Transformers #1: Introduction to Transformer

RPL CV/DL reading group

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23 Feb 2021

Transformers theme: schudule

- 23 Feb (today) (Sebastian): Introduction to the Transformer model
- 9 Mar (Federico): Transformer models for Image
- (tentative) 23 Mar (Yonk): Transformer models in different applications/domains
- (tentative) 6 Apr (Sofia): Alternative approaches to Transformer

Agenda

1. Taxonomy: attention, self-attention, Transformer?
   - Why attention?
   - Why Transformer?
   - **Discussion!**
2. Transformer
   - Transformer vs. RNN; Transformer in general
   - Some specifics for text
   - **Discussion!**
3. Some details about the Transformer & results
4. **Discussion!**

Taxonomy

Attention! - definition

"Attention is a technique that mimics cognitive attention" (Wikipedia)

"(Your) Attention is (our) profit" (Instagram) ⚠ Offical sources might deny it.

"The ability to focus on one thing and ignore others" (Alex Graves, 2020) - I might have taken it out of context :/

"**Looking at some places more than at others**" (Bujwid, 2021)

Why attention (in neural networks)?

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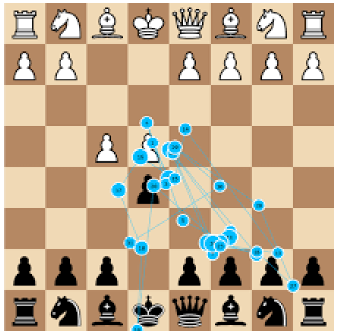

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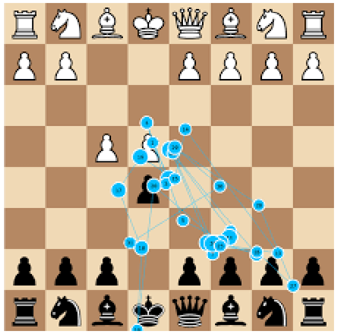


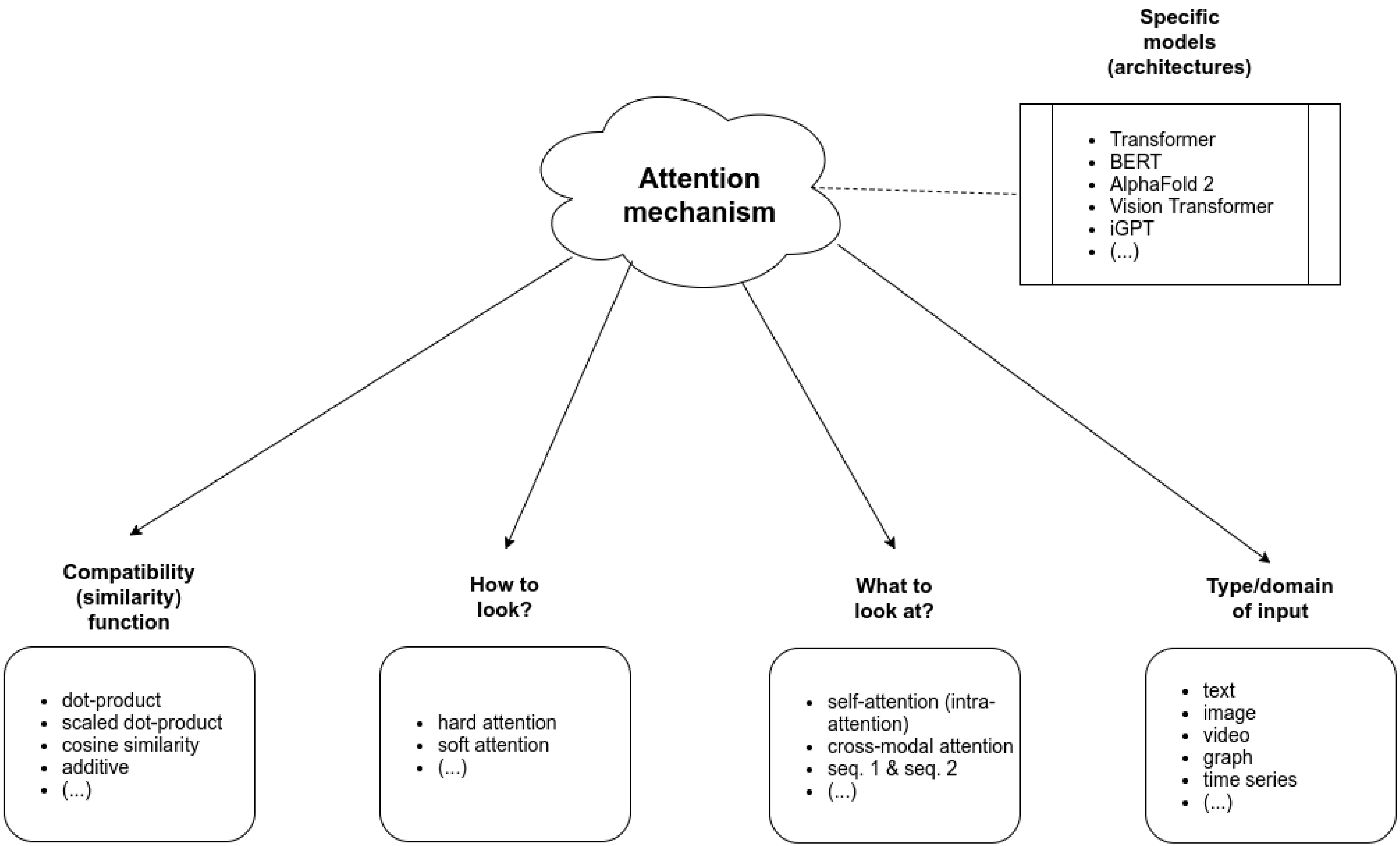
Anna är orolig för miljön så hon använder sin cykel året runt

(...) (...)

Anna is concerned about the environment so she uses ? bike all year round

(her)

Taxonomy

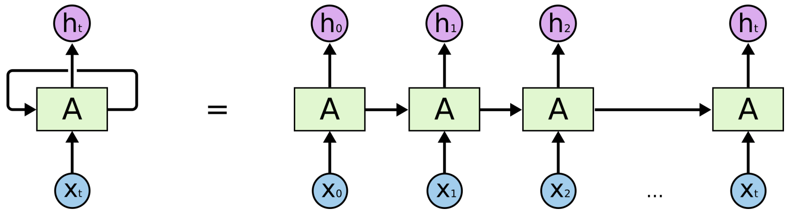

Specific models (architectures)
Transformer
BERT
AlphaFold 2
Vision Transformer
iGPT
(...)
Attention mechanism
Compatibility (similarity) function
dot-product
scaled dot-product
cosine similarity
additive
(...)
How to look?
hard attention
soft attention
(...)
What to look at?
self-attention (intra-attention)
cross-modal attention
seq. 1 & seq. 2
(...)
Type/domain of input
text
image
video
graph
time series
(...)

Why Transformer [1]?

Let's look at the issues with RNNs first!

Issue #1: Computational efficiency

This structure is not efficient on GPUs!



(Image from: http://colah.github.io/)

[1] Vaswani et al., "Attention Is All You Need," NeurIPS 2017

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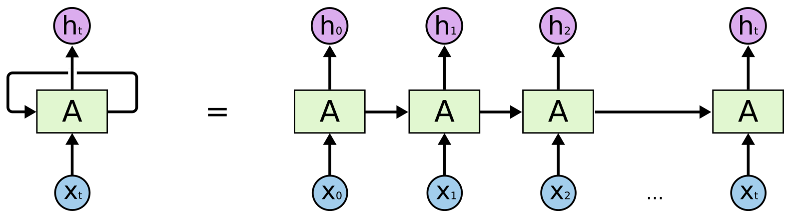

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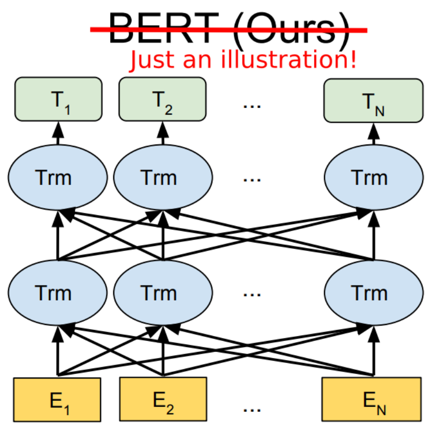
Solution #1: An architecture without sequential operations



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Issue #2: Long-term dependencies

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sv: Viskleken | *eng:* Telephone (game)

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Our unpublished results:

Doesn't work if too many kids.
(Sebastian, 199...)

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Solution #2: Always look at the whole sequence (or rather sub-sequence)

Transformer

Transformer: scaled dot-product self-attention

T - the number of tokens/elements
$Q \in \mathbb{R}^{T \times d}$ - queries
$K \in \mathbb{R}^{T \times d}$ - keys
$V \in \mathbb{R}^{T \times d_v}$ - values

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Self-attention when all Q, K, and V are a function of the same input sequence X.

- $Q = f_q(X)$, $K = f_k(X)$, $V = f_v(X)$
- Typically all linear functions

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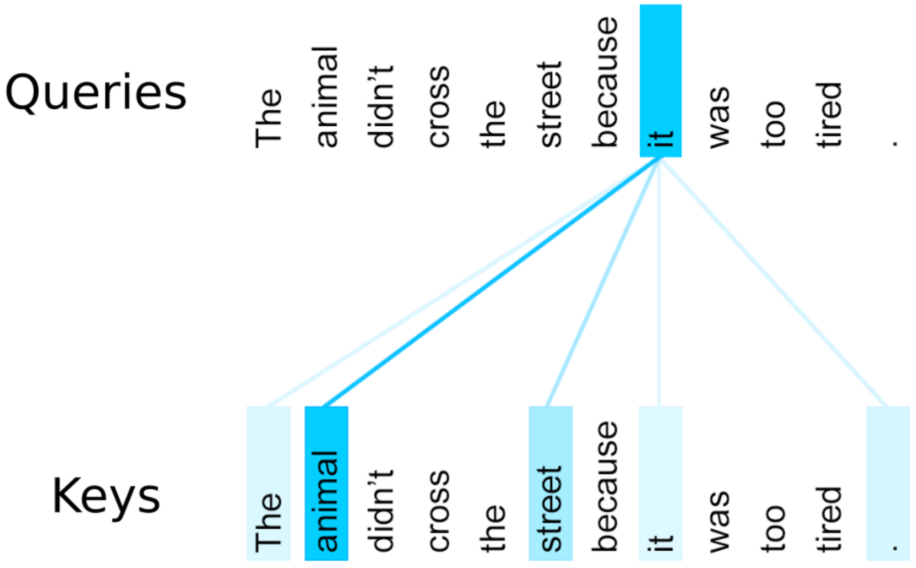
For each token (query!) compute the "compatibility" with other tokens (keys!):

$$\frac{QK^T}{\sqrt{d}} \qquad [\mathbb{R}^{T \times T}]$$

- Or any other $f(Q, K) \to \mathbb{R}^{T \times T}$



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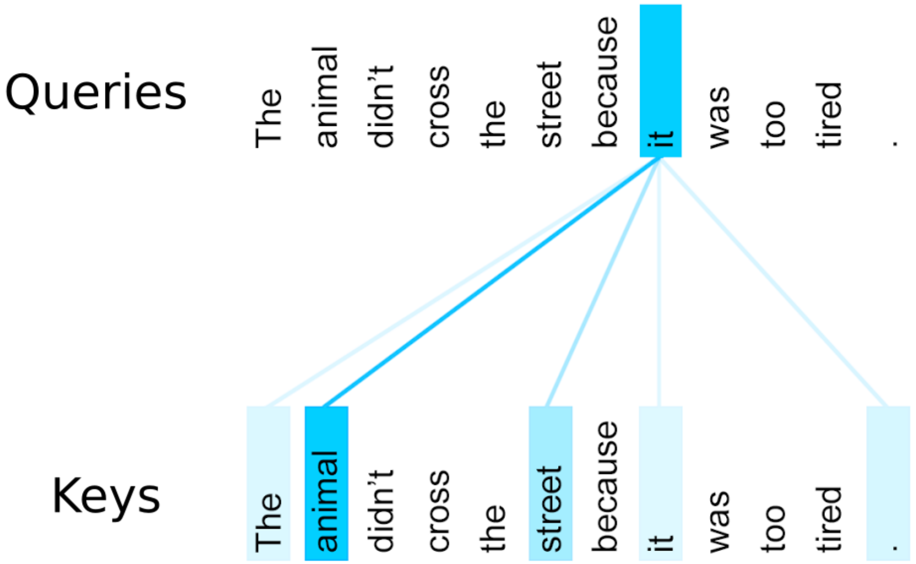
Normalize the "compatibility" for each query

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)$$



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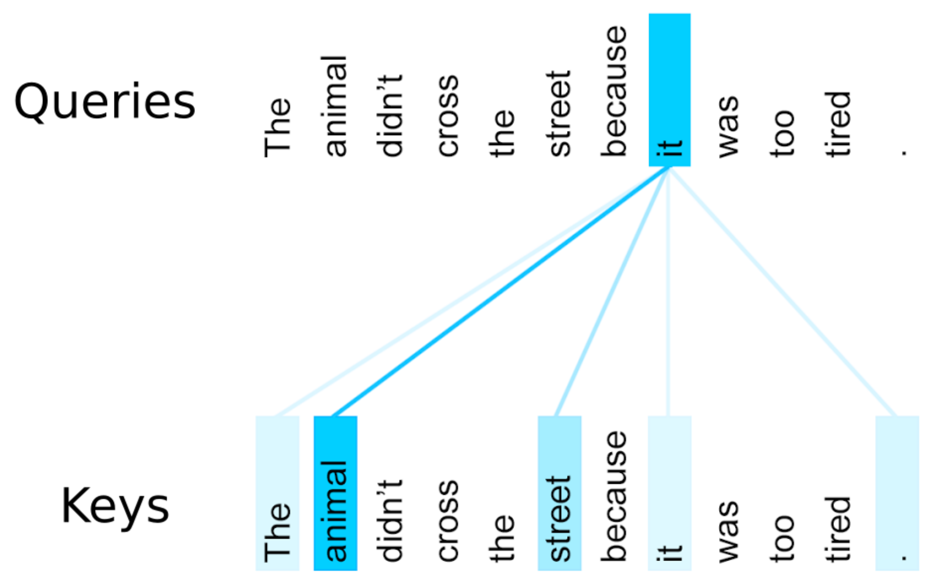
Compute new values:

$$\text{attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) V$$



Transformer: architecture

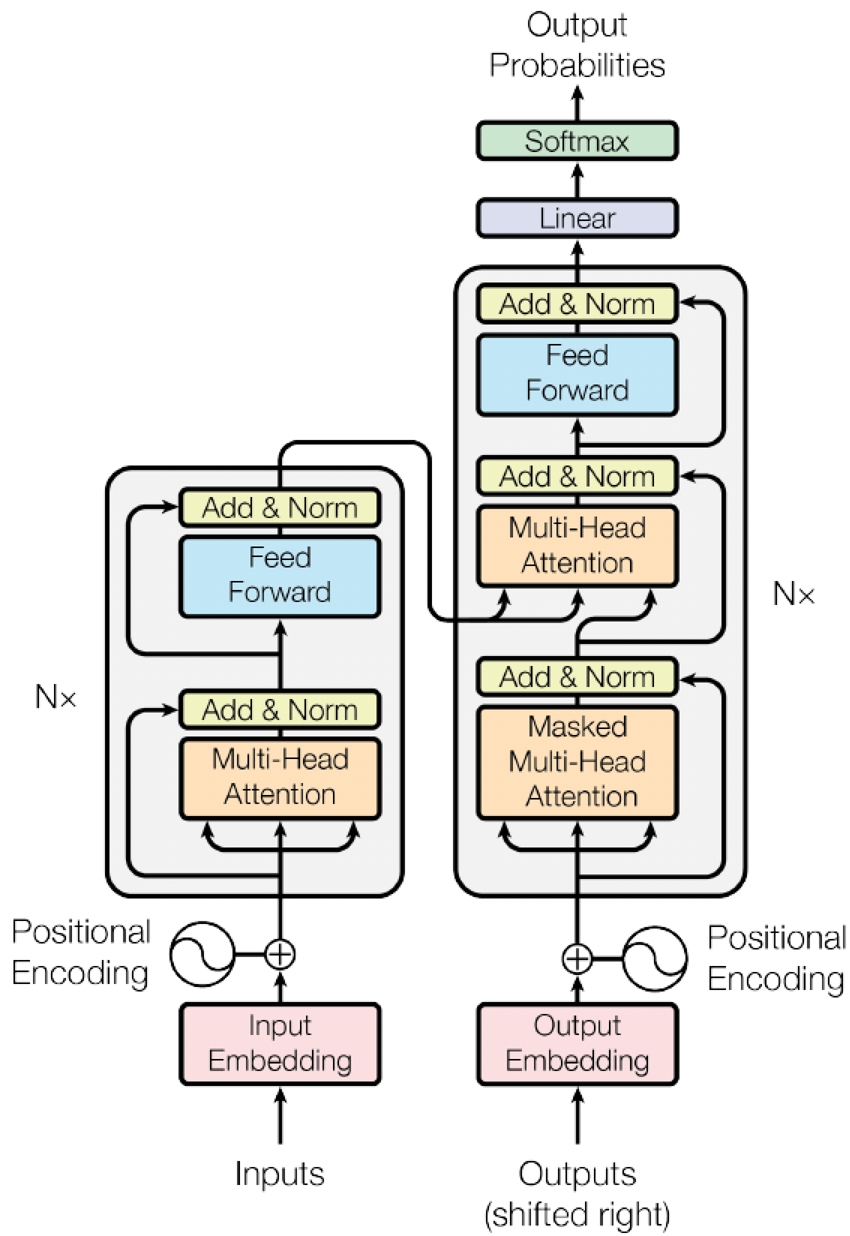


Figure 1: The Transformer - model architecture.

Some details

Complexity

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)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

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- More effective (controlling for #params)

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Interpretability?

Results

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 [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	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**	**41.8**	$2.3 \cdot 10^{19}$	

Thank you!

Discussion!