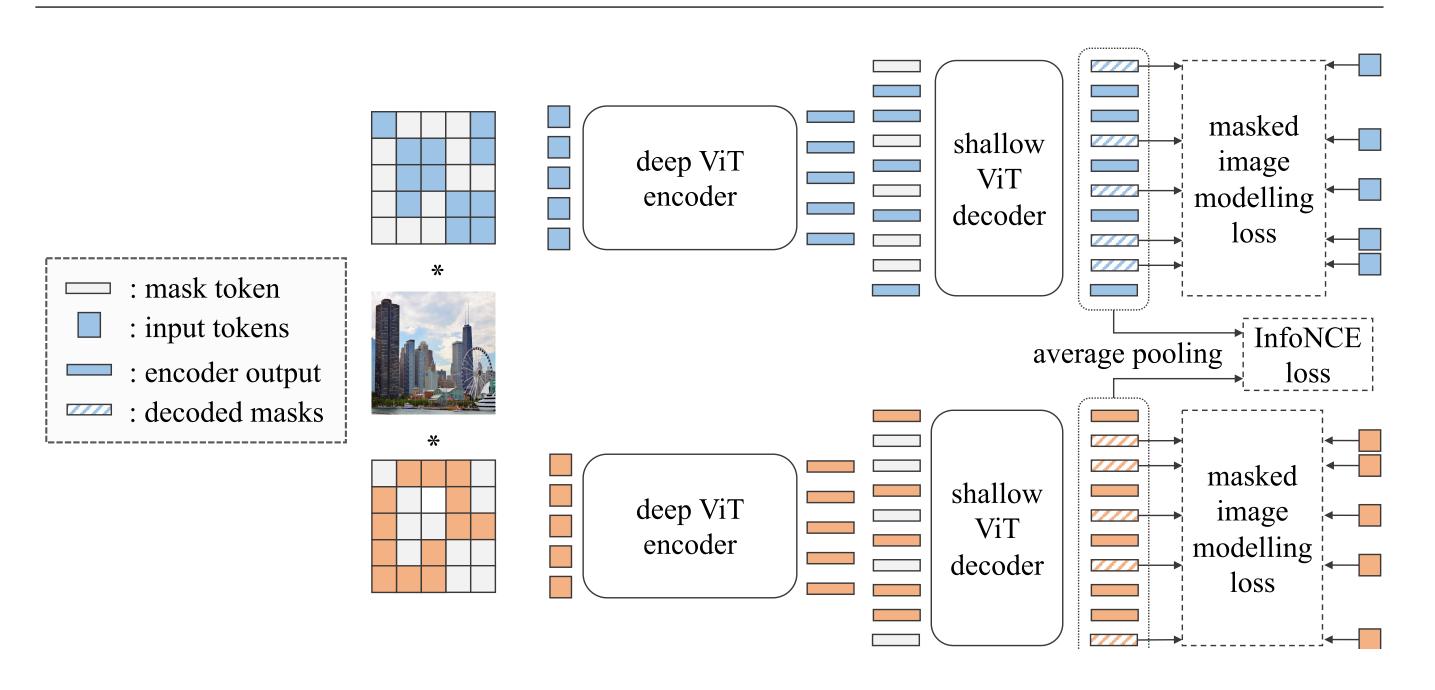


## **SplitMask**



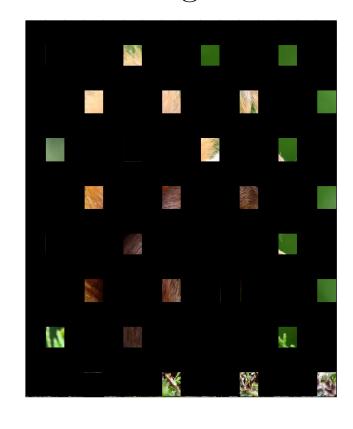
SplitMask is a denoising autoencoder that consists of three steps:

- Split: input image is split into 2 disjoint subsets and processed separately with a ViT encoder with shared parameters.
- Inpaint: the output is processed with a shallow decoder to predict missing patches in each branch.
- *Match*: The decoder outputs from both branches are contrastively trained to increase the similarity between their global descriptors (via Average pooling)

Method	Split	Inpaint	Match	Finetune	Lin.	Hours
BEiT [1]	X	✓	X	82.8	41.0	32.5
	<b>/</b>	<b>✓</b>	X	83.3	46.4	31.0
SplitMask	<b>✓</b>	X	$\checkmark$	79.3	4.0	32.5
	<b>/</b>	✓	✓	83.6	46.5	34.0

# Hypothesis

• Denoising Autoencoding methods (e.g. SplitMask, BEiT) are more sample efficient compared to joint embedding methods.





• Denoising Autoencoding methods are more robust to change in pre-training dataset nautre. They can be trained effectively using non-object centric datasets.

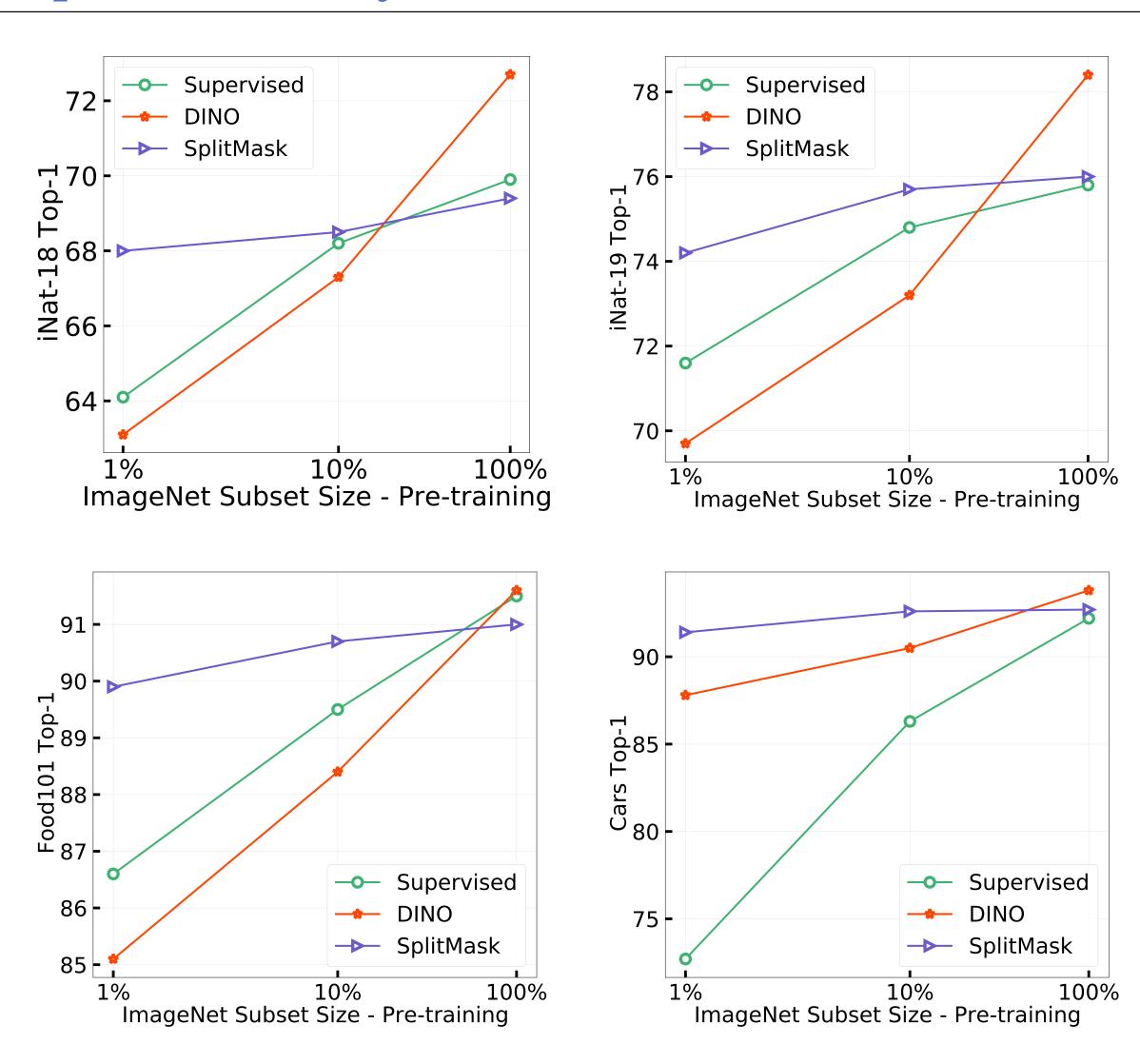
	IMNet $1\%$	IMNet 10%	IMNet Full	COCO
Method	epochs: 30k	epochs: 3k	epochs: 300	epochs: 3k
Supervised	71.6	75.0	75.8	
DINO [2]	70.1	73.1	78.4	71.9
BEiT [1]	74.1	74.5	75.2	74.4
SplitMask	74.8	<b>75.4</b>	75.4	76.3

# Visual word targets with no training

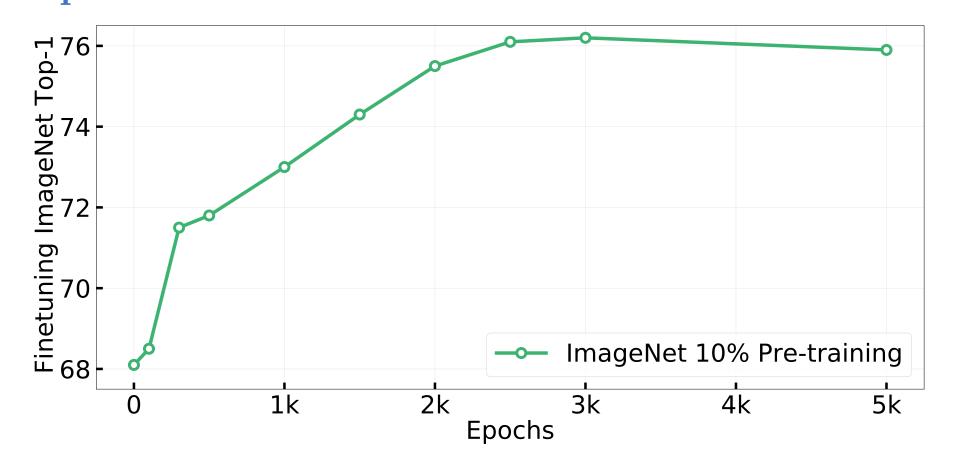
• Multiple simple methods that require no training can be used to generate the per-patch visual words, eliminating the need for pre-trained dVAE.

	DALL-E	Rand.	Proj.	Rand.	Patches	K-Means
iNat19	75.2	75	.2	7	5.3	75.0

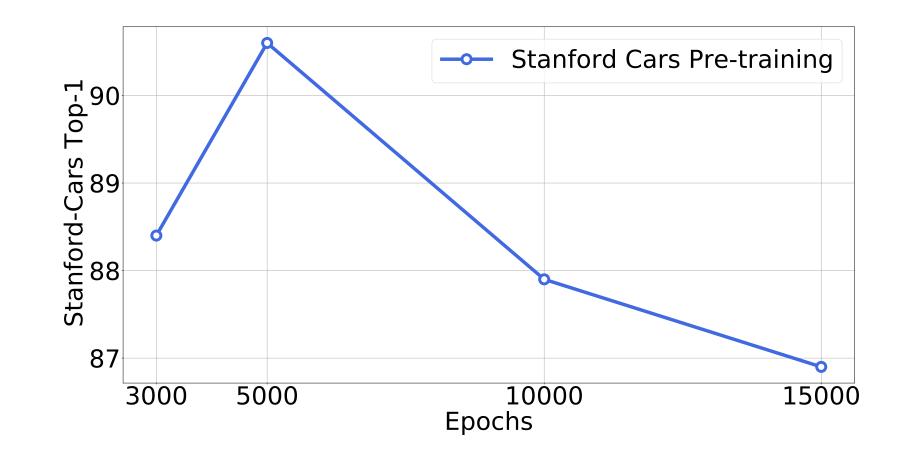
# Sample Efficiency



### How long to pre-train?



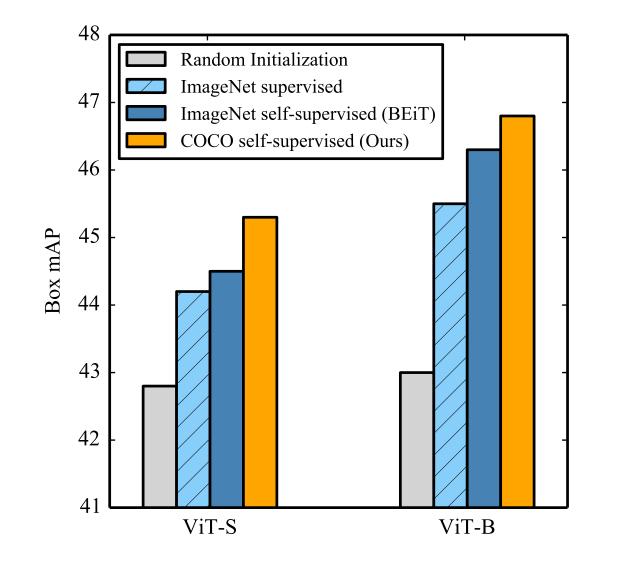
## Is training for longer always better?



## Results

SplitMask provides performance on par, and in some cases improved, when pre-trained on the target dataset indicating that denoising autoencoding methods do not rely on large scale datasets for successful pre-training.

## COCO Object Detection



## ADE20k Semantic Segmentation

Method	Pre	mIoU		
	Supervised	IMNet	ADE20k	
Random Init.	X	X	X	25.4
DeiT [3]	<b>✓</b>	X	X	46.1
BEiT [1]	X	<b>✓</b>	X	45.6
BEiT	X	X	$\checkmark$	45.6
SplitMask	×	X	✓	45.7

#### Classification

Method	Backbone	Supervised	Data	Used	iNat-18	iNat-19	Food 101	Cars
		pre-training	IMNet	Target	437k	265k	75k	8k
Random Init.		X	X	<b>√</b>	59.6	67.5	84.7	35.3
DeiT [3]		<b>✓</b>	<b>✓</b>	$\checkmark$	<u>69.9</u>	75.8	91.5	92.2
BEiT [1]	ViT-S	×	<b>✓</b>	<b>√</b>	68.1	75.2	90.5	92.4
BEiT		×	X	<b>√</b>	68.8	<u>76.1</u>	90.7	92.7
SplitMask		×	X	$\checkmark$	70.1	76.3	91.5	92.8
Random Init.		X	X	<b>√</b>	59.6	68.1	83.3	36.9
DeiT [3]		<b>✓</b>	<b>✓</b>	<b>√</b>	73.2	77.7	91.9	92.1
BEiT [1]	ViT-B	×	<b>✓</b>	<b>√</b>	71.6	78.6	91.0	93.9
BEiT		×	X	<b>√</b>	72.4	<u>79.3</u>	91.7	92.7
SplitMask		×	X	$\checkmark$	74.6	80.4	91.2	93.1

#### Robustness w.r.t pre-training dataset

• SplitMask shows a strong transfer performance regardless of the pre-training dataset used. Typically pre-training using the target dataset achieves the strongest result.

Finetuning $(\rightarrow)$ Pre-training $(\downarrow)$	iNat-19	iNat-18	Food 101	Cars
Rand Init.	67.5	59.6	84.7	35.3
IMNet	75.8	69.9	91.5	92.2
iNat-19	76.3	70.1	90.4	91.7
iNat-18	75.1	70.1	90.4	91.8
Food 101	75.1	68.6	$\boldsymbol{91.5}$	91.7
Cars	71.3	64.2	87.0	92.8
COCO	76.3	69.5	90.9	93.0

### References

- [1] Hangbo Bao, Li Dong, and Furu Wei. Beit: Bert pre-training of image transformers. arXiv preprint arXiv:2106.08254, 2021.
- [2] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. arXiv preprint arXiv:2104.14294, 2021.
- [3] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers and distillation through attention. arXiv preprint arXiv:2012.12877, 2020.