ImCLR: Implicit Contrastive Learning for Image Classification by John Chen

Abstract: Contrastive learning is an effective method for learning visual representations. In most cases, this involves adding an explicit loss function to encourage similar images to have similar representations, and different images to have different representations. In this paper, we introduce a clever construction for Implicit Contrastive Learning (ImCLR), primarily in the supervised setting: there, the network can implicitly learn to differentiate between similar and dissimilar images.

Furthermore, this requires almost no change to existing pipelines, which allows for easy integration and fair demonstration of effectiveness on a wide range of well-accepted benchmarks. Namely, there is no change to loss, no change to hyperparameters, and no change to general network architecture. We show that ImCLR improves the test error in the supervised setting across a variety of settings, including 3.24% on Tiny ImageNet, 1.30% on CIFAR-100, 0.14% on CIFAR-10, and 2.28% on STL-10. We show that this holds across different number of labeled samples, maintaining approximately a 2% gap in test accuracy down to using only 5% of the whole dataset. We further show that gains hold for robustness to common input corruptions and perturbations at varying severities with a 0.72% improvement on CIFAR-100-C, and in the semi-supervised setting with a 2.16% improvement with the standard benchmark Pi-model. We demonstrate that ImCLR is complementary to existing data augmentation techniques, achieving over 1% improvement on CIFAR-100 by combining ImCLR with CutMix over either baseline, and 2% by combining ImCLR with AutoAugment over either baseline. Finally, we perform an extensive ablation study to better understand the proposed algorithm.