Diverse Imagenet Models Transfer Better

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Abstract

A commonly accepted hypothesis is that models with higher accuracy on ImageNet perform better on other downstream tasks, leading to much research dedicated to optimizing ImageNet accuracy. Recently this hypothesis has been challenged by evidence showing that self-supervised models transfer better than their supervised counterparts, despite their inferior ImageNet accuracy. This calls for identifying the additional factors, on top of ImageNet accuracy, that make models transferable. In this work we show that high diversity of the filters learnt by the model promotes transferability jointly with ImageNet accuracy. Encouraged by the recent transferability results of self-supervised models, we use a simple procedure to combine self-supervised and supervised pretraining and generate models with both high diversity and high accuracy, and as a result high transferability. We experiment with several architectures and multiple downstream tasks, including both single-label and multi-label classification.

1. Introduction

The success of Deep Neural Networks (DNNS) in a variety of computer vision tasks is largely related to their ability to transfer feature representations learned on a pre-trained task to leverage others. A common practice is to pre-train a model on a large-scale supervised dataset such as ImageNet [70] and fine-tune it on the downstream (target) dataset that is typically of a smaller scale. This practice has systematically advanced the state-of-the-art in tasks such as image classification [52, 66], object detection [53, 65] and semantic segmentation [34, 53]. The pursuit after better pre-trained models coincided with pushing the state-of-the-art performance on ImageNet, as it was shown that supervised pre-trained models that perform better on ImageNet tend to perform better when fine-tuned on other tasks [44].

Recent works demonstrate that self-supervised pre-training (SSL) without any label information can also learn effective representations from upstream data (e.g., ImageNet) and even surpass supervised methods when transferring to downstream tasks. This success in transfer learning, despite their relatively poor performance on ImageNet [13, 15, 31, 33, 83] calls for identifying the additional factors, on top of ImageNet accuracy, that make models transferable.

While supervised training focuses on class-level discrimination, SSL focuses on instance discrimination, and models are trained to keep variants of the same instance close together in the representation space, and sometimes also, separated from different instances. On the other hand, supervised models learn meaningful high-level semantic features that are shared between instances of the same class, while SSL might capture irrelevant low level visual features (e.g., related to instance background). Thus high ImageNet performance guarantees that the features learnt are semantically meaningful and SSL learns diverse features. Those features are extracted for an input image by applying a composition of filters on it, that are determined by the model’s structure and learnt weights. This observation is supported by recent work that combines both supervised and self-supervised losses to improve transferability [37, 40], yet those require intervention in the self-supervision stage and the transferability is attributed to other less important factors than filter diversity such as the abstraction of the representations learned (measured by Centered Kernel Alignment (CKA) [43] between layers) and intra-class variations.

Our contribution is two-fold: (1) We suggest Filter Diversity as a calibration for the ImageNet accuracy for assessing the transferability of models.

\[ \text{CIS} = \text{Imagenet Accuracy} \times \text{Filter Diversity} \]  

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As we empirically validate that Calibrated Imagenet Score (CIS) better correlates with trasferability, i.e. the averaged log odds [44] over many downstream tasks (see Figure 1).

(2) We use a simple scheme for a Controlled Label Injection (CLI), that enables the injection of label information into any self-supervised pre-trained model in a controlled manner, for generating models of different filter diversity and Imagenet accuracy. The resulted models increase ImageNet performance while either improving or maintaining filter diversity of the self-supervised model. This both allows us to make observations about the connection between the CIS and transferability, while at the same time this leads to models with higher transferability.

We validate our approach over both CNNs (ResNets [35]) and vision transformers (ViT [25]), several self-supervised pre-training methods (e.g., MoCo-v2 [14], SimCLR [13], SwA V [10], DINO [10] and MAE [32]), two formulations of Filter Diversity, several downstream vision tasks, including multi-label classification on the MS-COCO [51] dataset and a variety of 14 single-label classification datasets.

2. Related Work

2.1. Transfer learning

Transfer learning was shown to be highly effective in transferring knowledge from upstream (source) datasets to typically much smaller datasets given that their domains are similar [59], [36] searched for the properties that make a dataset a good choice for transfer learning. [44] showed that when it comes to supervised models, ImageNet accuracy score is highly correlated with performance over downstream tasks, confirming the common practice of selecting pre-trained models for transfer learning based on their Imagenet accuracy. We show that when self-supervised models are included, the correlation significantly drops, calling for improved measures for selection. The architecture and depth of CNNs were also shown to impact transfer performance [6]. The effects of the pre-training loss function were studied by [37,40,42], and the importance of projector heads design and data augmentation to control the trade-off between performance on the upstream task and transferability is shown by [71,79]. Improved Imagenet score might actually lead to worse transfer learning results when used as fixed feature extractor, while the choice of the loss has little effect when networks are fully fine-tuned on the new tasks as shown by [42]. A combination of contrastive and supervised learning was shown to improve transfer leaning performance [37,40], but the factors driving the performance are still not completely understood. Centered Kernel Alignment (CKA) [43] was utilized by [42] to show that differences among loss functions are apparent only in the last few layers of the network, and [37] further showed that contrastive models contain more low level and mid-level features in those layers. [28,37,42] connect this to intra-class variations, concluding that representations with higher class separation obtain higher accuracy on the upstream task, but their features are less useful for downstream tasks. In this work, we identify filter diversity as a more important factor that implies on the transferability of the model, even in the more practical use-case of fine-tuning the pretrained models on the downstream tasks. [62] quantifies transferability between a source model and a target dataset by class separation measures over the embeddings of the target images, while filter diversity introduced in this paper is an intrinsic property of the model that does not depend on the data.

2.2. Self-Supervised Learning

SSL is a subset of unsupervised learning, where neural networks are explicitly trained with automatically generated labels. In earlier works, labels were generated by diverse pre-text tasks such as prediction of rotation [41], colorization [85], patches positions [24] and others [38]. More recent methods can be roughly divided to contrastive methods [13,14,31,33] and clustering methods [2,10,50]. Notably, MoCo-v2 [14], SimCLR [13], SwA V [10] have shown a dramatic improvement in representation quality learned from unlabeled Imagenet images, surpassing the performance of modern supervised methods over various downstream tasks [27]. They also showed that while self-supervised features seems to discard color information, their attentive focus is higher compared to their supervised counterparts. This motivated the proposals of hybrid methods. [40] proposed a new contrastive loss to leverage the label information and [37] combined it with both contrastive and cross-entropy losses. However, it is yet unclear what self-supervised features should be maintained and how in order to improve resulting models’ transferability. In this work, we propose a measure that captures the diversity of the information encoded in different networks, and a simple method to inject supervised label information to a pre-trained SSL model, in a way that maintains this diversity in order to improve transfer learning performance.

2.3. Filter Diversity

It has been shown that a significant portion of filters extracted by DNNs are redundant [5,7,11,21,68]. By simply training on a low-rank decomposition of the weight matrices, [20] demonstrated that a fraction of the parameters is sufficient to reconstruct the entire network. [3] estimated the number of redundant filters in each layer, by hierarchically clustering those according to their relative cosine distances in filter space. [4,67] proposed regularizing correlated filters based on their relative cosine distances to yield a network with diverse filters, with less overfitting, and better generalization. [1,58] use determinantal point pro-
cesses to select a subset of diverse neurons or connections and subsequently fuse the redundant ones into the selected ones for the purpose of pruning. Differently from the aforementioned, which deal mainly with reducing overfitting and pruning, in this work we focus on the importance of learning diverse filters for the purpose of transfer learning.

3. Filter Diversity Measures

Previous work connected the transferability of a model to data-dependent measures, such as the abstraction of representations learnt for the upstream data and the variations in its embedding space [37, 42], the number of non-zero elements in the activations [42] and robustness to corrupted data [37]. Considering that transfer learning deals with different, sometimes unknown in advance, downstream tasks, we instead search for a connection to an intrinsic data-independent property of the model. Intuitively, the more diverse the information learnt by the pre-trained model is, the more likely this information can be utilized in transfer learning to a larger variety of downstream tasks. With this intuition, since the information learnt by the pre-trained model is encoded in its weights, we need a way to quantify the diversity of filters learnt by the pre-trained model.

We adapt two measures, illustrated in Figure 2, both of which view the weights of the various neural layers as vectors in a metric space. The measures quantify the scatter of those vectors in the filter space. We describe in more detail the first measure, which is based on clusterability properties of the filters. The second measure, based on spectral analysis of the filters distribution, is presented in more details in Appendix E for brevity. Empirical evaluation with both measures leads to similar conclusions and validates the importance of filter diversity for transferability (Figure 1).

3.1. Clustering Filter Diversity

The first measure we adapt to evaluate filter diversity is based on assessing the organization of the filters into clusters, and is inspired by [3]. Filters that are grouped together into tight clusters imply low diversity, while filters that are sparsely spread imply high diversity. We next extend this idea to measure the overall clusterability of a deep neural network’s filters across all of its layers.

Let $W = \{w_1, \ldots, w_n\} \in \mathbb{R}^{d \times n}$ be a weight matrix whose columns $\{w_i\}_{i=1}^n$ are its filters. We apply the agglomerative clustering approach of [23, 78], while adjusting it to fit our purpose. The clustering continues agglomeratively, merging two clusters $C_a$ and $C_b$ as long as their average mutual cosine similarity $S_C(C_a, C_b)$ [49, 57] crosses some threshold $\tau$:

$$S_C(C_a, C_b) = \sum_{(w_a, w_b) \in C_a \otimes C_b} \cos(w_a, w_b) \frac{1}{|C_a| \cdot |C_b|} \geq \tau \quad (2)$$

The cluster ratio between the number of clusters and the number of filters for a given threshold $\tau$ quantifies the resulted clusterability, as illustrated in Figure 2 (Left). Due to different neural layers of the same model learning different levels of abstractions, a single threshold $\tau$ value does not fit all. Hence, differently from [3], we evaluate the clusterability of the entire model by averaging the cluster ratio of all layers across a spectrum of threshold values. For the full technical details and illustrations see Appendix D.

3.2. Spectral Filter Diversity

Another way to evaluate the distribution of filters is suggested next, based on spectral analysis of the filter vectors. Principal component analysis (PCA) [29] is an effective approach for evaluating variance along principal directions in the filter space. Low diversity implies that the filter distribution can be captured by a small number of principal directions, while high diversity implies requiring many principal directions, as illustrated in Figure 2 (Right) while the technical details and exact calculations are provided in Appendix E for brevity. Table 1 shows that both measures of Filter Diversity improve the correlation of the Calibrated Imagenet Score with the transferability in both cases of linear probing and finetuning, while for the former the spectral version is favourable, and for the latter the clustering based...
The scheme has two stages. It starts with Self-supervised Learning (SSL). Then, we gradually introduce supervision by injecting label information into any self-supervised pre-trained model in a controlled manner, and through that increases ImageNet accuracy while at the same time either improving or maintaining filter diversity of the self-supervised model. We show empirically that this scheme leads to models with higher transferability.

Denote by $f_{W_B}$ and $g_{W_{FF}}$ the backbone model and the classification model on top of it, with weights $W_B$ and $W_{FF}$ respectively, such that $\hat{y} = g_{W_{FF}}(f_{W_B}(x))$ holds for an input sample $x$ and its predicted label $\hat{y}$. The backbone weights $W_B$ were trained by any self-supervised method and $W_{FF}$ is randomly initialized.

We fine-tune the weights by training with controlled supervision, according to Algorithm 1. Considering that the classifier for pre-training is to be replaced eventually, the backbone weights $W_B$ are updated once every $T$ updates of the classifier $W_{FF}$, thus the classifier is encouraged to undertake most of the classification burden, and only some of it is passed through to the backbone, whose weights change more slowly. While other valid implementation alternatives for CLI might result this desired effect, e.g., assigning a higher learning rate to the classifier, the chosen implemen-
tation is analysed empirically (Section 4.2) and shows to be effective (Section 5.2). Effectively, $T = 1$ is a standard fine-tuning and $T \to \infty$ is linear probing. Hence, the diversity is maintained for a large enough control cycle $T$, when starting from models of high filter diversity.

**Algorithm 1 Controlled Label Injection (CLI)**

**input** Self-supervised pretrained weights $W_B$.
Upstream train set $D_{train}$, Control cycle $T$

**Fine-tuning steps $T$, Learning rate $\eta$**
1: $W_{FF} \leftarrow$ RandomInit()
2: for $t = 1, \ldots, T$ do
3: Sample an i.i.d train batch $(x_t, y_t) \sim D_{train}$
4: $W_{FF} \leftarrow W_{FF} - \eta \nabla_{W_{FF}} \mathcal{L}_{CE}(g_{W_{FF}}(f_{W_{FF}}(x_t)), y_t)$
5: if $\text{mod}(t, T) == 0$ then
6: $W_B \leftarrow W_B - \eta \nabla_{W_B} \mathcal{L}_{CE}(g_{W_B}(f_{W_B}(x_t)), y_t)$
7: end if
8: end for

**output** $W_B$

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**Table 1.** The Spearman ($\rho$), Pearson ($r$), $R^2$ and Kendall-tau ($\tau$) correlation coefficients between transferability and standard or Calibrated ImageNet Score (CIS) computed with the proposed filter diversity measures. Both diversity based CIS measures show significantly higher correlation than the plain ImageNet accuracy, with an advantage to Spectral Filter Diversity for linear probing and to Clustering Filter Diversity for finetune.

|               | Linear Probing |          |          |          | Finetune |          |          |          |
|---------------|----------------|----------|----------|----------|----------|----------|----------|----------|
|               | $\rho$ | $r$ | $R^2$ | $\tau$ | $\rho$ | $r$ | $R^2$ | $\tau$ |
| ImageNet Score | 0.55 | 0.73 | 0.13 | 0.38 | 0.74 | 0.81 | 0.47 | 0.53 |
| Spectral CIS   | 0.91 | 0.89 | 0.74 | 0.75 | 0.89 | 0.83 | 0.56 | 0.72 |
| Cluster CIS    | 0.89 | 0.88 | 0.71 | 0.72 | 0.93 | 0.88 | 0.70 | 0.77 |

Figure 4. The CLI Scheme: control the injected label information to the backbone by updating it more/less frequently for less/more diverse pretrained SSL models respectively.

### 4.2. Empirical Analysis of the CLI Procedure

Figure 5 shows the impact of the control cycle. Starting from a SSL pretrained model of high filter diversity (SwAV), we apply Algorithm 1 with different control cycle values. At the left side we show the similarity between the learnt representations of the final model and: (i) the original SSL model, and (ii) a fully supervised model. The similarity is measured by the average Centered Kernel Alignment (CKA) [43] between all pairs of stages of two Resnet50 models. When the label injection is high (low control cycle $T$) the similarity to the initial SSL model is low and the similarity to a fully supervised model is high. Our experiments show that the best transferability is obtained when those similarities are similar. At the right side of the figure, we empirically validate that the proposed label injection scheme improves Imagenet accuracy while maintaining most of the filter diversity of the input SSL model (SwAV). This is true up to a certain tipping point ($T = 3$ in this case), where the transferability is the highest and right after the aggressive label injection ruins the initial filter diversity and thus the Calibrated Imagenet Score drops together with the transferability.

Figure 3 (Left) shows how the control label injection can start off from different SSL pre-trained models of both low (MoCo-v2) and high (SwAV) filter diversity and generate models of different levels of Imagenet accuracy and filter diversity for different control cycle values. Those generated models allow us to make observations about the connection between Imagenet Score and Filter Diversity to the transferability through the Calibrated Imagenet Score, as shown in Figure 1. The trajectory for every origin SSL model traverses the Calibrated Imagenet Score contour lines towards more transferable regions, as expressed by the circle’s size.

This is further shown for more SSL methods applied on CNN in Figure 6, where the connection between the control cycle, Filter Diversity, CIS and transferability is shown. Notably, SSL models of low filter diversity benefit from the maximal label injection, while the filter diversity of highly diverse models is to be maintained by strengthening label injection for increasing the Imagenet accuracy right up to the point where the diversity drops. Those control cycle values are aligned with the points of highest CIS and ultimately highest transferability. Besides, SSL method undergoing CLI, two supervised models are presented, the first is trained shortly for 200 epochs and the second is trained longer for 600 epochs. Longer supervised training increases both Imagenet accuracy and Filter Diversity.
5. Experimental Settings

5.1. Downstream Datasets

We evaluated models for multi-label image classification on the popular MS-COCO [51] dataset and another 14 single-label image classification datasets ranging in training set size from 1,020 to 80,800 images (20 to 5,000 images per class; Table 2). These datasets covered a wide range of image classification tasks, including superordinate-level object classification (CIFAR-10 [46], CIFAR-100 [46], Caltech-256 [30]); fine-grained object classification of different kinds (Food-101 [8], NABirds [75], Stanford Cars [45], FGVC Aircraft [56], OxfordIIIT Pets [63], Oxford Flowers-102 [61], Stanford Dogs [39], CUB-200 [77]); texture classification (DTD [16]); and scene classification (MIT indoor 67 [64], SUN397 [81]).

5.2. Comparison to Other Supervised and SSL Combining Methods

5.2.1 Improved Transferability for CNN

Tables 3 and 4 compare the transfer learning performance of Resnet50 pretrained models across 15 downstream tasks, specified in Table 2, and averaged following [44] (see Appendix A) for linear probing and finetuning respectively. The compared models include pure supervised and unsupervised (MoCo-v2, SwAV, SimCLR, DINO) learning, supervised constrastive learning (SupCon [40]), a pre-training combining supervised and self-supervised losses (CE+SelfSupCon [37]) and label injected models following Algorithm 1. The behaviour for linear probing and fine-tuning is similar. Specifically, certain label injected models transfer best. As SwAV and DINO benefit from high filter diversity (see Figure 3), once label injected to the point of high Calibrated Imagenet score (see Figure 6) it transfers better than all the rest both in terms of overall transferability score and for the most downstream datasets individually. Since MoCo-v2 and SimCLR have relatively low filter diversity (see Figure 3), those benefit from more label injection that increases both their Imagenet accuracy and filter diversity together, as shown in Figure 6. Indeed, those attain the best transferability at $T = 1$. Those observations call for further future research about the underlying mechanisms that make different SSL methods resulting in different levels of filter diversity, as discussed in section 7.
6. Feature Importance for Transfer Learning

In this section we empirically analyze the importance of different factors to transferability. We consider the calibrated Imagenet Score (CIS) and the previously suggested for the case of linear probing.

Table 2. Datasets examined in transfer learning

| Pretrain | ImNet | Animal | Bird | CUB | Caltech | Cas | DTD | Dog | Flowers | Food | Text | ImageNet |
|----------|-------|--------|------|-----|---------|-----|-----|-----|---------|------|------|----------|
| Supervised | 78.7 | 46.4 | 60.9 | 93.0 | 77.1 | 71.5 | 89.1 | 67.4 | 69.5 | 90.4 | 86.5 | 70.0 | 78.7 | 93.0 | 63.1 | 7.3 |
| SupCon [40] | 73.9 | 30.9 | 56.6 | 94.9 | 79.2 | 69.0 | 88.3 | 72.6 | 70.2 | 90.5 | 89.1 | 68.6 | 79.3 | 92.5 | 63.6 | 12.6 |
| CE + SelfSupCon [37] | 77.3 | 40.2 | 52.8 | 93.3 | 76.3 | 63.0 | 87.3 | 58.1 | 67.6 | 94.0 | 85.6 | 67.4 | 76.6 | 92.6 | 61.3 | 3.9 |
| MoCo-v2 | 61.9 | 30.9 | 38.9 | 93.4 | 76.4 | 53.8 | 83.5 | 59.3 | 69.7 | 68.0 | 85.3 | 68.5 | 76.0 | 84.6 | 60.6 | -31 |
| MoCo-v2 (T = 1) | 78.7 | 35.8 | 55.9 | 92.4 | 74.6 | 65.6 | 87.3 | 52.7 | 67.8 | 91.6 | 80.6 | 65.4 | 76.3 | 93.1 | 60.5 | -12.4 |
| MoCo-v2 (T = 4) | 76.0 | 41.3 | 57.3 | 92.2 | 74.4 | 66.2 | 87.0 | 57.0 | 66.9 | 87.5 | 83.5 | 67.2 | 76.9 | 91.9 | 60.8 | -11.8 |
| SwAV | 72.0 | 52.0 | 53.3 | 93.2 | 77.8 | 66.7 | 86.5 | 71.0 | 71.4 | 76.4 | 90.6 | 73.2 | 81.6 | 88.9 | 65.1 | 0.3 |
| SwAV (T = 1) | 79.2 | 44.0 | 62.8 | 93.3 | 77.4 | 71.2 | 89.2 | 64.2 | 70.7 | 91.1 | 86.6 | 70.2 | 80.1 | 93.3 | 63.5 | 8.9 |
| SwAV (T = 4) | 78.1 | 53.4 | 65.7 | 93.1 | 78.8 | 73.2 | 89.8 | 69.8 | 72.2 | 87.0 | 90.4 | 73.2 | 81.6 | 93.1 | 65.8 | 18.1 |
| DINO | 75.0 | 54.8 | 54.8 | 93.7 | 78.6 | 68.9 | 87.1 | 74.5 | 72.7 | 75.9 | 92.5 | 74.7 | 81.7 | 89.3 | 66.1 | 8.1 |
| DINO (T = 1) | 77.6 | 46.0 | 63.4 | 93.5 | 78.3 | 73.2 | 89.2 | 66.2 | 71.0 | 90.9 | 87.0 | 71.2 | 80.9 | 93.8 | 64.2 | 13.1 |
| DINO (T = 4) | 77.5 | 53.8 | 66.0 | 93.8 | 79.5 | 74.3 | 89.7 | 70.5 | 73.0 | 86.9 | 91.8 | 74.8 | 82.2 | 93.3 | 66.0 | 22.6 |
| SimCLR | 68.1 | 43.4 | 35.3 | 89.1 | 69.0 | 50.5 | 82.4 | 56.2 | 65.4 | 65.4 | 85.2 | 62.2 | 72.4 | 83.8 | 58.2 | -48.0 |
| SimCLR (T = 1) | 78.1 | 47.8 | 61.1 | 93.8 | 77.7 | 71.3 | 88.7 | 65.8 | 70.9 | 88.9 | 87.5 | 70.5 | 80.2 | 92.9 | 64.0 | 8.9 |
| SimCLR (T = 4) | 75.0 | 50.4 | 55.3 | 93.7 | 77.6 | 67.5 | 85.7 | 66.8 | 69.8 | 82.4 | 88.0 | 69.2 | 77.0 | 91.3 | 63.0 | -1.5 |

Table 3. Linear probing performance of different CNN models, including different levels of label injected models) fit on the downstream datasets in terms of top-1 accuracy (%) and the overall transferability score. The models are grouped by the underlying base SSL method. The best performance of each column appears in bold and the best in each group is underlined. Label injected models transfer best.

5.2.2 Improved Transferability for ViT

Similar results are shown for vision transformers (ViT) in Table 5 and Appendix L. Specifically, label injected ViT models obtain better transfer learning performance than their pure SSL counterparts. Notably, for all the SSL methods examined for ViT, the maximal label injection strength results in the best transferability. Interestingly, this is also true for DINO applied to ViT, when this is not true when applied to CNNs. This observation invites future research on the reasons why ViT tend to learn less diverse filters than CNNs when pre-trained with the same SSL method, see section 7 for a further discussion.
Table 4. Performance of different CNN models fine-tuned on the downstream datasets in terms of top-1 accuracy (%) (averaged over 3 runs) and the overall transferability score. The models are grouped by the underlying base SSL method. The best performance of each column appears in **bold** and the best in each group is *underlined*. Label injected models transfer best.

| Pretrain | ImageNet | Caltech | CIFAR10 | CIFAR100 | SIFT | SIFT-DT | Aircraft | CIFAR100 | Chairs | Flowers | Pets | Cars | Dogs | SUN | Transfer | COCO |
|----------|-----------|---------|---------|----------|------|--------|----------|----------|--------|---------|------|-----|------|-----|--------|-------|
| Supervised | 83.0 | 89.9 | 98.6 | 89.6 | 82.3 | 70.8 | 60.8 | 87.9 | 83.2 | 79.6 | 91.3 | 93.8 | 85.4 | **91.5** | 68.1 | -0.101 |
| MAE | 78.2 | 93.0 | 98.8 | 90.6 | 84.3 | 73.2 | 73.1 | **90.6** | **85.4** | **86.2** | 94.4 | **94.8** | 89.8 | 89.5 | 71.1 | 0.131 |
| MAE (T = 1) | 81.3 | 92.2 | 99.8 | 90.1 | 84.5 | 73.2 | 73.4 | 89.0 | 85.0 | 85.6 | 94.6 | 94.6 | 89.2 | 88.2 | 71.0 | 0.095 |
| MAE (T = 4) | 78.2 | 87.2 | 97.8 | 86.9 | 83.7 | 72.1 | **80.6** | 87.5 | 83.2 | 74.5 | **98.7** | 89.6 | **93.8** | 80.1 | 67.6 | -0.187 |
| DINO | 83.2 | **93.1** | **99.0** | **91.2** | 84.7 | 74.6 | 72.1 | 89.9 | **86.3** | 84.9 | 94.7 | 94.3 | 89.4 | 90.5 | **71.5** | **0.148** |
| DINO (T = 1) | 82.3 | 92.8 | 98.8 | 91.0 | **84.7** | **75.2** | 71.2 | 90.0 | 85.8 | 85.2 | 95.4 | 94.7 | 89.1 | 88.3 | 71.5 | 0.131 |
| DINO (T = 4) | 89.1 | **97.7** | 98.9 | 90.7 | 84.7 | 74.6 | 72.1 | 89.9 | 86.3 | 84.9 | 94.7 | 94.3 | 89.4 | 90.5 | **71.5** | **0.148** |

Table 5. Performance of different ViT models fine-tuned on the downstream datasets in terms of top-1 accuracy (%) and the overall transferability score. The models are grouped by the underlying base SSL method. The best performance of each column appears in **bold** and the best in each group is *underlined*. Label injected models transfer best.

7. Discussion and Future Work

While we showed that models with high diversity transfer better, a natural extension would be to better understand how and why some training methods produce higher diversity than others. Indeed [4] uses an explicit diversity regularization. We don’t expect a diversity regularization during training to work well since diversity encourages high complexity models. In comparison, standard regularization restrict model complexity as a balance to the models overparametrization. Indeed, there are many ways the network can increase the diversity metric with no real change to the model behavior. One such trivial way to increase the Spectral Filter Diversity is to scale each filter \( W_i = \frac{W_i}{\|W_i\|} \) and then insert \( \|W_i\| \) into subsequent BatchNorm. Similarly, Cluster Diversity is based on cosine similarity, which is scale agnostic, thus filters that are redundant, or close to zero can be set to orthogonal vectors with epsilon scale. We hope this paper motivates future work in ways to increase real filter diversity, and transferability.

8. Conclusions

In this paper, we analyse the importance of different properties of pre-trained models to their transferability. We identify the notion of filter diversity as one of the key factors for transferability, together with the performance on the upstream task. A simple fine-tuning procedure is used for improving the transferability of given self-supervised pre-trained models, by injecting controlled supervision to those, while maintaining their filter diversity and improving their performance on the upstream task. Our study holds for different popular architectures of CNNs and ViTs and self-supervised methods, two different formulations for capturing filter diversity and many downstream tasks of multi-label and single-label classification over more than 15 different datasets.
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