When Source-Free Domain Adaptation Meets Learning with Noisy Labels

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UDA and SFDA

Unsupervised Domain Adaptation (UDA)

$$D_S = \{(\boldsymbol{x}_i^S, y_i^S)\}_{i=1}^N \;+\; D_T = \{(\boldsymbol{x}_i^T)\}_{i=1}^M$$

$$\Downarrow$$

$$f_T(\boldsymbol{x})$$

Source-Free Domain Adaptation (SFDA)

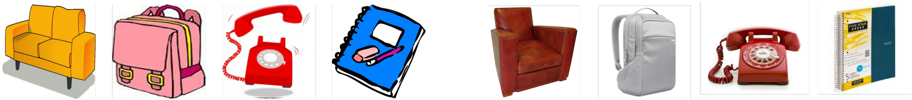
$$D_S = \{(\boldsymbol{x}_i^S, y_i^S)\}_{i=1}^N$$

$$\Downarrow \text{ Source Training}$$

$$f_S(\boldsymbol{x}) \;+\; D_T = \{(\boldsymbol{x}_i^T)\}_{i=1}^M$$

$$\Downarrow \text{ Target Adaptation}$$

$$f_T(\boldsymbol{x})$$



(a) Clipart: Clipart Images

(b) Real World: Regular Images captured with a Camera

Figure 1: Examples of Office-Home Dataset [1]: $p_S(X, Y) \neq p_T(X, Y)$

[1] Source: Venkateswara et al., Deep Hashing Network for Unsupervised Domain Adaptation. CVPR 2017.

Label Noise in SFDA

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$\Downarrow$ Source Training

$$f_S(\boldsymbol{x}) \; + \; D_T = \{(\boldsymbol{x}_i^T)\}_{i=1}^M$$

$\Downarrow$ Target Adaptation

$$f_T(\boldsymbol{x})$$

- **Two-Stage Training process**:
  Source Training $\Rightarrow$ **Target Adaptation**
- Key Point: Quality of the **Pseudo-Labels**
  - Domain Shift $\Rightarrow$ Severe Noise in Pseudo Labels
  - Incorrect Neighborhood/Cluster Information $\Rightarrow$ Noise Accumulation (Fig2)

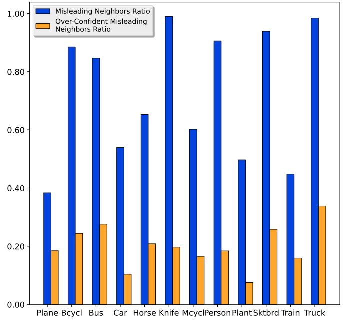

Figure 2: Neighbors Label Noise in SFDA Problem

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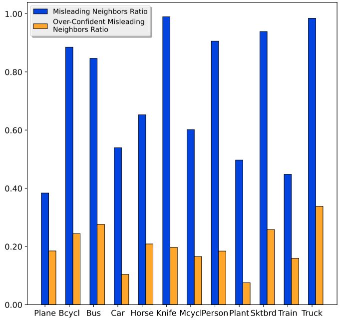

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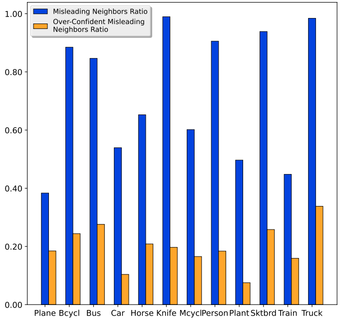

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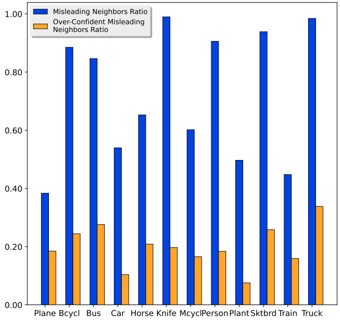

Figure 2: Neighbors Label Noise in SFDA Problem

$\Downarrow$

Incorrectly Assigned Pseudo Labels = Noisy Labels

We propose to **formulate SFDA as a Learning with Label Noise (LLN) problem.**

LLN

Learning with Label Noise (LLN)

- Given a set of **NOISY** training data $\bar{S}$
  - $\bar{S} = (\boldsymbol{x_i}, \bar{y}_i)_{i=1}^{n}$
  - $\boldsymbol{x_i}$: input data
  - $\bar{y}_i$: possibly corrupted label
  - y_i: ground-truth label
- To learn a **Noise-Robust** classifier
  $\Longrightarrow$ correctly label the new input data.

Figure 3: Example of Learning with Label Noise on Office-Home Dataset. The first row represents the ground-truth label; the second row is the possibly corrupted label.

Current Limitations of LLN methods in SFDA

Different Label Noises in LLN and in SFDA Settings

- Label Noise in **LLN** (Xiao et al., 2015):
  - generated by *human annotators* or *image search engines*
  - mislabeling rate for a sample is **bounded**
  - general LLN methods: **Noise-Robust** Losses
- Label Noise in **SFDA**:
  - generated by the *source model* due to the distribution shift
  - mislabeling rate can be out of control and **unbounded**

TWO **PROBLEMS** for *correctly* applying **LLN approaches** to **SFDA**:

1. Can general noise-robust LLN methods, based on the *Bounded Noise*, be effective for SFDA problems where the label noise has different properties?
2. If NOT, what kinds of LLN methods can be helpful?

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Unbounded Label Noise in SFDA

Theoretical Analysis 1 - Unbounded Label Noise in Source Free Domain Adaptation

Definition: Bounded and Unbounded Label Noises

With X as the input feature, Y as the ground-truth label, and $\tilde{Y}$ as the noisy label, we define the **Bounded Label Noise** scenario as:

$$\Pr[\tilde{Y} = i | Y = i, X = \boldsymbol{x}] > \Pr[\tilde{Y} = j | Y = i, X = \boldsymbol{x}], \ \forall \boldsymbol{x} \in \mathcal{X}, i \neq j$$

, and the **Unbounded Label Noise** scenario as:

$$\Pr[\tilde{Y} = j | Y = i, X = \boldsymbol{x}] \to 1, \ \exists \mathcal{S} \subset \mathcal{X}, \ \forall \boldsymbol{x} \in \mathcal{S}, i \neq j$$

- **Bounded**: A sample $\boldsymbol{x}$ has the highest probability of being in the correct class (i)
- **Unbounded**: Mislabeling rate of a sample x can be very high.

Existence of Unbounded Label Noise In SFDA (Th 3.1)

Under some mild assumptions, there exists a non-empty region $\mathbf{R} \subset \mathcal{X}$, for $(\boldsymbol{x}, y) \sim \mathcal{D}_T$, if $\boldsymbol{x} \in \mathbf{R}$, then

$$\Pr[f_S(\boldsymbol{x}) \neq y] \geq 1 - \delta,$$

where $\delta \in (0, 1)$ (i.e., $\delta = 0.01$), f_S is the optimal source classifier.

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where $\delta \in (0, 1)$ (i.e., $\delta = 0.01$), f_S is the optimal source classifier.

- **Theorem 3.1**: Due to the Domain Shift, **Unbounded Label Noise** exists in SFDA.

Theoretical Analysis 1 - Unbounded Label Noise in Source Free Domain Adaptation

Unsuitable LLN Losses for Unbounded Label Noise (Lemma 3.2)

Given a **bounded noise-robust loss ℓ_{LLN}** and an input sample x, we have:

$$\Pr\left[f_T^\star(\boldsymbol{x}) \neq \tilde{f}_T^\star(\boldsymbol{x})\right] \geq 1-\delta, \forall \boldsymbol{x} \in \mathbf{R}$$

where $f_T^\star$ and $\tilde{f}_T^\star$ are the global minimizers of $R(f_T)$ and $\widetilde{R}(f_T)$, the risks of the function f_T under **clean data** and **unbounded noisy data**, respectively.

- **Lemma 3.2**: many existing **Noise-Robust Loss based LLN methods**, which rely on the Bounded Label Noise assumption, are **NOT** the most suitable solutions for **SFDA**.

TWO **PROBLEMS** for *correctly* applying **LLN approaches** to **SFDA**:

1. Can general noise-robust LLN methods, based on the *Bounded Noise*, be effective for SFDA problems where the label noise has different properties? $\Rightarrow$ NO
2. If NOT, what kinds of LLN methods can be helpful?

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Early-Time Training Phenomenon in SFDA

Theoretical Analysis 2 - Early-time Training Phenomenon (ETP) exists in Unbounded Label Noise Scenario

ETP - Early-time Training Phenomenon

The **Early-time Training Phenomenon** describes the training dynamics of the classifier that preferentially **fits the clean samples** and therefore has **higher prediction accuracy for mislabeled samples** *during the early-training stage.* (Liu et al., 2020)

Existence of ETP in SFDA (Th 4.1)

In the **Unbounded Label Noise** scenario, given a set of mislabeled samples, $B = \{(\boldsymbol{x}, \tilde{y})\}$, and a classifier θ, there exists a proper time T, and a constant c_0 such that for any $0 < \sigma < c_0$, the **prediction accuracy** $\kappa(B; \theta_T)$ can satisfy the following inequality with probability $1 - o_p(1)$:

$$\kappa(B; \theta_T) \geq 1 - \exp\{-\frac{1}{200} g(\sigma)^2\},$$

where $g(\sigma)$ is a monotone decreasing function with $g(\sigma) \rightarrow \infty$ $(\sigma \rightarrow 0)$, and σ is the cluster variance.

$\Longrightarrow$ In **SFDA**,

- the **Early Adaptation Phase** is critical;
- the **Early-Time Predictions** for some easily mislabeled data could be **more promising**.

Method

Early Learning Regularization (ELR) Term (Liu et al., 2020)

$$\mathcal{L}_{\text{ELR}}(\theta_t) = \log\left(1 - \bar{y}_t^\top f(\boldsymbol{x}; \theta_t)\right)$$

where $f(\boldsymbol{x}; \theta_t)$ is the probabilistic output for the sample $\boldsymbol{x}$, and $\bar{y}_t = \beta \bar{y}_{t-1} + (1-\beta) f(\boldsymbol{x}; \theta_t)$ is the moving average prediction for $\boldsymbol{x}$.

Final Method Proposed in SFDA

Given *any* SFDA objective function $\mathcal{L}_{\text{SFDA}}$, the overall objective function is given by:

$$\mathcal{L} = \mathcal{L}_{\text{SFDA}} + \lambda \mathcal{L}_{\text{ELR}},$$

Gradient Analysis in SFDA

$$\frac{\mathrm{d}\mathcal{L}_{\text{ELR}}(\theta_t)}{\mathrm{d}f(\mathrm{x};\theta_t)} = -\frac{\bar{y}_t}{1-\bar{y}_t^\top f(\boldsymbol{x};\theta_t)}$$

- $\mathcal{L}_{\text{ELR}} \downarrow \Rightarrow \left|\frac{\mathrm{d}\mathcal{L}_{\text{ELR}}(\theta_t)}{\mathrm{d}f(\mathrm{x};\theta_t)}\right| \uparrow \Rightarrow \mathcal{L}_{\text{ELR}}$ dominates param updating
  $\Rightarrow$ Enforce the alignment of $f(\mathrm{x};\theta_t)$ with $\bar{y}_t$ rather than **noisy labels**

Experimental Results

Observation of Performance Drop

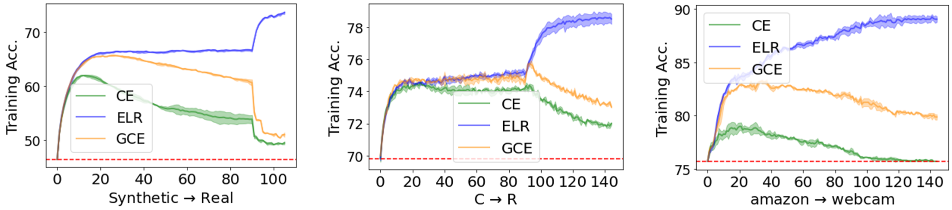

Figure 4: Performance Drop of LLN methods in Adaptation process (VisDA, DomainNet, Office-31)

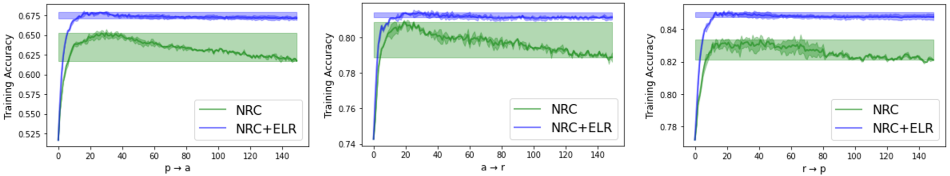

Figure 5: Performance Drop of SFDA methods in Adaptation process (Office-Home)

Main Experimental Results

- Office-Home
- VisDA-2017
- DomainNet

Method	SF	Ar→Cl	Ar→Pr	Ar→Rw	Cl→Ar	Cl→Pr	Cl→Rw	Pr→Ar	Pr→Cl	Pr→Rw	Rw→Ar	Rw→Cl	Rw→Pr	**Avg**
MCD (Saito et al., 2018b)	✗	48.9	68.3	74.6	61.3	67.6	68.8	57.0	47.1	75.1	69.1	52.2	79.6	64.1
CDAN (Long et al., 2018)	✗	50.7	70.6	76.0	57.6	70.0	70.0	57.4	50.9	77.3	70.9	56.7	81.6	65.8
SAFN (Xu et al., 2019a)	✗	52.0	71.7	76.3	64.2	69.9	71.9	63.7	51.4	77.1	70.9	57.1	81.5	67.3
Symnets (Zhang et al., 2019a)	✗	47.7	72.9	78.5	64.2	71.3	74.2	64.2	48.8	79.5	74.5	52.6	82.7	67.6
MDD (Zhang et al., 2019b)	✗	54.9	73.7	77.8	60.0	71.4	71.8	61.2	53.6	78.1	72.5	**60.2**	82.3	68.1
TADA (Wang et al., 2019a)	✗	53.1	72.3	77.2	59.1	71.2	72.1	59.7	53.1	78.4	72.4	60.0	82.9	67.6
BNM (Cui et al., 2020)	✗	52.3	73.9	80.0	63.3	72.9	74.9	61.7	49.5	79.7	70.5	53.6	82.2	67.9
BDG (Yang et al., 2020)	✗	51.5	73.4	78.7	65.3	71.5	73.7	65.1	49.7	81.1	74.6	55.1	84.8	68.7
SRDC (Tang et al., 2020)	✗	52.3	76.3	81.0	**69.5**	76.2	78.0	**68.7**	53.8	81.7	**76.3**	57.1	85.0	71.3
RSDA-MSTN (Gu et al., 2020)	✗	53.2	77.7	81.3	66.4	74.0	76.5	67.9	53.0	82.0	75.8	57.8	**85.4**	70.9
Source Only	✓	44.6	67.3	74.8	52.7	62.7	64.8	53.0	40.6	73.2	65.3	45.4	78.0	60.2
+ELR	✓	52.4	73.5	77.3	62.5	70.6	71.0	61.1	50.8	78.9	71.7	56.7	81.6	67.3
SHOT (Liang et al., 2020)	✓	57.1	78.1	81.5	68.0	78.2	78.1	67.4	54.9	82.2	73.3	58.8	84.3	71.8
+ELR	✓	**58.7**	**78.9**	**82.1**	68.5	79.0	77.5	68.2	57.1	81.9	74.2	59.5	84.9	**72.6**
G-SFDA (Yang et al., 2021b)	✓	55.8	77.1	80.5	66.4	74.9	77.3	66.5	53.9	80.8	72.4	59.7	83.2	70.7
+ELR	✓	56.4	77.6	81.1	67.1	75.2	77.9	65.9	55.0	81.2	72.1	60.0	83.6	71.1
NRC (Yang et al., 2021a)	✓	56.3	77.6	81.0	65.3	78.3	77.5	64.5	56.0	82.4	70.0	57.1	82.9	70.8
+ELR	✓	58.4	78.7	81.5	69.2	**79.5**	**79.3**	66.3	**58.0**	**82.6**	73.4	59.8	85.1	**72.6**

Figure 6: Accuracies (%) on Office-Home for ResNet50-based methods

Main Experimental Results

- Office-Home
- **VisDA-2017**
- DomainNet

Method	SF	plane	bcycl	bus	car	horse	knife	mcycl	person	plant	sktbrd	train	truck	**Per-class**
DANN (Ganin et al., 2016)	✗	81.9	77.7	82.8	44.3	81.2	29.5	65.1	28.6	51.9	54.6	82.8	7.8	57.4
DAN (Long et al., 2015)	✗	87.1	63.0	76.5	42.0	90.3	42.9	85.9	53.1	49.7	36.3	85.8	20.7	61.1
ADR (Saito et al., 2018a)	✗	94.2	48.5	84.0	72.9	90.1	74.2	92.6	72.5	80.8	61.8	82.2	28.8	73.5
CDAN (Long et al., 2018)	✗	85.2	66.9	83.0	50.8	84.2	74.9	88.1	74.5	83.4	76.0	81.9	38.0	73.9
SAFN (Xu et al., 2019a)	✗	93.6	61.3	84.1	70.6	94.1	79.0	91.8	79.6	89.9	55.6	89.0	24.4	76.1
SWD (Lee et al., 2019)	✗	90.8	82.5	81.7	70.5	91.7	69.5	86.3	77.5	87.4	63.6	85.6	29.2	76.4
MDD (Zhang et al., 2019b)	✗	-	-	-	-	-	-	-	-	-	-	-	-	74.6
MCC (Jin et al., 2020)	✗	88.7	80.3	80.5	71.5	90.1	93.2	85.0	71.6	89.4	73.8	85.0	36.9	78.8
STAR (Lu et al., 2020)	✗	95.0	84.0	84.6	73.0	91.6	91.8	85.9	78.4	94.4	84.7	87.0	42.2	82.7
RWOT (Xu et al., 2020)	✗	95.1	80.3	83.7	**90.0**	92.4	68.0	92.5	82.2	87.9	78.4	**90.4**	**68.2**	84.0
Source Only	✓	60.9	21.6	50.9	67.6	65.8	6.3	82.2	23.2	57.3	30.6	84.6	8.0	46.6
+ELR	✓	95.4	45.7	89.7	69.8	94.1	97.1	**92.9**	80.1	89.7	52.8	83.3	4.3	74.6
SHOT (Liang et al., 2020)	✓	94.3	88.5	80.1	57.3	93.1	94.9	80.7	80.3	91.5	89.1	86.3	58.2	82.9
+ELR	✓	95.8	84.1	83.3	67.9	93.9	**97.6**	89.2	80.1	90.6	90.4	87.2	48.2	84.1
G-SFDA (Yang et al., 2021b)	✓	96.0	87.6	85.3	72.8	95.9	94.7	88.4	79.0	92.7	93.9	87.2	43.7	84.8
+ELR	✓	**97.3**	89.1	**89.8**	79.2	**96.9**	97.5	92.2	**82.5**	**95.8**	**94.5**	87.3	34.5	**86.4**
NRC (Yang et al., 2021a)	✓	96.9	89.7	84.0	59.8	95.9	96.6	86.5	80.9	92.8	92.6	90.2	60.2	85.4
+ELR	✓	97.1	**89.7**	82.7	62.0	96.2	97.0	87.6	81.2	93.7	94.1	90.2	58.6	85.8

Figure 6: Accuracies (%) on VisDA-C (Synthesis → Real) for ResNet101-based methods

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- VisDA-2017
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MCD (Saito et al., 2018b)	✗	61.9	69.3	56.2	79.7	56.6	53.6	83.3	58.3	60.9	81.7	56.2	66.7	65.4
DANN (Ganin et al., 2016)	✗	63.4	73.6	72.6	86.5	65.7	70.6	86.9	73.2	70.2	85.7	75.2	70.0	74.5
DAN (Long et al., 2015)	✗	64.3	70.6	58.4	79.4	56.7	60.0	84.5	61.6	62.2	79.7	65.0	62.0	67.0
COAL (Tan et al., 2020)	✗	73.9	75.4	70.5	89.6	70.0	71.3	89.8	68.0	70.5	88.0	73.2	70.5	75.9
MDD (Zhang et al., 2019b)	✗	77.6	75.7	**74.2**	89.5	74.2	**75.6**	90.2	76.0	**74.6**	86.7	72.9	73.2	78.4
Source Only	✓	53.7	71.6	52.9	70.8	49.5	58.3	85.2	59.6	59.1	30.6	74.8	65.7	61.0
+ELR	✓	70.2	81.7	61.7	79.9	63.8	67.0	90.0	72.1	66.8	85.1	78.5	68.8	73.8
SHOT (Liang et al., 2020)	✓	73.3	80.1	65.8	**91.4**	74.3	69.2	91.9	77.0	66.2	87.4	81.3	75.0	77.7
+ELR	✓	**78.0**	81.9	67.4	91.1	**75.9**	71.0	92.6	79.3	68.0	88.7	84.8	77.0	**79.7**
G-SFDA (Yang et al., 2021b)	✓	65.8	78.9	60.2	80.5	64.7	64.6	89.3	69.9	63.6	86.4	78.8	71.1	72.8
+ELR	✓	69.4	80.9	60.6	81.3	67.2	66.4	90.2	73.2	64.9	87.6	82.1	71.0	74.6
NRC (Yang et al., 2021a)	✓	69.8	81.1	62.9	83.4	74.4	66.3	90.3	73.4	65.2	88.2	82.2	75.8	76.4
+ELR	✓	75.6	**82.2**	65.7	91.2	77.2	68.5	**92.7**	**79.8**	67.5	**89.3**	**85.1**	**77.6**	79.4

Figure 6: Accuracies (%) on DomainNet for ResNet50-based methods

Summary

In this work, we

1. *Distinguish* Label Noises in **SFDA** from **Traditional LLN Settings**;
2. *Justify* the existence of **ETP** in **Unbound Label Noise**;
3. *Identify* **effective** LLN methods for **SFDA**;
4. *Introduce* the **ELR** term to enhance SFDA performance.

We hope this work can **INSPIRE** more research on

- Exploring the Training Dynamic of Early-Time Adaptation
- and Utilizing the Early-Time Training Phenomenon in Unbounded Label Noise.

Thanks!

Poster Session 4: May 2, 16:30 - 18:30 #144

Project Code