C-SFDA: A Curriculum Learning Aided Self-Training Framework for Efficient Source Free Domain Adaptation

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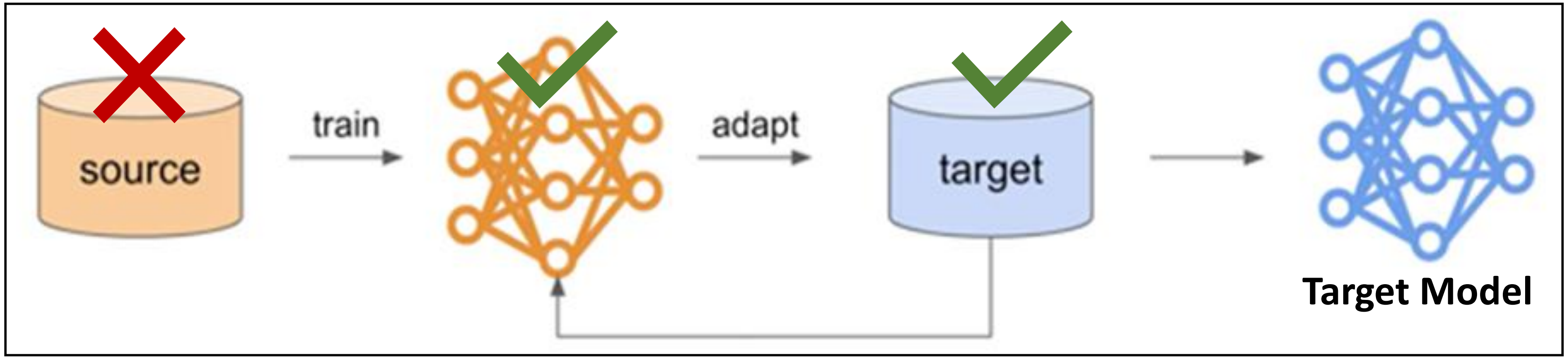
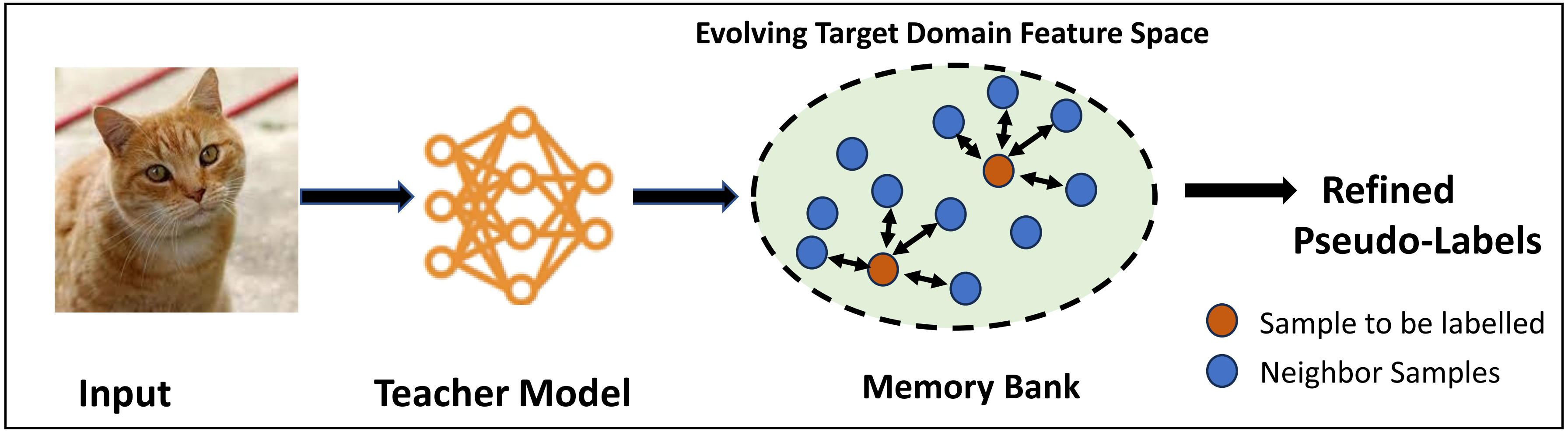
Overview

Addressed Task: Source Free Domain adaptation



Source-Free Domain Adaptation

- While adaptation, access to source data is not available.
- Pre-trained Source Model and unlabeled target data is available.



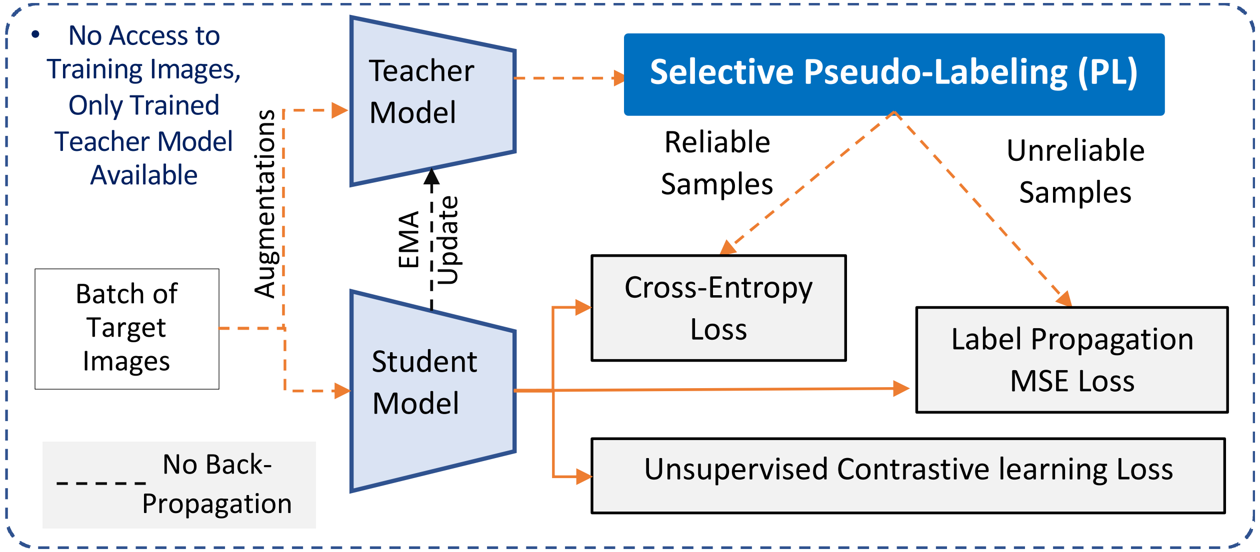
Existing SOTA: Memory-based Pseudo-Labelling

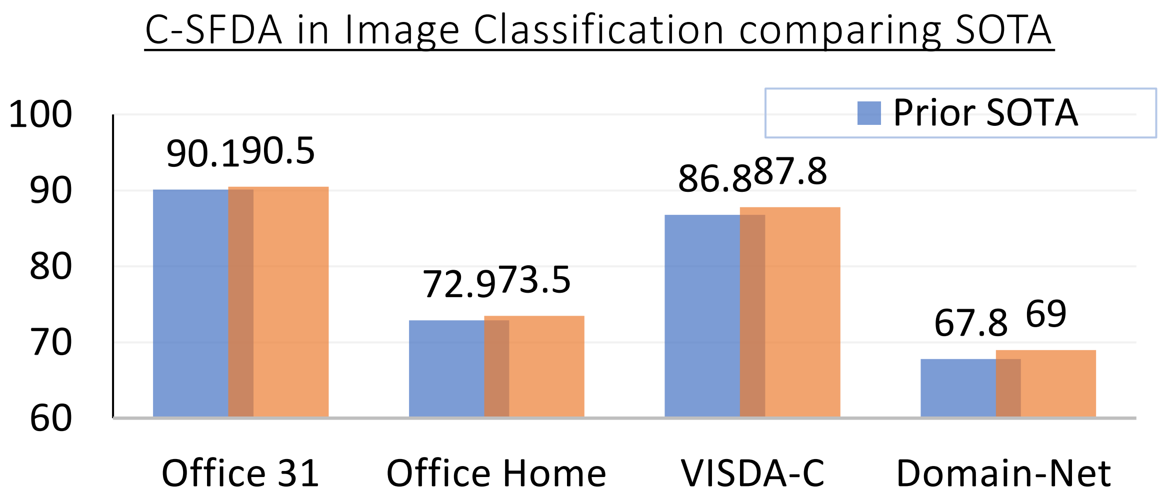
State-of-the-art Methods

- Follows self- training strategy
- Use memory bank and nearest neighboring techniques
- Struggles in resource-constraint scenarios

Proposed Method

Can we design a memory-bank-free SFDA approach that can guide the self-training with highly precise pseudo-labels?





Proposed Framework

- Curriculum learning-aided selective self-training strategy.
- Prioritizes learning from highly reliable pseudo-labels and propagating label information to less reliable ones.

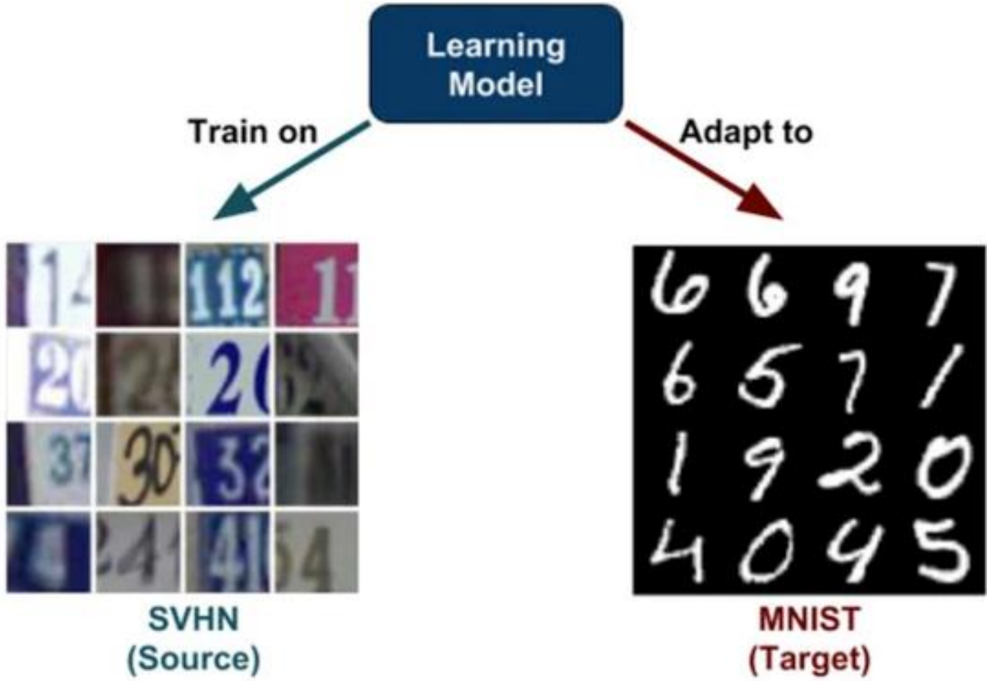
SOTA Performance

- Image Classification
- Semantic Segmentation
- Online Test-time Adaptation

Introduction

- Overview on Domain Adaptation
- Self-Training Framework
- Our Proposed Method
- Experimental Results
- Conclusion.

What is Domain Adaptation?



With Labels

With Labels

Supervised Domain Adaptation

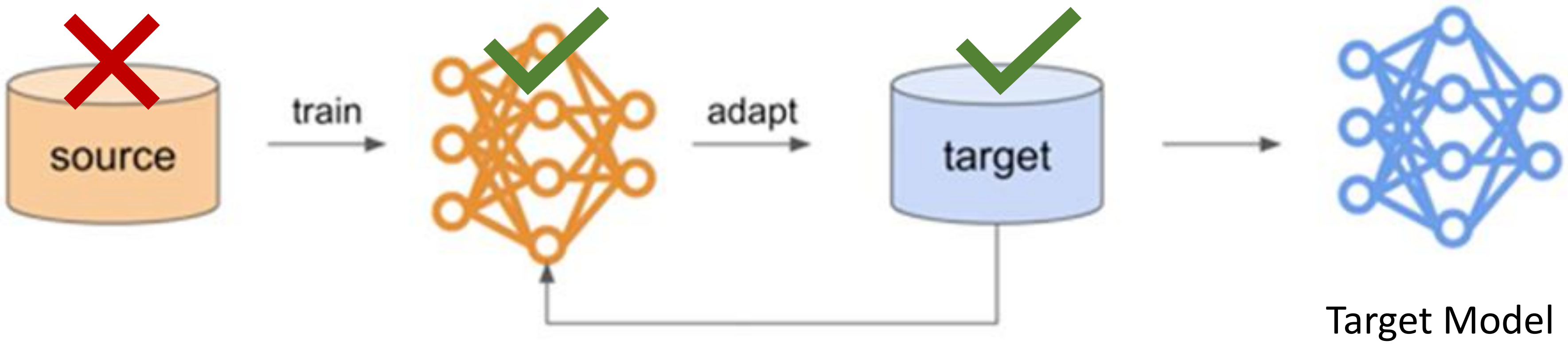
Source (With Labels)

Adapt to

Target (No Labels)

Unsupervised Domain Adaptation (UDA)

Source-Free Domain Adaptation (SFDA)



Target Model

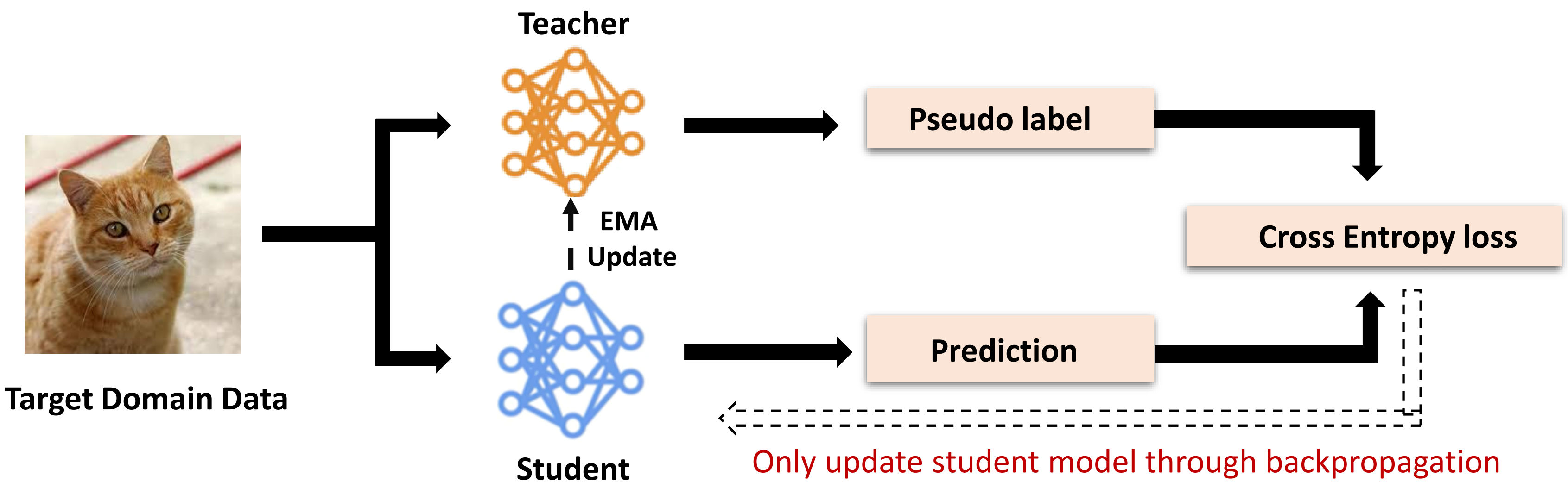
Source-Free Domain Adaptation-

- While adapting to target domain, access to source data is no longer available.
- No way to estimate the domain shift which is crucial in designing hyper-parameters.
- Most challenging domain adaptation setup and struggles under large domain shift.

Motivation

SOTA techniques follow self- training strategy where-

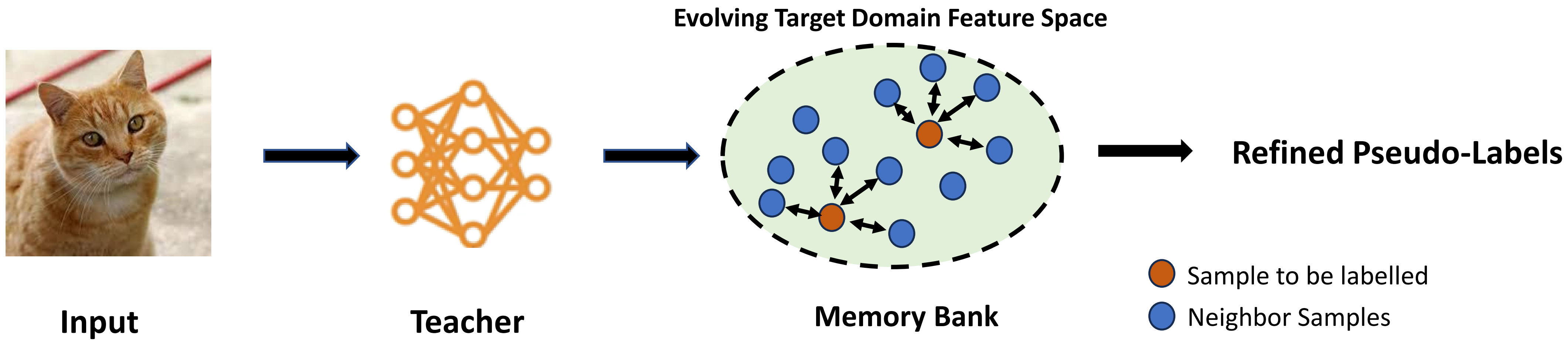
- ❑ Teacher model provides pseudo-label (PL) for the student model.
- ❑ Depending on the domain shift, the quality pseudo-label can vary.
- ❑ Bad quality pseudo-labels deteriorates the performance of student model.



Classical Pseudo-Labelling

Motivation

- To improve the pseudo-label quality existing SFDA techniques-
  - ➢ Use memory bank and nearest neighboring techniques for pseudo-label refinement.
  - ➢ Samples are labelled based on their *N* nearest neighbor's predictions.



Memory-based Pseudo-Labelling

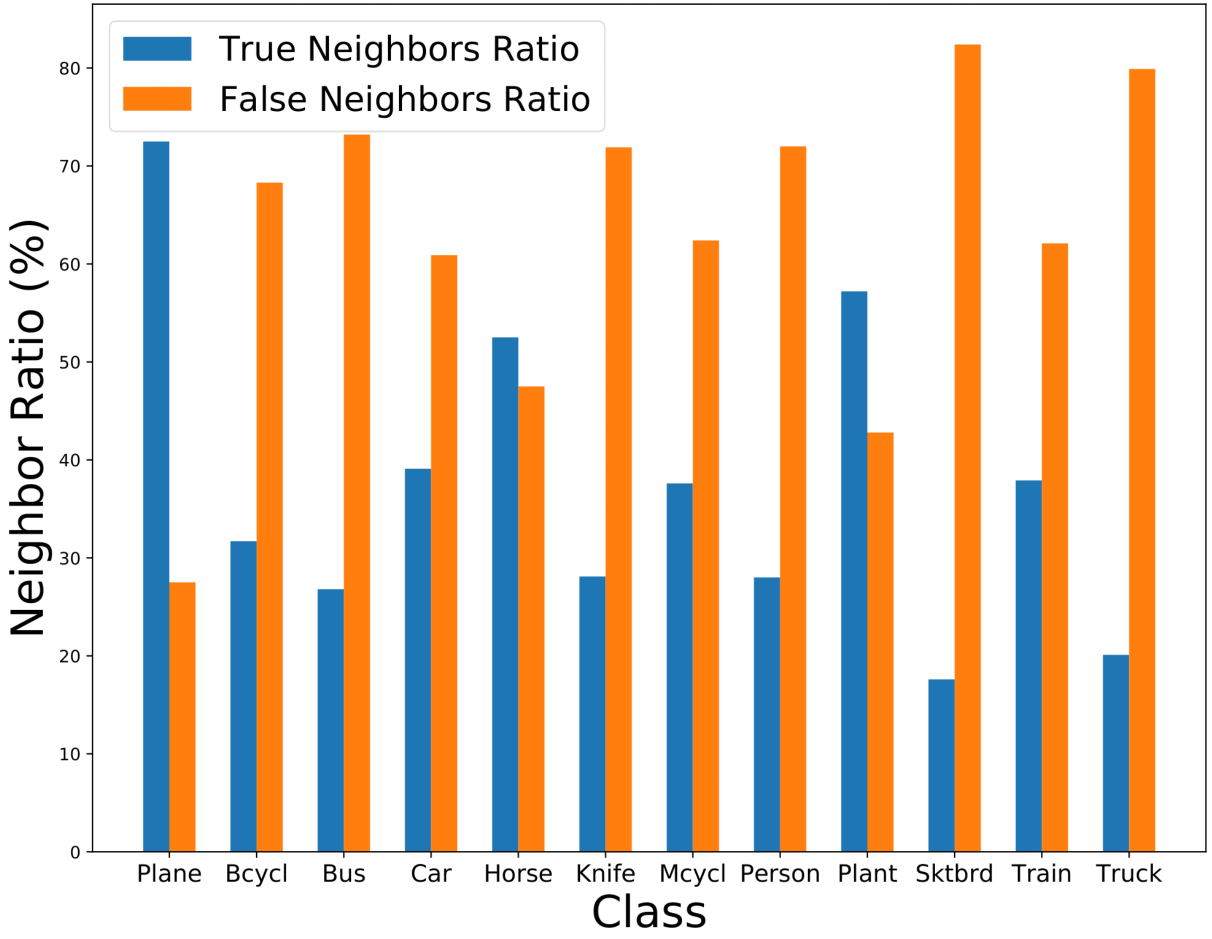
Motivation

❖ **Challenges with Nearest Neighboring-**

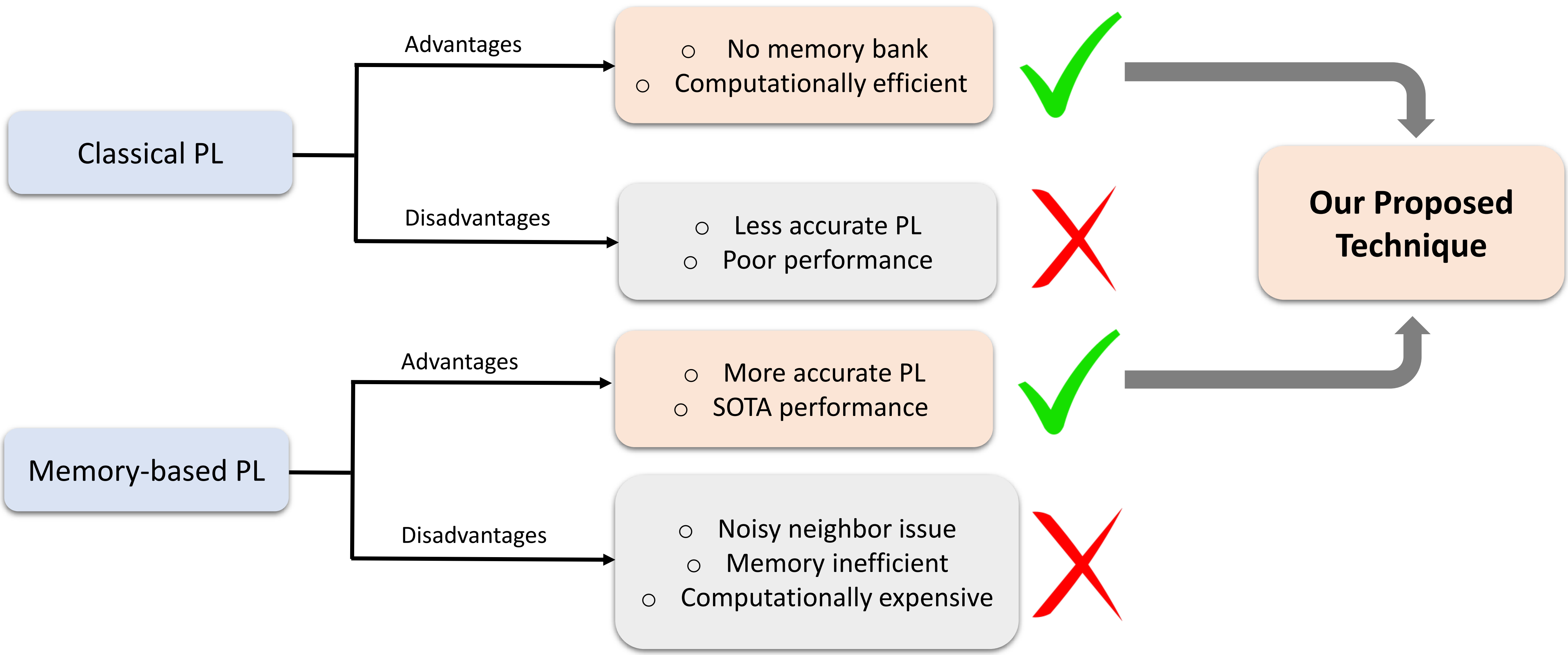
- ✓ May have false/misleading neighbors.
- ✓ Refined pseudo-labels will be mostly noisy.
- ✓ Severely impacts the classes with large domain gap.

❖ **Struggles under-**

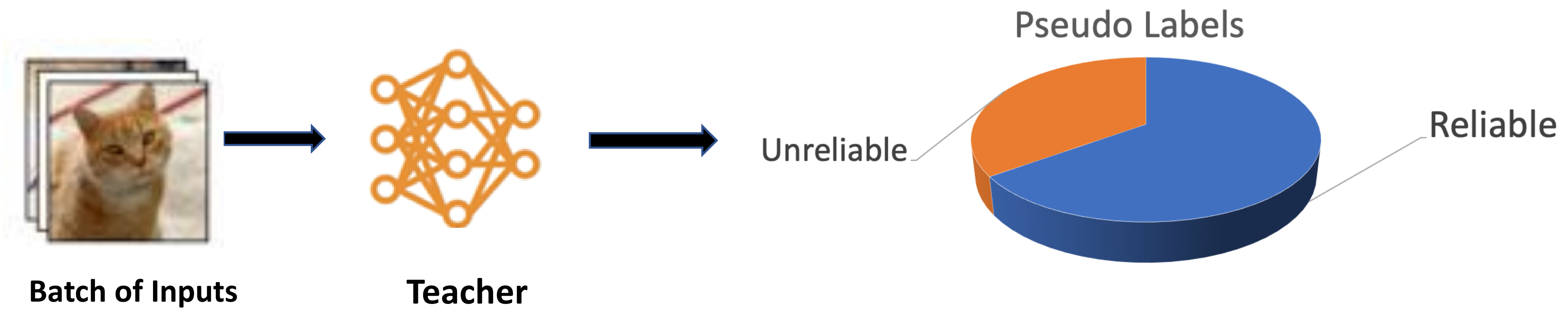
- ✓ Memory resource constraint.
- ✓ Limited computation.



Contribution



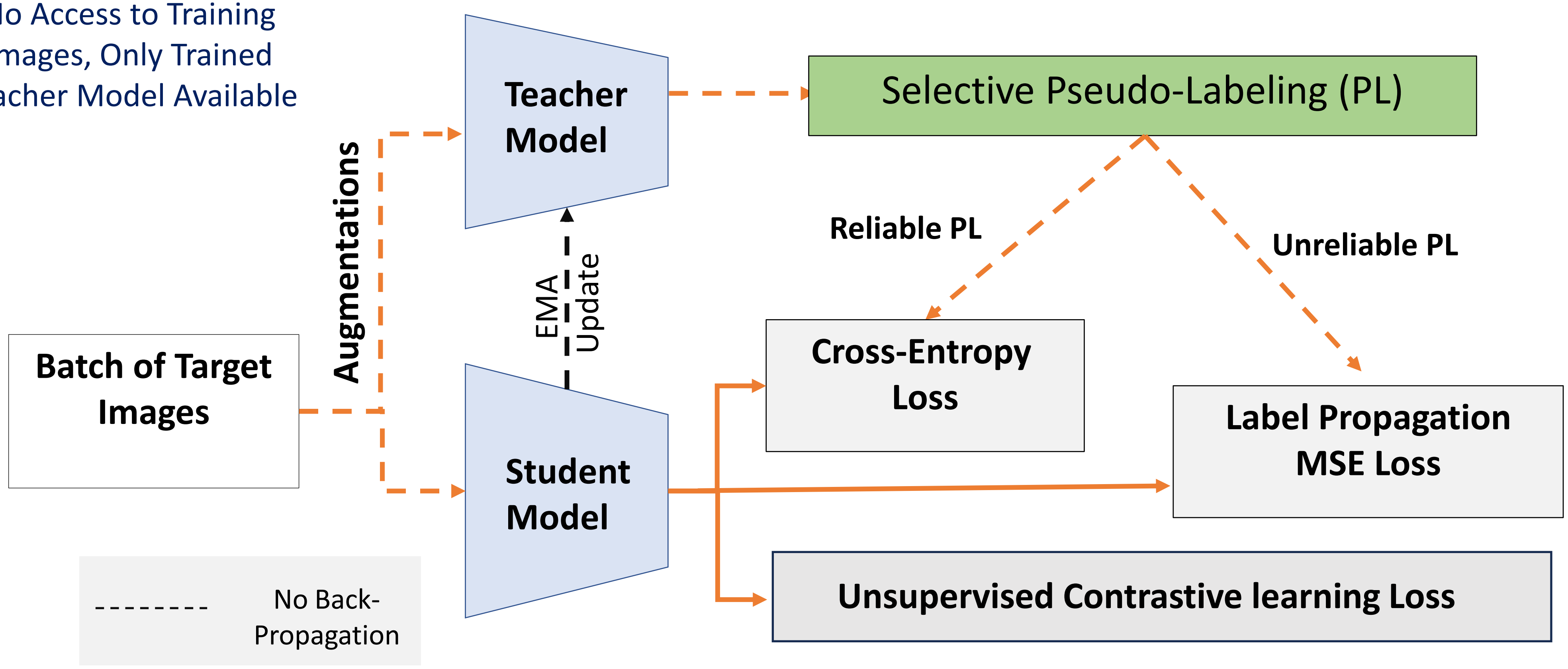
Method Overview



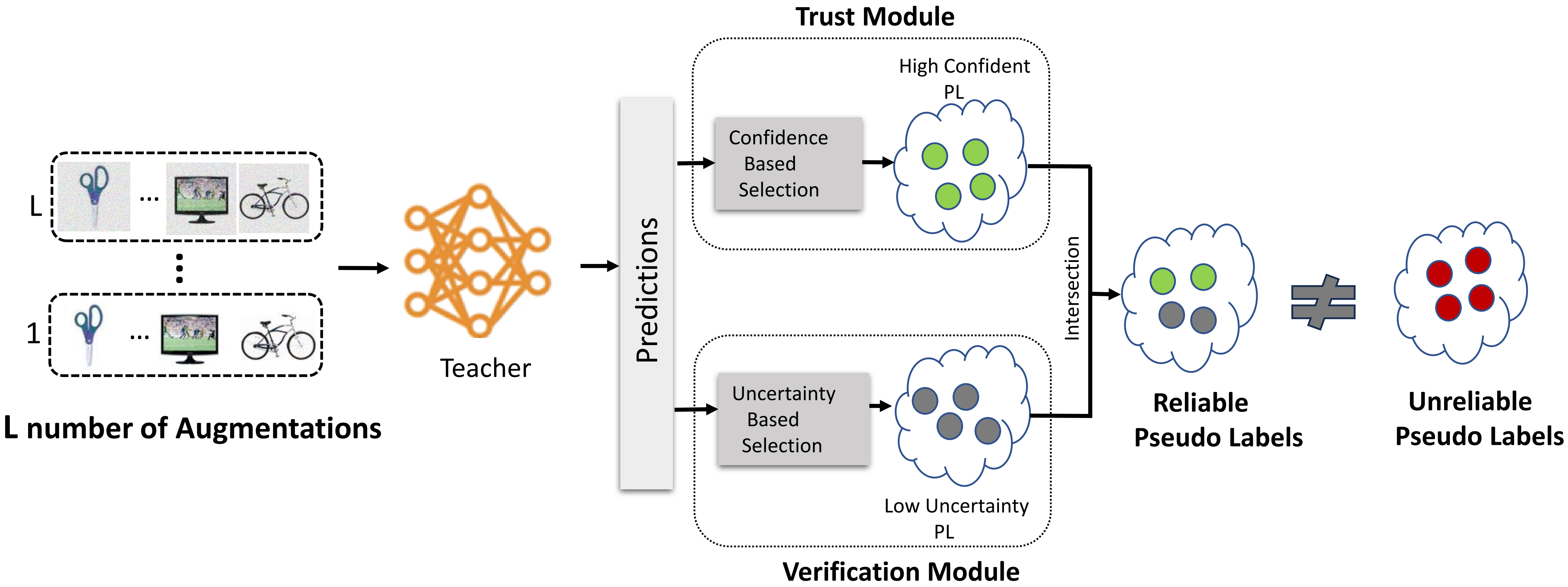
- **Intuition:** Should not trust all the pseudo-labels -
    - For some samples, generated pseudo-labels are always wrong.
    - Memorization of such unreliable or noisy labels leads to poor performance.
- **Concern:** Can we identify the unreliable ones?

Method Overview

- No Access to Training Images, Only Trained Teacher Model Available



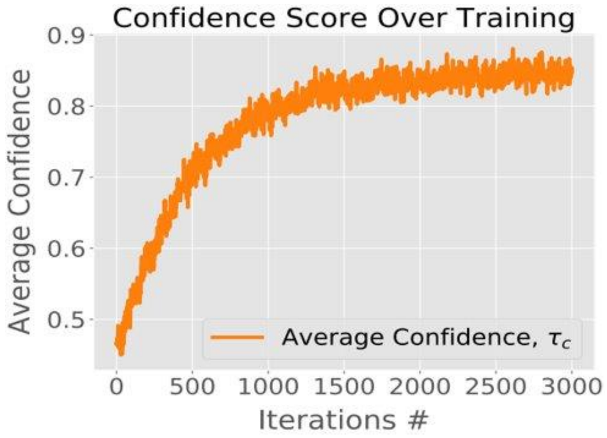
Selective Pseudo-Labeling (PL)



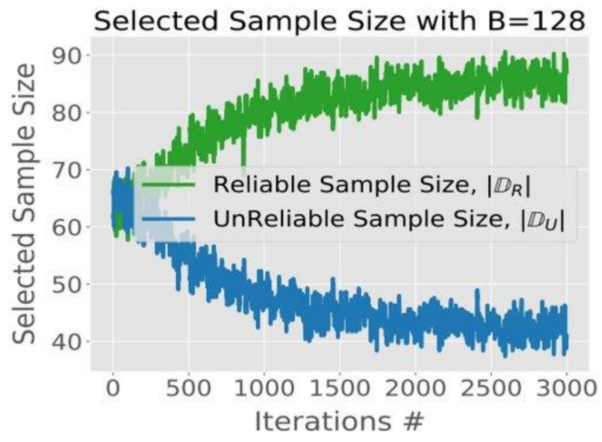
Statistical Results

Due to our selective pseudo-labelling-

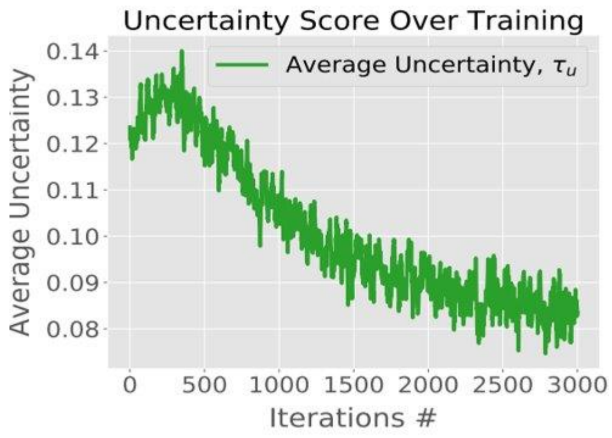
- ❑ Average confidence score increases **(a).**
- ❑ Average uncertainty score decreases **(b)**.
- ❑ We select more samples with better precision **(c).**
- ❑ Overall accuracy improves significantly **(d).**



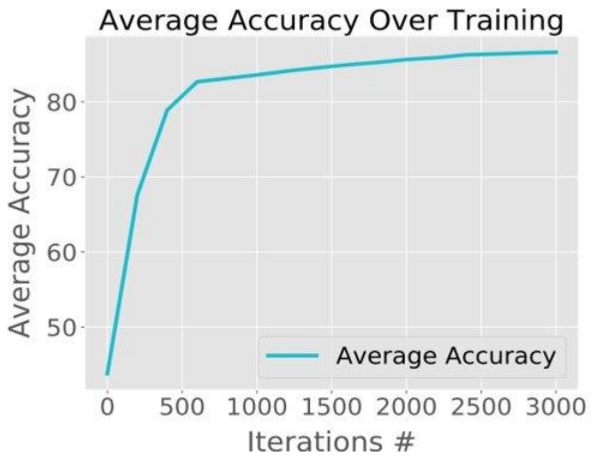
(a)



(c)



(b)



(d)

Experiments

- Image Recognition
  - ✓ Office 31
  - ✓ Office Home
  - ✓ VISDA-C
  - ✓ Domain-Net

- Semantic Segmentation
  - ✓ GTA5 --> CityScapes
  - ✓ SYNTHIA--> CityScapes
  - ✓ CityScapes --> Dark Zurich

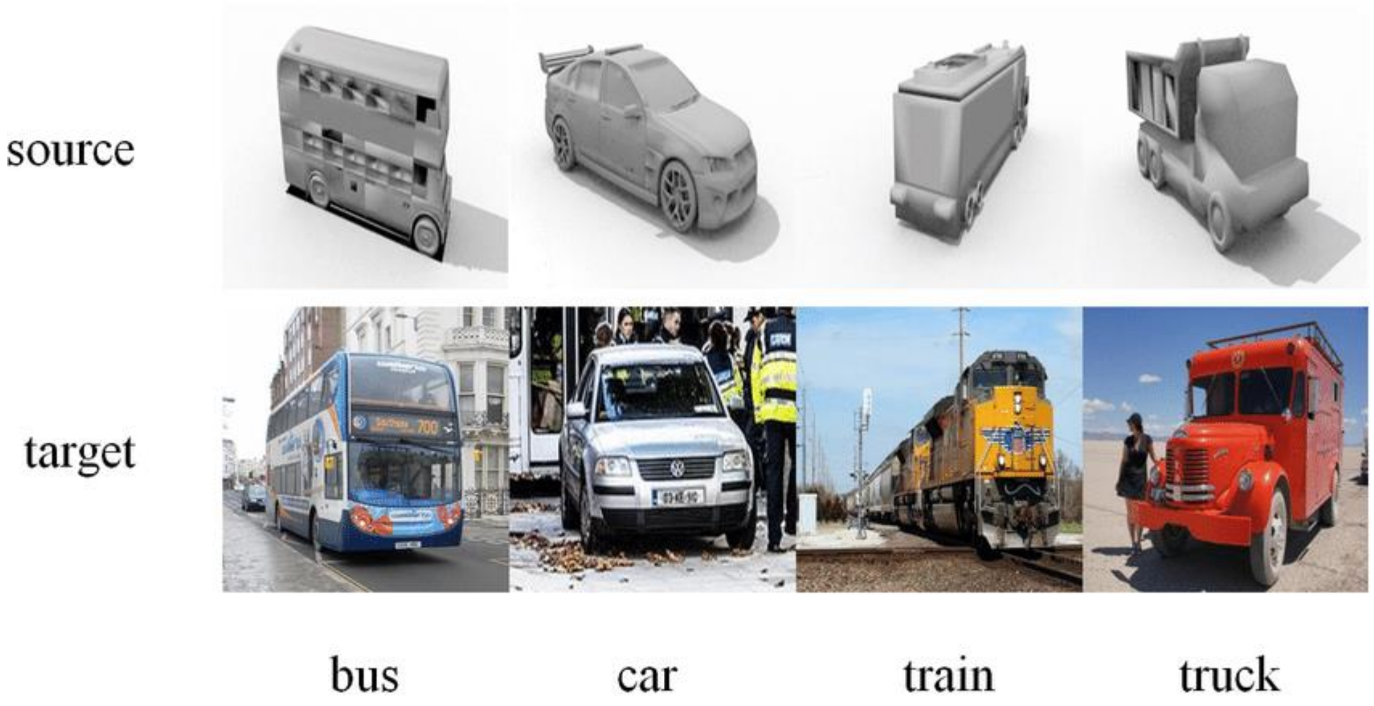
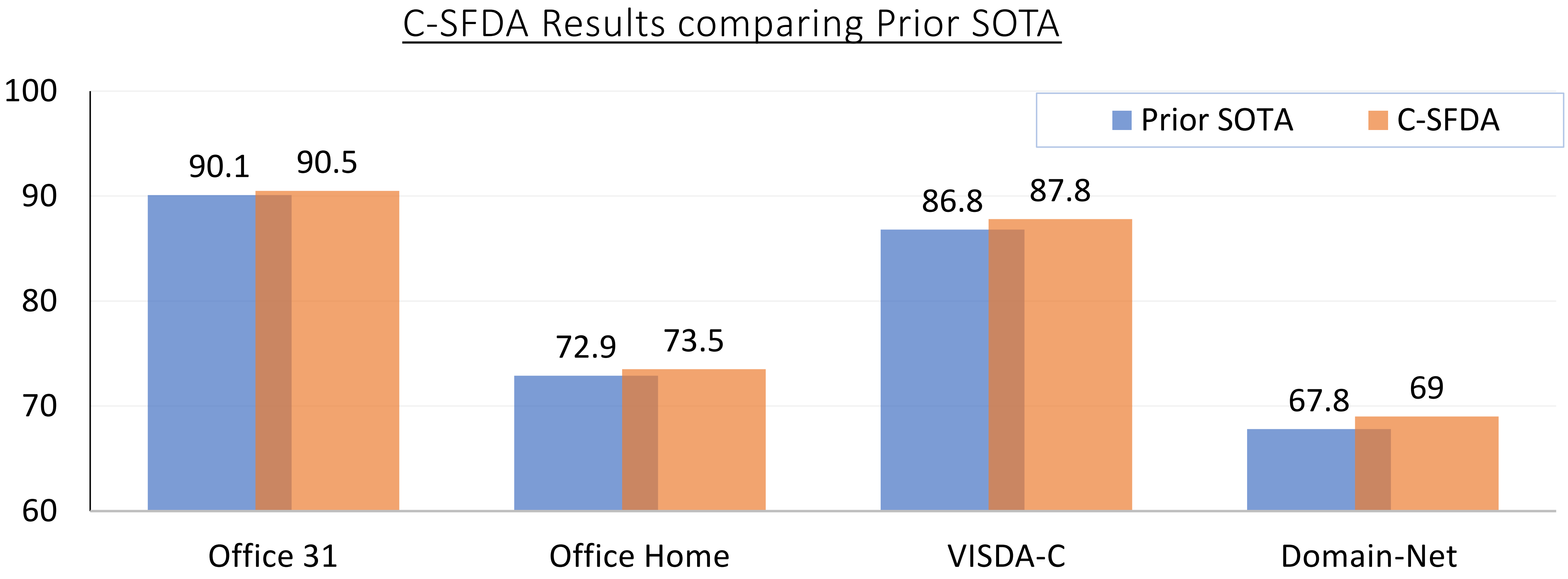
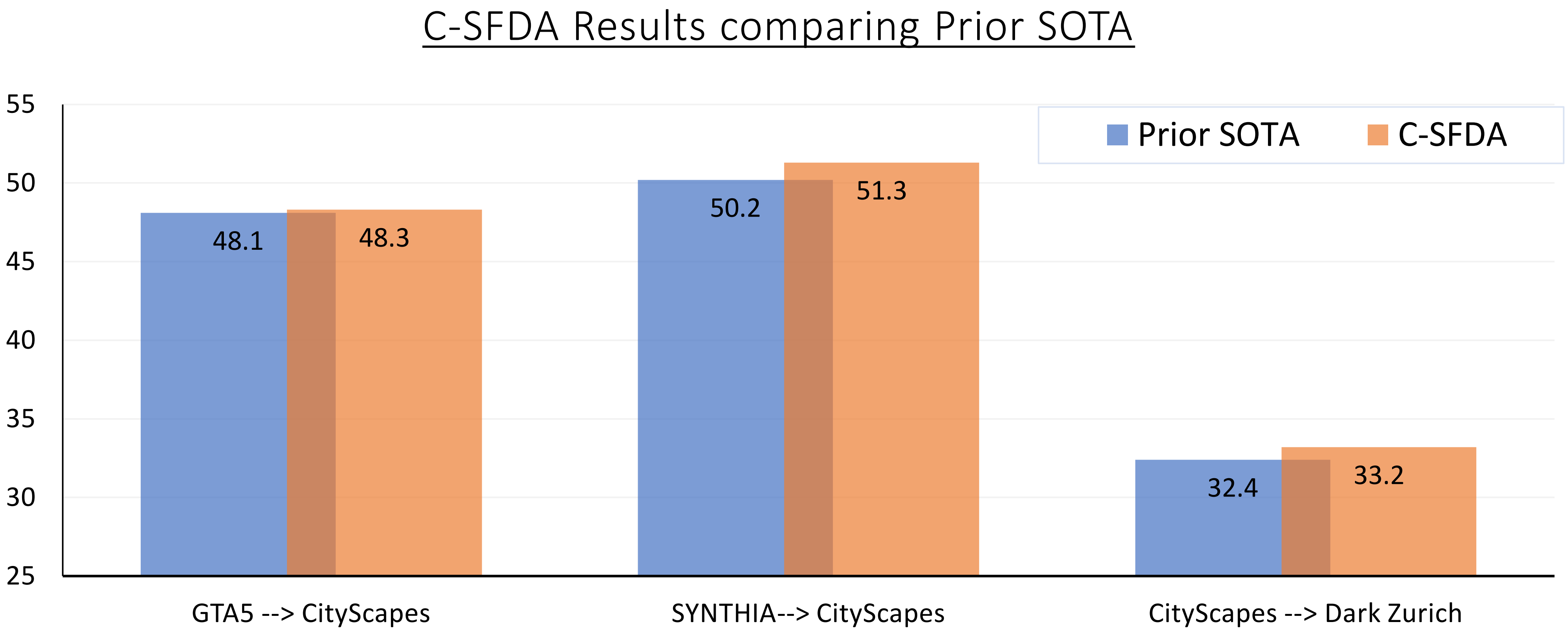


Figure: Example Source and Target Domains from VISDA-C

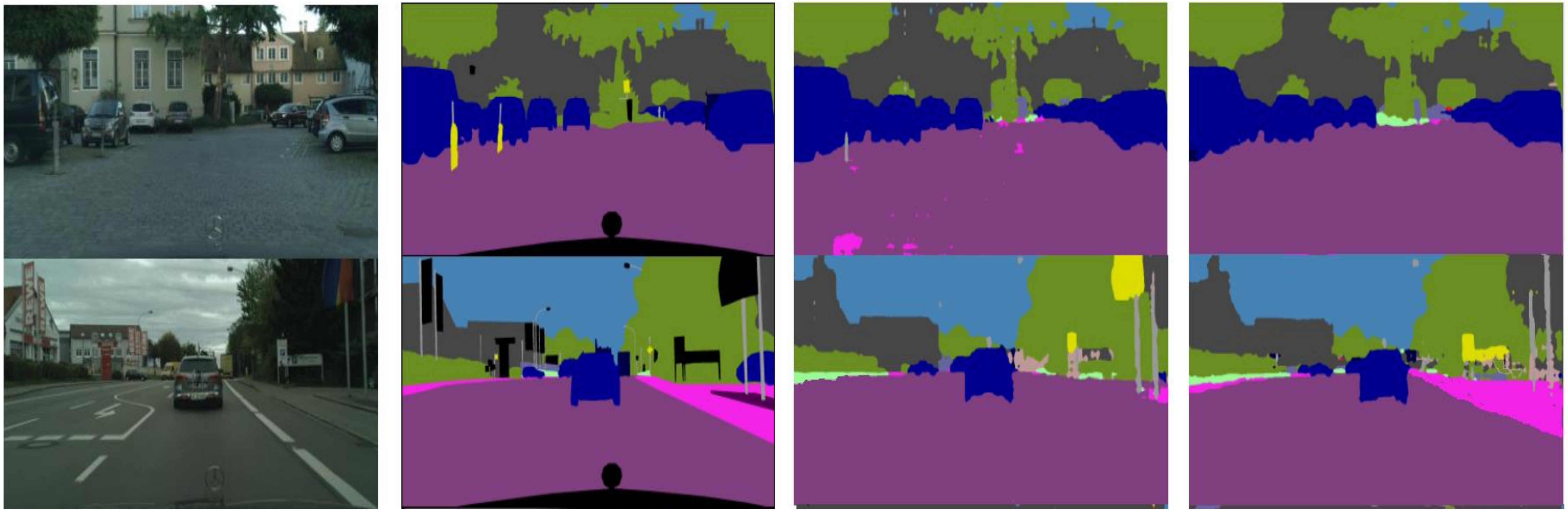
Image Classification Results



Semantic Segmentation Results



Semantic Segmentation Qualitative Results



Target Domain Image　GT　SOTA Baseline HCL　Ours

Conclusion

- ✓ We address the source-free domain adaptation problem.
- ✓ Our proposed method is based on self-training framework.
- ✓ We do not use any memory bank for pseudo-labelling.
- ✓ Our method is simple but highly effective.
- ✓ We achieve SOTA performance on several domain adaptation benchmarks.