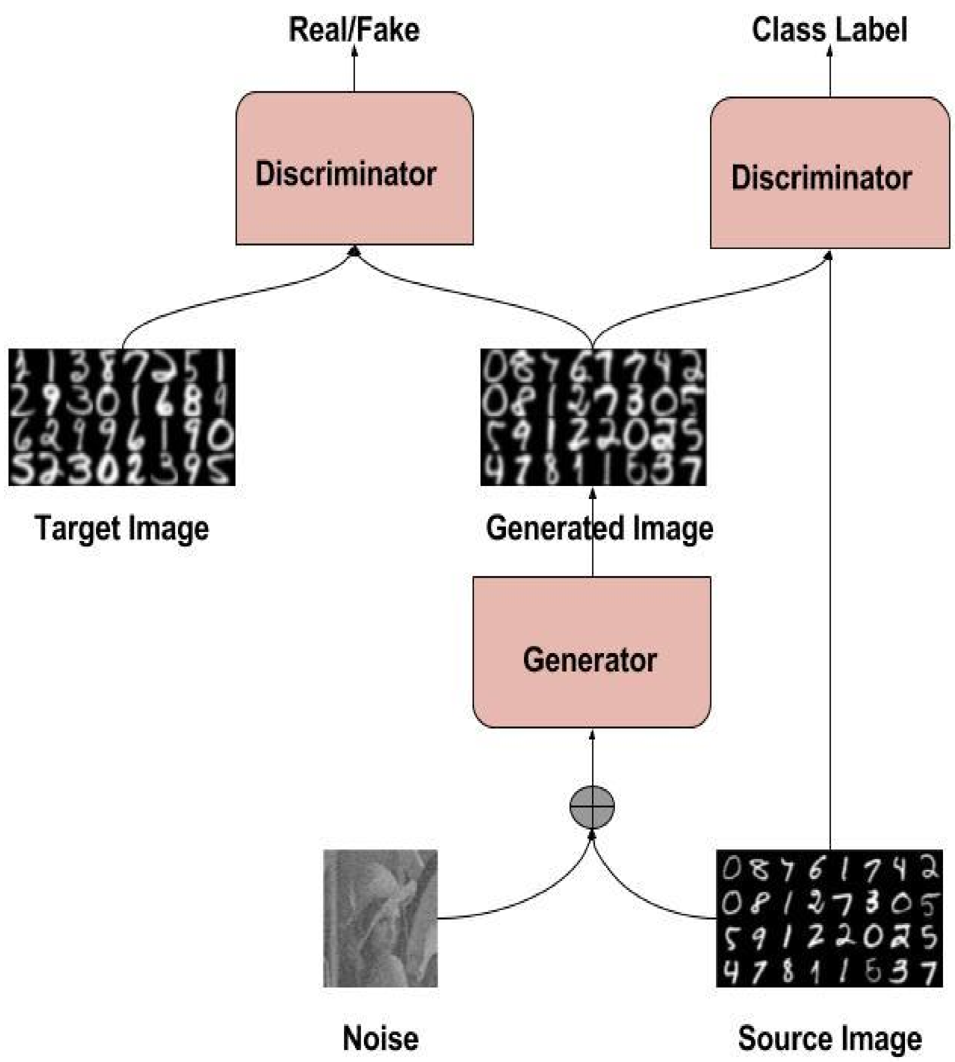

Unsupervised Domain Adaptation Using GANs

Group 10 :

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Unsupervised Pixel Level Domain Adaptation using GANs

Why is Domain Adaptation important?

- Different distribution of source dataset and target dataset. Models trained on such dataset do not generalize well
- Annotated dataset is difficult to obtain. Requires a lot of human effort
- Domain adaptation technique should not depend upon task at hand. In many approaches, domain adaptation and task-specific architecture are coupled

PixelDA GAN :

- Generator contains residual connections, that maintain resolution of original image, as compared to other approaches which use deconvolution for upsampling

Advantages :

- Decoupling from task-specific architecture
- Generalization across label spaces
- Stable Training by utilizing task specific loss on both source and target images

★ *Bousmalis, Konstantinos, et al. "Unsupervised pixel-level domain adaptation with generative adversarial networks."* [arXiv:1612.05424 (2016)]

Quantitative Results

Source Dataset: MNIST

Target Dataset: MNIST-M, USPS

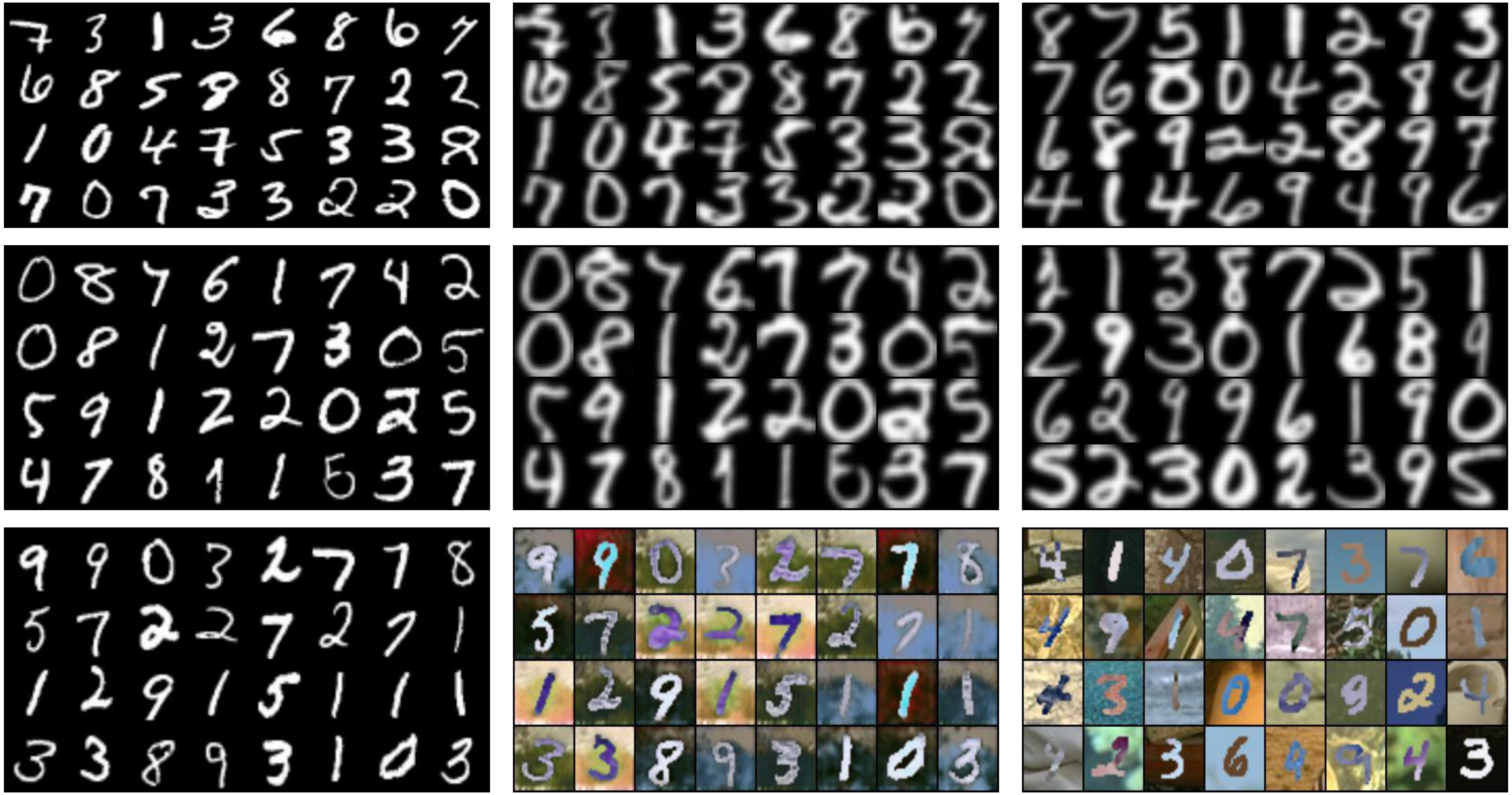
GAN Models:

I. PixelDA GAN
II. Least Square GAN

Model	MNIST -> USPS	MNIST -> MNIST-M
Source-Only	78.9 % (56.8 %)	63.6 %
Least Square GAN	**97.2 %**	82.12 %
PixelDA GAN	96.36 %	**96.66 %**
Target-Only	96.5 % (99.0 %)	95.9 % (97.2 %)

Table: Mean classification accuracy (%) for digit dataset (test only). The “Source-only” and “Target-only” rows are the results on the target domain when using no domain adaptation and training only on the source or the target domain respectively. We note that our Source and Target only baselines resulted in different numbers than published in the paper which we also indicate in parenthesis

Qualitative Results



USPS - Least Square GAN

USPS - PixelDA GAN

MNISTM - PixelDA GAN

Source Samples(MNIST)

Fake Samples

Target Samples