Less Confusion More Transferable:
Minimum Class Confusion for Versatile Domain Adaptation

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Abstract

Domain Adaptation (DA) transfers a learning model from a labeled source domain to an unlabeled target domain which follows different distributions. There are a variety of DA scenarios subject to label sets and domain configurations, including closed-set and partial-set DA, as well as multi-source and multi-target DA. It is notable that existing DA methods are generally designed only for a specific scenario, and may underperform for scenarios they are not tailored to. Towards a versatile DA method, a more universal inductive bias other than the domain alignment should be explored. In this paper, we delve into a missing piece of existing methods: class confusion, the tendency that a classifier confuses the predictions between the correct and ambiguous classes for target examples. We unveil that less class confusion explicitly indicates more class discriminability and implicitly implies more domain transferability in all the above scenarios.

Based on the more universal inductive bias, we propose a general loss function: Minimum Class Confusion (MCC). It can be characterized by (1) a non-adversarial DA method without explicitly deploying domain alignment, enjoying fast convergence speed (about $3 \times$ faster than mainstream adversarial methods); (2) a versatile approach that can handle Closed-Set, Partial-Set, Multi-Source, and Multi-Target DA, outperforming the state-of-the-art methods in these scenarios, especially on the largest and hardest dataset to date (7.25% on DomainNet). In addition, it can also be used as a general regularizer that is orthogonal and complementary to a variety of existing DA methods, accelerating convergence and pushing those readily competitive methods to a stronger level. We will release our code for reproducibility.

1. Introduction

Deep Neural Network (DNN) excels at learning discriminative representations from a large set of labeled data, leading to unprecedented successes in a wide range of machine learning tasks [6, 29, 14]. However, DNN often suffers from the scarcity of labeled data in real-world applications.
Figure 2. The error matrix of different models on Visda-2017 [35]. (a)–(b): Source Only model tested on the source and target domains, indicating severe class confusion of examples on the target domain. (c)–(d): Models trained with entropy minimization (MinEnt) [12] and MCC respectively, showing that MCC can largely alleviate class confusion on the target domain and performs much better than MinEnt.

DA (PDA) [2, 55] where the source label set subsumes the target one, Multi-Source DA (MSDA) [59, 51] with multiple source domains, and Multi-Target DA (MTDA) [34] with multiple target domains. As existing UDA methods cannot be directly applied to these challenging scenarios, various methods [2, 3, 55, 51, 34] have been proposed for each specific scenario. With well-designed architectures or losses, these methods work quite well in their own scenarios.

However, in practical applications, complicated data acquired in the real-world makes it difficult to confirm the label sets and domain configurations. Therefore, we may be stuck in choosing a proper method tailored to the right DA scenario. The most ideal solution to escape from this dilemma is a versatile DA method that can handle all the above scenarios. Unfortunately, existing DA methods are generally designed only for a specific scenario and may underperform for scenarios they are not tailored to. For instance, PADA [3], a classic PDA method, excels at selecting out outlier classes, but suffers from internal domain shift in MSDA and MTDA and underperforms in these scenarios, while DADA [34], an outstanding method tailored to MTDA, cannot be directly applied to PDA or MSDA. Therefore, incapable of being directly applied into other scenarios, existing DA methods are not versatile enough to meet the practical requirements.

Towards a versatile DA method, a more universal induc- tive bias other than the domain alignment should be explored. In this paper, we delved into the error matrices of the target domain and found that the classifier trained on the source domain may confuse to distinguish the correct class from a similar class, such as car and truck. As shown in Figure 2(b), the probability that a source-only model misclassifies cars as trucks on the target domain is over 25%. Further, we analyzed the error matrices in other DA scenarios and drew the same conclusion. These findings give us a fresh perspective to tackle domain adaptation: class confusion, the tendency that a classifier confuses the predictions between the correct and ambiguous classes for target examples.

Further, we unveil that less class confusion explicitly indicates more class discriminability and implicitly implies more domain transferability in all the above scenarios. However, we still need to face a new challenge that the ground-truth class confusion needs to be calculated based on the labels in the target domain, which is inaccessible in UDA. Fortunately, an instance weighted inner product of the classifier predictions with their transposes naturally reveal the confusion relationship between different classes. Therefore, we can define class confusion from this perspective, enabling it to be computed just based on the classifier predictions. To this end, we propose a novel loss function: Minimum Class Confusion (MCC), which can be characterized as a novel and versatile DA approach without explicitly deploying feature alignment, enjoying fast convergence speed. In addition, it can also be used as a general regularizer that is orthogonal and complementary to various existing DA methods, further accelerating and improving those readily competitive methods. Our contributions are summarized as follows:

- We unveil that class confusion is a common missing piece of existing DA methods and discover that less class confusion implies more transferability.
- We propose a novel loss function: Minimum Class Confusion (MCC), which is versatile to handle four different DA scenarios, including closed-set, partial-set, multi-source, and multi-target.
- We conduct extensive experiments on four standard datasets, and demonstrate that MCC can outperform the state-of-the-art methods in four DA scenarios, especially on the largest and hardest dataset to date (7.25% on DomainNet). It also enjoys an obvious (about 3×) faster convergence speed than mainstream DA methods.

2. Related Work

Unsupervised Domain Adaptation (UDA). Most existing domain adaptation researches focus on UDA, giving birth to many competitive methods. Most mainstream UDA methods based on DNNs can be classified into two categories: (1) Moment Matching and (2) Adversarial Training.

(1) Moment Matching methods aim to minimize the distribution discrepancy between the two domains. Deep
Coral [43] align second-order statistics of the two distributions. DDC [47] and DAN [23] utilizes Maximum Mean Discrepancy [13], JAN [26] leverages Joint Maximum Mean Discrepancy. SWD [20] introduces Sliced Wasserstein Distance and CAN [19] uses Contrastive domain discrepancy.

(2) Adversarial Training methods borrow the spirit of Generative Adversarial Network [11], aiming at learning domain invariant features in an adversarial manner. DANN [8] introduces a domain discriminator to distinguish source and target features, while the feature extractor strives to fool the domain discriminator. ADDA [46], MADA [32] and MCD [39] extends such architecture to multiple feature extractors and classifiers. Akin to Conditional Generative Adversarial Networks [28], CDAN [24] proposes to align features in a conditional adversarial manner. CyCADA [16] adapts features in both pixel and feature level. TADA [50] proposes a transferable attention mechanism. SymNet [57] introduces a symmetric classifier, and DTA [21] learns discriminative features with adversarial dropout.

Recently, other novel methods are proposed to tackle domain adaptation from new perspectives. For instance, SE [7] is based on teacher-student [44] model. TPN [31] introduces a prototypical network. TAT [22] proposes a novel transferable adversarial training method. BSP [5] penalizes the largest singular values of features in order to boost feature discriminability. AFN [52] unveils that those features with larger norm are more transferable and enlarges feature norm. Some methods [42, 18, 60, 61] also utilize self-training or pseudo label. These methods enlighten the road of domain adaptation from new perspectives.

Partial Domain Adaptation (PDA). In PDA, the target label space is a subspace of source label space, deteriorating negative transfer [30]. SAN [2], IWAN [55]. PADA [3] and ETN [4] introduces various weighting mechanisms to select out outlier classes in the source domain, while AFN [52] enlarges feature norms to alleviate negative transfer.

Multi-Source Domain Adaptation (MSDA). In MSDA, there are multiple source domains that may be significantly different. MDAN [59] provides solid theoretical insights for MSDA. Deep Cocktail Network [51] (DCTN) introduces a k-way domain classifier while M^3SDA [33] proposed a moment-matching model for MSDA.

Multi-Target Domain Adaptation (MTDA). In MTDA, multiple target domains are included. DADA [34] enjoys strong performance in this task by learning domain-invariant features with well-designed network architecture and losses.

In this paper, we aim at proposing a versatile method for all the four scenarios above and compare its performance with these state-of-the-art methods respectively.

3. Approach

In this paper, we aim at proposing a novel loss function, Minimum Class Confusion (MCC), as a versatile approach to four domain adaptation scenarios. (1) Unsupervised Domain Adaptation (UDA) [8], the standard scenario, constitutes a labeled source domain $\mathcal{S} = \{(x_i^s, y_i^s)\}_{i=1}^n$ and an unlabeled target domain $\mathcal{T} = \{x_i^t\}_{i=1}^n$, where $x^s$ is an example and $y_i^s$ is the associated label. (2) Partial Domain Adaptation (PDA) [3] extends UDA by letting the source domain labeled set subsume the target domain label set. (3) Multi-Source Domain Adaptation (MSDA) [33] extends UDA by expanding to S labeled source domains $\{S_1, S_2, ..., S_3\}$. (4) Multi-Target Domain Adaptation (MTDA) [34] extends UDA by expanding to T unlabeled target domains $\{T_1, T_2, ..., T_T\}$. Hereafter, we denote by $a_i$, $a_j$, and $A_{ij}$ the i-row, the j-th column and the $ij$-th entry of matrix $A$ respectively.

3.1. Minimum Class Confusion

To minimize class confusion, we need to find out some proper criteria to measure the pairwise class confusion on the target domain. Different from previous methods such as CORAL [43] that place focus on features, we explore the classifier predictions. First, we denote the classifier output of the target domain as $\hat{Y}_i = G(F(X_i)) \in \mathbb{R}^{B \times |C|}$, where $B$ is the batch size of the target data, $|C|$ is the number of source classes, $F$ is the feature extractor and $G$ is the classifier. We focus on the classification predictions $\hat{Y}$ and omit the domain subscript $t$ for clarity. The probability $\hat{Y}_{ij}$ that the i-th instance belongs to the j-th class is given by

$$\hat{Y}_{ij} = \frac{\exp (Z_{ij}/T)}{\sum_{j=1}^{|C|} \exp (Z_{ij}/T)},$$

where $Z_{ij}$ is the logit output of the classifier layer (before the softmax function) and $T$ is the temperature [15] for scaling. Obviously, Eq. (1) boils down to the vanilla softmax function when $T = 1$. Hence, $\hat{Y}_{ij}$ reveals the relationship between the i-th instance and the j-th class. A natural question arises: Can we quantify the class confusion relationship by using $\hat{Y}$? This paper gives a positive answer.

First, we note that the examples in the target domain are not equally important for computing class confusion. Those examples with higher certainty in class predictions given by the classifier are more reliable and should contribute more to the pairwise class confusion. We use the entropy functional $H(p) \triangleq -\sum p \log p$ in information theory as an uncertainty measure of distribution $p$. The entropy (uncertainty) $H(\hat{Y}_{i})$ of predicting the i-th example by the classifier is defined as

$$H(\hat{Y}_{i}) = -\sum_{j=1}^{C} \hat{Y}_{ij} \log \hat{Y}_{ij},$$

While the entropy is a measure of uncertainty, what we want is a probability distribution that places a larger probability on the examples with larger certainty of class predictions. A
where $\mathbf{W}$ is the corresponding diagonal matrix. Note that we take the de facto transformation to probability is the softmax function

$$W_{ii} = \frac{B (1 + \exp(-H(\hat{y}_i)))}{\sum_{i' = 1}^{B} (1 + \exp(-H(\hat{y}_{i'})))}, \quad (3)$$

where $W_{ii}$ is the probability quantifying the importance of the $i$-th example for computing the class confusion, and $\mathbf{W}$ is the corresponding diagonal matrix. Note that we take the opposite value of the entropy to reflect the certainty. Laplace Smoothing [41] (i.e. adding a constant 1 to each addend of the softmax function) is used to form a heavier-tailed weight distribution, which is suitable for highlighting more certain examples as well as avoiding overly penalizing the others. For better manipulation, the probability over the examples in each batch of size $B$ is rescaled to sum up to $B$ such that the average weight for each example is 1.

Second, we recall that $\hat{Y}$ reveals the relationship between the $i$-th example and the $j$-th class. By prioritizing on the examples with more certain class predictions, we define the pairwise class confusion between two classes $j$ and $j'$ as

$$C_{jj'} = \hat{y}_j^\top \mathbf{W} \hat{y}_{j'}. \quad (4)$$

Let's delve into the definition of the class confusion in Eq. (4). Note that $\hat{y}_j$ denotes the probabilities of the $B$ examples in each batch to come from the $j$-th class. The class confusion is defined as the inner product between $\hat{y}_j$ and $\hat{y}_{j'}$ weighted by $\mathbf{W}$, the certainties of class predictions for the $B$ examples. So it measures the possibility of simultaneously classifying the $B$ examples into the $j$-th and the $j'$-th classes.

The batch-based definition of the class confusion in Eq. (4) is native for the mini-batch SGD optimization. However, when the number of classes is large, it will run into a severe class imbalance in each batch. To tackle this problem, we adopt a normalization technique widely used in Random Walk [49]:

$$\tilde{C}_{jj'} = \frac{C_{jj'}}{\sum_{j''=1}^{|C|} C_{jj''}}. \quad (5)$$

Taking the idea of Random Walk, the normalized class confusion in Eq. (5) has a neat interpretation: It is probable to walk from one class to another (resulting in wrong classification) if the two classes have a high class confusion.

Finally, let's come back to designing the final loss. Recall that $\tilde{C}_{jj'}$ well measures the confusion between classes $j$ and $j'$. We only need to minimize the cross-class confusion, i.e. $j \neq j'$. In other words, the ideal situation is that no examples are ambiguously classified into two classes at the same time. We define the Minimum Class Confusion (MCC) loss as

$$L_{MCC}(\hat{Y}_t) = \sum_{j=1}^{|C|} \sum_{j' \neq j} |C_{jj'}|. \quad (6)$$

Since the class confusion in Eq. (5) has been normalized, minimizing the between-class confusion in Eq. (6) readily implies that the within-class confusion is maximized. Eq. (6) is a universal loss that is pluggable to all existing approaches.

### 3.2. Less Confusion More Transferable

Based on the proposed Minimum Class Confusion (MCC) loss function, we further elaborate a more universal inductive bias towards designing versatile domain adaptation methods: less confusion, more discriminable, and more transferable.

- It is intuitively reasonable that when the classes are less confused, they are more easily discriminated.
Our key observation is that, if the labels are available in both source and target domains, we can train a joint network with the cross-entropy loss. Then the features learned by the network from both domains will be implicitly aligned with the class supervision (supported by the oracle results of A-distance in Figure 7), not requiring explicit feature alignment. This is a strong inductive bias of deep networks with built-in transferability.

Since the labels are unavailable in the target domain, we only add the cross-entropy loss in the source domain, and impose our MCC loss in the target domain to boost the discriminability. Based on the built-in transferability of deep networks, the representations of the same class from the source and target domains will be implicitly aligned by MCC, thereby boosting the transferability.

The above propositions will be justified in the empirical studies (Section 4). We want to emphasize that the inductive bias of less confusion in this work is more universal than that of domain alignment in prior work. As discussed in Section 2, many prior methods explicitly align features from the source and target domains, facing the risk of deteriorating the feature discriminability and impeding the transferability [5]. Further, the inductive bias of less confusion is general and applicable to a variety of domain adaptation scenarios, while that of domain alignment will suffer when the domains cannot be aligned naturally (e.g. the partial-set DA scenarios).

3.3. Versatile Approach to Domain Adaptation

The main motivation of the MCC loss is to design a versatile approach to a variety of domain adaptation scenarios. As elaborated above, by combining the cross-entropy loss on the source domain labeled data and the MCC loss on the target domain unlabeled data, the deep network will be guided to explicitly improve the discriminability of the target data and implicitly boost the transferability across domains. Hence, there is no need for explicit feature alignment.

Denote by \( \hat{y}_s = G(F(x_s)) \) the class prediction for each source domain instance \( x_s \), by \( \hat{y}_t = G(F(x_t)) \) the class predictions for a batch (size \( B \)) of target domain instances \( X_t \). The versatile approach (termed also by MCC) proposed for a variety of domain adaptation scenarios is formulated as

\[
\min_{F,G} \mathbb{E}_{(x_s,y_s) \in S} L_{CE}(\hat{y}_s, y_s) + \mu \mathbb{E}_{X_t \subset T} L_{MCC}(\hat{y}_t), \tag{7}
\]

where \( L_{CE} \) is the cross-entropy loss, \( \mu \) is a hyper-parameter for the importance of the MCC loss. With the joint loss, the feature extractor \( F \) and the classifier \( G \) of the deep adaptation model are trained end-to-end by back-propagation.

The deep adaptation model in Eq. (7), without any extra modifications or techniques, is versatile enough to tackle the four typical domain adaptation scenarios.

- **Unsupervised Domain Adaptation (UDA).** Eq. (7) is formulated natively for this vanilla scenario.
- **Partial Domain Adaptation (PDA).** Since no explicit domain alignment is deployed, there is no worry about the misalignment between source outlier classes and target classes as [3]. Hence, Eq. (7) can also be directly applied to PDA. In PDA, the source label set subsumes the target label set, and the MCC loss is computed on \( \hat{Y}_t \in \mathbb{R}^{B \times |C|} \) (\(|C|\) is the number of source classes). However, compared to the confusion between the target classes, the confusion between the source outlier classes on the target domain will be negligible in the MCC loss.

- **Multi-Source Domain Adaptation (MSDA).** Prior methods of MSDA consider multiple source domains as different domains, capturing the internal source domain shifts, and a simple merge of all source domains proves fragile. However, based on the built-in transferability in Section 3.2, we can safely merge \( S \) source domains as \( S \leftarrow S_1 \cup \cdots \cup S_S \) to enable implicit domain alignment, yielding a much simpler but effective MSDA approach.

- **Multi-Target Domain Adaptation (MTDA).** Based on similar idea as MSDA, also note that the MCC loss is the same for different target domains, we can safely merge \( T \) target domains as \( T \leftarrow T_1 \cup \cdots \cup T_T \) to enable implicit domain alignment.

We will show by empirical studies that Eq. (7), without extra modifications, is simple and effective for all scenarios.

3.4. Regularization to Existing DA Methods

Since the MCC loss is defined on the target domain with the less confusion inductive bias, which is different from the widely used domain alignment inductive bias, our method is naturally orthogonal and complementary to the previous methods, pushing those already competitive methods to a stronger level. The MCC loss in Eq. (6) can be serving as a regularization term pluggable into existing methods.

Take the domain alignment framework [8] based on the adversarial training as an example, integrating the MCC loss:

\[
\min_{F,G} \max_D \mathbb{E}_{(x_s,y_s) \in S} L_{CE}(\hat{y}_s, y_s) + \mu \mathbb{E}_{X_t \subset T} L_{MCC}(\hat{y}_t) - \lambda \mathbb{E}_{x \in S \cup T} L_{CE}(D(f), d), \tag{8}
\]

where the last equation stands for the domain discriminator \( D \) that strives to distinguish the source from the target, and \( d \) is the domain label, \( f = F(x) \) is the features learned to confuse the domain discriminator. The overall framework is a minimax game between two players \( F \) and \( D \) with \( \lambda \) to be the balancing hyper-parameter. Note that the classifier \( G \) is not involved in the adversarial training, hence it is easy to directly integrate the MCC loss into the framework. The MCC
loss can also be readily integrated into other representative frameworks e.g. moment matching [23] and large norm [52].

4. Experiments

We evaluate MCC with many state-of-the-art transfer learning methods on MTDa, MSDa, PDA and UDA scenarios. We will release our code for reproducibility.

4.1. Setup

We used four real-world datasets: (1) Office-31 [37]: a classical domain adaptation dataset with 31 categories and 3 domains: Amazon (A), Webcam (W) and DSLR (D); (2) Office-Home [48]: a more difficult dataset with 65 categories and 4 domains: Art (A), Clip Art (C), Product (P) and Real World (R). The domain gap of Office-Home is significantly larger than that of Office-31; (3) VisDA-2017 [35]: a simulation-to-real dataset with 12 categories and more than 280,000 images, and (4) DomainNet [33]: the largest and hardest domain adaptation dataset till now, with approximately 0.6 million images from 345 categories and 6 domains: Clipart (C), Infograph (I), Painting (P), Quickdraw (Q), Real (R) and Sketch (S).

Our methods were implemented based on PyTorch. Deep Embedded Validation (DEV) [54] was conducted to select hyper-parameters. Then, we set $\mu = 1.0$ in all experiments, which generally works well as the value of MCC is comparable to cross-entropy loss. For a fair comparison, we report the results of other algorithms according to the original paper. We run each experiment for 5 times.

4.2. Results

Multi-Target Domain Adaptation. The performance of MCC in MTDa is evaluated on DomainNet, the most difficult dataset to date. As shown in Table 1, many competitive methods are not effective in this challenging dataset. However, our simple yet effective method outperforms the current state-of-the-art method DADA [34] by a big margin (7.3%).

Multi-Source Domain Adaptation. When evaluated our method in MSDa, we adopt the source combine strategy for MCC and compare it with existing DA algorithms that are specifically designed for MSDa on DomainNet. As shown in Table 2, source combine strategy is fragile for MSDa as many mainstream DA methods suffer from negative transfer. However, with such a naive strategy, MCC can significantly outperform M$^3$SDA [33], the state-of-the-art method tailored to MSDa scenario, by a big margin (5.0%).

Partial Domain Adaptation. Since the existence of outlier source classes, PDA is known as a challenging scenario. For a fair comparison, we follow the setting in PADA [3] and AFN [52], where the first 25 categories in alphabetic order are taken as the target domain. As shown in Table 3, our method on Office-Home can also outperform AFN [52] which is the strongest PDA method to date.

Unsupervised Domain Adaptation. We evaluate MCC in UDA on standard benchmark datasets. (1) Visda-2017. As reported in Table 4, when applied as a domain adaptation method, MCC surpass the state-of-the-art UDA algorithms. (2) Office-31. As shown in Table 6 (standard deviation is reported in the supplementary material), MCC can outperform all the other algorithms. It is noteworthy that MCC does not induce any additional learnable parameters, while other algorithms may involve complicated network architectures with extra parameters and training skills.

4.3. Analyses

A General Regularizer. In addition, MCC can be used as a regularization term for various DA methods. We apply it to mainstream domain adaptation methods, and compare its performance with entropy minimization (MinEnt) [12] and Batch Spectral Penalization (BSP) [5]. As shown in Table 5 and Table 7 (standard deviation is reported in the supplementary material), MCC implies larger improvements than MinEnt and BSP to various kinds of DA methods. It is noteworthy that MCC can push the accuracy of CDAN to a higher level of over 80% on Visda-2017.

Convergence Speed. We show the accuracy curve of the whole training procedure in Figure 5. MCC enjoys faster convergence speed. Besides, when used as a regularization term for existing domain adaptation methods, MCC can also largely accelerate convergence. Totally, both MinEnt and BSP take approximately 10000 iterations to converge, while MCC takes about 2500 iterations, which is about 3 $\times$ faster.

Synthetic Dataset. We explore the performance of MCC on Two Moon, whose target samples are generated by rotating the source samples by 30°. We plot the decision boundary of the classifiers to compare the performance of MCC
Table 3. Accuracy (%) on Office-Home for PDA (ResNet-50).

| Method (S:T) | A:C  | A:P  | A:R  | C:A  | C:P  | C:R  | P:A  | P:C  | P:R  | R:A  | R:P  | Avg  |
|--------------|------|------|------|------|------|------|------|------|------|------|------|------|
| ResNet [14]  | 38.6 | 60.8 | 75.2 | 39.9 | 48.1 | 52.9 | 49.7 | 30.9 | 70.8 | 65.4 | 41.8 | 53.7 |
| DAN [23]     | 44.4 | 61.8 | 74.5 | 41.8 | 54.2 | 54.1 | 46.9 | 38.1 | 68.4 | 64.4 | 51.5 | 74.3 |
| JAN [26]     | 45.9 | 61.2 | 68.9 | 50.4 | 59.7 | 61.0 | 45.8 | 43.4 | 70.3 | 63.9 | 52.4 | 76.8 |
| PADA [3]     | 51.2 | 67.0 | 78.7 | 52.2 | 53.8 | 59.0 | 52.6 | 43.2 | 78.8 | 73.7 | 56.6 | 77.1 |
| AFN [52]     | 58.9 | 76.3 | 81.4 | 70.4 | 73.0 | 77.8 | 72.4 | 55.3 | 80.4 | 75.8 | 60.4 | 79.9 |
| MCC          | 57.5 | 82.0 | 86.4 | 70.7 | 70.6 | 78.2 | 76.5 | 61.7 | 86.5 | 82.0 | 64.5 | 84.0 |

Table 4. Accuracy (%) on VisDA-2017 for UDA (ResNet-101).

| Method | plane | bcybl | bus | car  | horse | knife | mcyle | person | plant | sktbrd | train | truck | mean  |
|--------|-------|-------|-----|------|-------|-------|-------|--------|-------|--------|-------|-------|-------|
| ResNet [14] | 55.1  | 53.3  | 61.9 | 59.1  | 80.6  | 17.9  | 79.7  | 31.2  | 81.0  | 26.5  | 73.5  | 8.5   | 52.4  |
| MinEnt [12] | 80.3  | 75.5  | 75.8 | 48.3  | 77.9  | 27.3  | 69.7  | 40.2  | 46.5  | 46.6  | 79.3  | 16.0  | 57.0  |
| DANN [8]  | 81.9  | 77.7  | 82.8 | 44.3  | 81.2  | 29.5  | 65.1  | 28.6  | 51.9  | 54.6  | 82.8  | 7.8   | 57.4  |
| DAN [23]  | 87.1  | 63.0  | 76.5 | 42.0  | 90.3  | 42.9  | 85.9  | 53.1  | 49.7  | 36.3  | 85.8  | 25.8  | 71.9  |
| MCD [39] | 87.0  | 60.9  | 83.7 | 64.0  | 88.9  | 79.6  | 84.7  | 76.9  | 88.6  | 40.3  | 83.0  | 25.8  | 71.9  |
| CDAN [24] | 85.2  | 66.9  | 83.0 | 50.8  | 84.2  | 74.9  | 88.1  | 74.5  | 83.4  | 76.0  | 81.9  | 38.0  | 73.9  |
| ADR [38] | 87.8  | 79.5  | 83.7 | 65.3  | 92.3  | 61.8  | 88.9  | 73.2  | 87.8  | 60.0  | 85.5  | 32.3  | 74.8  |
| AFN [52] | 93.6  | 61.3  | 84.1 | 70.6  | 94.1  | 79.0  | 91.8  | 79.6  | 89.9  | 55.6  | 89.0  | 24.4  | 76.1  |
| MCC      | 88.1  | 80.3  | 80.5 | 71.5  | 90.1  | 93.2  | 85.0  | 71.6  | 89.4  | 73.8  | 85.0  | 36.9  | 78.8  |

Figure 4. Decision boundaries of Two Moon dataset where blue points indicate target domain, and different classes of the source domain are shown in purple and yellow. MCC attains a better decision boundary than MinEnt.

Figure 5. Training curves and \( \epsilon_{\text{ideal}} \) values. MCC enjoys higher convergence speed and shows lower \( \epsilon_{\text{ideal}} \) values, which implies higher feature discriminability.

**Feature Discriminability.** Ben-David et al. [1] derived the expected error \( \mathbb{E}_T(h) \) of a hypothesis \( h \) on the target domain \( \mathbb{E}_T(h) \leq \mathbb{E}_S(h) + \frac{1}{2} d_{H\Delta H}(S, T) + \epsilon_{\text{ideal}} \) by three terms: (a) expected error of \( h \) on the source domain, \( \mathbb{E}_S(h) \); (b) the A-distance \( d_{H\Delta H}(S, T) \), a measure of domain discrepancy; and (c) the error \( \epsilon_{\text{ideal}} \) of the ideal joint hypothesis \( h^* \) on both source and target domains. BSP [5] states out that \( \epsilon_{\text{ideal}} \) represents the feature discriminability. As Figure 5 shows, the \( \epsilon_{\text{ideal}} \) value of MCC is lower than that of mainstream DA methods. When used as a regularizer, MCC can attain a lower \( \epsilon_{\text{ideal}} \) value than MinEnt [12] and BSP [5], revealing that MCC can further enhance feature discriminability.

**Hyperparameter Sensitivity.** Temperature scaling \( T \) and the trade-off \( \mu \) of regularization term are the only two hyperparameters of MCC and MinEnt when applying them to existing DA methods. We take hyper-parameters around the optimal hyper-parameter \([T^*, \mu^*]\) for each regularizer to test its hyperparameter sensitivity. Consider the task \( A \rightarrow W \).
Table 5. Accuracy (%) on VisDA-2017 as a regularizer for UDA (ResNet-101).

| Method       | A-W | D-W | W-D | A-D | D:A | W:A | Avg |
|--------------|-----|-----|-----|-----|-----|-----|-----|
| DANN [8]     |     |     |     |     |     |     |     |
| CDAN [24]    |     |     |     |     |     |     |     |
| DANN + BSP [5] |   |     |     |     |     |     |     |
| DANN + MCC   |     |     |     |     |     |     |     |
| AFN [52]     |     |     |     |     |     |     |     |
| JAN [26]     |     |     |     |     |     |     |     |
| MADA [32]    |     |     |     |     |     |     |     |
| MinEnt [12]  |     |     |     |     |     |     |     |
| SimNet [36]  |     |     |     |     |     |     |     |
| GTA [40]     |     |     |     |     |     |     |     |
| CDAN [24]    |     |     |     |     |     |     |     |
| MCC          | 95.4 | 98.6 | 100.0 | 95.6 | 72.6 | 73.9 | 89.4 |

Figure 6. The hyper-parameter sensitivity $A \rightarrow W$ on Office-31. The performance of MCC is above 94% under different hyper-parameters, while that of MinEnt collides under some parameters near the optimal ones, showing that MCC is less sensitive to hyper-parameters and consistently better than MinEnt.

Table 6. Accuracy (%) on Office-31 for UDA (ResNet-50).

| Method       | A-W | D-W | W-D | A-D | D:A | W:A | Avg |
|--------------|-----|-----|-----|-----|-----|-----|-----|
| ResNet [14]  |     |     |     |     |     |     |     |
| DAN [23]     | 80.5 | 97.1 | 99.6 | 78.6 | 63.6 | 62.8 | 80.4 |
| RTN [25]     | 84.5 | 96.8 | 99.4 | 77.5 | 66.2 | 64.8 | 81.6 |
| DANN [8]     | 82.0 | 96.9 | 99.1 | 79.7 | 68.2 | 67.4 | 82.2 |
| ADDA [46]    | 86.2 | 96.2 | 98.4 | 77.8 | 69.5 | 68.9 | 82.9 |
| JAN [26]     | 85.4 | 97.4 | 99.8 | 84.7 | 68.6 | 70.0 | 84.3 |
| MADA [32]    | 90.0 | 97.4 | 99.6 | 87.8 | 70.3 | 66.4 | 85.2 |
| MinEnt [12]  | 92.5 | 98.0 | 99.8 | 92.6 | 70.3 | 63.1 | 86.1 |
| SimNet [36]  | 88.6 | 98.2 | 99.7 | 85.3 | 73.4 | 71.6 | 86.2 |
| GTA [40]     | 89.5 | 97.9 | 99.8 | 87.7 | 72.8 | 71.4 | 86.5 |
| CDAN [24]    | 94.1 | 98.6 | 100.0 | 92.9 | 71.0 | 69.3 | 87.7 |
| MCC          | 95.4 | 98.6 | 100.0 | 95.6 | 72.6 | 73.9 | 89.4 |

Figure 7. A-Distance [1] and t-SNE visualization of features of the last $fc$-layer of task $A \rightarrow W$ on Office-31 in UDA scenario and task $P \rightarrow R$ on Office-Home in PDA scenario. Gray: Source Outlier Classes, Blue: Source Share Classes, Red: Target Classes.

Specifically deploying feature alignment, MCC can make features much more transferable across domains. More visualization results are included in the supplementary material.

### 5. Conclusion

In this paper, we unveil that less class confusion implies more transferability, which is a general discovery for Versatile Domain Adaptation. To this end, we propose a novel loss function: Minimum Class Confusion (MCC). MCC can be applied as a versatile domain adaptation method that can handle various DA scenarios. Extensive empirical results prove that our method can outperform state-of-the-art methods in four DA scenarios respectively, enjoying faster convergence. Meanwhile, MCC can also be used as a general regularizer for existing domain adaptation methods, further improving performance and accelerating training.
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