A Appendix

We provide in this supplementary file complementary 1-shot results of Table 1, and results for class splitting on the ImageNet benchmark. We also present a comparison of the chosen relabeling algorithms to K-means and finally give details about the MiniIN-6k dataset and the used MoCo features.

A.1 Results of using MiniIN-6k on different benchmark

We report in Table 2, complementary 1-shot results to the ones in table 1 on both miniImagenet and CUB datasets, using four different feature backbones. These results are consistent with the observations made on the impact of the base training data on the five shot accuracy.

		MiniIN			CUB		
	Base data / Algo.	MiniIN N=38400 $C=64$	MiniIN6K Random N=38400 $C=64$	MiniIN6K $N{\approx}7{,}1.10^6$ C=6000	CUB N=5885 $C=100$	MiniIN6K* Random N=38400 $C=64$	MiniIN6K* $N{\approx}6{,}8.10^6$ $C=5704$
WRN	CC	61.62±0.17	58.49±2.29	85.40±0.15	76.73±0.40	41.62±0.93	73.51±0.21
Conv4	CC	48.62±0.09	46.87±0.70	56.09±0.16	61.21±0.16	39.65±0.71	47.01±0.26
ResNet10	CC	59.06±0.35	56.06±1.74	74.42±0.20	74.48±0.42	40.92±0.51	57.81±0.43
ResNet18	CC	60.85±0.17	57.51±1.79	81.42±0.20	76.13±0.39	40.90±0.86	63.14±0.93

Table 2: One shot, 5-way accuracy on MiniIN and CUB using different base training data and backbones. CC: Cosine Classifier. WRN: Wide ResNet28-10. MiniIN6K Random: 600 images from 64 classes sampled randomly from MiniIN6K. We evaluate the variances over 3 different runs, each run compute the few-shot performance on 10k sampled episodes. MiniIN6K*: MiniIN6K without images from bird categories.

A.2 Class selection with similarity to test classes

Similarly to the Fig 3a, we show results of selecting closest or farthest classes to CUB test classes using different features in Fig 7. Similar observations can be drawn.

A.3 Number of classes and images trade-off on IN benchmark

Similarly to Fig 4, we show results of sampling datasets from IN6k of 500k or 50k images and with different number of classes. Using 50k images, we observe that there is an optimal trade-off between the number of classes and number of images. While for 500k, the optimal number of classes might be larger than the maximum possible using IN6k (i.e 6000)

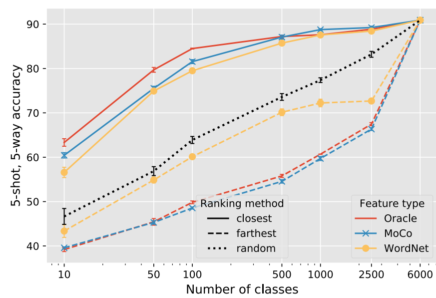


Fig. 7: Five-shot accuracy on CUB when sampling classes from miniIN-6K **closest/farthest** to the CUB test set or randomly.

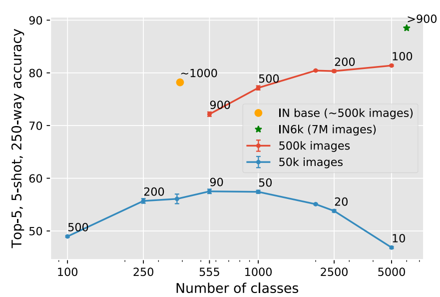


Fig. 8: Trade-off between the number of classes and images per class for a fixed image budget on the IN benchmark. Each point is annotated with its corresponding number of images per class.

In Table 3, we present results on the impact of splitting classes of the training dataset using oracle features on the ImageNet-1k high resolution benchmark as defined in [19]. Splitting classes improves the 5-shot performance by 2% and the 1-shot performance by barely 0.93% using ResNet-34.

	base	split 2	split 4	split 8	IN6k
1-shot	57.56±0.20	58.12±0.00	58.49±0.17	57.78±0.01	70.94±0.07
5-shot	78.15±0.23	79.13±0.03	80.10±0.15	80.30±0.07	88.50±0.05

Table 3: Top-5, 250-way few shot accuracy on the ImageNet-1k benchmark using the 389 base training classes - 497350 images (base), and split versions of this dataset into 2,4 and 8 splits and also using the large IN6k dataset (7135118 images). Results are averaged over 3 different runs.

A.4 Comparing splitting and grouping strategies to K-means

In Figure 9, we show how the used splitting and grouping methods compare to a simple K-means algorithm (leading to unbalanced clusters). We observe that the balanced class relabeling leads to a better performance than the K-means based relabeling, justifying our choice for the presented experiments. These results use oracle features to compute image features for class splitting.

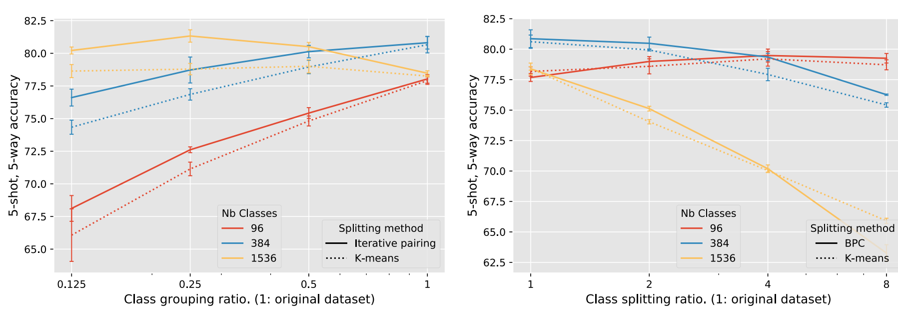


Fig. 9: Comparing our balanced splitting and grouping methods (Bisection along Principal Component for splitting classes, and Iterative pairing for grouping classes) to K-means on the MiniIN benchmark.

A.5 Details about MoCo features

We use the self-supervised features on ImageNet using a ResNet-50 backbone from [41][1] unofficial implementation of Momentum Contrast for unsupervised visual representation learning [20].

A.6 Details about miniIN6K

We created the ImageNet-6K dataset by sampling the largest 6000 classes from ImageNet-22K excluding the Imagenet-1K classes. Each class contains at least 900 images and a maximum of 2248 available images per class with a total of 7135116 images. We will share the list of images in the IN6K dataset.

A.7 Class sampling bias

In Fig. 10, we show the correlation between the distance to miniIN test classes of miniIN6k classes grouped into 10 bins of increasing class diversity or validation performance. We observe that most diverse classes are closest to miniIN test classes than least diverse ones.

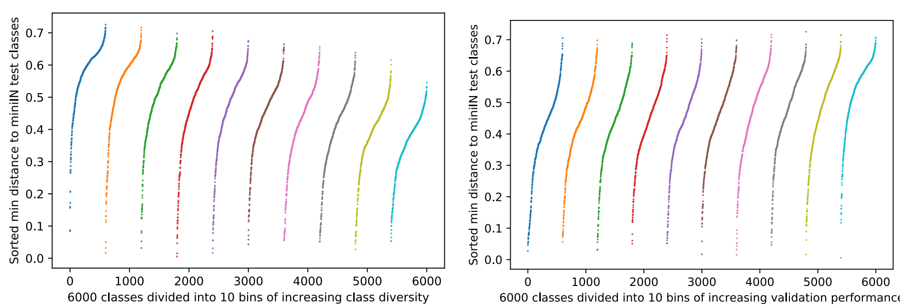


Fig. 10: Class similarity between miniIN6k classes and miniIN test classes. MiniIN6k classes (x-axis) are grouped in 10 bins of increasing class diversity or validation accuracy. We observe that class similarity to test classes correlates with both class diversity and class validation accuracy, thus the importance of avoiding this bias during class selection.

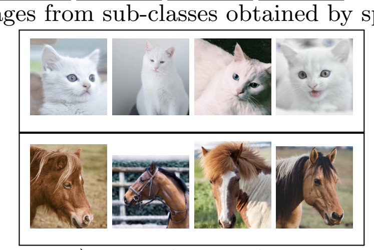
A.8 Class grouping and splitting

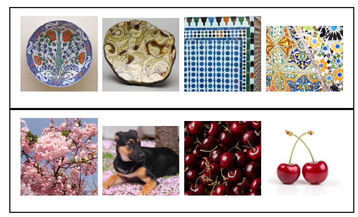
We display examples of resulting grouped and split classes.

[1] Moco features from https://github.com/HobbitLong/CMC/

(a) Images from meta-classes obtained by grouping four dataset classes.

(b) Images from sub-classes obtained by splitting classes "Sunflower" and "Tulips".





c) Least diverse classes (Horse, Angora cat ...)

d) Most diverse classes (Arabesque, cherry...)

Fig. 11: a) Images from **meta-classes obtained by grouping** dataset classes using pre-trained features. Each line represents a meta-class. b) Examples of **sub-classes obtained by splitting** dataset classes using pre-trained features. Each column represents a sub-class. c), d) Images from least or most diverse classes from miniIN6k, with one line per class.

A.9 Image credits of Figure 11

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