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Original Paper

Deep Unsupervised Domain Adaptation: A Review of Recent Advances and Perspectives

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ABSTRACT

Deep learning has become the method of choice to tackle real-world problems in different domains, partly because of its ability to learn from data and achieve impressive performance on a wide range of applications. However, its success usually relies on two assumptions: (i) vast troves of labeled datasets are required for accurate model fitting, and (ii) training and testing data are independent and identically distributed. Its performance on unseen target domains, thus, is not guaranteed, especially when encountering out-of-distribution data at the adaptation stage. The performance drop on data in a target domain is a critical problem in deploying deep neural networks that are successfully trained on data in a source domain. Unsupervised domain adaptation (UDA) is proposed to counter this, by leveraging both labeled source domain data and unlabeled target domain data to carry out various tasks in the target domain. UDA has yielded promising results on natural image processing, video analysis, natural language processing, time-series data analysis, medical image analysis, etc. In this review, as a rapidly evolving

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topic, we provide a systematic comparison of its methods and applications. In addition, the connection of UDA with its closely related tasks, e.g., domain generalization and out-of-distribution detection, has also been discussed. Furthermore, deficiencies in current methods and possible promising directions are highlighted.

Keywords: Deep learning, unsupervised domain adaptation, transfer learning, adversarial training, self training.

1 Introduction

Deep learning is a subfield of machine learning, which aims at discovering multiple levels of distributed representations of input data via hierarchical architectures [73]. For the past several years, there has been an explosion of deep learning-based approaches, where deep learning has substantially improved state-of-the-art approaches to diverse machine learning problems and applications [123]. In particular, deep learning has transformed conventional signal processing approaches into simultaneously learning both features and a prediction model in an end-to-end fashion [7]. Although supervised deep learning is the most prevalent and successful approach for a variety of tasks, its success hinges on (i) vast troves of labeled training data and (ii) the assumption of independent and identically distributed (*i.i.d.*) training and testing datasets [99]. Because reliable labeling of massive datasets for various application domains is often expensive and prohibitive, for a task without sufficient labeled datasets in a target domain, there is strong demand to apply trained models, by leveraging rich labeled data from a source domain [286]. This learning strategy, however, suffers from shifts in data distributions, i.e., domain shift, between source and target domains [302]. As a result, the performance of a trained model can be severely degraded, when encountering out-of-distribution (OOD) data, i.e., a source distribution differs from a target distribution [25]. For example, the performance of a disease diagnostic system, applied to a population in a target domain that is different from a population in a source domain, cannot be guaranteed.

To counter this, unsupervised domain adaptation (UDA) is proposed as a viable solution to migrate knowledge learned from a labeled source domain to unseen, heterogeneous, and unlabeled target domains [155, 167], as shown in Figure 1. UDA is aimed at mitigating domain shifts between source and target domains [118]. The solution to UDA is primarily classified into statistic moment matching (e.g., maximum mean discrepancy (MMD) [174]), domain style transfer [234], self-training [148, 165, 321], and feature-level adversarial learning [66, 81, 82, 171].

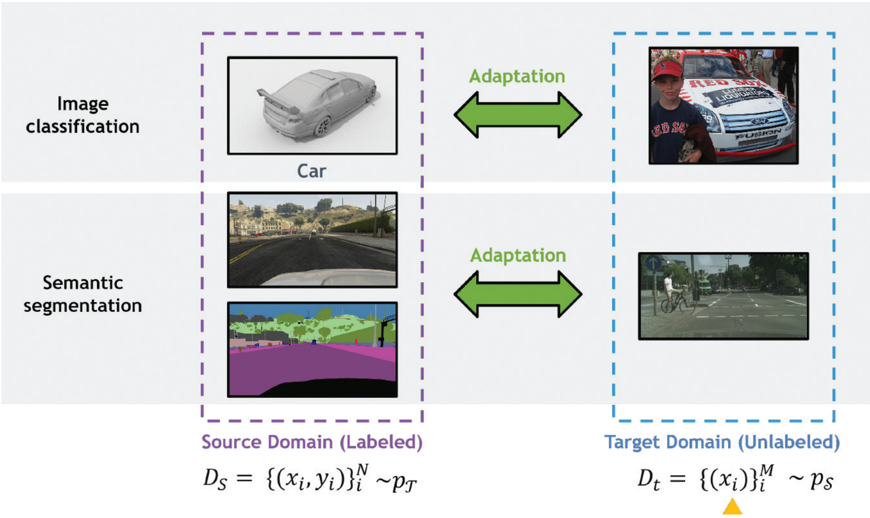

Figure 1: A taxonomy of transfer learning approaches based on the availability of labeled data in a source or target domain.

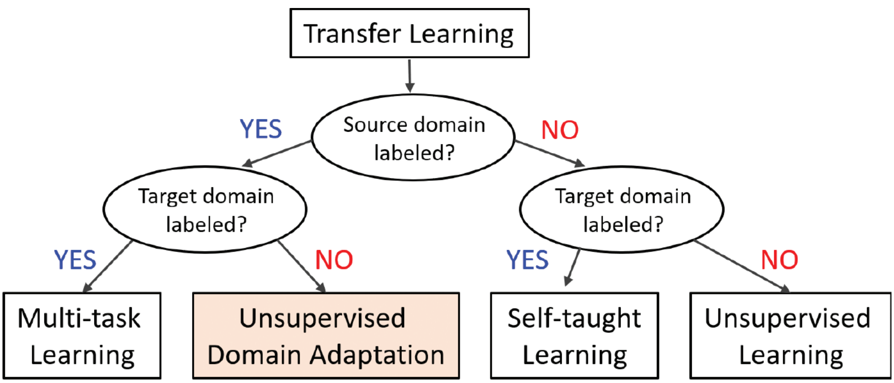

Figure 2: Illustration of the UDA classification and segmentation with the examples on the VisDA17 challenge database. The target domain data are unlabeled, as indicated by the orange triangle.

There are several previous review papers focusing on domain adaptation [6, 8, 13, 49, 118, 119, 215, 249, 270, 275, 315, 316], and the broader problem of transfer learning [45, 122, 204, 237, 251, 306]. As shown in Figure 2, domain adaptation can be seen as a special case of transfer learning, with the assumption that labeled data are available only in a source domain [204]. In

Table 1: Comparison with the previous UDA survey papers.

Surveys	Deep UDA	Generative mapping	Normalization	Ensemble	Self-training	Self-supervision	Low density
Beijbom [6]	×	×	×	×	×	×	×
Sun *et al.* [249]	×	×	×	×	×	×	×
Csurka [49]	√	×	×	×	×	×	×
Wang and Deng [270]	√	√	×	×	×	×	×
Zhao *et al.* [316]	√	√	×	×	×	×	×
Kouw and Loog [119]	√	√	×	×	√* (no deep)	×	×
Wilson and Cook [275]	√	√	√	√	×	×	√
Ramponi and Plank [215]	√	√	×	×	√	×	×
Zhang [309]	√	√	√	×	√	×	√
Guan and Liu [75]	√	√	×	×	×	×	×
Ours	√	√	√	√	√	√	√

this review paper, we aim to provide a wide coverage of models and algorithms for UDA from a theoretical and practical point of view. This review also touches on emerging approaches, especially those developed recently, providing a thorough comparison of different techniques as well as a discussion of the connection of unique components and methods with unsupervised deep domain adaptation. The coverage of UDA, especially deep learning-based UDA, has been limited in the general transfer learning reviews. Many prior reviews of domain adaption do not incorporate deep learning approaches; however, deep learning-based approaches have been the mainstream of UDA. In addition, some reviews do not touch deeply on domain mapping [49, 118, 119], normalization statistic-based [49, 119, 315, 316], ensemble-based [49, 119, 270, 316], or self-training-based methods [275]. Moreover, some of them only focus on limited application areas, such as visual data analytics [49, 202, 270] or natural language processing (NLP) [215]. In this review, we provide a holistic view of this promising technique for a wide range of application areas, including natural image processing, video analysis, NLP, time-series data analysis, medical image analysis, and climate and geosciences. The topics with which other review papers dealt are summarized in Table 1.

The rest of the paper is organized as follows. We first analyze possible domain shifts in UDA in Section 2. Then, various recent UDA methods are discussed and compared to each other in Section 3. Next, we show how UDA is applied to multiple application areas in Section 4. In Section 5, we highlight promising future directions. Finally, we conclude this paper in Section 6.

2 Overview

In this section, without loss of generality, we first introduce terms and notations as well as a formal definition of UDA. In UDA, there are an underlying source domain distribution $p_s(x,y) \in p_{\mathcal{S}}$ and a different target domain distribution $p_t(x,y) \in p_{\mathcal{T}}$. Then, a labeled dataset $\mathcal{D}_{\mathcal{S}}$ is selected *i.i.d.* from $p_s(x,y)$, and an unlabeled dataset $\mathcal{D}_{\mathcal{T}}$ is selected *i.i.d.* from the marginal distribution $p_t(x)$. The goal of UDA is to improve a generalization ability of a trained model in a target domain, by learning on both $\mathcal{D}_{\mathcal{S}}$ and $\mathcal{D}_{\mathcal{T}}$. We note that $\mathcal{Y} = \{1, 2, \ldots, c\}$ is the set of the class labels for discriminative tasks, e.g., classification and segmentation. In contrast, $\mathcal{Y}$ can be continuous values, sentences, images, or languages in generative tasks [67]. UDA [66, 258] is motivated by the following theorem [118]:

Theorem 1. *For a hypothesis h*

$$\begin{aligned}\mathcal{L}_t(h) \le\ & \mathcal{L}_s(h) + d[p_{\mathcal{S}}, p_{\mathcal{T}}] \\ & + \min[\mathbb{E}_{x\sim p_s}|p_s(y|x) - p_t(y|x)|, \mathbb{E}_{x\sim p_t}|p_s(y|x) - p_t(y|x)|]. \end{aligned} \tag{1}$$

Here, $\mathcal{L}_s(h)$ and $\mathcal{L}_t(h)$ are predefined losses with a hypothesis h in source and target domains, respectively. $d[\cdot]$ represents a divergence measure, e.g., the Jensen–Shannon (JS) divergence in the case of conventional adversarial UDA [232]. Of note, the third term on the right hand, $\min[\mathbb{E}_{x\sim p_s}|p_s(y|x) - p_t(y|x)|, \mathbb{E}_{x\sim p_t}|p_s(y|x) - p_t(y|x)|]$, is a negligible value, for which the error in a source domain $\mathcal{L}_s(h)$ and the divergence between two domains is considered an upper bound of the error in a target domain $\mathcal{L}_t(h)$. $\mathcal{L}_s(h)$ can be minimized, using recent advances in supervised learning, e.g., advanced deep feature extractor networks. Overall, UDA methods aim at minimizing the divergence between two domains to lower the upper bound of the generalization error in the target domain $\mathcal{L}_t(h)$.

Domain shifts can be categorized into four types [118], as shown in Figure 3. Existing work primarily focuses on a single shift only, by assuming that other shifts remain invariant across domains. The covariate shift w.r.t. $p(x)$ is to align the marginal distribution for all of the data samples. At a more fine-grained level, the conditional shift is used to align the shift of $p(x|y)$, which is a more realistic setting than the covariate shift only setting, since different classes could have their own shift protocols. For instance, some street lamps glitter, while other lamps are dim at night [143]. However, estimating $p_t(x|y)$ without $p_t(y)$ is ill-posed [307]. Moreover, the label shift [21], a.k.a. target shift, indicates the sample proportion of involved classes is different between two domains. Furthermore, the concept shift [118] can arise, when classifying, for example, tomato as a vegetable or fruit in different countries; it is, however, usually not a common problem in popular object classification or semantic segmentation tasks. As such, this review mainly focuses on the covariate shift alignment in UDA, as is most commonly studied. The challenges of aligning the other shifts and their combinations are also discussed as directions for future research.

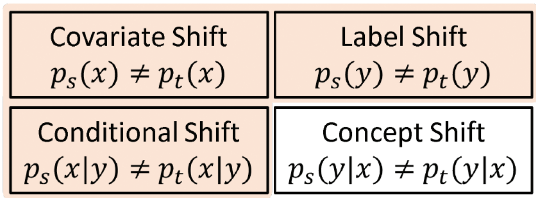

Figure 3: A summary of four possible domain shifts. The red mask indicates the most common domain shift scenarios in UDA [143]. Note that $p(x)$ can be aligned, if $p(x|y)$ is aligned with the law of total probability [307].

3 Methodology

The past few years have witnessed a proliferation of UDA methods, following the rapid growth of neural network research. Popular approaches include domain alignment with statistic divergence and adversarial training, generative domain mapping, normalization statistics alignment, ensemble-based methods, and self-training, as summarized in Figure 4. In addition, these approaches can be combined to further enhance performance on a variety of tasks. In this section, we discuss each category in more detail as well as their combinations and connections.

3.1 Statistic Divergence Alignment

Learning domain invariant feature representations is the most widely used philosophy in many deep UDA methods, which hinges on minimizing domain discrepancy in a latent feature space. To achieve this goal, choosing a proper divergence measure is at the core of these methods. Widely used measures include MMD [224], correlation alignment (CORAL) [247], contrastive domain discrepancy (CDD) [105], Wasserstein distance [145], graph matching loss [287], etc.

Following the hypothesis of a two-sample statistical test, MMD measures the distribution divergence with observed samples. Specifically, the mean of a smooth function w.r.t. the samples from two domains are compared, where a larger mean difference indicates a larger domain discrepancy. Conventionally, the unit ball in characteristic reproducing kernel Hilbert spaces (RKHS)—as a means of analyzing and comparing distributions—is used as the smooth function, which provides a zero population if and only if the two distributions

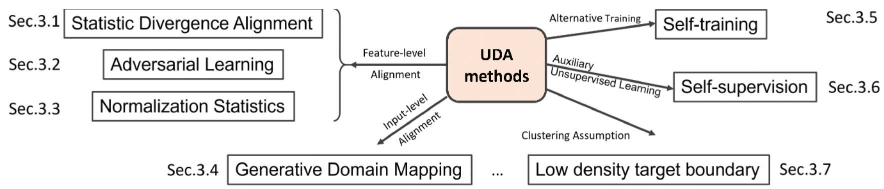

Figure 4: A summary of the main stream UDA methods discussed in this paper.

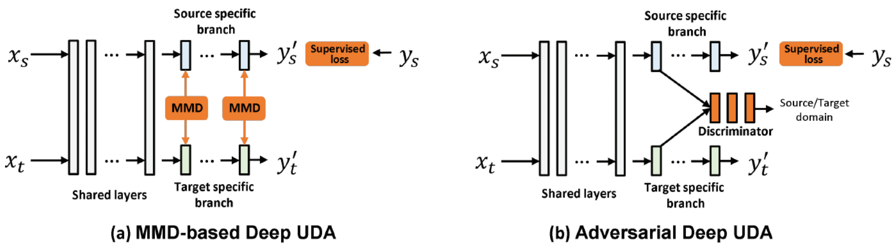

Figure 5: Different architectures of (a) MMD-based UDA (e.g., DAN [173]), and (b) adversarial training based deep UDA (e.g., domain-adversarial neural networks (DANN) [66]).

are equal. In practice, the alignment component serves as another classifier akin to a task classifier. In what follows, MMD can be calculated and minimized between the outputs of the classifiers' layers [224], as shown in Figure 5(a). Following vanilla MMD, multiple kernel MMD (MK-MMD) [173] and joint MMD (JMMD) [175] are further proposed to achieve a more robust MMD estimation.

Similar to MMD, CORAL is proposed, based on a polynomial kernel [247]. CORAL is defined as the difference of the second-order statistics, i.e., covariances, across the features of two domains. To measure the difference of the covariances, different distances have been explored, e.g., squared matrix Frobenius norm [248], an Euclidean distance measure in mapped correlation alignment [311], log-Euclidean distances [272], and geodesic distances [193]. CORAL has also been generalized to possibly infinite-dimensional covariance matrices in RKHS [312]. The statistics beyond the first-order, e.g., MMD, and second-order, e.g., CORAL, are further investigated for more accurate CORAL estimation [27].

To achieve class conditioned distribution alignment, CDD [105] is proposed to incorporate the class label into MMD. By minimizing CDD, cross-class divergence is enlarged, while within-class divergence is minimized. Considering that the label in a target domain is missing in UDA, contrastive adaptation networks (CAN) [105] is proposed to alternatively estimate the target domain label with clustering, while minimizing CDD.

In addition, the Wasserstein distance [68, 80, 156, 170], a.k.a. optimal transportation distance or earth mover's distance [145, 149], could be another alternative to measure the distribution divergence. The joint distribution optimal transport (JDOT) is proposed to measure the Wasserstein distance between two feature distributions [48]. As a deep learning framework, DeepJDOT is further proposed to achieve an end-to-end UDA [50].

Furthermore, graph matching has been used as a divergence measure, which aims at finding an optimal correspondence between two graphs [287]. With a batch of samples, the feature extraction can be regarded as nodes in an undirected graph. The distance between two nodes represents their similarity. The domain divergence is defined as the matching cost between the graphs in source and target domain batches [51, 52].

3.2 Adversarial Learning

Instead of choosing a divergence measure, such as MMD, recent work focuses on adaptively learning a measure of divergence. With recent advances in generative adversarial networks (GAN), adversarial training is widely used to achieve domain invariant feature extraction.

Following Theorem 1, to efficiently minimize the upper bound, i.e., the right-hand side of Equation (1), adversarial UDAs are used to minimize across domain divergence at the feature level with guidance of a discriminator as an adaptively learned divergence measure. Specifically, as shown in fig. 5(b), in [66, 258], a feature extractor $f(\cdot)$ is applied onto x to extract a feature representation $f(x) \in \mathbb{R}^K$. We would expect that $d[p_s(f(x)), p_t(f(x))]$ could be a small value. Targeting this goal, in addition to training a classifier Cls to correctly classify source data, $f(\cdot)$ is also optimized to encourage the source and target feature distributions to be similar to each other, following the supervision signal from a domain discriminator $Dis : \mathbb{R}^K \to (0, 1)$. We note that the classifier $Cls : \mathbb{R}^K \times \mathcal{Y} \to (0, 1)$ outputs the probability of an extracted feature $f(x)$ being a class y among c categories, i.e., $C(f(x), y) = p(y|f(x); Cls)$. The objective of different modules can be

$$\max_{Cls} \underset{x\sim p_s}{\mathbb{E}} \log C(f(x), y) \tag{2}$$

$$\max_{Dis} \underset{x\sim p_s}{\mathbb{E}} \log(1 - Dis(f(x)) + \underset{x\sim p_t}{\mathbb{E}} \log Dis(f(x)) \tag{3}$$

$$\max_{f} \underset{x\sim p_s}{\mathbb{E}} \log C(f(x), y) + \lambda \underset{x\sim p_t}{\mathbb{E}} \log(1 - Dis(f(x)), \tag{4}$$

where $\lambda \in \mathbb{R}^+$ is used to balance between the two loss terms. Following the conventional adversarial UDA methods, the three *max* strategy [232, 254] can be leveraged, and the three objectives above are used to update the corresponding three modules, respectively. In Equation (3), if $f(x)$ is a source domain feature, then $Dis(f(x))$ is trained to produce 0 and vice versa. Note that maximizing $\underset{x\sim p_t}{\mathbb{E}} \log Dis(f(x))$ for Dis in Equation (3), while maximizing

$\mathop{\mathbb{E}}_{x \sim p_t} \log(1 - Dis(f(x)))$ for f in Equation (4) has made this formula a $minmax$ adversarial game.

Specifically, domain adversarial neural network (DANN) [66] utilizes the gradient reversal layer as a domain discriminator Dis. In addition, adversarial discriminative domain adaptation (ADDA) [258] is proposed to initialize the target model with source domain training, followed by adversarial adaptation, which amounts to the target domain-specific classifier. Other than minimizing cross-entropy based domain confusion losses, Tzeng *et al.* [257] propose enforcing the prediction as a uniform distribution of binary bins. Assuming that the samples are the same, these two domain discriminative losses are essentially equivalent to each other [73]. Similarly, Motiian *et al.* [194] group the domains and classes as four pairs, by utilizing a four-class classifier for the domain discriminative network. The feature generator is further developed in [261] to achieve source domain feature augmentation.

Instead of modeling the domain divergence with the JS divergence as in conventional adversarial UDA [232], a discriminator for estimating the Wasserstein distance is further proposed [239]. Following the recent Wasserstein GAN [1], the Wasserstein distance can be used as a better distance measure, especially to cope with large discrepancies. This is because the JS-divergence cannot differentiate the distance between distributions if there is no overlap between two distributions. In Saito *et al.* [229], there are two discriminators to maximize the discrepancy of each class in the target domain, which renders the target domain features to have a wider class-wise boundary region to facilitate the classification.

3.3 Normalization Statistics

In modern deep neural networks, batch normalization (BN) layers have played an important role in achieving faster training [100], smoother optimization, and more stable convergence [279], due to its insensitivity to initialization [235]. In each normalization layer, there are two low-order batch statistics, including mean and variance, and two learnable high-order batch statistics, including scaling and bias.

Some early work assumes that the BN statistics of mean and variance inherit domain knowledge. As the early attempt of applying BN to domain adaptation, AdaBN [134], as illustrated in Figure 6(a), is proposed to achieve UDA, by modulating BN statistics from a source domain to a target domain. In AdaBN, once training is completed, the parameters and weights learned during the training, except for BN layers, are fixed. As a result, BN layers can be simply added to a target domain, without having an interaction with the source domain [134]. In addition, AutoDIAL [20] is further proposed as a generalized AdaBN, which retrains the network weights simultaneously with additional domain alignment layers.

Recent work [22, 183, 185, 271] demonstrates that the low-order batch statistics, including the mean and variance, are domain-specific, because of the divergence of feature representations across two domains. Note that simply forcing the mean and variance to be the same between source and target domains is likely to lose expressiveness of networks [305]. Besides, once the low-order BN statistics discrepancy has been partially mitigated, the high-order BN statistics can be shareable between two domains [185, 271]. Note that all of the aforementioned approaches [22, 183, 185, 271, 305] need joint training on source domain data. Recently, OSUDA [159, 166], as shown in Figure 6(b), propose reducing the domain discrepancy by means of a momentum-based adaptive low-order batch statistics progression strategy and an explicit high-order BN statistics consistency loss for source-free UDA segmentation.

3.4 Generative Domain Mapping

Rather than aligning features in a latent space, an alternative can be directly rendering the target domain data at the data level. The classifier or segmentation network can be trained on the generated target domain data from source domain data alongside their labels [242]. In addition, the network can be trained simultaneously with GANs [11, 91], as shown in Figure 7(b).

Cycle reconstruction for image style translation plays an important role for unpaired translation tasks [113, 294, 318]. However, it is challenging to efficiently constrain local structures, thus leading to significant distortions in the translated images and their segmentations [290]. To address this, Yang *et al.* [290] extract a modality-independent neighborhood descriptor (MIND) feature $M(x_t)$ and $M(G_{TC}(x_t))$ of x_t and $G_{TC}(x_t)$ with a manually defined extractor M, and minimize their reconstruction loss $||M(x_t) - M(G_{TC}(x_t))||_1$. [163] propose a general structure feature extractor f in lieu of M. To achieve more fine-grained class-wise image mapping, conditional GANs have been widely used for generative domain mapping.

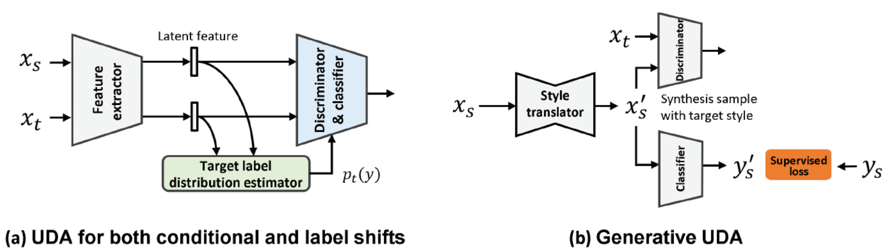

Figure 6: Different architectures for BN-based methods, e.g., (a) AdaBN [134] and OSUDA [159, 166].

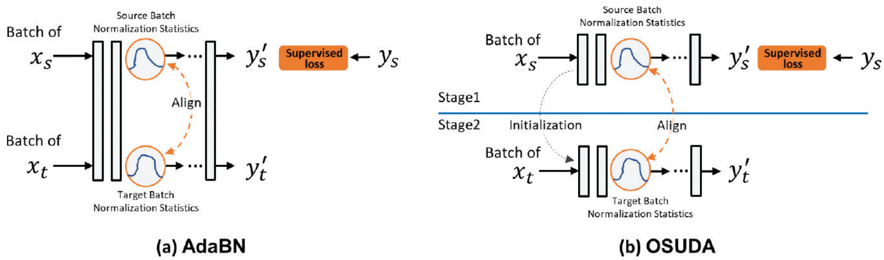

Figure 7: Different architectures for (a) adversarial UDA with Conditional and Label Shift (CLS) [143], and (b) generative adversarial UDA [11].

3.5 Self-training

Unlike approaches that reduce domain discrepancy with a divergence measure, self-training is proposed as an alternative training scheme, by utilizing unlabeled target domain data to achieve domain adaptation [321]. Self-training is based on a round-based alternative training scheme, which is originally developed for semi-supervised training and has recently been adapted for UDA. There are two steps involved in deep self-training based UDA: (1) creating a set of pseudo-labels in the target domain, and (2) retraining the network using the generated pseudo-labels with target domain data.

Recently, self-training-based approaches have surpassed adversarial training-based approaches in several deep UDA tasks [188, 241, 273]. Whereas self-training was initially presented as part of semi-supervised learning [255], recently proposed deep self-training methods combine feature embedding with alternative learning in a unified manner, thus yielding flexible domain adaptation [321].

A crucial issue in self-training-based approaches, however, is that pseudo-labels in the target domain could be noisy; and thus it is likely that a large proportion could be unreliable. To mitigate this issue, selecting the prediction with high confidence is essential. To this end, in classification or segmentation tasks with softmax output unit, a possible solution would be to gauge the confidence as the maximum value of histogram [321]. Additionally, to tackle the problem of the noisy and unreliable pseudo-labels, Zou *et al.* [321] construct a more conservative pseudo-label in order to smooth the one-hot hard label to a soft label vector. Liu *et al.* [148] further resort to an additional supervision signal of an energy-based model for regularization, which is independent of the pseudo-label. Mei *et al.* [187] explore instance-wise self-training for UDA.

In addition to the discriminative tasks, such as classification and segmentation, Mei *et al.* [165] further extend self-training to a generative task, by controlling the confident pseudo-label of continuous pixel value with a Bayesian uncertainty mask. In learning-based tasks, two kinds of uncertainty exist, including an aleatoric uncertainty and an epistemic uncertainty [54, 97, 108]. Specifically, the aleatoric uncertainty is caused by the uncertainty from noisy training data observations, whereas the epistemic uncertainty is caused by models that are not sufficiently trained. In self-training, the pseudo-labels are typically noisy, thus leading to the aleatoric uncertainty. In addition, the epistemic uncertainty in self-training is caused by a limited number iterations for model training and a limited number of target domain training samples. Therefore, taking both uncertainties into account is vital to build a robust model with a holistic uncertainty calibration.

3.6 Self-supervision

Another solution to UDA is to incorporate auxiliary self-supervision tasks into the network training. Self-supervised learning hinges on only unlabeled data to prescribe a pretext learning task, such as context prediction or image rotation, for which a target objective can be computed without supervision [117]. This group of work assumes that alignment can be achieved by carrying out source domain classification and reconstruction of target domain data [70] or both source and target domain data [12]. In Ghifary *et al.* [70], a deep reconstruction-classification network is optimized with a pair-wise squared reconstruction loss. In particular, the scale-invariant mean squared error reconstruction loss is introduced in Bousmalis *et al.* [12] to train its domain separation networks.

In addition to the conventional reconstruction tasks [171], new self-supervision tasks have been proposed, e.g., image rotation and jigsaw predictions [283]. Kim *et al.* [111] propose both in-domain and across-domain self-supervision to achieve UDA with fewer source domain labels. Lian *et al.* [137] propose a self-motivated pyramid curriculum for segmentation.

3.7 Low Density Target Boundary

Several UDA approaches based on a popular clustering assumption [24] are proposed in the context of semi-supervised training, which indicates target domain samples from the same class are likely to be distributed closely as a cluster. The target domain class-wise decision boundaries should be located in the low-density regions [82]. To this end, Shu *et al.* [243] propose virtual adversarial domain adaptation. In addition, after training, a decision-boundary iterative refinement step with a teacher is further applied to refine the decision boundary in a target domain [243]. Kumar *et al.* [121] combine variational adversarial training with a conditional entropy loss to achieve a low-density boundary and avoid overfitting in unlabeled data. Similarly, an entropy loss has been applied to AutoDIAL [20]. Other than the feature level, generative methods at the image level have also been developed to make the decision boundary lie in a lower density region [274].

Saito *et al.* [227] propose adversarial dropout regularization, which is seen as the difference between two dropout networks as a discriminator to generate target discriminative features. Lee *et al.* [127] extend the adversarial dropout for convolutional layers with a channel drop rather than an element drop. TDDA [71] focuses on task-discriminative alignment for UDA.

3.8 Other Methods

DEV [298] is proposed to achieve UDA via model selection. The prototype with clustering is utilized in Pan *et al.* [205] for class-wise adaptation. Liu *et al.* [155, 167] further extend the class-wise prototype to fine-grained subtypes. Wu *et al.* [278] apply dual mixup regularization to adversarial UDA. Domain randomization is proposed in Kim *et al.* [114], Rodriguez and Mikolajczyk [220] to randomly generate source domain data with a different style to achieve a decent generalization ability in a target domain. To further utilize unlabeled data, a mean teacher has been used in Cai *et al.* [15], Deng *et al.* [53]. The inter/intra object correlation is explored in a graph reasoning framework for domain adaptation in Xu *et al.* [284]. Liu *et al.* [160] utilize the self-semantic contour as an intermediate feature to facilitate domain adaptation.

3.9 Combinations and Connections

Several aforementioned approaches can be combined with each other to exploit complementary optimization. Both feature-level adversarial alignment and image-level generative mapping can be combined sequentially, e.g., GraspGAN [10], or jointly, e.g., CyCADA [103]. Following AdaBN, several works have shown that the BN alignment can be added on top of other UDA methods [10, 63, 105, 129]. The BN alignment and entropy minimization for low-density target boundary are combined for source data free UDA [159, 166]. Adversarial domain-invariant feature alignment has been applied on different levels, following an ensemble scheme [121]. Low-density target boundary and domain-invariant feature learning are jointly learned in Lee *et al.* [124], Saito *et al.* [229]. Kang *et al.* [106] combine generative image mapping with the alignment of model attention. PANDA [95] integrates adversarial training with prototype-based normalization.

4 Applications

UDA has been successfully applied to a variety of application areas, including perception and understanding of images, video analysis, NLP, time-series data analysis, medical image analysis, and climate and geosciences. While some works are based on general principles of UDA, other works are targeted to tackle specific applications under consideration, by exploiting the characteristics of training and testing datasets. In this section, we do not intend to provide a comprehensive review, but rather opt to highlight examples of trends in UDA for various application areas, given the presence of a huge body of work and a number of excellent prior reviews.

4.1 Image Analysis

Natural image analysis is the most explored area in UDA, due to the availability of large-scale visual databases. Depending on the label and corresponding output, popular tasks include image classification, e.g., object recognition and face recognition, object detection, semantic segmentation, image generation, image caption, etc.

4.1.1 Image Classification

Classification or recognition of object categories has been a fundamental task in computer vision. As such, numerous attempts have been made to use deep learning and UDA for the classification. For instance, Long *et al.* [175] use AlexNet [120] backbone for the task, where the approach is compared against the source model, the DANN method [65], and the variations of MMD, e.g., DDC [259], DAN [173], JAN [175], and RTN [176]. Zellinger *et al.* [301] compare their CMD methods with other discrepancy-based methods, e.g., DDC [259], deep CROAL [248], DLID [43], AdaBN [135], and adversarial DANN [65]. In addition to the object classification, UDA of face recognition is another hot research topic, in which the most important shifts include pose, illumination, expression, age, ethnicity, and imaging modality [150, 151, 157]. Among these shifts, the expression, ethnicity, and imaging modality have discrete variations, while other attributes have continuous variations [141, 154]. In Kan *et al.* [104], a bi-shifting auto-encoder framework is proposed for face identification with the domain shifts of view, ethnicity, and sensor. Hong *et al.* [92] generate different face views for domain adaptation. Sohn *et al.* [245] achieve adversarial UDA for video face recognition.

There are several widely adopted benchmarks for classification tasks. As for databases to test the domain shift in natural images, Office-31 dataset [225] is widely used, which contains data from three different sources, i.e., Amazon (A), DSLR (D), and Webcam (W). As for image synthesis to achieve real image domain adaptation, VisDA17 [209] is a preferred choice. DomainNet [208] is the largest domain adaptation dataset to date, which consists of $-0.6\,\mathrm{M}$ images with 345 sub-classes from 24 meta-classes.

In addition to classification with discrete labels, several tasks have ordinal class labels [142, 144]. In the case of medical diagnosis, it is likely that the labels are discrete and distributed successively. As such, UDA for ordinal classification needs to induce a non-trivial ordinal distribution first, prior to projecting the data onto a latent space. In Liu *et al.* [152, 153], a recursively conditional Gaussian distribution is adapted to ordered constraint modeling, which admits a tractable joint distribution prior.

4.1.2 Image Detection

In addition to recognizing objects, image detection has been further investigated, by localizing objects in a wide view of field with a bounding-box [202]. Deep object detection has been an integral part of several tasks, e.g., surveillance, augmented/mixed reality (AR/MR), autonomous driving, and human-computer interface.

Adversarial feature alignment has been utilized for UDA object detection in [40, 93, 228, 244, 262]. In addition, adversarial generative mapping at the image level has been applied in [28, 94, 220, 300, 303]. In several works [74, 109, 112, 130, 222, 313], the pseudo-label based self-training is adopted for progressive adaptation.

For UDA in image detection, popular domain adaptation scenarios include adaptation of cross weather conditions, synthetic to real imagery, etc. For example, domain adaptation is performed from Cityscapes [46] to Foggy Cityscapes [230], which is rendered from Cityscapes, by adding the fog noise. In addition, several works [285] use SIM10k dataset as the source domain and the Cityscapes dataset as the target domain.

4.1.3 Image Segmentation

Image segmentation aims at pixel-wise classification [161, 250]. Rather than indicating the rough position of the object like a detection task, segmentation provides fine-grained delineation to support subsequent operations. Compared with the sample wise classification in UDA, it is difficult to apply the low-density target region and prototype based UDA methods. Since each pixel needs to be represented as a point in the feature space, it is difficult to scale up to large-scale data. Instead, adversarial training at both feature and image levels have been widely used [187, 256, 299]. Self-training based methods have also been developed for semantic segmentation [29, 147].

A typical task is to adapt the large-scale labeled game engine rendered data, i.e., GTA5 [217], to the real-world data, i.e., Cityscapes [46], for which there are a total of 19 shared labels for semantic segmentation. In a source domain, there are a total of 24,000 labeled game engine rendered images from Grand Theft Auto 5. As the standard evaluation protocol [291], all of the samples in the GTA5 dataset are used as the source domain, while the training set of Cityscape with a total of 2975 images is used as the target domain training set. The testing set of Cityscapes has a total of 500 images.

4.1.4 Image Generation

Generative models have been widely applied to diverse tasks, e.g., entertainment, image harmonization/stylization, and data completion and augmentation [158, 162, 264, 282, 288, 289].

The image style synthesis task itself can be regarded as a cross-domain translation task, when the input involves another style or domain. To address this, GAN-based methods have been widely used for cross-domain image generation tasks [85]. Self-training has also been applied to the image synthesis task. For example, Liu *et al.* [165] leverage self-training for the image synthesis task, which also considers both epistemic and aleatoric uncertainties [54]. Specifically, Liu *et al.* [165] aim at cross modality synthesis using paired sets of images acquired from two different sites.

The typical evaluation in He *et al.* [85] adopt the T1-weighted to T2-weighted MRI translation across three IXI centers.[1] In addition, the paired cine and tagged tongue MRI in two private datasets are used in Liu *et al.* [165].

4.2 Medical Image Analysis

Medical image analysis has been a major application ground for image analysis methods, due to its wide usage in real-life imaging problems. In addition, a variety of imaging modalities are used in a clinical setting, each of which poses unique challenges. An increasing amount of deep network-based methods have been proposed to achieve enhanced computational speed and better algorithmic performance over traditional medical image analysis methods. UDA has been successfully adopted in image segmentation, classification, and generation tasks in addition to a few other varying applications.

Perone *et al.* [210] use a self-ensembling technique in semantic image segmentation, demonstrating that it can improve model generalization. Their method is evaluated using a small number of magnetic resonance imaging (MRI) datasets, serving as a proof-of-concept of the advantage of UDA in medical imaging, rather than showing an actual application in a more extensive real-life medical problem. Ouyang *et al.* [201] report UDA for multi-domain medical image segmentation via a VAE-based feature prior matching, which features data efficiency. It is applied to a multi-modality cardiac image dataset to achieve segmentation. Zou *et al.* [320] propose UDA with the so-called Dual-Scheme Fusion Network, where both source-to-target and target-to-source connections are built to help bridge the gap between domain differences for improved performance. It is applied to the segmentation of both brain tumors and cardiac data, yielding decent results. He *et al.* [84] achieve cross-device retinal OCT segmentation. Liu *et al.* [160] facilitate cross-modality brain tumor segmentation with self-semantic contouring. Additionally, more methods

[1] https://brain-development.org/ixi-dataset/

have been proposed to improve the segmentation UDA networks from within their structures. To enable flexibility of two-way adaptations, Ning *et al.* [198] propose a bidirectional UDA framework based on disentangled representation learning. It achieves decent performances in both the forward adaptation direction, such as from MRI to computed tomography (CT), and the backward direction, such as from CT back to MRI. The popular evaluation setting is to use the MMWHS challenge dataset as the source domain and the MMAS dataset as the target domain, respectively [319].

It often poses a challenge to share medical data for collaboration due to sensitive patient information. To address the privacy concern of the large-scale and well-labeled medical data in the source domain, Liu *et al.* [166, 169] adapt a pre-trained "off-the-shelf" segmentation model without source domain data at the adaptation stage. The test-time adaptable segmentation networks have been developed to achieve UDA in a source-free manner [85, 107]. In addition, He *et al.* [85] show that their method can be generalized to image translation UDA tasks.

Besides, recent years have seen increased usage of UDA to solve segmentation problems using a variety of imaging modalities, such as CT, MRI, X-ray imaging [310] and optical coherence tomography imaging [132, 268]. Additionally, UDA has been used in medical image classification [2, 180] and diagnosis [308]. For instance, Liu *et al.* [155, 167] explore the subtype of congenital heart disease [269]. The disease level has been investigated in Liu *et al.* [152, 153], in which the Kaggle Diabetic Retinopathy (KDR)[2] is used as the source domain, and the recent Indian Diabetic Retinopathy Image Dataset (IDRiD) dataset [212] is used as the target domain.

4.3 Video Analysis

Video data contain rich spatial and temporal semantic information. However, it is challenging to collect and annotate a large volume of video data to learn useful spatiotemporal features. Annotation of all video frames is labor-intensive and time-consuming for different target applications and devices [131, 207, 231]. Accordingly, UDA has been applied to video analysis tasks, including action recognition [31, 34, 42, 203], person re-identification [189], action segmentation [32, 33], video captioning [36], video quality assessment [35], and video artifact reduction [78].

Because there are few well-organized video datasets in early work, an image-to-video adaptation method is proposed to use a large-scale image dataset to train a model for video analysis. Sohn *et al.* [245] improve accuracy in face recognition using a video through image-to-video domain adaptation as in Figure 8(a). They attempt to overcome the difference of visual quality between still images and video frames. Liu *et al.* [172] propose a deep image-to-video

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[2] https://www.kaggle.com/c/diabetic-retinopathy-detection

adaptation and fusion network (DIVAFN) to enhance accuracy in video action recognition, by transferring knowledge learned from images. In addition, UCF-HMDB$_{full}$ and Kinetics-Gameplay [31] have been collected to promote video domain adaptation and benchmark the performance in the presence of large domain discrepancy.

Most pre-trained networks for video analysis tend to perform poorly, when a pre-trained model encounters unseen temporal dynamics on the target side. There is prior work to resolve the problems in video action recognition, by overcoming domain discrepancies along the spatial and temporal directions. Chen *et al.* [31] propose a temporal attentive adversarial adaptation network (TA^{3}N) in Figure 8(b). They attempt to align two domains spatio-temporally, by encoding spatio-temporal features using an attention mechanism. Choi *et al.* [42], Pan *et al.* [203], and Chen *et al.* [34] improve the attention mechanism for better alignment. Video UDA on action recognition is extended to more realistic settings, using videos collected from surveillance cameras [195] and drones [41].

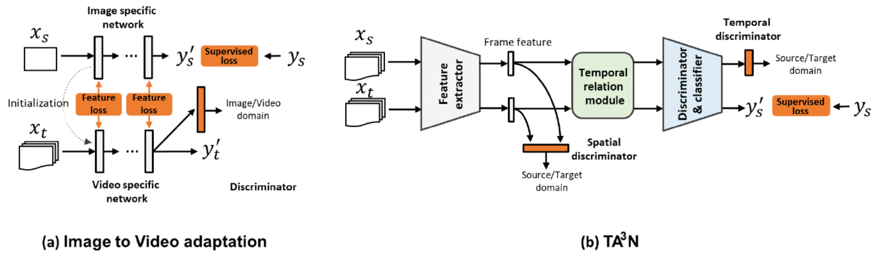

Figure 8: (a) Example of image-to-video adaptation [245] and (b) example of UDA for video analysis [31].

UDA is actively studied for video scene analysis and restoration. Chen *et al.* [30] propose VideoGAN to focus on the translation of video-based data and transfer the data across different domains. Guizilini *et al.* [76] present a video segmentation method using self-learning to bridge a domain gap between simulated and real videos. UDA is also applied to face recognition [60], person re-identification [189], and video captioning [36]. In addition to the analysis of high-level semantics, there is prior work for UDA in low-level video processing. Chen *et al.* [35] and Ham *et al.* [78] present various UDA methods for video quality assessment and video artifact reduction. They attempt to provide reliable performance of a network, when the visual quality of a video frame is different between source and target domains.

The typical evaluation datasets for image-to-video adaptation include UCF-Olympic, UCF-HMDBsmall, UCF-HMDBfull, and Kinetics-Gameplay [31]. In addition, the Kinetics and NEC-DRONE datasets are utilized for evaluation of video UDA on action recognition [41]. For the video quality assessment, UDA approaches are evaluated on DIV2K, BSD68, and Set12 datasets [78].

4.4 Natural Language Processing

Similar to the visual data processing, the necessity of developing UDA methods has emerged in NLP [238], partly because it is costly and demanding to annotate the sheer volume of language data.

Sentiment analysis is the most explored application to develop UDA methods in NLP [215]. In early attempts of UDA in NLP, Ganin *et al.* [66] propose a domain-adversarial neural network (DANN). UDA is carried out by adding a domain classifier that is connected to a feature extractor through a gradient reversal layer. It has motivated several studies [72, 136, 219, 239]. Shen *et al.* [239] utilize the adversarial training to minimize the estimated Wasserstein distance between source and target samples. Rocha and Cardoso [219] indicate that the adversarial training method can be more effective, when the source and target language datasets contain several content variations in addition to the language shift. Furthermore, UDA methods are applied to perform various NLP tasks, including dependency parsing [221, 236], POS (part-of-speech) tagging [55, 139], relation extraction [64, 218, 240], trigger identification [196], language identification [136], political data classification [55], etc.

Pre-training has become a key ingredient to deploy an NLP model due to the inherent complexity of the structure of language and the nature of NLP tasks [215, 238]. In recent NLP studies, it is a standard training strategy to fine-tune a transformer-based model with a small amount of data for a target application. A large-scaled language dataset is used for pre-training in the source domain, and task-specific data become the target domain in the context of UDA. With the domain shift, adaptive pre-training has been proposed to compensate for the classical pre-training, such as BERT [14]. AdaptBERT [79] performs domain-adaptive fine-tuning to adapt contextualized embedding by masked language modeling from the target domain. Gururangan *et al.* [77] use both domain-adaptive pre-training and task-specific pre-training methods.

Image captioning is an interdisciplinary area to connect computer vision and NLP. A typical solution to UDA for image captioning would be to leverage a convolutional encoder for extracting the necessary latent information of visual scenes, followed by adopting a text generator, e.g., recurrent neural networks. Similarly, Chen *et al.* [38] use adversarial training for the paired source domain data and unpaired target domain data. Zhao *et al.* [317] develop a dual learning scheme to fine-tune a source domain model trained on a limited dataset to the target domain. Because the output of an image captioning model is a sentence, it poses a challenge to model a conditional distribution. A possible solution would be to encode a sentence label with an additional recurrent neural network as in Che *et al.* [25].

The sentiment classification UDA, across English, Chinese, and Arabic with the dataset in [39], is used for evaluation [219]. The English OntoNotes 5.0 and the Universal Dependencies datasets are used for dependency parsing

UDA evaluation [221]. In addition, the English portion of ACE2005 dataset is used for relation extraction UDA evaluation, which covers a total of 6 genres and 11 relation types.

4.5 Time Series Data Analysis

Various UDA strategies are exploited for tasks using time series data. Among others, with time series medical data, such as electroencephalogram (EEG), electrocardiogram (ECG), and multivariate healthcare data, UDA has been applied to perform sleep classification [61, 297, 314], arrhythmia classification [199, 267], motor imagery [216, 252], etc. Especially, these methods attempt to tackle the distribution discrepancy between different datasets and between subjects, because medical data vary depending on demographic features such as age, sex, and illness. For example, Yoo *et al.* [297] apply both adversarial training and self-training with three different domain discriminators, including domain, subject, and stage discriminators, as shown in Figure 9(a), to preserve local structures of sleep stages as shown in Figure 9(b).

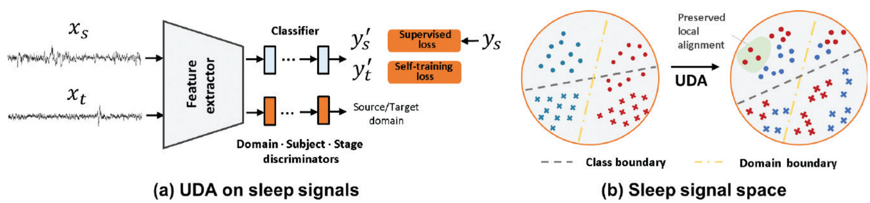

Figure 9: (a) Example of UDA for sleep classification [297] and (b) sleep signal space.

Existing work on emotion recognition [83, 86, 133, 296], speech recognition [3, 110, 184, 265], and imagined speech recognition [102] also brings the concept of UDA. Moreover, the effectiveness of UDA is explored for applications that use industrial time series data, including human action recognition [23, 59, 101, 233], inertial tracking [26], driving maneuver prediction [253], anomaly detection [191], fault diagnosis [177], and lifetime prediction [47, 214].

Besides, time-series UDA approaches are developed to effectively capture the temporal dependencies of time series data that may be neglected, by visual data-based methods. For instance, based on DANN, recurrent domain adversarial neural network (R-DANN) and variational recurrent adversarial deep domain adaptation (VRADA) [213] are proposed by exploiting the long short-term memory (LSTM) network [89] and variational RNN [44] as a feature extractor, respectively. More models, such as a sparse associative structure alignment (SASA) model [16] and a convolutional deep domain adaptation model for time series data (CoDATS) [276], are developed to improve time series UDA performance.

For sleep signal UDA, the Montreal Archive of Sleep Studies is used as the source domain, while the Sleep-EDF database and Sleep-EDF-st database are used as the target domain [297]. For emotion recognition, the DEAP dataset and DREAMER dataset are usually used as the benchmarks [86].

4.5.1 Climate science and Geosciences

In recent years, deep learning has been applied to numerous applications on the Earth science, e.g., climate science and geosciences [17]. Similar to the other application areas, the perception of remote sensing data can also have the problem of domain shift, across location and time. In Huang *et al.* [98], UDA across active and passive satellite data is developed for cloud type detection. Notably, the active spaceborne Lidar sensor CALIOP onboard CALIPSO satellite has better representation capability and sensitivity to aerosol types and cloud phases, while the passive spectroradiometer sensor VIIRS onboard Suomi-NPP satellite has wide swaths and better spatial coverage. Mengqiu *et al.* [190] propose a UDA method to bridge the gap between the abundant labeled land fog data and the unlabeled sea fog data for sea fog detection. Soto *et al.* [246] exploit the cycleGAN-based UDA approach [318] for deforestation detection in the Amazon forest.

In addition, UDA has been widely explored in many applications on geoscience research. Nasim *et al.* [197] investigate a UDA approach to mitigate the domain gap between seismic images of the F3 block 3D dataset from offshore Netherlands and Penobscot 3D survey data from Canada, which utilizes the EarthAdaptNet to semantically segment the seismic images, when a few classes have data scarcity. The teacher-student network has been used in Hu *et al.* [96] for the classification of the Sentinel-2 images across cities, e.g., Moscow and Munich. Hu *et al.* [178] conduct experiments on Satelite Image Time Series (SITS) classification using existing natural image-based UDA methods and find that those UDA methods are ineffective, due to the temporal nature of SITS. Nyborg *et al.* [200] propose an explicit UDA method that learns the temporal shift of SITS for crop classification and introduce a dataset for cross-region adaptation from SITS in four different regions in Europe. Ma and Zhang [179] introduce a UDA approach for corn-yield prediction using time-series vegetation indices and weather observations.

5 Promising Directions

As stated above, advanced deep UDA methods have been widely applied to numerous tasks and applications. In this section, we point to a number of underexplored areas that are of great theoretical and practical importance, which can be promising future research directions.

5.1 Realistic Shift Assumption

Most of the current UDA methods have focused on the alignment of covariate shift. As analyzed in Section 1, however, there exist four kinds of possible shifts in real-world applications [119]. While numerous works are proposed in the literature to address conditional or covariate shifts, label and concept shifts have not been investigated extensively. Notably, approaches for the adversarial feature alignment of the covariate shift and approaches without considering the conditional shift have been outperformed by several competing approaches, e.g., self-training [321], dropout [227], and moment matching methods [205] in most of the benchmarks. As such, it is important to incorporate both conditional and covariate shifts, as it is ill-posed to take one of them into consideration [118, 307]. In Liu *et al.* [143], theoretical analysis and methodology under the conditional and label shift assumptions are discussed in adversarial learning-based UDA.

It is, therefore, necessary to incorporate more realistic assumptions of the domain shifts, depending on real-world tasks at hand.

5.2 Partial/Open-set Domain Adaptation

Partial UDA can be seen as a special category of label shifts, in which some classes have zero probability in a target domain. Due to the mismatch of categories between source and target domains, conventional UDA approaches may result in negative transfer [18, 19, 116]. Similarly, open-set UDA or universal UDA are presented under the assumption that there are novel classes in a target domain; this approach thus could lead to novel class discovery or out-of-distribution detection [206].

Lipton *et al.* [140] propose a test distribution estimator to detect the label shift. Azizzadenesheli *et al.* [4] introduce a regularization approach to correct the label shift. Chen *et al.* [37] cast the problem of the label shift as an optimal transportation-based UDA task, which is closely related to the class imbalance problem in the MMD framework. Wu *et al.* [277] propose an asymmetrically-relaxed alignment approach using the adversarial UDA. However, these approaches assume that there is no conditional shift.

As noted above, partial UDA can be regarded as a special case of the label shifts. Therefore, developing more general label shift UDA methods for both small label distribution shift and partial UDA can be more practical for real-world applications. In addition, novel class/subtype discovery could be incorporated into the open-set UDA.

5.3 Source-free Domain Adaptation

Data privacy has been a critical concern over cross-center collaboration, especially in the medical domain. Conventional UDA requires the large scale and well-labeled source domain data to be shared, which may cause issues over source domain data leakage and intellectual property [5]. To address this, Liu *et al.* [159, 166] propose a source-free UDA approach with white-box domain adaptation to delineate anatomic structures in medical imaging data. Specifically, that work leverages an off-the-shelf pre-trained segmentation model to adapt to a target domain, by migrating its batch normalization statistics. In addition, recently, Yin *et al.* [295] propose a deep inversion technique to demonstrate that original training data can be recovered from knowledge used in the course of white-box domain adaptation [304]. To address this, a recent work [169] uses black-box UDA segmentation, for which no prior knowledge of network weights is needed for adaptation. Liu *et al.* [168] further propose that a target domain network structure could be different from a trained source domain model to achieve UDA for segmentation.

Source-free domain adaptation is also closely related to test time adaptation, in that we encounter a single or a few test samples that are different from source domain data [62, 165, 223, 266]. To accommodate continuously changing environments, we expect that frameworks employed would be source-free, involve low-cost training in mobile devices, and avoid catastrophic forgetting [90, 181, 280, 281].

Therefore, UDA under a more strict data sharing setting can be a promising direction, which only shares the pre-trained white/black-box source domain model. We note that the model sharing is also related to the federated learning, which is another important transfer learning problem [292].

5.4 Continuous and Test Time Adaptation

Existing work on UDA usually assumes that several stationary domains exist for which prior work attempts to achieve domain adaptation between discrete distributions. In real-world environments, however, the change in distributions could be continuous. For example, when one drives from Seattle to Boston, one will cross snow-capped mountains, deserts, plateaus, flatlands, hilly areas, etc. There is, however, no distinct boundaries between these environments, and thus the shift is smoothly evolving. Therefore, one needs to consider lifelong learning to progressively adapt a trained model to new environments [146].

There is a need to build well organized and gradually changing UDA datasets. In addition, the mixup or interpolation technology [171] would be useful to hallucinate the intermediate data between two largely different domains to facilitate UDA.

5.5 Adaptation in Foundation Model Era

Foundation models [9] are recently surged as a hot topic to utilize super large labeled data, which can incorporate sufficiently variant data. In addition, they are robust to the covariate shift in many cases. Then, one can ask: if we have a sufficiently large training set with diverse data distributions, can they generalize well on all of the implementation scenarios? Though applying domain generalization may address the covariate and conditional label shifts, it is challenging to alleviate the label shift, without access to target domain data. In addition, the concept shift can also cause a problem, even though there are sufficient training data.

UDA methods to deal with label shift can be an important direction in the era of foundation models. In addition, it is interesting to investigate the generality of different foundation models.

5.6 Semi-supervised Domain Adaptation

While there have been great advances in UDA, due to diverse target domains, the performance of UDA is not satisfactory in many cases [164]. In such circumstances, labeling a small set of target domain data could be a viable solution [260]. Along this direction, semi-supervised domain adaptation (SSDA) is proposed, as it can leverage both labeled source and target data as well as unlabeled target data. Further, several SSDA classification methods have been proposed to use instance constraints [58], subspace learning [293], entropy minimax [226], adversarial attack [115], etc. These methods are based on discriminative class boundaries for image classification, which, however, cannot be directly applied to segmentation. In Liu *et al.* [164], the asymmetric co-training is proposed to achieve semi-supervised domain adaptation for medical image segmentation.

The unified framework for both SSL and UDA is able to utilize both labeled and unlabeled target domain data. The alternative training based methods, e.g., self-training, have been applied to these two tasks, which can have a great potential for semi-supervised domain adaptation. Semi-supervised domain adaptation for object detection and image generation, however, are largely underexplored.

5.7 Domain Generalization

Most of the prior work on UDA assumes that there is a single source domain, while recent work has shown that network generalization can be further improved with multiple source domain sets [192]. By observing varying datasets, networks can learn domain invariant cues. Domain generalization further removes the requirement of unlabeled target domain data in multi-source UDA [186]. There are two main streams for domain generalization tasks. The first stream is to learn domain invariant features [69]. For example, Li *et al.* [128, 141] utilize adversarial training to mitigate the domain divergence. The second stream targets to fuse the domain-specific feature representations.

For instance, Mancini *et al.* [182] develop the domain-specific classifiers with multiple independent models. Then, the domain agnostic components are fused to form the domain-wise classification probability. Ding and Fu [57] match the low-rank structure of domain-specific features. Liu *et al.* [146] further align the conditional distribution with a variational inference scheme.

Domain generalization is usually considered a multi-task learning problem [141], by exploring multiple source domains. How to achieve good test time adaptation for an unseen domain can be a challenging problem. For example, the label shift can be adaptively corrected in test time implementation as in Liu *et al.* [146].

5.8 Out-of-distribution Detection

OOD detection or deep OOD detection has recently been an active research topic [25]. If the domain shift is too large for reliable adaptation, a more reasonable choice would be to reject significant outliers rather than to make adapted predictions with high uncertainty. While detecting the OOD samples in a low-dimensional space has been well-studied [211], it is still challenging to detect OOD in high-dimensional complex data, e.g., images [138]. For example, Hendrycks and Gimpel [87] identify that trained DNNs usually have higher maximum softmax output for in-distribution examples than anomalous ones. A possible improvement of this baseline would be to consider both the in-distribution and out-of-distribution training samples during training [88]. However, enumerating all possible OOD distributions before deployment is usually not possible. Liang *et al.* [138] propose that the difference between maximum probabilities in softmax distributions on ID/OOD samples can be made more significant, by means of adversarial perturbation pre-processing during training.

Devries and Taylor [56] augment the classifier with a confidence estimation branch, and adjust the objective using the predicted confidence score for training. Lee *et al.* [125] train a classifier simultaneously with a GAN, with an additional objective to encourage low confidence in generated samples. Hendrycks *et al.* [88] use real OOD samples instead of generated ones to train the detector. Vyas *et al.* [263] label a part of training data as OOD samples to train a classifier, where that approach dynamically changes the partition of ID and OOD samples. These improvements based on [87] typically need to retrain a classifier with modified structures or optimization objectives. Recently, Lee *et al.* [126] propose a new framework for anomaly detection. A number of methods [126, 138, 263] need OOD samples for tuning hyper-parameter selection, e.g., the threshold for verification. DVN [25] aims to verify the predictions of a trained deep model, by estimating $p(x|y)$ rather than $p(x)$.

It remains an exciting open problem of how to train good density estimators on complex datasets, which is an important module for OOD detection. In addition, the connection and difference between OOD sample and adversarial attack samples also need further explorations.

6 Conclusion

In this paper, we have systematically reviewed deep learning-based UDA approaches. Deep learning has already surpassed its predecessors in a variety of fields, and future research in deep learning will strive toward the seamless deployment of trained models in a source domain into unseen and new target domains. Toward this goal, we provided a comprehensive summary of recent deep UDA approaches along with the merits and demerits of those approaches. Furthermore, several successful applications of deep UDA methods were reviewed. Finally, several challenges of the current deep UDA approaches were identified, which could serve as promising future directions.

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