

# Improving Visual Representation Learning through Perceptual Understanding



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Fred Hoffman



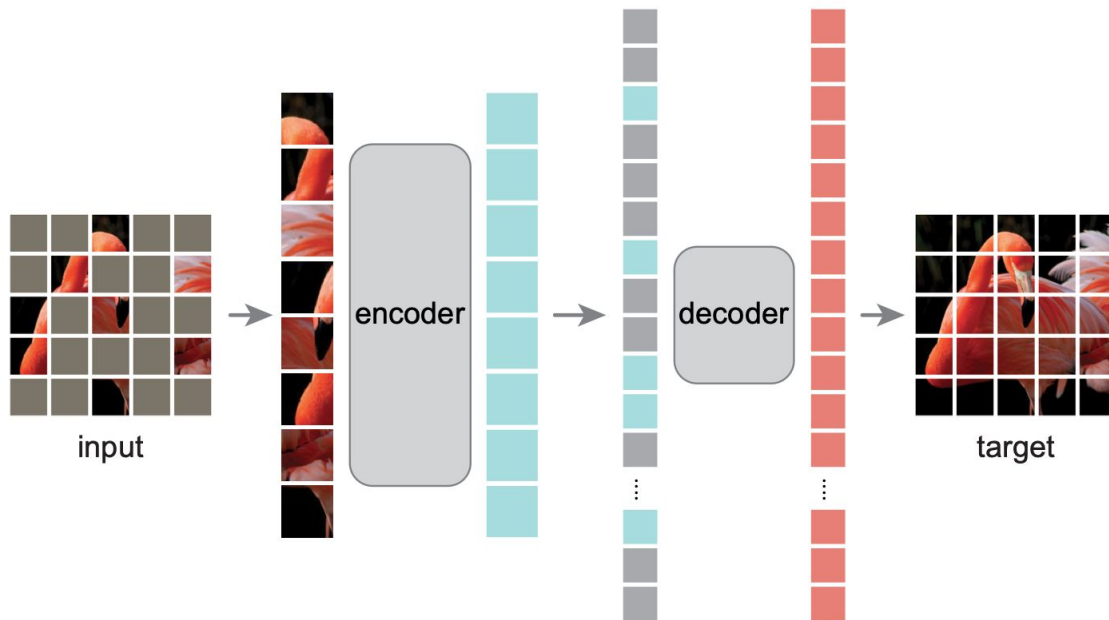
Ken Chatfield

WED-PM-204



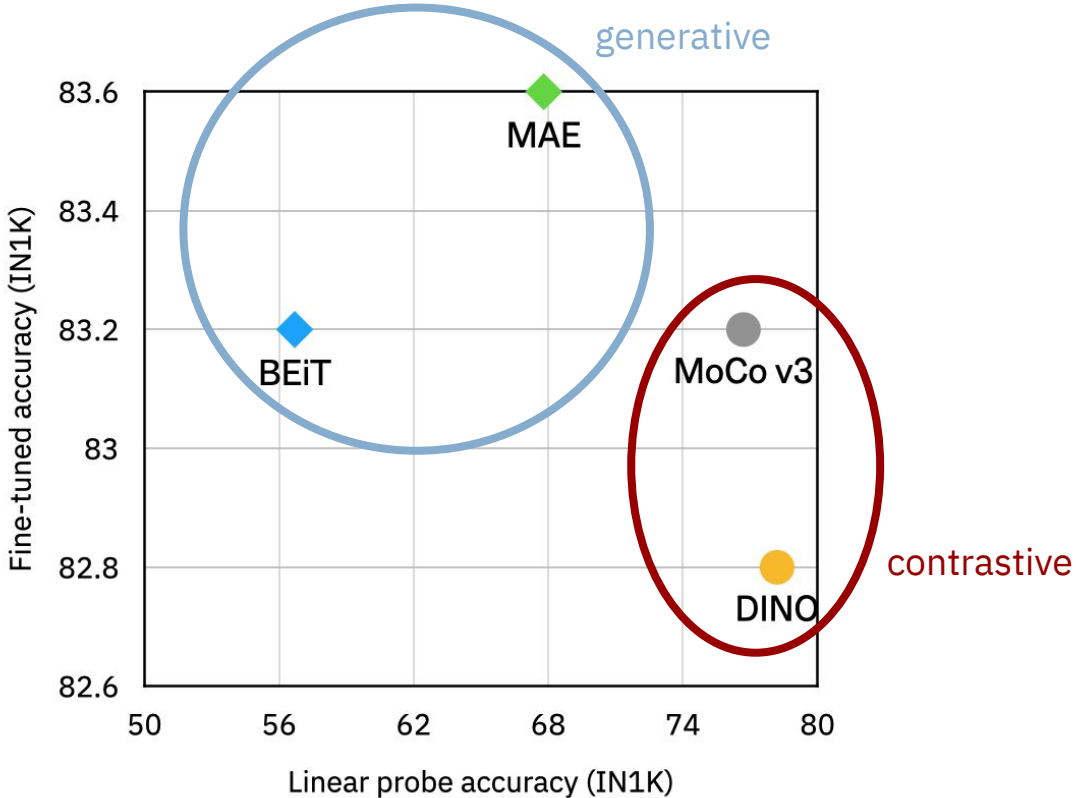
Tractable

The self-supervised revolution in NLP has made it to vision

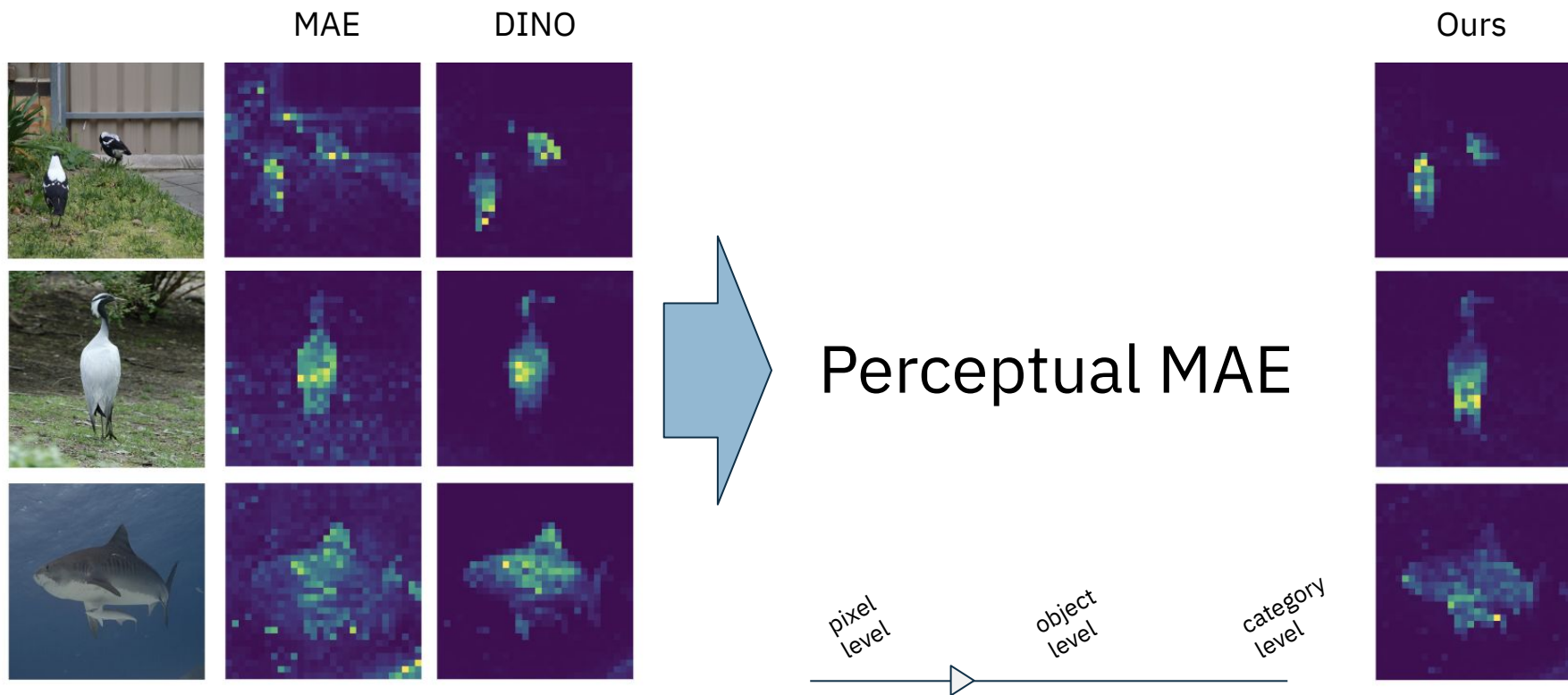


*Masked Autoencoders are Scalable Visual Learners*  
Kaimeng He et al. (CVPR 2022)

Problem: generative SSL still underperforms when not fine-tuning



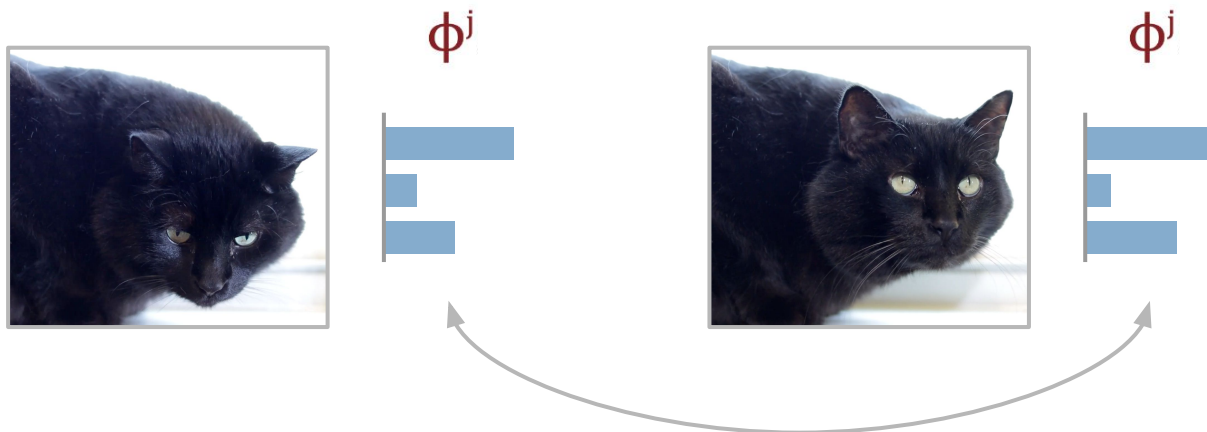
Our aim: incorporate learning higher-level features into masked autoencoders



How? We add an explicit image-level perceptual penalty to the loss

$$L^G = || G(I_m) - I ||_1 + L_{\text{feat}}^G$$

Perceptual loss by **feature matching**:



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*Trick: where  $\phi$  is an adversarial discriminator*

Image-level adversarial term

*Penalise reconstruction which can be distinguished from real image*



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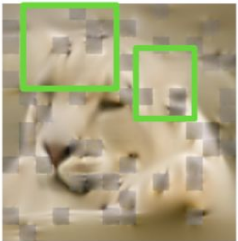
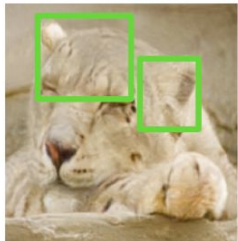
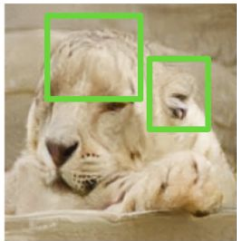
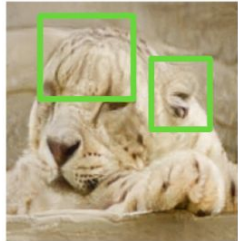
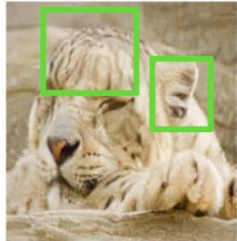


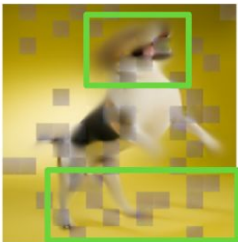
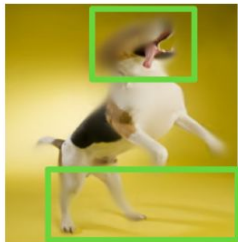
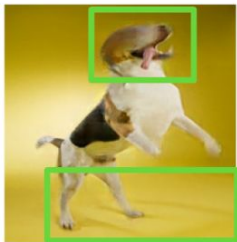
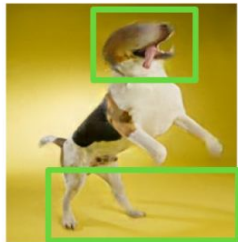
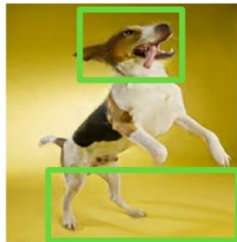
Image-level adversarial term

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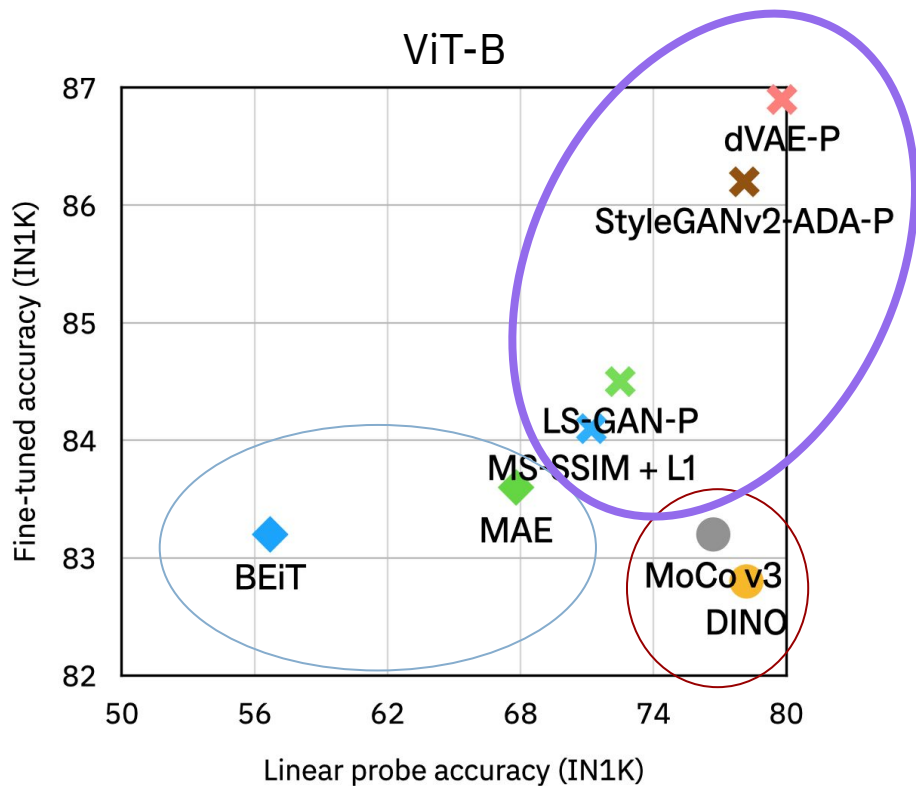
Plus from the generative adversarial toolbox:

- multi-scale gradients
- perceptual path reg.
- adaptive discriminator augmentation (ADA)

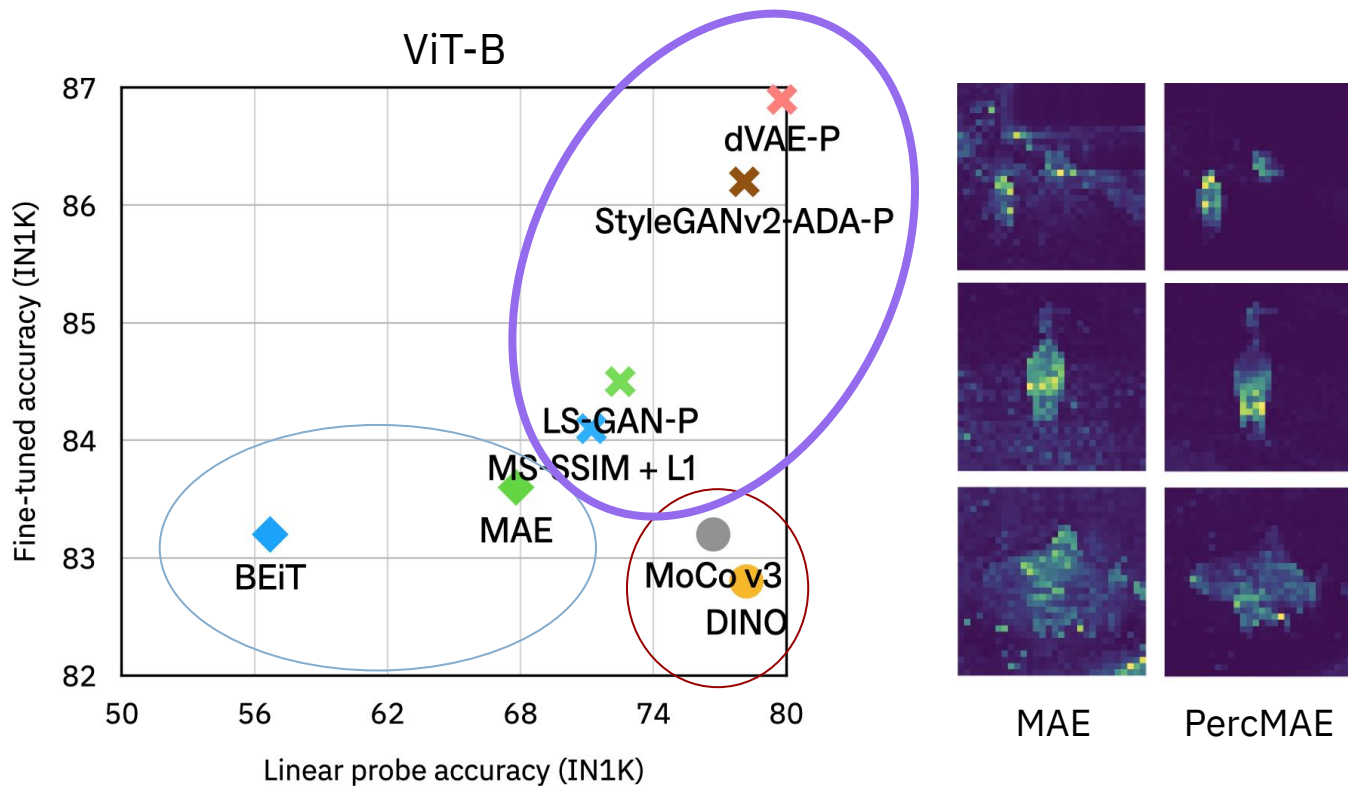
Not only does this improve decoder reconstruction

		MAE	MS-SSIM	LS-GAN-P	MSG-GAN-P	StyleGANv2- ADA-P		
								
								
	L1	0.25	0.21	0.16	0.11	0.06		
	IS	6.33	8.01	16.2	32.1	36.8		

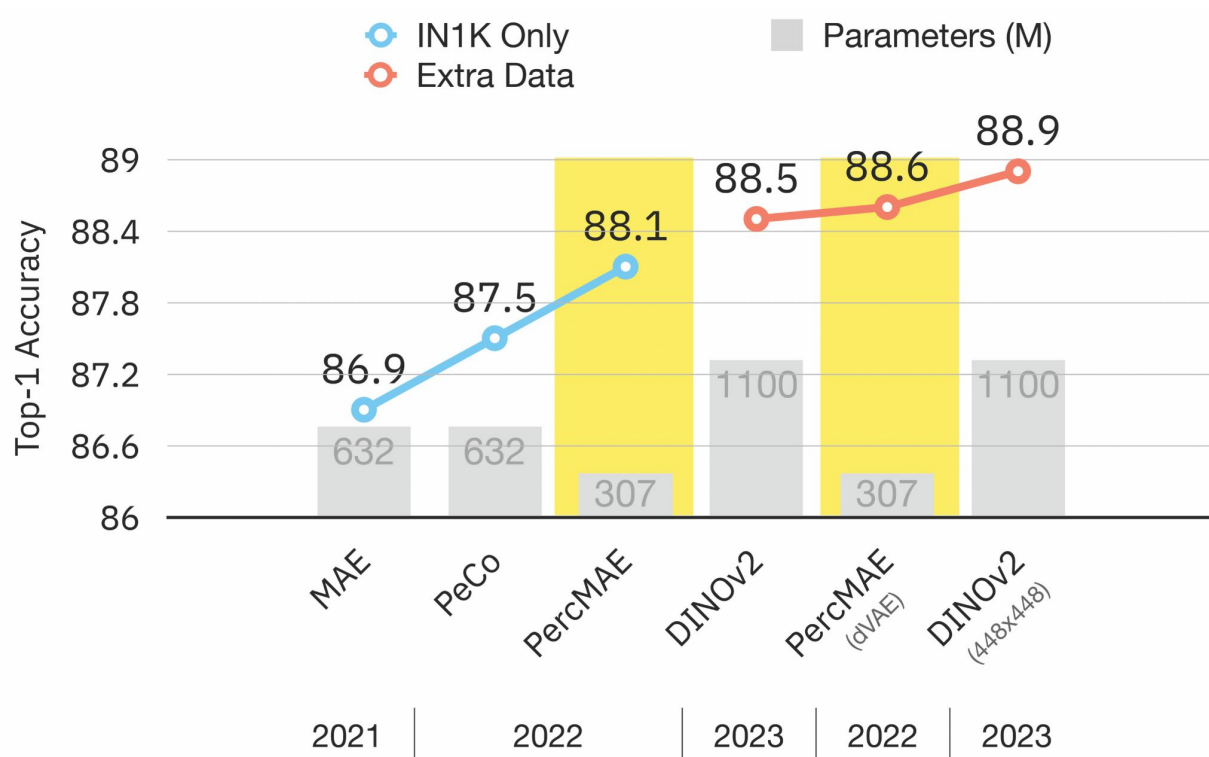
But also boosts both fine-tuned and few-shot settings for classification



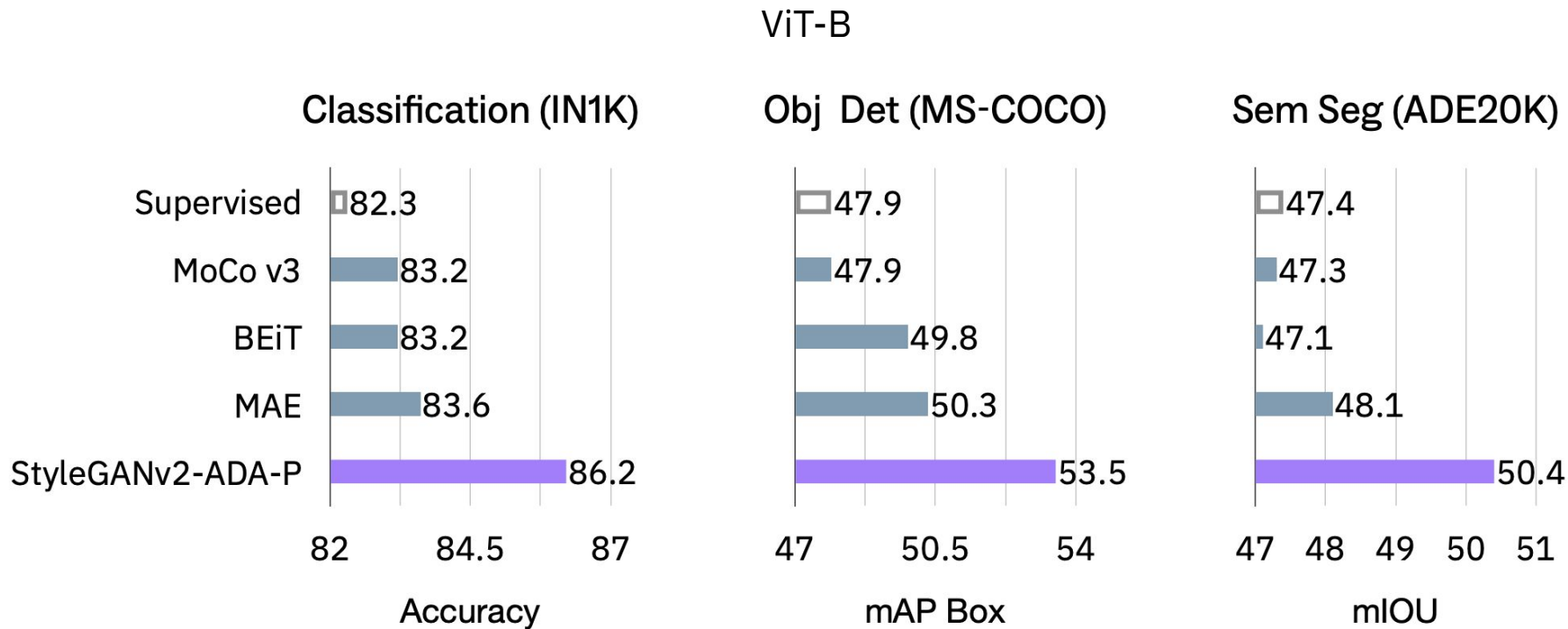
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All whilst being much more data and compute efficient than alternate methods



## And generalises across tasks



Poster session:  
WED-PM-204

<https://github.com/tractableai/perceptual-mae>