Debiased Learning from Naturally Imbalanced Pseudo-Labels

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Code

Contributions

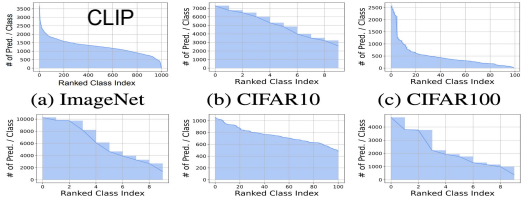
First Insight: Pseudo-labels by machines are naturally imbalanced, just like ground-truth labels by humans.

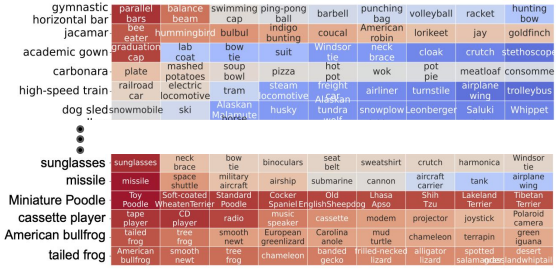
First debiased learning algorithm for pseudo-labels w/o knowing actual classification margins.

New SOTA on ImageNet: +9% on zero-shot, +26% on 0.2% semi-supervised learning; a universal add-on.

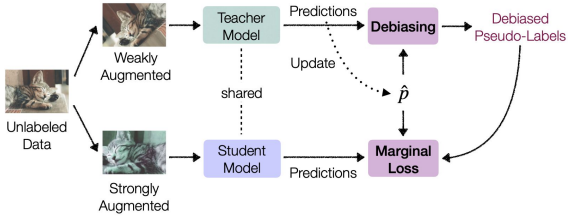
Pseudo-Labels Are Naturally Imbalanced

due to intrinsic data similarity, even when the model is trained and tested on balanced data; pseudo-labeled tail classes have stronger inter-class confusion.



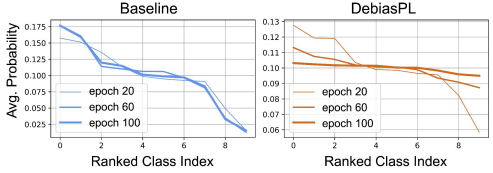


Our Debiased Pseudo-Labeling



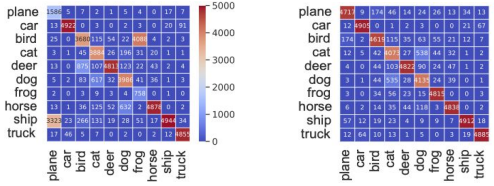
Adaptive debiasing on weak augmentations: Offset to reduce the class bias, more on pseudo-labeled **head** classes

$$\tilde{f}_i = f(\alpha(x_i)) - \lambda \log \hat{p}, \quad \hat{p} \leftarrow m\hat{p} + (1-m)\frac{1}{\mu B}\sum_{1}^{\mu B} p_k$$



Adaptive margin on strong augmentations: Offset to reduce inter-class confusion, more on pseudo-labeled **tail** classes

$$\mathcal{L}_{\text{AML}} = -\log \frac{e^{(z_{\hat{y}_i} - \Delta_{\hat{y}_i})}}{e^{(z_{\hat{y}_i} - \Delta_{\hat{y}_i})} + \sum_{k \neq \hat{y}_i}^{C} e^{(z_k - \Delta_k)}} \qquad \Delta_j = \lambda \log(\tfrac{1}{\hat{p}_j})$$



New SOTA: Large Gains, Robust, Simple & Lean