Domain Adaptation with Dynamic Open-Set Targets

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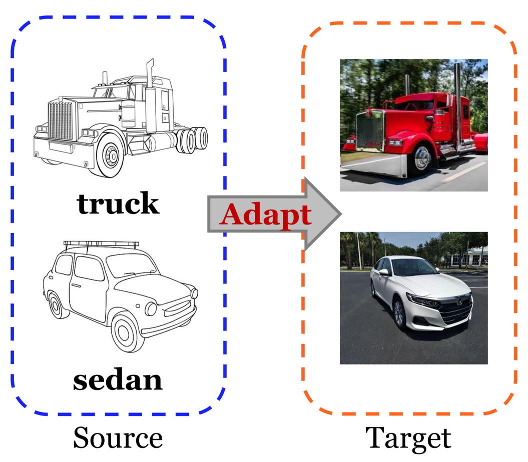
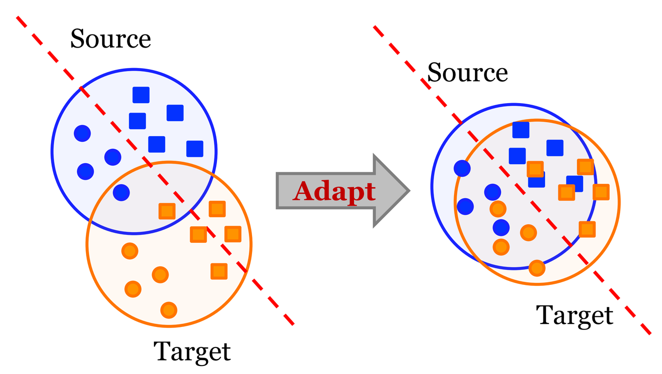
Background

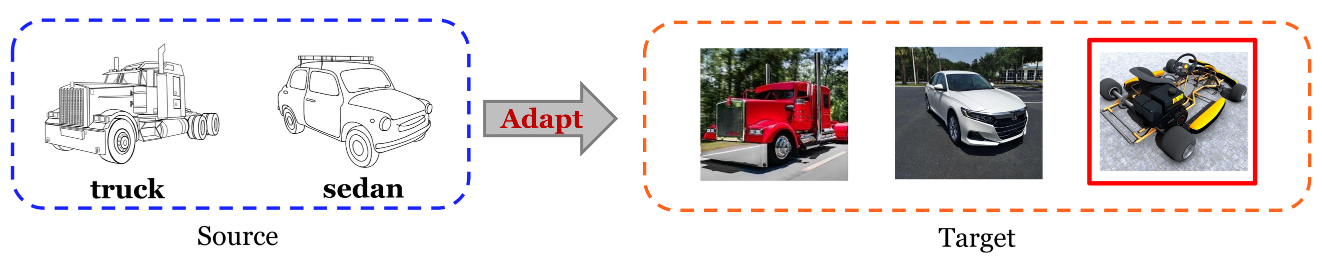
❑ Unsupervised domain adaptation



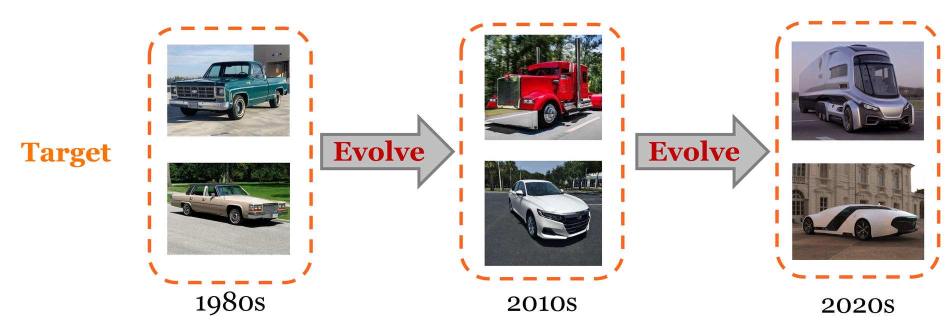


❑ Limitations in some real-world scenarios

- Open-set scenario: "unknown" category in the target domain



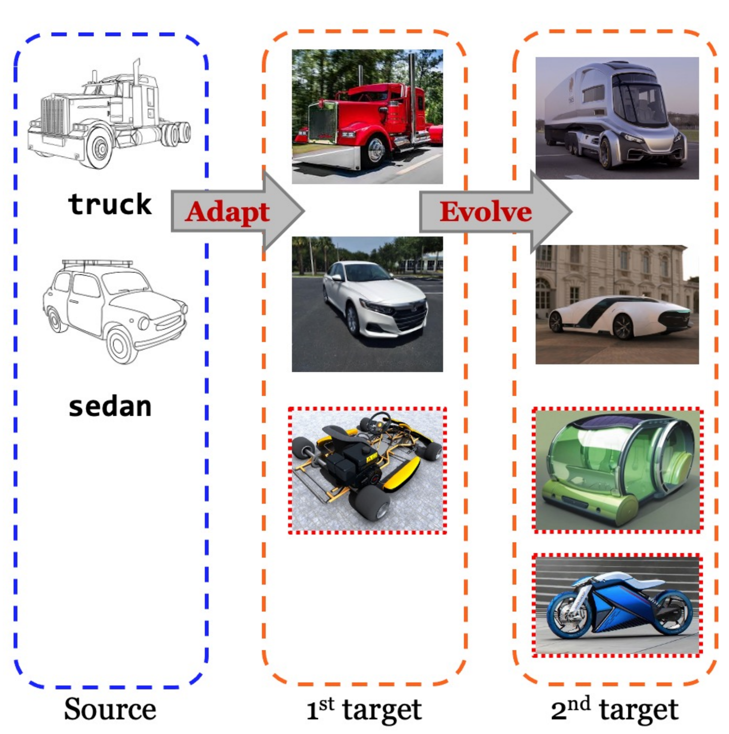
- Dynamic adaptation scenario: time-evolving target domain



Problem Definition

❑ **Dynamic open-set domain adaptation**

- Given: (1) A static source domain (fully labeled); and (2) A **time-evolving** target domain (unlabeled) with **novel unseen classes**
- Goal: (1) Classify the data of known classes correctly; (2) Identify the data of unseen classes as "unknown"



❑ **Challenges:**

- **Evolving distribution:** The target distribution is evolving
- **Varying class proportions:** The ratio of known target examples changes

Theoretical Analysis

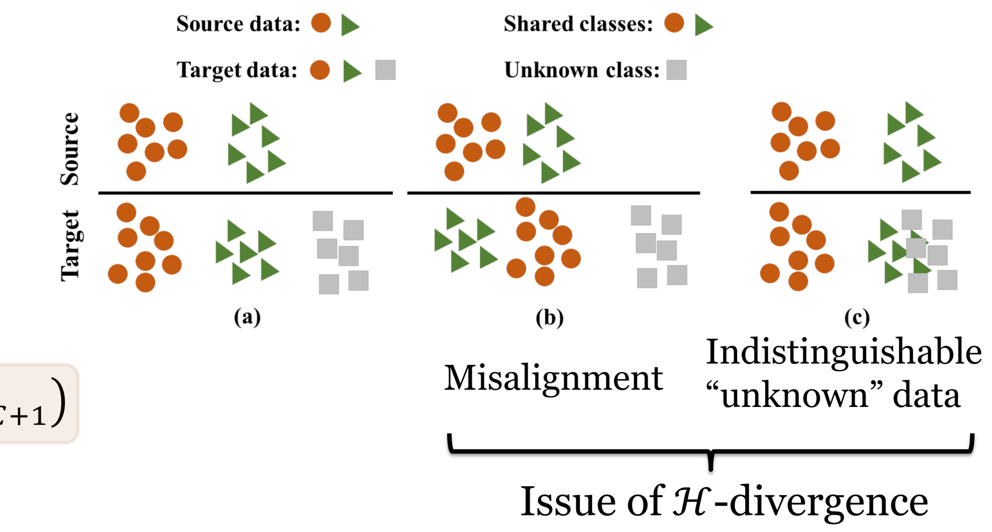
❑ **Distribution shift under open-set targets**

- Existing $\mathcal{H}$-divergence ⇒ (b)(c)

$$d_{\mathcal{H}\Delta\mathcal{H}}(\mathbb{Q}_X^s, \mathbb{P}_X^t) = \sup_{h,h'\in\mathcal{H}} \left|\Pr_{\mathbb{Q}_X^s}[B] - \Pr_{\mathbb{P}_X^t}[B]\right|$$

- **Proposed open-set discrepancy ⇒ (a)**

$$d_{OS}(\mathbb{Q}^s, \mathbb{P}^t) = d_{\mathcal{C}}(\mathbb{Q}^s, \mathbb{P}_{\le C}^t) - \rho \cdot d_{\mathcal{H}\Delta\mathcal{H}}(\mathbb{Q}_X^s, \mathbb{P}_{X|Y=C+1}^t)$$



❑ **PU-learning under open-set targets**

- Positive: source examples (C shared classes)
- Unlabeled: target examples (C shared classes or "unknown" class)
- Specially, if there is no distribution shift,

$$\epsilon_t(h) = (1-\pi_{C+1}^t)\cdot\epsilon_s(h) + \underbrace{\mathbb{E}_{x\sim\mathbb{P}_X^t}[L(h(x), y=C+1)] - (1-\pi_{C+1}^t)\mathbb{E}_{x\sim\mathbb{Q}_X^s}[L(h(x), y=C+1)]}_{\text{Positive-unlabeled open-set risk}}$$

$\pi_{C+1}^t = \mathbb{P}^t(y = C+1)$

❑ **Error upper bound on $\epsilon_{t_{N+1}}(h)$**

- Classification error on historical task
  - **Learn class membership on shared classes**
- Open-set distribution discrepancy $d_{OS}(\cdot,\cdot)$
  - **Measure distribution shift**
- PU-learning based open-set risk Δ_{PU}
  - **Identify the "unknown" class in the target domain**

Theorem 1: Assume that the loss function $L(\cdot,\cdot)$ is bounded, i.e., $|L(\cdot,\cdot)| \le M$. For any hypothesis $h\in\mathcal{H}$ and $\sum_{j=0}^N \alpha_j = 1$ where $\alpha_j \ge 0$ $(j = 0,1,\cdots,N)$, the expected error $\epsilon_{t_{N+1}}(h)$ of the target task at the $(N+1)^{\text{th}}$ time stamp is bounded as:

$$\epsilon_{t_{N+1}}(h) \le \left(1-\pi_{C+1}^{t_{N+1}}\right)\left(\sum_{j=0}^N \alpha_j \mathbb{E}_{(x,y)\sim\mathbb{P}_{\le C}^{t_j}}[L(h(x),y)] + 4M\sum_{j=0}^N \alpha_j d_{OS}\left(\mathbb{P}_{\le C}^{t_j}, \mathbb{P}^{t_{N+1}}\right)\right) + \Delta_{PU} + CONST$$

where $\Delta_{PU} = \mathbb{E}_{x\sim\mathbb{P}_X^{t_{N+1}}}[L(h(x), y=C+1)] - \left(1-\pi_{C+1}^{t_{N+1}}\right)\sum_{j=0}^N \alpha_j \mathbb{E}_{(x,y)\sim\mathbb{P}_{\le C}^{t_j}}[L(h(x), y=C+1)]$ is the positive-unlabeled open-set risk.

Proposed Algorithm: OuterAdapter

❑ **Objective function**

- PU loss: **Discriminative feature learning under open-set targets**

$$\min_\theta \sum_{j=0}^N \frac{\left(1-\pi_{C+1}^{t_{N+1}}\right)\alpha_j}{n_{t_j}} \sum_{i=1}^{n_{t_j}} \left(L\left(h\left(x_{t_j}^i\right), \hat{y}_{t_j}^i;\theta\right) - L\left(h\left(x_{t_j}^i\right), y=C+1;\theta\right)\right) + \frac{1}{m_{t_{N+1}}}\sum_{i=1}^{m_{t_{N+1}}} L\left(h(x_{t_{N+1}}^i), y=C+1;\theta\right)$$

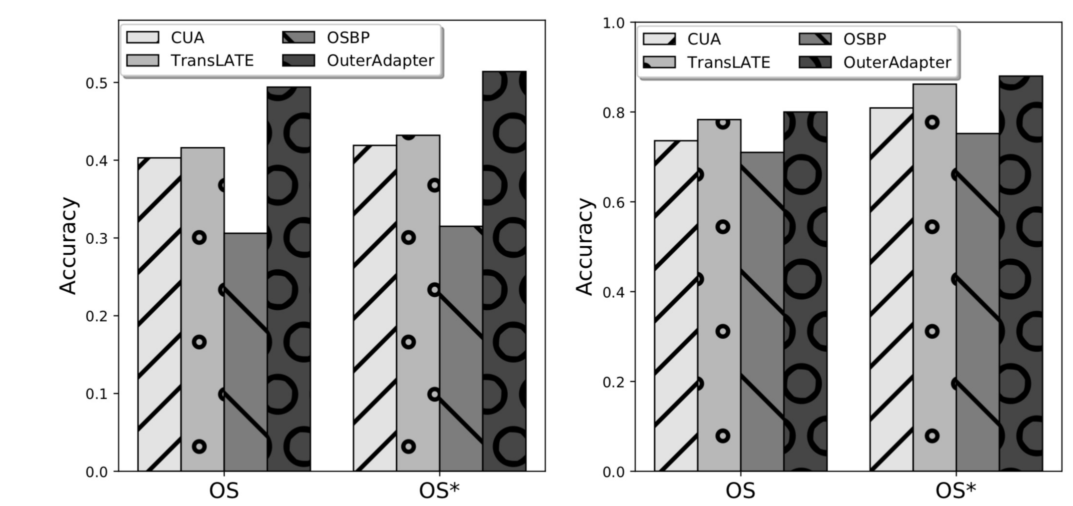
$$+\beta\sum_{j=0}^N \alpha_j d_{OS}\left(\mathbb{P}_{\le C}^{t_j}, \mathbb{P}^{t_{N+1}};\theta\right)$$

- $\mathcal{OS}$-divergence: **Domain-invariant feature learning**

Evaluation

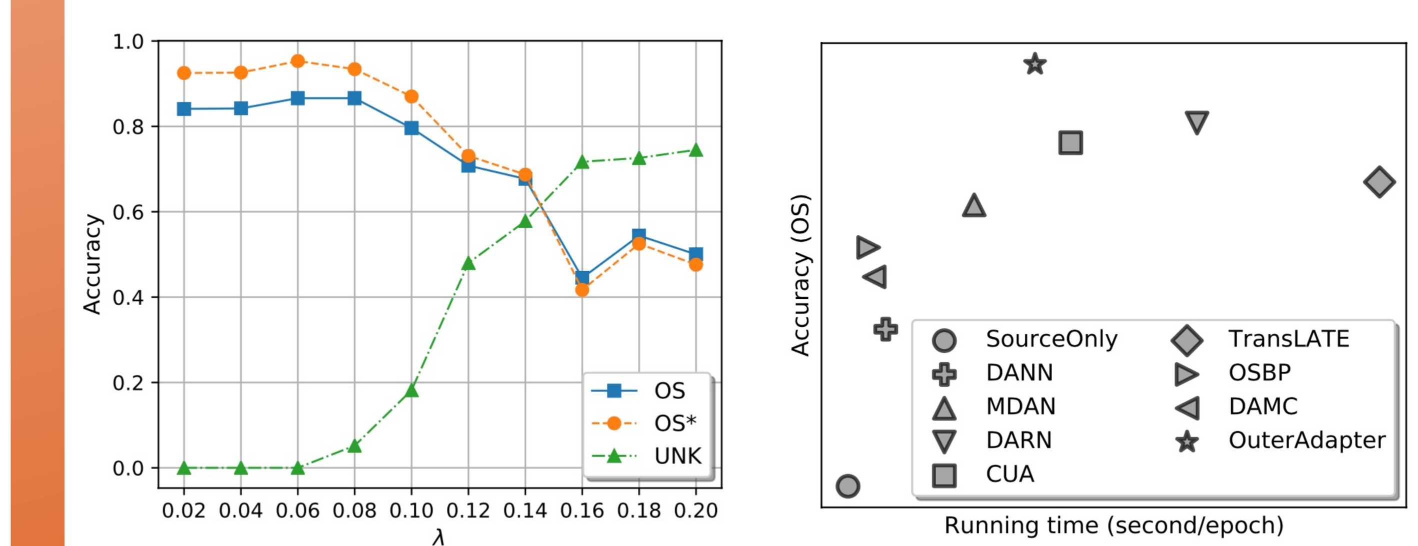
❑ Effectiveness:

- **OS**: Average classification accuracy over all the classes
- **OS***: Average classification accuracy over all the known classes



(a) Art→Clipart (b) DSLR→Webcam

❑ Hyper-parameter sensitivity and computational efficiency:



Conclusion

❑ **Problem**: A novel dynamic open-set domain adaptation problem is studied where novel unknown classes might appear over time.
❑ **Analysis**: We derive the generalization error bounds based on the proposed $\mathcal{OS}$-divergence.
❑ **Algorithm**: A novel PU-learning based algorithm OuterAdapter is proposed to minimize the error upper bound.
❑ **Evaluation**: Extensive experiments confirm the effectiveness and efficiency of the OuterAdapter algorithm.

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