Semi-Supervised Domain Adaptation via Selective Pseudo Labeling and Progressing Self-Training

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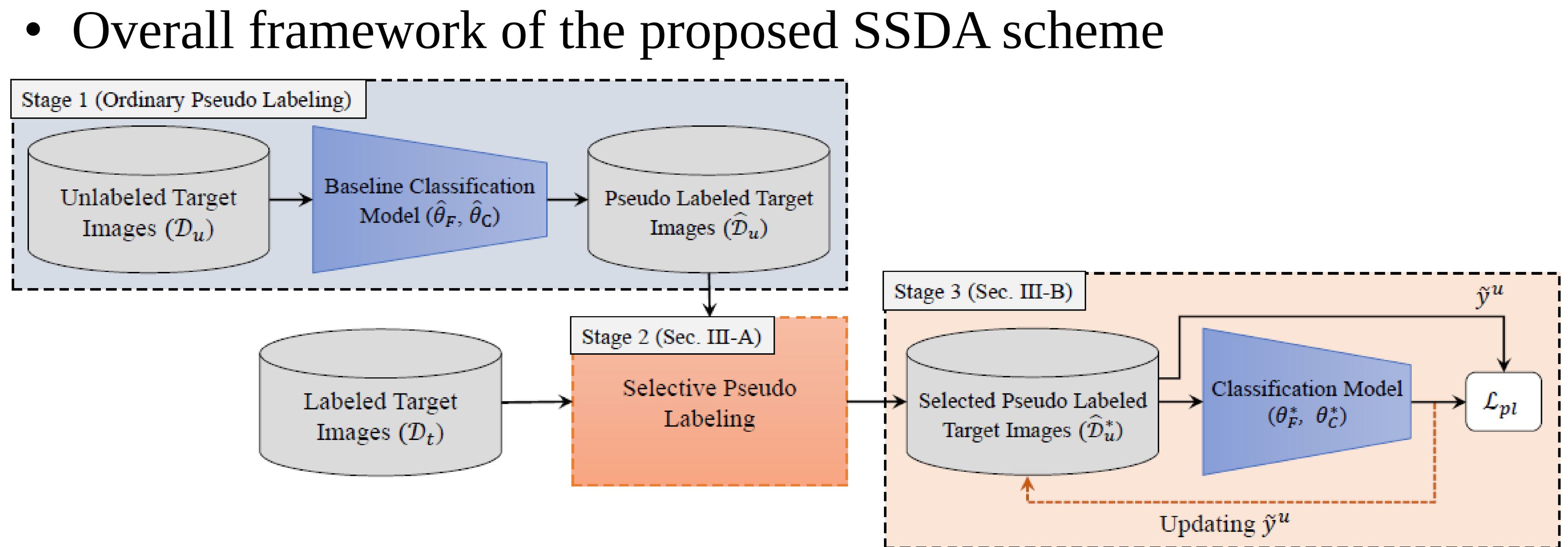
Introduction & Related Work

- A fundamental limitation of deep convolutional neural network (DCNN): Due to the strong dependency on training data, DCNN is fragile to domain shifts.
  - ✓ Domain shift: Statistical difference of data distributions between two domains.

- Unsupervised domain adaptation (UDA)
  - ✓ Feature-level and Pixel-level adaptation approaches.
  - ✓ Limitation: Discriminative power in target domain is not guaranteed and not robust to large domain shift.
- Semi-supervised domain adaptation (SSDA)
  - ✓ In comparison with UDA, a few labeled images are additionally given for training.
- Previous SSDA method: Minimax entropy (MME [14])
  - ✓ Update to increase entropy w.r.t classifier.
  - ✓ Update to decrease entropy w.r.t feature extractor.
- Limitation of previous SSDA method
  - ✓ Solely adopt labeled target images for embedding ordinary supervised loss, overlooking the potential usefulness of the few yet informative data.
  - ✓ Our motivation: We propose to exploit the labeled target images more actively by treating them as 'golden' samples for SSDA.

Proposed Method

- Overall framework of the proposed SSDA scheme



- Our method consists of the following three steps
  - ✓ Step #1: Training a baseline network for generating pseudo labels.
  - ✓ Step #2: Selective pseudo labeling.
  - ✓ Step #3: Label noise-robust training via progressive self-training.
- Step #1: Pseudo labeling via a baseline method
  - ✓ MME [14] is adopted as the baseline method.
  - ✓ Assign pseudo labels to unlabeled images.

Proposed Method (Continued)

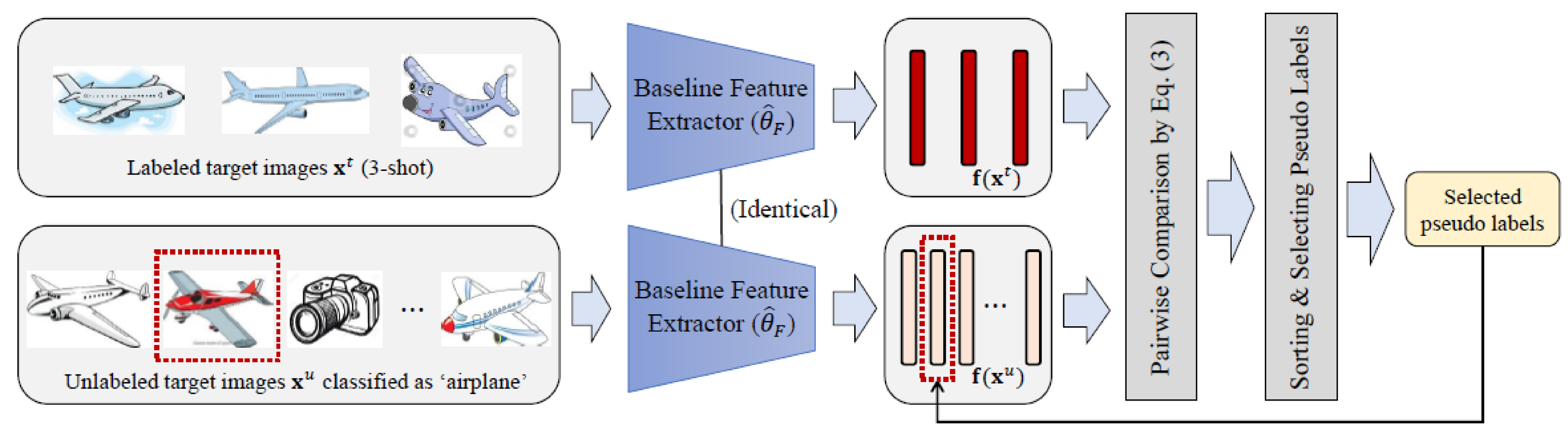
- Step #2: Selective pseudo labeling
  - ✓ Applied independently for each image category.
  - ✓ For the j-th unlabeled image, a pairwise distance is calculated.

$$d_j = \frac{1}{n_t'}\sum_{i=1}^{n_t'}\left\|\mathrm{f}(\mathrm{x}_i^t) - \mathrm{f}(\mathrm{x}_j^u)\right\|_1$$

  - ✓ Sort the unlabeled images based on d_j and determine n_u' samples as pseudo labels.

$$n_u' = \left\lceil r_u \frac{n_u}{K} \right\rceil$$

  - ✓ The pipeline of the selective pseudo labeling scheme.



- Step #3: Label noise-robust learning via progressive self-training
  - ✓ The selected pseudo labels are still not completely reliable (i.e., noisy).
  - ✓ Inspired by [17], we alternately update the network and the noisy labels set.
- Final objective function
  - ✓ We conduct SSDA by combining the baseline method and our proposed scheme.

Experimental Results & Analysis

- Experimental setups
  - ✓ Datasets: LSDAC [3], Office-Home [18], and Office [19].
  - ✓ Baseline network architectures: AlexNet [27], VGG-16 [28] , and ResNet-34 [29].
  - ✓ Implementation: PyTorch 1.1.0 & NVIDIA Titan-X.
- DA methods in comparison
  - ✓ S+T, DANN [4], ADR [20], CDAN [5], ENT [21], MME [14].
- Comparative evaluation results
  - ✓ Results on the LSDAC dataset (ResNet-34)

	S+T	DANN	ADR	CDAN	ENT	MME	Ours
1-shot	56.9	58.4	57.6	62.5	62.6	66.4	**69.0**
3-shot	60.0	60.7	60.4	66.5	67.6	68.9	**71.0**

  - ✓ Results on the Office-Home dataset (VGG-16)

	S+T	DANN	ADR	CDAN	ENT	MME	Ours
1-shot	57.4	60.0	57.4	55.8	51.6	62.7	**63.9**
3-shot	62.9	63.9	63.0	61.8	64.8	67.6	**68.6**

  - ✓ Results on the Office dataset (VGG-16)

	S+T	DANN	ADR	CDAN	ENT	MME	Ours
1-shot	68.7	69.8	69.4	65.9	70.6	73.4	**76.4**
3-shot	73.3	75.0	73.7	72.9	75.3	77.0	**78.1**

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