SFU NatLangLab

CMPT 413/713: Natural Language Processing

Transformers and Self-Attention

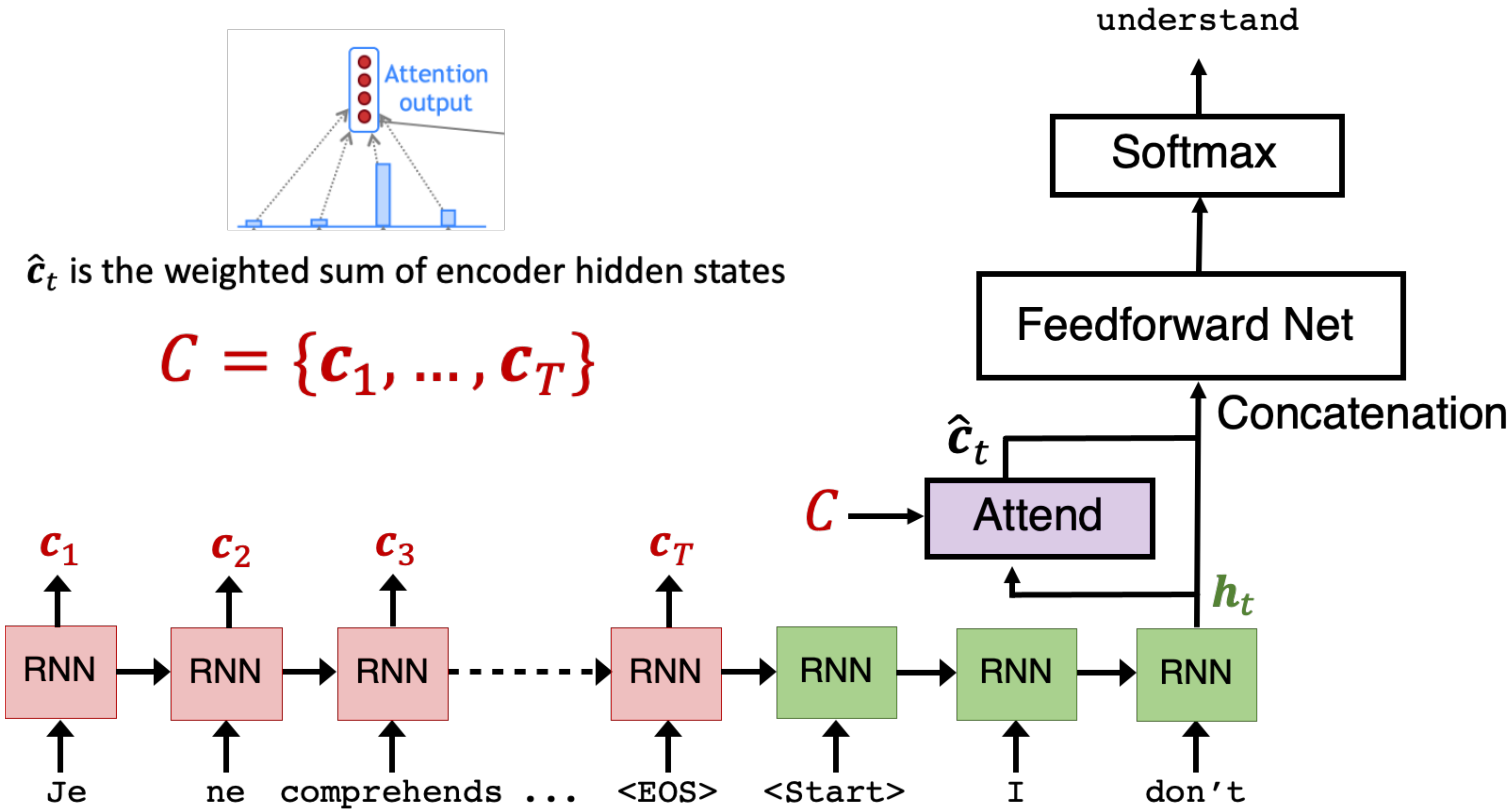
Spring 2024

2024-02-12

Adapted from slides from Danqi Chen and Karthik Narasimhan
(with some content from slides from Chris Manning and Abigail See)

Review of attention in sequence to sequence models

Attentive machine translation summary

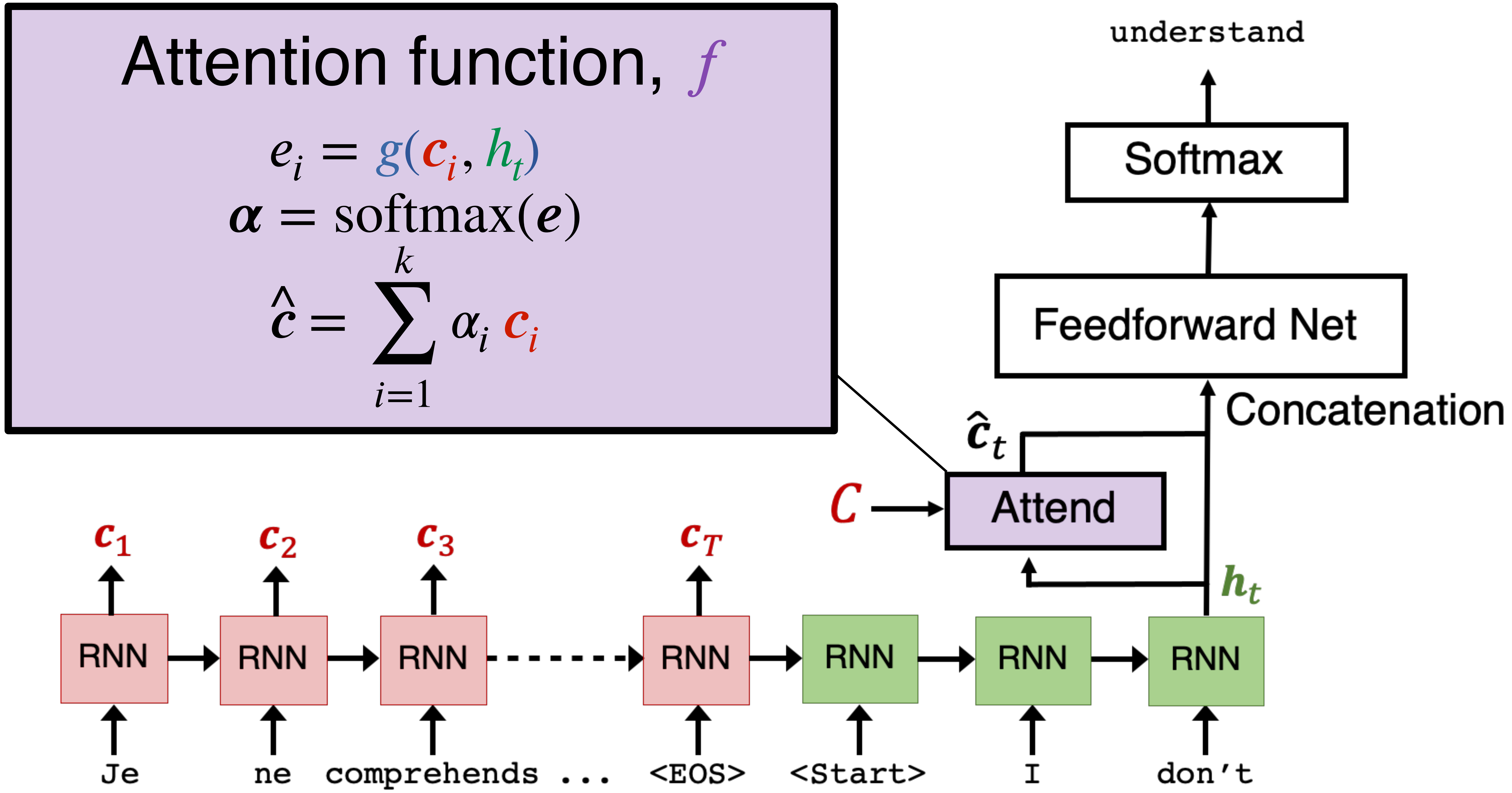


$\hat{c}_t$ is the weighted sum of encoder hidden states

$$C = \{c_1, \dots, c_T\}$$

(slide credit: Peter Anderson)

Attentive machine translation summary



(slide credit: Peter Anderson)

Summary of attention

Attention function, f

$$e_i = g(\boldsymbol{c}_i, \boldsymbol{z})$$
$$\boldsymbol{\alpha} = \mathrm{softmax}(\boldsymbol{e})$$
$$\hat{\boldsymbol{c}} = \sum_{i=1}^{k} \alpha_i \, \boldsymbol{c}_i$$

Attention scores: $\boldsymbol{e}$ (unnormalized)

Attention weights: $\boldsymbol{\alpha}$ (normalized)

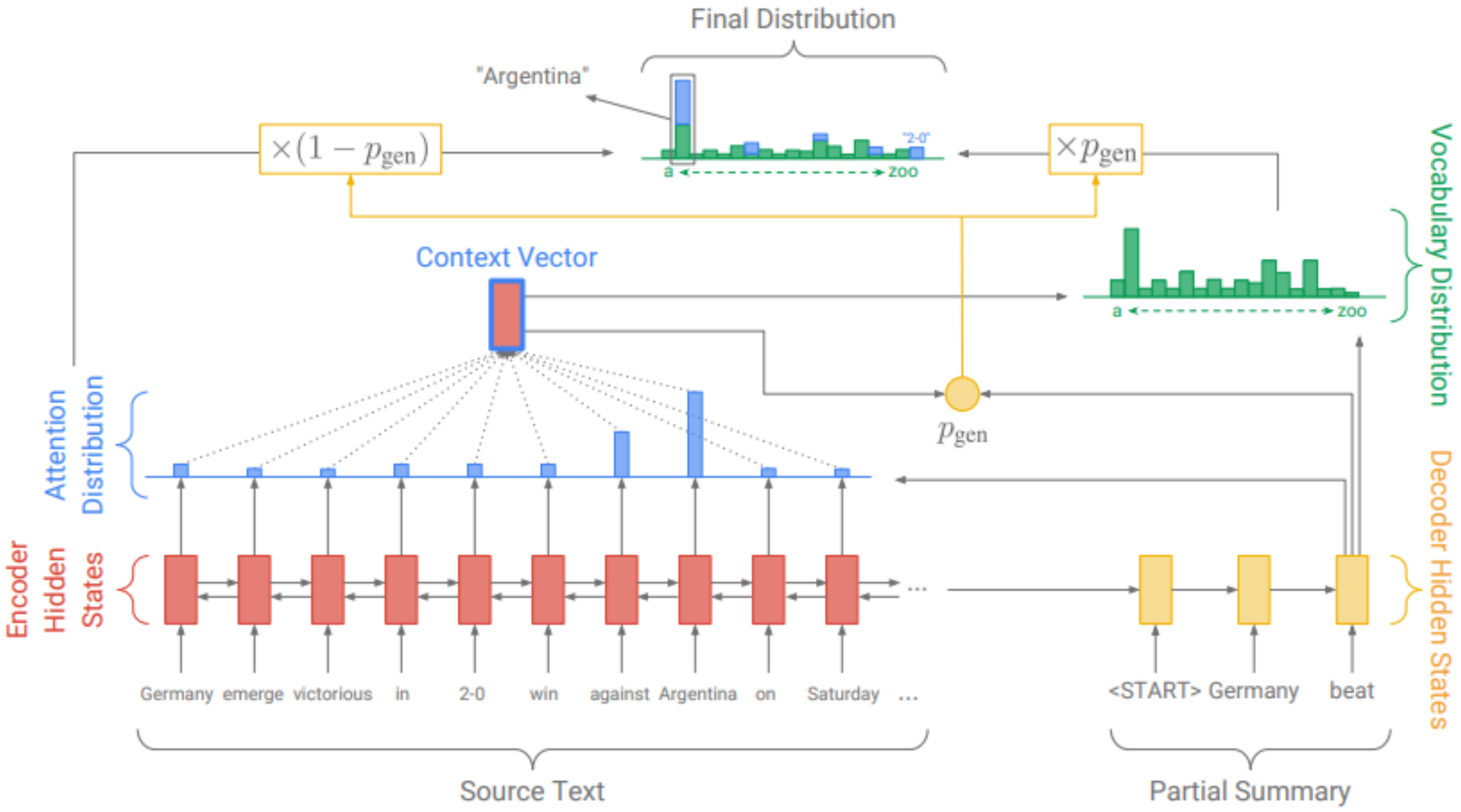
Final attention output

Weighted sum of context features (or values)

Attention score $e_i = g(\boldsymbol{c}_i, \boldsymbol{z})$
how well does the attention candidate $\boldsymbol{c}_i$ match the query $\boldsymbol{z}$

- **Dot-product attention**:
  $$g(c_i, z) = z^\top c_i$$
- **Neural network**
  $$g(c_i, z) = v^\top \tanh\left(W_1 c_i + W_2 z\right)$$

Attention can be used to copy from input

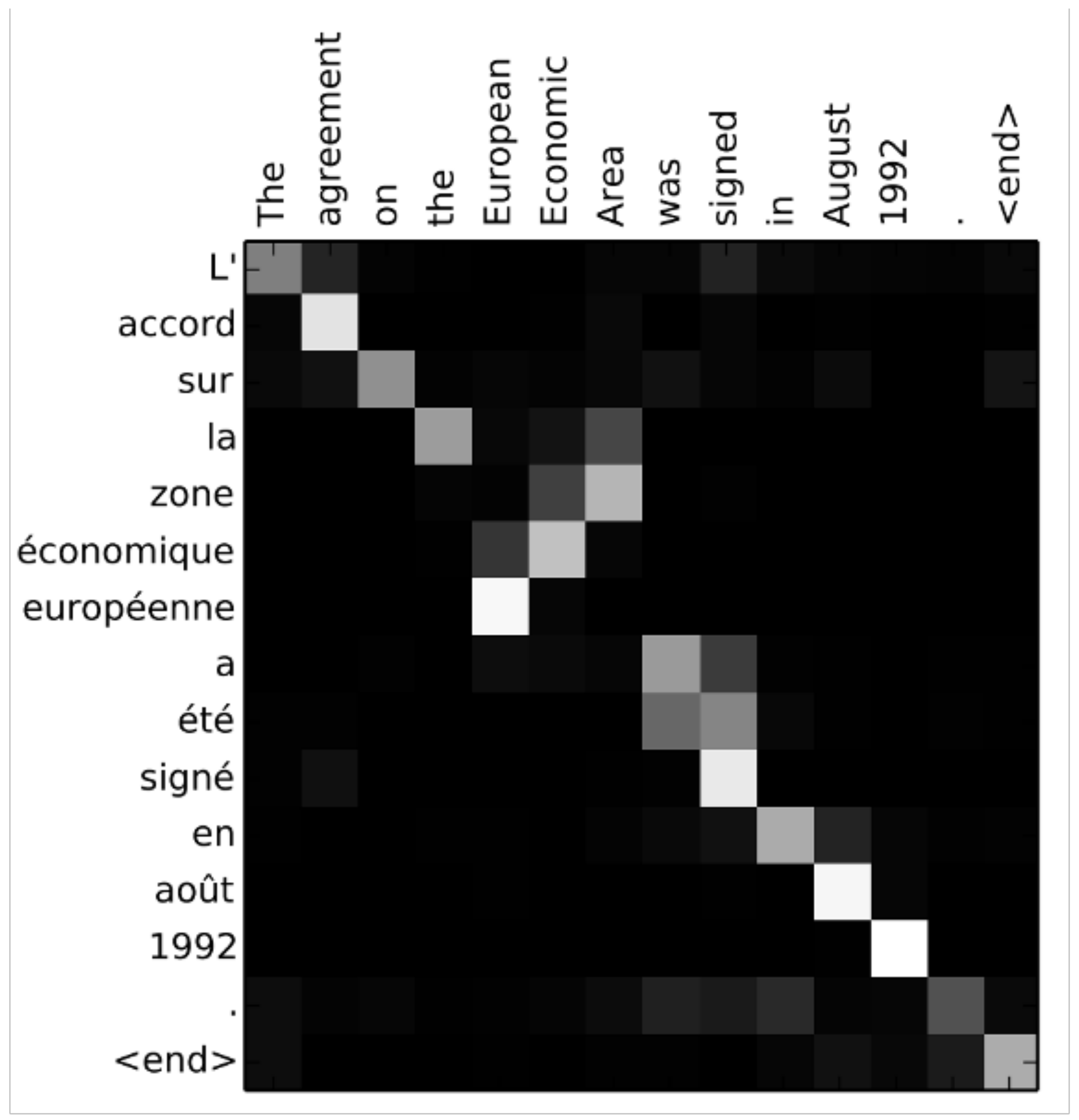


- Probability of generating from vocabulary or copying from input
- Probability of copying specific word (similar to attention)

(See et al, 2017)

Motivation of attention

- How much does this attention candidate match the query vector?
- Motivated by biological attention and alignment in machine translation

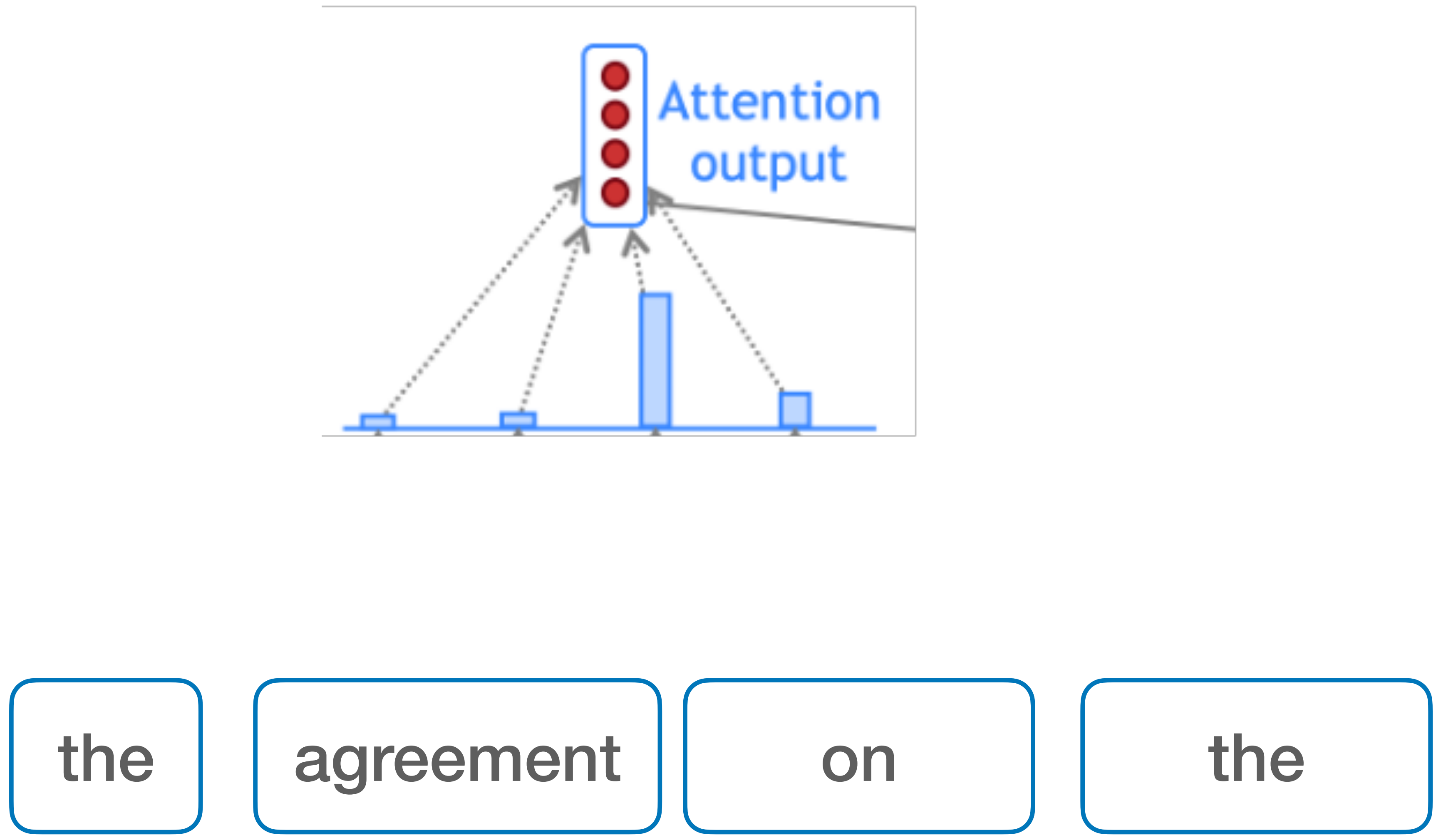


generated (French)

source (English)

Attention weights α_i (0 = black, 1 = white)

get a representation that is a weighted sum over the attention candidates based on a query vector



Attention is a *general* deep learning technique

- Given a set of value vectors and a query vector, **attention** is a way to compute a **weighted sum** of the values dependent on the query.
  - The query determines what values to focus on,
    - We say: the query "*attends*" to the values
  - In NMT, each decoder hidden state (query) attends to all the encoder hidden state (values)
- A more general form: use a set of keys and values
  - The keys are used to compute the **attention scores**
  - The values are used to compute the **output vector**

Attention is always computed the same way

- Assume that we have a set of key-value pairs $\mathbf{k}_1, \ldots, \mathbf{k}_n \in \mathbb{R}^{d_k}$, $\mathbf{v}_1, \ldots, \mathbf{v}_n \in \mathbb{R}^{d_v}$, and a query vector $\mathbf{q} \in \mathbb{R}^{d_q}$

- Computing attention consists of the following steps:
  - Compute the attention scores: $\boxed{e_i = g(\mathbf{k}_i, \mathbf{q}), \mathbf{e} \in \mathbb{R}^n}$
  - Take softmax to get the attention distribution

$$\alpha = \mathrm{softmax}(\mathbf{e}) \in \mathbb{R}^n$$

  - Use attention distribution to take weighted sum of values

$$\hat{\mathbf{c}} = \sum_{i-1}^{n} = \alpha_i \mathbf{v}_i \in \mathbb{R}^{d_v}$$

Query-Value-Key view of attention

Attention function, f

$$e_i = g(\boldsymbol{c}_i, \boldsymbol{z})$$
$$\boldsymbol{\alpha} = \text{softmax}(\boldsymbol{e})$$
$$\hat{\boldsymbol{c}} = \sum_{i=1}^{k} \alpha_i \, \boldsymbol{c}_i$$

→

Attention function, f

$$e_i = g(\boldsymbol{k}_i, \boldsymbol{q})$$
$$\boldsymbol{\alpha} = \text{softmax}(\boldsymbol{e})$$
$$\hat{\boldsymbol{c}} = \sum_{i=1}^{k} \alpha_i \, \boldsymbol{v}_i$$

Projected query,key,value →

$$\boldsymbol{q} = W_Q \, \boldsymbol{z}$$
$$\boldsymbol{k}_i = W_K \, \boldsymbol{c}_i$$
$$\boldsymbol{v}_i = W_V \, \boldsymbol{c}_i$$

→

Matrix form

$$\boldsymbol{q} = W_Q \, \boldsymbol{z}$$
$$K = W_K \, C^T$$
$$V = W_V \, C^T$$

$$C \in \mathbb{R}^{N \times d_C}$$

General form of attention: key-value-query

- **Attention** is a way to compute a **weighted sum** of the values dependent on the query and the corresponding keys.
  - All of these (key value query) are represented using **vectors**
    - The query and key are used for addressing (contains partial information). While the values provide more complete information
    - The weighted sum is a **selective summary** of the information found in the values.
    - It is a way to obtain a **fixed-sized representation** of an arbitrary set of representations (values) based on some other representation (the query)

Different types of attention

Soft vs Hard Attention

- Soft: Each attention candidate is weighted by α_i

$$\hat{\boldsymbol{v}} = \sum_{i=1}^{k} \alpha_i \, \boldsymbol{v}_i$$

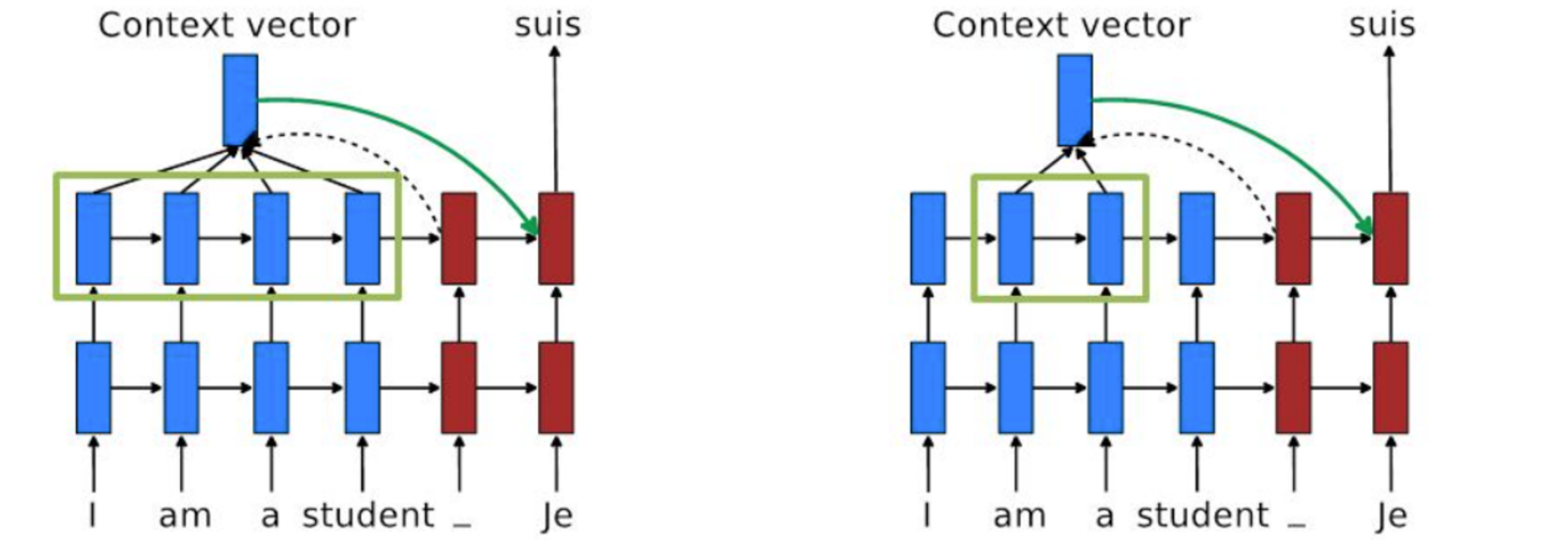
  - Easy to train (smooth and differentiable)
  - But can be expensive over large input

- Hard: Use α_i as a sample probability to pick *one* attention candidate as input to subsequent layers
  - Trainable with REINFORCE approaches (Xu et al. ICML 2015), or Gumbel-Softmax (Jang et al. ICLR 2017)

Xu et al. ICML 2015

Global vs Local Attention

- Global: attention over the entire input
- Local: attention over a window (or subset) of the input

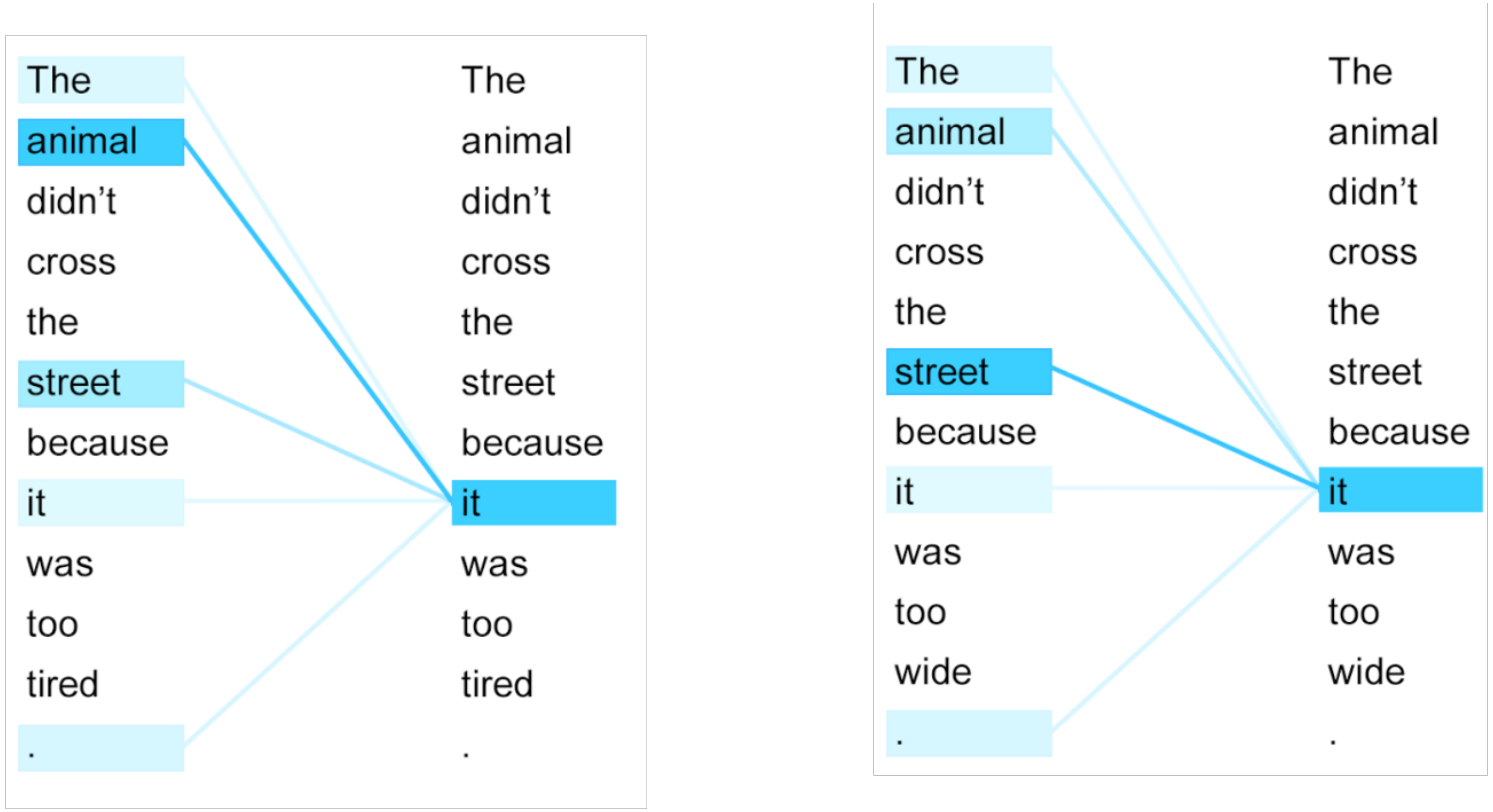


Global: ***all*** source states. Local: ***subset*** of source states.

Luong et al, 2015

Self-Attention

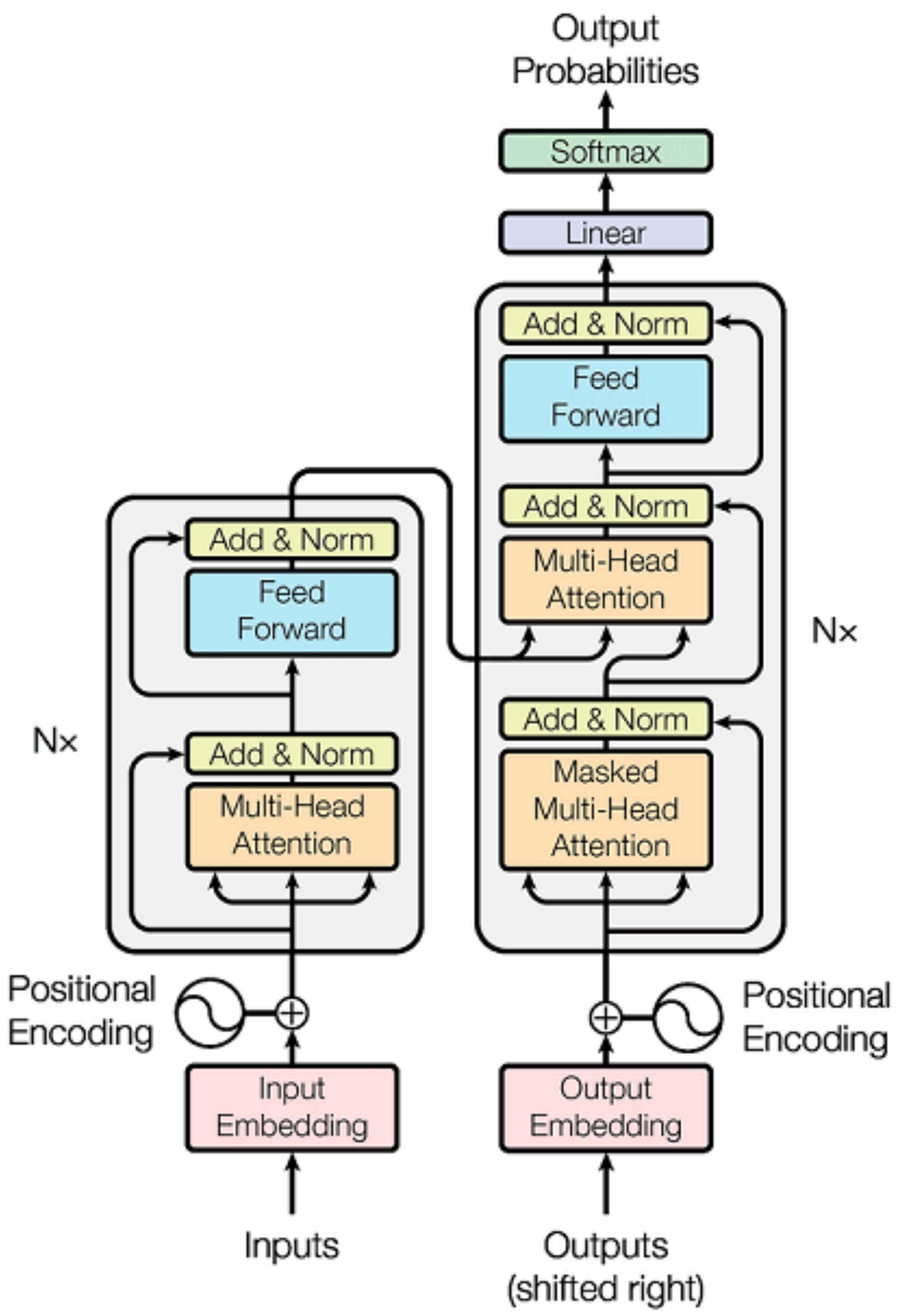
- Attention (correlation) with different parts of itself



https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

- Transformers: modules with scaled dot-product self-attention

Transformers: self-attention

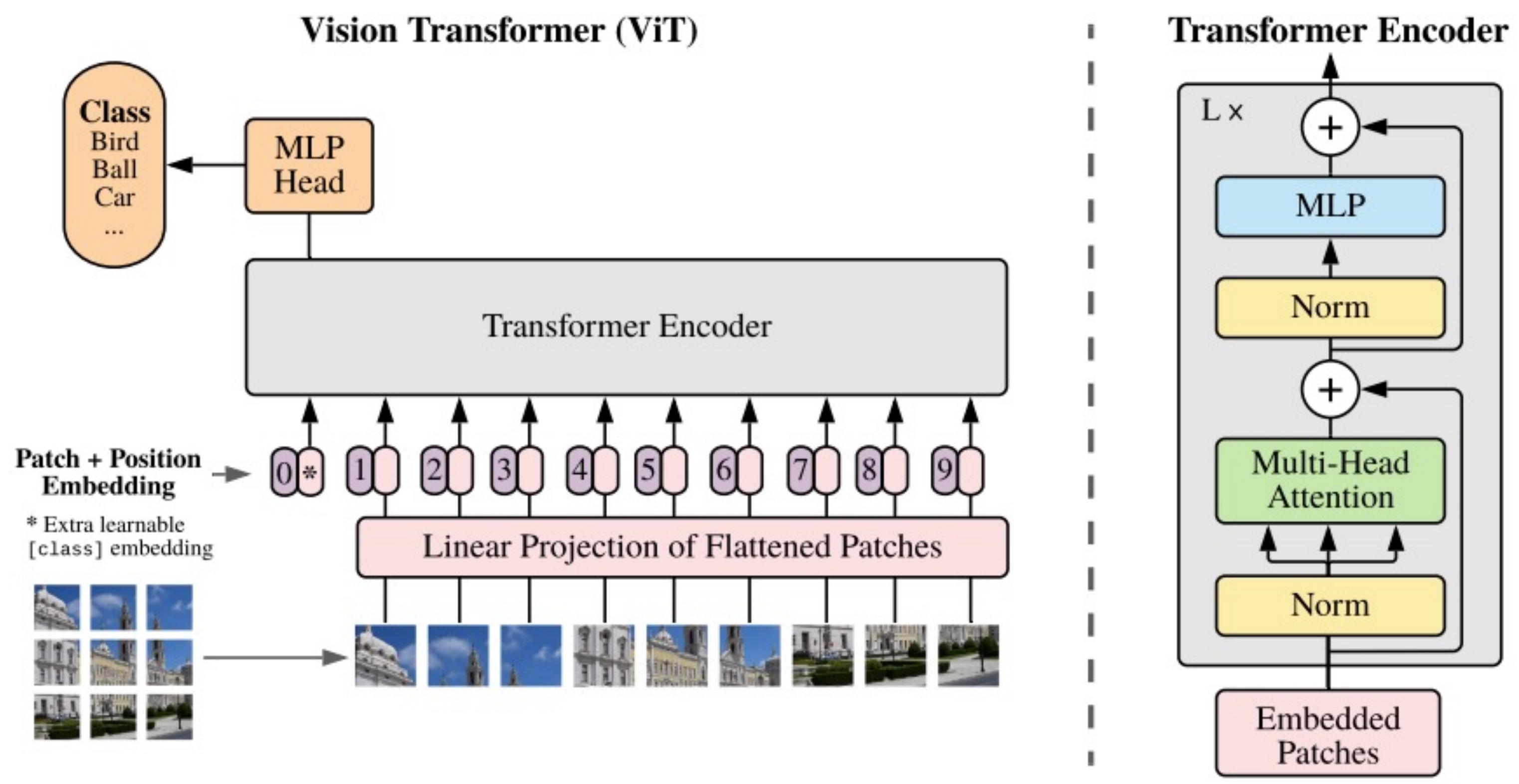


- More recent models (e.g. Transformer, Vaswani et al., 2017) have replaced RNNs entirely with attention mechanisms
- Theoretically limiting (since recurrence can help handle arbitrarily long sequences)
- Huge gains in practical performance

Transformers

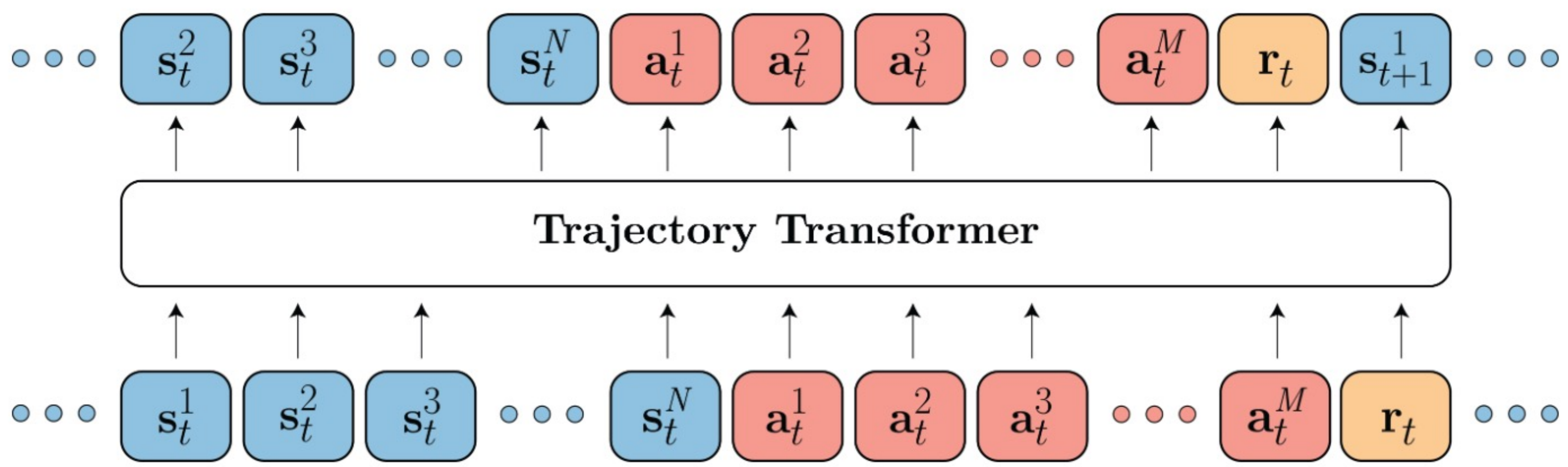
Transformers are everywhere!

- Vision

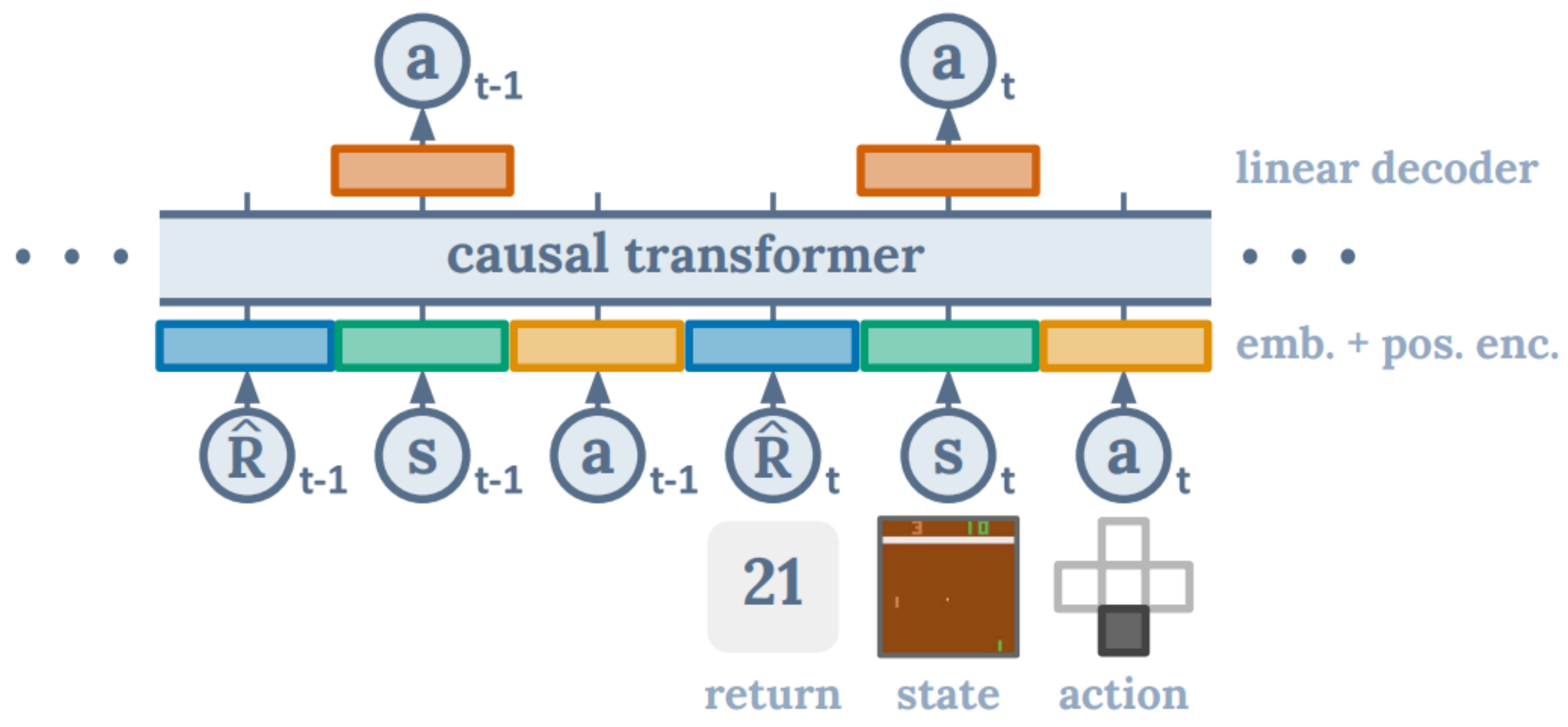


An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale, Dosovitskiy et al, ICLR 2021

- Reinforcement Learning



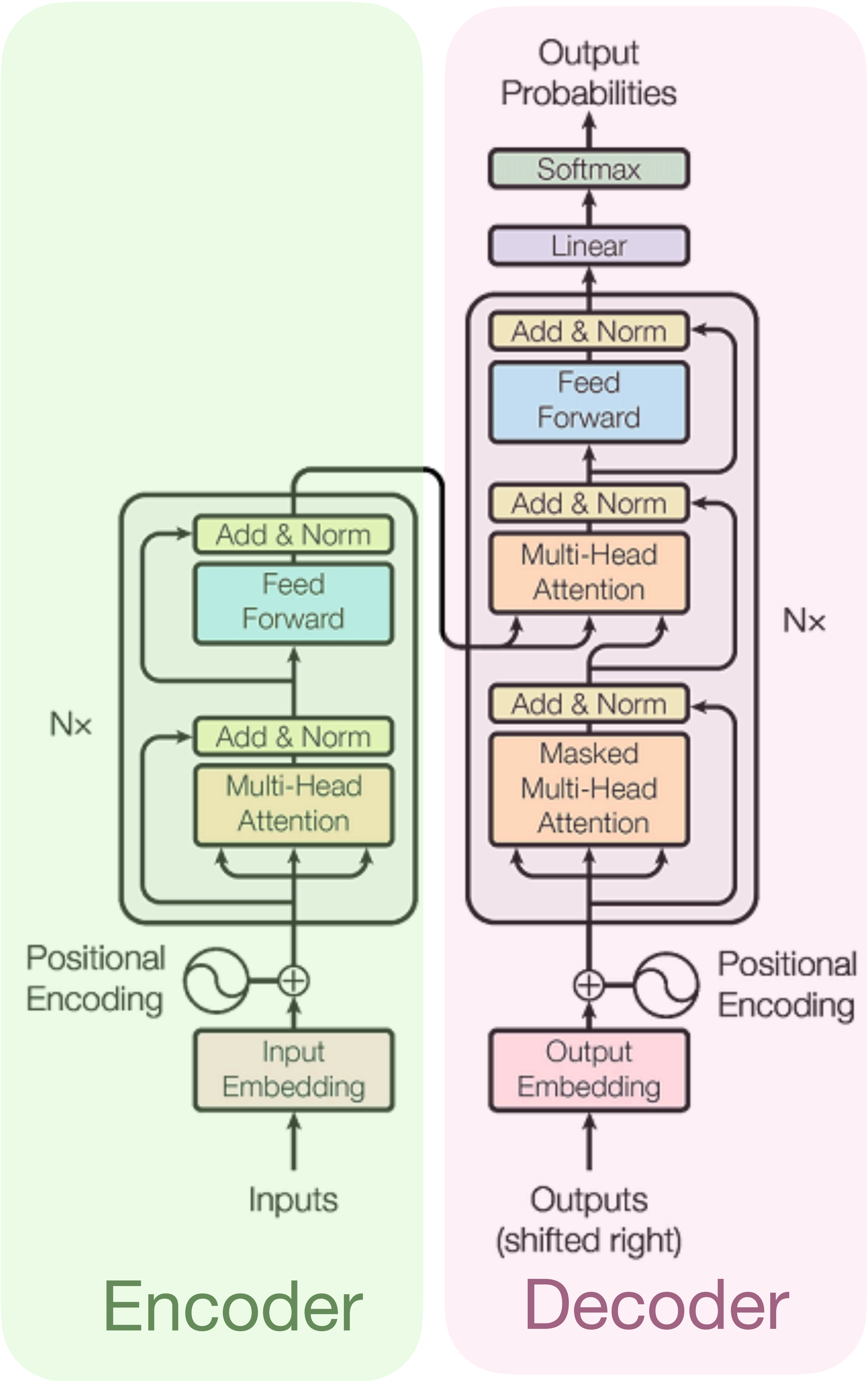
Trajectory Transformer [Janner et al, 2021]



Decision Transformer [Chen et al, 2021]

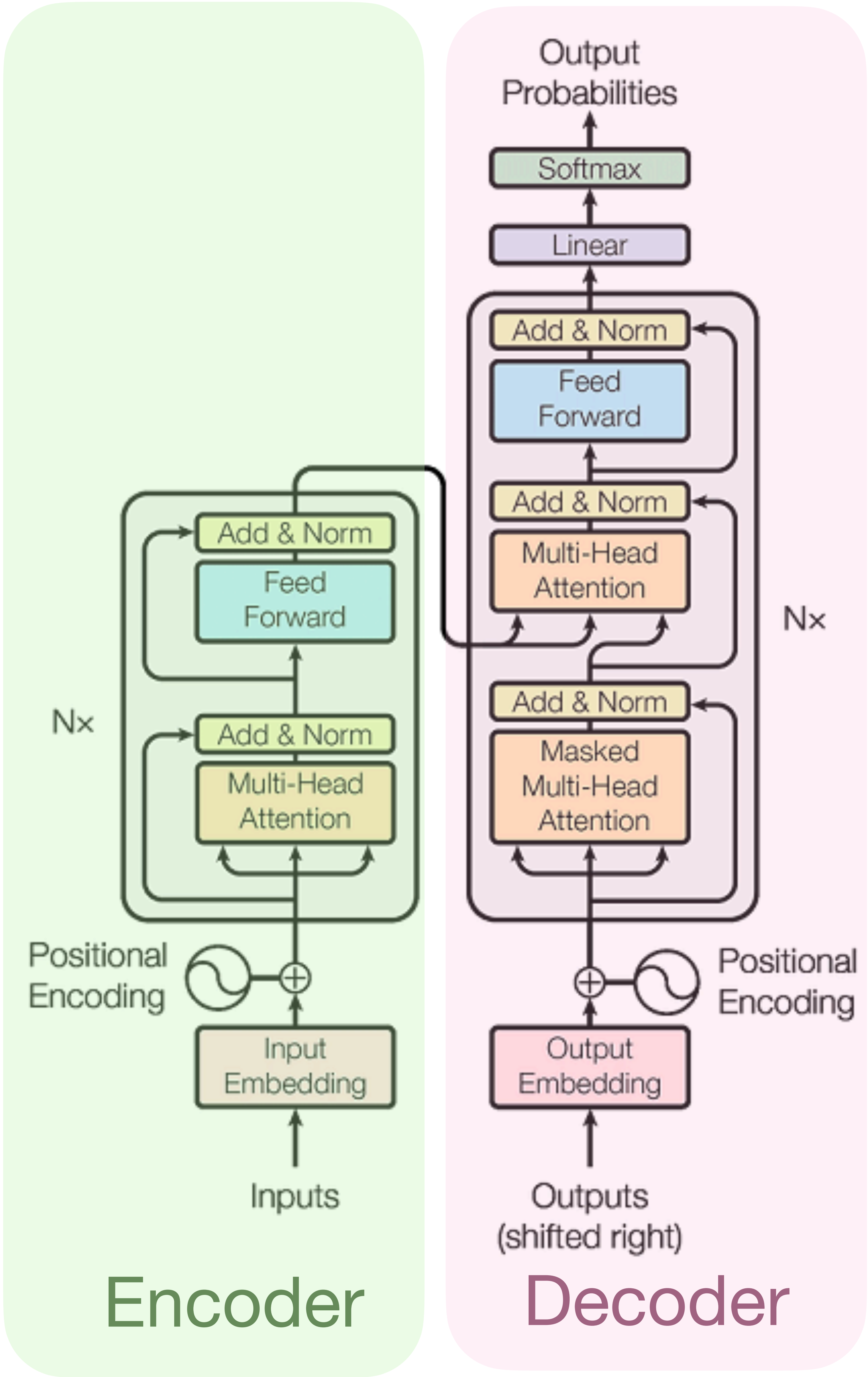
Transformers

- NIPS'17: Attention is All You Need
- Originally proposed for NMT (encoder-decoder framework)
- Used in most LLMs!
- Key idea: **Multi-head self-attention**
- No recurrence structure any more so it trains much faster



Understanding transformers

- From attention to self-attention
- From self-attention to multi-headed self-attention
- Transformer encoder
- Transformer decoder
- Putting the pieces together



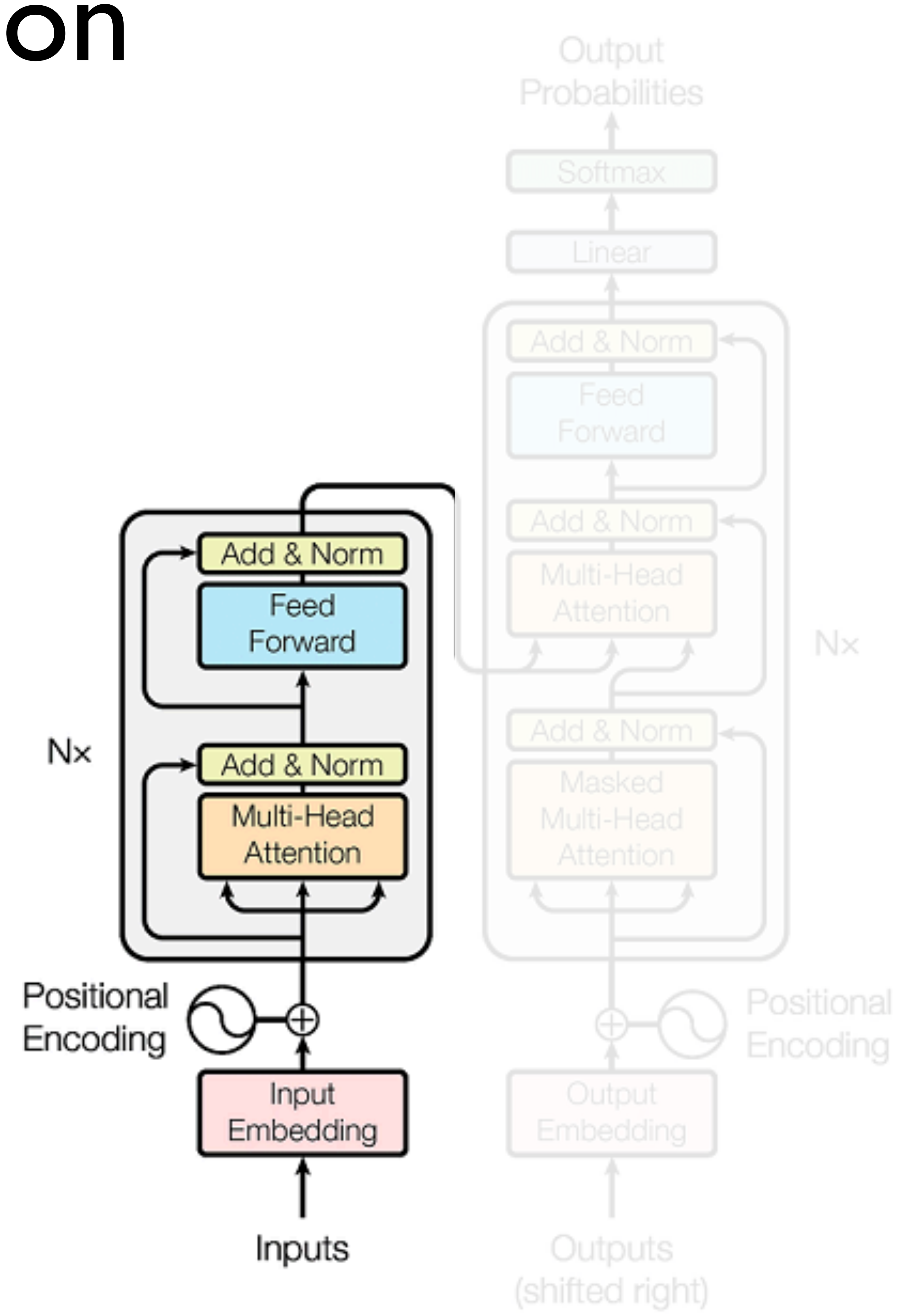
Multi-head self-attention

- Each Transformer block has two-sublayers
  - Multi-Head self-attention
  - 2 layer feedforward NN (with ReLU)

- Each sublayer has a residual connection and a layer normalization
  - LayerNorm(x+SubLayer(x))

Helps the training process!

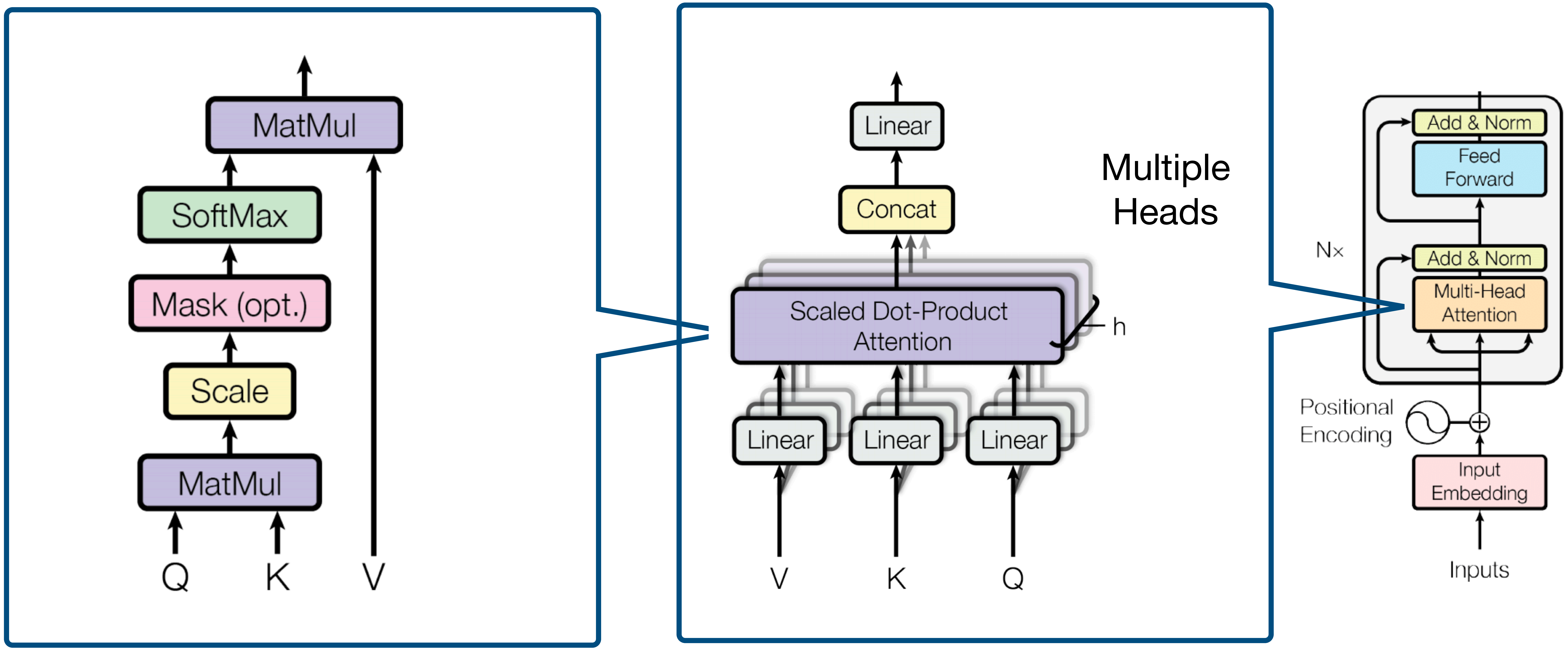
- Input layer has a positional encoding



Multi-head self-attention

Scaled Dot-Product Attention

self-attention



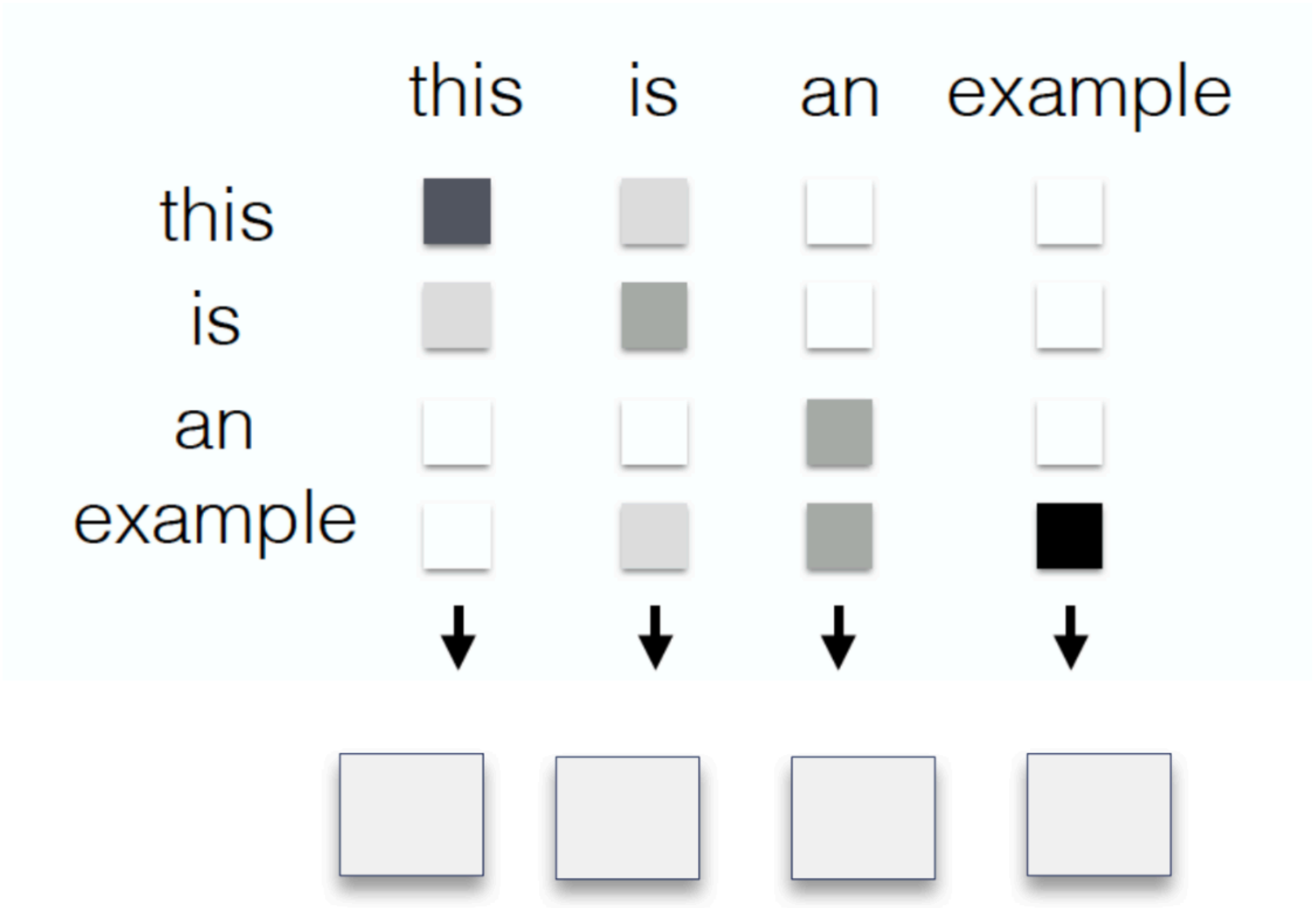
Attention Is All You Need https://arxiv.org/pdf/1706.03762.pdf

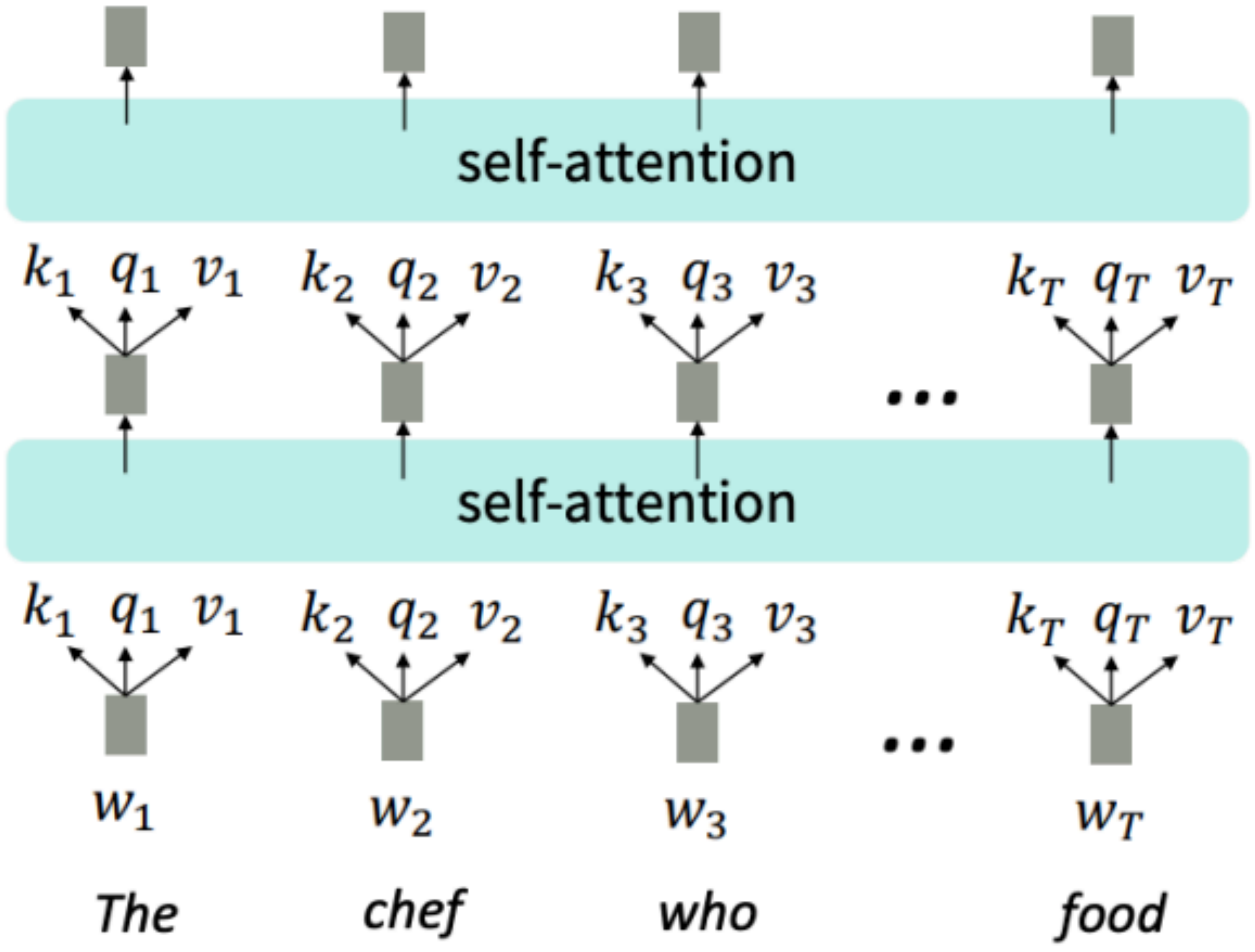
Self Attention

(also referred to as Intra-Attention)

- **Self-attention**: let's use each word as query and compute the attention with all the other words (other words are the keys and values)

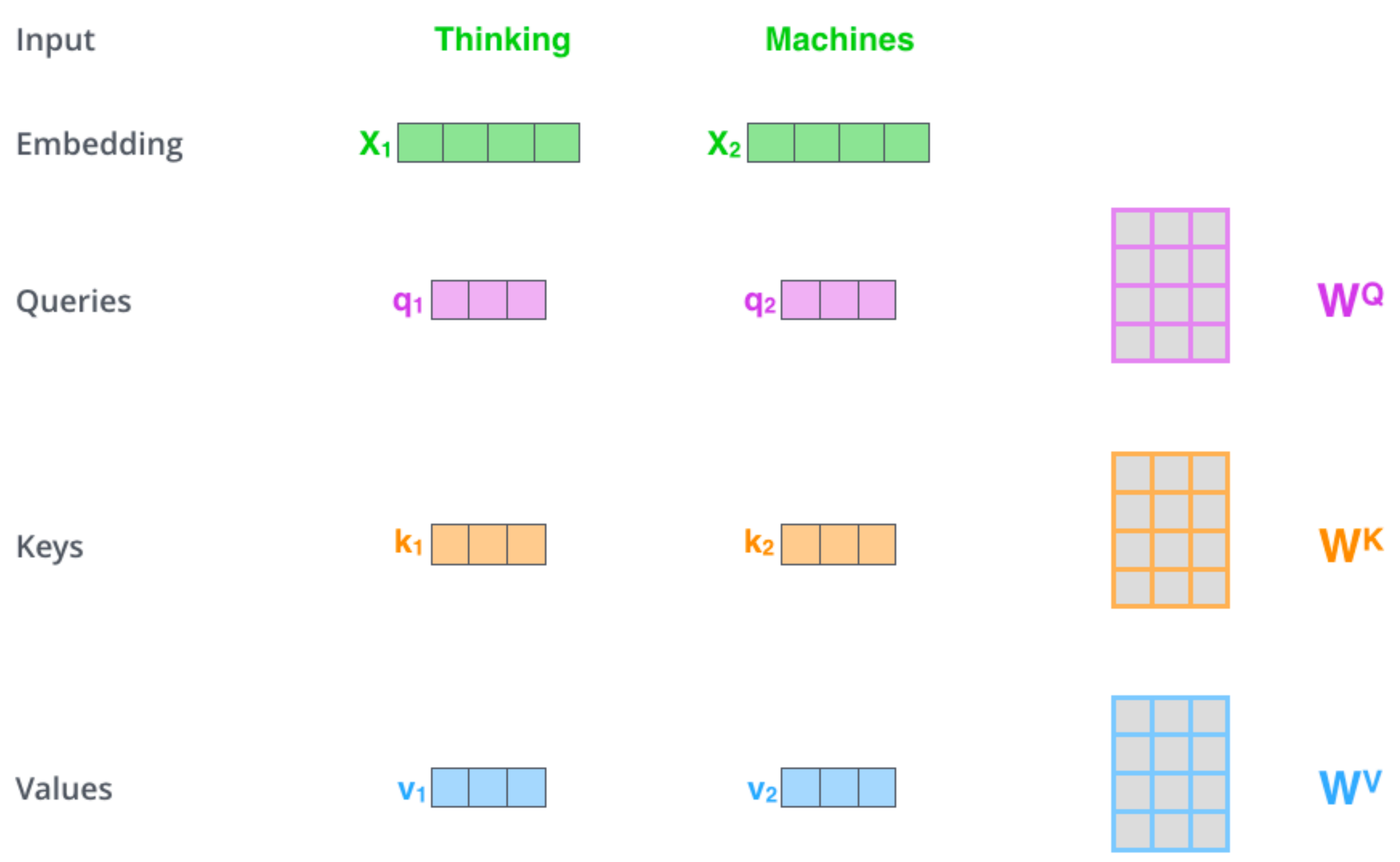
= the word vectors themselves select each other



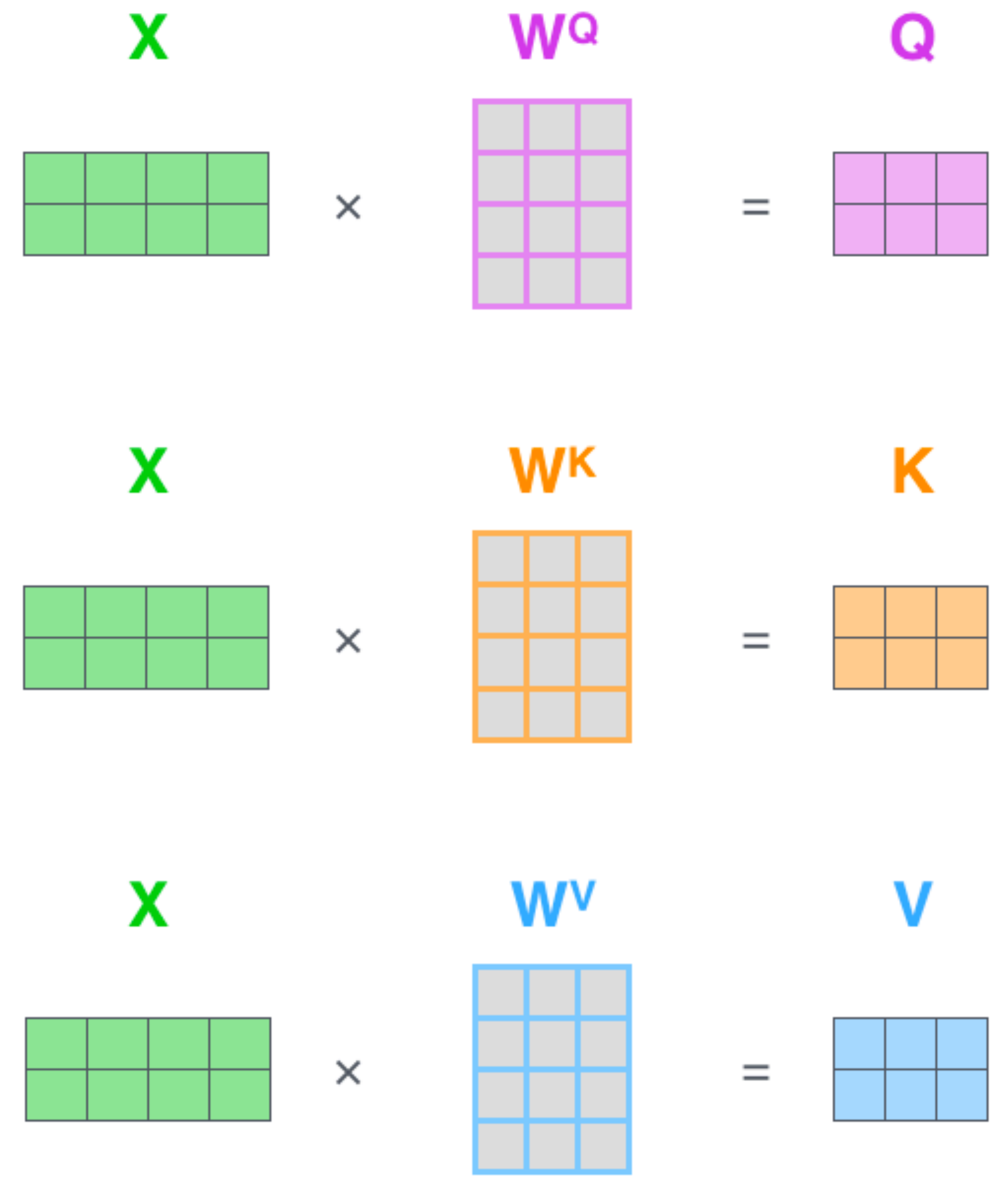


How to get key-value-query for each word?

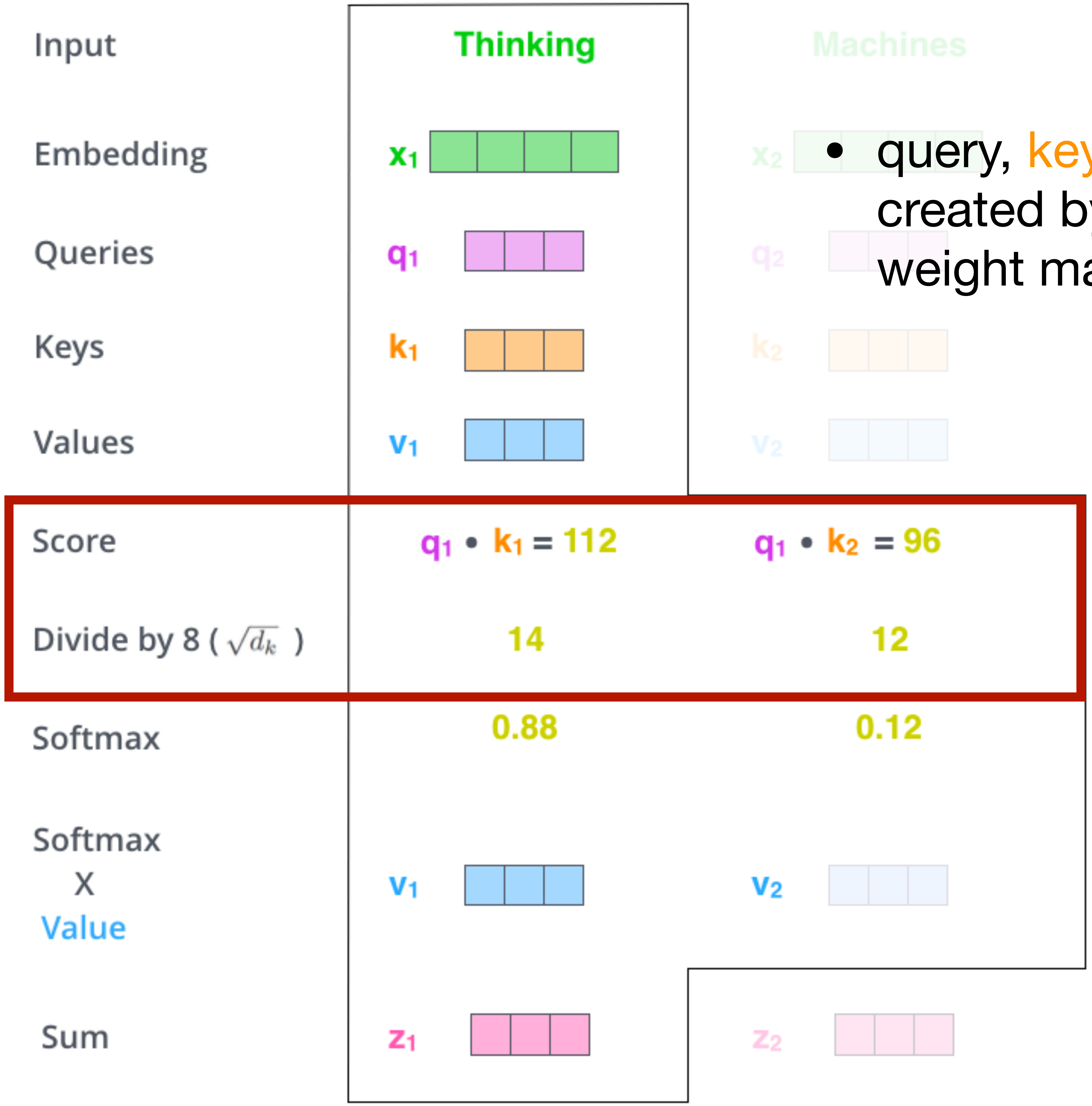
- For each word, we have vectors for the key-value-query
- These vectors are created by multiplying the word embedding by trained weight matrices



Stack into matrices and compute all at once!



(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)



- query, key, and value vectors created by multiplying learned weight matrices with embedding

- Can be any kind of attention function
- For transformers, this is the scaled dot-product attention

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

Recall: types of attention

- Assume keys $\mathbf{k}_1, \mathbf{k}_2, \ldots, \mathbf{k}_n$ and query $\mathbf{q}$

1. **Dot-product attention** (assumes equal dimensions for $\mathbf{k}_i$ and $\mathbf{q}$):

$$g(\mathbf{k}_i, \mathbf{q}) = \mathbf{q}^T \mathbf{k}_i \in \mathbb{R}$$

Simplest (no extra parameters)

Does not work well for large dimensions

more efficient (matrix multiplication)

2. **Bilinear / multiplicative attention:**

$$g(\mathbf{k}_i, \mathbf{q}) = \mathbf{k}^T \mathbf{W} \mathbf{k}_i \in \mathbb{R}$$, where $\mathbf{W}$ is a weight matrix

More flexible than dot-product (W is trainable)

3. **Additive attention (essentially MLP):**

$$g(\mathbf{k}_i, \mathbf{q}) = \mathbf{w}^T \tanh\left(\mathbf{W}_1 \mathbf{k}_i + \mathbf{W}_2 \mathbf{q}\right) \in \mathbb{R}$$

where $\mathbf{W}_1, \mathbf{W}_2$ are weight matrices and $\mathbf{w}$ is a weight vector

Perform better for larger dimensions

Scaled dot-product attention

- Assume keys $\mathbf{k}_1, \mathbf{k}_2, \ldots, \mathbf{k}_n$ and query $\mathbf{q}$

1. **Dot-product attention** (assumes equal dimensions for $\mathbf{k}_i$ and $\mathbf{q}$):

$$g(\mathbf{k}_i, \mathbf{q}) = \mathbf{q}^T \mathbf{k}_i \in \mathbb{R}$$

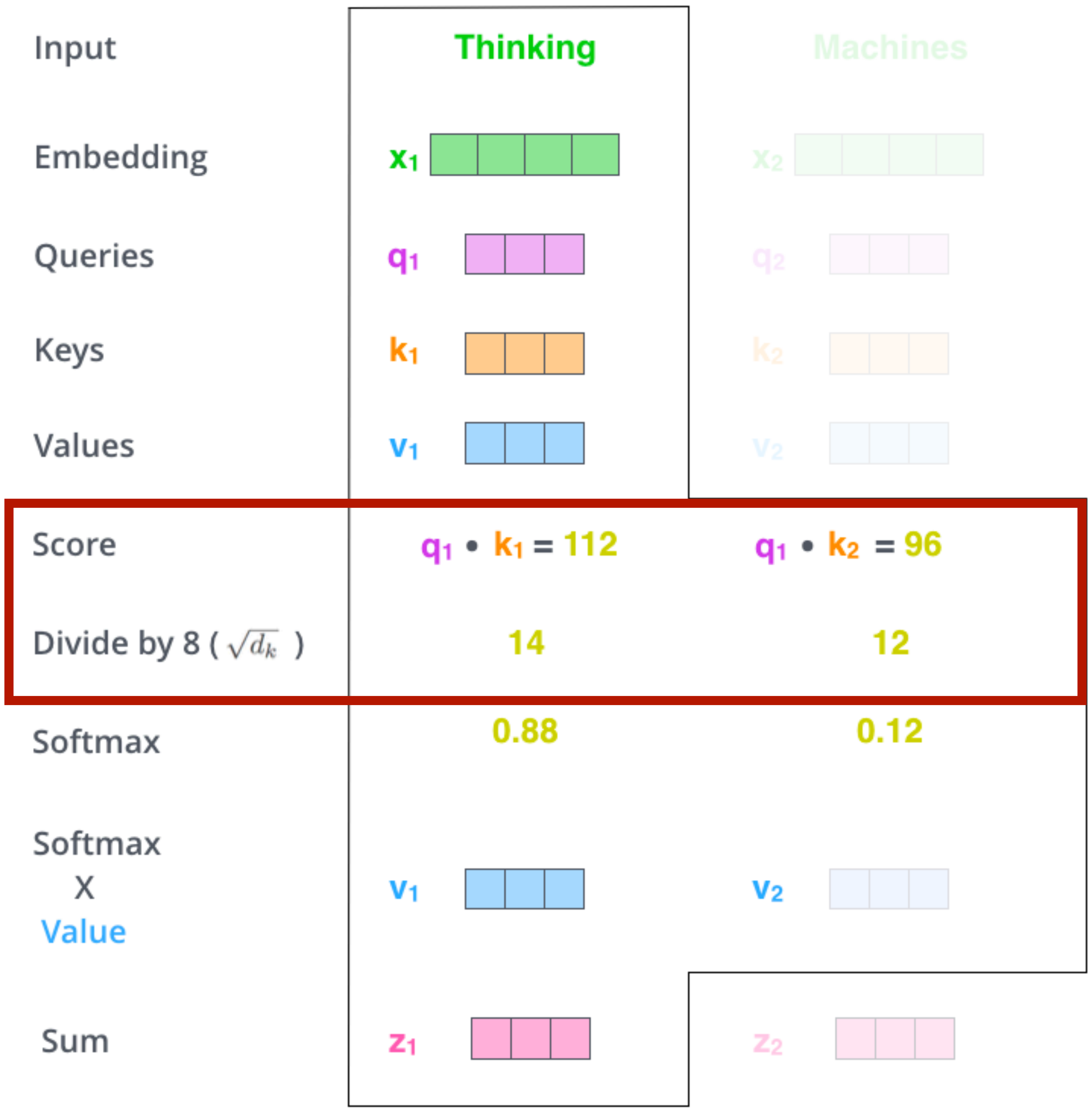
Scale of dot product increases
as dimension gets larger
Perform poorly for large *d*
Softmax has small gradient

2. **Scaled dot-product attention:**

$$g(\mathbf{k}_i, \mathbf{q}) = \frac{\mathbf{q}^T \mathbf{k}_i}{\sqrt{d}} \in \mathbb{R}$$

Scaled dot product will perform well
for larger dimensions

Scaling factor: d = dimension of hidden state



- Can be any kind of attention function
- For transformers, this is the scaled dot-product attention

- z_1 is the final vector of attended values for "Thinking" as the query

(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

Self-attention in equations

- A self-attention layer maps a sequence of input vectors $\mathbf{x}_1, \ldots, \mathbf{x}_n \in \mathbb{R}^{d_1}$ to a sequence of n vectors: $\mathbf{y}_1, \ldots, \mathbf{y}_n \in \mathbb{R}^{d_2}$
  - Note: this is similar as an RNN layer and can be used to replace an RNN layer
- First, construct a set of queries, keys, and values:

$$\mathbf{q}_i = W^Q \mathbf{x}_i, W^Q \in \mathbb{R}^{d_q \times d_1}$$
$$\mathbf{k}_i = W^K \mathbf{x}_i, W^K \in \mathbb{R}^{d_k \times d_1}$$
$$\mathbf{v}_i = W^V \mathbf{x}_i, W^V \in \mathbb{R}^{d_v \times d_1}$$

- Second, for each $\mathbf{q}_i$, compute attentions scores and attention distribution

$$\alpha_{i,j} = \text{softmax}\left(\frac{\mathbf{q}_i \cdot \mathbf{k}_j}{\sqrt{d_k}}\right)$$

Scaled dot-product so $d_k = d_q$

- Finally, compute the weighted sum:

$$\mathbf{y}_i = \sum_{j=1}^{n} \alpha_{i,j} \mathbf{v}_j \in \mathbb{R}^{d_v}$$

$d_v = d_2$

Self-attention: matrix notation

$$X \in \mathbb{R}^{n \times d_1}$$

$$Q = XW^Q, W^Q \in \mathbb{R}^{d_1 \times d_q}$$

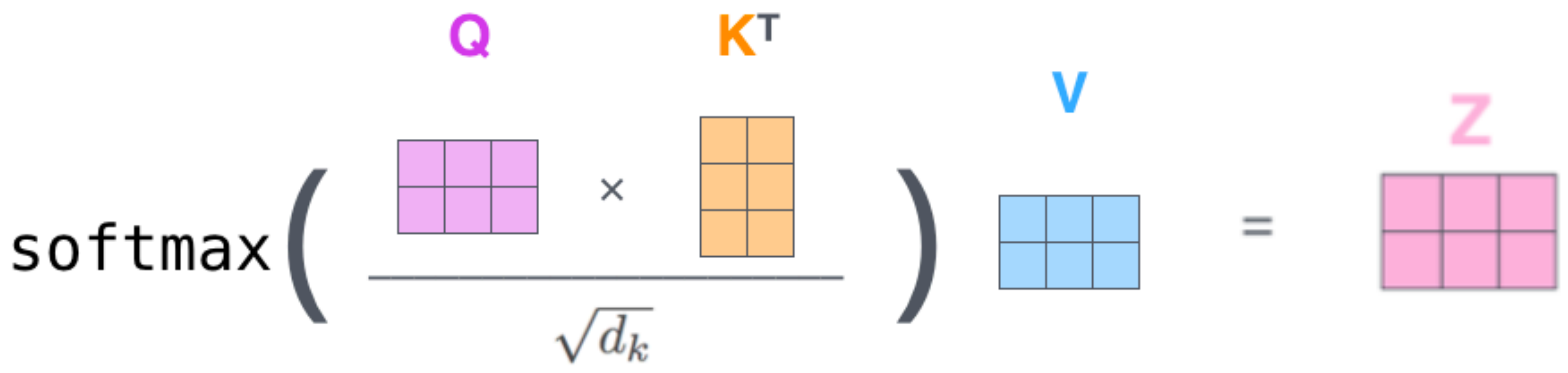
$$K = XW^K, W^K \in \mathbb{R}^{d_1 \times d_k}$$

$$V = XW^V, W^V \in \mathbb{R}^{d_1 \times d_v}$$

Note: the notation on this slide are following the original paper
(= the transpose of the matrices in the previous slide)

$$\boxed{\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{\overset{n \times d_q}{Q}\,\overset{d_k \times n}{K^T}}{\sqrt{d_k}}\right)\underset{n \times d_v}{V}}$$

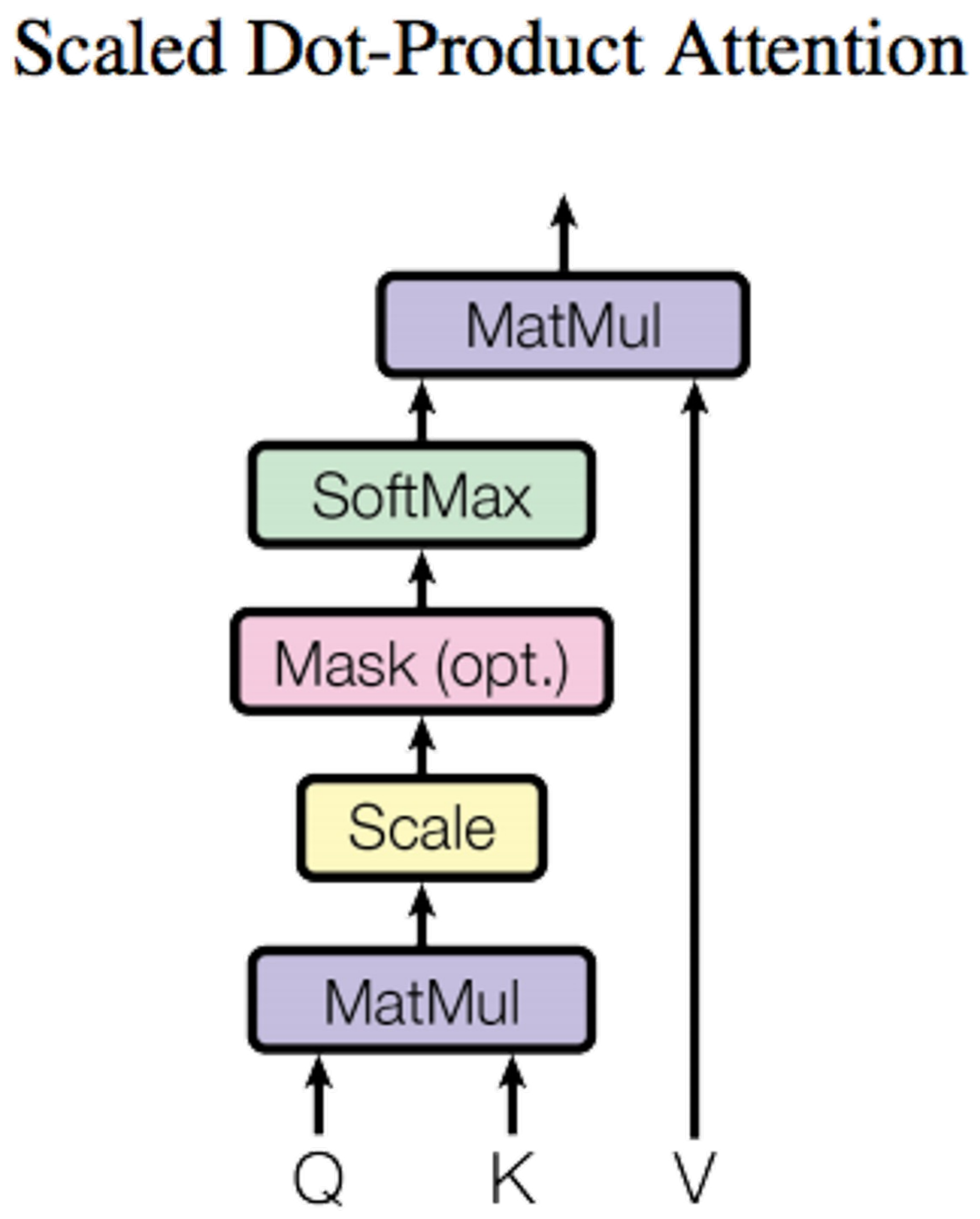
Be careful to make sure
the softmax is over the correct dimension



(figure credit: [Jay Alammar](http://jalammar.github.io/illustrated-transformer/) http://jalammar.github.io/illustrated-transformer/)

Scaled Dot Product Attention

Efficient, stable training



Let $Z \in \mathbb{R}^{M \times d_z}$ be a matrix of task context vectors to attend to

Let $C \in \mathbb{R}^{N \times d_C}$ be a matrix of input vectors to attend over

$\boldsymbol{SDPAttention(Z, C)}$:

$Q = W_Q Z^T$ $\quad W_Q \in \mathbb{R}^{d_q \times d_Z}$ $\quad d_q = d_k$

$K = W_K C^T$ $\quad W_K \in \mathbb{R}^{d_k \times d_C}$

$V = W_V C^T$ $\quad W_V \in \mathbb{R}^{d_v \times d_C}$

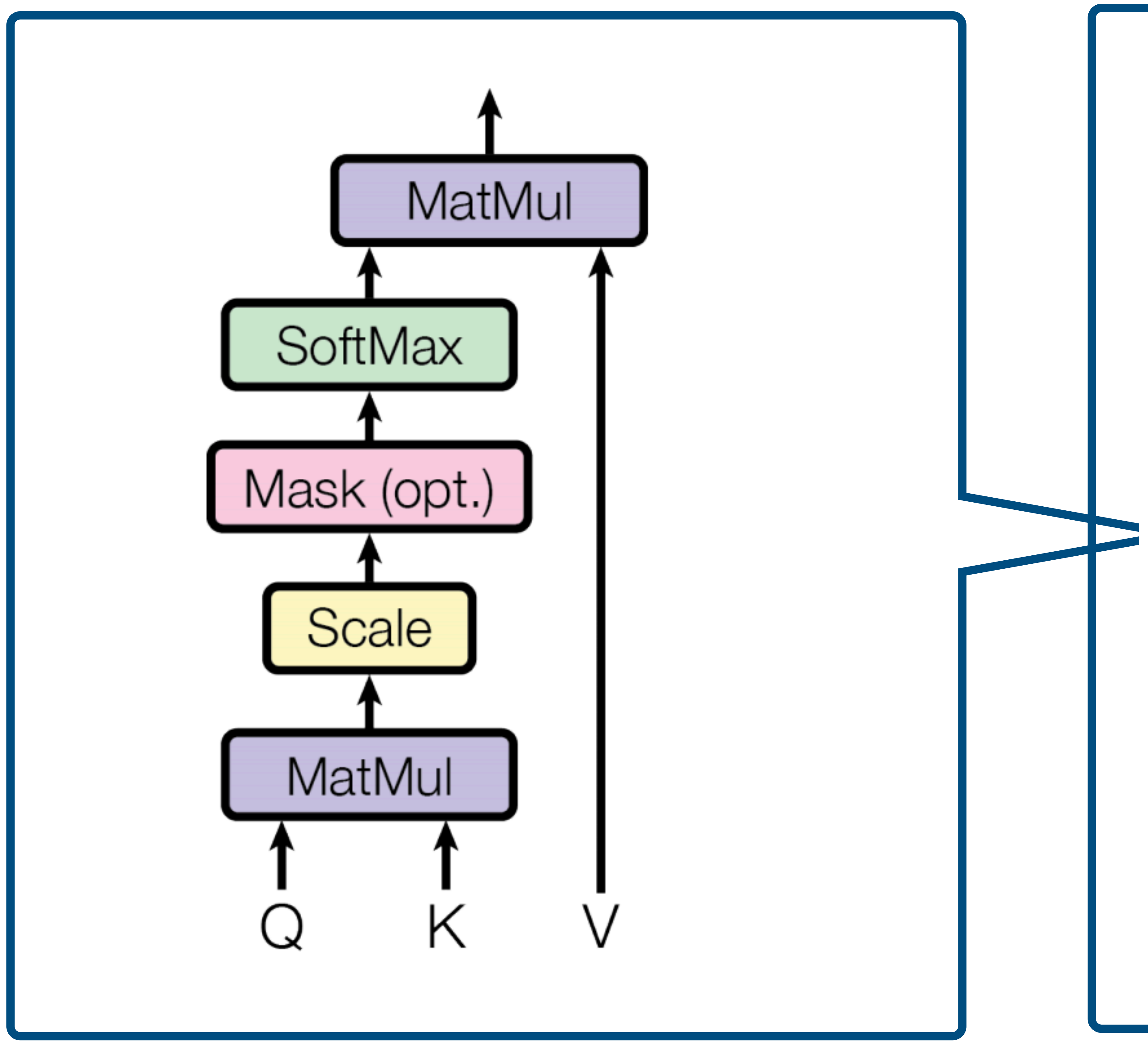
Return $\boxed{\hat{V} = softmax\left(\frac{Q^T K}{\sqrt{d_k}}\right) V}$

$\hat{V} \in \mathbb{R}^{M \times d_v}$ be a matrix of attended values

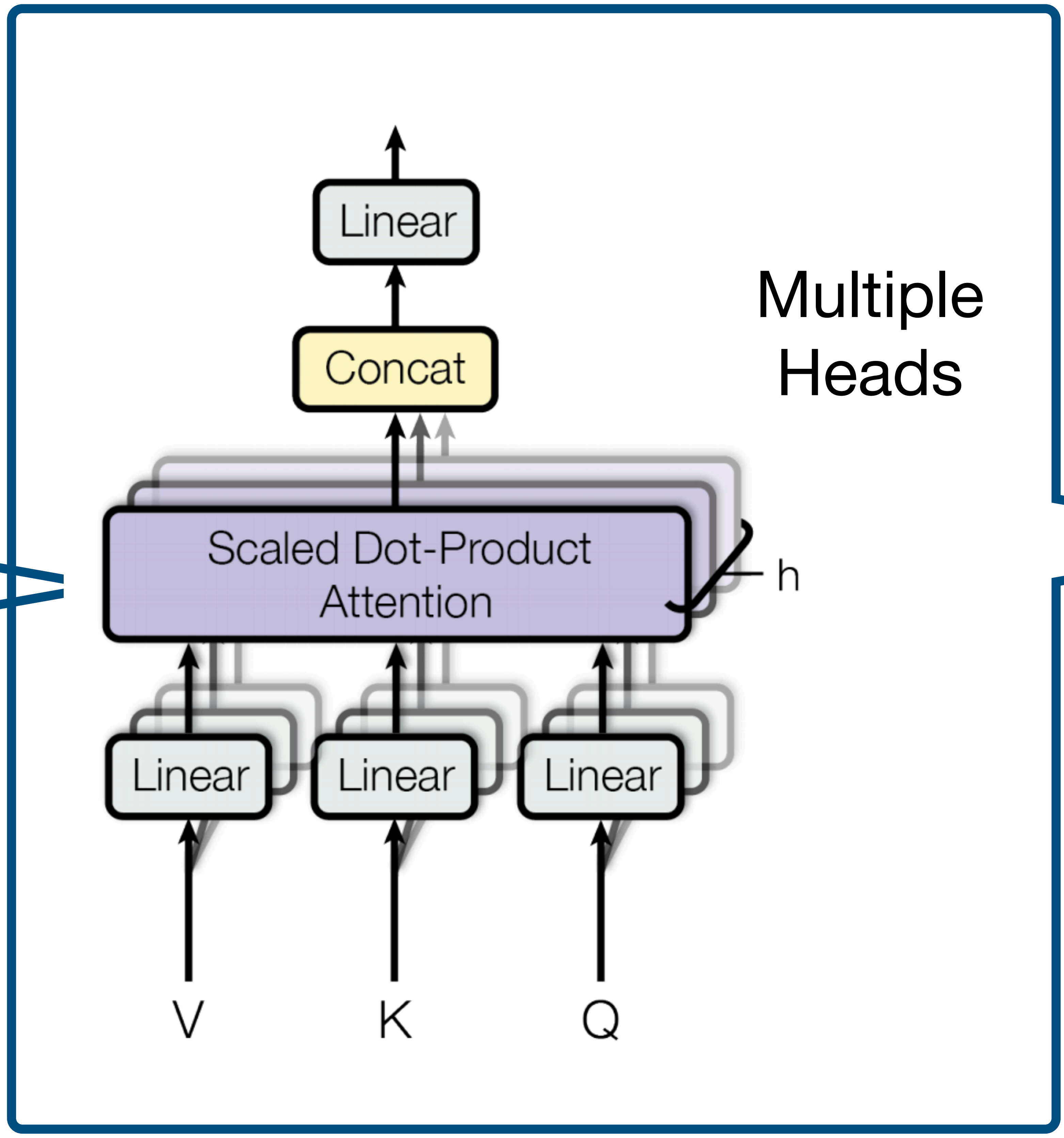
Attention Is All You Need https://arxiv.org/pdf/1706.03762.pdf

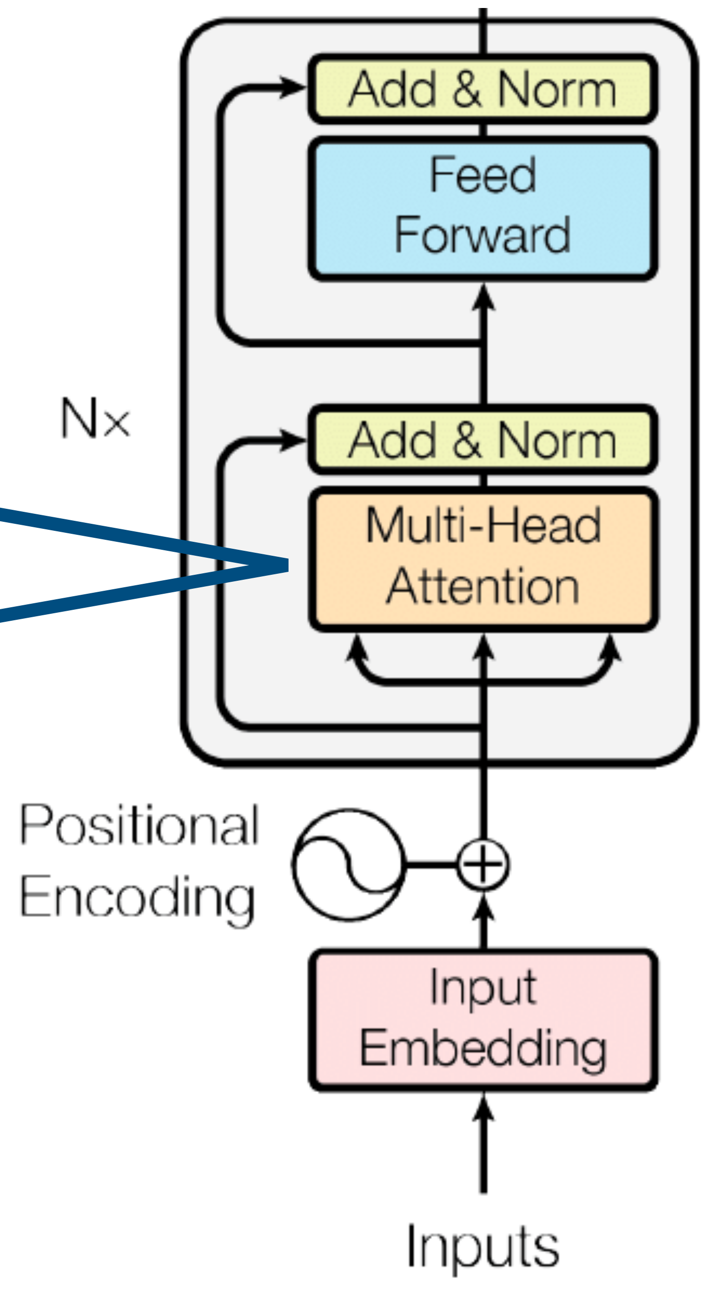
Multi-head self-attention

Scaled Dot-Product Attention



self-attention





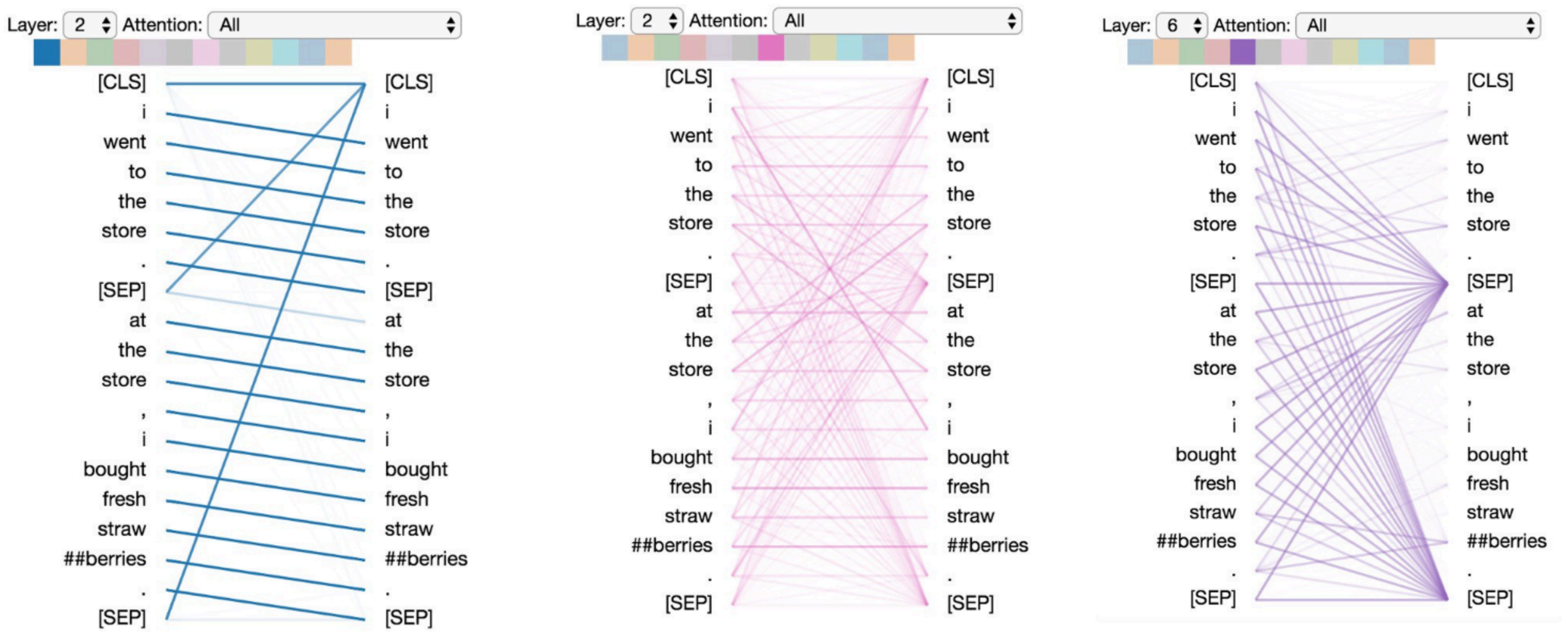
Attention Is All You Need https://arxiv.org/pdf/1706.03762.pdf

Multi-head self-attention

One head is not expressive enough. Let's have multiple heads!

$$\text{Multihead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O$$
$$\text{head}_i = A(XW_i^Q, XW_i^K, XW_i^V)$$

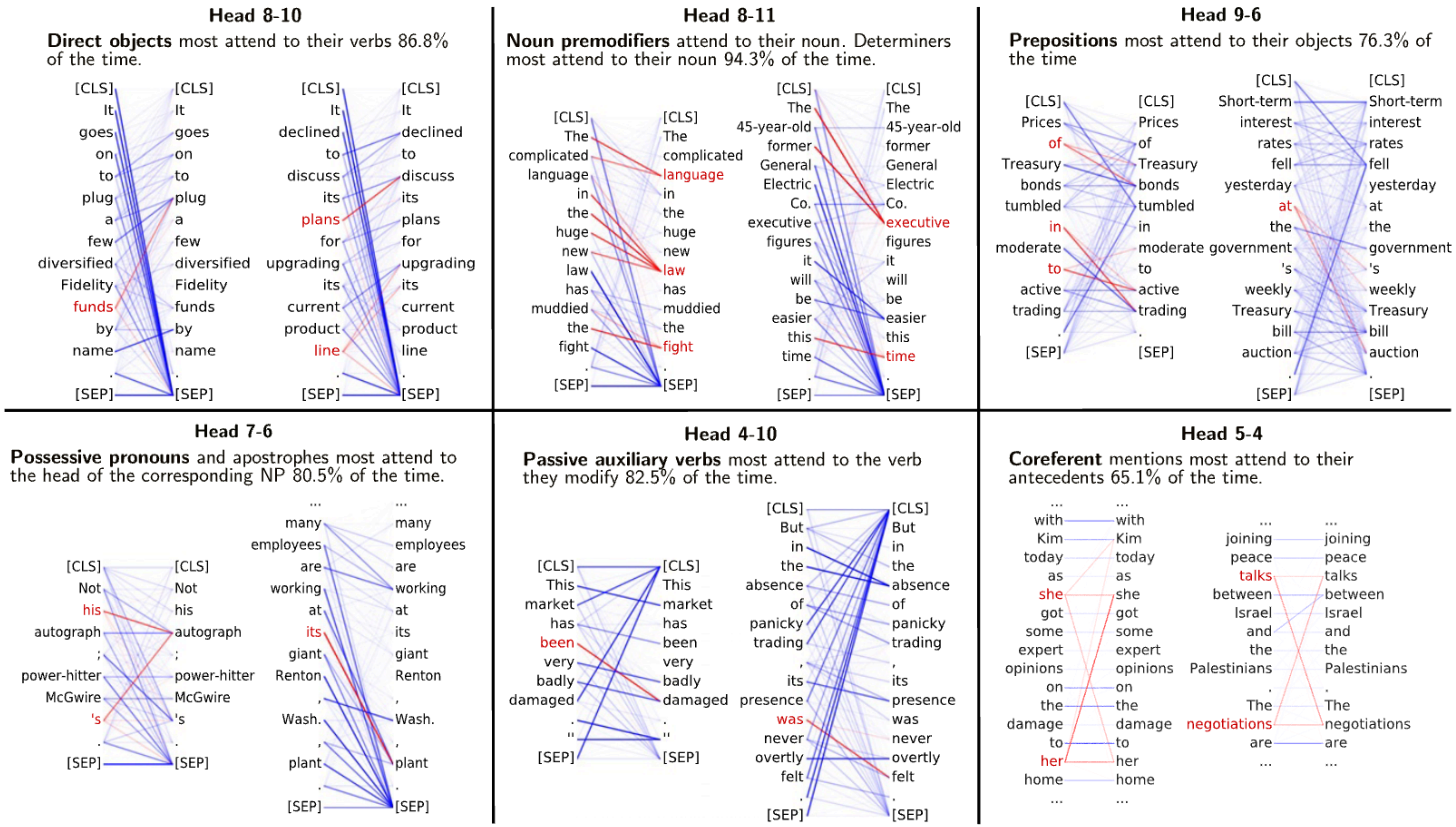
In practice, $h = 8$,
$d = d_{out}/h, W^O \in \mathbb{R}^{d_{out} \times d_{out}}$



https://github.com/jessevig/bertviz

Why different heads?

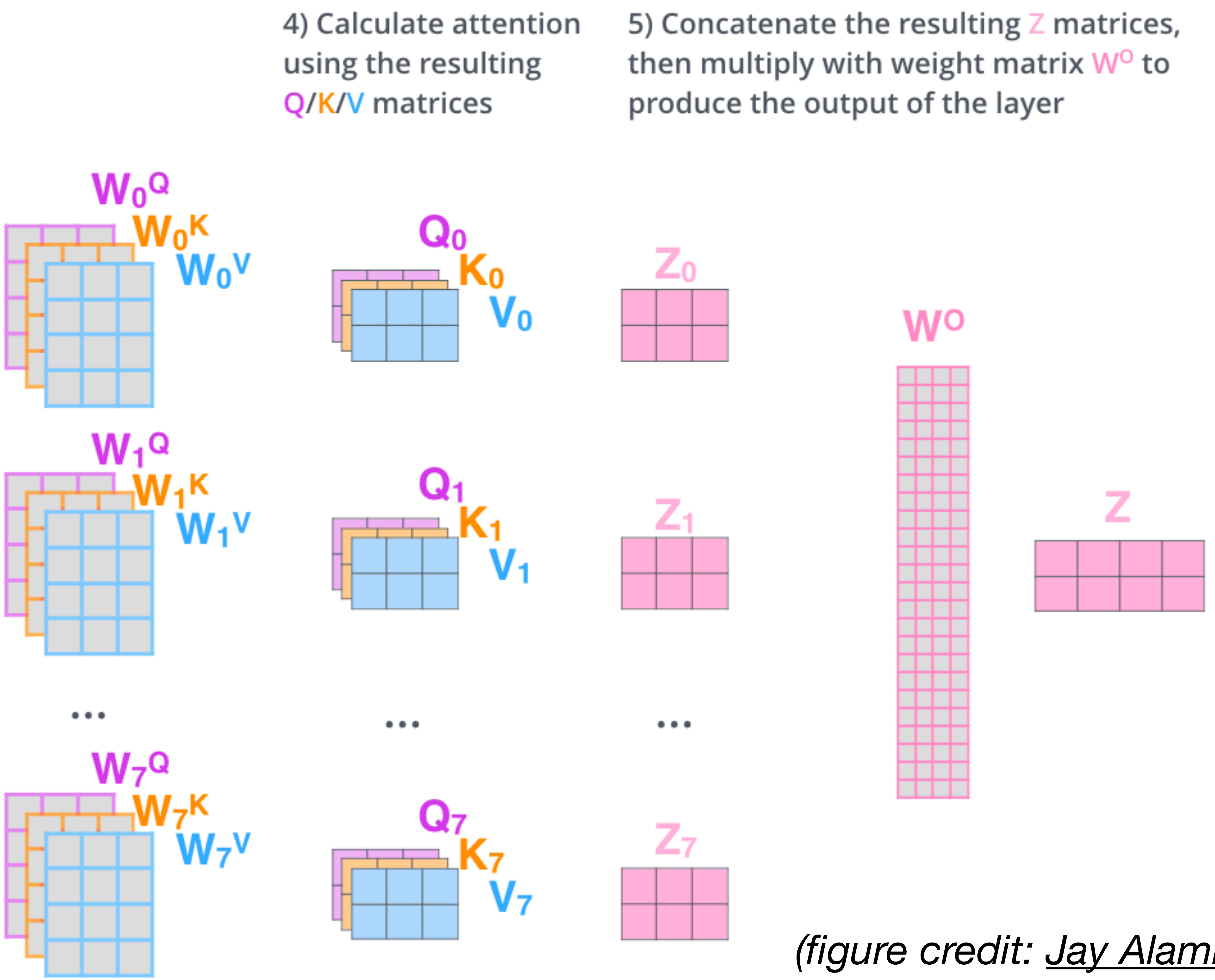
- Different heads learn to attend to different things



Emergent linguistic structure in artificial neural networks trained by self-supervision, Manning et al, PNAS 2019

Multiple heads

- Multiple (different) representations for each query, key, and values
- Different weight matrices —> different vectors
- Different ways for the words to interact with each other



(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

Multi-head attention

$$\text{Multihead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O$$

$$\text{head}_i = A(XW_i^Q, XW_i^K, XW_i^V)$$

- In practice, we use a reduced dimension for each head.

$$W_i^Q \in \mathbb{R}^{d_1 \times d_q}, W_i^K \in \mathbb{R}^{d_1 \times d_k}, W_i^V \in \mathbb{R}^{d_1 \times d_v}$$

$$d_q = d_k = d_v = d/h$$

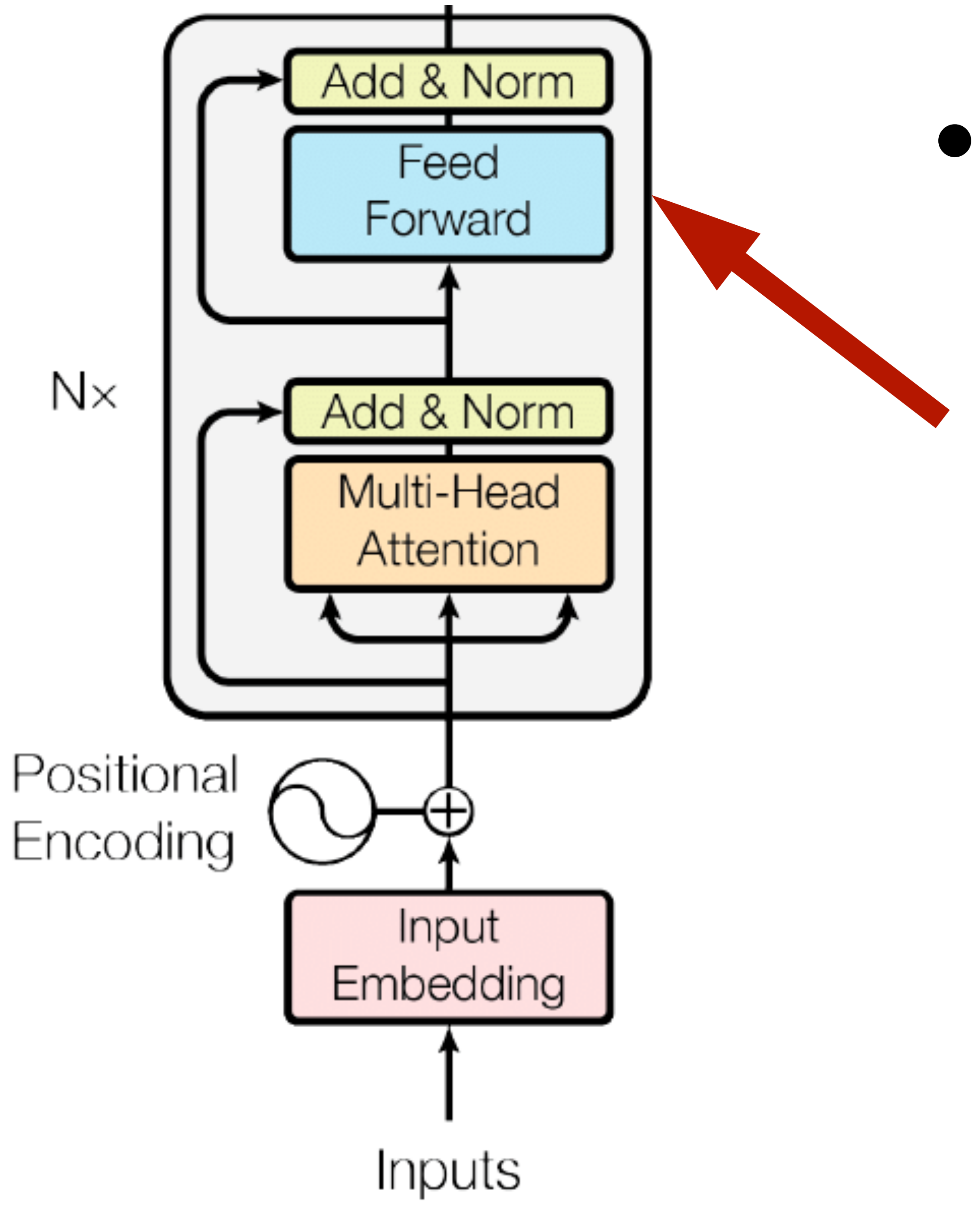
d = hidden size, h = # of heads

$$W^O \in \mathbb{R}^{d \times d_2}$$

If we stack multiple layers, usually $d_1 = d_2 = d$

- The total computational cost is similar to that of single-head attention with full dimensionality

Transformer Encoder



- Each Transformer block has two sub-layers
  - Multi-head attention
  - 2-layer feedforward NN (with ReLU)

Without FFNN: No non-linearity!

Adding nonlinearities

- There is no elementwise nonlinearities in self-attention; stacking more self-attention layers just re-averages value vectors

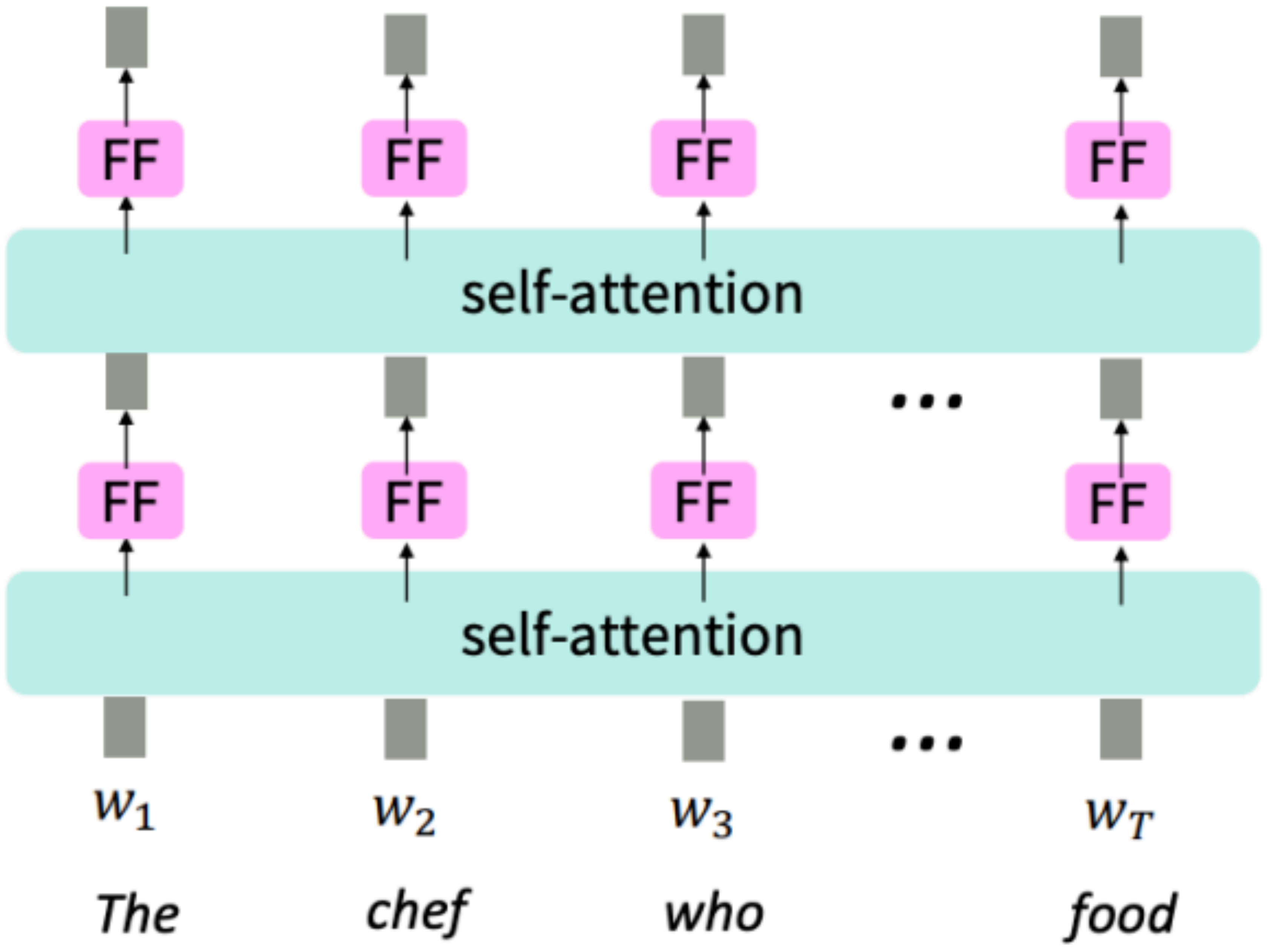
- Simple fix: add a feed-forward network to post-process each output vector

$$\mathrm{FFN}(\mathbf{x}_i) = W_2\mathrm{ReLU}(W_1\mathbf{x}_i + \mathbf{b}_1) + \mathbf{b}_2$$

$$W_1 \in \mathbb{R}^{d_{ff} \times d}, \mathbf{b}_1 \in \mathbb{R}^{d_{ff}}$$

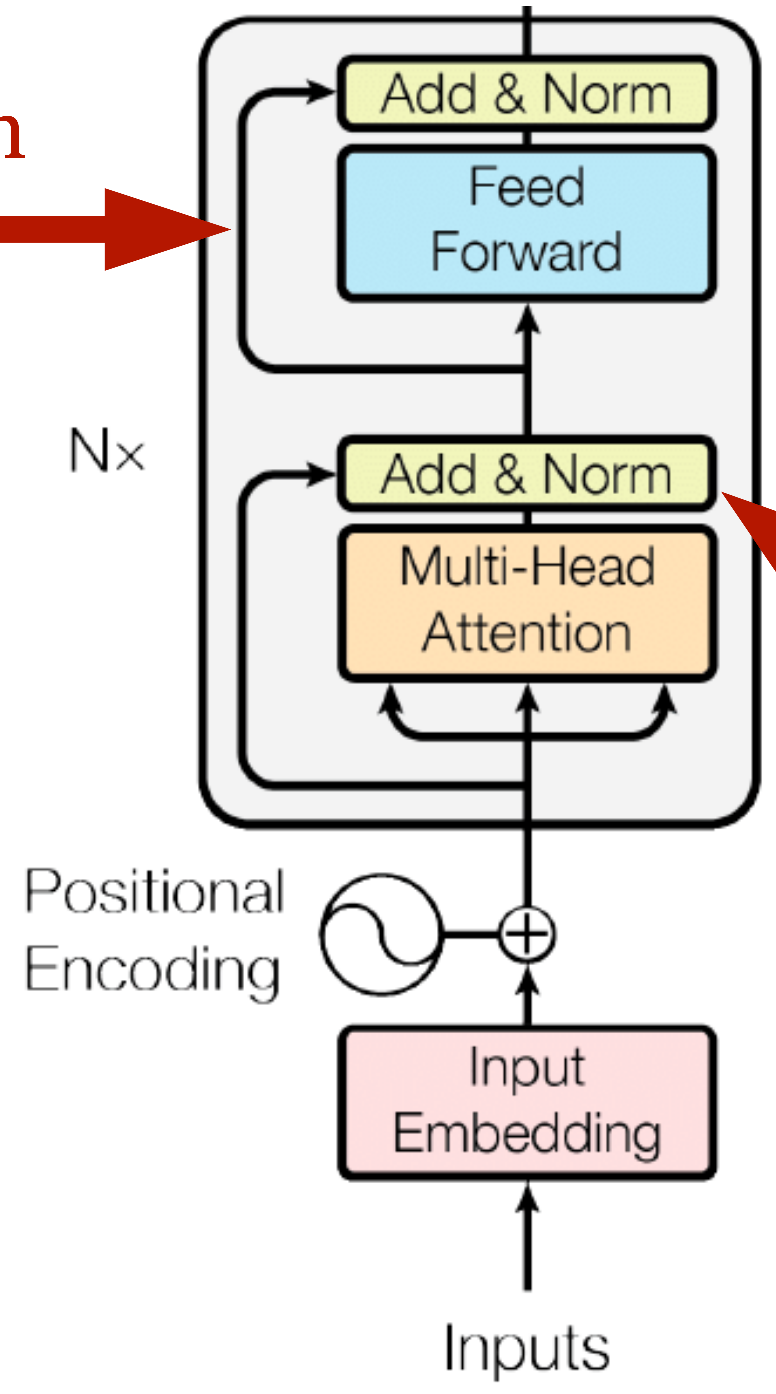
$$W_2 \in \mathbb{R}^{d \times d_{ff}}, \mathbf{b}_2 \in \mathbb{R}^{d}$$

In practice, they use $d_{ff} = 4d$



Transformer Encoder

residual connection



- Each Transformer block has two sub-layers
  - Multi-head attention
  - 2-layer feedforward NN (with ReLU)

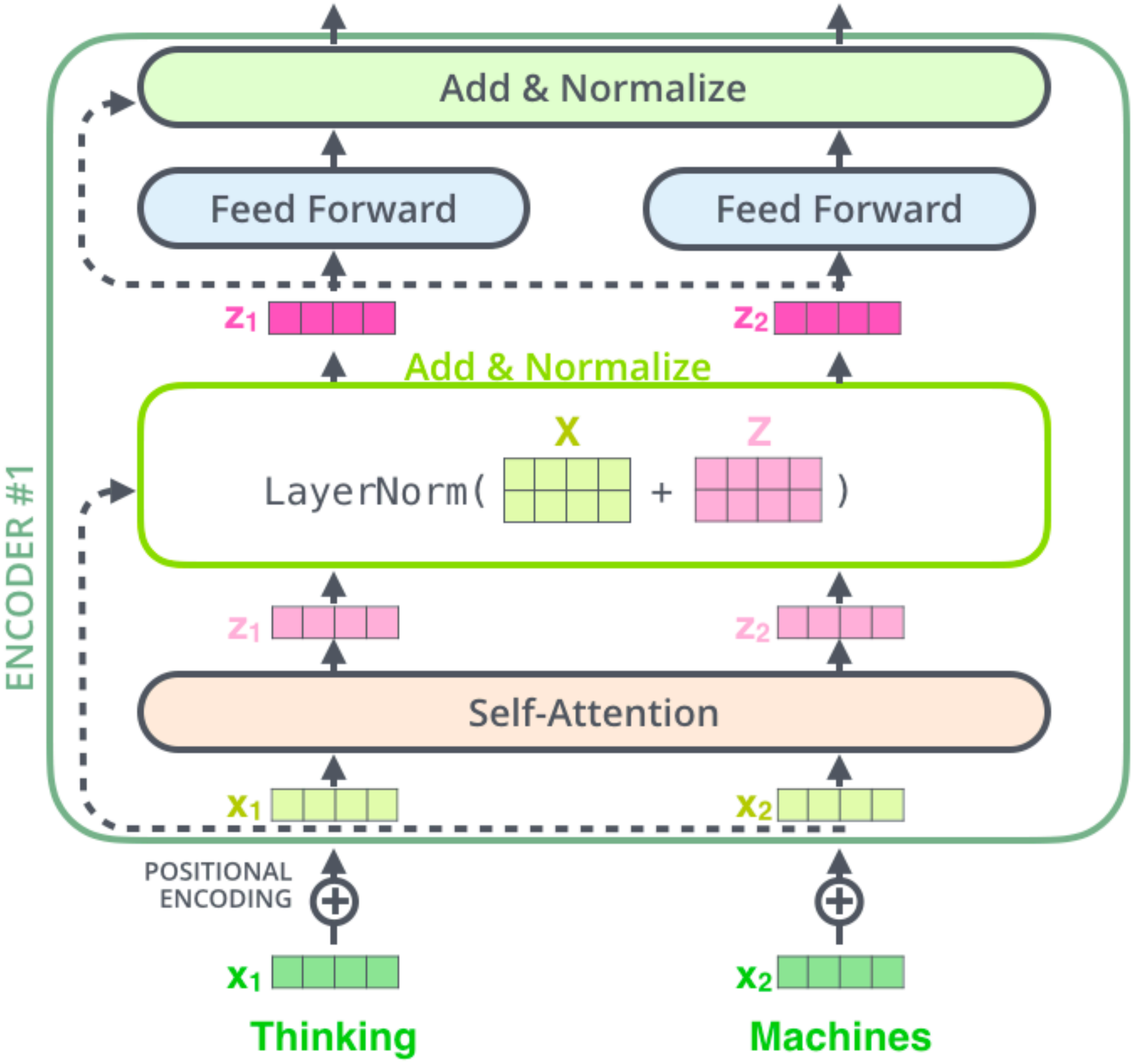
- Each sublayer has a residual connection and a layer normalization

$$\mathrm{LayerNorm}(x + \mathrm{SubLayer}(x))$$

(He et al, 2016): Residual connections

(Ba et al, 2016): Layer Normalization

Residual connections and Layer Normalization



(figure credit: Jay Alammar http://jalammar.github.io/illustrated-transformer/)

LayerNorm

- changes input features to have mean 0 and variance 1 per layer.
- Adds two more parameters

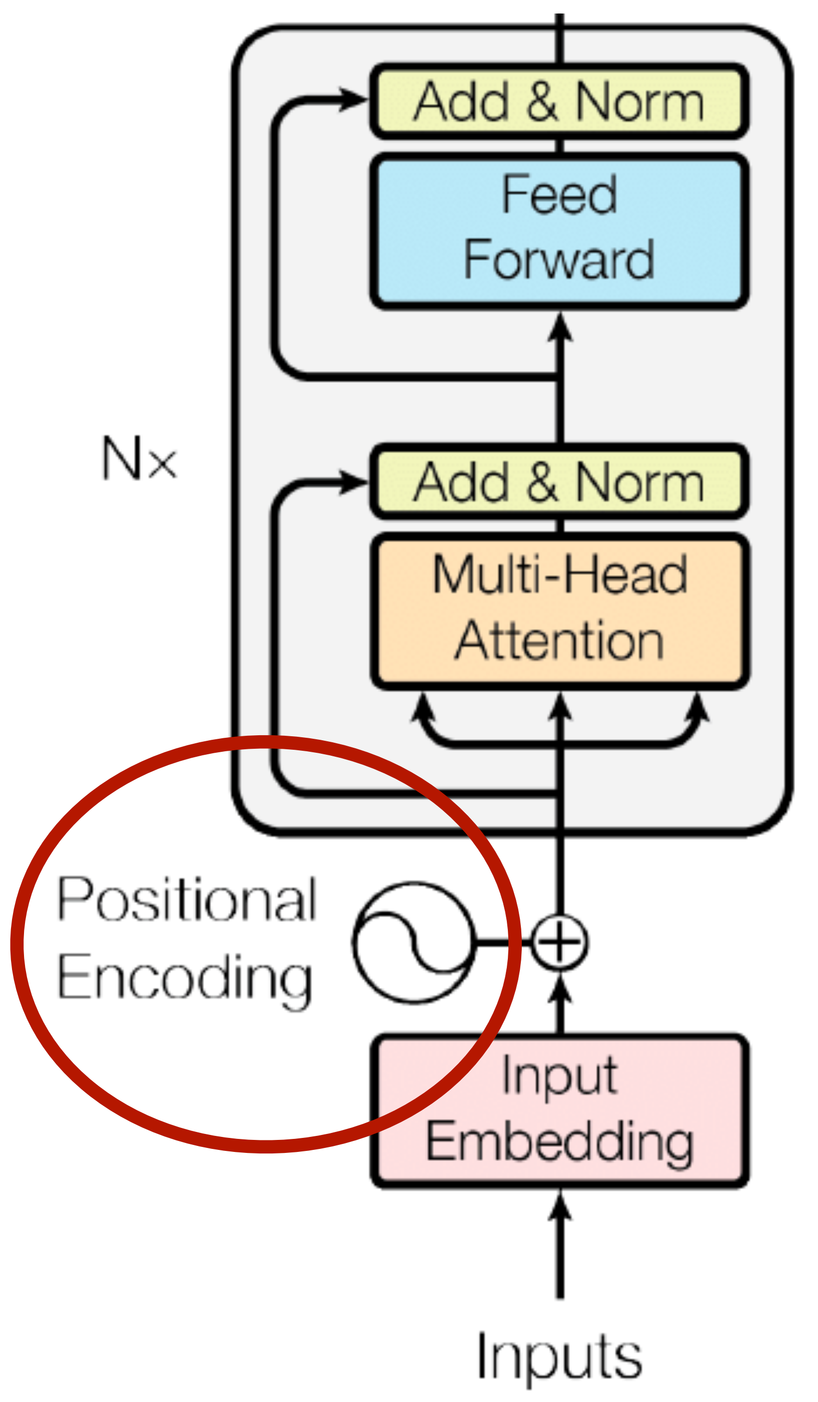
$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \qquad \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}\left(a_i^l - \mu^l\right)^2}$$

$$h_i = \frac{g_i}{\sigma_i}(a_i - \mu_i) + b_i$$

- For more stable and efficient training

(Ba et al, 2016): Layer Normalization

Transformer Encoder



- Each Transformer block has two sub-layers
  - Multi-head attention
  - 2-layer feedforward NN (with ReLU)
- Each sublayer has a residual connection and a layer normalization

$$\mathrm{LayerNorm}(x + \mathrm{SubLayer}(x))$$

- Input layer has a positional encoding

Necessary for the model to know the position of the token

(He et al, 2016): Residual connections

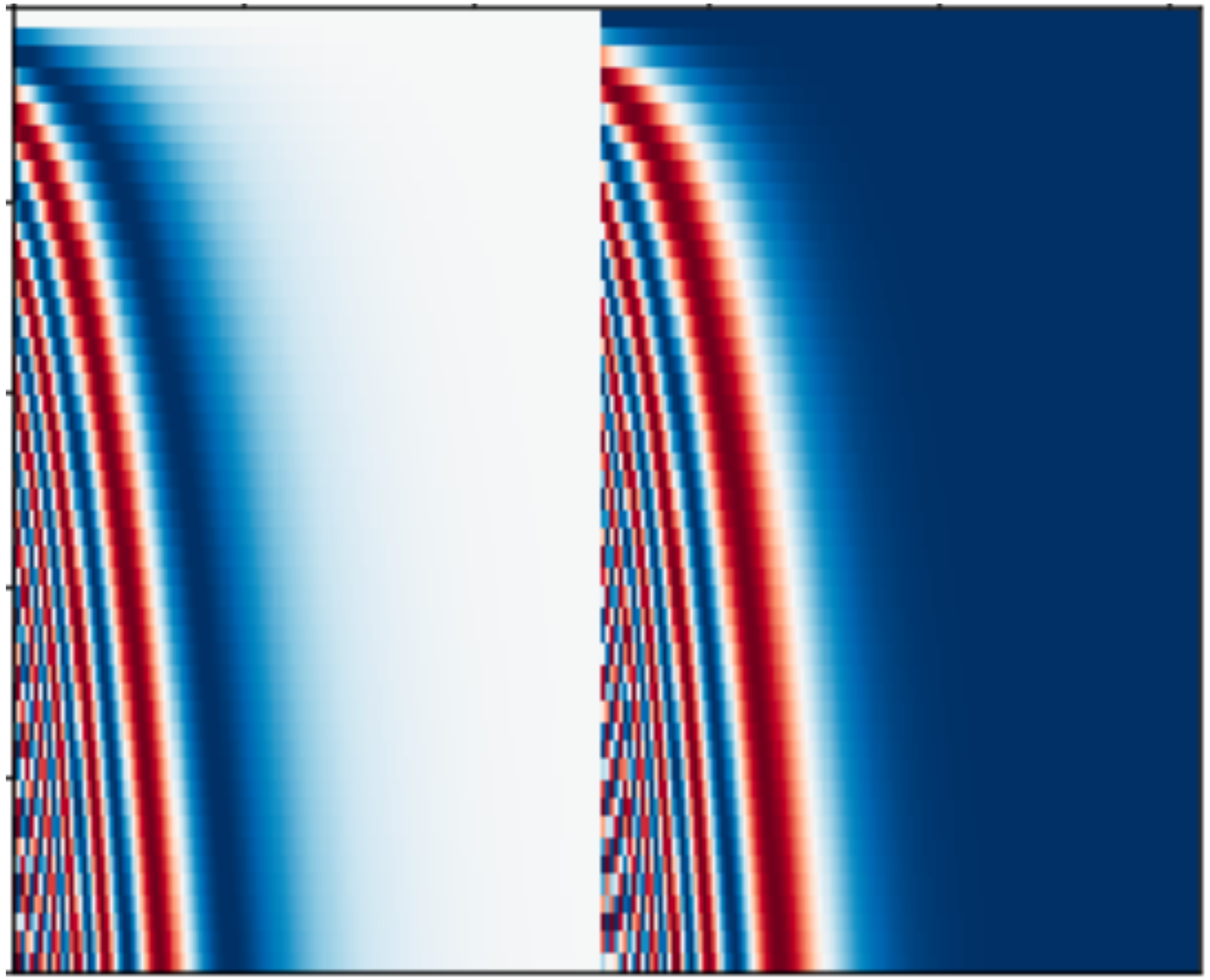
(Ba et al, 2016): Layer Normalization

Positional encoding

$$\overrightarrow{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases}$$

$$\omega_k = \frac{1}{10000^{2k/d}}$$

$$\overrightarrow{p_t} = \begin{bmatrix} \sin(\omega_1 . t) \\ \cos(\omega_1 . t) \\ \\ \sin(\omega_2 . t) \\ \cos(\omega_2 . t) \\ \\ \vdots \\ \\ \sin(\omega_{d/2} . t) \\ \cos(\omega_{d/2} . t) \end{bmatrix}_{d \times 1}$$



Sine Cosine

t = position

d = embedding dimension

i = embedding index (0 to d-1)

Positional encoding

$$\vec{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases}$$

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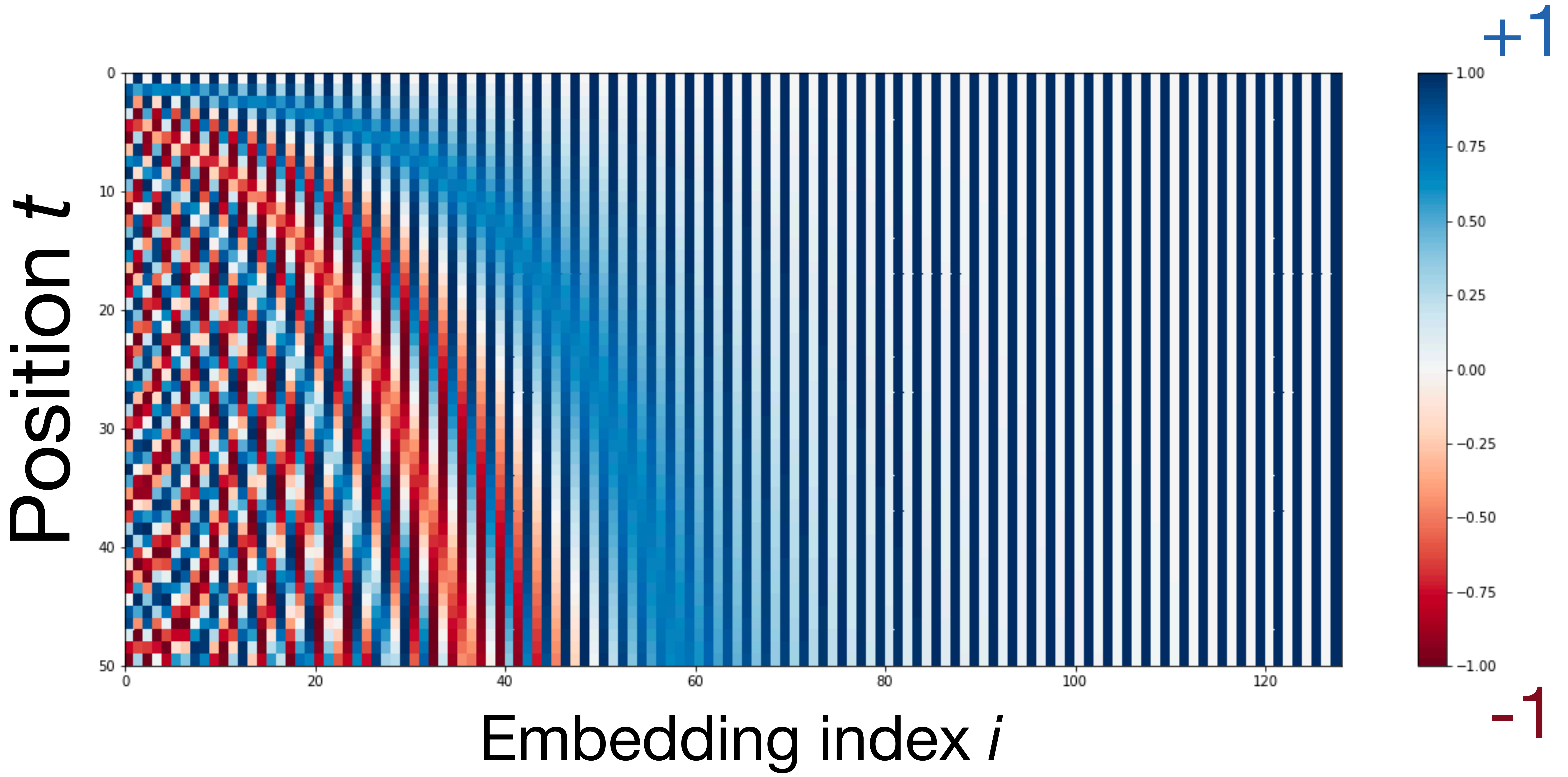


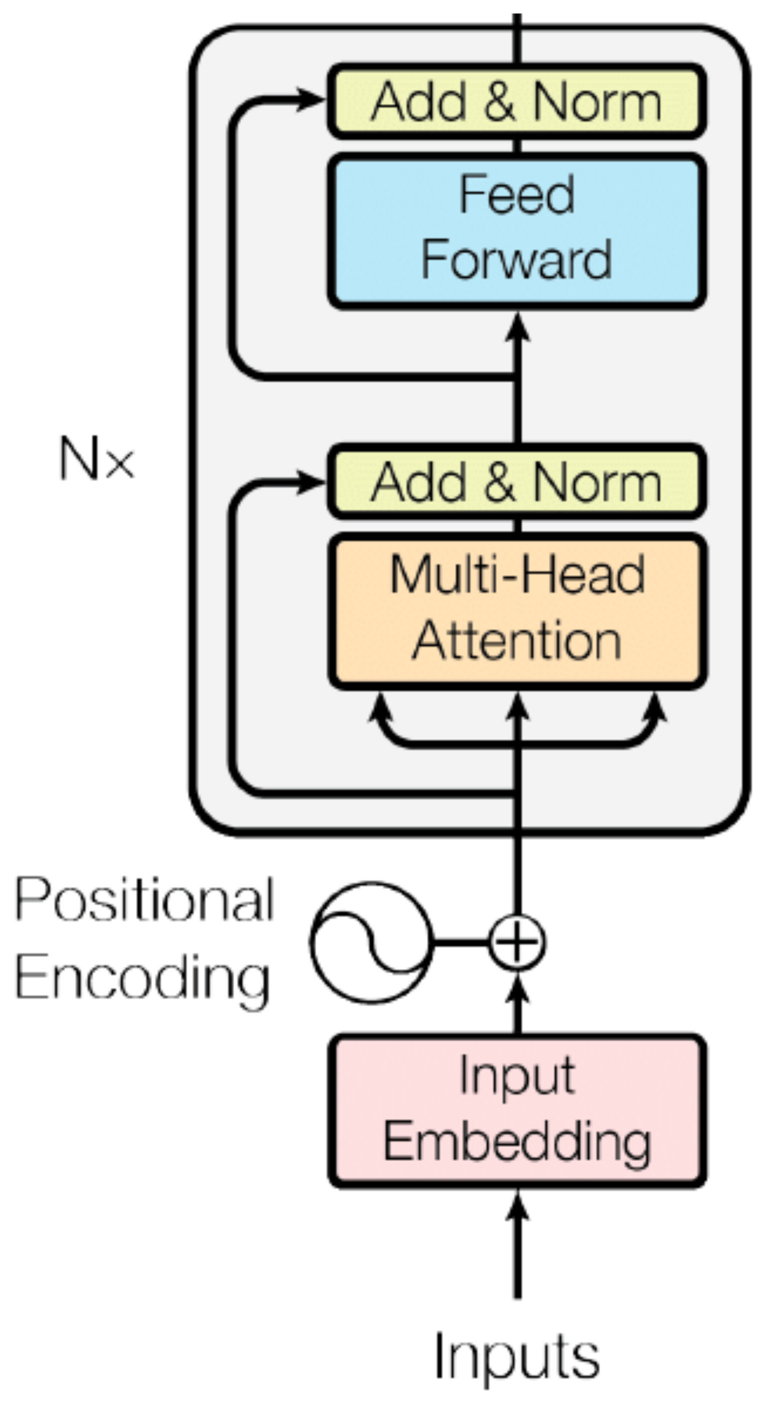
t = position

d = embedding dimension

i = embedding index (0 to d-1)

Transformer encoder

Transformer
Non-recurrent, deep model with attention

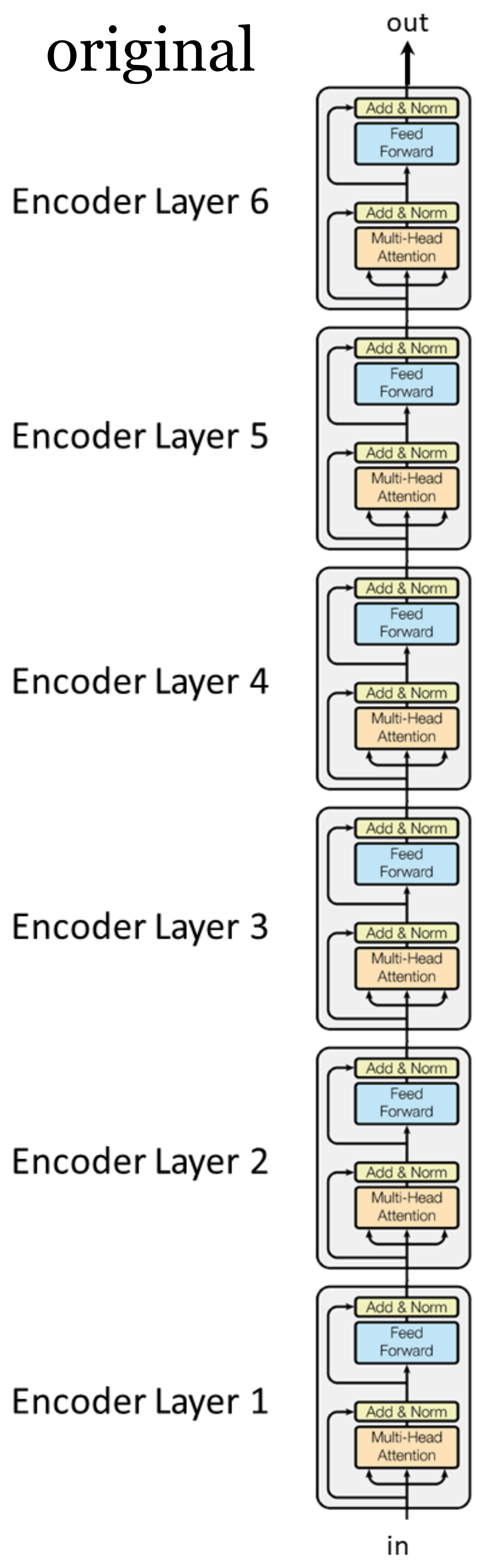


- Each Transformer block has two sub-layers
  - Multi-head attention
  - 2-layer feedforward NN (with ReLU)
- Each sublayer has a residual connection and a layer normalization

$$\text{LayerNorm}(x + \text{SubLayer}(x))$$

- Input layer has a positional encoding
- Input embedding is byte pair encoding (BPE)

original

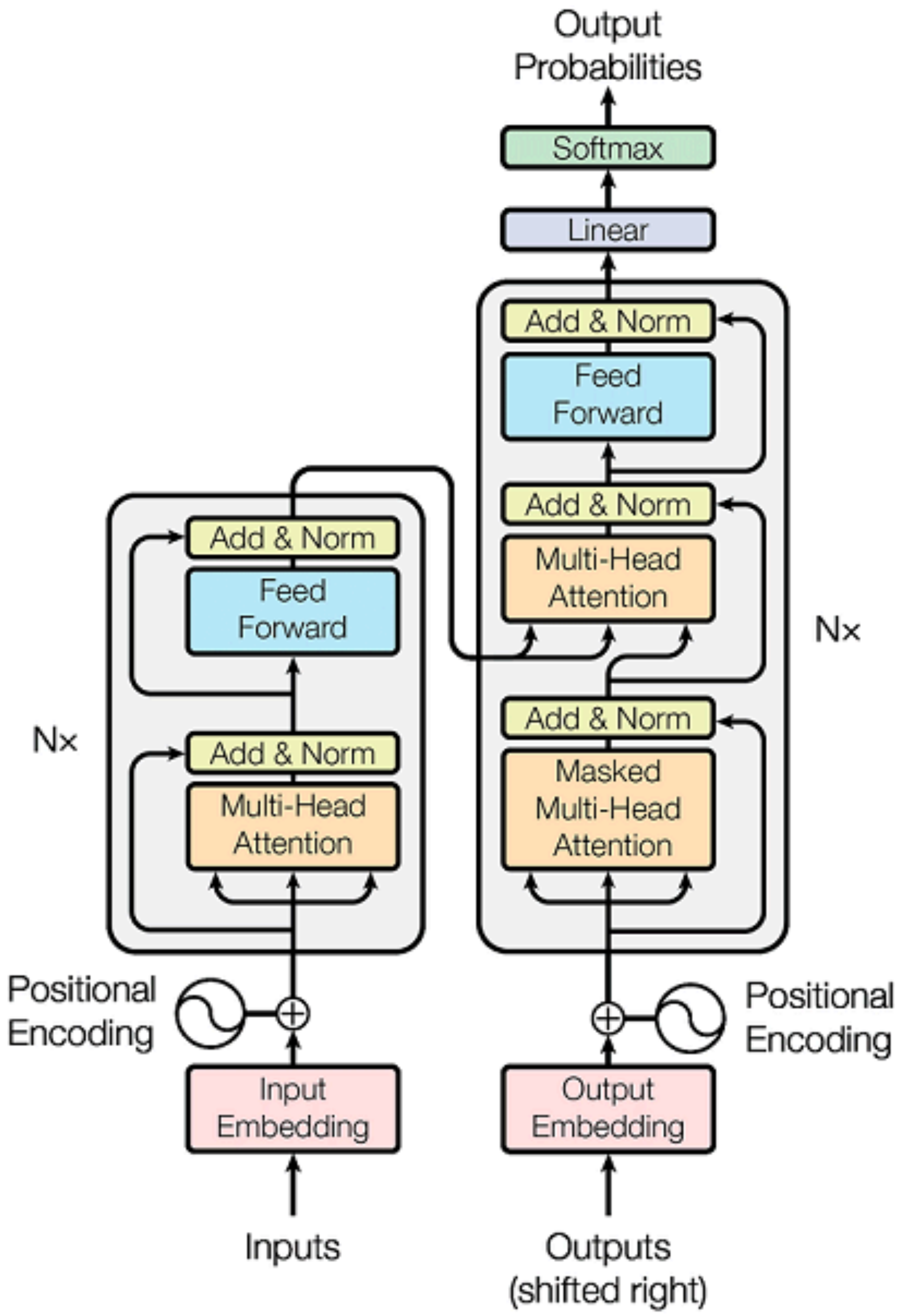


- BERT_base: 12 layers, 12 heads, hidden size = 768, 110M parameters
- BERT_large: 24 layers, 16 heads, hidden size = 1024, 340M parameters

(He et al, 2016): Residual connections

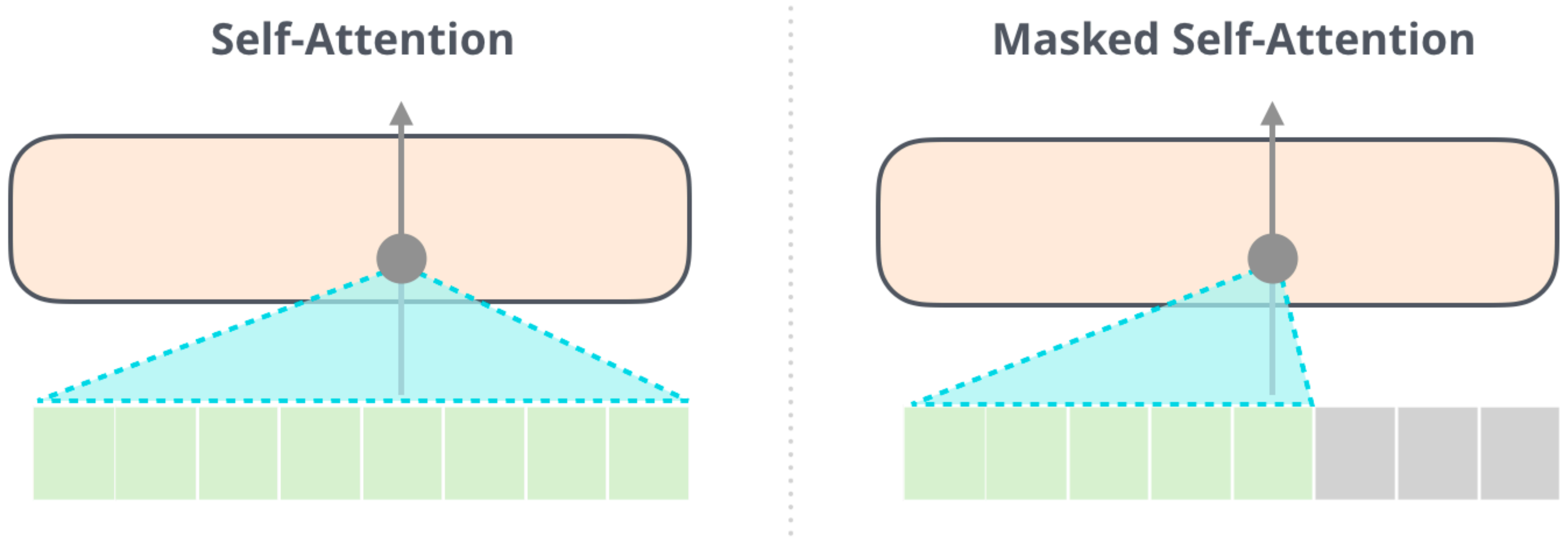
(Ba et al, 2016): Layer Normalization

Transformer decoder



- Encoder-Decoder Attention, where queries come from previous decoder layer and keys and values come from output of encoder

- Masked decoder self-attention on previously generated outputs



(figure credit: Jay Alammar
http://jalammar.github.io/illustrated-gpt2/)

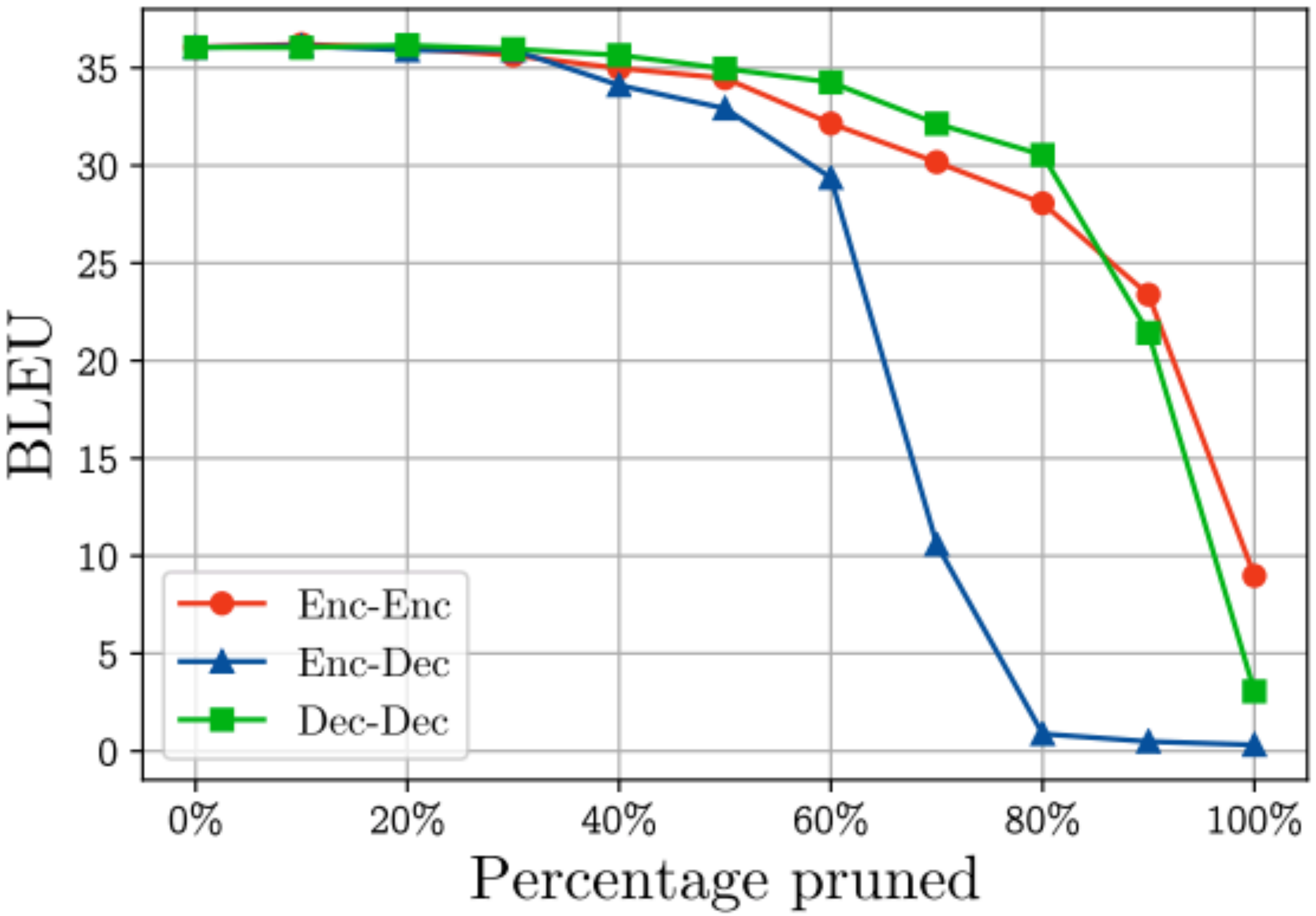
- also 6 layers (in original paper)

Do we need all these heads?

3 types of attention: Enc-Enc, Enc-Dec, Dec-Dec

6 layers, 16 heads each layer for each type

- Can we prune away some of the heads of a trained model during test time?



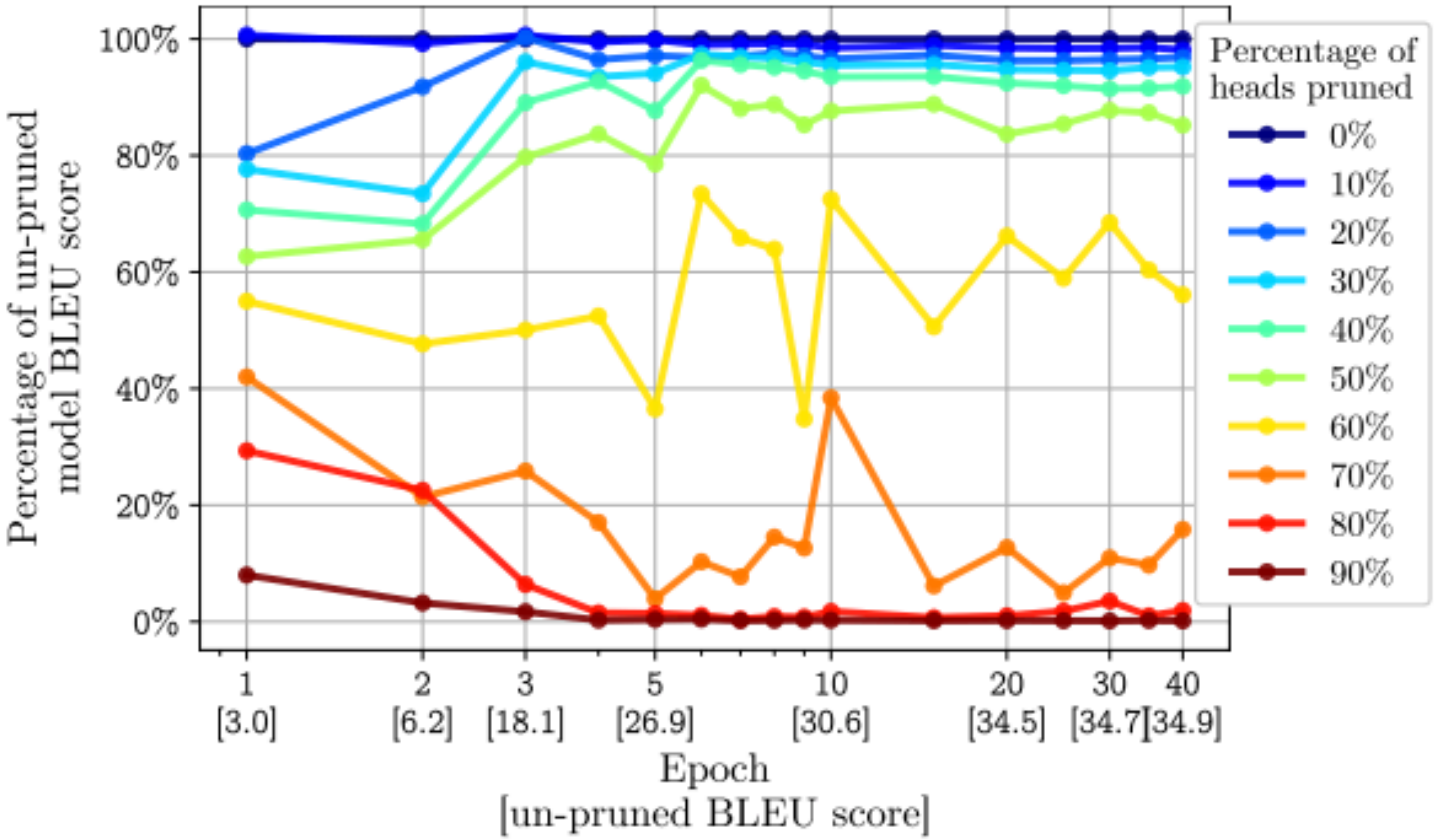
Are Sixteen Heads Really Better than One?
Michel, Levy, and Neubig, NeurIPS 2019

Do we need all these heads?

3 types of attention: Enc-Enc, Enc-Dec, Dec-Dec

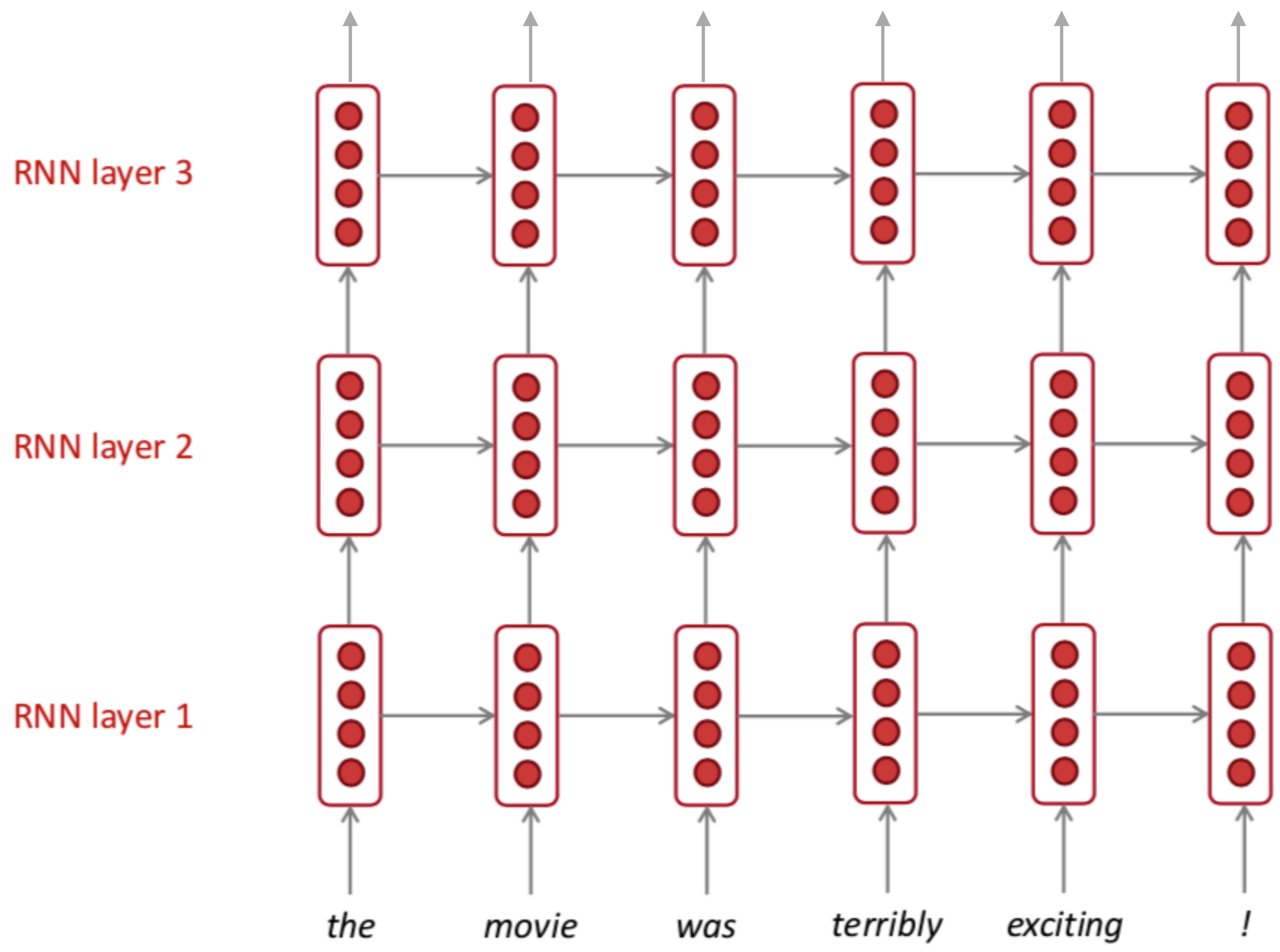
6 layers, 16 heads each layer for each type

- Can we train a good MT model with less heads?

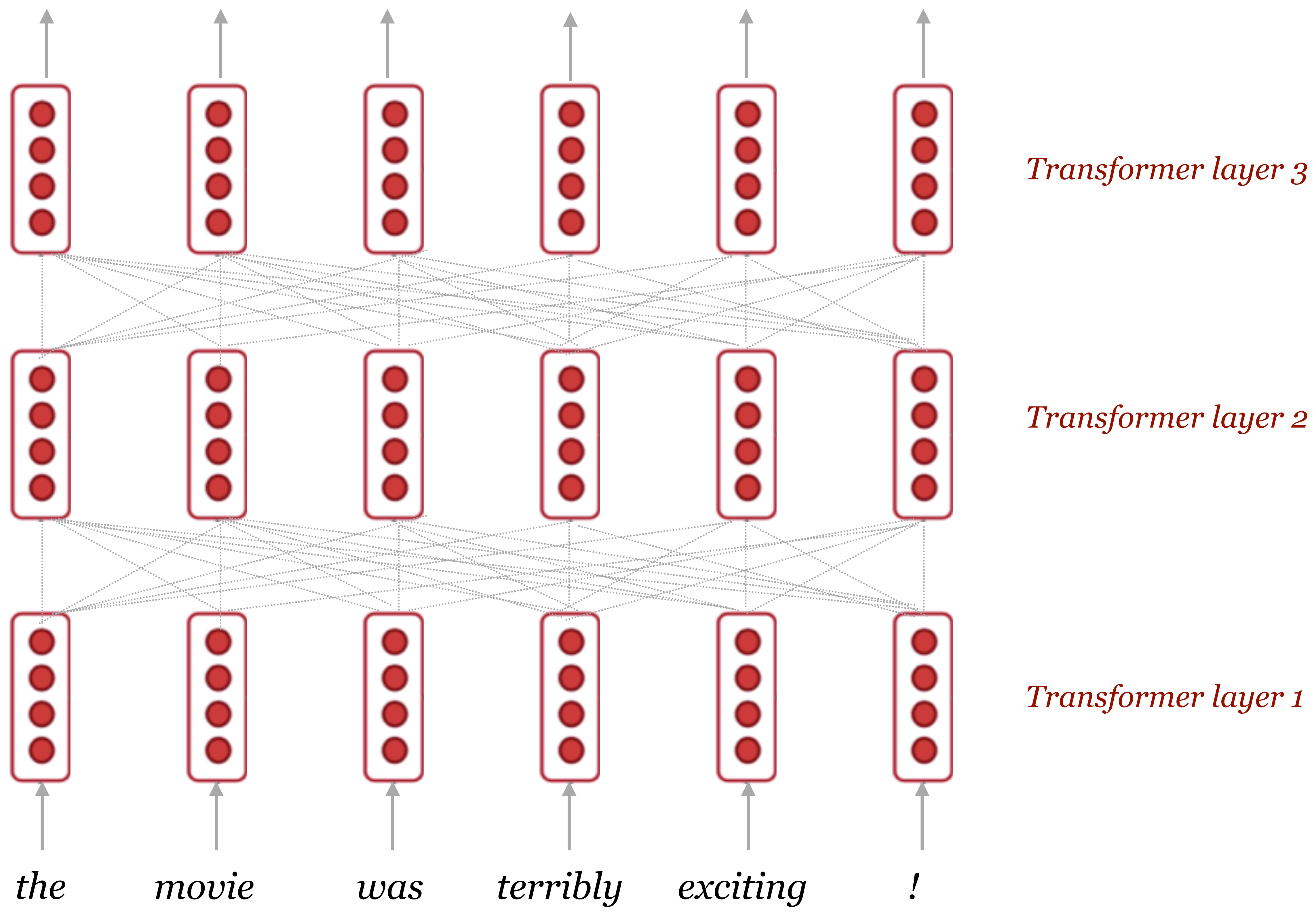


Are Sixteen Heads Really Better than One?
Michel, Levy, and Neubig, NeurIPS 2019

RNNs vs Transformers



RNN



Transformer

Useful Resources

Pytorch (https://pytorch.org/docs/stable/nn.html#transformer-layers)

nn.Transformer:

```
>>> transformer_model = nn.Transformer(nhead=16, num_encoder_layers=12)
>>> src = torch.rand((10, 32, 512))
>>> tgt = torch.rand((20, 32, 512))
>>> out = transformer_model(src, tgt)
```

nn.TransformerEncoder:

```
>>> encoder_layer = nn.TransformerEncoderLayer(d_model=512, nhead=8)
>>> transformer_encoder = nn.TransformerEncoder(encoder_layer, num_layers=6)
>>> src = torch.rand(10, 32, 512)
>>> out = transformer_encoder(src)
```

The Annotated Transformer:

http://nlp.seas.harvard.edu/2018/04/03/attention.html

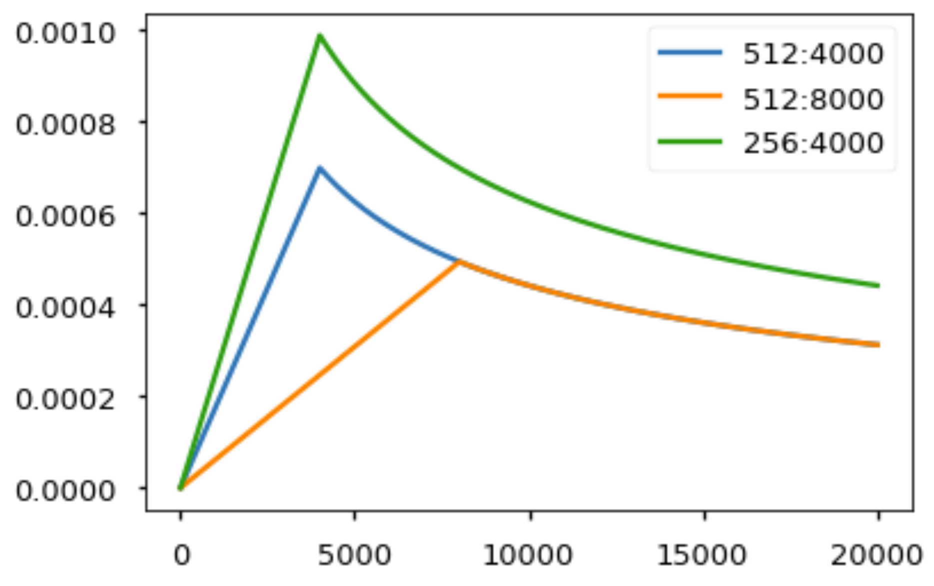
A Jupyter notebook which explains how Transformer works line by line in PyTorch!

🤗 **Transformers**

https://github.com/huggingface/transformers

Other details

- Learning rate with warmup and decay



- Label smoothing

Perfomance on machine translation

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

Attention is all you need
Vaswani et al, NeurIPS 2017

Transformer Pros and Cons

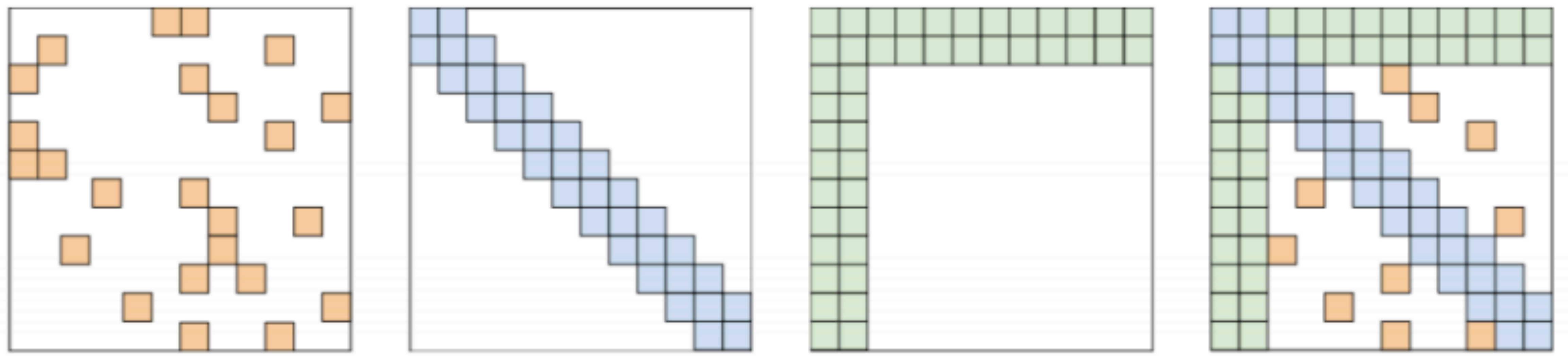
- Pros
  - Easier to capture dependencies: we draw attention between every pair of words
  - Easier to parallelize (matrix operations)

$$Q = XW^Q, W^Q \in \mathbb{R}^{d_1 \times d_q}$$

$$K = XW^K, W^K \in \mathbb{R}^{d_1 \times d_k}$$

$$V = XW^V, W^V \in \mathbb{R}^{d_1 \times d_v}$$

- Cons
  - Quadratic computation in self-attention
    - Can become very slow when the sequence length is large



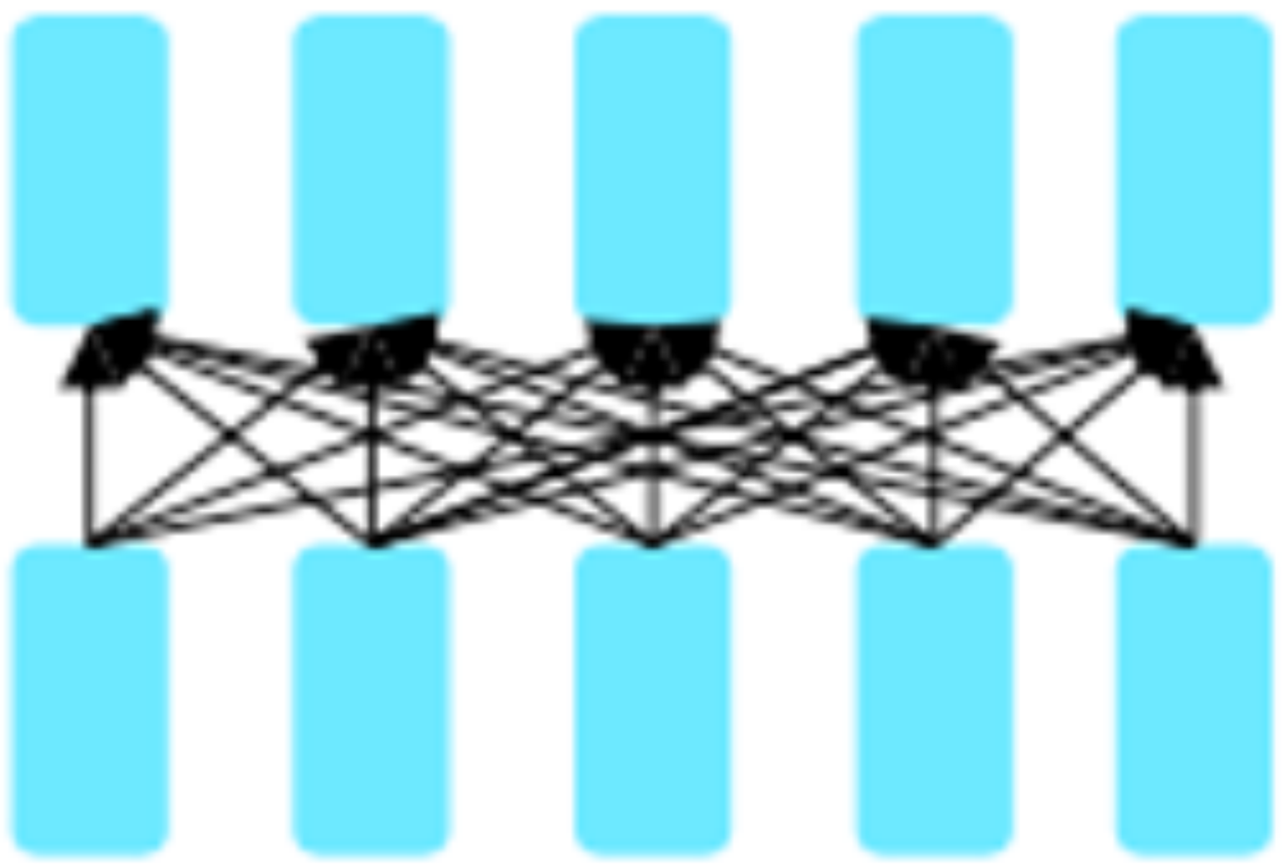
(a) Random attention (b) Window attention (c) Global Attention (d) BIGBIRD

- Are these positional representations enough to capture positional information?

Transformers for pretraining

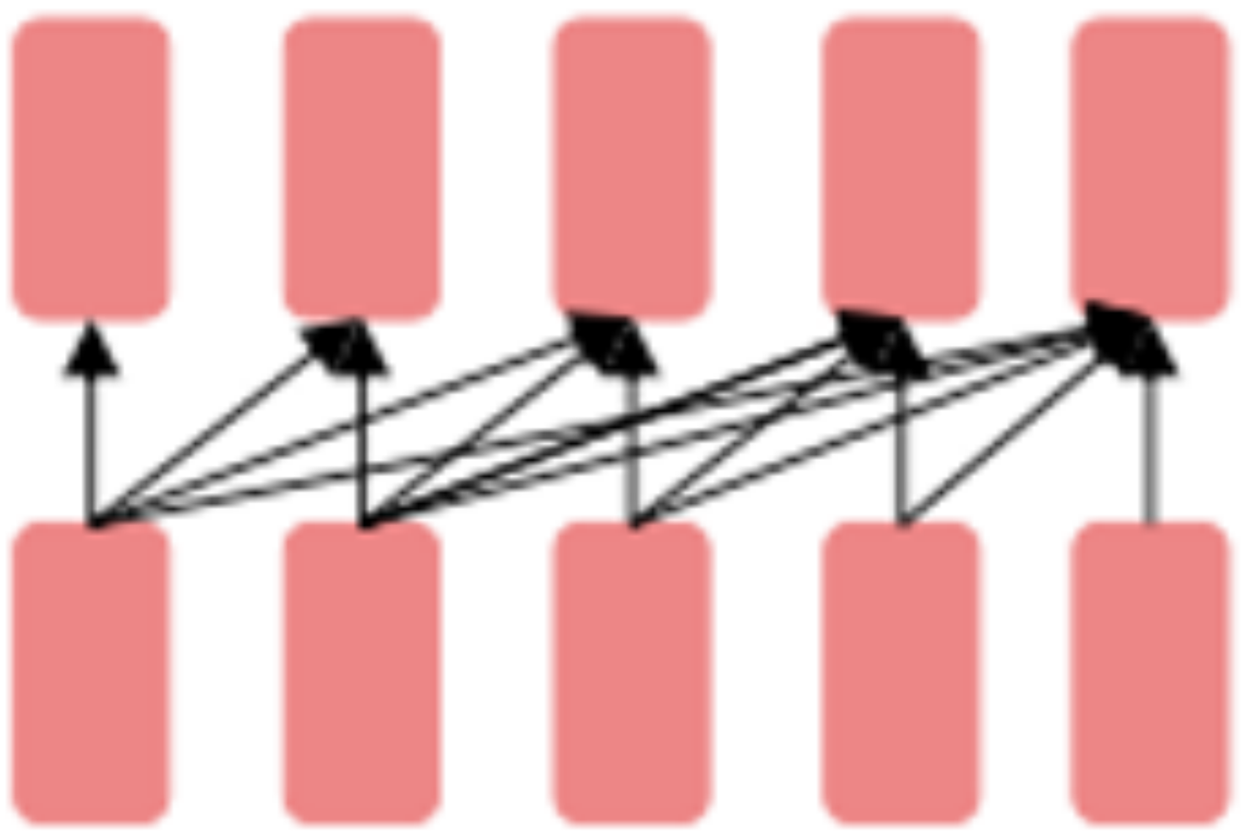
- Self-supervised Transformer based models shattered language understanding benchmarks in NLP in 2018.
- Trained on large text corpus with self-supervised objectives and then transferred.

Encoder only



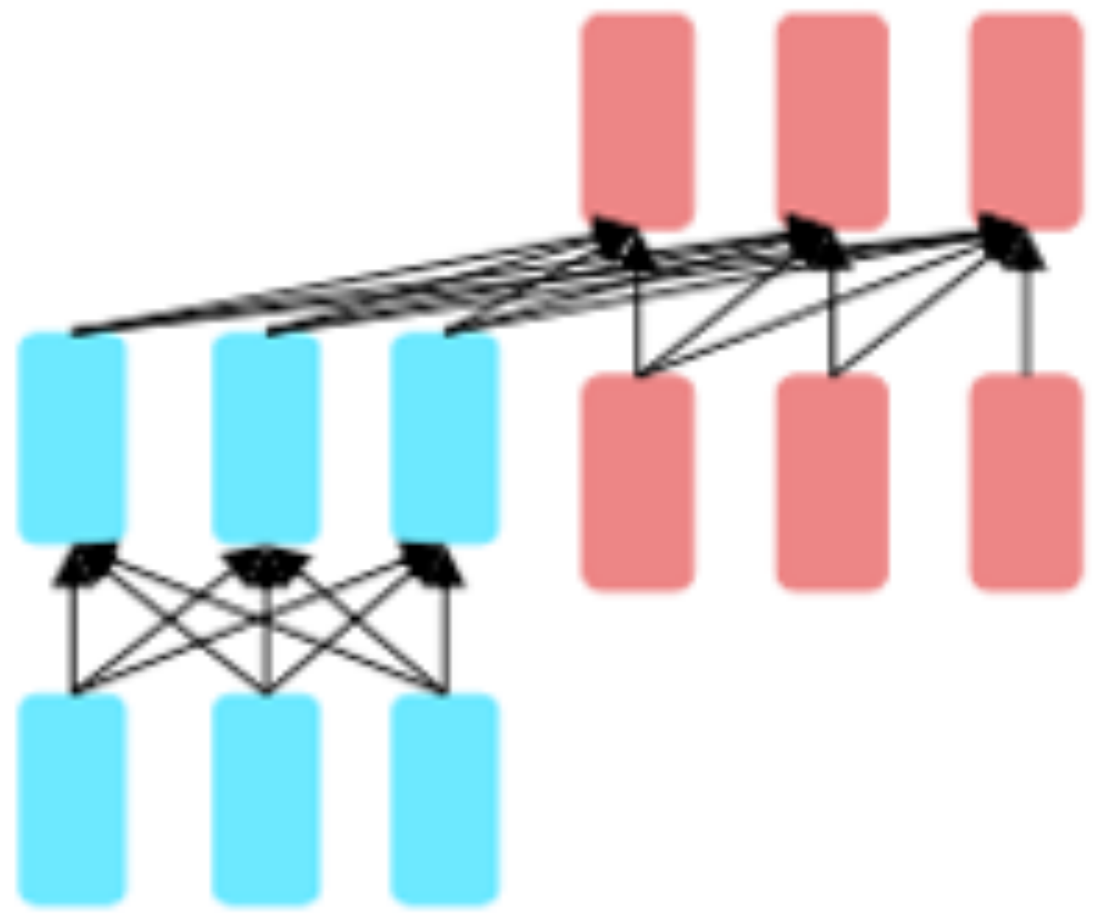
- Masked language models
- Bidirectional context
- BERT + variants (e.g. RoBERTa)

Decoder only



- Language models
- Can't condition on future words, good for generation
- GPT-2, GPT-3, LaMDA

Encoder-Decoder



- Combine benefits of both
- Original Transformer, UniLM, BART, T5, Meena

Slide adapted from: Stanford CS224n, John Hewitt