Машинное обучение

Лекция 10

Seq2seq learning, Attention

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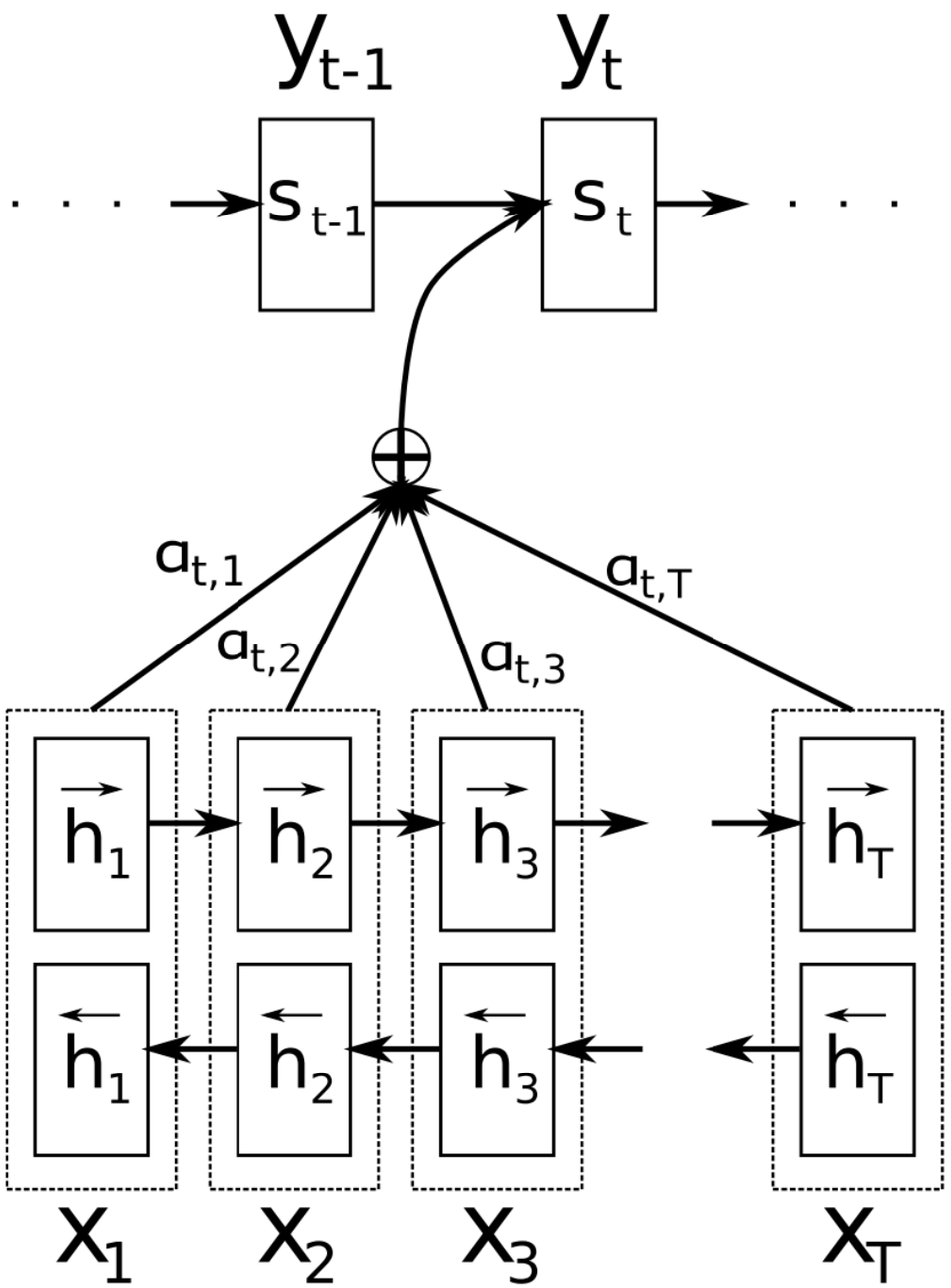
2019

Recap: Attention



Скрытый слой RNN

$$s_i = f(s_{i-1}, y_{i-1}, c_i).$$

Взвешенная сумма

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j.$$

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

$$e_{ij} = a(s_{i-1}, h_j)$$

Neural Machine Translation by Jointly Learning to Align and Translate

А что если без RNN?

А что если без RNN?

Но ведь нам нужно обрабатывать последовательности…

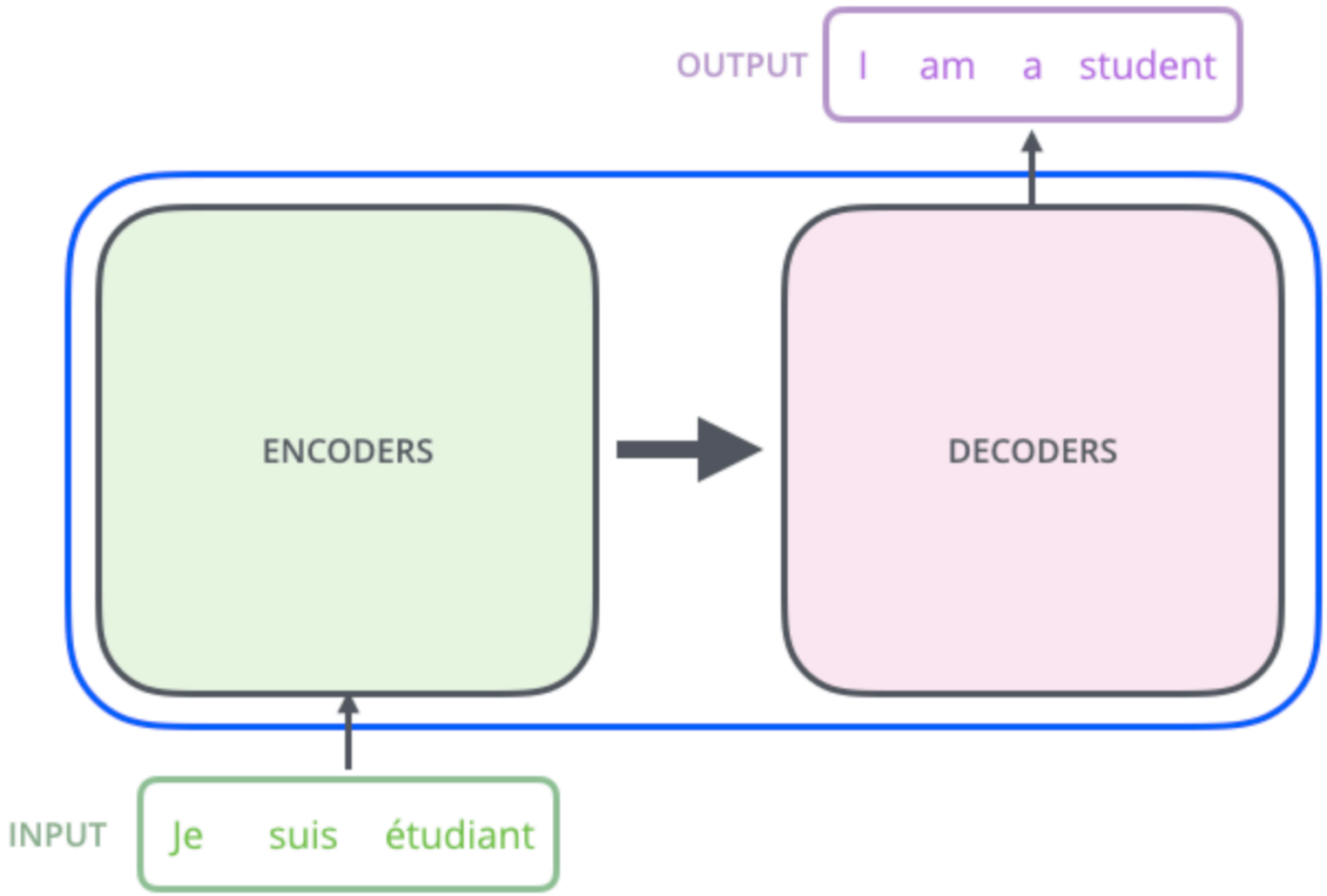
Self-Attention

The Illustrated Transformer

Self-Attention

The Illustrated Transformer

Self-Attention



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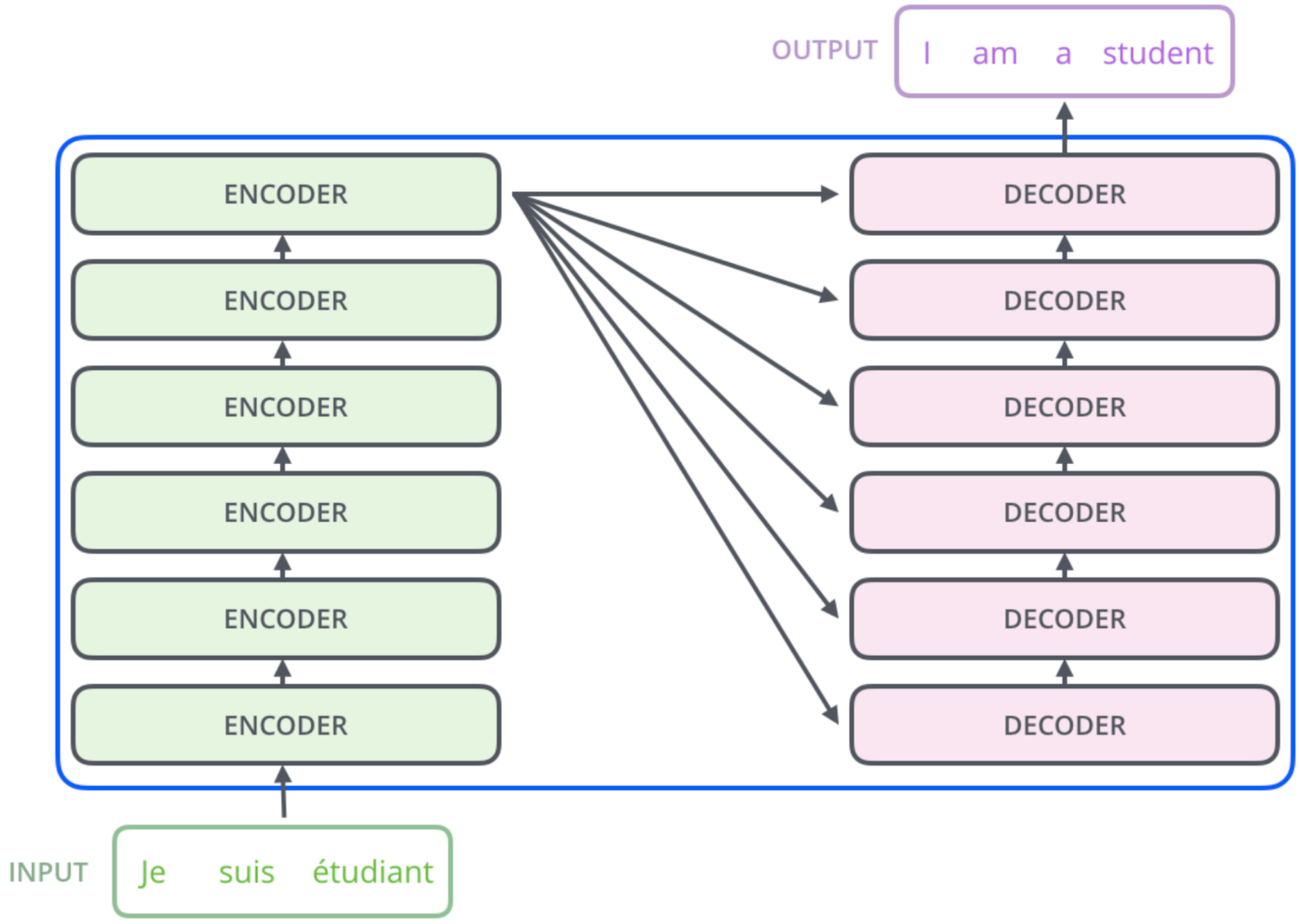
Self-Attention



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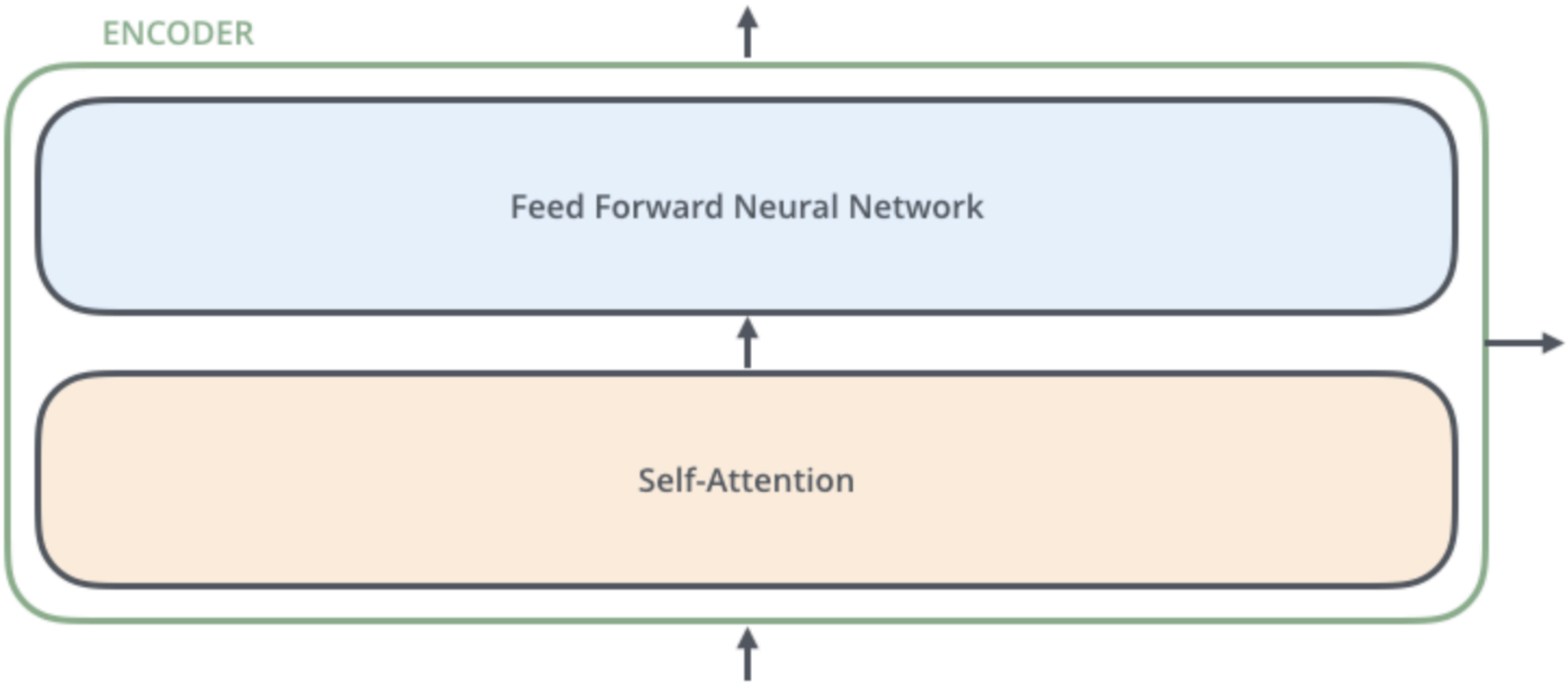

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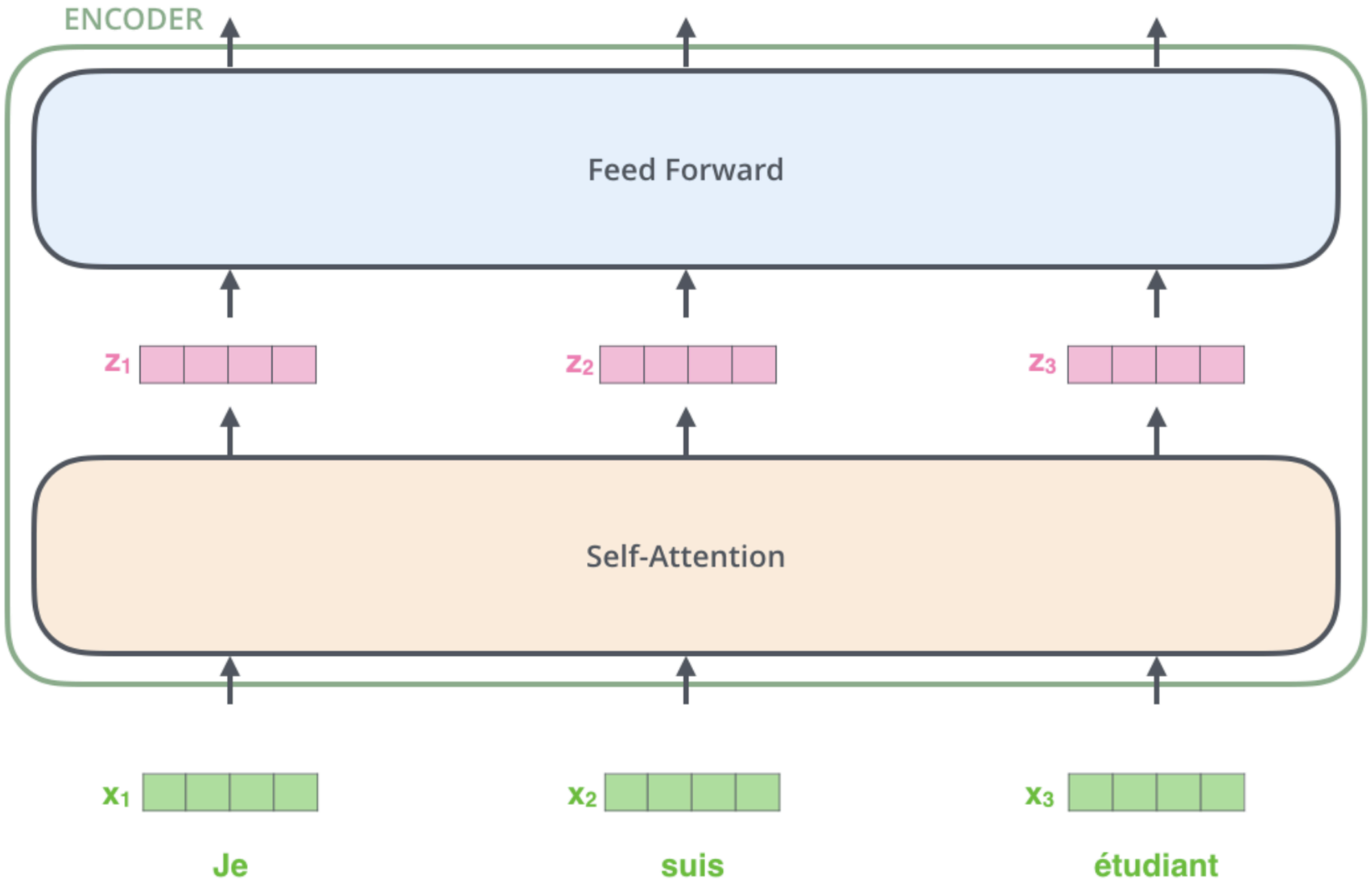
Self-Attention



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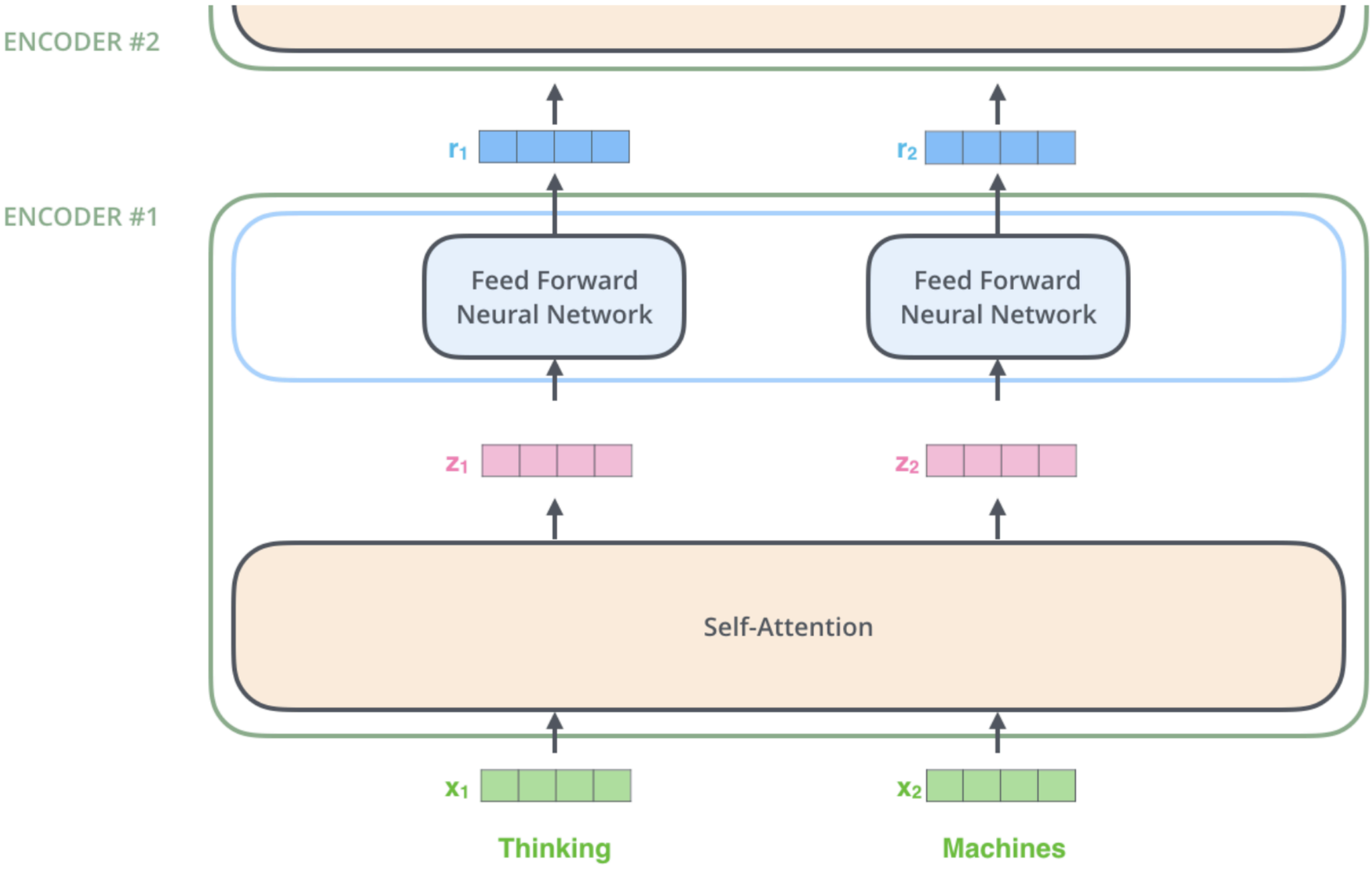
Self-Attention



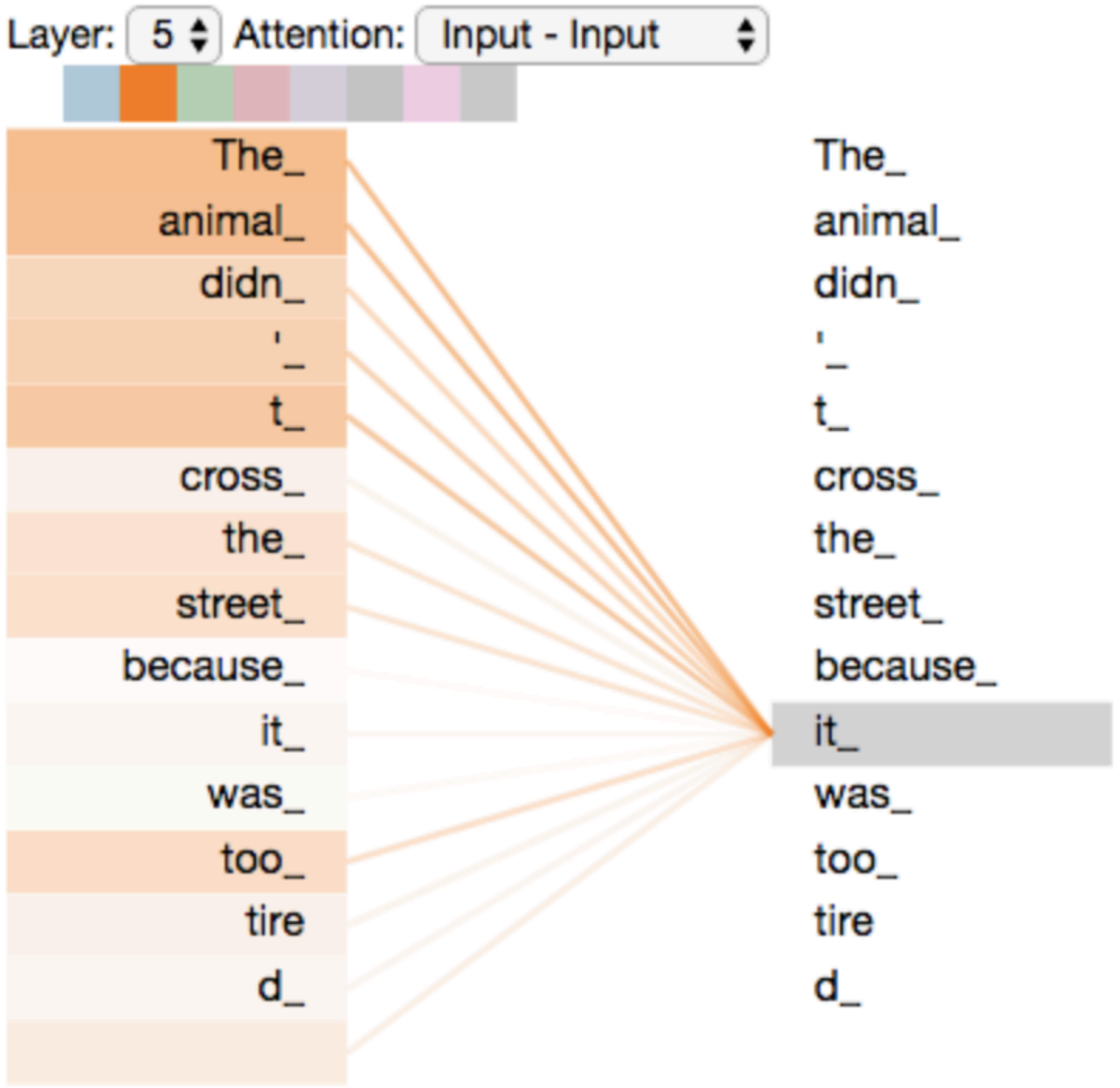
The Illustrated Transformer

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

?

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

Self-Attention



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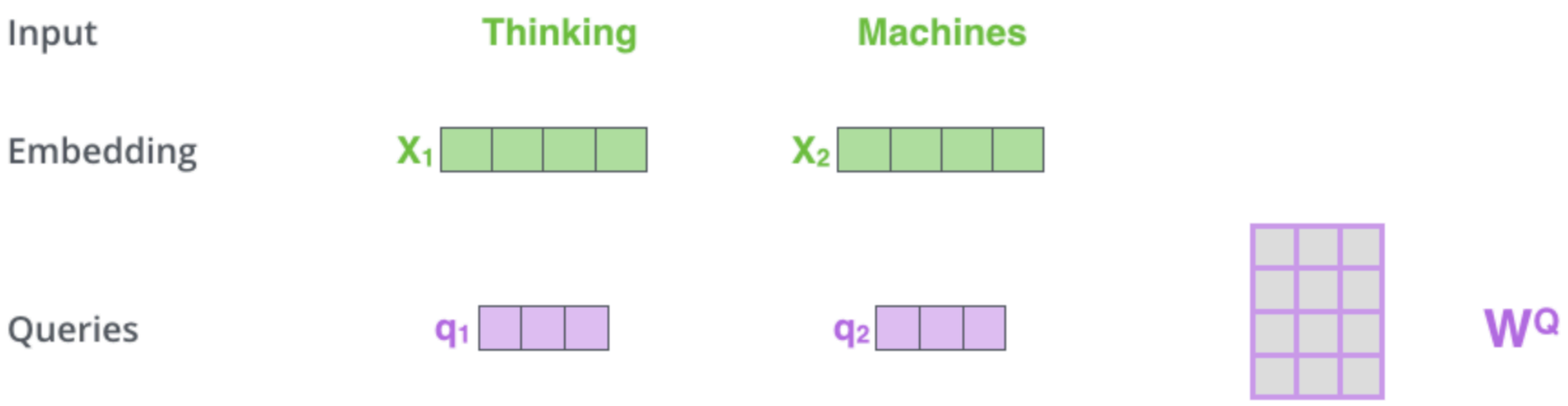
Шаг 1 - Векторы Queries, Keys, Values



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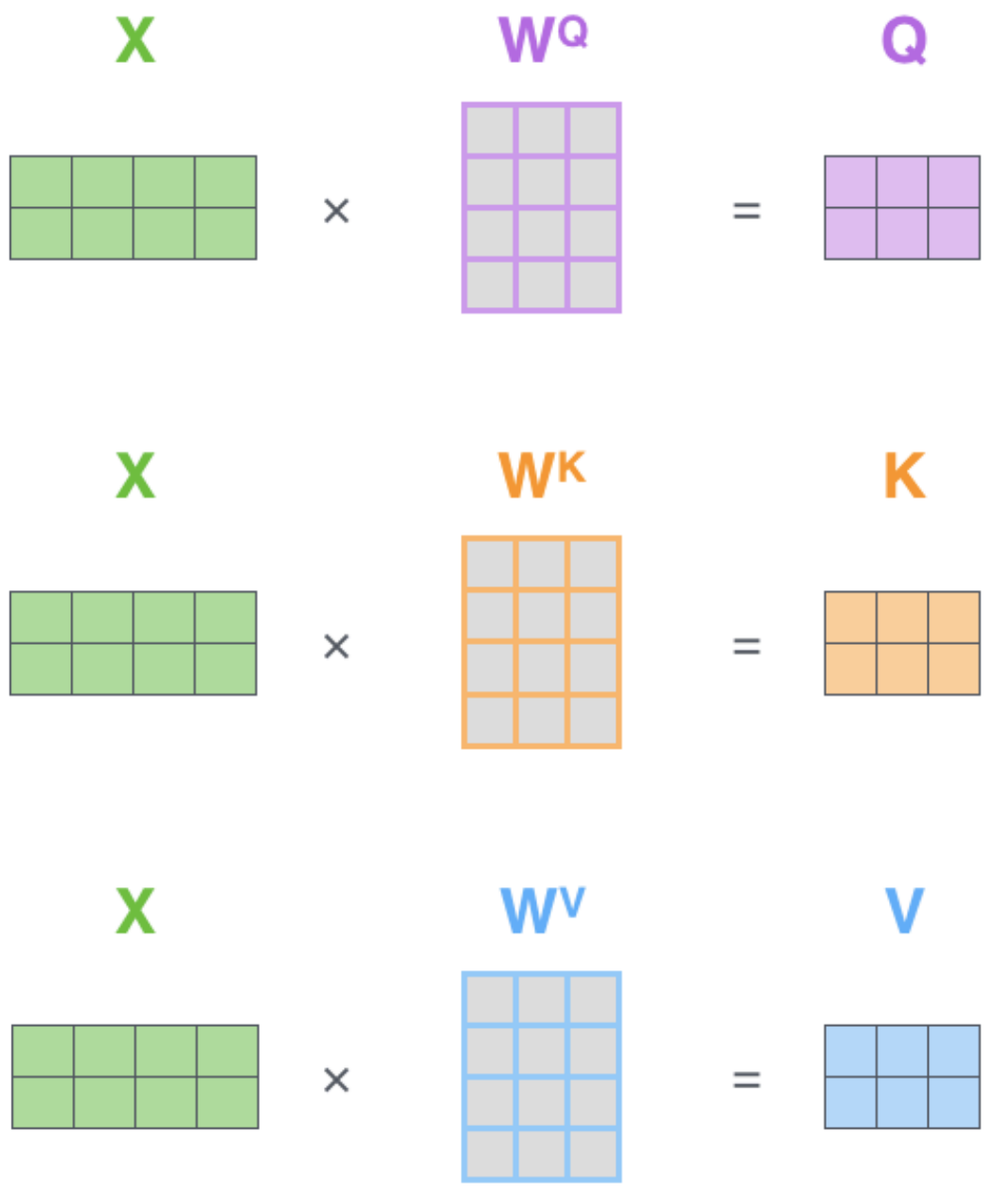
Шаг 1 - Векторы Queries, Keys, Values



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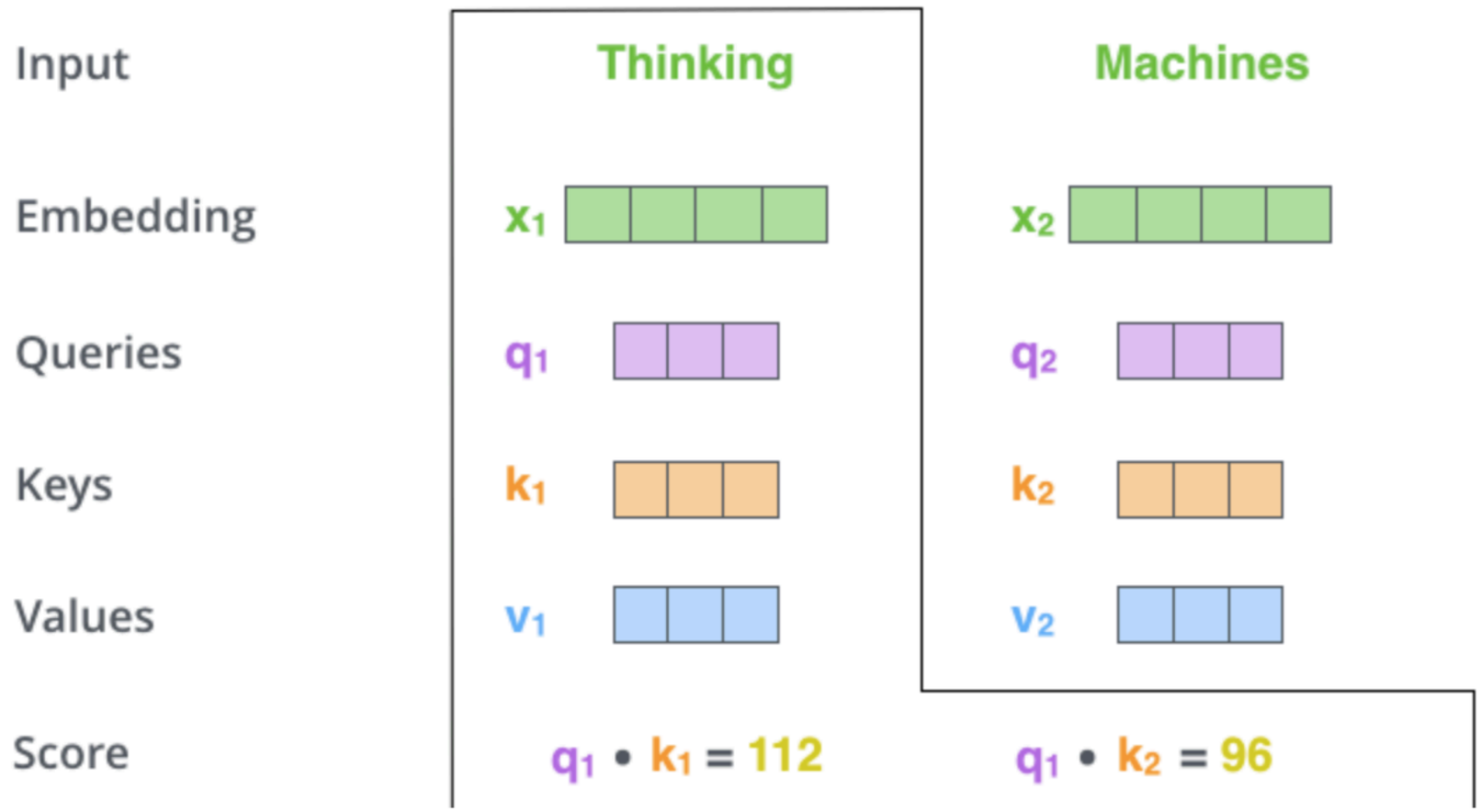
Шаг 2 - Вычисление Score



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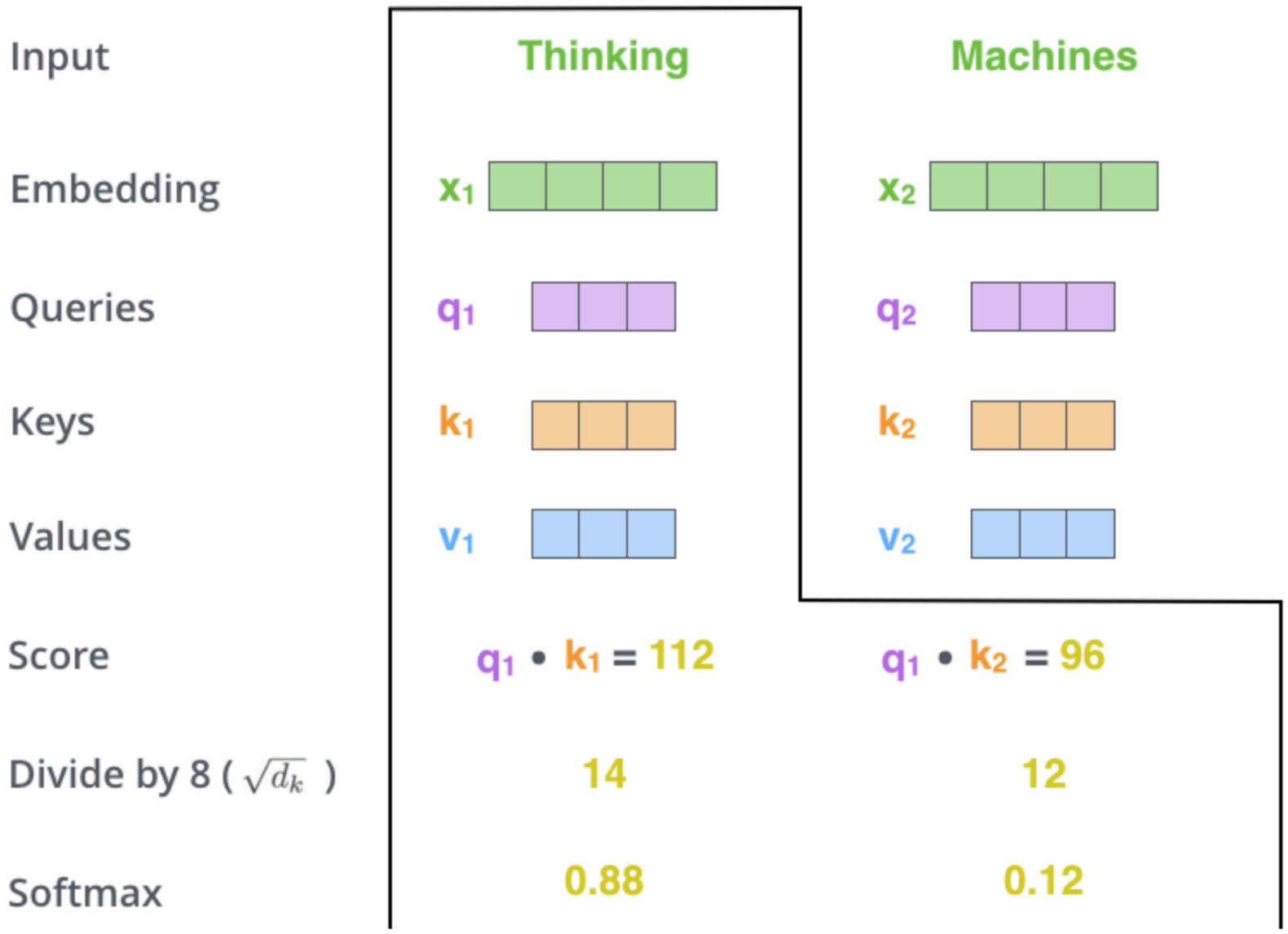
Шаг 3: Делим Скор на sqrt(d)
Шаг 4: Softmax



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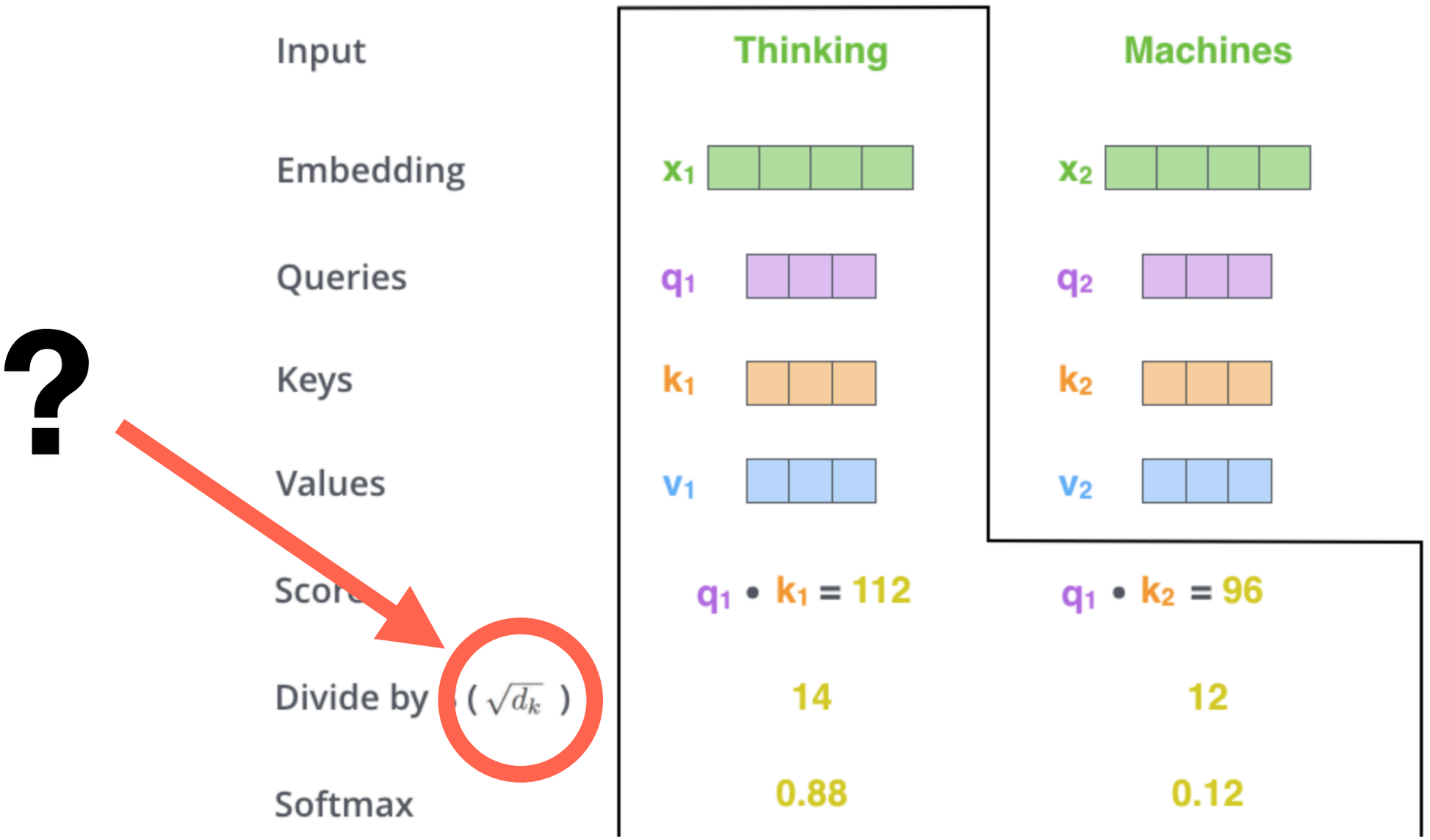
Шаг 3: Делим Скор на sqrt(d)
Шаг 4: Softmax



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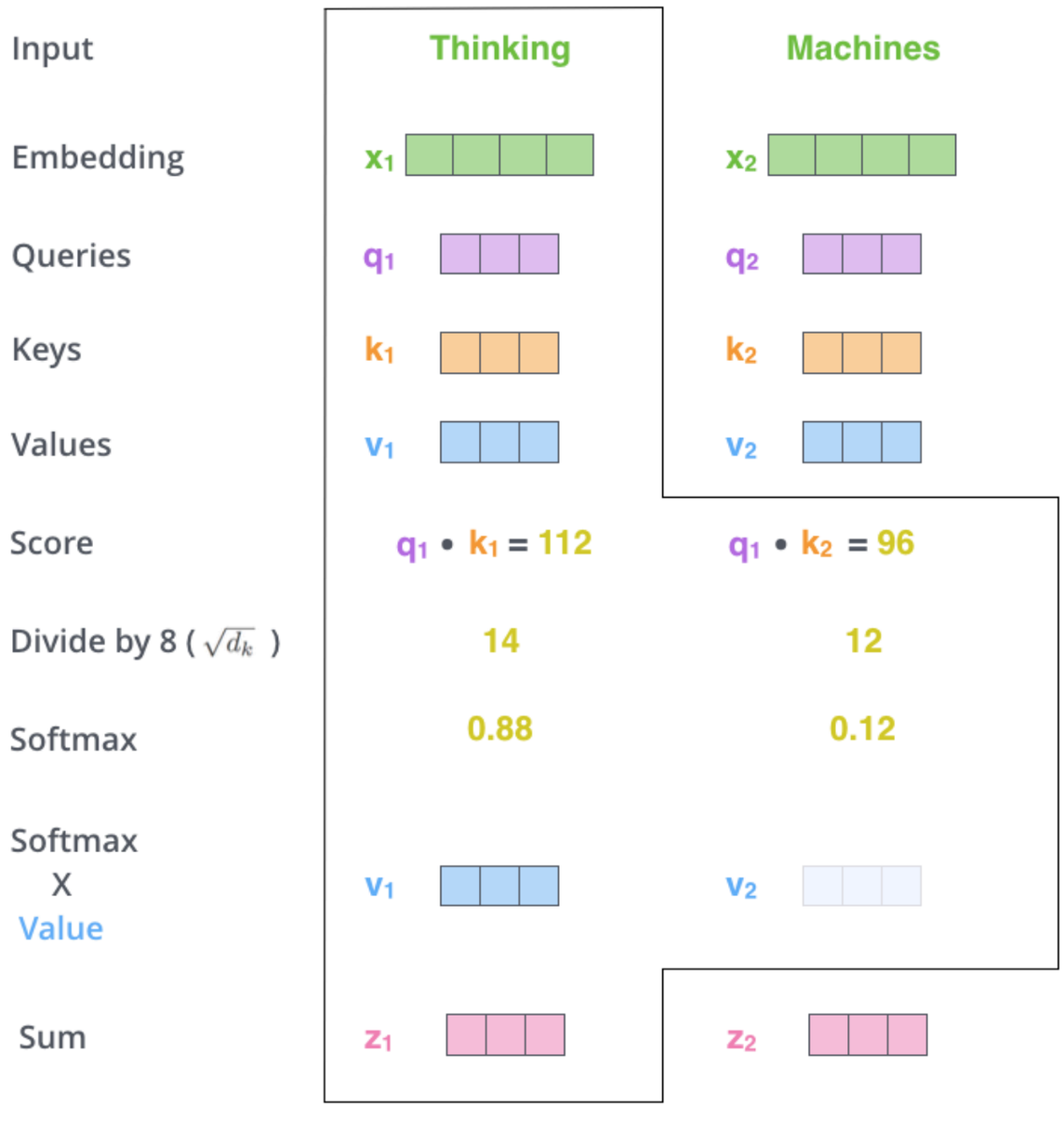
Шаг 5: Умножение каждого Values вектора на значение softmax
Шаг 6: Суммирование векторов



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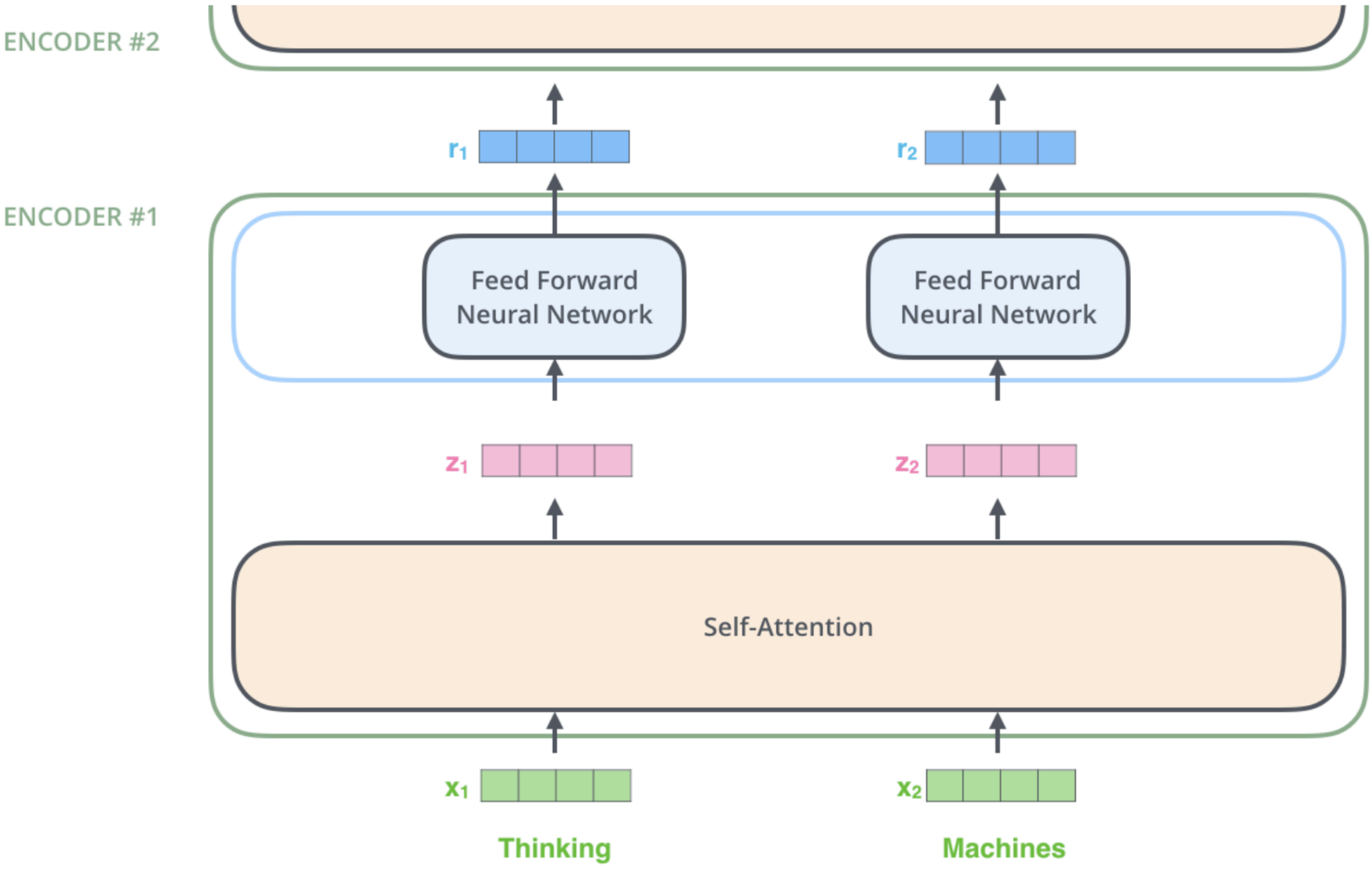
Self-Attention



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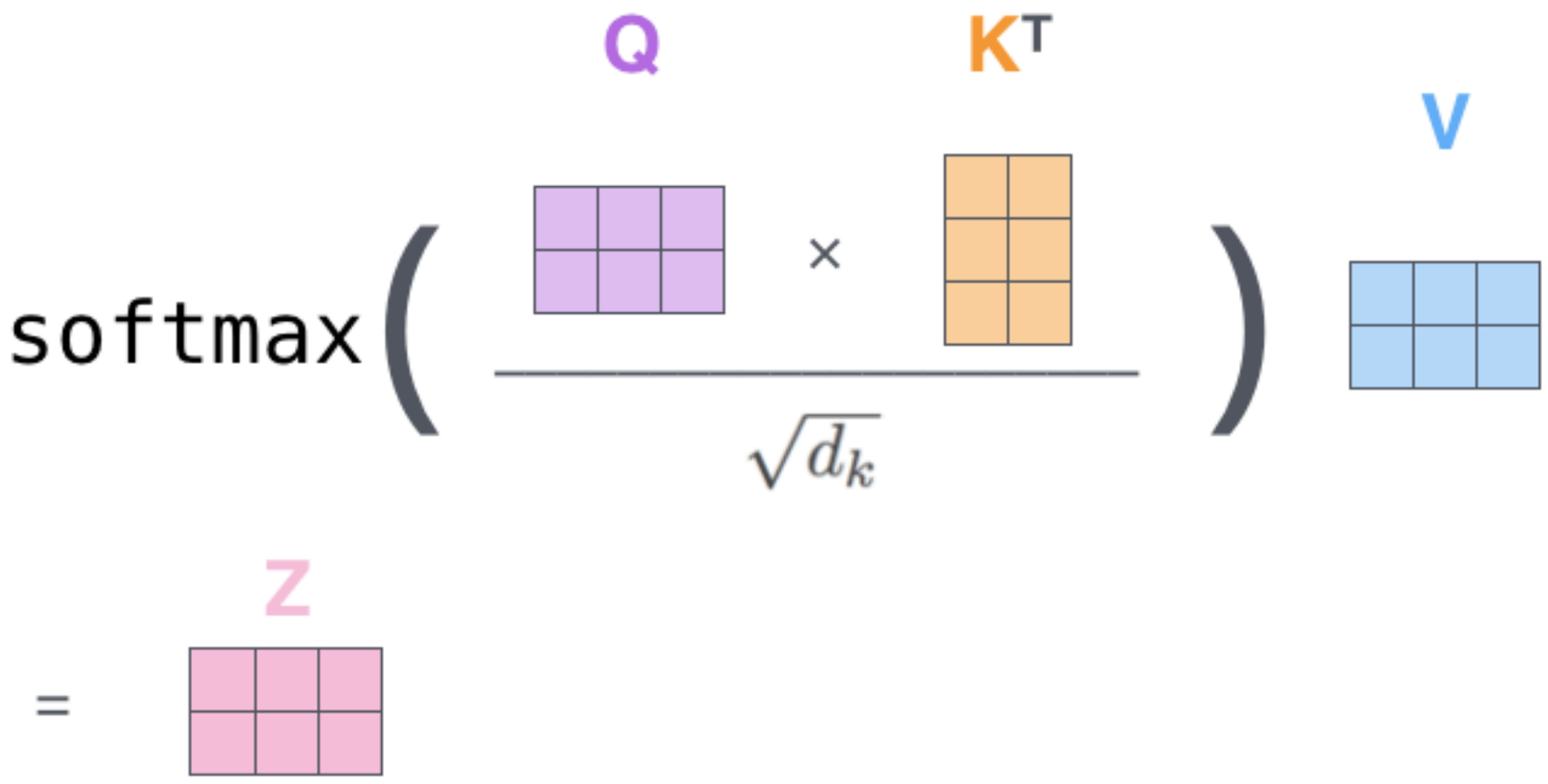
Self-Attention



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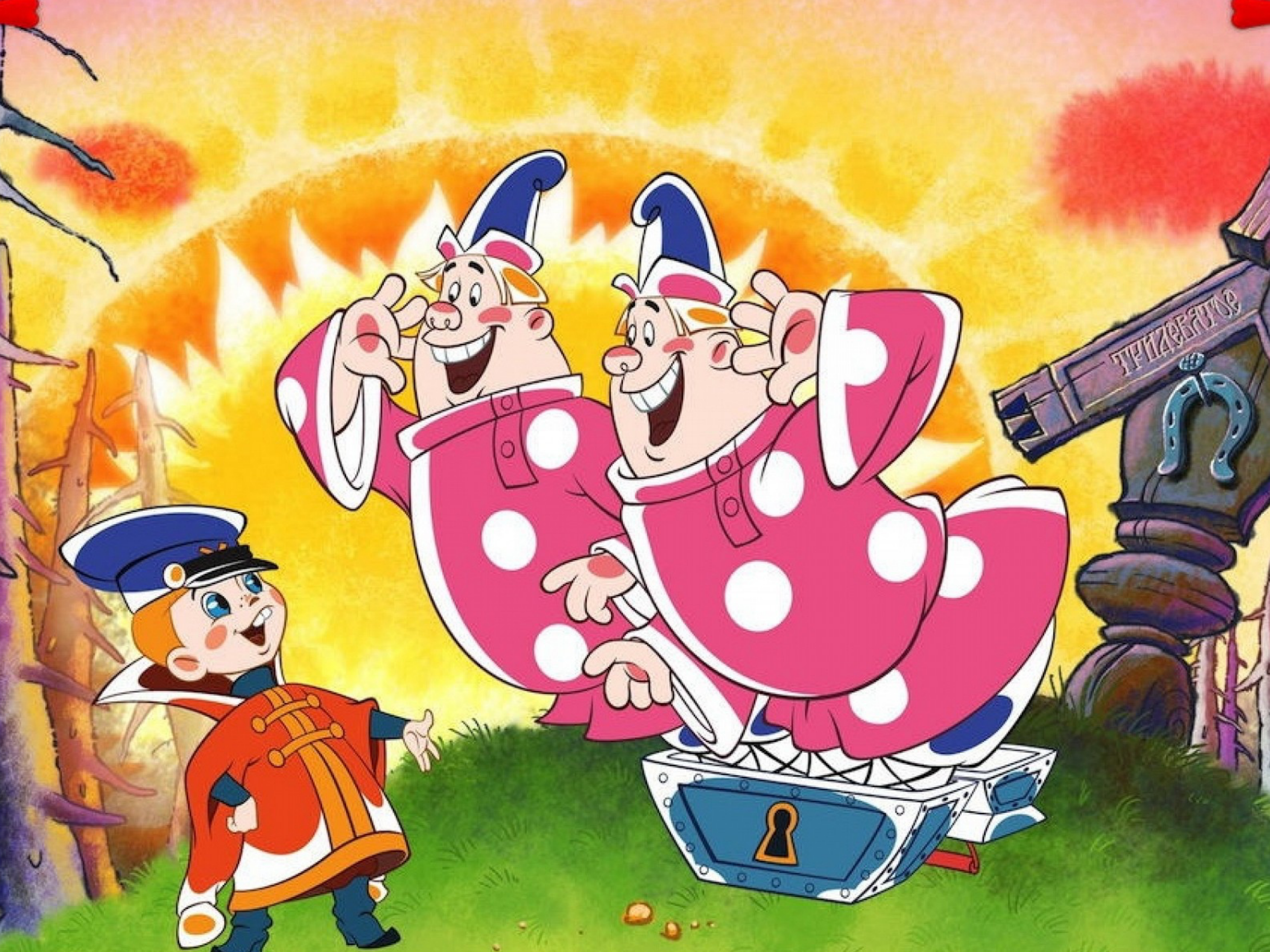
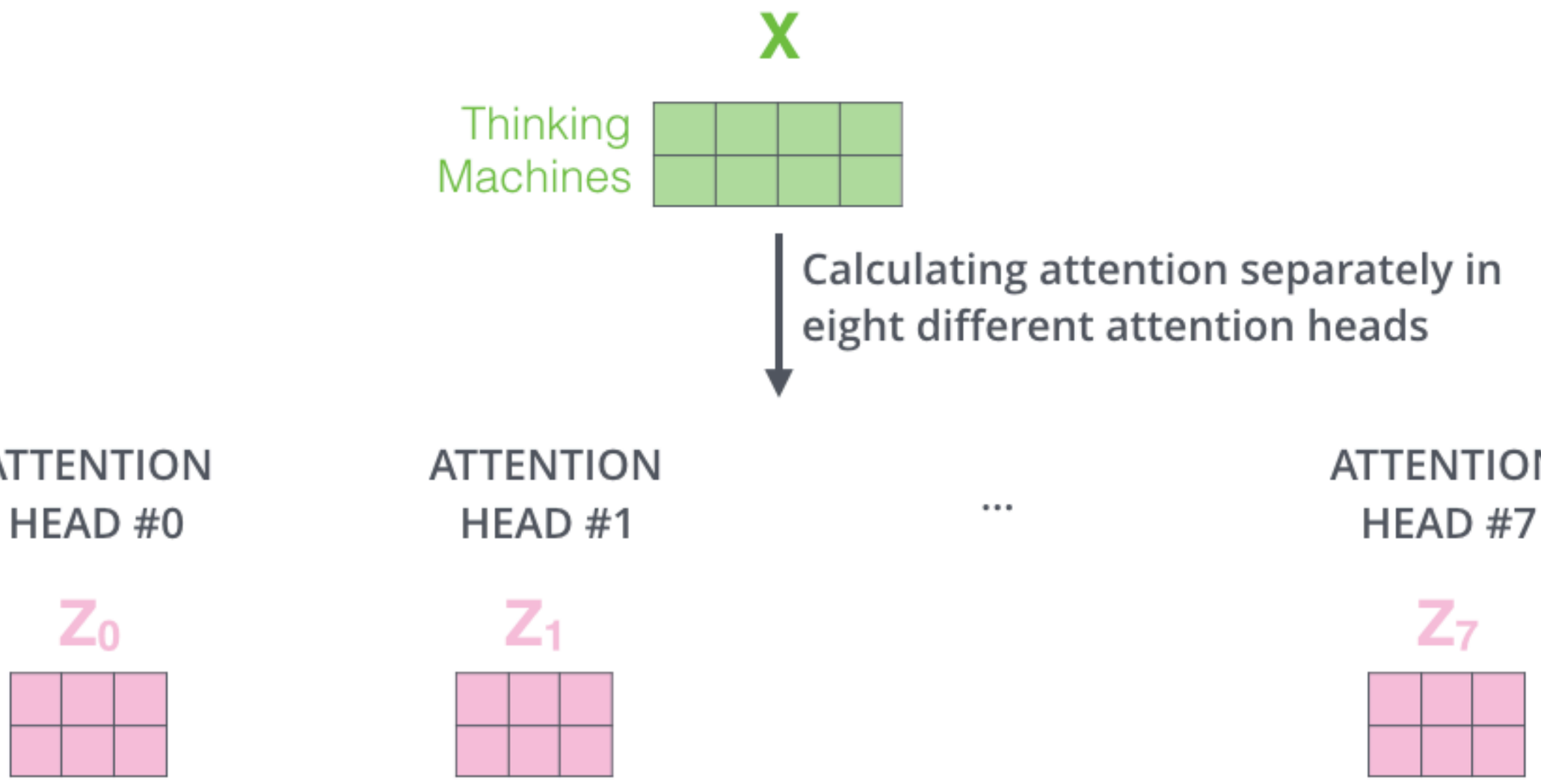

ТРИЗВЕЗДОВ

Multihead Self-Attention



The Illustrated Transformer

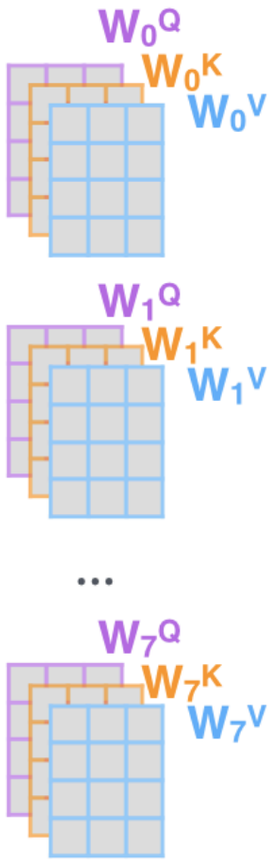
Multihead Self-Attention

1) This is our input sentence*

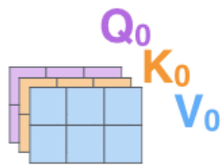
Thinking
Machines

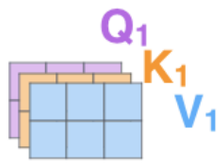
2) We embed each word*

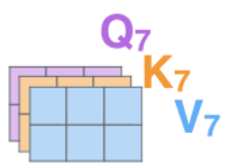
3) Split into 8 heads. We multiply X or R with weight matrices



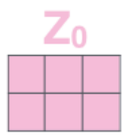
4) Calculate attention using the resulting Q/K/V matrices

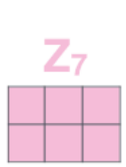


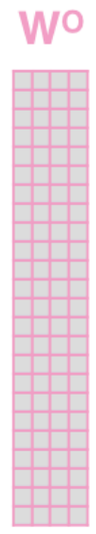


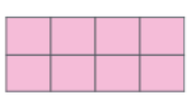


5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer









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

...

...

...

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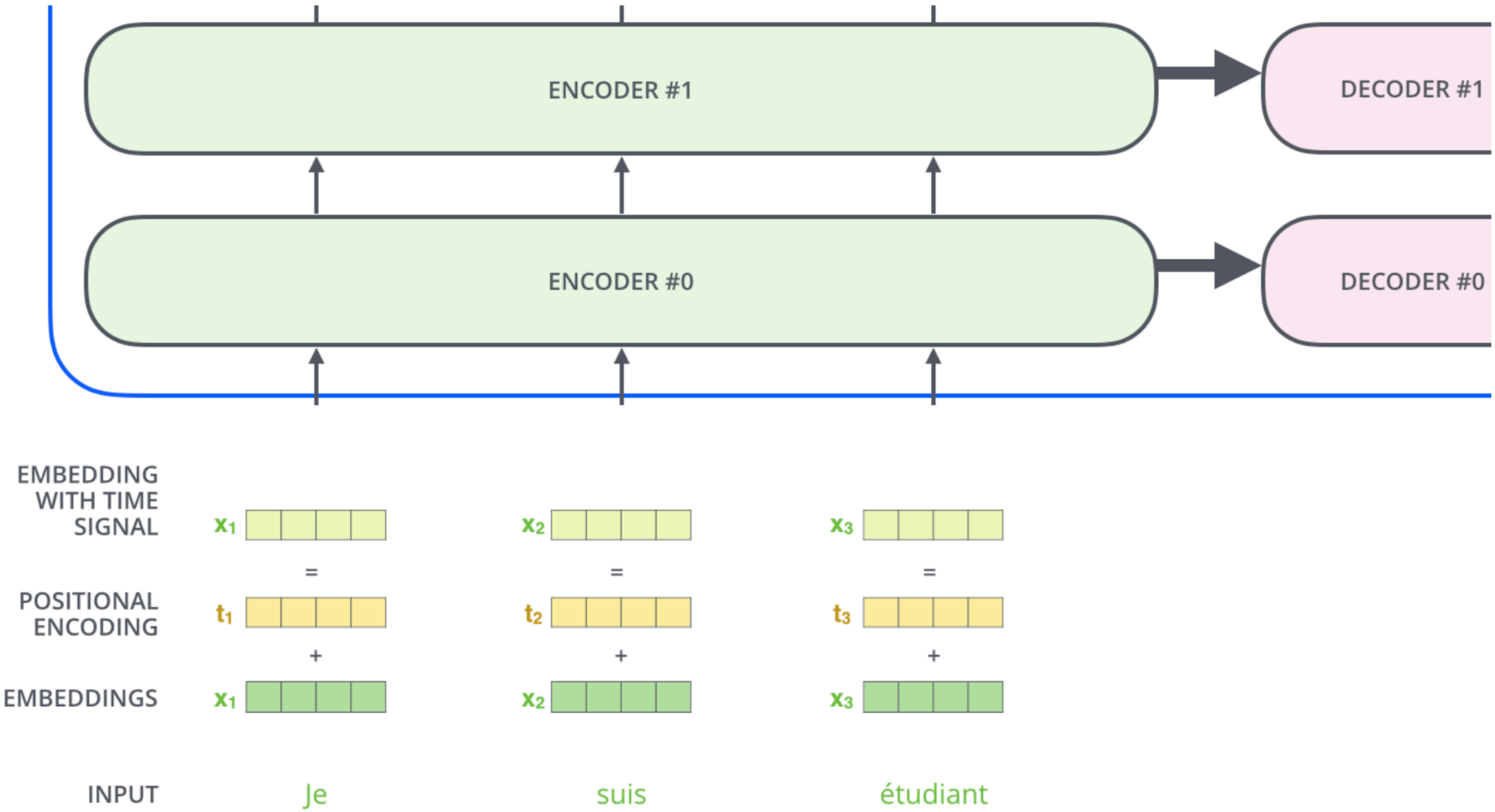
Но ведь нам нужно обрабатывать последовательности…

Positional Encoding



The Illustrated Transformer

Positional Encoding

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

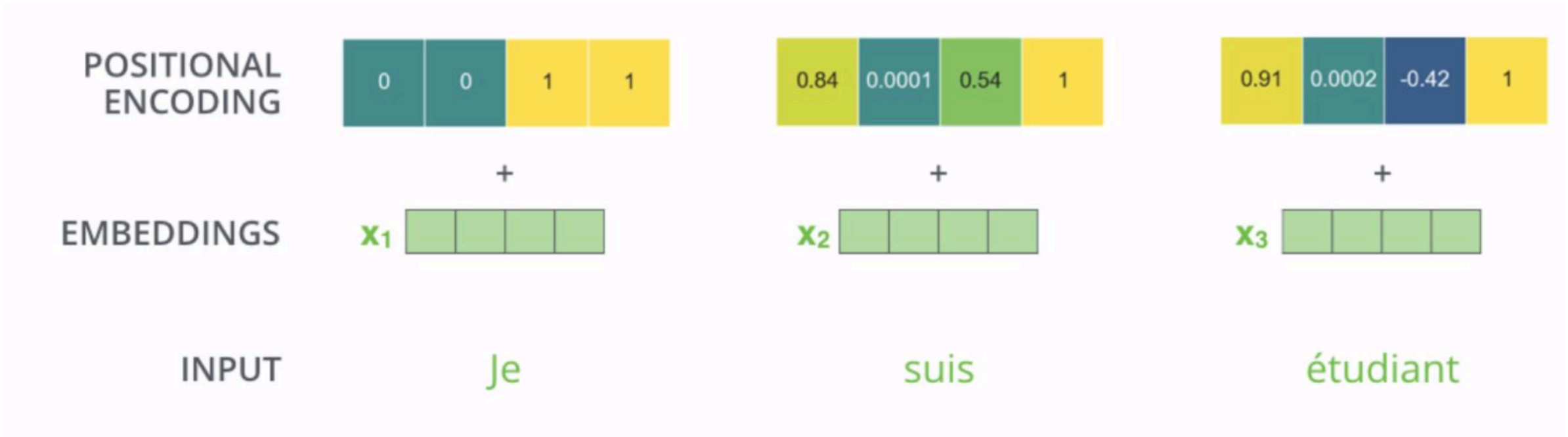
$$PE_{(pos,\ 2i+1)} = cos(pos\ /\ 10000^{2i\ /\ d_{\text{model}}})$$

- *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

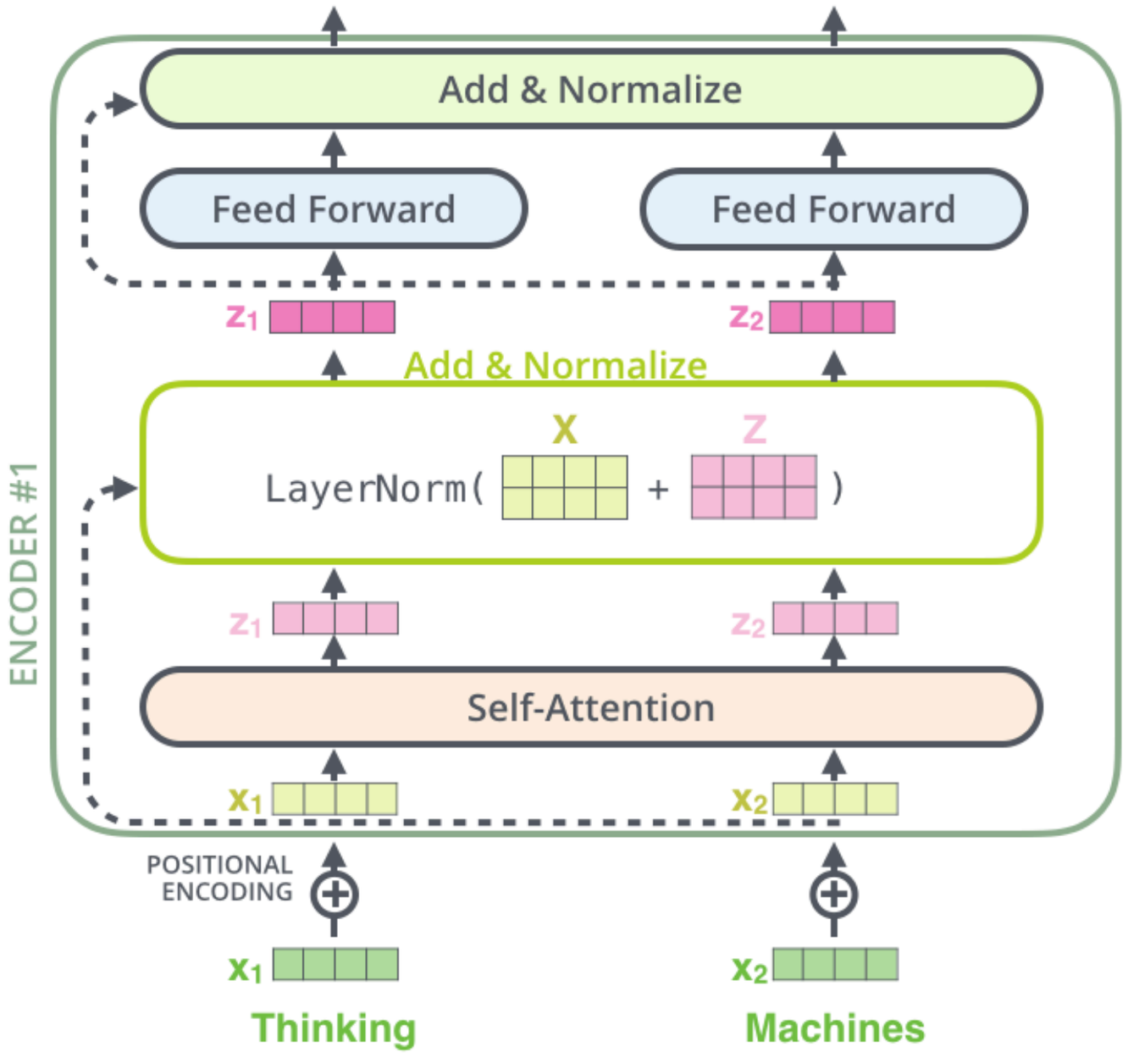
https://github.com/ml-mipt/ml-mipt/blob/advanced/week04_Transformer/week04_Transformer.pdf

Positional Encoding

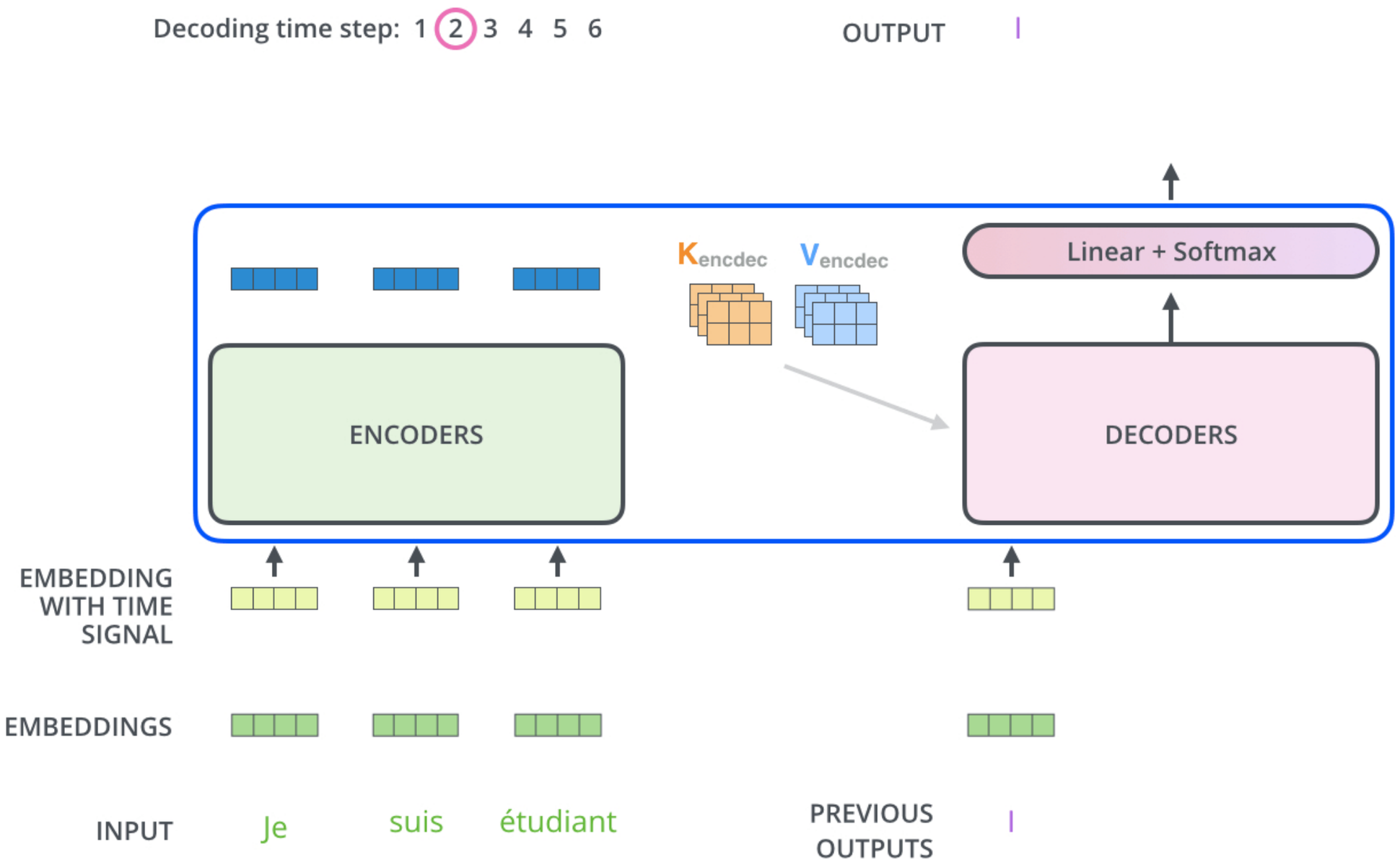


https://github.com/ml-mipt/ml-mipt/blob/advanced/week04_Transformer/week04_positional_encoding_carriers.ipynb

The Residuals & layer-normalization



Self-Attention



The Illustrated Transformer

Output Probabilities

Softmax

Linear

Stage 5

Add & Norm

Feed Forward

Stage 4

Add & Norm

Multi-Head Attention

Add & Norm

Masked Multi-Head Attention

Stage 3

Nx

Add & Norm

Feed Forward

Add & Norm

Multi-Head Attention

ge 2 Nx

sitional coding

Input Embedding

Inputs

Positional Encoding

Output Embedding

Outputs (shifted right)