Attention Is All You Need

a.k.a. «Sequence models are overrated»

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Sequence processing tasks

When there's a sequence and you need to process it

We all know them, we all love them

- Machine translation:
  Translating one sequence of words into another.
- Sentiment analysis:
  Classification of sequences
- Text-to-speech and speech-to-text:
  Translation with some caveats
- And many, many more.
- We will focus on sequence-to-sequence tasks in this presentation.

Machine translation is nontrivial

- Natural language is complex and complicated;
- There is about a khgjillion ways to say the same thing differently;
- Sentences can have wildly varying lengths;
- Connected words don't have to be close;
- And yet the word order is crucial;
- The connections between words are not always straightforward
- Nor are their meanings.

Try translating this:

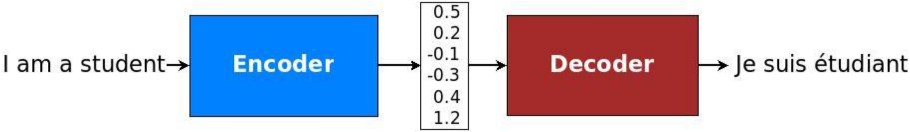
- “The horse raced past the barn fell.”
- “The old man the boat.”
- “The complex houses married and single soldiers and their families.”

How do we cope with this?

- Hard-coded rule-based translation is horrible.
- Statistical systems are better, but still quite bad.
- Deep learning to the rescue!

Generally, Deep-Learning based models consist of an encoder and a decoder:

- Encoder encodes the word sequence into some internal representation;
- Decoder decodes that representation inte a sequence of words in another language.



RNNs: the original seq2seq

By this point you should be familiar with them.

- Encoder iterates over the input sequence, building some internal vector representation of it;
- Decoder decodes that vector into a full sequence in another language.

Pros and cons:

+ Can adequately model sequences;
+ Can model (medium-)long-term dependencies;
– Not very good at very long-term dependencies;
– Is forced to compress a whole sentence into a single vector;
– Non-parallelizable; slow.

RNNs with attention

- Encoder iterates over the input sequence, generating a sequence of representations;
- Decoder selects and combines embeddings at each step to produce a full sequence in another language.

Pros and cons:

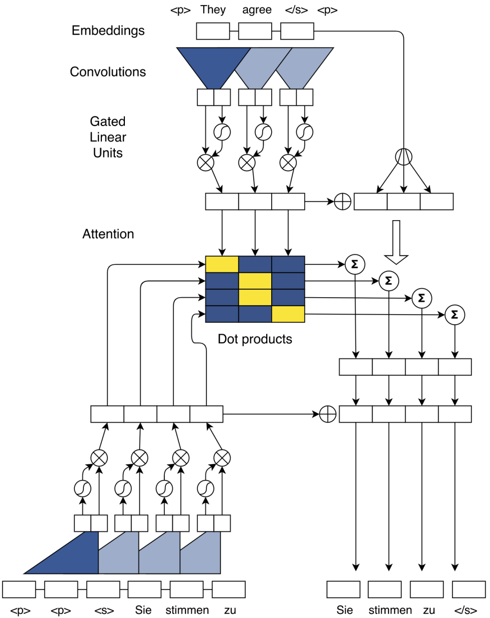
+ Are better at long-term dependencies between input and output;
+ No longer compresses; the latent space is much larger;
− Still non-parallelizable and slow.

CNNs

Encoder and decoder are CNNs instead of RNNs.
Pros and cons:

+ Are even better at long-term dependencies, since there is no bottleneck in the form of RNN's inner state;
+ Parallelizable; fast;
– Since CNN neurons have limited perception field, networks have to be very deep or use other tricks.
– For the same reason, there always is a maximum distance where model can "connect" words.

ConvS2S architecture



Main trends

- RNNs are good as an initial "baseline", but they have major drawbacks;
- Everything is better with attention;
- Additionally, we would like as much parallelization as possible;
- And no bottlenecks;
- And no limits on sequence length.

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What can we use?

- RNNs are out of the question — they have major bottlenecks;
- CNNs are also out — they have limited perception;
- ???
- Can we make a sequence model without actually using anything sequential?

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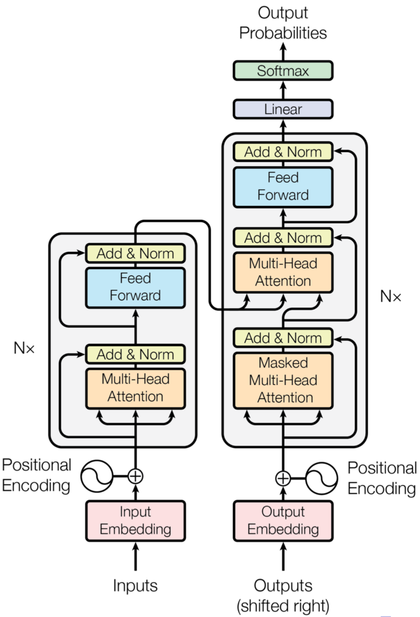
- Can we make a sequence model without actually using anything sequential?
- Yes, and attention is our best friend.

Enter Transformer

Transformer is a work of several researchers, mostly from Google.
Main features:

- Consists entirely of fully-connected layers and attention;
- Attention is applied not only between encoder and decoder, but within them as well;
- Since fully-connected layers have no way of knowing the position in the sequence, *positional embeddings* are employed;
- An entirely new attention mechanism: *Multi-head attention*;
- Residual connections, layer normalization, dropouts, label smoothing...

Transformer architecture

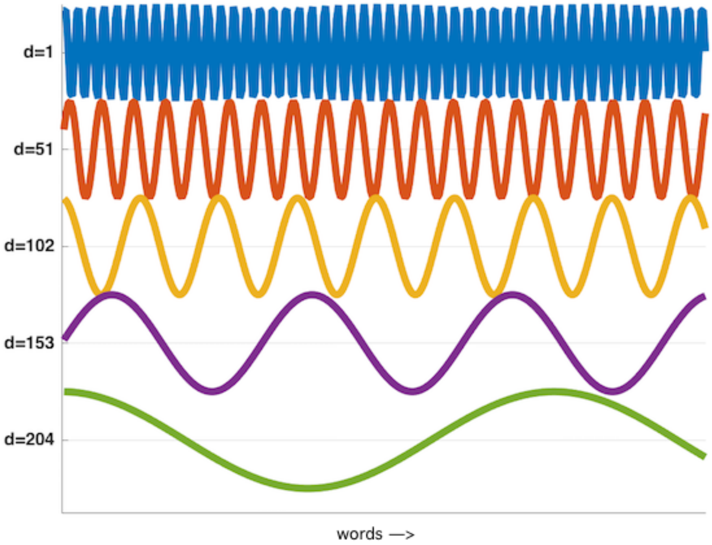


Input

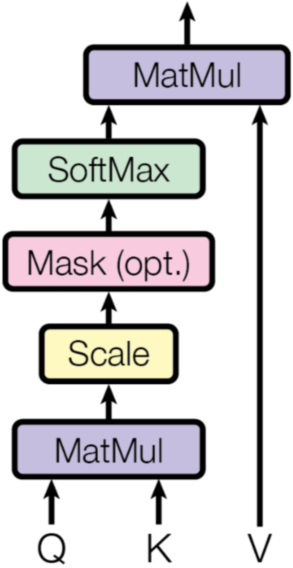
- Input and output are preprocessed using BPE (byte-pair encoding); the words are split into sub-word tokens, which are then fed into the network.
- In order to give the model a sence of location, positional embeddings are used:
  If $\mathbf{w} = (w^{(1)}, w^{(2)}, \ldots, w^{(\ldots)})$ is a sequence of word embeddings, then $\mathbf{x} = (w^{(1)} + p^{(1)}, w^{(2)} + p^{(2)}, \ldots)$ is a sequence of positionally embedded words;

$$\begin{cases} p_{2i}^{(k)} = \sin\left(\dfrac{k}{10^{\frac{8i}{d_{\text{model}}}}}\right) \\ p_{2i+1}^{(k)} = \cos\left(\dfrac{k}{10^{\frac{8i}{d_{\text{model}}}}}\right) \end{cases}$$

Positional embeddings



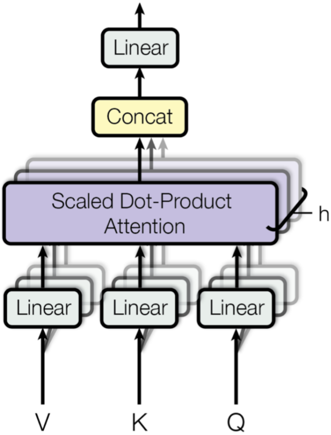
Attention



Basic building block of Multihead attention is *Scaled dot-product attention*:

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

Attention

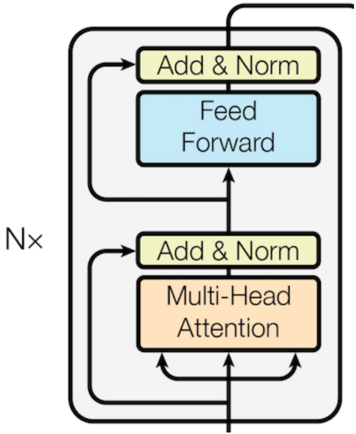


Multihead attention is simply a concatenation of several slightly different scaled dot-product attentions:

$$\text{Multihead}(Q, K, V) = (H_1, \ldots, H_h)^T W^O$$

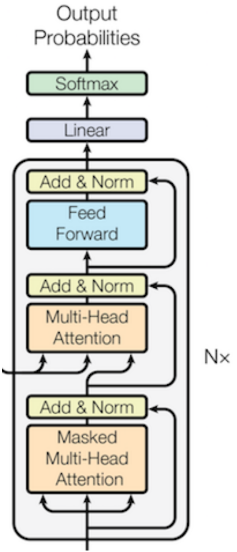
$$H_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Encoder



- Encoder consists of N identical blocks;
- Each block consists of an attention layer and a feedforward layer with residual connections inbetween;
- The keys, values and queries all come from the previous block; this is *self-attention*;

Decoder

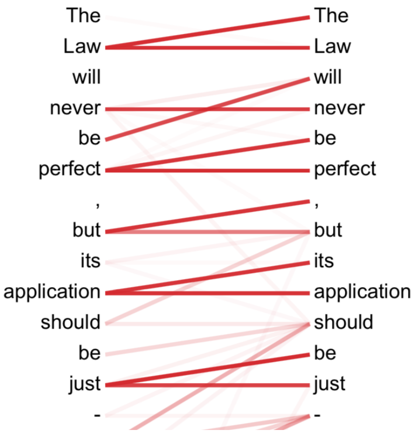


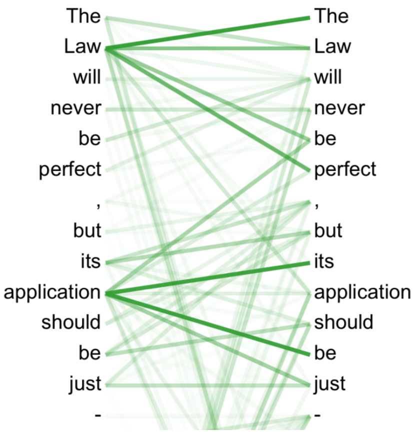
- Decoder consists of N identical blocks;
- Each block consists of:
    - Self-attention layer;
    - Attention over encoder outputs;
    - Feedforward layer;
- In the attention over encoder outputs, keys and values come from encoder, but queries are generated by the decoder.

Why does this work better?

- This architecture is easily parallelized: the only sequential part is how every word of output depends on all previous words;
- It does not employ any unusual operations; most operations are easily parallelized and heavily optimized matrix multiplications;
- The path between any two sequence items has constant length, as opposed to linear in RNNs and CNNs.
- Heavy dependence on attention makes results more interpretable, possibly giving insight into how the model "looks" at the text.

Self-attention

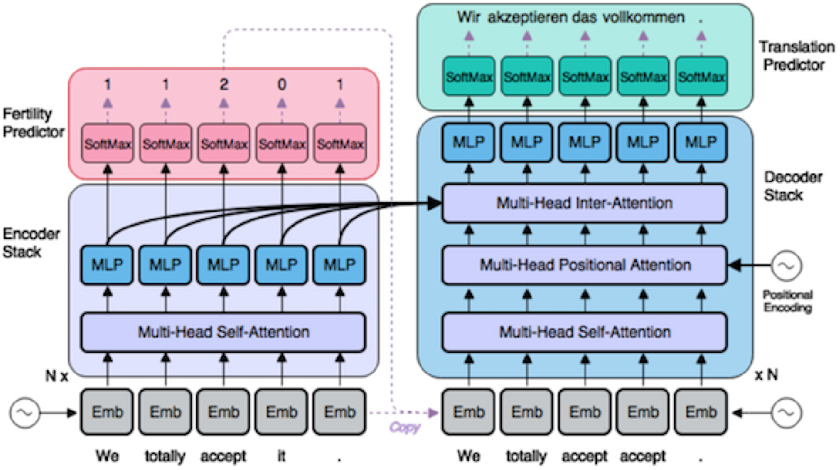




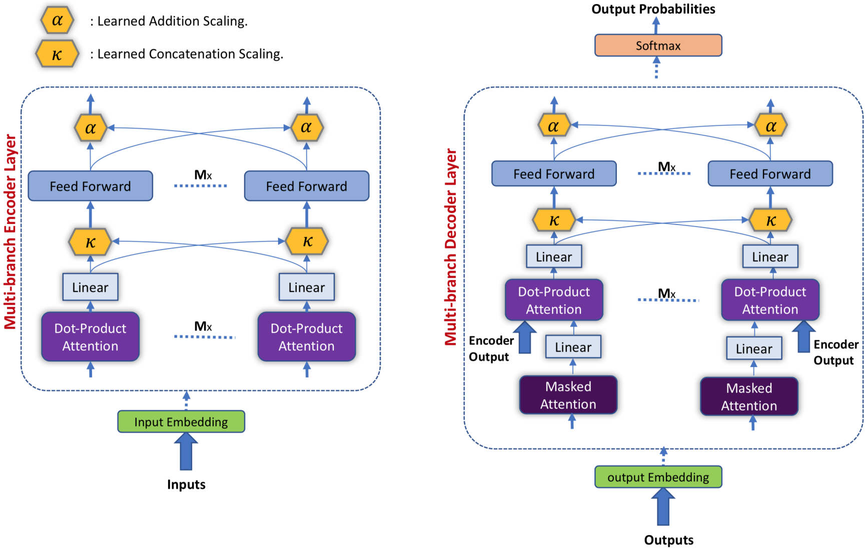
Results

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**	$2.3 \cdot 10^{19}$	

Non-autoregressive Transformer



Weighted Transformer



References I

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