Self-Supervision

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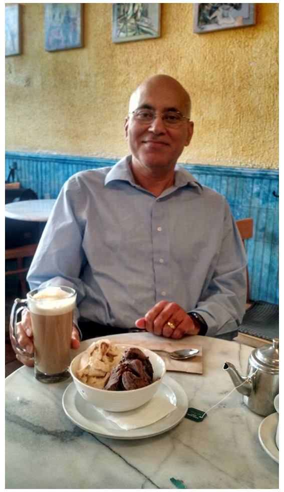
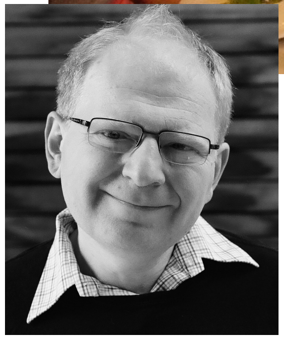
CS 543 / ECE 549

Is semantic supervision necessary to learn good representations?

- Manual labeling doesn't scale, suffers from biases
- Plenty of unlabeled visual data already, and growing really fast
- *And subject of the Gelato Bet:*
- *If, by the first day of autumn (Sept 23) of 2015, a method will exist that can match or beat the performance of R-CNN on Pascal VOC detection, without the use of any extra, human annotations (e.g. ImageNet) as pre-training, Mr. Malik promises to buy Mr. Efros one (1) gelato (2 scoops: one chocolate, one vanilla).*





The Gelato Bet

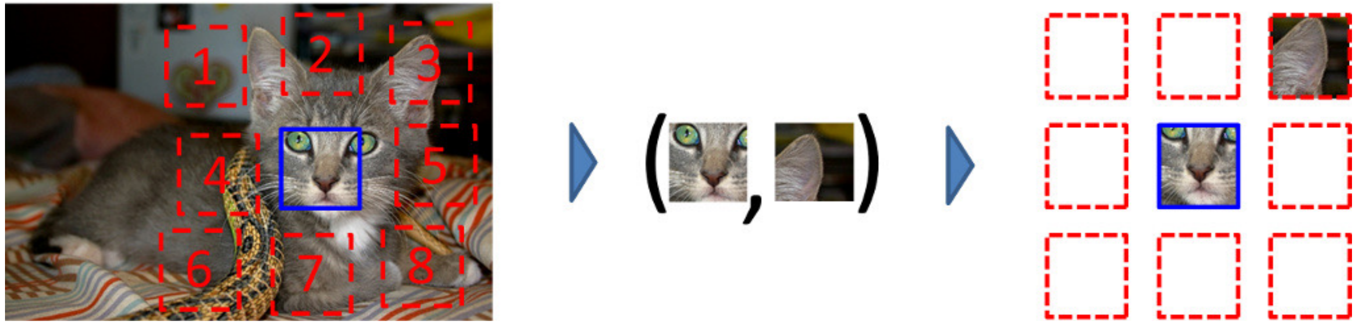
Pre-train representations on a pre-text task

E.g. Colorization

After pre-training, use representation for down-stream tasks.

Many other possibilities,

- Spatial relationship between pair of patches



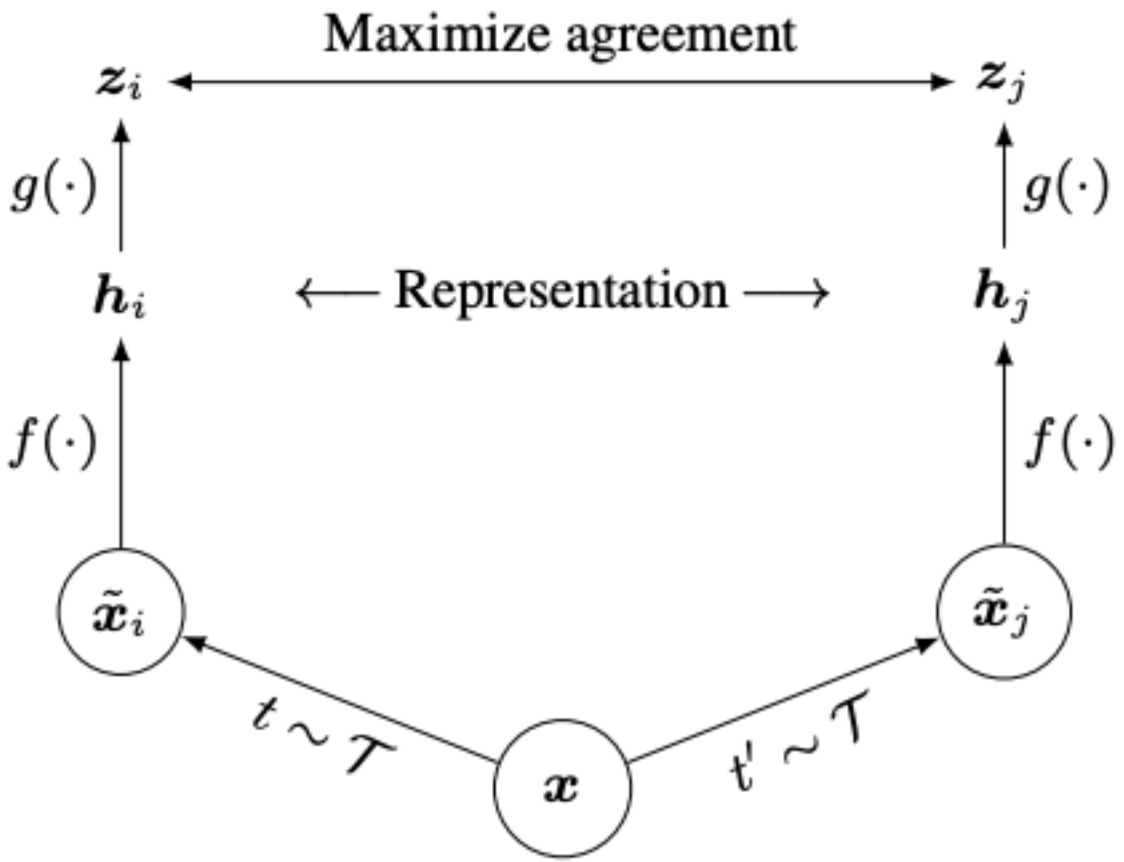
- Predict sound / frame ordering in a video
- Encourage two augmentations of same image to be closer to each other than to another image
- Predict hidden image patches from context

[Split-Brain Autoencoders: Unsupervised Learning by Cross-Channel Prediction](), Zhang et al. CVPR 2017
[Context as Supervisory Signal: Discovering Objects with Predictable Context](), Doersch et al. ICCV 2015

Contrastive Learning

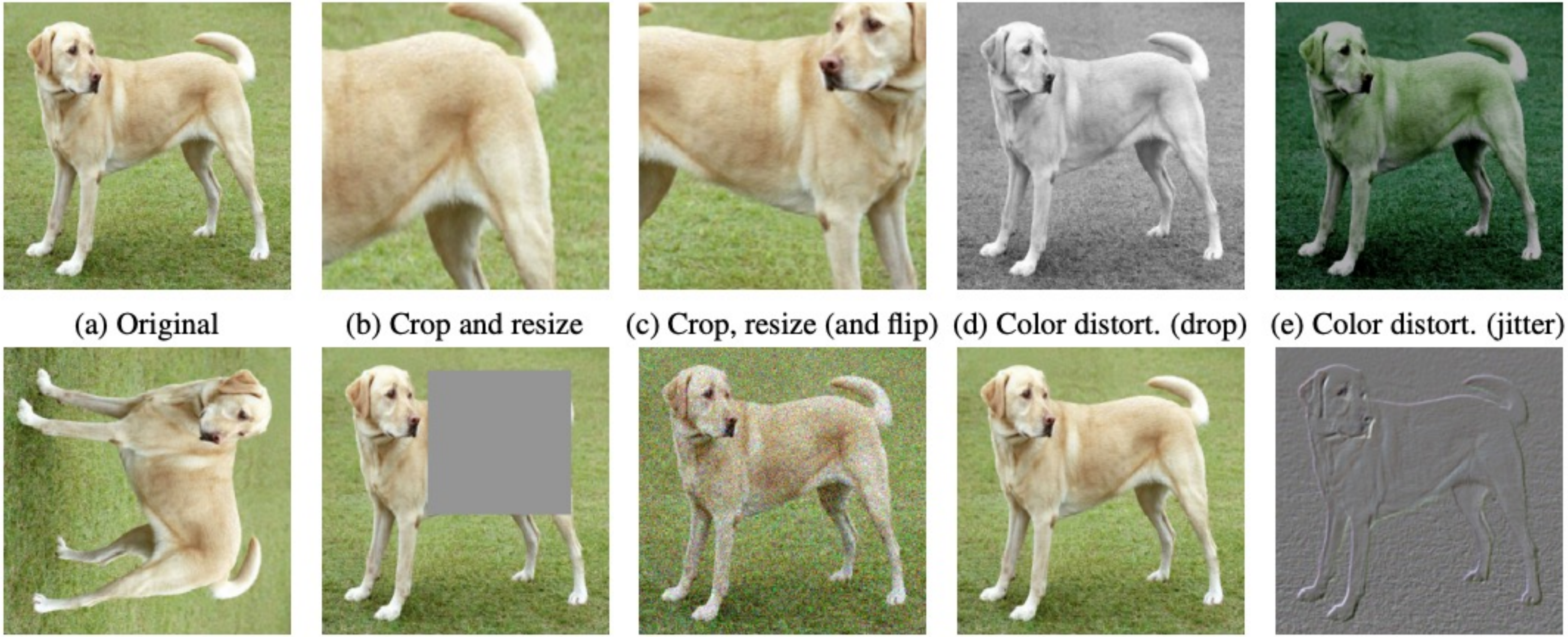
- Encourage two augmentations of an image to be close.
- Using acontrastive loss:

$$\ell_{i,j} = -\log \frac{\exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\mathrm{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$



A Simple Framework for Contrastive Learning of Visual Representations, Chen et al. ICML 2020
See also: Momentum Contrast for Unsupervised Visual Representation Learning, He et al. CVPR 2020

Augmentations

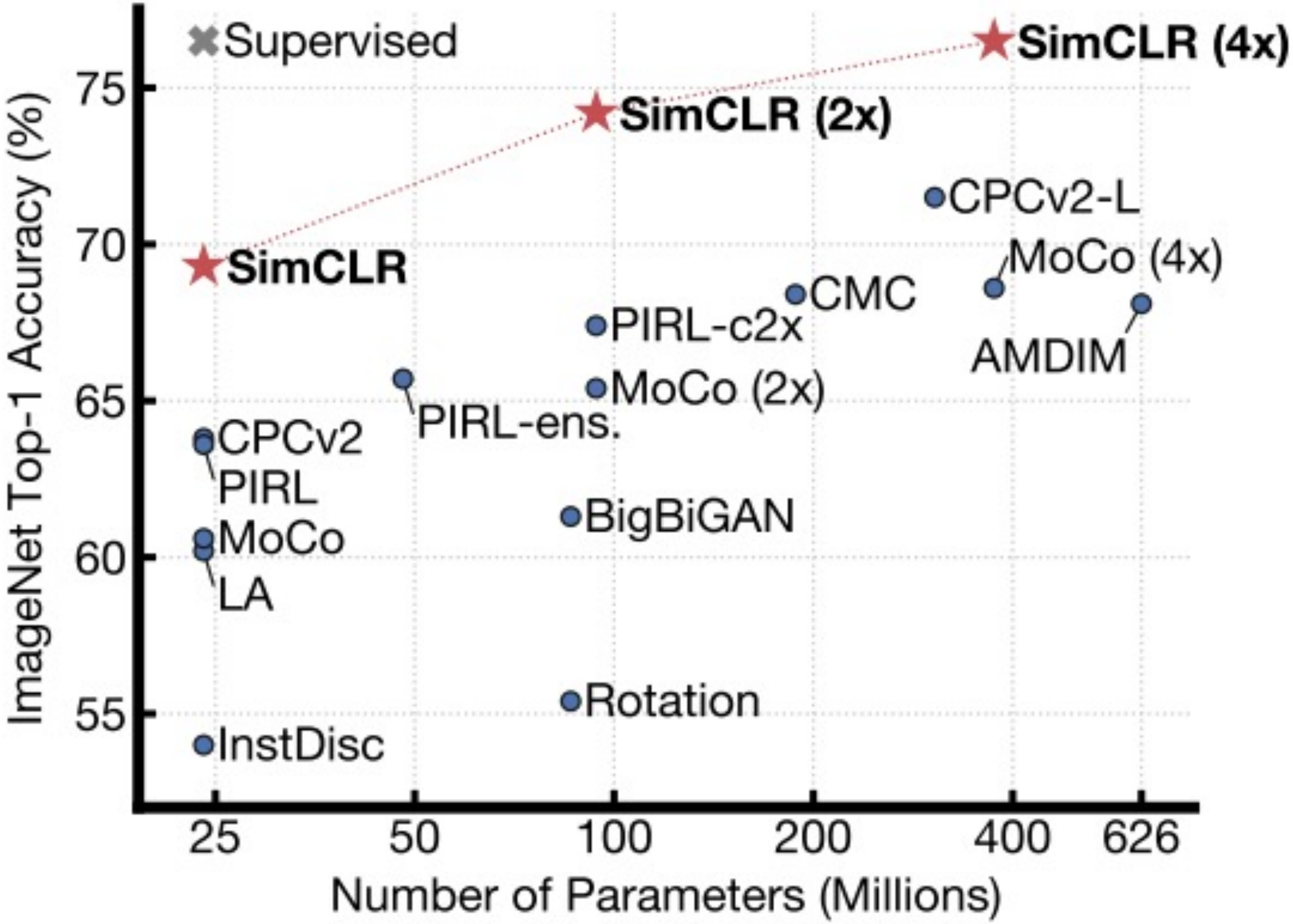


(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering

A Simple Framework for Contrastive Learning of Visual Representations, Chen et al. ICML 2020

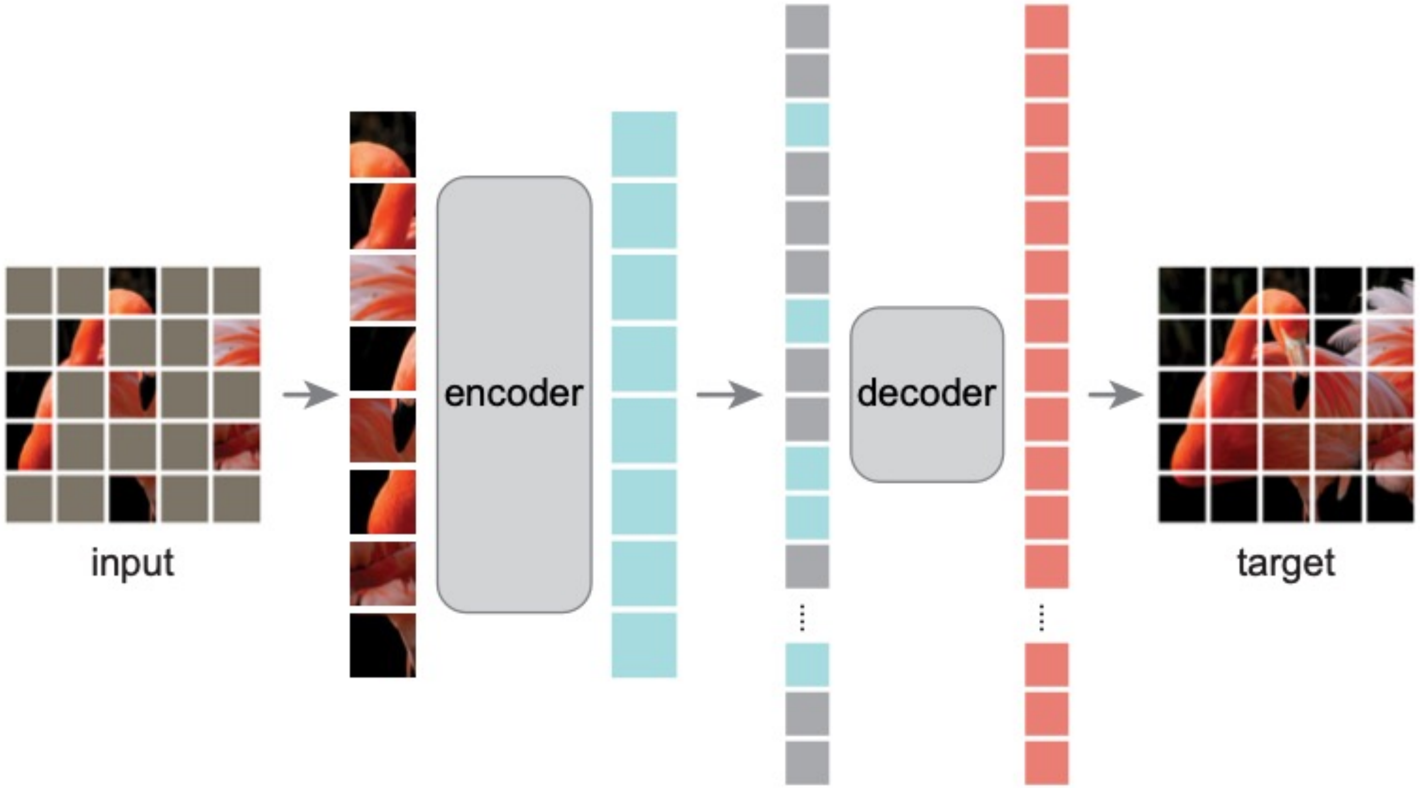
Results



A Simple Framework for Contrastive Learning of Visual Representations, Chen et al. ICML 2020

Masked Auto-Encoders

- Mask out image patches, predict masked patches from visible patches.
- Pre-train encoder & decoder.
- Use encoder as an image representation.



[Masked Autoencoders Are Scalable Vision Learners](), He et al. CVPR 2022

Better than semantic supervision on ImageNet 1K!

method	pre-train data	AP^box ViT-B	AP^box ViT-L	AP^mask ViT-B	AP^mask ViT-L
supervised	IN1K w/ labels	47.9	49.3	42.9	43.9
MoCo v3	IN1K	47.9	49.3	42.7	44.0
BEiT	IN1K+DALLE	49.8	**53.3**	44.4	47.1
MAE	IN1K	**50.3**	**53.3**	**44.9**	**47.2**

Table 4. **COCO object detection and segmentation** using a ViT Mask R-CNN baseline. All entries are based on our implementation. Self-supervised entries use IN1K data *without* labels. Mask AP follows a similar trend as box AP.

method	pre-train data	ViT-B	ViT-L
supervised	IN1K w/ labels	47.4	49.9
MoCo v3	IN1K	47.3	49.1
BEiT	IN1K+DALLE	47.1	53.3
MAE	IN1K	**48.1**	**53.6**

Table 5. **ADE20K semantic segmentation** (mIoU) using UperNet. BEiT results are reproduced using the official code. Other entries are based on our implementation. Self-supervised entries use IN1K data *without* labels.

dataset	ViT-B	ViT-L	ViT-H	ViT-H_{448}	prev best
iNat 2017	70.5	75.7	79.3	**83.4**	75.4 [55]
iNat 2018	75.4	80.1	83.0	**86.8**	81.2 [54]
iNat 2019	80.5	83.4	85.7	**88.3**	84.1 [54]
Places205	63.9	65.8	65.9	**66.8**	66.0 [19]†
Places365	57.9	59.4	59.8	**60.3**	58.0 [40]‡

Table 6. **Transfer learning accuracy on classification datasets**, using MAE pre-trained on IN1K and then fine-tuned. We provide system-level comparisons with the previous best results.

†: pre-trained on 1 billion images. ‡: pre-trained on 3.5 billion images.

Masked Autoencoders Are Scalable Vision Learners, He et al. CVPR 2022

Improves performance on ImageNet itself

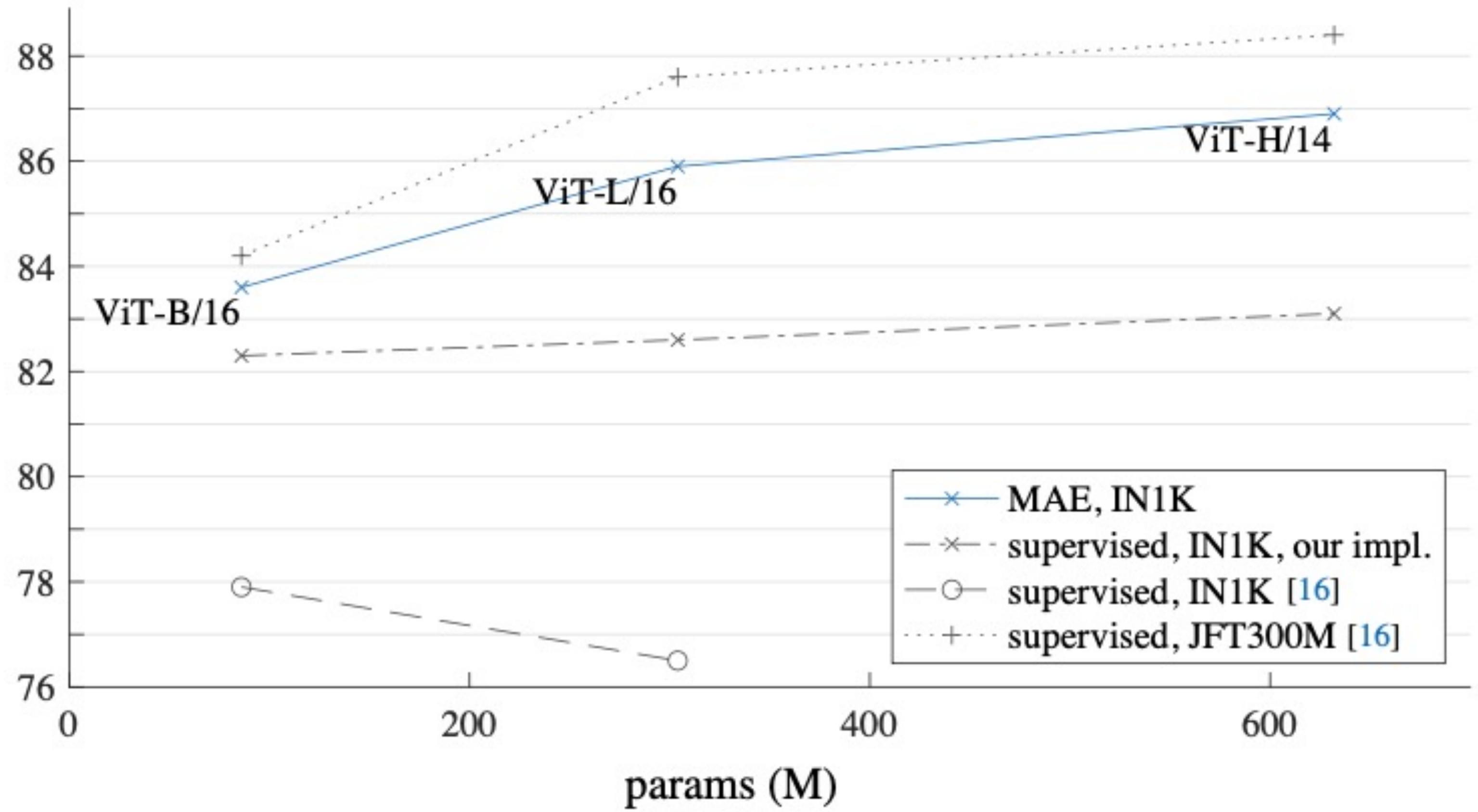


Figure 8. **MAE pre-training *vs*. supervised pre-training**, evaluated by fine-tuning in ImageNet-1K (224 size). We compare with the original ViT results [16] trained in IN1K or JFT300M.

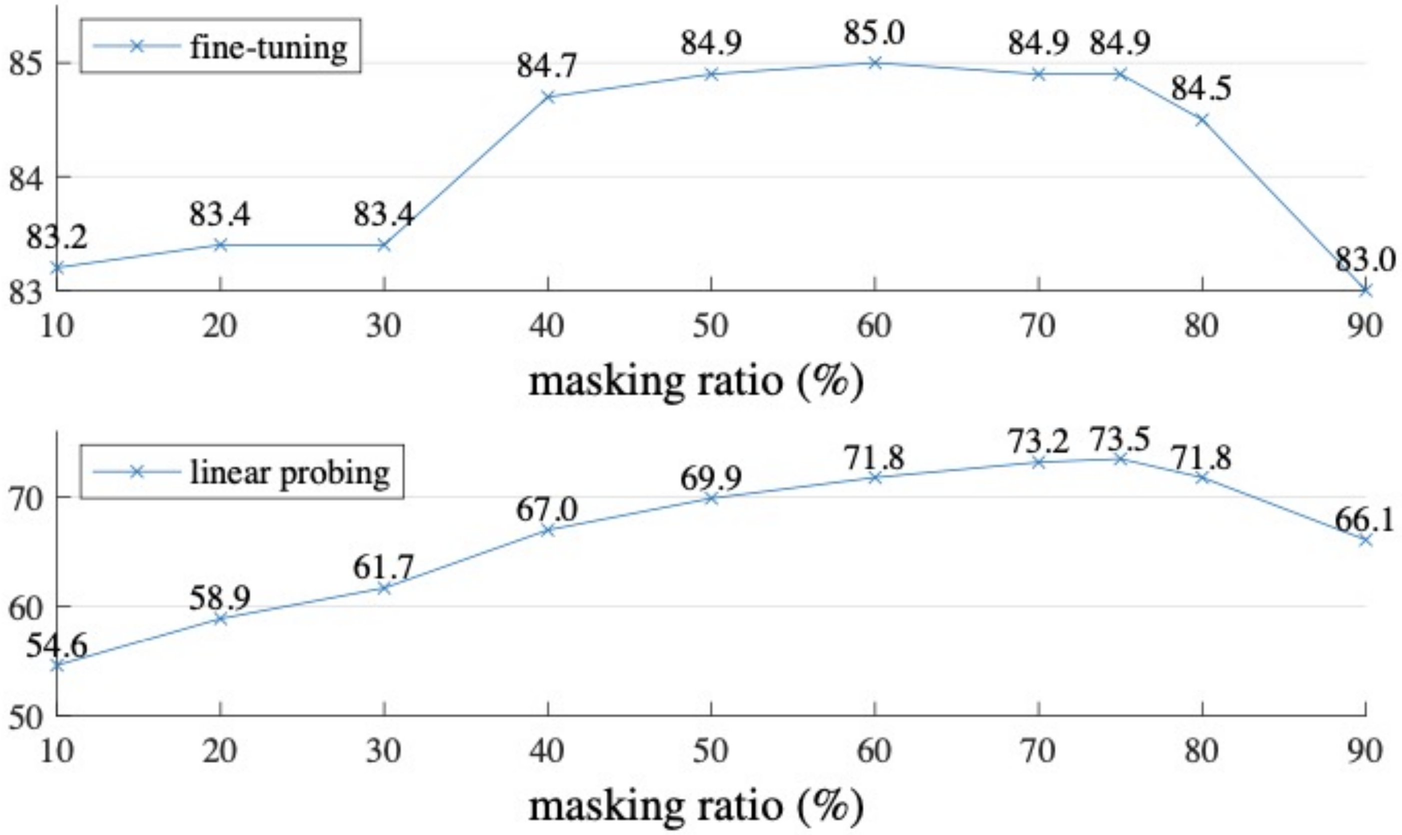
[Masked Autoencoders Are Scalable Vision Learners](), He et al. CVPR 2022

Better than past self-supervision approaches

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	<u>83.6</u>	<u>85.9</u>	<u>86.9</u>	**87.8**

Masked Autoencoders Are Scalable Vision Learners, He et al. CVPR 2022

Ablations



Need high masking ratio for good learning.
NLP models use 15-20% masking ratio.

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

Faster and better to not input masked out patches to encoder

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

Normalized pixels are a better target than discrete tokens / PCA coefficients

[Masked Autoencoders Are Scalable Vision Learners](), He et al. CVPR 2022