ABSTRACT

Recent masked image modeling (MIM) has received much attention in self-supervised learning (SSL), which requires the target model to recover the masked part of the input image. Although MIM-based pre-training methods achieve new state-of-the-art performance when transferred to many downstream tasks, the visualizations show that the learned representations are less separable, especially compared to those based on contrastive learning pre-training. This inspires us to think whether the linear separability of MIM pre-trained representation can be further improved, thereby improving the pre-training performance. Since MIM and contrastive learning tend to utilize different data augmentations and training strategies, combining these two pretext tasks is not trivial. In this work, we propose a novel and flexible pre-training framework, named MimCo, which combines MIM and contrastive learning through two-stage pre-training. Specifically, MimCo takes a pre-trained contrastive learning model as the teacher model and is pre-trained with two types of learning targets: patch-level and image-level reconstruction losses.

Extensive transfer experiments on downstream tasks demonstrate the superior performance of our MimCo pre-training framework. Taking ViT-S as an example, when using the pre-trained MoCov3-ViT-S as the teacher model, MimCo only needs 100 epochs of pre-training to achieve 82.53% top-1 finetuning accuracy on ImageNet-1K, which outperforms the state-of-the-art self-supervised learning counterparts.
CSCS CONCEPTS
• Computing methodologies → Image representations.

KEYWORDS
self-supervised learning, pre-training, contrastive learning, mask image modeling

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1 INTRODUCTION
With the development of deep neural networks [22] and transformers [38], masked language modeling (MLM) has achieved great success and emerged as an important self-supervised pre-training approach for language models in natural language processing (NLP). For instance, BERT [11] innovatively proposes to randomly mask a part of the input sequence and learn to predict or reconstruct these masked tokens, which has almost become the standard pre-training paradigm in NLP. Inspired by the success of MLM, recently, masked image modeling (MIM) has achieved fast development in visual pre-training tasks, showing the potential to be an important training paradigm for self-supervised learning in vision.

MIM is a task of randomly masking some patches of an input image and learning to reconstruct the masked patches. ViT [14] and BEiT [3] propose to perform MIM in self-supervised pre-training with vision transformer (ViT) [14]. BEiT first proposes to use a trained discrete variational autoencoder (dVAE) [33] to build a visual vocabulary, imitating the language vocabulary in NLP, which provides promising performance in visual pre-training. Following BEiT, very recently, several MIM literature have been proposed to further promote the self-supervised learning in vision. Some methods [19, 45] propose to directly regress the raw pixels of the masked patches in a simple and effective way. Other methods [13, 40, 47] turn to improve the semantic of visual tokens.

Although state-of-the-art MIM-based self-supervised learning methods achieve impressive performance when transferred to downstream tasks, they suffer from poor linear separability of learned representations, as shown in Figure 3. The linear separability of representations is highly correlated with transfer performance for tasks that require frozen features, such as image retrieval. It is not surprising that recent MIM-based pre-training work [45] has limited performance on these downstream tasks. In contrast, the learned representations are more linearly separable based on the contrastive learning pre-training paradigm, e.g., MoBY [43] and MoCov3 [9]. This motivates us to combine these two pre-training paradigms of MIM and contrastive learning and propose a new pre-training framework.

However, introducing contrastive learning into MIM is not trivial since MIM and contrastive learning tend to utilize different data augmentations and training strategies. In this work, we propose a novel and flexible pre-training framework, named MimCo. As show in Figure 1, MimCo is pre-trained in two stages. In the first stage, the contrastive teacher model is pre-trained based on contrastive learning methods, such as MoCov3 [9], MoBY [43], etc. In the second stage, MimCo is pre-trained with MIM, and the contrastive teacher model will not be updated, which is similar to the role of dVAE [33] in BEiT [3]. Through decoupling the MIM and contrastive learning paradigms, MimCo is more flexible and efficient during pre-training. First, MIM and contrastive learning are two different pre-training paradigms, differing vastly from data augmentations to training hyperparameters. Thus pre-training them individually is more convenient and flexible. Second, advances in contrastive learning based pre-training will benefit MimCo by simply replacing the contrastive teacher with a new and better model.

To take full advantage of the contrastive teacher model, we further propose two types of reconstruction losses. The first is the patch-level reconstruction loss. For the masked patches, we take the corresponding features of the contrastive teacher model as reconstruction targets. Compared to directly predicting the patch features [40], we propose to reconstruct the patch features through a contrastive loss, which performs better. The second is the image-level reconstruction loss, which reconstructs the overall features of the masked image. The image-level reconstruction, also implemented as a contrastive loss, helps improve the linear separability of learned representations, as shown in Table 9.

Overall, this work makes the following contributions:

- We propose a novel and flexible pre-training framework, named MimCo, which takes a contrastive learning pre-trained model as the teacher model. Compared with recent MIM pre-training methods, MimCo owns more separable representations and better transfer performances.
- To take full advantage of the contrastive teacher model, we propose two reconstruction losses, i.e., patch-level and image-level, which are experimentally verified to be effective.
- Extensive experiments on many downstream tasks, including classification, object detection, instance segmentation, and semantic segmentation demonstrate that our MimCo pre-training framework can achieve superior transfer performance against state-of-the-art methods.

2 RELATED WORK
During the booming of deep learning, recent years have witnessed remarkable progress of self-supervised learning (SSL) [12, 17, 27, 29, 30, 39, 46].

Contrastive Learning Pre-training. Recently, one line of research focus on contrastive learning [1] based pre-training methods, and plenty of literature [4, 7, 15, 18, 20, 37, 41, 43, 44] have been proposed, which dominate the previous self-supervised visual representation learning. These methods learn discriminative representation by attracting similar instances and dispelling dissimilar instances, based on two or multiple different augmented views of one image. For instance, SimCLR [7] proposes a simple framework to promote the performance of self-supervised learning by maximizing the mutual information between two augmented views of an image. MoCo [20] uses a momentum encoder to maintain consistent representations of negative pairs drawn from a memory bank, which enables building a large and consistent dictionary on-the-fly that facilitates contrastive unsupervised learning. BYOL [18] proposes a metric-learning manner, which uses a moving average
network to produce prediction targets as a means of stabilizing the bootstrap step. MoBY [43] proposes an elegant combination of MoCo [20] and BYOL [18], with a proper training recipe and lighter tricks, MoBY can achieve high performance. Our method takes the contrastive learning pre-trained model as the teacher model and aims to improve the performance of MIM pre-training.

**Masked Image Modeling Pre-training.** Masked language modeling (MLM) methods [11, 32] often mask some part of the input sequence and then train the models to model the missing portion. MLM methods have been a popular language model pre-training paradigm in NLP. Inspired by the great success of modern MLM methods in NLP, very recently, another line of research on self-supervised visual learning tends to masked image modeling (MIM). iGPT [6] trains a sequence Transformer [38] to auto-regressively predict the next pixels and learns state-of-the-art representations for low resolution datasets. ViT [14] proposes to predict mean color of each corrupted patch using their respective patch representations with ViT. BEiT [3] proposes to use a pre-trained discrete variational autoencoder (dVAE) [33], which can be seen as a offline tokenizer, to encode masked patches. Following BEiT [3], MAE [19] develops an asymmetric encoder-decoder architecture to reconstruct the normalized masked patches. SimMIM [45] proposes a simple framework to reconstruct the raw pixels. iBOT [47] performs masked image modeling via self-distillation by introducing an online tokenizer. PeCo [13] proposes to learn a perceptual codebook, which exhibits better semantic meanings of the visual tokens. MaskFeat [40] presents masked feature prediction with HOG [10] for self-supervised pre-training of video models. Our method is complementary to the MIM methods.

**Self-supervised Learning and Knowledge Distillation.** Knowledge distillation (KD) [2, 23] aims to distill knowledge from a well-trained model (teacher) to another model (student). Typical KD methods usually leverage the intermediate features or the output logits of a teacher model to supervise the training of a student model. Hinton et al. [23] first proposes to distill knowledge from teacher’s output logits into smaller student model. FitNets [34] extend this idea to distill the knowledge via minimizing the intermediate features learned by the teacher and the student model. Recently, some works introduce the KD methods into self-supervised learning [8, 16, 24, 28, 35, 28] proposes a knowledge transfer method to decouple the pre-training model and the final task model based on clustering the learned features. [35] proposes to use contrastive loss to learn cross-modality consistency. CompRes [24] compresses an already learned deep self-supervised teacher model into a smaller student model by mimicking the relative similarity of data points in the teacher’s embedding space. SEED [16] first trains a large network in a self-supervised fashion, and then trains a small network to mimic the similarity score distribution inferred by the large network over a set of instances. DINO [5] proposes to simplify self-supervised training by directly predicting the output of a teacher network, which is built with a momentum encoder. In this work, we propose to extract knowledge from pre-trained contrastive teacher models when performing MIM pre-training.

### 3 APPROACH

We inspire our method by improving the performance of MIM pre-training with the assistance of contrastive learning. Instead of combining MIM and contrastive learning via multi-task learning, we propose a novel two-stage pre-training framework that is more flexible and achieves higher performance. In this section, we elaborate the framework, learning targets, and implementation details of MimCo, respectively.

#### 3.1 Framework

MimCo is pre-trained in two-stages. In the first stage, we use contrastive learning methods, such as MoCoV3 [9], MoBY [43], etc., to pre-train on the ImageNet-1K dataset. The pre-trained model will be used as the contrastive teacher model in our MimCo pre-training, as shown in Figure 1. We refer readers to these works for more details, and in our experiments, we directly use the open-source models from these works.

As shown in Figure 1, MimCo mainly consists of a learnable encoder \( f \), a frozen contrastive teacher model \( f' \), and two sets of contrastive learning modules. During pre-training, for each training sample \( x \), we first randomly generate a mask \( m \) using the same masking strategy as in SimMIM [45]. Then, the contrastive teacher model takes as input the non-masked image and extracts features \( f'(x) \), while the learnable encoder extracts features \( f(x,m) \) for the masked image using the generated mask \( m \). The non-masked features \( f'(x) \) will be used as the targets to reconstruct the masked feature \( f(x,m) \) through patch-level and image-level reconstruction losses, which will be described in the next section. After pre-training, only the learnable encoder is applied to non-masked images to extract representations for downstream tasks.

#### 3.2 Learning Targets

In this section, we elaborate the learning targets of MimCo, including the patch-level and image-level reconstruction losses. Algorithm 1 provides the pseudo-code of MimCo for these learning targets.

**Patch-level Reconstruction Loss.** Similar to other MIM-based SSL work [19, 45], we reconstruct knowledge for those masked patches of input sample \( x \). MaskFeat [40] verifies that reconstructing the features of the pre-trained model via \( \ell_1 \)-loss is better than directly reconstructing the raw pixels or HOG features. Unlike MaskFeat, we experimentally find that reconstructing the features via contrastive loss is superior to \( \ell_1 \)-loss, as shown in Table 7. To be specific, we adopt a contrastive learning loss to model the similarity of the local patches between masked and non-masked images. Following MoBY [43], a projector \( p^p_2 \) (2 layer convolution), a predictor \( p^p_2 \) (2 layer convolution), and a momentum projector \( p^p_2 \) (2 layer convolution) are introduced when computing the contrastive loss, as shown in Figure 1. Formally, the patch-level reconstruction loss \( \mathcal{L}_{\text{patch}} \), can be computed as follows. For convenience, we show the \( \mathcal{L}_{\text{patch}} \) computed on one input sample \( x \).

\[
\mathcal{L}_{\text{patch}} = \frac{1}{M} \sum_{i=1}^{M} - \log \frac{\exp(q_i \cdot k_{i,i} / r)}{\sum_{j=1}^{K} \exp(q_i \cdot k_{i,j} / r)}
\]  
\[\text{(1)}\]
in which:
\[
\begin{align*}
q_i &= p^p_i(p^f_i(f(x, m))))_i, \\
k_{i,+} &= p^p_i(f(x)),
\end{align*}
\]
where \(M\) denotes the total number of masked patches of a sample \(x, m \in \mathbb{R}^{1 \times 3 \times H \times W}\) is the randomly generated mask applied to \(x\).
\(\{p^p_i(p^f_i(f(x, m))), p^p_i(f(x))\} \in \mathbb{R}^{C \times H \times W}\) are the output features of the predictor \(p^p_i\) and momentum predictor \(p^p_i\), respectively. \(P\) denotes the patch size in ViTs and should take the stride value into consideration in Swins, which has downsampling operations. \(q_i, k_{i,+}\) are the feature vectors corresponding to \(i\)th masked patch from the learnable encoder and frozen teacher model, respectively. \(k_j\) is the \(j\)th feature vector in the key queue. \(K\) is the length of the key queue (4096 by default). \(\tau\) is a temperature term (0.2 by default).
Since patch features are very redundant, for image \(x\), we instead put the average feature of all patch features of the teacher model into the key queue.

**Image-level Reconstruction Loss.** As compensation for the patch-level reconstruction loss, which only focuses on local patch reconstruction, the image-level reconstruction loss here focuses on reconstruction from the global view. We adopt a contrastive loss to encourage the global features between masked and non-masked images to be as similar as possible. The difference from other contrastive learning-based SSL works [9, 43] is that instead of taking two views of a sample as a positive pair, we take the non-masked view \(x\) and the masked view \((x, m)\) as a positive pair. For convenience, we denote the projector, predictor, and momentum projector as \(p^p_1, p^p_2\), and \(p^p_3\), respectively, which are all 2 layer MLP.

The image-level reconstruction loss \(L_{image}\) is computed as:
\[
L_{image} = -\log \frac{\exp(q \cdot k_+ / \tau)}{\exp(q \cdot k_+ / \tau) + \sum_{i=1}^K \exp(q \cdot k_i / \tau)},
\]
in which:
\[
\begin{align*}
q &= p^p_2(p^f_1(f(x, m))), \\
k_+ &= p^p_3(f(x)),
\end{align*}
\]
where \(q, k_+, k_i\) are all 1-D feature vectors. \(k_i\) is the feature of un-masked images in the key queue. \(K\) is the length of the key queue (4096 by default). \(\tau\) is a temperature term (0.2 by default).

### 3.3 Implementation

**Architecture.** We use the Vision Transformers [14] and Swin Transformers [25] as the backbone. For ViTs, we conduct experiments on ViT-S and ViT-B with patch size set to 16. For Swins, we conduct experiments on Swin-T and Swin-B with patch size set to 4 and window size set to 7.

**Pre-training Setup.** We by default pre-train MimCo on ImageNet-1K training set with AdamW [26] optimizer and a batch size of 2048. For ViT-S and ViT-B, we use the MoCoV3 [9] pre-trained models as the contrastive teacher models. For Swin-T and Swin-B, we use the MoBY [43] pre-trained models as the contrastive teacher models. If not specified, we pre-train all architectures with 100 epochs. The learning rate is linearly warmed up during the first 10 epochs to its base value scaled with the total batch size: \(lr = 10^{-3} \times \text{batch size} / 512\), and the weight decay is 0.05. A light data augmentation strategy is used: random resize cropping with scale range of [0.67, 1] and a aspect ratio range of [3/4, 4/3], followed by a random flipping and a color normalization steps. Following SimMIM [45], the default masking strategy of MimCo is: a random masking strategy with a patch size of 32×32 and a mask ratio of 60%.

### 4 EXPERIMENTS

We first transfer MimCo to downstream tasks, following the standard evaluation protocols adopted in prior arts. For the classification task on ImageNet-1K, we evaluate the quality of MimCo pre-training with Swin-T, Swin-B, ViT-S and ViT-B as backbones. For other dense tasks, including instance detection and segmentation on MS-COCO, semantic segmentation on ADE20K, we use Swin-T as the backbone to evaluate the transfer performance of MimCo pre-training. We then give a brief ablation study on the crucial composition of MimCo.

#### 4.1 Transferring Performance on Downstream Tasks

**Classification on ImageNet-1K.** Previous work [19, 45] have shown that the accuracy of linear probing is not always consistent with that of finetuning, especially for MIM-based pretraining methods. In this work, we directly study the finetuning accuracy.
Table 1: Finetuning accuracy on ImageNet-1K. Sup. denotes the supervised baselines. † denotes using multi-crop augmentation. ‡ denotes our pre-training results using official code.

| Method         | Arch.     | Extra model          | Pre-train Epochs | Effective Epochs | Top-1 acc (%) |
|----------------|-----------|----------------------|-------------------|------------------|---------------|
| Sup. [25]      | Swin-T    |                      | 800               | 800              | 81.2          |
| SimMIM [45]    | Swin-T    |                      | 300               | 600              | 81.4          |
| MoBY [43]      |           | MoBY-Swin-T-300e     | 100               | 700              | 81.7          |
| MimCo (Ours)   |           | MoBY-Swin-T-300e     | 300               | 900              | 81.9          |
| Sup. [25]      | Swin-B    |                      |                   |                  | 83.5          |
| SimMIM [45]    | Swin-B    |                      | 100               | 100              | 83.5          |
| SimMIM [45]    |           |                      | 800               | 800              | 84.0          |
| MoBY [43]      |           | MoBY-Swin-B-300e     | 300               | 600              | 83.1†         |
| MimCo (Ours)   |           | MoBY-Swin-B-300e     | 100               | 700              | 84.0          |
| MimCo (Ours)   |           | MoBY-Swin-B-300e     | 300               | 900              | 84.3          |
| Sup. [36]      | ViT-S/16  | dVAE                 | 800               | 800              | 79.9          |
| BEiT [3]       |           |                      | 800               | 3200             | 81.4          |
| DINo [5]       |           |                      | 800               | 3200             | 82.0†         |
| iBOT [47]      |           |                      | 300               | 600              | 81.4          |
| iBOT [47]      |           |                      | 100               | 700              | 82.5          |
| MimCo (Ours)   |           | MoCov3-ViT-S/16-300e | 300               | 900              | 82.7          |
| Sup. [36]      | ViT-B/16  |                      | 800               | 800              | 81.8          |
| BEiT [3]       |           |                      | 800               | 1600             | 83.2          |
| DINo [5]       |           |                      | 400               | 1600             | 83.6†         |
| MAE [19]       |           |                      | 1600              | 1600             | 83.6          |
| SimMIM [45]    |           |                      | 800               | 800              | 83.8          |
| MoCov3 [9]     |           |                      | 400               | 1600             | 83.8†         |
| MimCo (Ours)   |           | MoCov3-ViT-B/16-300e | 300               | 600              | 83.2          |
| MimCo (Ours)   |           | MoCov3-ViT-B/16-300e | 100               | 700              | 83.7          |
| MimCo (Ours)   |           | MoCov3-ViT-B/16-300e | 300               | 900              | 83.9          |

As shown in Table 1, when pre-trained with 100 epochs, MimCo achieves top-1 accuracies of 81.7%, 84.0%, 82.5%, and 83.7% with Swin-T, Swin-B, ViT-S/16, and ViT-B/16, respectively, outperforming the contrastive teacher models and performing on par with state-of-the-art methods. When pre-trained with 300 epochs, MimCo achieves top-1 accuracies of 81.9%, 84.3%, 82.7%, and 83.9% with Swin-T, Swin-B, ViT-S/16, and ViT-B/16, respectively, reaching new state-of-the-art results.

Due to different training strategies, different methods with the same pre-training epochs actually see different total numbers of images. For fair comparison of pre-training efficiency, we follow iBOT [47] and use effective pre-training epochs, defined as actual pre-training epochs multiplied with a scaling factor accounting for
extra trained images. Taking ViT-S as the encoder, as shown in Figure 2, our MimCo achieves a better balance between transfer performance and effective pre-training epochs compared to other pre-training methods.

Object Detection and Instance Segmentation. Mask R-CNN [21] is adopted in the evaluation, following the implementation of [25]. Table 2 shows a comparison of the learned representations of MimCo and other counterparts. MimCo pre-trained with 100 epochs achieves 43.9% AP and 40.1% AP on object detection and instance segmentation, respectively, outperforming sup. and MoBY [43] pre-training. When pre-trained with 300 epochs, the AP for object detection and instance segmentation are further improved to 44.9% and 40.7%, respectively.

Table 2: Results of object detection and instance segmentation finetuned 12 epochs on MS-COCO dataset. We use Mask R-CNN framework with Swin-T as the backbone. * denotes our training result using the official code.

| Method      | Pre-train Epochs | mAPbbox (%) | mAPmask (%) |
|-------------|------------------|-------------|-------------|
| Sup. [25]   | 100              | 41.6*       | 38.4*       |
| Sup. [25]   | 300              | 43.7        | 39.8        |
| MoBY [43]   | 100              | 41.5        | 38.3        |
| MoBY [43]   | 300              | 43.6        | 39.6        |
| MimCo (Ours)| 100              | 43.9        | 40.1        |
| MimCo (Ours)| 300              | 44.9        | 40.7        |

Semantic Segmentation. The UPerNet [42] segmentation approach and the ADE20K dataset are adopted in the evaluation, following MoBY [43]. Table 3 shows the comparison of MimCo and other pre-training methods on this evaluation. When pre-trained with 300 epochs, MimCo achieve an mIoU of 45.40%, outperforming supervised and other self-supervised pre-training methods.

Table 3: Transfer performance comparison of ADE20K semantic segmentation. All models are fine-tuned for 160K iterations on the ADE20K dataset, with Swin-T and ViT-B/16 as the backbone and UperNet as the segmentation framework.

| Backbone | Method      | Pre-train Epochs | mIoU (%) |
|----------|-------------|------------------|----------|
| Swin-T   | Sup. [25]   | 800              | 44.51    |
|          | SimMIM [45] | 800              | 40.47    |
|          | MoBY [43]   | 300              | 44.06    |
|          | MimCo (Ours)| 100              | 44.44    |
|          | MimCo (Ours)| 300              | 45.40    |
| ViT-B/16 | Sup. [25]   | 800              | 46.6     |
|          | BEiT [3]    | 800              | 45.8     |
|          | MAE [19]    | 1600             | 48.1     |
|          | MimCo (Ours)| 300              | 48.91    |

Nearest Neighbor Retrieval. As shown in Figure 3, we visualize the learned features of pre-trained models using T-SNE tools. We randomly choose 10 classes of ImageNet-1K dataset to visualize for simplicity, the visualization of learned representation shows that our MimCo significantly improves the linear separability of representations compared to SimMIM [45] and MAE [19]. We further evaluate MimCo on the nearest neighbor retrieval task, which is highly correlated with the linear separability of learned representations. We consider the revisited [31] Oxford and Paris image retrieval datasets. They contain 3 different splits of gradual difficulty with query/database pairs. We report the Mean Average Precision (mAP) for the Medium (M) and Hard (H) splits. We compare MimCo with SimMIM [45] following the evaluation protocol as in DINO [5]. As reported in Table 4, MimCo achieves significantly better performance on this task, further validating that the linear separability of the learned representation is improved.

Table 4: Effect of pre-trained features on nearest neighbor retrieval when using Swin-T as the backbone. The model weights of SimMIM is from our pre-trained model based on the official released code.

| Method     | Pre-train Epochs | ROx | RPar |
|------------|------------------|-----|------|
|            |                  | M   | H   | M   | H   |
| SimMIM [45]| 800              | 4.23| 1.53| 8.06| 3.13|
| MimCo (Ours)| 100             | **30.16**| 7.91| 50.82| 21.31|
| MimCo (Ours)| 300             | 28.73| 7.81| **51.51**| **22.14**|

4.2 Ablation Study

Unless otherwise specified, all ablation experiments are pre-trained for 100 epochs on ImageNet-1K dataset with Swin-T as the backbone.

Mask Ratio. For pre-training, we follow the masking strategy in SimMIM [45] by default, which uses a patch size of 32×32 and a mask ratio of 60%. Considering that this masking strategy may not be suitable for our MimCo framework, we study how masking strategy affect the effectiveness of pre-training. We mainly analysis
the effect of mask ratio and report the finetuning accuracy on ImageNet-1K in Table 5. We empirically find that the mask ratio of 60% performs better, and we use it for all other experiments.

Table 5: Effect of mask ratio in our pre-training framework. The patch size is fixed to 32×32. All experiments are performed with Swin-T as the backbone.

| Mask ratio | Top-1 acc (%) |
|------------|---------------|
| 50%        | 81.56         |
| 60%        | **81.66**     |
| 70%        | 81.54         |

Finetuning Recipes on ImageNet-1K. Following the practice of previous work, we search several critical parameters (mainly the drop path rate and layer-wise learning rate decay) for the best finetuning performance. The ablation results are reported in Table 6.

Table 6: Different finetuning recipes on ImageNet-1K. "L.D." denotes layer-wise learning rate decay, "D.P.R." denotes drop path rate.

| Arch. | Pre-train Epochs | D.P.R. | L.D. | Top-1 acc (%) |
|-------|------------------|--------|------|---------------|
| Swin-T | 100              | 0.2    | 0.75 | 80.94         |
|        |                   | 0.1    | 0.65 | 81.58         |
|        |                   | 0.1    | 0.75 | **81.66**     |
|        |                   | 0.1    | 0.85 | 81.61         |
|        | 0.15              | 0.75   |      | 83.79         |
|        | 0.20              | 0.75   |      | 83.88         |
|        | 0.25              | 0.75   |      | 83.80         |
|        | 0.20              | 0.80   |      | **84.04**     |
|        | 0.20              | 0.85   |      | 83.94         |
| Swin-B | 100              | 0.2    | 0.75 | 82.28         |
|        |                   | 0.1    | 0.65 | 82.34         |
|        |                   | 0.1    | 0.75 | **82.53**     |
|        |                   | 0.1    | 0.85 | 82.49         |
|        | 0.2               | 0.75   |      | 83.86         |
|        | 0.1               | 0.65   |      | **83.89**     |
|        | 0.1               | 0.7    |      | 83.64         |
|        | 0.1               | 0.75   |      | 83.65         |
| VIT-S  | 100              | 0.2    | 0.75 | 83.86         |
|        |                   | 0.1    | 0.65 | **83.89**     |
|        |                   | 0.1    | 0.7  | 83.64         |
|        |                   | 0.1    | 0.75 | 83.65         |
| VIT-B  | 300              | 0.2    | 0.65 | 83.86         |
|        |                   | 0.1    | 0.65 | **83.89**     |
|        |                   | 0.1    | 0.7  | 83.64         |
|        |                   | 0.1    | 0.75 | 83.65         |

Reconstruction Losses. We first compare our patch-level reconstruction loss with existing work, and then we further experimentally verify the effectiveness of introducing additional image-level reconstruction loss. MaskFeat [40] verifies that reconstructing the features of the pre-trained model with \(\ell_1\)-loss outperforms reconstructing other targets, including RGB values and HOG features, so we directly compare with the \(\ell_1\)-loss feature reconstructions. As shown in Table 7, the accuracy of patch reconstruction using contrastive loss reaches 81.55%, outperforming 81.35% of reconstructing patch features with \(\ell_1\)-loss.

To reveal the importance of additional image-level reconstruction loss \(L_{image}\) (defined in Equation 3), we conduct factor-by-factor experiments in this section. As shown in Table 8, loss \(L_{patch}\) and loss \(L_{image}\) achieve 81.55% and 81.59% top-1 accuracies, respectively, outperforming the supervised pre-training of 81.2% and the MoBY teacher model of 81.40%. When using both losses, MimCo achieves the best results of 81.66% top-1 accuracy.

Table 7: Comparison of losses for reconstructing teacher model features at patch-level. All experiments are pre-trained for 100 epochs and use Swin-T as the backbone.

| Patch reconstruction loss | Extra model | Top-1 acc (%) |
|---------------------------|-------------|---------------|
| \(\ell_1\) loss [40]     | MoBY-Swin-T-300e | 81.35         |
| Contrastive loss (ours)  |             | **81.55**     |

Table 8: Ablation experiments on the patch- and image-level reconstruction loss terms of MimCo. Image classification results finetuned on ImageNet-1K are reported. All experiments are pre-trained for 100 epochs and use Swin-T as the backbone.

| Reconstruction losses | ImageNet-1K Top-1 (%) |
|-----------------------|-----------------------|
| ✓                     | 81.55                 |
| ✓                     | 81.59                 |
| ✓ ✓                   | 81.66                 |

Table 9: Ablation experiments on the patch- and image-level reconstruction loss terms of MimCo. The results on the revisited Oxford and Paris image retrieval datasets are reported. All experiments are pre-trained for 100 epochs and use Swin-T as the backbone.

| Reconstruction losses | Image Retrieval |
|-----------------------|-----------------|
| \(L_{patch}\)        | \(L_{image}\)  |
| ✓                     | ROx M  | H  | RPar M | H   |
| ✓                     | 22.46  | 5.5 | 39.16  | 14.55 |
| ✓ ✓                   | 31.58  | 9.04 | 53.26  | 24.07 |
| ✓ ✓ ✓                 | 30.16  | 7.91 | 50.82  | 21.31 |

Comparison with Multi-task Learning. A simple solution to combine contrastive learning and MIM is through multi-task learning. We use "SimMIM + MoBY" to represent combining two pre-training methods of SimMIM [45] and MoBY [43] through multi-task learning. As shown in Table 10, our MimCo achieves higher performance than the naive multi-task learning method under the same effective pre-training epoch.

Remove Mask Operation. To investigate whether MIM plays an important role in our pre-training framework, we try to remove...
Table 10: Comparison with multi-tasking learning approach. All models take Swin-T as the backbone and are finetuned for 100 epochs on the ImageNet-1K dataset.

| Method             | Extra model  | Pre-train Epochs | Effective Epochs | Top-1 acc (%) |
|--------------------|--------------|------------------|------------------|---------------|
| SimMIM + MoBY      | -            | 100              | 300              | 81.06         |
| SimMIM + MoBY      | -            | 300              | 900              | 81.29         |
| MimCo (Ours)       | MoBY-Swin-T-300e | 100          | 700              | 81.66         |
| MimCo (Ours)       | MoBY-Swin-T-300e | 300          | 900              | 81.86         |

Table 11: Effect of masking input in our pre-training framework. All experiments are performed with Swin-T as the backbone.

| Masking image input | Top-1 acc (%) |
|---------------------|---------------|
| ✓                   | 81.23         |
|                     | 81.66         |

The masking operation. In fact, our pre-training framework degenerates to a knowledge distillation framework when the masking operation is removed. As shown in Table 11, without masking input, the performance degenerates from 81.66% to 81.23%, indicating the critical role of masking operation in our framework.

5 DISCUSSION

What Semantic Patterns Does MimCo Learn? To further help reveal what patterns does MIM learn, we follow the visualization of iBOT [47] to explore the learned patterns of the pre-trained models of SimMIM [45], MAE [19], and our MimCo via visualization, respectively. Specifically, we use the pre-trained ViT S/16 models and visualize the top-36 most similar patches (among different images) with the highest cosine similarity on ImageNet-1K validation set. To better understand each little patch, we visualize a 80×80 context for each 16×16 patch (highlight in orange color). As depicted in Figure 4, the top left patch in each pattern layout is used as the query patch. For all patterns, the MIM methods SimMIM [45] and MAE [19] tend to group the patches with similar colors regardless of their semantic meaning. This might be because they use the raw pixels as the learning target of the masked patches, which force the model to focus on learning the low-level details (e.g., color) and ignore high-level semantics. It is worth noting that, our MimCo is capable of excavating more clear and meaningful semantic patterns. e.g., head of person, head of birds, and colorful flowers. In addition to specific objects, the first row shows that MimCo can successfully group text on different backgrounds. The results indicate that MimCo can learn both low-level details and high-level semantics at the same time.

6 CONCLUSIONS

This work proposes a novel MIM pre-training framework, named MimCo, which leverages contrastive teacher models to improve the linear separability of learned representations, thereby improving pre-training performance. MimCo is flexible and efficient: 1) the contrastive teacher model can be flexibly substituted; 2) simple weak data augmentation is used for pre-training; 3) MimCo achieves state-of-the-art transfer performance with fewer effective pre-training epochs. We hope that our strong results and flexible pre-training framework will facilitate pre-training research, especially combining different pre-training pretext tasks such as contrastive learning and MIM.
