Unsupervised Multi-Target Domain Adaptation Through Knowledge Distillation

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Abstract

Unsupervised domain adaptation (UDA) seeks to alleviate the problem of domain shift between the distribution of unlabeled data from the target domain w.r.t. labeled data from source domain. While the single-target domain scenario is well studied in UDA literature, the Multi-Target Domain Adaptation (MTDA) setting remains largely unexplored despite its practical importance. For instance, in video surveillance applications, each camera of a distributed network corresponds to a different non-overlapping viewpoint (target domain). MTDA problem can be addressed by adapting one specialized model per target domain, although this solution is too costly in many real-world applications. It has also been addressed by blending target data for multi-domain adaptation to train a common model, yet this may lead to a reduction in model specificity and accuracy. In this paper, we propose a new unsupervised MTDA approach to train a common CNN that can generalize well across multiple target domains. Our approach – the Multi-Teacher MTDA (MT-MTDA) – relies on multi-teacher knowledge distillation (KD) in order to distill target domain knowledge from multiple teachers to a common student. Inspired by a common education scenario, a different target domain is assigned to each teacher model for UDA, and these teachers alternatively distill their knowledge to one common student model. The KD process is performed in a progressive manner, where the student is trained by each teacher on how to perform UDA, instead of directly learning domain adapted features. Finally, instead of directly combining the knowledge from each teacher, MT-MTDA alternates between teachers that distill knowledge in order to preserve the specificity of each target (teacher) when learning to adapt the student. MT-MTDA is compared against state-of-the-art methods on Office-Home, Office31, and Digits-5 datasets, and empirical results show that our proposed model can provide a considerably higher level of accuracy across multiple target domains.
1 Introduction

Deep Learning (DL) architectures, and in particular Convolutional Neural Networks (CNNs), have achieved state-of-the-art performance in many visual recognition applications such as image classification, object detection, and segmentation [10]. Despite their success, several factors limit their deployment in real-world industrial applications. Among these factors is the problem of domain shift, where the distribution of original training data (source domain) diverges w.r.t data from the operational environment (target domain). This problem often translates to a notable decline in performance once the DL model has been deployed in the target domain.

In order to address this problem, DL models for domain adaptation have been proposed to align a discriminant source model with the target domain using data captured from the target domain [6, 8, 18, 24]. In unsupervised domain adaptation (UDA), a large amount of unlabeled data is often assumed to have been collected from the target domain to avoid the costly task of annotating data. Currently, several conventional and DL models have been proposed for the single target domain adaptation (STDA) setting, using unlabeled data that is collected from a single target domain. These models rely on different approaches, ranging from the optimization of a statistical criterion to the integration of an adversarial network, in order to learn robust domain-invariant representations from source and target domain data. However, the multi-target domain adaptation (MTDA) scenario, i.e., unlabeled data from multiple target domains, remains almost unexplored despite many real-world applications. For example, in video-surveillance applications, a DL model for, e.g., person re-identification, should normally be adapted to multiple different camera viewpoints (target domains) within a large distributed non-overlapping network of cameras.

Extension of STDA techniques to the MTDA setting is not straightforward, and they may perform poorly on multiple target domains. Although MTDA problems can be solved by producing one model per target domain, this approach becomes costly and impractical in applications with a growing number of target domains. In such cases, a MTDA approach should ideally yield a common DL model that is compact and has been adapted to perform accurately across all target domains. To adapt a common multi-target DL model, one recent MTDA approach consists in blending all the target datasets together for UDA, which may lead to a reduction in the model’s specificity and accuracy [5]. While the current approach provides an interesting direction in adapting a common model to multiple target domains, we argue that directly adapting a model to multiple target domains can affect the performance since there are limitations on a model’s capacity to learn and generalize in diverse target domains. Other works on MTDA have focused on the problem of unshared categories between target domains [27], nevertheless, it is not considered in this work since it’s outside the scope of this paper.

In this paper, a novel MTDA learning strategy referred to as Multi-Teacher MTDA (MT-MTDA) is proposed to train a common CNN to perform well across multiple target domains. Our strategy relies on knowledge distillation to efficiently transfer information from several different target domains, each one associated with a specialized teacher, to a single common multi-target model. Figures 1(a)-(c) illustrate the different MTDA strategies from literature, evolving from strategies that adapt a single CNN per target domain, to strategies that adapt a common CNN across all target domains. Our novel MT-MTDA approach (illustrated in Figure 1(d)) is inspired by a common education scenario, where each teacher is responsible for a single subject (i.e. target domain), and these teachers sequentially educate a student to learn all the subjects.

In our MT-MTDA approach: (1) Since only the student performance is important after training, we can resort to complex architecture for the teacher model; (2) These complex teachers can provide a higher capacity to generalize toward a single target domain instead of having one model learning multiple target domains; (3) The student model learns compressed knowledge from teachers across target domains, instead of directly learning to generalize on multiple domains; and (4) MT-MTDA can benefit from different STDA algorithms since each teacher adapt to only one target.

We also propose an efficient alternative for the fu-
of knowledge from multiple teachers. State-of-the-art techniques for multi-teacher knowledge distillation rely on average or sum operations to directly combine the information derived by teachers [21]. To preserve the specificity of individual teachers, we let our student model learn to adapt from each teacher separately and sequentially from teacher to teacher. We argue that having better preservation of target specificity we can obtain better results.

Finally, we present a comprehensive evaluation of the proposed MT-MTDA and state-of-the-art strategies on the Digit-five, Office31 and OfficeHome benchmark datasets, and show that MT-MTDA consistently achieves a high level of accuracy across multiple target domains with different networks as backbone architectures.

2 Related Work:

Single Target Domain Adaptation. STDA is an unsupervised transfer learning task that focuses on adapting a model such that it can generalize well on an unlabeled target domain data while using a labeled source domain dataset. DL models for UDA seek to learn discriminant and domain-invariant representations from source and target data [23]. They are either based on either adversarial [8], discrepancy [16], or reconstruction-based approaches [7]. Taking advantage of adversarial training, several methods [8, 22, 17, 5] have been proposed using either gradient reversal [8] or a combination of feature extractor and domain classifier to encourage domain confusion. Discrepancy-based approaches [16, 14] rely on measures between source and target distributions that can be minimized in order to generalize on the target domain. In [16], authors minimize the Maximum Mean Discrepancy (MMD) between target and source features in order to find domain invariant features. On the other hand, [14] assume that task knowledge is already learned and the domain adaptation is done on the batch normalization layer in order to correct the domain shift. Lastly, another set of domain adaptation techniques focus on the mapping of the source domain to target domain data or vice versa [2]. These techniques are often based on the use of Generative Adversarial Network (GAN) in order to find a mapping between source and target.

Multi Target Domain Adaptation. MTDA is a set of domain adaptation techniques that improves upon the single target domain adaptation by adapting a single model to teacher target domains. Currently, multi-target domain adaptation still remains largely unexplored with many open research questions. The paper of [9] proposes an approach that can adapt a model to multiple target domains by maximizing the mutual information between domain labels and domain-specific features while minimizing the mutual information between the shared features. Recently, [4] proposed to blend multiple target domains together and minimize the discrepancy between the source and the blended targets. Additionally, the authors employ an unsupervised meta-learner in combination with a meta target domain discriminator in order to blend the target domains. While these methods achieve good performance, they fail to take advan-

Figure 1: Illustration of different STDA and MTDA strategies for training CNNs across multiple target domains. $S$ is the labeled source dataset, while $T_i$ are the unlabelled target datasets for $i = 1, 2..., n$. 
tage of existing STDA techniques, which have been extensively researched. Another important common point to existing methods is that they try to capture the representation of all the target domains using a common feature extractor directly from the data, which can degrade the final accuracy because of the limited capacity of this common model. In our paper, we overcome this issue by performing domain adaptation separately on different models and distilling a compressed knowledge to a common model. In addition, our experiments show that current mixed target approaches still struggle with blending target domains in the feature space. We can gain more by preserving each domain specificity using STDA on different models.

Knowledge Distillation (KD). KD techniques allow for model compression by transferring knowledge from a teacher model, usually complex, to a smaller compact student model. The two main approaches of transferring knowledge between teacher and student models consist in minimizing the difference between logits [12, 15], and between features maps [26, 20, 11]. Techniques from the first approach focus on measuring logits obtained from a temperature-based softmax and then minimize the distance between the logits of the teacher and the student [12]. More recently, techniques like [11] minimize the distance between the intermediate feature maps of the teacher and student using a partial L2 distance. In contrast with other techniques, these features are obtained using a margin ReLU that accounts for negative values of feature map. Techniques for multi-teacher knowledge distillation focus on the fusion of distilled knowledge. In [21], the authors use multiple teachers in the scenario of single target domain adaptation and employ a fusion scheme that sums the output of each teacher to apply distillation. Recently, a STDA model has been proposed using KD to learning a compressed model that is adapted to perform well for a given target domain [19].

3 Proposed Method

3.1 Domain Adaptation of Teachers:

In this paper, the RevGrad [8] technique is employed since it is the basis for many popular methods [1, 4], although it can be easily replaced by other STDA techniques. Let us define the source domain as \( S = \{x_s, y_s\} \) where \( x_s \) is input pattern, and \( y_s \) its corresponding label. The set of target domains is defined as \( T = \{T_1, T_2, ..., T_n\} \), each one defined as \( T_i = \{x_i\} \). For each target domain \( T_i \), we define a teacher model \( \Phi_i \), and each of these teachers will be adapted to a corresponding target domain using the UDA technique proposed in [8]. The domain adaptation of the teacher relies on a domain classifier, a gradient reversal layer (GRL), and the domain confusion loss:

\[
L_{DC}(\Phi_i, S, T_i) = \frac{1}{N_s + N_t} \sum_{x \in S \cup T_i} L_{CE}(D_i(\Phi_i(x)), d_i) \tag{1}
\]

where \( \phi_i(x) \) is the output from the feature extractor of teacher network \( \Phi_i \), before the fully connected layers, \( D_i \) is the domain classifier for the corresponding teacher network, \( d_i \) the domain label (source or target), \( N_s \) is the number of samples in the source domain \( S \), and \( N_t \) is the number of samples in the target domain \( T_i \).

The final domain adaptation loss is then defined as:

\[
L_{DA}(\Phi_i, S, T_i) = \frac{1}{N_s} \sum_{x_s, y_s \in S} L_{CE}(\Phi_i(x_s), y_s) + \gamma \cdot L_{DC}(\Phi_i, T_i) \tag{2}
\]

The first term (cross-entropy loss) allows the supervised training of the teacher model on the source domain that ensures the consistency of domain confusion. The second term is controlled by a hyper-parameter \( \gamma \) that regulates the importance of the domain confusion loss which is maximized using a gradient reversal layer. Figure 2 illustrates how GRL is applied for UDA.

3.2 Knowledge Distillation from Teacher to Student:

In this paper, we employ knowledge distillation based on logits as in [12]. The Figure 3 illustrates the overall process of distillation on both target and source domains. Logits from a teacher/student model are fed...
to a temperature-based softmax function, in combination with a KL divergence loss on both the teacher and student outputs:

$$L_{\text{Source}}(\Phi_i, \Theta, S) = \frac{1}{N_s} \sum_{x_s, y_s \in S} L_{KL}(\Phi_i(x_s, \tau), \Theta(x_s, 1)) + \alpha \cdot L_{CE}(\Theta(x_s, 1), y_s) \tag{3}$$

where $\Theta$ represents our student model with $\tau$ the temperature hyper-parameter the softmax, and $\alpha$ the hyper-parameter to regulate the importance of the cross-entropy term. Even though the second term of Eq. 3 may perform well with data from the source domain because it has labels, we add the domain confusion loss (Eq. 1) on the target domain to provide consistency during target distillation:

$$L_{\text{Target}}(\Phi_i, \Theta, T_i) = \frac{1}{N_t} \sum_{x_t \in T_i} L_{KL}(\Phi_i(x_t, \tau), \Theta(x_t, 1)) + \alpha \cdot L_{DC}(\Theta, T_i) \tag{4}$$

3.3 Multi-Teacher Multi-Target DA:

For progressive UDA of teacher models and transfer of knowledge from teacher to the student model, we adopt an exponential growing rate to gradually transfer the importance of UDA to KD. The growth rate is defined as:

$$g = \frac{\log(f/s)}{N_e} \tag{5}$$

where $s$ the starting value, $f$ the final value, and $N_e$ the number of total epochs. This growth rate will used to calculate the value of $\beta$ in the overall loss function for optimization of one teacher:

$$L(\Phi_i, \Theta, S, T_i) = (1 - \beta)L_{DA}(\Phi_i, T_i) + \beta L_{\text{Source}}(\Phi_i, \Theta, S) + \beta L_{\text{Target}}(\Phi_i, \Theta, T_i) \tag{6}$$

With $\beta$, the value that balances between the importance of the domain adaptation loss and the distillation loss, is then defined as $\beta = s \cdot \exp^g e$, where $e$ represent the current epoch. Our approach, MT-MTDA, instead of using deterministic fusion functions, such as average fusion, employs an alternative learning scheme for knowledge distillation from multiple teachers. This alternative scheme is done by sequentially looping through each teacher at batch level, as described in the following algorithm:

**Algorithm 1: Multi-Teacher Multi-Target Domain adaptation (MT-MTDA)**

- **input**: A source domain dataset $S$, a set of target dataset $T_0, T_1, \ldots T_n$
- **output**: A student model adapted to $n$ targets

  Initialize a set of teachers models $\Phi = \{\Phi_0, \Phi_1, \ldots \Phi_n\}$
  Initialize a student model $\Theta$

  for $e \leftarrow 1$ to $N_e$ do
    for $x_s \in S$ and $x_t \in \{T_0, T_1, \ldots T_n\}$ do
      Get the set of data of target domains $X_t$
      for $x_t^i \in X_t$ and $\Phi_i \in \Phi$ do
        Optimize $(1 - \beta)L_{DA}(\Phi_i, T_i)$ for $\Phi_i$ using $x_s, x_t^i$
        Optimize the loss of equation $\beta L_{\text{Source}}(\Phi_i, \Theta, S)$ for $\Phi_i$ and $\Theta$ using $x_s$\n        Optimize the loss of equation $\beta L_{\text{Target}}(\Phi_i, \Theta, T_i)$ for $\Phi_i$ and $\Theta$ using $x_t^i$
      end
    end
    Update $\beta = s \cdot \exp^g e$
  end
  Evaluate the model

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1 Note that our method can work with any other technique.
Figure 4: Illustration of the proposed learning technique.

Figure 4 illustrates the overall pipeline for our MT-MTDA approach. While all teachers share the same source dataset, the figure shows that each teacher has its own target dataset with their own domain adaptation loss.

4 Experiments

4.1 Datasets:

Our experiments are performed on the 3 challenging datasets described below.

1) Digit-five: This dataset regroups a set of 5 digits datasets: MNIST (mt), MNIST-M (mm), SVHN (sv), USPS (up) and Synthetic Digits (sy). Each one has each 10 classes that represent all the digits. For the evaluation on this dataset, we follow the same protocol as in [5] for a fair comparison. We use 25000 samples for training on mt, mm, sv, sy and 9000 for testing. On the up dataset we use the entire dataset as a domain.

2) Office31: This dataset has 3 subsets – Amazon (A), DSLR (D) and Webcam (W). Images are taken respectively from the Amazon website, a DSLR camera and a webcam. These datasets all have 31 common classes and around 4000 images in total. We followed the standard evaluation protocol, a domain is chosen as a source, and the rest as targets. The performance of the model is evaluated using classification accuracy over all target domains.

3) OfficeHome: This dataset contains 4 subsets: Art (Ar), Clip Art (Cl), Real World (Rw) and Product (Pr). It has a total of 15,500 images for 65 object categories that are usually found in office or home settings. We follow the same evaluation protocol for Office31 for this dataset.

4.2 Implementation Details:

For the implementation of MT-MTDA, we use the same number of optimizers as teacher models. These optimizers are responsible for the UDA of each teacher. Additionally, we add another optimizer for the knowledge distillation of the student. MT-MTDA is compared to a lower bound, that’s only trained on source and tested on target, the current state-of-the-art in MTDA – AMEANS [5] and to baseline methods such as RevGrad [8] which is the basis of our MTDA method. We also use other baselines like DAN [16] or ADDA [22] in some cases for additional comparison. For the Digits-five dataset, we employ a LeNet backbone with ResNet50 as teacher. As for the comparison on Office31 and OfficeHome, we use AlexNet backbone with ResNet50 as teacher models, and as for the comparison on the ResNet50 backbone, we use a ResNext101 as teachers. Our backbone CNNs follows the choices in [5]. All these models start with pre-trained weights from ImageNet, except for LeNet.

As for our hyper-parameters, we selected them based on their overall result in cross-validation in all the scenarios instead of having a set of dedicated hyper-parameters for each scenario. The details of our hyper-parameters can be found in the Supplementary Material. We report the average classification accuracy obtained by all implemented models over 3 replications, from all the target domains. For other baselines, we report their best published result for fair comparison. Additional results are shown and analysed, along with a weighted average accuracy version of MT-MTDA in the Supplementary Material. The code of our approach can be found at: https://github.com/Anon6272/MT-MTDA

4.3 Results and Discussion:

Table 1 shows the average classification accuracy of the MT-MTDA versus baseline and state-of-the-art method.
Table 1: Accuracy of MT-MTDA and reference methods on the Digits-Five dataset.

| Models          | mt → mm, sv, up, sy | mm → mt, mm, sv, up, sy | sv → mt, mm, up, sy | sy → mt, mm, up, sy | up → mt, sv, mm, sy | Average |
|-----------------|----------------------|-------------------------|---------------------|---------------------|---------------------|---------|
| Source only     | 36.0                 | 57.3                    | 67.1                | 74.9                | 36.9                | 54.6    |
| ADDA[22]        | 52.5                 | 58.9                    | 46.4                | 67.0                | 34.8                | 51.9    |
| DAN[16]         | 38.8                 | 58.9                    | 56.1                | 63.8                | 27.0                | 48.0    |
| RevGrad[8]      | 60.2                 | 66.0                    | 64.7                | 69.2                | 44.1                | 60.1    |
| AMEANS[5]       | 61.2                 | 66.9                    | 67.2                | 73.3                | 47.5                | 63.2    |
| MT-MTDA (ours)  | 58.6                 | 71.0                    | 67.6                | 75.6                | 51.0                | 64.7    |

ods on the Digits-Five dataset. We observe that our technique provides a higher level of accuracy, on average than the other approaches. In the first scenario, where our method performs poorly, further analysis on separate target domains (in Supplemental Material) indicates that our teacher models did not adapt well to the MNIST-M and Synthetic datasets. This is mainly due to our selection of hyper-parameters, which was based on the all-scenario setting instead of individual cases. This explains why, for our first scenario, the result lags behind current baselines. It is possible, however, to overcome this problem by optimizing each scenario with a different set of hyper-parameters, including each teacher.

Table 2: Accuracy of MT-MTDA and reference methods on the Office31 dataset.

| Models          | Backbone | A → D, W | D → A, W | W → A, D | Average |
|-----------------|----------|-----------|-----------|-----------|---------|
| Source only     | AlexNet  | 62.7      | 74.3      | 74.4      | 70.1    |
| DAN[16]         | 65.2      | 77.3      | 74.7      | 71.6      | 69.4    |
| RevGrad[8]      | 67.4      | 75.8      | 75.8      | 75.8      | 75.8    |
| AMEANS[5]       | 69.9      | 78.0      | 78.1      | 78.1      | 78.1    |
| MT-MTDA (Ours)  | ResNet50  | 72.2      | 76.9      | 77.6      | 76.3    |
| Source only     | ResNet50  | 68.9      | 70.9      | 80.0      | 76.4    |
| DAN[16]         | 71.9      | 73.0      | 85.0      | 77.6      | 77.6    |
| RevGrad[8]      | 73.0      | 77.1      | 87.7      | 80.7      | 80.7    |
| AMEANS[5]       | 75.8      | 84.2      | 84.3      | 86.2      | 84.2    |
| MT-MTDA (Ours)  | 77.9      | 85.7      | 84.0      | 85.2      | 85.2    |

Tables 2 and 3 present the average classification accuracy of the MT-MTDA versus baseline and state-of-the-art methods on Office31 and OfficeHome data, respectively. In both cases, we observe that MT-MTDA typically outperforms the current state-of-the-art methods. With the AlexNet backbone, the improvements are significant, which can be explained by the advantage of using KD from multiple complex teachers, leading to a better generalization on a single target domain. We can observe that on Office31, AMEANS performs slightly better than MT-MTDA with the larger ResNet50 backbone. We believe that this is due to the limitations of domain adaptation on teacher models with MT-MTDA. We further discuss this point in the ablation study where we compare and discuss the performance of teacher and student in 4.4.

Overall, our MT-MTDA technique outperforms better both the baselines and state-of-the-art techniques. From Tables 1 and 2, we noticed that our model generally provides the highest accuracy on a compact backbone CNN, mainly because of the teacher’s complexity and our knowledge distillation process. This is further confirmed by a comparison with the baseline RevGrad[8] technique adapted directly on multi-target domains. Additionally, the improvements in accuracy that our methods brings decrease when the complexity gap between the teachers and student is smaller. In this case, the performance bottleneck is the teacher and the distillation algorithm. We further discuss this point in the ablation study, when comparing between student and teacher models.

From Figure 5 (please see a higher resolution image in Supplemental Material), we observe that the feature representation learned with MT-MTDA better separates Office31 features, compared to other reference methods. Furthermore, MT-MTDA also separates class samples from different target domains in a better way than AMEANS. For comparison purposes, representations of other baselines are provided in the Supplementary Material. We noted that in current state-of-the-art methods, the target domains do not blend well with each other since the feature extractor can still differentiate them quite well based on the t-SNE.

4.4 Ablation Study

Detailed Comparison of Each Target Domain.

For this experiment, compare MT-MTDA in a setting
Table 3: Accuracy of proposed and reference methods on OfficeHome dataset

| Models  | Backbone | At → Cl, Pr, Rw | Cl → At, Pr, Rw | Pr → At, Cl, Rw | Rw → At, Cl, Pr | Average |
|---------|----------|------------------|------------------|------------------|------------------|---------|
| Source only | AlexNet | 38.8 | 41.8 | 39.8 | 37.9 | 34.9 |
| DAN[16] | 39.7 | 41.6 | 37.8 | 40.5 | 34.3 |
| RevGrad[8] | 42.2 | 43.8 | 40.9 | 41.7 | 37.2 |
| AMEANS[5] | 44.6 | 45.6 | 41.4 | 49.3 | 45.2 |
| MT-MTDA (Ours) | 48.8 | 48.7 | 42.9 | 55.8 | 49.1 |
| Source only | ResNet50 | 49.1 | 41.8 | 41.1 | 43.4 | 41.1 |
| DAN[16] | 55.6 | 55.1 | 51.9 | 56.1 | 52.8 |
| RevGrad[8] | 58.4 | 57.0 | 52.0 | 63.0 | 57.1 |
| AMEANS[5] | 64.3 | 64.2 | 59.2 | 66.4 | 63.4 |
| MT-MTDA (Ours) | 64.6 | 66.4 | 59.2 | 67.1 | 64.3 |

Figure 5: T-SNE visualization of Office31 data, where features are learned using MT-MTDA and AMEANS. Best viewed in color
where each target domain has a specific model. We compare our result on separate target domains with RevGrad [8], but trained on a single target domain adaptation task. We also compared with the current best STDA algorithm, to our knowledge, in order to evaluate the effect of having a better STDA for the teacher model in our method.

Table 4: Average accuracy baseline STDA methods for individual target datasets vs MTDA methods on Office31 dataset using AlexNet

| Method                  | A → D   | A → W   | A → D,W | A → D,W | Average |
|-------------------------|---------|---------|---------|---------|---------|
| Upper-Bound             | 98.1    | 77.6    | 83.1    | 87.9    | 85.9    |
| AMEANS                  | 97.6    | 77.1    | 82.2    | 86.6    | 84.7    |
| Source only             | 77.1    | 77.1    | 77.1    | 77.1    | 77.1    |

Table 5 shows that while our algorithm does not perform as well as the state-of-the-art in STDA, it requires less computational power and memory since it only uses one model for all the target models instead of having a specific model for each target domain, i.e., two models in this case. This means that MTDA methods would typically scale better than current STDA methods since the number of models does not depend on the number of target models. Additionally, DM-ADA [25] shows that our algorithm can still be further improved since we can replace the STDA algorithm we are using on the teacher models (RevGrad [8]) with almost any other STDAs. The table also shows the cosine distance in order to quantify the domain shift between source and target features for each UDA problem. Results show that the UDA problems in Office31 have a similar level difficulty.

Comparison with the Upper-Bound. In this experiment, we compare the results obtained on Office31 with an upper bound, trained in a supervised way using labels of all the target domains mixed together training on multiple targets. The lower-bound is the same as in the main experiments, a model trained only on the source data.

From Table 5 we observe that the proposed MT-MTDA approach outperforms both the lower baseline and the state-of-the-art method [5], by nearly 8% and 3%, as average. In contrast, the gap with full supervision is still large, indicating that there is still room for improvement to bridge this gap.

Teachers vs Student Performances. We now compare the performances of our with the student in order to explore the impact of knowledge distillation. For this experiment, we aggregate the result of each separate teacher in each scenario together and compare it with the result of our student. This comparison was performed on the Office31 dataset (additional results on OfficeHome can be found in the Supplementary Material).

Table 6: Comparison with of teachers accuracy vs students

| Module      | A → D   | A → W   | A → D,W | Average |
|-------------|---------|---------|---------|---------|
| Upper-Bound | 98.1    | 77.6    | 83.1    | 85.9    |
| AMEANS      | 97.6    | 77.1    | 82.2    | 84.7    |
| Source only | 77.1    | 77.1    | 77.1    | 77.1    |

From Table 6 the gap in accuracy is small and the student is almost at the same level as the teachers, except for the case of A → D,W. This indicates that our student model has learned how to adapt to multi-target domains from each separate teacher without an explicit fusion scheme. The first scenario of A → D,W shows a particular case where knowledge distillation helps improving domain adaptation. This behavior is also found when using ResNet50 as backbone architecture and seems to happen when the gap between the teachers and student is very small. Additionally, from the ResNet50 backbone, we can see that the bottleneck can be found on teacher models and its domain adaptation since the student is stuck with a very similar accuracy as the teachers.

Consistency on Target Knowledge Distillation. In this section, we want to compare the performance of our algorithm to see whether the consistency loss...
added to the target knowledge distillation actually helps to improve the performance. To this end, we removed the second term of the target knowledge distillation, Eq. 4, completely and we run our algorithm with the same settings as before on the scenario with an AlexNet as backbone on Office31 dataset.

Table 7: Accuracy of proposed method with target distillation consistency vs without

| Models                      | A \rightarrow D,W | D \rightarrow A,W | W \rightarrow A,D | Average |
|-----------------------------|-------------------|------------------|------------------|---------|
| MT-MTDA without CST        | 73.8              | 74.3             | 76.7             | 75.6    |
| MT-MTDA with CST           | 74.9              | 77.6             | 78.3             | 77.6    |

From the Table 7, it seems that having a consistency term on the target distillation loss only brings a small boost in performance. This aligns with our main results since the hyper-parameter that controls this consistency term is set to a small value.

Comparison with Other Fusion Methods. To demonstrate the benefits of the proposed feature fusion strategy, we compare our alternative fusion scheme with other baselines fusion methods, e.g., the sum or the mean of the output. The hyper-parameters for all the cases remain the same to those of the main experiment, with the only difference being the output of all the teachers is summed/averaged and then distilled to the student.

Table 10 shows that the proposed alternative distillation works better than either fusion by sum or average. This means that the proposed alternative scheme transfers learned knowledge better than the baseline methods in the particular case of MTDA. In addition, this shows that the student does not need an explicit fusion scheme in order to learn target domain knowledge from multiple teachers.

Comparison with Blended Targets Domains. For this experiment, we compare the scenario of having multiple teachers with each a different target domain versus a scenario with one teacher adapting on a mixed target domain. In order to run MT-MTDA with mixed target, we merge all the target domains into a single target domain, where a single teacher is then assigned to this mixed target domain. We run this study on the Office31 dataset with the same hyper-parameters as in the main experiment.

From the results of Table 11 we can observe that the accuracy of a mixed target domain using our algorithm is significantly lower than the results with a multi-teacher approach. This suggests that even with a complex teacher network, a good generalization on a mixed target domain is hard to achieve and a multi-teacher scenario is preferable.

Impact of Number of Target Domains. We now investigate the impact of increasing the number of domains on the student model. This experiment starts with a STDA setting of our algorithm and slowly increase the number of domains until reaching the maximum. We decided to do this experiment on the scenario with Ar dataset as source in OfficeHome dataset since it has more than two target domains and the dataset is bigger than Digits-Five.

From Table 8 we can see that while the performance degrades on the target domain Pr, we notice a slight increase in accuracy of the other cases. This means that, with our method, training multiple target domains together can boost the performance of some separate target domains. The decrease of performance in the case of Pr also indicates that there might be a saturation in learning capacity. In this case, we can say that the target domains Cl and Rw improved at the expense of Pr.

Order of Target Domains. We propose to evaluate whether the order of target domains impacts the performance of the final model. Similarly to the previous experiment, we decided to use the scenario with Ar as the source domain in OfficeHome dataset since there are more than 2 target domains. Table 9 reports the results of individual target domains when their orders are different. These results indicate that even though the order of the domains leads to different average results, the difference between the configurations is marginal, of nearly 0.3%, with a standard deviation equal to 0.1. These results indicate that the order of target domains has little impact, if any, on the final result of the trained models.

5 Conclusion

In this paper, we propose an unexplored way of doing MTDA, that takes advantage of multiple teachers
Table 8: Comparison with of accuracy on separate domains with gradual increase in domains. The order in the target domains indicates the order in which they were integrated into the training.

| Order | Accuracy |
|-------|----------|
| 1. Ar | 34.0     |
| 2. Cl | 33.3     |
| 3. Pr | 33.0     |
| 4. Rw | 34.1     |

Table 9: Accuracy of each target domain and standard deviation between these accuracies.

| Order | Accuracy | StdDev |
|-------|----------|--------|
| 1. Cl | 34.1 | 0.4   |
| 2. Pr | 52.6 | 0.3   |
| 3. Rw | 59.7 | 0.4   |

Table 10: Accuracy of proposed method with different fusions.

| Model | Average |
|-------|---------|
| MT-MTDA Mean | 75.1 |
| MT-MTDA Deviation | 65.4 |
| MT-MTDA Sum | 67.1 |

Table 11: Accuracy of proposed method using a single teacher vs multiple teachers.

| Model | Average |
|-------|---------|
| MT-MTDA Single | 82.5 |
| MT-MTDA Deviation | 74.9 |

in order to distill knowledge from multiple domains into a single student. The results from our experiment show that our method outperforms the current state-of-the-art, especially when using compact models, which can facilitate the use in many types of real-time applications. From our experiment, we identify several bottlenecks that can impede generalization of a compact model to multiple domains: 1) the STDA algorithm determines the accuracy of teacher models and 2) The transfer of target domain knowledge which needs to be improved when the student model is compact. Since STDA is a popular area of research, our future work will focus on how to transfer target domain knowledge.

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Supplementary Material

A Experimental Methodology

A.1 Hyper-parameters

From Table 12, you can find all the hyper-parameters that was used for different datasets and backbones. We selected these hyper-parameters based on a standard cross-validation process. These hyper-parameters are selected based on the overall result in all the scenarios instead of each scenario.

A.2 Evaluation metrics

In the paper of [5], the authors first proposed an accuracy metrics that take in account the different sizes of each target domain in order to have a balanced accuracy score at the end. This accuracy is defined as:

\[ Acc = \sum_{i=0}^{n} w_i Acc_i \]  

(7)

With \( w_i \) calculated as \( w_i = \frac{N_i}{\sum_{j=0}^{n} N_j} \). The problem with this accuracy is that it can hide the poor performance of a target domain that’s small. The authors from the same paper proposed to use another accuracy which is the same one we used in our main paper where the same weight is used for each target domain. This is also referred as the equal-weight classification accuracy in the paper of [5]. This is accuracy is calculated as:

\[ Acc^{EQ} = \frac{1}{n} \sum_{i=0}^{n} Acc_i \]  

(8)

Additionally, we also give our result based on the Equation 7 and on each target domain in order to highlight where our algorithm can fail.

B Results and Discussion

B.1 Further analysis on Digits-Five

As indicated in our results for Table 1, we analyzed the accuracy of each target domain in order to show where’s our drop in accuracy.

From Table 13, we can see that the drop in performance in the scenario previously noted in the main paper is due to the decline of the domain adaptation on both \( mt \to mm \) and \( mt \to sy \). Further analysis of these two domain adaptation shows that our common hyper-parameters do no work well for these two cases since we can get better performance using other hyper-parameters. However, these parameters would yield lower performance on other scenarios therefore we choose to remain on the same hyper-parameters as before. This indicates that in order to have better performance, it’s best to have a different hyper-parameters set for each scenario and even each teacher.

B.2 Weighted Accuracy

In this section, we present our average accuracy using Equation 7. We compare with the weighted accuracy reported in the paper of [5] for a fair comparison.

From Tables 14, 15, 16, our weighted results are still consistent with our equal-weight results in the main paper. Our method performs better than current state-of-the-art method in all cases except on Office31 with ResNet50. These results show that our method does not improve upon state-of-the-art by having a good accuracy on an easy case of domain adaptation with huge amount of data but it improves in more general manner.

B.3 Additional Comparison on Each Target

As mentioned in the main paper, we present more results on each separate target domain comparing to a standard STDA baseline [8] on OfficeHome using AlexNet.

From Table 17, we can draw a similar conclusion of the main paper. Our method performs in average better than multiple STDA on different target domains. This shows that we can have one model handling different target domains without sacrificing computational power or memory.
**Table 12:** Hyper-parameters for our algorithms for each backbone and dataset

| Hyper parameters | Digits-Five LeNet | Office31 Alexnet | OfficeHome Alexnet | Office31 ResNet50 | OfficeHome ResNet50 |
|------------------|------------------|------------------|--------------------|-------------------|---------------------|
| N                | 100              | 100              | 200                | 100               | 200                 |
| batch size       | 64               | 16               | 8                  | 16                | 8                   |
| α                | 20               | 20               | 20                 | 20                | 20                  |
| σ                | 0.1              | 0.1              | 0.1                | 0.1               | 0.1                 |
| J                | 0.8              | 0.8              | 0.8                | 0.8               | 0.8                 |
| UDA Learning Rate| 0.0005           | 0.001            | 0.001              | 0.001             | 0.001               |
| KD Learning Rate | 0.0005           | 0.001            | 0.001              | 0.001             | 0.001               |
| weight decay     | 0.0005           | 0.0005           | 0.0005             | 0.0005            | 0.0005              |

**Table 13:** Accuracy of each target domain on Digits-Five dataset with LeNet as Backbone.

| Domain | mt | mm | sv | up | sy |
|--------|----|----|----|----|----|
| Student Acc | 96.3 | 69.1 | 85.8 | 87.0 | 55.5 |
| Source only | 26.9 | 56.0 | 67.2 | 73.8 | 36.9 |
| ADDA | 43.7 | 55.9 | 40.4 | 66.1 | 34.8 |
| DAN | 31.3 | 53.1 | 48.7 | 63.3 | 27.0 |
| RevGrad | 52.4 | 64.0 | 65.3 | 66.6 | 44.3 |
| AMEANS | 56.2 | 65.2 | 67.3 | 71.3 | 47.5 |
| MT-MTDA (ours) | 54.3 | 73.4 | 67.1 | 73.1 | 64.0 |

**Table 14:** Weighted accuracy of proposed and baseline methods on Digits-Five dataset with AlexNet as Backbone.

| Models | A → D,W | D → A,W | W → A,D | Average |
|--------|---------|---------|---------|---------|
| Source only | 62.4 | 60.8 | 57.2 | 60.1 |
| DAN | 68.2 | 58.7 | 55.6 | 60.8 |
| RevGrad | 74.1 | 56.6 | 55.0 | 62.6 |
| AMEANS | 74.5 | 62.8 | 59.7 | 65.7 |
| MT-MTDA (ours) | 82.4 | 62.4 | 61.9 | 68.9 |

**Table 15:** Weighted accuracy of proposed and baseline methods on Office31 dataset.

| Models | Backbone | A → D,W | D → A,W | W → A,D | Average |
|--------|----------|---------|---------|---------|---------|
| Source only | 68.6 | 70.0 | 66.5 | 68.4 |
| DAN | 78.0 | 64.4 | 66.7 | 69.7 |
| RevGrad | 78.2 | 72.2 | 69.8 | 73.4 |
| AMEANS | 90.1 | 77.0 | 73.4 | 80.2 |
| MT-MTDA (ours) | 87.8 | 75.4 | 72.8 | 78.7 |

**Table 16:** Weighted accuracy of proposed and baseline methods on OfficeHome dataset.

| Models | Student | Ar → Cl, Pr, Rw | Cl → Ar, Pr, Rw | Pr → Ar, Cl, Rw | Rw → Ar, Cl, Pr | Average |
|--------|---------|----------------|----------------|----------------|----------------|---------|
| Source only | 33.4 | 35.6 | 34.7 | 39.8 | 33.7 |
| DAN | 42.4 | 45.1 | 34.1 | 48.4 | 44.2 |
| RevGrad | 44.6 | 47.6 | 32.8 | 50.2 | 46.3 |
| AMEANS | 48.8 | 50.1 | 44.0 | 56.0 | 49.7 |
| MT-MTDA (ours) | 48.8 | 50.1 | 44.0 | 56.0 | 49.7 |
| Source only | 47.6 | 42.6 | 44.2 | 51.3 | 46.4 |
| DAN | 55.6 | 56.6 | 48.5 | 56.7 | 54.3 |
| RevGrad | 58.4 | 58.1 | 52.9 | 62.1 | 57.9 |
| AMEANS | 64.3 | 65.5 | 59.5 | 66.7 | 64.0 |
| MT-MTDA (ours) | 64.6 | 67.1 | 59.0 | 66.4 | 64.3 |
Table 17: Average accuracy of proposed and baseline STDA methods for individual and overall target datasets on OfficeHome dataset using AlexNet

| Method   | Ar → Cl | Ar → Pr | Ar → Rw | Avg  | Cl → Ar | Cl → Pr | Cl → Rw | Avg  | Pr → Ar | Pr → Cl | Pr → Rw | Avg  | Rw → Ar | Rw → Cl | Rw → Pr | Avg  |
|----------|---------|---------|---------|-------|---------|---------|---------|-------|---------|---------|---------|-------|---------|---------|---------|-------|
| RevGrad STDA | 30.4  | 45.2  | 54.3  | 45.1  | 30.2  | 54.1  | 55.1  | 45.4  | 31.6  | 39.7  | 59.3  | 43.5  | 41.7  | 46.4  | 55.2  | 52.6  |
| AMEANS   | 34.7  | 52.0  | 55.8  | 58.8  | 40.7  | 52.0  | 53.7  | 48.7  | 38.3  | 46.7  | 53.5  | 42.0  | 32.0  | 42.1  | 46.8  | 45.7  |

B.4 TSNE Visualization

In this section, we add the TSNE of RevGrad[8] and DAN[16] and provide a higher resolution of the previous TSNE. From Figure 6, we can see that features between different target domains can be mixed together even when there’s a blending mechanism like in [6].
Figure 6: T-SNE visualization of all baselines methods versus MT-MTDA (ours)