Vision & Learning
Joint Laboratory

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Dipartimento di Ingegneria e Scienza dell'Informazione

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Introduction to Deep Domain Adaptation for Visual Recognition

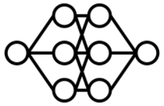
Stéphane Lathuilière

Outline

- Why we need domain adaptation?
- Domain shift
- Common Domain Adaptation scenarios
- Benchmarks
- History
- Recent Methods (Deep learning)
  - Image translation methods
  - Feature alignment/confusion
  - Batchnorm-based

Parks and Birds

PARCO
NATURA
VIVA
Nature, all ways.



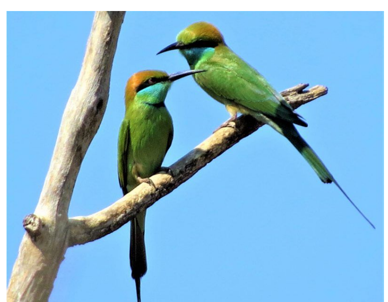
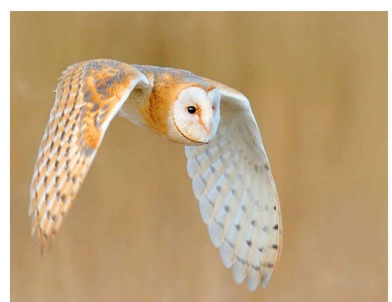
Is there a bird?





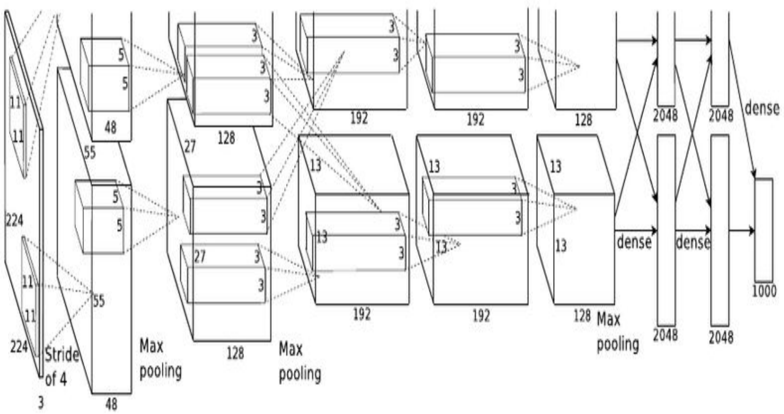


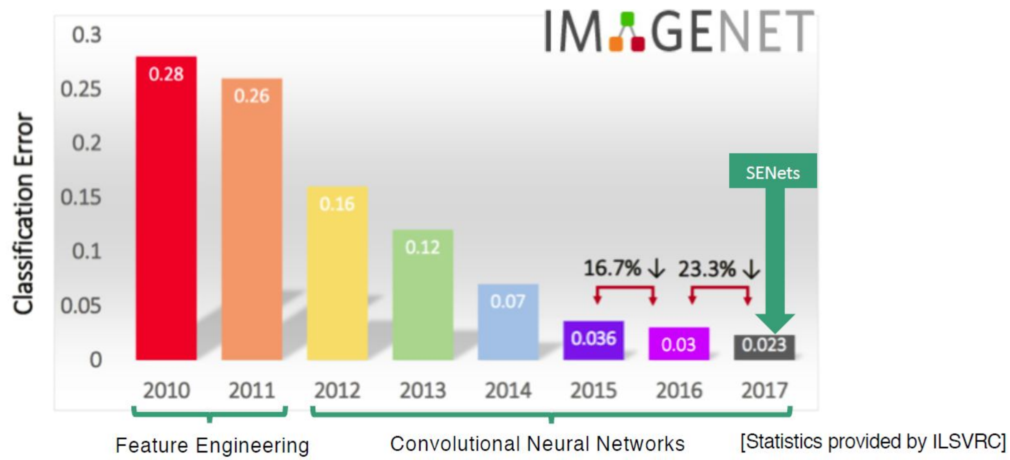



Why are we so good?

Deep Learning Revolution



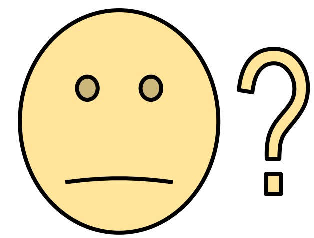


Krizhevsky, A., Sutskever, I. & Hinton, G. E. Imagenet Classification with Deep Convolutional Neural Networks. *NIPS*, 2012.

…back to birds

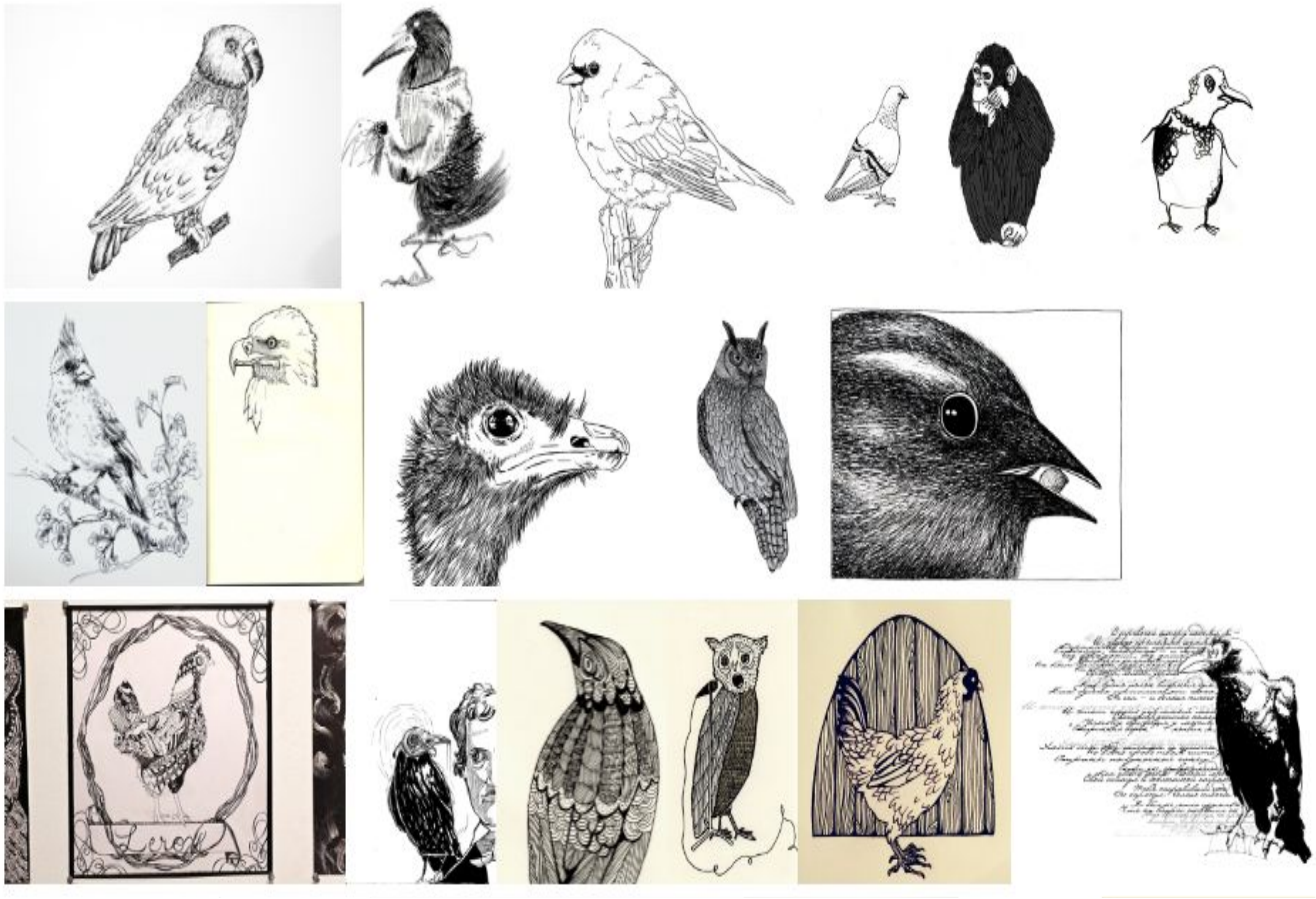
Training on:

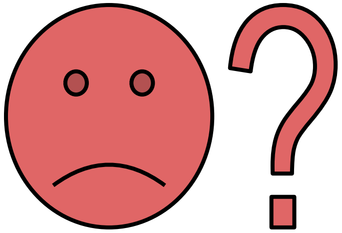
Is there a bird?



https://bam-dataset.org/

Is there a bird?





https://bam-dataset.org/

Domain Shift: why do we care about?

Appearance changes due to seasonal and time changes.

Z. Chen et al., "Deep Learning Features at Scale for Visual Place Recognition". ICRA 2017.

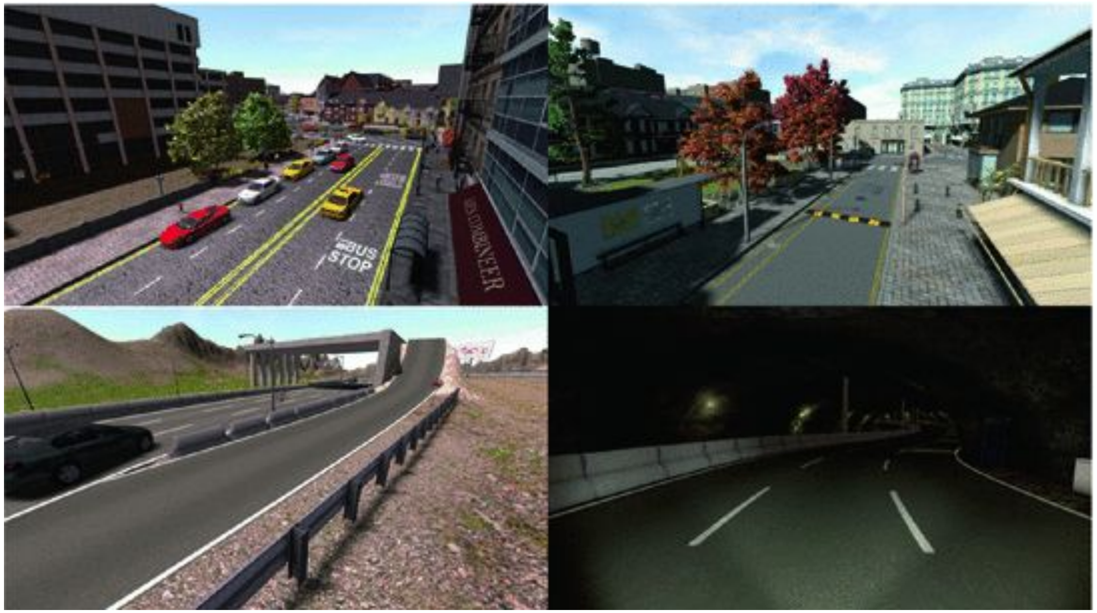
Domain Shift: why do we care about?

Appearance changes due to different sensors.

S. Hwang et al., "Multispectral Pedestrian Detection: Benchmark Dataset and Baseline", CVPR, 2015.

Domain Shift: why do we care about?

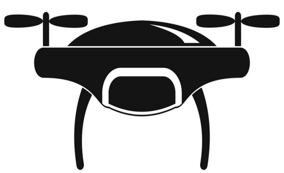
Use of synthetic data



http://synthia-dataset.net/

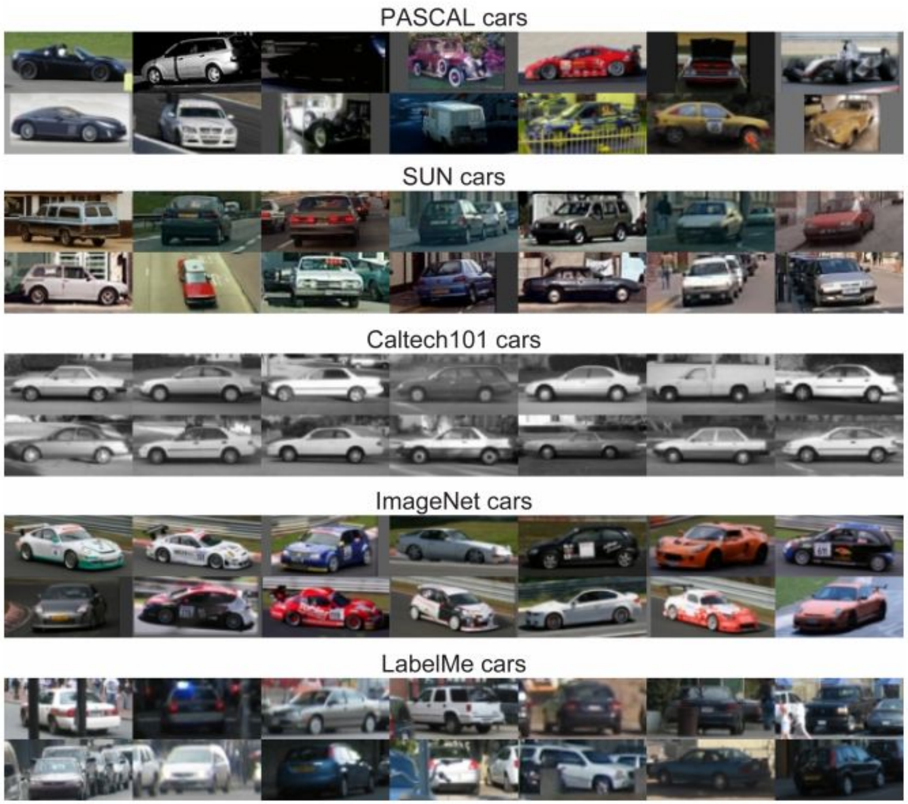
Domain Shift: why do we care about?

Overcoming costly/unfeasible data collection



https://www.zdnet.com/article/robots-to-the-rescue-searching-for-survivors-checking-on-structural-damage-in-japan/

Domain shift and dataset bias



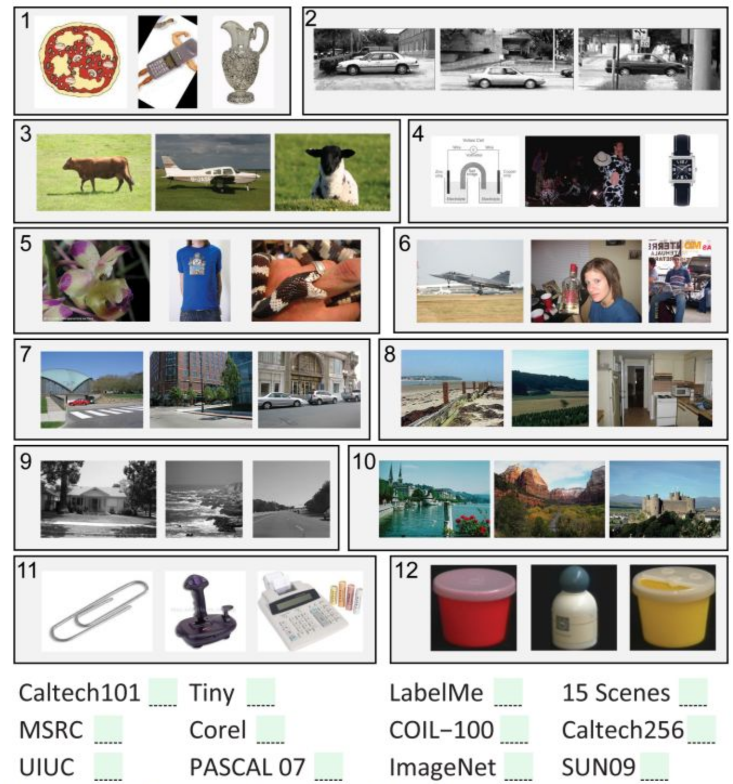


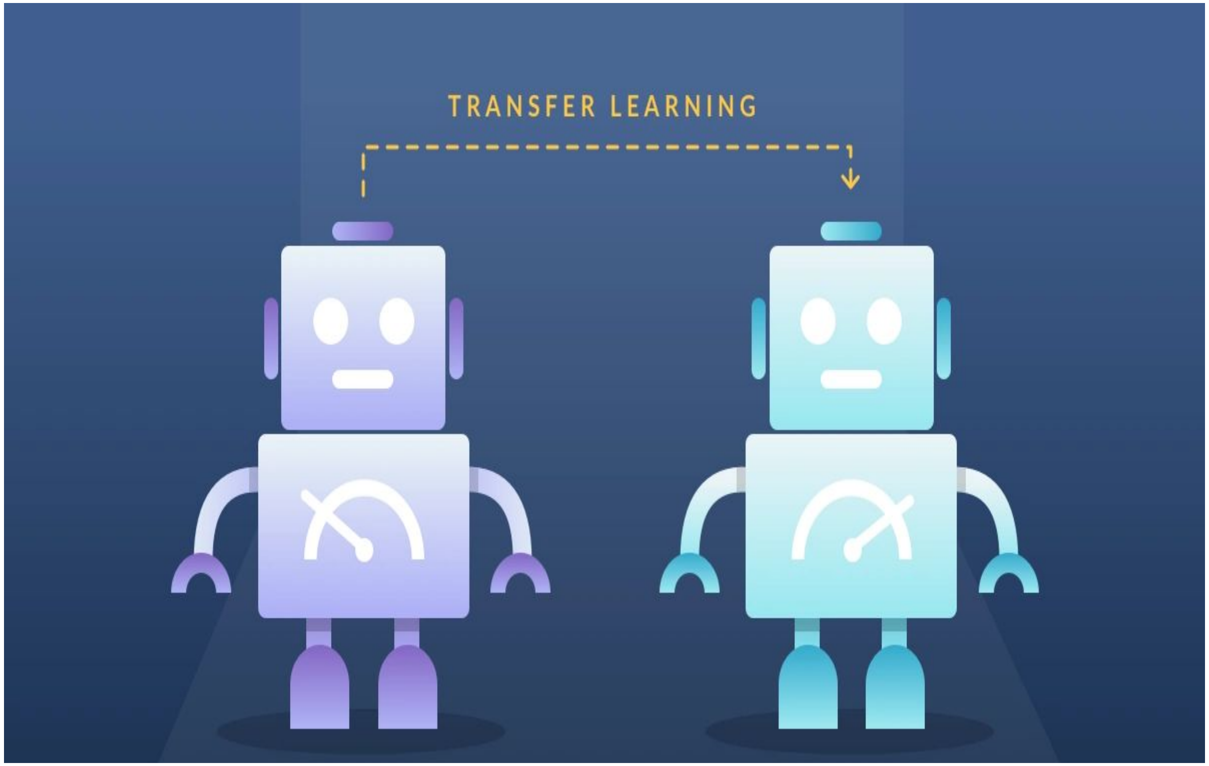
Figure 1. Name That Dataset: Given three images from twelve popular object recognition datasets, can you match the images with the dataset? (answer key below)

Torralba and Efros .,"Unbiased look at dataset bias, CVPR, 2011.

How to solve this problem?

Transferring Knowledge

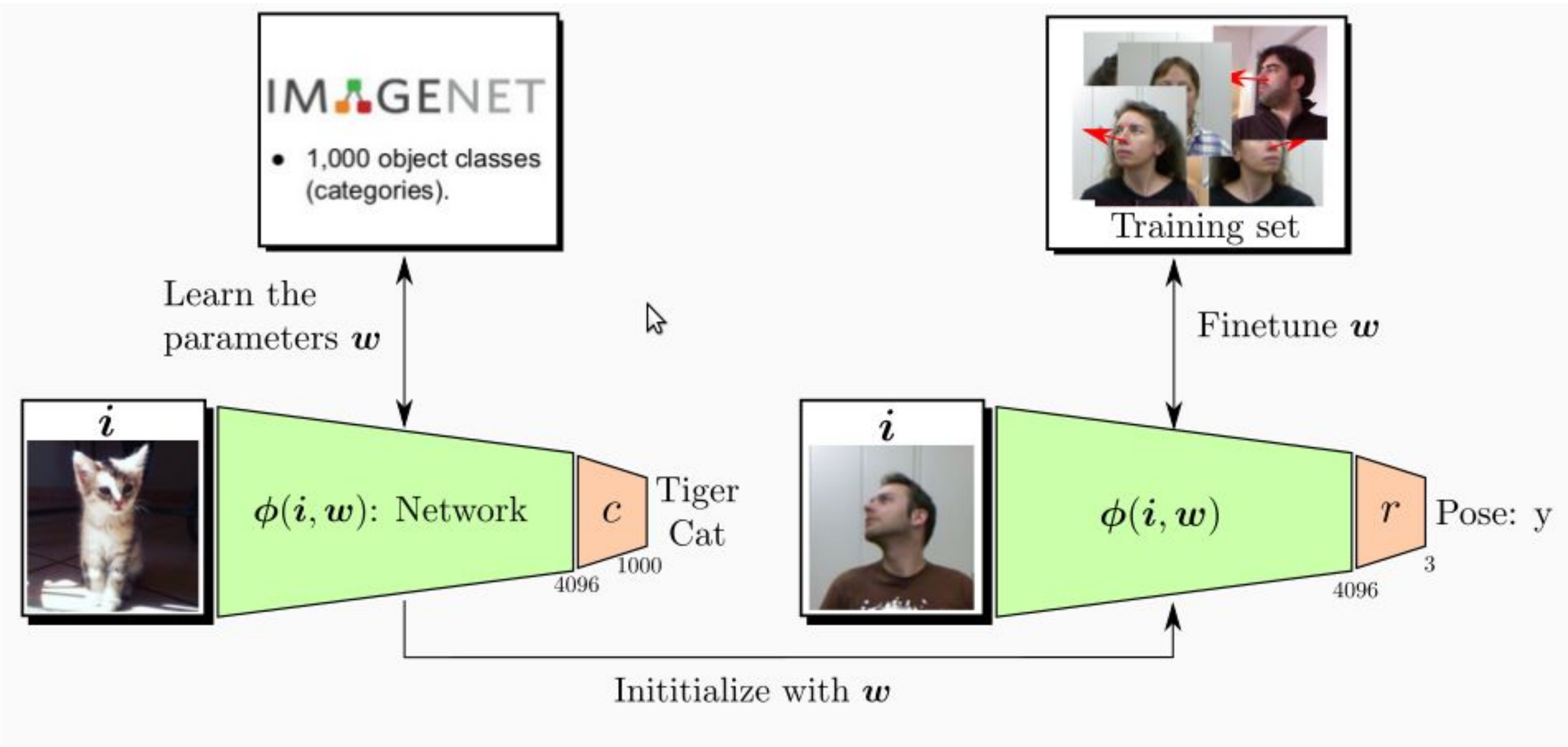
Exploit transfer learning techniques.



Source image: https://www.datacamp.com/community/tutorials/transfer-learning

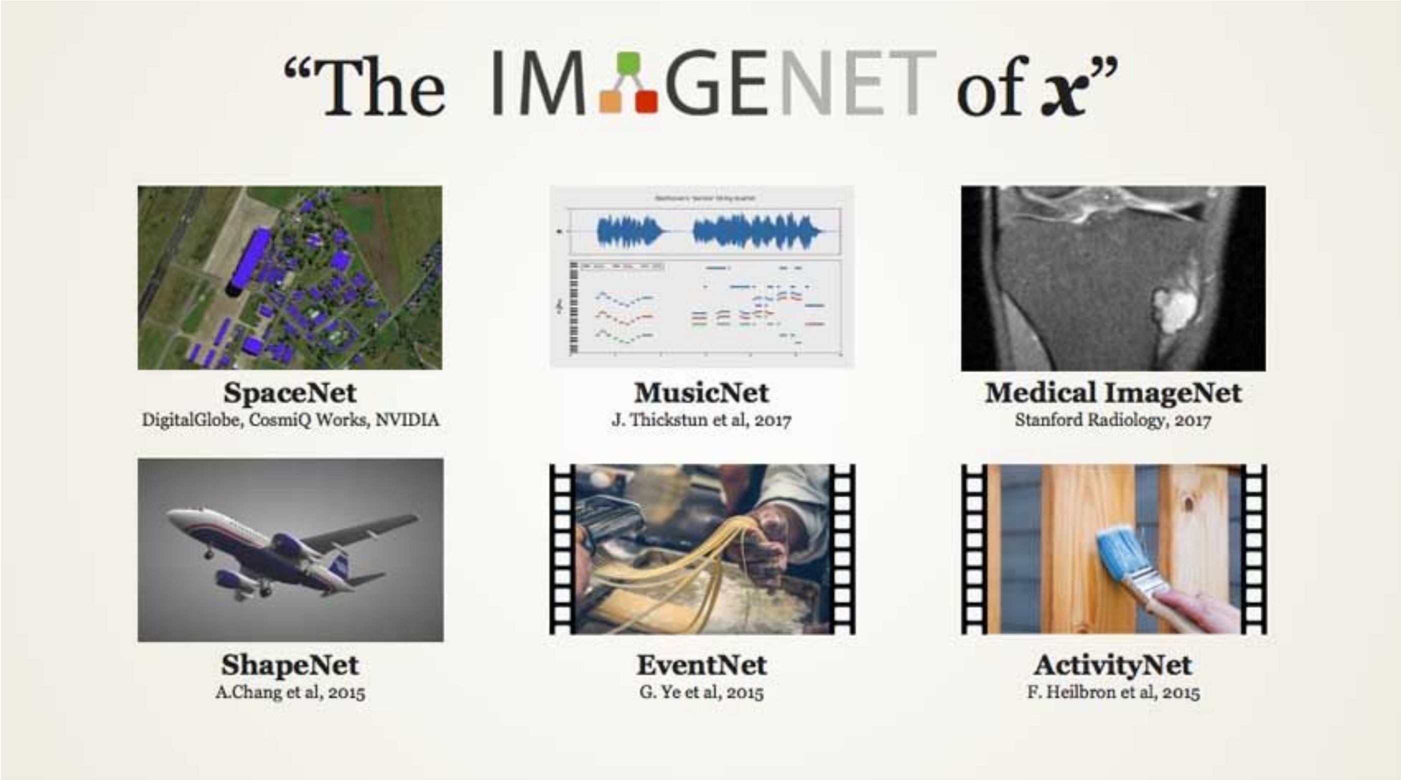
Solution 1: Transfer learning

More general than DA



Data annotation

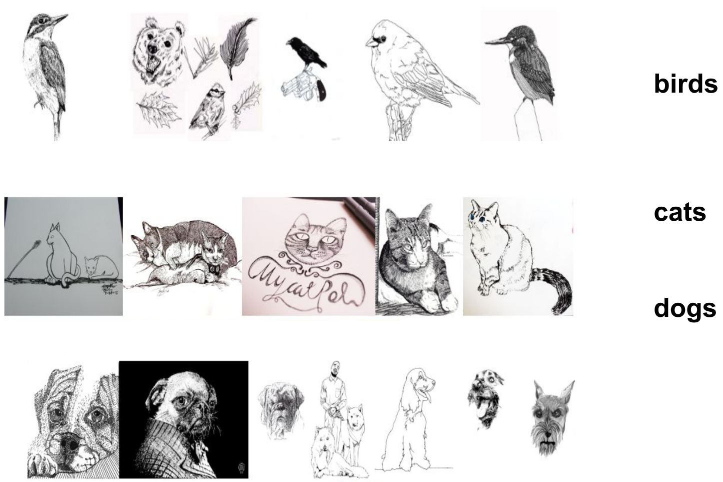
- Data collection is costly
- We cannot annotate everything.



Slide credit: [Fei-Fei Li]

Solution 1: Data annotation

Annotate data in the **target scenario** and fine-tune....



Data annotation

Solution 2

Domain Adaptation!

A bit of notation

$\mathcal{X}$ Feature space 

$\mathcal{Y}$ Output space {0,1,2,3,4,5,6,7,8,9}

$X \in \mathcal{X}$ Input variable 

$Y \in \mathcal{Y}$ Output variable 3

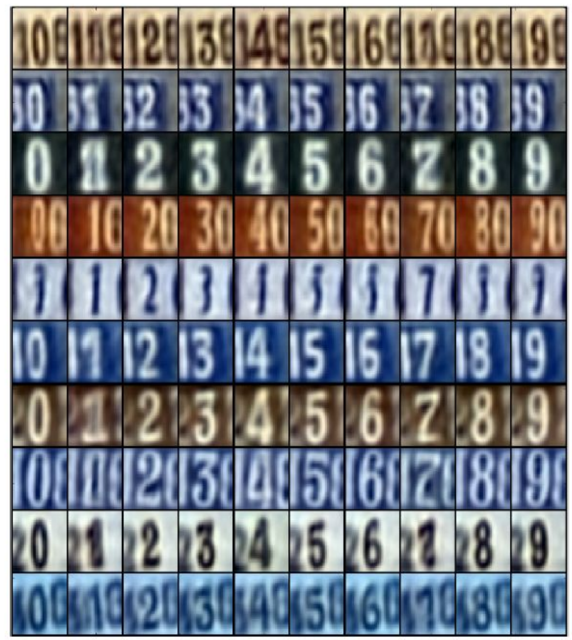
$D = \{\mathcal{X}, P(X)\}$ Domain

$T = \{\mathcal{Y}, P(Y|X)\}$ Task

F. Orabona & T. Tommasi. Tutorial on Domain Adaptation and Transfer Learning. In ECCV 2014.

Domain adaptation

MNIST



SVHN

The Domain Adaptation (DA) Problem

Source Domain

$$D^s = \{\mathcal{X}^s, P(X^s)\}$$

$$T^s = \{\mathcal{Y}^s, P(Y^s|X^s)\}$$

Target Domain

$$D^t = \{\mathcal{X}^t, P(X^t)\}$$

$$T^t = \{\mathcal{Y}^t, P(Y^t|X^t)\}$$

DA problem

$$D^s \neq D^t$$

$$T^s = T^t$$

F. Orabona & T. Tommasi. Tutorial on Domain Adaptation and Transfer Learning. In ECCV 2014.

The Domain Adaptation (DA) Problem

Source Domain

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DA problem

$$\mathcal{X}^s \neq \mathcal{X}^t$$

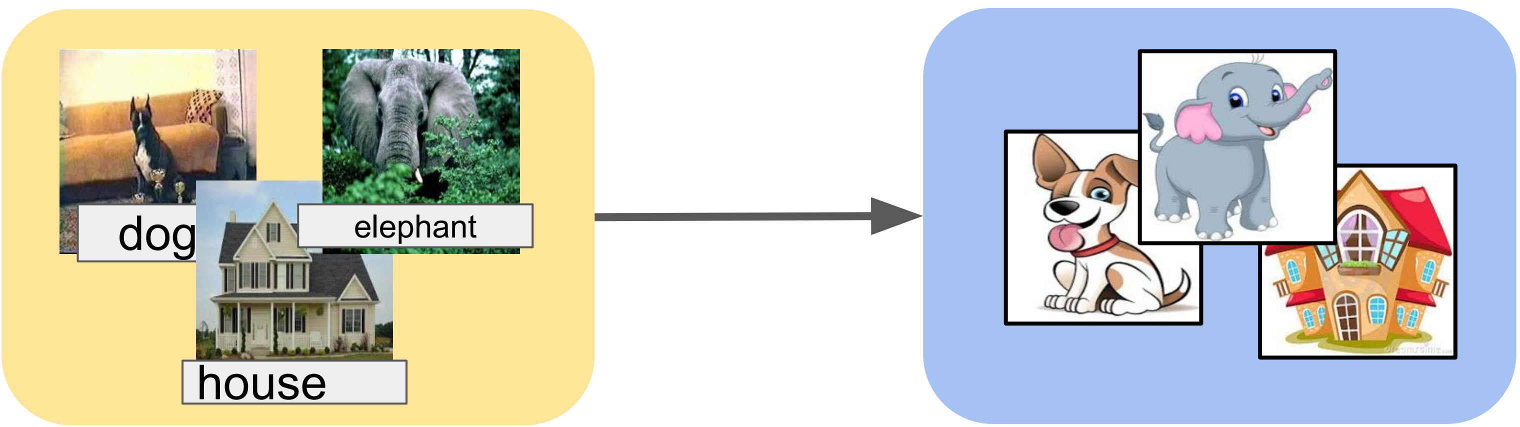
$$P(X^s) \neq P(X^t)$$

$$\mathcal{Y}^s = \mathcal{Y}^t$$

DA Landscape: unsupervised DA

Labelled
Source Domain

Unlabelled
Target Domain



$$P(X^s) \neq P(X^t)$$
$$\mathcal{Y}^s = \mathcal{Y}^t$$

Real images vs Cartoons

{elephant, dog, house}

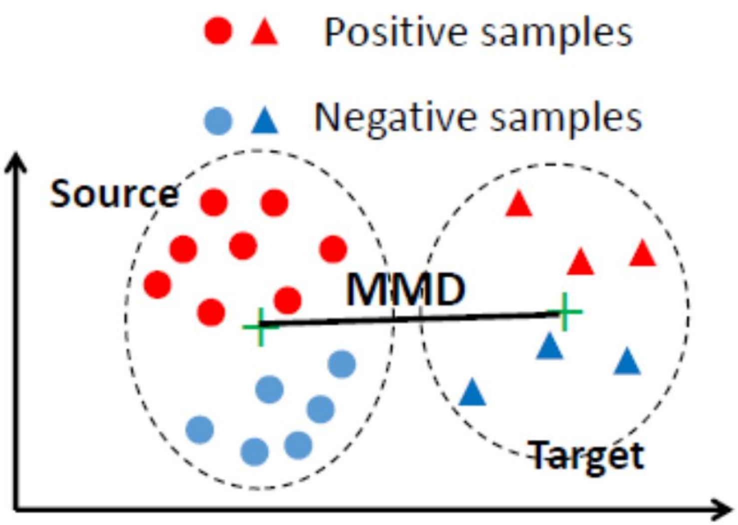
http://www.eecs.qmul.ac.uk/~dl307/project_iccv2017

Where are we now?

A bit of history - before the Deep Learning Revolution

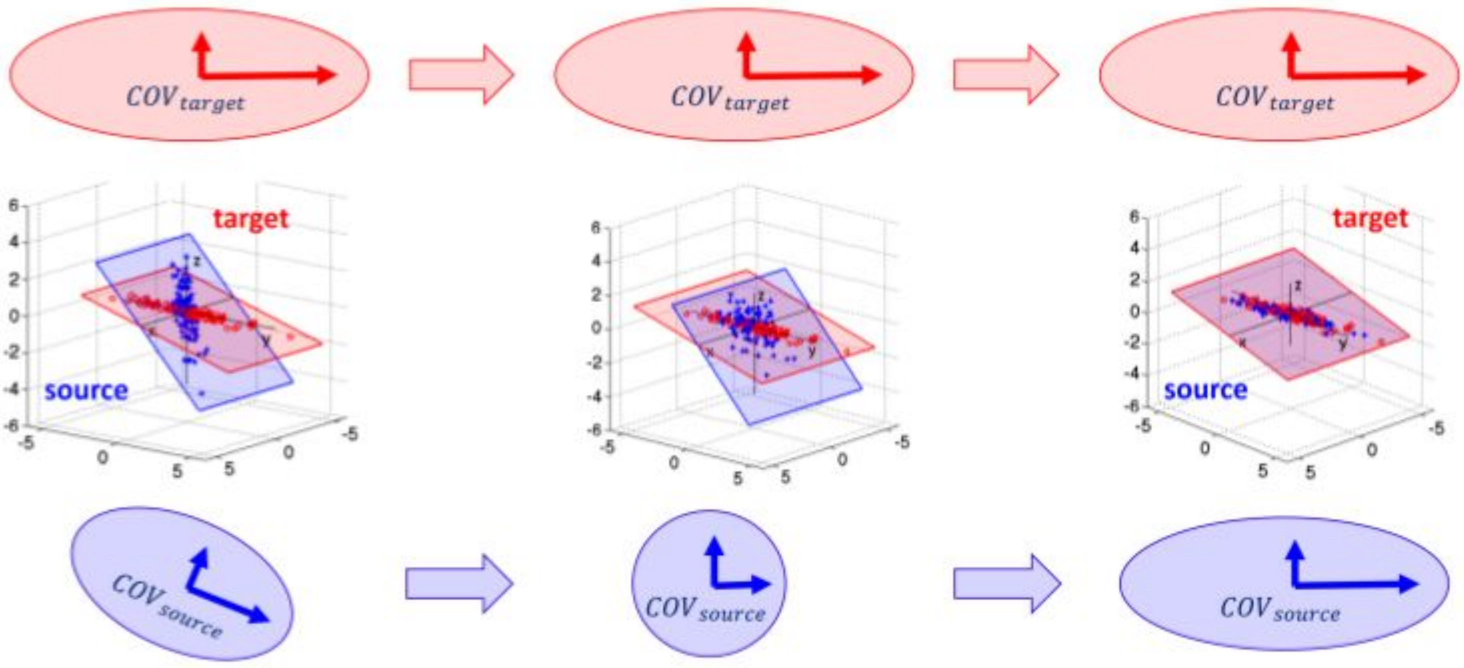
A bit of history - before the Deep Learning Revolution:
Maximum Mean Discrepancy

$$\mathrm{MMD}^2 = \left\| \frac{1}{n^s} \sum_{i=1}^{n^s} \phi(x_i^s) - \frac{1}{n^t} \sum_{i=1}^{n^t} \phi(x_i^t) \right\|^2$$



Gretton, A., et al. . "A kernel method for the two-sample-problem". In NIPS. 2007.
F. Orabona & T. Tommasi. Tutorial on Domain Adaptation and Transfer Learning. In ECCV 2014.

A bit of history - before the Deep Learning Revolution: CORAL

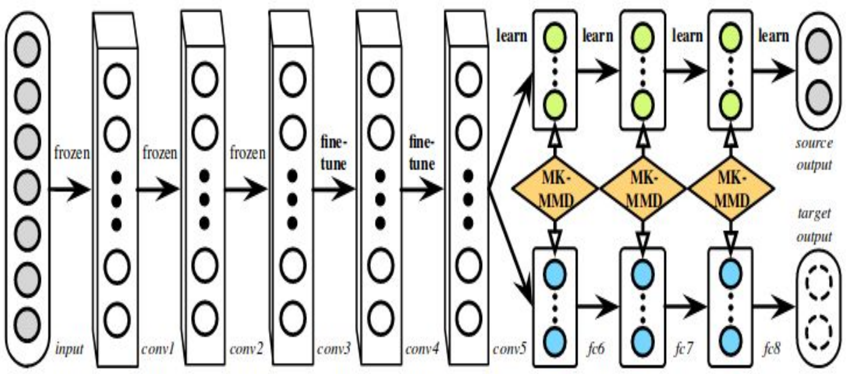


Sun, B., et al. “Correlation alignment for unsupervised domain adaptation”. In Domain Adaptation in Computer Vision Applications (pp. 153-171), 2017..

Deep Domain Adaptation

Discrepancy-based methods

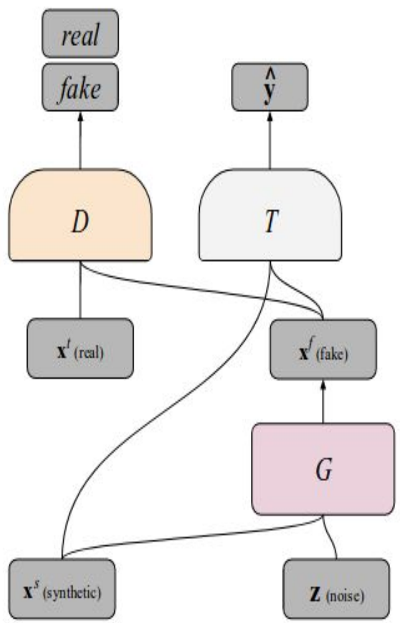
- Align the source and target distributions using maximum mean discrepancy (MMD), correlation alignment (CORAL), Kullback Leibler (KL) divergence, etc.
- Notable examples:
  - Deep Adaptation Networks [Long et al. ICML 2015]
  - Deep Correlation Alignment [Sun et al. ECCV 2016]
  - Associative DA [Haeusser, et al. ICCV 2017]

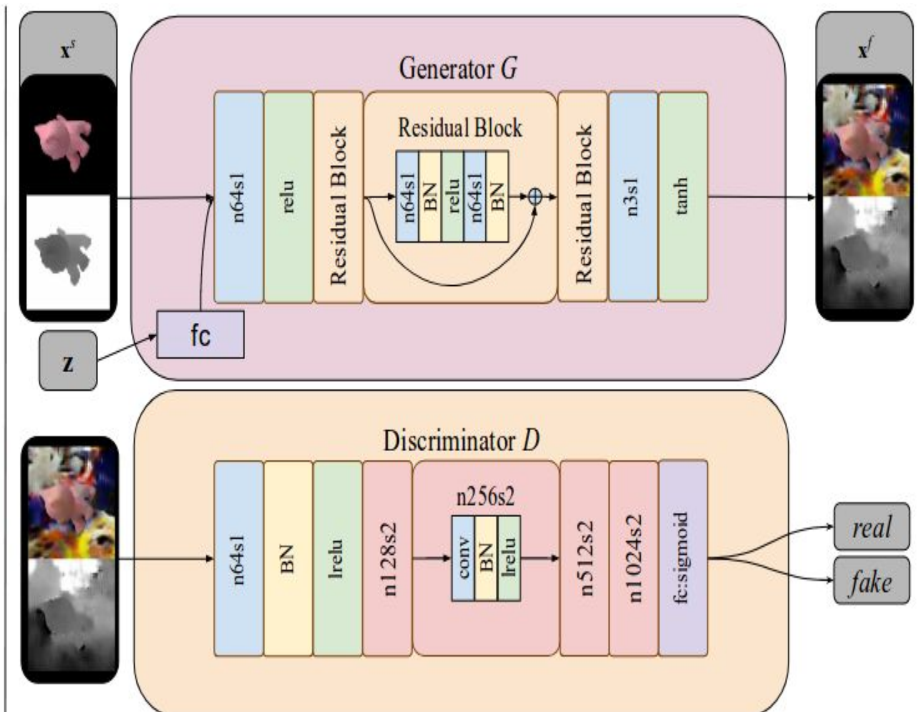


Domain Adaptation through Image Translation

Adversarial-based methods

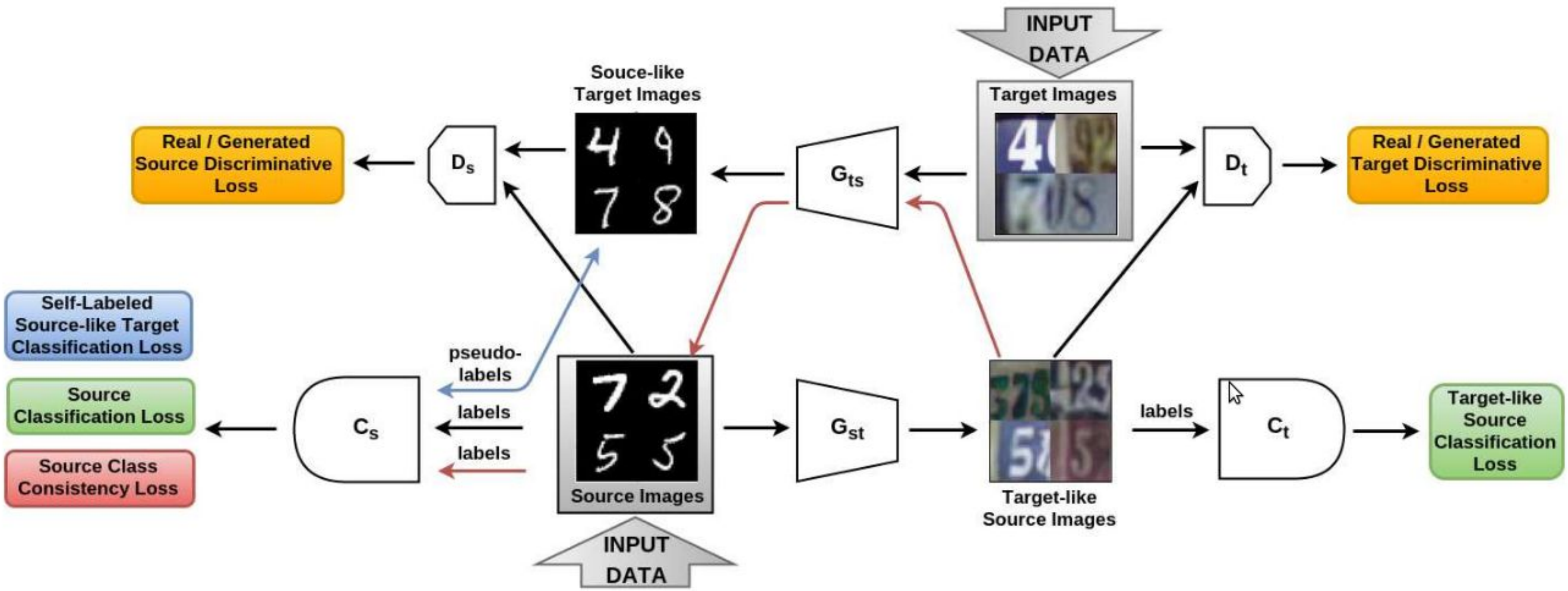
- Combine the discriminative model with GANs.
- Use source images to generate simulated samples that are similar to the target samples and preserve the annotation information of the source domain.





- Notable examples:
  - Pixel-level DA [Bousmalis et al. CVPR 2017]
  - SBADA-GAN [Russo et al. CVPR 2018]
  - CyCADA [Hoffman et al. ICML 2018]

Cycle GAN for DA: SBADAGAN

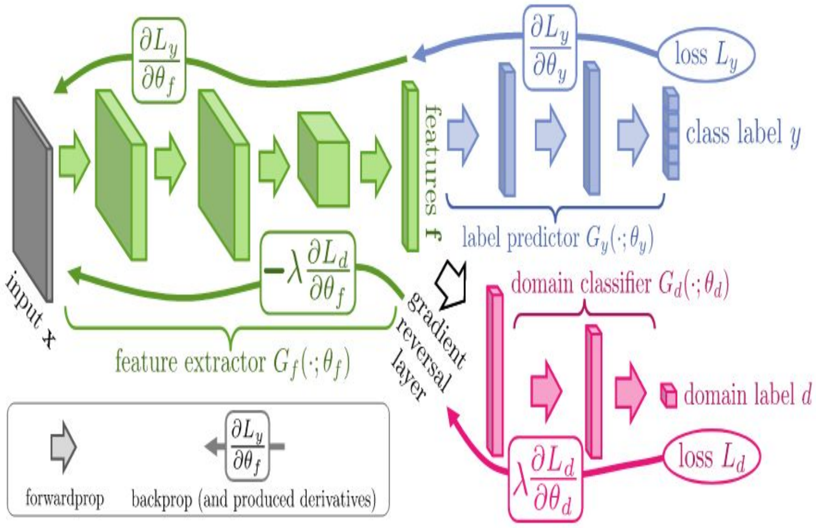


From source to target and back: Symmetric Bi-Directional Adaptive GANPaolo Russo1, Fabio M. Carlucci, Tatiana Tommasi and Barbara Caputo CVPR 2018

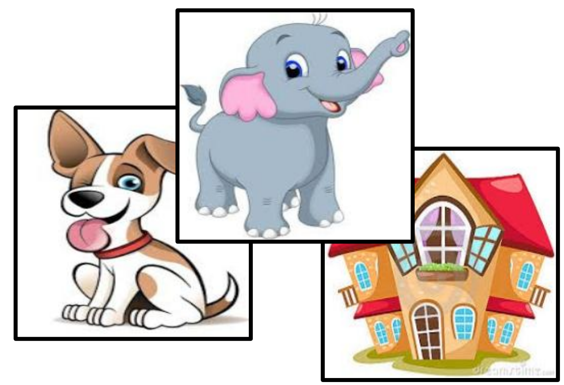
Adversarial Domain Adaptation

Adversarial-based methods

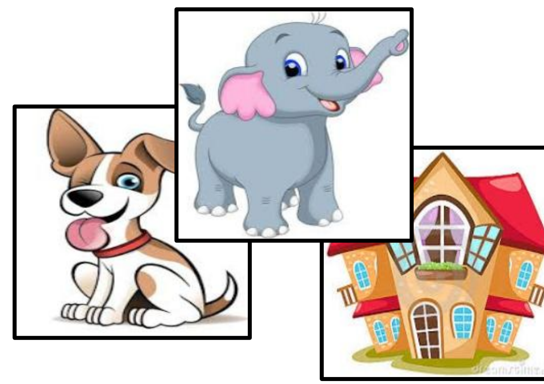
- Employ an adversarial objective to ensure that the network cannot distinguish between the source and target domains
- Notable examples:
  - Domain Adversarial NN [Ganin et al. JMLR 2016]
  - Adversarial Discriminative DA [Tzeng et al. CVPR 2017]
  - Deep Cocktail Network [Xu et al. CVPR 2018]



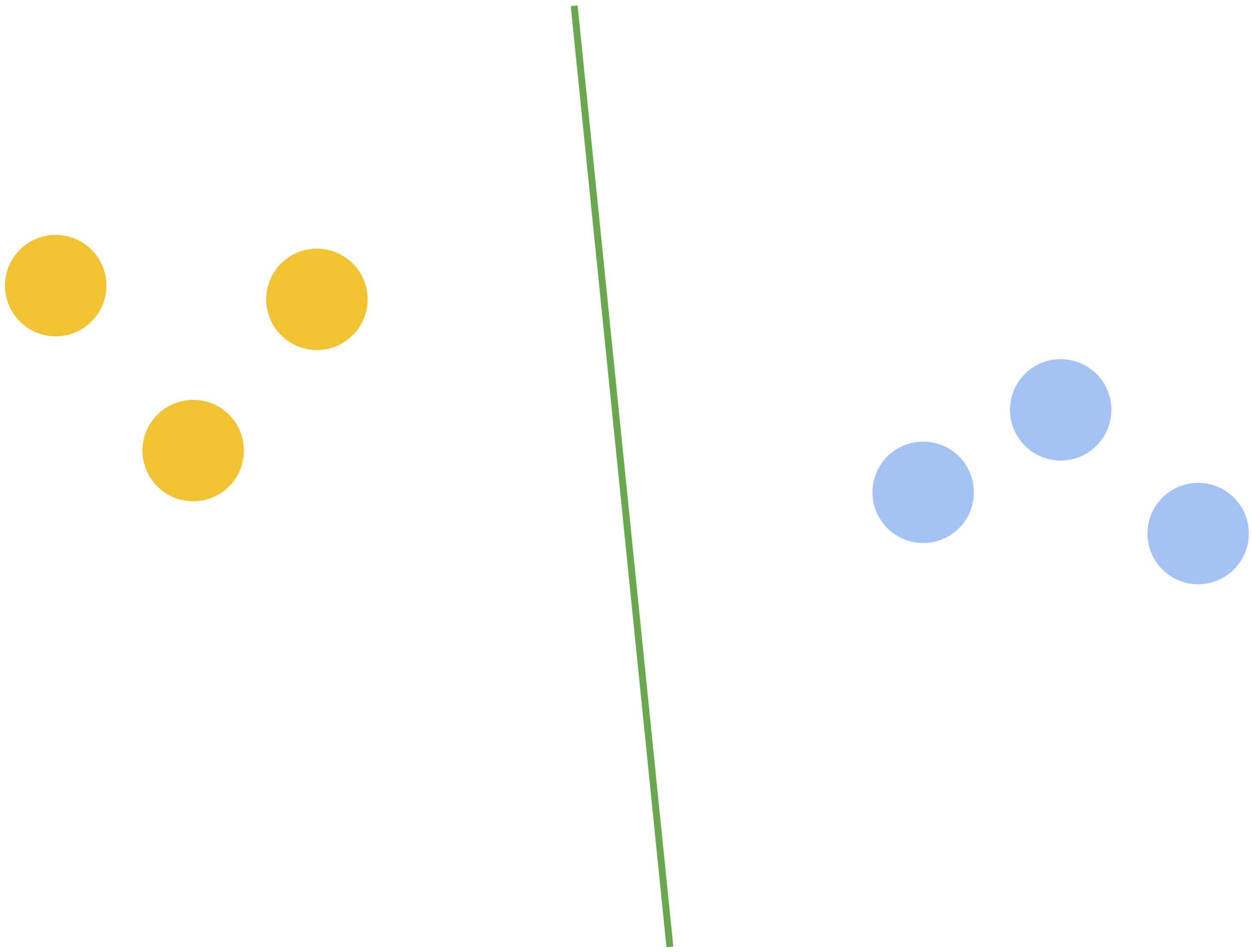
Domain Classification



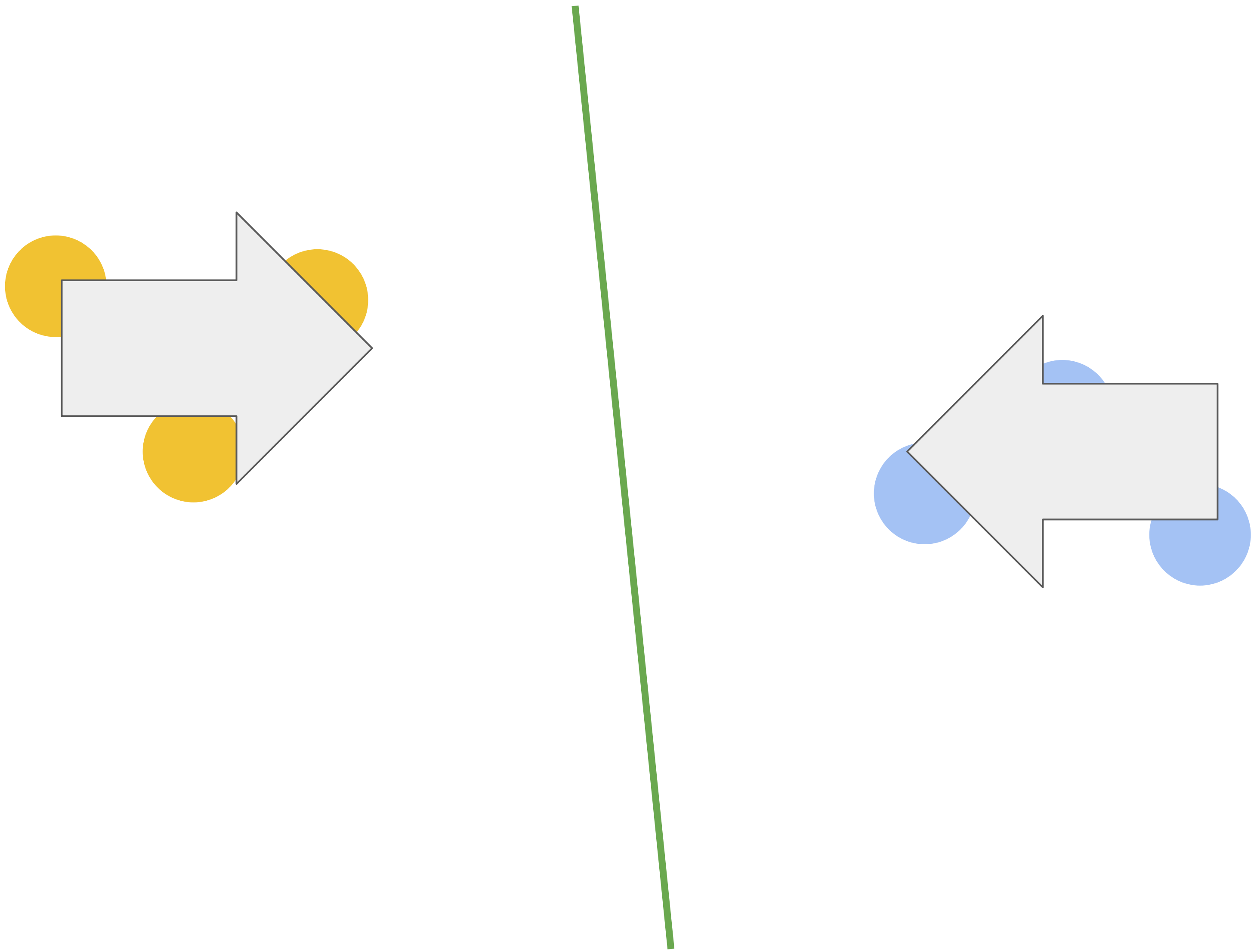
Domain Classification



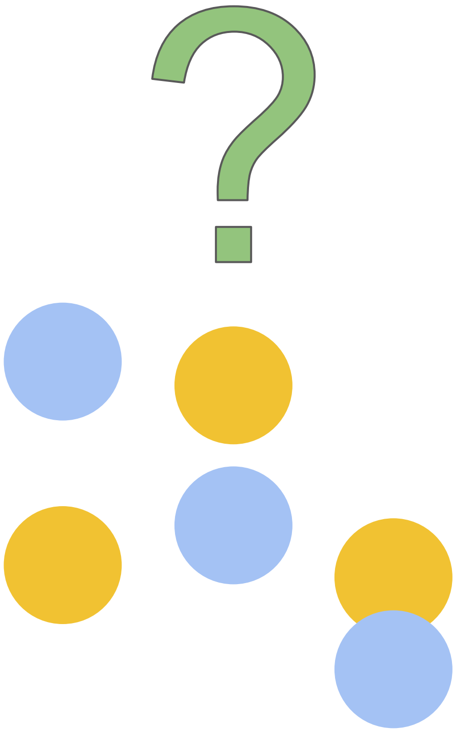
Domain Classification



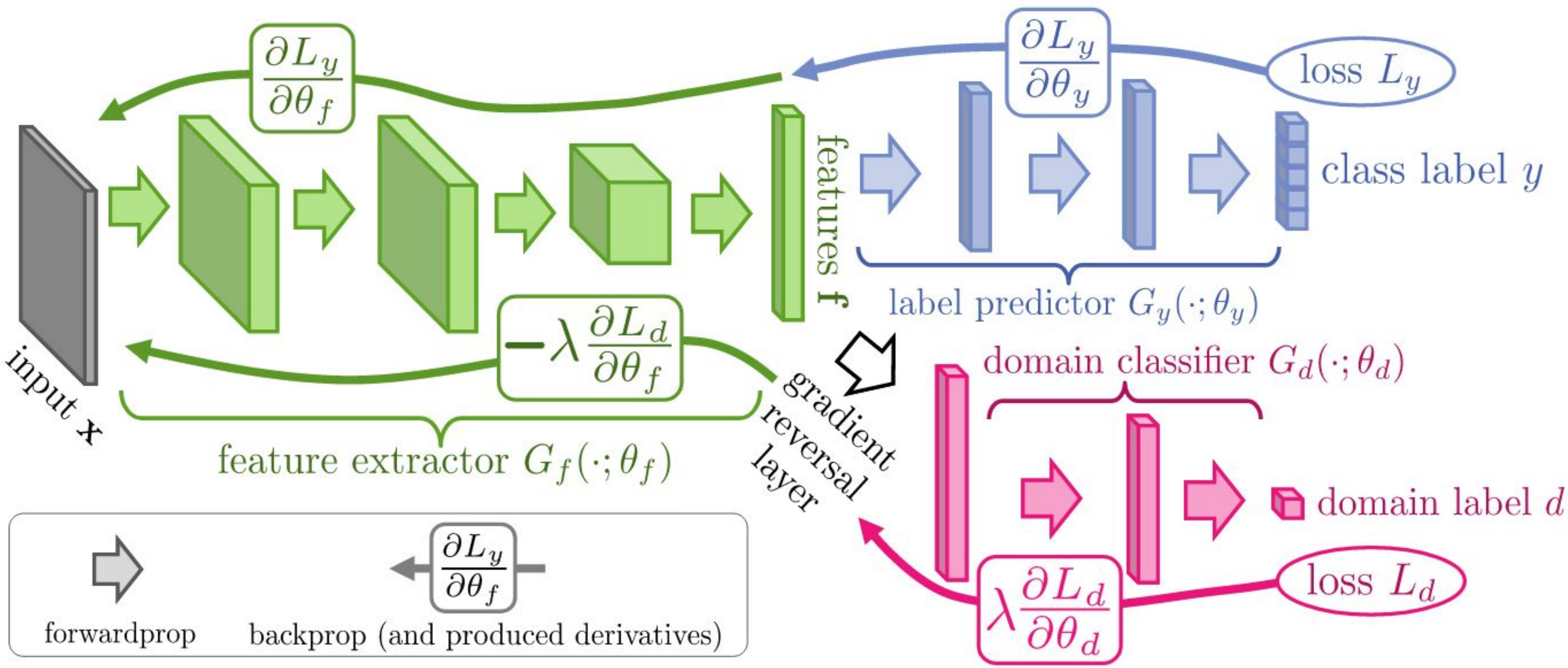
Domain Classification



Domain Classification

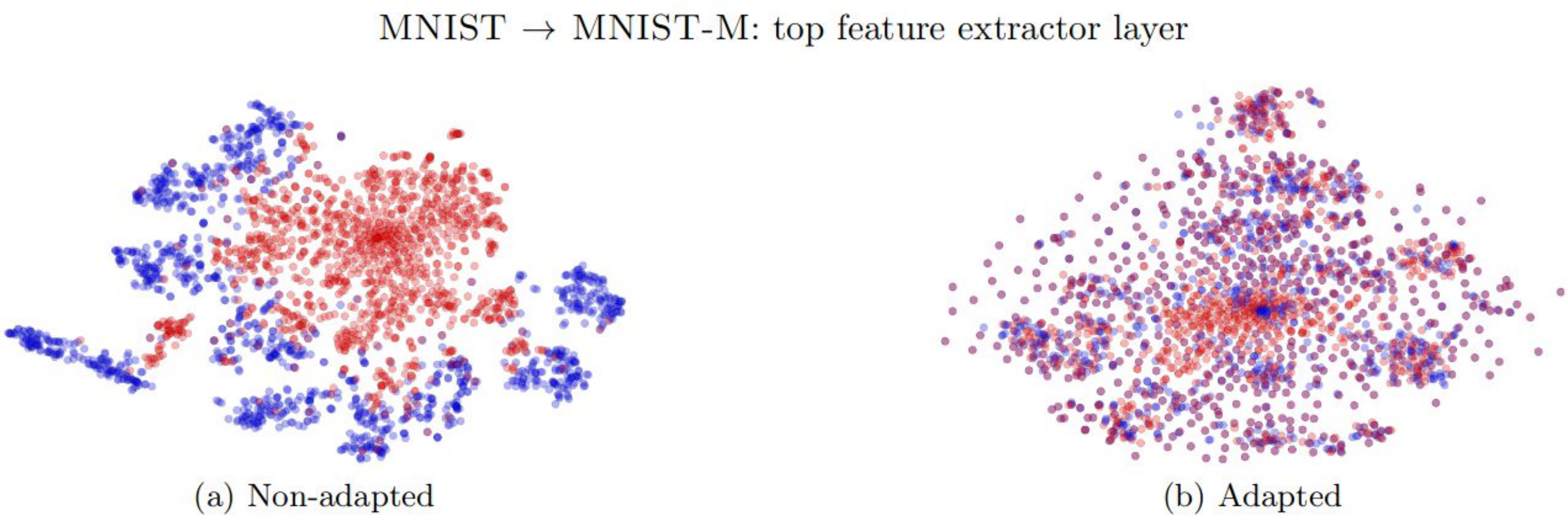


Domain Adversarial Training



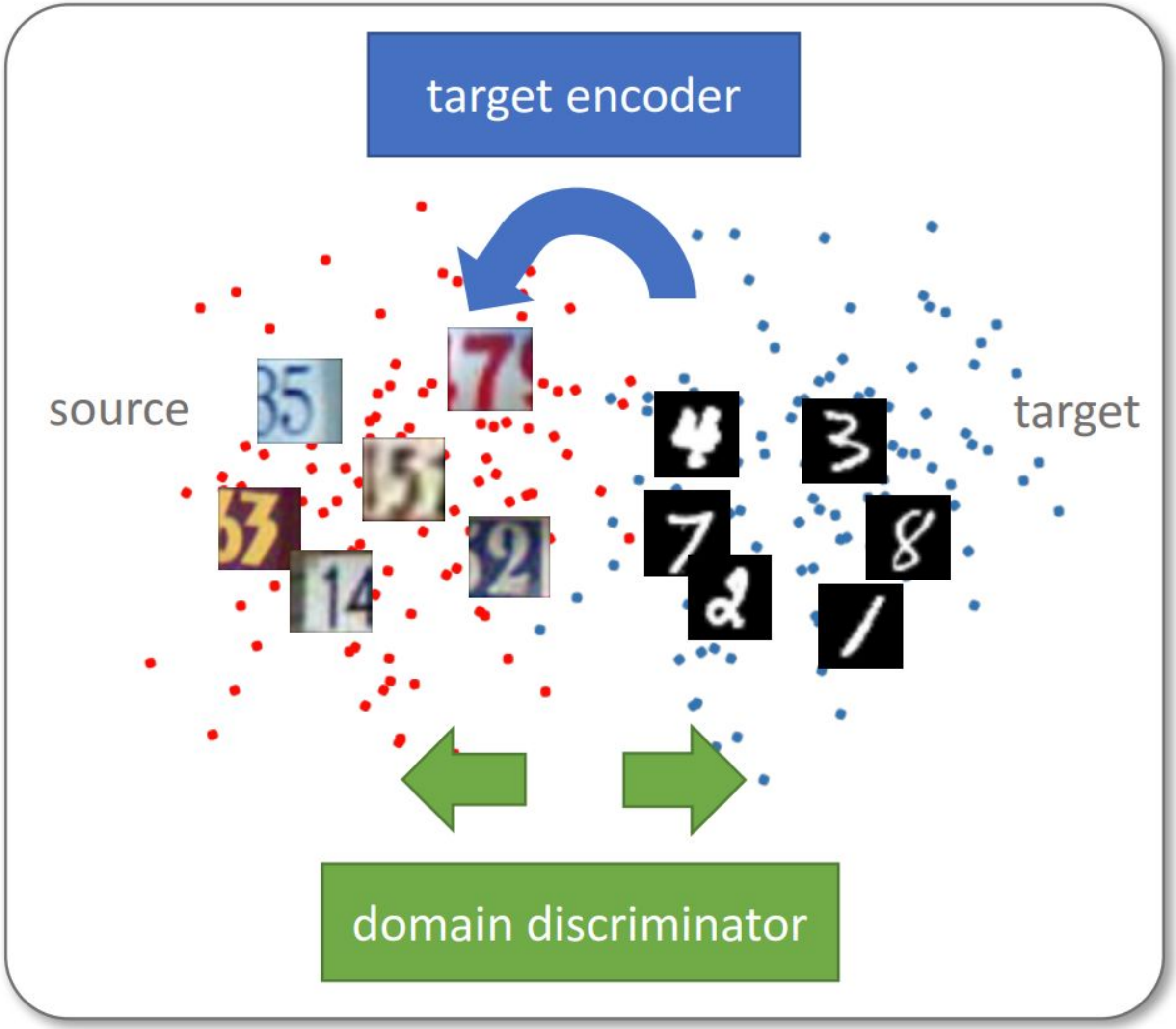
Ganin, Y., et al. "Domain-adversarial training of neural networks". The Journal of Machine Learning Research, 17(1), 2096-2030, 2016..

Domain Adversarial Training



Ganin, Y., et al. "Domain-adversarial training of neural networks". The Journal of Machine Learning Research, 17(1), 2096-2030, 2016..

ADDA

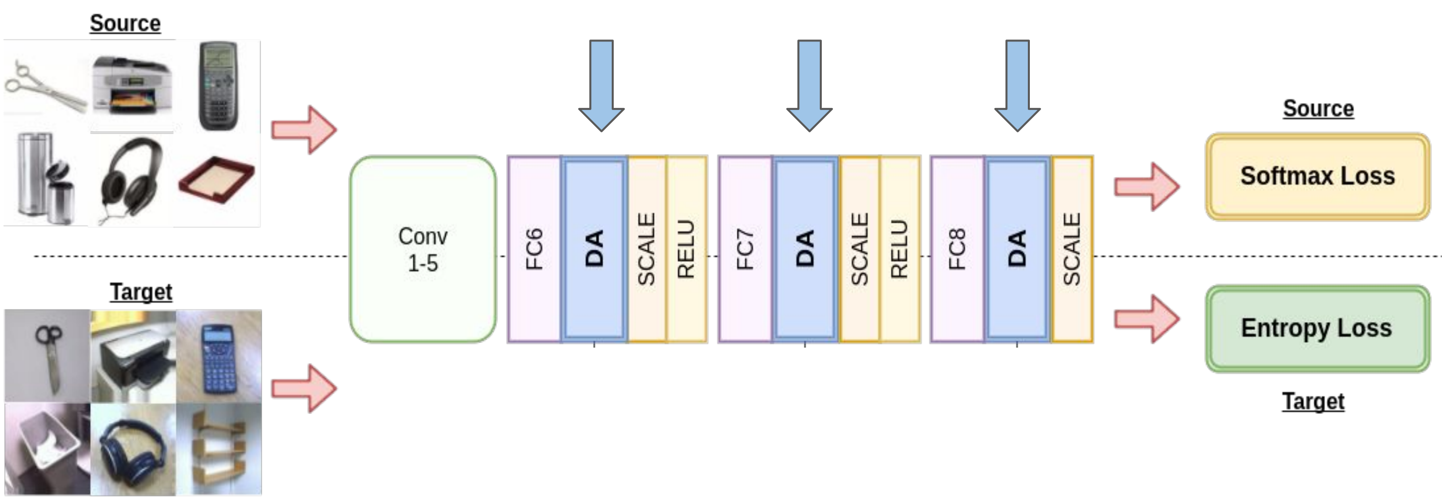


Tzeng, E., Hoffman, J., Saenko, K., & Darrell, T., " Adversarial discriminative domain adaptation". In CVPR 2017.

Domain Adaptation through Batch Normalization

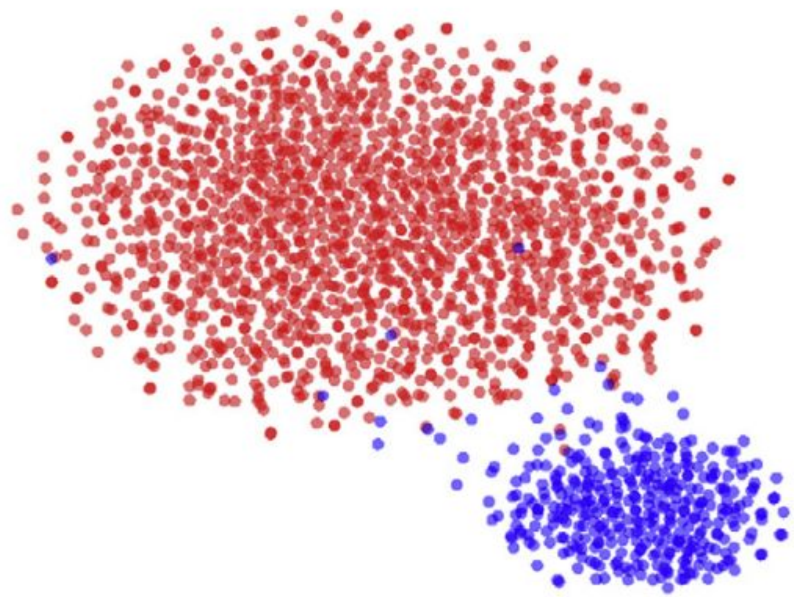
Adaptation with Alignment Layers

- Key Idea: Learn domain-agnostic representations by adjusting the architecture of the deep network
- Introduce domain distribution alignment layers.



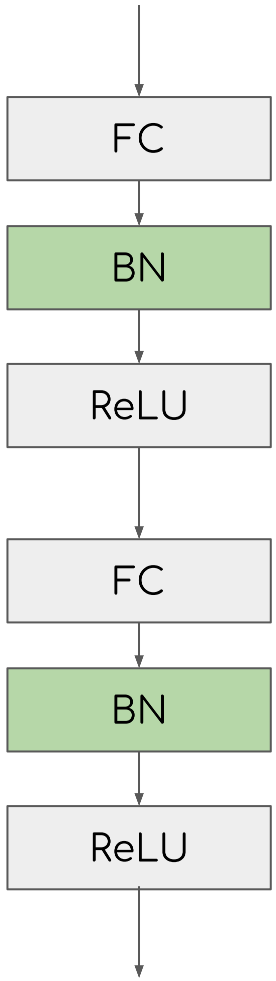
Carlucci, F. M., Porzi, L., Caputo, B., Ricci, E., & Rota Bulò, S. (2017). "AutoDIAL: Automatic Domain Alignment Layers". *ICCV*.

How the problem looks like



Li et al. (2017) “Revisiting Batch Normalization For Practical Domain Adaptation”, ICLR-WS.

Some Background: Batch Normalization



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_\mathcal{B} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

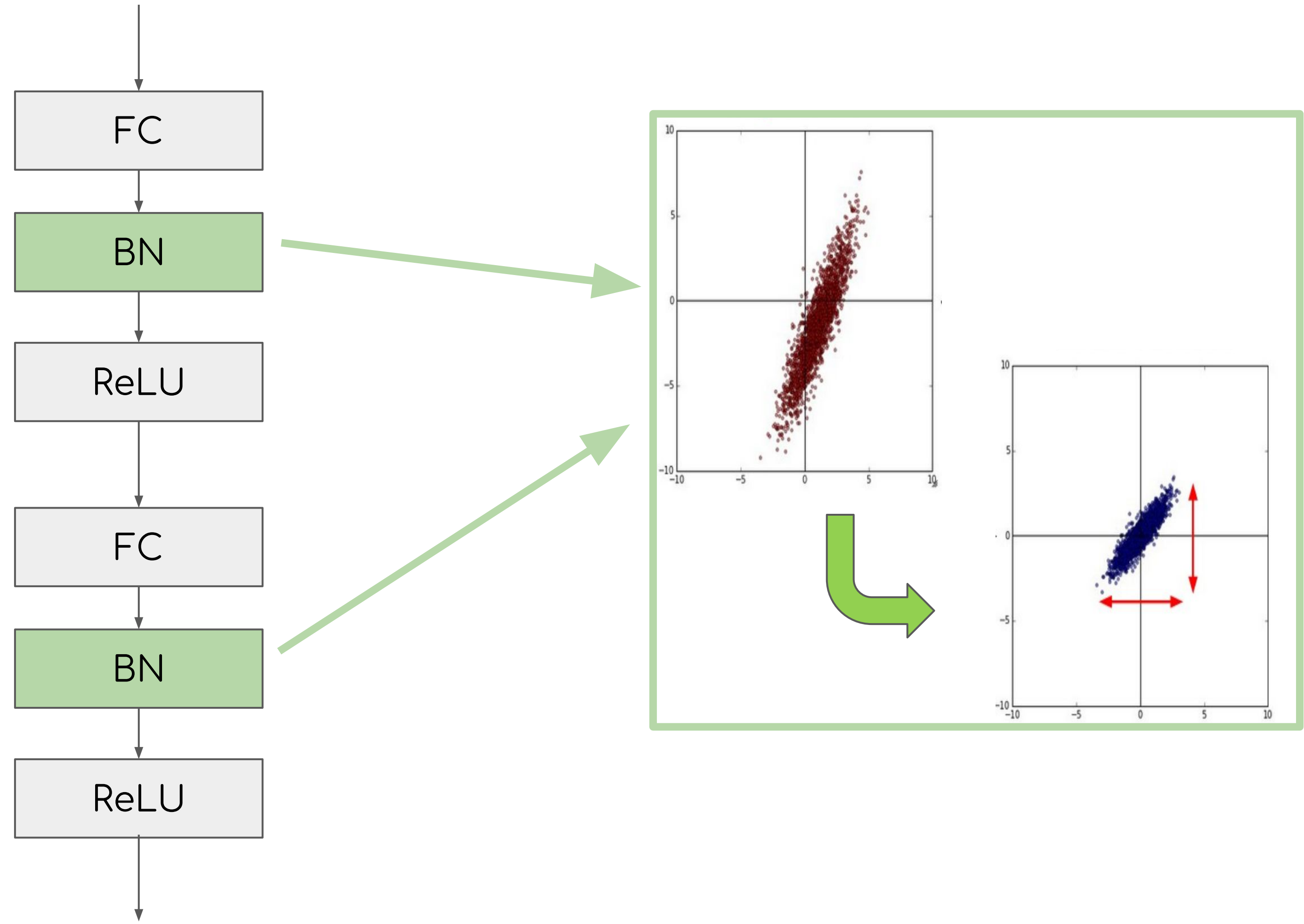
$$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_\mathcal{B})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_\mathcal{B}}{\sqrt{\sigma_\mathcal{B}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

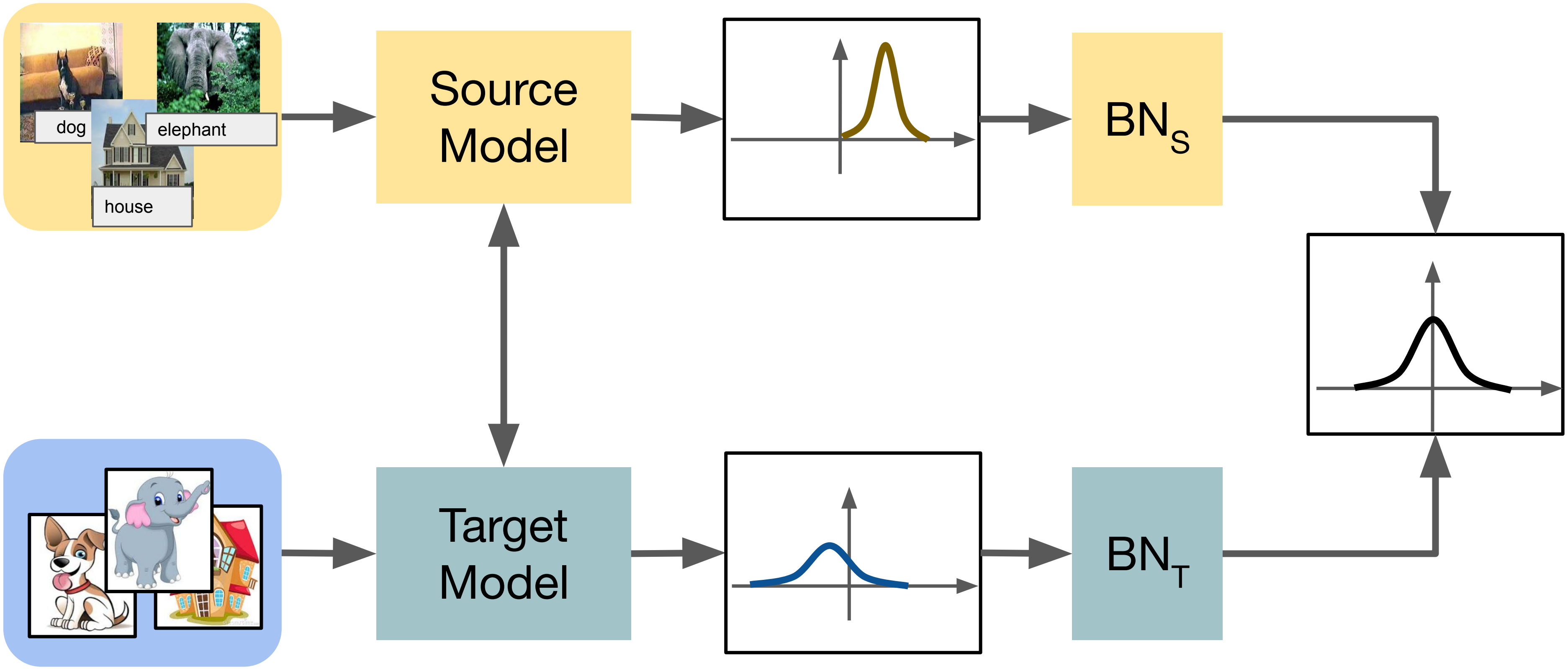
Ioffe, S., & Szegedy, C. "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift: Automatic Domain Alignment Layers". *ICML 2015.*
http://cs231n.github.io/neural-networks-2/#batchnorm

Some Background: Batch Normalization



Ioffe, S., & Szegedy, C. "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift: Automatic Domain Alignment Layers". *ICML 2015.*
http://cs231n.github.io/neural-networks-2/#batchnorm

DA through Batch Normalization



Carlucci, F. M., Porzi, L., Caputo, B., Ricci, E., & Rota Bulò, S. "AutoDIAL: Automatic Domain Alignment Layers". *ICCV 2017.*
Carlucci, F. M., Porzi, L., Caputo, B., Ricci, E., & Rota Bulò, S. "Just dial: Domain alignment layers for unsupervised domain adaptation". ICIAP 2017.

What’s next?

Ongoing and Future Works

- Deep open world recognition with domain shift.
  - The closed-world assumption (same class for source and target is too strict)
  - More challenging than online DA

Mancini, M., Karaoguz, H., Ricci, E., Jensfelt, P., & Caputo, B. "Towards Web Aided Deep Open World Recognition". ICRA 2019.

Online Adaptation for Depth Estimation

Online Adaptation

- No supervision
- Continuously changing distributions
- Online learning

Zhang, Z., Lathuilière, S., Pilzer, A., Sebe, N., Ricci, E., & Yang, J. (2019). Online Adaptation through Meta-Learning for Stereo Depth Estimation. *arXiv preprint arXiv:1904.08462. (under review).*

Questions?