Domain Adaptation

CS 330

Course Reminders

Optional homework 4 due next **Monday**.

Project milestone due next **Wednesday**

Azure: If you are close to running out of credits,
proactively request more in private Ed post.

Plan for Today

Domain Adaptation

- Problem statements
- Algorithms
    - Data reweighting
    - Feature alignment
    - Domain translation

Goal for by the end of lecture: Understand different domain adaptation methods and when to use one vs. another

Problem Settings Recap

Multi-Task Learning

Solve multiple tasks $\mathcal{T}_1, \cdots, \mathcal{T}_T$ at once.

$$\min_\theta \sum_{i=1}^{T} \mathcal{L}_i(\theta, \mathcal{D}_i)$$

Transfer Learning

Solve target task $\mathcal{T}_b$ after solving source task(s) $\mathcal{T}_a$

by *transferring* knowledge learned from $\mathcal{T}_a$

Meta-Learning Problem

Transfer Learning with Many Source Tasks

Given data from $\mathcal{T}_1, \ldots, \mathcal{T}_n$, solve new task $\mathcal{T}_{\text{test}}$ more quickly / proficiently / stably

What is domain adaptation?

Perform well on target domain $p_T(x, y)$,
using training data from source domain(s) $p_S(x, y)$

A form of transfer learning, with **access to target domain data during training** ("transductive" learning)

Unsupervised domain adaptation: access to unlabeled target domain data

Semi-supervised domain adaptation: access to unlabeled and labeled target domain data

Supervised domain adaptation: access to labeled target domain data.

We will focus on ***unsupervised domain adaptation***.

What is domain adaptation?

Perform well on target domain $p_T(x, y)$,

using training data from source domain(s) $p_S(x, y)$

A form of transfer learning, with **access to target domain data during training**

(“transductive” learning)

Unsupervised domain adaptation: access to unlabeled target domain data

Common assumptions:

- Source and target domain only differ in domain of the function, i.e. $p_S(y \mid x) = p_T(y \mid x)$
- There exists a single hypothesis with low error.

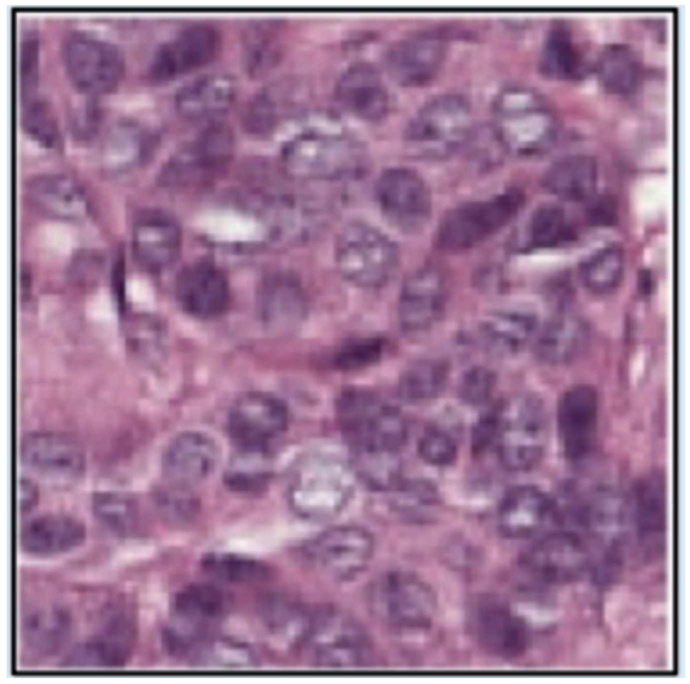
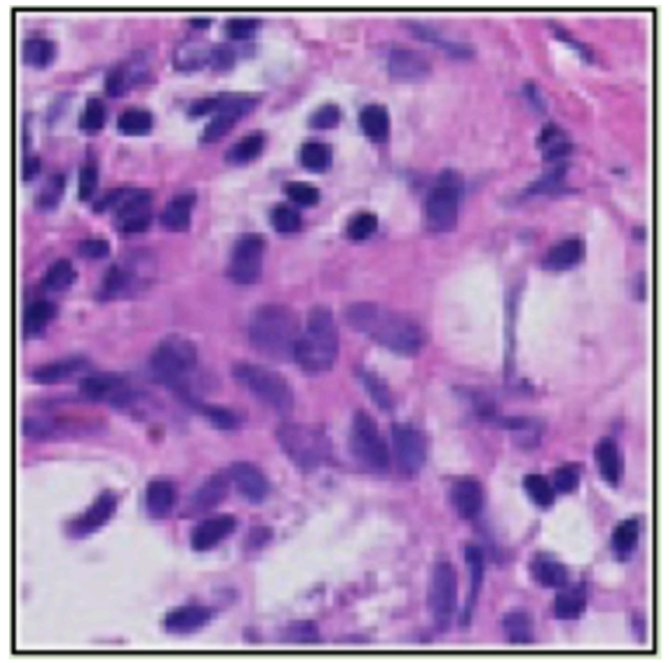
A “domain” is a special case of a “task”

A task: $\mathscr{T}_i \triangleq \{p_i(\mathbf{x}), p_i(\mathbf{y} \mid \mathbf{x}), \mathscr{L}_i\}$ A domain: $d_i \triangleq \{p_i(\mathbf{x}), p(\mathbf{y} \mid \mathbf{x}), \mathscr{L}\}$

Example domain adaptation problems

Tumor detection & classification

Source hospital Target hospital

varying imaging techniques, different demographics

Land use classification

Source region Target region

appearance of buildings, plants; weather conditions, pollution

Text classification, generation

Source corpus Target corpus

Simple English Wikipedia

arXiv

PubMed

differing sentence structure, vocabulary, word use

Domains can also be:

- people/users
- points in time
- institutions
  (schools, companies, universities)

Revisiting assumptions:

- Access to target domain data during training.
- There exists a single hypothesis $f(y \mid x)$ with low error.

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  - **Data reweighting**
  - Feature alignment
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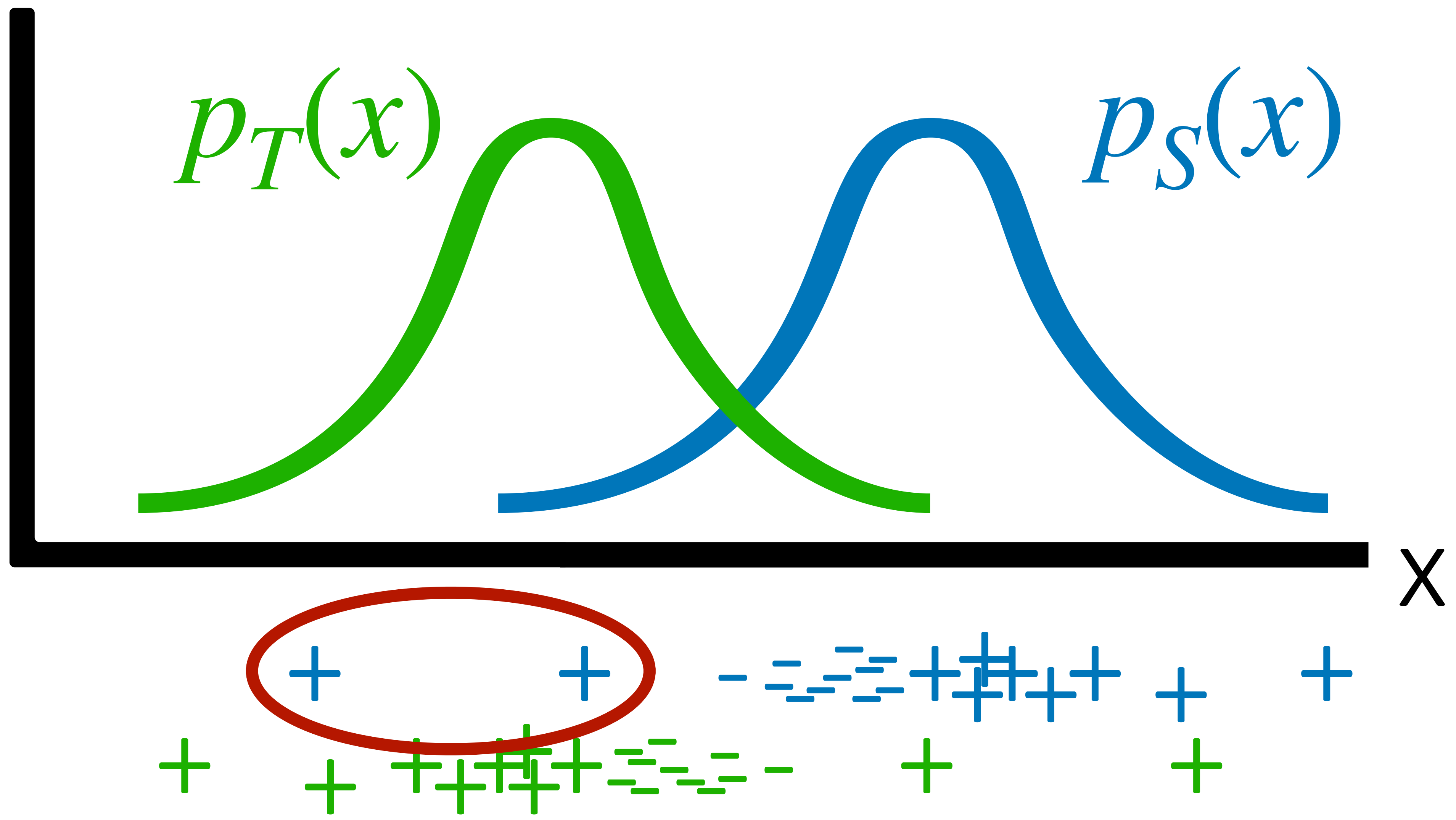
Toy domain adaptation problem



e.g. sample selection bias

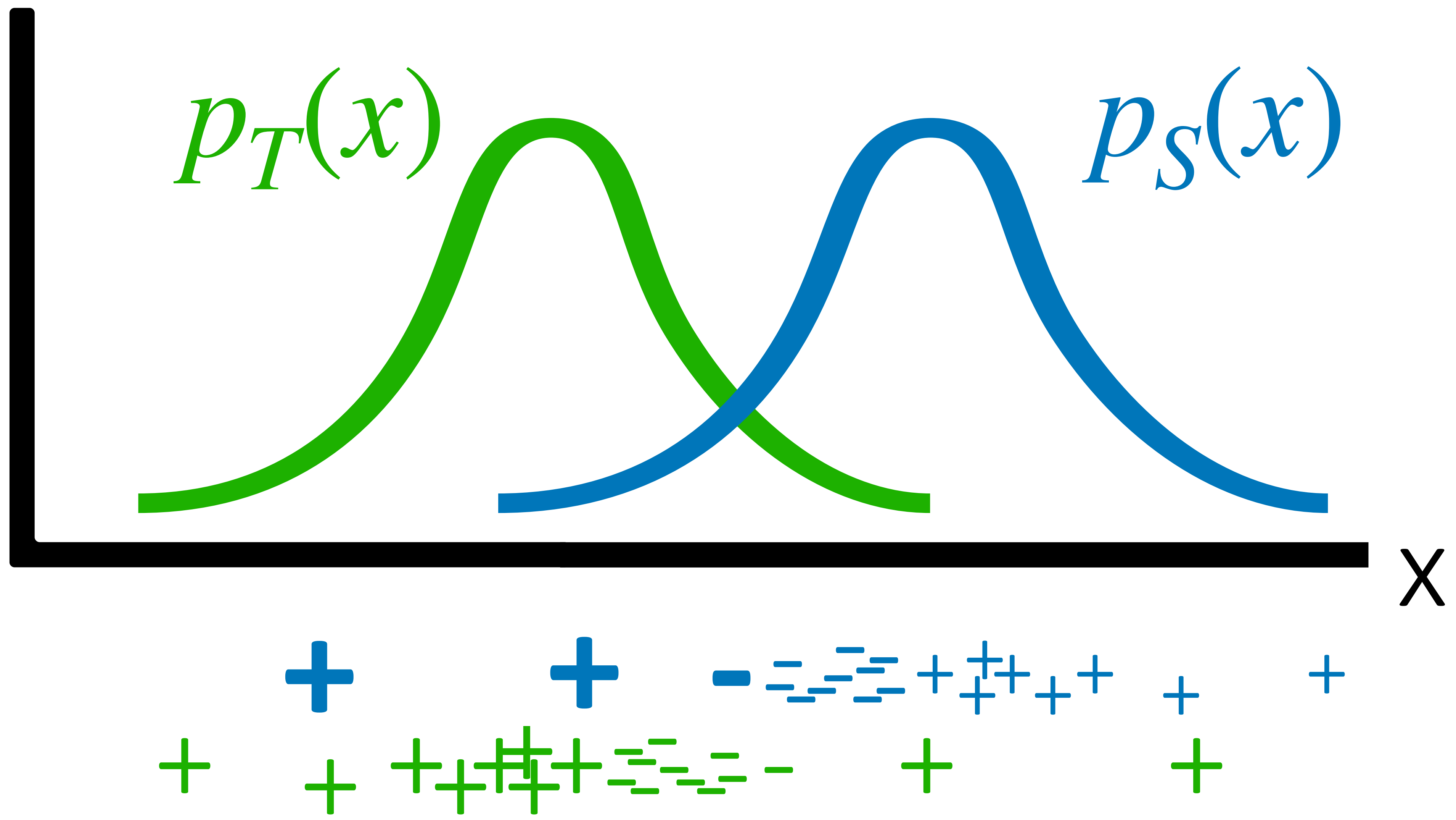
Problem: Classifier trained on $p_S(x)$ pays little attention to examples with high probability under $p_T(s)$

How can we learn a classifier that does well on $p_T(x)$?

(using labeled data from $p_S(x)$ & unlabeled data from $p_T(x)$)

Problem adapted from Blitzer & Daume ICML '10

Toy domain adaptation problem



e.g. sample selection bias

Problem: Classifier trained on $p_S(x)$ pays little attention to examples with high probability under $p_T(s)$

Solution: Upweight examples with high $p_T(x)$ but low $p_S(x)$

Why does this make sense mathematically?

Problem adapted from Blitzer & Daume ICML '10

Domain adaptation via importance sampling

Empirical risk minimization on source data: $\min_\theta \mathbb{E}_{p_S(x,y)}[L(f_\theta(x), y)]$

Goal: ERM on target distribution: $\min_\theta \mathbb{E}_{p_T(x,y)}[L(f_\theta(x), y)]$

$$\begin{aligned}
\mathbb{E}_{p_T(x,y)}[L(f_\theta(x), y)] &= \int p_T(x, y) L(f_\theta(x), y) dxdy \\
&= \int p_T(x, y) \frac{p_S(x, y)}{p_S(x, y)} L(f_\theta(x), y) dxdy \\
&= \mathbb{E}_{p_S(x,y)} \left[\frac{p_T(x, y)}{p_S(x, y)} L(f_\theta(x), y) \right]
\end{aligned}$$

Note: $p(y \mid x)$ cancels out if it is the same for source & target

Solution: Upweight examples with high $p_T(x)$ but low $p_S(x)$

Domain adaptation via importance sampling

$$\min_{\theta} \mathbb{E}_{p_S(x,y)} \left[\frac{p_T(x)}{p_S(x)} L(f_\theta(x), y) \right]$$

How to estimate the importance weights $\frac{p_T(x)}{p_S(x)}$?

Option 1: Estimate likelihoods $p_T(x)$ and $p_S(x)$, then divide. But, difficult to estimate accurately.

Can we estimate the ratio ***without*** training a generative model?

Bayes rule:

$$p(x \mid \text{target}) = \frac{p(\text{target} \mid x) p(x)}{p(\text{target})}$$

$$p(x \mid \text{source}) = \frac{p(\text{source} \mid x) p(x)}{p(\text{source})}$$

$$\frac{p_T(x)}{p_S(x)} = \frac{p(x \mid \text{target})}{p(x \mid \text{source})} = \frac{p(\text{target} \mid x) p(\text{source})}{p(\text{source} \mid x) p(\text{target})}$$

a constant

can estimate with binary classifier!

Bickel, Bruckner, Scheffer. Discriminative Learning Under Covariate Shift. JMLR '09

Domain adaptation via importance sampling

$$\min_{\theta} \mathbb{E}_{p_S(x,y)}\left[\frac{p_T(x)}{p_S(x)} L(f_\theta(x), y)\right]$$

$$\frac{p_T(x)}{p_S(x)} = \frac{p(x \mid \text{target})}{p(x \mid \text{source})} = \frac{p(\text{target} \mid x)p(\text{source})}{p(\text{source} \mid x)p(\text{target})}$$

a constant

can estimate with binary classifier!

Full algorithm:

1. Train binary classifier $c(\text{source} \mid x)$ to discriminate between source and target data.
2. Reweight or resample data $\mathscr{D}_S$ according to $\dfrac{1 - c(\text{source} \mid x)}{c(\text{source} \mid x)}$.
3. Optimize loss $L(f_\theta(x), y)$ on reweighted or resampled data.

Bickel, Bruckner, Scheffer. Discriminative Learning Under Covariate Shift. JMLR '09

What assumption does this make?

$$\min_{\theta} \mathbb{E}_{p_S(x,y)} \left[\frac{p_T(x)}{p_S(x)} L(f_\theta(x), y) \right]$$

Source $p_S(x)$ needs to cover the target $p_T(x)$.

Formally: if $p_T(x) \neq 0$, then $p_S(x) \neq 0$.

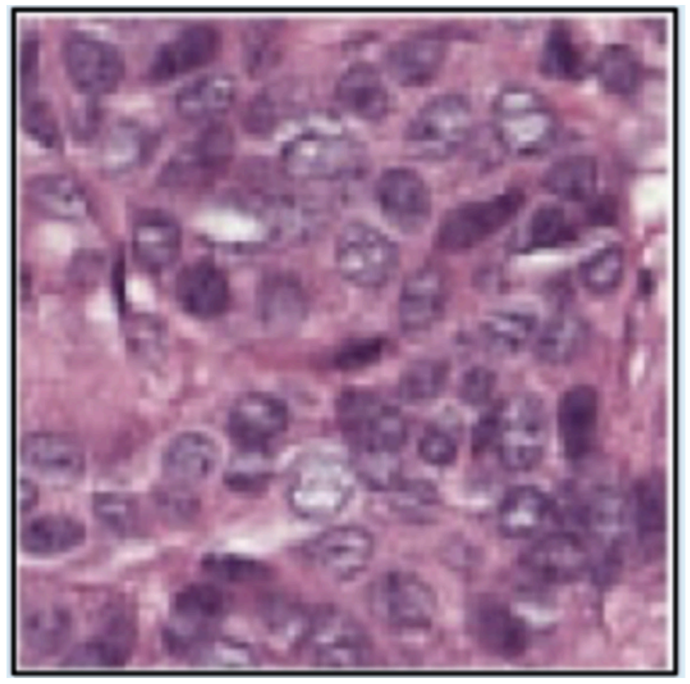
Text classification, generation

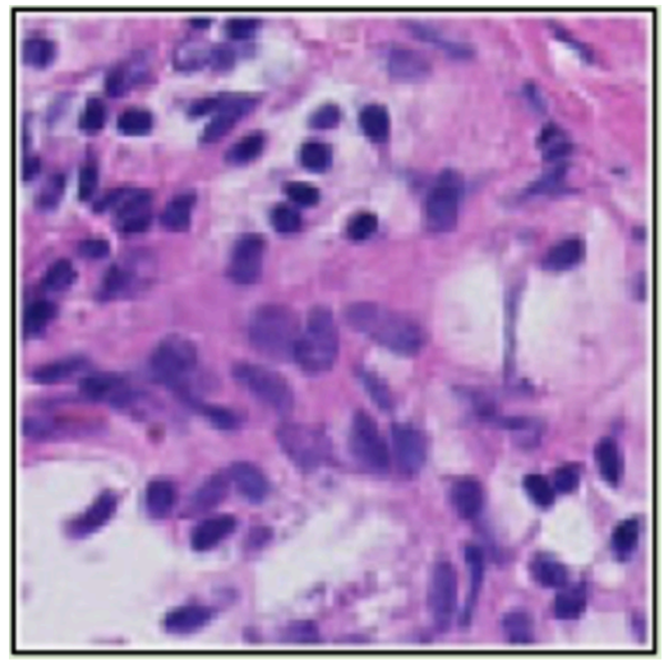
Source corpus Target corpus

—> May have enough coverage of distr.

Tumor detection & classification

Source hospital Target hospital





—> Source probably won't cover target distr!

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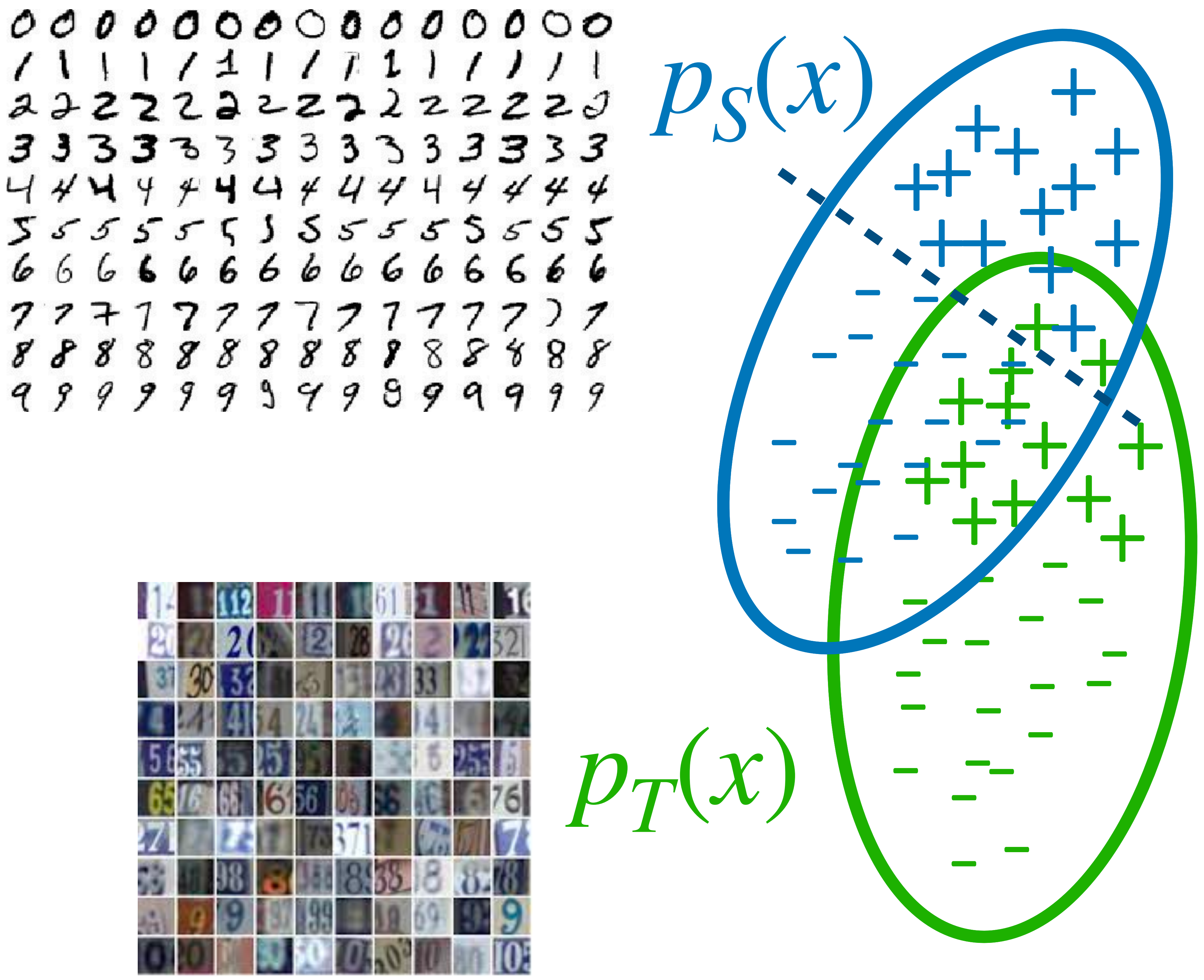
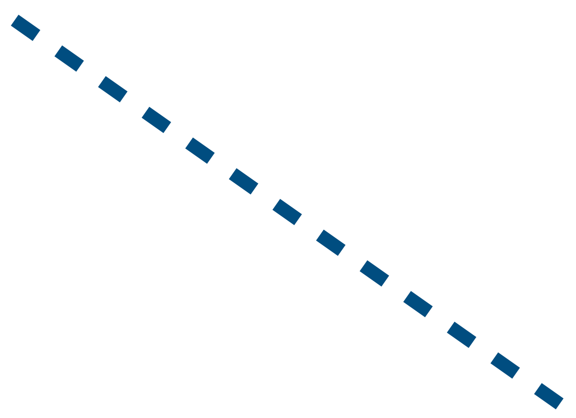
Domain adaptation if support is not shared?



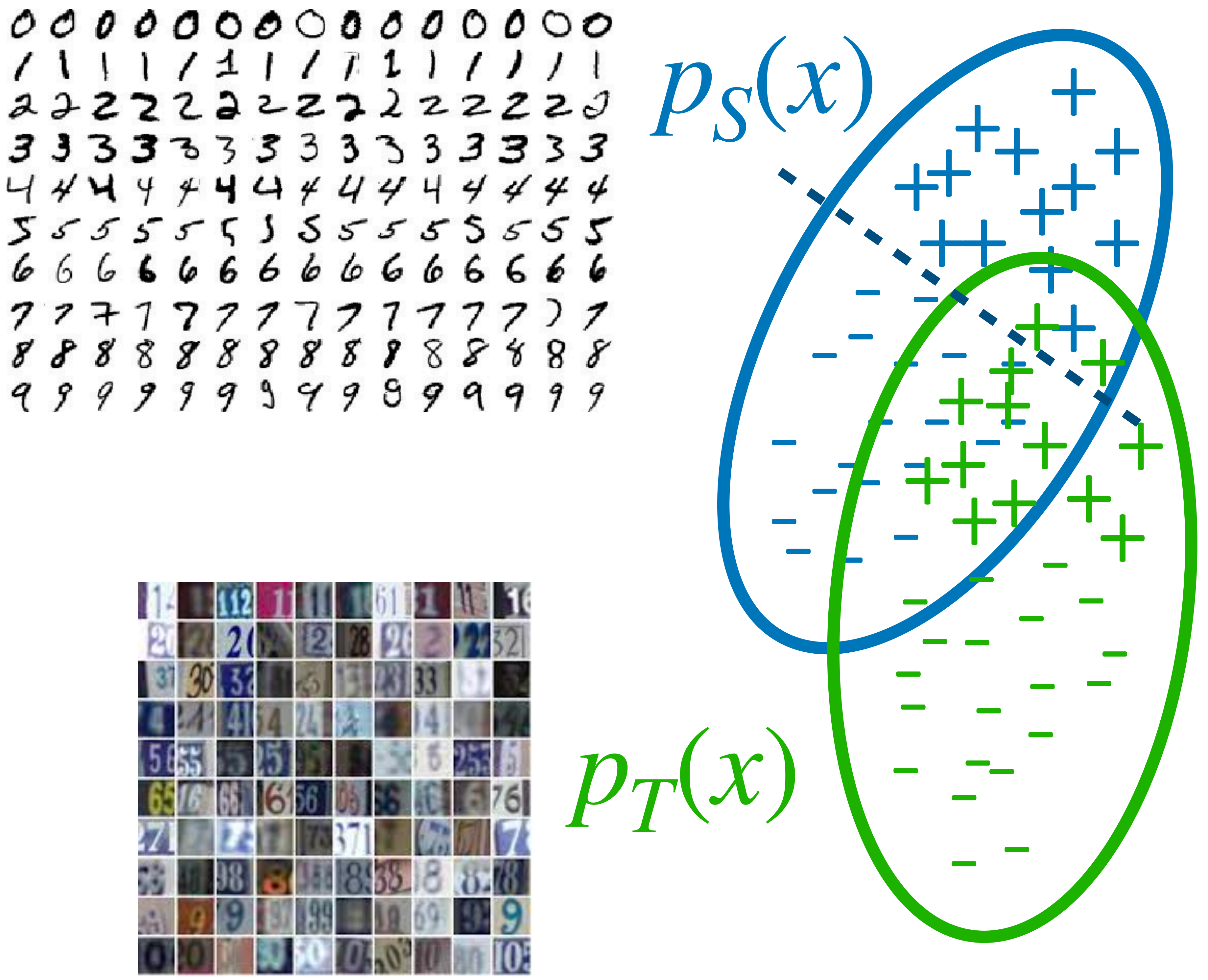
Can we align the features?



Source classifier in ***aligned feature space*** is more accurate in target domain.

How to align the features?

Domain adaptation if support is not shared?



How to align the features?

Source encoder f_{θ_S} Target encoder f_{θ_T}

Need to match features at *population-level*.

i.e. make encoded samples $f_{\theta_S}(x), x \sim p_S(\cdot)$

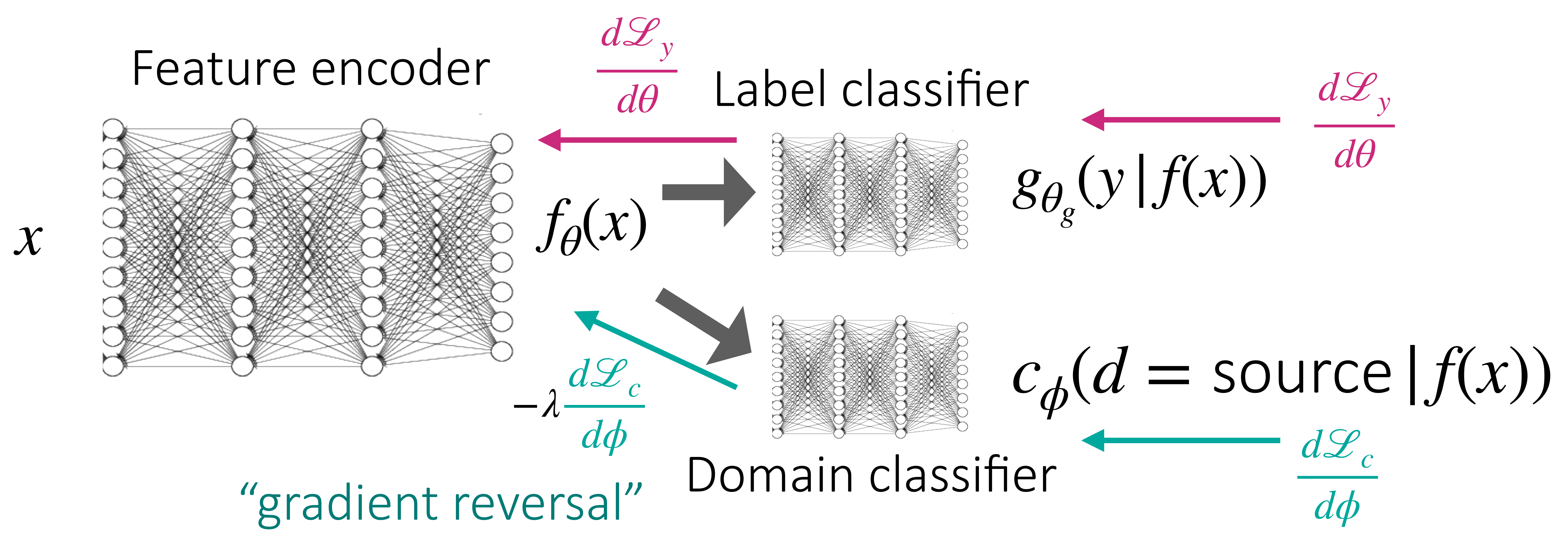
indistinguishable from $f_{\theta_T}(x), x \sim p_T(\cdot)$

Key idea: Try to fool a domain classifier $c(d = \text{source} \mid f(x))$.

If samples are indistinguishable to discriminator, then distributions are the same.

Domain adaptation via feature alignment

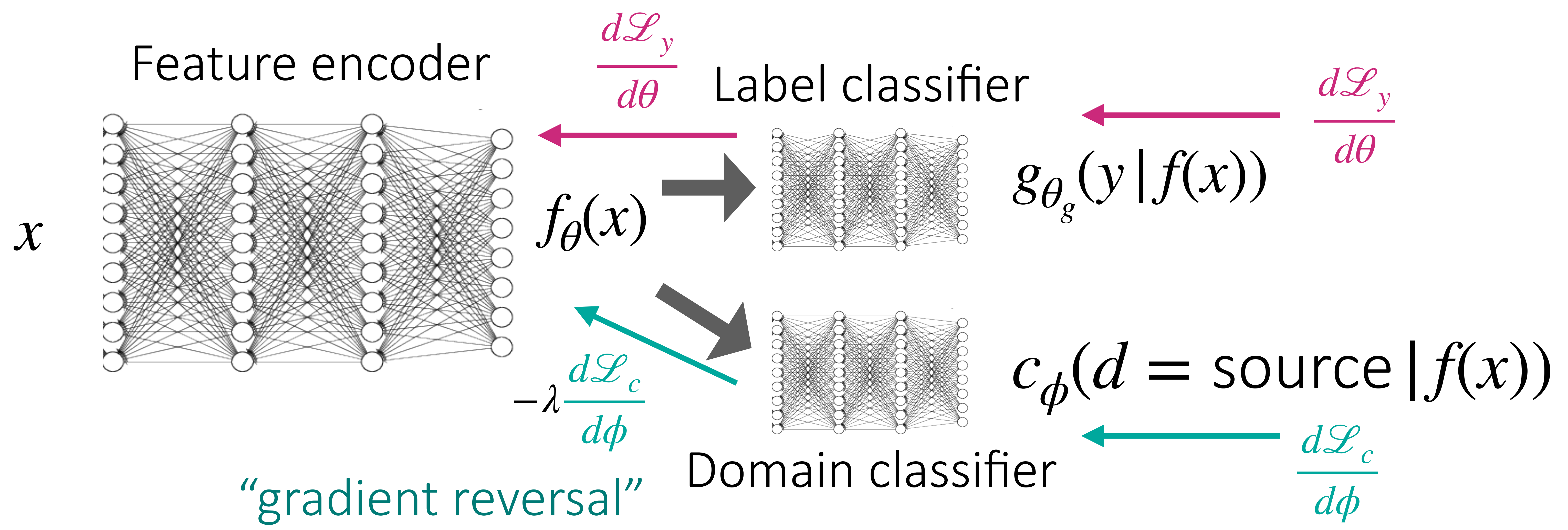
Key idea: Try to fool a domain classifier $c(d = \text{source} \mid f(x))$.



Minimize label prediction error & maximize "domain confusion"

Tzeng et al. Deep Domain Confusion. arXiv '14
Ganin et al. Domain-Adversarial Training of Neural Networks. JMLR '16

Domain adaptation via feature alignment



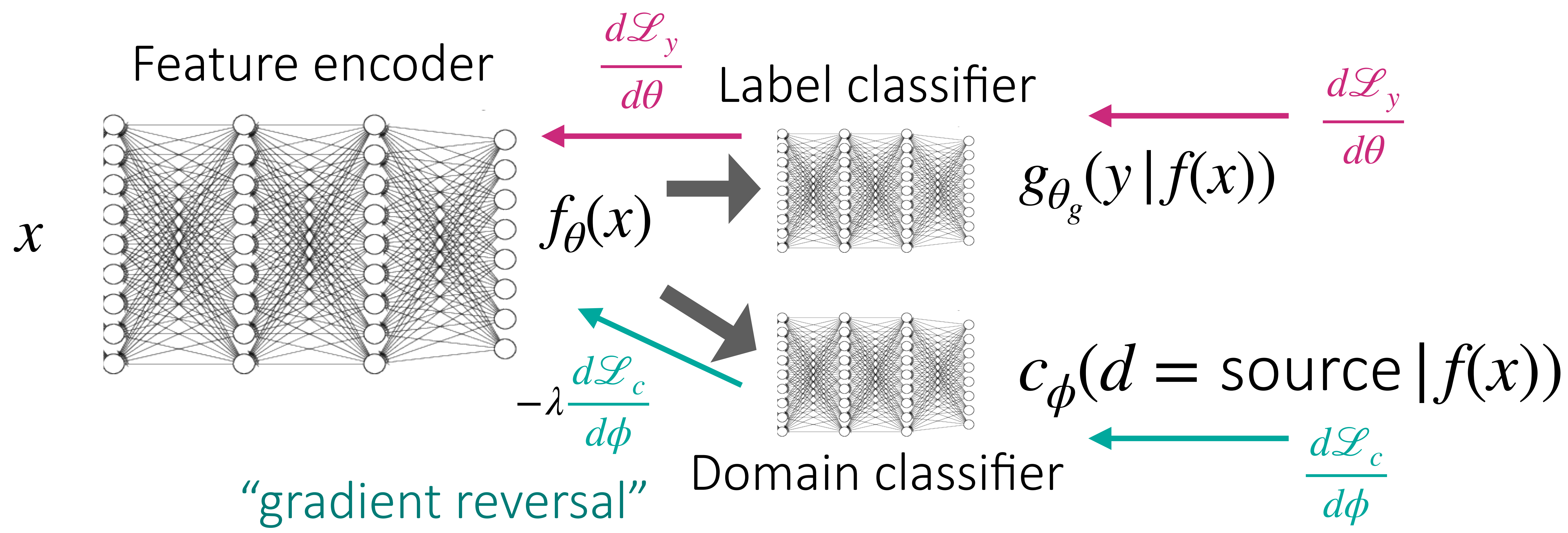
Full algorithm:

1. Randomly initialize encoder(s) f_θ, label classifier g_{θ_g}, domain classifier c_ϕ
2. Update domain classifier: $\min_\phi \mathcal{L}_c = -\mathbb{E}_{x \sim D_S}[\log c_\phi(f(x))] - \mathbb{E}_{x \sim D_T}[1 - \log c_\phi(f(x))]$.
3. Update label classifier & encoder: $\min_{\theta, \theta_g} \mathbb{E}_{(x,y)\sim D_S}[L\left(g_{\theta_g}(f_\theta(x)), y\right)] - \lambda \mathcal{L}_c$
4. Repeat steps 2 & 3.

Tzeng et al. Deep Domain Confusion. arXiv '14

Ganin et al. Domain-Adversarial Training of Neural Networks. JMLR '16

Domain adaptation via feature alignment



Can learn separate source and target encoder

Source encoder f_{θ_S} Target encoder f_{θ_T}

Make encoded samples $f_{\theta_S}(x), x \sim p_S(\cdot)$

indistinguishable from $f_{\theta_T}(x), x \sim p_T(\cdot)$

—> can give model more flexibility

Different forms of domain adversarial training.

Option 1: Maximize domain classifier loss (gradient reversal, same as GANs)

Option 2: Optimize for 50/50 guessing

Tzeng et al. Deep Domain Confusion. arXiv '14

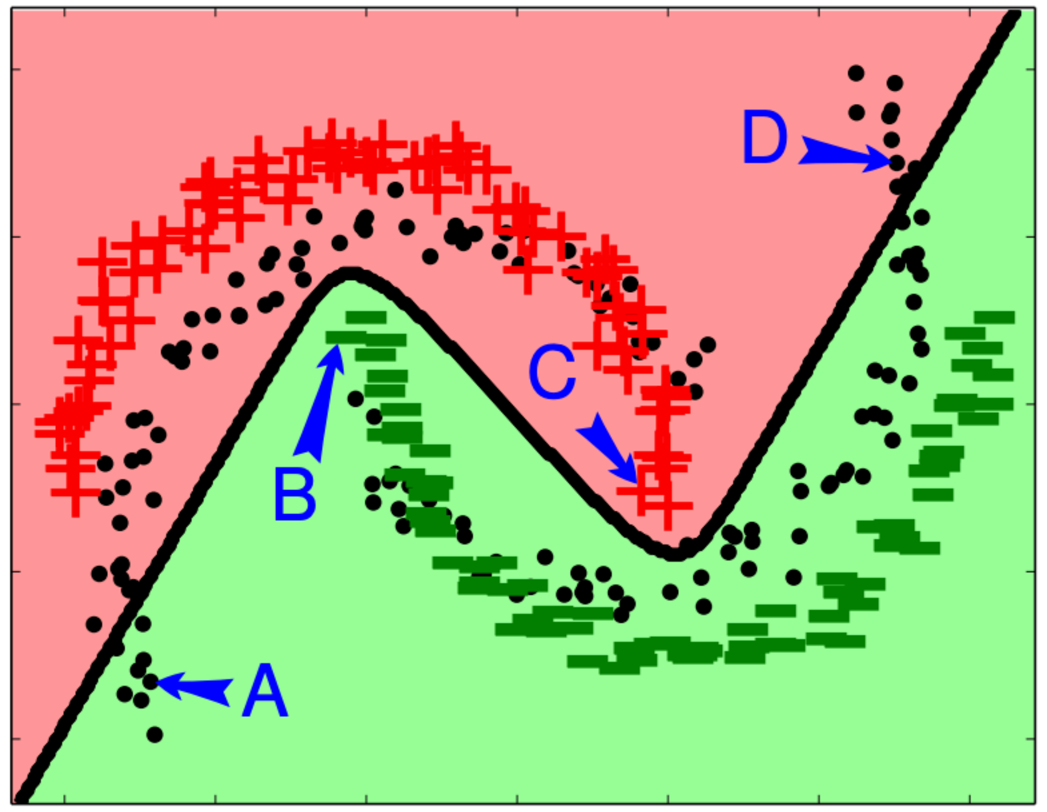
Ganin et al. Domain-Adversarial Training of Neural Networks. JMLR '16

Domain adaptation via feature alignment

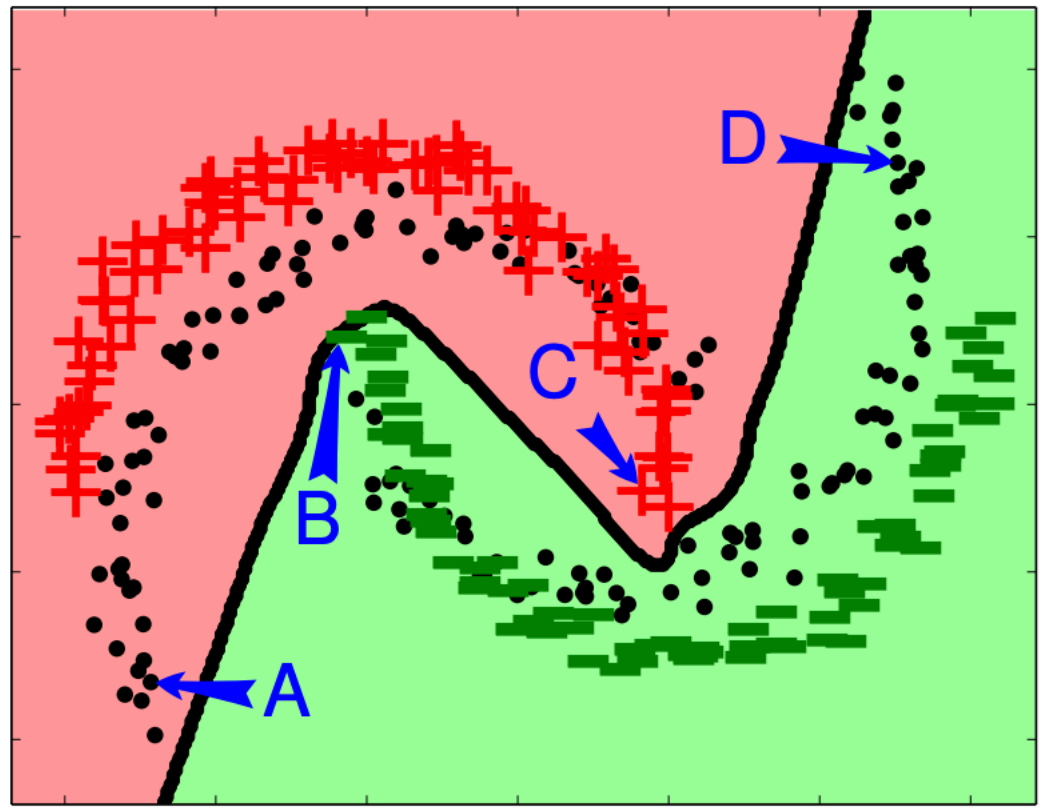
Toy example

source domain: +, —

target domain data: •



standard NN training

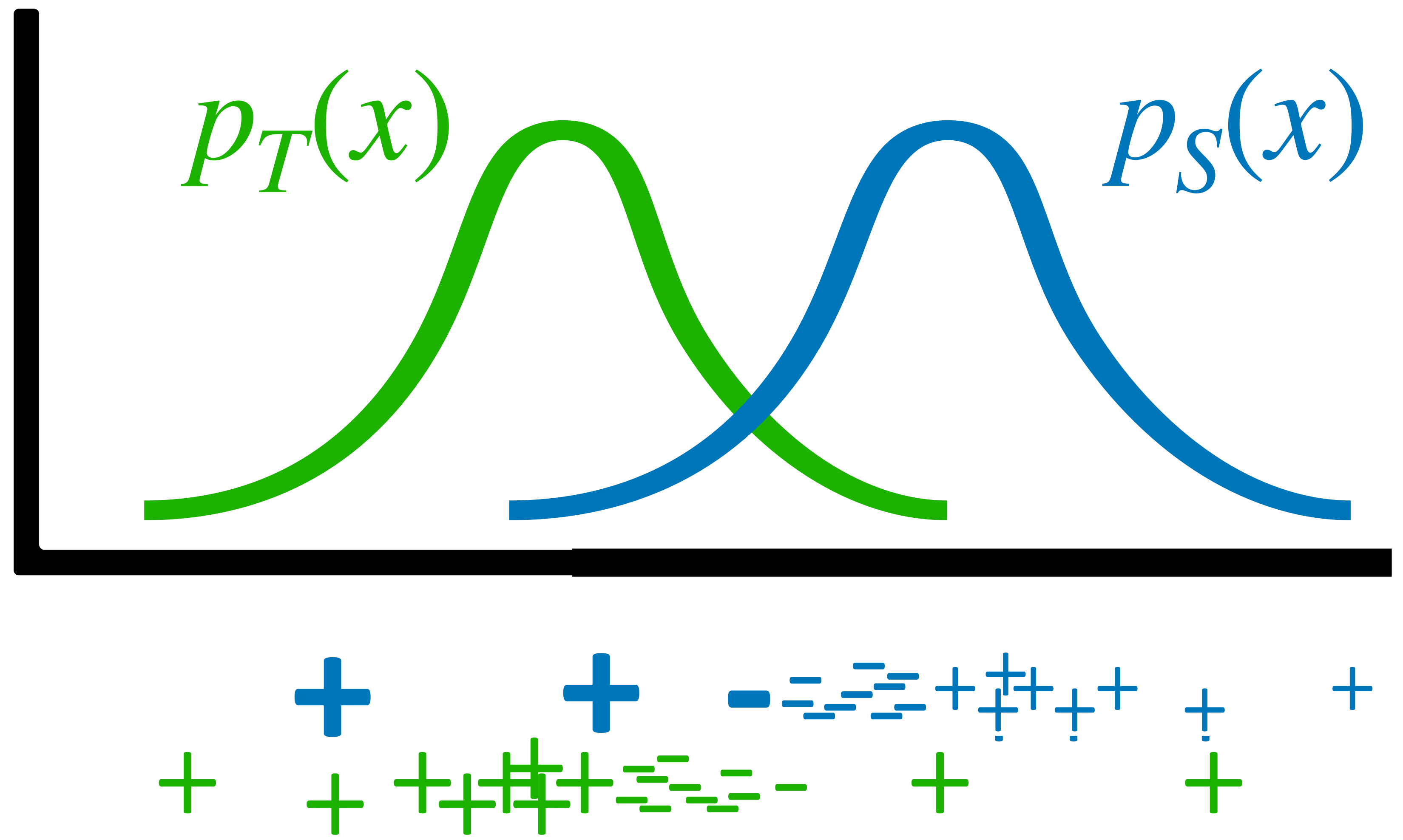


domain adversarial training

Method	Source / Target	MNIST / MNIST-M	Syn Numbers / SVHN	SVHN / MNIST	Syn Signs / GTSRB
Source only		.5225	.8674	.5490	.7900
DANN		**.7666** (52.9%)	**.9109** (79.7%)	**.7385** (42.6%)	**.8865** (46.4%)
Train on target		.9596	.9220	.9942	.9980

Ganin et al. Domain-Adversarial Training of Neural Networks. JMLR '16

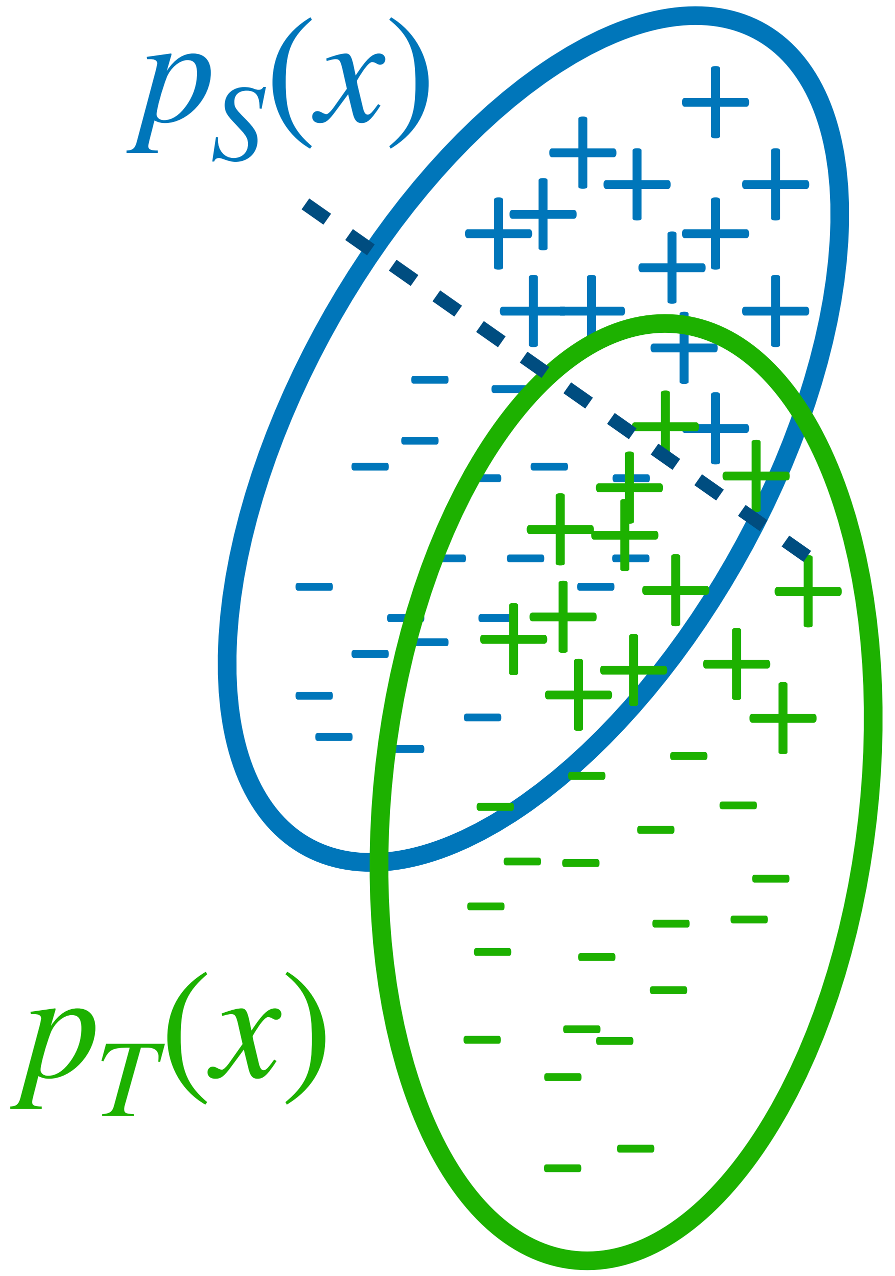
Importance weighting



$$\min_{\theta} \mathbb{E}_{p_S(x,y)}\left[\frac{p_T(x)}{p_S(x)} L(f_\theta(x), y)\right]$$

+ simple, can work well
— requires source distr. to cover target

Feature alignment



+ fairly simple to implement, can work quite well
+ doesn't require source data coverage
— involves adversarial optimization
— requires clear alignment in data

Plan for Today

Domain Adaptation
- Problem statements
- Algorithms
  - Data reweighting
  - Feature alignment
  - **Domain translation**

Goal for by the end of lecture: Understand different domain adaptation methods and when to use one vs. another

What if it is hard to align features?

Idea: translate between domains

i.e. $F : X_S \to X_T$ or $G : X_T \to X_S$

If you could translate source examples to target examples:

1. Translate labeled source dataset to target domain with F.
2. Train predictor on translated dataset.
3. Deploy predictor.

Alternatively, if you could translate from target to source:

1. Train predictor on source dataset.
2. Translate target example to source domain with G.
3. Evaluate predictor on translated example.

Key question: How to translate between domains?

Domain Translation with CycleGAN

Idea: translate between domains

i.e. $F : X_S \to X_T$ or $G : X_T \to X_S$

Key question: How to translate between domains?

Step 1: Train F to generate images from $p_T(x)$

and G to generate images from $p_S(x)$

Using GAN objective: $\mathscr{L}_{\text{GAN}} = \mathbb{E}_{x \sim p_T(\cdot)}[\log D_T(x)] + \mathbb{E}_{x \sim p_S(\cdot)}[1 - \log D_T(F(x))]$

Challenge: The mapping is underconstrained, can be arbitrary.

Can we encourage models to learn a consistent, bijective mapping?

Step 2: Train F and G to be cyclically consistent.

$F(G(x)) \approx x$ and $G(F(x)) \approx x$

Zhu, Park, Isola, Efros. CycleGAN. ICCV 2017

Domain Translation with CycleGAN

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Step 2: Train F and G to be cyclically consistent.

$F(G(x)) \approx x$ and $G(F(x)) \approx x$

i.e. $\mathbb{E}_{x \sim p_S(\cdot)} \|G(F(x)) - x\|_1 + \mathbb{E}_{x \sim p_T(\cdot)} \|F(G(x)) - x\|_1$

Full objective: $\mathscr{L}_{\text{GAN}}(F, D_T) + \mathscr{L}_{\text{GAN}}(G, D_S) + \lambda \mathscr{L}_{\text{cyc}}(F, G)$

Zhu, Park, Isola, Efros. CycleGAN. ICCV 2017

Domain Translation with CycleGAN

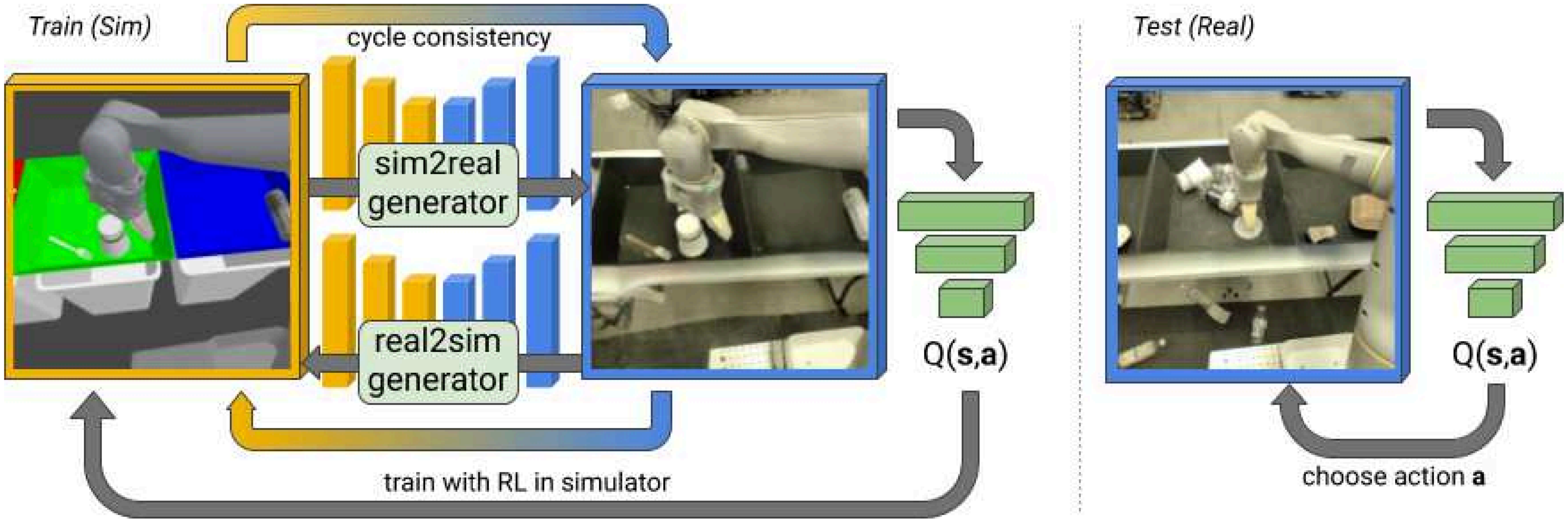
Idea: translate between domains

i.e. $F : X_S \rightarrow X_T$ or $G : X_T \rightarrow X_S$

Zhu, Park, Isola, Efros. CycleGAN. ICCV 2017

CycleGAN for Domain Adaptation

Robotics sim2real policy adaptation



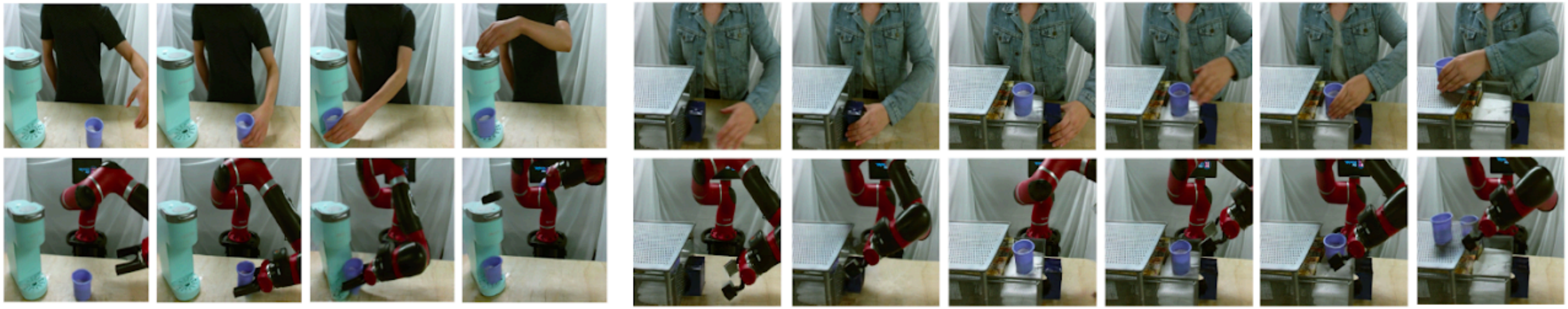
Simulation-to-Real Model	Robot 1 Grasp Success
Sim-Only [19]	21%
Randomized Sim [19]	37%
GAN	29%
CycleGAN	61%
GraspGAN	63%
RL-CycleGAN	**70%**

Rao, Harris, Irpan, Levine, Ibarz, Khansari. RL-CycleGAN. CVPR 2020

CycleGAN for Domain Adaptation

Human-robot domain adaptation

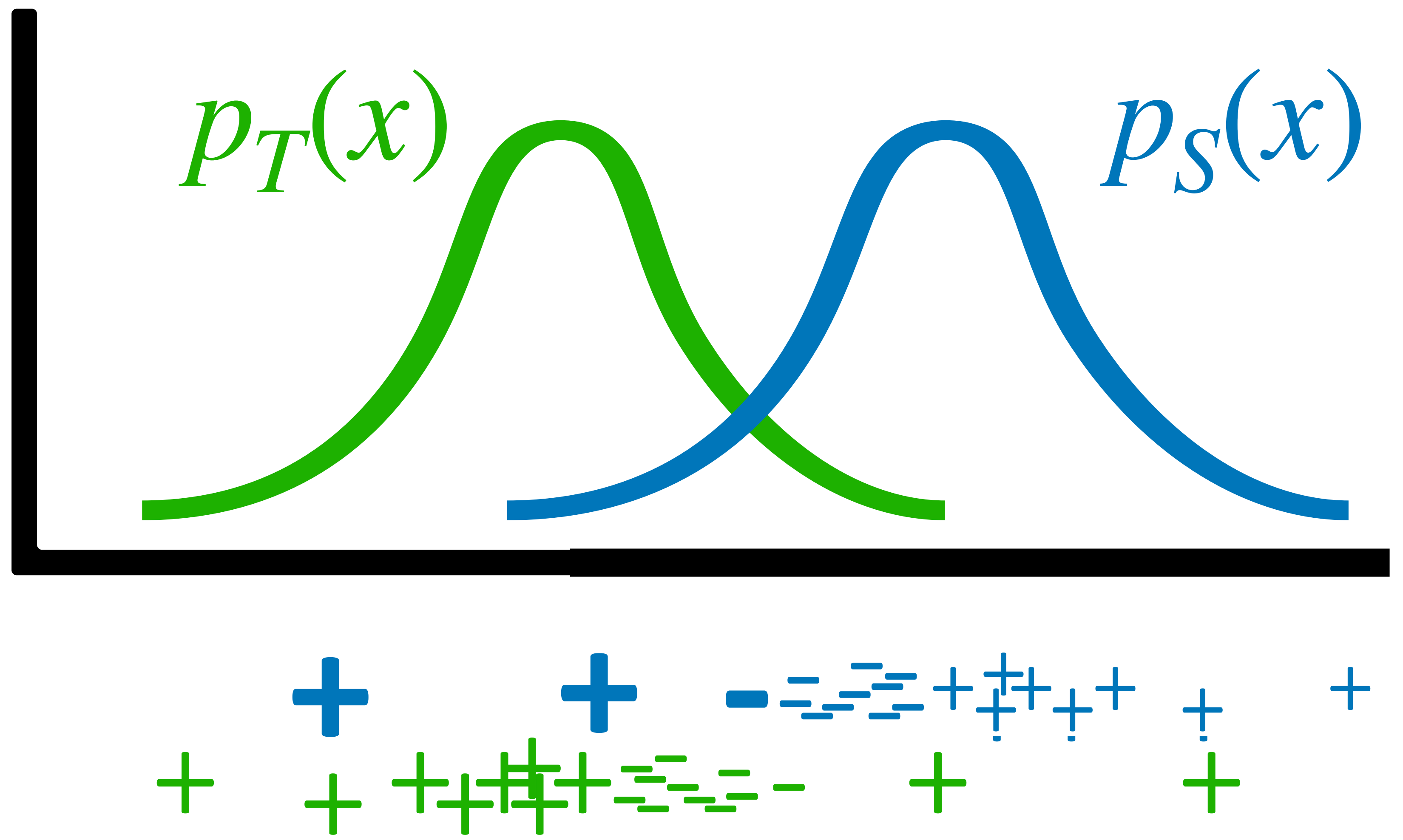
Input human images



Generated images in robot domain

Smith, Dhawan, Zhang, Abbeel, Levine. RSS 2020

Importance weighting

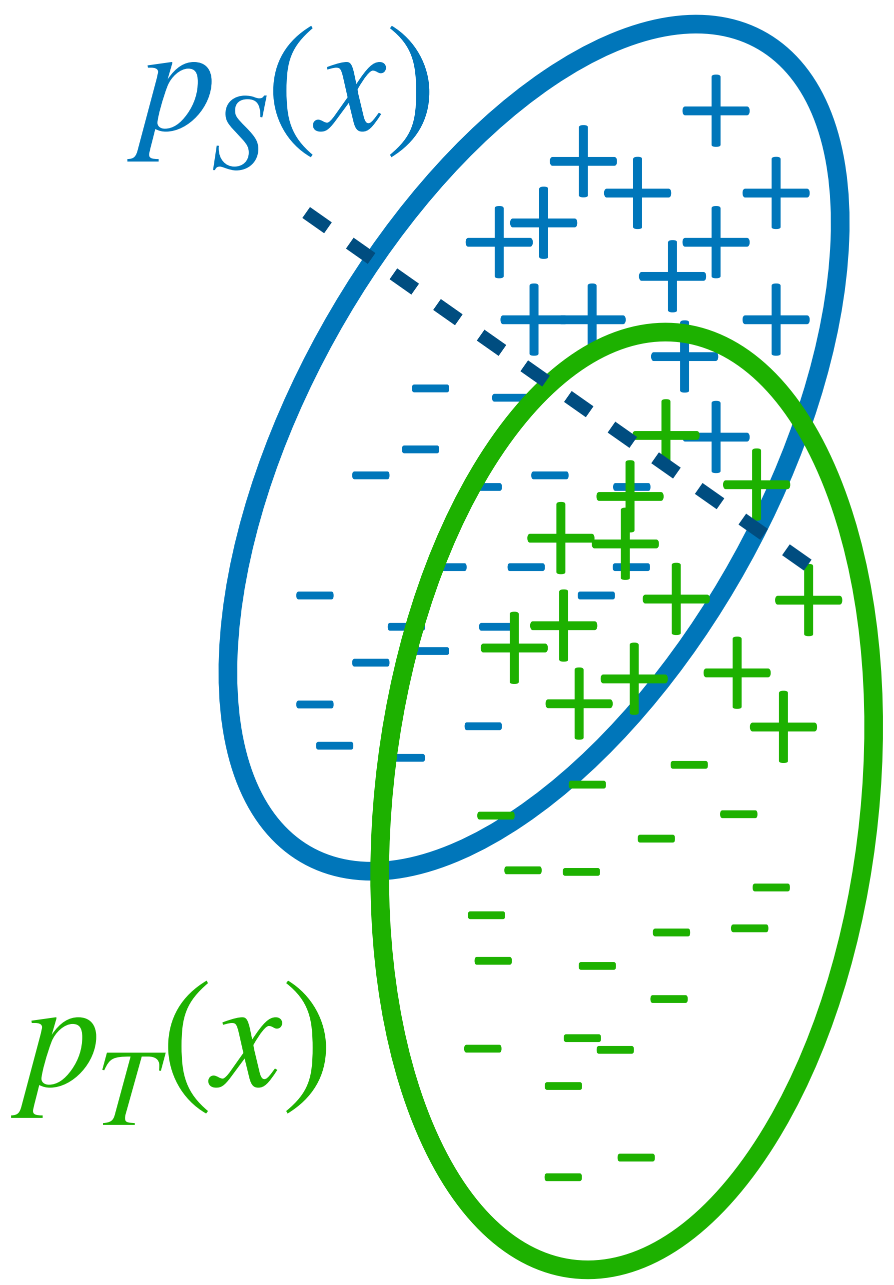


$$\min_\theta \mathbb{E}_{p_S(x,y)}\left[\frac{p_T(x)}{p_S(x)} L(f_\theta(x), y)\right]$$

\+ simple, can work well

— requires source distr. to cover target

Feature alignment



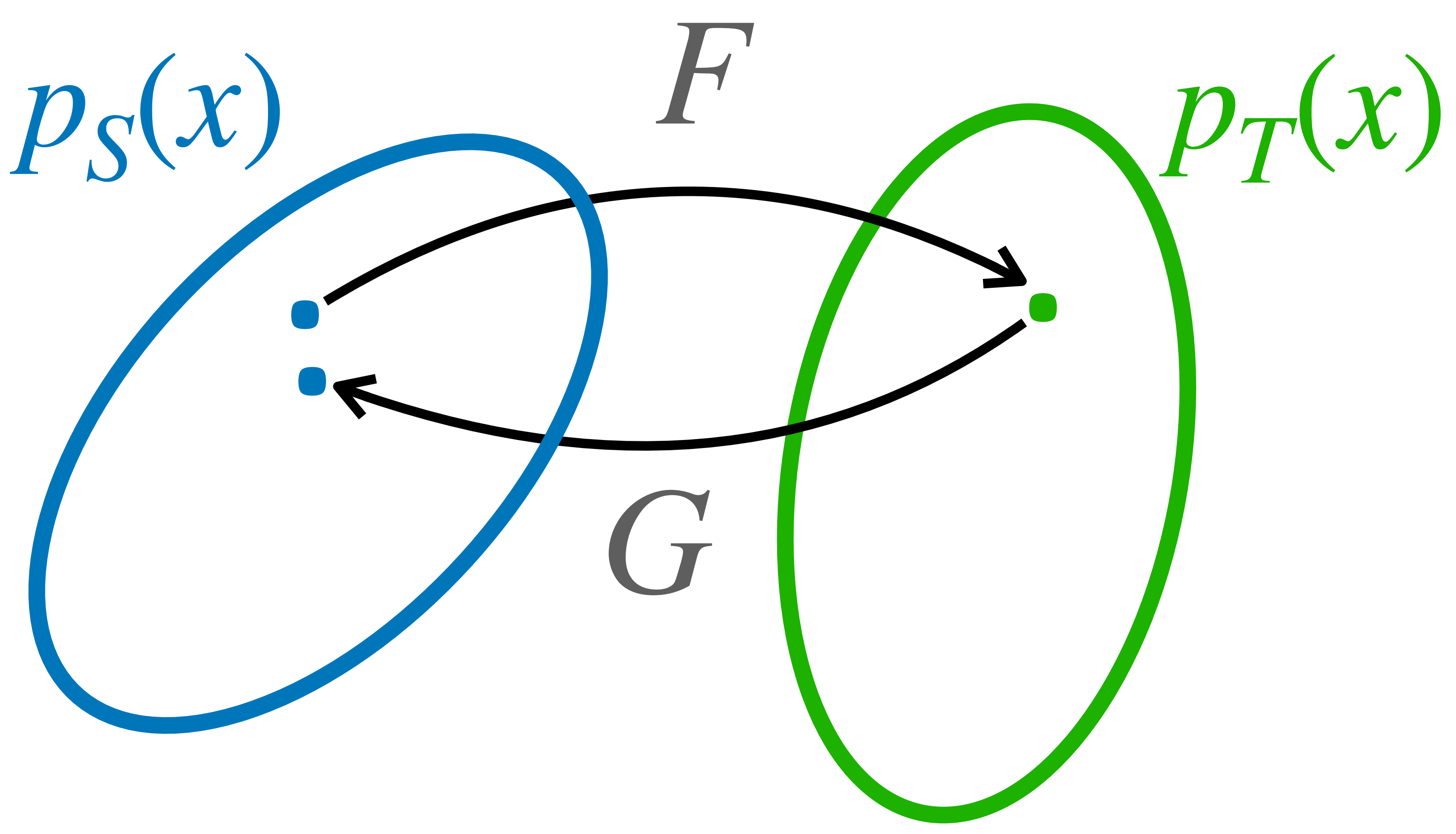
\+ fairly simple to implement, can work quite well

\+ doesn't require source coverage

— involves adversarial optimization

— requires clear alignment in data

Domain translation



\+ conceptually neat, can work quite well

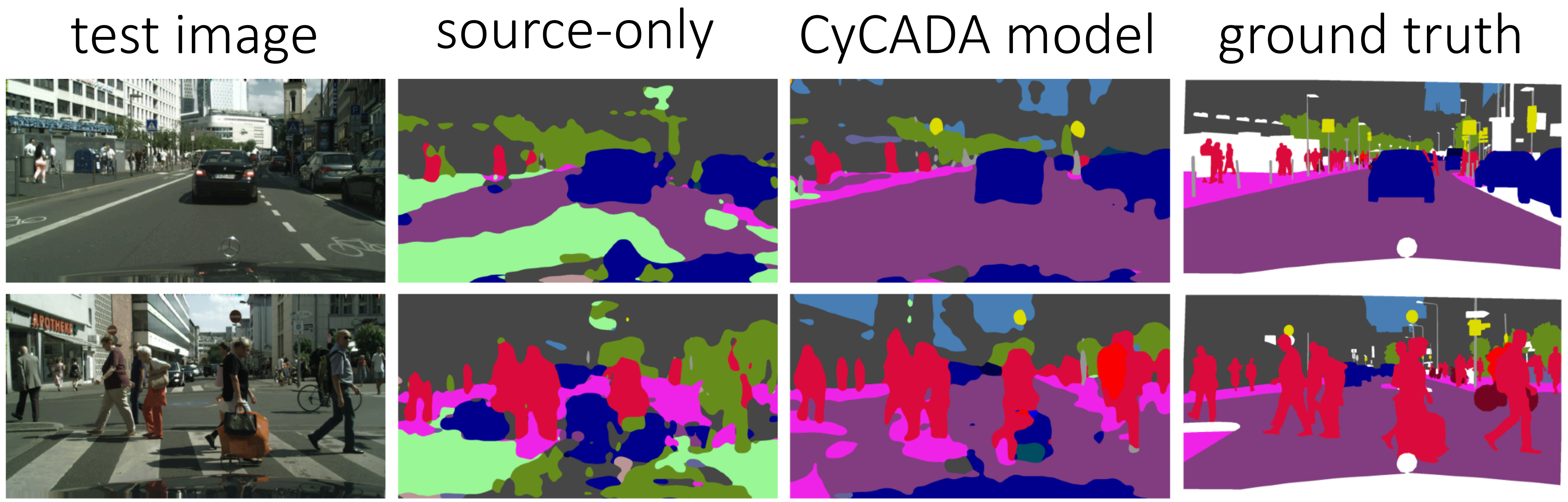
\+ interpretable (easier to debug, cool pictures)

-- involves generative modeling & adversarial optimization

-- requires clear alignment in data

CycleGAN & DANN for Domain Adaptation

CyCADA: incorporates both cycle consistency & domain adversarial training



Character recognition

Model	USPS → MNIST	SVHN → MNIST
Source only	69.6 ± 3.8	67.1 ± 0.6
DANN (Ganin et al., 2016)	-	73.6
DTN (Taigman et al., 2017a)	-	84.4
CoGAN (Liu & Tuzel, 2016b)	89.1	-
ADDA (Tzeng et al., 2017)	90.1 ± 0.8	76.0 ± 1.8
PixelDA (Bousmalis et al., 2017b)	-	-
UNIT (Liu et al., 2017)	93.6	**90.5***
CyCADA (Ours)	**96.5 ± 0.1**	**90.4 ± 0.4**
Target Fully Supervised	99.2 ± 0.1	99.2 ±0.1

GTA5 → Cityscapes

	Architecture	road	sidewalk	building	wall	fence	pole	traffic light	traffic sign	vegetation	terrain	sky	person	rider	car	truck	bus	train	motorbike	bicycle	**mIoU**	**fwIoU**	**Pixel acc.**
Source only	A	26.0	14.9	65.1	5.5	12.9	8.9	6.0	2.5	70.0	2.9	47.0	24.5	0.0	40.0	12.1	1.5	0.0	0.0	0.0	17.9	41.9	54.0
FCN-wld (Hoffman et al., 2016)	A	70.4	32.4	62.1	14.9	5.4	10.9	14.2	2.7	79.2	21.3	64.6	44.1	4.2	70.4	8.0	7.3	0.0	3.5	0.0	27.1	-	-
CDA (Zhang et al., 2017b)	A	26.4	22.0	74.7	6.0	11.9	8.4	16.3	11.1	75.7	13.3	**66.5**	38.0	**9.3**	55.2	**18.8**	18.9	0.0	**16.8**	**14.6**	27.8	-	-
FCTN (Zhang et al., 2017a)	A	72.2	28.4	74.9	18.3	10.8	**24.0**	**25.3**	17.9	80.1	**36.7**	61.1	44.7	0.0	74.5	8.9	1.5	0.0	0.0	0.0	30.5	-	-
CyCADA (Ours)	A	**85.2**	**37.2**	**76.5**	**21.8**	**15.0**	23.8	22.9	**21.5**	**80.5**	31.3	60.7	**50.5**	9.0	**76.9**	17.1	**28.2**	**4.5**	9.8	0.0	**35.4**	**73.8**	**83.6**
Oracle - Target Supervised	A	96.4	74.5	87.1	35.3	37.8	36.4	46.9	60.1	89.0	54.3	89.8	65.6	35.9	89.4	38.6	64.1	38.6	40.5	65.1	60.3	87.6	93.1
Source only	B	42.7	26.3	51.7	5.5	6.8	13.8	23.6	6.9	75.5	11.5	36.8	49.3	0.9	46.7	3.4	5.0	0.0	5.0	1.4	21.7	47.4	62.5
CyCADA (Ours)	B	**79.1**	**33.1**	**77.9**	**23.4**	**17.3**	**32.1**	**33.3**	31.8	**81.5**	**26.7**	**69.0**	**62.8**	14.7	**74.5**	**20.9**	**25.6**	**6.9**	**18.8**	20.4	**39.5**	**72.4**	**82.3**
Oracle - Target Supervised	B	97.3	79.8	88.6	32.5	48.2	56.3	63.6	73.3	89.0	58.9	93.0	78.2	55.2	92.2	45.0	67.3	39.6	49.9	73.6	67.4	89.6	94.3

Table 4: Adaptation between GTA5 and Cityscapes, showing IoU for each class and mean IoU, freq-weighted IoU and pixel accuracy. CyCADA significantly outperforms baselines, nearly closing the gap to the target-trained oracle on pixel accuracy.

Hoffman et al. ICML 2018

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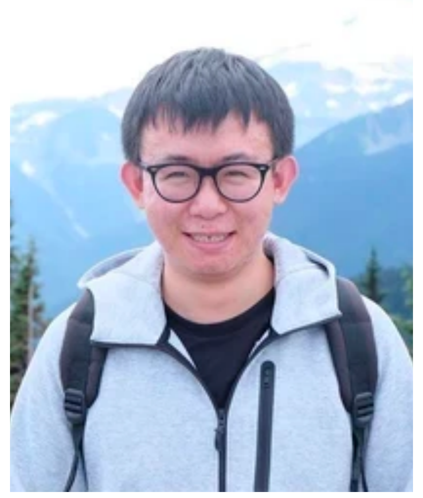
Azure: If you are close to running out of credits,
proactively request more in private Ed post.

Next time: Domain generalization



by Huaxiu Yao