Unknown Sample Discovery for Source Free Open Set Domain Adaptation

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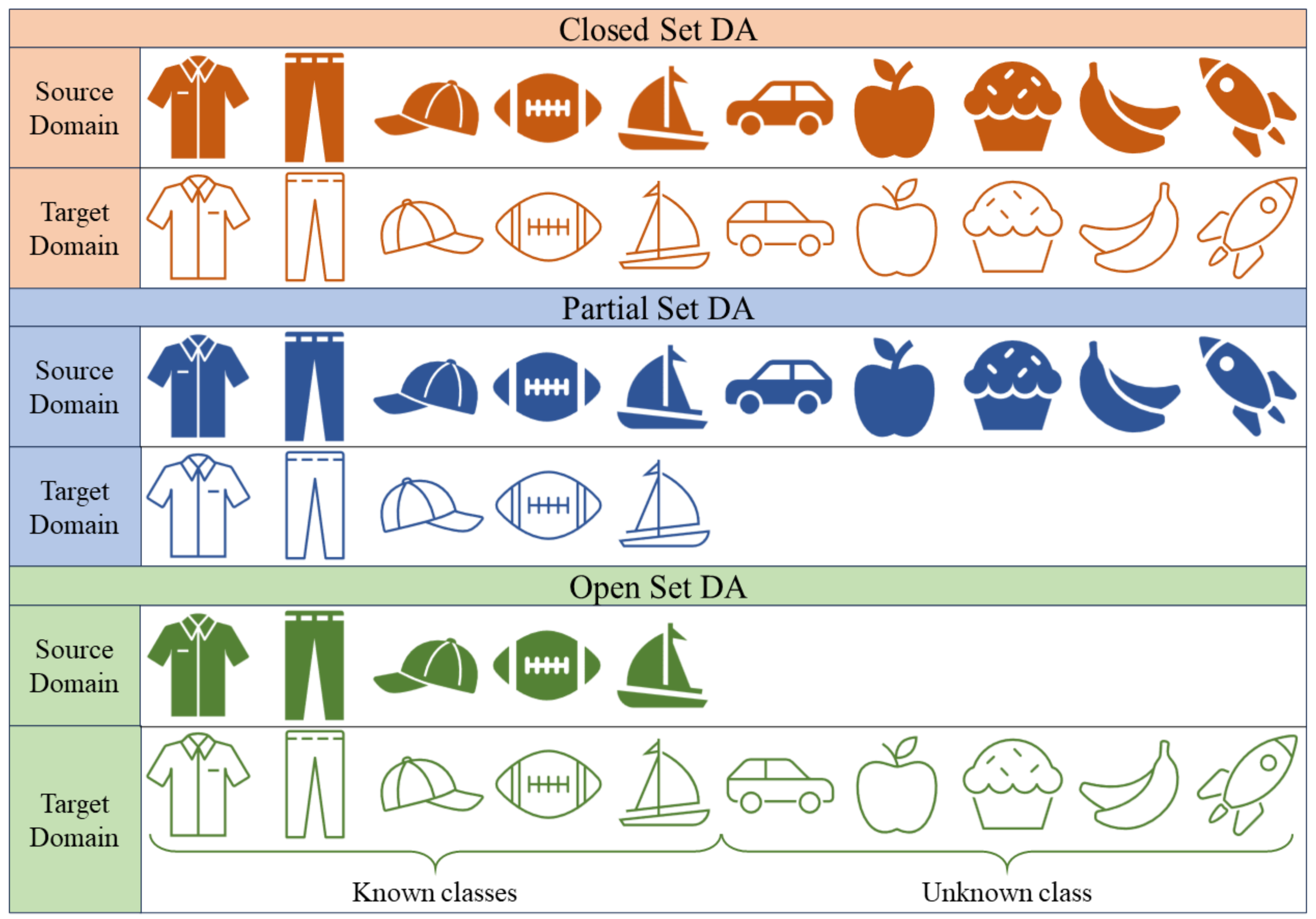
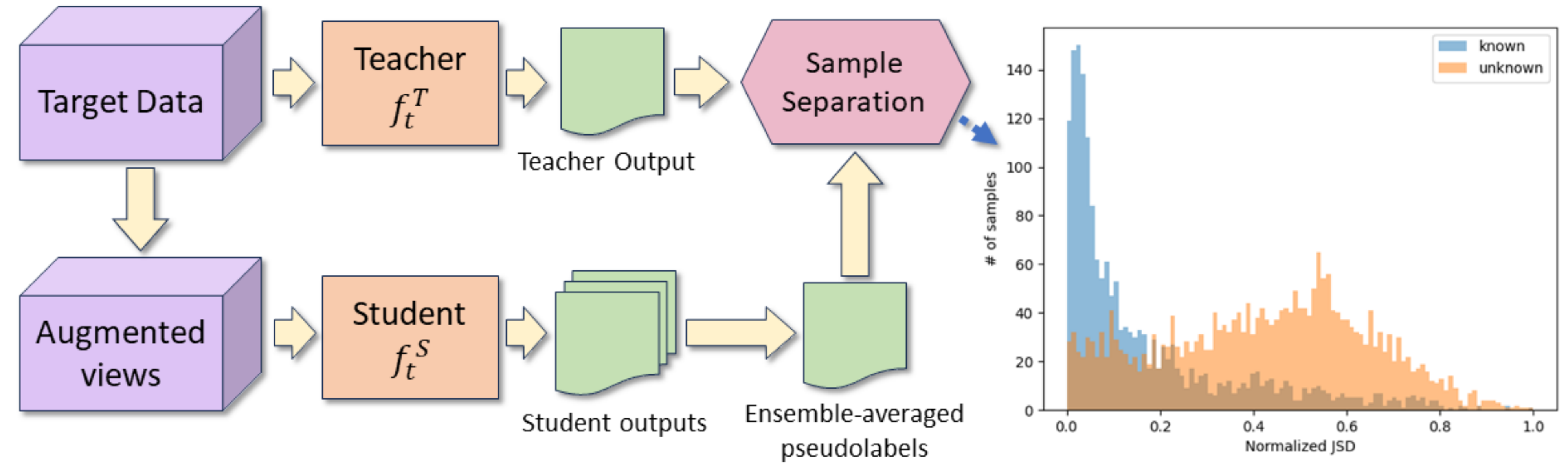
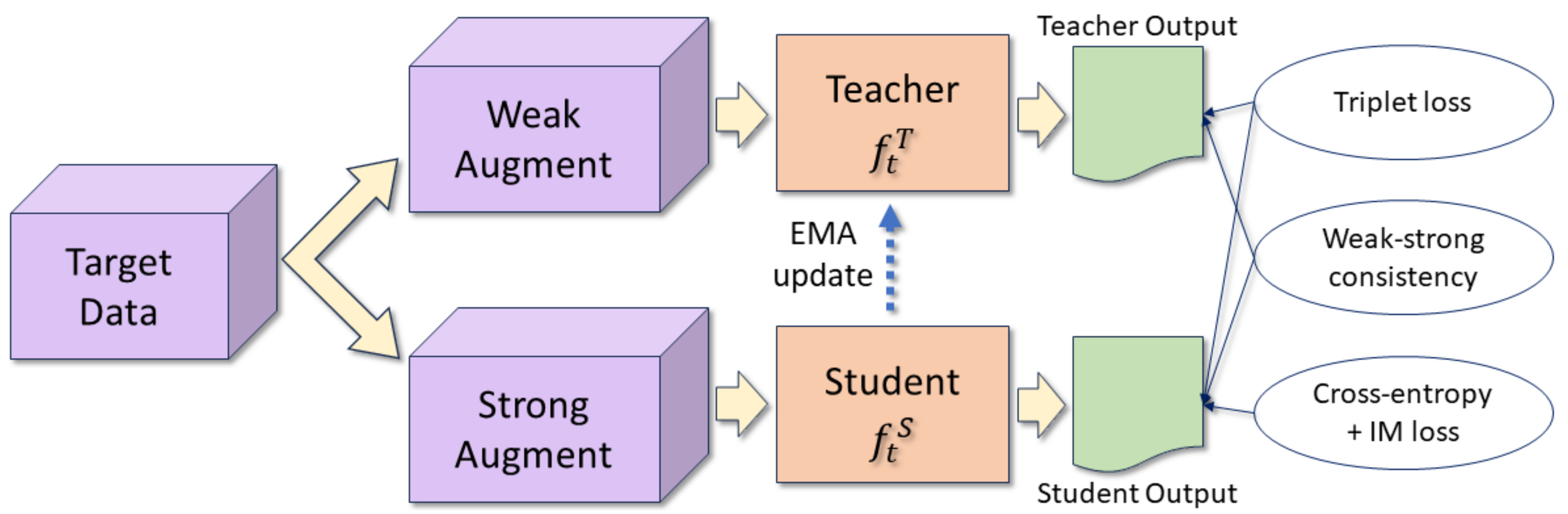
Abstract

Open Set Domain Adaptation (OSDA) aims to adapt a model trained on a source domain to a target domain that undergoes distribution shift and contains samples from novel classes outside the source domain. Test-time or source-free OSDA (SF-OSDA) techniques eliminate the need to access source domain samples, but current SF-OSDA methods utilize only the known classes in the target domain for adaptation and require access to the entire target domain even during inference after adaptation, to distinguish between known and unknown samples. In this paper, we introduce Unknown Sample Discovery (USD) as an SF-OSDA method that utilizes a temporally ensembled teacher model to conduct known-unknown target sample separation and adapts the student model to the target domain over all classes using co-training and temporal consistency between the teacher and the student. USD promotes Jensen-Shannon distance (JSD) as an effective measure for known-unknown sample separation. Our teacher-student framework significantly reduces error accumulation resulting from imperfect known-unknown sample separation, while curriculum guidance helps to reliably learn the distinction between target known and target unknown subspaces. USD appends the target model with an unknown class node, thus readily classifying a target sample into any of the known or unknown classes in subsequent post-adaptation inference stages. Empirical results show that USD is superior to existing SF-OSDA methods and is competitive with current OSDA models that require both source and target domains during adaptation.





Pseudolabel generation for the target samples and known-unknown sample separation based on Jensen-Shannon Distance (JSD).



Adaptation process for USD using co-training. The student model receives pseudolabels for the target samples (see figure above) and is optimized using a combination of triplet, weak-strong consistency, information maximization (IM) and cross-entropy losses. The teacher model is updated via exponential moving averages (EMA) at the end of each epoch.

Results

Method	SF	Office-31 OS*	Office-31 UNK	Office-31 HOS	Office-Home OS*	Office-Home UNK	Office-Home HOS	VisDA-C OS*	VisDA-C UNK	VisDA-C HOS
DANN	✗	87.1	68.3	75.9	52.6	77.1	60.7	52.1	-	-
CDAN	✗	88.3	63.9	73.4	54.5	74.6	61.4	-	-	-
STA	✗	84.3	64.8	72.5	61.8	63.3	61.1	62.4	82.4	71.0
OSBP	✗	87.2	80.4	83.7	64.1	66.3	64.7	50.9	81.7	62.7
PGL	✗	82.7	64.7	72.6	76.1	25.0	35.2	-	-	-
OSLPP	✗	89.3	85.6	87.4	63.8	71.7	67.0	-	-	-
UADAL	✗	84.8	92.1	88.1	62.6	78.0	68.7	-	-	-
SHOT [1]	✓	92.6	53.3	67.0	74.6	33.9	45.6	57.5*	12.1*	20.1*
AaD [2]	✓	72.4	91.2	80.4	58.2	71.9	63.6	32.0*	62.9*	42.4*
USD	✓	83.3	84.4	83.3	61.6	71.5	65.9	57.8	86.7	69.4

Evaluation Metric

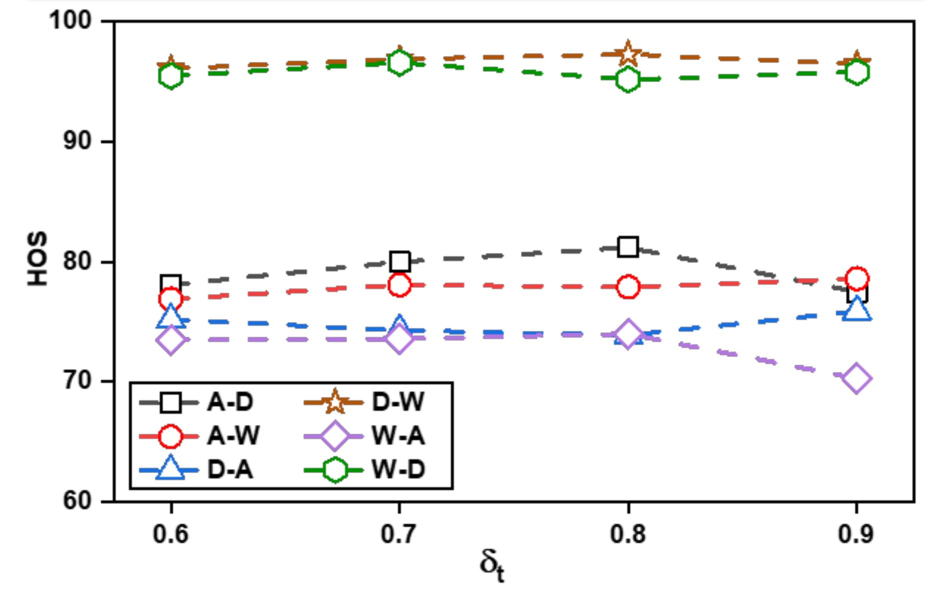
$$OS^* = \frac{1}{|C_s|}\sum_{i=1}^{|C_s|}\frac{|x_t : x_t \in \mathcal{D}_t^i \cap \tilde{y}_t^i = i|}{|x_t : x_t \in \mathcal{D}_t^i|}$$

$$UNK = \frac{|x_t : x_t \in \mathcal{D}_t^{|C_t|} \cap \tilde{y}_t^i = |C_t||}{|x_t : x_t \in \mathcal{D}_t^{|C_t|}|}$$

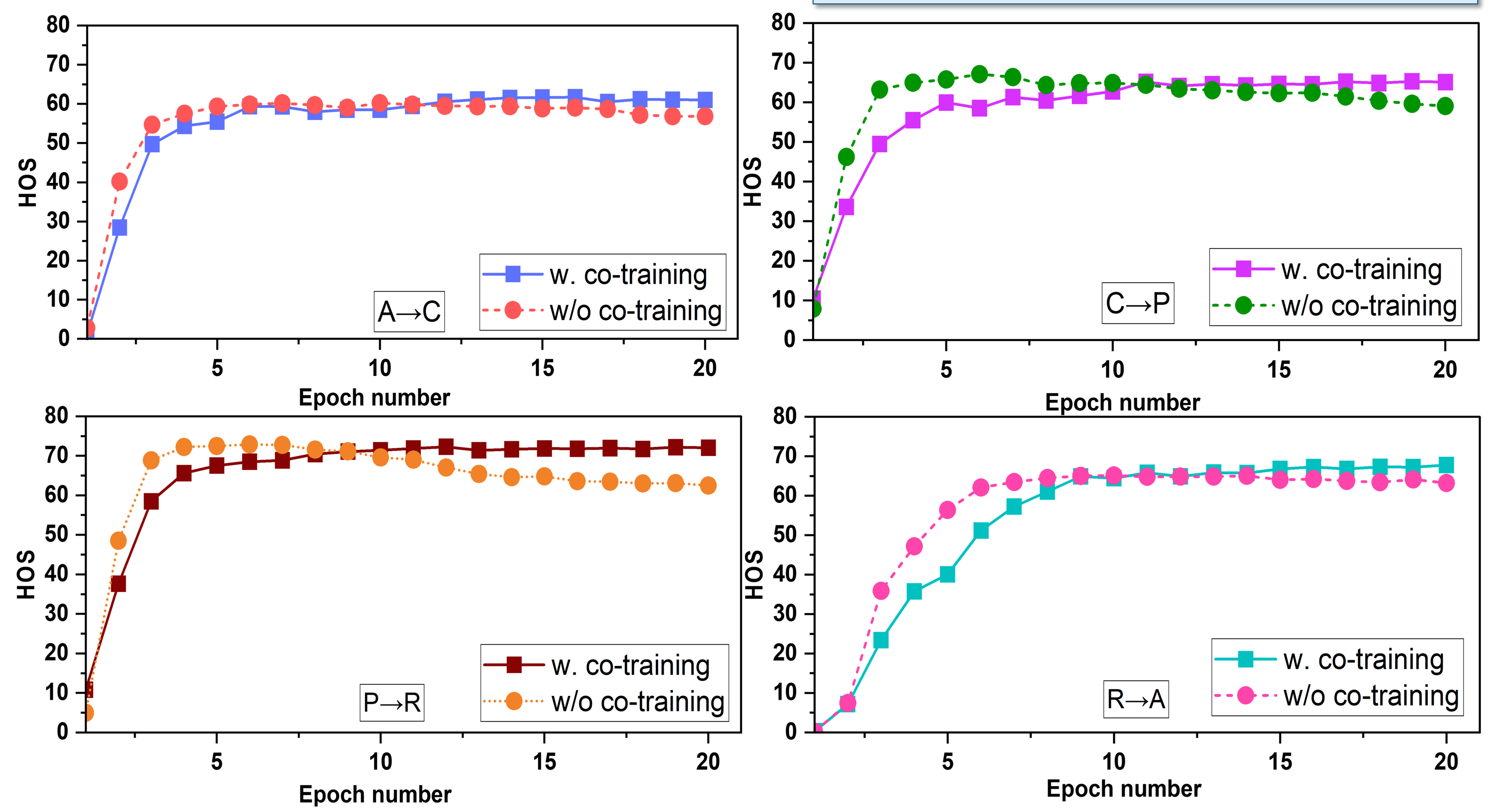
$$HOS = \frac{2 \times OS^* \times UNK}{OS^* + UNK}$$

OS* = mean per class for known classes
UNK = accuracy for the unknown class
HOS = harmonic mean betⁿ OS* and UNK

Ablation Study



Impact of JSD threshold δ_t (threshold to conservatively separate known-unknown samples) on HOS for Office-31 dataset



Impact of co-training on reducing error accumulation during adaptation on Office-Home dataset.

References

[1] Jian Liang, Dapeng Hu, and Jiashi Feng. Do we really need to access the source data? source hypothesis transfer for unsupervised domain adaptation. ICML 2020.

[2] Shiqi Yang, Yaxing Wang, Kai Wang, Shangling Jui, and Joost van de weijer. Attracting and dispersing: A simple approach for source-free domain adaptation, NuerIPS 2022.

Acknowledgements

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