Rethinking the Role of Pre-Trained Networks in Source-Free Domain Adaptation

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Institute for Infocomm Research I²R

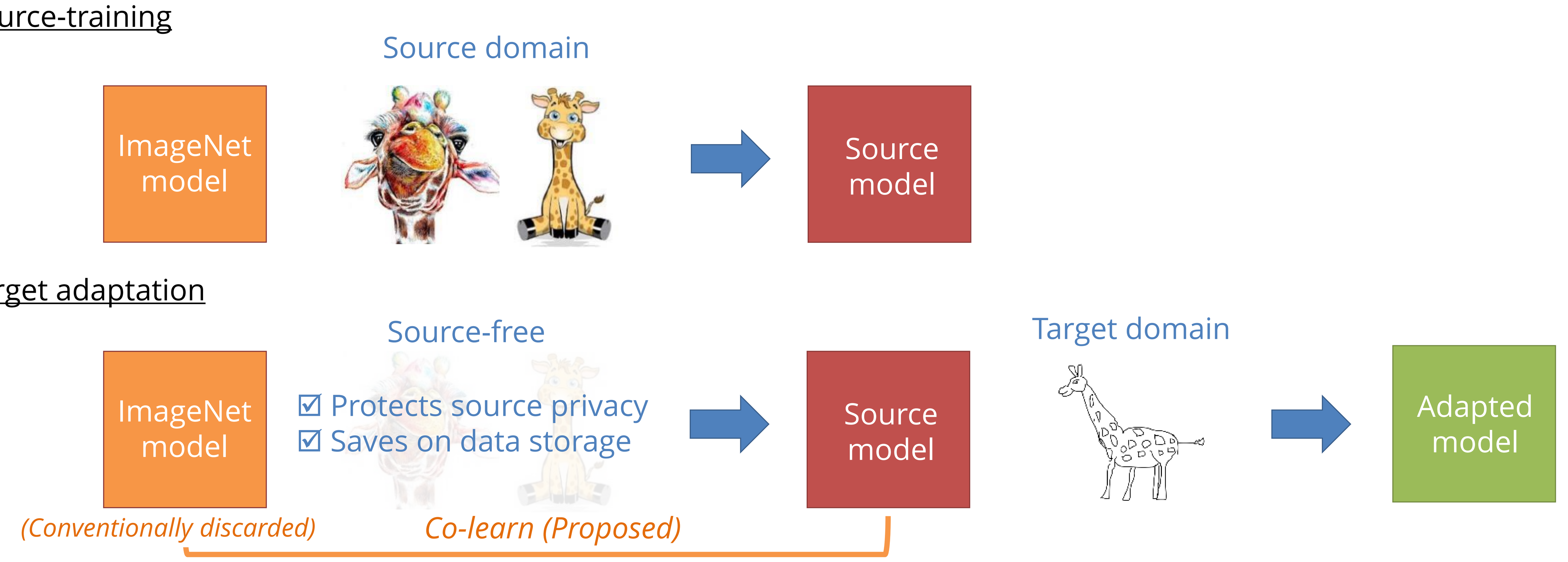
Wenyu Zhang[1], Li Shen[1], Chuan-Sheng Foo[1,2]

[1] Institute for Infocomm Research (I²R), Agency for Science, Technology and Research (A*STAR)
[2] Centre for Frontier AI Research (CFAR), Agency for Science, Technology and Research (A*STAR)

Source-Free Domain Adaptation (SFDA)

The success of deep learning in various applications is typically reliant on the assumption that train (source domain) and test (target domain) data distributions are the same. Deployments in real-world environments can encounter domain shift, hence we need reliable model adaptation to the target domain.

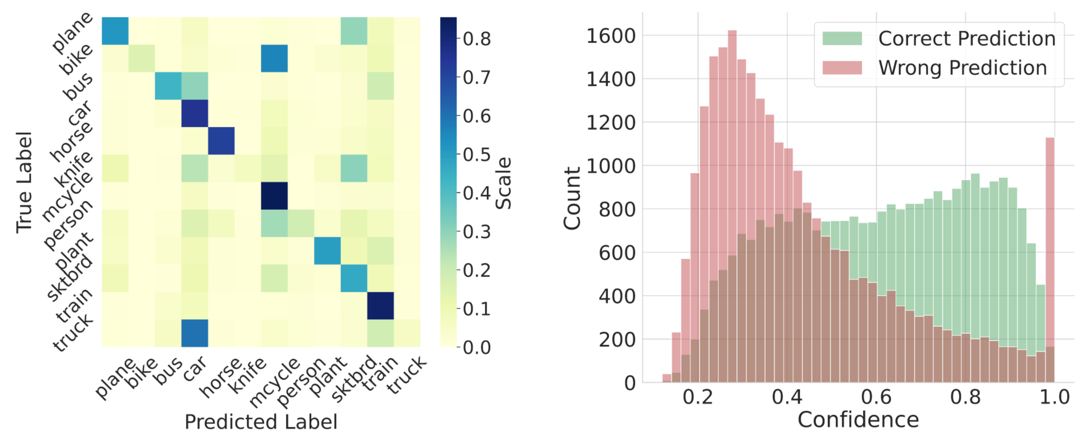
SFDA Framework



Problem of Source Model on Target Domain

Source-training can cause pre-trained networks to overfit to source distribution and forget pre-existing target information.

Example: VisDA-C source model produces unreliable pseudolabels on target samples, and is over-confident on a significant number of incorrect predictions.



Proposed Method

Adapt source model through co-learning to generate more reliable target pseudolabels.

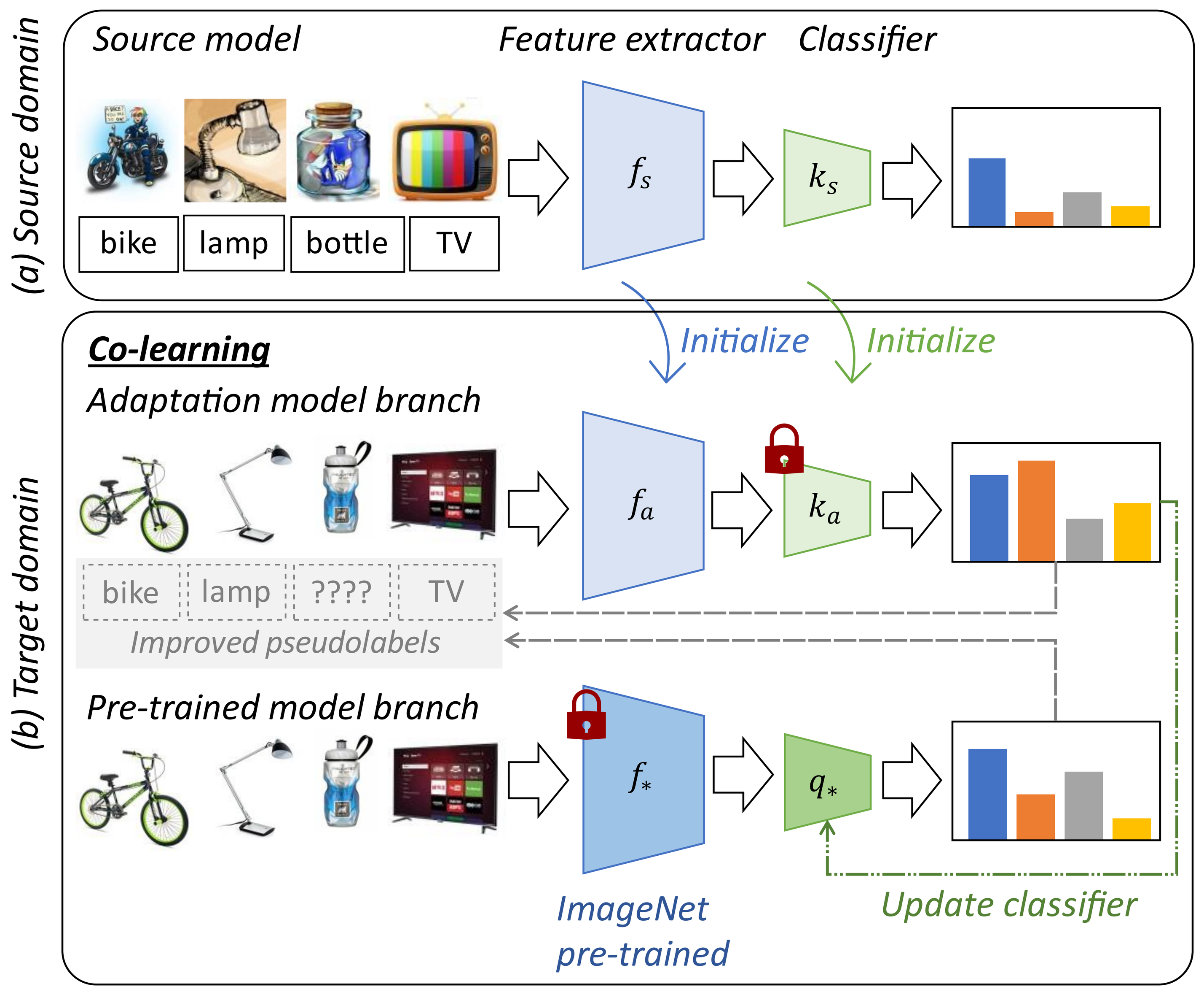
Initialization

- **Adaptation model branch** $\{f_a, k_a\}$ initialized by source model $\{f_s, k_s\}$
- **Pre-trained model branch** initialized by f_* and weighted nearest-centroid-classifier (NCC) task classifier q_*

Co-learning

- Alternate updates on the two branches by (1) finetuning f_a with confident pseudolabels, and (2) re-estimating centroids in q_*
- Improved pseudolabels by MatchOrConf scheme with confidence level γ

$\hat{\mathbf{y}}_\mathbf{a} = \hat{\mathbf{y}}_*$	$\mathbf{Conf}(\hat{\mathbf{y}}_\mathbf{a}) > \gamma$	$\mathbf{Conf}(\hat{\mathbf{y}}_*) > \gamma$	**Pseudolabel** $\tilde{\mathbf{y}}$
✓	✓/✗	✓/✗	$\hat{y}_a$
✗	✓	✓	-
✗	✓	✗	$\hat{y}_a$
✗	✗	✓	$\hat{y}_*$
✗	✗	✗	-



Experimental Setup

Datasets

Office-31: 3 domains: Amazon, Webcam, DSLR
Office-Home: 4 domains: Art, Clipart, Product, Real World
DomainNet: 4 domains: Clipart, Painting, Real, Sketch
VisDA-C: Synthetic-to-real transfer

Source model: ResNet-101 for VisDA-C, ResNet-50 for rest

Co-learning Network	# params
ResNet-50	26M
ResNet-101	45M
Swin-S	50M
ConvNeXt-S	50M
Swin-B	88M
ConvNeXt-B	89M

Results

Method	SF	Office-31	Office-Home	DomainNet	VisDA-C
GVB-GD	✗	89.3	70.4	-	-
GSDA	✗	89.7	70.3	-	-
CAN	✗	90.6	-	-	87.2
FixBi	✗	-	72.7	-	87.2
Source Only	✓	79.2	59.6	55.5	45.9
Co-learn (w/ ResNet)	✓	88.3	70.0	61.9	83.7
Co-learn (w/ Swin-B)	✓	**93.6**	**83.5**	**71.8**	**88.2**
SHOT	✓	88.7	71.9	67.3	82.4
w/ Co-learn (w/ ResNet)		88.8 (↑ 0.1)	72.4 (↑ 0.5)	67.3 (=)	84.1 (↑ 1.7)
w/ Co-learn (w/ Swin-B)		**90.9** (↑ 2.2)	**75.7** (↑ 3.8)	**71.4** (↑ 4.1)	**85.2** (↑ 2.8)
SHOT++	✓	89.2	72.7	69.3	86.8
w/ Co-learn (w/ ResNet)		89.1 (↓ 0.1)	73.3 (↑ 0.6)	69.2 (↓ 0.1)	87.4 (↑ 0.6)
w/ Co-learn (w/ Swin-B)		**91.2** (↑ 2.0)	**76.3** (↑ 3.6)	**72.9** (↑ 3.6)	**88.6** (↑ 1.8)
AaD	✓	89.7	71.8	68.3	87.7
w/ Co-learn (w/ ResNet)		90.3 (↑ 0.6)	72.7 (↑ 0.9)	70.2 (↑ 1.9)	88.2 (↑ 0.5)
w/ Co-learn (w/ Swin-B)		**93.0** (↑ 3.3)	**79.0** (↑ 7.2)	**72.7** (↑ 4.4)	**89.1** (↑ 1.4)

(Co-learning ResNet follows source model initialization)

Multi-source adaptation on Office-31

Method	→ A	→ D	→ W	Avg
CAiDA	75.7	98.8	93.2	89.2
w/ Co-learn (w/ ResNet-50)	76.8	99.0	93.2	89.7 (↑ 0.5)
w/ Co-learn (w/ Swin-B)	**79.3**	**99.6**	**97.4**	**92.1** (↑ 2.9)

Non-closed-set adaptation on Office-Home

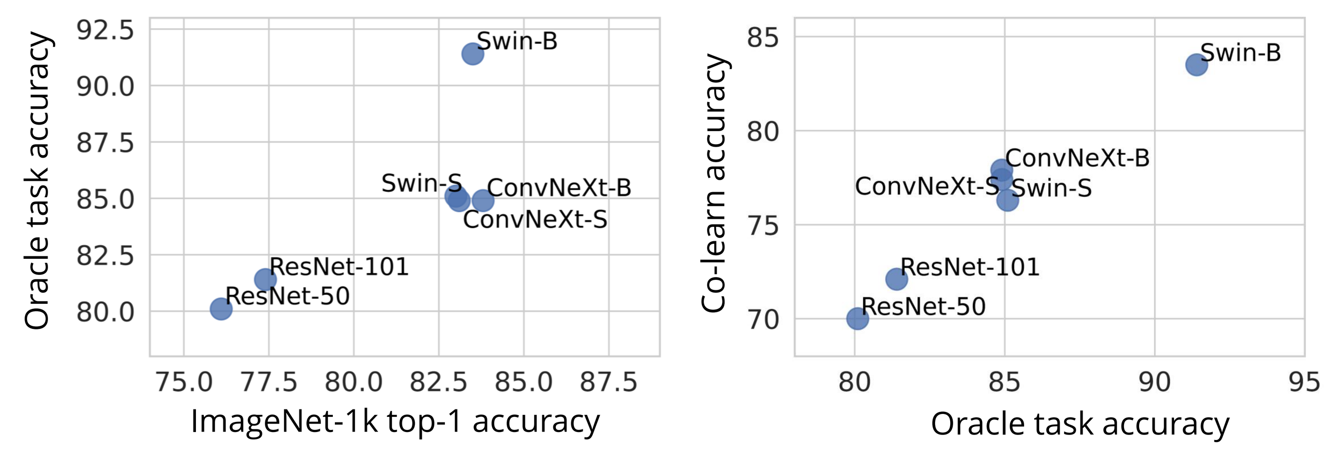
Method	Open-set	Partial-set	Open-partial
SFDA algorithm	65.1	78.3	78.3
w/ Co-learn (w/ ResNet-50)	66.0 (↑ 0.9)	78.6 (↑ 0.3)	**79.2** (↑ 0.9)
w/ Co-learn (w/ Swin-B)	**66.3** (↑ 1.2)	**79.8** (↑ 1.5)	79.0 (↑ 0.7)

(SHOT for open and partial-set, OneRing for open-partial)

Further Analysis:

Preferred characteristics of pre-trained networks for co-learning:

- Dataset similarity (input style and task)
- Robustness against covariate shift
- Different view of feature and classification decision



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