Adversarial Reweighting for Partial Domain Adaptation

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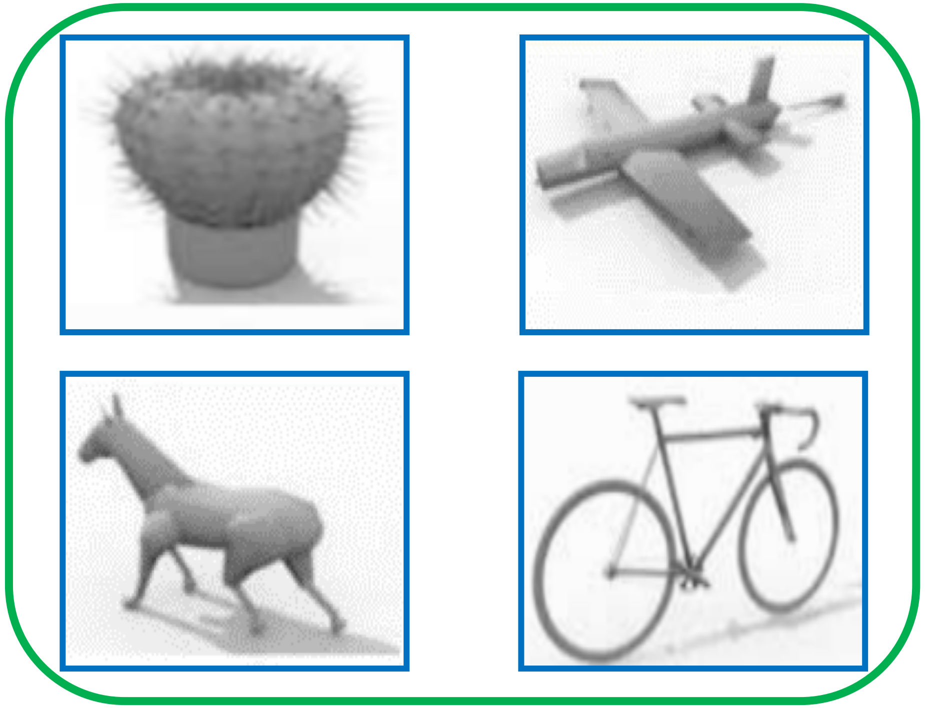
1. Partial Domain Adaptation

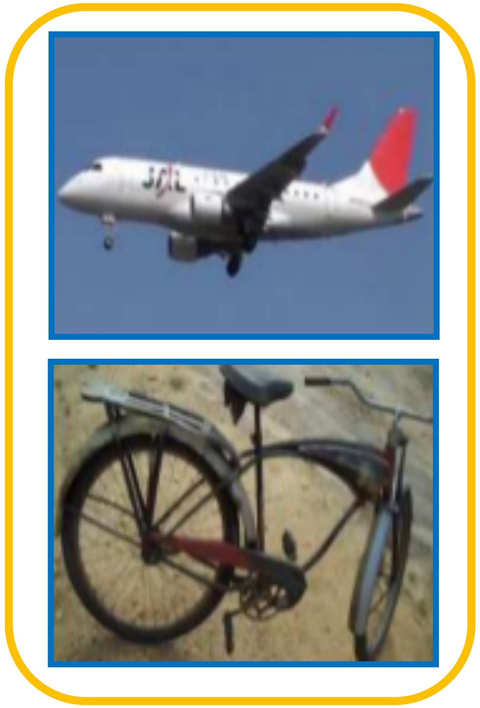
Problem Setting



Transfer

$P^s(x,y) \neq P^t(x,y)$

$\mathcal{Y}^t \subset \mathcal{Y}^s$



$(x_i^s, y_i^s) \sim P^s(x,y)$

$(x_j^t, \cdot) \sim P^t(x,y)$

1. Partial Domain Adaptation

An Unified Loss Framework for PDA Methods

Total Loss = Source Cross-entropy + Reweighted Distribution Alignment
+ Conditional Entropy

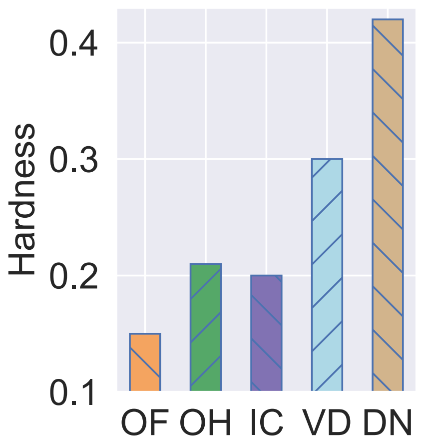
Table S-1: Comparisons of losses of feature-adaptation-based partial domain adaptation methods.

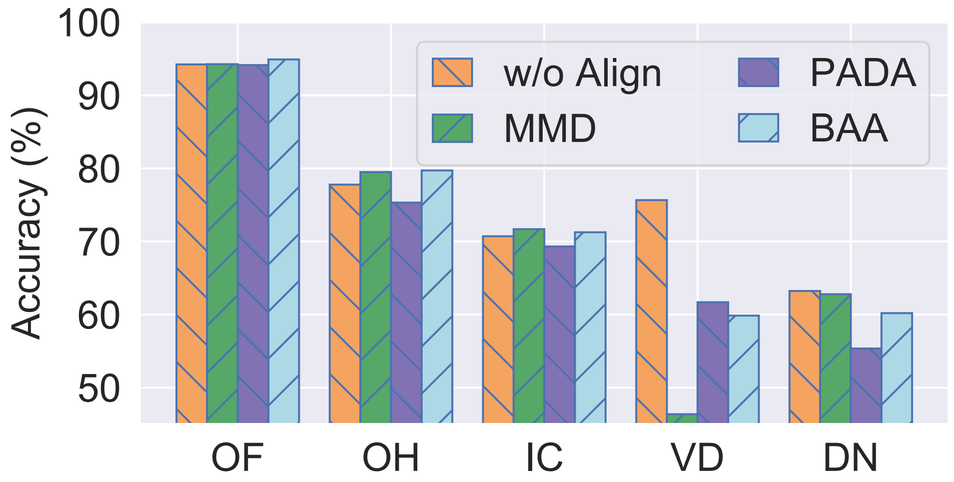
Method	Reweighting in CE	Reweighting Strategy	Distance Metric	Conditional Entropy
SAN [1]	✗	Classifier	JS	✓
IWAN [10]	✗	Discriminator	JS	✓
PADA [2]	✓	Classifier	JS	✗
ETN [3]	✓	Discriminator	JS	✓
DRCN [7]	✗	Classifier	MMD	✗
BAA [8]	✓	Classifier	JS	✓

1. Partial Domain Adaptation

Challenges of PDA Methods

➢ **We propose to measure the hardness of a dataset for PDA using the probability of target data misclassified as source-only classes.**



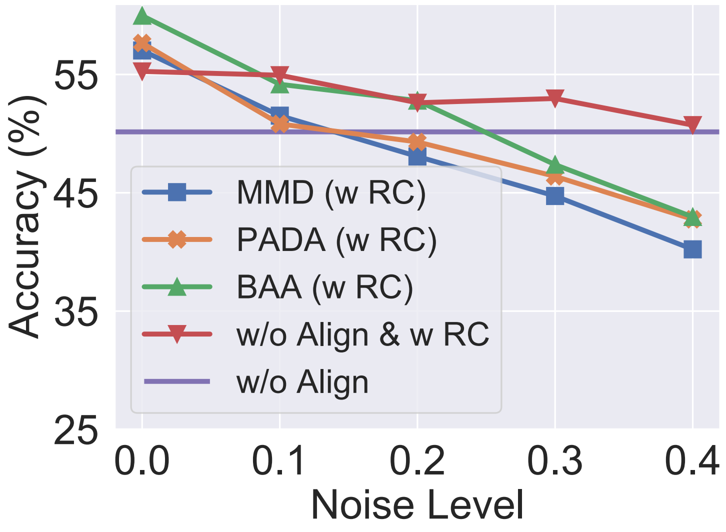


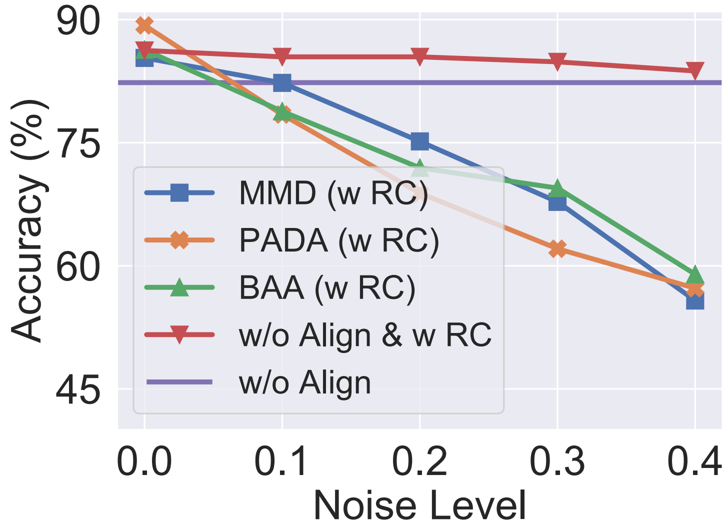
- Left figure. Hardness of Office-31 (OF), Office-Home (OH), ImageNet-Caltech (IC), VisDA-2017 (VD), DomainNet (DN).
- Right figure. Accuracy of different alignment losses on the above datasets.

➢ ***Negative transfer occurs on challenging datasets of VisDA-2017 (VD), DomainNet (DN).***

1. Partial Domain Adaptation

Challenges of PDA Methods



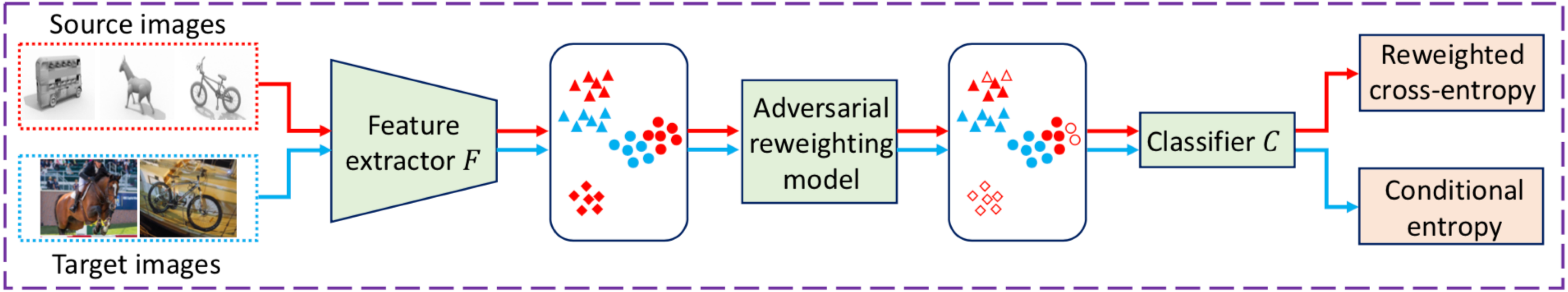


Results for *reweighted classification loss* (RC) and different *reweighted alignment losses* with generated source data weights with varying noise levels in the tasks S→R (left) and C→P (right).

- ***The reweighted alignment losses are not robust to weight noise.***
- ***Reweighting the classifier is more robust to weight noise.***

2. Adversarial Reweighting for PDA

Framework



$$\mathcal{L}(\theta_F, \theta_C, \mathbf{w}) = \frac{1}{n_s}\sum_{i=1}^{n_s} w_i \mathcal{J}(C(F(x_i^s;\theta_F);\theta_C), y_i^s) + \frac{1}{n_t}\sum_{j=1}^{n_t} H\left(C\left(F\left(x_j^t;\theta_F\right);\theta_C\right)\right)$$

2. Adversarial Reweighting for PDA

Adversarial Reweighting Model

$$\min_{\mathbf{w}\in\mathcal{W}} \max_{\theta_D\in\Theta} \frac{1}{n_s}\sum_{i=1}^{n_s} w_i D(z_i^s;\theta_D) - \frac{1}{n_t}\sum_{j=1}^{n_t} D\left(z_j^t;\theta_D\right)$$

where $\mathbf{w} = \left(w_1, w_2, \cdots, w_{n_s}\right)^T$.

- Given $\mathbf{w}$, θ_D is updated using mini-batch Adam algorithm.
- Given θ_D, $\mathbf{w}$ is learned by solving the following cone programming.

$$\min_{\mathbf{w}} \mathbf{d}^T\mathbf{w}$$

$$s.t. w_i \geq 0, \sum_{i=1}^{n_s}\left(w_i - 1\right)^2 \leq \rho n_s, \sum_{i=1}^{n_s} w_i = n_s.$$

where $d_i = D(z_i^s;\theta_D), \mathbf{d} = \left(d_1, d_2, \cdots, d_{n_s}\right)^T$.

3. Experiments

Office-Home

Method	Ar→Cl	Ar→Pr	Ar→Rw	Cl→Ar	Cl→Pr	Cl→Rw	Pr→Ar	Pr→Cl	Pr→Rw	Rw→Ar	Rw→Cl	Rw→Pr	Avg
ResNet-50 [15]	46.33	67.51	75.87	59.14	59.94	62.73	58.22	41.79	74.88	67.40	48.18	74.17	61.35
ADDA [39]	45.23	68.79	79.21	64.56	60.01	68.29	57.56	38.89	77.45	70.28	45.23	78.32	62.82
CDAN+E [24]	47.52	65.91	75.65	57.07	54.12	63.42	59.60	44.30	72.39	66.02	49.91	72.80	60.73
IWAN [46]	53.94	54.45	78.12	61.31	47.95	63.32	54.17	52.02	81.28	76.46	56.75	82.90	63.56
SAN [3]	44.42	68.68	74.60	67.49	64.99	77.80	59.78	44.72	80.07	72.18	50.21	78.66	65.30
PADA [4]	51.95	67.00	78.74	52.16	53.78	59.03	52.61	43.22	78.79	73.73	56.60	77.09	62.06
ETN [5]	59.24	77.03	79.54	62.92	65.73	75.01	68.29	55.37	84.37	75.72	57.66	84.54	70.45
DRCN [21]	54.00	76.40	83.00	62.10	64.50	71.00	70.80	49.80	80.50	77.50	59.10	79.90	69.00
SAFN [42]	58.93	76.25	81.42	70.43	72.97	77.78	72.36	55.34	80.40	75.81	60.42	79.92	71.83
RTNet$_{adv}$ [6]	63.20	80.10	80.70	66.70	69.30	77.20	71.60	53.90	84.60	77.40	57.90	85.50	72.30
BA^{3}US [22]	60.62	83.16	88.39	71.75	72.79	83.40	75.45	61.59	86.53	79.25	62.80	86.05	75.98
DPDAN [43]	59.40	–	79.04	–	–	–	–	–	81.79	76.77	58.67	82.18	–
Cls+Ent (w/ linear)	54.03	73.61	83.27	69.51	67.56	77.75	69.51	53.73	83.38	74.56	59.34	82.41	70.72
AR (w/ linear) (ours)	62.13	79.22	89.12	73.92	75.57	84.37	78.42	61.91	87.85	82.19	65.37	85.27	77.11
Cls+Ent	61.61	78.21	86.20	73.19	71.76	79.62	75.11	59.76	86.31	79.16	61.67	83.59	74.68
AR (ours)	67.40	85.32	90.00	77.32	70.59	85.15	78.97	64.78	89.51	80.44	**66.21**	86.44	78.29
Cls+Ent+AUS	63.34	81.12	86.14	74.01	76.53	79.79	77.69	62.57	86.42	78.33	62.69	84.38	76.08
AR+AUS (ours)	**68.24**	85.60	**90.61**	75.91	**77.54**	81.89	**81.73**	**66.39**	89.01	**83.65**	65.61	**86.95**	79.43
Cls+Ent+LS	62.99	83.59	87.30	74.20	73.05	81.67	79.25	63.46	87.85	78.97	64.54	84.76	76.80
AR+LS (ours)	65.67	**87.36**	89.62	**79.25**	75.01	**86.97**	80.81	65.79	**90.61**	80.81	65.25	86.12	**79.44**

3. Experiments

DomainNet

Method	C→P	C→R	C→S	P→C	P→R	P→S	R→C	R→P	R→S	S→C	S→P	S→R	Avg
ResNet-50 [15]	41.21	60.01	42.13	54.52	70.80	48.32	63.1	58.63	50.26	45.43	39.3	49.75	51.96
DANN [9]	27.83	36.64	29.91	31.79	41.98	36.58	47.64	46.81	40.85	25.82	29.54	32.72	35.68
CDAN+E [24]	37.46	48.26	46.61	45.50	60.96	52.63	62.01	60.63	54.74	35.37	38.50	43.63	48.86
SAN [3]	34.35	51.62	46.23	57.13	70.21	58.25	69.61	67.49	67.88	41.69	41.15	48.44	54.50
PADA [4]	22.49	32.85	29.95	25.71	56.47	30.45	65.28	63.35	54.17	17.45	23.89	26.91	37.41
BA^{3}US [22]	42.87	54.72	53.79	64.03	76.39	64.69	**79.99**	**74.31**	**74.02**	50.36	42.69	49.65	60.63
Cls+Ent (w/ linear)	50.14	64.05	**59.81**	65.26	76.12	69.50	75.54	69.74	68.55	50.63	54.95	54.44	63.23
AR (w/ linear) (ours)	**56.70**	**70.36**	58.56	65.63	74.80	**74.85**	75.22	71.17	69.08	**53.90**	**55.70**	**63.09**	**65.76**
Cls+Ent	49.40	65.69	58.89	65.92	74.82	70.77	75.87	70.72	68.26	50.45	**55.70**	62.23	64.06
AR (ours)	52.66	68.24	58.29	**66.78**	**77.53**	74.38	76.70	71.77	70.48	53.66	53.60	61.57	65.47

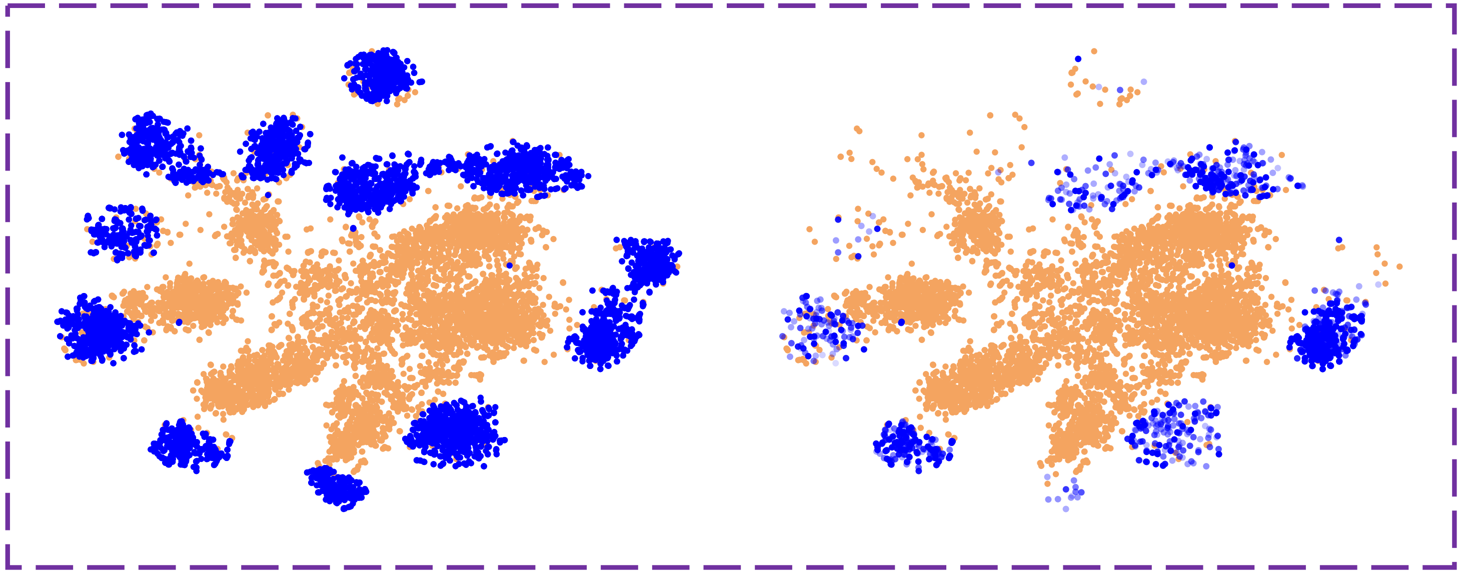
3. Experiments

Office, ImageNet-Caltech, and VisDA-2017

Method	Office-31							ImageNet-Caltech			VisDA-2017		
	A→D	A→W	D→A	D→W	W→A	W→D	Avg	C→I	I→C	Avg	R→S	S→R	Avg
ResNet-50 [15]	83.44	75.59	83.92	96.27	84.97	98.09	87.05	71.29	69.69	70.49	64.28	45.26	54.77
DAN [23]	61.78	59.32	74.95	73.90	67.64	90.45	71.34	60.13	71.30	65.72	68.35	47.60	57.98
DANN [9]	81.53	73.56	82.78	96.27	86.12	98.73	86.50	67.71	70.80	69.23	73.84	51.01	62.43
IWAN [46]	90.45	89.15	95.62	99.32	94.26	99.36	94.69	73.33	78.06	75.70	71.30	48.60	59.95
SAN [3]	94.27	93.90	94.15	99.32	88.73	99.36	94.96	75.26	77.75	76.51	69.70	49.90	59.80
PADA [4]	82.17	86.54	92.69	99.32	95.41	**100.0**	92.69	70.48	75.03	72.76	76.50	53.50	65.00
ETN [5]	95.03	94.52	96.21	**100.0**	94.64	**100.0**	96.73	74.93	83.23	79.08	–	–	–
DRCN [21]	86.00	88.50	95.60	**100.0**	95.80	**100.0**	94.30	78.90	75.30	77.10	73.20	58.20	65.70
RTNet$_{adv}$ [6]	96.20	97.60	92.30	**100.0**	95.40	**100.0**	97.20	–	–	–	–	–	–
BA^{3}US [22]	**99.36**	**98.98**	94.82	**100.0**	94.99	98.73	**97.81**	**83.35**	84.00	83.68	67.56	69.86	68.71
DPDAN [43]	96.27	96.82	**96.35**	**100.0**	95.62	**100.0**	97.51	–	–	–	–	65.26	–
Cls+Ent (w/ linear)	90.45	87.80	94.68	**100.0**	94.36	98.09	94.23	77.74	77.82	77.78	69.00	82.32	75.66
AR (w/ linear) (ours)	91.72	97.63	95.62	**100.0**	95.30	**100.0**	96.71	81.78	85.83	83.81	74.82	85.30	80.09
Cls+Ent	80.89	87.12	94.05	94.58	93.95	99.36	91.66	79.60	82.59	81.10	66.63	84.72	75.68
AR (ours)	96.82	93.54	95.51	**100.0**	**96.04**	99.67	96.93	82.24	**87.12**	**84.69**	**78.52**	**88.75**	**83.62**

3. Experiments

Weight Visualization



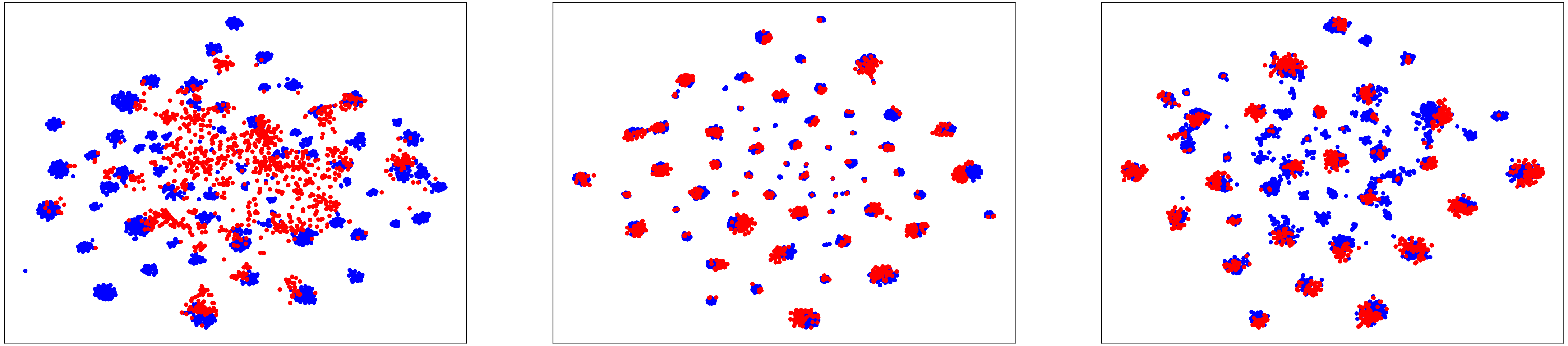
source vs target

weighted source vs target

average weights for each class

3. Experiments

Feature Visualization



ResNet-50 | Cls+Ent | AR (ours)

- Blue: source, red: target.

Thanks for your attention

Code: https://github.com/XJTU-XGU/Adversarial-Reweighting-for-Partial-Domain-Adaptation