Low-confidence Samples Matter for Domain Adaptation

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Abstract

Domain adaptation (DA) aims to transfer knowledge from a label-rich source domain to a related but label-scarce target domain. The conventional DA strategy is to align the feature distributions of the two domains. Recently, increasing researches have focused on self-training or other semi-supervised algorithms to explore the data structure of the target domain. However, the bulk of them depend largely on confident samples in order to build reliable pseudo labels, prototypes or cluster centers. Representing the target data structure in such a way would overlook the huge low-confidence samples, resulting in suboptimal transferability that is biased towards the samples similar to the source domain. To overcome this issue, we propose a novel contrastive learning method by processing low-confidence samples, which encourages the model to make use of the target data structure through the instance discrimination process. To be specific, we create positive and negative pairs only using low-confidence samples, and then re-represent the original features with the classifier weights rather than directly utilizing them, which can better encode the task-specific semantic information. Furthermore, we combine cross-domain mixup to augment the proposed contrastive loss. Consequently, the domain gap can be well bridged through contrastive learning of intermediate representations across domains. We evaluate the proposed method in both unsupervised and semi-supervised DA settings, and extensive experimental results on benchmarks reveal that our method is effective and achieves state-of-the-art performance. The code can be found in https://github.com/zhyx12/MixLRCo.

1. Introduction

Deep neural networks (DNNs) have shown considerable effectiveness in a variety of machine learning challenges [5, 28, 54]. However, the impressive performance gain heavily relies on the access to massive well-labeled training data. Additionally, manually annotating sufficient training data is often time and expense prohibitive in reality. Besides, another disadvantage of traditional deep learning is its inability to generalize to new datasets due to the domain shift problem [1, 2]. Domain adaptation (DA) addresses this issue by utilizing the knowledge of a label-rich domain (i.e., source domain) to assist the learning in a related but label-scarce domain (i.e., target domain). We investigate two scenarios in this paper: unsupervised DA (UDA) and semi-supervised DA (SSDA). The distinction is that the target domain has no labeled data (UDA) or only a small quantity of labeled data (SSDA). The most popular way to deal with the issue of domain shifting is to learn domain-invariant representations. We can classify these DA approaches as either discrepancy metric-based [41, 69, 81] or adversarial-based [9, 13, 38, 59, 68]. Recently, there have been more methods exploring the inherent structures of unlabeled target domains, such as self-training through pseudo labels [12, 26, 39, 96] and aligning prototypes across domains [4, 24, 50, 88]. To create reliable pseudo labels or prototypes in the target domain, the majority of them simply pick trustworthy samples according to some criteria, such as probability [4, 50] and sample ratio [96]. Consequently, the low-confidence samples are completely ignored in these methods. There are some approaches taking into account less reliable samples, such as self-penalization loss [47] and entropy minimization [14, 43, 55, 80, 91]. However, these methods only consider the probability or entropy of each individual sample and disregard the connections of these samples.

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Most methods do not process these low-confidence samples due to no obvious supervision signal such as pseudo-label. In light of the recent success of instance discrimination contrastive loss [6, 15] in unsupervised representation learning, one natural idea is to introduce it to the unlabeled target domain since it does not need semantic labels. It should be noted that most existing contrastive learning methods in domain adaptation are based on classes, where a sample should be close to those of the same category, and away from those of other categories. Thus, only high-confidence samples are used by resorting to pseudo labels. We use instance discrimination contrastive loss which is based on individual instances. However, as stated by previous works [25, 84], the instance discrimination has a basic flaw for domain adaptation: the semantic structure of the data is not encoded by the learned representations. This is because two instances, regardless of their semantics, are considered as negative pairs if they originate from different samples, and their similarity will be reduced.

To solve this problem, we delve into the feature similarities of samples within the same class and across classes. Fig. 1 depicts our findings. Specifically, for the low-confidence samples, the mean similarity within a class is smaller and that across classes is larger compared with the high-confidence samples. This phenomenon about the low-confidence samples is opposite to the ideal case (i.e., similarity within the same class is larger, and that across classes is smaller). But it may be appropriate for contrastive learning: given randomly sampled negative pairs, the contrastive loss will pay more attention to the samples across classes due to larger similarities, and will push them away from each other. Thus we propose to only use low-confidence samples for contrastive loss, which would alleviate the semantic conflict in contrastive learning. To further incorporate the task-specific semantic information, we propose to re-represent the original feature with the classifier weights rate the task-specific semantic information, we propose to mix up the samples for contrastive loss, which would alleviate the semantic conflict in contrastive learning.

MixLRCo. Here the model is encouraged to behave linearly across the source domain and target domain samples. This way is inspired by recent advances in self-supervised learning [23, 30, 60] that use mixup to generate positive or negative samples. In this work, we only use low-confidence target samples and random source samples for cross-domain mixup. What is more, the low-confidence target samples are given a higher weight than the source samples, which can keep the attention of contrastive learning to the data structure of the target domain.

Our contributions are summarized as follows:

• We propose a novel domain adaptation framework, LRCo, that explores the inherent structures of the target domain by performing contrastive learning on low-confidence samples. Additionally, a simple feature re-representation method is also proposed to encode the task-specific information.

• We extend LRCo by combining with the cross-domain mixup, which can reduce the domain discrepancy by producing intermediate samples across domains and contrastively learning their representations.

• We conduct extensive experiments on multiple UDA and SSDA benchmarks, and the results reveal that our proposed method achieves the state-of-the-art performance owing to better exploiting the low-confidence samples.

2. Related Work

2.1. Unsupervised Domain Adaptation

Unsupervised Domain Adaptation (UDA) [1, 2] is a technique for generalizing a model learnt from a labeled source domain to an unlabeled target domain. The mainstream approaches are to learn domain-invariant representations, and they can be classified into two coarse types. The first one specifically decreases the domain discrepancy represented by some distribution discrepancy metrics [41, 51, 64, 65, 69, 81]. Another common line of research is adversarial training [9, 13, 35, 38, 59, 68, 73]. These methods make use of all samples in both the source and target domains, which usually serve as a baseline for other advanced methods.

To increase discriminability, more recent DA methods attempt to investigate the data structure in unlabeled target domain. Self-training as a typical approach generates target domain pseudo labels [12, 26, 29, 36, 39, 43, 47, 49, 58, 89, 92, 96, 97]. Another category is to construct the prototypes [4, 50, 77, 78, 88, 94] or cluster centers [10, 24, 66] across domains and then perform class-wise alignment. Most of these approaches use a fixed probability threshold [12, 36, 50, 58, 78], a dynamic probability threshold [47, 89], a fixed sample ratio [29, 49, 92], a dynamic sample ratio [38, 96, 97], or a threshold of other metrics [4, 14, 26, 39] to choose trustworthy samples (i.e., high-confidence samples) and reject other low-confidence samples. To mitigate the harmful effect of noisy labels, it is reasonable to only utilize the reliable samples. However, less trustworthy samples are also important since they may reveal the structure of data space. Some techniques are proposed to maintain a global prototype bank [10, 24, 94]. The entropy weighted methods [40, 73] give greater weights to the samples with low entropy (i.e., high-confidence)
lower weights to the samples with high entropy (i.e., low-confidence). In both circumstances, the influence of incorrect predictions is assumed to be automatically reduced by the majority of correct predictions. But the explicit supervisions for low-confidence samples are still lacking.

Some approaches try to add more constraints to low-confidence samples. FixBi [47] proposes a self-penalization loss that enforces the maximum probability of the low-confidence samples to be zero. Low-confidence samples are also taken into account by entropy minimization [14,43,55,72,80,91] and virtual adversarial training [8,61]. These constraints are built based on the information (e.g., probability and entropy) of individual samples, while neglecting their relationships. Some methods [22,34,35] propose to use dark knowledge [17] (i.e., knowledge on incorrect DNN predictions), but their primary objective is to suppress incorrect predictions through inconsistency discovery. Different from these methods, we propose to learn the representation of low-confidence samples more effectively via an instance discrimination procedure.

2.2. Semi-Supervised Domain Adaptation

Semi-Supervised Domain Adaptation (SSDA) aims to reduce the discrepancy between the source and target distribution in the presence of limited labeled target samples. [57] first proposes to align the distributions using adversarial training on entropy. Based on MME, [20,27] further introduce virtual adversarial training [46] to learn more robust features. [31] presents a meta-learning framework for SSDA. [83] breaks down the SSDA problem into two sub-problems, namely, semi-supervised problem and UDA problem, and then proposes to learn consistent predictions using co-training. CDAC [32] proposes an adversarial adaptive clustering loss to group features of unlabeled target data into clusters and perform cluster-wise feature alignment across domains. CLDA [62] employs class-wise contrastive learning to reduce the inter-domain gap and instance level contrastive alignment to minimize the intra-domain discrepancy. ECACL [33] propose a holistic framework that incorporates multiple complementary domain alignment techniques. Among these methods, [32,33,44] adopt FixMatch [63] or its variants. In this work, we also use FixMatch to build a strong baseline, and add a regularization term [97] to get more reliable pseudo labels.

2.3. Contrastive Representation Learning

Contrastive Learning has shown remarkable advantages in self-supervised learning [6,11,15,18,45,48]. The contrastive loss measures the similarity of representation pairs and attempts to distinguish between positive and negative pairs. MoCo [15] maintains a queue of previously processed embeddings as negative memory bank. SimCLR [6] shows that large batch size and strong data augmentations has a comparable performance to the memory-based approaches. Here we adopt a similar architecture to MoCo [15] to perform contrastive learning.

In domain adaptation, most approaches [24,84] use contrastive loss on the basis of class-wise prototypes with a sample selection strategy. Only a few methods [25,56,62] use the instance discrimination based contrastive loss. [25] employs contrastive learning in a pre-train step before proceeding to a domain alignment stage. [62] suggests that the classifier can be used as a contrastive projection head [6]. [56] conducts temporal contrastive self-supervised learning over the graph representations. In contrast to previous efforts, we particularly concentrate on contrastive learning on low-confidence samples and at the same time propose a feature re-representation approach for encoding the task-specific semantic information.

2.4. Mixup Training Strategy

Mixup [87] and its variants [3,71,86] provide effective data augmentation strategies when paired with a cross-entropy loss for supervised and semi-supervised learning. In domain adaptation, there are several methods [42,47,76,79,82,83] applying mixup. [76,79] combines the domain-level mixup with domain adversarial training to learn a more continuous latent space across domains. [47,82,83] use the category-level mixup which requires the target domain pseudo labels. [42] proposes virtual mixup training by combining virtual adversarial training and mixup. In self-supervised learning, recent works have leveraged the idea of image space mixtures [30,60] and embedding space mixtures [23,95] to generate more valuable positive or negative samples. Our MixLRCo is inspired by these methods but implemented in a non-trivial way. Additionally, our approach is different from [56] that adopts the background mixing for video domain adaptation and treat each domain equally.

3. Preliminary

In this work, we focus on the unsupervised and semi-supervised domain adaptation problem in image classification. Formally, for both tasks, we are given a source domain \( D_s = \{ (x_s^i, y_s^i) \}_{i=1}^{n_s} \) with \( n_s \) labeled samples and an unlabeled target domain \( D_{tu} = \{ x_{tu}^j \}_{j=1}^{n_{tu}} \) with \( n_{tu} \) unlabeled samples, except in the semi-supervised setting, a small amount of extra labeled samples in the target domain are given \( D_{tl} = \{ (x_{tl}^k, y_{tl}^k) \}_{k=1}^{n_{tl}} \). The data in source and target domains are drawn from the joint distributions \( P(x_s, y_s) \) and \( Q(x_t, y_t) \) with \( P \neq Q \), respectively.

Inspired by [7,14,57,84], we build a cosine similarity based network. It consists of a feature extractor \( F \) and a classifier \( C \). The output probability can be obtained by

\[
p(x) = \sigma(\frac{\sum_k W^2 \cdot k(F(x))}{\gamma_{\text{max}}}),
\]

where \( \sigma \) indicates a softmax func-
tion, $W_C$ is classifier weights, $\ell_2(x) = \frac{x}{||x||}$ is the $\ell_2$-normalization function, and $T_{ce}$ is a temperature parameter.

Given this architecture, we build our method on the existing well-performed baseline. Generally speaking, the training objective can be summarized as

$$\ell_{ce} = -\sum_{i=1}^{K} y_i \log p(y = i|x),$$  

$$L_{baseline} = \mathbb{E}_{x \in D_1} \ell_{ce} + \lambda_{align} \mathbb{E}_{x \in D_1 \cup D_{tu}} \ell_{align},$$

where $D_1$ means labeled domain, and represents $D_s$ in UDA and $D_s \cup D_{il}$ in SSDA. $K$ is the number of classes. $\ell_{ce}$ is the standard cross-entropy loss, and $\ell_{align}$ is some specific loss to align representations across domains. Since forms of different baselines differ, we don’t give specific definition for $\ell_{align}$. $\lambda_{align}$ is the trade-off parameter.

4. Method

4.1. A Stronger Baseline

Inspired by previous works [32, 88, 93] in domain adaptation, we add FixMatch [63] to the existing method to construct a stronger baseline. Specifically, let $T(x)$ and $T'(x)$ denote the weakly and strongly augmented views for $x \in D_{tu}$, respectively. To generate more stable pseudo labels, we adopt a teacher-student framework. The teacher model (i.e., $F$ and $C$) is continuously updated by exponential moving average (EMA) [67] of the student model (i.e., $F$ and $C$). Here we use weight decay rate 0.99 for all experiments.

To obtain a pseudo-label, we first compute probability of a weak augmented view: $\hat{p}(T(x))$. Then we use $\hat{p} = \arg\max(\hat{p})$ as the pseudo label. The loss on the strongly augmented view can be presented as

$$\ell_{fm} = -\mathbb{I}(\max(\hat{p}) > \tau) \log p(y = \hat{p}|T'(x)),$$

where $\tau$ is the probability threshold. We can split the data in target domain $D_{tu}$ into $D_{tu}^h$ and $D_{tu}^l$ at each training step. The superscripts $h$ and $l$ are used to denote the high-confidence and low-confidence samples, respectively.

Although FixMatch improves the prediction consistency and provide more reliable pseudo labels, the wrong predictions are still severe due to domain discrepancy [39]. Here we follow [43, 88] to use the KLD regularization term in CRST [97]. It encourages the high-confidence output to be evenly distributed to all classes so that the prediction results do not overfit the pseudo labels.

$$\ell_{kld} = -\mathbb{I}(\max(\hat{p}) > \tau) \sum_{j=1}^{K} \frac{1}{K} \log p(y = j|T'(x_{tu})).$$

Here $\ell_{kld}$ is only applied to the high-confidence samples. Thus the overall loss function of our strong baseline can be presented as follows. Here we set $\lambda_{kld} = 0.1$ for all experiments.

$$L_{strong} = L_{baseline} + \mathbb{E}_{x \in D_{tu}^h} (\ell_{fm} + \lambda_{kld} \ell_{kld}).$$

4.2. Contrast Loss for Low-confidence Samples

Before introducing our new contrastive loss, we first review the contrastive loss used in self-supervised learning. Given an image $x_i \in D_{tu}$, we can obtain two differently augmented views $x_i^1, x_i^2$ as the query image and key image. Then the $\ell_2$-normalized features can be produced by $f_i, f_i = \ell_2(F(x_i^1)), \tilde{f}_i = \ell_2(\tilde{F}(x_i^2))$. The naive contrastive loss without other designs (e.g., projection head) can be presented as follows:

$$h(f_i, \tilde{f}_i) = \exp(\frac{f_i^T \tilde{f}_i}{T_{co}}),$$

$$\ell_{co} = -\log \frac{h(f_i, \tilde{f}_i)}{\sum_{\tilde{f}_j \in M} h(f_i, \tilde{f}_j)},$$

where $T_{co}$ is the temperature hyper-parameter for contrastive loss, and we use $h$ to denote the exponential of scaled cosine similarity. $M$ is the memory bank [15] which stores the processed features by the teacher feature extractor. Intuitively, this loss is the log form of a $(|M| + 1)$-way softmax-based classifier that tries to classify $f_i$ as $\tilde{f}_i$.

A drawback of the contrastive loss is that a pair of samples belonging to the same class could be treated as negatives. More specifically, for a balanced dataset, there are average $\frac{|M|}{K}$ samples in $M$ that belong to the same class as the query image but regarded as negative samples. This can not be changed as long as $M$ is randomly constructed, even if only high-confidence or only low-confidence samples are
considered\(^1\). However, as mentioned before, after inspecting the similarities of samples within same class and across classes, we argue that the low-confidence samples are more suitable for applying contrastive loss.

Instance discrimination contrastive loss works well in unsupervised representation learning, we tried directly applying it in feature space, but got limited improvement, which motivates us to encode task-specific semantic information. Here we propose a new strategy by re-representing the original feature with the classifier weights, where an attention mechanism is used.

\[
\text{Re}(f_i) = \sigma \left( \frac{W^C_{i} f_i}{T_{\text{re}}} \right) W_C, \quad r_i = \ell_2(\text{Re}(f_i)),
\]

\[
\text{Re}(\tilde{f}_i) = \sigma \left( \frac{W^C_{\text{re}} \tilde{f}_i}{T_{\text{re}}} \right) W_C, \quad \tilde{r}_i = \ell_2(\text{Re}(\tilde{f}_i)),
\]

where \(W_C\) and \(W^{\text{re}}_C\) are the weights of student classifier and teacher classifier. \(T_{\text{re}}\) is a temperature to scale the similarity, and we directly set \(T_{\text{re}} = T_{\text{ce}}\) without over-tuning this hyper-parameter. It should be noted that the conclusion obtained from Figure 1 still holds after feature re-representation. Here the classifier weights are regarded as the class prototypes, and we use them as a set of new coordinate to re-represent the original features. Thus the classifier weights are detached and not updated by the contrastive loss:

\[
\ell_{\text{lrco}} = - \log \frac{h(r_i, \tilde{r}_i)}{h(r_i, \tilde{r}_i) + \sum_{\tilde{r}_j \in M} h(r_i, \tilde{r}_j)},
\]

where \(M\) stores the re-represented features. Finally, the framework is shown in Fig. 2, and the overall loss is presented as

\[
\mathcal{L}_{\text{lrco}} = \mathcal{L}_{\text{strong}} + \lambda_{\text{re}} \mathbb{E}_{x \in D^{t}_{u}} \ell_{\text{lrco}}.
\]

Our feature re-representation is similar to Pronoun [19] which adopts prototype-based normalized output. The differences are two-folds: i. motivation: they aim to enhance the conditioning strength when constructing input for domain adversarial training, we aim to encode semantic information and alleviate semantic conflict. ii. They maintain global prototypes, and we directly adopt classifier weight.

### 4.3. Cross-Domain Mixup Contrastive Learning

For the low-confidence samples in the target domain, one of the reasons why they are difficult to be correctly classified is the low similarity with the source domain samples. Meanwhile, the aforementioned contrastive learning process only considers the structure of feature space in target domain and ignores the domain differences. Inspired by recent work [23, 30, 60, 95] which combine mixup [87] and contrastive learning, we propose cross-domain mixup contrastive learning to further boost the domain-shared feature learning as shown in Fig. 3. Specifically, given two differently augmented views \(x^1, x^2\) of the same image \(x_i \in D^t_u\), we randomly sample an image \(x_s\) from source domain, and also obtain two different views \(x^1_s, x^2_s\). Then we mixup the source samples and low-confidence target samples as query image. In order to make sure that the low-confidence target samples keep dominant, we adopt a similar strategy as in MixMatch [3] where a max operation is used upon the Beta distribution. Then the mixup process can be presented as

\[
\lambda \sim \text{Beta}(\alpha, \alpha), \quad \lambda' = \max(\lambda, 1 - \lambda), \quad x^m_i = \lambda x^1_i + (1 - \lambda) x^1_s
\]

where \(\alpha\) is the parameter controlling the shape of Beta distribution.

Then the mixed image \(x^m_i\) is sent to the student feature extractor, and \(x^2_s\) and \(x^2_s\) are sent to the teacher feature extractor. To obtain the the query feature \(r^m_i\) and the key feature \(\tilde{r}^m\), we conduct the following process

\[
\begin{align*}
\tilde{f}^m_i &= \ell_2(F(x^m_i)), \quad r^m_i = \ell_2(\text{Re}(\tilde{f}_i)), \\
\tilde{f}_s &= \ell_2(F(x^2_s)), \quad \tilde{r}_s = \ell_2(\text{Re}(\tilde{f}_s)), \\
\tilde{r}^m &= \lambda' \tilde{r}_i + (1 - \lambda') \tilde{r}_s.
\end{align*}
\]

Then the contrastive loss can be represented as

\[
\ell_{\text{mixlrco}} = - \log \frac{h(r^m_i, \tilde{r}^m)}{h(r^m_i, \tilde{r}^m) + h(r^m_i, \tilde{r}_s) + \sum_{\tilde{r}_j \in M} h(r^m_i, \tilde{r}_j)},
\]

where \(h\) follows the definition in Eq.(5). \(M\) still stores re-represented features of target domain low-confidence samples. This loss can be regarded as the log form of a \(|M| + 2\)-way softmax-based classifier that tries to classify \(r^m_i\) as \(\tilde{r}^m\).

We call the method combing LRCo and Mixup as MixL-
5. Experiments

5.1. Datasets and Scenarios

**Unsupervised DA:** Office-Home [70] is a challenging dataset for visual domain adaptation with 15,500 images in 65 categories. It has four significantly different domains: Artistic, Clipart, Product, and Real-World (abbr. R, C, A, and P). VisDA-2017 [52] is a large-scale dataset for synthetic-to-real domain adaptation. It contains 152,397 synthetic images for the source domain and 55,388 real-world images for the target domain.

**Semi-Supervised DA:** DomainNet [51] is initially a multi-source domain adaptation benchmark. Four domains are involved, i.e., Real, Clipart, Painting, and Sketch (abbr. R, C, P, and S). Each of them contains images of 126 categories. Office-Home consists of Real, Clipart, Art, and Product (abbr. R, C, A, and S) domains with 65 classes. For both datasets, the number of labeled target data is 1-shot or 3-shot per class.

5.2. Implementation Details

For the baseline model, we choose GVB [9] for UDA task and MME [57] for SSDA task. For the temperature \( T_{ce} \), we set it 0.03 for GVB to achieve comparable performance, and 0.05 for MME by following the original paper. The hyperparameters (denoted as \( \lambda_{align} \) in Eq.(1)) in the baseline method are directly used without any modification. As for the backbone network, we use ResNet50 [16] for UDA, and AlexNet [28] and ResNet34 [16] for SSDA.

For the strong baseline, an hyperparameter is probability threshold \( \tau \) in Eq.(2). We set \( \tau = 0.8 \) for DomainNet and \( \tau = 0.9 \) for Office-Home in the SSDA task selected by validation set. And for UDA task, we empirically control the proportion of high-confidence samples in 60%-80%.

RCo, and the final loss is presented as

\[
L_{mixlrco} = L_{strong} + \lambda_{co} \sum_{x \in D_u \cup D_t} \ell_{mixlrco}.
\] (12)

where \( \lambda_{co} \) is kept the same as in Eq. (8).

5.3. Comparison with State-of-the-Art

In this section, we compare our proposed method with other state-of-the-art methods for UDA and SSDA. Here **Source Only** in UDA task means the model trained only using labeled source data, and \( S + T \) in SSDA means the model trained by the labeled source and target data. The **Strong Baseline** represents the model denoted in Eq. (4) combining FixMatch-KLD and the used baselines (i.e., GVB [9] and MME [57]). **LRCo** represents the model corresponding to Eq. (8), and **MixLRCo** represents the model corresponding to Eq. (12).

### Table 1. Classification accuracy (%) of different UDA methods on Office-Home with ResNet-50 as backbone.

| Method                  | A→C | A→P | A→R | C→A | C→P | C→R | P→A | P→C | P→R | R→A | R→C | R→P | Acc  |
|-------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| Source-Only             | 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 |
| GVB (CVPR’20) [9]      | 57.0| 74.7| 79.8| 64.6| 74.1| 74.6| 65.2| 55.1| 81.0| 74.6| 59.7| 84.3| 70.4 |
| HDAN (NeurIPS’20) [21] | 56.8| 75.2| 79.8| 65.1| 73.9| 75.2| 66.3| 56.7| 81.8| 75.4| 59.7| 84.7| 70.9 |
| FixBi (CVPR’21) [47]   | 58.1| 77.3| 80.4| 67.7| 79.5| 78.1| 65.8| 57.9| 81.7| 76.4| 62.9| 86.7| 72.7 |
| ATDCC (CVPR’21) [37]   | 60.2| 77.8| 82.2| 68.5| 78.6| 77.9| 68.4| 58.4| 83.1| 74.8| 61.5| 87.2| 73.2 |
| MetaAlign(CVPR’21) [74] | 59.3| 76.0| 80.2| 65.7| 74.7| 75.1| 65.7| 56.5| 81.6| 74.1| 61.1| 85.2| 71.3 |
| SCDA (ICCV’21) [35]    | 60.7| 76.4| 82.8| 69.8| 77.5| 78.4| 68.9| 59.0| 82.7| 74.9| 61.8| 84.5| 73.1 |
| TCM (ICCV’21) [85]     | 58.6| 74.4| 79.6| 64.5| 74.0| 75.1| 64.6| 56.2| 80.9| 74.6| 60.7| 84.7| 70.7 |
| ToAlign (NeurIPS’21) [75]| 57.9| 76.9| 80.8| 66.7| 75.6| 77.0| 67.8| 57.0| 82.5| 75.1| 60.0| 84.9| 72.0 |
| CST (NeurIPS’21) [39]   | 59.0| 79.6| 83.4| 68.4| 77.1| 76.7| 68.9| 56.4| 83.0| 75.3| 62.2| 85.1| 73.0 |

### Table 2. Accuracies (%) of Synthetic → Real on VisDA-2017 for unsupervised domain adaptation methods using ResNet-50.

| Method                  | Acc  |
|-------------------------|------|
| GVB*                    | 74.5 |
| Strong Baseline         | 79.3 |
| LRCo (Ours)             | 81.3 |
| MixLRCo (Ours)          | 82.0 |

where \( \tau \in [0.93, 0.98] \) is used. For LRCo, there are three hyperparameters: temperature \( T_{co} \) in Eq. (5), memory bank size \( |M| \), and trade-off parameter \( \lambda_{co} \) in Eq.(8). We set \( T_{co} = 0.3 \), \( |M| = 512 \), \( \lambda_{co} = 0.5 \) for all experiments. For MixLRCo, the additional hyperparameter is \( \alpha \) of Beta distribution, and we set \( \alpha = 1.0 \) for both tasks.
in certain adaptation scenarios and drawbacks in others owing to the diversity of adaptation tasks. Since our methods are built on existing baseline, the weaknesses of baseline method are inherited to our LRCo and MixLRCo. However, for the average performance, our LRCo and MixLRCo can achieve SOTA performance.

Semi-supervised Domain Adaptation. Table 3 and Table 5 show the results on Office-Home and DomainNet, respectively. The baseline method MME is directly adopted since our architecture is the same as MME. Compared with SOTA methods, the Strong Baseline achieves comparable performance in Office-Home and relatively lower performance in larger-scale DomainNet. And our LRCo and MixLRCo can achieve new SOTA performance on both tasks.

5.4. Analysis and Discussion

Sample selection for contrastive Loss. We particularly consider different samples (i.e., high or low confidence samples) when computing contrastive loss in Sec. 4.2. Table 4 gives the results of different selections. In particular, the experiment 0 represents the Strong Baseline, and the experiment 5 is our LRCo. When the high-confidence samples appear in both positive and negative pairs (#1, 3, 7, 9), to avoid better semantic conflict, we discard the high-confidence samples in memory bank that share the same pseudo label as the high-confidence query sample. It can be seen that when adopting high-confidence samples as positive pairs (#1-3), the performance is always decreased. When the positives pairs are from low-confidence samples, the high-confidence negative samples in memory bank will hurt the performance (#4, 6). This is mainly because the high-confidence negative samples are closer to the class prototypes and the contrastive loss pushes the low-confidence samples away from them. When the positives pairs are from both low and high confidence samples (#7, 8, 9), the results cannot exceed our proposed LRCo (#5).

### Table 3. Accuracy(%) on Office-Home under the setting of 3-shot using Alexnet (A) and Resnet34 (R) as backbone networks.

| Method      | Method      | Net | 3-shot | 5-shot | 7-shot |
|-------------|-------------|-----|--------|--------|--------|
| MME (ICCV’19) [57] | Strong Baseline | A+T | 66.7 | 64.6 | 62.4 |
| APE (ECCV’20) [27] | LRCo (Ours) | A+T | 66.4 | 64.2 | 62.1 |
| CDAC (CVPR’21) [33] | MixLRCo (Ours) | A+T | 66.2 | 64.0 | 61.9 |
| ECACL-P (ICCV’21) [33] | MixLRCo (Ours) | A+T | 66.1 | 64.0 | 61.8 |
| MME (ICCV’19) [57] | Strong Baseline | R+T | 66.0 | 64.0 | 61.9 |
| APE (ECCV’20) [27] | LRCo (Ours) | R+T | 65.8 | 63.7 | 61.6 |
| CDAC (CVPR’21) [33] | MixLRCo (Ours) | R+T | 65.7 | 63.6 | 61.5 |
| ECACL-P (ICCV’21) [33] | MixLRCo (Ours) | R+T | 65.6 | 63.5 | 61.4 |

**Table 4. Accuracy of different sample selections for positive pairs and negative pairs. R→C in Office-Home is used for both UDA and SSDA.**

| # | Positive Pairs | Negative Pairs | UDA | SSDA |
|---|----------------|----------------|-----|------|
| 0 | High | Low | High | Low | 64.8 | 71.0 |
| 1 | ✓ | ✓ | ✓ | ✓ | 65.2 | 71.2 |
| 2 | ✓ | ✓ | ✓ | ✓ | 65.6 | 71.5 |
| 3 | ✓ | ✓ | ✓ | ✓ | 65.6 | 71.1 |
| 4 | ✓ | ✓ | ✓ | ✓ | 65.9 | 71.6 |
| 5 | ✓ | ✓ | ✓ | ✓ | 66.9 | 72.1 |
| 6 | ✓ | ✓ | ✓ | ✓ | 66.2 | 71.9 |
| 7 | ✓ | ✓ | ✓ | ✓ | 65.8 | 71.5 |
| 8 | ✓ | ✓ | ✓ | ✓ | 66.0 | 71.8 |
| 9 | ✓ | ✓ | ✓ | ✓ | 66.1 | 71.6 |

Necessity of re-representation. We investigate the necessity of feature re-representation in domain adaptation by comparing it with other choices. Table 6 shows the ablation results. It can be seen that our re-representation mechanism can extremely boost the performance. We also test re-representation without detaching classifier weights (i.e., update them with contrastive loss), and the performance will drop.

Different designs for MixLRCo. Our implementation for MixLRCo is non-trial since there are two key designs: a) only select the low-confidence samples in target domain for cross-domain mixup. b) keep the target domain samples dominant. The results of different choices are shown in Table 7. It can be seen that involving the target high-confidence samples always brings negative effect. When only using the target low-confidence samples, MixLRCo without target domination can achieve better performance than LRCo but lower than MixLRCo with target domination.

One may ask that the mixup of target high-confidence samples and source samples can also produce less confident samples, and why it performs worse. Here we explain it from the probabilities of different mixup samples. Fig. 4 shows the average value of the accumulation of top
### Table 5. Accuracy(%) on DomainNet under the settings of 1-shot and 3-shot using Alexnet (A) and Resnet34 (R) as backbone networks.

| Net          | Method                                      | R→C | R→P | P→C | C→S | S→P | R→S | P→R | Mean                  |
|--------------|---------------------------------------------|-----|-----|-----|-----|-----|-----|-----|-----------------------|
| S+T          | Source only                                 | 43.5| 47.1| 42.4| 45.0| 40.1| 44.9| 33.6| 36.4                  |
|              | Strong Baseline                             | 56.9| 59.9| 56.0| 57.2| 50.8| 54.6| 42.5| 47.3                  |
|              | MixLRCo (Ours)                              | 59.8| 64.0| 57.1| 59.1| 55.5| 62.8| 46.9| 51.4                  |
|              | MixLRCo (Ours)                              | 61.2| 64.4| 58.7| 59.8| 57.9| 63.8| 46.2| 52.4                  |
|              | Strong Baseline                             | 55.6| 60.0| 60.6| 62.2| 58.8| 59.4| 50.8| 55.0                  |
|              | Strong Baseline                             | 71.7| 73.9| 67.1| 69.1| 62.8| 73.0| 63.7| 66.3                  |
|              | Strong Baseline                             | 70.4| 76.6| 70.8| 72.1| 72.9| 76.7| 56.7| 63.1                  |
|              | Strong Baseline                             | 77.4| 79.6| 74.2| 75.1| 75.5| 79.3| 67.6| 69.9                  |
|              | Strong Baseline                             | 64.6| 65.9| 70.7| 72.2| 80.3| 80.8| 74.0| 75.2                  |
|              | Strong Baseline                             | 76.1| 77.7| 75.1| 75.7| 71.0| 76.4| 63.7| 69.7                  |
|              | Strong Baseline                             | 73.0| 75.7| 72.0| 72.9| 71.7| 75.6| 63.0| 66.3                  |
|              | Strong Baseline                             | 75.3| 79.0| 74.1| 77.3| 75.3| 79.4| 65.0| 70.6                  |
|              | Strong Baseline                             | 55.7| 60.2| 57.1| 59.4| 54.0| 58.2| 50.8| 55.0                  |
|              | Original feature                            | 64.8| 71.0| 65.7| 71.4| 66.2| 71.6| 66.9| 72.1                  |
|              | Re-representation (LRCo) w/o detach          |     |     |     |     |     |     |     |                      |
|              | Re-representation (LRCo)                     | 66.9| 72.1|     |     |     |     |     |                      |

### Table 6. Accuracy comparison of the original features and re-represented features in contrastive learning. R→C in Office-Home is used for both UDA and SSDA.

| Method                                      | UDA  | SSDA |
|---------------------------------------------|------|------|
| Strong Baseline                             | 64.8 | 71.0 |
| Original feature                            | 65.7 | 71.4 |
| Re-representation (LRCo) w/o detach          | 66.2 | 71.6 |
| Re-representation (LRCo)                     | 66.9 | 72.1 |

### Table 7. Accuracy of different designs for MixLRCo. R→C in Office-Home is used for both UDA and SSDA.

| #   | Target Samples | Target Domination | UDA  | SSDA |
|-----|----------------|-------------------|------|------|
| 0   |                |                   | 66.9 | 72.1 |
| 1   | ✓              |                   | 65.8 | 71.3 |
| 2   | ✓              | ✓                 | 65.9 | 71.5 |
| 3   | ✓              | ✓                 | 67.4 | 72.5 |
| 4   | ✓              | ✓                 | 67.7 | 73.1 |
| 5   | ✓              | ✓                 | 66.7 | 72.1 |
| 6   | ✓              | ✓                 | 67.0 | 72.3 |

### Figure 4. The accumulation of largest \( k \in \{1, 2, \ldots, 10\} \) probabilities of different mixed samples.

### Figure 5. The feature TSNE visualization under UDA Office-Home R→C.

### 6. Conclusion

In this paper, we propose a novel contrastive learning framework for unsupervised domain adaptation (UDA) and semi-supervised domain adaptation (SSDA) by exploiting the low-confidence samples in the target domain and making use of classifier weights to re-represent the features. Our proposed method can effectively alleviate the semantic conflict problem of the original contrastive loss. Furthermore, we propose to integrate the cross-domain mixup into contrastive learning, which can help to reduce the domain gap and further boost the performance. Extensive experiments show the effectiveness of the proposed method, which can achieve state-of-the-art UDA and SSDA performance.
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