MiniMax Entropy Network: Learning Category-Invariant Features for Domain Adaptation

Chaofan Tao¹, Fengmao Lv¹, Lixin Duan¹* and Min Wu²
¹Big Data Research Center, University of Electronic Science and Technology of China
²Institute for Infocomm Research, A*STAR
{tcftrees, lxduan}@gmail.com, fengmaolv@126.com, wumin@i2r.a-star.edu.cn

Abstract

How to effectively learn from unlabeled data from the target domain is crucial for domain adaptation, as it helps reduce the large performance gap due to domain shift or distribution change. In this paper, we propose an easy-to-implement method dubbed MiniMax Entropy Networks (MMEN) based on adversarial learning. Unlike most existing approaches which employ a generator to deal with domain difference, MMEN focuses on learning the categorical information from unlabeled target samples with the help of labeled source samples. Specifically, we set an unfair multi-class classifier named category discriminator, which classifies source samples accurately but be confused about the categories of target samples. The generator learns a common subspace that aligns the unlabeled samples based on the target pseudo-labels. For MMEN, we also provide theoretical explanations to show that the learning of feature alignment reduces domain mismatch at the category level. Experimental results on various benchmark datasets demonstrate the effectiveness of our method over existing state-of-the-art baselines.

1 Introduction

Though deep convolutional networks has gained great advancement in visual understanding over the past years [Bin et al., 2019; Tao et al., 2020; Chen et al., 2021; Tao et al., 2021], its training process heavily relies on numerous labeled samples. Since it is often prohibitively expensive to manually label a large-scale dataset for a certain learning task at hand, how to effectively relieve the annotation burden in deep learning remains an open issue.

In recent years, synthetic images, whose class labels can be cheaply generated with the recent advances of computer graphics techniques, are tentatively used to train models that can work in real-world scenarios, aiming to reduce the corresponding labelling consumption [Peng et al., 2017]. However, the domain discrepancy between the synthetic images (i.e. source domain) and the real-world photos (i.e. target domain) still severely degrades the performance of model. As theoretically discussed in [Ben-David et al., 2010], this discrepancy can lead to statistically unbounded risk for target tasks. To improve the model’s generalization ability across domains, domain adaptation has been widely studied especially for unsupervised domain adaptation.

Formally, unsupervised domain adaptation aims to achieve desirable results in the target domain through adaptation from labeled source dataset and unlabeled target dataset [Pan and Yang, 2010]. As indicated above, the distribution discrepancy forms the main bottleneck in domain adaptation. In order to learn a transfer model across domains, various approaches has been proposed including discrepancy-based methods [Long et al., 2015; Long et al., 2016; Bousmalis et al., 2016], reconstruction-based methods [Bousmalis et al., 2016; Sankaranarayanan et al., 2017] and adversarial-based methods [Ganin and Lempitsky, 2014; Tzeng et al., 2017]. Specifically, adversarial-based methods are widely implemented in recent years. As shown in Figure 1, Most of existing adversarial-based methods set a domain classi-
fier as discriminator to judge the origin of input samples, thereby pushing the model to generate domain-invariant feature representations. However, we argue that two issues exist in the existing works: (1) In classification tasks, the data distribution over intermediate representations are mixture of different clusters, but classic adversarial-based methods cannot precisely align the clusters with each specific category since domain labels have no categorical information; (2) To achieve good generalization performance over the target domain, the target samples need to be kept far way from the decision boundaries, but domain invariance can only account for global alignment. Therefore, it is essential to consider categorical information of target images during the learning process.

In this paper, we propose a novel adversarial training model dubbed MiniMax Entropy network (MMEN), which is implemented in an end-to-end fashion. The architecture of our model can be viewed as a variant of Domain-Adversarial Neural Networks (DANN) [Ganin and Lempitsky, 2014]. Instead of using a domain classifier as discriminator, we set an unfair multi-class classifier named category discriminator to incorporate category information into the adversarial procedure. As displayed in Figure 2, our model contains a shared feature generator $G$, a category discriminator $D$ and an auxiliary classifier $C$. The adversarial procedure is implemented through controlling the information entropy of the discriminator’s softmax predictions over target samples. It is noteworthy that this entropy quantity can reflect the discriminator’s confidence in the target samples’ label assignment [Krause et al., 2010]. During the training process, $D$ is trained to classify the source images confidently but be extremely confused about the category of the target images. In contrast, $G$ aims to generate features that assist the target samples to be classified by $D$ with high confidence. With the support of the source domain, $D$ is able to detect target samples that are not aligned with the source features of any categories, while $G$ will be guided to generate target features that mimic the source feature of each specific category. Through the minimax game between $G$ and $D$, our model can achieve domain invariance within each category, which can lead to discriminative features for the target domain.

Overall, the contributions of this work are listed as follows:

- We propose MMEN for unsupervised domain adaptation. MMEN is trained through a minimax game over the entropy of the category discriminator’s prediction, which encourages to achieve domain invariance within each category.

- Our model enjoys a concise framework and a clear training procedure. Therefore, our model is easy-to-implement and efficient compared with other methods.

- The experimental results outperform the existing state-of-the-art methods on various benchmark datasets. Then we make a completed evaluation.

## 2 Related Work

### 2.1 Unsupervised Domain Adaptation

How to perform unsupervised domain adaptation remains an open issue theoretically and practically. Since deep models tend to generate more transferable and informative features than the shallow models [Donahue et al., 2014], the recent domain adaptation methods primarily focus on achieving domain invariance in intermediate layers of convolutional neural networks. Specifically, methods that utilized maximum mean discrepancy (MMD) are representative, including [Long et al., 2015; Long et al., 2016; Bousmalis et al., 2016; Long et al., 2017] that align the distributions between different domains by subspace learning. [Long et al., 2015] proposed to reduce the domain discrepancy through embedding the intermediate features into reproducing kernel Hilbert space and then minimizing the means of data distribution between domains. In [Long et al., 2017], the MMD measurement was further implemented over the joint distributions of features and labels, aiming to correct both domain shift [Pan and Yang, 2010] and conditional shift [Zhang et al., 2013].

Besides MMD, adversarial-based methods for domain adaptation have sprung up recently with appearance of the generative adversarial networks (GAN) [Goodfellow et al., 2014]. In order to effectively bridge source domain and target domain, the previous methods [Ganin and Lempitsky, 2014; Tzeng et al., 2017; Chadha and Andreopoulos, 2018] primarily focused on learning domain-invariant representations, by which the distribution discrepancy between domains can be reduced. These methods utilized a domain classifier to achieve domain alignment in DNNs [Ganin and Lempitsky, 2014]. The domain classifier was trained to distinguish the origin of input based on feature representations, while the generator aimed to cheat the discriminator by generating features with small domain discrepancy. However, domain invariance does not necessarily imply discriminative features for target data.

Among the recent approaches, diverse adversarial-based methods attempted to inject task knowledge to their models indirectly. In [Chen et al., 2018], the author used target samples to alleviate the domain shift by re-weighting the distribution of source labels. In [Pei et al., 2018], the target pseudo-labels were employed to weight the loss on multiple subordinate domain classifiers. In [Zhang et al., 2018], selected target pseudo-labels were combined with learnable weight functions in the classification loss. Aforementioned methods ignore the feature distribution alignment for each specific category, which more or less degrade the model’s generalization ability over the target domain.

### 2.2 Loss Regularization

Loss regularization has been widely applied to benefit parameterized models of posterior probabilities from unlabeled data or partially labeled data [Grandvalet and Bengio, 2006]. [Krause et al., 2010] proposed to estimate the data distribution by entropy for clustering data and training a classifier simultaneously. [Huang et al., 2022] proposes a loss function for improving adversarial robustness. [Springenberg, 2015] modeled a discriminative classifier from unlabeled data by
maximizing the mutual information between inputs and predicted categories. In the field of domain adaptation, [Tzeng et al., 2015] once employed cross-entropy between target activation and soft labels to exploit semantic relationships in label space.

3 Method

Consider $X$ as the input space and $Y$ as the label space, source data $x_s$ and target data $x_t$ are drawn from marginal distribution $P(X_s)$ and $P(X_t)$ respectively. We use $\{(x_s,y_s)\}$ as source dataset, which belongs to source domain $D_s$. Then we use $\{x_t\}$ as unlabeled target dataset, which belongs to target domain $D_t$. It is assumed that the data in different domains share the feature space while following different marginal distributions $P(X_s) \neq P(X_t)$, named as domain shift. The aim of unsupervised domain adaptation is to train a flexible model $\eta: X \rightarrow Y$ that has low target risk $Pr_{(x_t,y_t) \sim D_t}[\eta(x_t) \neq y_t]$ using all given data.

3.1 Motivation

Most recent adversarial-based method treat the discriminator as a domain classifier that discriminates the domain of input. If we take a close look, the generator could not receive any target categorical information from the domain classifier during the learning process, thus the generator has problem aligning feature distribution in the level of category. Accordingly, these models could not guarantee that the generated features were categorically discriminative. For any specific category, the target features that far away from the source ones are likely to be classified into wrong class even with high confidence. To tackle this problem, we propose a method that utilize categorical information to help the generator to generate category-invariant feature.

Since the source data is labeled, a well-trained classifier $C$ for source data can be learned easily with convolution neural network. Target risk is potential to be reduced significantly with effective alignment. However, it is challenging to find a reasonable way for the classifier to score the prediction of target samples, since we have no access to the target labels. “Scoring” can be viewed as a soft label assignment. We find that soft label assignment can be achieved simply and efficiently by utilizing iteratively-updating pseudo-labels in an adversarial manner.

In our model, we set a category discriminator $D$ after the generator. The discriminator assigns the feature representation of each target sample to a probabilistic vector. $D$ is a multi-class predictor in this paper, but undertakes different responsibilities in different steps. $D$ is first pre-trained on the source samples to ensure the model obtain categorically discriminative representations of source and then make accurate predictions. During the step of category confusion, $D$ is streamed with both source samples and target samples, aiming to push the generator to align feature distribution in the level of category. Our method does not require to set domain labels for adversarial training.

3.2 Model Description

Category Confusion

In order to accomplish the aforementioned goals for classifier and discriminator, we first pre-train the model by classifying the source samples with available labels. We set the cross-entropy between true labels and probabilistic outputs as the classification loss, which is defined as follow:

$$
\min_{G,C,D} L_c = -\frac{1}{2n_s} \sum_{x_s}[y_s \cdot \log(C(G(x_s))) + y_n \cdot \log(D(G(x_s)))],
$$

where $n_s$ denotes the number of samples in source domain in a batch. Dot product is used as “$\cdot$”. It is an essential step for the model to take measure on target samples because the source only model can give plausible support on target samples at the start of adaptation.

The goal of our model is to jointly train the categorical discriminator $C$ and feature extractor $G$ and to generate category-invariant feature. As shown in the Figure 2, $C$ and $G$ hold different stands:

- **(D) Category Discriminator’s stand** Classify source samples accurately; Be uncertain of the predicted categories on target samples.
- **(G) Feature Generator’s stand** Generate category-invariant feature representations.

The discriminator need to judge the domain of input based on feature distribution, then classify source samples accurately and make unfair predictions on target samples. Unfair means the uncertainty about predicted category. The generator strives to align target representations that mistake the discriminator for the source to enjoy accurate predictions. If the distribution of generative target feature $P_t^g$ is consistent with the distribution of source feature $P_s^g$ in the level of both domain and category, the classifier can predict target samples correctly with high confidence.

In order to achieve uncertainty of the predicted categories, we need to estimate the degree of error predictions on target samples by discriminator, and feedback this information to the generator. Although the labels of target samples are inaccessible, we can utilize pseudo-labels $\hat{y}_t = D(G(x_t))$. A nature way to estimate the error predictions is to judge whether the cross-entropy of pseudo-labels $H(p(y|x_t))$ is sufficiently small, since it is minimized when the discriminator make certain predictions. Alternatively speaking, $H(p(y|x_t))$ is maximized when the distribution of class prediction is even (extremely confused). The cross-entropy of pseudo-labels $H(p(y|x_t))$ can be formalized as follow:

$$
H(p(y|x_t)) = -\frac{1}{n_t} \sum_{x_t} \hat{y}_t \cdot \log(D(G(x_t))),
$$

where $n_t$ denotes the number of samples in target domain in a batch. Assuming that there are $K$ categories in the dataset, then $\hat{y}_t$ is a $K$-dimensional vector denoting class-wise probability of a target sample, $\hat{y}_t(i) = p(y_i=1|x_t)$ for $i = 1, \cdots, K$.

Remember that we want the target feature to mimic the
source distribution, thereby utilizing the capacity of source model to infer the target labels. As we know, cross-entropy reflects the relationship between feature distribution and decision boundary. High cross-entropy of pseudo-labels \( H(p(y|x_t)) \) means that the generated target features are near the decision boundaries of category discriminator, thereby making the discriminator confused about the predicted categories. During the process of training, the category discriminator is expected to keep unfair. This setting guides the generator to generate category-invariant feature for high prediction certainty until the generated target features are fully aligned. Therefore, we maximize \( H(p(y|x_t)) \) for the D, which tends to assign target pseudo-labels that have equal probability to each category. By minimizing \( H(p(y|x_t)) \) for the G, it tends to generate source-alike feature for the target sample. Our final objective is:

\[
\min_G \max_D \lambda H(p(y|x_t)), \quad \min_{G,D,C} L_c, \quad \text{where } \lambda \text{ controls the trade-off between classification and category confusion.}
\]

**Training Procedure**

First, in order to make the classifier keep discriminative on source, we apply apply Eq.1 to train the source only network. Second, we use Eq.3 and Eq.4 to learn the generator G, the unfair category discriminator D and classifier C. Notice that classifier C is auxiliary used to enhance the categorical discriminability towards source samples. Our model works fine without C, we will discuss this phenomenon later.

It is worth noting that misuse of the noisy pseudo labels could have negative effects during the training procedure empirically. That is just the one that motivates us to leverage the pseudo labels through the mini-max game over entropies, but not directly assigning pseudo labels to target data. As the learning process develops, the aligned target feature will cause the cross entropy of pseudo labels decreases gradually, thereby generating relatively clean pseudo labels. The performance will be improved in cycle. We discuss that our model is capable of inferring target labels successfully step by step. Notice that our model does not need to filter bad target samples manually like setting an accuracy threshold. All target samples can be used during the training process.

Since C and G hold opposite stands on target samples, we optimize the model by iterative training. To balance the power of both sides, we set a hyper-parameter \( k = 4 \), which signifies the times of updating G before updating C in a batch. In the test phase, target samples are fed forward through G and C for final prediction.

**4 Experiments**

To evaluate the proposed method on several benchmark datasets, we employ classification accuracy as metric. The metric is defined as follow:

\[
\text{Accuracy} = \frac{|x_t : x_t \in X_t \land \hat{y}_t = y_t|}{|x_t : x_t \in X_t|}.
\]

All our experiments are implemented by PyTorch. We set the hyper-parameter \( k = 4 \) and coefficient \( \lambda = 0.1 \) in all the experiments. Results show the superiority of our method against state-of-the-art transfer learning methods.

**4.1 ImageCLEF-DA Dataset**

ImageCLEF-DA\(^1\) is a benchmark dataset for domain adaptation. We use 3 domains of data in the dataset, including ImageNet ILSVRC 2012 (I), Pascal VOC 2012 (P) and Caltech-256 (C). Each domain has 12 shared categories and each category has 50 images. We perform all transfer tasks across domains, namely I \( \rightarrow \) P, P \( \rightarrow \) I, I \( \rightarrow \) C, C \( \rightarrow \) I, C \( \rightarrow \) P and P \( \rightarrow \) C.

\(^1\)http://imageclef.org/2014/adaptation

![Diagram of the model](image.png)
We utilize ResNet50 [He et al., 2016] as our CNN architecture. For fair comparison, we compare the performance of MMEN with methods that based on ResNet50. Both classifier and category discriminator are three fully-connected layers (1000 → 1000 → 12) with batch normalization layers. The model is pre-trained based on ImageNet and then fine-tuned by source samples initially. SGD is used as the optimizer with learning rate $1 \times 10^{-3}$. The batch size of both source samples and target samples are 24 equally. We train our model 150 epoches totally.

### 4.2 Digits Dataset

MNIST [LeCun et al., 1998], SVHN [Netzer et al., 2011], and USPS [Hull, 1994] are three commonly used datasets in digit classification and domain adaptation. We perform three challenging transfer tasks SV → MN, MN → US and US → MN to evaluate our method.

We follow the shallow CNN architecture used in [Ganin and Lempitsky, 2014]. Batch normalization layers are employed on each layer. We use Adam [Kingma and Ba, 2014] as the optimizer and learning rate is $2 \times 10^{-4}$. Batch size is set as 128 for both source samples and target samples. We train our model 150 epoches totally.

### 4.3 Comparative Results

To verify the effectiveness of each module in our model, we consider several variants as follow:

- **G+D** We utilize the target pseudo labels to adversarially train the generator G and category discriminator D.
- **MMEN** Compared with ‘G+D’, we add an auxiliary classifier C during training. It is the full model of mini-max entropy network, namely MMEN.

We compare our results with the state-of-the-art methods, including ResNet50 [He et al., 2016], Deep Adaptation Network (DAN) [Long et al., 2015], Residual Transfer Network (RTN) [Long et al., 2016], Domain separation networks (DSN) [Bousmalis et al., 2016], Joint Adaptation Network (JAN) [Long et al., 2017], Domain-Adversarial Neural Networks (DANN) [Ganin and Lempitsky, 2014], Multi-Adversarial Domain Adaptation (MADA) [Pei et al., 2018], Re-weighted Adversarial Adaptation Network (RAAN) [Chen et al., 2018], Adversarial Discriminative Domain Adaptation (ADDA) [Tzeng et al., 2017] and its improved variant (iADDA) [Chadha and Andreopoulos, 2018].

As shown on Table 1 and Table 2, we can observe the comparative results. MMD-based methods DAN, RTN, DSN and JAN exhibit relatively low performance due to coarse-grained feature alignment. Compared with the adversarial-based methods DANN and ADDA that make adaptation on generator without any categorical information, our method improves the performance with a remarkable gap. The most recent methods MADA, RAAN and iADDA utilize task knowledge indirectly by re-weighting the loss function or mimicking fixed source encoder posteriors. By contrast, our model injects target knowledge directly and enables fine-grained feature alignment, therefore it outperforms state-of-the-art methods on various benchmark datasets. The easy-to-implement framework and competitive performance indicates that play minimax game over pseudo labels is an effective and efficient way for unsupervised domain adaptation. The auxiliary classifier C in MMEN enhance discriminability towards source samples. The module help stabilize the distribution that the target feature aims to align. Hence, MMEN obtains better performance compared with ‘G+D’.

### 5 Discussion

We use the activation of the last layer of generator as feature representations and project them by t-SNE embedding [Maaten and Hinton, 2008]. As shown in the Figure 3(a), we plot the feature distribution learned by source only model. Source features (violet) are distributed dispersedly with categories, which means the classifier can learn the decision boundary for source samples easily. However, target features (other different colors) are scattered irregularly with high ambiguity. In Figure 3(b), since domain classifier only care about the origin of input but ignore categorical information, the generator is only able to align feature in the level of domain globally. Hence, the classifier cannot classify target samples precisely. Contrast with Figure 3(c), target feature are aligned closely with source feature that share the same

### Table 1: Comparison of the performance (%) for unsupervised domain adaptation with the state-of-the-art methods.

| Model       | I→P | P→I | I→C | C→I | C→P | P→C | Avg.  |
|-------------|-----|-----|-----|-----|-----|-----|-------|
| ResNet50    | 74.8| 83.9| 91.5| 78.0| 65.5| 91.2| 80.7  |
| DAN         | 74.5| 82.2| 92.8| 86.3| 69.2| 89.8| 82.5  |
| RTN         | 74.6| 85.8| 94.3| 85.9| 71.7| 91.2| 83.9  |
| DANN        | 75.0| 86.0| 96.2| 87.0| 74.3| 91.5| 85.0  |
| JAN         | 76.8| 88.0| 94.7| 89.5| 74.2| 91.7| 85.8  |
| MADA        | 75.0| 87.9| 96.0| 88.8| 75.2| 92.2| 85.8  |
| **G+D**     | 76.2| 91.3| 94.8| 89.1| 72.9| 94.0| 86.4  |
| **MMEN**    | 77.8| 92.2| 95.8| 89.8| 75.8| 94.5| 87.7  |
| Oracle      | 95.5| 99.7| 100.0| 99.7| 95.5| 100.0| 98.4  |

### Table 2: Comparison of the performance (%) for unsupervised domain adaptation. S, M and U are the abbreviations of SVHN, MNIST and USPS respectively. Oracle denotes the target samples are trained in a fully supervised manner.

| Model       | S→M | M→U | U→M |
|-------------|-----|-----|-----|
| Source Only | 67.1| 76.7| 63.4|
| DANN        | 73.9| 77.5| -   |
| DSN         | 82.7| -   | -   |
| ADDA        | 76.0| 89.4| 90.1|
| RAAN        | 89.2| 89.0| 92.1|
| iADDA       | 92.7| 91.0| 94.8|
| **G+D**     | 97.2| 96.8| 96.6|
| **MMEN**    | 98.8| 97.8| 97.4|
| Oracle      | 99.5| 99.4| 99.3|
Figure 3: The feature distribution of samples in two domains are visualized by t-SNE in the task MNIST $\rightarrow$ USPS. Source features are marked in violet, and target features marked in other different colors represent different categories. The feature representations are scattered irregularly between domains learned by the Source Only model. Classic adversarial-based method DANN only take account of global feature alignment in the level of domain. By contrast, our model consider the category-level alignment. The feature representations that belongs to the same category but in different domains are close. Hence, the decision boundary of task-specific classifier can be easily learned.

Figure 4: Analysis of the category-level feature alignment in our model. For each category, we computer the distance of the feature center between source domain and target domain in the task MNIST $\rightarrow$ USPS. Compared with the performance learned by model pre-trained on the ImageNet, source only model and classic adversarial-based method DANN, our model successfully aligns the feature distribution in all categories.

Figure 5: The visualization of accuracy and training loss in the task P $\rightarrow$ I and P $\rightarrow$ C on the CLEF datasets. $H$ and $L_c$ denote cross-entropy of pseudo-labels and cross-entropy with true labels respectively. Accuracy denotes the performance on the classifier.

category but away from those have different categories. It indicates MMEN is able to generate category-invariant feature and enjoy categorical discriminability.

From Figure 5(a) and 5(b), we observe that cross-entropy of pseudo-labels $H(p(x_t))$ declines continuously with the decrease of cross-entropy $L_c$ between $y_t$ and target labels. We only use the target labels in this part for verification, which are not used during training. The former means that our model becomes more and more certain about target labels assignment. The latter indicates that our model successfully infers labels from unlabeled target samples. The simultaneous learning trends of $H(p(x_t))$ and $L_c$ verifies the feasibility of our model. Because of the property of unfairness, the category discriminator is uncertain about the category of target samples purposely but classify source samples correctly. To minimize the uncertainty of the prediction on target samples, the generator has to mimic the source distribution of specific category in the feature space. As the generated target features become more and more similar with source feature for each category, they can enjoy the classifier’s power to classify source samples. Hence, cross-entropy $L_c$ on target samples
decreases consecutively during the learning process.

In order to evaluate the category-level feature alignment, we compute the cluster center distance (CCD) \( \{d_1^c, d_2^c, ..., d_K^c\} \) of the same category between two domains in the feature space. \( d_k^c \) denotes the CCD of category \( k \) in the epoch \( e \). Large cluster center distance means that the feature representations are weakly aligned. Euclidean distance is used as the metric. We choose 1860 source samples and 1860 target samples in the task MNIST \( \rightarrow \) USPS. The value are normalized by dividing the CCD in pre-train model for each category. As shown in Figure 4, the CCD in source only model is large. It is understandable due to the fact that source only model does not align feature distribution. Compared with source only model and DANN, the CCD of all categories in the our model are smaller. This result verify that our model can align the feature distribution in the level of category.

In order to study the sensitivity of our approach, we search coefficient \( \lambda \) ranged from 0.01 to 2 and \( k \) ranged from 2 to 5 respectively in the task MNIST \( \rightarrow \) USPS. As reported in Table 3, the performance of our model are high and close with each other despite the variation of \( \lambda \) and \( k \). In addition, the discriminator \( D \) gets stronger quickly when \( \lambda \) gets larger or the times of updating generator in the inner loop \( k \) gets smaller. Hence, it causes vanishing gradient and incomplete feature alignment. Accordingly, performance drops slightly in this case. Generally speaking, our model is robust enough against the variation of hyper-parameter \( \lambda \) and \( k \).

Since source risk \( \Pr(x_s, y_s) \sim D, [\eta(x_s) \neq y_s] \) is considerably low after pre-training, we wonder whether a simple classifier can make accurate predictions on unlabeled samples under the premise of well-aligned feature. Therefore, we illustrate the results based on ResNet50 on the ImageCLEF-DA dataset firstly as shown in Figure 6, and then conduct unsupervised domain adaptations on classifier and category discriminator respectively based on the target feature leaned by MMEN. We observe that both classifier \( C \) and discriminator \( D \) defeat ResNet50 with large performance gap. Please notice that the classifier is not streamed with target data during training. The target feature is learned to distributed close with the source one, hence the source classifier \( C \) does not need to see the target domain data for good performance. It inspires us that fine-grained feature alignment plays a crucial role in domain adaptation. The well-aligned target features are eligible to utilize the power of source model to infer labels.

| \( \lambda \) | 0.01 | 0.02 | 0.05 | 0.1 | 0.2 | 0.5 | 1 | 2 |
|---|---|---|---|---|---|---|---|---|
| \( k=2 \) | 96.9 | 96.9 | 96.8 | 96.6 | 96.7 | 96.5 | 93.5 | 83.6 |
| \( k=3 \) | 97.6 | 97.4 | 96.9 | 97.2 | 97.7 | 97.4 | 93.7 | 91.6 |
| \( k=4 \) | 97.9 | 97.7 | 97.7 | 97.8 | 97.8 | 97.6 | 96.8 | 94.6 |
| \( k=5 \) | 98.1 | 98.4 | 98.0 | 97.8 | 97.8 | 97.8 | 96.9 | 94.8 |

Table 3: (MNIST \( \rightarrow \) USPS) Performance (%) for unsupervised domain adaptation varies with \( k \) and \( \lambda \).

Figure 6: Comparison of performance by ResNet50, classifier and category discriminator with feature leaned by MMEN.

6 Conclusion

We have proposed a simple yet effective method for unsupervised domain adaptation. In order to achieve fine-grained aligned feature representations, we inject the target categorical information from target samples directly. Although target labels are unavailable during the learning process, we utilize the cross-entropy of pseudo-labels to estimate the distribution of class-wise predictions. By setting an unfair category discriminator, we employ adversarial training procedure that push the generative target feature aligned with source feature for each category. Hence, the obtained feature representations enjoy invariance with the shift among categories in different domains. The experimental results demonstrate the superiority of our approach. Moreover, the target feature learned by MMEN exhibits flexible compatibility with source classifiers.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 62106204) and the Sichuan Natural Science Foundation (No. 2022NSFSC0911).

References

[Ben-David et al., 2010] Shai Ben-David, John Blitzer, Koby Crammer, Alex Kulesza, Fernando Pereira, and Jennifer Wortman Vaughan. A theory of learning from different domains. Machine learning, 79(1-2):151–175, 2010.

[Bin et al., 2019] Yi Bin, Yang Yang, Chaofan Tao, Zi Huang, Jingjing Li, and Heng Tao Shen. Mr-net: Exploiting mutual relation for visual relationship detection. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 8110–8117, 2019.

[Bousmalis et al., 2016] Konstantinos Bousmalis, George Trigeorgis, Nathan Silberman, Dilip Krishnan, and Dumitru Erhan. Domain separation networks. In Advances in Neural Information Processing Systems, pages 343–351, 2016.

[Chadha and Andreopoulos, 2018] Aaron Chadha and Yiannis Andreopoulos. Improving adversarial discriminative
domain adaptation. arXiv preprint arXiv:1809.03625, 2018.

[Chen et al., 2018] Qingchao Chen, Yang Liu, Zhaowen Wang, Ian Wassell, and Kevin Chetty. Re-weighted adversarial adaptation network for unsupervised domain adaptation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7976–7985, 2018.

[Chen et al., 2021] Cong Chen, Chaofan Tao, and Ngai Wong. Litetg: Efficient and lightweight graph transformers. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management, pages 161–170, 2021.

[Donahue et al., 2014] Jeff Donahue, Yangqing Jia, Oriol Vinyals, Judy Hoffman, Ning Zhang, Eric Tzeng, and Trevor Darrell. Decaf: A deep convolutional activation feature for generic visual recognition. In International conference on machine learning, pages 647–655, 2014.

[Ganin and Lempitsky, 2014] Yaroslav Ganin and Victor Lempitsky. Unsupervised domain adaptation by backpropagation. arXiv preprint arXiv:1409.7495, 2014.

[Goodfellow et al., 2014] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In Advances in neural information processing systems, pages 2672–2680, 2014.

[Grandvalet and Bengio, 2006] Yves Grandvalet and Yoshua Bengio. Entropy regularization. Semi-supervised learning, pages 151–168, 2006.

[He et al., 2016] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[Huang et al., 2022] Binxiao Huang, Chaofan Tao, Rui Lin, and Ngai Wong. Frequency regularization for improving adversarial robustness. arXiv preprint arXiv:2212.12732, 2022.

[Hull, 1994] Jonathan J. Hull. A database for handwritten text recognition research. IEEE Transactions on pattern analysis and machine intelligence, 16(5):550–554, 1994.

[Kingma and Ba, 2014] Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

[Krause et al., 2010] Andreas Krause, Pietro Perona, and Ryan G Gomes. Discriminative clustering by regularized information maximization. In Advances in neural information processing systems, pages 775–783, 2010.

[LeCun et al., 1998] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324, 1998.

[Long et al., 2015] Mingsheng Long, Yue Cao, Jianmin Wang, and Michael I Jordan. Learning transferable features with deep adaptation networks. arXiv preprint arXiv:1502.02791, 2015.

[Long et al., 2016] Mingsheng Long, Han Zhu, Jianmin Wang, and Michael I Jordan. Unsupervised domain adaptation with residual transfer networks. In Advances in Neural Information Processing Systems, pages 136–144, 2016.

[Long et al., 2017] Mingsheng Long, Han Zhu, Jianmin Wang, and Michael I Jordan. Deep transfer learning with joint adaptation networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 2208–2217. JMLR. org, 2017.

[Maaten and Hinton, 2008] Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. Journal of machine learning research, 9(Nov):2579–2605, 2008.

[Netzer et al., 2011] Yuval Netzer, Tao Wang, Adam Coates, Alessandro Bissacco, Bo Wu, and Andrew Y Ng. Reading digits in natural images with unsupervised feature learning. In NIPS workshop on deep learning and unsupervised feature learning, volume 2011, page 5, 2011.

[Pan and Yang, 2010] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10):1345–1359, 2010.

[Pei et al., 2018] Zhongyi Pei, Zhangjie Cao, Mingsheng Long, and Jianmin Wang. Multi-adversarial domain adaptation. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[Peng et al., 2017] Qingchao Chen, Yang Liu, Zhaowen Wang, and Michael I Jordan. Unsupervised domain adaptation with residual transfer networks. In Proceedings of the IEEE International Conference on Computer Vision, pages 7167–7176, 2017.

[Sankaranarayanan et al., 2017] Swami Sankaranarayanan, Yogesh Balaji, Carlos D. Castillo, and Rama Chellappa. Generate to adapt: Aligning domains using generative adversarial networks. CoRR, abs/1704.01705, 2017.

[Springenberg, 2015] Jost Tobias Springenberg. Unsupervised and semi-supervised learning with categorical generative adversarial networks. arXiv preprint arXiv:1511.06390, 2015.

[Tao et al., 2020] Chaofan Tao, Qinhong Jiang, Lixin Duan, and Ping Luo. Dynamic and static context-aware lstm for multi-agent motion prediction. In European Conference on Computer Vision, pages 547–563. Springer, 2020.

[Tao et al., 2021] Chaofan Tao, Rui Lin, Quan Chen, Zhaoyang Zhang, Ping Luo, and Ngai Wong. Fat: Learning low-bitwidth parametric representation via frequency-aware transformation. arXiv preprint arXiv:2102.07444, 2021.

[Tzeng et al., 2015] Eric Tzeng, Judy Hoffman, Trevor Darrell, and Kate Saenko. Simultaneous deep transfer across domains and tasks. In Proceedings of the IEEE International Conference on Computer Vision, pages 4068–4076, 2015.

[Tzeng et al., 2017] Eric Tzeng, Judy Hoffman, Kate Saenko, and Trevor Darrell. Adversarial discriminative domain adaptation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7167–7176, 2017.
[Zhang et al., 2013] Kun Zhang, Bernhard Schölkopf, Krikamol Muandet, and Zhikun Wang. Domain adaptation under target and conditional shift. In *International Conference on Machine Learning*, pages 819–827, 2013.

[Zhang et al., 2018] Weichen Zhang, Wanli Ouyang, Wen Li, and Dong Xu. Collaborative and adversarial network for unsupervised domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3801–3809, 2018.