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paper

## **Bi-Classifier Determinacy Maximization for Unsupervised Domain Adaptation**

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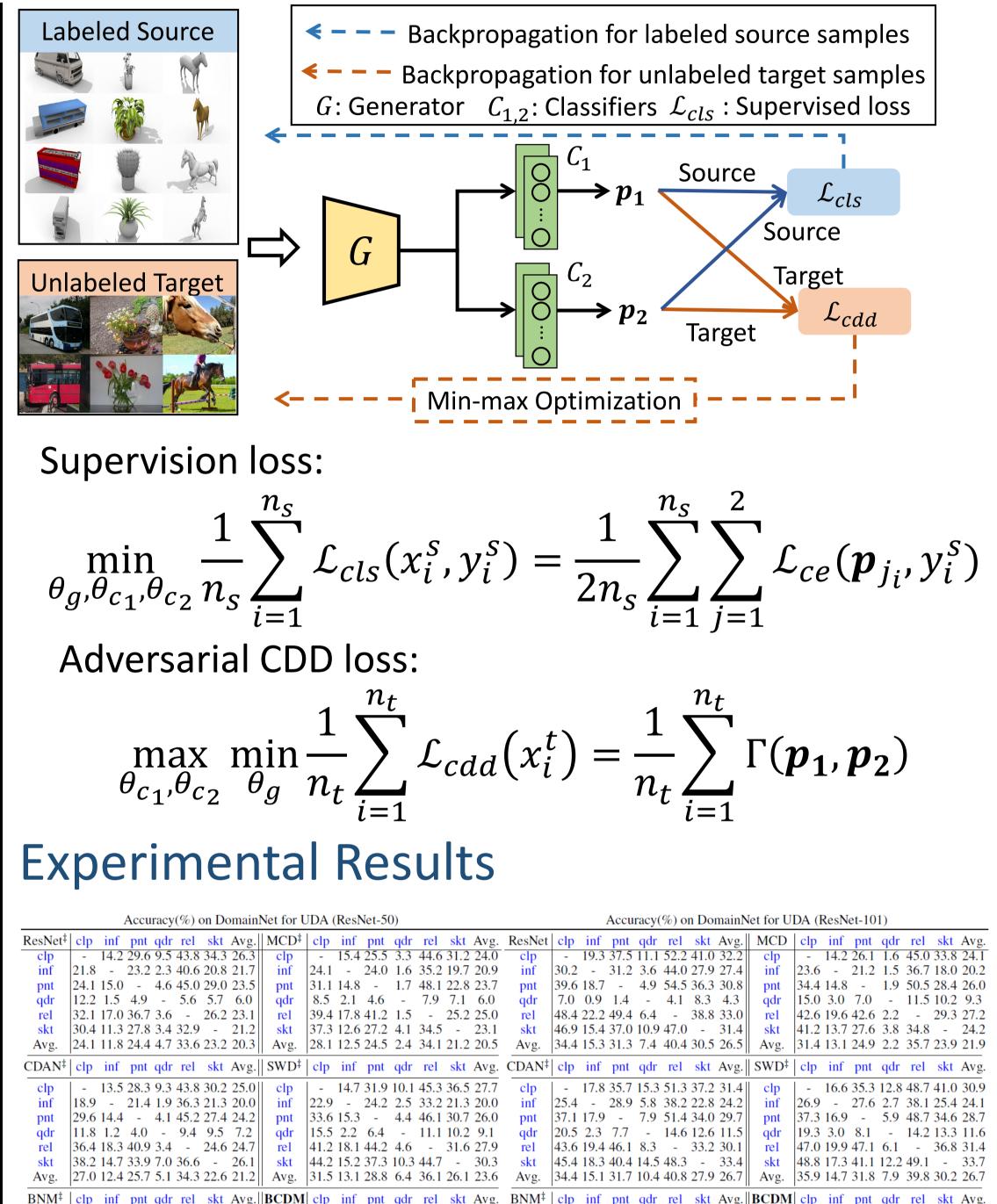


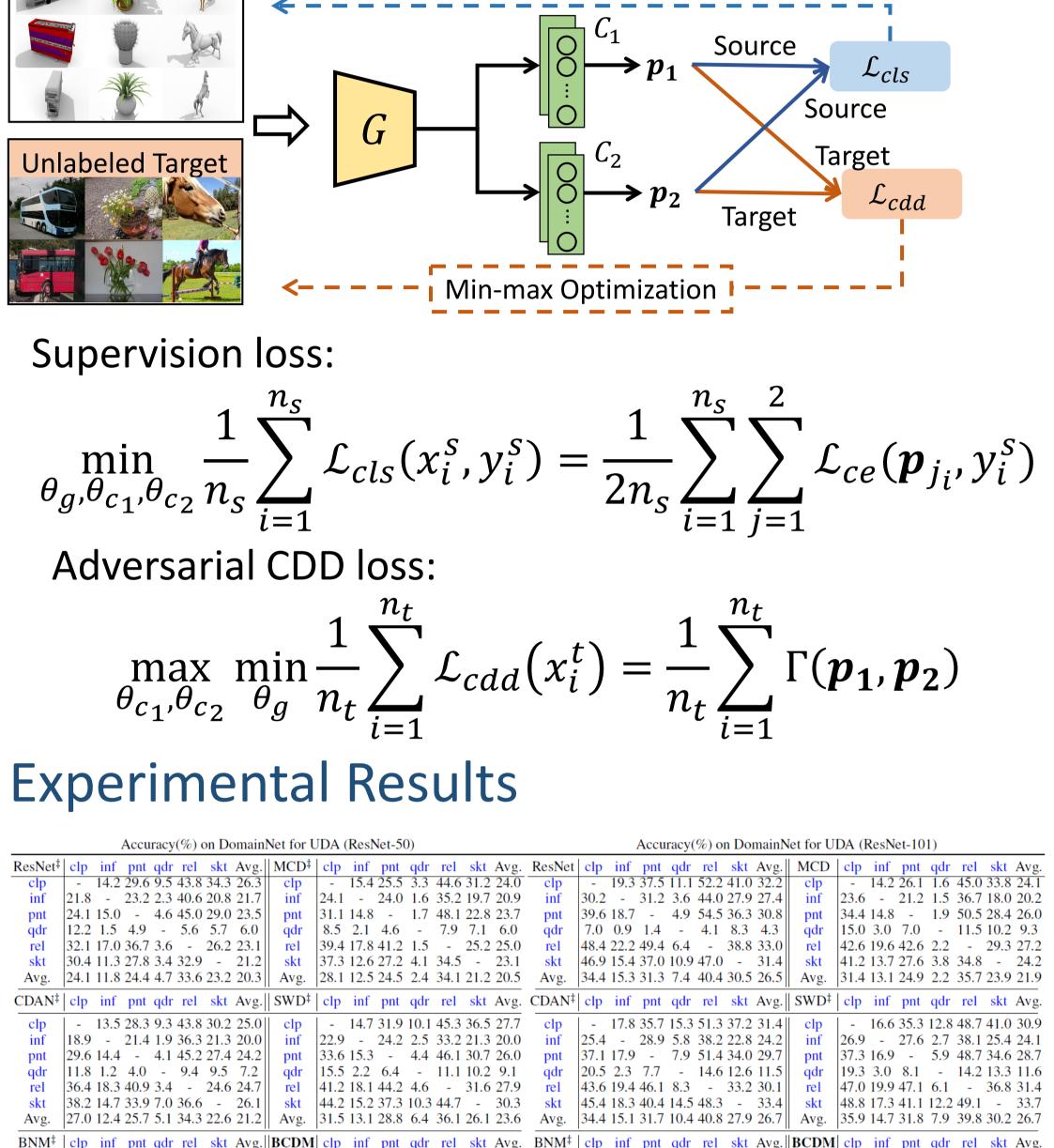
code

**Domain Adaptation** 

Target Source Domain Domain

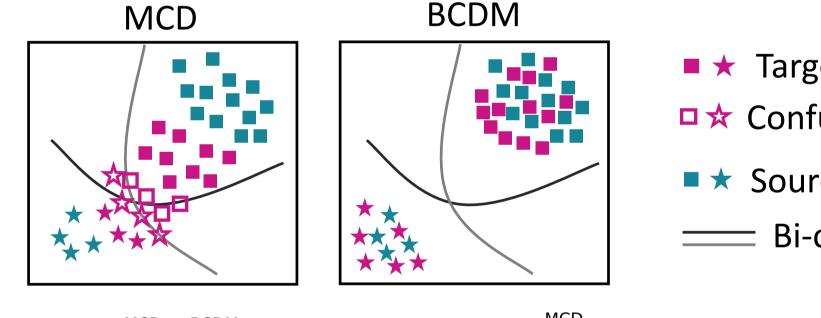
Labeled source data and unlabeled target data follow different joint distributions, i.e.,  $P(X_s, Y_s) \neq P(X_t, Y_t)$ .

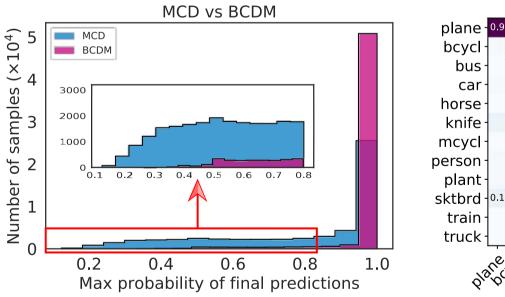


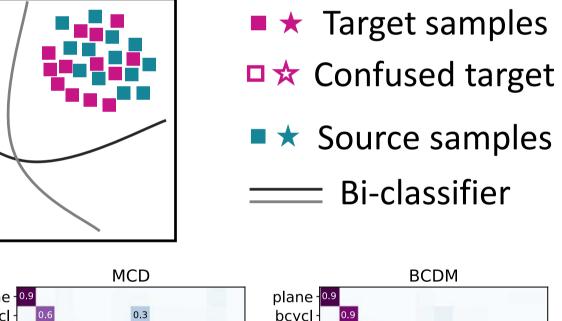


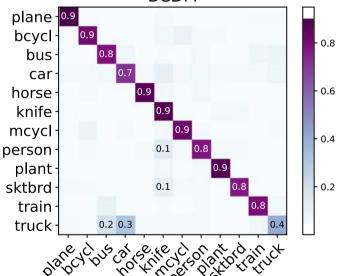
## **Bi-Classifier Adversarial**

There exist two popular paradigms to conduct adversarial domain adaptation either by constructing a domain discriminator or by utilizing two distinct classifiers. As for the second paradigm, the selection of classifier discrepancy loss between two taskspecific classifiers is critical for expected adaptability.









### **Classifier Determinacy Disparity**

BNM‡	clp	inf	pnt	qdr	rel	skt	Avg.	BCDM	clp	inf	pnt	qdr	rel	skt	Avg.	BNM <sup>‡</sup>	clp	inf	pnt	qdr	rel	skt	Avg.	BCDM	clp	inf	pnt	qdr	rel	skt Avg.
																														43.9 34.1
inf	26.6	-	28.5	2.4	38.5	18.1	22.8	inf	29.3	-	29.4	3.8	41.3	25.0	25.8	inf	24.6	-	27.8	7.9	35.0	22.0	23.5	inf	31.9	-	32.7	6.9	44.7	28.5 28.9
pnt	39.9	12.2	-	3.4	54.5	36.2	29.2	pnt	39.2	17.7	-	4.8	51.2	34.9	29.6	pnt	36.0	20.2	-	9.7	51.8	34.2	30.4	pnt	42.5	19.8	-	7.9	54.5	38.5 32.6
qdr	17.8	1.0	3.6	-	9.2	8.3	8.0	qdr	19.4	2.6	7.2	-	13.6	12.8	11.1	qdr	21.3	3.8	10.5	-	14.0	12.9	12.5	qdr	23.0	4.0	9.5	-	16.9	16.2 13.9
rel	48.6	13.2	49.7	3.6	-	33.9	29.8	rel	48.2	21.5	48.3	5.4	-	36.7	32.0	rel	43.4	21.7	47.0	9.9	-	32.9	31.0	rel	51.9	24.9	51.2	8.7	-	40.6 35.5
skt	54.9	12.8	42.3	5.4	51.3	-	33.3	skt	50.6	17.3	41.9	10.6	49.0	-	33.9	skt	43.1	19.1	39.5	15.6	47.0	-	32.7	skt	53.7	20.5	46.0	13.1	53.4	- 37.1
Avg.	37.6	10.3	31.4	4.2	40.9	27.3	25.3	Avg.	37.3	15.3	32.4	7.0	41.0	29.9	27.2	Avg.	33.7	16.8	32.1	11.8	39.6	27.7	26.9	Avg.	40.6	17.8	35.6	10.3	44.3	33.5 <b>30.4</b>

Given  $p_1$  and  $p_2$  as the bi-classifier softmax outputs, we investigate the classifier discrepancy by Biclassifier Prediction Relevance Matrix A:  $A = p_1 p_2^T$ . Therefore, we define the CDD loss as:

$$\Gamma(p_1, p_2) = \sum_{m,n=1}^{K} A_{mn} - \sum_{m=1}^{K} A_{mm} = \sum_{m \neq n}^{K} A_{mn}$$

- Non-negative;
- $\Gamma(p_1, p_2) = 0$  iff.  $p_1 = p_2$  and each of the probabilistic output is one-hot vector;
- Symmetric;
- Satisfies triangle inequality.

