NLP 102

Transformer

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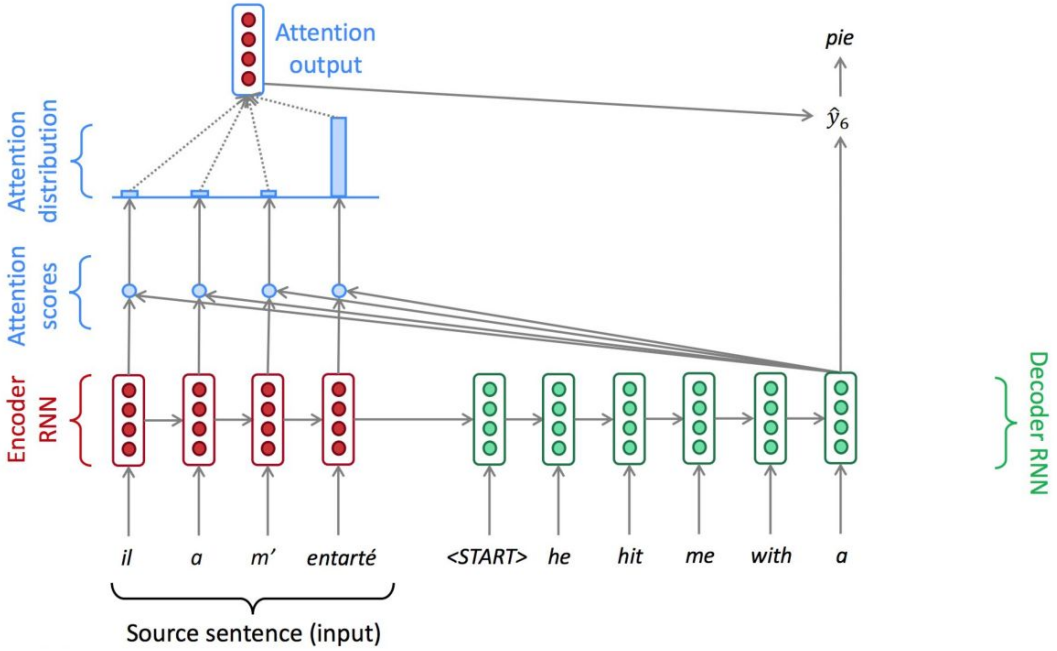
Overview

- Attention
- Global view on the transformer
- Self-Attention
- Positional Encoding
- Layer Normalization
- Questions

recap: Attention in seq2seq

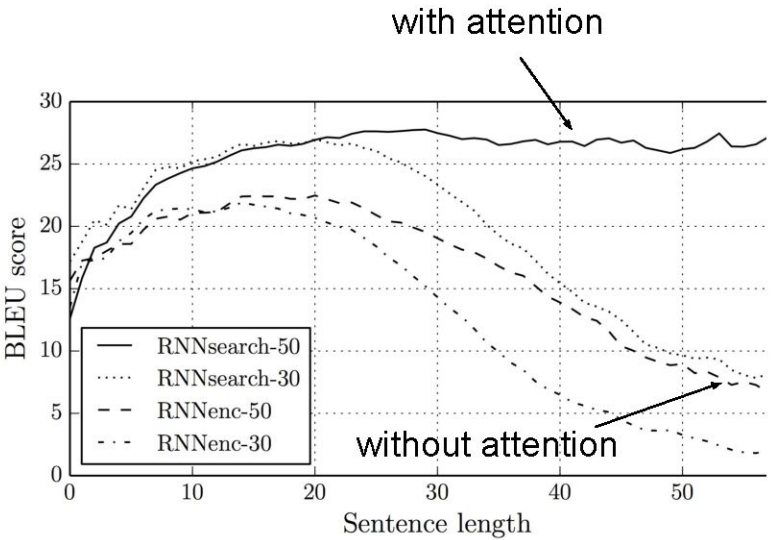


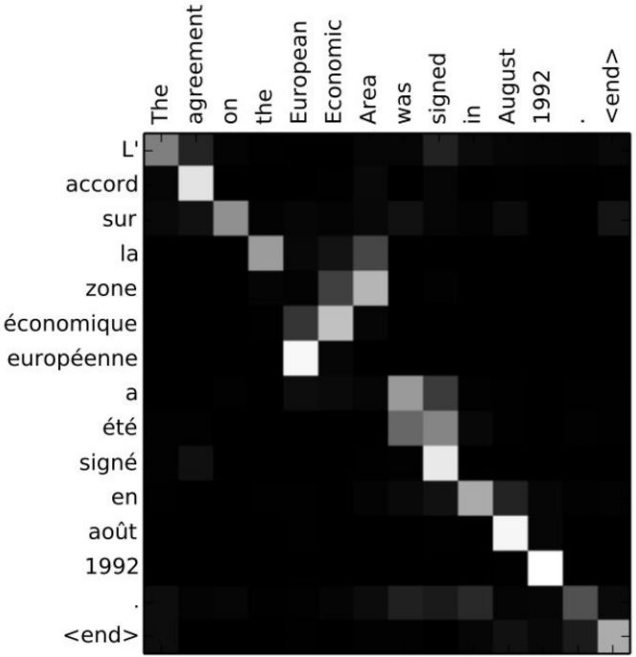
Attention variants

- Basic dot-product (the one discussed before): $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{h}_i \in \mathbb{R}$
- Multiplicative attention: $\boldsymbol{e}_i = \boldsymbol{s}^T \boldsymbol{W} \boldsymbol{h}_i \in \mathbb{R}$
  - $\boldsymbol{W} \in \mathbb{R}^{d_2 \times d_1}$ - weight matrix
- Additive attention: $\boldsymbol{e}_i = \boldsymbol{v}^T \tanh(\boldsymbol{W}_1 \boldsymbol{h}_i + \boldsymbol{W}_2 \boldsymbol{s}) \in \mathbb{R}$
  - $\boldsymbol{W}_1 \in \mathbb{R}^{d_3 \times d_1}, \boldsymbol{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ - weight matrices
  - $\boldsymbol{v} \in \mathbb{R}^{d_3}$ - weight vector

Attention advantages

- “Free” word alignment
- Better results on long sequences





The Transformer

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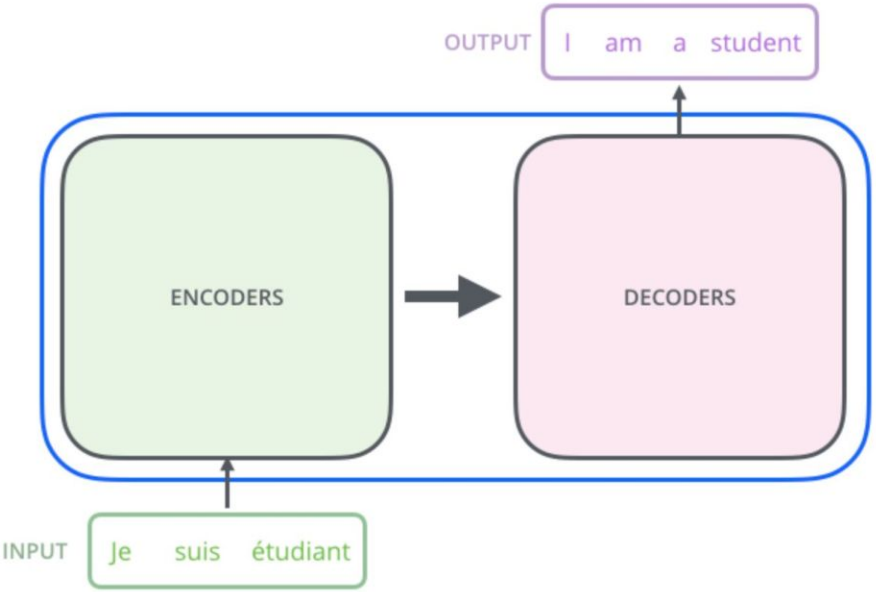
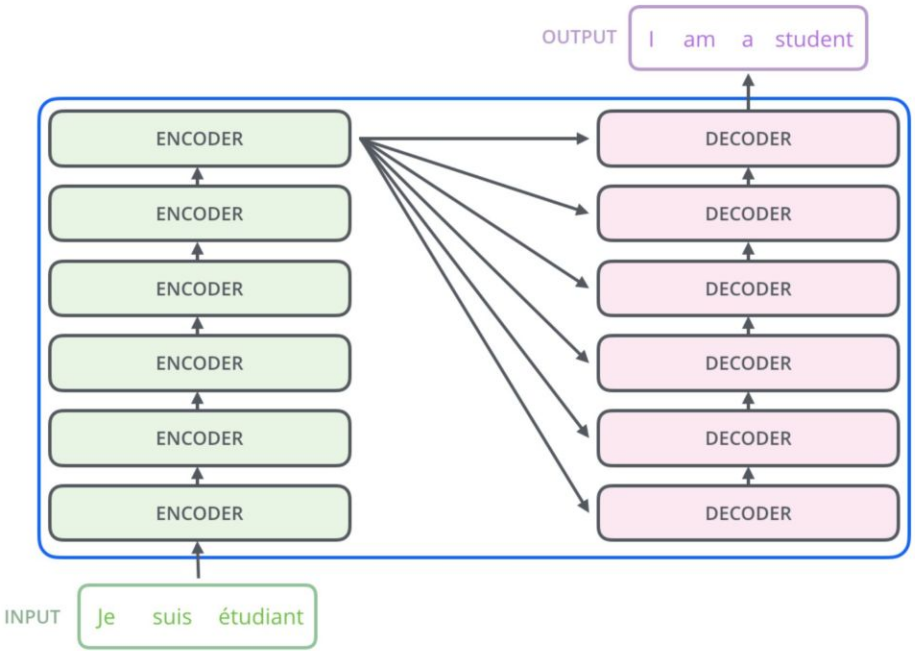
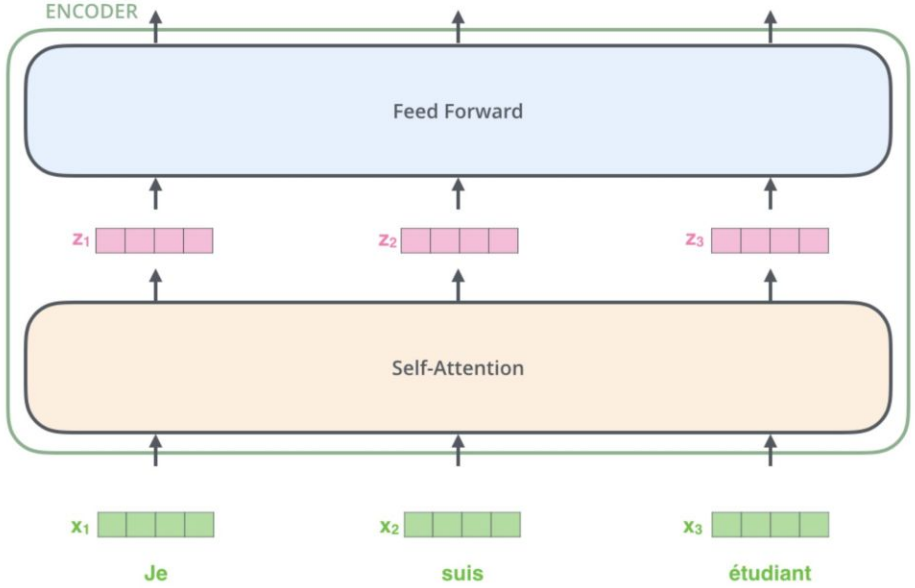


The Transformer



The Encoder Side



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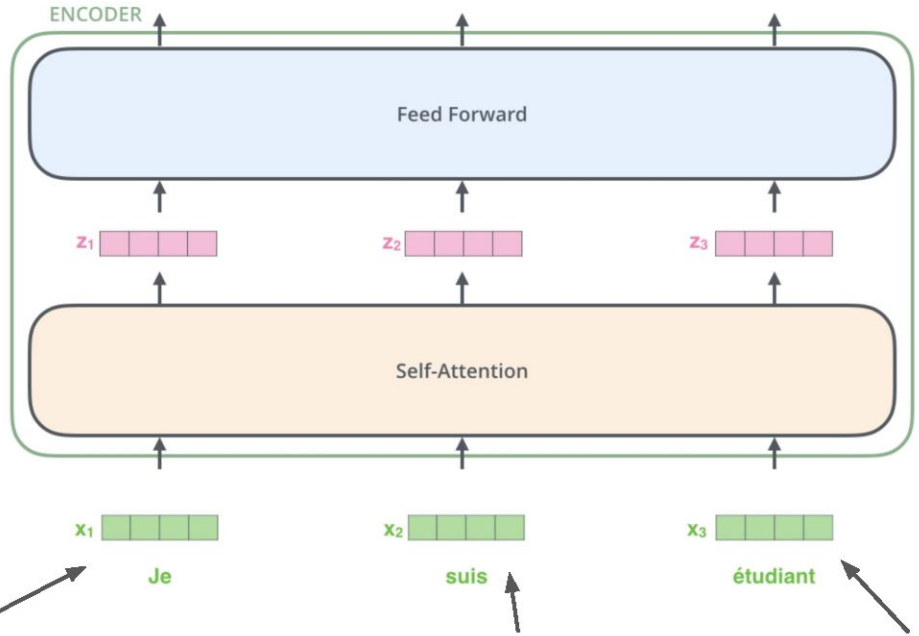
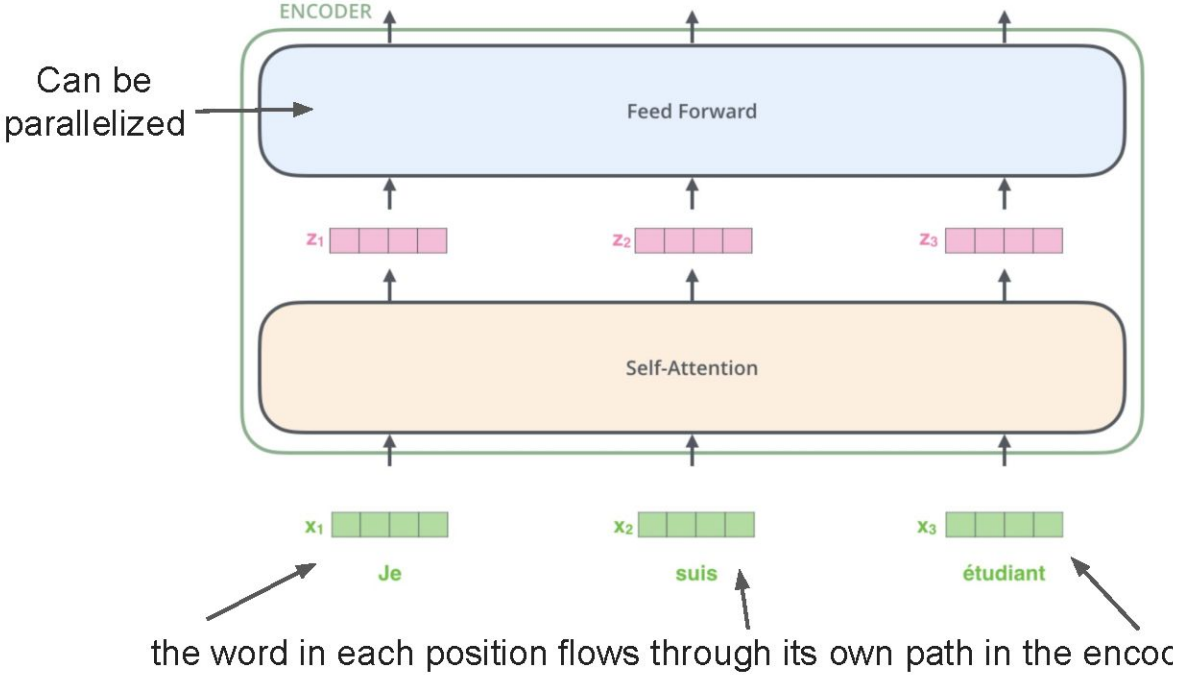


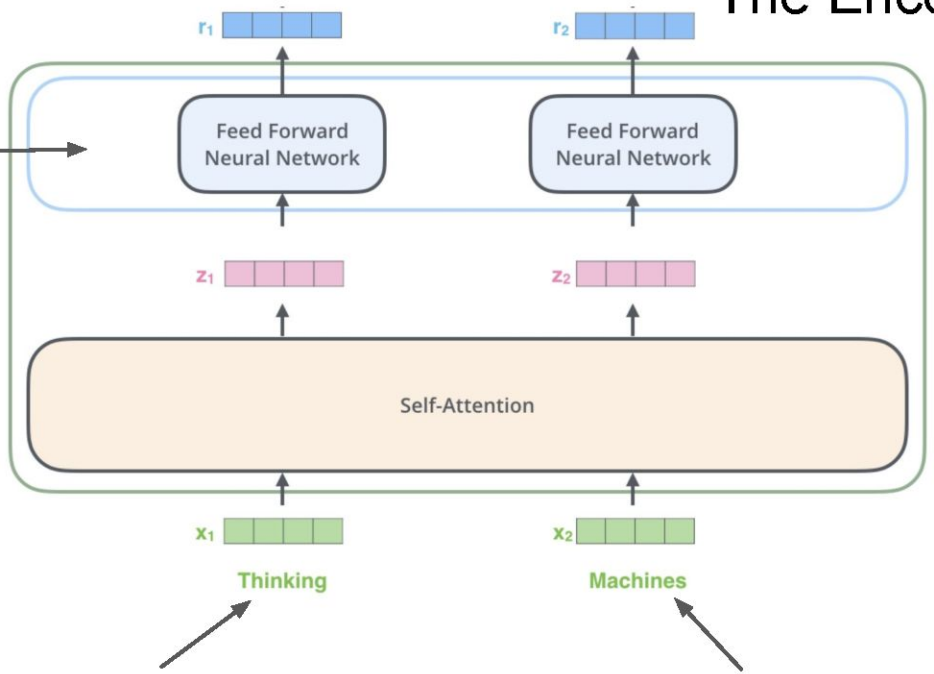
the word in each position flows through its own path in the encoc

The Encoder Side



The Encoder Side

Can be parallelized



the word in each position flows through its own path in the encoc

The Transformer: quick overview

- Proposed in the paper “Attention is All You Need” (Ashish Vaswani et al.)
- No recurrent or convolutional neural networks -> just attention
- Beats seq2seq in machine translation task
  - 28.4 BLEU on the WMT 2014 English-to-German translation task
- Much faster
- Uses **self-attention** concept

Self-Attention

Self-Attention at a High Level

"`The animal didn't cross the street because it was too tired`"

- What does “it” in this sentence refer to?

Self-Attention at a High Level

"`The animal didn't cross the street because it was too tired`"

- What does “it” in this sentence refer to?
- We want self-attention to associate “it” with “animal”

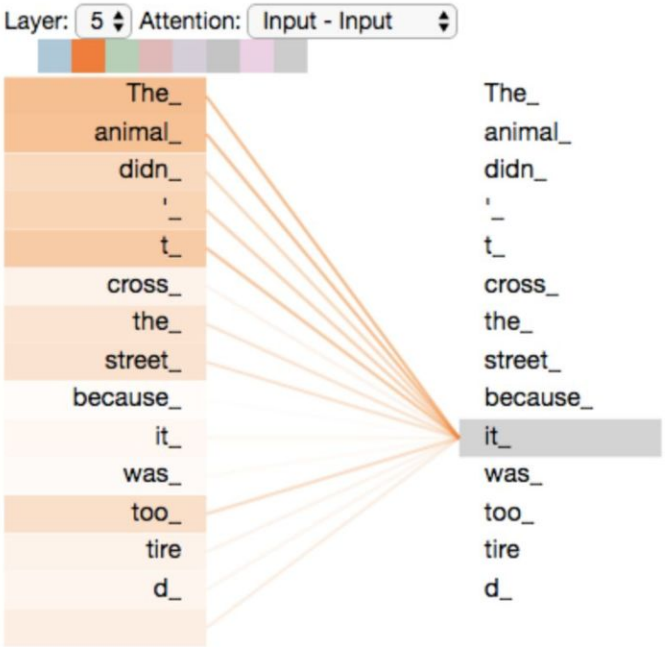
Self-Attention at a High Level

"`The animal didn't cross the street because it was too tired`"

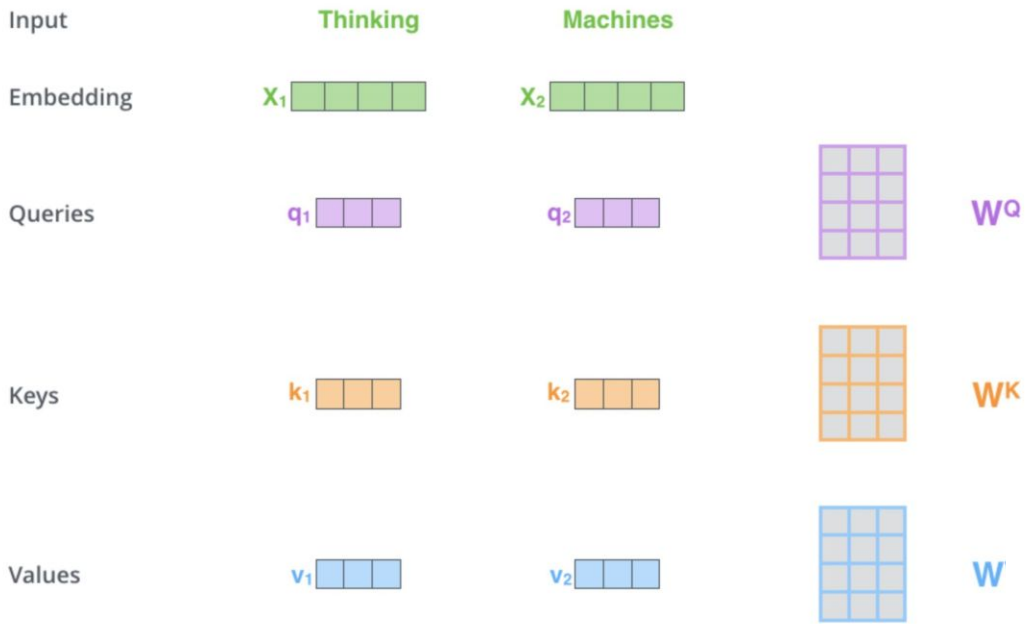
- What does “it” in this sentence refer to?
- We want self-attention to associate “it” with “animal”

- Self-attention is the method the Transformer uses to bake the “understanding” of other relevant words into the one we’re currently processing

Self-Attention at a High Level



Self-Attention: detailed explanation

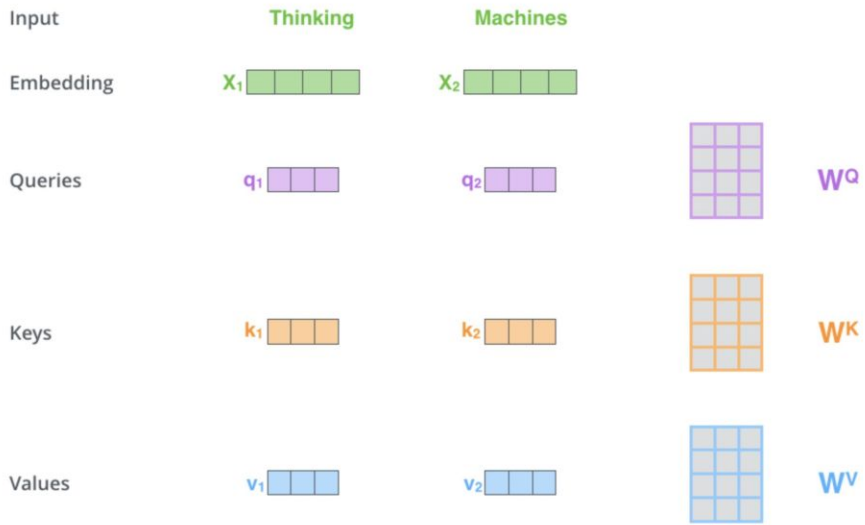


Self-Attention: detailed explanation

STEP 1:

create 3 vectors (Query, Key, Value)

from each of the encoder's input vectors



Self-Attention: detailed explanation

What are the “query”, “key”, and “value” vectors?

Self-Attention: detailed explanation

What are the “query”, “key”, and “value” vectors?

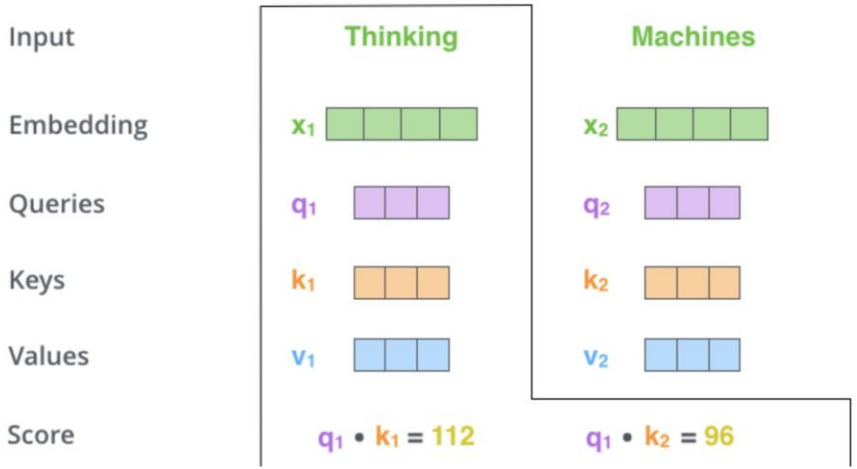
They’re abstractions that are useful for calculating and thinking about attention.

Self-Attention: detailed explanation

STEP 2:

calculate a score

(score each word of the input sentence against the current word)



Self-Attention: detailed explanation

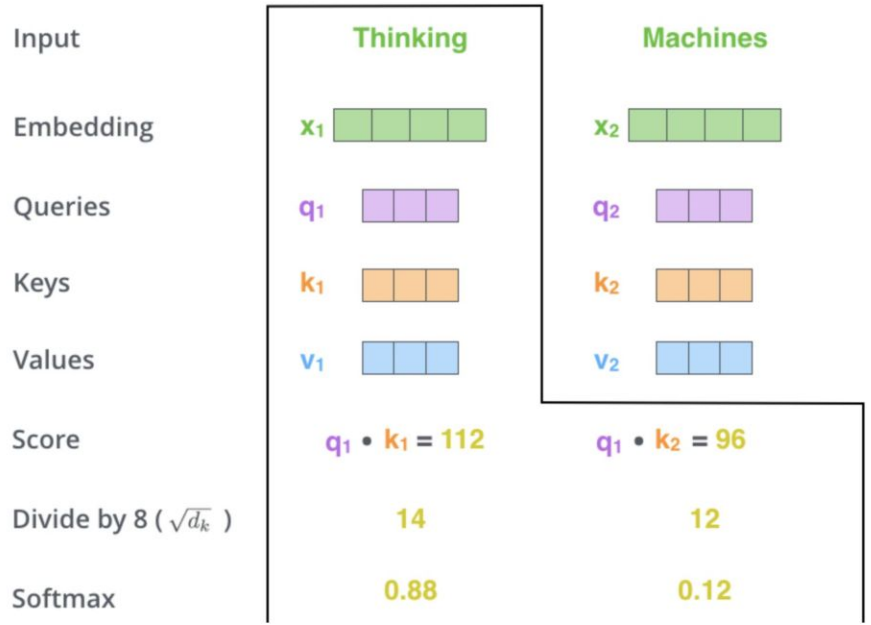
STEP 3:

divide the scores by 8

(the square root of the dimension of the key vectors)

STEP 4:

softmax



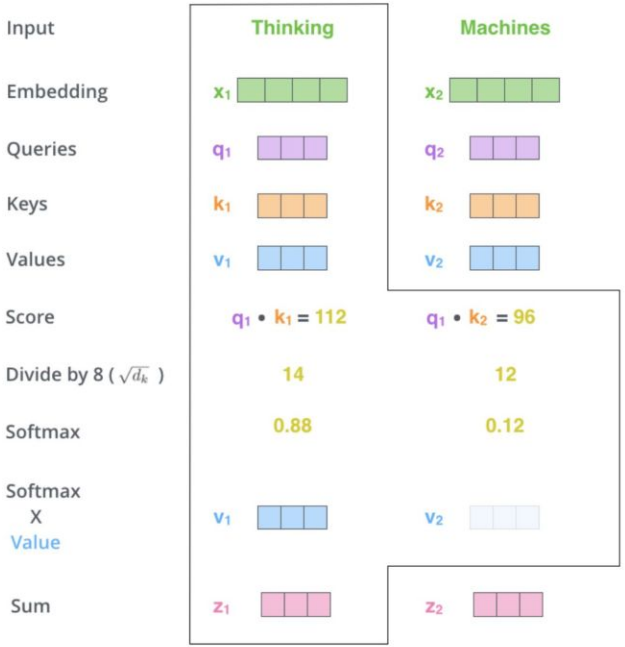
Self-Attention: detailed explanation

STEP 5:

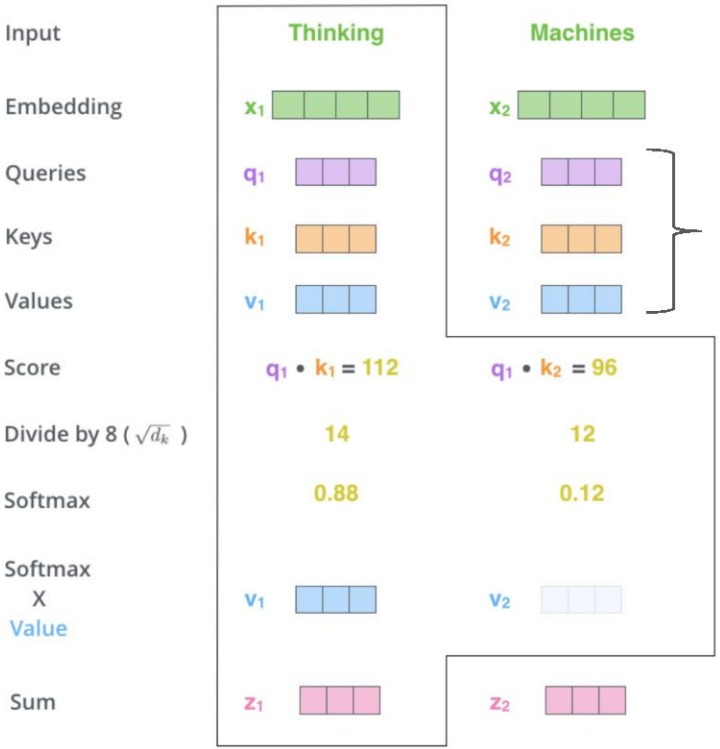
multiply each value vector by the softmax score

STEP 6:

sum up the weighted value vectors



Self-Attention



STEP 1: create Query, Key, Value

STEP 2: calculate scores

STEP 3: divide by $\sqrt{d_k}$

STEP 4: softmax

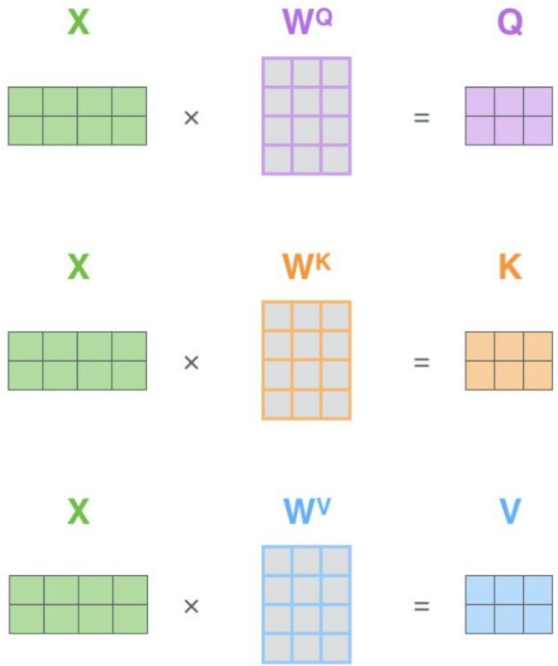
STEP 5: multiply each value vector by the softmax score

STEP 6: sum up the weighted value vectors

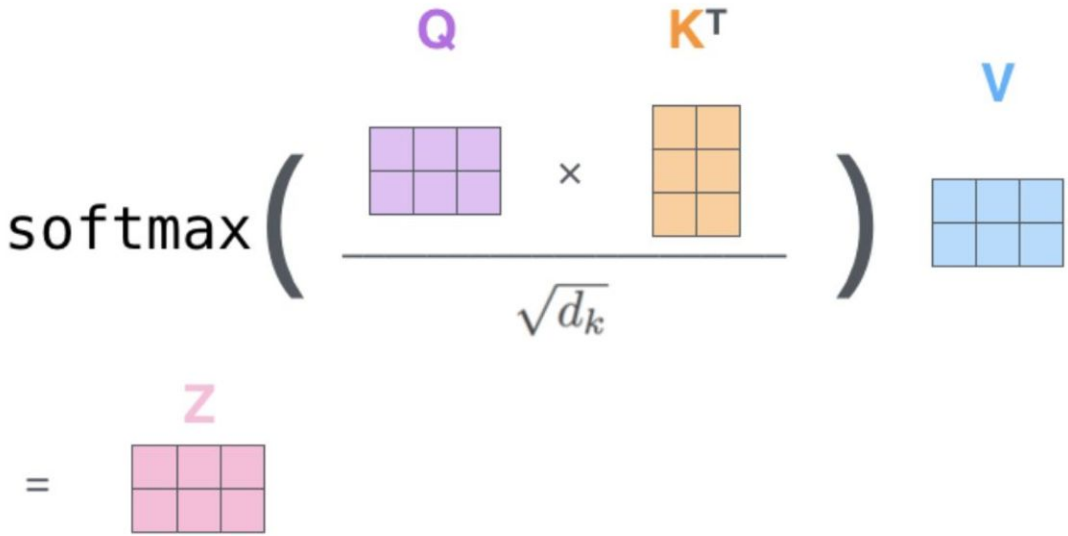
Self-Attention: Matrix Calculation

Pack embeddings into matrix **X**

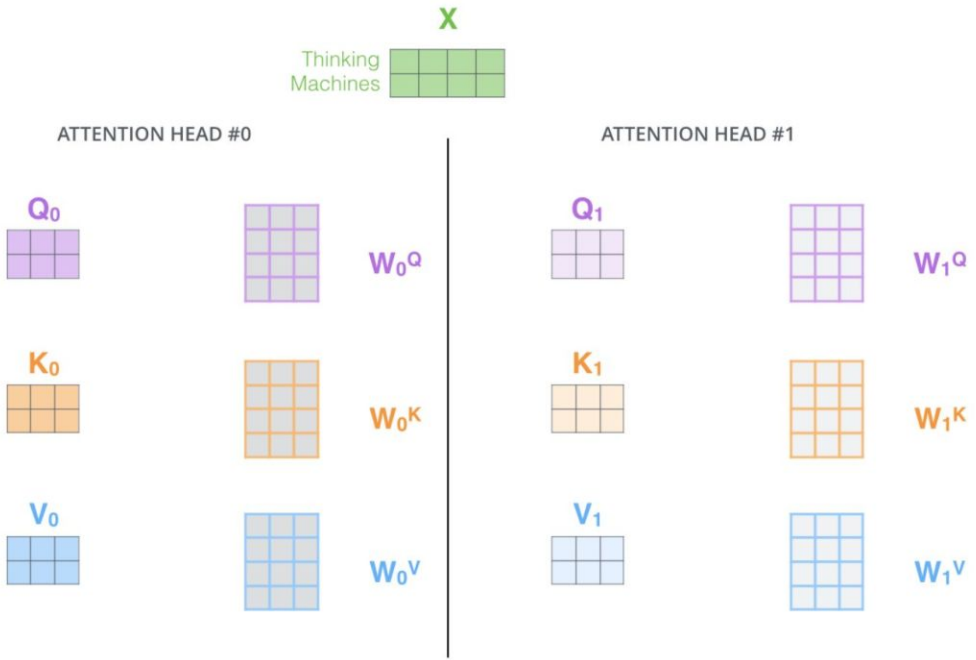
Multiply **X** by weight matrices we've trained (**Wk, Wq, Wv**)



Self-Attention: Matrix Calculation



Multi-Head Attention



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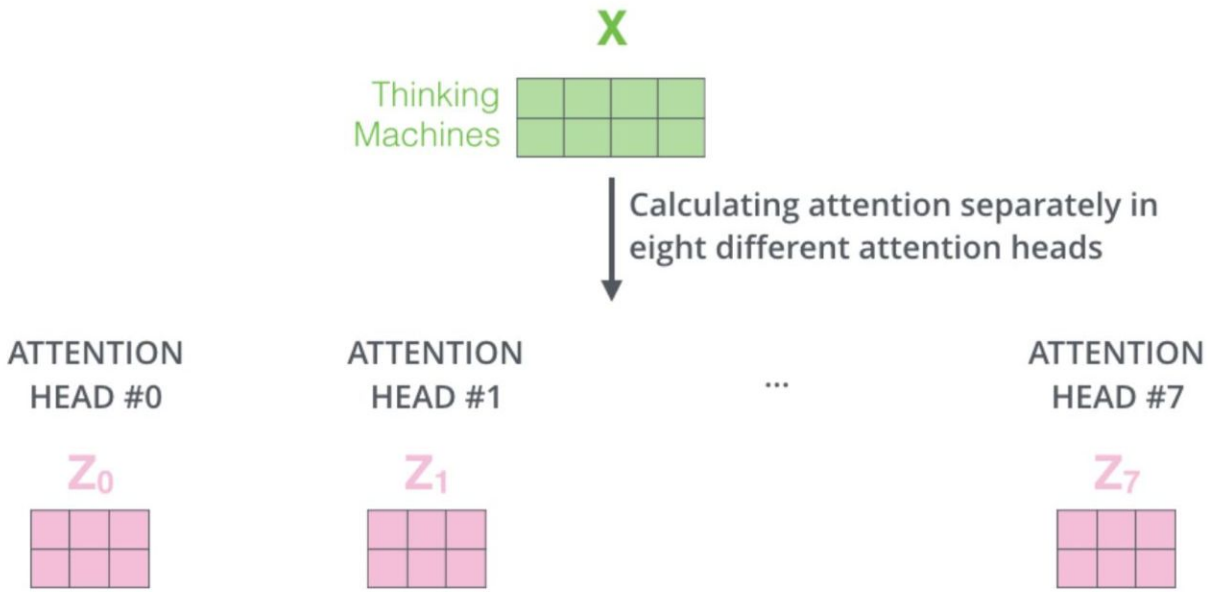


Multi-Head Attention

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

=

1) This is our input sentence*

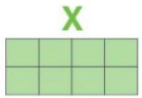
2) We embed each word*

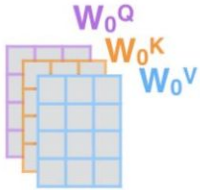
3) Split into 8 heads. We multiply X or R with weight matrices

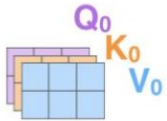
4) Calculate attention using the resulting Q/K/V matrices

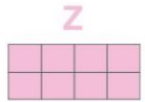
5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer

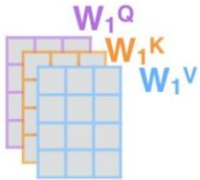
Thinking Machines

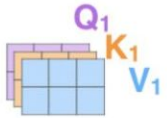




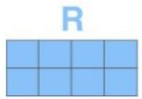


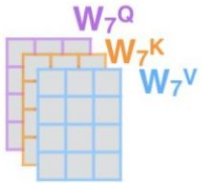




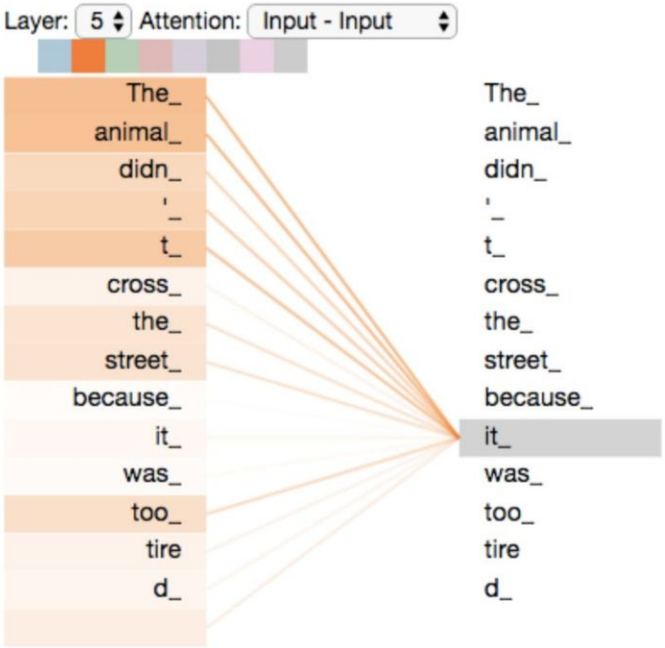


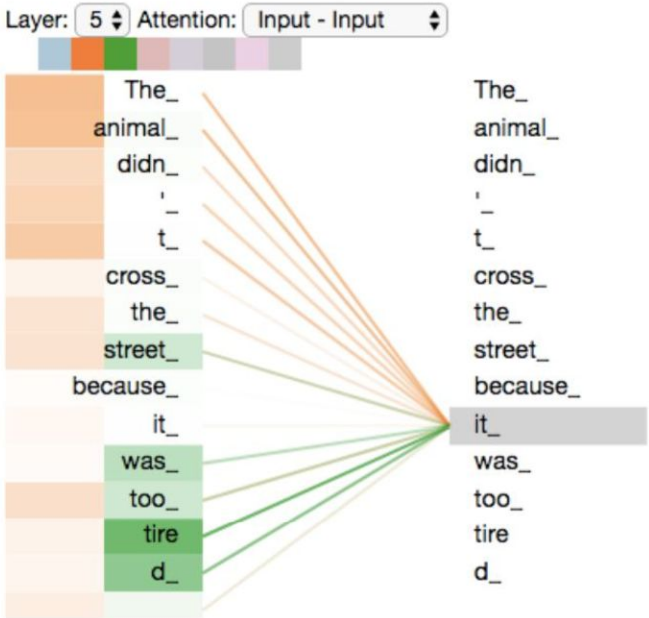
* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one



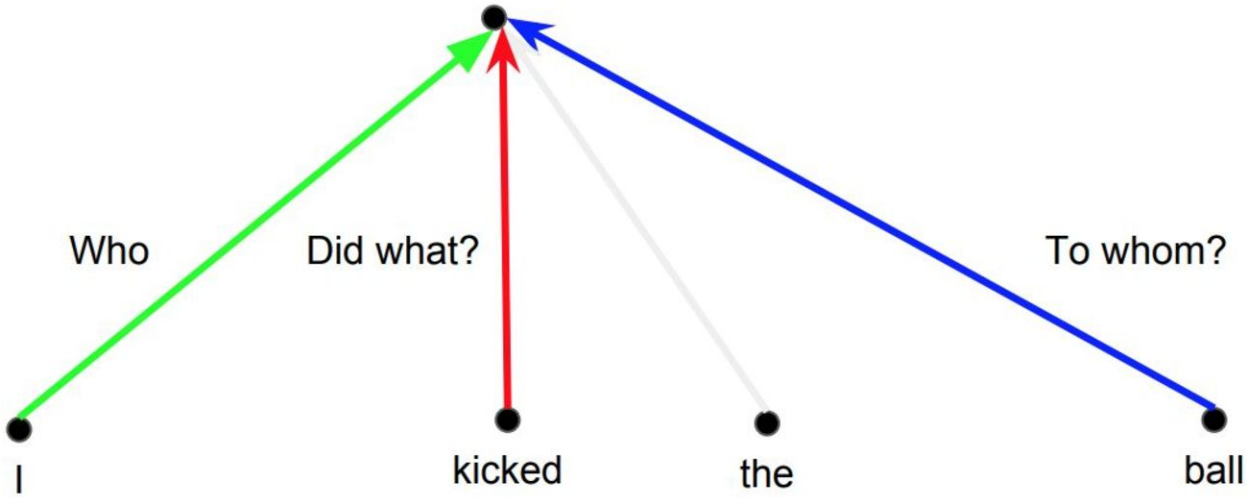


Multi-Head Attention

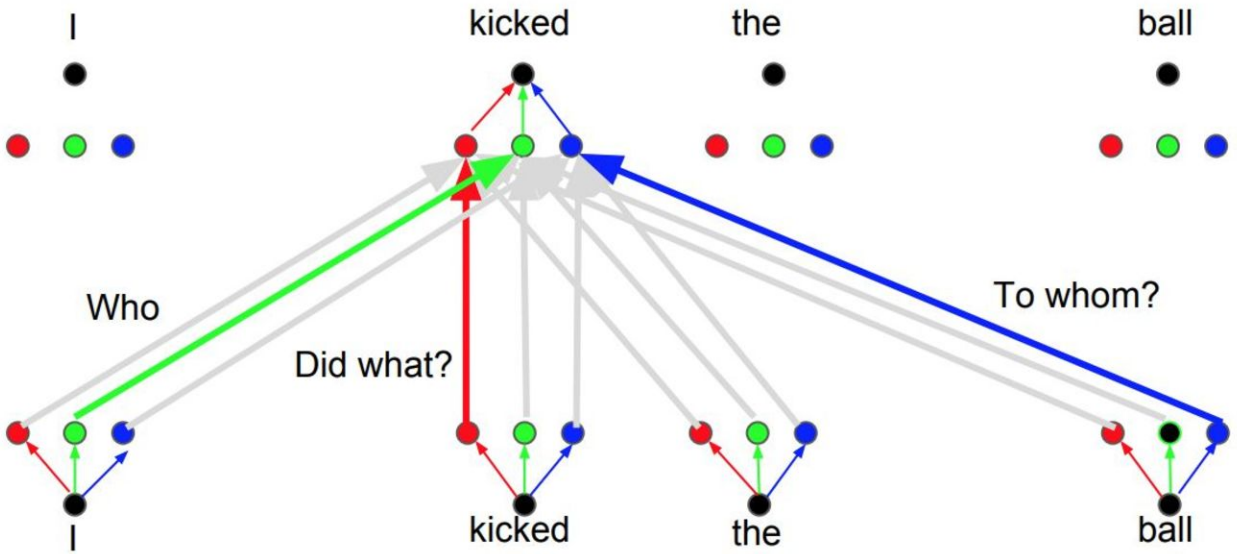




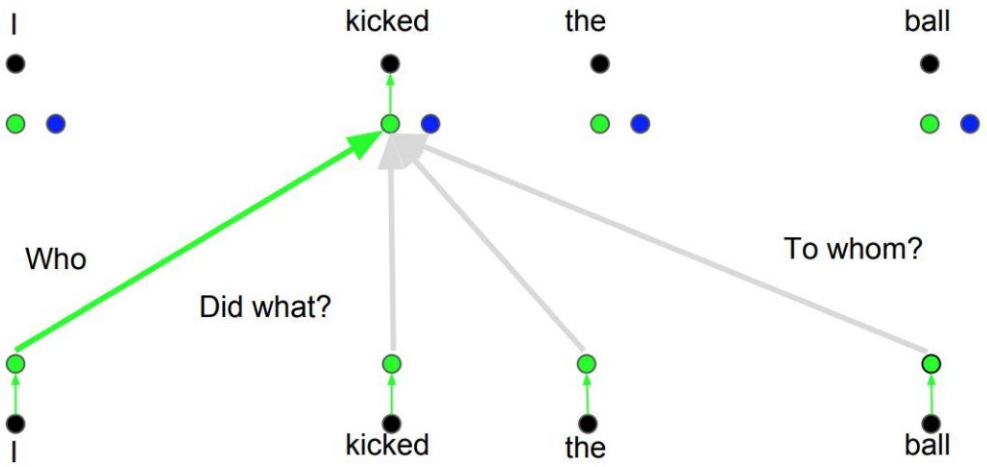
Why Multi-Head Attention?



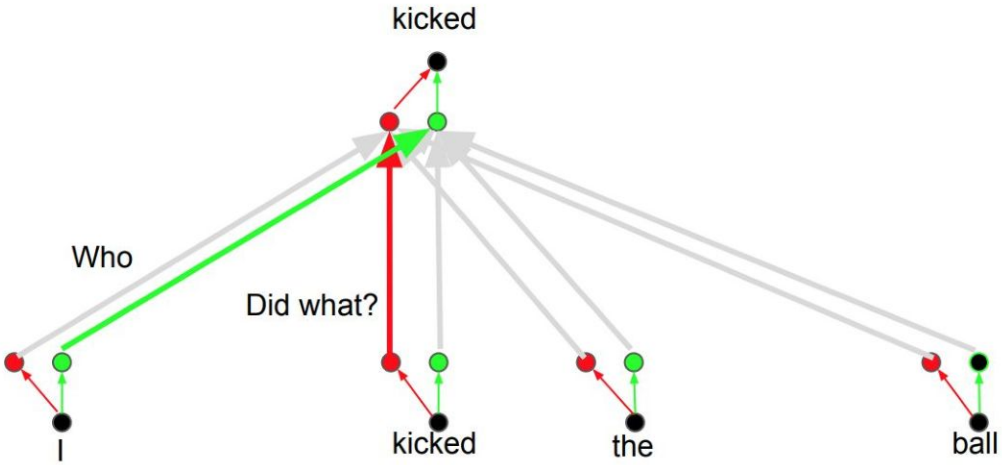
Why Multi-Head Attention?



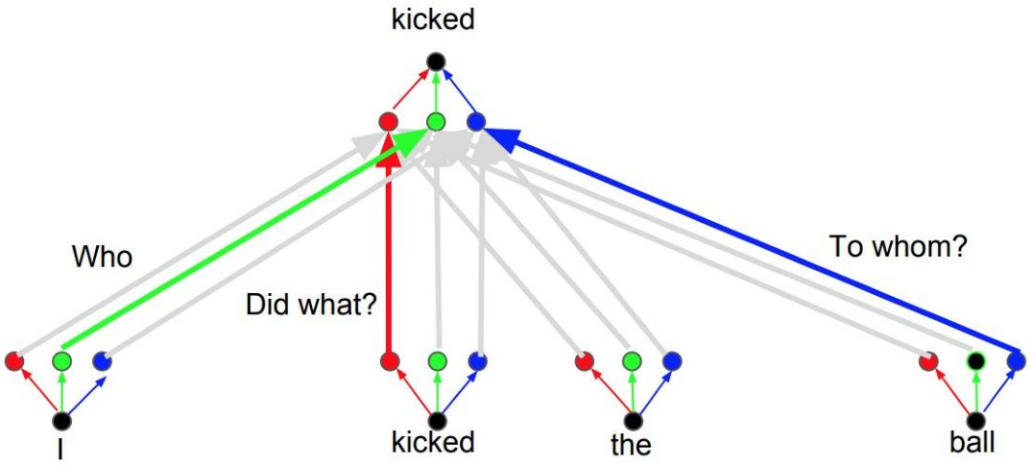
Attention head: Who



Attention head: Did What?

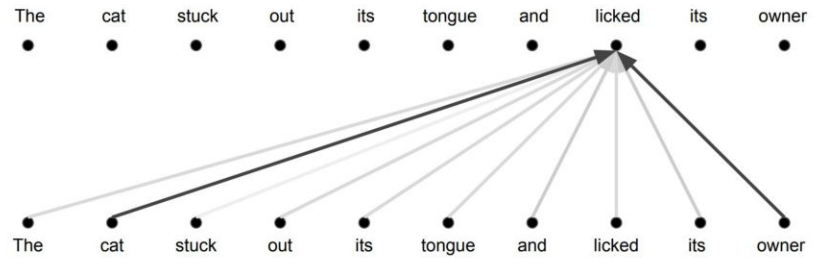


Attention head: To Whom?



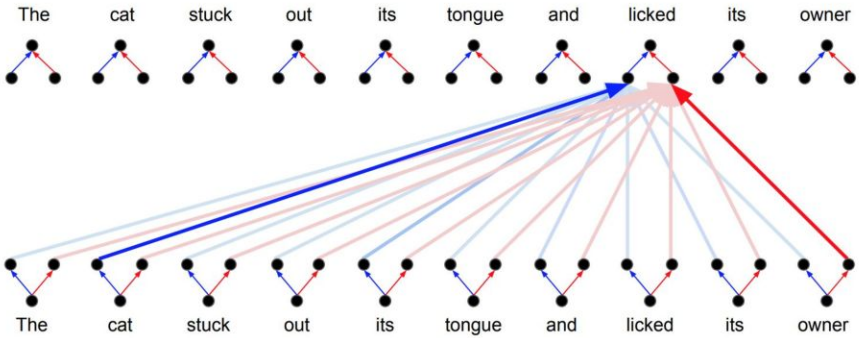
Attention vs. Multi-Head Attention

Attention: a weighted average



Multi-Head Attention:

parallel attention layers with different linear transformations on input and output.



Performance: WMT 2014 BLEU

	EN-DE	EN-FR
GNMT (orig)	24.6	39.9
ConvSeq2Seq	25.2	40.5
Transformer*	**28.4**	**41.8**

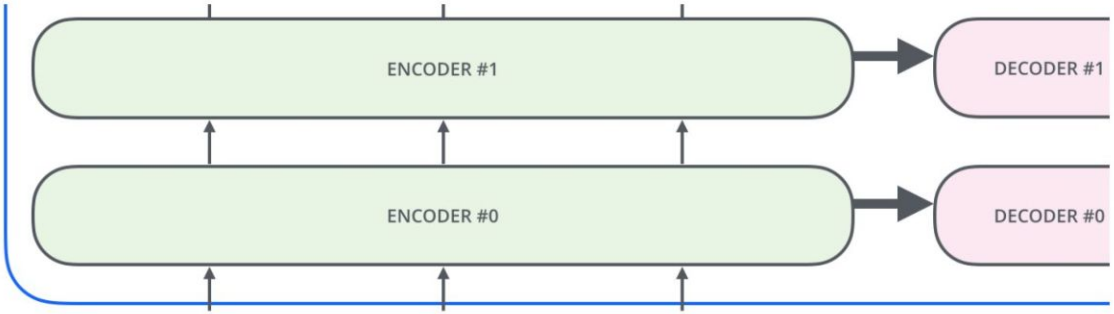
*Transformer models trained >3x faster than the others.

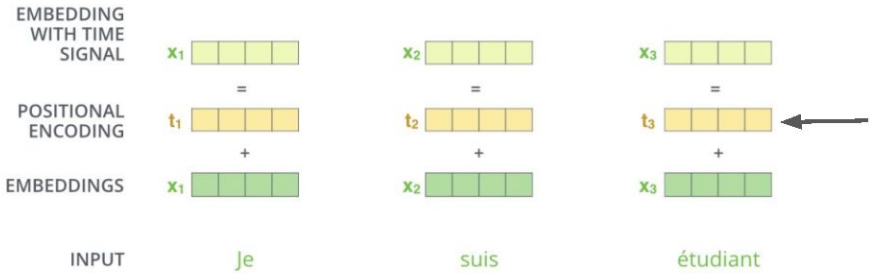
Research Challenges

- Constant ‘path length’ between any two positions.
- Unbounded memory.
- Trivial to parallelize (per layer).
- Models Self-Similarity.
- Relative attention provides expressive timing, equivariance, and extends naturally to graphs.

Positional Encoding

Positional Encoding





It provides meaningful distances between the embedding vectors once they're projected into Q/K/V vectors and during dot-product attention

Positional Encoding

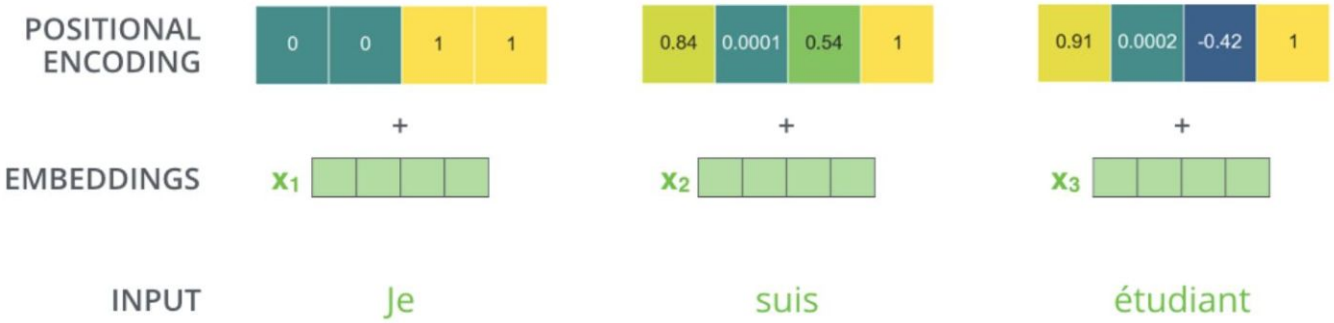
$$PE_{(pos,\ 2i)} = sin(pos / 10000^{2i\ /\ d_{\text{model}}})$$

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

- *pos* is the position
- *i* is the dimension.

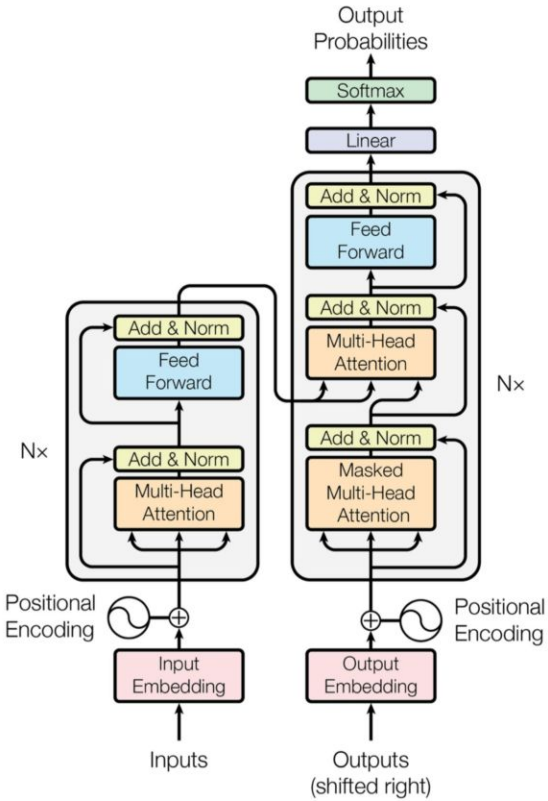
Each dimension of the positional encoding corresponds to a sinusoid.
The wavelengths form a geometric progression from 2pi to 2pi * 10 000

Positional Encoding

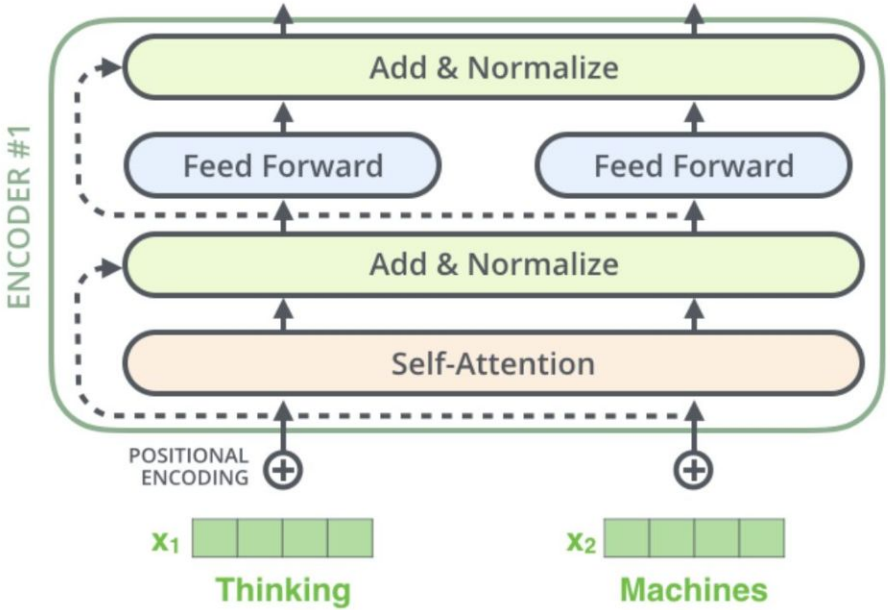


Layer Normalization

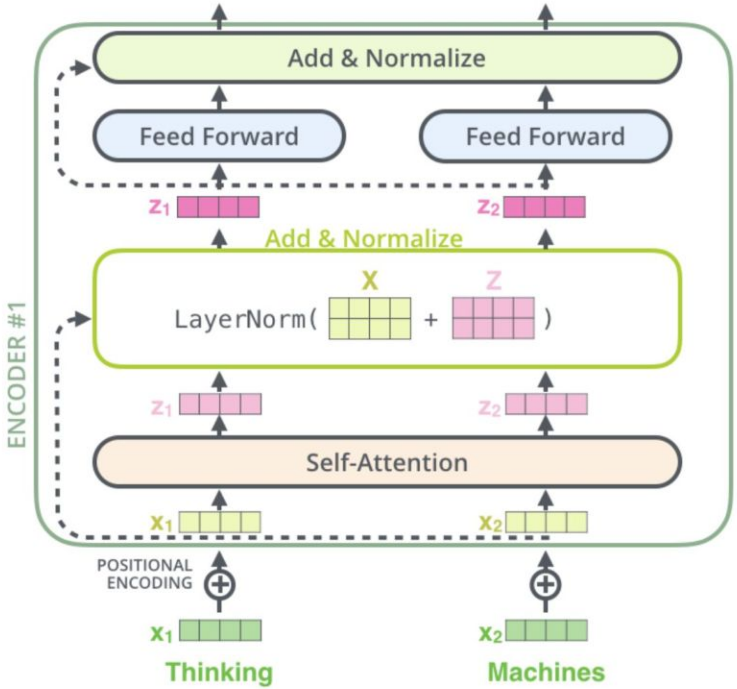
The Transformer: recap

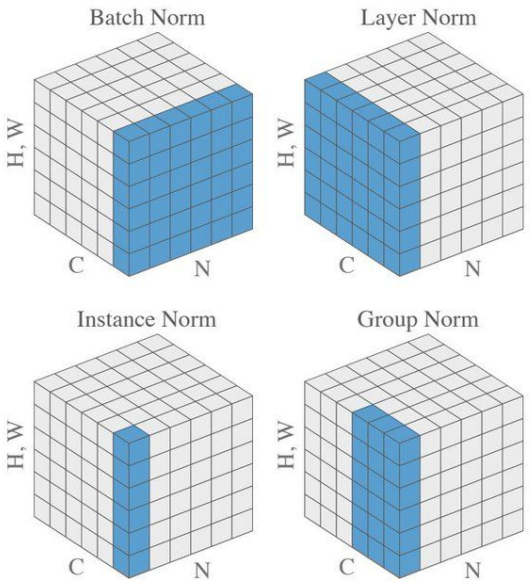


Layer Normalization

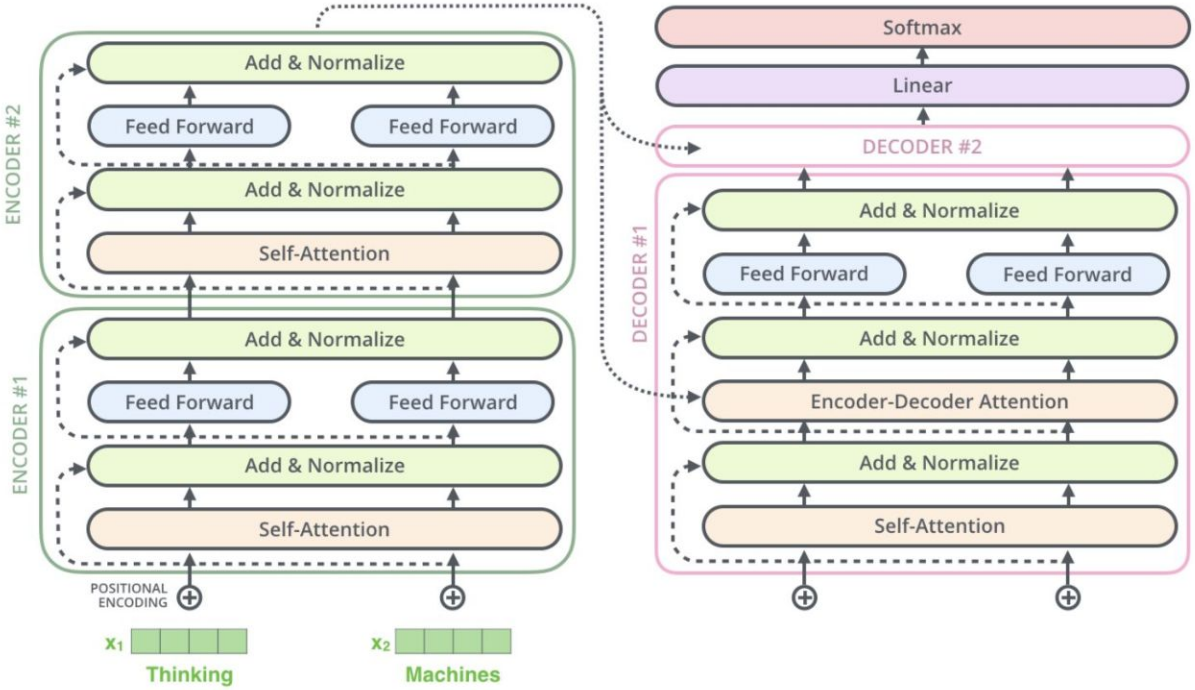


Layer Normalization



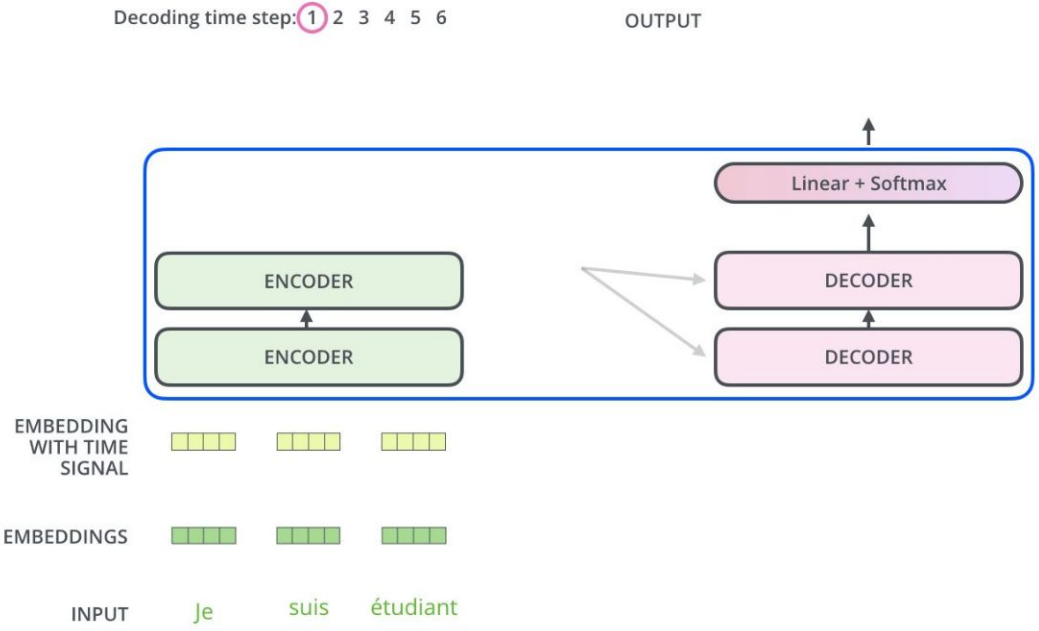


Layer Normalization

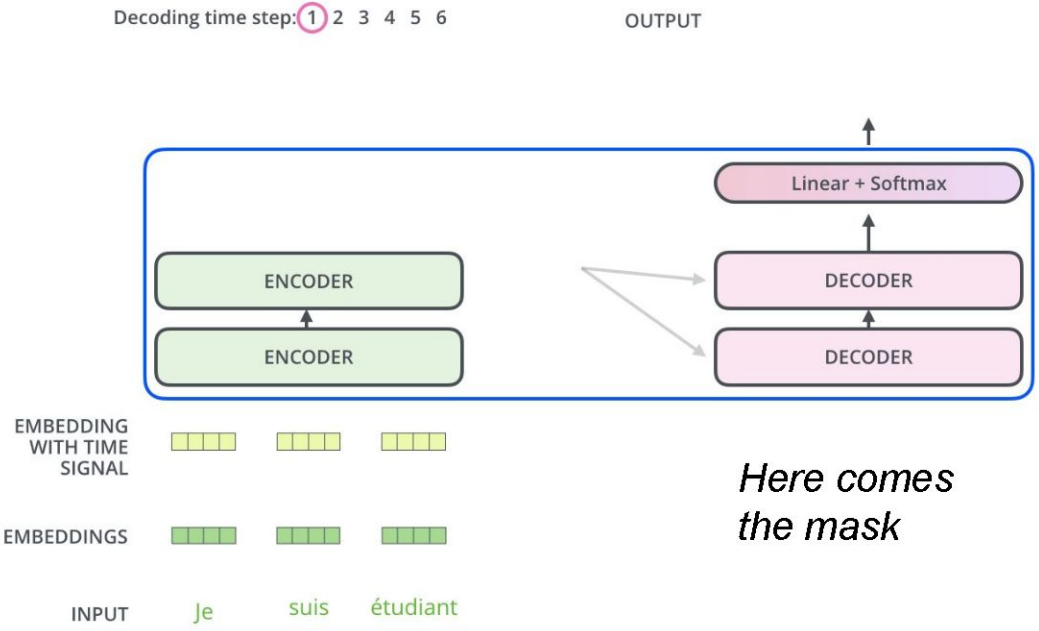


The Decoder

The Decoder Side

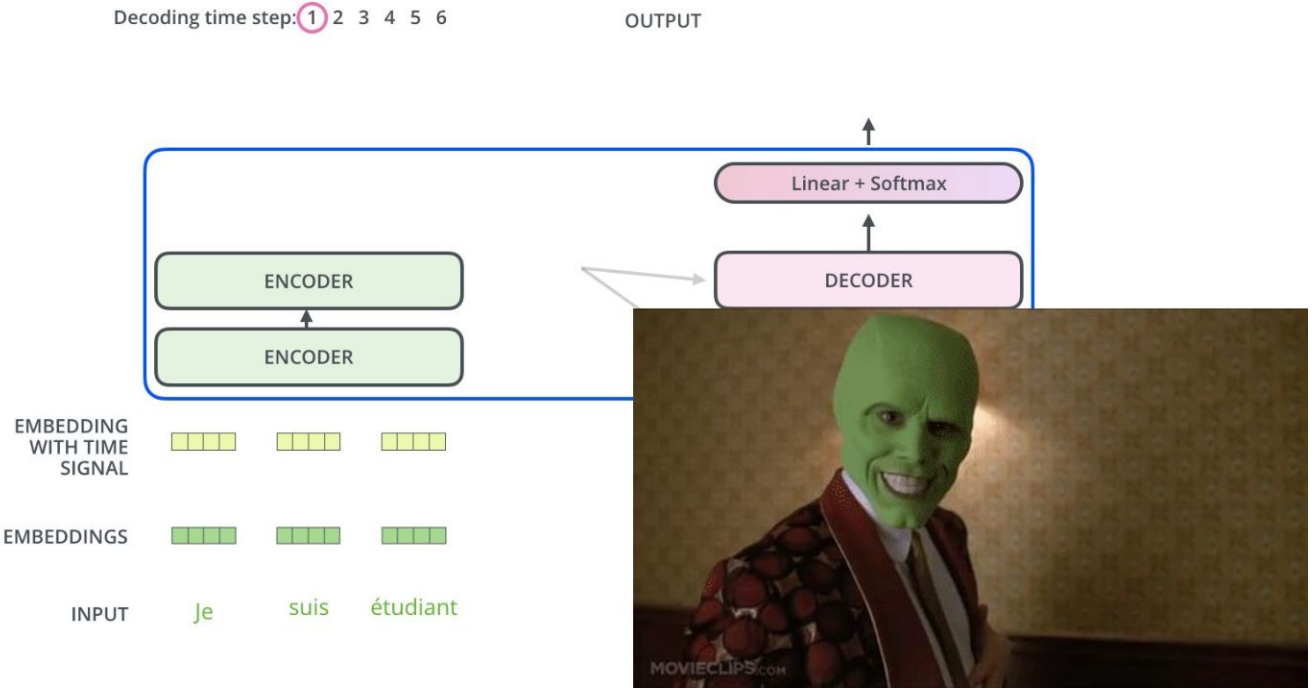


The Decoder Side

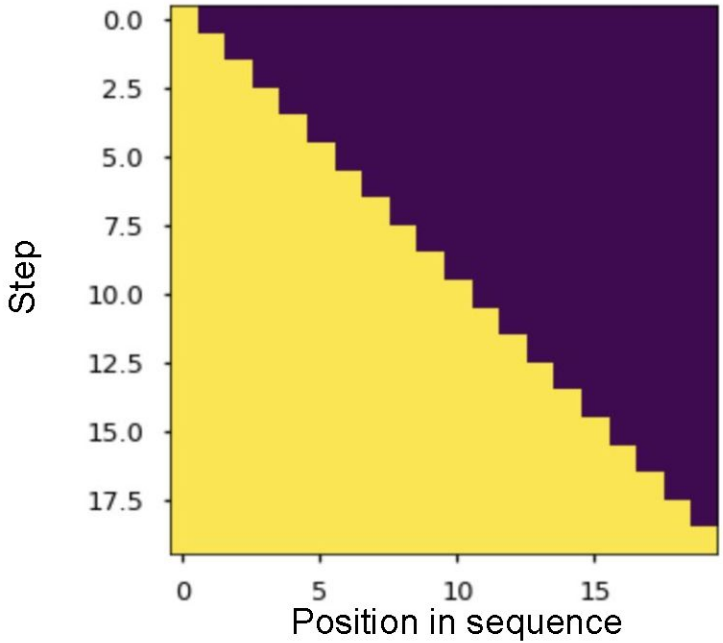


Here comes the mask

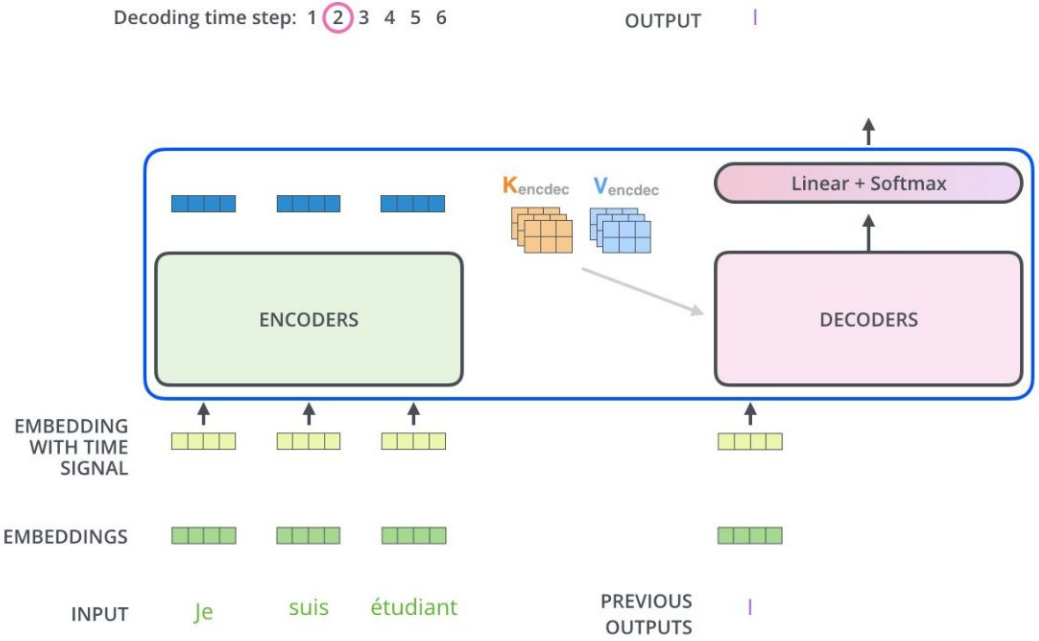
The Decoder Side



The masked decoder input



The Decoder Side



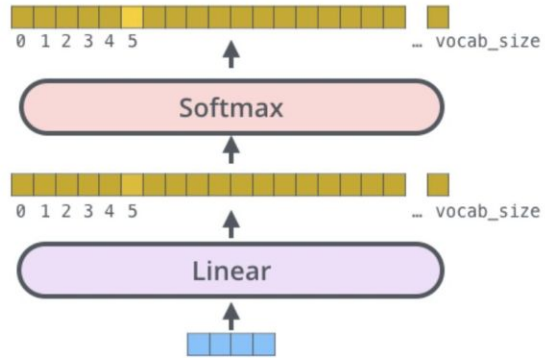
Final Linear and Softmax Layer

Which word in our vocabulary is associated with this index?

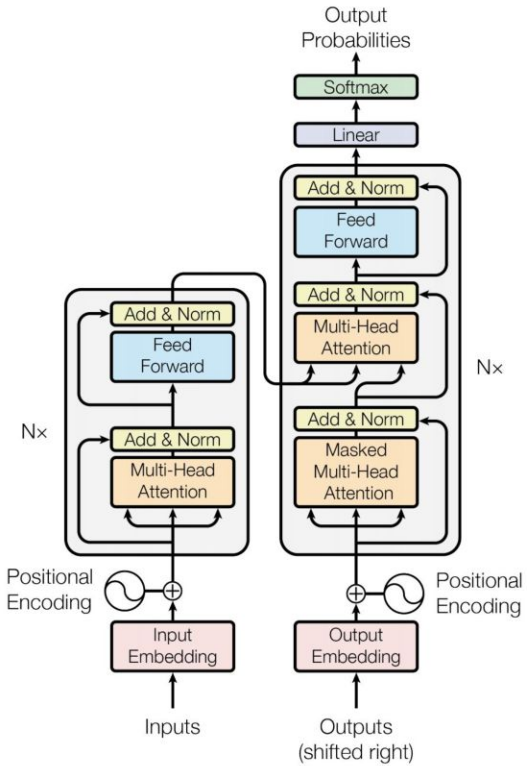
am

Get the index of the cell with the highest value **(argmax)**

5

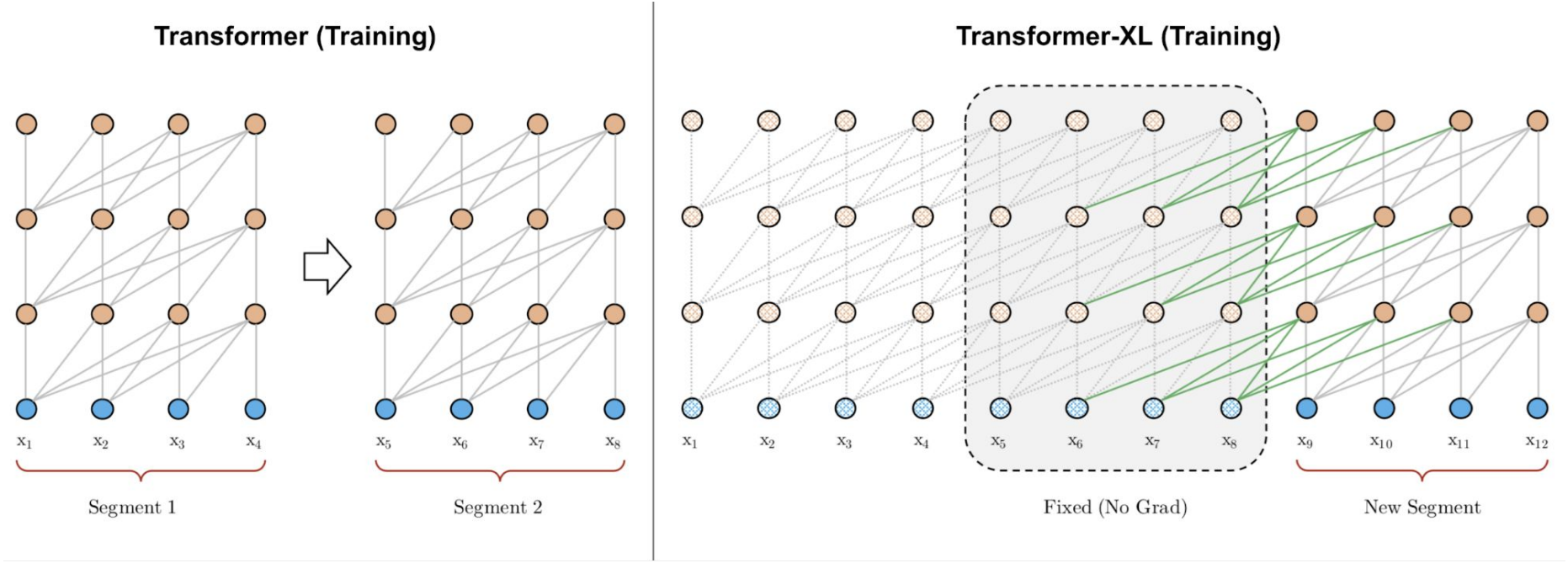


The Transformer



Improved Transformers

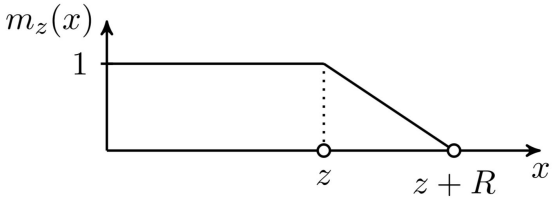
Transformer-XL



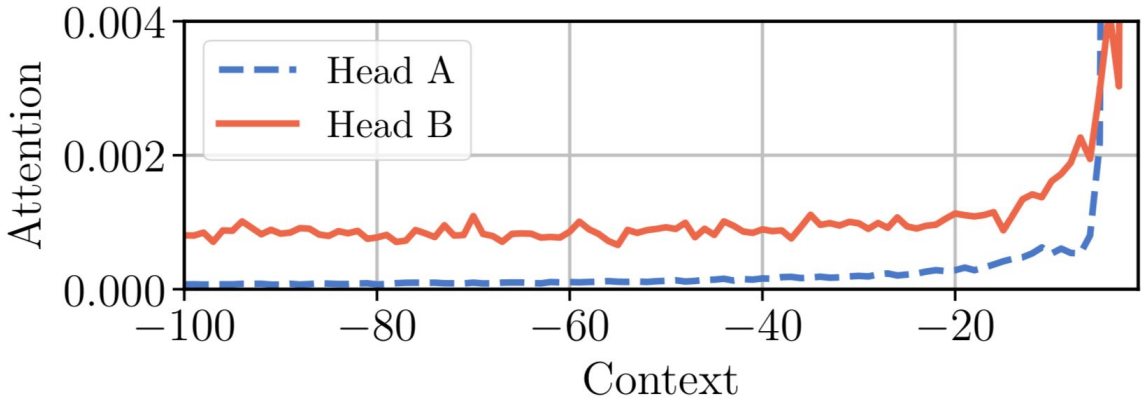
A comparison between the training phrase of vanilla Transformer & Transformer-XL
Transformer-XL paper

Adaptive Attention Span

$$m_z(x) = \text{clamp}(\frac{1}{R}(R + z - x), 0, 1)$$



$$a_{ij} = \frac{m_z(i-j)\exp(s_{ij})}{\sum_{r=i-s}^{i-1} m_z(i-r)\exp(s_{ir})}$$



Two attention heads in the same model, A & B, assign attention differently within the same context window. Head A attends more to the recent tokens, while head B look further back into the past uniformly.

[Adaptive attention Span paper]

Reformer

[Reformer Paper]

Problems

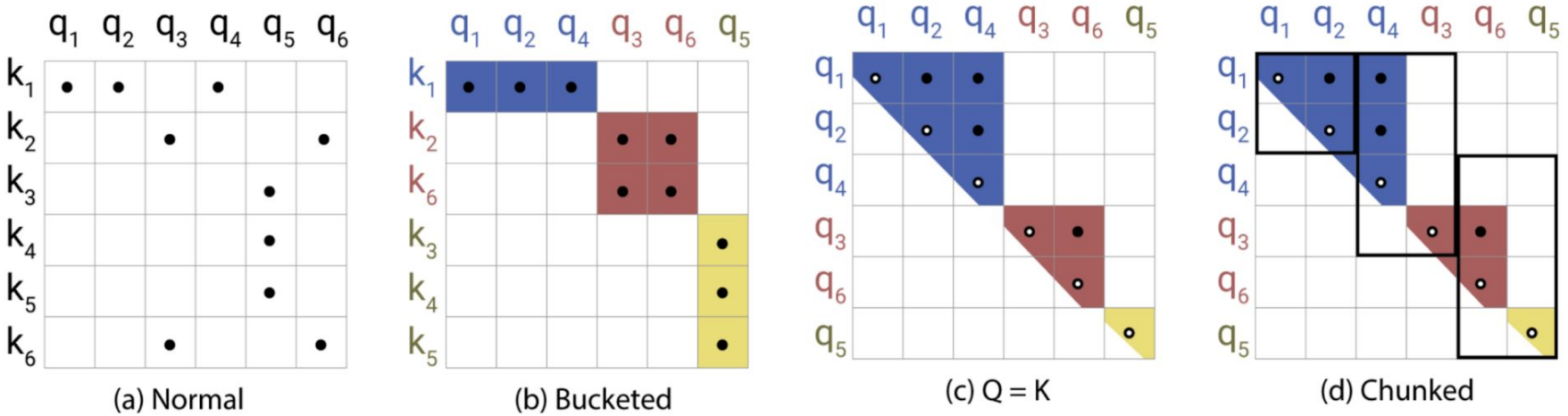
- Memory in a model with N layers is N-times larger than in a single-layer model because we need to store activations for back-propagation.
- The intermediate FF layers are often quite large.
- The attention matrix on sequences of length L often requires O(L2) in both memory and time.

Solution

- Replace the dot-product attention with locality-sensitive hashing (LSH) attention, reducing the complexity from O(L2) to O(LlogL).
- Replace the standard residual blocks with reversible residual layers, which allows storing activations only once during training instead of N times (i.e. proportional to the number of layers).

Sorting by hash

shared-QK



Reformer

[Reformer Paper]

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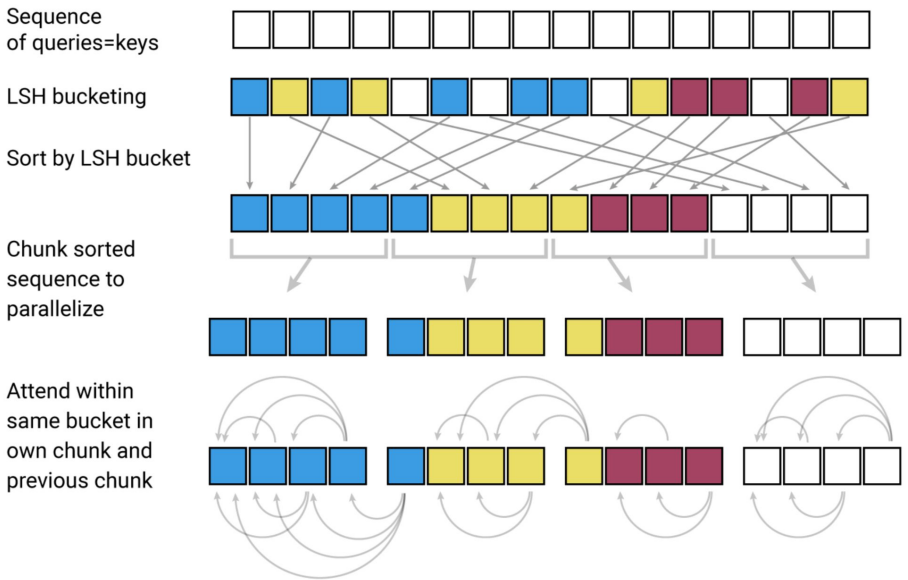

Reversible Residual Network?

$$y_1 = x_1 + F(x_2),\ y_2 = x_2 + G(y_1)$$

$$x_2 = y_2 - G(y_1),\ x_1 = y_1 - F(x_2)$$

$$Y_1 = X_1 + \text{Attention}(X_2),\ Y_2 = X_2 + \text{FeedForward}(Y_1)$$

The resulting reversible Transformer does not need to store activation in every layer.

Outro and Q&A

- Transformer is novel and very powerful architecture
- It is worth it to understand how Self-Attention works
- Physical analogues can help you