Masked Autoencoders Are Scalable Vision Learners

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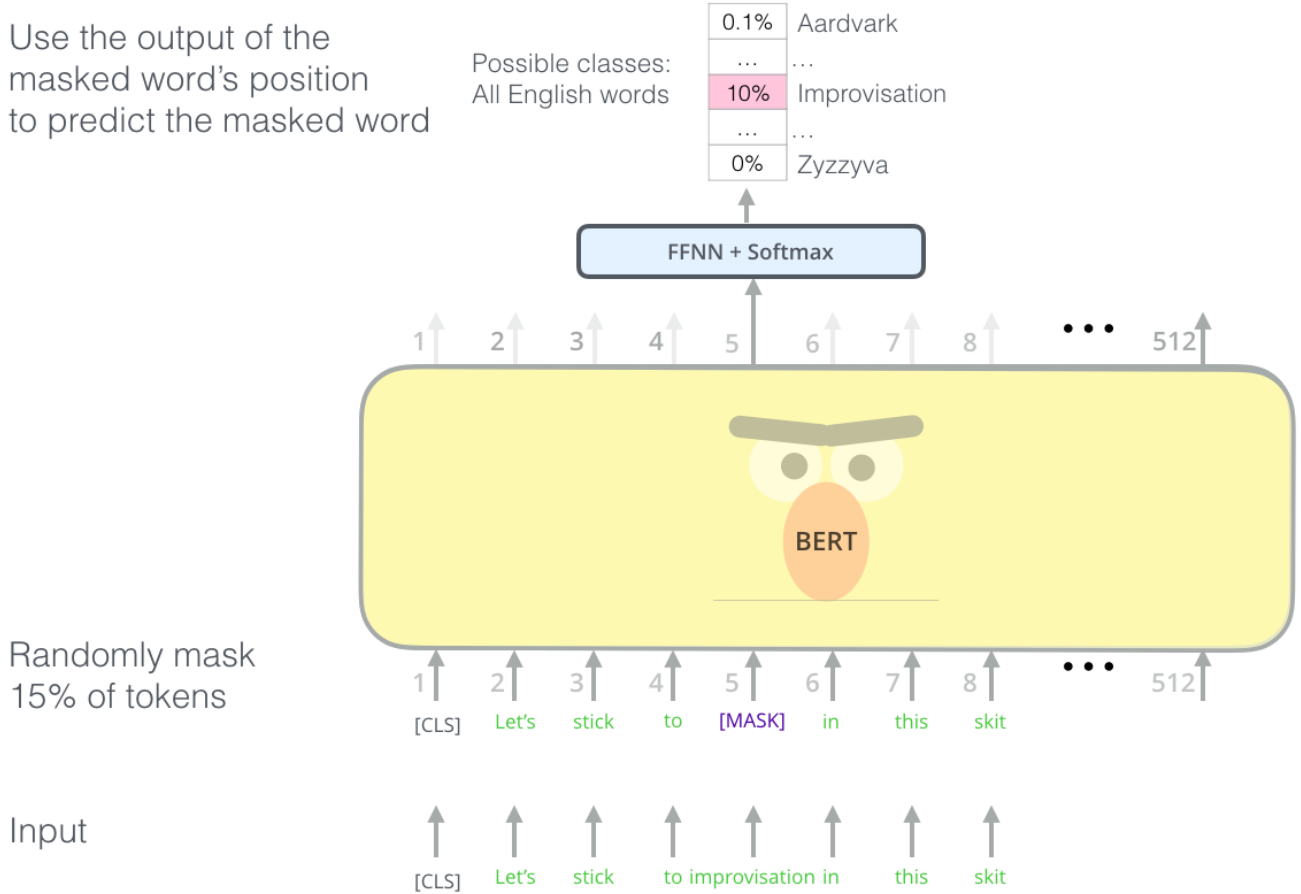
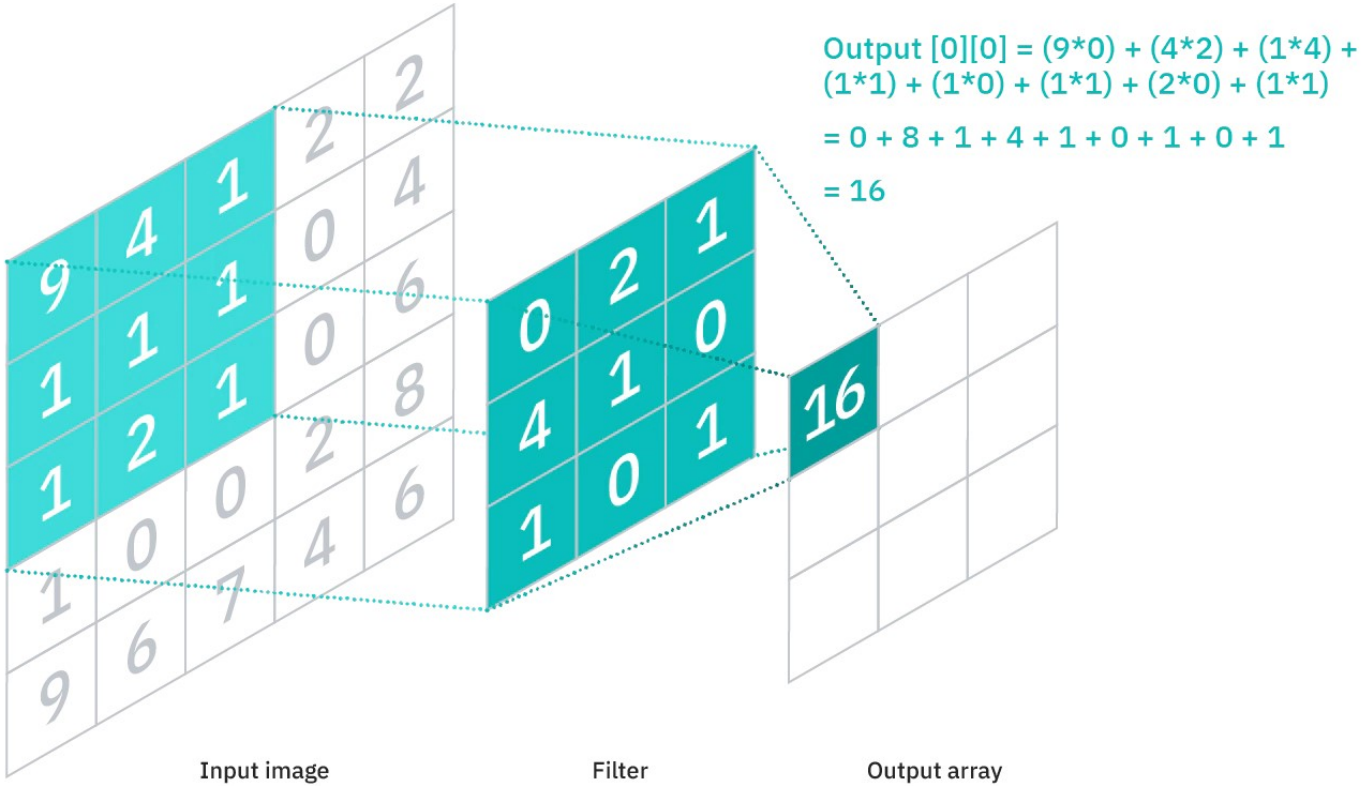
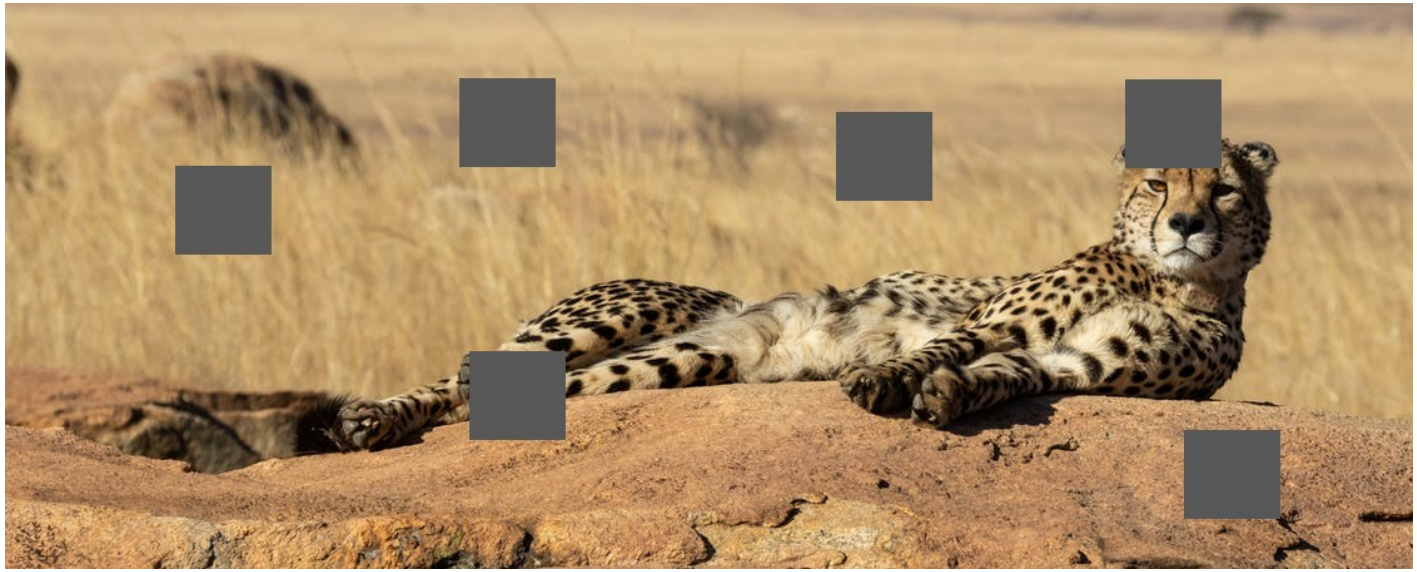


https://jalammar.github.io/illustrated-bert/

Convolutional networks:



[MASK] lies on a stone.



[MASK] lies on a stone.

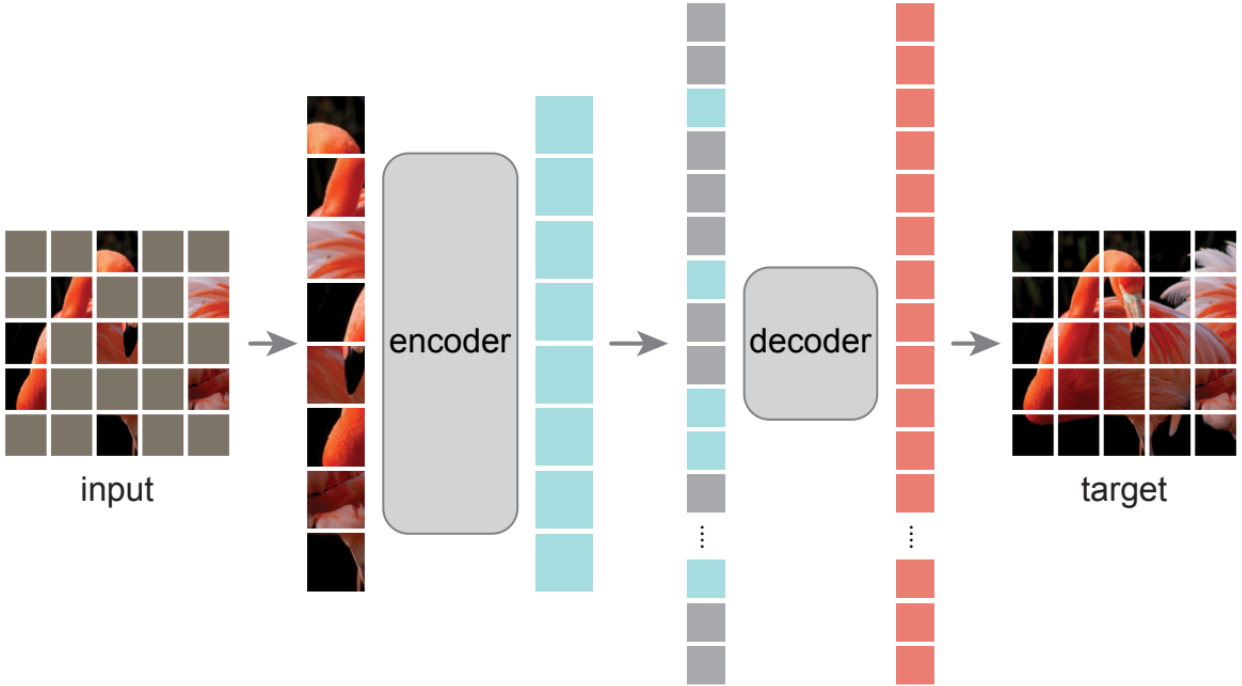
Semantic difference

Cheetah

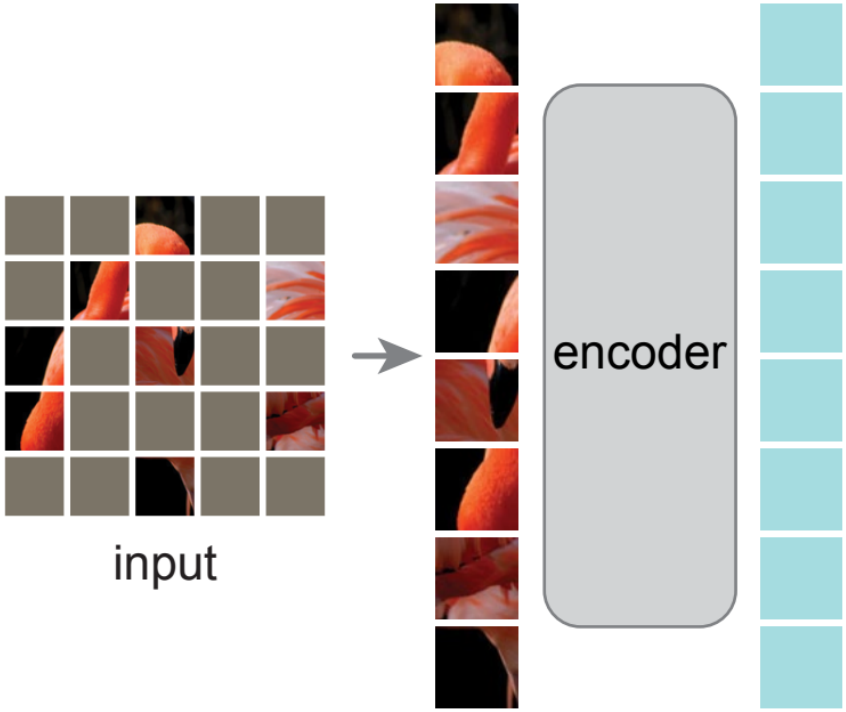
Stone

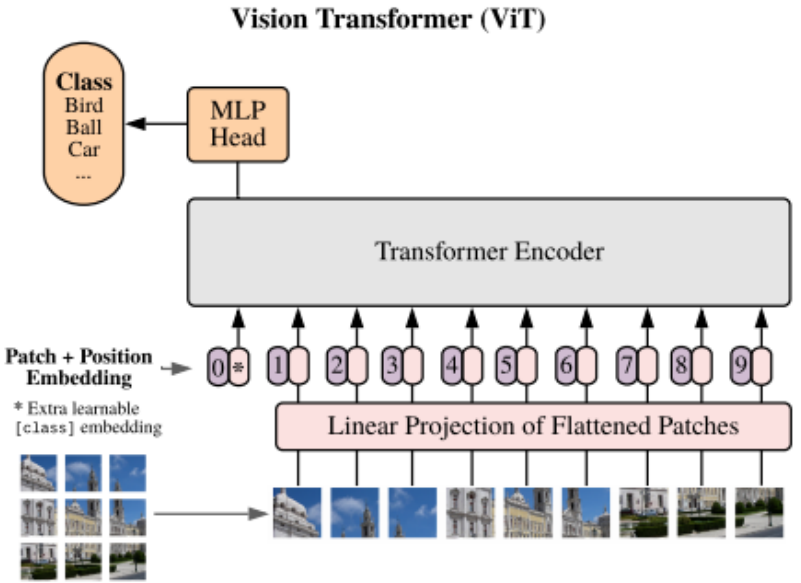
Grass

Masked Autoencoder (MAE)

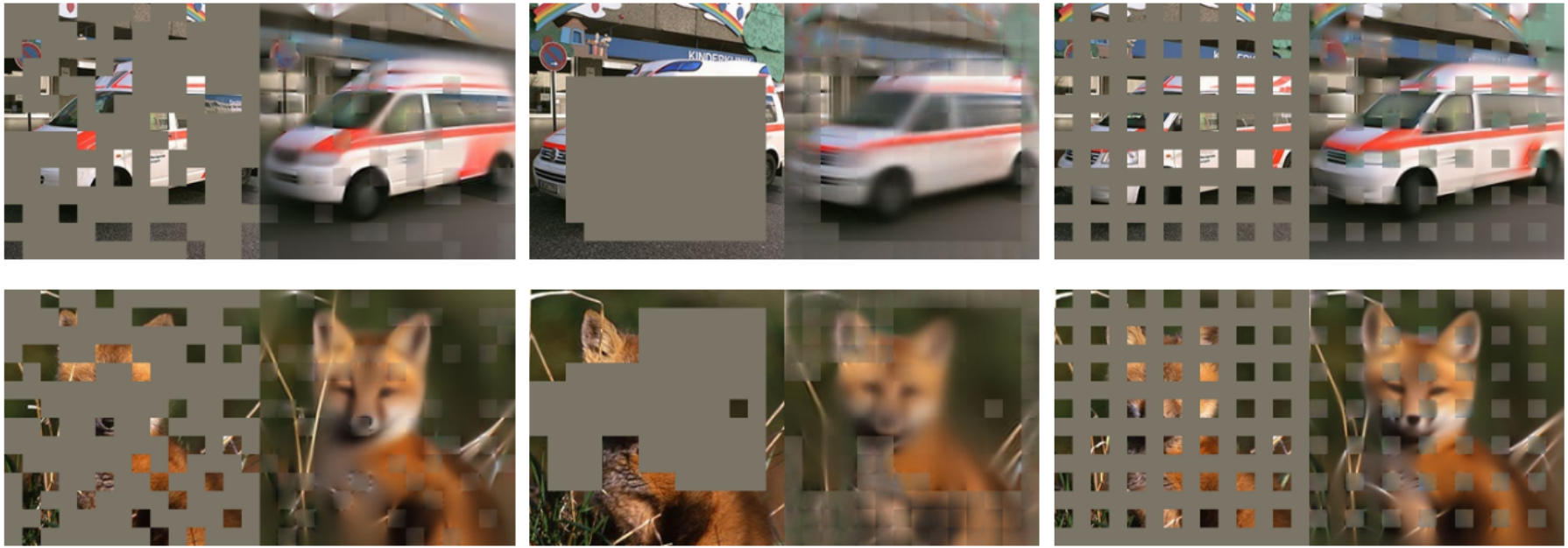


Encoder


input
encoder

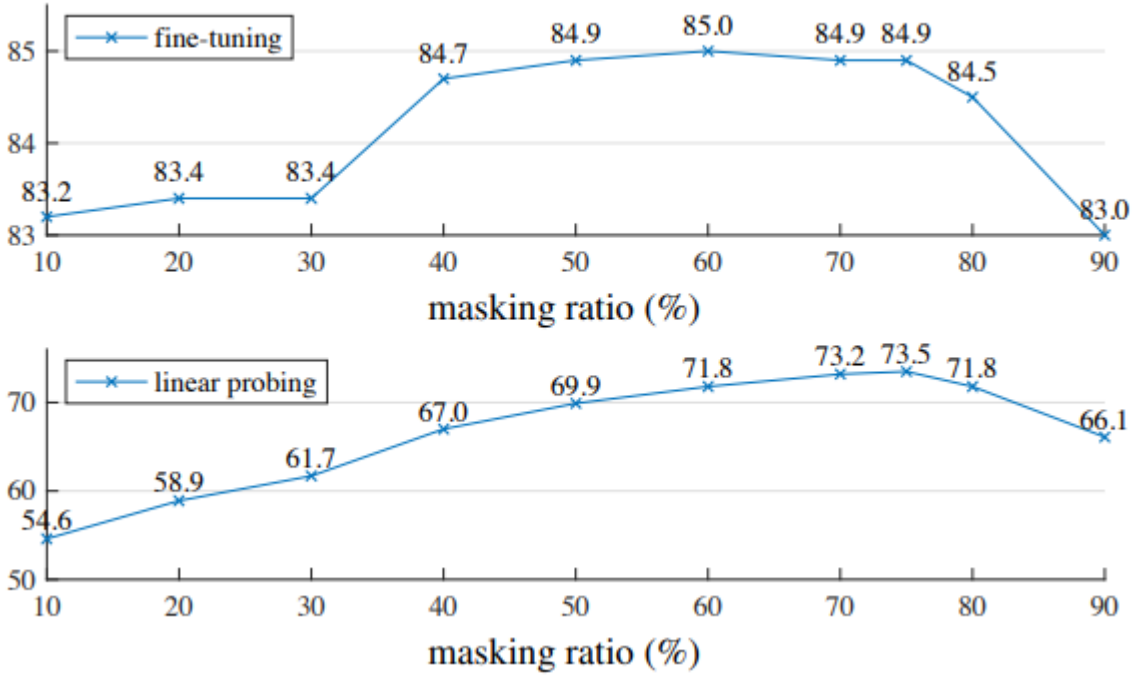

Vision Transformer (ViT)
Class
Bird
Ball
Car
...
MLP Head
Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0*
1
2
3
4
5
6
7
8
9
Linear Projection of Flattened Patches

Mask sampling strategy

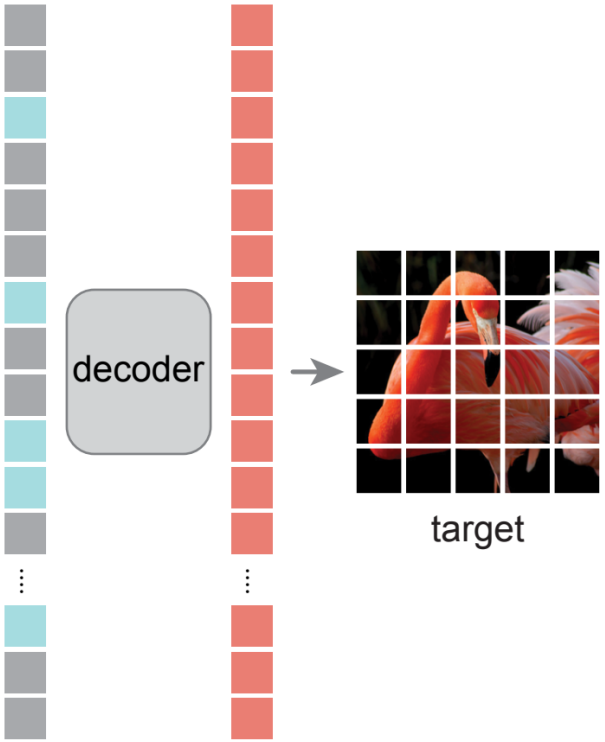


random 75% block 50% grid 75%

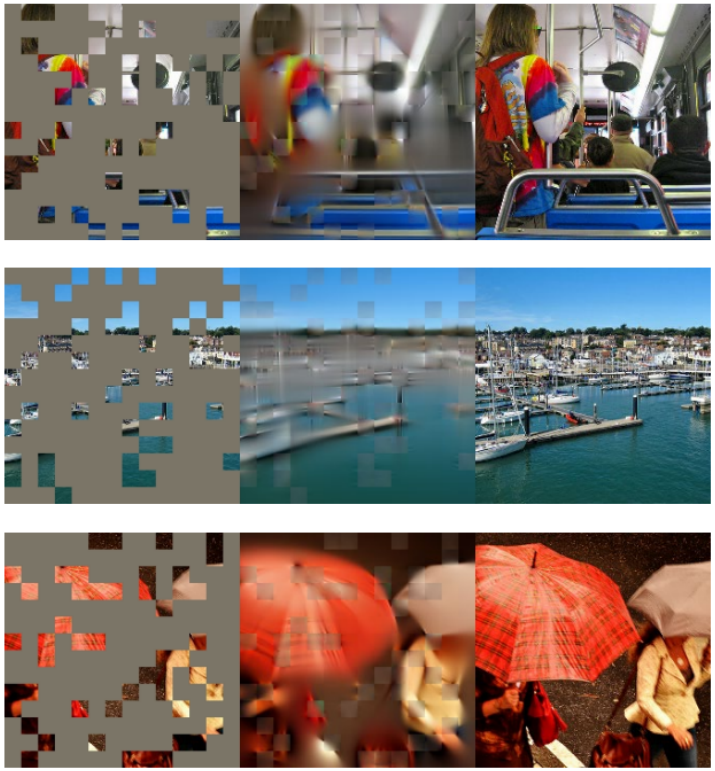
Masking ratio



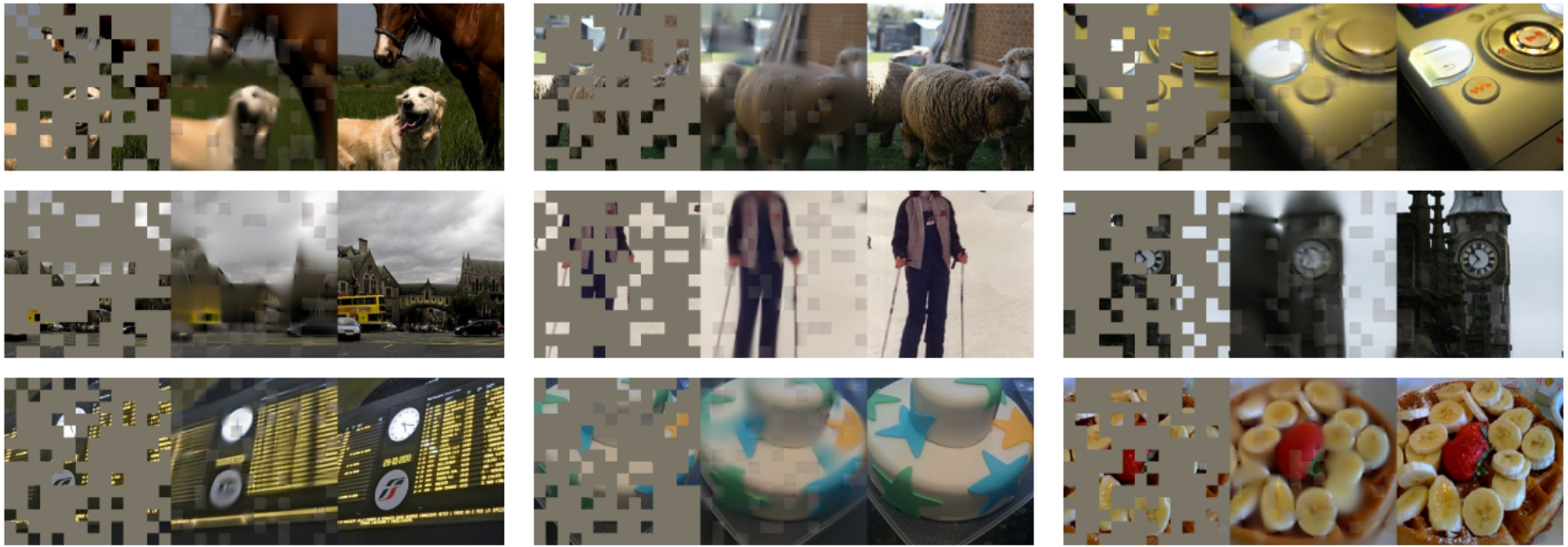
Decoder



Reconstruction results:



Reconstruction



Supervised training parameters

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

config	value
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	90
augmentation	RandomResizedCrop

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

config	value
optimizer	AdamW
base learning rate	1e-3
weight decay	0.05
optimizer momentum	β_1, β_2=0.9, 0.999
layer-wise lr decay [10, 2]	0.75
batch size	1024
learning rate schedule	cosine decay
warmup epochs	5
training epochs	100 (B), 50 (L/H)
augmentation	RandAug (9, 0.5) [12]
label smoothing [52]	0.1
mixup [69]	0.8
cutmix [68]	1.0
drop path [30]	0.1 (B/L) 0.2 (H)

Results - ViT-L

scratch, original [16]	scratch, our impl.	baseline MAE
76.5	82.5	84.9

Ablations

blocks	ft	lin
1	84.8	65.5
2	**84.9**	70.0
4	**84.9**	71.9
8	**84.9**	**73.5**
12	84.4	73.3

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

dim	ft	lin
128	**84.9**	69.1
256	84.8	71.3
512	**84.9**	**73.5**
768	84.4	73.1
1024	84.3	73.1

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

case	ft	lin	FLOPs
encoder w/ `[M]`	84.2	59.6	3.3×
encoder w/o `[M]`	**84.9**	**73.5**	**1**×

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

case	ft	lin
pixel (w/o norm)	84.9	73.5
pixel (w/ norm)	**85.4**	**73.9**
PCA	84.6	72.3
dVAE token	85.3	71.6

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

case	ft	lin
none	84.0	65.7
crop, fixed size	84.7	73.1
crop, rand size	**84.9**	**73.5**
crop + color jit	84.3	71.9

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

case	ratio	ft	lin
random	75	**84.9**	**73.5**
block	50	83.9	72.3
block	75	82.8	63.9
grid	75	84.0	66.0

(f) **Mask sampling**. Random sampling works the best. See Figure 6 for visualizations.

Compare with another methods

method	pre-train data	ViT-B	ViT-L	ViT-H	ViT-H_{448}
scratch, our impl.	-	82.3	82.6	83.1	-
DINO [5]	IN1K	82.8	-	-	-
MoCo v3 [9]	IN1K	83.2	84.1	-	-
BEiT [2]	IN1K+DALLE	83.2	85.2	-	-
MAE	IN1K	83.6	85.9	86.9	**87.8**

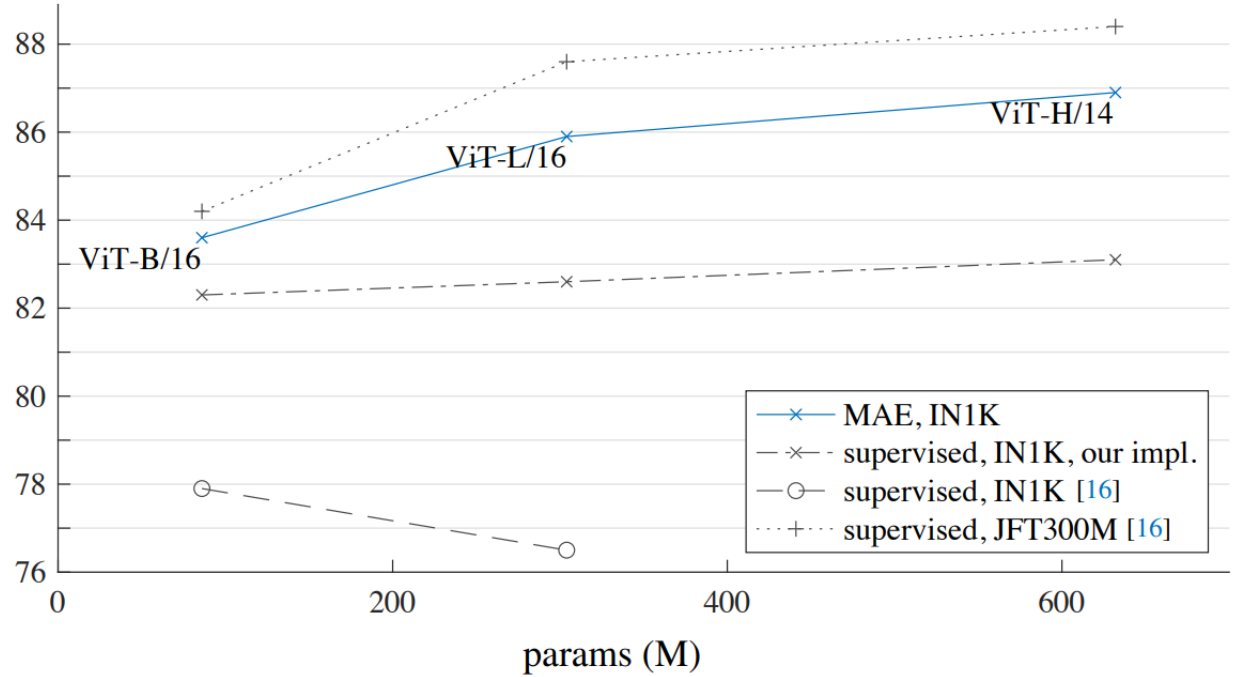


Figure 8. **MAE pre-training *vs*. supervised pre-training**, evaluated by fine-tuning in ImageNet-1K (224 size). We compare with the original ViT results [16] trained in IN1K or JFT300M.