Attention Is All You Need

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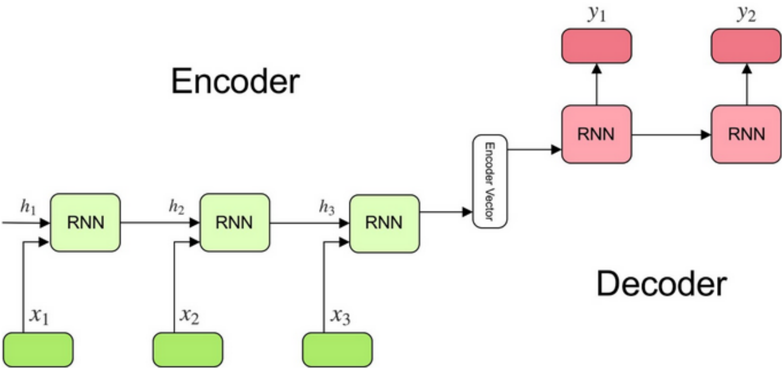
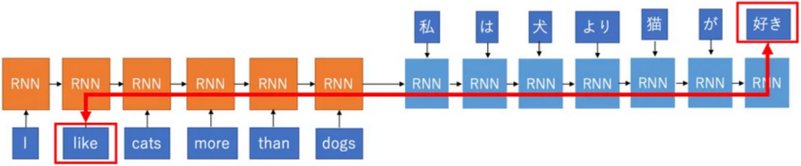
Sequence-to-Sequence models



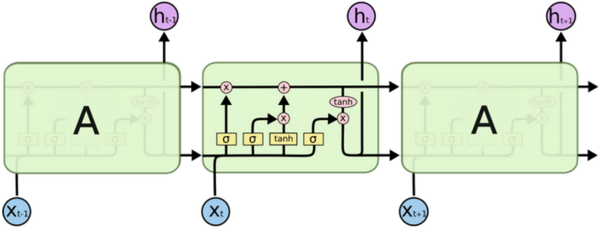
- most popular models
- language translation

RNNs



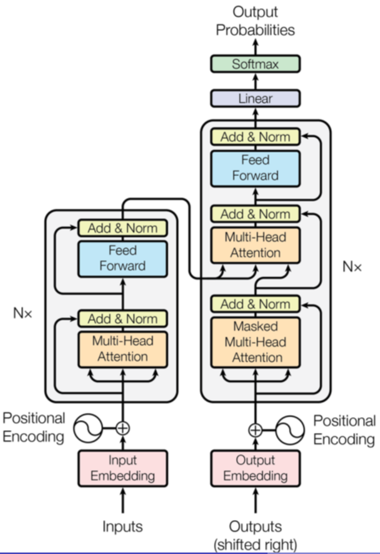
- feed-forward NNs rolled out through time (back-propagation through time)
- slow to train
- cannot deal with long sequences: vanishing/exploding gradients

LSTMs



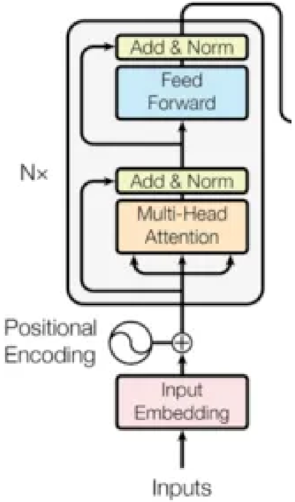
- Hochreiter and Schmidhuber (1997)
- path to allow past information to skip processing and move to next
- forget, input, output gating: better coping with longer sequences
- slower to train than RNNs: data passed sequentially, no parallelization

The Transformer model



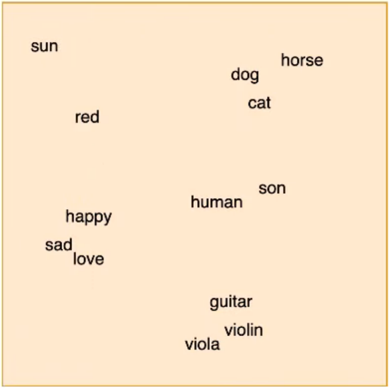
- same encoder-decoder model as RNNs
- the input sequence passed in parallel
- no concept of time-step (like RNNs that construct hidden state)

The Encoder



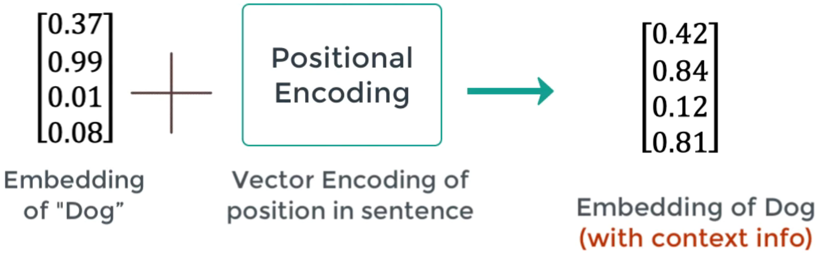
- Multi-Head Attention block
- Feed-Forward layer
- residual connection: learn the difference, supress vanishing gradient problem
- layer normalization

Problem with the embedding space



- words $\rightarrow$ vectors, closer to each other for similar words
- words in different sentences have different meanings
- positional encoder breaks the equality of different embeddings

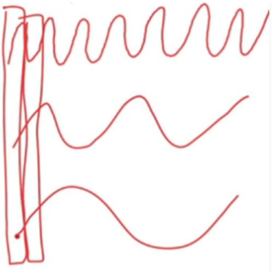
Positional Encoder



$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

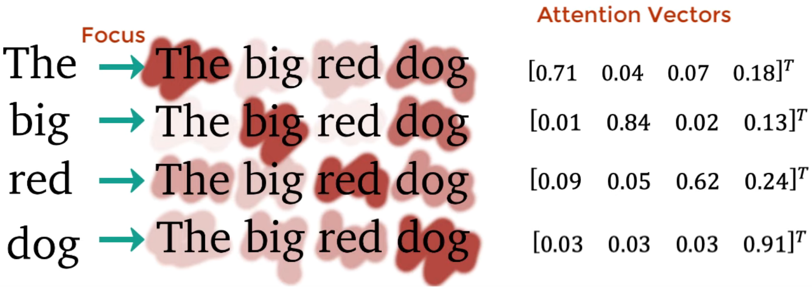
- vector containing context based of position of word in sentence

Positional Encoder functions



- some kind of continuous 'binary' encoding of position
- comparing positional encodings gives the distance between words
- wavelenghts of geometric progression between 2π and $10000 \cdot 2\pi$

Attention



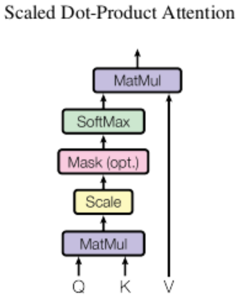
- (self) attention
- for every word, it computes the contextual relationships with other words in sentence

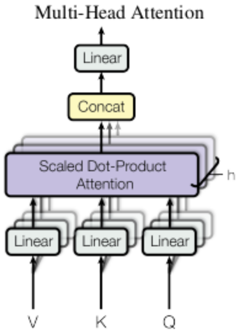
How Attention is computed: Scaled Dot-Product Attention

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

- dot-product determines cosine similarity between Key and Query
- as dot product tends to grow with dimensionality of the query and key, so scaling prevents explosion to huge values
- softmax determines a more like a 'one-hot' encoding, and basically a component from V gets selected
- some kind of indexing scheme

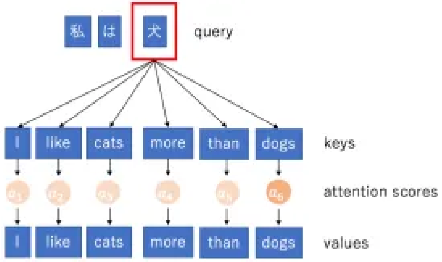
Multi-Head Attention





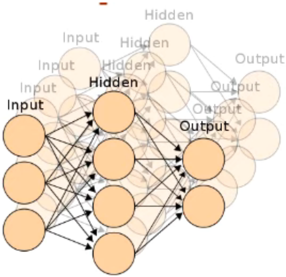
- computes the relevance of a set of Values based on Keys and Queries
- attention is used as a way for the model to focus on relevant information
- computes multiple attention vectors for every word (multi-head)

Multi-Head Attention (2)



- query is the word being decoded
- keys and values are the source sentence
- attention score represents the relevance (large for word 'dog')

Feed-forward NN



- looks for features into attention vectors
- non-linear mapping between input and output space, with ReLU in between:

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

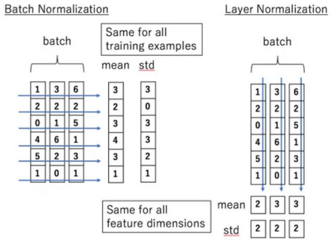
Layer Normalization

Batch normalization

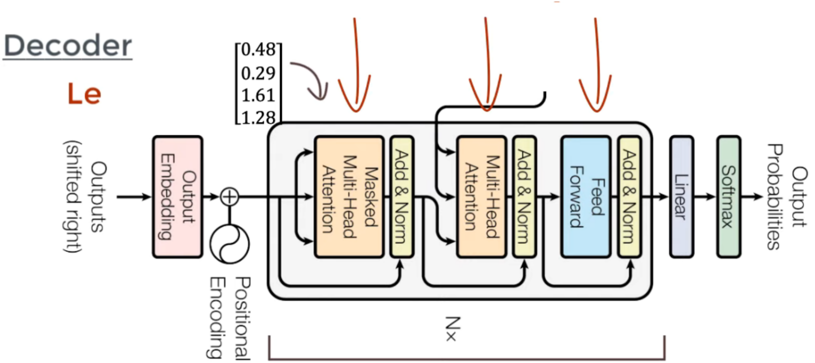
$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}$$
$$\sigma_j^2 = \frac{1}{m}\sum_{i=1}^{m}(x_{ij} - \mu_j)^2$$
$$\hat{x_{ij}} = \frac{x_{ij}-\mu_j}{\sqrt{\sigma_j^2+\epsilon}}$$

Layer normalization:

$$\mu_i = \frac{1}{m}\sum_{j=1}^{m} x_{ij}$$
$$\sigma_i^2 = \frac{1}{m}\sum_{j=1}^{m}(x_{ij} - \mu_i)^2$$
$$\hat{x_{ij}} = \frac{x_{ij}-\mu_i}{\sqrt{\sigma_i^2+\epsilon}}$$

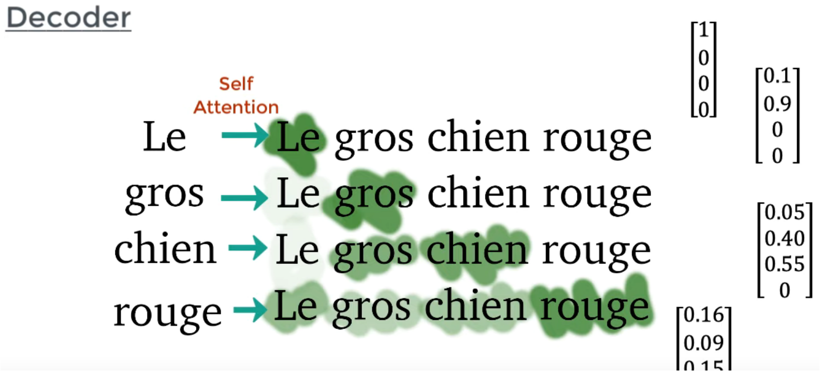


- BN: statistics computed across the batch, the same in batch
- LN: computed across features, independent of other samples
- smoothens the landscape loss; arbitrary batchsize



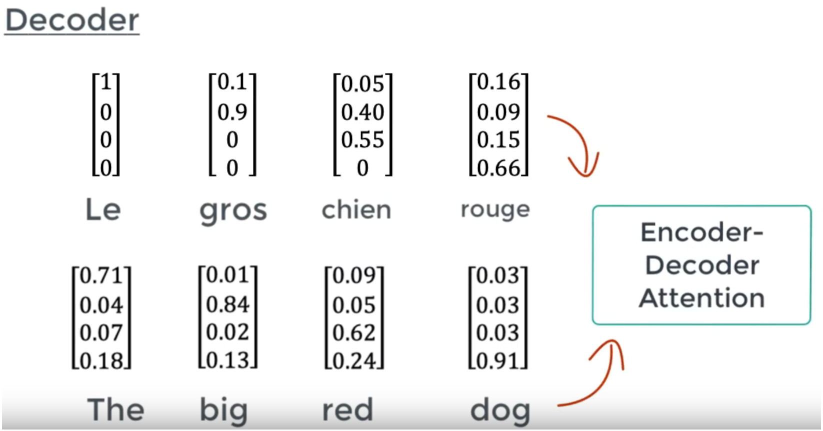
- positional encoding in the second language is performed
- three components similar to the encoder block

Block 1: Masked Multi-Head Attention

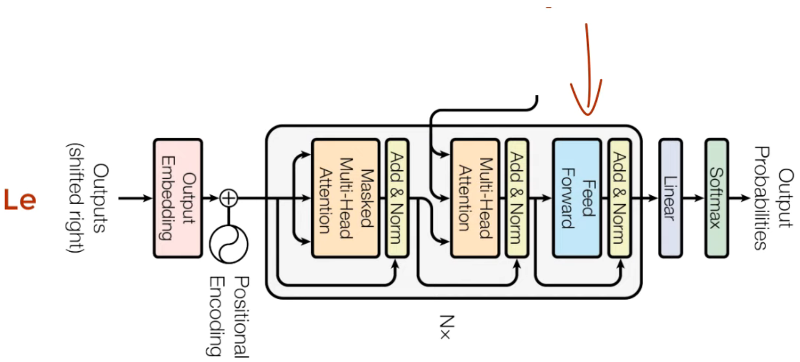


- generates attention vectors for every word to construct context
- generates only attention for previous words (no learning otherwise)

Block 2: Multi-Head Attention

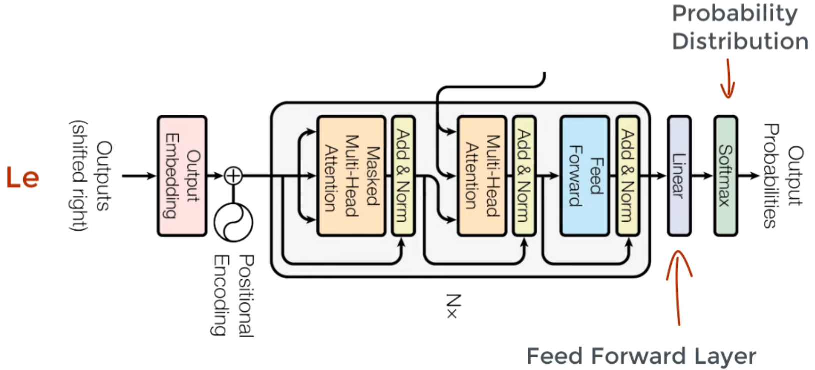


- gets positional-encoding vectors and vectors from the encoder
- output: attention vectors for every word in both languages
- generates similar attention vectors for both languages



- reduces dimensionality of the feature vector and computes features

Output



- feed-forward layer maps to the number of words in second language
- softmax transforms output to a probability distribution
- final word is the one given by the highest probability

Training procedure

- standard WMT 2014 English-German dataset, 4.5 million sentence pairs
- byte-paired encoding (37000 tokens vocabulary)
- 25000 tokens per batch
- 8 NVIDIA P100 GPUs, 12 hours for base model, 3.5 days large model (1024 as dimension, $d_{ff} = 4096$, heads=16)
- ADAM optimizer with varying LR
- residual dropout regularization

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

- outperforms previous SoA by more than 2.0 BLEU
- even base model surpasses all previously published models at a fraction of training cost of any previous model
- base model uses averaged model of last 5 checkpoints (20 checkpoints for big)

Conclusion

- first sequence transducer model based entirely on attention
- recurrent layers replaced with multi-headed self-attention
- significantly faster than traditional RNNs
- paper's code: `https://github.com/tensorflow/tensor2tensor`

Bibliography

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