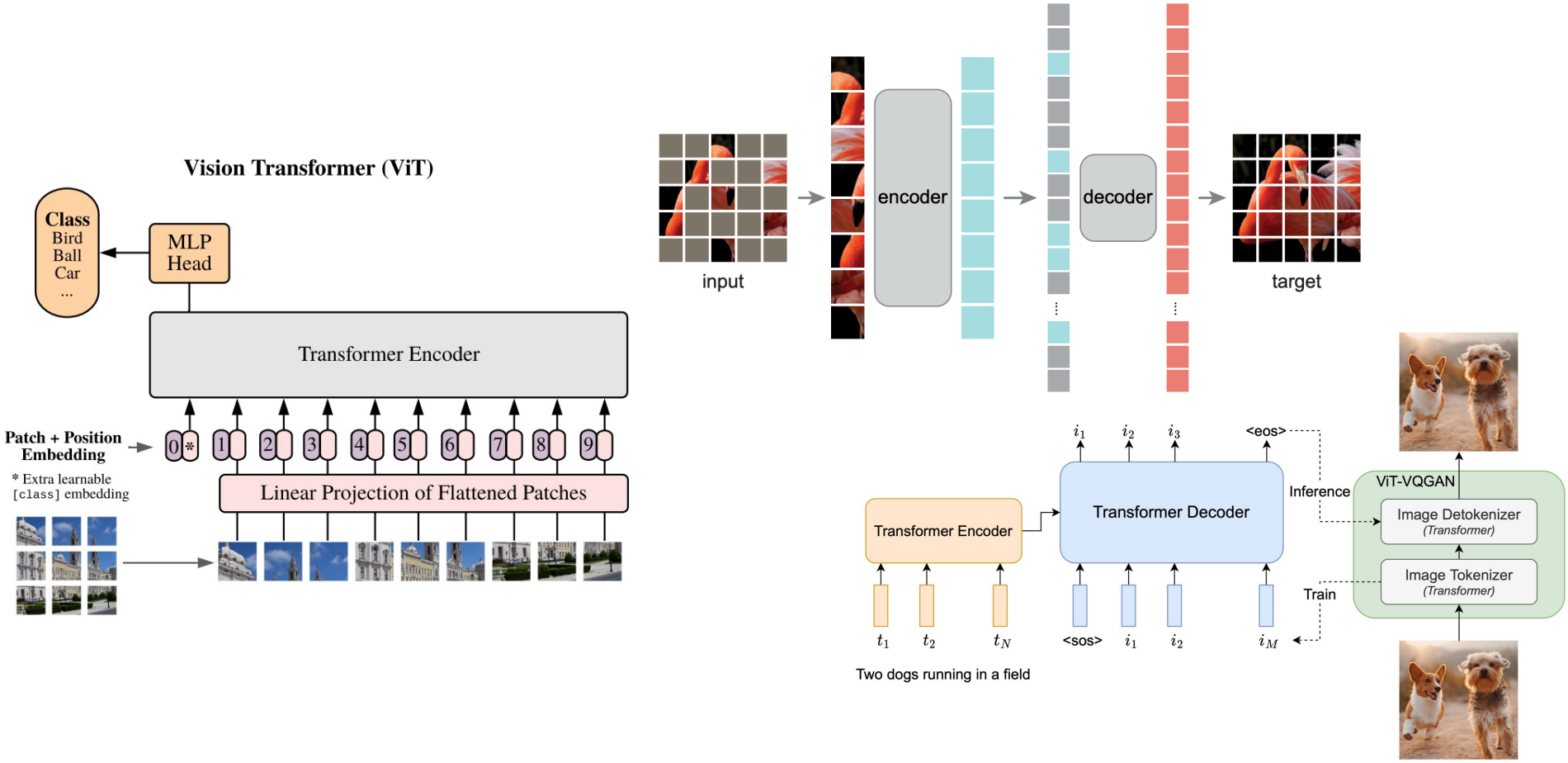
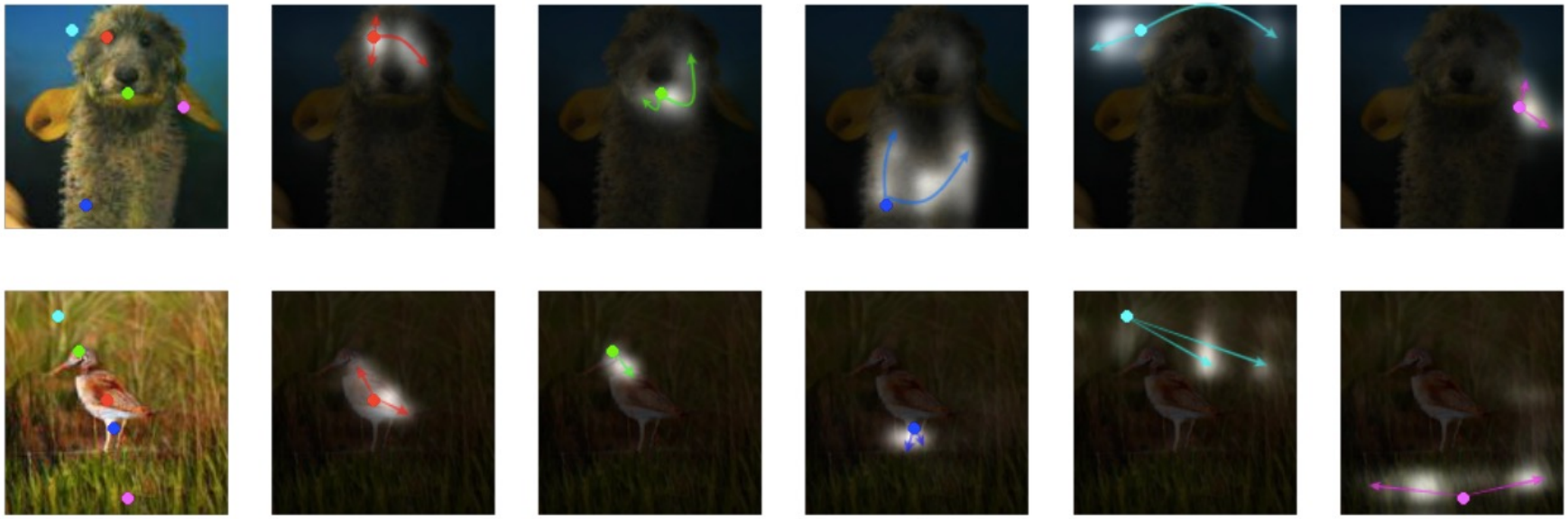
Transformers for image modeling



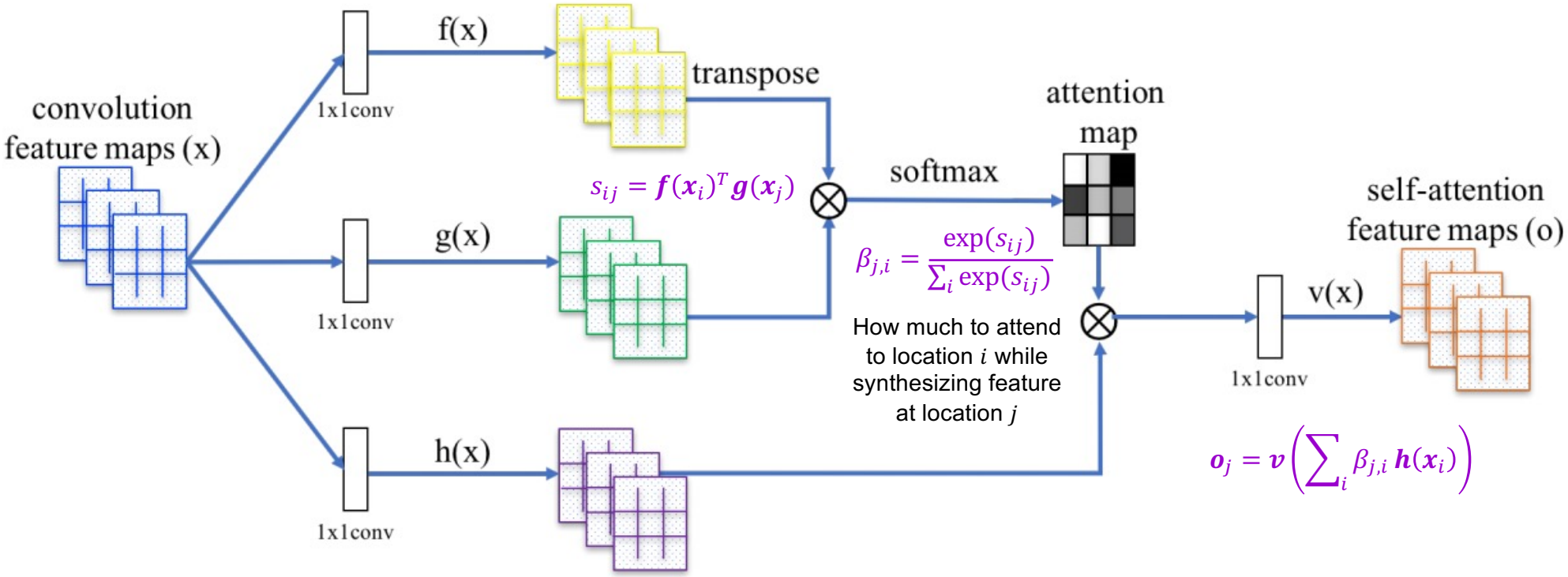
Self-attention for images: SAGAN

- Idea: self-attention produces adaptive receptive fields that can better capture non-local structure



H. Zhang, I. Goodfellow, D. Metaxas, A. Odena. Self-Attention Generative Adversarial Networks. ICML 2019

Self-attention for images: SAGAN



H. Zhang, I. Goodfellow, D. Metaxas, A. Odena. Self-Attention Generative Adversarial Networks. ICML 2019

Image-text cross-attention in diffusion models

- Text prompt is encoded by a language model and injected into the denoising U-Net using *cross-attention*

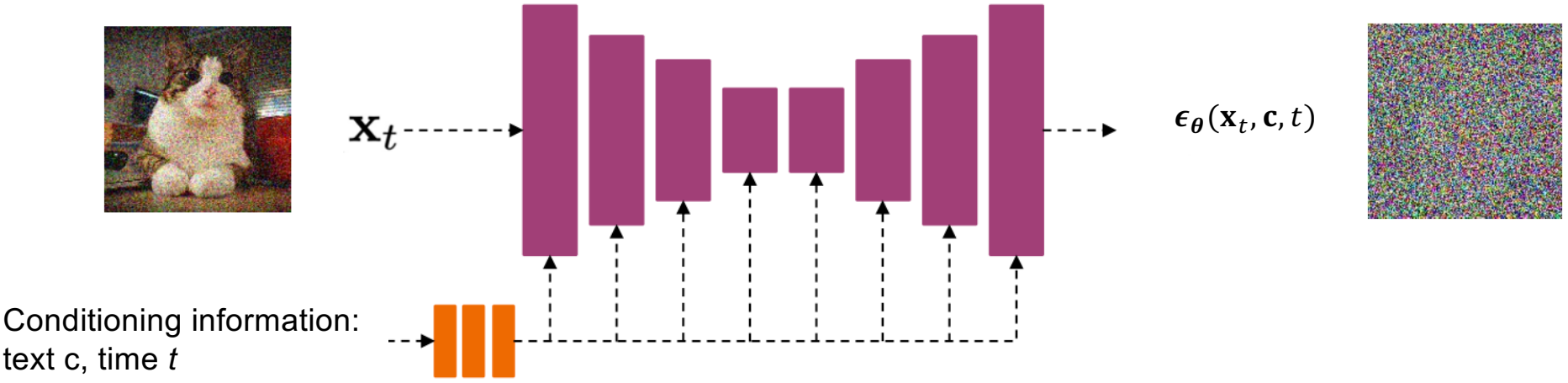


Image source

Image-text cross-attention in diffusion models

- Text prompt is encoded by a language model and injected into the denoising U-Net using *cross-attention*

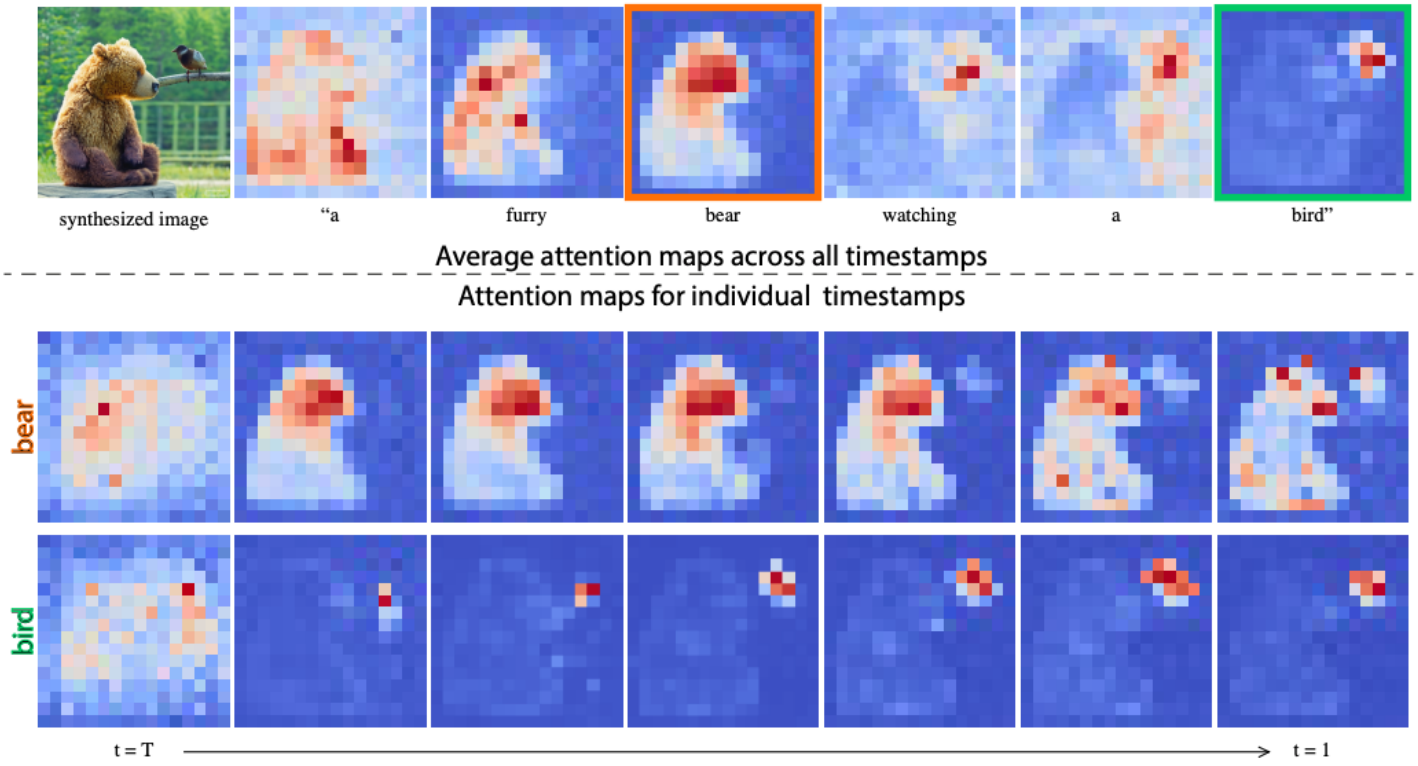
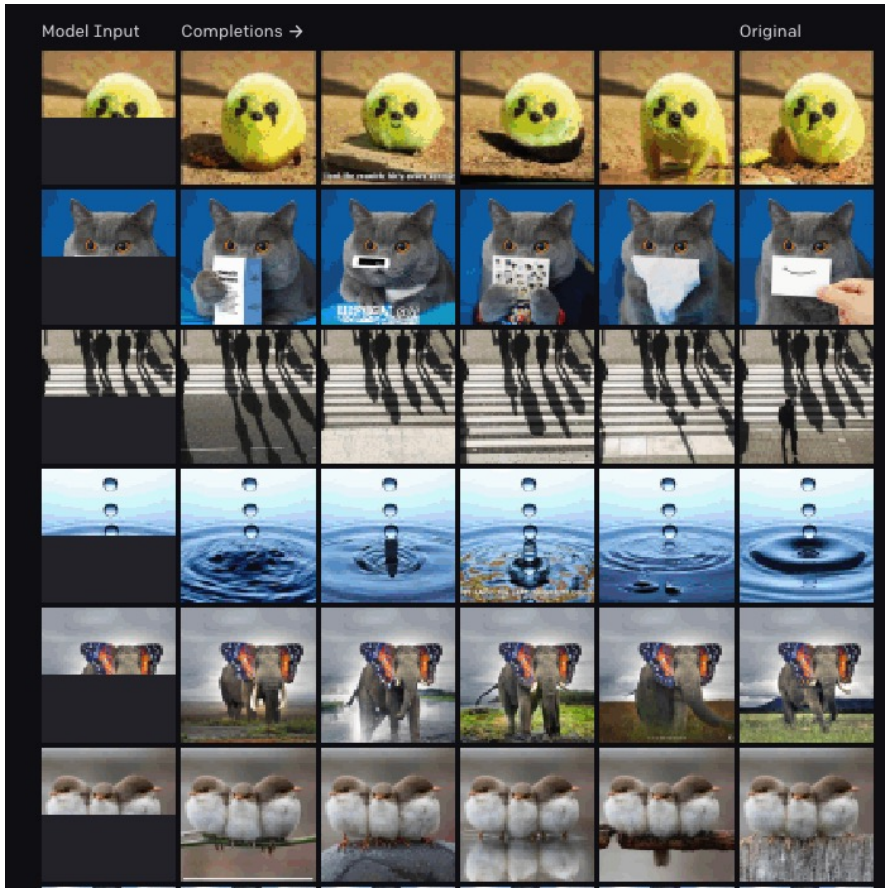


Image source

Transformers for image modeling: Outline

- Architectures
- Self-supervised learning
- Autoregressive text-to-image generation
- Trends

Image GPT – OpenAI

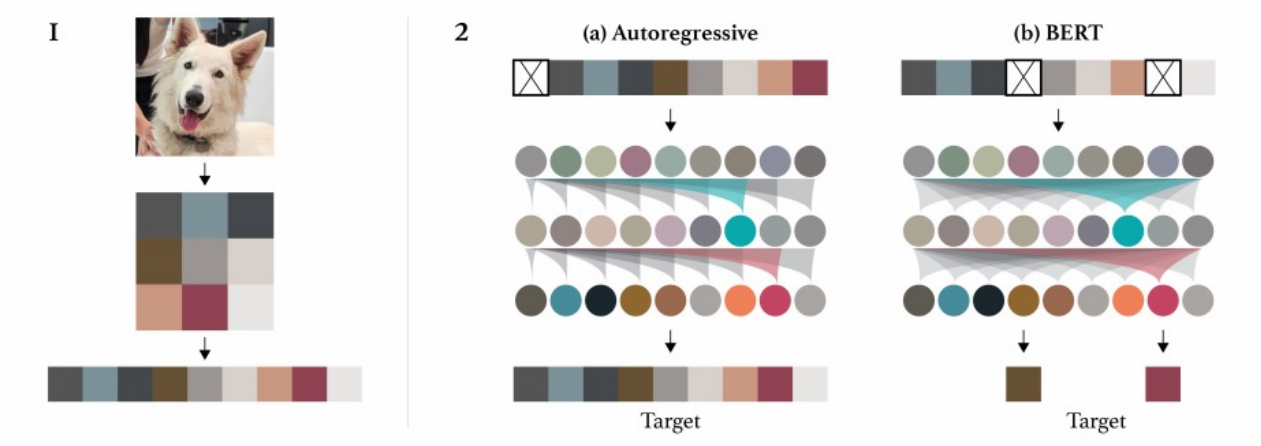


https://openai.com/blog/image-gpt/

M. Chen et al., Generative pretraining from pixels, ICML 2020

Image GPT

- Image resolution up to 64x64, color values quantized to 512 levels (9 bits), dense attention
- For transfer learning, average-pool encoded features across all positions



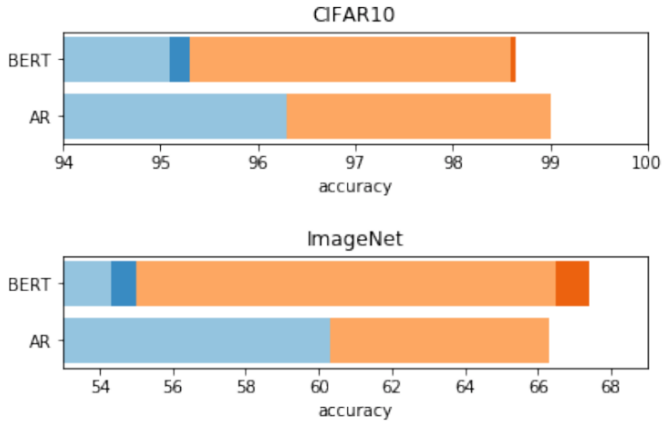


Figure 4. Comparison of auto-regressive pre-training with BERT pre-training using iGPT-L at an input resolution of $32^2 \times 3$. Blue bars display linear probe accuracy and orange bars display fine-tune accuracy. Bold colors show the performance boost from ensembling BERT masks. We see that auto-regressive models produce much better features than BERT models after pre-training, but BERT models catch up after fine-tuning.

M. Chen et al., Generative pretraining from pixels, ICML 2020

Image GPT

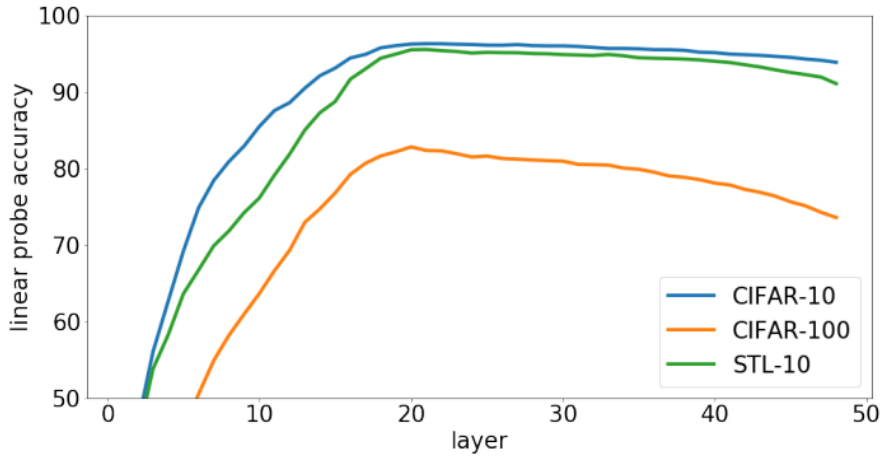


Figure 2. Representation quality depends on the layer from which we extract features. In contrast with supervised models, the best representations for these generative models lie in the middle of the network. We plot this unimodal dependence on depth by showing linear probes for iGPT-L on CIFAR-10, CIFAR-100, and STL-10.

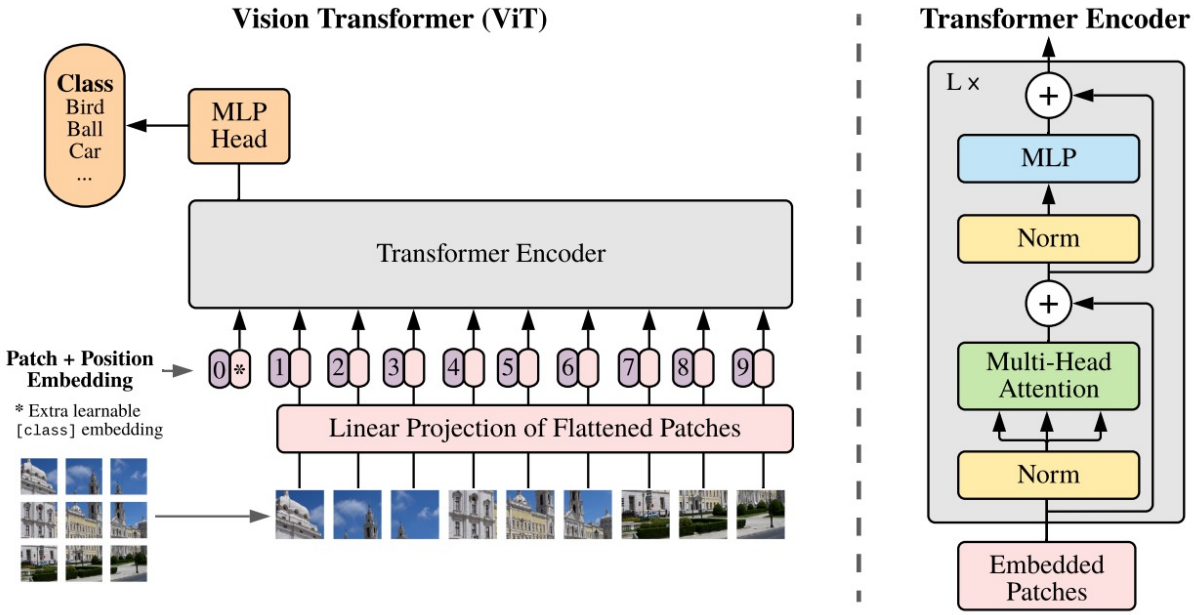
Table 2. Comparing linear probe accuracies between our models and state-of-the-art self-supervised models. A blank input resolution (IR) corresponds to a model working at standard ImageNet resolution. We report the best performing configuration for each contrastive method, finding that our models achieve comparable performance.

Method	IR	Params (M)	Features	Acc
Rotation	orig.	86	8192	55.4
iGPT-L	$32^2 \cdot 3$	1362	1536	60.3
BigBiGAN	orig.	86	8192	61.3
iGPT-L	$48^2 \cdot 3$	1362	1536	65.2
AMDIM	orig.	626	8192	68.1
MoCo	orig.	375	8192	68.6
iGPT-XL	$64^2 \cdot 3$	6801	3072	68.7
SimCLR	orig.	24	2048	69.3
CPC v2	orig.	303	8192	71.5
iGPT-XL	$64^2 \cdot 3$	6801	15360	72.0
SimCLR	orig.	375	8192	76.5

M. Chen et al., Generative pretraining from pixels, ICML 2020

Vision transformer (ViT) – Google

- Split an image into patches, feed linearly projected patches into standard transformer encoder
  - With patches of 14x14 pixels, you need 16x16=256 patches to represent 224x224 images



A. Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. ICLR 2021

Vision transformer (ViT)

- Trained in a supervised fashion, fine-tuned on ImageNet

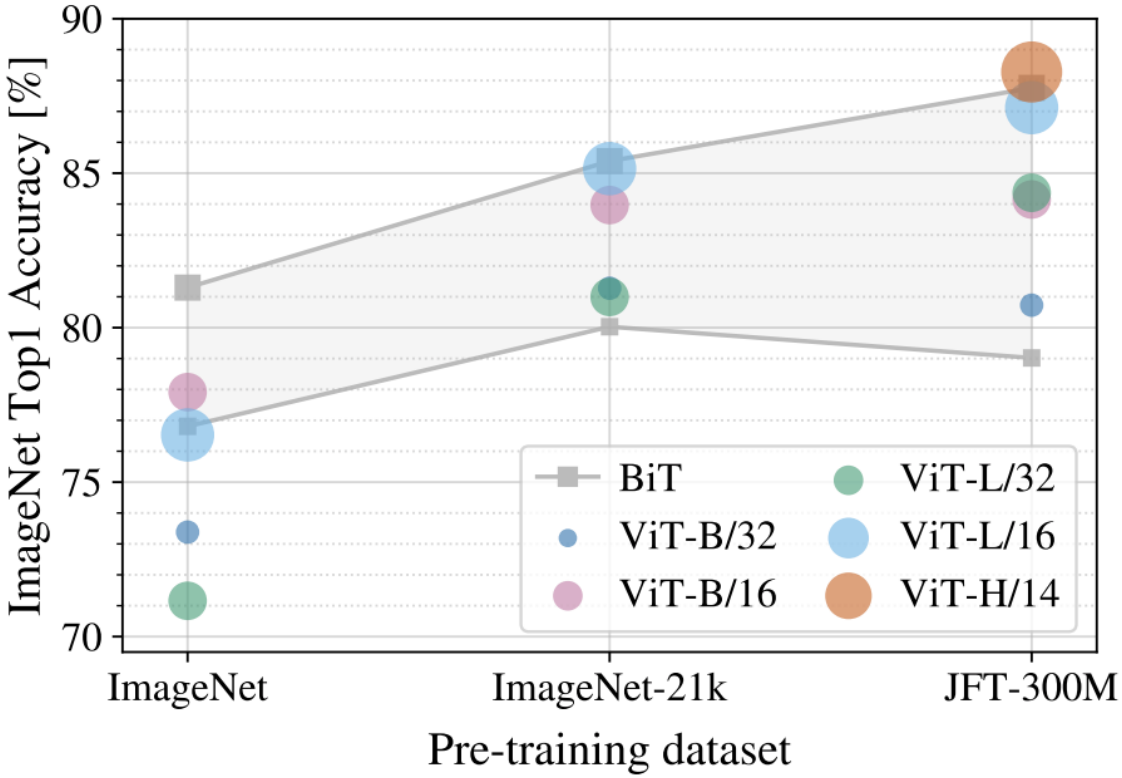


Figure 3: Transfer to ImageNet. While large ViT models perform worse than BiT ResNets (shaded area) when pre-trained on small datasets, they shine when pre-trained on larger datasets. Similarly, larger ViT variants overtake smaller ones as the dataset grows.

BiT: Big Transfer (ResNet)
ViT: Vision Transformer (Base/Large/Huge, patch size of 14x14, 16x16, or 32x32)

Internal Google dataset (not public)

A. Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. ICLR 2021

Hierarchical transformer: Swin

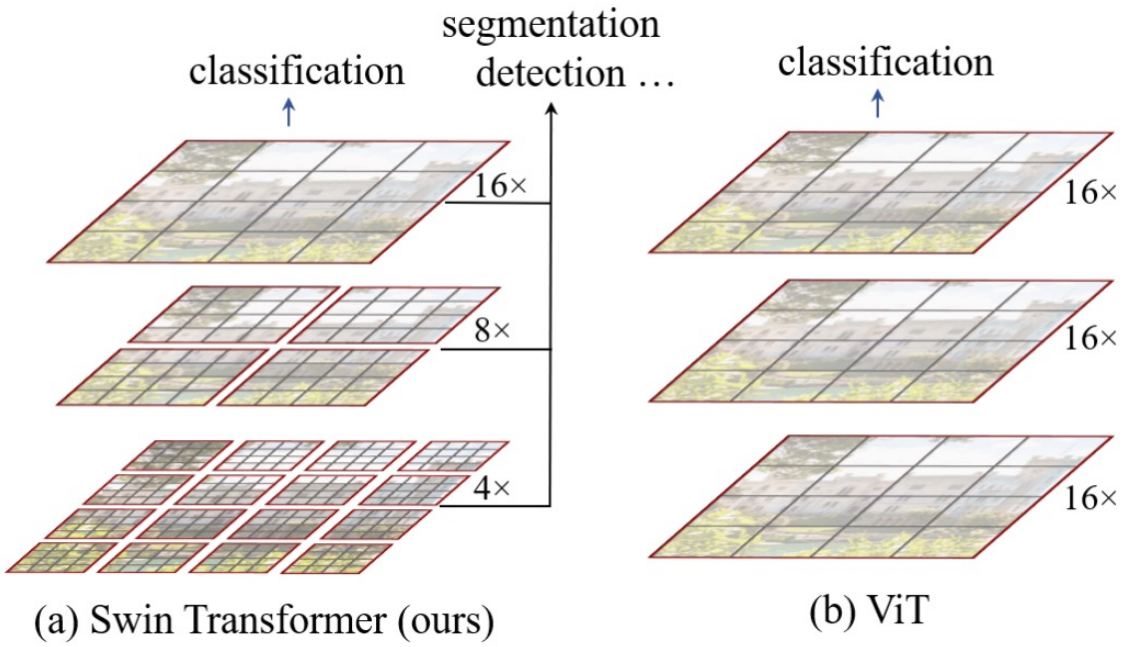
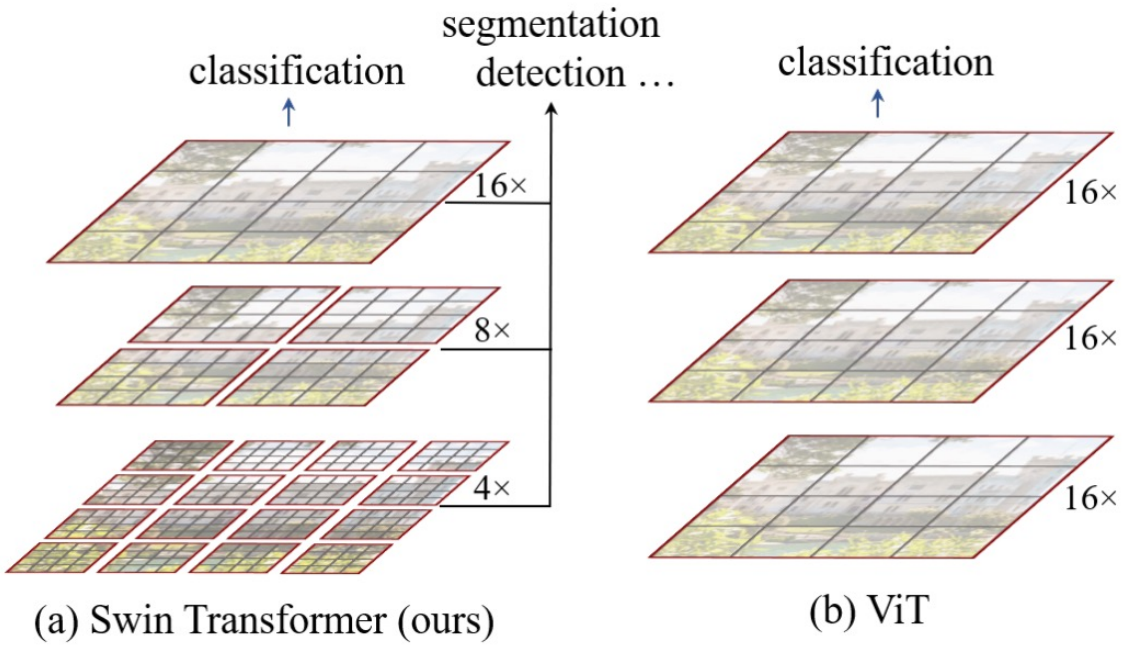


Figure 1. (a) The proposed Swin Transformer builds hierarchical feature maps by merging image patches (shown in gray) in deeper layers and has linear computation complexity to input image size due to computation of self-attention only within each local window (shown in red). It can thus serve as a general-purpose backbone for both image classification and dense recognition tasks. (b) In contrast, previous vision Transformers [19] produce feature maps of a single low resolution and have quadratic computation complexity to input image size due to computation of self-attention globally.

Z. Liu et al. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. ICCV 2021

Hierarchical transformer: Swin



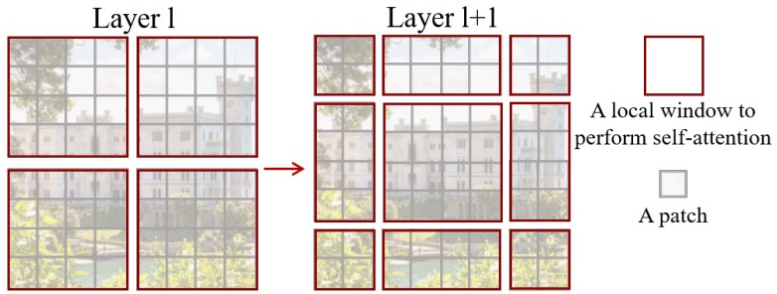


Figure 2. An illustration of the *shifted window* approach for computing self-attention in the proposed Swin Transformer architecture. In layer l (left), a regular window partitioning scheme is adopted, and self-attention is computed within each window. In the next layer $l + 1$ (right), the window partitioning is shifted, resulting in new windows. The self-attention computation in the new windows crosses the boundaries of the previous windows in layer l, providing connections among them.

Z. Liu et al. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. ICCV 2021

Swin results

(a) Regular ImageNet-1K trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [44]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [44]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [44]	224^2	84M	16.0G	334.7	82.9
ViT-B/16 [19]	384^2	86M	55.4G	85.9	77.9
ViT-L/16 [19]	384^2	307M	190.7G	27.3	76.5
DeiT-S [57]	224^2	22M	4.6G	940.4	79.8
DeiT-B [57]	224^2	86M	17.5G	292.3	81.8
DeiT-B [57]	384^2	86M	55.4G	85.9	83.1
Swin-T	224^2	29M	4.5G	755.2	81.3
Swin-S	224^2	50M	8.7G	436.9	83.0
Swin-B	224^2	88M	15.4G	278.1	83.5
Swin-B	384^2	88M	47.0G	84.7	84.5

(b) ImageNet-22K pre-trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
R-101x3 [34]	384^2	388M	204.6G	-	84.4
R-152x4 [34]	480^2	937M	840.5G	-	85.4
ViT-B/16 [19]	384^2	86M	55.4G	85.9	84.0
ViT-L/16 [19]	384^2	307M	190.7G	27.3	85.2
Swin-B	224^2	88M	15.4G	278.1	85.2
Swin-B	384^2	88M	47.0G	84.7	86.4
Swin-L	384^2	197M	103.9G	42.1	87.3

Table 1. Comparison of different backbones on ImageNet-1K classification. Throughput is measured using the GitHub repository of [62] and a V100 GPU, following [57].

COCO detection and segmentation

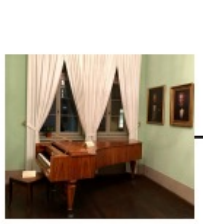
(a) Various frameworks

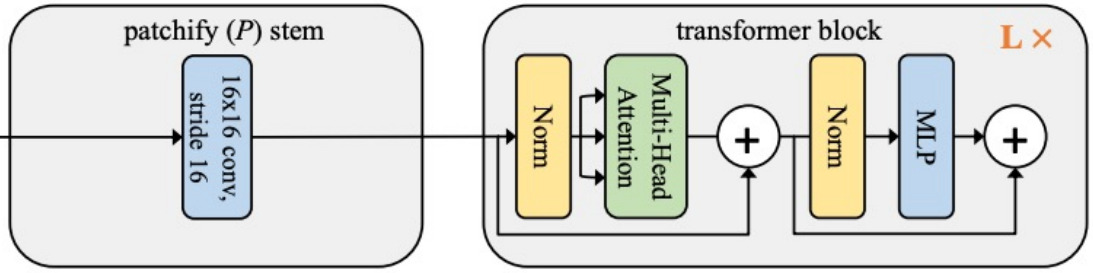
Method	Backbone	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	#param.	FLOPs	FPS
Cascade Mask R-CNN	R-50	46.3	64.3	50.5	82M	739G	18.0
	Swin-T	**50.5**	**69.3**	**54.9**	86M	745G	15.3
ATSS	R-50	43.5	61.9	47.0	32M	205G	28.3
	Swin-T	**47.2**	**66.5**	**51.3**	36M	215G	22.3
RepPointsV2	R-50	46.5	64.6	50.3	42M	274G	13.6
	Swin-T	**50.0**	**68.5**	**54.2**	45M	283G	12.0
Sparse R-CNN	R-50	44.5	63.4	48.2	106M	166G	21.0
	Swin-T	**47.9**	**67.3**	**52.3**	110M	172G	18.4

(b) Various backbones w. Cascade Mask R-CNN

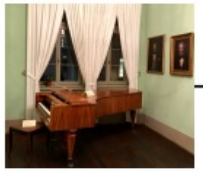
	AP^{box}	AP^{box}_{50}	AP^{box}_{75}	AP^{mask}	AP^{mask}_{50}	AP^{mask}_{75}	param	FLOPs	FPS
DeiT-S†	48.0	67.2	51.7	41.4	64.2	44.3	80M	889G	10.4
R50	46.3	64.3	50.5	40.1	61.7	43.4	82M	739G	18.0
Swin-T	**50.5**	**69.3**	**54.9**	**43.7**	**66.6**	**47.1**	86M	745G	15.3
X101-32	48.1	66.5	52.4	41.6	63.9	45.2	101M	819G	12.8
Swin-S	**51.8**	**70.4**	**56.3**	**44.7**	**67.9**	**48.5**	107M	838G	12.0
X101-64	48.3	66.4	52.3	41.7	64.0	45.1	140M	972G	10.4
Swin-B	**51.9**	**70.9**	**56.5**	**45.0**	**68.4**	**48.7**	145M	982G	11.6

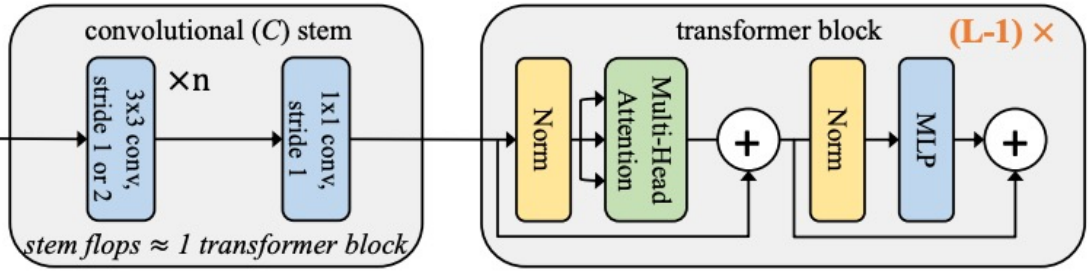
Hybrid of CNNs and transformers





Original ViT (baseline, termed ViT_P):
- *Sensitive to lr and wd choice*
- *Converges slowly*
- *Works with AdamW, but not SGD*
- *Underperforms sota CNNs on ImageNet*





Ours (termed ViT_C, same runtime):
- ✓ *Robust to lr and wd choice*
- ✓ *Converges quickly*
- ✓ *Works with AdamW, and also SGD*
- ✓ *Outperforms sota CNNs on ImageNet*

T. Xiao et al. Early convolutions help transformers see better. NeurIPS 2021

Outline

- Architectures
- Self-supervised learning

Masked autoencoders

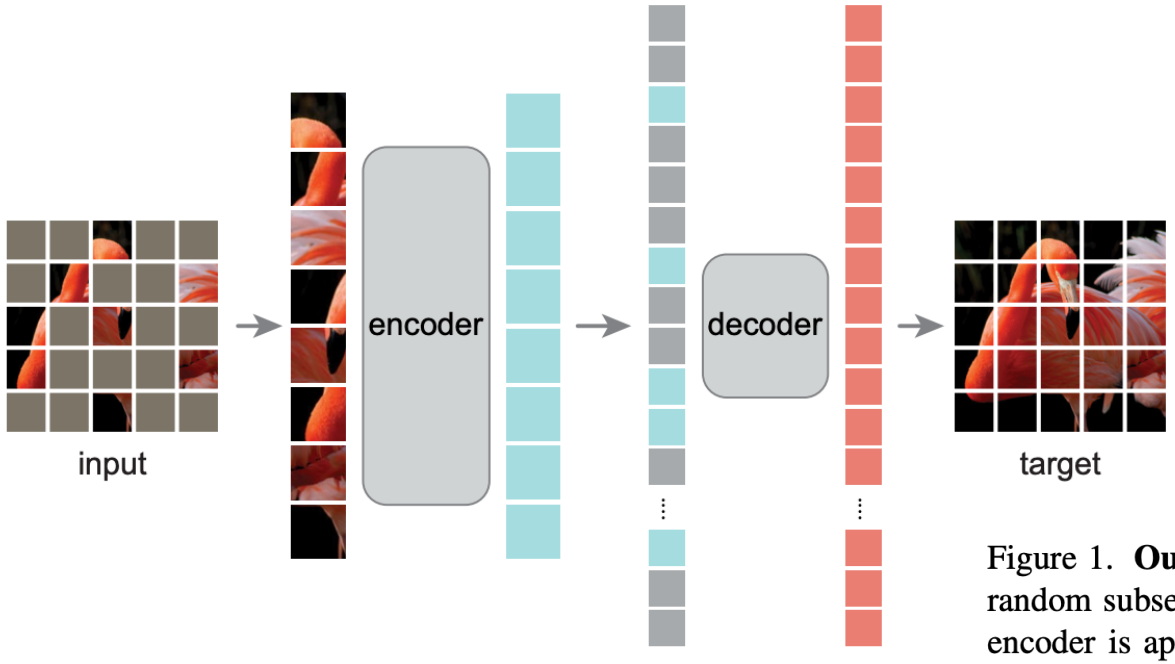


Figure 1. **Our MAE architecture**. During pre-training, a large random subset of image patches (*e.g.*, 75%) is masked out. The encoder is applied to the small subset of *visible patches*. Mask tokens are introduced *after* the encoder, and the full set of encoded patches and mask tokens is processed by a small decoder that reconstructs the original image in pixels. After pre-training, the decoder is discarded and the encoder is applied to uncorrupted images to produce representations for recognition tasks.

K. He et al. Masked autoencoders are scalable vision learners. CVPR 2022

Masked autoencoders

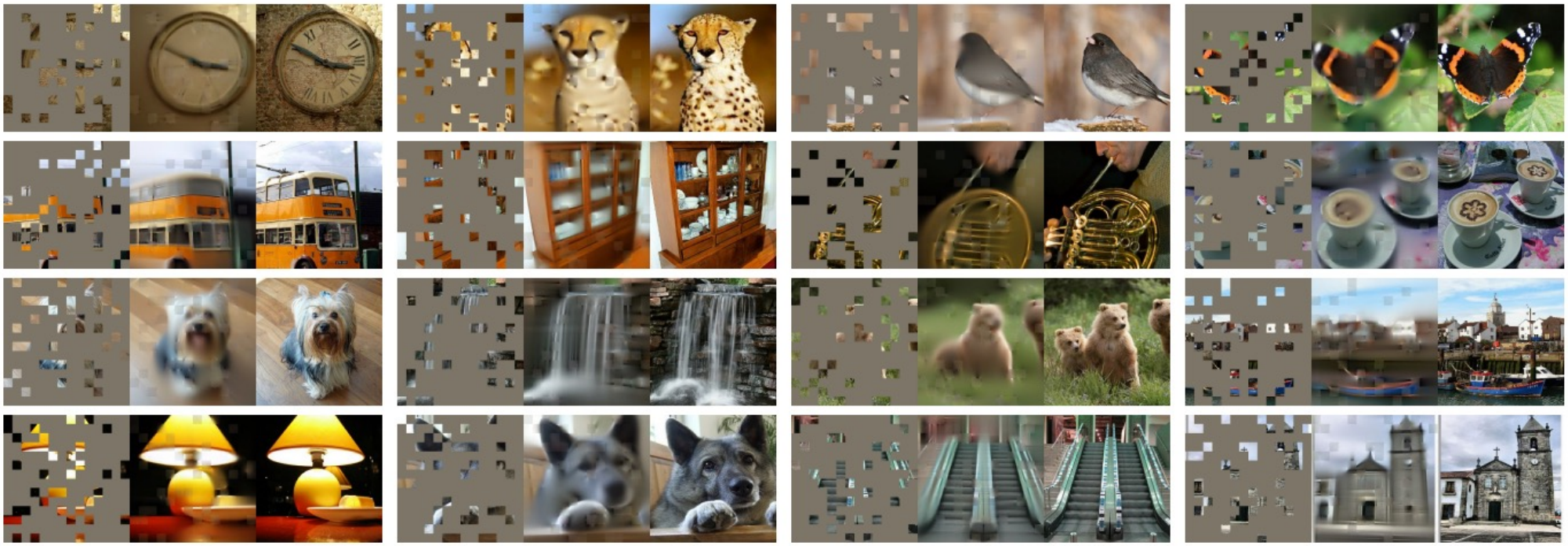


Figure 2. Example results on ImageNet *validation* images. For each triplet, we show the masked image (left), our MAE reconstruction† (middle), and the ground-truth (right). The masking ratio is 80%, leaving only 39 out of 196 patches. More examples are in the appendix.
†*As no loss is computed on visible patches, the model output on visible patches is qualitatively worse. One can simply overlay the output with the visible patches to improve visual quality. We intentionally opt not to do this, so we can more comprehensively demonstrate the method's behavior.*

K. He et al. Masked autoencoders are scalable vision learners. CVPR 2022

Masked autoencoders: Results

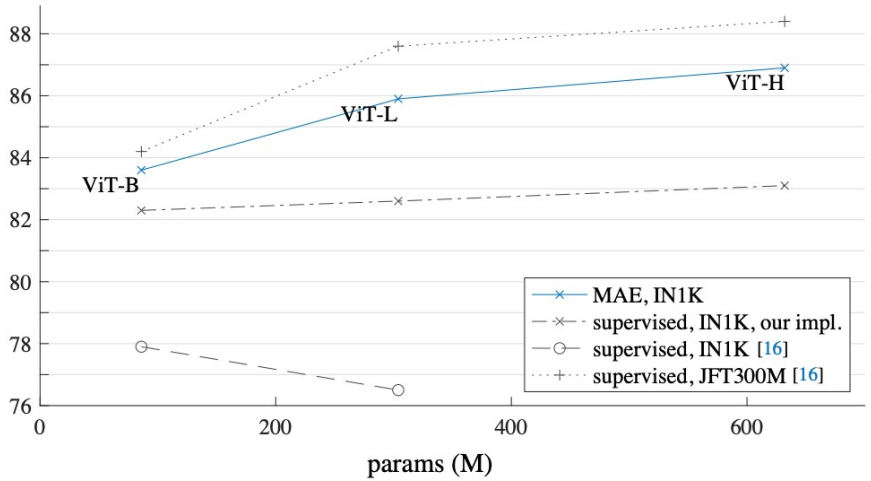


Figure 8. **MAE pre-training *vs*. supervised pre-training**, evaluated by fine-tuning in ImageNet-1K (224 size). We compare with the original ViT results [16] trained in IN1K or JFT300M.

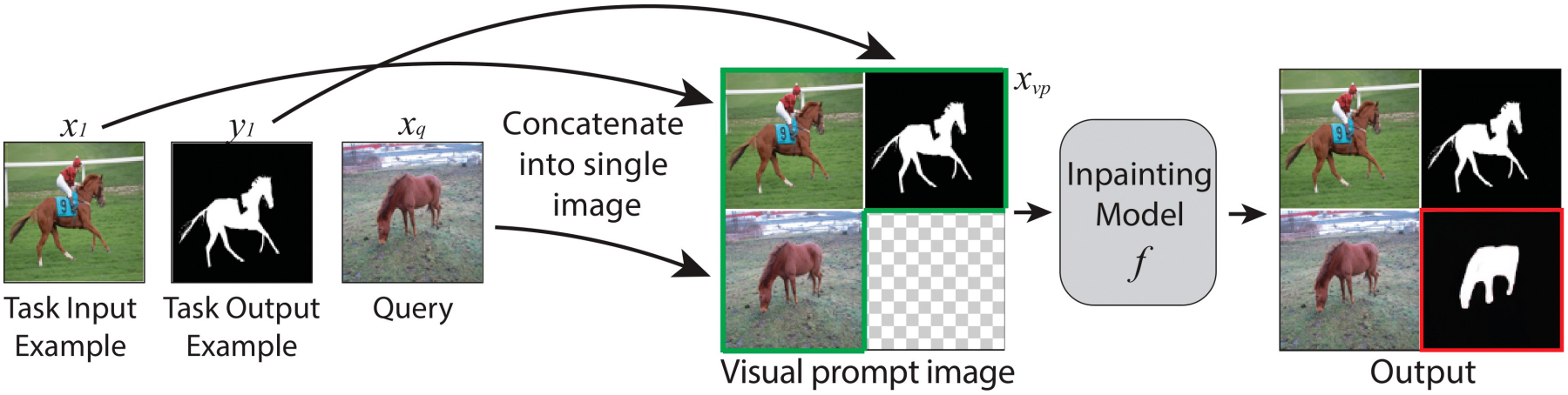
method	pre-train data	ViT-B	ViT-L	ViT-H	ViT-H_{448}
scratch, our impl.	-	82.3	82.6	83.1	-
DINO [5]	IN1K	82.8	-	-	-
MoCo v3 [9]	IN1K	83.2	84.1	-	-
BEiT [2]	IN1K+DALLE	83.2	85.2	-	-
MAE	IN1K	83.6	85.9	86.9	**87.8**

		AP^{box}		AP^{mask}	
method	pre-train data	ViT-B	ViT-L	ViT-B	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.

K. He et al. Masked autoencoders are scalable vision learners. CVPR 2022

Application: Visual prompting



A. Bar et al. Visual prompting via image inpainting. NeurIPS 2022

Application: Visual prompting

Figure 3: **Random images from our Computer Vision Figures dataset**. We curated a dataset of 88k unlabeled figures from Computer Vision academic papers. During training, we randomly sample crops from these figures, without any additional parsing.

Application: Visual prompting

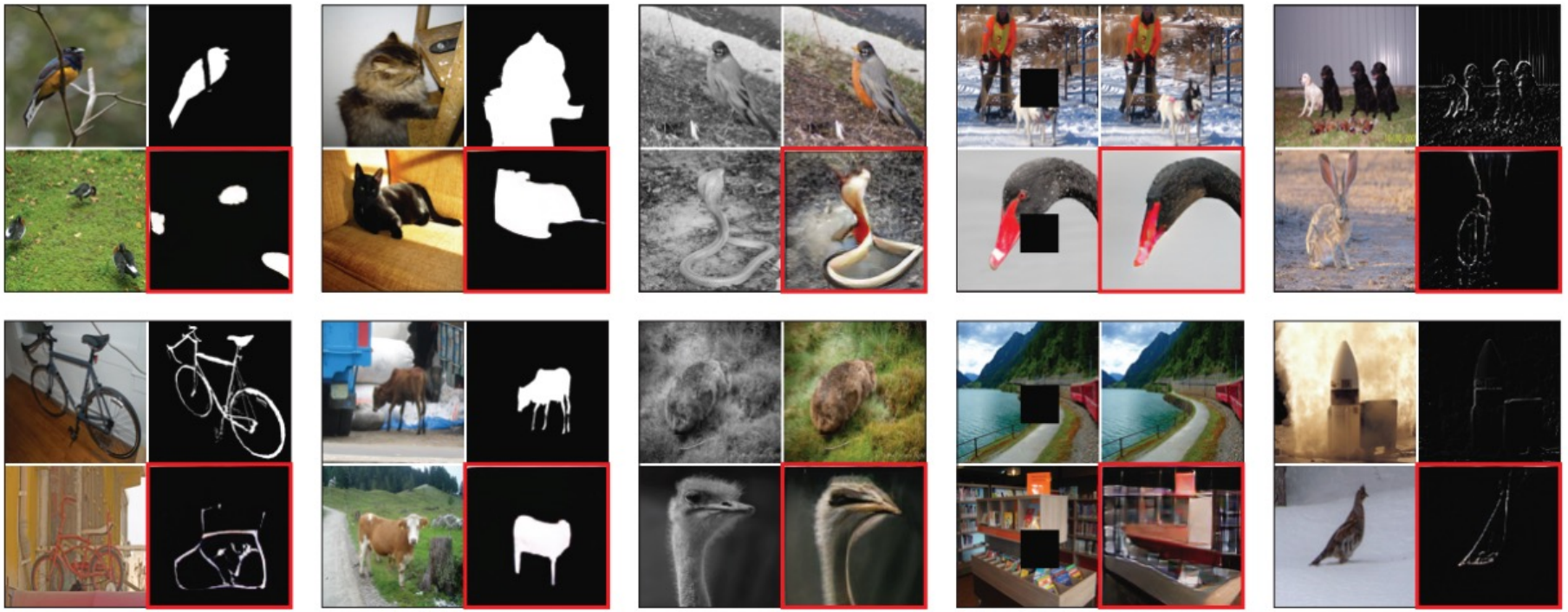


Figure 4: **Visual prompting prediction examples.** Each visual prompt was fed to an MAE-VQGAN model trained on the Figures dataset. For each visual prompt, the result is marked in red.

Application: Visual prompting

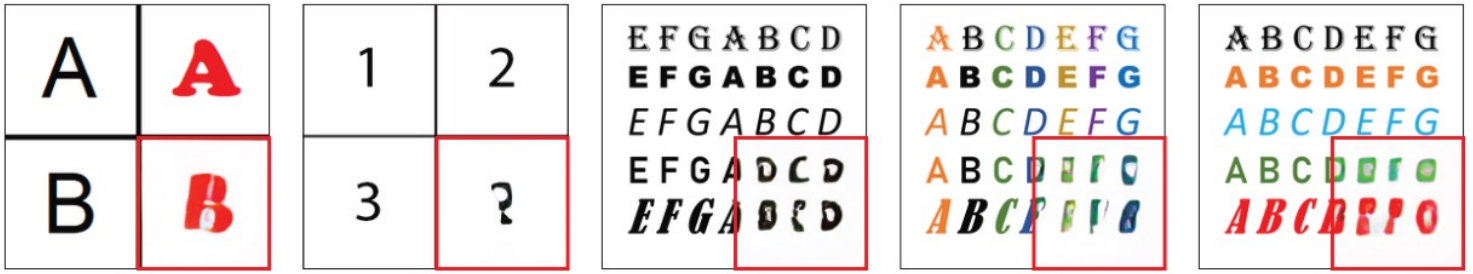


Figure 10: **Style and content extrapolation using MAE-VQGAN**. The model can extrapolate the style of a new content (a), but fails to predict a new content (b). The model struggles to extrapolate new style and content of longer sequences (c-e).

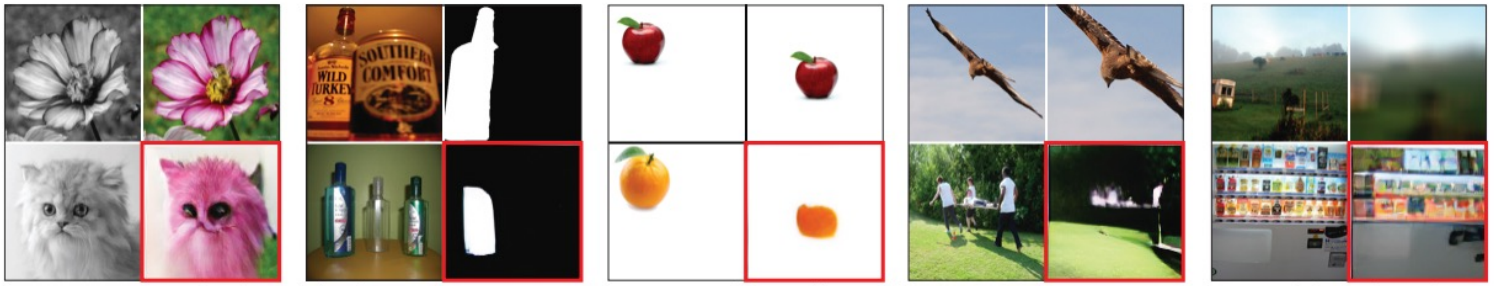


Figure 11: **Limitations and failure cases.** Single input-output example might be ambiguous and can lead to unintended completions. The MAE-VQGAN model performs worse given non-aligned input-output example, and by using a VQGAN vocabulary, it is limited in synthesizing out-of-distribution pixels (like blurry images).

DINO: Self-distillation with no labels

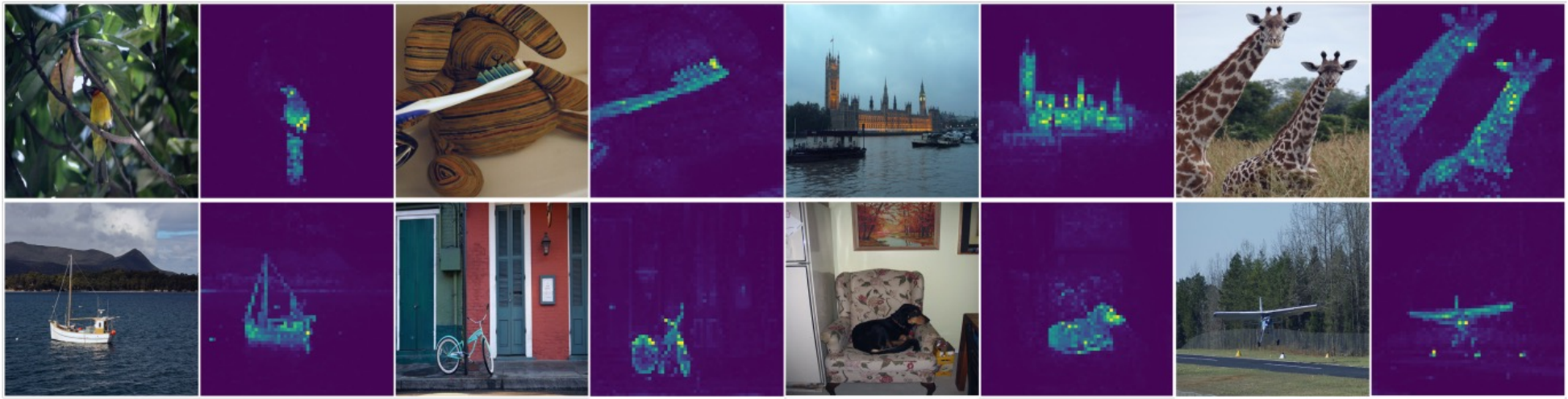


Figure 1: **Self-attention from a Vision Transformer with 8×8 patches trained with no supervision.** We look at the self-attention of the `[CLS]` token on the heads of the last layer. This token is not attached to any label nor supervision. These maps show that the model automatically learns class-specific features leading to unsupervised object segmentations.

M. Caron et al. Emerging Properties in Self-Supervised Vision Transformers. ICCV 2021

DINO: Self-distillation with no labels

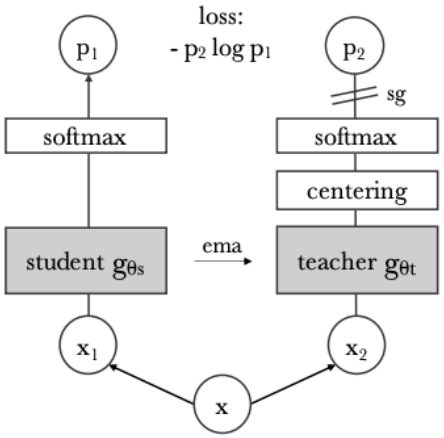


Figure 2: **Self-distillation with no labels.** We illustrate DINO in the case of one single pair of views (x_1, x_2) for simplicity. The model passes two different random transformations of an input image to the student and teacher networks. Both networks have the same architecture but different parameters. The output of the teacher network is centered with a mean computed over the batch. Each networks outputs a K dimensional feature that is normalized with a temperature softmax over the feature dimension. Their similarity is then measured with a cross-entropy loss. We apply a stop-gradient (sg) operator on the teacher to propagate gradients only through the student. The teacher parameters are updated with an exponential moving average (ema) of the student parameters.

Algorithm 1 DINO PyTorch pseudocode w/o multi-crop.

```
# gs, gt: student and teacher networks
# C: center (K)
# tps, tpt: student and teacher temperatures
# l, m: network and center momentum rates
gt.params = gs.params
for x in loader: # load a minibatch x with n samples
    x1, x2 = augment(x), augment(x) # random views

    s1, s2 = gs(x1), gs(x2) # student output n-by-K
    t1, t2 = gt(x1), gt(x2) # teacher output n-by-K

    loss = H(t1, s2)/2 + H(t2, s1)/2
    loss.backward() # back-propagate

    # student, teacher and center updates
    update(gs) # SGD
    gt.params = l*gt.params + (1-l)*gs.params
    C = m*C + (1-m)*cat([t1, t2]).mean(dim=0)

def H(t, s):
    t = t.detach() # stop gradient
    s = softmax(s / tps, dim=1)
    t = softmax((t - C) / tpt, dim=1) # center + sharpen
    return - (t * log(s)).sum(dim=1).mean()
```

M. Caron et al. Emerging Properties in Self-Supervised Vision Transformers. ICCV 2021

DINO: Self-distillation with no labels

Method	Arch.	Param.	im/s	Linear	k-NN
Supervised	RN50	23	1237	79.3	79.3
SCLR [11]	RN50	23	1237	69.1	60.7
MoCov2 [13]	RN50	23	1237	71.1	61.9
InfoMin [54]	RN50	23	1237	73.0	65.3
BarlowT [66]	RN50	23	1237	73.2	66.0
OBoW [21]	RN50	23	1237	73.8	61.9
BYOL [23]	RN50	23	1237	74.4	64.8
DCv2 [9]	RN50	23	1237	75.2	67.1
SwAV [9]	RN50	23	1237	**75.3**	65.7
DINO	RN50	23	1237	**75.3**	**67.5**
Supervised	ViT-S	21	1007	79.8	79.8
BYOL* [23]	ViT-S	21	1007	71.4	66.6
MoCov2* [13]	ViT-S	21	1007	72.7	64.4
SwAV* [9]	ViT-S	21	1007	73.5	66.3
DINO	ViT-S	21	1007	**77.0**	**74.5**

Table 2: **Linear and k-NN classification on ImageNet.** We report top-1 accuracy for linear and k-NN evaluations on the validation set of ImageNet for different self-supervised methods. We focus on ResNet-50 and ViT-small architectures, but also report the best results obtained across architectures. * are run by us. We run the k-NN evaluation for models with official released weights. The throughput (im/s) is calculated on a NVIDIA V100 GPU with 128 samples per forward. Parameters (M) are of the feature extractor.

M. Caron et al. Emerging Properties in Self-Supervised Vision Transformers. ICCV 2021

Outline

- Architectures
- Self-supervised learning
- Autoregressive text-to-image generation

DALL-E

- Learn a joint sequential transformer model that can be used to generate image based on text prompt

(a) a tapir made of accordion. a tapir with the texture of an accordion.

(b) an illustration of a baby hedgehog in a christmas sweater walking a dog

(c) a neon sign that reads "backprop". a neon sign that reads "backprop". backprop neon sign

A. Ramesh et al., Zero-Shot Text-to-Image Generation, arXiv 2021
https://openai.com/blog/dall-e/

DALL-E: Image encoding

- Train convolutional encoder and decoder to compress images to 32x32 grids of discrete tokens (each assuming 8192 values)

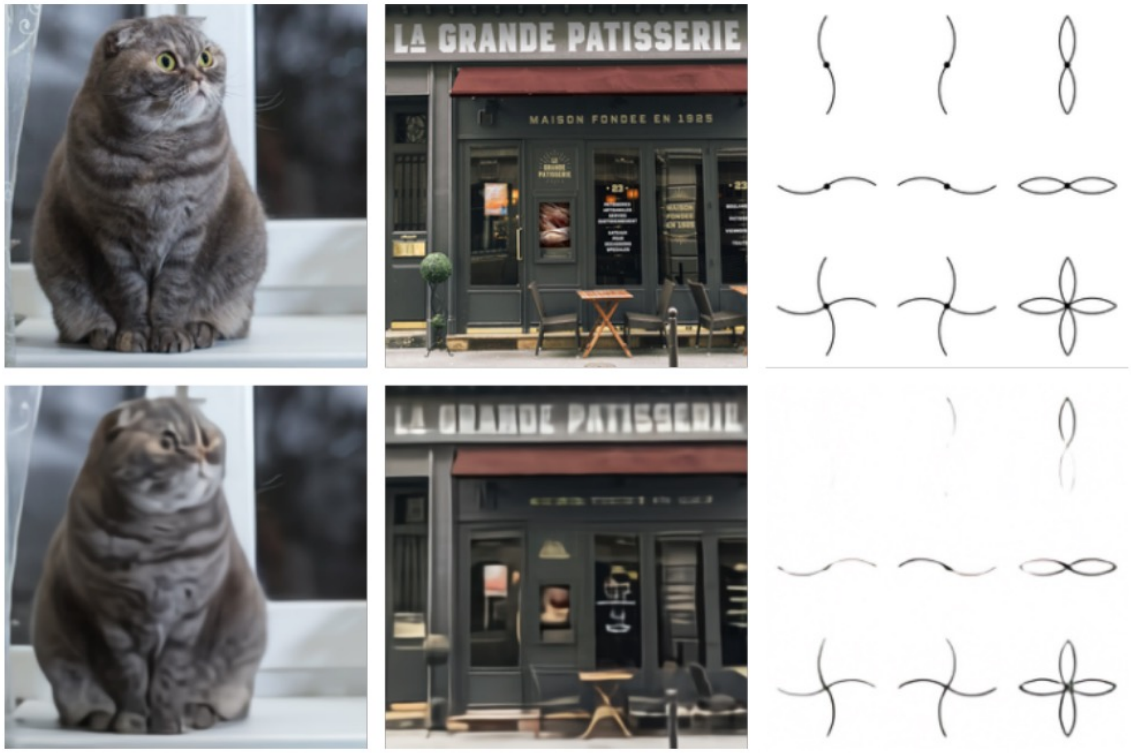
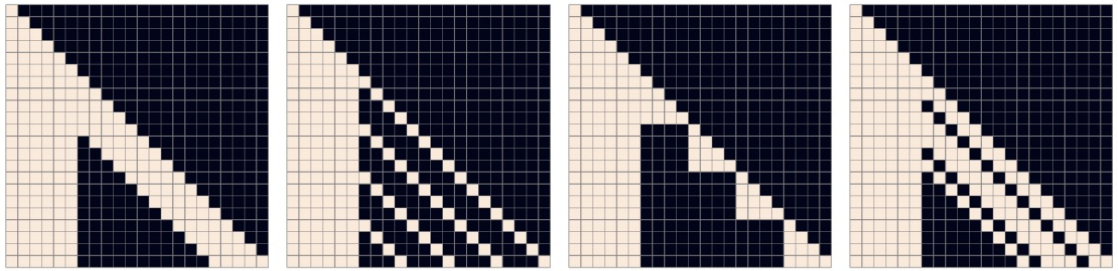


Figure 1. Comparison of original images (top) and reconstructions from the discrete VAE (bottom). The encoder downsamples the spatial resolution by a factor of 8. While details (e.g., the texture of the cat's fur, the writing on the storefront, and the thin lines in the illustration) are sometimes lost or distorted, the main features of the image are still typically recognizable. We use a large vocabulary size of 8192 to mitigate the loss of information.

DALL-E: Transformer architecture and training

- Concatenate up to 256 text tokens with 32x32=1024 image tokens, learn a transformer model with 64 layers and 12B parameters
- Dataset: 250M image-text pairs from the Internet
- Transformer model details
  - Decoder-only architecture
  - 64 self-attention layers,
  - 62 attention heads, sparse attention patterns
  - Mixed-precision training, distributed optimization



(a) Row attention mask. (b) Column attention mask. (c) Column attention mask with transposed image states. (d) Convolutional attention mask.

Figure 11. Illustration of the three types of attention masks for a hypothetical version of our transformer with a maximum text length of 6 tokens and image length of 16 tokens (i.e., corresponding to a 4×4 grid). Mask (a) corresponds to row attention in which each image token attends to the previous 5 image tokens in raster order. The extent is chosen to be 5, so that the last token being attended to is the one in the same column of the previous row. To obtain better GPU utilization, we transpose the row and column dimensions of the image states when applying column attention, so that we can use mask (c) instead of mask (b). Mask (d) corresponds to a causal convolutional attention pattern with wraparound behavior (similar to the row attention) and a 3×3 kernel. Our model uses a mask corresponding to an 11×11 kernel.

DALL-E: Generating images given text

- Output samples reranked using CLIP

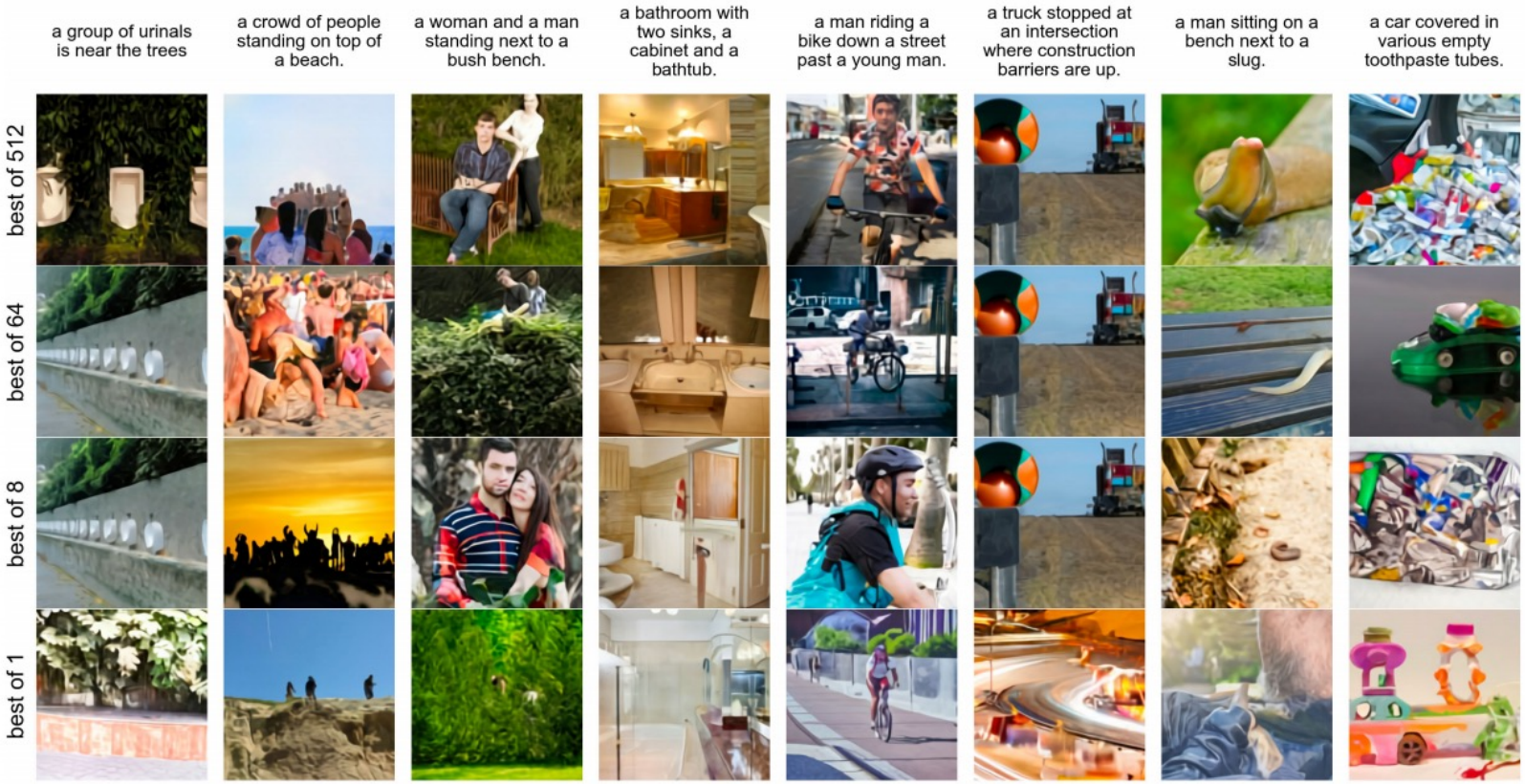
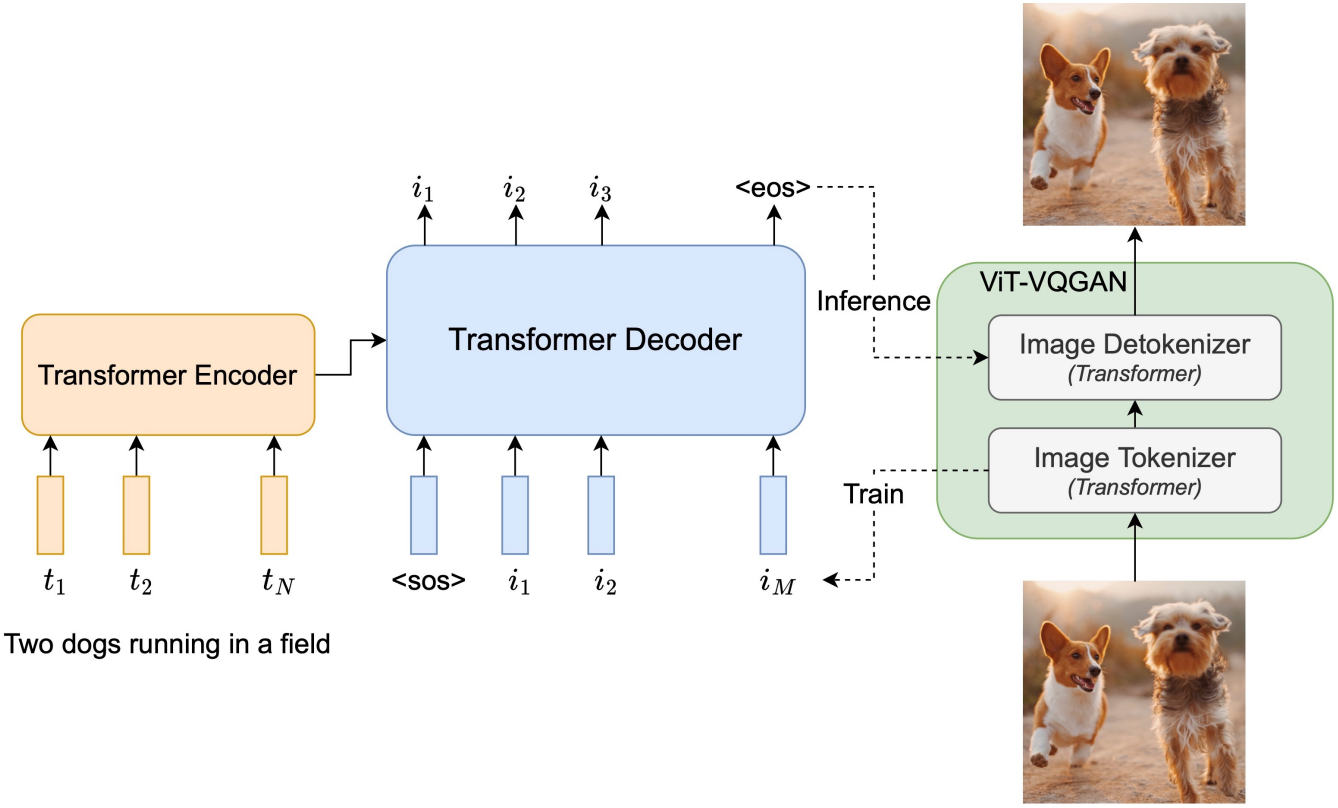


Figure 6. Effect of increasing the number of images for the contrastive reranking procedure on MS-COCO captions.

PARTI: Pathways auto-regressive text-to-image



J. Yu et al. [Scaling Autoregressive Models for Content-Rich Text-to-Image Generation.](#) arXiv 2022

PARTI

Model	Encoder Layers	Decoder Layers	Model Dims	MLP Dims	Heads	Total Params
Parti-350M	12	12	1024	4096	16	350M
Parti-750M	12	36	1024	4096	16	750M
Parti-3B	12	36	2048	8192	32	3B
Parti	16	64	4096	16384	64	20B

Parti-350M **Parti-750M** **Parti-3B** **Parti-20B**

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!

A green sign that says "Very Deep Learning" and is at the edge of the Grand Canyon. Puffy white clouds are in the sky.

PARTI

A. *A photo of a frog reading the newspaper named "Toaday" written on it. There is a frog printed on the newspaper too.*

B. *A portrait of a statue of the Egyptian god Anubis wearing aviator goggles, white t-shirt and leather jacket. The city of Los Angeles is in the background. Hi-res DSLR photograph.*

C. *A high-contrast photo of a panda riding a horse. The panda is wearing a wizard hat and is reading a book. The horse is standing on a street against a gray concrete wall. Colorful flowers and the word "PEACE" are painted on the wall. Green grass grows from cracks in the street. DSLR photograph. daytime lighting.*

PARTI

D. *A giant cobra snake made from X. X* $\in$ {*"salad", "pancakes", "sushi", "corn"*}

E. *A wombat sits in a yellow beach chair, while sipping a martini that is on his laptop keyboard. The wombat is wearing a white panama hat and a floral Hawaiian shirt. Out-of-focus palm trees in the background. DSLR photograph. Wide-angle view.*

F. *The saying "BE EXCELLENT TO EACH OTHER"* ..., (a) brick wall and alien (b) driftwood. (c) old wooden boat with reflection. (d) stained glass. (See text for full prompts.)

PARTI

G. *Three-quarters front view of a X Y Z coming around a curve in a mountain road and looking over a green valley on a cloudy day. DSLR photograph. X ∈ {blue, red, yellow}, Y ∈ {1977, 1997, 2017}, Z ∈ {Porsche 911, Corvette, Ford F-150}*

H. *A raccoon wearing formal clothes, wearing a tophat and holding a cane. The raccoon is holding a garbage bag. Oil painting in the style of X. X ∈ {"Rembrandt", "Vincent Van Gogh", "Hokusai", "pixel art", "pointillism", "abstract cubism", "Egyptian tomb heiroglyphics", "traditional Chinese painting", "Madhubani art"}*

I. *A photo of an Athenian vase with a painting of X playing Y in the style of Egyptian hieroglyphics. X ∈ {"pandas", "toucans", "pangolins"}, Y ∈ {"tennis", "soccer", "basketball"}*

PARTI

Approach	Model Type	MS-COCO FID (↓)		LN-COCO FID (↓)	
		Zero-shot	Finetuned	Zero-shot	Finetuned
Random Train Images [10]	-	2.47		-	
Retrieval Baseline	-	17.97	6.82	33.59	16.48
TReCS [46]	GAN	-	-	-	48.70
XMC-GAN [47]	GAN	-	9.33	-	14.12
DALL-E [2]	Autoregressive	∼28	-	-	-
CogView [3]	Autoregressive	27.1	-	-	-
CogView2 [61]	Autoregressive	24.0	17.7	-	-
GLIDE [11]	Diffusion	12.24	-	-	-
Make-A-Scene [10]	Autoregressive	11.84	7.55	-	-
DALL-E 2 [12]	Diffusion	10.39	-	-	-
Imagen [13]	Diffusion	**7.27**	-	-	-
Parti	Autoregressive	**7.23**	**3.22**	**15.97**	**8.39**

Table 5: Comparison with previous work on the MS-COCO (2014) [16] and Localized Narratives (COCO split) [29] validation sets. When available, we report results for both zero-shot and finetuned models. Retrieval models either perform retrieval over our training set ("zero-shot"), or the respective MS-COCO and LN-COCO training sets ("finetuned"). Parti samples 16 images per text prompt and uses a CoCa model to rank the outputs (Section 2.4). Similar to DALL-E 2 [12], we use guidance scale 1.2 for all above results. We report zero-shot FID score of other model sizes in Figure 9.

Outline

- Architectures
- Self-supervised learning
- Autoregressive text-to-image generation
- Trends

Trends

- Architectures
- Unification of tasks, datasets, modalities: “foundation models”
- Availability of increasingly powerful and reliable high-level primitives

Beyond transformers?

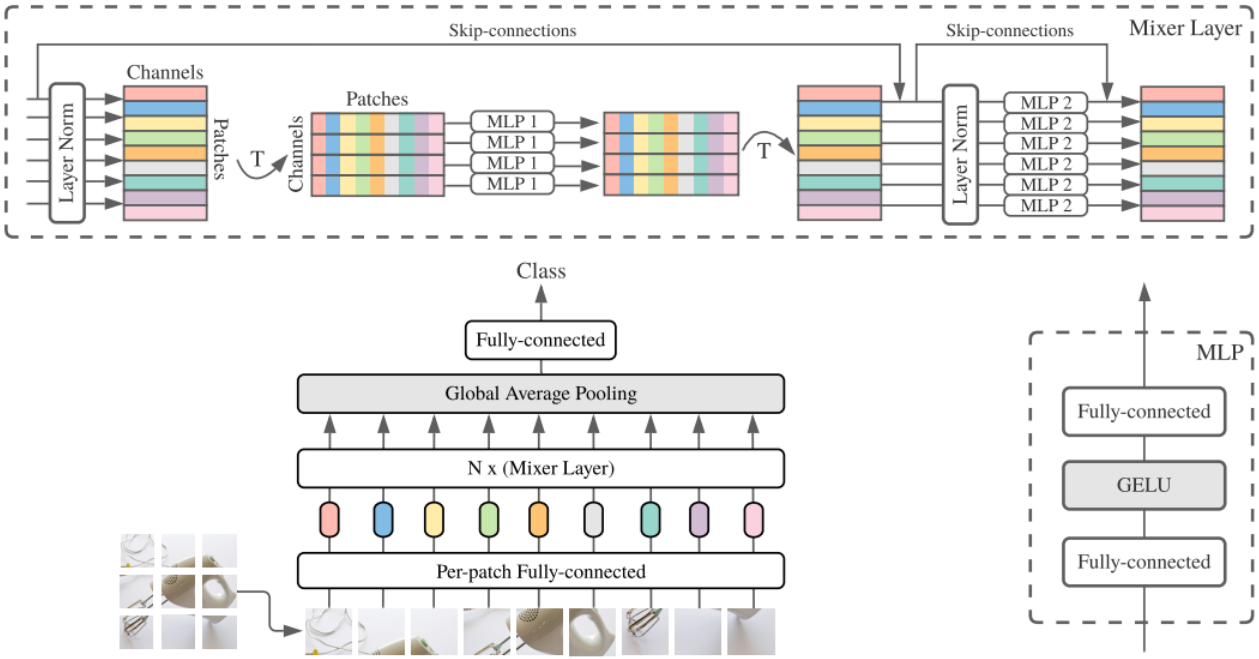


Figure 1: MLP-Mixer consists of per-patch linear embeddings, Mixer layers, and a classifier head. Mixer layers contain one token-mixing MLP and one channel-mixing MLP, each consisting of two fully-connected layers and a GELU nonlinearity. Other components include: skip-connections, dropout, and layer norm on the channels.

I. Tolstikhin et al. MLP-Mixer: An all-MLP Architecture for Vision. NeurIPS 2021

Or completely back to CNNs?

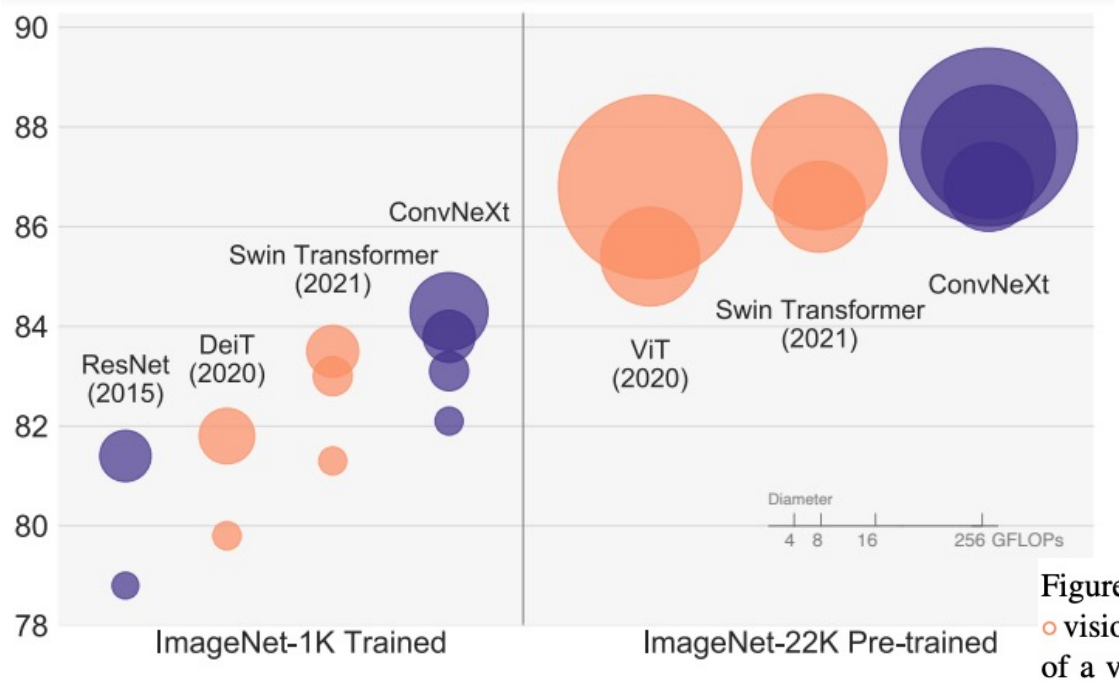


Figure 1. **ImageNet-1K classification** results for • ConvNets and ○ vision Transformers. Each bubble's area is proportional to FLOPs of a variant in a model family. ImageNet-1K/22K models here take $224^2/384^2$ images respectively. ResNet and ViT results were obtained with improved training procedures over the original papers. We demonstrate that a standard ConvNet model can achieve the same level of scalability as hierarchical vision Transformers while being much simpler in design.

Z. Liu et al. A ConvNet for the 2020s. CVPR 2022

Back to CNNs?

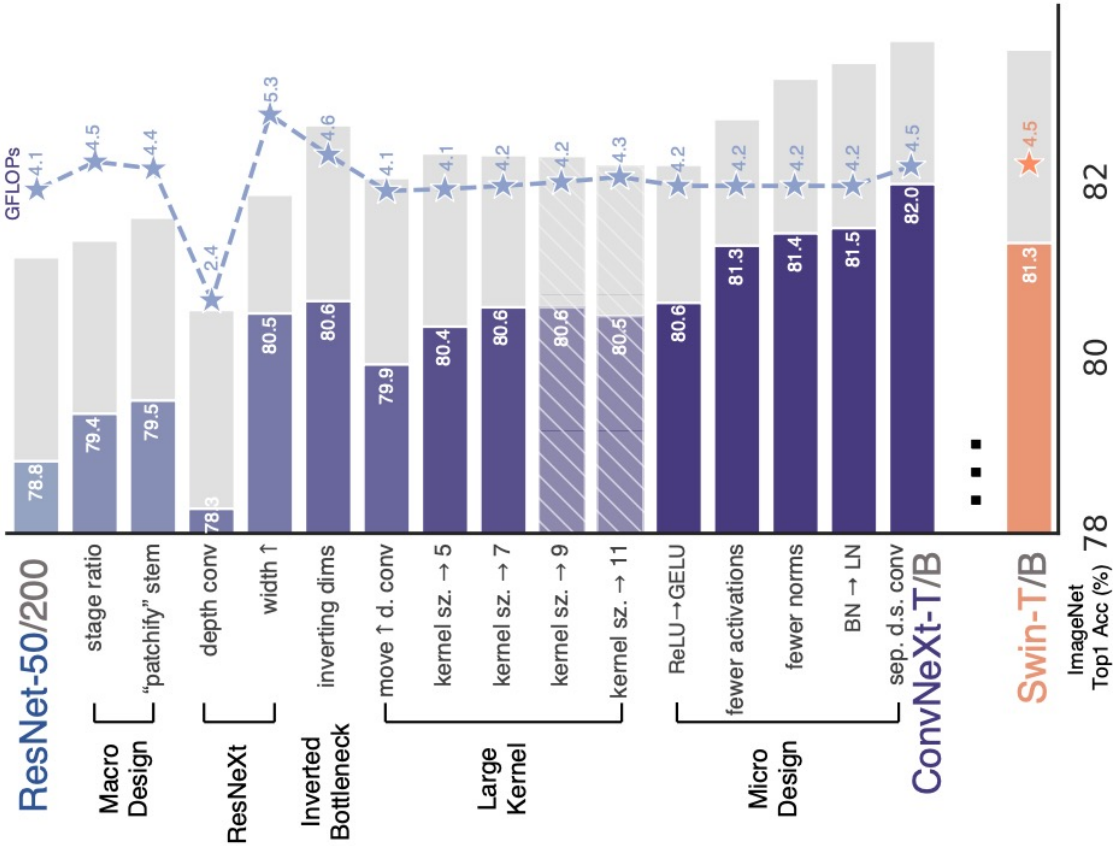
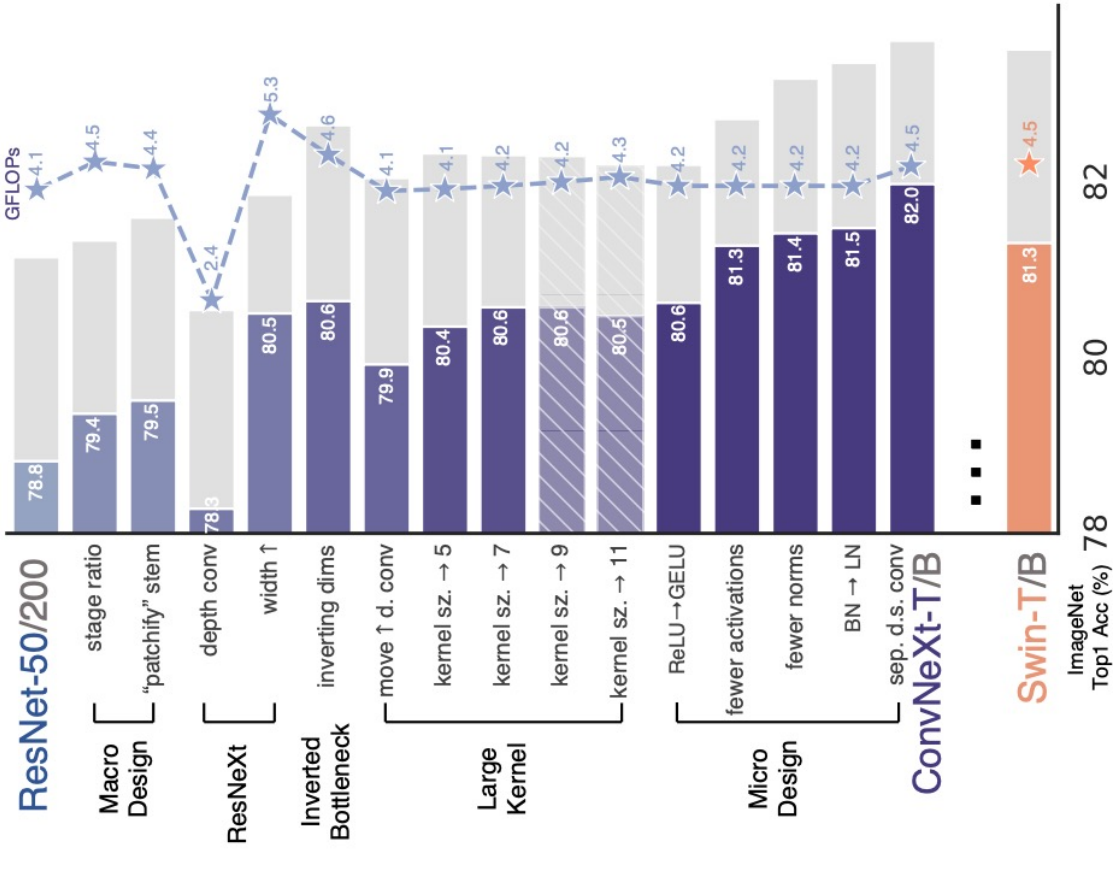
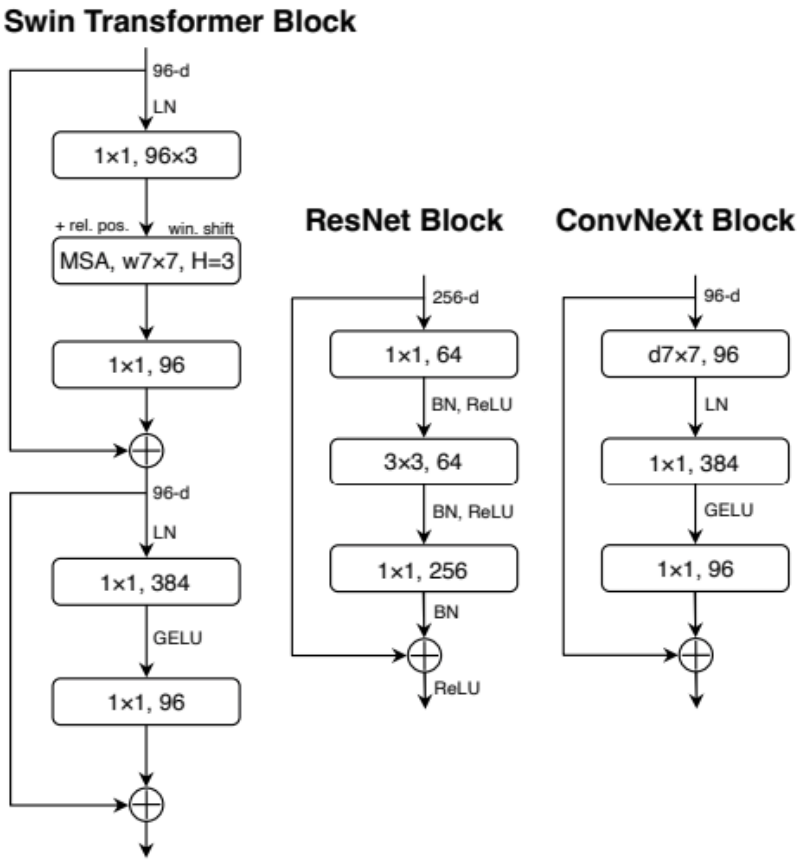


Figure 2. We modernize a standard ConvNet (ResNet) towards the design of a hierarchical vision Transformer (Swin), without introducing any attention-based modules. The foreground bars are model accuracies in the ResNet-50/Swin-T FLOP regime; results for the ResNet-200/Swin-B regime are shown with the gray bars. A hatched bar means the modification is not adopted. Detailed results for both regimes are in the appendix. Many Transformer architectural choices can be incorporated in a ConvNet, and they lead to increasingly better performance. In the end, our pure ConvNet model, named ConvNeXt, can outperform the Swin Transformer.

Z. Liu et al. A ConvNet for the 2020s. CVPR 2022

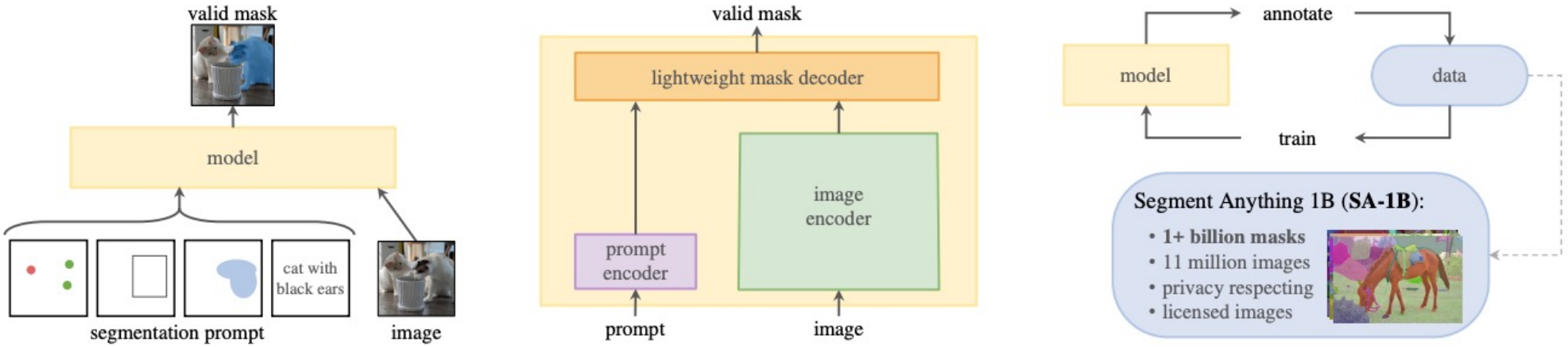
Back to CNNs?





Z. Liu et al. A ConvNet for the 2020s. CVPR 2022

Segment Anything Model



(a) **Task**: promptable segmentation (b) **Model**: Segment Anything Model (**SAM**) (c) **Data**: data engine (top) & dataset (bottom)

Figure 1: We aim to build a foundation model for segmentation by introducing three interconnected components: a promptable segmentation *task*, a segmentation *model* (SAM) that powers data annotation and enables zero-shot transfer to a range of tasks via prompt engineering, and a *data* engine for collecting SA-1B, our dataset of over 1 billion masks.

A. Kirillov et al. Segment Anything. arXiv 2023
https://segment-anything.com/

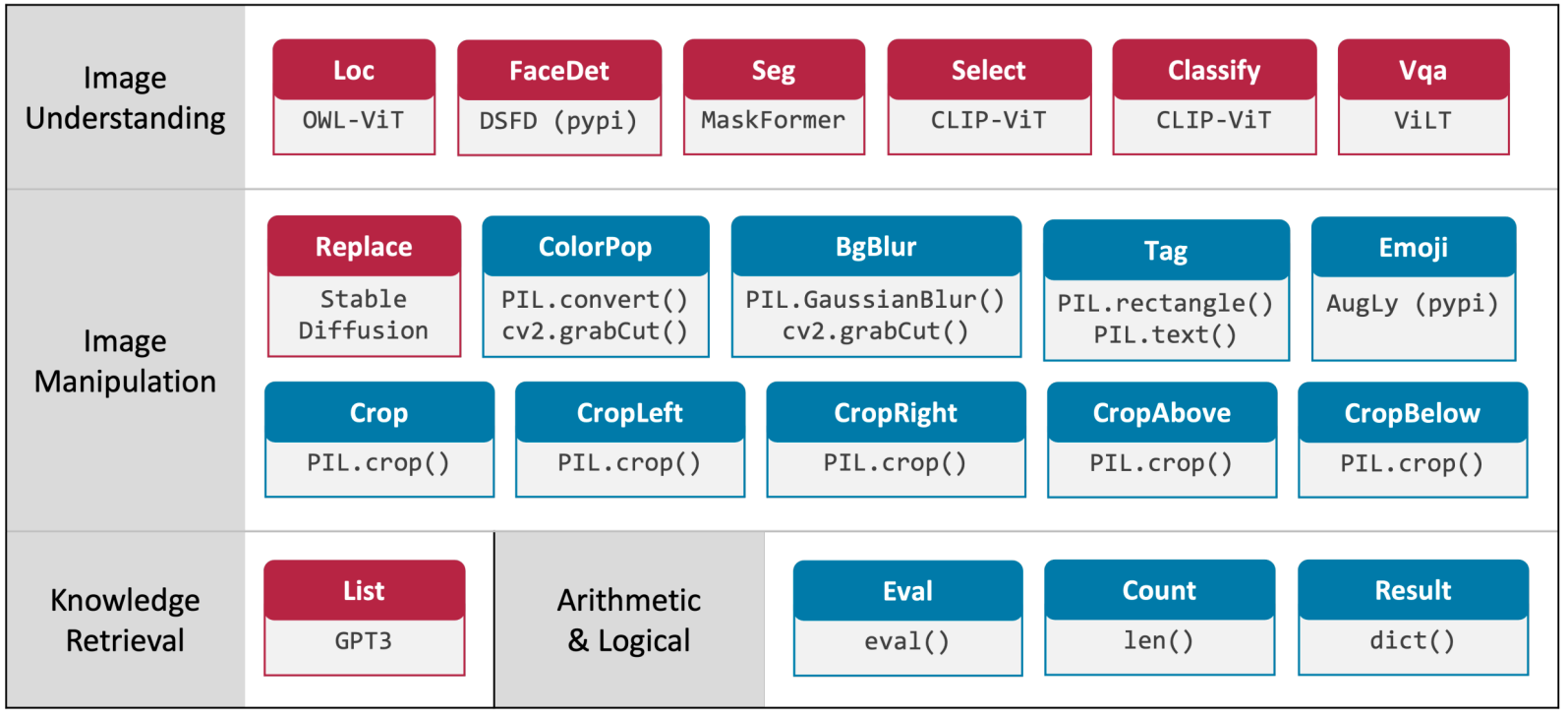
Visual Programming

Figure 1. **VISPROG is a modular and interpretable neuro-symbolic system for compositional visual reasoning.** Given a few examples of natural language instructions and the desired high-level programs, VISPROG generates a program for any new instruction using *in-context learning* in GPT-3 and then executes the program on the input image(s) to obtain the prediction. VISPROG also summarizes the intermediate outputs into an interpretable *visual rationale* (Fig. 4). We demonstrate VISPROG on tasks that require composing a diverse set of modules for image understanding and manipulation, knowledge retrieval, and arithmetic and logical operations.

T. Gupta and A. Kembhavi. Visual Programming: Compositional visual reasoning without training. CVPR 2023

Visual Programming

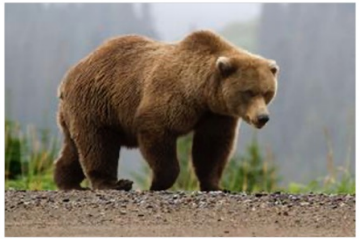
- Modules supported in VisProg



Visual Programming

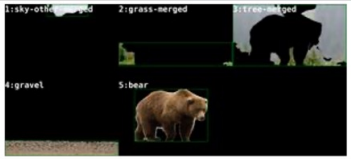
- Image editing with natural language

Instruction: Replace the ground with white snow and the bear with a white polar bear



Prediction:

```
← IMAGE
```




```
← OBJ0=Seg(
      image=IMAGE)
```

```
← OBJ1=Select(
      image=IMAGE,
      object=OBJ0,
      query='ground')
```

```
← IMAGE0=Replace(
      image=IMAGE,
      object=OBJ1,
      prompt='white snow')
```

```
← OBJ2=Seg(
      image=IMAGE0)
```

```
← OBJ3=Select(
      image=IMAGE0,
      object=OBJ2,
      query='bear')
```

```
← IMAGE1=Replace(
      image=IMAGE0,
      object=OBJ3,
      prompt='white polar bear')
```

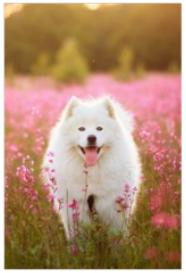
Visual Programming

- Reasoning about image pairs

Statement: At least three animals are in a flowered field

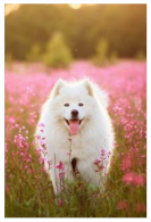
LEFT:

RIGHT:



Prediction: True

 ← LEFT

 ← RIGHT

```
2   ← ANSWER0=Vqa(
          image=LEFT,
          question='How many animals
          are in the flowered field?')

1   ← ANSWER1=Vqa(
          image=RIGHT,
          question='How many animals
          are in the flowered field?')

True ← ANSWER2=Eval(expr='{ANSWER0} + {ANSWER1} >= 3?')
           =Eval(expr='2 + 1 >= 3?')
```

Visual Programming

- Example results

Replace Leonardo DiCaprio with Leonardo DiCaprio wearing sunglasses

Create a color pop of the woman in blue and the woman in red and blur the background

Replace Anne Hathaway with Emma Watson and Meryl Streep with Jennifer Lawrence

Replace the desert by sandy beach

Replace the couch with a plush blue couch

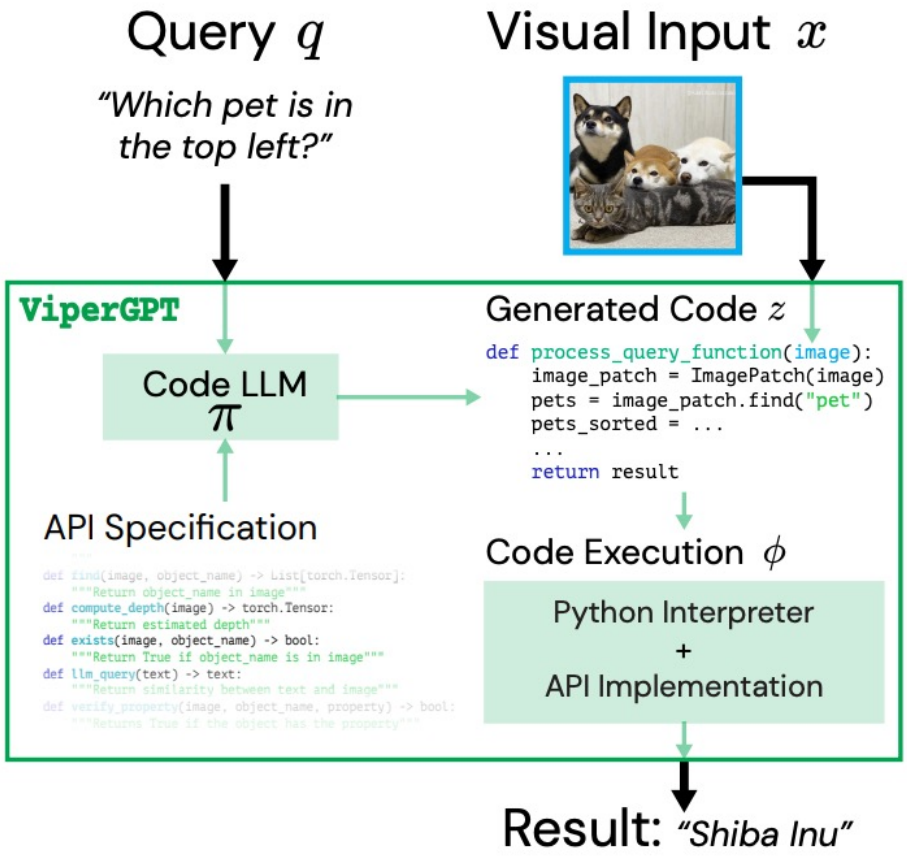
Tag the women leaders of Germany, Taiwan, and New Zealand

Tag the three female lead characters from Friends series

Tag these Scandinavian flags with their countries

Tag the painting of Girl with a Pearl Earring with its painter

ViperGPT



S. Menon et al. [ViperGPT: Visual Inference via Python Execution for Reasoning.](#) arXiv 2023

ViperGPT

Query: How many muffins can each kid have for it to be fair?

Generated Code

```
def execute_command(image):
    image_patch = ImagePatch(image)
    muffin_patches = image_patch.find("muffin")
    kid_patches = image_patch.find("kid")
    return str(len(muffin_patches) // len(kid_patches))
```

Execution

▶len(muffin_patches)=8
▶len(kid_patches)=2
▶8//2 = 4
Result: 4

Query: Drink with zero alcohol

```
def execute_command(image):
    image_patch = ImagePatch(image)
    drink_patches = image_patch.find("drink")
    for drink_patch in drink_patches:
        drink_name = drink_patch.simple_query("What is this?")
        alcoholic = llm_query(f"Does the {drink_name} have alcohol?")
        if alcoholic == "no":
            return drink_patch
    return None
```

▶drink_patches=

▶drink_name = 'tullamore dew'
▶alcoholic = 'yes'

▶drink_name = 'bacardi'
▶alcoholic = 'yes'

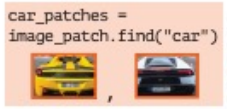
▶drink_name = 'gin'
▶alcoholic = 'yes'

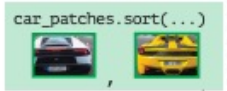
▶drink_name = 'dr pepper'
▶alcoholic = 'no'

Result:

Query: What would the founder of the brand of the car on the left say to the founder of the brand of the car on the right?


```
def execute_command(image):
    image_patch = ImagePatch(image)
    car_patches = image_patch.find("car")
    car_patches.sort(key=lambda car: car.horizontal_center)
    left_car = car_patches[0]
    right_car = car_patches[-1]
    left_car_brand = left_car.simple_query("What is the brand of this car?")
    right_car_brand = right_car.simple_query("What is the brand of this car?")
    left_car_founder = llm_query(f"Who is the founder of {left_car_brand}?")
    right_car_founder = llm_query(f"Who is the founder of {right_car_brand}?")
    return llm_query(f"What would {left_car_founder} say to {right_car_founder}?")
```



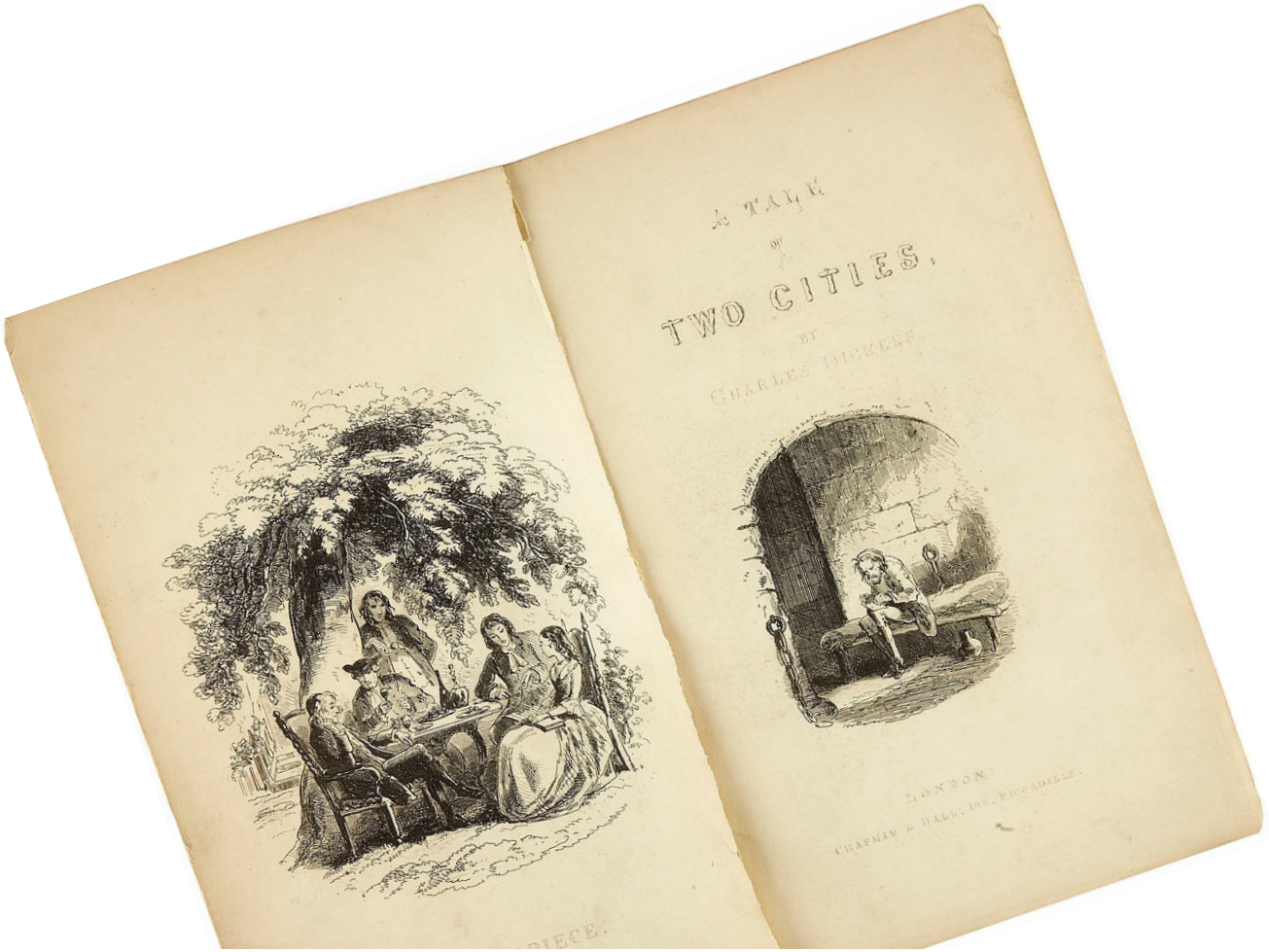


▶left_car_brand='lamborghini'
▶right_car_brand='ferrari'

▶left_car_founder='Ferruccio Lamborghini'
▶right_car_founder='Enzo Ferrari'

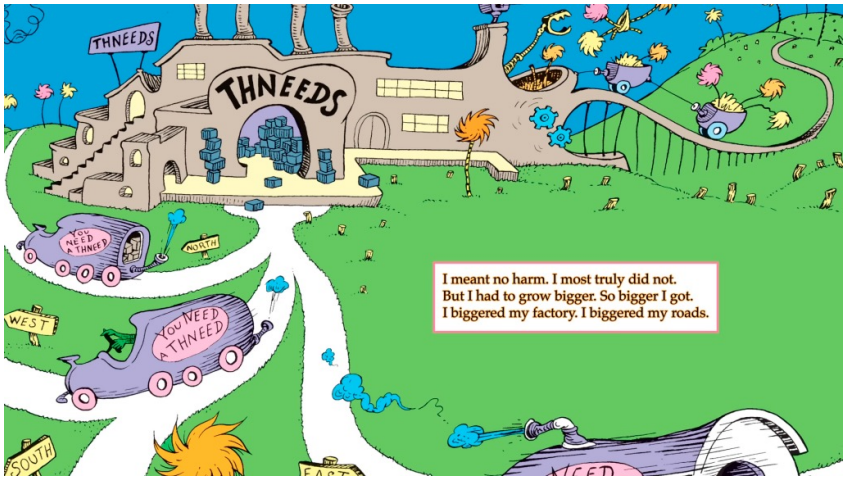
Result: *"Ferruccio Lamborghini might say, 'It's been an honor to be a rival of yours for so many years, Enzo. May our cars continue to push each other to be better and faster!' "*

So, where does this leave us?



Computer vision before deep learning

Computer vision now



Computer vision academics?