max planck institut
informatik

SIC Saarland Informatics Campus

# High Level Computer Vision

# Transformer Architecture & Computer Vision

# @ June 5, 2024

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**cms.sic.saarland/hlcvss24/**

**Max Planck Institute for Informatics & Saarland University,**
**Saarland Informatics Campus Saarbrücken**

# Transformer for Computer Vision Tasks

- Many Transformer Based Methods in the last Years… e.g. for
  - Image Classification [Dosovitskiy et al., 2020] [Touvron et al., 2020]
  - Object detection [Carion et al., 2020] [Zhu et al., 2020]
  - Image Segmentation [Ye et al., 2020] [Yie et al., 2021]
  - Image super resolution [Yang et al., 2020]
  - Video understanding [Sun et al., 2019] [Girdhar et al., 2019]
  - Image generation [Chen et al., 2020]
  - Visual question answering [Tan et al., 2019] [Su et al., 2019]
  - …

# Overview of Today's Lecture

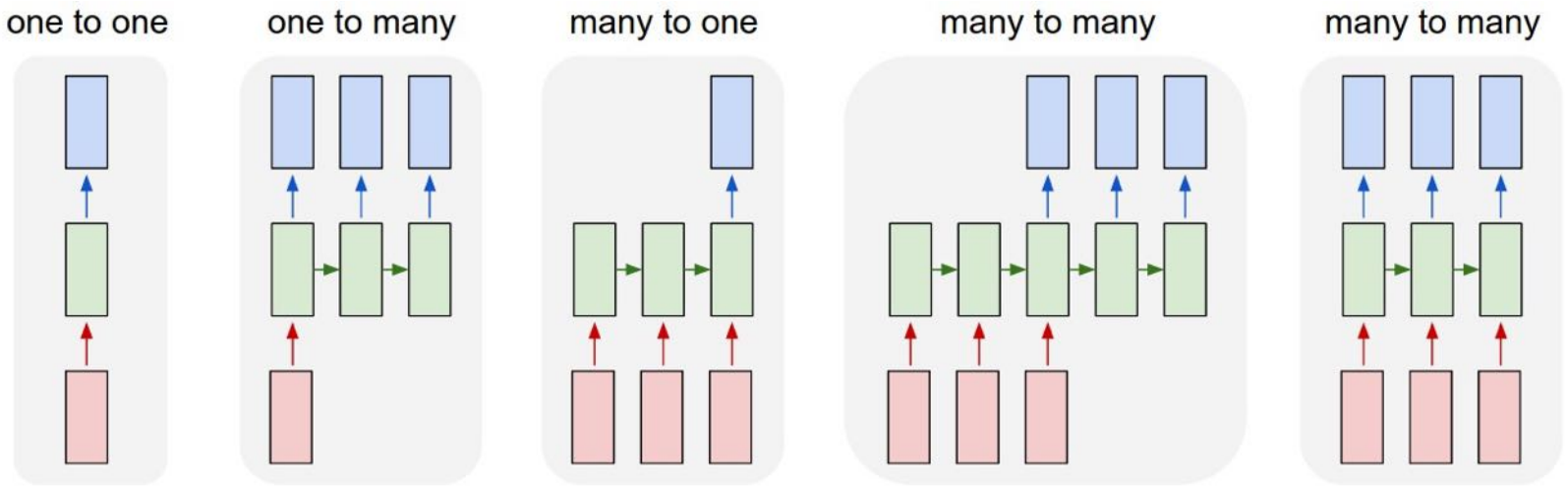
- Introduction of Transformer
  - Attention Is All You Need @ NeurIPS 2017 - https://arxiv.org/abs/1706.03762
- Vision Transformer (ViT) for Image Classification
  - An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale @ ICLR 2021 https://arxiv.org/abs/2010.11929
- Object Detection with Transformers (DETR)
  - DETR: End-to-End Object Detection with Transformers @ ECCV 2020 https://arxiv.org/abs/2005.12872
  - Deformable DETR: Deformable Transformers for End-to-End Object Detection @ ICLR 2021 https://arxiv.org/abs/2010.04159
- Swin Transformer
  - Swin Transformer: Hierarchical Vision Transformer using Shifted Windows @ ICCV 2021 https://arxiv.org/abs/2103.14030

*pictures are from http://jalammar.github.io/illustrated-transformer/*

# Transformer for Machine Translation

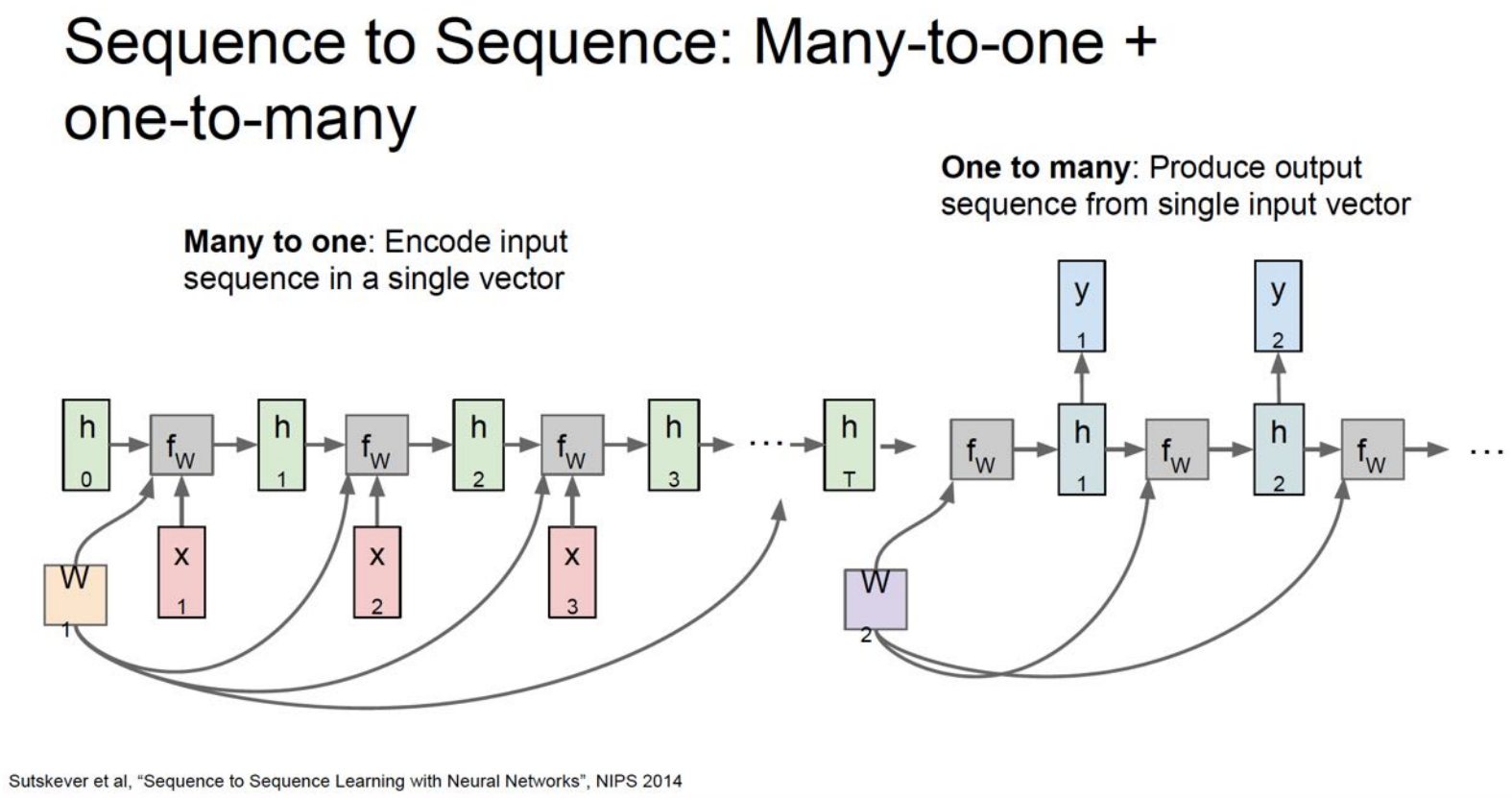

*Attention is all you need. Vaswani et al. NeurIPS 2017*

# Recurrent Networks offer a lot of flexibility:



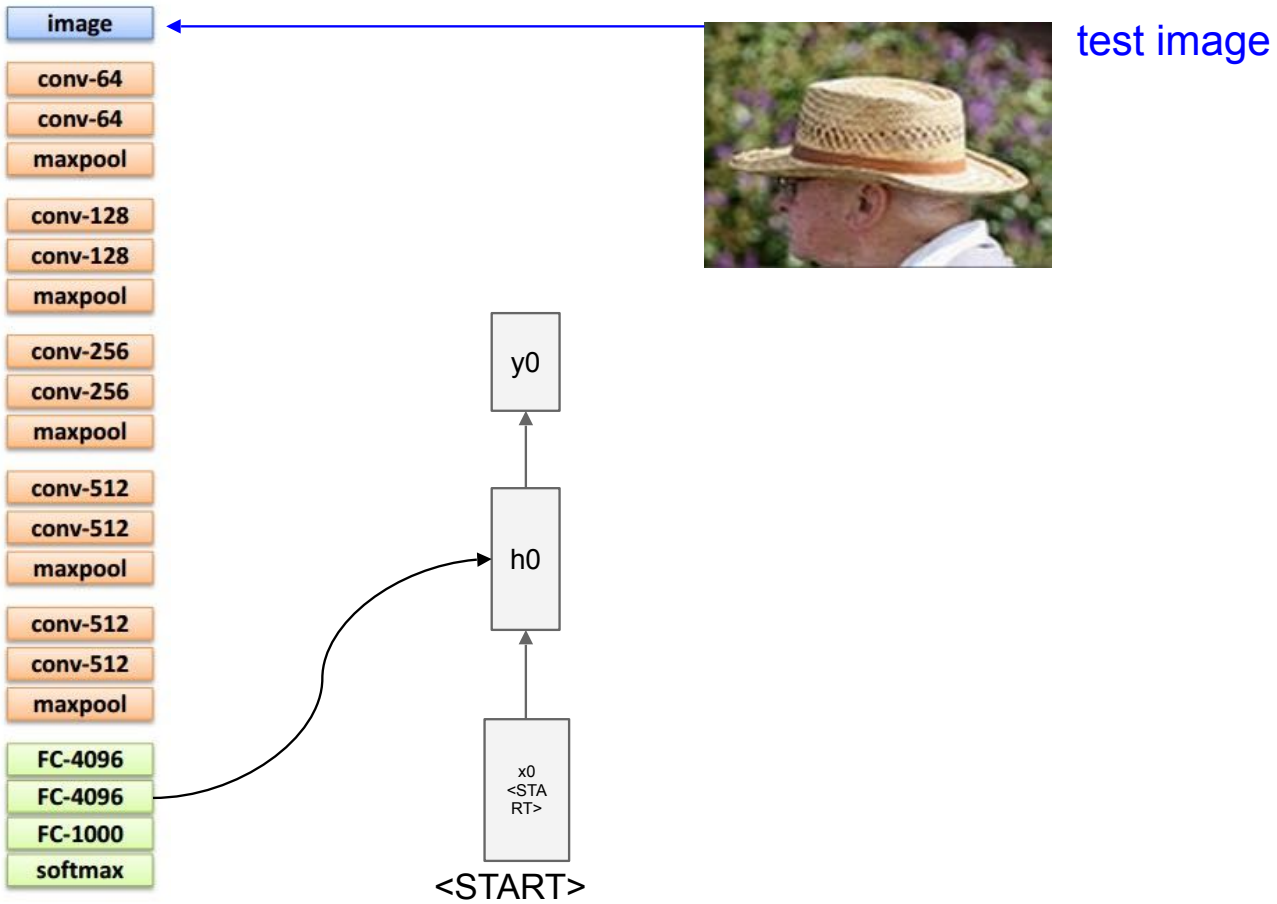

slide credit: Andrej Karpathy

# Sequence to Sequence (e.g. Language Translation)




slide credit: Fei-Fei, Justin Johnson, Serena Yeung

# Image Captioning = Image to Sentence Translation

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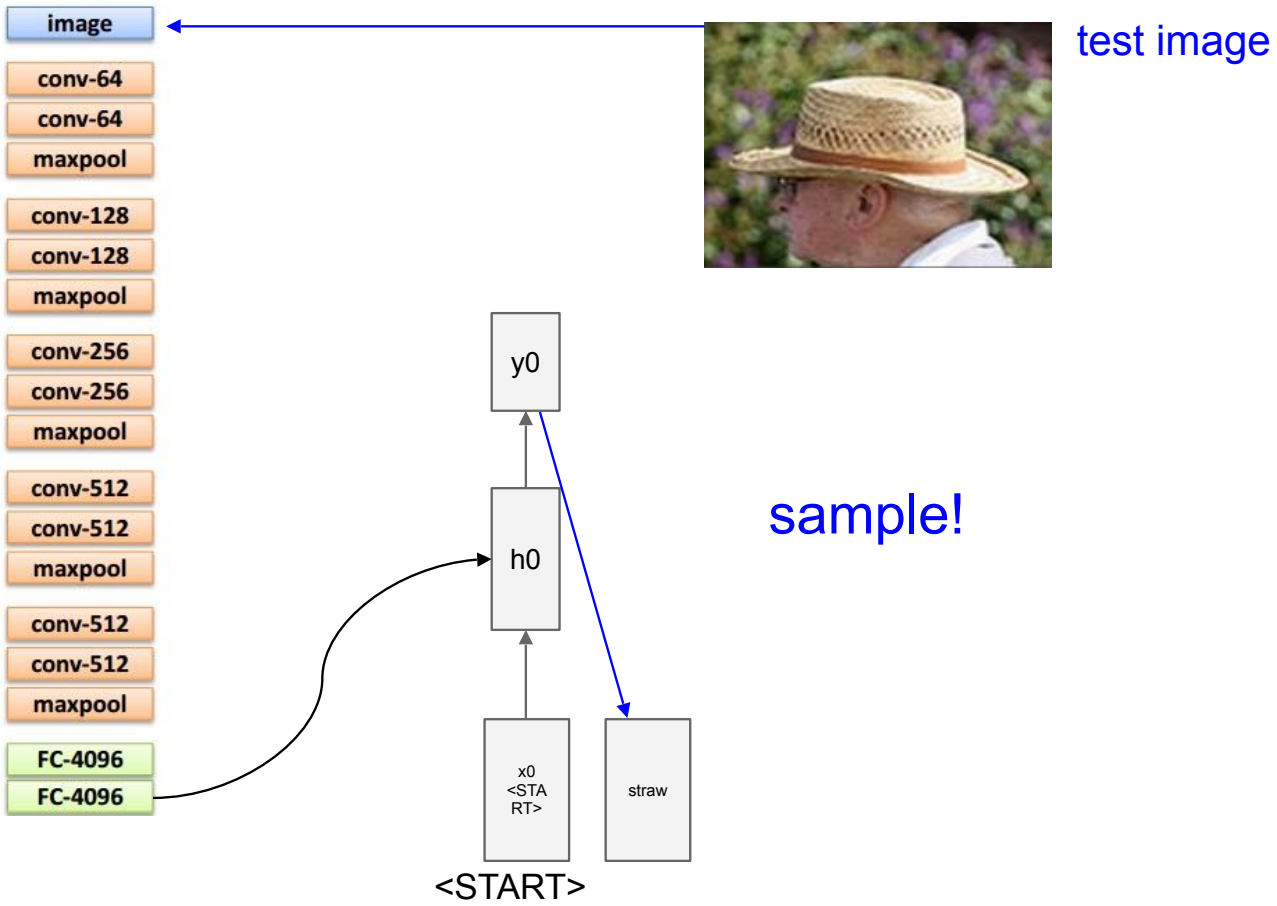


slide credit: Andrej Karpathy

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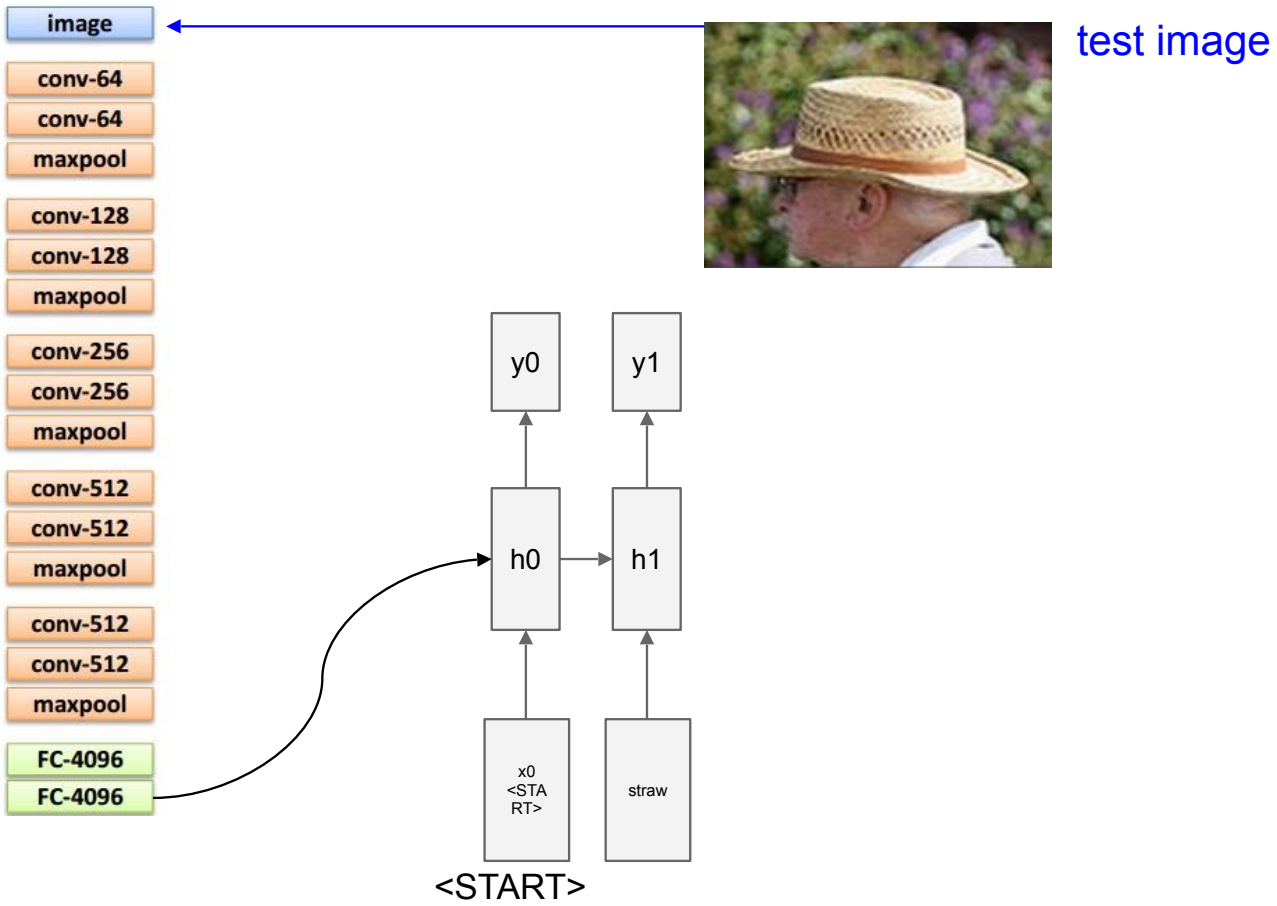


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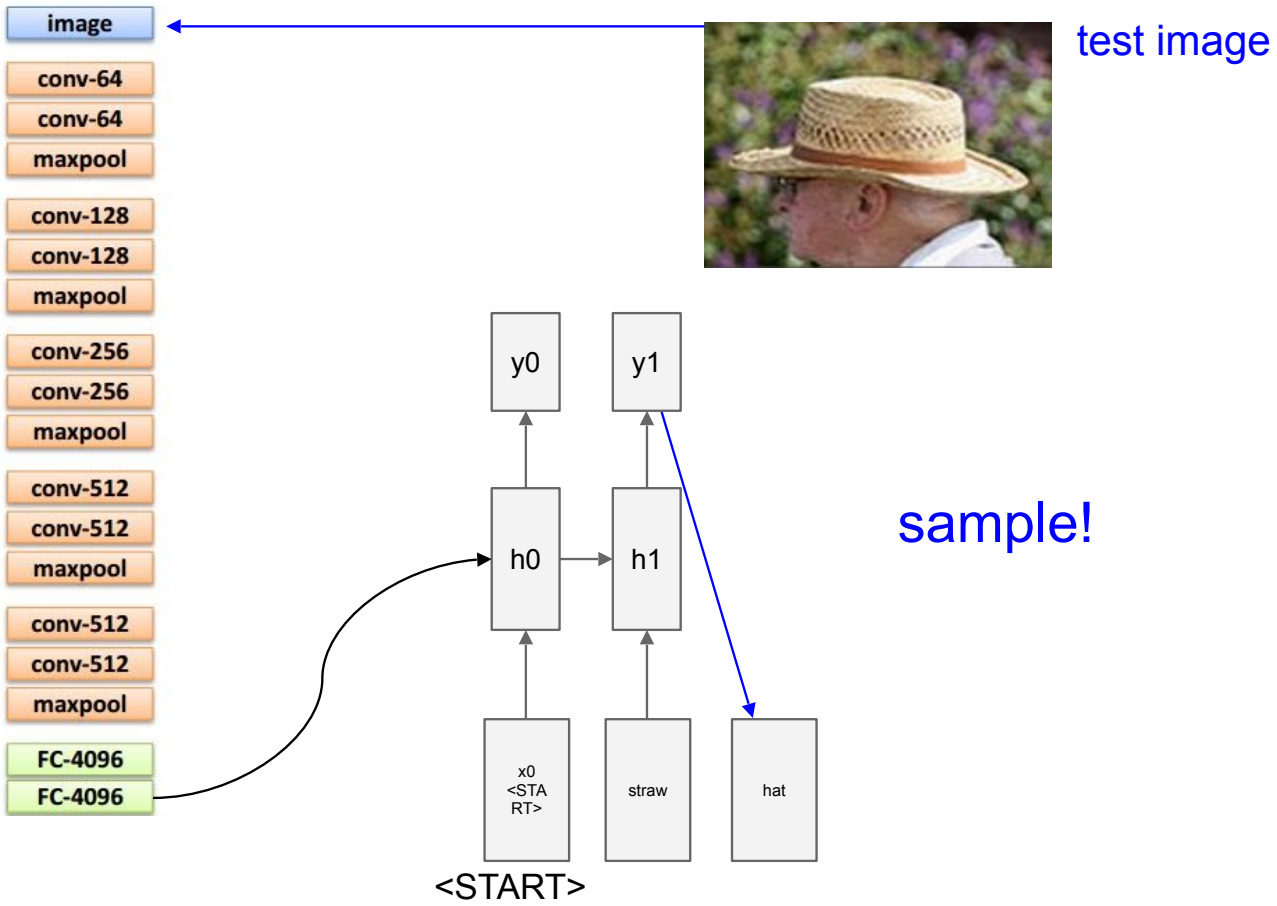


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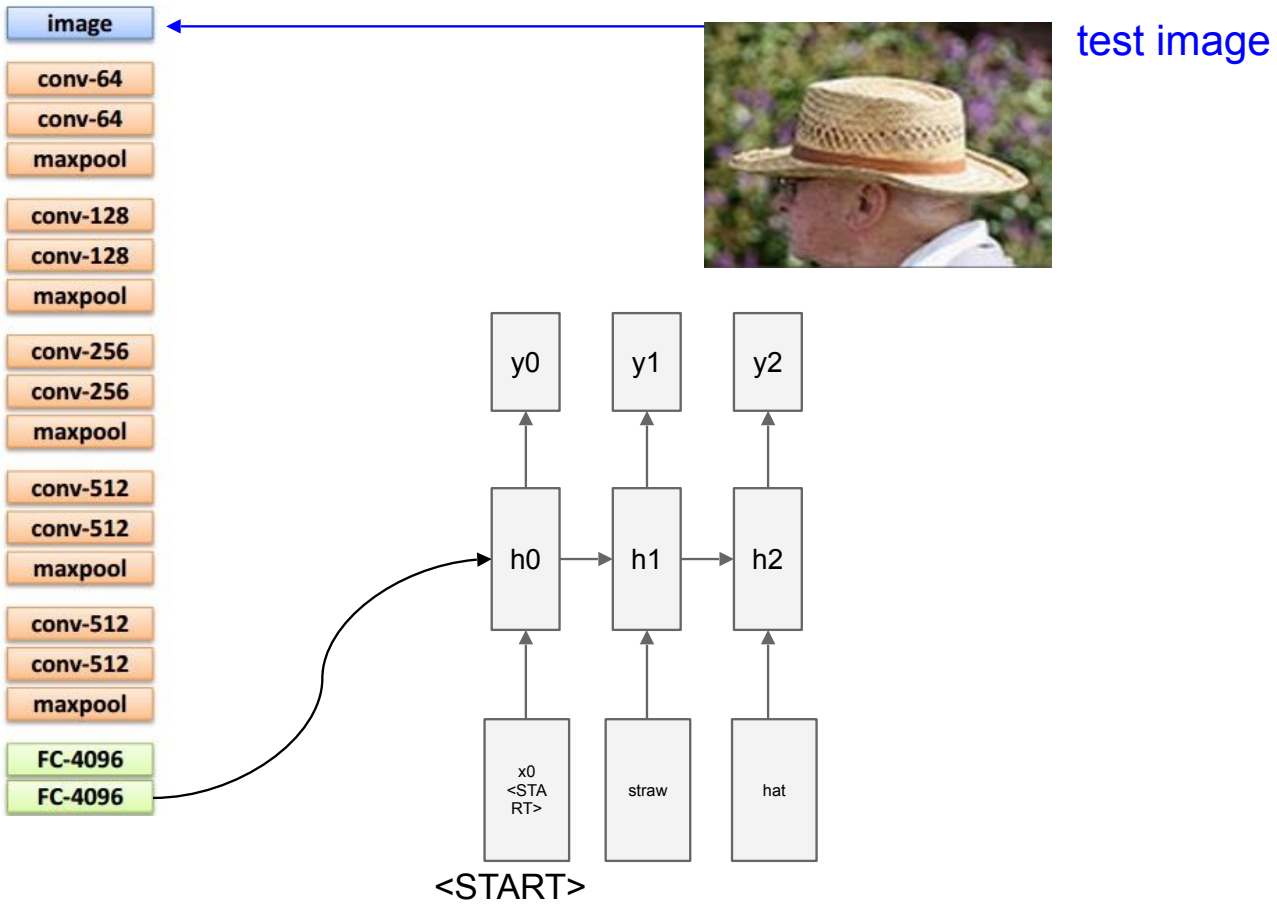


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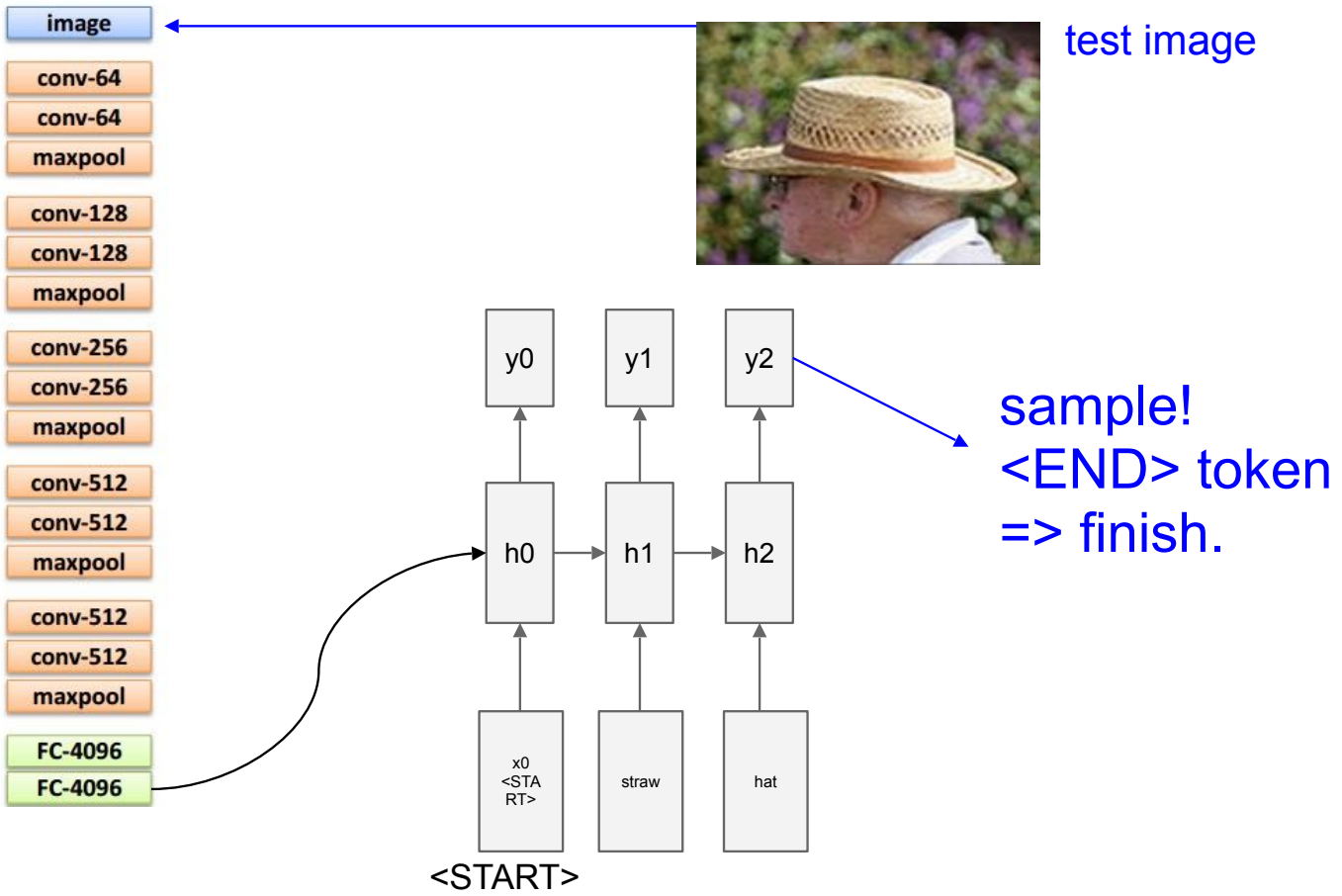


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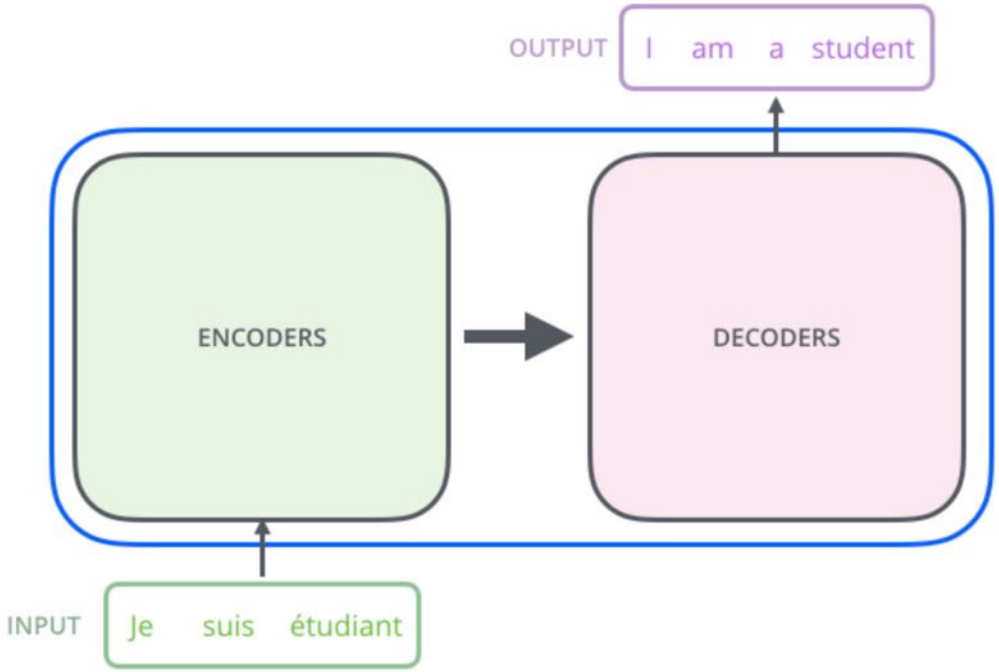
*pictures are from http://jalammar.github.io/illustrated-transformer/*

# Transformer: Architecture Overview

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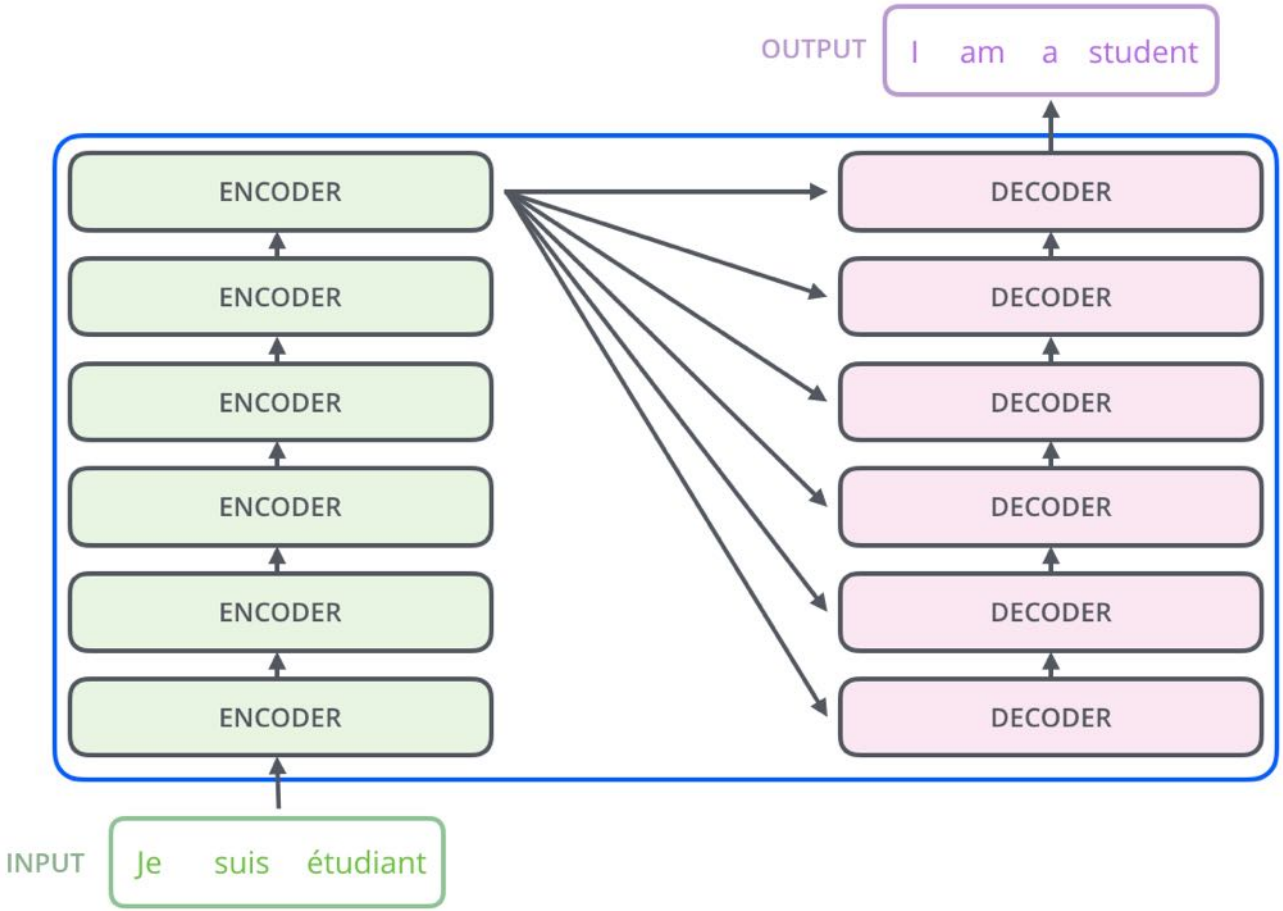
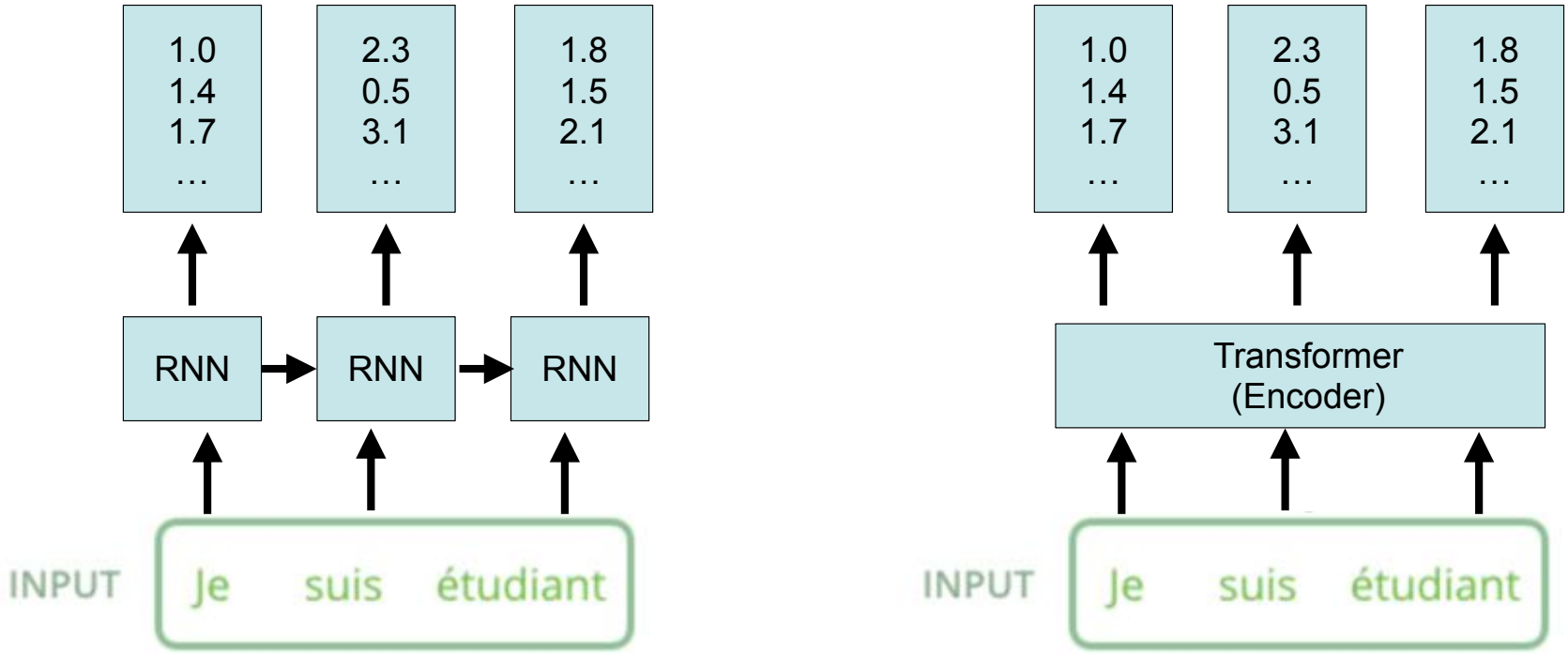


# Encoder — Difference RNN vs. Transformer Encoder

- Transformer Language: here, each word is a "**token**"

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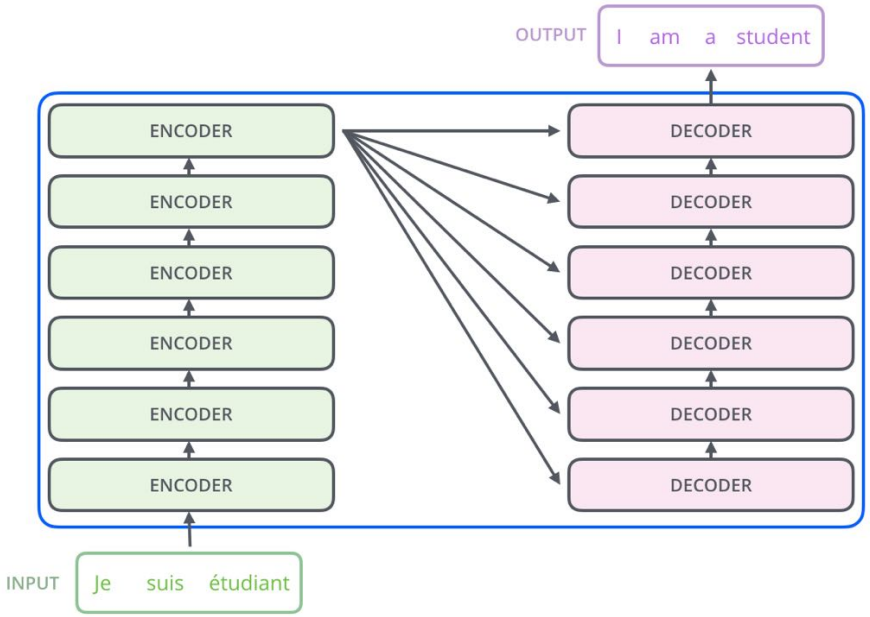


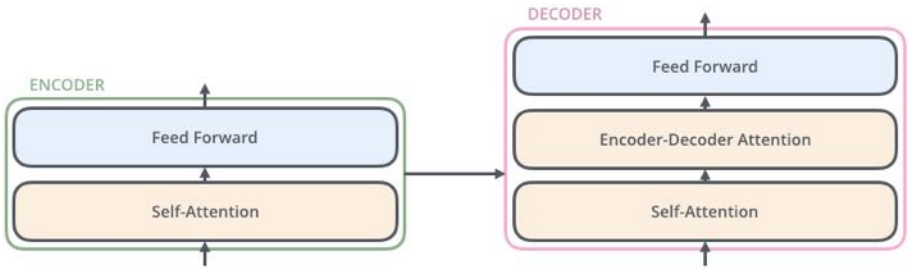


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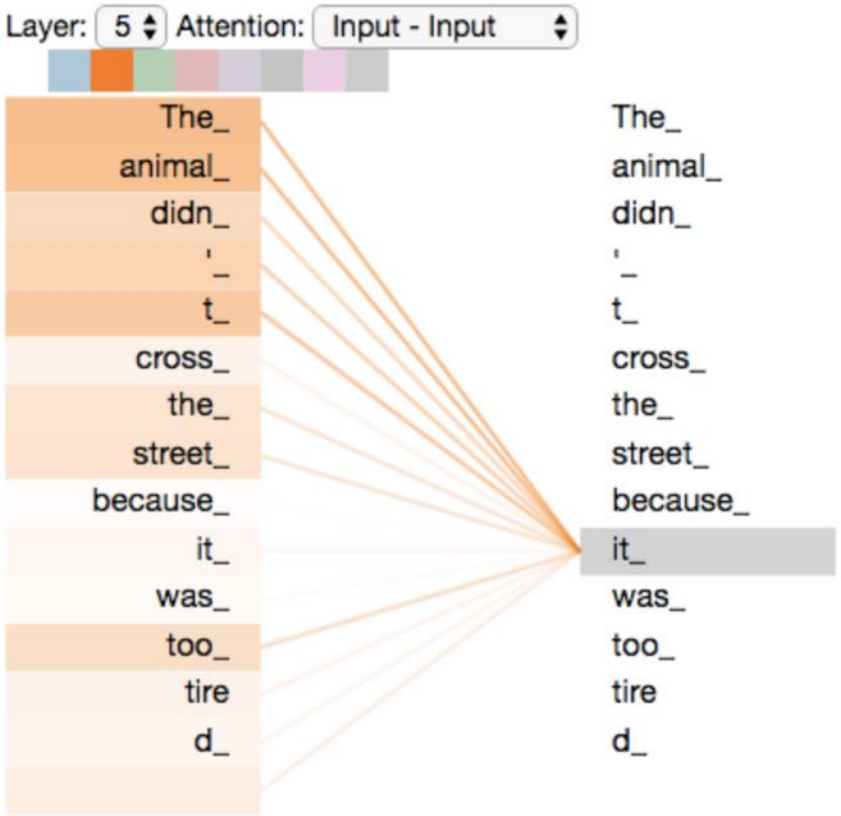
# What is Self-Attention?

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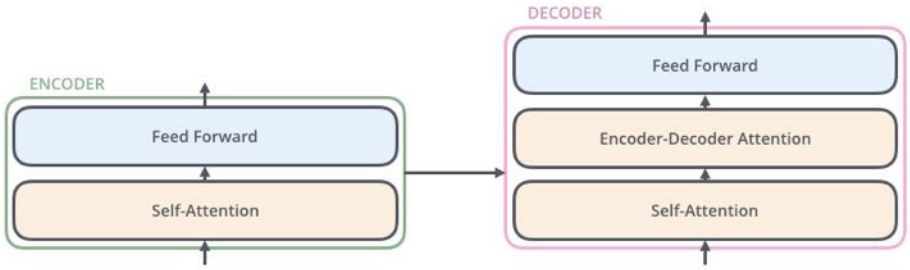


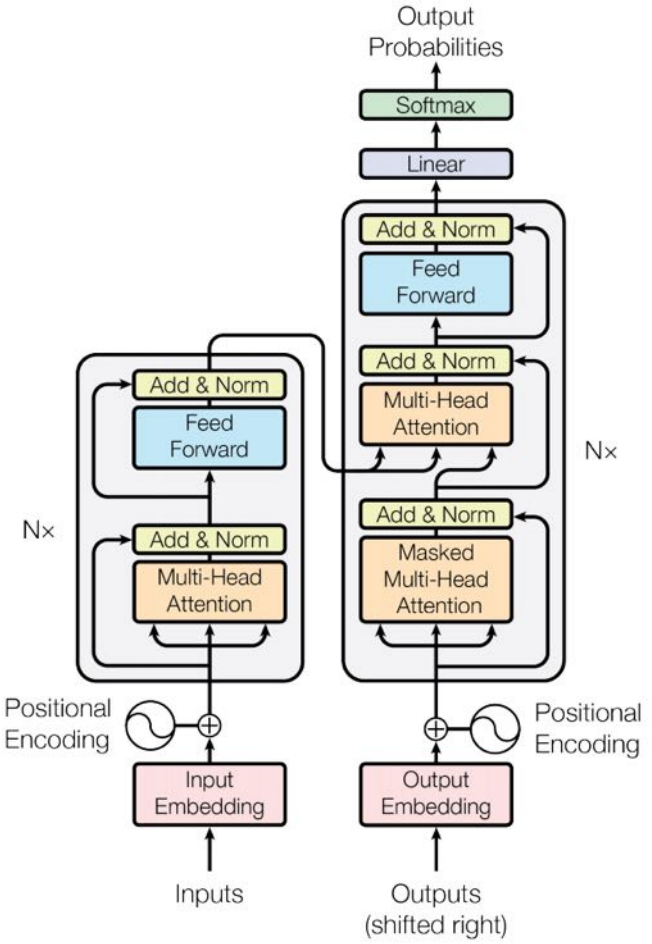


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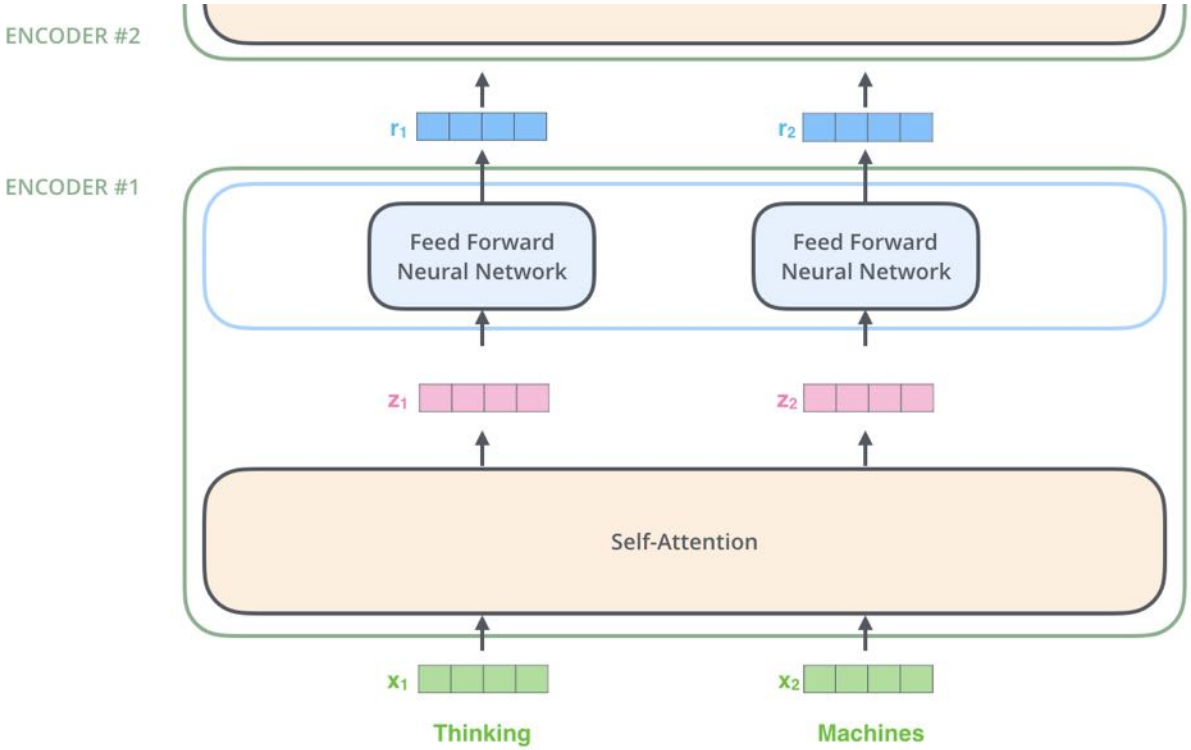
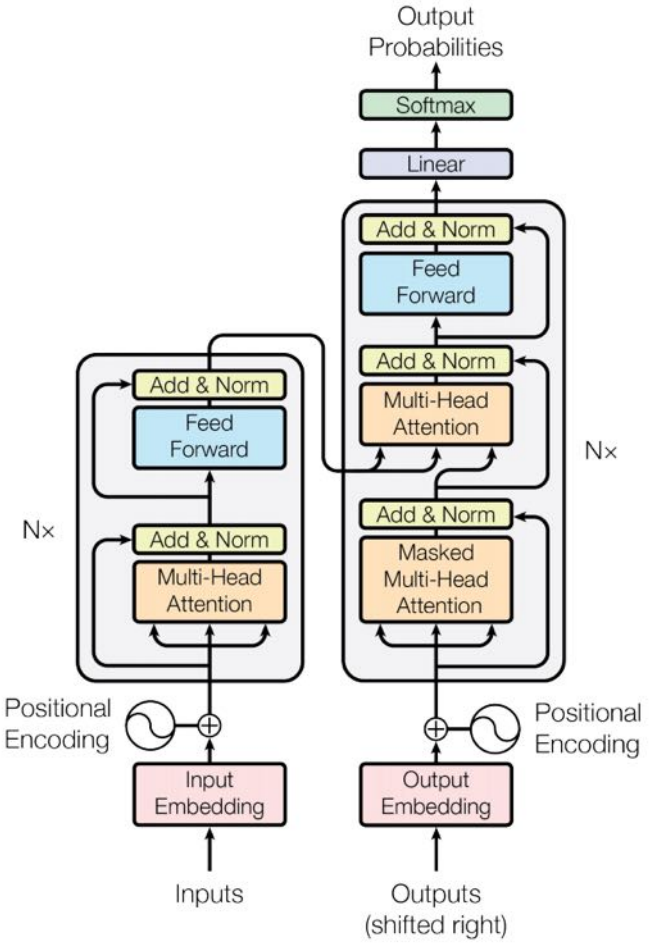
# Encoder — Consumes a Set of (Word) Tokens

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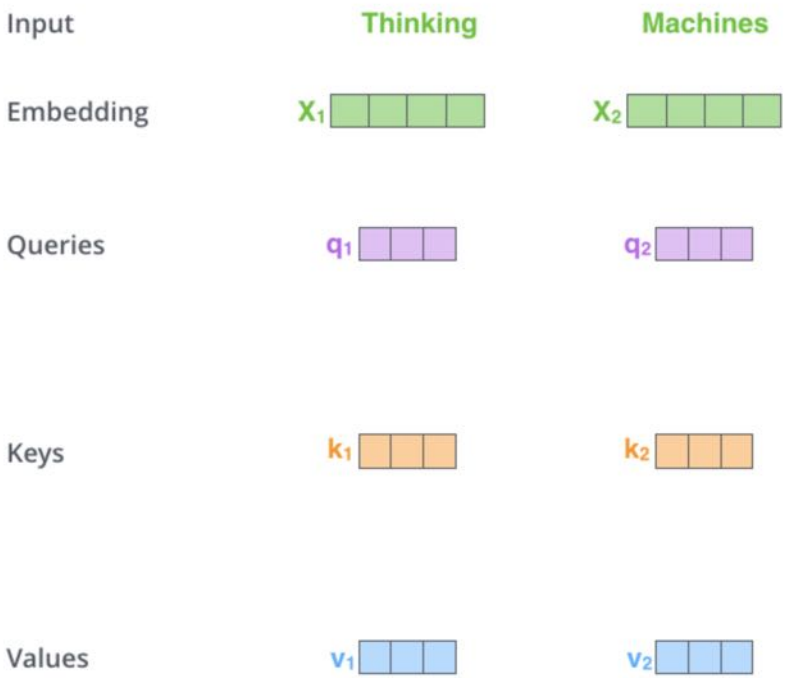
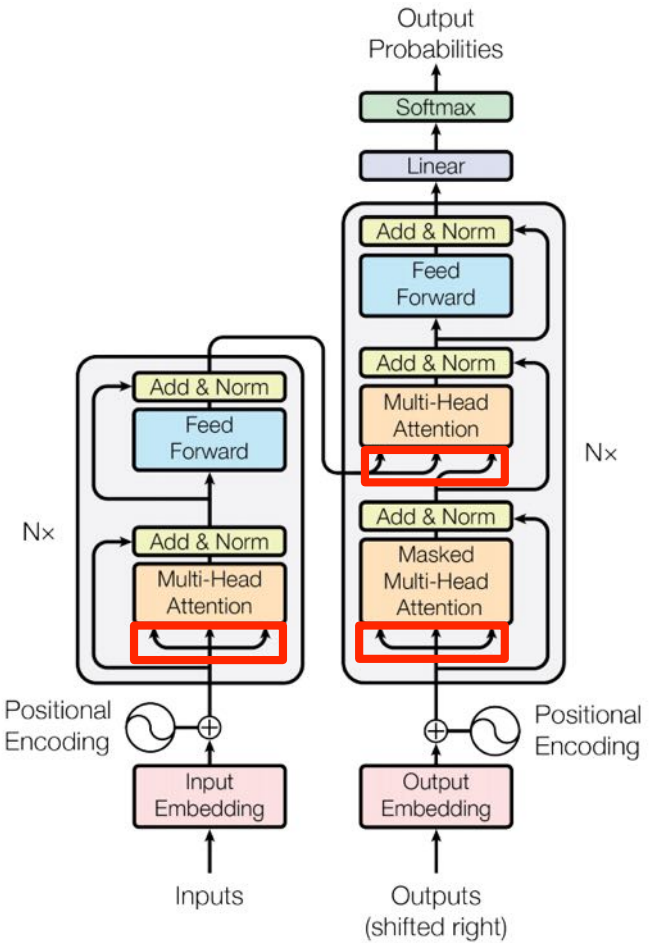
# Self-Attention: Query, Key and Value

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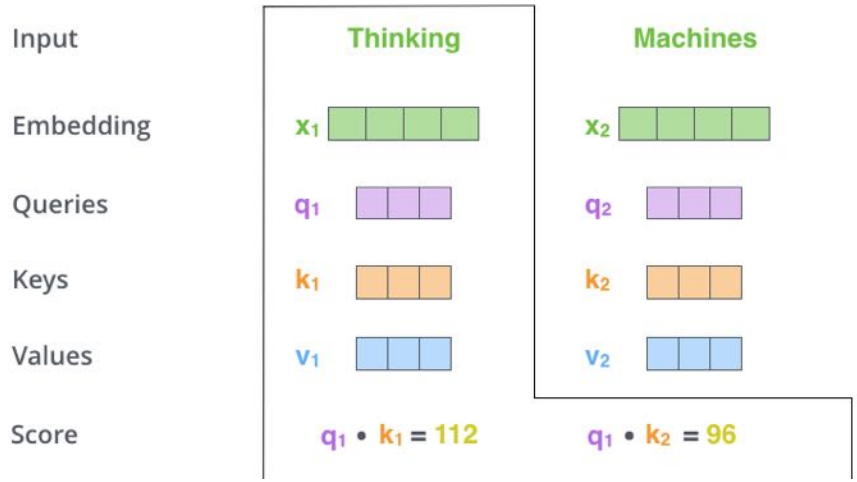


slide credit: Yongqin Xian

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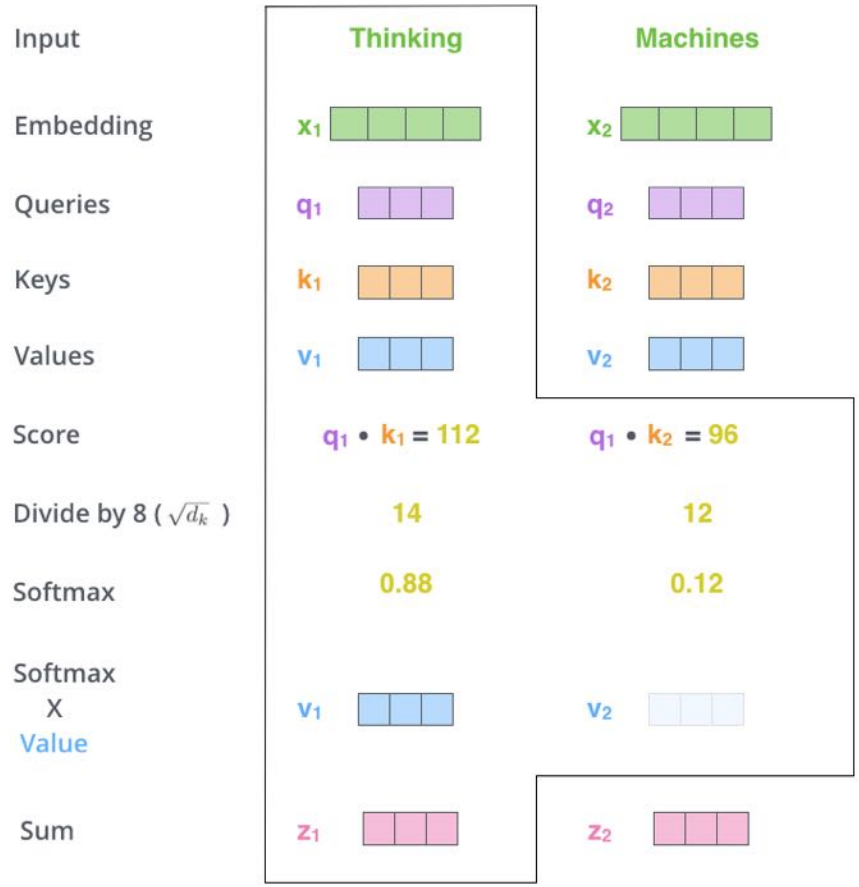


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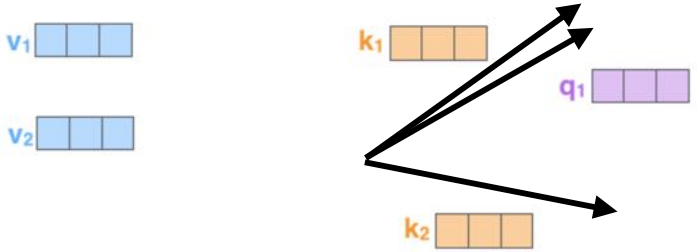


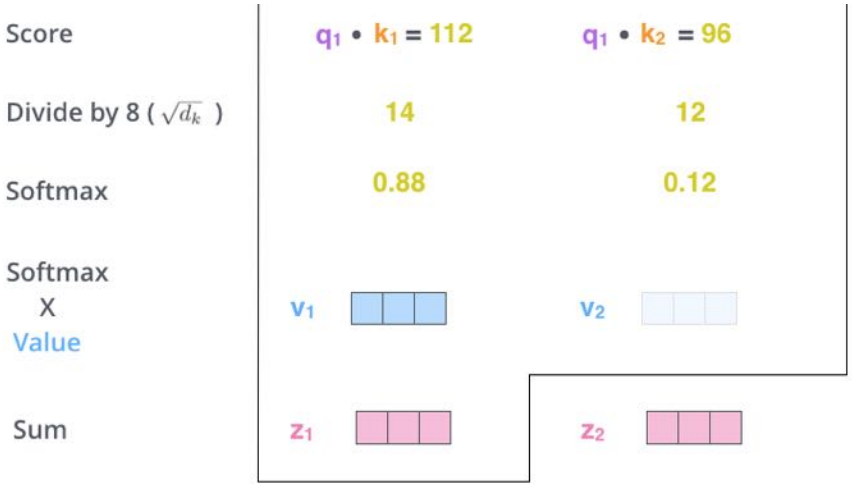

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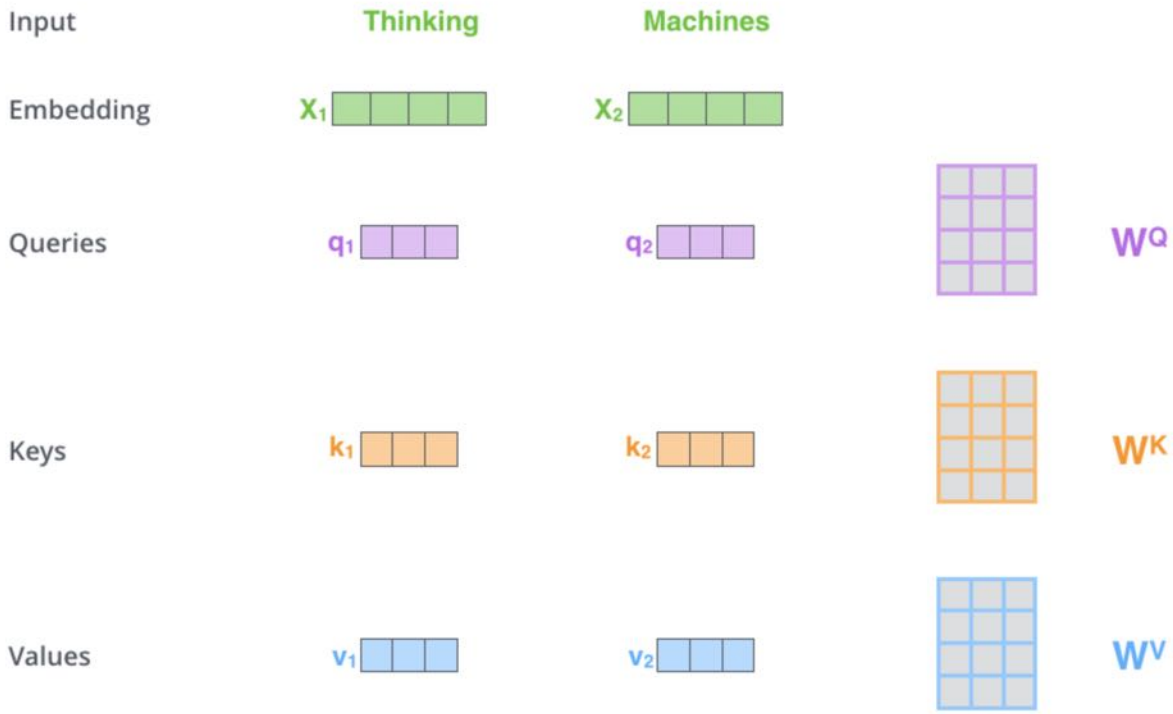


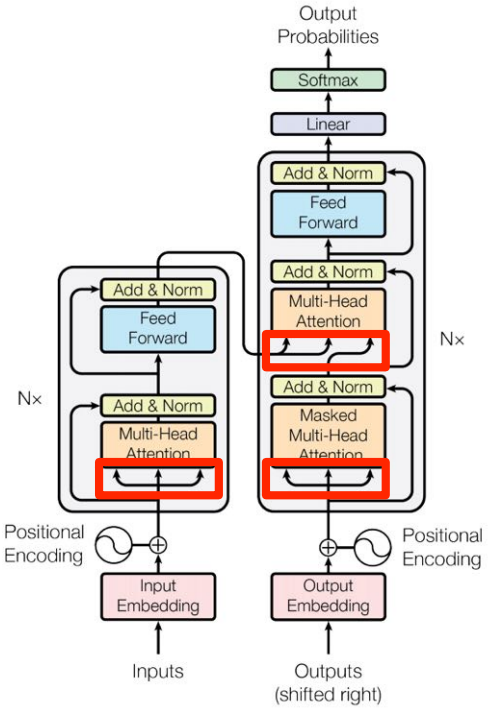


*Attention is all you need. Vaswani et al. NeurIPS 2017*

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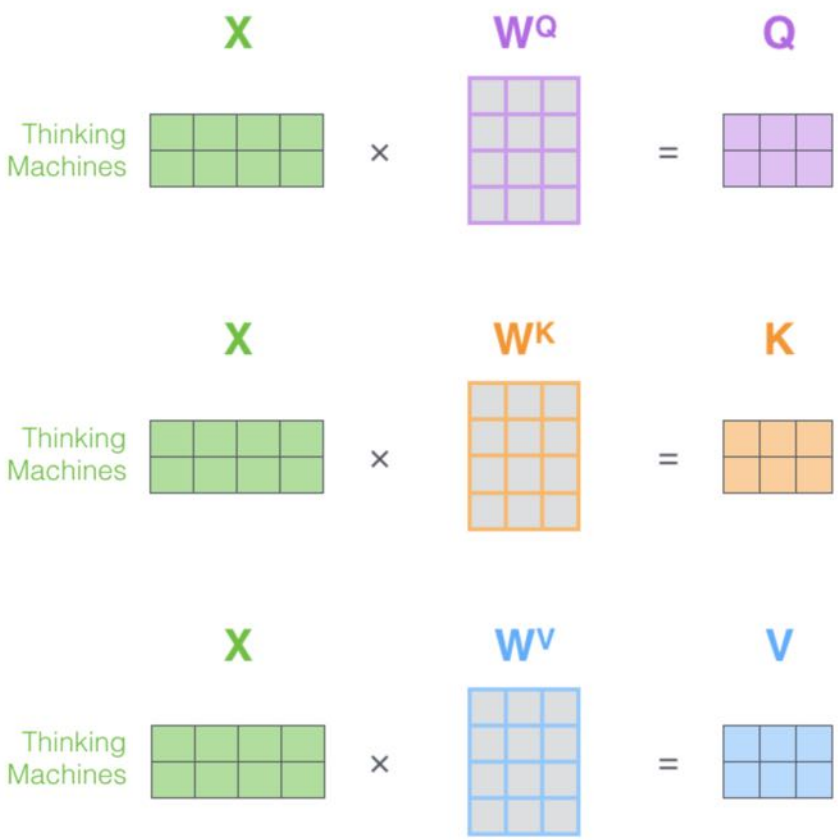


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slide credit: Yongqin Xian

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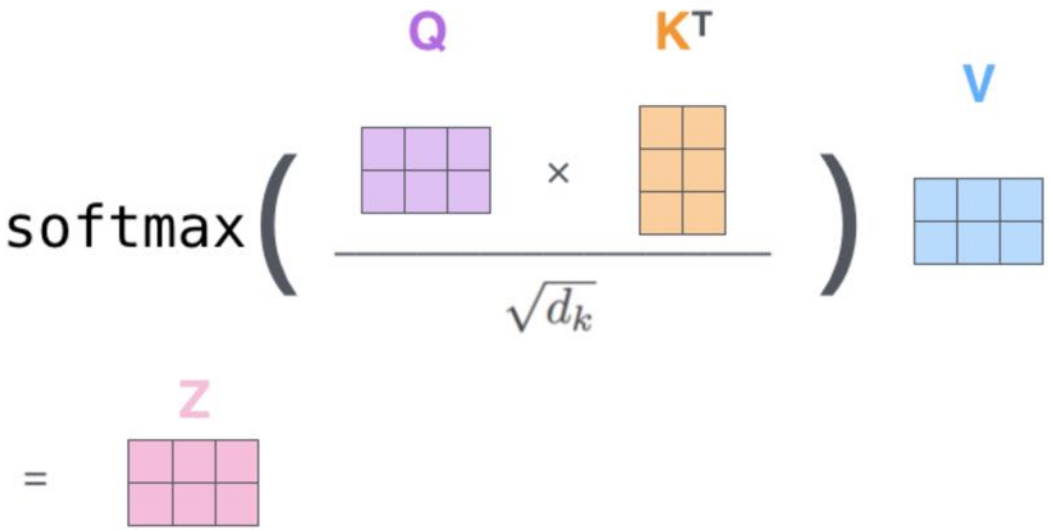
# Self-Attention: Output

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slide credit: Yongqin Xian

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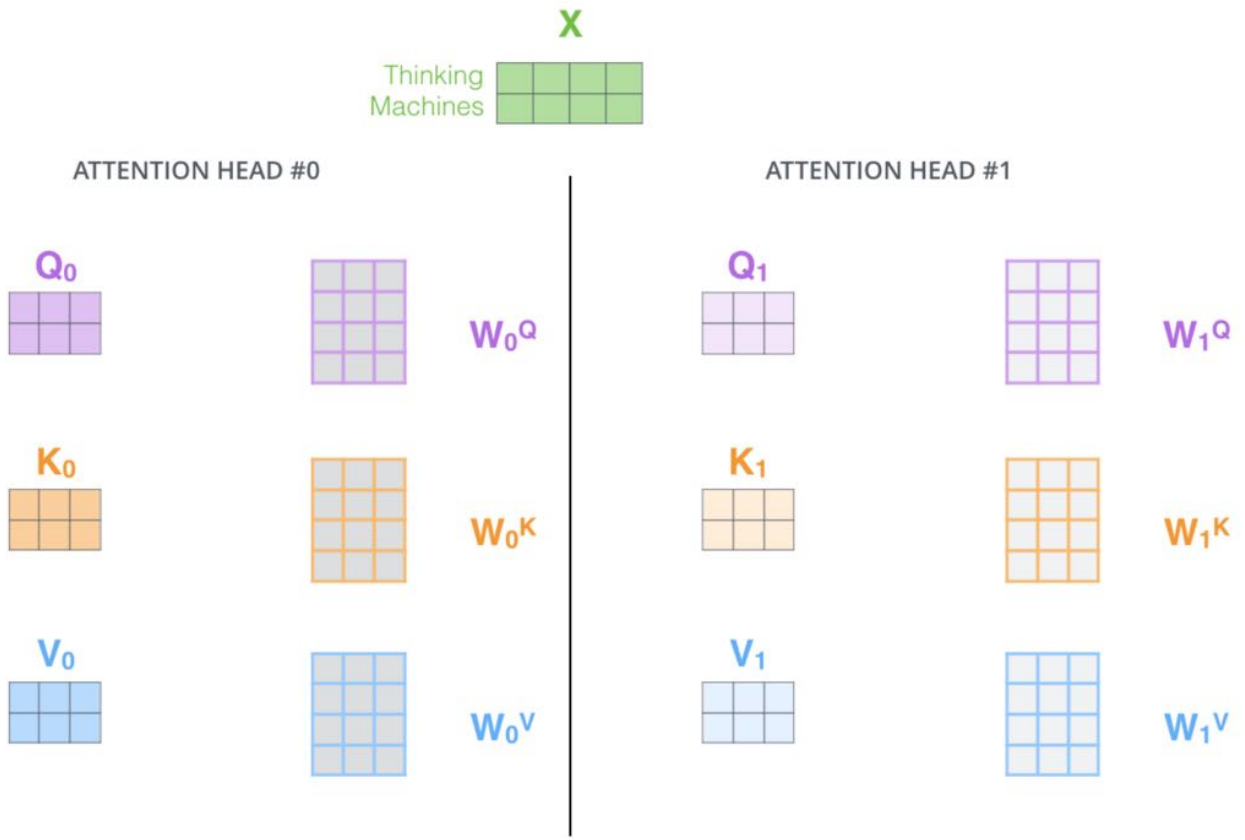
# Multi-Head Self-Attention

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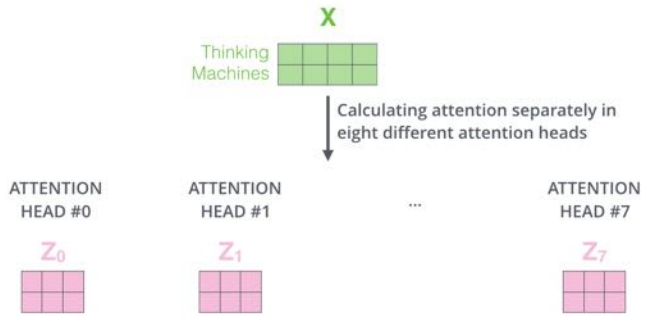


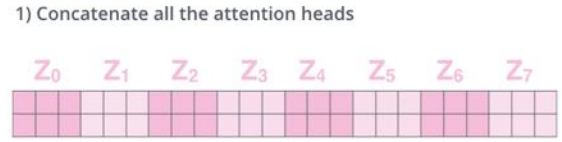


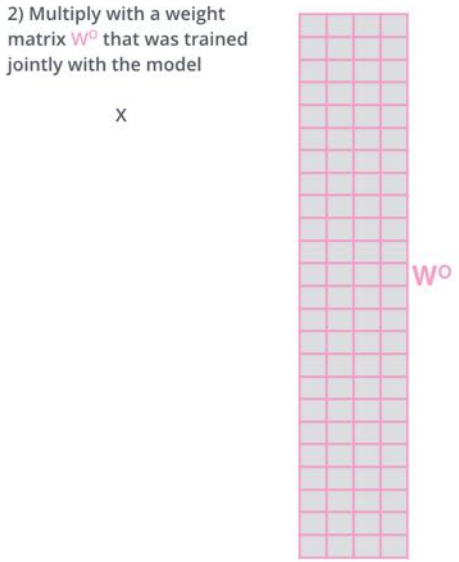


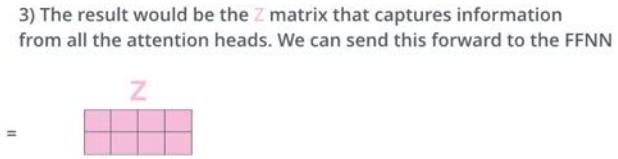

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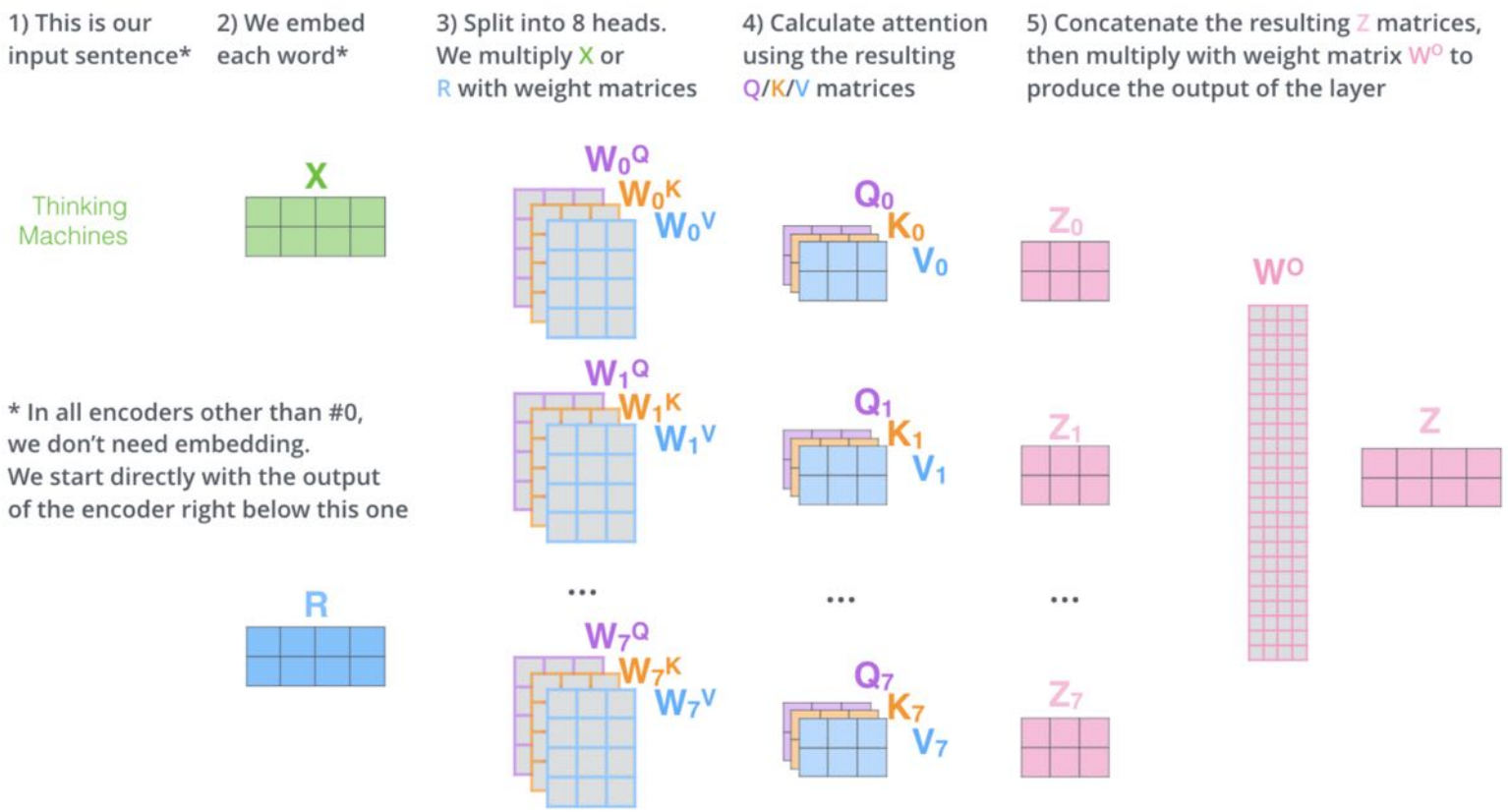


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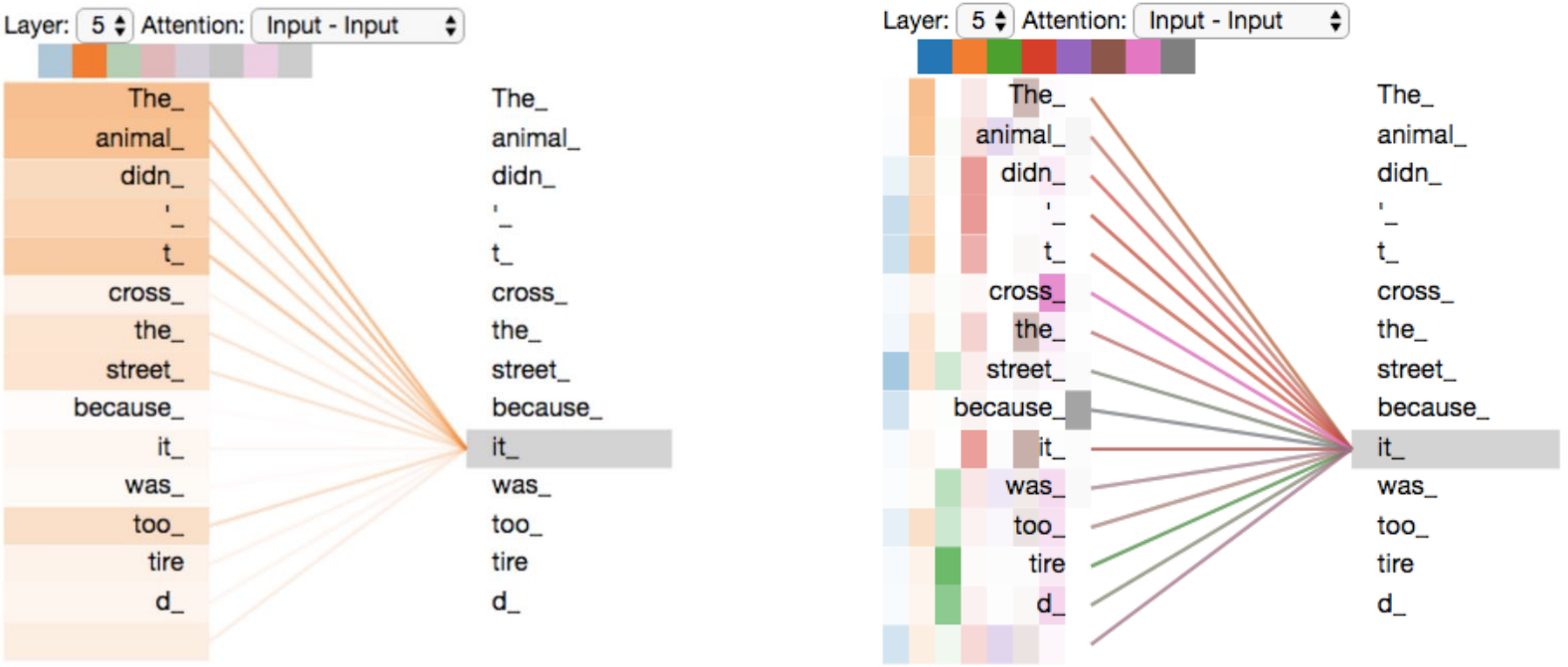
# Multi-Head Self-Attention — How to Interpret?

- One head vs. multi-head… hart to interpret

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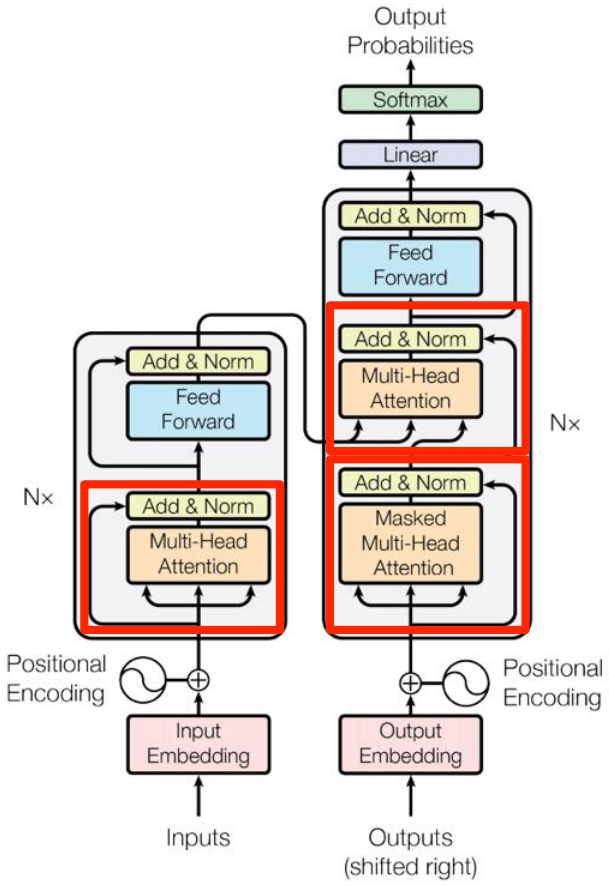
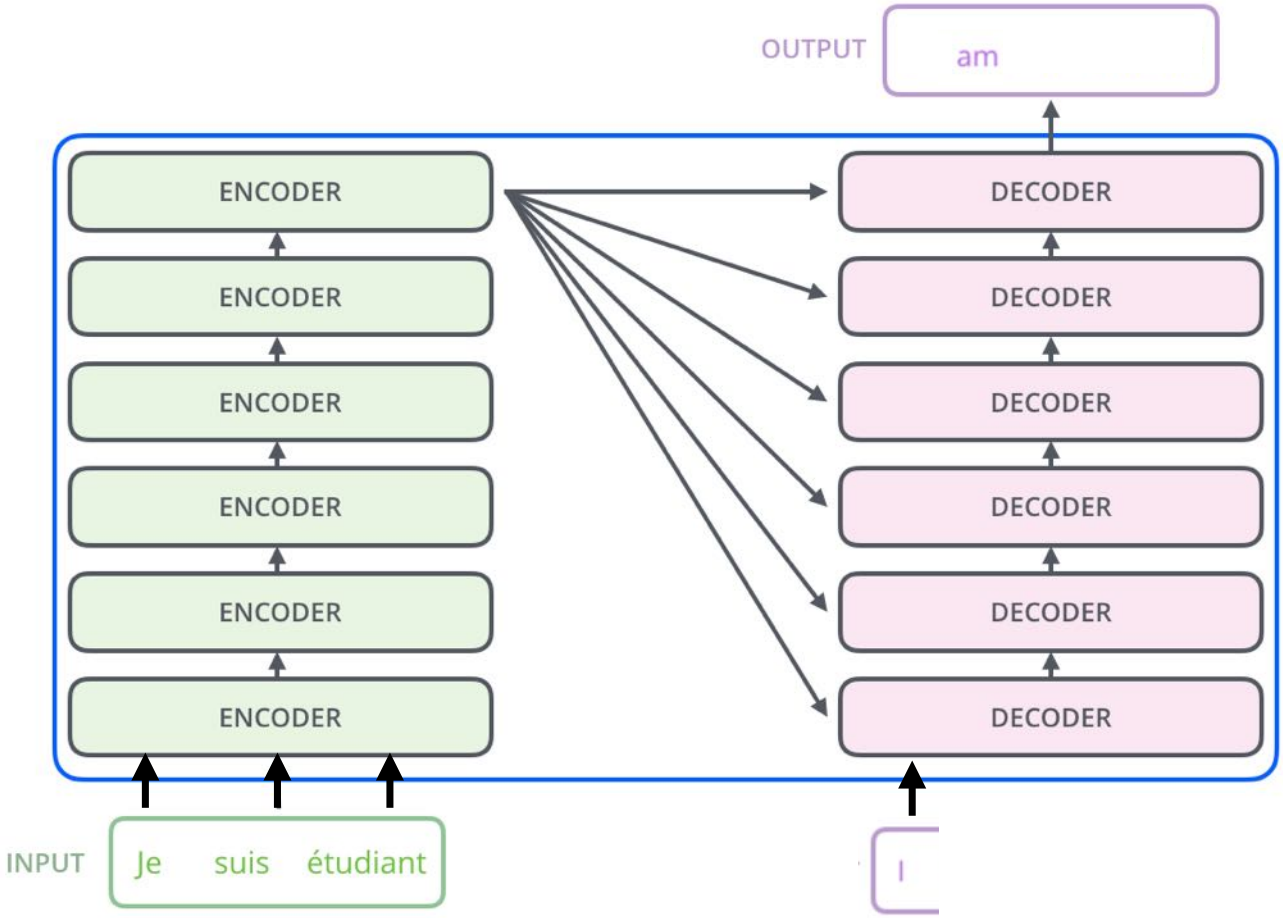
# Transformer Architecture — Aspects




- Residual connections (add & norm)
- Three Attention Mechanisms:
  - Encoder: Multi-Head (Self) Attention
    - see previous slides
  - (Encoder-Decoder) Multi-Head Attention
    - mechanism identical to the above
    - keys & values coming from encoder
    - queries coming from decoder
  - Decoder: Masked Multi-Head (Self) Attention
    - mechanism identical to the above
    - previous words are given as “queries”
    - future words are “masked”

*pictures are from http://jalammar.github.io/illustrated-transformer/*

# Illustration of Masking on the Decoder Side



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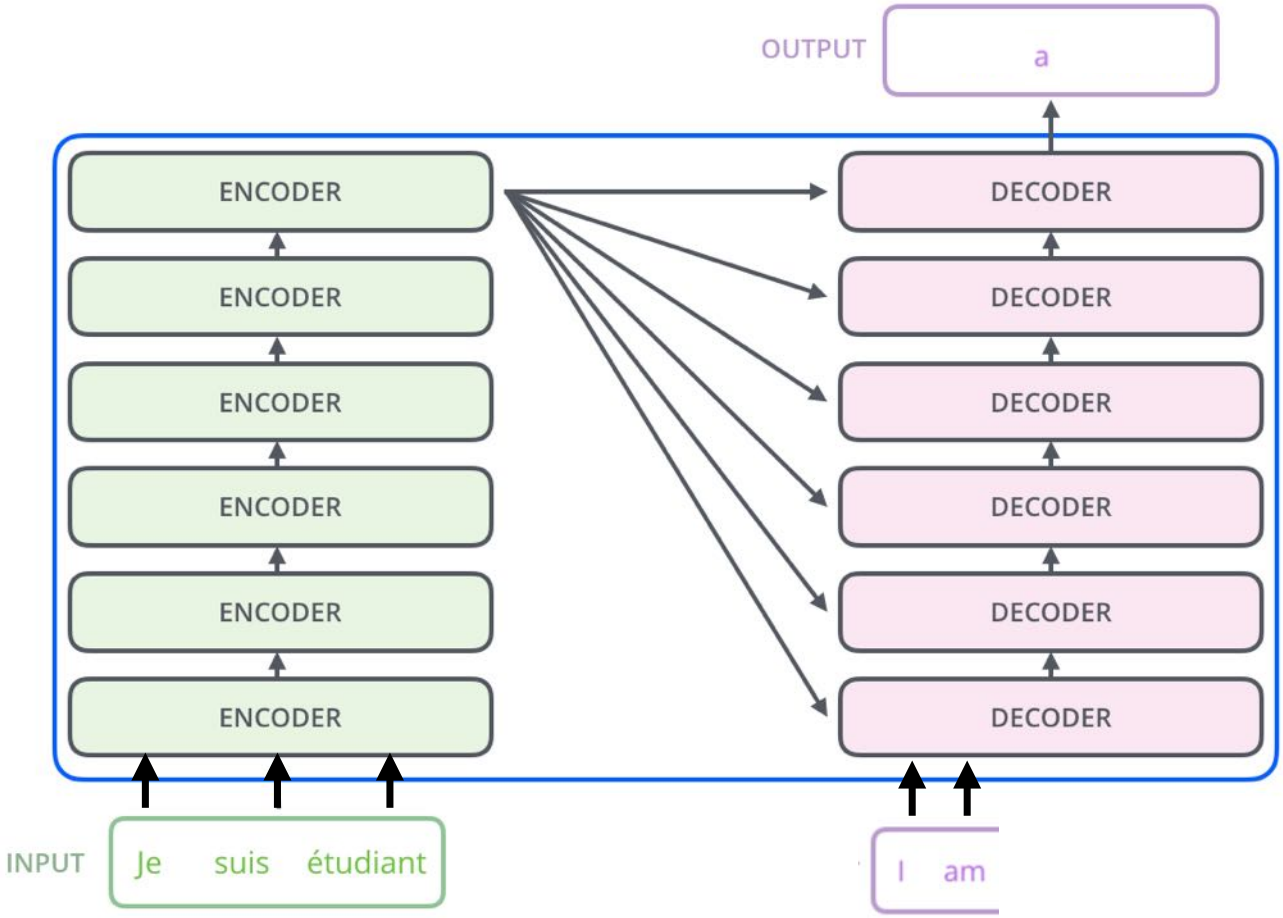

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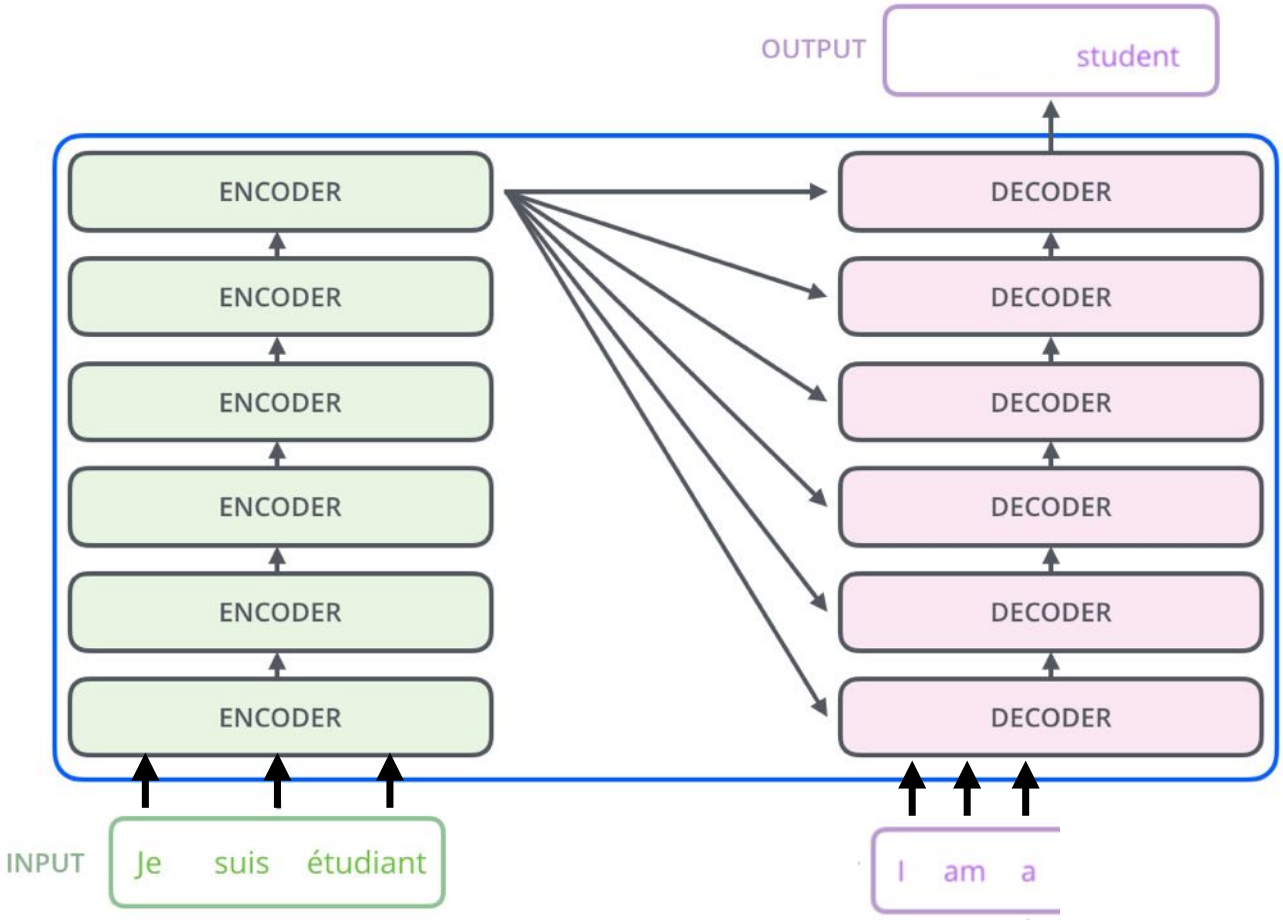
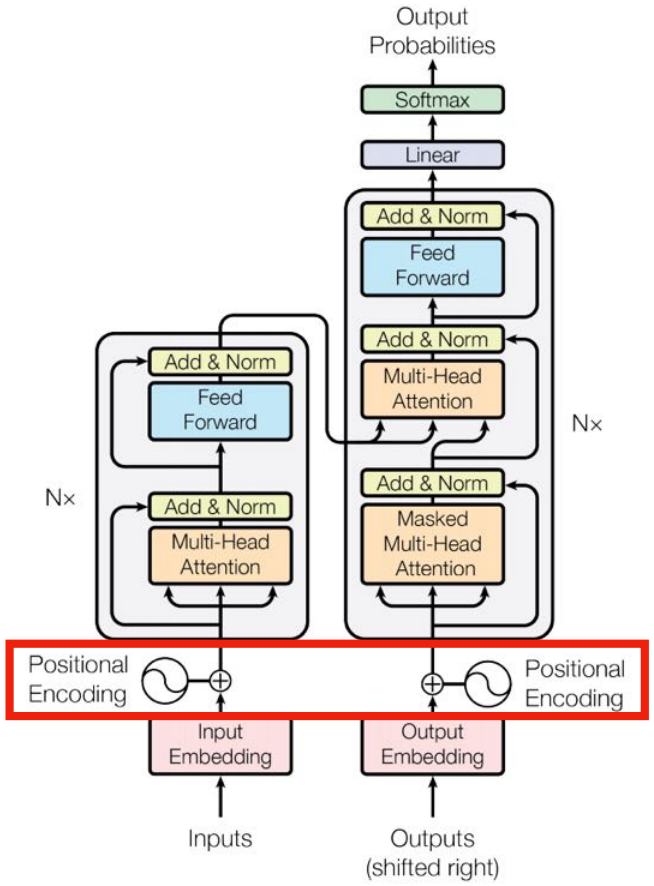


# Positional Encoding: Representing Order of Sequence

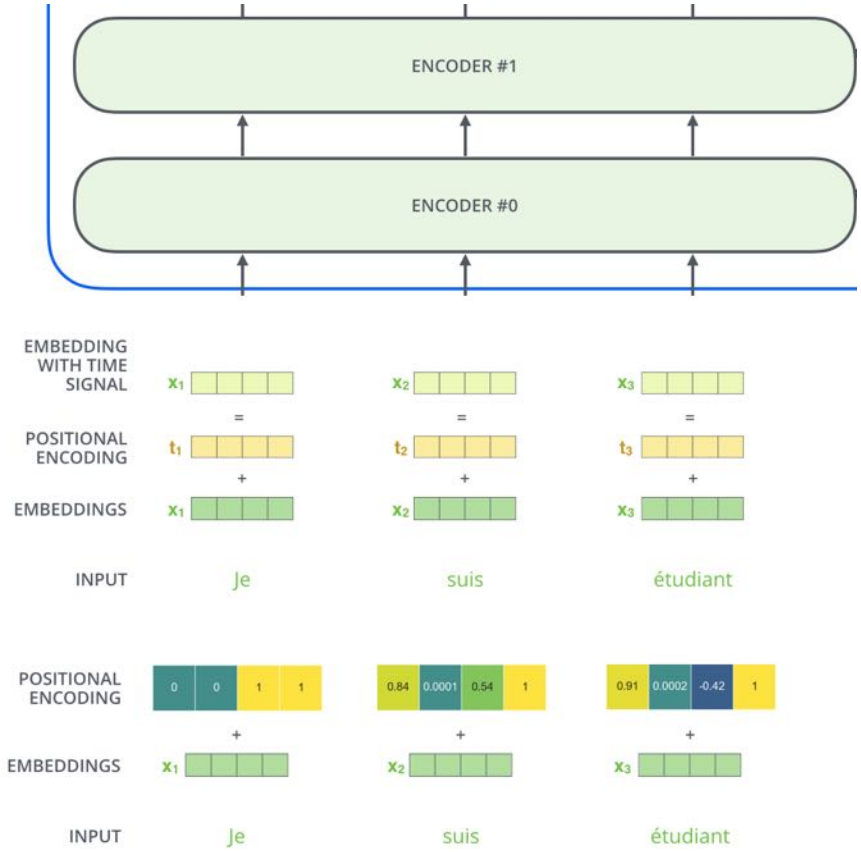



- unique encoding of each position
- consistent relative distance
- generalize to longer sequence

*Attention is all you need. Vaswani et al. NeurIPS 2017*

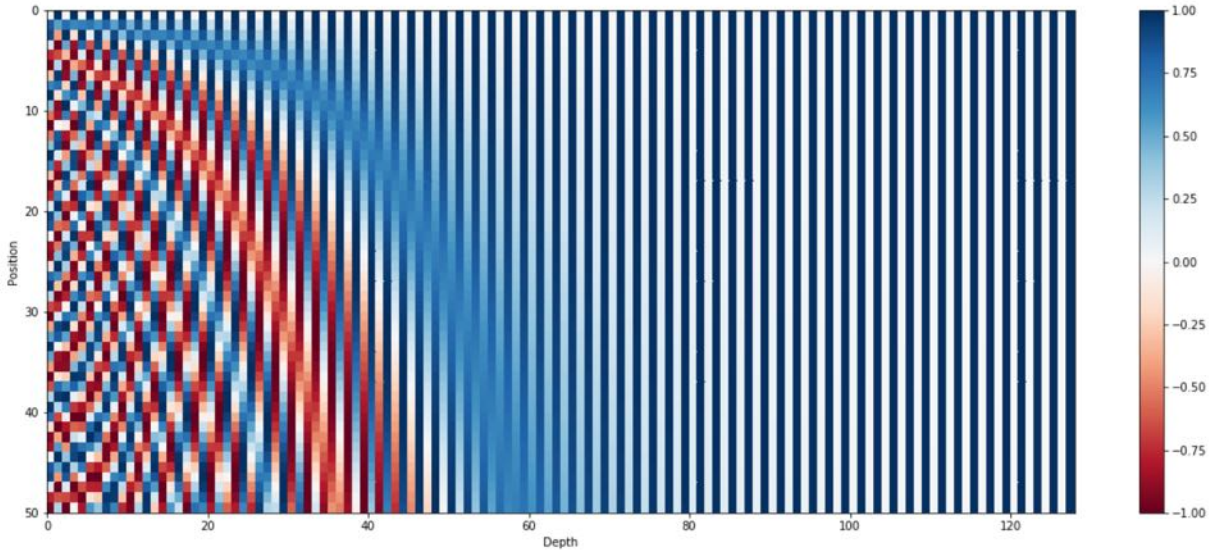
slide credit: Yongqin Xian

# Positional Encoding: Representing Order of Sequence



# Positional Encoding: Representing Order of Sequence

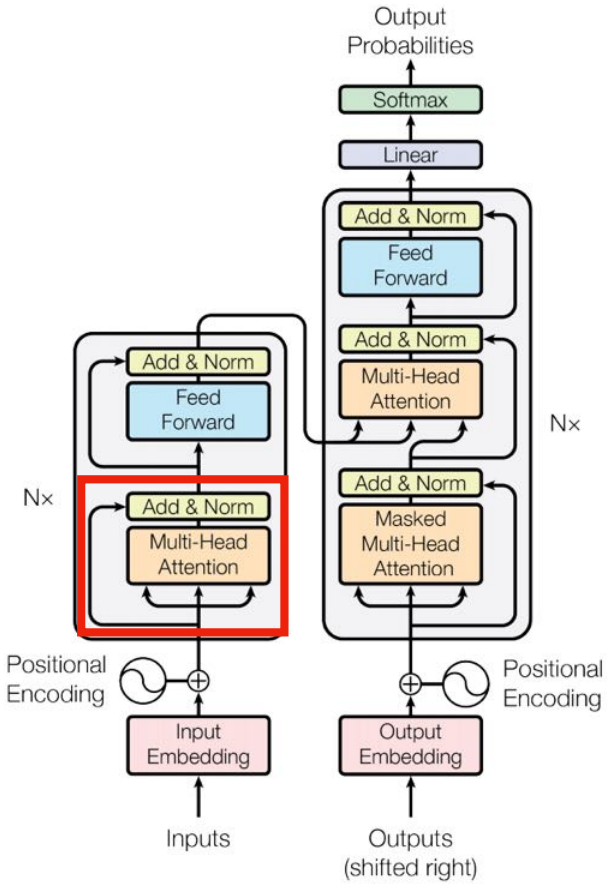
$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$




*Attention is all you need. Vaswani et al. NeurIPS 2017*

slide credit: Yongqin Xian

# Add & Norm

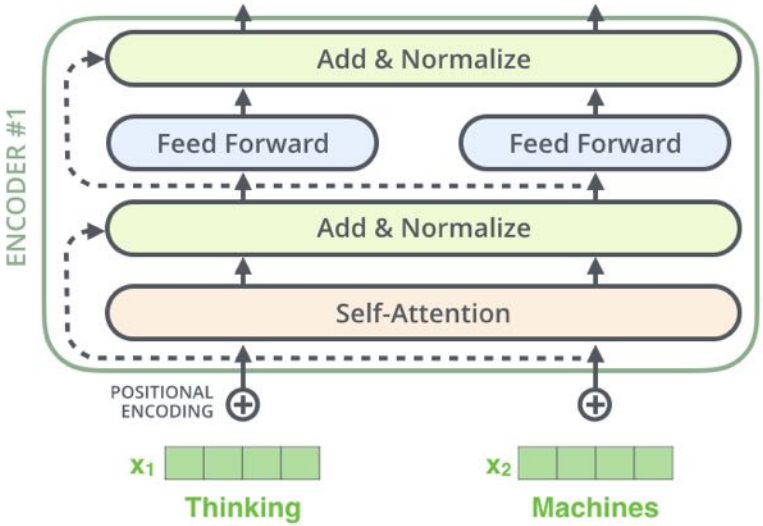


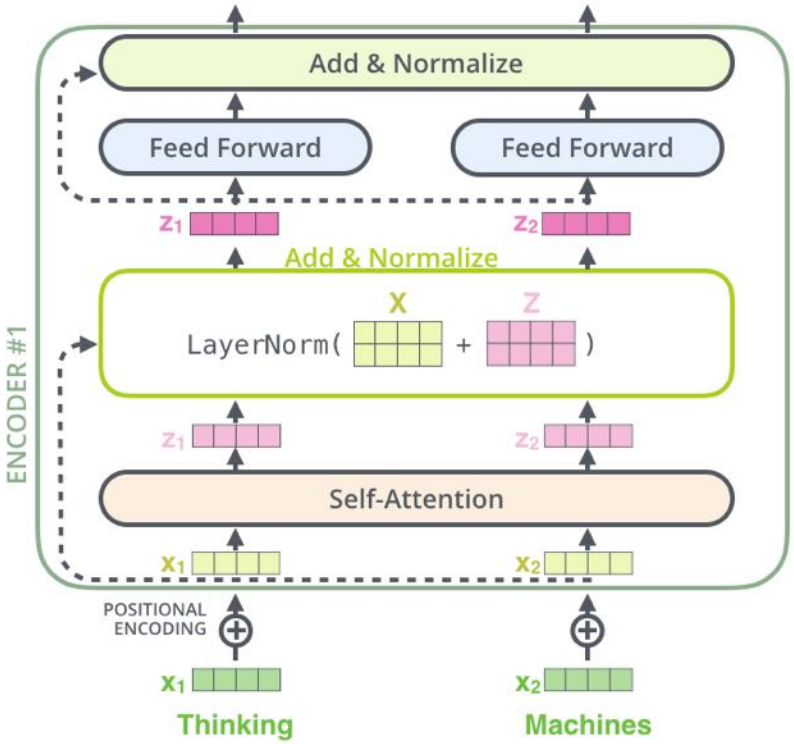

- residual connection
- normalization

*Attention is all you need. Vaswani et al. NeurIPS 2017*

slide credit: Yongqin Xian

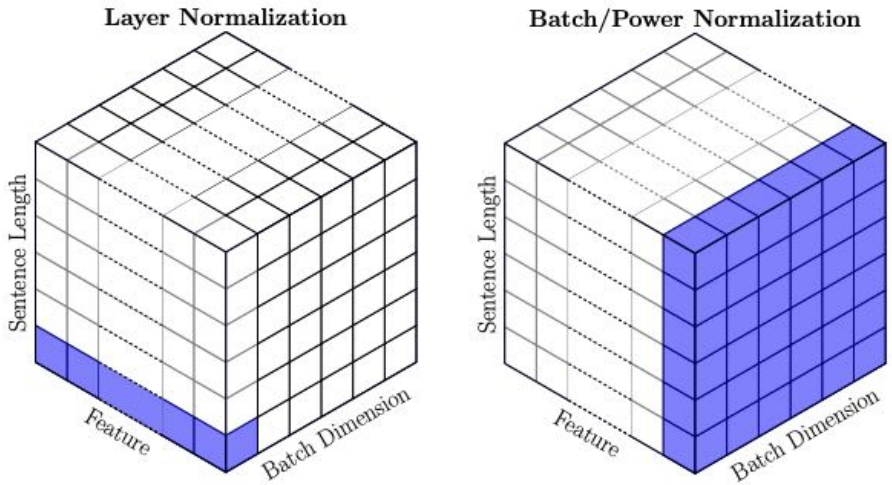
# Add & Norm


ENCODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
POSITIONAL ENCODING
x1
x2
Thinking
Machines

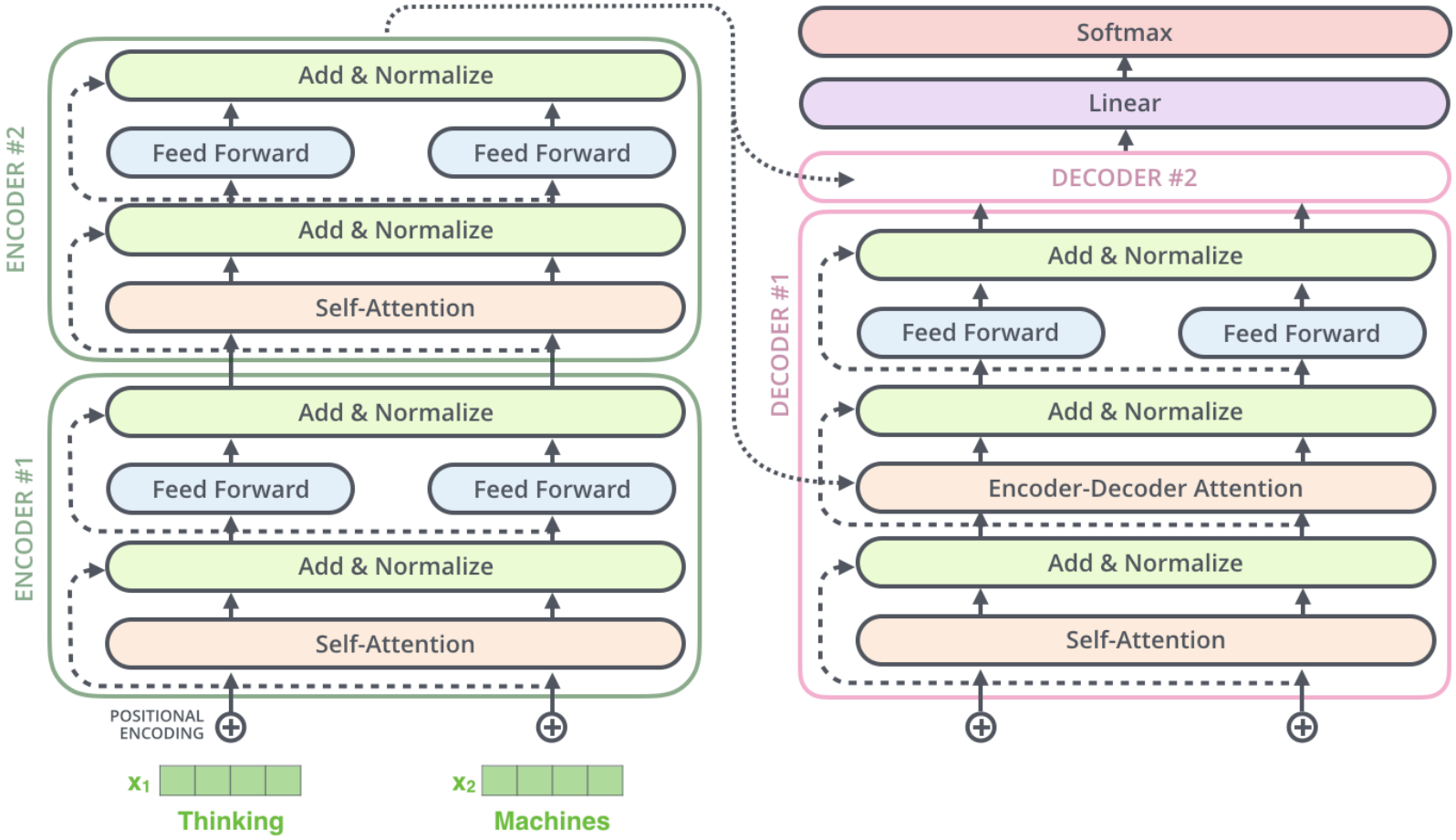

ENCODER #1
Add & Normalize
Feed Forward
Feed Forward
z1
z2
Add & Normalize
X
Z
LayerNorm( + )
z1
z2
Self-Attention
x1
x2
POSITIONAL ENCODING
x1
x2
Thinking
Machines

# Layernorm vs. Batchnorm

- Layernorm:
  - normalize each instance (word) independently
- Batchnorm
  - normalize each feature dimension (channel) over the entire batch



# “Complete Picture”



# Overview of Today's Lecture

- Introduction of Transformer
  - Attention Is All You Need @ NeurIPS 2017 - https://arxiv.org/abs/1706.03762

- **Vision Transformer (ViT) for Image Classification**
  - An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale @ ICLR 2021 https://arxiv.org/abs/2010.11929

- Object Detection with Transformers (DETR)
  - DETR: End-to-End Object Detection with Transformers @ ECCV 2020 https://arxiv.org/abs/2005.12872
  - Deformable DETR: Deformable Transformers for End-to-End Object Detection @ ICLR 2021 https://arxiv.org/abs/2010.04159

- Swin Transformer
  - Swin Transformer: Hierarchical Vision Transformer using Shifted Windows @ ICCV 2021 https://arxiv.org/abs/2103.14030

# Contributions

- Propose Vision Transformer (ViT) for image classification
  - without need for any CNNs
- ViT achieves state-of-art results for image classification
  - with lower computational costs

# Vision Transformer (ViT)

- What are sensible tokens for images?

*An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. ICLR 2021*

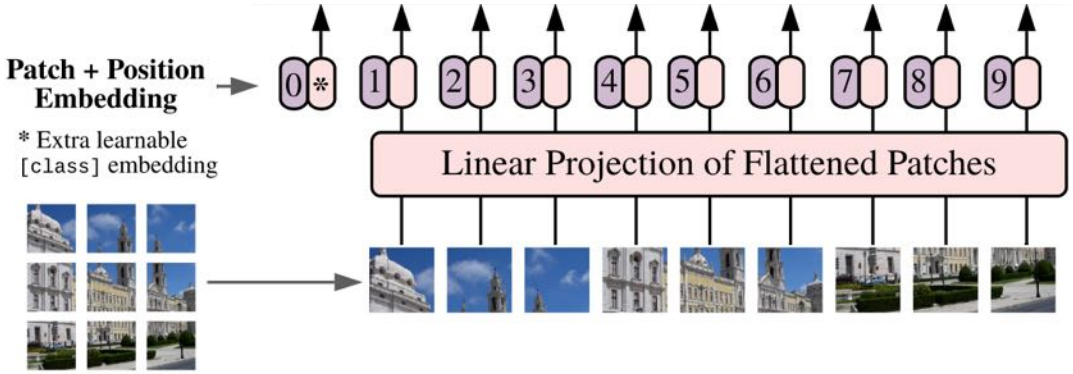
# Vision Transformer (ViT)

- What are sensible tokens for images?
  - Image Patches…
  - … here: each image patch of size 16x16

*An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. ICLR 2021*

# Vision Transformer (ViT)

- Positional encoding
  - learnable embedding for each patch position (sometimes also fixed positional encoding)
- Additional token for “class embedding”
  - learnable, its output embedding used for global image representation (and image classification — see next slide)

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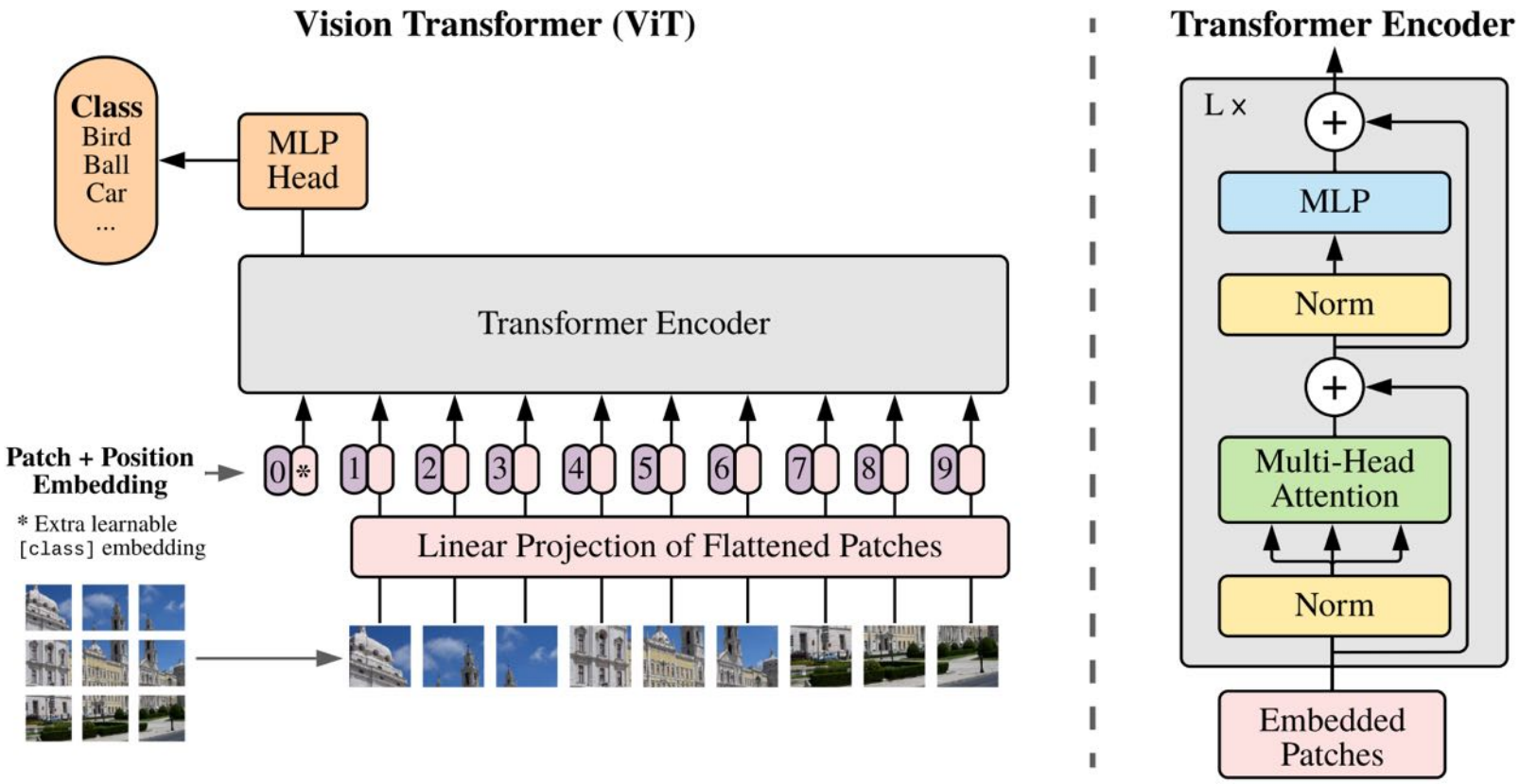
# Vision Transformer (ViT)

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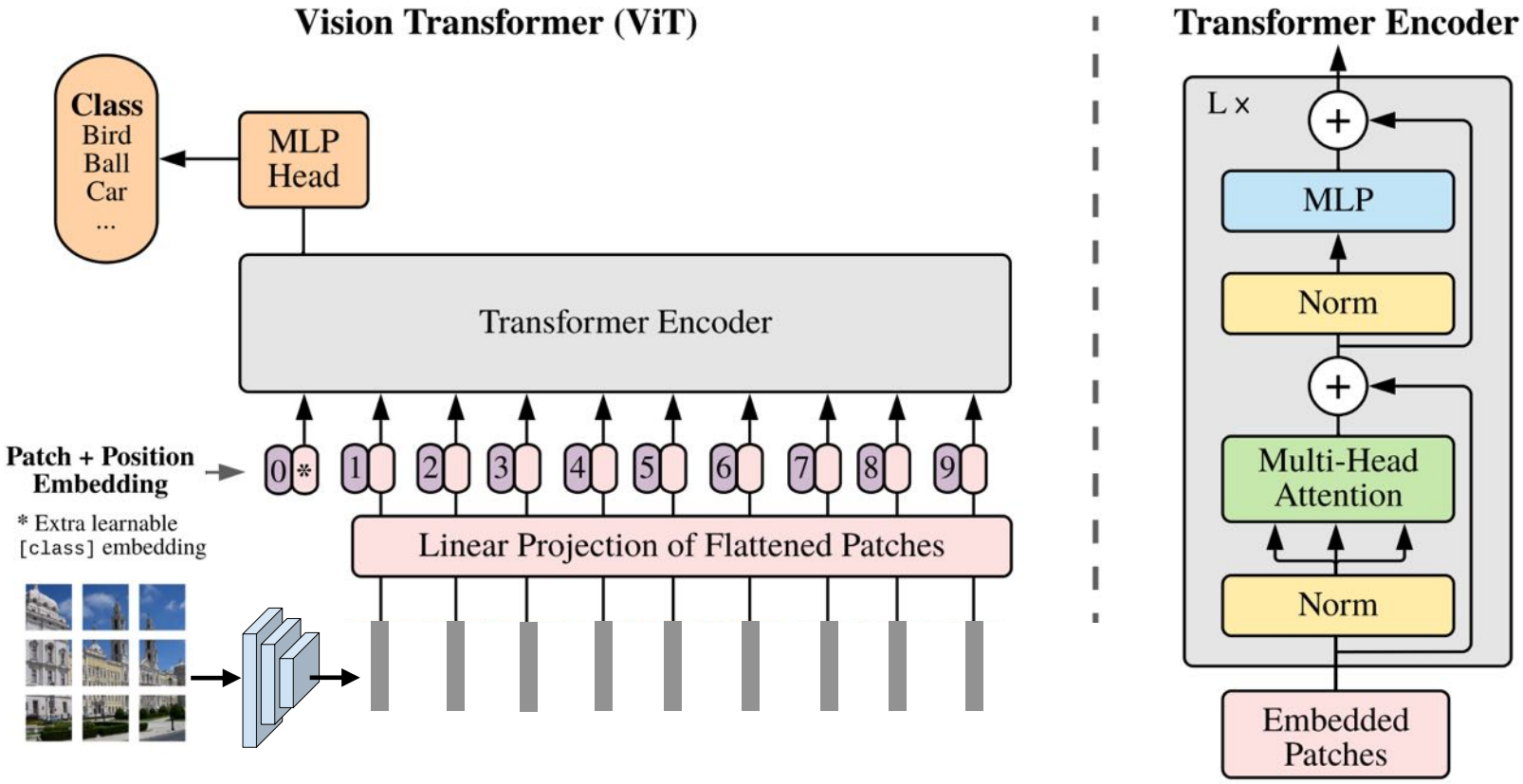
# Hybrid ViT Architecture (with CNN-embedding of image patches)




*An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. ICLR 2021*

# Experimental Setup

- Pretrained on large datasets with labels **finetune on Transformer**
  - ImageNet (1.4M images, 1K classes)
  - ImageNet 21K (14M images, 21K classes) [Deng et al., 2009]
  - JFT (303M images, 18K classes) [SUN et al., 2017]

- Finetuning for downstream tasks
  - replace the classification head with random weights
  - fine-tune the whole network

- Downstream tasks
  - ImageNet, CIFAR10/100, Oxford Pet/Flower, …
  - 19-task VTAB classification suite: 1000 samples per task [Zhai et al., 2019]

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slide credit: Yongqin Xian

# Model Variants

- ViT-variants: Base, Large, Huge

| 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 |

文本

- For comparison:
  - ResNet-50: 25M
  - ResNet-152: 60M
  - VGG16: 197M
- Notation in the following slide:
  - “ViT-L/16” means: ViT-Large model (see table, with 16x16 input patches)

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slide credit: Yongqin Xian

# Results (top-1 accuracies)

| | 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 |

- Comparisons
  - BiT-L (ResNet152x4): SOTA on other datasets, pretrained on JFT [Kolesnikov et al., 2020]
  - Noisy student: SOTA on ImageNet, pretrained with ImageNet + unlabeled JFT [Xie et al., 2020]

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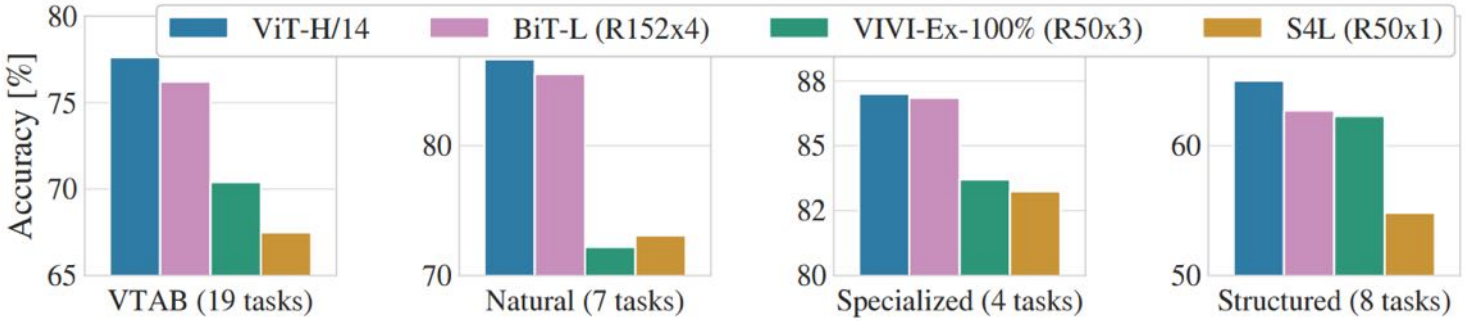
slide credit: Yongqin Xian

# Results on “Low-Shot” Transfer (1000 Examples per Task)




- Comparisons
  - BiT-L: SOTA, pretrained on JFT [Kolesnikov et al., 2020]
  - VIVI: ResNet, pretrained with ImageNet + youtube [Tschannen et al., 2020]
  - S4L: ResNet, semisupervised on ImageNet [Zhai et al., 2019]

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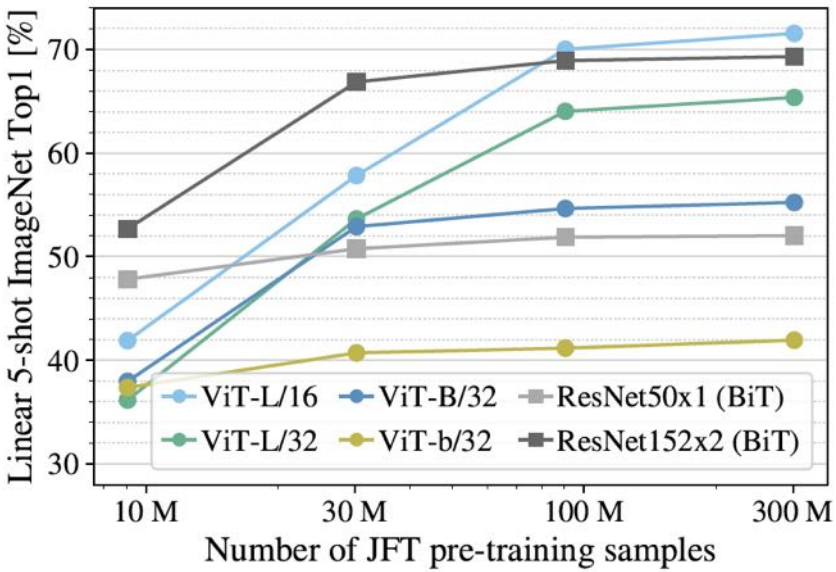
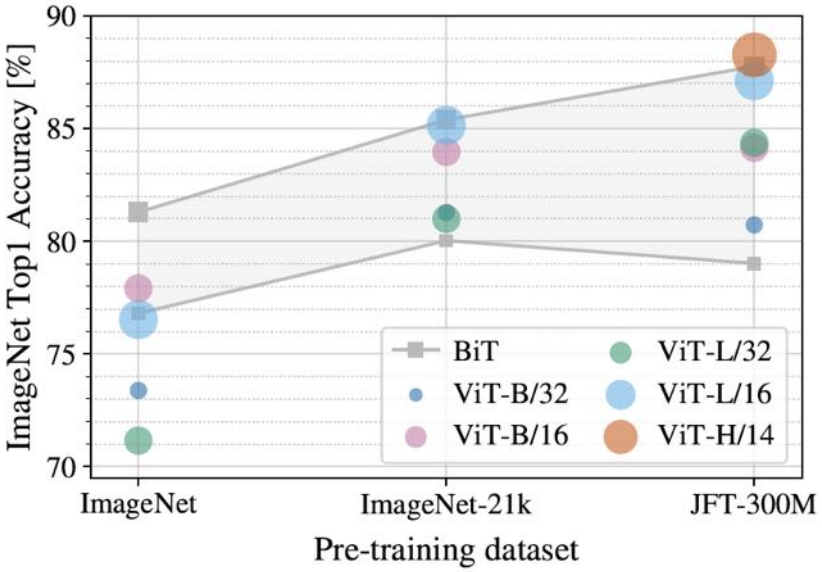
# Ablation on Dataset Size

- ViT requires large dataset to outperform CNNs

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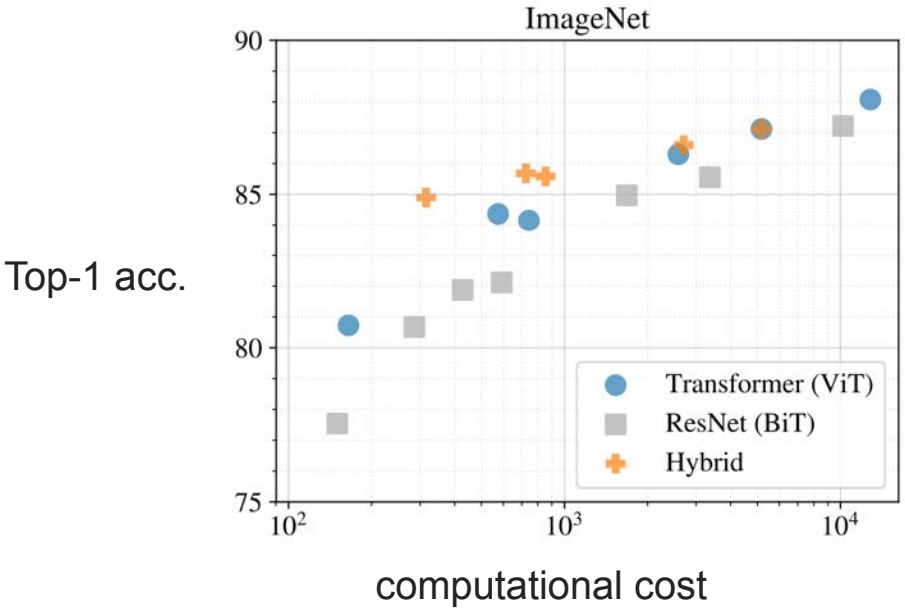
# Performance vs. Cost for Different Architectures




- ViT dominates ResNet on the performance-compute trade-off
- Hybrid outperforms ViT at small computational budget

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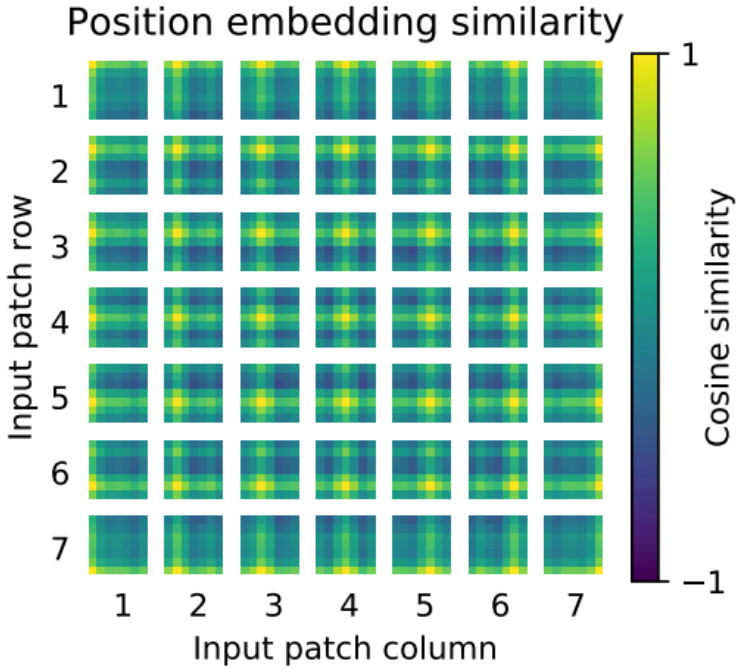
slide credit: Yongqin Xian

# Analysis of Positional Embedding

- Closer patches tend to have more similar positional embedding




| Pos. Emb. | Default/Stem |
|---|---|
| No Pos. Emb. | 0.61382 |
| 1-D Pos. Emb. | 0.64206 |
| 2-D Pos. Emb. | 0.64001 |

5-shot learning top-1 acc. on ImageNet

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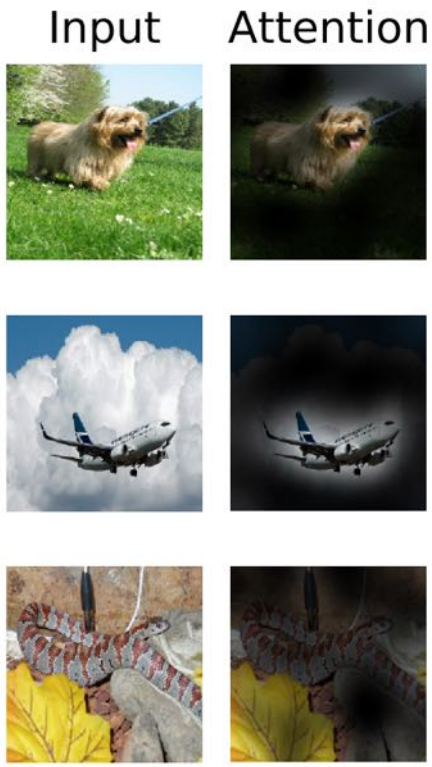
slide credit: Yongqin Xian

# Visualizing Attention




*An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. Dosovitskiy et al. ICLR 2021*

# Main Conclusion

- A pure transformer can achieve SOTA (state of the art) performance for image classification
  - without convolutional layers
  - with a more scalable and simpler architecture

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- Swin Transformer
  - Swin Transformer: Hierarchical Vision Transformer using Shifted Windows @ ICCV 2021 https://arxiv.org/abs/2103.14030

slide credit: Jaemin Jeong

# DETR: End-to-End Object Detection with Transformers

## DEtection + TRansformer

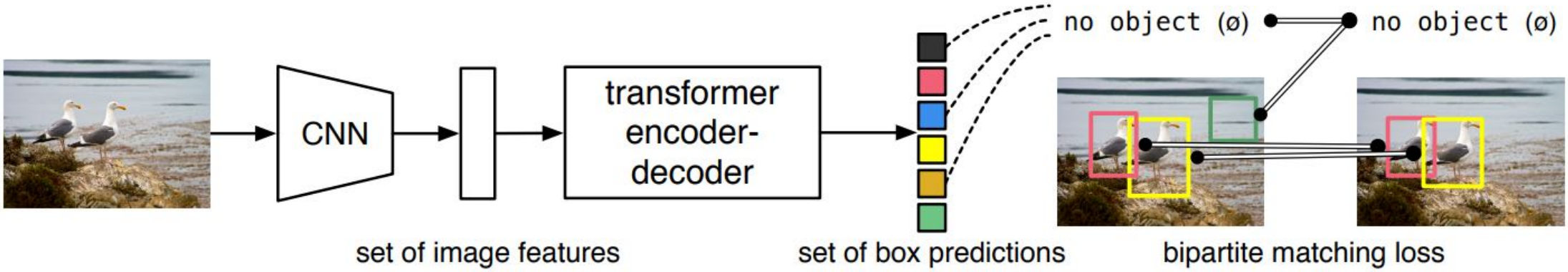
Nicolas Carion*, Francisco Massa*, Gabriel Synnaeve, Nicolas Usunier,
Alexander Kirillov, and Sergey Zagoruyko

Facebook AI

# Introduction

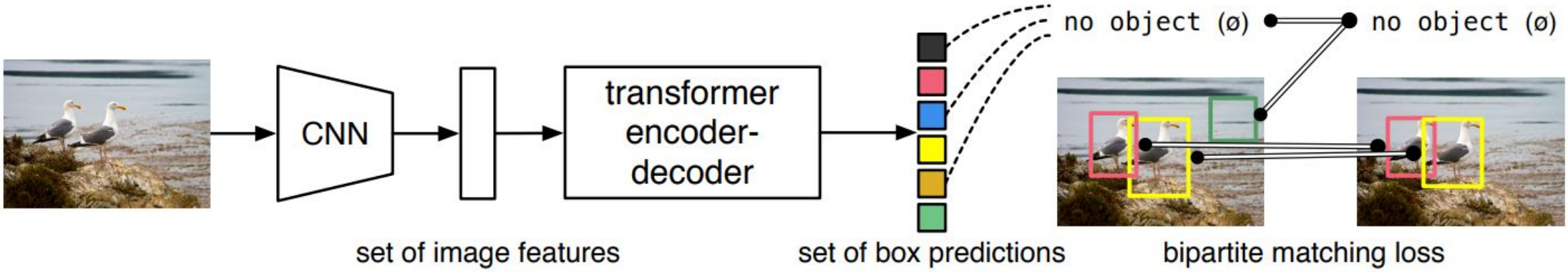
- CNN-based Object Detectors (such as Yolo, Faster-RCNN) :
  - use proposal regions, anchors, window centers,… as bounding box candidates
  - these object detectors are not really trained end-to-end because of necessary postprocessing such non-maximum suppression (standard NMS, Soft NMS, …)

- Object Detection with Transformers (DETR)
  - object detection pipeline that directly outputs a set of boxes from a Transformer
  - combination of a common CNN with a transformer architecture

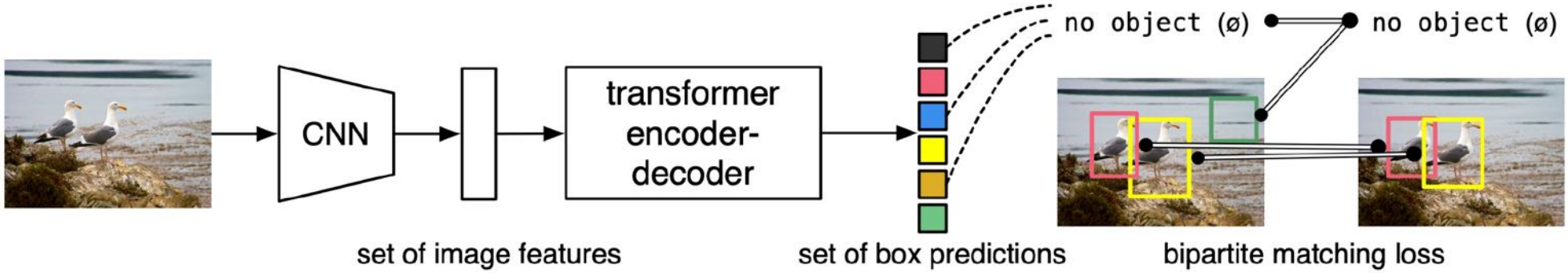


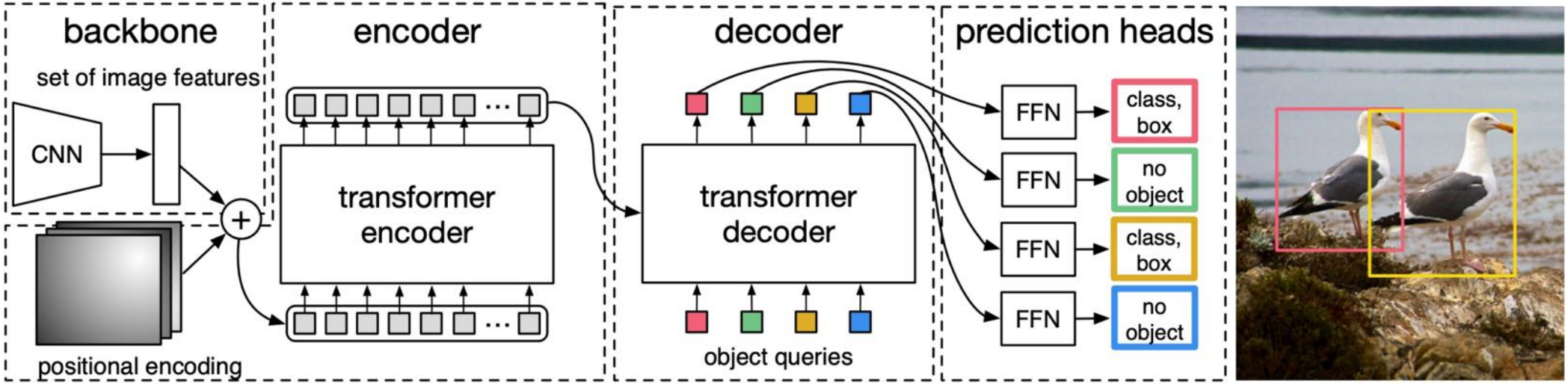
# DEtection with TRansformers (DETR)

- Two core aspects:
  - 1. Architecture that directly **predicts** the final **set of** all **detections** (in parallel & single pass)
  - 2. **Set prediction loss** that results in a unique matching of object predictions and ground truth bounding boxes
    - bipartite matching loss to uniquely assign predictions with ground truth boxes
    - predictions with no match should yield a “no object” class prediction (see figure)



# Object Detection with Transformers: DETR




Carion et al, "End-to-End Object Detection with Transformers", ECCV 2020

slide credit: Justin Johnson

# What are Object Queries?

- Object queries are the input of the decoder.
  - learnt embeddings
  - they use 100 (or 100s) of them

- Many think of them as “querying specific object classes, at specific locations, of a particular size, and of a particular aspect ratio” …
  - but at the end “just learnt”

slide credit: Jaemin Jeong

Table 1: Comparison with Faster R-CNN with a ResNet-50 and ResNet-101 backbones on the COCO validation set. The top section shows results for Faster R-CNN models in Detectron2 [50], the middle section shows results for Faster R-CNN models with GIoU [38], random crops train-time augmentation, and the long `9x` training schedule. DETR models achieve comparable results to heavily tuned Faster R-CNN baselines, having lower $AP_S$ but greatly improved $AP_L$. We use torchscript Faster R-CNN and DETR models to measure FLOPS and FPS. Results without R101 in the name correspond to ResNet-50.

| Model | GFLOPS/FPS | #params | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ |
|---|---|---|---|---|---|---|---|---|
| Faster RCNN-DC5 | 320/16 | 166M | 39.0 | 60.5 | 42.3 | 21.4 | 43.5 | 52.5 |
| Faster RCNN-FPN | 180/26 | 42M | 40.2 | 61.0 | 43.8 | 24.2 | 43.5 | 52.0 |
| Faster RCNN-R101-FPN | 246/20 | 60M | 42.0 | 62.5 | 45.9 | 25.2 | 45.6 | 54.6 |
| Faster RCNN-DC5+ | 320/16 | 166M | 41.1 | 61.4 | 44.3 | 22.9 | 45.9 | 55.0 |
| Faster RCNN-FPN+ | 180/26 | 42M | 42.0 | 62.1 | 45.5 | 26.6 | 45.4 | 53.4 |
| Faster RCNN-R101-FPN+ | 246/20 | 60M | 44.0 | 63.9 | **47.8** | **27.2** | 48.1 | 56.0 |
| DETR | 86/28 | 41M | 42.0 | 62.4 | 44.2 | 20.5 | 45.8 | 61.1 |
| DETR-DC5 | 187/12 | 41M | 43.3 | 63.1 | 45.9 | 22.5 | 47.3 | 61.1 |
| DETR-R101 | 152/20 | 60M | 43.5 | 63.8 | 46.4 | 21.9 | 48.0 | 61.8 |
| DETR-DC5-R101 | 253/10 | 60M | **44.9** | **64.7** | 47.7 | 23.7 | **49.5** | **62.3** |

slide credit: Jaemin Jeong

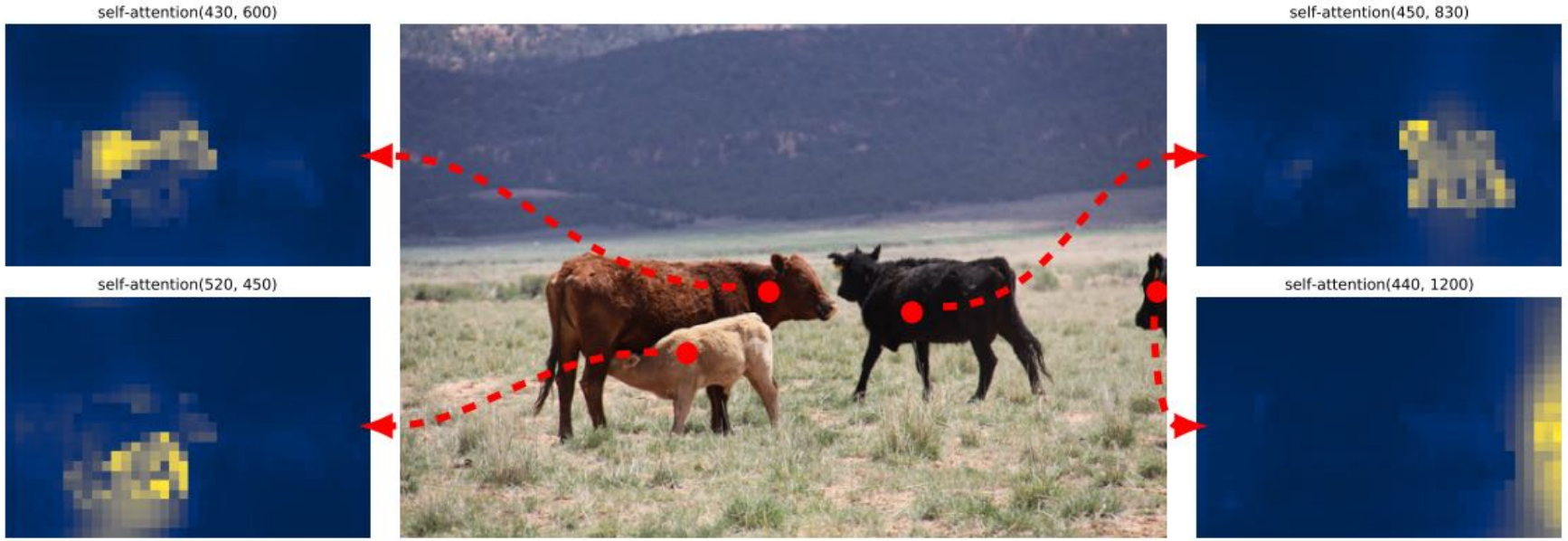
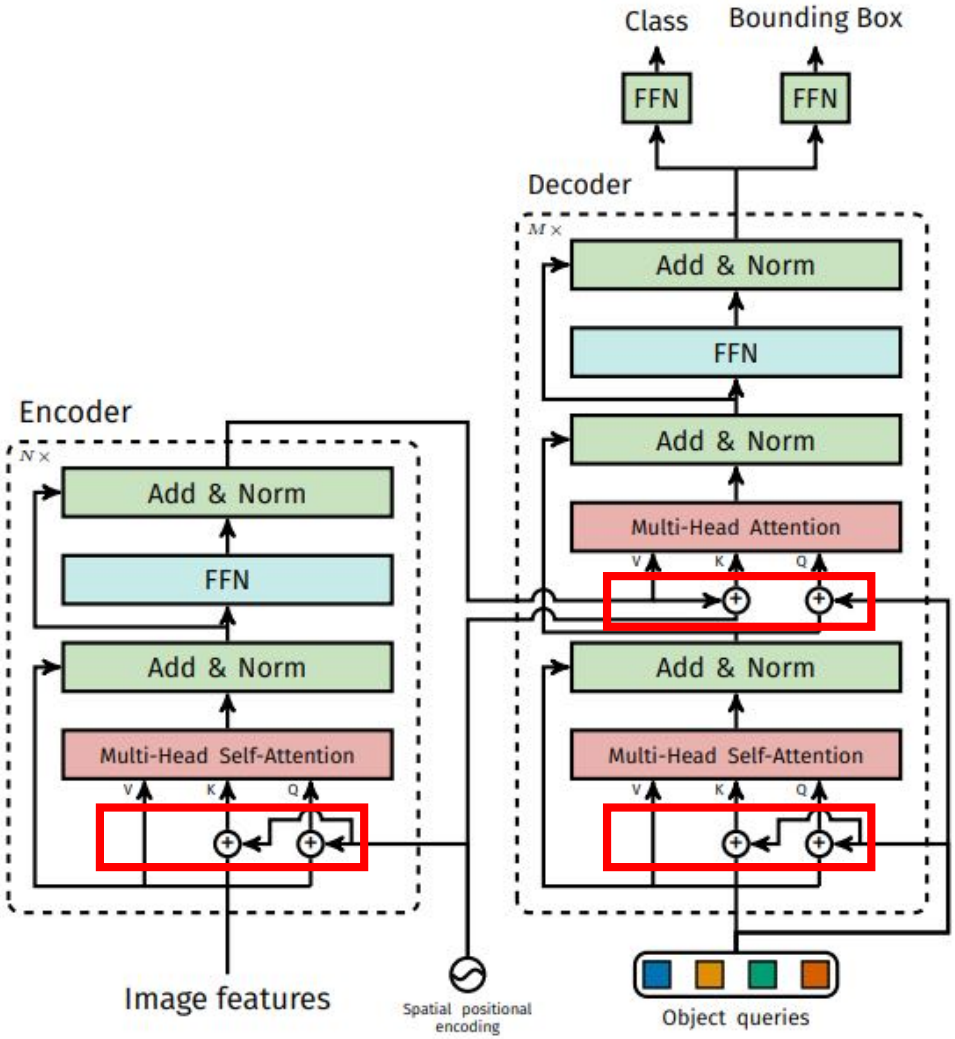
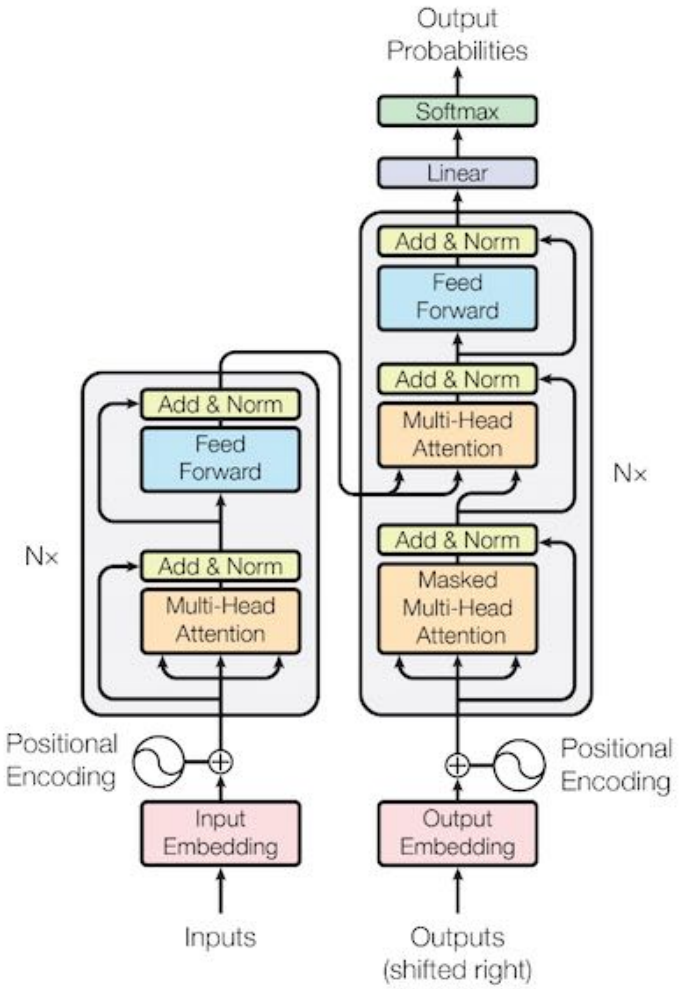



Fig. 3: Encoder self-attention for a set of reference points. The encoder is able to separate individual instances. Predictions are made with baseline DETR model on a validation set image.

slide credit: Jaemin Jeong



slide credit: Jaemin Jeong

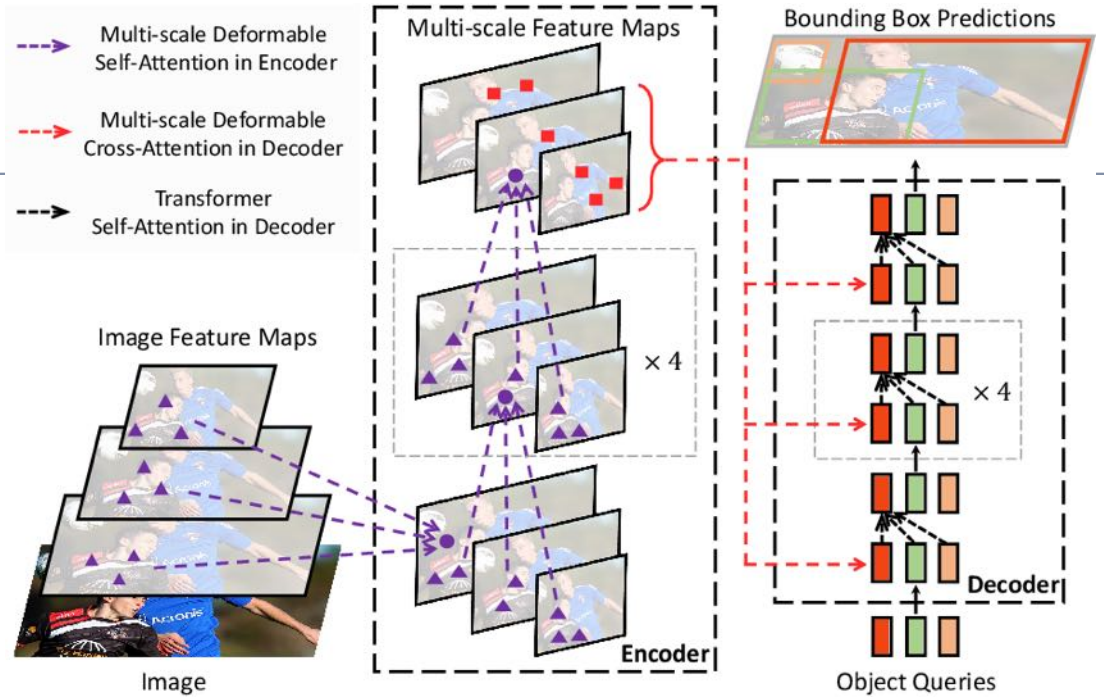
# Importance of positional encodings

Table 3: Results for different positional encodings compared to the baseline (last row), which has fixed sine pos. encodings passed at every attention layer in both the encoder and the decoder. Learned embeddings are shared between all layers. Not using spatial positional encodings leads to a significant drop in AP. Interestingly, passing them in decoder only leads to a minor AP drop. All these models use learned output positional encodings.

| spatial pos. enc. | | output pos. enc. | | | | |
|---|---|---|---|---|---|---|
| encoder | decoder | decoder | AP | $\Delta$ | $AP_{50}$ | $\Delta$ |
| none | none | learned at input | 32.8 | -7.8 | 55.2 | -6.5 |
| sine at input | sine at input | learned at input | 39.2 | -1.4 | 60.0 | -1.6 |
| learned at attn. | learned at attn. | learned at attn. | 39.6 | -1.0 | 60.7 | -0.9 |
| none | sine at attn. | learned at attn. | 39.3 | -1.3 | 60.3 | -1.4 |
| sine at attn. | sine at attn. | learned at attn. | **40.6** | - | **61.6** | - |

sine : fixed sine pos
learned : learnable

# Deformable DETR




| Method | Epochs | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ | params | FLOPs | FPS |
|---|---|---|---|---|---|---|---|---|---|---|
| Faster R-CNN + FPN | 109 | 42.0 | 62.1 | 45.5 | 26.6 | 45.4 | 53.4 | 42M | 180G | 26 |
| DETR | 500 | 42.0 | 62.4 | 44.2 | 20.5 | 45.8 | 61.1 | 41M | 86G | 28 |
| DETR-DC5 | 500 | 43.3 | 63.1 | 45.9 | 22.5 | 47.3 | 61.1 | 41M | 187G | 12 |
| DETR-DC5 | 50 | 35.3 | 55.7 | 36.8 | 15.2 | 37.5 | 53.6 | 41M | 187G | 12 |
| DETR-DC5+ | 50 | 36.2 | 57.0 | 37.4 | 16.3 | 39.2 | 53.9 | 41M | 187G | 12 |
| Deformable DETR | 50 | 43.8 | 62.6 | 47.7 | 26.4 | 47.1 | 58.0 | 40M | 173G | 19 |
| + iterative bounding box refinement | 50 | 45.4 | 64.7 | 49.0 | 26.8 | 48.3 | 61.7 | 40M | 173G | 19 |
| ++ two-stage Deformable DETR | 50 | 46.2 | 65.2 | 50.0 | 28.8 | 49.2 | 61.7 | 40M | 173G | 19 |

# Overview of Today's Lecture

- Introduction of Transformer
  - Attention Is All You Need @ NeurIPS 2017 - https://arxiv.org/abs/1706.03762
- Vision Transformer (ViT) for Image Classification
  - An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale @ ICLR 2021 https://arxiv.org/abs/2010.11929
- Object Detection with Transformers (DETR)
  - DETR: End-to-End Object Detection with Transformers @ ECCV 2020 https://arxiv.org/abs/2005.12872
  - Deformable DETR: Deformable Transformers for End-to-End Object Detection @ ICLR 2021 https://arxiv.org/abs/2010.04159
- **Swin Transformer**
  - Swin Transformer: Hierarchical Vision Transformer using Shifted Windows @ ICCV 2021 https://arxiv.org/abs/2103.14030

# Swin Transformer: Hierarchical Vision Transformer using Shifted Windows

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ICCV 2021 — Best Paper Award (Marr Prize)

slide credit: Justin Johnson

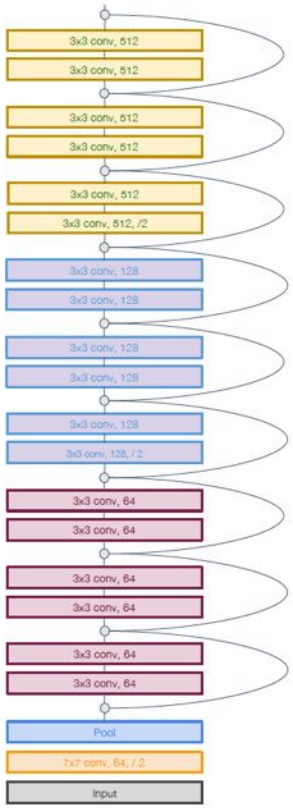
# ViT vs CNN

Stage 3:
256 x 14 x 14

Stage 2:
128 x 28 x 28

Stage 1:
64 x 56 x 56

Input:
3 x 224 x 224

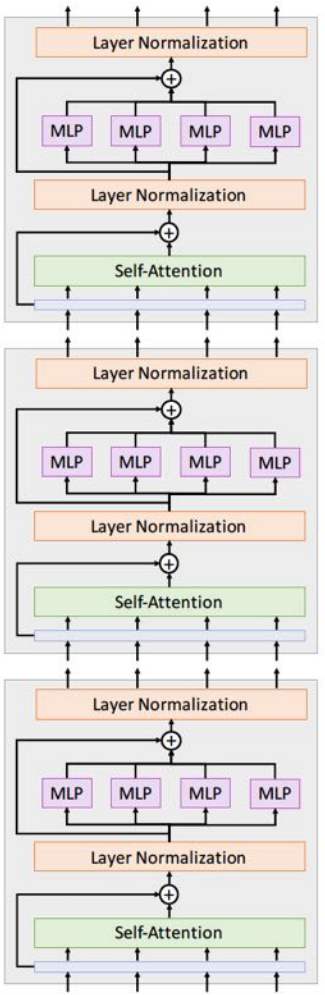



In most CNNs (including ResNets), **decrease** resolution and **increase** channels as you go deeper in the network (Hierarchical architecture)

Useful since objects in images can occur at various scales

In a ViT, all blocks have same resolution and number of channels (Isotropic architecture)

Can we build a **hierarchical** ViT model?




3rd block:
768 x 14 x 14

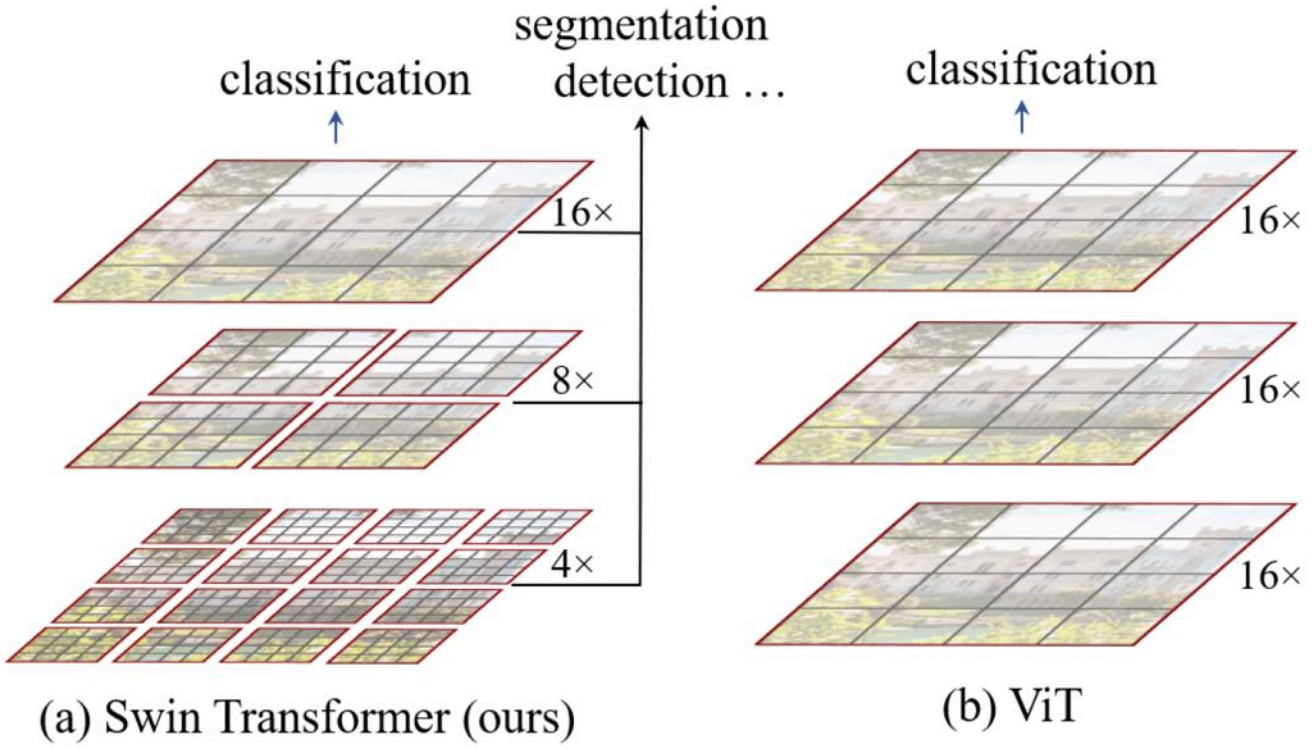
2nd block:
768 x 14 x 14

1st block:
768 x 14 x 14

Input:
3 x 224 x 224

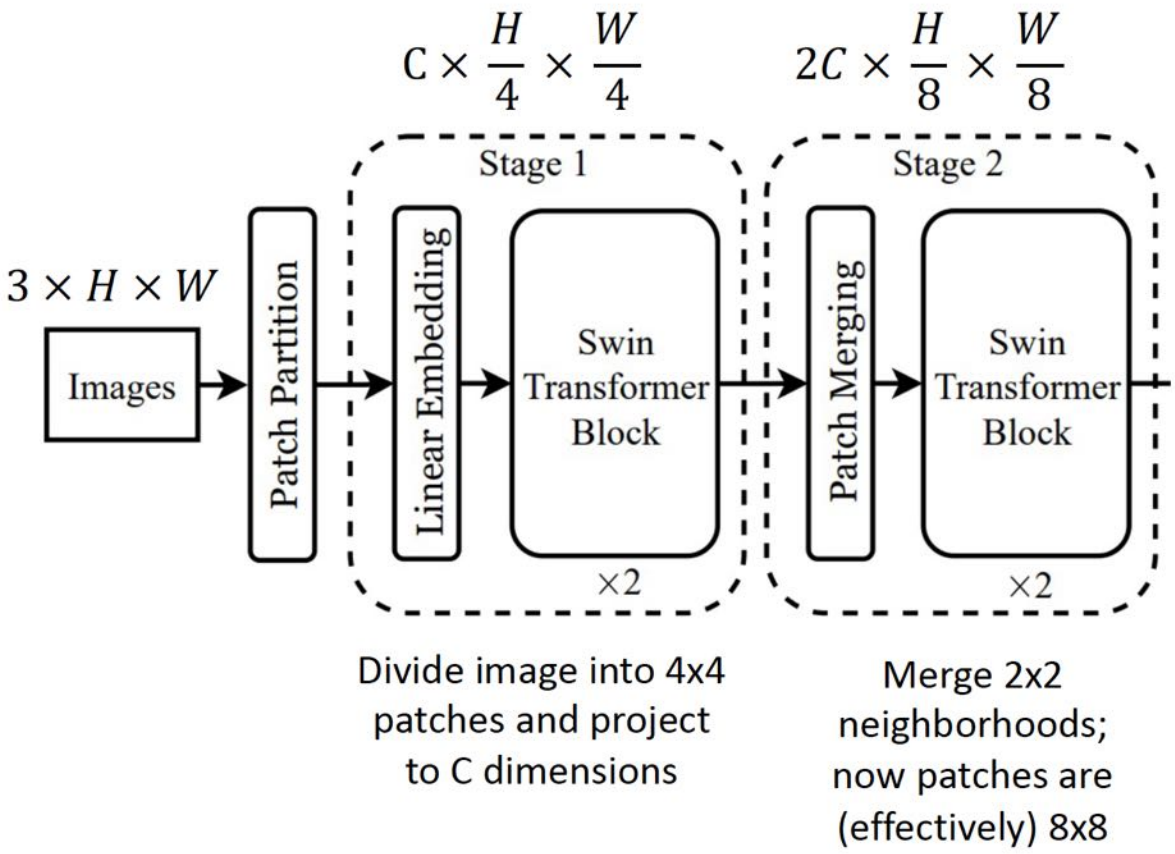
# Swin Transformer vs. Standard ViT (Vision Transformer)

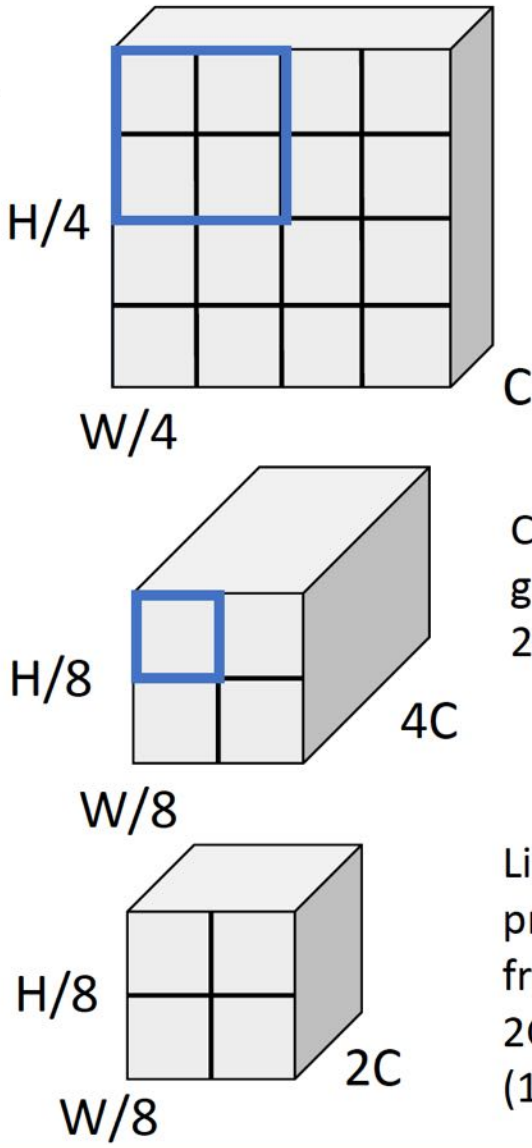
- Swin Transformer
  - hierarchical: token size increases from 4x4 to 16x16 pixels
  - architecture can be used for
    - image classification, but also
    - semantic segmentation and
    - object detection
    - instance segmentation
  - computationally more efficient than ViT



# Hierarchical ViT: Swin Transformer

slide credit: Justin Johnson

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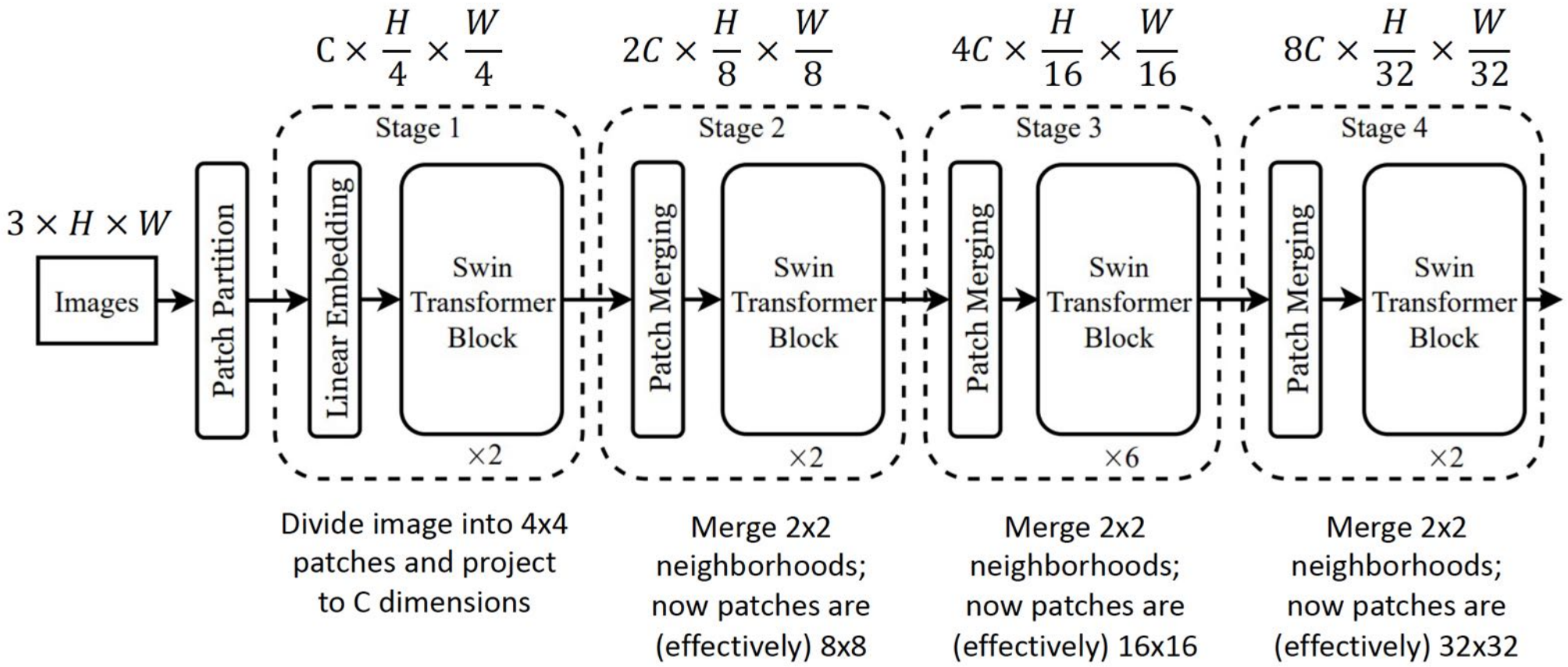
# Hierarchical ViT: Swin Transformer

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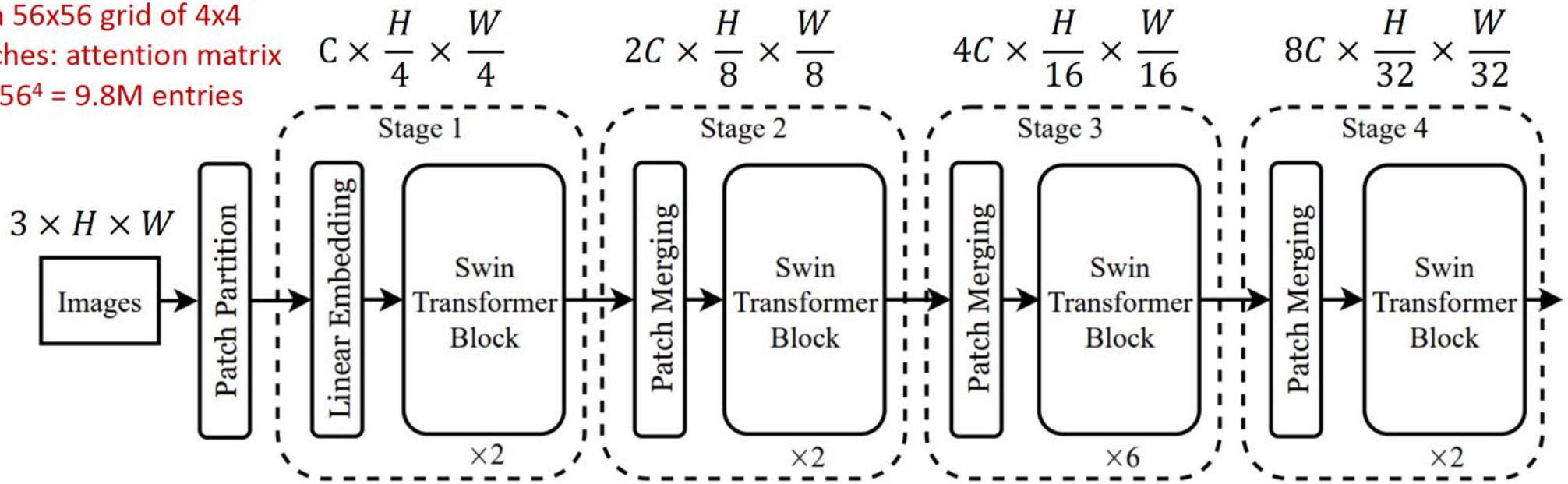
# Hierarchical ViT: Swin Transformer

**Problem**: 224x224 image with 56x56 grid of 4x4 patches: attention matrix has $56^4$ = 9.8M entries




**Solution**: don't use full attention, instead use attention over patches

Divide image into 4x4 patches and project to C dimensions

Merge 2x2 neighborhoods; now patches are (effectively) 8x8

Merge 2x2 neighborhoods; now patches are (effectively) 16x16

Merge 2x2 neighborhoods; now patches are (effectively) 32x32

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# Swin Transformer: Window Attention

With H x W grid of **tokens**, each attention matrix is $H^2W^2$ – **quadratic** in image size

Rather than allowing each **token** to attend to all other tokens, instead divide into **windows** of M x M tokens (here M=4); only compute attention within each window

Total size of all attention matrices is now: $M^4(H/M)(W/M) = M^2HW$

**Linear** in image size for fixed M!
Swin uses M=7 throughout the network

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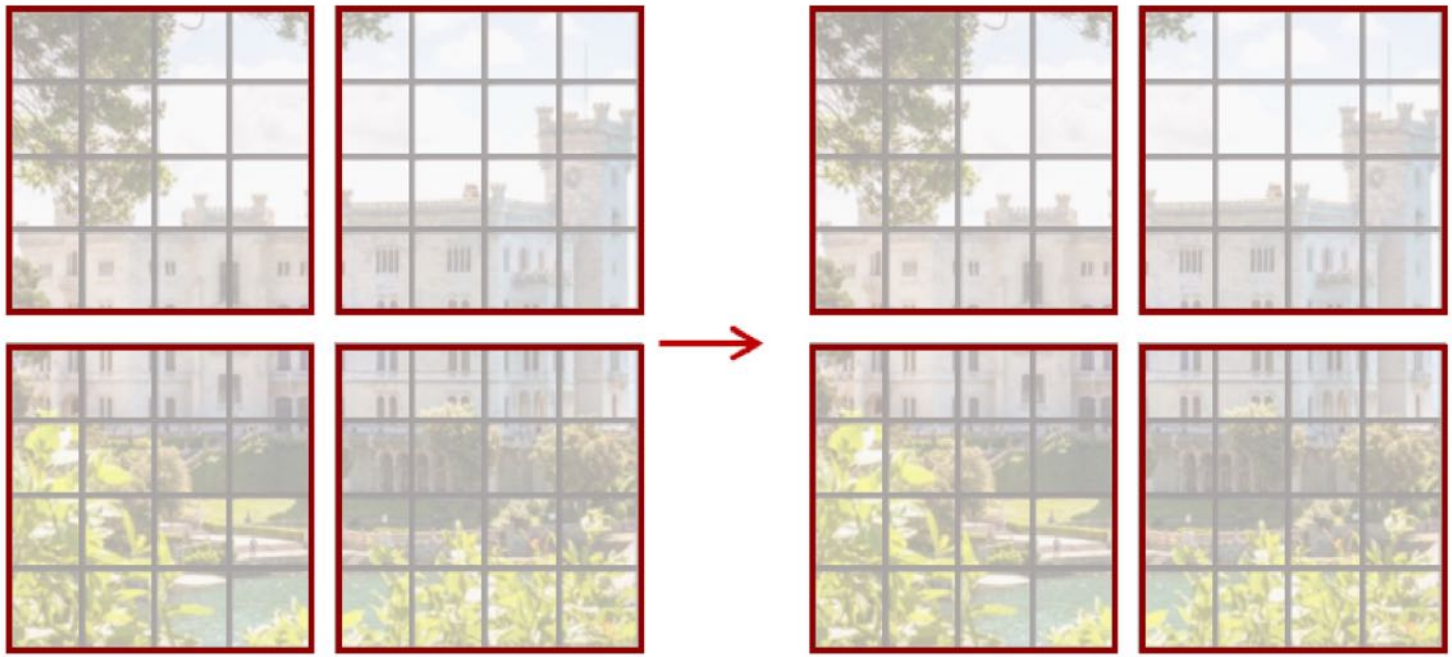
# Swin Transformer: Window Attention

**Problem**: tokens only interact with other tokens within the same window; no communication across windows



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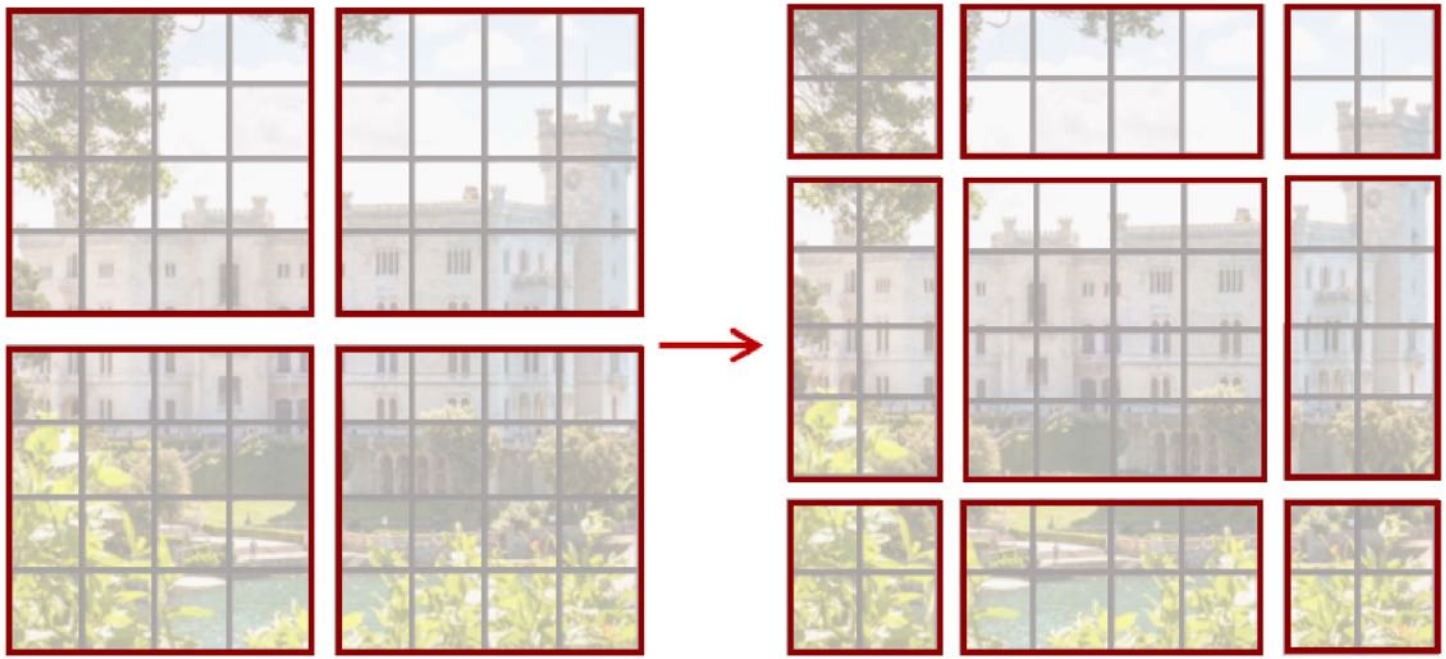
# Swin Transformer: Shifted Window Attention

**Solution**: Alternate between normal windows and shifted windows in successive Transformer blocks



Block L: Normal windows

Block L+1: Shifted Windows

Ugly detail: Non-square windows at edges and corners

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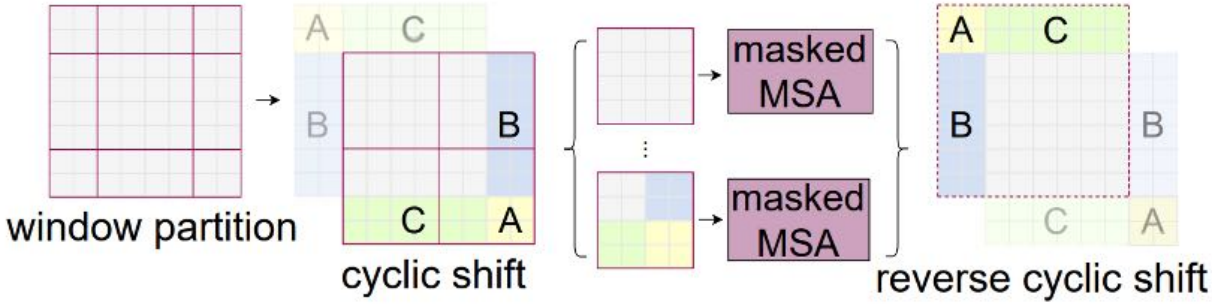
slide credit: Justin Johnson

# Efficient batch computation for shifted configuration

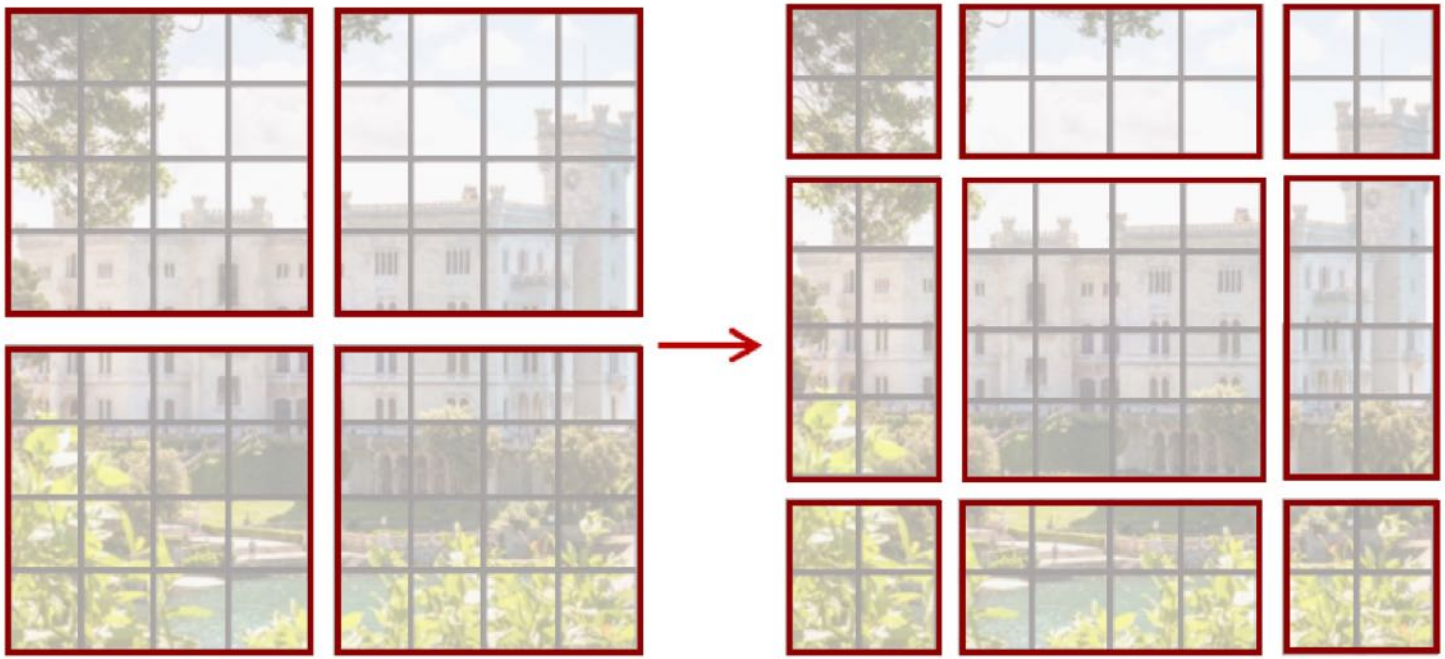
- First idea
  - add padding… works, but increased computation

- Their idea: cyclic-shift:



# Swin Transformer: Shifted Window Attention

**Solution**: Alternate between normal windows and shifted windows in successive Transformer blocks



Block L: Normal windows

Block L+1: Shifted Windows

Liu et al, "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows", ICCV 2021

Detail: Relative Positional Bias

ViT adds positional embedding to input tokens, encodes *absolute position* of each token in the image

Swin does not use positional embeddings, instead encodes *relative position* between patches when computing attention:

Attention with relative bias:

$$A = Softmax\left(\frac{QK^T}{\sqrt{D}} + B\right)V$$

$Q, K, V: M^2 \times D$ (Query, Key, Value)

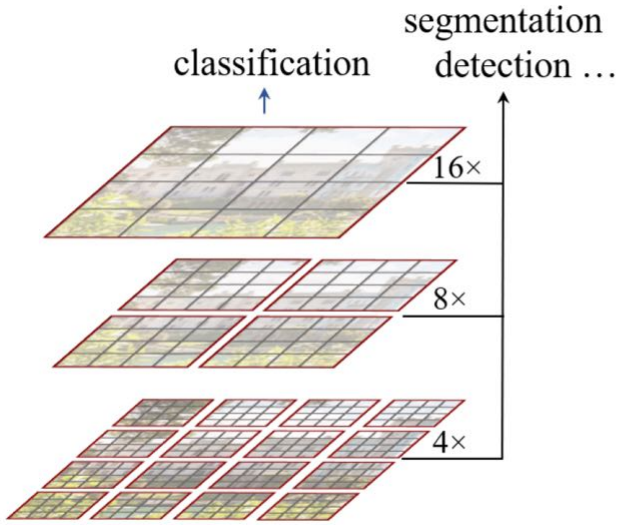
$B: M^2 \times M^2$ (learned biases)

slide credit: Justin Johnson

# Application to Various Tasks…

- General idea: think of (hierarchical tokens) as feature maps
  - allows to apply standard techniques for detection (e.g. Faster-RNN), instance segmentation (e.g. Mask-RCNN), semantic segmentation
    - ImageNet: classification
    - COCO: object detection
    - ADE20k: semantic segmentation

| | ImageNet | | COCO | | ADE20k |
|---|---|---|---|---|---|
| | top-1 | top-5 | $AP^{box}$ | $AP^{mask}$ | mIoU |
| w/o shifting | 80.2 | 95.1 | 47.7 | 41.5 | 43.3 |
| shifted windows | **81.3** | **95.6** | **50.5** | **43.7** | **46.1** |
| no pos. | 80.1 | 94.9 | 49.2 | 42.6 | 43.8 |
| abs. pos. | 80.5 | 95.2 | 49.0 | 42.4 | 43.2 |
| abs.+rel. pos. | 81.3 | 95.6 | 50.2 | 43.4 | 44.0 |
| rel. pos. w/o app. | 79.3 | 94.7 | 48.2 | 41.9 | 44.1 |
| rel. pos. | **81.3** | **95.6** | **50.5** | **43.7** | **46.1** |



(a) Swin Transformer (ours)