

Adversarial Discriminative Domain Adaptation

Eric Tzeng

University of California, Berkeley
etzeng@eecs.berkeley.edu

Kate Saenko

Boston University
saenko@bu.edu

Judy Hoffman

Stanford University
jhoffman@cs.stanford.edu

Trevor Darrell

University of California, Berkeley
trevor@eecs.berkeley.edu

Abstract

Adversarial learning methods are a promising approach to training robust deep networks, and can generate complex samples across diverse domains. They can also improve recognition despite the presence of domain shift or dataset bias: recent adversarial approaches to unsupervised domain adaptation reduce the difference between the training and test domain distributions and thus improve generalization performance. However, while generative adversarial networks (GANs) show compelling visualizations, they are not optimal on discriminative tasks and can be limited to smaller shifts. On the other hand, discriminative approaches can handle larger domain shifts, but impose tied weights on the model and do not exploit a GAN-based loss. In this work, we first outline a novel generalized framework for adversarial adaptation, which *subsumes* recent state-of-the-art approaches as special cases, and use this generalized view to better relate prior approaches. We then propose a previously unexplored instance of our general framework which combines discriminative modeling, untied weight sharing, and a GAN loss, which we call Adversarial Discriminative Domain Adaptation (ADDA). We show that ADDA is more effective yet considerably simpler than competing domain-adversarial methods, and demonstrate the promise of our approach by exceeding state-of-the-art unsupervised adaptation results on standard domain adaptation tasks as well as a difficult cross-modality object classification task.

1. Introduction

Deep convolutional networks, when trained on large-scale datasets, can learn representations which are generically useful across a variety of tasks and visual domains [1, 2]. However, due to a phenomenon known as *dataset bias* or *domain shift* [3], recognition models trained along with these representations on one large dataset do not generalize well to

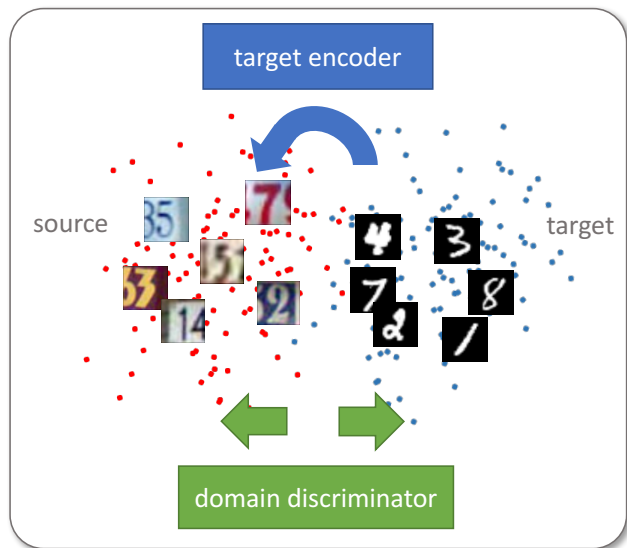


Figure 1: We propose an improved unsupervised domain adaptation method that combines adversarial learning with discriminative feature learning. Specifically, we learn a discriminative mapping of target images to the source feature space (target encoder) by fooling a domain discriminator that tries to distinguish the encoded target images from source examples.

novel datasets and tasks [4, 1]. The typical solution is to further fine-tune these networks on task-specific datasets—however, it is often prohibitively difficult and expensive to obtain enough labeled data to properly fine-tune the large number of parameters employed by deep multilayer networks.

Domain adaptation methods attempt to mitigate the harmful effects of domain shift. Recent domain adaptation methods learn deep neural transformations that map both domains

into a common feature space. This is generally achieved by optimizing the representation to minimize some measure of domain shift such as maximum mean discrepancy [5, 6] or correlation distances [7, 8]. An alternative is to reconstruct the target domain from the source representation [9].

Adversarial adaptation methods have become an increasingly popular incarnation of this type of approach which seeks to minimize an approximate domain discrepancy distance through an adversarial objective with respect to a domain discriminator. These methods are closely related to generative adversarial learning [10], which pits two networks against each other—a generator and a discriminator. The generator is trained to produce images in a way that confuses the discriminator, which in turn tries to distinguish them from real image examples. In domain adaptation, this principle has been employed to ensure that the network cannot distinguish between the distributions of its training and test domain examples [11, 12, 13]. However, each algorithm makes different design choices such as whether to use a generator, which loss function to employ, or whether to share weights across domains. For example, [11, 12] share weights and learn a symmetric mapping of both source and target images to the shared feature space, while [13] decouple some layers thus learning a partially asymmetric mapping.

In this work, we propose a novel unified framework for adversarial domain adaptation, allowing us to effectively examine the different factors of variation between the existing approaches and clearly view the similarities they each share. Our framework unifies design choices such as weight-sharing, base models, and adversarial losses and subsumes previous work, while also facilitating the design of novel instantiations that improve upon existing ones.

In particular, we observe that generative modeling of input image distributions is not necessary, as the ultimate task is to learn a discriminative representation. On the other hand, asymmetric mappings can better model the difference in low level features than symmetric ones. We therefore propose a previously unexplored unsupervised adversarial adaptation method, Adversarial Discriminative Domain Adaptation (ADDA), illustrated in Figure 1. ADDA first learns a discriminative representation using the labels in the source domain and then a separate encoding that maps the target data to the same space using an asymmetric mapping learned through a domain-adversarial loss. Our approach is simple yet surprisingly powerful and achieves state-of-the-art visual adaptation results on the MNIST, USPS, and SVHN digits datasets. We also test its potential to bridge the gap between even more difficult cross-modality shifts, without requiring instance constraints, by transferring object classifiers from RGB color images to depth observations. Finally, we evaluate on the standard Office adaptation dataset, and show that ADDA achieves strong improvements over competing methods, especially on the most challenging domain shift.

2. Related work

There has been extensive prior work on domain transfer learning, see e.g., [3]. Recent work has focused on transferring deep neural network representations from a labeled source datasets to a target domain where labeled data is sparse or non-existent. In the case of unlabeled target domains (the focus of this paper) the main strategy has been to guide feature learning by minimizing the difference between the source and target feature distributions [11, 12, 5, 6, 8, 9, 13, 14].

Several methods have used the Maximum Mean Discrepancy (MMD) [3] loss for this purpose. MMD computes the norm of the difference between two domain means. The DDC method [5] used MMD in addition to the regular classification loss on the source to learn a representation that is both discriminative and domain invariant. The Deep Adaptation Network (DAN) [6] applied MMD to layers embedded in a reproducing kernel Hilbert space, effectively matching higher order statistics of the two distributions. In contrast, the deep Correlation Alignment (CORAL) [8] method proposed to match the mean and covariance of the two distributions.

Other methods have chosen an adversarial loss to minimize domain shift, learning a representation that is simultaneously discriminative of source labels while not being able to distinguish between domains. [12] proposed adding a domain classifier (a single fully connected layer) that predicts the binary domain label of the inputs and designed a *domain confusion* loss to encourage its prediction to be as close as possible to a uniform distribution over binary labels. The gradient reversal algorithm (ReverseGrad) proposed in [11] also treats domain invariance as a binary classification problem, but directly maximizes the loss of the domain classifier by reversing its gradients. DRCN [9] takes a similar approach but also learns to reconstruct target domain images. Domain separation networks [15] enforce these adversarial losses to minimize domain shift in a shared feature space, but achieve impressive results by augmenting their model with private feature spaces per-domain, an additional dissimilarity loss between the shared and private spaces, and a reconstruction loss.

In related work, adversarial learning has been explored for generative tasks. The Generative Adversarial Network (GAN) method [10] is a generative deep model that pits two networks against one another: a generative model G that captures the data distribution and a discriminative model D that distinguishes between samples drawn from G and images drawn from the training data by predicting a binary label. The networks are trained jointly using backprop on the label prediction loss in a mini-max fashion: simultaneously update G to minimize the loss while also updating D to maximize the loss (fooling the discriminator). The advantage of GAN over other generative methods is that there is no

need for complex sampling or inference during training; the downside is that it may be difficult to train. GANs have been applied to generate natural images of objects, such as digits and faces, and have been extended in several ways. The BiGAN approach [16] extends GANs to also learn the inverse mapping from the image data back into the latent space, and shows that this can learn features useful for image classification tasks. The conditional generative adversarial net (CGAN) [17] is an extension of the GAN where both networks G and D receive an additional vector of information as input. This might contain, say, information about the class of the training example. The authors apply CGAN to generate a (possibly multi-modal) distribution of tag-vectors conditional on image features. GANs have also been explicitly applied to domain transfer tasks, such as domain transfer networks [18], which seek to directly map source images into target images.

Recently the CoGAN [13] approach applied GANs to the domain transfer problem by training two GANs to generate the source and target images respectively. The approach achieves a domain invariant feature space by tying the high-level layer parameters of the two GANs, and shows that the same noise input can generate a corresponding pair of images from the two distributions. Domain adaptation was performed by training a classifier on the discriminator output and applied to shifts between the MNIST and USPS digit datasets. However, this approach relies on the generators finding a mapping from the shared high-level layer feature space to full images in both domains. This can work well for say digits which can be difficult in the case of more distinct domains. In this paper, we observe that modeling the image distributions is not strictly necessary to achieve domain adaptation, as long as the latent feature space is domain invariant, and propose a discriminative approach.

3. Generalized adversarial adaptation

We present a general framework for adversarial unsupervised adaptation methods. In unsupervised adaptation, we assume access to source images \mathbf{X}_s and labels Y_s drawn from a source domain distribution $p_s(x, y)$, as well as target images \mathbf{X}_t drawn from a target distribution $p_t(x, y)$, where there are no label observations. Our goal is to learn a target representation, M_t and classifier C_t that can correctly classify target images into one of K categories at test time, despite the lack of in domain annotations. Since direct supervised learning on the target is not possible, domain adaptation instead learns a source representation mapping, M_s , along with a source classifier, C_s , and then learns to adapt that model for use in the target domain.

In adversarial adaptive methods, the main goal is to regularize the learning of the source and target mappings, M_s and M_t , so as to minimize the distance between the empirical source and target mapping distributions: $M_s(X_s)$ and

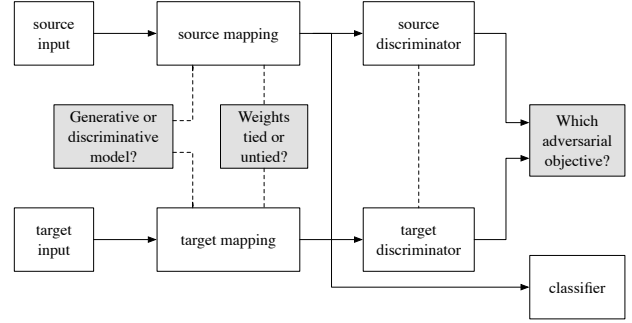


Figure 2: Our generalized architecture for adversarial domain adaptation. Existing adversarial adaptation methods can be viewed as instantiations of our framework with different choices regarding their properties.

$M_t(X_t)$. If this is the case then the source classification model, C_s , can be directly applied to the target representations, eliminating the need to learn a separate target classifier and instead setting, $C = C_s = C_t$.

The source classification model is then trained using the standard supervised loss below:

$$\min_{M_s, C} \mathcal{L}_{\text{cls}}(\mathbf{X}_s, Y_t) = \mathbb{E}_{(\mathbf{x}_s, y_s) \sim (\mathbf{X}_s, Y_t)} - \sum_{k=1}^K \mathbb{1}_{[k=y_s]} \log C(M_s(\mathbf{x}_s)) \quad (1)$$

We are now able to describe our full general framework view of adversarial adaptation approaches. We note that all approaches minimize source and target representation distances through alternating minimization between two functions. First a domain discriminator, D , which classifies whether a data point is drawn from the source or the target domain. Thus, D is optimized according to a standard supervised loss, $\mathcal{L}_{\text{adv}_D}(\mathbf{X}_s, \mathbf{X}_t, M_s, M_t)$ where the labels indicate the origin domain, defined below:

$$\begin{aligned} \mathcal{L}_{\text{adv}_D}(\mathbf{X}_s, \mathbf{X}_t, M_s, M_t) = & - \mathbb{E}_{\mathbf{x}_s \sim \mathbf{X}_s} [\log D(M_s(\mathbf{x}_s))] \\ & - \mathbb{E}_{\mathbf{x}_t \sim \mathbf{X}_t} [\log(1 - D(M_t(\mathbf{x}_t)))] \end{aligned} \quad (2)$$

Second, the source and target mappings are optimized according to a constrained adversarial objective, whose particular instantiation may vary across methods. Thus, we can derive a generic formulation for domain adversarial techniques below:

$$\begin{aligned} \min_D \mathcal{L}_{\text{adv}_D}(\mathbf{X}_s, \mathbf{X}_t, M_s, M_t) \\ \min_{M_s, M_t} \mathcal{L}_{\text{adv}_M}(\mathbf{X}_s, \mathbf{X}_t, D) \\ \text{s.t. } \psi(M_s, M_t) \end{aligned} \quad (3)$$

Method	Base model	Weight sharing	Adversarial loss
Gradient reversal [19]	discriminative	shared	minimax
Domain confusion [12]	discriminative	shared	confusion
CoGAN [13]	generative	unshared	GAN
ADDA (Ours)	discriminative	unshared	GAN

Table 1: Overview of adversarial domain adaption methods and their various properties. Viewing methods under a unified framework enables us to easily propose a new adaptation method, adversarial discriminative domain adaptation (ADDA).

In the next sections, we demonstrate the value of our framework by positioning recent domain adversarial approaches within our framework. We describe the potential mapping structure, mapping optimization constraints ($\psi(M_s, M_t)$) choices and finally choices of adversarial mapping loss, $\mathcal{L}_{\text{adv}_M}$.

3.1. Source and target mappings

In the case of learning a source mapping M_s alone it is clear that supervised training through a latent space discriminative loss using the known labels Y_s results in the best representation for final source recognition. However, given that our target domain is unlabeled, it remains an open question how best to minimize the distance between the source and target mappings. Thus the first choice to be made is in the particular parameterization of these mappings.

Because unsupervised domain adaptation generally considers target discriminative tasks such as classification, previous adaptation methods have generally relied on adapting discriminative models between domains [12, 19]. With a discriminative base model, input images are mapped into a feature space that is useful for a discriminative task such as image classification. For example, in the case of digit classification this may be the standard LeNet model. However, Liu and Tuzel achieve state of the art results on unsupervised MNIST-USPS using two generative adversarial networks [13]. These generative models use random noise as input to generate samples in image space—generally, an intermediate feature of an adversarial discriminator is then used as a feature for training a task-specific classifier.

Once the mapping parameterization is determined for the source, we must decide how to parametrize the target mapping M_t . In general, the target mapping almost always matches the source in terms of the specific functional layer (architecture), but different methods have proposed various regularization techniques. All methods initialize the target mapping parameters with the source, but different methods choose different constraints between the source and target mappings, $\psi(M_s, M_t)$. The goal is to make sure that the target mapping is set so as to minimize the distance between the source and target domains under their respective mappings, while crucially also maintaining a target mapping that is category discriminative.

Consider a layered representations where each layer parameters are denoted as, M_s^ℓ or M_t^ℓ , for a given set of equivalent layers, $\{\ell_1, \dots, \ell_n\}$. Then the space of constraints explored in the literature can be described through layerwise equality constraints as follows:

$$\psi(M_s, M_t) \triangleq \{\psi_{\ell_i}(M_s^{\ell_i}, M_t^{\ell_i})\}_{i \in \{1 \dots n\}} \quad (4)$$

where each individual layer can be constrained independently. A very common form of constraint is source and target layerwise equality:

$$\psi_{\ell_i}(M_s^{\ell_i}, M_t^{\ell_i}) = (M_s^{\ell_i} = M_t^{\ell_i}). \quad (5)$$

It is also common to leave layers unconstrained. These equality constraints can easily be imposed within a convolutional network framework through weight sharing.

For many prior adversarial adaptation methods [19, 12], all layers are constrained, thus enforcing exact source and target mapping consistency. Learning a symmetric transformation reduces the number of parameters in the model and ensures that the mapping used for the target is discriminative at least when applied to the source domain. However, this may make the optimization poorly conditioned, since the same network must handle images from two separate domains.

An alternative approach is instead to learn an asymmetric transformation with only a subset of the layers constrained, thus enforcing partial alignment. Rozantsev et al. [20] showed that partially shared weights can lead to effective adaptation in both supervised and unsupervised settings. As a result, some recent methods have favored untying weights (fully or partially) between the two domains, allowing models to learn parameters for each domain individually.

3.2. Adversarial losses

Once we have decided on a parametrization of M_t , we employ an adversarial loss to learn the actual mapping. There are various different possible choices of adversarial loss functions, each of which have their own unique use cases. All adversarial losses train the adversarial discriminator using a standard classification loss, $\mathcal{L}_{\text{adv}_D}$, previously stated in Equation 2. However, they differ in the loss used to train the mapping, $\mathcal{L}_{\text{adv}_M}$.

The gradient reversal layer of [19] optimizes the mapping to maximize the discriminator loss directly:

$$\mathcal{L}_{\text{adv}_M} = -\mathcal{L}_{\text{adv}_D}. \quad (6)$$

This optimization corresponds to the true minimax objective for generative adversarial networks. However, this objective can be problematic, since early on during training the discriminator converges quickly, causing the gradient to vanish.

When training GANs, rather than directly using the minimax loss, it is typical to train the generator with the standard loss function with inverted labels [10]. This splits the optimization into two independent objectives, one for the generator and one for the discriminator, where $\mathcal{L}_{\text{adv}_D}$ remains unchanged, but $\mathcal{L}_{\text{adv}_M}$ becomes:

$$\mathcal{L}_{\text{adv}_M}(\mathbf{X}_s, \mathbf{X}_t, D) = -\mathbb{E}_{\mathbf{x}_t \sim \mathbf{X}_t} [\log D(M_t(\mathbf{x}_t))]. \quad (7)$$

This objective has the same fixed-point properties as the minimax loss but provides stronger gradients to the target mapping. We refer to this modified loss function as the “GAN loss function” for the remainder of this paper.

Note that, in this setting, we use independent mappings for source and target and learn only M_t adversarially. This mimics the GAN setting, where the real image distribution remains fixed, and the generating distribution is learned to match it.

The GAN loss function is the standard choice in the setting where the generator is attempting to mimic another unchanging distribution. However, in the setting where both distributions are changing, this objective will lead to oscillation—when the mapping converges to its optimum, the discriminator can simply flip the sign of its prediction in response. Tzeng et al. instead proposed the domain confusion objective, under which the mapping is trained using a cross-entropy loss function against a uniform distribution [12]:

$$\begin{aligned} \mathcal{L}_{\text{adv}_M}(\mathbf{X}_s, \mathbf{X}_t, D) = & - \sum_{d \in \{s, t\}} \mathbb{E}_{\mathbf{x}_d \sim \mathbf{X}_d} \left[\frac{1}{2} \log D(M_d(\mathbf{x}_d)) \right. \\ & \left. + \frac{1}{2} \log(1 - D(M_d(\mathbf{x}_d))) \right]. \end{aligned} \quad (8)$$

This loss ensures that the adversarial discriminator views the two domains identically.

4. Adversarial discriminative domain adaptation

The benefit of our generalized framework for domain adversarial methods is that it directly enables the development of novel adaptive methods. In fact, designing a new method has now been simplified to the space of making three design

choices: whether to use a generative or discriminative base model, whether to tie or untie the weights, and which adversarial learning objective to use. In light of this view we can summarize our method, adversarial discriminative domain adaptation (ADDA), as well as its connection to prior work, according to our choices (see Table 1 “ADDA”). Specifically, we use a discriminative base model, unshared weights, and the standard GAN loss. We illustrate our overall sequential training procedure in Figure 3.

First, we choose a discriminative base model, as we hypothesize that much of the parameters required to generate convincing in-domain samples are irrelevant for discriminative adaptation tasks. Most prior adversarial adaptive methods optimize directly in a discriminative space for this reason. One counter-example is CoGANs. However, this method has only shown dominance in settings where the source and target domain are very similar such as MNIST and USPS, and in our experiments we have had difficulty getting it to converge for larger distribution shifts.

Next, we choose to allow independent source and target mappings by untying the weights. This is a more flexible learning paradigm as it allows more domain specific feature extraction to be learned. However, note that the target domain has no label access, and thus without weight sharing a target model may quickly learn a degenerate solution if we do not take care with proper initialization and training procedures. Therefore, we use the pre-trained source model as an initialization for the target representation space and fix the source model during adversarial training.

In doing so, we are effectively learning an asymmetric mapping, in which we modify the target model so as to match the source distribution. This is most similar to the original generative adversarial learning setting, where a generated space is updated until it is indistinguishable with a fixed real space. Therefore, we choose the inverted label GAN loss described in the previous section.

Our proposed method, ADDA, thus corresponds to the following unconstrained optimization:

$$\begin{aligned} \min_{M_s, C} \mathcal{L}_{\text{cls}}(\mathbf{X}_s, Y_s) = & - \mathbb{E}_{(\mathbf{x}_s, y_s) \sim (\mathbf{X}_s, Y_s)} \sum_{k=1}^K \mathbb{1}_{[k=y_s]} \log C(M_s(\mathbf{x}_s)) \\ \min_D \mathcal{L}_{\text{adv}_D}(\mathbf{X}_s, \mathbf{X}_t, M_s, M_t) = & - \mathbb{E}_{\mathbf{x}_s \sim \mathbf{X}_s} [\log D(M_s(\mathbf{x}_s))] \\ & - \mathbb{E}_{\mathbf{x}_t \sim \mathbf{X}_t} [\log(1 - D(M_t(\mathbf{x}_t)))] \\ \min_{M_t} \mathcal{L}_{\text{adv}_M}(\mathbf{X}_s, \mathbf{X}_t, D) = & - \mathbb{E}_{\mathbf{x}_t \sim \mathbf{X}_t} [\log D(M_t(\mathbf{x}_t))]. \end{aligned} \quad (9)$$

We choose to optimize this objective in stages. We begin

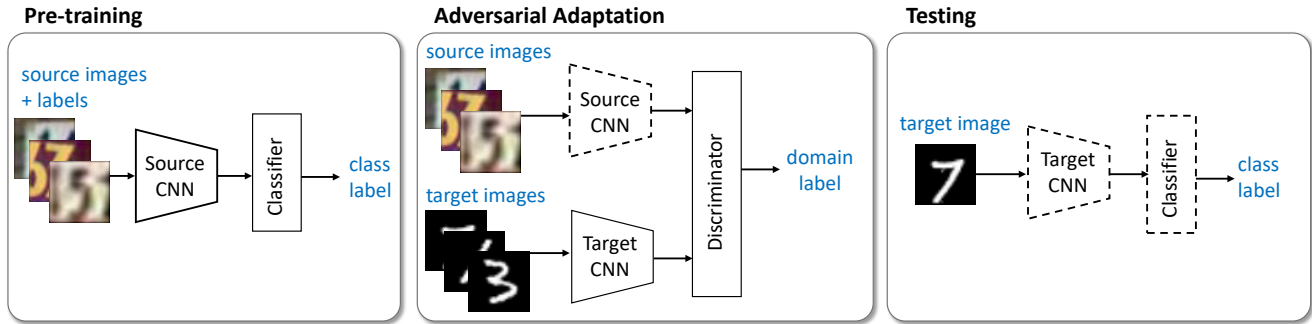


Figure 3: An overview of our proposed Adversarial Discriminative Domain Adaptation (ADDA) approach. We first pre-train a source encoder CNN using labeled source image examples. Next, we perform adversarial adaptation by learning a target encoder CNN such that a discriminator that sees encoded source and target examples cannot reliably predict their domain label. During testing, target images are mapped with the target encoder to the shared feature space and classified by the source classifier. Dashed lines indicate fixed network parameters.

by optimizing \mathcal{L}_{cls} over M_s and C by training using the labeled source data, \mathbf{X}_s and Y_s . Because we have opted to leave M_s fixed while learning M_t , we can thus optimize $\mathcal{L}_{\text{adv}_D}$ and $\mathcal{L}_{\text{adv}_M}$ without revisiting the first objective term. A summary of this entire training process is provided in Figure 3.

We note that the unified framework presented in the previous section has enabled us to compare prior domain adversarial methods and make informed decisions about the different factors of variation. Through this framework we are able to motivate a novel domain adaptation method, ADDA, and offer insight into our design decisions. In the next section we demonstrate promising results on unsupervised adaptation benchmark tasks, studying adaptation across visual domains and across modalities.

5. Experiments

We now evaluate ADDA for unsupervised classification adaptation across three different adaptation settings. We explore three digits datasets of varying difficulty: MNIST [21], USPS, and SVHN [22]. We additionally evaluate on the NYUD [23] dataset to study adaptation across modalities. Finally, we evaluate on the standard Office [24] dataset for comparison against previous work. Example images from all experimental datasets are provided in Figure 4.

For the case of digit adaptation, we compare against multiple state-of-the-art unsupervised adaptation methods, all based upon domain adversarial learning objectives. In 3 of 4 of our experimental setups, our method outperforms all competing approaches, and in the last domain shift studied, our approach outperforms all but one competing approach. We also validate our model on a real-world modality adaptation task using the NYU depth dataset. Despite a large domain shift between the RGB and depth modalities, ADDA

learns a useful depth representation without any labeled depth data and improves over the nonadaptive baseline by over 50% (relative). Finally, on the standard Office dataset, we demonstrate ADDA’s effectiveness by showing convincing improvements over competing approaches, especially on the hardest domain shift.

5.1. MNIST, USPS, and SVHN digits datasets

We experimentally validate our proposed method in an unsupervised adaptation task between the MNIST [21], USPS, and SVHN [22] digits datasets, which consist 10 classes of digits. Example images from each dataset are visualized in Figure 4 and Table 2. For adaptation between MNIST and USPS, we follow the training protocol established in [25], sampling 2000 images from MNIST and 1800 from USPS. For adaptation between SVHN and MNIST, we use the full training sets for comparison against [19]. All experiments are performed in the unsupervised settings, where labels in the target domain are withheld, and we consider adaptation in three directions: MNIST→USPS, USPS→MNIST, and SVHN→MNIST.

For these experiments, we use the simple modified LeNet architecture provided in the Caffe source code [21, 26]. When training with ADDA, our adversarial discriminator consists of 3 fully connected layers: two layers with 500 hidden units followed by the final discriminator output. Each of the 500-unit layers uses a ReLU activation function. Optimization proceeds using the Adam optimizer [27] for 10,000 iterations with a learning rate of 0.0002, a β_1 of 0.5, a β_2 of 0.999, and a batch size of 256 images (128 per domain). All training images are converted to greyscale, and rescaled to 28×28 pixels.

Results of our experiment are provided in Table 2. On the easier MNIST and USPS shifts ADDA achieves comparable performance to the current state-of-the-art, CoGANs [13],

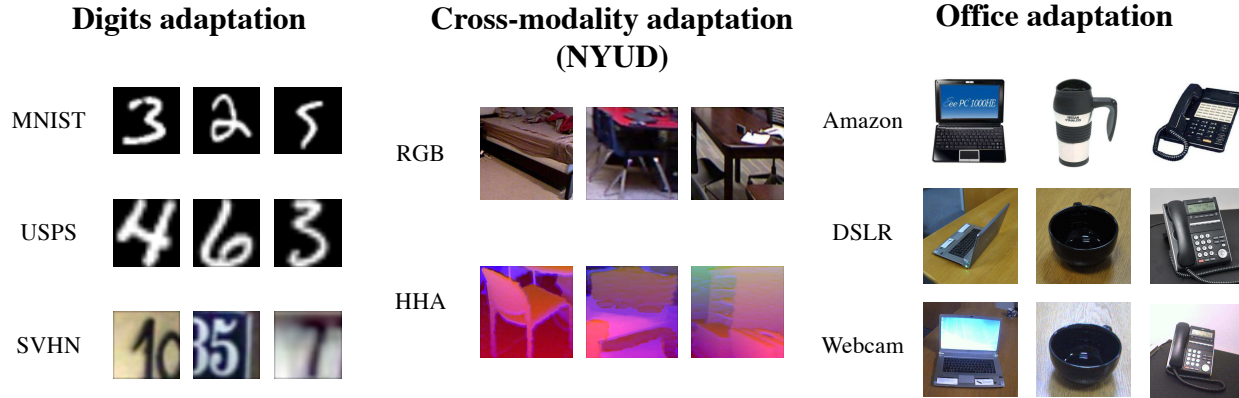


Figure 4: We evaluate ADDA on unsupervised adaptation across seven domain shifts in three different settings. The first setting is adaptation between the MNIST, USPS, and SVHN datasets (left). The second setting is a challenging cross-modality adaptation task between RGB and depth modalities from the NYU depth dataset (center). The third setting is adaptation on the standard Office adaptation dataset between the Amazon, DSLR, and Webcam domains (right).







Method	MNIST \rightarrow USPS	USPS \rightarrow MNIST	SVHN \rightarrow MNIST
	 \rightarrow 	 \rightarrow 	 \rightarrow 
Source only	0.752 ± 0.016	0.571 ± 0.017	0.601 ± 0.011
Gradient reversal	0.771 ± 0.018	0.730 ± 0.020	0.739 [19]
Domain confusion	0.791 ± 0.005	0.665 ± 0.033	0.681 ± 0.003
CoGAN	0.912 ± 0.008	0.891 ± 0.008	did not converge
ADDA (Ours)	0.894 ± 0.002	0.901 ± 0.008	0.760 ± 0.018

Table 2: Experimental results on unsupervised adaptation among MNIST, USPS, and SVHN.

despite being a considerably simpler model. This provides compelling evidence that the machinery required to generate images is largely irrelevant to enabling effective adaptation. Additionally, we show convincing results on the challenging SVHN and MNIST task in comparison to other methods, indicating that our method has the potential to generalize to a variety of settings. In contrast, we were unable to get CoGANs to converge on SVHN and MNIST—because the domains are so disparate, we were unable to train coupled generators for them.

5.2. Modality adaptation

We use the NYU depth dataset [23], which contains bounding box annotations for 19 object classes in 1449 images from indoor scenes. The dataset is split into a train (381 images), val (414 images) and test (654) sets. To perform our cross-modality adaptation, we first crop out tight bounding boxes around instances of these 19 classes present in the dataset and evaluate on a 19-way classification task over object crops. In order to ensure that the same instance is not seen in both domains, we use the RGB images from the train split as the source domain and the depth images from the val split as the target domain. This corresponds to 2,186 labeled

source images and 2,401 unlabeled target images. Figure 4 visualizes samples from each of the two domains.

We consider the task of adaptation between these RGB and HHA encoded depth images [28], using them as source and target domains respectively. Because the bounding boxes are tight and relatively low resolution, accurate classification is quite difficult, even when evaluating in-domain. In addition, the dataset has very few examples for certain classes, such as `toilet` and `bathtub`, which directly translates to reduced classification performance.

For this experiment, our base architecture is the VGG-16 architecture, initializing from weights pretrained on ImageNet [29]. This network is then fully fine-tuned on the source domain for 20,000 iterations using a batch size of 128. When training with ADDA, the adversarial discriminator consists of three additional fully connected layers: 1024 hidden units, 2048 hidden units, then the adversarial discriminator output. With the exception of the output, these layers use a ReLU activation function. ADDA training then proceeds for another 20,000 iterations, using the same hyperparameters as in the digits experiments.

We find that our method, ADDA, greatly improves classification accuracy for this task. For certain categories, like

	bathub	bed	bookshelf	box	chair	counter	desk	door	dresser	garbage bin	lamp	monitor	night stand	pillow	sink	sofa	table	television	toilet	overall
# of instances	19	96	87	210	611	103	122	129	25	55	144	37	51	276	47	129	210	33	17	2401
Source only	0.000	0.010	0.011	0.124	0.188	0.029	0.041	0.047	0.000	0.000	0.069	0.000	0.039	0.587	0.000	0.008	0.010	0.000	0.000	0.139
ADDA (Ours)	0.000	0.146	0.046	0.229	0.344	0.447	0.025	0.023	0.000	0.018	0.292	0.081	0.020	0.297	0.021	0.116	0.143	0.091	0.000	0.211
Train on target	0.105	0.531	0.494	0.295	0.619	0.573	0.057	0.636	0.120	0.291	0.576	0.189	0.235	0.630	0.362	0.248	0.357	0.303	0.647	0.468

Table 3: Adaptation results on the NYUD [23] dataset, using RGB images from the train set as source and depth images from the val set as target domains. We report here per class accuracy due to the large class imbalance in our target set (indicated in # instances). Overall our method improves average per category accuracy from 13.9% to 21.1%.

Method	$A \rightarrow W$	$D \rightarrow W$	$W \rightarrow D$
Source only (AlexNet)	0.642	0.961	0.978
Source only (ResNet-50)	0.626	0.961	0.986
DDC [5]	0.618	0.950	0.985
DAN [6]	0.685	0.960	0.990
DRCN [9]	0.687	0.964	0.990
DANN [19]	0.730	0.964	0.992
ADDA (Ours)	0.751	0.970	0.996

Table 4: Unsupervised adaptation performance on the Office dataset in the fully-transductive setting. ADDA achieves strong results on all three evaluated domain shifts and demonstrates the largest improvement on the hardest shift, $A \rightarrow W$.

counter, classification accuracy goes from 2.9% under the source only baseline up to 44.7% after adaptation. In general, average accuracy across all classes improves significantly from 13.9% to 21.1%. However, not all classes improve. Three classes have no correctly labeled target images before adaptation, and adaptation is unable to recover performance on these classes. Additionally, the classes of pillow and nightstand suffer performance loss after adaptation.

5.3. Office dataset

Finally, we evaluate our method on the benchmark Office visual domain adaptation dataset [24]. This dataset consists of 4,110 images spread across 31 classes in 3 domains: *amazon*, *webcam*, and *dslr*. Following previous work [19], we focus our evaluation on three domain shifts: *amazon* to *webcam* ($A \rightarrow W$), *dslr* to *webcam* ($D \rightarrow W$), and *webcam* to *dslr* ($W \rightarrow D$). We evaluate ADDA fully transductively, where we train on every labeled example in the source domain and every unlabeled example in the target.

Because the Office dataset is relatively small, fine-tuning a full network quickly leads to overfitting. As a result, we use ResNet-50 [30] as our base model due to its relatively low number of parameters and fine-tune only the lower layers of the target model, up to but not including conv5. Optimization

is done using SGD for 20,000 iterations with a learning rate of 0.001, a momentum of 0.9, and a batch size of 64. The adversarial discriminator consists of three fully connected layers of dimensions 1024, 2048, and 3072, each followed by ReLUs, and one fully connected layer for the final output. We present the results of this experiment in Table 4.

We see that ADDA is competitive on this adaptation task as well, achieving state-of-the-art on all three of the evaluated domain shifts. Although the base architecture ADDA uses is different from previous work, which typically fine-tunes using AlexNet as a base, by comparing the source-only baselines we see that the ResNet-50 architecture does not perform significantly better. Additionally, we see the largest increase on the hardest shift $A \rightarrow W$ despite ResNet-50's poor performance on that shift, indicating that ADDA is effective even on challenging real-world adaptation tasks.

6. Conclusion

We have proposed a unified framework for unsupervised domain adaptation techniques based on adversarial learning objectives. Our framework provides a simplified and cohesive view by which we may understand the similarities and differences between recently proposed adaptation methods. Through this comparison, we are able to understand the benefits and key ideas from each approach and to combine these strategies into a new adaptation method, ADDA.

We presented an evaluation across four domain shifts for our unsupervised adaptation approach. Our method generalizes well across a variety of tasks, achieving strong results on benchmark adaptation datasets as well as a challenging cross-modality adaptation task.

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