Boulder

Computer Vision; Advanced Topics; Domain Adaptation

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Learning Transferable Features with Deep Adaptation Networks

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Unsupervised Domain Adaptation

$\mathcal{D}_s = \{(x_i^s, y_i^s)\}_{i=1}^{n_s} \rightarrow$ source domain

$\mathcal{D}_t = \{x_j^t\}_{j=1}^{n_t} \rightarrow$ target domain

Build a classifier which can minimize target risk!

$y = c_\theta(x) \rightarrow$ classifier

$\varepsilon_t(\theta) = \Pr_{(x,y)\sim\mathcal{D}_t}[c_\theta(x) \neq y] \rightarrow$ target risk

Semi-supervised Adaptation

$\mathcal{D}_a = \{(x_i^a, y_i^a)\}_{i=1}^{n_a} \rightarrow n_a$ annotated examples of source and target domains

Multi-Layer Adaptation & Multi-Kernel MMD

MMD $\rightarrow$ Maximum Mean Discrepancy

$$\min_\theta \frac{1}{n_a}\sum_{i=1}^{n_a} J(c_\theta(x_i^a), y_i^a) + \lambda \sum_{l=l_1}^{l_2} d_k^2(\mathcal{D}_s^l, \mathcal{D}_t^l)$$

cross-entropy loss

layer indices ($l_1 = 6$ & $l_2 = 8$)

$\mathcal{D}_s^l = \{h_i^{sl} := \phi^l(x_i^s)\}_{i=1}^{n_s}$

$\mathcal{D}_t^l = \{h_j^{tl} := \phi^l(x_j^t)\}_{j=1}^{n_t}$

$k \rightarrow$ convex combination of m kernels

$$k = \sum_{u=1}^{m} \beta_u k_u, \sum_{u=1}^{m} \beta_u = 1, \beta_u \geq 0$$

$$k_u(h_i, h_j) = \exp(-\frac{\|h_i - h_j\|^2}{\gamma_u})$$

Gaussian kernels

$$d_k^2(\mathcal{D}_s^l, D_t^l) = \frac{1}{n_s^2}\sum_{i=1}^{n_s}\sum_{j=1}^{n_s} k(h_i^{sl}, h_j^{sl}) + \frac{1}{n_t^2}\sum_{i=1}^{n_t}\sum_{j=1}^{n_t} k(h_i^{tl}, h_j^{tl}) - \frac{2}{n_s n_t}\sum_{i=1}^{n_s}\sum_{j=1}^{n_t} k(h_i^{sl}, h_j^{tl})$$

incurs a complexity of $O(n^2)$

An unbiased estimate of MK-MMD can be computed with linear complexity (see the paper!)

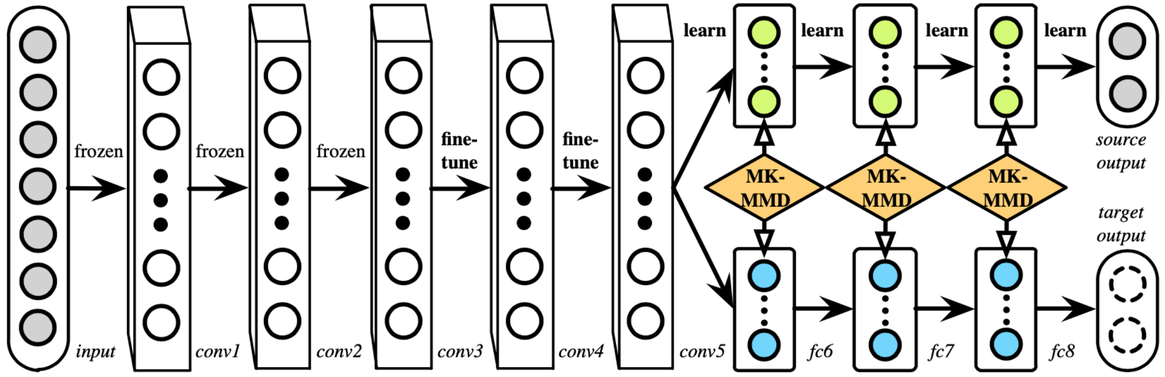
We can learn the optimal kernel parameters β_u by $\max_{k\in\mathcal{K}} d_k^2\left(\mathcal{D}_s^\ell, \mathcal{D}_t^\ell\right)\sigma_k^{-2}$

$\sigma_k \rightarrow$ estimation variance

Minimizing MMD is equivalent to maximizing the error of classifying the source from the target (two-sample classifier)

Accuracy on *Office-10 + Caltech-10* dataset with standard unsupervised adaptation protocol

Method	A → C	W → C	D → C	C → A	C → W	C → D	Average
TCA	42.7 ± 0.0	34.1 ± 0.0	35.4 ± 0.0	54.7 ± 0.0	50.5 ± 0.0	50.3 ± 0.0	44.6
GFK	41.4 ± 0.0	26.4 ± 0.0	36.4 ± 0.0	56.2 ± 0.0	43.7 ± 0.0	42.0 ± 0.0	41.0
CNN	83.8 ± 0.3	76.1 ± 0.5	80.8 ± 0.4	91.1 ± 0.2	83.1 ± 0.3	89.0 ± 0.3	84.0
LapCNN	83.6 ± 0.6	77.8 ± 0.5	80.6 ± 0.4	**92.1** ± 0.3	81.6 ± 0.4	87.8 ± 0.4	83.9
DDC	84.3 ± 0.5	76.9 ± 0.4	80.5 ± 0.2	91.3 ± 0.3	85.5 ± 0.3	89.1 ± 0.3	84.6
DAN_7	84.7 ± 0.3	78.2 ± 0.5	81.8 ± 0.3	91.6 ± 0.4	87.4 ± 0.3	88.9 ± 0.5	85.4
DAN_8	84.4 ± 0.3	80.8 ± 0.4	81.7 ± 0.2	91.7 ± 0.3	90.5 ± 0.4	89.1 ± 0.4	86.4
DAN_{SK}	84.1 ± 0.4	79.9 ± 0.4	81.1 ± 0.5	91.4 ± 0.3	86.9 ± 0.5	89.5 ± 0.3	85.5
DAN	**86.0** ± 0.5	**81.5** ± 0.3	**82.0** ± 0.4	92.0 ± 0.3	**92.0** ± 0.4	**90.5** ± 0.2	**87.3**



Accuracy on *Office-31* dataset with standard unsupervised adaptation protocol

Method	A → W	D → W	W → D	A → D	D → A	W → A	Average
TCA	21.5 ± 0.0	50.1 ± 0.0	58.4 ± 0.0	11.4 ± 0.0	8.0 ± 0.0	14.6 ± 0.0	27.3
GFK	19.7 ± 0.0	49.7 ± 0.0	63.1 ± 0.0	10.6 ± 0.0	7.9 ± 0.0	15.8 ± 0.0	27.8
CNN	61.6 ± 0.5	95.4 ± 0.3	99.0 ± 0.2	63.8 ± 0.5	51.1 ± 0.6	49.8 ± 0.4	70.1
LapCNN	60.4 ± 0.3	94.7 ± 0.5	**99.1** ± 0.2	63.1 ± 0.6	51.6 ± 0.4	48.2 ± 0.5	69.5
DDC	61.8 ± 0.4	95.0 ± 0.5	98.5 ± 0.4	64.4 ± 0.3	52.1 ± 0.8	52.2 ± 0.4	70.6
DAN_7	63.2 ± 0.2	94.8 ± 0.4	98.9 ± 0.3	65.2 ± 0.4	52.3 ± 0.4	52.1 ± 0.4	71.1
DAN_8	63.8 ± 0.4	94.6 ± 0.5	98.8 ± 0.6	65.8 ± 0.4	52.8 ± 0.4	51.9 ± 0.5	71.3
DAN_{SK}	63.3 ± 0.3	95.6 ± 0.2	99.0 ± 0.4	65.9 ± 0.7	53.2 ± 0.5	52.1 ± 0.4	71.5
DAN	**68.5** ± 0.4	**96.0** ± 0.3	99.0 ± 0.2	**67.0** ± 0.4	**54.0** ± 0.4	**53.1** ± 0.3	**72.9**

Amazon (A), Webcam (W), DSLR (D)

Long, Mingsheng, et al. "Learning transferable features with deep adaptation networks." *International conference on machine learning*. PMLR, 2015.

Domain-Adversarial Training of Neural Networks

Domain Adaptation

Data at training and test time come from similar but different distributions!

$X \rightarrow$ input space

$Y = \{0, 1, \ldots, L-1\} \rightarrow$ set of L possible labels

$\mathcal{D}_S \rightarrow$ source domain

$\mathcal{D}_T \rightarrow$ target domain

$\mathcal{D}_S, \mathcal{D}_T \rightarrow$ distributions over $X \times Y$

$S \rightarrow$ labeled source sample drawn i.i.d from $\mathcal{D}_S$

$T \rightarrow$ unlabeled target sample drawn i.i.d from $\mathcal{D}_T^X$

$\mathcal{D}_T^X \rightarrow$ marginal distribution of $\mathcal{D}_T$ over X

$S = \{(x_i, y_i)\}_{i=1}^n \sim (\mathcal{D}_S)^n$

$T = \{x_i\}_{i=n+1}^N \sim (\mathcal{D}_T^X)^{n'}$

$N = n + n' \rightarrow$ total number of samples

Build a classifier $\eta : X \rightarrow Y$ with a low target risk:

$\mathcal{R}_{\mathcal{D}_T}(\eta) = \Pr_{(x,y)\sim\mathcal{D}_T}(\eta(x) \neq y)$

Theorem

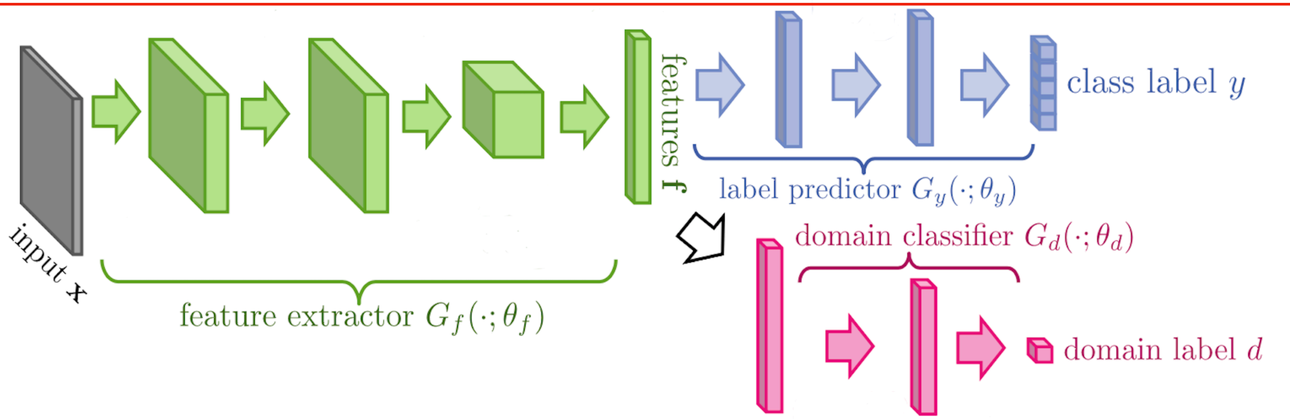
> For effective domain transfer to be achieved, predictions must be made based on features that cannot discriminate between the training (source) and test (target) domains.

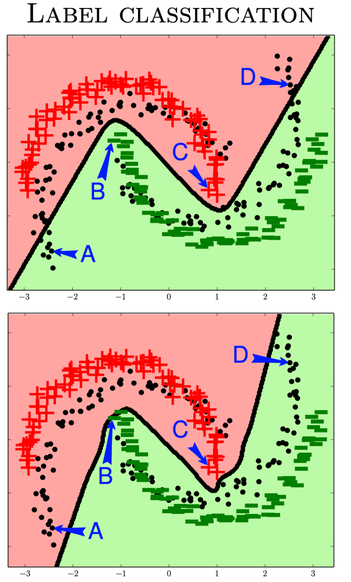
Domain-Adversarial Neural Network (DANN)

$G_f(\cdot;\theta_f) \rightarrow$ feature extractor

$G_y(\cdot;\theta_y) \rightarrow$ label predictor

$G_d(\cdot;\theta_d) \rightarrow$ domain classifier





$\mathcal{L}_y^i(\theta_f, \theta_y) = \mathcal{L}_y(G_y(G_f(x_i;\theta_f);\theta_y), y_i) \rightarrow$ prediction loss

$\mathcal{L}_d^i(\theta_f, \theta_d) = \mathcal{L}_d(G_d(G_f(x_i;\theta_f);\theta_d), d_i) \rightarrow$ domain loss

$\mathcal{L}_d(G_d(G_f(x_i)), d_i) = -d_i \log(G_d(G_f(x_i))) - (1-d_i)\log(1 - G_d(G_f(x_i)))$

$d_i = 1$ if $x_i \sim \mathcal{D}_T^X$

$d_i = 0$ if $x_i \sim \mathcal{D}_S^X$

$\mathcal{L}_y(G_y(G_f(x_i)), y_i) = -\log(G_y(G_f(x_i))_{y_i})$

$$(\hat{\theta}_f, \hat{\theta}_y) = \underset{\theta_f,\theta_y}{\operatorname{argmin}} E(\theta_f, \theta_y, \hat{\theta}_d)$$

$$\hat{\theta}_d = \underset{\theta_d}{\operatorname{argmax}} E(\hat{\theta}_f, \hat{\theta}_y, \theta_d)$$

$$E(\theta_f, \theta_y, \theta_d) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_y^i(\theta_f, \theta_y) - \lambda\left(\frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_d^i(\theta_f, \theta_d) + \frac{1}{n'}\sum_{i=n+1}^{N} \mathcal{L}_d^i(\theta_f, \theta_d)\right)$$

Unsupervised Hyper-parameter Selection

Split S into training set S' and validation set S_V

Split T into training set T' and validation set T_V

Use S' and T' to learn a classifier η

$\{(x, \eta(x))\}_{x\in T'} \rightarrow$ self labeled set (new source)

Unlabeled $S' \rightarrow$ new target

$\eta_r \rightarrow$ reverse classifier

Evaluate η_r on S_V

$\mathcal{R}_{S_V}(\eta_r) \rightarrow$ reverse validation risk

$S_V \rightarrow$ used for early stopping the training of η

$T_V \rightarrow$ used for early stopping the training of η_r

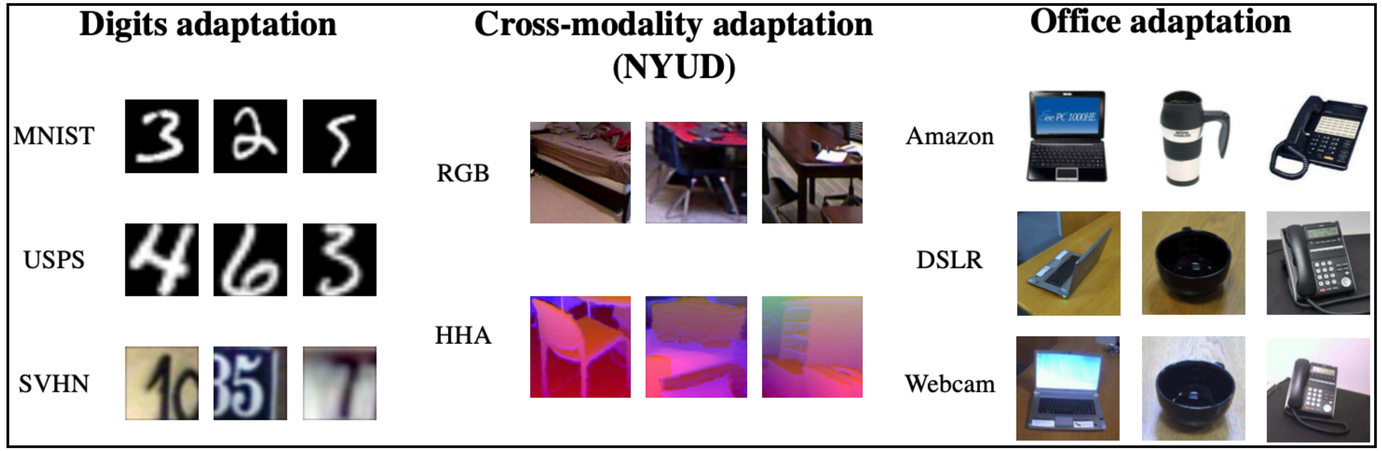
– document sentiment analysis

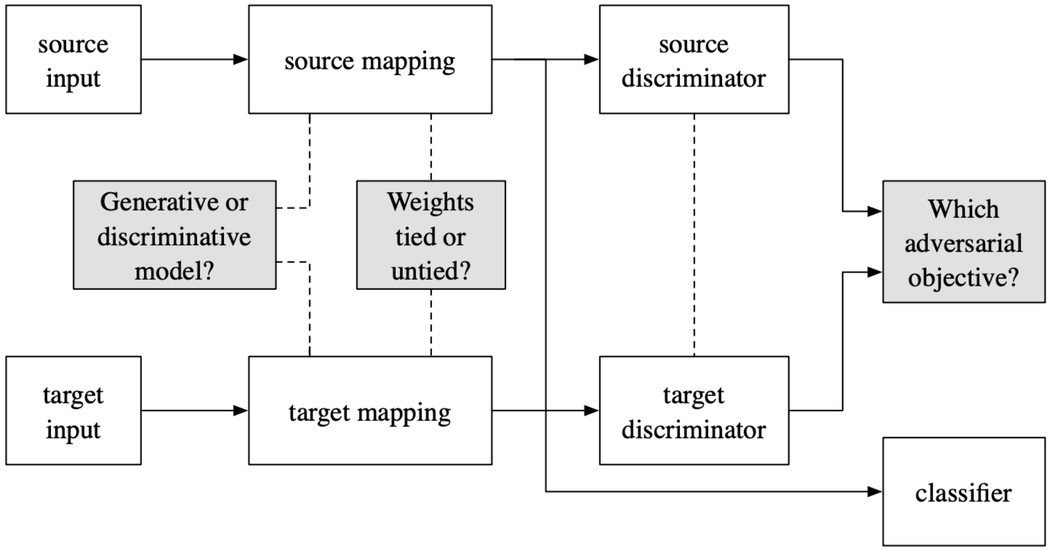
– image classification

–person re-identification

Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." *The journal of machine learning research* 17.1 (2016): 2096-2030.

Adversarial Discriminative Domain Adaptation





– dataset bias or domain shift

$(\mathbf{X}_s, Y_s) \rightarrow$ source images & labels $\quad \mathbf{X}_t \rightarrow$ target images (no labels)

$M_s, M_t \rightarrow$ source & target representation mappings

$C \rightarrow$ classifier $\quad K \rightarrow$ number of categories

$$\min_{M_s, C} \mathcal{L}_{\text{cls}}(\mathbf{X}_s, Y_s) =$$

$$- \mathbb{E}_{(\mathbf{x}_s, y_s) \sim (\mathbf{X}_s, Y_s)} \sum_{k=1}^{K} \mathbb{1}_{[k=y_s]} \log C(M_s(\mathbf{x}_s))$$

$$\min_{D} \mathcal{L}_{\text{adv}_D}(\mathbf{X}_s, \mathbf{X}_t, M_s, M_t) =$$

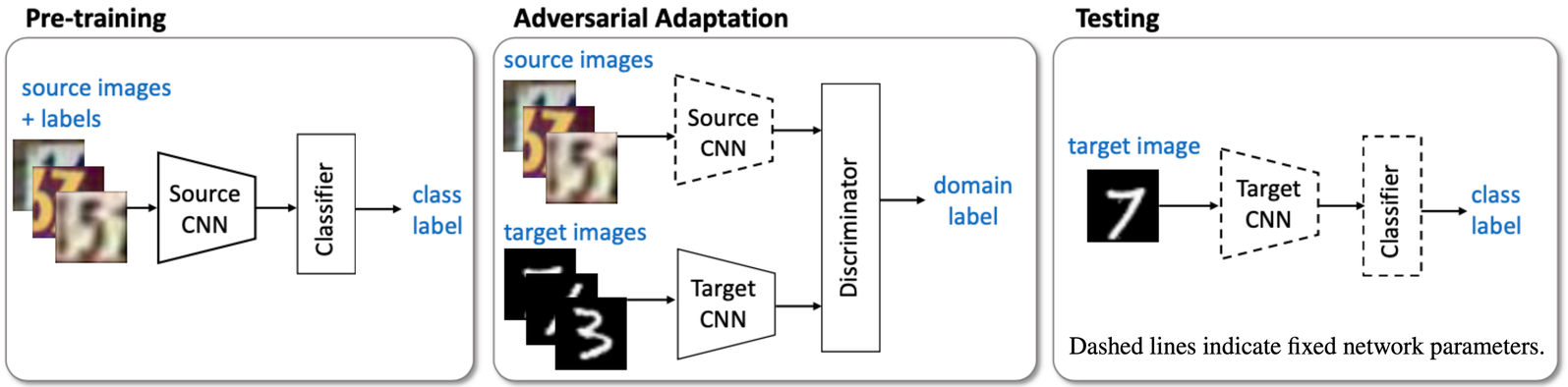
$$- \mathbb{E}_{\mathbf{x}_s \sim \mathbf{X}_s}[\log D(M_s(\mathbf{x}_s))] - \mathbb{E}_{\mathbf{x}_t \sim \mathbf{X}_t}[\log(1 - D(M_t(\mathbf{x}_t)))]$$

$$\min_{M_t} \mathcal{L}_{\text{adv}_M}(\mathbf{X}_s, \mathbf{X}_t, D) =$$

$$- \mathbb{E}_{\mathbf{x}_t \sim \mathbf{X}_t}[\log D(M_t(\mathbf{x}_t))].$$

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

Method	MNIST → USPS	USPS → MNIST	SVHN → MNIST
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



Tzeng, Eric, et al. "Adversarial discriminative domain adaptation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

Unsupervised Pixel-Level Domain Adaptation with Generative Adversarial Networks

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Synthetic data (game engines or renderers): ground-truth annotations are generated automatically
– map representations between the two domains
– learn to extract features that are domain–invariant
– transformation in the pixel space from one domain to the other

Unsupervised Pixel-level Domain Adaptation (PixelDA)

Assumption: The differences between the domains are primarily low-level (due to noise, resolution, illumination, color) rather than high-level (types of objects, geometric variations, etc).

$X^s = \{x_i^s, y_i^s\}_{i=1}^{N^s} \rightarrow$ labeled dataset of N^s samples from the source domain

$X^t = \{x_i^t\}_{i=1}^{N^t} \rightarrow$ unlabeled dataset of N^t samples from the target domain

$x^f = G(x^s, z; \theta_G) \rightarrow$ generator
└ adapted or fake image

$z \sim p_z \rightarrow$ noise vector

$X^f = \{G(x^s, z), y^s\} \rightarrow$ new dataset of any size
└ adapted dataset

The task-specific classifier can be trained as if the training and test data were from the same distribution.

Learning

$d = D(x; \theta_d) \rightarrow$ discriminator
└ likelihood that a given image has been sampled from the target domain

distinguish between "fake" images produced by the generator and "real" images from the target domain

$\hat{y} = T(x; \theta_T) \rightarrow$ classifier (assigns task specific labels $\hat{y}$ to images $x \in X^f \cup X^t$)

$$\min_{\boldsymbol{\theta}_G, \boldsymbol{\theta}_T} \max_{\boldsymbol{\theta}_D} \alpha \mathcal{L}_d(D, G) + \beta \mathcal{L}_t(G, T) + \gamma \mathcal{L}_c(G)$$

$$\mathcal{L}_d(D, G) = \mathbb{E}_{\mathbf{x}^t}[\log D(\mathbf{x}^t; \boldsymbol{\theta}_D)] + \mathbb{E}_{\mathbf{x}^s, \mathbf{z}}[\log(1 - D(G(\mathbf{x}^s, \mathbf{z}; \boldsymbol{\theta}_G); \boldsymbol{\theta}_D))]$$
└ domain loss

$$\mathcal{L}_t(G, T) = \mathbb{E}_{\mathbf{x}^s, \mathbf{y}^s, \mathbf{z}}\big[- \mathbf{y}^{s\top} \log T(G(\mathbf{x}^s, \mathbf{z}; \boldsymbol{\theta}_G); \boldsymbol{\theta}_T) - \mathbf{y}^{s\top} \log T(\mathbf{x}^s); \boldsymbol{\theta}_T \big]$$
└ task-specific loss (cross-entropy)

$y^s \rightarrow$ one-hot-encoding

Content–similarity loss

Prior knowledge: Single objects are rendered on black backgrounds and consequently we expect images adapted from these renderings to have similar foregrounds and different backgrounds from the equivalent source images.

$$\mathcal{L}_c(G) = \mathbb{E}_{\mathbf{x}^s, \mathbf{z}}\Big[\frac{1}{k} \left\| (\mathbf{x}^s - G(\mathbf{x}^s, \mathbf{z}; \boldsymbol{\theta}_G)) \circ \mathbf{m} \right\|_2^2 - \frac{1}{k^2} \left((\mathbf{x}^s - G(\mathbf{x}^s, \mathbf{z}; \boldsymbol{\theta}_G))^\top \mathbf{m} \right)^2 \Big]$$

masked-PMSE (pairwise mean squared error) loss

$m \in \mathbb{R}^k \rightarrow$ binary mask (foreground vs background)

Model	MNIST to USPS	MNIST to MNIST-M
Source Only	78.9	63.6 (56.6)
CORAL [41]	81.7	57.7
MMD [44, 31]	81.1	76.9
DANN [14]	85.1	77.4
DSN [5]	91.3	83.2
CoGAN [30]	91.2	62.0
Our PixelDA	**95.9**	**98.2**
Target-only	96.5	96.4 (95.9)

nearest neighbors in the MNIST-M training set of the generated samples

Bousmalis, Konstantinos, et al. "Unsupervised pixel-level domain adaptation with generative adversarial networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

CyCADA: Cycle-Consistent Adversarial Domain Adaptation

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Adversarial Adaptation Models:
– discovering domain invariant representations (feature space methods)
– mapping between unpaired image domains (image space methods)

Unsupervised Adaptation

$X_S \rightarrow$ source data $\quad Y_S \rightarrow$ source labels

$X_T \rightarrow$ target data $\quad$ no target labels!

Learn a model f_T that correctly predicts the label for the target data X_T

Pre-train Source Task Model

$$\mathcal{L}_{\text{task}}(f_S, X_S, Y_S) = -\mathbb{E}_{(x_s,y_s)\sim(X_S,Y_S)} \sum_{k=1}^{K} \mathbb{1}_{[k=y_s]} \log\left(\sigma(f_S^{(k)}(x_s))\right)$$

σ: softmax function

domain shift leads to reduced performance when evaluating on target data

Pixel-level Adaptation

$G_{S\rightarrow T} \rightarrow$ mapping from source to target

↳trained to produce target samples that fool adversarial discriminator D_T

$\mathcal{L}_{\text{GAN}}(G_{S\rightarrow T}, D_T, X_T, X_S) = \mathbb{E}_{x_t\sim X_T}[\log D_T(x_t)] + \mathbb{E}_{x_s\sim X_S}[\log(1 - D_T(G_{S\rightarrow T}(x_s)))]$

$\mathcal{L}_{\text{task}}(f_T, G_{S\rightarrow T}(X_S), Y_S) \rightarrow$ learn a target model f_T

No way to guarantee that $G_{S\rightarrow T}(x_s)$ preserves the structure and content of x_s!

$\mathcal{L}_{\text{GAN}}(G_{T\rightarrow S}, D_S, X_S, X_T)$

$\mathcal{L}_{\text{cyc}}(G_{S\rightarrow T}, G_{T\rightarrow S}, X_S, X_T) = \mathbb{E}_{x_s\sim X_S}[||G_{T\rightarrow S}(G_{S\rightarrow T}(x_s)) - x_s||_1]$

$+ \mathbb{E}_{x_t\sim X_T}[||G_{S\rightarrow T}(G_{T\rightarrow S}(x_t)) - x_t||_1]$

Prevent Label Flipping

semantic consistency $\leftarrow \mathcal{L}_{\text{sem}}(G_{S\rightarrow T}, G_{T\rightarrow S}, X_S, X_T, f_S) =$

$\mathcal{L}_{\text{task}}(f_S, G_{T\rightarrow S}(X_T), p(f_S, X_T))$

$+ \mathcal{L}_{\text{task}}(f_S, G_{S\rightarrow T}(X_S), p(f_S, X_S))$

$p(f, X) = \arg\max f(x)$

↳predicted label

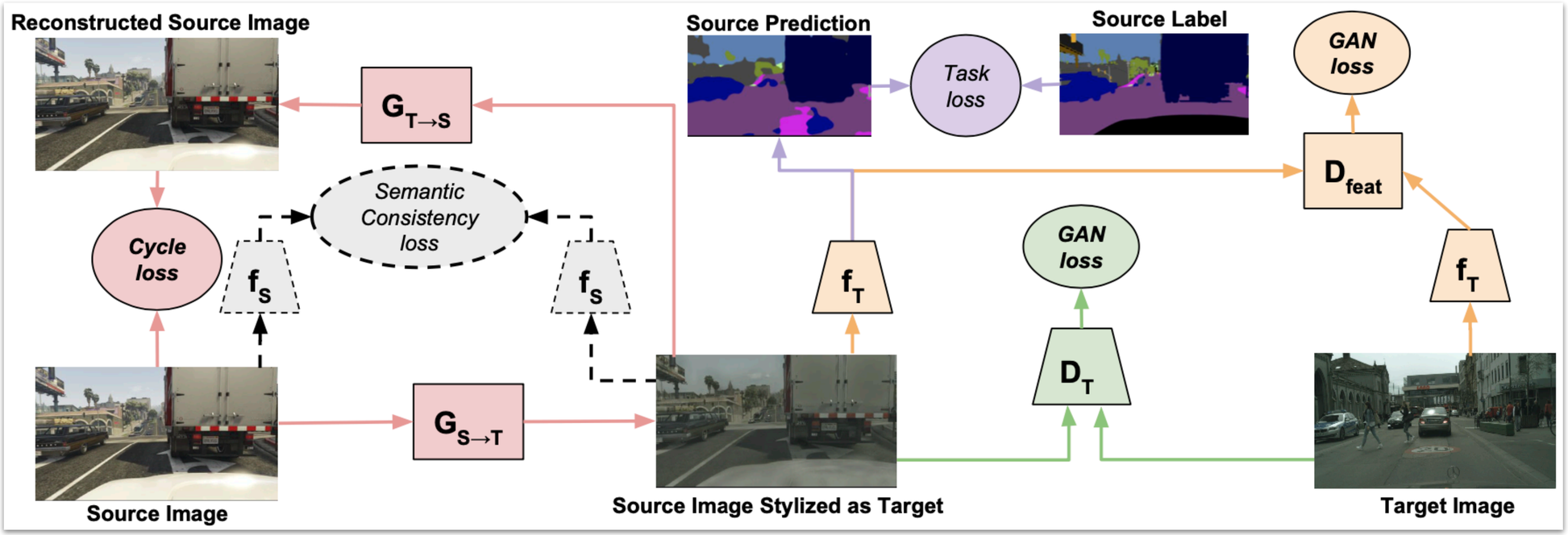
$f_S \rightarrow$ pretrained and fixed

Feature-level Adaptation

$\mathcal{L}_{\text{GAN}}(f_T, D_{\text{feat}}, f_S(G_{S\rightarrow T}(X_S)), X_T)$

Complete Objective

$$f_T^* = \arg\min_{f_T} \min_{\substack{G_{S\rightarrow T} \\ G_{T\rightarrow S}}} \max_{D_S, D_T} \mathcal{L}_{\text{CyCADA}}$$



SVHN→MNIST

Model	Accuracy (%)
Source only	67.1
CyCADA - no feat adapt, no semantic loss	70.3
CyCADA - no feat adapt	71.2
CyCADA - no cycle consistency	75.7
CyCADA - no pixel adapt	83.8
CyCADA (Full)	**90.4**
Target Fully Supervised	99.2

Hoffman, Judy, et al. "Cycada: Cycle-consistent adversarial domain adaptation." *International conference on machine learning*. PMLR, 2018.

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Questions?