

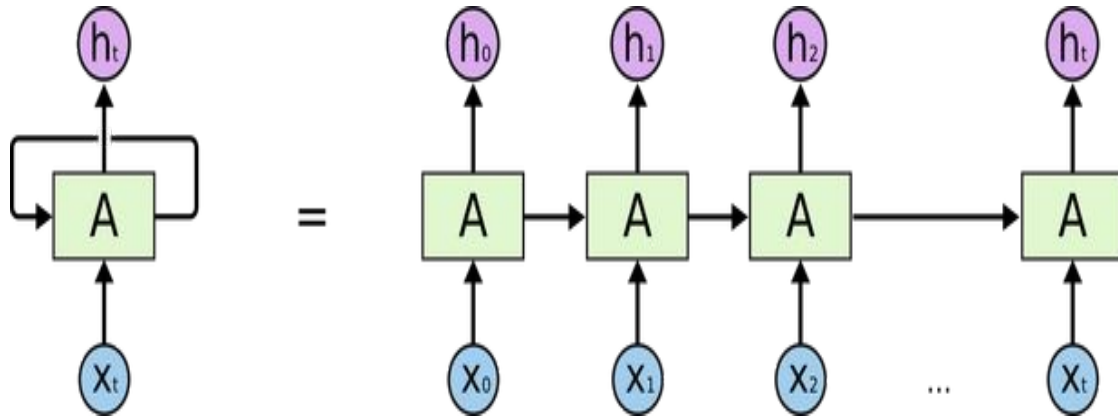


# NLP Session

# Topics

- RNN
- LSTM
- Transformers

# RNN



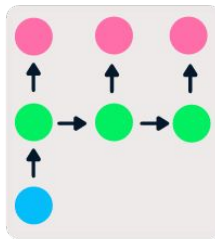
# Types of RNN

- One to One RNN
- One to Many RNN
- Many to One RNN
- Many to Many RNN

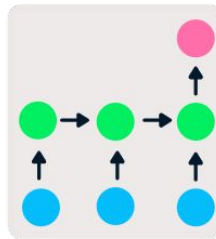
One to One



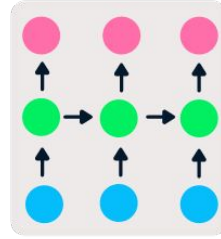
One to Many



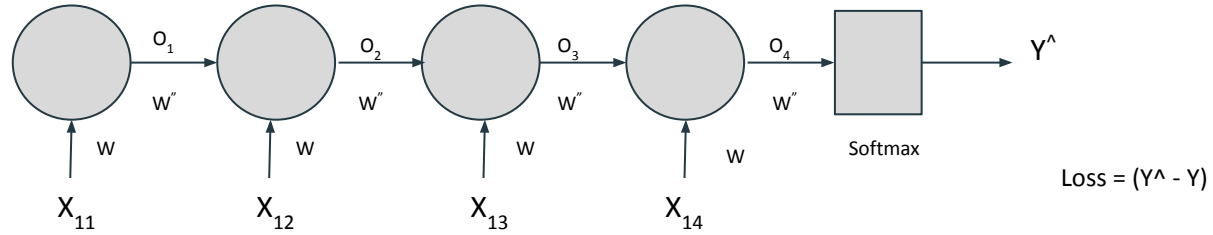
Many to One



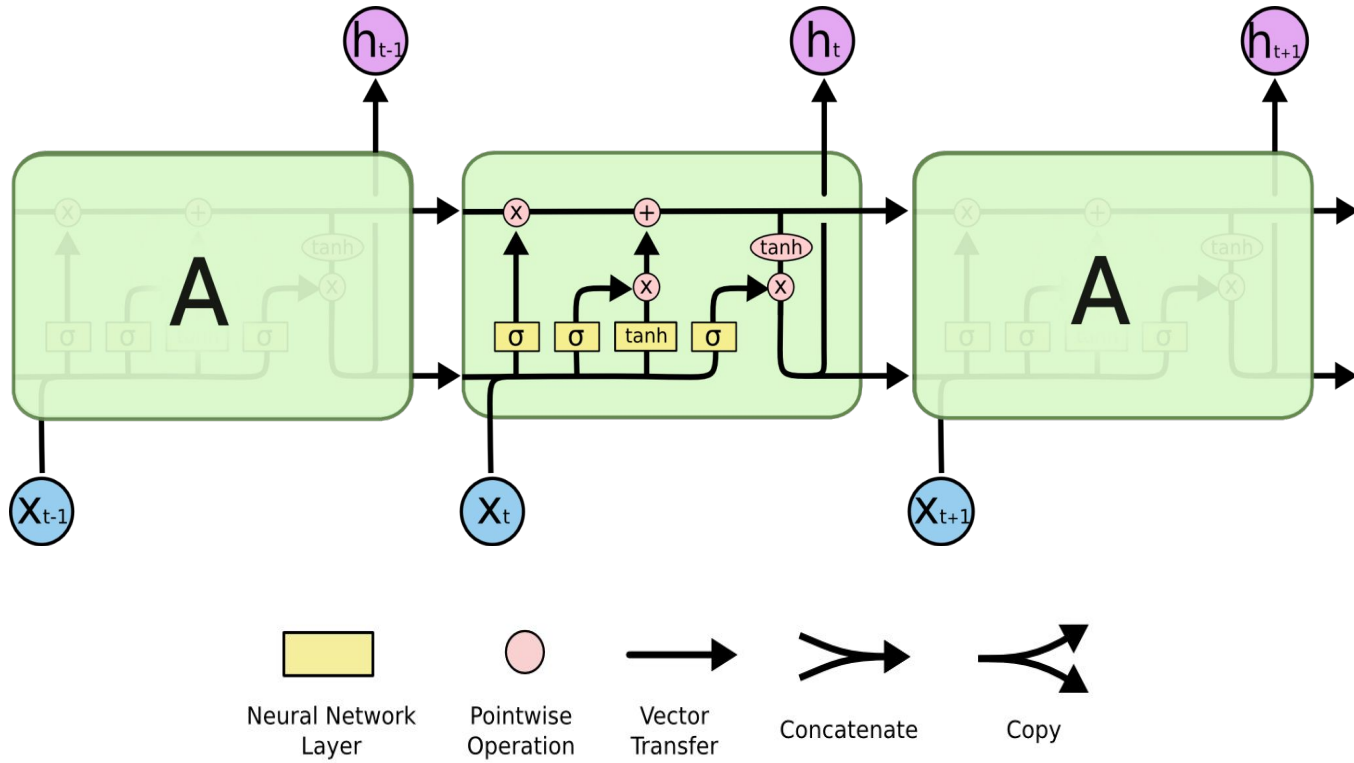
Many to Many



# Forward and Backward Propagation



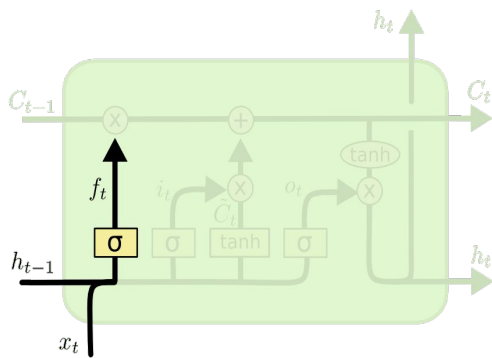
# LSTM



# Forget Gate Layer

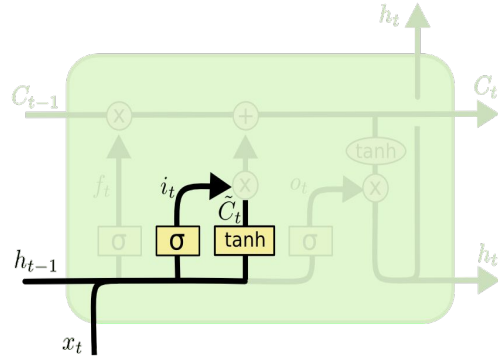
Example 1 - Rohan likes pizza but **he** does not like burger.

Example 2 - Rohan likes pizza but his **friend** likes burger.



$$f_t = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f)$$

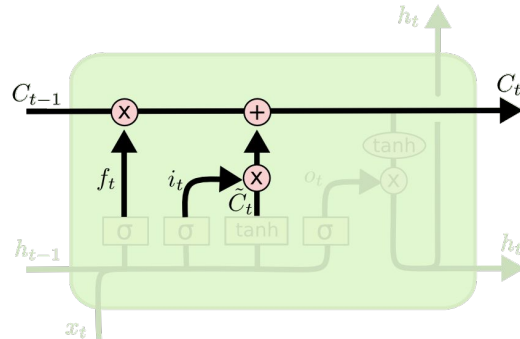
# Input Gate Layer



$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

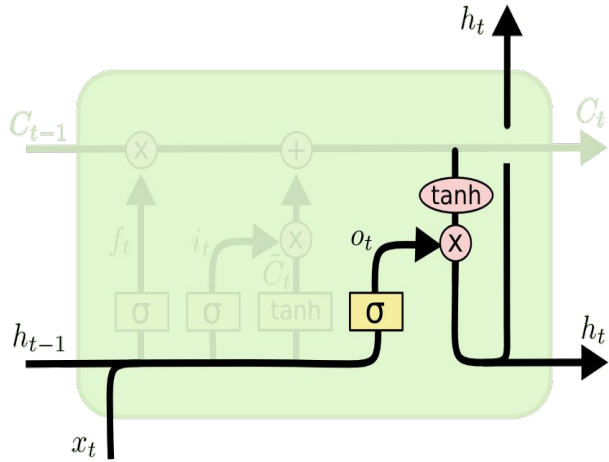
Combining



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$



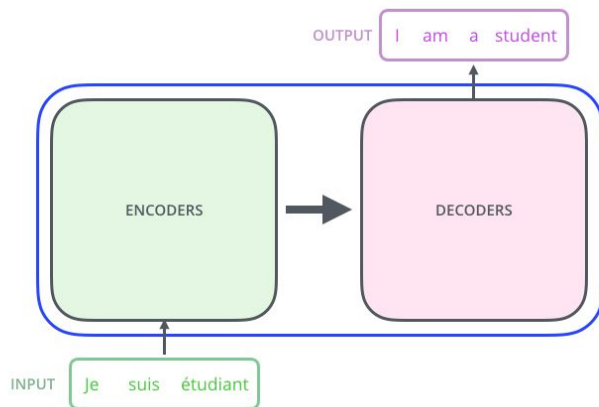
# Output Gate Layer

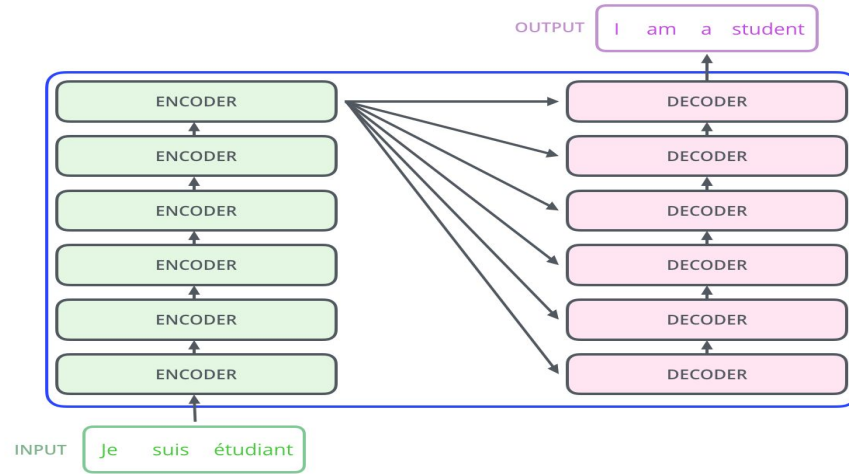


$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$

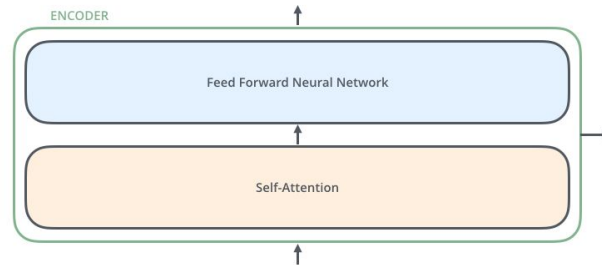
$$h_t = o_t * \tanh(C_t)$$

# Transformers





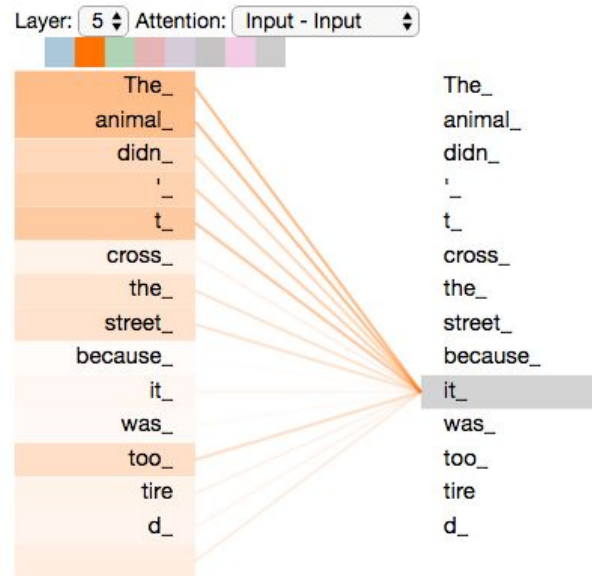
In Every Encoder -



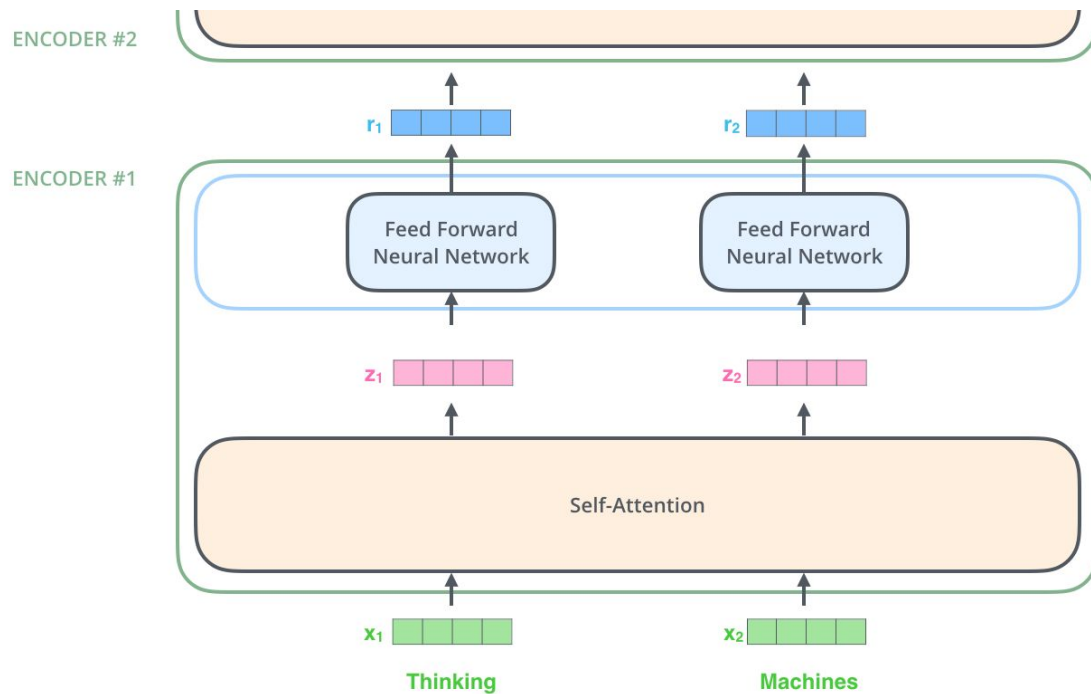
# Self - Attention

Why to use ?

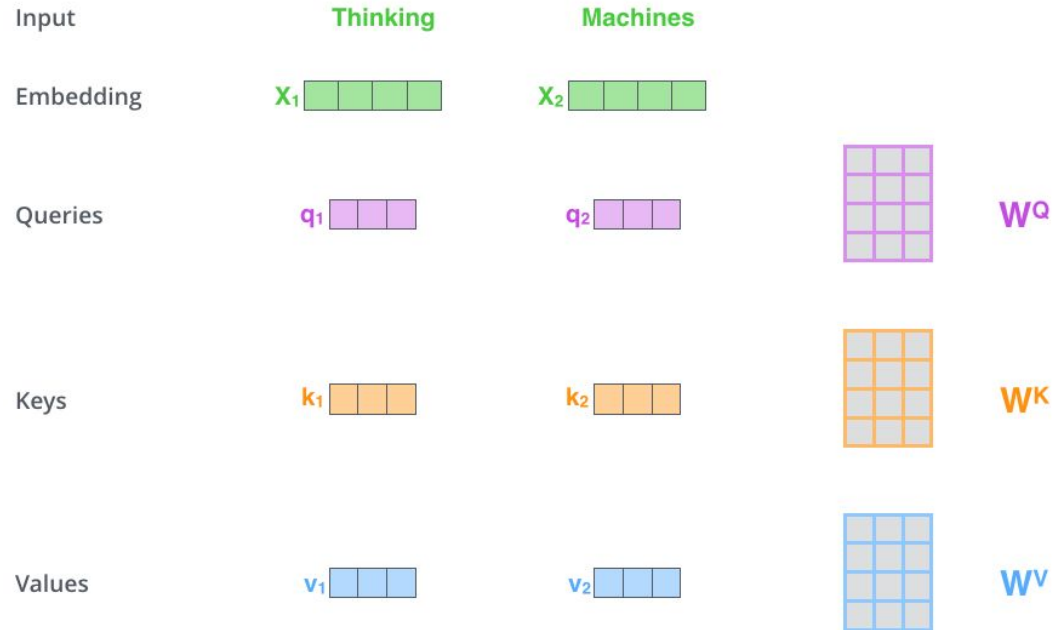
Example - The animal didn't cross the street because **it** was too tired



# Understanding self-attention



## Step 1 - To create Queries, key and values vector



## Step 2 - To calculate the score

Input

Embedding

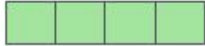
Queries

Keys

Values

Score

Thinking

$x_1$  

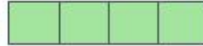
$q_1$  

$k_1$  

$v_1$  

$$q_1 \cdot k_1 = 112$$

Machines

$x_2$  

$q_2$  

$k_2$  

$v_2$  

$$q_1 \cdot k_2 = 96$$

### Step 3 - Divide the score by 8 and calculating the softmax

Input

Embedding

Queries

Keys

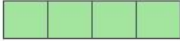
Values

Score

Divide by 8 (  $\sqrt{d_k}$  )

Softmax

Thinking

$x_1$  

$q_1$  

$k_1$  

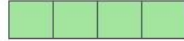
$v_1$  

$q_1 \cdot k_1 = 112$

14

0.88

Machines

$x_2$  

$q_2$  

$k_2$  

$v_2$  

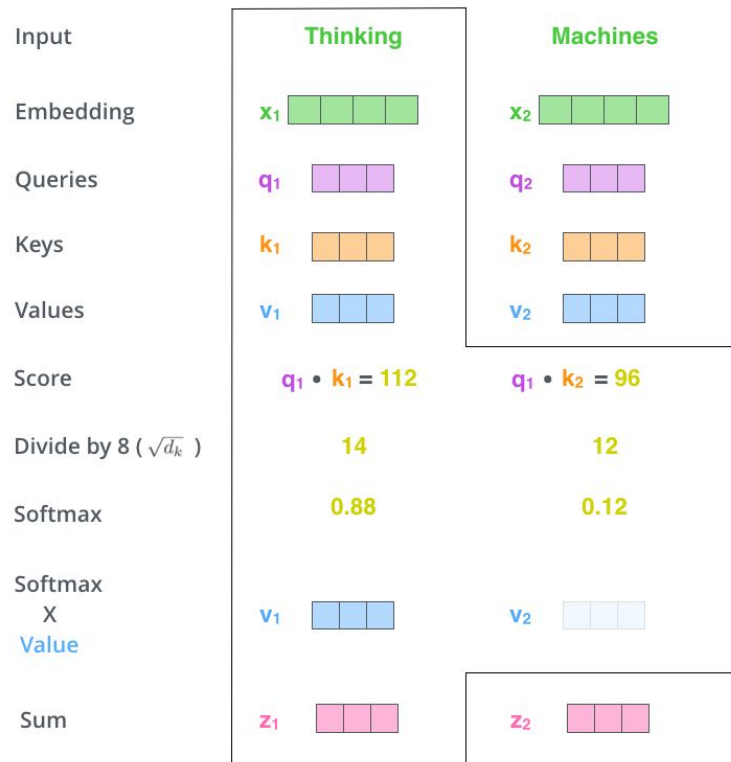
$q_2 \cdot k_2 = 96$

12

0.12



## Step 4 - Multiply the value vector with softmax



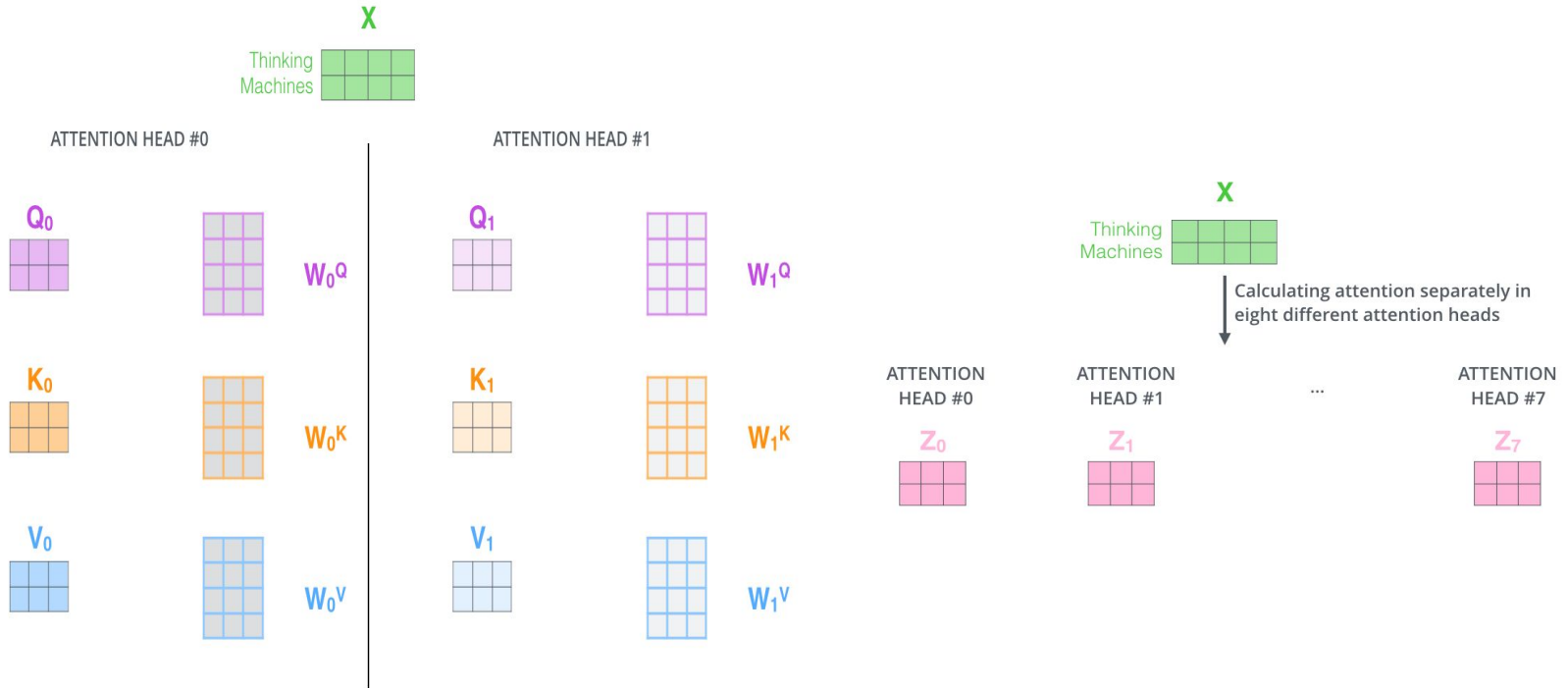
# Matrix Calculation of self-attention

$$\begin{matrix} \text{X} \\ \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} \end{matrix} \times \begin{matrix} \text{W}^{\text{Q}} \\ \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} \end{matrix} = \begin{matrix} \text{Q} \\ \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} \end{matrix}$$

$$\begin{matrix} \text{X} \\ \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} \end{matrix} \times \begin{matrix} \text{W}^{\text{K}} \\ \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} \end{matrix} = \begin{matrix} \text{K} \\ \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} \end{matrix}$$

$$\begin{matrix} \text{X} \\ \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} \end{matrix} \times \begin{matrix} \text{W}^{\text{V}} \\ \begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \square & \square & \square & \square \\ \hline \end{array} \end{matrix} = \begin{matrix} \text{V} \\ \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} \end{matrix}$$

# Multi-headed Attention



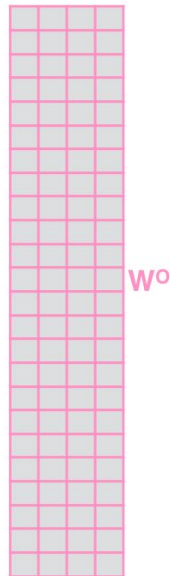
# Input to feed-forward neural network

1) Concatenate all the attention heads



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

$\times$

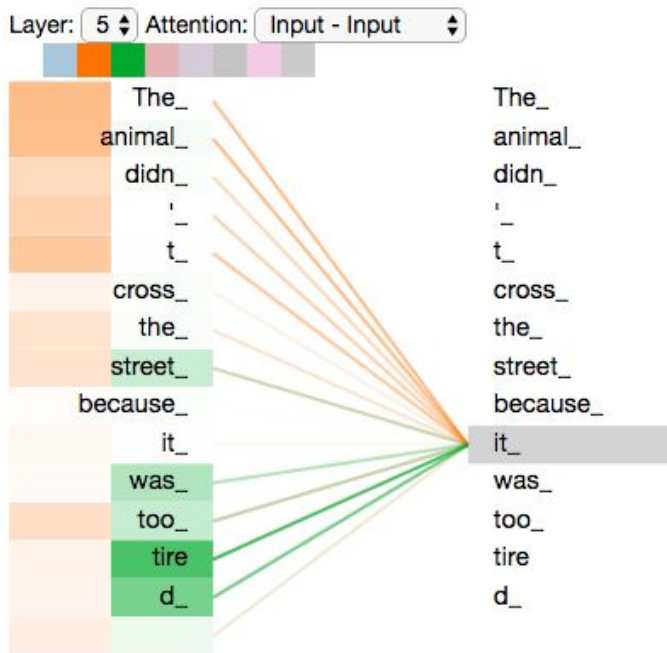


3) The result would be the  $Z$  matrix that captures information from all the attention heads. We can send this forward to the FFNN



# After Applying multi-headed attention

Example - The animal didn't cross the street because it was too tired



# Entire Process

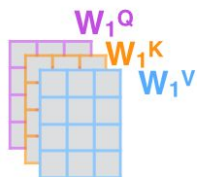
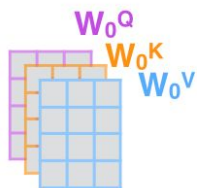
1) This is our input sentence\*

Thinking  
Machines

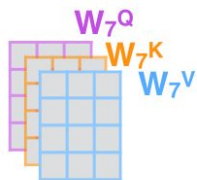
2) We embed each word\*



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

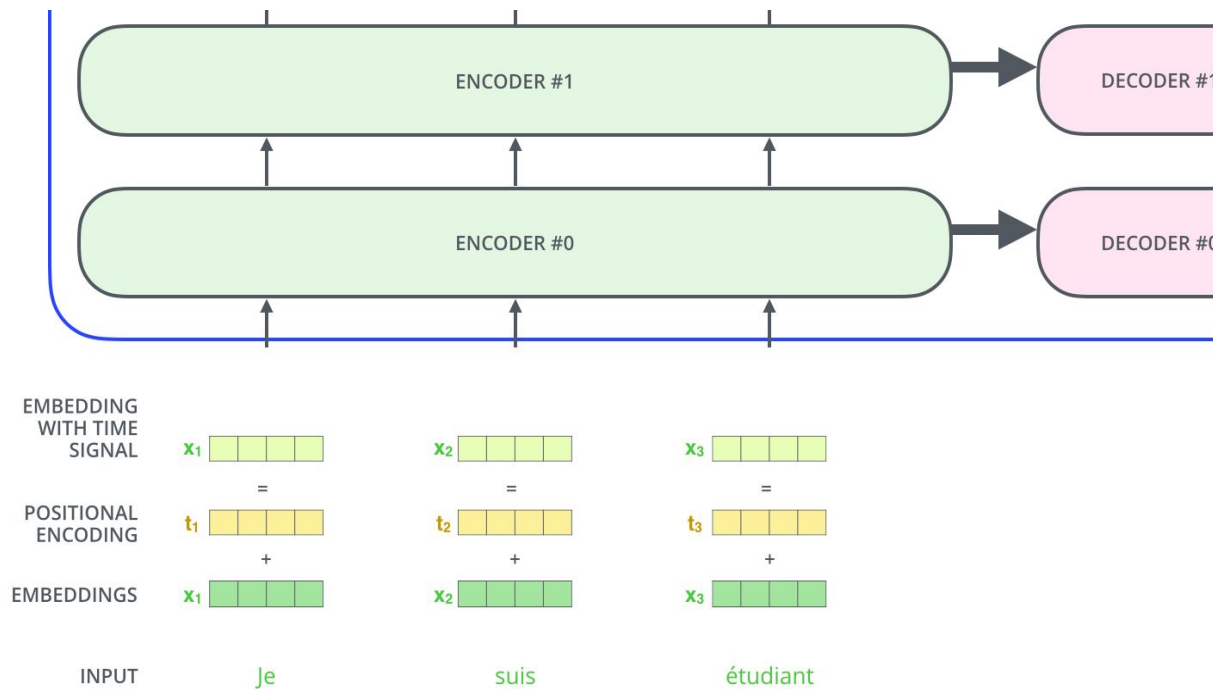


...

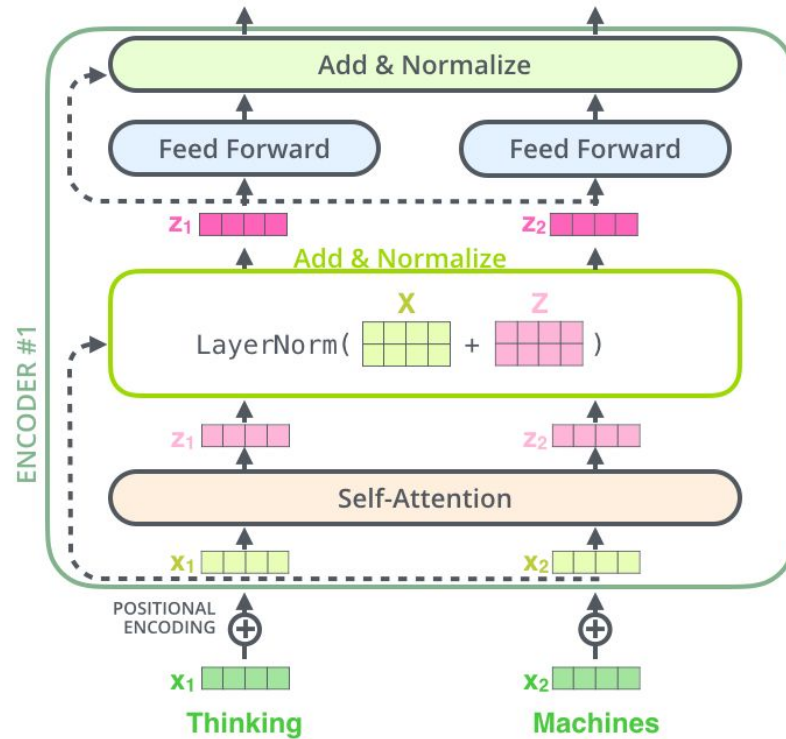


\* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one

# Positional Encodings

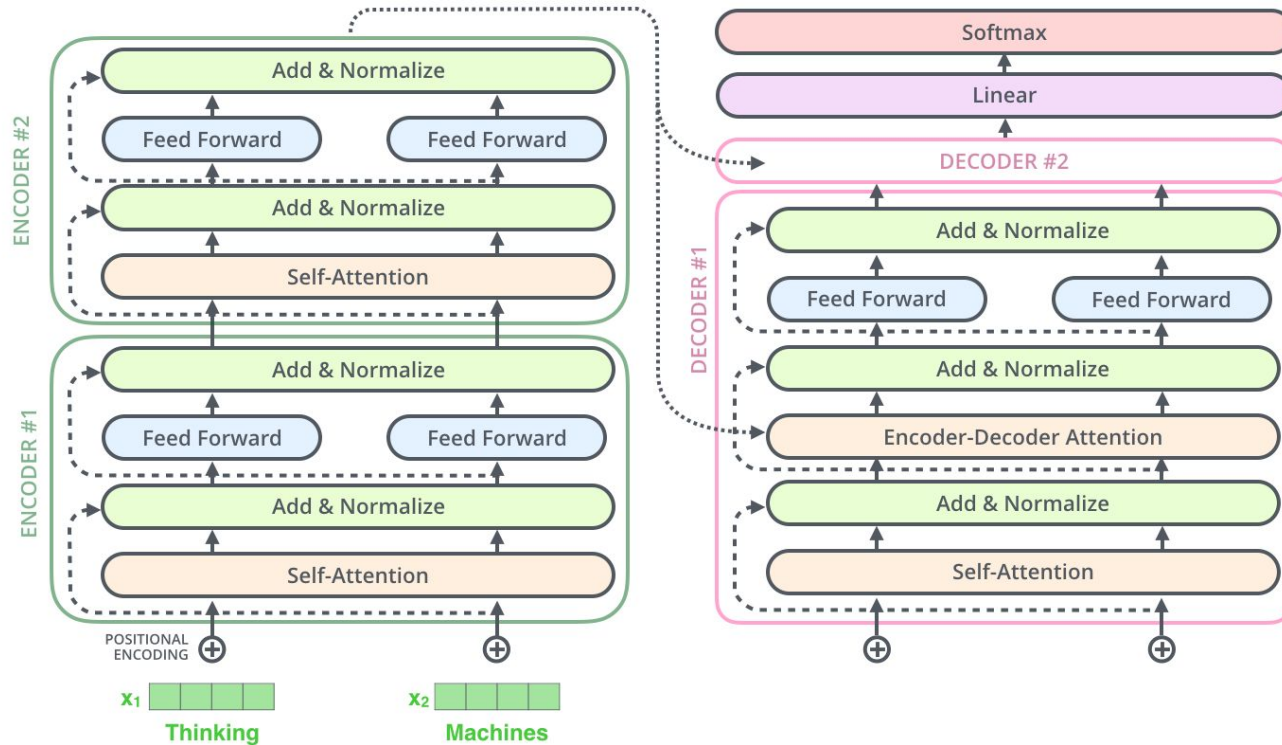


# Layer Normalization





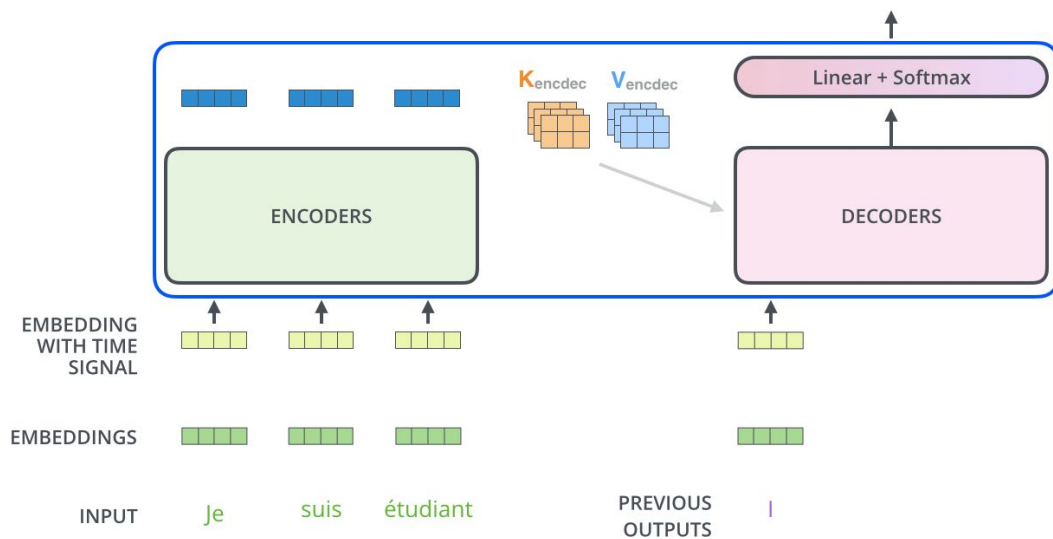
# Entire Process



# Output Visualization

Decoding time step: 1 2 3 4 5 6

OUTPUT |



Thank you