Machine Translation. Attention. Transformers

MIPT

4.03.2021

Anton Emelianov, Alena Fenogenova.

Today

- Machine Translation
- Seq2Seq
- Attention
- Early attention models
- Transformer
  - High-level
  - Deeper

Machine translation

How are you today? ⇒ Wie geht es dir heute?

x=(x_1,x_2,…,x_(T_x))

y=(y_1,y_2,…,y_(T_y))

Translation task => finding the target sequence that is the most probable given the input;

the target sequence that maximizes the conditional probability: $y^* = \arg\max_y p(y|x)$

Machine translation:

- between natural languages
- between programming languages
- any sequences of tokens

by **Machine translation** we will mean **any general sequence-to-sequence task**

Machine translation

Machine translation systems learn a function: $p(y|x, \theta)$

We try to find target sequence that maximizes the conditional probability:

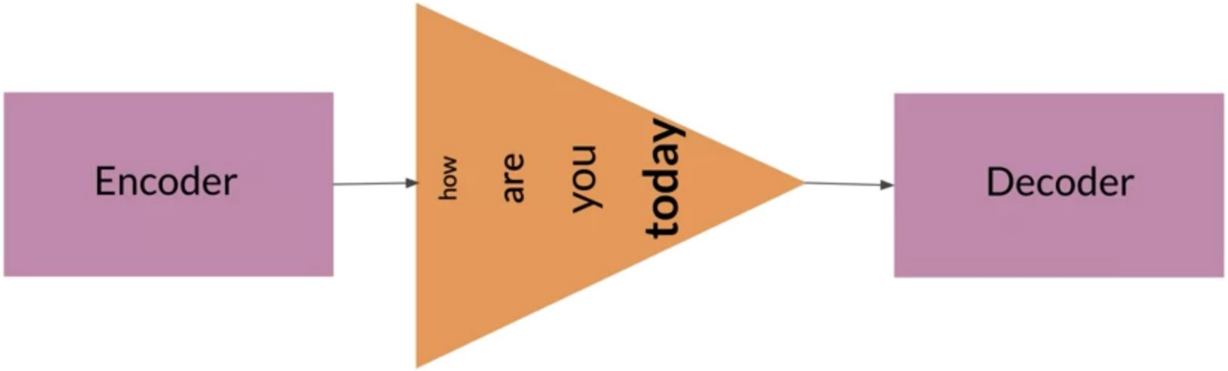
$$\hat{y} = \text{argmax}_y \, p(y|x, \theta)$$

where θ – model parameters that determine probability distibution

What to do?

1. modeling - how does the model for $p(y|x,\theta)$ look like?
2. learning - how to find the parameters θ?
3. inference - how to find the best y?

Machine translation



Seq2Seq

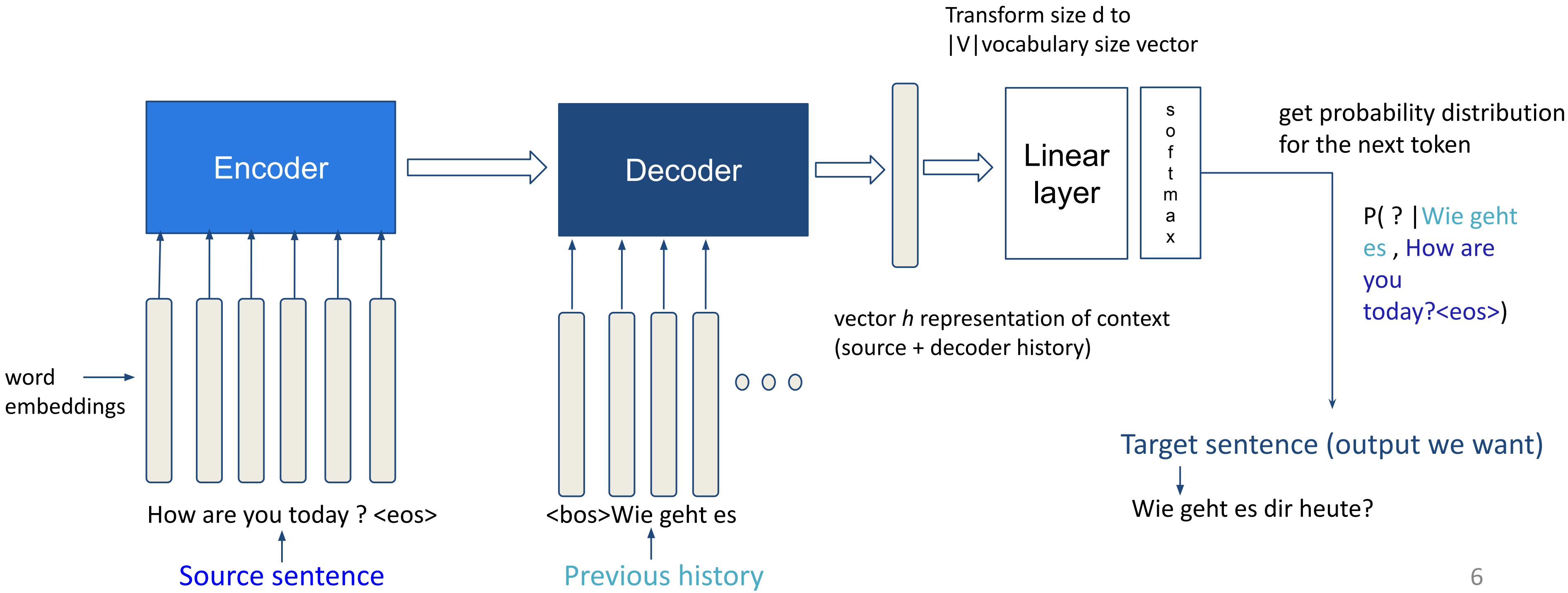
Introduced by Google in 2014

Encoder - reads source sequence and produces its representation;
Decoder - uses source representation from the encoder to generate the target sequence.

Maps variable-length sequences to fixed-length memory
Commonly used LSTMs, GRUs in encoder, decoder

Machine translation. Conditional LM

Language models estimate the *unconditional probability p(y)* of a sequence y, Sequence-to-sequence models need to estimate the *conditional probability p(y|x)* of a sequence y given a source x



Machine translation

Pipeline:

- feed source and previously generated target words into a network;
- get vector representation of context (both source and previous target) from the networks decoder;
- from this vector representation, predict a probability distribution for the next token.

Training:

we train to predict probability distributions of the next token given previous context (source and previous target tokens). At each step we maximize the probability a model assigns to the correct token.

Cross-entropy: looking for parameters

$$Loss(p^*, p) = -p^* \log(p) = -\sum_{i=1}^{|V|} p_i^* \log(p_i)$$

Seq2seq is optimized as a single system. Backpropagation operates “end-to-end”

Machine translation. Inference

Ok, everything is great, but **how to generate**?

How to find argmax?

$$y' = \arg\max_{y} p(y|x) = \arg\max_{y} \prod_{t=1}^{n} p(y_t|y_{<t}, x)$$

Actually, the total number of hypotheses is $|V|^n$

We don't try to find exact solution, we approximate it.

There are several methods to do it …

Machine translation. Inference

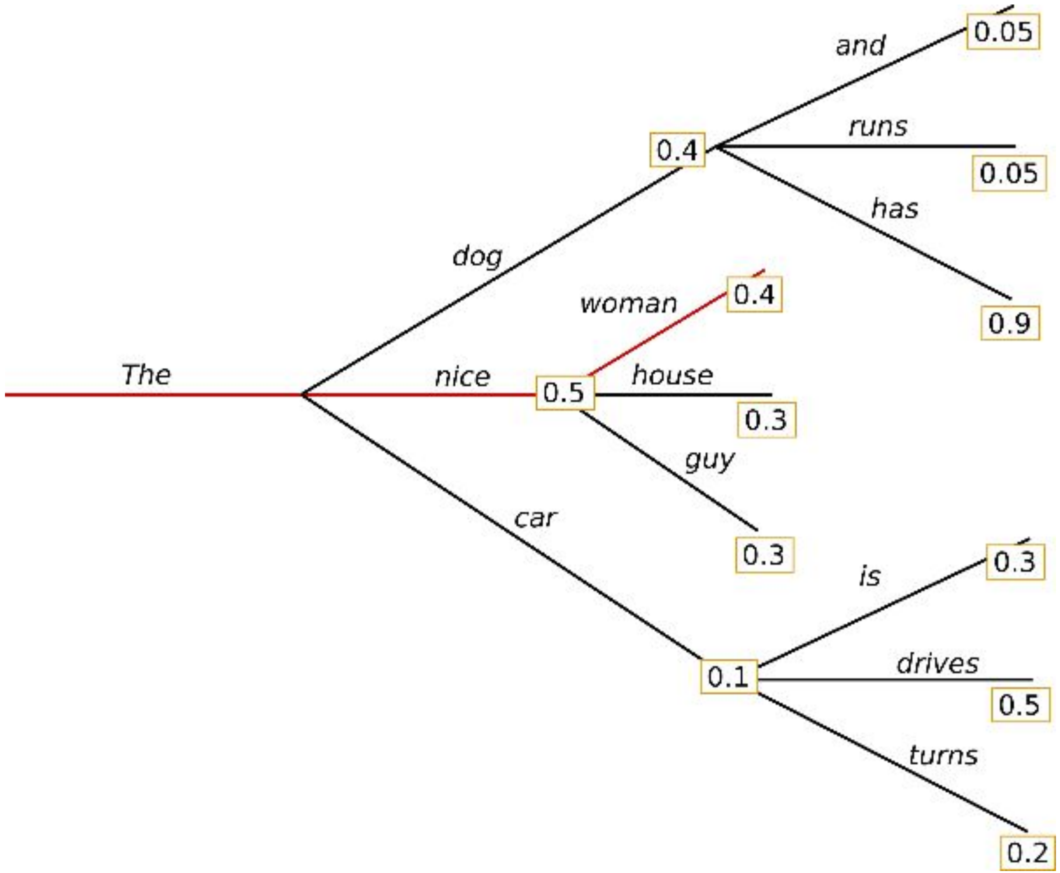
Greedy Decoding:

At each step, pick the most probable token

Take argmax on each step of the decoder

Problems:

- the best next token != best sequence
- has no way to undo decisions



Machine translation. Inference

Beam Search:

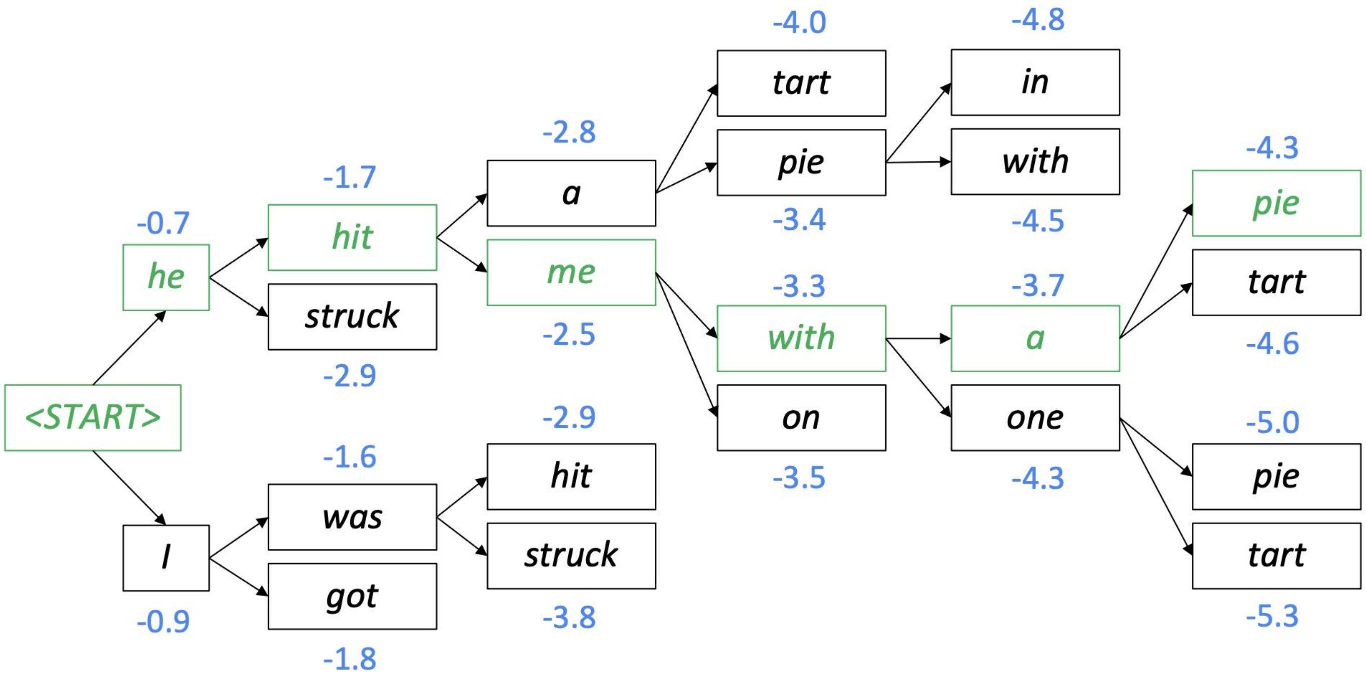
Keep
probable
translations
(hypotheses)

•

(in practice 4 to 10)

Example:

beam size k = 2



$$\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

Machine translation. Evaluation

BLEU (Bilingual Evaluation Understudy)

BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:

- n-gram precision (usually for 1, 2, 3 and 4-grams)
- Plus a penalty for too-short system translations

$$\frac{\text{(Sum over unique n-gram counts in the candidate)}}{\text{(total \# of words in candidate)}}$$

<u>Limitations</u>: semantics, the order of the n-grams in the sentence.

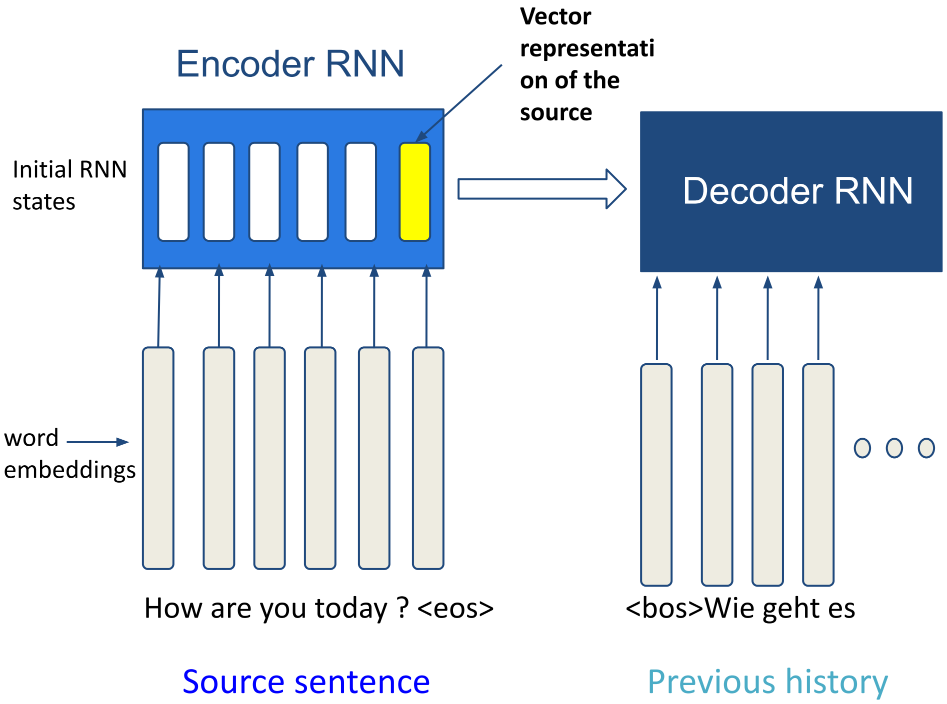
ROUGE (Recall Oriented Understudy for Gisting Evaluation)

[check quality of machine text for machine translation or summarization]

calculates precision and recall for machine texts by counting the n-gram overlap between the machine texts and a reference text

<u>Limitations</u>: meaning (does not understan concepts and themes)

Machine translation. Limitations



- for the encoder, it is hard to compress the sentence;
- for the decoder, different information may be relevant at different steps;
- how far we can see in the past is finite. RNN's tend to forget information from timesteps that are far behind.

The intermediate representation z cannot encode information from all the input timesteps **bottleneck problem**.

The stacked RNN layers usually create **vanishing gradient problem**

Attention

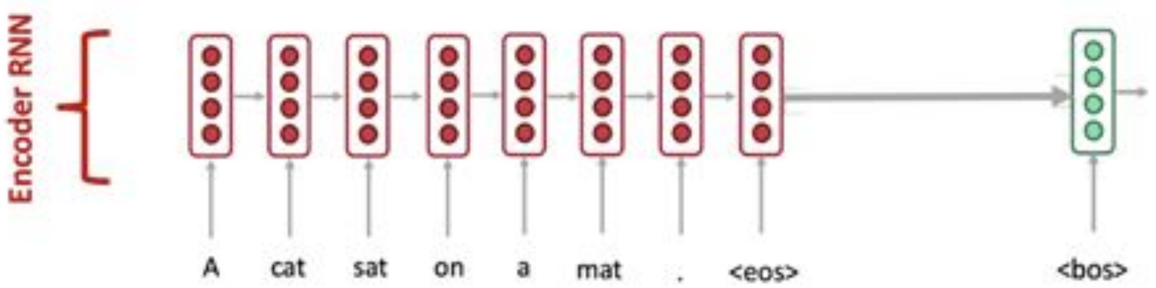
Attention:

At different steps, let a model "focus" on different parts of the source tokens (more relevant ones).

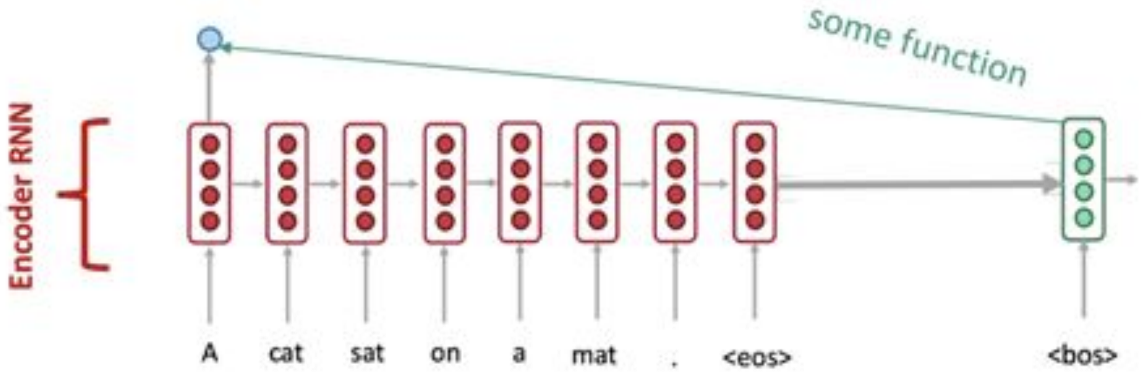
Core idea:

on each step of the decoder, use direct connection to the encoder to focus on a particular part of the source sequence

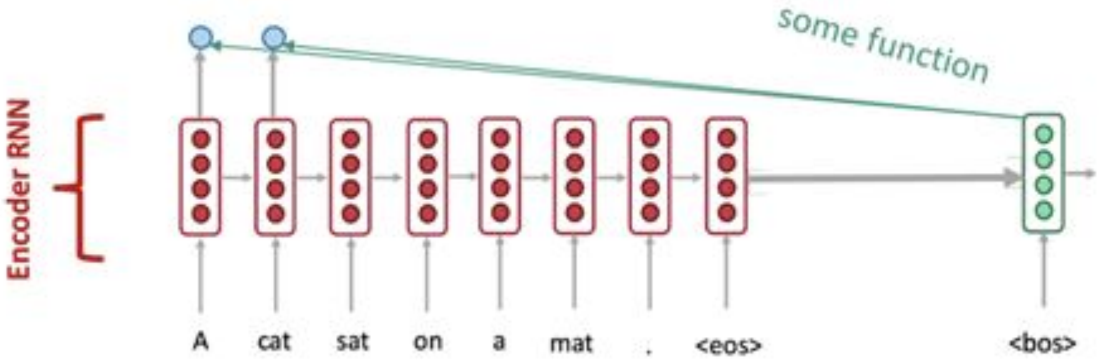
Attention



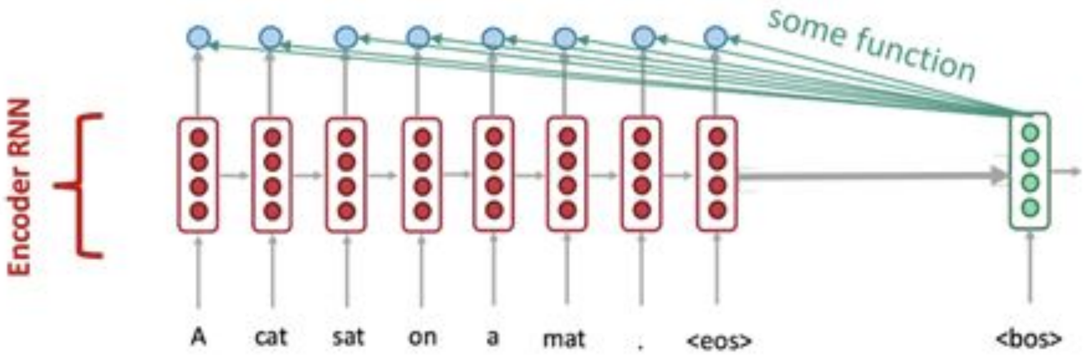
Attention



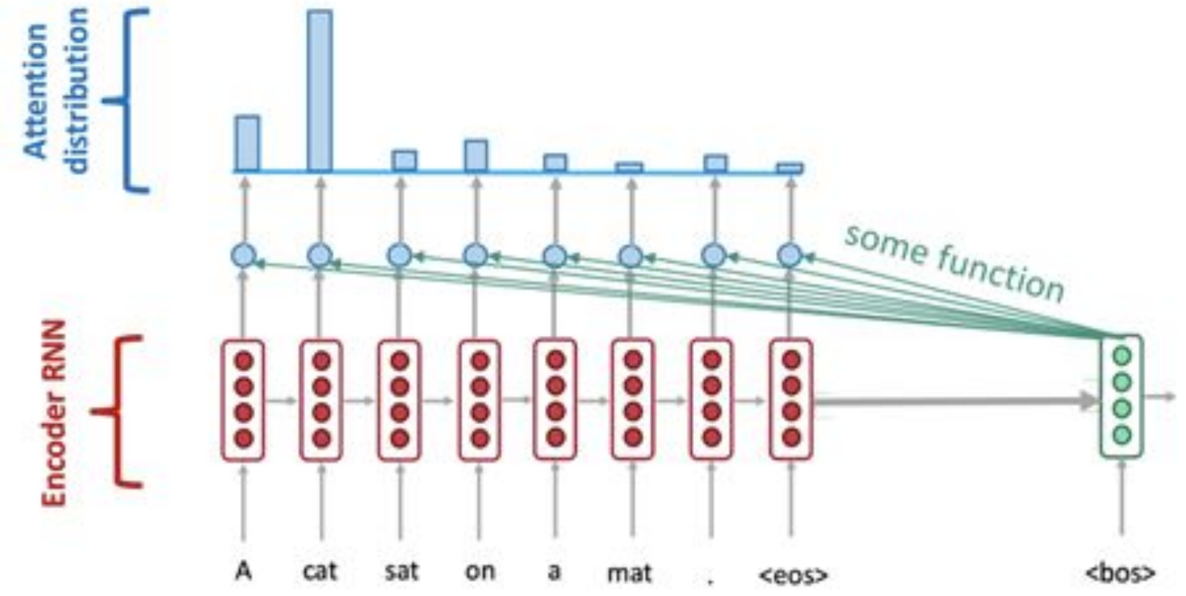
Attention



Attention

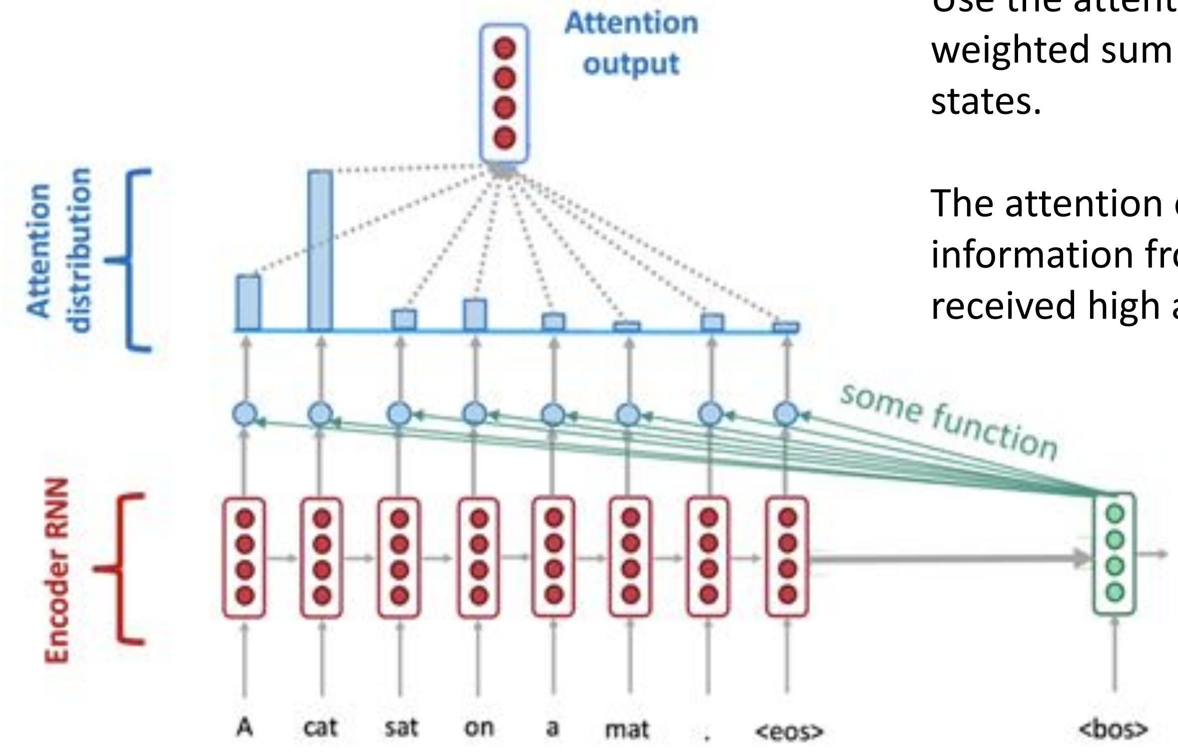


Attention



Attention distribution
some function
Encoder RNN
A
cat
sat
on
a
mat
.
<eos>
<bos>

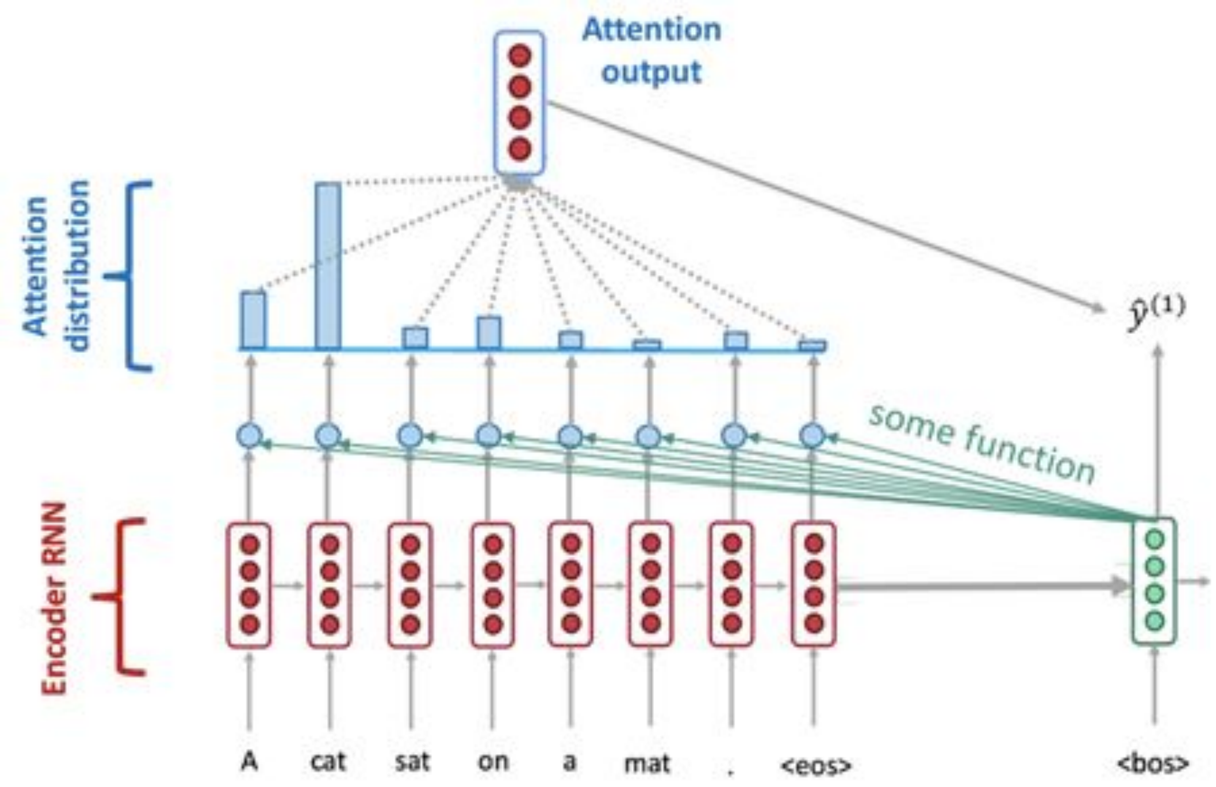
Attention



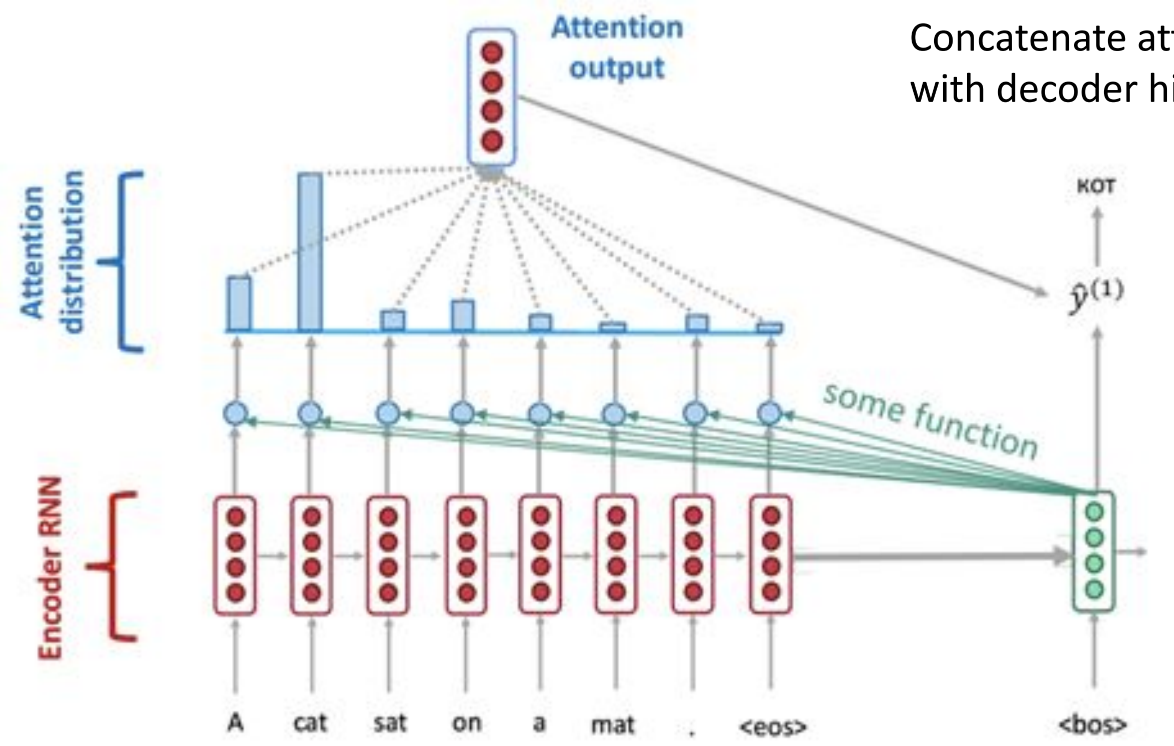
Use the attention distribution to take a weighted sum of the encoder hidden states.

The attention output mostly contains information from the hidden states that received high attention

Attention

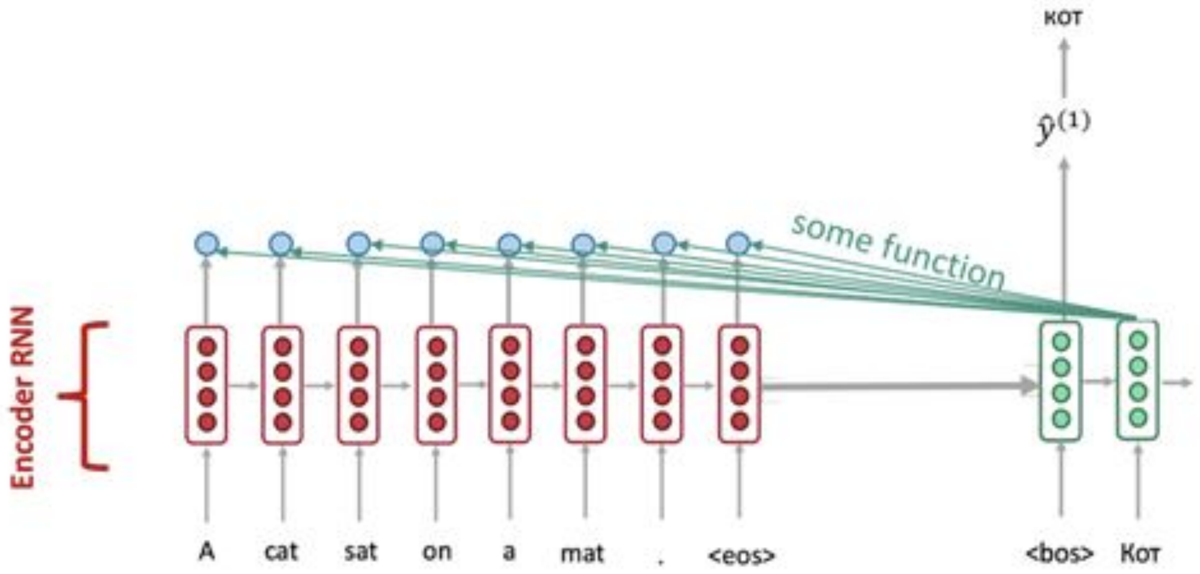

Attention output
Attention distribution
some function
$\hat{y}^{(1)}$
Encoder RNN
A
cat
sat
on
a
mat
.
<eos>
<bos>

Attention



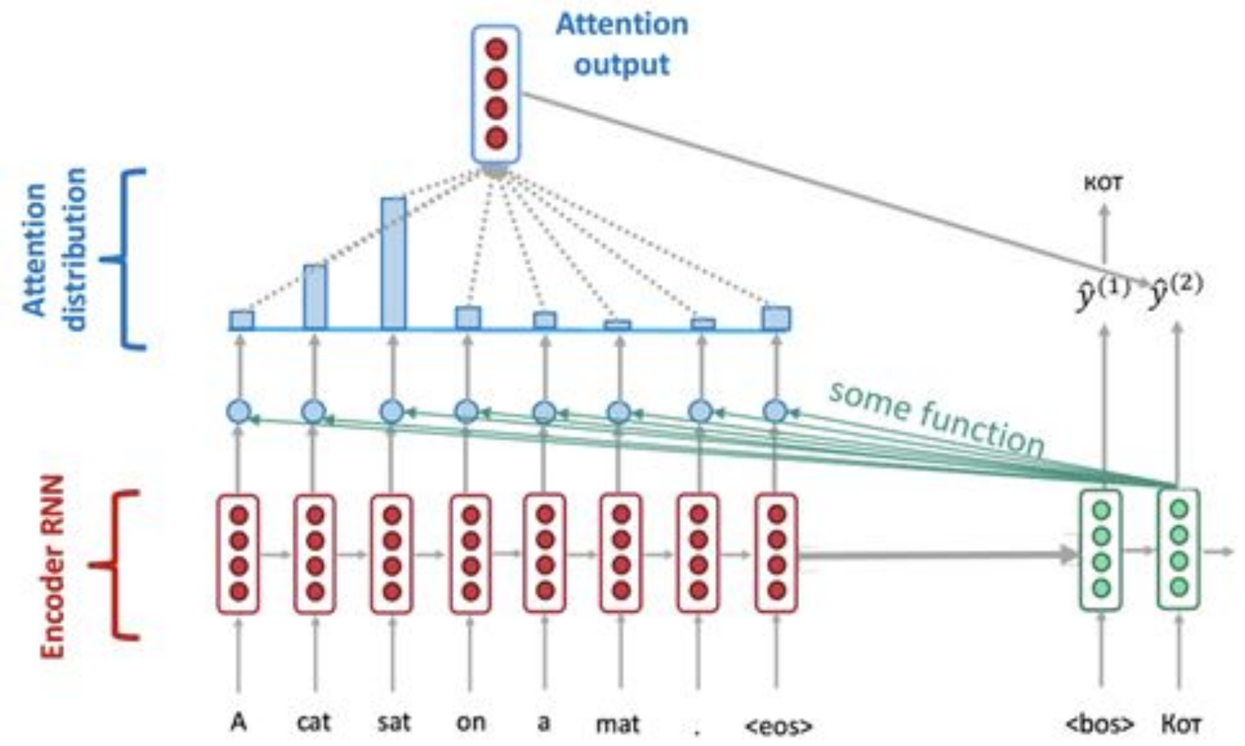
Concatenate attention output with decoder hidden state

Attention



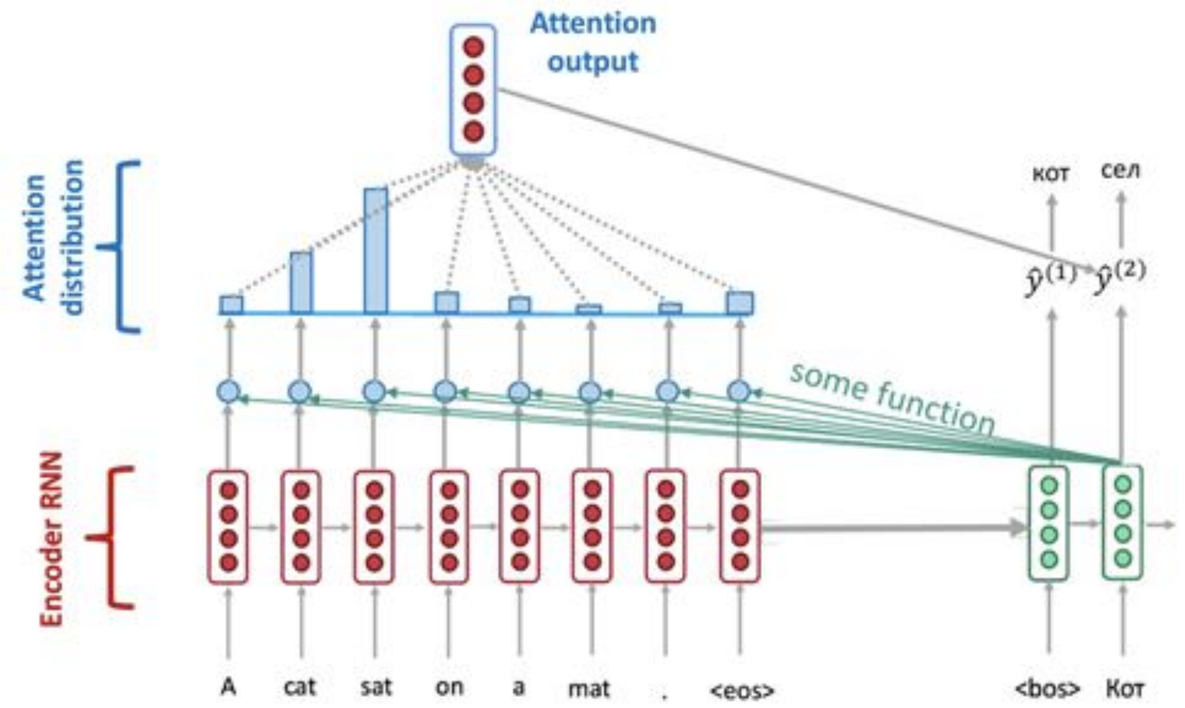
кот
$\hat{y}^{(1)}$
some function
Encoder RNN
A
cat
sat
on
a
mat
.
<eos>
<bos>
Кот

Attention



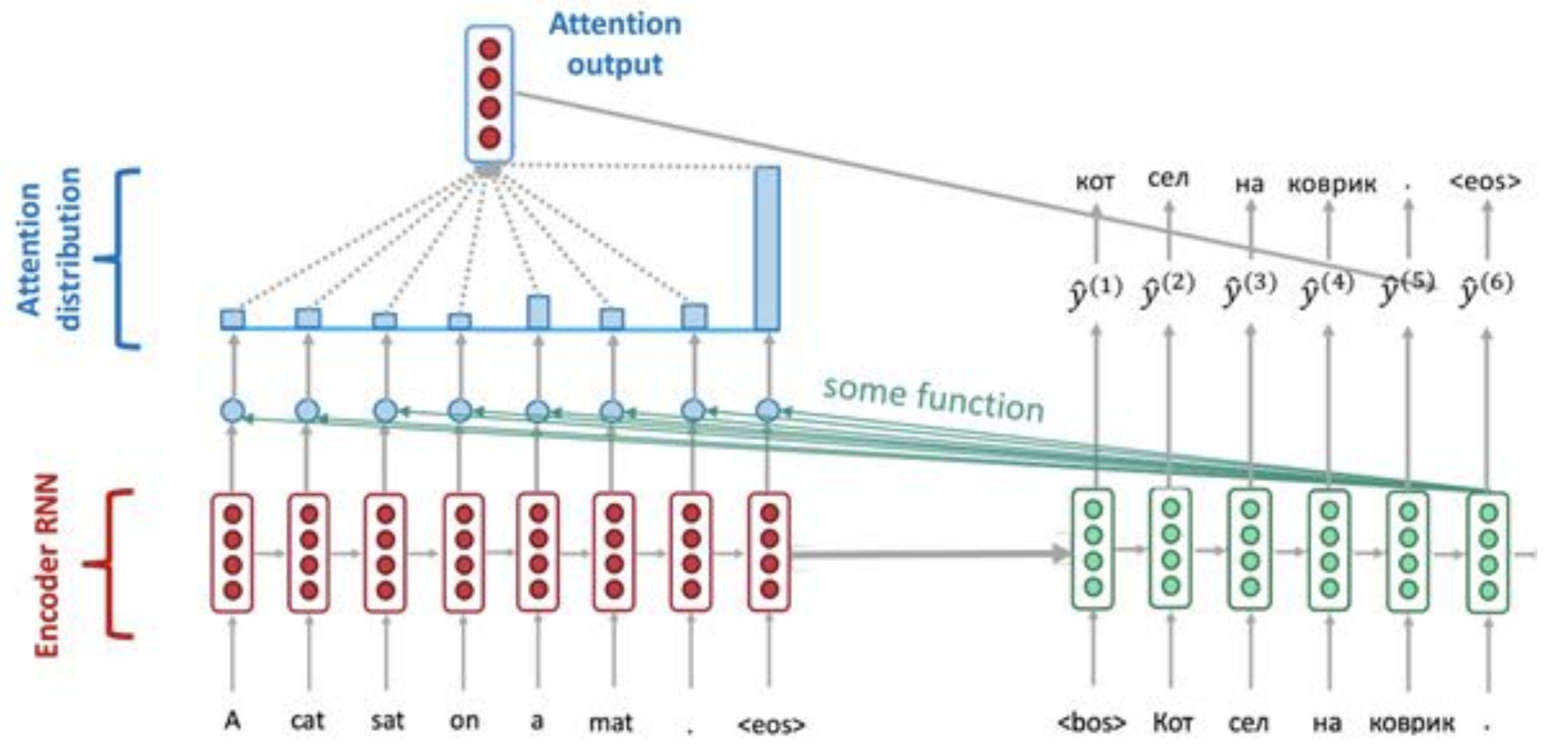
Attention output
Attention distribution
Encoder RNN
some function
кот
$\hat{y}^{(1)}$ $\hat{y}^{(2)}$
A
cat
sat
on
a
mat
.
<eos>
<bos>
Кот

Attention



Attention output
Attention distribution
Encoder RNN
some function
кот
сел
$\hat{y}^{(1)}$
$\hat{y}^{(2)}$
A
cat
sat
on
a
mat
.
<eos>
<bos>
Кот

Attention

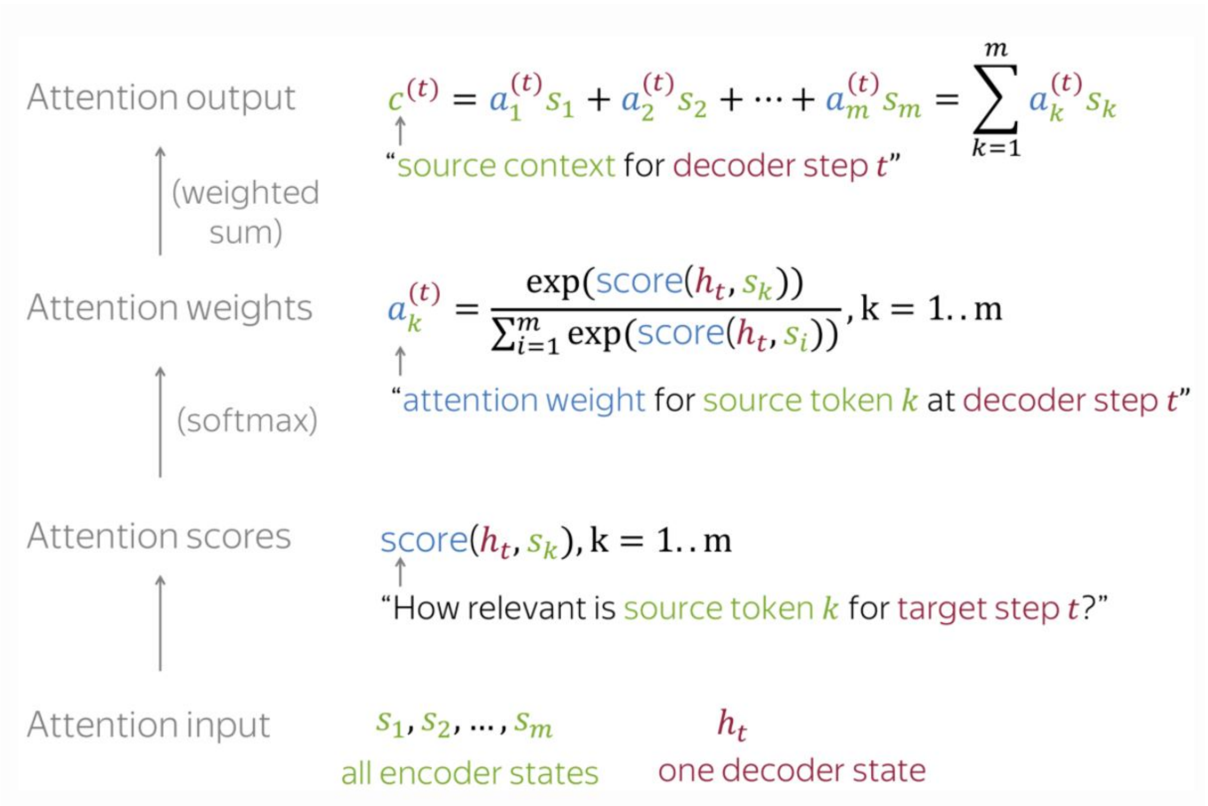


Attention output
Attention distribution
some function
Encoder RNN
кот
сел
на
коврик
.
<eos>
$\hat{y}^{(1)}$
$\hat{y}^{(2)}$
$\hat{y}^{(3)}$
$\hat{y}^{(4)}$
$\hat{y}^{(5)}$
$\hat{y}^{(6)}$
A
cat
sat
on
a
mat
.
<eos>
<bos>
Кот
сел
на
коврик
.

Attention

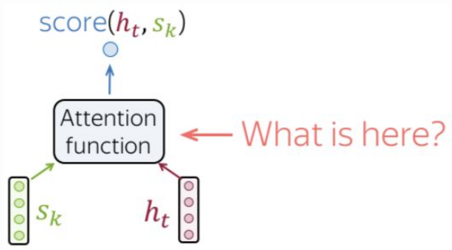
At each decoder step, attention:

- receives attention input
- computes attention scores
- computes attention weights: a probability distribution - softmax applied to attention scores;
- computes attention output: the weighted sum of encoder states with attention weights.



Attention variants

There are sevaral ways to compute attention score:



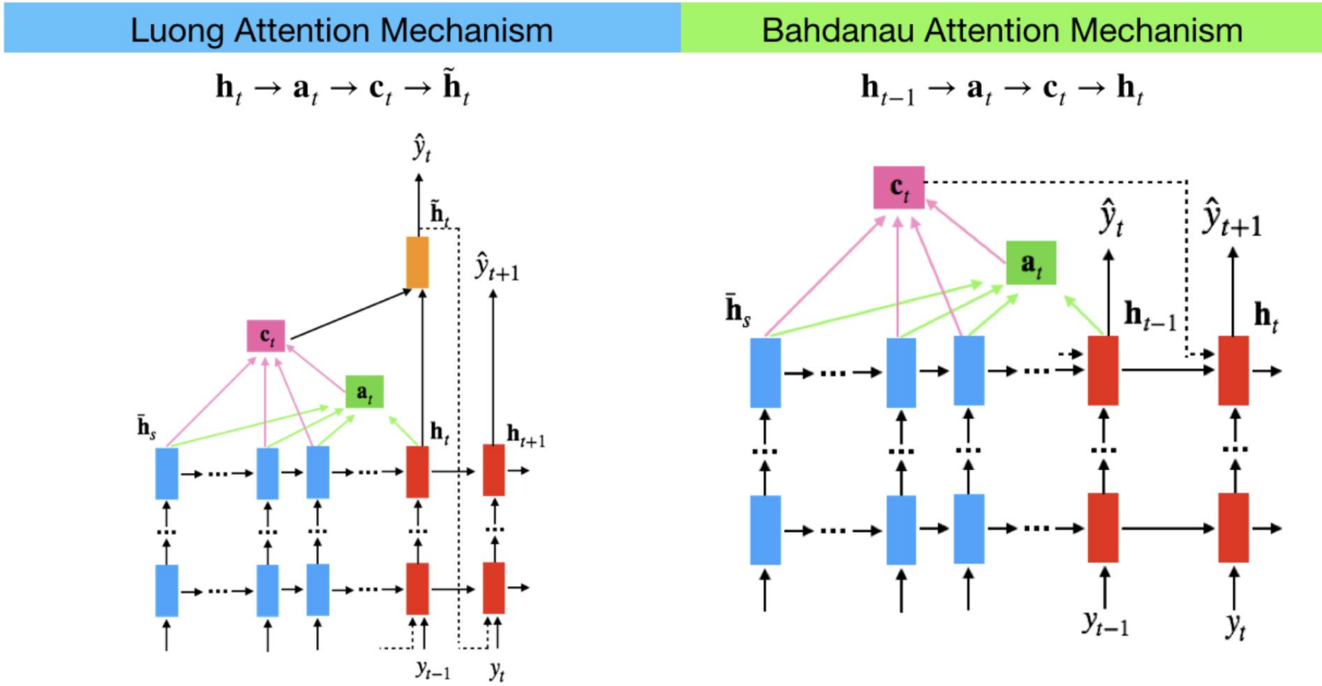
Name	Alignment score function
Content-base attention	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \text{cosine}[\boldsymbol{s}_t, \boldsymbol{h}_i]$
Additive(*)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \mathbf{v}_a^\top \tanh(\mathbf{W}_a[\boldsymbol{s}_t; \boldsymbol{h}_i])$
Location-Base	$\alpha_{t,i} = \text{softmax}(\mathbf{W}_a \boldsymbol{s}_t)$ Note: This simplifies the softmax alignment to only depend on the target position.
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.
Dot-Product	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \boldsymbol{h}_i$
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.

- dot-product - the simplest method;
- general or bilinear function (aka "Luong attention") from Effective Approaches to Attention-based Neural Machine Translation;
- additive or multi-layer perceptron (aka "Bahdanau attention");
- actually any function you want =).

Early attention models

Bahdanau attention (paper Neural Machine Translation by Jointly Learning to Align and Translate by Dzmitry Bahdanau, KyungHyun Cho and Yoshua Bengio);

Luong attention (the paper Effective Approaches to Attention-based Neural Machine Translation by Minh-Thang Luong, Hieu Pham, Christopher D. Manning.

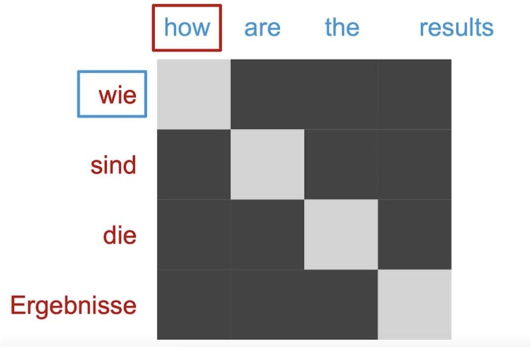


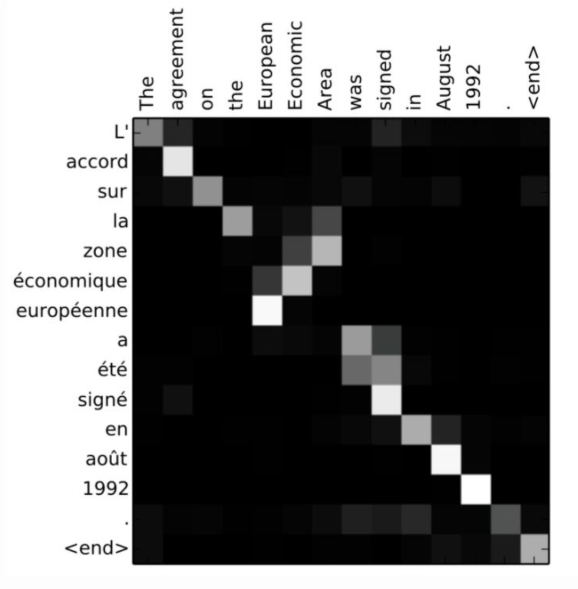
Luong	Bahdanau
$\mathbf{a}_t(s) = \text{align}(\mathbf{h}_t, \bar{\mathbf{h}}_s)$	$\mathbf{a}_t(s) = \text{align}(\mathbf{h}_{t-1}, \bar{\mathbf{h}}_s)$
$\mathbf{c}_t = \sum a_t \mathbf{h}_s$	$\mathbf{c}_t = \sum a_t \mathbf{h}_s$
$\tilde{\mathbf{h}}_t = \tanh(W_c[\mathbf{c}_t; \mathbf{h}_t])$	$\mathbf{h}_t = \text{RNN}(\mathbf{h}_{t-1}^{l-1}, [\mathbf{c}_t; \mathbf{h}_{t-1}])$

Practice here: https://github.com/spro/practical-pytorch/blob/master/seq2seq-translation/seq2seq-translation.ipynb

Attention is good

- Attention significantly improves NMT performance
  - It’s very useful to allow decoder to focus on certain parts of the source
- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability
  - attention distribution shows what the decoder was focusing on
  - Alignment





Transformer

Transformers

Attention is all you need =)

2017

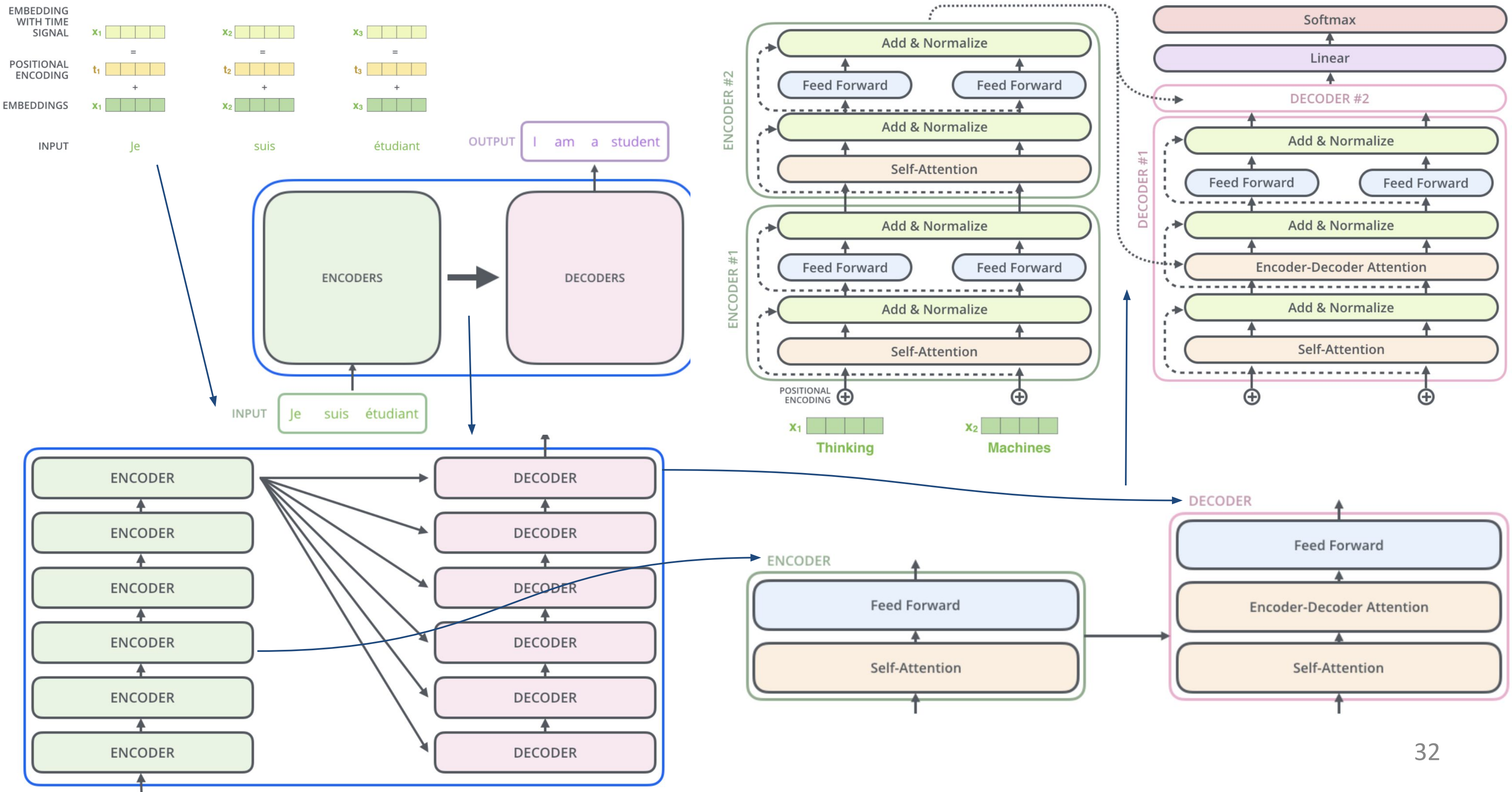
Previously:

- RNN encoder + RNN decoder, interaction via fix-sized vector
- RNN encoder + RNN decoder, interaction via attention

NOW:

attention + attention+ attention

Transformers. High-level



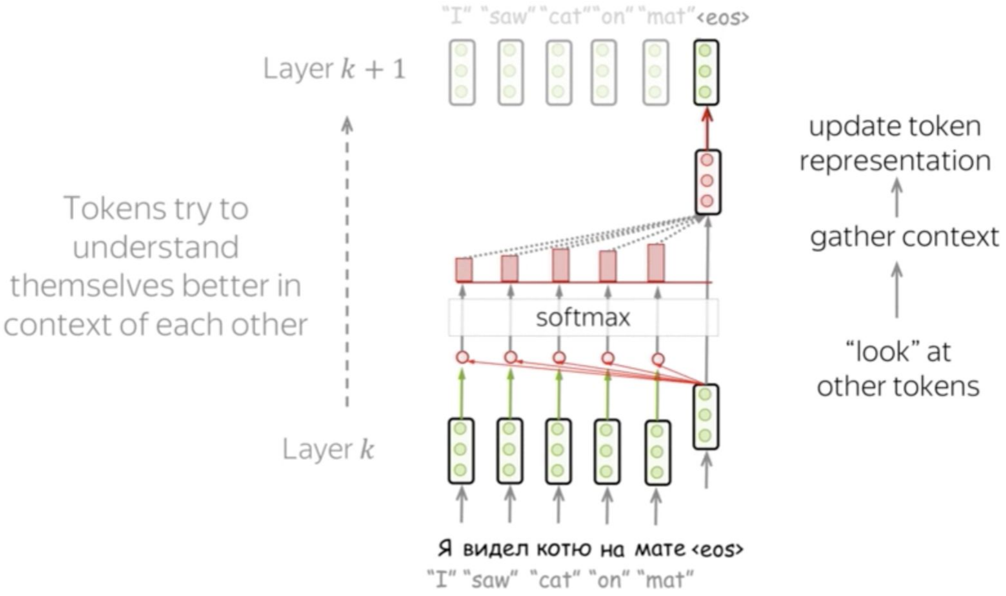
Transformers. Self-attention

Previously - one decoder state looked at all encoder states

NOW - each state looks at each other states

Self-attention:

- tokens interact with each other
- each token "looks" at other tokens
- gathers context
- updates the previous representation of "self"



In Parallel!

Transformers. Self-attention

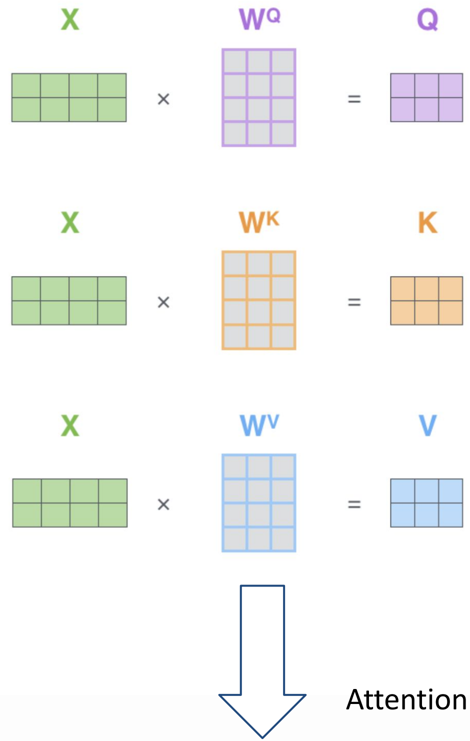
Query, Key and Value vectors:

Each vector receives three representations:

- query - asking for information;
- key - saying that it has some information;
- value - giving the information.

These matrices allow different aspects of the x vectors to be used/emphasized in each of the three roles

Attention matches the key and query by assigning a value to the place the key is most likely to be.



Attention weights

$$\mathrm{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathrm{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

Transformers. Masked self-attention

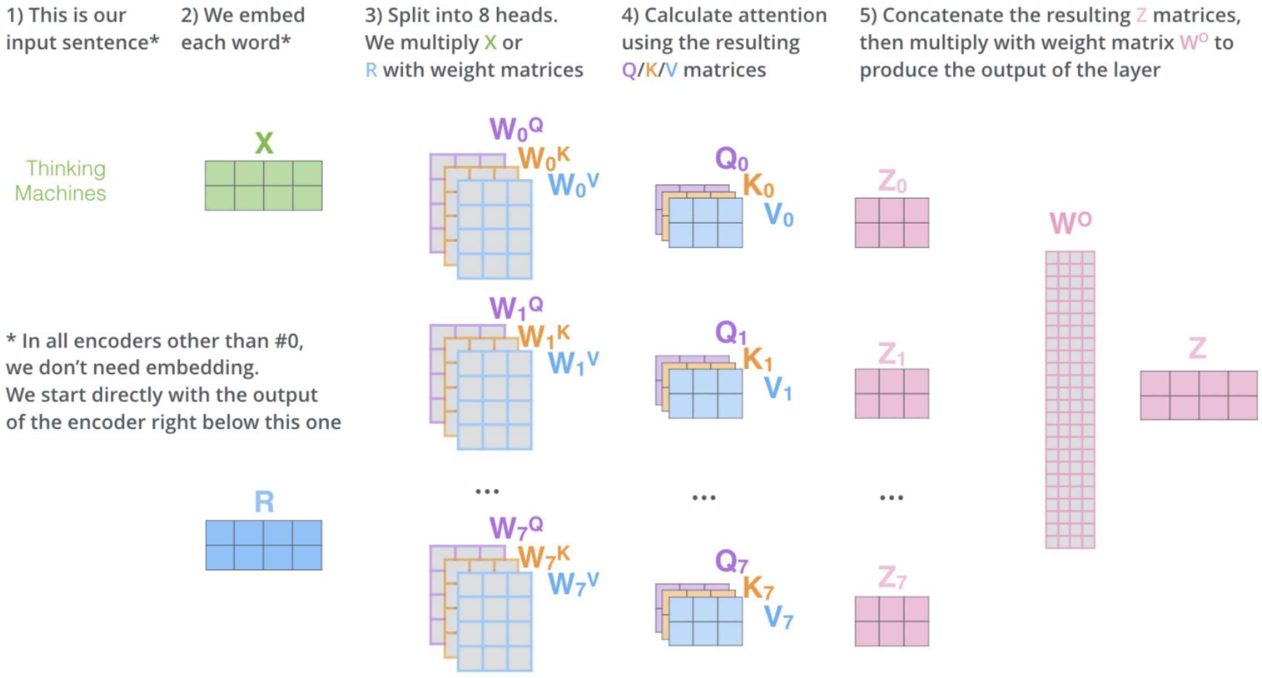
Decoder has different self-attention =>

Masked self-attention

- we generate one token at a time (we don’t have all source tokens at once like in encoder): during generation, we don't know which tokens we'll generate in future.
- to enable parallelization we forbid the decoder to look ahead - future tokens are masked out (setting them to -inf) before the softmax step in the self-attention calculation

Transformers. Multi-head attention

- We need to know different relationships between tokens in a sentence: syntactic relationships, lexical preferences, order, grammar issues like case or gender agreement.
- Instead of having one attention mechanism, multi-head attention has several "heads" which work independently and focus on different things.
- Heads works independently

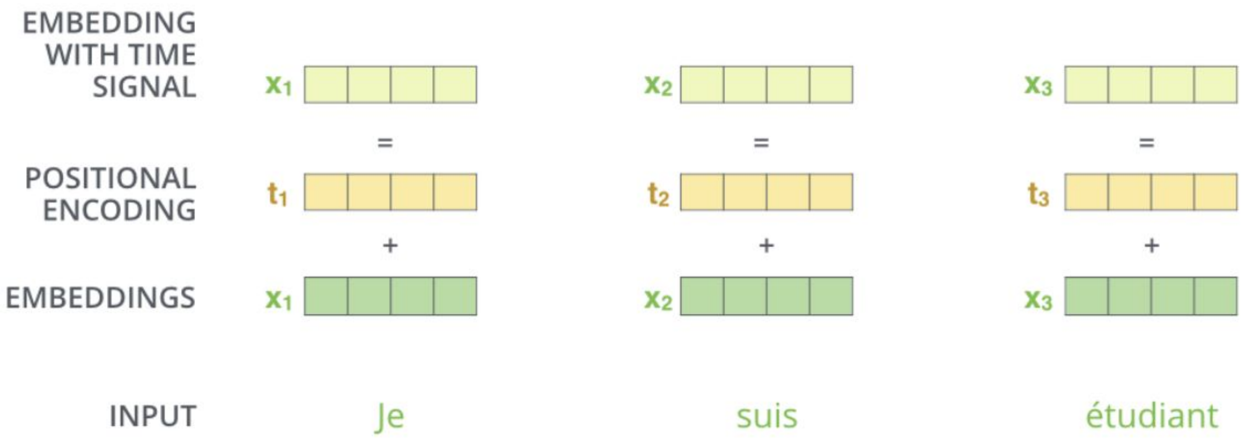


$$\mathrm{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)\mathbf{W}^O$$

$$\text{where head}_i = \mathrm{Attention}\left(\mathbf{QW}_i^Q, \mathbf{KW}_i^K, \mathbf{VW}_i^V\right)$$

Transformers. Positional encoding

- **positional encoding** provides *order information* to the model



The fixed positional encodings

used in the Transformer

$$PE(i, \delta) = \begin{cases} \sin\left(\frac{i}{10000^{2\delta'/d}}\right) & \text{if } \delta = 2\delta' \\ \cos\left(\frac{i}{10000^{2\delta'/d}}\right) & \text{if } \delta = 2\delta' + 1 \end{cases}$$

Transformers. Extra

- **Feed-forward blocks**

each layer has a feed-forward network block:

two linear layers with ReLU non-linearity between them

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2.$$

- **Residual connection (train better)**

Residual connections => add a block's input to its output

They ease the gradient flow through a network and allow stacking a lot of layers

* In the Transformer in the "Add & Norm" part, the "Add" part stands for the residual connection.

- **Layer Normalization (train faster)**

Normalizes vector representation of each example in batch. Improves convergence stability

Idea: cut down on uninformative variation in hidden vector values by normalizing to unit mean and standard deviation within each layer

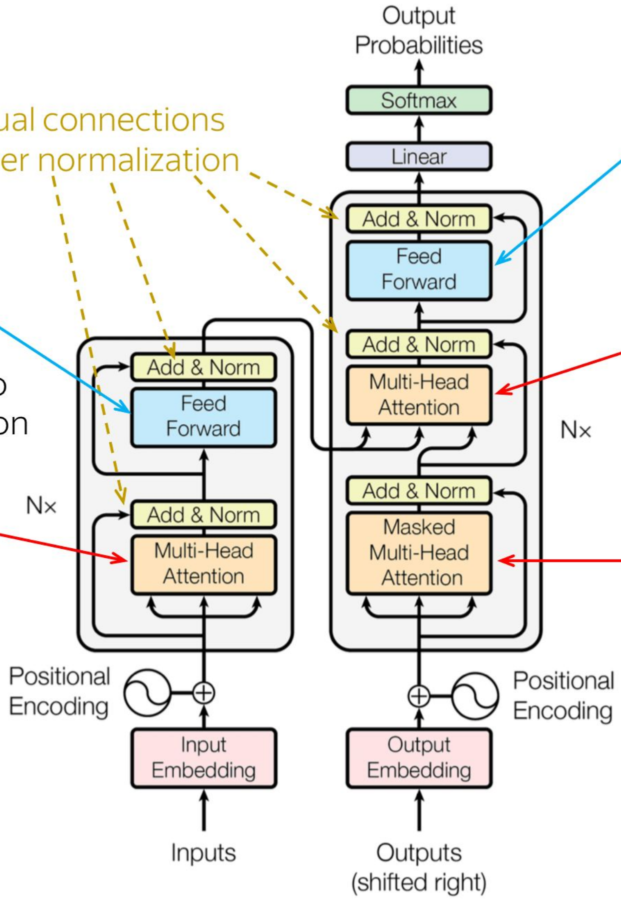
Transformers. One more time

Residual connections
and layer normalization

Feed-forward network:
after taking information from other tokens, take a moment to think and process this information

Encoder self-attention:
tokens look at each other

queries, keys, values are computed from encoder states



Feed-forward network:
after taking information from other tokens, take a moment to think and process this information

Decoder-encoder attention:
target token looks at the source

queries – from decoder states; keys and values from encoder states

Decoder self-attention (masked):
tokens look at the previous tokens

queries, keys, values are computed from decoder states

Transformers

Why are transformers good?

- No recurrence, distributed and independent representations at each block (all tokens can be processed at once)
- No long relations: for recurrent models - one training step requires O(len(source) + len(target)) steps, for Transformer, it's O(1), since all words interact at every layer.
- Fast learning: encoder and decoder can be parallel
- Self-Attention: model does not need to remember too much
- Multi-head attention allows to pay attention to different aspects
- The meaning heavily depends on the context

References

Transformers

Attention is all you need

Transformer survey

High-level

Jay Alammar:

- Transformers - http://jalammar.github.io/illustrated-transformer/
- Seq2seq with attention - https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

AI Summer https://theaisummer.com/transformer/

Deeper

- Stanford Lectures https://www.youtube.com/watch?v=IxQtK2SjWWM&ab_channel=StanfordUniversitySchoolofEngineering
- Lena Voita https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html
- https://lilianweng.github.io/lil-log/2020/04/07/the-transformer-family.html

With code:

- https://nlp.seas.harvard.edu/2018/04/03/attention.html
- https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/text/transformer.ipynb#scrollTo=1kLCla68EloE