CAE v2: Context Autoencoder with CLIP Target

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Abstract

Masked image modeling (MIM) learns visual representation by masking and reconstructing image patches. Applying the reconstruction supervision on the CLIP representation has been proven effective for MIM. However, it is still under-explored how CLIP supervision in MIM influences performance. To investigate strategies for refining the CLIP-targeted MIM, we study two critical elements in MIM, i.e., the supervision position and the mask ratio, and reveal two interesting perspectives, relying on our developed simple pipeline, context autoencoder with CLIP target (CAE v2). Firstly, we observe that the supervision on visible patches achieves remarkable performance, even better than that on masked patches, where the latter is the standard format in the existing MIM methods. Secondly, the optimal mask ratio positively correlates to the model size. That is to say, the smaller the model, the lower the mask ratio needs to be. Driven by these two discoveries, our simple and concise approach CAE v2 achieves superior performance on a series of downstream tasks. For example, a vanilla ViT-Large model achieves 81.7% and 86.7% top-1 accuracy on linear probing and fine-tuning on ImageNet-1K, and 55.9% mIoU on semantic segmentation on ADE20K with the pre-training for 300 epochs. We hope our findings can be helpful guidelines for the pre-training in the MIM area, especially for the small-scale models.

1. Introduction

Masked image modeling (MIM) [3] is at the center of self-supervised representation learning, showing good potentials on various downstream tasks, including image classification, semantic segmentation, object detection, and instance segmentation. It masks out some patches in the images with a pre-defined mask ratio and adds the reconstruction supervision on a set of patches at some specific positions, i.e., supervision position. Specifically, in most MIM methods [3, 10, 27, 53], the supervision positions are only associated with the masked patches, i.e., only adding the supervisions on the masked patches.

The reconstruction loss of MIM can be applied in different domains or targets, such as RGB [27, 53], HOG [48], discrete visual tokens [3, 10, 18, 22, 40], momentum encoders [13, 44, 51], and pretrained models [48, 49]. Recently, MVP [49] applies the reconstruction loss on the image representations of CLIP [42], i.e., minimizing the reconstruction error in the domain of CLIP representation. Benefiting from the rich multi-modality information and informative representation, the CLIP-targeted MVP performs very well.

Despite that, it is still under-explored how the detailed ways of applying CLIP in MIM affect performance. Unlike most MIM methods [3, 10, 27, 53] applying the reconstruction supervision on the masked patches, MVP supervises both masked and unmasked patches. It raises a question: how will the supervision position influence the CLIP-targeted MIM? On the other hand, the mask ratio performs differently for different supervision targets [3, 27]. With CLIP as the target, it is unclear how the mask ratio behaves.

In this paper, we study these two critical ingredients, i.e., supervision position and mask ratio, in MIM with the CLIP representation as the supervision. To conduct the study, we develop a simple MIM pipeline, i.e., context autoencoder with CLIP target (CAE v2). We will first analyze how the supervision position and the mask ratio influence the performance of CAE v2. Then, relying on the analyses, we implement CAE v2 as a concise yet effective MIM model, producing superior performance on various downstream tasks.

First, we study on the influence of the supervision position. Except for applying the CLIP supervision on the predictions of masked patches, we consider to directly supervise the latent representations of visible patches with CLIP features. Surprisingly, we find that the supervision only on visible patches achieves remarkable performance, even better than that on masked patches. It reveals that the
visible patches can effectively extract rich semantic information from CLIP, performing like the feature distillation. Moreover, combining the supervisions of masked and visible patches together like [49] brings slight performance improvement. Therefore, we advocate that the supervision on visible patches is a good way for the supervision position in the CLIP-targeted MIM.

Next we explore the behavior of the mask ratio. Recall that MAE [27] points out a high mask ratio (75%) is good for the balance of efficiency and effectiveness. Others like [3, 10] empirically set the mask ratio as 40-50%, and MVP simply follows [3]. Here we want to explore what is the optimal mask ratio in the CLIP-targeted MIM. We conduct a series of experiments on a battery of models with different sizes and sweep the mask ratio from 15% to 95%. The results are interesting, showing that the smaller models favor lower mask ratios, while larger models prefer higher ones. This provides a new perspective that the optimal mask ratio is positively correlated with the model size.

Based on the above analyses, our CAE v2 achieves superior performance on various scales of models. Especially, with 300 epoch pre-training, CAE v2 can boost a vanilla ViT-Large to 81.7% and 86.7% top-1 accuracy on linear probing and fine-tuning on ImageNet-1K, and 55.9% mIoU on ADE20K. We hope our analyses and findings can be useful guidelines for the future MIM studies, especially for the pre-training on lightweight models. In summary, our contributions are:

- We develop a simple CLIP-targeted MIM pipeline, namely CAE v2, to study the supervision position and the mask ratio;
- For the supervision position, we advocate that applying the supervision on visible patches is a good way;
- For the mask ratio, we present that the optimal mask ratio positively correlates with the model size;
- Driven by these analyses, our CAE v2 achieves superior performance on different scales of models on various downstream tasks.

2. CAE v2

With CLIP as the supervision target, this paper aims to study the two important elements in MIM, i.e., the supervision position and the mask ratio. We achieve this by developing a simple framework CAE v2, in which the supervision target is CLIP and the model structure is based on [10, 49] with some specific modifications. We introduce the details as follows.

2.1. Overview

The overview of our CAE v2 is illustrated in Figure 1. Let \( x \in D \) denote an input image. Following previous MIM methods [3, 10, 27, 48], CAE v2 first embeds \( x \) into a total length of \( N \) patches, which are then randomly masked by a specific proportion \( \gamma \). These \( N \) patches are naturally split into two non-overlapped sets, i.e., visible patches \( X_v \) and masked patches \( X_m \), where \( N = |v| + |m| \). The mask ratio is thus denoted as \( \gamma = |m| / N \). Following [10, 27], the encoder \( F \) maps the visible patches \( X_v \) to the latent representations \( Z_v \). The decoder \( \mathcal{H} \) predicts the latent representations \( Z_m \) for the masked patches from mask tokens \( E_m \). After that, the predictions of visible patches \( Y_v \) and masked patches \( Y_m \) are naturally split into two non-overlapped sets, \( Y_v \) and \( Y_m \).

For the target supervision, we directly input the intact image \( x \) into the CLIP vision model \( \mathcal{F} \) to generate the target supervision \( T \). \( T \) is then split into \( T_v \) and \( T_m \) corresponding to the absolute positions of \( X_v \) and \( X_m \). The optimization is applied on \( Y_v \) and \( T_v \), and we also study to add the supervision on \( Y_m \) and \( T_m \).
decoder, one MIM head, and one CLIP model.

**Encoder.** The encoder $\mathcal{F}$ only receives the visible patches $\mathbf{X}_v$ following [10, 27]. $\mathcal{F}$ maps the visible patches $\mathbf{X}_v$ to the latent representations $\mathbf{Z}_v$ across a stack of transformer blocks. The operation of $\mathcal{F}$ is based on self-attention. In this paper, we utilize a series of ViTs [21] to form the encoder, including ViT-Tiny, ViT-Small, ViT-Base, and ViT-Large.

**Decoder.** The decoder $\mathcal{G}$ predicts the latent representation $\mathbf{Z}_m$ for the masked patches from the mask tokens $\mathbf{E}_m$, conditioned on the visible latent representation $\mathbf{Z}_v$. It is inspired by the latent contextual regressor in CAE [10]. $\mathcal{G}$ performs as the same as cross-attention. Here, we utilize a lightweight decoder in CAE v2, i.e., one-layer transformer block$^1$.

**Head.** The head $\mathcal{H}$ maps the latent predictions $\mathbf{Z}_v$, and the latent representations $\mathbf{Z}_m$ to $\mathbf{Y}_v$ and $\mathbf{Y}_m$, respectively. $\mathbf{Y}_v$ and $\mathbf{Y}_m$ share the same form with the target supervisions $\mathbf{T}_v$ and $\mathbf{T}_m$. In this work, we only use a FC layer followed by a LN (layer norm) layer in $\mathcal{H}$.

**CLIP model.** The vision branch of CLIP model $\mathcal{F}$ generates the target supervisions $\mathbf{T}$. In the whole paper, we only use the ViT-Base of the CLIP model as $\mathcal{F}$. $\mathbf{T}$ is then split into the target supervisions for visible patches $\mathbf{T}_v$ and for masked patches $\mathbf{T}_m$ according to the absolute positions of $\mathbf{X}_v$ and $\mathbf{X}_m$.

### 2.3. Study, Discovery and Analysis

We pay attention to two critical elements in MIM, i.e., the supervision position and the mask ratio.

**Supervision position.** Most previous MIM methods [3, 10, 27] apply the reconstruction supervision on the predictions of masked patches. With CLIP as the target, MVP [49] supervises both visible and masked patches. Here, we do experiments to study how will the supervision position influence the CLIP-targeted MIM.

We systematically analyze three kinds of supervision positions based on CAE v2, i.e., only on the predictions of visible patches $\mathbf{Y}_m$, only on the predictions of masked patches $\mathbf{Y}_v$, and on both $\mathbf{Y}_v$ and $\mathbf{Y}_m$. The loss function can be formulated as follows:

$$L = \frac{\delta_v \cdot \ell(\mathbf{Y}_v, \mathbf{T}_v) + \delta_m \cdot \ell(\mathbf{Y}_m, \mathbf{T}_m)}{\delta_v \cdot |v| + \delta_m \cdot |m|}, \quad (1)$$

where $\ell$ is the loss function. By default, we use the cosine distance as the loss function. $\delta_v/\delta_m$ is the indicative function, controlling whether to use visible/masked patches for optimization. If $\delta_m = 1 - \delta_v = 1$, Eq. (1) reduces to only use the reconstruction loss for masked patches as in [3, 10, 27]. If $\lambda_m = 1 - \delta_v = 0$, the loss becomes the feature distillation loss for visible patches. When setting $\lambda_m = \delta_v = 1$, the optimization is imposed on both visible and masked patches as in [49].

From the experiments (see Table 1), we observe an interesting phenomenon: only applying the supervision on visible patches can achieve remarkable performance. We conjecture this benefit mainly comes from the powerful CLIP model by knowledge distillation. Intriguingly, the distillation loss works well on a subset of image patches, in which some contextual information are missing. Moreover, despite the relatively inferior performance when only using the reconstruction supervision on masked patches, it brings slightly positive improvement when combining the reconstruction supervision on the masked patches with the feature distillation loss on the visible patches. We believe that in this way, the supervision on masked patches performs as a regularization for the representation learning, which is beneficial to alleviating the over-fitting when training only on visible patches.

Our findings are different from the common sense in the current MIM methods [3, 10, 27] that only compute the loss on the masked patches, which is inherited from BERT [15] in the NLP area and has been verified by most current works. Therefore, in CLIP-targeted MIM, we provide a new perspective that the feature distillation on the partial image patches (here referred to visible patches) is a good choice for the model optimization.

**Mask ratio.** The MIM methods generally mask a specific percentage of patches on $\mathbf{x}$ as the input for the model training. For example, [27] utilizes the mask ratio of 75%, while [3, 49] and [10] empirically set the mask ratio as 40% and 50%. Driven by the above experience that the CLIP supervision on visible patches can achieve good results in our CAE v2, we naturally consider to study what is the optimal option for the mask ratio.

We begin from a high mask ratio $\gamma$, i.e., 75% as in [27]. We find that despite the reasonable performance on the large model (e.g., ViT-Base), it performs less than satisfactory on

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$^1$We find that one-layer transformer block as the decoder ready can produce promising performance. For parameter-friendly, we use this structure as the default setting. We do not analyze the influence of the depth of decoder, since it is not the main concern in this paper.
smaller models like ViT-Tiny/Small (see Figure 3). We thus gradually decrease the mask ratio, leading to more visible patches. The performance on all scales of models starts to improve at the beginning of reducing the mask ratio. This trend is especially true for the downstream task like semantic segmentation, verifying that the high mask ratio is not necessary in the CLIP-targeted MIM.

With the continued decreas of the mask ratio, the models with different sizes perform differently. We observe that the smaller models favor lower proportions of mask ratios, while the larger models prefer relatively higher ones. The underlying reason may be that it is hard for the small-size model to optimize on a small subset of patches where most contextual information are missing. So it is better to reduce the difficulty by using more visible patches, i.e., a lower mask ratio. On the contrary, large-scale models learn representations from plenty of patches easily. Therefore, a high mask ratio can make MIM harder to ease the over-fitting.

Based on the above observation, we point out that the optimal mask ratio is positively correlated with the model size. That is to say, the larger the model, the higher the mask ratio, and preferring more challenging work; otherwise, the smaller model favors a lower mask ratio. We believe that this discovery can be a useful guideline in the MIM pre-training area, especially for the small models.

Discussion. The most relevant work for ours is MVP [49]. It is noted that our CAE v2 is not contradictory to MVP, even though we both use CLIP as the target. We focus on the analyses under the CLIP-targeted MIM and propose new perspectives, while MVP highlights the rich information brought by the CLIP target. Specifically, in this work, we go further one step to study two important ingredients in MIM, including the supervision target and the mask ratio. First, we find only applying the CLIP supervision on visible patches already achieves comparable or even superior performance compared to the optimization on all patches as in MVP. Second, MVP inherits the mask ratio (40%) from [3] and applies it on both base- and large-size models. Differently, we study the effect of the mask ratios on a battery of models with different scales, and find the mask ratio is highly related to the model size. In addition, our CAE v2 with these two findings demonstrates large performance gains. We illustrate the detailed paradigms of our CAE v2 and MVP in Figure 2 for better comparisons.

3. Experiments
3.1. Settings
Model structures. We study a series of vision transformer backbones [21], including ViT-Tiny (12 layers with $dim=192$), ViT-Small (12 layers with $dim=384$), ViT-Base (12 layers with $dim=768$), and ViT-Large (24 layers with $dim=1024$). Note that for ViT-Tiny, we follow [47] to increase the number of heads from 3 to 12, which gives better results on ImageNet-1K [14]. For other models, we strictly follow the model configurations as in [21].

To eliminate the influence of different sizes of CLIP models, we adopt the vision branch ViT-Base/16 of CLIP\textsuperscript{2} as the target for all pre-training experiments with ViT-Tiny/Small/Base/Large [21].

Pre-training. Following most previous MIM methods [3, 10, 27, 47, 49], we use ImageNet-1K (IN-1K) dataset [14] for all pre-training experiments. The input images are with the size of $224 \times 224$ and partitioned into $14 \times 14$ patches with the patch size being $16 \times 16$. We apply random resized cropping and horizontal flipping during pre-training.

The pre-training settings are almost the same as CAE [10], except for the mask ratios that are analyzed in Section 3.2. By default, we use 15%, 25%, 50%, and 50% mask ratios on ViT-Tiny, ViT-Small, ViT-Base, and ViT-Large, respectively. We use AdamW [38] for optimization and train the CAE v2 for 300 epochs for all scales of ViTs [21]. The detailed pre-training settings are shown in the supplementary material.

\begin{table}[ht]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
Model & Supervision & IN-1K & ADE20K & \\
\hline
Y_m & Y_v & LIN & FT & mIoU & \\
\hline
ViT-Tiny & ✓ & - & 64.9 & 77.2 & 44.1 & \\
ViT-Small & ✓ & - & 73.9 & 82.4 & 49.6 & \\
ViT-Base & ✓ & - & 78.4 & 85.0 & 52.7 & \\
\hline
\end{tabular}
\caption{Table 1. Influences of the supervision position in our CAE v2. Default settings are marked in gray.}
\end{table}

\begin{table}[ht]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
Model & Loss type & IN-1K & ADE20K & \\
\hline
ViT-Tiny & MSE & 69.1 & 77.3 & 44.8 & \\
ViT-Small & MSE & 77.3 & 82.7 & 49.8 & \\
ViT-Base & MSE & 80.4 & 85.3 & 52.9 & \\
\hline
\end{tabular}
\caption{Table 2. Ablation on the loss type in our CAE v2. We use the cosine distance as the default loss function (marked in gray).}
\end{table}
Evaluation. We evaluate our CAE v2 on various downstream tasks. For image classification, we conduct evaluations on ImageNet-1K [14] with both linear probing (LIN) and fine-tuning (FT) protocols. Without specification, in all experiments, we conduct the linear probing for 90 epochs and the fine-tuning for 100 epochs. For semantic segmentation, we follow BEiT [3] to use UperNet [52] and report the mIoU on ADE20K [57] dataset. For objection detection and instance segmentation, we use COCO [35] as the evaluation dataset. We adopt both Mask R-CNN [29] and Cascade Mask R-CNN [5] frameworks and report APb and APc on the COCO val split. Please refer to the supplementary material for more training details on various downstream tasks.

3.2. Main Properties

We mainly explore two critical ingredients, the supervision position and the mask ratio, in CAE v2 when using CLIP as the supervision target. Compared with previous pre-training methods, we observe different properties and trends. In addition, we also give investigations on the loss types and the masking types. Details are given below.

Supervision position. Modern pre-training methods [3, 10, 27] only give supervision on masked patches, as they find that learning with visible patches is an easy task and may leak information, result in trivial solutions, and degenerate the representation learning. When using CLIP [42] as the pre-training target, the situation is different.

Table 1 provides the detailed results of the influence of the supervision position on ImageNet-1K [14] and ADE20K [57] based on CAE v2. Different from existing MIM methods [3, 10, 27], we observe that only adding supervision on visible patches already presents remarkable results on both linear probing, image classification fine-tuning, and semantic segmentation fine-tuning. While only adding supervision on masked patches [3, 10, 27] shows worse performance with linear probing (64.9% vs. 68.8% with ViT-Tiny, 73.9% vs. 77.3% with ViT-Small, and 78.4% vs. 80.5% with ViT-Base), but competitive results with image classification fine-tuning and semantic segmentation fine-tuning (Table 1). We conjecture that the rich semantics in CLIP [42] make the supervision on visible patches work as a knowledge distillation task. It is different from previous methods where the semantics in the target is not precise enough to provide strong supervision on visible patches. Moreover, by combining the supervision on visible patches and masked patches (the rows marked with gray in Table 1), we obtain a slight improvement over the one only with supervision on visible patches. Based on the observation, the supervision on masked patches in our CAE v2 can be considered as a regularization for representation learning with CLIP as the target.

Mask ratio. Given that the supervision on masked patches is a regularization for the learning of CAE v2, we suppose that it may not be appropriate to adopt a high mask ratio (75% in MAE [27], 40%-50% in BEiT [3], CAE [10], and MVP [49]) for all scales of ViTs. We study different mask ratios, ranging from 15% to 90% (see Figure 4), for a series of ViTs (Tiny, Small, and Base) with our CAE v2.

Figure 3 gives the performance of ViT-Tiny/ViT-Small/ViT-Base [21] under various mask ratios using three

![Figure 3](image-url)
evaluation methods: linear probing, image classification fine-tuning, and semantic segmentation fine-tuning. The results give a clear trend on the choice of mask ratios, i.e., the best mask ratio is positively related to the model size. From the curves in Figure 3, we also find that with the selected mask ratio exceeding the best mask ratio, the performances on downstream tasks drop quickly, especially fine-tuning. The evidence indicates the significance of our study on the mask ratio and provides a guideline for choosing mask ratios for different scales of ViTs. According to the experiments in Figure 3, we use a mask ratio of 15% for ViT-Tiny, 25% for ViT-Small, and 50% for ViT-Base.

Loss type. As the target of CAE v2 is the CLIP features, we explore the influence of different loss functions in the feature space. Table 2 shows the results of CAE v2 on different scales of models with different loss functions, including the mean square error (MSE), Smooth-l1 and the cosine distance. We only observe slight differences (≤0.5%) in performance on ImageNet1K [14]. On ADE20K [57], the variances are slightly bigger, indicating the loss function of using CLIP as the target gives more impact on challenging downstream tasks. We adopt the cosine distance loss as the default choice.

Mask sampling strategy. We also compare different mask sampling strategies in our CAE v2, i.e., random sampling [27] and block-wise sampling [3, 10, 49] (as shown in Figure 4). There are only ~0.1% gaps between these two sampling strategies on linear probing and image classification fine-tuning (see Table 3). When it comes to semantic segmentation, the block-wise sampling shows better performance than the random sampling. In CAE v2, we use block-wise sampling strategy by default.

### 3.3. Main Results

Based on the analyses of the supervision position in Section 2.3, we find that only applying the feature distillation supervision on visible patches can achieve good performance. We denote this format as CAE v2. Meanwhile, adding the reconstruction supervision on masked patches can further improve the performance, which is denoted as CAE v2+. We report both CAE v2 and CAE v2 + in this subsection.

#### Image classification on ImageNet-1K.

Table 4 shows the comparisons of different models with two evaluation methods: linear probing and fine-tuning.

With linear probing, CAE v2 shows significant improvements over previous methods with other targets, e.g., BEIT [3], MAE [27], CAE [10], and MaskFeat [48]. These gains are expected as CLIP features contain rich semantics than other targets. Compared with the methods (MVP [49] and BEIT V2 [40]) use CLIP as the target, CAE v2 can also give superior performance (on ViT-Base with 300 epoch pre-training, CAE v2 vs. MVP: 80.6% vs. 75.4% and CAE v2 vs. BEIT V2: 80.6% vs. 80.1%). When we fine-tune the pre-trained model on ImageNet-1K, CAE v2 achieves the best results among various methods across all scales of ViTs (Table 4). Specifically, CAE v2 achieves 85.3% top-1 accuracy, surpassing previous methods by large margins. Moreover, with ViT-Large, CAE v2 improves the performance to 86.7% top-1 accuracy.

#### Semantic segmentation on ADE20K.

Semantic segmentation is a challenging task that needs to classify all pixels to various semantic labels given an image. CLIP [42] as the target shows clear advantages in this task. As shown in Table 4, CAE v2 significantly improves the results over the methods pre-trained with other targets, e.g., by 2.7% mIoU over CAE [10] with ViT-Base. When comparing with CLIP [42], MVP [49], and BEIT V2 [40], CAE v2 outperforms them with the same or less pre-training epochs. The superior performance hold when we move to ViT-Large, with which CAE v2 achieves 55.9% mIoU on ADE20K [57].

#### Object detection and instance segmentation on COCO.

We evaluate the pre-trained models on COCO [35] with Mask R-CNN [29] (Table 5) and Cascade Mask R-CNN [5, 29] (Table 6). We report the results of 1× (12 epochs) training schedule. Compared with other pre-training methods, CAE v2 performs better under both two configurations. With Mask R-CNN, CAE v2 gives 4.9/3.0 points higher on ViT-Small and 2.0/0.9 points higher on ViT-Base on AP0/ARm than the previous best method [10]. The superior performance remain when adopting Cascade Mask.
| Methods using ViT-Tiny: | #Epochs | Target | IN-1K LIN | FT | mIoU |
|---------------------------|---------|--------|-----------|----|------|
| MAE-Tiny [47] | 400 | RGB | 23.4 | 76.2 | - |
| CAE [10] | 300 | DALL-E | 28.1 | 75.9 | 38.3 |
| Distilled MAE-lite [47] | 400 | RGB | - | 76.5 | - |
| CAE v2 | 300 | CLIP-B | 68.8 | 77.4 | 44.2 |
| CAE v2 + | 300 | CLIP-B | 69.3 | **77.8** | **44.7** |

| Methods using ViT-Small: | #Epochs | Target | IN-1K LIN | FT | mIoU |
|---------------------------|---------|--------|-----------|----|------|
| MoCo v3 [12] | 300 | Self-EMA | 73.1 | **81.7** | - |
| BEiT [3] | 300 | DALL-E | 15.7 | **81.7** | - |
| SplitMask [22] | 300 | DALL-E | - | 81.5 | - |
| CAE [10] | 300 | DALL-E | 51.8 | **82.0** | - |
| iBOT [58] | 3200 | Self-EMA | **77.9** | **82.3** | **45.4** |
| CAE v2 | 300 | CLIP-B | 77.3 | 82.8 | 49.1 |
| CAE v2 + | 300 | CLIP-B | 77.5 | **83.1** | **49.7** |

| Methods using ViT-Base: | #Epochs | Target | IN-1K LIN | FT | mIoU |
|---------------------------|---------|--------|-----------|----|------|
| MoCo v3 [12] | 300 | Self-EMA | 76.5 | 83.2 | 47.2 |
| DINO [7] | 400 | Self-EMA | 77.3 | 83.3 | 47.2 |
| iBOT [58] | 1600 | Self-EMA | 79.5 | 84.0 | 50.0 |
| BEiT [3] | 800 | DALL-E | 56.7 | 83.2 | 45.6 |
| SimMIM [53] | 800 | RGB | 56.7 | 83.8 | - |
| MAE [27] | 1600 | RGB | 68.0 | 83.6 | 48.1 |
| CAE [10] | 1600 | DALL-E | 70.4 | 83.9 | 50.2 |
| SdAE [13] | 300 | Self-EMA | 64.9 | 84.1 | 48.6 |
| SIM [44] | 1600 | Self-EMA | 76.4 | 83.8 | - |
| MaskFeat [48] | 1600 | HOG | - | 84.0 | - |
| SplitMask [22] | 300 | DALL-E | - | 83.6 | 45.7 |
| PeCo [18] | 800 | VQGAN | - | 84.5 | 48.5 |
| data2vec [2] | 800 | Self-EMA | - | 84.2 | - |
| CMAE [32] | 1600 | RGB | - | 84.7 | 50.1 |
| ExtreMA [51] | 300 | Self-EMA | 73.3 | 83.7 | 47.9 |
| CLIP [42] | - | Text | - | 84.9 | 51.1 |
| MaskCLIP [20] | 1600 | Text | 72.9 | 84.1 | 50.8 |
| MVP [49] | 300 | CLIP-B | 75.4 | 84.4 | 52.4 |
| BEIT V2 [40] | 300 | VQ-CLIP-B | 80.1 | 85.0 | 52.7 |
| CAE v2 | 300 | CLIP-B | 80.5 | 85.2 | **53.1** |
| CAE v2 + | 300 | CLIP-B | **80.6** | **85.3** | **52.9** |

| Methods using ViT-Large: | #Epochs | Target | IN-1K LIN | FT | mIoU |
|---------------------------|---------|--------|-----------|----|------|
| MoCo v3 [12] | 300 | Self-EMA | - | 84.1 | 49.1 |
| BEiT [3] | 1600 | DALL-E | - | 85.2 | 53.3 |
| iBOT [58] | 1200 | Self-EMA | 81.0 | 84.8 | - |
| MAE [27] | 1600 | RGB | 75.8 | 85.9 | 53.6 |
| CAE [10] | 1600 | DALL-E | 78.1 | 86.3 | 54.7 |
| data2vec [2] | 1600 | Self-EMA | - | 86.6 | - |
| MVP [49] | 300 | CLIP-B | - | 86.3 | 54.3 |
| BEIT V2 [40] | 300 | VQ-CLIP-B | - | 86.6 | 55.0 |
| CAE v2 | 300 | CLIP-B | **81.7** | **86.7** | **55.9** |

Table 4. Pre-training evaluation on the top-1 accuracy (%) on linear probing (LIN) and fine-tuning (FT) on ImageNet-1K [14], and mIoU (%) on ADE20K [57]. † denotes the fine-tuning epoch is 200 for ViT-Small. ‡ means our implementation using the officially released code. § means the results from [10]. All other results except for ours are from the original papers.
Table 5. Pre-training evaluation on object detection (DET) and instance segmentation (INS) on COCO [35]. Mask R-CNN [29] is adopted and trained with $1 \times$ schedule. All results except for CAE v2 are from [10]. #Epochs refers to the pre-training epochs on ImageNet-1K. $^\ast$ denotes multi-crop pre-training augmentation.

Table 6. Pre-training evaluation on object detection (DET) and instance segmentation (INS) on COCO [35] with Cascade Mask R-CNN [5]. All models are trained with the $1 \times$ schedule. All results except for CAE v2 are from [10], and the results of iBOT are from the original paper [58]. #Epochs refers to the effective pre-training epochs on ImageNet-1K. $^\ast$ denotes multi-crop pre-training augmentation.

### 4. Related Work

Masked image modeling (MIM) aims to learn transferable vision representations. It is inspired by the successful large-scale pre-training for transformers [46] with masked language modeling (MLM) [4, 8, 15, 17] in NLP and can serve as a pretext task in self-supervised vision pre-training [1, 6, 9, 11, 16, 19, 23, 25, 26, 28, 31, 33, 34, 36, 39, 54–56, 59]. MIM methods [2, 3, 27, 43, 48, 53] follow a mask-then-predict pipeline of (i) corrupting an image by masking several image patches based on a pre-defined mask ratio and (ii) learning to predict the missing content under specific supervision. CAE v2 uses the CLIP model [42] as the supervision target and studies on the above two aspects. Next, we discuss related works with respect to these two aspects.

**Supervision target.** There are several ways to represent the missing content when supervising a model. Existing MIM methods explore different supervision targets on their frameworks, including RGB pixels [24, 27], HOG descriptors [48], discrete visual tokens [3, 10, 18, 22, 40], and feature representation from momentum models [13, 44, 51]. Among these methods, supervision is added to the model’s predictions for masked patches. They give no supervision to the model’s predictions for unmasked patches (visible patches). Recently, MVP [49] explored changing the supervision target from other modalities and validated the effectiveness of the additional knowledge. In detail, MVP adopts the vision branch of the CLIP model [42] as the supervision target in MIM. Then MVP gives supervision on all patches of the image, including masked patches and unmasked patches. CAE v2 follows MVP [49] to use the CLIP model as the supervision target and go one step further to study the supervision position in this paper.

**Mask ratio.** The mask ratio is a hyper-parameter that needs hand-design in both MLM and MIM. In MLM, BERT [15] uses a relatively small mask ratio (15%) for pre-training. [50] argues that masking up to 40% may give higher performance. In MIM, a lot of works use a high mask ratio for pertaining. For example, MAE [27] utilizes a mask ratio of 75%, BEiT [3], CAE [10], and MVP [49] empirically set the mask ratio as 40% and 50%. In this paper, we study this interesting problem and provide a guideline for choosing the right mask ratio for different scales of ViTs.

Concurrent with our work, [30, 37, 41] also explores using CLIP to guide the MIM pre-training. MILAN [30] and dBOT [37] focus on the impact of target representations, that the CLIP containing multi-modality knowledge can provide more benefits to MIM. MaskDistill [41] works on the design of distillation loss in supervision. Differently, we investigate two aspects orthogonal to these works. We find that adding supervision on visible patches further helps visual learning compared to only supervising the masked patches. Moreover, we explore the relationship between mask ratio and model scales. These two findings provide useful guidelines for MIM pre-training.

### 5. Conclusion and Limitation

This paper studies two critical ingredients in MIM, i.e., the supervision position and the mask ratio, with CLIP as
the supervision target. With our simple pipeline CAE v2, we reveal two new insights: i) the feature distillation supervision on visible patches can achieve remarkable performance; ii) the optimal mask ratio is positively correlated to the model size. Following these two guidelines, our CAE v2 achieves superior performance on all scales of models on various downstream tasks.

**Limitation.** Limited by resources, we do not study on larger models, like ViT-Huge and ViT-Giant. We leave this exploration in the future.

**References**

[1] Mahmoud Assran, Mathilde Caron, Ishan Misra, Piotr Bojanowski, Florian Bordes, Pascal Vincent, Armand Joulin, Michael G. Rabbat, and Nicolas Ballas. Masked siamese networks for label-efficient learning. *ArXiv*, abs/2204.07141, 2022.

[2] Alexei Baevski, Wei-Ning Hsu, Qiantong Xu, Arun Babu, Jiatao Gu, and Michael Auli. data2vec: A general framework for self-supervised learning in speech, vision and language. In *ICML*, 2022.

[3] Hangbo Bao, Li Dong, and Furu Wei. BEiT: BERT pre-training of image transformers. In *ICLR*, 2022.

[4] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Satry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, T. J. Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeff Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. *ArXiv*, abs/2005.14165, 2020.

[5] Zhaowei Cai and Nuno Vasconcelos. Cascade r-cnn: Delving into high quality object detection. In *CVPR*, pages 6154–6162, 2018.

[6] Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. Deep clustering for unsupervised learning of visual features. In *ECCV*, pages 132–149, 2018.

[7] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *ICCV*, pages 9650–9660, 2021.

[8] Mark Chen, Alec Radford, Rewon Child, Jeffrey Wu, Heewoo Jun, David Luan, and Ilya Sutskever. Generative pre-training from pixels. pages 1691–1703. PMLR, 2020.

[9] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. *preprint arXiv:2002.05709*, 2020.

[10] Xiaokang Chen, Mingyu Ding, Xiaodi Wang, Ying Xin, Shentong Mo, Yunhao Wang, Shumin Han, Ping Luo, Gang Zeng, and Jingdong Wang. Context autoencoder for self-supervised representation learning. *ArXiv preprint arXiv:2202.03026*, 2022.

[11] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. *preprint arXiv:2003.04297*, 2020.

[12] Xinlei Chen, Saining Xie, and Kaiming He. An empirical study of training self-supervised vision transformers. In *ICCV*, pages 9640–9649, 2021.

[13] Yabo Chen, Yuchen Liu, Dongsheng Jiang, Xiaopeng Zhang, Wenrui Dai, Hongkai Xiong, and Qi Tian. Sdae: Self-distilled masked autoencoder. *ArXiv preprint arXiv:2208.00449*, 2022.

[14] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR*, pages 248–255, 2009.

[15] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In *NAACL*, pages 4171–4186. Association for Computational Linguistics, 2019.

[16] Carl Doersch, Abhinav Gupta, and Alexei A Efros. Unsupervised visual representation learning by context prediction. In *ICCV*, 2015.

[17] Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. Unified language model pre-training for natural language understanding and generation. In *NeurIPS*, pages 13042–13054, 2019.

[18] Xiaoyi Dong, Jianmin Bao, Ting Zhang, Dongdong Chen, Weiming Zhang, Lu Yuan, Dong Chen, Fang Wen, and Nenhai Yu. Peco: Perceptual codebook for bert pre-training of vision transformers. *ArXiv preprint arXiv:2111.12710*, 2021.

[19] Xiaoyi Dong, Jianmin Bao, Ting Zhang, Dongdong Chen, Weiming Zhang, Lu Yuan, Dong Chen, Fang Wen, and Nenhai Yu. Bootstrapped masked autoencoders for vision bert pretraining. *ArXiv*, abs/2207.07116, 2022.

[20] Xiaoyi Dong, Yinglin Zheng, Jianmin Bao, Ting Zhang, Dongdong Chen, Hao Yang, Ming Zeng, Weiming Zhang, Lu Yuan, Dong Chen, Fang Wen, and Nenhai Yu. Maskclip: Masked self-distillation advances contrastive language-image pretraining. *ArXiv*, abs/2208.12262, 2022.

[21] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *ICLR*, 2021.

[22] Alaaeldin El-Nouby, Gautier Izacard, Hugo Touvron, Ivan Laptev, Hervé Jégou, and Edouard Grave. Are large-scale datasets necessary for self-supervised pre-training? *ArXiv preprint arXiv:2112.10740*, 2021.

[23] Aleksandr Ermolov, Aliaksandr Siarohin, Enver Sangineto, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *ICLR*, 2021.

[24] Priya Goyal, Mathilde Caron, Benjamin Lefaudeux, Min Xu, Pengchao Wang, Vivek Pai, Mannat Singh, Vitaliy Laptev, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, and Nicu Sebe. Whitening for self-supervised representation learning. In *ICCV*, pages 4171–4186. Association for Computational Linguistics, 2019.

[25] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In *NAACL*, pages 4171–4186. Association for Computational Linguistics, 2019.
[57] Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In CVPR, pages 633–641, 2017.

[58] Jinghao Zhou, Chen Wei, Huiyu Wang, Wei Shen, Cihang Xie, Alan Yuille, and Tao Kong. ibot: Image bert pre-training with online tokenizer. ICLR, 2022.

[59] Qiang Zhou, Chaohui Yu, Hao Luo, Zhibin Wang, and Hao Li. Mimco: Masked image modeling pre-training with contrastive teacher. arXiv preprint arXiv:2209.03063, 2022.