Masked Autoencoders Are Scalable Vision Learners

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Abstract

This paper shows that masked autoencoders (MAE) are scalable self-supervised learners for computer vision. Our MAE approach is simple: we mask random patches of the input image and reconstruct the missing pixels. It is based on two core designs. First, we develop an asymmetric encoder-decoder architecture, with an encoder that operates only on the visible subset of patches (without mask tokens), along with a lightweight decoder that reconstructs the original image from the latent representation and mask tokens. Second, we find that masking a high proportion of the input image, e.g., 75%, yields a nontrivial and meaningful self-supervisory task. Coupling these two designs enables us to train large models efficiently and effectively: we accelerate training (by 3× or more) and improve accuracy. Our scalable approach allows for learning high-capacity models that generalize well: e.g., a vanilla ViT-Huge model achieves the best accuracy (87.8%) among methods that use only ImageNet-1K data. Transfer performance in downstream tasks outperforms supervised pre-training and shows promising scaling behavior.

1. Introduction

Deep learning has witnessed an explosion of architectures of continuously growing capability and capacity [33, 25, 57]. Aided by the rapid gains in hardware, models today can easily overfit one million images [13] and begin to demand hundreds of millions of—often publicly inaccessible—labeled images [16].

This appetite for data has been successfully addressed in natural language processing (NLP) by self-supervised pre-training. The solutions, based on autoregressive language modeling in GPT [47, 48, 4] and masked autoencoding in BERT [14], are conceptually simple: they remove a portion of the data and learn to predict the removed content. These methods now enable training of generalizable NLP models containing over one hundred billion parameters [4].

The idea of masked autoencoders, a form of more general denoising autoencoders [58], is natural and applicable in computer vision as well. Indeed, closely related research in vision [59, 46] preceded BERT. However, despite significant interest in this idea following the success of BERT, progress of autoencoding methods in vision lags behind NLP. We ask: what makes masked autoencoding different between vision and language? We attempt to answer this question from the following perspectives:

(i) Until recently, architectures were different. In vision, convolutional networks [34] were dominant over the last decade [33]. Convolutions typically operate on regular grids and it is not straightforward to integrate ‘indicators’ such as mask tokens [14] or positional embeddings [57] into convolutional networks. This architectural gap, however, has been addressed with the introduction of Vision Transformers (ViT) [16] and should no longer present an obstacle.

(ii) Information density is different between language and vision. Languages are human-generated signals that are highly semantic and information-dense. When training a model to predict only a few missing words per sentence, this task appears to induce sophisticated language understanding. Images, on the contrary, are natural signals with heavy spatial redundancy—e.g., a missing patch can be recovered from neighboring patches with little high-level un-
understanding of parts, objects, and scenes. To overcome this difference and encourage learning useful features, we show that a simple strategy works well in computer vision: masking a very high portion of random patches. This strategy largely reduces redundancy and creates a challenging self-supervisory task that requires holistic understanding beyond low-level image statistics. To get a qualitative sense of our reconstruction task, see Figures 2 – 4.

(iii) The autoencoder’s decoder, which maps the latent representation back to the input, plays a different role between reconstructing text and images. In vision, the decoder reconstructs pixels, hence its output is of a lower semantic level than common recognition tasks. This is in contrast to language, where the decoder predicts missing words that contain rich semantic information. While in BERT the decoder can be trivial (an MLP) [14], we found that for images, the decoder design plays a key role in determining the semantic level of the learned latent representations.

Driven by this analysis, we present a simple, effective, and scalable form of a masked autoencoder (MAE) for visual representation learning. Our MAE masks random patches from the input image and reconstructs the missing patches in the pixel space. It has an asymmetric encoder-decoder design. Our encoder operates only on the visible subset of patches (without mask tokens), and our decoder is lightweight and reconstructs the input from the latent representation along with mask tokens (Figure 1). Shifting the mask tokens to the small decoder in our asymmetric encoder-decoder results in a large reduction in computation. Under this design, a very high masking ratio (e.g., 75%) can achieve a win-win scenario: it optimizes accuracy while allowing the encoder to process only a small portion (e.g., 25%) of patches. This can reduce overall pre-training time by 3× or more and likewise reduce memory consumption, enabling us to easily scale our MAE to large models.

Our MAE learns very high-capacity models that generalize well. With MAE pre-training, we can train data-hungry models like ViT-Large/Huge [16] on ImageNet-1K with improved generalization performance. With a vanilla ViT-Huge model, we achieve 87.8% accuracy when fine-tuned on ImageNet-1K. This outperforms all previous results that use only ImageNet-1K data. We also evaluate transfer learning on object detection, instance segmentation, and semantic segmentation. In these tasks, our pre-training achieves better results than its supervised pre-training counterparts, and more importantly, we observe significant gains by scaling up models. These observations are aligned with those witnessed in self-supervised pre-training in NLP [14, 47, 48, 4] and we hope that they will enable our field to explore a similar trajectory.
2. Related Work

**Masked language modeling** and its autoregressive counterparts, e.g., BERT [14] and GPT [47, 48, 4], are highly successful methods for pre-training in NLP. These methods hold out a portion of the input sequence and train models to predict the missing content. These methods have been shown to scale excellently [4] and a large abundance of evidence indicates that these pre-trained representations generalize well to various downstream tasks.

**Autoencoding** is a classical method for learning representations. It has an encoder that maps an input to a latent representation and a decoder that reconstructs the input. For example, PCA and k-means are autoencoders [29]. Denoising autoencoders (DAE) [58] are a class of autoencoders that corrupt an input signal and learn to reconstruct the original, uncorrupted signal. A series of methods can be thought of as a generalized DAE under different corruptions, e.g., masking pixels [59, 46, 6] or removing color channels [70]. Our MAE is a form of denoising autoencoding, but different from the classical DAE in numerous ways.


**Self-supervised learning** approaches have seen significant interest in computer vision, often focusing on different pretext tasks for pre-training [15, 61, 42, 70, 45, 17]. Recently, contrastive learning [3, 22] has been popular, e.g., [62, 43, 23, 7], which models image similarity and dissimilarity (or only similarity [21, 8]) between two or more views. Contrastive and related methods strongly depend on data augmentation [7, 21, 8]. Autoencoding pursues a conceptually different direction, and it exhibits different behaviors as we will present.

3. Approach

Our masked autoencoder (MAE) is a simple autoencoding approach that reconstructs the original signal given its partial observation. Like all autoencoders, our approach has an encoder that maps the observed signal to a latent representation, and a decoder that reconstructs the original signal from the latent representation. Unlike classical autoencoders, we adopt an *asymmetric* design that allows the encoder to operate only on the partial, observed signal (without mask tokens) and a lightweight decoder that reconstructs the full signal from the latent representation and mask tokens. Figure 1 illustrates the idea, introduced next.

**Masking.** Following ViT [16], we divide an image into regular non-overlapping patches. Then we sample a subset of patches and mask (i.e., remove) the remaining ones. Our sampling strategy is straightforward: we sample random patches without replacement, following a uniform distribution. We simply refer to this as “random sampling”.

Random sampling with a high masking ratio (i.e., the ratio of removed patches) largely eliminates redundancy, thus creating a task that cannot be easily solved by extrapolation from visible neighboring patches (see Figures 2 – 4). The uniform distribution prevents a potential center bias (i.e., more masked patches near the image center). Finally, the highly sparse input creates an opportunity for designing an efficient encoder, introduced next.

**MAE encoder.** Our encoder is a ViT [16] but applied only on visible, unmasked patches. Just as in a standard ViT, our encoder embeds patches by a linear projection with added positional embeddings, and then processes the resulting set via a series of Transformer blocks. However, our encoder only operates on a small subset (e.g., 25%) of the full set. Masked patches are removed; no mask tokens are used. This allows us to train very large encoders with only a fraction of compute and memory. The full set is handled by a lightweight decoder, described next.

**MAE decoder.** The input to the MAE decoder is the full set of tokens consisting of (i) encoded visible patches, and (ii) mask tokens. See Figure 1. Each mask token [14] is a shared, learned vector that indicates the presence of a miss-
ing patch to be predicted. We add positional embeddings to all tokens in this full set; without this, mask tokens would have no information about their location in the image. The decoder has another series of Transformer blocks.

The MAE decoder is only used during pre-training to perform the image reconstruction task (only the encoder is used to produce image representations for recognition). Therefore, the decoder architecture can be flexibly designed in a manner that is independent of the encoder design. We experiment with very small decoders, narrower and shallower than the encoder. For example, our default decoder has <10% computation per token vs. the encoder. With this asymmetrical design, the full set of tokens are only processed by the lightweight decoder, which significantly reduces pre-training time.

**Reconstruction target.** Our MAE reconstructs the input by predicting the pixel values for each masked patch. Each element in the decoder’s output is a vector of pixel values representing a patch. The last layer of the decoder is a linear projection whose number of output channels equals the number of pixel values in a patch. The decoder’s output is reshaped to form a reconstructed image. Our loss function computes the mean squared error (MSE) between the reconstructed and original images in the pixel space. We compute the loss only on masked patches, similar to BERT [14].

We also study a variant whose reconstruction target is the normalized pixel values of each masked patch. Specifically, we compute the mean and standard deviation of all pixels in a patch and use them to normalize this patch. Using normalized pixels as the reconstruction target improves representation quality in our experiments.

**Simple implementation.** Our MAE pre-training can be implemented efficiently, and importantly, does not require any specialized sparse operations. First we generate a token for every input patch (by linear projection with an added positional embedding). Next we randomly shuffle the list of tokens and remove the last portion of the list, based on the masking ratio. This process produces a small subset of tokens for the encoder and is equivalent to sampling patches without replacement. After encoding, we append a list of mask tokens to the list of encoded patches, and unshuffle this full list (inverting the random shuffle operation) to align all tokens with their targets. The decoder is applied to this full list (with positional embeddings added). As noted, no sparse operations are needed. This simple implementation introduces negligible overhead as the shuffling and unshuffling operations are fast.

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1Computing the loss only on masked patches differs from traditional denoising autoencoders [58] that compute the loss on all pixels. This choice is purely result-driven: computing the loss on all pixels leads to a slight decrease in accuracy (e.g., ~0.5%).

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![Figure 5. Masking ratio. A high masking ratio (75%) works well for both fine-tuning (top) and linear probing (bottom). The y-axes are ImageNet-1K validation accuracy (%) in all plots in this paper.](image)

## 4. ImageNet Experiments

We do self-supervised pre-training on the ImageNet-1K (IN1K) [13] training set. Then we do supervised training to evaluate the representations with (i) end-to-end fine-tuning or (ii) linear probing. We report top-1 validation accuracy of a single 224×224 crop. Details are in Appendix A.1.

**Baseline: ViT-Large.** We use ViT-Large (ViT-L/16) [16] as the backbone in our ablation study. ViT-L is very big (an order of magnitude bigger than ResNet-50 [25]) and tends to overfit. The following is a comparison between ViT-L trained from scratch vs. fine-tuned from our baseline MAE:

<table>
<thead>
<tr>
<th>Masking ratio (%)</th>
<th>scratch, original [16]</th>
<th>scratch, our impl. baseline MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>76.5</td>
<td>82.5</td>
</tr>
<tr>
<td>60</td>
<td>66.1</td>
<td>84.9</td>
</tr>
</tbody>
</table>

We note that it is nontrivial to train supervised ViT-L from scratch and a good recipe with strong regularization is needed (82.5%, see Appendix A.2). Even so, our MAE pre-training contributes a big improvement. Here fine-tuning is only for 50 epochs (vs. 200 from scratch), implying that the fine-tuning accuracy heavily depends on pre-training.

### 4.1. Main Properties

We ablate our MAE using the default settings in Table 1 (see caption). Several intriguing properties are observed.

**Masking ratio.** Figure 5 shows the influence of the masking ratio. The optimal ratios are surprisingly high. The ratio of 75% is good for both linear probing and fine-tuning. This behavior is in contrast with BERT [14], whose typical masking ratio is 15%. Our masking ratios are also much higher than those in related works [6, 16, 2] in computer vision (20% to 50%).

The model infers missing patches to produce different, yet plausible, outputs (Figure 4). It makes sense of the gestalt of objects and scenes, which cannot be simply completed by extending lines or textures. We hypothesize that this reasoning-like behavior is linked to the learning of useful representations.

Figure 5 also shows that linear probing and fine-tuning results follow different trends. For linear probing, the ac-
Our MAE decoder can be flexibly designed from scratch (82.5%). For fine-tuning, the results are less sensitive to the ratios, and a wide range of masking ratios (40–80%) work well. All fine-tuning results in Figure 5 are better than training from scratch (82.5%).

**Decoder design.** Our MAE decoder can be flexibly designed, as studied in Table 1a and 1b.

Table 1a varies the decoder depth (number of Transformer blocks). A sufficiently deep decoder is important for linear probing. This can be explained by the gap between a pixel reconstruction task and a recognition task: the last several layers in an autoencoder are more specialized for reconstruction, but are less relevant for recognition. A reasonably deep decoder can account for the reconstruction specialization, leaving the latent representations at a more abstract level. This design can yield up to 8% improvement in linear probing (Table 1a, ‘lin’). However, if fine-tuning is used, the last layers of the encoder can be tuned to adapt to the recognition task. The decoder depth is less influential for improving fine-tuning (Table 1a, ‘ft’).

Interestingly, our MAE with a single-block decoder can perform strongly with fine-tuning (84.8%). Note that a single Transformer block is the minimal requirement to propagate information from visible tokens to mask tokens. Such a small decoder can further speed up training.

In Table 1b we study the decoder width (number of channels). We use 512-d by default, which performs well under fine-tuning and linear probing. A narrower decoder also works well with fine-tuning.

Overall, our default MAE decoder is lightweight. It has 8 blocks and a width of 512-d (gray in Table 1). It only has 9% FLOPs per token vs. ViT-L (24 blocks, 1024-d). As such, while the decoder processes all tokens, it is still a small fraction of the overall compute.

**Mask token.** An important design of our MAE is to skip the mask token [M] in the encoder and apply it later in the lightweight decoder. Table 1c studies this design.

If the encoder uses mask tokens, it performs worse: its accuracy drops by 14% in linear probing. In this case, there is a gap between pre-training and deploying: this encoder has a large portion of mask tokens in its input in pre-training, which does not exist in uncorrupted images. This gap may degrade accuracy in deployment. By removing the mask token from the encoder, we constrain the encoder to patches and thus improve accuracy.

Moreover, by skipping the mask token in the encoder, we greatly reduce training computation. In Table 1c, we reduce the overall training FLOPs by 3.3×. This leads to a 2.8× wall-clock speedup in our implementation (see Table 2). The wall-clock speedup is even bigger (3.5–4.1×), for a smaller decoder (1-block), a larger encoder (ViT-H), or both. Note that the speedup can be >4× for a masking ratio of 75%, partially because the self-attention complexity is quadratic. In addition, memory is greatly reduced, which can enable training even larger models or speeding up more by large-batch training. The time and memory efficiency makes our MAE favorable for training very large models.

**Table 1. MAE ablation experiments** with ViT-L/16 on ImageNet-1K. We report fine-tuning (ft) and linear probing (lin) accuracy (%). If not specified, the default is: the decoder has depth 8 and width 512, the reconstruction target is unnormalized pixels, the data augmentation is random resized cropping, the masking ratio is 75%, and the pre-training length is 800 epochs. Default settings are marked in gray.

<table>
<thead>
<tr>
<th>Decoder depth</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>blocks</td>
<td>84.8</td>
<td>84.9</td>
<td>84.9</td>
<td>84.9</td>
<td>84.4</td>
</tr>
<tr>
<td>ft</td>
<td>65.5</td>
<td>70.0</td>
<td>71.9</td>
<td>73.5</td>
<td>73.3</td>
</tr>
<tr>
<td>lin</td>
<td>69.1</td>
<td>71.3</td>
<td>73.3</td>
<td>73.1</td>
<td>73.1</td>
</tr>
</tbody>
</table>

(a) **Decoder depth.** A deep decoder can improve linear probing accuracy.

<table>
<thead>
<tr>
<th>Decoder width</th>
<th>128</th>
<th>256</th>
<th>512</th>
<th>768</th>
<th>1024</th>
</tr>
</thead>
<tbody>
<tr>
<td>dim</td>
<td>84.9</td>
<td>84.8</td>
<td>84.9</td>
<td>84.4</td>
<td>84.3</td>
</tr>
<tr>
<td>ft</td>
<td>69.1</td>
<td>71.3</td>
<td>73.3</td>
<td>73.1</td>
<td>73.1</td>
</tr>
<tr>
<td>lin</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(b) **Decoder width.** The decoder can be narrower than the encoder (1024-d).

<table>
<thead>
<tr>
<th>Mask token</th>
<th>encoder w/ [M]</th>
<th>encoder w/o [M]</th>
</tr>
</thead>
<tbody>
<tr>
<td>case</td>
<td>ft</td>
<td>lin</td>
</tr>
<tr>
<td>encoder w/ [M]</td>
<td>84.2</td>
<td>59.6</td>
</tr>
<tr>
<td>encoder w/o [M]</td>
<td>84.9</td>
<td>73.5</td>
</tr>
</tbody>
</table>

(c) **Mask token.** An encoder without mask tokens is more accurate and faster (Table 2).

<table>
<thead>
<tr>
<th>Mask sampling</th>
<th>random</th>
<th>block</th>
<th>grid</th>
</tr>
</thead>
<tbody>
<tr>
<td>ratio</td>
<td>ft</td>
<td>lin</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>83.9</td>
<td>72.3</td>
<td></td>
</tr>
<tr>
<td>75</td>
<td>84.0</td>
<td>66.0</td>
<td></td>
</tr>
</tbody>
</table>

(d) ** Reconstruction target.** Pixels as reconstruction targets are effective.

(e) **Data augmentation.** Our MAE works with minimal or no augmentation.

<table>
<thead>
<tr>
<th>encoder</th>
<th>dec. depth</th>
<th>ft acc</th>
<th>hours</th>
<th>speedup</th>
</tr>
</thead>
<tbody>
<tr>
<td>ViT-L, w/ [M]</td>
<td>8</td>
<td>84.9</td>
<td>15.4</td>
<td>2.8×</td>
</tr>
<tr>
<td>ViT-L</td>
<td>8</td>
<td>84.8</td>
<td>11.6</td>
<td>3.7×</td>
</tr>
<tr>
<td>ViT-H, w/ [M]</td>
<td>8</td>
<td>-</td>
<td>119.6</td>
<td>-</td>
</tr>
<tr>
<td>ViT-H</td>
<td>8</td>
<td>85.8</td>
<td>34.5</td>
<td>3.5×</td>
</tr>
<tr>
<td>ViT-H</td>
<td>8</td>
<td>85.9</td>
<td>29.3</td>
<td>4.1×</td>
</tr>
</tbody>
</table>

Table 2. **Wall-clock time** of our MAE training (800 epochs), benchmarked in 128 TPU-v3 cores with TensorFlow. The speedup is relative to the entry whose encoder has mask tokens (gray). The decoder width is 512, and the mask ratio is 75%. †: This entry is estimated by training ten epochs.
Reconstruction target. We compare different reconstruction targets in Table 1d. Our results thus far are based on pixels without (per-patch) normalization. Using pixels with normalization improves accuracy. This per-patch normalization enhances the contrast locally. In another variant, we perform PCA in the patch space and use the largest PCA coefficients (96 here) as the target. Doing so degrades accuracy. Both experiments suggest that the high-frequency components are useful in our method.

We also compare an MAE variant that predicts tokens, the target used in BEiT [2]. Specifically for this variant, we use the DALLE pre-trained dVAE [50] as the tokenizer, following [2]. Here the MAE decoder predicts the token indices using cross-entropy loss. This tokenization improves fine-tuning accuracy by 0.4% vs. unnormalized pixels, but has no advantage vs. normalized pixels. It also reduces linear probing accuracy. In §5 we further show that tokenization is not necessary in transfer learning.

Our pixel-based MAE is much simpler than tokenization. The dVAE tokenizer requires one more pre-training stage, which may depend on extra data (250M images [50]). The dVAE encoder is a large convolutional network (40% FLOPs of ViT-L) and adds nontrivial overhead. Using pixels does not suffer from these problems.

Data augmentation. Table 1e studies the influence of data augmentation on our MAE pre-training.

Our MAE works well using cropping-only augmentation, either fixed-size or random-size (both having random horizontal flipping). Adding color jittering degrades the results and so we do not use it in other experiments.

Surprisingly, our MAE behaves decently even if using no data augmentation (only center-crop, no flipping). This property is dramatically different from contrastive learning and related methods [62, 23, 7, 21], which heavily rely on data augmentation. It was observed [21] that using cropping-only augmentation reduces the accuracy by 13% and 28% respectively for BYOL [21] and SimCLR [7]. In addition, there is no evidence that contrastive learning can work without augmentation: the two views of an image are the same and can easily satisfy a trivial solution.

In MAE, the role of data augmentation is mainly performed by random masking (ablated next). The masks are different for each iteration and so they generate new training samples regardless of data augmentation. The pretext task is made difficult by masking and requires less augmentation to regularize training.

Mask sampling strategy. In Table 1f we compare different mask sampling strategies, illustrated in Figure 6.

Figure 6. Mask sampling strategies determine the pretext task difficulty, influencing reconstruction quality and representations (Table 1f). Here each output is from an MAE trained with the specified masking strategy. Left: random sampling (our default). Middle: block-wise sampling [2] that removes large random blocks. Right: grid-wise sampling that keeps one of every four patches. Images are from the validation set.

The dV AE encoder is a large convolutional network (40%) and adds nontrivial overhead. Using pixels without (per-patch) normalization. Using pixels with normalization improves accuracy. This per-patch normalization enhances the contrast locally. In another variant, we perform PCA in the patch space and use the largest PCA coefficients (96 here) as the target. Doing so degrades accuracy. Both experiments suggest that the high-frequency components are useful in our method.

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Figure 7. Training schedules. A longer training schedule gives a noticeable improvement. Here each point is a full training schedule. The model is ViT-L with the default setting in Table 1.
The MAE models in Table 3 are pre-trained for 1600 epochs for better accuracy (Figure 7). Even so, our total pre-training time is less than the other methods when trained on the same hardware. For example, training ViT-L on 128 TPU-v3 cores, our MAE’s training time is 31 hours for 1600 epochs and MoCo v3’s is 36 hours for 300 epochs [9].

Comparisons with supervised pre-training. In the original ViT paper [16], ViT-L degrades when trained in IN1K. Our implementation of supervised training (see A.2) works better, but accuracy saturates. See Figure 8.

Our MAE pre-training, using only IN1K, can generalize better: the gain over training from scratch is bigger for higher-capacity models. It follows a trend similar to the JFT-300M supervised pre-training in [16]. This comparison shows that our MAE can help scale up model sizes.

4.3. Partial Fine-tuning

Table 1 shows that linear probing and fine-tuning results are largely uncorrelated. Linear probing has been a popular protocol in the past few years; however, it misses the opportunity of pursuing strong but non-linear features—which is indeed a strength of deep learning. As a middle ground, we study a partial fine-tuning protocol: fine-tune the last several layers while freezing the others. This protocol was also used in early works, e.g., [65, 70, 42].

Figure 9 shows the results. Notably, fine-tuning only one Transformer block boosts the accuracy significantly from 73.5% to 81.0%. Moreover, if we fine-tune only “half” of the last block (i.e., its MLP sub-block), we can get 79.1%, much better than linear probing. This variant is essentially fine-tuning an MLP head. Fine-tuning a few blocks (e.g., 4 or 6) can achieve accuracy close to full fine-tuning.

In Figure 9 we also compare with MoCo v3 [9], a contrastive method with ViT-L results available. MoCo v3 has higher linear probing accuracy; however, all of its partial fine-tuning results are worse than MAE. The gap is 2.6% when tuning 4 blocks. While the MAE representations are less linearly separable, they are stronger non-linear features and perform well when a non-linear head is tuned.
These observations suggest that linear separability is not the sole metric for evaluating representation quality. It has also been observed (e.g., [8]) that linear probing is not well correlated with transfer learning performance, e.g., for object detection. To our knowledge, linear evaluation is not often used in NLP for benchmarking pre-training.

5. Transfer Learning Experiments

We evaluate transfer learning in downstream tasks using the pre-trained models in Table 3.

### Object detection and segmentation

We fine-tune Mask R-CNN [24] end-to-end on COCO [37]. The ViT backbone is adapted for use with FPN [36] (see A.3). We apply this approach for all entries in Table 4. We report box AP for object detection and mask AP for instance segmentation.

Compared to supervised pre-training, our MAE performs better under all configurations (Table 4). With the smaller ViT-B, our MAE is 2.4 points higher than supervised pre-training (50.3 vs. 47.9, \( \text{AP}_{\text{box}} \)). More significantly, with the larger ViT-L, our MAE pre-training outperforms supervised pre-training by 4.0 points (53.3 vs. 49.3).

The pixel-based MAE is better than or on par with the token-based BEiT, while MAE is much simpler and faster. Both MAE and BEiT are better than MoCo v3 and MoCo v3 is on par with supervised pre-training.

### Semantic segmentation

We experiment on ADE20K [72] using UperNet [63] (see A.4). Table 5 shows that our pre-training significantly improves results over supervised pre-training, e.g., by 3.7 points for ViT-L. Our pixel-based MAE also outperforms the token-based BEiT. These observations are consistent with those in COCO.

### Classification tasks

Table 6 studies transfer learning on the iNaturalists [56] and Places [71] tasks (see A.5). On iNat, our method shows strong scaling behavior: accuracy improves considerably with bigger models. Our results surpass the previous best results by large margins. On Places, our MAE outperforms the previous best results [19, 40], which were obtained via pre-training on billions of images.

### Pixels vs. tokens

Table 7 compares pixels vs. tokens as the MAE reconstruction target. While using dVAE tokens is better than using unnormalized pixels, it is statistically similar to using normalized pixels across all cases we tested. It again shows that tokenization is not necessary for our MAE.

6. Discussion and Conclusion

Simple algorithms that scale well are the core of deep learning. In NLP, simple self-supervised learning methods (e.g., [47, 14, 48, 4]) enable benefits from exponentially scaling models. In computer vision, practical pre-training paradigms are dominantly supervised (e.g. [33, 51, 25, 16]) despite progress in self-supervised learning. In this study, we observe on ImageNet and in transfer learning that an autoencoder—a simple self-supervised method similar to techniques in NLP—provides scalable benefits. Self-supervised learning in vision may now be embarking on a similar trajectory as in NLP.

On the other hand, we note that images and languages are signals of a different nature and this difference must be addressed carefully. Images are merely recorded light without a semantic decomposition into the visual analogue of words. Instead of attempting to remove objects, we remove random patches that most likely do not form a semantic segment. Likewise, our MAE reconstructs pixels, which are not semantic entities. Nevertheless, we observe (e.g., Figure 4) that our MAE infers complex, holistic reconstructions, suggesting it has learned numerous visual concepts, i.e., semantics. We hypothesize that this behavior occurs by way of a rich hidden representation inside the MAE. We hope this perspective will inspire future work.
Broader impacts. The proposed method predicts content based on learned statistics of the training dataset and as such will reflect biases in those data, including ones with negative societal impacts. The model may generate inexistent content. These issues warrant further research and consideration when building upon this work to generate images.

References

[33] Yanghao Li, Saining Xie, Xinlei Chen, Piotr Dollár, Kaiming He, and Ross Girshick. Benchmarking detection transfer learning with vision transformers. In preparation, 2021.
A. Implementation Details

A.1. ImageNet Experiments

ViT architecture. We follow the standard ViT architecture [16]. It has a stack of Transformer blocks [57], and each block consists of a multi-head self-attention block and an MLP block, both having LayerNorm (LN) [1]. The encoder ends with LN. As the MAE encoder and decoder have different width, we adopt a linear projection layer after the encoder to match it. Our MAE adds positional embeddings [57] (the sine-cosine version) to both the encoder and decoder inputs. Our MAE does not use relative position or layer scaling (which are used in the code of [2]).

We extract features from the encoder output for fine-tuning and linear probing. As ViT has a class token [16], to adapt to this design, in our MAE pre-training we append an auxiliary dummy token to the encoder input. This token will be treated as the class token for training the classifier in linear probing and fine-tuning. Our MAE works similarly well without this token (with average pooling).

Pre-training. The default setting is in Table 8. We do not use color jittering, drop path, or gradient clip. We use xavier_uniform [18] to initialize all Transformer blocks, following ViT’s official code [16]. We use the linear lr scaling rule [20]: $lr = \text{base lr} \times \text{batchsize} / 256$.

End-to-end fine-tuning. Our fine-tuning follows common practice of supervised ViT training. The default setting is in Table 9. We use layer-wise lr decay [10] following [2].

Linear probing. Our linear classifier training follows [9]. See Table 10. We observe that linear probing requires a very different recipe than end-to-end fine-tuning. In particular, regularization is in general harmful for linear probing. Following [9], we disable many common regularization strategies: we do not use mixup [69], cutmix [68], drop path [30], or color jittering, and we set weight decay as zero.

It is a common practice to normalize the classifier input when training a classical linear classifier (e.g., SVM [11]). Similarly, it is beneficial to normalize the pre-trained features when training the linear probing classifier. Following [15], we adopt an extra BatchNorm layer [31] without affine transformation (affine=False). This layer is applied on the pre-trained features produced by the encoder, and is before the linear classifier. We note that the layer does not break the linear property, and it can be absorbed into the linear classifier after training: it is essentially a re-parameterized linear classifier.\(^3\) Introducing this layer helps calibrate the feature magnitudes across different variants in our ablations, so that they can use the same setting without further lr search.

\(^3\)Alternatively, we can pre-compute the mean and std of the features and use the normalized features to train linear classifiers.

<table>
<thead>
<tr>
<th>config</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>optimizer</td>
<td>AdamW [39]</td>
</tr>
<tr>
<td>base learning rate</td>
<td>1.5e-4</td>
</tr>
<tr>
<td>weight decay</td>
<td>0.05</td>
</tr>
<tr>
<td>optimizer momentum</td>
<td>$\beta_1, \beta_2=0.9, 0.95$ [6]</td>
</tr>
<tr>
<td>batch size</td>
<td>4096</td>
</tr>
<tr>
<td>learning rate schedule</td>
<td>cosine decay [38]</td>
</tr>
<tr>
<td>warmup epochs</td>
<td>40</td>
</tr>
<tr>
<td>augmentation</td>
<td>RandomResizedCrop</td>
</tr>
</tbody>
</table>

Table 8. Pre-training setting.

<table>
<thead>
<tr>
<th>config</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>optimizer</td>
<td>LARS [66]</td>
</tr>
<tr>
<td>base learning rate</td>
<td>0.1</td>
</tr>
<tr>
<td>weight decay</td>
<td>0</td>
</tr>
<tr>
<td>optimizer momentum</td>
<td>0.9</td>
</tr>
<tr>
<td>batch size</td>
<td>16384</td>
</tr>
<tr>
<td>learning rate schedule</td>
<td>cosine decay</td>
</tr>
<tr>
<td>warmup epochs</td>
<td>10</td>
</tr>
<tr>
<td>training epochs</td>
<td>50, 100, 200</td>
</tr>
<tr>
<td>augmentation</td>
<td>RandomAug (9, 0.5) [12]</td>
</tr>
<tr>
<td>label smoothing</td>
<td>0.1</td>
</tr>
<tr>
<td>mixup</td>
<td>0.8</td>
</tr>
<tr>
<td>cutmix</td>
<td>1.0</td>
</tr>
<tr>
<td>drop path</td>
<td>0.1 (B/L) 0.2 (H)</td>
</tr>
</tbody>
</table>

Table 9. End-to-end fine-tuning setting.

Table 10. Linear probing setting. We use LARS with a large batch for faster training; SGD works similarly with a 4096 batch.

Partial fine-tuning. Our MAE partial fine-tuning (§4.3) follows the setting in Table 9, except that we adjust the number of fine-tuning epochs. We observe that tuning fewer blocks requires a longer schedule. We set the numbers of fine-tuning epochs as \{50, 100, 200\} and use the optimal one for each number of blocks tuned.

A.2. Supervised Training ViT-L/H from Scratch

We find that it is nontrivial to train supervised ViT-L/H from scratch on ImageNet-1K. The training is unstable. While there have been strong baselines with publicly available implementations [53] for smaller models, the recipes for the larger ViT-L/H are unexplored. Directly applying the previous recipes to these larger models does not work. A NaN loss is frequently observed during training.

We provide our recipe in Table 11. We use a wd of 0.3, a large batch size of 4096, and a long warmup, following the original ViT [16]. We use $\beta_2=0.95$ following [6]. We use the regularizations listed in Table 11 and disable others, following [64]. All these choices are for improving training stability. Our recipe can finish training with no NaN loss.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
config & value \\
\hline
optimizer & AdamW \[39\] \\
base learning rate & 1.5e-4 \\
weight decay & 0.05 \\
optimizer momentum & $\beta_1, \beta_2=0.9, 0.95$ [6] \\
batch size & 4096 \\
learning rate schedule & cosine decay [38] \\
warmup epochs & 40 \\
augmentation & RandomResizedCrop \\
\hline
\end{tabular}
\caption{Pre-training setting.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
config & value \\
\hline
optimizer & LARS [66] \\
base learning rate & 0.1 \\
weight decay & 0 \\
optimizer momentum & 0.9 \\
batch size & 16384 \\
learning rate schedule & cosine decay \\
warmup epochs & 10 \\
training epochs & 50, 100, 200 \\
augmentation & RandomAug (9, 0.5) [12] \\
label smoothing & 0.1 \\
mixup & 0.8 \\
cutmix & 1.0 \\
drop path & 0.1 (B/L) 0.2 (H) \\
\hline
\end{tabular}
\caption{End-to-end fine-tuning setting.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|}
\hline
config & value \\
\hline
optimizer & LARS [66] \\
base learning rate & 0.1 \\
weight decay & 0 \\
optimizer momentum & 0.9 \\
batch size & 16384 \\
learning rate schedule & cosine decay \\
warmup epochs & 10 \\
training epochs & 50, 100, 200 \\
augmentation & RandomResizedCrop \\
\hline
\end{tabular}
\caption{Linear probing setting. We use LARS with a large batch for faster training; SGD works similarly with a 4096 batch.}
\end{table}
The accuracy is 82.6% for ViT-L (81.5% w/o EMA), and 83.1% for ViT-H (80.9% w/o EMA). Both ViT-L and ViT-H show an overfitting trend if not using EMA.

As a by-product, our recipe for ViT-B has 82.3% accuracy (82.1% w/o EMA), vs. 81.8% in [53].

### A.3. Object Detection and Segmentation in COCO

We adapt the vanilla ViT for the use of an FPN backbone [36] in Mask R-CNN [24]. ViT has a stack of Transformer blocks that all produce feature maps at a single scale (e.g., stride 16). We equally divide this stack into 4 subsets and apply convolutions to upsample or downsample the intermediate feature maps for producing different scales (stride 4, 8, 16, or 32, the same as a standard ResNet [25]). FPN is built on these multi-scale maps.

For fair comparisons among different methods, we search for hyper-parameters for each entry in Table 4 (including all competitors). The hyper-parameters we search for are the learning rate, weight decay, drop path rate, and fine-tuning epochs. We will release code along with the specific configurations. For full model and training details, plus additional experiments, see [35].

### A.4. Semantic Segmentation in ADE20K

We use UperNet [63] following the semantic segmentation code of [2]. We fine-tune end-to-end for 100 epochs with a batch size of 16. We search for the optimal \( lr \) for each entry in Table 5 (including all competitors).

The semantic segmentation code of [2] uses relative position bias [49]. Our MAE pre-training does not use it. For fair comparison, we turn on relative position bias only during transfer learning, initialized as zero. We note that our BEiT reproduction uses relative position bias in both pre-training and fine-tuning, following their code.

### A.5. Additional Classification Tasks

We follow the setting in Table 9 for iNaturalist and Places fine-tuning (Table 6). We adjust the \( lr \) and fine-tuning epochs for each individual dataset.

### B. Comparison on Linear Probing Results

In §4.3 we have shown that linear probing accuracy and fine-tuning accuracy are largely uncorrelated and they have different focuses about linear separability. We notice that existing masked image encoding methods are generally less competitive in linear probing (e.g., than contrastive learning). For completeness, in Table 12 we compare on linear probing accuracy with masking-based methods.

Our MAE with ViT-L has 75.8% linear probing accuracy. This is substantially better than previous masking-based methods. On the other hand, it still lags behind contrastive methods under this protocol: e.g., MoCo v3 [9] has 77.6% linear probing accuracy for the ViT-L (Figure 9).

### C. Robustness Evaluation on ImageNet

In Table 13 we evaluate the robustness of our models on different variants of ImageNet validation sets. We use the same models fine-tuned on original ImageNet (Table 3) and only run inference on the different validation sets, without any specialized fine-tuning. Table 13 shows that our method has strong scaling behavior: increasing the model sizes has significant gains. Increasing the image size helps in all sets but IN-C. Our results outperform the previous best results (of specialized systems) by large margins.

In contrast, supervised training performs much worse (Table 13 bottom; models described in A.2). For example, with ViT-H, our MAE pre-training is 35% better on IN-A (68.2% vs 33.1%) than the supervised counterpart.

---

Table 11. Supervised training ViT from scratch.

<table>
<thead>
<tr>
<th>config</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>optimizer</td>
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<td>base learning rate</td>
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<td>weight decay</td>
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<td>batch size</td>
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<tr>
<td>learning rate schedule</td>
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<tr>
<td>warmup epochs</td>
<td>20</td>
</tr>
<tr>
<td>training epochs</td>
<td>300 (B), 200 (L/H)</td>
</tr>
<tr>
<td>augmentation</td>
<td>RandAug (9, 0.5) [12]</td>
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<tr>
<td>label smoothing</td>
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</tr>
<tr>
<td>mixup [69]</td>
<td>0.8</td>
</tr>
<tr>
<td>cutmix [68]</td>
<td>1.0</td>
</tr>
<tr>
<td>drop path [30]</td>
<td>0.1 (B), 0.2 (L/H)</td>
</tr>
<tr>
<td>exp. moving average (EMA)</td>
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</tr>
</tbody>
</table>

Table 12. Linear probing results of masked encoding methods. Our fine-tuning results are in Table 3. *1: our implementation.

<table>
<thead>
<tr>
<th>dataset</th>
<th>ViT-B</th>
<th>ViT-L</th>
<th>ViT-H</th>
<th>ViT-H aeΔ</th>
<th>prev best</th>
</tr>
</thead>
<tbody>
<tr>
<td>IN-Corruption ↓ [27]</td>
<td>51.7</td>
<td>41.8</td>
<td>33.8</td>
<td>36.8</td>
<td>42.3 [32]</td>
</tr>
<tr>
<td>IN-Adversarial [28]</td>
<td>35.9</td>
<td>57.1</td>
<td>68.2</td>
<td>76.7</td>
<td>35.8 [41]</td>
</tr>
<tr>
<td>IN-Rendition [26]</td>
<td>48.3</td>
<td>59.9</td>
<td>64.4</td>
<td>66.5</td>
<td>48.7 [41]</td>
</tr>
<tr>
<td>IN-Sketch [60]</td>
<td>34.5</td>
<td>45.3</td>
<td>49.6</td>
<td>50.9</td>
<td>36.0 [44]</td>
</tr>
</tbody>
</table>

Table 13. Robustness evaluation on ImageNet variants (top-1 accuracy, except for IN-C [27] which evaluates mean corruption error). We test the same MAE models (Table 3) on different ImageNet validation sets, without any specialized fine-tuning. We provide system-level comparisons with the previous best results.
Figure 10. **Uncurated random samples** on ImageNet validation images. For each triplet, we show the masked image (left), our MAE reconstruction (middle), and the ground-truth (right). The masking ratio is 75%.
Figure 11. **Uncurated random samples** on COCO validation images, using an MAE trained on ImageNet. For each triplet, we show the masked image (left), our MAE reconstruction (middle), and the ground-truth (right). The masking ratio is 75%.