Class-Imbalanced Semi-Supervised Learning with Inverse Auxiliary Classifier (Supplementary Material)

BMVC 2023 Submission # 908

1 Additional Training Curves

We visualize the training curves for the test accuracy throughout the training phase for the six CISSL algorithms [1, 2, 3, 4, 5, 6] with and without IAC respectively, on CIFAR-10 dataset with $N_1 = 500$, $M_1 = 4000$, $\gamma_l = 100$ and $\gamma_u = 100$ in Figure 1. This represents a typical scenario where the class distributions of labeled and unlabeled examples are consistent. As shown in Figure 1, although not overly conspicuous, the proposed IAC can enhance the performance of CISSL algorithms when the distributions of labeled and unlabeled data are consistent. This suggests that IAC is an effective plug-in module for CISSL.

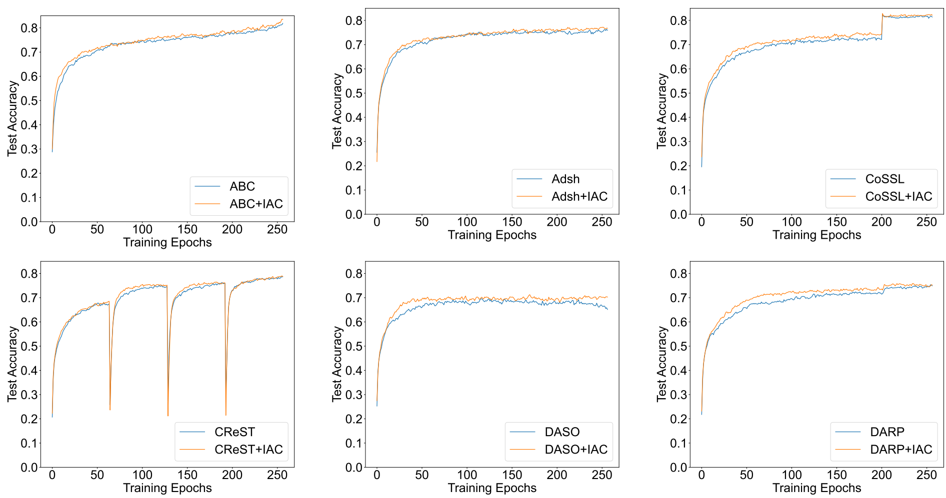

Figure 1: Training curves for the test accuracy on CIFAR-10, $N_1 = 500$, $M_1 = 4000$, $\gamma_l = 100$ and $\gamma_u = 100$.

Algorithm	CIFAR-10	CIFAR-100
FixMatch	9.88iter/sec	9.82iter/sec
w/IAC	9.48iter/sec	9.40iter/sec
CReST	9.88iter/sec	9.82iter/sec
w/IAC	9.48iter/sec	9.40iter/sec
Adsh	9.80iter/sec	9.53iter/sec
w/IAC	9.52iter/sec	9.34iter/sec
DASO	8.23iter/sec	7.82iter/sec
w/IAC	7.92iter/sec	7.34iter/sec
ABC	9.49iter/sec	9.33iter/sec
w/IAC	9.12iter/sec	8.89iter/sec
CoSSL	4.87iter/sec	3.51iter/sec
w/IAC	4.52iter/sec	3.26iter/sec

Table 1: Training cost on CIFAR-10 and CIFAR-100.

2 Running Cost Analysis

To evaluate the efficiency of IAC, we display the training cost in Table 1, where we measure floating point operations per second (FLOPS) using NVIDIA GeForce RTX 2080 Ti. As the proposed IAC appears to be a variant of ABC in structure, the time consumption when using IAC is relatively low. Table 1 shows that the training cost of our IAC, in terms of time, is similar to that of ABC. This cost is negligible compared to existing CISSL algorithms.

References

[1] Yue Fan, Dengxin Dai, Anna Kukleva, and Bernt Schiele. Cossl: Co-learning of representation and classifier for imbalanced semi-supervised learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14574–14584, 2022.

[2] Lan-Zhe Guo and Yu-Feng Li. Class-imbalanced semi-supervised learning with adaptive thresholding. In *International Conference on Machine Learning*, pages 8082–8094. PMLR, 2022.

[3] Jaehyung Kim, Youngbum Hur, Sejun Park, Eunho Yang, Sung Ju Hwang, and Jinwoo Shin. Distribution aligning refinery of pseudo-label for imbalanced semi-supervised learning. *Advances in neural information processing systems*, 33, 2020.

[4] Hyuck Lee, Seungjae Shin, and Heeyoung Kim. Abc: Auxiliary balanced classifier for class-imbalanced semi-supervised learning. *Advances in neural information processing systems*, 34, 2021.

[5] Youngtaek Oh, Dong-Jin Kim, and In So Kweon. Daso: Distribution-aware semantics-oriented pseudo-label for imbalanced semi-supervised learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9786–9796, 2022.

[6] Chen Wei, Kihyuk Sohn, Clayton Mellina, Alan Yuille, and Fan Yang. Crest: A class-rebalancing self-training framework for imbalanced semi-supervised learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10857–10866, 2021.