d-SNE: Domain Adaptation using Stochastic Neighborhood Embedding

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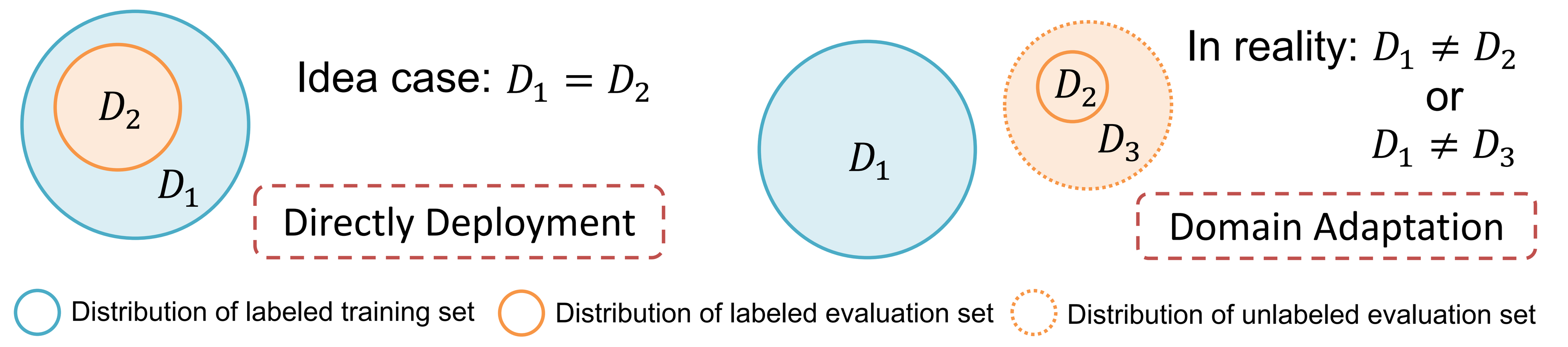
Motivation

There might be a performance gap between the training and testing set



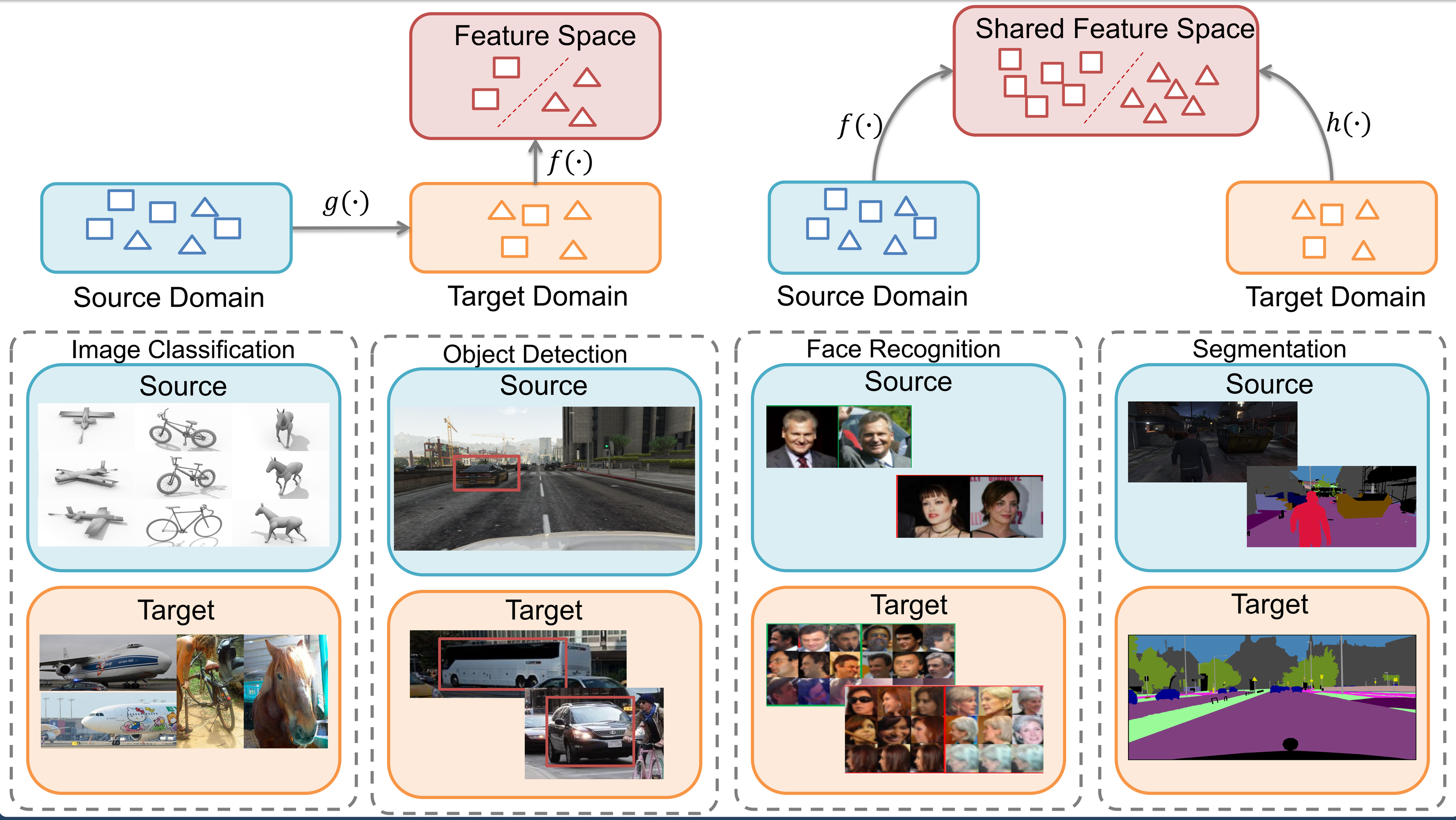
Problem Statement

Source domain $D^s = \{x^s, y^s\}_{i=1}^{N^s}$

Target domain $D^t = \{x^t, y^t\}_{j=1}^{N^t}, N^t \ll N^s$ or $D^t = \{x^t\}_{j=1}^{N^t}$

To improve the performance of an existing model M_{D^s} for D^t by adapting the knowledge of the model learned from D^s to D^t

Related Work



Method

Consider the distance between the features $\{\phi_{D^s}(x^s), \phi_{D^t}(x^t)\}$ from the source and target domain:

$$d(x^s, x^t) = \left|\left|\phi_{D^s}(x^s) - \phi_{D^t}(x^t)\right|\right|_2^2$$

The probability that target samples $x_j^t \in D^t$ has the same label as the source samples $x_i^s \in D^s$:

$$p_{ij} = \frac{e^{-d(x_i^s, x_j^t)}}{\sum_{x \in D^s} e^{-d(x, x_j^t)}} \xrightarrow{\text{Consider all samples in } D^s} p_j = \frac{\sum_{x \in D_k^s} e^{-d(x, x_j^t)}}{\sum_{x \in D^s} e^{-d(x, x_j^t)}}, D_k^s = \{\forall x_l^s | y_l^s = k\}$$

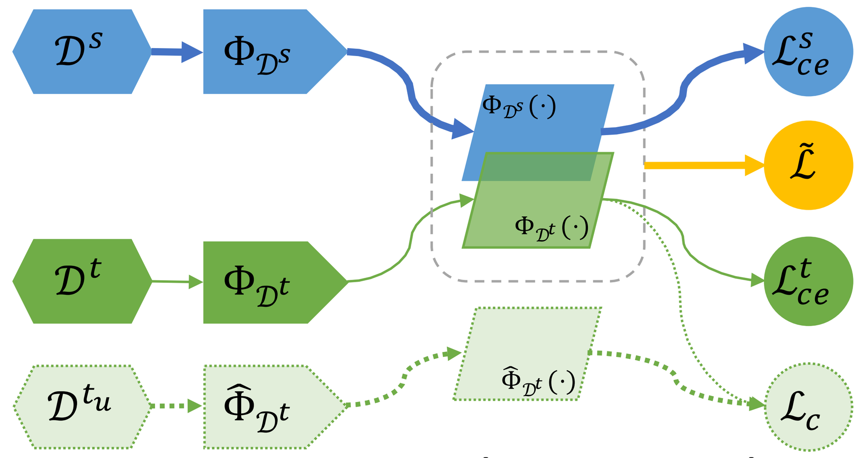
Given a target sample and label, the source domain D^s is split into two parts as a same-class set D_k^s and a different-class set $D_{\bar{k}}^s$. The objective function for the domain adaptation problem can be derived as:

$$\sum_{x_j \in D^t} \frac{1}{p_j} = \sum_{x_j \in D^t} \left(\frac{\sum_{x \in D_{\bar{k}}^s} e^{-d(x, x_j)}}{\sum_{x \in D_k^s} e^{-d(x, x_j)}} \right), \text{ for } k = y_i$$

Relaxation: minimize the log-likelihood:

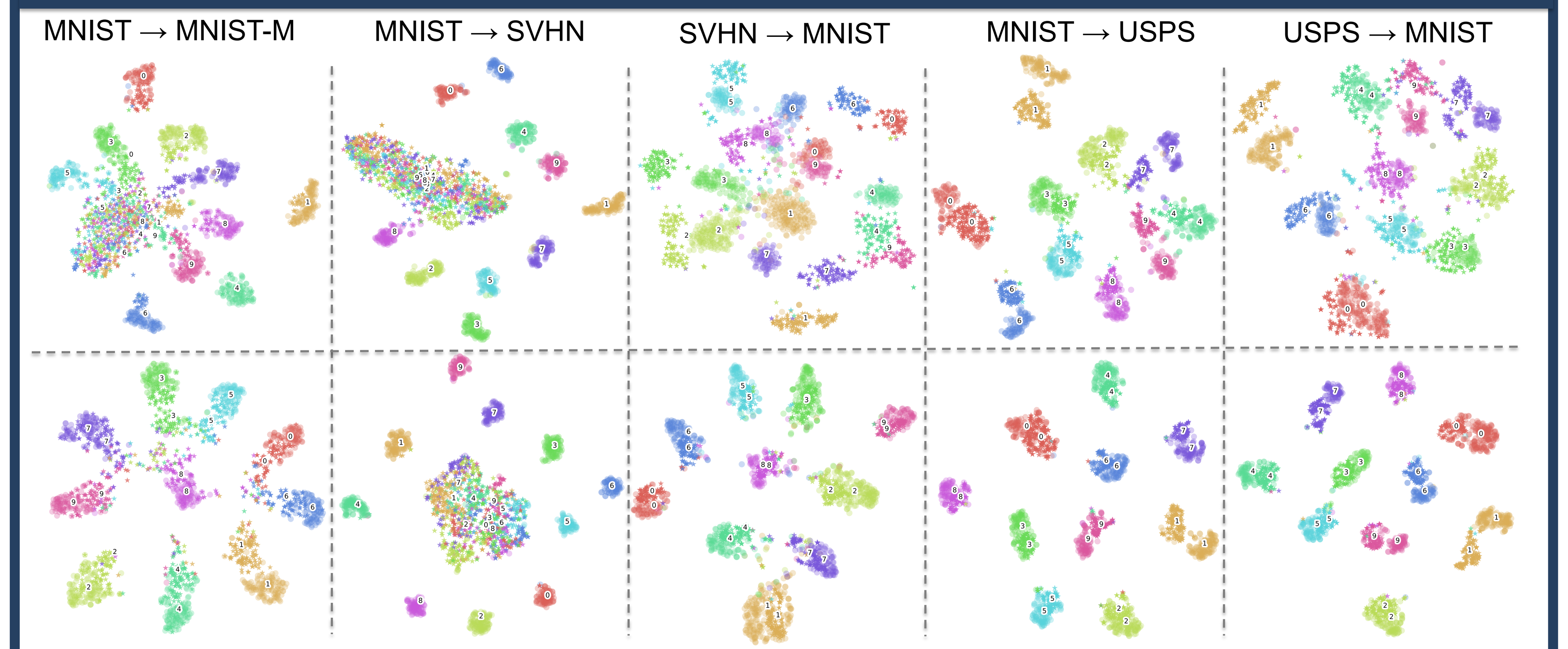
$$\tilde{L} = \sup_{x \in D_k^s} \{a | a \in d(x, x_j)\} - \inf_{x \in D_{\bar{k}}^s} \{a | a \in d(x, x_j)\}$$

for $k = y_i$



Extension: Semi-supervised Domain Adaptation using Mean-Teacher network

Experiments



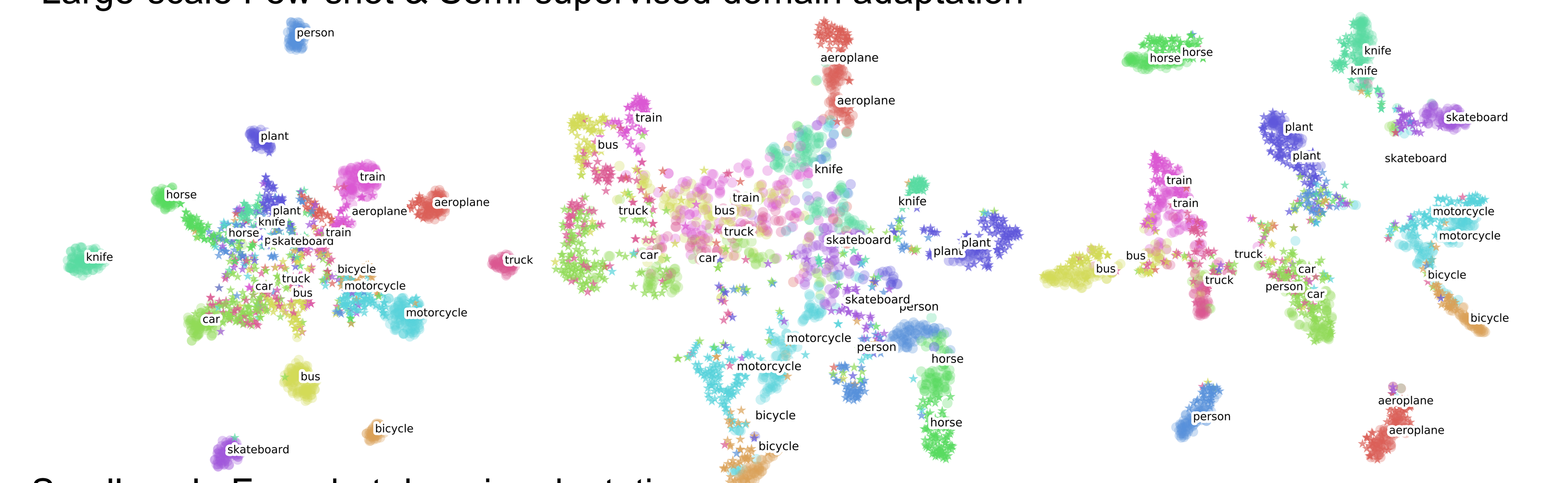
Experiments

Method	Setting	k	MNIST→ MNIST-M	MNIST→USPS	USPS→MNIST	MNIST→SVHN	SVHN→MNIST
DIRT-T	U		98.90	-	-	54.50	**99.40**
SE			-	98.23	99.54	71.40	92.00
SBADA-GAN			**99.40**	95.04	97.60	61.08	76.14
G2A			-	95.30	90.80	-	92.40
FADA	S	7	-	94.40	91.50	47.00	87.20
CCSA		10	78.29	97.22	95.71	37.63	94.57
d-SNE		7	84.62	97.53	97.52	53.19	95.68
		10	87.80	**99.00**	98.49	61.73	96.45
d-SNE	SS	10	94.12	-	-	**77.63**	97.60

Classification accuracy for domain adaptation methods on digits datasets. The unsupervised setting (U) uses all the images in the target domain. The supervised setting (S) uses 10 labeled samples per-class from the target domain.

Method	Setting	Source	Target
G2A	U	44.50	77.10
SE	SS	52.80	85.40
CCSA	S	52.80	76.89
d-SNE	S	52.80	80.66
	SS	52.80	**86.15**

- Large-scale Few-shot & Semi-supervised domain adaptation



- Small-scale Few-shot domain adaptation

Method	Setting	k	A → D	A → W	D → A	D → W	W → A	W → D
DRCN	U		68.70	67.10	56.00	96.40	54.09	99.00
G2A			87.70	89.50	72.80	97.90	71.40	99.80
CCSA	S	3	89.00	88.20	**71.80**	96.40	**72.10**	**97.60**
FADA		3	88.20	88.10	68.10	96.40	71.10	97.50
d-SNE (VGG16)		0	62.40	61.49	48.92	82.24	47.52	90.42
		3	**91.44**	**90.13**	71.06	**97.10**	71.74	97.46
d-SNE (ResNet101)		0	80.41	75.26	67.39	96.39	65.55	98.31
		3	**94.65**	**96.58**	**75.51**	**99.10**	**74.20**	**100.00**

Results of office31 experiments. d-SNE with ResNet-101 base network achieves the best results with only 3 samples in the target domain while d-SNE with VGG-16 base network outperforms the baselines in the majority of cases.