UCDAVIS
COLLEGE OF ENGINEERING
ELECTRICAL &
COMPUTER ENGINEERING

Attention & Vision Transformers

Kartik Patwari
Feb 11, 2026

*Acknowledgement: some slides are adapted from Philip Isola (phillipi@mit.edu)

CNNs Recap

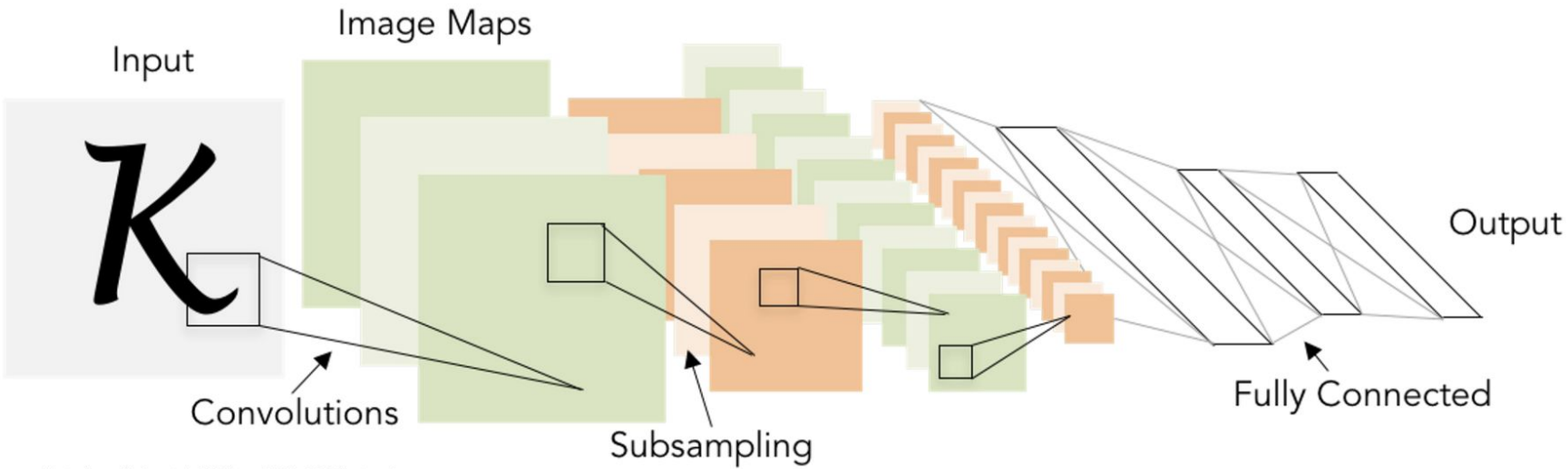
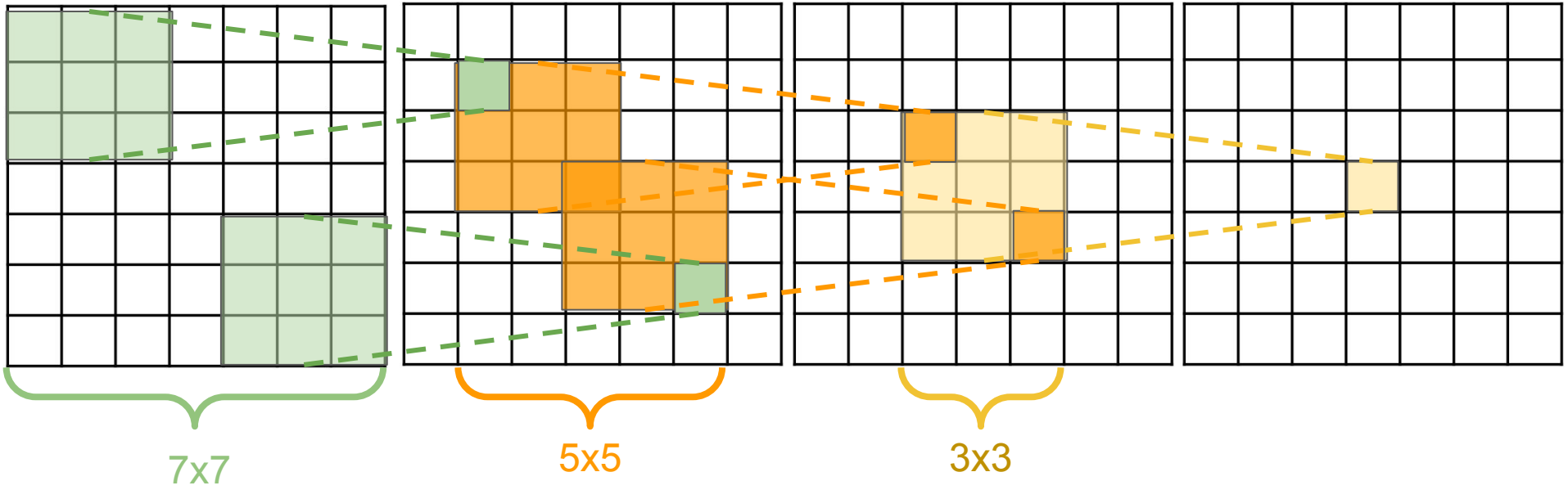
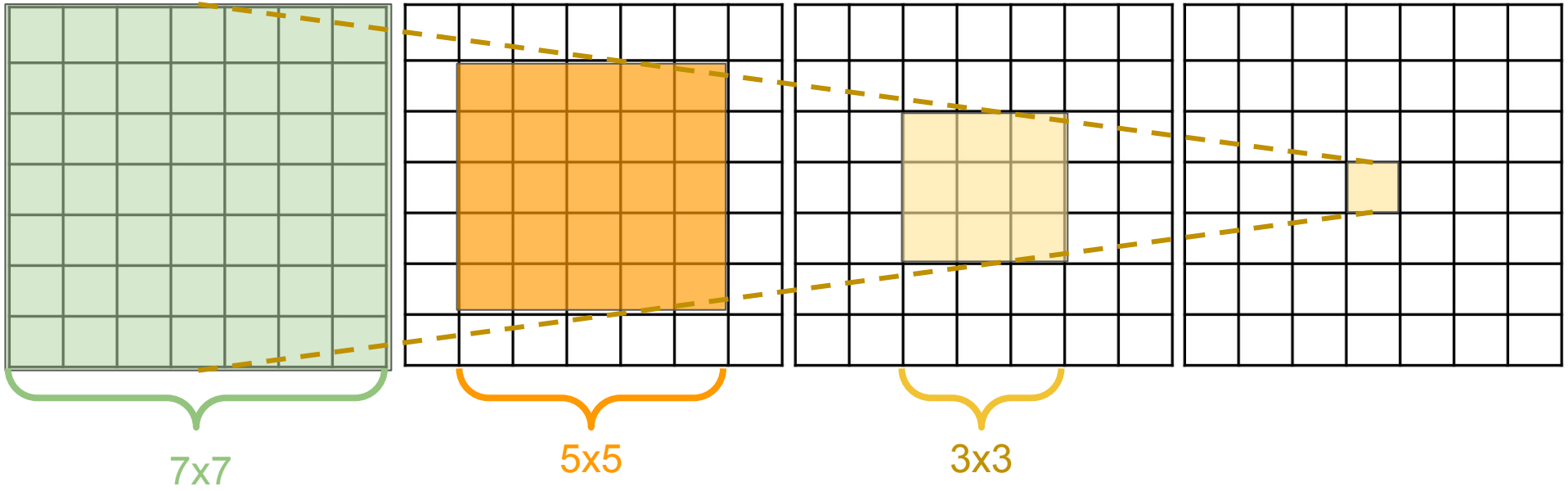


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

CNN Limitations: Receptive Fields

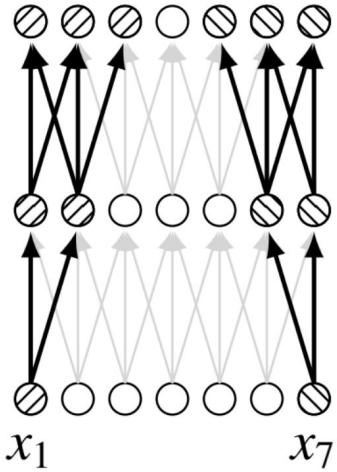


CNN Limitations: Receptive Fields

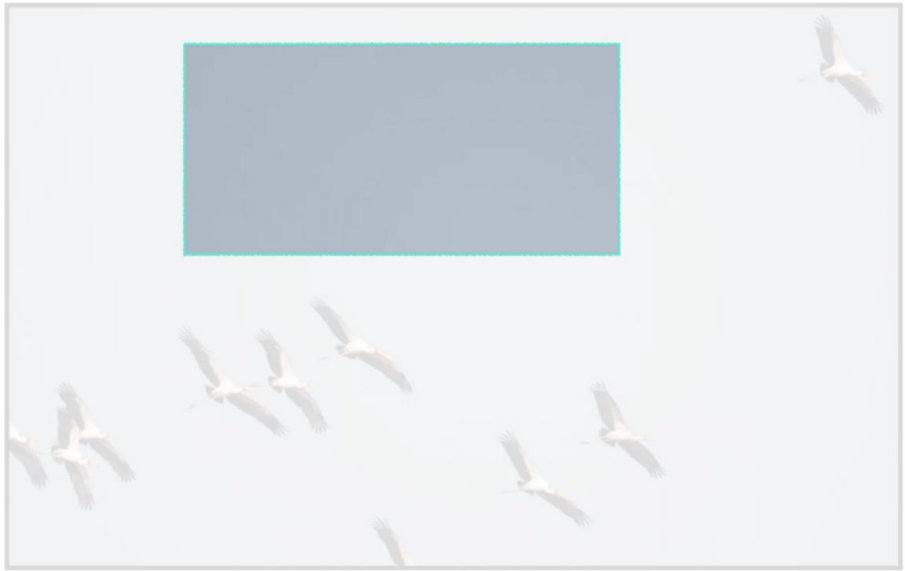


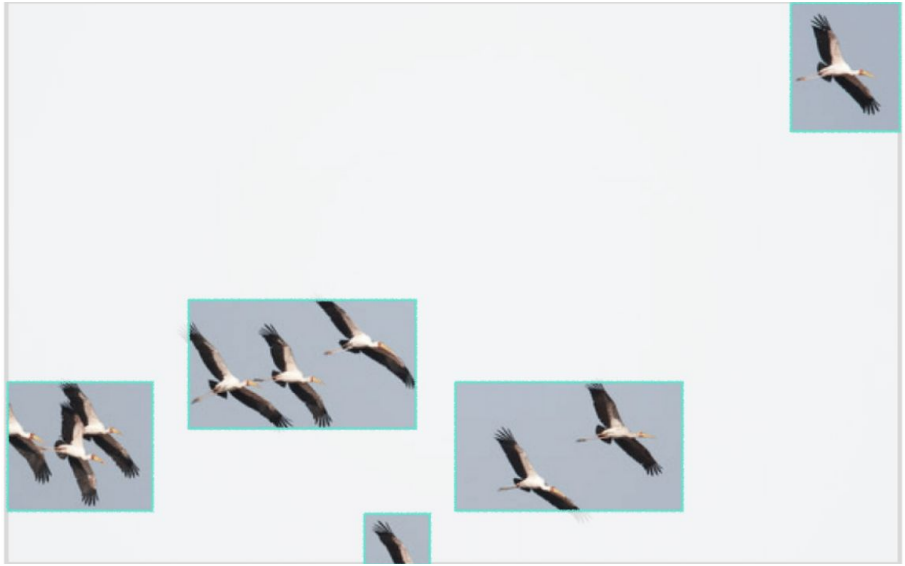
CNN Limitations

- CNNs are built around **locality**
- Not well suited to modeling **long distance relationships**
- Far image regions do not interact



Can we focus on specific regions?





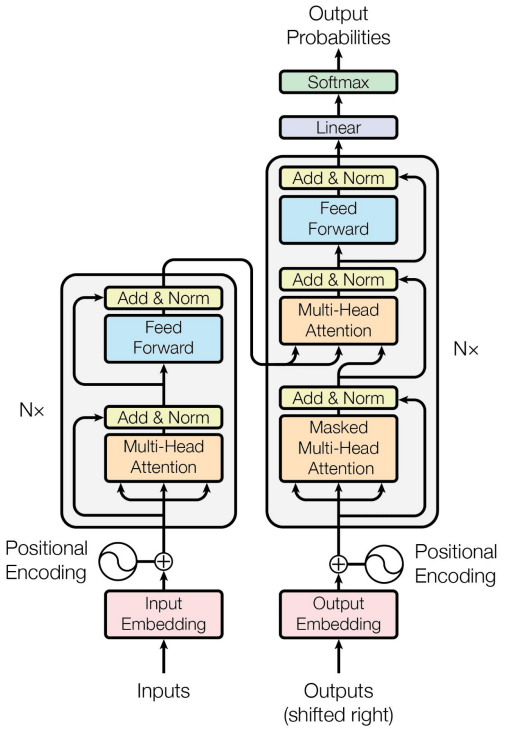
Attention Is All You Need

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 lukaszkaiser@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 solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

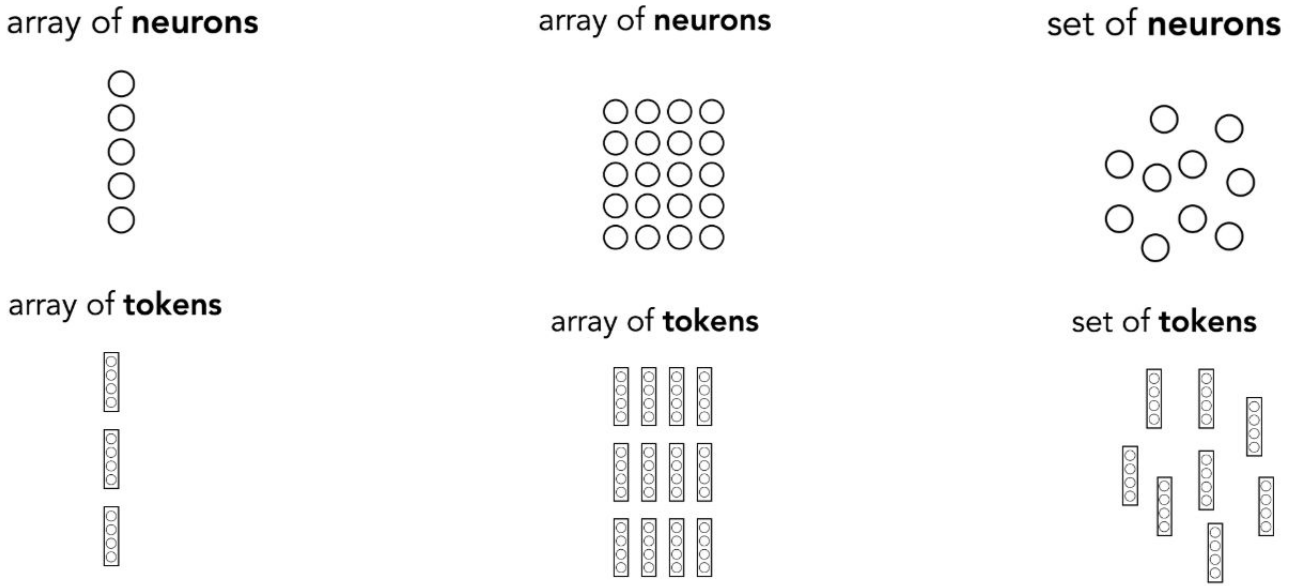


Attention Is All You Need: Attention, Transformers, ViTs

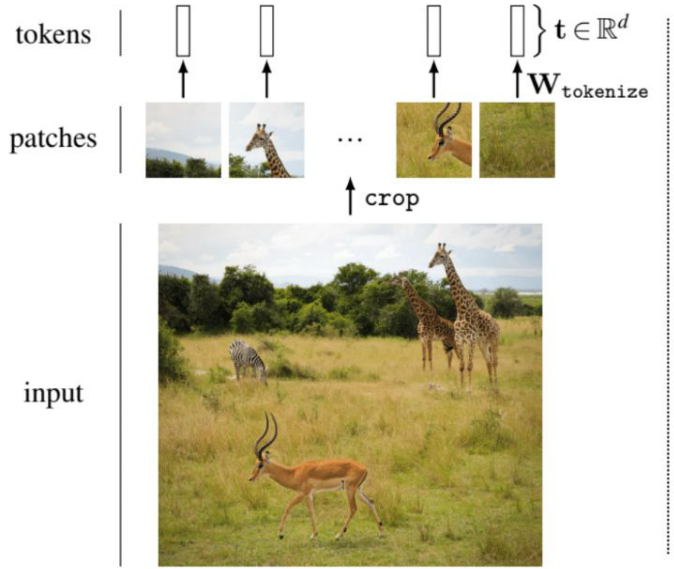
- Tokens
- Attention
- Self & Multi-head Attention
- Vision Transformers

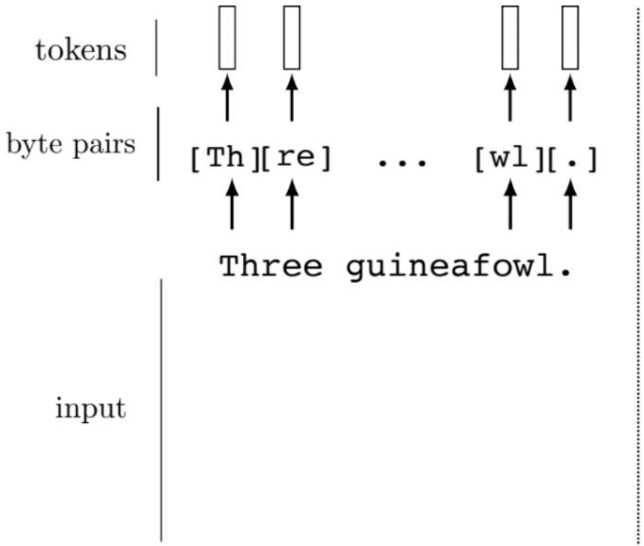
Tokens

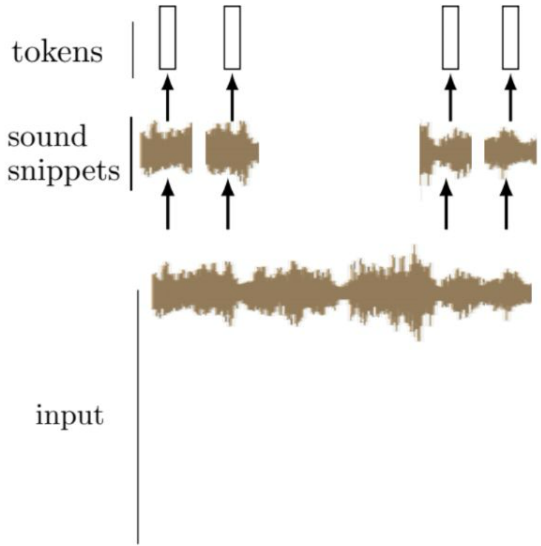
- Tokens can be seen as a vector of neurons
- Encapsulate bundle of information



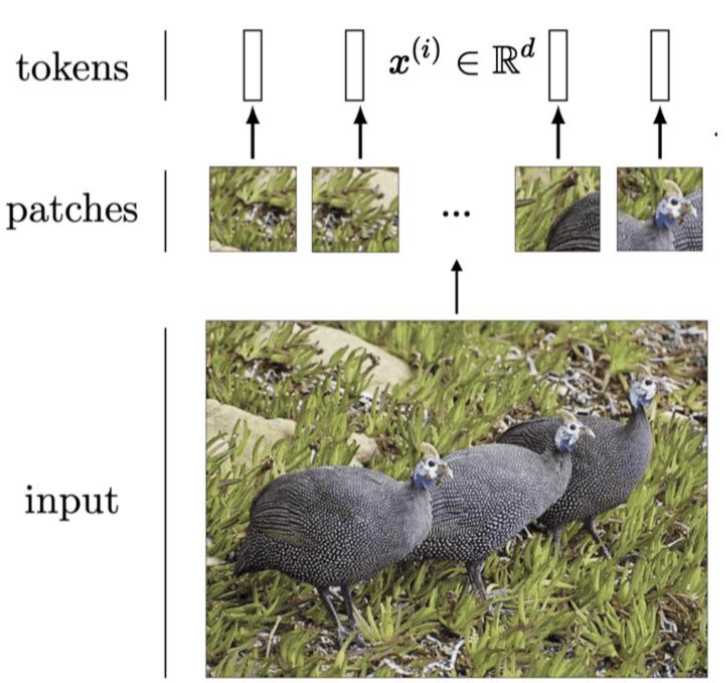
Tokenization

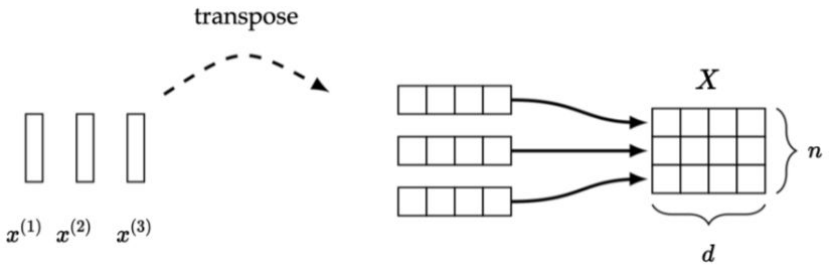






Tokenization





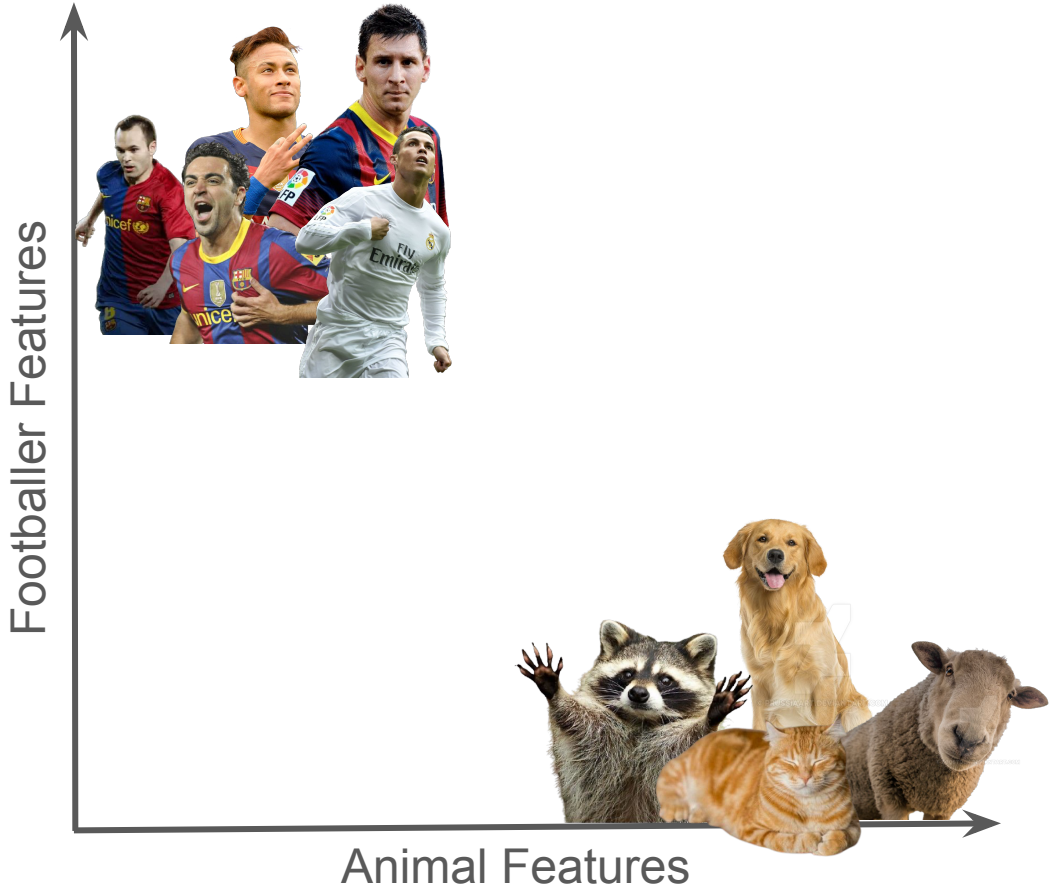
- d is the size of each token ($x^{(i)} \in \mathbb{R}^d$)
- n is the number of tokens

Attention: What should “goat” be?

Q: What does goat mean here? Animal

Q: What does goat mean here? Footballer (Greatest of all time)

Embedding Space

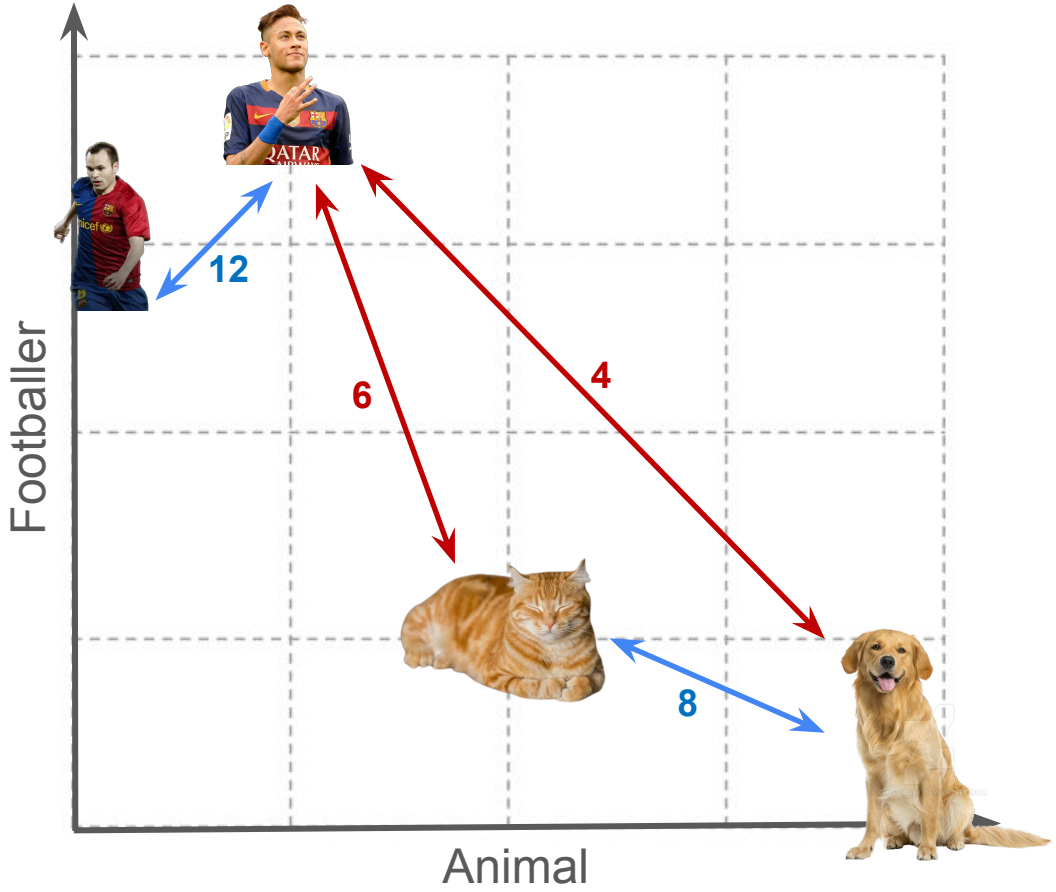


$$E = [Footballer\ feature, Animal\ feature]$$

Messi is the goat, not Ronaldo.

The sheep and goat are grazing.

Similarity: Dot Product



$$sim(\text{  }, \text{  }) = \begin{bmatrix}1\\4\end{bmatrix} \cdot \begin{bmatrix}0\\3\end{bmatrix} = 12$$

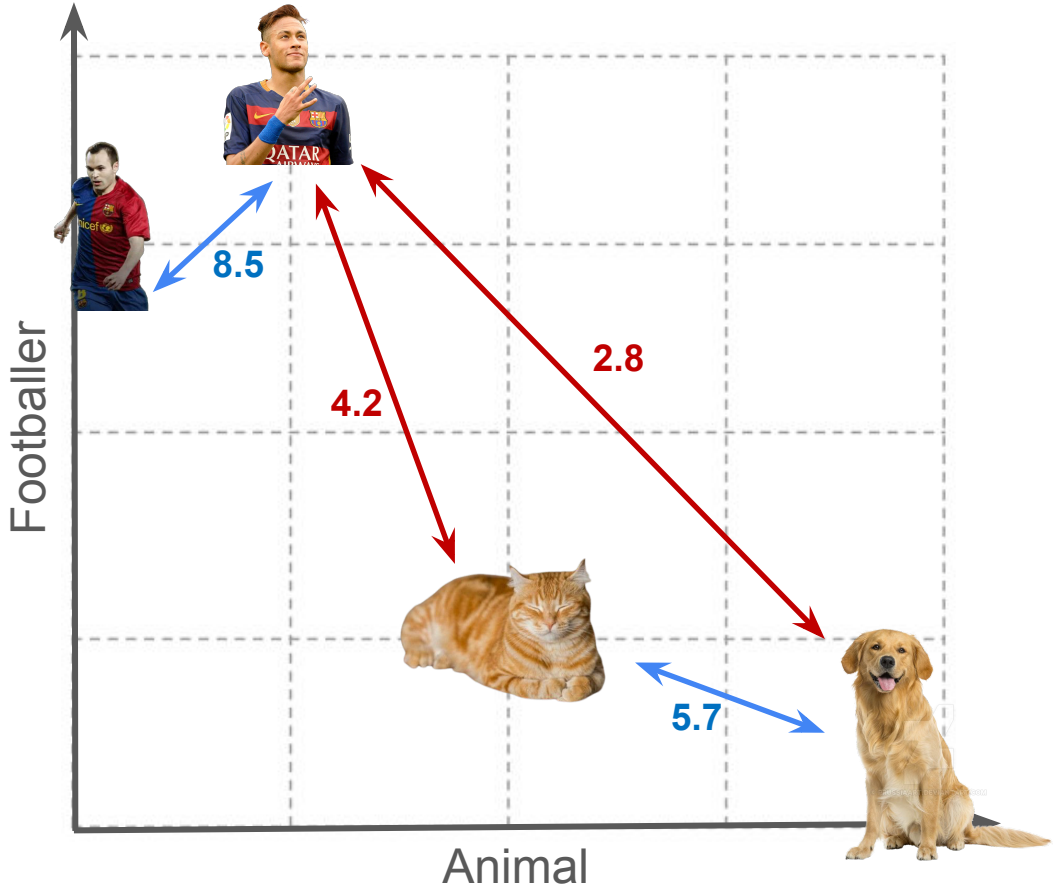
$$sim(\text{  }, \text{  }) = \begin{bmatrix}4\\0\end{bmatrix} \cdot \begin{bmatrix}2\\1\end{bmatrix} = 8$$

$$sim(\text{  }, \text{  }) = \begin{bmatrix}1\\4\end{bmatrix} \cdot \begin{bmatrix}4\\0\end{bmatrix} = 4$$

$$sim(\text{  }, \text{  }) = \begin{bmatrix}1\\4\end{bmatrix} \cdot \begin{bmatrix}2\\1\end{bmatrix} = 6$$

*Note: this is not euclidean distance

Similarity: Scaled Dot Product



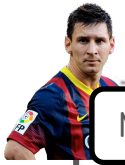
$$sim(\text{Neymar}, \text{Iniesta}) = \frac{\begin{bmatrix}1\\4\end{bmatrix} \cdot \begin{bmatrix}0\\3\end{bmatrix}}{\sqrt{2}} \sim 8.5$$

$$sim(\text{Dog}, \text{Cat}) = \frac{\begin{bmatrix}4\\0\end{bmatrix} \cdot \begin{bmatrix}2\\1\end{bmatrix}}{\sqrt{2}} \sim 5.7$$

$$sim(\text{Neymar}, \text{Dog}) = \frac{\begin{bmatrix}1\\4\end{bmatrix} \cdot \begin{bmatrix}4\\0\end{bmatrix}}{\sqrt{2}} \sim 2.8$$

$$sim(\text{Neymar}, \text{Cat}) = \frac{\begin{bmatrix}1\\4\end{bmatrix} \cdot \begin{bmatrix}2\\1\end{bmatrix}}{\sqrt{2}} \sim 4.2$$

What should “goat” be?



Messi

Ronaldo

Footballer

the

is

and

not

sheep

grazing

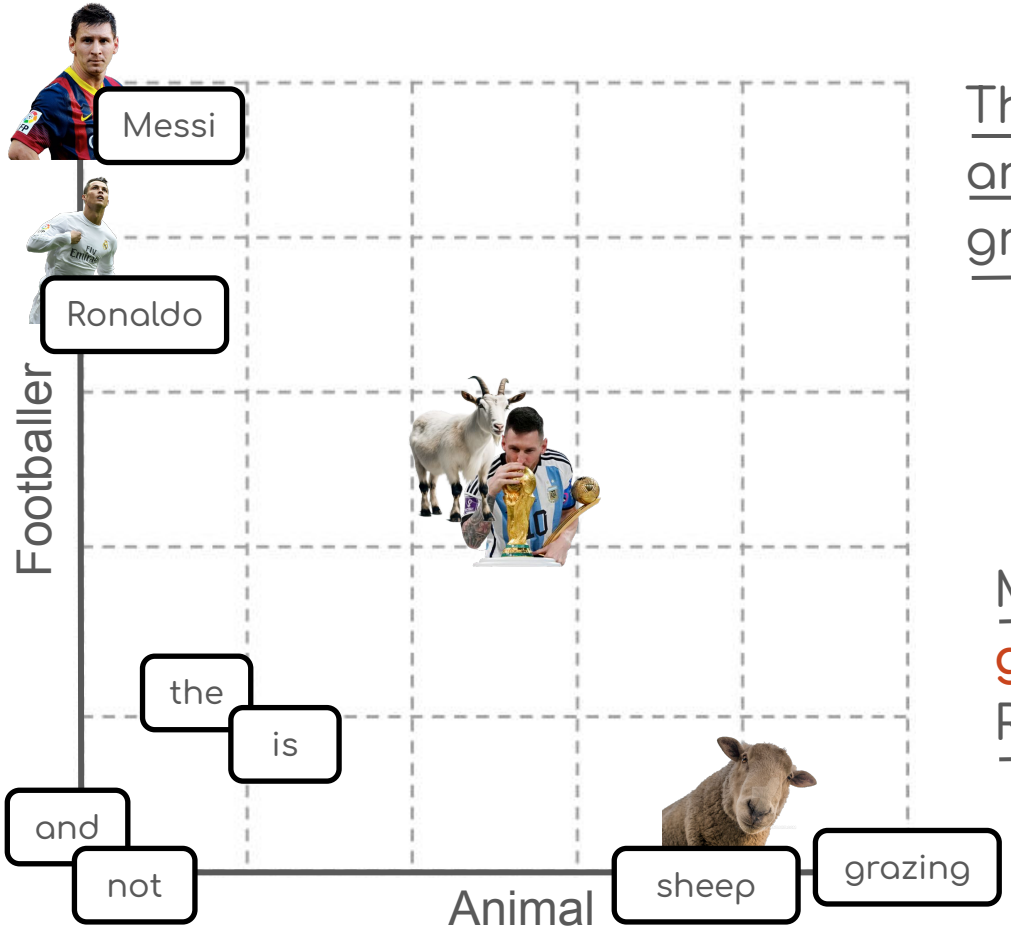
Animal

The sheep and goat are grazing.

Messi is the goat, not Ronaldo.

Word/Token	Embedding
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	???
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

What should “goat” be?



The sheep and goat are grazing.

Messi is the goat, not Ronaldo.

Word	Embedding
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	[2.5,2.5]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

What should “goat” be?

S_1: The sheep and goat are grazing.

$$Q, K, V = \begin{bmatrix} \text{the} & [1,1] \\ \text{sheep} & [4,0] \\ \text{and} & [0,0] \\ \text{goat} & [2.5,2.5] \\ \text{grazing} & [5,0] \end{bmatrix}$$

S_2: Messi is the goat, not Ronaldo.

$$Q, K, V = \begin{bmatrix} \text{Messi} & [0,5] \\ \text{is} & [1,1] \\ \text{goat} & [2.5,2.5] \\ \text{not} & [0,0] \\ \text{Ronaldo} & [0,4] \end{bmatrix}$$

Word	Q,K,V
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	[2.5,2.5]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

*Note: We take Q,K,V as same for this simple illustrative example

Attention: Calculate Scores

Attention scores are computed as the dot product of the **Query (Q)** of the target word (goat) with the **Keys (K)** of all words in the sentence.

$$Score = Q_{goat} \cdot K^T$$

$$Scores(S_1) = [2.5,2.5] \cdot \begin{bmatrix} [1,1] \\ [4,0] \\ [0,0] \\ [2.5,2.5] \\ [5,0] \end{bmatrix} = \begin{bmatrix} 5 \\ 10 \\ 0 \\ 12.5 \\ 12.5 \end{bmatrix}$$

S_1:

The sheep and goat are grazing.

$$Scores(S_2) = [2.5,2.5] \cdot \begin{bmatrix} [0,5] \\ [1,1] \\ [2.5,2.5] \\ [0,0] \\ [0,4] \end{bmatrix} = \begin{bmatrix} 12.5 \\ 5 \\ 12.5 \\ 0 \\ 10 \end{bmatrix}$$

S_2:

Messi is the goat, not Ronaldo.

Word	Q,K,V
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	[2.5,2.5]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

Attention: Scale Scores

We scale the scores by dividing by $\sqrt{d_k}$, where $d_k = 2$ (embedding dimension):

$$Scaled\ Score = \frac{Q_{goat} \cdot K^T}{\sqrt{d_k}}$$

$$Scaled\ Scores(S_1) = \begin{bmatrix} 5 \\ 10 \\ 0 \\ 12.5 \\ 12.5 \end{bmatrix} \Big/ \sqrt{2} = \begin{bmatrix} 3.55 \\ 7.08 \\ 0 \\ 8.85 \\ 8.85 \end{bmatrix}$$

S_1:

The sheep and goat are grazing.

$$Scaled\ Scores(S_2) = \begin{bmatrix} 12.5 \\ 5 \\ 12.5 \\ 0 \\ 10 \end{bmatrix} \Big/ \sqrt{2} = \begin{bmatrix} 8.85 \\ 3.55 \\ 8.85 \\ 0 \\ 7.08 \end{bmatrix}$$

S_2:

Messi is the goat, not Ronaldo.

Word	Q,K,V
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	[2.5,2.5]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

Attention: Softmax

We convert the scaled scores into probabilities using the **Softmax**.

$$Attention\ Score = softmax\left(\frac{Q_{goat} \cdot K^T}{\sqrt{d_k}}\right)$$

$$Attention\ Scores(S_1) = softmax\left(\begin{bmatrix}3.55\\7.08\\0\\8.85\\8.85\end{bmatrix}\right) = \begin{bmatrix}0.00\\0.08\\0.00\\0.46\\0.46\end{bmatrix}$$

S_1:

The sheep and goat are grazing.

$$Attention\ Scores(S_2) = softmax\left(\begin{bmatrix}8.85\\3.55\\8.85\\0\\7.08\end{bmatrix}\right) = \begin{bmatrix}0.43\\0\\0.43\\0\\0.14\end{bmatrix}$$

S_2:

Messi is the goat, not Ronaldo.

Word	Q,K,V
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	[2.5,2.5]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

Attention: Weighted Sum

The output for goat is the weighted sum of the **Value (V)** vectors.

$$Attention(Q,K,V) = \sum softmax\left(\frac{Q_{goat} \cdot K^T}{\sqrt{d_k}}\right) \cdot V$$

$$Attention\ (S_1) = \sum \begin{bmatrix}0.00\\0.08\\0.00\\0.46\\0.46\end{bmatrix} \cdot \begin{bmatrix}[1,1]\\[4,0]\\[0,0]\\[2.5,2.5]\\[5,0]\end{bmatrix} = \begin{bmatrix}3.77\\1.15\end{bmatrix}$$

S_1:

The sheep and goat are grazing.

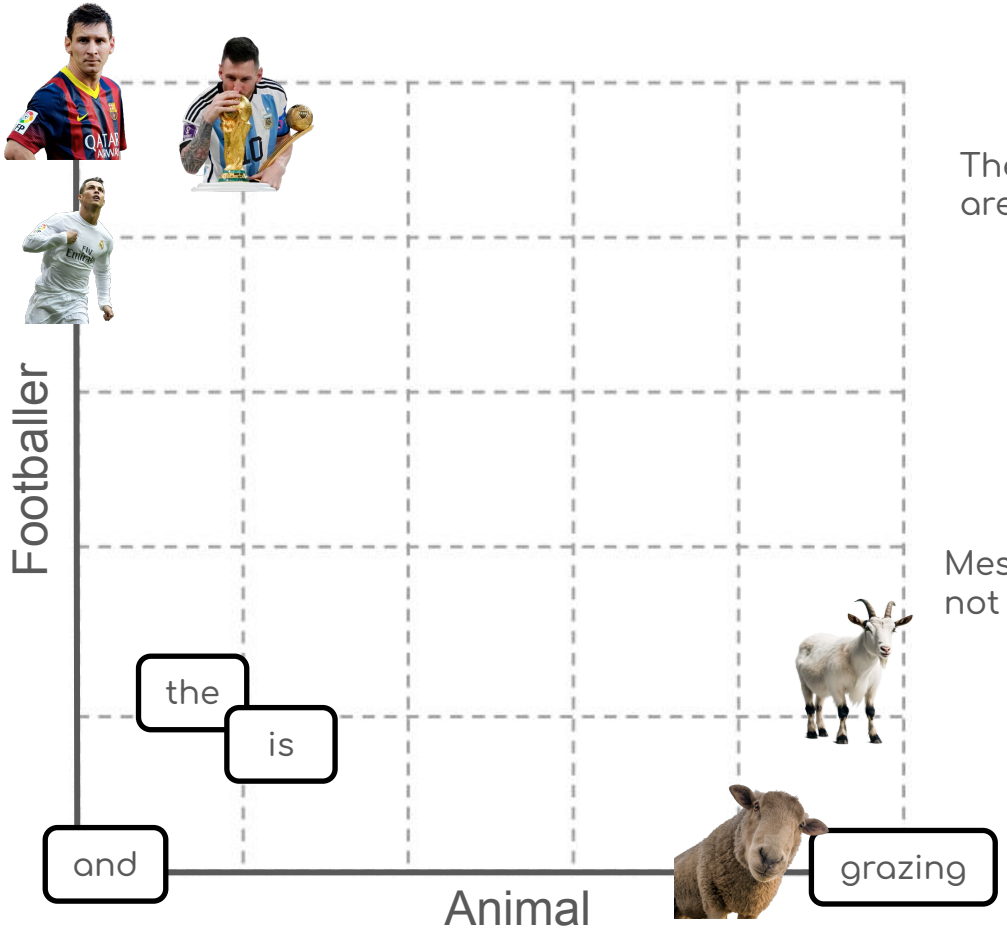
$$Attention\ (S_2) = \sum \begin{bmatrix}0.43\\0\\0.43\\0\\0.14\end{bmatrix} \cdot \begin{bmatrix}[0,5]\\[1,1]\\[2.5,2.5]\\[0,0]\\[0,4]\end{bmatrix} = \begin{bmatrix}1.08\\3.79\end{bmatrix}$$

S_2:

Messi is the goat, not Ronaldo.

Word	Q,K,V
the	[1,1]
sheep	[4,0]
and	[0,0]
goat	[2.5,2.5]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

What should “goat” be?



S_1:

The sheep and goat are grazing.

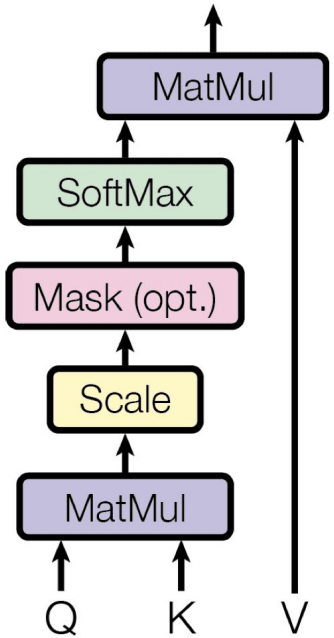
S_2:

Messi is the goat, not Ronaldo.

Word	Q,K,V
the	[1,1]
sheep	[4,0]
and	[0,0]
goat (S_1)	[3.77,1.15]
goat (S_2)	[1.08,3.79]
grazing	[5,0]
Messi	[0,5]
is	[1,1]
not	[0,0]
Ronaldo	[0,4]

Scaled Dot-Product Attention

- **Query (Q)**
  - The current word/token’s focus or what it's "asking for."
  - A **vector representing the intent of the query word.**
- **Key (K)**
  - The **identity** or "role" of each word in the context of the sentence.
  - A matrix where each row corresponds to a word and holds its **contextual representation**.
- **Value (V)**
  - The **information or content** associated with each word.
  - A matrix where each row corresponds to a word’s **content to aggregate if it’s attended to**.



Attention is a content-based lookup mechanism.

Attention: Single Query

1. Similarity score with key (k_j):

$$s_j = qk_j^T / \sqrt{d_k}$$

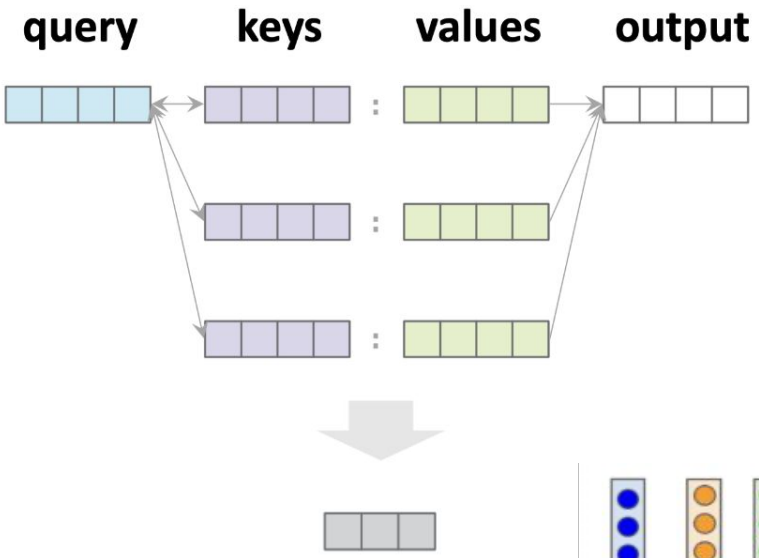
2. Attention weights:

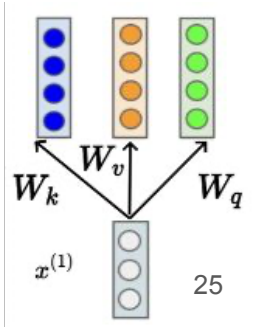
$$a = softmax(qk_j^T / \sqrt{d_k})$$

3. Output: Attention-weighted sum:

$$y = \sum_j a_j v_i$$

Note: Attention complexity grows as O(N²) with number of tokens.





Attention: Multiple Query

1. Similarity score with query (q_i) and key (k_j):

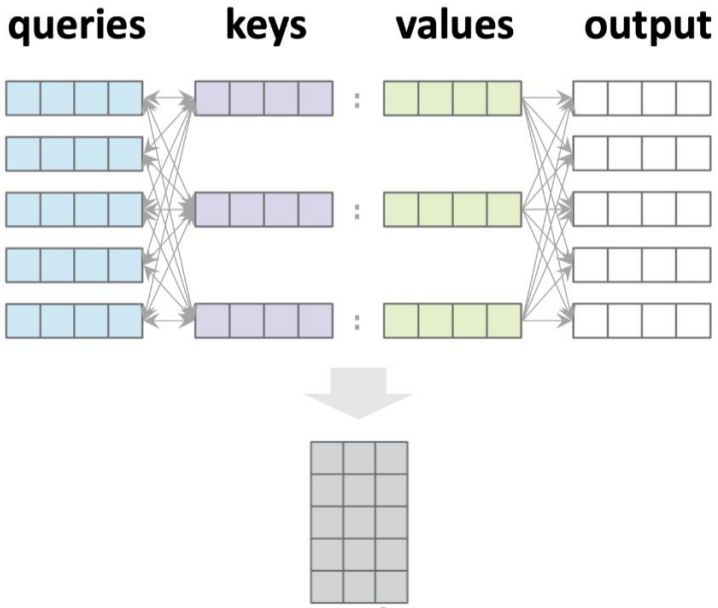
$$s_{ij} = q_i k_j^T / \sqrt{d_k}$$

2. Attention weights:

$$a_i = softmax(q_i k_j^T / \sqrt{d_k})$$

3. Output: Attention-weighted sum:

$$y_i = \sum_j a_{ij} v_i$$



Self-Attention

Let us take following sentence with new embeddings:
We will use all words as Q, K, and V

Messi is the goat, not Ronaldo.

$$a_i = softmax(q_i k_j^T / \sqrt{d_k})$$

Word	Q,K,V
Messi	[6,2]
is	[1,1]
the	[1,1]
goat	[5,3]
,	[0,0]
not	[1,0]
Ronaldo	[4,2]

Self-Attention

Messi is the goat, not Ronaldo.

Word	Q,K,V
Messi	[6,2]
is	[1,1]
the	[1,1]
goat	[5,3]
,	[0,0]
not	[1,0]
Ronaldo	[4,2]

Step 1: $s_{ij} = q_i k_j^T / \sqrt{d_k}$

	Messi	is	the	goat	,	not	Ronaldo
Messi	28.37	5.67	5.67	25.53	0	4.25	19.86

$$s_{messi,messi} = q_i k_j^T / \sqrt{d_k} = (6\times6 + 2\times2)/\sqrt{2} = 28.37$$

Self-Attention

Messi is the goat, not Ronaldo.

Word	s_{ij}
Messi	28.37
is	5.67
the	5.67
goat	25.53
,	0.00
not	4.25
Ronaldo	19.86

Step 2: $a_i = softmax(s_{ij})$

	Messi	is	the	goat	,	not	Ronaldo
Messi	0.94	0.0	0.0	0.06	0	0.0	0.0

$$a_{messi} = e^{28.37}/(e^{28.37} + e^{5.67} + e^{5.67} + e^{25.53} + e^{0} + e^{4.25} + e^{19.85}) \approx 0.94$$

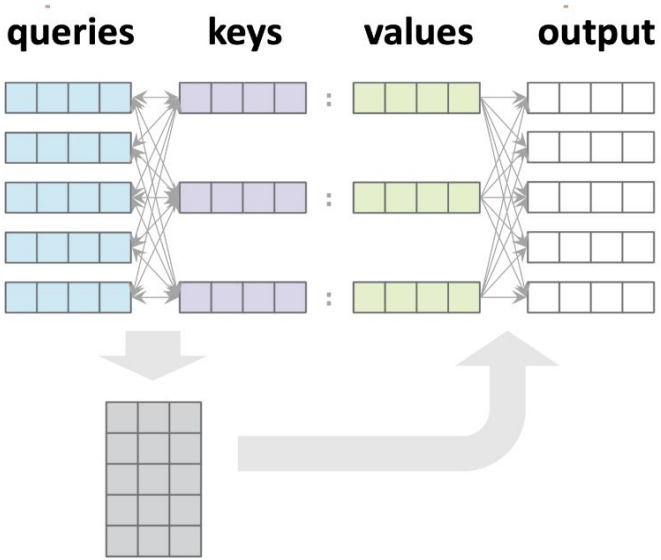
Self-Attention

Messi is the goat, not Ronaldo.

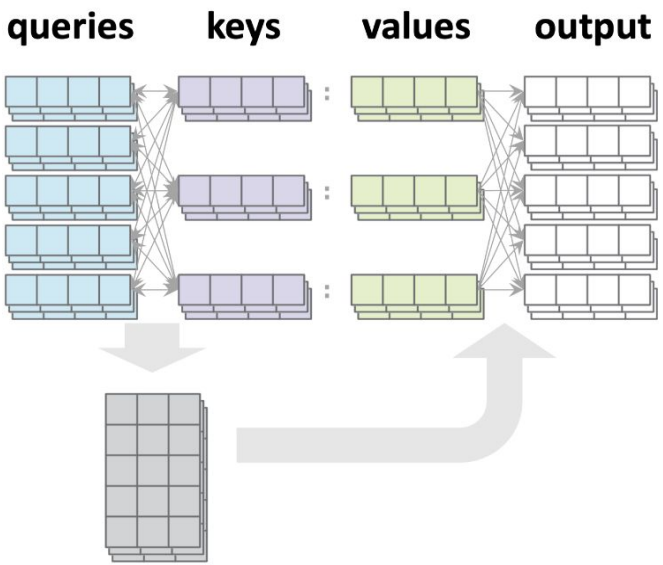
	Messi	is	the	goat	,	not	Ronaldo
Messi	0.94	0.0	0.0	0.06	0.0	0.0	0.0
is	0.44	0.01	0.01	0.44	0.0	0.0	0.11
the	0.44	0.01	0.01	0.44	0.0	0.0	0.11
goat	0.8	0.0	0.0	0.2	0.0	0.0	0.0
,	0.14	0.14	0.14	0.14	0.14	0.14	0.14
not	0.54	0.02	0.02	0.27	0.01	0.02	0.13
Ronaldo	0.0	0.0	0.0	0.2	0.0	0.0	0.8

Multi-head Attention

One head

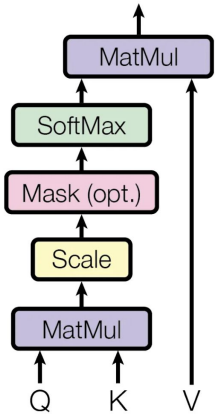


Multiple heads

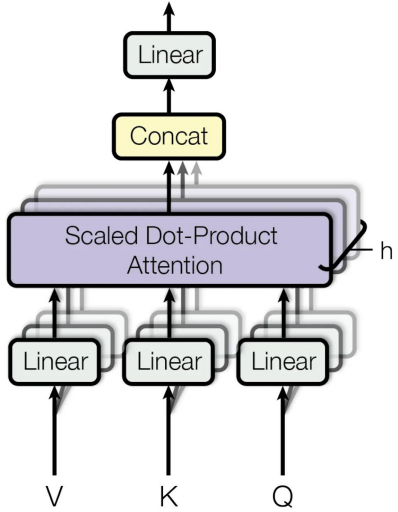


Multi-head Attention

Scaled Dot-Product Attention



Multi-Head Attention



$$Attention(Q, K, V) = \sum softmax\left(\frac{Q_{goat} \cdot K^T}{\sqrt{d_k}}\right) \cdot V$$

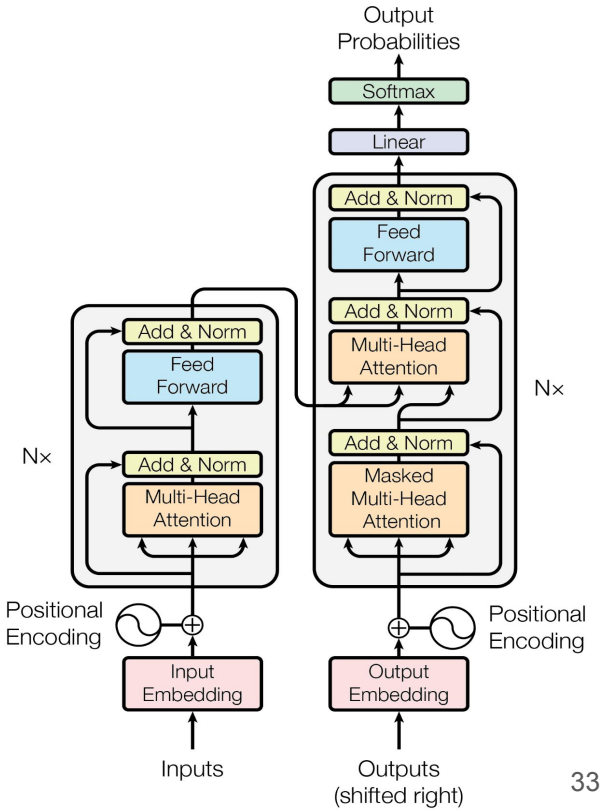
Using Attention: Transformers

Messi is the goat, not Ronaldo.

Messi est la chèvre, pas Ronaldo.

メッシはゴートで、ロナウドではありません。

梅西是山羊，不是罗纳尔多。



Vision Transformers

Published as a conference paper at ICLR 2021

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, neilhoulsby}@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 train.[1]

1 INTRODUCTION

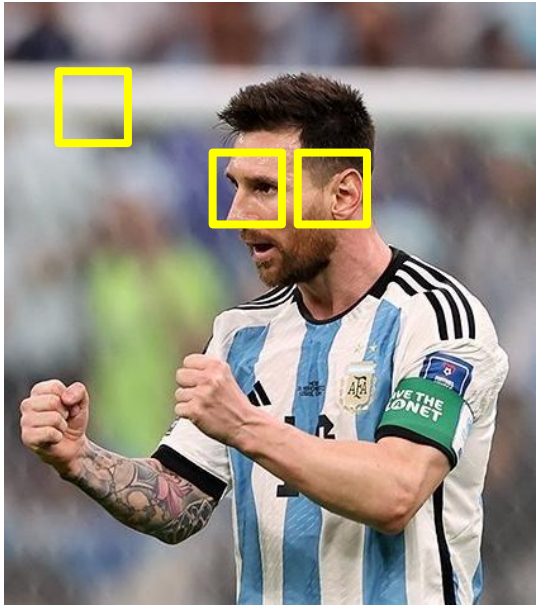
Self-attention-based architectures, in particular Transformers (Vaswani et al., 2017), have become the model of choice in natural language processing (NLP). The dominant approach is to pre-train on a large text corpus and then fine-tune on a smaller task-specific dataset (Devlin et al., 2019). Thanks to Transformers' computational efficiency and scalability, it has become possible to train models of unprecedented size, with over 100B parameters (Brown et al., 2020; Lepikhin et al., 2020). With the models and datasets growing, there is still no sign of saturating performance.

Visual Attention

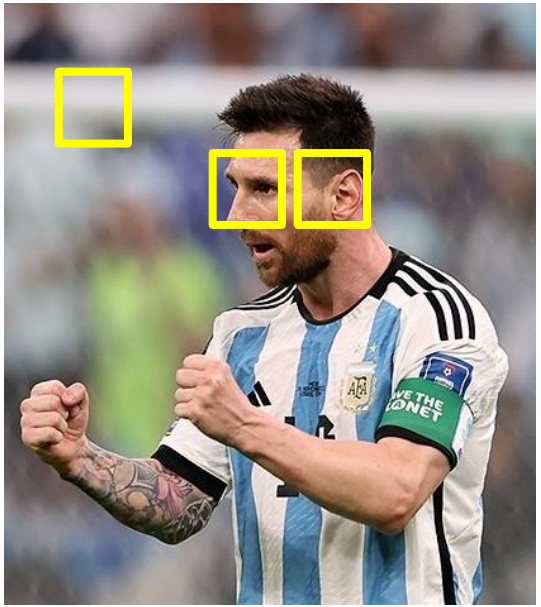
Query: “Which patches are relevant to me?”

Key: “What visual feature do I represent?”

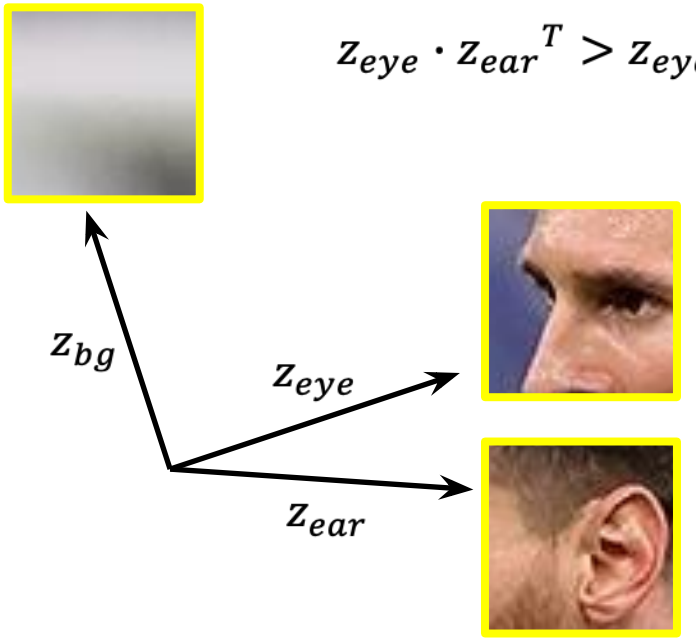
Value: “What visual information should I contribute?”



Visual Attention



Visual Attention: Dot-product Similarity



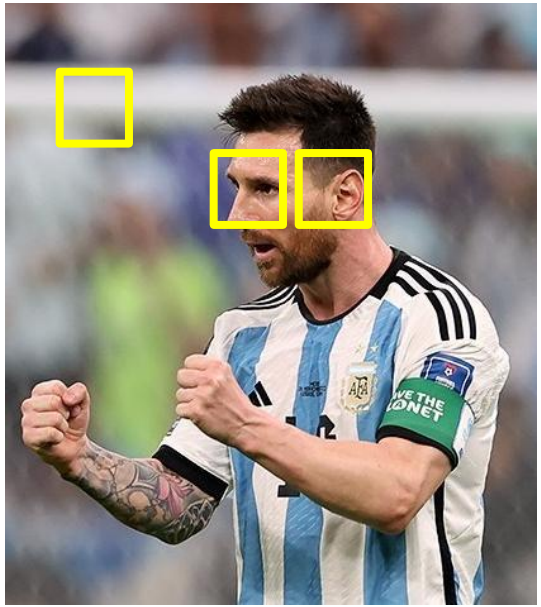
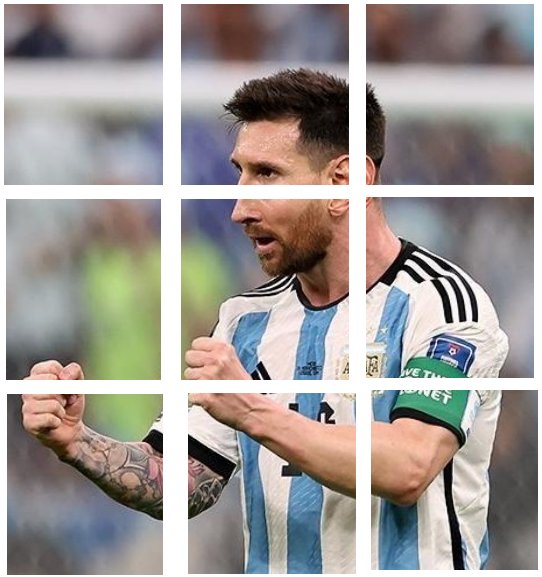


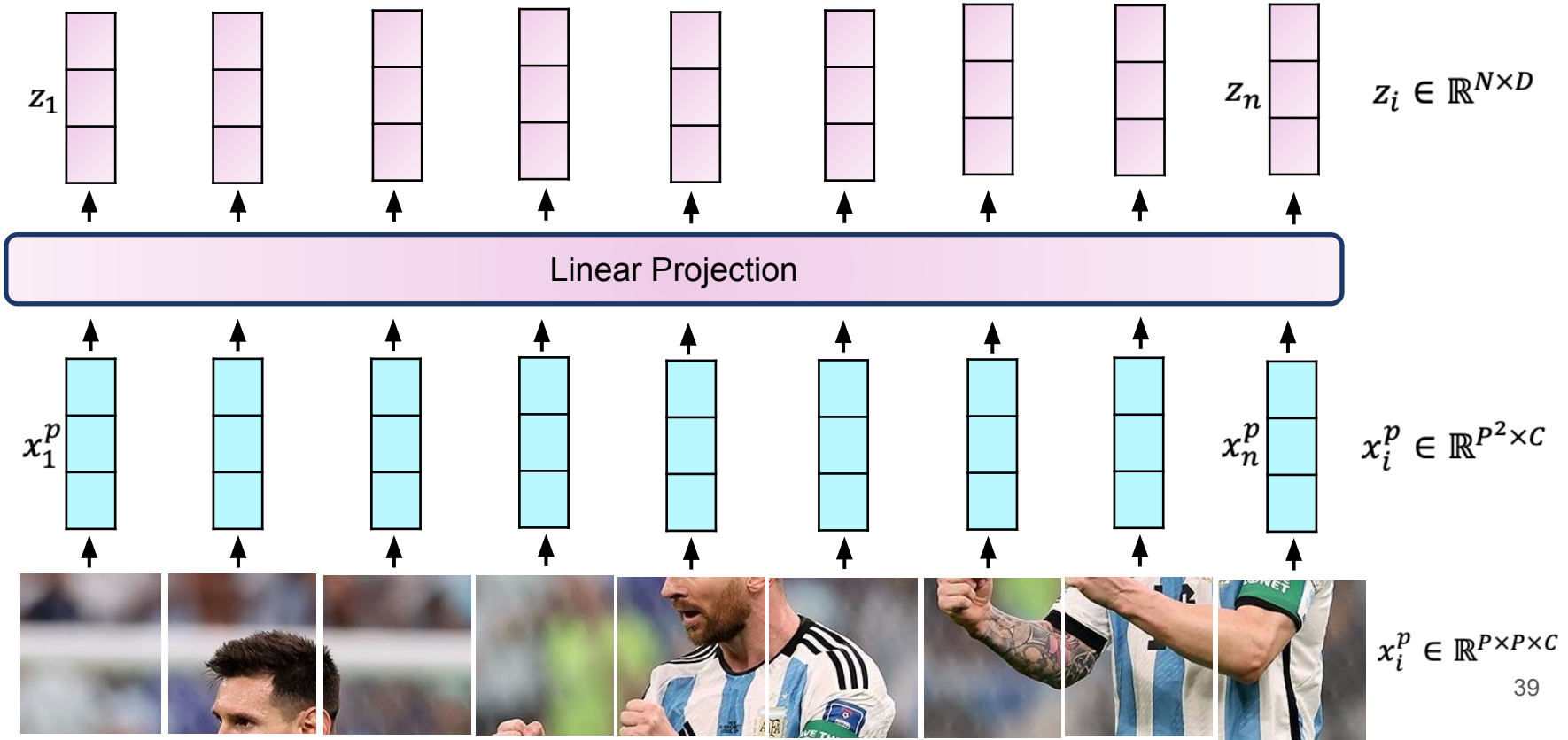
Image to Patches

$x \in \mathbb{R}^{W \times H \times C}$

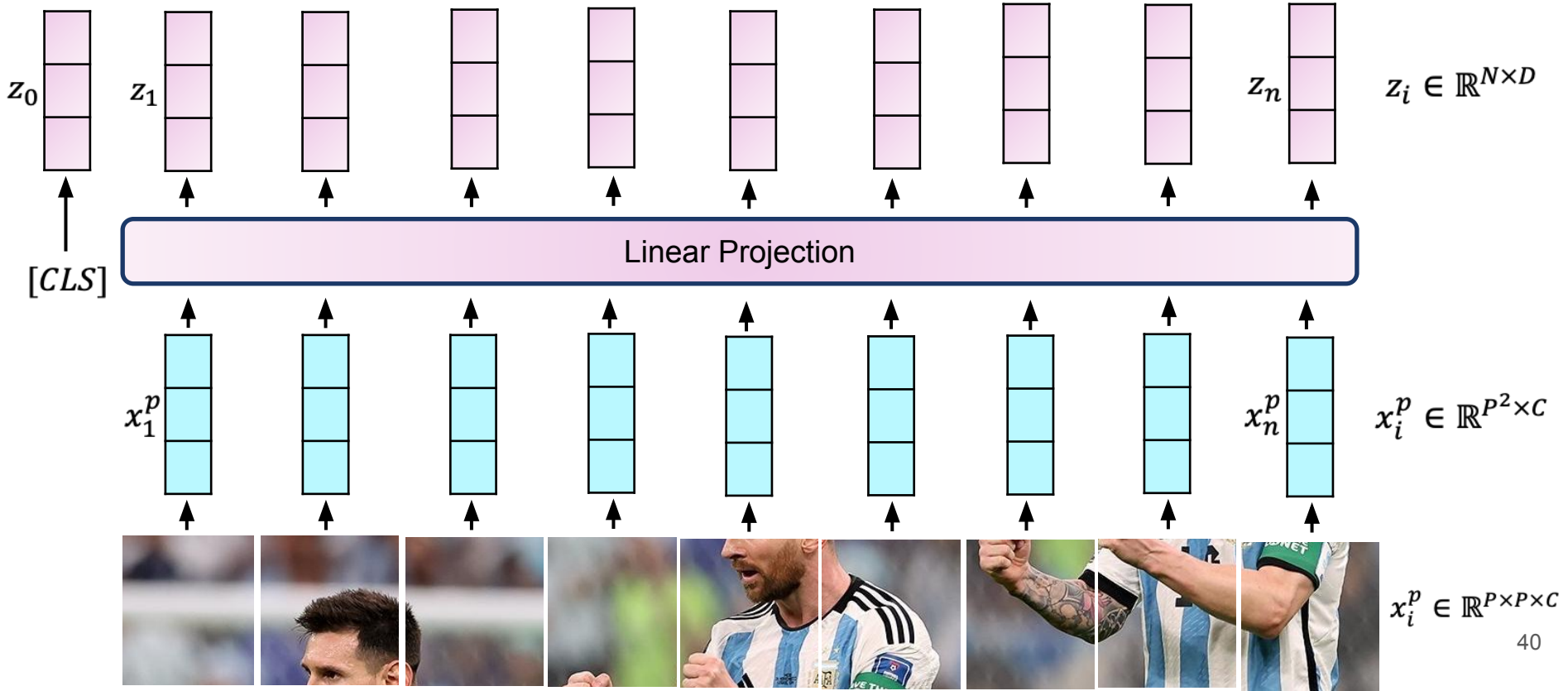


$x_i^p \in \mathbb{R}^{P \times P \times C}, i = 1 \ \ldots N$

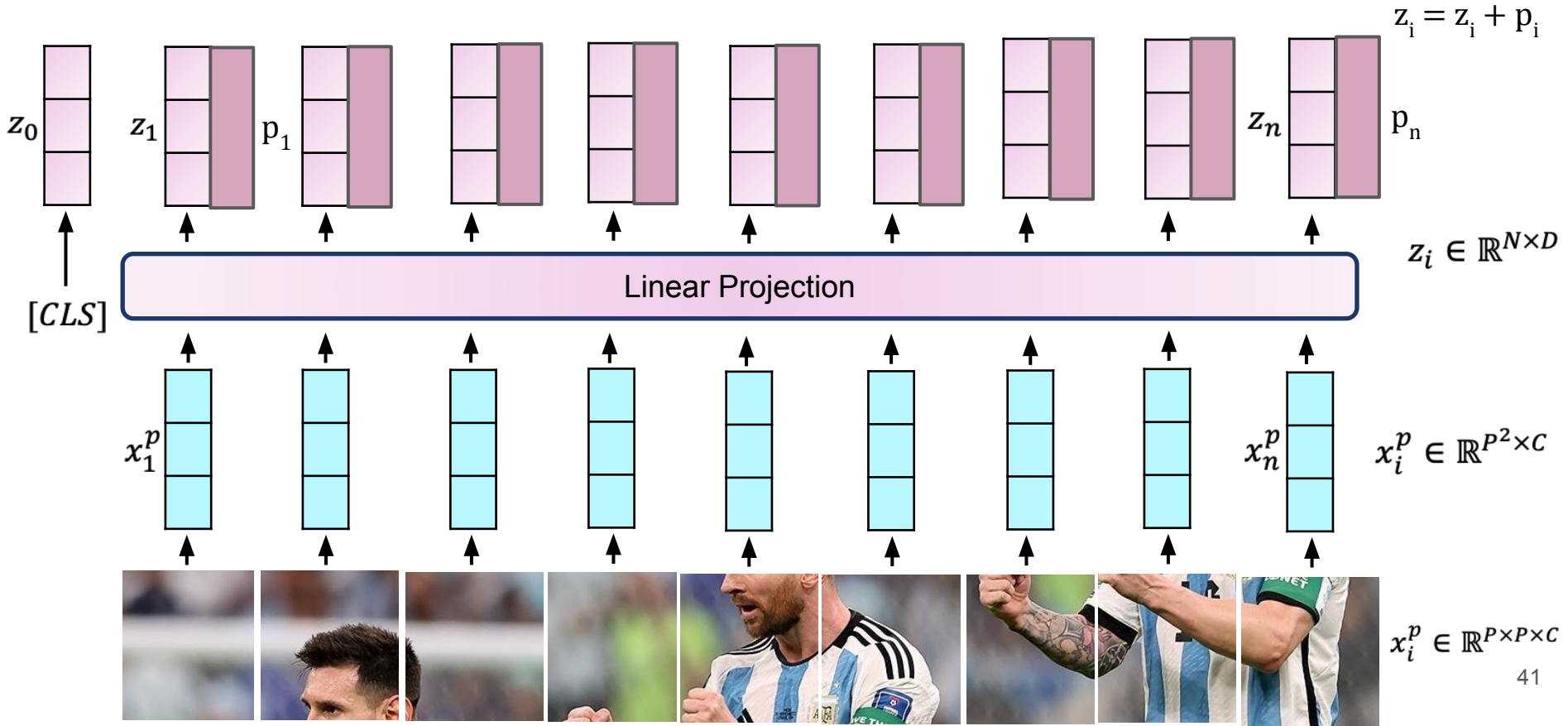
Linear Projection



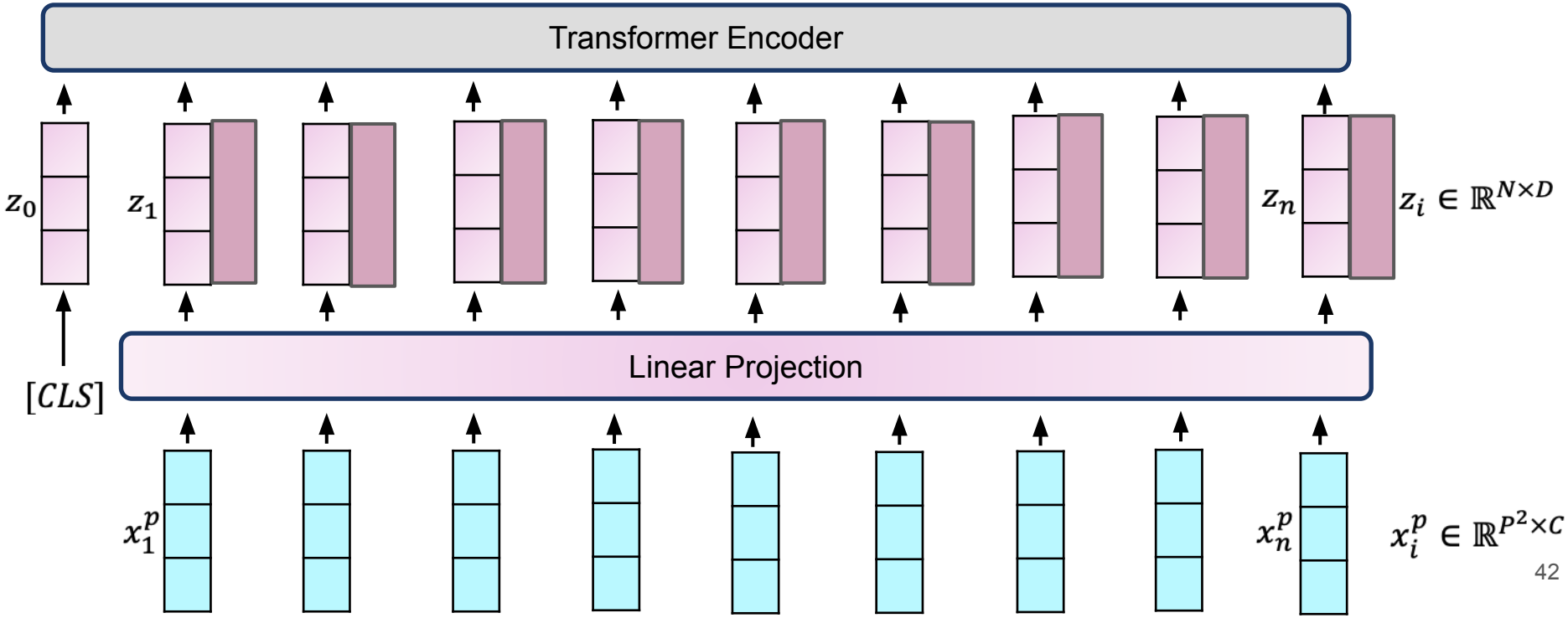
Global Representation (CLS token)



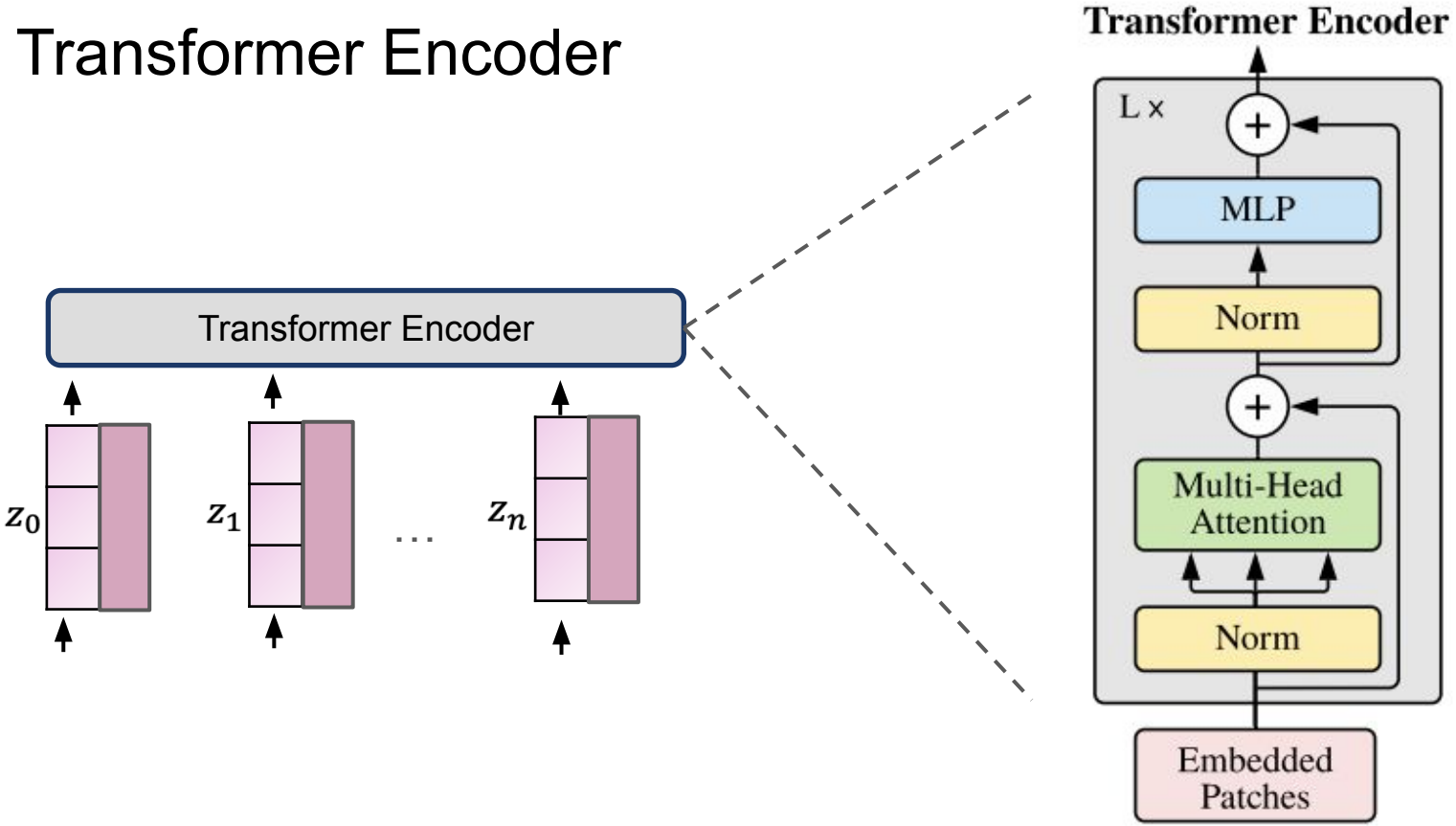
Positional Encoding



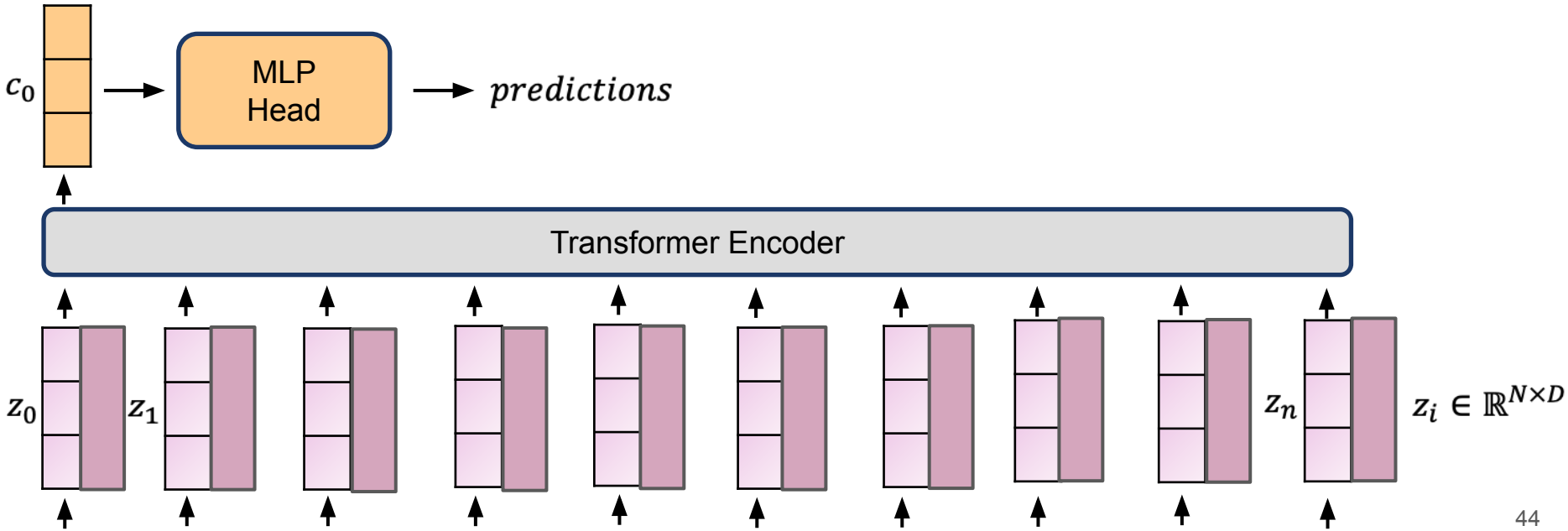
Transformer Encoder



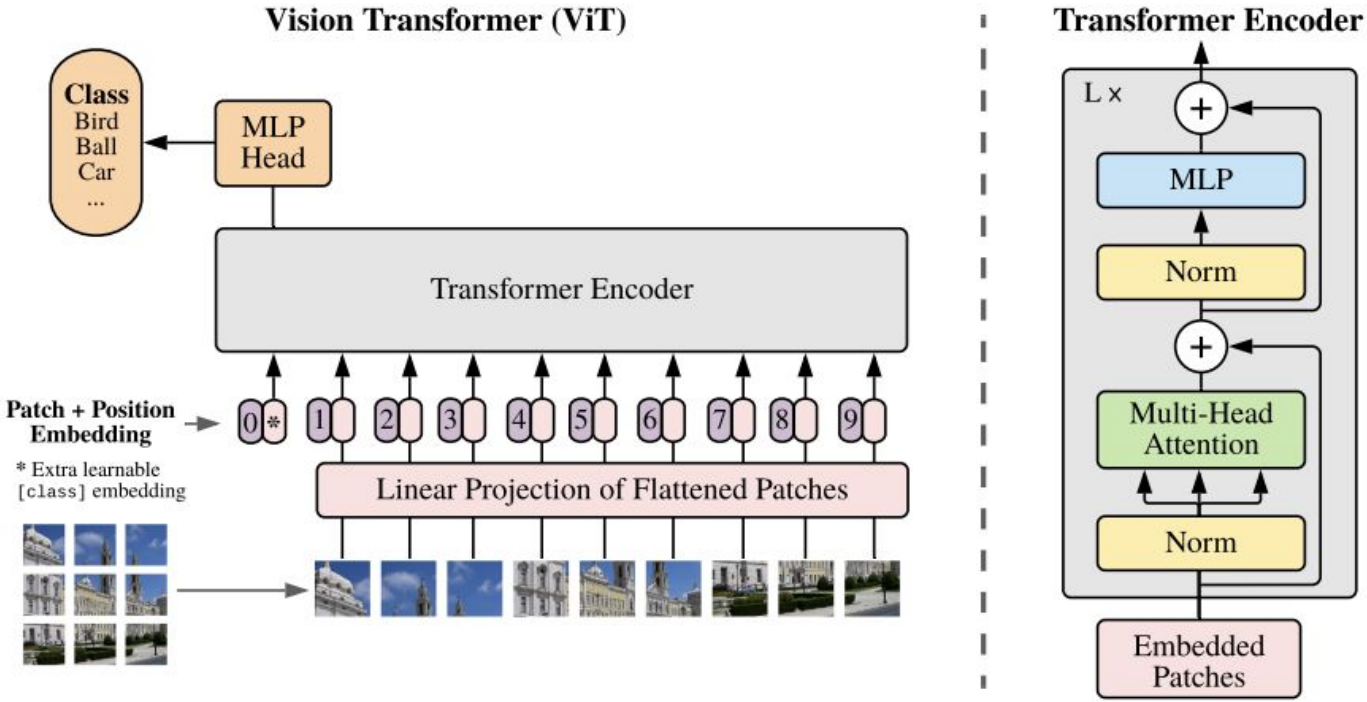
Transformer Encoder



Transformer Encoder and Classification



Vision Transformer (ViT)



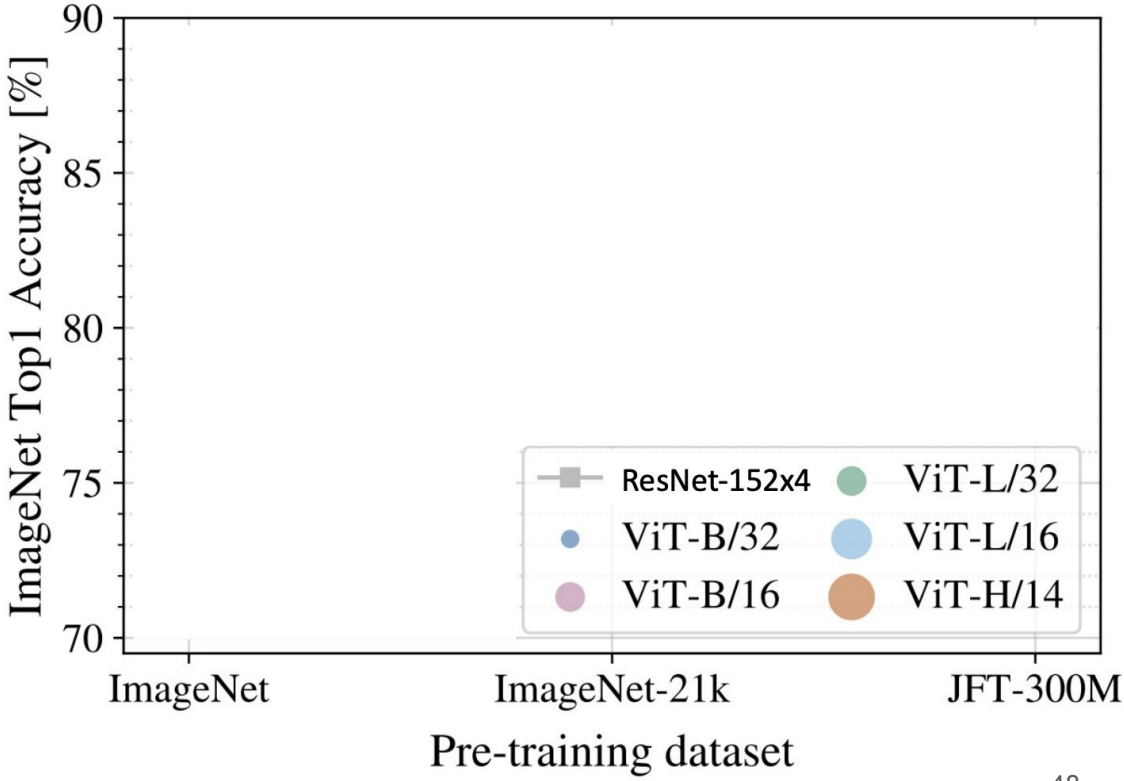
Dosovitskiy et al. “An Image is Worth16X16 Words: Transformers for Image Recognition at Scale” ICLR 2021

Vision Transformers Need More Data Than CNNs

- **CNNs**
  - Local receptive fields focus on nearby pixels
  - Built-in spatial hierarchy
  - Image structure encoded in architecture
- **Transformers**
  - Global attention from the start
  - No built-in locality or spatial assumptions
  - Must learn image structure from data

Vision Transformers Need More Data Than CNNs

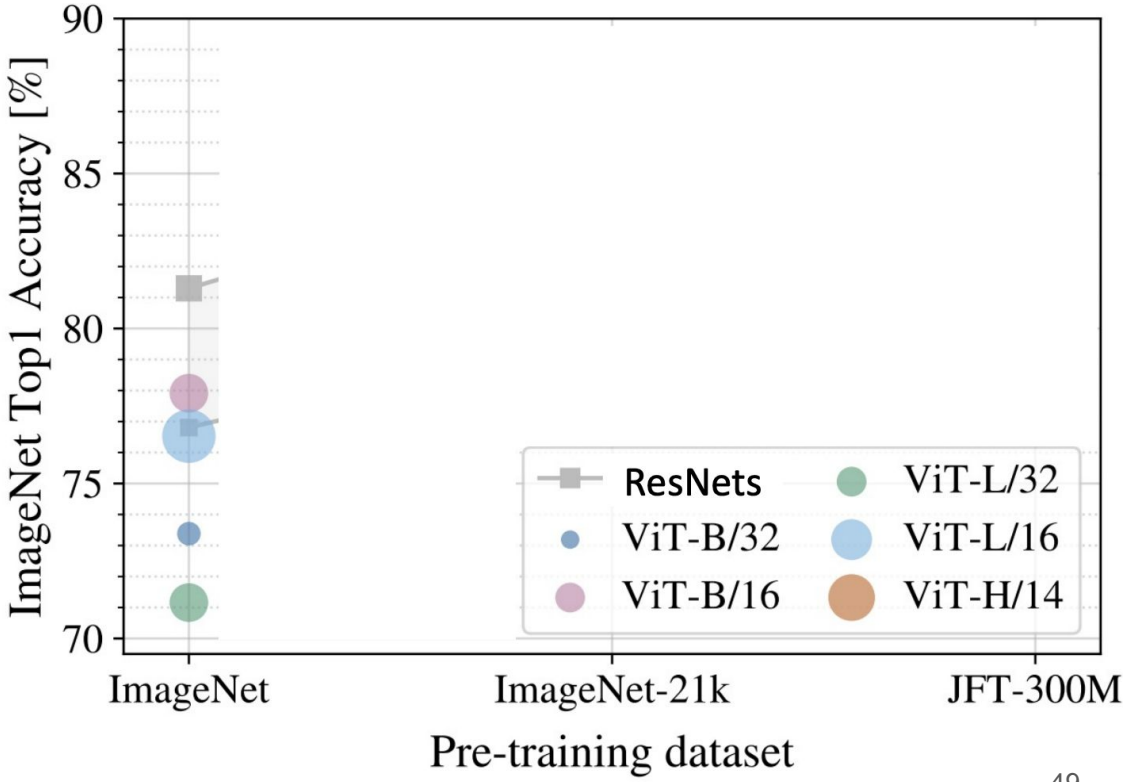
Let's compare ResNet (CNN) vs ViT accuracies for various datasets of different scales!



Vision Transformers Need More Data Than CNNs

ImageNet:

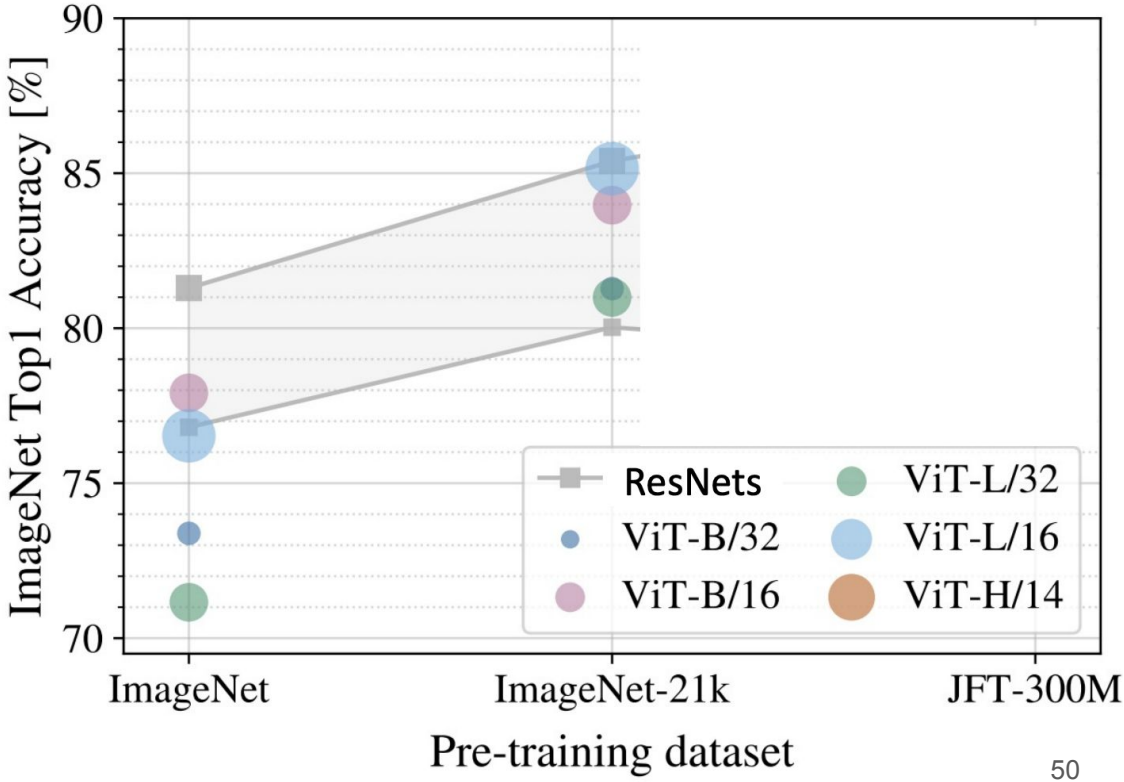
- 1k Classes
- 1.2M images



Vision Transformers Need More Data Than CNNs

ImageNet:
- 1k Classes
- 1.2M images

ImageNet-21k
- 21k classes
- 14M images

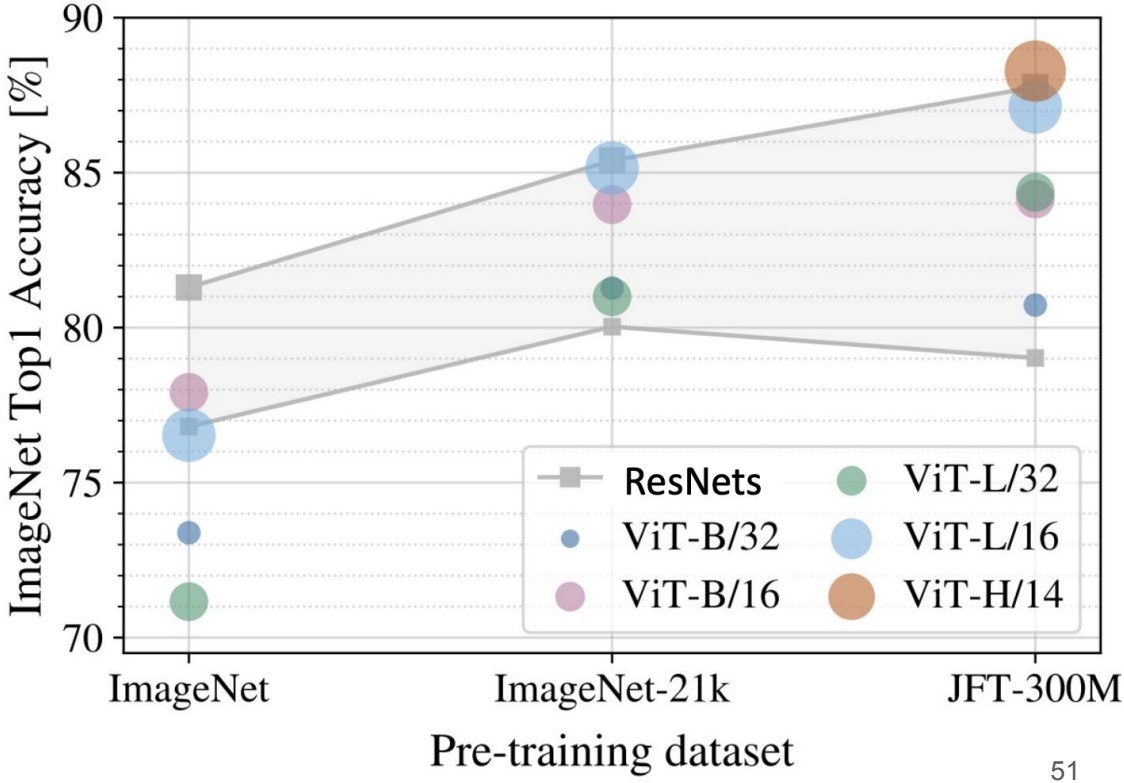


Vision Transformers Need More Data Than CNNs

ImageNet:
- 1k Classes
- 1.2M images

ImageNet-21k
- 21k classes
- 14M images

JFT-300M
- 300M images



Thank you
for your attention :)