#### **Domain Adaptation**

Once the distribution of training data is different from testing data... Domain shift: Training and testing data have different distributions.

■ Domain adaptation

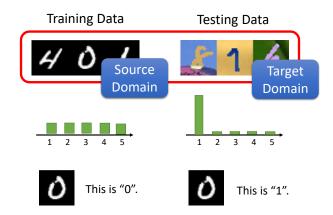
A part of transfer learning.

#### **Domain Shift**

Source domain: training data Target domain: testing data

#### **Domain Adaptation**

We need to know some knowledge of target domain.



#### Have data and little labeled:

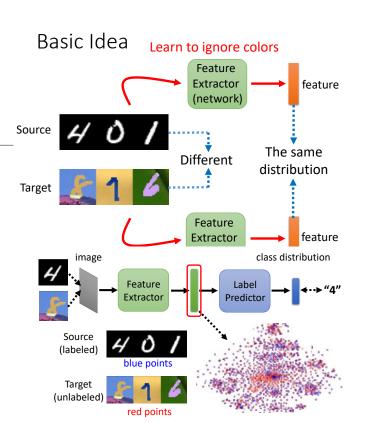
Idea: training a model by source data, then fine-tune the model by target data Challenge: **only limited target data**, **so be careful about overfitting** 

#### Large amount of unlabeled data

Basic idea: to find a feature extractor (also a network).
After passing the feature extractor, the final feature has no difference.

## Domain Adversarial Training

We need to define feature extractor layer range and label predictor layers by ourself. This is also a hyper parameter.



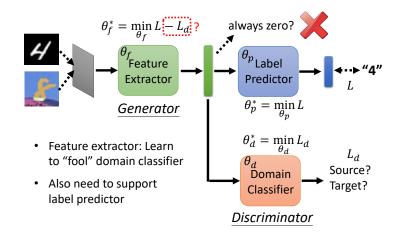
Method: now we take the outputs of feature extractor and see it's grouping to make sure it does not have difference.]

#### Basic idea (but not the best idea):

Extract the features to make domain classifier can not classify data by the features.

Feature extractor: Learn to fool domain classifier
Also need to support label predictor.

Feature extractor needs to generate proper feature vector to make label predictor generate correct label. Therefore features are not always 0.



Feature Extractor( $\theta_{f}$ ): Generate feature vector to make label predictor make correct prediction.

$$\theta_f^* = \min_{\theta_f} L - L_d$$

Label predictor: $(\theta_n)$  to predict the correct label classification

$$\theta_p^* = \min_{\theta_p} L$$

Domain Classifier( $\theta_d$ ): predict the source target

$$\theta_d^* = \underset{\theta_d}{minL}$$

Here L:loss

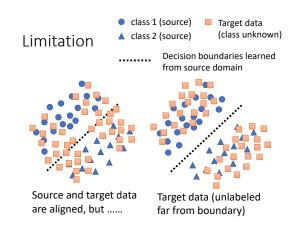
#### Limitation

We want to keep the target data away from the decision boundary as far as possible.

Export results are centered → far from boundary

Export results are similar → close to boundary

Used in Decision-boundary Iterative Refinement Training with a Teacher (DIRT-T)



Maximum Classifier Discrepancy

## Universal domain adaptation

Until now, we make assumption source domain have the same objects in target domain. But ...

The weights of label predictor and label predictor is critical to make sure the training balance.

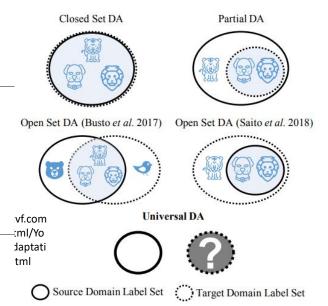
## Little and unlabeled data situation

Test time training (TTT)

### Target domain unknown: Domain Generalization

Expect our model can overcome the difference between domains.

# Considering Decision Boundary unlabeled Feature Extractor Label Predictor Label Predictor Large entropy Label Predictor Large entropy Label Predictor



## Once training data has one domain, testing data have multiple domains

Data augmentation.