CS378: Natural Language Processing
Lecture 16: Transformers

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Multi-Head Self-Attention

Multi-Head Self Attention

- Multiple "heads" analogous to different convolutional filters
- Let E = [sent len, embedding dim] be the input sentence. This will be passed through three different linear layers to produce three mats:
  - Query $Q = EW^Q$: these are like the **decoder hidden state** in attention
  - Keys $K = EW^K$: these control what gets attended to, along with the query
  - Values $V = EW^V$: these vectors get summed up to form the output

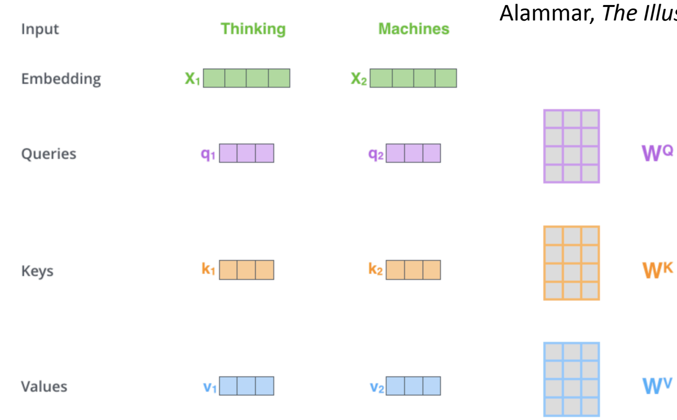
$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

dim of keys

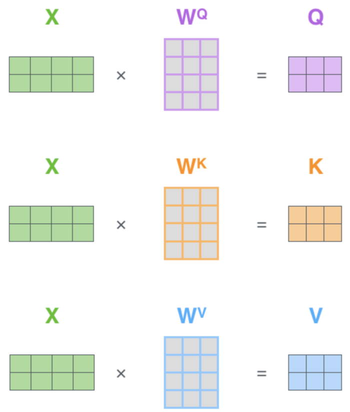
Vaswani et al. (2017)

Self-Attention

Alammar, *The Illustrated Transformer*

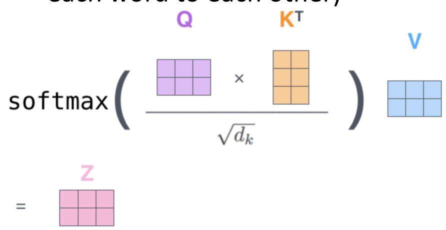


Self-Attention



Alammar, *The Illustrated Transformer*

sent len x sent len (attn for each word to each other)



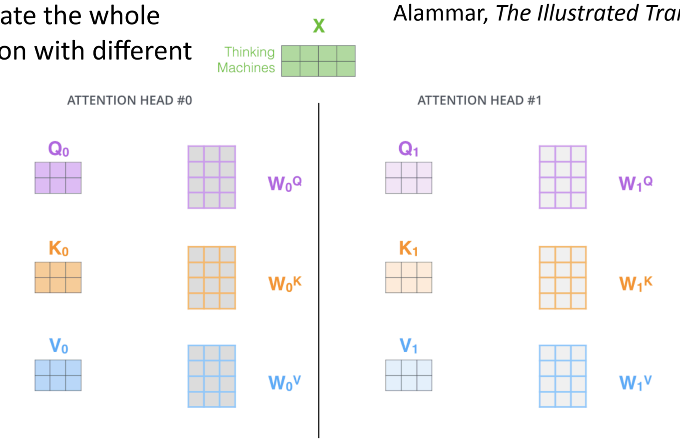
sent len x hidden dim

Z is a weighted combination of V rows

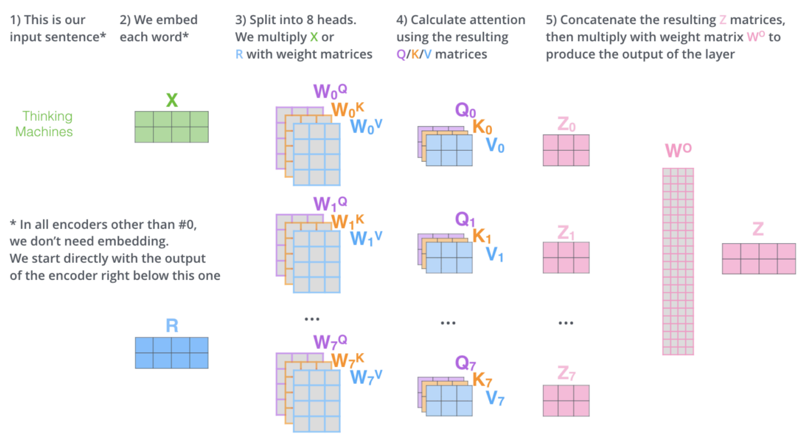
Multi-head Self-Attention

Just duplicate the whole computation with different weights:

Alammar, *The Illustrated Transformer*



Multi-head Self-Attention



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

- *n* = sentence length, *d* = hidden dim, *k* = kernel size, *r* = restricted neighborhood size
- **Quadratic complexity**, but O(1) sequential operations (not linear like in RNNs) and O(1) "path" for words to inform each other

Vaswani et al. (2017)

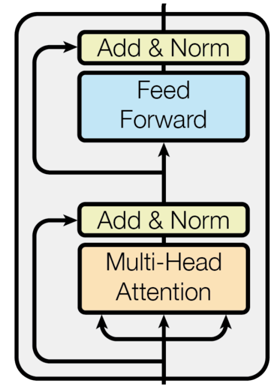
Transformers

Architecture

- Alternate multi-head self-attention with feedforward layers that **operate over each word individually**

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

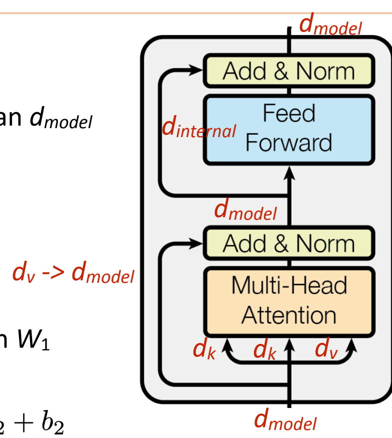
  - These feedforward layers are where most of the parameters are
- Residual connections in the model: input of a layer is added to its output
- Layer normalization: controls the scale of different layers in very deep networks (not needed in A4)



Dimensions

- Vectors: d_{model}
- Queries/keys: d_k , always smaller than d_{model}
- Values: separate dimension d_v , output is multiplied by W^O which is d_v x d_{model} so we can get back to d_{model} before the residual
- FFN can explode the dimension with W_1 and collapse it back with W_2

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$



Vaswani et al. (2017)

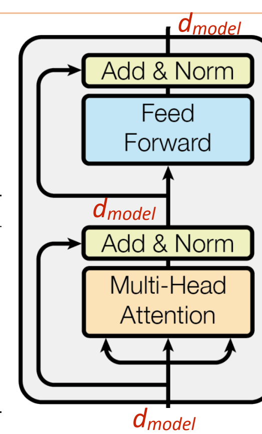
Transformer Architecture

	N	d_{model}	d_{ff}	h	d_k	d_v
base	6	512	2048	8	64	64

- From Vaswani et al.

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}
GPT-3 Small	125M	12	768	12	64
GPT-3 Medium	350M	24	1024	16	64
GPT-3 Large	760M	24	1536	16	96
GPT-3 XL	1.3B	24	2048	24	128
GPT-3 2.7B	2.7B	32	2560	32	80
GPT-3 6.7B	6.7B	32	4096	32	128
GPT-3 13B	13.0B	40	5140	40	128
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128

- From GPT-3; d_{head} is our d_k



Transformer Architecture

1	description	FLOPs / update	% FLOPS MHA	% FLOPS FFN	% FLOPS attn	% FLOPS logit
8	OPT setups					
9	760M	4.3E+15	35%	44%	14.8%	5.8%
10	1.3B	1.3E+16	32%	51%	12.7%	5.0%
11	2.7B	2.5E+16	29%	56%	11.2%	3.3%
12	6.7B	1.1E+17	24%	65%	8.1%	2.4%
13	13B	4.1E+17	22%	69%	6.9%	1.6%
14	30B	9.0E+17	20%	74%	5.3%	1.0%
15	66B	9.5E+17	18%	77%	4.3%	0.6%
16	175B	2.4E+18	17%	80%	3.3%	0.3%

Credit: Stephen Roller on Twitter

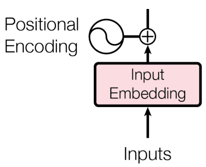
Transformers: Position Sensitivity

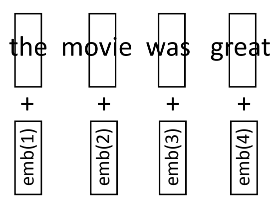
The ballerina is very excited that she will dance in the show.

- If this is in a longer context, we want words to attend *locally*
- But transformers have *no notion of position* by default

Vaswani et al. (2017)

Transformers: Position Sensitivity



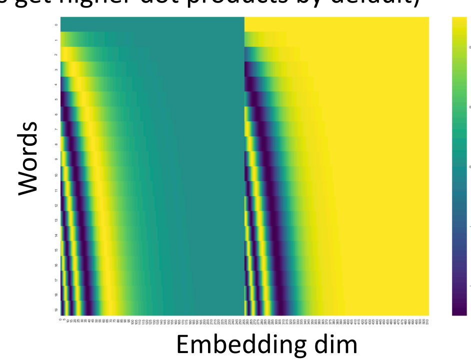


- Encode each sequence position as an integer, add it to the word embedding vector
- Why does this work?

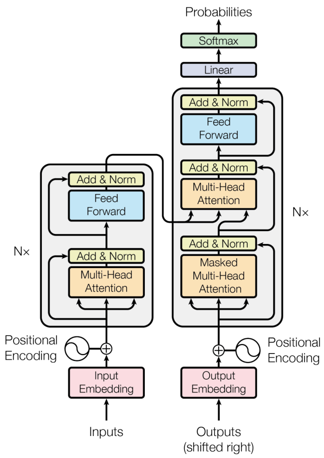
Transformers

Alammar, *The Illustrated Transformer*

- Alternative from Vaswani et al.: sines/cosines of different frequencies (closer words get higher dot products by default)



Transformers: Complete Model



- Original Transformer paper presents an **encoder-decoder** model
- Right now we don’t need to think about both of these parts — will return in the context of MT
- Can turn the encoder into a decoder-only model through use of a triangular causal attention mask (only allow attention to previous tokens)

Vaswani et al. (2017)