。MMAL [64] 最初是为领域适应设计的，并重新用于领域泛化。MMD-AAE [24] 是一种最近的领域泛化方法，通过 MMD 约束对齐特征来学习领域不变特征。CCSA [49] 使用语义对齐来正则化学习到的特征子空间。DSN [66] 通过将源域分解为私有和共享空间并通过重建信号学习它们来获得领域对齐。D-SAM [63] 是一种基于利用领域特定聚合模块的领域泛化方法。MASF [47] 通过基于梯度的元训练过程对语义特征进行正则化。EPI-FCR [37] 通过基于领域聚合方法的情景训练实现了领域泛化的领域不变特征。

4.3 Implementation Details

4.3 实施细节

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.

我们基于 PyTorch 深度学习框架实现了我们提出的方法。我们使用在 ImageNet 数据集上预训练的 AlexNet 或 ResNet-18 模型对网络进行微调。在训练过程中，所有卷积层和池化层都进行了微调，而分类器层则通过反向传播从头开始训练，适用于所有迁移任务。我们将分类器的学习率设置为其他层的 10 倍，因为它是从头开始训练的。我们使用带有 0.9 动量的迷你批量随机梯度下降 (SGD) 进行优化，并根据 [67] 进行学习率调整。我们设置 $\alpha = 1, \beta = 0.5, \gamma = 0.5$ ，批量大小 = 32 。我们遵循领域泛化的标准评估，并在训练期间使用所有带标签的源示例。需要注意的是，训练期间目标数据不可用。为了计算平均准确率，结果是通过运行每个迁移任务 5 次获得的。

4.4 Results

4.4 结果

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.

表 1 报告了在 PACS 数据集上四个迁移任务的分类准确率，使用在 ImageNet 上预训练的 AlxNet 架构。从表 1 中可以看出，我们的区分性领域不变方法在每个迁移任务上都取得了可比的结果，并且我们提出的方法在大多数最先进的方法中表现优于，除了 MASF 和 JiGen 方法。我们还观察到 DDIAN 提供了最高的整体效率，仅在源仅方法上取得了 6% 的进展。

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.

表 2 报告了使用 ResNet-18 在 PACS 数据集上四个迁移任务的分类性能，我们可以观察到，使用 ResNet-18 架构时，获得的结果如预期般全面增强。尽管如此，我们的系统仍然保持最高的整体效率，在源仅方法上提高了 3.4%。

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.

表 3 在领域泛化的背景下展示了 VLCS 数据集上四个迁移任务的分类性能。对于 VLCS 数据集，我们遵循 [37] 的相同协议，其中每个领域被分为训练集 (70%) 和测试集 (30%)，并进行留一法评估。从结果中我们观察到，我们的方法在领域泛化方面优于之前的最先进方法。在四个迁移领域泛化任务中，我们获得了 6.4% 相对于仅源方法的改进。

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, $C, S \rightarrow A; C, A, \vec{R} \rightarrow P$ 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.

表 4 显示了 Office-Home 数据集上四个迁移任务的分类准确率。从结果中可以看出，我们提出的方法在 P、$C, S \rightarrow A; C, A, \vec{R} \rightarrow P$ 和 $C, P, A \rightarrow R$ 迁移任务上取得了最高的结果，并且在 A、$P, R \rightarrow C$ 迁移任务上表现相当。DDIAN 在整体上也提供了最佳性能，相对于仅源方法有 3% 的改进，并且至少在之前的最先进方法 CIDDG、D-SAM 和 JiGen 上有 1.6% 的改进。

4.5 Ablation study

4.5 消融研究

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.

在本节中，我们进一步使用 PACS 数据集进行额外实验，以调查我们提出的领域泛化网络各个组件对性能的贡献。使用各个组件进行五次实验的平均准确率如表 5 所示。我们对三个独立组件进行了实验:DDIAN(全局领域对齐)、DDIAN(局部领域对齐) 和 DDIAN(区分特征)。我们去掉两个组件，保留一个组件，DDIAN(全局领域对齐) 意味着我们去掉局部领域对齐和区分特征组件，以观察全局领域对齐组件的贡献。DDIAN(局部领域对齐) 表示我们去掉全局领域对齐和区分特征，而 DDIAN(区分特征) 则表示我们去掉全局和局部领域对齐模块，仅保留与基线的区分特征组件。通过消融研究，我们观察到每个

独立组件的 DDIAN 都优于仅使用源数据的方法。还注意到，所有组件的 DDIAN 优于其他方法。根据消融研究的结果，我们得出结论，每个组件在实现领域不变特征和在未见目标数据上获得泛化方面都发挥着自己的作用。我们还发现，区分特征对于在未知目标领域上的泛化是有用的。

5 Conclusion

5 结论

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.

在本文中，我们解决了领域泛化问题，其中判别特征以对抗方式提取。对抗模块不仅对齐源领域的边际分布，还对齐领域的条件分布。引入了学习判别特征的方法，以应用特征空间以实现更好的类间可分性和类内紧凑性，这有助于预测类别和领域兼容性。有两个因素可以促进深度特征的判别性，从而实现领域无关模型。一方面，由于深度表示更好地聚类，进行领域对齐要容易得多。另一方面，由于改进的类间可分性，超平面和每个簇之间存在较大的距离。因此，错误分类散布在每个簇中间或靠近边缘的样本的可能性较小。我们在多个基准测试中证明了所提方法的有效性，并在大多数迁移任务中达到了最先进的性能。

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References

参考文献

[1] Minghao Chen, Shuai Zhao, Haifeng Liu, and Deng Cai. Adversarial-learned loss for domain adaptation. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 3521-3528, 2020.

[2] Seungmin Lee, Dongwan Kim, Namil Kim, and Seong-Gyun Jeong. Drop to adapt: Learning discriminative features for unsupervised domain adaptation. In Proceedings of the IEEE International Conference on Computer Vision, pages 91-100, 2019.

[3] Mohammad Mahfujur Rahman, Clinton Fookes, Mahsa Baktashmotlagh, and Sridha Sridharan. On Minimum Discrepancy Estimation for Deep Domain Adaptation, pages 81-94. Springer International Publishing, Cham, 2020.

[4] Hong Liu, Mingsheng Long, Jianmin Wang, and Michael Jordan. Transferable adversarial training: A general approach to adapting deep classifiers. In International Conference on Machine Learning, pages 4013-4022, 2019.

[5] Xinhong Ma, Tianzhu Zhang, and Changsheng Xu. Gcan: Graph convolutional adversarial network for unsupervised domain adaptation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8266-8276, 2019.

[6] Yabin Zhang, Bin Deng, Hui Tang, Lei Zhang, and Kui Jia. Unsupervised multi-class domain adaptation: Theory, algorithms, and practice. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020.

[7] Mohammad Mahfujur Rahman, Clinton Fookes, and Sridha Sridharan. Preserving semantic consistency in unsupervised domain adaptation using generative adversarial networks. arXiv e-prints, pages arXiv-2104, 2021.

[8] Wenjie Qiu, Wendong Chen, and Haifeng Hu. Partial domain adaptation based on shared class oriented adversarial network. Computer Vision and Image Understanding, 199:103018, 2020.

[9] Hang Su, Shaogang Gong, and Xiatian Zhu. Multi-perspective cross-class domain adaptation for open logo detection. Computer Vision and Image Understanding, 204:103156, 2021.

[10] Yingjun Du, Jun Xu, Huan Xiong, Qiang Qiu, Xiantong Zhen, Cees GM Snoek, and Ling Shao. Learning to learn with variational information bottleneck for domain generalization. In European Conference on Computer Vision, pages 200-216. Springer, 2020.

[11] Mohammad Mahfujur Rahman, Clinton Fookes, Mahsa Baktashmotlagh, and Sridha Sridharan. Multi-component image translation for deep domain generalization. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 579-588. IEEE, 2019.

[12] Mohammad Mahfujur Rahman, Clinton Fookes, Mahsa Baktashmotlagh, and Sridha Sridharan. Correlation-aware adversarial domain adaptation and generalization. Pattern Recognition, 100, 2020.

[13] Haoliang Li, Sinno Jialin Pan, Shiqi Wang, and Alex C Kot. Domain generalization with adversarial feature learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5400-5409, 2018.

[14] Fengchun Qiao, Long Zhao, and Xi Peng. Learning to learn single domain generalization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12556-12565, 2020.

[15] Jongbin Ryu, Gitaek Kwon, Ming-Hsuan Yang, and Jongwoo Lim. Generalized convolutional forest networks for domain generalization and visual recognition. In International Conference on Learning Representations, 2019.

[16] Kaiyang Zhou, Yongxin Yang, Timothy Hospedales, and Tao Xiang. Learning to generate novel domains for domain generalization. In European Conference on Computer Vision, pages 561-578. Springer, 2020.

[17] Hung-Yu Tseng, Hsin-Ying Lee, Jia-Bin Huang, and Ming-Hsuan Yang. Cross-domain few-shot classification via learned feature-wise transformation. arXiv preprint arXiv:2001.08735, 2020.

[18] Toshihiko Matsuura and Tatsuya Harada. Domain generalization using a mixture of multiple latent domains. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 11749-11756, 2020.

[19] Prithvijit Chattopadhyay, Yogesh Balaji, and Judy Hoffman. Learning to balance specificity and invariance for in and out of domain generalization. In European Conference on Computer Vision, pages 301-318. Springer, 2020.

[20] Seonguk Seo, Yumin Suh, Dongwan Kim, Jongwoo Han, and Bohyung Han. Learning to optimize domain specific normalization for domain generalization. arXiv preprint arXiv:1907.04275, 3(6):7, 2019.

[21] Shujun Wang, Lequan Yu, Caizi Li, Chi-Wing Fu, and Pheng-Ann Heng. Learning from extrinsic and intrinsic supervisions for domain generalization. In European Conference on Computer Vision, pages 159-176. Springer, 2020.

[22] Mohammad Mahfujur Rahman, Clinton Fookes, and Sridha Sridharan. Deep domain generalization with feature-norm network. arXiv e-prints, pages arXiv-2104, 2021.

[23] Ya Li, Xinmei Tian, Mingming Gong, Yajing Liu, Tongliang Liu, Kun Zhang, and Dacheng Tao. Deep domain generalization via conditional invariant adversarial networks. In ECCV, 2018.

[24] Haoliang Li, Sinno Jialin Pan, Shiqi Wang, and Alex C. Kot. Domain generalization with adversarial feature learning. In CVPR, 2018.

[25] Gilles Blanchard, Aniket Anand Deshmukh, Urun Dogan, Gyemin Lee, and Clayton Scott. Domain generalization by marginal transfer learning. arXiv preprint arXiv:1711.07910, 2017.

[26] Gilles Blanchard, Gyemin Lee, and Clayton Scott. Generalizing from several related classification tasks to a new unlabeled sample. In Advances in Neural Information Processing Systems (NIPS). 2011.

[27] Krikamol Muandet, David Balduzzi, and Bernhard Schölkopf. Domain generalization via invariant feature representation. In Proceedings of the International Conference on International Conference on Machine Learning (ICML), 2013.

[28] Muhammad Ghifary, David Balduzzi, W. Bastiaan Kleijn, and Mengjie Zhang. Scatter component analysis: A unified framework for domain adaptation and domain generalization. TPAMI, 39(7), 2017.

[29] Aditya Khosla, Tinghui Zhou, Tomasz Malisiewicz, Alexei Efros, and Antonio Torralba. Undoing the damage of dataset bias. In European Conference on Computer Vision (ECCV), Florence, Italy, October 2012.

[30] Muhammad Ghifary, W. Bastiaan Kleijn, Mengjie Zhang, and David Balduzzi. Domain generalization for object recognition with multi-task autoencoders. In IEEE International Conference on Computer Vision, (ICCV), 2015.

[31] Zheng Xu, Wen Li, Li Niu, and Dong Xu. Exploiting Low-Rank Structure from Latent Domains for Domain Generalization, pages 628-643. Springer International Publishing, Cham, 2014.

[32] Chen Fang, Ye Xu, and Daniel N. Rockmore. Unbiased metric learning: On the utilization of multiple datasets and web images for softening bias. In International Conference on Computer Vision, 2013.

[33] L. Niu, W. Li, D. Xu, and J. Cai. An exemplar-based multi-view domain generalization framework for visual recognition. IEEE Transactions on Neural Networks and Learning Systems, 29(2), 2018.

[34] L. Niu, W. Li, and D. Xu. Visual recognition by learning from web data: A weakly supervised domain generalization approach. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2774-2783, June 2015.

[35] Riccardo Volpi, Hongseok Namkoong, Ozan Sener, John C Duchi, Vittorio Murino, and Silvio Savarese. Generalizing to unseen domains via adversarial data augmentation. In Advances in Neural Information Processing Systems, pages 5334-5344, 2018.

[36] D. Li, Y. Yang, Y. Z. Song, and T. M. Hospedales. Deeper, broader and artier domain generalization. In IEEE International Conference on Computer Vision (ICCV), 2017.

[37] Yi-Zhe Song. Episodic training for domain generalization. In Proceedings of the International Conference on Computer Vision (ICCV 2019). Institute of Electrical and Electronics Engineers (IEEE), 2019.

[38] Yogesh Balaji, Swami Sankaranarayanan, and Rama Chellappa. Metareg: Towards domain generalization using meta-regularization. In Advances in Neural Information Processing Systems, pages 998-1008, 2018.

[39] Yiying Li, Yongxin Yang, Wei Zhou, and Timothy M Hospedales. Feature-critic networks for heterogeneous domain generalization. arXiv preprint arXiv:1901.11448, 2019.

[40] Fabio M Carlucci, Antonio D'Innocente, Silvia Bucci, Barbara Caputo, and Tatiana Tommasi. Domain generalization by solving jigsaw puzzles. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2229-2238, 2019.

[41] Shiv Shankar, Vihari Piratla, Soumen Chakrabarti, Siddhartha Chaudhuri, Preethi Jyothi, and Sunita Sarawagi. Generalizing across domains via cross-gradient training. arXiv preprint arXiv:1804.10745, 2018.

[42] Nader Asadi, Mehrdad Hosseinzadeh, and Mahdi Eftekhari. Towards shape biased unsupervised representation learning for domain generalization. arXiv preprint arXiv:1909.08245, 2019.

[43] Aniket Anand Deshmukh, Yunwen Lei, Srinagesh Sharma, Urun Dogan, James W Cutler, and Clayton Scott. A generalization error bound for multi-class domain generalization. arXiv preprint arXiv:1905.10392, 2019.

[44] Kei Akuzawa, Yusuke Iwasawa, and Yutaka Matsuo. Adversarial invariant feature learning with accuracy constraint for domain generalization. arXiv preprint arXiv:1904.12543, 2019.

[45] Thanh-Dat Truong, Chi Nhan Duong, Khoa Luu, Minh-Triet Tran, and Minh Do. Beyond domain adaptation: Unseen domain encapsulation via universal non-volume preserving models. arXiv preprint arXiv:1812.03407, 2018.

[46] Maximilian Ilse, Jakub M Tomczak, Christos Louizos, and Max Welling. Diva: Domain invariant variational autoencoders. arXiv preprint arXiv:1905.10427, 2019.

[47] Qi Dou, Daniel Coelho de Castro, Konstantinos Kamnitsas, and Ben Glocker. Domain generalization via model-agnostic learning of semantic features. In Advances in Neural Information Processing Systems, pages 6447-6458, 2019.

[48] Z. Ding and Y. Fu. Deep domain generalization with structured low-rank constraint. TIP, 27(1), 2018

[49] Saeid Motiian, Marco Piccirilli, Donald A. Adjeroh, and Gianfranco Doretto. Unified deep supervised domain adaptation and generalization. In IEEE International Conference on Computer Vision (ICCV), 2017

[50] Haohan Wang, Zexue He, Zachary C Lipton, and Eric P Xing. Learning robust representations by projecting superficial statistics out. arXiv preprint arXiv:1903.06256, 2019.

[51] Ya Li, Mingming Gong, Xinmei Tian, Tongliang Liu, and Dacheng Tao. Domain generalization via conditional invariant representation. In AAAI, 2018.

[52] Ya Li, Xinmei Tian, Mingming Gong, Yajing Liu, Tongliang Liu, Kun Zhang, and Dacheng Tao. Deep domain generalization via conditional invariant adversarial networks. In Proceedings of the European Conference on Computer Vision (ECCV), pages 624-639, 2018.

[53] Toshihiko Matsuura and Tatsuya Harada. Domain generalization using a mixture of multiple latent domains. arXiv preprint arXiv:1911.07661, 2019.

[54] Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. Domain-adversarial training of neural networks. JMLR, 17(1), 2016.

[55] Amena Khatun, Simon Denman, Sridha Sridharan, and Clinton Fookes. End-to-end domain adaptive attention network for cross-domain person re-identification. IEEE Transactions on Information Forensics and Security, 2021.

[56] Amena Khatun, Simon Denman, Sridha Sridharan, and Clinton Fookes. Joint identification-verification for person re-identification: A four stream deep learning approach with improved quartet loss function. Computer Vision and Image Understanding, 197:102989, 2020.

[57] Amena Khatun, Simon Denman, Sridha Sridharan, and Clinton Fookes. A deep four-stream siamese convolutional neural network with joint verification and identification loss for person re-detection. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 1292-1301. IEEE, 2018.

[58] Amena Khatun, Simon Denman, Sridha Sridharan, and Clinton Fookes. Semantic consistency and identity mapping multi-component generative adversarial network for person re-identification. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 2267-2276, 2020.

[59] Yandong Wen, Kaipeng Zhang, Zhifeng Li, and Yu Qiao. A discriminative feature learning approach for deep face recognition. In European conference on computer vision, pages 499-515. Springer, 2016.

[60] Ya Li, Xinmei Tian, Mingming Gong, Yajing Liu, Tongliang Liu, Kun Zhang, and Dacheng Tao. Deep domain generalization via conditional invariant adversarial networks. In ECCV, 2018.

[61] Konstantinos Bousmalis, George Trigeorgis, Nathan Silberman, Dilip Krishnan, and Dumitru Erhan. Domain separation networks. In NIPS. 2016.

[62] Da Li, Yongxin Yang, Yi-Zhe Song, and Timothy M. Hospedales. Learning to generalize: Meta-learning for domain generalization. In AAAI, 2018.

[63] Antonio D'Innocente and Barbara Caputo. Domain generalization with domain-specific aggregation modules. In German Conference on Pattern Recognition, pages 187-198. Springer, 2018.

[64] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning, 2017.

[65] Venkateswara Hemanth, Eusebio Jose, Chakraborty Shayok, and Panchanathan Sethuraman. Deep hashing network for unsupervised domain adaptation. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.

[66] Konstantinos Bousmalis, George Trigeorgis, Nathan Silberman, Dilip Krishnan, and Dumitru Erhan. Domain separation networks. In Proceedings of the International Conference on Neural Information Processing Systems (NIPS), 2016.

[67] Yaroslav Ganin and Victor Lempitsky. Unsupervised domain adaptation by backpropagation. In ICML, 2015.