An Image is Worth 16x16 Words:

Transformers for Image Recognition at Scale

Binder Jonas

Overview

- Introduction
- Vision Transformer
- Experiments
- State Today
- Conclusion
- Questions

Transformers

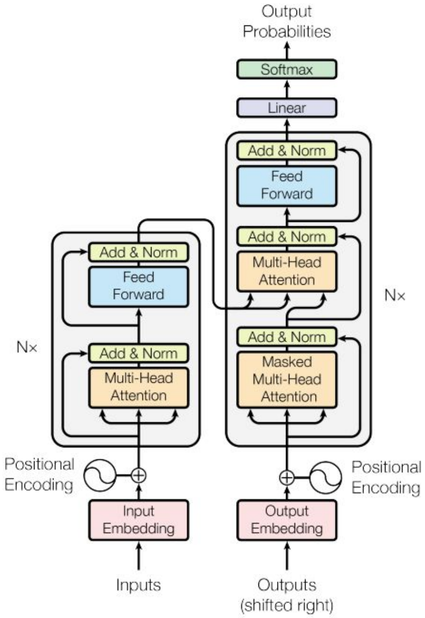
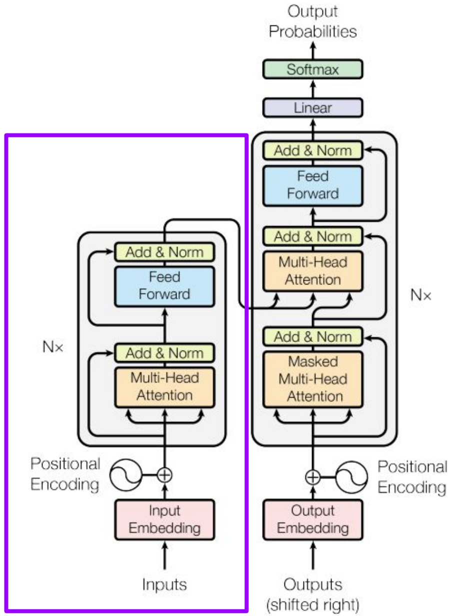


Figure 1: The Transformer - model architecture.

Source: Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, Illia Polosukhin. Attention is all you need. In NIPS 2017

Transformers



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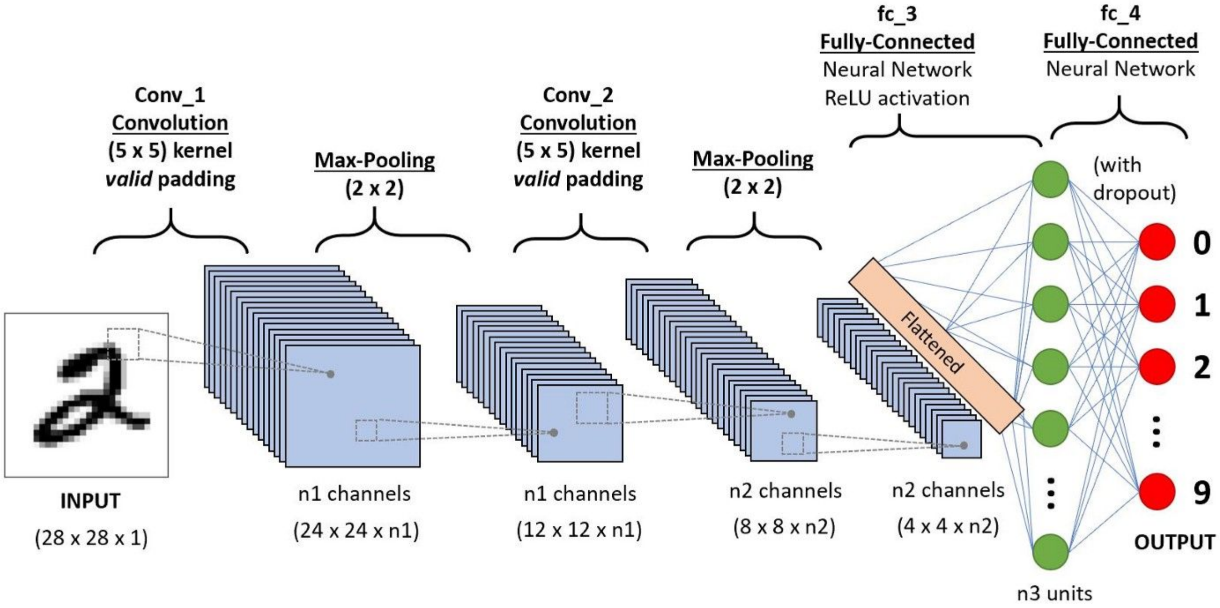
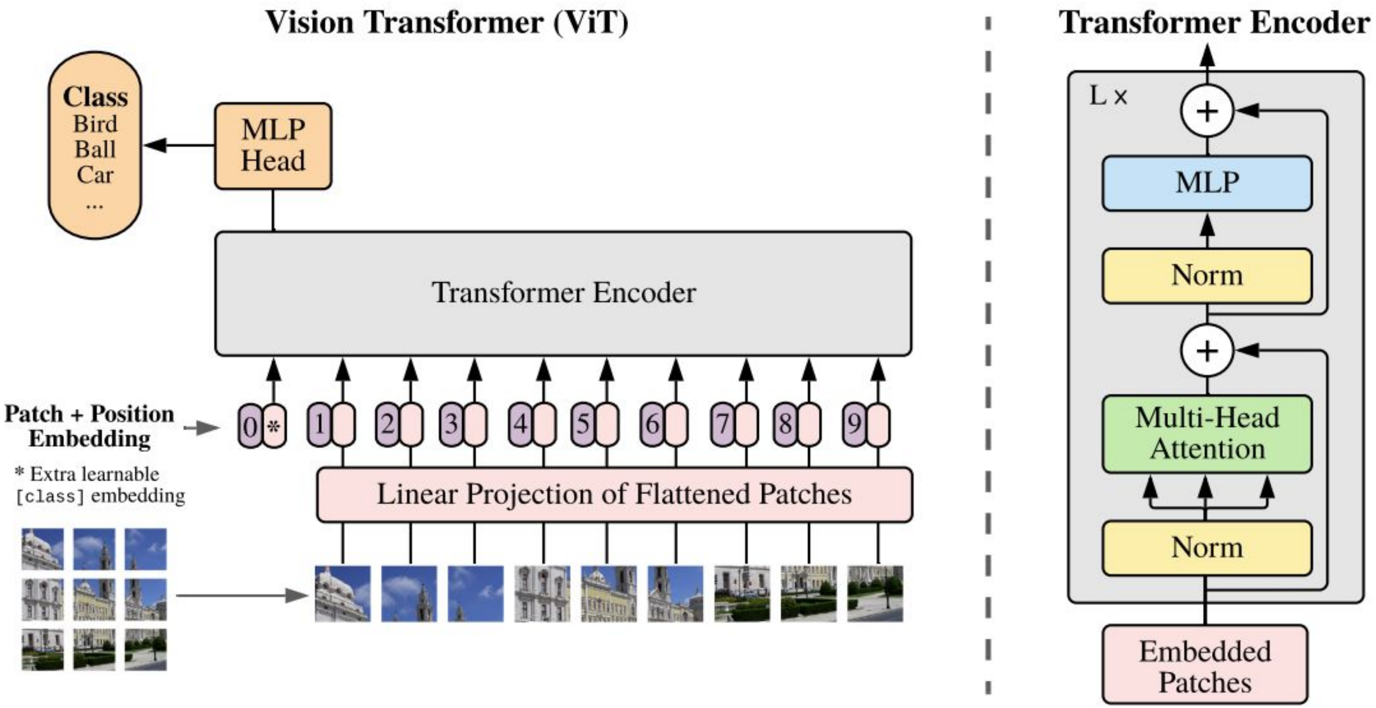
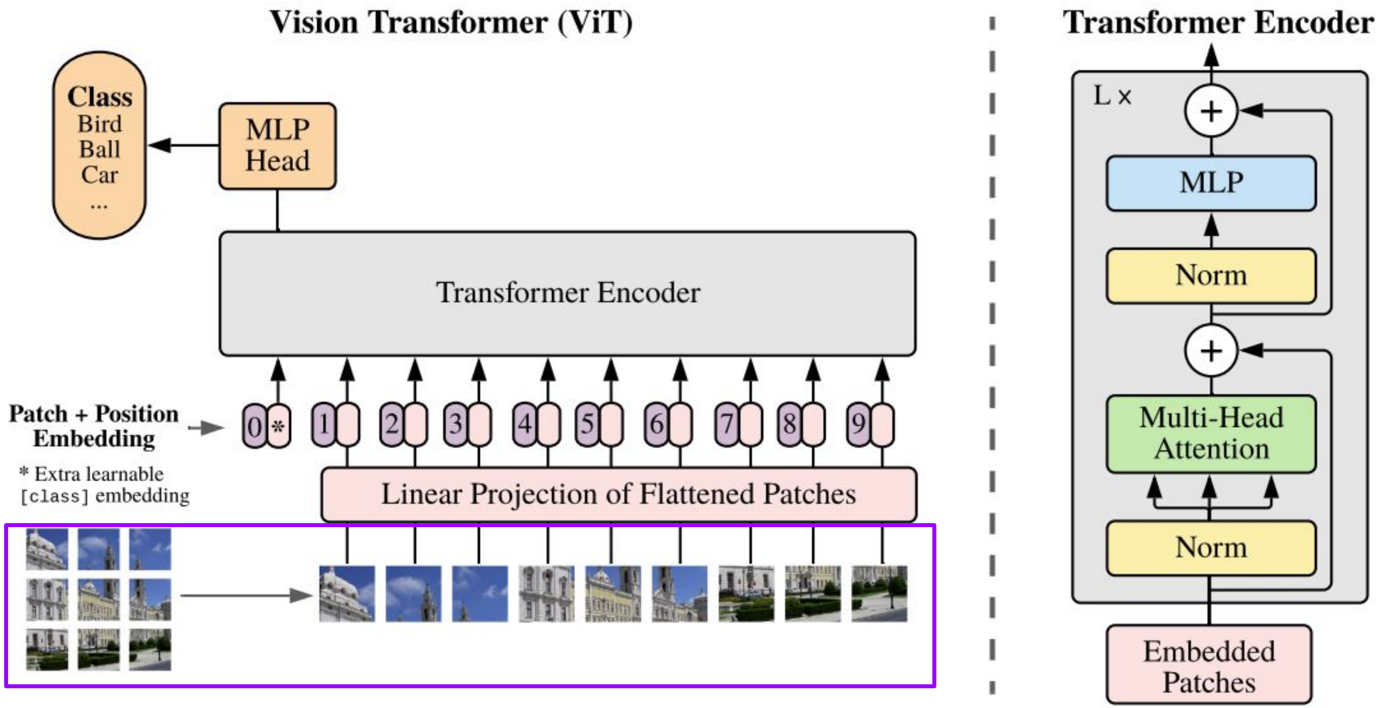
Convolutional Neural Networks (CNN)



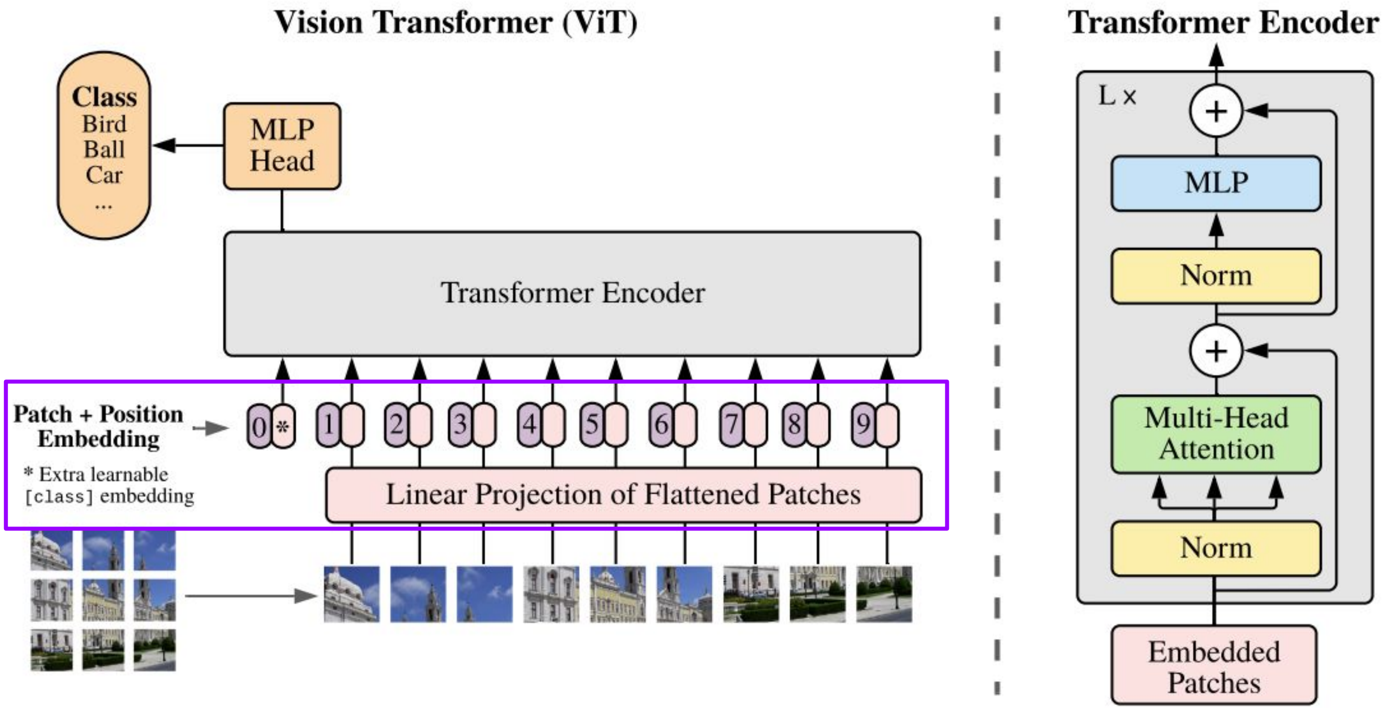
Vision Transformer



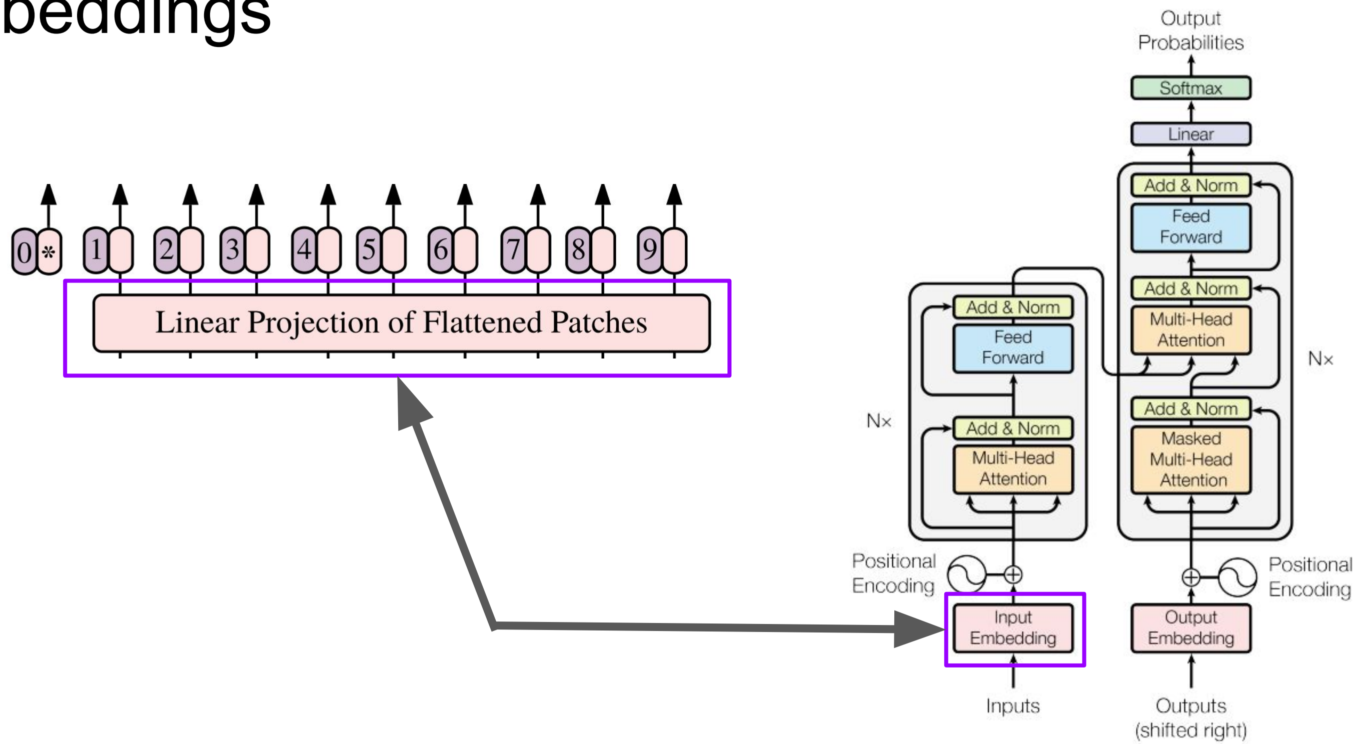
Vision Transformer



Vision Transformer



Patch Embeddings



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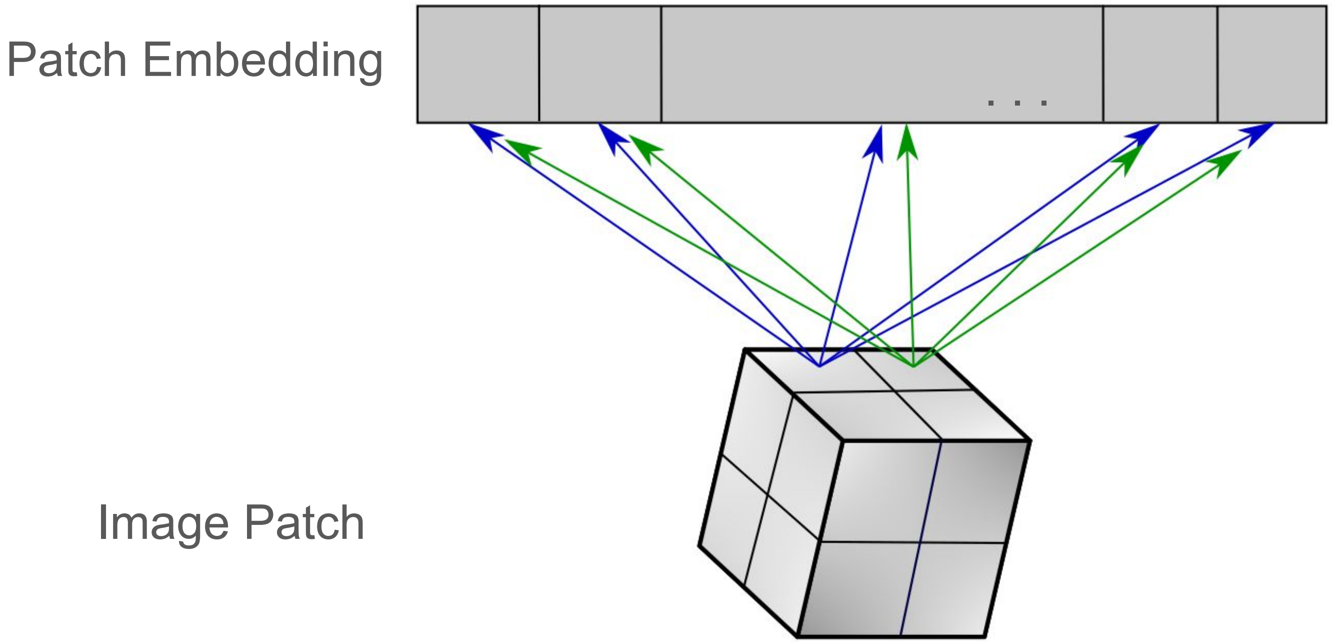
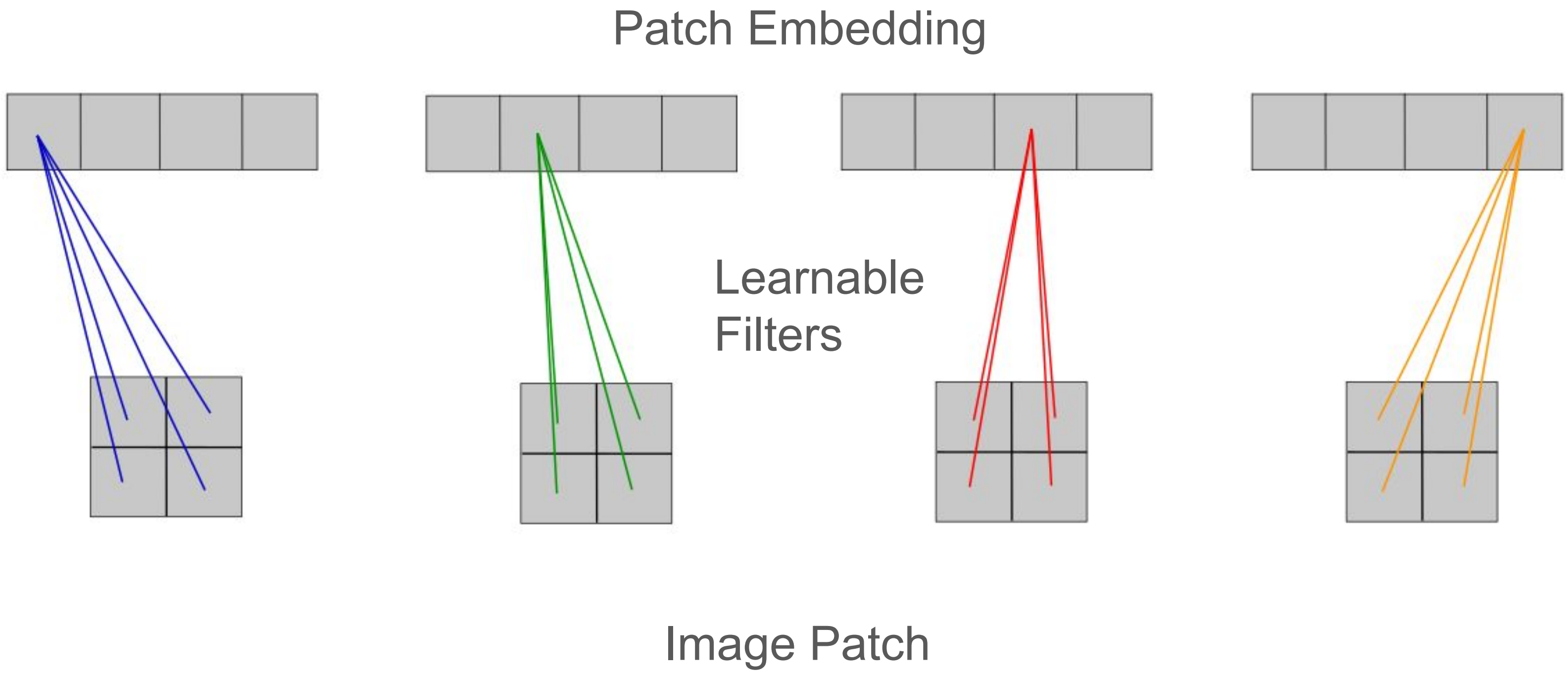
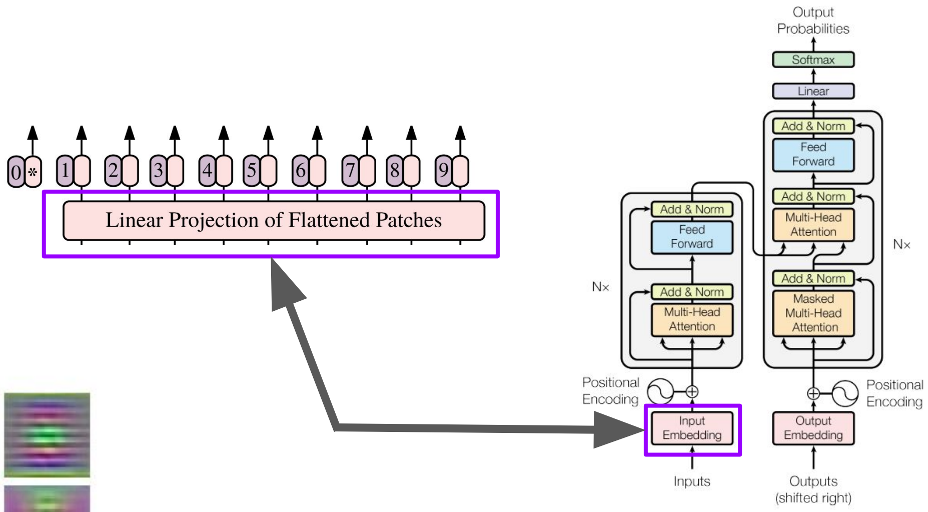
Linear Projection



Analogy to Convolution



Patch Embeddings



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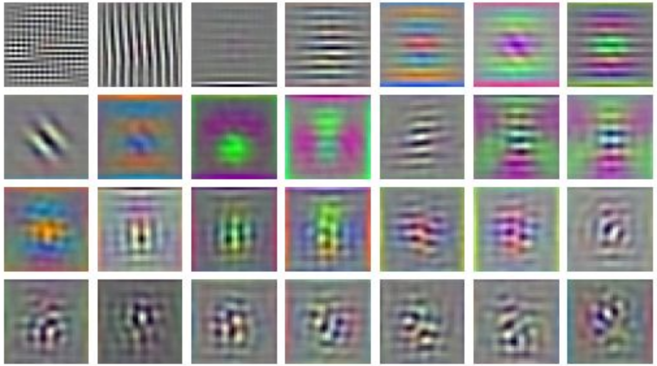
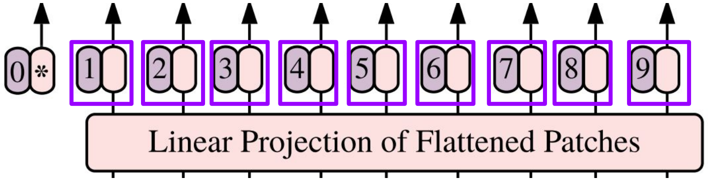
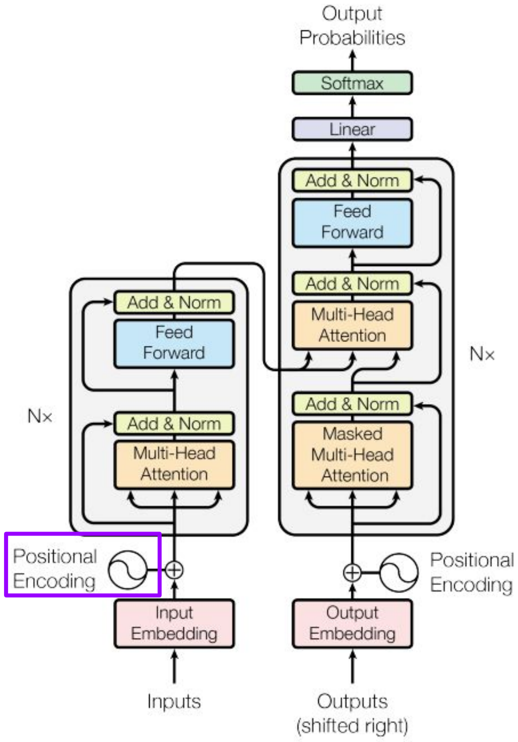
RGB embedding filters
(first 28 principal components)



Position Embeddings





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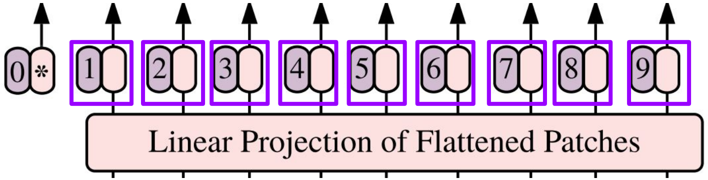
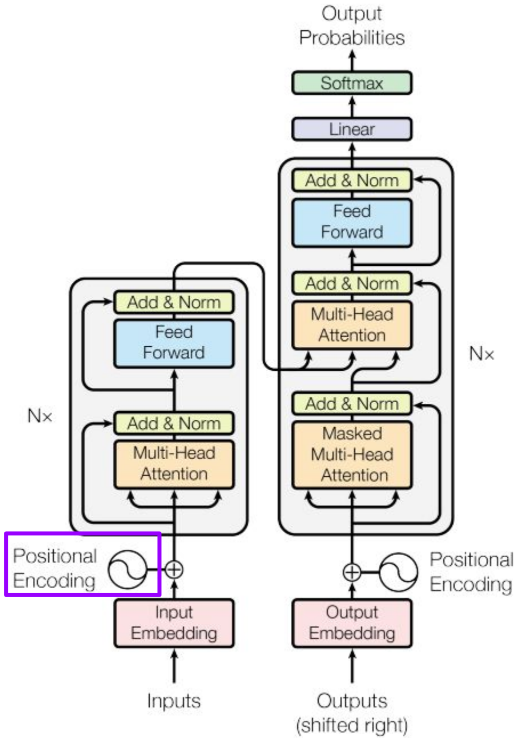
Position Embeddings



$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$



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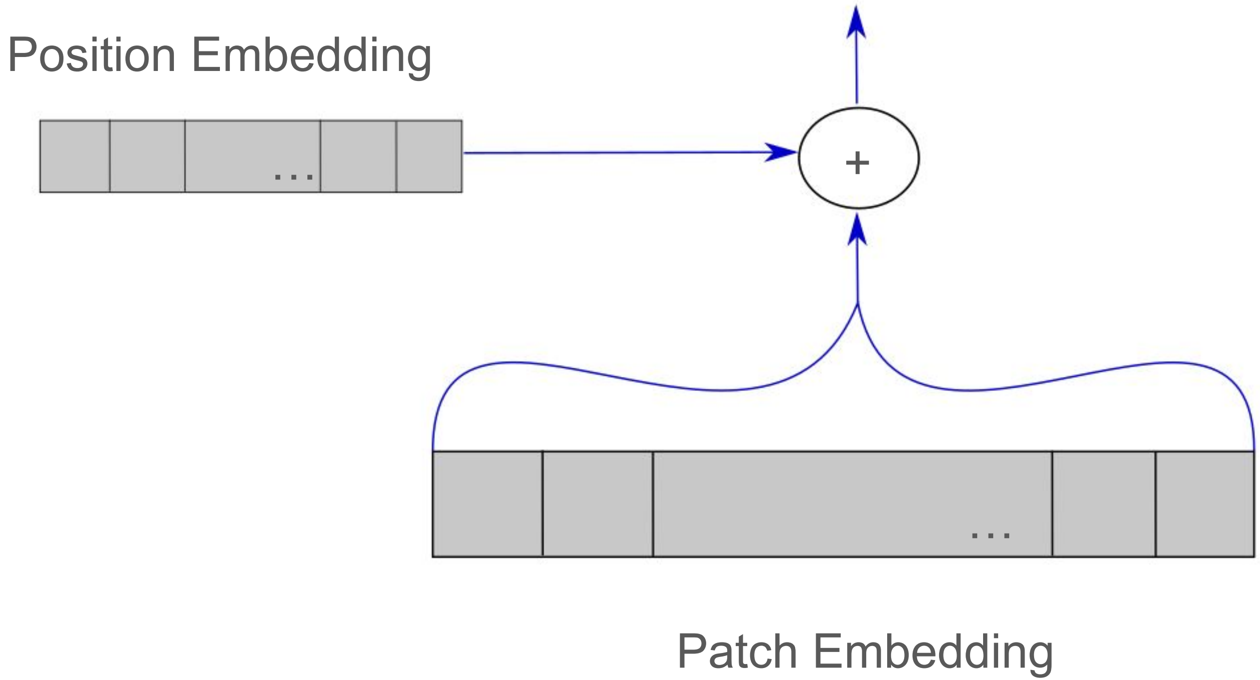
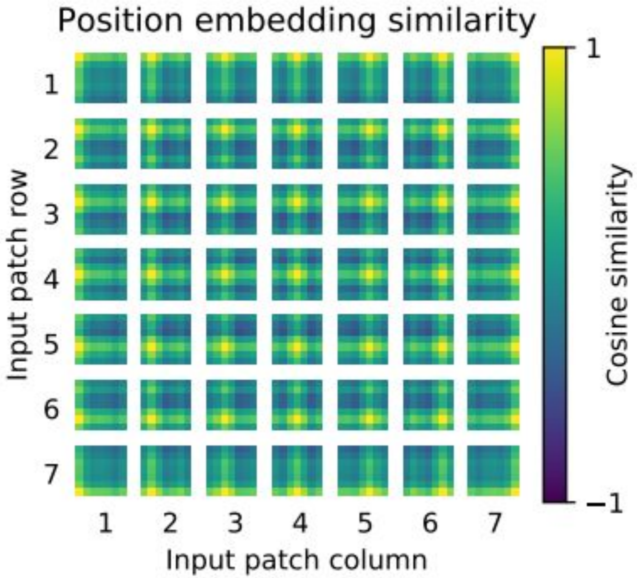
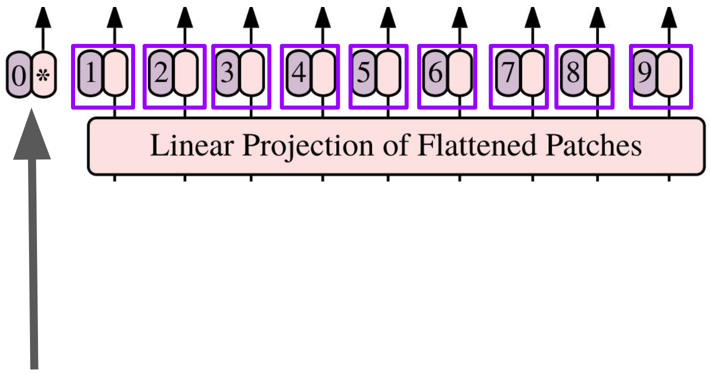
Position Embedding



Position Embeddings



Position Embeddings



Class Token

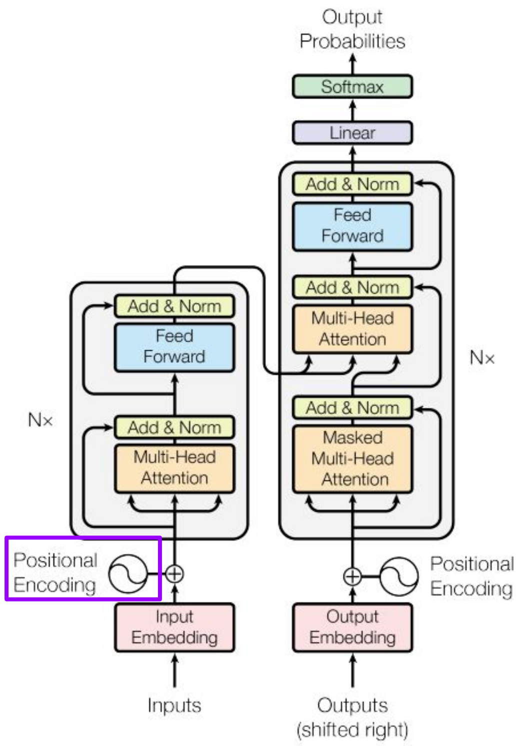
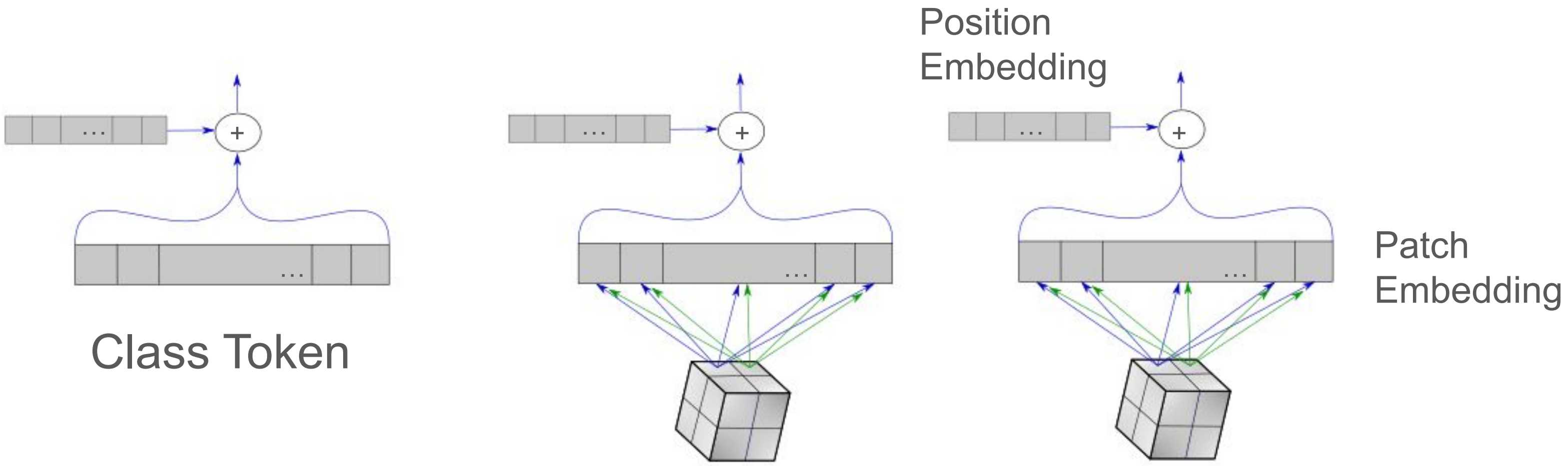


Figure 1: The Transformer - model architecture.

Whole Pipeline



Position Embeddings

$$\mathbf{z}_0 = [\mathbf{x}_{\text{class}};\, \mathbf{x}_p^1\mathbf{E};\, \mathbf{x}_p^2\mathbf{E};\, \cdots;\, \mathbf{x}_p^N\mathbf{E}] + \mathbf{E}_{pos}$$

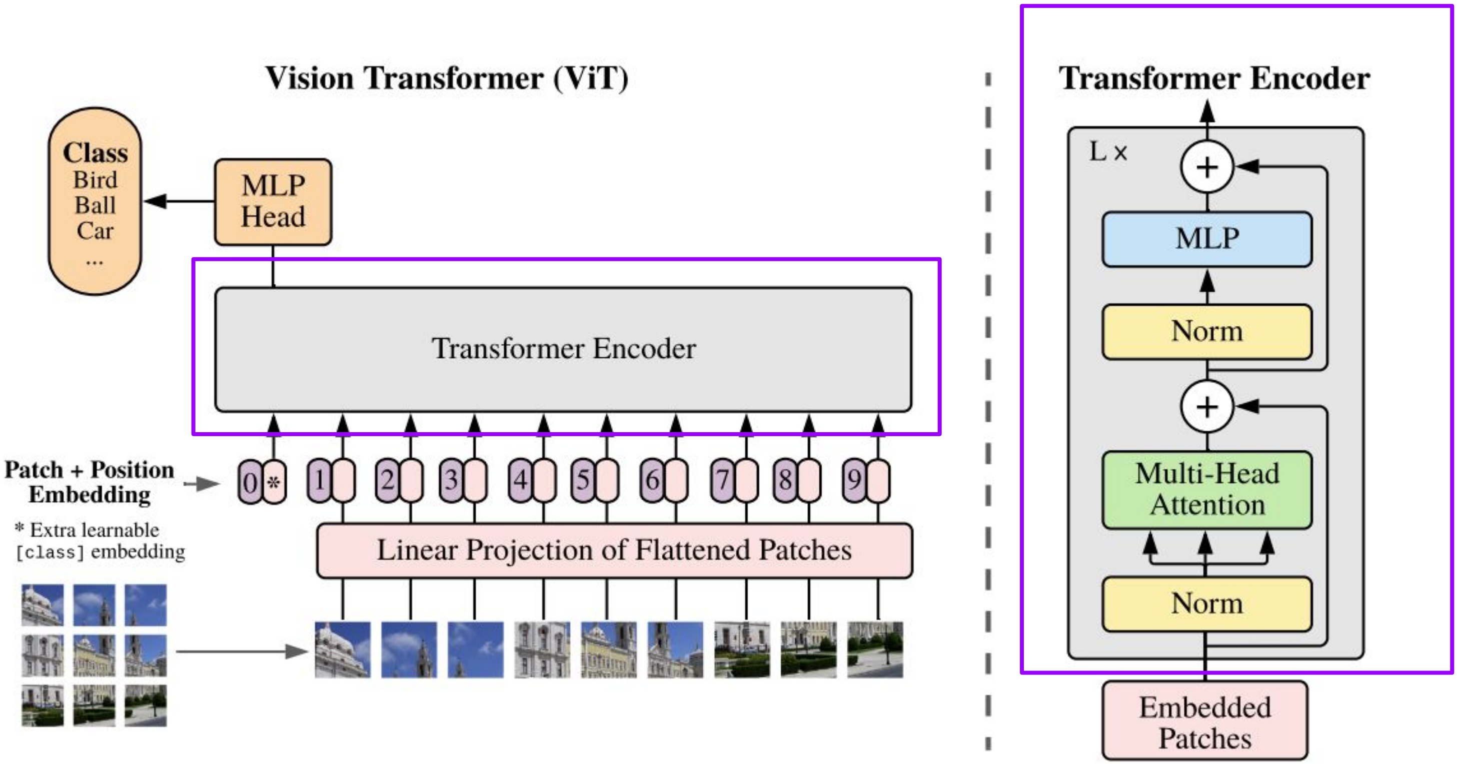
Class Token

Image Patch

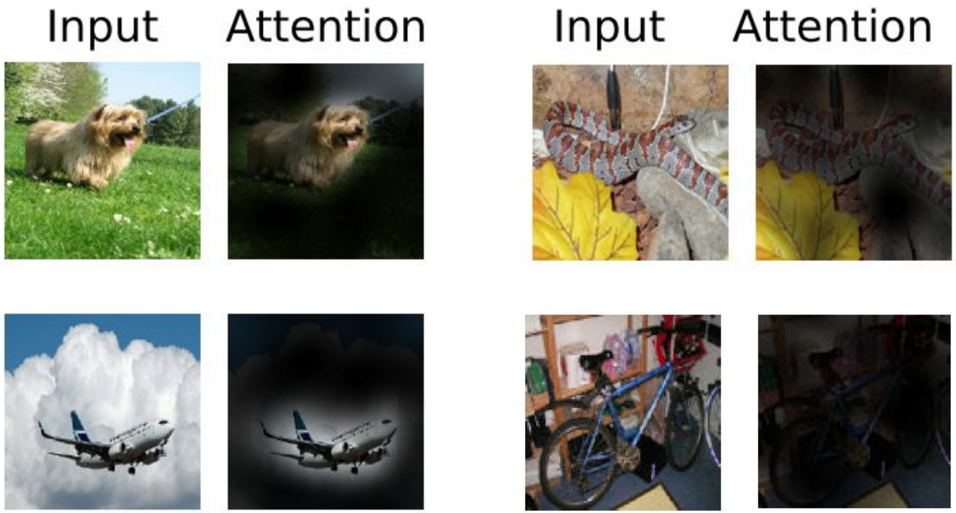
Embedding Filter

Positional Embedding

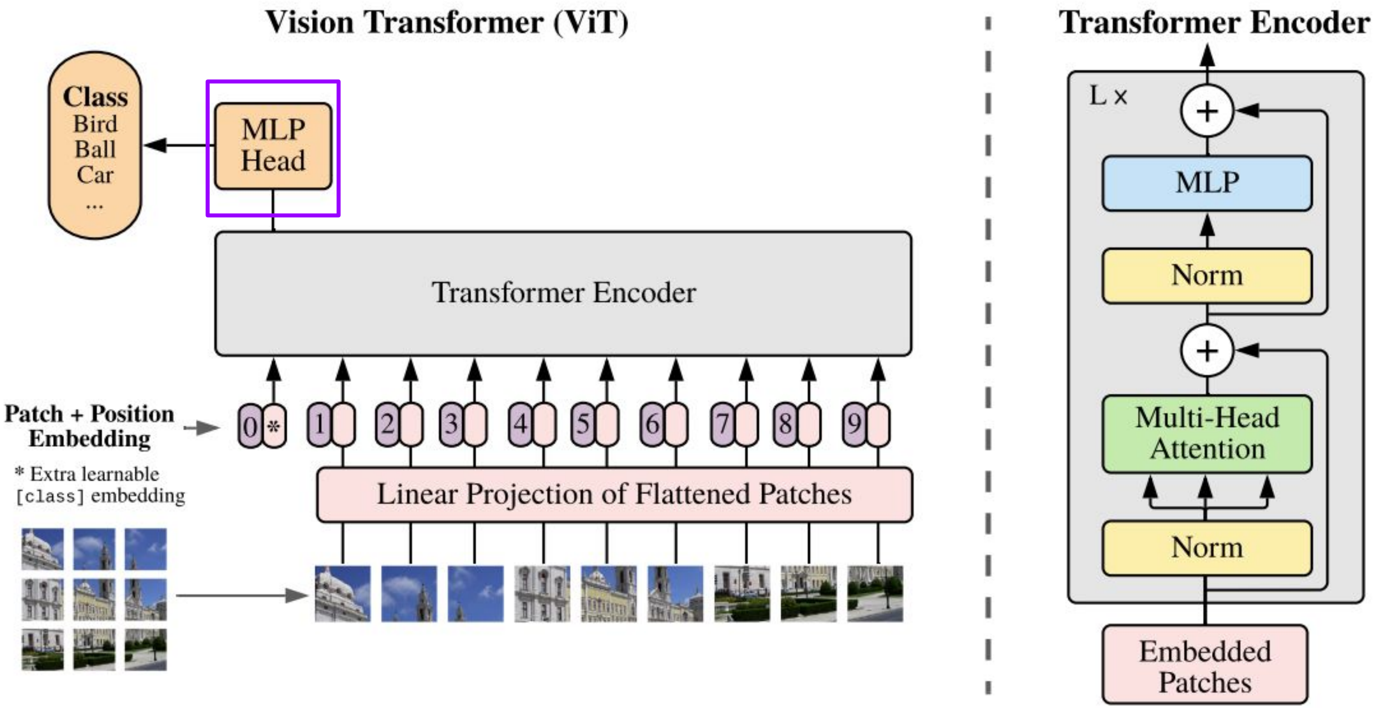
Transformer Encoder



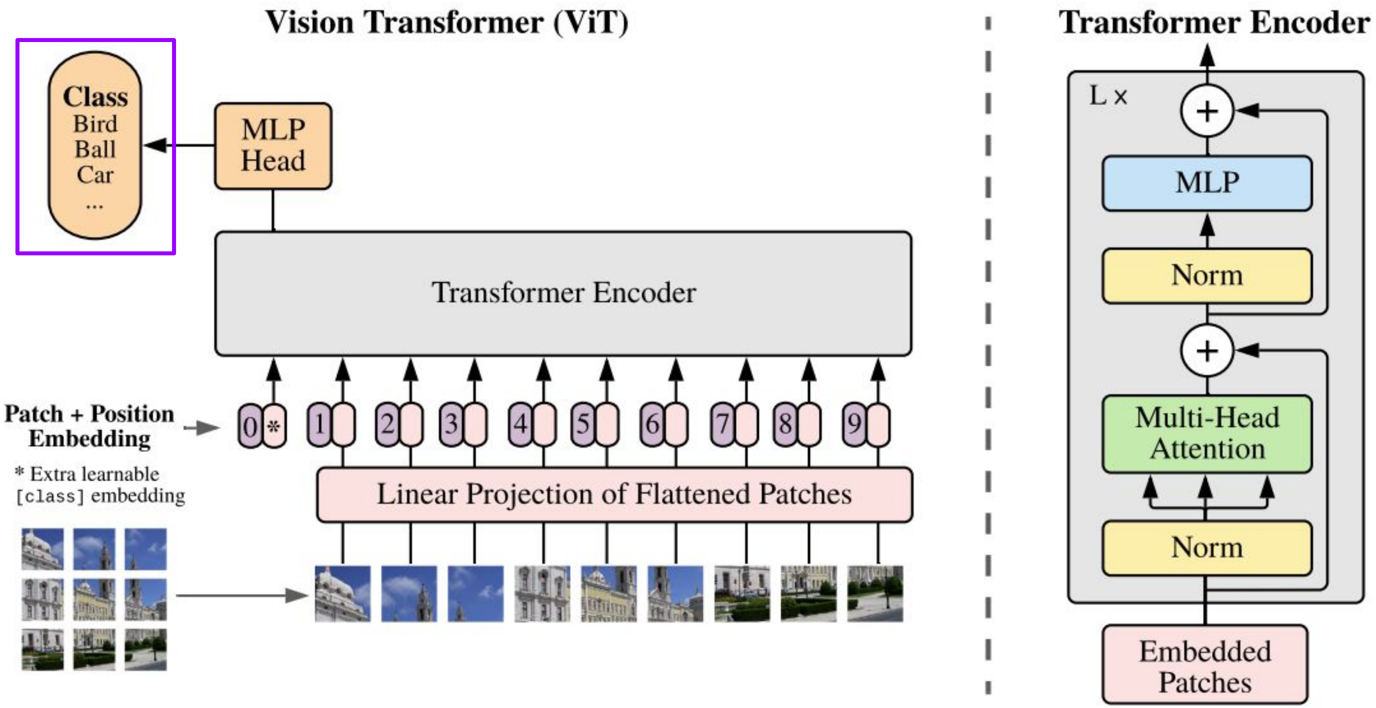
Visualization Attention



Multilayer Perceptron



Prediction



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 ×
MLP
Norm
Multi-Head
Attention
Norm
Embedded
Patches

Models

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

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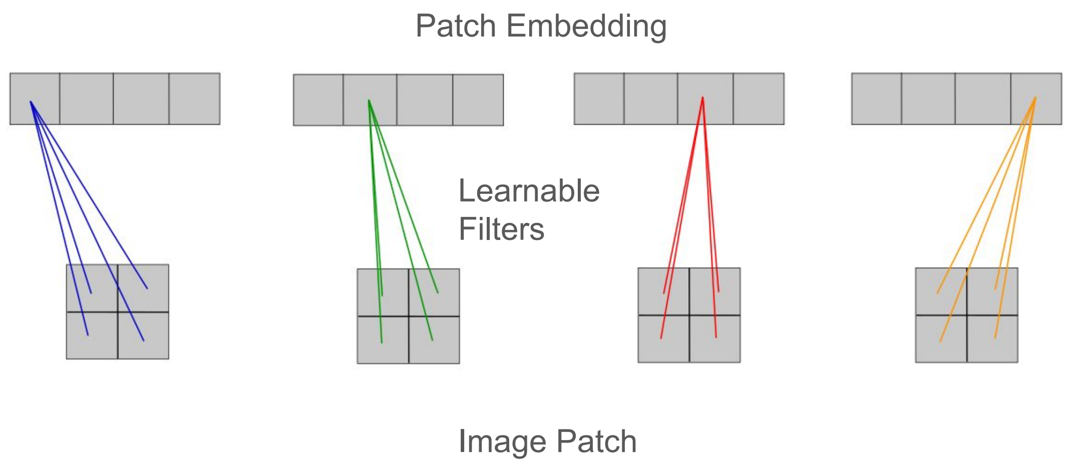
ViT-Huge	32	1280	5120	16	632M

Hidden Size Intuition

Patch Size: 16 x 16 x 3 ⟶ $16 * 16 * 3 = \boxed{768}$

⟶ 1 Filter per pixel



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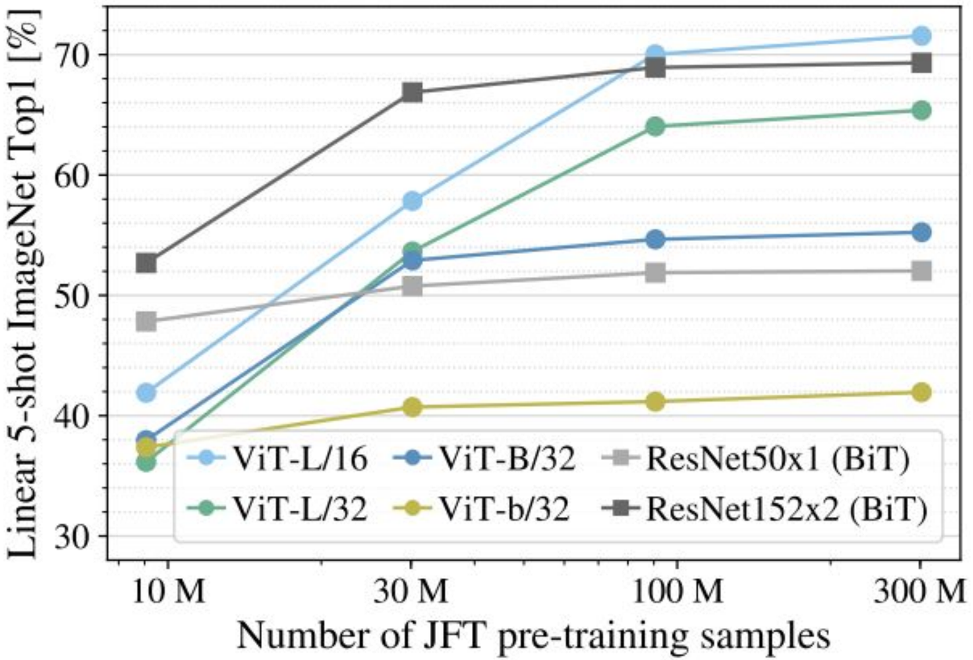
Results

Patch Size

	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

Pre-training vs. Performance



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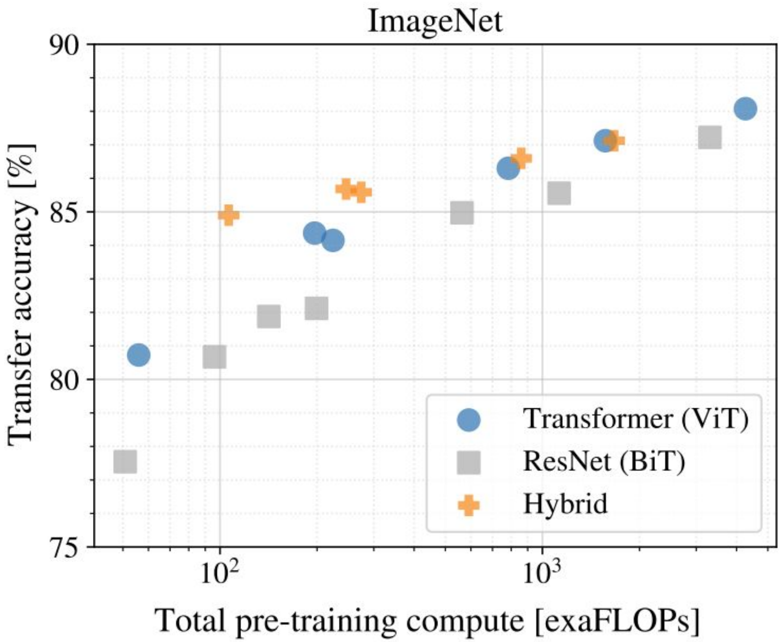
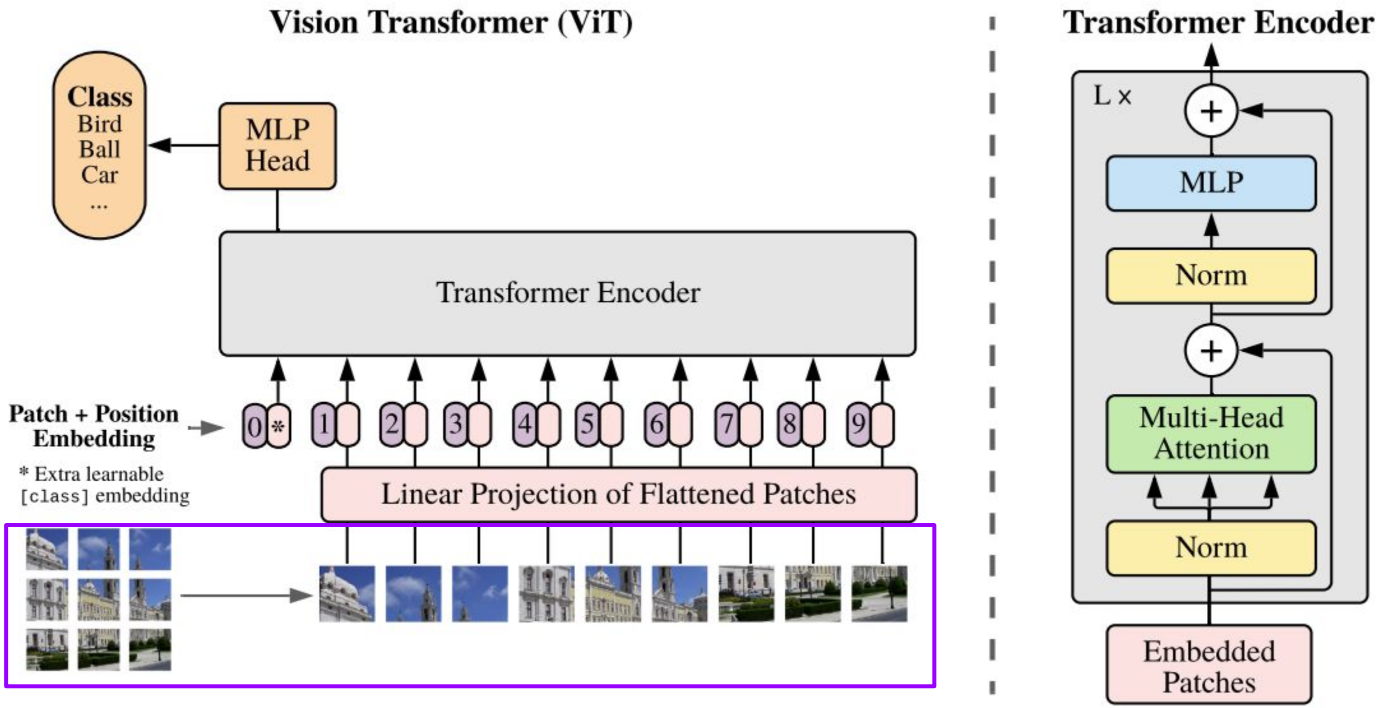
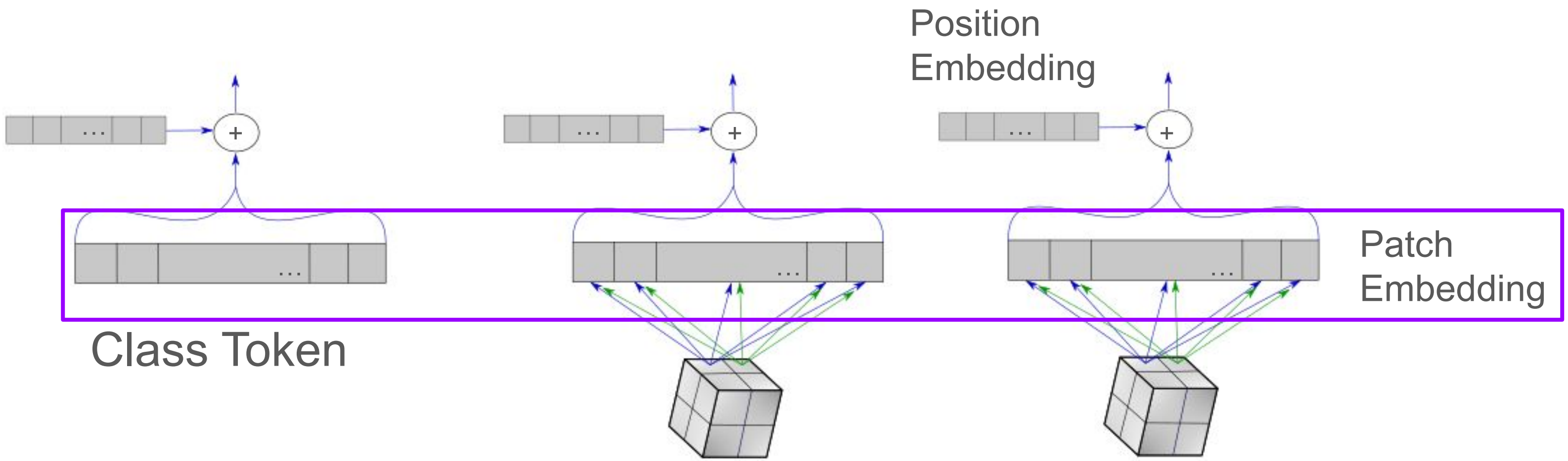
Pre-Training vs. Accuracy



Vision Transformer



Self Supervision



Results

- Only tested on smallest model (ViT-B/16)
- Faster convergence
- Worse performance than pretraining:
  - Training from scratch: 77.9%
  - With self-supervision:79.9%
  - With pre-training: 84.15%

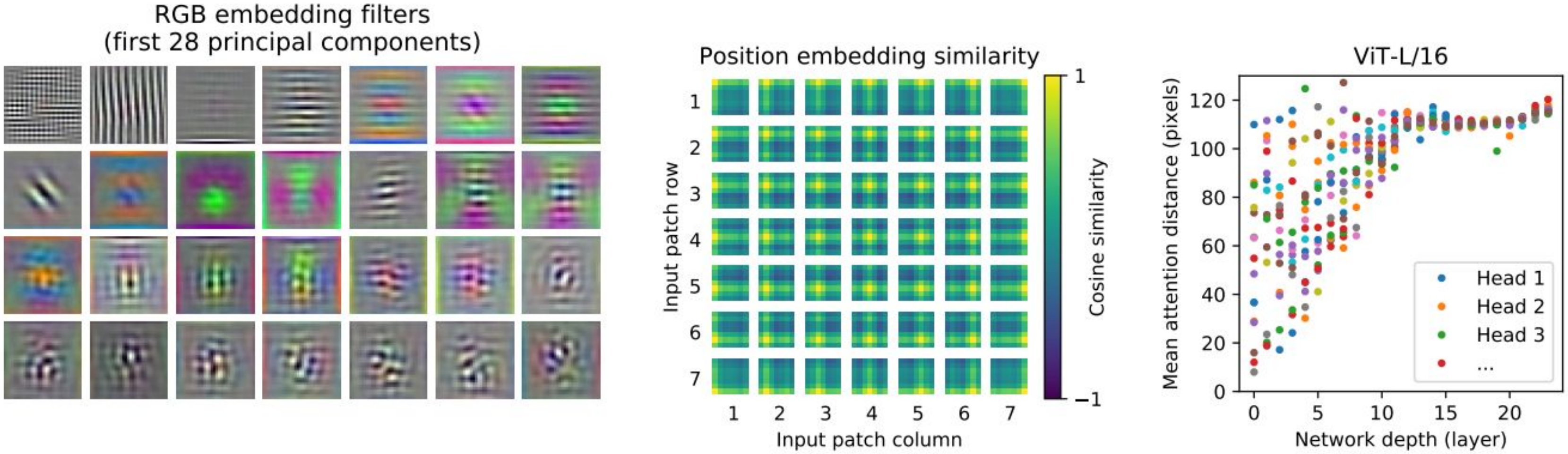
State Today

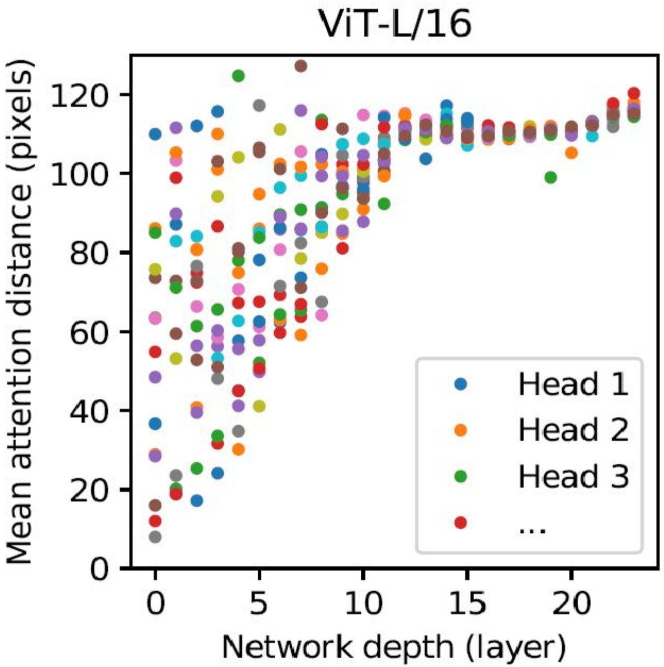
- Transformer methods are at the top of Leaderboards
- Lager Vision Transformer Vit-G/14 with larger pre-train set
- Transformers can also be used for detection and segmentation tasks
- Self-supervision in the next talk

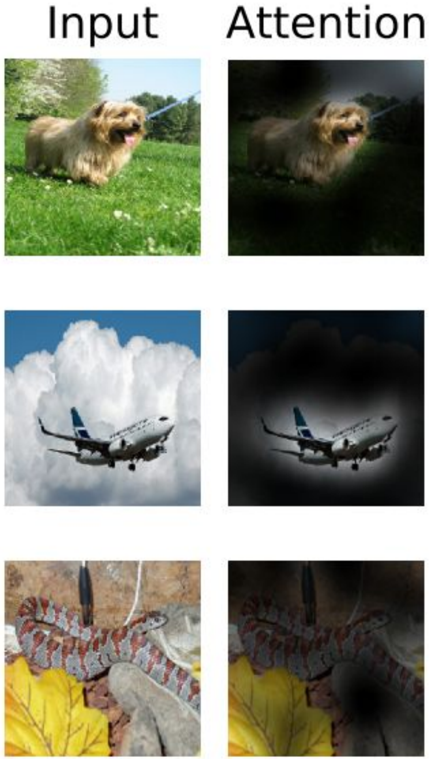
Conclusion

- It is possible to use Transformers for Image Classification
- Large pre-train datasets are needed
- Perform better than comparable ResNets with the same amount of compute
- Self-supervision is also possible

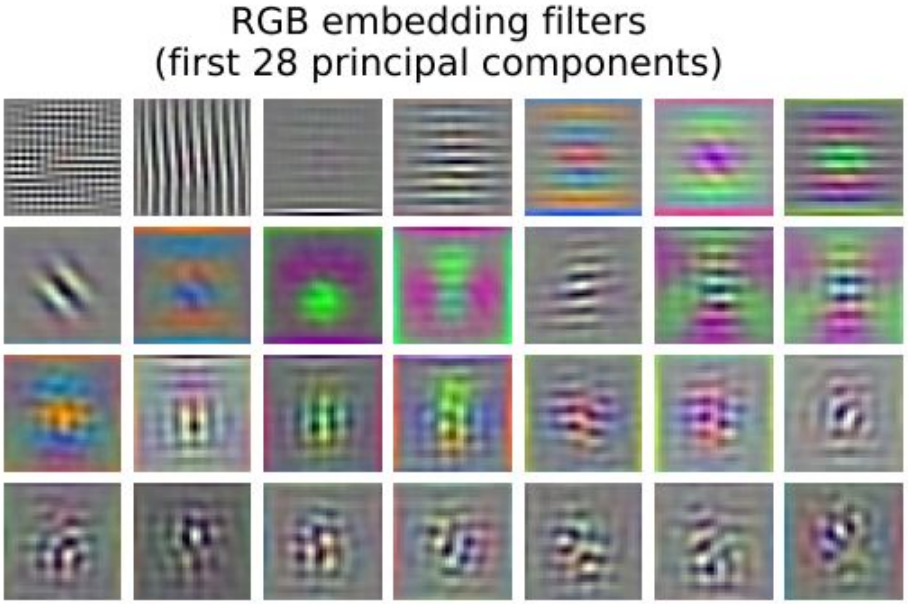
Appendix

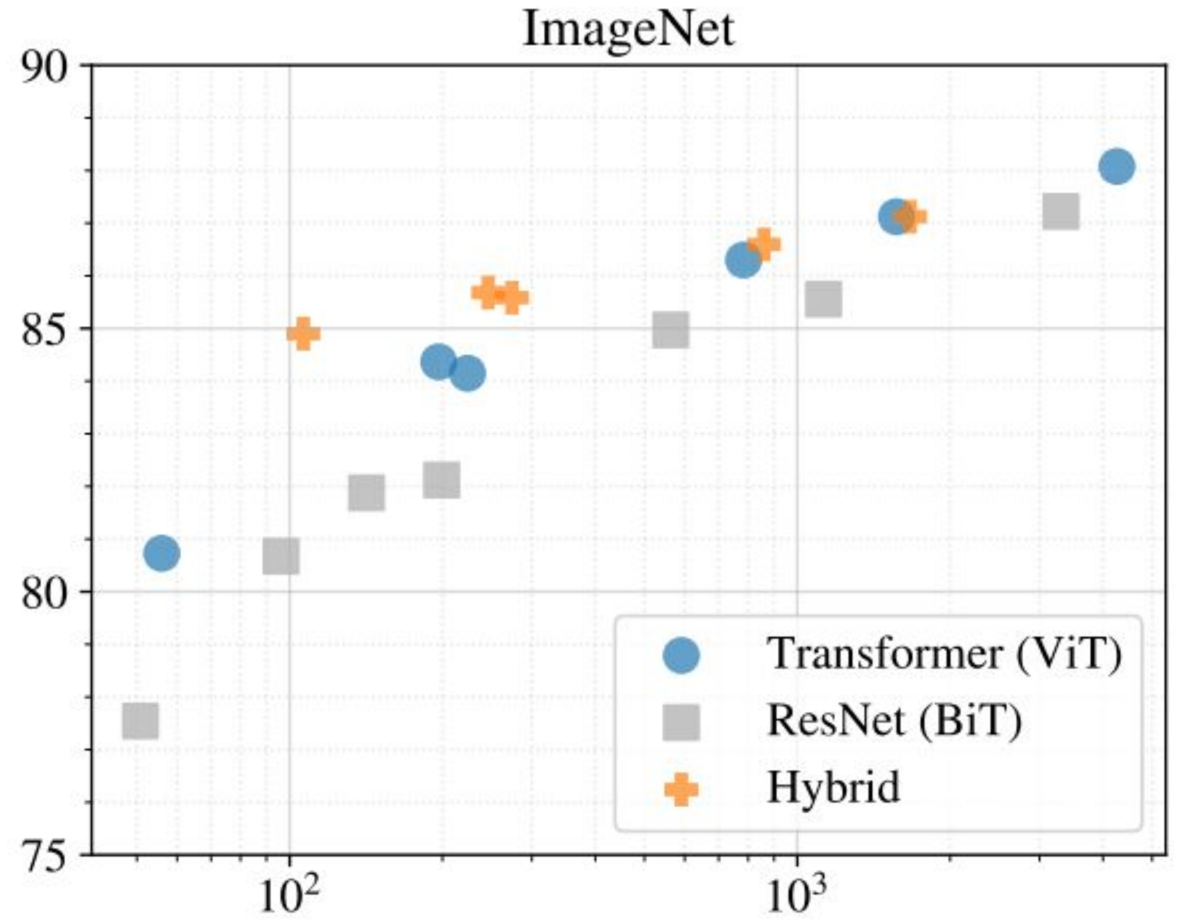

RGB embedding filters
(first 28 principal components)
Position embedding similarity
Input patch row
Input patch column
Cosine similarity
1
−1
ViT-L/16
Mean attention distance (pixels)
Network depth (layer)
Head 1
Head 2
Head 3
...

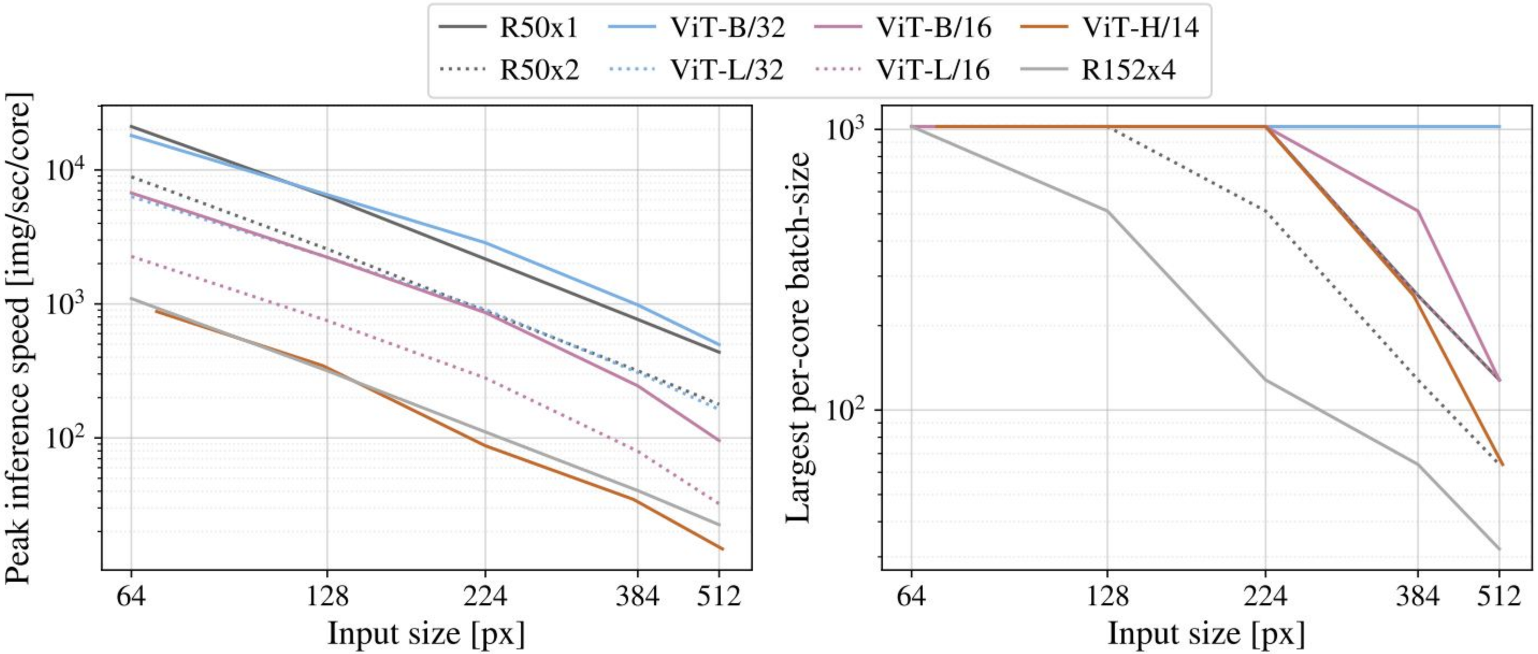

ViT-L/16
Mean attention distance (pixels)
Network depth (layer)
0
20
40
60
80
100
120
0
5
10
15
20
Head 1
Head 2
Head 3
...


Input
Attention

Patch Embeddings




ImageNet
90
85
80
75
10^2
10^3
Transformer (ViT)
ResNet (BiT)
Hybrid



R50x1
ViT-B/32
ViT-B/16
ViT-H/14
R50x2
ViT-L/32
ViT-L/16
R152x4
Peak inference speed [img/sec/core]
10^4
10^3
10^2
64
128
224
384
512
Input size [px]
Largest per-core batch-size
10^3
10^2
64
128
224
384
512
Input size [px]

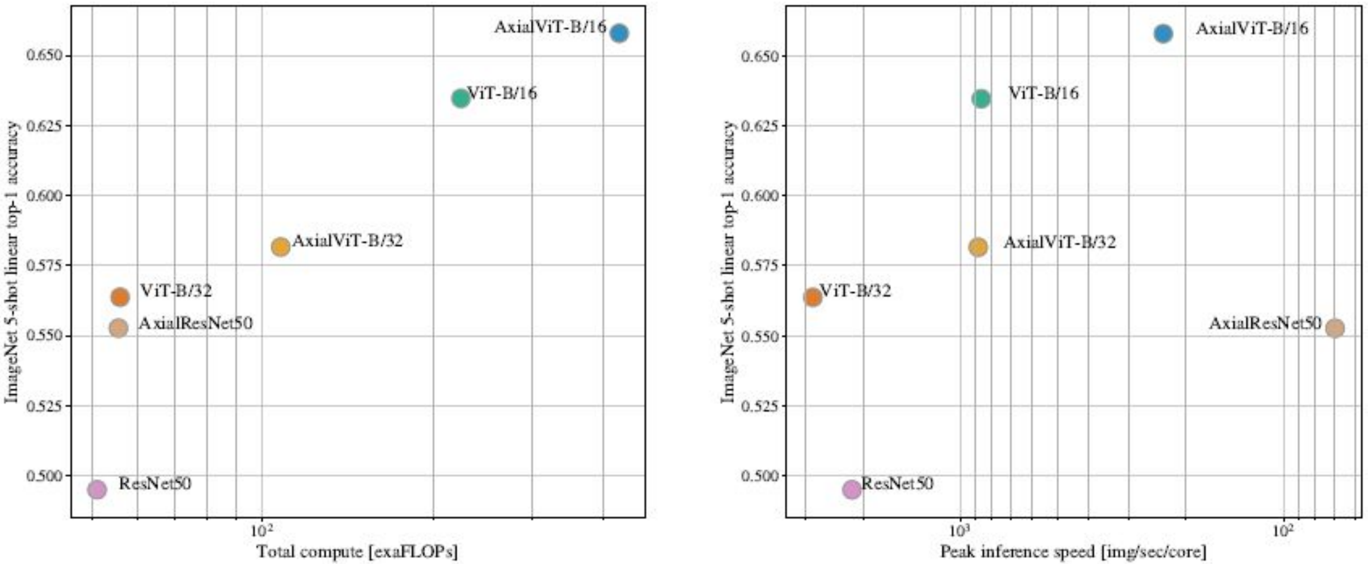
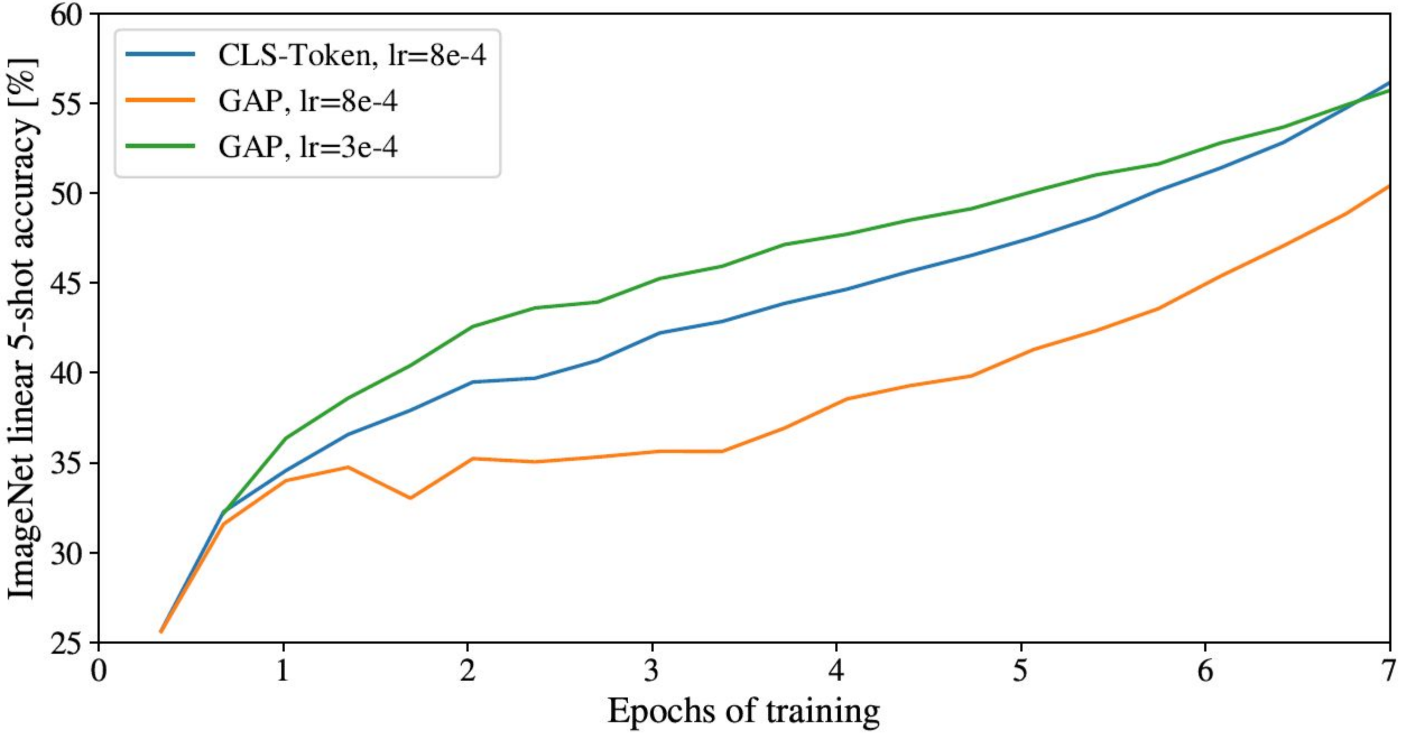


Figure 13: Performance of Axial-Attention based models, in terms of top-1 accuracy on ImageNet 5-shot linear, versus their speed in terms of number of FLOPs (**left**) and inference time (**left**).

		ViT-B/16	ViT-B/32	ViT-L/16	ViT-L/32	ViT-H/14
ImageNet	CIFAR-10	98.13	97.77	97.86	97.94	-
	CIFAR-100	87.13	86.31	86.35	87.07	-
	ImageNet	77.91	73.38	76.53	71.16	-
	ImageNet ReaL	83.57	79.56	82.19	77.83	-
	Oxford Flowers-102	89.49	85.43	89.66	86.36	-
	Oxford-IIIT-Pets	93.81	92.04	93.64	91.35	-
ImageNet-21k	CIFAR-10	98.95	98.79	99.16	99.13	99.27
	CIFAR-100	91.67	91.97	93.44	93.04	93.82
	ImageNet	83.97	81.28	85.15	80.99	85.13
	ImageNet ReaL	88.35	86.63	88.40	85.65	88.70
	Oxford Flowers-102	99.38	99.11	99.61	99.19	99.51
	Oxford-IIIT-Pets	94.43	93.02	94.73	93.09	94.82
JFT-300M	CIFAR-10	99.00	98.61	99.38	99.19	99.50
	CIFAR-100	91.87	90.49	94.04	92.52	94.55
	ImageNet	84.15	80.73	87.12	84.37	88.04
	ImageNet ReaL	88.85	86.27	89.99	88.28	90.33
	Oxford Flowers-102	99.56	99.27	99.56	99.45	99.68
	Oxford-IIIT-Pets	95.80	93.40	97.11	95.83	97.56

Pos. Emb.	Default/Stem	Every Layer	Every Layer-Shared
No Pos. Emb.	0.61382	N/A	N/A
1-D Pos. Emb.	0.64206	0.63964	0.64292
2-D Pos. Emb.	0.64001	0.64046	0.64022
Rel. Pos. Emb.	0.64032	N/A	N/A



CLS-Token, lr=8e-4
GAP, lr=8e-4
GAP, lr=3e-4
ImageNet linear 5-shot accuracy [%]
Epochs of training
60
55
50
45
40
35
30
25
0
1
2
3
4
5
6
7