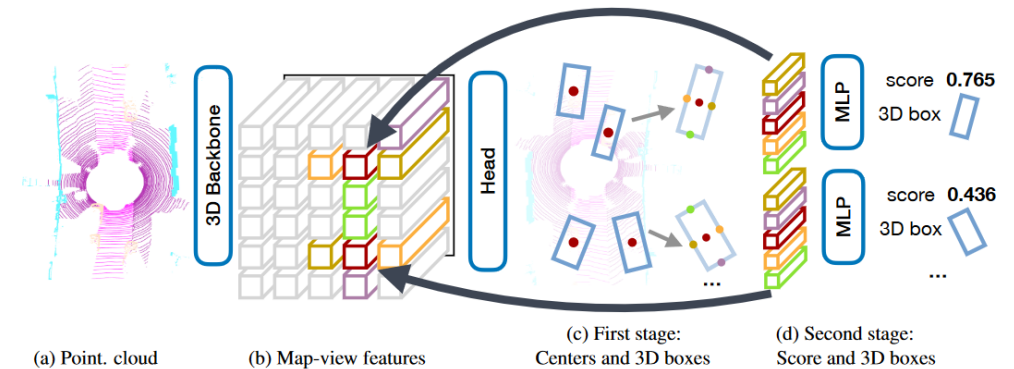


“Attention” and “Transformer” Architectures

James Hays

Recap – Lidar processing

- Popular CNN backbones aren't a direct fit for 3D point processing tasks.
- It's not clear how best to use deep learning on 3D data
 - Use a truly permutation invariant representation (PointNet)
 - Use a voxel representation (VoxelNet)
 - Use a bird's a view representation (PointPillars)
 - Create a range image (LaserNet)
- Multi-modal approaches (adding images, radar) help surprisingly little compared to lidar-only approaches.
- These alternate representations might be applicable more broadly, e.g. reasoning about depth estimates might be easier in bird's eye view (PseudoLidar)



CenterPoint, which is near state of the art for 3D object detection when using VoxelNet backbone.

Center-based 3D Object Detection and Tracking. Tianwei Yin, Xingyi Zhou, Philipp Krähenbühl. CVPR 2021

<https://paperswithcode.com/sota/3d-object-detection-on-nuscenes>

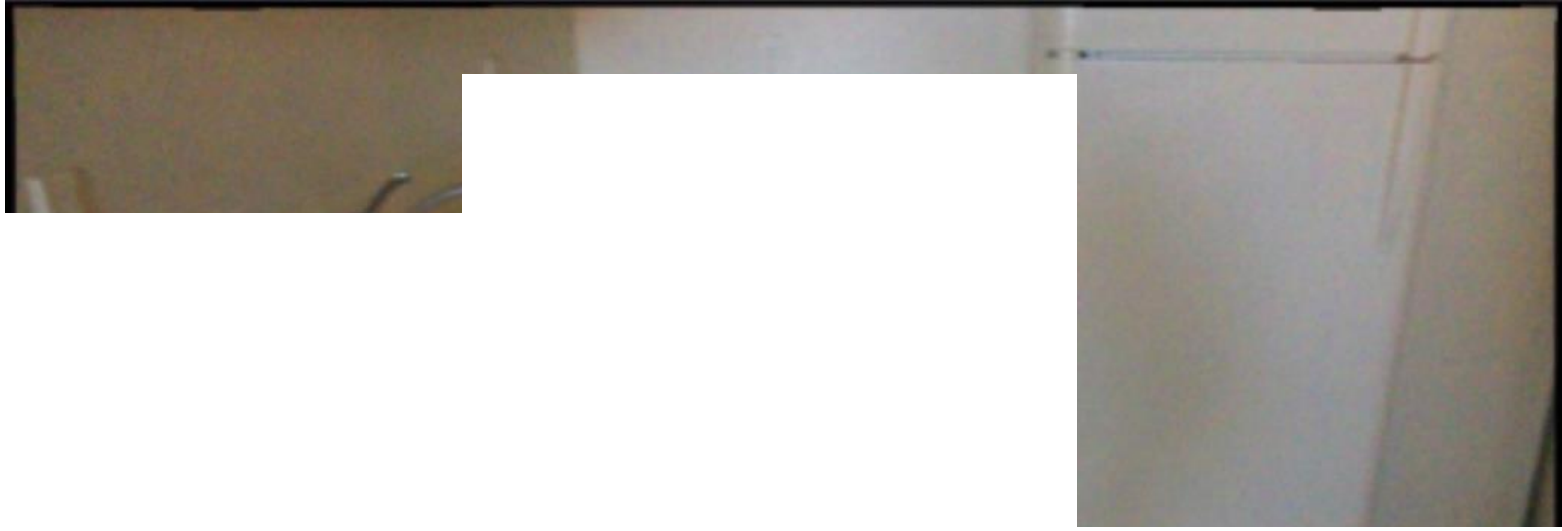
Outline

- Context and Receptive Field
- Going Beyond Convolutions in...
 - Text
 - Point Clouds
 - Images











Language understanding

... serve ...

Language understanding

... great **serve** from Djokovic ...



Language understanding

... be right back after I **serve** these salads ...





Brendan Dolan-Gavitt

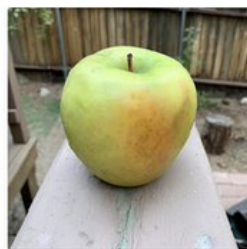
@moyix

The latest generation of adversarial image attacks is, uh, somewhat simpler to carry out [openai.com/blog/multimoda...](https://openai.com/blog/multimodal-adversarial-attacks)

Attacks in the wild

We refer to these attacks as *typographic attacks*. We believe attacks such as those described above are far from simply an academic concern. By exploiting the model's ability to read text robustly, we find that even *photographs of hand-written text* can often fool the model. Like the Adversarial Patch,²² this attack works in the wild; but unlike such attacks, it requires no more technology than pen and paper.

Attack text label iPod ▾



Granny Smith	85.6%
iPod	0.4%
library	0.0%
pizza	0.0%
toaster	0.0%
dough	0.1%



Granny Smith	0.1%
iPod	99.7%
library	0.0%
pizza	0.0%
toaster	0.0%
dough	0.0%

When we put a label saying "iPod" on this Granny Smith apple, the model erroneously classifies it as an iPod in the zero-shot setting.



Mark O. Riedl
@mark_riedl



Replying to @mark_riedl

In case of AI uprising...



6:42 PM · Mar 4, 2021 · Twitter for iPad



Mark O. Riedl
@mark_riedl



Replying to @mark_riedl

Upon further reflection, neural language models aren't always so good with negations. I recommend this instead

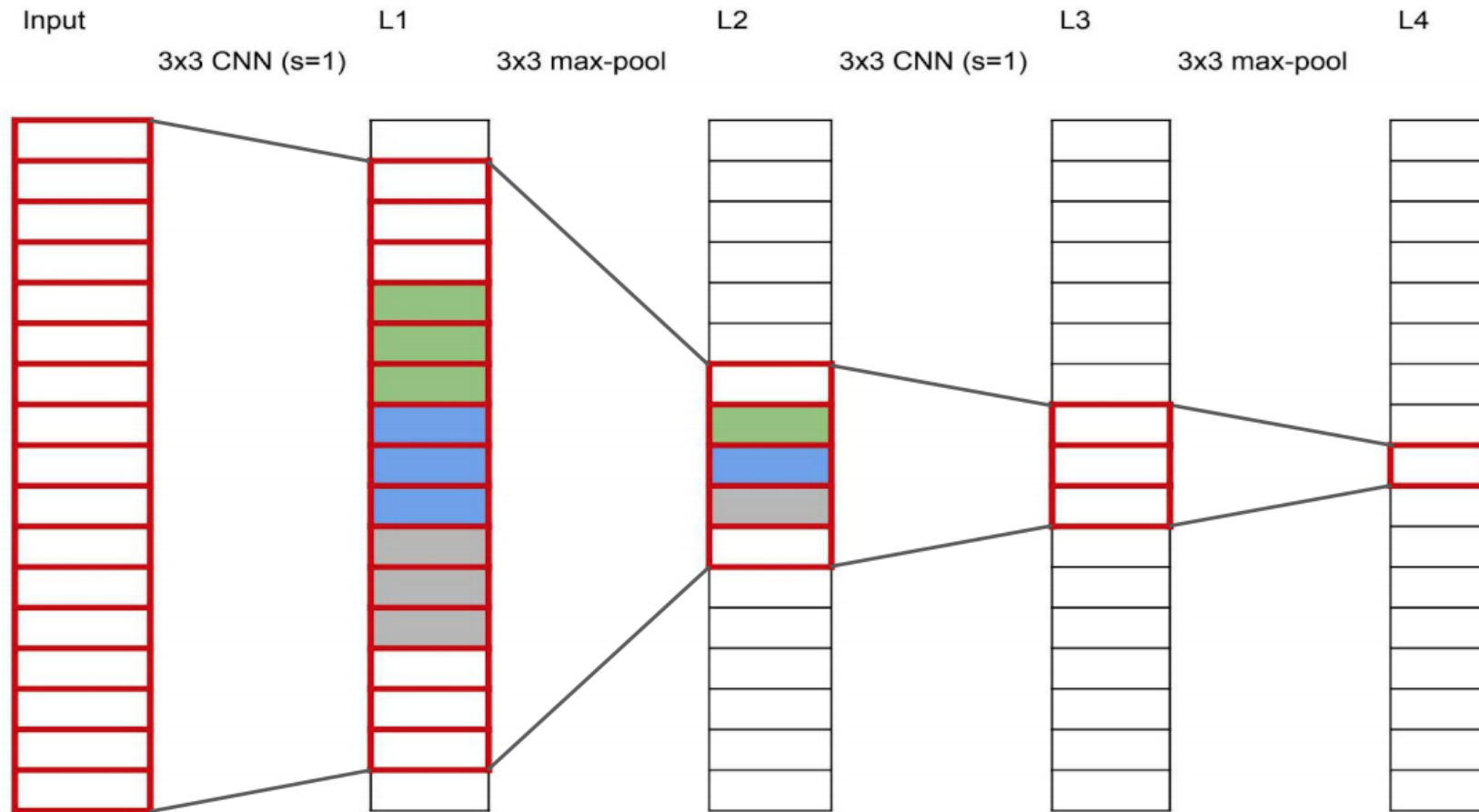


9:28 PM · Mar 4, 2021 · Twitter for iPad

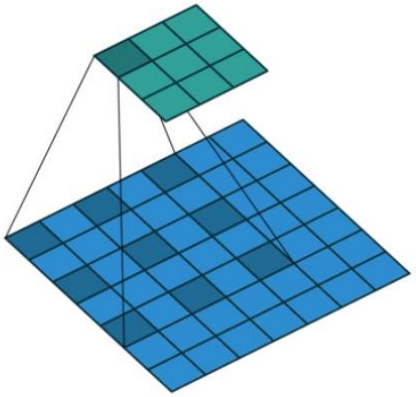
So how do we fix these problems?



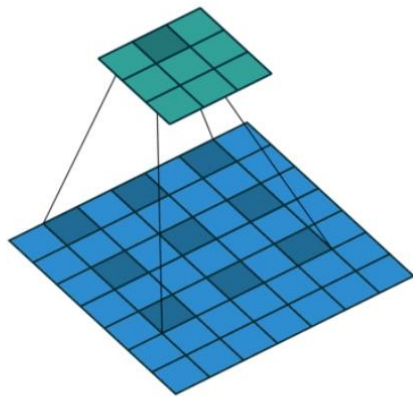
Receptive field



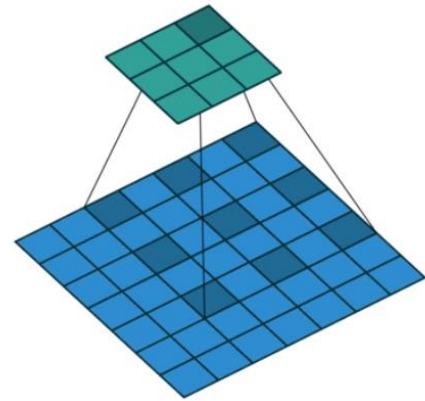
Dilated Convolution



No padding, no stride, dilation



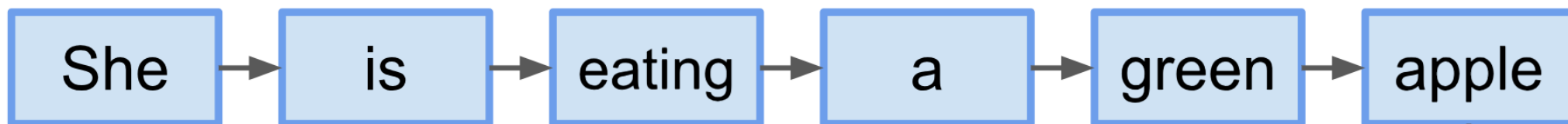
No padding, no stride, dilation



No padding, no stride, dilation

Sequence 2 Sequence models in language

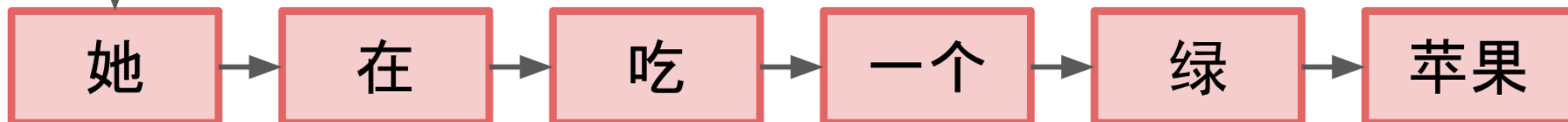
Encoder



Context vector (length: 5)

[0.1, -0.2, 0.8, 1.5, -0.3]

Decoder



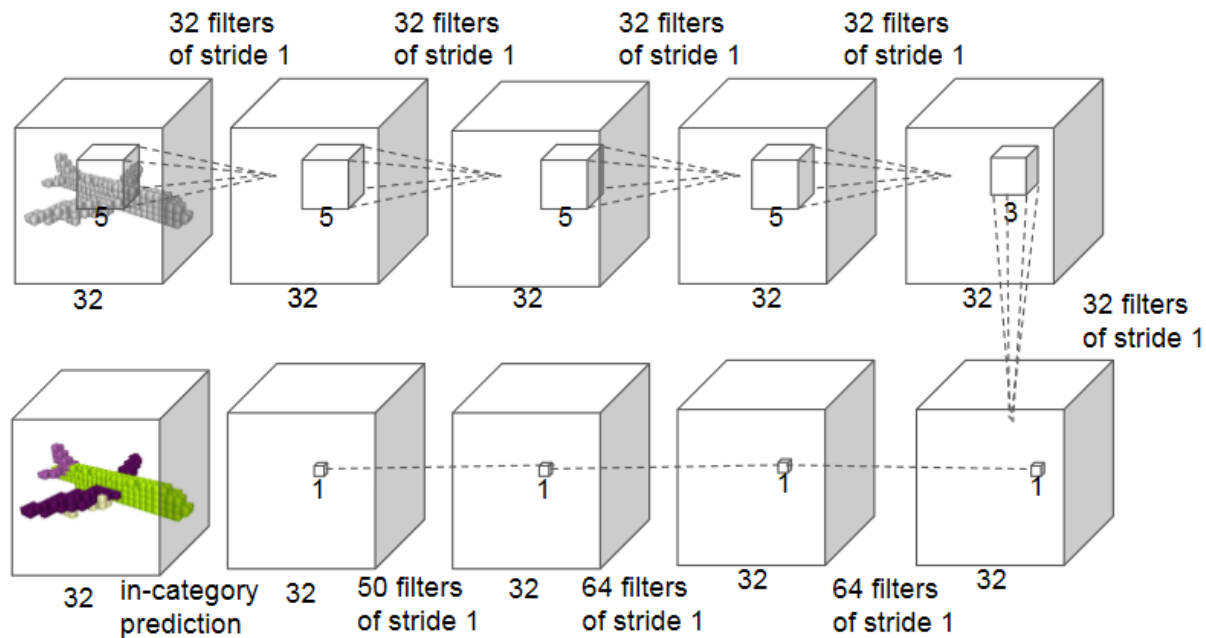


Figure 10. **Baseline 3D CNN** segmentatic network is fully convolutional and predicts p voxel.

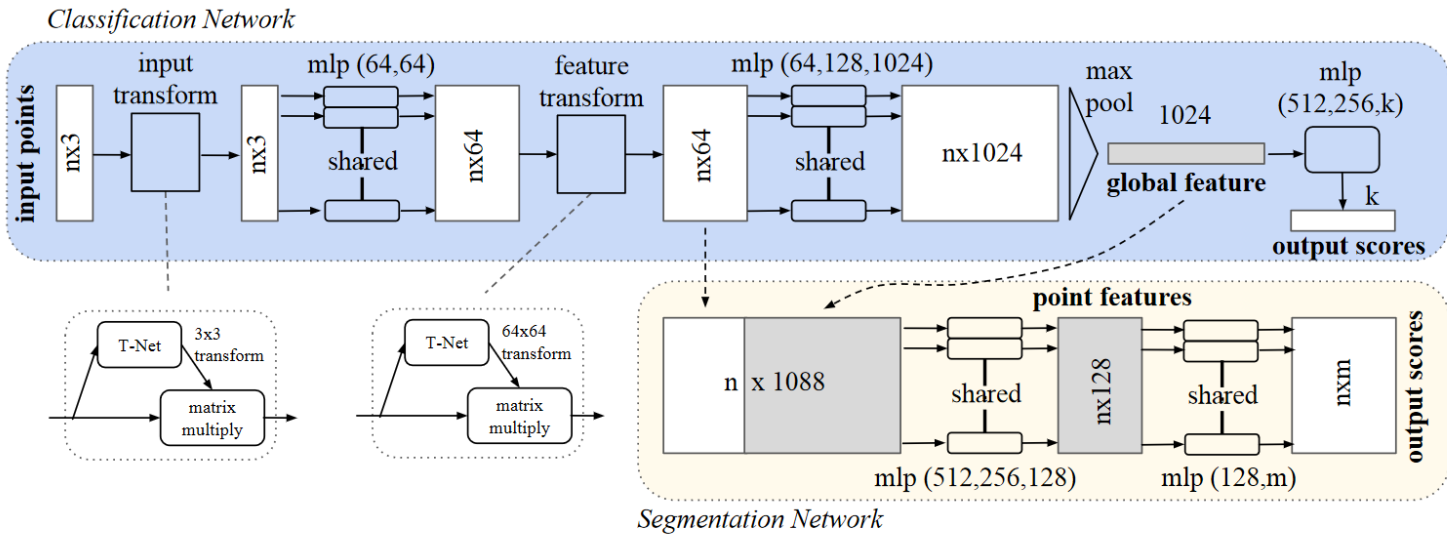


Figure 2. **PointNet Architecture.** The classification network takes n points as input, applies input and feature transformations, and then aggregates point features by max pooling. The output is classification scores for k classes. The segmentation network is an extension to the classification net. It concatenates global and local features and outputs per point scores. “mlp” stands for multi-layer perceptron, numbers in bracket are layer sizes. Batchnorm is used for all layers with ReLU. Dropout layers are used for the last mlp in classification net.

Outline

- Context and Receptive Field
- Going Beyond Convolutions in...
 - Text
 - Point Clouds
 - Images

Attention Is All You Need

Ashish Vaswani*
Google Brain
avaswani@google.com

Noam Shazeer*
Google Brain
noam@google.com

Niki Parmar*
Google Research
nikip@google.com

Jakob Uszkoreit*
Google Research
usz@google.com

Llion Jones*
Google Research
llion@google.com

Aidan N. Gomez* †
University of Toronto
aidan@cs.toronto.edu

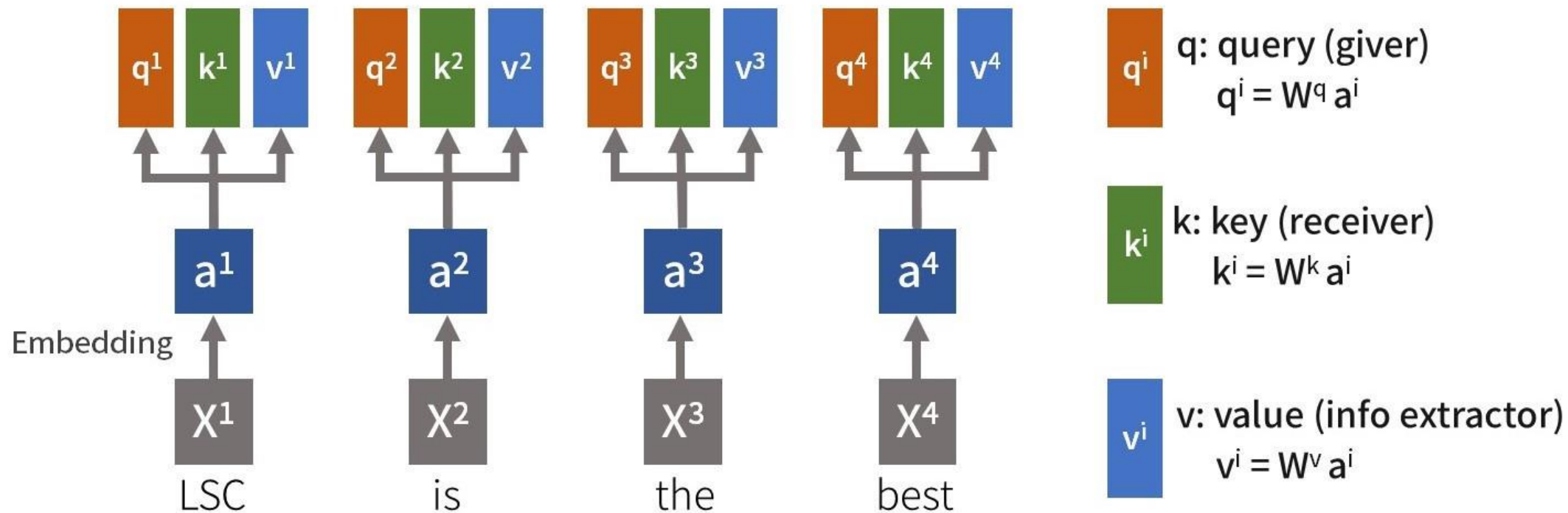
Łukasz Kaiser*
Google Brain
lukaszkaizer@google.com

Illia Polosukhin* †
illia.polosukhin@gmail.com

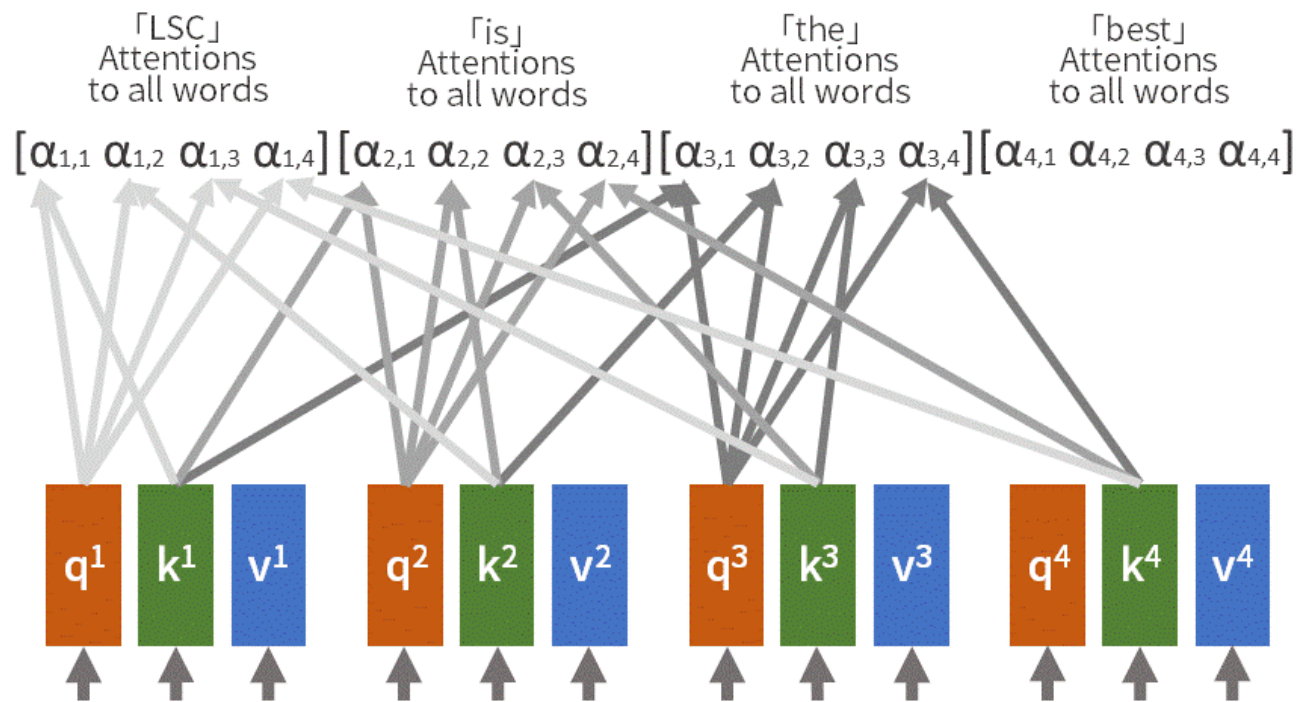
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based on the attention mechanism.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



Input: LSC is the best!



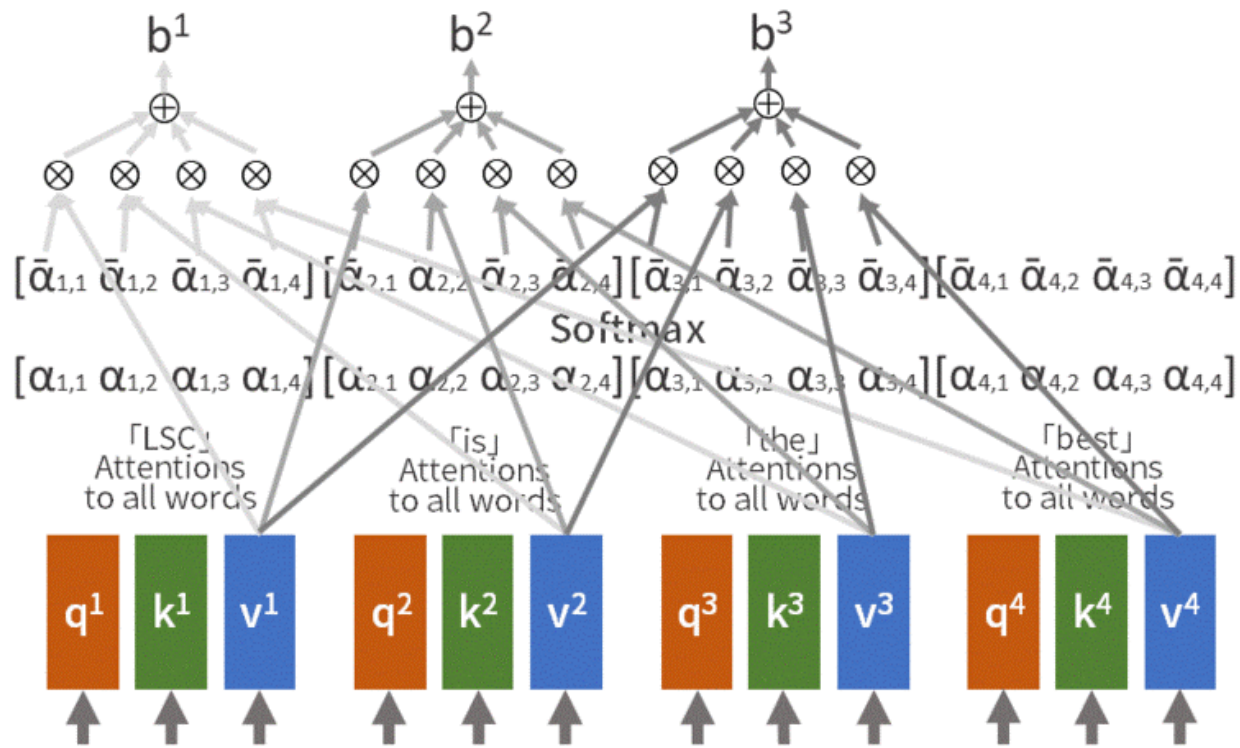
$$\alpha_{i,j} = \frac{q^i \cdot k^j}{\sqrt{d}}$$

d: dimension of q, k

A =

$$\begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} & \alpha_{1,3} & \alpha_{1,4} \\ \alpha_{2,1} & \alpha_{2,2} & \alpha_{2,3} & \alpha_{2,4} \\ \alpha_{3,1} & \alpha_{3,2} & \alpha_{3,3} & \alpha_{3,4} \\ \alpha_{4,1} & \alpha_{4,2} & \alpha_{4,3} & \alpha_{4,4} \end{bmatrix}$$

Attention Matrix

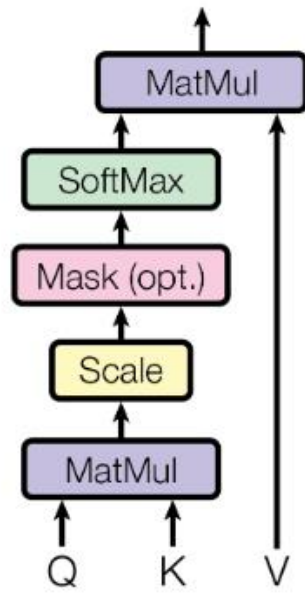


$$b^i = \sum_j \bar{\alpha}_{i,j} v^j$$

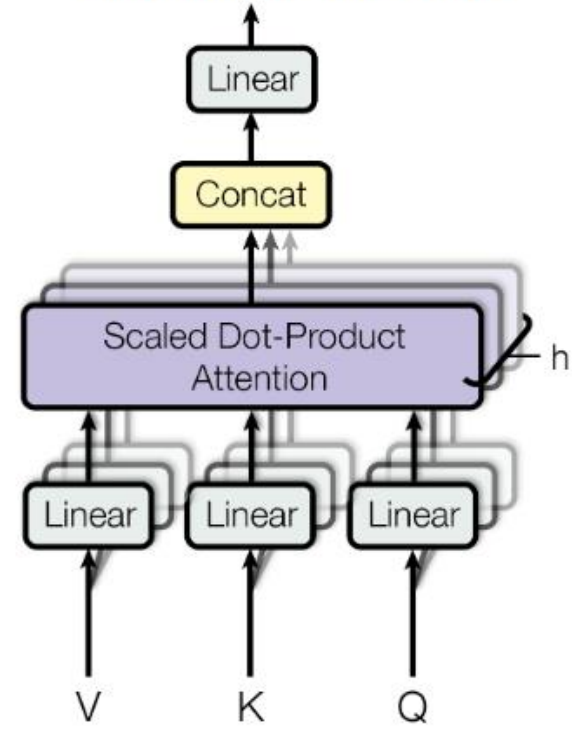
Complexity Comparison

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(\log_k(n))$

Scaled Dot-Product Attention



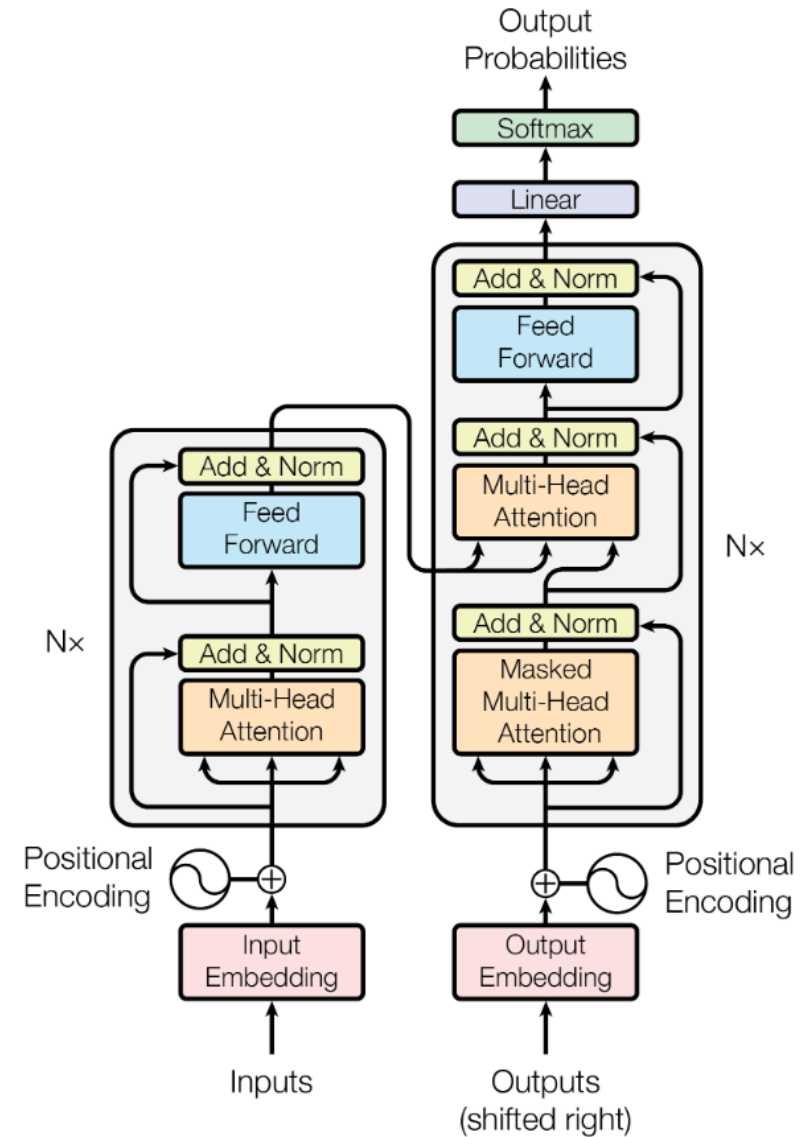
Multi-Head Attention



Transformer Architecture

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	41.29	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$3.3 \cdot 10^{18}$	
Transformer (big)	28.4	41.8	$2.3 \cdot 10^{19}$	



Outline

- Context and Receptive Field
- Going Beyond Convolutions in...
 - Text
 - Point Clouds
 - Images

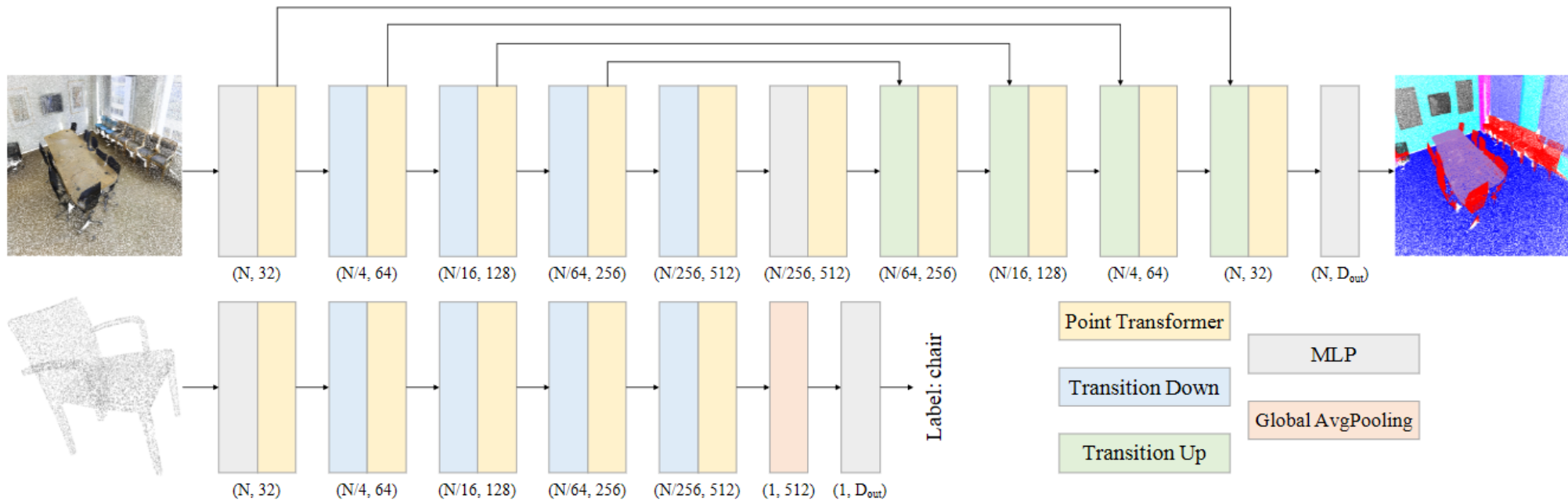
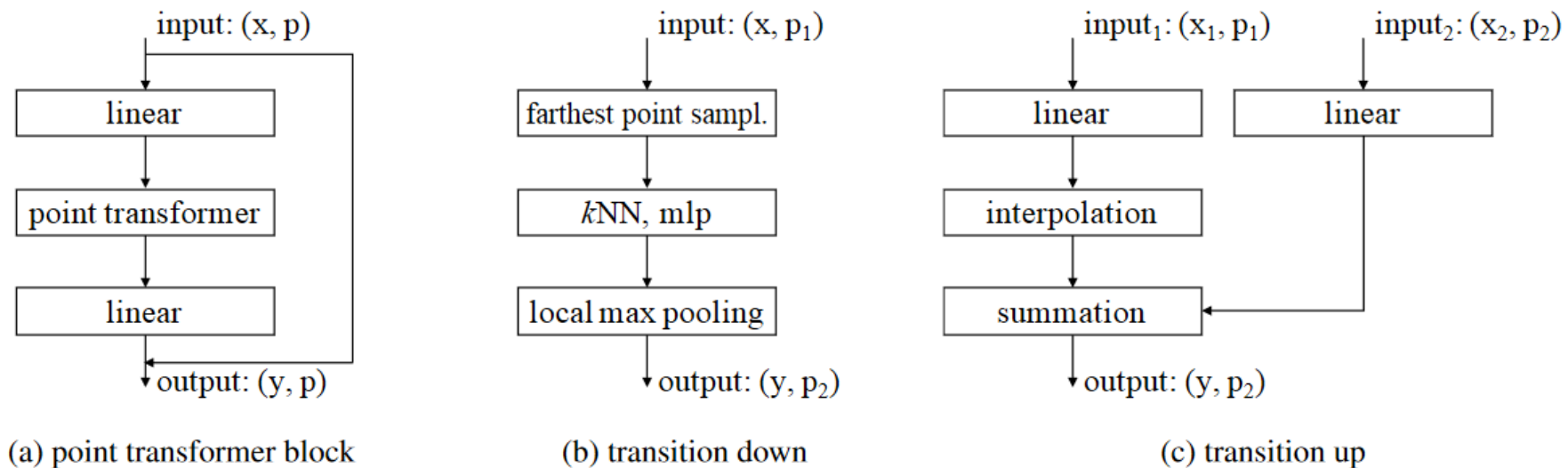


Figure 3. Point transformer networks for semantic segmentation (top) and classification (bottom).



Input

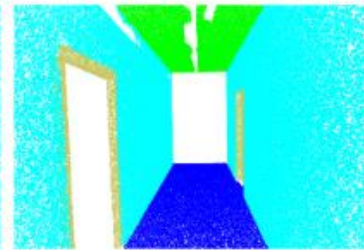
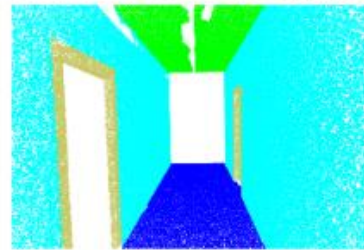
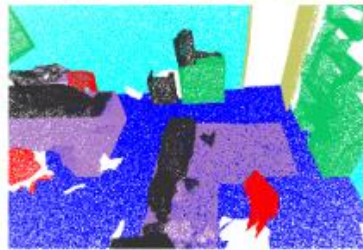
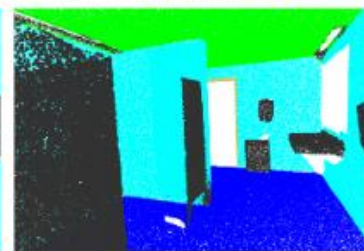
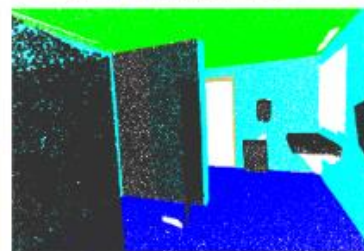
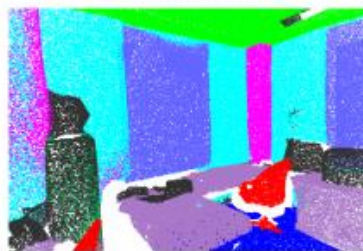
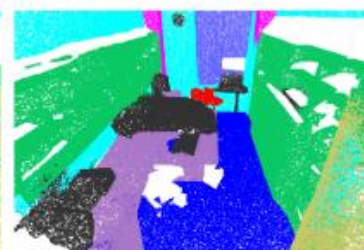
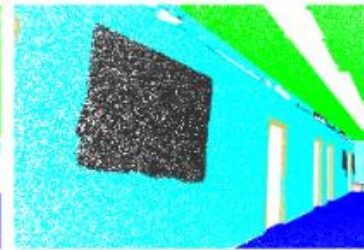
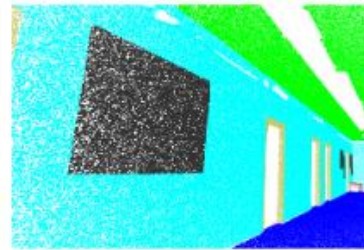
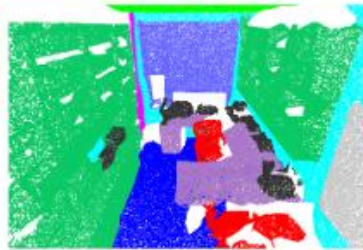
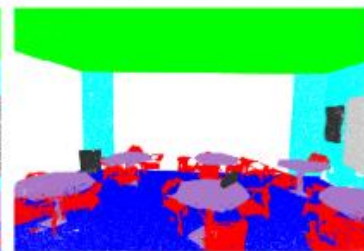
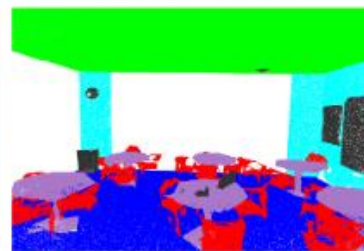
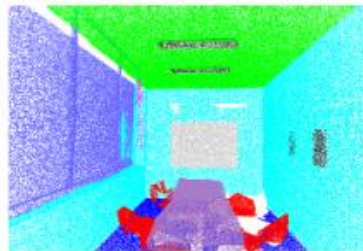
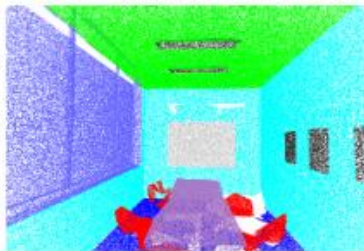
Ground Truth

Point Transformer

Input

Ground Truth

Point Transformer



■ ceiling
 ■ floor
 ■ wall
 ■ beam
 ■ column
 ■ window
 ■ door
 ■ table
 ■ chair
 ■ sofa
 ■ bookcase
 ■ board
 ■ clutter

Method	OA	mAcc	mIoU	ceiling	floor	wall	beam	column	window	door	table	chair	sofa	bookcase	board	clutter
PointNet [22]	–	49.0	41.1	88.8	97.3	69.8	0.1	3.9	46.3	10.8	59.0	52.6	5.9	40.3	26.4	33.2
SegCloud [32]	–	57.4	48.9	90.1	96.1	69.9	0.0	18.4	38.4	23.1	70.4	75.9	40.9	58.4	13.0	41.6
TangentConv [31]	–	62.2	52.6	90.5	97.7	74.0	0.0	20.7	39.0	31.3	77.5	69.4	57.3	38.5	48.8	39.8
PointCNN [18]	85.9	63.9	57.3	92.3	98.2	79.4	0.0	17.6	22.8	62.1	74.4	80.6	31.7	66.7	62.1	56.7
SPGraph [14]	86.4	66.5	58.0	89.4	96.9	78.1	0.0	42.8	48.9	61.6	84.7	75.4	69.8	52.6	2.1	52.2
PCCN [38]	–	67.0	58.3	92.3	96.2	75.9	0.3	6.0	69.5	63.5	66.9	65.6	47.3	68.9	59.1	46.2
PointWeb [50]	87.0	66.6	60.3	92.0	98.5	79.4	0.0	21.1	59.7	34.8	76.3	88.3	46.9	69.3	64.9	52.5
HPEIN [12]	87.2	68.3	61.9	91.5	98.2	81.4	0.0	23.3	65.3	40.0	75.5	87.7	58.5	67.8	65.6	49.4
MinkowskiNet [33]	–	71.7	65.4	91.8	98.7	86.2	0.0	34.1	48.9	62.4	81.6	89.8	47.2	74.9	74.4	58.6
KPConv [33]	–	72.8	67.1	92.8	97.3	82.4	0.0	23.9	58.0	69.0	81.5	91.0	75.4	75.3	66.7	58.9
PointTransformer	90.8	76.5	70.4	94.0	98.5	86.3	0.0	38.0	63.4	74.3	89.1	82.4	74.3	80.2	76.0	59.3

Table 1. Semantic segmentation results on the S3DIS dataset, evaluated on Area 5.

Method	input	mAcc	OA
3DShapeNets [43]	voxel	77.3	84.7
VoxNet [20]	voxel	83.0	85.9
Subvolume [23]	voxel	86.0	89.2
MVCNN [30]	image	–	90.1
PointNet [22]	point	86.2	89.2
PointNet++ [24]	point	–	91.9
SpecGCN [36]	point	–	92.1
PointCNN [18]	point	88.1	92.2
DGCNN [40]	point	90.2	92.2
PointWeb [50]	point	89.4	92.3
SpiderCNN [44]	point	–	92.4
PointConv [42]	point	–	92.5
KPConv [33]	point	–	92.9
InterpCNN [19]	point	–	93.0
PointTransformer	point	90.6	93.7

<https://paperswithcode.com/sota/3d-point-cloud-classification-on-modelnet40>

Table 3. Shape classification results on the ModelNet40 dataset.

Outline

- Context and Receptive Field
- Going Beyond Convolutions in...
 - Text
 - Point Clouds
 - Images

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

Alexey Dosovitskiy^{*,†}, Lucas Beyer^{*}, Alexander Kolesnikov^{*}, Dirk Weissenborn^{*},
Xiaohua Zhai^{*}, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer,
Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby^{*,†}

^{*}equal technical contribution, [†]equal advising

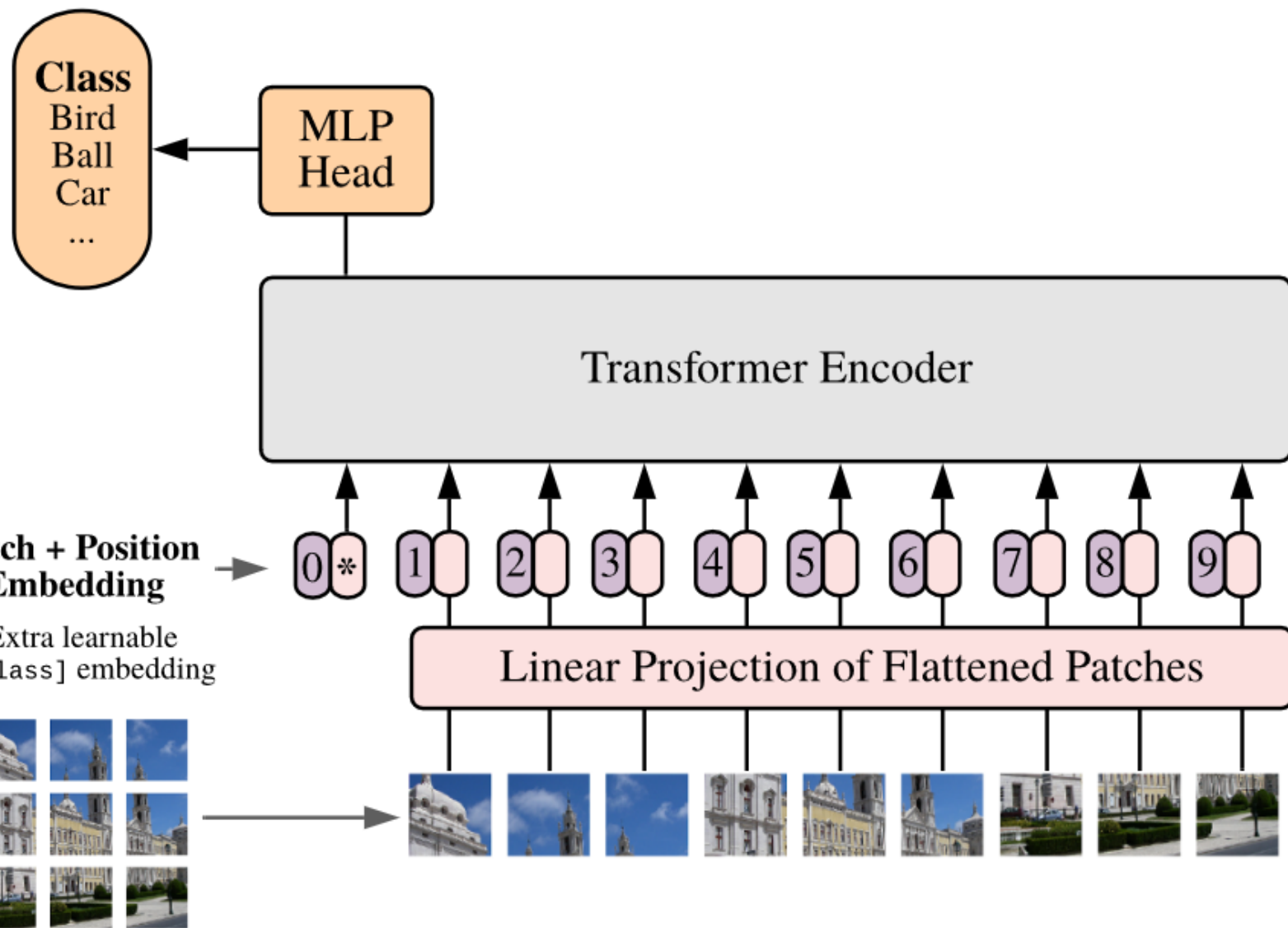
Google Research, Brain Team

{adosovitskiy, neilhoulby}@google.com

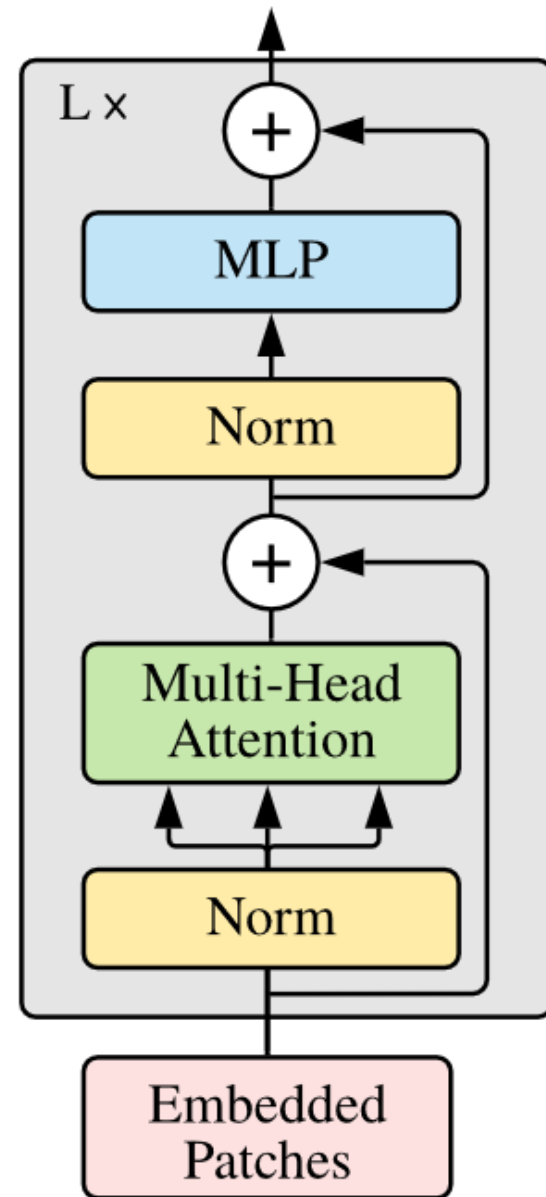
ABSTRACT

While the Transformer architecture has become the de-facto standard for natural language processing tasks, its applications to computer vision remain limited. In vision, attention is either applied in conjunction with convolutional networks, or used to replace certain components of convolutional networks while keeping their overall structure in place. We show that this reliance on CNNs is not necessary and a pure transformer applied directly to sequences of image patches can perform very well on image classification tasks. When pre-trained on large amounts of data and transferred to multiple mid-sized or small image recognition benchmarks (ImageNet, CIFAR-100, VTAB, etc.), Vision Transformer (ViT) attains excellent results compared to state-of-the-art convolutional networks while requiring substantially fewer computational resources to train¹

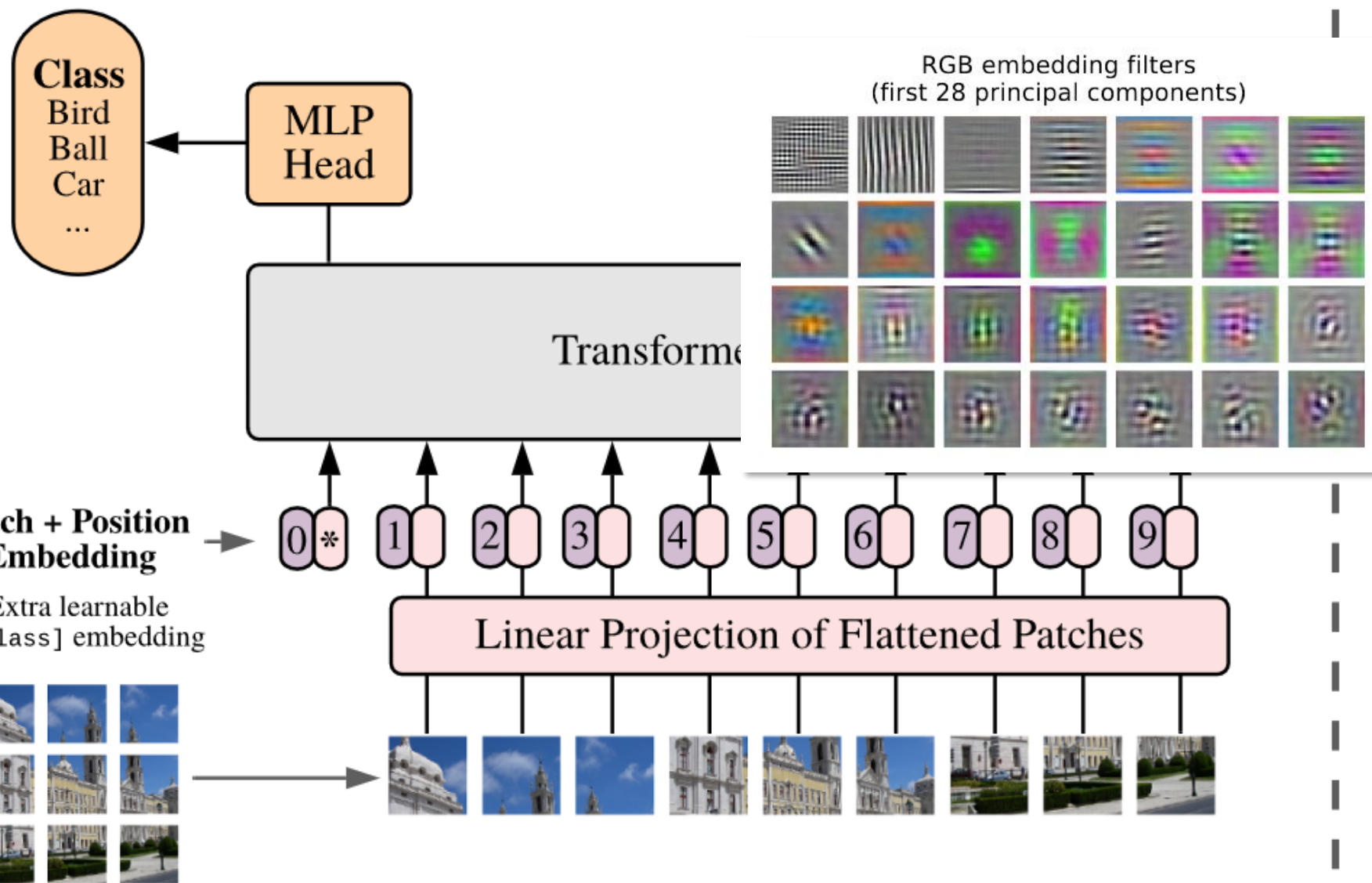
Vision Transformer (ViT)



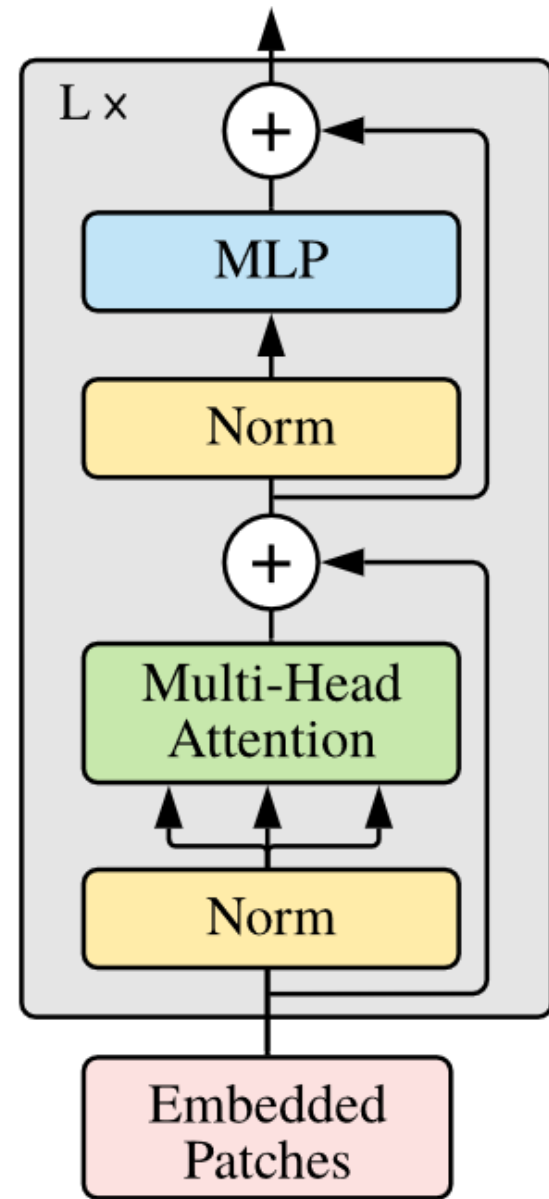
Transformer Encoder



Vision Transformer (ViT)



Transformer Encoder

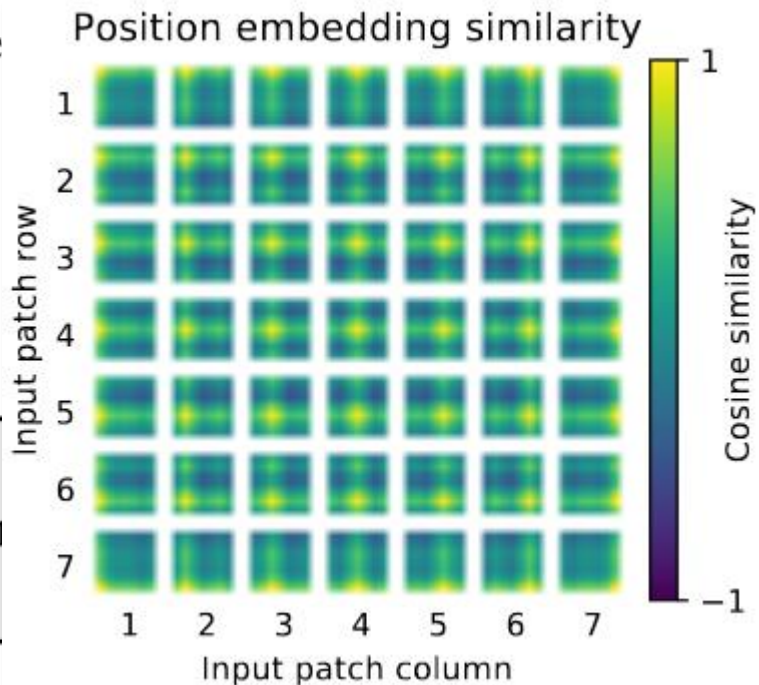


Vision Transformer

Class
Bird
Ball
Car
...

MLP
Head

Transformer



Transformer Encoder

$L \times$

+

MLP

Norm

+

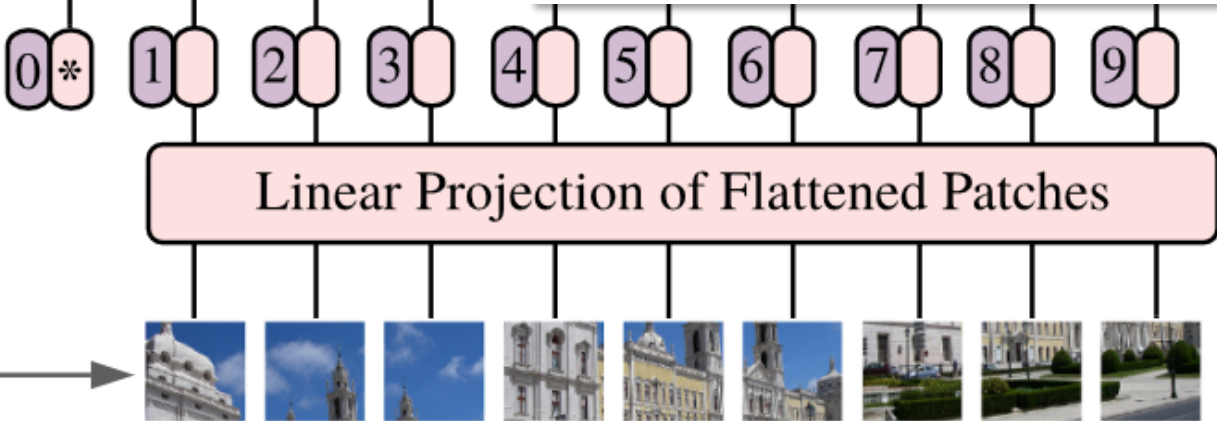
Multi-Head
Attention

Norm

Embedded
Patches

**Patch + Position
Embedding**

* Extra learnable
[class] embedding



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.

	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

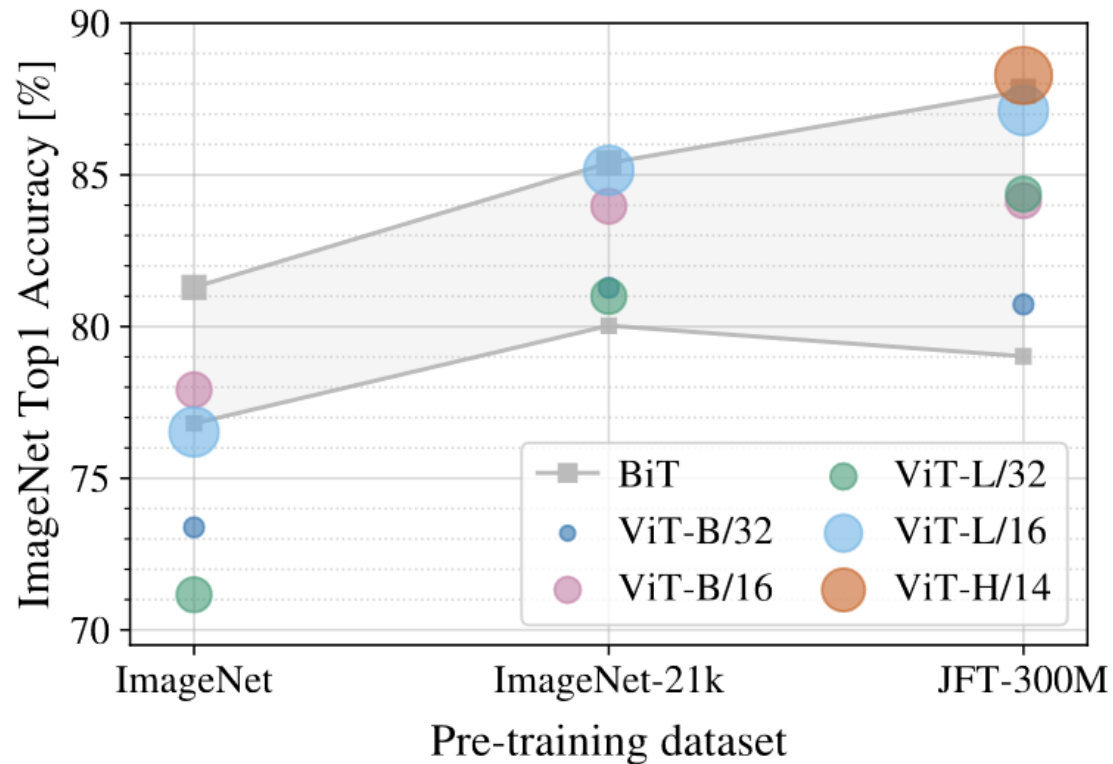


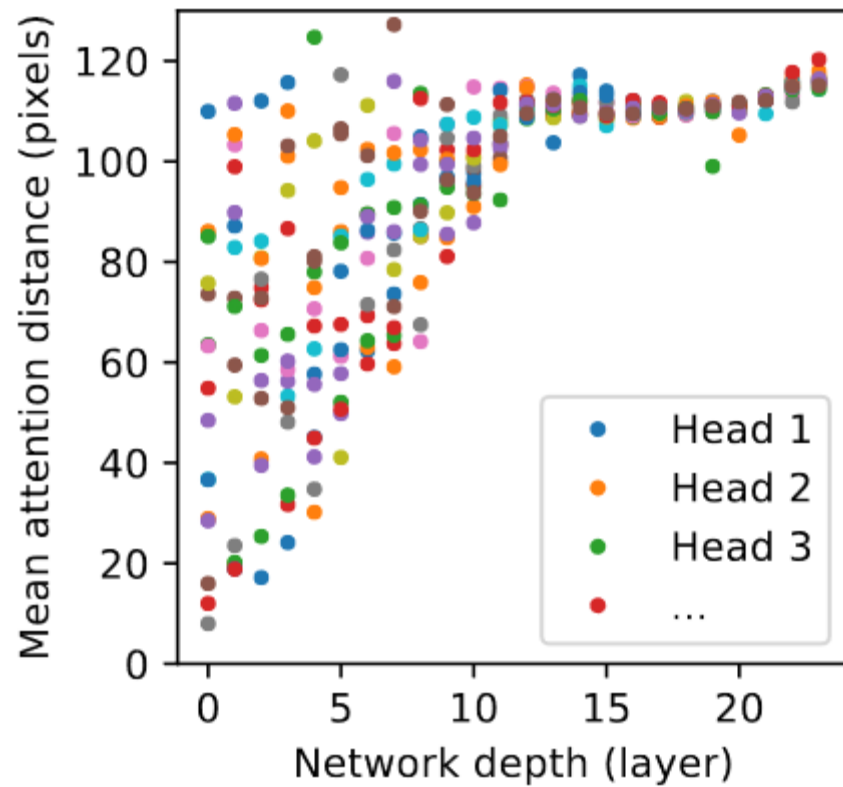
Figure 3: Transfer to ImageNet. While large ViT models perform worse than BiT ResNets (shaded area) when pre-trained on small datasets, they shine when pre-trained on larger datasets. Similarly, larger ViT variants overtake smaller ones as the dataset grows.

When trained on mid-sized datasets such as ImageNet, such models yield modest accuracies of a few percentage points below ResNets of comparable size. This seemingly discouraging outcome maybe expected: Transformers lack some of the inductive biases inherent to CNNs, such as translation equivariance and locality, and therefore do not generalize well when trained on insufficient amounts of data.

However, the picture changes if the models are trained on larger datasets (14M-300M images). We find that large scale training trumps inductive bias.

Dosovitskiy et al.

ViT-L/16



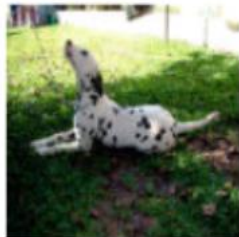
101



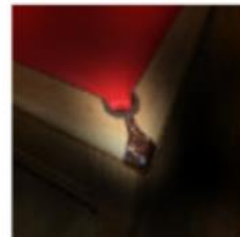
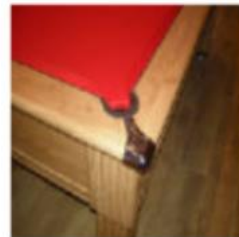
102



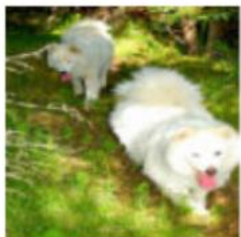
103



104



109



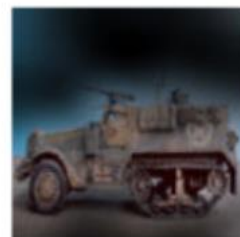
110



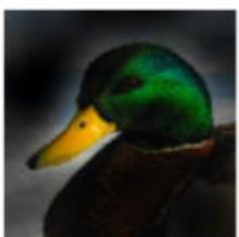
111



112



117



118



119



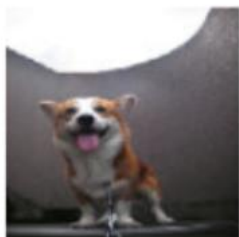
120



125



126

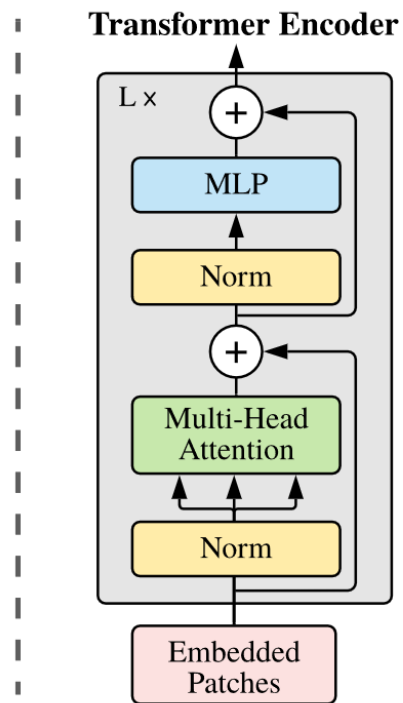
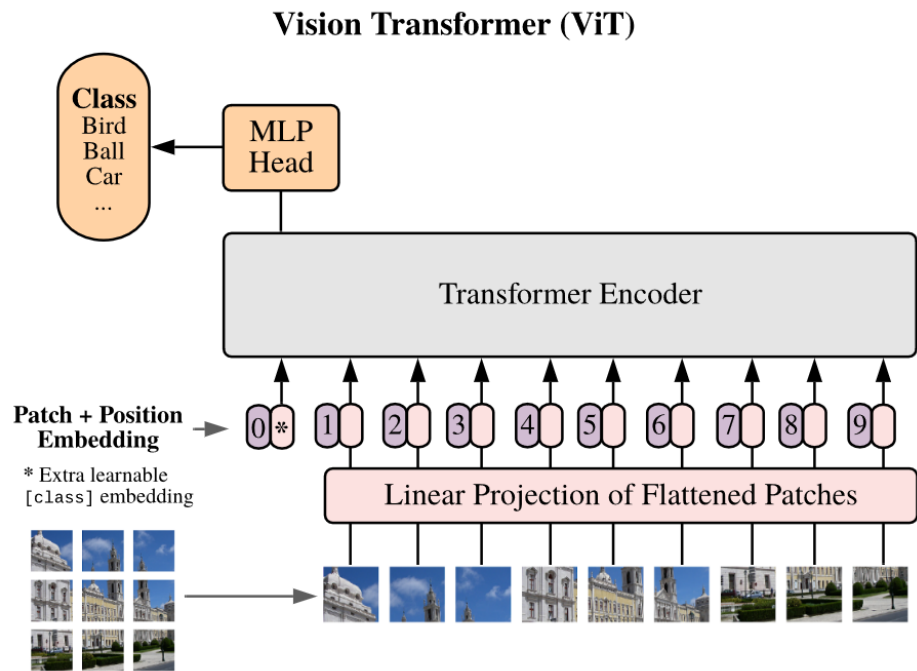


127

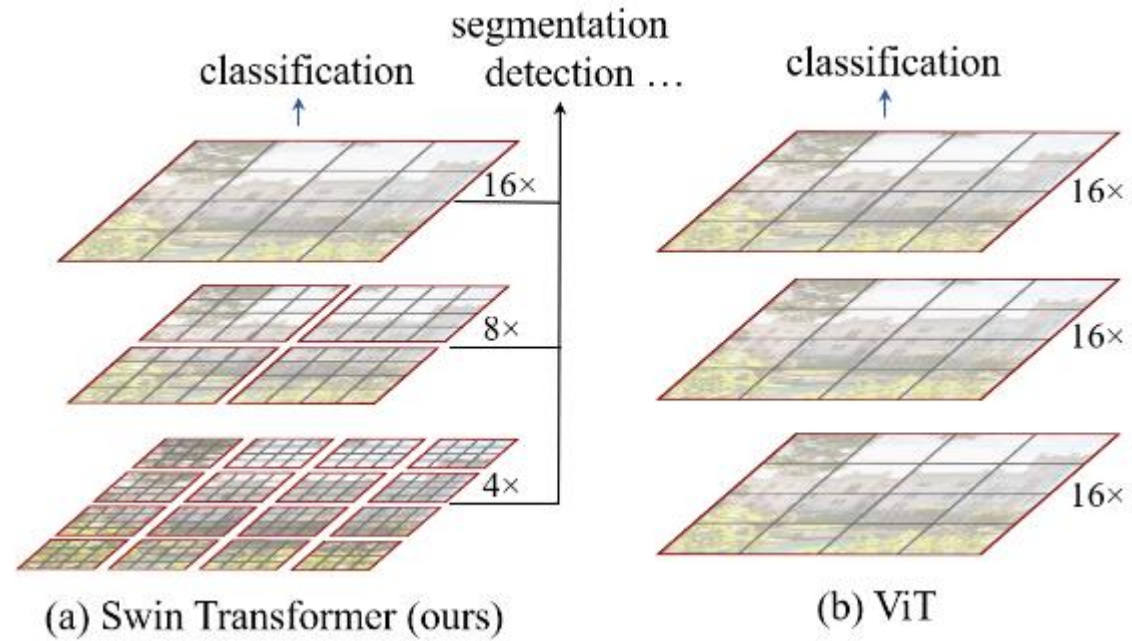


128





- This can't be ideal, right?



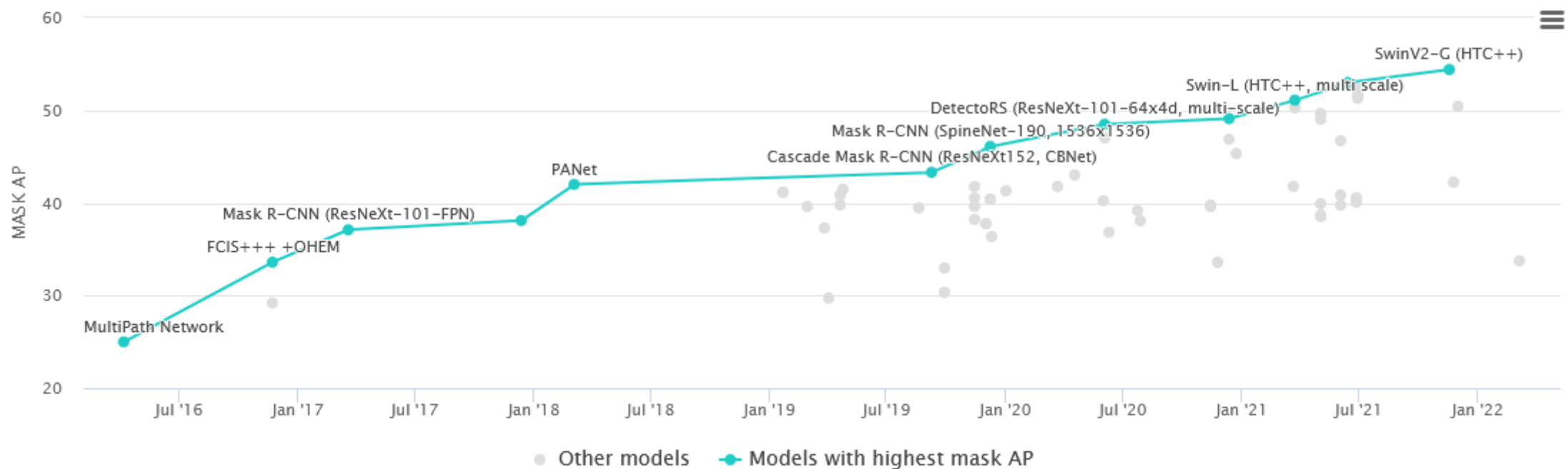
Swin Transformer: Hierarchical Vision Transformer using Shifted Windows

Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, Baining Guo

Instance Segmentation on COCO test-dev

Leaderboard Dataset

View by for



<https://paperswithcode.com/sota/instance-segmentation-on-coco>

A ConvNet for the 2020s

Zhuang Liu^{1,2*} Hanzi Mao¹ Chao-Yuan Wu¹ Christoph Feichtenhofer¹ Trevor Darrell² Saining Xie^{1†}

¹Facebook AI Research (FAIR) ²UC Berkeley

Code: <https://github.com/facebookresearch/ConvNeXt>

Abstract

The “Roaring 20s” of visual recognition began with the introduction of Vision Transformers (ViTs), which quickly superseded ConvNets as the state-of-the-art image classification model. A vanilla ViT, on the other hand, faces difficulties when applied to general computer vision tasks such as object detection and semantic segmentation. It is the hierarchical Transformers (e.g., Swin Transformers) that reintroduced several ConvNet priors, making Transformers practically viable as a generic vision backbone and demonstrating remarkable performance on a wide variety of vision tasks. However, the effectiveness of such hybrid approaches is still largely credited to the intrinsic superiority of Transformers, rather than the inherent inductive biases of convolutions. In this work, we reexamine the design spaces and test the limits of what a pure ConvNet can achieve. We gradually “modernize” a standard ResNet toward the design of a vision Transformer, and discover several key components that contribute to the performance difference along the way. The outcome of this exploration is a family of pure ConvNet models dubbed ConvNeXt. Constructed entirely from standard ConvNet modules, ConvNeXts compete favorably with Transformers in terms of accuracy and scalability, achieving 87.8% ImageNet top-1 accuracy and outperforming Swin Transformers on COCO detection and ADE20K segmentation, while maintaining the simplicity and efficiency of standard ConvNets.

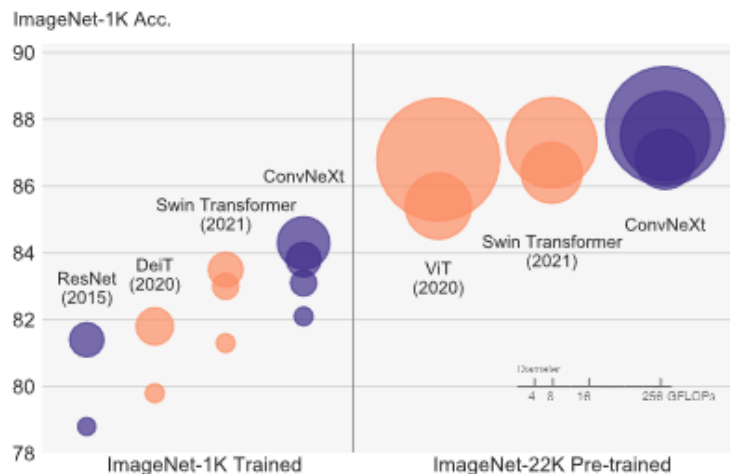


Figure 1. **ImageNet-1K classification** results for • ConvNets and ○ vision Transformers. Each bubble’s area is proportional to FLOPs of a variant in a model family. ImageNet-1K/22K models here take $224^2/384^2$ images respectively. ResNet and ViT results were obtained with improved training procedures 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.

visual feature learning. The introduction of AlexNet [40] precipitated the “ImageNet moment” [59], ushering in a new era of computer vision. The field has since evolved at a rapid speed. Representative ConvNets like VGGNet [64], Inceptions [68], ResNe(X)t [28, 87], DenseNet [36], MobileNet [34], EfficientNet [71] and RegNet [54] focused on different aspects of accuracy, efficiency and scalability, and popularized many useful design principles.

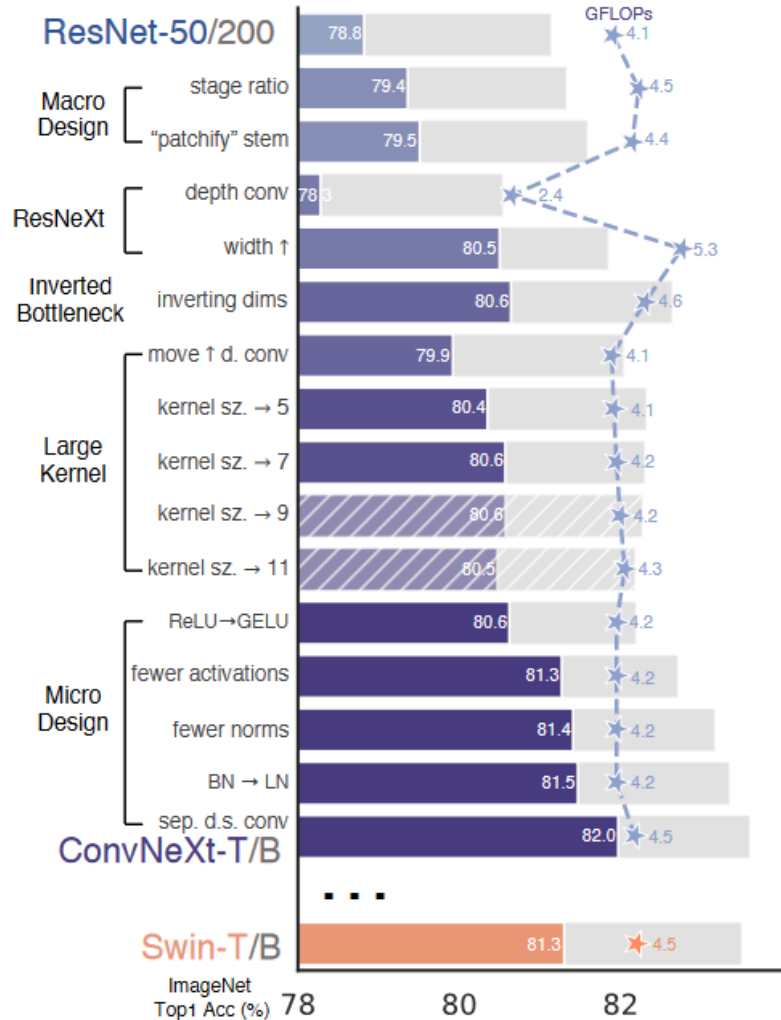


Figure 2. We modernize a standard ConvNet (ResNet) towards the design of a hierarchical vision Transformer (Swin), without introducing any attention-based modules. The foreground bars are model accuracies in the ResNet-50/Swin-T FLOP regime; results for the ResNet-200/Swin-B regime are shown with the 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.

backbone	FLOPs	FPS	AP ^{box}	AP ₅₀ ^{box}	AP ₇₅ ^{box}	AP ^{mask}	AP ₅₀ ^{mask}	AP ₇₅ ^{mask}
Mask-RCNN 3× schedule								
○ Swin-T	267G	23.1	46.0	68.1	50.3	41.6	65.1	44.9
● ConvNeXt-T	262G	25.6	46.2	67.9	50.8	41.7	65.0	44.9
Cascade Mask-RCNN 3× schedule								
● ResNet-50	739G	16.2	46.3	64.3	50.5	40.1	61.7	43.4
● X101-32	819G	13.8	48.1	66.5	52.4	41.6	63.9	45.2
● X101-64	972G	12.6	48.3	66.4	52.3	41.7	64.0	45.1
○ Swin-T	745G	12.2	50.4	69.2	54.7	43.7	66.6	47.3
● ConvNeXt-T	741G	13.5	50.4	69.1	54.8	43.7	66.5	47.3
○ Swin-S	838G	11.4	51.9	70.7	56.3	45.0	68.2	48.8
● ConvNeXt-S	827G	12.0	51.9	70.8	56.5	45.0	68.4	49.1
○ Swin-B	982G	10.7	51.9	70.5	56.4	45.0	68.1	48.9
● ConvNeXt-B	964G	11.4	52.7	71.3	57.2	45.6	68.9	49.5
○ Swin-B [‡]	982G	10.7	53.0	71.8	57.5	45.8	69.4	49.7
● ConvNeXt-B [‡]	964G	11.5	54.0	73.1	58.8	46.9	70.6	51.3
○ Swin-L [‡]	1382G	9.2	53.9	72.4	58.8	46.7	70.1	50.8
● ConvNeXt-L [‡]	1354G	10.0	54.8	73.8	59.8	47.6	71.3	51.7
● ConvNeXt-XL [‡]	1898G	8.6	55.2	74.2	59.9	47.7	71.6	52.2

Table 3. COCO object detection and segmentation results using Mask-RCNN and Cascade Mask-RCNN. [‡] indicates that the model is pre-trained on ImageNet-22K. ImageNet-1K pre-trained Swin results are from their Github repository [3]. AP numbers of the ResNet-50 and X101 models are from [45]. We measure FPS on an A100 GPU. FLOPs are calculated with image size (1280, 800).

Summary

- “Attention” models outperform recurrent models and convolutional models for sequence processing. They allow long range interactions.
- These models do best with LOTS of training data
- They seem like a good fit for point processing tasks, although maybe there isn’t enough data for them to outperform other methods.
- Naïve attention mechanisms have quadratic complexity with the number of input tokens, but there are often workarounds for this.
- For “traditional” image processing, it is not clear if Transformers outperform convolutional networks.