MemSAC: Memory Augmented Sample Consistency for Large-Scale Domain Adaptation

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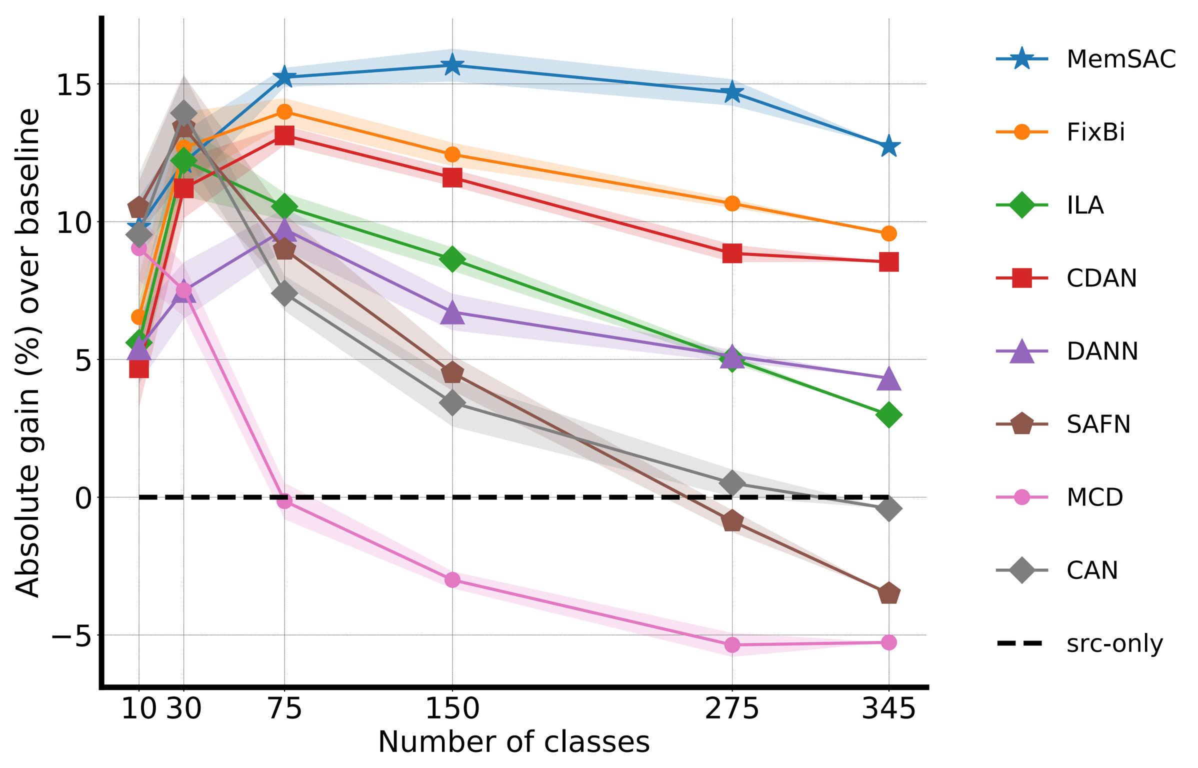
SCAN ME

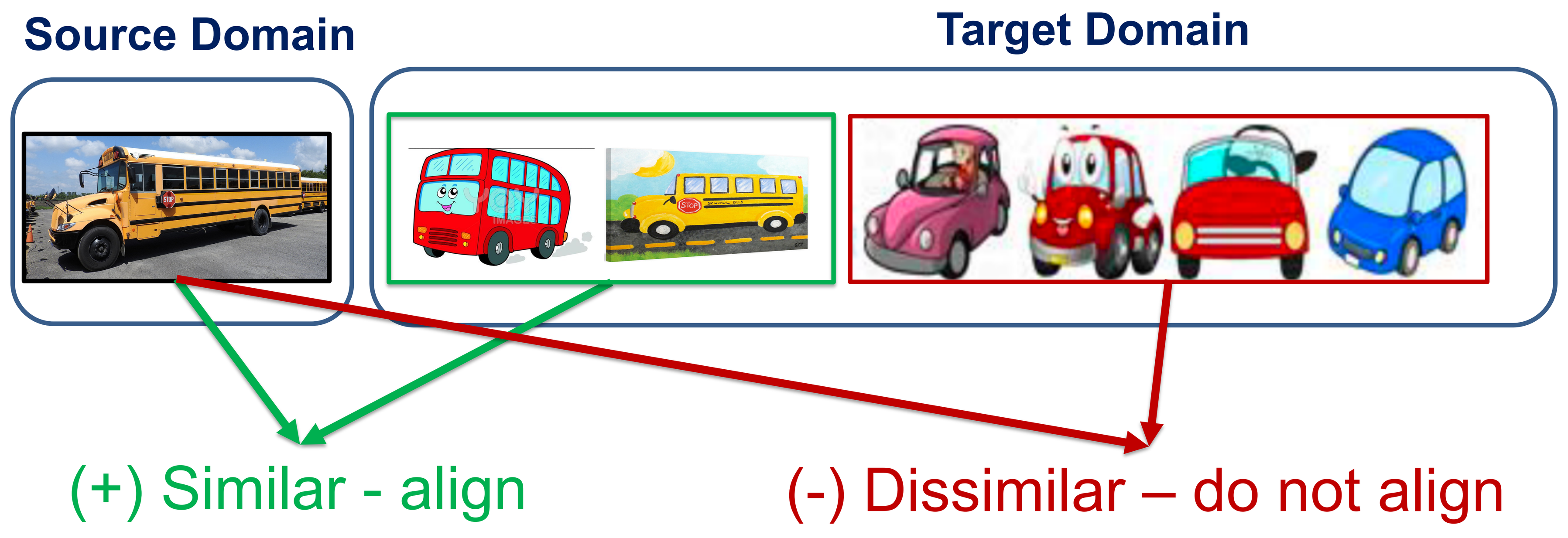
What is Domain Adaptation?

- Transfer trained model from a labeled source domain, like synthetic images, to an unlabeled target domain, like real images.
- *Assumption*: Source domain images are easier and cheaper to collect and annotate compared to target domain images.
- So, what is wrong with existing methods? **They do not scale well**!



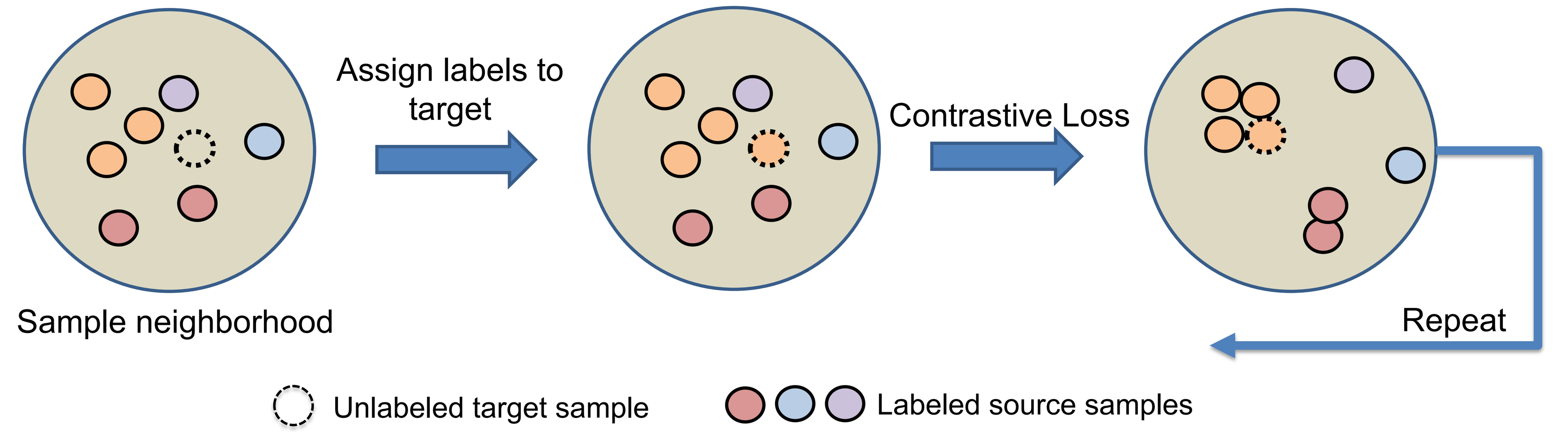
- In many use-cases **domain adaptation on many-class datasets** is important, and prior methods are limited by negative transfer.

Multi-Sample Contrastive (MSC) Learning



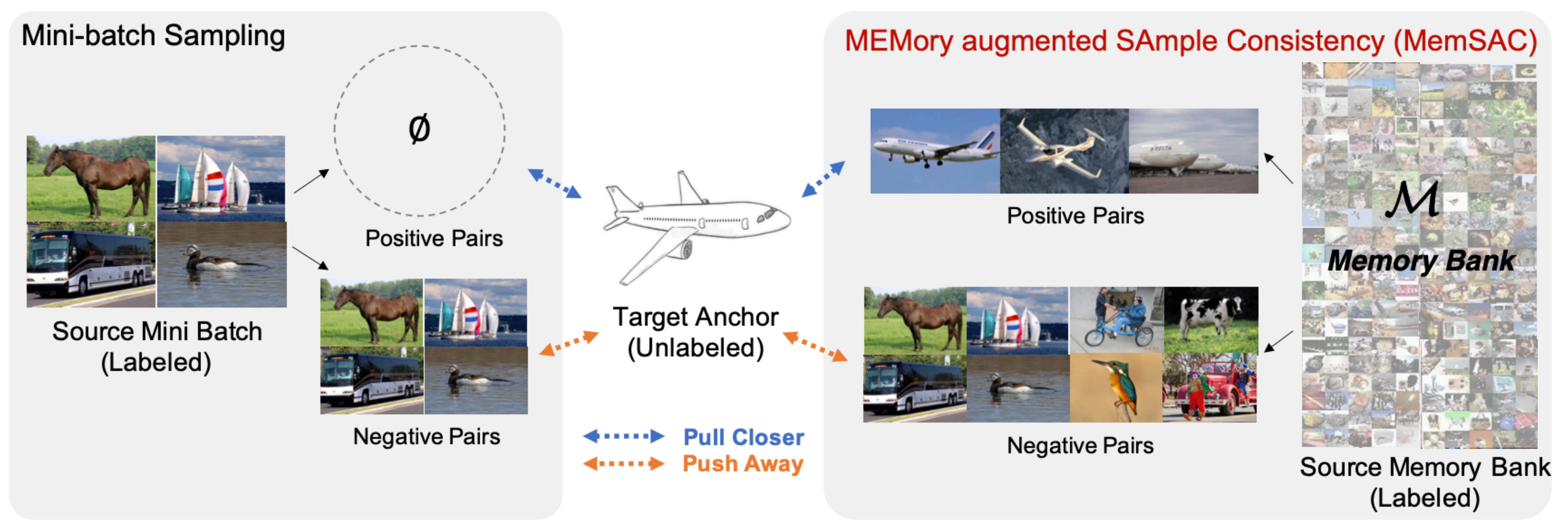
$$\mathcal{L}_{sc} = \frac{1}{|\mathcal{B}_t|}\sum_{j\in\mathcal{B}_t} -\log\left\{\sum_{i\in\mathcal{M}_+^j}\frac{\exp(\phi_{ij}/\tau)}{\sum_{i\in\mathcal{M}}\exp(\phi_{ij}/\tau)}\right\}$$

kNN pseudo-labeling on target samples

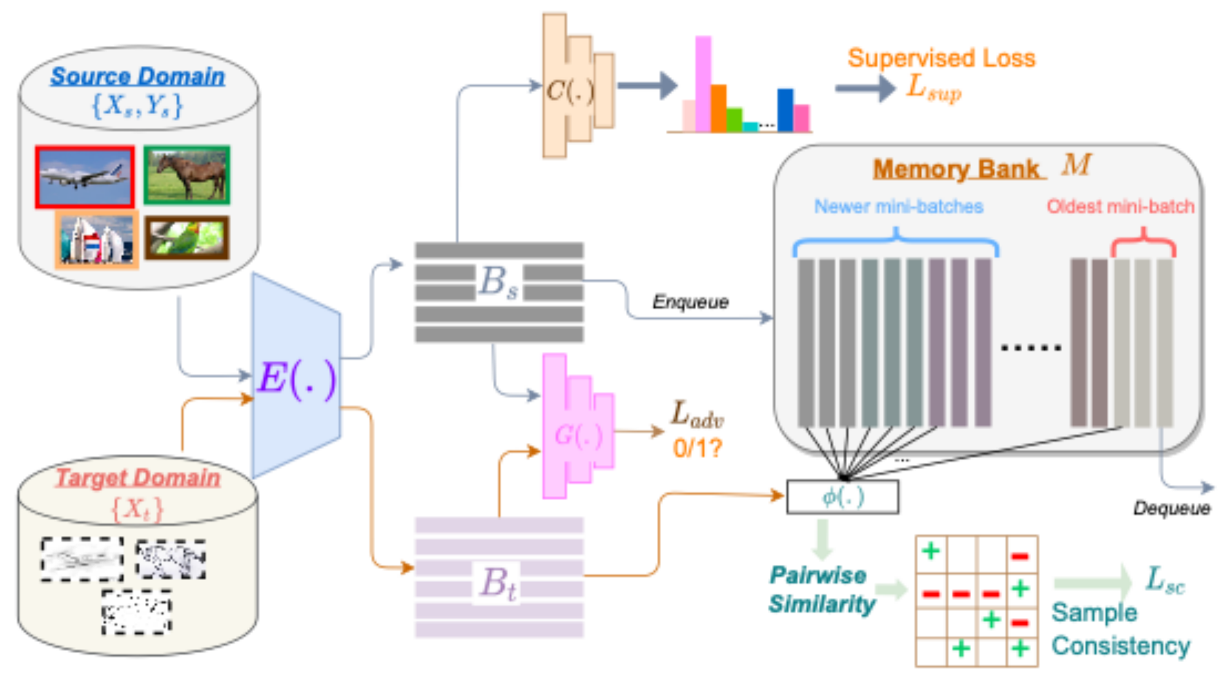


Memory Augmented Training for MSC

- ✗ With many-classes, regular sized mini-batches will not have sufficient positives and negatives.
- ✓ Our memory bank helps stores samples from previous batches enriching the positive and negative sample set.



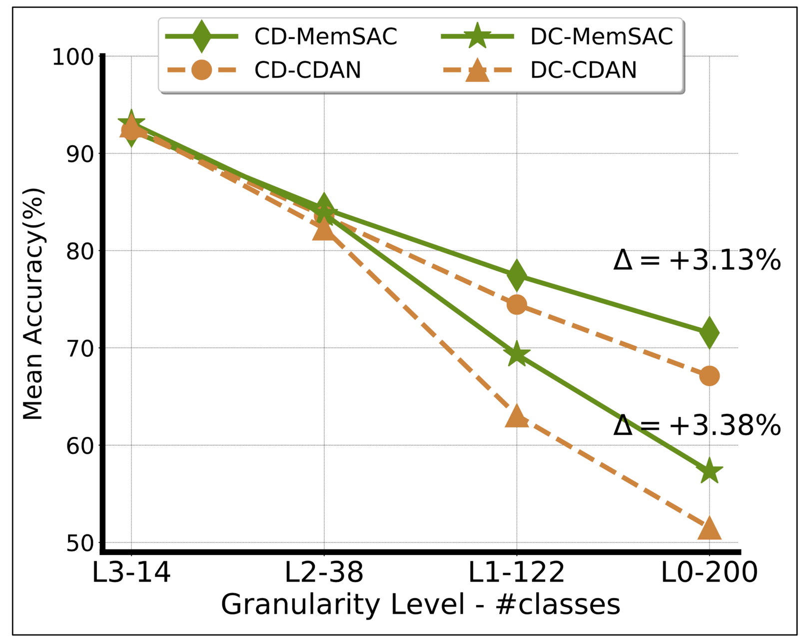
MemSAC Architecture



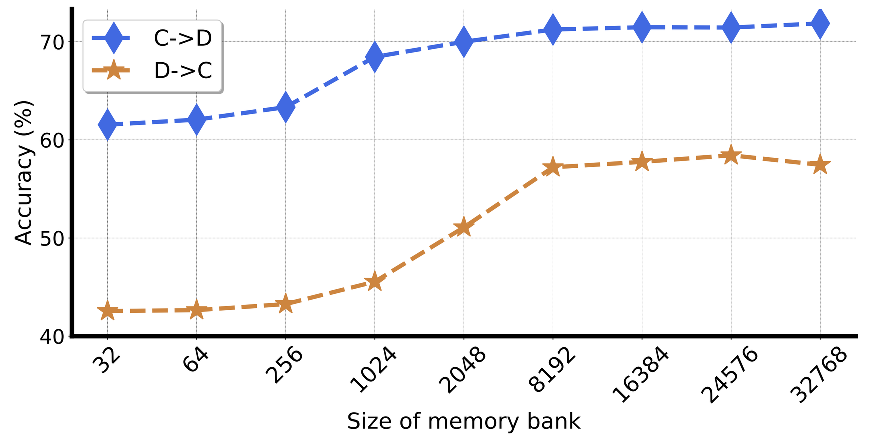
$$\min_{\theta} \mathcal{L}_{sup}(\mathcal{X}^s,\mathcal{Y}^s;\theta) + \lambda_{adv}\mathcal{L}_{adv}(\mathcal{X}^s,\mathcal{X}^t;\theta) + \lambda_{sc}\mathcal{L}_{sc}(\mathcal{X}^s,\mathcal{Y}^s,\mathcal{X}^t;\theta)$$

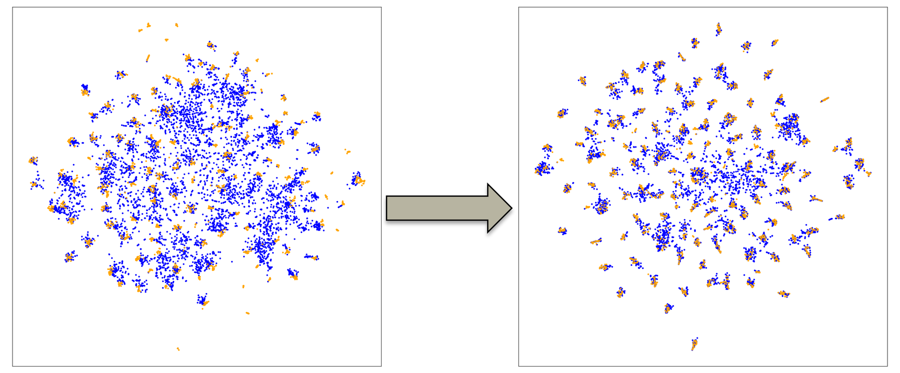
Results on Many-Class Adaptation

Method	DomainNet	Caltech-UCSD
Source Model	35.98	51.47
DANN	40.58	54.91
MCD	32.94	44.37
CDAN	43.24	60.98
PAN	43.03	62.96
ToAlign	45.45	57.48
MemSAC [Ours]	**47.26**	**67.95**

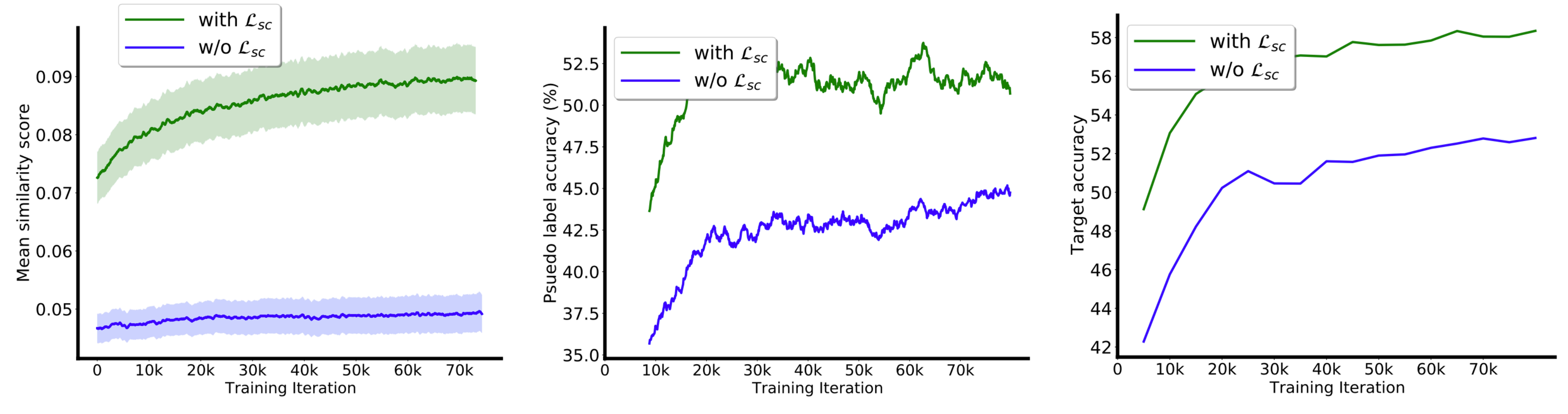


Our method is especially useful with finer-grained labels and many-class datasets.





improved alignment using MemSAC



(a) (b) (c)

MemSAC improves similarity score as well as accuracy

Limitations of our method

- The gains from MemSAC are limited when there are not many categories.
- Noisy pseudo-labels might hurt the training.