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A Balanced and Uncertainty-aware Approach for Partial Domain Adaptation

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Outline

1. Background
2. Method
3. Experiments

Problem Definition

- Deep learning across domains with different label spaces $\mathcal{C}_s \supset \mathcal{C}_t$
- Positive transfer across domains in **shared** label space $\mathcal{P}_{\mathcal{C}_t} \neq \mathcal{Q}_{\mathcal{C}_t}$
- Negative transfer across domains in **outlier** label space

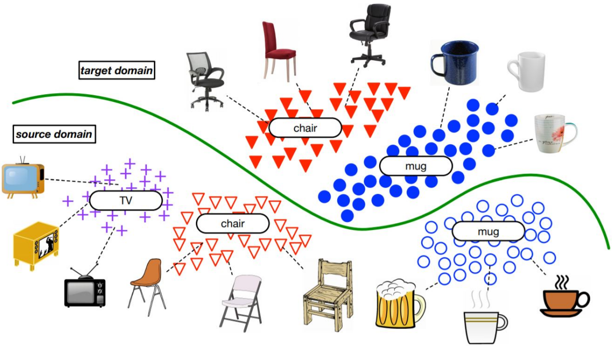

Figure 1: Test data and training data comes from different distributions!

*Credit to Cao et al. [slides at CVPR 2018].

Preliminary: Domain Adversarial Learning

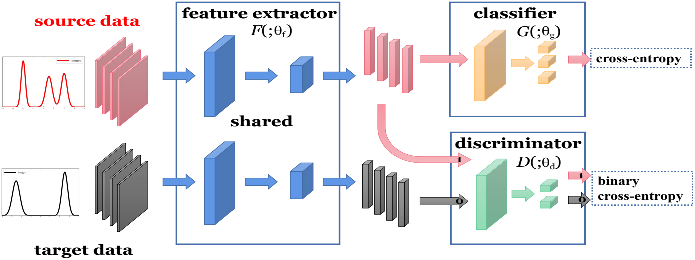

Figure 2: The framework of DANN.

$$
\begin{aligned}
&\min_{\theta_f,\theta_g} \max_{\theta_d} \mathcal{L}_{cls}(\theta_f,\theta_g) + \lambda\, \mathcal{L}_{adv}(\theta_f,\theta_d), \\
&\mathcal{L}_{adv}(\theta_f,\theta_d) = \frac{1}{n_s}\sum\nolimits_{i=1}^{n_s} \log[D(F(x_i^s))] + \frac{1}{n_t}\sum\nolimits_{j=1}^{n_t} \log[1 - D(F(x_j^t))], \\
&\mathcal{L}_{cls}(\theta_f,\theta_g) = \frac{1}{n_s}\sum\nolimits_{i=1}^{n_s} l_{ce}(G(F(x_i^s)), y_i^s).
\end{aligned}
\tag{1}
$$

Ganin, Yaroslav, and Victor Lempitsky. "Unsupervised domain adaptation by backpropagation." In Proc. ICML, 2015.

Preliminary: Partial Adversarial Domain Adaptation

Lessons:

1. How to promote positive transfer across domains in **shared** label space?
- Promote domain alignment between shared classes across domains and ignore the outlier classes $\mathcal{C}_s \backslash \mathcal{C}_t$ in the source domain **during alignment**.

2. Is the discriminative information contained in the source outlier classes $\mathcal{C}_s \backslash \mathcal{C}_t$ useful for domain adaptation?
- No, ignore the outlier classes $\mathcal{C}_s \backslash \mathcal{C}_t$ in the source domain **during the training of source classifier**.

* Cao, Zhangjie, et al. "Partial adversarial domain adaptation." In Proc. ECCV, 2018.

Preliminary: Partial Adversarial Domain Adaptation

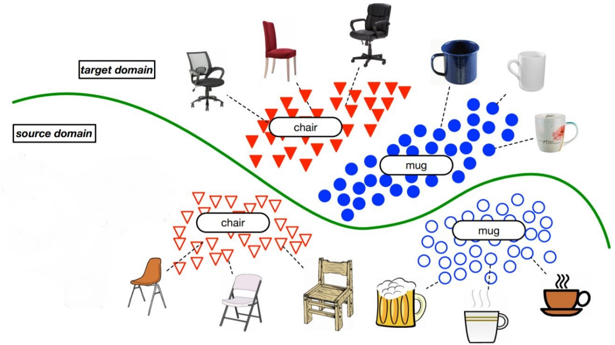

Figure 3: A closed-set domain adaptation problem.

Ideally, if we can correctly infer the label space of the target domain, the challenging partial domain adaptation problem would turn out to be a vanilla closed-set domain adaptation problem.

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* Cao, Zhangjie, et al. "Partial adversarial domain adaptation." In Proc. ECCV, 2018.

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Domain Adversarial Learning Revisited

Baseline method: Entropy-regularized DANN (E-DANN)

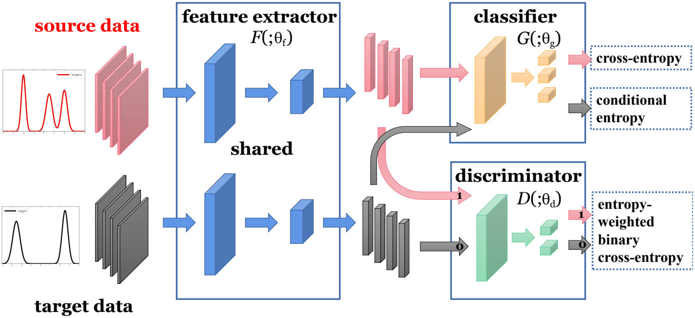


Figure 4: The framework of the baseline method E-DANN.

- ☑ conditional entropy minimization
- ☑ not all samples are equally important during alignment
- ☑ weighted source classification loss *(filtering out source outlier classes)*

Framework of Our Method (BA^{3}US)

Overview

1. Balanced Adversarial Alignment (BAA)
2. Adaptive Uncertainty Suppression (AUS)

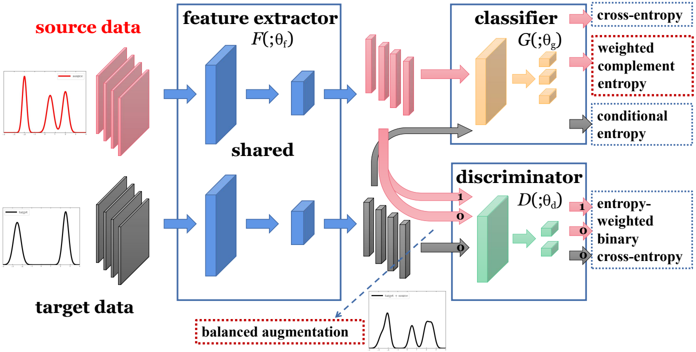
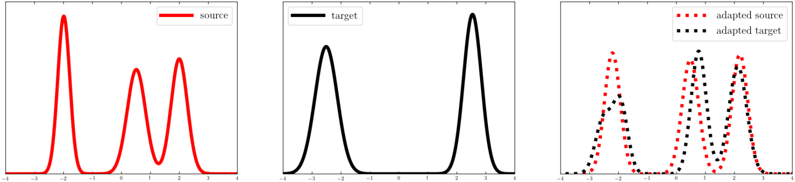


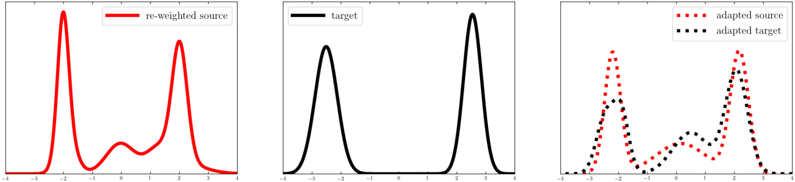
Figure 5: The framework of the proposed method BA^{3}US for partial domain adaptation.

Framework of Our Method (BA^{3}US)

1. Balanced Adversarial Alignment (BAA)



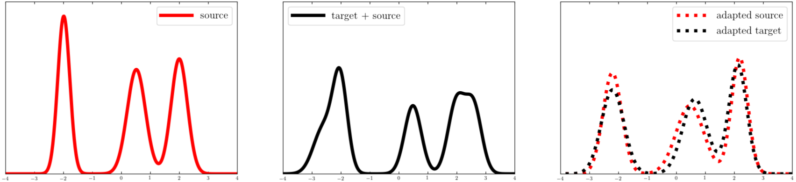
(a) vanilla setting



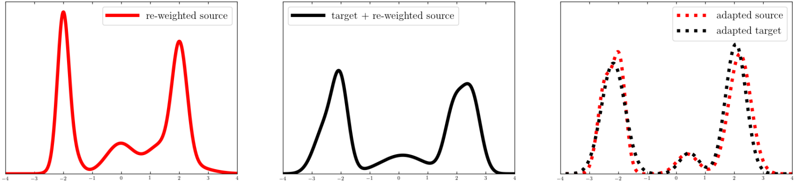
(b) previous source re-weighting scheme

Figure 6: An illustrating example of different schemes towards distribution alignment in PDA where the source contains one source outlier class. **Red: source distributions**, **black: target distributions**, *dashed: adapted distributions.*

1. Balanced Adversarial Alignment (BAA)



(c) proposed target augmentation scheme



(d) combination scheme in our BAA

Figure 7: An illustrating example of different schemes towards distribution alignment in PDA where the source contains one source outlier class. **Red: source distributions**, **black: target distributions**, *dashed: adapted distributions.*

Previous DA methods focus on strengthening the **feature transferability** by developing various domain alignment strategies, but they mostly ignore the **feature discriminability** in the source domain and simply employ the conventional cross-entropy loss.

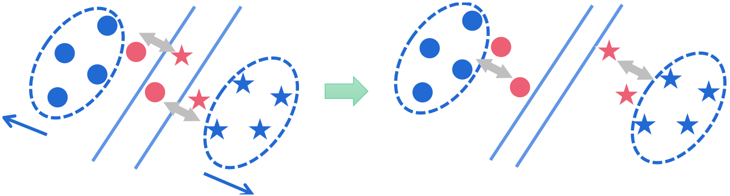


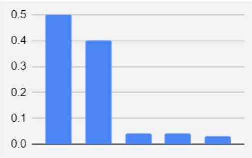
Figure 8: Mitigating the effects of **uncertainty propagation** from source. [blue: source, red: target, gray: adversarial alignment.]

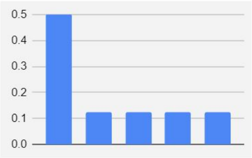
Framework of Our Method (BA^{3}US)

2. Adaptive Uncertainty Suppression (AUS)

Confidence-weighted complement entropy

- ☑ maximize the entropy of incorrect classes





- ☑ easy samples (larger $\hat{y}_a$) with lower weights

$$\mathcal{L}_{wce}(\theta_f, \theta_g) = \frac{\beta}{n_s \log(K-1)} \sum_{i=1}^{n_s} l_{wce}(G(F(x_i^s)), y_i^s),$$
$$\text{where } l_{wce}(\hat{y}, y) = (1-\hat{y}_a)^{\xi} \sum_{j \neq a} \frac{\hat{y}_j}{1-\hat{y}_a} \log(\frac{\hat{y}_j}{1-\hat{y}_a}), \tag{2}$$

* Chen, Hao-Yun, et al. "Complement Objective Training." In Proc. ICLR, 2019.

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Table 1: Accuracy (%) on **Office-Home** dataset for *partial domain adaptation* via ResNet-50. The best in **bold red**; the second best in *italic blue*. [65-classes → 25-classes]

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	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 (CVPR2017)	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 (NeurIPS2018)	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 (CVPR2018)	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 (CVPR2018)	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 (ECCV2018)	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 (CVPR2019)	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
SAFN (ICCV2019)	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
DRCN (TPAMI2020)	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
RTNet$_{adv}$ (**CVPR2020**)	**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
MCC (**ECCV2020**)	57.50	*82.00*	*86.40*	70.70	70.60	78.20	**76.50**	**61.70**	*86.50*	**82.00**	**64.50**	84.00	*75.10*
E-DANN	54.05	74.12	84.06	67.06	64.95	75.15	71.29	53.09	83.42	76.00	58.17	81.53	70.24
Ours (w/ BAA)	56.20	79.55	86.21	*70.86*	69.94	*81.06*	72.51	57.91	86.47	77.10	59.34	83.64	73.40
Ours (BA^{3}US)	*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**

Results on Office31 and ImageNet-Caltech

Table 2: Accuracy (%) on **Office31** and **ImageNet-Caltech** for *partial domain adaptation* via ResNet-50. The best in **bold red**; the second best in *italic blue*.

Method	Office31							ImageNet-Caltech		
	A → D	A → W	D → A	D → W	W → A	W → D	Avg.	I → C	C → I	Avg.
ResNet-50	$83.44_{\pm 1.12}$	$75.59_{\pm 1.09}$	$83.92_{\pm 0.95}$	$96.27_{\pm 0.85}$	$84.97_{\pm 0.86}$	$98.09_{\pm 0.74}$	87.05	$69.69_{\pm 0.78}$	$71.29_{\pm 0.74}$	70.49
ADDA (CVPR2017)	$83.41_{\pm 0.17}$	$75.67_{\pm 0.17}$	$83.62_{\pm 0.14}$	$95.38_{\pm 0.23}$	$84.25_{\pm 0.13}$	*99.85*$_{\pm 0.12}$	87.03	$71.82_{\pm 0.45}$	$69.32_{\pm 0.41}$	70.57
CDAN (NeurIPS2018)	$77.07_{\pm 0.90}$	$80.51_{\pm 1.20}$	$93.58_{\pm 0.07}$	$98.98_{\pm 0.00}$	$91.65_{\pm 0.00}$	$98.09_{\pm 0.00}$	89.98	$72.45_{\pm 0.07}$	$72.02_{\pm 0.13}$	72.24
IWAN (CVPR2018)	$90.45_{\pm 0.36}$	$89.15_{\pm 0.37}$	*95.62*$_{\pm 0.29}$	*99.32*$_{\pm 0.32}$	$94.26_{\pm 0.25}$	$99.36_{\pm 0.24}$	94.69	$78.06_{\pm 0.40}$	$73.33_{\pm 0.46}$	75.70
SAN (CVPR2018)	$94.27_{\pm 0.28}$	$93.90_{\pm 0.45}$	$94.15_{\pm 0.36}$	*99.32*$_{\pm 0.52}$	$88.73_{\pm 0.44}$	$99.36_{\pm 0.12}$	94.96	$77.75_{\pm 0.36}$	$75.26_{\pm 0.42}$	76.51
PADA (ECCV2018)	$82.17_{\pm 0.37}$	$86.54_{\pm 0.31}$	$92.69_{\pm 0.29}$	*99.32*$_{\pm 0.45}$	*95.41*$_{\pm 0.33}$	**100.0**$_{\pm 0.00}$	92.69	$75.03_{\pm 0.36}$	$70.48_{\pm 0.44}$	72.76
DRCN (TPAMI2020)	86.00	88.05	95.60	**100.0**	**95.80**	**100.0**	94.30	75.30	78.90	77.10
ETN (CVPR2019)	$95.03_{\pm 0.22}$	$94.52_{\pm 0.20}$	**96.21**$_{\pm 0.27}$	**100.0**$_{\pm 0.00}$	$94.64_{\pm 0.24}$	**100.0**$_{\pm 0.00}$	96.73	*83.23*$_{\pm 0.24}$	$74.93_{\pm 0.44}$	79.08
RTNet$_{adv}$ **(CVPR2020)**	*97.60*$_{\pm 0.10}$	*96.20*$_{\pm 0.30}$	$92.30_{\pm 0.10}$	**100.0**$_{\pm 0.00}$	$95.40_{\pm 0.10}$	**100.0**$_{\pm 0.00}$	96.90	-	-	-
E-DANN	$92.36_{\pm 0.00}$	$93.22_{\pm 0.00}$	$94.61_{\pm 0.05}$	**100.0**$_{\pm 0.00}$	$94.71_{\pm 0.05}$	$98.73_{\pm 0.00}$	95.60	$78.31_{\pm 0.81}$	$77.69_{\pm 0.25}$	78.00
Ours (w/ BAA)	$93.63_{\pm 0.00}$	$93.90_{\pm 0.00}$	$94.89_{\pm 0.09}$	**100.0**$_{\pm 0.00}$	$94.78_{\pm 0.00}$	**100.0**$_{\pm 0.00}$	*96.20*	$82.97_{\pm 0.49}$	*79.34*$_{\pm 0.08}$	*81.16*
Ours (BA^{3}US)	**99.36**$_{\pm 0.00}$	**98.98**$_{\pm 0.28}$	$94.82_{\pm 0.05}$	**100.0**$_{\pm 0.00}$	$94.99_{\pm 0.08}$	$98.73_{\pm 0.00}$	**97.81**	**84.00**$_{\pm 0.15}$	**83.35**$_{\pm 0.28}$	**83.68**

Parameter Sensitivity

$$\mathcal{L}_{wce}(\theta_f, \theta_g) = \frac{\beta}{n_s \log(K-1)} \sum_{i=1}^{n_s} l_{wce}(G(F(x_i^s)), y_i^s),$$

$$\text{where } l_{wce}(\hat{y}, y) = (1-\hat{y}_a)^{\xi} \sum_{j \neq a} \frac{\hat{y}_j}{1-\hat{y}_a} \log(\frac{\hat{y}_j}{1-\hat{y}_a}),$$

Parameters: trade-off parameter β and weight-controlling parameter ξ

Table 3: Sensitivity of parameter ξ.

Avg. (%)	0.0	0.1	0.3	0.5	0.7	0.9	1.0
Office-Home	75.32	75.88	**76.28**	*76.10*	*76.10*	75.81	75.98
Office31	97.68	97.71	97.65	97.67	97.64	**97.84**	*97.81*

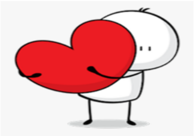
Table 4: Sensitivity of parameter β.

Avg. (%)	0.0	0.1	0.5	1.0	5.0	10.0
Office-Home	73.40	73.58	75.09	**75.98**	*75.69*	73.25
Office31	96.20	96.13	96.50	96.63	*97.81*	**97.83**

Summary

1. *To be balanced, augmentation along with selection is effective.*
2. *Uncertainty suppression in the source domain is critical for adaptation.*
3. *State-of-the-art results on partial domain adaptation benchmarks.*

★ Code is available at `https://github.com/tim-learn/BA3US/`.
If you require any further information, feel free to contact me.
Email: liangjian92@gmail.com



(a) Love

(b) Peace

(c) Health