Virtual Mixup Training for Unsupervised Domain Adaptation

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Abstract

We study the problem of unsupervised domain adaptation which aims to adapt models trained on a labeled source domain to a completely unlabeled target domain. Domain adversarial training is a promising approach and has been a basis for many state-of-the-art approaches in unsupervised domain adaptation. The idea of domain adversarial training is to align the feature space between the source domain and target domain by adversarially training a domain classifier and a feature encoder. Recently, cluster assumption has been applied to unsupervised domain adaptation and achieved strong performance. In this paper, we propose a new regularization method called Virtual Mixup Training (VMT), which is able to further constrain the hypothesis of cluster assumption. The idea of VMT is to impose a locally-Lipschitz constraint on the model by smoothing the output distribution along the lines between pairs of training samples. Unlike the traditional mixup model, our method constructs the combination samples without label information, allowing it to be applicable to unsupervised domain adaptation. The proposed method is generic and can be combined with existing methods using domain adversarial training. We combine VMT with a recent state-of-the-art model called VADA, and extensive experiments demonstrate that VMT significantly improves the performance of VADA on several domain adaptation benchmark datasets. For the challenging task of adapting MNIST to SVHN, when not using instance normalization, VMT improves the accuracy of VADA by over 30%. When using instance normalization, our model achieves an accuracy of 96.4%, which is very close to the accuracy (96.5%) of the train-on-target model. Code will be made publicly available.

1 Introduction

Deep neural networks have launched a profound reformation in a wide variety of fields such as image classification [19], detection [12], and segmentation [23]. However, the performance of deep neural networks is often based on large amounts of labeled training data. In real-world tasks, generating labeled training data can be very expensive and may not always be feasible. One approach to this problem is to learn on a related labeled source data and generalize to the unlabeled target data, which is known as domain adaptation. We in this work consider the problem of unsupervised domain adaptation where the training samples in the target domain are completely unlabeled.

For unsupervised domain adaptation, Ganin et al. [10] proposed to learn domain-invariant features between the source domain and target domain by domain adversarial training, which has been a basis

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of numerous domain adaptation methods [41, 20, 34, 30, 43]. Most of the follow-up studies focus on how to align the domain-invariant features better, including the approaches of adversarial discriminative adaptation [41], maximizing classifier discrepancy [30], and class conditional alignment [43, 20].

Recently, Shu et al. [34] have successfully combined cluster assumption [15] with domain adversarial training and achieved strong performance. They also pointed out that the locally-Lipschitz constraint is critical to the performance of cluster assumption. Without the locally-Lipschitz constraint, the classifier may abruptly change its predictions in the vicinity of the training samples due to the high-capacity of the classifier even though the cross-domain features are well aligned. To this end, they adopted the virtual adversarial training [27] to constrain the local Lipschitzness on both the source domain and target domain. In this paper, we follow this line and propose a new method to constrain the local Lipschitzness.

Inspired by the virtual labels used in literature [27], we propose the Virtual Mixup Training (VMT) model, which extends mixup [44] to use the virtual labels, thereby allowing it to be applicable to unsupervised domain adaptation. Here virtual labels mean that the labels are the current estimate of the classifier. Specifically, we first construct convex combinations, denoted as \((\tilde{x}, \tilde{y})\), of pairs of training samples and their virtual labels, and then define a penalty term that punishes the difference between the prediction of the combined sample \(f(\tilde{x})\) and the combined virtual label \(\tilde{y}\). This penalty term produces a linear change of the output distribution in-between training samples. As a result, it leads to imposing the locally-Lipschitz constraint to the classifier. Note that VMT can be applied to both the target and source domains. For the source domain, we also replace the real labels with the virtual labels, without using the label information of the source domain. Therefore although the original mixup [44] is used for data augmentation, our proposed method is not a data augmentation approach because VMT does not utilize the label information.

In the experiments, we combine VMT with a recent state-of-the-art model called VADA [34], and evaluate on several commonly used benchmark datasets, including MNIST, MNIST-M, SVHN, Synthetic Digits, CIFAR-10, and STL. The experimental results show that VMT is able to improve the performance of VADA in all tasks. For the most challenging task, MNIST \(\rightarrow\) SVHN without instance normalization, our model improves VADA’s accuracy from 54.5% to 86.4%. When using instance normalization, our model achieves an accuracy of 96.4%, which is very close to the accuracy (96.5%) of the train-on-target model.

2 Related Work

Domain adaptation. Domain adaptation has gained extensive attention in recent years due to its advantage of utilizing unlabeled data. A theoretical analysis of domain adaptation is presented in [3]. Early works [33, 25] tried to minimize the discrepancy distance between the source and target feature distributions. Long et al. [24] and Sun & Saenko [36] extended this method by matching higher order statistics of the two distributions. Huang et al. [18], Tzeng et al. [40], and Ganin et al. [10] proposed to project the source and target feature distributions into some common space and match the learned features as close as possible. Specifically, Ganin et al. [10] proposed the domain adversarial training to learn domain-invariant features, which has been a basis of numerous domain adaptation methods [41, 30, 43, 34, 20]. Tzeng et al. [41] generalized a framework based on domain adversarial training and proposed to combine the discriminative model and GAN loss [13]. Saito et al. [30] proposed to maximize the discrepancy of two different classifiers to learn not only domain-invariant but also class-specific features. Xie et al. [43] also proposed to learn class-specific features by assigning virtual labels to the target samples and aligning the class centroids between the source and target domains. Shu et al. [34] proposed to combine the cluster assumption [15] with domain adversarial training. They also adopted virtual adversarial training [27] to constrain the local Lipschitzness of the classifier, as [15] pointed out that locally-Lipschitz constraint is critical to the performance of the cluster assumption. Kumar et al. [20] extended [34] by using co-regularization [35] to align class-specific features. We also follow the line of [34] and propose a new method to constrain the local Lipschitzness.

There are also many other promising models including domain separation networks [6], reconstruction-classification networks [11], tri-training [29], and self-ensembling [9]. Another effective direction to domain adaptation is through the image-to-image translation [37, 7, 22, 26, 28, 17].
where the source samples are translated to the target domain within the same class and the translated target samples can be used to train the classifier.

**Local Lipschitzness.** Grandvalet and Bengio [15] pointed out that local Lipschitzness is critical to the performance of the cluster assumption. Ben-David and Urner [2] also showed in theory that Lipschitzness can be viewed as a way of formalizing the cluster assumption. Constraining local Lipschitzness has been proven the effectiveness in semi-supervised learning [1, 31, 38, 21, 27] and domain adaptation [9, 34]. Generally, these methods smooth the output distribution of the model by constructing surrounding points of the original points and enforcing consistent predictions between the surrounding and original points. Specifically, Bachman et al. [1], Sajjadi et al. [31], and Laine & Aila [21] utilized the randomness of some network layers, including stochastic augmentation, dropout, and randomized pooling, to construct the surrounding points. Tarvainen & Valpola [38] and French et al. [9] proposed to construct two different networks and enforce the two networks to output consistent predictions for the same input. Miyato et al. [27] proposed to use the adversarial examples [14] as the surrounding points.

**Mixup.** Zhang et al. [44] proposed a regularization method called mixup to improve the generalization of neural network architectures. Mixup generates convex combinations of pairs of training examples and their labels, favoring smooth output distribution of the model. A similar idea is presented in [39] for image classification. Verma et al. [42] extended mixup by mixing on the output of a random hidden layer. Guo et al. [16] proposed to learn the mixing policy by an additional network instead of the random policy.

**Virtual labels.** Virtual (or pseudo) labels have been widely used in semi-supervised learning [4, 27] and domain adaptation [8, 29, 43]. Basically, virtual labels are the current predictions of the classifier. Chen et al. [8] and Saito et al. [29] proposed to first use multiple classifiers to assign virtual labels to the target samples, and then train the classifier using the target samples with virtual labels. Xie et al. [43] proposed to calculate the class centroids of virtual labels to reduce the bias caused by the false virtual labels. However, these methods heavily rely on the accuracy of the virtual labels as these methods utilize the information of the class types of the virtual labels. The most related method to our proposed model is virtual adversarial training [27], both of which do not care about the class types of the virtual labels. Virtual adversarial training treats the virtual labels as the ground truth labels for the adversarial examples, and penalizes the difference between the predictions of the original sample and its adversarial example.

## 3 Method

### 3.1 Background

#### 3.1.1 Domain Adversarial Training

We first describe domain adversarial training [10] which is a basis of our model. Let $\mathcal{X}_s$ and $\mathcal{Y}_s$ be the distributions of input sample $x$ and label $y$ from the source domain, and let $\mathcal{X}_t$ be the input distribution of the target domain. Suppose a classifier $f = g \circ h$ can be decomposed into a feature encoder $g$ and an embedding classifier $h$. The input $x$ is first mapped through the feature encoder $g : \mathcal{X} \rightarrow \mathcal{Z}$, and then through the embedding classifier $h : \mathcal{Z} \rightarrow \mathcal{Y}$. On the other hand, a domain discriminator $d : \mathcal{Z} \rightarrow (0, 1)$ maps the feature vector to the domain label $(0, 1)$. The domain discriminator $d$ and feature encoder $g$ are trained adversarially: $d$ tries to distinguish whether the input sample $x$ is from the source domain or target domain, while $g$ aims to generate indistinguishable feature vectors of samples from the source and target domains. The objective of domain adversarial training can be formalized as follows:

$$\min_f \mathcal{L}_y(f; \mathcal{X}_s, \mathcal{Y}_s) + \lambda_d \mathcal{L}_d(g; \mathcal{X}_s, \mathcal{X}_t),$$

where

\[
\mathcal{L}_y(f; \mathcal{X}_s, \mathcal{Y}_s) = \mathbb{E}_{(x,y) \sim (\mathcal{X}_s, \mathcal{Y}_s)} \left[ y^\top \ln f(x) \right],
\]

\[
\mathcal{L}_d(g; \mathcal{X}_s, \mathcal{X}_t) = \sup_d \mathbb{E}_{x \sim \mathcal{X}_s} \left[ \ln d(g(x)) \right] + \mathbb{E}_{x \sim \mathcal{X}_t} \left[ \ln (1 - d(g(x))) \right],
\]

and $\lambda_d$ is used to adjust the weight of $\mathcal{L}_d$. 

3
3.1.2 Cluster Assumption

Cluster assumption states that the input data contains clusters, and if points are in the same cluster, they come from the same class [15]. It has been widely used in semi-supervised learning [15, 31, 27], and recently been applied to unsupervised domain adaptation [34]. Shu et al. [34] adopted conditional entropy to enforce the behavior of cluster assumption:

$$\mathcal{L}_c(f; \mathcal{X}) = -\mathbb{E}_{x \sim \mathcal{X}} \left[ f(x)^\top \ln f(x) \right].$$

(2)

In practice, another critical component is the local Lipschitzness of the classifier. Without the locally-Lipschitz constraint, the classifier may abruptly change its predictions in the vicinity of the training samples. To this end, Shu et al. [34] adopted virtual adversarial training [27] to impose the locally-Lipschitz constraint:

$$\mathcal{L}_v(f; \mathcal{X}) = \mathbb{E}_{x \sim \mathcal{X}} \left[ \max_{\|r\| \leq \epsilon} \text{D}_{\text{KL}}(f(x)\|f(x + r)) \right].$$

(3)

3.2 Virtual Mixup Training

Following the line of forcing cluster assumption, we propose the Virtual Mixup Training (VMT), a novel approach to enforce the local Lipschitzness. Mixup [44] has shown the effectiveness in smoothing the output distribution of neural networks for many supervised problems. The idea of mixup is to encourage the classifier to behave linearly in-between training samples by applying the following convex combinations of samples:

$$\tilde{x} = \lambda x_i + (1 - \lambda)x_j,$$
$$\tilde{y} = \lambda y_i + (1 - \lambda)y_j,$$

(4)

where $\lambda \sim \text{Beta}(\alpha, \alpha)$, for $\alpha \in (0, \infty)$. However, for unsupervised domain adaptation, we have no direct information about $y_i$ and $y_j$ of the target domain. Inspired by [27], we replace $y_i$ and $y_j$ with the approximations, $f(x_i)$ and $f(x_j)$, which are the current predictions by the classifier $f$. Literally, we call $f(x_i)$ and $f(x_j)$ virtual labels, and formalize our proposed VMT as follows:

$$\tilde{x} = \lambda x_i + (1 - \lambda)x_j,$$
$$\tilde{y} = \lambda f(x_i) + (1 - \lambda)f(x_j),$$

(5)

where $\lambda \sim \text{Beta}(\alpha, \alpha)$, for $\alpha \in (0, \infty)$. We want the classifier $f$ to behave linearly along the lines between $x_i$ and $x_j$. Therefore the prediction of $\tilde{x}$, i.e. $f(\tilde{x})$, should be consistent with $\tilde{y}$. Based on this, we arrive at the objective of VMT given by:

$$\mathcal{L}_m(f; \mathcal{X}) = \mathbb{E}_{x \sim \mathcal{X}} \left[ \text{D}_{\text{KL}}(\tilde{y} \| f(\tilde{x})) \right].$$

(6)

Note that VMT can be applied to either the target or source domain. For the source domain, we also replace $y_i$ and $y_j$ with the virtual labels, without using the label information. Although the original mixup [44] is used for data augmentation, VMT is not a data augmentation approach because we do not utilize the label information. Combining VMT with VADA [34], we can get the following objective:

$$\min_f \mathcal{L}_{y,d} + \lambda_s [\mathcal{L}_m(f; \mathcal{X}_s) + \mathcal{L}_v(f; \mathcal{X}_s)] + \lambda_t [\mathcal{L}_m(f; \mathcal{X}_t) + \mathcal{L}_v(f; \mathcal{X}_t)] + \mathcal{L}_c(f; \mathcal{X}_t),$$

(7)

where $\mathcal{L}_{y,d} = \mathcal{L}_y(g; \mathcal{X}_s, \mathcal{X}_t) + \lambda_d \mathcal{L}_d(g; \mathcal{X}_s, \mathcal{X}_t)$, and $(\lambda_s, \lambda_t)$ are used to adjust the weights of the penalty terms on the source and target domains. Except for $\alpha$ in Eq. 5 which is fixed as 1 in our experiments, we do not introduce additional hyperparameters, compared with VADA [34], and the hyperparameters $(\lambda_d, \lambda_s, \lambda_t)$ are easy to choose empirically.

Our proposed VMT can be understood as to smooth the output distribution of the classifier, imposing the locally-Lipschitz constraint to the classifier. Local Lipschitzness has been proven the effectiveness in favoring the cluster assumption [15, 34]. We empirically show in Section 4.3 that VMT is
orthogonal to another locally-Lipschitz-constraint technique, virtual adversarial training [27]. VMT can be combined with virtual adversarial training to further improve the performance.

Like mixup [44], the implementation of VMT is also simple, and introduces a low computational cost. Despite its simplicity, VMT achieves a new state-of-the-art performance on several benchmark datasets, and especially for the task of adapting MNIST to SVHN without instance normalization, VMT is able to improve the accuracy of VADA by over 30%.

4 Experiments

For the evaluation, we focus on the visual domain adaptation and evaluate our model on several benchmark datasets including MNIST, MNIST-M, Synthetic Digits (SYN), Street View House Numbers (SVHN), CIFAR-10, and STL-10.

4.1 Implementation Detail

Architecture. We use identical network architectures as the ones in VADA [34] for a fair comparison. In particular, a small CNN is used for the tasks of digits, and a larger CNN is used for adaptation tasks between CIFAR-10 and STL-10.

Hyperparameters. We fix $\alpha$ in Eq. 6 as 1 for all experiments. For $\lambda_d$ and $\beta$, we follow [34] to restrict the hyperparameter search to $\lambda_d = \{0, 10^{-2}\}$ and $\beta = \{10^{-3}, 10^{-2}\}$. For $\lambda_\phi$ and $\lambda_t$, we restrict the hyperparameter search to $\lambda_\phi = \{0, 10^{-2}, 10^{-1}, 0.5, 1\}$ and $\lambda_t = \{10^{-2}, 10^{-1}, 1\}$.

Iterative refinement training. In literature [34], an iterative refinement training technique called DIRT-T is proposed for further optimizing the cluster assumption on the target domain. We find this strategy is also very effective for our model. Specifically, we first initialize with a trained VMT model using Eq. 7, and then iteratively minimize the following objective on the target domain:

$$\min_{f_n} \lambda_t L_t(f_n; \mathcal{X}_t) + \beta \mathbb{E} [D_{KL}(f_n-1(x)||f_n(x))],$$

where $L_t = L_m + L_v + L_c$. We report the results of using or without using DIRT-T in the following experiments.

Baselines. We primarily compare our model with two baselines: VADA [34] and Co-DA [20]. Co-DA is also based on VADA, which used a co-regularization method to make a better domain alignment. We also show the results of several other recently proposed unsupervised domain adaptation models for comparison.

Other detail. Following [34], we replace gradient reversal [10] with the strategy [13] of alternating updates between the domain discriminator and feature encoder. We also follow [34] to apply the instance normalization to the input images and report the performances of using or without using the instance normalization. We use Adam Optimizer (learning rate $= 0.001$, $\beta_1 = 0.5$, $\beta_2 = 0.999$) with an exponential moving average (momentum $= 0.998$) to the parameter trajectory. The implementation of our model is based on the official implementation of VADA [34], and the code will be made publicly available.

4.2 Model Evaluation

We evaluate VMT on the following unsupervised domain adaptation tasks, and the results are shown in Table 1. Our proposed VMT achieves state-of-the-art performance for all the tasks.

MNIST $\rightarrow$ SVHN. We first evaluate VMT on the adaptation task from MNIST to SVHN. Adapting from MNIST to SVHN is usually treated as a challenging task [10, 34] since the intrinsic dimensionality of MNIST is significantly lower than SVHN. It is especially difficult when the input is not instance-normalized, as shown in Table 1. For MNIST $\rightarrow$ SVHN without instance normalization, VADA removes conditional entropy minimization as it behaves unstable and finds a degenerate solution quickly [34]. We find this problem no longer exists in our model, and thus we remain conditional

\textsuperscript{3}https://github.com/RuiShu/dirt-t
Table 1: Test set accuracy on visual domain adaptation benchmark datasets. For all tasks, VMT improves the accuracy of VADA and achieves state-of-the-art performance.

| Source Target | MNIST SVHN MNIST MNIST-M SVHN CIFAR STL CIFAR |
|---------------|-----------------------------------------------|
| MMD [24]      | - 71.1 76.9 88.0 96.5 55.0 86.4 58.7 96.5 |
| DANN [10]     | 35.7 71.1 81.5 90.3 66.4 58.7 |
| DRCN [11]     | 40.1 82.7 83.2 91.2 86.7 92.9 |
| DSN [5]       | - 82.7 83.2 91.2 66.4 58.7 |
| kNN-Ad [32]   | 40.3 78.8 86.7 - - - |
| PixelDA [7]    | - - 98.2 - - |
| ATT [22]      | 52.8 86.2 94.2 92.9 - - |
| II-model (aug) [9] | 71.4 92.0 94.2 76.3 64.2 |

Without Instance-Normalized Input:

| Source-Only  | 27.9 77.0 58.5 86.9 76.3 63.6 |
| VADA [34]    | 47.5 97.9 97.7 94.8 80.0 73.5 |
| Co-DA [20]   | 55.3 98.8 99.0 96.1 81.4 76.4 |
| VMT (ours)   | 67.9 98.9 99.0 96.3 81.6 78.5 |
| VADA+DIRT-T [34] | 54.5 99.4 98.9 96.1 75.3 |
| Co-DA+DIRT-T [20] | 63.0 99.4 99.1 96.5 77.6 |
| VMT+DIRT-T (ours) | 86.4 99.5 99.2 96.5 - 79.2 |

With Instance-Normalized Input:

| Source-Only  | 40.9 82.4 59.9 88.6 77.0 62.6 |
| VADA [34]    | 73.3 94.5 95.7 94.9 78.3 71.4 |
| Co-DA [20]   | 81.7 98.7 98.0 96.0 80.6 74.7 |
| VMT (ours)   | 89.5 99.1 98.2 96.3 80.9 77.0 |
| VADA+DIRT-T [34] | 76.5 99.4 98.7 96.2 - 73.3 |
| Co-DA+DIRT-T [20] | 88.0 99.4 98.8 96.5 - 75.9 |
| VMT+DIRT-T (ours) | 96.4 99.6 98.9 96.5 - 78.0 |

For MNIST → SVHN, we observe significant improvements over the baselines. Especially for the setting of without instance normalization, VMT+DIRT-T outperforms VADA+DIRT-T by 31.9% and outperforms Co-DA+DIRT-T by 23.4%, and VMT outperforms VADA and Co-DA by 20.4% and 12.6%, respectively. For the setting of with instance normalization, VMT+DIRT-T achieves an accuracy of 96.4%. Moreover, we train a classifier on the target domain (i.e., SVHN) with labels revealed using the same network architecture and same settings, and it is treated as an upper bound for domain adaptation methods. This train-on-target model achieves an accuracy of 96.5%. The accuracy of VMT+DIRT-T (96.4%) is very close to the upper bound (96.5%).

**SVHN → MNIST.** For this task, it is much easier than MNIST → SVHN. VADA already achieves a high accuracy (97.9%) for this task. VMT still improves the accuracy of VADA by 4.6% and 1% for with and without instance normalization, respectively. VMT+DIRT-T has a similar performance as VADA+DIRT-T. Compared with Co-DA, VMT performs similarly for this task.

**MNIST → MNIST-M.** We then evaluate on the adaptation task from MNIST to MNIST-M, where the images in MNIST-M are constructed by blending the MNIST digits with randomly cropped color patches from the BSDS500 dataset. For this task, VMT improves the accuracy of VADA by 2.5% and 1.3% for with and without instance normalization respectively and has a similar performance as Co-DA.

**SYN DIGITS → SVHN.** We also evaluate on the adaptation task from Synthetic Digits to SVHN. The Synthetic Digits dataset is constructed by rendering digit images using standard fonts and varying the position, orientation, background, stroke color, and amount of blur. Similar to the task of entropy minimization during training. For MNIST → SVHN, we observe significant improvements over the baselines. Especially for the setting of without instance normalization, VMT+DIRT-T outperforms VADA+DIRT-T by 31.9% and outperforms Co-DA+DIRT-T by 23.4%, and VMT outperforms VADA and Co-DA by 20.4% and 12.6%, respectively. For the setting of with instance normalization, VMT+DIRT-T achieves an accuracy of 96.4%. Moreover, we train a classifier on the target domain (i.e., SVHN) with labels revealed using the same network architecture and same settings, and it is treated as an upper bound for domain adaptation methods. This train-on-target model achieves an accuracy of 96.5%. The accuracy of VMT+DIRT-T (96.4%) is very close to the upper bound (96.5%).
To analyze the role of VMT on the source domain, i.e., \( L_c \) in Eq. 7, we present an ablation study in Table 3. We conduct this study through the most challenging task, MNIST \( \rightarrow \) SVHN. From Table 3, we have the following three observations. First, VMT on the target domain plays a critical role as \( \{ L_c, L_m(X_t) \} \) gets much higher accuracy than \( \{ L_c, L_m(X_s) \} \). This is reasonable because our final target is to classify the samples from the target domain. Second, adding \( L_m(X_s) \) to \( \{ L_c, L_m(X_t) \} \) is able to further improve the performance by 3.5%. This may be because applying MNIST \( \rightarrow \) MNIST-M, we observe a reasonable improvement of VMT over VADA and a similar performance between VMT and Co-DA.

**CIFAR-10 \( \rightarrow \) STL-10.** For CIFAR-10 and STL-10, there are nine overlapping classes between the two datasets. Following [9, 34, 20], we remove the non-overlapping classes and remain the nine overlapping classes. For this task, VMT improves the accuracy of VADA by 2.6% and 1.6% for with and without instance normalization respectively and performs similarly to Co-DA. Note that DIRT-T has no effect on this task, because STL-10 contains a very small training set, making it difficult to estimate conditional entropy.

**STL-10 \( \rightarrow \) CIFAR-10.** We finally evaluate on the adaptation task from STL-10 to CIFAR-10. For this task, VMT outperforms VADA by about 5% and outperforms Co-DA by about 2% for with and without instance normalization. When using DIRT-T, VMT+DIRT-T outperforms VADA+DIRT-T by 4.7% and 3.9% and outperforms Co-DA+DIRT-T by 2.1% and 1.6% for with and without instance normalization, respectively.

### 4.3 Comparing with Virtual Adversarial Training

As stated in Section 5.1,2 virtual adversarial training (VAT) [27] is another approach to impose the locally-Lipschitz constraint, as used in literature [34]. We conduct comparison experiments between VAT and our proposed VMT and show the results in Table 2. VMT achieves higher accuracy than VAT for all the tasks, and it demonstrates that VMT surpasses VAT in constraining the local Lipschitzness. Furthermore, combining VMT and VAT is able to further improve the performance. This shows that VMT is orthogonal to VAT, and they can be used together to constrain the local Lipschitzness.

### 4.4 Analysis of VMT on the Source Domain

To analyze the role of VMT on the source domain, i.e., \( L_c(f; X_s) \) in Eq. 7 we present an ablation study in Table 3. We conduct this study through the most challenging task, MNIST \( \rightarrow \) SVHN. From Table 3, we have the following three observations. First, VMT on the target domain plays a critical role as \( \{ L_c, L_m(X_t) \} \) gets much higher accuracy than \( \{ L_c, L_m(X_s) \} \). This is reasonable because our final target is to classify the samples from the target domain. Second, adding \( L_m(X_s) \) to \( \{ L_c, L_m(X_t) \} \) is able to further improve the performance by 3.5%. This may be because applying

| Source Target | MNIST | SVHN | MNIST | MNIST-M | SYN | CIFAR | STL | CIFAR |
|---------------|-------|------|-------|---------|-----|-------|-----|-------|
| With Instance-Normalized Input: |       |      |       |         |     |       |     |       |
| \( \{ L_c \} \) | 66.8  | 83.1 | 93.8  | 93.4    | 79.1| 68.6  |     |       |
| \( \{ L_c, L_m \} \) | 73.3  | 94.5 | 95.7  | 94.9    | 78.3| 71.4  |     |       |
| \( \{ L_c, L_m(X_s) \} \) | 85.9  | 98.6 | 96.4  | 95.6    | 80.5| 75.2  |     |       |
| \( \{ L_c, L_m(X_t), L_m(X_s) \} \) | 89.5  | 99.1 | 98.2  | 96.3    | 80.9| 77.0  |     |       |

Table 2: Test set accuracy in comparison experiments between VAT and VMT. \( L_c \) denotes the conditional entropy loss, \( L_c \) denotes the VAT loss, and \( L_m \) denotes the VMT loss. \( \{ L_c, L_m \} \) means that we only use \( L_y, d, L_c \), and \( L_m \) in Eq. 7 setting the weights of the other losses to 0. The results of \( \{ L_c \} \) and \( \{ L_c, L_v \} \) are duplicated from [34].

| Method | \( \{ L_c \} \) | \( \{ L_c, L_m(X_s) \} \) | \( \{ L_c, L_m(X_t) \} \) | \( \{ L_c, L_m(X_s), L_m(X_t) \} \) |
|--------|----------------|-----------------------------|-----------------------------|---------------------------------|
| Accuracy | 70.2 | 68.4 | 82.4 | 85.9 |

Table 3: Test set accuracy on the adaptation task of MNIST \( \rightarrow \) SVHN with instance-normalized input. \( L_c \) denotes the conditional entropy loss, and \( L_m(X_s) \) and \( L_m(X_t) \) denote the VMT loss on the source and target domain respectively. For example, \( \{ L_c, L_m(X_s) \} \) means that we only use \( L_y, d, L_c \), and \( L_m(X_s) \) in Eq. 7 setting the weights of the other losses to 0. The accuracy of \( \{ L_c \} \) is different to [34] as we set \( \lambda_t \) to 0.1 for MNIST \( \rightarrow \) SVHN with instance-normalized input.
VMT on both the source and target domains can generate similar output distributions for the source and target domains, thus further improving the performance on the target domain. Third, combining $L_{m} (X_s)$ alone with $L_{c}$ has a negative impact on the performance, reducing the accuracy from 70.2% to 68.4%.

5 Conclusion

In this paper, we proposed a novel method, called virtual mixup training, for unsupervised domain adaptation. VMT is designed to constrain the local Lipschitzness, which further improves the performance of the cluster assumption \[15, 34\]. The idea of VMT is to make linearly-change predictions along the lines between pairs of training samples. In particular, we first construct convex combinations of training samples and their virtual labels, and then add a penalty term that punishes the difference between the prediction of the combined point and combined virtual label. VMT significantly improves the performance of a recent state-of-the-art model called VADA, which is based on the cluster assumption. For a challenging adaptation task from MNIST to SVHN, our model achieves an accuracy of 96.4%, which is very close to the accuracy (96.5%) of the train-on-target model. Given the strong performance of VMT, we would like to explore the use of VMT in semi-supervised and supervised learning, which we leave as future work.

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