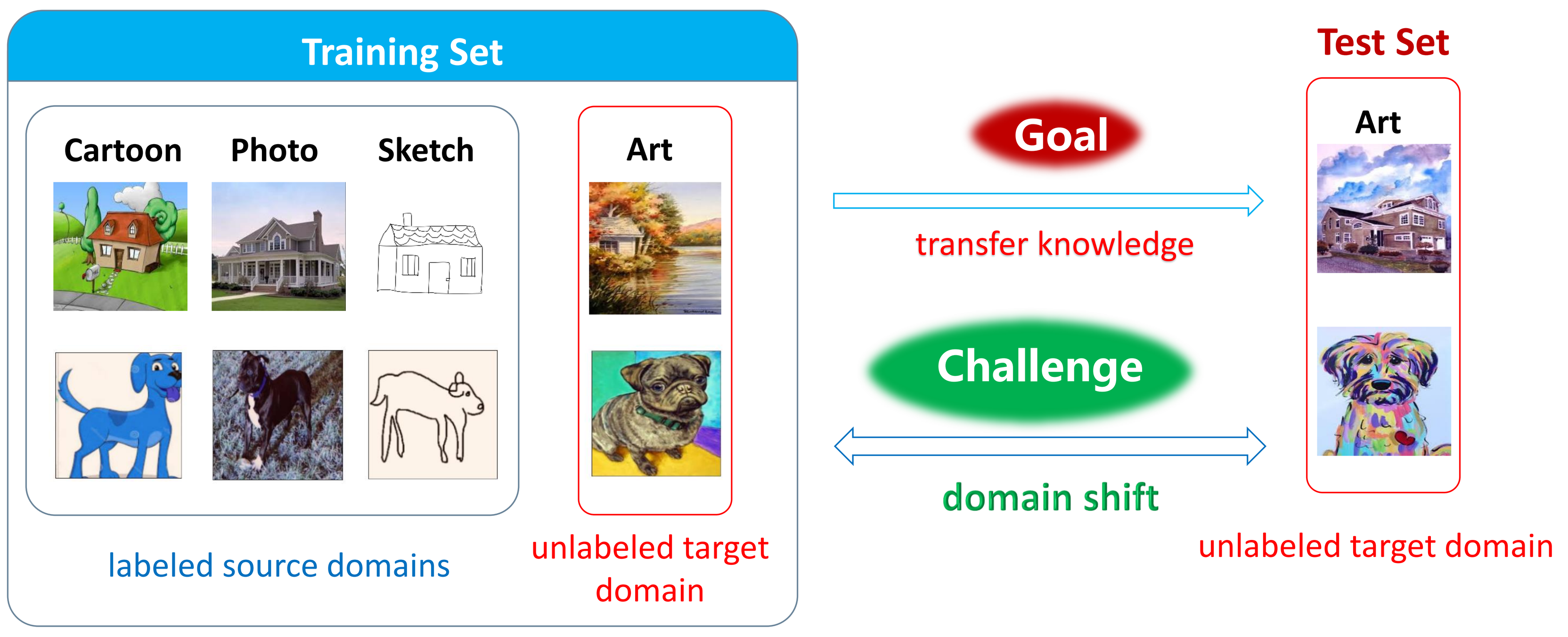
Robust Target Training for Multi-Source Domain Adaptation

Zhongying Deng, Da Li, Yi-Zhe Song, Tao Xiang

z.deng@surrey.ac.uk

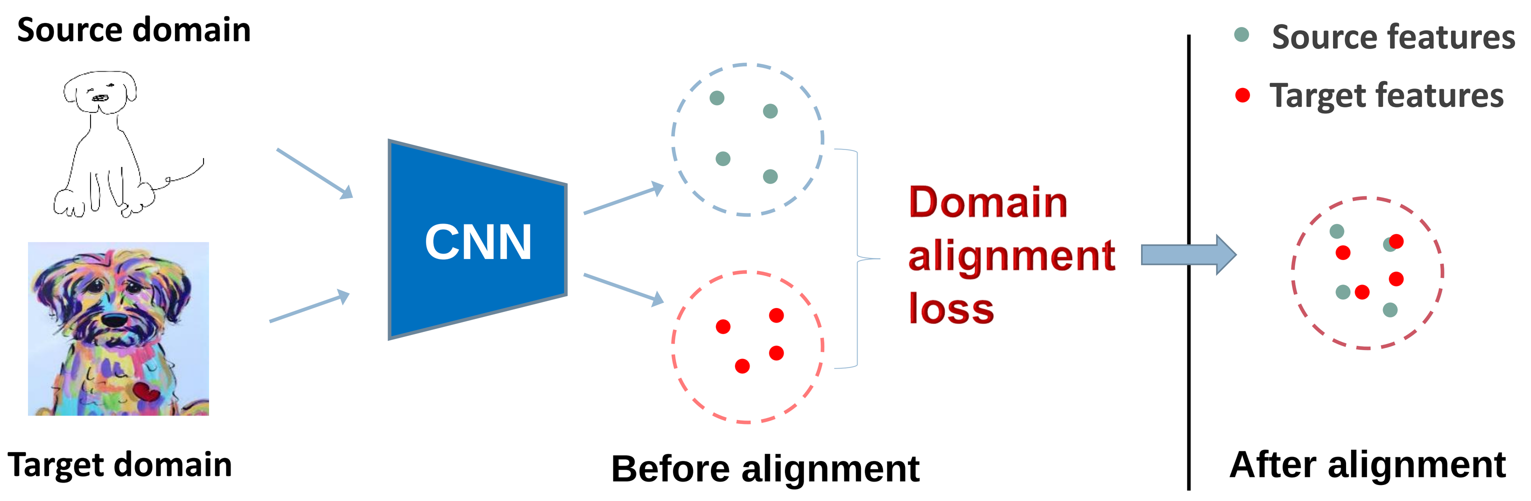
Code: https://github.com/Zhongying-Deng/BORT2

Multi-Source Domain Adaptation



Motivation

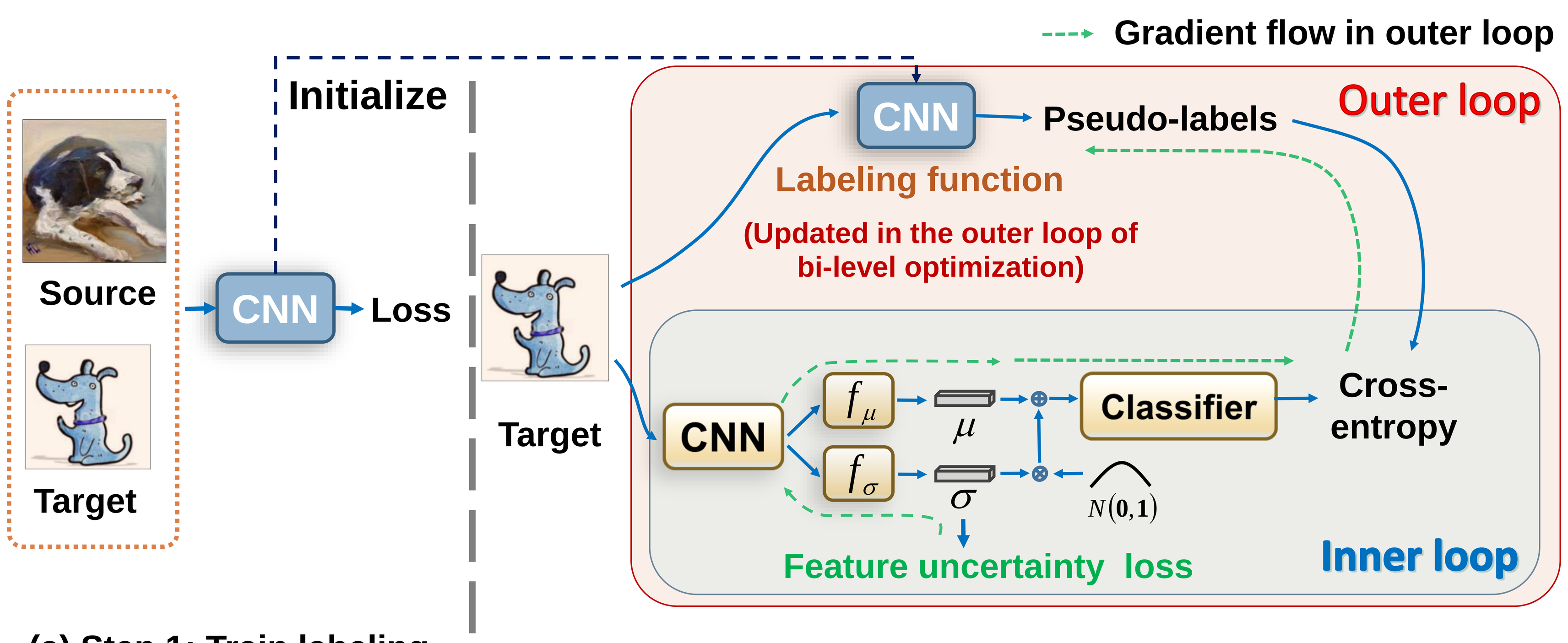
- To reduce the domain shift, most existing methods try to align feature distributions across domains.



1. **Negative transfer**: source domain knowledge reduces the performance in target
2. **Source-domain-bias**: e.g., statistics in BN layers can be highly source-domain biased
3. **Target domain re-training (using pseudo-labels) to alleviate source-domain bias**
4. Pseudo-label may contain noise
5. Train noise-robust model and improve the quality of pseudo-labels

Proposed Method

- **Motivation:** A second step training on target domain to alleviate source-domain bias
- **Key:** **Train noise-robust model and improve the quality of pseudo-labels**



(a) Step 1: Train labeling function on both source and target domains

(b) Step 2: Train noise-robust model only on the pseudo-labeled target domain

Bi-level Optimization based Robust Target Training (BORT^2)

Step 1 can be trained using any existing multi-source domain adaptation (MSDA) methods

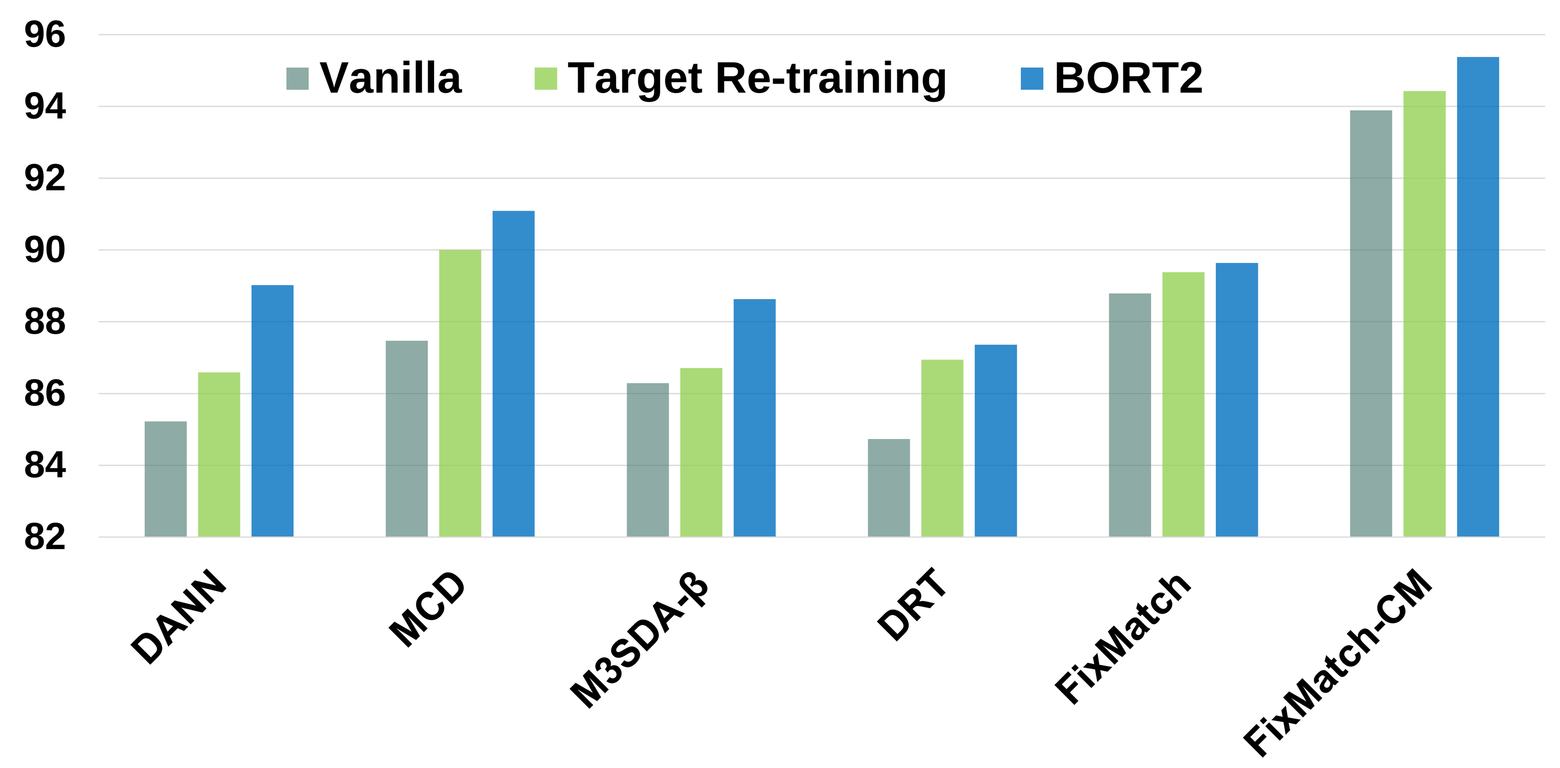
- E.g.,DANN, M3SDA, DRT.

Step 2 is the **bi-level optimization** built on **feature uncertainty estimation**

- A stochastic CNN layer in the noise-robust target model is used to model each target instance feature as a Gaussian distribution
- The variance of the Gaussian measure the label uncertainty as per [1]
- In the inner loop, the feature uncertainty can help the cross-entropy loss to identify low-quality pseudo-labels
- Low-quality pseudo-labels are downplayed to train a noise-robust model
- The outer loop treat the labeling function as hyper network, which is optimized to minimize feature uncertainty loss using bi-level optimization
- Low feature uncertainty usually implies higher probability of pseudo-labels.

Experiments

Comparison to baseline models



- A naïve second step training on the target domain using pseudo-labels can improve the performance of existing MSDA methods.
- BORT^2 further improve the performance.

Comparison to the state of the art

Results on PACS

One-step training methods may suffer from source-domain-bias

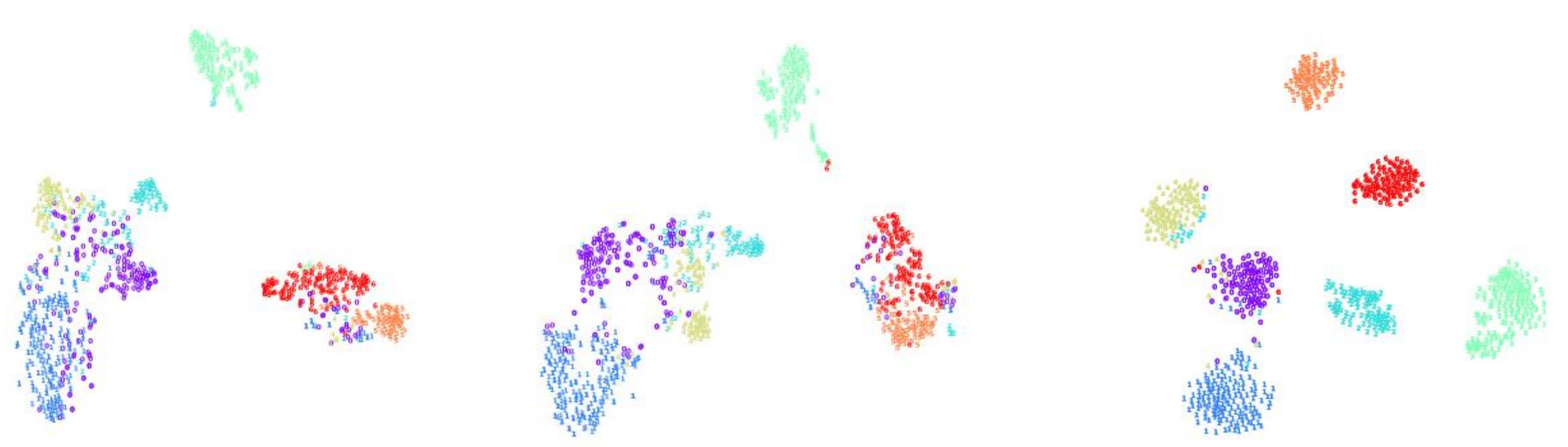
Method	Art.	Cartoon	Sketch	Photo	Avg.
Oracle	99.53	99.84	99.53	99.92	99.71
Source-only	81.22	78.54	72.54	95.45	81.94
MDAN [35]	83.54	82.34	72.42	92.91	82.80
DCTN [31]	84.67	86.72	71.84	95.60	84.71
M^{3}SDA-β [22]	84.20	85.68	74.62	94.47	84.74
MDDA [36]	86.73	86.24	77.56	93.89	86.11
LtC-MSDA [30]	90.19	90.47	81.53	97.23	89.85
DAC-Net [6]	91.39	91.39	84.97	97.93	91.42
BORT^2 (*Ours*)	**95.02**	**94.51**	**93.23**	**98.74**	**95.38**

Results on DomainNet

Method	Clipart	Infograph	Painting	Quickdraw	Real	Sketch	Avg.
Oracle	79.7±0.16	41.0±0.18	71.4±0.11	72.6±0.70	83.7±0.13	70.59±0.06	69.8
Source-only [22]	47.6±0.52	13.0±0.41	38.1±0.45	13.3±0.39	51.9±0.85	33.7±0.54	32.9
DANN [8]	45.5±0.59	13.1±0.72	37.0±0.69	13.2±0.77	48.9±0.65	31.8±0.62	32.6
DCTN [31]	48.6±0.73	23.5±0.59	48.8±0.63	7.2±0.46	53.5±0.56	47.3±0.47	38.2
MCD [24]	54.3±0.64	22.1±0.70	45.7±0.63	7.6±0.49	58.4±0.65	43.5±0.57	38.5
M^{3}SDA-β [22]	58.6±0.53	26.0±0.89	52.3±0.55	6.3±0.58	62.7±0.51	49.5±0.76	42.6
CMSS [32]	64.2±0.18	28.0±0.20	53.6±0.39	16.0±0.12	63.4±0.21	53.8±0.35	46.5
LtC-MSDA [30]	63.1±0.50	28.7±0.70	56.1±0.50	16.3±0.50	66.1±0.60	53.8±0.60	47.4
DRT [14]	69.7±0.24	**31.0**±0.56	59.5±0.43	9.9±1.03	68.4±0.28	59.4±0.21	49.7
DAC-Net [6]	72.5±0.04	27.6±0.10	57.8±0.06	23.0±0.14	66.7±0.10	59.5±0.12	51.2
STEM [21]	72.0	28.2	**61.5**	25.7	**72.6**	60.2	**53.4**
BORT^2 (*Ours*)	**74.0**±0.04	29.1±0.19	59.6±0.06	**28.0**±0.02	69.3±0.04	**60.3** ±0.14	**53.4**

- BORT^2 obtains state-of-the-art performance on PACS and DomainNet.

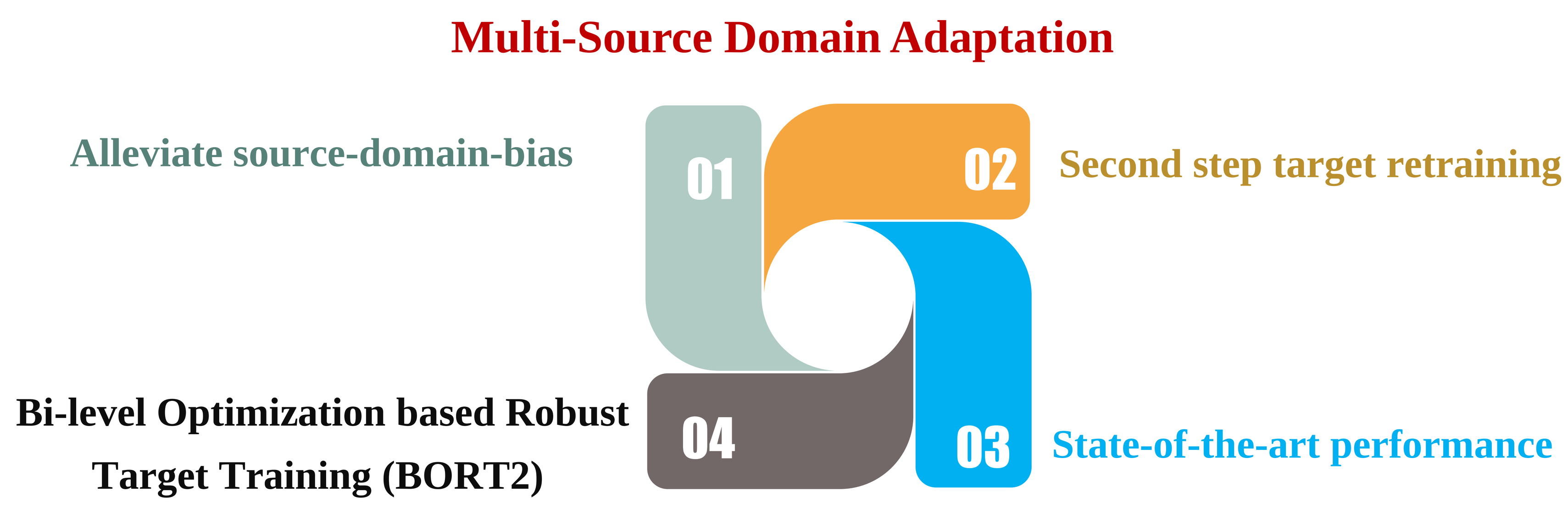
Feature visualizations on the target domain



M^{3}SDA (ICCV'19) DRT (CVPR'21) BORT^2

- BORT^2 extracts more discriminative features

Conclusions



[1] Tianyuan Yu *et al*. Robust person re-identification by modelling feature uncertainty. In ICCV, 2019