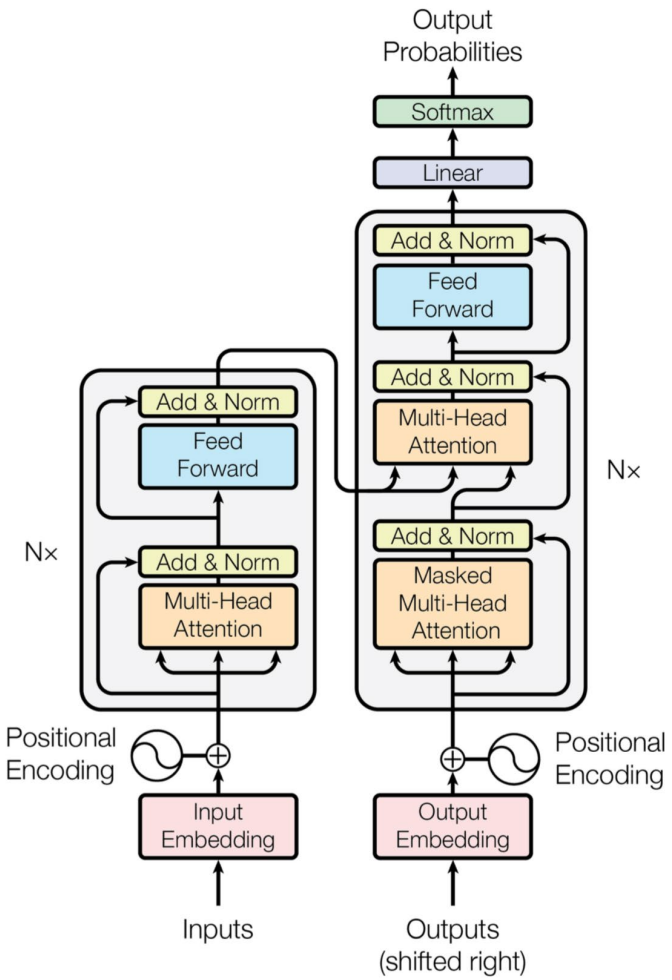
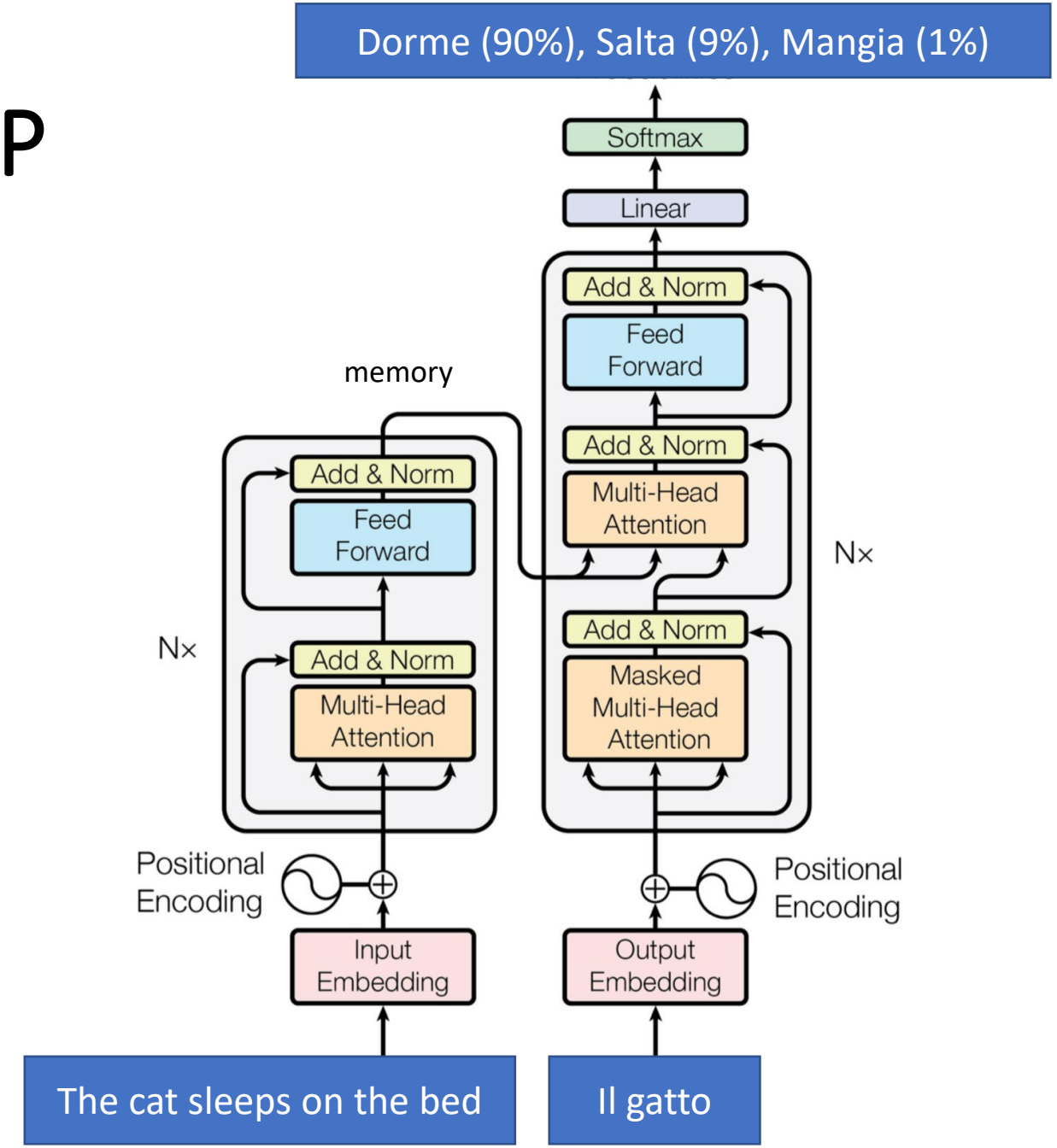
Vision and Perception

Transformers In Vision

SAPIENZA
UNIVERSITÀ DI ROMA


Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

The transformer in NLP



Summary

- From RNNs to Transformers
- Tranformer’s attention and self-attention mechanism
- Transformer Encoder
- From Text to Images: Vision Transformers
- The scale and data problem
- Hybrid Transformers

History

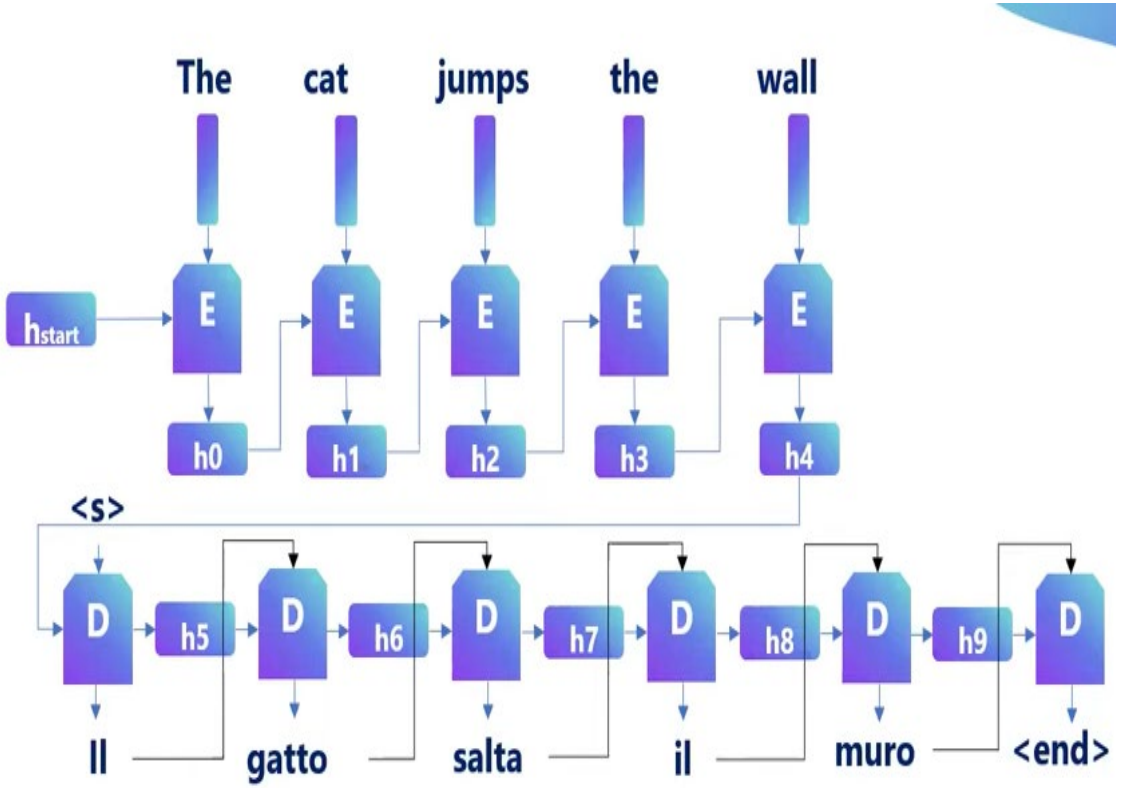
- 2017 Introduced transformers in NLP
- 2020 Vision Transformers
- 2021 Transformers for video understanding
- Now used everywhere!

Recurrent Networks (RNNs)

- Recurrent models generate a sequence of hidden states h_t, as a function of the previous hidden state h_{t-1} and the input for position t

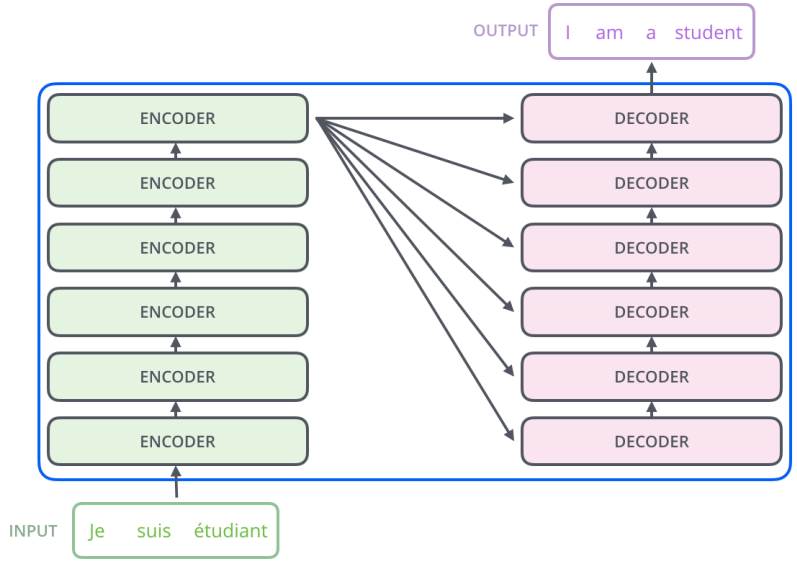
Problems:

1. We forget tokens too far in the past
2. This inherently sequential nature **precludes parallelization** within training examples
   - Need to wait the previous token to compute the next hidden state

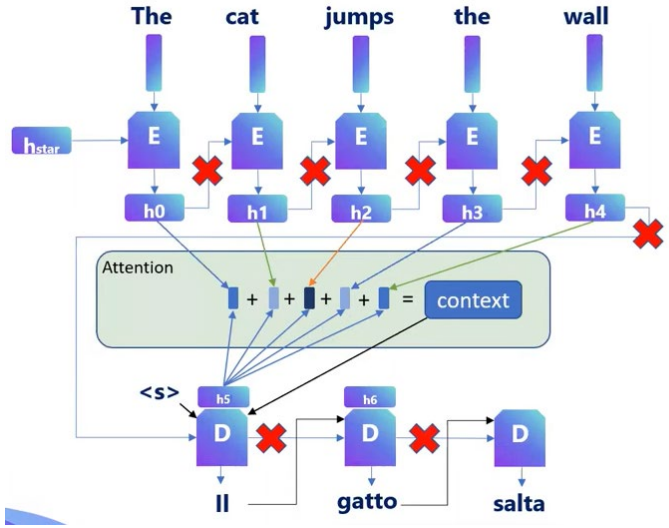


How to solve those problems?

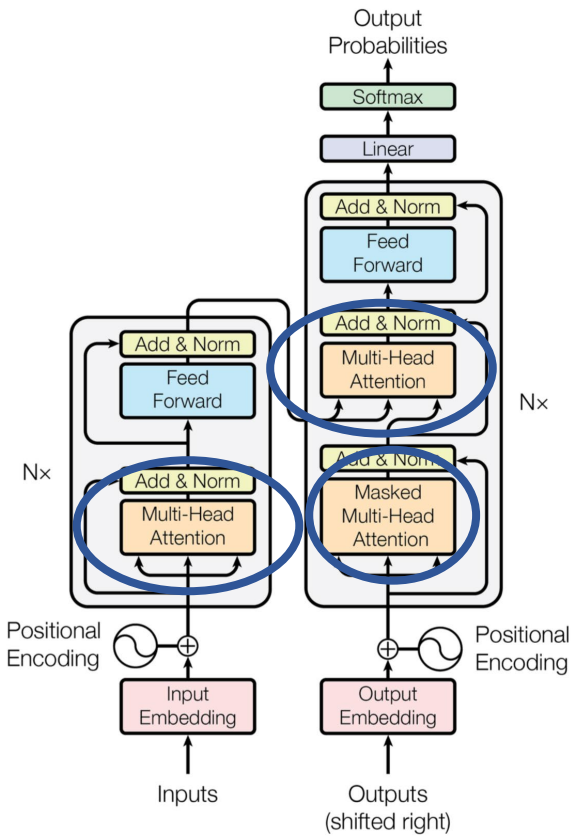
- Problem 1: Add an attention mechanism
- Problem 2 : Remove recurrent connections



- Paper from 2017: «Attention is all you need»



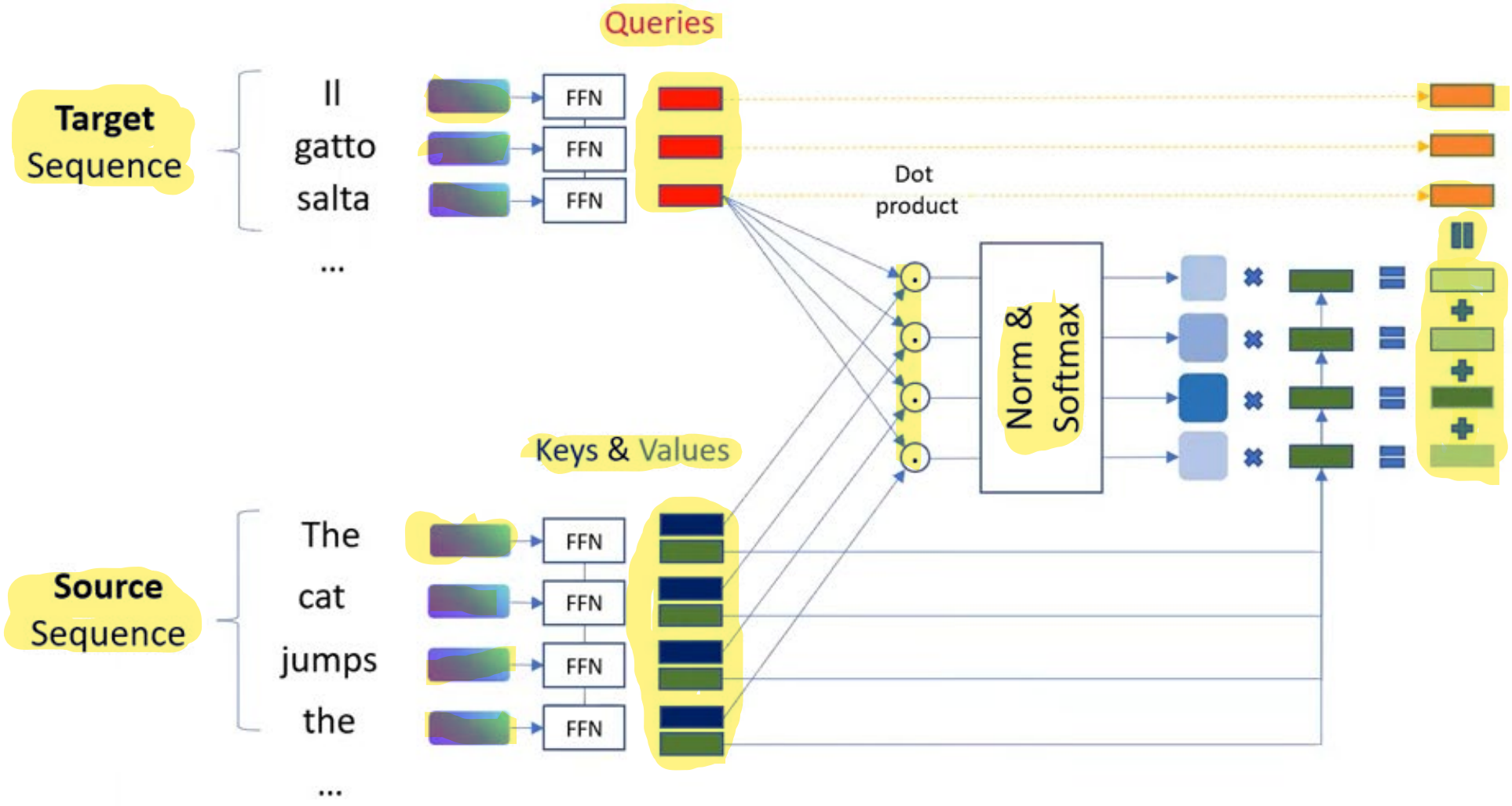
Attention is all you need



The Transformer is a simple network architecture based on the attention mechanism which **boosts the speed** with which these models can be trained

[Vaswani et al., 2017]

Transformer's Attention mechanism

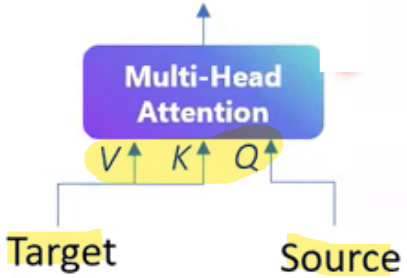


Target tokens (from the point of view of the source sequence)

Attention and Self-Attention

Attention

- Source ≠ Target
  - Queries from **Source**
  - Key, Values from **Target**



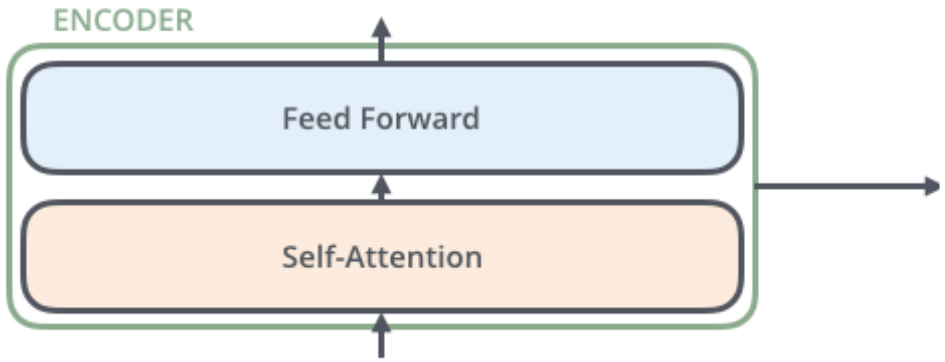
- Captures **inter-**sequence dependencies

Self-Attention

- Source = Target
  - Key, Queries, Values obtained from the same sentence

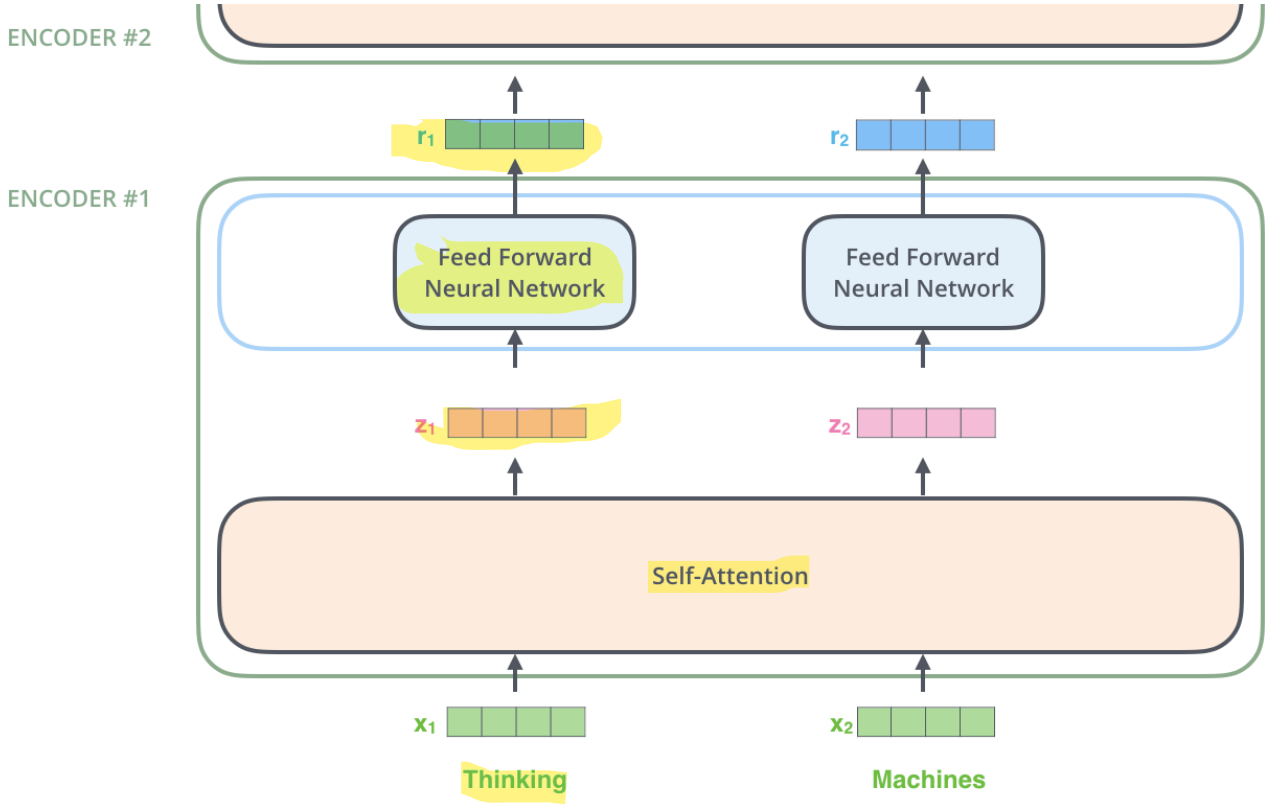
- Captures **intra-**sequence dependencies

Attention is all you need



- The encoders are **all identical** in structure (yet they do not share weights)
- The *self-attention layer* helps the encoder to **look at other words** in the input sentence as it encodes a specific word
- The outputs of the self-attention layer are fed to a feed-forward neural network

The encoder



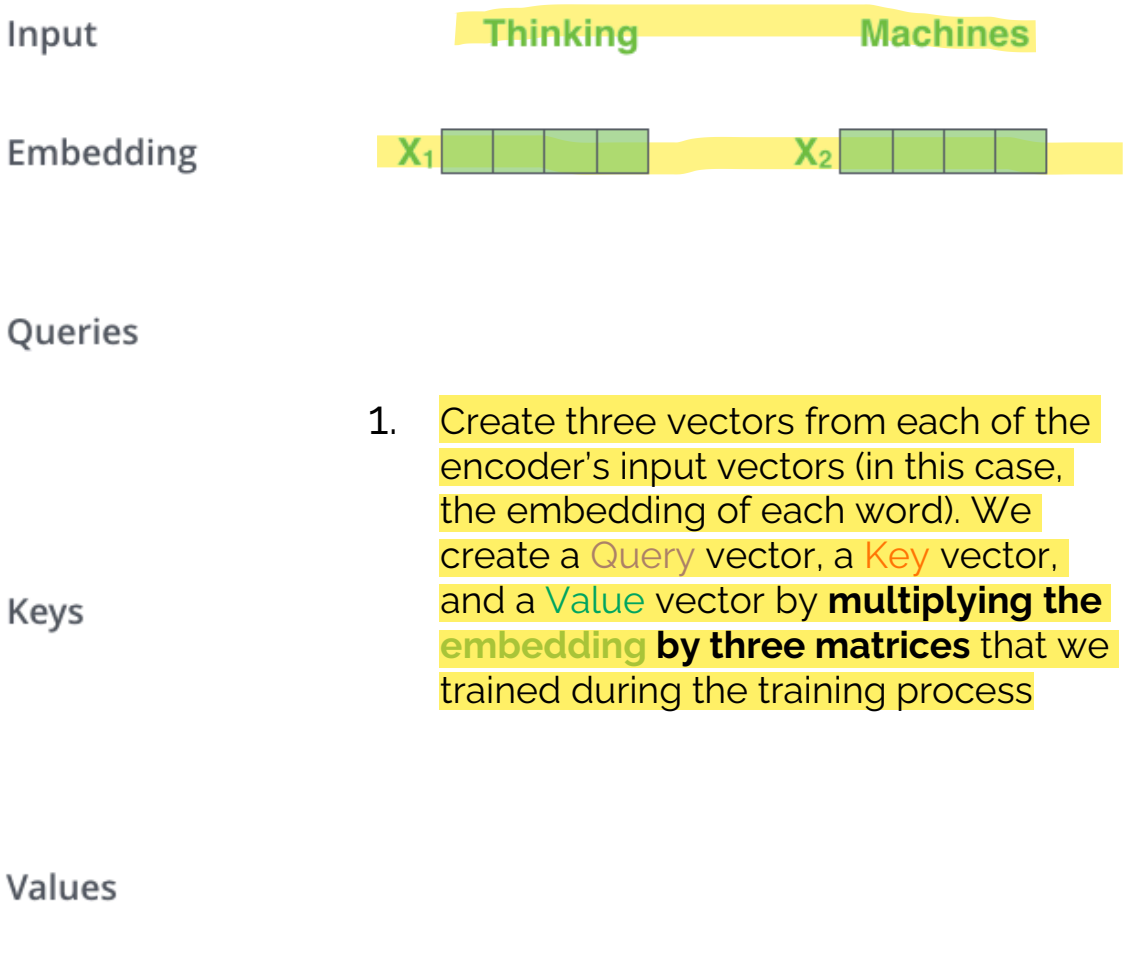
Key property of the Transformer: each word flows through its own path in the encoder.

- There are dependencies between these paths in the self-attention layer.
- The feed-forward layer does not have those dependencies and thus the various paths can be executed in parallel while flowing through the feed-forward layer

An encoder receives a list of vectors as input. It processes this list by passing these vectors into a ‘self-attention’ layer, then into a feed-forward neural network, then sends out the output upwards to the next encoder.

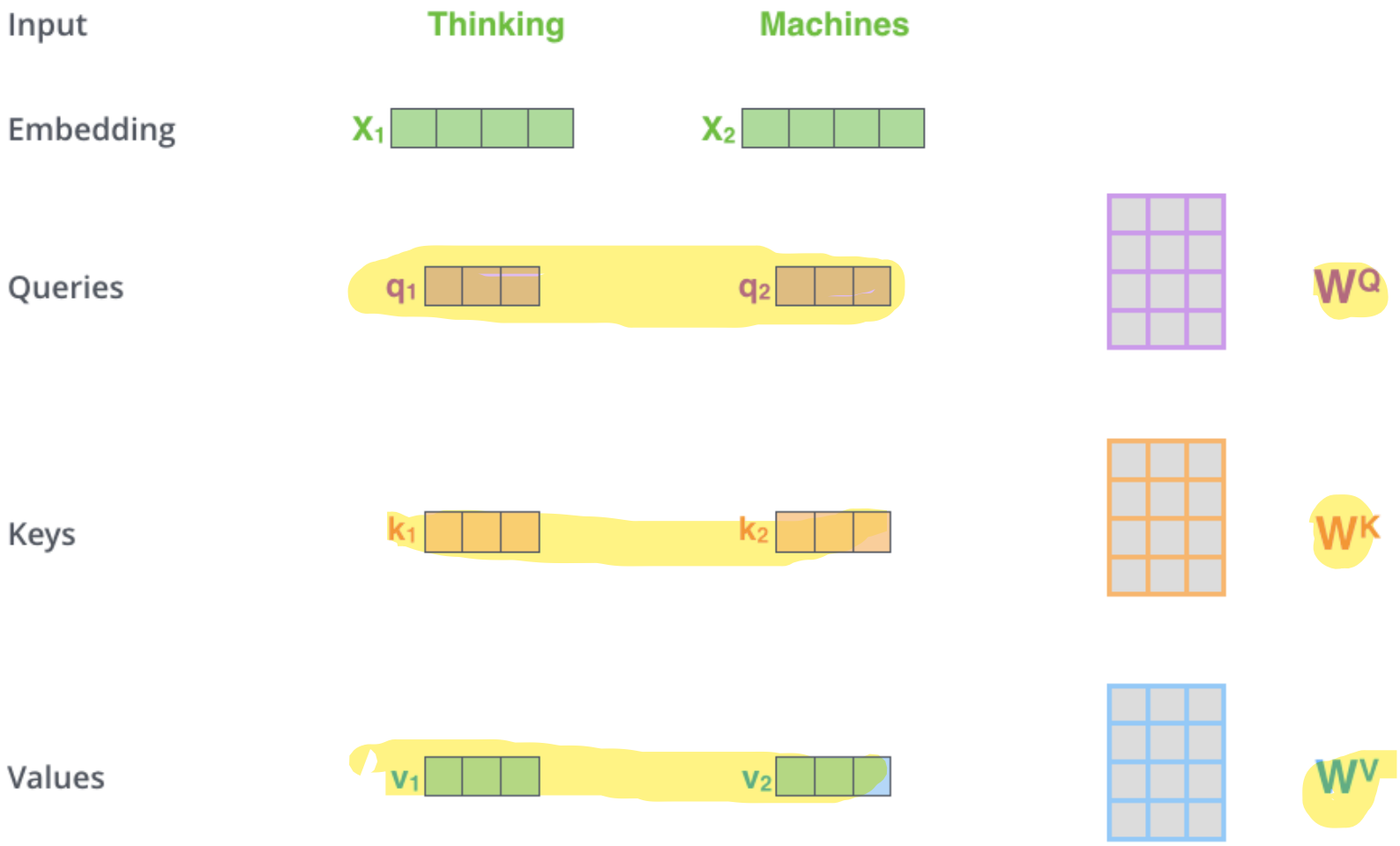
Self-attention

- As the model processes each word (each position in the input sequence), self attention allows it to look at other positions in the input sequence for clues that can help lead to a better encoding for this word.
- Captures **intra-sequence** dependencies

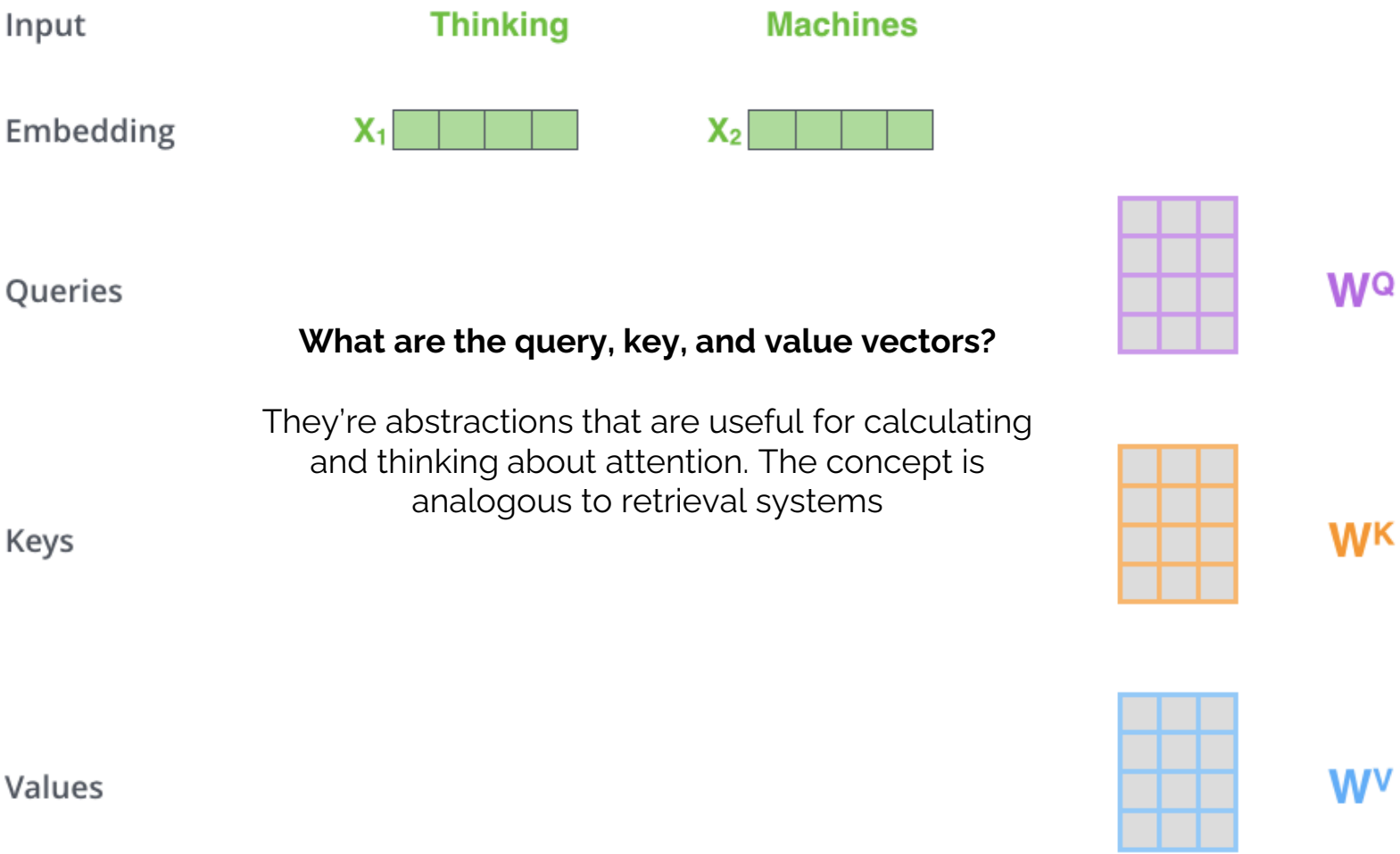


1. Create three vectors from each of the encoder's input vectors (in this case, the embedding of each word). We create a Query vector, a Key vector, and a Value vector by **multiplying the embedding by three matrices** that we trained during the training process

Self-attention



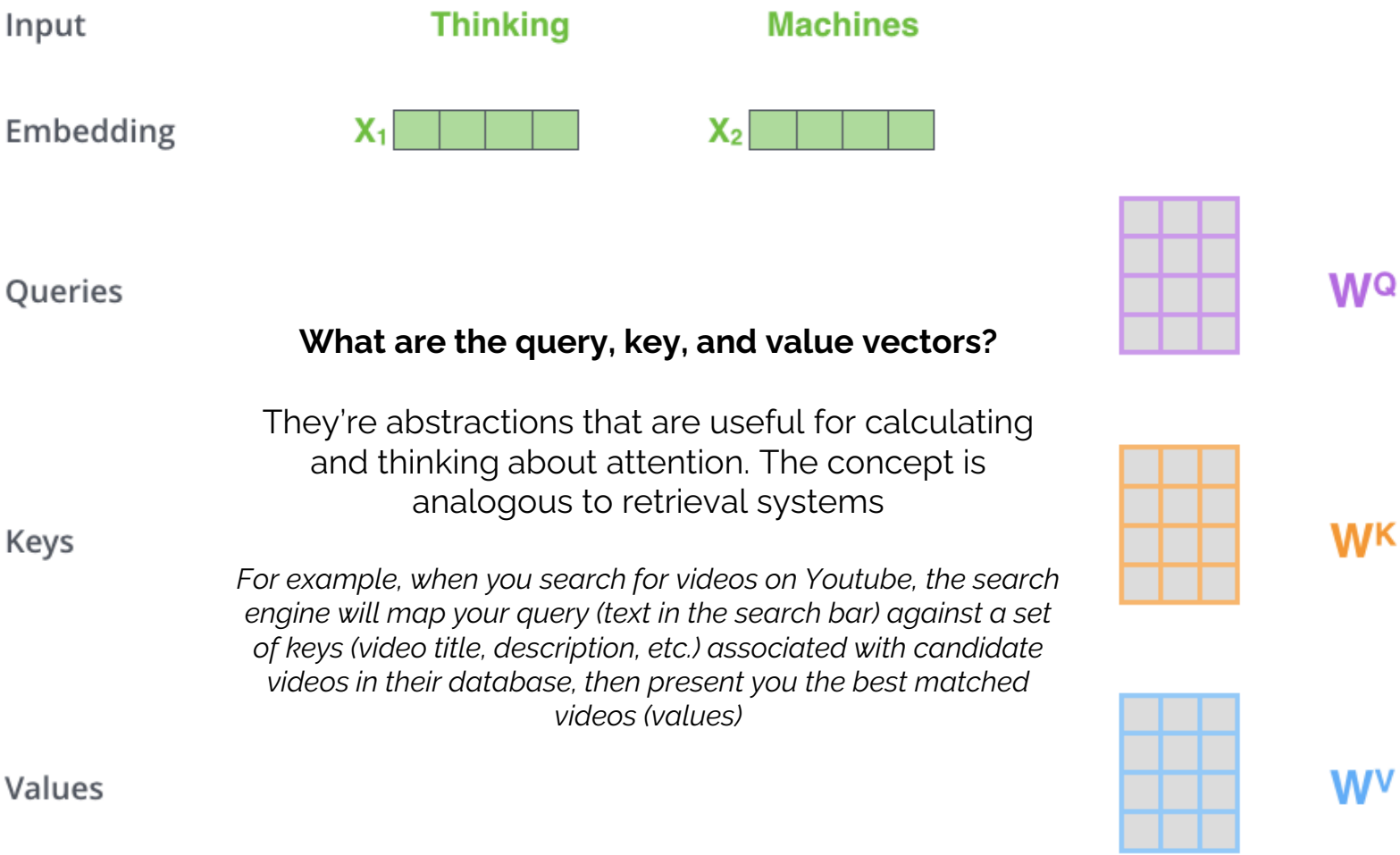
Self-attention



What are the query, key, and value vectors?

They're abstractions that are useful for calculating and thinking about attention. The concept is analogous to retrieval systems

Self-attention

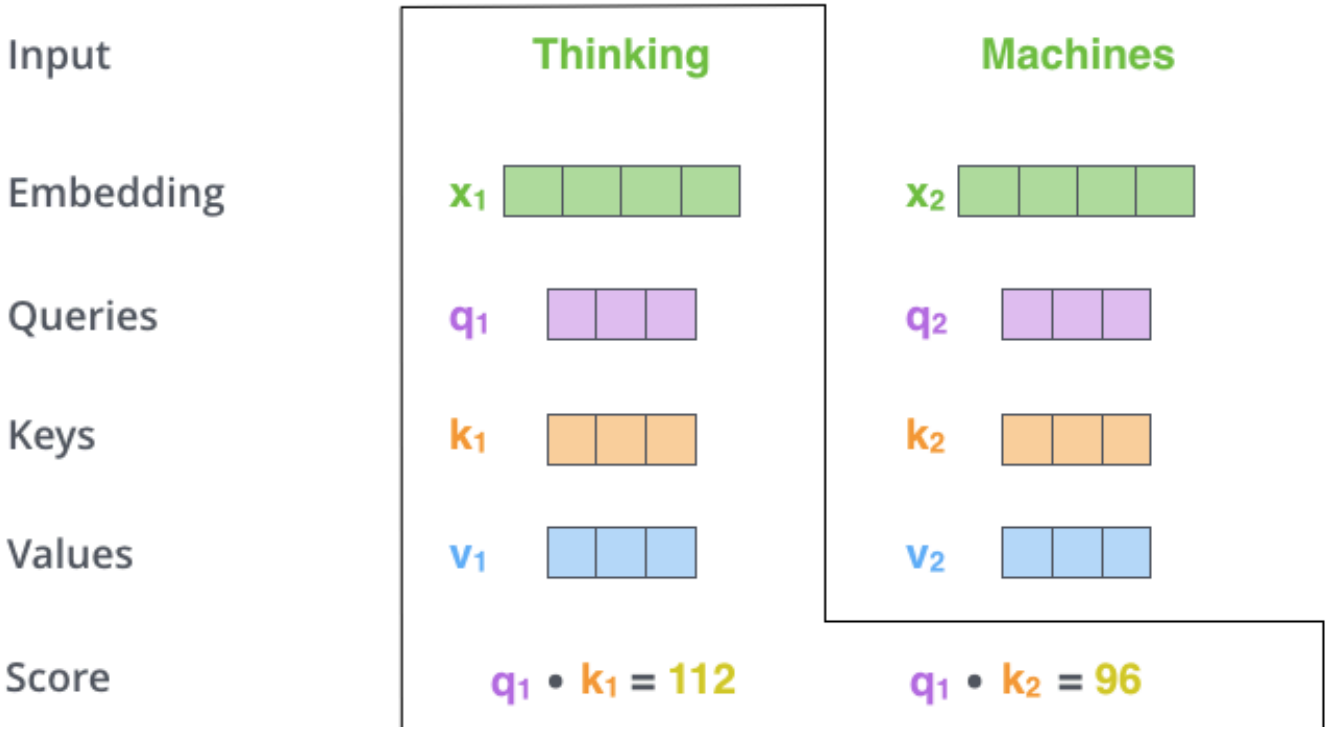


What are the query, key, and value vectors?

They're abstractions that are useful for calculating and thinking about attention. The concept is analogous to retrieval systems

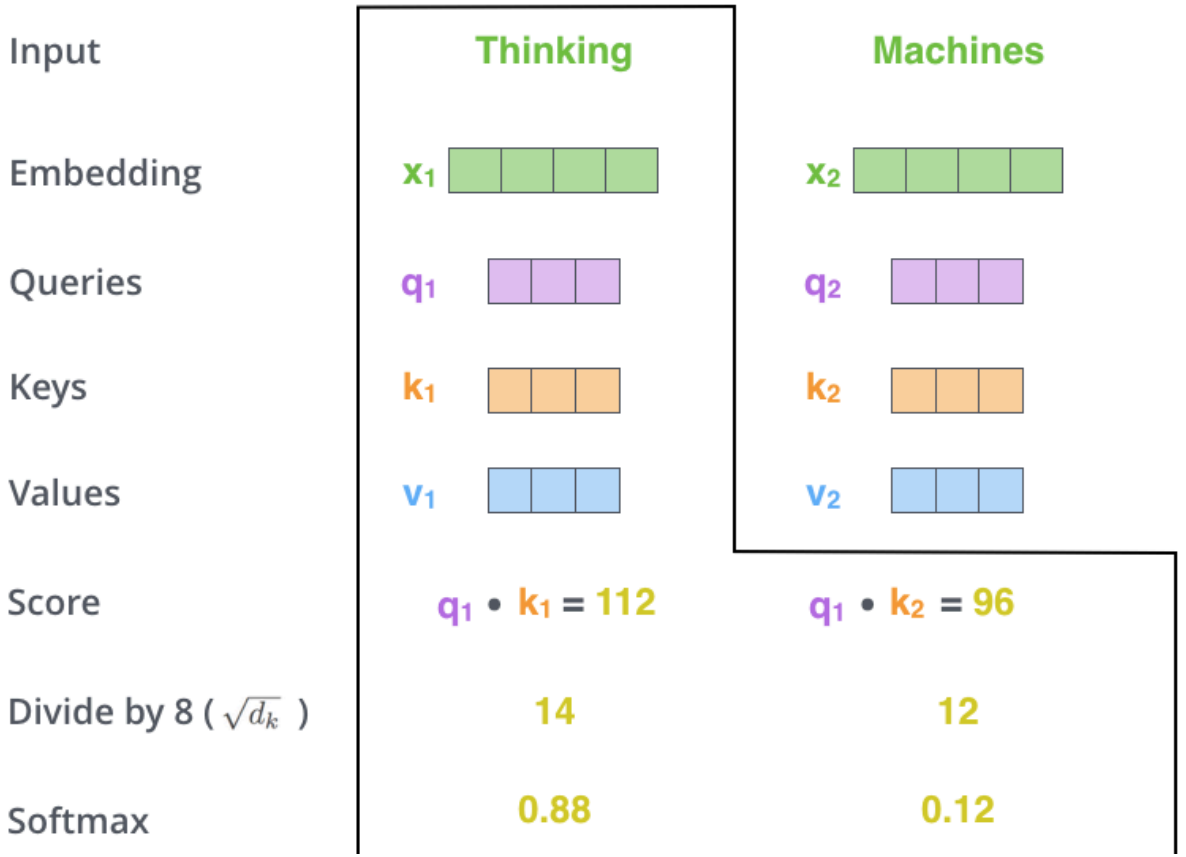
For example, when you search for videos on Youtube, the search engine will map your query (text in the search bar) against a set of keys (video title, description, etc.) associated with candidate videos in their database, then present you the best matched videos (values)

Self-attention



2. Calculate the **score** by taking the **dot product** of the query vector with the key vector of the respective word we're scoring

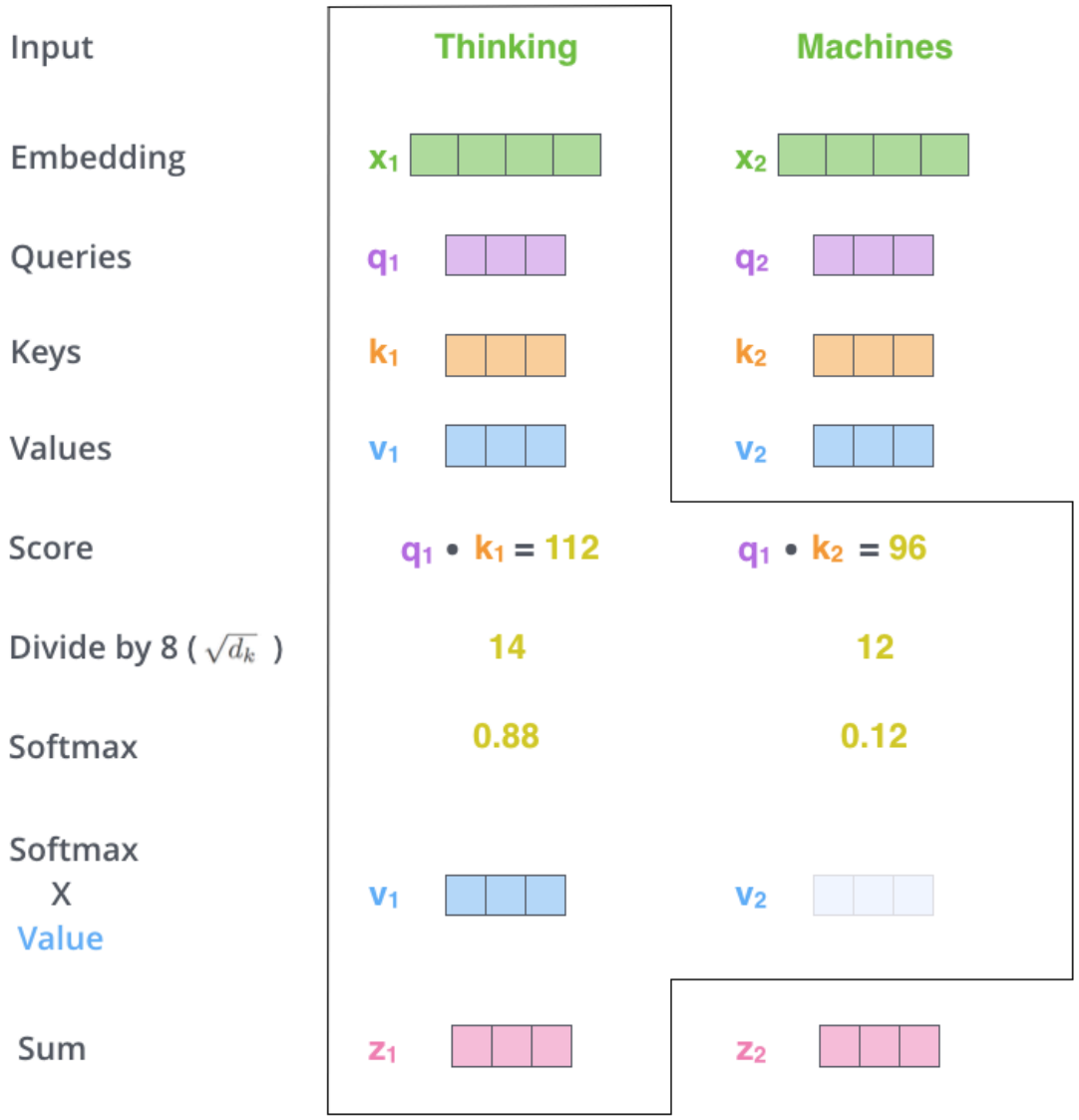
Self-attention



3. **Divide** the scores by the **square root** of the **dimension of the key** vectors (64 in the paper). This leads to having more stable gradients.
4. Pass the result through a **softmax** operation (softmax score determines how much each word will be expressed at this position)

Self-attention

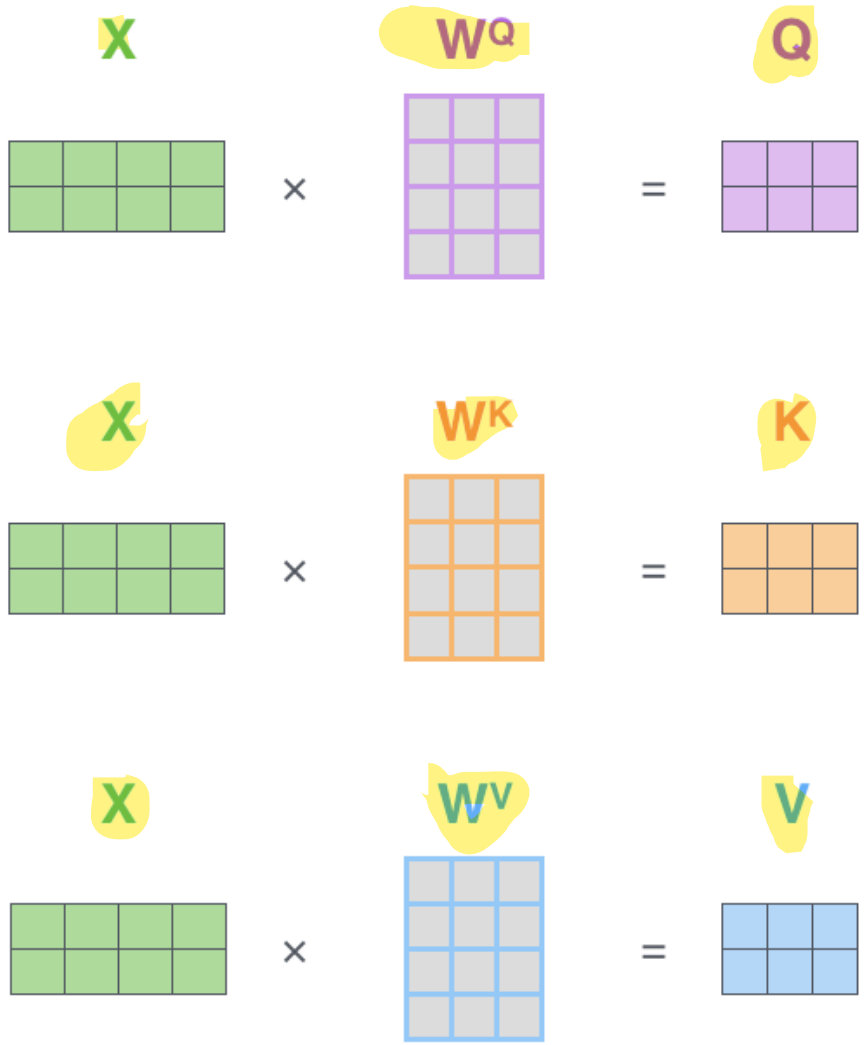
5. **Multiply** each value vector by the softmax score. The intuition here is to keep intact the values of the word(s) we want to **focus** on, and drown-out irrelevant words
6. **Sum** up the weighted value vectors



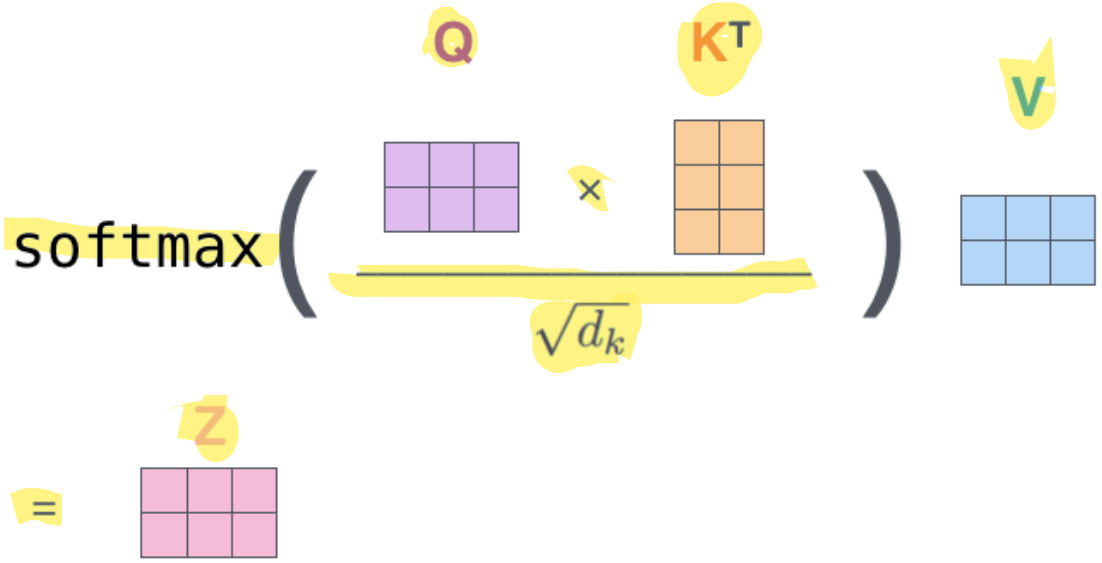
Self-attention: matrix calculation

This calculation is done in matrix form for faster processing!

The first step is to calculate the Query, Key, and Value matrices. We do that by packing our embeddings into a matrix X and multiplying it by the weight matrices we have trained (WQ, WK, WV).



Self-attention: matrix calculation

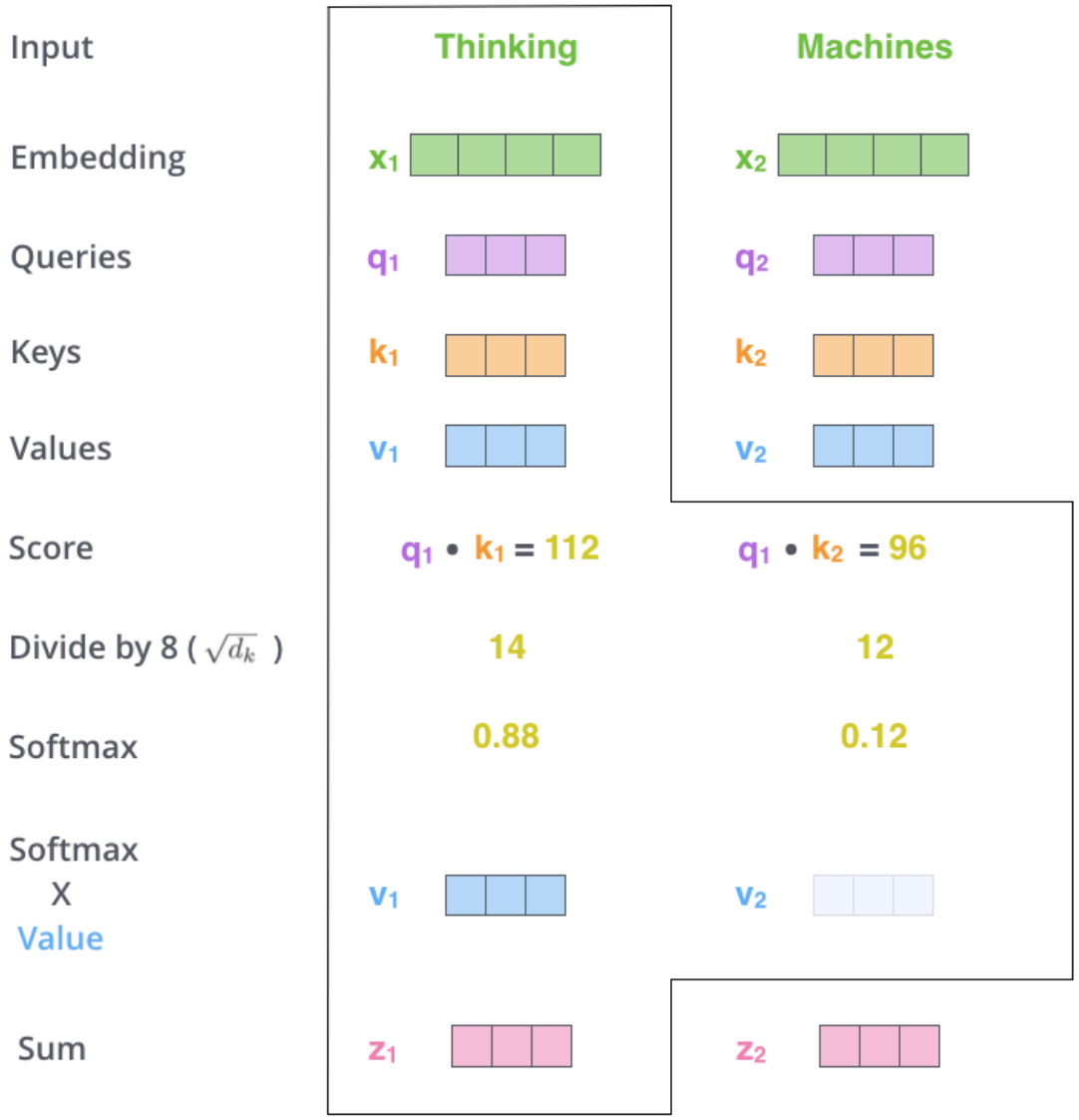


Self-attention: limitation

Note

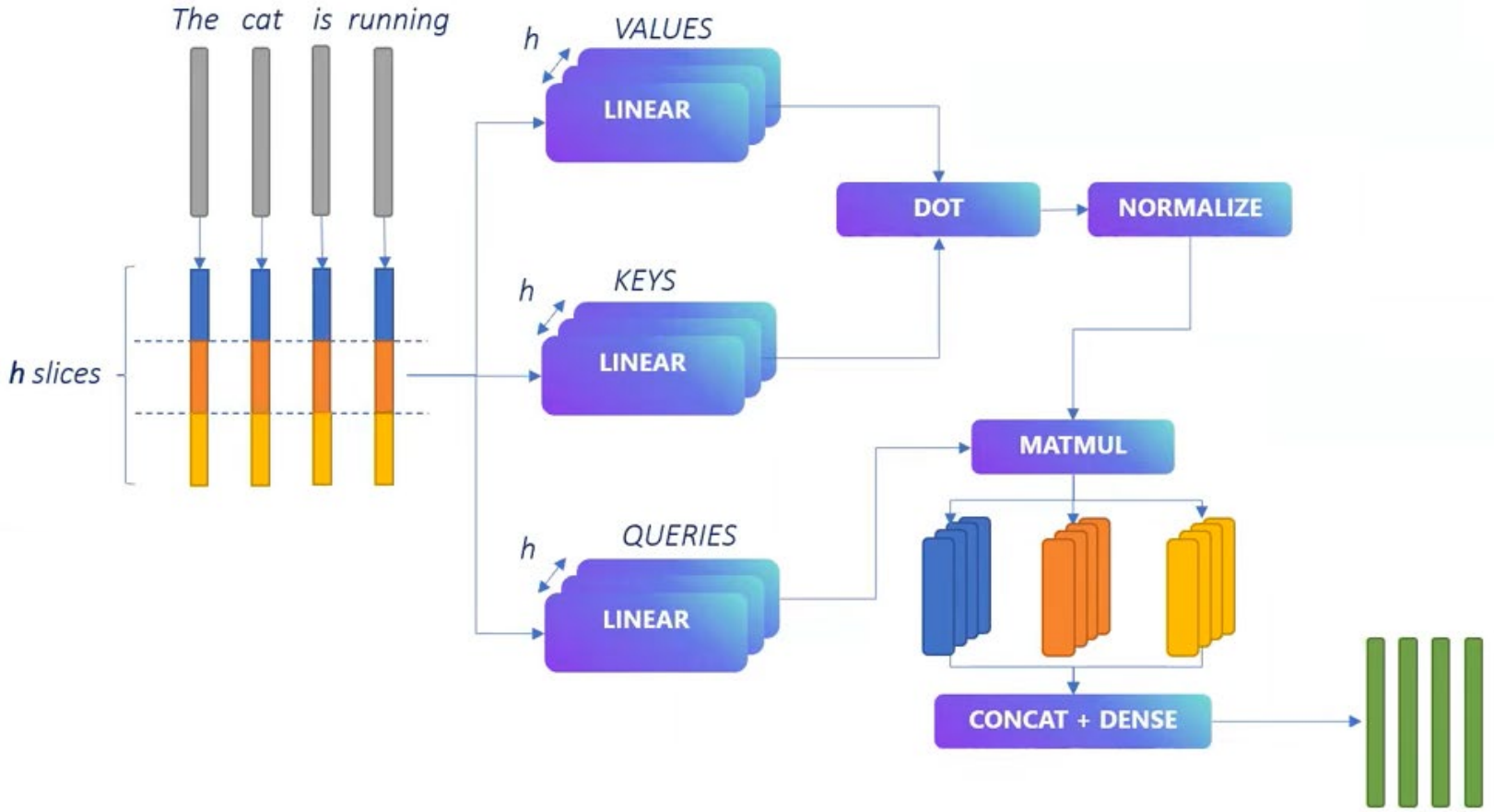
z_1 contains a little bit of every other encoding, but it could be **dominated by the the actual word itself**

It would be useful if we're translating a sentence like "***The animal*** *didn't cross the street because* ***it*** *was too tired*", we would want to know which word "it" refers to



Multi-head attention

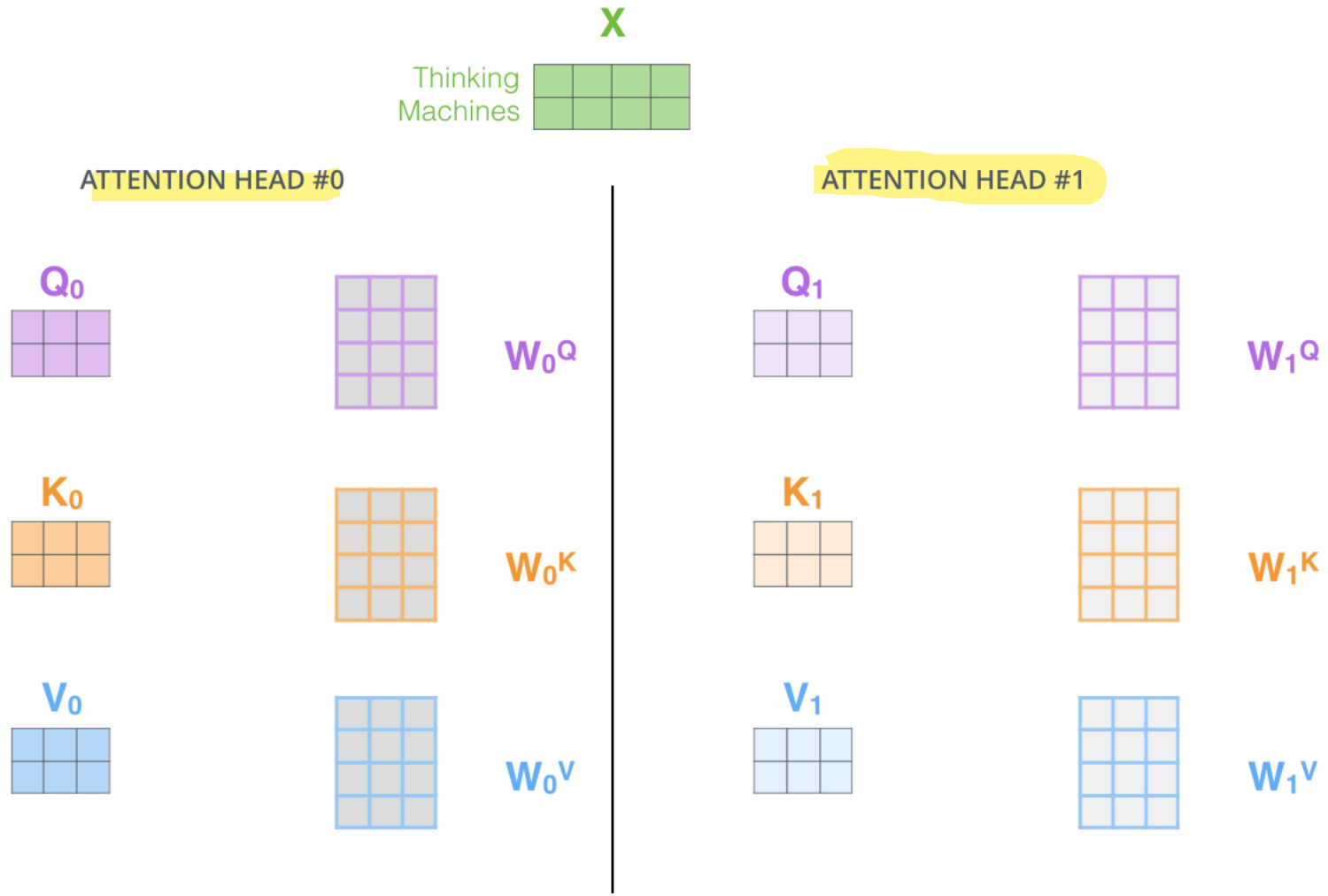
Multiple instantiations of the attention mechanism



Multi-head attention

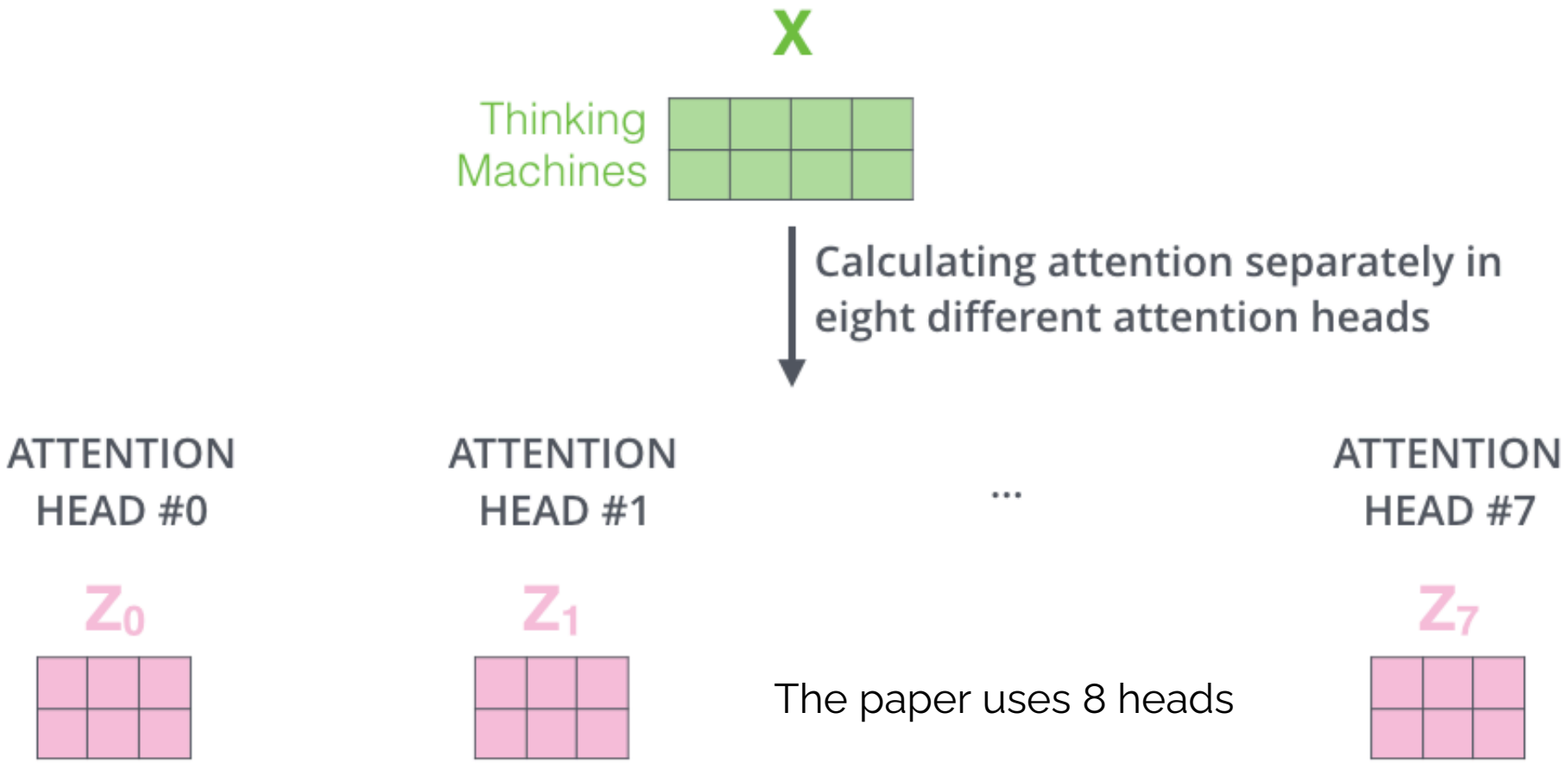
1. It expands the model's ability to focus on **different positions**

2. It gives the attention layer **multiple "representation subspaces"**

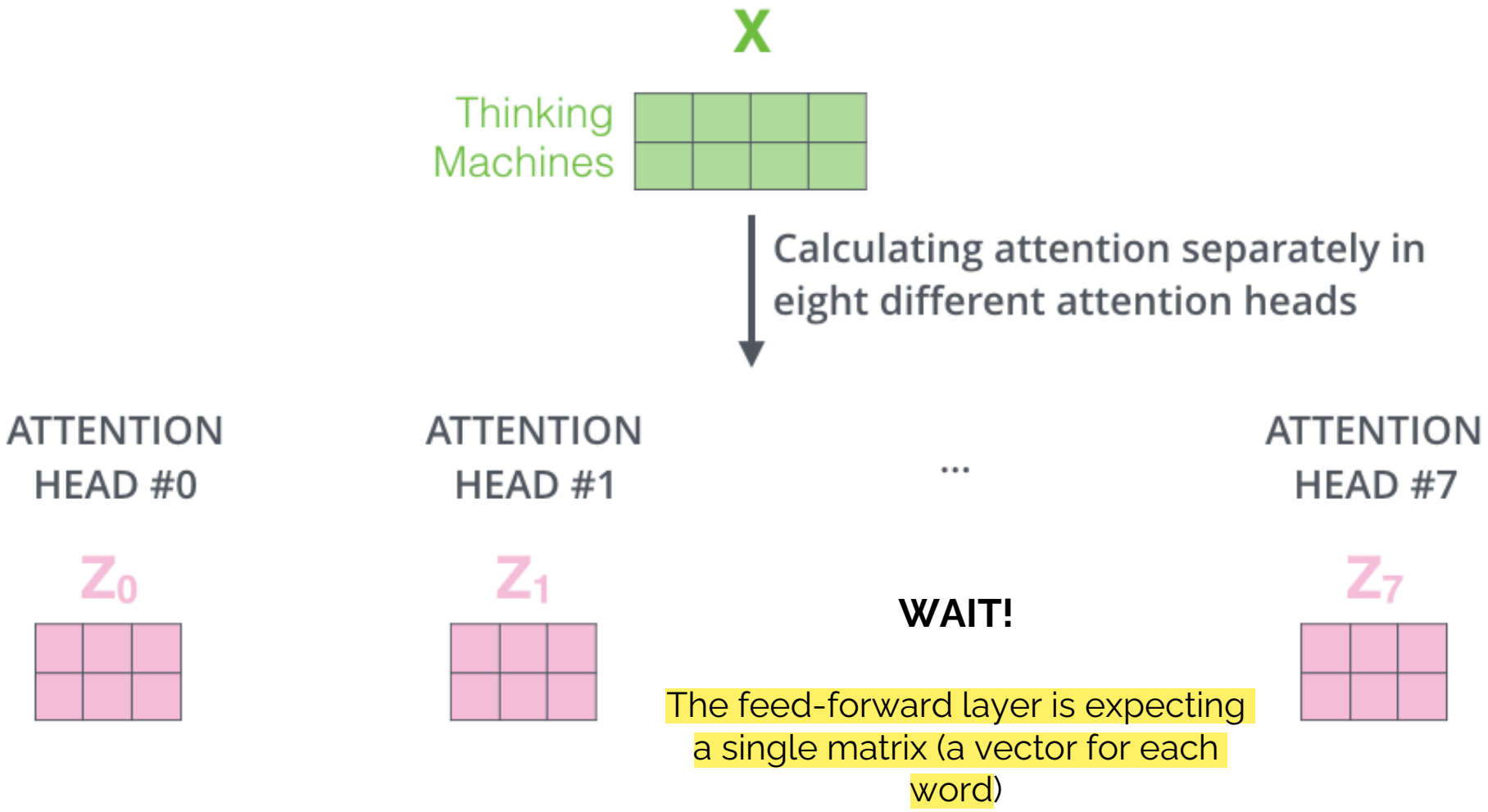


Each of these sets is randomly initialized. Then, after training, each set is used to project the input embeddings (or vectors from lower encoders/decoders) into a different representation subspace

Multi-head attention

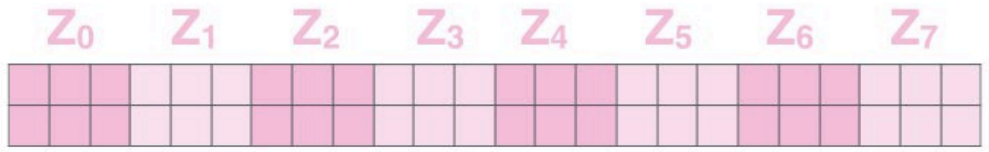


Multi-head attention



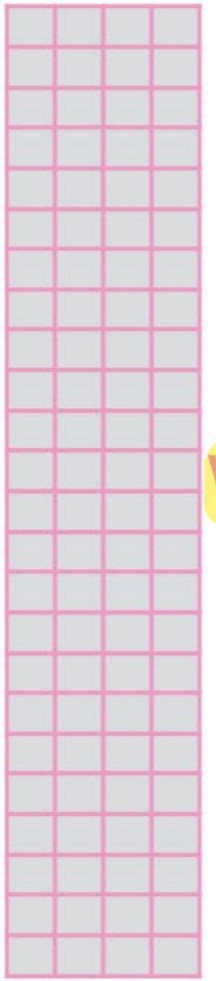
Multi-head attention

1) Concatenate all the attention heads



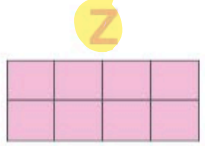
2) Multiply with a weight matrix W^O that was trained jointly with the model

X

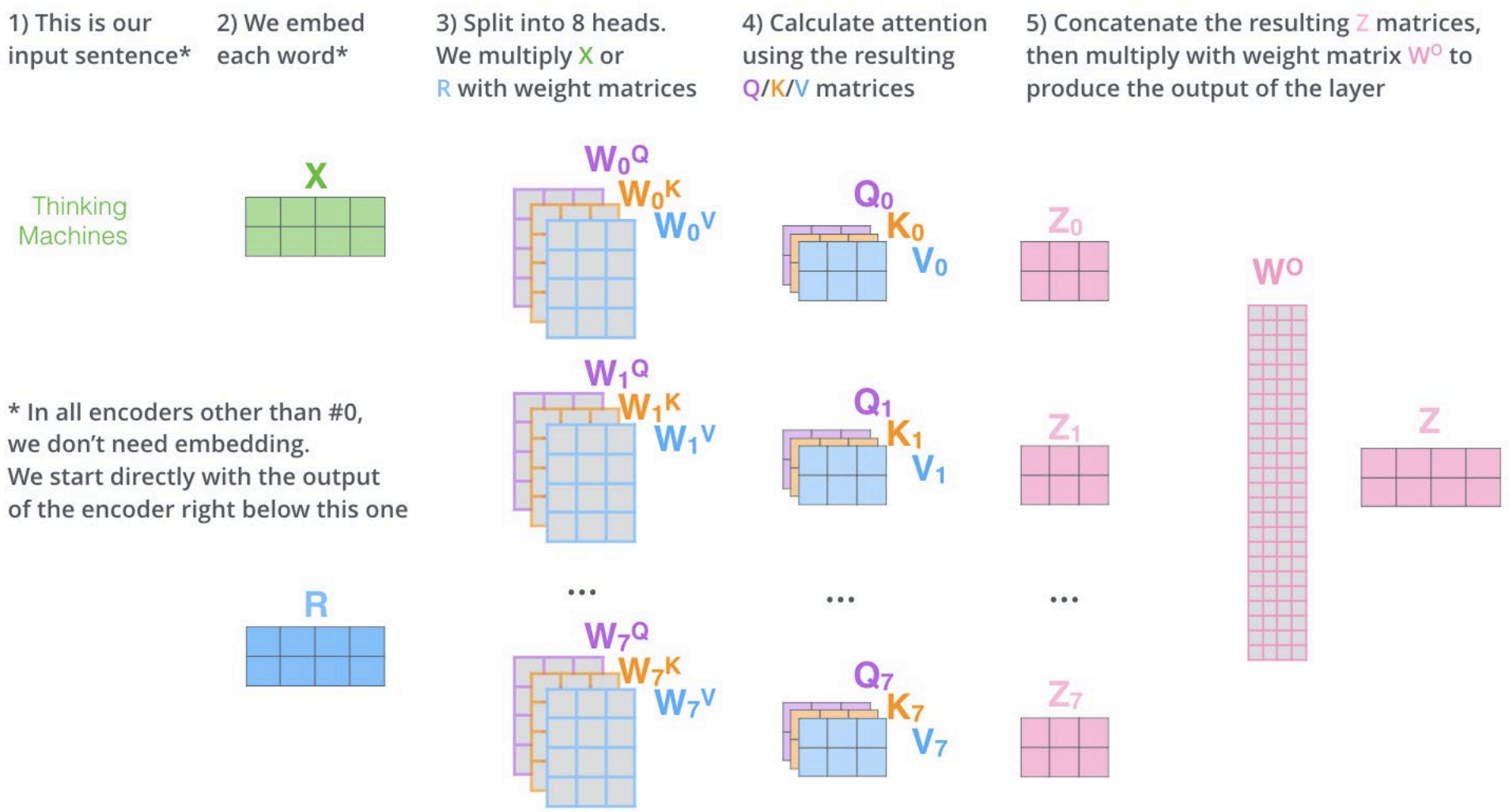


3) The result would be the Z matrix that captures information from all the attention heads. We can send this forward to the FFNN

=

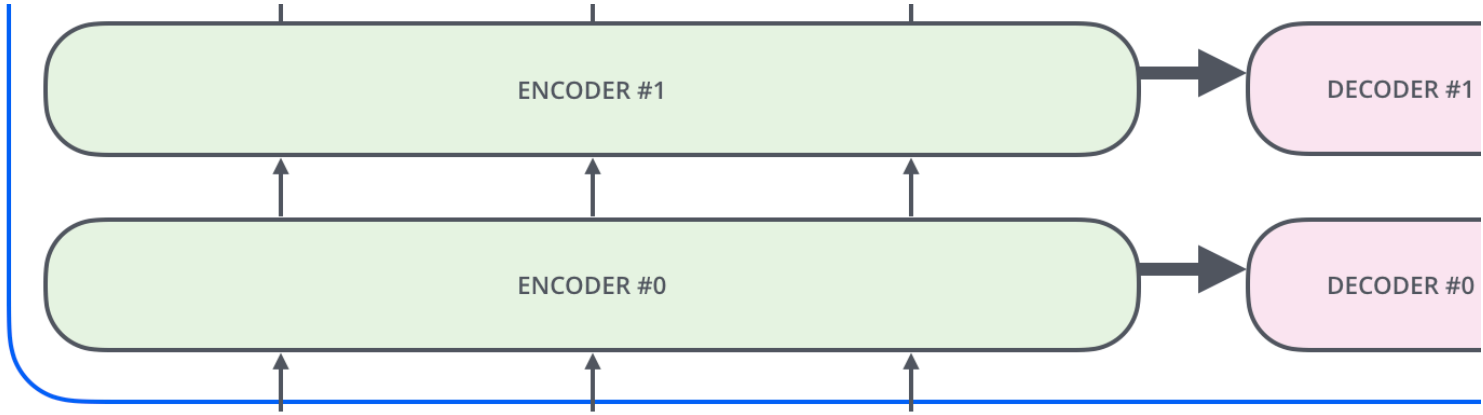


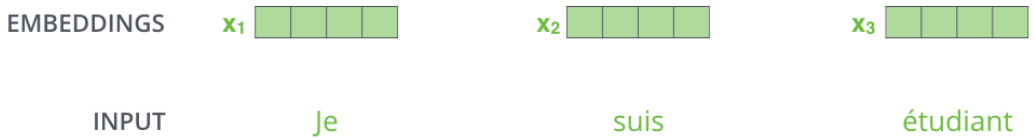
Multi-head attention: put all together!



Positional Encoding

One thing that's missing from the model as we have described it so far is a way to account for the **order of the words** in the input sequence!

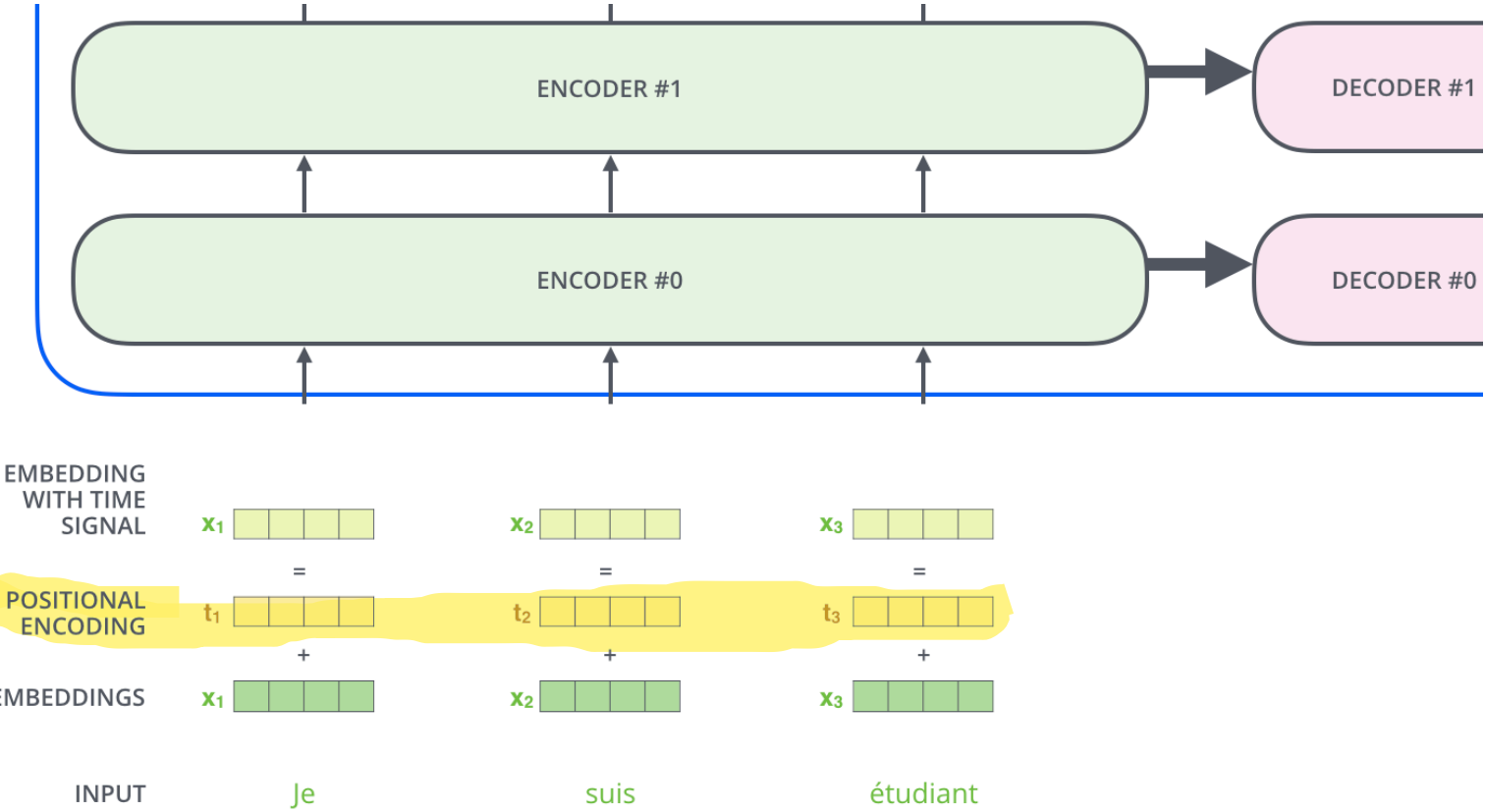




Positional Encoding

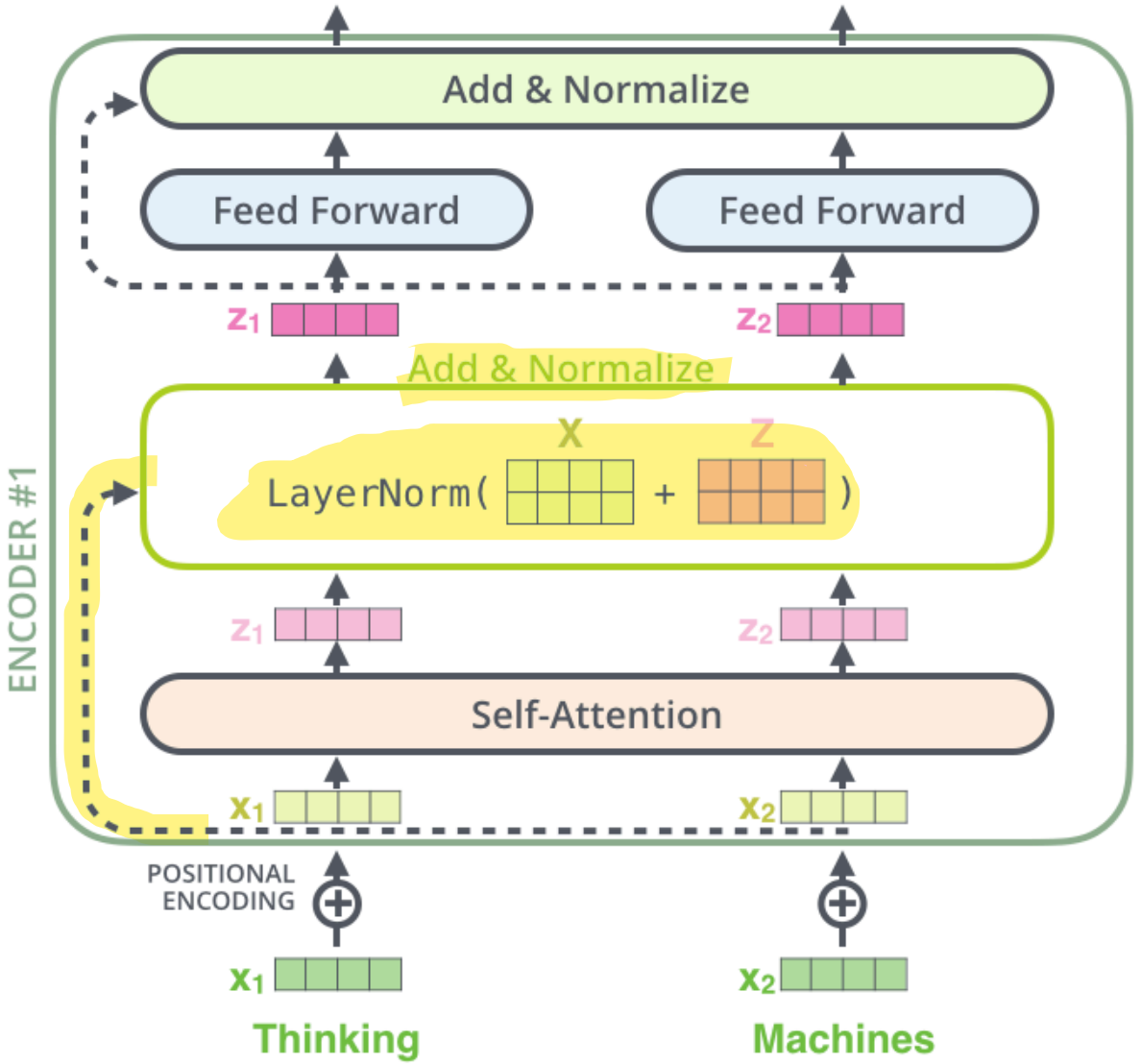
One thing that's missing from the model as we have described it so far is a way to account for the **order of the words** in the input sequence!

To address this, the transformer adds a vector to each input embedding which helps it determine the position of each word

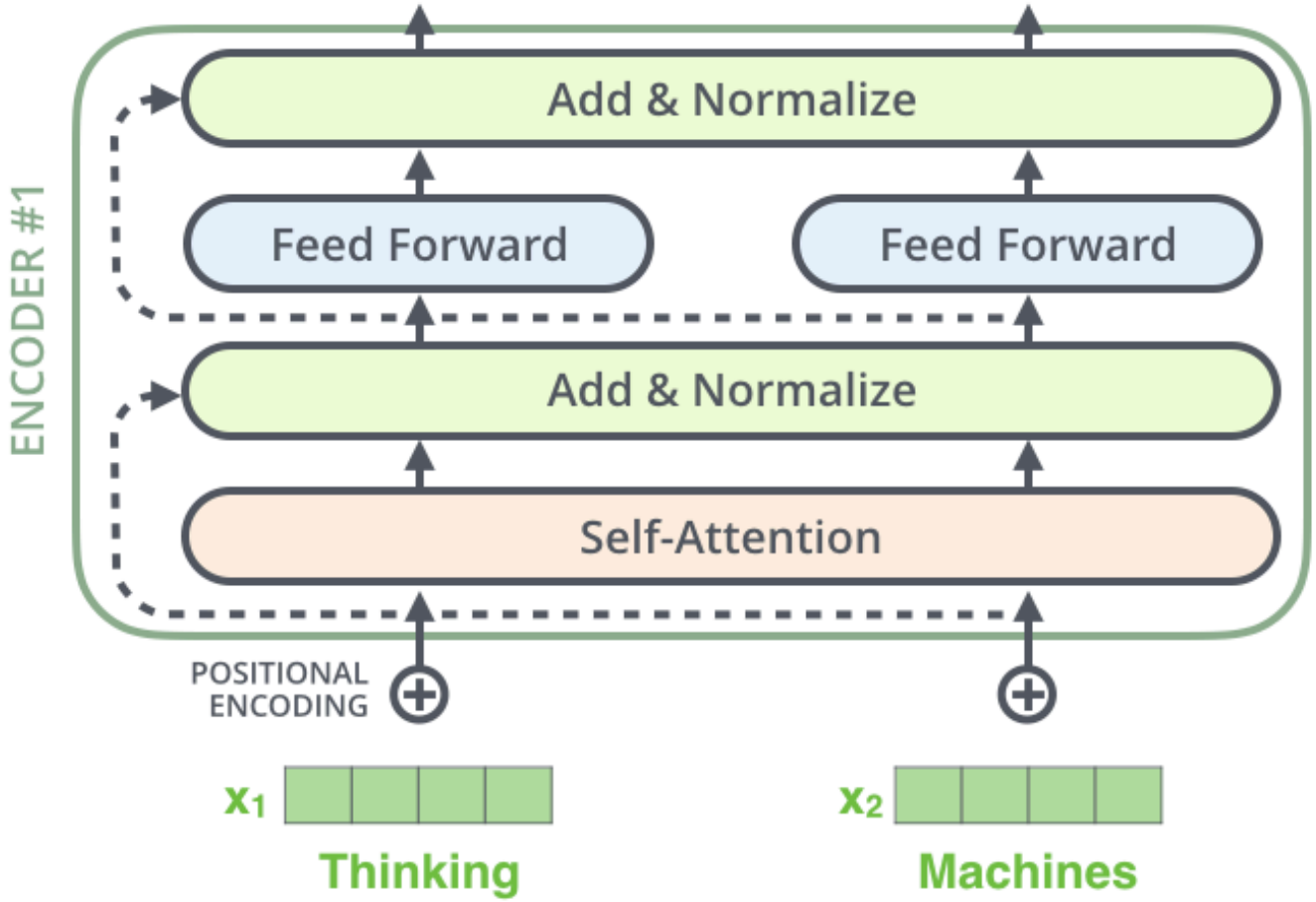


The residuals

Each sub-layer (self-attention, feed forward neural net) in each encoder has a residual connection around it, and is followed by a **layer-normalization** step



The encoder


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

Comparison to other layers

- Self-attention layers were found to be **faster than recurrent layers** for shorter sequence lengths, and can be restricted to consider only a neighbourhood in the input sequence for very long sequence lengths

- The number of sequential operations required by a recurrent layer is based upon the **sequence length**, whereas this number remains **constant** for a self-attention layer

- Tracking long-term dependencies with convolutional layers would require the use of **large kernels**, or **stacks of convolutional layers** that could increase the computational cost. However, a single layer of MHA has a receptive field of n (*i.e. sequence length*), while the convolutive layer has a receptive field of k (*i.e. kernel size*)

The transformer network: key concepts

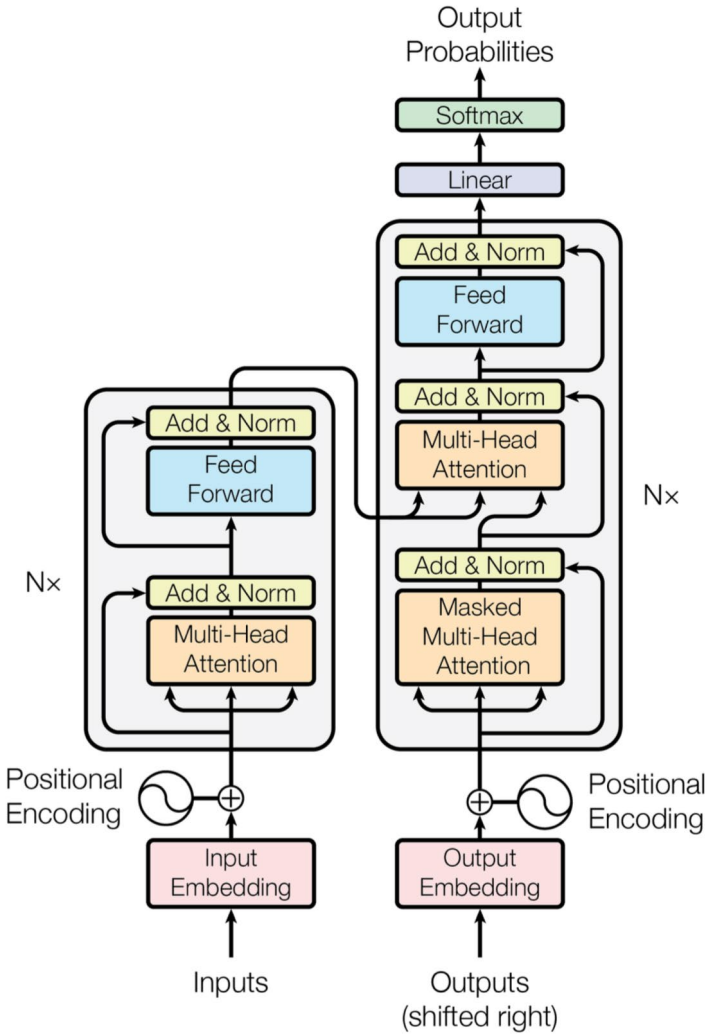
- The **encoder attends to all words** in the input sequence, irrespective if they precede or succeed the word under consideration

- The decoder receives as input its own predicted y_{t-1}

- At the second sublayer, the decoder also receives the output of the encoder, which now allows the decoder to **attend to all of the words in the input sequence**

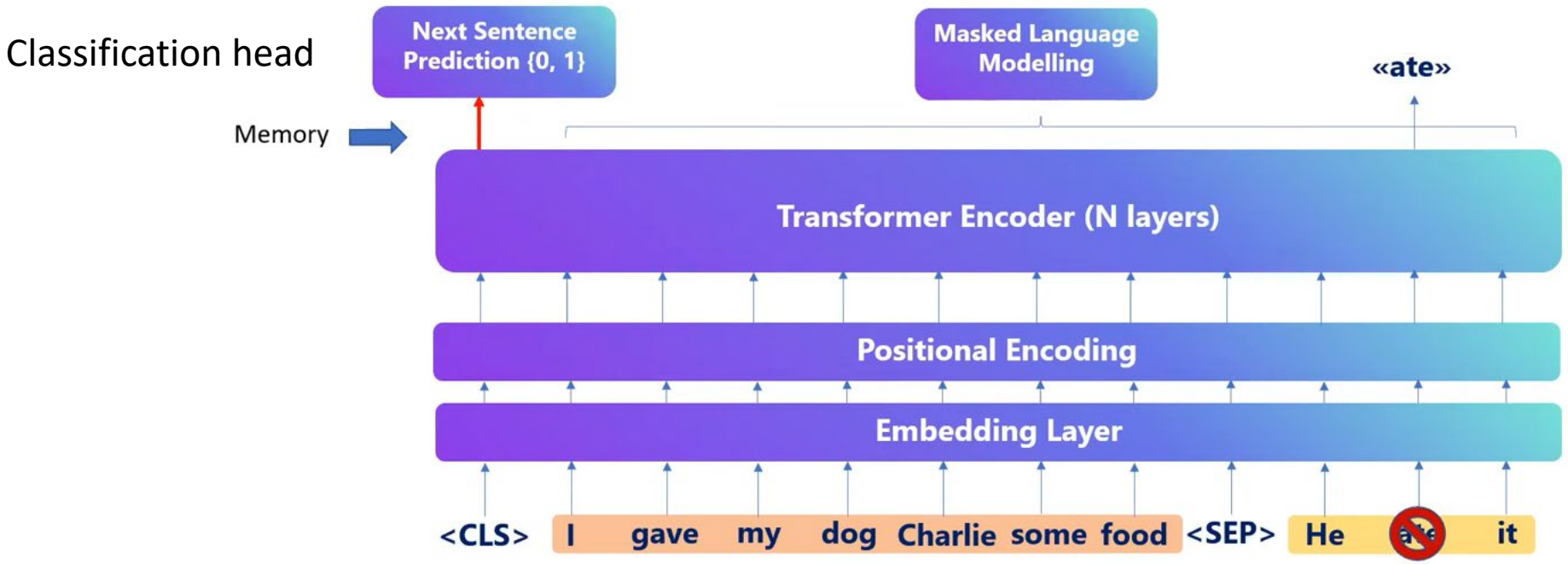
The transformer network: limitations

- Self- Attention calculation is O(n^2)
- Is possible to construct an Attention map



Transformer Encoder

- BERT (Devlin et al. 2018)



sentence-level representation for classification

Expanding the universe of self-attention

- **Attention** dominates **language**
- **Convolution** dominates (dominated?) **vision**
- Can we bring **attention** to **vision**?

Why self-attention for vision?

Attention Models: Motivation

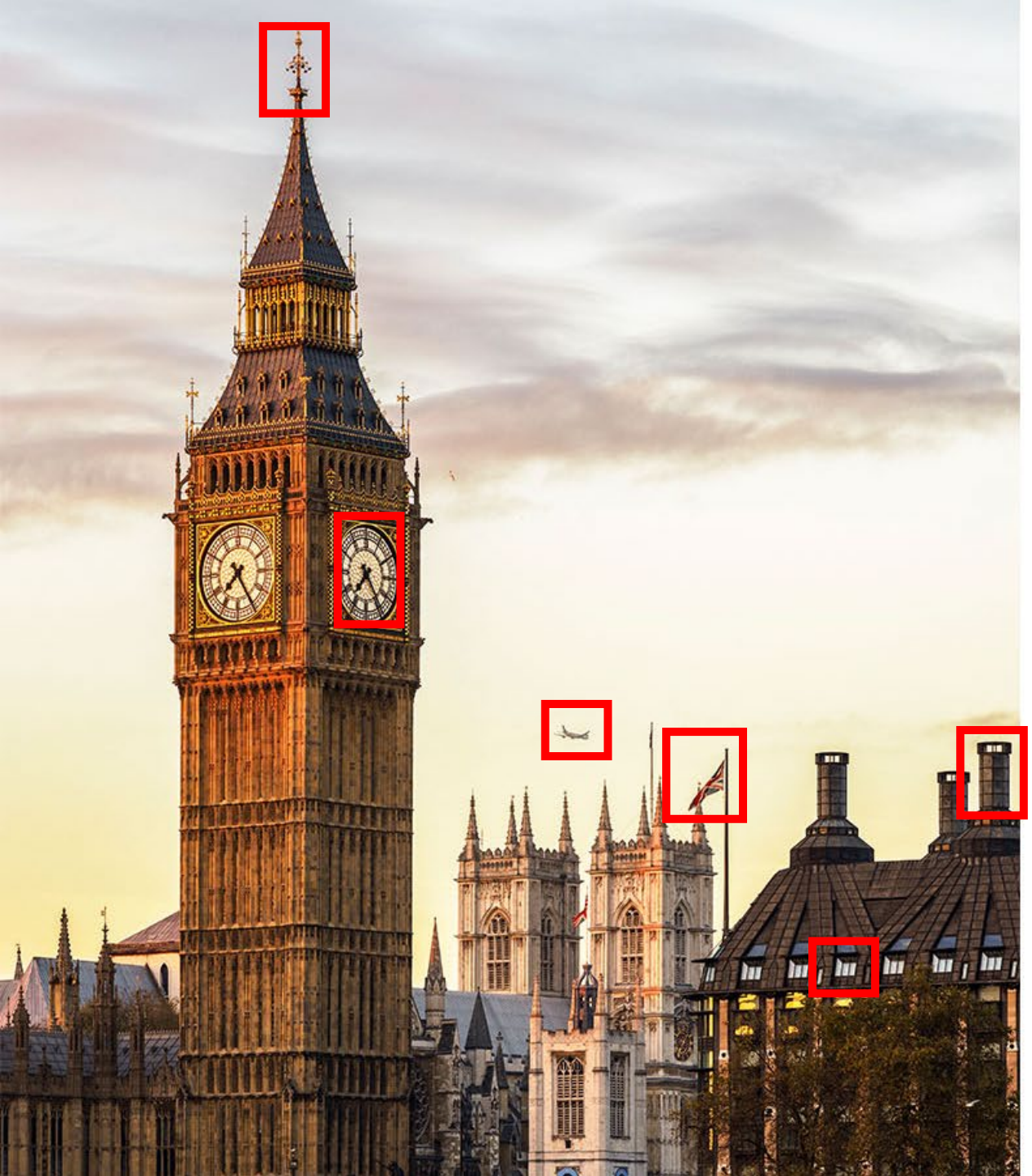
Can we use self-attention in images?

- What are the images patches relevent to a given query pacth
- Concentrate on relevant parts of the image
- Given non local nature of S-A enable to discover relationship between spatial distant image patches

Possible motivations

- Modeling long-range interactions between words (pixels).
- Useful for longer sentences (images).
- Different heads can model different kinds of interactions between words (pixels)
- Self-attention can model the self-similarity within images

FIND THE DIFFERENCES



Who is wearing glasses?

Where is the child sitting?

Is the umbrella upside down?

How many children are in the bed?

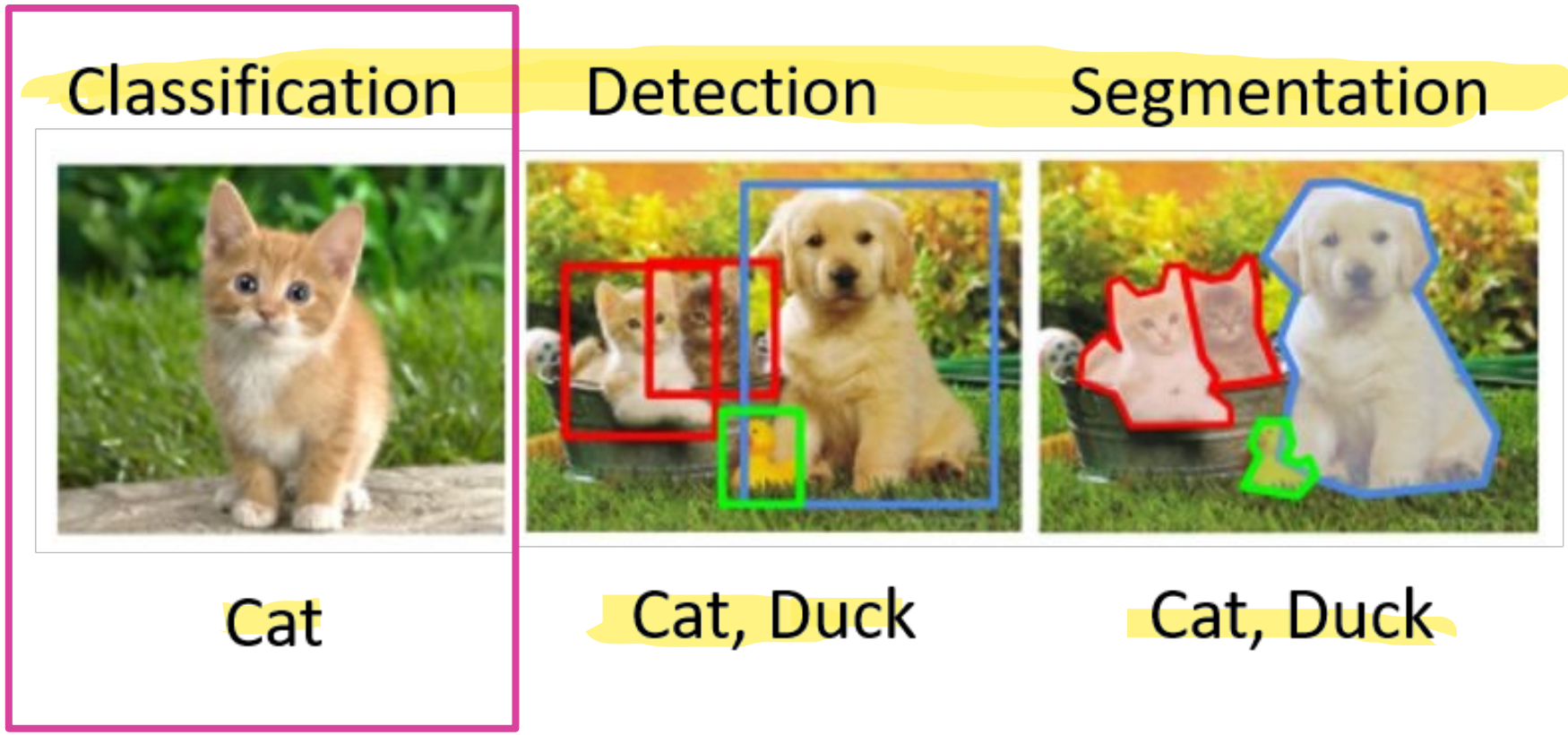
Text prompt

an armchair in the shape of an avocado [...]

AI-generated images

View more images or edit prompt

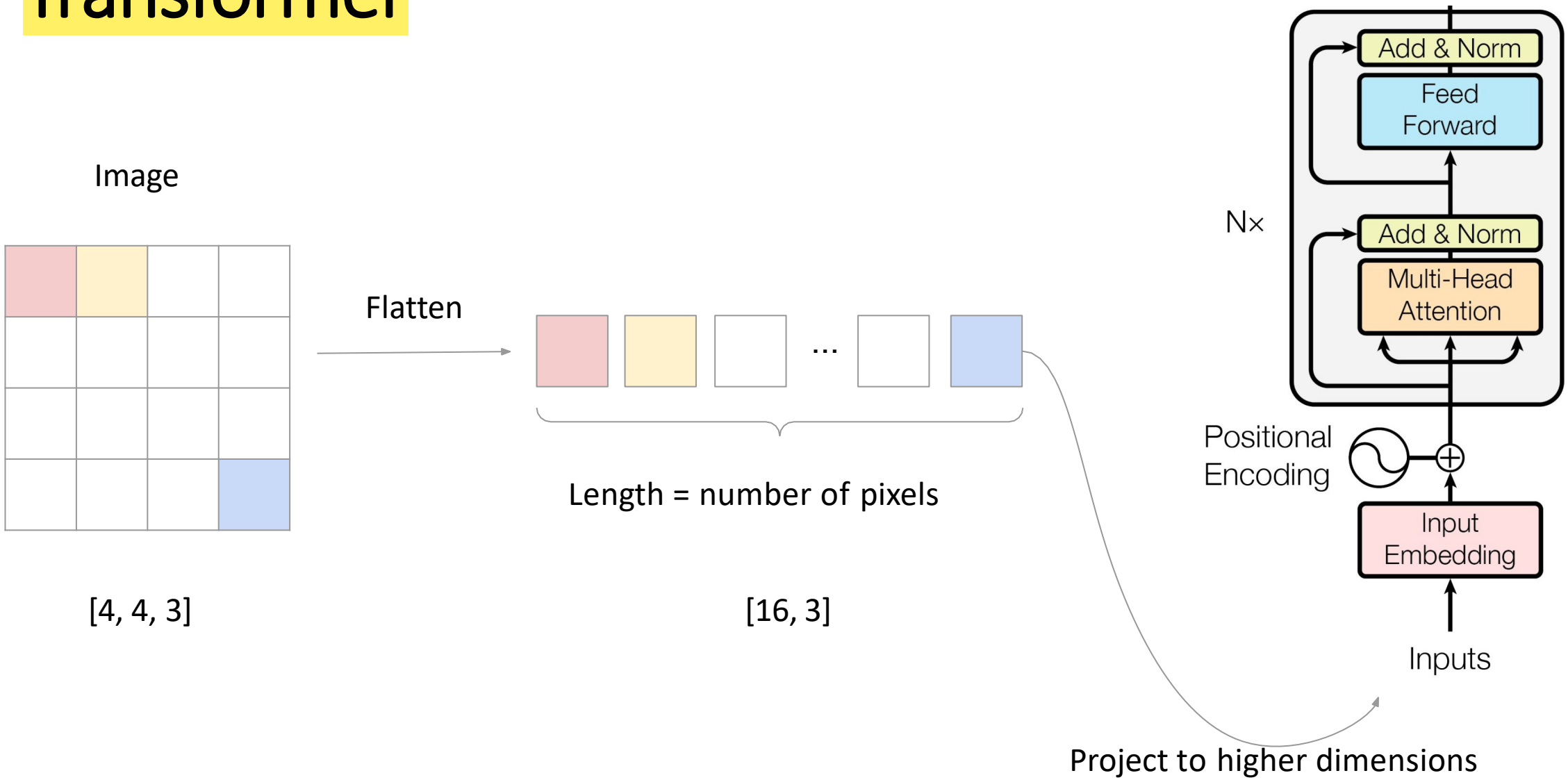
Vision tasks



Source

How do we design vision attention models?
Adapt a pre-existing method

Idea: treat each pixel as a token, and pass to Transformer

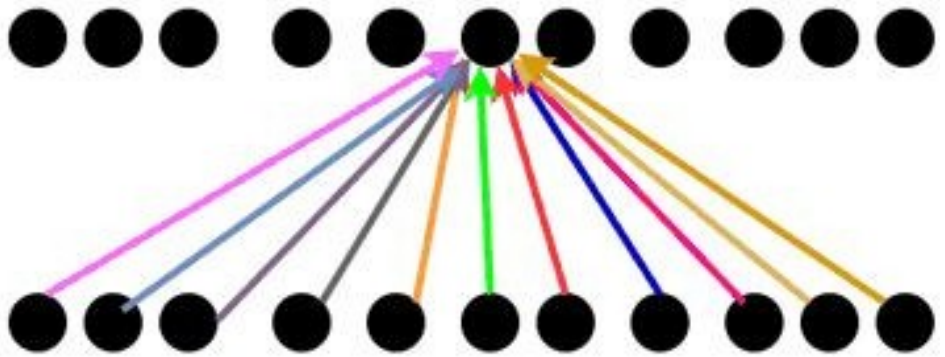


Problem: it’s too expensive!

- For a 256x256 images, there 62500 pixels
- Attention cost scales quadratically with the input length
- So 3906250000 calculations!!!

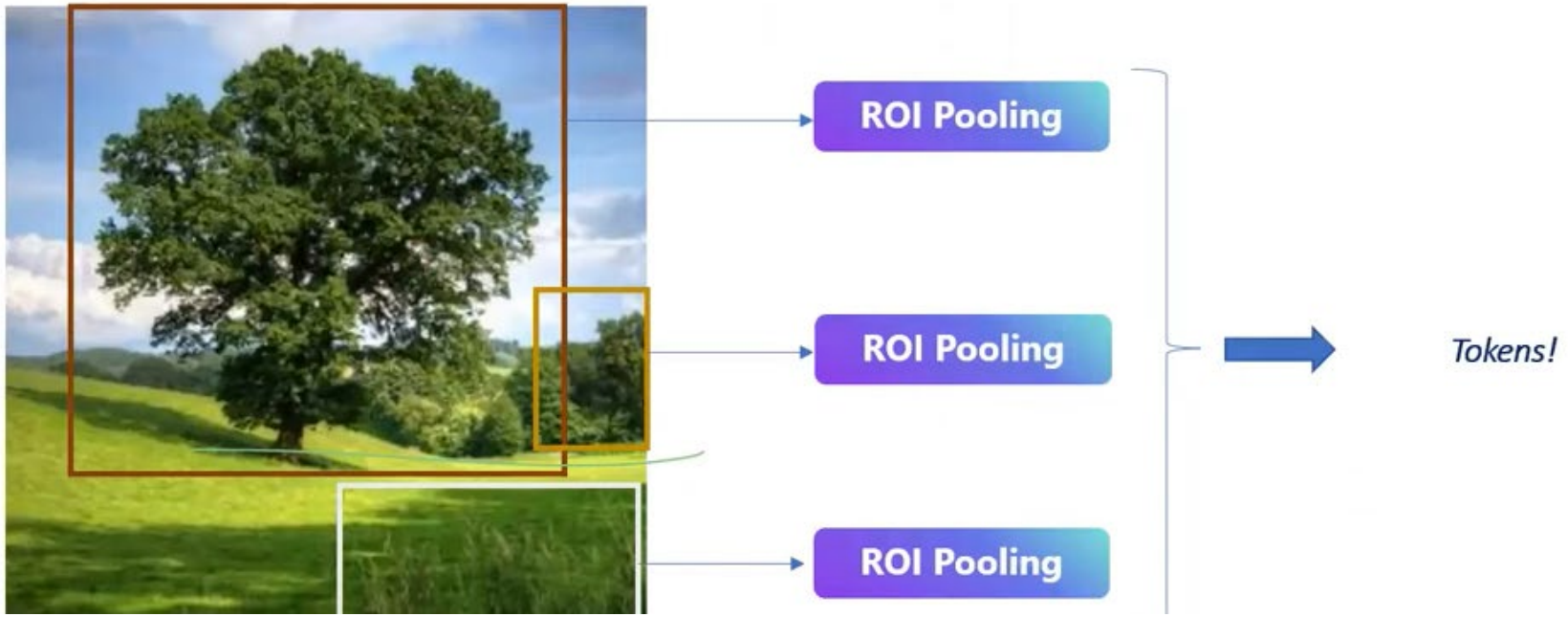
256px

256px



Transformers in Computer Vision

- Tokens as the features from an object detector



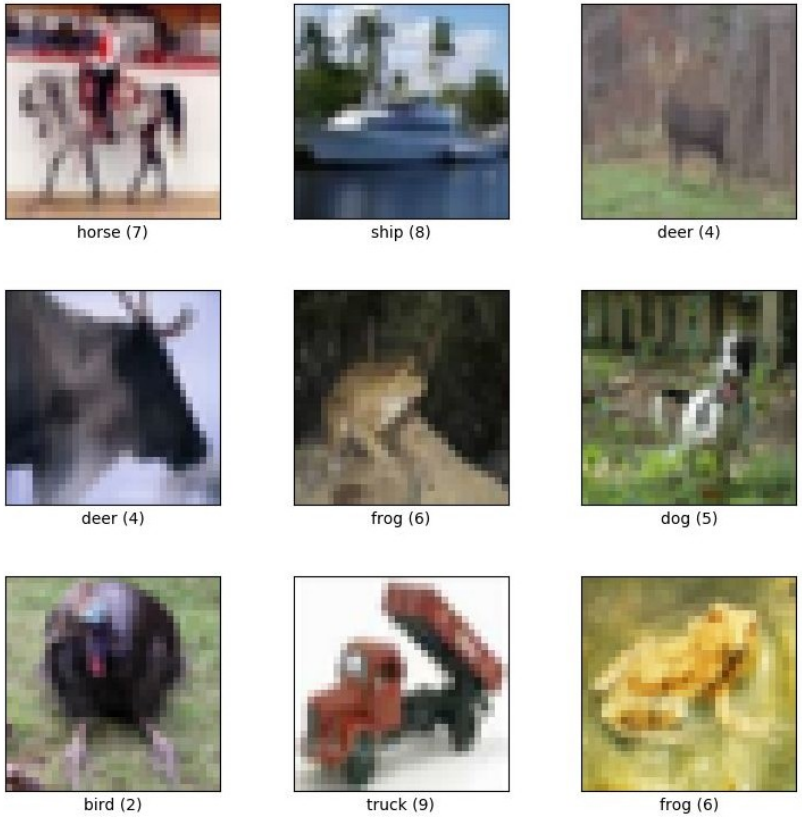
Used in visual textual matching

Idea: use a smaller image size

- Will reduce the input length, which makes the Transformer cheaper

Source

Problem: loses a lot of detail

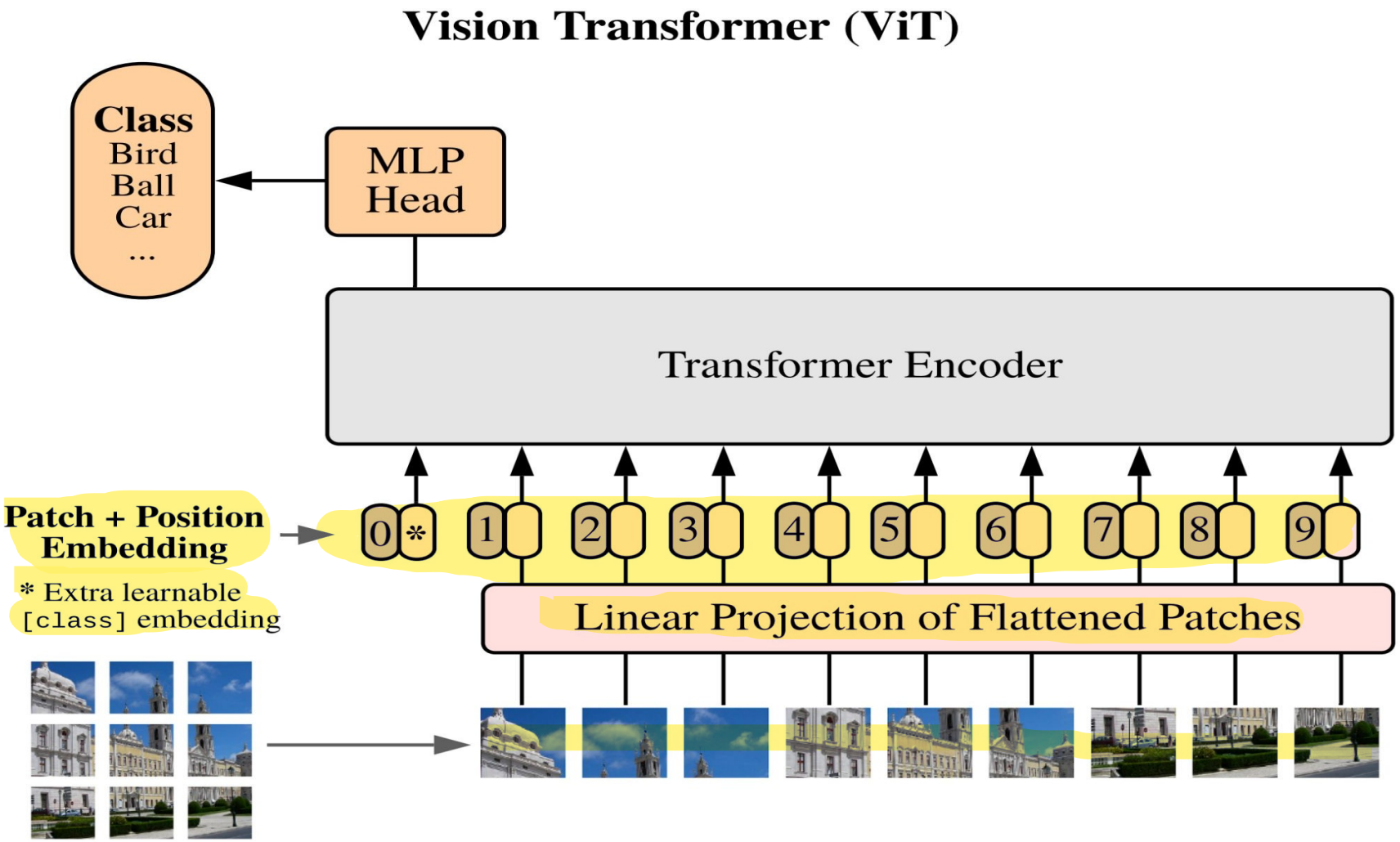


Source

Vision Transformers (ViTs)

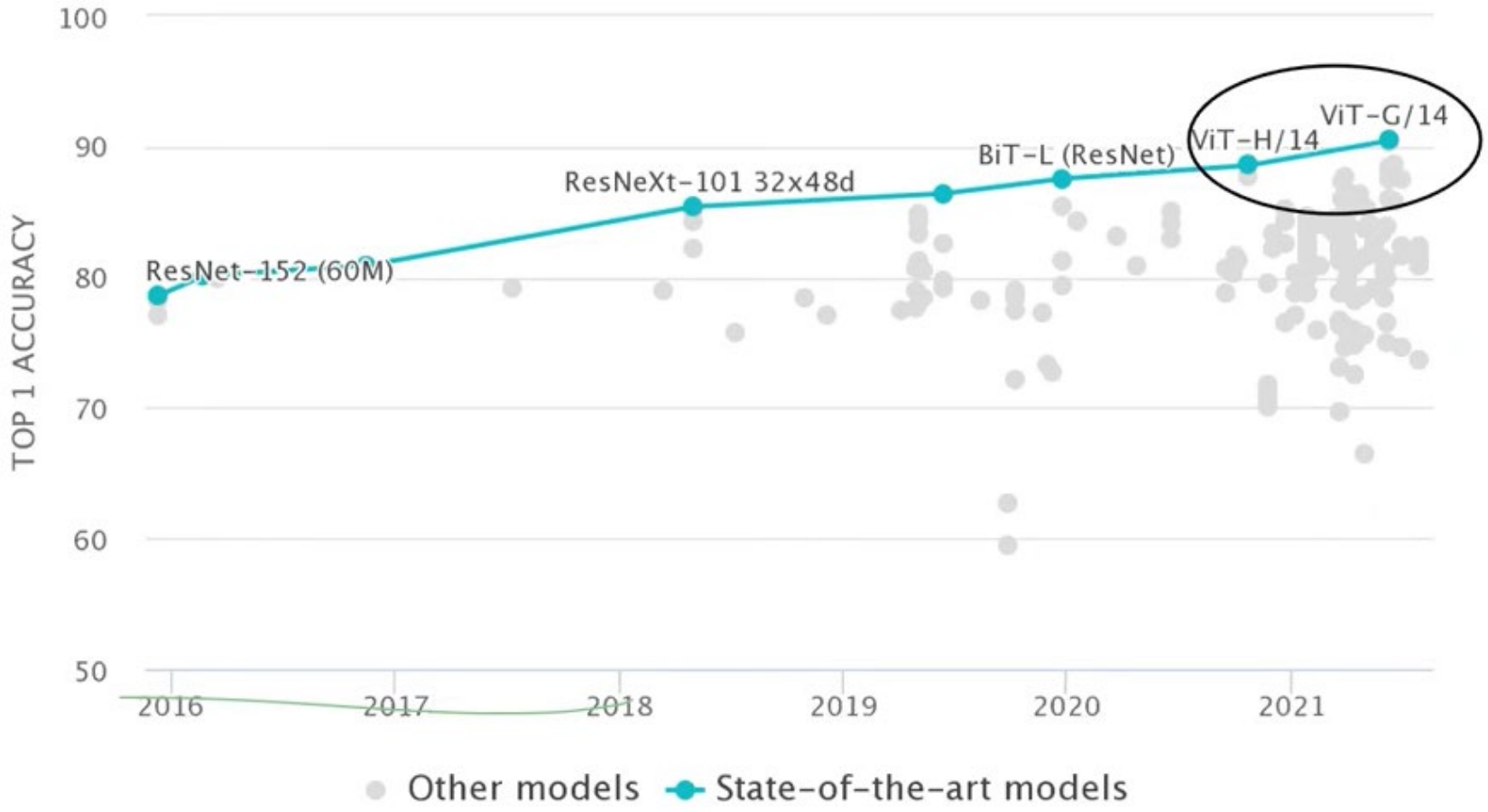
«An image is worth 16x16 words» paper

Vision Transformer



Dosovitskiy et al. 2020

Image classification on ImageNet



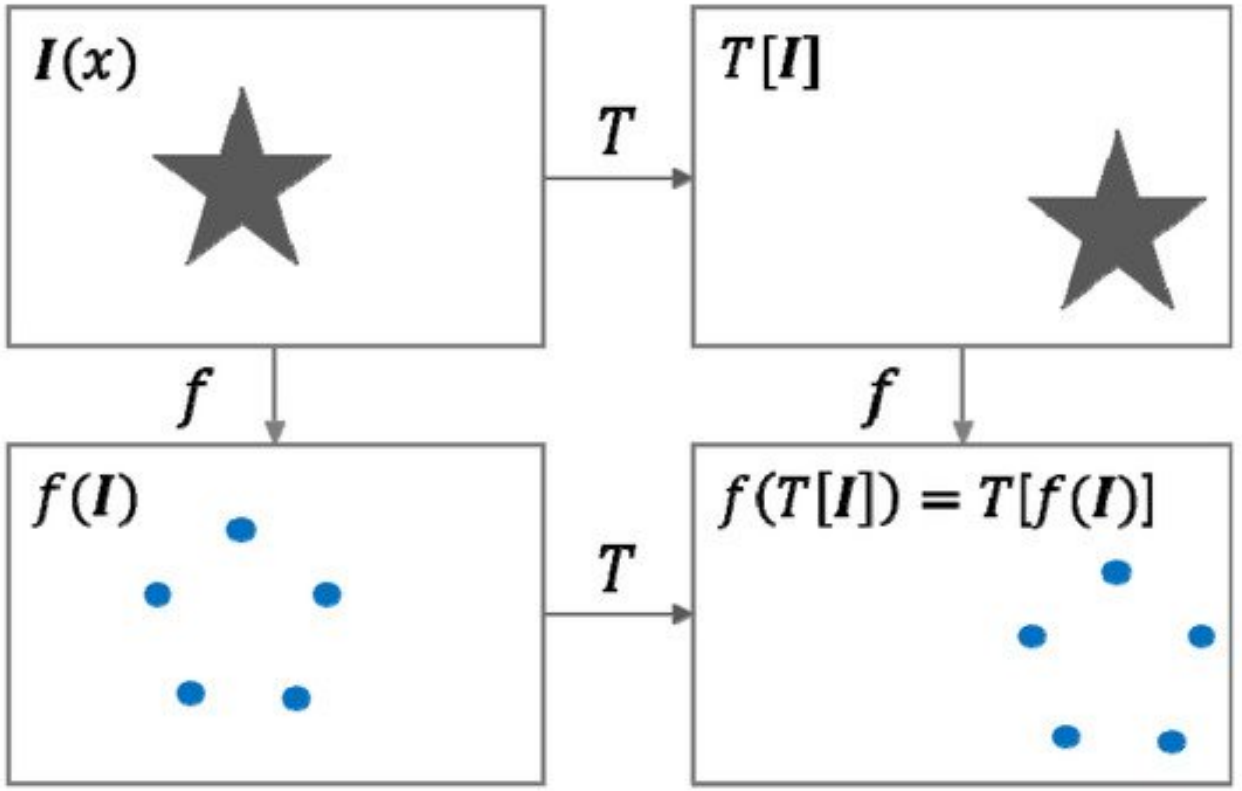
Key concepts

- **Applying a Transformer Directly to Images**
  - with the fewest possible modifications
  - provide the sequence of linear embeddings of the patches as an input
  - image patches = tokens (words) in NLP

- **Small Scale Training**
  - achieved accuracies below ResNets of comparable size
  - Transformers lack some inductive biased inherent to CNNs (such as translation equivariance and locality)
    - Convolutions are translation invariant, locality sensitive, and lack a global understanding of images.
    - Transformers can be used in convolutional pipelines to produce global representations of images.

  Large Scale Training
  - surpass inductive bias
  - excellent results when pre-trained and transferred

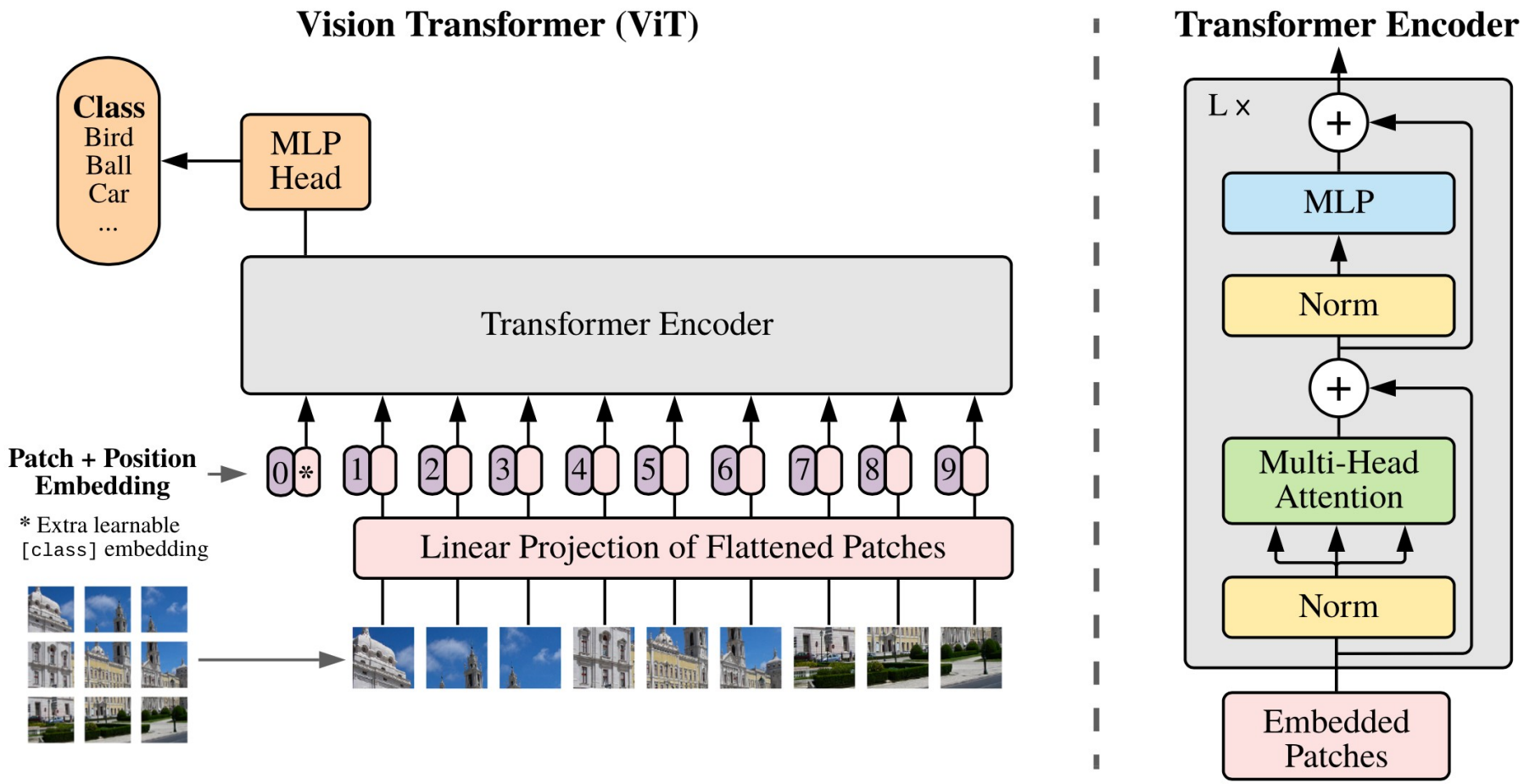
Translational Equivariance



Invariance means that you can recognize an entity (i.e. object) in an image, even when its appearance or position varies.
Translation in computer vision implies that each image pixel has been moved by a fixed amount in a particular direction.

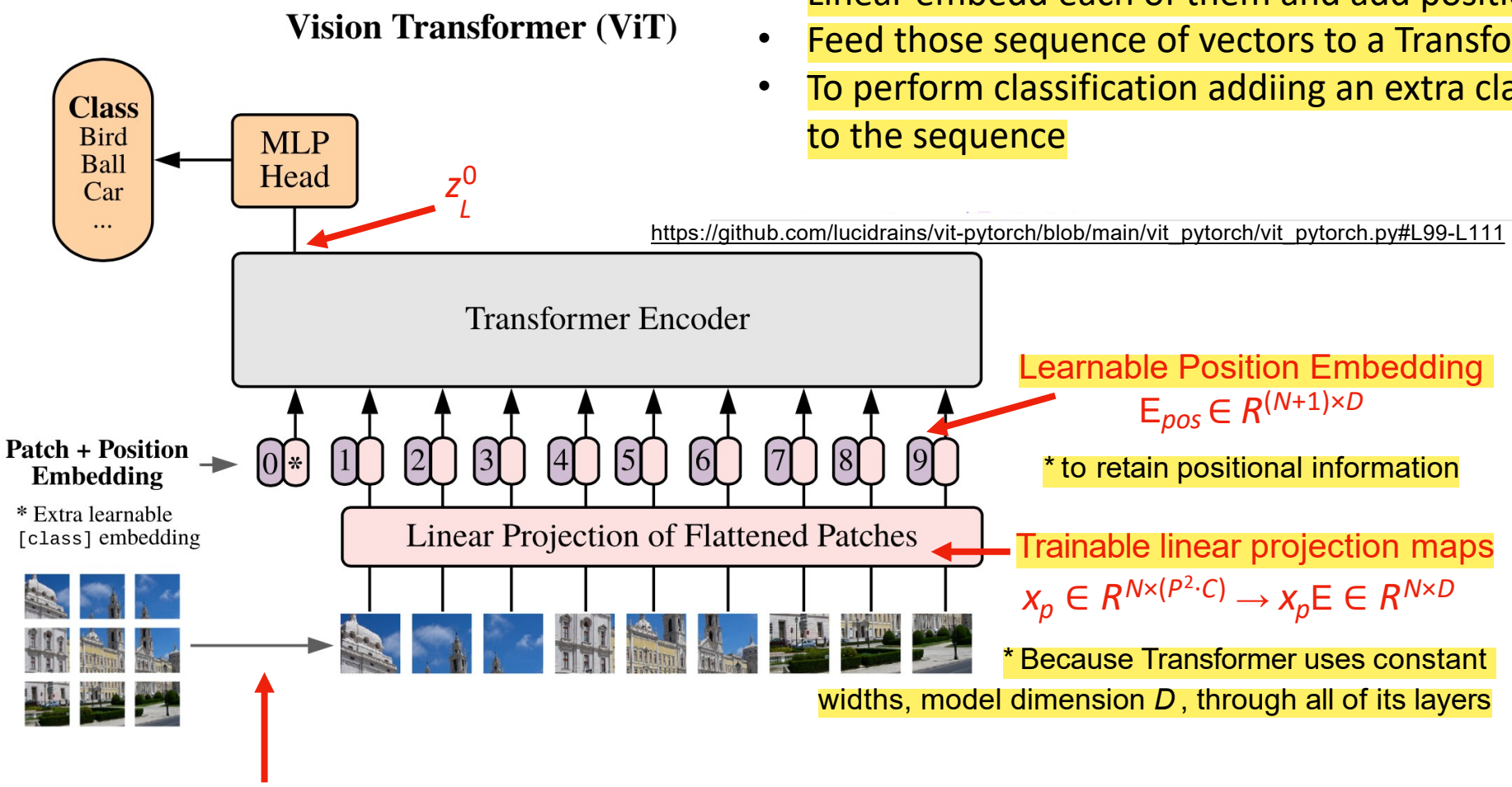
ViT

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
Norm
Embedded Patches

Method

- Split an image in fixed size patches
- Linear embedd each of them and add position embedding
- Feed those sequence of vectors to a Transformer Encoder
- To perform classification addiing an extra classification token to the sequence



https://github.com/lucidrains/vit-pytorch/blob/main/vit_pytorch/vit_pytorch.py#L99-L111

Learnable Position Embedding

$E_{pos} \in R^{(N+1)\times D}$

* to retain positional information

Trainable linear projection maps

$x_p \in R^{N\times(P^2\cdot C)} \rightarrow x_p E \in R^{N\times D}$

* Because Transformer uses constant widths, model dimension D, through all of its layers

Step by step

1. Split an image into patches
2. Flatten the patches
3. Produce lower-dimensional linear embeddings from the flattened patches
4. Add positional embeddings
5. Feed the sequence as an input to a standard transformer encoder
6. Pretrain the model with image labels (fully supervised on a huge dataset)
7. Finetune on a smaller dataset for image classification

Experiments

- **Datasets**

  Pre-training

  - ILSVRC-2012 ImageNet dataset : 1k classes / 1.3M images
  - ImageNet-21k : 21k classes / 14M images
  - JFT : 18k classes / 303M images

  Downstream (Fine-tuning)

  -ImageNet, ImageNet ReaL, CIFAR-10/100, Oxford-IIIT Pets, Oxford Flowers-102, VTAB

- **Model Variants**

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

Datasets

	# 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

- **Comparison to State of the Art**

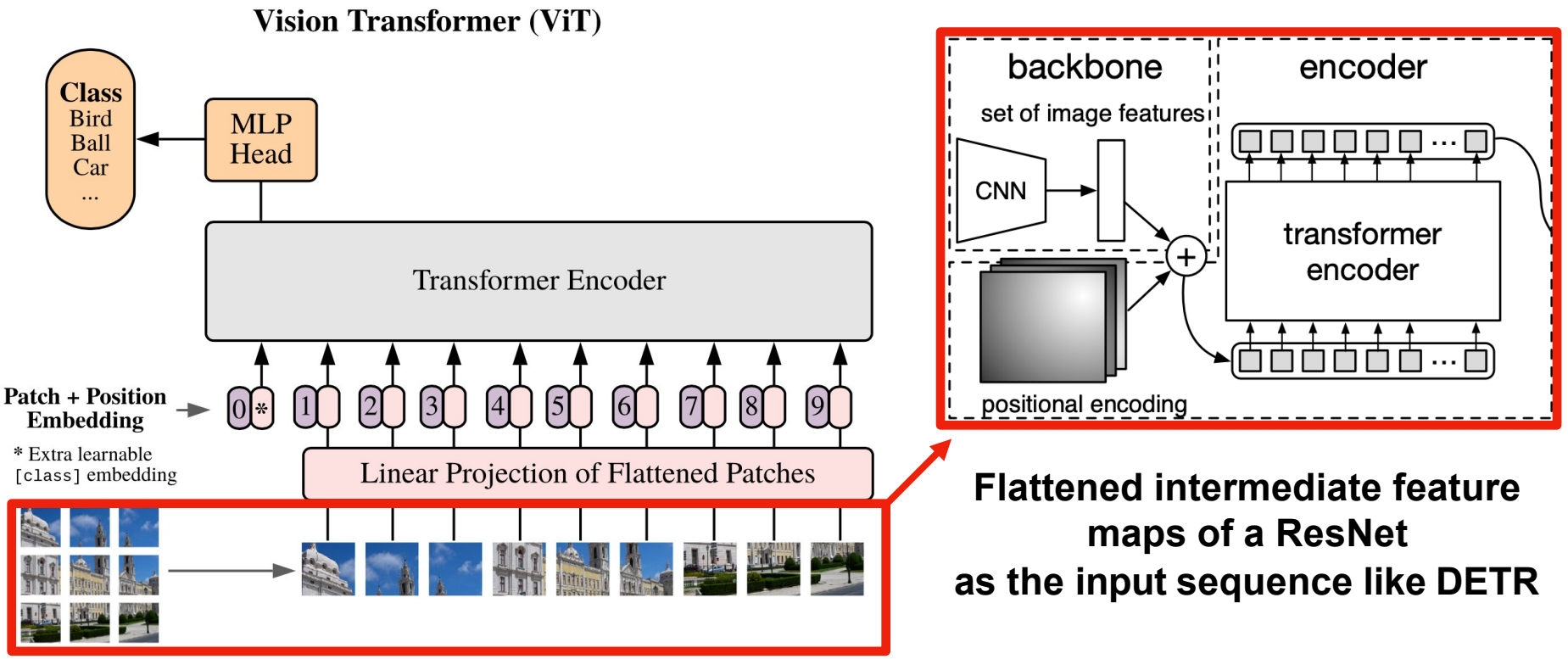
	Ours (ViT-H/14)	Ours (ViT-L/16)	BiT-L (ResNet152x4)	Noisy Student (EfficientNet-L2)
ImageNet	88.36	87.61 ± 0.03	87.54 ± 0.02	$88.4/\mathbf{88.5}^*$
ImageNet ReaL	**90.77**	90.24 ± 0.03	90.54	90.55
CIFAR-10	**99.50** ± 0.06	99.42 ± 0.03	99.37 ± 0.06	–
CIFAR-100	**94.55** ± 0.04	93.90 ± 0.05	93.51 ± 0.08	–
Oxford-IIIT Pets	**97.56** ± 0.03	97.32 ± 0.11	96.62 ± 0.23	–
Oxford Flowers-102	99.68 ± 0.02	**99.74** ± 0.00	99.63 ± 0.03	–
VTAB (19 tasks)	**77.16** ± 0.29	75.91 ± 0.18	76.29 ± 1.70	–
TPUv3-days	2.5k	0.68k	9.9k	12.3k

Table 2: Comparison with state of the art on popular image classification datasets benchmarks. Vision Transformer models pre-trained on the JFT300M dataset often match or outperform ResNet-based baselines while taking substantially less computational resources to pre-train. *Slightly improved 88.5% result reported in Touvron et al. (2020).

* BiT-L : Big Transfer, which performs supervised transfer learning with large ResNets
* Noisy Student : a large EfficientNet trained using semi-supervised learning

Kolesnikov et al. Big Transfer (BiT): General Visual Representation Learning. ECCV 2020
Xie et al. Self-training with noisy student improves imagenet classification. CVPR 2020

Hybrid Architecture



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

Conclusion and Challenges

- **Application of Transformers to Image Recognition**

  - no image-specific inductive biases in the architecture

  - interpret an image as sequence of patches and process it by a standard Transformer encoder (self-attention and layer norm)

  - it is highly scalable and highly parallelizable

  - faster training, larger models, better performance across vision and language tasks

  - matches or exceeds the S.O.T.A being cheap to pre-train

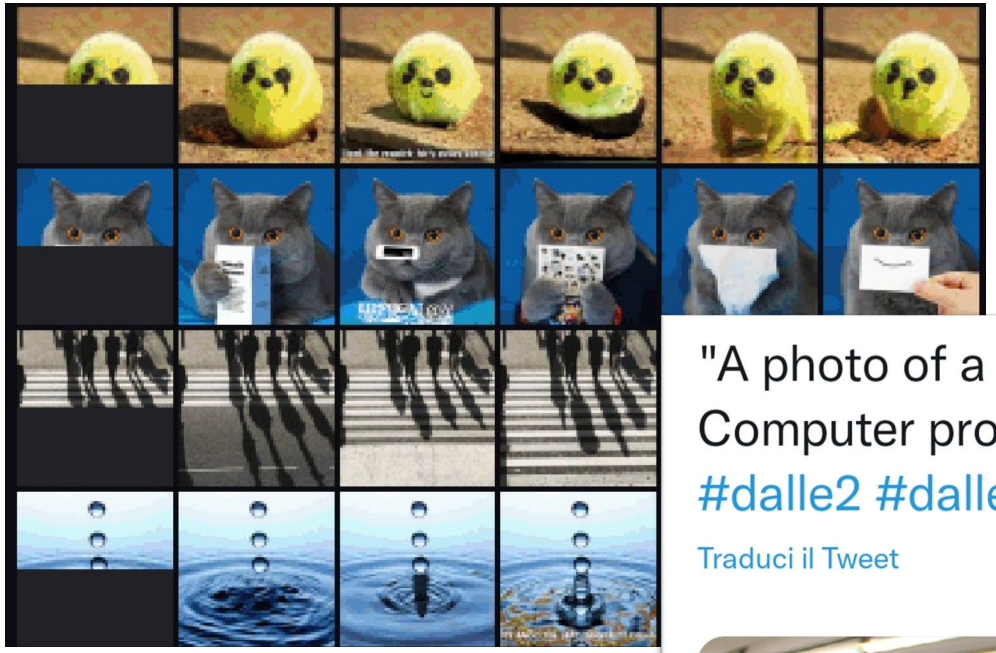
- **Challenges**

  - The scale and data problem

Survey of self-attention applications in Computer Vision

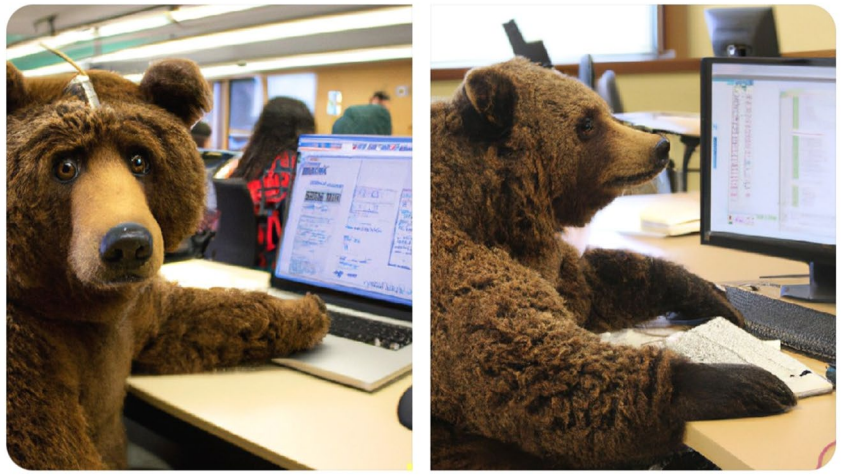
Some cool applications

- **Image GPT** (Generative Pretraining from Pixels), uses transformer for pixel level image completion, just like other GPT for text completion
- **Dall-e 2** https://openai.com/dall-e-2/

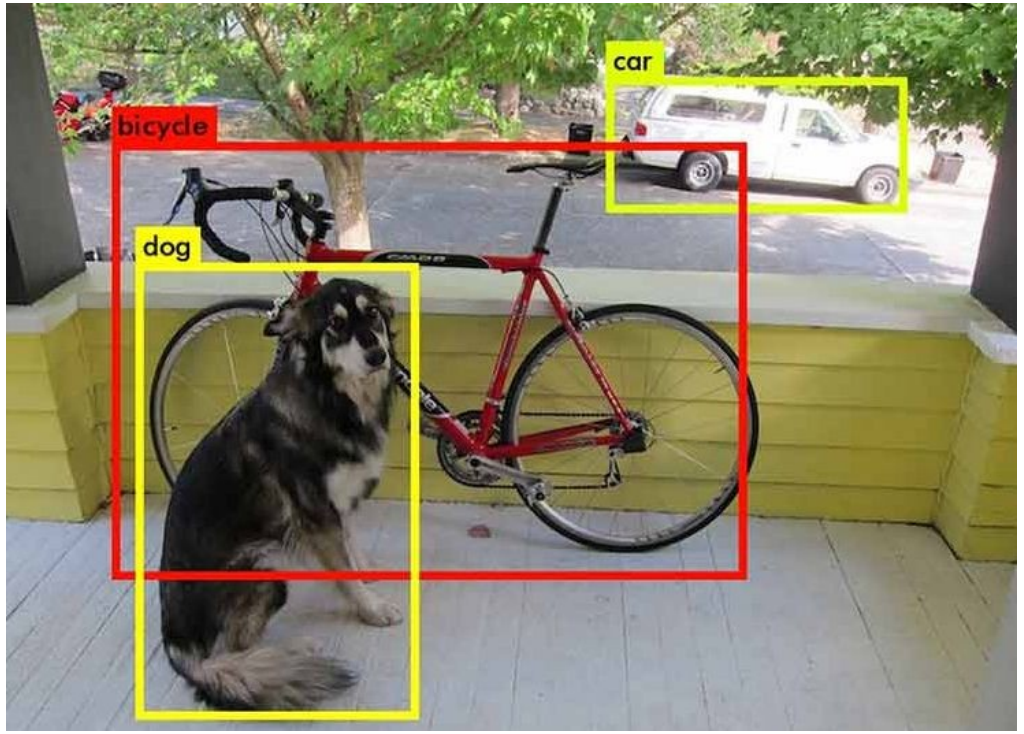


"A photo of a confused grizzly bear in Computer programming class" #dalle2 #dalle

Traduci il Tweet

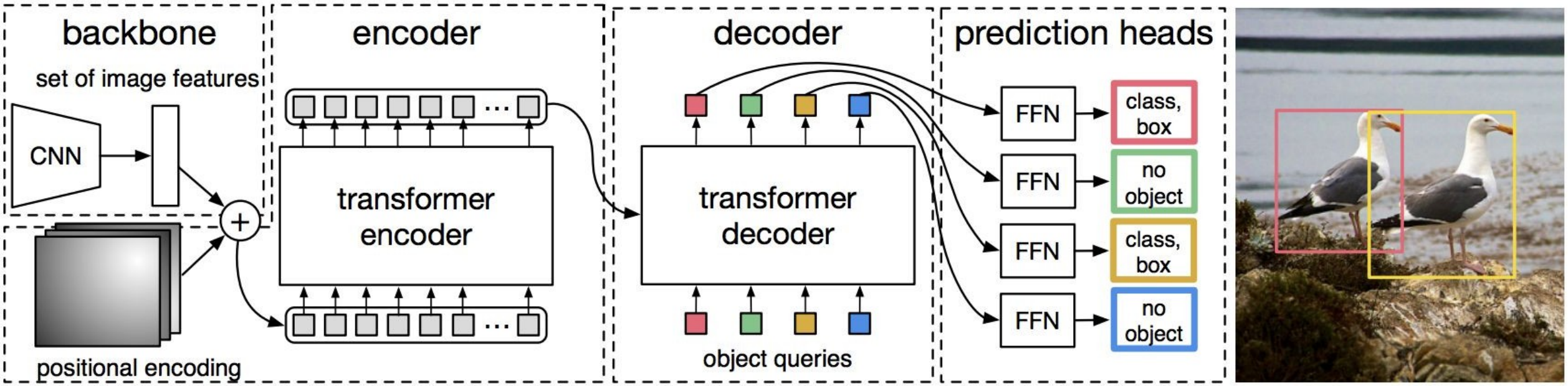


Transformers for Object Detection



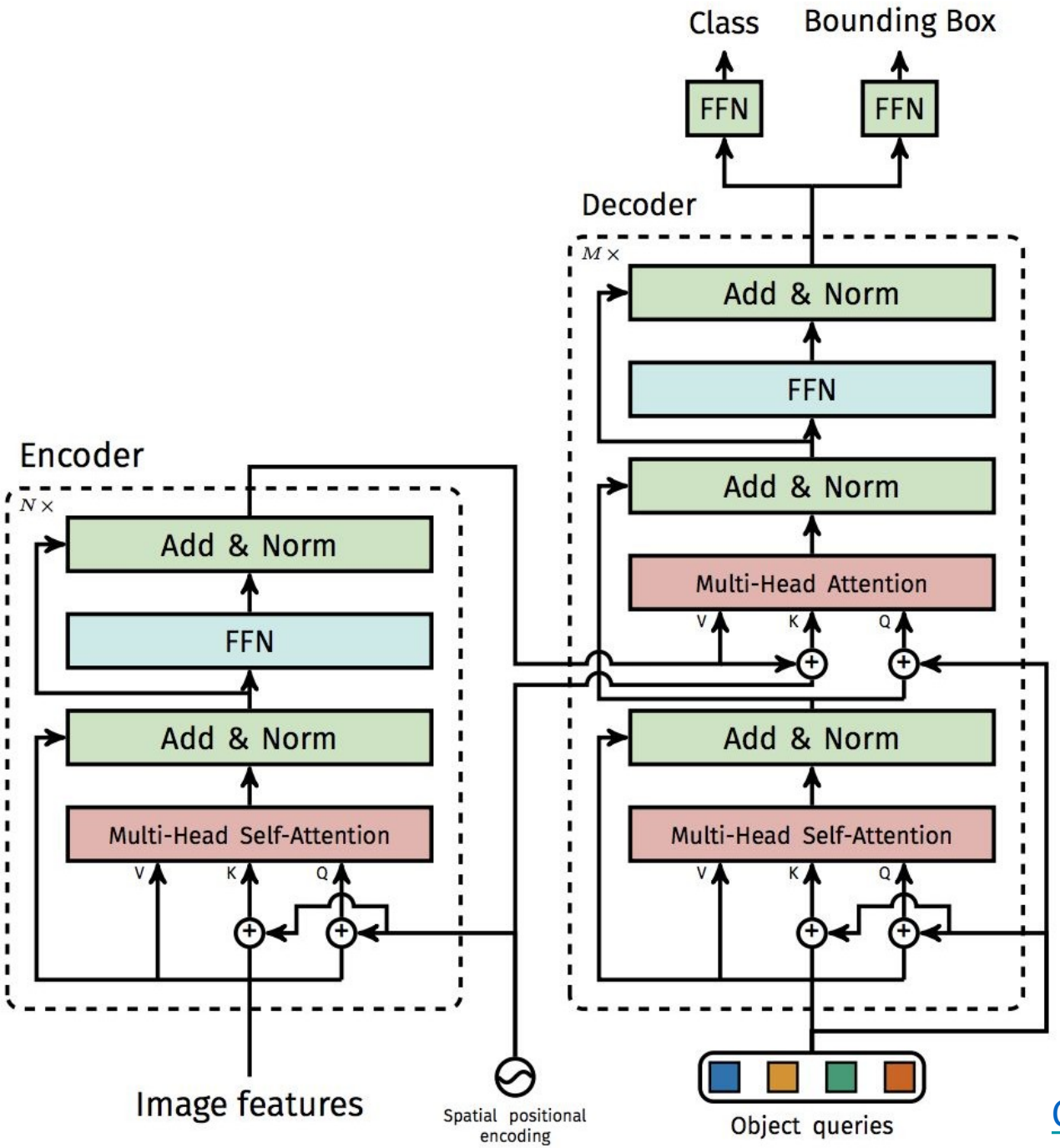
Carion et al 2020

DETR: End-to-End Object Detection with Transformers



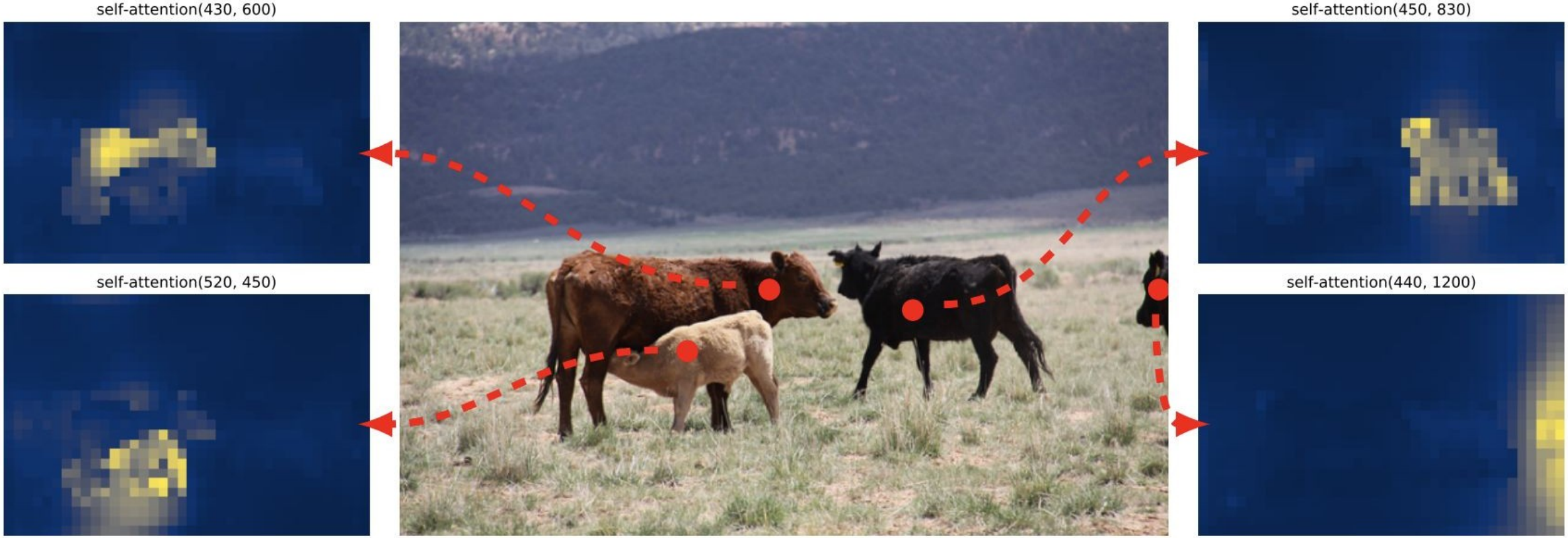
Carion et al 2020

DETR



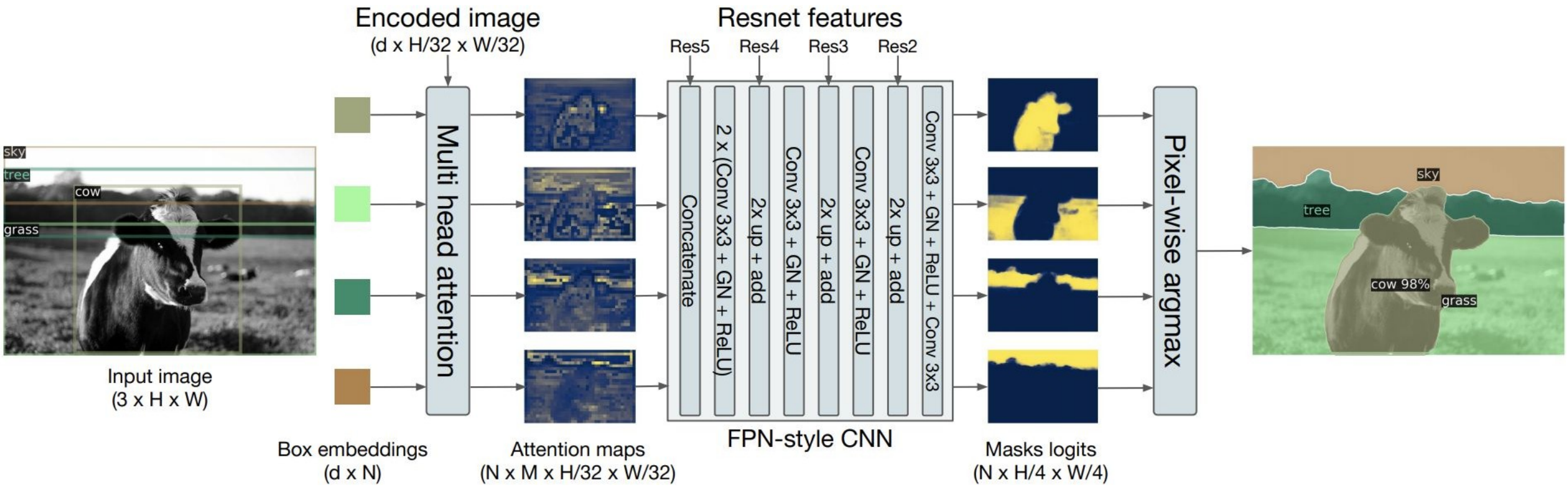
Carion et al 2020

DETR



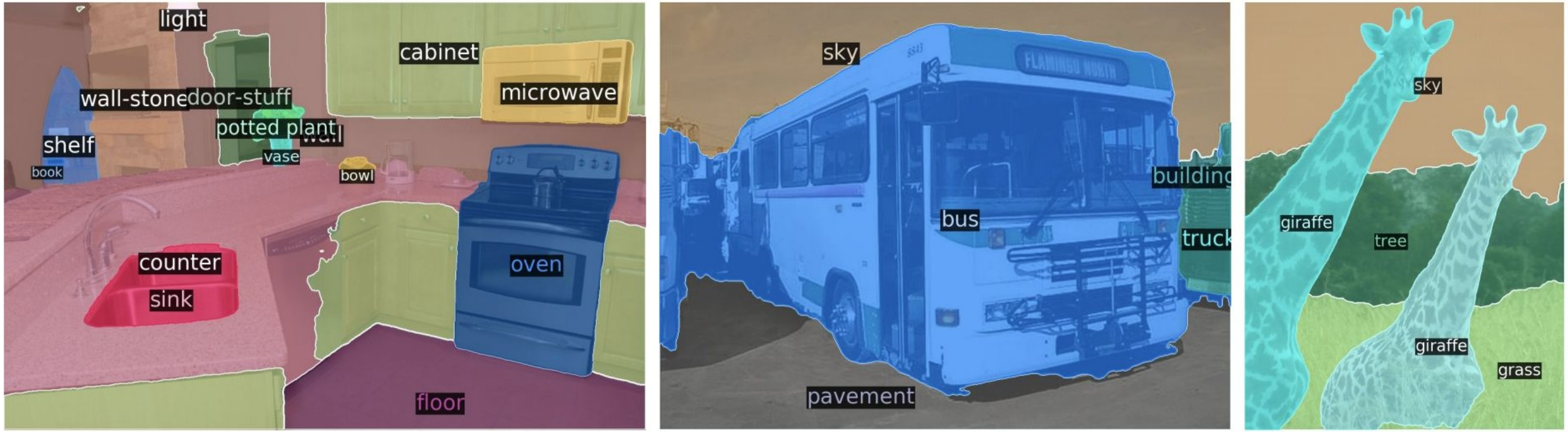
Carion et al 2020

DETR can be modified to perform panoptic segmentation



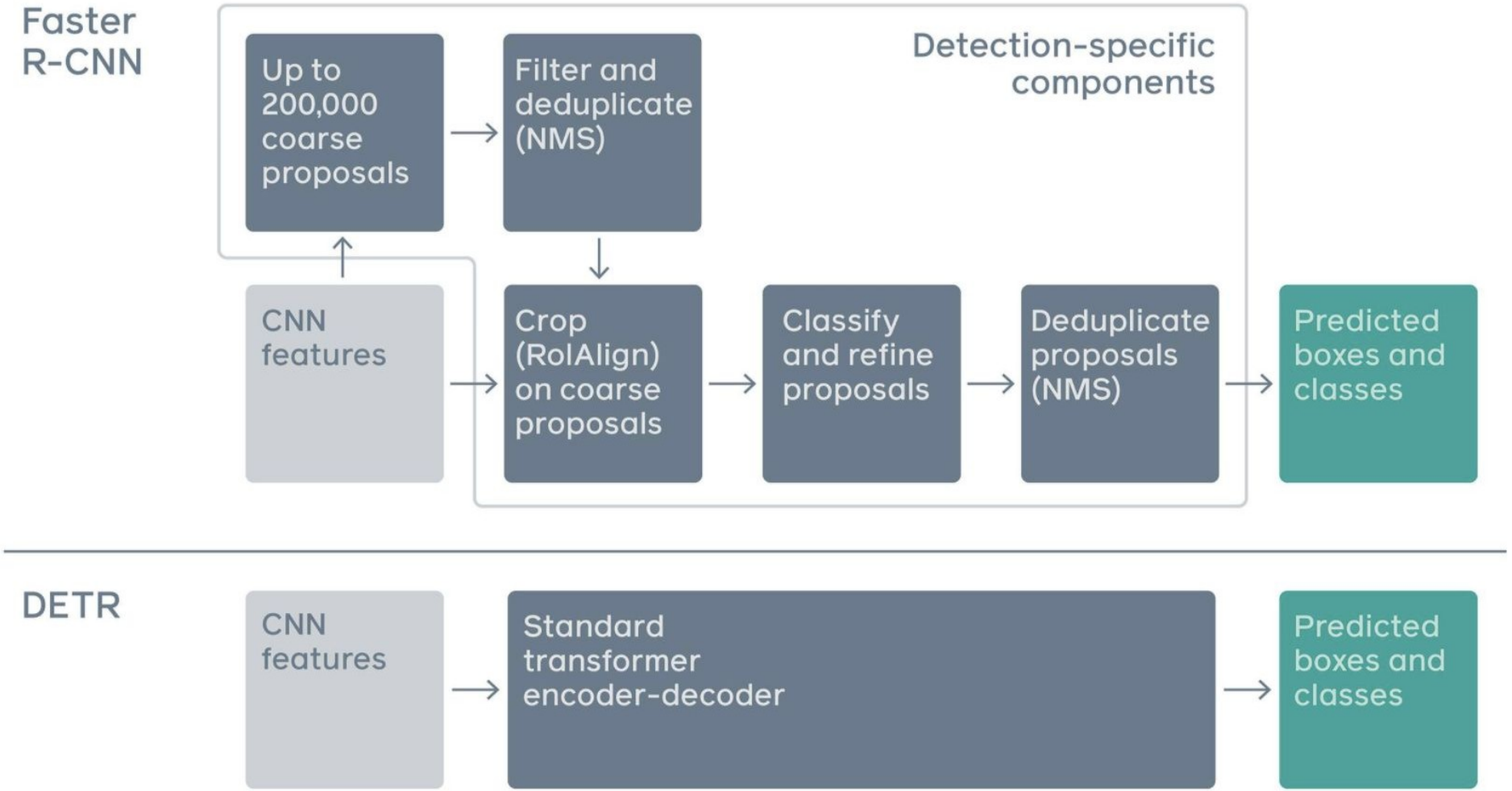
Carion et al 2020

DETR can be modified to perform panoptic segmentation



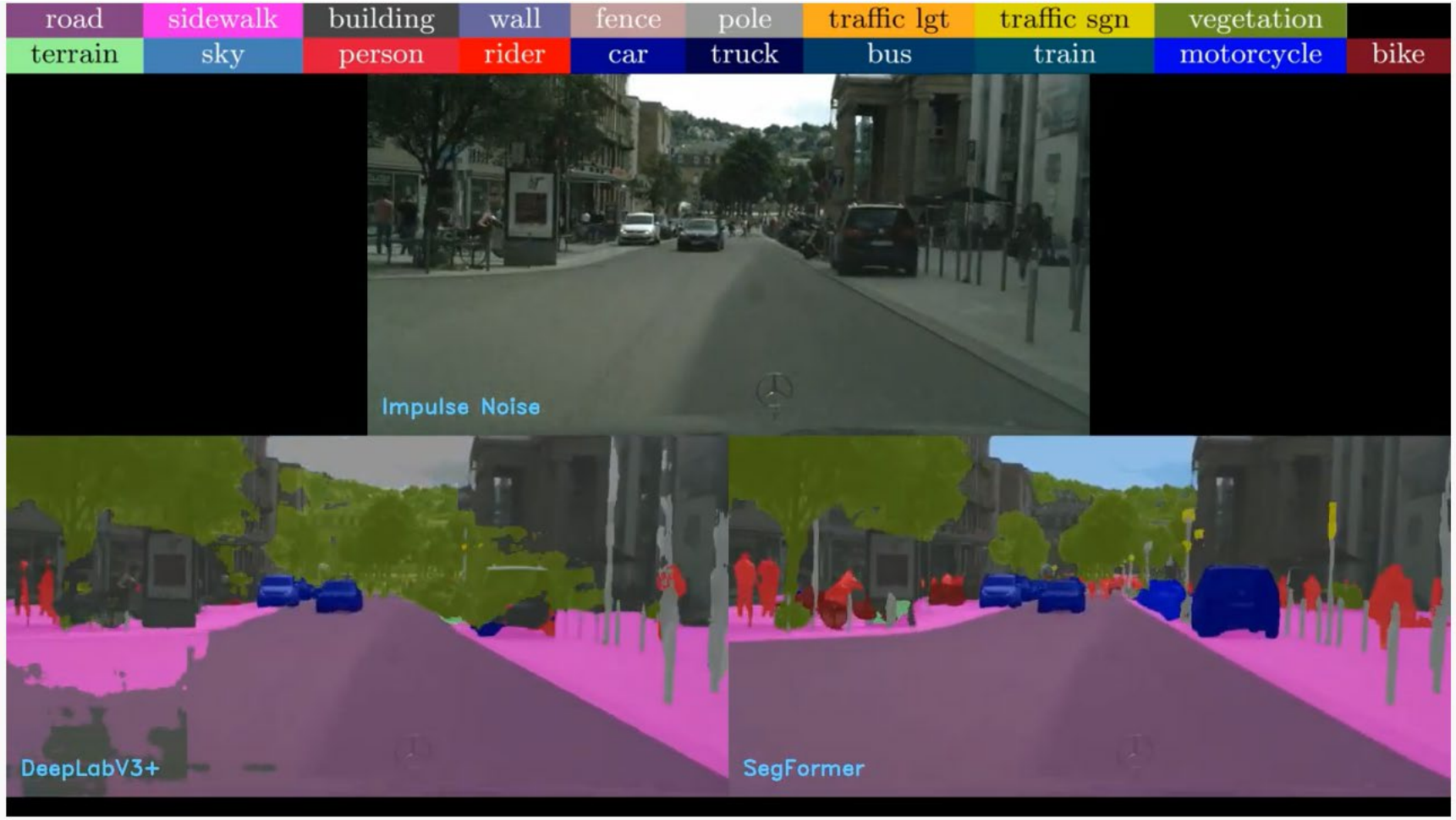
Carion et al 2020

DETR Inference Code is simpler



Carion et al 2020

Transformers for Semantic Segmentation

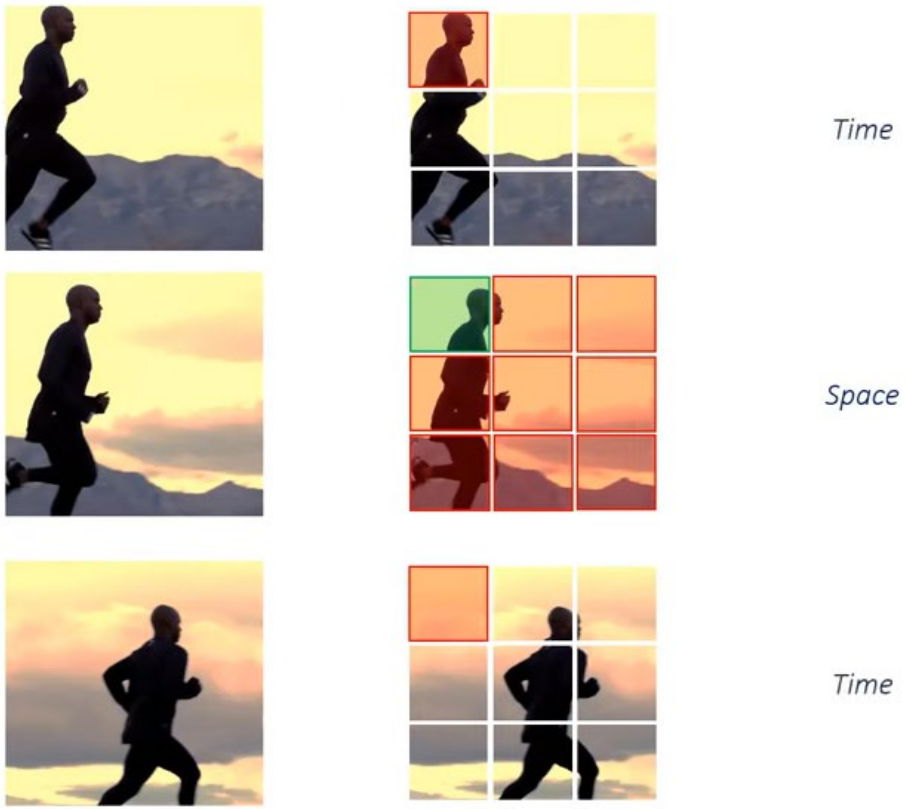


https://www.youtube.com/watch?v=J0MoRQzZe8U

Transformers for Video Recognition

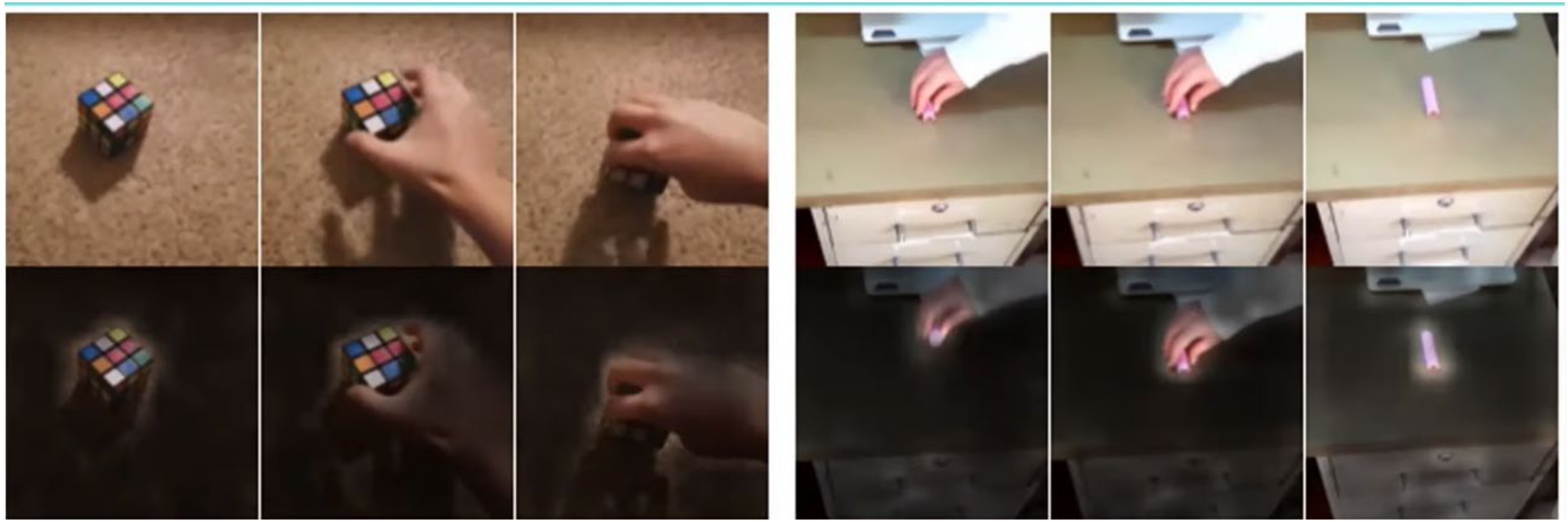
TimeSformer

Combine space and time attention with Divided Space-Time Attention



https://arxiv.org/abs/2102.05095

TimeSformer

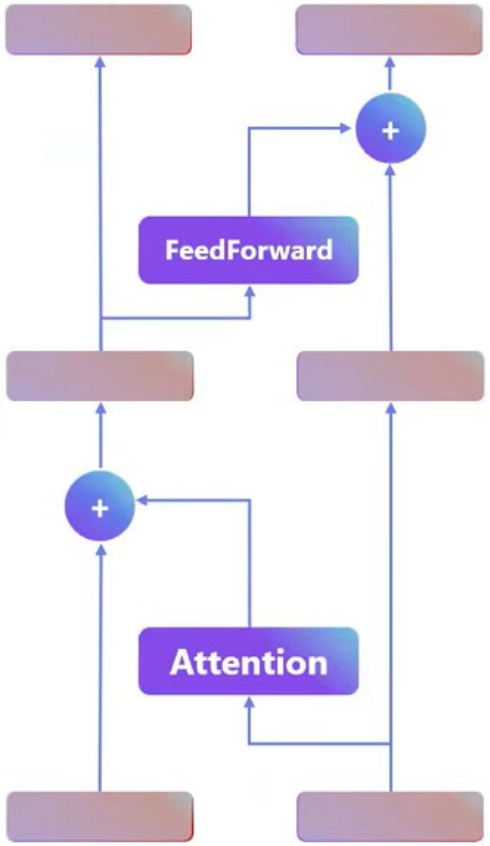


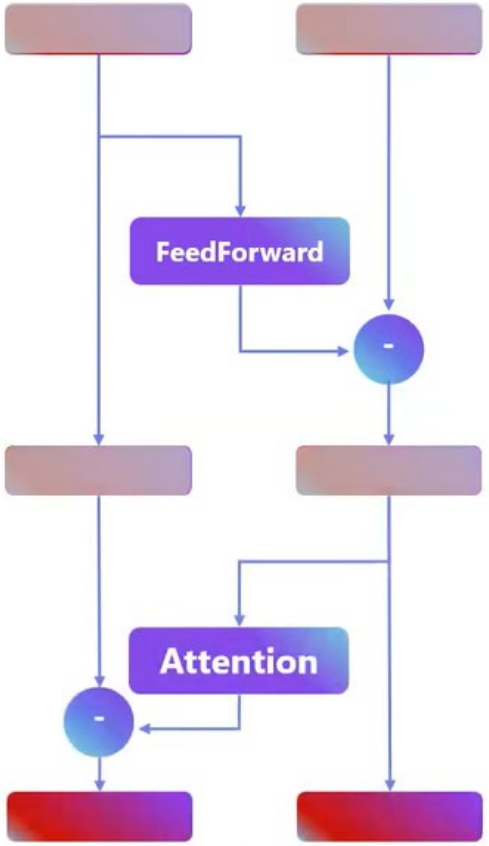
Focus on the main object
Track the object through the frames

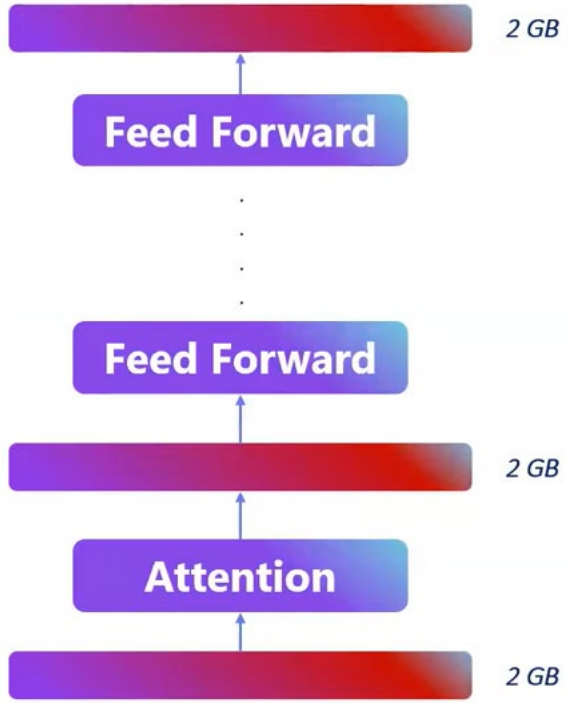
Efficient Transformer

Tranformers in the original form use a lot of memory

Only those finals tokens are stored





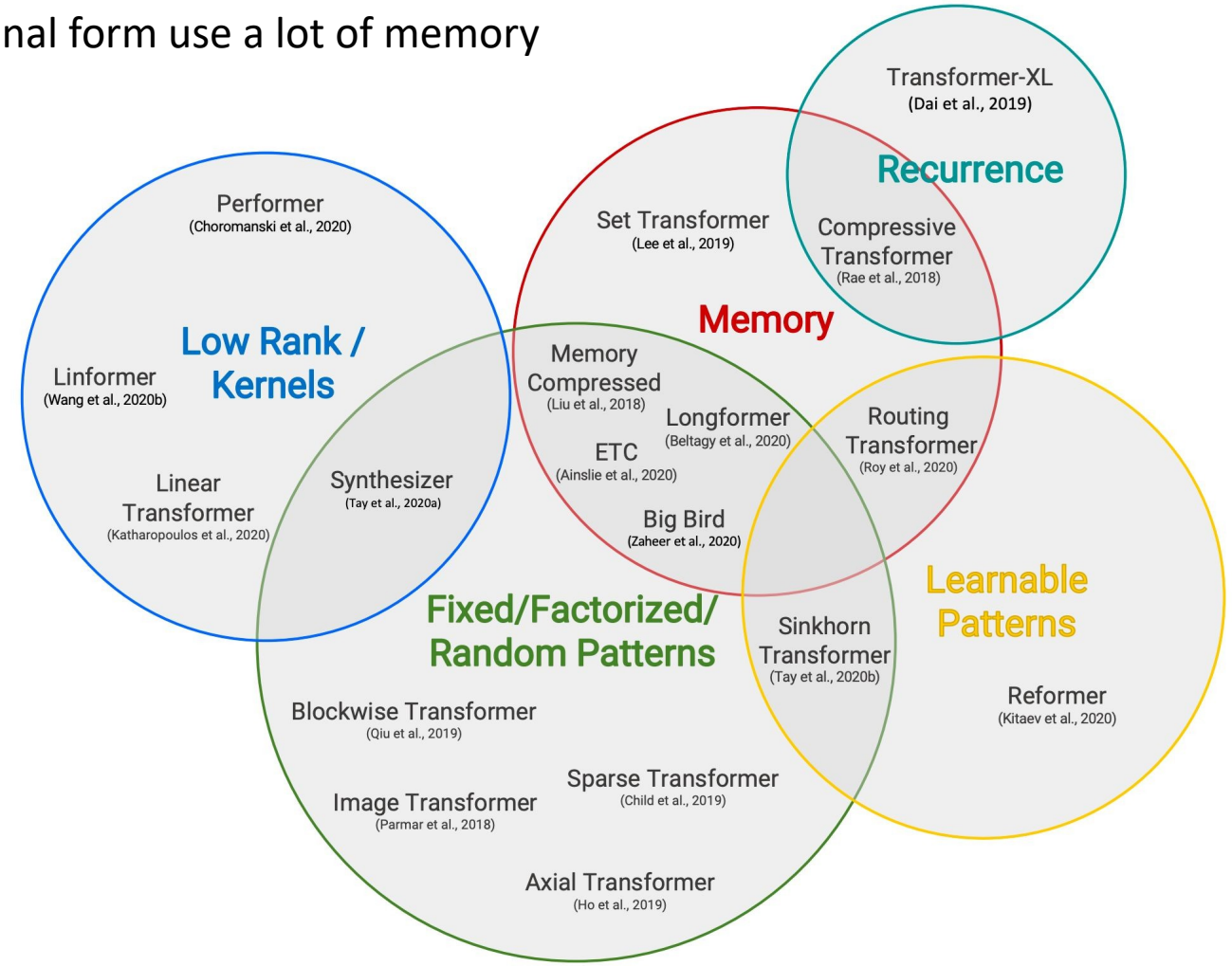


List of the input tokens
At each step a tensor is produced to mantain in memory

https://arxiv.org/abs/2001.04451

Lot of ideas to try out!

Tranformers in the original form use a lot of memory

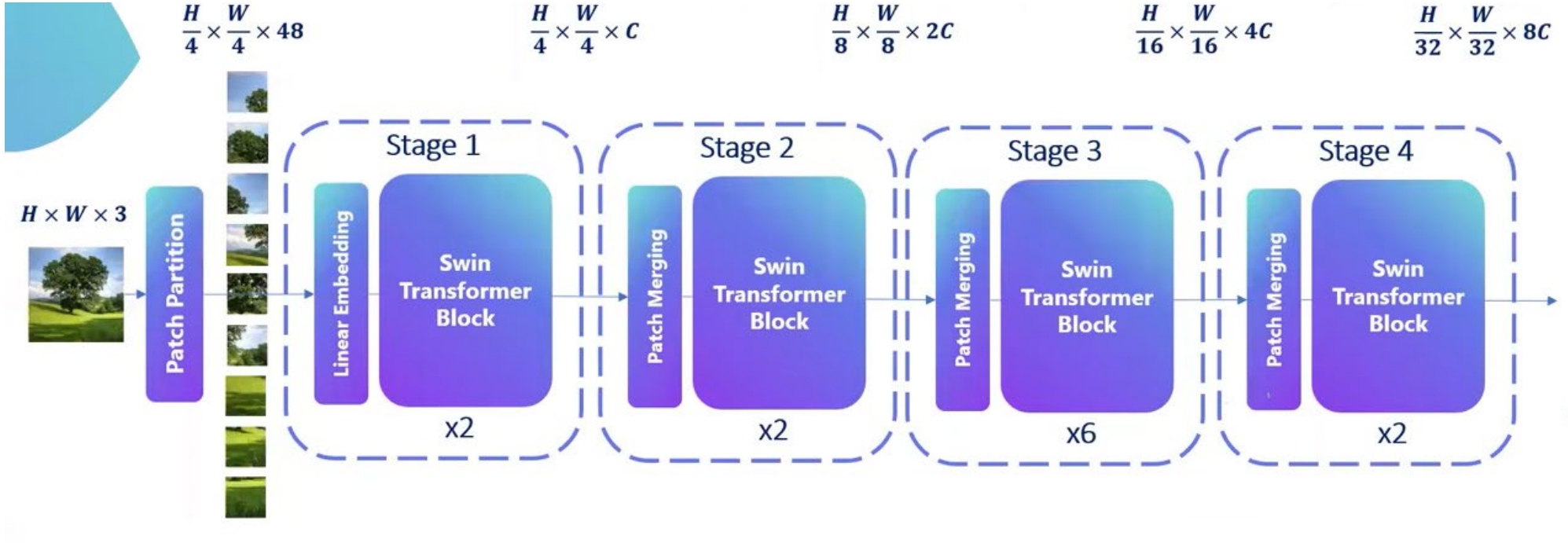


Tay et al. 2020. Efficient Transformers: A Survey.

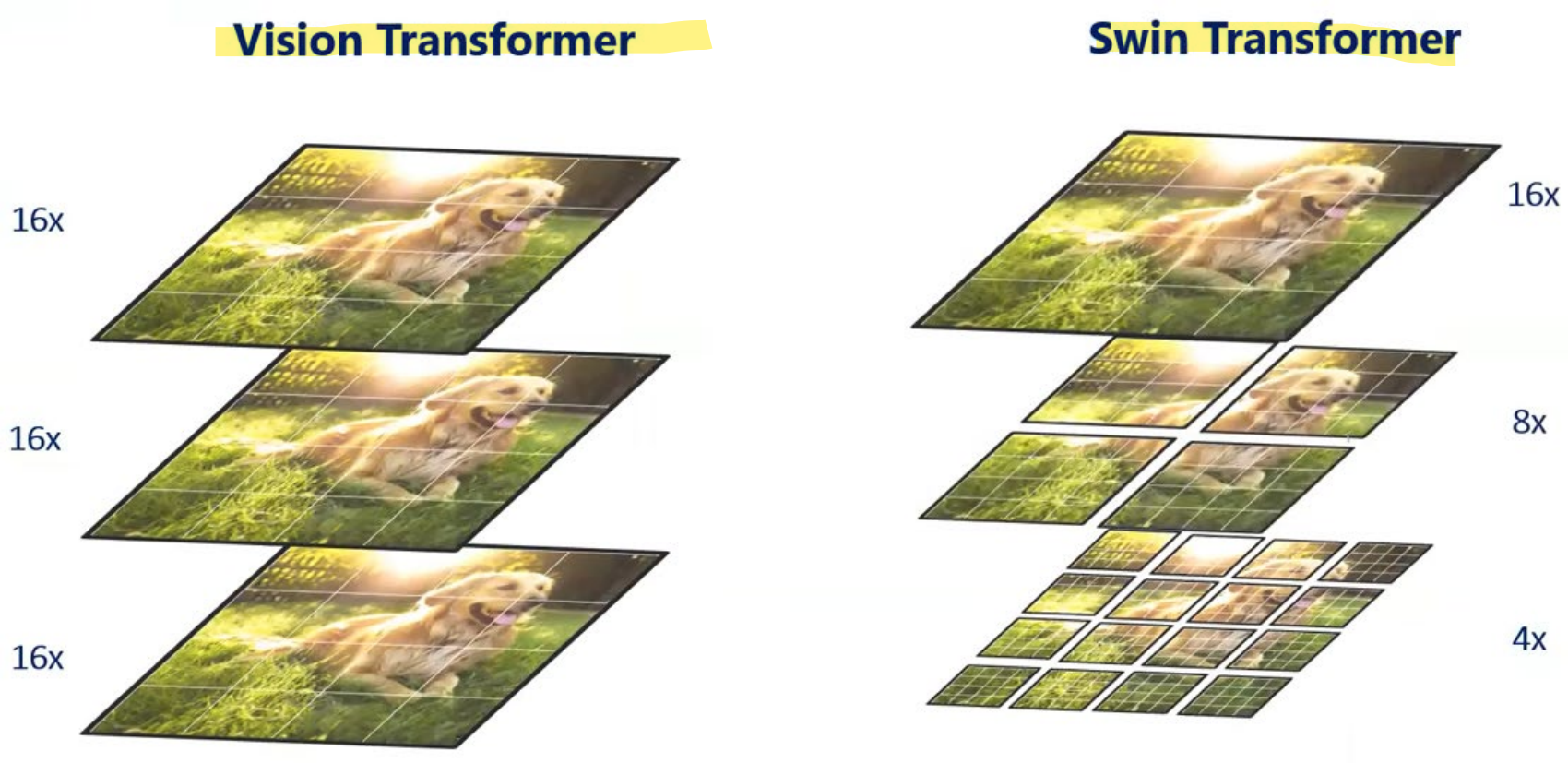
Multi-Scale Features in Transformers

Swin Trasformer

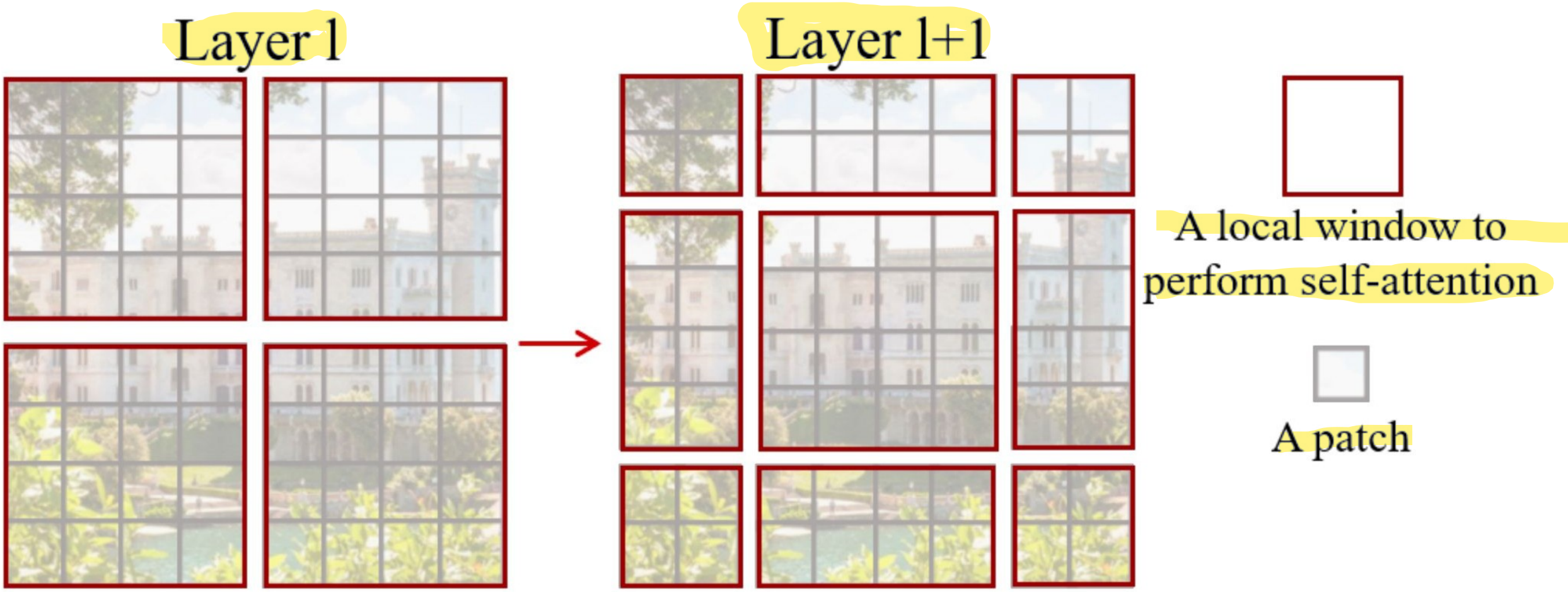
Shifted-window based self-Attention



Swin Transformer



Swin Transformer: Shifted window



Liu et al. 2021

Swin Transformer

youtube.com/watch?v=FQVS_0Bja6o

State of the art on COCO dataset https://paperswithcode.com/sota/object-detection-on-coco

Transformers for Self-Supervised Learning

DINO

Supervised baseline DINO

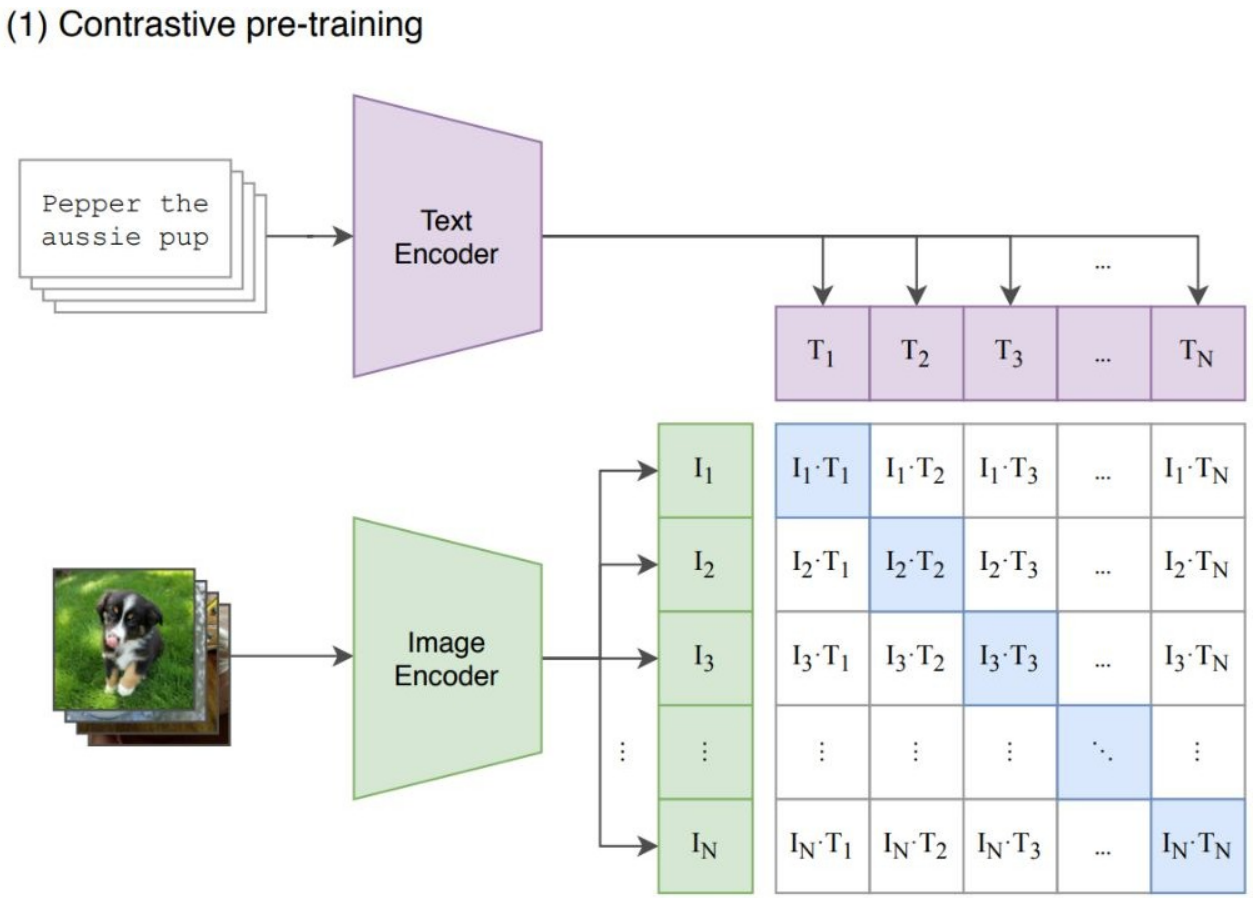
https://www.youtube.com/watch?v=h3ij3F3cPIk

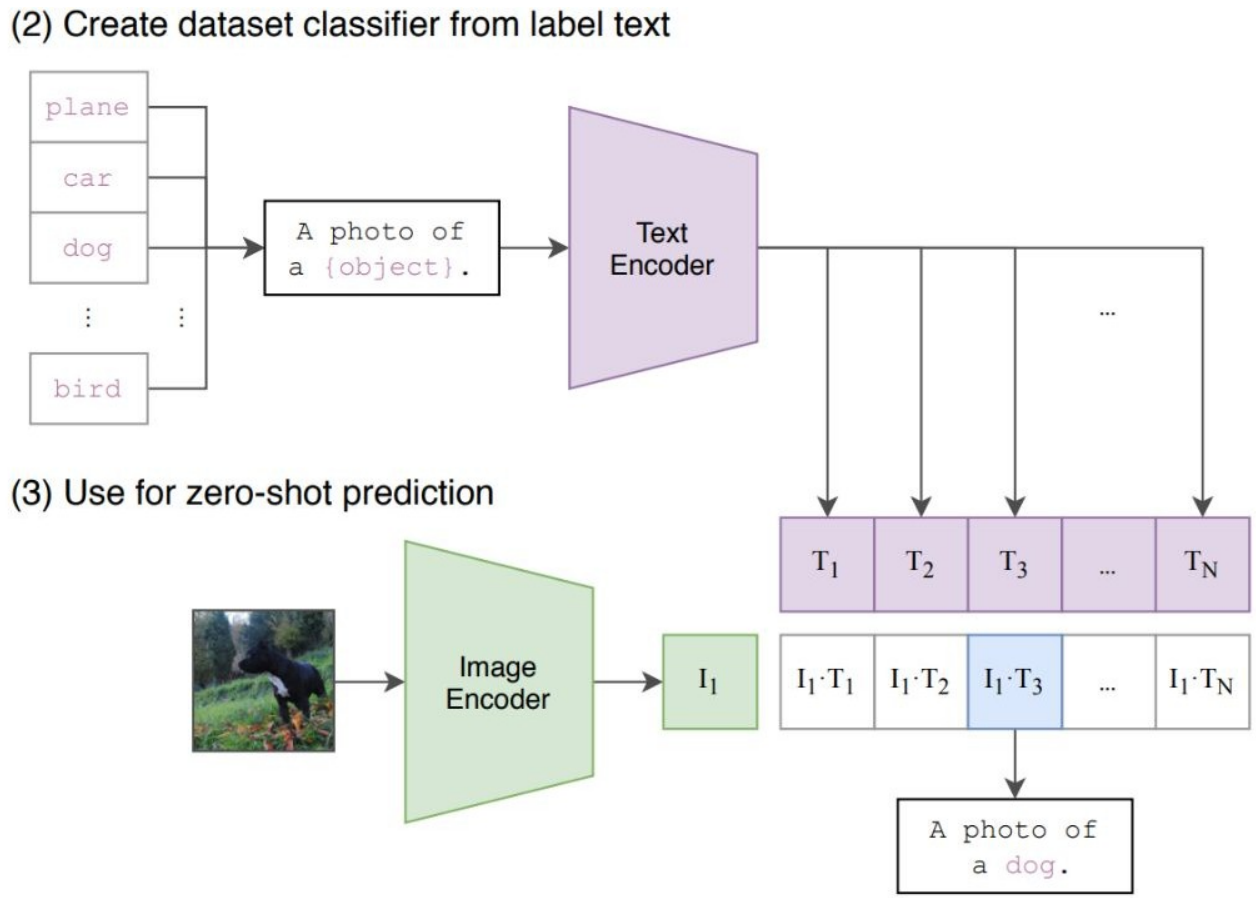
The network learns through a process called ‘self-distillation’. There is a teacher and student network both having the same architecture, a **Vision Transformer(ViT)**.

Caron et al 2020

Transformers for Multi-Modal Learning

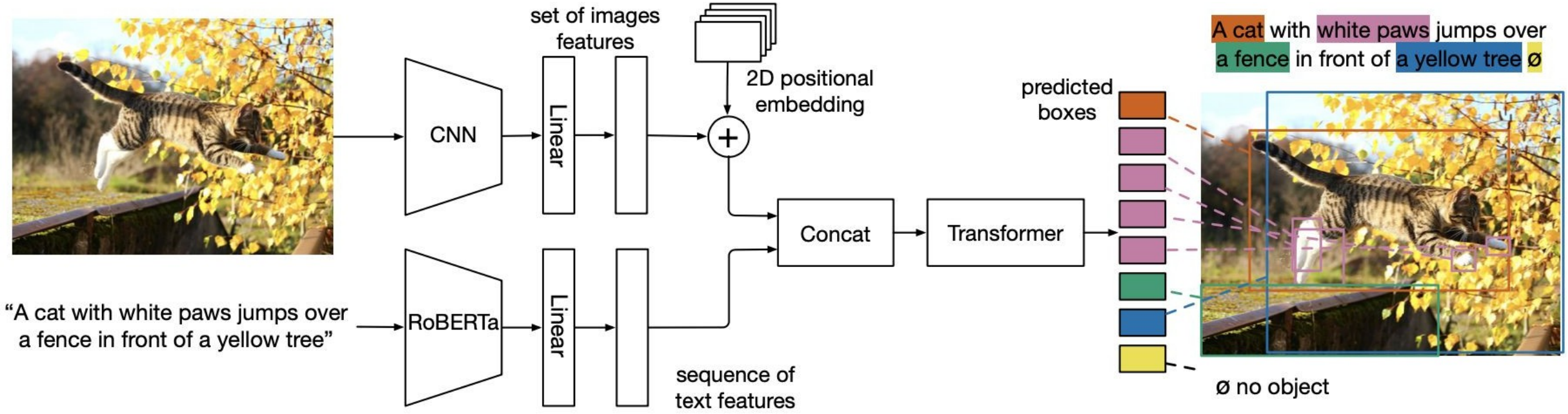
CLIP (*Contrastive Language–Image Pre-training)*





[Radford et al 2021]

Multimodal DETR (M-DETR)

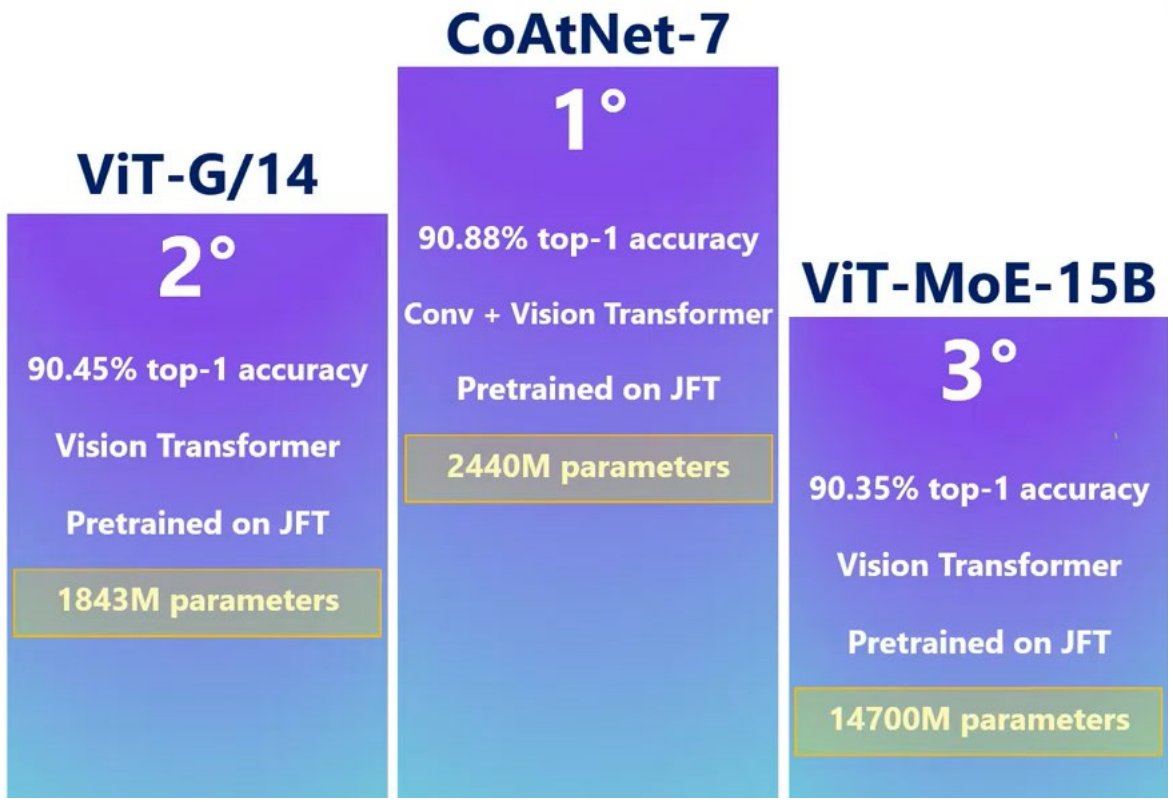


Kamath et al 2021

M-DETR

Kamath et al 2021

ImageNet ranking (2022)



CoAtNet: Marrying Convolution and Attention for All Data Sizes
https://proceedings.neurips.cc//paper/2021/file/20568692db622456cc42a2e853ca21f8-Paper.pdf

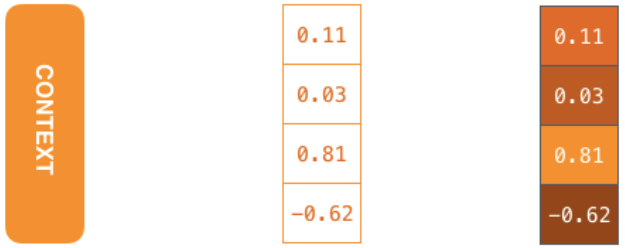
Takeaways

- Pure attention models require a lot of data OR data-augmentations and regularization for ~SoTA performance
- Hybrid and (or) multi-scale models perform best (efficient for the same high accuracy) across all data regimes
- Huge promise for multimodal (combining with language)

Transformer networks: summary

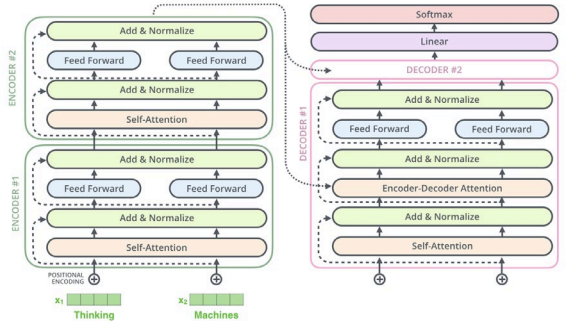
Foundations

- **Attention** allows to focus on relevant parts of the input
- **Query, key, and value vectors** obtained by multiplying the embedding by three matrices



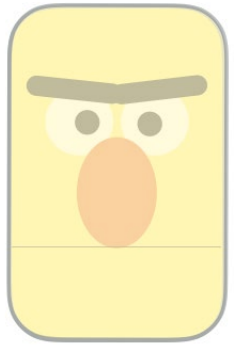
Transformer

- The encoder **attents to all words with self-attention**
- The decoder receives as input its own predicted the output of the encoder



Applications

- BERT
- VIT
- Wav2Vec



Credits: Ashish Vaswani, Prajit Ramachandran, and Aravind Srinivas, Jay Alammar, Simone Scardapane, Jaemin Jeong, Choi Dongmin, Coccomini, Messina