

12

Attention :

Long Short-term Memory (LSTM)

RNN →

Forget gate:

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

Input gate:

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

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

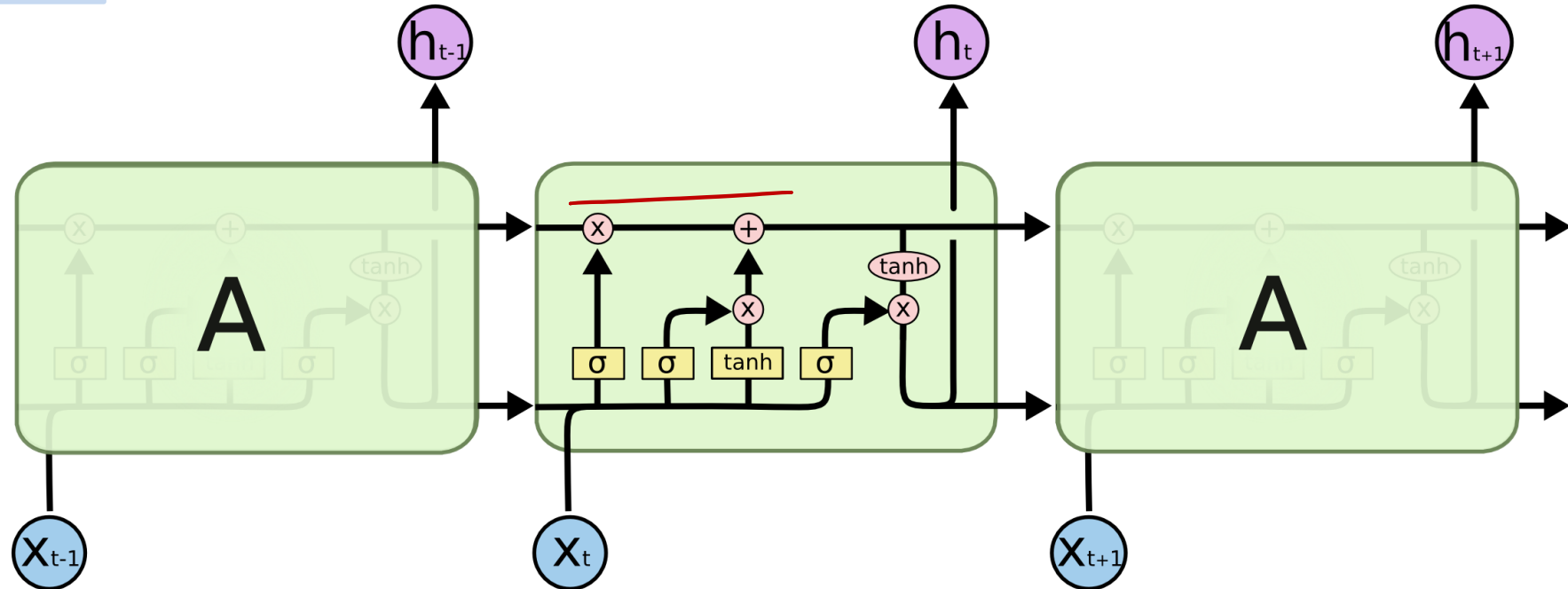
Cell update:

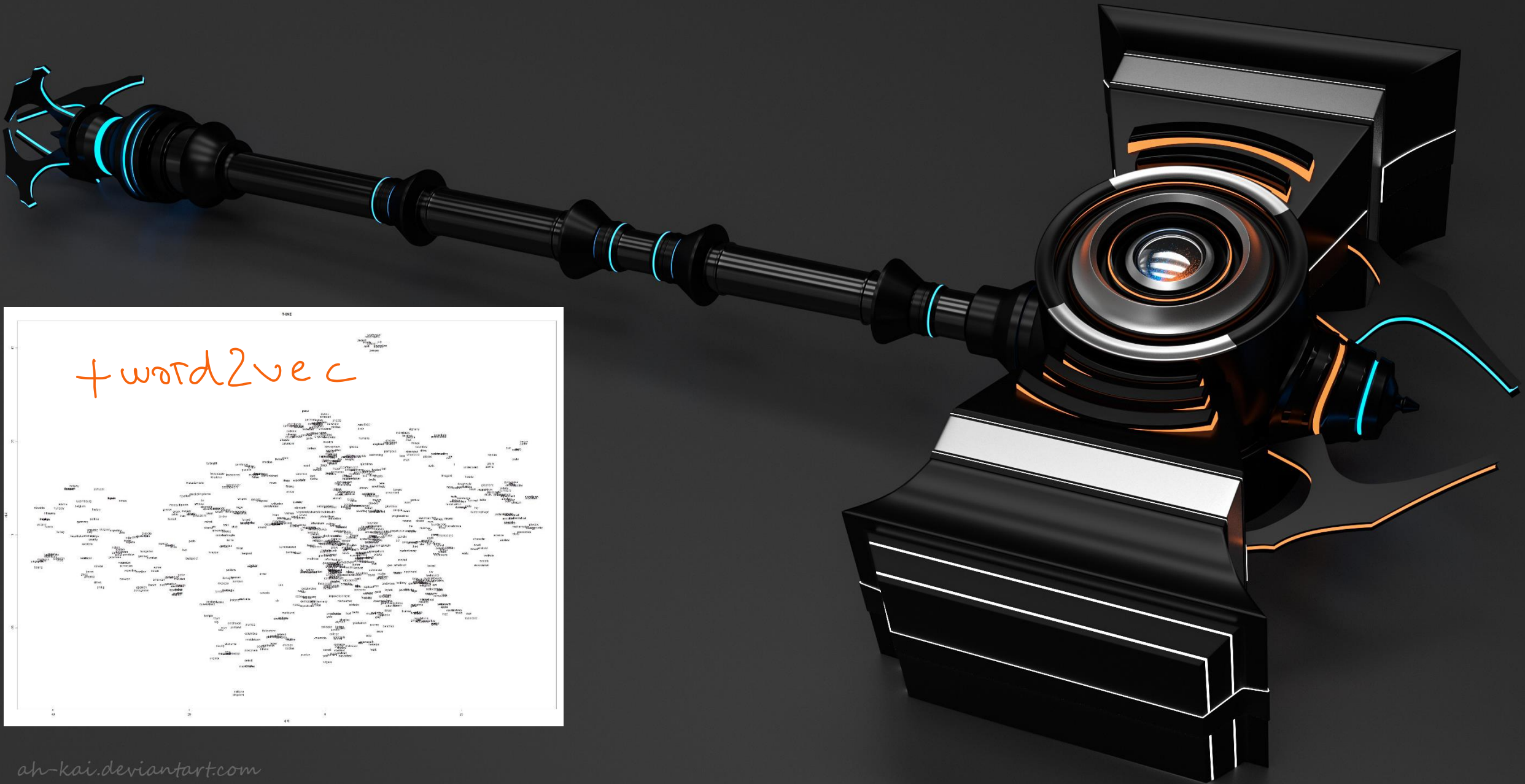
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Output gate:

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

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

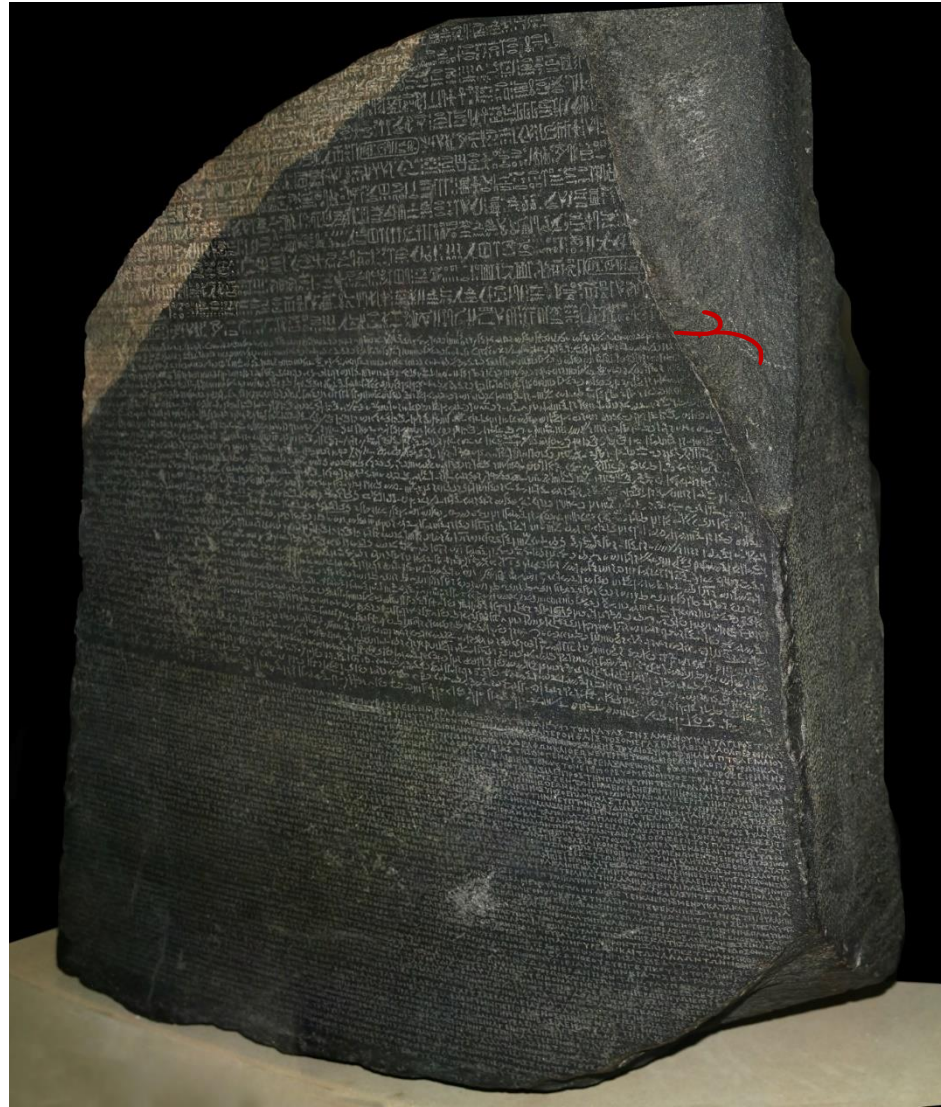




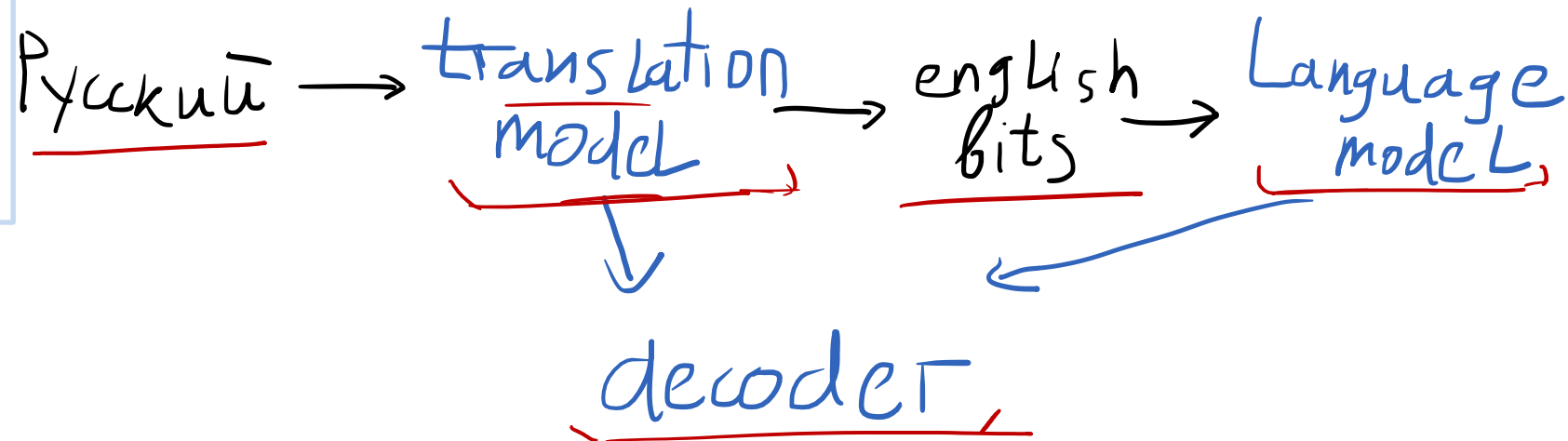
Машинный перевод

Machine Translation

Rosetta Stone







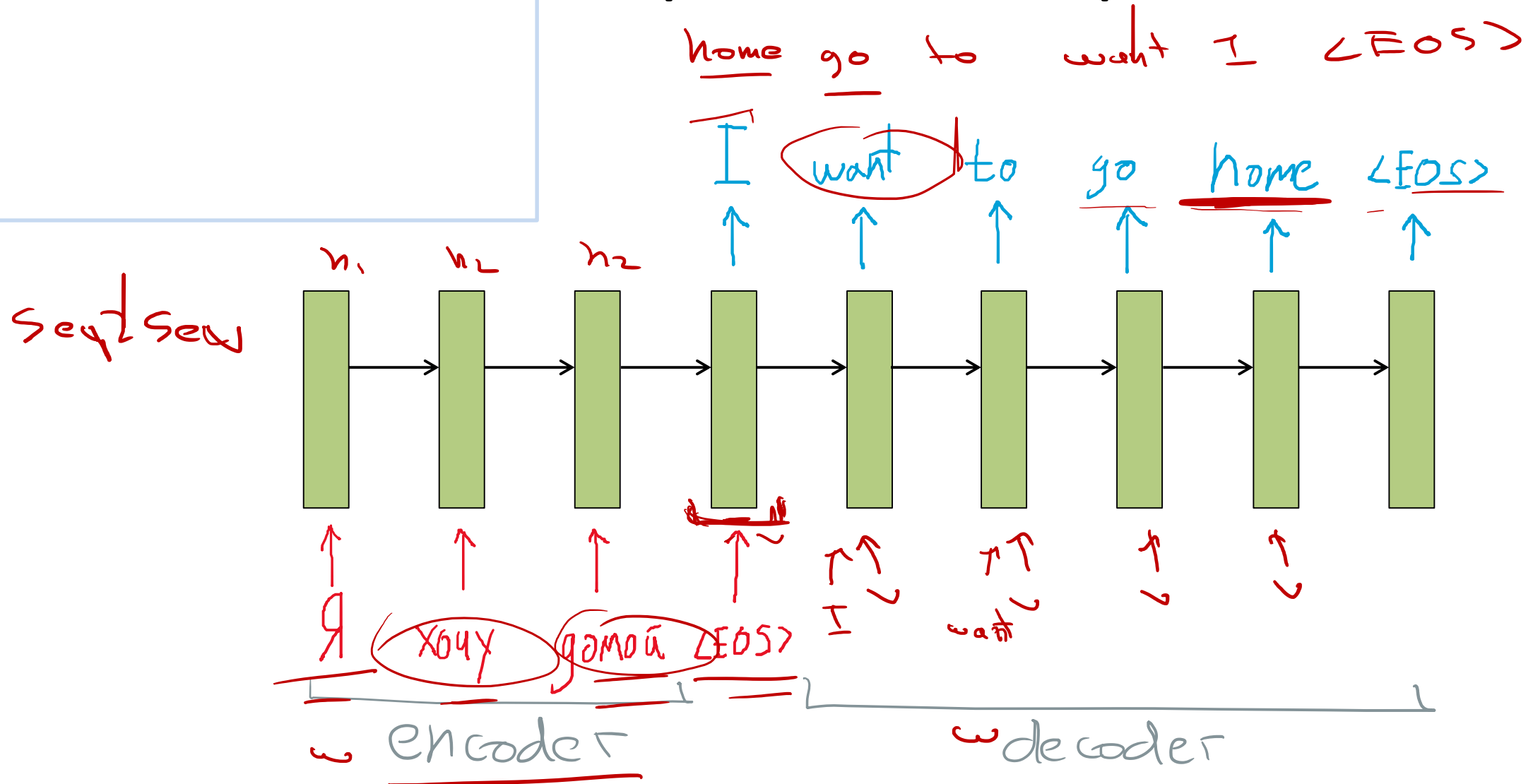
Good → Доброе
morning → утро

Oh → Офигеть
wow

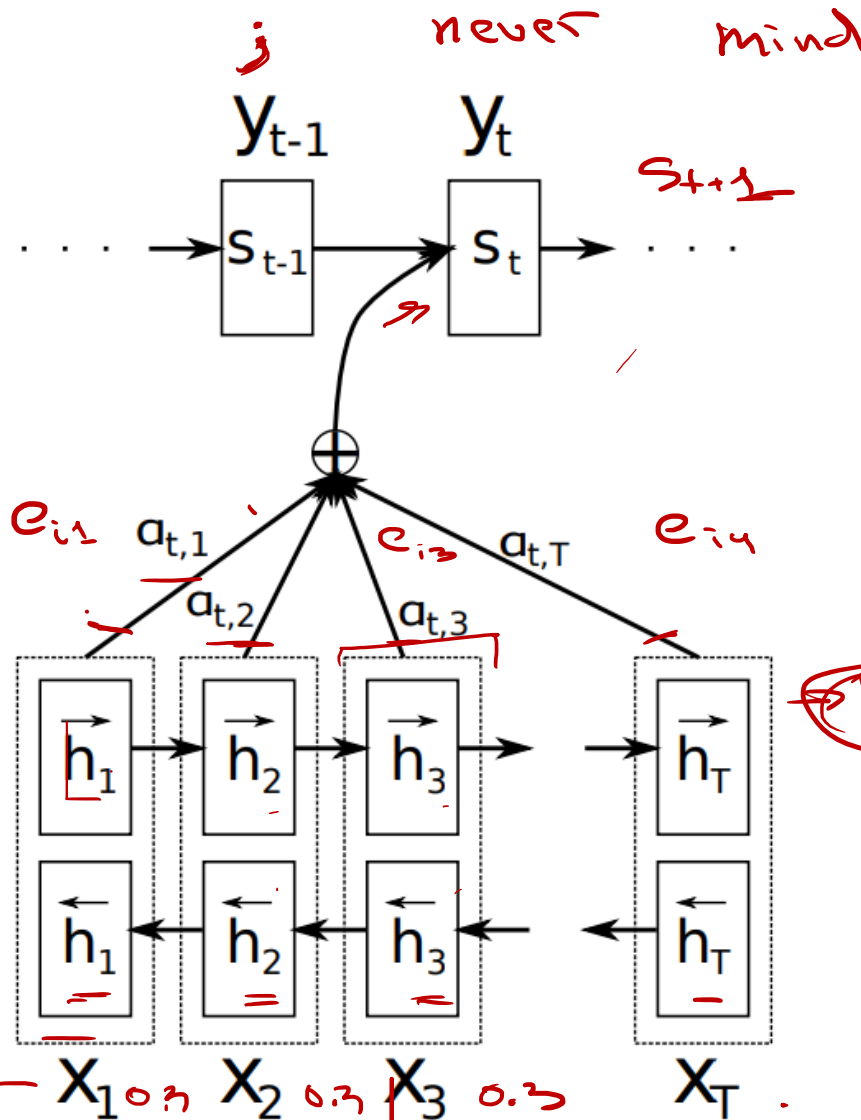
Goodbye → До
→ свидания

Never
mind → Не
обращай
внимания

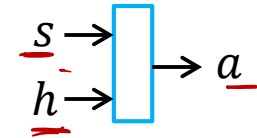
Sequence to Sequence



Attention



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



$$\underline{a(s, h)} = \underline{s \cdot h}$$

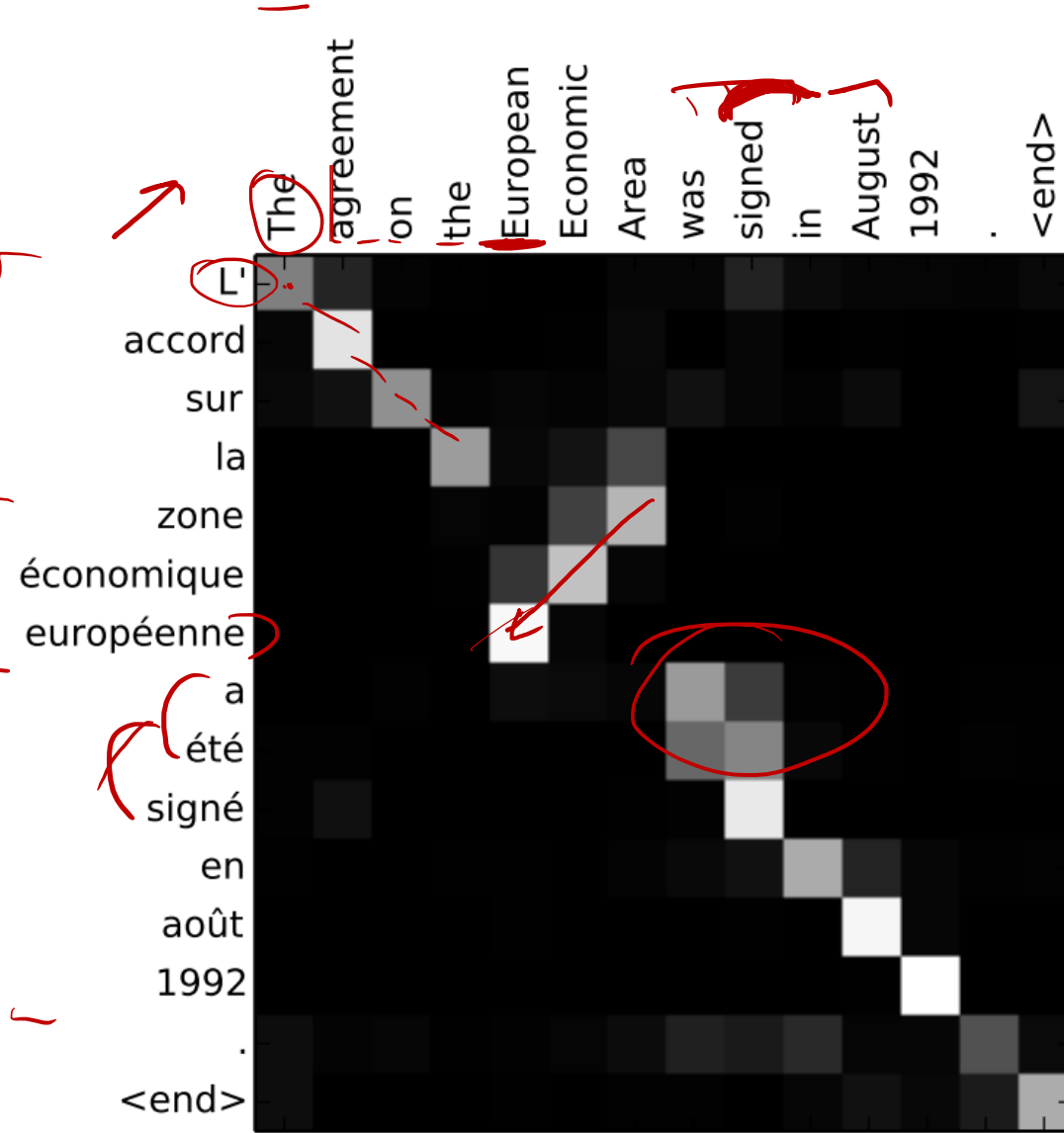
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

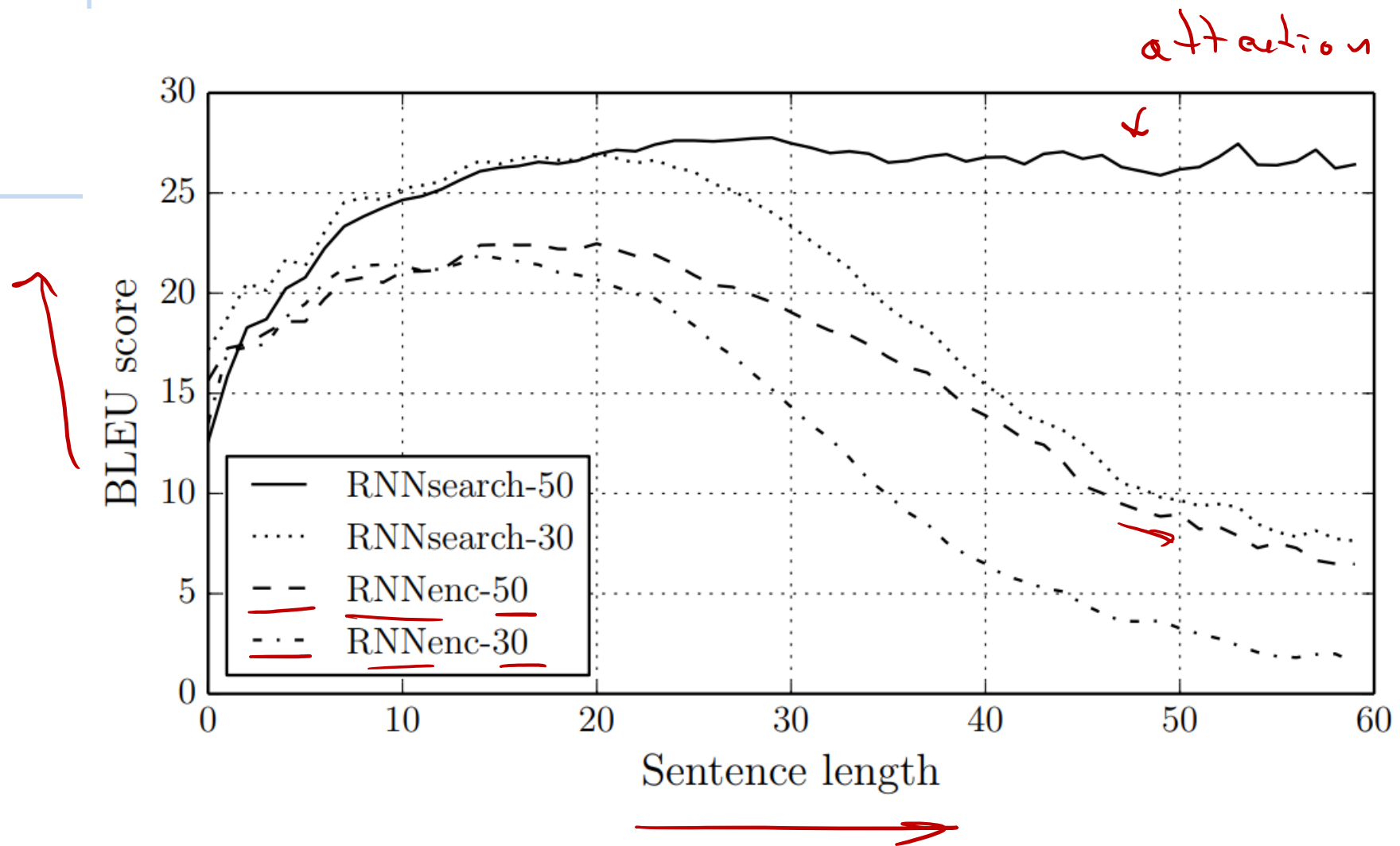
$$\underline{c_i} = \sum_{j=1}^{T_x} \alpha_{ij} \underline{h_j}$$

h
= s₀

Encoder

He Open GLSL





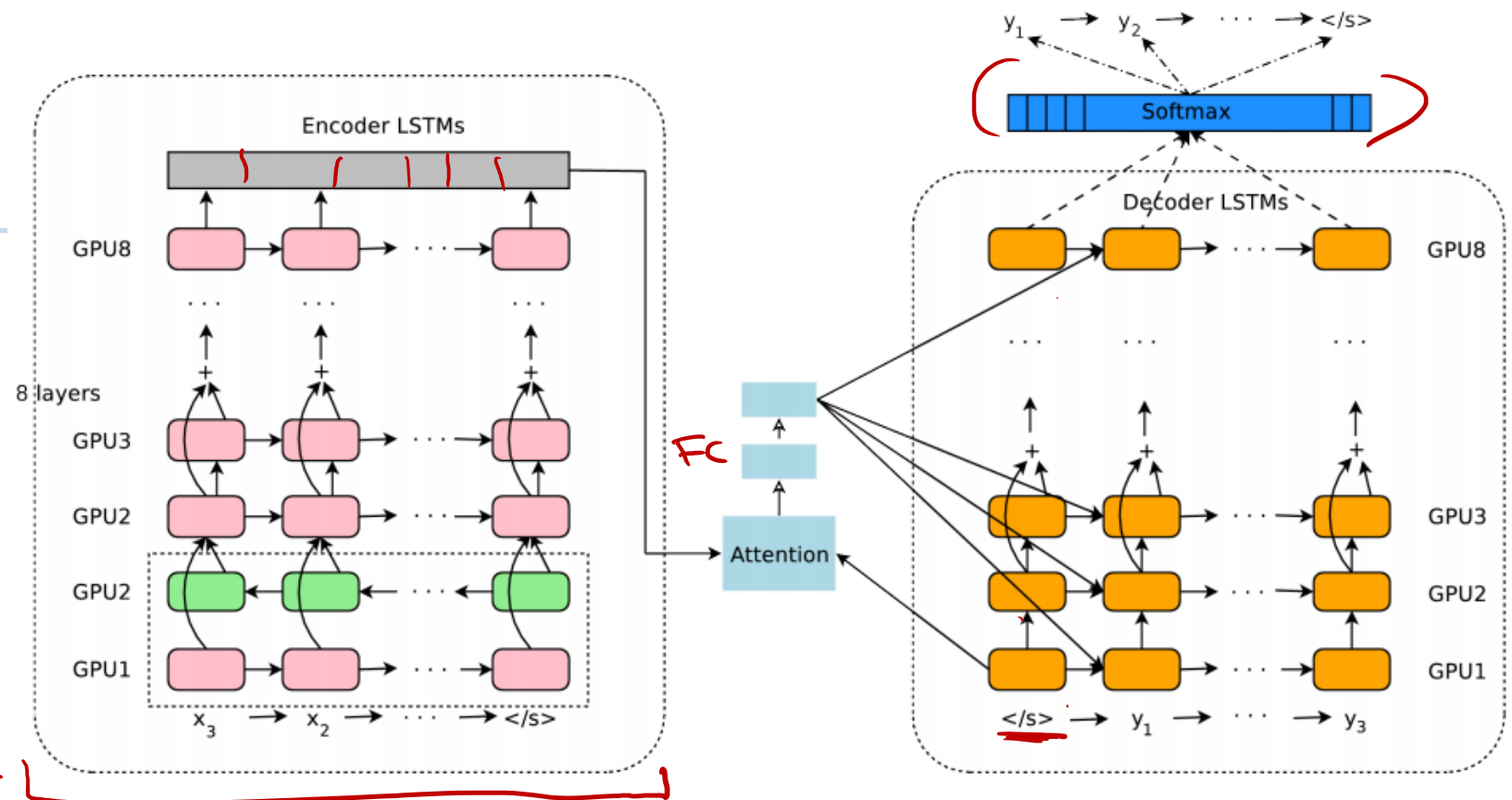


more awesome stuff at ThumbPress.com

Google Translate

66✓

enc



- Word: Jet makers feud over seat width with big orders at stake
- wordpieces: _J et _makers _fe ud _over _seat _width _with _big _orders _at _stake

90

{ Kilimanjaro is 19,710 feet of the mountain covered with snow, and it is said that the highest mountain in Africa. Top of the west, “Ngaje Ngai” in the Maasai language, has been referred to as the house of God. The top close to the west, there is a dry, frozen carcass of a leopard. Whether the leopard had what the demand at that altitude, there is no that nobody explained. }

no one

Kilimanjaro is a mountain of 19,710 feet covered with snow and is said to be the highest mountain in Africa. The summit of the west is called “Ngaje Ngai” in Masai, the house of God. Near the top of the west there is a dry and frozen dead body of leopard. No one has ever explained what leopard wanted at that altitude.



Image captioning



A bird is flying over
a body of water.



A woman is throwing a
frisbee in a park.

Figure 2. Attention over time. As the model generates each word, its attention changes to reflect the relevant parts of (top row) vs “hard” (bottom row) attention. (Note that both models generated the same captions in this example.)

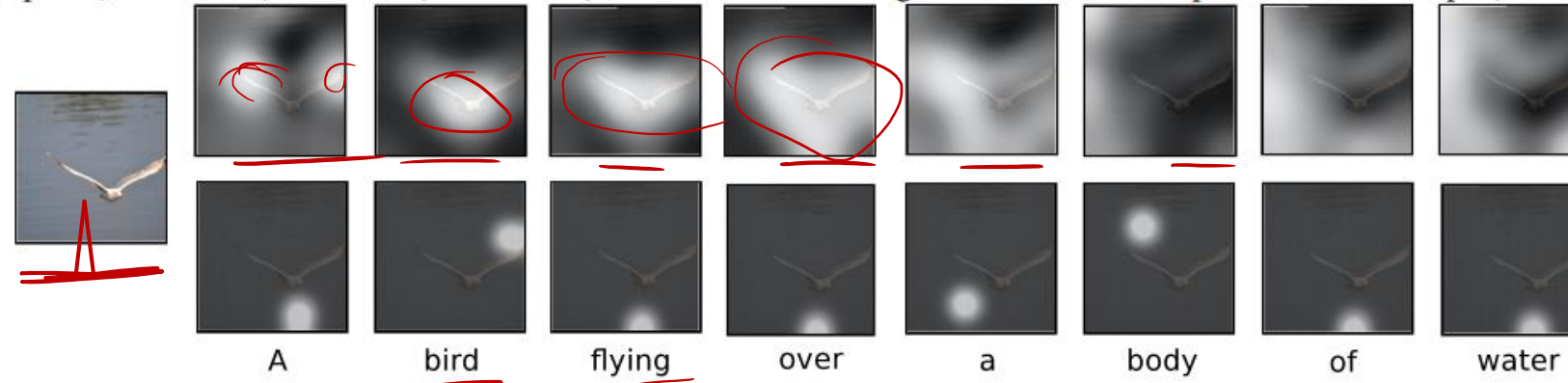


Figure 3. Examples of attending to the correct object (white indicates the attended regions, underlines indicated the correct words).



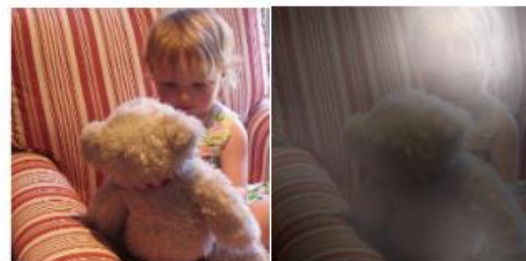
A woman is throwing a frisbee in a park.



A dog is standing on a hardwood floor.



A stop sign is on a road with mountains in the background.



A little girl sitting on a bed with a teddy bear.



A group of people sitting on a boat in the water.

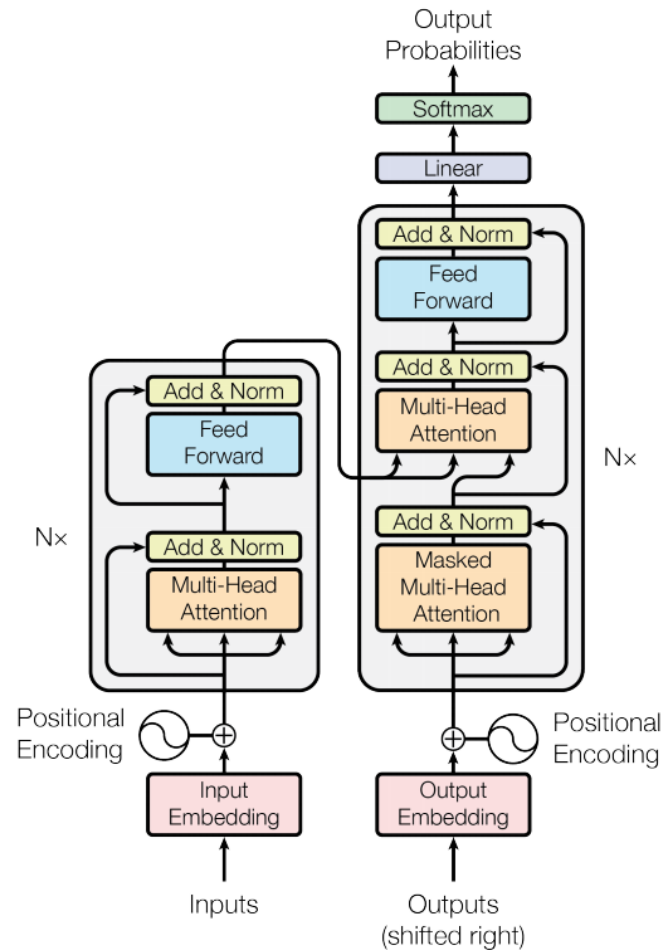


A giraffe standing in a forest with trees in the background.



THIS IS GREAT!
NOT ONLY AM I NOT LEARNIN',

Attention is All You Need



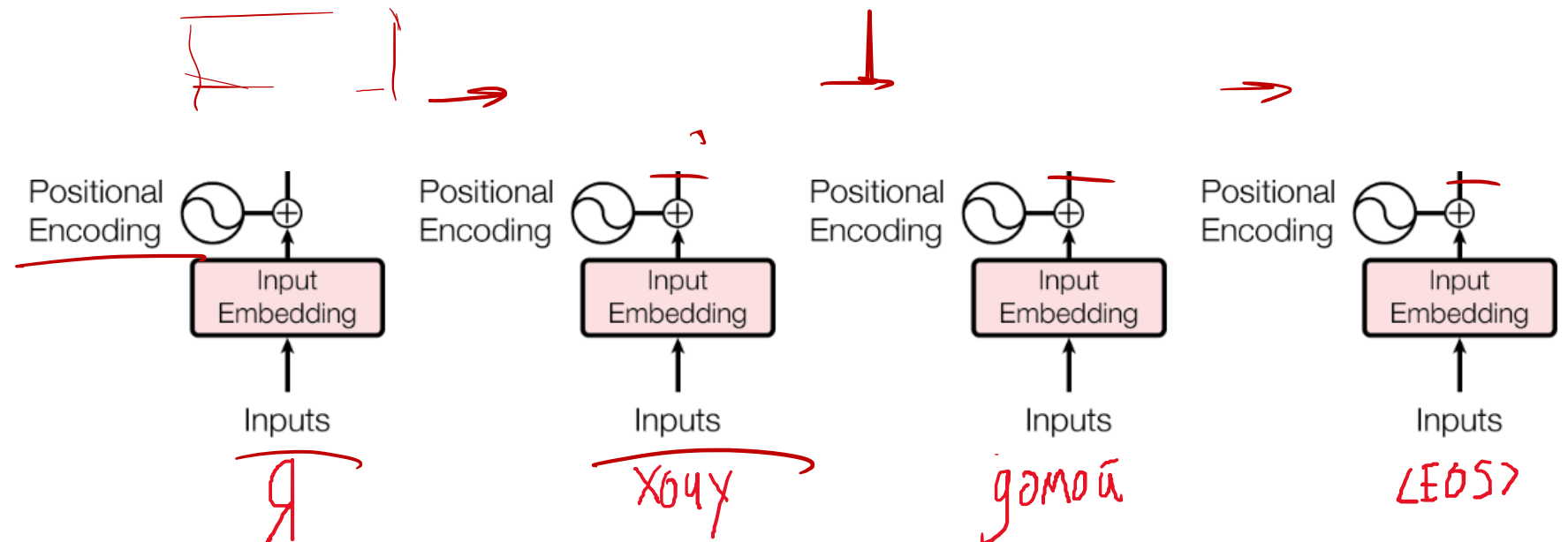
Вот тут я про него рассказываю

<https://habrahabr.ru/post/341240/>

Figure 1: The Transformer - model architecture.

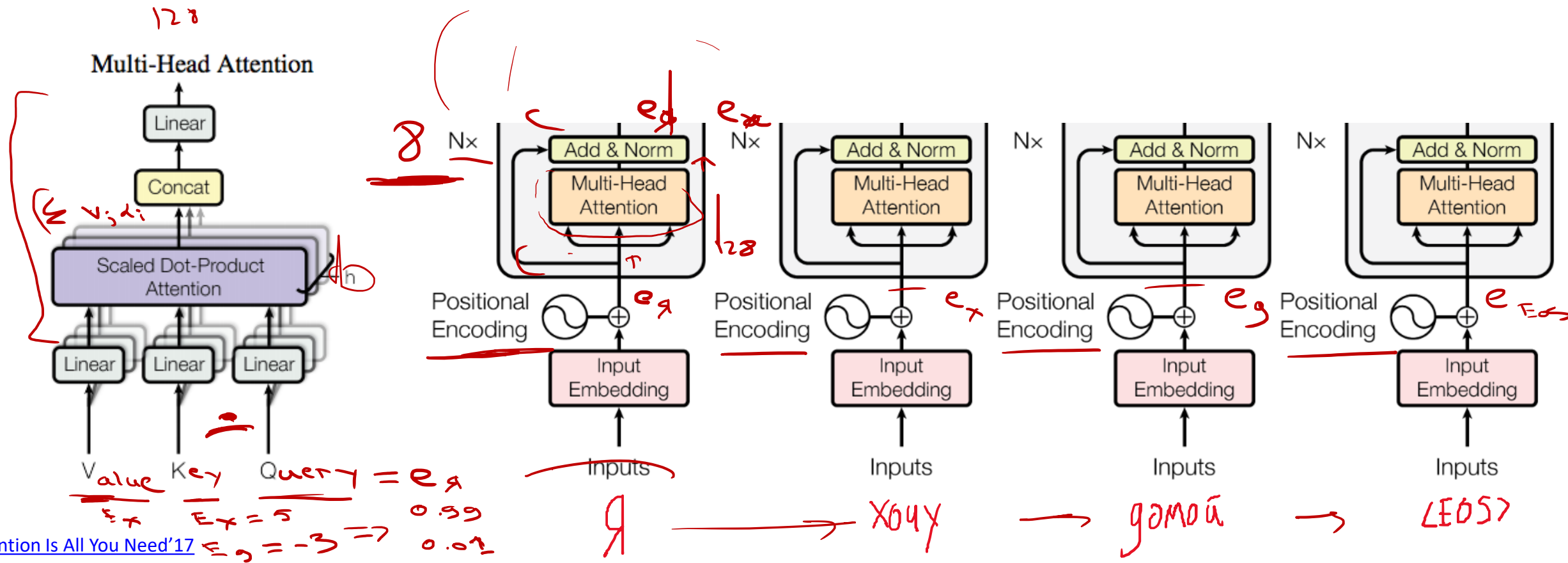
Transformer

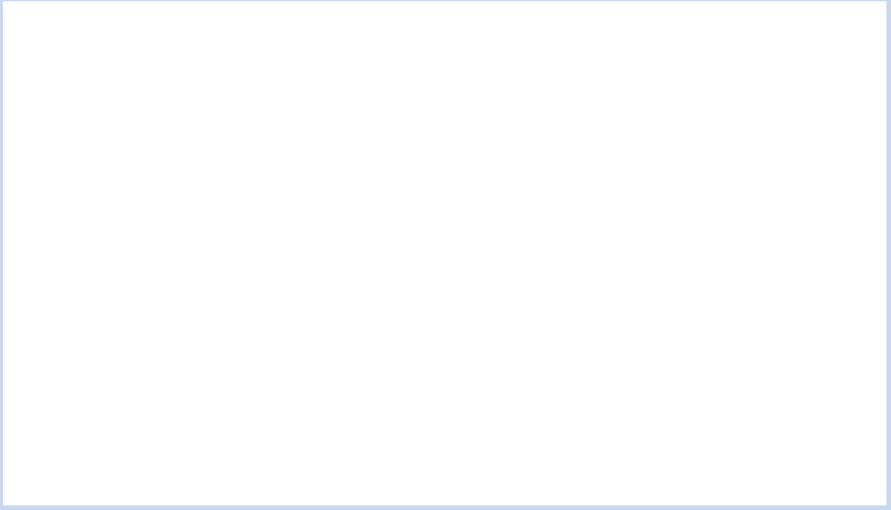
Encoder



Transformer

Encoder





$n = 1$

$n = 2$

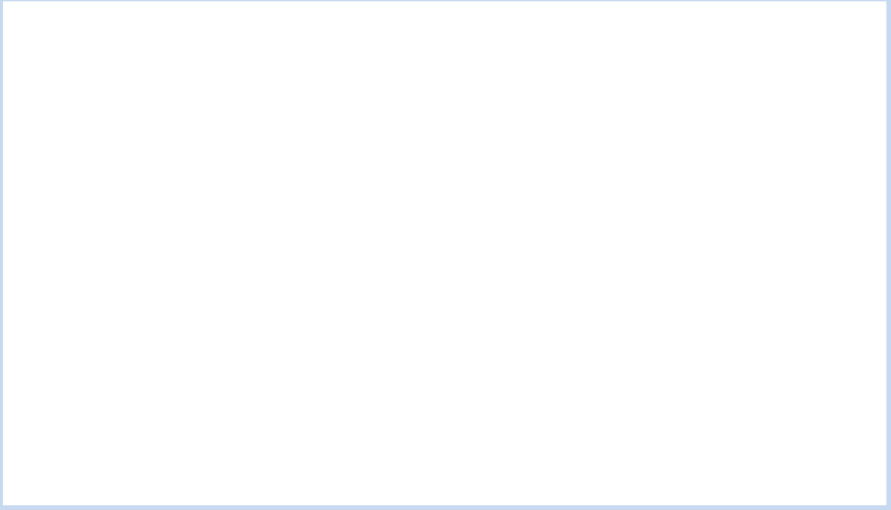
C

Decoder

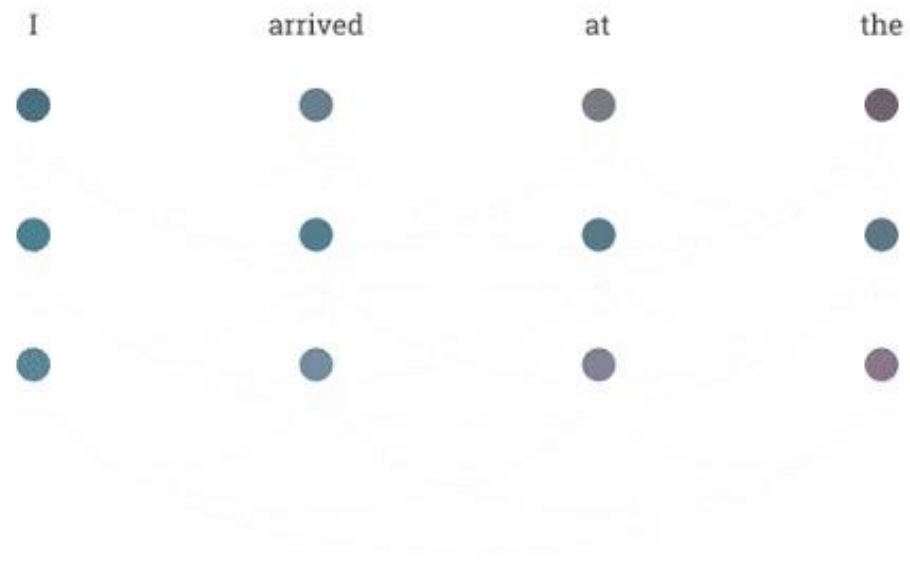


<start>





Encoding



АРХИТЕКТУРА



ПРОСТО ТЕРМОЯД

Use the output of the masked word's position to predict the masked word

Possible classes:
All English words

| | |
|------|---------------|
| 0.1% | Aardvark |
| ... | ... |
| 10% | Improvisation |
| ... | ... |
| 0% | Zyzzzyva |

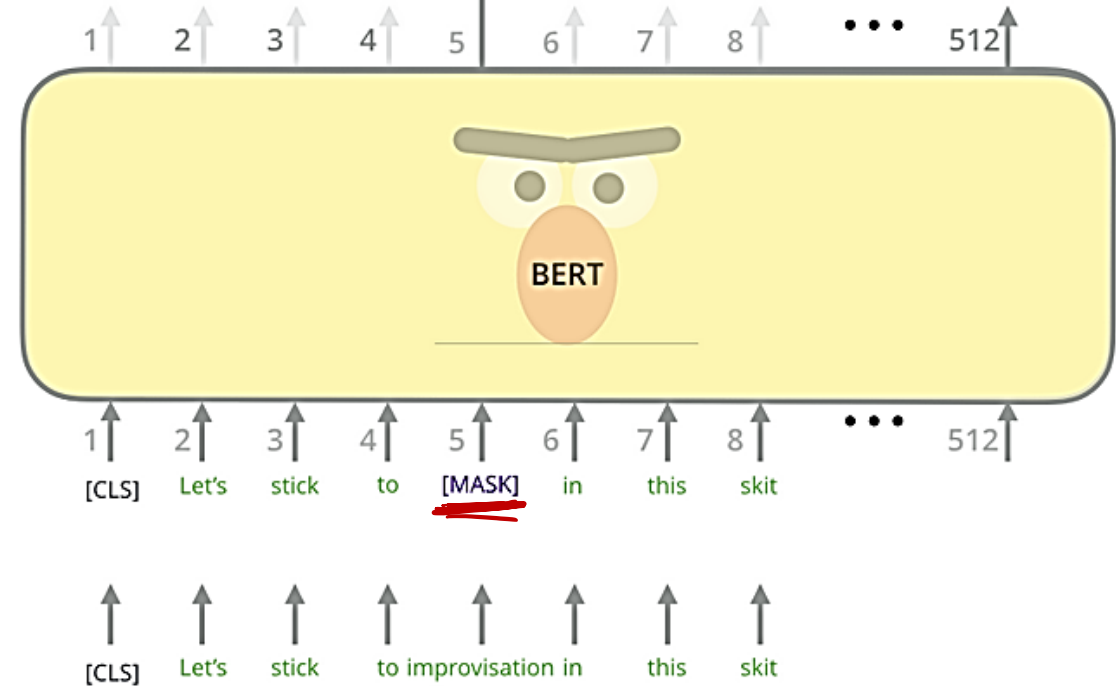
FFNN + Softmax

Encoder
320M parameters
24 transformer blocks

transformer encoder

Randomly mask
15% of tokens

Input

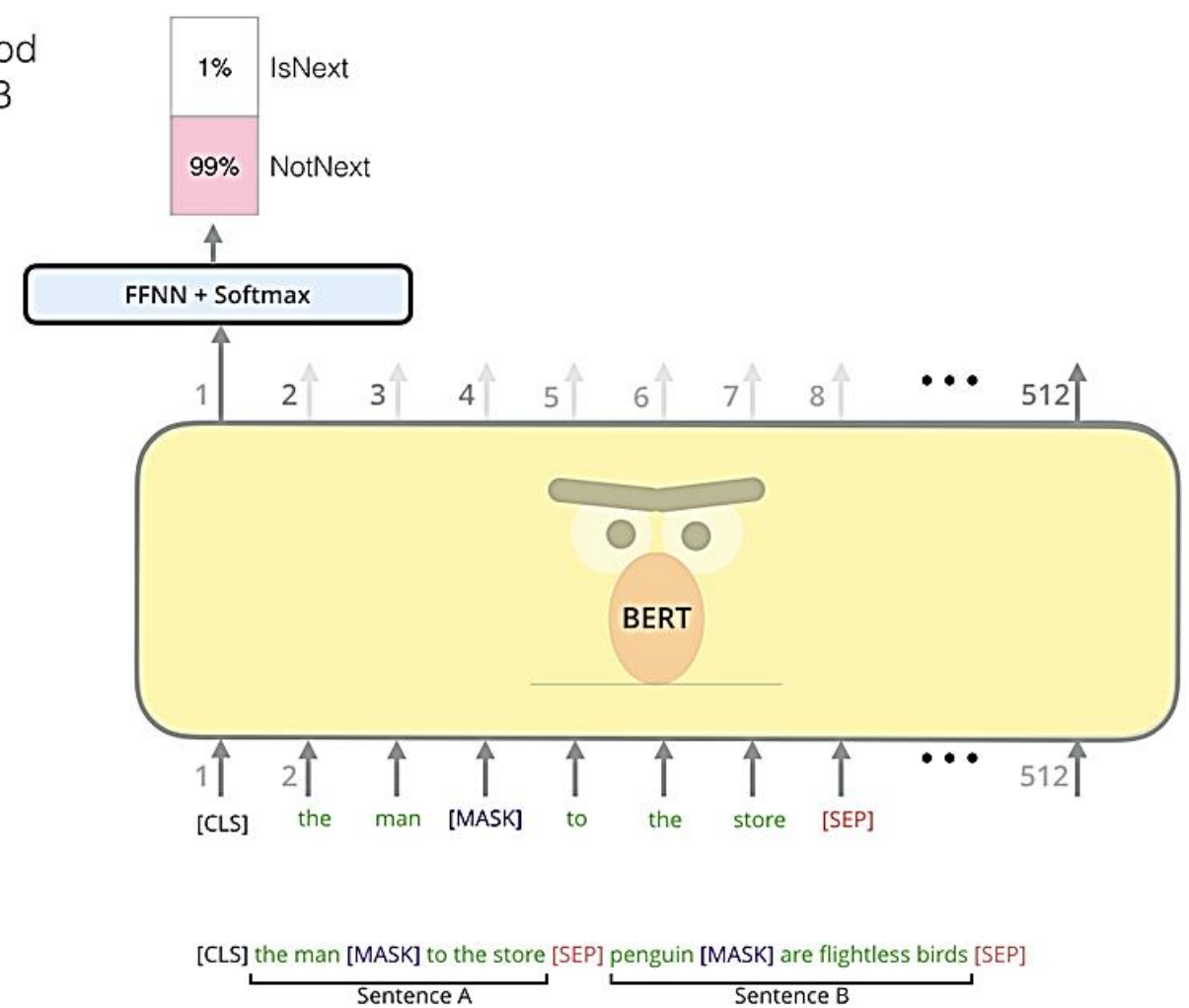


BERT's clever language modeling task masks 15% of words in the input and asks the model to predict the missing word.

[Image source](#)

**BACK
TO
THE PRESENT**

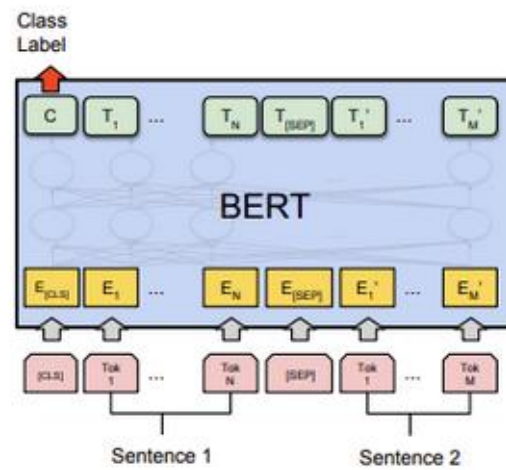
Predict likelihood
that sentence B
belongs after
sentence A



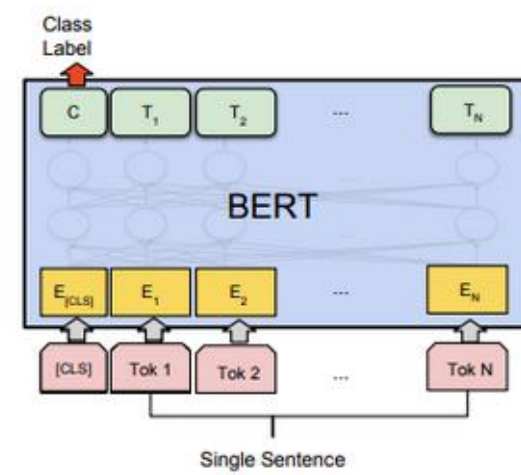
The second task BERT is pre-trained on is a two-sentence classification task. The tokenization is oversimplified in this graphic as BERT actually uses WordPieces as tokens rather than words --- so some words are broken down into smaller chunks.

[Image source](#)

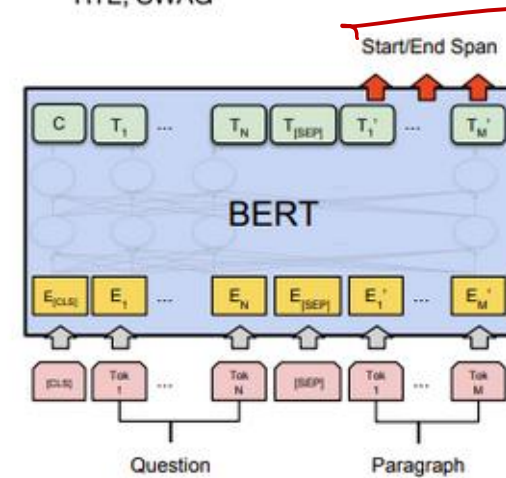
**BACK
TO THE PRESENT**



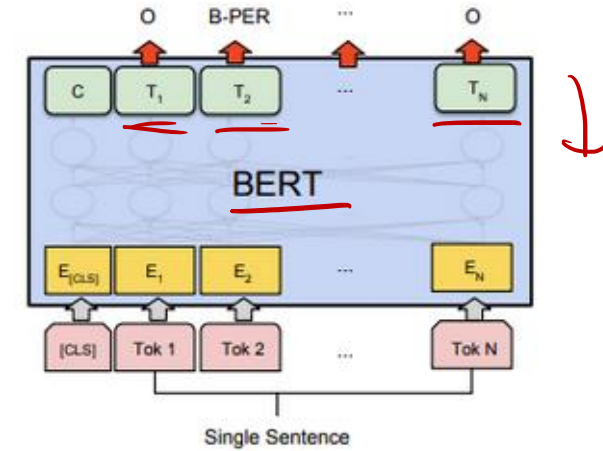
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



(b) Single Sentence Classification Tasks:
SST-2, CoLA



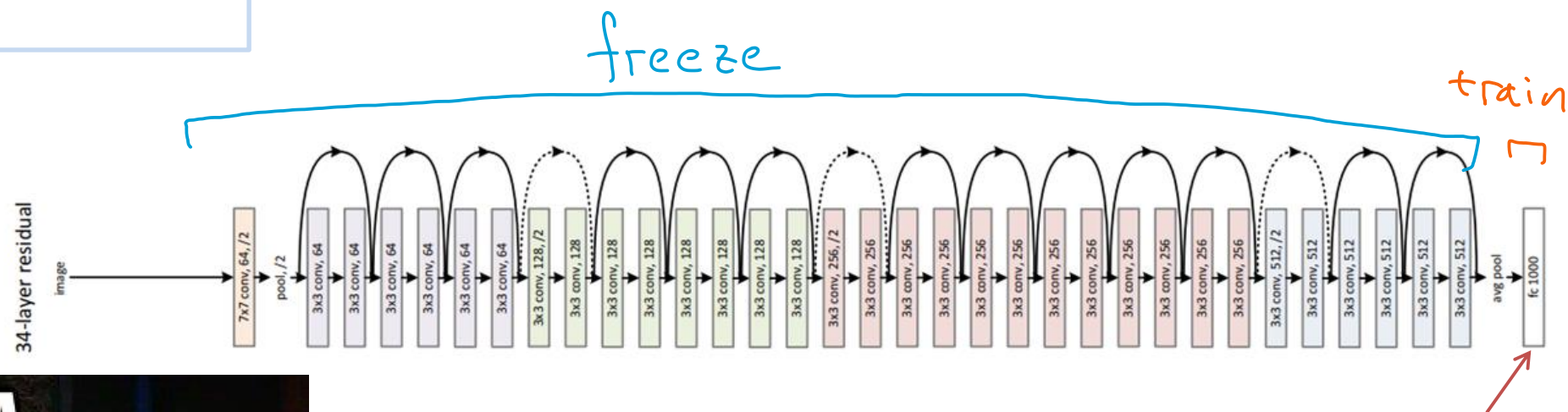
(c) Question Answering Tasks:
SQuAD v1.1



(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

BACK
TO THE PRESENT

Transfer learning в NLP!



Линейный классификатор



BERT_{LARGE}

КОГДА
ДОЖДАЛСЯ

risovach.ru

BACK
TO THE PRESENT

Question Answering

Because of the complexity of medications including specific indications, effectiveness of treatment regimens, safety of medications (i.e., drug interactions) and patient compliance issues (in the hospital and at home) many pharmacists practicing in hospitals gain more education and training after pharmacy school through a pharmacy practice residency and sometimes followed by another residency in a specific area. Those pharmacists are often referred to as clinical pharmacists and they often specialize in various disciplines of pharmacy. For example, there are pharmacists who specialize in hematology/oncology, HIV/AIDS, infectious disease, critical care, emergency medicine, toxicology, nuclear pharmacy, pain management, psychiatry, anti-coagulation clinics, herbal medicine, neurology/epilepsy management, pediatrics, neonatal pharmacists and more.

Where do pharmacists acquire more preparation following pharmacy school?

Ground Truth Answers: a pharmacy practice residency | pharmacy practice residency | pharmacy practice residency

What do clinical pharmacists specialize in?

Ground Truth Answers: various disciplines of pharmacy | various disciplines of pharmacy | various disciplines of pharmacy

What is one issue that adds to the complexity of a pharmacist's job?

Ground Truth Answers: effectiveness of treatment regimens | effectiveness of treatment regimens | effectiveness of treatment regimens

Which pharmacists are likely to seek additional education following pharmacy school?

Ground Truth Answers: pharmacists practicing in hospitals | pharmacists practicing in hospitals | clinical pharmacists

Where do pharmacists not go following pharmacy school?

Question Answering

Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph. How will your system compare to humans on this task?

| Rank | Model | EM | F1 |
|-------------------|--|--------|--------|
| | Human Performance Stanford University (Rajpurkar & Jia et al. '18) | 86.831 | 89.452 |
| 1 Jan 15, 2019 | BERT + MMFT + ADA (ensemble) Microsoft Research Asia | 85.082 | 87.615 |
| 2 Jan 10, 2019 | BERT + Synthetic Self-Training (ensemble) Google AI Language https://github.com/google-research/bert | 84.292 | 86.967 |
| 3 Dec 13, 2018 | BERT finetune baseline (ensemble) Anonymous | 83.536 | 86.096 |
| 4 Dec 16, 2018 | Lunet + Verifier + BERT (ensemble) Layer 6 AI NLP Team | 83.469 | 86.043 |
| 4 Dec 21, 2018 | PAML+BERT (ensemble model) PINGAN GammaLab | 83.457 | 86.122 |

Language Modeling

1B Words / Google Billion Word benchmark

The [One-Billion Word benchmark](#) is a large dataset derived from a news-commentary site. The dataset consists of 829,250,940 tokens over a vocabulary of 793,471 words. Importantly, sentences in this model are shuffled and hence context is limited.

| Model | Test perplexity | Number of params | Paper / Source | Code |
|---|-----------------|------------------|---|--------------------------|
| Transformer-XL Large (Dai et al., 2018) <i>under review</i> | 21.8 | 0.8B | Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context | Official |
| Transformer-XL Base (Dai et al., 2018) <i>under review</i> | 23.5 | 0.46B | Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context | Official |
| Transformer with shared adaptive embeddings - Very large (Baevski and Auli, 2018) | 23.7 | 0.8B | Adaptive Input Representations for Neural Language Modeling | Link |
| 10 LSTM+CNN inputs + SNM10-SKIP (Jozefowicz et al., 2016) <i>ensemble</i> | 23.7 | 43B? | Exploring the Limits of Language Modeling | Official |

OpenAI GPT-2'19

SYSTEM PROMPT
(HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION
(MACHINE-WRITTEN,
10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

