An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

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Outline

1. Introduction
2. Objectives
3. Related Work
4. Method
5. Experiments
6. Conclusion

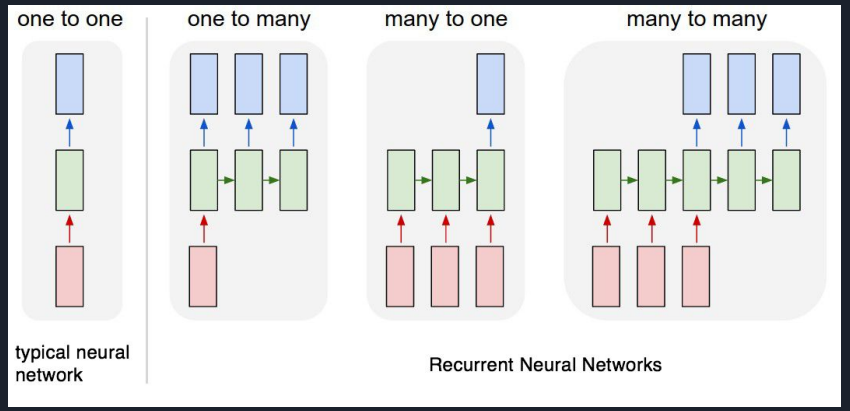
Introduction

- Using transformers for Natural Language Processing (NLP) involves pre-training and fine-tuning
- Previous use of transformers for computer vision lacked scalability and generalization
- Pure transformer applied to image patches – similar to NLP, but with patches instead of words
- Transformer pre-trained on huge (14 million to 300 million images) datasets

Objectives

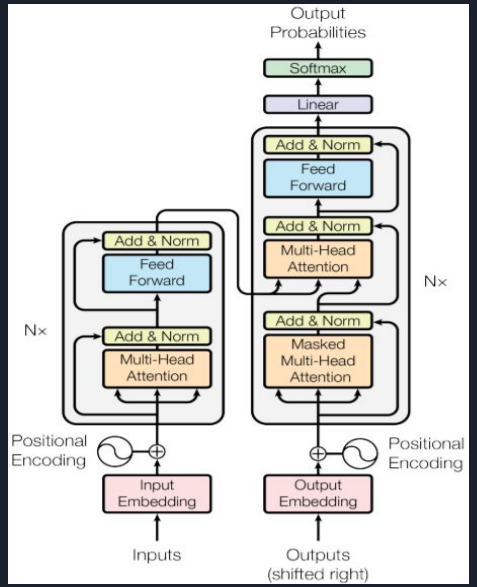
- Apply transformers used for Natural Language Processing to computer vision problems - Vision Transformer (ViT)
- Utilize transformers without relying on CNNs
- Demonstrate results with a number of models and datasets
- Achieve comparable or improved results with transformers compared to CNNs
- Lower the computational complexity

Related Work



Andre Karpathy (http://karpathy.github.io/2015/05/21/rnn-effectiveness/)

- Recurrent Neural Networks first handled sequence data, then LSTMs
  - Slow training
  - limited memory i.e. small window size
- Transformers in NLP Tasks
  - *Attention Is All You Need* introduced the transformer in 2017
  - Transformers allow parallel training of longer sequences
  - BERT and GPT serve as the inspiration from NLP tasks



Attention Is All You Need (NuerIPS (NIPS), 2017

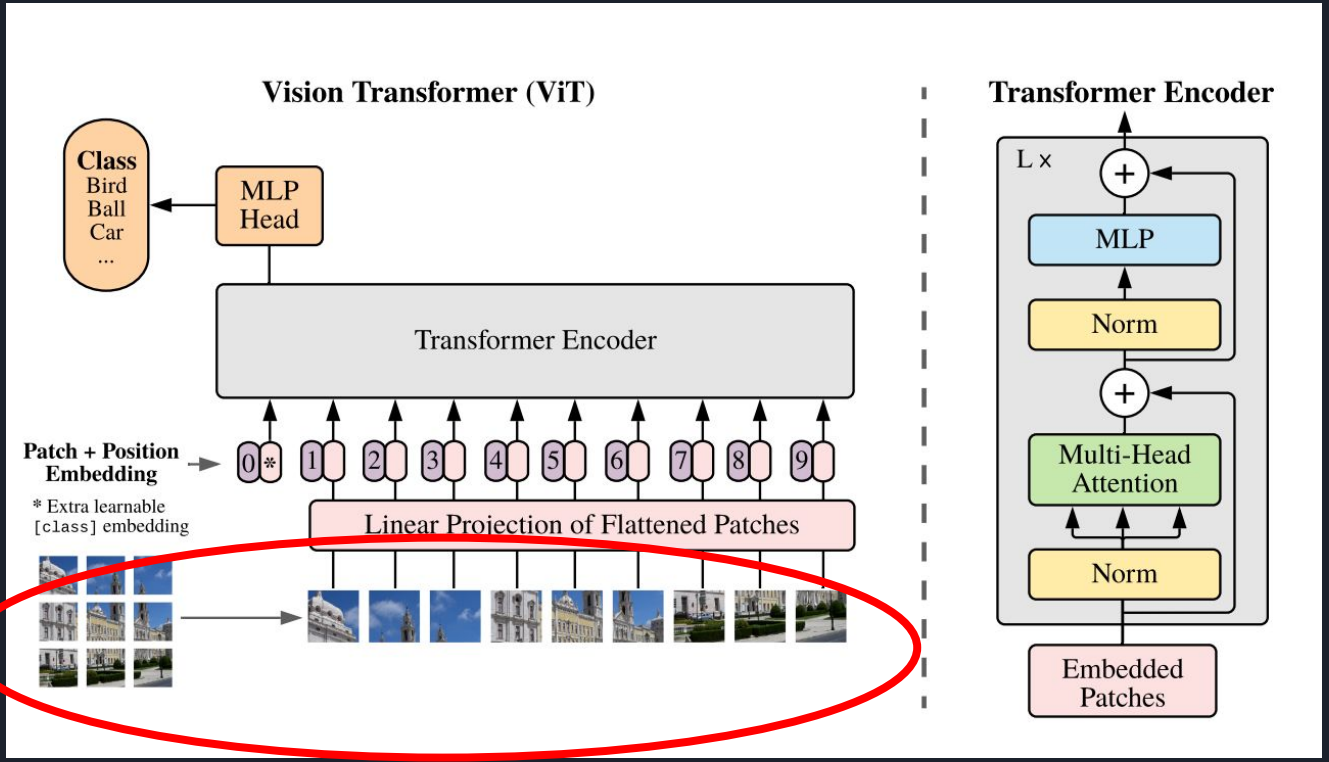
Comparison to State of the Art on ImageNet

- Convolutional Neural Networks dominated classification tasks until recently
- Transformers have recently overtaken state of the art with caveats like extra data or hybrid models

Model Category	Model Name	ImageNet Top-1 Accuracy	Reference
Transformer	ViT-H/14	88.55%*	"AN IMAGE IS WORTH 16X16 WORDS…" (ICLR, 2021)
CNN	EfficientNet-L2	90.2%*	"Meta Psuedo Labels" (EfficientNet-L2) (CVPR, 2021)
Transformer	ViT-G/14	90.45%*	"Scaling Vision Transformers (ArXiv, 2021)
Hybrid CNN-Transformer	CoAtNet-7	90.88%*	"CoAtNet: Marrying Convolution and Attention for All Data Sizes" (NuerIPS, 2021)

*trained with additional data from Google's Internal Datasets (JFT-300M & JFT-3B)

Method


Vision Transformer (ViT)
Class
Bird
Ball
Car
...
MLP Head
Transformer Encoder
Patch + Position Embedding
* Extra learnable [class] embedding
0 * 1 2 3 4 5 6 7 8 9
Linear Projection of Flattened Patches
Transformer Encoder
L x
MLP
Norm
Multi-Head Attention
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Embedded Patches


1 2 3
4 5 6
7 8 9


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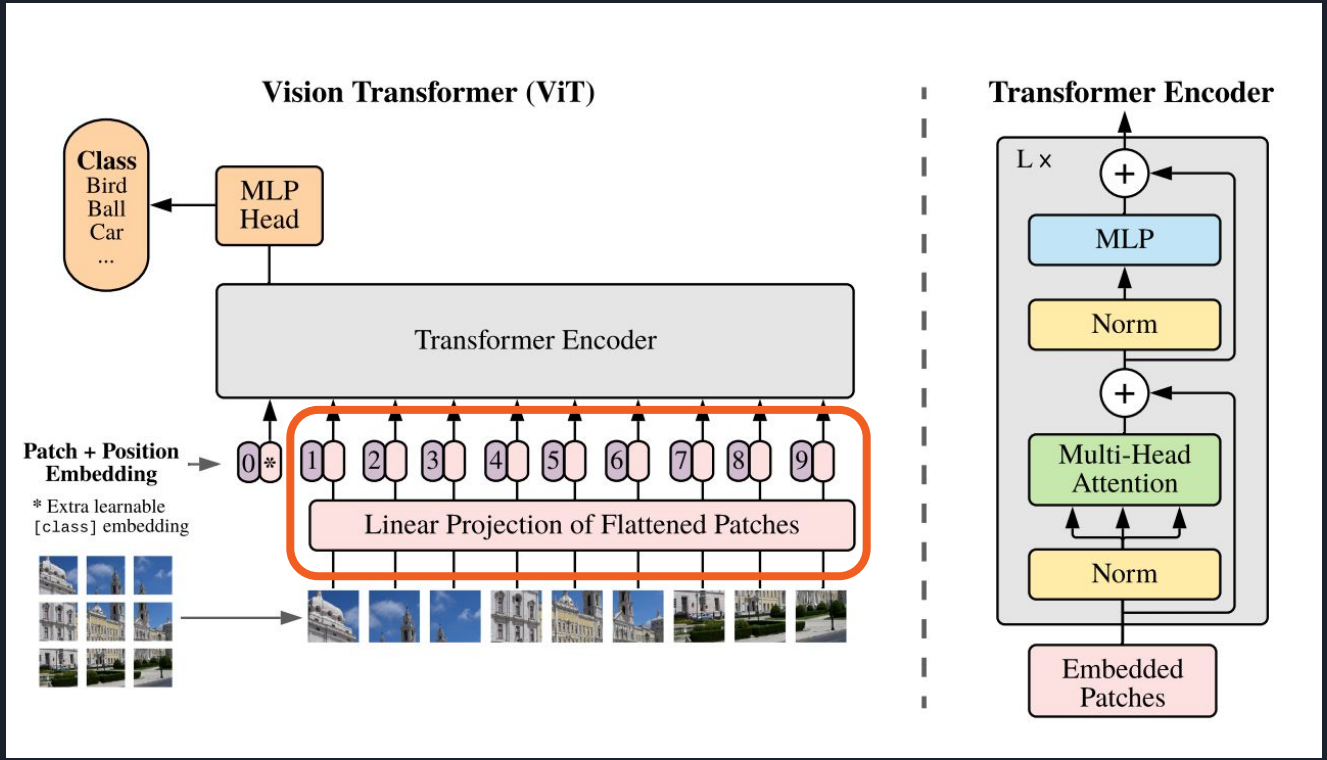
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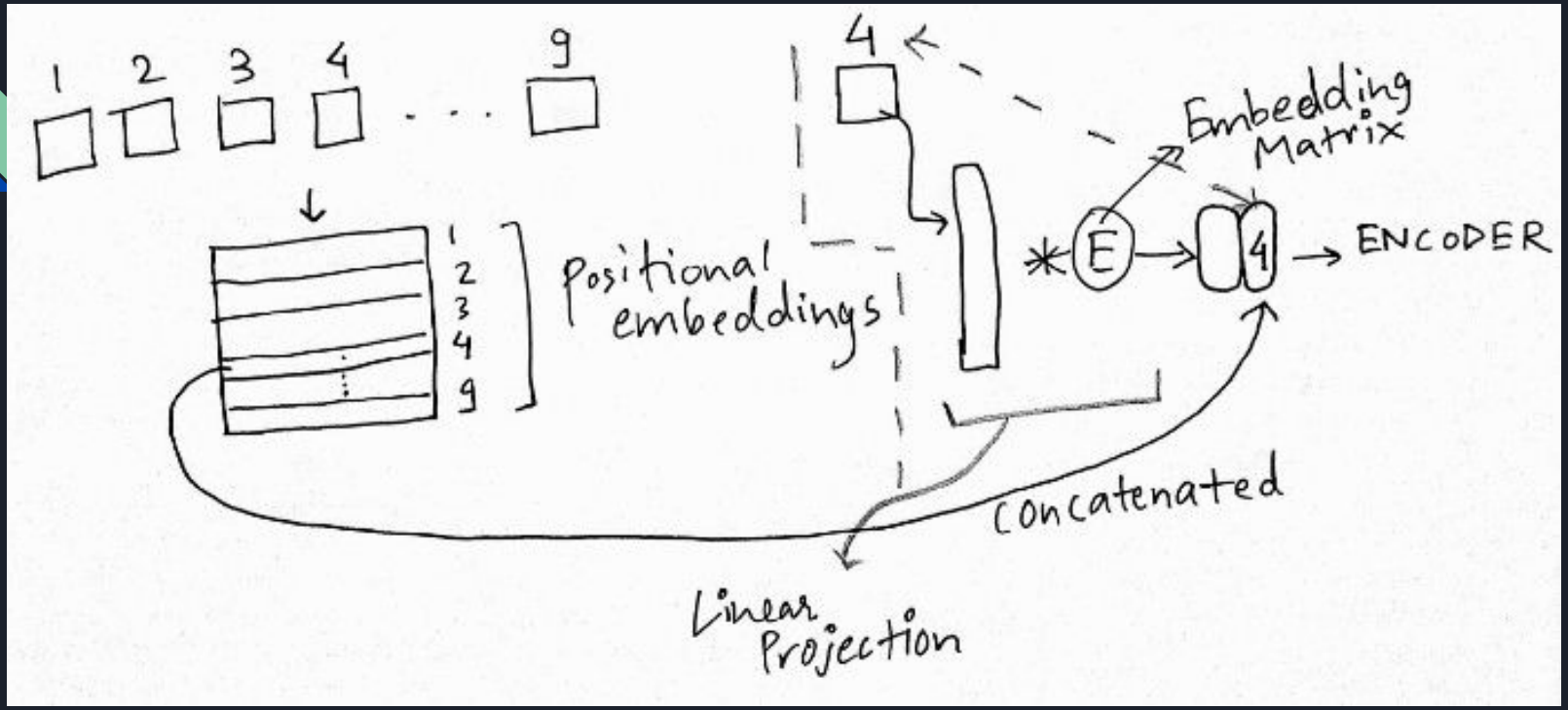
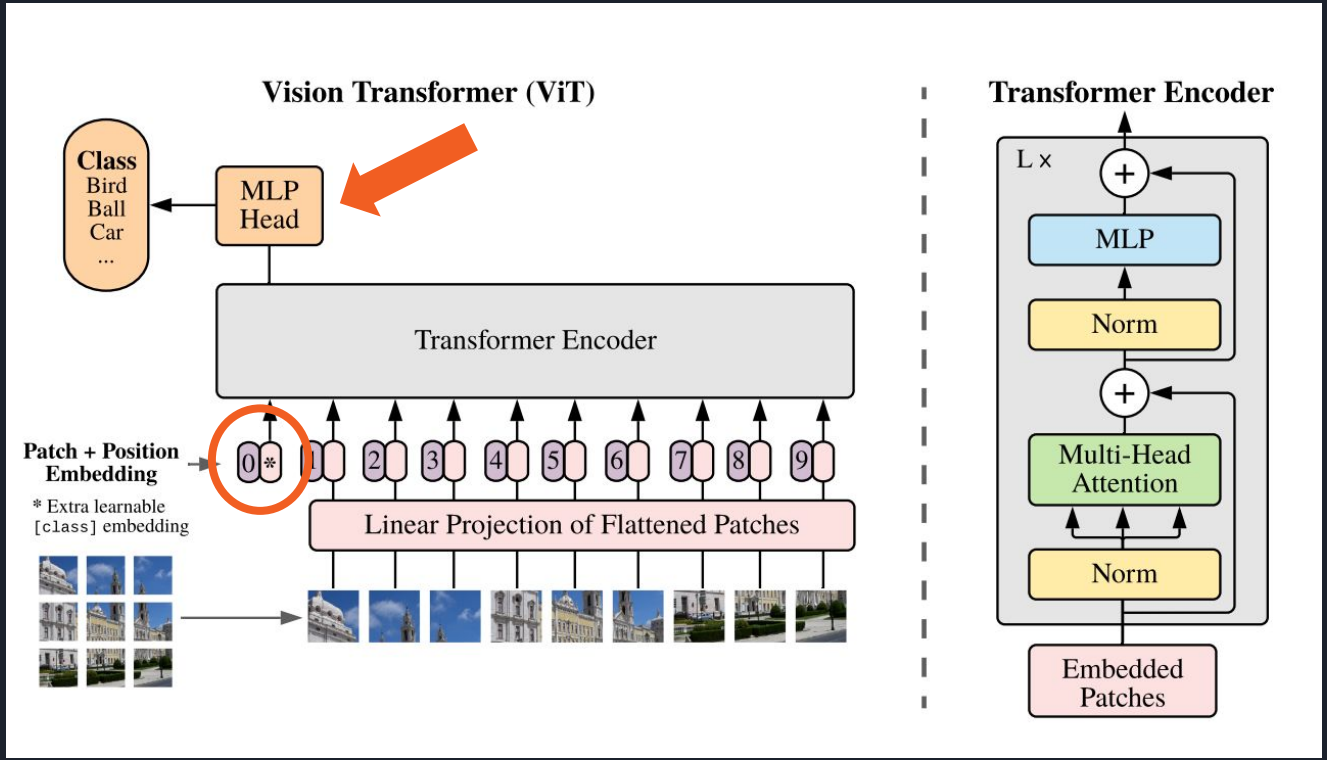


$$\mathbf{x}_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$$

Source: https://medium.com/analytics-vidhya/vision-transformers-bye-bye-convolutions-e929d022e4ab

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}};\ \mathbf{x}_p^1\mathbf{E};\ \mathbf{x}_p^2\mathbf{E};\ \cdots;\ \mathbf{x}_p^N\mathbf{E}] + \mathbf{E}_{pos}, \qquad \mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D},\ \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D}$$

Method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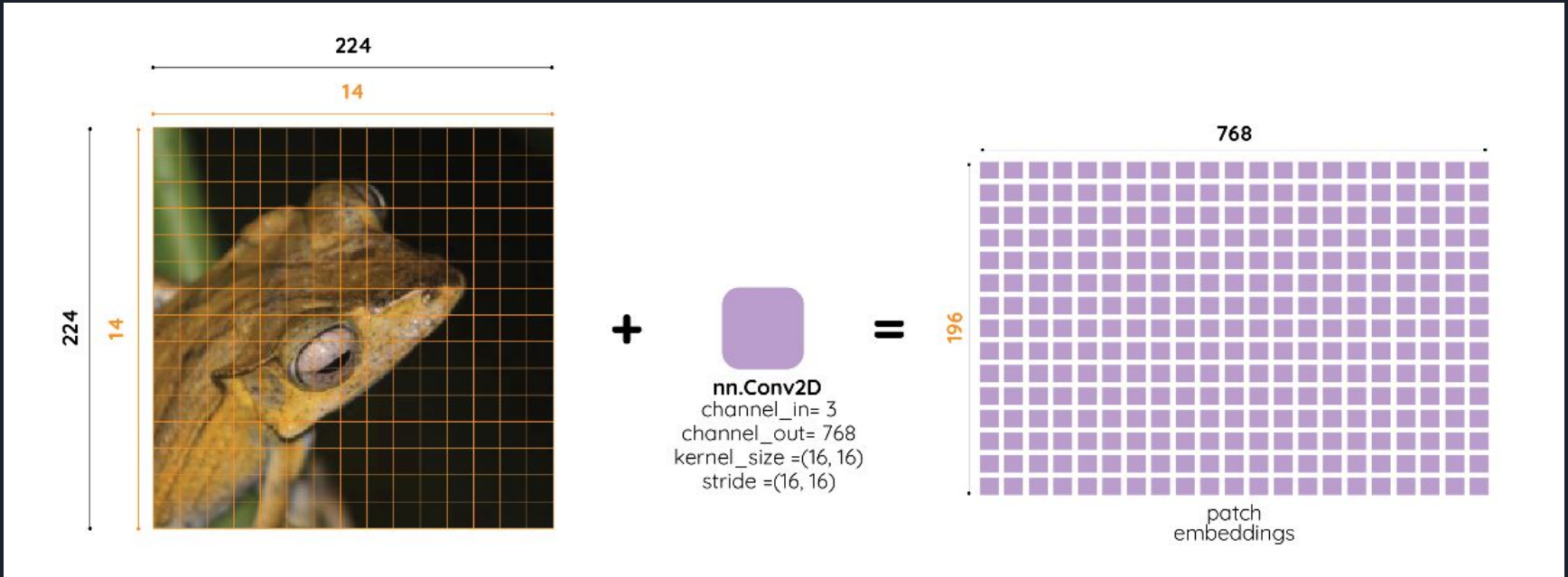
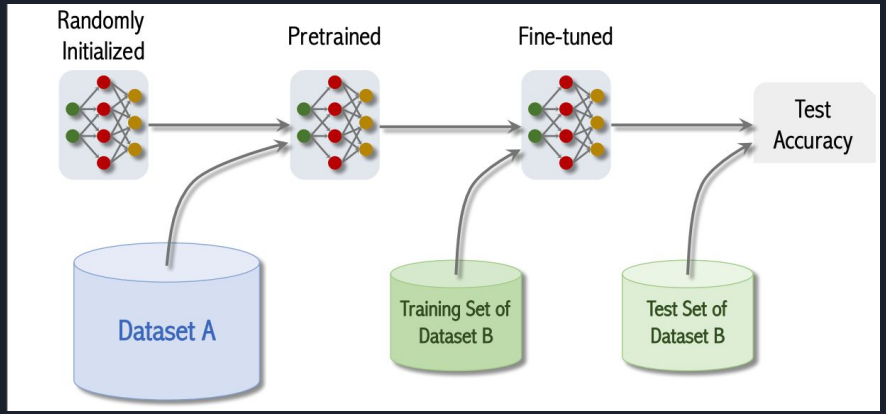
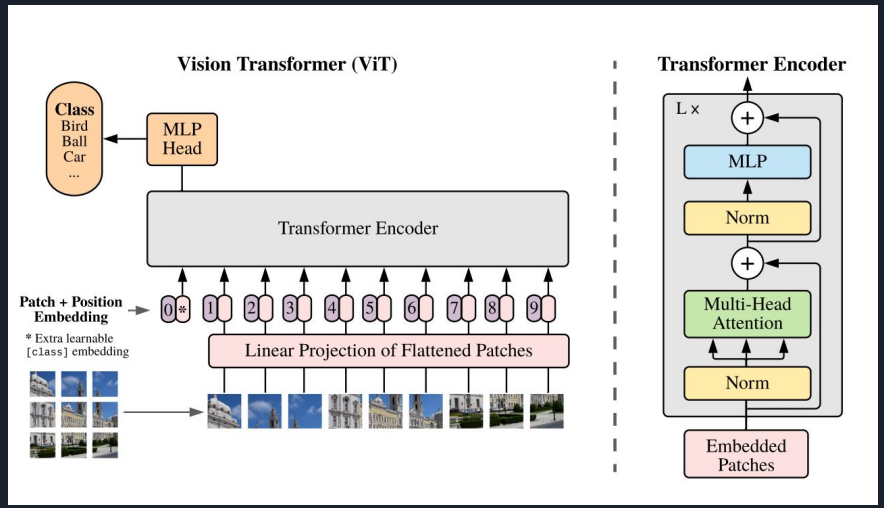
Hybrid Architecture



Source: https://amaarora.github.io/2021/01/18/ViT.html

Method: Fine-Tuning and Higher Resolution





Source: https://www.youtube.com/watch?v=HZ4j_U3FC94

Experiments: Setup: Explanation of Datasets and Model Variants - Datasets

- Pre-training Datasets
  - ILSVRC-2012 ImageNet (i.e., ImageNet), ~1000 classes, ~1.3 million images
  - ImageNet-21k, ~21000 classes, ~14 million images
  - JFT, ~18000 classes, ~303 million images

- Fine-tuning Datasets
  - ImageNet - both original validation labels and Reassessed Labels (ReaL)
  - CIFAR-10/100, ~60000 images each
  - Oxford-IIIT Pets, ~7400 images
  - Oxford Flowers-102, ~7100 images
  - VTAB: natural, specialized, structured
- Preprocessing
  - Pre-training: image cropped, random horizontal mirroring, resize to 224x224
  - Fine-tuning: Images resized to 448x448, random crop of 384x384
  - Random horizontal flips

Experiments: Setup: Explanation of Datasets and Model Variants - Model Variants

- ViT Model Variants
  - Base - 32x32 and 16x16
  - Large - 32x32 and 16x16
  - Huge - 14x14

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

Table 1: Details of Vision Transformer model variants.

- CNNs (ResNet (BiT))
  - ResNet(50, 101, 152, 200)
  - Batch Normalization replaced with Group Normalization
- Hybrids
  - Use ResNet50 output from stage 4
  - Output (feature maps) fed to ViT with patch size of 1 pixel

Experiments: Setup: Explanation of Datasets and Model Variants - Training and Fine Tuning

- Training
  - Uses Adam optimizer with β_1 = 0.9 and β_2 = 0.999
  - Batch size 4096
  - Weight decay 0.1
  - Linear learning rate warmup and decay

- Fine-tuning
  - SGD with momentum
  - Batch size 512
  - Cosine learning rate decay
  - No weight decay

	ResNet50		ResNet152x2	
Dataset	Adam	SGD	Adam	SGD
ImageNet	77.54	78.24	84.97	84.37
CIFAR10	97.67	97.46	99.06	99.07
CIFAR100	86.07	85.17	92.05	91.06
Oxford-IIIT Pets	91.11	91.00	95.37	94.79
Oxford Flowers-102	94.26	92.06	98.62	99.32
Average	89.33	88.79	94.01	93.72

Experiments: Setup: Explanation of Datasets and Model Variants - Metrics

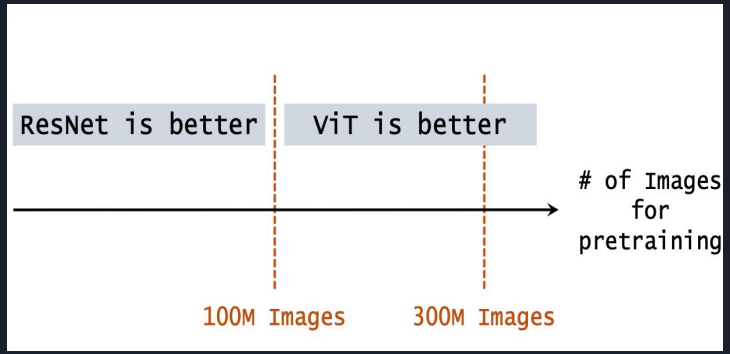
- Metrics
  - Fine-tuning accuracy: results after fine-tuning
  - Few-shot accuracy: results using a small subset of data (used for quick evaluations)

Experiments: Pre-training Data Requirements

	# of Images	# of Classes
ImageNet (Small)	1.3 Million	1 Thousand
ImageNet-21K (Medium)	14 Million	21 Thousand
JFT (Big)	300 Million	18 Thousand

Experiments: Scaling Study

	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** ± 0.04	87.76 ± 0.03	85.30 ± 0.02	87.54 ± 0.02	88.4/88.5*
ImageNet ReaL	**90.72** ± 0.05	90.54 ± 0.03	88.62 ± 0.05	90.54	90.55
CIFAR-10	**99.50** ± 0.06	99.42 ± 0.03	99.15 ± 0.03	99.37 ± 0.06	–
CIFAR-100	**94.55** ± 0.04	93.90 ± 0.05	93.25 ± 0.05	93.51 ± 0.08	–
Oxford-IIIT Pets	**97.56** ± 0.03	97.32 ± 0.11	94.67 ± 0.15	96.62 ± 0.23	–
Oxford Flowers-102	99.68 ± 0.02	**99.74** ± 0.00	99.61 ± 0.02	99.63 ± 0.03	–
VTAB (19 tasks)	**77.63** ± 0.23	76.28 ± 0.46	72.72 ± 0.21	76.29 ± 1.70	–
TPUv3-core-days	2.5k	0.68k	0.23k	9.9k	12.3k



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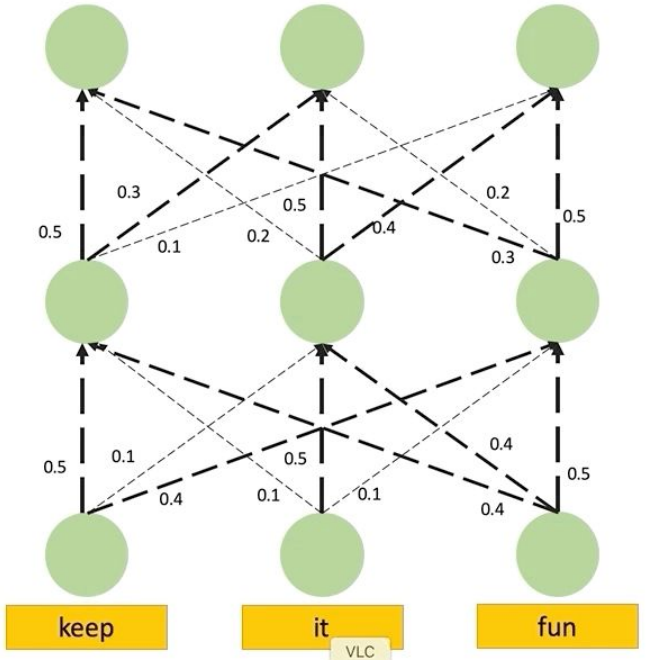
Inspecting Vision Transformers

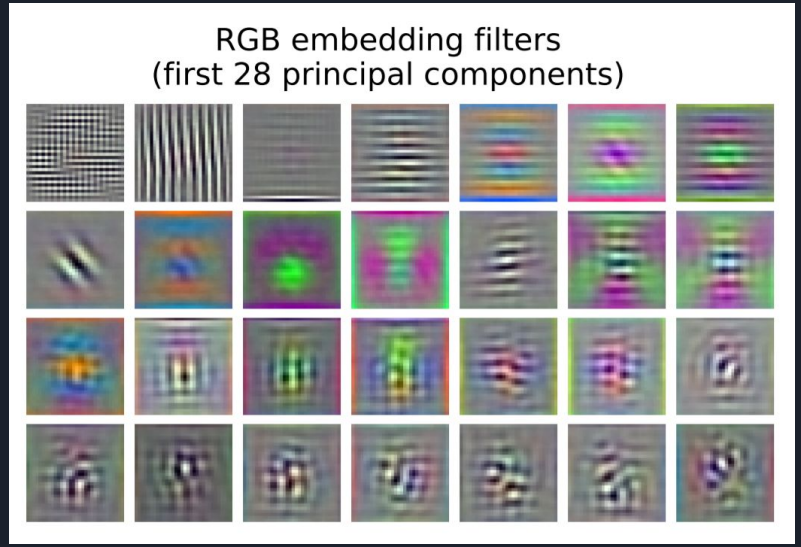
Attention Rollout (Samira Abnar, 2020)



Visualization of Embedding Filters

What does the model learn?

- Calculate PCA on the embedding E i.e. create new features that summarize information from all feature vectors
- The learned filter look similar to low level CNN feature maps (left)
- The transformer is learning visual information in a familiar way to CNNs e.g. lines for edge detection in various orientations



What Does The Position Embedding Learn?

- Recall the Position Embedding is a matrix with N+1 Rows by D features

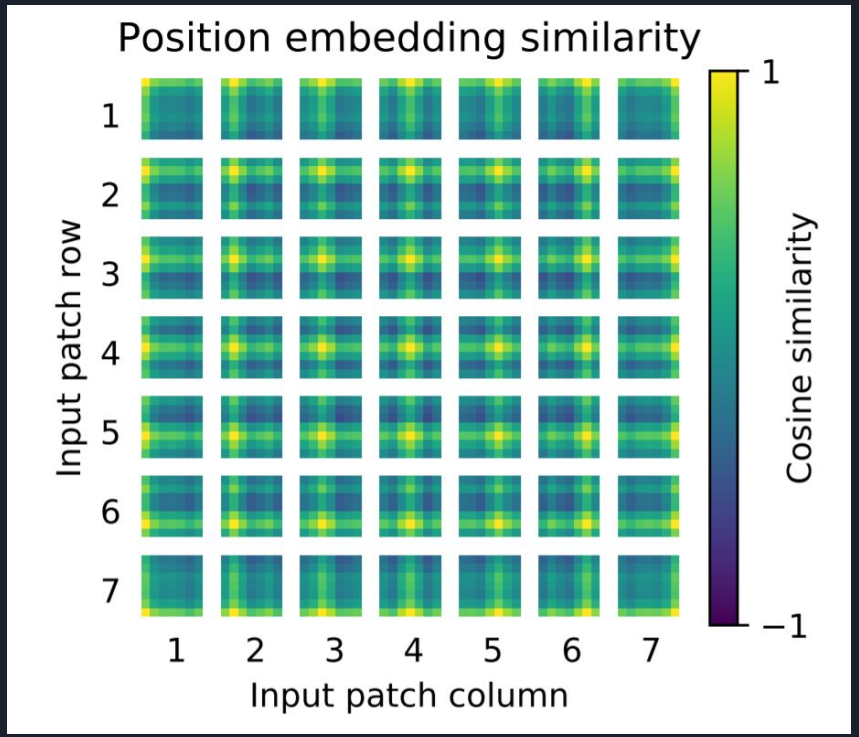
$$\mathbf{E}_{pos} \in \mathbb{R}^{(N+1)\times D}$$

- For all patches N
  - Compute similarity between each row vector and itself

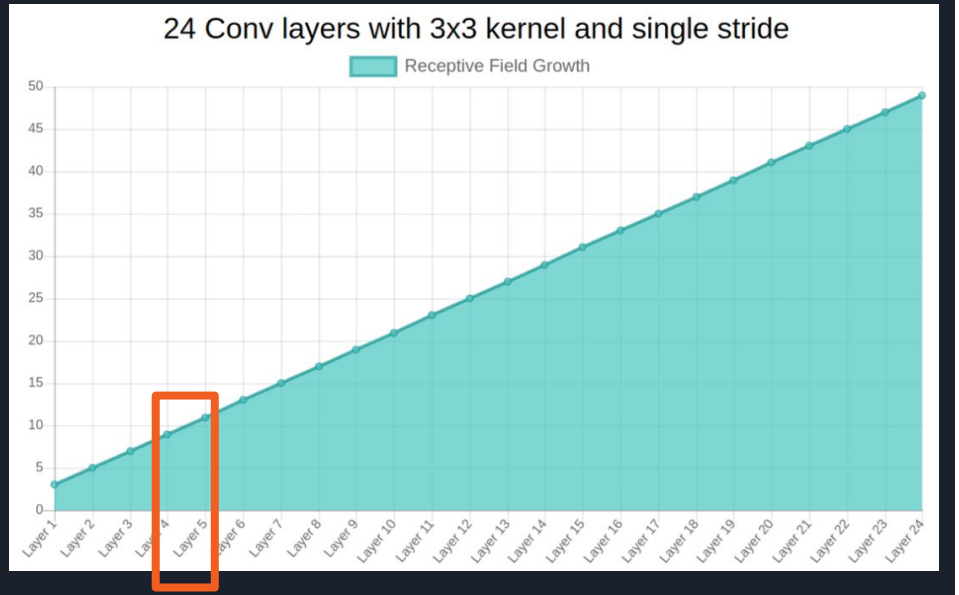
$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

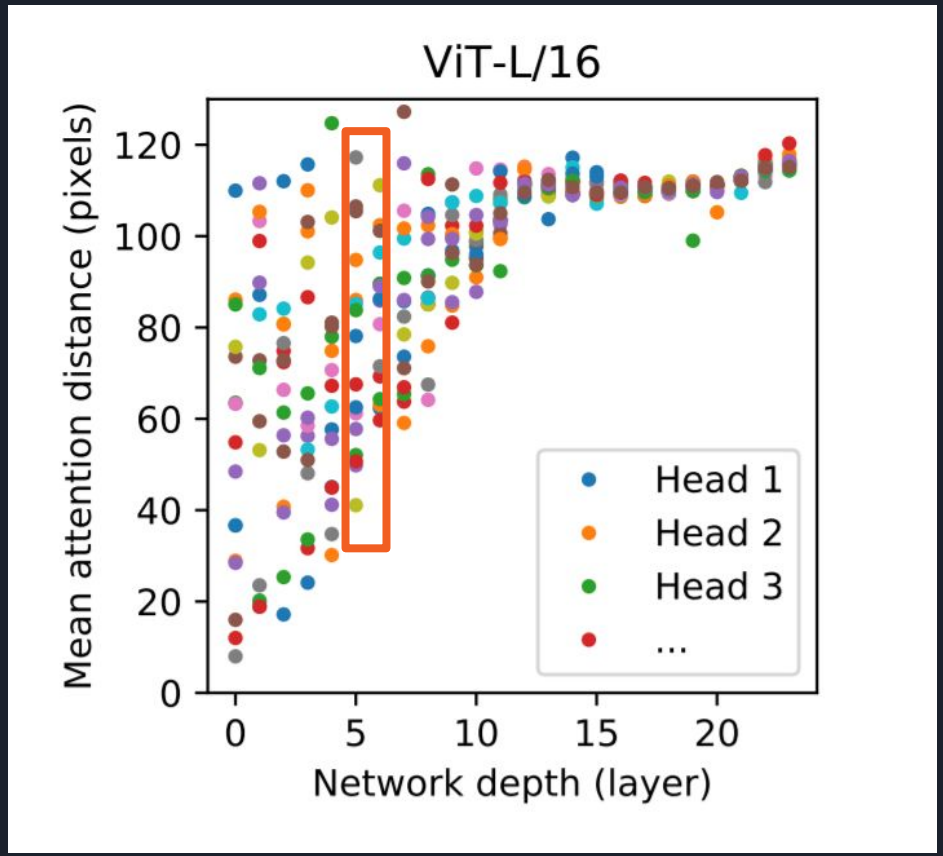
- Plotting the similarities show that the embedding is highly correlated between the rows and columns of its original 2-D position.

ViT-L/32

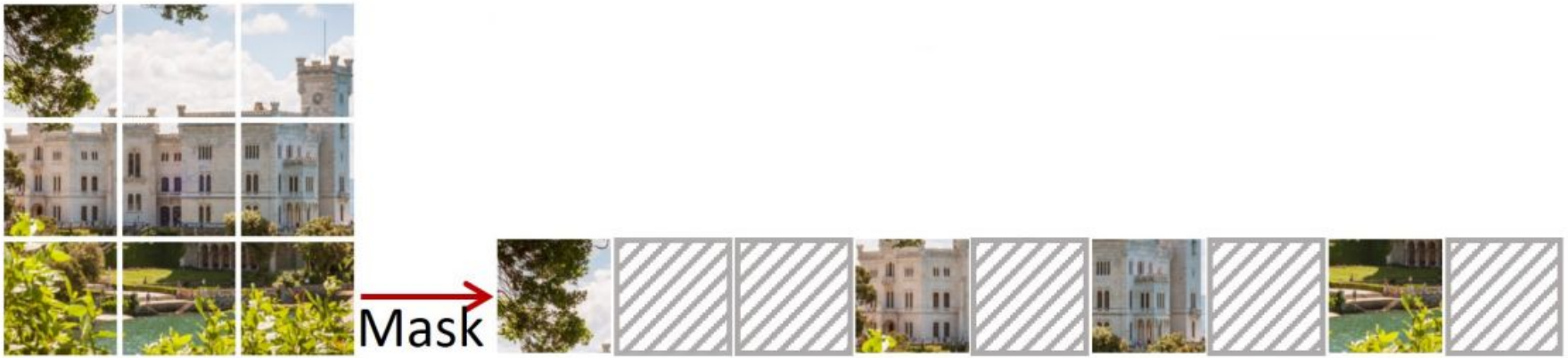


Attention Distance Over Layer Depth





Self-Supervision



Source: https://arxiv.org/pdf/2111.09886.pdf

Conclusion - Advantages

- Self-Attention
- Parallelized training over other sequence models
- Can learn spatial mapping of where patches were pulled
- Attention is widely spread across pixels even at early layers, revealing global understanding
- Diagrams are clear and well-made

Conclusion - Disadvantages

- Trained on additional data that is internal to Google
- Extremely large networks, not suited for deployment on edge computing

Computing Z_0 - *Output of the Embedding*