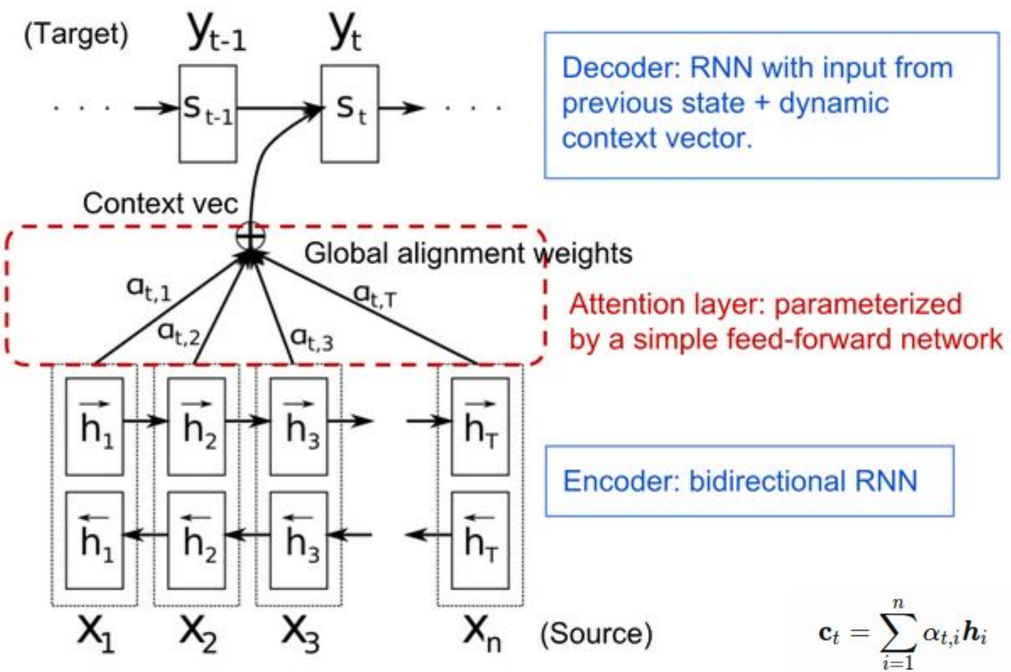
Трансформер

(в схемах и мемах)

Мотивация

- Обучение RNN - трудоёмкая задача
- Хотим избавиться от RNN, не теряя возможность учитывать дальнодействующие зависимости между словами
- Оказывается, что можно обойтись механизмом Внимания



Additive Attention

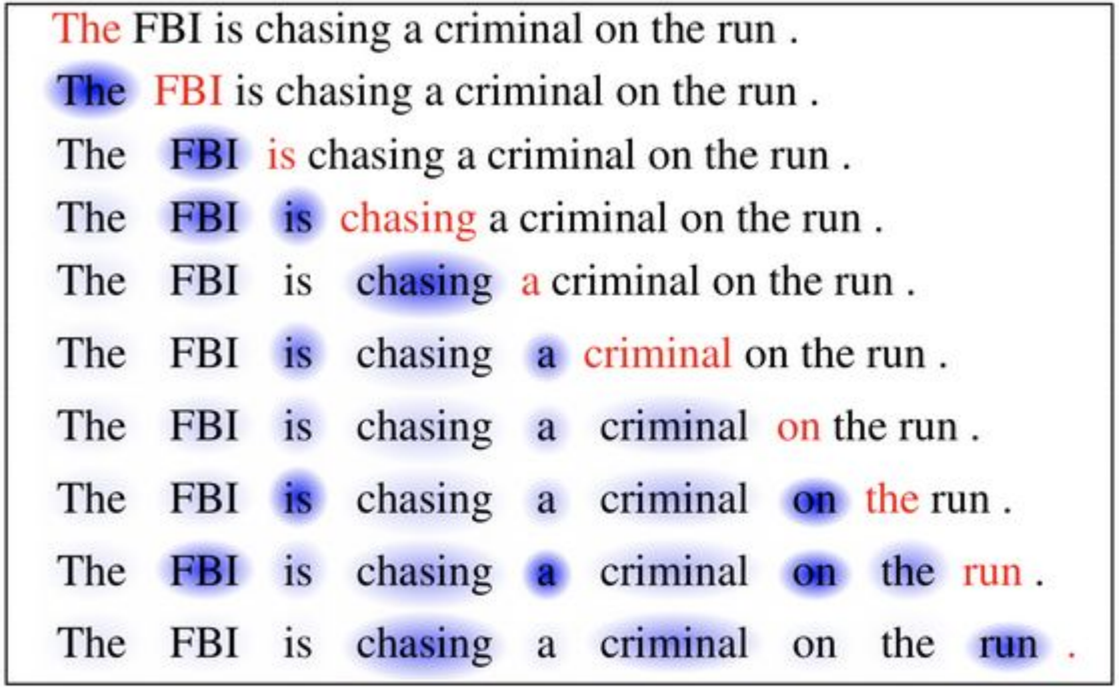
$$\boldsymbol{h}_i = [\overrightarrow{\boldsymbol{h}}_i^\top ; \overleftarrow{\boldsymbol{h}}_i^\top]^\top, i = 1, \dots, n$$

$$\boldsymbol{s}_t = f(\boldsymbol{s}_{t-1}, y_{t-1}, \mathbf{c}_t)$$

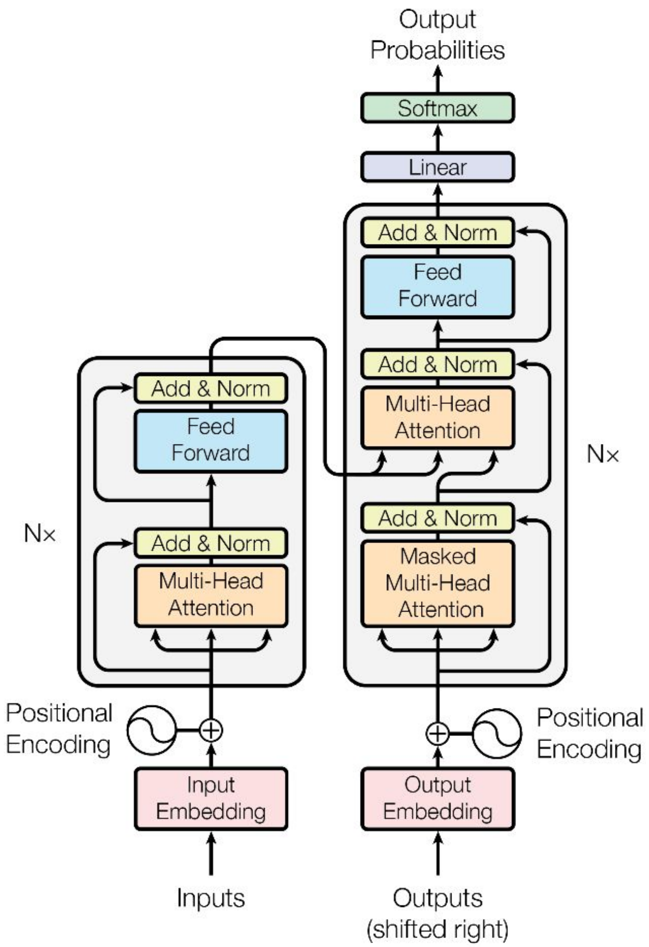
$$\mathbf{c}_t = \sum_{i=1}^{n} \alpha_{t,i} \boldsymbol{h}_i \quad \text{; Context vector for output } y_t$$

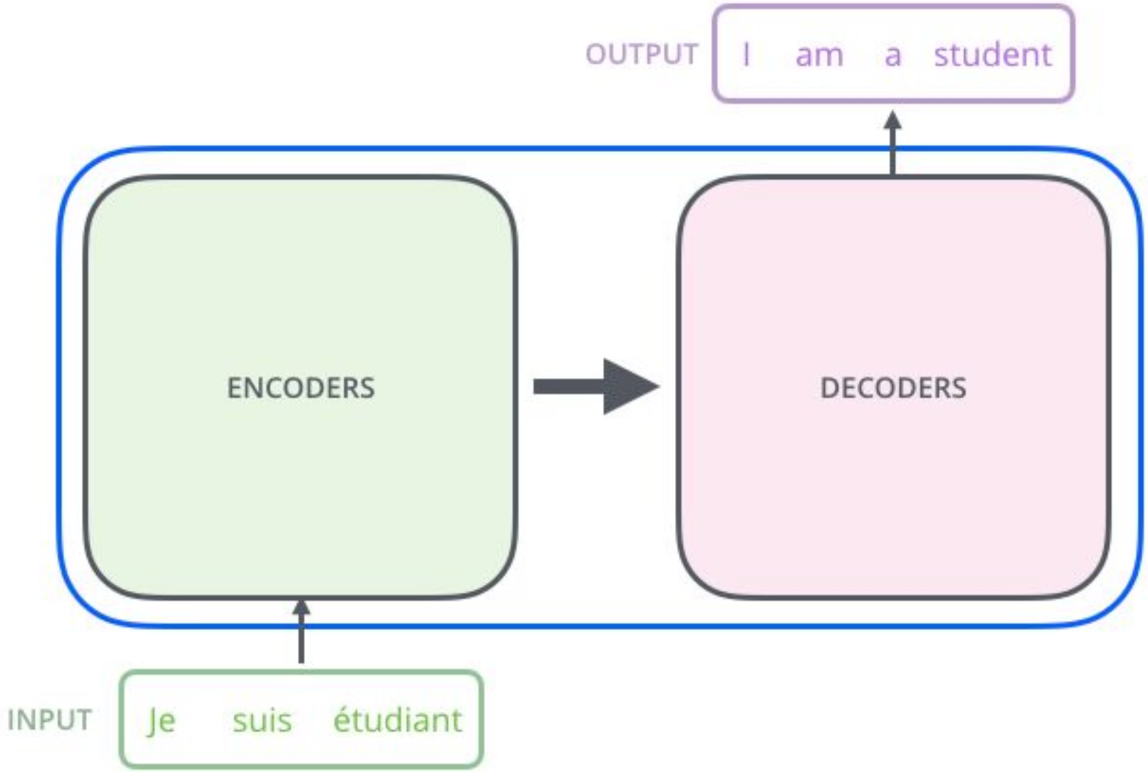
$$\alpha_{t,i} = \text{align}(y_t, x_i) \quad \text{; How well two words } y_t \text{ and } x_i \text{ are aligned.}$$

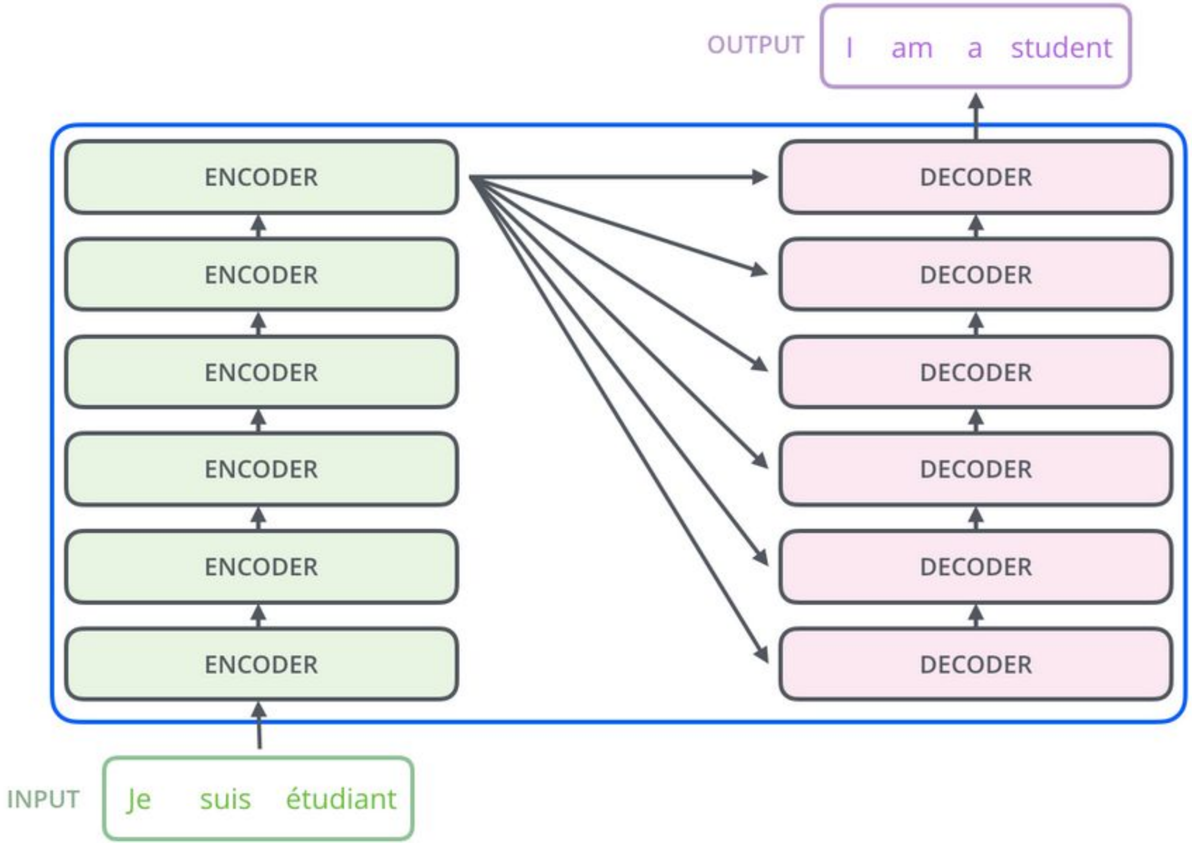
$$= \frac{\exp(\text{score}(\boldsymbol{s}_{t-1}, \boldsymbol{h}_i))}{\sum_{i'=1}^{n} \exp(\text{score}(\boldsymbol{s}_{t-1}, \boldsymbol{h}_{i'}))} \quad \text{; Softmax of some predefined alignment score..}$$

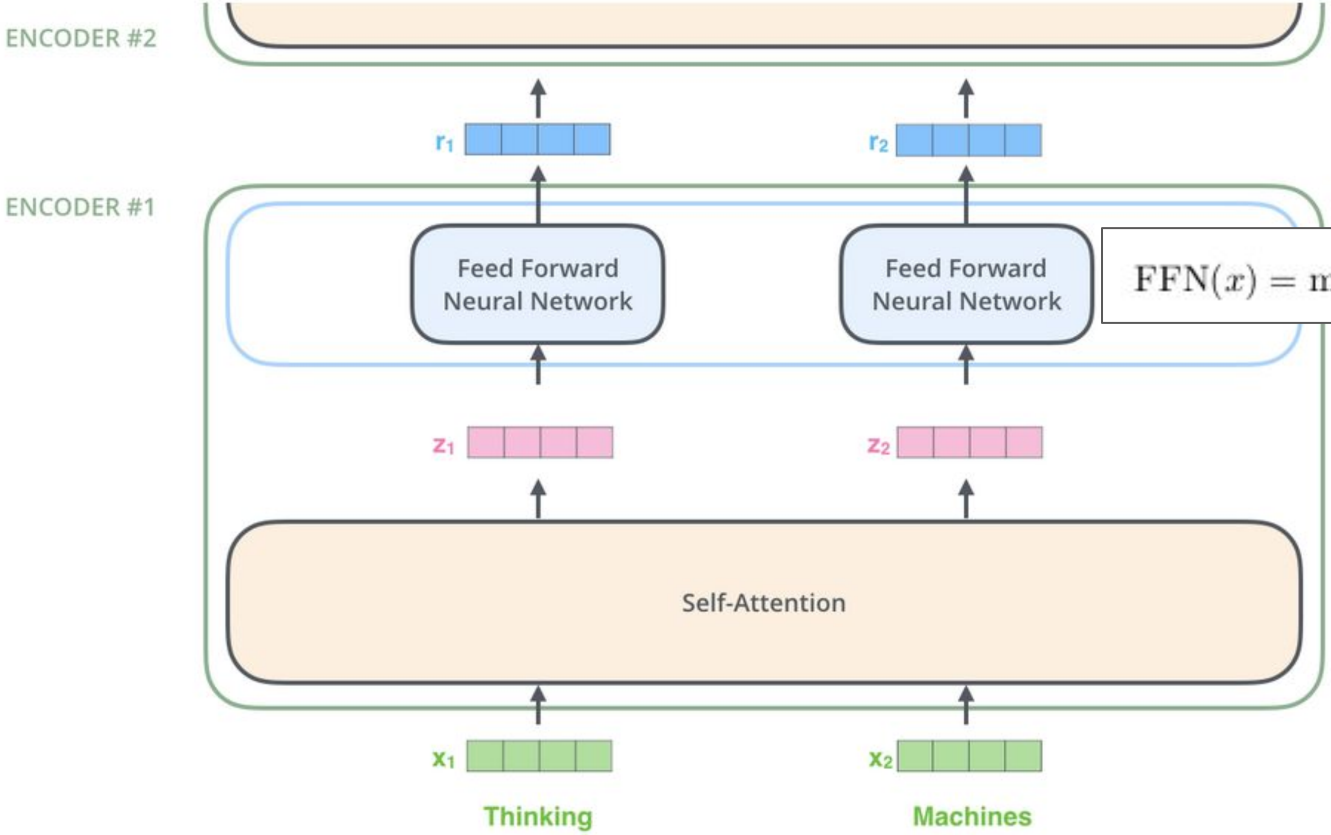

The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .
The FBI is chasing a criminal on the run .

Name	Alignment score function	Citation
Content-base attention	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \text{cosine}[\boldsymbol{s}_t, \boldsymbol{h}_i]$	Graves2014
Additive(*)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \mathbf{v}_a^\top \tanh(\mathbf{W}_a[\boldsymbol{s}_t; \boldsymbol{h}_i])$	Bahdanau2015
Location-Base	$\alpha_{t,i} = \text{softmax}(\mathbf{W}_a \boldsymbol{s}_t)$ Note: This simplifies the softmax alignment to only depend on the target position.	Luong2015
General	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \mathbf{W}_a \boldsymbol{h}_i$ where $\mathbf{W}_a$ is a trainable weight matrix in the attention layer.	Luong2015
Dot-Product	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \boldsymbol{h}_i$	Luong2015
Scaled Dot-Product(^)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \frac{\boldsymbol{s}_t^\top \boldsymbol{h}_i}{\sqrt{n}}$ Note: very similar to the dot-product attention except for a scaling factor; where n is the dimension of the source hidden state.	Vaswani2017

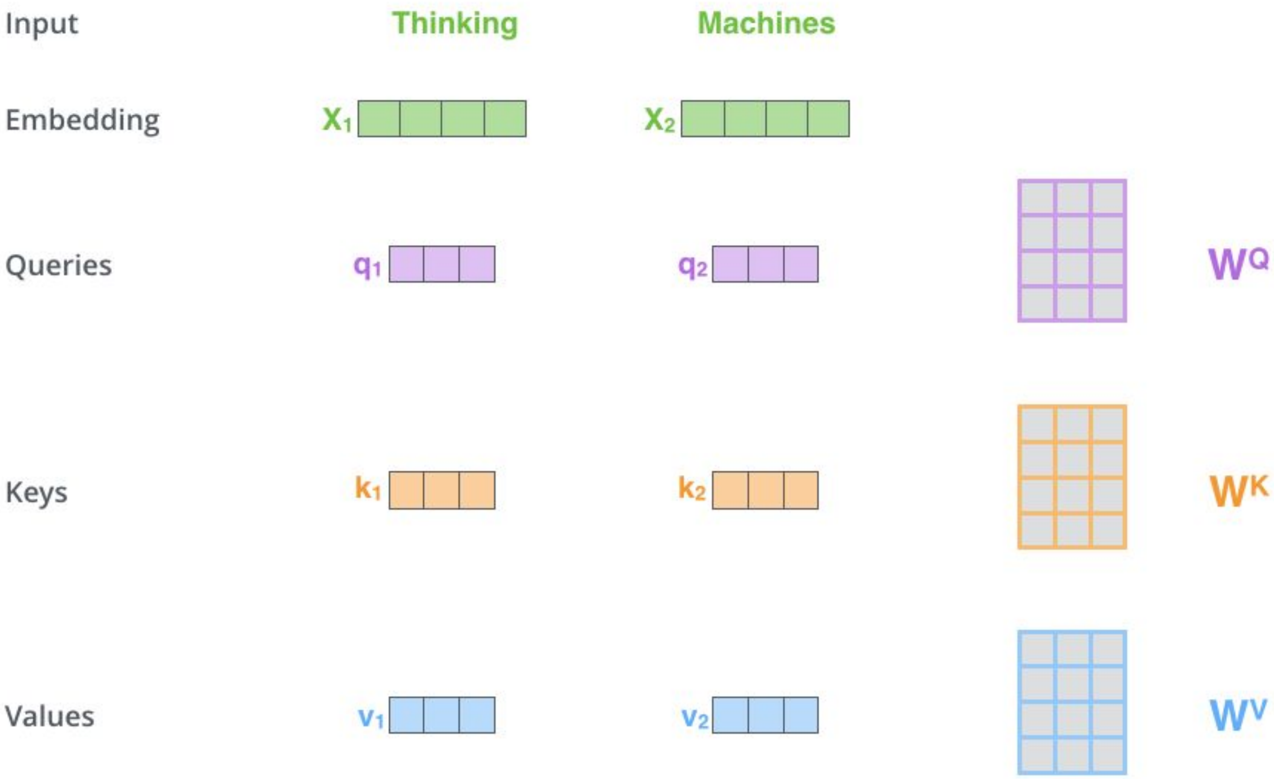

Output
Probabilities
Softmax
Linear
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Add & Norm
Masked
Multi-Head
Attention
Add & Norm
Feed
Forward
Nx
Add & Norm
Multi-Head
Attention
Positional
Encoding
Positional
Encoding
Input
Embedding
Output
Embedding
Inputs
Outputs
(shifted right)


OUTPUT
I am a student
ENCODERS
DECODERS
INPUT
Je suis étudiant

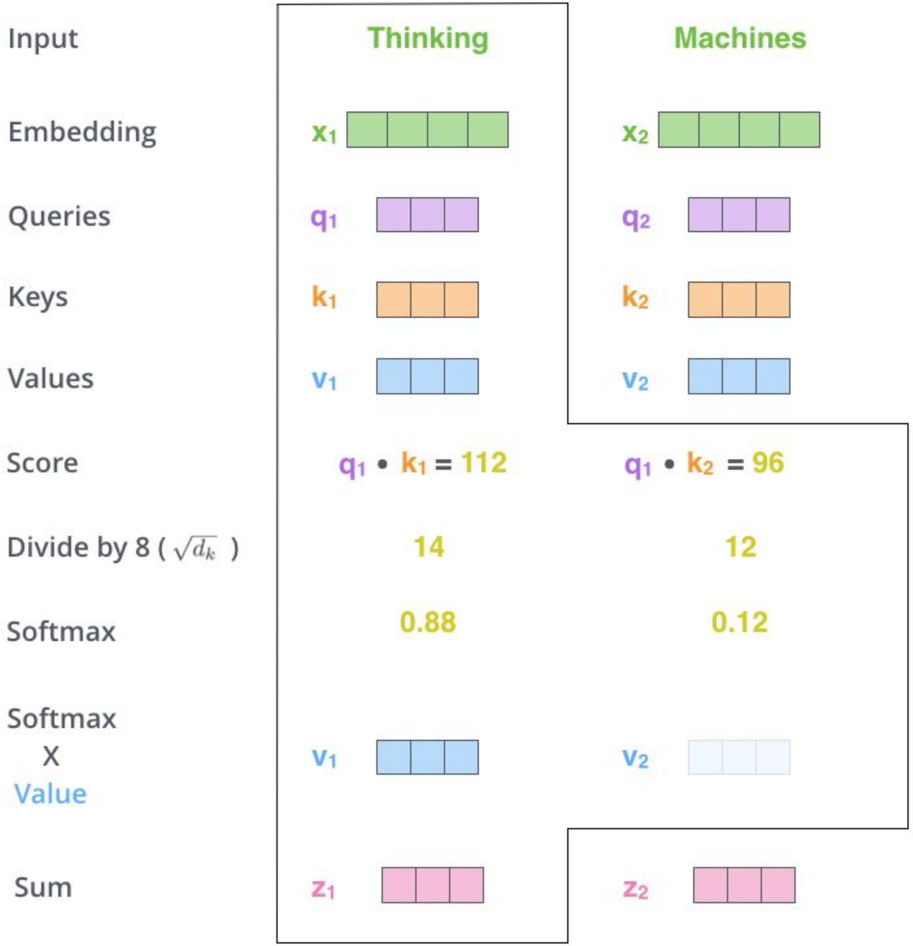

OUTPUT
I am a student
ENCODER
ENCODER
ENCODER
ENCODER
ENCODER
ENCODER
DECODER
DECODER
DECODER
DECODER
DECODER
DECODER
INPUT
Je suis étudiant

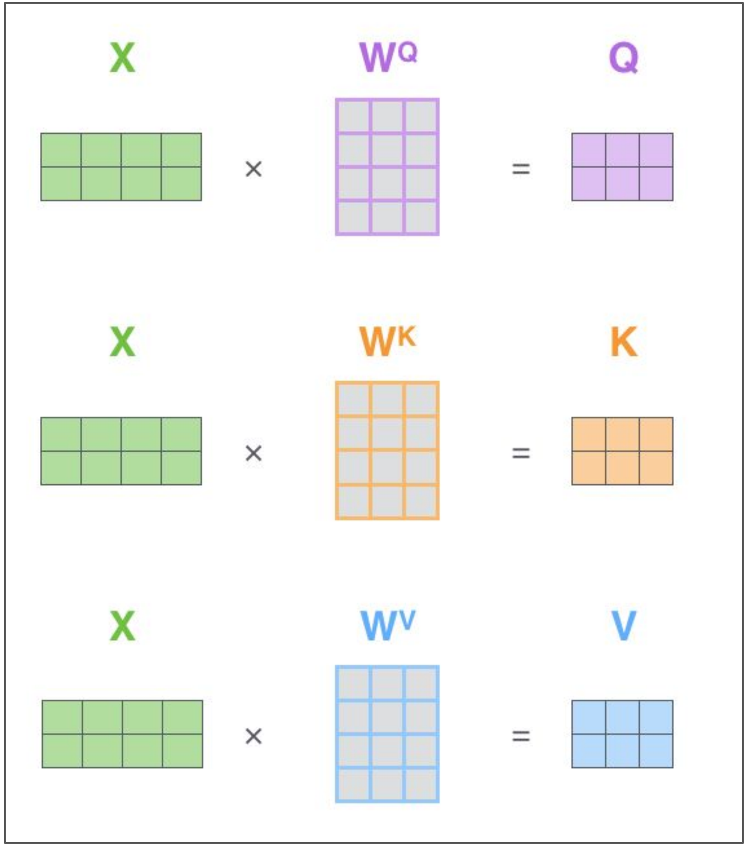


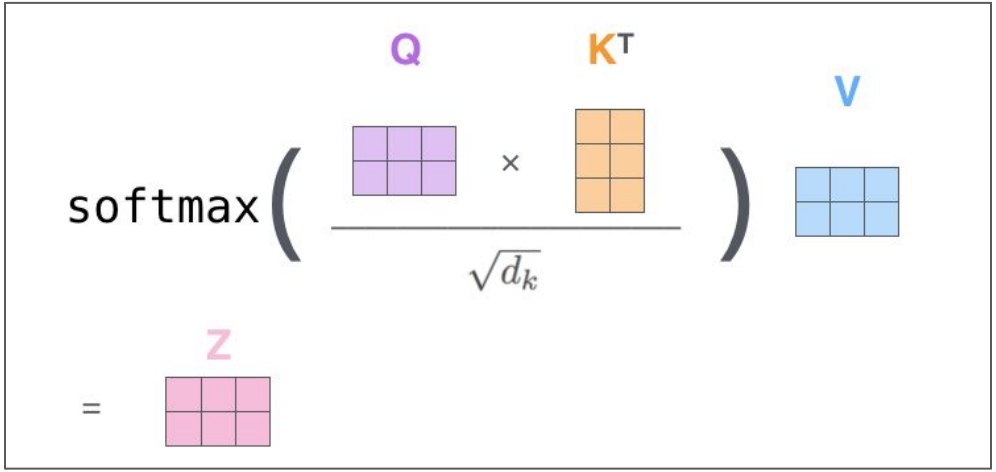
$$\mathrm{FFN}(x) = \max(0, \mathbf{z}W_1 + b_1)W_2 + b_2$$



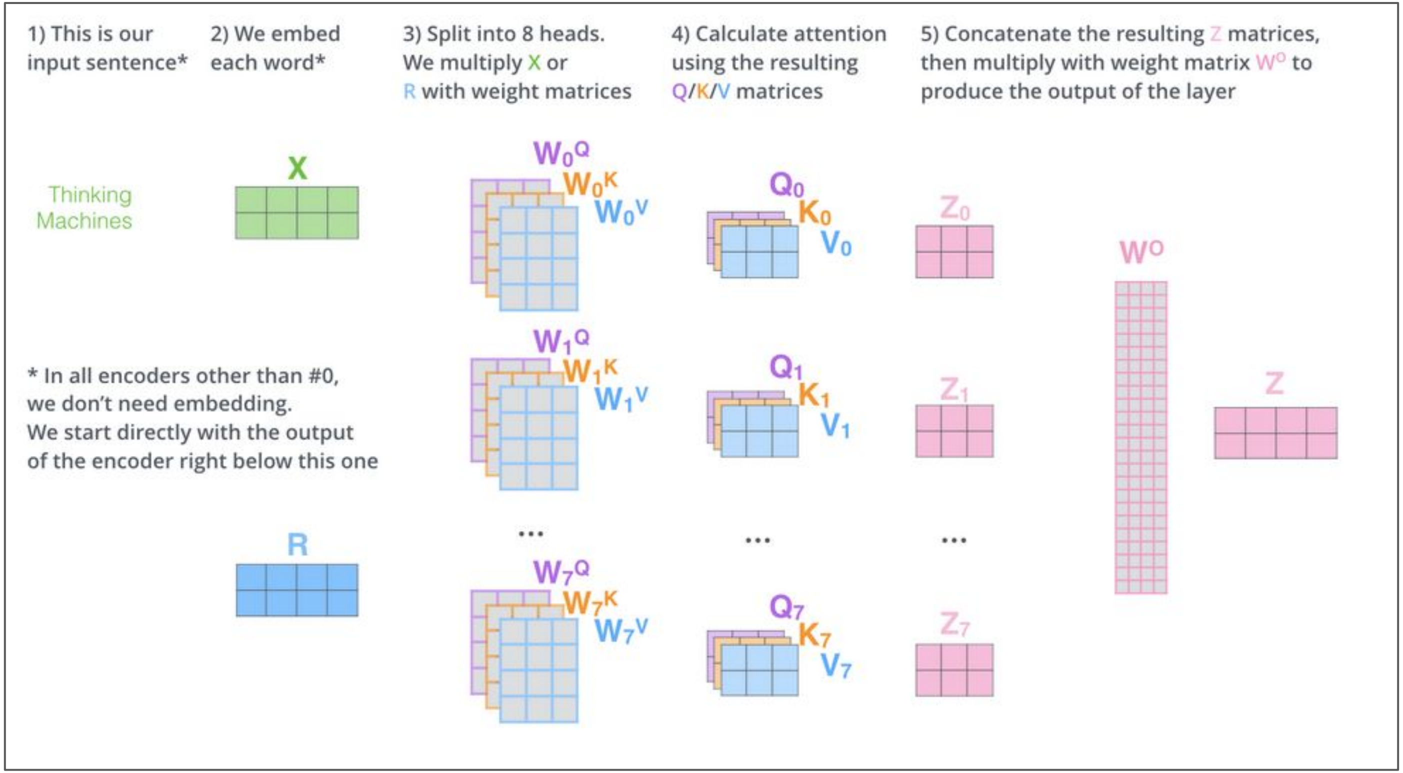
Input
Thinking
Machines
Embedding
X_1
X_2
Queries
q_1
q_2
W^Q
Keys
k_1
k_2
W^K
Values
v_1
v_2
W^V


Input
Thinking
Machines
Embedding
x_1
x_2
Queries
q_1
q_2
Keys
k_1
k_2
Values
v_1
v_2
Score
$q_1 \bullet k_1 = 112$
$q_1 \bullet k_2 = 96$
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12
Softmax
X
Value
v_1
v_2
Sum
z_1
z_2





$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{n}})\mathbf{V}$$



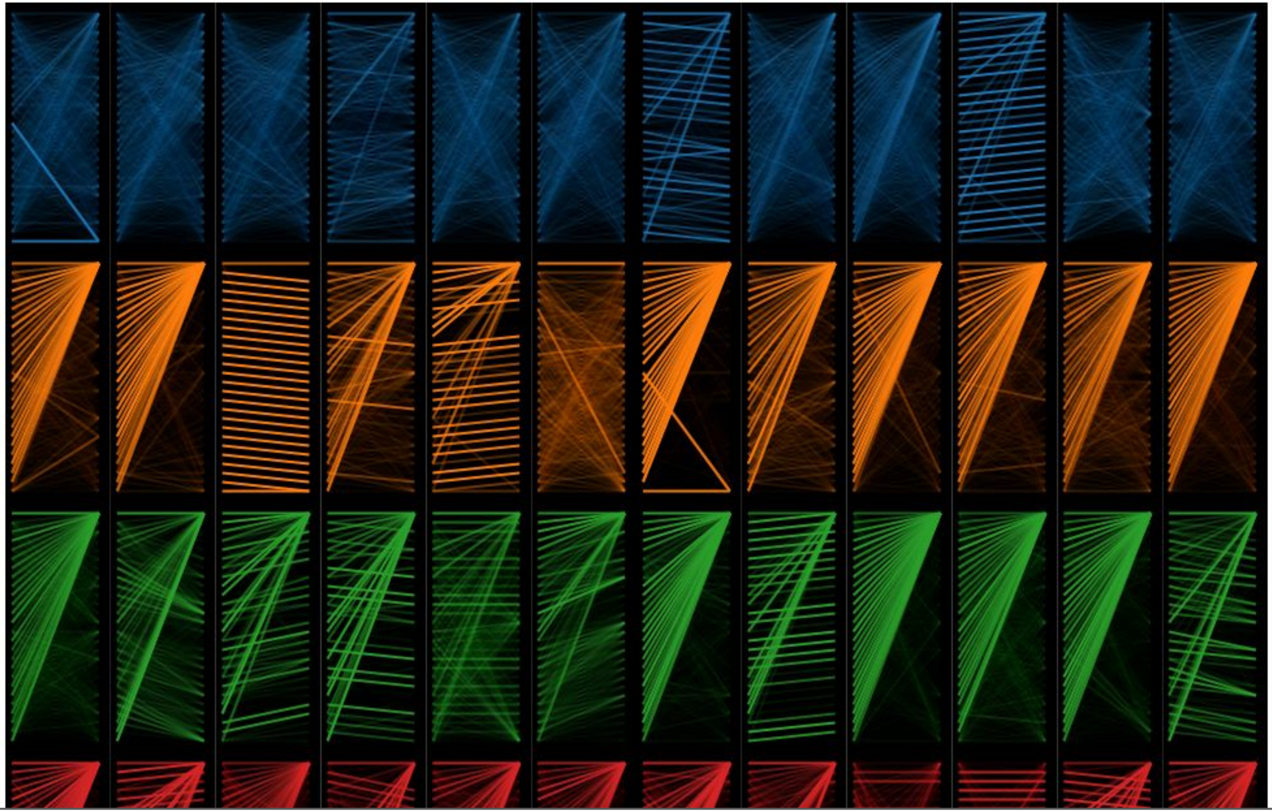
$$\mathrm{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = [\mathrm{head}_1; \ldots; \mathrm{head}_h]\mathbf{W}^O$$

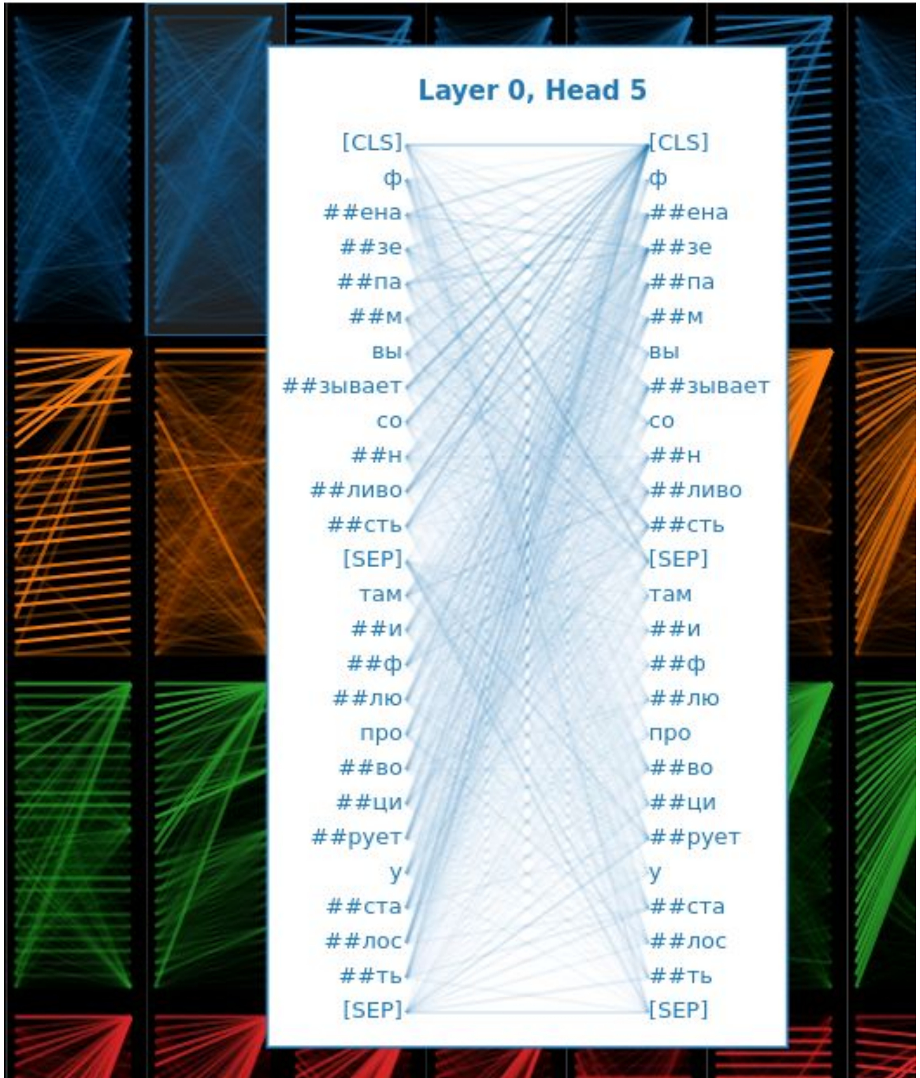
$$\text{where } \mathrm{head}_i = \mathrm{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V)$$

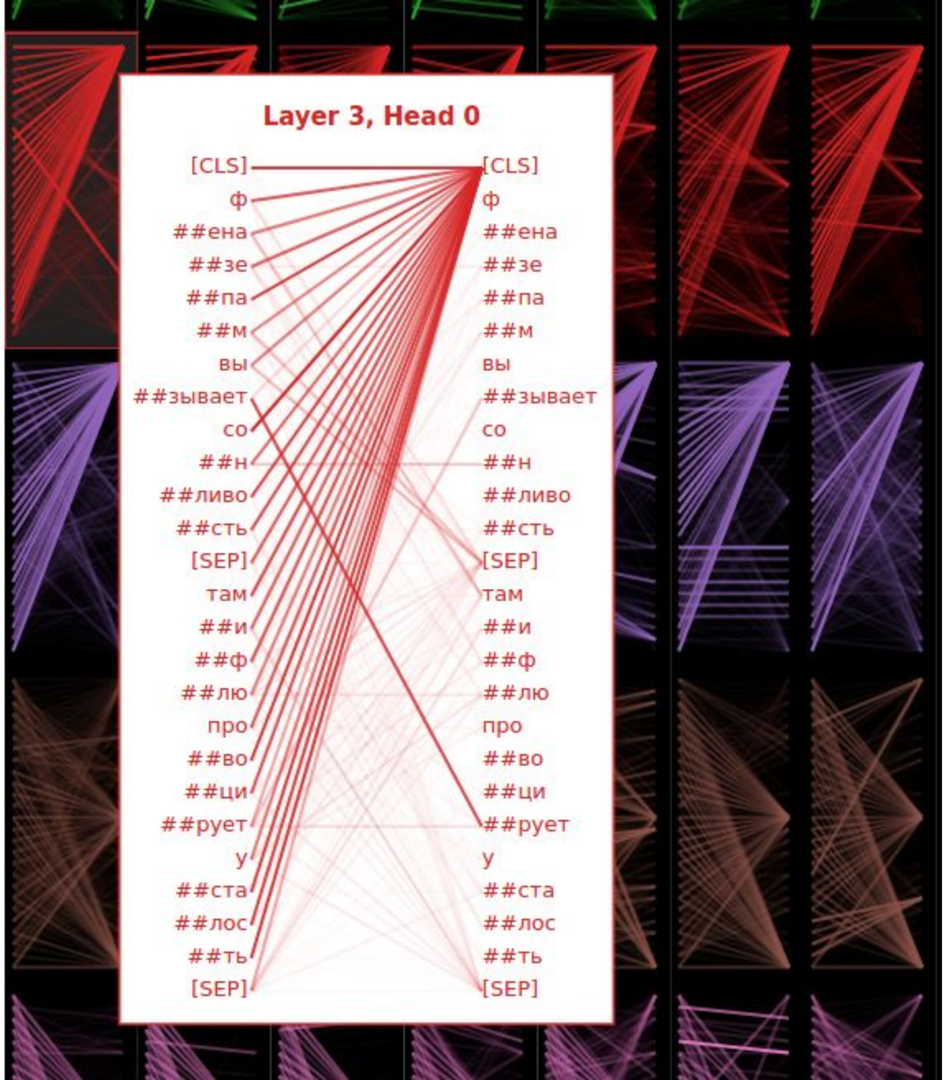
where $\mathbf{W}_i^Q$, $\mathbf{W}_i^K$, $\mathbf{W}_i^V$, and $\mathbf{W}^O$ are parameter matrices to be learned.

```python
from bertviz import model_view

call_html()
model_view(attention, tokens)
```



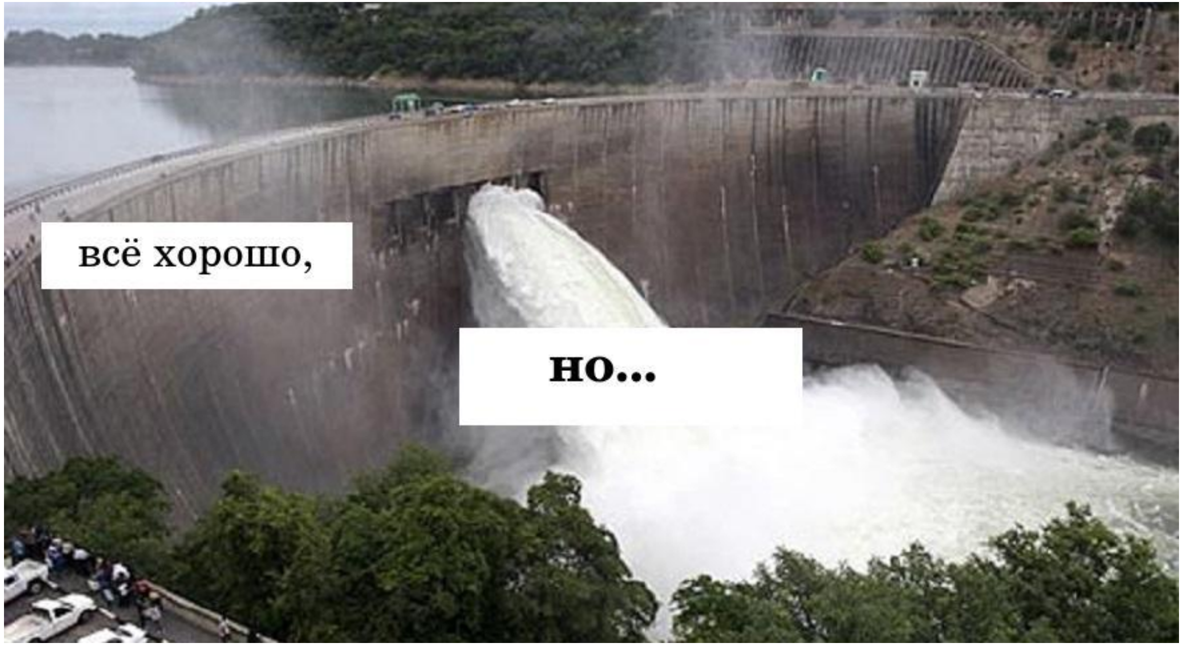

Layer 0, Head 5
[CLS]
ф
##ена
##зе
##па
##м
вы
##зывает
со
##н
##ливо
##сть
[SEP]
там
##и
##ф
##лю
про
##во
##ци
##рует
у
##ста
##лос
##ть
[SEP]

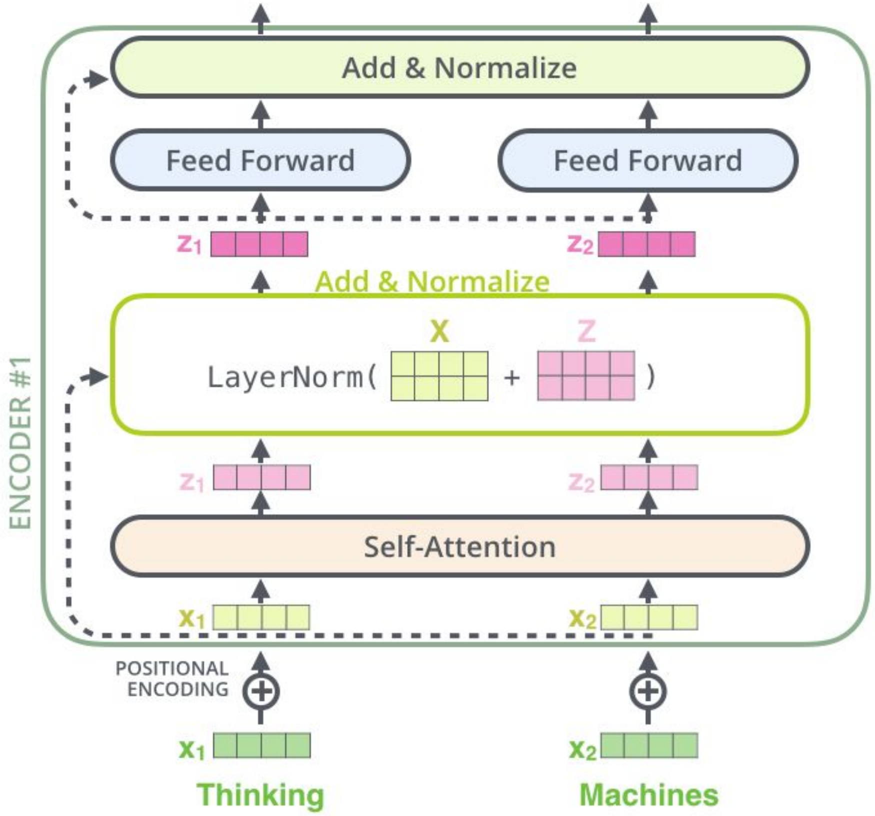


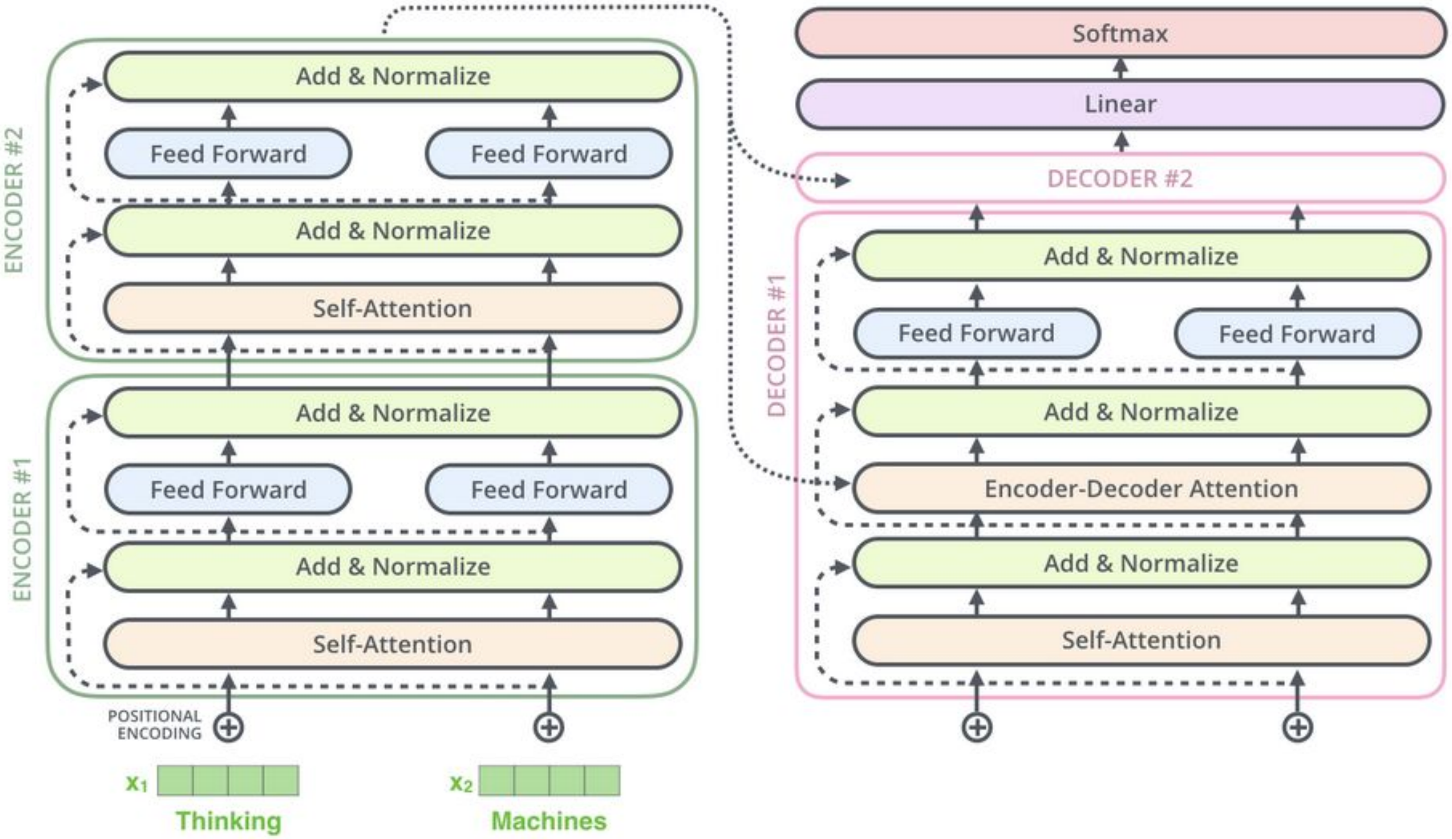
Layer 3, Head 0
[CLS]
ф
##ена
##зе
##па
##м
вы
##зывает
со
##н
##ливо
##сть
[SEP]
там
##и
##ф
##лю
про
##во
##ци
##рует
у
##ста
##лос
##ть
[SEP]

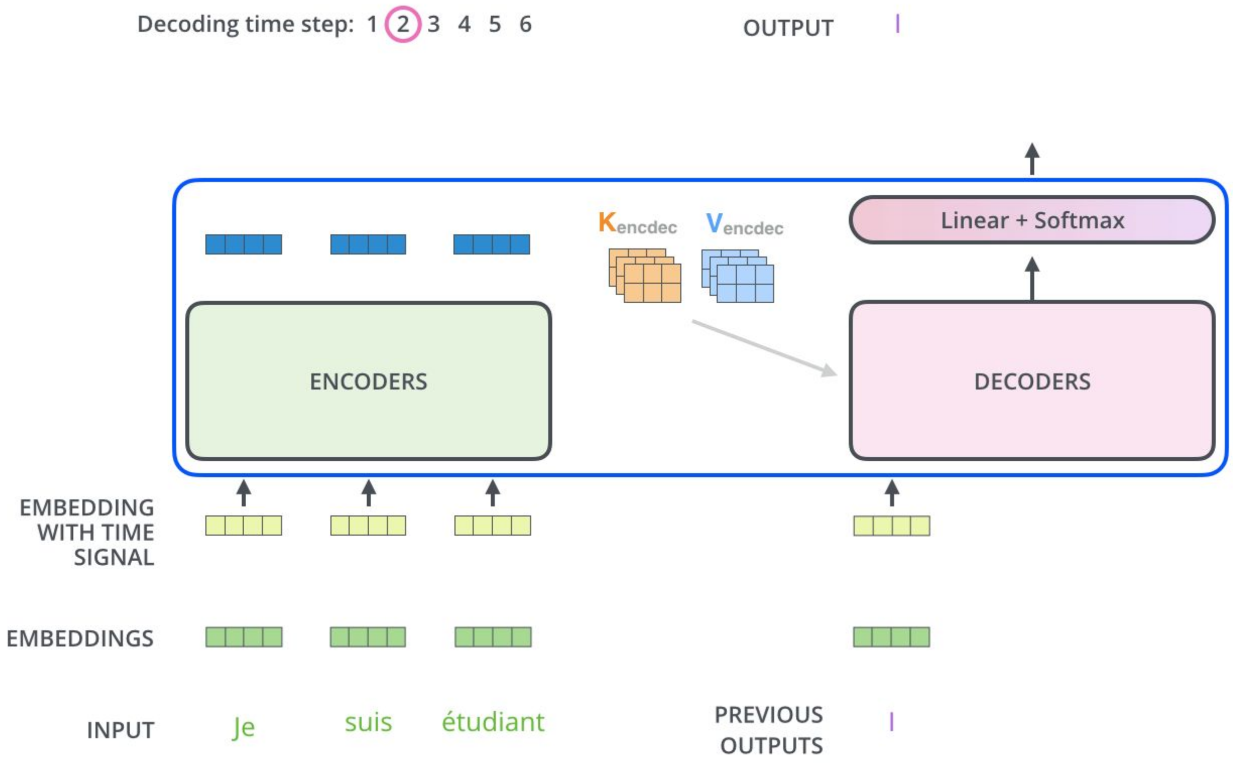
Ну всё, можно уже стакать слои?

Ну всё, можно уже стакать слои?

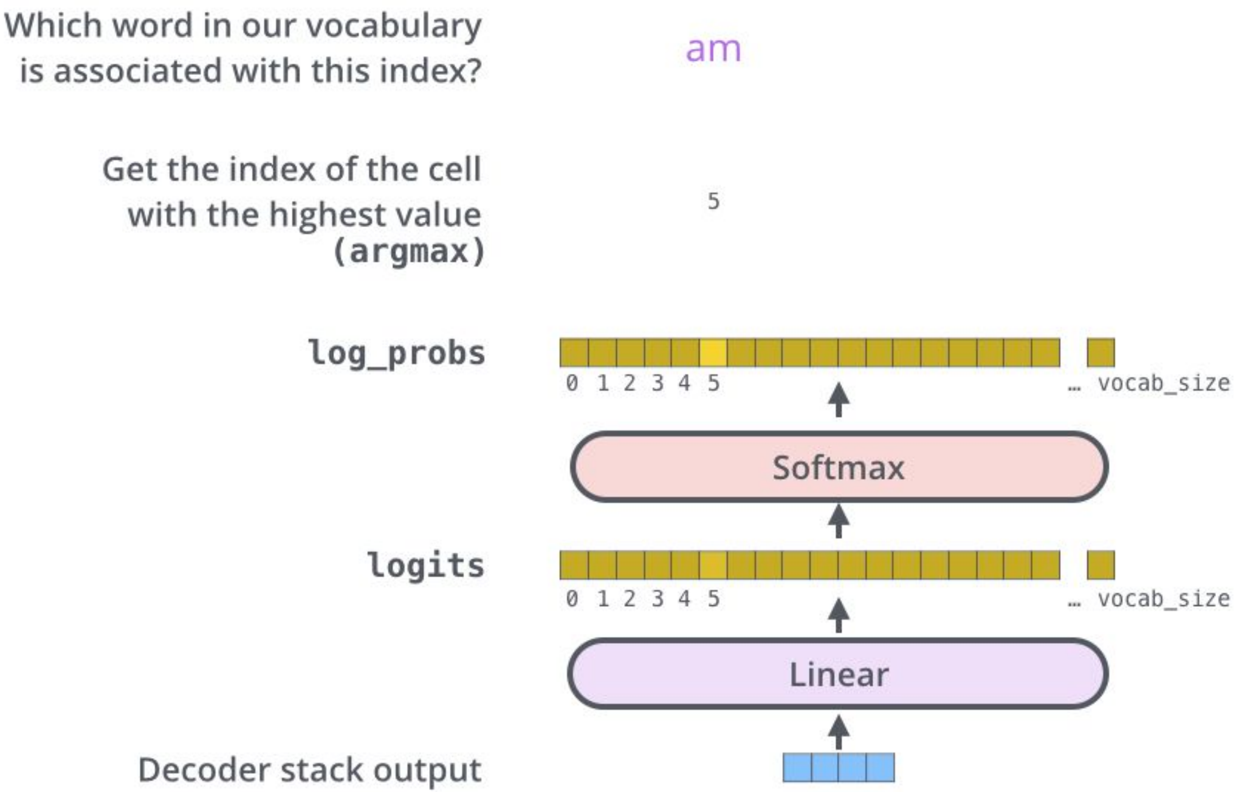



Add & Normalize
Feed Forward
Feed Forward
z1
z2
Add & Normalize
X
Z
LayerNorm(+)
z1
z2
Self-Attention
x1
x2
ENCODER #1
POSITIONAL
ENCODING
x1
x2
Thinking
Machines


Softmax
Linear
DECODER #2
ENCODER #2
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
ENCODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
POSITIONAL ENCODING
x1
Thinking
x2
Machines
DECODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Encoder-Decoder Attention
Add & Normalize
Self-Attention



Decoding time step: 1 2 3 4 5 6
OUTPUT
I
Kencdec
Vencdec
Linear + Softmax
ENCODERS
DECODERS
EMBEDDING WITH TIME SIGNAL
EMBEDDINGS
INPUT
Je
suis
étudiant
PREVIOUS OUTPUTS
I

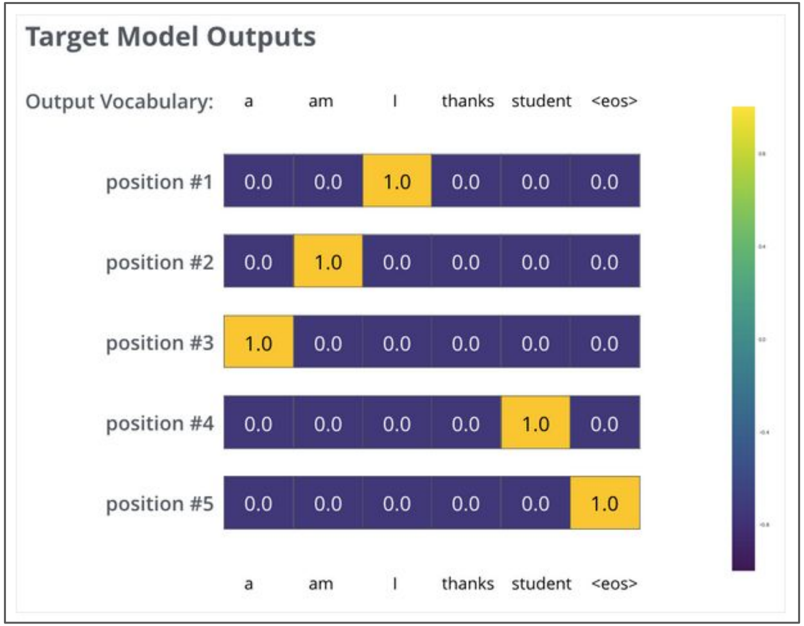

Which word in our vocabulary is associated with this index?
am
Get the index of the cell with the highest value (argmax)
5
log_probs
0 1 2 3 4 5 … vocab_size
Softmax
logits
0 1 2 3 4 5 … vocab_size
Linear
Decoder stack output

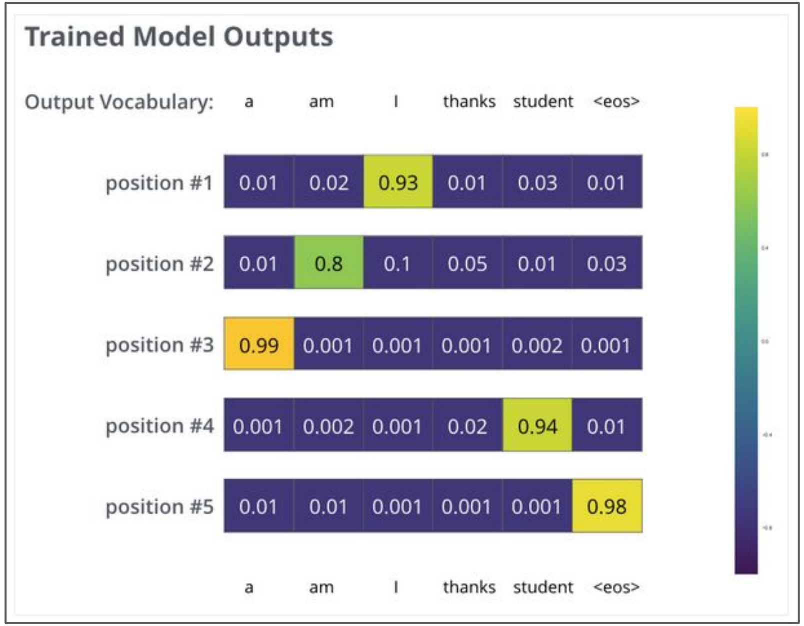
Output Vocabulary

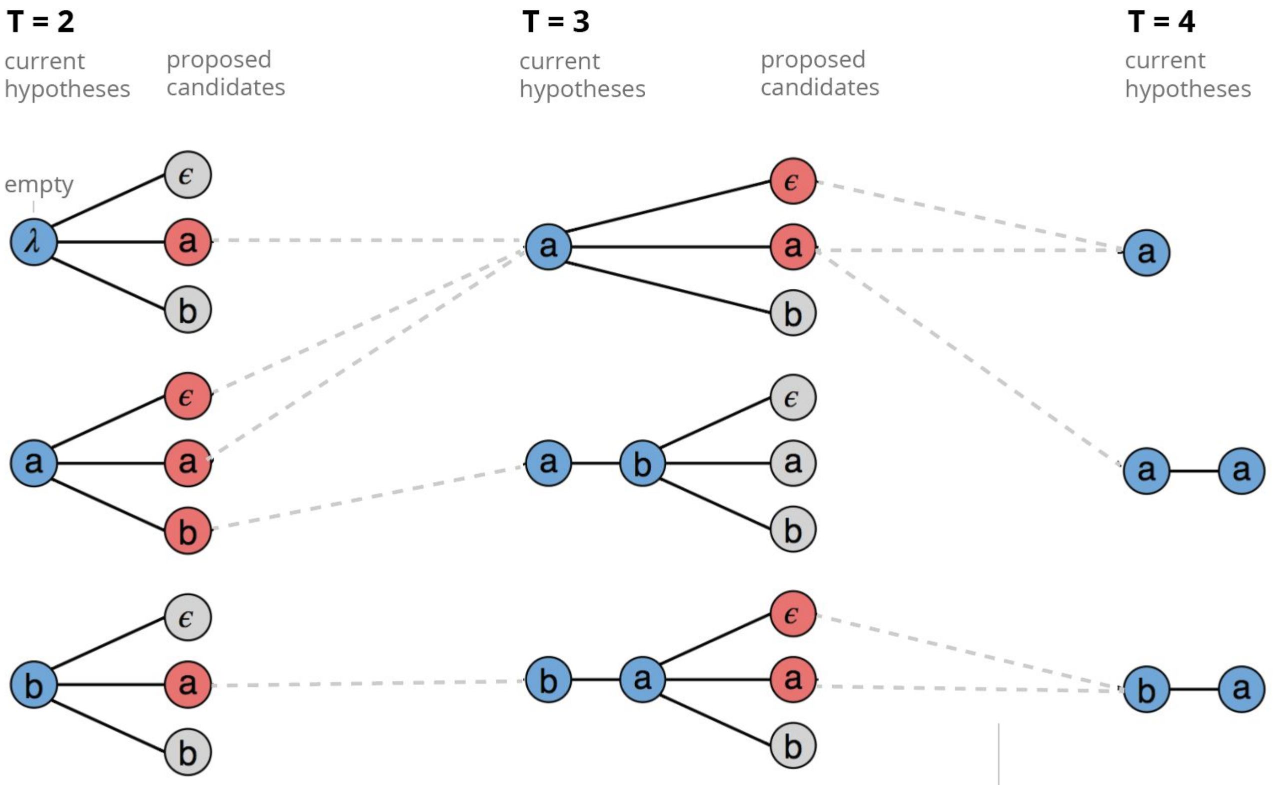
WORD	a	am	I	thanks	student	<eos>
INDEX	0	1	2	3	4	5

One-hot encoding of the word “am”

0.0	1.0	0.0	0.0	0.0	0.0







CTC beam search algorithm with an output alphabet {ε,a,b} and a beam size of three.

Multiple extensions can merge in to the same hypothesis.

Positional Encoding

- Смотрим на весь ввод сразу - теряем информацию о порядке слов
- Нужна функция, сопоставляющая слову его относительную позицию во входной последовательности
- Наивные варианты имеют ряд недостатков

Positional Encoding

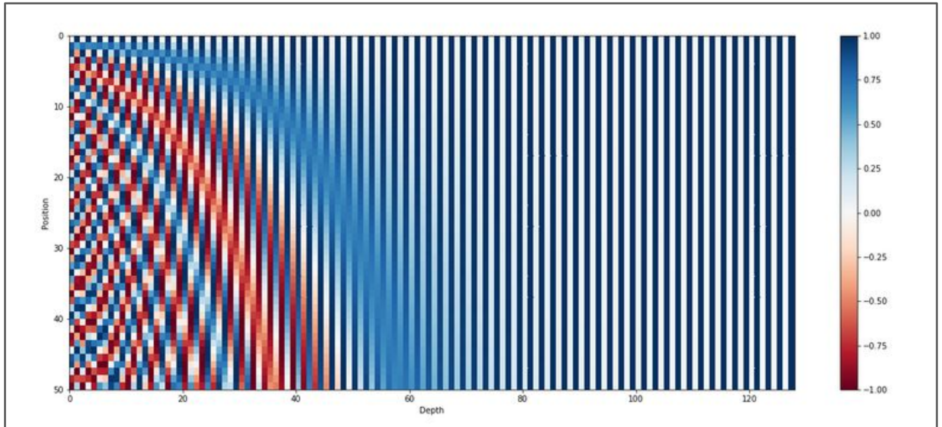
Что требуется от функции?

- Должна сопоставлять уникальную кодировку для каждого временного шага (позиции слова в предложении).
- Расстояние между любыми двумя временными шагами должно быть одинаковым в предложениях разной длины.
- Наша модель должна без каких-либо усилий обобщаться на более длинные предложения. Значения функции должны быть ограниченными.
- Отображение должно быть детерминированным.

Желаемая функция

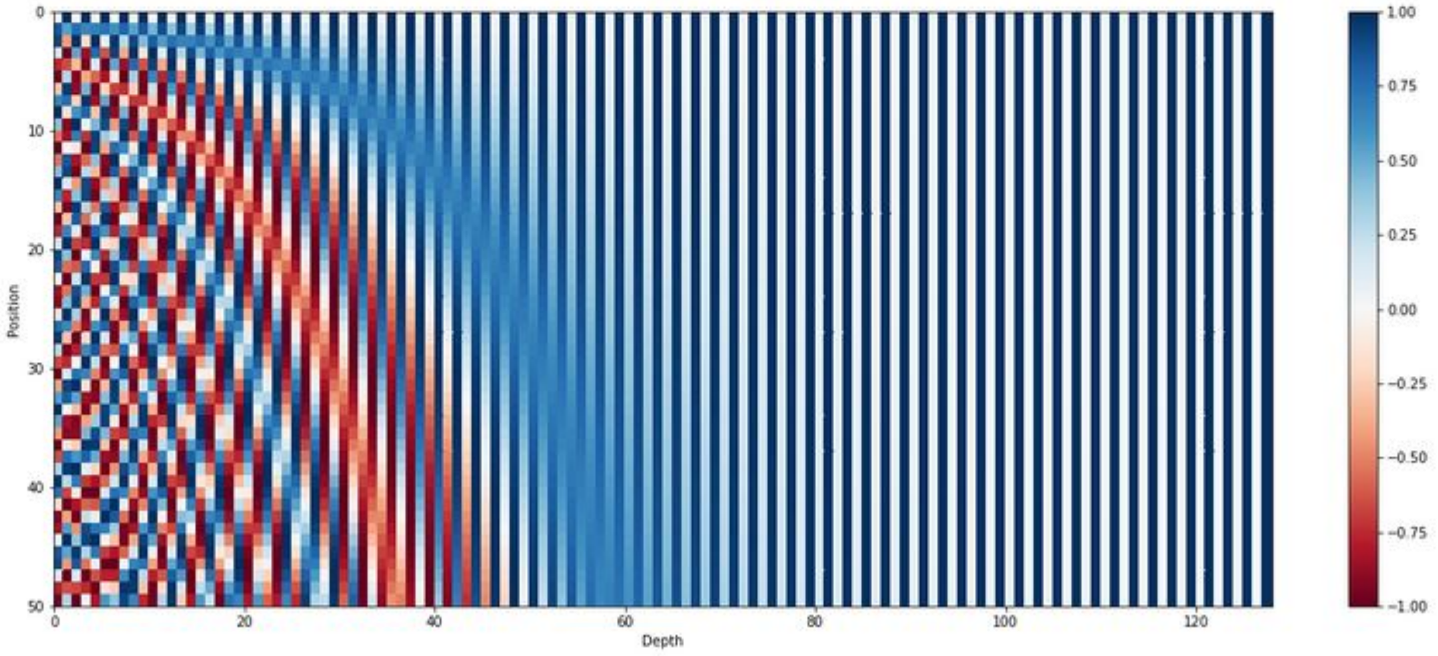
$$\vec{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases}$$

$$\omega_k = \frac{1}{10000^{2k/d}}$$

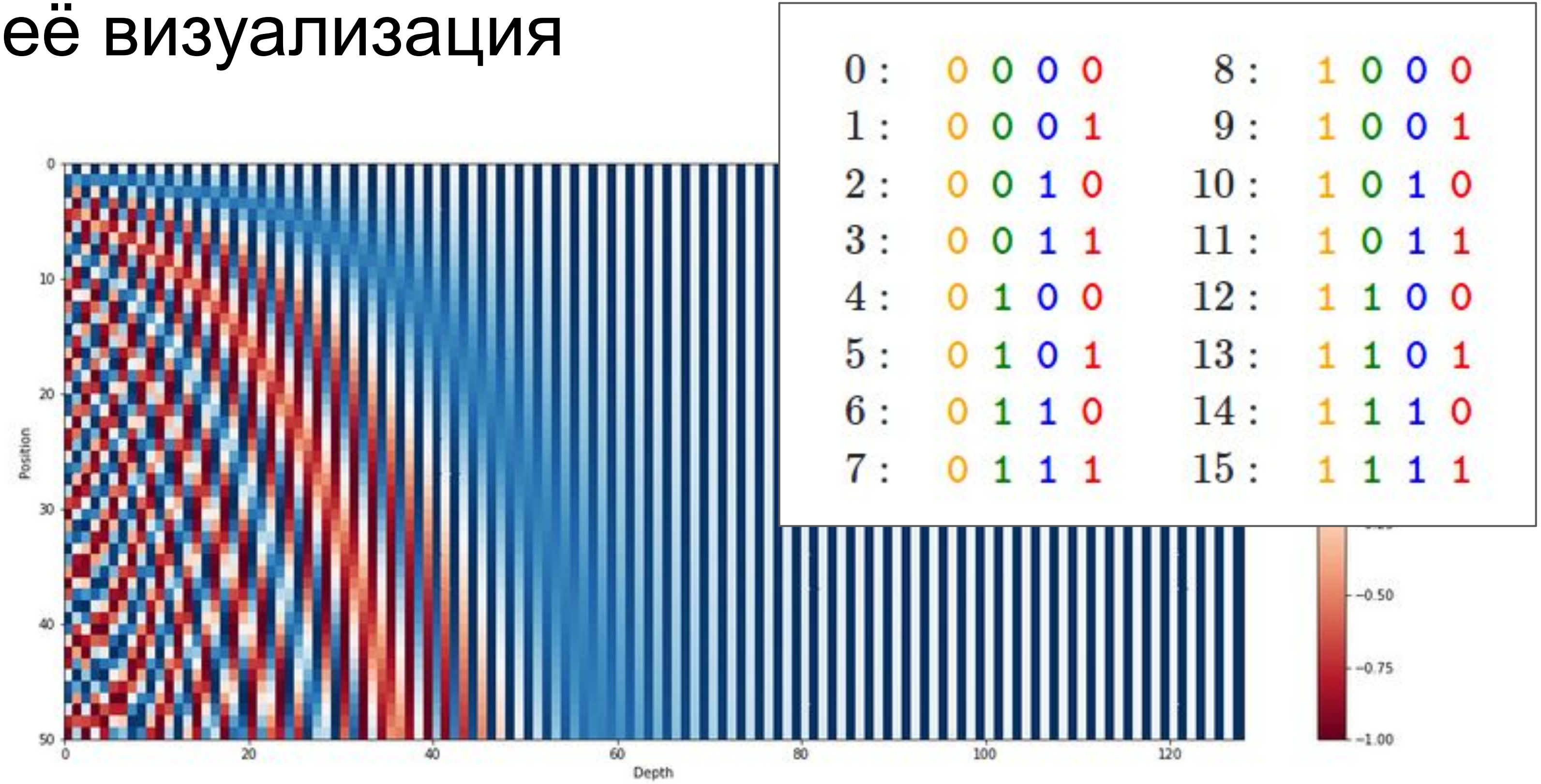


$$\vec{p_t} = \begin{bmatrix} \sin(\omega_1 . t) \\ \cos(\omega_1 . t) \\ \\ \sin(\omega_2 . t) \\ \cos(\omega_2 . t) \\ \\ \vdots \\ \\ \sin(\omega_{d/2} . t) \\ \cos(\omega_{d/2} . t) \end{bmatrix}_{d \times 1}$$

...И её визуализация



...И её визуализация



0 :	0	0	0	0	8 :	1	0	0	0
1 :	0	0	0	1	9 :	1	0	0	1
2 :	0	0	1	0	10 :	1	0	1	0
3 :	0	0	1	1	11 :	1	0	1	1
4 :	0	1	0	0	12 :	1	1	0	0
5 :	0	1	0	1	13 :	1	1	0	1
6 :	0	1	1	0	14 :	1	1	1	0
7 :	0	1	1	1	15 :	1	1	1	1

Label Smoothing + Residual Dropout

Formula of Label Smoothing

Label smoothing replaces one-hot encoded label vector *y_hot* with a mixture of *y_hot* and the uniform distribution:

```
y_ls = (1 - α) * y_hot + α / K
```

where K is the number of label classes, and α is a hyperparameter that determines the amount of smoothing. If $\alpha = 0$, we obtain the original one-hot encoded *y_hot*. If $\alpha = 1$, we get the uniform distribution.

Заключение

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Заключение

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

Ссылки на материалы

Вот они, слева направо!

https://arxiv.org/abs/1706.03762

https://www.youtube.com/watch?v=dQw4w9WgXcQ

https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html#whats-wrong-with-seq2seq-model

http://jalammar.github.io/illustrated-transformer/

https://kazemnejad.com/blog/transformer_architecture_positional_encoding/#what-is-positional-encoding-and-why-do-we-need-it-in-the-first-place

Thank you for your Attention ;)

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