Domain Adaptation Meets Disentangled Representation Learning and Style Transfer

Hoang Tran Vu and Ching-Chun Huang
Department of Electrical Engineering, National Chung Cheng University, Taiwan

Abstract. In order to solve the unsupervised domain adaptation problem, some methods based on adversarial learning are proposed recently. These methods greatly attract people’s eyes because of the better ability to learn the common representation space so that the feature distributions among many domains are ambiguous and non-discriminative. Although there are many discussions and results, the success of the methods implicitly funds on the assumption that the information of domains are fully transferrable. If the assumption is not satisfied, the influence of negative transfer may degrade domain adaptation. In this paper, we proposed to relieve the negative effects by not only adversarial learning but also disentangled representation learning, and style transfer. In detail, our architecture disentangles the learned features into common parts and specific parts. The common parts represent the transferrable feature space, whereas the specific parts characterize the unique style of each individual domain. Moreover, we proposed to exchange specific feature parts across domains for image style transfer. These designs allow us to introduce five types of training objectives to enhance domain adaptation and realize style transfer. In our experiments, we evaluated domain adaptation on three standard digit datasets MNIST, USPS and SVHN. The results show that our architecture can be adaptive well to full transfer learning and partial transfer learning. As a side product, the trained network also demonstrates high potential to generate style-transferred images.

Keywords: Transfer learning, Disentangled representation learning, Domain adaptation, Partial transfer learning, Style transfer.

1 Introduction

Recently, the powerful supervised learning algorithms such as Deep Convolutional Neural Networks (CNNs) have achieved significant successes especially on classification tasks. However, the successes are highly dependent on large labeled training datasets. If we apply a trained network to testing samples from other new domains, the classification performance often drops significantly. The problem is owing to the domain discrepancies (also known as domain shift) among the corresponding feature distributions. Therefore, to adapt to a new domain, most network models need to be rebuilt from scratch or be refined by using newly collected training data. However, collecting and labeling new datasets
is extremely expensive and time-consuming. It would be nice to decrease the demand on relabeling extra training data.

To address the aforementioned issue, some transfer learning methods for domain adaptation have been proposed in the past decade. Most of the methods aim at reducing the domain shift or minimizing the difference among domain feature distributions. The key idea is to learn deep feature transformations to map inputs from different domains into a common feature space so that the extracted features are both domain-invariant and class-discriminative. Some metrics of domain shift have been used in these methods such as maximum mean discrepancy (MMD) [1][2], multi kernel variant of MMD (MK-MMD) [3], and correlation distances [4]. By minimizing the metrics, these previous works can adapt to different domains in a statistical manner.

Recently, along with the success and understanding of the Generative Adversarial Network (GAN) [5] for many generative tasks, researchers have turned to borrow the idea of adversarial learning to perform domain adaptation. Based on adversarial learning, domain adaptation problem is modeled as a minimax game between a domain classifier (discriminator) and a feature extractor. The feature extractor is trained to extract features which can not only minimize the classification loss (usually in the source domain) but also fool the domain discriminator. Though funding on adversarial learning, each adaptation method proposed different novelties. They may transfer and adapt features from source domain to target domain, from target to source, or both directions. In addition, there are some other design choices such as whether to utilize a generator, where to introduce the domain discriminator (in the image domain or feature domain), what loss function to use, how to maximize the loss function, or whether to share network weights across domains.

Most aforementioned methods focus on learning the common feature representation to bridge and transfer learnable knowledge from a source domain to a target domain [6][7][8][9][10][11]. The success of these methods implicitly funds on the assumption that the information from a source domain are fully transferrable. However, some domain specific features are only suitable to characterize the domain properties. Negative effects may happen and degrade domain adaptation if the domain specific features are transferred. Moreover, partial transfer learning [12] is another new concern where the target label space is a subset of the source label space. For this new problem, simplify matching the whole source and target domains as the previous methods would also result in negative transfer due to the effects of outlier source classes.

The designed idea of our framework is illustrated in Fig. 1. To relieve the negative transfer problem, we aim to answer the fundamental question what to transfer, which is now getting more attention and has recently reported in a few works [13][14]. Following by what to transfer, we eventually proposed a deep feature decomposition framework for unsupervised domain adaptation to answer how to transfer. The designed deep framework allows us to learn the multiple disentanglable feature components which are further divided into a common feature part and a specific part. The common features show the shared and
Fig. 1: We propose an adversarial unsupervised adaptation framework which disentangles the feature domain into multiple semantic parts and allows to exchange the feature across domains to generate style-transferred images. With the feed-back design, semantic consistency and multi-level adversarial losses, our framework shows how style transfer and disentangled representation learning can be used for domain adaptation.

highly-relative image contents between two domains. Thus, the domain feature distributions of the common parts are expected to be matched after domain adaption. The specific features mainly reveal the domain property such as style and appearance. By transferring messages through the common part rather that the specific parts, we could achieve better transfer learning between two domains with less negative propagation. Furthermore, instead of directly ignoring the specific features, we proposed to integrate image style transfer into our domain adaptation framework. By well utilizing the specific feature to synthesize new images with style transfer from source to target and vice versa, in this paper, we show how style transfer can improve domain adaptation in a better way. It may also be the first of its kind to mutually connect domain adaptation and style transfer in a unified generative framework.

To evaluate the proposed idea for disentangled representation learning, domain adaptation, and style transfer, in this paper, we train our framework to complete the unsupervised domain adaptation task for handwritten digit recognition. Comparing performance with other methods in the same task, our experimental results show better performance in terms of classification accuracy and domain adaptation. Our architecture is also adaptive well to full transfer learning and partial transfer learning. These achievements are majorly founded on the design features and contributions of our new framework, which are summarized as follows:
1. **Disentangled Representation Learning**: We disentangle the feature maps in-to multiple semantic parts both in source and target domains. Each individual part contributes to different tasks. The common part is used for domain adaptation and the specific part is used for style Transfer. Finally, domain adaptation and style Transfer are connected and mutually support in order to achieve better performance.

2. **Domain Adaptation**: Our framework can be applied to solve the unsupervised domain adaptation problem. By disentangling the features, we aim to answer the questions *what to transfer* and *what not to transfer* and therefore we can reduce the influence of negative message transfer. In detail, we prefer to transfer only the common component instead of the specific characteristics.

3. **Style Transfer**: We propose a new method for feature/style exchange across domains. It means that if we combine the specific part of one domain with the common part of the other domain to form a new feature representation, we can generate a style-transferred image through a GAN-based framework. Therefore, our framework can also be extended to solve multi-domain image-to-image translation problems, which is style transfer.

4. **Multi-level adversarial learning**: We combine adversarial learning and generative adversarial networks in a unified architecture to jointly match domain distributions in both image-level and feature-level.

5. **Novel objective losses**: Based on the ability to generate a style-transferred image, we propose a novel feed-back loss and a semantic consistency loss. By introducing these objective losses, we can help to enhance the transferability of the learned common parts and preserve the semantic information during style transfer.

6. **Cluster-based distribution**: In our GAN-based framework, the discriminators not only aim to distinguish between source images and target images but also try to classify the input data. With this design, the discriminators could be more powerful and help our system to match the *cluster-based distribution* between source and target domains instead of matching the whole *domain distribution* as the traditional discriminator. This design feature enables our framework to solve the partial transfer problem.

The paper is organized as follows: Section 2 summarizes the related works. Section 3 presents the proposed method. Section 4 shows the details of objective losses used in the proposed framework. Section 5 presents the dataset and the experimental results. Finally, we make our conclusion in Section 6.

## 2 Related Works

**Domain Adaptation**: A large number of domain adaptation methods have been proposed over the recent years. We divide them into two main groups: 1) finding the mapping between source and target domains, and 2) finding the shared latent space between two domains. For the first group, some methods focus on learning the map-ping from a source domain to a target domain in
the feature level [7] or the image level [8]. Some other methods choose to learn the inverse mapping from target to source [6]. Recently, to make the adaptation system more robust and general, the authors in [9] proposed to combine both mapping directions in a unified architecture. For the second group, researchers focus on minimizing the distance between two domains in feature space by using some domain shift metrics such as first order feature space statistic [12], and higher order feature space statistic [14]. More recently, domain shift between two domains could be further reduced by applying adversarial learning. The main concept is to find the shared latent space so that a strong domain classifier could not distinguish source samples and target samples. There are variants of training strategies for adversarial learning. In [10], the authors point out that simply maximizing domain confusion to match the whole feature distributions of two domains could not make sure the corresponding local class distributions of domains are matched. Thus, they proposed to combine a domain confusion loss and softmax cross-entropy loss to train the network so that the network could transfer knowledge not only across domains but also tasks. However, the method still needs sparsely labeled data in target domain. In [6], the authors proposed an unsupervised adversarial discriminative domain adaptation framework. According to their result, an adversarial learning framework based on asymmetric feature mappings for source and target can outperform the one based on a symmetric mapping. To realize adversarial learning, the choice of adversarial loss function is another issue. In [11], the authors directly treat the domain discriminator loss as the adversarial loss to learn the optimal feature mapping; while the authors in [6] train the optimal feature mapping with the standard discriminator loss function with inverted labels.

Disentangled Representation Learning: Recently, the research group in [13] argued that most of the conventional domain adaptation methods learn the common representations of source and target domains without considering the negative influence from the domain specific characteristics. If the network transfers the negative effects, we may not be able to learn a well generalized common feature representation. Therefore, the authors proposed a two-stage neural network learning algorithm to learn a multi-part hidden layer where individual parts can be disentangled or combined for different tasks in different domains. Also aiming at answering the fundamental question what to transfer, Domain Separation Network [14], proposed to integrate a private network to learn the private subspace for each domain and a shared network to extract the shared representation subspace across domains. After domain separation, the standard adversarial loss and classification loss can be applied only in the shared subspace. To robustly train the domain separation network, a difference loss and a reconstruction loss are also introduced. The difference loss forces the private subspace and shared subspace to be independent. By using the reconstruction loss, they also hope the separated new feature spaces could still keep most of the image content.

Partial Transfer Learning: Partial transfer learning was proposed by [12], where the target domain label space is a subspace of the source domain la-
bel space. Because the extra source classes might cause negative transfer when classifying the target domain, it makes the domain adaptation problem more challenging. Thus, instead of matching the whole source and target domains as these previous methods, a method focuses more on matching the corresponding local class distributions among domains are necessary. Moreover, a source class distribution without its corresponding target class should not be matched. In this work, in order to solve the partial transfer problem, instead of using single-discriminator domain adversarial network, the authors proposed to use multi-discriminator domain adversarial network, each discriminator is responsible for matching the source and target domain data associated with each label.

3 The Structure of the Proposed Domain Adaptation Network

In this paper, we firstly focus on the problem of unsupervised domain adaptation, where we are provided source data $X_S$, source labels $Y_S$, and target data $X_T$, but no target label. Particularly, we aim to train a target domain classifier $F_C$ that can correctly predict the label for the target data $X_T$ by leveraging the source data $X_S$ and source labels $Y_S$. Unlike the conventional setting of domain adaptation, we pay further attention on (a) transfer learning of common feature components and (b) partial transfer learning. For case (a), we argue that disentangled representation learning is necessary to decompose the common feature parts and specific parts of domains. For case (b), we design our framework to match the cluster-based distributions between source and target domains instead of matching the whole domain distribution. Finally, we proposed to exchange the specific feature parts across domains and synthesize style-transferred images.
These style-transferred images are further used to improve domain adaptation and partial transfer learning.

Our framework is illustrated in Fig. 2. We design a deep framework that allows us to learn multiple disentanglable feature components represented by multiple feature maps among some relative (image) domains. To simplify the disentangled representation learning problem, we start from two domains, source \((x_S)\) and target \((x_T)\). For disentangled representation learning, we separate the hidden feature maps into common parts and specific parts. In Fig. 2, \(F_S\) and \(F_T\) denote the feature extractors which map the source and target images into the feature domain respectively. The generators in the source and target domains, \(G_S\) and \(G_T\), are responsible for image reconstruction based on the extracted features. To solve the unsupervised domain adaptation problem in a better way, we have introduced two key function modules in our feature extraction and image generation framework:

- **Disentangled Representation Learning**: The feature extraction networks, \(F_S\) and \(F_T\), have the ability to disentangle the feature maps into different semantic parts including the common parts \((C_S\) and \(C_T\)) and specific parts \((S_S\) and \(S_T\)). We denote the decomposition processes as \(C_S = F^C_S(x_S), C_T = F^C_T(x_T), S_S = F^S_S(x_S),\) and \(S_T = F^S_T(x_T)\). As an instance, in our digit classification experiments, the common parts imply the semantic features of digits; the specific parts mainly reveal the domain style such as the writing style and appearance. Each part could be utilized in a different way to connect two domains and finally helps to transfer knowledge for domain adaptation. Thus, our system can realize the classification task without supervised labels in the target domain.

- **Feature exchange across domains**: We combine the specific part of one domain with the common part of the other domain to synthesize a new feature representation as shown in Fig. 2. The operator is named as feature exchange. Next, based on a learnable GAN-based network, our system can generate a style-transferred image given a synthesized feature representation. The style-transferred image, keeping the original image content but different image style, would play important roles to bridge domains. This process also enable our system to transfer the labels from source to target.

Besides feature extractors and generators, our framework also consists of three discriminators and one standard classifier as illustrated in Figure 2. Based on the supervised labels in the source domain, the standard classifier (\(F_C\)) and the source common features should be well trained in order to correctly classify the source domain samples. In addition, three adversarial discriminators \(D_S, D_T\) and \(D_F\) are introduced for representation adaptation in both the image level and feature level. \(D_S\) aims to distinguish between real source images \(X_S\) and style-transferred target image, denoted as \(\{G_S(S_S, C_T)\}\). Here, \(G_S(S_S, C_T)\) means a style-transferred target image is generated by a the generator \(G_S\) given the cascade of source specific parts \(S_S\) and target common parts \(C_T\). In the similar way, \(D_T\) aims to discriminate between \(X_T\) and \(\{G_T(S_T, C_S)\}\). By introducing \(D_S\) and \(D_T\), we have used adversarial learning in the image level and therefore
the synthesized and style-transferred image should not be distinguished from the real ones. This property is quite helpful for domain adaptation, which would be explained later. Moreover, we also apply adversarial learning in the feature level by $D_F$, which is designed to distinguish between the common parts $C_S$ and $C_T$ of source and target domains. With the helps of the adversarial discriminators $D_F$, we can match the feature distribution of the source common part $C_S$ and the target common part $C_T$.

4 Objective Losses and Training for Domain Adaptation

To train our domain adaptation network, we designed and implemented 5 types of objective losses. We summary them as follows and explain the design details in the following subsections.

1. **Adversarial Loss** [15] is applied to unify the common feature distributions of source and target domains in both the image and feature levels.

2. **Feedback and Reconstruction Loss** is a new objective term proposed in this work. Funded on style transfer, we use many synthesized style-transferred images to enhance the consistence of the generators $\{G_i\}_{i=S,T}$ and the extractors $\{F_i\}_{i=S,T}$. Unlike the reconstruction loss in an auto-encoder setting, our feedback and reconstruction loss is measured in the feature level and allows our network to adapt two domains through style transfer.

3. **Semantic Consistency Loss** is also a new objective term proposed in this work due to the introduction of style transfer for domain adaptation. The loss is used to measure the classification consistency between the discriminator $D_S$ and $D_T$. Given a testing target sample $X_T$ and its style-transferred image $G_S(S_S, C_T)$, if our network is trained well, the output of the source discriminator $D_S(G_S(S_S, C_T))$ should be consistent with the target discriminator $D_T(X_T)$. This design allows our network to transfer the class supervision from source to target and train the target discriminator (with the classification function) without target labels. In the training phase, to reduce the semantic consistency loss, our feature extraction networks $F$ are forced to well disentangle the Common and Specific feature components. Meanwhile, the generators $G$ are forced to perform style transfer well.

4. **Entropy Minimization Losses** [16] is applied in our training procedure as post parameter refinement. The loss enforces the classification outputs to be precise with less uncertainty. It helps the intra-cluster distributions of the common feature parts to be compact and inter-cluster distributions to be separable and thereby it makes the transfer process easier.

5. **Classification Loss**, the conventional loss function, is used to measure the correctness of the standard classifier ($F_C$) used in the source domain. To minimize the source prediction errors given the labeled data, the feature extractor $F_S$ should be well trained.
4.1 Adversarial Loses

Our domain adaptation framework works like the conditional \cite{17} in which the conditional variables are common parts $C$ and specific parts $S$. However, we do not use any random noise as GAN inputs. All the features come from data themselves. For domain adaptation, we apply adversarial losses \cite{15} and design three adversarial discriminators ($D_S, D_T, D_F$) to jointly match the statistic distributions of two domains in both the image and feature levels. However, our discriminators not only aim to distinguish between source and target domains but also try to classify the input data. Similar to the design in \cite{18}, our adversarial discriminators are $(N_C + 1)$-way classifiers with $N_C$ binary nodes to indicate $N_C$ content classes and an extra class for type discrimination. For $D_S$ and $D_T$, the extra class represents a real (1) or synthesized (0) image; For $D_F$, it indicates the source (1) or target (0) domain. With this design, the discriminators could be more powerful and help our system to match the cluster-based distribution between domains instead of matching the whole domain distribution as the traditional discriminator \cite{5}. Note that, due to image style transfer, our network can still train $D_T$ even though we do not have supervised labels in the target domain. Indeed, the label information is borrowed from the annotation in the source domain.

Accordingly, we have defined three adversarial losses for training: (a) the feature level loss $L_{\text{adv.fea}}$, (b) the image-level loss in the source domain $L_{\text{adv.img}}^S$, and (c) the image-level loss in the target domain $L_{\text{adv.img}}^T$.

**Feature Level Loss ($L_{\text{adv.fea}}$)** Here, $L_{\text{adv.fea}}$ is relative to feature extractors $F_S, F_T$, and especially the feature discriminator $D_F$. Since our discriminator plays two roles at the same time, a type classifier and a content classifier, $L_{\text{adv.fea}}$ is composed of a type loss $L_{\text{type}D_F}$ and a classification loss $L_{\text{cls}D_F}$ as defined in equation (1).

$$L_{\text{adv.fea}}(F_S, F_T, D_F) = L_{\text{type}D_F}(F_S, F_T, D_F) + L_{\text{cls}D_F}(F_S, D_F).$$

In \cite{1}, the type loss $L_{\text{type}D_F}$ is defined by a standard 2-class likelihood function, where the class labels are the original domain. That is

$$L_{\text{type}D_F}(F_S, F_T, D_F) = E_{x_S} \log(D_F^{N_C+1}(F^C_S(x_S))) + E_{x_T} \log(1 - D_F^{N_C+1}(F^C_T(x_T))).$$

Here, $D_F^{(N_C+1)}(\cdot)$, the $(N_C + 1)$th output of discriminator $D_F$, works as a domain classifier and predicts the domain label (1 for source and 0 for target) for each input sample. $F^C_S(x_S)$ and $F^C_T(x_T)$ are the common feature parts of a source sample $x_S$ and a target sample $x_T$. $E_{x_S}$ and $E_{x_T}$ are the expectation operators; practically, we draw samples from data distributions $P(x_S)$ and $P(x_T)$. In our network, the discriminator $D_F$ should be well trained to correctly indicate the domain of an input sample so that the loss $L_{\text{type}D_F}$ could be maximized. However, the feature extractors $F_S$ and $F_T$ are trained to greatly confuse the
discriminator $D_F$ and minimize $L_{type,D_F}$. On the other hand, we use cross entropy to define the classification loss $L_{cls,D_F}$, which has used in equation (3). That is,

$$L_{cls,D_F}(F_S, D_F) = -E_{x_S} \sum_{i=0}^{N_C} y^i_S \cdot \log(\sigma(D^i_F(F^C_S(x_S)))).$$  

where $D^i_F(\cdot)$, the $i^{th}$ output of discriminator $D_F$, works as a content classifier and predicts the probability of the $i^{th}$ class. $y^i_S$ is the supervised label for the input sample $x_S$. $y^i_S = 1$ if $x_S$ belongs to the $i^{th}$ class; otherwise, $y^i_S = 0$. In (3), $\sigma(\cdot)$ denotes the softmax function, which is used to make sure the summation of $N$ class probabilities is 1. Since only source domain has label information, we only consider source samples for training in this loss. During the learning phase, $F_S$ and $F_T$ are trained to minimize the classification loss $L_{cls,D_F}$.

Source Domain Image-level Loss ($L^S_{adv, img}$) Like $L_{adv, fea}$, $L^S_{adv, img}$ is also composed of a type loss $L_{type,D_S}$ and a classification loss $L_{cls,D_S}$. Since the adversarial loss is highly relative to $F_S, F_T, G_S,$ and $D_S$, we define it as

$$L^S_{adv, img}(F_S, F_T, G_S, D_S) = L_{type,D_S}(F_S, F_T, G_S, D_S) + L_{cls,D_S}(D_S),$$

The type loss $L_{type,D_S}$ related to discriminator $D_S$ is defined by a 2-class likelihood function, but now the class labels are the image types (1 for a real image and 0 for a generated image). That is

$$L_{type,D_S}(F_S, F_T, G_S, D_S) = E_{x_S} \log(D_S^{N_C+1}(x_S)) + E_{S,S,C_T} \log(1 - D_S^{N_C+1}(G_S(S_S, C_T))).$$

In (5), $D_S^{(N_C+1)}(\cdot)$ is a type classifier used to discriminate a real or synthesized image. $G_S(S_S, C_T)$ generates an image by cascading a source specific feature $S_S$ and a target common feature $C_T$. $S_S$ and $C_T$ are samples drawn from the source specific feature (style) manifold and the target common feature distribution. Note that $S_S = F^S_S(x_S)$ and $C_T = F^T_T(x_T)$. Particularly, $S_S$ and $C_T$ are extracted by randomly selecting $x_S$ and $x_T$ and the feature extractors. For training, our goal is to tune the discriminator $D_S$ to correctly classify the image type in order to maximize $L_{type,D_S}$. At the same time, $F_S, F_T$, and $G_S$ are trained to confuse the discriminator $D_S$ and minimize $L_{type,D_S}$. In return, our network could decompose features well and generate vivid images.

The second term in (4), $L_{cls,D_S}(D_S)$, is the image classification loss for source discriminator $D_S$. We define of $L_{cls,D_S}(D_S)$ in equation (6).

$$L_{cls,D_S}(D_S) = -E_{x_S} \sum_{i=0}^{N_C} y^i_S \cdot \log(\sigma(D^i_S(x_S))).$$

Similar to equation (3), $D^i_S(\cdot)$ is probability of the $i^{th}$ content class, $y^i_S$ is the supervised class label, $\sigma(\cdot)$ denotes the softmax function, and $E_{x_S}$ is the expectation operator over possible $x_S$. To minimize $L_{cls,D_S}(D_S)$, $D_S$ is trained to well classify the input image samples.
Target Domain Image-level Loss ($L_{adv, img}^T$) Target adversarial loss $L_{adv, img}^T$ shares the same design concept as $L_{adv, img}^S$. It is defined as

$$L_{adv, img}^T(F_S, F_T, G_T, D_T) = L_{type,D_T}(F_S, F_T, G_T, D_T) + L_{cls,D_T}(F_S, F_T, G_T, D_T),$$

where the type loss $L_{type,D_T}$ and image content classification loss $L_{cls,D_T}$ are

$$L_{type,D_T}(F_S, F_T, G_T, D_T) = E_{x_T} \log(D_T^{NC+1}(x_T)) + E_{S_T,C_S} \log(1 - D_T^{NC+1}(G_T(S_T,C_S))).$$

and

$$L_{cls,D_T}(F_S, F_T, G_T, D_T) = -E_{S_T,C_S} \sum_{i=0}^{NC} y^S_i \cdot \log(\sigma(D_T^i(G_T(S_T,C_S)))).$$

Here, since $C_S = F_S^C(x_S)$ and $S_T = F_T^S(x_T)$, both $L_{type,D_T}$ and $L_{cls,D_T}$ are relative to $F_S$ and $F_T$. By randomly sampling the dataset to have samples $x_S$ and $x_T$, we could extract $C_S$ and $S_T$. Finally, it is worth mentioning that the supervised class label $y^S_i$ for training the target discriminator $D_T$ is borrowed from the source domain. In [9], we generate many target-style images with source labels so that $D_T$ could be trained. By minimizing all the losses, we expect $F_S$ and $F_T$ could well separate common features and specific features, $G_T$ could generate vivid style-transferred images, and $D_T$ can perform image classification well.

4.2 Feedback Losses and Reconstruction Losses

Because our framework is designed in the form of a convolutional auto-encoder, in order to make sure the learned features are generalized enough, we also proposed to minimize the reconstruction losses for both domains. Here, we apply the traditional mean squared error (MSE) as follows for the reconstruction task in both domains.

$$L_{recon}^S(G_S, F_S) = E_{x_S} ||x_S - G_S(F_S(x_S))||^2.$$

$$L_{recon}^T(G_T, F_T) = E_{x_T} ||x_T - G_T(F_T(x_T))||^2.$$

In our training procedure, $G_S, F_S, G_T$, and $F_T$ are learned to minimize the two reconstruction loss.

Besides, we proposed the feedback losses. Although conceptually similar to reconstruction losses, the feedback losses could further help to connect both domains. As shown in Fig. 2 to enhance the transferability of the learned common parts, we proposed to exchange feature components across domains and generate style-transferred images through a GAN-based framework. Funded on this property and inspired by the cycle-consistency loss [19], it becomes possible to introduce feedback losses to enforce the learning of feature extractors.
(F_T, F_S) and image generators (G_T, G_S). In detail, we input a combined feature map \((S_S, C_T)\) to a generator \(G_S\) and generate a source-style image. Ideally, if we input the synthesized image into feature extractor \(F_S\) and get its feature map \(S'_S, C'_T\), we would hope the two feature maps \(S'_S, C'_T\) and \(S_S, C_T\) are consistent. That is, we expect \(F_S^S(G_S(S_S, C_T)) \approx S_S\) and \(F_S^C(G_S(S_S, C_T)) \approx C_T\). This feedback constraint could be integrated in our learning step by imposing an L2 penalty term according to the feedback errors. The similar concept could also be applied to the target domain. Therefore, in our system, we have the following two feedback losses.

\[
L_{feedback}^F(F_S, F_T, G_S) = E_{S_S, C_T}(\|S_S - F_S^S(G_S(S_S, C_T))\|^2_2 + \|C_T - F_S^C(G_S(S_S, C_T))\|^2_2). \tag{12}
\]

\[
L_{feedback}^T(F_S, F_T, G_T) = E_{S_T, C_S}(\|S_T - F_T^S(G_T(S_T, C_S))\|^2_2 + \|C_S - F_T^C(G_T(S_T, C_S))\|^2_2). \tag{13}
\]

### 4.3 Semantic consistency loss

Most of the relative works for domain adaptation rely on distribution matching. In this work, we find the possibility to transfer sample labels for domain adaptation when disentangled learning meets style transfer. As we have mentioned in the previous subsection, we train our network to be able to generate target style images whose contents come from source images. This allows the generated target images to inherit the source labels and enables the transfer of sample labels. Furthermore, based on the supervised label transfer, discriminators \(D_S\) and \(D_T\) could be trained. By leveraging \(D_S\) and \(D_T\), we proposed a new semantic consistency loss to improve domain adaptation.

Note that, discriminators \(D_S\) and \(D_T\) not only distinguish real and style-transferred images but also predict the class of each input data. If our network is well trained, we expect the classification result \(D_S(G_S(S_S, C_T|X_T)\) of the generated style-transferred image \(G_S(S_S, C_T|X_T)\) should be consistent with \(D_T(X_T)\), where \(C_T|X_T\) means a common feature vectors extracted from its corresponding sample \(X_T\) by \(C_T = F_C^C(x_T)\). Note that generated image \(G_S(S_S, C_T|X_T)\) is supposed to have the same image content like the input target image \(X_T\). Therefore, in order to encourage this kind of semantic consistency, we introduce the semantic consistency loss as follows:

\[
L_{sem}(F_S, F_T, G_S, D_S, D_T) = E_{S_S, X_T}\|[D_T^{1\rightarrow NC}(X_T) - D_S^{1\rightarrow NC}(G_S(S_S, C_T|X_T))\|^2_2. \tag{14}
\]

In (14), both \(D_T^{1\rightarrow NC}(.)\) and \(D_S^{1\rightarrow NC}(.)\) output a classification vector with \(N_C\) components. Mean squared error is used to measure the difference of vectors.

**Semantic consistency loss** plays the important role to connect both domains. To reduce the semantic consistency loss, our feature extraction networks \(F\) are forced to well disentangle the Common and Specific feature components. Meanwhile, the generators \(G\) are forced to perform style transfer well.
4.4 Entropy minimization losses

The classification ability of the discriminators $D_S, D_T$ and $D_F$ is a critical point in our network. However, so far, we only base on the source sample annotation for training. The result might be acceptable for $D_S$ and $D_F$ but might not be perfect for $D_T$ due to the lack of true labels. Thus, to enhance the classification ability, we look for the help from unsupervised methods [20] and integrate the concept of entropy minimization [16] into our network training.

Note that the output of $\sigma(D_{1 \rightarrow NC}^1(x_i^s))$ is a normalized classification vector of an input sample $x_i^s$, where its $j$th element $D^j_s(x_i^s)$ indicates the probability of the $j$th class and $D_s \in \{D_S, D_T, D_F\}$. The softmax function $\sigma(.)$ is used to make sure the probability summation is equal to 1. If we treat the output vector as a probability distribution, its entropy can be measured by

$$H(\sigma(D_{1 \rightarrow NC}^1(x_i^s))) = -\sum_{j=1}^{NC} \sigma(D^j_s(x_i^s)).\log(\sigma(D^j_s(x_i^s))),$$

(15)

where $H(.)$ is the standard entropy function and $NC$ is the class number. For an input sample $x_i^s$, if the corresponding entropy is small, it implicitly means the sample is well classified from an unsupervised viewpoint. Thus, we might enhance the classification ability by minimize the summarization of the entropies of many samples. To utilize this property in our training, we define the three entropy loss terms corresponding to three discriminators $D_S, D_T,$ and $D_F$ as follows:

$$L_{Entropy}(F_S, F_T, G_S, D_S, D_T, D_F) = E_{Ss,C_T} H(\sigma(D_{1 \rightarrow NC}^1(G_S(s_i^S, c_T^i)))) + E_{x_T} H(\sigma(D_{1 \rightarrow NC}^1(c_T^i)))$$

(16)

By minimizing the entropy penalty in (16), our system has two achievements. (1) We can train the three discriminators, the classification part, by unlabeled target samples. (2) The feature extractors are trained to from a well-clustered feature distribution over many classes. These properties improve domain adaptation especially in the partial transfer case. To understand the importance of entropy minimization, we visualize the learned features (common parts and specific parts) when training with and without $L_{Entropy}$ in Fig. 6b and Fig. 6c. We may find the margins among the clusters are clear and well separated when the effect of $L_{Entropy}$ is considered in the training process.

4.5 Classification loss

The last loss we apply in our learning is the standard classification loss. It uses the labeled source samples to train the classifier $F_C$ in the common feature domain and predict the final output label for a given testing sample. For the $NC$-way classification, the multiple-class classification loss, also known as the cross-entropy, are defined as

$$L_{cls}(F_S, F_C) = -E_{CS} \sum_{i=0}^{NC} y_i^s.log(\sigma(F_C^{i}(C_S))).$$

(17)
In the training phase, the learned network is also required to minimize the cross-entropy loss.

5 Experiment and Discussion

5.1 Setup

In order to evaluate the effectiveness of our framework, we validate it by performing domain adaptation on three standard digit datasets MNIST [20], USPS [21], and SVHN [22] which contain 10 classes of digits.

USPS dataset has a training set of 7291 images and a test set of 2007 images of size 16x16.

MNIST dataset consists of 60000 training examples and 10000 test examples of size 28x28.

SVHN dataset contains 73257 digits for training and 26032 digits for testing of size 32x32.

With these datasets, we take into account the following unsupervised transfer scenarios. (1) MNIST → USPS/ USPS → MNIST: because USPS and MNIST follow very different distribution, to accelerate experiments, we follow the training protocol created in [23], randomly sampling 1800 images in USPS and 2000 images in MNIST. To reduce the high variance effect in performance of random sampling, we run each experiment five times and report the average performance. (2) SVHN → MNIST: we use the full training sets. All images were rescaled into 32x32 and pixels were normalized to [0, 1] values, and only the labels from source are available during training.

Two transfer learning problems are focused in our experiments are full transfer learning and partial transfer learning where the target label space is a subset of source label space. For the case of partial transfer learning, we randomly select 5 classes to form the target domain data, and only the scenario MNIST → USPS is considered.

Architecture. For all of these experiments, we simply modify LeNet architecture provided in Caffe source code [24] as our extractors. The extractor pipeline has three 5x5 convolution layers covering 64, 128, and 256 kernels respectively, followed by ReLU and pooling. With 256 kernels in the output, we use 128 kernels to learn specific features and the rest for common features. For the generators, we use the same structure as DCGAN [25] with 4 full convolutional layers containing 512, 256, 128 and 1 kernels correspondingly, each followed by ReLU and up-sampling layer. The output is the generated image. The feature-level discriminator contains three fully connected layers of size 128, 128 and 11, each followed by ReLU except the last one. The image-level discriminators have three convolutional layers with 64, 128 and 256 kernels, followed by two fully connected layers of size 128 and 11.
Table 1: Experimental results on unsupervised adaptation

| Source only | **MNIST → USPS** | **USPS → MNIST** | **SVHN → MNIST** |
|-------------|------------------|------------------|------------------|
| CORAL [4]   | 81.7             | 57.1 ± 1.7       | 60.1 ± 1.1       |
| MMD [2]     | 81.1             |                 | 71.1             |
| DANN [7]    | 85.1             | 73.0 ± 2.0       | 73.9             |
| DSN [14]    | 91.3             |                 | 82.7             |
| CoGAN [26]  | 91.2             | 89.1 ± 0.8       | No converge      |
| ADDA [6]    | 89.4 ± 0.2       | 90.1 ± 0.8       | 76.0 ± 1.8       |
| GenToAdapt [18] | 92.5 ± 0.7       | **90.8 ± 1.3**   | 84.7 ± 0.9       |
| DRCN [29]   | 91.8 ± 0.09      | 73.7 ± 0.04      | 82.0 ± 0.16      |
| **Our method** | **94.14 ± 0.45** | 88.3 ± 1.06      | **90.23**        |

Fig. 3: Feature visualization

(a) USPS → MNIST  
(b) SVHN → MNIST

5.2 Full transfer learning

The results of our experiment are provided in Table 1, we observe that our method performs well in all scenarios, especially achieves the highest performance in both MNIST → USPS and SVHN → MNIST cases.

**Feature visualization.** To demonstrate the distributions of our learned features, we use t-SNE [27] projection. As shown in Fig. 3, the common features from target and source domains are matched together and grouped into 10 main clusters clearly, especially for the simple case USPS → MNIST. This means that our framework not only can learn the common features which cannot be distinguished between domains but also have ability to match the cluster-based distributions of two domains. On the contrary, the specific features from target and source domains are separated well and far away from common features. It means that our framework can learn the domain specific characteristics and
these characteristics are different from the common features even we did not apply any difference loss such as orthogonality constraint on these features.

**With and without semantic consistency loss.** In Fig. 4, we show the comparison of the style-transferred images produced by the generators $G_S$ and $G_T$ with and without semantic consistency loss. Without semantic consistency, the style-transferred images (Fig. 4c and 4d) seem to have the same style as the real one, but they fail at preserving the semantic information. They might deliver ambiguous information to the classifier and discriminators. As shown in (Fig. 4c and 4d), with semantic consistency loss, the style-transferred images successfully both preserve the semantic information and depict the style information.

![Fig. 4: With and without semantic consistency loss](image)

To show the common and specific parts in image domain. In Fig. 5, we show some examples for SVHN $\rightarrow$ MNIST case. We also try to show the common and specific parts in image domain by inhibiting the remaining part before inputting to the Generators. For example, if we want to show the common parts, we will set all specific parts equal to zero then concatenate them and input into the corresponding Generator. As shown in the Fig. 5e and 5f, the common part of each domain only store the information of ”digits”. Meanwhile, the specific parts encode the style information such as the contrast, color, size, ... as shown clearly in Fig. 5g. For the target’s specific part shown in Fig. 5h, all the images are almost same because the style of all the images in target domain (MNIST) are same. This experiment partly demonstrates our aforementioned statements about our framework’s abilities to learn disentangled representations and transfer the style across domain.

![Fig. 5: Show the common and specific parts in image domain](image)
5.3 Partial Transfer Learning

In order to quickly test whether our framework is capable of solving partial transfer learning problem, we still use the digit datasets and randomly select 5 classes to form the target domain data (USPS), and apply our framework with 3 different settings: (1) without feedback losses, (2) without entropy minimization losses and (3) proposed method. Based on the results in Table 2 and the t-SNE visualization in Fig. 6, we can understand the importance of $L_{feedback}$ and $L_{Entropy}$ in our framework especially for partial transfer learning case. As aforementioned, by enhancing the harmony and the stability of extractors and generators, $L_{feedback}$ improves the performance significantly by 14.28%. Without $L_{feedback}$, the outlier source clusters seem to cause certain difficulties to transferring process, as shown in Fig. 6a, the corresponding common clusters between source and target are not aligned well and some clusters are mismatched. With $L_{feedback}$, as shown in Fig. 6b, the corresponding classes between source and target are matched, however it still has ambiguous areas between classes. In Fig. 6c, we can recognize that $L_{Entropy}$ solves this problem and boosts the performance.
(5.28%) by clustering semantic classes together and thereby increasing the distance between clusters and then reducing the ambiguity. Moreover, comparing the performance and the feature distribution of our method for two transferring cases (full transferring and partial transferring), we can partly assert that our network can solve the partial transferring problem efficiently.

|                         | MNIST → USPS |
|-------------------------|--------------|
| Without $L_{feedback}$ and $L_{Entropy}$ | 75.22%       |
| Without $L_{Entropy}$   | 89.50%       |
| Proposed method         | **94.78%**   |

6 Conclusion

In this paper, we proposed a unified framework for unsupervised domain adaptation that can disentangle the feature domain into multi parts in order to answer the questions what to transfer and what not to transfer. To simplify the problem, we separate the feature domain into two main parts: common features between source and target domains, and specific features of each domain. The common features are used to embed the content information that are useful for classification purpose across domains, and the specific features are used to encode the domain specific characteristics that are useful for style transfer or multi-domain image-to-image translation problem. To enhance the transferability of common features and match the common distribution between domains for in both feature and image levels, we proposed the novel idea for feature exchange and multiple levels adversarial learning. Besides, we also introduced the feedback design and semantic consistency loss to improve the harmony and the stability of the parts in the architecture. Last but not least, entropy minimization losses were applied in our framework as a refining method to encourage the self-clustering ability in target domain and thereby make the transfer process easier. The experiments confirm the power of our network in solving both of full transfer problem and partial transfer problem. Besides, results also show the potential of our network in image style transfer application. We plan to extend this work by testing it on other domain adaptation challenges and multi-domain image-to-image translation problems.
Fig. 6: Visualization of learned features when partial transferring from MNIST to USPS.
References

1. Gretton, A., Smola, A., Huang, J., Schmittfull, M., Borgwardt, K., Schölkopf, B. In: Covariate shift and local learning by distribution matching. MIT Press, Cambridge, MA, USA (2009) 131–160
2. Tzeng, E., Hoffman, J., Zhang, N., Saenko, K., Darrell, T.: Deep domain confusion: Maximizing for domain invariance. CoRR abs/1412.3474 (2014)
3. Long, M., Cao, Y., Wang, J., Jordan, M.I.: Learning transferable features with deep adaptation networks. In: Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37. ICML’15, JMLR.org (2015) 97–105
4. Sun, B., Saenko, K.: Deep coral: Correlation alignment for deep domain adaptation. In: ECCV 2016 Workshops. (2016)
5. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative adversarial nets. In Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N.D., Weinberger, K.Q., eds.: Advances in Neural Information Processing Systems 27. Curran Associates, Inc. (2014) 2672–2680
6. Tzeng, E., Hoffman, J., Darrell, T., Saenko, K.: Adversarial discriminative domain adaptation. In: Computer Vision and Pattern Recognition (CVPR). (2017)
7. Ganin, Y., Ustinova, E., Ajakan, H., Germain, P., Larochelle, H., Laviolette, F., Marchand, M., Lempitsky, V.: Domain-adversarial training of neural networks. J. Mach. Learn. Res. 17(1) (January 2016) 2096–2030
8. Bousmalis, K., Silberman, N., Dohan, D., Erhan, D., Krishnan, D.: Unsupervised pixel-level domain adaptation with generative adversarial networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017) 95–104
9. Russo, P., Carlucci, F.M., Tommasi, T., Caputo, B.: From source to target and back: symmetric bi-directional adaptive gan. CoRR abs/1705.08824 (2017)
10. Tzeng, E., Hoffman, J., Darrell, T., Saenko, K.: Simultaneous deep transfer across domains and tasks. CoRR abs/1510.02192 (2015)
11. Ganin, Y., Lempitsky, V.: Unsupervised domain adaptation by backpropagation. In: Proceedings of the 32Nd International Conference on International Conference on Machine Learning - Volume 37. ICML’15, JMLR.org (2015) 1180–1189
12. Cao, Z., Long, M., Wang, J., Jordan, M.I.: Partial transfer learning with selective adversarial networks. CoRR abs/1707.07901 (2017)
13. J, G., Bhatt, H.S., Sinha, M., Roy, S.: Multi-part representation learning for cross-domain web content classification using neural networks. In: Proceedings of the 28th ACM Conference on Hypertext and Social Media. HT ’17, New York, NY, USA, ACM (2017) 305–314
14. Bousmalis, K., Trigeorgis, G., Silberman, N., Krishnan, D., Erhan, D.: Domain separation networks. In Lee, D.D., Sugiyama, M., Luxburg, U.V., Guyon, I., Garnett, R., eds.: Advances in Neural Information Processing Systems 29. Curran Associates, Inc. (2016) 343–351
15. Hoffman, J., Wang, D., Yu, F., Darrell, T.: Fcns in the wild: Pixel-level adversarial and constraint-based adaptation. CoRR abs/1612.02649 (2016)
16. Grandvalet, Y., Bengio, Y.: Semi-supervised learning by entropy minimization. In Saul, L.K., Weiss, Y., Bottou, L., eds.: Advances in Neural Information Processing Systems 17. MIT Press (2005) 529–536
17. Mirza, M., Osindero, S.: Conditional generative adversarial nets. CoRR abs/1411.1784 (2014)
18. Sankaranarayanan, S., Balaji, Y., Castillo, C.D., Chellappa, R.: Generate To Adapt: Aligning Domains using Generative Adversarial Networks. ArXiv e-prints (April 2017)
19. Zhu, J.Y., Park, T., Isola, P., Efros, A.A.: Unpaired image-to-image translation using cycle-consistent adversarial networks. arXiv preprint arXiv:1703.10593 (2017)
20. Lecun, Y., Bottou, L., Bengio, Y., Haffner, P.: Gradient-based learning applied to document recognition. In: Proceedings of the IEEE. (1998) 2278–2324
21. Hull, J.J.: A database for handwritten text recognition research. IEEE Trans. Pattern Anal. Mach. Intell. 16(5) (May 1994) 550–554
22. Netzer, Y., Wang, T., Coates, A., Bissacco, A., Wu, B., Ng, A.Y.: Reading digits in natural images with unsupervised feature learning. In: NIPS Workshop on Deep Learning and Unsupervised Feature Learning 2011. (2011)
23. Long, M., Wang, J., Ding, G., Sun, J., Yu, P.: Transfer feature learning with joint distribution adaptation. In: Proceedings of the IEEE International Conference on Computer Vision, Institute of Electrical and Electronics Engineers Inc. (1 2013) 2200–2207
24. Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S., Darrell, T.: Caffe: Convolutional architecture for fast feature embedding. In: Proceedings of the 22Nd ACM International Conference on Multimedia. MM ’14, New York, NY, USA, ACM (2014) 675–678
25. Radford, A., Metz, L., Chintala, S.: Unsupervised representation learning with deep convolutional generative adversarial networks. CoRR abs/1511.06434 (2015)
26. Liu, M.Y., Tuzel, O.: Coupled generative adversarial networks. In Lee, D.D., Sugiyama, M., Luxburg, U.V., Guyon, I., Garnett, R., eds.: Advances in Neural Information Processing Systems 29. Curran Associates, Inc. (2016) 469–477
27. van der Maaten, L., Hinton, G.: Visualizing high-dimensional data using t-sne. Journal of Machine Learning Research 9: 25792605 (Nov 2008)
7 Supplementary Material

7.1 CNN architectures

Fig. 7: The feature extractor architecture.

Fig. 8: The generator architecture.

Fig. 9: Image-level discriminator architecture.
7.2 Training details

Our training schedule is divided into three main steps:

- **Step 1**: We first warm-up our network by training it without $L_{\text{Entropy}}$ 4000 iterations with random initialization and the learning rate 0.001.
- **Step 2**: We initialize target networks weights by the trained source networks weights and also train without $L_{\text{Entropy}}$ other 20,000 iterations with the learning rate 0.001.
- **Step 3**: We refine the network by training for 2000 iterations with $L_{\text{Entropy}}$ loss and learning rate 0.0001.

During training, we can repeat step 2 and step 3 to achieve better initialization. As the network converges, we can also reduce the learning rate by ten times and continue training to get higher performance.