BOSTON UNIVERSITY

Deep Learning for Data Science
DS 542

Lecture 17
Vision Transformers

Slides originally by Thomas Gardos.
Images from [Understanding Deep Learning] unless otherwise cited.

Topics

- Transformers Recap
- ImageGPT
- Vision Transformer (ViT)
- CLIP – Contrastive Learning w/ Image Pre-Training
- MAE - Masked Autoencoders
- JEPA - Joint-Embedding Predictive Architecture
- REPA - Representation Alignment

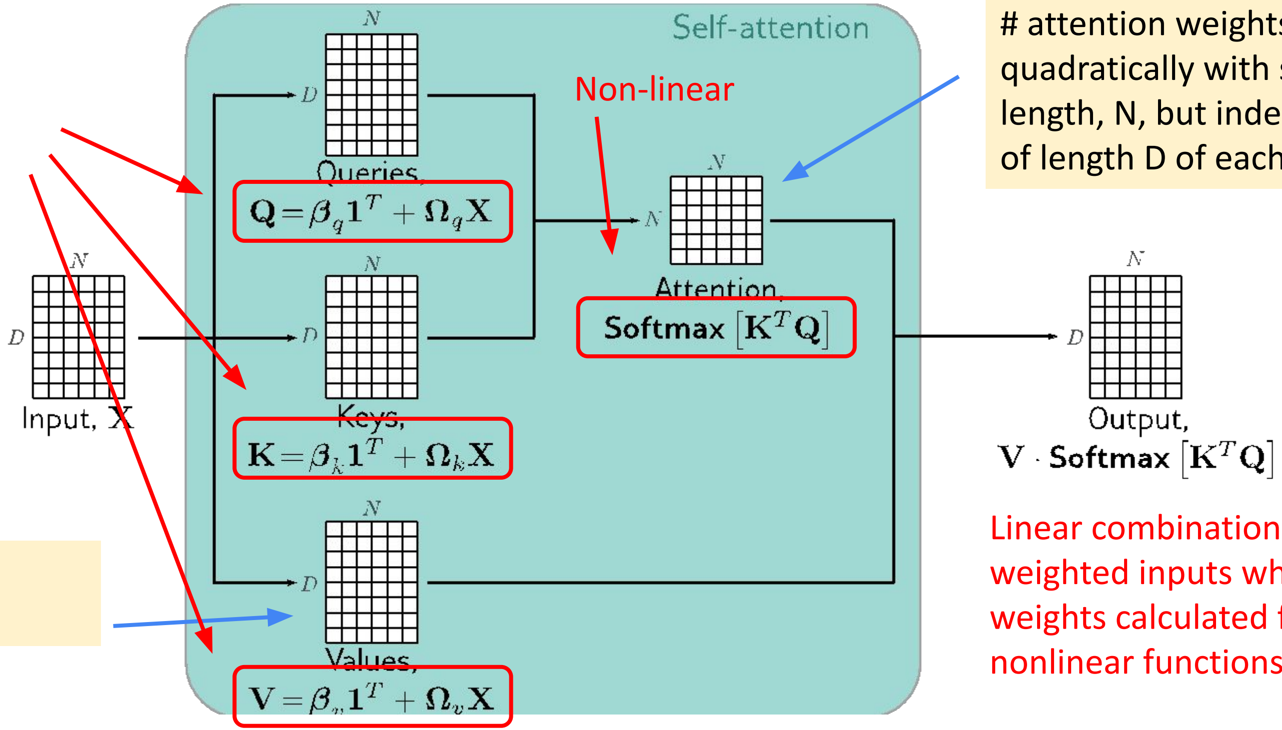
Recurring theme: more semantic loss functions
→ better performance and faster training

Transformers Recap

Hypernetwork – 1 branch calculates weights of other branch

Linear
&
Can be calculated in parallel

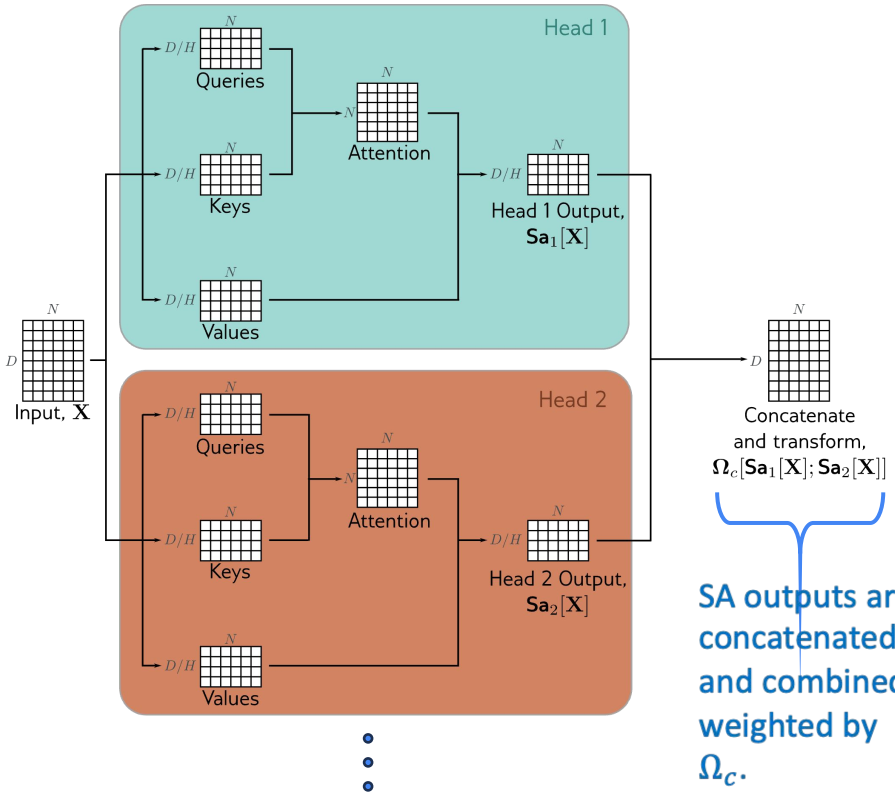
attention weights scales quadratically with sequence length, N, but independent of length D of each input



Scales linearly with sequence length, N

Linear combination of weighted inputs where weights calculated from nonlinear functions

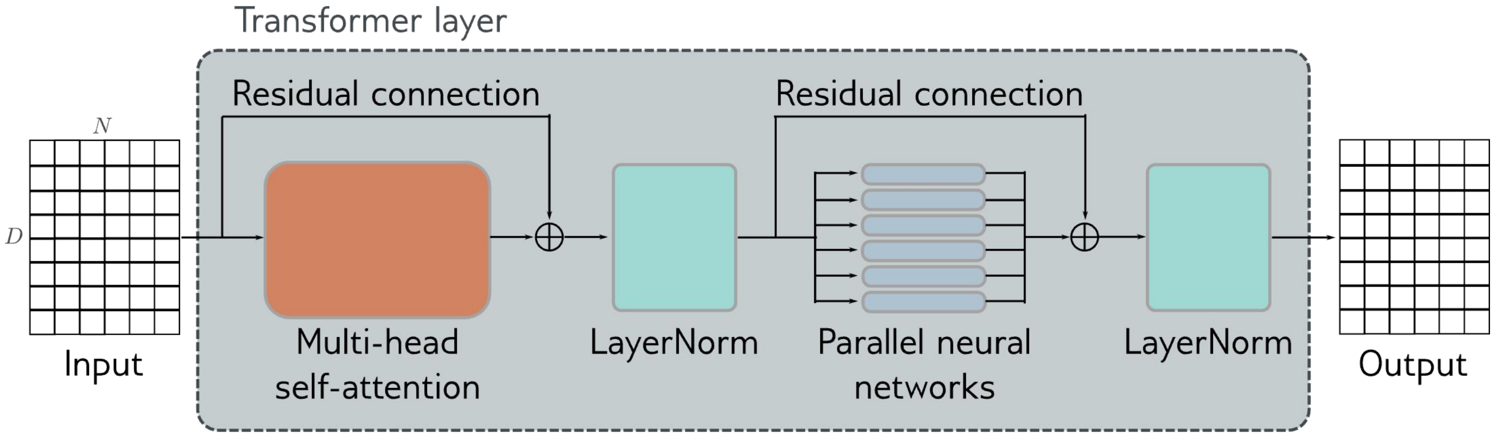
Multi-Head Self Attention



SA outputs are concatenated and combined weighted by Ω_c.

- Multiple self-attention heads are usually applied in parallel
- "allows model to jointly attend to info from different representation subspaces at different positions"
- Original paper used 8 heads
- All can be executed in parallel

Transformer Layer -- Complete



Transform Layer

$$
\begin{aligned}
\mathbf{X} &\leftarrow \mathbf{X} + \mathbf{MhSa}[\mathbf{X}] \\
\mathbf{X} &\leftarrow \mathbf{LayerNorm}[\mathbf{X}] \\
\mathbf{x}_n &\leftarrow \mathbf{x}_n + \mathbf{mlp}[\mathbf{x}_n] \\
\mathbf{X} &\leftarrow \mathbf{LayerNorm}[\mathbf{X}],
\end{aligned}
$$

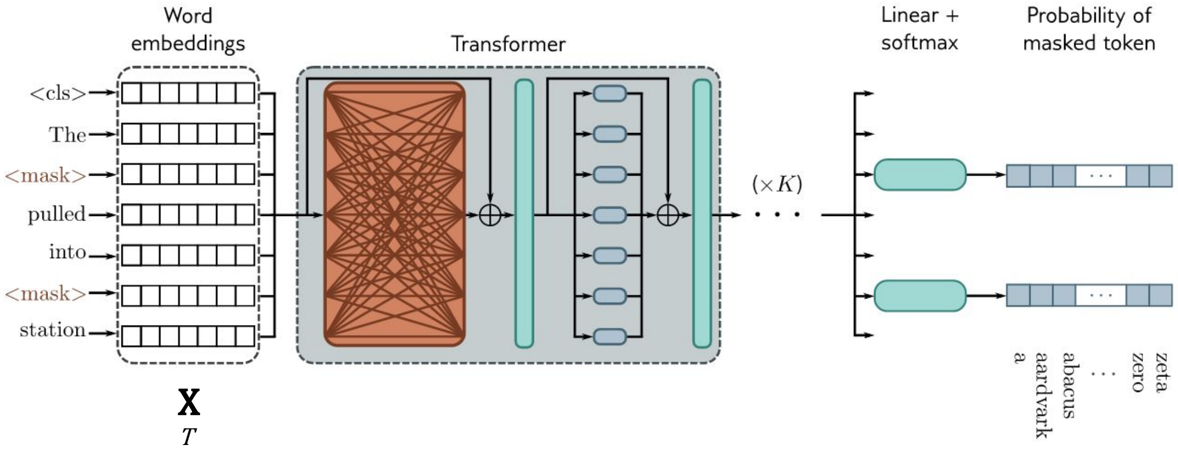
LayerNorm

$$y = \frac{x - \mathbf{E}[x]}{\sqrt{\mathbf{Var}[x] + \epsilon}} * \gamma + \beta$$

Calculated column-wise

Encoder Pre-Training

Special <cls> token used for aggregate sequence representation for classification

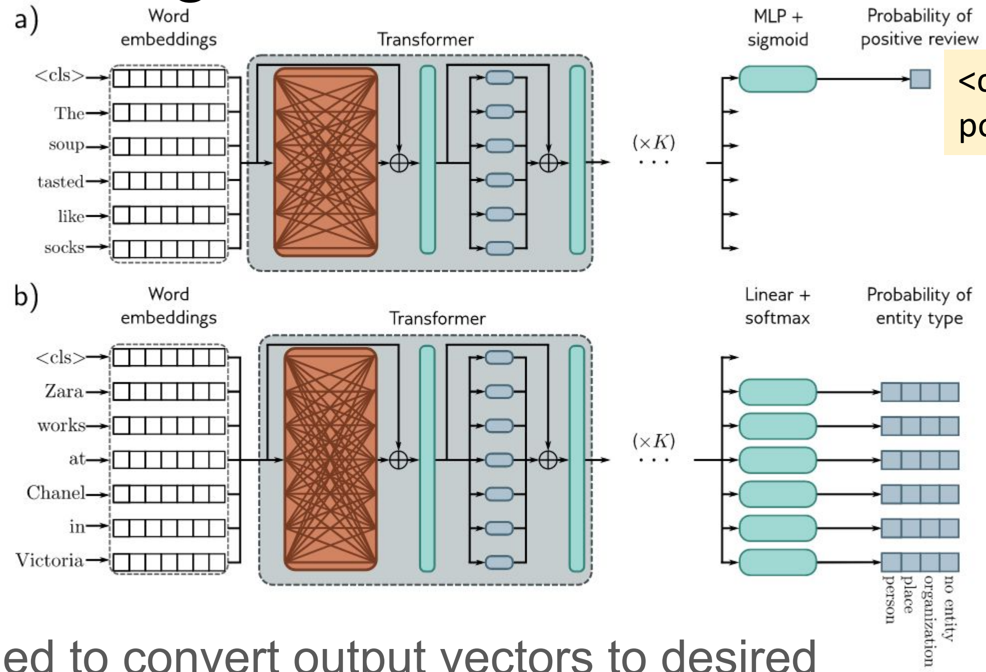


- A small percentage of input embedding replaced with a generic <mask> token
- Predict missing token from output embeddings
- Added linear layer and softmax to generate probabilities over vocabulary
- Trained on BooksCorpus (800M words) and English Wikipedia (2.5B words)

Encoder Fine-Tuning

Sentiment Analysis

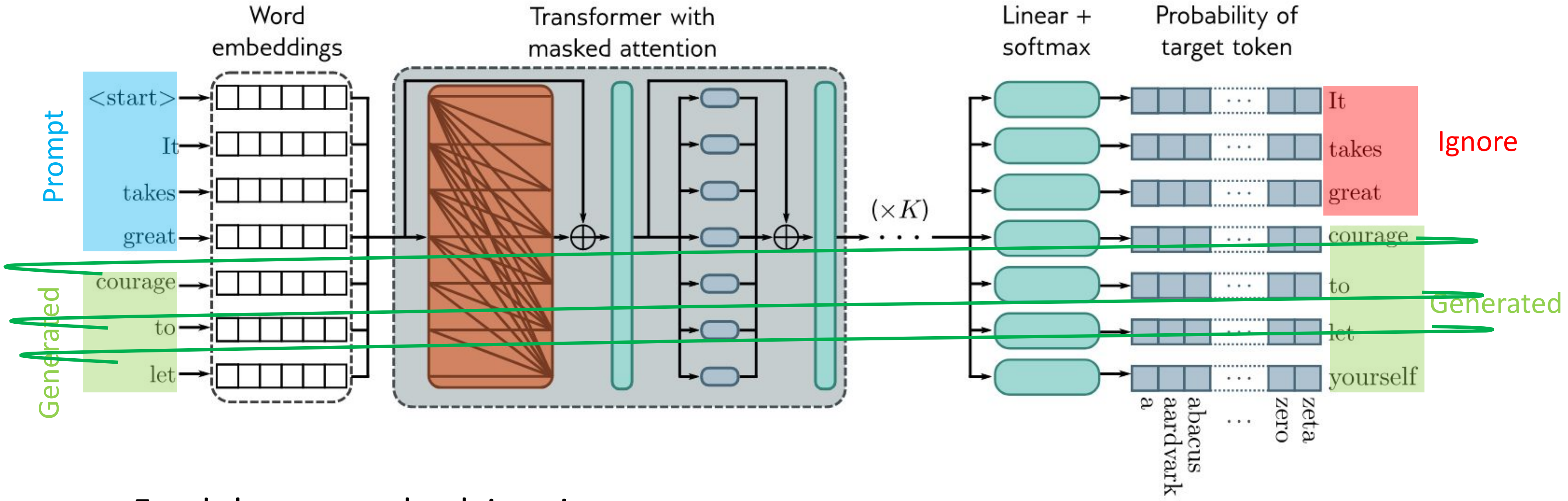
Named Entity Recognition (NER)



<cls> token position

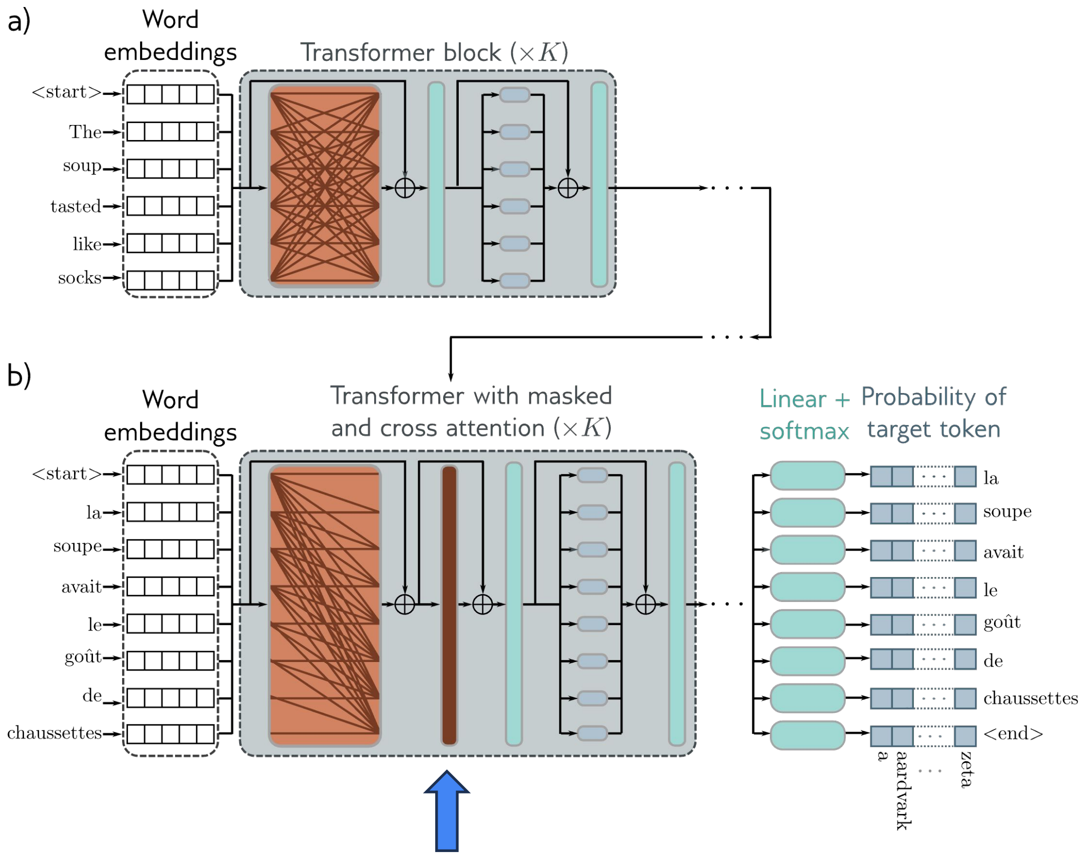
- Extra layer(s) appended to convert output vectors to desired output format
- 3rd Example: Text span prediction -- predict start and end location of answer to a question in passage of Wikipedia, see https://rajpurkar.github.io/SQuAD-explorer/

Decoder: Text Generation (Generative AI)



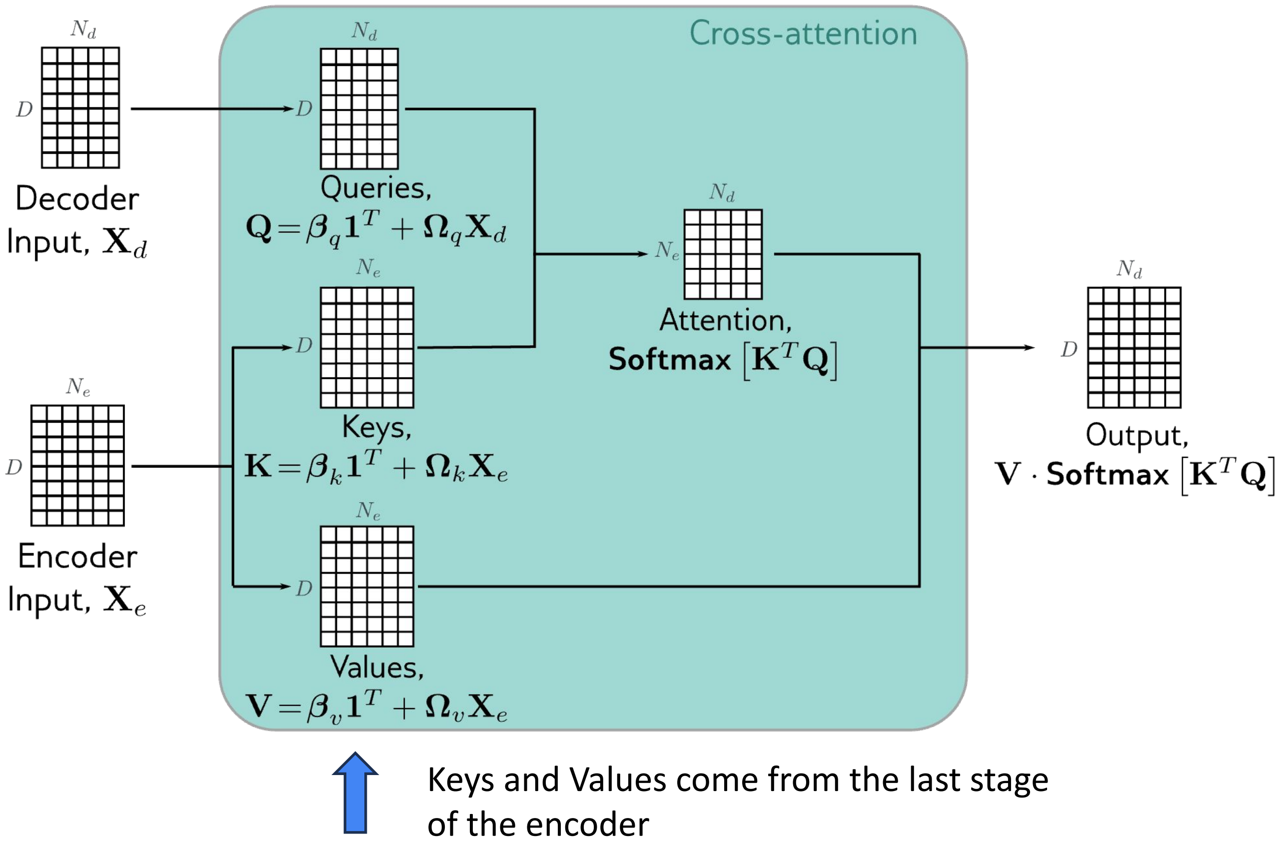
- Feed the output back into input

Encoder Decoder Model



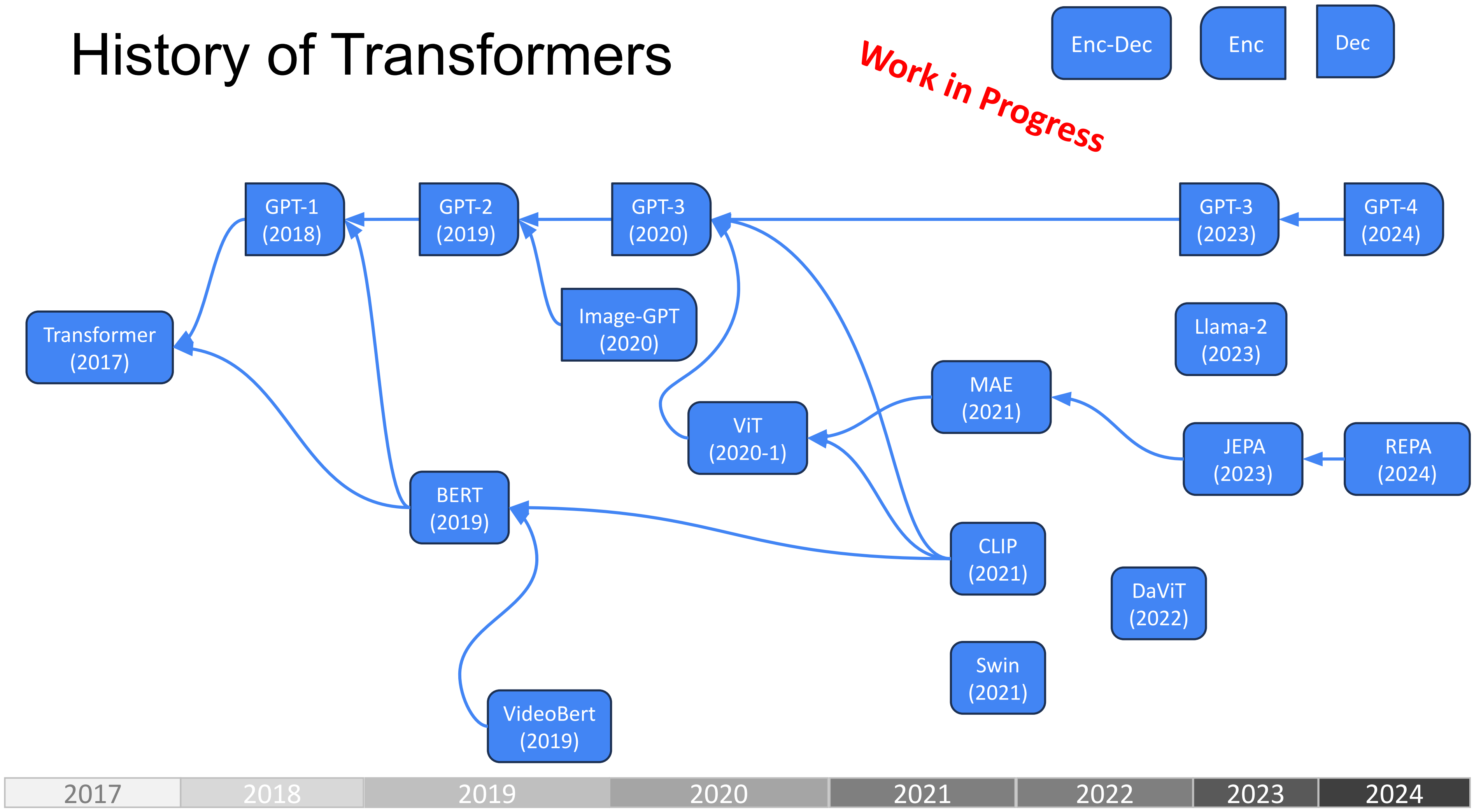
- The transformer layer in the decoder of the encoder-decoder model has an extra stage
- Attends to the input of the encoder with *cross attention* using Keys and Values from the output of the encoder

Cross-Attention

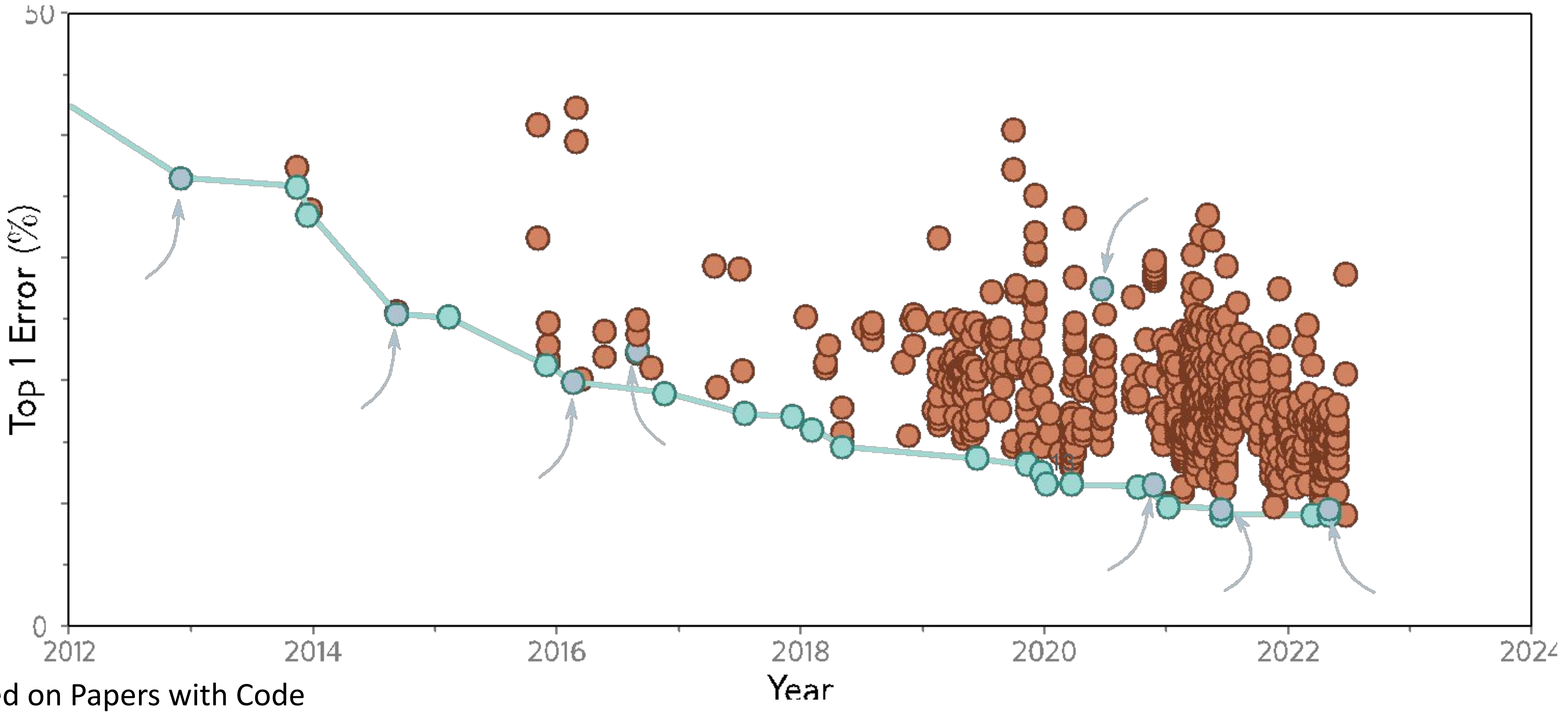


Keys and Values come from the last stage of the encoder

History of Transformers

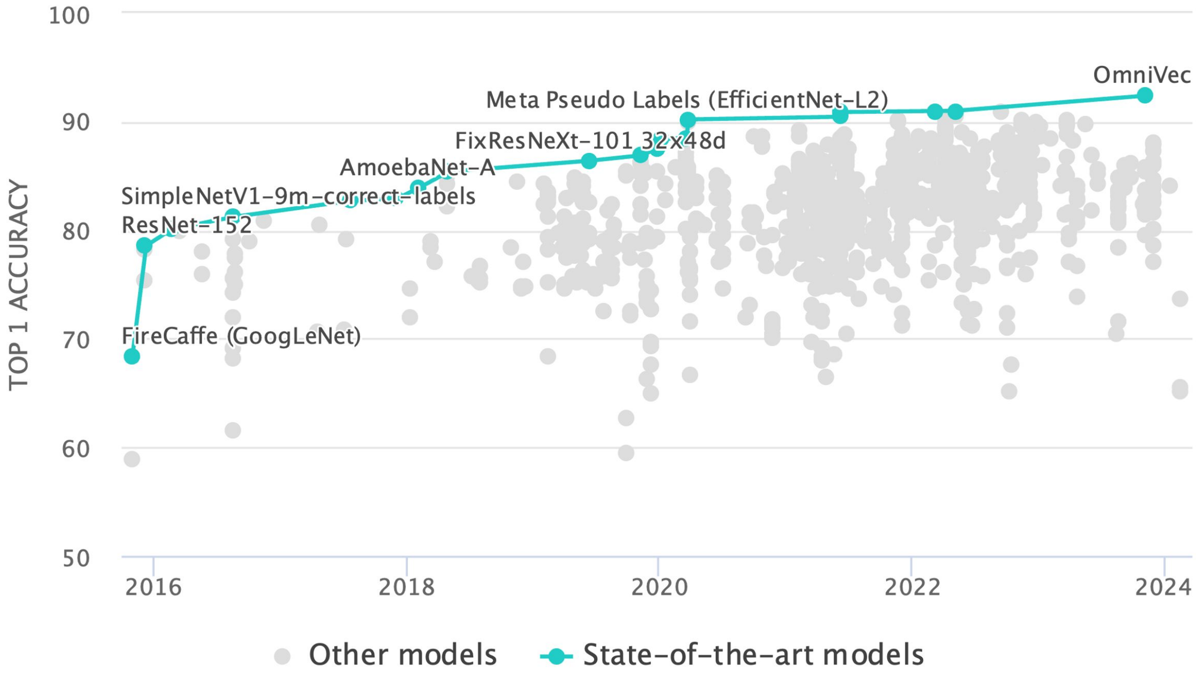


ImageNet History – Top-1 Error



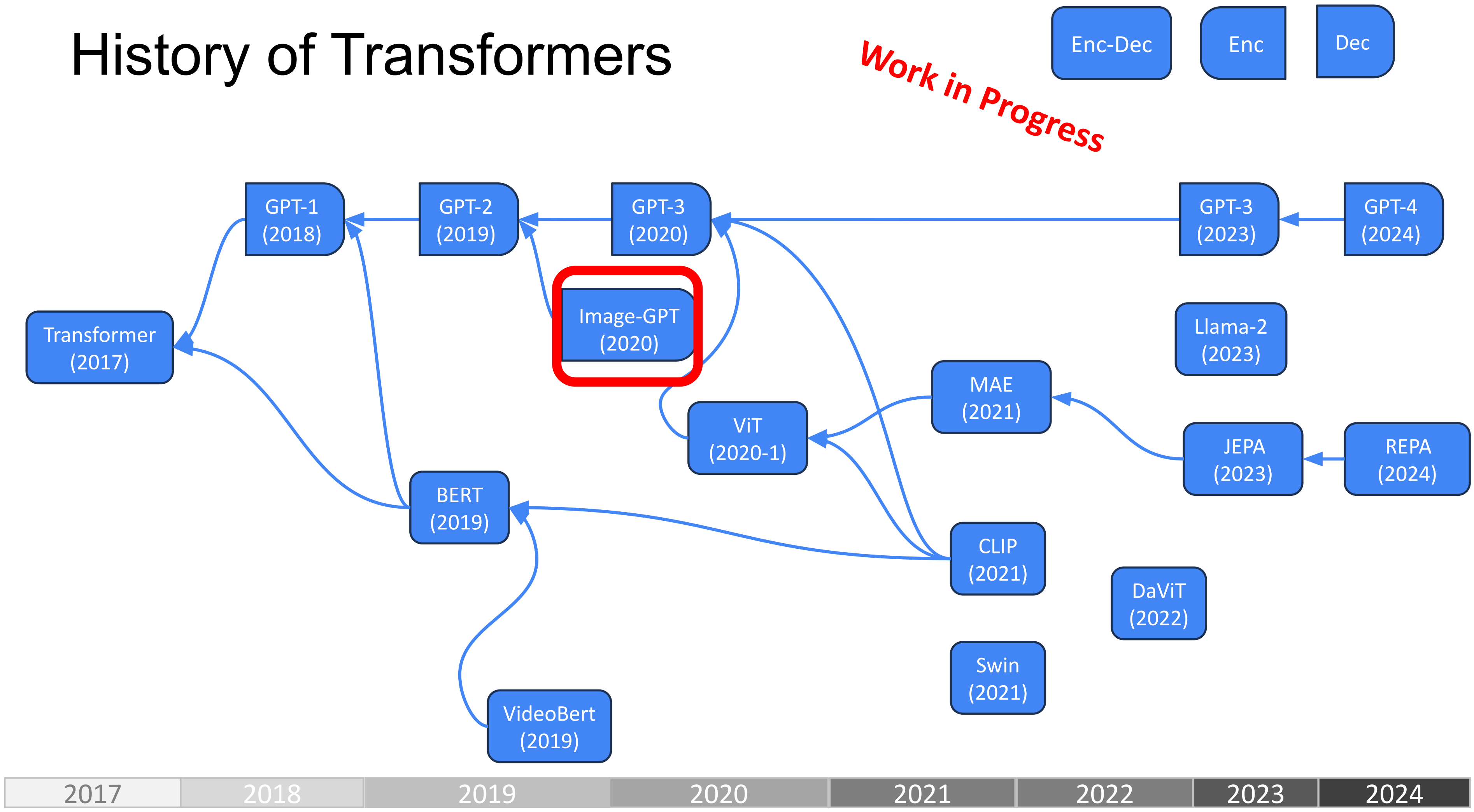
Based on Papers with Code

ImageNet Top-1 Accuracy



https://paperswithcode.com/sota/image-classification-on-imagenet

History of Transformers



OpenAI

Image GPT – June 2020

- Train GPT-2 scale sequence Transformer to auto-regressively predict pixels, w/o 2D input structure
- Use GPT-2 with only minor changes
- ImageNet Top-1 72% accuracy (not great), trained on ImageNet and web images
- Primary objective is to explore the representation accuracy of internal features

https://openai.com/research/image-gpt
https://github.com/openai/image-gpt (deprecated)
https://huggingface.co/docs/transformers/model_doc/imagegpt

M. Chen *et al.*, "Generative Pretraining from Pixels," OpenAI, Technical Report, Jun. 2020.

- Reduced resolution to reduce context size:
  32×32, 48×48 or 64×64
- Also reduced color palette from $3\times8 = 24$ bit to a 9-bit (512 colors) color palette by clustering (R, G, B) pixels with $k = 512$.

Image GPT – Inputs

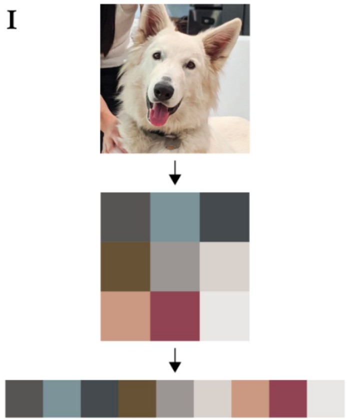


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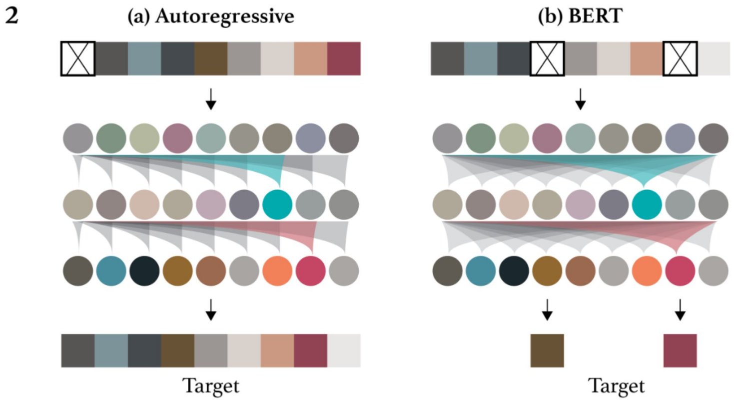
Image GPT – Training Objectives



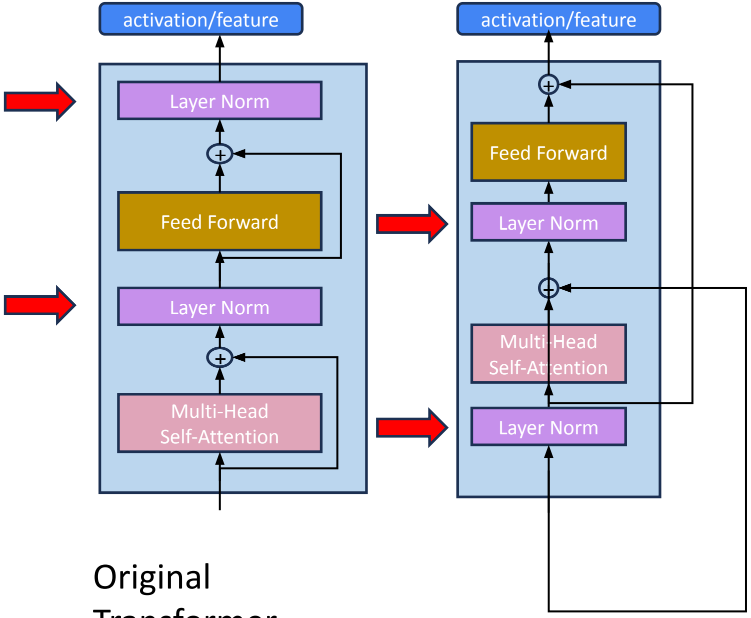
- Tried training with either *Autoregressive* or *BERT* style training objective

https://openai.com/research/image-gpt
https://github.com/openai/image-gpt (deprecated)
https://huggingface.co/docs/transformers/model_doc/imagegpt

M. Chen *et al.*, “Generative Pretraining from Pixels,” OpenAI, Technical Report, Jun. 2020.

Image GPT – Transformer Layer

OpenAI



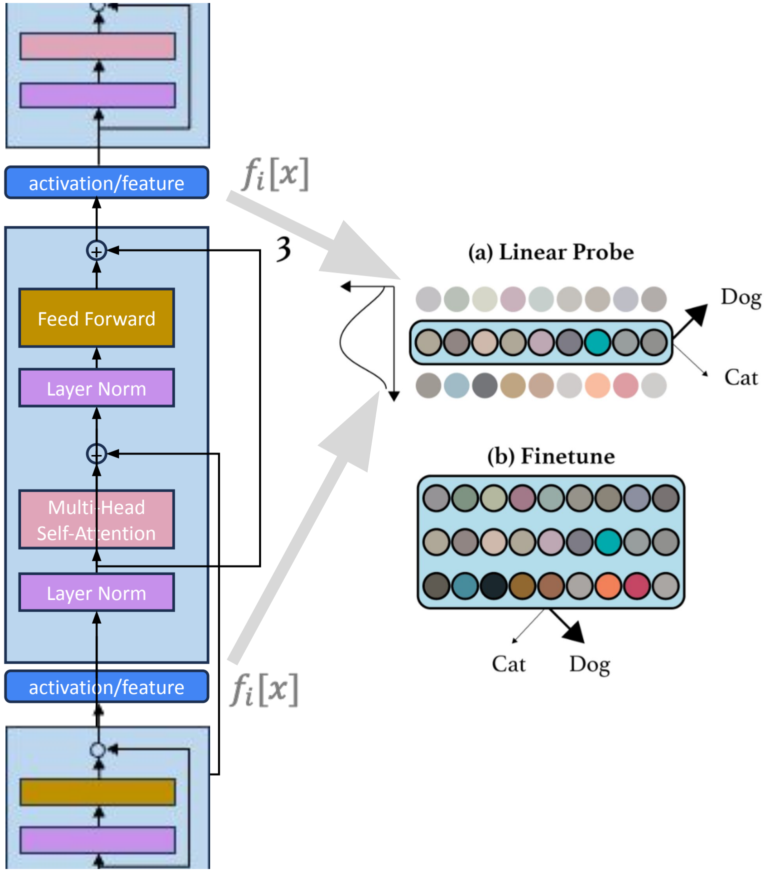
Original Transformer

ImageGPT Transformer

- LayerNorm moved to precede Self-Attention and Feed Forward block
- In the residual path

Image GPT – Linear Probes

OpenAI

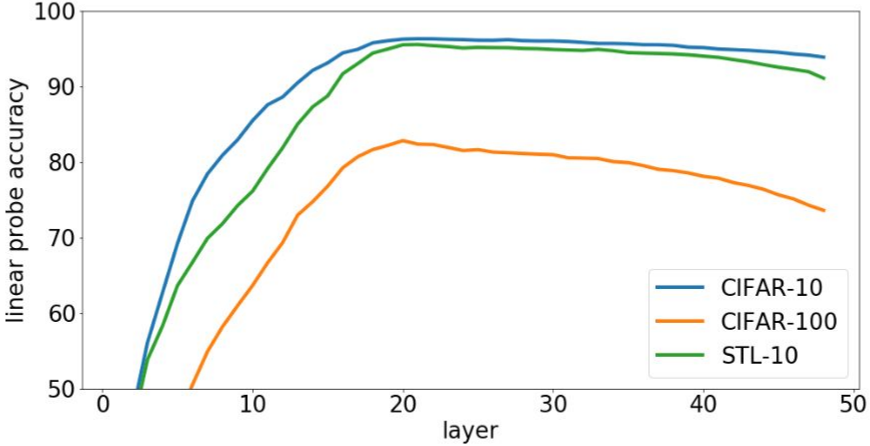


- Use pre-trained model as a "feature extractor"
- Activations after each layer ➔ Features
  - call i^{th} feature: $f_i[x]$
- Good features should linearly separate the classes of transfer tasks
- ➔ linear classifier trained on $(f_i[x], Y)$
- Do this with each feature and see which performs best

Image GPT – Representation Quality

Size	Layers	d	# parms
iGPT-S	24	512	76M
iGPT-M	36	1024	455M
iGPT-L	48	1536	1.4B
iGPT-XL	60	3072	6.8B

iGTP-L



- Classification representation quality by feature layer
- Best representation seems to lie in the middle
- As opposed to supervised-training where the best representations lie at the end of the network

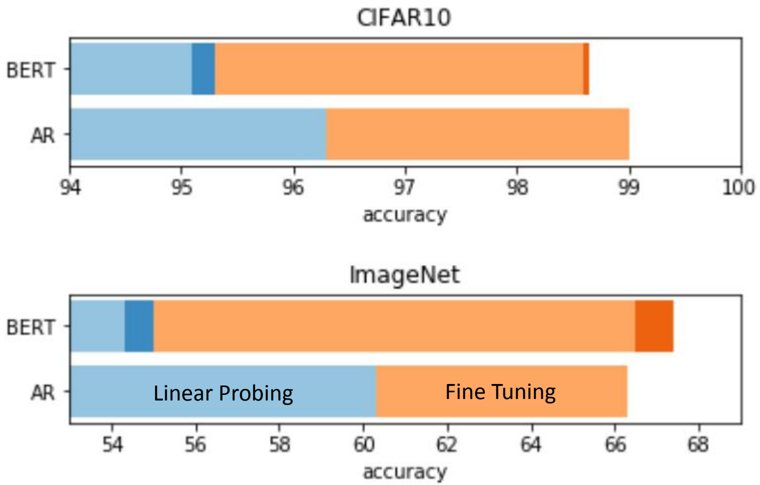
Image-GPT –

Perhaps generative model operates in two phases:

1. The 1st phase gathers information from surrounding context in order to build a more global representation.
2. In 2nd phase, contextualized input is used to solve conditional next pixel prediction task.

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

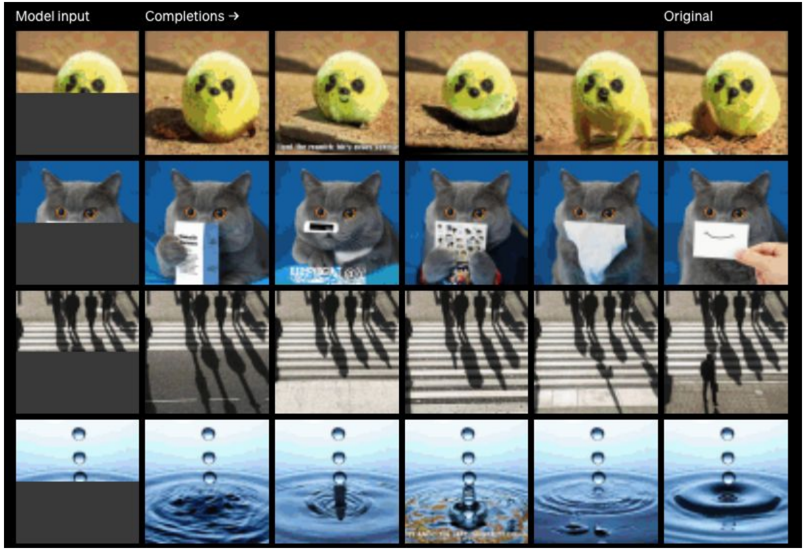
Image GPT – Fine-tuning for Classification



- Fine-tuning on the target dataset further improves accuracy
- Fine-tuning the entire model outperformed fine-tuning the best linear probe feature

Image GPT – AR Pixel Prediction Results

Input Completions Original



Input Completions Original

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

Image GPT – Sampling the Distribution

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

Image GPT – Pros and Cons

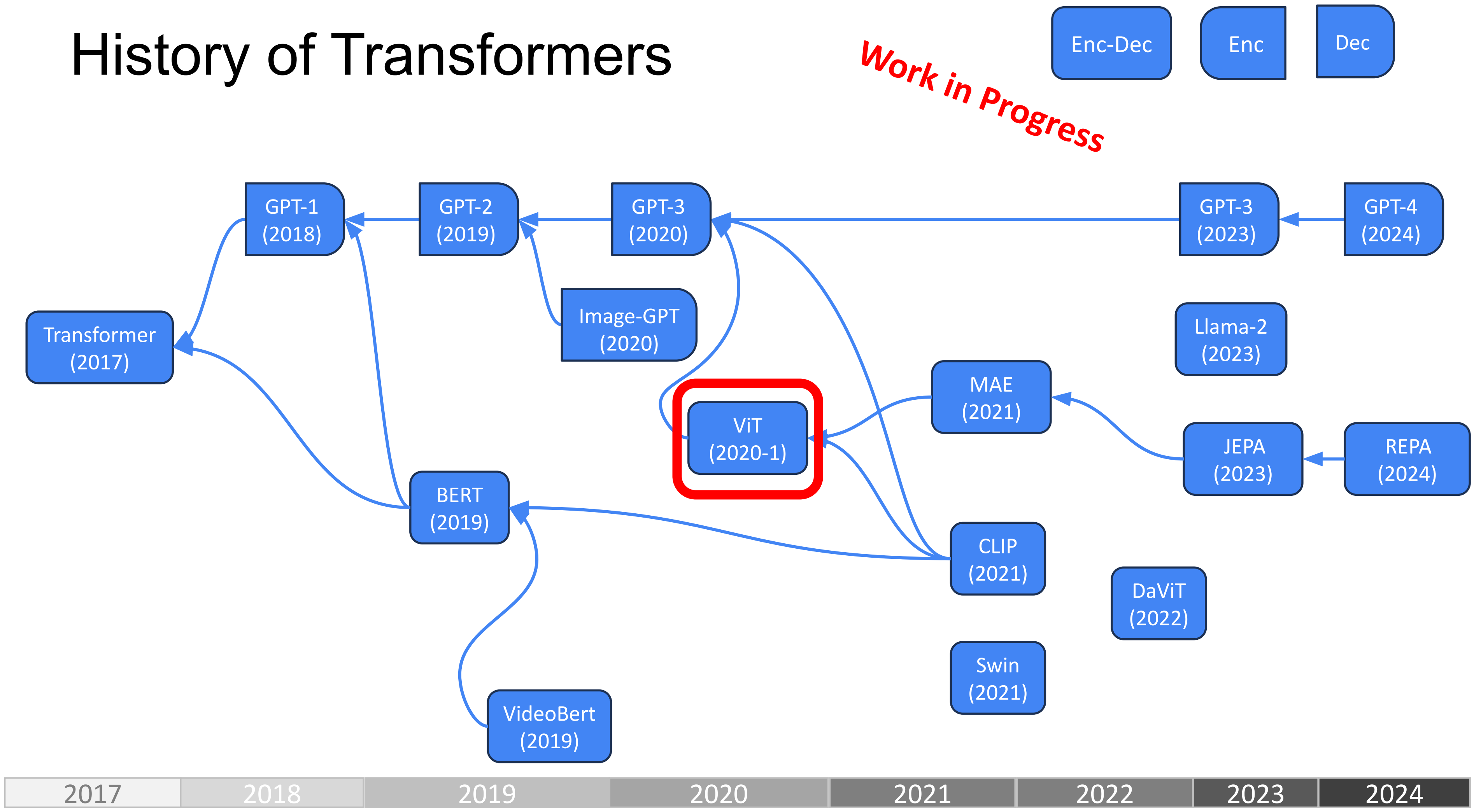
Pro:

- Gave insights into the representational power of Transformers with unsupervised training

Con:

- Worked on downscaled images of size 32x32 to 64x64

History of Transformers



Vision Transformer (ViT) – June 2021

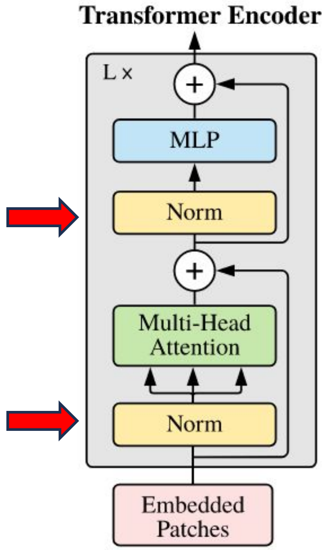
- Overcomes resolution limitation of ImageGPT by using patches
- Follows scalable NLP Transformer architectures to benefit from efficient implementations
- ImageNet Top-1 accuracy: 88.55%
- Performs poorly if just trained on ImageNet
  - can be expected since Transformers lack the inductive bias of CNNs
- Competitive when pre-trained on very large datasets (e.g. 14M – 300M) images – all supervised at this point

Large scale training trumps inductive bias???

https://arxiv.org/abs/2010.11929v2
https://github.com/google-research/vision_transformer

Be wary of method claims based on different data sets and compute.

Vision Transformer (ViT) – June 2021



- Uses same Transformer layer as ImageGPT and scalable NLP Transformers

https://arxiv.org/abs/2010.11929v2
https://github.com/google-research/vision_transformer

ViT: Putting it all together

1. Divide image into $P \times P$ patches

ViT: Putting it all together

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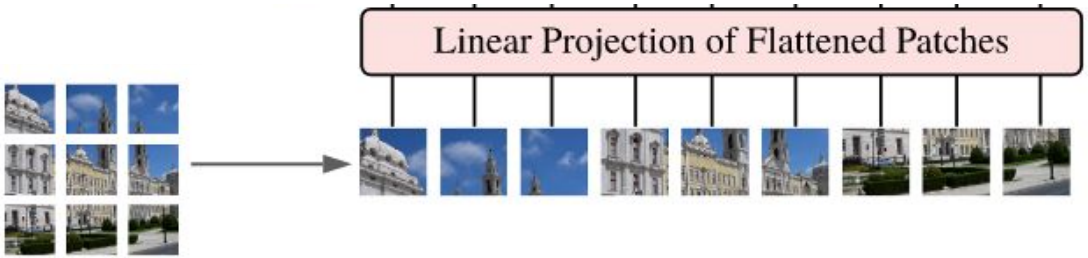
2. Create sequence of length $N = HW/P^2$

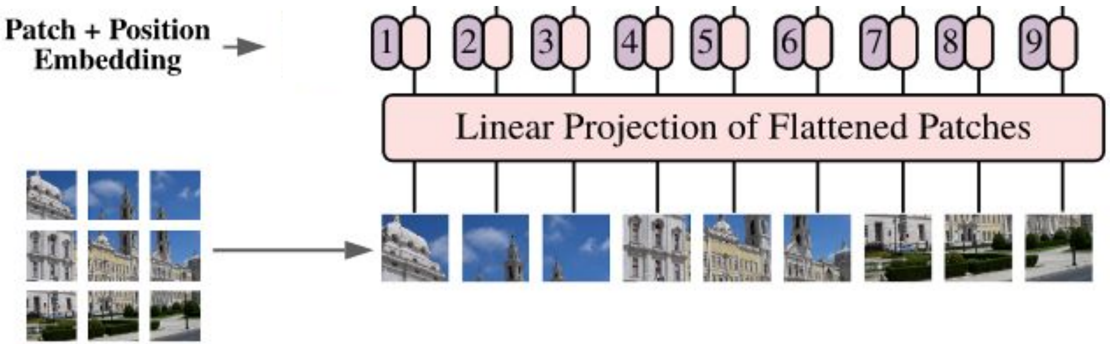
ViT: Putting it all together

1. Divide image into $P \times P$ patches
2. Create sequence of length $N = HW/P^2$
3. Flatten the patches and map to D dimensions with a trainable linear projection



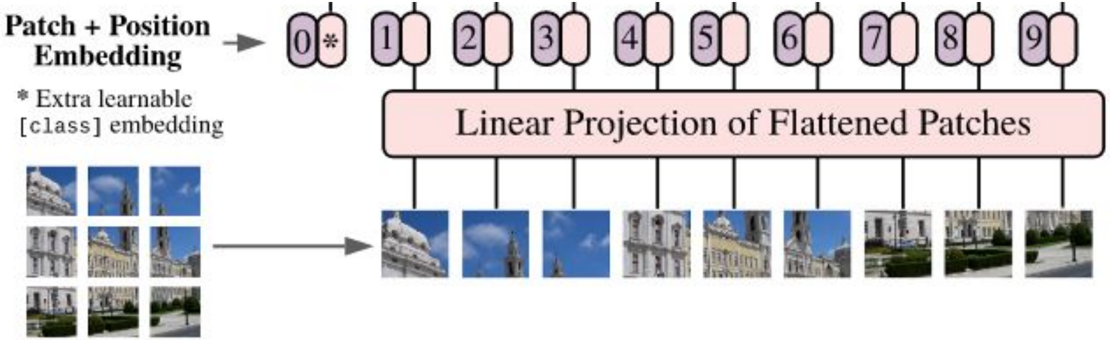
ViT: Putting it all together

1. Divide image into $P \times P$ patches
2. Create sequence of length $N = HW/P^2$
3. Flatten the patches and map to D dimensions with a trainable linear projection
4. Add a learned 1-D position embedding

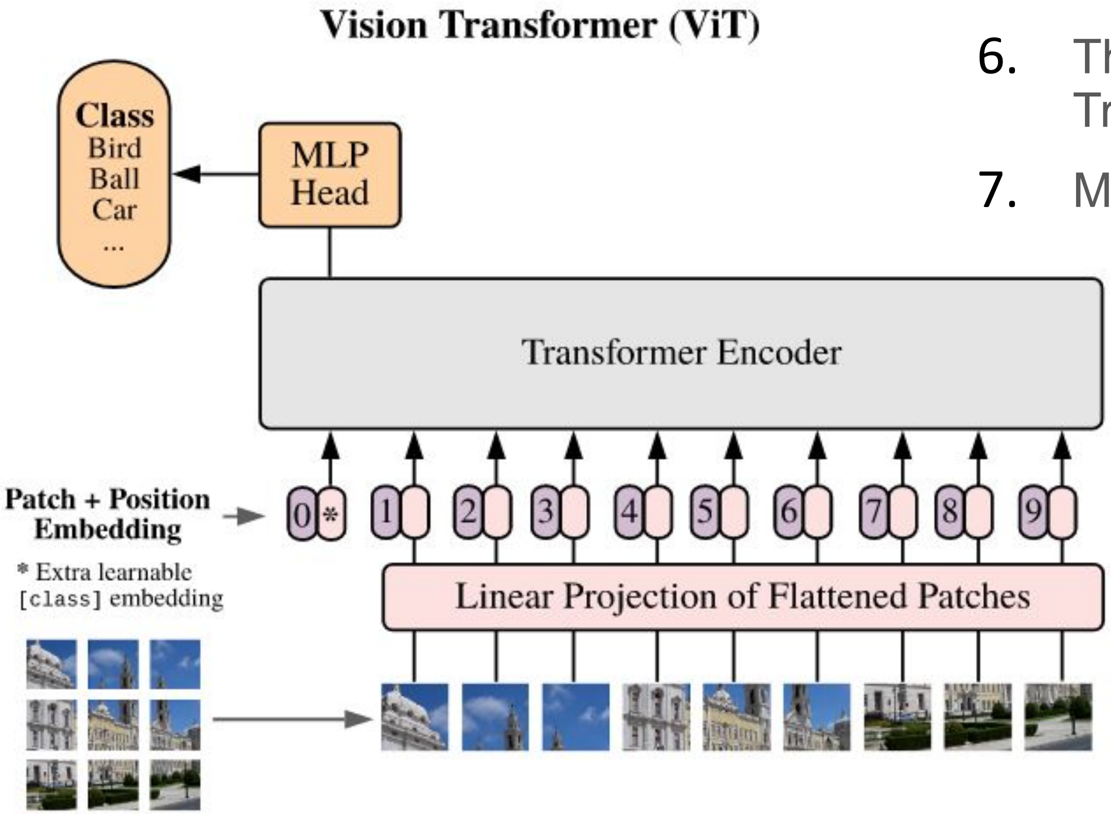


ViT: Putting it all together

1. Divide image into $P \times P$ patches
2. Create sequence of length $N = HW/P^2$
3. Flatten the patches and map to D dimensions with a trainable linear projection
4. Add a learned 1-D position embedding
5. Include a learnable [class] embedding



ViT: Putting it all together



6. Then through a multi-layered Transformer encoder to a
7. MLP classification head.

ViT Training Datasets & Model Variants

Dataset	# Classes	# Images
ILSVRC-2012	1K	1.3M
ImageNet-21K	21K	14M
JFT	18K	303M

Model	Layers	Hidden size D	MLP size	Heads	Params	
ViT-Base	12	768	3072	12	86M	Same as BERT
ViT-Large	24	1024	4096	16	307M	Same as BERT
ViT-Huge	32	1280	5120	16	632M	New for ViT

Notation: ViT-L/16 -- "Large" variant with 16×16 input size.

Note: $16\times16\times3 = 768$

ViT: Image Classification Results

Pre-Trained On

	Ours-JFT (ViT-H/14)	Ours-JFT (ViT-L/16)	Ours-I21k (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	**88.55** $\pm$ 0.04	87.76 $\pm$ 0.03	85.30 $\pm$ 0.02	87.54 $\pm$ 0.02	88.4/88.5*
ImageNet ReaL	**90.72** $\pm$ 0.05	90.54 $\pm$ 0.03	88.62 $\pm$ 0.05	90.54	90.55
CIFAR-10	**99.50** $\pm$ 0.06	99.42 $\pm$ 0.03	99.15 $\pm$ 0.03	99.37 $\pm$ 0.06	–
CIFAR-100	**94.55** $\pm$ 0.04	93.90 $\pm$ 0.05	93.25 $\pm$ 0.05	93.51 $\pm$ 0.08	–
Oxford-IIIT Pets	**97.56** $\pm$ 0.03	97.32 $\pm$ 0.11	94.67 $\pm$ 0.15	96.62 $\pm$ 0.23	–
Oxford Flowers-102	99.68 $\pm$ 0.02	**99.74** $\pm$ 0.00	99.61 $\pm$ 0.02	99.63 $\pm$ 0.03	–
VTAB (19 tasks)	**77.63** $\pm$ 0.23	76.28 $\pm$ 0.46	72.72 $\pm$ 0.21	76.29 $\pm$ 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k

ViT: Visualizing Internals

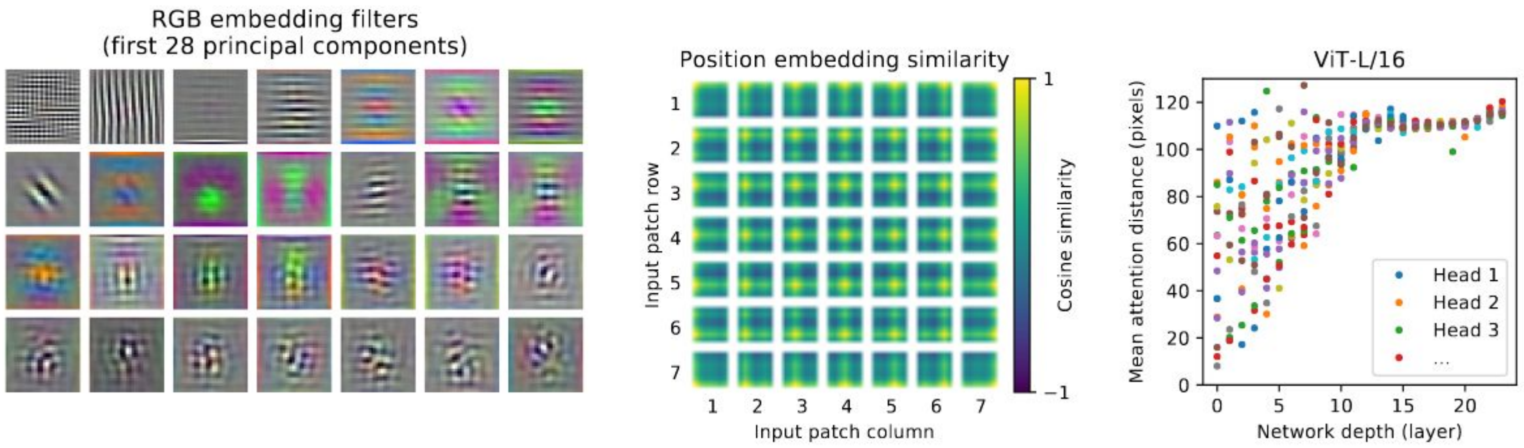


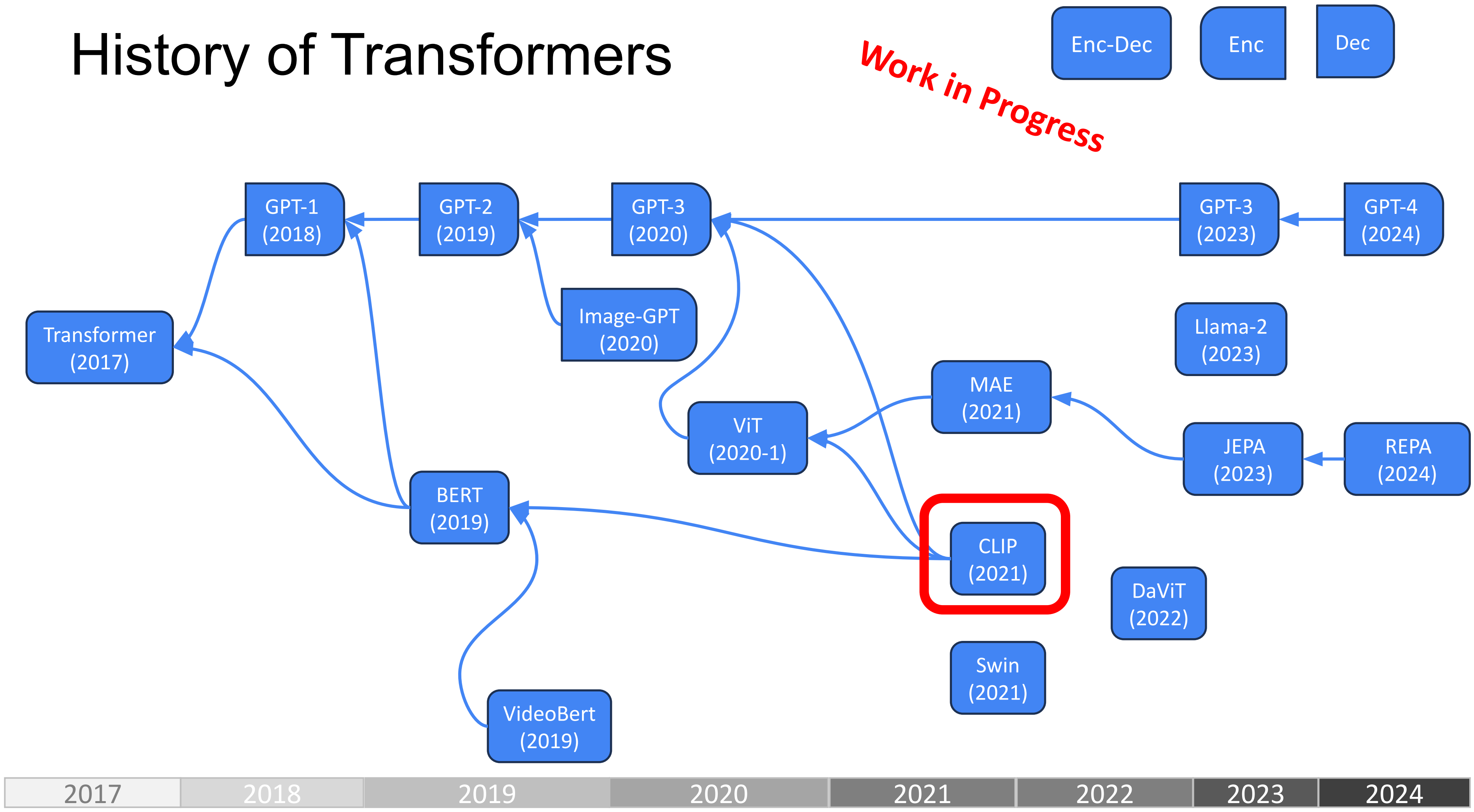
Figure 7: **Left:** Filters of the initial linear embedding of RGB values of ViT-L/32. **Center:** Similarity of position embeddings of ViT-L/32. Tiles show the cosine similarity between the position embedding of the patch with the indicated row and column and the position embeddings of all other patches. **Right:** Size of attended area by head and network depth. Each dot shows the mean attention distance across images for one of 16 heads at one layer. See Appendix D.7 for details.

Scaling Vision Transformers (2022)

- Explore scaling up and down
- Achieves new state-of-the-art on ImageNet top-1: 90.45% *with 2B parameter model*

X. Zhai, A. Kolesnikov, N. Houlsby, and L. Beyer, “Scaling Vision Transformers,” presented at the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, pp. 12104–12113. Accessed: Mar. 18, 2024.

History of Transformers



CLIP (2021) – Contrastive Language Image Pretraining

- Learn directly from raw text about images
- Created a new 400m (image, text) pair dataset called WebImageText (WIT) scraped from the internet
- “Simple” pre-training task:
  - Predict which caption goes with which image from scratch on a dataset of 400 million (image, text) pairs
  - Efficient and scalable
  - Learn state-of-the-art image representations from scratch
- Zero-shot transfer to many image classification datasets
- Shows promise for zero-shot transfer for other tasks: e.g. OCR, facial expression recognition, …

A. Radford *et al.*, “Learning Transferable Visual Models From Natural Language Supervision,” in *Proceedings of the 38th International Conference on Machine Learning*, PMLR, Jul. 2021, pp. 8748–8763. https://proceedings.mlr.press/v139/radford21a.html

CLIP (2021) – Contrastive Language Image Pretraining

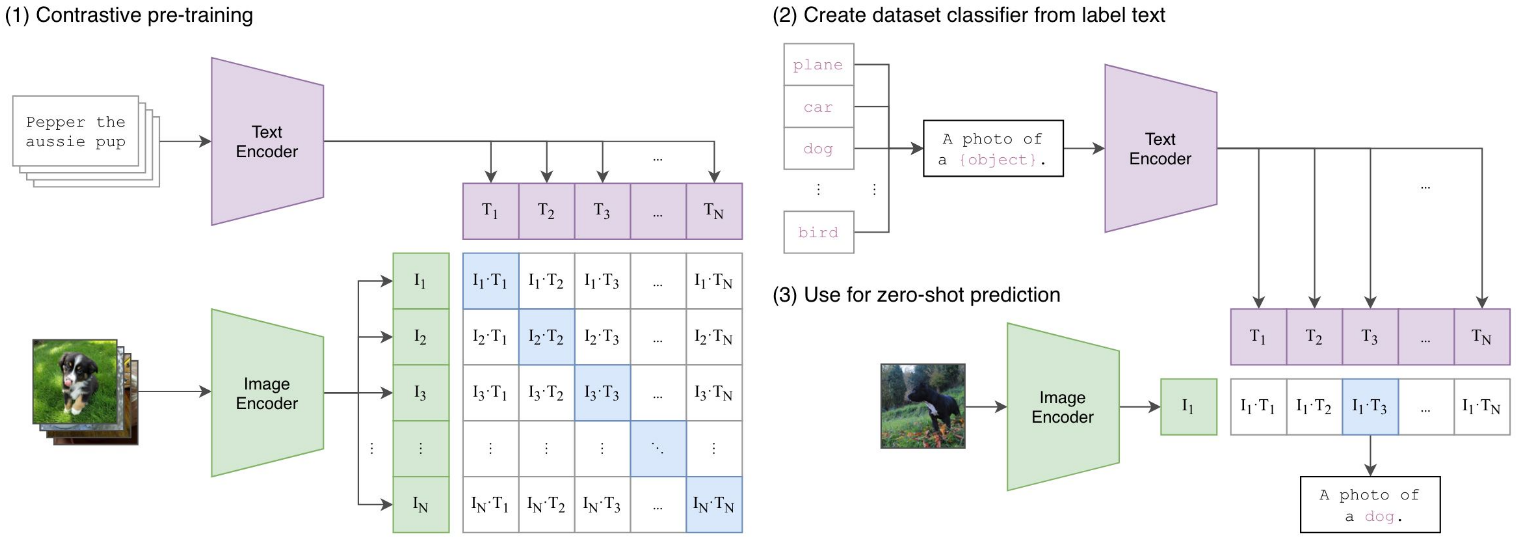
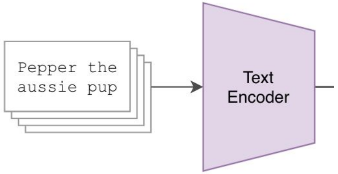


Figure 1. Summary of our approach. While standard image models jointly train an image feature extractor and a linear classifier to predict some label, CLIP jointly trains an image encoder and a text encoder to predict the correct pairings of a batch of (image, text) training examples. At test time the learned text encoder synthesizes a zero-shot linear classifier by embedding the names or descriptions of the target dataset's classes.

CLIP (2021) – Text Encoder



Embedding

- lower-cased byte pair encoding (BPE)
- bracketed with `[SOS]` and `[EOS]` tokens

Transformer

- 12-layer
- 512-wide
- 8 attention heads

CLIP (2021) – Image Encoder

Trained and compared 5 ResNets and 3 vision transformers

- ResNet50, ResNet101, RN50x4, x16, x64
- ViT-B/32, ViT-B/16 and ViT-L/14

Best model: ViT-L/14@336px

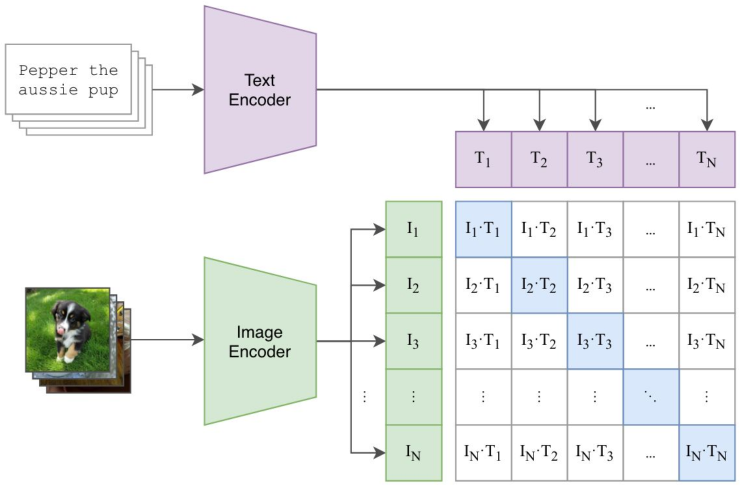
- e.g. ViT-Large with 336x336 pixel resolution and 14x14 patch resolution

Found vision transformers ~3x more compute efficient than CLIP ResNets

- RN50x64 took 18 days on 592 V100 GPUs
- ViT took 12 days on 256 V100 GPUS

CLIP (2021) – Contrastive Language Image Pretraining

(1) Contrastive pre-training



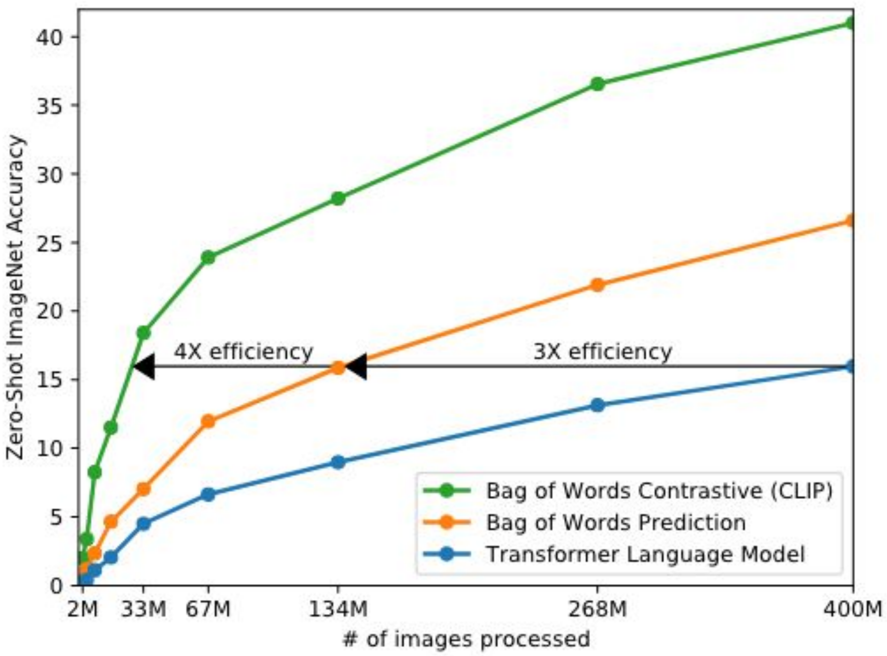

```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

Figure 3. Numpy-like pseudocode for the core of an implementation of CLIP.

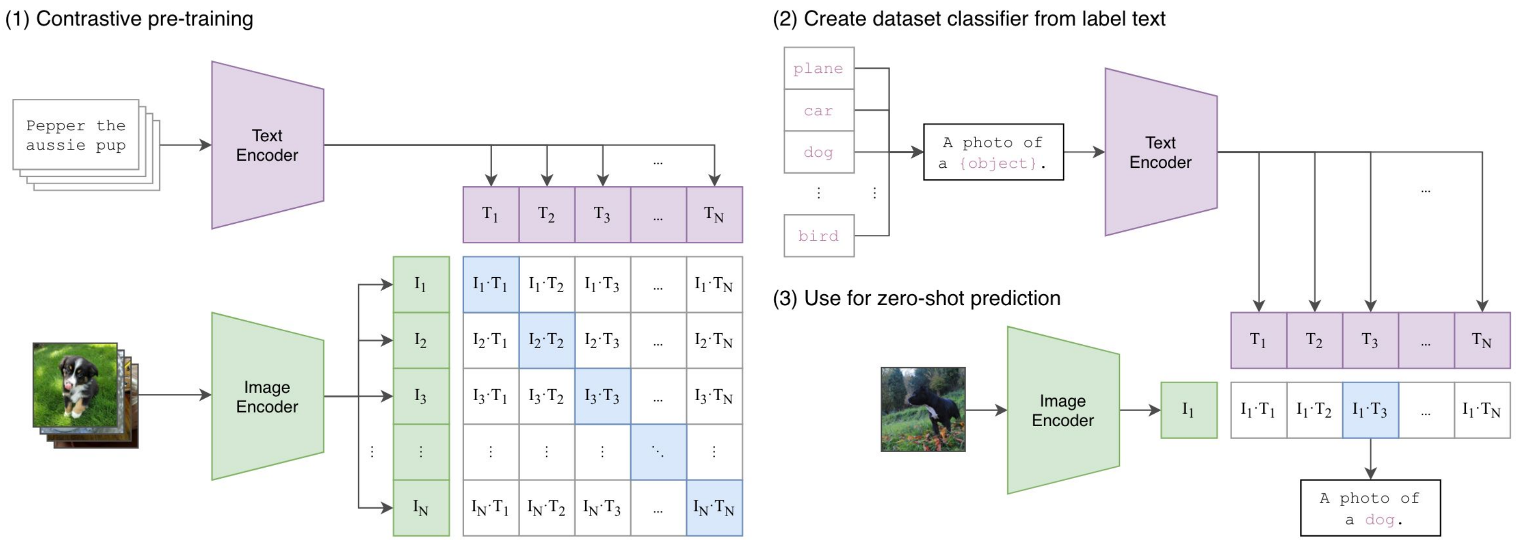
CLIP (2021) – Contrastive Loss

- Initially tried to train to predict caption of image (blue curve)
- bag-of-words encoding of same text is 3X more efficient (orange) curve
- Contrastive Objective improved another 4X (green curve)

Contrastive Loss: Maximize cosine similarity measure between matching (image, text) pairs and simultaneously minimize similarity between non-matching pairs



CLIP (2021) – Zero-Shot Image Classification



CLIP (2021) – Zero-Shot Image Classification

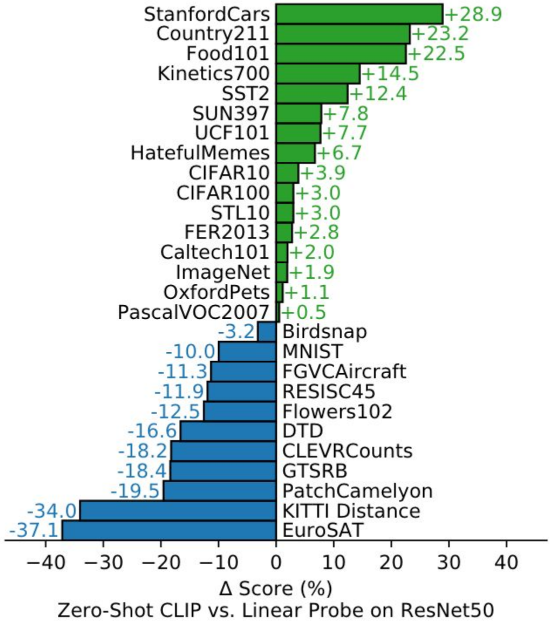
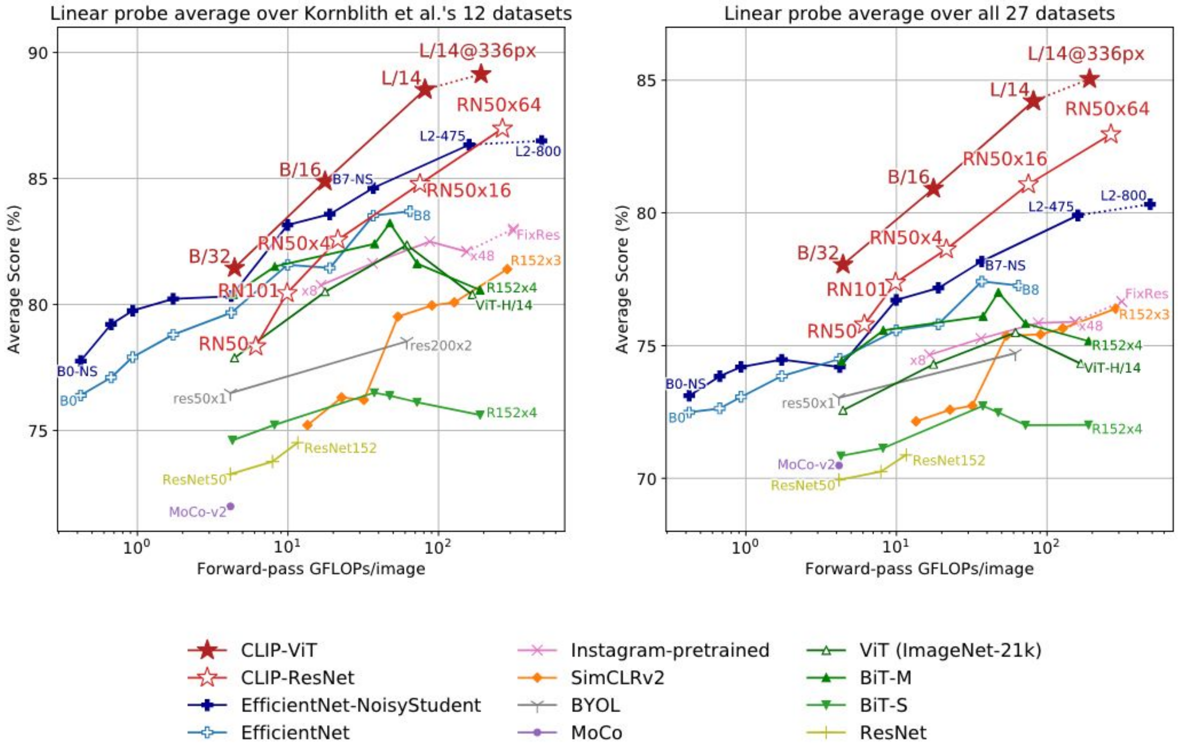


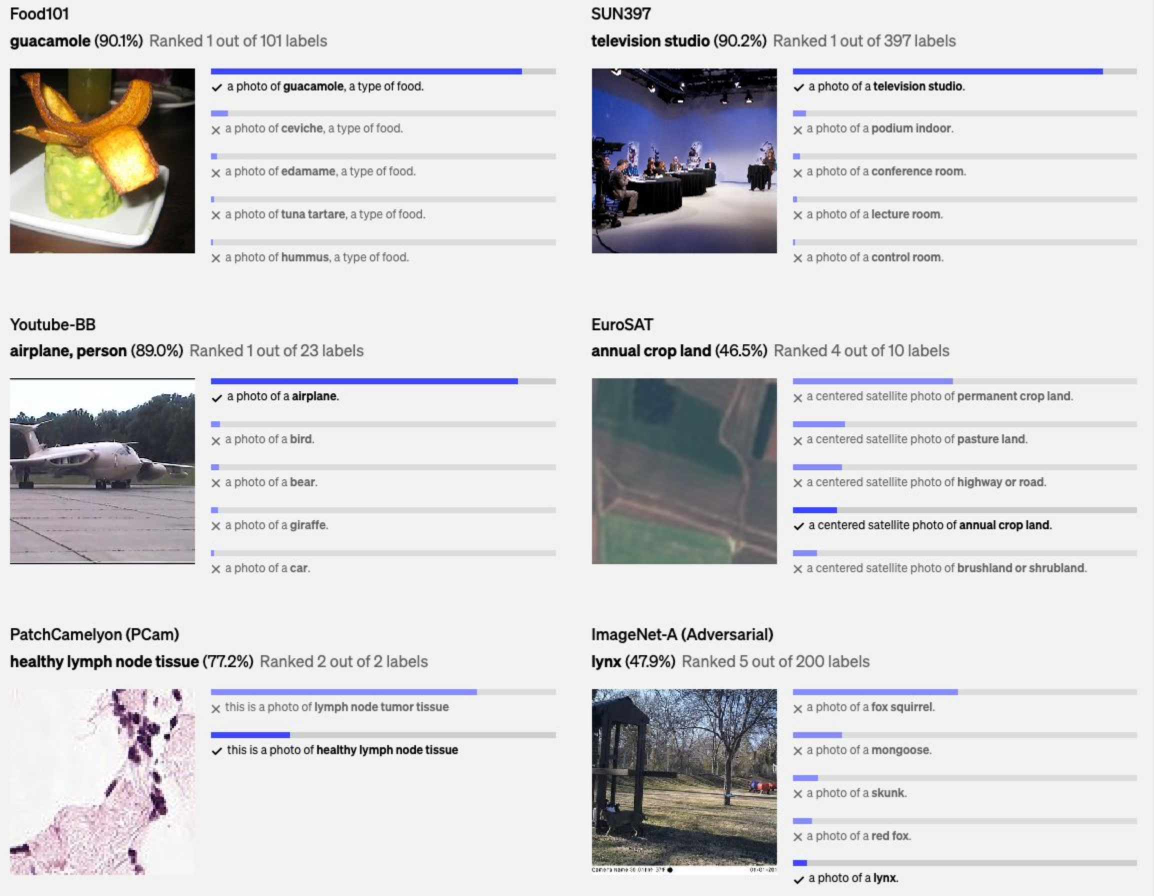
Figure 4. **Zero-shot CLIP is competitive with a fully supervised baseline.** Across a 27 dataset eval suite, a zero-shot CLIP classifier outperforms a fully supervised linear classifier fitted on ResNet50 features on 16 datasets, including ImageNet.

- Evaluated across 27(!!) datasets
- Compared to ResNet50 trained in supervised manner
- Beat ResNet50 on 16 of the 27
- Produced new SoTA on STL10 (99.3%)

CLIP (2021) – Compute Efficiency

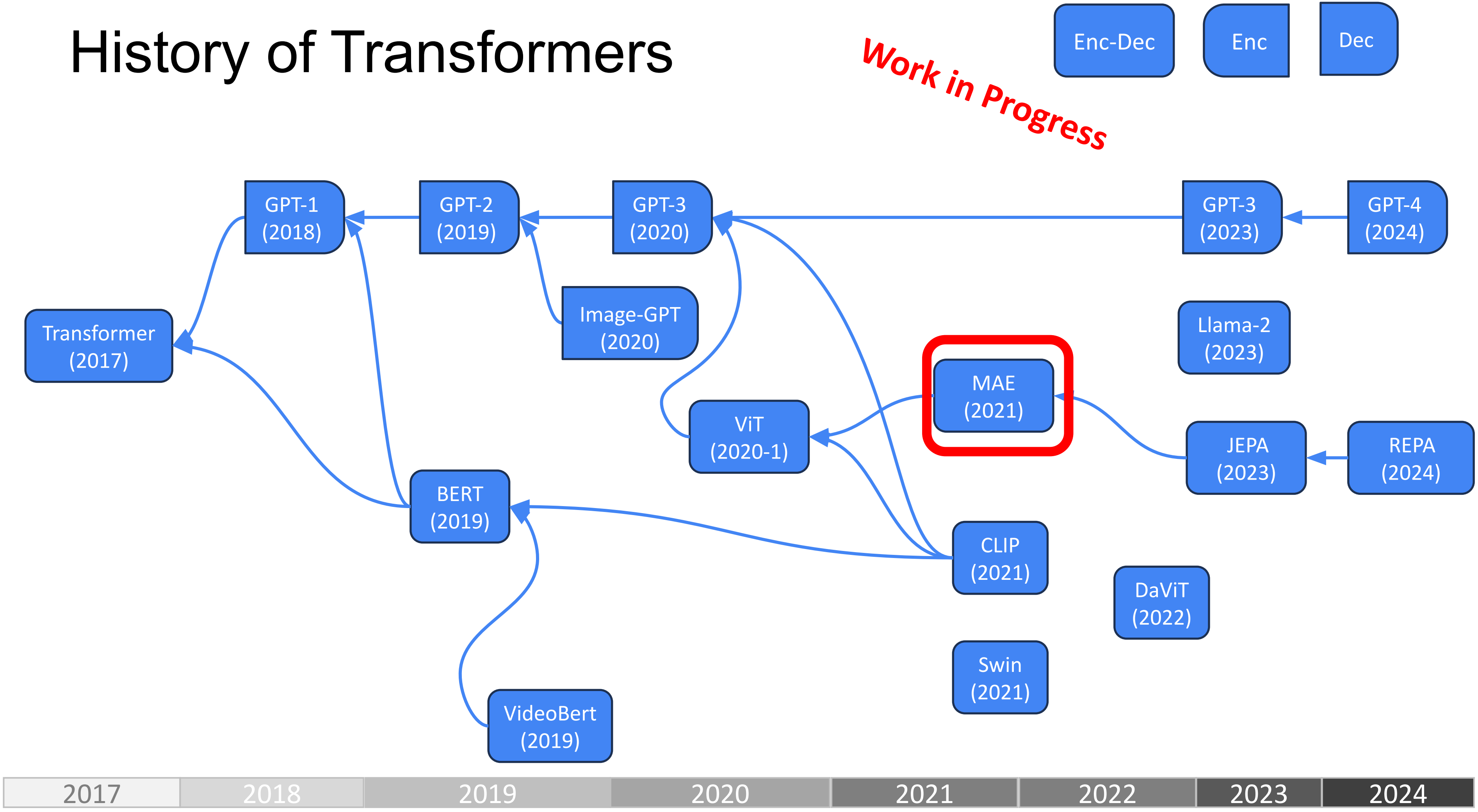


CLIP(2021) – Zero-Shot Classification Examples



History of Transformers

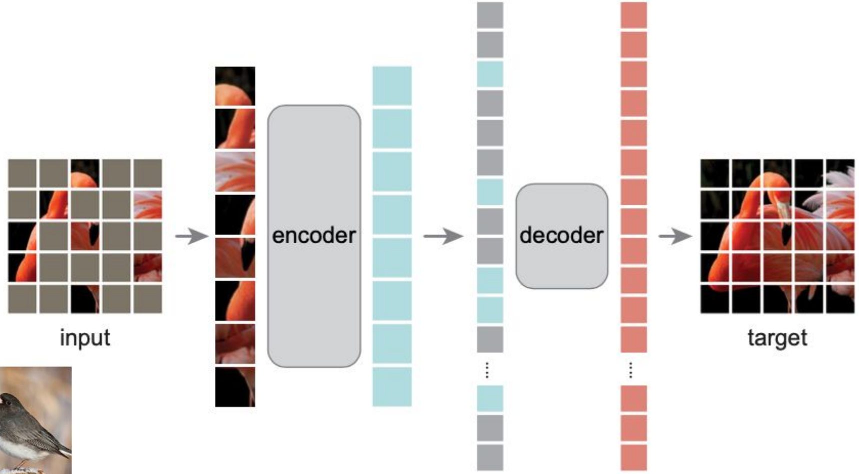
Work in Progress

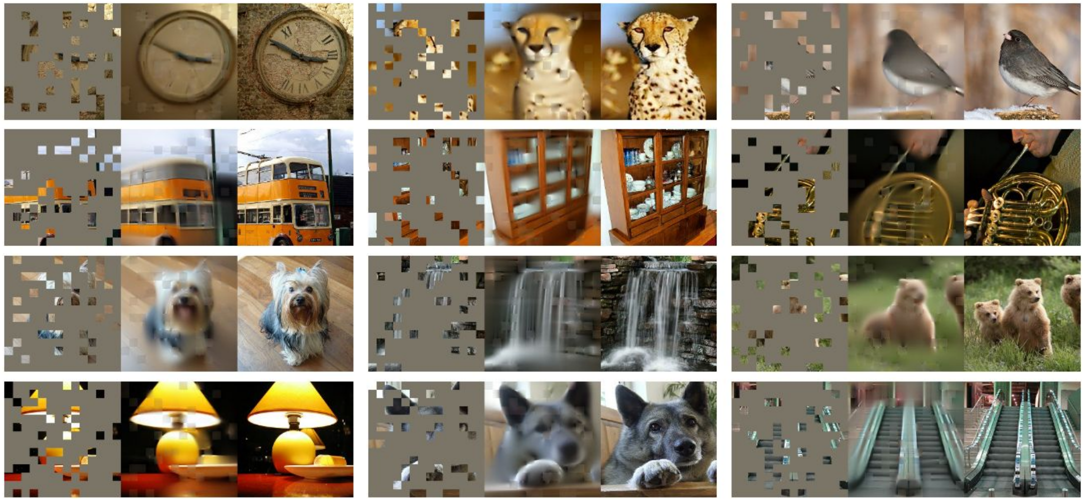


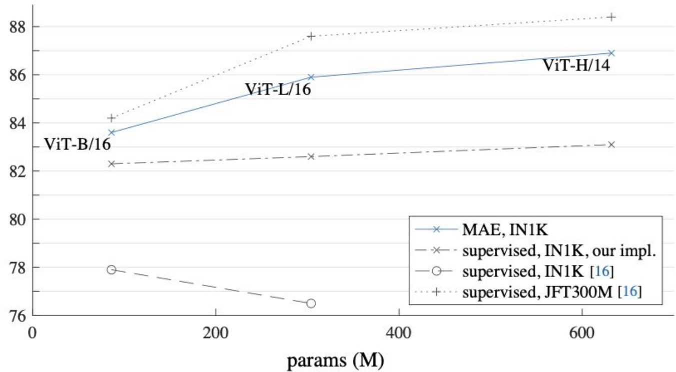
Masked Autoencoders are Scalable Vision Learners

Key idea:

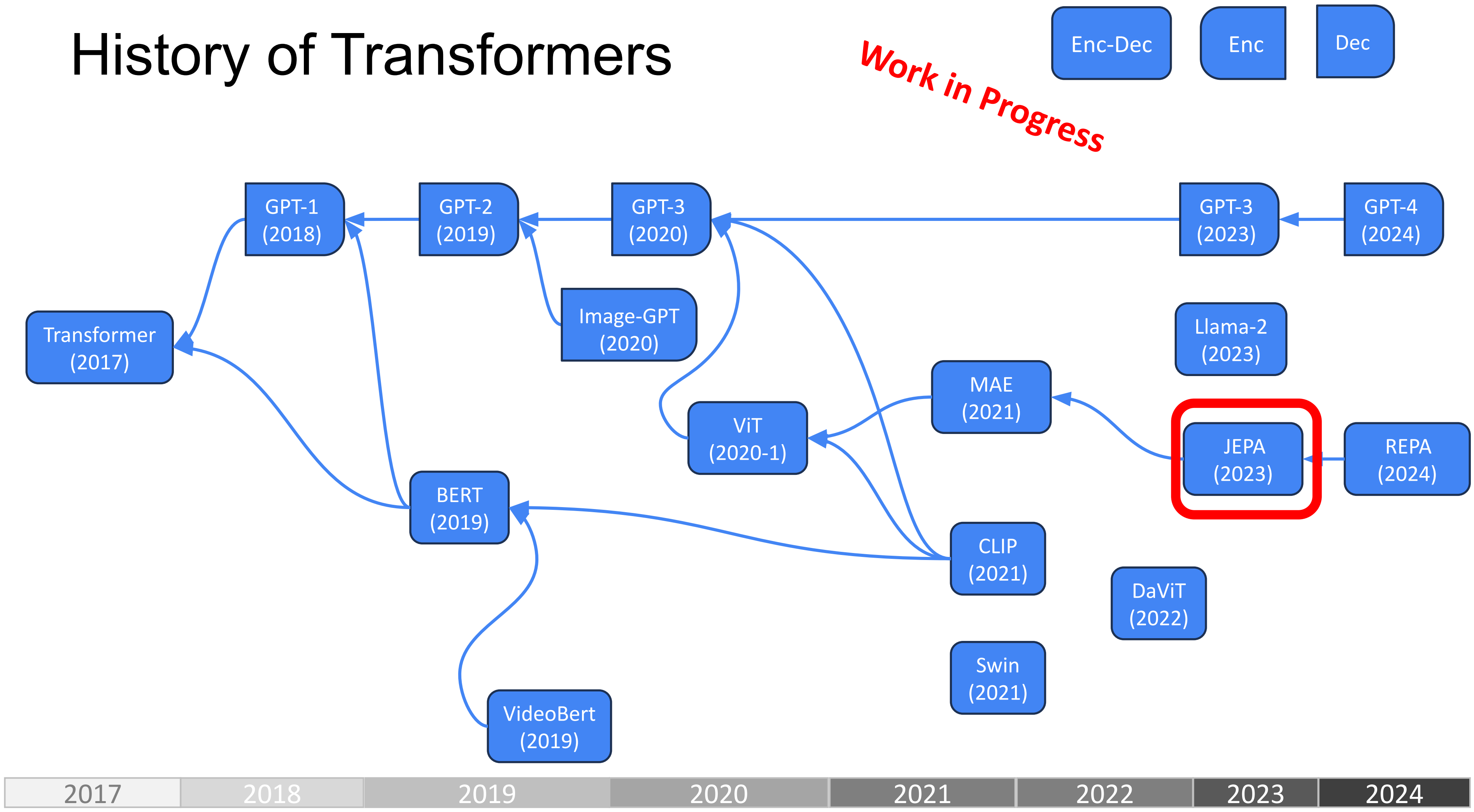
- Encode latent codes for blocks and mask them out, train on recovering pixels from the unmasked blocks.







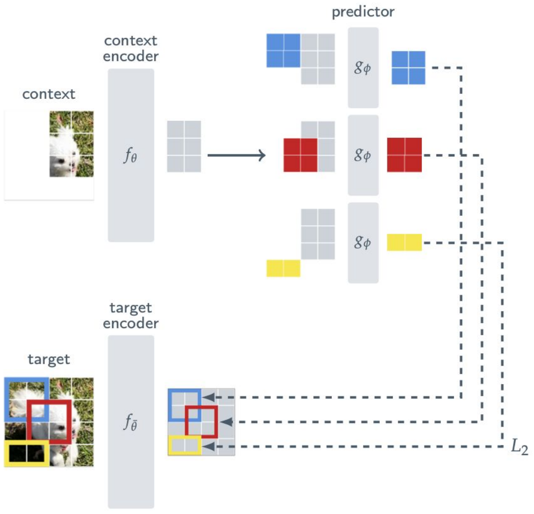
History of Transformers

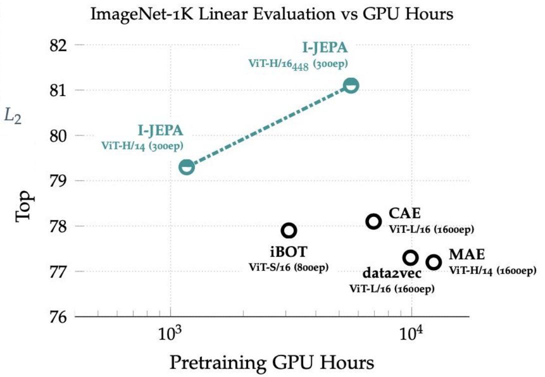


Self-Supervised Learning from Images with a Joint-Embedding Predictive Architecture

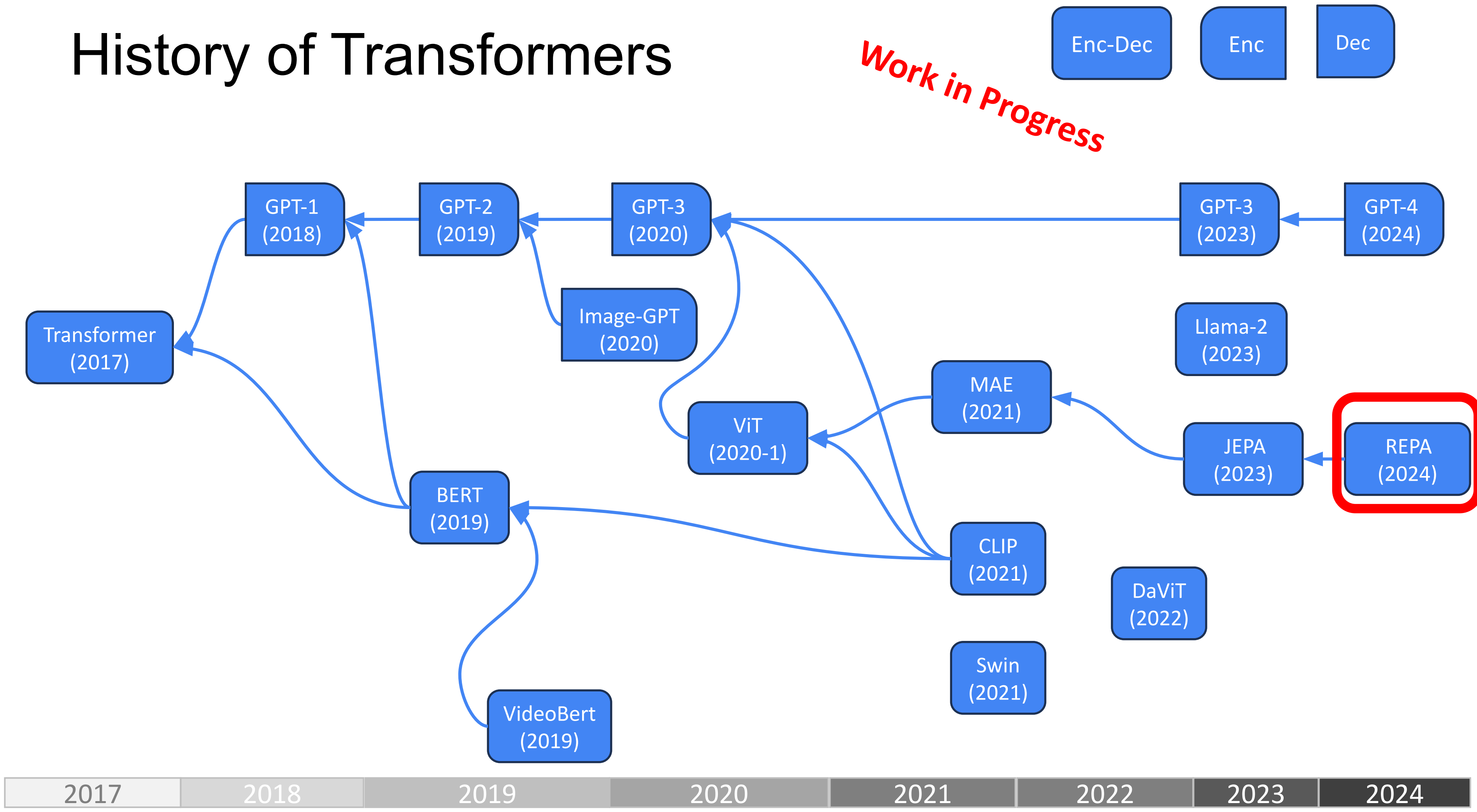
Key idea:

- Divide image into blocks and map them to latent representations
- Given one block's latent representation, predict the surrounding representations.
- But don't let representation collapse!





History of Transformers



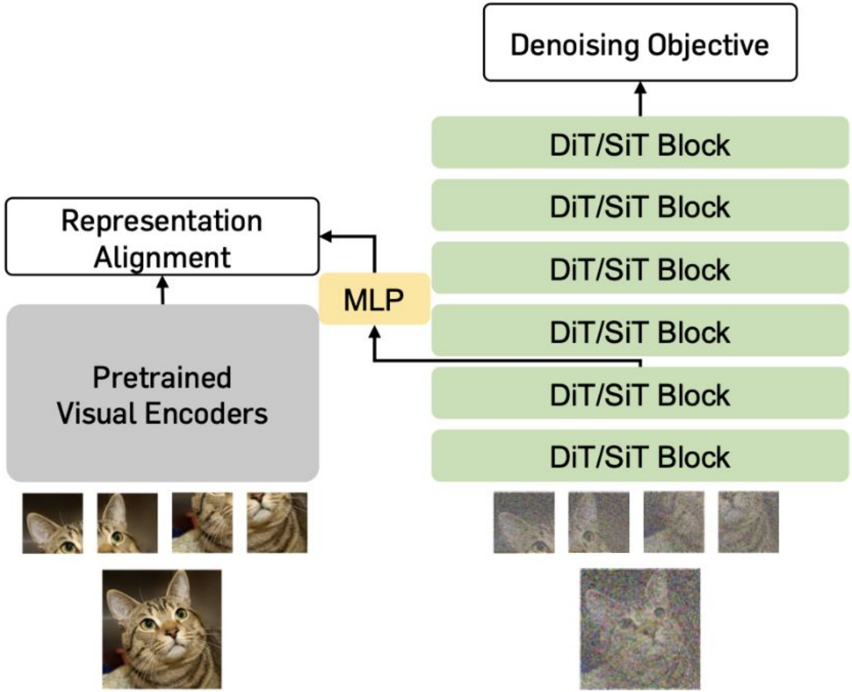
Representation Alignment for Generation: Training Diffusion Transformers Is Easier Than You Think

Preprint released 2024-10-09

Key idea:

- Bootstrap image generation model by training representation to reconstruct representation of existing model.

(We will cover diffusion in ~3 weeks.)



Feedback?