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Dual collaboration for decentralized multi-source domain adaptation

Key words: Multi-source domain adaptation; Data decentralization; Domain shift; Negative transfer

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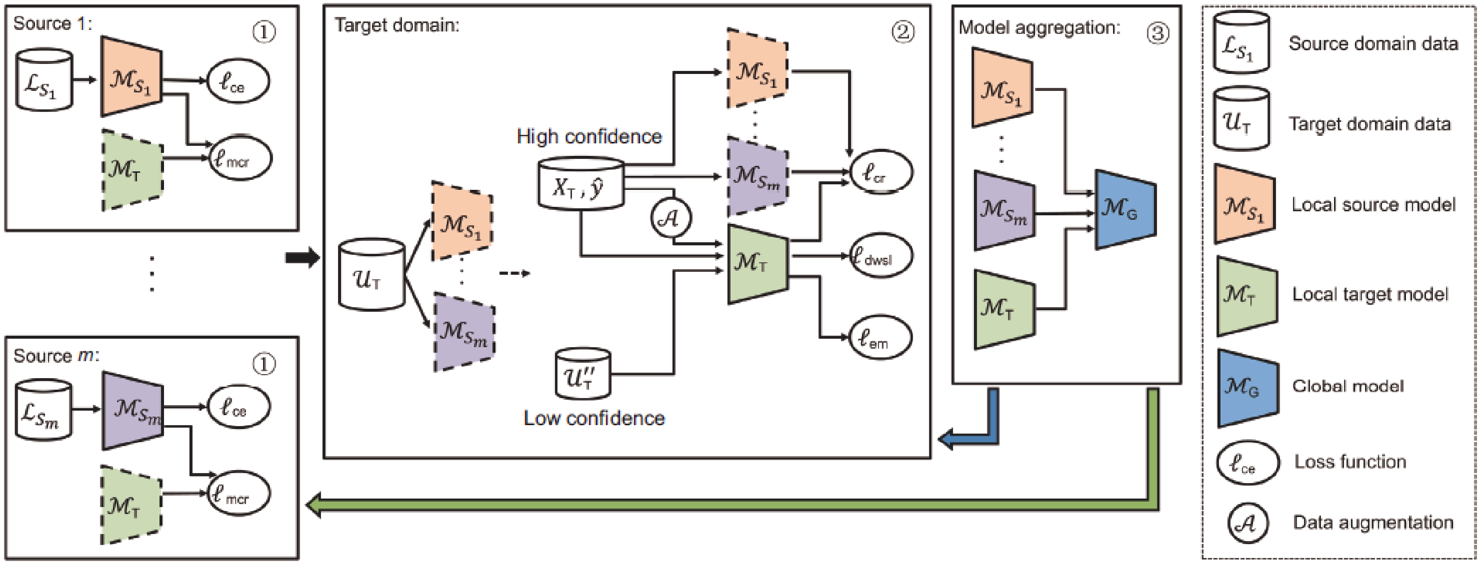
Motivation

- Due to data privacy and storage cost concerns, the data from different domains are isolated and cannot be accessed by other domains, which presents a great challenge for the conventional unsupervised multi-source domain adaptation (UMDA) methods.
- First, the source models inevitably generate inaccurate pseudo-labels for fine-tuning or distilling knowledge in the unlabeled target domain, which reduces the domain adaptation performance.
- Second, the source models tend to overfit their domain data under the data decentralization scenario, which leads to the source models shifting away from the distribution of target domain data.

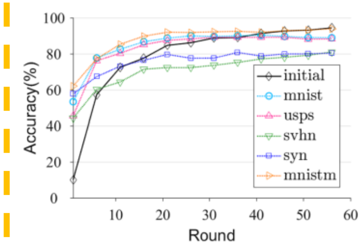
Main idea

- A dual collaboration framework is proposed to reduce the domain gap between the decentralized source domains and target domain.
- On the decentralized target domain, we propose a domain weighted soft label (DWSL) strategy to generate pseudo-labels and improve the discrimination of the target domain model by fully using the unlabeled target domain data.
- On the decentralized source domains, we regularize local source models toward the target domain model during training to reduce the domain gap.
- Experiments have been conducted on standard multi-source domain adaptation datasets, indicating the superior performance of our dual collaboration multi-source domain adaptation (DC-MDA).

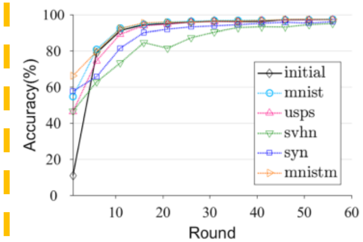
Method



Overall framework



w/o MCR



w/ MCR

☐ Target domain training

- ☐ Cross-entropy loss is adopted for training the pseudo-labeled target domain ℓ_{dwsl}
- ☐ Consistency regularization (CR) is adopted to improve the discrimination ℓ_{cr}
- ☐ Entropy minimization (EM) is adopted to utilize the low-confident unlabeled data ℓ_{em}

$$\ell_{\text{tar}} = \ell_{\text{dwsl}} + \ell_{\text{cr}} + \ell_{\text{em}}.$$

☐ Source domain training

- ☐ Cross-entropy loss is adopted for training local source model ℓ_{ce}
- ☐ Model consistency regularization (MCR) is used to overcome negative transfer ℓ_{mcr}

$$\ell_{\text{src}} = \ell_{\text{ce}} + \lambda \ell_{\text{mcr}}$$

☐ Model aggregation

$$\mathcal{M}_{\text{G}} = \frac{1}{m+1}\left(\sum_{j=1}^{m} \frac{N_{S_j}}{N_{\text{tot}}}\mathcal{M}_{S_j} + \frac{N_{\text{T}}}{N_{\text{tot}}}\mathcal{M}_{\text{T}}\right)$$

Major results

Compared with the SOTA

Table 1 Classification accuracy (mean±std) on the Digit-5 dataset

Method	Classification accuracy (%)					Avg (%)
	mt	mm	sv	sy	up	
Source-only	92.3±0.9	63.7±0.8	71.5±0.8	83.4±0.8	90.7±0.5	80.3
DAN (Long et al., 2015)	96.3±0.5	63.8±0.7	62.5±0.7	85.4±0.8	94.2±0.9	80.4
DANN (Ganin and Lempitsky, 2015)	97.6±0.8	71.3±0.6	63.5±0.8	85.3±0.8	92.3±0.9	82.0
DCTN (Xu et al., 2018)	96.2±0.8	70.5±1.2	77.6±0.4	86.8±0.8	92.8±0.3	84.8
M3SDA (Peng et al., 2019)	98.4±0.7	72.8±1.1	81.3±0.9	89.6±0.6	96.1±0.8	87.7
MDAN (Zhao H et al., 2018)	97.2±1.0	75.7±0.8	82.2±0.8	85.2±0.6	93.3±0.5	86.7
MDDA (Zhao SC et al., 2020)	98.8±0.4	78.6±0.6	79.3±0.8	89.7±0.7	93.9±0.5	88.1
CMSS (Yang LY et al., 2020)	99.0±0.1	75.3±0.6	88.4±0.6	93.7±0.2	97.7±0.1	90.8
ABMSDA (Zuo et al., 2021)	99.3±0.1	73.4±0.7	88.2±0.5	97.7±0.2	97.1±0.9	91.1
LtC-MSDA (Wang H et al., 2020)	99.0±0.4	85.6±0.8	83.2±0.6	93.0±0.5	98.3±0.4	91.8
T-SVDNet (Li RH et al., 2021)	99.3±0.1	91.2±0.7	84.9±1.5	95.7±0.3	98.6±0.2	93.9
STEM (Nguyen et al., 2021)	99.4	89.7	89.9	97.5	98.4	95.0
DAEL (Zhou et al., 2021)	99.5±0.0	93.8±0.1	92.5±0.2	**97.9±0.0**	98.7±0.8	96.5
SHOT (Liang et al., 2020)	98.2±0.4	80.2±0.4	84.5±0.3	91.1±0.2	97.1±0.3	90.2
DECISION (Ahmed et al., 2021)	99.2	93.0	82.6	97.5	97.8	94.0
FADA (Peng et al., 2020)	91.4±0.7	62.5±0.7	50.5±0.3	71.8±0.5	91.7±1.0	73.6
SFDA (Wang B et al., 2022)	99.1	72.3	86.0	90.4	98.1	89.2
COPA (Wu and Gong, 2021)	99.4	89.8	91.0	97.5	**99.2**	95.4
KD3A (Feng et al., 2021)	99.2±0.1	87.3±0.2	85.6±0.2	89.4±0.3	98.5±0.3	92.0
DC-MDA	**99.6±0.0**	**97.1±0.2**	**93.2±1.1**	97.6±0.4	98.8±0.1	**97.3**

The best results are in bold

Table 2 Classification accuracy (mean) on the Office31 dataset

Method	Accuracy (%)			Avg (%)
	A	D	W	
Source-only	51.6	92.0	97.1	80.2
DCTN (Xu et al., 2018)	54.9	99.6	96.9	83.8
M3SDA (Peng et al., 2019)	55.4	99.4	96.2	83.7
MDAN (Zhao H et al., 2018)	55.2	99.2	95.4	83.3
MDDA (Zhao SC et al., 2020)	56.2	99.2	97.2	84.2
LtC-MSDA (Wang H et al., 2020)	56.9	99.6	97.2	84.6
SHOT (Liang et al., 2020)	75.0	97.8	94.9	89.3
DECISION (Ahmed et al., 2021)	75.4	99.6	98.4	91.1
KD3A (Feng et al., 2021)	71.9	99.8	98.7	90.1
DC-MDA	**75.8**	**100**	**100**	**91.9**

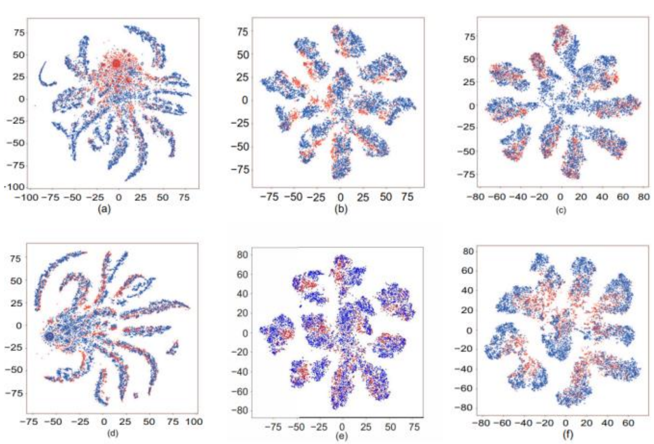
The best results are in bold

Table 3 Classification accuracy (mean) on the Office-Caltech10 dataset

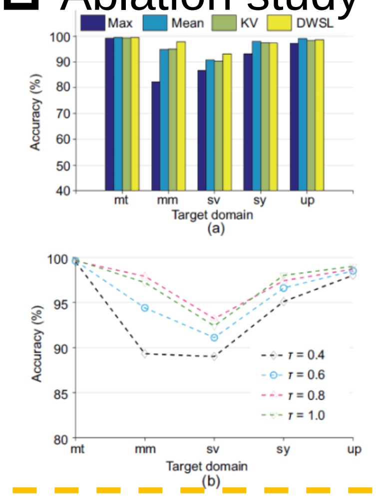
Method	Accuracy (%)				Avg (%)
	A	C	D	W	
Source-only	86.1	87.8	98.3	99.0	92.8
DCTN (Xu et al., 2018)	92.7	90.2	99.0	99.4	95.3
M3SDA (Peng et al., 2019)	94.5	92.2	99.2	99.5	96.4
CMSS (Yang LY et al., 2020)	96.6	93.7	99.3	99.6	97.2
STEM (Nguyen et al., 2021)	**98.4**	94.2	**100**	**100**	98.2
SHOT (Liang et al., 2020)	96.4	96.2	98.5	99.7	97.7
DECISION (Ahmed et al., 2021)	95.9	95.9	**100**	99.6	98.0
FADA (Peng et al., 2020)	84.2	88.7	87.1	88.1	87.1
COPA (Wu and Gong, 2021)	95.8	94.6	99.6	99.8	97.5
KD3A (Feng et al., 2021)	97.4	96.4	98.4	99.7	97.9
DC-MDA	96.9	**97.2**	**100**	**100**	**98.5**

The best results are in bold

Feature visualization



Ablation study



Conclusions

- In this paper, we propose a novel DC-MDA method for decentralized multi-source domain adaptation.
- In our method, we overcome the data decentralization and domain shift challenges by training the target domain model with the collaboration of source domain models and training the source domain models with the collaboration of the target model.
- For the domain shift challenge, our method improves the discrimination of the local target model and the transferable performance of local source models with the collaboration from other domain models to obtain a model that works well on the target domain.

Yikang WEI is currently pursuing the PhD degree with the College of Intelligence and Computing, Tianjin University, Tianjin, China. His current research interests include some machine learning methods and computer vision applications, such as domain adaptation, transfer learning, and federated learning.

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