Semi-supervised learning made simple with self-supervised clustering Supplementary material

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1. More implementation details

1.1. ImageNet-1k

Pre-training. On ImageNet-1k, we train Suave with ResNet-50 backbone a projection head with hidden and output dimensions 2048 and 128, respectively. The number of prototypes is set to 1000 as the number of classes. We train with mini-batches composed of 256 unlabeled and 128 labeled images. The training lasts for 100 epochs; each epoch consumes all the unlabeled images once. We optimize using LARS with a learning rate of linearly increased from 0 to 0.4 throughout 5 epochs and then decreased to 0.001 with a cosine scheduler. The cross-entropy loss is regularized with a weight decay of 10^{-6}. Also, the ground-truth labels are smoothed with a factor of 0.01. The pseudo-labels, instead, are computed via three iterations of the Sinkhorn-Knopp algorithm [4] applied to the detached logits (output of the network) extended with a queue of 3840 embeddings buffered from previous mini-batches. The logits used for pseudo labeling are first peaked using a temperature (ϵ parameter) of 0.05, while the logits used as predictions are peaked with a temperature of 0.1 before computing the loss. On the unlabeled images, we use multi-crop [2] with two large crops (random crop range (0.14, 1)) of size 224^2 and eight small crops (random crop range (0.08, 0.14)) of size 96^2. We extend each batch with mixed images generated from MixUp [8, 9] with probability 1.0, applying either MixUp or CutMix with probability 0.5 and degree of mixing (known as lambda) drawn from $\mathrm{Beta}(1, 1)$. The augmentation recipe of unlabeled images is the exact same as SwAV [2] (color jittering with intensity 0.8 and probability 0.8, random grayscaling with probability 0.2, and Gaussian blurring with probability 0.5). For labeled images, the Inception-style [7] augmentations adopted consist of random cropping with range (0.08, 1), horizontal flip with probability 0.5, color jittering with intensity 0.4 and probability 0.8, and grayscaling with probability 0.2.

Fine-tuning. The fine-tuning runs for 3/5 epochs when using 1%/10% of the labels with the same semi-supervised setting of the pre-training. Note that the hyper-parameters are kept the same unless specified in the following. The network is fully initialized with the pre-trained weights, except for the prototypes layer, which is randomly initialized. We adopt a smaller learning rate, 0.02, with no linear warm-up and a final value of 0.0002 after cosine decreasing. Also, we reduce the intensity of the augmentations; on the labeled images, we reduce color jittering intensity to 0.1 (keeping probability 0.8) and disable grayscaling; on the unlabeled, we turn off multi-crops, generating only two crops per image with crop range of (0.08, 1), and drop off the color distortions and the blurring.

Simplified training recipe for Daino. For Daino experiments with ViT-S/16 backbone [5] we adopt the default DINO [3] pre-training recipe[1] for most hyper-parameters except for a few modification that we report in the following. We perform semi-supervised pre-training for 60 epochs, initializing the ViT backbone weights with the DINO pre-trained ones (800 epochs checkpoint); the teacher momentum is set to 0.990; the teacher temperature is raised from 0.04 to 0.07 during the first 10 epochs; the student temperature is fixed to 0.1; we do not freeze the last layer because the labeled loss help to avoid clustering collapse; we set the learning rate to 0.00024 and warm it up linearly for the first 4 epochs; each mini-batch is composed of 1024 unlabeled and 512 labeled images; the labeled images are extended using MixUp [8,9] with probability 1.0 as in the Suave recipe; we augment the unlabeled images with multi-crop obtaining two large crops (crop range (0.25,1)) and eight small crops (crop range (0.05,0.25)); other data augmentations are maintained as in the original DINO. Note that no fine-tuning is explored for Daino.

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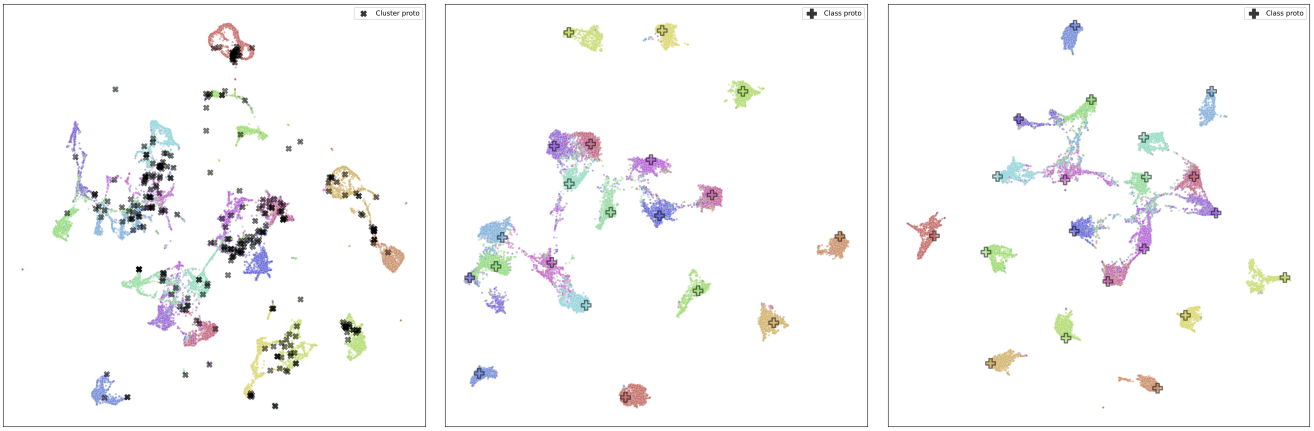
[1] see https://dl.fbaipublicfiles.com/dino/dino_deitsmall16_pretrain/args.txt



(a) SwAV / SwAV-linear (b) SwAV-finetuned (c) Suave

Figure 1. Latent space comparison via UMAP dimensionality reduction. This figure depicts the real-data counterpart of Figure 1 of the main paper. Twenty randomly picked classes are shown and coded by different colors. (a) shows the latent space shared by SwAV and SwAV-linear (which only trains a linear layer for the classification while keeping frozen all the rest of the network). In (a), we also show a random sample of 300 cluster prototypes marked by a red "X". (b) and (c) show the latent space of SwAV fully fine-tuned and Suave pre-trained and fine-tuned with 1% of the labels, respectively. Here, the class prototypes are marked by "+".

1.2. CIFAR100

For CIFAR100 we use a slightly different recipe with respect to ImageNet. First, we do not perform fine-tuning (neither supervised nor semi-supervised), as we found that it does not improve performance. Semi-supervised training is performed with unlabeled batch size 128 and labeled batch size 100 for 200 epochs. For both Suave and Daino, the backbone is initialized using weights obtained by unsupervised training of SwAV for 500 epochs on the same dataset. In addition, we use multi-crop with 4 local crops of size $(0.1, 0.6)$ and 2 global crops of size $(0.6, 1.0)$. Similarly to ImageNet, we use label smoothing with coefficient 0.01. The learning rate for LARS is set to 2.8 and a weight decay of $3 \cdot 10^{-6}$ is applied. The ϵ coefficients are set to 0.086 and 0.07 for Suave and Daino respectively. For both methods we also use a momentum encoder with momentum 0.99. We apply image mixing techniques as data augmentation as for ImageNet, with the only difference that we also mix local crops on CIFAR100. All the other hyperparameters are kept the same as described before.

2. Additional results

We present further comparisons with the state-of-the-art in Sec. 2.1 and show additional visualizations in Sec. 2.2.

2.1. Pre-training results

In Tab. 1 we report results on ImageNet-1k after semi-supervised pretraining (without fine-tuning) using the same classifier as the one that was trained during pre-training (PAWS uses a nearest-neighbor classifier, we use a linear classifier). The results clearly show that, despite a much smaller batch size, Suave is able to match or outperform PAWS, even without fine-tuning.

Table 1. Results without fine-tuning on ImageNet-1k.

Method	Epochs	Batch size		Acc@1	
		Unlab.	Lab.	10%	1%
PAWS-NN [1]	100	4096	6720	71.0	61.5
	200	4096	6720	71.9	63.2
	300	4096	6720	73.1	64.2
Suave	(100)100	256	128	71.9	62.2
	(200)100	256	128	72.7	63.1
	(800)100	256	128	73.4	64.1

2.2. Latent representations

In Fig. 1, we report the real-data counterpart of Figure 1 of the main paper, computed with UMAP [6]. The latent vectors are taken from the bottleneck layer (output of the projection head) of the models trained with 1% of the labels. All the models are initialized with SwAV pre-trained at 800 epochs. We observe a neat difference between (a), where classes are less isolated/separable, and (b-c), where, instead, classes are well separated. Moreover, by visually comparing (b) and (c), we notice a slightly better class separation obtained by Suave (c). However, we remark that the random classes shown may not highlight the difference of the models at best, as Suave outperforms SwAV-finetuned of $\sim$9%p.

References

[1] Mahmoud Assran, Mathilde Caron, Ishan Misra, Piotr Bojanowski, Armand Joulin, Nicolas Ballas, and Michael Rabbat. Semi-supervised learning of visual features by non-parametrically predicting view assignments with support samples. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021. 2

[2] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. *Advances in Neural Information Processing Systems*, 33:9912–9924, 2020. 1

[3] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9650–9660, 2021. 1

[4] Marco Cuturi. Sinkhorn distances: Lightspeed computation of optimal transport. *Advances in neural information processing systems*, 26, 2013. 1

[5] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2021. 1

[6] Leland McInnes, John Healy, and James Melville. Umap: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426*, 2018. 2

[7] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015. 1

[8] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 6023–6032, 2019. 1

[9] Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In *International Conference on Learning Representations*, 2018. 1