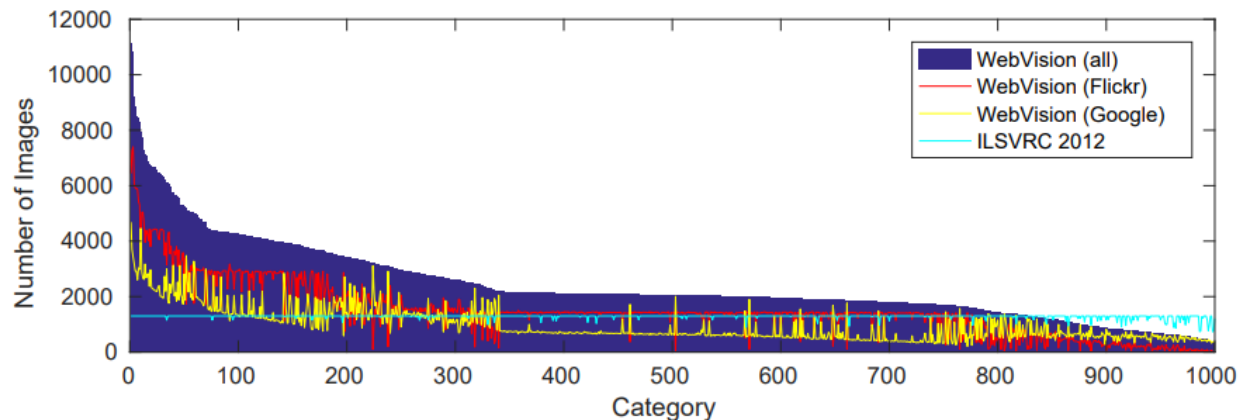


Multiplicative Logit Adjustment Approximates Neural-Collapse- Aware Decision Boundary Adjustment

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Long-Tailed Recognition (LTR)

- Real-world class distributions are often dominated by classes with overwhelmingly small sample sizes (Long-Tailed Data).
 - Zipf's law[Reed, 2001]
- Problems: Naïve training ...
 - Biases the classes with large numbers of training samples (Head classes).
 - Degrades accuracy of classes with small number of samples (Tail classes).
 - Degrades overall accuracy.



The number of images per category of the WebVision dataset.
(<https://data.vision.ee.ethz.ch/cvl/webvision/dataset2017.html>)

Logit Adjustment (LA)

Post-hoc adjustment methods for LTR that modify the logits.

- Additive LA (ALA) [Menon+, ICLR2020]

$$g_k(\mathbf{x}) - \gamma_+ \log n_k$$

- γ_+ : A hyperparameter.
- Based on a Fisher-consistent loss.
 - Assumes that the sample numbers n_k approach infinity.

- Multiplicative LA (MLA) [Kim+, 2020]

$$n_k^{-\gamma_{\times}} g_k(\mathbf{x})$$

- γ_{\times} : A hyperparameter.
- Heuristic-based with no theoretical guarantees yet.
- Outperforms ALA in certain cases [Hasegawa+, ICLR2024].

Our work

- Research Question

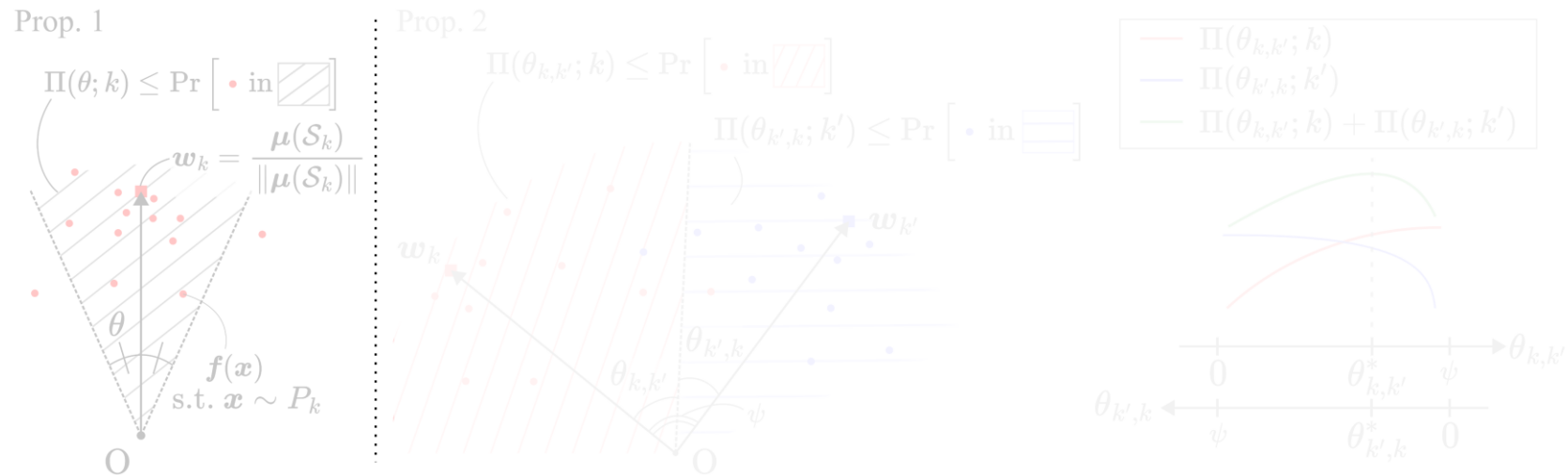
- Is there a theoretical foundation behind the effectiveness of MLA?

- Contribution

- Provide a near-optimality of MLA with our three-step theory.
 - Validate experimentally that the theory holds under realistic conditions.

Three-Step Theory

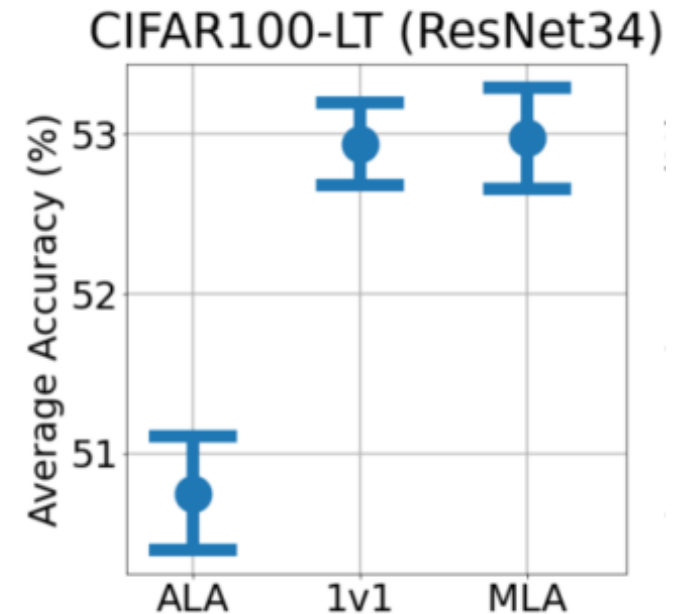
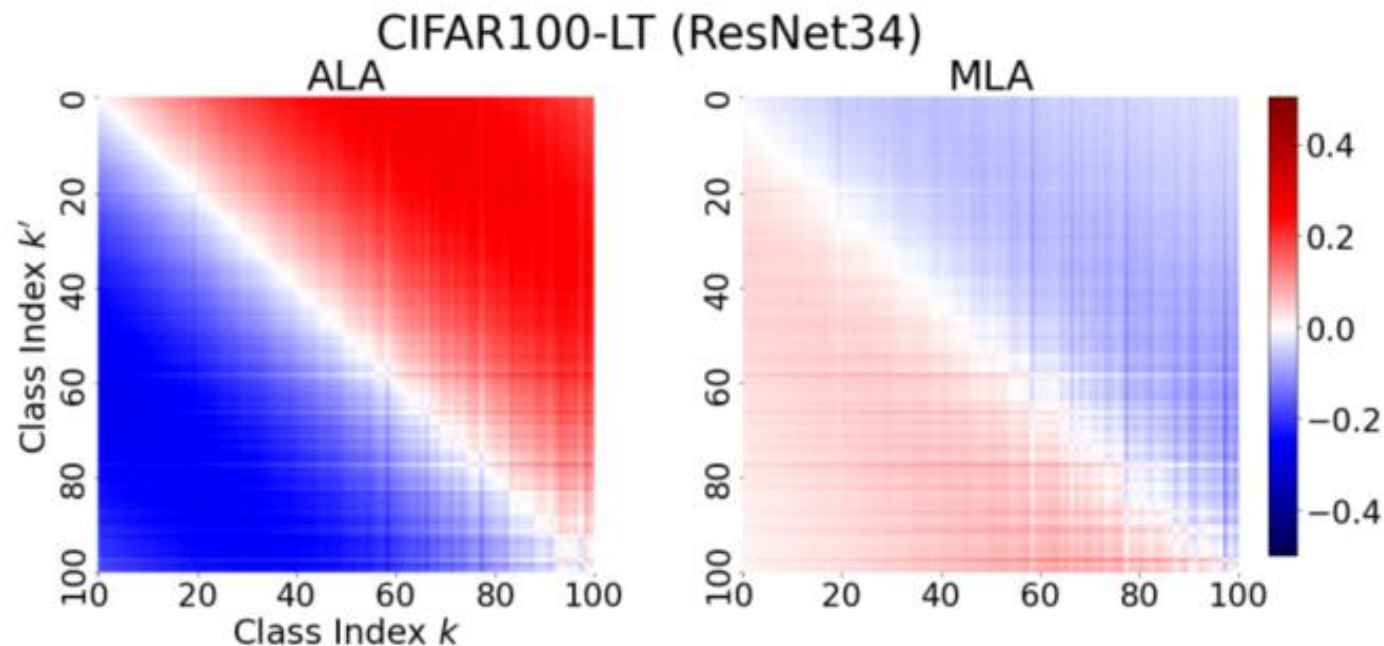
1. Feature spread estimation based on neural collapse [Papayan+, PNAS2020].
2. Decision boundary optimization (1vs1Adjuster).



3. Approximation of 1vs1Adjuster to MLA.

Experiment: Validating the Approximation

- Verify the approximation from the following two perspectives.
 1. The angles of decision boundaries.
 2. The test accuracy.



Links

- Our paper
 - <https://arxiv.org/abs/2409.17582>
- Our github repository
 - <https://github.com/HN410/MLA-Approximates-NCDBA>

