Cycle Self-Training for Semi-Supervised Object Detection with Distribution Consistency Reweighting

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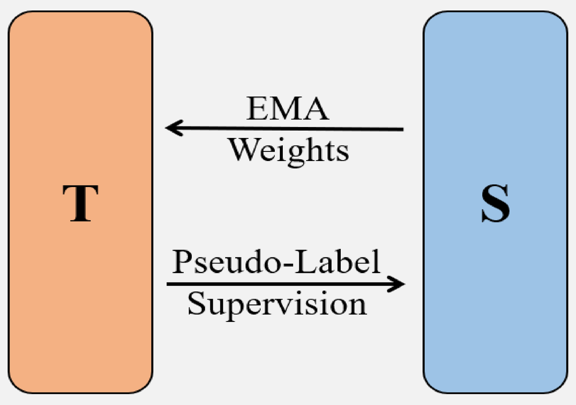
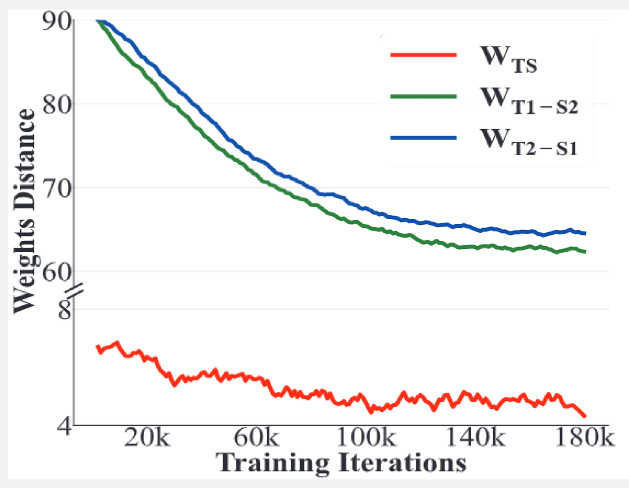
Background

- The pseudo-labeling based model consists of two components: a teacher model and a student model. However, the teacher is tightly **coupled with** the student due to the exponential moving average.

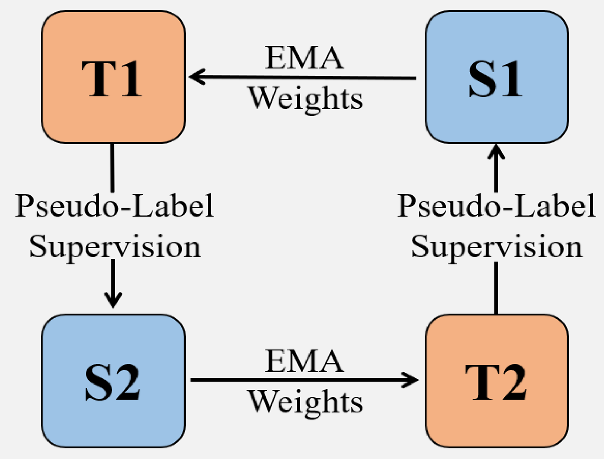


- Moreover, the teacher is prone to generate biased pseudo-labels towards dominant classes, making the **imbalanced problem** in detection even more severe

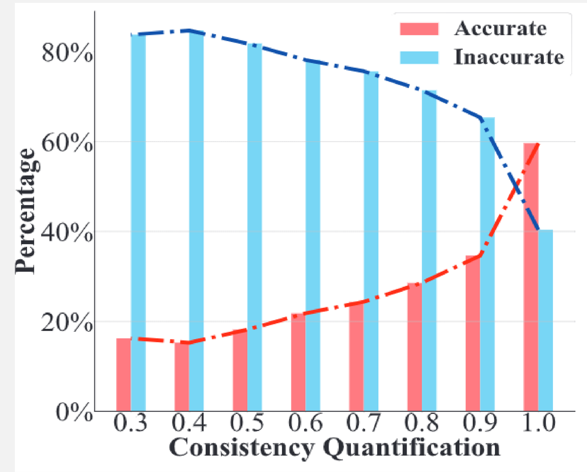


Introduction

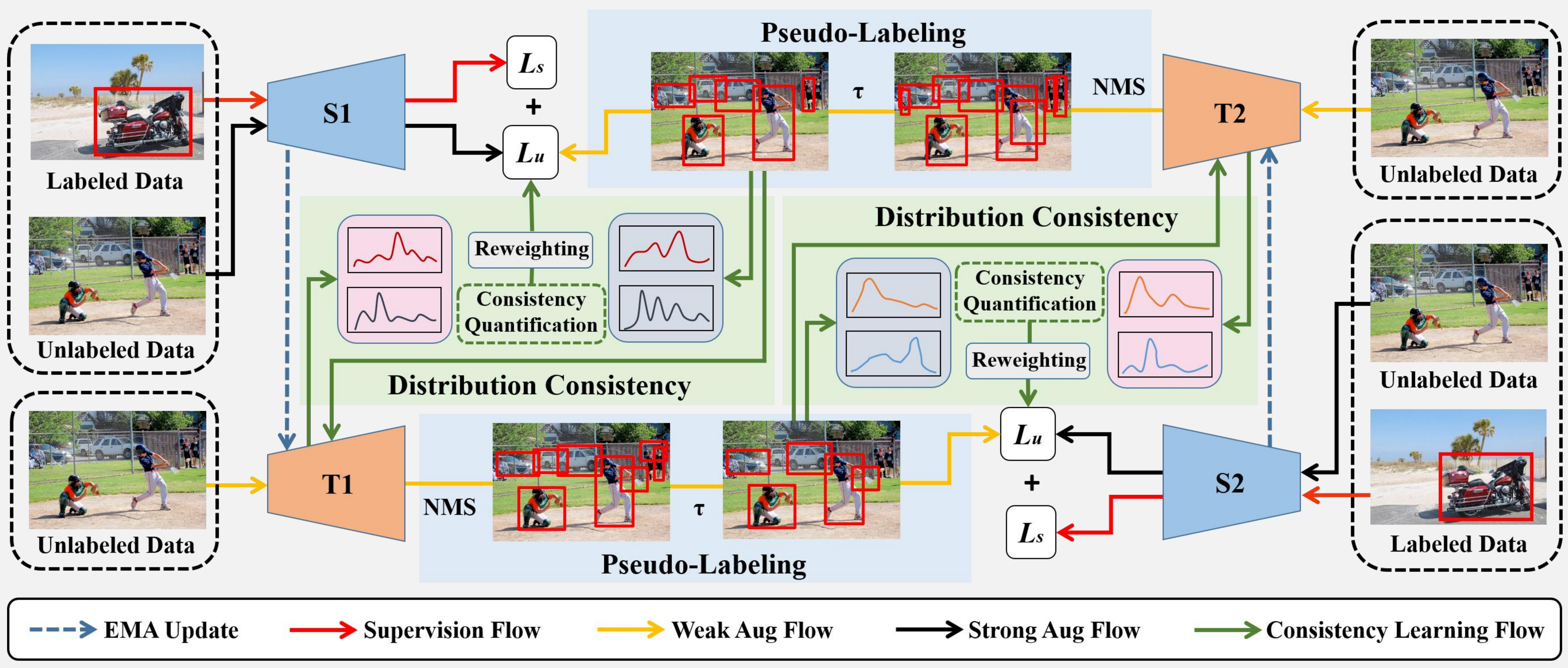
- To address the tightly coupling problem, we introduce a **Cycle Self-Training framework (CST)**, which consists of two teacher networks and two student networks.



- To tackle the confirmation bias problem, we propose a **Distribution Consistency Reweighting (DCR)**, where pseudo-labels are learned based on consistency.



Cycle Self-Training Framework

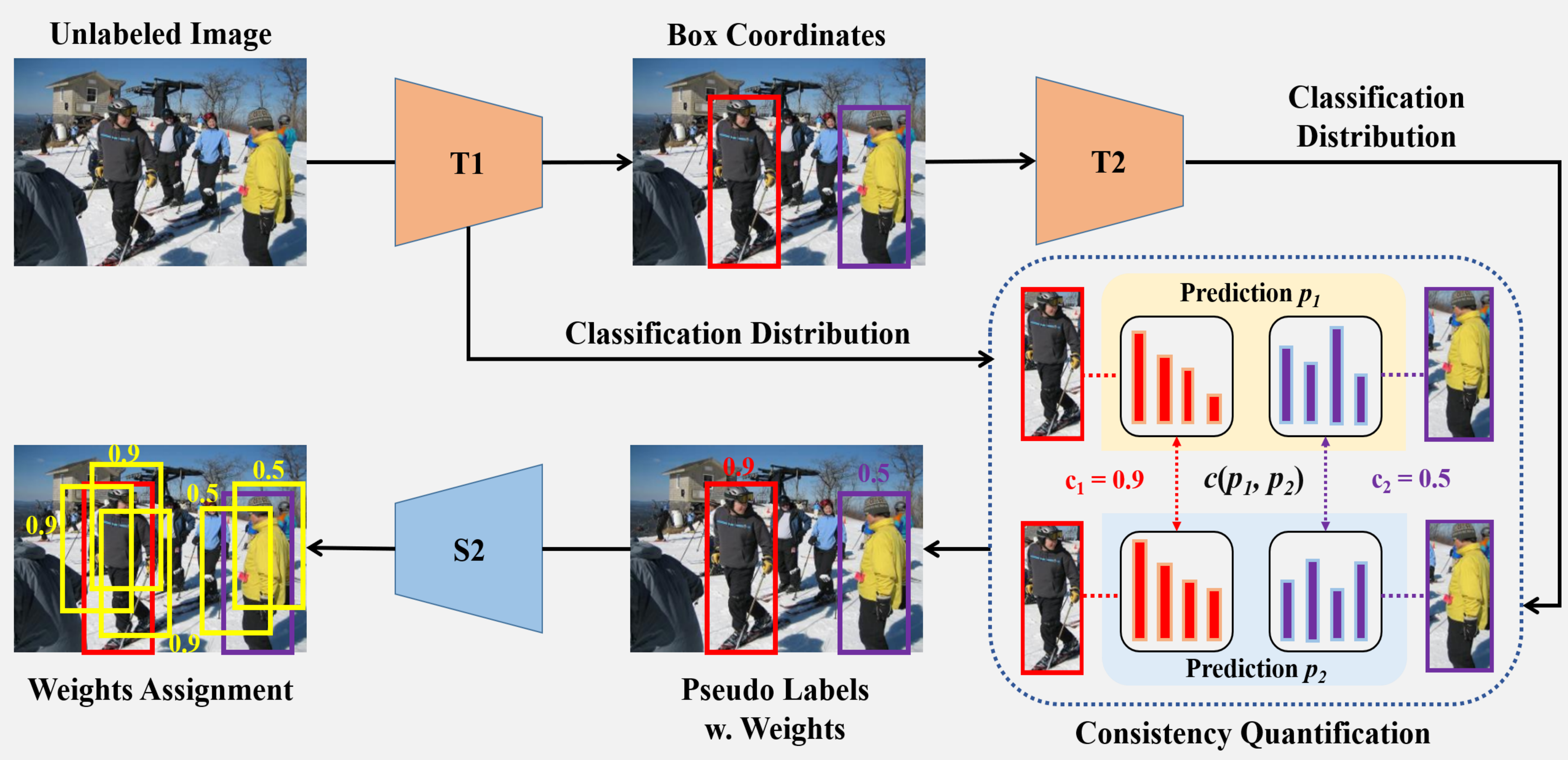


The overview of the **Cycle Self-Training (CST) framework**. Labeled and unlabeled images form the training data batch. In each iteration, the teacher T1 (T2) perform pseudo-labeling on weak augmented images to train the student S2 (S1) with strong augmented images. And the student S1 (S2) is utilized to update the teacher T1 (T2) via EMA to **alleviate the coupling effect.**

Total Loss: Supervised & Unsupervised Losses

$$L = L_s + \alpha L_u \quad \begin{cases} L_s = \frac{1}{N}\sum_{i=1}^{N}\left(L_{cls}\left(x_i^l, y_i^l\right) + L_{reg}\left(x_i^l, y_i^l\right)\right) \\ L_u = \frac{1}{N}\sum_{i=1}^{N} c_i L_{cls}\left(x_i^u, y_i^u\right) \end{cases}$$

Distribution Consistency Reweighting Strategy



The structure of **Distribution Consistency Reweighting (DCR)**. Pseudo-labels generated by the teacher T1 are measured by the teacher T2 to perform consistency quantification $c(p1,p2)$ of classification distribution, and subsequently acts on the weights assignment for the student S2。

Consistency Quantification: L1 Distance or JS Divergence

$$c_i(p_1^i, p_2^i) = 2\times\left(1-\sigma\left(\left\|p_1^i - p_2^i\right\|_1\right)\right) \qquad c_i(p_1^i, p_2^i) = JS\left(\left\|p_1^i - p_2^i\right\|_1\right)^{\beta}$$

- Normalize the L1 distance to 0.5 ~1 with a sigmoid mapping function. Then a linear normalization is performed.
- Because the JS values are in the range 0 ~1, we only utilize a tunable focusing parameter β =2.

Experiments & Comparisons

Methods	Reference	1% COCO	2% COCO	5% COCO	10% COCO	100% COCO
Supervised	-	9.05±0.16	12.70±0.15	18.47±0.22	23.86±0.81	37.63
CSD [13]	NeurIPS-19	10.51±0.06 (+1.46)	13.93±0.12 (+1.23)	18.63±0.07 (+0.16)	22.46±0.08 (-1.40)	38.87 (+1.24)
STAC [34]	ArXiv-20	13.97±0.35 (+4.92)	18.25±0.25 (+5.55)	24.38±0.12 (+5.86)	28.64±0.21 (+4.78)	39.21 (+1.58)
Instant-Teaching [47]	CVPR-21	18.05±0.15 (+9.00)	22.45±0.15 (+9.75)	26.75±0.05 (+8.28)	30.40±0.05 (+6.54)	40.20 (+2.57)
ISMT [45]	CVPR-21	18.88±0.74 (+9.83)	22.43±0.56 (+9.73)	26.37±0.24 (+7.90)	30.53±0.52 (+6.67)	39.64 (+2.01)
Humble Teacher [37]	CVPR-21	16.96±0.38 (+7.91)	21.72±0.24 (+9.02)	27.70±0.75 (+9.23)	31.61±0.28 (+7.75)	42.37 (+4.74)
Combating Noise [41]	NeurIPS-21	18.41±0.10 (+9.36)	24.00±0.15 (+11.30)	28.96±0.29 (+10.49)	32.43±0.20 (+8.57)	43.20 (+5.57)
Soft Teacher [44]	ICCV-21	20.46±0.39 (+11.41)	-	30.74±0.08 (+12.27)	34.04±0.14 (+10.18)	44.50 (+6.87)
CPL [19]	AAAI-22	19.02±0.25 (+9.97)	23.34±0.18 (+10.64)	28.40±0.15 (+9.93)	32.23±0.14 (+8.37)	43.30 (+5.67)
MUM [14]	CVPR-22	21.88±0.12 (+12.83)	24.84±0.10 (+12.14)	28.52±0.09 (+10.05)	31.87±0.30 (+8.01)	42.11 (+4.48)
Unbiased Teacher [25]	ICLR21	20.75±0.12 (+11.70)	24.30±0.07 (+11.60)	28.27±0.11 (+9.80)	31.50±0.10 (+7.64)	41.30 (+3.67)
CST (ours)	-	21.80±0.18 (+12.75)	25.97±0.15 (+13.27)	29.51±0.13 (+11.04)	32.39±0.21 (+8.53)	41.80 (+1.17)
CST* (ours)	-	**22.43±0.14 (+13.38)**	**26.74±0.10 (+14.04)**	**30.58±0.08 (+12.11)**	**33.65±0.17 (+9.79)**	**43.12 (+5.49)**

Methods	Reference	PASCAL VOC		VOC-additional	
		AP	AP_{50}	AP	AP_{50}
Supervised	-	45.3	76.3	45.3	76.3
CSD [13]	NeurIPS-19	-	74.7	-	75.1
STAC [34]	ArXiv-20	44.6	77.4	46.0	79.1
Instant-Teaching [48]	CVPR-21	48.7	78.3	49.7	79.0
ISMT [45]	CVPR-21	46.2	77.2	49.6	77.7
Humble Teacher [37]	CVPR-21	**53.0**	**80.9**	**54.4**	81.3
Combating Noise [41]	NeurIPS-21	49.3	80.6	50.2	**81.4**
CPL [19]	AAAI-22	52.4	76.9	54.0	77.6
MUM [15]	CVPR-22	50.2	78.9	52.3	80.5
Unbiased Teacher [25]	ICLR-21	48.7	77.4	50.3	78.8
CST (ours)	-	50.3	78.1	52.3	79.6
CST* (ours)	-	**51.5**	**78.7**	**53.5**	**80.5**

- The performance of semi-supervised object detection methods for 1%, 2%, 5%, 10%, 100% MS-COCO protocols.
- The performance compared with our CST method for VOC/VOC-additional dataset.

Ablations & Qualitative Results

CST	DCR	AP (%)
		20.1
✓		21.4
	✓	21.2
✓	✓	**21.9**

Quantification Style	AP (%)
JS Divergence	21.5
L1 Distance	**21.9**

Combinations for DCR	AP (%)
(T1 ↔ S1) , (T2 ↔ S2)	21.6
(T1 ↔ S2) , (T2 ↔ S1)	21.4
(T1 ↔ T2) , (T2 ↔ T1)	**21.9**

- Either of the two components can give a favorable improvement.
- L1 Distance better balances weights compared to JS Divergence.
- The computation between T1 and T2 achieves better performance.

(a) Supervised (b) Unbiased Teacher (c) Our CST (d) Our CST*