Diverse Learner: Exploring Diverse Supervision for Semi-supervised Object Detection

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1 Proof: teacher loses its distinctiveness in the later training process.

In the conventional teacher-student framework, we note the parameter of teacher and student model at iteration t as θ_{tea}^{t} and θ_{stu}^{t}, respectively.

we have exponential moving average, when $t_1 = t_0 + 1$

$$\theta_{tea}^{t_1} = \alpha\theta_{tea}^{t_0} + (1-\alpha)\theta_{stu}^{t_1} \tag{1}$$

$$= \alpha\theta_{tea}^{t_0} + (1-\alpha)(\theta_{stu}^{t_0} + \Delta\theta_{stu}^{t_1}) \tag{2}$$

when $t_2 = t_0 + 2$

$$\theta_{tea}^{t_2} = \alpha\theta_{tea}^{t_1} + (1-\alpha)\theta_{stu}^{t_2} \tag{3}$$

$$= \alpha\theta_{tea}^{t_1} + (1-\alpha)(\theta_{stu}^{t_1} + \Delta\theta_{stu}^{t_2}) \tag{4}$$

$$= \alpha(\alpha\theta_{tea}^{t_0} + (1-\alpha)(\theta_{stu}^{t_0} + \Delta\theta_{stu}^{t_1}) + (1-\alpha)(\theta_{stu}^{t_1} + \Delta\theta_{stu}^{t_2}) \tag{5}$$

$$= \alpha^2\theta_{tea}^{t_0} + (1-\alpha)(\alpha\theta_{stu}^{t_0} + \theta_{stu}^{t_1}) + (1-\alpha)(\alpha\Delta\theta_{stu}^{t_1} + \Delta\theta_{stu}^{t_2}) \tag{6}$$

we hypothesis that in later training process,

$$\Delta\theta_{stu}^{t_0} \to 0 \tag{7}$$

we have

$$\Delta\theta_{stu}^{t_1}, \Delta\theta_{stu}^{t_2} \to 0 \tag{8}$$

$$\theta_{stu}^{t_2} \approx \theta_{stu}^{t_1} \approx \theta_{stu}^{t_0} \tag{9}$$

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so

$$\theta_{tea}^{t_2} = \alpha^2\theta_{tea}^{t_0} + (1-\alpha)(\alpha\theta_{stu}^{t_0} + \theta_{stu}^{t_1}) \quad (10)$$
$$= \alpha^2\theta_{tea}^{t_0} + (1-\alpha^2)\theta_{stu}^{t_0} \quad (11)$$

so when $t_n = t_0 + n$, we have

$$\theta_{tea}^{t_n} = \alpha^n\theta_{tea}^{t_0} + (1-\alpha^n)\theta_{stu}^{t_0} \quad (12)$$

from $\alpha < 1$, when n is large, we have $\alpha^n \to 0$ and $1 - \alpha^n \to 1$, so

$$\theta_{tea}^{t_n} \to \theta_{stu}^{t_0} \quad (13)$$

2 Data augmentation.

For a fair comparison, we follow the data augmentation setting of Soft Teacher. The details are shown in Table 1.

Table 1. Details of weak data augmentations and strong data augmentations applied in our framework. We denote pseudo label-aware augmentation as PLAE.

Augmentation	Weak Augmentation	Strong Augmentation
Horizon Flip	p=0.5	p=0.5
Rand Resize	short edge$\in(0.5, 1.5)$	short edge$\in(0.5, 1.5)$
Solarize Jitter	-	p=0.25, ratio$\in(0, 1)$
Brightness Jitter	-	p=0.25, ratio$\in(0, 1)$
Contrast Jitter	-	p=0.25, ratio$\in(0, 1)$
Sharpness Jitter	-	p=0.25, ratio$\in(0, 1)$
Translation	-	p=0.3, translation ratio$\in(0, 0.1)$
Rotate	-	p=0.3, angle$\in(0, 30^o)$
Shift	-	p=0.3, angle$\in(0, 30^o)$
Rand erasing	-	num$\in(1, 5)$,ratio$\in(0.05, 0.2)$
PLAE	-	p=0.5, ratio$\in(0.02, 0.3)$

3 Hyper-parameters.

Hyper parameter details are shown in Table 2.

4 Mutual learning's performance under 10% labeled setting.

To demonstrate the superiority of diverse learner, we compare the performance of diverse learner and mutual learning under 10% labeled setting. As shown

Table 2. Meanings and values of hyper-parameters.

Hyper-parameter	Description	Partially labeled	Fully Labeled
l	Lower threshold	0.8	0.8
u	Upper threshold	0.9	0.9
	Unsupervised loss weight	4	2
	EMA rate	0.999	0.999
b_l	Batch size for labeled data	32	32
b_u	Batch size for unlabeled data	8	32
	Learning rate	0.01	0.01
t	Training iterations	180k	720k

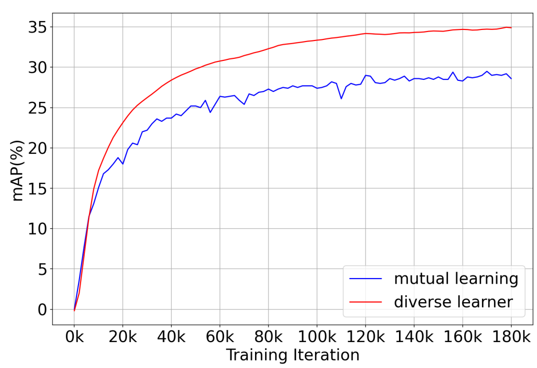

Fig. 1. The mAP value curves of mutual learning and diverse learner under 10% labeled coco setting.

in Figure 1, we observe that despite a larger amount number of labeled data compared to 1% labeled setting, mutual learning still comes with a continuous fluctuations. On the contrary, diverse learner maintains a smooth growth curve and obtain 5.9% mAP improvement.

5 Qualitative comparison with Soft teacher.

We qualitatively verify the effect of our proposed diverse learner by comparing it against Soft teacher. Concretely, we set a same threshold $\delta = 0.8$ to filter pseudo labels of foreground objects under 1% labeled data setting on COCO dataset. As shown in Figure 2, obviously, diverse learner generates a much larger amount of high quality pseudo labeled foreground objects.

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Fig. 2. The comparison of pseudo labeled foreground objects with Soft teacher under 1% labeled setting on COCO dataset. We use the same threshold $= 0{:}8$ for Diverse learner and Soft teacher. The class name of the pseudo labeled foreground objects are omitted for simplicity concern. (a)Diverse leaner; (b)Soft teacher.