Augmented Cyclic Adversarial Learning for Domain Adaptation

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Abstract

Training a model to perform a task typically requires a large amount of data from the domains in which the task will be applied. However, it is often the case that data are abundant in some domains but scarce in others. Domain adaptation deals with the challenge of adapting a model trained from a data-rich source domain to perform well in a data-poor target domain. In general, this requires learning plausible mappings between domains. CycleGAN is a powerful framework that efficiently learns to map inputs from one domain to another using adversarial training and a cycle-consistency constraint. However, the conventional approach of enforcing cycle-consistency via reconstruction may be overly restrictive in cases where one or more domains have limited training data. In this paper, we propose an augmented cyclic adversarial learning model that enforces the cycle-consistency constraint through an external task specific model, which encourages the preservation of task-relevant content as opposed to exact reconstruction. We explore digit classification with MNIST and SVHN in a low-resource setting in supervised, semi and unsupervised situation. In low-resource supervised setting, the results show that our approach improves absolute performance by 14% and 4% when adapting SVHN to MNIST and vice versa, respectively, which outperforms unsupervised domain adaptation methods that require high-resource unlabeled target domain. Moreover, using only few unsupervised target data, our approach can still outperforms many high-resource unsupervised models. In speech domains, we also adopt a speech recognition model from each domain as the task specific model. Our approach improves absolute performance of speech recognition by 2% for female speakers in the TIMIT dataset, where the majority of training samples are from male voices.

1 Introduction

Domain adaptation (Huang et al., 2007; Xue et al., 2008; Ben-David et al., 2010) aims to generalize a model from source domain to a target domain. Typically, the source domain has a large amount of training data, whereas the data are scarce in the target domain. This challenge is typically addressed by learning a mapping between domains, which allow data from the source domain to enrich the available data for training in the target domain. One way of learning such mappings is through Generative Adversarial Networks (GANs Goodfellow et al., 2014) with cycle-consistency constraint (CycleGAN Zhu et al., 2017), which enforces that mapping of an example from the source to the target and then back to the source domain would result in the same example (and vice versa for a target example). Due to this constraint, CycleGAN learns to preserve the “content” from the source domain while only

1Here the content refers to the invariant properties of the data with respect to a task. For example, in image classification the semantic information of an image would be its class. Thus, different task on the same data would result in different semantic information. In this paper we use content and semantic information interchangeably.

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transferring the ‘style’ to match the distribution of the target domain. This is a powerful constraint, and various works (Yi et al., 2017; Liu et al., 2017; Hoffman et al., 2018) have demonstrated its effectiveness in learning cross domain mappings.

Enforcing cycle-consistency is appealing as a technique for preserving semantic information of the data with respect to a task, but implementing it through reconstruction may be too restrictive when data are imbalanced across domains. This is because the reconstruction error encourages exact match of samples from the reverse mapping, which may in turn encourage the forward-mapping to keep the sample close to the original domain. Normally, the adversarial objectives would counter this effect; however, when data from the target domain are scarce, it is very difficult to learn a powerful discriminator that can capture meaningful properties of the target distribution. Therefore, the resulting mappings learned is likely to be sub-optimal. Importantly, for the learned mapping to be meaningful, it is not necessary to have the exact reconstruction. As long as the ‘semantic’ information is preserved and the ‘style’ matches the corresponding distribution, it would be a valid mapping.

To address this issue, we propose an augmented cyclic adversarial learning model for domain adaptation. In particular, we replace the reconstruction objective with a task specific model. The model learns to preserve the ‘semantic’ information from the data samples in a particular domain by minimizing the loss of the mapped samples for the task specific model. On the other hand, the task specific model also serves as an additional source of information for the corresponding domain and hence supplements the discriminator in that domain to facilitate better modeling of the distribution. The task specific model can also be viewed as an implicit way of disentangling the information essential to the task from the ‘style’ information that relates to the data distribution of different domain. We show that our approach improves the performance by 40% as compared to the baseline on digit domain adaptation. We improve the phoneme error rate by ~ 5% on TIMIT dataset, when adapting the model trained on one speech from one gender to the other.

1.1 Related Work

Our work is broadly related to domain adaptation using neural networks. When labels are available in the target domain, a common approach is to utilize the label information in target domain to minimize the discrepancy between source and target domain (Hu et al., 2015; Tzeng et al., 2015; Gebru et al., 2017; Hoffman et al., 2016; Gupta et al., 2016; Ge and Yu, 2017). For example, Hu et al. (2015) applies the marginal Fisher analysis criteria and Maximum Mean Discrepancy (MMD) to minimize the distribution difference between source and target domain. Tzeng et al. (2015) proposed to add a domain classifier that predicts domain label of the inputs, with a domain confusion loss. Gebru et al. (2017) leverages attributes by using attribute and class level classification loss with attribute consistent loss to fine-tune the target model. Our method also employs models from both domains, however, our models are used to assist adversarial learning for better learning of the target domain distribution. In addition, our final model is obtained by training on data from target domain as well as the transferred data from the source domain, rather than fine-tuning a source/target domain model.

More recently, various work have taken advantage of the substantial generation capabilities of the GAN framework and applied them to domain adaptation (Liu and Tuzel, 2016; Bousmalis et al., 2017; Yi et al., 2017; Tzeng et al., 2017; Kim et al., 2017; Hoffman et al., 2018). However, most of these works focus on unsupervised domain adaptation, which may be unsuitable for situations where the target domain data are limited. Bousmalis et al. (2017) use a GAN to adapt data from the source to target domain while simultaneously training a classifier on both the source and adapted data. Our method also employs task specific models; however, we use the models to augment the CycleGAN formulation. We show that having cycles in both directions (i.e. from source to target and vice versa) is important in the case where the target domain has limited data (see sec. 4). Tzeng et al. (2017) propose adversarial discriminative domain adaptation (ADDA), where adversarial learning is employed to match the representation learned from the source and target domain. Our method also utilizes pre-trained models from each domain, but we only implicitly match the representation distributions rather than explicitly enforcing representational similarity. Cycle-consistent adversarial domain adaptation (CyCADA Hoffman et al., 2018) is perhaps the most similar work to our own. This approach uses both $\ell_1$ and semantic consistency to enforce cycle-consistency. An important difference in our work is that we also include another cycle that starts from the target domain. This is important because, if the target domain is of low resource, the adaptation from source to target may fail due to the difficulty in learning a good discriminator in the target domain.
Our model is closely related to CycleGAN (Zhu et al., 2017), where the model learns to map between domains through adversarial learning and cycle-consistent constraint. Using classification to assist GAN training has also been explored previously (Springenberg, 2015; Sricharan et al., 2017; Kumar et al., 2017). Springenberg (2015) proposed CatGAN, where the discriminator is converted to a multi-class classifier. We extend this idea to any task specific model, and use this model to preserve task specific information regarding the data.

2 Preliminaries

2.1 Generative Adversarial Network

To learn the true data distribution \( P_{data}(X) \) in a nonparametric way, Goodfellow et al. (2014) proposed the generative adversarial network (GAN). In this framework, a discriminator network \( D(x) \) learns to discriminate between the data produced by a generator network \( G(z) \) and the data sampled from the true data distribution \( P_{data}(X) \), whereas the generator models the true data distribution by learning to confuse the discriminator. Under certain assumptions (Goodfellow et al., 2014), the generator would learn the true data distribution when the game reaches equilibrium. Training of GAN is in general done by alternately optimizing the following objective for \( D \) and \( G \).

\[
\min_G \max_D V(G, D) = \mathbb{E}_{x \sim P_{data}(X)}[\log D(x)] + \mathbb{E}_{z \sim P_z(Z)}[\log (1 - D(G(z)))]
\] (1)

2.2 CycleGAN

CycleGAN (Zhu et al., 2017) extends this framework to multiple domains, \( P_S(X) \) and \( P_T(X) \), while learning to map samples back and forth between them. Adversarial learning is applied such that the result mapping from \( G_{S \rightarrow T} \) will match the target distribution \( P_T(X) \), and similarly for the reverse mapping from \( G_{T \rightarrow S} \). This is accomplished by the following adversarial objectives:

\[
\mathcal{L}_{adv}(G_{S \rightarrow T}, D_T) = \mathbb{E}_{x \sim P_T(X)}[\log D_T(x)] + \mathbb{E}_{x \sim P_S(X)}[\log (1 - D_T(G_{S \rightarrow T}(x)))]
\] (2)

\[
\mathcal{L}_{adv}(G_{T \rightarrow S}, D_S) = \mathbb{E}_{x \sim P_S(X)}[\log D_S(x)] + \mathbb{E}_{x \sim P_T(X)}[\log (1 - D_S(G_{T \rightarrow S}(x)))]
\] (3)
CycleGAN also introduces cycle-consistency, which enforces that each mapping is able to invert the other. In the original work, this is achieved by including the following reconstruction objective:

\[
\mathcal{L}_{cyc}(G_{S\rightarrow T}, G_{T\rightarrow S}) = \mathbb{E}_{x \sim P_S(X)} \left[ \| G_{T\rightarrow S}(G_{S\rightarrow T}(x)) - x \|_1 \right] + \mathbb{E}_{x \sim P_T(X)} \left[ \| G_{S\rightarrow T}(G_{T\rightarrow S}(x)) - x \|_1 \right]
\]

(4)

Learning the CycleGAN model involves optimizing a weighted combination of the above objectives 2, 3 and 4.

3 Augmented Cyclic Adversarial Learning

Enforcing cycle-consistency using a reconstruction objective (e.g. eq. 4) may be too restrictive and potentially results in sub-optimal mapping functions. This is because the learning dynamics of CycleGAN balance two contrastive forces. The adversarial objective encourages the mapping functions to generate samples that are close to the true distribution. At the same time, the reconstruction objective encourages identity mapping. Balancing these objectives may work well in the case where both domains have a relatively large number of training samples. However, problems may arise in case of domain adaptation, where data within the target domain are relatively sparse.

Let \( P_S(X) \) and \( P_T(X) \) denote source and target domain distribution, respectively, and samples from \( P_T(X) \) are limited. In this case, it will be difficult for the discriminator \( D_T \) to model the actual distribution \( P_T(X) \). A discriminator model with sufficient capacity will quickly overfit and the resulting \( D_T \) will act like delta function on the sample points from \( P_T(X) \). Attempts to prevent this by limiting the capacity or using regularization may easily induce over-smoothing and underfitting such that the probability outputs of \( D_T \) are only weakly sensitive to the mapped samples. In both cases, the influence of the reconstruction objective should begin to outweigh that of the adversarial objective, thereby encouraging an identity mapping. More generally, even if we are are able to obtain a reasonable discriminator \( D_T \), the support of the distribution learned through it would likely to be small due to limited data. Therefore, the learning signal \( G_{S\rightarrow T} \) gets from \( D_T \) would be limited. To sum up, limited data within \( P_T(X) \) would make it less likely that the discriminator will encourage meaningful cross domain mappings.

The root of the above issue in domain adaptation is two fold. First, exact reconstruction is a too strong objective for enforcing cycle-consistency. Second, learning a mapping function to a particular domain which solely depends on the discriminator for that domain is not sufficient. To address these two problems, we propose to 1) use a task specific model to enforce the cycle-consistency constraint, and 2) use the same task specific model in addition to the discriminator to train more meaningful cross domain mappings. In more detail, let \( M_S \) and \( M_T \) be the task specific models trained on domains \( P_S(X, Y) \) and \( P_T(X, Y) \), and \( \mathcal{L}_{task} \) denotes the task specific loss. Our cycle-consistent objective is then:

\[
\mathcal{L}_{relax-cyc}(G_{S\rightarrow T}, G_{T\rightarrow S}, M_S, M_T) = \mathbb{E}_{(x, y) \sim P_{S}(X, Y)} \left[ \mathcal{L}_{task}(M_S(G_{T\rightarrow S}(G_{S\rightarrow T}(x)), y)) \right]
\]

\[
+ \mathbb{E}_{(x, y) \sim P_{T}(X, Y)} \left[ \mathcal{L}_{task}(M_T(G_{S\rightarrow T}(G_{T\rightarrow S}(x)), y)) \right]
\]

(5)

Here, \( \mathcal{L}_{task} \) enforces cycle-consistency by requiring that the reverse mappings preserve the semantic information of the original sample. Importantly, this constraint is less strict than when using reconstruction, because now as long as the content matches that of the original sample, the incurred loss will not increase. (Some style consistency is implicitly enforced since each model \( M \) is trained on data within a particular domain.) This is a much looser constraint than having consistency in the original data space, and thus we refer to this as the relaxed cycle-consistency objective.

To address the second issue, we augment the adversarial objective with corresponding objective:

\[
\mathcal{L}_{aug}(G_{T\rightarrow S}, D_S, M_S) = \mathbb{E}_{x \sim P_S(X)} \left[ \log(D_S(x)) \right]
\]

\[
+ \mathbb{E}_{x \sim P_T(X)} \left[ \log(1 - D_S(G_{T\rightarrow S}(x))) \right]
\]

\[
+ \mathbb{E}_{(x, y) \sim P_S(x, y)} \left[ \mathcal{L}_{task}(M_S(x, y)) \right]
\]

\[
+ \mathbb{E}_{(x, y) \sim P_T(x, y)} \left[ \mathcal{L}_{task}(M_S(G_{T\rightarrow S}(x), y)) \right]
\]

(6)

\[
\mathcal{L}_{aug}(G_{S\rightarrow T}, D_T, M_T) = \mathbb{E}_{x \sim P_T(X)} \left[ \log(D_T(x)) \right]
\]

\[
+ \mathbb{E}_{x \sim P_S(X)} \left[ \log(1 - D_T(G_{S\rightarrow T}(x))) \right]
\]

\[
+ \mathbb{E}_{(x, y) \sim P_T(x, y)} \left[ \mathcal{L}_{task}(M_T(x, y)) \right]
\]

\[
+ \mathbb{E}_{(x, y) \sim P_S(x, y)} \left[ \mathcal{L}_{task}(M_T(G_{S\rightarrow T}(x), y)) \right]
\]

(7)
Similar to adversarial training, we optimize the above objective by maximizing $D_S (D_T)$ and minimizing $G_{T\rightarrow S} (G_{S\rightarrow T})$ and $M_S (M_T)$. With the new terms, the learning of mapping functions $G$ get assists from both the discriminator and the task specific model. The task specific model learns to capture conditional probability distribution $P_S (Y|X)$ ($P_T (Y|X)$), that also preserves information regarding $P_S (X)$ ($P_T (X)$). This conditional information is different than the information captured through the discriminator $D_S (D_T)$. The difference is that the model is only required to preserve useful information regarding $X$ respect to predicting $Y$, for modeling the conditional distribution, which makes learning the conditional model a much easier problem. In addition, the conditional model mediates the influence of data that the discriminator does not have access to ($Y$), which should further assist learning of the mapping functions $G_{T\rightarrow S} (G_{S\rightarrow T})$.

### 3.1 Application to Domain Adaptation

In this paper, we adopt our approach to effectively augment the limited data in the target domain with adapted data from the source domain. Ultimately, we aim to improve the performance of the task specific model in the target domain $M_T$. To apply the approaches describe above, we follow two steps. First, with the available data from source domain, we pre-train the source domain task specific models $M_S$. Second, we train a model to map examples between domains, making use of $M_S$ and $M_T$ where appropriate, while training $M_S$ and $M_T$ jointly, using target labeled data and mapped training source examples: $T' \leftarrow \{(G_{S\rightarrow T}(x), y) | x, y \in P_S (X, Y)\}$. In effect, domain adaptation describes the improvement in the performance of $M_T$ gained in the final step.

### 4 Experiments

In this section, we evaluate our proposed model on domain adaptation for visual and speech recognition. We continue the convention of referring to the data domains as ‘source’ and ‘target’, where target denotes the domain with limited training data. Visual domain adaptation is evaluated using the MNIST Lecun et al. (1998) and Street View House Numbers (SVHN) datasets Netzer et al. (2011). Adaptation on speech is evaluated on the domain of gender within the TIMIT dataset Garofolo et al. (1993), which contains broadband 16kHz recordings of 6300 utterances (5.4 hours) of phonetically-balanced speech. The male/female ratio of speakers across train/validation/test sets is approximately 70% to 30%. Therefore, we treat male speech as the source domain and female speech as the target domain.

#### 4.1 Model Ablations

To get an idea of the contribution from each component of our model, in this section we perform a series of ablations and present the results in Table 1. We perform these ablations by treating SVHN as the source domain and MNIST as the target domain. We down sample the MNIST training data so only 10 samples per class are available during training, which is only 0.17% of full training data. The testing performance is calculated on the full MNIST test set. We use a modified LeNet for all experiments in this ablation. The Modified LeNet consists of two convolutional layers with 20 and 50 channels, followed by a dropout layer and two fully connected layers of 50 and 10 dimensionality.

There are various ways that one may utilize cycle-consistency or adversarial training to do domain adaptation from components of our model. One way is to use adversarial training on the target domain to ensure matching of distribution of adapted data, and use the task specific model to ensure the ‘content’ of the data from the source domain is preserved. This is the model described in Bousmalis et al. (2017), except their model is originally unsupervised. This model is denoted as $S \rightarrow T$ in Table 1. It is also interesting to examine the importance of the double cycle, which is proposed in Zhu et al. (2017) and adopted in our work. Theoretically, one cycle would be sufficient to learn the mapping between domains; therefore, we also investigate performance of one cycle only models, where one direction would be from source to target and then back, and similarly for the other direction. These models are denoted as $(S \rightarrow T \rightarrow S)$-One Cycle and $(T \rightarrow S \rightarrow T)$-One Cycle in Table 1, respectively. To test the effectiveness of the relaxed cycle-consistency (eq. 5) and augmented adversarial loss (eq. 6 and 7), we also test one cycle models while progressively adding these two losses. Interestingly, the one cycle relaxed and one cycle augmented models are similar to the model proposed in Hoffman et al. (2018) when their model performs mapping from source to target domain and then back. The difference is that their model is unsupervised and includes more losses at different levels.
As can be seen from Table 1, the simple conditional model performed surprisingly well as compared to more complicated cyclic counterparts. This may be attributed to reduced complexity, since it only needs to learn one set of mapping. As expected, the single cycle performance is poor when the target domain is of limited data due to inefficient learning of discriminator in the target domain (see section 3). When we change the cycle to the other direction, where there are abundant data in the target domain, the performance improves, but is still worse than the simple one without cycle. This is because the adaption mapping (i.e. \( G_{S \rightarrow T} \)) is learned only through the generated samples from \( G_{T \rightarrow S} \), which likely deviate from the real examples in practice. This observation also suggests that it would be beneficial to have cycles in both directions when applying the cycle-consistency constraint, since then both mappings can be learned through real examples. The trends get reversed when we are using relaxed implementation of cycle-consistency from the reconstruction error with the task specific losses. This is because now the power of the task specific model is crucial to preserve the content of the data after the reverse mapping. When the source domain dataset is sufficiently large, the cycle-consistency gets preserved. As such, the resulting learned mapping functions would preserve meaningful semantics of the data while transferring the styles to the target domain, and vice versa. In addition, it is clear that augmenting the discriminator with task specific loss is helpful for learning adaptations. Furthermore, the information added from the task specific model is clearly beneficial for improving the adaptation performance, without this none of the models outperforms the baseline model, where no adaptation is performed. Last but not least, it is also clear from the results that using task specific model improves the overall adaptation performance.

Table 1: Ablation study results from SVHN (Source) to MNIST (Target). See text for more details. Note: The MNIST domain is limited to only 10 images per class (0.17% of full training dataset). Experiments were performed 4 times with different random sampling for MNIST.

| Domain Adaptation Model               | Test Accuracy (%) |
|---------------------------------------|-------------------|
| No Adaptation (trained on SVHN)       | 71.11             |
| Target Model (trained on MNIST)       | 79.22±3.98        |
| SVHN+MNIST-(100)                      | 85.62±1.15        |
| \(S \rightarrow T\)                   | 69.91±1.56        |
| \((S \rightarrow T) \rightarrow S\)-One Cycle | 46.32±2.09        |
| \(T \rightarrow S \rightarrow T\)-One Cycle | 58.34±2.49        |
| \((S \rightarrow T) \rightarrow S\)-Relaxed-Cyc (Ours) | \textbf{72.51±1.71} |
| \(T \rightarrow S \rightarrow T\)-Relaxed-Cyc (Ours) | 43.56±2.92        |
| \((S \rightarrow T) \rightarrow S\)-Augmented-Cyc (Ours) | \textbf{79.40±0.73} |
| \(T \rightarrow S \rightarrow T\)-Augmented-Cyc (Ours) | 49.81±0.53        |
| CycleGAN                              | 45.54±1.05        |
| Relaxed-Cyc (Ours)                    | 88.62±1.77        |
| Augmented-Cyc (Ours)                  | \textbf{93.90±0.33} |

4.2 Visual Domain Adaptation

In this section, we experiment on domain adaptation in the task of digit recognition. In each experiment, we select one domain (MNIST or SVHN) to be the target and sub-sample to a few examples per class, using the full other dataset as the source domain. We also experiment with two different task specific models \( M \): specifically, DenseNet (Huang et al., 2017, representing a relatively simple architecture) and a modified LeNet (representing a relatively simple architecture, see section 4.1). To compare the results, we perform the same experiments using CycleGAN as well as the relaxed version of the cycle-consistent objective (Relaxed-Cyc, see eq. 5 in section 3). For the former, \( \ell_1 \) reconstruction loss is replaced with the model loss in order to encouraging cycle-consistency.

Table 2 and 3 show the results on augmenting the low resource MNIST and SVHN with the complementary high resource domain. This approach improves test performance of the target classifier by a large margin, compared to when trained only using the target domain data. We observe that training a more complicated deep model for the target domain weakens this effect. As
shown in Table 2, using DenseNet as a classifier on MNIST (target) achieves $\approx 24\%$ lower test classification accuracy than using a variant of LeNet. This difference likely reflects differences in the two architectures’ degree of overfitting. Overfitting will produce a false gradient signal during cycle adversarial learning (when classifying the adapted source examples). Based on this observation, we use the comparatively simpler LeNet architecture with SVHN as the target domain (see Table 3). Using our proposed approach, SVHN test performance improves by $27\%$ over domain adaptation using CycleGAN. We also include some qualitative results when performing domain adaptation from SVHN (source) to MNIST (target), as shown in Figure 2.

To further evaluate the performance of our approach with unsupervised domain adaptation models, where a large unlabeled target domain is required, Table 4 indicates the performance comparison. We evaluate our approach on SVHN→MNIST and MNIST→SVHN adaptation with different sizes of labeled target domain. It is shown that Augmented cyclic learning adaptation outperforms the state of the art unsupervised approaches using only less than $1\%$ of labeled training samples of target domain. It is worth mentioning that Shu et al. (2018) improved their VADA adversarial model using natural gradient as teacher-student training, which is not directly comparable to adversarial approaches. Moreover, the source-only baseline of (Shu et al., 2018) is stronger than reported unsupervised approaches, as well as our baseline. Moreover, Figure 3 depicts the improvement on generalization performance of target model using Augmented cyclic adaptation, with variable labeled target domain on MNIST and SVHN datasets.

**Extension to Semi and Unsupervised learning** Our proposed domain adaptation is not only constrained to supervised domain adaptation. By using source classifier as pseudo-labeler of target data, our method can be easily extended to unsupervised setting. The unsupervised results are presented in the first column of Table 5, when using only 500 unlabeled samples our method already outperforms several unsupervised methods that utilizes the full dataset as shown in Table 4. We also evaluated our method in semi-supervised scenario and the results are in Table 5.

### 4.3 Speech Domain Adaptation

We also apply our proposed model to domain adaptation in speech recognition. We use the TIMIT dataset, where the male to female speaker ratio is about $7:3$ and thus we choose the data subset from male speakers as the source and the subset from female speakers as the target domain. We evaluate test performance on the standard TIMIT test set and use phoneme error rate (PER) as the evaluation metric. Spectrogram representation of audio is chosen for model evaluation. As demonstrated by Hosseini-Asl et al. (2018), multi-discriminator training significantly impacts adaptation performance. Therefore, we used the multi-discriminator architecture as the discriminator for the adversarial loss.

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Figure 2: Qualitative comparison of domain adaptation for experimental models. Each column illustrates the mapping performed by each of the models from the original SVHN image (source domain) to MNIST (target domain, 100 samples in total). It can be seen that the augmented cycle-consistent model is able to preserve most of the semantic information, while still approximately match the target distribution.
Table 2: Visual domain adaptation results from SVHN to MNIST (Low resource). No adaptation denotes model trained on the source domain (SVHN) and target model refers to model trained on the target domain (MNIST). Note: MNIST (Low resource) domain contains only 10 images per class (100 examples in total), the experiments was performed 4 times with different random sampling for MNIST.

| Domain Adaptation Model | MNIST Test (%) | DenseNet |
|-------------------------|----------------|----------|
| No Adaptation           | 71.11          | 56.92    |
| Target Model            | 79.22±3.98     | 39.89±0.84|
| CycleGAN                | 45.54±1.05     | 28.52±1.65|
| Relaxed-Cyc (Ours)      | 84.62±1.77     | 44.36±3.42|
| Augmented-Cyc (Ours)    | **93.90±0.33** | **69.47±4.66** |

Figure 3: Performance comparison of proposed Augmented cyclic adversarial learning using different numbers of labeled training sample in target domain. (Best viewed in color)

Table 3: Visual domain adaptation results from MNIST to SVHN (Low resource). No adaptation denotes model trained on the source domain (MNIST) and target model refers to model trained on the target domain (SVHN). Note: SVHN (Low resource) domain contains only 50 images per class (500 examples in total), the experiments was performed 4 times with different random sampling for SVHN.

| Domain Adaptation Model | SVHN Test (%) | LeNet (modified) |
|-------------------------|--------------|------------------|
| No Adaptation           | 38.03        |                  |
| Target Model (0.68%)    | 70.20±2.35   |                  |
| CycleGAN                | 66.75±2.02   |                  |
| Relaxed-Cyc (Ours)      | 72.13±0.91   |                  |
| Augmented-Cyc (Ours)    | **74.61±0.43** |                |

in our evaluation. Our task specific model is the pretrained speech recognition model within each domain in this set of experiments.

The result are shown in Table 6. We observe significant performance improvements over the baseline model as well as comparable or better performance as compared to previous methods. It is interesting to note that the performance of the proposed model on the adapted male almost matches the baseline model performance, where the model is trained on true female speech. In addition, the performance gap in this case is significant as compared to other methods, which suggests the adapted distribution is indeed close to the true target distribution. In addition, when combined with more data, our model further out performs the baseline by a noticeable margin.
Table 4: Visual domain adaptation results for *unsupervised high-resource* and *supervised low-resource* target domains. *Note:* Augmented-Cyc(n) indicate using n labeled samples of target domain are used for training domain adaptation model. No augmentation is used in training Augmented-Cyc model. VADA (Shu et al., 2018) used a stronger *source-only* baseline on SVHN→MNIST (82.4 accuracy) compared to other approaches.

| Model                      | SVHN→MNIST | MNIST→SVHN |
|----------------------------|-------------|-------------|
| Source Only                | 71.11       | 38.03       |

*unsupervised high-resource*

| Model                      | SVHN→MNIST | MNIST→SVHN |
|----------------------------|-------------|-------------|
| DANN (Ganin et al., 2016)  | 73.6        | 35.7        |
| SBADA-GAN (Russo et al., 2018) | 76.1    | 61.1        |
| ADDA (Tzeng et al., 2017)  | 76.0±1.8    | -           |
| TRUDA (Sener et al., 2016) | 78.8        | 40.3        |
| DRCN (Ghifary et al., 2016) | 82.0±0.2    | 40.1±0.1    |
| DTN (Taigman et al., 2017) | 84.4        | -           |
| ATT (Saito et al., 2017)   | 86.2        | 52.8        |
| DIFA (Volpi et al., 2018)  | 89.7±2.0    | -           |
| CyCADA (Hoffman et al., 2018) | 90.4±0.4  | -           |
| I2I Adapt - DenseNet (Murez et al., 2018) | 92.2    | -           |
| Gen-to-Adapt (Sankaranarayanan et al., 2018) | 92.4±0.9  | -           |
| DupGAN (Hu et al., 2018)   | 92.46       | 62.65       |
| Self-ensembling (MT+CT) (French et al., 2018) | 93.3±5.88  | 42.0±5.7    |
| ADR (Saito et al., 2018)   | 95.0±1.87   | -           |
| MECA (Moreiro et al., 2018) | 95.2      | -           |
| VADA (Shu et al., 2018)    | 94.5        | 73.3        |
| DAassoc (Häusser et al., 2017) | 95.68±1.54 | 33.87±4.02 |

*supervised low-resource*

| Model                      | SVHN→MNIST | MNIST→SVHN |
|----------------------------|-------------|-------------|
| FADA (Motiian et al., 2017) (10) | 72.8        | 37.7        |
| Augmented-Cyc (10) (Ours)   | 79.01±1.03  | 49.59±1.78  |
| FADA (Motiian et al., 2017) (50) | 86.1       | 46.1        |
| Augmented-Cyc (50) (Ours)   | 89.91±0.68  | 50.91±0.36  |
| FADA (Motiian et al., 2017) (70) | 87.2       | 47.0        |
| Augmented-Cyc (70) (Ours)   | 90.23±0.12  | 53.27±0.94  |
| Augmented-Cyc (100) (Ours)  | 93.90±0.33  | 61.50±1.05  |
| Augmented-Cyc (200) (Ours)  | 95.43±0.27  | 65.84±0.21  |
| Augmented-Cyc (300) (Ours)  | 96.43±0.11  | 70.83±0.62  |
| Augmented-Cyc (400) (Ours)  | 96.83±0.10  | 73.35±0.06  |
| Augmented-Cyc (500) (Ours)  | 97.23±0.05  | 74.61±0.43  |
| Augmented-Cyc (1000) (Ours) | **97.99±0.07 (98.07)** | **79.13±0.46 (79.82)** |

Full Target dataset: 99.49±0.02 (99.52) 93.38±0.07 (93.43)

Table 5: Unsupervised and semi-supervised results on MNIST

| Total # samples available | 0% | 10% | 50% | 90% | 100% |
|---------------------------|----|-----|-----|-----|------|
| n=100                     | 81.43 | 77.63 | 91.16 | 94.15 | 94.21 |
| n=200                     | 80.19 | 85.84 | 93.28 | 95.44 | 95.60 |
| n=500                     | **84.26** | 87.22 | 96.18 | 96.84 | 97.27 |
| n=1000                    | **86.49** | 91.75 | 96.85 | 97.63 | 98.07 |

5 Conclusion and Future Work

In this paper, we propose to use augmented cycle-consistency adversarial learning for domain adaptation and introduce a task specific model to facilitate learning domain related mappings. We enforce
Table 6: Speech domain adaptation results on TIMIT. We treat male and female voices for the source and target domains, respectively, based on the intrinsic imbalance of speaker genders in the dataset (about 7:3 male/female ratio). For the evaluation metric, lower is better.

| Training Set          | Domain Adaptation Model          | Female (PER) |   |   |
|-----------------------|----------------------------------|--------------|---|---|
|                       |                                  |              | Val | Test |
| Male                  |                                  | 35.70        | 30.69 |   |
| Female (Baseline model)|                                  | 24.51        | 23.22 |   |
| Adapted Male          | CycleGAN                         | 32.95        | 30.07 |   |
| Adapted Male          | FHVAE (Hsu et al., 2017)         | –            | 26.2 |   |
| Adapted Male          | MD-CycleGAN (Hosseini-Asl et al., 2018) | 28.80 | 25.45 |   |
| Adapted Male          | Augmented-Cyc (Ours)             | 24.86        | 23.46 |   |
| Female + Adapted Male | MD-CycleGAN (Hosseini-Asl et al., 2018) | 21.15 | 19.08 |   |
| Female + Adapted Male | Augmented-Cyc (Ours)             | **20.32**    | **19.02** |   |
| All Data              | No Adaptation                    | 20.63        | 20.52 |   |
| All Data + Adapted Male| MD-CycleGAN (Hosseini-Asl et al., 2018) | 20.26 | 19.60 |   |
| All Data + Adapted Male| Augmented-Cyc (Ours)             | **20.02**    | **18.44** |   |

cycle-consistency using a task specific loss instead of the conventional reconstruction objective. Additionally, we use the task specific model as an additional source of information for the discriminator in the corresponding domain. We demonstrate the effectiveness of our proposed approach by evaluating on two domain adaptation tasks, and in both cases we achieve significant performance improvement as compared to the baseline.

Extending the definition of target task to fully unsupervised tasks, such as reconstruction loss using autoencoder, or self-supervision, e.g. speech modeling using wavenet (van den Oord et al., 2016), or language modeling using recurrent or transformer networks (Radford et al., 2018). Therefore, our proposed method would work on all settings for domain adaptation.

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Appendix A  Speech Domain Models Implementation

In this section, the detail of CycleGAN and speech model architectures are explained. The size of the convolution layer are denoted by the tuple \((C, F, T, SF, ST)\), where \(C, F, T, SF,\) and \(ST\) denote number of channels, filter size in frequency dimension, filter size in time dimension, stride in frequency dimension and stride in time dimension respectively. Architecture of CycleGAN model is based on Zhu et al. (2017) with modifications mentioned in Hosseini-Asl et al. (2018). Both generators in CycleGAN are based on U-net Ronneberger et al. (2015) architecture with 4 layers of convolution of sizes \((8,3,1,1), (16,3,1,1), (32,3,2,2), (64,3,2,2)\), followed by corresponding deconvolution layers. To increase stability of adversarial training, as proposed by Hosseini-Asl et al. (2018), the discriminator output is modified to predict a single scalar as real/fake probability. Discriminator has 4 convolution layers of sizes \((8,4,2,2), (16,4,2,2), (32,4,2,2), (64,4,2,2)\), as default kernel and stride sizes in Hosseini-Asl et al. (2018). ASR model is implemented based on Zhou et al. (2017), which is trained only with maximum likelihood. The model includes one convolutional layer of size \((32,41,11,2,2)\), and five residual convolution blocks of size \((32,7,3,1,1), (32,5,3,1,1), (32,3,3,1,1), (64,3,3,2,1), (64,3,3,1,1)\) respectively. Convolutional layers are followed by 4 layers of bidirectional GRU RNNs with 1024 hidden units per direction per layer. Finally, a fully-connected hidden layer of size 1024 is used as the output layer.

A.1 Qualitative Evaluation of Domain Adaptation

In this section we show some qualitative results on transcriptions produced from different models.

### Table 7: ASR prediction improvement on low resource Female domain (TIMIT), when augmented with adapted audios from high resource Male domain

| Test on Female | True | No adaptation | CycleGAN | Augmented-Cycle Model |
|----------------|------|---------------|----------|-----------------------|
| Train on Female + (Male →Female) | True sil dh ah m a r n n h n s l d uw a n n h n s l p a y d x r e w e h s l g l s e h n s l d i h n d h s a h n s l sil | No adaptation sil dh ah m a r n n h n s l d uw a m s i l b a y e r w i h s l b z l i h s i d n d n n s a n s l sil | CycleGAN sil dh ih m a r n n h n s l d ih ah n d h s i d h s s l p a y d h r e h s l d h i d h s h n s l d i h n s i l n s l a y n s l sil | Augmented-Cycle Model sil dh ah m a r n n h n s l d uw a n n h n s l b a y d x y e r w e h s l b i h s i s n s l d i h n s a h n s l sil |
| | sil iy v i h n a h s h m s l p l v a h s l k a e sil b y i h l e h r i y s l k a h n s l t e y n n s l t s s h m s l b i z s l sil | sil iy v i h n a h s h m s l v o w s l k a e sil b y i h l e h r i y s l k e h n s l t e y n s h m s l b i z s l sil | sil iy v i h n a h s h m s l p l v o w s l k a e sil b y i h l e h r i y s l k e h n s l t e y n s h m s l b i z s l sil | Augmented-Cycle Model sil iy v i h n a h s h m s l p l v o w s l k a e sil b y i h l e h r i y s l k e h n s l t e y n s h m s l b i z s l sil |
| | sil dh ah f a a s i l p r h v i h n n s l d i h m f r a h m e r v a a v i h n g a a n s l t a a m s l sil | sil dh ah f a a s i l p r h v i h n n s l d i h m e r v a a v i h n g a a n s l t a a m s l sil | sil dh ah f a a s i l p r h v i h n n s l d i h m e r v a a v i h n g a a n s l t a a m s l sil | Augmented-Cycle Model sil dh ah f a a s i l p r h v i h n n s l d i h m e r v a a v i h n g a a n s l t a a m s l sil |
| | sil iy v i h s t a a l s i l p r h v i h n n s l d i h m f r a h m e r v a a v i h n g a a n s l t a a m s l sil | sil iy v i h s t a a l s i l p r h v i h n n s l d i h m e r v a a v i h n g a a n s l t a a m s l sil | sil iy v i h s t a a l s i l p r h v i h n n s l d i h m e r v a a v i h n g a a n s l t a a m s l sil | Augmented-Cycle Model sil iy v i h s t a a l s i l p r h v i h n n s l d i h m e r v a a v i h n g a a n s l t a a m s l sil |
| | sil dh ah f a a s i l p r h v i h n n s l d i h m f r a h m e r v a a v i h n g a a n s l t a a m s l sil | sil dh ah f a a s i l p r h v i h n n s l d i h m f r a h m e r v a a v i h n g a a n s l t a a m s l sil | sil dh ah f a a s i l p r h v i h n n s l d i h m f r a h m e r v a a v i h n g a a n s l t a a m s l sil | Augmented-Cycle Model sil dh ah f a a s i l p r h v i h n n s l d i h m f r a h m e r v a a v i h n g a a n s l t a a m s l sil |
| | True sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil | No Adaptation sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil | CycleGAN sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil | Augmented-Cycle Model sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil |
| | sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil | sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil | sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil | Augmented-Cycle Model sil ch iy s l s i l t a a l s i l k i h n g z r a h n d h f e r s s l i s l t a y m d h e r w a a r n s l s l sil |
| | True sil d o w n s l d u w s l c h a a r t i s l y i s l d e r d x i y s i l d i h s h i h z s l s l sil | No Adaptation sil d o w n s l d u w s l c h e r e t l y s i l t e r d x i y s i l d e y s i l d e h s i h z s l s l sil | CycleGAN sil d o w n s l d u w s l c h a a r t i s l y i s l d e r d x i y s i l d e h s i h z s l s l sil | Augmented-Cycle Model sil d o w n s l d u w s l c h e r e t l y s i l t e r d x i y s i l d e h s i h z s l s l sil |
| | sil d o w n s l d u w s l c h a a r t i s l y i s l d e r d x i y s i l d e h s i h z s l s l sil | sil d o w n s l d u w s l c h e r e t l y s i l t e r d x i y s i l d e y s i l d e h s i h z s l s l sil | sil d o w n s l d u w s l c h e r e t l y s i l t e r d x i y s i l d e h s i h z s l s l sil | Augmented-Cycle Model sil d o w n s l d u w s l c h e r e t l y s i l t e r d x i y s i l d e h s i h z s l s l sil |
| | True sil k a e l s i l y i h m e y s i l s i l b o w n z n s i l t i y s i l t r a a n g s i l s l sil | No Adaptation sil k a e l s i l y i h m e y s i l s i l b o w n z n s i l t i y s i l t r a a n g s i l s l sil | CycleGAN sil k a e l s i l y i h m e y s i l s i l b o w n z n s i l t i y s i l t r a a n g s i l s l sil | Augmented-Cycle Model sil k a e l s i l y i h m e y s i l s i l b o w n z n s i l t i y s i l t r a a n g s i l s l sil |