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Multi-source domain adaptation handling inaccurate label spaces

Keqiuyin Li, Jie Lu *, Hua Zuo, Guangquan Zhang

Australian Artificial Intelligence Institute, University of Technology Sydney, 81 Broadway, Ultimo, 2007, Sydney, NSW, Australia

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ABSTRACT

Domain adaptation with inaccurate label is a challenging and interesting topic in transfer learning, dealing with source and target domains with shift label spaces. Most existing domain adaptation methods assume aware label distributions among source and target domains. However, this cannot always be guaranteed in reality. Furthermore, existing multi-domain adaptation methods rarely deal with label heterogeneity among source domains. Thus, in this paper, we propose a multi-source domain adaptation method handling Inaccurate label (IncLabDA) during transfer. The proposed method designs a module that can transfer knowledge from multi-source domains with both homogeneous and heterogeneous label spaces in universal scenario. Anchors are generated from pre-trained model to build data-matching via a contrastive method avoiding to referring original data. In addition, class center consistency combined with clustering strategy considering both global and local confidences is adopted to recognize out-of-distribution samples. By removing source private classes and target unknown samples, highly confident target samples are collected to self-supervise the adaptation. At the same time, constraints enlarging the distance among target known classes and between the known and unknown samples are applied to enhance the performance of the proposed model. Experiments on real-world datasets validate the superiority of the IncLabDA model.

1. Introduction

Unsupervised domain adaptation is an attractive method for solving task(s) from label-scarce target domain(s) by leveraging the knowledge learned from label-rich source domain(s) [1,2]. To transfer knowledge across domains, reducing the data gap [3] or correcting distribution shift [4] between source and target domains is a commonly employed solution, including reducing the discrepancy between instances [5], features [6,7] and parameters [8]. According to the number of source and target domains, the most commonly explored domain adaptation scenarios include single-source single-target [9–11], single-source multi-target [12,13], multi-source single-target [14,15] and multi-source multi-target domain adaptation. Based on the shareness of source and target labels, there are four groups for unsupervised domain adaptation: closed-set [16,17], partial [18], open-set [19,20] and universal domain adaptation [21].

Closed-set domain adaptation transfers source knowledge to the target domain where the source and target domains have the same label space which has been widely explored [22]. Partial domain adaptation deals with knowledge transfer across domains where the source label space is larger than that of the target domain [23]. Open-set domain adaptation is designed to handle transfer learning where the target domain contains more categories than the source domain [24]. It has to classify known classes (classes shared by source and target domains) and unknown classes (target private classes). To detect unknown samples, hard rejection and soft rejection based on a threshold defined by clustering or entropy assumption are developed [25].

Universal domain adaptation handles a more challenging scenario where source and target domains have private categories respectively [26]. Compared with partial and open-set domain adaptation, universal domain adaptation has to classify known classes without introducing too much unrelated information of source private classes, and distinguish target unknown classes simultaneously. Combining relevance measurement and entropy assumption is a popular method to identify known classes and unknown classes [27]. Most existing universal domain adaptation methods rely on access to the source data to achieve transfer across domains. However, source data is not always available due to privacy issues, especially in real applications. Besides, there can be multiple source domains for a target domain. Transferring information from multi-source domains and the label heterogeneity issue among multi-source domains remain unsolved.

To address universal domain adaptation without source data, encouraged by source-absent domain adaptation, data generation is employed to generated source data, including positive and negative samples [28]. Positive samples are used to adapt source and target data while negative samples are used to train unknown classifier. However,

* Corresponding author.
E-mail addresses: keqiuyin.li@uts.edu.au (K. Li), jie.lu@uts.edu.au (J. Lu), hua.zuo@uts.edu.au (H. Zuo), guangquan.zhang@uts.edu.au (G. Zhang).

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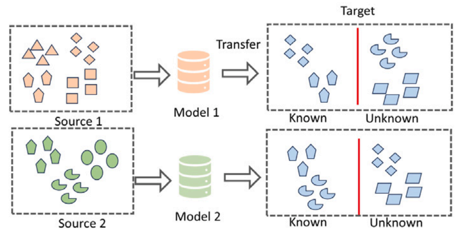
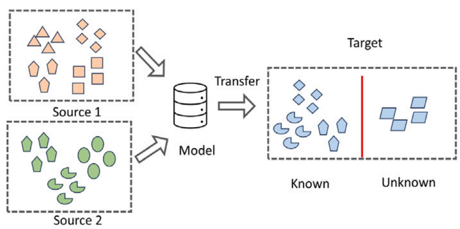


(a) Inaccurate label in single-source domain



(b) Inaccurate label in multi-source domain

Fig. 1. Inaccurate label in domain adaptation with single and multiple source domains.

these method requires a very large number of generated outliers to distinguish unknown classes. In addition, when there are multiple source domains, existing methods cannot be applied efficiently, especially when the source domains have different label spaces. As shown in Fig. 1(a), where colors indicate different domains while shapes indicate labels. Given multi-source domains, existing universal domain adaptation methods transfer knowledge from a single source domain. This requires training individual source model in every source domain, the individual source model can only classify samples from the classes shared by the corresponding source and target domains. Training individual model requires learning more parameters and the individual model cannot classify all known classes. That is why we propose multi-source domain adaptation model to tackle inaccurate label. As shown in Fig. 1(b), the purpose of this work is to leverage knowledge from the source domains to identify more transferable information. If the model can tackle source domains with heterogeneous label spaces, it has the ability to handle multi-source domains with the same label space.

In summary, existing works have several main limitations: (1). Many methods rely on data matching and assume that the source and target domains share the same label space, which poses challenges in scenarios where source data is unavailable and label shifts occur. (2). Several studies focusing on addressing label shifts are tailored to specific scenarios, which restricts their applicability in handling complex label shifts across various situations. (3). Only a few existing studies concentrate on universal source-free domain adaptation, but they rarely address adaptation from multiple source domains. Additionally, there is a lack of research on handling multiple source domains with distinct label spaces in a source-free universal setting.

To solve the mentioned limitations, in this paper, we propose a multi-source domain adaptation method handling inaccurate label (InCLabDA) in source-source and source-target domains. A challenging setting where most existing domain adaptation methods can fail to deal with. The proposed method learns one model to predict multiple tasks from both source and target domains. It leverages source invariant information that can be transferred among domains to predict target known classes. At the same time, it designs a category discriminator union to assist in generating class anchors and detecting outliers during matching target data to source categories. The category discriminator can guarantee the flexibility of the proposed model to handle multi-source domains with homogeneous and heterogeneous label spaces. Both target unknown classes and source private classes are identified when pseudo-labeling target samples, which is expected to improve the classification performance on known and unknown classes.

Our contributions are summarized as follows:

- We introduce a model capable of learning multiple tasks for domain adaptation in scenarios with inaccurate label spaces. This model offers flexibility in addressing multiple label shifts, whether the source data is accessible or inaccessible. It eliminates the necessity to train separate models for each source domain by integrating both global and local information through a global classifier and category discriminators. The global classifier is proficient in identifying all known categories in source domains without the need for training individual models, while the category discriminator excels at handling label shifts in the source domains when applied to a new (target) domain. This approach effectively mitigates bias stemming from unshared categories in the source domains.
- We devise an anchor generation function to establish class anchors using contrastive learning via leveraging the cross-entropy information from both the global and category levels. This function groups known samples close to the anchors while ensuring separation between samples from different categories. This approach proves advantageous for known sample classification and unknown sample identification in the target domain, particularly when confronted with multiple source domains featuring distinct label spaces, a challenge that many existing domain adaptation methods struggle to address.
- We introduce a threshold based on the probability vectors predicted by the global classifier and category discriminator. This is coupled with a confident target sample selection scheme to minimize noise in the pseudo labels by grouping source and target anchors. This approach facilitates the self-training of the target domain using pseudo labels provided by clustering with a high quality to adapt the source model.

The remainder of this paper is organized as follows. Section 2 briefly describes the related work on universal domain adaptation with and without source access. Section 3 provides details of the proposed multi-domain adaptation method for uncertain label spaces. The experiment results and analysis on real-world visual datasets are displayed in Section 4. Section 5 summarizes the research and proposes potential directions for future study.

2. Related work

This section introduces previous studies on universal domain adaptation with and without source data, followed by a discussion of typical techniques in source-absent domain adaptation.

2.1. Universal domain adaptation with source access

Universal domain adaptation has to handle the data shift between source and target domains as well as between known and unknown classes. One-vs-all network learns the decision boundary determined by the inter-class and intra-class distance to reject unknown target samples whose class entropy is high [29]. It builds two classifiers, an open-set classifier to provide the threshold of unknown samples, and a closed-set classifier to predict known samples. Hard negative classifier sampling and open-set entropy minimization are employed to adapt the source model to the target domain. The universal multi-source domain adaptation network combines the hypothesis predictions of multiple source classifiers to learn the pseudo-margin of target samples, which is further applied to divide known and unknown classes [30]. It adopts a target margin register to optimize an empirical vector which calculates the reliability of sample belonging to the known classes. Both class-wise and sample-wise reliabilities are considered to build the weighting mechanism to measure the possibility of a class being known or unknown.

2.2. Data-free universal domain adaptation

Universal source-free domain adaptation is the first work to handle transfer with domain-shift and category-shift simultaneously without access to source data [28]. It builds a two-step learning process to guarantee the positive transfer across domains, including the procurement stage and deployment stage. The procurement stage generates negative samples for the known source classes to learn a model which has the ability to encounter category-gap. The deployment stage designs a source similarity metric to measure the weight vector of a sample being positive and trains a domain-specific feature extractor to force the target data to the feature space of shared labels. Universal model adaptation learns a two-head classifier from the source domain and applies it to the target domain with an informative consistency score to divide known and unknown samples in the target domain [31]. In the source model training procedure, a closed-set classifier is learned to predict the soft-max class probability, while in the model adaptation process, a threshold defined by the mean informative consistency is used to select unknown samples.

2.3. Typical techniques in data-free domain adaptation

Pseudo-labeling and data generation are two techniques widely used in data-free domain adaptation [32,33]. Avatar prototype generation and adaptation aligns the source and target domains by matching the generated source and target prototypes [34]. To generate class prototypes that can separate samples from different categories, in the source domain, a contrastive loss based on InfoNCE is used to enlarge the distance among categories. In the target domain, target prototypes are calculated using a self-supervised pseudo-labeling strategy. To collect highly confident target pseudo labels, it combines neighborhood clustering loss and class entropy based on the normalized similarity of features to reduce pseudo label noise. Weighted contrastive alignment is proposed based on the pseudo-labeled data to align target samples to the source categories using a class-wise method.

Existing methods rarely consider domain adaptation when there are multiple source domains with heterogeneous label spaces. Many multi-domain adaptation methods train independent source models and predict the target task by combining the outputs of all source classifiers, which is not always efficient in real applications, especially when the number of source domains is very large. Furthermore, existing domain adaptation methods assume label spaces of source and target are known, but in real situations, it is normal that the label overlaps of source and target cannot be aware. To address these problems, in this paper, we propose multi-source domain adaptation model with inaccurate label spaces. The proposed model is flexible enough to handle multiple source domains with homogeneous and heterogeneous label spaces. By unifying source knowledge, the proposed method learns one model to handle multiple tasks.

3. Method

3.1. Overview

We deal with Inaccurate label in multi-domain adaptation, where source domains with both homogeneous and heterogeneous label spaces are considered. In this scenario, the overlaps among source and target labels cannot be ensured. This requires the source model must have the ability to handle multiple label uncertainties, which means model generality and detecting out-of-distribution samples.

The proposed method is illustrated in Fig. 2. Fig. 2(a) indicates the model training on vendor-side, which is trained on multiple source domains by leveraging the feedback from source model without sharing data. Considering multi-source domain can have different label spaces, to guarantee that the model can handle source heterogeneity avoiding introducing independent parameters, a global classifier with a category discriminator union are designed to provide constraint for its own source classes and reduce the influence of unshared classes. Fig. 2(b) indicates the generation of highly representative anchors. Contrastive learning is adopted here to generate anchor by finding nearest samples to the class center. Fig. 2(c) is the procedure of target adaptation on client-side. To perform the pre-trained model on target task, classifier layers are frozen while the backbone is fine-tuned under the supervision of self-training and data-matching. To match data, generated anchors are adopted to reduce their distance. To self-supervise the training, unshared classes are identified to reduce pseudo label noise and collect high confident target labels.

3.2. Source model training

To avoid training an independent source model in each source domain, we propose a unified learning model to handle multiple tasks. It is important to guarantee that the model can be performed on multiple source domains with both homogeneous and heterogeneous label spaces. To achieve this, denote the source label space as $C_s = C_{s_1} \cup \cdots \cup C_{s_k}$, a classifier $P \in \mathbb{R}^{C_s}$ is trained based on multiple source domains, where C_s indicates C_s-dimension. Besides, to reduce the influence of unshared classes and better identify outliers, a category discriminator union $\{P_c\}_{c=1}^{C_s}$ is designed to provide binary predictions of each class. The classifier P and P_c can be trained by minimizing the error between the outputs and the ground-truth smoothing labels, which is expressed as:

$$L_s = \sum_{k}^{K}(L(P(\phi(\boldsymbol{x}_{s_k})), \boldsymbol{y}_{s_k}) + \sum_{c=1}^{C_s} L(P_c(\phi(\boldsymbol{x}_{s_k})), I(\boldsymbol{y}_{s_k}, c))), \tag{3.1}$$

where L is the entropy loss, $I(\boldsymbol{y}_{s_k}, c) = 1_{y_{s_k}=c}$ indicates binary class label.

3.3. Anchor generation

During source model training, to avoid to load large size source data to adapt target data, we generate anchors from the known labels as $G(\boldsymbol{y}_s)$, $\boldsymbol{y}_s \in C_s$ to match the source and target distributions. Since multiple source domains contain label heterogeneity, how the anchors mitigate the influence resulting from the absence of the unshared category and retain information from shared category can affect the source anchor generation. Category discriminators determining whether a sample belonging inside or outside of a category is helpful. The advantage of employing a category discriminator is that it remains unaffected by the absence of certain categories. This is because, apart from samples belonging to the same category, all other samples are treated as negative samples. If all category discriminators from one source classify a sample as an outlier, we can conclude that this source does not contain the category reflected by the sample. When generating anchors for the corresponding category, we can simply skip the absent sources to avoid introducing additional noise.

The generated anchors are further expected to meet two criteria: firstly, the generated class anchor should be classified into the corresponding categories, and secondly, samples from the same category should be close to the corresponding anchors.

To fulfill these criteria, we employ contrastive learning constructed by infoGAN [9] to generate representative anchors. Contrastive learning is a method that emphasizes extracting meaningful representations by comparing positive and negative pairs of instances. It operates under the assumption that similar instances should be closer to each other in a learned embedding space, whereas dissimilar instances should be distanced.

For the first condition, as illustrated in Fig. 2(b), we utilize the source label as input fed to generator G to produce the anchors. These generated anchors (outputs) are optimized to be closer if they are similar and farther if dissimilar. The similarity is measured using cosine distance, which calculates the angle between the anchors. Furthermore,

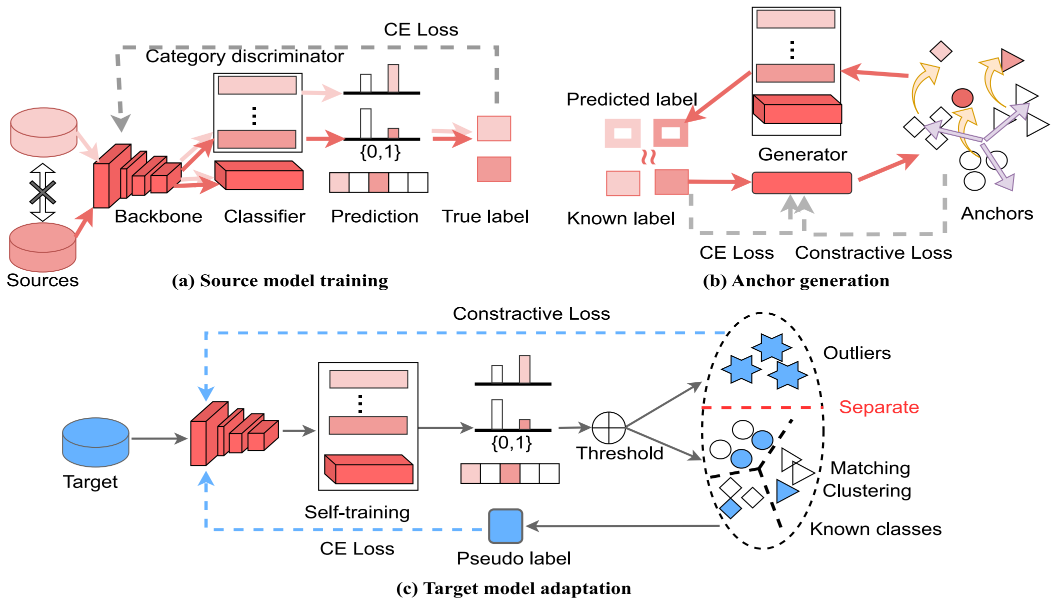


Fig. 2. The procedure of the proposed method. (a). IncLabDA is trained on multi-source domains. (b). Anchors are generated based on contrastive learning. (c). Adaptation is designed based on self-supervision and contrastive matching.

they are expected to be classified as insiders of their respective categories by the classifier P and the discriminator P_c, which are optimized by minimizing the cross-entropy loss returned by P and P_c to ensure that their labels gain both global- and local-level constraints. Thus, The data generator satisfying the first condition is updated as:

$$L_G = L(P(\phi(G(\mathbf{y}_s))), \mathbf{y}_s) + L(P_c(\phi(G(\mathbf{y}_s))), I(\mathbf{y}_s, c)). \tag{3.2}$$

For the second condition, as demonstrated in previous research [16], the class center proves robust enough to represent transferable information of each class compared to the entire dataset. We aim to minimize the distance between generated anchors and their respective class centers. which is expressed as:

$$L_c = \sum_{c=1}^{C_s} \left\| \frac{1}{m} \sum_{i=1}^{m} \phi(G(y_s^{ci})) - \sum_{i=1}^{b} P_c(\phi(\mathbf{x}_{s_k}^i))\phi(\mathbf{x}_{s_k}^i) \right\|^2. \tag{3.3}$$

m is number of anchors in each class, b is batchsize.

To enhance the representation of the anchors, we enlarge the distance between anchors from different classes to learn clear boundaries among classes. Denote a positive sample as $\hat{\mathbf{x}}^+$ and a negative sample as $\hat{\mathbf{x}}^-$, contrastive loss [35] is employed to separate anchors from different classes, which is:

$$L_{con} = -log \frac{exp(\psi(\hat{\mathbf{x}}, \hat{\mathbf{x}}^+)/\tau)}{exp(\psi(\hat{\mathbf{x}}, \hat{\mathbf{x}}^+)/\tau) + \sum_{i=1}^{C_s-1} exp(\psi(\hat{\mathbf{x}}, \hat{\mathbf{x}}^{i-})/\tau)}, \tag{3.4}$$

where ψ is a distance measurement calculating the similarity between samples and τ is the temperature factor.

The total loss of optimizing the source data generator is then expressed as:

$$L_{gen} = L_G + L_c + L_{con}. \tag{3.5}$$

3.4. Target model adaptation

In adaptation procedure, to perform the source model on the target domain, we adopt cluster matching to group the target samples to the source categories which can classify known samples. At the same time, we learn thresholds to identify both source private classes and unknown target samples to reduce the influence of unshared categories. Detecting unshared samples in our scenario poses several challenges. Firstly, both the source and target domains exhibit distribution shifts. This implies that utilizing a pre-trained source model without data access to predict target labels can introduce significant noise initially. Secondly, the target domain lacks labels, making it impossible to gather any information about the unknown samples. Consequently, the classifier tends to assign labels from known classes to these unknown samples, despite their true origin being from unfamiliar classes. To achieve unshared category detection, target samples are pseudo-labeled first to provide self-supervision for extracting invariant information and selecting known target samples. To collect highly confident target pseudo labels, both the predictions of clustering and classification are considered to reduce the noise in pseudo labels.

Out-of-distribution and known samples are distinguished by learning a threshold defined by a_o, an information score inspired by information maximization loss. Since obtaining target classes through data-level alignment is challenging due to inaccessible source data, we opt to use model outputs — predictions indicating the probability of belonging to each class — to determine optimal target outputs. After feeding the target samples to the pre-trained model and category discriminators, denote the predicted outputs of classifier P as $\boldsymbol{\omega}_G = [\omega_G^1, \dots, \omega_G^{C_s}]$ and that of category discriminator as $\boldsymbol{\omega}_S = [\omega_S^1, \dots, \omega_S^{C_s}]$ which indicate the probability vectors indicating the degrees of a target sample belonging to the source classes. Since there are unshared classes, if all pseudo target labels are used to calculate target clustering centers, unrelated information can degrade the classification performance. To avoid this, we first define information score a_o that divides uncertainty categories from the target domain, which is:

$$a_o = \frac{\sum -(\boldsymbol{\omega}_G + \boldsymbol{\omega}_S)\log(P(\phi(\mathbf{x}_t)))}{2\log(C_s)}. \tag{3.6}$$

Through the calculation of a_o, we derive the information score for each target sample. To distinguish between known and out-of-distribution samples, we utilize k-means clustering to divide all samples into two clusters. If the maximum probability value of a target sample is higher, meaning a lower information score than a_o, we regard it as a sample from the shared classes. Otherwise, we regard it as a sample from the private classes with label $C_s + 1$, and these outliers are not used to calculate clustering centers.

After removing the outliers defined by a_o, we gather target samples with label space C_s. This sample set can include target unknown samples which are given source unshared labels. To identify these target samples, we first adopt another threshold $a_p^c = \mathrm{med}\{\omega_{max}^{ci}\}_{i=1}^{n_c}$ to select target samples with highly confident pseudo labels, which is set experimentally as the median value of the maximum probabilities of all samples belonging to the same category based on our previous research. ω^c_{max} is maximum probability returned by classifiers, n_c is the number of target samples divided into the cth class. We group samples whose maximum probabilities are larger than a^c_p as confident target samples.

Target clustering centers are calculated based on these selected target samples, which is:

$$\boldsymbol{v}^c_t = \frac{\sum_{i=1}^{\hat{n}_c}(\boldsymbol{\omega}^i_G + \boldsymbol{\omega}^i_S)\cdot\phi(\boldsymbol{x}^i_t)}{\sum_{i=1}^{\hat{n}_c}(\boldsymbol{\omega}^i_G + \boldsymbol{\omega}^i_S)}. \tag{3.7}$$

Furthermore, if the target domain is adapted to the source domain, where the distributions of source and target are matched, the following assumption should hold true: the target clustering centers and source anchor centers belonging to the same category should be closest to each other. Based on this assumption, we take the mean values of all source anchors from the same category as their centers, and we calculate the similarity between target clustering centers and generated anchors which returns the class index r of the target clustering center which is closest to the cth center. If the cth target cluster center gets the closest class anchor as $\hat{\boldsymbol{v}}^c$, where $r = c$, we regard that the cth class is a common category of source and target domains. Denote the final common label set as $\mathcal{C}$, the clustering label $\tilde{\boldsymbol{y}}_t$ of a target sample is defined by finding the nearest clustering center $\boldsymbol{v}^c_t$.

Select the same pseudo labels returned by clustering and classification, the target cluster centers and pseudo labels are then updated as:

$$\begin{aligned} \boldsymbol{v}^c_t &= \frac{\sum_{i=1}^{\hat{n}'_c}\mathbb{1}_{\tilde{\boldsymbol{y}}^i_t=c}\cdot\phi(\boldsymbol{x}^i_t)}{\sum_{i=1}^{\hat{n}'_c}\mathbb{1}_{\tilde{\boldsymbol{y}}^i_t=c}}, \\ \tilde{\boldsymbol{y}}_t &= \arg\min_c \mathrm{Dis}(\phi(\boldsymbol{x}_t), \boldsymbol{v}^c_t), \\ \boldsymbol{v}_t &= \{\boldsymbol{v}^c_t\}_{c\in\mathcal{C}}. \end{aligned} \tag{3.8}$$

$\hat{n}'_c$ is the number of samples in the cth class stored in the memory bank.

Employing the pseudo labels obtained by Eq. (3.8), freeze the classifier layer, the source model is adapted to the target domain using a self-supervision strategy by fine-tuning the feature extractor ϕ, where information maximization loss is employed to balance the domain:

$$L_t = L_\phi((P(\phi(\boldsymbol{x}_t))), \tilde{\boldsymbol{y}}_t) + \sum \bar{\boldsymbol{p}}_t \log(\bar{\boldsymbol{p}}_t),\ \ \boldsymbol{x}_t \in \mathcal{D}'. \tag{3.9}$$

where $\bar{\boldsymbol{p}}_t = \frac{1}{\sum_{c=1}^{C}\hat{n}'_c}\sum_{i=1}^{\sum_{c=1}^{C}\hat{n}'_c} P(\phi(\boldsymbol{x}^i_t))$.

Except for the label-level constraint controlled by self-supervision, to better transform the target data distribution to the source feature space, data-level constraints are adopted to group samples from the same classes, and enlarge the distance among known target classes as well as between known and unknown samples. To match the target samples to the shared source classes, the distance between target samples and the generated anchors is minimized by:

$$L_{st} = \left\| \sum_{i=1}^{b} P(\phi(\boldsymbol{x}^i_t))\phi(\boldsymbol{x}^i_t) - \frac{1}{m}\sum_{i=1}^{m}\phi(G(\boldsymbol{y}^{ci}_s)) \right\|^2, c \in C. \tag{3.10}$$

To separate known classes from each other, contrastive loss is adopted on the pseudo-labeled data, which is:

$$L_{cont} = -log \sum_{c\in C} \frac{exp(\psi(\boldsymbol{x}_t, \boldsymbol{x}^{c+}_t)/\tau)}{exp(\psi(\boldsymbol{x}_t, \boldsymbol{x}^{+}_t)/\tau) + \sum_{i\neq c} exp(\psi(\boldsymbol{x}_t, \boldsymbol{x}^{i-}_t)/\tau)}. \tag{3.11}$$

To better define out-of-distribution samples, we enlarge the distance between the samples in memory bank $\mathcal{D}'_t$ and the unknown samples defined by Eq. (3.6). We rank the unknown samples by their entropy assumptions and select $\frac{1}{3}$ of the samples with the highest entropy loss, denoted as $\mathcal{D}^u_t = \{\boldsymbol{x}^{ui}_t\}_{i=1}^{n^u}$. We maximize the distance between the known and unknown samples by:

$$L_{uk} = \arg\max_\phi \left\| \frac{1}{\sum_{c=1}^{C}\hat{n}'_c}\sum_{i=1}^{\sum_{c=1}^{C}\hat{n}'_c} h(\phi(\boldsymbol{x}^i_t)) - \frac{1}{n^u}\sum_{j=1}^{n^u} h(\phi(\boldsymbol{x}^{uj}_t)) \right\|^2_{\mathcal{H}}. \tag{3.12}$$

The total loss function of adapting source model to target domain is:

$$L_{total} = L_t + \beta L_{st} + \gamma L_{cont} + \lambda L_{uk}. \tag{3.13}$$

The processing of the proposed unified learning model for source-absent multi-domain adaptation is described in Algorithms 3.1 and 3.2.

Algorithm 3.1 IncLabDA: Source model training.

1: **Input:** Source domains;
2: **for** $\epsilon = 1,\ \epsilon < \mathcal{I}_s,\ \epsilon{+}{+},$ **do**
3: Update classifiers by unifying source knowledge as in equation (3.1);
4: Calculate entropy-loss of source data generator as in equation and (3.2);
5: Calculate contrastive loss of source data generator as in equations (3.3) and (3.4);
6: Update source data generator as in equation (3.5);
7: **end for**
8: **Output:** Source model, source category discriminator, source generator.

Algorithm 3.2 IncLabDA: Target model adaptation.

1: **Input:** Source model, source category discriminator, source generator, target domain;
2: **for** $\epsilon = 1,\ \epsilon < \mathcal{I}_t,\ \epsilon{+}{+},$ **do**
3: Learn the threshold to identify unknown samples as in equation (3.6);
4: Calculate target class centers as in equation (3.7);
5: Update target class centers and pseudo labels as in equation (3.8);
6: Adapt target data to source feature space controlled by source generator as equation (3.10);
7: Calculate contrastive loss on target domain as equation (3.11);
8: Enlarge distance of known and unknown classes as equation (3.12);
9: Fine-tune feature extractor as equation (3.13);
10: **end for**
11: **Output:** Target labels.

4. Experiments

In this section, the proposed IncLabDA model is validated on three popular real-world visual datasets including Office31, OfficeHome and DomainNet. All the experiments are classification tasks under the multi-source domain adaptation scenario, where both source domains with homogeneous and heterogeneous label spaces are applied to validate the proposed method. Harmonic mean (HM) on the accuracy of known and unknown classes is employed to measure the performance of the proposed IncLabDA model. The results are the mean values of three repeat runs on each task.

All the experiments are classification tasks under the multi-source domain adaptation scenario, where both source domains with homogeneous and heterogeneous label spaces are applied to validate the proposed method. Harmonic mean (HM) on the accuracy of known

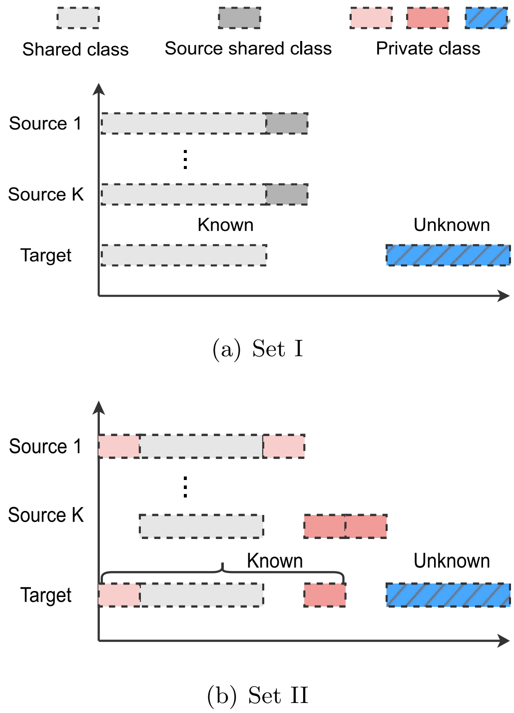


Fig. 3. Settings of universal source-absent multi-domain adaptation.

Table 1
Label set division under homogeneous and heterogeneous settings. In source domain, the division is listed as source shared/private classes. In target domain, the division is listed as known/unknown classes.

Dataset	Domain	Set I	Set II
Office31	S1	20	6/7
	S2	20	6/7
	T	10/11	10/11
OfficeHome	S1	15	4/7
	S2	15	4/7
	S3	15	4/7
	T	10/50	10/40
DomainNet	S	200	
	T	150/145	

and unknown classes is employed to measure the performance of the proposed unified learning model. The results are the mean values of three repeat runs on each task. The experiment settings are shown in Fig. 3. For multi-source domains with homogeneous label space (Set I), we follow the work in [21,26] to set the known and unknown classes. For multi-source domains with heterogeneous label spaces (Set II), the label set of the source and target domains are shown in Table 1.

The compared baselines include heterogeneous single source and multi-source domain adaptation methods with and without source data. Methods with source access include:

- RTN: Residual transfer networks [36];
- IWAN: Importance weighted adversarial nets [37];
- PADA: Partial adversarial domain adaptation [38];
- ATI: Open set domain adaptation for image and action recognition [39];
- OSBP: Open set domain adaptation by backpropagation [40];
- UAN: Universal domain adaptation [26];
- CMU: Learning to detect open classes for universal domain adaptation [41];
- DANCE: Universal domain adaptation via self-supervision [27];
- DCC: Domain consensus clustering for universal domain adaptation [21];
- OVA: One vs. all net [29].
- DCTN: Deep cocktail networks for universal multi-source domain adaptation [42].

Source-absent methods include:

- SHOT: Source hypothesis transfer with information maximization [43];
- USFDA: Universal source-free domain adaptation [28];
- UMAD: Universal model adaptation under domain and category shift [31];
- OneRing: One ring [44];
- UB2DA: Universal black-box domain adaptation [45].
- SF-FDN: Fuzzy multi-source-free domain adaptation [16];
- FuzUMSFDA: Universal data-free multi-domain adaptation [46];
- LEAD: Learning decomposition for universal multi-source-free domain adaptation [47];
- Um2B: Universal multi-domain adaptation from black-boxes [48].

Results of the partial (PADA) and open-set (ATI, OSBP) domain adaptation baselines are re-run under universal settings. All the compared results are obtained from previous publications. For single source-free domain adaptation methods, we take the average predictions from all source domains as the multi-source results similar to previous studies.

$ResNet50$ is employed as the backbone on datasets Office31 and OfficeHome complemented by PyTorch, while $ResNet101$ is applied on DomainNet. Parameters are updated based on backpropagation with stochastic gradient descent. Hyperparameters are updated based on backpropagation with stochastic gradient descent, values defined followed by Ganin and Lempitsky [49].

4.1. Results and analysis

Table 2 presents the HM on tasks from DomainNet and OfficeHome, while Table 3 displays the results for tasks from Office-31. The proposed model (IncLabDA) achieves the highest average performance on most tasks and datasets. On DomainNet and OfficeHome, IncLabDA outperforms both baselines with and without source data. The average HM is improved by 4.0% and 2.2% compared to non-data-free baselines, and by 0.2% and 1.2% compared to data-free baselines, respectively. On Office-31, there is a 3.0% improvement compared to non-data-free methods, while it achieves the second-best performance compared to data-free methods. Furthermore, compared to other baselines, the proposed method can handle more complex settings for universal domain adaptation.

As claimed in previous studies [41,44], classification accuracy may lack measurement of the performance on unknown classes. However, considering many existing methods only provide classification accuracy results, we also compare classification accuracy on the datasets OfficeHome and Office31 to provide sufficient validation of the proposed IncLabDA. Tables 4 and 5 show the classification accuracy of the proposed method and the baselines. It can be seen that the proposed IncLabDA still outperforms the existing methods on both datasets.

Tables 6 and 7 show the HM of the proposed methods and baselines where multi-source domains have heterogeneous label spaces. It can be seen that the proposed IncLabDA performs better than the other methods. Heterogeneous source label spaces are rarely explored in previous universal domain adaptation methods. One advantage of the proposed method is that it can handle both homogeneous and heterogeneous source label spaces without training an independent model in each source domain. Many previous universal domain adaptation methods cannot deal with multiple source domains simultaneously. For a target task, if there are multiple source domains, they have to adapt each pair of source and target domains to predict the target task. The proposed IncLabDA learns one model to predict multiple tasks, it is flexible enough to leverage knowledge from multiple source domains to explore more information to complete the target task.

Table 2
HM (%) on datasets OfficeHome and DomainNet of the IncLabDA and baselines.

Method	SF	OfficeHome					DomainNet
		R	P	C	A	Avg	Avg
RTN	×	45.6	44.4	38.3	43.3	42.9	30.1
IWAN	×	47.6	46.2	41.5	45.7	45.3	32.8
PADA	×	44.1	42.3	34.2	40.2	40.2	27.1
ATI	×	46.6	45.2	41.0	44.6	44.4	30.4
OSBP	×	46.2	45.7	40.6	45.3	44.5	32.0
UAN	×	59.2	58.2	50.6	58.3	56.6	41.0
CMU	×	64.5	63.6	55.0	63.3	61.6	48.3
DANCE	×	41.7	52.6	45.4	50.2	47.3	–
DCC	×	70.1	68.4	**68.9**	73.2	70.2	49.2
OVA	×	79.1	74.9	59.5	71.3	71.2	49.8
SHOT	✓	41.0	31.0	33.9	56.7	40.7	32.6
UMAD	✓	78.2	73.7	59.1	69.4	70.1	47.1
OneRing	✓	78.8	72.1	62.7	73.4	71.8	51.3
UB2DA	✓	76.3	70.0	61.1	74.3	70.4	49.3
SF-FDN	✓	66.2	61.3	57.9	67.0	63.1	–
FuzUMSFDA	✓	74.7	66.9	62.3	73.9	69.5	–
LEAD	✓	85.3	79.4	61.3	73.8	75.0	50.8
Um2B	✓	83.5	79.5	59.8	74.6	74.4	–
IncLabDA	✓	**81.7**	**76.5**	65.6	**76.8**	**75.2**	**52.0**

Table 3
HM (%) on datasets Office-31 of the IncLabDA and baselines.

Method	SF	D	W	A	Avg
RTN	×	52.7	52.4	48.5	51.2
IWAN	×	53.0	52.1	49.7	51.6
PADA	×	52.8	51.1	46.0	50.0
ATI	×	53.0	51.8	48.7	51.2
OSBP	×	54.2	52.9	50.0	52.3
UAN	×	65.6	64.6	60.2	63.5
CMU	×	74.3	73.3	71.8	73.1
DANCE	×	90.7	89.9	79.1	86.6
DCC	×	88.6	78.9	73.1	80.2
SHOT	✓	79.0	77.8	68.2	75.0
USFDA	✓	83.4	85.2	86.0	84.9
UMAD	✓	88.2	84.1	**88.9**	87.0
OneRing	✓	**90.9**	89.5	85.2	88.5
UB2DA	✓	84.4	85.4	91.0	86.9
FuzUMSFDA	✓	86.9	89.4	86.9	87.7
LEAD	✓	89.3	87.9	86.3	87.8
Um2B	✓	97.5	89.8	87.2	**91.5**
IncLabDA	✓	90.3	**93.7**	84.8	89.6

Table 4
Accuracy (%) on datasets OfficeHome of the IncLabDA and baselines with homogeneous source label spaces.

Method	SF	R	P	C	A	Avg
RTN	×	86.0	77.0	60.0	68.7	72.9
IWAN	×	85.6	77.1	56.5	74.3	73.4
PADA	×	77.8	71.6	40.0	62.3	62.9
ATI	×	85.3	77.1	57.0	73.8	73.3
OSBP	×	76.8	65.9	49.1	63.8	63.9
UAN	×	86.7	80.3	61.7	**79.5**	77.1
SHOT	✓	70.1	68.4	**68.9**	73.2	70.2
USFDA	✓	87.6	81.3	62.2	77.1	77.1
UB2DA	✓	92.9	84.2	57.3	76.8	77.7
Um2B	✓	85.6	74.4	54.8	71.9	71.7
IncLabDA	✓	**90.2**	**85.4**	59.5	76.3	**77.9**

4.2. Ablation study

Tables 8 and 9 show the results of the ablation study on the dataset OfficeHome with homogeneous and heterogeneous source labels respectively. We evaluate three modules in the domain adaptation procedure when training the target model: the influence of matching target data to generated source data is reflected by loss function L_{st}, the influence of contrastive learning is reflected by loss function L_{cont}, the influence of separating known and unknown classes is reflected by loss function L_{uk}.

It can seen that the model trained without contrastive loss L_{cont} performs worst under the three settings, which indicates that the contrastive loss which forces samples from the same class to be close to each other and separates samples from different classes is the most important module for the proposed method. The performance of the model without loss function L_{uk} shows a larger decrease in most settings. This indicates that the operation to enlarge the distance between the known and unknown classes also plays an essential role in guaranteeing the transfer performance. The employment of generated matching can have a positive influence on the proposed IncLabDA. Without adapting target data to source generated centers controlled by L_{st}, the value of HM reduced under all settings.

To better demonstrate the function of the proposed method in addressing inaccurate labels, we conducted an ablation study to test the strategy for detecting out-of-distribution and source private samples. We used "w/o a_o" to indicate experiments employing traditional entropy assumption to replace the proposed a_o for identifying unknown samples, while "w/o a_p" indicates experiments without selecting high-confidence samples to calculate centers when detecting source private samples using center consistency.

Table 5
Accuracy (%) on datasets Office31 of the IncLabDA and baselines with homogeneous source label spaces.

Method	SF	D	W	A	Avg
ResNet	×	85.7	82.8	80.1	82.9
IWAN	×	87.1	87.6	85.2	86.6
PADA	×	86.3	82.3	69.0	79.2
ATI	×	87.2	86.0	80.2	84.5
OSBP	×	79.3	69.9	53.9	67.7
UAN	×	92.3	90.2	85.3	89.2
DCTN	✓	**98.3**	**97.8**	76.3	90.7
SHOT	✓	88.6	78.9	73.1	80.2
USFDA	✓	93.1	90.4	87.1	90.2
OneRing	✓	92.1	86.8	81.5	86.8
UB2DA	✓	93.3	90.6	**91.2**	91.7
Um2B	✓	**96.4**	94.1	90.1	**93.5**
IncLabDA	✓	95.3	94.7	86.5	92.2

Table 6
HM (%) on dataset Office-31 of the IncLabDA and baselines with heterogeneous source label spaces.

Method	SF	D	W	A	Avg
ResNet	✓	82.7	71.7	54.3	69.6
SHOT	✓	76.7	77.7	71.6	75.3
CAiDA	✓	88.8	67.3	80.8	79.0
DCC	✓	88.2	83.0	72.3	81.2
IncLabDA	✓	**95.4**	**90.7**	**81.3**	**89.1**

Table 7
HM (%) on dataset OfficeHome of the IncLabDA and baselines with heterogeneous source label spaces.

Method	SF	R	P	C	A	Avg
ResNet	✓	78.5	**71.4**	51.8	64.9	66.7
SHOT	✓	73.8	66.9	54.3	71.0	66.5
CAiDA	✓	41.9	42.7	42.6	53.5	45.2
DCC	✓	**79.0**	72.3	53.7	65.7	67.7
IncLabDA	✓	73.1	70.9	**59.2**	**73.2**	**69.1**

Table 8
Ablation study (HM (%)) on dataset OfficeHome with homogeneous source labels.

Method	R	P	C	A	Avg
W/o L_{st}	82.2	75.4	64.4	**76.9**	74.7
W/o L_{cont}	78.4	72.1	62.3	74.8	71.9
W/o L_{uk}	81.7	75.5	61.7	76.3	73.8
Proposed	**81.7**	**76.5**	**65.6**	76.8	**75.2**

Table 9
Ablation study (HM (%)) on dataset OfficeHome with heterogeneous label spaces.

Method	R	P	C	A	Avg
W/o L_{st}	**73.4**	**70.9**	**59.2**	71.9	68.9
W/o L_{cont}	68.5	64.4	54.3	69.3	64.1
W/o L_{uk}	72.7	70.7	57.9	71.9	68.3
Proposed	73.1	**70.9**	**59.2**	**73.2**	**69.1**

Table 10
Ablation study (%) on datasets OfficeHome in addressing inaccurate labels.

Method	R	P	C	A	Avg
W/o a_o	80.3	75.4	64.5	76.0	74.1
W/o a_p	80.9	75.8	63.1	76.2	74.0
Proposed	**81.7**	**76.5**	**65.6**	**76.8**	**75.2**

Table 11
HM (%) on dataset OfficeHome with and without category discriminator under homogeneous (Homo) and heterogeneous (Heter) source label settings.

Setting	Method	R	P	C	A	Avg
Homo	W/o P_c	80.1	73.3	62.4	74.0	72.5
	Proposed	**81.7**	**76.5**	**65.6**	**76.8**	**75.2**
Heter	W/o P_c	**74.1**	67.6	57.2	70.1	67.3
	Proposed	73.1	**70.9**	**59.2**	**73.2**	**69.1**

The results are shown in Table 10. It can be seen that without either a_o or a_p, the model's performance decreases.

4.3. Influence of category discriminator

In this section, we validate the influence of category discriminator. We remove this module during the source model training and transfer the source model without the category discriminator to the target domain to test its performance. The results are shown in Table 11. It can be seen that the category discriminator has a positive influence on the proposed method even under the setting where source domains have the same label spaces. The category discriminator can learn specific source information especially that which is contained in unshared classes, and it also has the advantage of combining the knowledge of shared source categories.

4.4. Visualization analysis

This section provides a visualization analysis of the proposed method under homogeneous and heterogeneous settings. Taking task R from the dataset OfficeHome as an example, Figs. 4 and 5 show the T-SNE visualization of the proposed method and baseline SHOT. "Source only" refers to the model without domain adaptation based on $ResNet50$. It can be seen that the proposed method can divide target samples from known classes with clear decision boundaries. For unknown classes, compared with the source-only model without transfer in which the known and unknown classes are mixed up, and the baseline SHOT, where too many unknown classes are classified as known classes, when applying the proposed method, the unknown classes are grouped together with a few known samples, which indicates the superiority of the proposed method.

4.5. Model complexity analysis

In this section, we provide analysis of model complexity and calculate complexity of the proposed IncLabDA and two multi-source-free baselines SF-FDN AND FuzUMSFDA. Model complexity includes time and space complexities. Since the proposed model and baselines are based on the same backbone (ResNet) and embedding layer, whose time and space complexities are $32.8\times10^8+5.2\times10^5$ and $109\times10^6+5.3\times10^5$ respectively. The model complexities mainly differ from classification layers.

Table 12
Comparison of runtime and space on OfficeHome.

Method	Time	GPU memory	Model size	Performance
SF-FDN	2120.7	11 396	100 696.7	63.1
FuzUMSFDA	3309.2	19 484	100 848.4	69.5
IncLabDA	2912.8	14 130	96 416.2	75.2

For SF-FDN and FuzUMSFDA, they employ fuzzy rules as classifier, according to number of fuzzy rules, denoted as L_k, where k is source number, the time complexity is $(256\cdot C_s)\times L_k$, space complexity is $(256\cdot(C_s+1))\times L_k$. FuzUMSFDA has an extra attention layer, whose time and space complexities are $2K\cdot\lfloor K/2\rfloor$ and $(2K+1)\cdot\lfloor K/2\rfloor+K$ respectively.

In summary, the time complexity of the whole SF-FDN is $32.8\times10^8+5.2\times10^5+(256\cdot C_s)\times L_k$, with the space complexity of $109\times10^6+5.3\times10^5+(256\cdot(C_s+1))\times L_k$. For FuzUMSFDA, the time complexity is $32.8\times10^8+5.2\times10^5+(256\cdot C_s)\times L_k+2K\cdot\lfloor K/2\rfloor$, and the space complexity is $109\times10^6+5.3\times10^5+(256\cdot(C_s+1))\times L_k+(2K+1)\cdot\lfloor K/2\rfloor+K$. As for IncLabDA, its time complexity is $32.8\times10^8+5.2\times10^5+256\cdot C_s$, and the space complexity is $109\times10^6+5.3\times10^5+256\cdot(C_s+1)$.

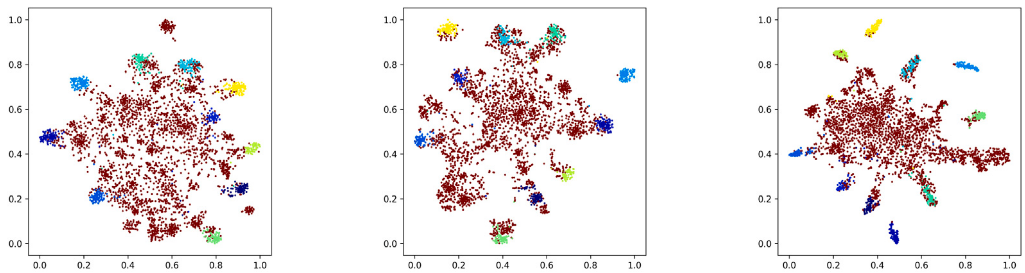
Table 12 presents the runtime and space requirements for SF-FDN, FuzUMSFDA, and the proposed IncLabDA, all conducted on an RTX-6000 GPU with a batch size of 32. It is evident that the proposed method has the smallest model size and the highest performance. However, in terms of runtime and space, IncLabDA requires more than SF-FDN. The reason is that the proposed method includes additional losses (e.g., L_{uk}, L_{cont}) to handle label shifts, whereas SF-FDN ignores them. As a result, IncLabDA requires more time and space to handle these additional losses when updating parameters.

5. Conclusion

This paper proposes a multi-source domain adaptation model for handling inaccurate label spaces. The IncLabDA has the ability to tackle both multi-source domains with homogeneous and heterogeneous label spaces without introducing an individual model of each source domain. It is also flexible enough to adapt pre-trained model to the target domain when the source original data cannot be accessed by generating highly representative anchors. The experiments on real-world datasets show that the IncLabDA outperforms existing domain adaptation methods especially when multiples source domains have different label spaces where most methods failed.

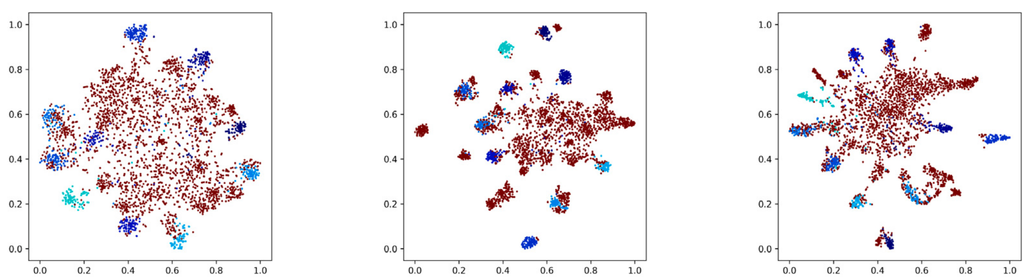
Our proposed method has broad applications across various areas, enabling models to generalize effectively across diverse datasets without the need for labeled data from each specific source, such as medical imaging in Healthcare, where there are often data from different hospitals or imaging modalities, each with its own labeling scheme. Our method could be employed to adapt models trained on data from one hospital or imaging modality to work effectively with data from other sources, even when the label spaces differ, and protect patients' privacy simultaneously. Another potential application is autonomous driving system, it collects data from diverse sensors and cameras, each potentially following unique labeling conventions owing to distinct sensor setups or environmental conditions. Employing our method enables autonomous driving models to seamlessly adjust to novel sensor configurations or environments, eliminating the necessity for labeled data from these specific sources.

In the future, we will tackle the sample imbalance problem among classes and source domains. Generally, there are always very large number of unknown samples compared with known samples, so it is easy for the unknown samples to dominate the training of the models which results in the failure of transfer. This problem is worth solving to improve the transfer performance.



(a) Source only (b) SHOT (c) Proposed

Fig. 4. T-SNE visualization on target domain RealWorld from dataset OfficeHome under homogeneous setting.



(a) Source only (b) SHOT (c) Proposed

Fig. 5. T-SNE visualization on target domain RealWorld from dataset OfficeHome under heterogeneous setting.

CRediT authorship contribution statement

Keqiuyin Li: Data curation, Methodology, Software, Writing – original draft. **Jie Lu:** Funding acquisition, Supervision. **Hua Zuo:** Supervision. **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.

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Keqiuyin Li is a Postdoctoral Research Associate in Australian Artificial Intelligence Institute, University of Technology Sydney, Australia. She received her Ph.D. from the University of Technology Sydney, Sydney, Australia, in 2023. Her research interests include transfer learning and image super-resolution.

Jie Lu (F'18) is an Australian Laureate Fellow, IFSA Fellow, ACS Fellow, Distinguished Professor, and the Director of Australian Artificial Intelligence Institute (AAII) at the University of Technology Sydney, Australia. Her main research expertise is in transfer learning, concept drift, fuzzy systems, decision support systems and recommender systems. She has published over 500 papers in IEEE Transactions and other leading journals and conferences. She is the recipient of two IEEE Transactions on Fuzzy Systems Outstanding Paper Awards (2019 and 2022), NeurIPS2022 Outstanding Paper Award, Australia's Most Innovative Engineer Award (2019), Australasian Artificial Intelligence Distinguished Research Contribution Award (2022), Australian NSW Premier's Prize on Excellence in Engineering or Information & Communication Technology (2023), and the Officer of the Order of Australia (AO) 2023.

Hua Zuo is an Australian DECRA Fellow and Senior Lecturer with the Faculty of Engineering and Information Technology, University of Technology Sydney, Australia. She received her Ph.D. from the University of Technology Sydney, Sydney, Australia, in 2018. Her research interests include transfer learning and fuzzy systems. She is a Member of the Decision Systems and eService Intelligence (DeSI) Research Laboratory at the Australian Artificial Intelligence Institute (AAII), University of Technology Sydney.

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.