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# **Class Discriminative Adversarial Learning for Unsupervised Domain Adaptation**

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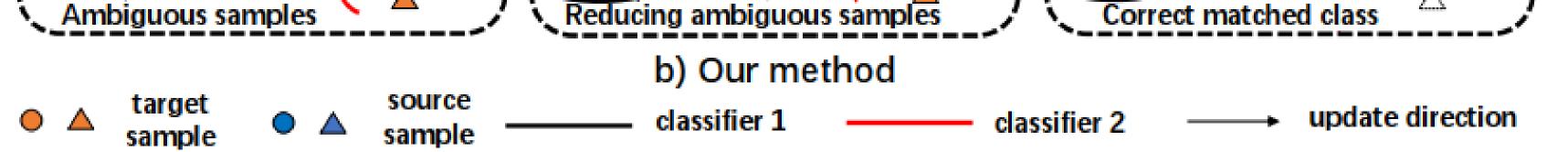
Problem & Proposed method	Experiments							
» Problem statement	» Experimental results							
	MCD [33] CVPR18 77.3 89.2 92.7 88.2 71.0 92.3 85.1							
Source data	MCD+ECI Ours 79.3 ±0.2 92.5 ±0.1 96.3 ±0.1 90.5±0.2 78.0±0.2 94.8±0.1 88.6							
	SWD [16] CVPR19 78.3 90.3 93.2 89.7 73.3 93.8 86.4							
with labels How to 🥎	SWD+ECI Ours 79.8±0.1 92.7±0.2 96.8±0.0 92.9±0.1 77.3±0.2 96.5±0.1 89.3   CDAL Ours 80.4±0.1 93.7±0.1 97.8±0.0 93.3±0.1 80.2±0.3 97.5±0.2 90.5							
fine-tune	The performance of our method on ImageCLEF							



Train a adapted model that works well in target domain

» Overview of proposed	method	
Samples and two classifiers	Maximize discrepancy	Minimize discrepancy
Ambiguous samples a) Tradition	New ambiguous samples	Wrong matched class
Samples and two classifiers	Expertise-aware classifier interferen	ce Minimize discrepancy
Ambiguous samples	Reducing ambiguous samples	Correct matched class

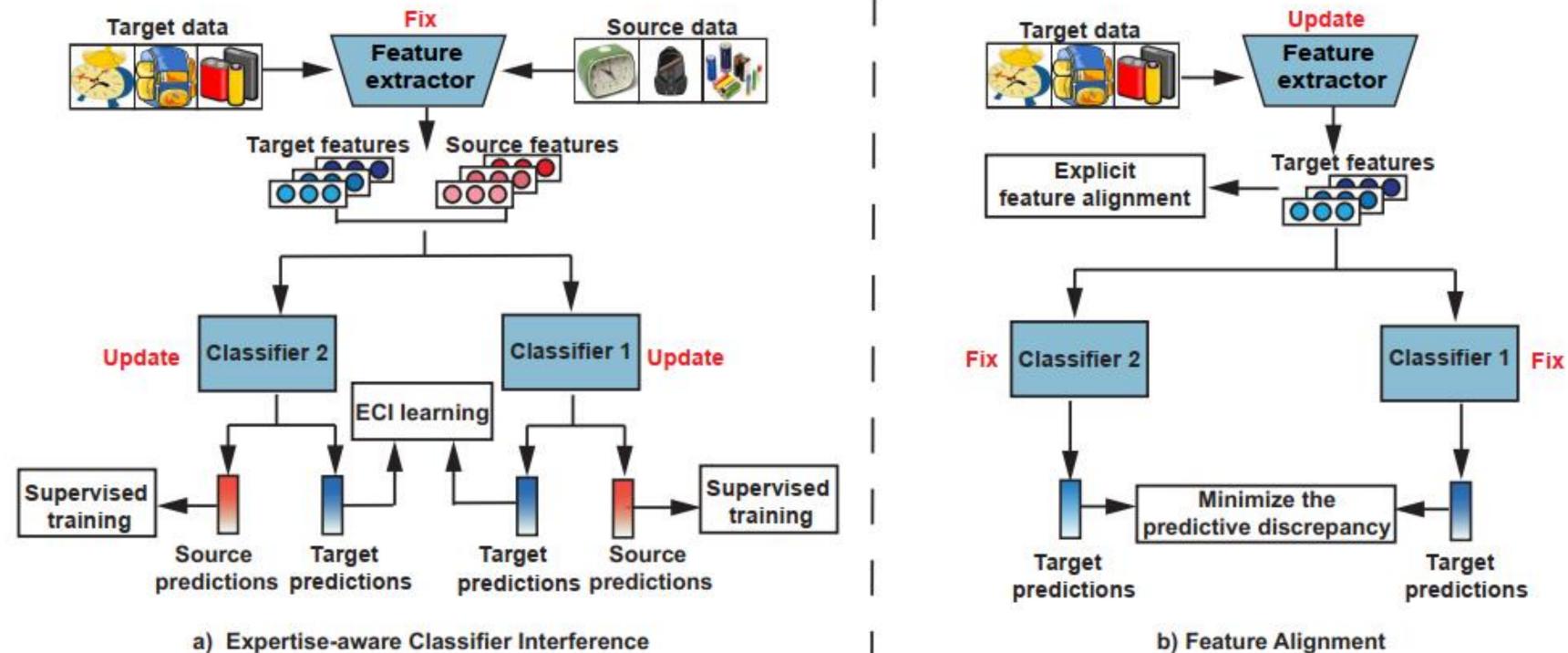
MCD[33]	CVPR18	48.9	68.3	74.6	61.3	67.6	68.8	57.0	47.1	75.1	69.1	52.2	79.6	Г
MCD+ECI	Ours	57.4	74.0	78.6	62.3	73.7	75.0	64.4	54.5	81.1	73.3	60.3	83.7	
SWD[16]	CVPR19	51.3	70.3	75.0	56.2	69.4	71.6	59.8	53.8	80.2	71.1	59.2	83.4	
SWD+ECI	Ours	58.0	75.4	79.0	64.1	73.3	74.9	64.6	54.1	81.1	72.5	60.5	83.8	L
CDAL	Ours	59.5 ±0.3	77.8 ±0.1	80.0 ±0.1	67.0 ±0.2	77.1 ±0.2	76.6 ±0.0	66.6 ±0.2	56.2 ±0.1	81.8 ±0.0	74.3 ±0.1	60.6 ±0.0	84.6 ±0.1	1
The p	perfo	rma	anc	e c	ofo	urn	net	tho	d o	n O	ffic	ce-ł	lor	r
MCD[33]	CVPR18	87.0	60.9	83.7	64.0 8	88.9 7	9.6	84.7	76.9	88.6	40.3	83.0	25.8	T
MCD+ECI	Ours	93.4	77.2	76.9				83.4	74.8	84.7	72.3	85.8	55.2	Ļ
SWD[16] SWD+ECI	CVPR19 Ours	90.8 93.6	82.5 78.6	81.7 76.7				86.3 83.4	77.5 75.7	87.4 85.2	63.6 75.6	85.6 85.8	29.2 57.0	
CDAL	Ours	95.0 97.5	84.9	81.0				90.6	80.9	96.2	94.9	88.2	48.7	ł
» Abla	atior	ı st	ud	ies	5									
						I→	C	C-	→ī	C-	→P	P	→C	-
Metho		I→	P	P-	→I	I→	_	C-	-		→P		→C	
			P		→I	I→ 93.	_	C- 88	-		→P 6.8		→C 93.0	
Metho		I→	•P .0	P-	→I 9.7	-	2	-	.6	6		9		
Metho PSE	od	I→ 74	•P .0 .3	P- 89	→I 9.7 9.2	93.	2	88	.6 .2	6 7	6.8	9	93.0	_
Metho PSE MCD	od •ECI	I→ 74 77. <b>79</b>	P .0 .3 .3	P- 89 89 <b>9</b> 2	→I 9.7 9.2	93. 92. <b>96</b> .	2 7 .3	88 88 <b>90</b>	.6 .2 .5	6 7 7	6.8 1.0 <b>8.0</b>	9 9	93.0 92.3 9 <b>4.8</b>	
Metho PSE MCD MCD+	od •ECI blatic	I→ 74 77 79 01 S	P .0 .3 .3	P- 89 89 92 dy (	→I 9.7 9.2	93. 92. 96.	2 7 .3	88 88 90 tho	.6 .2 .5	60 71 71 01 S	6.8 1.0 <b>8.0</b>	ond	93.0 92.3 9 <b>4.8</b>	<u> </u>
Metho PSE MCD MCD+ The a	od •ECI blatic	I→ 74 77 79 0n s	P .0 .3 .3 stuc	P- 89 89 92 dy (	→I 0.7 0.2 0.5	93. 92. 96.	2 .7 .3 me	88 88 90 tho	.6 .2 .5 od c	6 7 7 7 0 1 S	6.8 1.0 8.0	ond P	93.0 92.3 9 <b>4.8</b>	

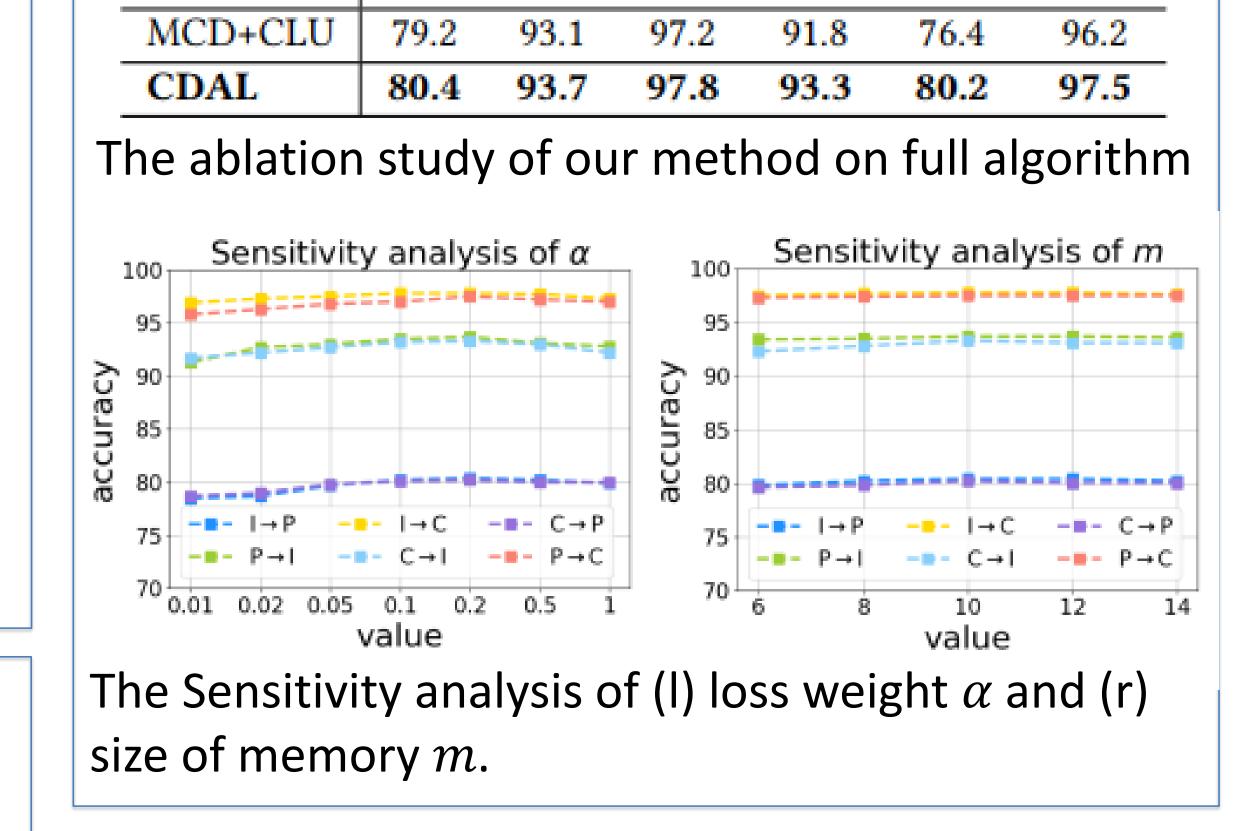


### **» Our contributions:**

- Propose a novel Class Discriminative Adversarial Learning (CDAL) framework.
- CDAL can more effectively improve the discrimination ability of both adapted classifiers whilst reasoning away ambiguous target samples during training.
- Extensive experiments show that CDAL outperforms state-of-the-art methods by a clear margin on three standard datasets.

#### **»** Architecture of CDAL Fix Target data Feature extractor Target features Source features





## Conclusion and others

### **»** Conclusion

- Investigate the problem of ambiguous target samples in the biclassifier adversarial learning;
- Propose a Class Discriminative Adversarial Learning method which employs an ECI strategy and a representation regularization.

An illustration of our Class Discriminative Adversarial Learning (CDAL) method. In the first step, the model (including the feature extractor and two classifiers) is trained by labeled source samples. (a) In the second step, the feature extractor is fixed while the two classifiers are updated by the proposed Expertise-aware Classifier Interference (ECI) strategy. Note, the supervised training supervisory on source domain is applied to preserve the classification ability. (b) In the third step, the feature extractor is then optimized by minimizing the discrepancy between the two fixed classifiers. Feature alignment is also applied across domains.

#### » Citation

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#### **» Reproducibility**

Code is available at: <u>https://github.com/buerzlh/CDAL</u>.

#### » Contact

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