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

Xiaofeng Liu\textsuperscript{a}, Chaehwa Yoo\textsuperscript{b}, Fangxu Xing\textsuperscript{a}, Hyejin Oh\textsuperscript{b}, Georges El Fakhri\textsuperscript{a}, Je-Won Kang\textsuperscript{b}, Jonghye Woo\textsuperscript{a}

\textsuperscript{a} Gordon Center for Medical Imaging, Massachusetts General Hospital and Harvard Medical School, Boston, MA, USA
\textsuperscript{b} Dept. of Electronic and Electrical Engineering and Graduate Program in Smart Factory, Ewha Womans University, Seoul, South Korea

Editor: C.C. Jay Kuo

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 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 (Goodfellow et al., 2016). 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 (LeCun et al., 2015). 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 (Bengio et al., 2013). 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 (Huo et al., 2022). 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 (Xu and Yan, 2022). This learning strategy, however, suffers from shifts in data distributions, i.e., domain shift, between source and target domains (Zhang et al., 2022). 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 (Che et al., 2021). 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 (Liu et al., 2021i, 2022g), as shown in Fig. 2. UDA is aimed at mitigating domain shifts between source and target domains (Kouw, 2018). The solution to UDA is primarily classified into statistic moment matching (e.g., maximum mean discrepancy (MMD) (Long et al., 2018)), domain style transfer (Sankaranarayanan et al., 2018), self-training (Zou et al., 2019; Liu et al., 2021e1), and feature-level adversarial learning (Ganin et al., 2016; He et al., 2020a b Liu et al., 2018).

There are several previous review papers focusing on domain adaptation (Beijbom, 2012; Bungum and Gambäck, 2011 Betlehem et al., 2015; Sun et al., 2015; Wang and Deng, 2018; Csurka, 2017; Zhao et al., 2018; Kouw, 2018; Kouw and Loog, 2019; Zhao et al., 2020b; Wilson and Cook, 2020; Ramponi and Plank, 2020), and the broader problem of transfer learning (Pan and Yang, 2009; Cook et al., 2013; Lazaric, 2012 Shao et al., 2014; Tan et al., 2018; Zhang et al., 2019b). As shown in Fig. 1, domain adaptation can be seen as a special

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

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.

case of transfer learning, with the assumption that labeled data are available only in a source domain (Pan and Yang, 2009). In 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 (Csurka, 2017; Kouw, 2018; Kouw and Loog, 2019), normalization statistic-based (Csurka, 2017; Kouw and Loog, 2019; Zhao et al., 2018, 2020b), ensemble-based (Csurka, 2017; Wang and Deng, 2018; Kouw and Loog, 2019; Zhao et al., 2018), or self-training-based methods (Wilson and Cook, 2020). Moreover, some of them only focus on limited application areas, such as visual data analytics (Wang and Deng, 2018; Csurka, 2017; Oza et al., 2021) or natural language processing (NLP) (Ramponi and Plank, 2020). 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 Sec. 2. Then, various recent UDA methods are discussed and compared to each other in Sec. 3. Next, we show how UDA is applied to multiple application areas in Sec. 4. In Sec. 5, we highlight promising future directions. Finally, we conclude this paper in Sec. 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 \( p_s(x, y) \) and a different target domain distribution \( p_t(x, y) \). Then, a labeled dataset \( D_S \) is selected \( i.i.d. \) from \( p_s(x, y) \), and an unlabeled dataset \( D_T \) 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 \( D_S \) and \( D_T \). 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 (Ge et al., 2021a). UDA (Ganin et al., 2016; Tzeng et al., 2017) is motivated by the following theorem (Kouw, 2018):

**Theorem 1** For a hypothesis \( h \)

\[
L_s(h) \leq L_t(h) + d[p_S, p_T] + \min[\mathbb{E}_{x \sim p_s}[p_s(y|x) - p_t(y|x)], \mathbb{E}_{x \sim p_t}[p_s(y|x) - p_t(y|x)]].
\]

Here, \( L_s(h) \) and \( L_t(h) \) 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 (Salimans et al., 2016). 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 \( L_s(h) \) and the divergence between two domains is considered an upper bound of the error in a target domain \( L_t(h) \). \( L_s(h) \) 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 \( L_t(h) \).

Domain shifts can be categorized into four types (Kouw, 2018), as shown in Fig. 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
Figure 3: A summary of four possible domain shifts. The red mask indicates the most common domain shift scenarios in UDA (Liu et al., 2021b). Note that $p(x)$ can be aligned, if $p(x|y)$ is aligned with the law of total probability (Zhang et al., 2013).

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 (Liu et al., 2021b). However, estimating $p_t(x|y)$ without $p_t(y)$ is ill-posed (Zhang et al., 2013). Moreover, the label shift (Chan and Ng, 2005), a.k.a. target shift, indicates the sample proportion of involved classes is different between two domains. Furthermore, the concept shift (Kouw, 2018) 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.

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 Fig. 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 (Rozantsev et al., 2018), correlation alignment (CORAL) (Sun et al., 2016), contrastive domain discrepancy (CDD) (Kang et al., 2019), Wasserstein distance (Liu et al., 2020b), graph matching loss (Yan et al., 2016), 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 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 (Rozantsev et al., 2018), as shown in Fig. 5(a). Following vanilla MMD, multiple kernel MMD (MK-MMD) (Long et al., 2015) and joint MMD (JMMD) (Long et al., 2017) are further proposed to achieve a more robust MMD estimation.

Similar to MMD, CORAL is proposed, based on a polynomial kernel (Sun et al., 2016). 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 (Sun and Saenko, 2016), an Euclidean distance measure in mapped correlation alignment (Zhang et al., 2018b), log-Euclidean distances (Wang et al., 2017), and geodesic distances (Morerio et al., 2017). CORAL has also been generalized to possibly infinite-dimensional covariance matrices in RKHS (Zhang et al., 2018c). The statistics beyond the first-order, e.g., MMD, and second-order, e.g., CORAL, are further investigated for more accurate CORAL estimation (Chen et al., 2020a).

To achieve class conditioned distribution alignment, CDD (Kang et al., 2019) 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) (Kang et al., 2019) is proposed to alternatively estimate the target domain label with clustering, while minimizing CDD.

In addition, the Wasserstein distance (Liu et al., 2020d; Han et al., 2020; Liu et al., 2019c; Ge et al., 2021b; Liu et al., 2019c), a.k.a. optimal transportation distance or earth mover’s distance (Liu et al., 2020b; c), 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 (Courty et al., 2017). As a deep learning framework, DeepJDOT is further proposed to achieve an end-to-end UDA (Damodaran et al. 2018).

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

Figure 5: Different architectures of (a) MMD-based UDA (e.g., DAN (Long et al., 2015)), and (b) adversarial training based deep UDA (e.g., domain-adversarial neural networks (DANN) (Ganin et al., 2016)).

Furthermore, graph matching has been used as a divergence measure, which aims at finding an optimal correspondence between two graphs (Yan et al., 2016). 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 (Das and Lee, 2018a, b).

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 Eq. (1), adversarial UDAs are used to minimize 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 Ganin et al. (2016); Tzeng et al. (2017), 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 $Dis: \mathbb{R}^K \rightarrow (0,1)$. We note that the classifier $Cls: \mathbb{R}^K \times \mathcal{Y} \rightarrow (0,1)$ 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

$$\max_{Cls} \mathbb{E}_{x \sim p_s} \log C(f(x), y)$$  \hspace{1cm} (2)

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

$$\max_{f} \mathbb{E}_{x \sim p_s} \log C(f(x), y) + \lambda \mathbb{E}_{x \sim p_t} \log (1 - Dis(f(x)))$$  \hspace{1cm} (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 (Tran et al., 2019; Salimans et al. 2016)
can be leveraged, and the three objectives above are used to update the corresponding three modules, respectively. In Eq. (3), if \( f(x) \) is a source domain feature, then \( \text{Dis}(f(x)) \) is trained to produce 0 and vice versa. Note that maximizing \( \mathbb{E}_{x \sim p_t} \log \text{Dis}(f(x)) \) for \( \text{Dis} \) in Eq. (3), while maximizing \( \mathbb{E}_{x \sim p_t} \log(1 - \text{Dis}(f(x))) \) for \( f \) in Eq. (4) has made this formula a \textit{minmax} adversarial game.

Specifically, domain adversarial neural network (DANN) (Ganin et al., 2016) utilizes the gradient reversal layer as a domain discriminator \( \text{Dis} \). In addition, adversarial discriminative domain adaptation (ADDA) (Tzeng et al., 2017) 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. (2015) propose to enforce 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 (Goodfellow et al., 2016). Similarly, Motiian et al. (2017) 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 Volpi et al. (2018) to achieve source domain feature augmentation.

Instead of modeling the domain divergence with the JS divergence as in conventional adversarial UDA (Salimans et al., 2016), a discriminator for estimating the Wasserstein distance is further proposed (Shen et al., 2018). Following the recent Wasserstein GAN (Adler and Lunz, 2018), 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. (2018), 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 (Ioffe and Szegedy, 2015), smoother optimization, and more
Figure 7: Different architectures for BN-based methods, e.g., (a) AdaBN (Li et al., 2018c) and OSUDA (Liu et al., 2021m, 2022b).

Recent work (Chang et al., 2019; Maria Carlucci et al., 2017; Wang et al., 2019; Mancini et al., 2018b) 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 (Zhang et al., 2020a). Besides, once the low-order BN statistics discrepancy has been partially mitigated, the high-order BN statistics can be shareable between two domains (Maria Carlucci et al., 2017; Wang et al., 2019). Note that all of the aforementioned approaches (Chang et al., 2019; Maria Carlucci et al., 2017; Zhang et al., 2020a; Wang et al., 2019; Mancini et al., 2018b) need joint training on source domain data. Recently, OSUDA (Liu et al., 2021m, 2022b), as shown in Fig. 7(b), is proposed to reduce 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.
(Shrivastava et al., 2017). In addition, the network can be trained simultaneously with GANs (Bousmalis et al., 2017; Hoffman et al., 2018), as shown in Fig. 6(b).

Cycle reconstruction for image style translation plays an important role in unpaired translation tasks (Zhu et al., 2017; Kim et al., 2017; Yi et al., 2017). However, it is challenging to efficiently constrain local structures, thus leading to significant distortions in the translated images and their segmentations (Yang et al., 2020a). To address this, Yang et al. (2020a) 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 $||M(x_t) - M(G_{TC}(x_t))||_1$. Liu et al. (2022e) propose to learn 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.

### 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 (Zou et al., 2019). 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 (Wei et al., 2021; Mei et al., 2020b; Shin et al., 2020). Whereas self-training was initially presented as part of semi-supervised learning (Triguero et al., 2015), recently proposed deep self-training methods combine feature embedding with alternative learning in a unified manner, thus yielding flexible domain adaptation (Zou et al., 2019).

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 (Zou et al., 2019). Additionally, to tackle the problem of the noisy and unreliable pseudo-labels, Zou et al. (2019) propose to construct a more conservative pseudo-label in order to smooth the one-hot hard label to a soft label vector. Liu et al. (2021e) further resort to an additional supervision signal of an energy-based model for regularization, which is independent of the pseudo-label. Mei et al. (2020a) propose to explore instance-wise self-training for UDA.

In addition to the discriminative tasks, such as classification and segmentation, Liu et al. (2021l) 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 (Der Kiureghian and Ditlevsen, 2009; Kendall and Gal, 2017; Hu et al., 2019). 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 of 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 (Kolesnikov et al., 2019). This group of work assumes that alignment can be achieved by carrying out source domain classification and reconstruction of target domain data (Ghifary et al. 2016) or both source and target domain data (Bousmalis et al., 2016). In Ghifary et al. (2016), 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. (2016) to train its domain separation networks.

In addition to the conventional reconstruction tasks (Liu et al., 2018), new self-supervision tasks have been proposed, e.g., image rotation and jigsaw predictions (Xu et al., 2019a). Kim et al. (2020a) propose both in-domain and across-domain self-supervision to achieve UDA with fewer source domain labels. Lian et al. (2019) propose a self-motivated pyramid curriculum for segmentation.

### 3.7 Low density target boundary

Several UDA approaches based on a popular clustering assumption (Chapelle and Zien, 2005) 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 (He et al., 2020b). To this end, Shu et al. (2018) 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 (Shu et al., 2018). Kumar et al. (2018) propose to 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 (Carlucci et al., 2017). 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 (Wei and Hsu, 2018).

Saito et al. (2017) 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. (2019b) extend the adversarial dropout for convolutional layers with a channel drop rather than an element drop. TDDA (Gholami et al., 2019) focuses on task-discriminative alignment for UDA.
3.8 Other Methods

DEV (You et al., 2019) is proposed to achieve UDA via model selection. The prototype with clustering is utilized in Pan et al. (2019) for class-wise adaptation. Liu et al. (2021i, 2022g) further extend the class-wise prototype to fine-grained subtypes. Wu et al. (2020) propose to apply dual mixup regularization to adversarial UDA. Domain randomization is proposed in Rodriguez and Mikolajczyk (2019); Kim et al. (2019b) 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. (2019); Deng et al. (2021). The inter/intra object correlation is explored in a graph reasoning framework for domain adaptation in Xu et al. (2020). Liu et al. (2022c) propose to 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 (Bousmalis et al., 2018), or jointly, e.g., CyCADA (Judy et al., 2018). Following AdaBN, several works have shown that the BN alignment can be added on top of other UDA methods (Li, 2018; Bousmalis et al., 2018; French et al. 2017; Kang et al., 2019). The BN alignment and entropy minimization for low-density target boundary are combined for source data free UDA (Liu et al., 2021m, 2022b). Adversarial domain-invariant feature alignment has been applied on different levels, following an ensemble scheme (Kumar et al., 2018). Low-density target boundary and domain-invariant feature learning are jointly learned in Lee et al. (2019a); Saito et al. (2018). Kang et al. (2018) combine generative image mapping with the alignment of model attention. PANDA (Hu et al., 2020a) 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. (2017) use AlexNet (Krizhevsky et al., 2012) backbone for the task, where the approach is compared against the source model, the DANN method (Ganin and Lempitsky, 2015), and the variations of MMD, e.g., DDC (Tzeng et al., 2014), DAN (Long et al., 2015), JAN (Long et al., 2017) and RTN (Long et al., 2016). Zellinger et al. (2017) compare their CMD methods with other discrepancy-based methods, e.g., DDC (Tzeng et al., 2014), deep CROAL (Sun and Saenko, 2016), DLID (Chopra et al., 2013), AdaBN (Li et al., 2016)) and adversarial DANN (Ganin and Lempitsky, 2015). 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 (Liu et al., 2021f,g, 2017). Among these shifts, the expression, ethnicity, and imaging modality have discrete variations, while other attributes have continuous variations (Liu et al., 2019b, 2021a). In Kan et al. (2015), a bi-shifting auto-encoder framework is proposed for face identification with the domain shifts of view, ethnicity, and sensor. Hong et al. (2017) generate different face views for domain adaptation. Sohn et al. (2017) propose to 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 (Saenko et al., 2010) 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 (Peng et al., 2017) is a preferred choice. DomainNet (Peng et al., 2019b) is the largest domain adaptation dataset to date, which consists of ~0.6M images with 345 sub-classes from 24 meta-classes.

In addition to classification with discrete labels, several tasks have ordinal class labels (Liu et al., 2019a, 2020a). 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. (2021h, 2022a), 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 (Oza et al., 2021). 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 Chen et al. (2018c); Saito et al. (2019b); Sindagi et al. (2020); Hsu et al. (2020a); VS et al. (2021). In addition, adversarial generative mapping at the image level has been applied in Zhang et al. (2019a); Rodriguez and Mikolajczyk (2019); Hsu et al. (2020b); Chen et al. (2020b); Yu et al. (2022). In RoyChowdhury et al. (2019); Khodabandeh et al. (2019); Kim et al. (2019a); Zhao et al. (2020a); Li et al. (2021b); Gu et al. (2022), 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 (Cordts et al., 2016) to Foggy Cityscapes (Sakaridis et al., 2018), which is rendered from Cityscapes, by adding the fog noise. In addition, several works (Xu et al., 2019b) 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 (Tajbakhsh et al., 2020; Liu et al., 2022d). 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 (Yu and Koltun, 2015; Tsai et al., 2018; Mei et al., 2020a). Self-training based methods have also been developed for semantic segmentation (Chen et al., 2019b; Liu et al., 2021d).

A typical task is to adapt the large-scale labeled game engine rendered data, i.e., GTA5 (Richter et al., 2016), to the real-world data, i.e., Cityscapes (Cordts et al., 2016), 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 (Yang et al., 2020b), all of the samples in the GTA5 dataset are used as the source domain, while the training set of Cityscape with a total of 2,975 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 (Yang et al., 2018, 2019a; Liu et al., 2021k, j; Wang et al.; Xing et al., 2022).

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 (He et al., 2021b). Self-training has also been applied to the image synthesis task. For example, Liu et al. (2021l) propose to leverage self-training for the image synthesis task, which also considers both epistemic and aleatoric uncertainties (Der Kiureghian and Ditlevsen, 2009). Specifically, Liu et al. (2021l) aim at cross modality synthesis using paired sets of images acquired from two different sites.

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. (2019) 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 real medical problems. Ouyang et al. (2019) 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. (2020) 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. (2020c) propose to achieve cross-device retinal OCT segmentation. Liu et al. (2022c) propose to facilitate cross-modality brain tumor segmentation with self-semantic contouring. Additionally, more methods have been proposed to improve the segmentation UDA networks from within their structures. To enable flexibility of two-way adaptations, Ning et al. (2021) propose a bidirectional UDA framework based on disentangled representation learning. It achieves decent performances in both the forward adaptation direction, from MRI to computed tomography (CT), and the backward direction, from CT 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 (Zhuang and Shen, 2016).

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. (2021m, 2022h) propose to 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 (He et al., 2021b; Karani et al., 2021). In addition, He et al. (2021b) 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 (Zhang et al. (2018a)) and optical coherence tomography imaging (Wang et al., 2021b; Li et al., 2021a). Additionally, UDA has been used in medical image classification (Ahn et al., 2020; Mahapatra et al., 2021) and diagnosis (Zhang et al., 2020b). For instance, Liu et al. (2021i, 2022g) propose to explore the subtype of congenital heart disease (Wang et al., 2021c). The disease level has been investigated in Liu et al. (2021h, 2022a), in which the Kaggle Diabetic Retinopathy (KDR)\(^1\) is used as the source domain, and the recent Indian Diabetic Retinopathy Image Dataset (IDRiD) dataset (Porwal et al., 2018) is used as the target domain.

The evaluation database used in He et al. (2021b) for T1-weighted to T2-weighted MRI translation is brain MRI datasets from three IXI centers\(^2\). In addition, paired cine and tagged tongue MRI data in two clinical sites datasets are used in Liu et al. (2021l).

---

1. https://www.kaggle.com/c/diabetic-retinopathy-detection
2. https://brain-development.org/ixi-dataset/
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 (Li et al. (2019a); Peng et al. (2019a); Saleh et al. (2019)). Accordingly, UDA has been applied to video analysis tasks, including action recognition (Chen et al. (2019c); Choi et al. (2020b); Pan et al. (2020); Chen et al. (2022)), person re-identification (Mekhazni et al. (2020)), action segmentation (Chen et al. (2020e,d)), video captioning (Chen et al. (2021b)), video quality assessment (Chen et al., 2021a), and video artifact reduction (Ham et al., 2021).

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. (2017) improve accuracy in face recognition using a video through image-to-video domain adaptation as in Fig. 8(a). They attempt to overcome the difference of visual quality between still images and video frames. Liu et al. (2019d) propose a deep image-to-video adaptation and fusion network (DIVAFN) to enhance accuracy in video action recognition, by transferring knowledge learned from images. In addition, UCF-HMDB\textsubscript{full} and Kinetics-Gameplay (Chen et al., 2019c) 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. (2019c) propose a temporal attentive adversarial adaptation network (TA\textsuperscript{3}N) in Fig. 8(b). They attempt to align two domains spatio-temporally, by encoding spatio-temporal features using an attention mechanism. Choi et al. (2020b), Pan et al. (2020), and Chen et al. (2022) improve the attention mechanism for better alignment. Video UDA on action recognition is extended to more realistic settings, using videos collected from surveillance cameras (Mou et al., 2021) and drones (Choi et al., 2020a).
UDA is actively studied for video scene analysis and restoration. Chen et al. (2020c) propose VideoGAN to focus on the translation of video-based data and transfer the data across different domains. Guizilini et al. (2021) 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 (Ekladious et al., 2020), person re-identification (Mekhazni et al., 2020), and video captioning (Chen et al., 2021b). In addition to the analysis of high-level semantics, there is prior work for UDA in low-level video processing. Chen et al. (2021a) and Ham et al. (2021) 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 (Chen et al., 2019c). In addition, the Kinetics and NEC-DRONE datasets are utilized for evaluation of video UDA on action recognition (Choi et al., 2020a). For the video quality assessment, UDA approaches are evaluated on DIV2K, BSD68, and Set12 datasets (Ham et al., 2021).

4.4 Natural Language Processing

Similar to the visual data processing, the necessity of developing UDA methods has emerged in NLP (Sharir et al., 2020), 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 (Ramponi and Plank, 2020). In early attempts of UDA in NLP, Ganin et al. (2016) 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 (Li et al., 2019b; Shen et al., 2018; Rocha and Cardoso, 2019; Ghosal et al., 2020). Shen et al. (2018) utilize the adversarial training to minimize the estimated Wasserstein distance between source and target samples. Rocha and Cardoso (2019) 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 (Sato et al., 2017; Rotman and Reichart, 2019), POS (part-of-speech) tagging (Desai et al., 2019; Lim et al., 2020), relation extraction (Fu et al., 2017; Rios et al., 2018; Shi et al., 2018), trigger identification (Naik and Rose, 2020), language identification (Li et al., 2019b), political data classification (Desai et al., 2019), 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 (Sharir et al., 2020; Ramponi and Plank, 2020). 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 (Burstein et al., 2019). AdaptBERT (Han and Eisenstein, 2019) performs domain-adaptive fine-tuning to adapt contextualized embedding by masked language modeling from the target
domain. Gururangan et al. (2020) propose to 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. (2017) propose to use adversarial training for the paired source domain data and unpaired target domain data. Zhao et al. (2017) 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. (2021).

The sentiment classification UDA, across English, Chinese, and Arabic with the dataset in Chen et al. (2018b), is used for evaluation (Rocha and Cardoso, 2019). The English OntoNotes 5.0 and the Universal Dependencies datasets are used for dependency parsing UDA evaluation (Rotman and Reichart, 2019). 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 (Zhao et al., 2021; Yoo et al., 2021; Fan et al., 2022), arrhythmia classification (Niu et al., 2020; Wang et al., 2021a), motor imagery (Raza and Samothrakis, 2019; Tang and Zhang, 2020), 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. (2021) apply both adversarial training and self-training with three different domain discriminators, including domain, subject, and

---

Figure 9: (a) Example of UDA for sleep classification (Yoo et al., 2021) and (b) sleep signal space.
stage discriminators, as shown in Fig. 9(a), to preserve local structures of sleep stages as shown in Fig. 9(b).

Existing work on emotion recognition (Li et al., 2018b; Yin et al., 2020b; He et al., 2021a, 2022), speech recognition (Wang et al., 2018; Manohar et al., 2018; Khurana et al., 2021; Anoop et al., 2021), and imagined speech recognition (Jimenez-Guarneros and Gomez-Gil, 2021) 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 (Jiang et al., 2018; Chang et al., 2020; Du et al. 2019; Sanabria et al., 2021), inertial tracking (Chen et al., 2019a), driving maneuver prediction (Tonutti et al., 2019), anomaly detection (Michau and Fink, 2021), fault diagnosis (Lu et al., 2021), and lifetime prediction (da Costa et al., 2020; Ragab et al., 2020).

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) (Purushotham et al., 2017) are proposed by exploiting the long short-term memory (LSTM) network (Hochreiter and Schmidhuber, 1997) and variational RNN (Chung et al., 2015) as a feature extractor, respectively. More models, such as a sparse associative structure alignment (SASA) model (Cai et al., 2021) and a convolutional deep domain adaptation model for time series data (CoDATS) (Wilson et al., 2020), are developed to improve time series UDA performance.

For sleep signal UDA, the Montreal Archive of Sleep Studies (MASS) is used as the source domain, while the Sleep-EDF database and Sleep-EDF-st database are used as the target domain (Yoo et al., 2021). For emotion recognition, the DEAP dataset and DREAMER dataset are usually used as the benchmarks (He et al., 2022).

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 (Camps-Valls et al., 2021). 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. (2020), 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. (2022) 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. (2020) exploit the cycleGAN-based UDA approach (Zhu et al., 2017) for deforestation detection in the Amazon forest.

In addition, UDA has been widely explored in many applications on geoscience research. Nasim et al. (2022) 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. (2020b) for the classification of the Sentinel-2 images across cities, e.g., Moscow and
Munich. Lucas et al. (2020) conduct experiments on Satellite 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. (2022) 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 (2021) 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 Sec. 1, however, there exist four kinds of possible shifts in real-world applications (Kouw and Loog, 2019). 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 (Zou et al., 2019), dropout (Saito et al., 2017), and moment matching methods (Pan et al., 2019) 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 (Zhang et al., 2013; Kouw, 2018). In Liu et al. (2021b), 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 (Cao et al., 2018b,a; Kim et al., 2020b). Similarly, open-set UDA and 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 (Panareda Busto and Gall, 2017).

Lipton et al. (2018) propose a test distribution estimator to detect the label shift. Azizzadenesheli et al. (2019) introduce a regularization approach to correct the label shift. Chen et al. (2018a) 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. (2019a) 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 (Bateson et al., 2020). To address this, Liu et al. (2021m, 2022b) 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. (2020a) 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 (Zhang et al., 2021). To address this, a recent work (Liu et al., 2022h) uses black-box UDA segmentation, for which no prior knowledge of network weights is needed for adaptation. Liu et al. (2022i) 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 (Royer and Lampert, 2015; Fredericks et al., 2014; Wang et al., 2020; Liu et al., 2021l). 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 (Hoffman et al., 2014; Wulfmeier et al., 2018; Wu et al., 2019b; Mancini et al., 2019).

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 (Yang et al., 2019b).

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 (Liu et al., 2021c).

There is a need to build well organized and gradually changing UDA datasets. In addition, the mixup or interpolation technology (Liu et al., 2018) 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 (Bommasani et al., 2021) 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 (Liu et al., 2022f). In such circumstances, labeling a small set of target domain data could be a viable solution (Van Engelen and Hoos, 2020). 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 (Donahue et al., 2013), subspace learning (Yao et al., 2015), entropy minimax (Saito et al., 2019a), adversarial attack (Kim and Kim, 2020), etc. These methods are based on discriminative class boundaries for image classification, which, however, cannot be directly applied to segmentation. In Liu et al. (2022f), 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 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 (Montesuma and Mboula, 2021). 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 (Matsuura and Harada, 2020). There are two main streams for domain generalization tasks. The first stream is to learn domain invariant features (Ghifary et al., 2017). For example, Li et al. (2018a); Liu et al. (2021a) utilize adversarial training to mitigate the domain divergence. The second stream targets to fuse the domain-specific feature representations. For instance, Mancini et al. (2018a) 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 (2017)
propose to match the low-rank structure of domain-specific features. Liu et al. (2021c) further propose to align the conditional distribution with a variational inference scheme.

Domain generalization is usually considered a multi-task learning problem (Liu et al., 2021a), 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. (2021c).

5.8 Out-of-distribution Detection

OOD detection or deep OOD detection has recently been an active research topic (Che et al., 2021). 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 (Pimentel et al., 2014), it is still challenging to detect OOD in high-dimensional complex data, e.g., images (Liang et al., 2018). For example, Hendrycks and Gimpel (2017) 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 (Hendrycks et al., 2019). However, enumerating all possible OOD distributions before deployment is usually not possible. Liang et al. (2018) 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 (2018) augment the classifier with a confidence estimation branch, and adjust the objective using the predicted confidence score for training. Lee et al. (2018a) train a classifier simultaneously with a GAN, with an additional objective to encourage low confidence in generated samples. Hendrycks et al. (2019) propose to use real OOD samples instead of generated ones to train the detector. Vyas et al. (2018) 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 Hendrycks and Gimpel (2017) typically need to retrain a classifier with modified structures or optimization objectives. Recently, Lee et al. (2018b) propose a new framework for anomaly detection. A number of methods (Liang et al., 2018; Vyas et al., 2018. Lee et al., 2018b) need OOD samples for tuning hyper-parameter selection, e.g., the threshold for verification. DVN (Che et al., 2021) 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.

References

Jonas Adler and Sebastian Lunz. Banach wasserstein gan. *Advances in Neural Information Processing Systems*, 31, 2018.

Euijoon Ahn, Ashnil Kumar, Michael Fulham, Dagan Feng, and Jinman Kim. Unsupervised domain adaptation to classify medical images using zero-bias convolutional auto-encoders and context-based feature augmentation. *IEEE transactions on medical imaging*, 39(7):2385–2394, 2020.

CS Anoop, AP Prathosh, and AG Ramakrishnan. Unsupervised domain adaptation schemes for building asr in low-resource languages. In *2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 342–349. IEEE, 2021.

Kamyar Azizzadenesheli, Anqi Liu, Fanny Yang, and Animashree Anandkumar. Regularized learning for domain adaptation under label shifts. *ICLR*, 2019.

Mathilde Bateson, Hoel Kervadec, Jose Dolz, Herve Lombaert, and Ismail Ben Ayed. Source-relaxed domain adaptation for image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 490–499. Springer, 2020.

Oscar Beijbom. Domain adaptations for computer vision applications. *arXiv preprint arXiv:1211.4860*, 2012.

Yoshua Bengio, Aaron Courville, and Pascal Vincent. Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, 35(8):1798–1828, 2013.

Terence Betlehem, Wen Zhang, Mark A Poletti, and Thushara D Abhayapala. Personal sound zones: Delivering interface-free audio to multiple listeners. *IEEE Signal Processing Magazine*, 32(2):81–91, 2015.

Rishi Bommasani, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*, 2021.

Konstantinos Bousmalis, George Trigeorgis, Nathan Silberman, Dilip Krishnan, and Dumitru Erhan. Domain separation networks. *Advances in neural information processing systems*, 29, 2016.

Konstantinos Bousmalis, Nathan Silberman, David Dohan, Dumitru Erhan, and Dilip Krishnan. Unsupervised pixel-level domain adaptation with generative adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3722–3731, 2017.
Deep Unsupervised Domain Adaptation

Konstantinos Bousmalis, Alex Irpan, Paul Wohlhart, Yunfei Bai, Matthew Kelcey, Mrinal Kalakrishnan, Laura Downs, Julian Ibarz, Peter Pastor, Kurt Konolige, et al. Using simulation and domain adaptation to improve efficiency of deep robotic grasping. In 2018 IEEE international conference on robotics and automation (ICRA), pages 4243–4250. IEEE, 2018.

Lars Bungum and Björn Gambäck. A survey of domain adaptation in machine translation: Towards a refinement of domain space. In Proceedings of the India-Norway Workshop on Web Concepts and Technologies, volume 112, 2011.

Jill Burstein, Christy Doran, and Thamar Solorio. Proceedings of the 2019 conference of the north american chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers). In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 2019.

Qi Cai, Yingwei Pan, Chong-Wah Ngo, Xinmei Tian, Lingyu Duan, and Ting Yao. Exploring object relation in mean teacher for cross-domain detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 11457–11466, 2019.

Ruichu Cai, Jiawei Chen, Zijian Li, Wei Chen, Keli Zhang, Junjian Ye, Zhuozhang Li, Xiaoyan Yang, and Zhenjie Zhang. Time series domain adaptation via sparse associative structure alignment. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, pages 6859–6867, 2021.

Gustau Camps-Valls, Devis Tuia, Xiao Xiang Zhu, and Markus Reichstein. Deep learning for the Earth Sciences: A comprehensive approach to remote sensing, climate science and geosciences. John Wiley & Sons, 2021.

Zhangjie Cao, Mingsheng Long, Jianmin Wang, and Michael I Jordan. Partial transfer learning with selective adversarial networks. In CVPR, pages 2724–2732, 2018a.

Zhangjie Cao, Lijia Ma, Mingsheng Long, and Jianmin Wang. Partial adversarial domain adaptation. In Proceedings of the European Conference on Computer Vision (ECCV), pages 135–150, 2018b.

Fabio Maria Carlucci, Lorenzo Porzi, Barbara Caputo, Elisa Ricci, and Samuel Rota Bulo. Autodial: Automatic domain alignment layers. In 2017 IEEE international conference on computer vision (ICCV), pages 5077–5085. IEEE, 2017.

Yee Seng Chan and Hwee Tou Ng. Word sense disambiguation with distribution estimation. In IJCAI, volume 5, pages 1010–5, 2005.

Woong-Gi Chang, Tackgeun You, Seonguk Seo, Suha Kwak, and Bohyung Han. Domain-specific batch normalization for unsupervised domain adaptation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7354–7362, 2019.
Youngjae Chang, Akhil Mathur, Anton Isopoussu, Junehwa Song, and Fahim Kawsar. A systematic study of unsupervised domain adaptation for robust human-activity recognition. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 4(1):1–30, 2020.

Olivier Chapelle and Alexander Zien. Semi-supervised classification by low density separation. In *International workshop on artificial intelligence and statistics*, pages 57–64. PMLR, 2005.

Tong Che, Xiaofeng Liu, Site Li, Yubin Ge, Ruixiang Zhang, Caiming Xiong, and Yoshua Bengio. Deep verifier networks: Verification of deep discriminative models with deep generative models, 2021.

Changhao Chen, Yishu Miao, Chris Xiaoxuan Lu, Linhai Xie, Phil Blunsom, Andrew Markham, and Niki Trigoni. Motiontransformer: Transferring neural inertial tracking between domains. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 8009–8016, 2019a.

Chao Chen, Zhiliang Fu, Zhihong Chen, Sheng Jin, Zhaowei Cheng, Xinyu Jin, and Xian-Sheng Hua. Homm: Higher-order moment matching for unsupervised domain adaptation. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 3422–3429, 2020a.

Chaoqi Chen, Zebiao Zheng, Xinghao Ding, Yue Huang, and Qi Dou. Harmonizing transferability and discriminability for adapting object detectors. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8869–8878, 2020b.

Cheng Chen, Qi Dou, Hao Chen, Jing Qin, and Pheng-Ann Heng. Synergistic image and feature adaptation: Towards cross-modality domain adaptation for medical image segmentation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 865–872, 2019b.

Jiawei Chen, Yuexiang Li, Kai Ma, and Yefeng Zheng. Generative adversarial networks for video-to-video domain adaptation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 3462–3469, 2020c.

Min-Hung Chen, Zsolt Kira, Ghassan AlRegib, Jaekwon Yoo, Ruxin Chen, and Jian Zheng. Temporal attentive alignment for large-scale video domain adaptation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 6321–6330, 2019c.

Min-Hung Chen, Baopu Li, Yingze Bao, and Ghassan AlRegib. Action segmentation with mixed temporal domain adaptation. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 605–614, 2020d.

Min-Hung Chen, Baopu Li, Yingze Bao, Ghassan AlRegib, and Zsolt Kira. Action segmentation with joint self-supervised temporal domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9454–9463, 2020e.

26
Peipeng Chen, Yuan Gao, and Andy J Ma. Multi-level attentive adversarial learning with temporal dilation for unsupervised video domain adaptation. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1259–1268, 2022.

Pengfei Chen, Leida Li, Jinjian Wu, Weisheng Dong, and Guangming Shi. Unsupervised curriculum domain adaptation for no-reference video quality assessment. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5178–5187, 2021a.

Qingchao Chen, Yang Liu, Zhaowen Wang, Ian Wassell, and Kevin Chetty. Re-weighted adversarial adaptation network for unsupervised domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 7976–7985, 2018a.

Qingchao Chen, Yang Liu, and Samuel Albanie. Mind-the-gap! unsupervised domain adaptation for text-video retrieval. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 1072–1080, 2021b.

Tseng-Hung Chen, Yuan-Hong Liao, Ching-Yao Chuang, Wan-Ting Hsu, Jianlong Fu, and Min Sun. Show, adapt and tell: Adversarial training of cross-domain image captioner. In *Proceedings of the IEEE international conference on computer vision*, pages 521–530, 2017.

Xilun Chen, Yu Sun, Ben Athiwaratkun, Claire Cardie, and Kilian Weinberger. Adversarial deep averaging networks for cross-lingual sentiment classification. *Transactions of the Association for Computational Linguistics*, 6:557–570, 2018b.

Yuhua Chen, Wen Li, Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Domain adaptive faster r-cnn for object detection in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3339–3348, 2018c.

Jinwoo Choi, Gaurav Sharma, Mamunohan Chandraker, and Jia-Bin Huang. Unsupervised and semi-supervised domain adaptation for action recognition from drones. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1717–1726, 2020a.

Jinwoo Choi, Gaurav Sharma, Samuel Schulter, and Jia-Bin Huang. Shuffle and attend: Video domain adaptation. In *European Conference on Computer Vision*, pages 678–695. Springer, 2020b.

Sumit Chopra, Suhrid Balakrishnan, and Raghuraman Gopalan. Dlid: Deep learning for domain adaptation by interpolating between domains. In *ICML workshop on challenges in representation learning*, volume 2. Citeseer, 2013.

Junyoung Chung, Kyle Kastner, Laurent Dinh, Kratarth Goel, Aaron C Courville, and Yoshua Bengio. A recurrent latent variable model for sequential data. *Advances in neural information processing systems*, 28, 2015.

Diane Cook, Kyle D Feuz, and Narayanan C Krishnan. Transfer learning for activity recognition: A survey. *Knowledge and information systems*, 36(3):537–556, 2013.
Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3213–3223, 2016.

Nicolas Courty, Remi Flamary, Amaury Habrard, and Alain Rakotomamonjy. Joint distribution optimal transportation for domain adaptation. Advances in Neural Information Processing Systems, 30, 2017.

Gabriela Csurka. Domain adaptation for visual applications: A comprehensive survey. arXiv preprint arXiv:1702.05374, 2017.

Paulo Roberto de Oliveira da Costa, Alp Akçay, Yingqian Zhang, and Uzay Kaymak. Remaining useful lifetime prediction via deep domain adaptation. Reliability Engineering & System Safety, 195:106682, 2020.

Bharath Bhushan Damodaran, Benjamin Kellenberger, Remi Flamary, Devis Tuia, and Nicolas Courty. Deepjdot: Deep joint distribution optimal transport for unsupervised domain adaptation. In Proceedings of the European Conference on Computer Vision (ECCV), pages 447–463, 2018.

Debasmit Das and CS Lee. Graph matching and pseudo-label guided deep unsupervised domain adaptation. In International conference on artificial neural networks, pages 342–352. Springer, 2018a.

Debasmit Das and CS George Lee. Unsupervised domain adaptation using regularized hyper-graph matching. In 2018 25th IEEE International Conference on Image Processing (ICIP), pages 3758–3762. IEEE, 2018b.

Jinhong Deng, Wen Li, Yuhua Chen, and Lixin Duan. Unbiased mean teacher for cross-domain object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4091–4101, 2021.

Armen Der Kiureghian and Ove Ditlevsen. Aleatory or epistemic? does it matter? Structural safety, 31(2):105–112, 2009.

Shrey Desai, Barea Sinno, Alex Rosenfeld, and Junyi Jessy Li. Adaptive ensembling: Unsupervised domain adaptation for political document analysis. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4718–4730, 2019.

Terrance Devries and Graham W. Taylor. Learning confidence for out-of-distribution detection in neural networks. 2018.

Zhengming Ding and Yun Fu. Deep domain generalization with structured low-rank constraint. TIP, 2017.

28
Jeff Donahue, Judy Hoffman, Erik Rodner, Kate Saenko, and Trevor Darrell. Semi-supervised domain adaptation with instance constraints. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 668–675, 2013.

Hao Du, Tian Jin, Yongping Song, and Yongpeng Dai. Unsupervised adversarial domain adaptation for micro-doppler based human activity classification. IEEE geoscience and remote sensing letters, 17(1):62–66, 2019.

George Ekladious, Hugo Lemoine, Eric Granger, Kaveh Kamali, and Salim Moudache. Dual-triplet metric learning for unsupervised domain adaptation in video face recognition. In 2020 International Joint Conference on Neural Networks (IJCNN), pages 1–9. IEEE, 2020.

Jiahao Fan, Hangyu Zhu, Xinyu Jiang, Long Meng, Chen Chen, Cong Fu, Huan Yu, Chenyuan Dai, and Wei Chen. Unsupervised domain adaptation by statistics alignment for deep sleep staging networks. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30:205–216, 2022.

Erik M Fredericks, Byron DeVries, and Betty HC Cheng. Towards run-time adaptation of test cases for self-adaptive systems in the face of uncertainty. In Proceedings of the 9th International Symposium on Software Engineering for Adaptive and Self-Managing Systems, pages 17–26, 2014.

Geoffrey French, Michal Mackiewicz, and Mark Fisher. Self-ensembling for visual domain adaptation. arXiv preprint arXiv:1706.05208, 2017.

Lisheng Fu, Thien Huu Nguyen, Bonan Min, and Ralph Grishman. Domain adaptation for relation extraction with domain adversarial neural network. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 425–429, 2017.

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

Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. Domain-adversarial training of neural networks. The Journal of Machine Learning Research, 17(1):2096–2030, 2016.

Yubin Ge, Ly Dinh, Xiaofeng Liu, Jinsong Su, Ziyao Lu, Ante Wang, and Jana Diesner. Baco: A background knowledge-and content-based framework for citing sentence generation. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1466–1478, 2021a.

Yubin Ge, Site Li, Xuyang Li, Fangfang Fan, Wanqing Xie, Jane You, and Xiaofeng Liu. Embedding semantic hierarchy in discrete optimal transport for risk minimization. In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 2835–2839. IEEE, 2021b.
Muhammad Ghifary, W Bastiaan Kleijn, Mengjie Zhang, David Balduzzi, and Wen Li. Deep reconstruction-classification networks for unsupervised domain adaptation. In *European conference on computer vision*, pages 597–613. Springer, 2016.

Muhammad Ghifary, David Balduzzi, W Bastiaan Kleijn, and Mengjie Zhang. Scatter component analysis: A unified framework for domain adaptation and domain generalization. *IEEE T-PAMI*, 2017.

Behnam Gholami, Pritish Sahu, Minyoung Kim, and Vladimir Pavlovic. Task-discriminative domain alignment for unsupervised domain adaptation. In *ICCV*, 2019.

Deepanway Ghosal, Devamanyu Hazarika, Abhinab Roy, Navonil Majumder, Rada Mihalcea, and Soujanya Poria. Kingdom: Knowledge-guided domain adaptation for sentiment analysis. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3198–3210, 2020.

I. Goodfellow, Y. Bengio, and A. Courville. Deep Learning. MIT press, 2016.

Qiao Gu, Brian Okorn, and David Held. Ossid: Online self-supervised instance detection by (and for) pose estimation. *IEEE Robotics and Automation Letters*, 2022.

Hao Guan and Mingxia Liu. Domain adaptation for medical image analysis: a survey. *IEEE Transactions on Biomedical Engineering*, 2021.

Vitor Guizilini, Jie Li, Rareș Ambruș, and Adrien Gaidon. Geometric unsupervised domain adaptation for semantic segmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8537–8547, 2021.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A Smith. Don't stop pretraining: Adapt language models to domains and tasks. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8342–8360, 2020.

Yu-Jin Ham, Chaehwa Yoo, and Je-Won Kang. Training compression artifacts reduction network with domain adaptation. In *Applications of Digital Image Processing XLIV*, volume 11842, page 118420U. International Society for Optics and Photonics, 2021.

Xiaochuang Han and Jacob Eisenstein. Unsupervised domain adaptation of contextualized embeddings for sequence labeling. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4238–4248, 2019.

Yuzhuo Han, Xiaofeng Liu, Zhenfei Sheng, Yutao Ren, Xu Han, Jane You, Risheng Liu, and Zhongxuan Luo. Wasserstein loss-based deep object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 998–999, 2020.

Gewen He, Xiaofeng Liu, Fangfang Fan, and Jane You. Classification-aware semi-supervised domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 964–965, 2020a.
Gewen He, Xiaofeng Liu, Fangfang Fan, and Jane You. Image2audio: Facilitating semi-supervised audio emotion recognition with facial expression image. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 912–913, 2020b.

Wenwen He, Yalan Ye, Yunxia Li, Tongjie Pan, and Li Lu. Online cross-subject emotion recognition from ecg via unsupervised domain adaptation. In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pages 1001–1005. IEEE, 2021a.

Yufan He, Aaron Carass, Yihao Liu, Shiv Saidha, Peter A Calabresi, and Jerry L Prince. Adversarial domain adaptation for multi-device retinal oct segmentation. In Medical Imaging 2020: Image Processing, volume 11313, page 1131309. International Society for Optics and Photonics, 2020c.

Yufan He, Aaron Carass, Lianrui Zuo, Blake E Dewey, and Jerry L Prince. Autoencoder based self-supervised test-time adaptation for medical image analysis. Medical image analysis, 72:102136, 2021b.

Zhipeng He, Yongshi Zhong, and Jiahui Pan. An adversarial discriminative temporal convolutional network for eeg-based cross-domain emotion recognition. Computers in biology and medicine, 141:105048, 2022.

Dan Hendrycks and Kevin Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. ICLR, 2017.

Dan Hendrycks, Mantas Mazeika, and Thomas Dietterich. Deep anomaly detection with outlier exposure. ICLR, 2019.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 1997.

Judy Hoffman, Trevor Darrell, and Kate Saenko. Continuous manifold based adaptation for evolving visual domains. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 867–874, 2014.

Judy Hoffman, Eric Tzeng, Taesung Park, Jun-Yan Zhu, Phillip Isola, Kate Saenko, Alexei A Efros, and Trevor Darrell. Cycada: Cycle-consistent adversarial domain adaptation. In ICML, 2018.

Sungeun Hong, Woobin Im, Jongbin Ryu, and Hyun S Yang. Sspp-dan: Deep domain adaptation network for face recognition with single sample per person. In 2017 IEEE International Conference on Image Processing (ICIP), pages 825–829. IEEE, 2017.

Cheng-Chun Hsu, Yi-Hsuan Tsai, Yen-Yu Lin, and Ming-Hsuan Yang. Every pixel matters: Center-aware feature alignment for domain adaptive object detector. In European Conference on Computer Vision, pages 733–748. Springer, 2020a.
Han-Kai Hsu, Chun-Han Yao, Yi-Hsuan Tsai, Wei-Chih Hung, Hung-Yu Tseng, Maneesh Singh, and Ming-Hsuan Yang. Progressive domain adaptation for object detection. In Proceedings of the IEEE/CVF winter conference on applications of computer vision, pages 749–757, 2020b.

Dapeng Hu, Jian Liang, Qibin Hou, Hanshu Yan, Yunpeng Chen, Shuicheng Yan, and Jiashi Feng. Panda: Prototypical unsupervised domain adaptation. ECCV, 2020a.

Jingliang Hu, Lichao Mou, and Xiao Xiang Zhu. Unsupervised domain adaptation using a teacher-student network for cross-city classification of sentinel-2 images. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 43:1569–1574, 2020b.

Shi Hu, Daniel Worrall, Stefan Knegt, Bas Veeling, Henkjan Huisman, and Max Welling. Supervised uncertainty quantification for segmentation with multiple annotations. In MICCAI, pages 137–145. Springer, 2019.

Xin Huang, Sahara Ali, Chenxi Wang, Zeyu Ning, Sanjay Purushotham, Jianwu Wang, and Zhibo Zhang. Deep domain adaptation based cloud type detection using active and passive satellite data. In 2020 IEEE International Conference on Big Data (Big Data), pages 1330–1337. IEEE, 2020.

Xinyue Huo, Lingxi Xie, Hengtong Hu, Wengang Zhou, Houqiang Li, and Qi Tian. Domain-agnostic prior for transfer semantic segmentation. arXiv preprint arXiv:2204.02684, 2022.

Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In International conference on machine learning, pages 448–456, 2015.

Wenjun Jiang, Chenglin Miao, Fenglong Ma, Shuochao Yao, Yaqing Wang, Ye Yuan, Hongfei Xue, Chen Song, Xin Ma, Dimitrios Koutsonikolas, et al. Towards environment independent device free human activity recognition. In Proceedings of the 24th Annual International Conference on Mobile Computing and Networking, pages 289–304, 2018.

Magdiel Jimenez-Guarneros and Pilar Gomez-Gil. Standardization-refinement domain adaptation method for cross-subject eeg-based classification in imagined speech recognition. Pattern Recognition Letters, 141:54–60, 2021.

Hoffman Judy, Tzeng Eric, Park Taesung, Zhu Jun-Yan, Isola Phillip, Saenko Kate, Efros Alexei, and Darrell Trevor. Cycada: Cycle-consistent adversarial domain adaptation. In ICML, pages 1994–2003, 2018.

Meina Kan, Shiguang Shan, and Xilin Chen. Bi-shifting auto-encoder for unsupervised domain adaptation. In Proceedings of the IEEE international conference on computer vision, pages 3846–3854, 2015.

Guoliang Kang, Liang Zheng, Yan Yan, and Yi Yang. Deep adversarial attention alignment for unsupervised domain adaptation: the benefit of target expectation maximization. In Proceedings of the European conference on computer vision (ECCV), pages 401–416, 2018.
Guoliang Kang, Lu Jiang, Yi Yang, and Alexander G Hauptmann. Contrastive adaptation network for unsupervised domain adaptation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4893–4902, 2019.

Neerav Karani, Ertunc Erdil, Krishna Chaitanya, and Ender Konukoglu. Test-time adaptable neural networks for robust medical image segmentation. Medical Image Analysis, 68:101907, 2021.

Alex Kendall and Yarin Gal. What uncertainties do we need in bayesian deep learning for computer vision? arXiv:1703.04977, 2017.

Mehran Khodabandeh, Arash Vahdat, Mani Ranjbar, and William G Macready. A robust learning approach to domain adaptive object detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 480–490, 2019.

Sameer Khurana, Niko Moritz, Takaaki Hori, and Jonathan Le Roux. Unsupervised domain adaptation for speech recognition via uncertainty driven self-training. In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 6553–6557. IEEE, 2021.

Donghyun Kim, Kuniaki Saito, Tae-Hyun Oh, Bryan A Plummer, Stan Sclaroff, and Kate Saenko. Cross-domain self-supervised learning for domain adaptation with few source labels. arXiv preprint arXiv:2003.08264, 2020a.

Seunghyeon Kim, Jae-Hoon Choi, Taekyung Kim, and Changick Kim. Self-training and adversarial background regularization for unsupervised domain adaptive one-stage object detection. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6092–6101, 2019a.

Taeksoo Kim, Moonsu Cha, Hyunsoo Kim, Jung Kwon Lee, and Jiwon Kim. Learning to discover cross-domain relations with generative adversarial networks. In International Conference on Machine Learning, pages 1857–1865. PMLR, 2017.

Taekyung Kim and Changick Kim. Attract, perturb, and explore: Learning a feature alignment network for semi-supervised domain adaptation. In European Conference on Computer Vision, pages 591–607. Springer, 2020.

Taekyung Kim, Minki Jeong, Seunghyeon Kim, Seokeon Choi, and Changick Kim. Diversify and match: A domain adaptive representation learning paradigm for object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12456–12465, 2019b.

Youngeun Kim, Sungeun Hong, Seunghan Yang, Sungil Kang, Yunho Jeon, and Jiwon Kim. Associative partial domain adaptation. arXiv preprint arXiv:2008.03111, 2020b.

Alexander Kolesnikov, Xiaohua Zhai, and Lucas Beyer. Revisiting self-supervised visual representation learning. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 1920–1929, 2019.
Wouter M Kouw. An introduction to domain adaptation and transfer learning. *arXiv preprint arXiv:1812.11806*, 2018.

Wouter M Kouw and Marco Loog. A review of domain adaptation without target labels. *IEEE transactions on pattern analysis and machine intelligence*, 43(3):766–785, 2019.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25, 2012.

Abhishek Kumar, Prasanna Sattigeri, Kahini Wadhawan, Leonid Karlinsky, Rogerio Feris, Bill Freeman, and Gregory Wornell. Co-regularized alignment for unsupervised domain adaptation. *Advances in Neural Information Processing Systems*, 31, 2018.

Alessandro Lazaric. Transfer in reinforcement learning: a framework and a survey. In *Reinforcement Learning*, pages 143–173. Springer, 2012.

Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553):436–444, 2015.

Chen-Yu Lee, Tanmay Batra, Mohammad Haris Baig, and Daniel Ulbricht. Sliced wasserstein discrepancy for unsupervised domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10285–10295, 2019a.

Kimin Lee, Honglak Lee, Kibok Lee, and Jinwoo Shin. Training confidence-calibrated classifiers for detecting out-of-distribution samples. *ICLR*, 2018a.

Kimin Lee, Kibok Lee, Honglak Lee, and Jinwoo Shin. A simple unified framework for detecting out-of-distribution samples and adversarial attacks. *NIPS*, 2018b.

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/CVF International Conference on Computer Vision*, pages 91–100, 2019b.

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

Jerry Li. Twin-gan–unpaired cross-domain image translation with weight-sharing gans. *arXiv preprint arXiv:1809.00946*, 2018.

Wei Li, Wei Wei, Lei Zhang, Cong Wang, and Yanning Zhang. Unsupervised deep domain adaptation for hyperspectral image classification. In *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium*, pages 1–4. IEEE, 2019a.

Xiaohui Li, Sijie Niu, Xizhan Gao, Tingting Liu, and Jiwen Dong. Unsupervised domain adaptation with self-selected active learning for cross-domain oct image segmentation. In *International Conference on Neural Information Processing*, pages 585–596. Springer, 2021a.
Yang Li, Wenming Zheng, Yuan Zong, Zhen Cui, Tong Zhang, and Xiaoyan Zhou. A bi-hemisphere domain adversarial neural network model for eeg emotion recognition. *IEEE Transactions on Affective Computing*, 12(2):494–504, 2018b.

Yanghao Li, Naiyan Wang, Jianping Shi, Jiaying Liu, and Xiaodi Hou. Revisiting batch normalization for practical domain adaptation. *arXiv preprint arXiv:1603.04779*, 2016.

Yanghao Li, Naiyan Wang, Jianping Shi, Xiaodi Hou, and Jiaying Liu. Adaptive batch normalization for practical domain adaptation. *Pattern Recognition*, 80:109–117, 2018c.

Yitong Li, Timothy Baldwin, and Trevor Cohn. What’s in a domain? learning domain-robust text representations using adversarial training. In *Proceedings of NAACL-HLT*, pages 474–479, 2019b.

Yu-Jhe Li, Xiaoliang Dai, Chih-Yao Ma, Yen-Cheng Liu, Kan Chen, Bichen Wu, Zijian He, Kris Kitani, and Peter Vadja. Cross-domain object detection via adaptive self-training. *arXiv preprint arXiv:2111.13216*, 2021b.

Qing Lian, Fengmao Lv, Lixin Duan, and Boqing Gong. Constructing self-motivated pyramid curriculums for cross-domain semantic segmentation: A non-adversarial approach. *ICCV*, 2019.

Shiyu Liang, Yixuan Li, and R. Srikant. Enhancing the reliability of out-of-distribution image detection in neural networks. *ICLR*, 2018.

KyungTae Lim, Jay Yoon Lee, Jaime Carbonell, and Thierry Poibeau. Semi-supervised learning on meta structure: Multi-task tagging and parsing in low-resource scenarios. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 8344–8351, 2020.

Zachary Lipton, Yu-Xiang Wang, and Alexander Smola. Detecting and correcting for label shift with black box predictors. In *ICML*, 2018.

Xiaofeng Liu, BVK Vijaya Kumar, Jane You, and Ping Jia. Adaptive deep metric learning for identity-aware facial expression recognition. In *CVPR Workshops*, pages 20–29, 2017.

Xiaofeng Liu, Yang Zou, Lingsheng Kong, Zhihui Diao, Junliang Yan, Jun Wang, Site Li, Ping Jia, and Jane You. Data augmentation via latent space interpolation for image classification. In *24th International Conference on Pattern Recognition (ICPR)*, pages 728–733, 2018.

Xiaofeng Liu, Xu Han, Yukai Qiao, Yi Ge, Site Li, and Jun Lu. Unimodal-uniform constrained wasserstein training for medical diagnosis. In *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops*, pages 0–0, 2019a.

Xiaofeng Liu, Site Li, Lingsheng Kong, Wanqing Xie, Ping Jia, Jane You, and BVK Kumar. Feature-level frankenstein: Eliminating variations for discriminative recognition. In *CVPR*, 2019b.
Xiaofeng Liu, Yang Zou, Tong Che, Peng Ding, Ping Jia, Jane You, and BVK Kumar. Conservative wasserstein training for pose estimation. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8262–8272, 2019c.

Xiaofeng Liu, Fangfang Fan, Lingsheng Kong, Zhihui Diao, Wanqing Xie, Jun Lu, and Jane You. Unimodal regularized neuron stick-breaking for ordinal classification. Neurcomputing, 2020a.

Xiaofeng Liu, Yuzhuo Han, Song Bai, Yi Ge, Tianxing Wang, Xu Han, Site Li, Jane You, and Jun Lu. Importance-aware semantic segmentation in self-driving with discrete wasserstein training. In AAAI, pages 11629–11636, 2020b.

Xiaofeng Liu, Wenzuan Ji, Jane You, Georges El Fakhri, and Jonghye Woo. Severity-aware semantic segmentation with reinforced wasserstein training. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12566–12575, 2020c.

Xiaofeng Liu, Yunhong Lu, Xiongchang Liu, Song Bai, Site Li, and Jane You. Wasserstein loss with alternative reinforcement learning for severity-aware semantic segmentation. IEEE Transactions on Intelligent Transportation Systems, 2020d.

Xiaofeng Liu, Yang Chao, Jane J You, C-C Jay Kuo, and Bhagavatula Vijayakumar. Mutual information regularized feature-level frankenstein for discriminative recognition. IEEE T-PAMI, 2021a.

Xiaofeng Liu, Zhenhua Guo, Site Li, Fangxu Xing, Jane You, C-C Jay Kuo, Georges El Fakhri, and Jonghye Woo. Adversarial unsupervised domain adaptation with conditional and label shift: Infer, align and iterate. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 10367–10376, 2021b.

Xiaofeng Liu, Bo Hu, Linghao Jin, Xu Han, Fangxu Xing, Jinsong Ouyang, Jun Lu, Georges El Fakhri, and Jonghye Woo. Domain generalization under conditional and label shifts via variational bayesian inference. In IJCAI, 2021c.

Xiaofeng Liu, Bo Hu, Linghao Jin, Xu Han, Fangxu Xing, Jinsong Ouyang, Jun Lu, Georges El Fakhri, and Jonghye Woo. Domain generalization under conditional and label shifts via variational Bayesian inference. IJCAI, 2021d.

Xiaofeng Liu, Bo Hu, Xiongchang Liu, Jun Lu, Jane You, and Lingsheng Kong. Energy-constrained self-training for unsupervised domain adaptation. In 2020 25th International Conference on Pattern Recognition (ICPR), pages 7515–7520. IEEE, 2021e.

Xiaofeng Liu, Linghao Jin, Xu Han, Jun Lu, Jane You, and Lingsheng Kong. Identity-aware facial expression recognition in compressed video. In 2020 25th International Conference on Pattern Recognition (ICPR), pages 7508–7514. IEEE, 2021f.

Xiaofeng Liu, Linghao Jin, Xu Han, and Jane You. Mutual information regularized identity-aware facial expression recognition in compressed video. Pattern Recognition, 2021g.
Xiaofeng Liu, Site Li, Yubin Ge, Pengyi Ye, Jane You, and Jun Lu. Recursively conditional
gaussian for ordinal unsupervised domain adaptation. In *Proceedings of the IEEE/CVF
International Conference on Computer Vision*, pages 764–773, 2021h.

Xiaofeng Liu, Xiongchang Liu, Bo Hu, Wenxuan Ji, Fangxu Xing, Jun Lu, Jane You,
C-C Jay Kuo, Georges El Fakhri, and Jonghye Woo. Subtype-aware unsupervised domain
adaptation for medical diagnosis. *AAAI*, 2021i.

Xiaofeng Liu, Fangxu Xing, Georges El Fakhri, and Jonghye Woo. A unified conditional
disentanglement framework for multimodal brain mr image translation. In *2021 IEEE
18th International Symposium on Biomedical Imaging (ISBI)*, pages 10–14. IEEE, 2021j.

Xiaofeng Liu, Fangxu Xing, Jerry L Prince, Aaron Carass, Maureen Stone, Georges El Fakhri,
and Jonghye Woo. Dual-cycle constrained bijective vae-gan for tagged-to-cine magnetic
resonance image synthesis. In *2021 IEEE 18th International Symposium on Biomedical
Imaging (ISBI)*, pages 1448–1452. IEEE, 2021k.

Xiaofeng Liu, Fangxu Xing, Maureen Stone, Jiachen Zhuo, Timothy Reese, Jerry L Prince,
Georges El Fakhri, and Jonghye Woo. Generative self-training for cross-domain unsu-
pervised tagged-to-cine mri synthesis. In *International Conference on Medical Image
Computing and Computer-Assisted Intervention*, pages 138–148. Springer, 2021l.

Xiaofeng Liu, Fangxu Xing, Chao Yang, Georges El Fakhri, and Jonghye Woo. Adapting
off-the-shelf source segmenter for target medical image segmentation. In *International
Conference on Medical Image Computing and Computer-Assisted Intervention*, pages
549–559. Springer, 2021m.

Xiaofeng Liu, Site Li, Yubin Ge, Pengyi Ye, Jane You, and Jun Lu. Ordinal unsupervised do-
main adaptation with recursively conditional gaussian imposed variational disentanglement.
In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2022a.

Xiaofeng Liu, Fangxu Xing, Georges El Fakhri, and Jonghye Woo. Memory consistent
unsupervised off-the-shelf model adaptation for source-relaxed medical image segmentation.
In *Medical Image Analysis*, 2022b.

Xiaofeng Liu, Fangxu Xing, Georges El Fakhri, and Jonghye Woo. Self-semantic contour
adaptation for cross modality brain tumor segmentation. *IEEE International Symposium
on Biomedical Imaging (ISBI)*, 2022c.

Xiaofeng Liu, Fangxu Xing, Thibault Marin, Georges El Fakhri, and Jonghye Woo. Vari-
tional inference for quantifying inter-observer variability in segmentation of anatomical
structures. *arXiv preprint arXiv:2201.07106*, 2022d.

Xiaofeng Liu, Fangxu Xing, Jerry L Prince, Maureen Stone, Georges El Fakhri, and Jonghye
Woo. Structure-aware unsupervised tagged-to-cine mri synthesis with self disentanglement.
*arXiv preprint arXiv:2202.12474*, 2022e.

Xiaofeng Liu, Fangxu Xing, Nadya Shusharina, Ruth Lim, C-C Jay Kuo, Georges El Fakhri,
and Jonghye Woo. Act: Semi-supervised domain-adaptive medical image segmentation
with asymmetric co-training. In *MICCAI*, 2022f.
Xiaofeng Liu, Chaehwa Yoo, Fangxu Xing, C.-C. Jay Kuo, Georges El Fakhri, and Jonghye Woo. Subtype-aware dynamic unsupervised domain adaptation. *IEEE Transactions on Neural Networks and Learning Systems*, 2022g.

Xiaofeng Liu, Chaehwa Yoo, Fangxu Xing, C.-C. Jay Kuo, Georges El Fakhri, and Jonghye Woo. Unsupervised domain adaptation for segmentation with black-box source model. *SPIE Medical Imaging 2022: Image Processing*, 2022h.

Xiaofeng Liu, Chaehwa Yoo, Fangxu Xing, C.-C. Jay Kuo, Georges El Fakhri, and Jonghye Woo. Unsupervised black-box model domain adaptation for brain tumor segmentation. *Frontiers in Neuroscience*, 2022i.

Yang Liu, Zhaoyang Lu, Jing Li, Tao Yang, and Chao Yao. Deep image-to-video adaptation and fusion networks for action recognition. *IEEE Transactions on Image Processing*, 29:3168–3182, 2019d.

Mingsheng Long, Yue Cao, Jianmin Wang, and Michael I Jordan. Learning transferable features with deep adaptation networks. *ICML*, 2015.

Mingsheng Long, Han Zhu, Jianmin Wang, and Michael I Jordan. Unsupervised domain adaptation with residual transfer networks. In *Advances in Neural Information Processing Systems*, pages 136–144, 2016.

Mingsheng Long, Han Zhu, Jianmin Wang, and Michael I Jordan. Deep transfer learning with joint adaptation networks. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 2208–2217. JMLR. org, 2017.

Mingsheng Long, Zhangjie Cao, Jianmin Wang, and Michael I Jordan. Conditional adversarial domain adaptation. In *Advances in Neural Information Processing Systems*, pages 1647–1657, 2018.

Nannan Lu, Hanhan Xiao, Yanjing Sun, Min Han, and Yanfen Wang. A new method for intelligent fault diagnosis of machines based on unsupervised domain adaptation. *Neurocomputing*, 427:96–109, 2021.

Benjamin Lucas, Charlotte Pelletier, Daniel Schmidt, Geoffrey I Webb, and François Petitjean. Unsupervised domain adaptation techniques for classification of satellite image time series. In *IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium*, pages 1074–1077. IEEE, 2020.

Yuchi Ma and Zhou Zhang. Multi-source unsupervised domain adaptation on corn yield prediction. In *AI for Agriculture and Food Systems*, 2021.

Dwarikanath Mahapatra, Ruwan Tennakoon, et al. Gcn based unsupervised domain adaptation with feature disentanglement for medical image classification. 2021.

Massimiliano Mancini, Samuel Rota Bulo, Barbara Caputo, and Elisa Ricci. Best sources forward: domain generalization through source-specific nets. In *ICIP*, 2018a.
Massimiliano Mancini, Lorenzo Porzi, Samuel Rota Bulo, Barbara Caputo, and Elisa Ricci. Boosting domain adaptation by discovering latent domains. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3771–3780, 2018b.

Massimiliano Mancini, Samuel Rota Bulo, Barbara Caputo, and Elisa Ricci. Adagraph: Unifying predictive and continuous domain adaptation through graphs. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6568–6577, 2019.

Vimal Manohar, Pegah Ghahremani, Daniel Povey, and Sanjeev Khudanpur. A teacher-student learning approach for unsupervised domain adaptation of sequence-trained asr models. In *2018 IEEE Spoken Language Technology Workshop (SLT)*, pages 250–257. IEEE, 2018.

Fabio Maria Carlucci, Lorenzo Porzi, Barbara Caputo, Elisa Ricci, and Samuel Rota Bulo. Autodial: Automatic domain alignment layers. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 5067–5075, 2017.

Toshihiko Matsuura and Tatsuya Harada. Domain generalization using a mixture of multiple latent domains. *AAAI*, 2020.

Ke Mei, Chuang Zhu, Jiaqi Zou, and Shanghang Zhang. Instance adaptive self-training for unsupervised domain adaptation. *ECCV*, 2020a.

Ke Mei, Chuang Zhu, Jiaqi Zou, and Shanghang Zhang. Instance adaptive self-training for unsupervised domain adaptation. *ECCV*, 2020b.

Djebril Mekhazni, Amran Bhuiyan, George Ekladious, and Eric Granger. Unsupervised domain adaptation in the dissimilarity space for person re-identification. In *European Conference on Computer Vision*, pages 159–174. Springer, 2020.

XU Mengqiu, WU Ming, GUO Jun, Chuang Zhang, WANG Yubo, and MA Zhanyu. Sea fog detection based on unsupervised domain adaptation. *Chinese Journal of Aeronautics*, 35(4):415–425, 2022.

Gabriel Michau and Olga Fink. Unsupervised transfer learning for anomaly detection: Application to complementary operating condition transfer. *Knowledge-Based Systems*, 216:106816, 2021.

Eduardo Fernandes Montesuma and Fred Maurice Ngole Mboula. Wasserstein barycenter for multi-source domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16785–16793, 2021.

Pietro Morero, Jacopo Cavazza, and Vittorio Murino. Minimal-entropy correlation alignment for unsupervised deep domain adaptation. *arXiv preprint arXiv:1711.10288*, 2017.

Saeid Motiian, Quinn Jones, Seyed Iranmanesh, and Gianfranco Doretto. Few-shot adversarial domain adaptation. *Advances in neural information processing systems*, 30, 2017.
Quanzheng Mou, Longsheng Wei, Conghao Wang, Dapeng Luo, Songze He, Jing Zhang, Huimin Xu, Chen Luo, and Changxin Gao. Unsupervised domain-adaptive scene-specific pedestrian detection for static video surveillance. *Pattern Recognition*, 118:108038, 2021.

Aakanksha Naik and Carolyn Rose. Towards open domain event trigger identification using adversarial domain adaptation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7618–7624, 2020.

M Quamer Nasim, Taannistha Maiti, Ayush Srivastava, Tarry Singh, and Jie Mei. Seismic facies analysis: a deep domain adaptation approach. *IEEE Transactions on Geoscience and Remote Sensing*, 60:1–16, 2022.

Munan Ning, Cheng Bian, Dong Wei, Shuang Yu, Chenglang Yuan, Yaohua Wang, Yang Guo, Kai Ma, and Yefeng Zheng. A new bidirectional unsupervised domain adaptation segmentation framework. In *International Conference on Information Processing in Medical Imaging*, pages 492–503. Springer, 2021.

Lisha Niu, Chao Chen, Hui Liu, Shuwang Zhou, and Minglei Shu. A deep-learning approach to ecg classification based on adversarial domain adaptation. In *Healthcare*, volume 8, page 437. Multidisciplinary Digital Publishing Institute, 2020.

Joachim Nyborg, Charlotte Pelletier, Sébastien Lefèvre, and Ira Assent. Timematch: Unsupervised cross-region adaptation by temporal shift estimation. *ISPRS Journal of Photogrammetry and Remote Sensing*, 188:301–313, 2022.

Cheng Ouyang, Konstantinos Kamnitsas, Carlo Biffi, Jinming Duan, and Daniel Rueckert. Data efficient unsupervised domain adaptation for cross-modality image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 669–677. Springer, 2019.

Poojan Oza, Vishwanath A Sindagi, Vibashan VS, and Vishal M Patel. Unsupervised domain adaptation of object detectors: A survey. *arXiv preprint arXiv:2105.13502*, 2021.

Boxiao Pan, Zhangjie Cao, Ehsan Adeli, and Juan Carlos Niebles. Adversarial cross-domain action recognition with co-attention. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 11815–11822, 2020.

Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

Yingwei Pan, Ting Yao, Yehao Li, Yu Wang, Chong-Wah Ngo, and Tao Mei. Transferrable prototypical networks for unsupervised domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2239–2247, 2019.

Pau Panareda Busto and Juergen Gall. Open set domain adaptation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 754–763, 2017.

Jiangtao Peng, Weiwei Sun, Li Ma, and Qian Du. Discriminative transfer joint matching for domain adaptation in hyperspectral image classification. *IEEE Geoscience and Remote Sensing Letters*, 16(6):972–976, 2019a.
Xingchao Peng, Ben Usman, Neela Kaushik, Judy Hoffman, Dequan Wang, and Kate Saenko. Visda: The visual domain adaptation challenge, 2017.

Xingchao Peng, Qinxun Bai, Xide Xia, Zijun Huang, Kate Saenko, and Bo Wang. Moment matching for multi-source domain adaptation. *ICCV*, 2019b.

Christian S Perone, Pedro Ballester, Rodrigo C Barros, and Julien Cohen-Adad. Unsupervised domain adaptation for medical imaging segmentation with self-ensembling. *NeuroImage*, 194:1–11, 2019.

Marco A. F. Pimentel, David A. Clifton, Clifton Lei, and Lionel Tarassenko. A review of novelty detection. *Signal Processing*, 99(6):215–249, 2014.

Prasanna Porwal, Samiksha Pachade, Ravi Kamble, Manesh Kokare, Girish Deshmukh, Vivek Sahasrabuddhe, and Fabrice Meriaudeau. Indian diabetic retinopathy image dataset (idrid): a database for diabetic retinopathy screening research. *Data*, 3(3):25, 2018.

S. Purushotham, Wilka Carvalho, Tanachat Nilanon, and Yan Liu. Variational recurrent adversarial deep domain adaptation. In *ICLR*, 2017.

Mohamed Ragab, Zhenghua Chen, Min Wu, Chuan Sheng Foo, Chee Keong Kwoh, Ruqiang Yan, and Xiaoli Li. Contrastive adversarial domain adaptation for machine remaining useful life prediction. *IEEE Transactions on Industrial Informatics*, 17(8):5239–5249, 2020.

Alan Ramponi and Barbara Plank. Neural unsupervised domain adaptation in nlp—a survey. *arXiv preprint arXiv:2006.00632*, 2020.

Haider Raza and Spyridon Samothrakis. Bagging adversarial neural networks for domain adaptation in non-stationary eeg. In *2019 International Joint Conference on Neural Networks (IJCNN)*, pages 1–7. IEEE, 2019.

Stephan R Richter, Vibhav Vineet, Stefan Roth, and Vladlen Koltun. Playing for data: Ground truth from computer games. In *ECCV*, 2016.

Anthony Rios, Ramakanth Kavuluru, and Zhiyong Lu. Generalizing biomedical relation classification with neural adversarial domain adaptation. *Bioinformatics*, 34(17):2973–2981, 2018.

Gil Rocha and Henrique Lopes Cardoso. A comparative analysis of unsupervised language adaptation methods. In *Proceedings of the 2nd Workshop on Deep Learning Approaches for Low-Resource NLP (DeepLo 2019)*, pages 11–21, 2019.

Adrian Lopez Rodriguez and Krystian Mikolajczyk. Domain adaptation for object detection via style consistency. *arXiv preprint arXiv:1911.10033*, 2019.

Guy Rotman and Roi Reichart. Deep contextualized self-training for low resource dependency parsing. *Transactions of the Association for Computational Linguistics*, 7:695–713, 2019.
Aruni RoyChowdhury, Prithvijit Chakrabarty, Ashish Singh, SouYoung Jin, Huaizhu Jiang, Liangliang Cao, and Erik Learned-Miller. Automatic adaptation of object detectors to new domains using self-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 780–790, 2019.

Amelie Royer and Christoph H Lampert. Classifier adaptation at prediction time. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1401–1409, 2015.

Artem Rozantsev, Mathieu Salzmann, and Pascal Fua. Beyond sharing weights for deep domain adaptation. *IEEE transactions on pattern analysis and machine intelligence*, 41(4):801–814, 2018.

Kate Saenko, Brian Kulis, Mario Fritz, and Trevor Darrell. Adapting visual category models to new domains. In *European conference on computer vision*, pages 213–226. Springer, 2010.

Kuniaki Saito, Yoshitaka Ushiku, Tatsuya Harada, and Kate Saenko. Adversarial dropout regularization. *arXiv preprint arXiv:1711.01575*, 2017.

Kuniaki Saito, Kohei Watanabe, Yoshitaka Ushiku, and Tatsuya Harada. Maximum classifier discrepancy for unsupervised domain adaptation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3723–3732, 2018.

Kuniaki Saito, Donghyun Kim, Stan Sclaroff, Trevor Darrell, and Kate Saenko. Semi-supervised domain adaptation via minimax entropy. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8050–8058, 2019a.

Kuniaki Saito, Yoshitaka Ushiku, Tatsuya Harada, and Kate Saenko. Strong-weak distribution alignment for adaptive object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6956–6965, 2019b.

Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Semantic foggy scene understanding with synthetic data. *International Journal of Computer Vision*, 126(9):973–992, 2018.

Khaled Saleh, Ahmed Abobakr, Mohammed Attia, Julie Iskander, Darius Nahavandi, Mohammed Hossny, and Saeid Nahvandi. Domain adaptation for vehicle detection from bird’s eye view lidar point cloud data. In *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops*, pages 0–0, 2019.

Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans. In *Advances in neural information processing systems*, pages 2234–2242, 2016.

Andrea Rosales Sanabria, Franco Zambonelli, and Juan Ye. Unsupervised domain adaptation in activity recognition: A gan-based approach. *IEEE Access*, 9:19421–19438, 2021.

Swami Sankaranarayanan, Yogesh Balaji, Carlos D Castillo, and Rama Chellappa. Generate to adapt: Aligning domains using generative adversarial networks. In *CVPR*, 2018.
Shibani Santurkar, Dimitris Tsipras, Andrew Ilyas, and Aleksander Madry. How does batch normalization help optimization? *Advances in neural information processing systems*, 31, 2018.

Motoki Sato, Hitoshi Manabe, Hiroshi Noji, and Yuji Matsumoto. Adversarial training for cross-domain universal dependency parsing. In *Proceedings of the CoNLL 2017 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies*, pages 71–79, 2017.

Ling Shao, Fan Zhu, and Xuelong Li. Transfer learning for visual categorization: A survey. *IEEE transactions on neural networks and learning systems*, 26(5):1019–1034, 2014.

Or Sharir, Barak Peleg, and Yoav Shoham. The cost of training nlp models: A concise overview. *arXiv preprint arXiv:2004.08900*, 2020.

Jian Shen, Yanru Qu, Weinan Zhang, and Yong Yu. Wasserstein distance guided representation learning for domain adaptation. In *Thirtysecond AAAI conference on artificial intelligence*, 2018.

Ge Shi, Chong Feng, Lifu Huang, Boliang Zhang, Heng Ji, Lejian Liao, and He-Yan Huang. Genre separation network with adversarial training for cross-genre relation extraction. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1018–1023, 2018.

Inkyu Shin, Sanghyun Woo, Fei Pan, and In So Kweon. Two-phase pseudo label densification for self-training based domain adaptation. In *European Conference on Computer Vision*, pages 532–548. Springer, 2020.

Ashish Shrivastava, Tomas Pfister, Oncel Tuzel, Joshua Susskind, Wenda Wang, and Russell Webb. Learning from simulated and unsupervised images through adversarial training. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2107–2116, 2017.

Rui Shu, Hung H Bui, Hirokazu Narui, and Stefano Ermon. A dirt-t approach to unsupervised domain adaptation. In *ICLR*, 2018.

Vishwanath A Sindagi, Poojan Oza, Rajeev Yasarla, and Vishal M Patel. Prior-based domain adaptive object detection for hazy and rainy conditions. In *European Conference on Computer Vision*, pages 763–780. Springer, 2020.

Kihyuk Sohn, Sifei Liu, Guangyu Zhong, Xiang Yu, Ming-Hsuan Yang, and Manmohan Chandraker. Unsupervised domain adaptation for face recognition in unlabeled videos. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 3210–3218, 2017.

PJ Soto, GAOP Costa, RQ Feitosa, PN Happ, MX Ortega, J Noa, CA Almeida, and Christian Heipke. Domain adaptation with cyclegan for change detection in the amazon forest. *ISPRS Archives; 43, B3*, 43(B3):1635–1643, 2020.

Baochen Sun and Kate Saenko. Deep coral: Correlation alignment for deep domain adaptation. In *ECCV*, 2016.
Baochen Sun, Jiashi Feng, and Kate Saenko. Return of frustratingly easy domain adaptation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 30, 2016.

Shiliang Sun, Honglei Shi, and Yuanbin Wu. A survey of multi-source domain adaptation. *Information Fusion*, 24:84–92, 2015.

Nima Tajbakhsh, Laura Jeyaseelan, Qian Li, Jeffrey N Chiang, Zhihao Wu, and Xiaowei Ding. Embracing imperfect datasets: A review of deep learning solutions for medical image segmentation. *Medical Image Analysis*, 63:101693, 2020.

Chuanqi Tan, Fuchun Sun, Tao Kong, Wenchang Zhang, Chao Yang, and Chunfang Liu. A survey on deep transfer learning. In *International conference on artificial neural networks*, pages 270–279. Springer, 2018.

Xingliang Tang and Xianrui Zhang. Conditional adversarial domain adaptation neural network for motor imagery eeg decoding. *Entropy*, 22(1):96, 2020.

Michele Tonutti, Emanuele Ruffaldi, Alessandro Cattaneo, and Carlo Alberto Avizzano. Robust and subject-independent driving manoeuvre anticipation through domain-adversarial recurrent neural networks. *Robotics and Autonomous Systems*, 115:162–173, 2019.

Luan Tran, Kihyuk Sohn, Xiang Yu, Xiaoming Liu, and Mannmohan Chandraker. Gotta adapt'em all: Joint pixel and feature-level domain adaptation for recognition in the wild. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2672–2681, 2019.

Isaac Triguero, Salvador Garcia, and Francisco Herrera. Self-labeled techniques for semi-supervised learning: taxonomy, software and empirical study. *Knowledge and Information Systems*, 42(2):245–284, 2015.

Yi-Hsuan Tsai, Wei-Chih Hung, Samuel Schulter, Kihyuk Sohn, Ming-Hsuan Yang, and Mannmohan Chandraker. Learning to adapt structured output space for semantic segmentation. In *CVPR*, 2018.

Eric Tzeng, Judy Hoffman, Ning Zhang, Kate Saenko, and Trevor Darrell. Deep domain confusion: Maximizing for domain invariance. *arXiv preprint arXiv:1412.3474*, 2014.

Eric Tzeng, Judy Hoffman, Trevor Darrell, and Kate Saenko. Simultaneous deep transfer across domains and tasks. In *Proceedings of the IEEE international conference on computer vision*, pages 4068–4076, 2015.

Eric Tzeng, Judy Hoffman, Kate Saenko, and Trevor Darrell. Adversarial discriminative domain adaptation. In *CVPR*, 2017.

Jesper E Van Engelen and Holger H Hoos. A survey on semi-supervised learning. *Machine Learning*, 109(2):373–440, 2020.

Riccardo Volpi, Pietro Morerio, Silvio Savarese, and Vittorio Murino. Adversarial feature augmentation for unsupervised domain adaptation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5495–5504, 2018.
Vibashan VS, Vikram Gupta, Poojan Oza, Vishwanath A Sindagi, and Vishal M Patel. Mega-cda: Memory guided attention for category-aware unsupervised domain adaptive object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4516–4526, 2021.

Apoorv Vyas, Nataraj Jammalamadaka, Xia Zhu, Dipankar Das, and Theodore L. Willke. Out-of-distribution detection using an ensemble of self supervised leave-out classifiers. ECCV, 2018.

Chen Wang, Jing Wang, Xiaofeng Liu, Manzhu Xu, Fangyun Wang, Lin Zheng, Huahua Dong, Binbin Wang, Xin Zhang, and Wanqing Xie. Advanced congenital heart disease diagnosis based on automatic generation of echocardiogram. Available at SSRN 3916770.

Chengjia Wang, Gillian Macnaught, Giorgos Papanastasiou, Tom MacGillivray, and David Newby. Unsupervised learning for cross-domain medical image synthesis using deformation invariant cycle consistency networks. In International Workshop on Simulation and Synthesis in Medical Imaging, pages 52–60. Springer, 2018.

Dequan Wang, Evan Shelhamer, Shaoteng Liu, Bruno Olshausen, and Trevor Darrell. Tent: Fully test-time adaptation by entropy minimization. arXiv preprint arXiv:2006.10726, 2020.

Guojin Wang, Ming Chen, Zijian Ding, Jiawei Li, Huazhong Yang, and Ping Zhang. Intercal patient eeg arrhythmia heartbeat classification based on unsupervised domain adaptation. Neurocomputing, 454:339–349, 2021a.

Jing Wang, Yi He, Wangyi Fang, Yiwei Chen, Wanyue Li, and Guohua Shi. Unsupervised domain adaptation model for lesion detection in retinal oct images. Physics in Medicine & Biology, 66(21):215006, 2021b.

Jing Wang, Xiaofeng Liu, Fangyun Wang, Lin Zheng, Fengqiao Gao, Hanwen Zhang, Xin Zhang, Wanqing Xie, and Binbin Wang. Automated interpretation of congenital heart disease from multi-view echocardiograms. Medical Image Analysis, 69:101942, 2021c.

Mei Wang and Weihong Deng. Deep visual domain adaptation: A survey. Neurocomputing, 312:135–153, 2018.

Ximei Wang, Ying Jin, Mingsheng Long, Jianmin Wang, and Michael Jordan. Transferable normalization: Towards improving transferability of deep neural networks. arXiv preprint arXiv:2019, 2019.

Yifei Wang, Wen Li, Dengxin Dai, and Luc Van Gool. Deep domain adaptation by geodesic distance minimization. In Proceedings of the IEEE International Conference on Computer Vision Workshops, pages 2651–2657, 2017.

Colin Wei, Kendrick Shen, Yining Chen, and Tengyu Ma. Theoretical analysis of self-training with deep networks on unlabeled data. arXiv preprint arXiv:2010.03622, 2021.

Kai-Ya Wei and Chiou-Ting Hsu. Generative adversarial guided learning for domain adaptation. In BMVC, page 100, 2018.
Garrett Wilson and Diane J Cook. A survey of unsupervised deep domain adaptation. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 11(5):1–46, 2020.

Garrett Wilson, Janardhan Rao Doppa, and Diane J Cook. Multi-source deep domain adaptation with weak supervision for time-series sensor data. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1768–1778, 2020.

Yifan Wu, Ezra Winston, Divyansh Kaushik, and Zachary Lipton. Domain adaptation with asymmetrically-relaxed distribution alignment. In *International Conference on Machine Learning*, pages 6872–6881, 2019a.

Yuan Wu, Diana Inkpen, and Ahmed El-Roby. Dual mixup regularized learning for adversarial domain adaptation. *ECCV*, 2020.

Yuxin Wu and Kaiming He. Group normalization. In *Proceedings of the European conference on computer vision (ECCV)*, pages 3–19, 2018.

Zuxuan Wu, Xin Wang, Joseph E Gonzalez, Tom Goldstein, and Larry S Davis. Ace: Adapting to changing environments for semantic segmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2121–2130, 2019b.

Markus Wulfmeier, Alex Bewley, and Ingmar Posner. Incremental adversarial domain adaptation for continually changing environments. In *2018 IEEE International conference on robotics and automation (ICRA)*, pages 4489–4495. IEEE, 2018.

Fangxu Xing, Xiaofeng Liu, Jay Kuo, Georges Fakhri, and Jonghye Woo. Brain mr atlas construction using symmetric deep neural inpainting. *IEEE Journal of Biomedical and Health Informatics*, 2022.

Jiaolong Xu, Liang Xiao, and Antonio M Lopez. Self-supervised domain adaptation for computer vision tasks. *IEEE Access*, 7:156694–156706, 2019a.

Minghao Xu, Hang Wang, Bingbing Ni, Qi Tian, and Wenjun Zhang. Cross-domain detection via graph-induced prototype alignment. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12355–12364, 2020.

Pengcheng Xu, Prudhvi Gurram, Gene Whipps, and Rama Chellappa. Wasserstein distance based domain adaptation for object detection. *arXiv preprint arXiv:1909.08675*, 2019b.

Yayun Xu and Hua Yan. Cycle-reconstructive subspace learning with class discriminability for unsupervised domain adaptation. *Pattern Recognition*, page 108700, 2022.

Junchi Yan, Xu-Cheng Yin, Weiyao Lin, Cheng Deng, Hongyuan Zha, and Xiaokang Yang. A short survey of recent advances in graph matching. In *Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval*, pages 167–174, 2016.

Chao Yang, Yuhang Song, Xiaofeng Liu, Qingming Tang, and C-C Jay Kuo. Image inpainting using block-wise procedural training with annealed adversarial counterpart. *arXiv preprint arXiv:1803.08943*, 2018.
Chao Yang, Xiaofeng Liu, Qingming Tang, and C-C Jay Kuo. Towards disentangled representations for human retargeting by multi-view learning. *arXiv preprint arXiv:1912.06265*, 2019a.

Heran Yang, Jian Sun, Aaron Carass, Can Zhao, Junghoon Lee, Jerry L Prince, and Zongben Xu. Unsupervised mr-to-ct synthesis using structure-constrained cyclegan. *IEEE transactions on medical imaging*, 39(12):4249–4261, 2020a.

Jihan Yang, Ruijia Xu, Ruiyu Li, Xiaojuan Qi, Xiaoyong Shen, Guanbin Li, and Liang Lin. An adversarial perturbation oriented domain adaptation approach for semantic segmentation. 2020b.

Qiang Yang, Yang Liu, Yong Cheng, Yan Kang, Tianjian Chen, and Han Yu. Federated learning. *Synthesis Lectures on Artificial Intelligence and Machine Learning*, 13(3):1–207, 2019b.

Ting Yao, Yingwei Pan, Chong-Wah Ngo, Houqiang Li, and Tao Mei. Semi-supervised domain adaptation with subspace learning for visual recognition. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 2142–2150, 2015.

Zili Yi, Hao Zhang, Ping Tan, and Minglun Gong. Dualgan: Unsupervised dual learning for image-to-image translation. In *Proceedings of the IEEE international conference on computer vision*, pages 2849–2857, 2017.

Hongxu Yin, Pavlo Molchanov, Jose M Alvarez, Zhizhong Li, Arun Mallya, Derek Hoiem, Niraj K Jha, and Jan Kautz. Dreaming to distill: Data-free knowledge transfer via deepinversion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8715–8724, 2020a.

Yufeng Yin, Baiyu Huang, Yizhen Wu, and Mohammad Soleymani. Speaker-invariant adversarial domain adaptation for emotion recognition. In *Proceedings of the 2020 International Conference on Multimodal Interaction*, pages 481–490, 2020b.

Chaehwa Yoo, Hyang Woon Lee, and Jewon Kang. Transferring structured knowledge in unsupervised domain adaptation of a sleep staging network. *IEEE Journal of Biomedical and Health Informatics*, 2021.

Kaichao You, Ximei Wang, Mingsheng Long, and Michael Jordan. Towards accurate model selection in deep unsupervised domain adaptation. In *Proceedings of the twenty-first international conference on Machine learning*. ACM, 2019.

Fisher Yu and Vladlen Koltun. Multi-scale context aggregation by dilated convolutions. *arXiv preprint arXiv:1511.07122*, 2015.

Fuxun Yu, Di Wang, Yinpeng Chen, Nikolaos Karianakis, Tong Shen, Pei Yu, Dimitrios Lymberopoulos, Sidi Lu, Weisong Shi, and Xiang Chen. Sc-uda: Style and content gaps aware unsupervised domain adaptation for object detection. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 382–391, 2022.
Werner Zellinger, Thomas Grubinger, Edwin Lughofner, Thomas Natschläger, and Susanne Saminger-Platz. Central moment discrepancy (cmd) for domain-invariant representation learning. *arXiv preprint arXiv:1702.08811*, 2017.

Anran Zhang, Yandan Yang, Jun Xu, Xianbin Cao, Xiantong Zhen, and Ling Shao. Latent domain generation for unsupervised domain adaptation object counting. *IEEE Transactions on Multimedia*, 2022.

Dan Zhang, Jingjing Li, Lin Xiong, Lan Lin, Mao Ye, and Shangming Yang. Cycle-consistent domain adaptive faster rcnn. *IEEE Access*, 7:123903–123911, 2019a.

Haojian Zhang, Yabin Zhang, Kui Jia, and Lei Zhang. Unsupervised domain adaptation of black-box source models. *arXiv preprint arXiv:2101.02839*, 2021.

Jian Zhang, Lei Qi, Yinghuan Shi, and Yang Gao. Generalizable semantic segmentation via model-agnostic learning and target-specific normalization. *arXiv preprint arXiv:2003.12296*, 2020a.

Jing Zhang, Wanqing Li, Philip Ogunbona, and Dong Xu. Recent advances in transfer learning for cross-dataset visual recognition: A problem-oriented perspective. *ACM Computing Surveys (CSUR)*, 52(1):1–38, 2019b.

Kun Zhang, Bernhard Schölkopf, Krikamol Muandet, and Zhikun. Domain adaptation under target and conditional shift. In *ICML*, 2013.

Yifan Zhang, Ying Wei, Qingyao Wu, Peilin Zhao, Shuaicheng Niu, Junzhou Huang, and Mingkui Tan. Collaborative unsupervised domain adaptation for medical image diagnosis. *IEEE Transactions on Image Processing*, 29:7834–7844, 2020b.

Youshuan Zhang. A survey of unsupervised domain adaptation for visual recognition. *arXiv preprint arXiv:2112.06745*, 2021.

Yue Zhang, Shun Miao, Tommaso Mansi, and Rui Liao. Task driven generative modeling for unsupervised domain adaptation: Application to x-ray image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 599–607. Springer, 2018a.

Yun Zhang, Nianbin Wang, Shaobin Cai, and Lei Song. Unsupervised domain adaptation by mapped correlation alignment. *IEEE Access*, 6:44698–44706, 2018b.

Zhen Zhang, Mianzhi Wang, Yan Huang, and Arye Nehorai. Aligning infinite-dimensional covariance matrices in reproducing kernel hilbert spaces for domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3437–3445, 2018c.

Ganlong Zhao, Guanbin Li, Ruijia Xu, and Liang Lin. Collaborative training between region proposal localization and classification for domain adaptive object detection. In *European Conference on Computer Vision*, pages 86–102. Springer, 2020a.
Deep Unsupervised Domain Adaptation

Ranqi Zhao, Yi Xia, and Yongliang Zhang. Unsupervised sleep staging system based on domain adaptation. *Biomedical Signal Processing and Control*, 69:102937, 2021.

Sicheng Zhao, Bichen Wu, Joseph Gonzalez, Sanjit A Seshia, and Kurt Keutzer. Unsupervised domain adaptation: From simulation engine to the realworld. *arXiv preprint arXiv:1803.09180*, 2018.

Sicheng Zhao, Bo Li, Pengfei Xu, and Kurt Keutzer. Multi-source domain adaptation in the deep learning era: A systematic survey. *arXiv preprint arXiv:2002.12169*, 2020b.

Wei Zhao, Wei Xu, Min Yang, Jianbo Ye, Zhou Zhao, Yabing Feng, and Yu Qiao. Dual learning for cross-domain image captioning. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 29–38, 2017.

Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pages 2223–2232, 2017.

Xiahai Zhuang and Juan Shen. Multi-scale patch and multi-modality atlases for whole heart segmentation of mri. *Medical image analysis*, 31:77–87, 2016.

Danbing Zou, Qikui Zhu, and Pingkun Yan. Unsupervised domain adaptation with dual-scheme fusion network for medical image segmentation. In *IJCAI*, pages 3291–3298, 2020.

Yang Zou, Zhiding Yu, Xiaofeng Liu, and BVK Kumar. Confidence regularized self-training. *ICCV*, 2019.