Multi-Level Features Contrastive Network for Unsupervised Domain Adaptation
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Abstract
Unsupervised domain adaptation aims to train a model from the labeled source domain to make predictions on the unlabeled target domain when the data distribution of the two domains is different. As a result, it needs to reduce the data distribution difference between the two domains to improve the model’s generalization ability. Existing methods tend to align the two domains directly at the domain-level, or perform class-level domain alignment based on deep feature. The former ignores the relationship between the various classes in the two domains, which may cause serious negative transfer, the latter alleviates it by introducing pseudo-labels of the target domain, but it does not consider the importance of performing class-level alignment on shallow feature representations. In this paper, we develop this work on the method of class-level alignment. The proposed method reduces the difference between two domains dramatically by aligning multi-level features. In the case that the two domains share the label space, the class-level alignment is implemented by introducing Multi-Level Feature Contrastive Networks (MLFC-Net). In practice, since the categories of samples in target domain are unavailable, we iteratively use clustering algorithm to obtain the pseudo-labels, and then minimize Multi-Level Contrastive Discrepancy (MLCD) loss to achieve more accurate class-level alignment. Experiments on three real-world benchmarks ImageCLEF-DA, Office-31 and Office-Home demonstrate that MLFCNet compares favorably against the existing state-of-the-art domain adaptation methods.

Introduction
Many computer vision tasks have been made significant progress by deep neural networks(DNNs), especially in the field of supervised learning. One of the important reasons for the great success is that DNNs can learn transferable feature representations in large-scale labeled datasets, such as ImageNet (Deng et al. 2009). Unfortunately, the model trained on large-scale labeled dataset is generally sensitive to domain shifts, that is to say it cannot be generalized well to data that not lies inside the training data distribution (Torralba and Efros 2011). How to improve the generalization performance of the model has become one of the hottest research topics.

One of the possible solutions is to manually mark some samples on the target domain and then use these samples to fine-tune the model. However, marking a number of samples that can fine-tune the model is expensive and time-consuming, which is not suit for every ad-hoc target domain or task. Recent studies have shown that unsupervised domain adaptation can effectively mitigate the domain shift in data distributions (Tzeng et al. 2017; Saenko et al. 2010; Ben-David et al. 2010, 2006). A majority of successful methods rely on domain-level alignment using minimize the discrepancy between the source and target domain in the deep neural network, where the discrepancy is measured by Maximum Mean Discrepancy (MMD) (Long et al. 2015), Joint MMD (JMMD) (Long et al. 2017) and cross-covariance (Long et al. 2018). Although these methods have yielded promising results, most of them did not use the label information of the source domain, which belonged to the class-agnostic method. These methods are likely to ignore the finer class specific structure of the samples, which
will cause noisy predictions near classifier boundaries (Fig. 1). Some subsequent works [Häusser et al. 2017; Pei et al. 2018; Wu et al. 2018; Deng, Luo, and Zhu 2019; Kang et al. 2019; Pan et al. 2019] alleviated this problem by assigning pseudo-labels to the target domain samples to perform class-level alignment. However, these methods do not consider the importance of shallow feature alignment, leading to negative alignment.

In order to further align the source domain and target domain at the class-level, we propose to perform class-level alignment on the multi-level features representations. Specifically, inspired by Contrastive Domain Discrepancy (CDD) [Kang et al. 2019], we introduce a new Multi-Level Contrastive Discrepancy (MLCD) to minimize the intra-class discrepancy and maximize the inter-class discrepancy at multiple levels.

It should be noted that two technical issues have been effectively solved by previous works [Kang et al. 2019; Tang, Chen, and Jia 2020; Luo et al. 2019]. The first issue is that the labels of the target domain samples are unknown, and the pseudo-label of each sample needs to be estimated by using the output of the network. The second issue is that during the mini-batch training, for c-th class, the mini-batch may only contain samples form one domain, which requires a special training paradigm. Unfortunately, there is still a technical problem needs to be solved, that the size of the shallow feature map generally is very large. That means we cannot directly align the shallow feature maps of the two domains at the class-level.

In this paper, we propose Multi-Level Feature Contrastive Network (MLFCNet) to facilitate the optimization with MLCD. During the training, in addition to minimizing the cross entropy, we also need to assign labels to the samples in the target domain through clustering, and then adjust the feature representations according to MLCD metric. After clustering, we will remove those ambiguous target data and classes. Due to the center of the target domain is more and more accurate, the number of samples considered will continue to increase. The iterative learning strategy can better help the optimization of the algorithm.

The effectiveness of MLFCNet is reflected by improved adaptation accuracy on three public UDA benchmarks: ImageCLEF-DA [3], Office-31 [Saenko et al. 2010] and Office-Home [Venkateswara et al. 2017]. The experimental results show that our method performs favorably against the state-of-the-art UDA methods.

We finally summarize our contributions as follows.

- We propose a new optimization direction for unsupervised domain adaptation, which performs class-level alignment at multiple levels, and introduce a new discrepancy Multi-Level Contrastive Discrepancy (MLCD).
- We propose a network Multi-Level Feature Contrastive Network to facilitate the end-to-end training with MLCD.
- Our method achieves the competitive performance compared to the state-of-the-art on the ImageCLEF-DA, Office-31 and Office-Home benchmark.

### Related Work

#### Domain Adaptation Based on Domain-Level Alignment

Unsupervised domain adaptive methods based on domain-level can be roughly categorized as two categories: methods based on directly minimizing some notion of distance or discrepancy between the domains and methods based on adversarial learning. The former is represented by DAN [Long et al. 2015] and JAN [Long et al. 2017], which proposes to minimize the Maximum Mean Discrepancy (also known as MMD) to reduce the discrepancy between the two domains, such methods can be regarded as statistic moments-based methods. The latter is mainly inspired by GANs [Goodfellow et al. 2014] and is generally referred to as a method based on adversarial learning. This series of works [Ganin and Lempitsky 2015; Ganin et al. 2016; Tzeng et al. 2017] aim to learn the indistinguishable feature representations in the source and target domains through adversarial learning. Specifically, these methods usually train a domain discriminator to distinguish whether the sample comes from the source domain or the target domain, and train the generator to generate feature that can confuse the discriminator. Through continuous confrontation training, the feature gap between the two domains is finally reduced.

In a word, these methods belong to domain-level alignment. By aligning global distributions of source and target domain to learn align features between the two domains, so that a classifier trained in source domain can be used in target domain.

#### Domain Adaptation Based on Class-Level Alignment

The domain adaptation based on domain-level alignment cannot guarantee alignment between the respective categories, which may lead to more serious negative transfer. e.g. features of airplanes in target domain might be mapped near features of kites in source domain. Recent work consider the use of class specific properties to alleviate this problem [Luo et al. 2019; Pan et al. 2019; Kang et al. 2019]. Due to the target domain is unlabeled, these works need to train a co-regularization network or use clustering algorithm to assign labels to the target domain samples, and then align the deep feature representations at the class-level. These methods generally map the deep feature of same class samples from the source domain and target domain nearby in some way. This is problematic. Because the shallow feature of samples will be lost in training, and the deep feature representations that if they are not close enough, the samples at the classification boundary may be classified as negative samples. In contrast, MLFCNet aims to perform class-level alignment on multi-level features extracted from deep neural network. It can effectively alleviate the problem of ambiguous data and improve the performance of unsupervised domain adaptation. It requires spherical K-means Clustering to assign pseudo-labels, and then explicitly minimize the MLCD.

### Proposed Method

In the problem of unsupervised domain adaptation (UDA), we have a labeled source domain \( \mathcal{S} = \left\{ (x_i, y_i) \right\}_{i=1}^{n_s} \) with \( n_s \) samples, where \( \mathcal{S} \sim \mathcal{P}_s \) along with
Multi-Level Features

Figure 2: Feature maps of different levels will be downsampled to the same resolution.

an unlabeled target domain \( T = \{ \mathcal{X}_t \} = \{ x_t^j \}_{j=1}^{n_t} \) with \( n_t \) samples, where \( T \sim \mathcal{P}_t \), and \( \mathcal{P}_s \neq \mathcal{P}_t \). \( x^s, x^t \) represent the input data, and \( y^s \in \{ 0, 1, \cdots, C-1 \} \) denote the source data label of \( C \) classes. The task is to train a deep neural network \( \varphi \) using \( S \) and \( T \) that can make predictions \( \{ \hat{y}^t \} \) on \( T \).

We define \( \varphi_l(x) \) as the outputs of layer \( l \in \mathcal{L} \) in the deep neural network. In this section, we first review the unsupervised domain adaptation on class-level alignment, and then introduce our new domain discrepancy. Finally, we will clarify the architecture and training process of the proposed network.

Overview of Class-Level Domain Alignment

In order to quantitatively describe the difference between the two data distributions with their mean embedding in the reproducing kernel Hilbert space (RKHS) [Mendelson 2002]. MMD is usually used as a measurement method. i.e.

\[
D_H(\mathcal{P}_t, \mathcal{P}_s) := \sup_{f \in \mathcal{H}} \left( E_{x \sim \mathcal{P}_t} [f(x)] - E_{x' \sim \mathcal{P}_s} [f(x')] \right) \quad (1)
\]

where \( \mathcal{H} \) is the RKHS related to the positive definite kernel function. Domain-level alignment generally uses direct or adversarial learning methods to reduce MMD. However, these methods ignore the relationship between the categories in the two domains, which may cause negative transfer. Recently, many studies have proved that if category information is introduced, the performance of domain adaptation can be effectively improved by minimizing the MMD of two domain conditional distributions. i.e.

\[
D_H(\mathcal{P}_t, \mathcal{P}_s) := \sup_{f \in \mathcal{H}} \left( E_{x \sim \mathcal{P}_t} [f(x) | \mathcal{Y}_s] - E_{x' \sim \mathcal{P}_s} [f(x') | \hat{\mathcal{Y}}_t] \right) \quad (2)
\]

where the pseudo-label of target domain \( \hat{\mathcal{Y}}_t \) is unknown. In this kind of method, the pseudo-label is assigned to each unlabeled target sample. The pseudo-labeled target domain samples will be used with the source domain samples to learn an improved classification model.

Multi-Level Contrastive Discrepancy

We propose to take the class information into account, and then perform the operation of maximizing the inter-class domain discrepancy and minimizing the intra-class domain discrepancy within multi-level features to achieve better class-level alignment. The proposed Multi-Level Contrastive Discrepancy (MLCD) loss is established on the MMD of two domain conditional distributions. We define \( \hat{\varphi}(x) \) as the multi-level outputs of the deep neural network, supposing \( \eta_{cc}(y, y') = \begin{cases} 1 & \text{if } y = c, y' = c' \\ 0 & \text{otherwise} \end{cases} \), for two classes \( c_1, c_2 \) (which can be same or different), the \( D_H(\mathcal{P}_t, \mathcal{P}_s) \) given by:

\[
\hat{D}_c \hat{c}_2(\hat{\mathcal{Y}}_t, \hat{\varphi}) = \sum_{i=1}^{n_t} \sum_{j=1}^{n_t} \eta_{c_1 c_2}(y^s_i, y^t_j) k(\hat{\varphi}(x^s_i), \hat{\varphi}(x^t_j)) + \sum_{i=1}^{n_s} \sum_{j=1}^{n_t} \eta_{c_1 c_2}(y^s_i, y^t_j) k(\hat{\varphi}(x^s_i), \hat{\varphi}(x^t_j)) - 2 \sum_{i=1}^{n_s} \sum_{j=1}^{n_t} \eta_{c_1 c_2}(y^s_i, y^t_j) k(\hat{\varphi}(x^s_i), \hat{\varphi}(x^t_j)) \quad (3)
\]

where \( k(x_1, x_2) \) denote the positive definite kernel function and \( \hat{\varphi}(x) = (1 - \lambda) \varphi_n(x) + \lambda \Delta_{c=1} \varphi_l(x) \). The \( \Delta_{c=1} \) is a series of downsampling and concatenating operations. Note that the ground-truth labels of target domain are not available, so we adopt spherical K-means to assign target labels \( \hat{\mathcal{Y}}_t \), forming pairs for contrastive learning of multi-level features. Since the clustering algorithm is sensitive to initialization, we set the number of clusters to the number of classes \( C \). For \( c \)-th class, the target cluster \( O_{c}^t \) is initialized as the source cluster center \( O_{c}^s \), i.e. \( O_{c}^t \leftarrow O_{c}^s \). There are two reasons for this: 1) features used are multi-level and contain rich similar semantic information, the centers of \( c \)-th class from the source and target domains are approximation. 2) with the alignment of class-level, this approximation will be more accurate. Cosine dissimilarity is adopted to assignment of each target sample. After clustering, each target domain samples \( x^t \) is associated with a pseudo-label \( \hat{y}^t \). i.e. \( dist(\hat{\varphi}(x^t), O_{c}^t) < \text{threshold} \), where \( dist(x_1, x_2) = \frac{1}{2} (1 - \frac{||x_1 - x_2||_2}{||x_1||_2||x_2||_2}) \) threshold \( \in [0, 1] \) is a constant. We will remove the ambiguous samples, which are far from its assigned clustered centers to reduce the noise of pseudo-labels. Eq (3) defines two kinds of multi-level features discrepancy, 1) when \( c_1 = c_2 = c \), it measures multi-level intra-class features discrepancy; 2) when \( c_2 \neq c_2 \), it becomes multi-level inter-class features discrepancy. The MLCD can be given by:

\[
\hat{D}_{\text{mlcd}} = \frac{1}{C} \sum_{c=1}^{C} \hat{D}_{cc}(\hat{\mathcal{Y}}_t, \hat{\varphi}) - \frac{1}{C(C-1)} \sum_{c=1}^{C} \sum_{c' \neq c} \hat{D}_{cc'}(\hat{\mathcal{Y}}_t, \hat{\varphi}) \quad (4)
\]

The discrepancy in the feature representations of intra-
Multi-Level Feature Contrastive Network

For multi-level features alignment, we use pre-trained ResNet-50 (He et al. 2016) from ImageNet (Deng et al. 2009) as the backbone and replace the last fully-connected (FC) layer with task-specific ones, then fine-tune the network by source domain data.

In the deep convolution neural network, the shallow convolution layer will extract feature with high resolution and weak semantics, while the deep convolution layer is on the contrary and the general feature extracted by convolution layer are more transferable (Long et al. 2015, 2017). Inspired by this, we retain the multi-level features and align them at the class-level at the same time. In practice, we downsample the feature map with high resolution, then concatenate it with the smaller feature map, and finally add it with the deep feature map to obtain multi-level features (Fig. 2). This is reasonable because shallow feature have high resolution, the overhead of directly aligning them will be unacceptable. In particular, the sample concatenation preserves the relative position relationship of multi-level features, and there will be no alignment error. We name our network Multi-Level Feature Contrastive Network (MLFCNet). The network architecture is shown in Figure 3.

We need to train the whole network by minimize cross-entropy loss and MLCD loss. Since the network has multiple FC layers, the overall MLCD loss is

$$L_{mlcd} = \sum_{i=1}^{L} \hat{D}_i^{mlcd}$$  \hspace{1cm} (5)

Besides, the network is trained to classify the source images using cross entropy loss $L_{ce}$

$$L_{ce} = -\frac{1}{n_s} \sum_{i=1}^{n_s} \log P(y^s_i | x^s_i)$$  \hspace{1cm} (6)

where $y^s_i$ is the ground-truth label of source domain sample $x^s_i$, $P(y^s_i | x^s_i)$ denotes the predicted probability of label $y$ with the network parameterized by $\theta$, given input $x$.

Combining Eq (5) and Eq (6), the overall objective can be formulated as

$$\min_{\theta} L = L_{ce} + \beta L_{mlcd}$$  \hspace{1cm} (7)

where $\beta$ is the weight of the penalty term as the previous work (Kang et al. 2019). As the minimizing $L$, the features will be aligned by class at multi-level, and the intra-class domain discrepancy is minimized and inter-class domain discrepancy is maximized.

Algorithm 1 shows the training process of MLFCNet. The algorithm is executed in a mini-batch, which may cause the $c$-th samples contained in a mini-batch to come from only one of the source domain or the target domain. Once this happens, the intra-class discrepancy could not be estimated, resulting in reduced training efficiency. The previous class-level alignment work (Kang et al. 2019) solved this problem through class-aware sampling. Simply put, only those classes whose number is greater than a constant $N_0$ will be sampled each time target domain samples are assigned. This approach is adopted in the parper.
Table 1: Accuracy(%) on ImageCLEF-DA Dataset (ResNet-50)

| Method         | I → P  | P → I  | I → C  | C → I  | C → P  | P → C  | Avg   |
|----------------|--------|--------|--------|--------|--------|--------|-------|
| Source Model   | 74.8±0.3 | 83.9±0.1 | 91.5±0.3 | 78.0±0.2 | 65.5±0.3 | 91.2±0.3 | 80.7   |
| DAN            | 74.5±0.4 | 82.2±0.2 | 92.8±0.2 | 86.3±0.4 | 69.2±0.4 | 89.8±0.4 | 82.5   |
| DANN           | 75.0±0.6 | 86.0±0.3 | 96.2±0.4 | 87.0±0.5 | 74.3±0.5 | 91.5±0.6 | 85.0   |
| JAN            | 76.8±0.4 | 88.0±0.2 | 94.7±0.2 | 89.5±0.3 | 74.2±0.3 | 91.7±0.3 | 85.8   |
| CDAN+E         | 77.7±0.3 | 90.7±0.2 | 97.7±0.3 | 91.3±0.3 | 74.2±0.2 | 94.3±0.3 | 87.7   |
| TAT            | 78.8±0.2 | 92.0±0.2 | 97.5±0.3 | 92.0±0.3 | 78.2±0.4 | 94.7±0.4 | 88.9   |
| SAFN+ENT       | 79.3±0.1 | 93.3±0.4 | 96.3±0.4 | 91.7±0.0 | 77.6±0.1 | 95.3±0.1 | 88.9   |
| SymNets        | 80.2±0.3 | 93.6±0.2 | 97.0±0.3 | 93.4±0.3 | 78.7±0.3 | 96.4±0.1 | 89.9   |
| SRDC           | 80.8±0.3 | 94.7±0.2 | 97.8±0.2 | 94.1±0.2 | 80.0±0.3 | 97.7±0.1 | 90.9   |
| MLFCNet(ours)  | 87.2±0.3 | 98.0±0.2 | 99.1±0.1 | 98.9±0.2 | 88.1±0.9 | 99.9±0.1 | 95.3   |

Table 2: Accuracy(%) on Office-31 Dataset (ResNet-50)

| Method         | A → W  | D → W  | W → D  | A → D  | D → A  | W → A  | Avg   |
|----------------|--------|--------|--------|--------|--------|--------|-------|
| Source Model   | 77.8±0.2 | 96.9±0.1 | 99.3±0.1 | 82.1±0.2 | 64.5±0.2 | 66.1±0.2 | 81.1   |
| DAN            | 81.3±0.3 | 97.2±0.0 | 99.8±0.0 | 83.1±0.2 | 66.3±0.0 | 66.3±0.1 | 82.3   |
| DANN           | 81.7±0.2 | 98.0±0.2 | 99.8±0.0 | 83.9±0.7 | 66.4±0.2 | 66.0±0.3 | 82.6   |
| VADA           | 86.5±0.5 | 98.2±0.4 | 99.7±0.2 | 86.7±0.4 | 70.1±0.4 | 70.5±0.4 | 85.4   |
| MSTN           | 91.3     | 98.9    | 100     | 90.4    | 72.7    | 65.6    | 86.5   |
| MCD            | 88.6±0.2 | 98.5±0.1 | 100.0±0.0 | 92.2±0.2 | 69.5±0.1 | 69.7±0.3 | 86.5   |
| SAFN+ENT       | 90.1±0.8 | 98.6±0.2 | 99.8±0.0 | 90.7±0.5 | 73.0±0.2 | 70.2±0.3 | 87.1   |
| iCAN           | 92.5     | 98.8    | 100     | 90.1    | 72.1    | 69.9    | 87.2   |
| CDAN+E         | 94.1±0.1 | 98.6±0.1 | 100.0±0.0 | 92.9±0.2 | 71.0±0.3 | 69.3±0.3 | 87.2   |
| MSTN+DSBN      | 92.7     | 99      | 100     | 92.2    | 71.7    | 74.4    | 88.3   |
| TADA           | 94.3±0.3 | 98.7±0.1 | 99.8±0.2 | 91.6±0.3 | 72.9±0.2 | 73.0±0.3 | 88.4   |
| TAT            | 92.5±0.3 | 99.3±0.1 | 100.0±0.0 | 93.2±0.2 | 73.1±0.3 | 72.1±0.3 | 88.4   |
| SymNets        | 90.8±0.1 | 98.8±0.3 | 100.0±0.0 | 93.9±0.5 | 74.6±0.6 | 72.5±0.5 | 88.4   |
| BSP+CDAN       | 93.3±0.2 | 98.2±0.2 | 100.0±0.0 | 93.0±0.2 | 73.6±0.3 | 72.6±0.3 | 88.5   |
| MDD            | 94.5±0.3 | 98.4±0.1 | 100.0±0.0 | 93.5±0.2 | 74.6±0.3 | 72.2±0.1 | 88.9   |
| CAN            | 94.5±0.3 | 99.1±0.2 | 99.8±0.2 | 95.0±0.3 | 78.0±0.3 | 77.0±0.3 | 90.6   |
| SRDC           | 95.7±0.2 | 99.2±0.1 | 100.0±0.0 | 95.8±0.2 | 76.7±0.3 | 77.1±0.1 | 90.8   |
| SCAL+SPL       | 95.8±0.3 | 99.2±0.4 | 100.0±0.0 | 94.6±0.1 | 77.5±0.2 | 76.0±0.2 | 90.5   |
| MLFCNet(ours)  | 95.5±0.5 | 99.2±0.1 | 100.0±0.0 | 96.3±0.1 | 78.6±0.3 | 78.8±0.1 | 91.3   |

Experiment

Datasets

We evaluate MLFCNet against state-of-the-art algorithms on three public domain adaptation benchmarks. ImageCLEF-DA consists of 3,000 images belonging to 12 common categories shared by three popular datasets: Caltech-256(C), ImageNet ILSVRC2-12(I), and PASCAL VOC2012(P). This dataset includes a total of 6 tasks: I → P, P → I, I → C, C → I, C → P, P → C. Office-31(Saenko et al.) is a real-world dataset, which widely adopted by adaptation methods, containing three distinct domains: Amazon(A), DSLR(D) and Webcam(W). This dataset includes a total of 6 tasks: A → W D → W, W → D, A → D, D → A, W → A. Office-Home is more challenging benchmark dataset, with 65 classes shared by four distinct domains: Artistic images(Ar), Clip Art(Cl), Product images(Pr), and Real-World images(Rw). This dataset includes a total of 12 tasks: Ar → Cl, Ar → Pr, Ar → Rw, Cl → Ar, Cl → Pr, Cl → Rw, Pr → Ar, Pr → Cl, Pr → Rw, Rw → Ar, Rw → Cl, Rw → Pr.

Implementation Details

We use pretrained ResNet-50[He et al.2016] from ImageNet as the base feature extractor and replace the last fully connected(FC) layer with task-specific FC layer. Mini-batch stochastic gradient descent(SGD) is used for training the model. The learning rate is the same as the previous work(Ganin and Lempitsky2015,Long et al.2015,2017), i.e., the $\eta_p = \eta_0 \frac{m}{(1+ap)}$, the $\eta_0$ is the initial learning rate, $p$ linearly increases from 0 to 1. We set $\eta_0 = 0.001$ for convolutional layers and $\eta_0 = 0.01$ for FC layer. For all tasks, $a = 10$, $b = 0.75$ and $\beta = 0.3$. The $\lambda$ is set to 0.5 for ImageCLEF-DA, 0.25 for Office-31 and Office-Home. The thresholds are set to 1.0 to all tasks of ImageCLEF-DA and Office-Home, 0.05 for Office-31 tasks A→D, A→W, D→W, W→D, 0.8 for D→A, W→A.

Comparison with State-of-the-art

ImageCLEF-DA. In Table 1, we compared our method on ImageCLEF-DA with typical domain-level and class-
level alignment UDA algorithms: DAN(Long et al. 2015), DANN(Ganin et al. 2016), JAN(Long et al. 2017), DWT-MECC(Long et al. 2018), TAT(Liu et al. 2019), SAFN(Xu et al. 2019), SymNets(Zhang et al. 2019b), SRDC(Tang, Chen, and Jia 2020). We showed the results for adaptation using our method with MLFCNet loss. We observed that we outperform prior methods by a significant margin. On some relatively simple transfer tasks, such as P→I, we observed an improvement from 94.7 to 98, indicating the usefulness of our MLFCNet loss with MLFCNet. Similar improvements can be observed for 1→C, C→I, P→C. What’s more important is that our method has still made a significant improvement in the more difficult transfer tasks 1→P and C→P, boosts the accuracy of the best method(Tang, Chen, and Jia 2020) by 6.4% and 8.1% respectively. On all six transfer tasks of ImageCLEF-DA, the average accuracy is improved by 4.4% compared with the previous best method.

Office-31(Saenko et al. 2010). We compared our method on Office-31 with typical domain-level and class-level alignment UDA algorithms: DAN(Long et al. 2015), DANN(Ganin et al. 2016), VADA(Shu et al. 2018), MCD(Saito et al. 2018), SAFN+ENT(Xu et al. 2019), iCAN(Zhang et al. 2018), CDAN+E(Long et al. 2018), MDD(Zhang et al. 2019a), CAN(Kang et al. 2019), SRDC(Tang, Chen, and Jia 2020), SCAL+SPL(Wang et al. 2021). Table 2 lists the average classification accuracies on six transfer tasks of Office-31. We can observe that MLFCNet achieves better average accuracy than other compared methods, verifying the efficacy of MLFCNet.

Office-Home(Venkateswara et al. 2017). We compared our method on Office-Home with typical domain-level and class-level alignment UDA algorithms: DAN(Long et al. 2015), DANN(Ganin et al. 2016), JAN(Long et al. 2017), DWT-MEC(Roy et al. 2019), CDAN+E(Long et al. 2018), TAT(Liu et al. 2019), SAFN(Xu et al. 2019), TADA(Wang et al. 2019), SymNets(Zhang et al. 2019b), MDD(Zhang et al. 2019a), CAN(Kang et al. 2019), SRDC(Tang, Chen, and Jia 2020), SCAL+SPL(Wang et al. 2021). Results on Office-Home are shown in Table 3. Clearly, we outperformed other approaches by large margins on 11 out of 12 tasks. Furthermore, our methods brings a rise of improvement by 28.4% over the source only model(ResNet-50). Compared with the methods of domain-level alignment, such as DAN, our model achieves extra gain of 18.2%. Besides, our method has 3.2% and 2.5% improvements over the class-level alignment methods SRDC(Tang, Chen, and Jia 2020) and SCAL+SPL(Wang et al. 2021) respectively.

| Methods                          | Ar→Cl | Ar→Pr | Ar→Rw | Cl→Ar | Cl→Pr | Cl→Rw | Pr→Ar | Pr→Cl | Pr→Rw | Rw→Ar | Rw→Cl | Avg  |
|---------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Source Model                    | 34.9  | 50.0  | 58.0  | 37.4  | 41.9  | 46.2  | 38.5  | 31.2  | 60.4  | 53.9  | 41.2  | 59.9 | 46.1 |
| DAN                             | 43.6  | 57.0  | 67.9  | 45.8  | 56.5  | 60.4  | 44.0  | 43.6  | 67.7  | 63.1  | 51.5  | 74.3 | 56.3 |
| DANN                            | 45.6  | 59.3  | 70.1  | 47.0  | 58.9  | 60.6  | 46.1  | 43.7  | 68.5  | 63.2  | 51.8  | 76.8 | 57.6 |
| JAN                             | 45.9  | 61.2  | 68.9  | 50.4  | 59.7  | 61.0  | 45.8  | 43.4  | 70.3  | 63.9  | 52.4  | 76.8 | 58.3 |
| DWT-MEC                         | 50.3  | 72.1  | 77.0  | 59.6  | 69.3  | 70.2  | 58.3  | 48.1  | 77.3  | 69.3  | 53.6  | 82.0 | 65.6 |
| CDAN+E                          | 50.7  | 70.6  | 76.0  | 57.6  | 70.0  | 70.0  | 57.4  | 50.9  | 77.3  | 70.9  | 56.7  | 81.6 | 65.8 |
| TAT                             | 51.6  | 69.5  | 75.4  | 59.4  | 69.5  | 68.6  | 59.5  | 50.5  | 76.8  | 70.9  | 56.6  | 81.6 | 65.8 |
| BSP+CDAN                        | 52.0  | 68.6  | 76.1  | 58.0  | 70.3  | 70.2  | 58.6  | 50.2  | 77.6  | 72.2  | 59.3  | 81.9 | 66.3 |
| SAFN                            | 52.0  | 71.7  | 76.3  | 64.2  | 69.9  | 71.9  | 63.7  | 51.4  | 77.1  | 70.9  | 57.1  | 81.5 | 67.3 |
| TADA                            | 53.1  | 72.3  | 77.2  | 59.1  | 71.2  | 72.1  | 59.7  | 53.1  | 78.4  | 72.4  | 60.0  | 82.9 | 67.6 |
| SymNets                         | 47.7  | 72.9  | 78.5  | 64.2  | 71.3  | 74.2  | 64.2  | 48.8  | 79.5  | 74.5  | 52.6  | 82.7 | 67.6 |
| MDD                             | 54.9  | 73.7  | 77.8  | 60.0  | 71.4  | 71.4  | 61.2  | 53.6  | 78.1  | 72.5  | 60.2  | 82.3 | 68.1 |
| SRDC                            | 52.3  | 76.3  | 81.0  | 69.5  | 76.2  | 72.0  | 68.7  | 53.8  | 81.7  | 76.3  | 57.1  | 85.0 | 71.3 |
| SCAL+SPL                        | 57.3  | 77.5  | 80.7  | 68.8  | 77.9  | 79.3  | 65.2  | 55.9  | 81.7  | 75.0  | 61.0  | 83.9 | 72.0 |
| MLFCNet(ours)                   | 62.6  | 79.6  | 84.8  | 71.4  | 79.2  | 79.8  | 69.4  | 58.1  | 84.5  | 75.4  | 63.7  | 85.7 | 74.5 |

Table 3: Accuracy(%) on Office-Home Dataset(ResNet-50)
Ablations and Analysis

Importance of MLCD Loss. We compared our method with the model trained using deep feature contrastive discrepancy only, to verify the importance of MLCD loss. The results are shown in Table 4. It can be seen that the average accuracy of class-level alignment on multi-level features is better than deep feature only, and using the four-layer features is always the best. It is worth noting that using only deep feature for contrastive learning is much lower than using two-layer features (5.4%), but the improvement after more than two-layer features is relatively small.

Table 4: Accuracy(%) on ImageCLEF-DA Dataset(ResNet-50). F1,F2,F3,F4 denote the different level feature map.

|       | F1     | F2     | F3     | F4     | I     |
|-------|--------|--------|--------|--------|-------|
|       |        |        |        |        | P → P |
| ✓ ✓ ✓ | 79.0   | 93.9   | 97.1   | 92.6   | 78.1  |
| ✓ ✓ ✓ | 87.0   | 98.4   | 99.8   | 98.3   | 86.8  |
| ✓ ✓ ✓ | 87.9   | 98.1   | 99.1   | 98.1   | 87.6  |
| ✓ ✓ ✓ | 87.2   | 98.0   | 99.1   | 98.9   | 88.1  |
|       |        |        |        |        | Avg   |
| ✓ ✓ ✓ | 77.3   | 95.8   | 95.8   | 90.5   | 76.8  |
| ✓ ✓ ✓ | 85.6   | 97.3   | 99.3   | 97.0   | 87.1  |
| ✓ ✓ ✓ | 86.5   | 97.0   | 99.5   | 97.3   | 87.5  |
| ✓ ✓ ✓ | 87.0   | 98.3   | 99.2   | 97.5   | 87.5  |

Table 5: Accuracy(%) on ImageCLEF-DA Dataset(ResNet-18). F1,F2,F3,F4 denote the different level feature map.

|       | F1     | F2     | F3     | F4     | I     |
|-------|--------|--------|--------|--------|-------|
|       |        |        |        |        | P → P |
| ✓ ✓ ✓ | 77.3   | 95.8   | 95.8   | 90.5   | 76.8  |
| ✓ ✓ ✓ | 85.6   | 97.3   | 99.3   | 97.0   | 87.1  |
| ✓ ✓ ✓ | 86.5   | 97.0   | 99.5   | 97.3   | 87.5  |
| ✓ ✓ ✓ | 87.0   | 98.3   | 99.2   | 97.5   | 87.5  |
|       |        |        |        |        | Avg   |
| ✓ ✓ ✓ | 77.3   | 95.8   | 95.8   | 90.5   | 76.8  |
| ✓ ✓ ✓ | 85.6   | 97.3   | 99.3   | 97.0   | 87.1  |
| ✓ ✓ ✓ | 86.5   | 97.0   | 99.5   | 97.3   | 87.5  |
| ✓ ✓ ✓ | 87.0   | 98.3   | 99.2   | 97.5   | 87.5  |

Table 5: Accuracy(%) on ImageCLEF-DA Dataset(ResNet-18). F1,F2,F3,F4 denote the different level feature map.

Visualization of Feature Distribution. We visualized features of the last FC layer of ResNet backbone using t-SNE (Van der Maaten and Hinton 2008) in Fig. 4. It can be clearly seen that only the comparative learning of deep feature is not aligned well, while MLFCNet can learn highly discriminative features and maintain clear class boundaries.

Hyper-parameter Sensitivity. As shown in Fig. 5, we studied the sensitivity of MLFCNet to the balance weight coefficient $\lambda$ on tasks $C \rightarrow P$ and $C \rightarrow I$. Generally, our model is not sensitive to the change of $\lambda$, it can be seen that our method is better than the baseline method DAN (the blue dash curve). As $\lambda$ get larger, the accuracy increases steadily, and the accuracy polyline tends to be flat after $\lambda$ reaches 0.5.

Figure 5: The sensitivity of accuracy of MLFCNet to $\lambda$ on two example tasks. Right: $C \rightarrow P$ and Left: $C \rightarrow I$. The trends for other tasks are similar.

Conclusion

In this paper, we proposed Multi-Level Feature Contrastive Network to perform class-level alignment for UDA. Through the comparative learning of multi-level features, the feature representations from source and target domain can be aligned in a more accurate way. Accordingly, we introduced a new metric, Multi-Level Contrastive Discrepancy (MLCD), to minimize the intra-class discrepancy and maximize the inter-class discrepancy at multiple levels. Extensive experimental results convincingly demonstrate that the MLFCNet outperforms the state-of-the-arts on a wide range of unsupervised domain adaptive classification.

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