Self-Adaptive Partial Domain Adaptation

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Abstract—Partial Domain adaptation (PDA) aims to solve a more practical cross-domain learning problem that assumes target label space is a subset of source label space. However, the mismatched label space causes significant negative transfer. A traditional solution is using soft weights to increase weights of source shared domain and reduce those of source outlier domain. But it still learns features of outliers and leads to negative immigration. The other mainstream idea is to distinguish source domain into shared and outlier parts by hard binary weights, while it is unavailable to correct the tangled shared and outlier classes. In this paper, we propose an end-to-end Self-Adaptive Partial Domain Adaptation(SAPDA) Network. Class weights evaluation mechanism is introduced to dynamically selfrectify the weights of shared, outlier and confused classes, thus the higher confidence samples have the more sufficient weights. Meanwhile it can eliminate the negative transfer caused by the mismatching of label space greatly. Moreover, our strategy can efficiently measure the transferability of samples in a broader sense, so that our method can achieve competitive results on unsupervised DA task likewise. A large number of experiments on multiple benchmarks have demonstrated the effectiveness of our SAPDA.

Index Terms—adversarial learning, transfer learning, partial domain adaptation, semi-supervised learning

I. INTRODUCTION

TRANSFER learning concentrates on knowledge transfer learned on labelled source domain to unlabeled target domain by narrowing the distance among source and target domains. As one of the core approaches for transfer learning, domain adaptation aims to relieve the need for labelled data. There are two classes of methods to deal with it. The first is maximum mean discrepancy (MMD) which manages to maximize the distance between the mean of the two domains in some high dimensional mapping space. The second is the adversarial learning method, which attempts to extract the domain invariant features among the domains. Here, a basic assumption for domain adaptation is source and target domain share the same label space. Whereas, this assumption is hard to satisfy in practice.

Recently, partial domain adaptation task has been projected. Different from standard domain adaptation, PDA assumes that source label space contains target label space. This assumption relaxes the constraint of standard DA method that two domains have the same label space. Different from standard domain adaptation(Standard DA), PDA enables the transfer of knowledge from a domain with plenty of labels to another without labels, where source label space contains target one. Since large-scale annotated datasets such as Google Open Images and ImageNet-1k are available, PDA can be applied to many practical applications.

Partial domain adaptation task contains two crucial points. Firstly, compared with standard DA, PDA is more challenging because target label space is a subset of source label space and is unknown. The common subset of label space between different domains is denoted as shared domain while the part only including source label space is defined as outlier domain. During training of the PDA, an important issue is to select samples belonging to the shared domain. This dilemma can cause negative transfer if we misclassify some classes in the outlier domain to the shared one. Under this circumstance, some target samples can be wrongly grouped into these outlier domain. Secondly, the gap between source shared and target domain should be narrowed during training. Thus, we need to promote a universal framework to deal with it. Some previous methods are proposed to handle PDA by weighing classes or samples in a domain adversarial network. They increase weights of the shared classes while decrease weights of outlier classes. In ideal situations, weights of the shared classes should be 1, and those of the outlier classes should be 0. However, they all use probability-weights as class weights. Even though the weights of the source shared classes are meaningfully higher than the source outlier’s, they are far away from 1. As a result, negative transfer still can not be avoided in these methods. Moreover, when the discrepancy among different domains are huge, the boundary between the shared and outlier domain is not clear. So if we just cluster source domain into two groups named as shared and outlier domains, some samples on the boundary are easily to be misclassified, which may lead to aligning features from target domain to outlier domain in the following training steps. As a consequence, it will result in performance degradation. To copy with the difficulties of partial domain adaptation, an end to end Self-Adaptive Partial Domain Adaptation (SAPDA) network is proposed. Previous PDA methods only cluster source classes into shared and outlier classes, but the samples on the boundary can be easily misclassified when the discrepancy between different domains is huge, which can cause negative transfer greatly. To deal with this problem, in this paper, SAPDA self-adaptively clustered source label space into different groups. When the number of group is three, our model can not only select out the high-confidence samples as shared and outlier classes, but can also put the samples that are difficult to distinguish into the confused classes. In this way, when the shared and outlier classes are not easy to distinguish, our model can
effectively narrow the general gap between high-confident source shared classes and target classes while ignoring the effects of confused classes temporarily. If the groups are only two, SAPDA considered that it has enough confidence to select all the shared and outlier classes clearly. Samples in the same group share the same weights. The higher the weight is, the more possible the sample belongs to shared domain. Meanwhile, the self-adaptive weighted mechanism updates each 500 iterations, which can dynamically correct incorrect clustering weights. In this way, we can avoid misclassification due to the entanglement between shared and outlier domain, and eliminate negative transfer greatly.

SAPDA builds weighted adversarial network to straiten the gap between weighted source and target features, and reduce negative transfer of outlier domain. We carry out comprehensive experiments on five representative domain adaptation benchmark datasets.

II. RELATED WORK

A. Domain Adaptation

Domain adaptation is an approach that tries to build domain invariance between different domains, and mitigates the burden of annotating target data. A recent study has indicated that deep neural networks can learn invariant representations. These invariant representations can help knowledge transfer between domains.

Even if deep neural networks can disentangle complex data distributions, the discrepancy across domains can not be removed. Hence, recent works focus on how to connect deep neural network and domain adaptation. Two main approaches are proposed to handle it. The first approach tries to match the high order statistic features by adding an adaptation layer \[46 \] \[25 \] \[24 \] \[39 \] \[19 \]. The second one tries to extract common features cross domains by appending a domain discriminator \[9 \] \[15 \] \[47 \] \[46 \] \[28 \].

Recently, how to combine domain adaptation to realistic application has also get more and more attention. Domain adaptation has been designed as an universal module, applying to object detection \[2 \] \[6 \] \[33 \], semantic segmentation \[29 \] \[38 \] and person re-id \[45 \] \[41 \]. They have made a great contribution to alleviate the lack of labels in practical application.

B. Partial Domain Adaptation

Partial domain adaptation assumes target label space is a subset of source label space \[14 \]. Some methods have been presented to deal with PDA problems. Selective Adversarial Network (SAN) \[3 \] employs numerous adversarial networks and relative importance mechanisms to filter outlier classes. Partial Adversarial Domain Adaptation (PADA) \[4 \] modifies SAN by adding class-level relative importance index to source classifier to build a general adversarial network. Importance Weighted Adversarial Nets (IWAN) \[43 \] utilizes an attached domain discriminator to evaluate the sample-level weight and further adds the weight to adversarial network. Example Transfer Network (ETN) \[5 \] uses an auxiliary adversarial network to evaluate sample-level weight and to add the weight on adversarial network. These approaches can effectively process PDA compared with traditional methods.

These methods all use probability-weights to find out whether the class belongs to shared classes. However, in practice, if one class is subject to shared classes, the weight hardly achieves 1. This phenomenon can cause negative transfer. Moreover, when the discrepancy between domains is huge, the boundary between shared and outlier is not clear. So it is hard to classify the samples on the boundary. In other words, if we divide source domain into shared domain and outlier one directly, some of them are easy to misclassify. This paper proposes Self Adaptive Partial Domain Adaptation (SAPDA) that clusters source classes automatically into several different groups according to class probability-weights. Samples in the same group share the same weights. If there are more than two groups, sample weights are obtained by the means
of the class probability-weights in the group. Specially, if the groups are only two, sample weights are given as 1 or 0. Furthermore, we utilize Calinsk-Harabaze index [1] to evaluate the optimal number of groups we cluster into. In this way, we can guarantee a good classification.

III. SELF-ADAPTIVE PARTIAL DOMAIN ADAPTATION

A. Preliminaries

In PDA, we define $C_s$ as the source label space, $C_t$ as the target label space. Source domain is defined as $D_s = \{(x_i^s, y_i^s)\}_{i=1}^{n_s}$ of $n_s$ labeled samples with $|C_s|$ classes, while target domain is defined as $D_t = \{x_i\}_{i=1}^{n_t}$ of $n_t$ unlabeled samples with $|C_t|$ classes. Under the PDA setting, $C_s$ contains $C_t$. Source label $C_s$ consists of two parts, shared label space $C_{sh}$ and outlier one $C_{so}$. $C_{sh}$ is the same as target label space $C_t$, which means they have the same set of label classes. Outlier label space $C_{so}$ is the unique part of $C_s$, that to say, $C_{so} = C_s \setminus C_{sh}$. $D_{sh}$ is source-shared domain and $D_{so}$ is source-outlier domain.

Different from previous PDA methods, we introduce $D_{conf}$ as the domain of samples that are hard to distinguish. On the one hand, if our novel self-adaptive weight mechanism can classify all the source sample into source shared and outlier classes confidently, then we have $D_s = D_{so} \cup D_{sh}$. On the other hand, if our model is not confident enough to clearly distinguish the samples around the border, we cluster these confused samples into a separate cluster. Under this circumstance, $D_s = D_{so} \cup D_{sh} \cup D_{conf}$. Our self-adaptive weight updates each 500 iterations.

We assume that source domain $D_s$ and target domain $D_t$ are sampled from distributions $p_{sh}$ and $p_{t}$ respectively. Similarly, $p_{sh}$ denotes the distribution of source-shared domain $D_{sh}$ and $p_{t}$ denotes the distribution of source-outlier domain $D_t$.

In PDA task, the key issue includes two parts: firstly, due to shared and outlier classes are unknown in advance, it is essential to select out unrelated source data belonging to $D_{so}$ in order to decrease negative transfer. Secondly, we will try to narrow the gap between $D_{sh}$ and $D_t$. These two issues should be dealt simultaneously.

Our architecture of SAPDA is shown in Fig. 2. Class weight $w_i$ is the core variable of our proposed method. It denotes the probability that the sample $x_i$ comes from the source shared domain. Samples in the same group of classes (either in shared group, outlier group or confused group) share the same $w_i$. $w_i$ acts on some modules, including the domain discriminator $G_d$, the source classifier $G_c$ and the cluster classifier $G_c$. It aims to help the network focus on shared domain samples and exclude outlier samples. In the following subsections, we will introduce each modules of the model and how $w_i$ help them to focus on shared domain samples.

In subsection B, we introduce the basic building blocks of our model, including feature extractor $G_f$, $G_c$, $G_d$ and $G_{cl}$.

In subsection C, we specify how the self-adaptive class weights evaluation mechanism $G_w$ computes $w_i$. In a nutshell, $G_w$ takes $D_c$ as input and outputs $w_i$. $D_c$ is a $|C_s|$-dimension vector. It is the average of outputs from source classifier $G_c$ of all target samples. That is, $W_c = \frac{1}{n} \sum_{i=1}^{n} \{G_c(G_f(x_i))\}$. $W_c[i]$ represents the possibility of the $i$-th source domain class being part of the shared classes $C_{sh}$. We use $W_c$ to compute $w_i$.

In subsection D, we explore how $w_i$ acts on $G_c$ and $G_d$ as a weight value. The influence of $w_i$ is that $G_c$ and $G_d$ is guided to focus on the shared domain samples and not the outlier ones. In this way, positive transfer contributed by samples in $D_{sh}$ is enhanced and negative transfer caused by samples in $D_{so}$ is mitigated.

In subsection E, we explain why and how $w_i$ is used as cluster label for cluster classifier $G_{cl}$.

B. Basic building blocks

Feature extractor $G_f$ extracts features $f_i$ from input image samples $x_i$. That is, $f_i = G_f(x_i)$.

Source classifier $G_c$ takes extracted features as input and outputs $|C_s|$-dimension vectors $g_i$. That is, $g_i = G_c(G_f(x_i))$ and $|g_i| = |C_s|$. $g_i[j]$ represents the possibility of sample $x_i$ belonging to the $j$-th source domain classes. The loss of $G_c$ is denoted as:

**Fig. 2.** Our SAPDA framework. $G_f$ is the feature extractor, $G_d$ is the domain discriminator, $G_c$ is the source classifier, $W_c$ is the class weight vector. $G_w$ is the self-adaptive class weights evaluation mechanism, $w_i$ is the class weight. $G_{cl}$ is the cluster classifier. The red and blue flows are from source and target domains respectively.
by justifying,
cluster [8]. Hence, we need to find out the minimal \( \delta_2^k \) to effectively cluster the elements in \( W_c \) under the circumstance of \( k \) clusters. Since \( \sum_{m=1}^{k} \sum_{j \in S_m} W_c^{2}[j] \) is independent of \( k \), minimizing \( \delta_2^k \) is equivalent to:

\[
\max \left\{ \sum_{m=1}^{k} \sum_{j \in S_m} W_c^{2}[j] \right\}
\]

(8)

Hence, when \( \sum_{m=1}^{k} \sum_{j \in S_m} W_c^{2}[j] \) achieves its maximum, the optimal cluster results are obtained under the condition of \( k \) groups.

**Step 2. Determine the optimal number of groups**

Now that we have got cluster results for different cluster number \( k \in \{1, 2, 3\} \), the next step is to find out which cluster number is the best.

We utilize the Calinski-Harabasz index (CH index) [1] to compute the optimal \( k \). The CH index depicts the tightness through the intra-class dispersion matrix and the separation through the inter-class dispersion matrix. The inter-class dispersion matrix \( B(k) \) is given by:

\[
B(k) = \sum_{m=1}^{C} \frac{|S_m|}{|C_s|} (\alpha_m - \frac{\sum_{j \in S_m} W_c[j]}{|C_s|})(\alpha_m - \frac{\sum_{j \in S_m} W_c[j]}{|C_s|})^T
\]

(9)

We also set

\[
T_m = \frac{\sum_{j \in S_m} W_c[j]}{|S_m|}
\]

(10)

The intra-class dispersion matrix \( S(k) \) is given by:

\[
S(k) = \frac{1}{k} \sum_{m=1}^{k} \sum_{j \in S_m} (W_c[j] - T_m)(W_c[j] - T_m)^T
\]

(11)

and the CH index is defined as

\[
CH(k) = \frac{\text{tr} B(k)/(k-1)}{\text{tr} S(k)/(|C_s| - k)}
\]

(12)

Here, \( k \) is the current cluster group number, \( \text{tr} S(k) \) is the trace of the intra-class dispersion matrix, while \( \text{tr} B(k) \) represents the trace of the inter-class dispersion matrix.

Under the condition of \( k \) groups, the larger \( CH(k) \) is, the smaller the intra-group distance is, the greater inter-group distance is, the better the clustering result is.

Hence, we get the follow relation:

\[
k^* = \arg \max_k CH(k)
\]

(13)

**Step 3. Evaluate self-rectifying class weights \( w_i \)**

If the best group number \( k^* = 3 \), source classes are clustered into three groups: shared classes \( S_1 \), outlier classes \( S_2 \) and confused classes \( S_3 \). For any source sample \( (x^s_i, y^s_i) \), its weight \( w_i \) is provided as:

\[
w_i = \begin{cases} 1 & (x_i, y_i) \in S_1 \\ 0 & (x_i, y_i) \in S_2 \\ \alpha_{m=3} & (x_i, y_i) \in S_3 \end{cases}
\]

(14)

In this case, Our model not only maintains the discriminative ability to the identified shared samples and outlier ones, but also avoids misjudging the difficult-to-identify samples.

If \( k^* = 2 \), it just includes two groups \( S_1(D_{sh}) \) and \( S_2(D_{so}) \), \( w_i \) can be defined as:

\[
w_i = \begin{cases} 1 & (x_i, y_i) \in S_1 \\ 0 & (x_i, y_i) \in S_2 \end{cases}
\]

(15)

In this situation, the model believes it can distinguish the shared classes and outlier classes clearly, so the weights of shared samples are 1, and the weights of the outlier ones are 0. As a result, we can exclude the impact of the outlier classes as much as possible.

Specially, if best group number is \( k^* = 1 \), the model perceives the label space of source and target domains are the same. Partial domain adaptation degrades to standard domain adaptation. All the its weights \( w_i \) are 1.

**D. Weighted Source Classifier and Domain Classifier**

**Weighted Source Classifier**

The major challenge in PDA is that the class space of target domain is a subset of source ones [14], so source classifiers \( G_c \) have poor results in target domain tasks due to the negative transfer caused by outlier classes.

Recall that \( w_i \) represents the probability of sample \( x_i \) belonging to shared classes. Using \( w_i \) as weight values, we can solve the above problem by paying less attention to the outlier classes and only focus on the shared classes. On the other hand, we use an extra weight \( m_i \) to draw together samples from the same class in \( D_{sh} \) and \( D_t \) and push away outlier samples. In summary, we propose weighted source classifier whose loss is defined as follows:

\[
L_{ad}(G_c) = \frac{1}{n_s} \sum_{i=1}^{n_s} w_i(x^s_i)m_i(x^s_i)L(G_c(G_f(x^s_i)), y_i)
\]

(16)

where

\[
m(x) = 1 + e^{-H(x)}
\]

\[
H(x) = -\sum p(x) \log p(x)
\]

(17)

\[
p(x) = G_c(G_f(x))
\]

Here, the information entropy loss is employed in both domains so that they are harder to be misclassified. Because the target samples are unlabeled, they are much easier to tangle domains so that they are harder to be misclassified. Because the target samples are unlabeled, they are much easier to tangle domains so that they are harder to be misclassified.

**Weighted Domain Adaptation Framework**

In subsection B, we introduce a paradigm involving \( G_d \) and \( G_f \) that learns domain-invariant features. Though this paradigm is effective, negative transfer will arise if we apply it to partial domain adaptation directly. Because there is still incongruity between source and target label spaces.

Therefore, we similarly use weight values \( w_i \) and \( m_i \) to enhance positive transfer and alleviate negative transfer. Specifically, weights for samples in \( D_{sh} \) are promoted and weights for samples in \( D_{so} \) are decreased. The weighted adversarial domain adaptation framework for PDA can be defined as follows:

\[
\min_{G_f \sim G_d} \max_{G_d} L_{ad}(G_f, G_d)
\]

(18)
The higher $w_i$ is, the more likely the sample is from shared classes.

E. Cluster Classifier

As mentioned in subsection B, $G_{cl}$ classify samples into shared, outlier and confused clusters. $G_{cl}$ helps the model recognize shared domain samples by separating each cluster. The problem is that cluster labels is not originally available like class labels. As a solution, we use $w_i$ as cluster labels. The reason is that, as indicated by Eq. (14) and Fig. 3, samples from the same cluster, and extends the distance among samples from different clusters.

During training, if $k^* = 2$, $L_{cl}$ can be set as follows:

$$L_{cl}(G_{cl}) = \frac{1}{n_s} \sum_{i=1}^{n_s} L(G_{cl}(G_f(x_i^s), 1)) + \frac{1}{n_t} \sum_{i=1}^{n_t} L(G_{cl}(G_f(x_i^t), 1))$$

In Eq. (20) $n_{sh}$ is denoted as the number of samples from shared domain, and $n_{ot}$ as the number of samples from outlier domain. We have $n_{sh} + n_{ot} = n_s$.

By this means, source shared and target samples can be clustered together. At the same time, outlier ones can be separated, which decreases negative transfer greatly.

Moreover, if our SAPDA regards the situation as a standard domain adaptation setting, source and target domain share the same cluster label 1. In this situation, $L_{cl}$ can be written as follow:

$$L_{cl}(G_{cl}) = \frac{1}{n_s} \sum_{i=1}^{n_s} L(G_{cl}(G_f(x_i^s), 1)) + \frac{1}{n_t} \sum_{i=1}^{n_t} L(G_{cl}(G_f(x_i^t), 1))$$

F. Self-adaptive Partial Domain Adaptation

A novel self-adaptive partial domain adaptation framework is proposed to handle PDA task. This framework can self-adaptively cluster source domain into different groups to progressively measure the transferability of source classes on sample level by weighting samples in the same group equally, and jointly learn domain-invariant features across different domains. The complete algorithm is as follow:

\begin{align}
\text{Algorithm 1: SAPDA} \\
\text{Input:} & \text{ labeled source data } \{ (x_i^s, y_i^s) \}_{i=1}^{n_s} \text{ and unlabeled target data } \{ x_i^t \}_{i=1}^{n_t} \\
\text{Output:} & \text{ predicted labels } \{ y_i^t \}_{i=1}^{n_t} \\
\text{Initialization:} & \text{ } w_i \leftarrow 1 \text{ for all samples} \\
\text{for} & \text{ iteration } (i) = 1, 2, \ldots, 16000 \text{ do} \\
& 1) \text{ Extract features from one batch:} \\
& (f_1^s, \ldots, f_{batch}^s; f_1^t, \ldots, f_{batch}^t) \\
& = G_f(x_1^s, \ldots, x_{batch}^s, x_1^t, \ldots, x_{batch}^t) \\
& 2) \text{ Classify each samples in one batch and use eq.(16) to calculate loss:} \\
& (g_1^s, \ldots, g_{batch}^s; g_1^t, \ldots, g_{batch}^t) \\
& = G_c(f_1^s, \ldots, f_{batch}^s; f_1^t, \ldots, f_{batch}^t) \\
& 3) \text{ Uses eq.} (18) \text{ to calculate loss for classifier } G_d \\
& 4) \text{ Uses eq.} (19)/(20)/(21) \text{ to calculate loss for } G_{cl} \\
& 5) \text{ Loss back propagation} \\
\text{if} & i \% 500 == 0 \text{ then} \\
& a) \text{ Update } W_c \text{ using } W_c = \frac{1}{n_s} \sum_{i=1}^{n_s} (G_c(G_f(x_i^s))). \\
& b) \text{ Update } w_i \text{ using eq.(14)/(15) or } w_i \leftarrow 1 \text{ for all samples} \\
\text{end if} \\
\text{end for}
\end{align}

IV. EXPERIMENT

To illustrate the performance of SAPDA, we conduct some experiments on four benchmark compared with previous standard and partial domain adaptation methods.

A. Set up

Office-31 [32] dataset is a classic dataset for domain adaptation. It involves three domains: DSLR, Amazon, and Webcam, we denote them as D31, A31 and W31 respectively. They are set as source domains. There are 10 categories [10] shared by Caltech-256 [11] and Office-31 dataset. These 10 categories, denoted as W10, A10 and D10, are set as target domain. Moreover, Caltech-256 are also set as source domain and A10, W10 and D10 are set as target domain on three tasks.

Caltech-Office dataset utilizes 10 classes shared by Caltech-256 and Office-31 as source domain, denoted as W10, D10, A10 and C10, the first 5 classes in these 10 categories, denoted as W5, D5, A5 and C5, are set as target domain.

Office-Home dataset [37] is a much more intriguing dataset with the huger domain gap. It includes 65 categories with four
TABLE I
ACCURACY OF PARTIAL DA TASKS ON Caltech-Office (10 classes → 5 classes).

| Method      | Caltech-Office (10 classes → 5 classes) | Avg     |
|-------------|-----------------------------------------|---------|
| ResNet [12] | 45.62                                   | 63.61   |
| DaNN [9]    | 51.01                                   | 68.90   |
| RTN [27]    | 50.04                                   | 62.35   |
| Iwan [43]   | 52.18                                   | 62.35   |
| San [3]     | 52.06                                   | 80.58   |
| Pada [4]    | 53.53                                   | 85.54   |
| EtN [5]     | 57.09                                   | 88.93   |
| Sapda [4]   | 94.52                                   | 96.49   |
| Avg         |                                         | 75.64   |

TABLE II
ACCURACY OF PARTIAL DOMAIN ADAPTATION TASKS ON Office-31

| Method      | Office-31 | Avg     |
|-------------|-----------|---------|
| ResNet [12] | 45.62     | 63.61   |
| DaNN [9]    | 51.01     | 68.90   |
| RTN [27]    | 50.04     | 62.35   |
| Iwan [43]   | 52.18     | 62.35   |
| San [3]     | 52.06     | 80.58   |
| Pada [4]    | 53.53     | 85.54   |
| EtN [5]     | 57.09     | 88.93   |
| Sapda [4]   | 94.52     | 96.49   |
| Avg         | 96.61     | 97.73   |

TABLE III
ACCURACY OF PARTIAL DOMAIN ADAPTATION TASKS ON VisDA2017(12 classes → 6 classes) and Caltech-Office(256 classes → 10 classes)

| Method      | VisDA2017 | Caltech-Office |
|-------------|-----------|---------------|
| ResNet [12] | 45.62     | 61.33         |
| DaNN [9]    | 51.01     | 68.90         |
| RTN [27]    | 50.04     | 62.35         |
| Iwan [43]   | 52.18     | 62.35         |
| San [3]     | 52.06     | 80.58         |
| Pada [4]    | 53.53     | 85.54         |
| EtN [5]     | 57.09     | 88.93         |
| Sapda [4]   | 94.52     | 96.49         |
| Avg         | 95.83     | 95.83         |

TABLE IV
ACCURACY OF PARTIAL DA TASKS ON Office-Home (65 classes → 25 classes).

| Method      | Office-Home | Avg     |
|-------------|-------------|---------|
| ResNet-50 [12] | 46.33     | 48.18   |
| DaNN [9]    | 43.76      | 44.30   |
| RTN [27]    | 49.31      | 43.57   |
| Iwan [43]   | 53.94      | 45.37   |
| San [3]     | 53.94      | 45.37   |
| Pada [4]    | 53.94      | 45.37   |
| EtN [5]     | 53.94      | 45.37   |
| Sapda [4]   | 94.52      | 96.49   |
| Avg         | 95.83      | 95.83   |

domains: Artistic, Product images, Real-World and Clip Art. We define 65 classes in four domains as source domain Ar, Pr, Rw and Cl. Four domains with the first 25 classes are donated as target domain.

VisDA-2017 dataset is one of the most challenging dataset in domain adaptation, the synthetic data to real-image track is evaluated here. Under our partial domain adaptation setting, the first 6 classes are chosen as target domain and Synthetic
12 \rightarrow \text{Real6} task is conducted as $S \rightarrow R$.

The proposed SAPDA is compared with present standard DA and PDA methods. Among all the experiments, both standard DA and PDA methods are performed on PDA setting. ResNet-50 are used as the base backbone for all the methods except for AlexNet. Meanwhile, classic supervised learning methods like ResNet-50 train on the labeled source domain and test on the unlabeled target domain.

Furthermore, plenty of ablation experiments are carried on by assessing four variants of SAPDA: 1) SAPDA w/o self-adaptive class weights evaluation mechanism is the variant without self-adaptive class weights evaluation, degenerating to PADA with cluster classifier. 2) SAPDA w/o cluster classifier is the variant without cluster classifier. 3) SAPDA with shared, outlier and confused classes is the variant takes the weights with shared, outlier and confused classes. 4) SAPDA with shared and outlier classes is the variant that takes the weights with only shared and outlier classes.

Our implementation is based on PyTorch, and fine-tune pretrained ResNet-50 \[\text{[12]}\]. Similar to DaNN, a bottleneck layer is added after the feature extractor. Bottleneck layer, outlier discriminator $G_d$, domain discriminator $G_d$ and feature extractor $G_f$ are trained from square one. Mini-batch stochastic gradient descent are used during the training. We also select the same learning rate as DaNN. The learning rate is coordinated during training following $p = \frac{\eta \cdot t^{\alpha}}{((1 + p)^{\eta})^\alpha}$, where $\eta$ and $\alpha$ are changed with importance-weighted cross-validation \[\text{[34]}\], and $p$ is the hyper-parameter optimized based on the dataset.

B. Result

The classification results on Office-10-Caltech5, a set of Office-31 and VisDA-2017, a set of Caltech256-Office10 and Office-Home are respectively shown in Table \[\text{[V]}\]. We also perform some ablation experiments in Table \[\text{V}\]. The results indicate our SAPDA outperforms all the standard DA and PDA methods.

We also have some insightful observations. (1) supervised methods like AlexNet and ResNet perform better on standard DA method under PDA setting, it shows negative transfer has negative impact on the accuracy when the features from outlier source classes are learned by standard DA methods such as DaNN and DAN. (2) RTN utilizes the entropy minimization criterion to modify the problem. Hence, it is an improvement over ResNet, but there is still some negative transfer on most tasks. (3) Since the weight mechanism can select the shared classes and promote their weights, PDA methods achieve better result than ResNet-50 and other standard DA methods. (4) Our SAPDA outperforms both standard DA and PDA methods, demonstrating that our self-adaptive weight mechanism can effectively utilize the confused class to avoid misjudging confused samples.

We further discover different components of SAPDA by contrast with the results of SAPDA variants in Tables \[\text{V}\] (1) SAPDA outperforms SAPDA w/o self-adaptive class weights evaluation mechanism, proving that using self-adaptive class weights evaluation mechanism can select out reasonable outlier classes, further weaken the negative impact of outlier data, and force the source classifier to pay attention to data pertaining to the target label space. (2) SAPDA outperforms SAPDA w/o cluster classifier, showing the cluster classifier can gather different classes more tightly to avoid misclassification partly. (3) SAPDA with shared, outlier and confused classes gets the worst results on almost each task especially on the tasks D31 \rightarrow W10 and W31 \rightarrow D10. On these two tasks, because of the gap between different classes is small, it is easy for model to select out shared and outlier classes. But when we cluster source classes into shared, outlier and confused classes, neither the shared classes can be weighted as 1, nor the outlier classes are weighted as 0. This phenomenon can cause negative transfer, reducing accuracy, which also illustrate the necessity of putting $W_e$ to the expected values. Meanwhile, the result on task $S \rightarrow R$ performs much better than SAPDA with

| Method | Office-31 | Average |
|--------|-----------|---------|
| SAPDA w/o self-adaptive class weights evaluation mechanism | 92.46 |
| SAPDA w/o cluster classifier | 96.33 |
| SAPDA with shared, outlier and confused classes | 94.76 |
| SAPDA with shared and outlier classes | 96.79 |
| SAPDA | 97.73 |

| Method | Office-Home | Average |
|--------|-------------|---------|
| SAPDA w/o self-adaptive class weights evaluation mechanism | 50.9 |
| SAPDA w/o cluster classifier | 58.6 |
| SAPDA with shared, outlier and confused classes | 65.8 |
| SAPDA with shared and outlier classes | 66.6 |
| SAPDA | 66.9 |

**TABLE V**

**ACCURACY ON PARTIAL DA TASKS OF SAPDA AND ITS VARIANTS ON Office-31 (31 CLASSES \rightarrow 10 CLASSES)**

| Method | Office-Home | Average |
|--------|-------------|---------|
| SAPDA w/o self-adaptive class weights evaluation mechanism | 46.1 |
| SAPDA w/o cluster classifier | 57.6 |
| SAPDA with shared, outlier and confused classes | 58.3 |
| SAPDA with shared and outlier classes | 64.1 |
| SAPDA | 66.9 |

**TABLE VI**

**ACCURACY OF STANDARD DA TASKS ON Office-Home (65 CLASSES \rightarrow 65 CLASSES).**
shared, outlier and confused classes. This shows that in a more challenging task, arbitrarily converting the soft $W_c$ to a binary value can easily cause the difficult-to-discern shared classes to be misjudged as outlier classes or vice versa. This result also illustrates the necessity of self cluster weights mechanism. (4) SAPDA with shared and outlier classes achieves close result to SAPDA on Office-31 dataset, but does not perform well on more difficult VisDA-2017. It indicates the self cluster weights mechanism can play a much more important role when the task is much more harder.

Moreover, we also apply our method to the standard domain adaptation problem, which is shown in Table VII, because our sample weight evaluation mechanism became a transferability degree measurement mechanism, which also helped to improve the classification accuracy under this setting.

### TABLE VII

| hyper $\beta$ | $A \rightarrow W$ | $A \rightarrow D$ | Avg on Office-31 |
|---------------|------------------|------------------|------------------|
| 0.01          | 95.77            | 96.90            | 96.54            |
| 0.02          | 95.74            | 97.30            | 96.22            |
| 0.05          | 95.81            | 97.22            | 96.98            |
| 0.1           | **96.61**        | **97.45**        | **97.73**        |
| 0.5           | **96.61**        | 96.90            | 97.02            |
| 1             | 95.77            | 97.22            | 96.87            |

**C. Analysis**

**Class Weight:** Fig. 4(a)-(d) shows class weight histograms for task $A$ (31 classes) $\rightarrow W$ (10 classes). They are learned by finetuning ResNet-50, DaNN, PADA and our SAPDA respectively. The blue bins are weights for shared classes and the red are the weights for outlier classes.

**Feature Visualization:** Fig 5(a)-(d) are the feature visualization results by the t-SNE embeddings [7] for ResNet, DaNN, PADA and SAPDA. The blue points, the green points and the red points represents source shared, source outlier and target samples respectively. Based on these four graphs, we can get some insightful observation: (1) ResNet-50 can only classifier a few target samples into correct categories due to finetune, while DaNN almost cannot distinguish target samples into correct classes implies that mismatch between different label spaces deteriorate the accuracy. (2) PADA can cluster most target samples
into correct classes but the bound between shared and outlier classes is not distinct, which can still cause misclassification. (3) Our SAPDA can not only distinguish target samples into correct classes, but also cluster source outlier classes together while the distance between other clusters is far. In this way, target samples can almost be misclassified.

**Number of Clusters:** Task W31 to A10 achieves the worst performance among the six tasks of Office-31 dataset, which means it is the most difficult task for our framework. Hence, in Fig.6 we utilize this task to shows the number of clusters w.r.t. to iterations. The left ordinate is the accuracy of the task w.r.t. to iterations, and the right ordinate is the number of cluster groups of the task w.r.t. to iterations.

We have some interesting observations from this figure. Even if we set the number of clusters ranging from 1 to 3, the actual number of clusters selected by the network only includes two or three under PDA setting. This phenomenon reflects that when it is a little hard to classify some mixed samples, the framework clusters our source data into three groups, while when the gap between shared and outlier classes is obvious, the framework can classify the shared and outlier classes easily, the number of cluster groups is two. (2) When the accuracy improves significantly, our network believes it has enough ability to handle the task, the number of cluster groups decreases from three to two. Once the accuracy decreases, the network can find out some of the classes having been misclassified, the number of cluster groups can increase from two to three. In this way, the misclassified classes can be adjusted until all the classes have been arranged into the correct groups. This phenomenon implies that our framework has the ability to self-adaptive correct weights for source classes.

**Target Class:** We carry out some experiments with different target classes. Fig.7 shows DaNN performs worse as the number of target categories reduces. It indicates the influence of negative transfer caused by incongruity between different label spaces. Performance of SAN declines slowly and steadily, suggesting that the SAN has the potential to eliminate the effects of outlier classes. IWAN performs ordinary compared with SAN. Our SAPDA performs generally better than the other methods. Besides, when the number of target classes decreases, our model can achieve higher accuracy, showing our mechanism can not only select out outlier classes, but can also promote performance.

**Sensitive Analysis:** In order to better analyze the sensitivity of our model to hyperparameter $\beta$, in Table VII, we observed the influence of different $\beta$ on experimental results on the Office-31 dataset. It is not difficult to find that the experimental results are best when $\beta = 0.1$. Although other $\beta$ also affect the results, the overall results are relatively stable.

**Convergence Performance:** As shown in Fig.8, compared with it previous methods, our SAPDA does not only converge fast but also converges to highly accurate solutions, implying the robustness and efficiency of our SAPDA.

V. CONCLUSION

This paper presents an end to end Self-Adaptive Partial Domain Adaptation framework. It self-adaptively clusters source classes into different groups, and samples in the same group having the same weights. In this way, weighted adversarial network progressively quantifies the transferability of source examples, and simultaneously learns domain-invariant features across source and target domains. Experiments show effectiveness of our model and superiority over several benchmarks.

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