Aligning Domain-specific Distribution and Classifier for Cross-domain Classification from Multiple Sources

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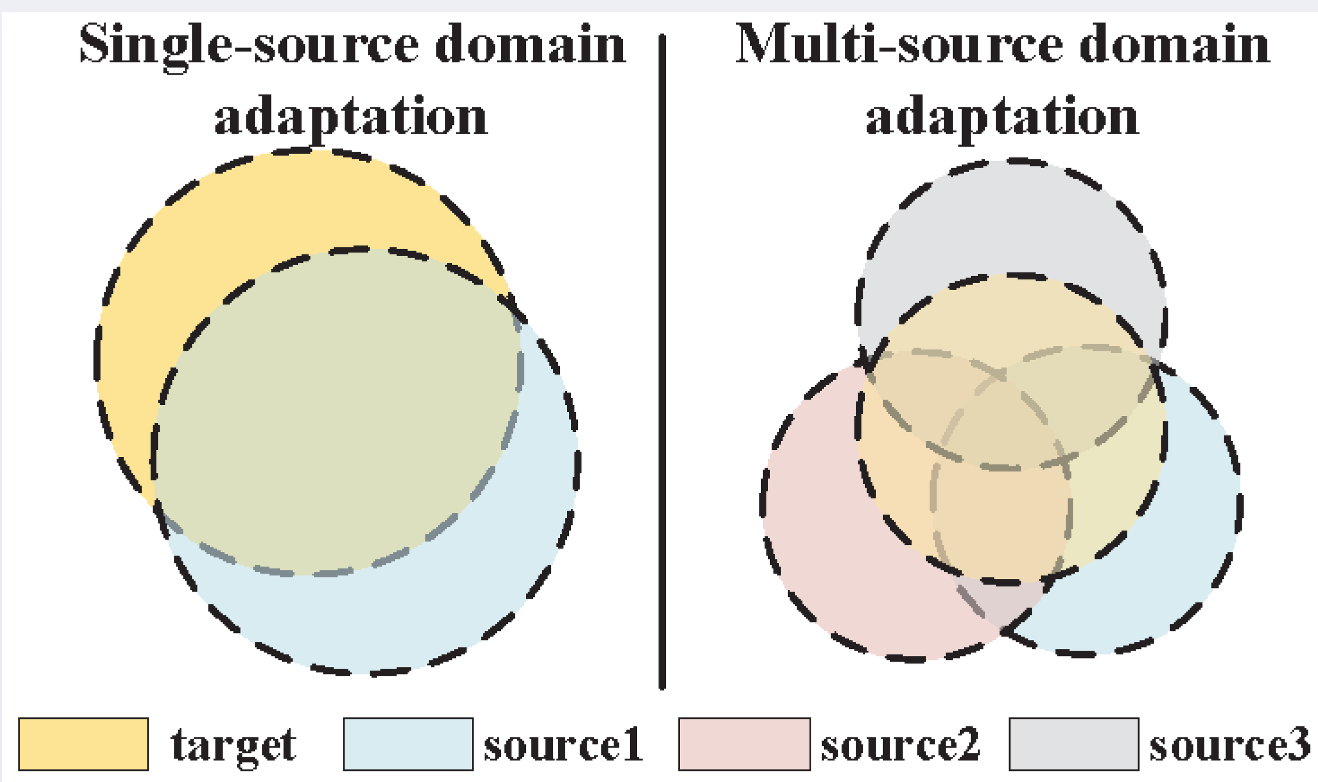
Introduction

In Single-source Unsupervised Domain Adaptation (SUDA), the distribution of source and target domains cannot be matched very well.

In Multi-source Unsupervised Domain Adaptation (MUDA), due to the shift between multiple source domains, it is much harder to match distributions of all source domains and target domains.

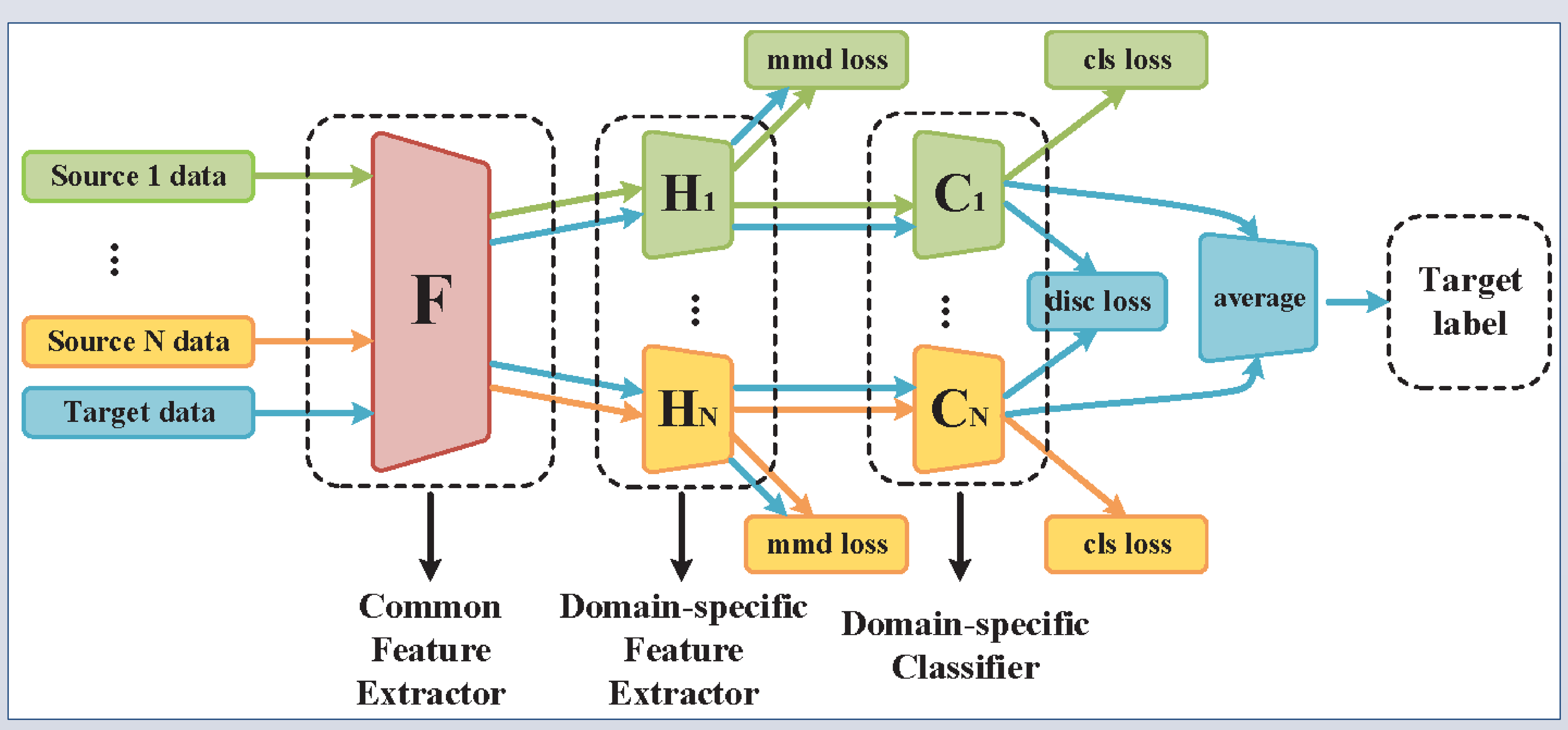


Previous deep MUDA methods have two common problems.

- The first problem is that they try to map all source and target domain data into a common feature space to learn common domain-invariant representations.
- The second problem is that they assume that the target domain data can be classified correctly by multiple domain-specific classifiers because they are aligned with the source domain data.

Model

Network Structure



Two-stage alignment Framework (MFSAN):

- Common feature extractor
- Domain-specific feature extractor
- Domain-specific classifier

The first stage: align domain-specific distribution with MMD.

The second stage: align the output of domain-specific classifiers with L1 distance.

cls loss

$$\mathcal{L}_{cls} = \sum_{j=1}^{N} \mathbf{E}_{x \sim X_{sj}} J(C_j(H_j(F(\mathbf{x}_i^{sj}))), \mathbf{y}_i^{sj})$$

mmd loss

$$D_{\mathcal{H}}(p,q) \triangleq \|\mathbf{E}_p[\phi(\mathbf{x}^s)] - \mathbf{E}_q[\phi(\mathbf{x}^t)]\|_{\mathcal{H}}^2$$

disc loss

$$\mathcal{L}_{disc} = \frac{2}{N \times (N-1)} \sum_{j=1}^{N-1} \sum_{i=j+1}^{N} \mathbf{E}_{x \sim X_t}[|C_i(H_i(F(x_k))) - C_j(H_j(F(x_k)))|],$$

Experiment

Dataset: ImageCLEF-DA、Office-31 and Office-Home

Results

Table 1: Performance Comparison of Classification Accuracy (%) on Office-31 Dataset.

Standards	Method	A,W → D	A,D → W	D,W → A	Avg
Single Best	ResNet	99.3	96.7	62.5	86.2
	DDC	98.2	95.0	67.4	86.9
	DAN	99.5	96.8	66.7	87.7
	D-CORAL	99.7	98.0	65.3	87.7
	RevGrad	99.1	96.9	68.2	88.1
	RTN	99.4	96.8	66.2	87.5
Source Combine	DAN	99.6	97.8	67.6	88.3
	D-CORAL	99.3	98.0	67.1	88.1
	RevGrad	99.7	98.1	67.6	88.5
Multi-Source	DCTN	99.3	98.2	64.2	87.2
	MFSAN_{disc}	99.7	97.9	68.1	88.6
	MFSAN_{mmd}	**99.9**	98.3	71.5	89.9
	MFSAN	99.5	**98.5**	**72.7**	**90.2**

Table 2: Performance Comparison of Classification Accuracy (%) on Image-CLEF Dataset.

Standards	Method	I,C → P	I,P → C	P,C → I	Avg
Single Best	ResNet	74.8	91.5	83.9	83.4
	DDC	74.6	91.1	85.7	83.8
	DAN	75.0	93.3	86.2	84.8
	D-CORAL	76.9	93.6	88.5	86.3
	RevGrad	75.0	**96.2**	87.0	86.1
	RTN	75.6	95.3	86.9	85.9
Source Combine	DAN	77.6	93.3	92.2	87.7
	D-CORAL	77.1	93.6	91.7	87.5
	RevGrad	77.9	93.7	91.8	87.8
Multi-Source	DCTN	75.0	95.7	90.3	87.0
	MFSAN_{disc}	78.0	95.0	92.5	88.5
	MFSAN_{mmd}	78.7	94.8	93.1	88.9
	MFSAN	**79.1**	95.4	**93.6**	**89.4**

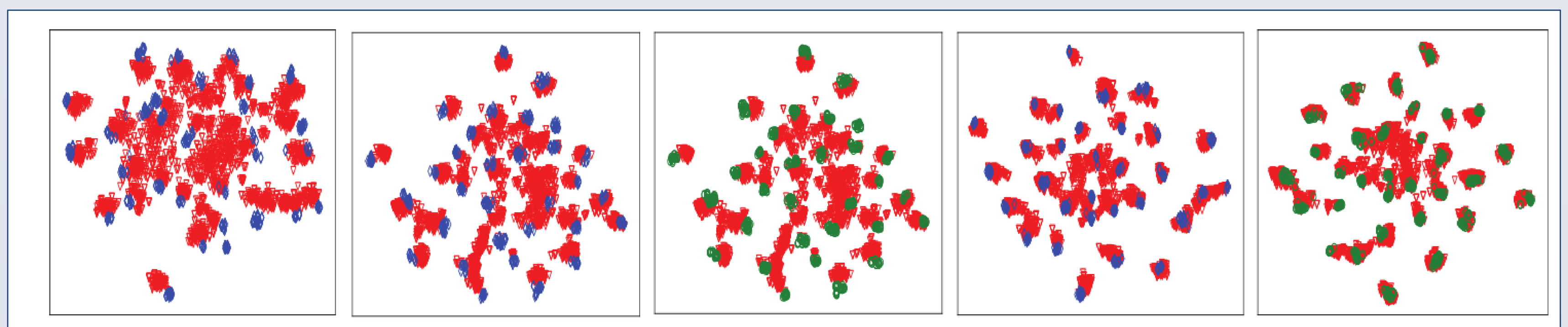
Table 4: Classification Accuracy (%) on Office-31 Dataset for MFSAN with and without diss Loss.

Standards	Method	A,W → D	A,D → W	D,W → A	Avg
MFSAN_{mmd}	S1	97.7	95.0	68.3	87.0
	S2	85.5	89.0	71.0	81.8
	Avg	99.9	98.3	71.5	89.9
MFSAN	S1	97.3	97.6	72.5	89.1
	S2	96.6	97.7	72.4	88.9
	Avg	99.5	**98.5**	**72.7**	**90.2**

Table 3: Performance Comparison of Classification Accuracy (%) on Office-Home Dataset.

Standards	Method	C,P,R → A	A,P,R → C	A,C,R → P	A,C,P → R	Avg
Single Best	ResNet	65.3	49.6	79.7	75.4	67.5
	DDC	64.1	50.8	78.2	75.0	67.0
	DAN	68.2	56.5	80.3	75.9	70.2
	D-CORAL	67.0	53.6	80.3	76.3	69.3
	RevGrad	67.9	55.9	80.4	75.8	70.0
Source Combine	DAN	68.5	59.4	79.0	82.5	72.4
	D-CORAL	68.1	58.6	79.5	**82.7**	72.2
	RevGrad	68.4	59.1	79.5	**82.7**	72.4
Multi-Source	MFSAN_{disc}	69.8	60.2	80.2	81.0	72.8
	MFSAN_{mmd}	71.1	61.9	79.3	80.8	73.3
	MFSAN	**72.1**	**62.0**	**80.3**	81.8	**74.1**

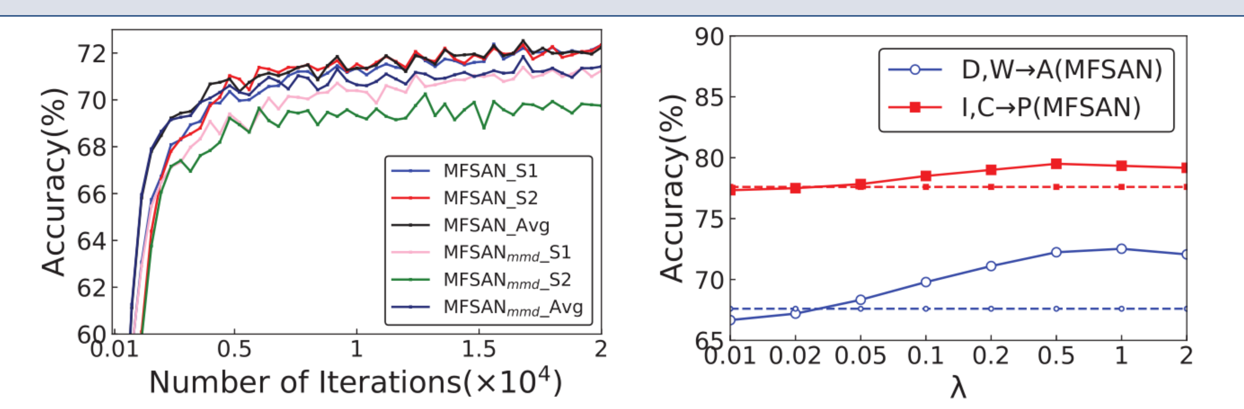
Feature visualization



(a) DAN (Single Source): D, A (b) DAN (Source Combine): D, A (c) DAN (Source Combine): W, A (d) MFSAN: D, A (e) MFSAN: W, A

Figure 3: The Visualization of Latent Representations of Source and Target Domains.

Algorithm Convergence and Parameter Sensitivity



(a) Convergence (b) Accuracy w.r.t λ

Figure 4: Algorithm Convergence and Parameter Sensitivity.

The results from MFSAN with disc loss have a smaller gap among classifiers and they achieve higher accuracy.

Conslusion

In this paper, we proposed a Multiple Feature Space Adaptation Network (MFSAN). MFSAN uses two-stage alignment to overcome two common problems exiting in previous deep MUDA methods.

- Align domain-specific distribution.
- Align the output of domain-specific classifiers. This ensure the same target sample predicted by different classifiers could get the same prediction.