

Domain Adaptation

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2023/04/26

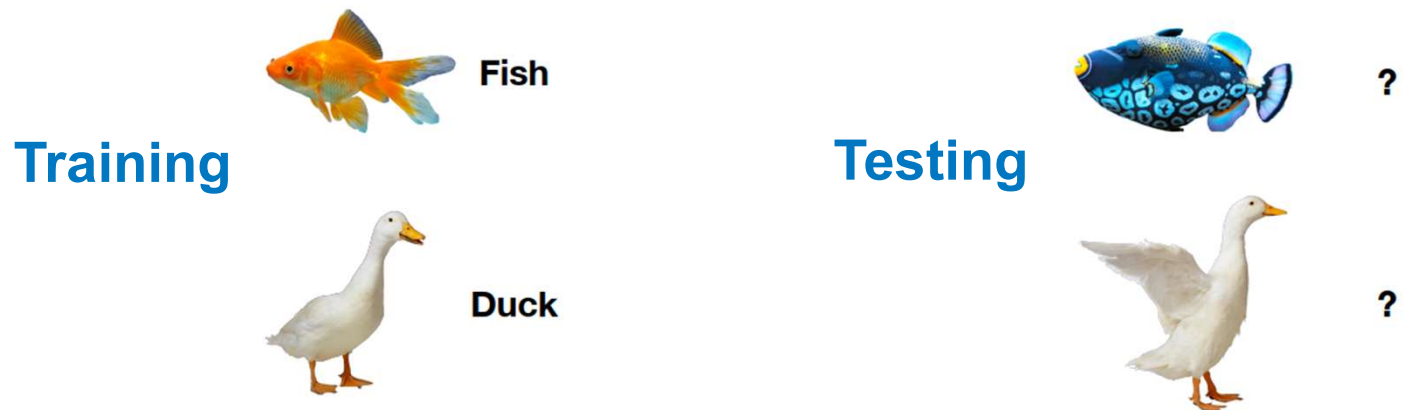
Overview

- Domain Adaptation Foundation
- Domain Adaptation Method
 - Discrepancy-based methods
 - Adversarial-based methods
- Multi-source Domain Adaptation Methods
- Universal Domain Adaptation Methods

A caveat in naive ML

★ The common assumption in ML is:

1. **Annotated** training data is available.
2. Training and testing data is drawn from **same feature space** with **same distribution**.



Not enough training data, No labels for training data...

?

Training



Testing



?



?

Training



Testing

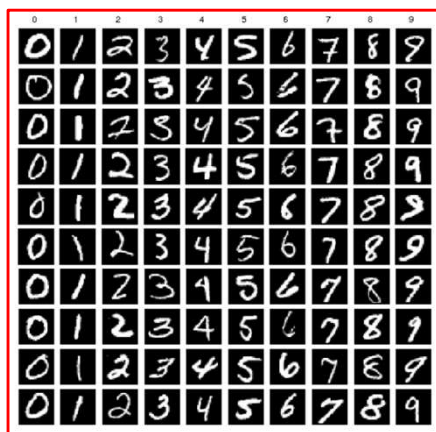
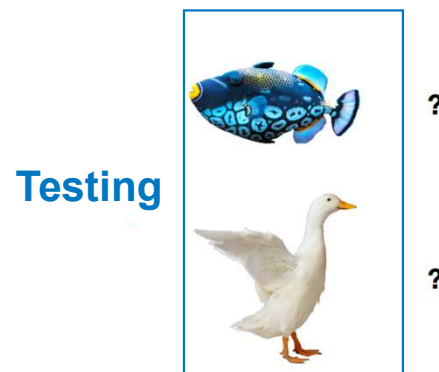


?



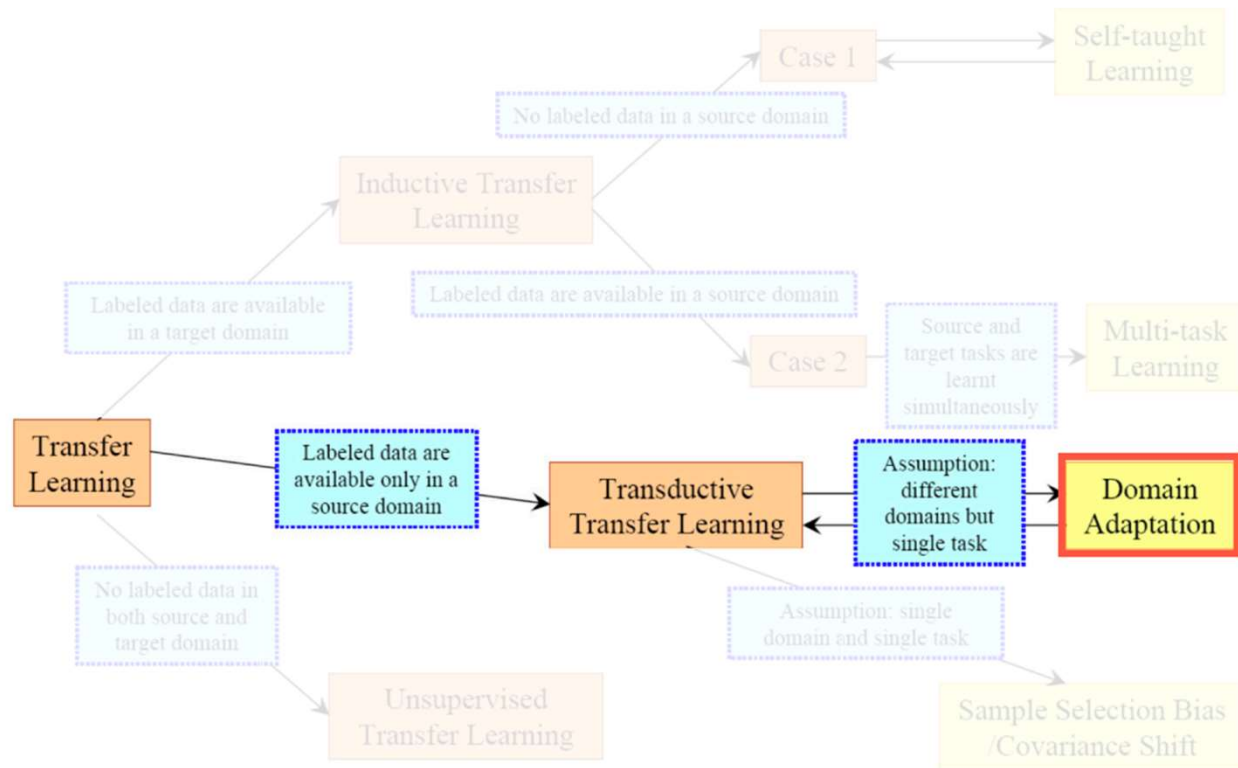
?

Why Domain Adaptation?



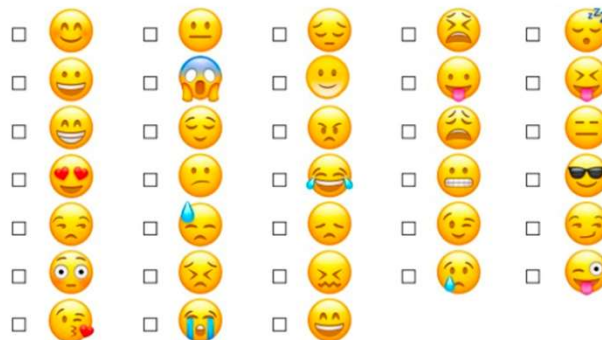
ACC 5%

Transfer learning vs Domain Adaptation

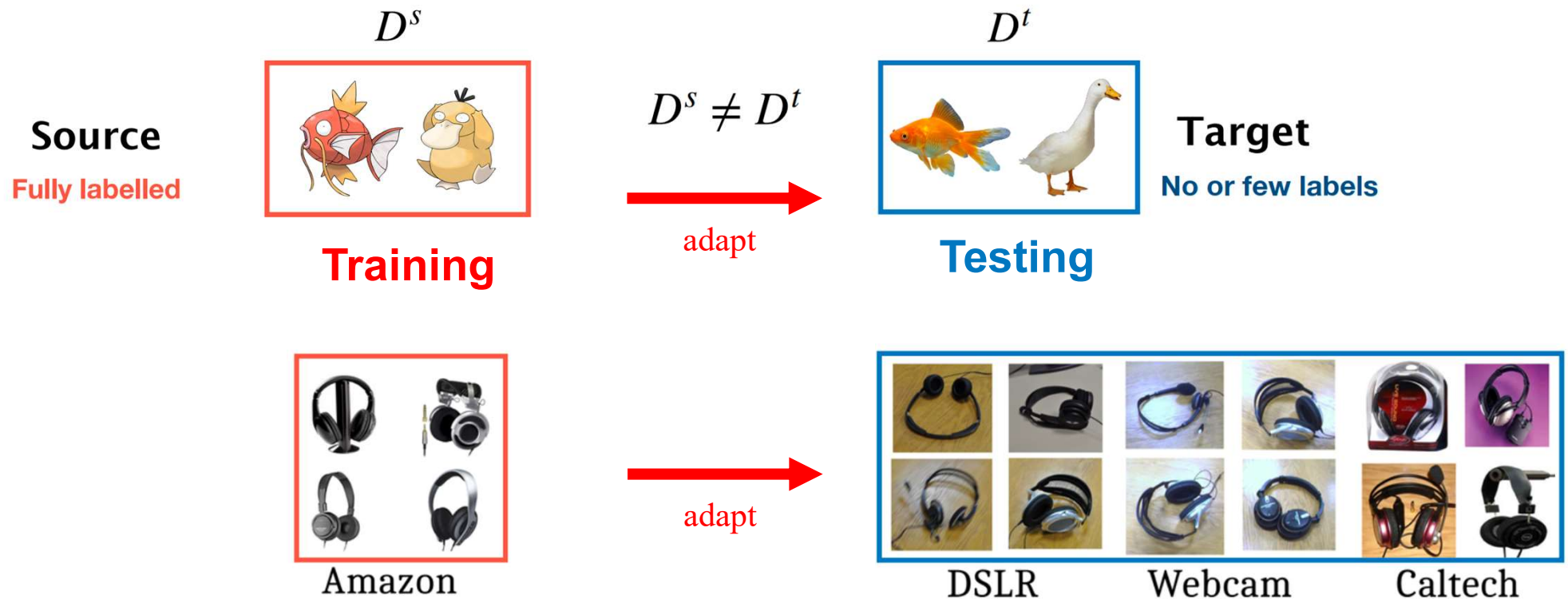


Intuitive Definition of Domain

Domain D



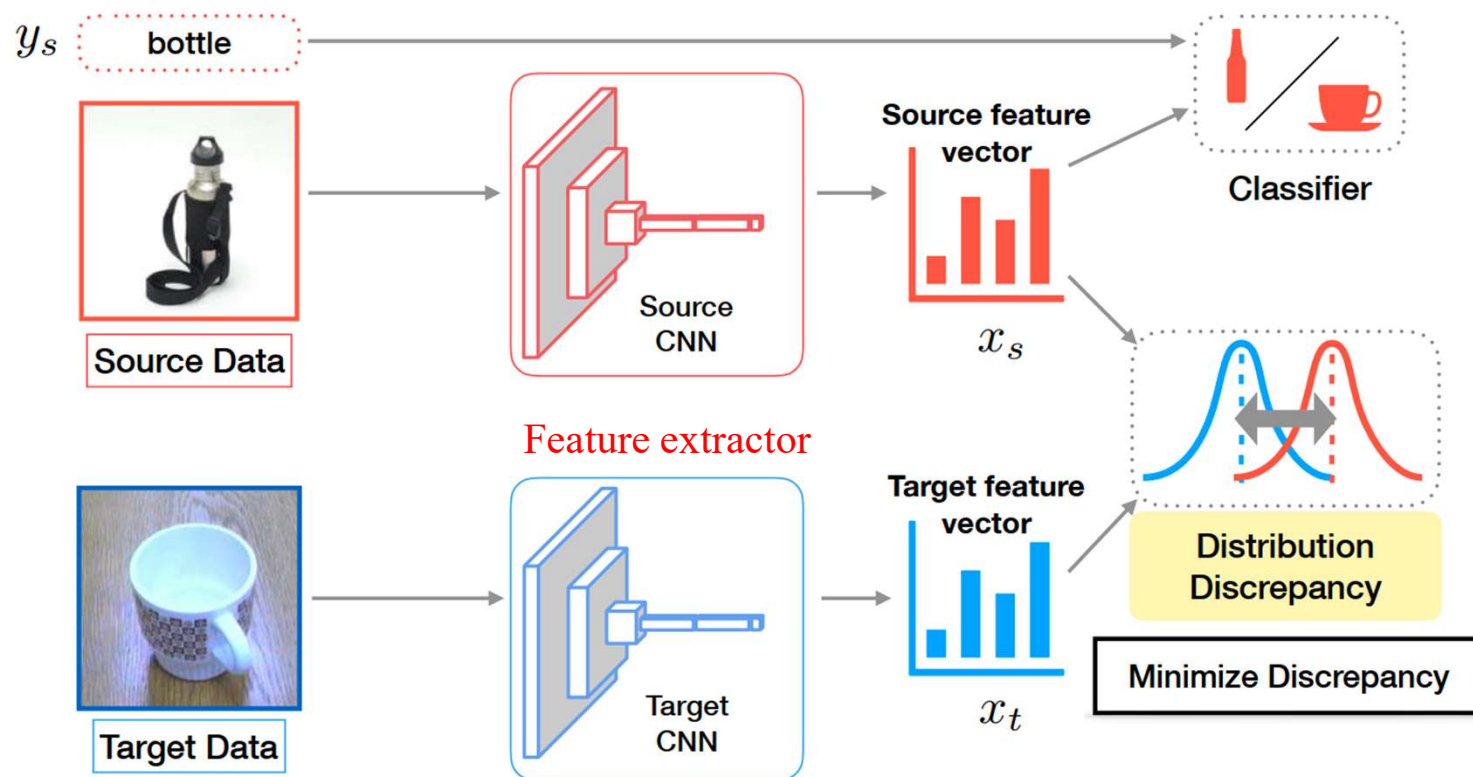
Domain Adaptation: Train on **Source** Test on **Target**



Overview

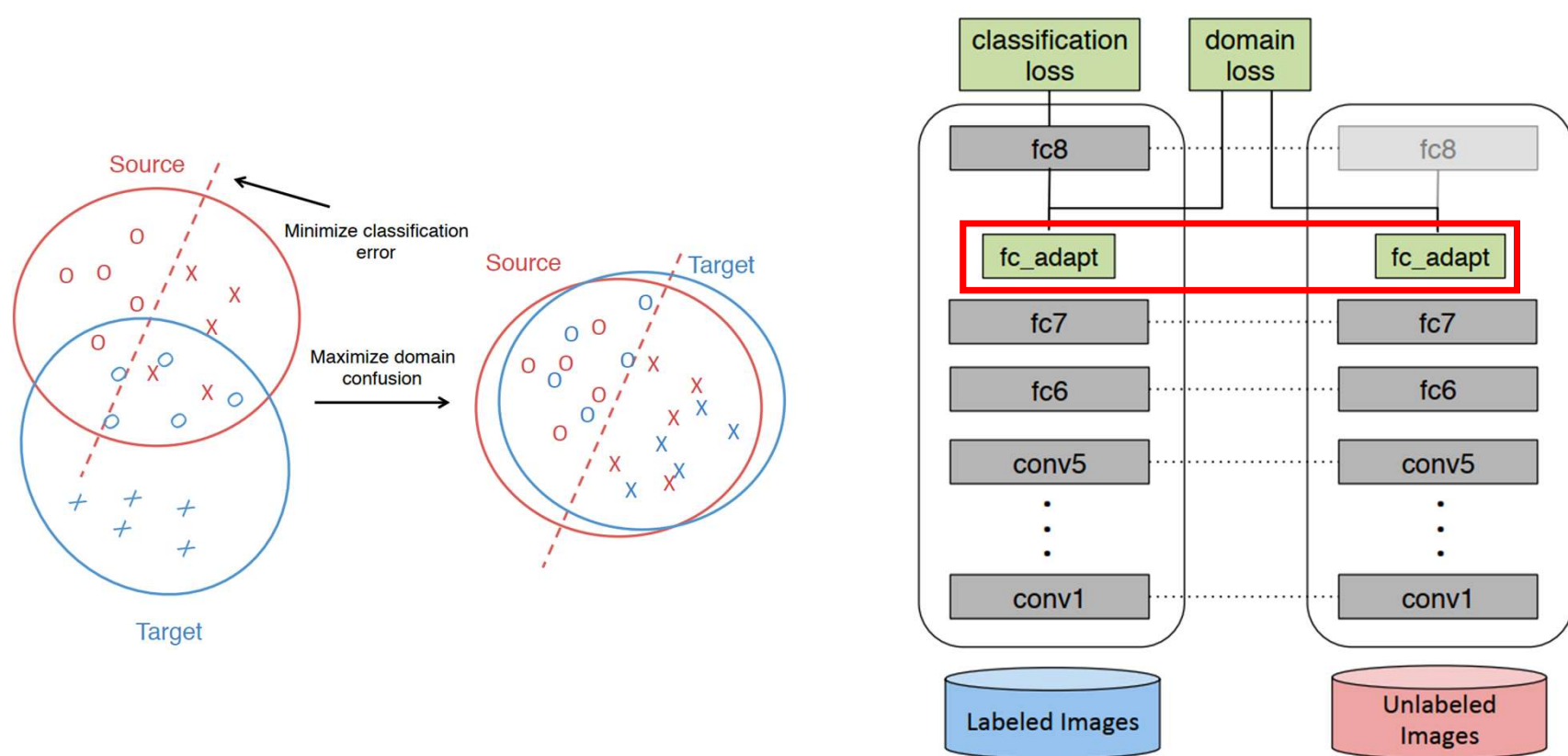
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Discrepancy-based methods



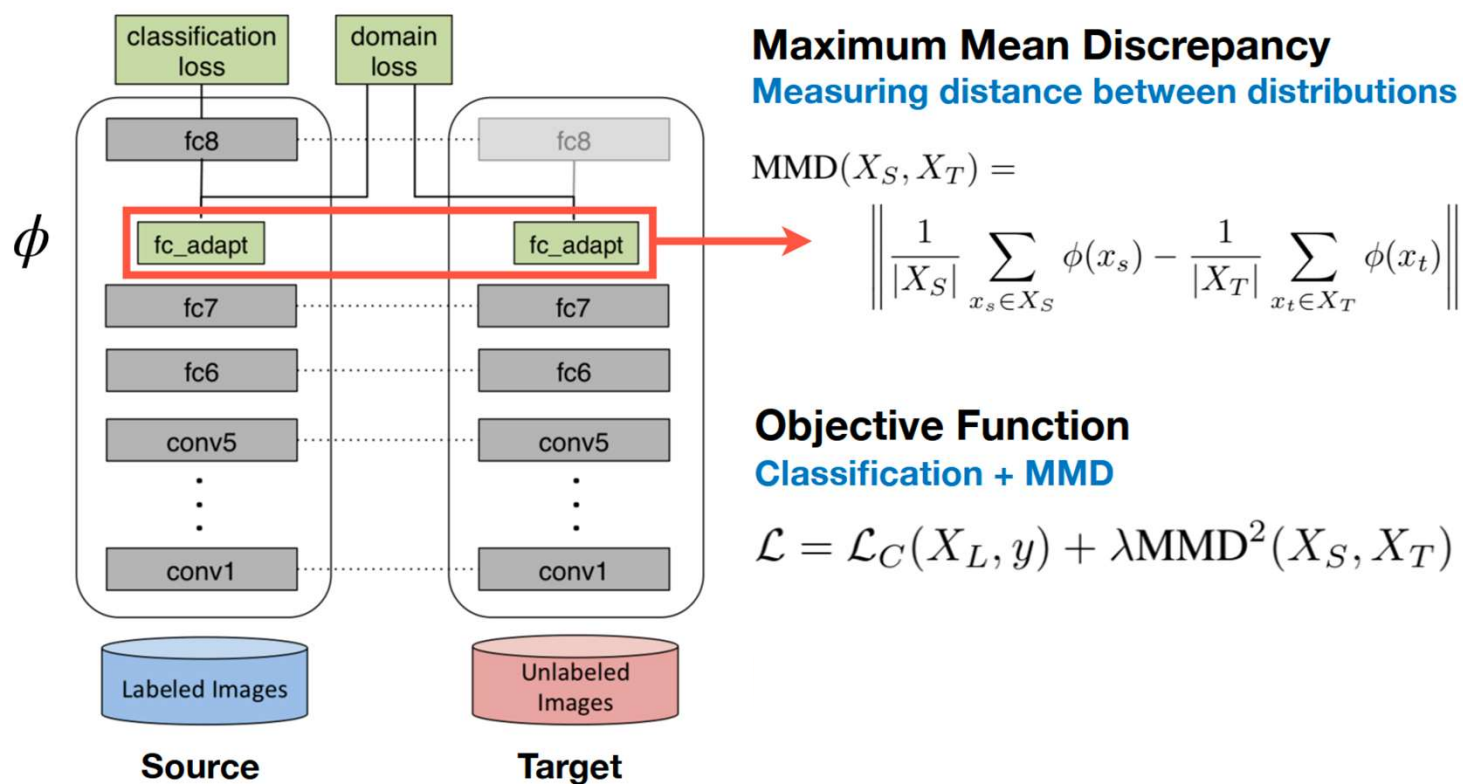
Slide credit: Judy Hoffman

Deep Domain Confusion

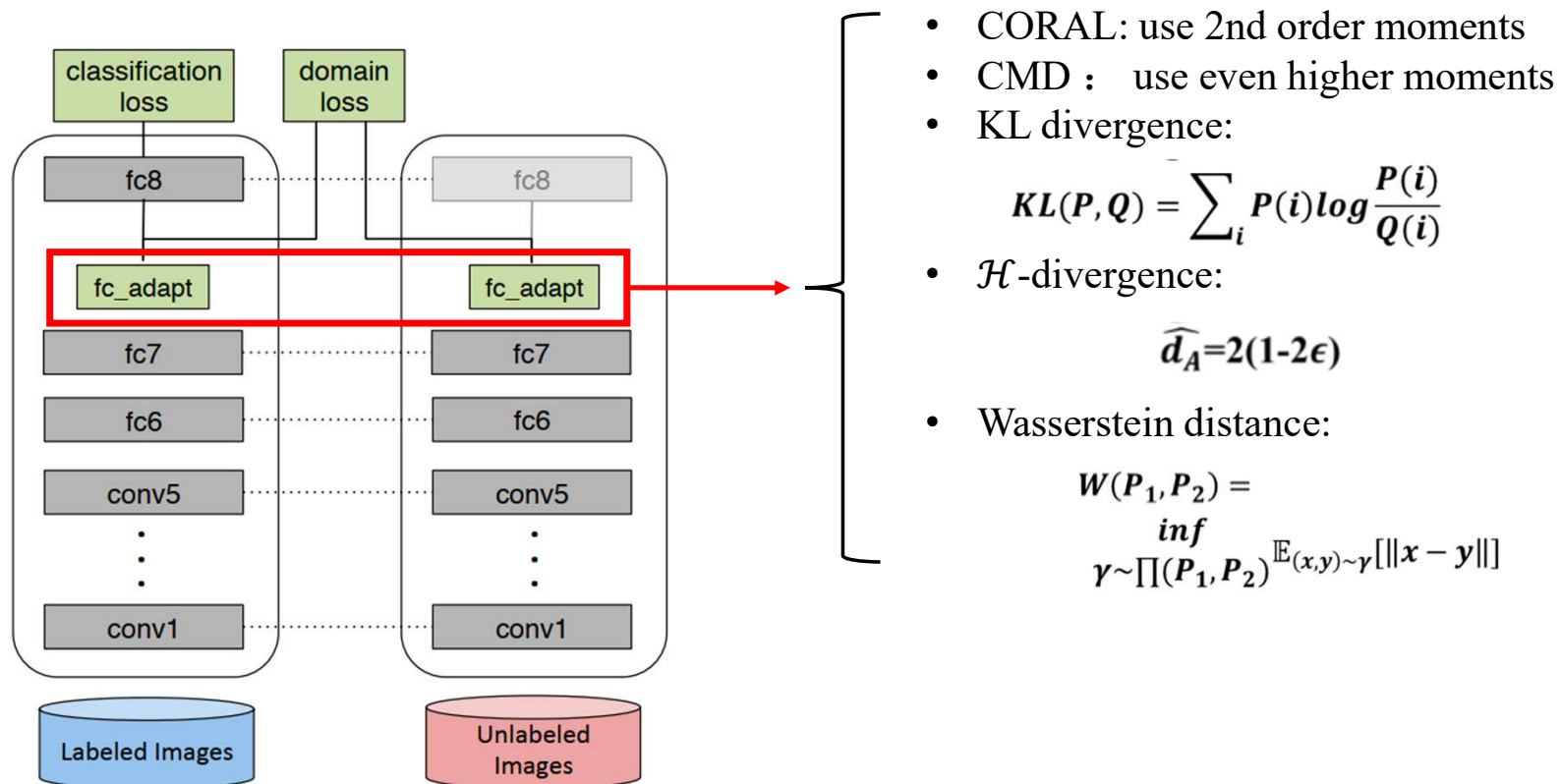


[CoRR 2014] Deep Domain Confusion- Maximizing for Domain Invariance

MMD: Max Mean Discrepancy



Other Discrepancy-based methods



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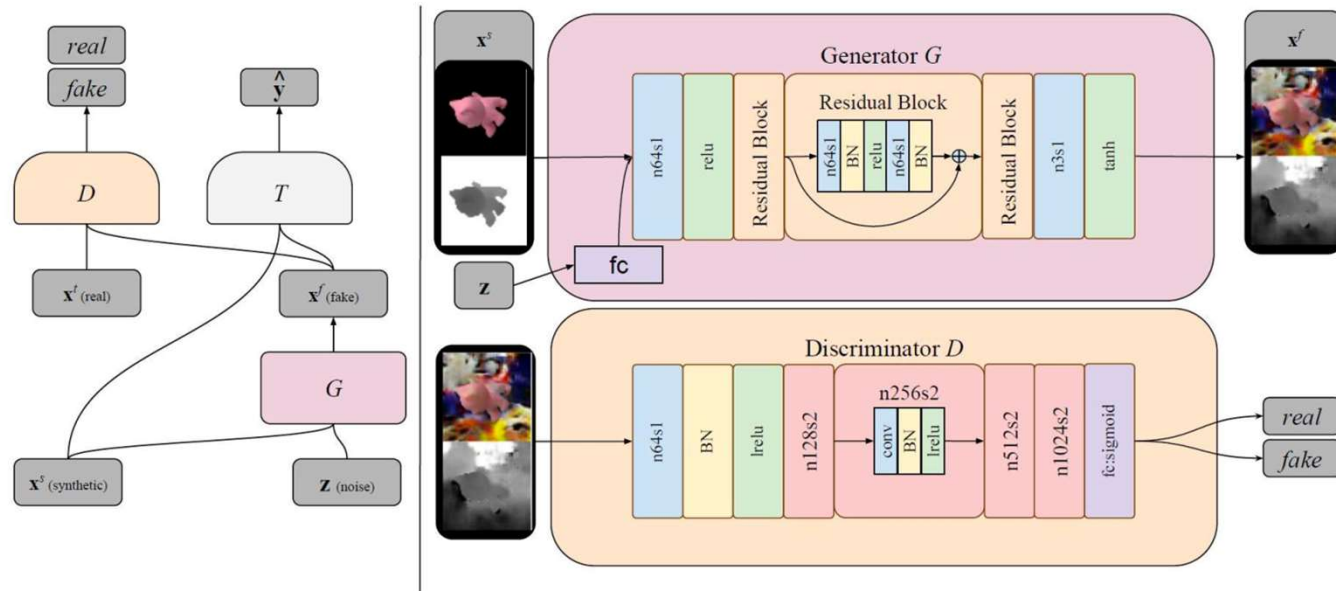
Generative Model: Pixel-level GANs



(a) Image examples from the Linemod dataset.

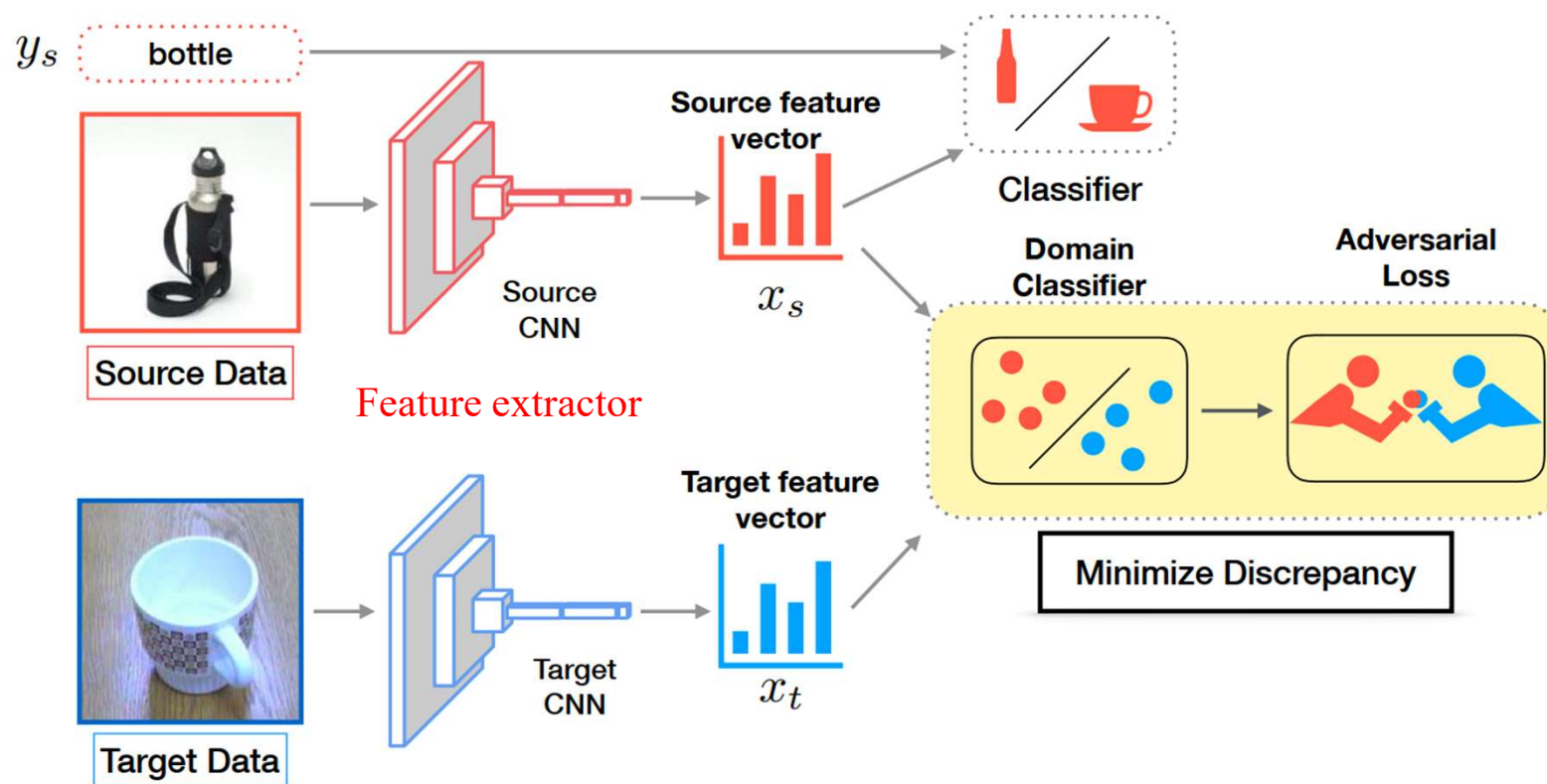


(b) Examples generated by our model, trained on Linemod.



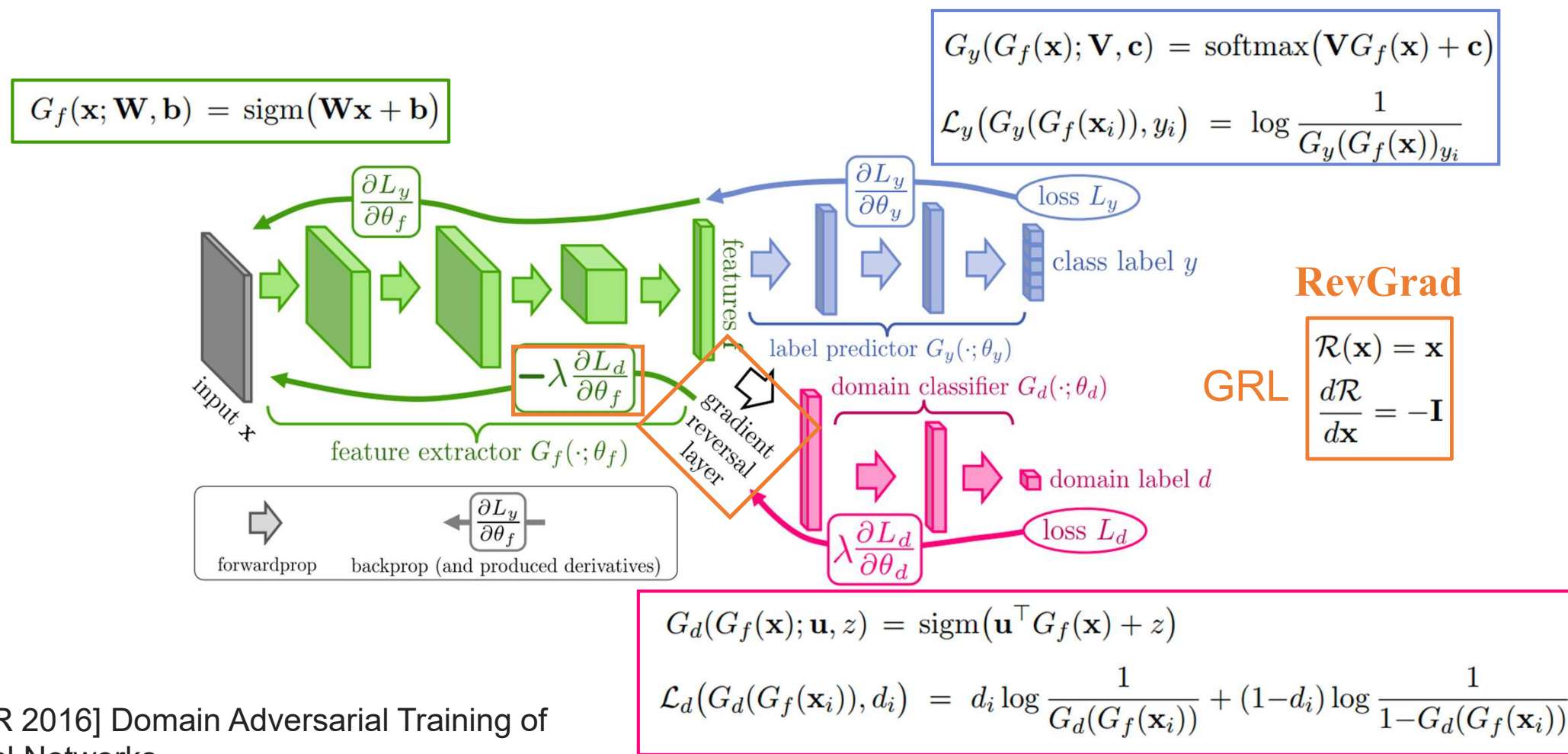
[CVPR 2017] Unsupervised pixel-level domain adaptation with generative adversarial networks

Discriminative Model

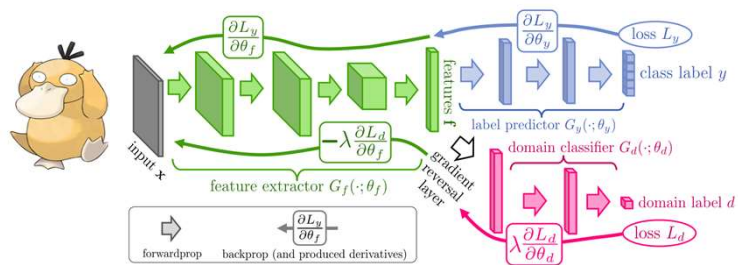


Slide credit: Judy Hoffman

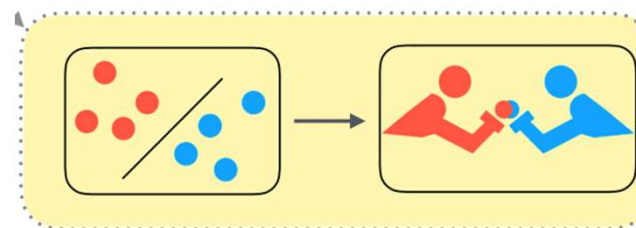
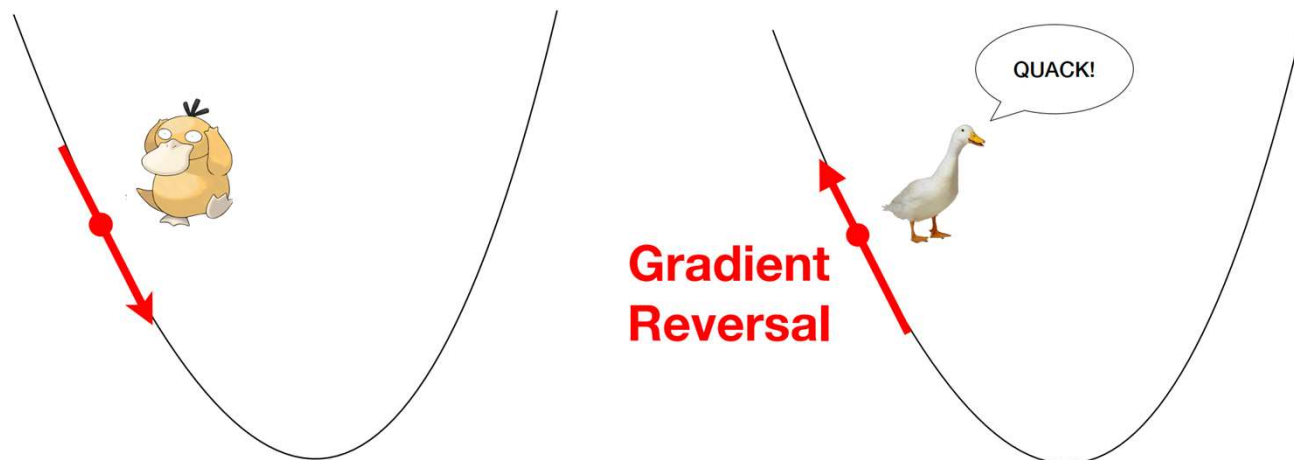
DANN: Domain Adversarial Training of Neural Networks



RevGrad

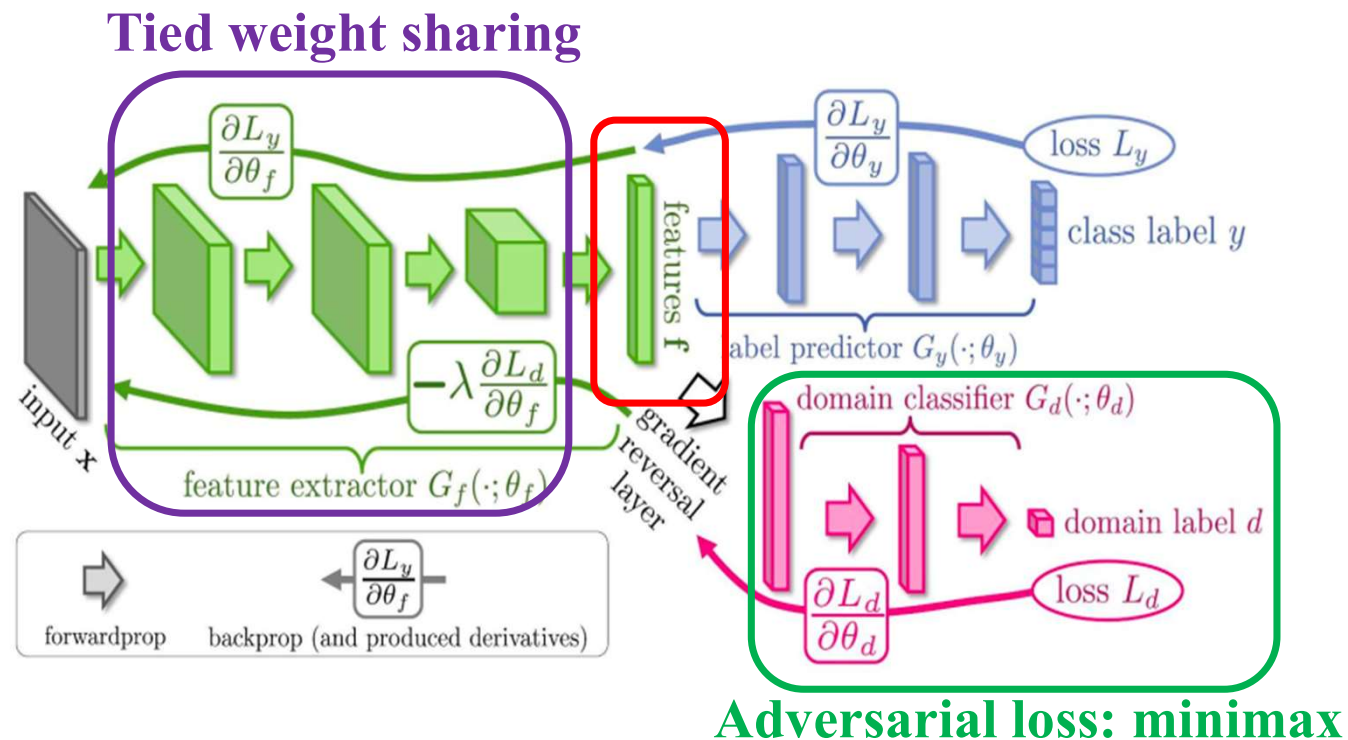


Loss of domain classifier



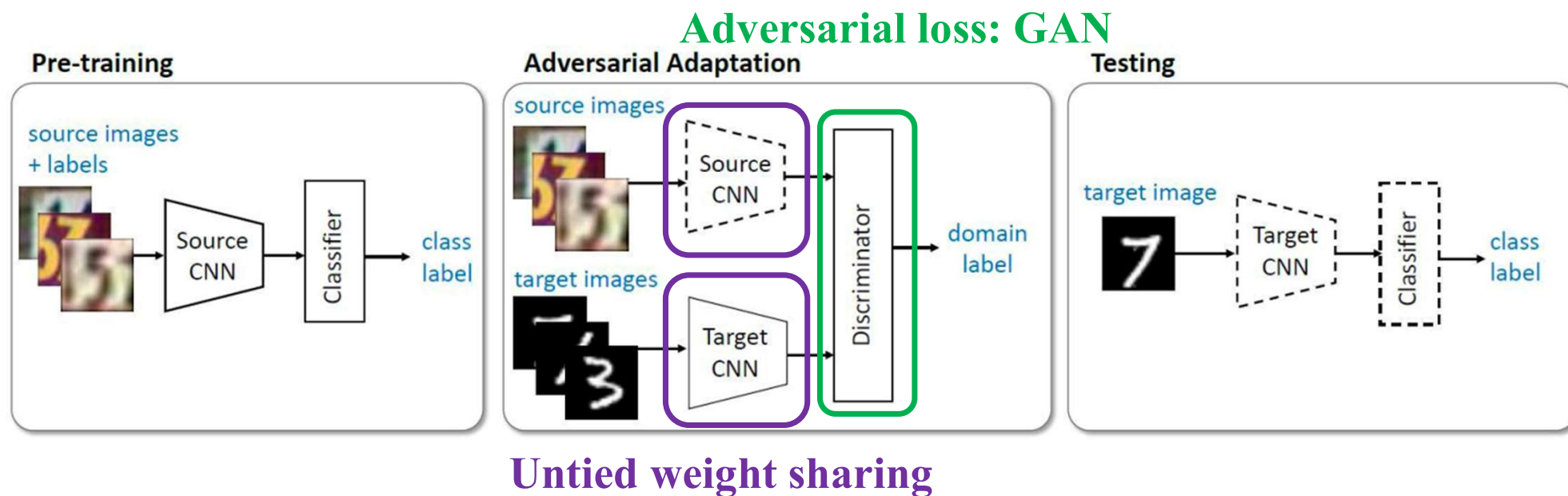
Slide credit: Chonghao Zhao

DANN: Domain Adversarial Training of Neural Networks



[JMLR 2016] Domain Adversarial Training of Neural Networks

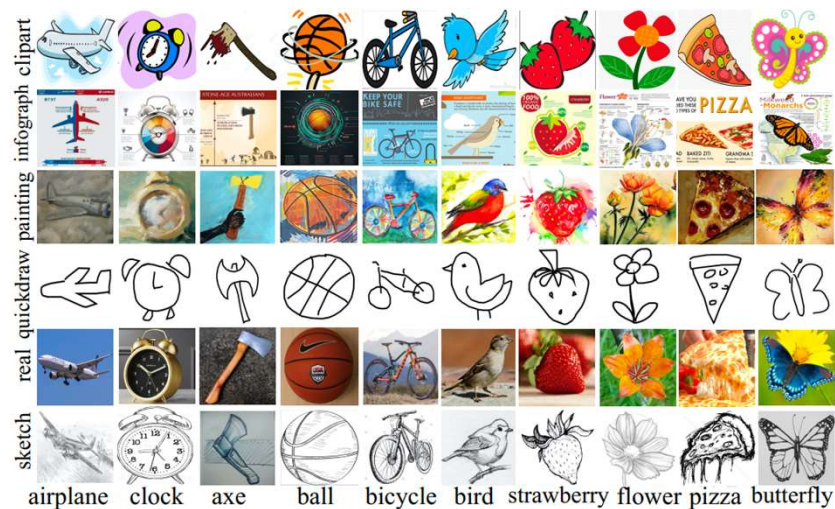
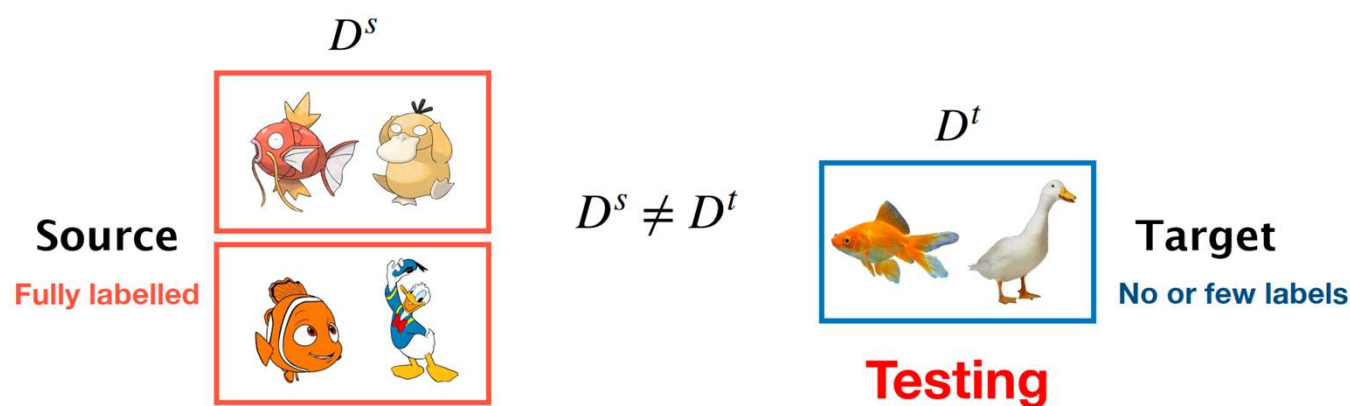
ADDA: Adversarial Discriminative Domain Adaptation



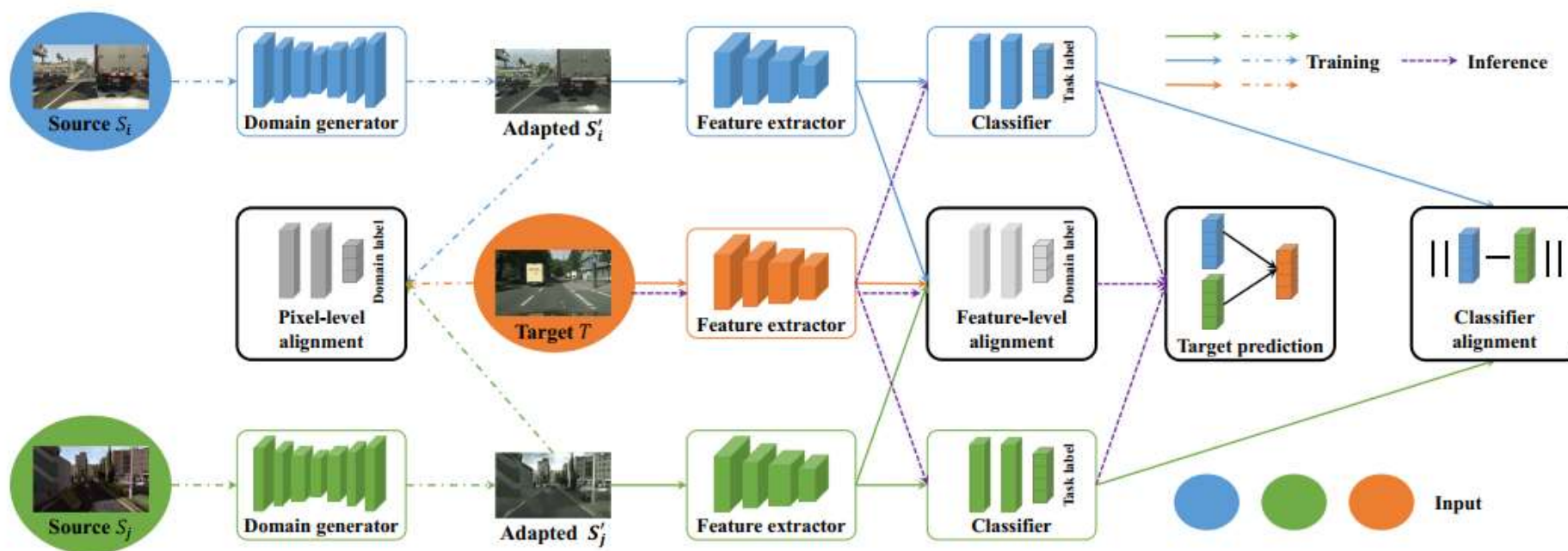
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- **Multi-source Domain Adaptation Methods**
- Universal Domain Adaptation Methods

Multi-source Domain Adaptation

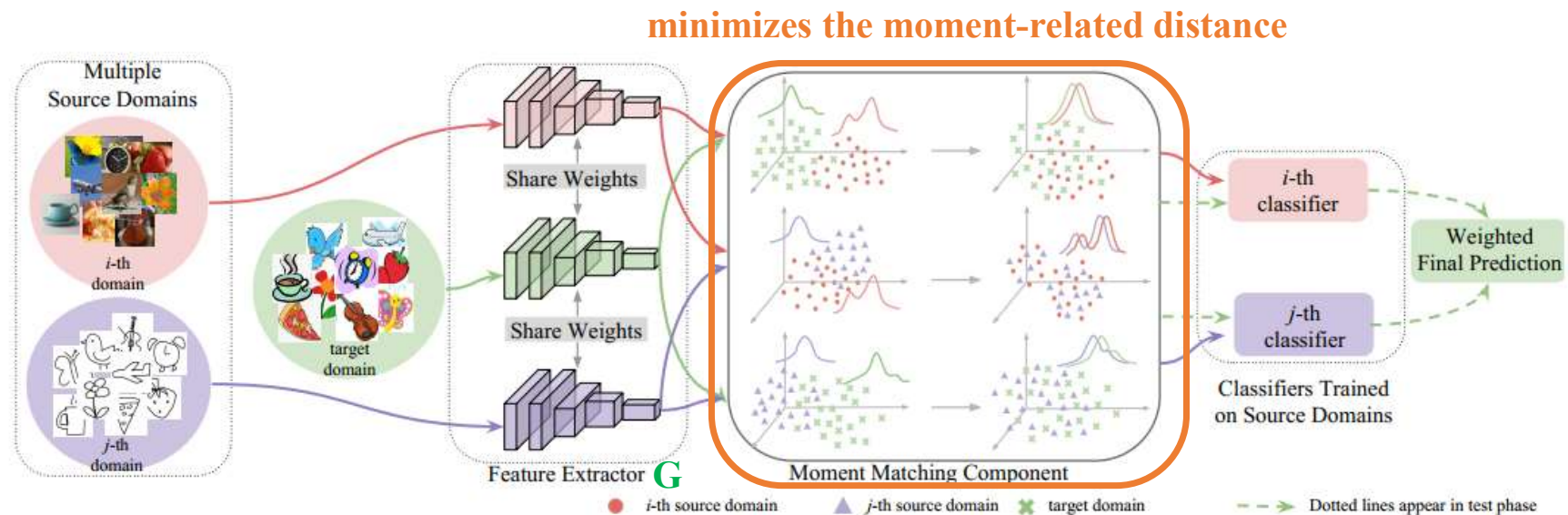


Multi-source Domain Adaptation



[arXiv 2020] Multi-source Domain Adaptation in the Deep Learning Era: A Systematic Survey

M3SDA: Moment Matching for Multi-Source Domain Adaptation



cross-entropy loss

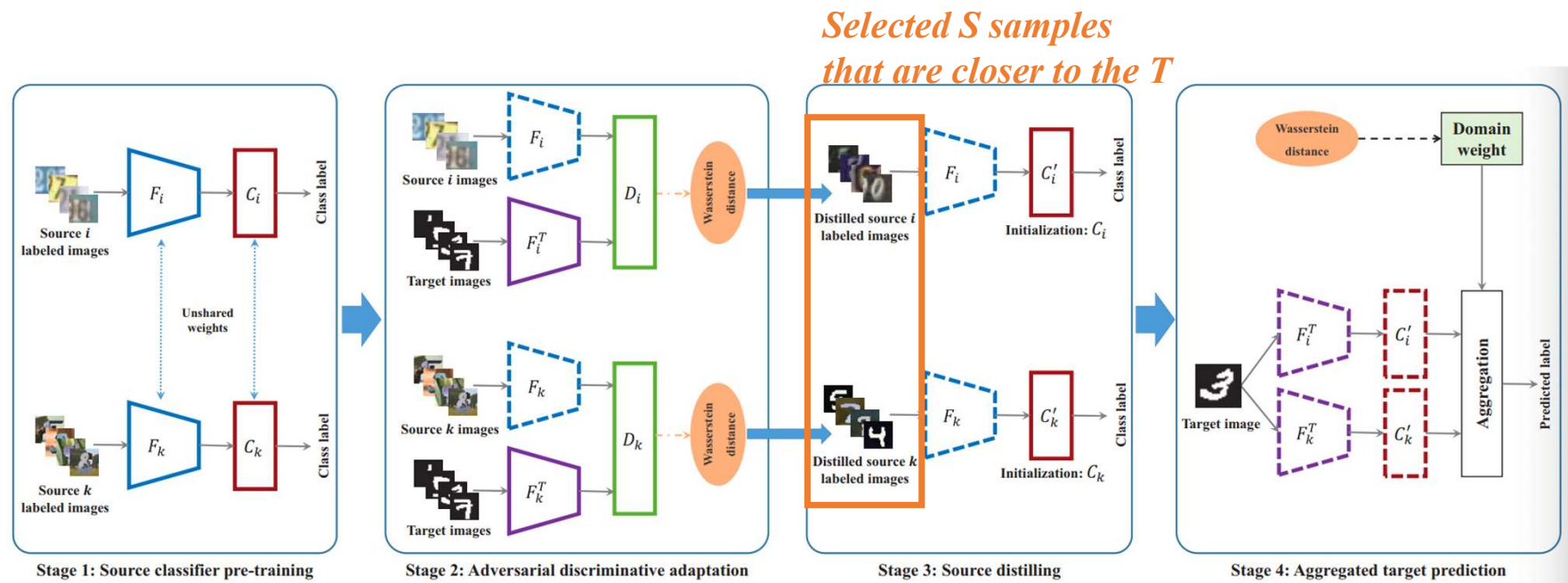
$$\min_{G, C} \sum_{i=1}^N \mathcal{L}_{\mathcal{D}_i} + \lambda \min_G MD^2(\mathcal{D}_S, \mathcal{D}_T)$$

Feature alignment

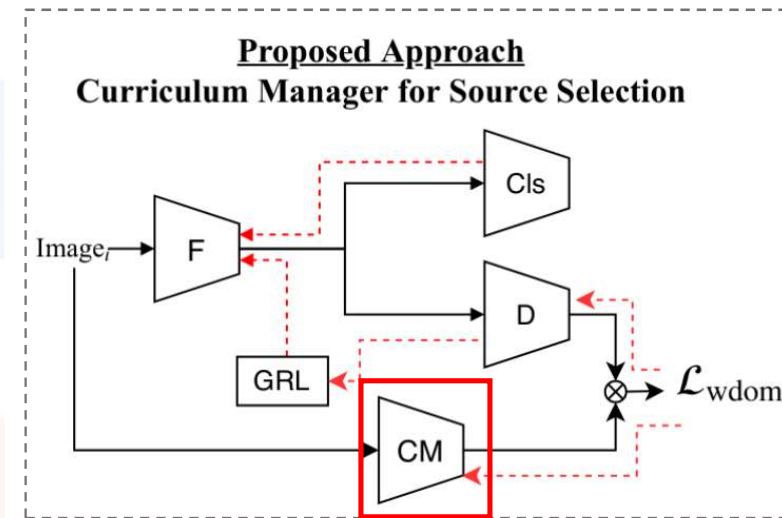
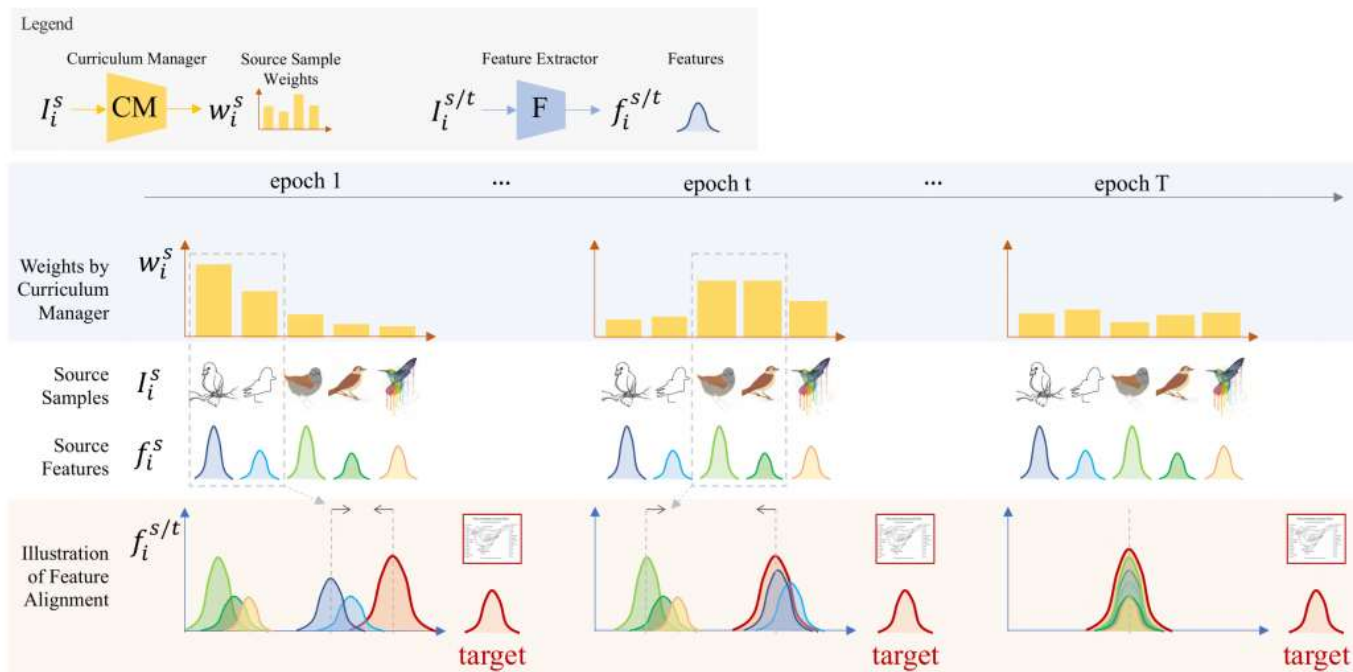
$$MD^2(\mathcal{D}_S, \mathcal{D}_T) = \sum_{k=1}^2 \left(\frac{1}{N} \sum_{i=1}^N \|\mathbb{E}(\mathbf{X}_i^k) - \mathbb{E}(\mathbf{X}_T^k)\|_2 \right. \\ \left. + \binom{N}{2}^{-1} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \|\mathbb{E}(\mathbf{X}_i^k) - \mathbb{E}(\mathbf{X}_j^k)\|_2 \right).$$

[ICCV 2019] Moment Matching for Multi-Source Domain Adaptation

MDDA: Multi-source Distilling Domain Adaptation



CMSS: Curriculum Manager for Source Selection



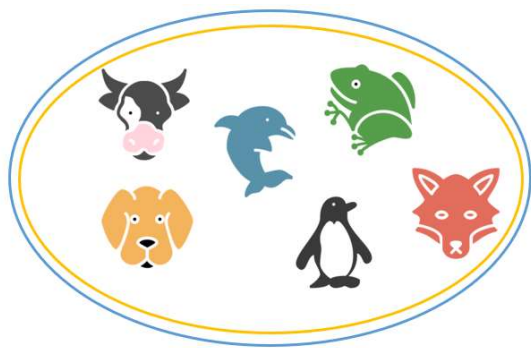
Generate weight vector of training samples

[ECCV 2020] Curriculum Manager for Source Selection in Multi-Source Domain Adaptation

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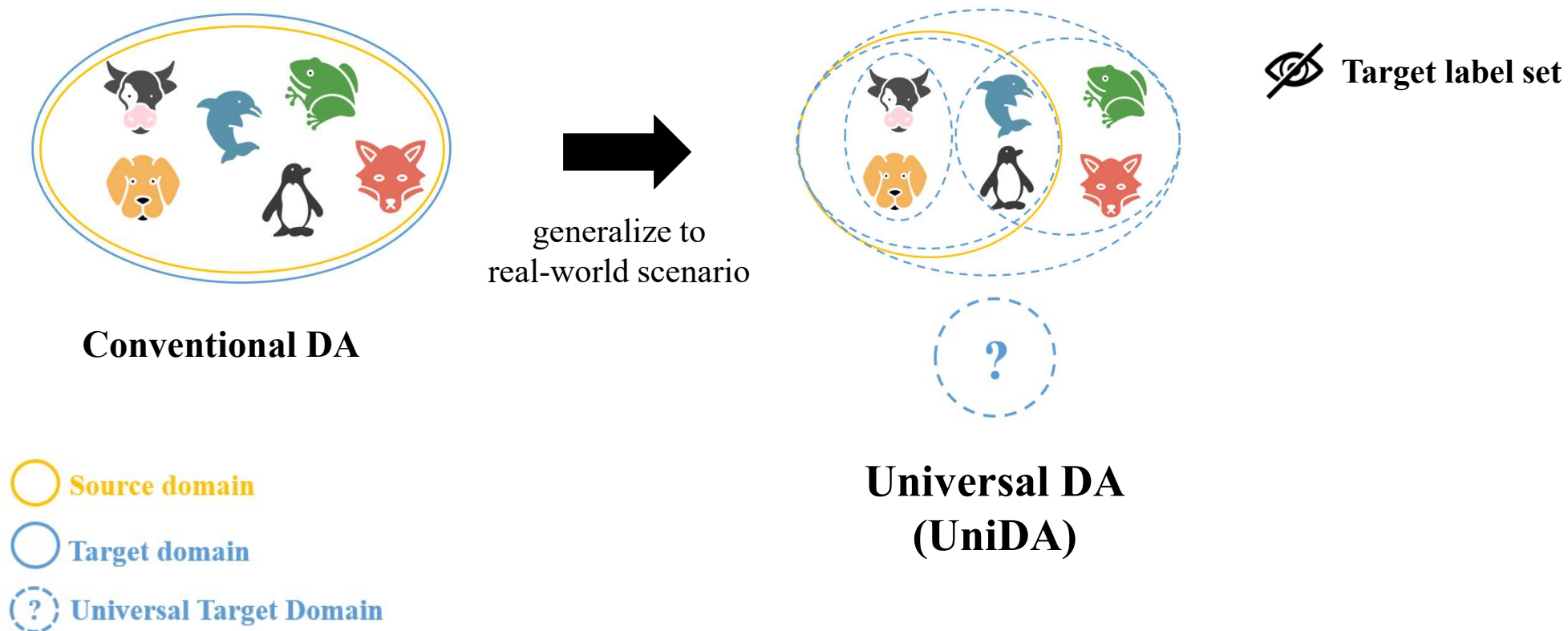
What is Universal Domain Adaptation?



Conventional DA

-  **Source domain**
-  **Target domain**
-  **Universal Target Domain**

What is Universal Domain Adaptation?



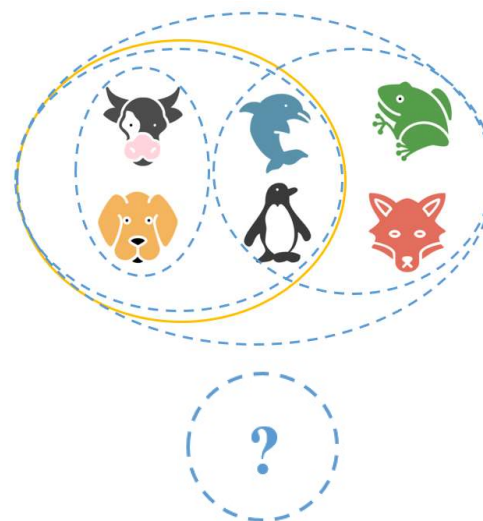
What is Universal Domain Adaptation?



Conventional DA



generalize to
real-world scenario



**Universal DA
(UniDA)**

 Target label set

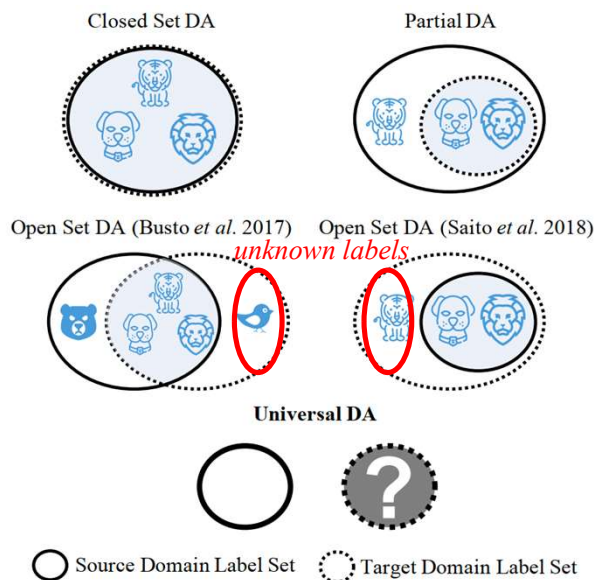


? common classes

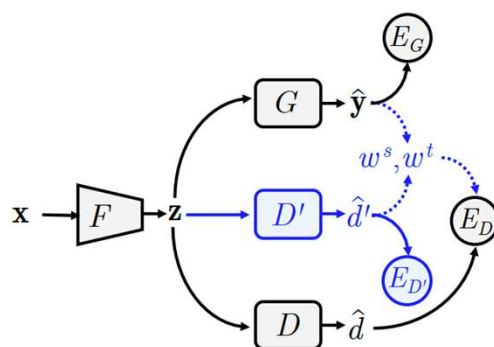
? private classes

 **More challenging!**

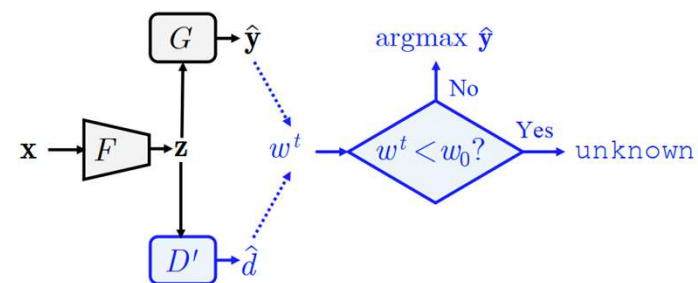
UAN: Universal Adaptation Network



Training phase



Testing phase



▢ conv layer □ fc layer ○ loss → computation flow weighting mechanism

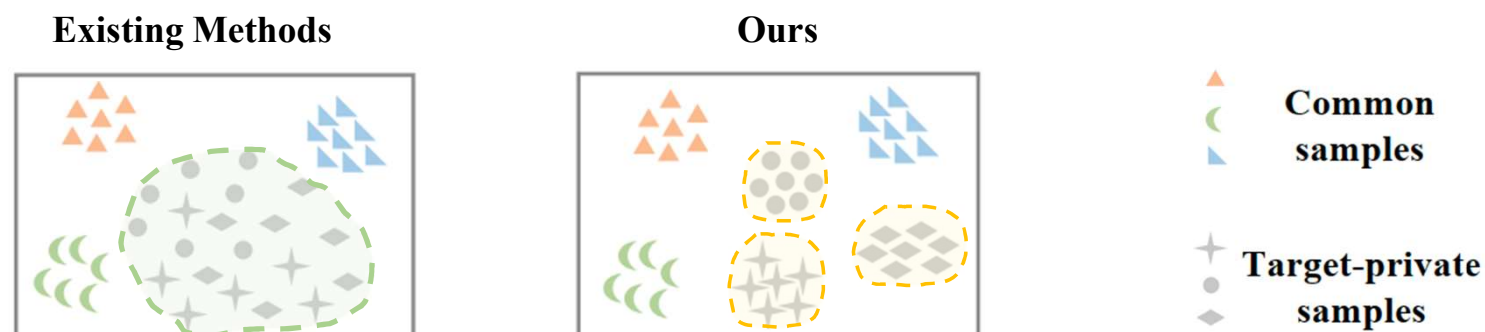
$$E_G = \mathbb{E}_{(\mathbf{x}, \mathbf{y}) \sim p} L(\mathbf{y}, G(F(\mathbf{x})))$$

$$E_{D'} = -\mathbb{E}_{\mathbf{x} \sim p} \log D'(F(\mathbf{x})) \\ - \mathbb{E}_{\mathbf{x} \sim q} \log (1 - D'(F(\mathbf{x})))$$

$$E_D = -\mathbb{E}_{\mathbf{x} \sim p} w^s(\mathbf{x}) \log D(F(\mathbf{x})) \\ - \mathbb{E}_{\mathbf{x} \sim q} w^t(\mathbf{x}) \log (1 - D(F(\mathbf{x})))$$

$$\max_D \min_{F, G} E_G - \lambda E_D \\ \min_{D'} E_{D'}$$

Existing Methods



ignore the intrinsic structure of target domain

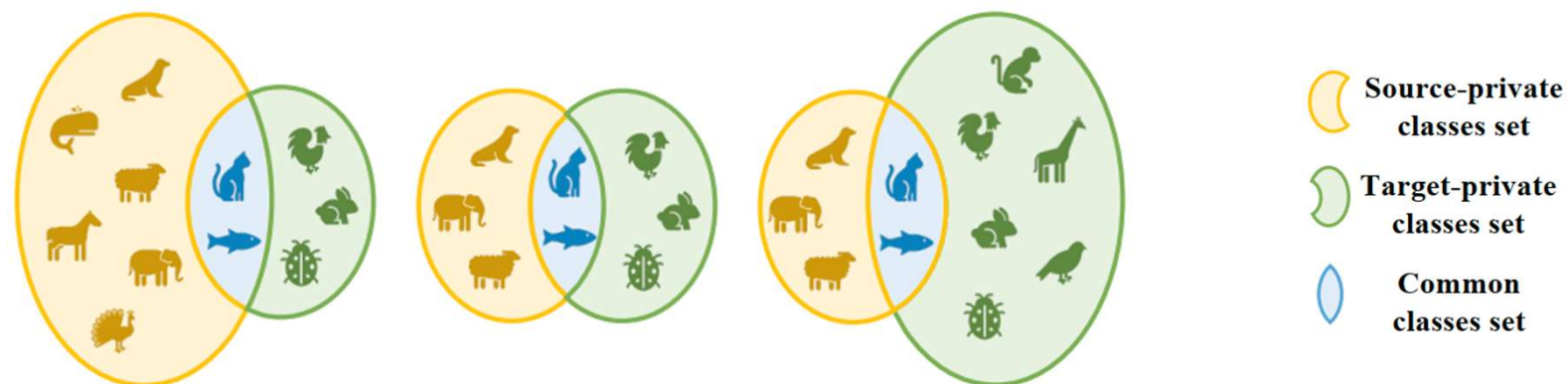


deteriorate target representation and model performance



learn a not well-generalized model to target domain

Existing Methods

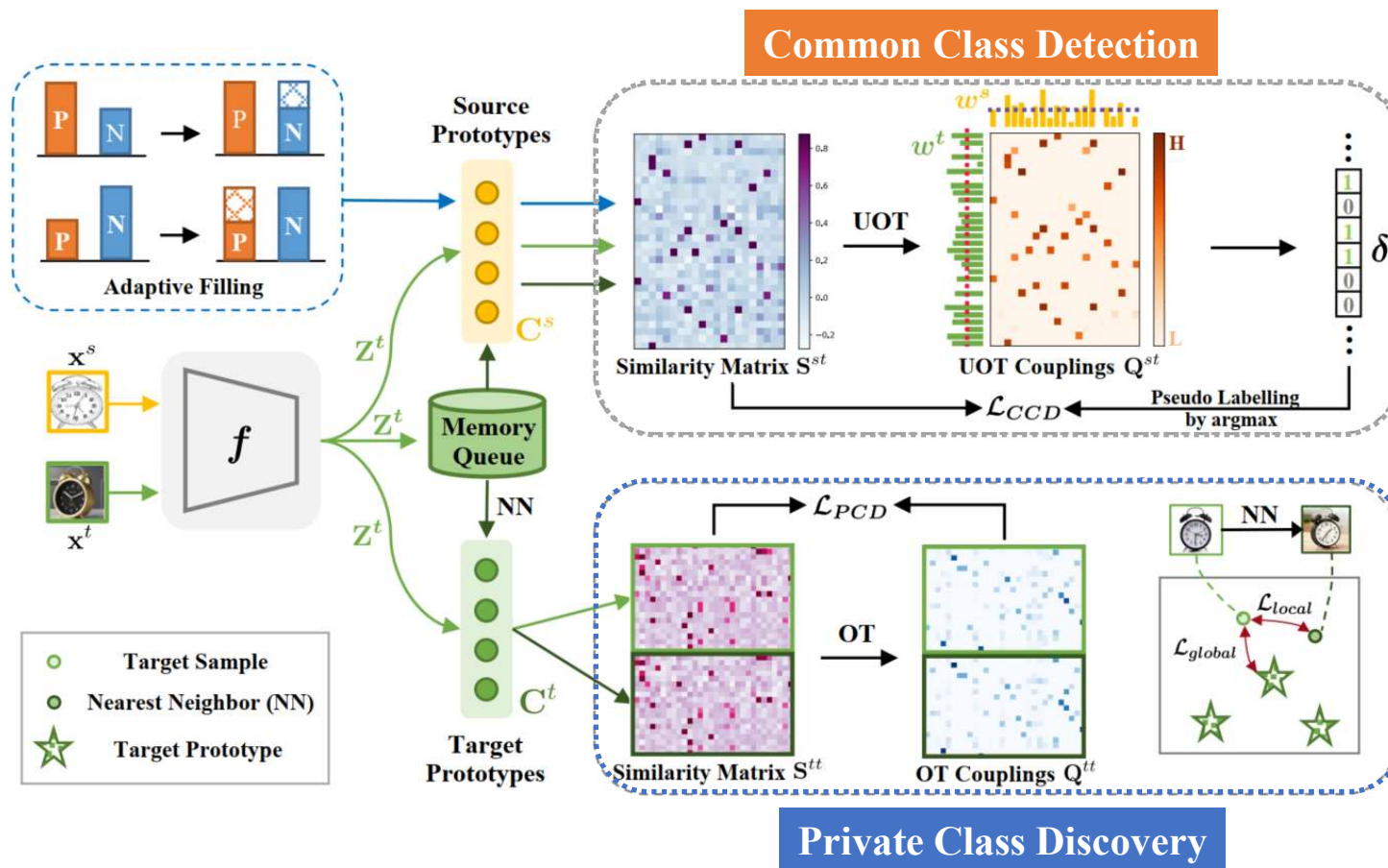


diverse ratios of common categories



very sensitive to threshold values

Unified OT Framework for UniDA



Questions?