Class-Balanced Loss Based on Class Volume for Long-Tailed Object Recognition

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Introduction

- Real-world datasets often exhibit a long-tailed class distribution.
- It is important to address this imbalance issue for robust real-world application.
- Otherwise classifiers tend to be biased towards the dominating classes and perform poorly on the tail classes.

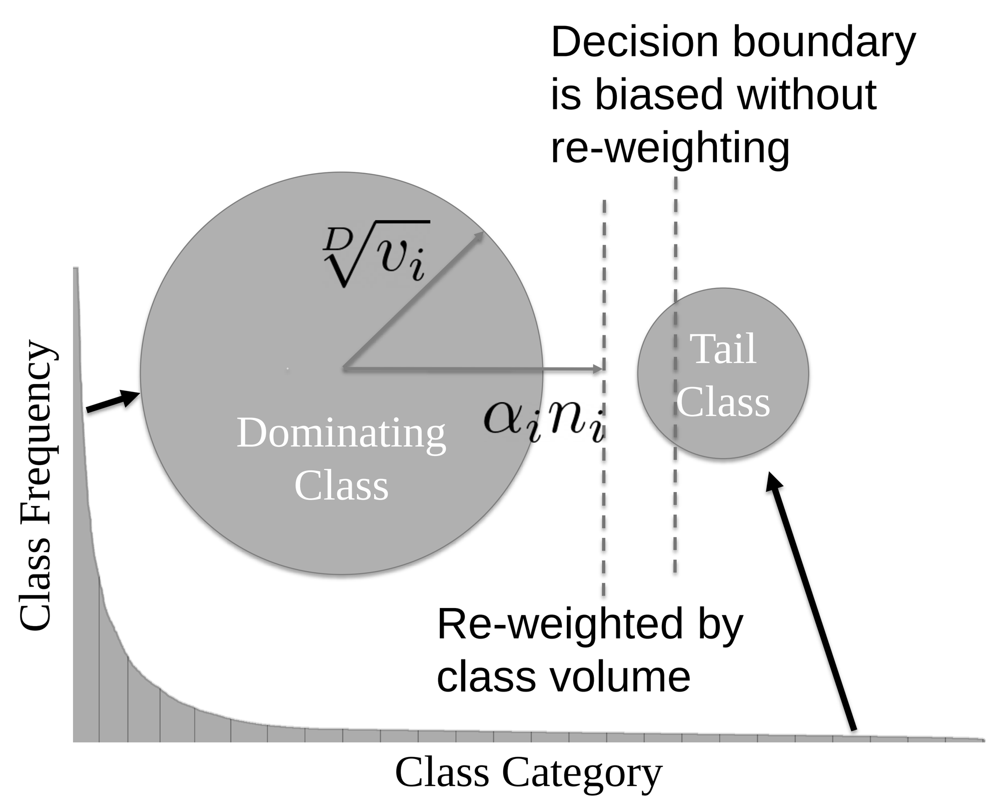
	Transfer Learning	Re-weighting	
		Existing	Ours
Within-class diversity	✓		✓
Generalization		✓	✓
Adaptive to data	✓		✓
Lightweight		✓	✓

Class Volume

① $v_i = \prod_{k=1}^{D} \sigma_{i,k}$

② $\alpha_i = \beta \dfrac{\sqrt[D]{v_i}}{n_i}$

③ $\beta = \dfrac{\sum_{j=1}^{C} n_j}{\sum_{i=1}^{C} \sqrt[D]{v_i}}$

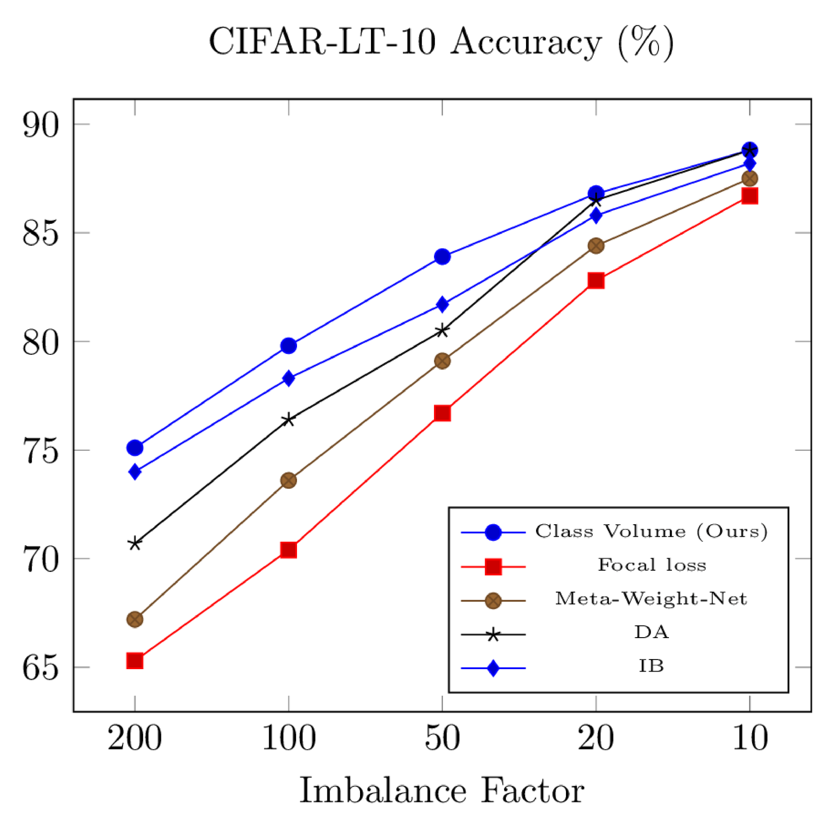


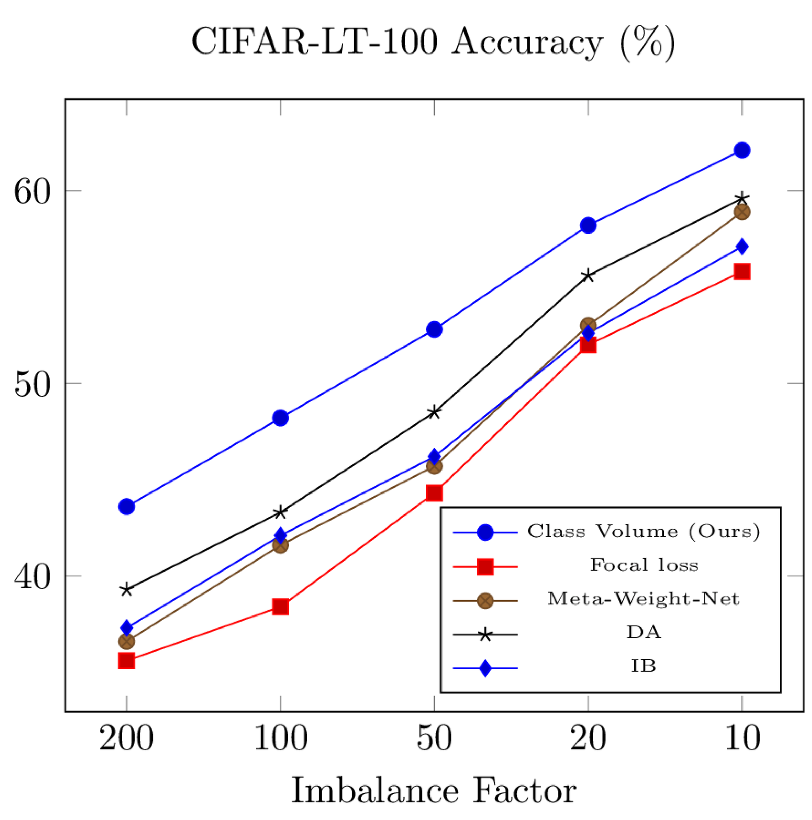
Class-balanced loss re-weights the loss function by a re-weighting factor α_i for each class i.

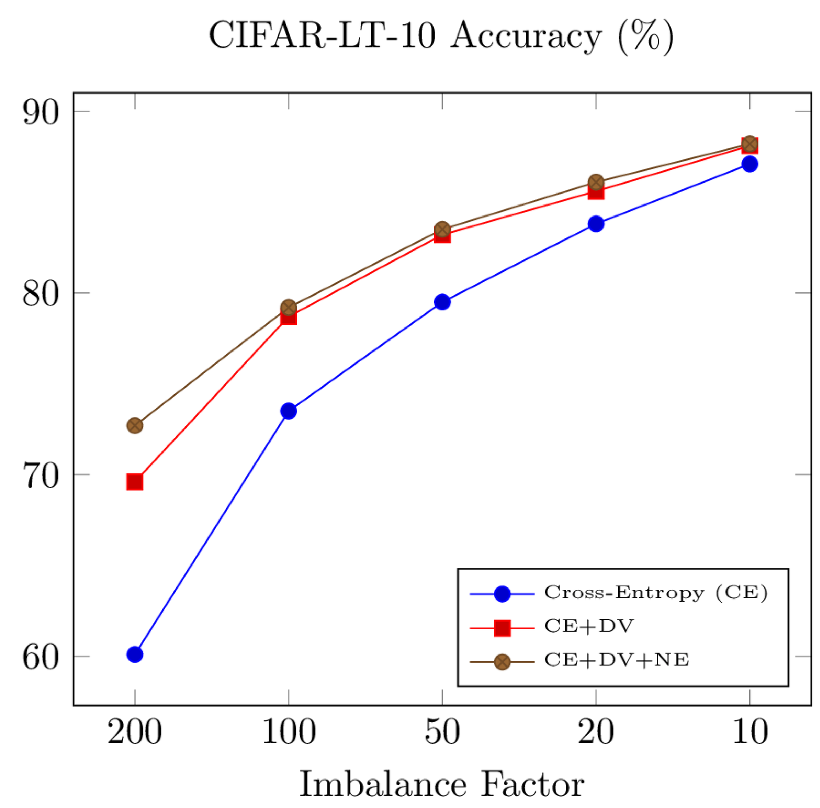
1. We define class volume v_i to estimate the class boundary. $\sigma_{i,k}$ is the standard deviation of the kth logit for samples in class i.
2. The re-weighting factor α_i can be viewed as a training sample's power of influence to the decision boundary.
   The aggregated power of influence $\alpha_i n_i$ estimates the distance from a class to the decision boundary.
   The re-weighting factor is assigned such that the distance to the decision boundary is proportional to the radius of the class volume.
3. Re-weighting factors are then normalized using β to preserve the expected loss:

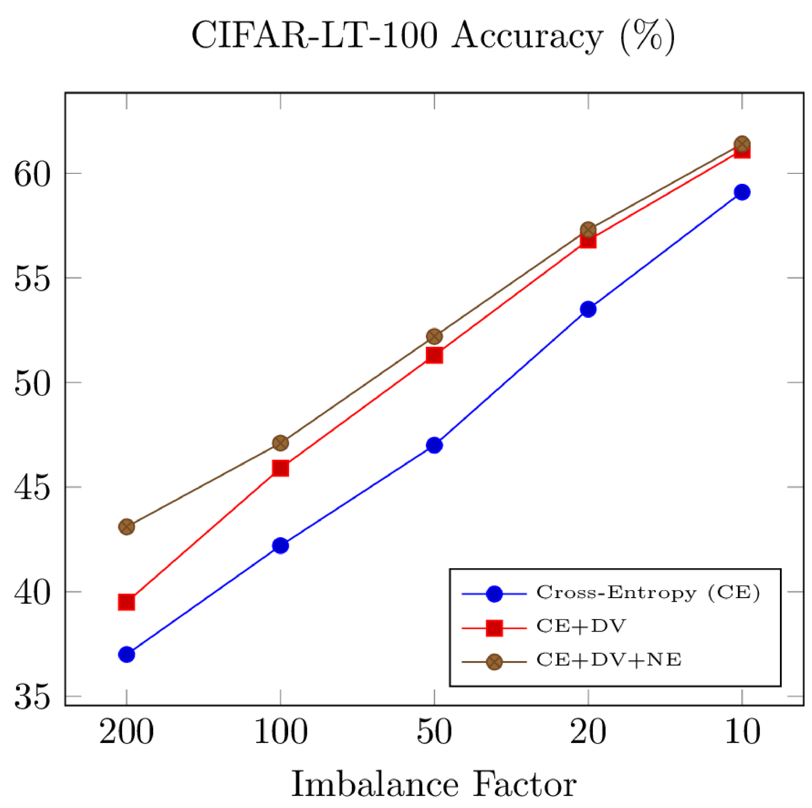
$$E(\alpha\ell) = E(\ell)$$

Results









Ablation study
CE: The baseline Cross-Entropy loss.
+DV: Re-weight the loss by class volume estimated from Distribution Variance.
+NE: Normalize the re-weighting factors to preserve the Expected loss.

Dataset	Backbone	Method	Overall	Many-shot	Medium-shot	Few-shot
ImageNet-LT	R50	VL-LTR	69.9	78.6	66.3	47.8
		Ours	70.3 ↑	74.4 ↓	70.1 ↑	55.2 ↑
	ViT-B	VL-LTR	77.0	84.8	73.8	57.3
		Ours	77.4 ↑	82.2 ↓	76.6 ↑	64.9 ↑
Places-LT	R50	VL-LTR	48.1	53.0	47.1	36.5
		Ours	48.7 ↑	45.5 ↓	50.3 ↑	48.1 ↑
	ViT-B	VL-LTR	50.2	54.2	48.4	43.4
		Ours	50.8 ↑	49.3 ↓	52.8 ↑	50.0 ↑
iNat2018	R50	VL-LTR	74.4	78.5	75.1	72.6
		Ours	76.4 ↑	75.2 ↓	76.5 ↑	76.4 ↑
	ViT-B	VL-LTR	76.0	81.1	77.4	73.4
		Ours	78.0 ↑	79.5 ↓	78.3 ↑	77.1 ↑

- The overall accuracy is improved.
- The classification bias is reduced.

Conclusion

- Class volume concept captures the bias introduced by both class imbalance and within-class diversity imbalance.
- Generalizable to all existing architectures.
- Adaptive to data without introducing any additional hyper-parameter.
- Lightweight. Does not add significant implementation effort or computation overhead.