

SOLVING THE LONG-TAILED PROBLEM VIA INTRA- AND INTER-CATEGORY BALANCE

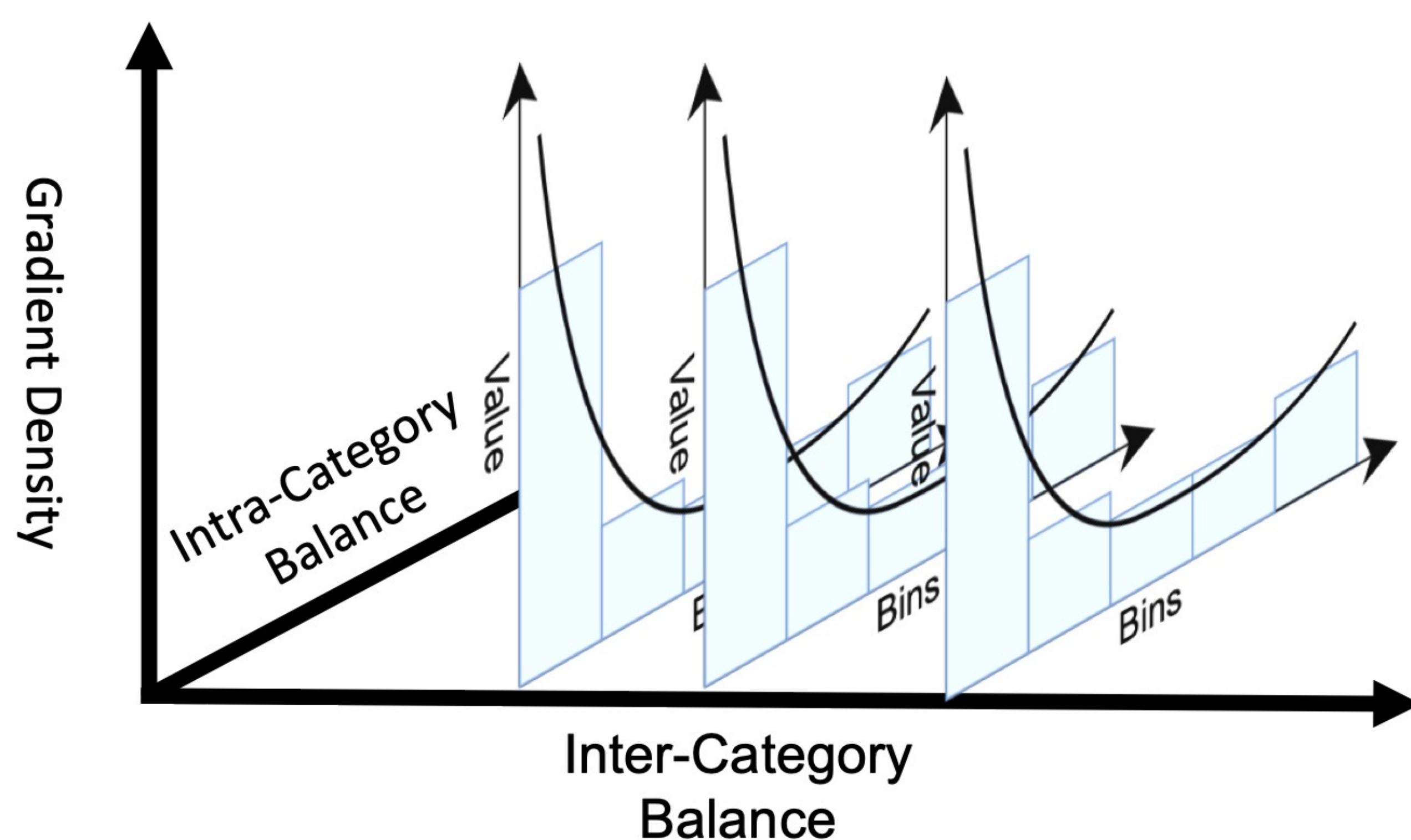
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Introduction

- Benchmark datasets for visual recognition assume that data is uniformly distributed, while real-world datasets obey long-tailed distribution.
- Current approaches handle the long-tailed problem only focus on inter-category balance.
- We propose a novel gradient harmonized mechanism with category-wise adaptive precision decouple the difficulty and sample size imbalance, which are correspondingly solved via intra- and inter-category balance strategies.

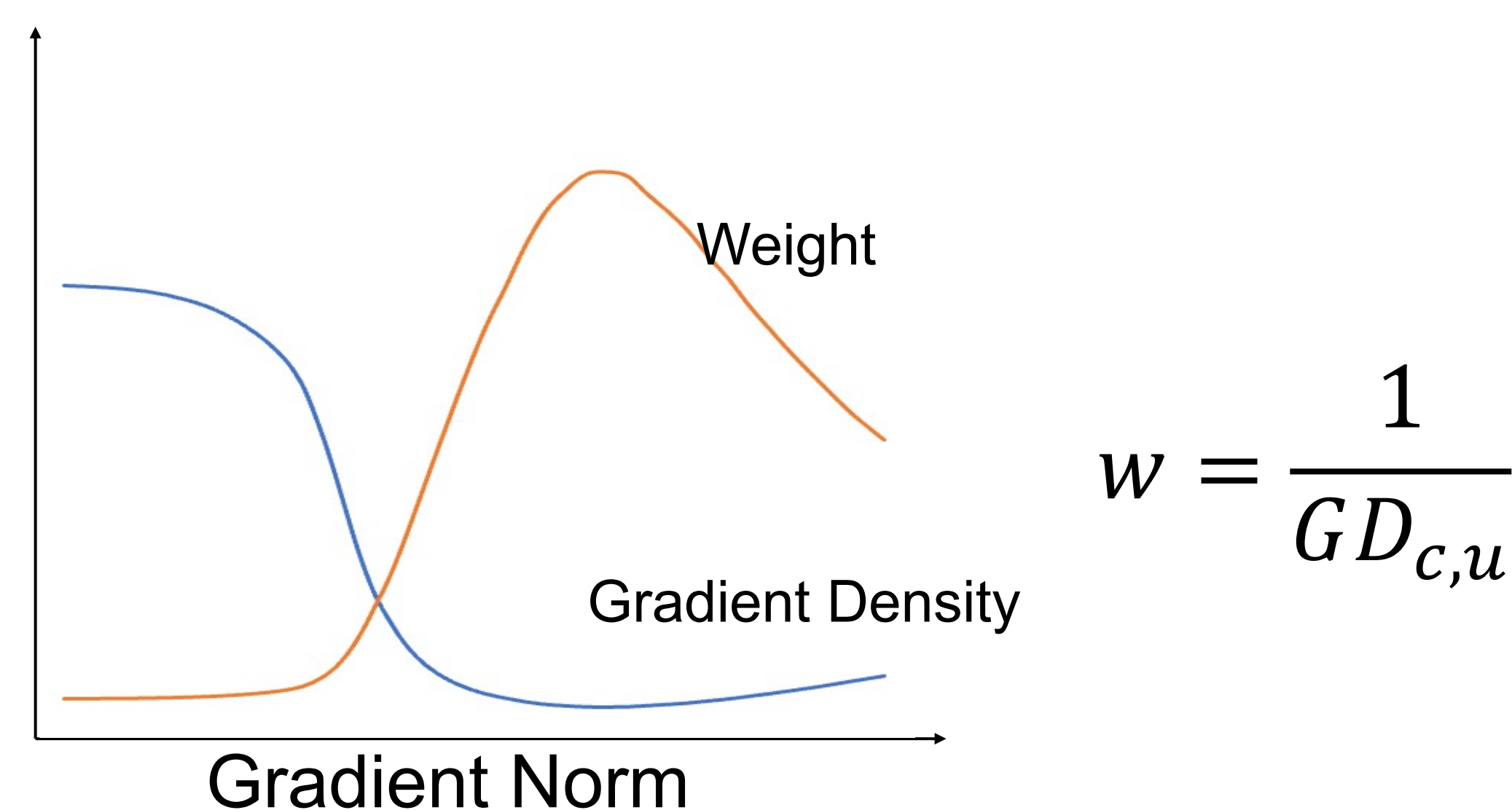
Category-wise GHM



Category-wise GHM dependently count gradient density for each category, thus we can obtain the exact difficulty distribution for each category. Besides, it decouples difficulty and sample size imbalance.

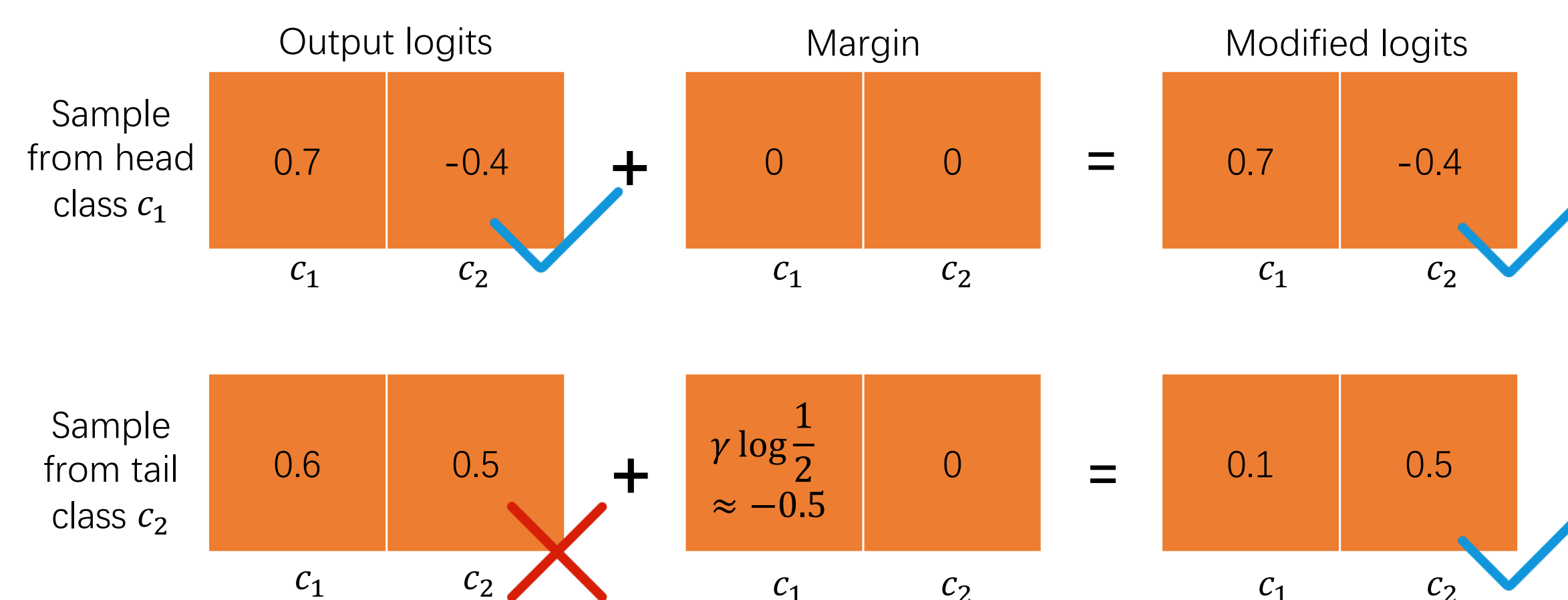
Intra- and Inter-Category Balance

- Intra-category balance emphasize hard samples while reducing the weight of simple samples and outliers in each category according to the gradient density.



- Inter-category balance correct the classification boundary shift by adding margins to the logits.

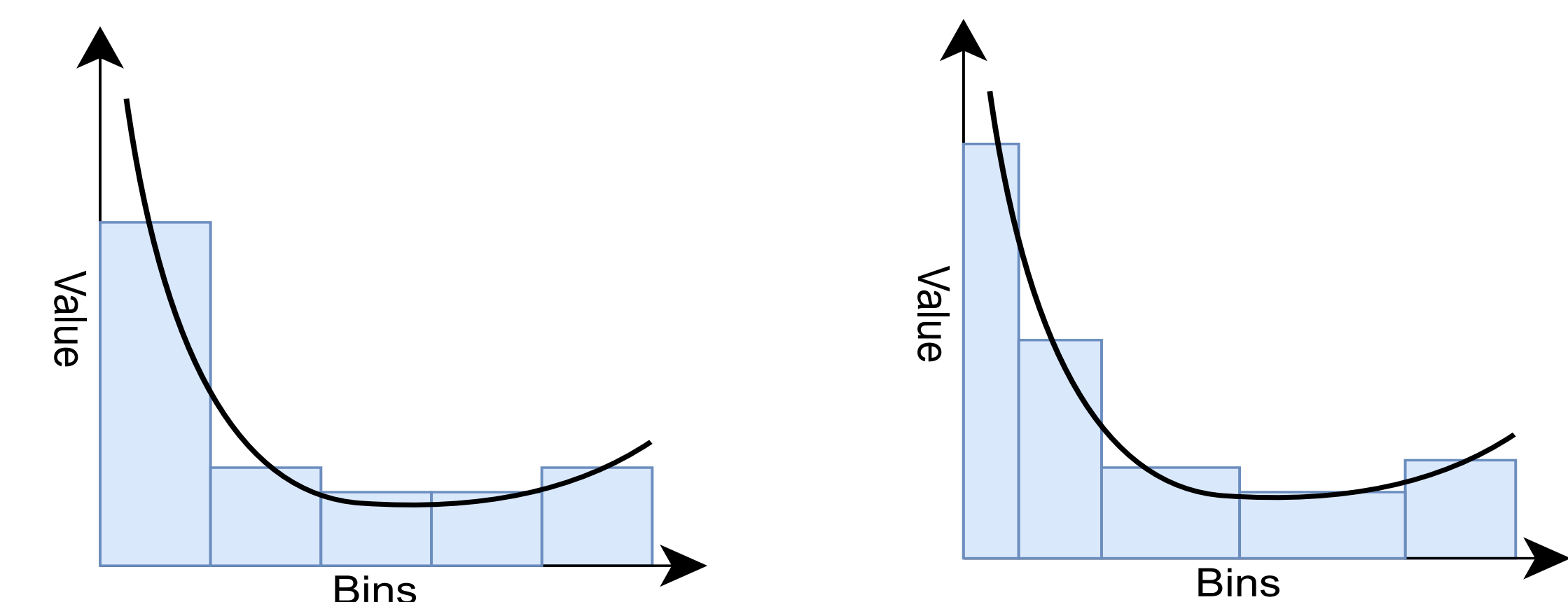
$$M_{c_1, c_2} = \gamma \log[\min(1, S_{c_2}/S_{c_1})]$$



- The final loss function combines intra- and inter-category balance.

$$\mathcal{L} = - \sum_{m \in \mathcal{C}} \left[W_{m,i} \cdot y_m \log \left(\frac{e^{z_m}}{\sum_{n \in \mathcal{C}} e^{z_n + M_{m,n}}} \right) \right]$$

Adaptive Precision



Adaptively adjust the precision of different bins to achieve higher approximation accuracy, thus improve the performance.

Results

Experiments with different imbalance factors

Table 1. Top-1 accuracy (%) of ResNet-32 with various loss function on long-tailed CIFAR-10/100 and TinyImageNet. Imbalance factor means the ratio of sample size of head classes to tail classes.

Dataset	Long-Tailed CIFAR-10				Long-Tailed CIFAR-100				Long-Tailed TinyImageNet			
	500	100	10	1	500	100	10	1	500	100	10	1
Softmax	59.76	71.74	86.69	93.00	30.90	38.77	57.21	71.00	31.42	39.06	54.51	63.32
Class Balanced	58.50	73.82	87.18	92.71	31.23	39.12	56.45	70.75	30.90	39.48	54.17	63.06
Focal [23]	57.72	72.43	86.70	92.66	30.31	38.12	56.12	70.13	30.93	39.23	54.00	63.22
GHM [24]	41.50	51.66	67.87	79.35	12.85	14.02	24.49	34.04	8.00	8.03	9.92	10.13
Effective Number [18]	57.97	71.47	87.13	92.98	30.40	39.32	57.37	70.75	30.90	39.48	54.17	63.06
Equalization [19]	58.29	72.61	87.08	93.04	30.82	39.84	58.14	71.66	29.63	37.39	52.75	62.84
Seesaw [20]	64.48	75.18	87.76	93.03	33.63	40.87	57.83	71.35	34.07	40.98	54.60	63.05
ours	66.13	75.39	87.29	92.75	33.85	41.59	57.81	71.41	34.79	42.66	55.35	63.21

Experiments on large-scale real-world datasets

Table 2. Top-1 accuracy (%) of ResNet-50 on long-tailed ImageNet and iNaturalist2017 dataset. Categories are divided into four groups and sample size gradually decreases from "Many" to "Rare".

	Long-Tailed ImageNet(imbalance factor=100)					iNaturalist2017(imbalance factor=435)				
	Many	Medium	Few	Rare	Over All	Many	Medium	Few	Rare	Over All
Softmax	63.91	48.07	22.15	12.55	36.67	84.92	69.88	50.21	40.63	54.64
ClassBalance	63.30	47.71	22.26	12.63	36.48	85.29	70.66	50.88	41.31	55.31
Focal[23]	62.70	47.70	23.42	12.86	36.67	84.41	70.01	51.96	41.13	55.15
EffectiveNumber[18]	63.86	47.91	23.42	13.70	37.22	87.77	72.96	54.45	44.49	58.25
Seesaw[20]	63.51	48.69	24.37	15.52	38.02	87.48	73.60	55.64	46.78	59.15
ours	63.61	48.73	25.78	16.95	38.77	87.84	73.59	56.75	48.02	59.85

Ablations

Table 3. Top-1 accuracy (%) of ResNet-50 on long-tailed ImageNet. "A" and "R" represent intra-category balance and inter-category balance respectively. Besides, "U" and "AU" represent URA and AURA respectively.

	ImageNet-LT(imbalance factor=100)				
	Many	Medium	Few	Rare	Over All
Softmax	63.91	48.07	22.15	12.55	36.67
R	63.51	48.69	24.37	15.52	38.02
A+U	63.93	48.32	22.60	13.44	37.07
R+A+U	63.55	48.67	25.16	16.30	38.42
R+A+AU	63.61	48.73	25.78	16.95	38.77

