

Rethinking Class-Balanced Methods for Long-Tailed Visual Recognition from a Domain Adaptation Perspective

- Supplementary Materials -

Outline

- Multiple runs of experiments on CIFAR-LT-10 under different imbalance factors (IFs). (Section A).
- Detailed comparison of various methods on large-scale long-tailed datasets (Section B).

A. Multiple runs on CIFAR-LT-10

In this experiment, we further validate our approach by running each setting 5 times with different random seeds. Table 1 shows the mean top-1 errors (%) and the standard deviations under the imbalance factor of 200, 100, and 50. We can see that the mean error rates are consistent with the results provided in Table 2 of the main paper.

B. Detailed comparison of various methods on large-scale long-tailed datasets

In this section, we present the top-1 errors (%) of various methods for ImageNet-LT, Places-LT, and iNaturalist 2018¹. As the experiment setups of the existing works vary by network initialization, the sampling strategy of mini-batches, losses, trainable layers of a network, etc., it is hard to have a fair comparison by the end results. Hence, besides their top-1 errors, we also report the experiment setups for each method. Tables 2, 3, and 4 show the results of the different methods on ImageNet-LT, Places-LT, and iNaturalist 2018, respectively. Our approach outperforms the class-balanced weighting scheme for both the cross-entropy loss and the focal loss, as we observed in the main paper. Moreover, our results are on par with best reported ones except on ImageNet-LT. Finally, we stress that almost all existing methods employ a class-balanced weighting or sampling strategy no matter what their main techniques are to tackle the long-tailed problem. Hence, given our consistent improvements over the class-balanced weighting, we expect

¹While we include the comparison on iNaturalist 2018 due to that most existing related works report results on this dataset, we reiterate that we advocate the use of iNaturalist 2017, instead of 2018, in this and future work due to the extremely small validation set of iNaturalist 2018.

the methods which have benefited from the class-balancing can gain further from our two-component weighting.

References

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Table 1. Multiple runs of our approach by using the cross-entropy loss on CIFAR-LT-10. The results are top-1 errors% on the test sets.

Imbalance factor	200	100	50
Cross-entropy training	34.32	29.64	25.19
Class-balanced cross-entropy loss [2]	31.11	27.63	21.95
Class-balanced fine-tuning	33.76	28.66	22.56
Class-balanced fine-tuning*	33.92	28.67	22.58
L2RW [6]	33.75	27.77	23.55
L2RW [6]*	33.49	25.84	21.07
Meta-weight net [7]	32.8	26.43	20.9
Ours with cross-entropy loss	29.32 ± 0.23	23.71 ± 0.22	19.45 ± 0.28

Table 2. Test top-1 errors (%) of different methods on ImageNet-LT. * indicates the re-run results.

Methods	NN	Initialization	Sampling	Loss	Stage-1 Trainable Variables	Stage-2 Trainable Variables	Results
Vanilla Model	ResNet-10	No-pretrain	Class-Balanced	CE	All	-	80.0
Vanilla Model [4]	ResNet-10	No-pretrain	Class-Balanced	Focal	All	-	69.8
Vanilla Model	ResNet-10	No-pretrain	Class-Balanced	Lifted	All	-	69.2
Vanilla Model [8]	ResNet-10	No-pretrain	Class-Balanced	Range	All	-	69.3
Joint [3]	ResNet-10	No-pretrain	Class-Balanced	CE	All	All	65.2
NCM [3]	ResNet-10	No-pretrain	Class-Balanced	CE	All	Classifier layer	64.5
cRT [3]	ResNet-10	No-pretrain	Class-Balanced	CE	All	Classifier layer	58.2
τ -normalized [3]	ResNet-10	No-pretrain	Class-Balanced	CE	All	Classifier layer	<u>59.4</u>
OLTR* [5]	ResNet-10	No-pretrain	Class-Balanced	CE	All	All	65.6
OLTR [5]	ResNet-10	No-pretrain	Class-Balanced	CE	All	All	64.4
Ours	ResNet-10	No-pretrain	None	CE	All	Classifier layer	63.5
Ours	ResNet-10	No-pretrain	None	Focal	All	Classifier layer	63.3
Vanilla Model	ResNet-50	No-pretrain	None	CE	All	-	59.0
CB [2]	ResNet-50	No-pretrain	None	CE	All	-	58.2
Joint [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	All	58.4
NCM [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	Classifier layer	55.7
cRT [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	Classifier layer	<u>52.7</u>
τ -normalized [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	Classifier layer	53.3
Ours	ResNet-50	No-pretrain	None	CE	All	Classifier layer	52.0

Table 3. Test top-1 errors (%) of different methods on Places-LT. * indicates the re-run results.

Methods	NN	Initialization	Sampling	Loss	Stage-1 Trainable Variables	Stage-2 Trainable Variables	Results
Vanilla Model	ResNet-152	ImageNet	Class-Balanced	CE	FC layers Last Block + FC	-	72.1 69.7
Vanilla Model [4]	ResNet-152	ImageNet	Class-Balanced	Focal	FC layers Last Block + FC	-	67.0 66.5
Vanilla Model	ResNet-152	ImageNet	Class-Balanced	Lifted	FC layers	-	64.8
Vanilla Model [8]	ResNet-152	ImageNet	Class-Balanced	Range	FC layers	-	64.9
Joint [3]	ResNet-152	ImageNet	Class-Balanced	CE	Last block + FC	Last block + FC	69.8
NCM [3]	ResNet-152	ImageNet	Class-Balanced	CE	Last block + FC	Classifier layer	63.7
cRT [3]	ResNet-152	ImageNet	Class-Balanced	CE	Last block + FC	Classifier layer	63.3
τ -normalized [3]	ResNet-152	ImageNet	Class-Balanced	CE	Last block + FC	Classifier layer	62.1
OLTR* [5]	ResNet-152	ImageNet	Class-Balanced	CE	Last block + FC	FC + memory	64.8
OLTR [5]	ResNet-152	ImageNet	Class-Balanced	CE	Last block + FC	FC + memory	64.1
Ours	ResNet-152	ImageNet	None	CE	Last block + FC	Classifier layer	62.9
Ours	ResNet-152	ImageNet	None	Focal	Last block + FC	Classifier layer	<u>62.2</u>

Table 4. Test top-1 errors (%) of different methods on iNaturalist 2018.

Methods	NN	Initialization	Sampling	Loss	Stage-1 Trainable Variables	Stage-2 Trainable Variables	Results
Vanilla Model	ResNet-50	No-pretrain	None	CE	All	-	42.9
Vanilla Model	ResNet-50	ImageNet+iNat'17	None	CE	All	-	36.2
LDAM [1]	ResNet-50	No-pretrain	None	LDAM	All	-	35.4
LDAM-DRW [1]	ResNet-50	No-pretrain	None	LDAM	All	-	32.0
CB [2]	ResNet-50	ImageNet+iNat'17	None	CE	All	-	34.7
CB [2]	ResNet-50	No-pretrain	None	Focal	All	-	38.9
Joint [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	All	38.3
NCM [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	Classifier layer	41.8
cRT [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	Classifier layer	34.8
τ -normalized [3]	ResNet-50	No-pretrain	Class-Balanced	CE	All	Classifier layer	34.4
Ours	ResNet-50	ImageNet+iNat'17	None	CE	All	All	<u>32.4</u>
Ours	ResNet-50	ImageNet+iNat'17	None	Focal	All	All	<u>32.3</u>
Vanilla Model	ResNet-101	ImageNet+iNat'17	None	CE	All	-	34.3
CB [2]	ResNet-101	ImageNet+iNat'17	None	CE	All	-	32.7
Ours	ResNet-101	ImageNet+iNat'17	None	CE	All	All	31.5