The Enforced Transfer: An Instance-Based Divide-and-Conquer Unsupervised Domain Adaptation Algorithm

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Abstract
Existing Domain Adaptation (DA) algorithms train target models to classify all samples in the target domain, but it fails to recognize the possibility that, within the target domain, some samples are closer to the source domain and thus should be classified by source domain models. In this paper, we develop a novel unsupervised DA algorithm, the Enforced Transfer, which employs an out-of-distribution detection algorithm to decide which model (i.e., source domain or target domain) to apply on the testing instance, i.e., divide-and-conquer. Instead of choosing the models at the instance-level, we make the choice of models at the layers of deep models. On three types of DA tasks, we outperform the state-of-the-art algorithms.

Introduction
Domain Adaptation (DA) has drawn a lot of interest because it deals with the problem that arises within a core assumption of machine learning: machine learning always assumes that the testing samples are from the domain of the training samples. This assumption often results in the fact that the machine learning model’s testing performance is significantly worse than its validation performance when the training and testing samples are from different distributions or domains.

Existing DA algorithms\(^1\) train target models and then use the target models to classify all samples in the target dataset. While this approach attempts to address the problem that the source and the target data are from different distributions, it fails to recognize the possibility that, within the target domain, some samples are closer to the distribution of the source domain than the distribution of the target domain.

So, how do we deal with the scenario aforementioned, in which some samples in the target domain are closer to the distribution of the source domain than the target domain, despite that they are originally from the target domain? A straightforward idea is to use an out-of-distribution detection algorithm to decide if, during the testing phase, a given sample is closer to the distribution of the source domain or the target domain. In the first case, this sample is given to a machine learning classifier trained on source samples. In the second case, this sample is given to a machine learning classifier trained on target samples. Since during the setting of unsupervised domain adaptation, the labels of the target domain are not available, we use pseudo-labels obtained from applying an existing unsupervised domain adaptation algorithm, ADDA (Tzeng et al. 2017), on the target data, to train a classifier in supervised fashion on the target domain.

It is widely known that the first few layers in a neural network extract low-level features, so the aforementioned approach can be extended from classifying samples in two different scenarios to classifying the samples’ activations after an empirically determined layer in two different scenarios.

The Enforced Transfer implements this idea. We inject an Enforced Transfer Cell (ETC) (Figure 1) after a layer that combines adversarial domain adaptation with out-of-distribution detection. First, we train a source encoder and a dense net with the source encoder’s output as its input using source samples’ activations after that convolutional layer, end-to-end. The adversarial domain adaptation consists of an encoder (that is also a generator) and a discriminator. The generator/encoder (called the target encoder) tries to deceive the discriminator by masking the target samples’ activations in the way that the discriminator may consider them as the source encoder’s output (by processing an activation from the source domain). The discriminator tries to differentiate if a given activation is a result of this generator or not. The discriminator is part of the out-of-distribution detection subroutine that decides if an activation should be sent to a dense net trained on the source or a dense net trained on the target. The target dense net is trained end-to-end with the target encoder. The purpose of using GAN is that, in case that the out-of-distribution detection subroutine fails to correctly assign an activation to be processed by the source or target dense net, its encoded values is still similar enough to the source/target activations that the dense net is less likely to misclassify it.

One question that may arise with this idea is that, if this GAN can make the encoded representations similar enough to the source domain, why would we have out-of-distribution problem, as we could just apply the target encoder on all target activations and send them to the source dense net? We cannot do so because during testing time, there could be samples that are closer to the distribution of
the source domain. In this case, using the target encoder to encode samples closer to the distribution of the source domain (rather than the target domain) does not make sense. The contributions of this paper are:

- We identify the problem of existing domain adaptation algorithms that use a target model to classify all target samples and consequently ignore that some samples might be closer to the distribution of the source rather than target.
- We provide empirical results on three categories of domain adaptation problems and our solution outperforms various state-of-the-art domain adaptation algorithms in these three categories. First, we evaluate the Enforced Transfer on a domain adaptation task on the acoustic modality by domain adapting from a dataset consisting of emotional utterances to a dataset that contains audio samples of speech in which, sometimes, the speakers are in verbal conflicts (We equate anger to conflict speech and other emotions to non-conflict speech). Second, we evaluate the Enforced Transfer on the domain adaptation tasks that takes digit datasets such as MNIST as the source and another digit dataset such as USPS as the target. Third, we evaluate the Enforced Transfer on domain-adapting on CIFAR-10 to STL-10. The Enforced Transfer outperforms all the state-of-the-art DA algorithms that we are compared against.

Related Work

Transfer Learning and Domain Adaptation

A large amount of work has been done on Domain Adaptation by minimizing the dis-similarity between the distributions of the source and target domain. The common measurements of domain dis-similarity include KL-distance, maximum mean discrepancy (MMD). Extensive research on transfer learning is dedicated to minimizing the dis-similarity measurements (Zhao, Qiu, and He 2021). The minimization of dis-similarity measurements is also used with other measurements, such as classification loss on source to find features that both discriminate and are domain-invariant (Tzeng et al. 2014). However, the minimization of MMD of domains jeopardizes the locality structure of samples and potentially reduces the effectiveness of transfer learning (Zhang et al. 2019b). Also, feature discriminability is also decreased due to the unintentional minimization of joint variance of features from source and target sets (Wang et al. 2020). Recently, Adversarial Discriminative Domain Adaptation (ADDA) (Tzeng et al. 2017) and (Deep Coral) (Sun and Saenko 2016) has garnered significant interest, being used as a state-of-the-art baselines by many works (Zhang et al. 2019a), (Shao and Zhong 2020).

One thing worth noting is that the aforementioned algorithms all ignore the possibility that a target sample might be closer to the distribution of the source than the target. Because they ignore the possibility, they use the target model to classify all samples. This proposed work, the Enforced Transfer, differs from them because we do not ignore the "uniqueness" of each sample. If a sample is closer to the distribution of the source, then a network trained on the source samples will classify it. If a sample is closer to the distribution of the target, then a network trained on the target samples will classify it.

Out-Of-Distribution Detection

A lot of attention has been paid to detect abnormal samples so that they can be intercepted before being sent to a neural network. Specifically, (Hendrycks and Gimpel 2016), (Lee et al. 2018), and (Liang, Li, and Srikant 2017) are three state-of-the-art approaches to detect out-of-distribution samples. Liang et al. (Liang, Li, and Srikant 2017) observe that fabricating small perturbations into samples as well as using temperature scaling can separate the softmax scores of in-distribution and out-of-distribution samples. Lee et al. (Lee et al. 2018) use Mahalanobis distance to separate in-distribution samples from out-of-distribution ones.

Lee et al. (Lee et al. 2018) provide a comparison of the three approaches and the performances of the three approaches are indicated in Table 1 from which we observe that the Mahalanobis distance based approach outperforms Softmax Probability (Hendrycks and Gimpel 2016) and ODIN (Liang, Li, and Srikant 2017). Therefore, in the rest of the paper, we use the Mahalanobis distance based approach for out-of-distribution detection. For details, see Section 3.3.

|                     | Softmax Probability | Mahalanobis | ODIN     |
|---------------------|---------------------|-------------|----------|
| Accuracy            | 85.06%              | 95.75%      | 91.08%   |

Table 1: The performances of the three state-of-the-art out-of-distribution detection algorithms. The measurement is accuracy. The performances are obtained when training ResNet on CIFAR-10 and SVHN samples are used as out-of-distribution samples.

There has not been enough works on incorporating out-of-distribution detection with transfer learning or Domain Adaptation. Perera et al. (Perera and Patel 2019) use an out-of-distribution dataset to improve the performance of a classifier on in-distribution samples, which is the only work that intends to combine the two knowledge fields. Our work, the Enforced Transfer, is one of the first approaches that use out-of-distribution to improve the performance of Domain Adaptation.

Enforced Transfer

State-of-the-art domain adaptation algorithms usually develop a target classifier and send all samples in the target domain during testing to this target classifier for further classification. There are several ways to get a target classifier as proposed by various works that are augmentation-based (Liu, Tian, and Xu 2019), feature alignment-based (Ren et al. 2019), classifier-alignment-based (Heraht et al. 2019) approaches, and adversarial-domain-adaptation-based (Tzeng et al. 2017). However, unlike our Enforced Transfer, this methodology ignores the uniqueness of each sample: some target samples might be closer to the distribution...
of the source data samples than the target samples. In this case, using the target classifier to classify samples that are closer to the source domain’s distribution does not make sense, even though those source-like samples are from the target domain.

We hypothesize that there are samples in the target dataset that are actually closer to the distribution of samples in the source domain, $p_s(x_s)$, Note that the distribution is not $p_s(x_s, y_s)$ because we do not care about the labels of the samples. As a result, despite coming from the target domain, these samples should be processed by a model trained on the source domain. We present a framework, the Enforced Transfer (ET) for adversarial supervised adaptation, that can send a sample (during testing phase) to a set of dense layers trained on the source domain or a set of dense layers trained on the target domain.

The Enforced Transfer starts with a deep convolutional neural net (CNN) which is a model trained on a source dataset. We choose CNN because it has garnered huge interests in the field of computer vision recently; also, its first layers extract low-level features. We then interject a new domain adaptation cell, called the Enforced Transfer Cell (ETC), after a single convolutional layer as described below. For a source model with $n$ convolutional layers, there are $n$ ways to interject the Enforced Transfer Cell, so $n$ Enforced Transfer architecture can be obtained.

![Figure 1: The dotted square includes the Enforced Transfer Cell. This image shows the ETC injected after the second convolutional layer of a CNN. Where to put the ETC is empirically determined (there are multiple Enforced Transfer architecture obtained and which architecture is the final solution is empirically determined). Let’s say there are $n$ layers and there will be $n$ experiments each of which results in an Enforced Transfer solution with only one ETC. Then the $n$ Enforced Transfer architecture is empirically evaluated on the validation set and the best performing one will be the final Enforced Transfer solution that has only one ETC after a certain layer.](image)

The Target Encoder and the Discriminator
Together with the discriminator $C$ within the Probe (we will talk about the Probe in the following sections), the Target encoder, $E_{target}$ or $E_t$, is a part in a generative adversarial network (GAN). The target encoder is the generator that tries to generate a mapping for a sample $x$ in $X_t$. Such that the discriminator $C$ cannot tell whether this mapping is a result given by the target encoder on a target sample or the source encoder on a source sample. In other words, $E_t$ maps $X_t$ to the feature space of $E_s(X_s)$.

To achieve this goal, the source encoder (whose training is described below) and the source domain is used for the training of this GAN that consists of the target encoder and the discriminator. Meanwhile, the discriminator $C$, trained against $E_t$, will try its best to differentiate vectors that are
the result of the source encoder from vectors that are the result of the target encoder.

One goal of this step is to obtain a good discriminator that is good at telling apart samples closer to the source domain from samples that are closer to the target domain. This discriminator is part of the Probe that decides if, during testing, a sample should be sent to a model (the source dense net) trained on samples from the source domain or a model (the target dense net) trained on samples from the target domain.

Another goal of using GAN is to leverage the source dataset which is usually large to help train the target encoder. If we do not use GAN, we will have to directly train a target encoder using the target samples’ activations. In Domain Adaptation and Transfer Learning, the target dataset usually has way less samples than the source. Training the target encoder without leveraging the source dataset (recall that the target encoder is trained to masquerade target samples into the result of the source encoder) produces a classification result. Note that the training of the discriminator (recall that the target encoder is trained to masquerade target samples into the distribution of the source encoder’s processing on source activations) results in a target encoder trained with less data.

The Target Dense Net
The target dense net, $D_{target}$ or $D_t$, is trained using $E_t$ (whose training is described below). During training, for every sample $x_t$ in the target domain, we calculate $E_t(x_t)$. Then we use the target encoder’s outputs as the training inputs for the target dense net. The target dense net then produces a classification result. Note that training the target dense net requires target labels and in unsupervised domain adaptation, target labels are not available. We mitigate the problem by training using the pseudo-labels of the target domains instead. The target domain’s pseudo-labels are obtained after applying an existing unsupervised domain adaptation algorithm RSDA on it.

The Probe that Consists of the Discriminator and the Out-of-Distribution Detection Subroutine
The obtaining of the out-of-distribution detection subroutine is not included in training because it does not require training as it is purely statistics-based. Now we would like to see if a given sample is in-distribution with the source data or in-distribution with the target data, using the out-of-distribution detection subroutine, during the testing phase.

In other words, we would like to see how a sample deviates from the source $X_s$ and the target $X_t$ (Note that $X_s$ is the set of activations of the source samples by the ith convolutional layer). We use the discriminator $C$ to measure how a sample deviates from the both distributions.

For the incoming $x$ (the activation after the ith convolutional layer of the original source classifier), we calculate the discriminator’s processing on both $E_s(x)$ and $E_t(x)$. Then, we concatenate the vector $C(E_s(x))$ and $C(E_t(x))$. We call the aforementioned operations the Critique on a sample $x$ by the discriminator $C$. The Critique exists as a way to utilize the discriminator to decide the in-distribution-ness of a sample. By concatenating the two vectors together, the out-of-distribution detection subroutine leverages both the information by the source encoder and the target encoder.

With the definition of the Critique, we are able to obtain two distributions using the Critique as shown in Table 2.

Each column represents a Critique distribution (source or target). During testing, a sample’s Critique is used to compare with the two Critique distributions to decide in which (Critique) distribution it falls into and whether $D_s$ or $D_t$ should be used to classify it. Note that the out-of-distribution subroutine that uses the discriminator does not occur during the training of the discriminator $C$. It is only used during the testing phase to determine if an activation is closer to the source or the target.

| Source Critique Distribution | Target Critique Distribution |
|------------------------------|------------------------------|
| $C(E_s(X_s)) $ $||$ $C(E_t(X_s)) $ | $C(E_s(X_t)) $ $||$ $C(E_t(X_t)) $ |

Table 2: The Critique distributions of the source and the target. Again, C is the discriminator. The source Critique distribution is illustrated by the concatenation $([],)$ of $C(E_s(X_s))$ and $C(E_t(X_s))$. The target Critique distribution is illustrated by the concatenation of $C(E_s(X_t))$ and $C(E_t(X_t))$.

Formally, a Critique for a sample $x$ is given as Equation 1. The Critique in Equation 1 measures how an incoming sample deviates from the source and the target distributions.

$$c(x) = C(E_s(x))$ $||$ $C(E_t(x))$$ (1)

The Critique is a vector, but we want a discrete result. The Critique should tell us if a sample $x$ is in-distribution with the source, in-distribution with the target, both, or neither. To convert the vector into a discrete result, we ask how typical this vector is, compared to the Critiques resulted by every sample in $X_s$ and every sample in $X_t$. In other words, we calculate how out-of-distribution this vector is, compared to the Critiques resulting from every sample in $X_s$ and every sample in $X_t$.

The next step is to calculate $c(x)$ for all $x$ in $X_s$, using Equation 1 after which we are able to calculate the empirical mean of the Critiques or Critiques on the entire source domain as denoted in Equation 2.

$$\hat{\mu}_s = \frac{1}{N_s} \sum_{j=1}^{N_s} C(E_s(x_j))$ $||$ $C(E_t(x_j)) = \frac{1}{N_s} \sum_{j=1}^{N_s} c(x_j)$$ (2)

Similarly, we can calculate the empirical mean of the Critiques or Critiques on the entire target domain, as denoted in Equation 3.

$$\hat{\mu}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} C(E_s(x_j))$ $||$ $C(E_t(x_j)) = \frac{1}{N_t} \sum_{j=1}^{N_t} c(x_j)$$ (3)

With the empirical mean for the Critiques on $X_s$, the set of activations on the entire source domain after the ith convolutional layer of the source classifier, and the empirical mean for the Critiques on $X_t$, the set of activations on the entire target domain after the ith convolutional layer of the
source classifier, we are able to calculate the empirical covariance matrices for the Critiques of the source and target domains as Equations 4 and 5.

\[ \tilde{\Sigma}_s = \frac{1}{N_s} \sum_{j=1}^{N_s} (c(x_j) - \tilde{\mu}_s)(c(x_j) - \tilde{\mu}_s)^\top \]  

\[ \tilde{\Sigma}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} (c(x_j) - \tilde{\mu}_s)c(x_j) - \tilde{\mu}_t)^\top \]  

We calculate the empirical covariance matrices and empirical means as distribution parameters to formulate the two distributions, one for the source domain and one for the target domain, of the Critiques. With the distribution parameters of the source domain, we can calculate how each Critique obtained from each sample in the source domain deviates from the distribution of all Critiques obtained from all samples in the source domain. Similarly, we are able to calculate how each Critique obtained from each sample in the target domain deviates from the distribution of all Critiques obtained from all samples in the target domain. The deviation is measured by the Mahalanobis distance. In other words, For each sample in the source, its Mahalanobis distance is calculated using Equation 6.

\[ \tilde{M}_s(x) = (c(x) - \tilde{\mu}_s)^\top \tilde{\Sigma}_s^{-1}(c(x) - \tilde{\mu}_s) \]  

\[ \tilde{M}_t(x) = (c(x) - \tilde{\mu}_t)^\top \tilde{\Sigma}_t^{-1}(c(x) - \tilde{\mu}_t) \]  

Up until now, we are able to obtain a set consisting of the Mahalanobis distances of all samples in the source domain, and a set consisting of the Mahalanobis distance of all samples in the (training set) of the target domain. We denote these two sets \( \tilde{M}_s(x) \) and \( \tilde{M}_t(x) \). We proceed to calculate the means \((\mu_s, \mu_t)\) and standard deviations \((\sigma_s, \sigma_t)\) of \( \tilde{M}_s(x) \) and \( \tilde{M}_t(x) \).

Recall that our initial task is to convert the Critique on an unknown sample \( x \) from a vector into a class: in-distribution with the source, in-distribution with the target, in-distribution with both, or out-of-distribution of both. In this final step, we convert the Critique \( c(x) \) into a class: For an unknown sample with its Critique by the discriminator, we test to see if its Critique’s Mahalanobis distance of the source domain is within the distribution of \( \tilde{M}_s(x) \), given the mean and standard deviations of \( \tilde{M}_s(x) \). Similarly, we can test to see if its Critique value’s Mahalanobis distance of the target domain is within the distribution of \( \tilde{M}_t(x) \). For the Probe to decide that a given sample \( x \) is in the source domain, \( x \) must satisfy the following condition Equation 8 whereas \( \lambda_s \) is empirically decided. \( \mu_s \) is the mean of the Mahalanobis distances of all samples in the source domain:

\[ \mu_s - \lambda_s \cdot \sigma_s \leq \tilde{M}_s(x) \leq \mu_s + \lambda_s \cdot \sigma_s \]  

Similarly, for the Probe to decide if a given sample \( x \) is in the target domain, \( x \) must satisfy the following condition, Equation 9 where as \( \lambda_t \) is empirically decided. \( \mu_t \) is the mean of the Mahalanobis distances of all samples in the target domain.

\[ \mu_t - \lambda_t \cdot \sigma_t \leq \tilde{M}_t(x) \leq \mu_t + \lambda_t \cdot \sigma_t \]  

**Evaluation**

We first evaluate Enforced Transfer on a domain adaptation task on an acoustic modality: we domain-adapt from a dataset consisting of emotional utterances to a dataset that contains audio samples of speech in which, sometimes, the speakers are in a verbal conflict (we map the anger emotion to conflict and other emotions to non-conflict). Then, to demonstrate that the Enforced Transfer not only works on domain-adapting from the domain of emotions to the domain of conflict speech, but also in other fields such as computer vision, we compare the Enforced Transfer against eight other state-of-the-art deep domain adaptation algorithms on two standard benchmarks on computer vision: domain adaptation from MNIST to USPS and from SVHN to MNIST. We also compare the Enforced Transfer solution against five state-of-the-art domain adaptation solutions on a more complex task - to domain-adapt from the dataset STL-10 to CIFAR-10, each of which consists of 10 classes of images such as ships and birds. Since the Enforced Transfer out-performs compared algorithms on these three types of domain adaptation tasks, this provides some evidence that our approach is a generic domain adaptation solution.

**The Domain Adaptation Task on the Acoustic Modality**

**The Source Dataset** In the following paragraphs we describe our source dataset in the domain adaptation task on the acoustic modality. The EMOTION dataset contains the all samples from the following 5 public datasets: RAVDESS (Livingstone and Russo 2018), CREMA-D (Cao et al. 2014), EMA (Lee et al. 2005), TESS (Dupuis and Pichora-Fuller 2010), and SAVIE (Haq and Jackson 2010). In addition we extend these 5 datasets with samples that are distorted to account for environmental conditions by artificially adding environmental distortions into the clean samples from the original five datasets. The reverberation effect is described by the combination of the decay factor, diffusion, and wet/dry ratio. EMOTION consists of training and testing sets. In the training set, there are 8,816 samples in the anger class, 8,786 samples in the happiness class, 7,742 samples in the neutral class, 8,811 samples in the sadness class, and 5,761 samples in the disgust/joy class. In the testing set, there are 1,942 samples in the anger class, 1,966 samples in the happiness class, 1,697 samples in the neutral class, 1,947 samples in the sadness class, and 1,292 samples in the fear/disgust class.

**The Target Dataset** Our target dataset, CONFLICT, is the dataset where we want to apply the Enforced Transfer solution so that the source classifier trained on EMOTION can be re-purposed. It is collected from real home environments in
which 19 couples talk (collected with approved IRB) about topics that they previously disagree on and have their conversation recorded. In total, there are 3027 training samples and 1009 testing samples.

**Comparison with State-of-the-Art Baselines** In this experiment, shown in the Table 3, we compare the Enforced Transfer with the scenario in which no domain adaptation or transfer learning is used (No DA/TL) and three baselines: direct training (directly training the a model on the data from the target dataset), two selected state-of-the-art approaches, ADDA and ADDA with CORAL loss. Each of the audio samples on which we test the situation in which no DA/TL is used, the three baselines, and the Enforced Transfer contains environmental distortions and/or overlapped speech. The usage of CORAL loss (in Deep CORAL) and ADDA has garnered a lot of interests in the field of DA/TL; in this paragraph we briefly describe these two approaches. CORAL loss proposes that the domain-shift can be mitigated by using linear transformations to align the second-order statistics of the two domains. ADDA proposes to encode the target samples to the feature space of the source and have a domain discriminator that tries to distinguish encoded target samples from source samples. ADDA and ADDA with CORAL loss achieve in F1 scores of 38.29% and 63.28% respectively.

| Env. Distortion | F1   |
|-----------------|------|
| No TL/DA        | 77.25% |
| Trained on target | 85.82% |
| ADDA + CORAL    | 63.28% |
| ADDA            | 38.29% |
| ET              | 93.10% |

Table 3: The performance of four baselines against the Enforced Transfer on data that has overlapped speech and environmental distortions.

As shown in Table 3, No TL/DA’s performance is 77.25%, a value that is higher than the state-of-the-art solutions ADDA and ADDA with CORAL loss. No TL/DA stands for that we directly apply the source classifier on the target samples. In the case of domain-adapting from a classifier of emotions to conflict detection, no TL/DA suggests that we directly apply the mood classifier on the conflict samples and the performance is calculated based on that anger denotes conflict while other emotions denote no conflict. ADDA performance was 38.29%, which is lower than the no TL/DA by 38.96%. ADDA with CORAL loss achieved a significantly higher performance, 63.28%. Since with have more than 7000 samples in the target dataset, we also directly train a classifier using only the target sample and yield an F1 score of 85.82%, which is higher than ADDA by 47.53% and ADDA combined with CORAL loss by 22.54%. Still, it is 7.28% lower than the Enforced Transfer’s performance.

Our Enforced Transfer results in an improvement over ADDA with CORAL loss by 29.82%. The Enforced Transfer’s high performance of an F1 score of 93.10% is obtained when we construct the Enforced Transfer after $f_i$ while $i = 1$. The large improvement that the Enforced Transfer has over ADDA shows that the Enforced Transfer is effective at recognizing testing samples in the target domain that are closer to the source distribution.

In the following paragraphs, we describe the four potential Enforced Transfer architectures performance - that is, when the Enforced Transfer is constructed after not only the first but also the second, third, and fourth convolutional layers of the original source classifier.

**Four Potential Enforced Transfer architectures’ Performance for Conflict** Table 4 shows the four potential Enforced Transfer architectures. Table 5 shows that the Enforced Transfer achieves the best performance when we apply it after the 1st convolutional layer.

When we only use $D_s$, the fully connected layers trained on the source domain, to classify samples from the target domain, we obtain the highest F1 score if we inject the Enforced Transfer Cell after the 4th convolutional layer. This is because the source classifier (that provides the convolutional layers) extracted high-level features after the deepest convolutional layer, and these high-level feature extractor trained on source are highly compatible with $D_s$ trained on source, hence the highest performance.

When we only use $D_t$, the fully connected layers trained on the target domain, we obtain the highest F1 score 90.34% if we inject the ETC after the first convolutional layer from the original source classifier. However, this value is still outperformed by that when we inject the complete ETC (using both $D_s$ and $D_t$) by 2.76%.

After the first convolutional layer, the Enforced Transfer achieves an F1 score of 82.75% when we only use the source dense nets but the performance is increased to 93.10% when we use both the source and target dense nets: The Probe decides if a given input is likely from the source and target domain. In other words, the F1 score is increased by 10.35% when we take into account the uniqueness of each sample (some testing samples are closer to the distribution of the source samples and some testing samples are closer to the distribution of the target samples). This indicates that the Probe is highly effective at determining if a sample is more similar to the samples in the source domain or the samples in the target domain. This observation also indicates that taking sample uniqueness into consideration results in better performance of detecting conflicts than not doing so.

**Office-31** In Table 4, we compare our Enforced Transfer against ResNet-50 (He et al. 2016) and nine other state-of-the-art domain adaptation algorithms using the dataset Office-31. Office-31 contains three subdomains: Amazon (A), Webcam (W), and Dslr (D). Each domain contains 31 classes of everyday office objects such as rulers or projectors. There are 4,110 images in total in Office-31. Across the three domains, six domain adaptation tasks can be formed, as shown in Table 4. The performance of each algorithm is measured in the accuracy that is the percentage of samples that are correctly classified by the algorithm out of all the samples in the testing set.

On the six domain adaptation tasks, we have achieved the state-of-the-art performance on five of them, except for the
In Table 5, we compare the Enforced Transfer algorithm against ResNet-50 and eight other state-of-the-art domain adaptation algorithms on Office-Home. Office-Home has four subdomains: Product (Pr), Art (Ar), Clipart (Cl), and Real World (Rw). There are 15,500 images in Office-Home, each of which is of a typical object that can be found in an office or home, such as flowers. Twelve domain adaptation algorithms can be formed based on the four subdomains. The performance of each algorithm is measured in the accuracy that is the percentage of samples that are correctly classified by the algorithm out of all the samples in the testing set.

Out of the twelve domain adaptation tasks, we outperform the next best-performing algorithm on six of them. On the task of Ar → Rw, the state-of-the-art, RSDA-MSTN, outperforms us by 1.6%. Again, RSDA fails to deal with the situation in which the pseudo-labels are not very accurate and the pseudo-label loss is very large. On the task Pr → Ar, the state-of-the-art, SRDC, outperforms us by 1.9%. SRDC proposes to alleviate the risk of damaging the intrinsic domain discrimination resulted from finding domain-aligned features. However, the proposition to minimize the KL divergence between the distribution of predictive labels and the distribution of auxiliary labels is a rather naive approach, as the authors fail to compare their algorithm with other measurements to minimize that as the Jensen–Shannon divergence.

**Conclusion**

To demonstrate that the Enforced Transfer is generic, we evaluate it on three types of domain adaptation tasks against various state-of-the-art algorithms. The Enforced Transfer outperforms all of them, which suggests that the observation that a sample’s uniqueness need to be taken into consideration is important during testing: some samples from the target dataset might be closer to the distribution of the source domain than the target domain, despite its origin.
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