DisCo: Remedy Self-supervised Learning on Lightweight Models with Distilled Contrastive Learning

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Abstract

While Self-Supervised representation Learning (SSL) has received widespread attention from the community, recent researches argue that its performance will suffer a cliff fall when the model size decreases. Since current SSL methods mainly rely on contrastive learning to train the network, in this work, we propose a simple yet effective method termed Distilled Contrastive Learning (DisCo) to ease the issue. Specifically, we find the final inherent embedding of the mainstream SSL methods contains the most fruitful information, and propose to distill the final embedding to maximally transmit a teacher’s knowledge to a lightweight model by constraining the last embedding of the student to be consistent with that of the teacher. In addition, we find that there exists a phenomenon termed Distilling BottleNeck and propose to enlarge the embedding dimension to alleviate this problem. Since the MLP only exists during the SSL phase, our method does not introduce any extra parameter to lightweight models during the downstream task deployment. Experimental results demonstrate that our method surpasses the state-of-the-art on all lightweight models by a large margin. Particularly, when ResNet-101/ResNet-50 is used respectively as a teacher to teach EfficientNet-B0, the linear result of EfficientNet-B0 on ImageNet is improved by 22.1% and 19.7% respectively, which is very close to ResNet-101/ResNet-50 with much fewer parameters. Code is available at https://github.com/Yuting-Gao/DisCo-pytorch.

1. Introduction

Deep learning has achieved great success in computer vision tasks, including image classification, object detection,

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come the mainstream due to their superior results. These methods are constantly refreshing the SOTA results with relatively large networks, but are unsatisfactory on some lightweight models at the same time. For example, the number of parameters of MobileNet-v3-Large/ResNet-152 is 5.2M/57.4M [25, 22], and the corresponding linear evaluation top-1 accuracy on ImageNet [36] using MoCo-V2 [10] is 36.2%/74.1%. Compared to their fully supervised counterparts 75.2%/78.57%, the results of MobileNet-v3-Large is far from satisfying. Meanwhile in real scenarios, sometimes only lightweight models can be deployed due to the limited hardware resources. Therefore, improving the ability of self-supervised representation learning on small models is of great significance.

Knowledge distillation [24] is an effective way to transfer the knowledge learned by a large model (teacher) to a small model (student). Recently, some self-supervised representation learning methods use knowledge distillation to improve the efficacy of small models. SimCLR-V2 [9] uses logits in the fine-tuning stage to transfer the knowledge in a task-specific way. CompRess [1] and SEED [18] mimic the similarity score distribution between a teacher and a student model over a dynamically maintained queue. Though distillation is effective, two factors affect the result prominently, i.e., which knowledge is most needed by the student and how to deliver it. In this work, we propose new insights towards these two aspects.

In the current mainstream contrastive learning based SSL methods, a multi-layer perceptron (MLP) is added after the encoder to obtain a low-dimensional embedding. Training loss and the accuracy evaluation are both performed on this embedding. We thus hypothesize that this final embedding contains the most fruitful knowledge and should be regarded as the first choice for knowledge transfer. To achieve this, we propose a simple yet effective Distilled Contrastive Learning (DisCo) framework to transfer this knowledge from large models to lightweight models in the pre-training stage. Specifically, DisCo takes the MLP embedding obtained by the teacher as the knowledge and injects it into the student by constraining the corresponding embedding of the student to be consistent with that of the teacher using MSE loss. In addition, we find that a budgeted dimension of the hidden layer in the MLP of the student may cause a knowledge transmission bottleneck. We term this phenomenon as Distilling Bottleneck and present to enlarge the embedding dimension to alleviate this problem. This simple yet effective operation relates to the capability of model generalization in the setting of self-supervised learning from the Information Bottleneck [40] perspective. It is worth noting that our method only introduces a small number of additional parameters in the pre-training phase, but during the fine-tuning and deployment stage, there is no extra computational burden since the MLP layer is removed.

Experimental results demonstrate that DisCo can effectively transfer the knowledge from the teacher to the student, making the representations extracted by the student more generalized. Our approach is simple and incorporate it into existing contrastive based SSL methods can bring significant gains. Our contributions are summarized as follows:

- We propose a simple yet effective self-supervised distillation method to boost the representation abilities of lightweight models.
- We discover that there exists a phenomenon termed Distilling BottleNeck in the self-supervised distillation stage and propose to enlarge the embedding dimension to alleviate this problem.
- We achieve state-of-the-art SSL results on lightweight models. Particularly, the linear evaluation results of EfficientNet-B0 [38] on ImageNet is quite close to ResNet-101/ResNet-50, while the number of parameters of EfficientNet-B0 is only 9.4%/16.3% of ResNet-101/ResNet-50.

2. Related Work

2.1. Self-supervised Learning

Self-supervised learning (SSL) is a generic framework that learns high semantic patterns from the data itself without any tags from human beings. Current methods mainly rely on three paradigms, i.e., pretext tasks, contrastive based and clustering based.

Pretext tasks. Approaches based on pretext paradigm focus on designing more effective surrogate tasks, including Exampler-CNN [15] that identifies whether patches are cropped from the same image, Rotation [26] that predicts the rotation degree of the input image, Jigsaw [31] that places the shuffled patches back to the original position, and Context encoder [33] that recovers the missing part of the input image conditioned on its surrounding.

Contrastive based. Contrastive based approaches have shown impressive performance on self-supervised representation learning, which enforce different views of the same input to be closer in feature space [11, 9, 8, 23, 20, 10, 19, 41, 42, 45]. SimCLR [8, 9] indicates that self-supervised learning can be boosted by applying strong data augmentation, training with larger batch size of negative samples, and adding projection head (MLP) after the global average pooling. However, SimCLR relies on very large batch size to achieve comparable performance, and cannot be applied widely to many real-world scenarios. MoCo [20, 10] considers contrastive learning as a look-up dictionary, using a memory bank to maintain consistent representations of negative samples. Thus, MoCo can achieve superior performance without large batch size, which is more feasible to
implement. BYOL [19] introduces a predictor to one branch of the network to break the symmetry and avoid the trivial solution. DINO [6] applies contrastive learning to vision transformers.

**Clustering based.** Clustering is one of the most promising approaches for unsupervised representation learning. DeepCluster [3] uses k-means assignments to generate pseudo-labels to iteratively group the features and update the weight of the network. DeeperCluster [4] scales to large uncurated datasets to capture complementary statistics. Different from previous works, to maximize the mutual information between pseudo labels and input data, SeLa [2] cast the pseudo-label assignment as an instance of optimal transport. SwAV [5] formulates to map representations to prototype vectors, which is assigned online and is capable to scale to larger datasets.

Although the mainstream methods SimCLR-V2, MoCo-V2, BYOL and SwAV belong to different self-supervised categories, they have four things in common: 1) two views for one image, 2) two encoders for feature extraction, 3) two projection heads to map the representations into a lower dimension space, and 4) the two low-dimensional embeddings are regarded to be a pair of positive samples, which can be considered as a contrast process. However, all of these methods suffer a performance cliff fall on lightweight models, which is what we try to remedy in this work.

### 2.2. Knowledge Distillation

Knowledge distillation (KD) tries to transfer the knowledge from a larger teacher model to a smaller student model. According to the form of knowledge, it can be classified into three categories, logits-based, feature-based, and relation-based.

**Logits-based.** Logits refers to the output of the network classifier. KD [24] proposes to make the student mimic the logits of the teacher by minimizing the KL-divergence of the class distribution.

**Feature-based.** Feature-based methods directly transfer the knowledge from the intermediate layers of the teacher to student. FitNets [35] regards the intermediate representations learned by the teacher as hints and transfers the knowledge to a thinner and deeper student through minimizing the mean square error between the representations. AT [44] proposes to use the spatial attention of the teacher as the knowledge and let the student pay attention to the area that the teacher is concerned about. SemCKD [7] adaptively selects the more appropriate representation pairs of the teacher and student.

**Relation-based.** Relation-based approaches explore the relationship between data instead of the output of a single instance. RKD [32] transfers the mutual relationship of the input data within one batch with distance-wise and angle-wise distillation loss from the teacher to the student. IRG [29] proposes to use the relationship the graph to further express the relational knowledge.

### 2.3. SSL meets KD

Recently, some works combine self-supervised learning and knowledge distillation. CRD [39] introduces a contrastive loss to transfer pair-wise relationship across different modalities. SSKD [43] lets the student mimic transformed data and self-supervision tasks to transfer richer knowledge. The above-mentioned works take self-supervision as an auxiliary task to further boost the process of knowledge distillation under fully supervised setting. CompRes[1] and SEED [18] tried to employ knowledge distillation as a means to improve the self-supervised visual representation learning capability of small models, which utilize the negative sample queue in MoCo [20] to constrain the distribution of positive sample over negative samples of the student to be consistent with that of the teacher. However, CompRes and SEED heavily rely on MoCo framework, which means that a memory bank always has to be preserved during the distillation process. Our method also aims to boost the self-supervised representation learning ability on lightweight models by distilling, however, we do not restrict the self-supervised framework and are thus more flexible. Furthermore, our method surpass SEED with a large margin on all lightweight models under the same setting.

### 3. Method

In this section, we introduce the proposed Distilled Contrastive Learning (DisCo) framework on lightweight models. We first give some preliminaries on contrastive based SSL and then introduce the overall architecture of DisCo and how DisCo transfers the knowledge from the teacher to the student. Finally, we present how DisCo can be combined with the existing contrastive based SSL methods.

#### 3.1. Preliminary on Contrastive Learning Based SSL

Mainstream contrastive learning based SSL methods have four common characteristics.

**Two views:** one input image $x$ is transformed into two views $v$ and $v'$ by two drastic data augmentation operations.

**Two encoders:** two augmented views are input to two encoders of the same structure, one is a learnable base encoder $s(\cdot)$ and the other $m(\cdot)$ is updated according to the base encoder, either shared or momentum updated. The encoder here can use any network architecture, such as the commonly used ResNet. Given an input image, the extracted representation obtained from the last global average pooling of the encoder is denoted as $Z$, and its dimension is $D$. 
Figure 2. The framework of the proposed method DisCo. One image is first transformed into two views by two drastic data augmentation operations. In addition to the original contrastive SSL part, a self-supervised pre-trained teacher is introduced, and the final embeddings obtained by the learnable student and the frozen teacher are required to be consistent for each view. Repr. stands for representation.

**Projection head:** both encoders are followed by a small projection head \( p(\cdot) \) that maps the representation \( Z \) to a low-dimensional embedding \( E \), which contains several linear layers. This procedure can be formulated as \( E = p(Z) = W_n \cdot \cdots (\sigma(W_1)Z) \), where \( W \) is the weight parameter of the linear layer, \( n \) is the number of layers, which is greater than or equal to 1, and \( \sigma \) is the non-linear function ReLU.

The importance of the projection head has been addressed in SimCLR-V2 and MoCo-V2. Following MoCo-V2, the default configuration of the projection head is two linear layers, in which the first layer maintains the original feature dimension \( D \), and the second layer reduces the dimension to 128.

**Loss function:** after obtaining the final embeddings of these two views, they are regarded as a pair of positive samples to calculate the loss.

### 3.2. Overall Architecture

The framework of DisCo is shown in Figure 2, consisting of three encoders followed by the projection head. The **Student** \( s(\cdot) \) in center is the encoder that we want to improve, the **Mean Student** \( m(\cdot) \) is updated according to \( s(\cdot) \), and **Teacher** \( t(\cdot) \) is the self-supervised pre-trained large encoder that is used as teacher in distillation.

For each input image \( x \), it is first transformed into two views \( v \) and \( v' \) by two drastic data augmentation operations. On the one hand, \( v \) is input to \( s(\cdot) \) and \( t(\cdot) \), generating two representations \( Z_v = s(v), Z_t = t(v) \), then after the projection head, these two representations are mapped to low-dimensional embeddings, \( E_v = p_v(Z_v), E_t = p_t(Z_t) \) respectively. On the other hand, \( v' \) is input to \( s(\cdot) \), \( m(\cdot) \) and \( t(\cdot) \) simultaneously, after encoding and projecting, three low-dimensional vectors \( E'_v = p_v(s(v')) \), \( E'_m = p_m(m(v')) \), and \( E'_t = p_t(t(v')) \) are obtained.

\[ \mathcal{L}_{dis} = ||E_v - E_t||^2 + ||E'_v - E'_t||^2 \]  

(1)

To verify that the embedding \( E \) contains the most meaningful knowledge, we experiment with several other commonly used distillation schemes in Table 5. The results prove that the knowledge we transmitted and the way it is transferred are indeed the most effective.

**Distilling Bottleneck.** In our distillation experiment, we found an interesting phenomenon. When the encoder of the student is ResNet-18/34 and the default MLP configuration is adopted, that is, the dimension of embedding output by the encoder is projected from \( D \) to \( D \) and then to 128, the results of DisCo is not satisfactory. We assume that this degradation is caused by the fact that the dimension of the hidden layer in the MLP is too small, and term this phenomenon as **Distilling Bottleneck**. In Figure 3, we exhibit the default configuration of the projection head of ResNet-18/34, EfficientNet-B0/B1, MobileNet-v3-Large, and ResNet-50/101/152. It can be seen that the dimension of the hidden layer of ResNet-18/34 is too small compared to other networks.

To alleviate the Distilling Bottleneck problem, we expand the dimension of the hidden layer in MLP. It’s worth noting that this operation only introduces a small number of parameters at the self-supervised distillation stage, and the MLP will be directly discarded during fine-tuning and
deployment, which means no extra computational burden is brought. We experimentally verified that such a simple operation can bring significant gains in Table 4.

This operation can be explained from the Information Bottleneck (IB) [40] perspective. IB is utilized in [37, 12] to understand how deep networks work by visualizing mutual information \( I(X; T) \) and \( I(T; Y) \) in the information plane, where \( I(X; T) \) is the mutual information between input and output, and \( I(T; Y) \) is the mutual information between output and label. The training of deep networks can be described by two-phases: the first fitting phase, where the network memorizes the information of input, resulting in the growth of \( I(X; T) \) and \( I(T; Y) \); the subsequent compression phase, where the network removes irrelevant information of input for better generalization, resulting in the decrease of \( I(X; T) \). Generally, in the compression phase, \( I(X; T) \) can present the model’s capability of generalization while \( I(T; Y) \) can present the model’s capability of fitting label [12]. We visualize the compression phase of our model with different dimensions of the hidden layer in the pre-training distillation stage in the information plane on one downstream transferring classification task. The results in Figure 6 shows two interesting phenomenons:

i. Models with different dimensions of the hidden layer have very similar \( I(T; Y) \), suggesting that models have the nearly equal capability of fitting the labels.

ii. The Model with larger dimension in the hidden layer has smaller \( I(X; T) \), suggesting a stronger capability of generalization.

These phenomenons show that MLP indeed relates to the capability of model generalization in the setting of self-supervised transfer learning.

### 3.4. Overall Objective Function

The overall objective function is defined as follows:

\[
\mathcal{L} = \mathcal{L}_{\text{dis}} + \lambda \mathcal{L}_{\text{co}}
\]

where \( \mathcal{L}_{\text{dis}} \) comes from the distillation part, \( \mathcal{L}_{\text{co}} \) can be the contrastive loss of any SSL method, and \( \lambda \) is a hyperparameter that controls the weights of the distillation loss and contrastive loss. In our experiments, \( \lambda \) is set to 1. Due to the simplicity of implementation, we use MoCo-V2 as the testbed in the experiments without additional explanation.

### 4. Experiments

#### 4.1. Settings

**Dataset.** All the self-supervised pre-training experiments are conducted on ImageNet [36]. For downstream classification tasks, experiments are carried out on Cifar10 and Cifar100 [27]. For downstream detection tasks, experiments are conducted on PASCAL VOC [17] and MS-COCO [28], with train-val/test and train2017/val2017 for training/testing respectively. For downstream segmentation tasks, the proposed method is verified on MS-COCO.

**Teacher Encoders.** Four large encoders are used as teachers, ResNet-50(22.4M), ResNet-101(40.53M), ResNet-152(55.4M), and ResNet-50*2(55.5M), where X(Y) denotes that the encoder X has Y millions of parameters and the Y does not consider the linear layer.

**Student Encoders.** Five widely used small yet effective networks are used as student, EfficientNet-B0(4.0M), MobileNet-v3-Large(4.2M), EfficientNet-B1(6.4M), ResNet-18(10.7M) and ResNet-34(20.4M).

**Teacher Pre-training Setting.** ResNet-50/101/152 are pre-trained using MoCo-V2 with default hyper-parameters. Following SEED, ResNet-50 and ResNet-101 are trained for 200 epochs, and ResNet-152 is trained for 400 epochs. ResNet-50*2 is pre-trained by SwAV, which is an open-source model 1 and trained for 800 epochs.

**Self-supervised Distillation Setting.** The projection head of all the student networks has two linear layers, with the dimension being 2048 and 128. The configuration of the learning rate and optimizer is set the same as MoCo-V2, and without a specific statement, the model is trained for 200 epochs. During the distillation stage, the teacher is frozen.

**Student Fine-tuning Setting.** For linear evaluation on ImageNet, the student is fine-tuned for 100 epochs. Initial learning rate is 3 for EfficientNet-B0/EfficientNet-B1/MobileNet-v3-Large, and 30 for ResNet-18/34. For linear evaluation on Cifar10 and Cifar100, the initial learning rate is 3 and all the models are fine-tuned for 100 epochs. SGD is adopted as the optimizer and the learning rate is decreased by 10 at 60 and 80 epochs for linear evaluation. For downstream detection and segmentation tasks, following SEED [18], all parameters are fine-tuned. For the detection task on VOC, the initial learning rate is 0.1 with 200 warm-up iterations and decays by 10 at 18k, 22.2k steps. The detector is trained for 48k steps with a batch size of 32. Following SEED, the scales of images are randomly sampled from [400, 800] during the training and is 800 at the inference. For the detection and instance segmentation on COCO, the model is trained for 180k iterations with the initial learning rate 0.11, and the scales of images are randomly sampled from [600, 800] during the training.

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1https://github.com/facebookresearch/swav
4.2. Linear Evaluation

We conduct linear evaluation on ImageNet to validate the effectiveness of our method. As shown in Table 1, student models distilled by DisCo outperform the counterparts pre-trained by MoCo-V2 (Baseline) with a large margin. Besides, DisCo surpasses the state-of-the-art SEED over various student models with teacher ResNet-50/101/152 under the same setting, especially on MobileNet-v3-Large distilled by ResNet-50 with a difference of 9.2% at top-1 accuracy. When using R50*2 as the teacher, SEED distills 800 epochs while DisCo distills 200 epochs. Subscript in green represents the improvement compared to MoCo-V2 baseline.

Table 1. ImageNet test accuracy (%) using linear classification on different student architectures. ♦ denotes the teacher/student models are pre-trained with MoCo-V2, which is our implementation and † means the teacher is pre-trained by SwAV, which is an open-source model. When using R50*2 as the teacher, SEED distills 800 epochs while DisCo distills 200 epochs. Subscript in green represents the improvement compared to MoCo-V2 baseline.

| Method          | S        | T        | Eff-b0 | Eff-b1 | Mob-v3 | R-18 | R-34 |
|-----------------|----------|----------|--------|--------|--------|------|------|
|                 | T-1  | T-5  | T-1  | T-5  | T-1  | T-5  | T-1  | T-5  | T-1  | T-5  | T-1  | T-5  |
| Supervised      |        |        |       |       |       |      |      |      |      |      |      |      |
| MoCo-V2 (Baseline)♦ | 46.8  | 72.2  | 48.4  | 73.8  | 36.2  | 62.1  | 52.2  | 77.6  | 56.8  | 81.4  |        |      |
| SSL Distillation |        |        |       |       |       |      |      |      |      |      |      |      |
| SEED[18]        | R-50 (67.4) | 61.3  | 82.7  | 61.4  | 83.1  | 55.2  | 80.3  | 57.6  | 81.8  | 58.5  | 82.6  |        |      |
| DisCo (ours)    | R-50 (67.4) ♦ | 66.5  | 87.6  | 66.6  | 87.5  | 64.4  | 86.2  | 60.6  | 83.7  | 62.5  | 85.4  |        |      |
|                 | R-101 (70.3) † | 63.0  | 83.8  | 63.4  | 84.6  | 59.9  | 83.5  | 58.9  | 82.5  | 61.6  | 84.9  |        |      |
|               | R-101 (69.1) ♦ | 68.9  | 88.9  | 69.0  | 89.1  | 65.7  | 86.7  | 62.3  | 85.1  | 64.4  | 86.5  |        |      |
|                 | R-152 (74.2) † | 65.3  | 86.0  | 67.3  | 86.9  | 61.4  | 84.6  | 39.5  | 83.3  | 62.7  | 85.8  |        |      |
|               | R-152 (74.1) † | 67.8  | 87.0  | 73.1  | 91.2  | 63.7  | 84.9  | 65.5  | 86.7  | 68.1  | 88.6  |        |      |
|                 | R50*2 (77.3) † | 67.6  | 87.4  | 68.0  | 87.6  | 68.2  | 88.2  | 65.0  | 84.9  | 65.7  | 86.8  |        |      |
|               | R50*2 (77.3) † | 69.1  | 88.9  | 64.0  | 84.6  | 58.9  | 81.4  | 65.2  | 86.8  | 67.6  | 88.6  |        |      |

is very close to the teacher, while the number of parameters of EfficientNet-B0 is only 9.4%/16.3% of ResNet-101/ResNet-50.

4.3. Semi-supervised Linear Evaluation

Following SEED, we evaluate our method under the semi-supervised setting. Two 1% and 10% sampled subsets of ImageNet training data (~12.8 and ~128 images per class respectively) [8] are used for fine-tuning the student models. As is shown in Figure 4, student models distilled by DisCo outperform baseline under any amount of labeled data. Furthermore, DisCo also shows the consistency under different fractions of annotations, that is, students always benefit from larger models as teachers. More labels will be helpful to improve the final performance of the student model, which is expected.

Figure 4. ImageNet top-1 accuracy (%) of semi-supervised linear evaluation with 1%, 10% and 100% training data. Points where the number of teacher network parameters are 0 are the results of the MoCo-V2 without distillation.
Table 2. Object detection and instance segmentation results on VOC07 test and COCO val2017 with ResNet-34 as backbone. \(\dagger\) means our implementation. Subscript in green represents the improvement compared to MoCo-V2 baseline.

| S | T | Method     | Object Detection | Instance Segmentation |
|---|---|------------|------------------|----------------------|
|   |   |            | VOC              | COCO                 |
|   |   |            | \(AP^{bb}\) | \(AP^{mm}\) | \(AP^{bb}\) | \(AP^{mm}\) | \(AP^{bb}\) | \(AP^{mm}\) |
| ×  | - | MoCo-V2 [21] | 53.6 79.1 58.7 | 38.1 56.8 40.7 | 33.0 53.2 35.3 |
| R-50 | SEED [18] | 53.7 79.4 39.2 | 38.4 57.0 41.0 | 33.3 53.2 35.3 |
| R-34 | - | DisCo (ours) | 56.5 80.6 62.5 | 40.0 59.1 43.4 | 34.9 56.3 37.1 |
| R-101 | SEED [18] | 54.1 79.8 39.1 | 38.5 57.3 41.4 | 33.6 54.1 35.6 |
| R-152 | - | DisCo (ours) | 56.1 80.3 61.8 | 40.0 59.1 43.2 | 34.7 55.9 37.4 |
|      |   | (2.5\(\dagger\)) (2.3\(\dagger\)) (2.5\(\dagger\)) | (1.9\(\dagger\)) (2.3\(\dagger\)) (2.7\(\dagger\)) | (1.9\(\dagger\)) (3.1\(\dagger\)) (1.8\(\dagger\)) |

Figure 5. Top-1 accuracy of students transferred to Cifar100 without and with distillation from different teachers.

4.4. Transfer to Cifar10/Cifar100

In order to analyze the generalization of representations obtained by DisCo, we further conduct linear evaluation on Cifar10 and Cifar100 with ResNet-18/EfficientNet-B0 as student and ResNet-50/ResNet101/ResNet152 as a teacher. Since the image resolution of the Cifar dataset is 32 × 32, all the images are resized to 224 × 224 with bicubic resampling before feeding into the model, following [18]. The results are shown in Figure 5, it can be seen that the proposed DisCo surpasses the MoCo-V2 baseline by a large margin with different student and teacher architectures on and Cifar100. In addition, our method also has a significant improvement compared to SEED. It is worth noting that as the teacher becomes better, the improvement brought by DisCo is more obvious. The performance trend on Cifar10 is consistent with that on Cifar100, see section 2 in the supplementary material for details.

4.5. Transfer to Detection and Segmentation

We also conduct experiments on detection and segmentation tasks for generalization analysis. C4 based Faster R-CNN [34] are used for objection detection on VOC and Mask R-CNN [21] are used for objection detection and instance segmentation on COCO. The results are shown in Table 2. On object detection, our method can bring obvious improvement on both VOC and COCO datasets. Furthermore, as SEED [18] claimed, the improvement on COCO is relatively minor compared to VOC since COCO training dataset has 118k images while VOC has only 16.5k training images, thus, the gain brought by weight initialization is relatively small. On the instance segmentation task, DisCo also shows superiority.

4.6. Distilling BottleNeck Phenomenon

In the self-supervised distillation stage, we first tried to distill small models with default MLP configuration of MoCo-V2 using ResNet-50 as a teacher, and the results are shown in Table 3, denoted by DisCo\(*\). It is worth noting that the dimensions of the hidden layer in DisCo\(*\) are exactly as same as SEED. It can be seen that compared to SEED, DisCo\(*\) shows superior results on EfficientNet-B0, and MobileNet-v3-Large, and has comparable results on ResNet-18. Then we expand the dimension of the hidden layer in the MLP of the student to be consistent with that of the teacher, that is, 2048\(D\), it can be seen that the results can be further improved, which is recorded in the third row. In particular, this expansion operation brings 3.5% and 3.6% gains for ResNet-18 and ResNet-34 respectively.

Table 3. Linear evaluation top-1 accuracy (%) on ImageNet.

| Method | Eff-b0 | Mob-v3 | R-18 | R-34 |
|--------|--------|--------|------|------|
| SEED   | 61.3   | 55.2   | 57.6 | 58.5 |
| DisCo* | 66.5±0.9 | 64.4±0.6 | 60.6±3.5 | 62.5±3.6 |

Theoretical Analysis from IB perspective. In Figure 6, on the downstream Cifar10 classification task, we visualize the compression phase of ResNet-18/34 with different hidden dimensions distilled by the same teacher in the information plane. Following [12], we use binning strategy [30] to estimate mutual information. It can be seen that when we adjust the hidden dimension in the MLP of
ResNet-18 and ResNet-34 from 512D to 2048D, the value of $I(X;T)$ becomes smaller while $I(T;Y)$ is basically unchanged, which suggests that enlarging the hidden dimension can make the student model more generalized in the setting of self-supervised transfer learning.

Figure 6. Mutual information paths from transition points to convergence points in the compression phase of training. T denotes transition points, and C(X%) denotes convergent points with X% top-1 accuracy on Cifar10. Points with similar I(T;Y) but smaller I(X;T) are better generalized.

4.7. Ablation Study

In this section, we testify the effectiveness of two important modules in DisCo, i.e. the distillation loss and the expansion of the hidden dimension of MLP, and the results are shown in Table 4. It can be seen that distillation loss can bring about essential changes, and the result will be greatly improved. Even with only distillation loss, good results can be achieved. Furthermore, as the hidden dimension increases, the top-1 accuracy also increases, but when the dimension is already large, the growth trend will slow down.

Table 4. Linear evaluation top-1 accuracy (%) on ImageNet. MLP-d means the hidden dimension of MLP and - denotes the hidden layer of the MLP is directly removed.

| Loss $L_{co}$ | Loss $L_{dis}$ | MLP-d | Eff-b0 | Mob-v3 | R-18 |
|---------------|---------------|-------|--------|--------|------|
| Baseline      | 1280/1280/512 | 46.8  | 36.2   | 52.2   |      |
| Effectiveness of loss ✓ | ✓ | 1280/1280/512 | 65.6  | 58.9   | 54.5  |
| Effectiveness of MLP-d ✓ | ✓ | 1280/1280/512 | 65.6  | 63.7   | 57.1  |
| ✓ | ✓ | 512/512/512 | 62.5  | 62.8   | 57.1  |
| ✓ | ✓ | 1024/1024/1024 | 65.0  | 63.8   | 59.2  |
| ✓ | ✓ | 2048/2048/2048 | 66.5  | 64.4   | 60.6  |

4.8. Comparison against other Distillation

In order to verify the effectiveness of the proposed method, we compare with three widely used distillation schemes, namely, 1) Attention transfer denoted by AT [44], 2) Relational knowledge distillation denoted by RKD [32] 3) Knowledge distillation denoted by KD [24]. AT and RKD are feature-based and relation-based respectively, which can be utilized during the self-supervised pre-training stage. KD is a logits-based method, which can only be used at the supervised fine-tuning stage. The comparison results are shown in Table 5. Single-Knowledge means using one of these approaches individually, and it can be seen that all distillation approaches can bring improvement to the baseline but the gain from DisCo is the most significant, which indicates the knowledge that DisCo chosen to transfer and the way of transmission is indeed more effective. Then, we also try to transfer multi-knowledge from teacher to student by combining DisCo with other schemes. It can be seen that integrating DisCo with AT/RKD/KD can boost the performance a lot, which further proves the effectiveness of DisCo.

Table 5. Linear evaluation top-1 accuracy (%) on ImageNet compared with different distillation methods.

| Method                        | Eff-b0 | Eff-b1 | Mob-v3 | R-18 |
|-------------------------------|--------|--------|--------|------|
| Baseline                      |        |        |        |      |
| MoCo-V2                       | 46.8   | 48.4   | 36.2   | 52.2 |
| Single-Knowledge              |        |        |        |      |
| AT                            | 57.1   | 58.2   | 51.0   | 56.2 |
| RKD                           | 48.3   | 50.3   | 36.9   | 56.4 |
| KD                            | 46.5   | 48.5   | 37.3   | 51.5 |
| DisCo (ours)                  | 66.5   | 66.6   | 64.4   | 60.6 |
| Multi-Knowledge               |        |        |        |      |
| AT + DisCo                    | 66.7   | 66.3   | 64.1   | 60.0 |
| RKD + DisCo                   | 66.8   | 66.5   | 64.4   | 60.6 |
| KD + DisCo                    | 65.8   | 65.9   | 65.2   | 60.6 |

4.9. More SSL Methods

In order to demonstrate the versatility of our method, we further experiment with two SSL methods that are quite different from the MoCo-V2 baseline we used in the previous sections. i) SwAV is used to testify the compatibility towards the learning paradigm, in which the difference is measured between clusters instead of instances (see supplementary section 3); ii) DINO is used to testify the compatibility towards the backbone type, in which the encoder is a vision transformer instead of the commonly used CNN, as is shown in Table 6. It can be seen that DisCo is not limited to specific SSL methods, and can bring significant improvement under most of the popular SSL frameworks.

Table 6. Linear evaluation top-1 accuracy (%) on ImageNet with DINO as testbed. ViT-tiny[14] and XCiT-tiny[16] are pretrained by DINO for 100 epochs.

| Teacher Model | Acc | ViT-tiny | XCiT-tiny |
|---------------|-----|---------|----------|
| -             | -   | 63.2    | 67.0     |
| ViT-tiny[14]  | 77  | 68.4(5.2) | -        |
| XCiT-tiny[16] | 77.8| -       | 71.1(4.1) |

5. Conclusion

In this paper, we propose Distilled Contrastive Learning (DisCo) to remedy self-supervised learning on lightweight...
models. The proposed method constraints the final embedding of the lightweight student to be consistent with that of the teacher to maximally transmit the teacher’s knowledge. DisCo is not limited to specific contrastive learning methods and can remedy student performance by a large margin.

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