Neurocomputing 564 (2024) 126921

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Survey Paper

Source-Free Unsupervised Domain Adaptation: Current research and future directions

Ningyuan Zhang, Jie Lu *, Keqiuyin Li, Zhen Fang, Guangquan Zhang

Australian Artificial Intelligence Institute, Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney, NSW 2007, Australia

ARTICLE INFO

Communicated by N. Zeng

Keywords:
Transfer Learning
Unsupervised Domain Adaptation
Source-free
Deep learning

ABSTRACT

In the field of Transfer Learning, Source-Free Unsupervised Domain Adaptation (SFUDA) emerges as a practical and novel task that enables a pre-trained model to adapt to a new unlabeled domain without access to the original training data. The advancement of SFUDA has profoundly reshaped the algorithmic design of domain adaptation methods. Given the novelty and limited exploration of SFUDA, conducting a comprehensive survey is imperative to showcase methodological advancements, identify existing gaps, and uncover potential trends in this field. This paper provides an extensive review of SFUDA, encompassing methods and applications. First, based on the learning objectives during adaptation, different SFUDA methods fall into three categories: (i) *Self-Tuning*, (ii) *Feature Alignment*, and (iii) *Sample Generation*, with further sub-categorization within each category. Additionally, the strengths and limitations of each category are discussed, and various application areas where SFUDA can yield significant benefits are summarized. Finally, drawing from extensive observations and insights, potential future directions for SFUDA research are analyzed, with a focus on identifying emerging trends and key areas for further exploration.

1. Introduction

Deep neural models have achieved remarkable success across various tasks and modalities [1]. However, training a deep neural model from scratch requires substantial labeled data and computational resources, making it impractical to train domain/task-specific deep models for each domain/task. This raises a fundamental question: Can the knowledge learned from one dataset/task (the source domain) be applied to other datasets/tasks (the target domains)? In response to this question, *Transfer Learning* has emerged, leveraging previously acquired knowledge from the source domain to enhance model performance in target domains [2]. The importance of transfer learning lies in the effective re-usage of source domain knowledge, making transfer learning an appealing machine learning approach that can reduce the need for extensive annotation and training. According to the relations between the source and target domains and tasks, three different paradigms have been identified under transfer learning [3]: (i) *Inductive Transfer Learning*, where the target task differs from the source task but labels for the target domain are available. (ii) *Unsupervised Transfer Learning*, where the target task is different from the source task, and labels for both the source and target domains are unavailable. (iii) *Transductive Transfer Learning*, where the source and target tasks are the same, but the source and target domains are different, and there is no labeled data in the target domain.

This paper focuses on a sub-field within transductive transfer learning known as *Unsupervised Domain Adaptation* (*UDA*), which addresses the challenge of *Domain Shift*, where the source and target domains follow different distributions [4]. UDA has garnered significant attention for its unique ability to tackle domain shifts without target annotations. Its feasibility relies on the inherent similarity between the source and target domains [5]. With the aim of training a model for the target domain using labeled source data and unlabeled target data, existing UDA methods achieve adaptation by aligning the statistical moments between the feature distributions extracted from the source and target domains [6–8]. Alternatively, some methods [9–11] incorporate domain discriminators into the learning process to distinguish between source and target features, while also guiding the feature extractor to generate similar features for both source and target samples to "fool" the domain discriminators.

While conventional Unsupervised Domain Adaptation (UDA) methods are effective at mitigating domain shifts, they face a significant practical limitation: they require the simultaneous input of both source and target samples into the deep model for adaptation. However, in

* Corresponding author.
E-mail addresses: ningyuan.zhang@student.uts.edu.au (N. Zhang), jie.lu@uts.edu.au (J. Lu), keqiuyin.li@uts.edu.au (K. Li), zhen.fang@uts.edu.au (Z. Fang), guangquan.zhang@uts.edu.au (G. Zhang).

https://doi.org/10.1016/j.neucom.2023.126921
Received 11 July 2023; Received in revised form 19 September 2023; Accepted 8 October 2023
Available online 10 October 2023

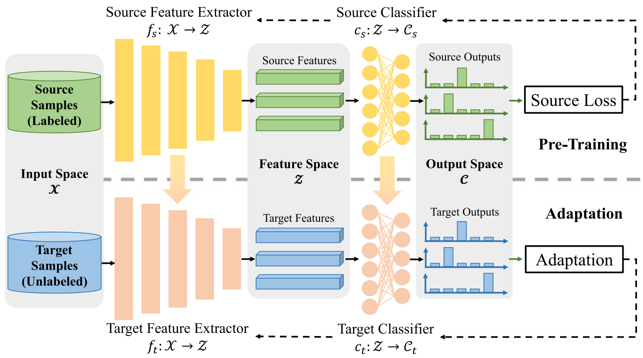

Fig. 1. Workflow of SFUDA Methods (taking the vanilla SFUDA setup for demonstration): During pre-training, a source model (composed of a feature extractor and a classifier) will be trained by the labeled source samples. During Adaptation, the target model will be initialized by the pre-trained source model and adapted given the unlabeled target domain.

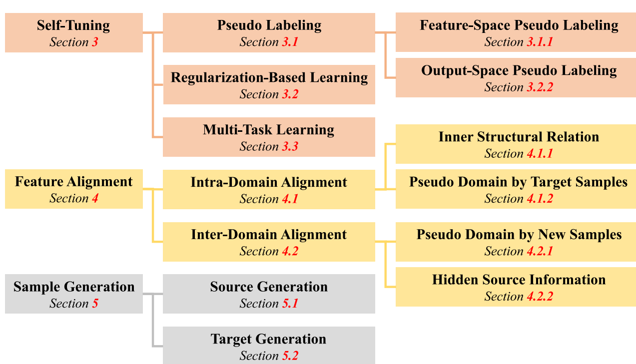

Fig. 2. Classification of SFUDA Methods: Based on the adaptation objectives of SFUDA methods, SFUDA methods are classified into Self-tuning, Feature Alignment, and Sample Generation categories, with finer categorizations within each category.

real-world scenarios, accessing source data can be challenging, especially when it contains sensitive or private information or when computational devices have limited resources to store and process both source and target data simultaneously. This challenge has catalyzed the emergence of a novel domain adaptation setup known as *Source-Free Unsupervised Domain Adaptation* (*SFUDA*), whose importance lies in the elimination of the need for the simultaneous access of the source and target data. SFUDA achieves this by breaking its workflow into two distinct stages (as demonstrated in Fig. 1): (i) the *Pre-Training* stage, where annotated source samples are used to pre-train the model, and (ii) the *Adaptation* stage, where source samples are inaccessible, and the model adapts to the target domain using only unlabeled target samples. The separation of pre-training and adaptation in SFUDA aligns it more closely with real-world scenarios, significantly enhancing its practical implications. Consequently, SFUDA has found a wide range of applications across various fields.

SFUDA was initially proposed in 2016 [12], but the concept of "source-free" was not extensively explored until the milestone work SHOT [13] was introduced in 2020. After 2020, Zhao et al. [14] and Farahani et al. [15] presented surveys covering UDA methods. However, they did not delve into SFUDA methods, as their surveys were published during the early stages of SFUDA's development. Liu et al. [16] included the early-emerged SFUDA methods in their in-depth review of UDA methods. They also identified "source-free" as a potential future direction for UDA advancement. Csurka et al. [17] conducted a comprehensive survey on UDA methods designed for image segmentation and briefly summarized SFUDA methods for segmentation. Moreover, Liu et al. [18] addressed SFUDA methods and applications within a subsection of a survey focused on data-free knowledge transfer. However, these surveys did not exclusively focus on SFUDA and were conducted during the early stages of SFUDA's emergence, underscoring the need for a timely taxonomy and comprehensive coverage of SFUDA methods. In light of this gap, this paper aims to offer a comprehensive, timely, and phased review of the field of SFUDA. In summary, the following contributions are made to the research community:

(1) **A Comprehensive Review of SFUDA**: This paper provides a structured overview of the methodological advancements in SFUDA. It categorizes SFUDA methods into three primary categories based on adaptation objectives, with further sub-categorization within each category (as depicted in Fig. 2). Furthermore, it explores the practical applications of SFUDA, highlighting its relevance and significance across various fields. This comprehensive coverage fills the gap left by previous studies that had not delved deeply into the topic of SFUDA.
(2) **Discussions and Future Directions**: Building on the structured review of SFUDA methods, this paper engages in critical discussions and analysis of different approaches, providing the research community with a deeper understanding of the field. Additionally, the paper outlines potential research directions for SFUDA, offering valuable guidance to researchers aiming to advance the field.

The structure of this paper is outlined as follows: In Section 2, the problem formulation and different setups under SFUDA are detailed; an in-depth discussion of the taxonomy used throughout this survey is also provided. In Sections Section 3, 4, and 5, SFUDA methods falling into each category are reviewed. Section 6 offers a critical analysis of different SFUDA approaches. In Section 7, various applications that benefit from the utilization of SFUDA techniques are highlighted. Finally, Section 8 summarizes the paper and highlights the future directions.

2. Preliminaries

Taking the image classification task as an example, this section elaborates on the problem formulation and setups under SFUDA and delves into the taxonomy for categorizing SFUDA methods.

2.1. Problem formulation

Let $\mathcal{X}$ be the input space, $\mathcal{C}_s$ or $\mathcal{C}_t$ be the source or target label space, and $|\mathcal{C}_s|$ or $|\mathcal{C}_t|$ be the numbers of source or target classes. Symbol x is used to represent the sample from input space $\mathcal{X}$, and y is used to represent the label from label space $\mathcal{C}_s$ or $\mathcal{C}_t$. A source domain consists of N_s labeled source samples, i.e., $\mathcal{D}_s = \left\{(x_s^1, y_s^1), \dots, (x_s^{N_s}, y_s^{N_s})\right\}$. Similarly, a target domain consists of N_t unlabeled target samples, i.e., $\mathcal{D}_t = \left\{x_t^1, \dots, x_t^{N_t}\right\}$. In order to clarify the problem formulation, the workflow of SFUDA is divided into two stages: pre-training and adaptation.

Stage 1. Pre-Training. With the aim of minimizing the empirical risk on the source domain $\mathcal{D}_s$, a source model $h_s : \mathcal{X} \to \mathcal{C}_s$ is obtained. The pre-trained source model h_s, parameterized by θ_{h_s}, consists of two sub-modules: a feature extractor $f_s : \mathcal{X} \to \mathcal{Z}$ (parameterized by θ_{f_s}, $\mathcal{Z}$ is the feature space) and a classifier $c_s : \mathcal{Z} \to \mathcal{C}_s$ (parameterized by θ_{c_s}).

Stage 2. Adaptation. During adaptation, the target model $h_t = c_t \circ f_t$ is initialized with the pre-trained source weights θ_{h_s}. Subsequently, h_t is adapted to the target domain with the aim of minimizing the empirical target-domain error:

$$\widehat{\mathrm{err}}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \mathcal{L}_{0-1}(h_t(x_t^i), y_t^i) \tag{1}$$

where $y_t^i \in \mathcal{C}_t$ represents the inaccessible ground-truth label of the target sample x_t^i, and $\mathcal{L}_{0-1}(\cdot, \cdot)$ is the zero–one loss.

Table 1
Different Setups in SFUDA: $C_s\&C_t$: the relation between source and target label spaces; $|C_s|\&|C_t|$: the relation between numbers of source and target classes; θ_{h_s}?: whether the source pre-trained model weights are accessible during adaptation; M_s?: the number of source domains; M_t?: the number of target domains.

Setup	$C_s\&C_t$	$\|C_s\|\&\|C_t\|$	θ_{h_s}?	M_s?	M_t?
Vanilla	$C_s = C_t$	$\|C_s\| = \|C_t\|$	√	= 1	= 1
Partial-set	$C_s \supset C_t$	$\|C_s\| > \|C_t\|$	√	= 1	= 1
Open-set	$C_s \subset C_t$	$\|C_s\| < \|C_t\|$	√	= 1	= 1
Universal	$C_s \cap C_t \neq \emptyset$	?	√	= 1	= 1
Black-box	$C_s = C_t$	$\|C_s\| = \|C_t\|$	×	= 1	= 1
Multi-source	$C_s = C_t$	$\|C_s\| = \|C_t\|$	√	> 1	= 1
Multi-target	$C_s = C_t$	$\|C_s\| = \|C_t\|$	√	= 1	> 1

2.2. Setups

There are various setups under SFUDA, each posing distinct constraints on different conditions. An overview of these setups is presented in Table 1.

Vanilla: This is the most common setup where the source and target domain share the same label space ($C_s = C_t$). The pre-trained weights can be used to initialize the target model.

Partial-Set: In this scenario, the source label space is a superset of the target label space ($C_t \subset C_s$) [19], while other conditions remain consistent with the vanilla setup.

Open-Set: In the open-set setup, the source label space is a subset of the target label space ($C_s \subset C_t$) [20], with all other conditions remaining consistent with the vanilla setup.

Universal: The universal setup makes no assumptions about the relationship between the source and target label spaces. Both domains can have overlapping or private classes [21].

Black-Box: In the black-box setup, access to the pre-trained weights is unavailable during adaptation [22]. Consequently, the target model's adaptation relies solely on the predictions made on the target domain.

Multi-Source/Target: These setups involve the existence of multiple source domains for model pre-training [23] or multiple target domains for model adaptation [24].

2.3. Taxonomy

The challenge in classifying SFUDA methods lies in their complex algorithmic processes. These methods often integrate various techniques, resulting in complex connections between different approaches. Therefore, this survey blocks the differences in the algorithmic process, categorizing SFUDA methods based solely on their learning objectives during adaptation.

When analyzing the adaptation objectives, two fundamental questions are considered: (i) Where does the loss signal originate? (ii) What models are learned after adaptation? By answering the questions, the existing SFUDA literature can be divided into distinct sub-categories with well-defined boundaries. The brief answers to these questions with respect to each sub-category can be viewed in Table 2.

It is important to note that the taxonomy presented in this survey is not the only way of classifying SFUDA methods. Alternative perspectives are equally valid. Furthermore, as SFUDA continues to evolve, new methods may emerge that do not neatly fit into the categories outlined in this survey. The objective of this survey is to provide a timely, comprehensive, and phased review of SFUDA, contributing to its development.

3. Self-tuning methods

This section introduces the largest category of SUFDA: self-tuning, which adapts the model by self-created supervision signals. Depending on the adaptation objectives, self-tuning can be further divided into three sub-categories: (i) the *Pseudo Labeling* (Section 3.1) sub-category that assigns pseudo labels to target samples and adapts the model based on the supervision of the pseudo labels; (ii) the *Regularization-Based Learning* (Section 3.2) sub-category that adapts the model only by regularization terms; and (iii) the *Multi-Task Learning* (Section 3.3) sub-category that combines multiple tasks to adapt the model.

3.1. Pseudo labeling

Pseudo labeling [25] was proposed for semi-supervised learning [26] initially. It trains a model on a partially labeled dataset and utilizes the model to generate labels for the remaining samples. Within the SFUDA framework, pseudo labeling can be employed to adapt the model by having the pre-trained source model infer pseudo labels for target samples. However, with the presence of domain shifts, the inferred pseudo labels may be contaminated with unknown noise. Consequently, many pseudo labeling methods focus on enhancing the robustness and trustworthiness of the pseudo labels.

Regarding adaptation objectives, the error between pseudo labels and target predictions is the loss signals generated by pseudo labeling methods. After adaptation, only the target model is learned. Based on the space in which pseudo labels are generated, pseudo labeling methods can be further divided into: (i) *Feature-Space Pseudo Labeling* (Section 3.1.1) that generates pseudo labels based on feature space relations, and (ii) *Output-Space Pseudo Labeling* (Section 3.1.2) that generates pseudo labels based on output predictions.

3.1.1. Feature-space pseudo labeling

Feature-space pseudo labeling methods explore the clustering structure of target features to infer pseudo labels, aiming to bypass the source bias of the pre-trained model. Deriving from the existing literature, a three-step workflow (illustrated in Fig. 3a) can be outlined:

- *Centroids Construction*: To build class centroids in the target feature space, and assign pseudo labels to target samples based on their relations to the centroids.
- *Label Refinement, Filtering, or Weighing*: To reduce label noise and alleviate source bias, enhancing the quality and reliability of the pseudo labels.
- *Model Adaptation*: To adapt the target model using the pseudo-labeled target samples.

Step 1. Centroids Construction. The key to this step lies in how to build more distinguished and reliable class centroids that are robust to domain shifts and source bias. Weighted k-means clustering [27] is an effective method for constructing class centroids in the feature space, leveraging target features as clustering entities and target outputs as clustering weights. This approach has found widespread adoption in feature-space pseudo labeling methods [13,28–37]. Among these methods, most of them utilize all target samples to build the class centroids. However, it would be beneficial to take the trustworthiness of each target sample into consideration during the construction process. To this end, Song et al. [37] and Tian et al. [36] perform weighted k-means clustering exclusively on low-entropy features to build the class centroids. Drawing inspirations from category learning [38,39], which suggests that objects with high similarities are likely to belong to the same category, Tang et al. [28] treat nearest features as fundamental clustering units during clustering and label assignment.

Beyond weighted k-means clustering, an alternative method for constructing centroids is to class-wisely average the low-entropy target features [40–42], building discriminative and class-balanced centroids. Furthermore, in the search for a representation of data-structure-wise probability in the feature space, Lee et al. [43] adopt Gaussian Mixture Modeling (GMM) [44] to construct class centroids, treating each target class as an individual Gaussian distribution.

While the majority of the methods create one representative centroid for each target class, the "centroid" of a target class is not necessarily limited to a single representative feature. Kim et al. [45]

Table 2
To adapt the target model: **Pseudo Labeling** methods minimize the error between target predictions and pseudo labels; **Regularization-Based Learning** methods minimize the loss calculated by regularization terms; **Multi-Task Learning** methods combine multiple tasks containing pseudo labeling, feature alignment, and self-supervised auxiliary tasks; **Inner Structural Relation** aligns target samples with their positive/negative peers; **Pseudo Domain by Target Samples** methods align target samples with source-like target samples; **Pseudo Domain by New Samples** methods align target samples with generated source-like samples; **Hidden Source Information** methods align the target information with information stored in the source model; **Source Generation** translates target samples into source-like samples that can be classified by the source model; **Target Generation** generates labeled target samples and then trains the target model.

Sub-Category	Model(s) learned	Summary of loss signals	Notes
Pseudo Labeling	h_t	$\mathcal{L}_{0-1}(h_t(x_t), \hat{y}_t)$	$\hat{y}_t$: Target Pseudo Label
Regularization-Based Learning	h_t	$\mathcal{L}_{reg}(x_t)$	$\mathcal{L}_{reg}$: Regularization Loss
Multi-Task Learning	h_t	$\mathcal{L}_{0-1}(h_t(x_t), \hat{y}_t) + \mathcal{L}_{align} + \mathcal{L}_{at}$	$\mathcal{L}_{align}$: Alignment Loss; $\mathcal{L}_{at}$: Auxiliary Task Loss
Inner Structural Relation	h_t	$\mathcal{L}_{align}(x_t, x_t^{\pm ref})$	$x_t^{\pm ref}$: Positive/Negative Peer of a Target Sample x_t
Pseudo Domain by Target Samples	h_t	$\mathcal{L}_{align}(x_t, x_{\tilde{t}})$	$x_{\tilde{t}}$: Source-Like Target Samples
Pseudo Domain by New Samples	$g_s\&h_t$	$\mathcal{L}_{align}(x_t, \tilde{x}_s)$	g_s: Source Generation Model; $\tilde{x}_s$: Generated Source-Like Samples
Hidden Source Information	h_t	$\mathcal{L}_{algin}(I_{D_t}, I_{h_s})$	I_{h_s}: Source Model Information; I_{D_t}: Target Domain Information
Source Generation	g_{t2s}	$\mathcal{L}_{0-1}(h_s(g_{t2s}(x_t)), \tilde{y}_s)$	g_{t2s}: Source Translation Model; $\tilde{y}_s$: Generated Source Label
Target Generation	$g_t\&h_t$	$\mathcal{L}_{0-1}(h_t(\tilde{x}_t), \tilde{y}_t)$	g_t: Target Generation Model; $\tilde{x}_t/\tilde{y}_t$: Generated Target Sample/Label

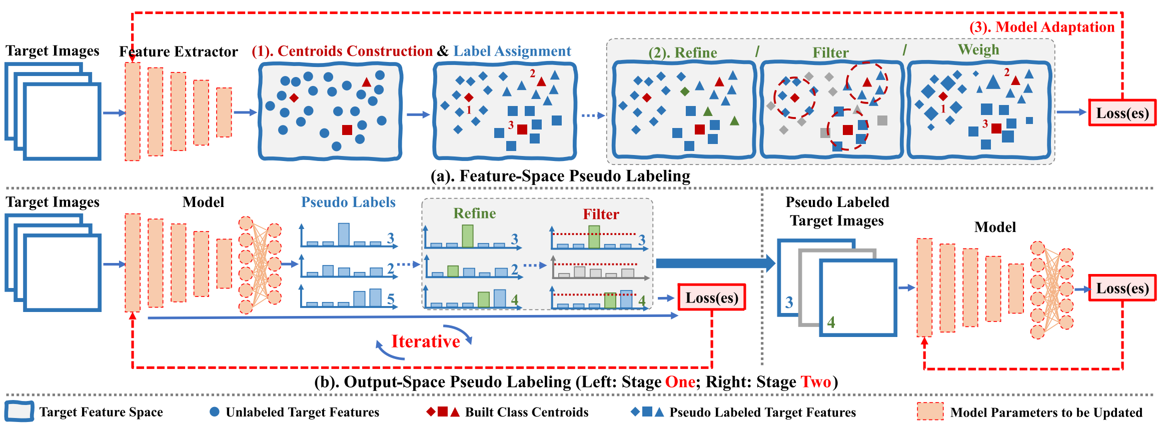

Fig. 3. **(a). Feature-Space Pseudo Labeling**: The workflow consists of (i) Centroids Construction, (ii) Label Refinement, Filtering, or Weighing, and (iii) Model Adaptation. **(b). Output-Space Pseudo Labeling**: *Stage One*: Label generation and model adaptation are carried out simultaneously in an iterative manner. *Stage Two*: After stage one, a cleaner set of pseudo labels can be obtained. A new/existing target model will then be trained/finetuned by the cleaner set of pseudo labels. Methods whose workflow spans the two stages are termed as Two-Stage methods.

and Dong et al. [46] directly adopt confident target features as "centroids" for a target class, without further averaging or clustering, preserving the intrinsic structural information of the target features.

After the class centroids are constructed, the feature-space pseudo labels can be assigned to the target samples according to their relations to the class centroids.

Step 2. Label Refinement, Filtering, or Weighing. Due to domain shifts, the assigned pseudo labels could be noisy. Label refinement is a way to mitigate such noise by correcting the pseudo labels for potentially mislabeled target samples. Wang et al. [29] propose neighbor consistency to correct target labels according to the label consistency among neighboring features. On the other hand, Guan et al. [41] and Qu et al. [42] take per-class information into consideration and adopt within-class k-means clustering to correct the labels for target features lying around the decision boundaries.

Beyond refinement, label noise can also be reduced through label filtering, which selects high-quality labels by a proper metric and threshold. In the case of feature-space pseudo labeling, the metric and threshold can be decided by feature distances. For instance, ambiguous target features that do not have a prominent shortest-to-centroid distance can be discarded [40,45].

To handle label noise while preserving the integrity of the pseudo-labeled target domain, label weighing can be employed. The key lies in the search for a proper metric that reflects the level of importance of a pseudo-labeled target sample. A simple metric would be the output entropy of a target sample, Song et al. [37] derive adaptive weights for the target samples from the class-wise entropy distributions of the target domain. While Kumar et al. [31] obtain the label weights from the feature space according to a target sample's label consistency across training steps. Combining the information across the output and feature space, Lee et al. [43] quantify the label weights by combining the confidence of pseudo labels and the consistency between pseudo labels and output predictions. The label weights are then used to sample-wisely weigh the final adaptation loss.

Step 3. Model Adaptation. With the pseudo-labeled target domain and the pre-trained model prepared, adaptation is then performed, mostly by a cross-entropy loss. Regarding the updating strategy for model weights, Wang et al. [29] introduce an innovative approach where the weights in the target feature extractor are divided into domain-invariant or domain-specific weights. The weights are then actively or passively updated using the loss signals created by the final cross-entropy loss.

3.1.2. Output-space pseudo labeling

Output-space pseudo labeling methods obtain pseudo labels for target samples in the output space using the predictions from the classifier. This approach enables the pre-trained model to be adapted with integrity, facilitating more strict setups such as the black-box setup. However, output-space pseudo labeling methods generate pseudo labels at the very end of the model, injecting the entire source bias into the pseudo labels. Therefore, the key aspect in designing output-space pseudo labeling methods lies in improving the quality of the pseudo labels to prevent error accumulation and mitigate source bias.

To address this aspect, output-space pseudo labeling methods usually "borrow opinions" from extra models. For example, Feng et al. [47] introduce an extra teacher model whose weights and BN statistics are

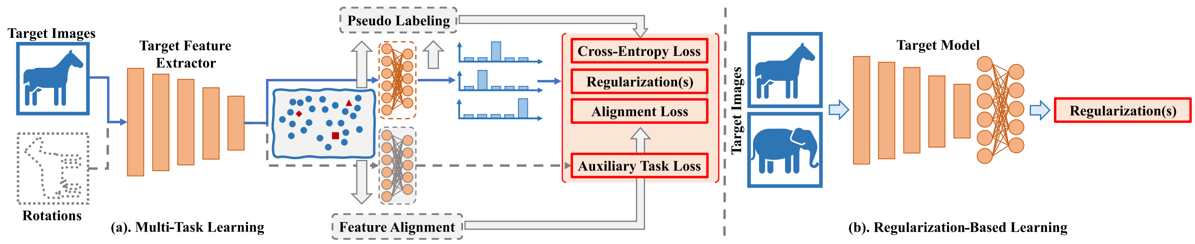

Fig. 4. (a). Multi-Task Learning methods adopt multiple sub-tasks (Auxiliary Task, Feature Alignment, and Pseudo Labeling) to adapt the model. **(b). Regularization-Based Learning** methods adapt the target model under the sole guidance of regularization terms.

the exponential moving average [48] of those of the target model to infer pseudo labels and avoid catastrophic forgetting [49] for the target model. Ahmed et al. [50] introduce extra models by replicating the pre-trained source model. They have the replicated models individually tuned in a negative learning [51] manner to "forget" potentially incorrect classes. The outputs of the models are then ensembled to enhance the quality of the pseudo labels. Instead of using a single pre-trained model, Sevyer et al. [52] enrich the diversity by ensembling the multiple pre-trained source models with different architectures to improve the label quality. The aforementioned methods utilize the pre-trained source models to enrich the label prediction, with the source model being the primary knowledge provider. To explore knowledge beyond the source model, Zhang et al. [53] incorporate a public-available pre-trained transformer [54] to jointly infer the pseudo labels with the source pre-trained model, and design a confidence-based filtering strategy to choose the pseudo labels between the pre-trained transformer and the source pre-trained model.

Similar to feature-space pseudo labeling methods, the inferred labels can be further filtered or weighed to reduce the noise. A fundamental filtering strategy is to directly discard pseudo-labeled target samples based on prediction confidence [50,55]. However, the confidence threshold needs to be leveraged carefully as different target classes tend to suffer different levels of label noise. To this end, Zhang et al. [22] estimate per-class label noise rate according to target prediction scores, and design per-class adaptive threshold to filter the label noise. In terms of label weighing, Kundu et al. [56] assign positive or negative weights to target samples based on their similarities to the source categories, pushing the target data closer to or away from the source clusters under the universal setup.

Unlike other methods that generate labels and adapt the model alternately, methods introduced above [50,53] follow a *Two-Stage* workflow that involves a stage one where cleaner pseudo labels are generated in an iterative manner same as other methods, and a stage two where the cleaner labels are used to train or finetune a new or existing model (Fig. 3b). Also following the two-stage workflow and aiming to provide a set of cleaner pseudo labels, Chen et al. [57] re-initialize the BN statistics to enhance the target model and adopt cluster-wise label consistency [58] to refine the pseudo labels; while Yan et al. [59] introduce diversity to the inferred labels by ensembling the outputs of a target sample and its augmentations. Paying attention to the transferability of individual target samples, Pei et al. [60] quantify the transferability of the target samples using uncertainty estimations. They encourage the target model to forget less-transferable target samples and remember more transferable ones during the first stage to enhance the target model.

A summary of the pseudo labeling methods can be viewed in the upper half of Table 3.

3.2. Regularization-based learning

Regularizations play a crucial role in stabilizing the training process and enhancing the generalizability of models without relying on label information. They are widely employed by SFUDA methods, serving as a modular component in the adaptation loss to adapt the target model along with other tasks. In this survey, methods that create loss signals from only the regularization terms and learn only the target model, are classified as regularization-based learning methods (Fig. 4b).

This subsection introduces novel regularization terms adopted by regularization-based learning methods:

- *Information Maximization* (IM) [61], introduced to SFUDA by Liang et al. [13], consists of an entropy minimization and a diversity maximization term, enhancing the discriminability while maintaining the diversity for the model.
- *Jacobian Norm*, proposed by Li et al. [62], encourages model smoothness by enforcing consistency between target samples and perturbed target samples.
- *Early Learning*, introduced to SFUDA by Yi et al. [63], forces the model's current predictions to align with earlier predictions, based on the early learning phenomenon that models tend to remember easy samples in early training stages [64].

In the literature, the above-introduced regularizations can be used alone to tune the model [62,63,65,66]. While Tian et al. [67] propose a method that adapts the target model by multiple regularizations to maintain balance, discriminability, and diversity concurrently.

3.3. Multi-task learning

During adaptation, it is not necessary to restrict the adaptation process to one task (such as pseudo labeling) only. Instead, multiple tasks can be incorporated to boost adaptation. Multi-task learning methods (Fig. 4a) aim to learn only the target model during adaptation. They create loss signals from multiple sources: (i) the error between pseudo labels and target predictions (pseudo labeling sub-task); (ii) the supervision generated by self-supervised auxiliary sub-tasks; or (iii) the discrepancy between target features and reference features (feature alignment sub-task, will be further elaborated in Section 4). This sub-section reviews the sub-category in terms of sub-tasks:

(1) Auxiliary Task. Self-supervised learning [89] is a powerful technique enabling deep models to learn semantic information without labeled data, by creating self-supervised auxiliary tasks. Among these tasks, rotation prediction [90] that randomly rotates target images and incorporates a task-specific classifier to classify the rotation degrees, has gained significant popularity among multi-task learning methods [74–77], aiding the target model to learn rich target semantics [91].

However, conventional self-supervised auxiliary tasks are not specifically designed and may not be optimal for SFUDA. This highlights a gap, necessitating the exploration of more SFUDA-compatible auxiliary tasks. To address the gap, Kundu et al. [73] theoretically verified that a higher domain similarity and a higher task similarity between the auxiliary task and the adaptation task would help close the domain discrepancy. Based on the findings, they introduce a sticker-based auxiliary task that has the model to predict a sticker's location, rotation, and category, given a sticker-intervened image. Such specially tailored auxiliary tasks can better fit the specialties of SFUDA, thereby enhancing the generalization ability of the model.

Table 3
Abstraction and benchmark comparison for Pseudo Labeling (**Up**) and Multi-Task Learning (**Down**) methods. **Centroids**: How a method builds class centroids, whether it makes full usage of the target domain (Full $\mathcal{D}_t$?), and the tricks for centroids construction (W for weighted k-means clustering; A for averaging; G for Gaussian Mixture Modeling; ×for no clustering or averaging). **Pseudo Label**: The space on which the labels are generated, and whether the generated pseudo labels are further refined, filtered, or weighed. **Align?**: Whether a method includes a Feature Alignment sub-task. **Auxiliary Tasks**: The self-supervised auxiliary sub-tasks a method adopts. **Accuracy**: The performance of a method on *Office31* [68] (ResNet-50 [69]), *OfficeHome* [70] (ResNet-50), and *VisDA* [71] (ResNet-101).

Method	Centroids		Pseudo label				Align?	Auxiliary task(s)	Accuracy		
	Full $\mathcal{D}_t$?	W?	Space?	Refine?	Filter?	Weigh?			Office31	OfficeHome	VisDA
[13]	√	W	F	–	–	–	–	–	88.6	71.8	82.9
[28]	√	W	F	–	–	–	–	–	88.6	72.6	84.5
[29]	√	W	F	√	–	–	–	–	90.1	72.5	83.1
[30]	√	W	F	–	–	–	–	–	90.7	79.3	83.0*
[31]	√	W	F	√	–	–	–	–	89.4*	76.0*	84.4
[32]	√	W	F	–	–	–	–	–	89.0	72.2	85.6
[36]	×	W	F	–	–	–	–	–	90.1	72.7	84.4
[37]	×	W	F	–	–	√	–	–	89.4	72.2	–
[33]^{bf}	√	W	F	–	–	–	–	–	85.5	66.7	–
[34]^{ms}	√	W	F	–	–	–	–	–	91.1	75.5	–
[35]^{ms}	√	W	F	–	–	√	–	–	91.2	75.0	–
[40]	×	A	F	–	√	–	–	–	–	64.9	76.4
[41]	×	A	F	√	–	–	–	–	89.5	72.8	85.6
[42]	×	A	F	√	–	–	–	–	89.4	72.5	85.8
[43]	√	G	F	–	–	√	–	–	90.3	72.5	86.9
[45]	×	×	F	–	√	–	–	–	87.2	65.7	76.7
[46]^{ms}	×	×	F	–	–	–	–	–	91.6	76.2	–
[47]	–	–	O	–	–	–	–	–	87.3	70.8	85.7
[52]	–	–	O	–	–	–	–	–	90.0	72.5	83.8
[72]	–	–	O	–	–	–	–	–	91.1	74.1	88.1
[55]^{o}	–	–	O	–	√	–	–	–	94.5	69.6	64.7
[22]^{B}	–	–	O	–	√	–	–	–	87.9	–	80.1
[56]^{u}	–	–	O	–	–	√	–	–	90.2	77.0	63.9
[50]	–	–	O	√	√	–	–	–	–	–	84.2
[57]	–	–	O	√	√	–	–	–	–	–	85.8
[53]	–	–	O	√	√	–	–	–	93.6	83.6	88.4
[60]	–	–	O	√	√	–	–	–	90.3	73.2	87.3
[59]	–	–	O	√	–	–	–	–	89.5	–	82.8
[73]	–	–	–	–	–	–	–	Sticker Intervention	90.7	74.0	88.2
[74]	–	–	–	–	–	√	√	Image Rotation	90.1	72.8	84.3
[75]	√	W	F	√	–	–	√	Image Rotation	–	73.2	87.7
[76]	√	W	F	–	–	–	–	Image Rotation	89.2	73.0	87.3
[77]	√	W	F	–	–	–	–	Image Rotation	–	72.9	87.8
[78]	√	W	F	–	–	–	√	–	89.3	–	83.4
[79]	√	W	F	–	–	–	√	–	–	72.8	87.3
[80]	√	W	F	–	–	–	√	–	–	71.6	86.0
[81]^{A}	√	W	F	–	–	–	√	–	83.5	58.0	65.0
[82]	√	W	F	–	–	–	√	–	–	72.0	85.2
[83]^{ms}	×	W	F	–	–	–	√	–	91.9	75.7	–
[84]	–	–	O	–	–	√	√	–	89.8	–	83.5
[85]	–	–	O	–	√	–	√	–	90.5	73.5	87.8
[86]^{B}	×	W	O & F	–	√	–	√	–	90.6	71.6	–
[87]^{uB}	–	–	O	–	–	–	√	–	91.7	77.7	–
[88]^{I}	–	–	O	–	√	–	√	–	–	65.4	76.7

Notes *: Accuracy obtained using a different backbone; ^{ms}: method designed for *multi-source* UDA setup;
^{I}: method designed for imbalanced situation; ^{A}: method designed for dealing adversarial target samples;
^{u}: method designed for universal UDA setup; ^{B}: method designed for black-box setup;
^{bf}: method designed for back-propagation-free setup; ^{o}: method designed for *open-set* UDA setup;.

(2) Feature Alignment. Feature alignment sub-tasks offer a distinct view promoting adaptation by direct operations on target features. They align the target features with suitable alignment references, equipping the target model with an alternative perspective to explore the underlying target semantics hidden in the structure of the target data. Within multi-task learning, several methods have adopted feature alignment as a sub-task to explore the target data structure. For example, works in [74,75,79,86] propose to split the target domain into a confident and a non-confident subset and have the confident subset to serve as a pseudo source domain to attract the non-confident target features. Instead of target domain division, Zhao et al. [78] and Huang et al. [84] align target features with historical target features to maintain the source hypothesis during adaptation. While Lee and Lee [82], and Karim et al. [85] align target features with target augmentation features to promote model smoothness and maintain model diversity. Moreover, Agarwal et al. [81] and Li et al. [88] have the feature alignment sub-task to support pseudo-labeling tasks, aiding in achieving intra-class compactness and inter-class separation during the adaptation process of pseudo-labeling, by pulling target features from the same class closer and pushing those from different classes apart. Innovatively, Li et al. [83] inject fuzzy rules into the source models to generate prototypical source features. During adaptation, alignment is performed between the prototypical source features and the prototypical target features extracted by the source fuzzy rules. Zong et al. [80] go beyond specific features and consider the decision boundaries of source classifiers as negative references, pushing target samples away from these boundaries.

(3) Pseudo Labeling. As a fundamental task of SFUDA, pseudo labeling plays a crucial role as a sub-task in the context of multi-task learning, guiding the joint adaptation of the target model alongside other sub-tasks both in the feature space [75–83,86] and output space [84–88]. In Section 3.1, a comprehensive introduction to pseudo labeling has been provided, demonstrating its workflow and various novel tricks. Hence, the specific aspects of the pseudo labeling sub-task within multi-task learning will not be further detailed. However, in the second half of Table 3, a concise summary is provided, outlining the

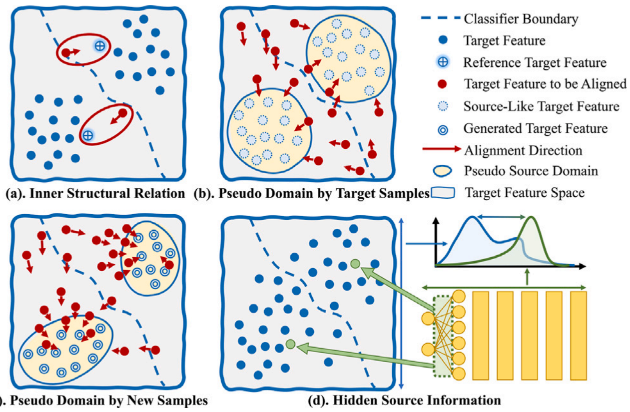

Fig. 5. An overview of Feature Alignment sub-categories: **(a). Inner Structural Relation** aligns target features according to their relations. **(b). Pseudo Domain by Target Samples** builds a pseudo domain by low-entropy target features, then performs alignment between the two domains. **(c). Pseudo Domain by New Samples** builds a pseudo domain by generating source-like samples, then performs alignment between the two domains. **(d). Hidden Source Information** aligns the information extracted from the target domain with the information hidden in the source model (marked as the yellow blocks on the bottom right). The figure demonstrated two types of hidden information: source classifier weights that serve as natural source class centroids (marked as green circles), and statistics information stored in the source model (marked as the green curve in the two-dimensional axis).

essential sub-tasks of multi-task learning methods as well as the corresponding benchmark performance. This summary serves as a handy overview of the pseudo labeling sub-task within the broader context of multi-task learning.

4. Feature alignment methods

Some conventional UDA methods focus on extracting similar features for source and target samples that share similar semantics, which can be seen as the alignment between source and target features. In the context of SFUDA, although source samples are inaccessible, alignment can still be performed between target samples and the intrinsic information hidden within the target data structure (*Intra-Domain Alignment*, Section 4.1), or between target samples and information exploited beyond the target domain (*Inter-Domain Alignment*, Section 4.2).

4.1. Intra-domain alignment

Information embedded in the target data structure can serve as a valuable indicator guiding the adaptation process. Intra-domain alignment methods specifically focus on exploring the target data structure and searching for alignment references within the target domain. These methods generate loss signals based on the discrepancy between rich-semantic target features and other target features, and they only learn the target model. Within this sub-category, two types of alignment references are identified: (i) Rich-semantic target features selected based on the *Inner Structural Relations* among target features (Section 4.1.1); (ii) A *Pseudo Domain* constructed by source-like *Target Samples* (Section 4.1.2). Once the reference is established, alignment can be carried out to adapt the model. A visual demonstration of these two types of references in the feature space can be observed in Fig. 5a&b, respectively. Furthermore, a summary and benchmark comparison of the intra-domain alignment methods can be viewed in the first half of Table 4.

4.1.1. Inner structural relation

Inner structural relation methods perform alignment among paired target features channeled by feature space structural relations. They tend to follow an "explore-then-align" manner:

Step 1. Alignment Reference Exploration. The structural information in the target feature space primarily resides in the nearest neighbor features. Target features and the corresponding top-k nearest neighbor features can be treated as positive pairs to be pulled closer [92–96]. However, in some cases, training a discriminative model by only bringing positive pairs closer is insufficient. Constructing negative pairs that are pushed apart is also essential to ensure a more discriminative feature structure. Yang et al. [94] and Wu et al. [95] regard target features and their corresponding non-top-k nearest neighbors as negative pairs. In addition, Chen et al. [96] further interpolate the nearest neighbors to select pairs of target features that fail to establish meaningful relations as negative pairs.

Step 2. Target Feature Alignment. With the positive and negative pairs established, the next step is to align the target features. To bring the positive pairs closer, a common strategy is to maximize their prediction consistency [92–95], with the effect of bringing a pair of positive features closer in the feature space. During the process of bringing positive pairs closer, different pairs can be assigned varying levels of importance. For instance, Wu et al. [95] assign greater weights to nearest neighbor pairs with higher cosine similarity, while Yang et al. [92] assign greater weights to pairs of reciprocal nearest neighbors [97], supported by empirical evidence that they are more likely to belong to the same class. Conversely, to push negative pairs apart, a common strategy is to minimize their prediction consistency [94,95]. Another approach is to minimize the contrastive loss, which pushes negative pairs apart while simultaneously bringing positive pairs closer [96].

4.1.2. Pseudo domain by target samples

Methods falling into this sub-category select target samples that exhibit source-like statistics to create a pseudo source domain. Subsequently, the problem of SFUDA can be converted into a conventional UDA problem, allowing existing UDA algorithms to function in the source-free setting. These methods typically adopt a "select-then-align" approach:

Step 1. Target Sample Selection. This step aims to select source-like target samples to construct a pseudo source domain. The key lies in defining appropriate metrics that quantify the degree of source similarity exhibited by the target samples. A straightforward method is to directly choose low-entropy or high-confidence target samples as the pseudo source domain [98–100]. While in the multi-source setup where rich domain-level knowledge [101] can be leveraged, Shen et al. [102] combine predictions and feature information from each source model to compute confidence scores, which are then aggregated to form a metric for dividing the target domain. Beyond selecting target samples according to confidence scores, feature-space relations are still helpful in picking up source-like target samples. Ding et al. [103] treat the weights of the source classifier as centroids of source classes and choose target features close to these weights to form the pseudo source domain.

Step 2. Domain Alignment. Once the pseudo source domain is established, the next step is to minimize the discrepancy between the pseudo source domain and the remaining target domain. Given the presence of two domains, conventional UDA methods, such as Domain Adversarial Learning [118], and Bi-Classifier Determinacy Maximization [119] can be employed to bridge the gap between the two domains [98,100,102]. While Yang et al. [104] propose a novel "bait" classifier to disagree with the source classifier on low-confidence target samples while maintaining agreement on high-confidence target samples, drawing inspirations from Maximum Classifier Discrepancy [120]. The disagreement & agreement operations will then force the low-confidence target samples to cross the decision boundary to be aligned with the high-confidence ones. In addition, Ding et al. [103] suggest aligning the two domains through cross-domain mix-up. Specifically, they intermix samples from the two distinct domains and enforce alignment between the resultant prediction outputs and the mixed pseudo labels.

Table 4
An abstraction and benchmark comparison of the **Feature Alignment** methods. **Intra/Inter**: Indicates whether the alignment reference is within (intra) or beyond (inter) the target domain. **PD?**: Indicates whether a method builds a pseudo domain for alignment. **Alignment**: The alignment references and the methods conducted for alignment. **Accuracy**: The performance of a method tested on *Office31* [68] (ResNet-50), *OfficeHome* [70] (ResNet-50), and *VisDA* [71] (ResNet-101).

Method	Intra/Inter	PD?	Alignment		Accuracy		
			Reference	Method	Office31	OfficeHome	VisDA
[92]	Intra	×	Nearest Target Features	$\max$(Prediction Consistency)	89.4	72.2	85.9
[93]	Intra	×	Nearest Target Features	$\max$(Prediction Consistency)	–	71.3	85.4
[94]	Intra	×	Nearest Target Features	$\min\max$(Prediction Consistency)	89.9	72.7	88.0
[95]	Intra	×	Nearest Target Features	$\min\max$(Prediction Consistency)	91.5	76.1	88.7
[96]	Intra	×	Nearest Target Features	$\min$(Contrastive Loss)	89.9	72.4	87.7
[98]	Intra	√	High-Confidence Target Samples	$\min\max$(Adversarial Loss)	–	72.1	84.1
[102]^{ms}	Intra	√	High-Confidence Target Samples	$\min\max$(Adversarial Loss)	91.3	77.3	–
[100]	Intra	√	High-Confidence Target Samples	$\min\max$(Classifier Determinacy Disparity)	89.9	72.2	87.5
[104]	Intra	√	High-Confidence Target Samples	$\min\max$(Prediction Consistency)	88.9	71.5	81.8
[103]	Intra	√	Near-Centroids Target Features	$\min$(Inter-domain Mixup Loss)	90.1	72.8	85.7
[105]	Inter	√	Generated Samples	$\min\max$(Adversarial Loss)	83.5	–	–
[106]	Inter	√	Generated Samples	$\min\max$(Adversarial Loss)	86.2	–	–
[107]	Inter	√	Generated Features	$\min$(Contrastive Loss)	89.9	71.6	86.0
[108]	Inter	√	Generated Outputs	$\min\max$(Adversarial Loss)	88.1	70.8	81.9
[109]	Inter	√	GMM-Sampled Features	$\min$(Wasserstein Distance)	88.4	–	76.9
[110]	Inter	√	GMM-Sampled Features	$\min$(Contrastive Loss)	90.1	72.9	86.5
[111]	Inter	√	GMM-Sampled Features	$\min\max$(Adversarial Loss)	89.7	71.4	85.3
[112]	Inter	√	Restyled Target Samples	$\min\max$(Adversarial Loss)	89.2	69.8	82.1
[113]	Inter	√	Restyled Target Samples	$\max$(Prediction Consistency)	87.7	–	81.4
[114]	Inter	×	Source Classifier Weights	$\min$(Moving Costs)	90.0	71.8	–
[115]	Inter	×	Source Classifier Weights	$\min$(Contrastive Loss)	89.3	–	87.5
[116]	Inter	×	Source Model Statistics	$\min$(KL-Divergence)	89.1	–	–
[117]	Inter	×	Source Model Statistics	$\min$(KL-Divergence)	–	–	83.1

Notes ^{ms}: the performance is obtained under the *multi-source* UDA setup;.

4.2. Inter-domain alignment

Inter-domain alignment methods seek alignment references beyond the target domain. They generate loss signals by identifying disparities between the generated or hidden source information and the target information. After adaptation, the target model is learned, and in certain cases, the generation model used to produce the source information is also acquired. In this sub-category, two types of alignment references are identified: (i) A *Pseudo Source Domain* constructed by generating new source-like samples (Section 4.2.1); (ii) The *Hidden Source Information* extracted from the source model. An overview of these two references is illustrated in Fig. 5c&d. Moreover, a summary and benchmark comparison of these methods is presented in the second half of Table 4.

4.2.1. Pseudo domain by new samples

Methods belonging to this sub-category build a pseudo source domain with generated data and simultaneously learn a generation model and the target model. They typically adopt a "generate-then-align" approach:

Step 1. Pseudo Domain Generation. In this step, a pseudo source domain is created using techniques such as GANs [121], GMMs [44], or other methods. The key to generation is to find proper information/supervision for the generation process such that the generated data effectively represents the source domain. When utilizing GANs to create the pseudo source domain without accessing the source data and target labels, a robust form of supervision comes from pre-trained source models, aiding GANs to generate source samples [105,106,113], prototypical source features [107], or even source-like predictions [108]. Alternatively, when using GMMs to generate source-like features [109–111,122], to ensure that sufficient statistical information of the source domain is captured, GMMs can be built by the source statistics calculated during source pre-training [109], or by statistics derived from target centroids and near-centroid target features [110], or by treating the source classifier weights directly as means for the Gaussian Models [111]. In addition to generative models and Gaussian modeling, Yao et al. [112] create source-like samples by progressively transforming target images into source images, accomplished by freezing the source model and back-propagating gradients to the input images.

Step 2. Domain Alignment. This step shares significant similarity with the corresponding step in the pseudo domain by target samples sub-category (Section 4.1.2). It involves employing conventional alignment techniques, such as contrastive learning, domain adversarial learning [118], or minimizing the Sliced Wasserstein distance [123], to bridge the domain gap. Yeh et al. [122], however, introduce a novel tri-level alignment procedure to address domain discrepancy. Specifically, they conduct input, feature, and output level alignment during both the inference process that maps target data to labels and the generation process that maps labels to reconstructed target samples, to adapt the model.

4.2.2. Hidden source information

The source model often contains valuable information representing the source domain. Hidden source information methods tap into this resource, extracting similar information from the target domain and aligning it with the stored source information. There are two main types of hidden source information:

Type 1. Source Classifier Weights can naturally act as source class centroids [124]. When employing source classifier weights as alignment references, the similar information to be extracted is the target features. Wang et al. [115] employ contrastive learning to encourage target features to be close to the potentially correct source classifier weights while pushing them away from potentially incorrect weights. Similarly, Tanwisuth et al. [114] propose a bi-directional moving cost, minimizing pairwise costs between target features and weight vectors and pushing the target features towards the classifier weights.

Type 2. Statistical Information stored in the source model can also encapsulate source domain representations. A common type of statistical information is the means and variances stored in the Batch Normalization (BN) layers of the source model. Correspondingly, the relevant target information would be the means and variances computed from the target domain. Adaptation can then be achieved through aligning BN statistics between target features and the source model [116]. Beyond BN statistics, Eastwood et al. [117] embed a soft binning [125] distribution within the source model during pre-training. This distribution approximates the marginal source feature distribution in an efficient and flexible manner. Adaptation is then achieved by aligning the marginal distribution extracted from target features with the distribution embedded in the source model.

Table 5
Evaluation framework for SFUDA methods.

Sub-Category	Method	Models Learned: Loss components	Inference	Office31	OfficeHome	VisDA
Pseudo Labeling	Liang et al. [13]	$\mathbf{h_t}$: $\mathcal{L}_{ce}$	$\mathbf{h_t}(x_t)$	88.6	71.8	82.9
Regularization-Based Learning	Yi et al. [63]	$\mathbf{h_t}$: $\mathcal{L}_{elr}$	$\mathbf{h_t}(x_t)$	84.9	67.3	74.6
Multi-Task Learning	Liang et al. [76]	$\mathbf{h_t}$: $\mathcal{L}_{ce} + \mathcal{L}_{rce}$	$\mathbf{h_t}(x_t)$	89.2	73.0	87.3
Inner Structural Relation	Yang et al. [94]	$\mathbf{h_t}$: $\mathcal{L}_{pc}$	$\mathbf{h_t}(x_t)$	89.9	72.7	88.0
Pseudo Domain by Target Samples	Du et al. [98]	$\mathbf{h_t}$: $\mathcal{L}_{ce} + \mathcal{L}_{Dadv}$	$\mathbf{h_t}(x_t)$	–	72.1	84.1
Pseudo Domain by New Samples	Kurmi et al. [105]	$\mathbf{g_s}$: $\mathcal{L}_{ce} + \mathcal{L}_{Gadv}$; $\mathbf{h_t}$: $\mathcal{L}_{ce} + \mathcal{L}_{Dadv}$	$\mathbf{h_t}(x_t)$	83.5	–	–
Hidden Source Information	Ishii and Sugiyama [116]	$\mathbf{h_t}$: $\mathcal{L}_{sm}$	$\mathbf{h_t}(x_t)$	89.1	–	–
Source Generation	Jeon et al. [126]	$\mathbf{g_{t2s}}$: $\mathcal{L}_{ce}$	$\mathbf{h_s}(\mathbf{g_{t2s}}(x_t))$	–	–	–
Target Generation	Li et al. [127]	$\mathbf{g_t}$: $\mathcal{L}_{ce} + \mathcal{L}_{Gadv}$; $\mathbf{h_t}$: $\mathcal{L}_{ce}$	$\mathbf{h_t}(x_t)$	89.6	–	81.6

h_t: Target Prediction Model; h_s: Source Prediction Model; g_s: Source Generation Model; g_t: Target Generation Model; $\mathbf{g_{t2s}}$: Source Translation Model
$\mathcal{L}_{ce}$: Cross-Entropy; $\mathcal{L}_{elr}$: Early Learning Regularization; $\mathcal{L}_{rce}$: Rotation Classification Cross-Entropy; $\mathcal{L}_{pc}$: Prediction Consistency;
$\mathcal{L}_{Dadv}$: Domain Adversarial Loss; $\mathcal{L}_{Gadv}$: Generative Adversarial Loss; $\mathcal{L}_{sm}$: Statistics Matching Loss.

5. Sample generation methods

Due to the strict constraints imposed by the "source-free" and "unsupervised" conditions, many SFUDA methods design complex adaptation algorithms to counter domain shifts under such strict conditions. Innovatively, this complexity can be bypassed by directly generating labeled samples. Depending on the generated data, sample generation methods can be further divided into three sub-categories: (i) the *Source Generation* (Section 5.1) sub-category that trains a generator g to translate target samples into source-like samples, serving as a preprocessing step to prepare the target samples to be classified by the source models; (ii) the *Target Generation* (Section 5.2) sub-category that generates labeled target samples to directly train the target model; and (iii) the *Intermediate Domain Generation* sub-category that generates an intermediate domain to bridge the source and target domain. Notably, Kundu et al. [128] propose a unique approach involving the creation of an intermediate domain through a mixing process. This intermediate domain is utilized to pre-train the source model, following which a typical SFUDA method is employed on the intermediate target domain to achieve adaptation. By building an intermediate domain, it is expected that the transferability between the source and target domains is enhanced [129], thereby boosting the performance of existing adaptation methods. In the following, methods that generate source/target samples are introduced to elaborate the basic ideas.

5.1. Source generation

The source generation sub-category focuses solely on learning the generation model g, which translates target samples into source-like samples during adaptation. Loss signals are generated as the pre-trained source model endeavors to recognize the translated "source" sample. Therefore, the key challenge is to effectively capture the source information to ensure reliable translation. To this end, under the multi-source setup, Jeon et al. [126] employ an autoencoder [130] as the generator g, comprising a feature extractor and multiple decoders. They take the pre-trained source models as supervision to have the auto-encoder effectively capture the source knowledge. Innovatively, the generator g does not have to be limited to generative models. Sahoo et al. [131] utilize a predictive network as the "generator" g to predict the shift parameters for target images, assuming that target data are natural-shifted source samples. Given the predicted shift parameters, the target images are then shifted to the source style and fed into the source model for classification.

5.2. Target generation

Target generation methods learn the target model as well as the generation model during adaptation, utilizing the differences between generated target samples and original target samples as the loss signals for the generation model, while the generated labeled target samples as direct supervision for the target model, reducing the reliance on complex adaptation algorithms. The main challenge in target generation is to generate samples that retain the characteristics of the target domain. Such key challenge can be addressed by employing a generator and discriminator pair [127,132], where the generator takes noise-injected labels as input and generates samples that are indistinguishable from the real target samples for the discriminator, and the discriminator aims to differentiate between target samples and generated samples. Besides the discriminator, Li et al. [127] additionally incorporate source model supervision to enhance the semantic similarity between the generated sample and the corresponding input label.

6. Discussions

In this section, Table 5 presents an evaluation framework featuring one representative method from each sub-category, illustrating the contrasts between sub-categories. Beyond showcasing the benchmark performance, the framework delves into three key facets: (i) the models learned during adaptation; (ii) the losses employed to train each model; and (iii) the inference pipeline after adaptation. This evaluation framework provides readers with a snapshot of the principal distinctions, performance, and general computational requisites associated with each sub-category. In the following, discussions are provided to highlight each method's strengths and limitations, based on which, insights on individual methods are provided to help readers gain a deeper understanding of the field of SFUDA.

6.1. Self-tuning

(1) Strengths. Regarding the pseudo labeling methods: they integrate class information to accomplish category-level adaptation [133]. They do not require excessive computational resources and are relatively easy to implement, allowing the model to be adapted in the same way it was pre-trained. The simplicity of pseudo labeling makes it applicable to various setups under SFUDA. While regularization-based learning methods provide even greater flexibility and simplicity, compatible with different model architectures and adaptation tasks [62, 63]. Moreover, regularization terms can help the model pay attention to specific model attributes and cultivate special model characteristics, adapting the model in a flexible and efficient way. Multi-task learning methods offer the advantage of learning domain-invariant representations through the simultaneous execution of multiple sub-tasks. This approach allows the model to capture diverse aspects of the data and provides multiple perspectives for learning. The complexity and diversity of the sub-tasks also facilitate the design of task-specific methods that can be applied to various setups and applications.

(2) Limitations. Pseudo labeling methods are sensitive to uncontrollable domain shifts [134] and unpredictable class imbalances. Inaccurate or unreliable pseudo labels can misguide the adaptation process, while training on imbalanced data may result in adverse class bias [135], impairing the adaptation performance. From the performance shown in Table 5, it is obvious that relying solely on regularization terms would hardly yield strong performance. Moreover, the incorporation of extra regularizations and multiple sub-tasks may introduce additional trade-off hyperparameters that require manual selection. The selection and optimization of these hyperparameters can be challenging and may necessitate extensive experiments. Additionally, the inclusion of multiple tasks during adaptation may lead to increased computational load and prolonged adaptation processes.

(3) Insights. For pseudo labeling methods, the uncontrollable domain shifts and unpredictable class imbalances could be eased by more generalizable source models. Potential solutions, such as uncertainty estimations, fuzzy rules, powerful backbones, model ensembling, or innovative data augmentation techniques, could be explored to enhance generalizability. For regularization-based learning methods, a promising direction is to tailor the regularizations based on the task-specificity of SFUDA, making them more specialized and effective as plug-and-play modules for SFUDA techniques. Regarding multi-task learning methods, a valuable direction is to identify and reconcile any inherent conflicts among individual sub-tasks

6.2. Feature alignment

(1) Strengths. Intra-domain alignment methods offer a straightforward approach by aligning within the target domain. They leverage local similarities and data structures without incurring additional computations from generation operations. Meanwhile, inter-domain alignment methods enable the target model to extend its scope beyond the target domain, injecting more diverse knowledge into the target model to facilitate effective adaptation.

(2) Limitations. Feature alignment methods may require the use of memory banks to store target features, generated data, or generation models. This could reduce memory efficiency during adaptation, limiting their applicability on constrained devices. For pseudo domain by new samples methods, they usually require learning extra generation models, which introduce additional trainable parameters and divide the adaptation process into a generation and an alignment stage, increasing the computation load and complexity of the adaptation stage. With hidden source information methods, challenges may arise when the source and target models exhibit structural differences, thus limiting the scalability of the target model.

(3) Insights. For intra-domain alignment methods, future research could focus on advanced techniques to select more dependable target features. Exploring methods that consider local density, robust distance metrics, and outlier detection techniques may contribute to refining the alignment process. For inter-domain alignment methods, future research could delve into more effective generative models and novel data augmentation strategies to enhance the quality and diversity of the generated samples. Additionally, exploring more representative information and embedding it appropriately in the source model might offer a viable direction for further research.

6.3. Sample generation

(1) Strengths. Sample generation methods can alleviate the need for extensive adaptation techniques and simplify the adaptation process [212]. Source generation methods can enable the utilization of existing source models without modification, empowering the source model to process target samples directly and maximally preserving the source knowledge. Furthermore, target generation methods can increase the number of available training samples, providing more diverse and informative training samples for adaptation.

(2) Limitations. It is important for sample generation methods to accurately capture the intrinsic characteristics of the samples during generation [213]; failure to do so could lead to impaired adaptation results. Additionally, sample generation methods often require the usage of generation models, introducing extra trainable parameters into the adaptation stage. During inference, source generation introduces an additional translation stage before prediction [131], thereby limiting practicality and prolonging the inference pipeline.

(3) Insights. Enhancing the quality of the generated samples is crucial for the success of sample generation methods. Future research can focus on developing more sophisticated generation models that better capture the desired domain characteristics. Furthermore, exploring innovative strategies such as data augmentation and image denoising could offer alternative ways to generate high-quality samples that align with either the source or target domain.

7. Applications

SFUDA has emerged as a flexible and practical solution for tackling domain shifts in various real-world applications and data modalities. Although SFUDA has been applied to diverse fields, its primary application remains centered in the field of computer vision. Hence, this section delves into the applications of SFUDA concerning three key tasks: *Segmentation*, *Detection*, and *Classification*, encompassing computer vision applications as well as extending beyond. In addition, a summary of benchmark datasets, as well as an overview of various applications adopting SFUDA, can be viewed in Table 6 and 7, respectively.

7.1. Segmentation

Segmentation is a foundational task in computer vision that involves pixel-level classification to divide an image into meaningful and distinct regions or segments. It enables various real-world applications such as autonomous driving, medical imaging, and video surveillance.

For conventional segmentation models operating on RGB images, domain shifts often arise from diverse weather conditions, background scenes, and disparities between synthetic and real images. In the literature, there are methods designed to adapt pre-trained RGB segmentation models [172–180]. In the task of road segmentation, adverse weather conditions pose a significant challenge, causing the performance of segmentation models pre-trained on normal weather conditions to drop significantly in adverse weather scenarios. Moreover, road segmentation models are often deployed on constrained devices such as vehicles or surveillance cameras, making it impractical to store the source data on the deployment devices. Additionally, segmentation requires precise pixel-level annotations for effective model training, making it infeasible to label newly distributed test data that emerge after model deployment. In the face of these challenges, Kothandaraman et al. [172] employ entropy minimization to bridge the domain gap between clean weather and adverse weather images. They then adopt output-space pseudo labeling to adapt the pre-trained segmentation model, bypassing the need for access to source data and target annotations. Consequently, the pre-trained model's segmentation performance, measured by mIoU, experiences a remarkable uplift of 23.99% on a real dataset collected under foggy weather.

Beyond conventional RGB images, there are SFUDA methods designed to adapt segmentation models for medical images [181–189]. In the task of brain skull stripping, domain shifts typically arise from variations in medical images sourced from distinct clinical sites or generated by different equipment, restricting the performance of a stripping model when it encounters brain MRIs from different vendors. Moreover, the sensitivity of medical images to privacy concerns restricts the sharing of source data across clinical sites, further underscoring the importance of employing SFUDA techniques. To address these difficulties, Dinsdale et al. [181] build a Gaussian Mixture Model (GMM) on source features during pre-training, serving as an abstraction of the source domain, thereby eliminating the need for sharing medical images. They then align the GMM built on target features with that of source features to adapt the stripping model to MRIs acquired by scanners from different vendors. As a result, they achieve an impressive enhancement of 14% in the pre-trained model's segmentation performance.

Table 6
A collection of benchmarking datasets for domain adaptation.

Task	Data	Dataset	Classes	Samples	Domain summary
Segmentation	RGB Image	Composed Dataset	–	40541	4: GTA5 [136]; Citscapes [137]; SYNTHIA [138]; NTHU [139]
Detection	RGB Image	Composed Dataset	–	28442	5: Citscapes [137]; Foggy Cityscapes [140]; KITTI [141]; SIM10k [142]; VOC2007 [143]
	RGB Image	Multi-Paintings [144]	6	4500	3: clipart1k; Comic2k; Watercolor2k
	Point Cloud	Composed Dataset	–	271630	3: Waymo [145]; nuScenes [146]; KITTI [141]
Classification	RGB Image	Digits	10	∼700000	5: MNIST [147]; SVHN [148]; USPS [149]; MNIST-M [118]; SYN [118]
	RGB Image	Office31 [68]	31	4110	3: Amazon; DSLR; Webcam
	RGB Image	OfficeHome [70]	65	15588	4: Art; Clipart; Product; Real World
	RGB Image	VisDA [71]	12	280157	2: Synthetic; Real
	RGB Image	DomainNet [150]	345	∼600000	6: Clipart, Infograph, Painting, Quickdraw, Real, Sketch
	RGB Image	Office-Caltech-10 [151]	10	2533	4: Amazon, DSLR, Webcam, Caltech10
	RGB Image	ImageCLEF-DA [152]	12	2400	4: Caltech; ImageNet; Pascal; Bing
	RGB Image	PACS [153]	7	9991	4: Art painting, Cartoon, Photo, Sketch
	Point Cloud	PointDA-10 [154]	10	32788	3: ModelNet-10; ShapeNet-10; ScanNet-10
	Video	Face Anti-Spoofing	–	7130	4: Replay-Attack [155]; Oulu-NPU [156]; CASIA-MFSD [157]; MSU-MFSD [158]
	Video	UCF–Olympic	6	1145	2: UCF101 [159]; Olympic [160]
	Video	UCF–HMDB$_{full}$ [161]	12	3209	2: UCF101 [159]; HMDB [162]
	Video	Sports-DA [163]	23	40718	3: UCF101 [159]; Sports-1M [164]; Kinetics [165]
	Video	Daily-DA [163]	8	18949	4: ARID [166]; HMDB [162]; Moments-in-Time [167]; Kinetics [165]
	Text	Composed QA Dataset	–	∼650000	4: SQuAD [168]; HotpotQA [169]; Natural Questions [170]; NewsQA [171]

Table 7
Real-world applications utilizing SFUDA.

Tasks	Data	Applications
Segmentation	RGB Image	Road segmentation [172]
	RGB Image	Semantic Segmentation [173–179]
	RGB Image	Video Semantic Segmentation [180]
	Medical Image	Brain Tissue Segmentation [181,182]
	Medical Image	Organ Segmentation [183–187]
	Medical Image	Spinal Cord Segmentation [188]
	Medical Image	Polyp Segmentation [189]
Detection	RGB Image	Object Detection [190–192]
	Point Cloud	Point Cloud Detection [193–195]
	Passive Millimeter-Wave Images	Concealed-Object Detection [196]
Classification	Medical Image	Autism Diagnosis [197]
	Medical Image	Pneumonia Diagnosis [198]
	EEG Data	Motor Imagery Classification [199]
	EEG Data	Seizure Subtype Classification [200]
	Video	Video Action Recognition [201–203]
	Video	Face Anti-Spoofing [204]
	Sensory Data	Machinery Fault Diagnosis [205,206]
	RGB Image	Blind Image Quality Assessment [207]
	Sound	Bird Species Sound Classification [208]
	Text	Question-Answering [209,210]
	Hyperspectral Image	Hyperspectral Image Classification [211]

7.2. Detection

Detection is another critical task in computer vision that supports various applications. It involves the identification and localization of objects of interest within images or videos.

In the literature, there are methods designed for detection models pre-trained on RGB images [190–192], and for detection models pre-trained on 3D point cloud data [193–195]. However, in this subsection, the introduction of methods for RGB detection models will be omitted as they share great similarities with segmentation methods in terms of challenges and motivations. In the task of 3D point cloud detection, changes in environmental conditions, object appearances, and point cloud attributes (such as density, frequency, resolution, and ranges) not only cause distribution shifts between source and target samples but also affect the distribution of source and target annotations. Moreover, in real-world 3D detection scenarios, obtaining high-quality labeled source data can be challenging or impractical. In response to these challenges, Saltori et al. [193] apply temporal coherency to estimate scale-transformation parameters that scale the target data to address annotation shifts. They generate pseudo-labels on the scaled target samples to adapt the model to handle sample shifts. As a result, they boost the detection performance of a pre-trained PointRCNN [214] 3D detection model by 22.6% in terms of average precision.

In the task of detecting concealed objects, passive millimeter-wave (PMMW) imagers provide a touch-free method by leveraging temperature differences between the background and objects. PMMW imagers operate in two types of imaging conditions: cold background and warm background. These conditions introduce domain shifts due to the intrinsic differences in image characteristics. To address the domain shifts caused by different backgrounds, Yang et al. [196] propose a self-tuning method that utilizes pseudo-labeling and adversarial learning to adapt a pre-trained concealed-object detector, resulting in a remarkable 8.16% boost in detection performance.

7.3. Classification

Classification, being the most fundamental task in deep learning, is widely recognized as a prominent application where SFUDA has been successfully employed. While benchmark image classification tasks have been extensively studied, real-world classification tasks across various industries and applications are also in great demand for SFUDA methods to address domain shift challenges.

Electroencephalogram (EEG) data, a multi-channel time-varying signal, is a valuable medical resource. Various tasks can be performed based on EEG data, such as Motor Imagery Classification [199] and Seizure Subtype Classification [200]. However, EEG data sampled from different patients/subjects often exhibit significant individual differences, which can lead to negative transfer when applying EEG classification models to new subjects. Additionally, the presence of private information in EEG data restricts the sharing of source EEG data. In the task of motor imagery classification, Zhang and Wu [199] address these challenges by constructing an intermediate domain based on the outputs of the pre-trained model. They then perform feature alignment to adapt the model under inter-subject domain shifts without leaking the source data or model parameters. As a result, they achieve a maximum classification accuracy improvement of 3.71% compared to other SFUDA methods.

Rotating machinery fault diagnosis is another classification task that operates on sensory data and plays a vital role in ensuring the reliable operation of machinery equipment. In real production scenarios, different working conditions of machinery equipment introduce domain shifts to fault diagnosis models. Additionally, the requirement for expert knowledge to label fault diagnosis data further limits the practicality of labeling newly distributed data after model deployment. To transfer the pre-trained fault diagnosis model to a different working condition, Yue et al. [205] employ a combination of feature-space pseudo labeling techniques and information maximization regularization to help the model adapt to the domain shifts, resulting in a significant performance improvement of 21.86% compared to the pre-trained model.

Beyond the applications mentioned, SFUDA techniques have proven successful in various fields and modalities. Action recognition [201–203], face anti-spoofing [204], hyperspectral image classification [211], blind image quality assessment [207], bird species sound classification [208] and question-answering [209,210] are among the diverse applications reaping benefits from the application of SFUDA methods.

8. Summary and future directions

This survey employs a coarse-to-fine approach, transitioning from a coarse overview to a detailed exploration of the methodological advancements in Source-Free Unsupervised Domain Adaptation (SFUDA). The existing SFUDA methods are systematically classified into three primary categories: self-tuning, feature alignment, and sample generation, according to their respective adaptation objectives. Moreover, each of these categories is subdivided into finer sub-categories, which are further dissected based on distinct workflows or characteristics. This hierarchical structure allows the survey to move from a general depiction of the SFUDA workflow to an intricate examination of method categorizations and their corresponding sub-categories. This structured approach aims to equip readers with both a comprehensive overview and an in-depth comprehension of SFUDA. Beyond the methodological aspects, this survey delves into the exploration of practical applications where SFUDA can offer significant advantages, illustrating the potential of SFUDA. Furthermore, drawn from the comprehensive reviews and analysis presented throughout the paper, the visions for the future trends of SFUDA can be outlined as follows.

(1) Catastrophic Forgetting. The non-reliance on source data largely enhances the practicality of SFUDA. However, it also poses a challenge related to the Catastrophic Forgetting [49] issue in SFUDA methods. An empirical study by Feng et al. [47] reveals that many SFUDA methods exhibit a notable performance drop in the source domain after adapting to a target domain. However, in real-world deployment scenarios, testing samples may not always neatly follow the target distribution but can follow various distributions, including those encountered during model training. Therefore, a promising avenue for future research could focus on developing SFUDA methods that enable adaptation to new domains without forgetting the knowledge learned from previous domains.

(2) Self-Supervised Learning. While self-supervised learning techniques enable the model to learn target semantics without requiring annotations, the literature reveals a scarcity of studies dedicated to the development of self-supervised learning methods [73] specially designed for SFUDA. Furthermore, it remains unclear how self-supervised learning sub-tasks can better utilize the knowledge acquired in the source domain and cooperate effectively with other SFUDA sub-tasks to further enhance adaptation performance. To address these challenges, future research endeavors may delve into the creation of self-supervised learning methods that leverage pre-trained source models optimally and are tailored to collaborate seamlessly with other SFUDA sub-tasks, thereby facilitating model adaptation.

(3) Architectures. The advancements in Transformer models [215] have demonstrated their efficacy across various tasks and modalities, offering a range of pre-trained transformers tailored to different downstream tasks. However, most SFUDA methods are designed for CNN architectures, such as the ResNet series [69]. The structural difference between CNNs and Transformers presents a challenge when applying existing SFUDA methods to pre-trained Transformers. Therefore, in future research, investigating the adaptation of transformer-based architectures and designing methods tailored for pre-trained transformers would be a worthwhile endeavor.

(4) Foundation Models. With the emergence of advanced Transformer models, a large amount of foundation models has emerged [216–219], demonstrating remarkable zero-shot and generalization capabilities across various tasks and modalities. These foundational models often comprise billions of parameters, which presents a significant challenge on how SFUDA techniques can adapt them in a parameter-efficient way when they are applied to domains in which they do not perform optimally. Hence, it is imperative that future research focuses on devising methods explicitly tailored to the efficient adaptation of large foundational models within the SFUDA framework.

These future visions highlight potential research directions that need further explorations and advancements. Hopefully, this survey could serve as a "way pointer" to guide future research endeavors and foster breakthroughs in the field of SFUDA.

CRediT authorship contribution statement

Ningyuan Zhang: Conceptualization, Data curation, Formal analysis, Visualization, Writing – original draft. **Jie Lu:** Conceptualization, Supervision, Funding acquisition, Formal analysis, Writing – review & editing. **Keqiuyin Li:** Conceptualization, Supervision, Formal analysis, Writing – review & editing. **Zhen Fang:** Conceptualization, Supervision, Formal analysis, Writing – review & editing. **Guangquan Zhang:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

The work was supported by the Australian Research Council (ARC) under grant FL190100149.

References

[1] S. Pouyanfar, S. Sadiq, Y. Yan, H. Tian, Y. Tao, M.P. Reyes, M.-L. Shyu, S.-C. Chen, S.S. Iyengar, A survey on deep learning: Algorithms, techniques, and applications, ACM Comput. Surv. 51 (5) (2018) 1–36.

[2] J. Lu, H. Zuo, G. Zhang, Fuzzy multiple-source transfer learning, IEEE Trans. Fuzzy Syst. 28 (12) (2019) 3418–3431.

[3] S.J. Pan, Q. Yang, A survey on transfer learning, IEEE Trans. Knowl. Data Eng. 22 (10) (2009) 1345–1359.

[4] Z. Fang, J. Lu, F. Liu, G. Zhang, Semi-supervised heterogeneous domain adaptation: Theory and algorithms, IEEE Trans. Pattern Anal. Mach. Intell. 45 (1) (2022) 1087–1105.

[5] K. Li, J. Lu, H. Zuo, G. Zhang, Multidomain adaptation with sample and source distillation, IEEE Trans. Cybern. (2023).

[6] B. Sun, K. Saenko, Deep coral: Correlation alignment for deep domain adaptation, in: European Conference on Computer Vision, Springer, 2016, pp. 443–450.

[7] M. Long, Y. Cao, J. Wang, M. Jordan, Learning transferable features with deep adaptation networks, in: International Conference on Machine Learning, PMLR, 2015, pp. 97–105.

[8] C. Chen, Z. Fu, Z. Chen, S. Jin, Z. Cheng, X. Jin, X.-S. Hua, Homm: Higher-order moment matching for unsupervised domain adaptation, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, No. 04, 2020, pp. 3422–3429.

[9] Y. Ganin, V. Lempitsky, Unsupervised domain adaptation by backpropagation, in: International Conference on Machine Learning, PMLR, 2015, pp. 1180–1189.

[10] Y. Zhang, F. Liu, Z. Fang, B. Yuan, G. Zhang, J. Lu, Learning from a complementary-label source domain: theory and algorithms, IEEE Trans. Neural Netw. Learn. Syst. 33 (12) (2021) 7667–7681.

[11] E. Tzeng, J. Hoffman, K. Saenko, T. Darrell, Adversarial discriminative domain adaptation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 7167–7176.

[12] B. Chidlovskii, S. Clinchant, G. Csurka, Domain adaptation in the absence of source domain data, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 451–460.

[13] J. Liang, D. Hu, J. Feng, Do we really need to access the source data? source hypothesis transfer for unsupervised domain adaptation, in: International Conference on Machine Learning, PMLR, 2020, pp. 6028–6039.

[14] S. Zhao, X. Yue, S. Zhang, B. Li, H. Zhao, B. Wu, R. Krishna, J.E. Gonzalez, A.L. Sangiovanni-Vincentelli, S.A. Seshia, et al., A review of single-source deep unsupervised visual domain adaptation, IEEE Trans. Neural Netw. Learn. Syst. (2020).

[15] A. Farahani, S. Voghoei, K. Rasheed, H.R. Arabnia, A brief review of domain adaptation, Adv. Data Sci. Inf. Eng. (2021) 877–894.

[16] X. Liu, C. Yoo, F. Xing, H. Oh, G. El Fakhri, J.-W. Kang, J. Woo, et al., Deep unsupervised domain adaptation: a review of recent advances and perspectives, APSIPA Trans. Signal Inf. Process. 11 (1) (2022).

[17] G. Csurka, R. Volpi, B. Chidlovskii, Unsupervised domain adaptation for semantic image segmentation: a comprehensive survey, 2021, arXiv preprint arXiv:2112.03241.

[18] Y. Liu, W. Zhang, J. Wang, J. Wang, Data-free knowledge transfer: A survey, 2021, arXiv preprint arXiv:2112.15278.

[19] Z. Cao, K. You, M. Long, J. Wang, Q. Yang, Learning to transfer examples for partial domain adaptation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 2985–2994.

[20] Z. Fang, J. Lu, F. Liu, J. Xuan, G. Zhang, Open set domain adaptation: Theoretical bound and algorithm, IEEE Trans. Neural Netw. Learn Syst. 32 (10) (2020) 4309–4322.

[21] K. You, M. Long, Z. Cao, J. Wang, M.I. Jordan, Universal domain adaptation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 2720–2729.

[22] H. Zhang, Y. Zhang, K. Jia, L. Zhang, Unsupervised domain adaptation of black-box source models, 2021, arXiv preprint arXiv:2101.02839.

[23] S. Zhao, B. Li, P. Xu, K. Keutzer, Multi-source domain adaptation in the deep learning era: A systematic survey, 2020, arXiv preprint arXiv:2002.12169.

[24] B. Gholami, P. Sahu, O. Rudovic, K. Bousmalis, V. Pavlovic, Unsupervised multi-target domain adaptation: An information theoretic approach, IEEE Trans. Image Process. 29 (2020) 3993–4002.

[25] D.-H. Lee, et al., Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks, in: Workshop on Challenges in Representation Learning, ICML, Vol. 3, No. 2, 2013, p. 896.

[26] X.J. Zhu, Semi-Supervised Learning Literature Survey, University of Wisconsin-Madison Department of Computer Sciences, 2005.

[27] M. Caron, P. Bojanowski, A. Joulin, M. Douze, Deep clustering for unsupervised learning of visual features, in: Proceedings of the European Conference on Computer Vision, ECCV, 2018, pp. 132–149.

[28] S. Tang, Y. Yang, Z. Ma, N. Hendrich, F. Zeng, S.S. Ge, C. Zhang, J. Zhang, Nearest neighborhood-based deep clustering for source data-absent unsupervised domain adaptation, 2021, arXiv preprint arXiv:2107.12585.

[29] F. Wang, Z. Han, Y. Gong, Y. Yin, Exploring domain-invariant parameters for source free domain adaptation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 7151–7160.

[30] G. Yang, H. Tang, Z. Zhong, M. Ding, L. Shao, N. Sebe, E. Ricci, Transformer-based source-free domain adaptation, 2021, arXiv preprint arXiv:2105.14138.

[31] V. Kumar, R. Lal, H. Patil, A. Chakraborty, CoNMix for source-free single and multi-target domain adaptation, 2022, arXiv preprint arXiv:2211.03876.

[32] J. Cao, Y. Liu, W. Bai, J. Ding, L. Li, Nasty-SFDA: Source free domain adaptation from a nasty model, in: ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, IEEE, 2023, pp. 1–5.

[33] O. Bohdal, D. Li, Samsung AI Center, T. Hospedales, Feed-Forward Source-Free Domain Adaptation via Class Prototypes.

[34] S.M. Ahmed, D.S. Raychaudhuri, S. Paul, S. Oymak, A.K. Roy-Chowdhury, Unsupervised multi-source domain adaptation without access to source data, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 10103–10112.

[35] K. Li, J. Lu, H. Zuo, G. Zhang, Source-free multi-domain adaptation with generally auxiliary model training, in: 2022 International Joint Conference on Neural Networks, IJCNN, IEEE, 2022, pp. 1–8.

[36] Q. Tian, S. Peng, T. Ma, Source-free unsupervised domain adaptation with trusted pseudo samples, ACM Trans. Intell. Syst. Technol. (2022).

[37] Z. Song, L. Chen, H. Sun, G. Kou, SS8: Source data-free domain adaptation via deep clustering with weighted self-labelling, in: 2022 IEEE International Conference on Networking, Sensing and Control, ICNSC, IEEE, 2022, pp. 1–6.

[38] F.G. Ashby, W.T. Maddox, Human category learning, Annu. Rev. Psychol. 56 (2005) 149–178.

[39] W.S. Deng, V.M. Sloutsky, The development of categorization: effects of classification and inference training on category representation, Dev. Psychol. 51 (3) (2015) 392.

[40] Y. Kim, D. Cho, S. Hong, Towards privacy-preserving domain adaptation, IEEE Signal Process. Lett. 27 (2020) 1675–1679.

[41] X. Guan, H. Sun, N. Liu, H. Zhou, Polycentric clustering and structural regularization for source-free unsupervised domain adaptation, 2022, arXiv preprint arXiv:2210.07463.

[42] S. Qu, G. Chen, J. Zhang, Z. Li, W. He, D. Tao, BMD: A general class-balanced multicentric dynamic prototype strategy for source-free domain adaptation, 2022, arXiv preprint arXiv:2204.02811.

[43] J. Lee, D. Jung, J. Yim, S. Yoon, Confidence score for source-free unsupervised domain adaptation, in: International Conference on Machine Learning, PMLR, 2022, pp. 12365–12377.

[44] R.O. Duda, P.E. Hart, et al., Pattern Classification and Scene Analysis, Vol. 3, Wiley New York, 1973.

[45] Y. Kim, D. Cho, K. Han, P. Panda, S. Hong, Domain adaptation without source data, IEEE Trans. Artif. Intell. 2 (6) (2021) 508–518.

[46] J. Dong, Z. Fang, A. Liu, G. Sun, T. Liu, Confident anchor-induced multi-source free domain adaptation, Adv. Neural Inf. Process. Syst. 34 (2021) 2848–2860.

[47] H. Feng, Z. Yang, H. Chen, T. Pang, C. Du, M. Zhu, W. Chen, S. Yan, Cosda: Continual source-free domain adaptation, 2023, arXiv preprint arXiv:2304.06627.

[48] A. Tarvainen, H. Valpola, Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results, Adv. Neural Inf. Process. Syst. 30 (2017).

[49] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A.A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska, et al., Overcoming catastrophic forgetting in neural networks, Proc. Nat. Acad. Sci. 114 (13) (2017) 3521–3526.

[50] W. Ahmed, P. Morerio, V. Murino, Cleaning noisy labels by negative ensemble learning for source-free unsupervised domain adaptation, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2022, pp. 1616–1625.

[51] Y. Kim, J. Yim, J. Yun, J. Kim, Nlnl: Negative learning for noisy labels, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 101–110.

[52] L.R. Sevyeri, I. Sheth, F. Farahnak, A. See, S.E. Kahou, T. Fevens, M. Havaei, Source-free domain adaptation requires penalized diversity, 2023, arXiv preprint arXiv:2304.02798.

[53] W. Zhang, L. Shen, C.-S. Foo, Co-learning with pre-trained networks improves source-free domain adaptation, 2022, arXiv preprint arXiv:2212.07585.

[54] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, B. Guo, Swin transformer: Hierarchical vision transformer using shifted windows, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 10012–10022.

[55] J.N. Kundu, N. Venkat, A. Revanur, R.V. Babu, et al., Towards inheritable models for open-set domain adaptation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 12376–12385.

[56] J.N. Kundu, N. Venkat, R.V. Babu, et al., Universal source-free domain adaptation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 4544–4553.

[57] W. Chen, L. Lin, S. Yang, D. Xie, S. Pu, Y. Zhuang, W. Ren, Self-supervised noisy label learning for source-free unsupervised domain adaptation, 2021, arXiv preprint arXiv:2102.11614.
[58] K. Han, A. Vedaldi, A. Zisserman, Learning to discover novel visual categories via deep transfer clustering, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 8401–8409.
[59] H. Yan, Y. Guo, C. Yang, Augmented self-labeling for source-free unsupervised domain adaptation, in: NeurIPS 2021 Workshop on Distribution Shifts: Connecting Methods and Applications, 2021.
[60] J. Pei, Z. Jiang, A. Men, L. Chen, Y. Liu, Q. Chen, Uncertainty-induced transferability representation for source-free unsupervised domain adaptation, 2022, arXiv preprint arXiv:2208.13986.
[61] A. Krause, P. Perona, R. Gomes, Discriminative clustering by regularized information maximization, Adv. Neural Inf. Process. Syst. 23 (2010).
[62] W. Li, M. Cao, S. Chen, Jacobian norm for unsupervised source-free domain adaptation, 2022, arXiv preprint arXiv:2204.03467.
[63] L. Yi, G. Xu, P. Xu, J. Li, R. Pu, C. Ling, A.I. McLeod, B. Wang, When source-free domain adaptation meets learning with noisy labels, 2023, arXiv preprint arXiv:2301.13381.
[64] S. Liu, J. Niles-Weed, N. Razavian, C. Fernandez-Granda, Early-learning regularization prevents memorization of noisy labels, Adv. Neural Inf. Process. Syst. 33 (2020) 20331–20342.
[65] J. Liang, D. Hu, R. He, J. Feng, Distill and fine-tune: Effective adaptation from a black-box source model, vol. 1, no, 3, 2021, arXiv preprint arXiv:2104.01539.
[66] S. Roy, M. Trapp, A. Pilzer, J. Kannala, N. Sebe, E. Ricci, A. Solin, Uncertainty-guided source-free domain adaptation, in: Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXV, Springer, 2022, pp. 537–555.
[67] Q. Tian, S. Peng, H. Sun, J. Zhou, H. Zhang, Source-free unsupervised domain adaptation with maintaining model balance and diversity, Comput. Electr. Eng. 104 (2022) 108408.
[68] K. Saenko, B. Kulis, M. Fritz, T. Darrell, Adapting visual category models to new domains, in: Computer Vision–ECCV 2010: 11th European Conference on Computer Vision, Heraklion, Crete, Greece, September 5-11, 2010, Proceedings, Part IV 11, Springer, 2010, pp. 213–226.
[69] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770–778.
[70] H. Venkateswara, J. Eusebio, S. Chakraborty, S. Panchanathan, Deep hashing network for unsupervised domain adaptation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 5018–5027.
[71] X. Peng, B. Usman, N. Kaushik, J. Hoffman, D. Wang, K. Saenko, Visda: The visual domain adaptation challenge, 2017, arXiv preprint arXiv:1710.06924.
[72] Q. Peng, Z. Ding, L. Lyu, L. Sun, C. Chen, Toward better target representation for source-free and black-box domain adaptation, 2022, arXiv preprint arXiv:2208.10531.
[73] J.N. Kundu, S. Bhambri, A. Kulkarni, H. Sarkar, V. Jampani, R.V. Babu, Concurrent subsidiary supervision for unsupervised source-free domain adaptation, in: European Conference on Computer Vision, Springer, 2022, pp. 177–194.
[74] H. Xia, H. Zhao, Z. Ding, Adaptive adversarial network for source-free domain adaptation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 9010–9019.
[75] H.-W. Yeh, T. Westfechtel, J.-B. Huang, T. Harada, Boosting source-free domain adaptation via confidence-based subsets feature alignment, in: 2022 26th International Conference on Pattern Recognition, ICPR, IEEE, 2022, pp. 2857–2863.
[76] J. Liang, D. Hu, Y. Wang, R. He, J. Feng, Source data-absent unsupervised domain adaptation through hypothesis transfer and labeling transfer, IEEE Trans. Pattern Anal. Mach. Intell. (2021).
[77] I. Diamant, R.H. Jennings, O. Dror, H.V. Habi, A. Netzer, Reconciling a centroid-hypothesis conflict in source-free domain adaptation, 2022, arXiv preprint arXiv:2212.03795.
[78] X. Zhao, R. Stanislawski, P. Gardoni, M. Sulowicz, A. Glowacz, G. Krolczyk, Z. Li, Adaptive contrastive learning with label consistency for source data free unsupervised domain adaptation, Sensors 22 (11) (2022) 4238.
[79] Z. Zhang, W. Chen, H. Cheng, Z. Li, S. Li, L. Lin, G. Li, Divide and contrast: Source-free domain adaptation via adaptive contrastive learning, 2022, arXiv preprint arXiv:2211.06612.
[80] Z. Zong, J. He, L. Zhang, H. Huan, Domain gap estimation for source free unsupervised domain adaptation with many classifiers, 2022, arXiv preprint arXiv:2207.05785.
[81] P. Agarwal, D.P. Paudel, J.-N. Zaech, L. Van Gool, Unsupervised robust domain adaptation without source data, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2022, pp. 2009–2018.
[82] J. Lee, G. Lee, Feature alignment by uncertainty and self-training for source-free unsupervised domain adaptation, 2022, arXiv preprint arXiv:2208.14888.
[83] K. Li, J. Lu, H. Zuo, G. Zhang, Source-free multi-domain adaptation with fuzzy rule-based deep neural networks, IEEE Trans. Fuzzy Syst. (2023).
[84] J. Huang, D. Guan, A. Xiao, S. Lu, Model adaptation: Historical contrastive learning for unsupervised domain adaptation without source data, Adv. Neural Inf. Process. Syst. 34 (2021) 3635–3649.
[85] N. Karim, N.C. Mithun, A. Rajvanshi, H.-p. Chiu, S. Samarasekera, N. Rahnavard, C-SFDA: A curriculum learning aided self-training framework for efficient source free domain adaptation, 2023, arXiv preprint arXiv:2303.17132.
[86] C. Liu, L. Zhou, M. Ye, X. Li, Self-alignment for black-box domain adaptation of image classification, IEEE Signal Process. Lett. 29 (2022) 1709–1713.
[87] B. Deng, Y. Zhang, H. Tang, C. Ding, K. Jia, On universal black-box domain adaptation, 2021, arXiv preprint arXiv:2104.04665.
[88] X. Li, J. Li, L. Zhu, G. Wang, Z. Huang, Imbalanced source-free domain adaptation, in: Proceedings of the 29th ACM International Conference on Multimedia, 2021, pp. 3330–3339.
[89] L. Jing, Y. Tian, Self-supervised visual feature learning with deep neural networks: A survey, IEEE Trans. Pattern Anal. Mach. Intell. 43 (11) (2020) 4037–4058.
[90] S. Gidaris, P. Singh, N. Komodakis, Unsupervised representation learning by predicting image rotations, 2018, arXiv preprint arXiv:1803.07728.
[91] B. Wallace, B. Hariharan, Extending and analyzing self-supervised learning across domains, in: European Conference on Computer Vision, Springer, 2020, pp. 717–734.
[92] S. Yang, J. van de Weijer, L. Herranz, S. Jui, et al., Exploiting the intrinsic neighborhood structure for source-free domain adaptation, Adv. Neural Inf. Process. Syst. 34 (2021) 29393–29405.
[93] S. Yang, Y. Wang, J. van de Weijer, L. Herranz, S. Jui, Generalized source-free domain adaptation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 8978–8987.
[94] S. Yang, Y. Wang, K. Wang, S. Jui, et al., Attracting and dispersing: A simple approach for source-free domain adaptation, in: Advances in Neural Information Processing Systems, 2022.
[95] C. Wu, G. Cao, Y. Li, X. Xi, W. Cao, H. Wang, When source-free domain adaptation meets label propagation, 2023, arXiv preprint arXiv:2301.08413.
[96] Y. Chen, X. Zhu, Y. Li, Y. Li, Y. Wei, H. Fang, Contrast and clustering: Learning neighborhood pair representation for source-free domain adaptation, 2023, arXiv preprint arXiv:2301.13428.
[97] D. Qin, S. Gammeter, L. Bossard, T. Quack, L. Van Gool, Hello neighbor: Accurate object retrieval with k-reciprocal nearest neighbors, in: CVPR 2011, IEEE, 2011, pp. 777–784.
[98] Y. Du, H. Yang, M. Chen, J. Jiang, H. Luo, C. Wang, Generation, augmentation, and alignment: A pseudo-source domain based method for source-free domain adaptation, 2021, arXiv preprint arXiv:2109.04015.
[99] S. Yang, Y. Wang, J. van de Weijer, L. Herranz, S. Jui, Unsupervised domain adaptation without source data by casting a bait, vol. 1, no. 2, 2020, p. 5, arXiv preprint arXiv:2010.12427.
[100] T. Chu, Y. Liu, J. Deng, W. Li, L. Duan, Denoised maximum classifier discrepancy for sourcefree unsupervised domain adaptation, in: Thirty-Sixth AAAI Conference on Artificial Intelligence, Vol. 2, AAAI-22, 2022.
[101] K. Li, J. Lu, H. Zuo, G. Zhang, Dynamic classifier alignment for unsupervised multi-source domain adaptation, IEEE Trans. Knowl. Data Eng. 35 (5) (2022) 4727–4740.
[102] M. Shen, Y. Bu, G. Wornell, On the benefits of selectivity in pseudo-labeling for unsupervised multi-source-free domain adaptation, 2022, arXiv preprint arXiv:2202.00796.
[103] Y. Ding, L. Sheng, J. Liang, A. Zheng, R. He, ProxyMix: Proxy-based mixup training with label refinery for source-free domain adaptation, 2022, arXiv preprint arXiv:2205.14566.
[104] S. Yang, Y. Wang, L. Herranz, S. Jui, J. van de Weijer, Casting a bait for offline and online source-free domain adaptation, Comput. Vis. Image Underst. (2023) 103747.
[105] V.K. Kurmi, V.K. Subramanian, V.P. Namboodiri, Domain impression: A source data free domain adaptation method, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021, pp. 615–625.
[106] Y. Liu, X. Wei, Y. Lu, C. Zhao, X. Qiao, Source free domain adaptation via combined discriminative GAN model for image classification, in: 2022 International Joint Conference on Neural Networks, IJCNN, IEEE, 2022, pp. 1–8.
[107] Z. Qiu, Y. Zhang, H. Lin, S. Niu, Y. Liu, Q. Du, M. Tan, Source-free domain adaptation via avatar prototype generation and adaptation, 2021, arXiv preprint arXiv:2106.15326.
[108] S. Chhabra, H. Venkateswara, B. Li, Generative alignment of posterior probabilities for source-free domain adaptation, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2023, pp. 4125–4134.
[109] M. Rostami, A. Galstyan, Sequential unsupervised domain adaptation through prototypical distributions, 2020.
[110] N. Ding, Y. Xu, Y. Tang, C. Xu, Y. Wang, D. Tao, Source-free domain adaptation via distribution estimation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 7212–7222.
[111] J. Tian, J. Zhang, W. Li, D. Xu, Vdm-da: Virtual domain modeling for source data-free domain adaptation, IEEE Trans. Circuits Syst. Video Technol. (2021).
[112] H. Yao, Y. Guo, C. Yang, Source-free unsupervised domain adaptation with surrogate data generation, in: Proceedings of NeurIPS 2021 Workshop on Distribution Shifts: Connecting Methods and Applications, 2021.

[113] Y. Hou, L. Zheng, Visualizing adapted knowledge in domain transfer, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 13824–13833.
[114] K. Tanwisuth, X. Fan, H. Zheng, S. Zhang, H. Zhang, B. Chen, M. Zhou, A prototype-oriented framework for unsupervised domain adaptation, Adv. Neural Inf. Process. Syst. 34 (2021) 17194–17208.
[115] R. Wang, Z. Wu, Z. Weng, J. Chen, G.-J. Qi, Y.-G. Jiang, Cross-domain contrastive learning for unsupervised domain adaptation, IEEE Trans. Multimed. (2022).
[116] M. Ishii, M. Sugiyama, Source-free domain adaptation via distributional alignment by matching batch normalization statistics, 2021, arXiv preprint arXiv:2101.10842.
[117] C. Eastwood, I. Mason, C.K. Williams, B. Schölkopf, Source-free adaptation to measurement shift via bottom-up feature restoration, 2021, arXiv preprint arXiv:2107.05446.
[118] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. Marchand, V. Lempitsky, Domain-adversarial training of neural networks, J. Mach. Learn. Res. 17 (1) (2016) 2096–2030.
[119] S. Li, F. Lv, B. Xie, C.H. Liu, J. Liang, C. Qin, Bi-classifier determinacy maximization for unsupervised domain adaptation., in: AAAI, Vol. 2, 2021, p. 5.
[120] K. Saito, K. Watanabe, Y. Ushiku, T. Harada, Maximum classifier discrepancy for unsupervised domain adaptation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 3723–3732.
[121] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial networks, Commun. ACM 63 (11) (2020) 139–144.
[122] H.-W. Yeh, B. Yang, P.C. Yuen, T. Harada, Sofa: Source-data-free feature alignment for unsupervised domain adaptation, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021, pp. 474–483.
[123] R. Flamary, N. Courty, D. Tuia, A. Rakotomamonjy, Optimal transport for domain adaptation, IEEE Trans. Pattern Anal. Mach. Intell. 1 (2016).
[124] K. Saito, D. Kim, S. Sclaroff, T. Darrell, K. Saenko, Semi-supervised domain adaptation via minimax entropy, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 8050–8058.
[125] J. Dougherty, R. Kohavi, M. Sahami, Supervised and unsupervised discretization of continuous features, in: Machine Learning Proceedings 1995, Elsevier, 1995, pp. 194–202.
[126] H. Jeon, S. Lee, U. Kang, Unsupervised multi-source domain adaptation with no observable source data, PLoS One 16 (7) (2021) e0253415.
[127] R. Li, Q. Jiao, W. Cao, H.-S. Wong, S. Wu, Model adaptation: Unsupervised domain adaptation without source data, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 9641–9650.
[128] J.N. Kundu, A.R. Kulkarni, S. Bhambri, D. Mehta, S.A. Kulkarni, V. Jampani, V.B. Radhakrishnan, Balancing discriminability and transferability for source-free domain adaptation, in: International Conference on Machine Learning, PMLR, 2022, pp. 11710–11728.
[129] Z. Fang, J. Lu, G. Zhang, An extremely simple algorithm for source domain reconstruction, IEEE Trans. Cybern. (2023).
[130] J. Masci, U. Meier, D. Cireşan, J. Schmidhuber, Stacked convolutional auto-encoders for hierarchical feature extraction, in: Artificial Neural Networks and Machine Learning–ICANN 2011: 21st International Conference on Artificial Neural Networks, Espoo, Finland, June 14-17, 2011, Proceedings, Part I 21, Springer, 2011, pp. 52–59.
[131] R. Sahoo, D. Shanmugam, J. Guttag, Unsupervised domain adaptation in the absence of source data, 2020, arXiv preprint arXiv:2007.10233.
[132] P. Morerio, R. Volpi, R. Ragonesi, V. Murino, Generative pseudo-label refinement for unsupervised domain adaptation, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2020, pp. 3130–3139.
[133] Y. Li, L. Guo, Y. Ge, Pseudo labels for unsupervised domain adaptation: A review, Electronics 12 (15) (2023) 3325.
[134] H. Liu, J. Wang, M. Long, Cycle self-training for domain adaptation, Adv. Neural Inf. Process. Syst. 34 (2021) 22968–22981.
[135] M. Buda, A. Maki, M.A. Mazurowski, A systematic study of the class imbalance problem in convolutional neural networks, Neural Netw. 106 (2018) 249–259.
[136] S.R. Richter, V. Vineet, S. Roth, V. Koltun, Playing for data: Ground truth from computer games, in: Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, the Netherlands, October 11-14, 2016, Proceedings, Part II 14, Springer, 2016, pp. 102–118.
[137] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, B. Schiele, The cityscapes dataset for semantic urban scene understanding, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3213–3223.
[138] G. Ros, L. Sellart, J. Materzynska, D. Vazquez, A.M. Lopez, The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3234–3243.
[139] Y.-H. Chen, W.-Y. Chen, Y.-T. Chen, B.-C. Tsai, Y.-C. Frank Wang, M. Sun, No more discrimination: Cross city adaptation of road scene segmenters, in: Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 1992–2001.
[140] C. Sakaridis, D. Dai, L. Van Gool, Semantic foggy scene understanding with synthetic data, Int. J. Comput. Vis. 126 (2018) 973–992.
[141] A. Geiger, P. Lenz, C. Stiller, R. Urtasun, Vision meets robotics: The kitti dataset, Int. J. Robot. Res. 32 (11) (2013) 1231–1237.
[142] M. Johnson-Roberson, C. Barto, R. Mehta, S.N. Sridhar, K. Rosaen, R. Vasudevan, Driving in the matrix: Can virtual worlds replace human-generated annotations for real world tasks? 2016, arXiv preprint arXiv:1610.01983.
[143] M. Everingham, L. Van Gool, C.K. Williams, J. Winn, A. Zisserman, The pascal visual object classes (voc) challenge, Int. J. Comput. Vision 88 (2010) 303–338.
[144] N. Inoue, R. Furuta, T. Yamasaki, K. Aizawa, Cross-domain weakly-supervised object detection through progressive domain adaptation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5001–5009.
[145] P. Sun, H. Kretzschmar, X. Dotiwalla, A. Chouard, V. Patnaik, P. Tsui, J. Guo, Y. Zhou, Y. Chai, B. Caine, et al., Scalability in perception for autonomous driving: Waymo open dataset, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 2446–2454.
[146] H. Caesar, V. Bankiti, A.H. Lang, S. Vora, V.E. Liong, Q. Xu, A. Krishnan, Y. Pan, G. Baldan, O. Beijbom, Nuscenes: A multimodal dataset for autonomous driving, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 11621–11631.
[147] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86 (11) (1998) 2278–2324.
[148] Y. Netzer, T. Wang, A. Coates, A. Bissacco, B. Wu, A.Y. Ng, Reading digits in natural images with unsupervised feature learning, 2011.
[149] J.J. Hull, A database for handwritten text recognition research, IEEE Trans. Pattern Anal. Mach. Intell. 16 (5) (1994) 550–554.
[150] X. Peng, Q. Bai, X. Xia, Z. Huang, K. Saenko, B. Wang, Moment matching for multi-source domain adaptation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 1406–1415.
[151] B. Gong, Y. Shi, F. Sha, K. Grauman, Geodesic flow kernel for unsupervised domain adaptation, in: 2012 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, 2012, pp. 2066–2073.
[152] B. Caputo, H. Müller, J. Martinez-Gomez, M. Villegas, B. Acar, N. Patricia, N. Marvasti, S. Üsküdarlı, R. Paredes, M. Cazorla, et al., Imageclef 2014: Overview and analysis of the results, in: Information Access Evaluation. Multilinguality, Multimodality, and Interaction: 5th International Conference of the CLEF Initiative, CLEF 2014, Sheffield, UK, September 15-18, 2014. Proceedings 5, Springer, 2014, pp. 192–211.
[153] D. Li, Y. Yang, Y.-Z. Song, T.M. Hospedales, Deeper, broader and artier domain generalization, in: Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 5542–5550.
[154] C. Qin, H. You, L. Wang, C.-C.J. Kuo, Y. Fu, Pointdan: A multi-scale 3d domain adaption network for point cloud representation, Adv. Neural Inf. Process. Syst. 32 (2019).
[155] I. Chingovska, A. Anjos, S. Marcel, On the effectiveness of local binary patterns in face anti-spoofing, in: 2012 BIOSIG-Proceedings of the International Conference of Biometrics Special Interest Group (BIOSIG), IEEE, 2012, pp. 1–7.
[156] Z. Boulkenafet, J. Komulainen, L. Li, X. Feng, A. Hadid, OULU-NPU: A mobile face presentation attack database with real-world variations, in: 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition, FG 2017, IEEE, 2017, pp. 612–618.
[157] Z. Zhang, J. Yan, S. Liu, Z. Lei, D. Yi, S.Z. Li, A face antispoofing database with diverse attacks, in: 2012 5th IAPR International Conference on Biometrics, ICB, IEEE, 2012, pp. 26–31.
[158] D. Wen, H. Han, A.K. Jain, Face spoof detection with image distortion analysis, IEEE Trans. Inf. Forensics Secur. 10 (4) (2015) 746–761.
[159] K. Soomro, A.R. Zamir, M. Shah, UCF101: A dataset of 101 human actions classes from videos in the wild, 2012, arXiv preprint arXiv:1212.0402.
[160] J.C. Niebles, C.-W. Chen, L. Fei-Fei, Modeling temporal structure of decomposable motion segments for activity classification, in: Computer Vision–ECCV 2010: 11th European Conference on Computer Vision, Heraklion, Crete, Greece, September 5-11, 2010, Proceedings, Part II 11, Springer, 2010, pp. 392–405.
[161] M.-H. Chen, Z. Kira, G. AlRegib, J. Yoo, R. Chen, J. Zheng, Temporal attentive alignment for large-scale video domain adaptation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 6321–6330.
[162] H. Kuehne, H. Jhuang, E. Garrote, T. Poggio, T. Serre, HMDB: a large video database for human motion recognition, in: 2011 International Conference on Computer Vision, IEEE, 2011, pp. 2556–2563.
[163] Y. Xu, J. Yang, H. Cao, K. Wu, M. Wu, Z. Li, Z. Chen, Multi-source video domain adaptation with temporal attentive moment alignment network, IEEE Trans. Circuits Syst. Video Technol. (2023).
[164] A. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, L. Fei-Fei, Large-scale video classification with convolutional neural networks, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 1725–1732.
[165] W. Kay, J. Carreira, K. Simonyan, B. Zhang, C. Hillier, S. Vijayanarasimhan, F. Viola, T. Green, T. Back, P. Natsev, et al., The kinetics human action video dataset, 2017, arXiv preprint arXiv:1705.06950.

[166] Y. Xu, J. Yang, H. Cao, K. Mao, J. Yin, S. See, Arid: A new dataset for recognizing action in the dark, in: Deep Learning for Human Activity Recognition: Second International Workshop, DL-HAR 2020, Held in Conjunction with IJCAI-PRICAI 2020, Kyoto, Japan, January 8, 2021, Proceedings 2, Springer, 2021, pp. 70–84.

[167] M. Monfort, A. Andonian, B. Zhou, K. Ramakrishnan, S.A. Bargal, T. Yan, L. Brown, Q. Fan, D. Gutfreund, C. Vondrick, et al., Moments in time dataset: one million videos for event understanding, IEEE Trans. Pattern Anal. Mach. Intell. 42 (2) (2019) 502–508.

[168] P. Rajpurkar, J. Zhang, K. Lopyrev, P. Liang, Squad: 100,000+ questions for machine comprehension of text, 2016, arXiv preprint arXiv:1606.05250.

[169] Z. Yang, P. Qi, S. Zhang, Y. Bengio, W.W. Cohen, R. Salakhutdinov, C.D. Manning, Hotpotqa: A dataset for diverse, explainable multi-hop question answering, 2018, arXiv preprint arXiv:1809.09600.

[170] T. Kwiatkowski, J. Palomaki, O. Redfield, M. Collins, A. Parikh, C. Alberti, D. Epstein, I. Polosukhin, J. Devlin, K. Lee, et al., Natural questions: a benchmark for question answering research, Trans. Assoc. Comput. Linguist. 7 (2019) 453–466.

[171] A. Trischler, T. Wang, X. Yuan, J. Harris, A. Sordoni, P. Bachman, K. Suleman, Newsqa: A machine comprehension dataset, 2016, arXiv preprint arXiv:1611.09830.

[172] D. Kothandaraman, R. Chandra, D. Manocha, SS-SFDA: Self-supervised source-free domain adaptation for road segmentation in hazardous environments, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 3049–3059.

[173] J.N. Kundu, A. Kulkarni, A. Singh, V. Jampani, R.V. Babu, Generalize then adapt: Source-free domain adaptive semantic segmentation, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 7046–7056.

[174] Y. Liu, W. Zhang, J. Wang, Source-free domain adaptation for semantic segmentation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 1215–1224.

[175] I.B. Akkaya, U. Halici, Self-training via metric learning for source-free domain adaptation of semantic segmentation, 2022, arXiv preprint arXiv:2212.04227.

[176] M. Klingner, J.-A. Termöhlen, J. Ritterbach, T. Fingscheidt, Unsupervised batchnorm adaptation (ubna): A domain adaptation method for semantic segmentation without using source domain representations, in: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2022, pp. 210–220.

[177] C.-Y. Yang, Y.-J. Kuo, C.-T. Hsu, Source free domain adaptation for semantic segmentation via distribution transfer and adaptive class-balanced self-training, in: 2022 IEEE International Conference on Multimedia and Expo, ICME, IEEE, 2022, pp. 1–6.

[178] Y. Zhao, Z. Zhong, Z. Luo, G.H. Lee, N. Sebe, Source-free open compound domain adaptation in semantic segmentation, IEEE Trans. Circuits Syst. Video Technol. 32 (10) (2022) 7019–7032.

[179] D. Zhao, S. Wang, Q. Zang, D. Quan, X. Ye, L. Jiao, Towards better stability and adaptability: Improve online self-training for model adaptation in semantic segmentation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2023, pp. 11733–11743.

[180] S.-Y. Lo, P. Oza, S. Chennupati, A. Galindo, V.M. Patel, Spatio-temporal pixel-level contrastive learning-based source-free domain adaptation for video semantic segmentation, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2023, pp. 10534–10543.

[181] N.K. Dinsdale, M. Jenkinson, A.I. Namburete, Sfharmony: Source free domain adaptation for distributed neuroimaging analysis, 2023, arXiv preprint arXiv:2303.15965.

[182] Y. Li, R. Dan, S. Wang, Y. Cao, X. Luo, C. Tan, G. Jia, H. Zhou, Y. Zhang, Y. Wang, et al., Plug-and-play shape refinement framework for multi-site and lifespan brain skull stripping, in: Machine Learning in Medical Imaging: 13th International Workshop, MLMI 2022, Held in Conjunction with MICCAI 2022, Singapore, September 18, 2022, Proceedings, Springer, 2022, pp. 81–90.

[183] M. Bateson, H. Kervadec, J. Dolz, H. Lombaert, I.B. Ayed, Source-free domain adaptation for image segmentation, Med. Image Anal. 82 (2022) 102617.

[184] J. Hong, Y.-D. Zhang, W. Chen, Source-free unsupervised domain adaptation for cross-modality abdominal multi-organ segmentation, Knowl.-Based Syst. 250 (2022) 109155.

[185] S. Kondo, Source-free unsupervised domain adaptation with norm and shape constraints for medical image segmentation, 2022, arXiv preprint arXiv:2209.01300.

[186] C. Li, W. Chen, X. Luo, Y. He, Y. Tan, Adaptive pseudo labeling for source-free domain adaptation in medical image segmentation, in: ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, IEEE, 2022, pp. 1091–1095.

[187] Y. Wang, J. Cheng, Y. Chen, S. Shao, L. Zhu, Z. Wu, T. Liu, H. Zhu, FVP: Fourier visual prompting for source-free unsupervised domain adaptation of medical image segmentation, 2023, arXiv preprint arXiv:2304.13672.

[188] S. Hu, Z. Liao, Y. Xia, ProSFDA: Prompt learning based source-free domain adaptation for medical image segmentation, 2022, arXiv preprint arXiv:2211.11514.

[189] C. Yang, X. Guo, Z. Chen, Y. Yuan, Source free domain adaptation for medical image segmentation with fourier style mining, Med. Image Anal. 79 (2022) 102457.

[190] L. Xiong, M. Ye, D. Zhang, Y. Gan, Y. Liu, Source data-free domain adaptation for a faster R-CNN, Pattern Recognit. 124 (2022) 108436.

[191] X. Li, W. Chen, D. Xie, S. Yang, P. Yuan, S. Pu, Y. Zhuang, A free lunch for unsupervised domain adaptive object detection without source data, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 35, No. 10, 2021, pp. 8474–8481.

[192] V. VS, P. Oza, V.M. Patel, Instance relation graph guided source-free domain adaptive object detection, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2023, pp. 3520–3530.

[193] C. Saltori, S. Lathuiliére, N. Sebe, E. Ricci, F. Galasso, Sf-uda 3d: Source-free unsupervised domain adaptation for lidar-based 3d object detection, in: 2020 International Conference on 3D Vision, 3DV, IEEE, 2020, pp. 771–780.

[194] D. Hegde, V.M. Patel, Attentive prototypes for source-free unsupervised domain adaptive 3d object detection, 2021, arXiv preprint arXiv:2111.15656.

[195] D. Hegde, V. Sindagi, V. Kilic, A.B. Cooper, M. Foster, V. Patel, Uncertainty-aware mean teacher for source-free unsupervised domain adaptive 3d object detection, 2021, arXiv preprint arXiv:2109.14651.

[196] H. Yang, Z. Yang, A. Hu, C. Liu, T.J. Cui, J. Miao, Source-free domain adaptive detection of concealed objects in passive millimeter-wave images, IEEE Trans. Instrum. Meas. (2023).

[197] T. Han, X. Gong, F. Feng, J. Zhang, Z. Sun, Y. Zhang, Privacy-preserving multi-source domain adaptation for medical data, IEEE J. Biomed. Health Inf. (2022).

[198] Y. Feng, Y. Luo, J. Yang, Cross-platform privacy-preserving CT image COVID-19 diagnosis based on source-free domain adaptation, Knowl.-Based Syst. 264 (2023) 110324.

[199] W. Zhang, D. Wu, Lightweight source-free transfer for privacy-preserving motor imagery classification, IEEE Trans. Cogn. Dev. Syst. (2022).

[200] C. Zhao, R. Peng, D. Wu, Source-free domain adaptation (SFDA) for privacy-preserving seizure subtype classification, IEEE Trans. Neural Syst. Rehabil. Eng. (2023).

[201] Y. Xu, J. Yang, H. Cao, K. Wu, M. Wu, Z. Chen, Source-free video domain adaptation by learning temporal consistency for action recognition, in: Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXXIV, Springer, 2022, pp. 147–164.

[202] Y. Xu, J. Yang, M. Wu, X. Li, L. Xie, Z. Chen, EXTERN: Leveraging endo-temporal regularization for black-box video domain adaptation, 2022, arXiv preprint arXiv:2208.05187.

[203] Y. Huang, X. Yang, J. Zhang, C. Xu, Relative alignment network for source-free multimodal video domain adaptation, in: Proceedings of the 30th ACM International Conference on Multimedia, 2022, pp. 1652–1660.

[204] Y. Liu, Y. Chen, W. Dai, M. Gou, C.-T. Huang, H. Xiong, Source-free domain adaptation with contrastive domain alignment and self-supervised exploration for face anti-spoofing, in: Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XII, Springer, 2022, pp. 511–528.

[205] K. Yue, W. Li, J. Li, Z. Chen, R. Huang, Source-free partial domain adaptation in rotating machinery fault diagnosis using deep hypothesis domain adaptation network, in: 2022 International Conference on Sensing, Measurement & Data Analytics in the Era of Artificial Intelligence, ICSMD, IEEE, 2022, pp. 1–6.

[206] Y. Zhang, Z. Ren, K. Feng, K. Yu, M. Beer, Z. Liu, Universal source-free domain adaptation method for cross-domain fault diagnosis of machines, Mech. Syst. Signal Process. 191 (2023) 110159.

[207] J. Liu, X. Li, S. An, Z. Chen, Source-free unsupervised domain adaptation for blind image quality assessment, 2022, arXiv preprint arXiv:2207.08124.

[208] M. Boudiaf, T. Denton, B. van Merriënboer, V. Dumoulin, E. Triantafillou, In search for a generalizable method for source free domain adaptation, 2023, arXiv preprint arXiv:2302.06658.

[209] M. Yin, B. Wang, Y. Dong, C. Ling, Source-free domain adaptation for question answering with masked self-training, 2022, arXiv preprint arXiv:2212.09563.

[210] Z. Zhao, Y. Xie, J. Xie, Z. Lin, Y. Li, Y. Shen, Source-free unsupervised domain adaptation for question answering, in: ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, IEEE, 2023, pp. 1–5.

[211] Z. Xu, W. Wei, L. Zhang, J. Nie, Source-free domain adaptation for cross-scene hyperspectral image classification, in: IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium, IEEE, 2022, pp. 3576–3579.

[212] K. Bousmalis, N. Silberman, D. Dohan, D. Erhan, D. Krishnan, Unsupervised pixel-level domain adaptation with generative adversarial networks, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 3722–3731.

[213] Y. Zhang, Z. Gan, K. Fan, Z. Chen, R. Henao, D. Shen, L. Carin, Adversarial feature matching for text generation, in: International Conference on Machine Learning, PMLR, 2017, pp. 4006–4015.

[214] S. Shi, X. Wang, H. Li, Pointrcnn: 3d object proposal generation and detection from point cloud, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, pp. 770–779.

[215] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, Adv. Neural Inf. Process. Syst. 30 (2017).
[216] A. Radford, J.W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, et al., Learning transferable visual models from natural language supervision, in: International Conference on Machine Learning, PMLR, 2021, pp. 8748–8763.
[217] A. Kirillov, E. Mintun, N. Ravi, H. Mao, C. Rolland, L. Gustafson, T. Xiao, S. Whitehead, A.C. Berg, W.-Y. Lo, et al., Segment anything, 2023, arXiv preprint arXiv:2304.02643.
[218] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever, et al., Language models are unsupervised multitask learners, Openai Blog 1 (8) (2019) 9.
[219] B. Wang, A. Komatsuzaki, GPT-J-6B: A 6 billion parameter autoregressive language model, 2021, Software.

Ningyuan Zhang is a Ph.D. candidate at the Australian Artificial Intelligence Institute, University of Technology Sydney, Australia. His research interest includes source-free domain adaptation and cross-modality transfer learning.

Jie Lu (F'18) is an Australian Laureate Fellow, IFSA Fellow, Distinguished Professor, and the Director of the Australian Artificial Intelligence Institute (AAII) at the University of Technology Sydney, Australia. She received the Ph.D. degree from Curtin University in 2000. Her main research expertise is in transfer learning, concept drift, fuzzy systems, decision support systems, and recommender systems. She has been awarded 12 Australian Research Council (ARC) discovery and linkage grants and led 20 industry projects. She has published over 500 papers in IEEE Transactions and other leading journals and conferences. Many of her research results have been successfully transferred to industry. She has delivered 40 keynote speeches at international conferences, supervised 50 Ph.D. students to completion, served as Editor-In-Chief for Knowledge-Based Systems, and received national and international awards including the IEEE Transactions on Fuzzy Systems Outstanding Paper Awards (2018 and 2022).

Keqiuyin Li received the Ph.D. degree in computer science from the University of Technology Sydney, Sydney, Australia, in 2023. She is a research associate working on the Australian research council laureate project in Decision Systems and e-Service Intelligent (DeSI) lab at the Australian Artificial Intelligence Institute (AAII) at the University of Technology Sydney, Australia. Her research interest is mainly in transfer learning.

Zhen Fang received his Ph.D. degree from the Australian Artificial Intelligence Institute, University of Technology Sydney, Australia, in 2021. He is a member of the Decision Systems and e-Service Intelligence (DeSI) Research Laboratory, Australian Artificial Intelligence Institute, University of Technology Sydney. His research interests include transfer learning and out-of-distribution learning. He has published several papers related to transfer learning and out-of-distribution learning in NeurIPS, ICML, TPAMI.

Guangquan Zhang is an Australian Research Council (ARC) QEII Fellow, Associate Professor, and the Director of the Decision Systems and e-Service Intelligent (DeSI) Research Laboratory at the Australian Artificial Intelligence Institute, University of Technology Sydney, Australia. He received his Ph.D. in applied mathematics from Curtin University, Australia, in 2001. From 1993 to 1997, he was a full Professor in the Department of Mathematics, Hebei University, China. His main research interests lie in fuzzy multi-objective, bilevel and group decision-making, fuzzy measures, transfer learning, and concept drift adaptation. He has published six authored monographs and over 500 papers including some 300 articles in leading international journals. He has supervised 40 Ph.D. students to completion and mentored 15 Postdoc fellows. Prof Zhang has won ten very competitive ARC Discovery grants and many other research projects. His research has been widely applied in industries.