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Multi-Source Domain Adaptation with Incomplete Source Label Spaces

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Abstract

Domain adaptation is a practicable tool in real world application where there exists data scarcity. Multi-source domain adaptation attracts increasing attention due to its ability to enrich transfer knowledge by combining information from multiple domains. However, knowledge transfer can trigger privacy concerns by accessing source data. In addition, multiple domains can have label heterogeneity problem. In this paper, to solve the mentioned problems, we conduct an incomplete multi-source domain adaptation (IMSDA) method which can address transfer learning with and without the access to source data. As far as we are aware, this is the first work handling source-free incomplete domain adaptation. To take the benefits of multiple sources, multi-task learning is adopted to learn a general source model which can perform on multiple domains. A data matching strategy with and without source data forcing target sample to source latent feature space is developed to combine with self-supervision to adapt source model to the target domain. Experiments on real-world datasets indicate the superiority of the proposed method.

Keywords: Transfer learning; domain adaptation; machine learning; image classification

1. Introduction

Machine learning, especially deep learning, attracts increasing attention in both academia and industry due to its ability to extract robust features and learn from its own errors [6, 19]. To train a well-performed model, it is a general assumption that the training (source) and testing (target) data must be drawn from the same distribution. As well, there must be a large size of source data to train the model. However, collecting source data satisfying these requirements cannot always be achieved in reality. First, collecting enough high-quality training data can raise high expense. In addition, in many applications such as healthcare and bank service, the data cannot be public due to privacy issues [10, 2]. To solve this problem, transfer learning is developed to deal with data scarcity and data shift [22, 18].

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Transfer learning leverages the gained knowledge from a source domain to facilitate learning a new but similar target task [13]. Domain adaptation is an important branch of transfer learning. The aim is to adapt a pre-trained model on labeled source domain(s) to an unlabeled or limited labeled target domain by filling the domain gaps [15]. To reduce source and target data shift, four types of approaches are developed, including feature-based, instance-based, parameter-based and relationship-based approaches. Feature-based approaches, in which both homogeneous and heterogeneous features are involved, adapt domains by reducing the distribution discrepancy between source and target data [20]. To measure the discrepancy, commonly used metric learning methods include maximum mean discrepancy [12] and Wasserstein distance [29]. Instance-based approaches match data by finding the most similar source samples to the target domain and give these samples a larger weights during training [11]. Parameter-based approaches transfer the source model weights directly to the target domain by fine-tuning, which is gaining popularity in recent research due to its flexibility of handling domain adaptation with and without the access to source data [16, 17, 5]. Relationship-based approaches bridge the data gaps by revealing the similar logic between source and target domains, the most explored algorithm is Markov logic [31].

According to the overlap of source and target label spaces, it can be divided into four types: the closed set [4], open-set [7, 9], partial [27] and universal domain adaptation [23]. Under closed set scenario, source and target label spaces contain the same categories. In other three settings, source and target domains include different classes. The open-set scenario indicates that the source categories extract only the portions of the target label space, partial scenario means target label space includes the source label space, while in universal scenario, both source and target domains have their own private spaces. The central problem of open-set, partial and universal domain adaptation is to detect private classes in corresponding domain and identify the shared classes in both domains.

Incomplete domain adaptation is a special setting of open-set transfer learning with multiple source domains [8]. For every single source domain, its label space is a proper subset of the target label space, but the union of all source label spaces can contain all target categories. This is a challenge and urgent problem to be solved since the label heterogeneity is common in real world applications. Fewer existing domain adaptation methods address incomplete domain adaptation. The main reason is that incomplete domain adaptation usually involves multiple source domains with heterogeneous label spaces, this is a complex setting in transfer learning because it requires to handle both multiple sources and different label spaces simultaneously under data shift.

Existing incomplete domain adaptation methods train independent source models which requires a large number of parameters especially when adopting deep neural networks [26]. In addition, previous studies never consider the unavailability of source data, which is a general solution for protecting data privacy [3]. To solve the mentioned problems, in this paper, we design an incomplete multi-source domain adaptation method handling heterogeneous source label spaces, named IMSDA. The proposed method taking the advantages of multi-task learning to learn a general model which can perform well on multiple domains, and develops a flexible adaptation strategy to handle domain adaptation with and without the access to source data. The main contributions of the proposed method are as following:

- An incomplete multi-source domain adaptation that trains one model to learn multiple tasks. Compared with existing incomplete domain adaptation methods, the proposed method reduces the number of source parameters by learning a general source model rather than individual source models.
- An adaptation strategy that is flexible to both domain adaptation with source data and source-free domain adaptation. This is first work to address incomplete multi-source domain adaptation without the access to source data. The proposed method can achieve transfer without accessing source data where existing incomplete domain adaption strategy relying on data matching cannot be applied.
- The proposed method is easy to apply to existing domain adaptation methods which cannot handle label heterogeneity and improves their performance. Validation on real world datasets indicates its practicality.

The rest of this paper is designed as follows: Section 2 introduces previous related work of multi-source domain adaptation and incomplete domain adaptation. Section 3 details the proposed incomplete multi-source domain adaptation method under both settings with and without the access to source data. Section 4 displays the application of the proposed method on visual tasks in real world. Section 5 summarizes the proposed method and lists potential future work.

2. Related Works

2.1. Multi-Source Domain Adaptation

To handle the challenge problem, the source diversity, in multi-source domain adaptation, a theoretical guaranteed algorithm is proposed to mix the local source teacher models which is expected to generate a global performed model to handle mixture domains [21]. To bridge the source and target domain gap, it learns a generator by forcing a student model to mimic the source teacher expert, where adversarial learning is employed to reduce the data shift. Federated learning becomes attractive due to its ability to train a model without leaking data in domain adaptation considering data privacy [28]. FedHealth is the first federated transfer learning method to handle the real-world wearable healthcare [2]. It trains the cloud model based on public datasets first, then fine-tunes the pre-trained cloud model on every source server privately where only parameters are shared but without original data information. Finally, to reduce the distribution divergence between the fine-tuned cloud model (source) and the new user (target), convolution neural networks are adopted to extract features where the correlation between source and target features is minimized.

2.2. Incomplete Domain Adaptation

Incomplete domain adaptation has been explored employing both shallow- and deep-based model structures. Incomplete multi-source transfer learning develops two directional knowledge transfer, including cross-domain transfer and cross-source transfer [3]. Latent low-rank transfer guided by iterative structure learning is proposed to deal with missing categories in every source domain based on the target data. Manifold regularizer and effective multi-source alignment work together to compensate unshared source categories in one source to the others. Deep cocktail network deals with domain shift by developing a multi-way adversarial learning strategy and the source specific perplexity scores based on the assumption that the combination of source distributions can represent the target distribution [26]. Pseudo-labeled target samples are conducted with labeled source data to update the training of multi-source category classifiers.

3. The Proposed Model

In this paper, an incomplete multi-source domain adaptation approach is designed to handle knowledge transfer with and without accessing the source data. Denote source domain as $\mathcal{D}_{s_k} = \{\boldsymbol{x}^i_{s_k}, \boldsymbol{y}^i_{s_k}\}_{i=1}^{n_{s_k}}$, where $\boldsymbol{y}_{s_k} \in C_{s_k}$, $\{\boldsymbol{x}_{s_k}, \boldsymbol{y}_{s_k}\}$ is data pair with sample and label, n_{s_k} is the number of samples, k is the index of source domain, C_{s_k} indicates the source label space. The target domain is denoted as $\mathcal{D}_t = \{\boldsymbol{x}^i_t\}_{i=1}^{n_t}$, where $\boldsymbol{x}_t$ is unlabeled target sample, n_t is the number of target samples. The aim of incomplete multi-source domain adaptation is to learn a function P_s to predict the target label $\boldsymbol{y}_t \in C_t$, where $C_t = \cup_{k=1}^{K} C_{s_k}$. The common label space is denoted as $C = \cap_{k=1}^{K} C_{s_k}$.

3.1. Source Model Training

In this paper, to take the advantage of transferring knowledge from multiple source domains and multi-task learning, a general model is trained by combining source information. Here we employ a pre-trained deep model, denoted as ϕ, to extract invariant features among multiple source domains. The classifier P_s can be trained with regard to the risk minimization principle [24], of which the objective function is minimizing the errors between the outputs of P_s and the ground-truth source labels in each source domain. The function can be expressed as:

$$\begin{gathered} P_s = \underset{\substack{P \\ (\boldsymbol{x}_{s_k}, \boldsymbol{y}_{s_k}) \in \mathcal{D}_{s_k}}}{\arg\min} L(P_s(\phi(\boldsymbol{x}_{s_k})), \boldsymbol{y}_{s_k}), \\ k = 1, \cdots, K. \end{gathered} \tag{1}$$

L is cross-entropy loss:

$$\begin{aligned} L &= -\frac{1}{n_{s_k}} \sum_{i=1}^{n_{s_k}} \boldsymbol{y}_{s_k}^i \log(P_s(\phi(\boldsymbol{x}_{s_k}^i))), \\ k &= 1, \cdots, K. \end{aligned} \tag{2}$$

3.2. Pseudo Label Collection

To ensure that the proposed method is flexible to handle data-free incomplete multi-source domain adaptation, self-supervision is adopted to guarantee the model can learn from its own errors. To achieve this, initial pseudo target labels are collected by applying the pre-learned source model to the target domain combined with deep k-means clustering. Initial target clustering centers are calculated based on probability of a target sample belonging to the source category returned by source classifier, which is:

$$\boldsymbol{v}_t^c = \frac{\sum_{i=1}^{n_t^c} P_s(\phi(\boldsymbol{x}_t^i))_c \cdot \phi(\boldsymbol{x}_t^i)}{\sum_{i=1}^{n_t^c} P_s(\phi(\boldsymbol{x}_t^i))_c}. \tag{3}$$

n_t^c is the number of target samples predicted to be in the c class, $P_s(\phi(\boldsymbol{x}_t^i))_c$ indicates the corresponding agreement degree.

With the processing of training, to improve the quality of clusters which is expected to predict high confident pseudo target labels, the target cluster centers and pseudo labels are then updated using deep k-means clustering as:

$$\begin{aligned} \boldsymbol{v}_t^c &= \frac{\sum_{i=1}^{n_t^c} \mathbb{1}_{\tilde{\boldsymbol{y}}_t^i = c} \cdot \phi(\boldsymbol{x}_t^i)}{\sum_{i=1}^{n_t^c} \mathbb{1}_{\tilde{\boldsymbol{y}}_t^i = c}}, \\ \hat{\boldsymbol{y}}_t &= \arg\min_c \mathrm{Dis}(\phi(\boldsymbol{x}_t), \boldsymbol{v}_t). \end{aligned} \tag{4}$$

$\tilde{\boldsymbol{y}}_t$ is the predicted target label by the source classifier P_s, $\hat{\boldsymbol{y}}_t$ is the pseudo target label estimated by clustering, where Dis means consine distance, which is advantageous to measure the angle similarity even when the two similar vectors are far apart by the Euclidean distance.

3.3. Model Adaptation

To perform the pre-trained source model on the target domain, in this section, we design two data-matching strategies to handle the model adaptation with and without the access to source data. Target class center is calculated first to match with source domain. The target class center is expressed as:

$$\boldsymbol{v}_b^c = \frac{\sum_{i=1}^{n_b} P_s(\phi(\boldsymbol{x}_t^i))_c \cdot \phi(\boldsymbol{x}_t^i)}{\sum_{i=1}^{n_b} P_s(\phi(\boldsymbol{x}_t^i))_c}. \tag{5}$$

n_b is the batch size during training. The target class center calculated here is soft center which can avoid the situation if there is no target sample belonging to a class in the sample batch.

3.3.1. Source Center Generation with Source Data

Assuming the cluster (class) centers of source and target domains should be similar to each other in the same latent feature space. When the source data can be accessed, the source class center can be calculated as:

$$\boldsymbol{v}_s^c = \begin{cases} \frac{1}{K}\sum_{k=1}^{K} \frac{\sum_{i=1}^{n_{s_k}^c} \mathbb{1}_{\boldsymbol{y}_{s_k}^i = c} \cdot \phi(\boldsymbol{x}_{s_k}^i)}{\sum_{i=1}^{n_t^c} \mathbb{1}_{\tilde{\boldsymbol{y}}_{s_k}^i = c}}, c \in C, \\ \frac{\sum_{i=1}^{n_{s_k}^c} \mathbb{1}_{\boldsymbol{y}_{s_k}^i = c} \cdot \phi(\boldsymbol{x}_{s_k}^i)}{\sum_{i=1}^{n_t^c} \mathbb{1}_{\tilde{\boldsymbol{y}}_{s_k}^i = c}} . c \notin C, k = 1, \cdots, K. \end{cases} \\ c \in \cup_{k=1}^{K} C_{s_k}. \tag{6}$$

3.3.2. Source Center Generation without Source Data

When the source data is unavailable, source class center is calculated from the classifier parameter with the assumption that the classifier weight vector can act as cluster center [25]. Then the source class center is expressed as the normalization of classifier weights:

$$\boldsymbol{v}_s^c = (\mathrm{Norm}(P_s))_c \tag{7}$$

The loss function of matching source and target centers is:

$$L_c = \sum_{c=1}^{C} ||\boldsymbol{v}_t^c - \boldsymbol{v}_s^c||^2. \tag{8}$$

By freezing the classifier layer, pseudo target labels are applied to self-supervise the adaptation by self-training the feature extractor ϕ, which is:

$$\phi = \arg\min_{\phi} L_\phi(P_s(\phi(\boldsymbol{x}_t)), \hat{\boldsymbol{y}}_t), \tag{9}$$

where

$$L_\phi = -\frac{1}{n_t}\sum_{i=1}^{n_t} \hat{y}_t^i \log(P_s(\phi(\boldsymbol{x}_t^i))). \tag{10}$$

The total loss function of adapting the model with incomplete source label spaces to the target domain is:

$$L_{total} = L_\phi + L_c \tag{11}$$

4. Experiments

In this section, we test the proposed IMSDA in two visual datasets, including Office-31 and Office-Home. Office-31 has three tasks $A, W2D$; $A, D2W$; $D, W2A$, containing 4110 images sharing 31 categories. Office-Home has four tasks $A, C, P2R$, $A, C, R2P$, $A, P, R2C$ and $C, P, R2A$, including 15588 images sharing 65 categories.

All experiments take $ResNet50$ as the backbone Learning rate η is $\eta = \frac{\eta_0}{(1+10\epsilon)^{0.75}}$, where $\eta_0 = 0.01$, ϵ is the training progress changing linearly from 0 to 1, the momentum is 0.9, weight decay is $5e-4$. The smoothing parameter $\mu = 0.1$.

The compared methods are as following:

- TL-IMS: Incomplete multi-source transfer learning [3];
- DCTN: Deep cocktail network with category shift [26];
- MFSAN: Domain-specific distribution and classifier alignment [30];
- MSCLDA: Multi-source contribution learning domain adaptation [14];
- DECISION: Multiple source models adaptation without source data [1];
- CAiDA: Conficent anchor-induced domain adaptation with multi-source data-free models [5].

4.1. Results and Analysis

Taking ResNet50 as backbone, the results on datasets Office-31 and Office-Home are displayed in Tabels 1 and 2. It shows that the proposed method IMSDA obtains the best accuracy in both setting with and without the access to source data. The accuracy of IMSDA on Office-31 with source data is 88%, improved by 4.2% compared with the second best performance. In source-free setting, we compare IMSDA with two typical multi-source-free methods, IMSDA gains accuracy 88.4%, which is 12.2% higher than the baselines. By applying the proposed method to CAiDA, it can be seen that the accuracy has been significantly improved. On dataset Office-Home, IMSDA achieve highest accuracy 70.9% and 71.0% under setting with and without source data respectively. The reason why our result is significantly higher than most baselines is that the proposed method employs a multi-task learning strategy to fill gaps of incomplete source label spaces, and self-supervision is adopted in the proposed method to enhance the transfer.

Table 1. Classification accuracy (%) of the proposed IMSDA and baselines with incomplete source label spaces on Office-31.

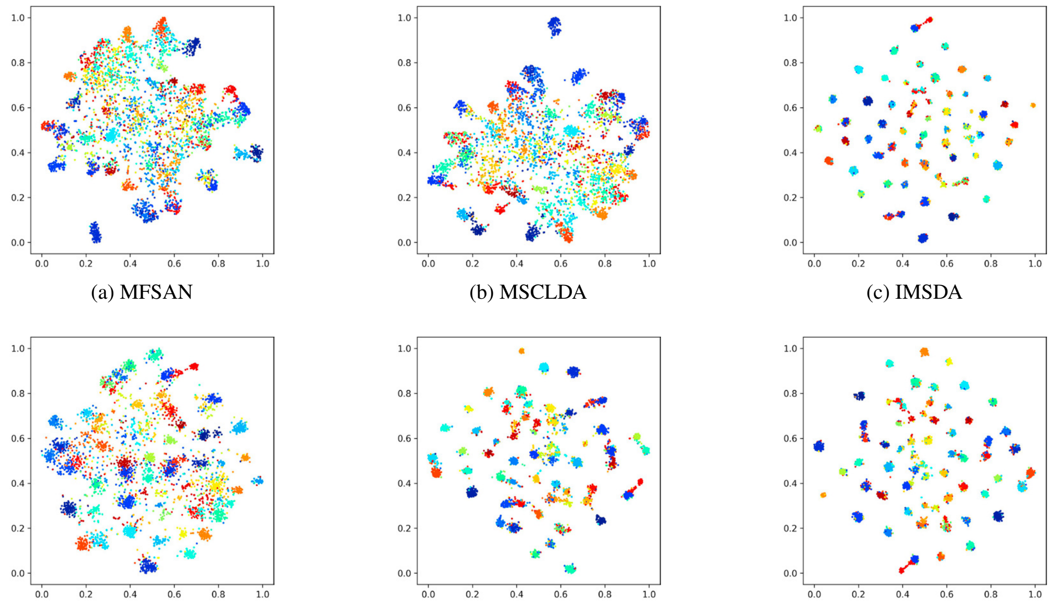
Method	SF	A, W2D	A, D2W	W, D2A	Avg
TL-IMS	✗	51.5	61.3	42.6	51.8
MFSAN	✗	87.3	86.3	59.4	77.7
MSCLDA	✗	84.9	83.4	58.3	75.5
DCTN	✗	**99.6**	**96.9**	54.9	83.8
IMSDA	✗	97.2	94.2	**72.5**	**88.0**
DECISION	✓	87.8	86.3	51.8	75.3
CAiDA	✓	91.7	82.1	54.8	76.2
Source only	✓	89.8	87.2	58.3	78.4
CAiDA+ours	✓	97.4	**94.6**	72.8	88.3
IMSDA	✓	**98.2**	94.2	**72.9**	**88.4**

4.2. Visualization Analysis

T-distributed stochastic neighbor embedding (T-SNE) is used to visualize target features in a two-dimension space by marking different classes in different colors. Fig. 1 shows the data visualization in the latent feature space (classification features) of target domain. It can be seen that the proposed IMSDA divides target samples clearly from other classes. The source-free IMSDA generally performs better than baselines with the access to source data. Indicating the proposed method employing self-supervision can learn invariant information better than data matching.

Table 2. Classification accuracy (%) of the proposed IMSDA and baselines with incomplete source label spaces on Office-Home.

Method	SF	A,C,P2R	A,C,R2P	A,P,R2C	C,P,R2A	Avg
MFSAN	✗	61.7	58.5	45.2	50.8	54.1
MSCLDA	✗	59.4	57.1	41.3	48.7	51.6
IMSDA	✗	**78.6**	**79.7**	**55.8**	**69.4**	**70.9**
DECISION	✓	48.0	34.9	29.1	33.9	36.5
CAiDA	✓	33.0	29.2	24	30.1	29.1
Source only	✓	68.8	66.7	44.4	56.4	59.1
CAiDA+ours	✓	78.4	78.8	55.3	69.6	70.5
IMSDA	✓	**78.9**	**79.4**	**55.9**	**69.8**	**71.0**



(a) MFSAN (b) MSCLDA (c) IMSDA

(d) Source only (e) CAiDA+ours (f) IMSDA

Fig. 1. T-SNE visualization on target domain RealWorld from dataset OfficeHome.Figures (a), (b) and (c) indicate the models trained with the access to source data. Figures (d), (e) and (f) indicate models without the access to source data.

5. Conclusion

This paper develops an incomplete multi-source domain adaptation method addressing cross-domain knowledge transfer with and without the access to source data. The advantages of multi-task learning is considered to learn a general source model which can reduce the number of parameters in multi-source domain adaptation while enriching the transfer information. A data matching strategy is built to flexibly deal with model adaptation with and without source data, where self-supervision is combined to enhance the model performance. Data privacy is concerned in many applications. In the future, the more strict source-free domain adaptation setting will be explored to protect data during transfer.

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