Applied Deep Learning

Transformer

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Sequence Encoding

Basic Attention

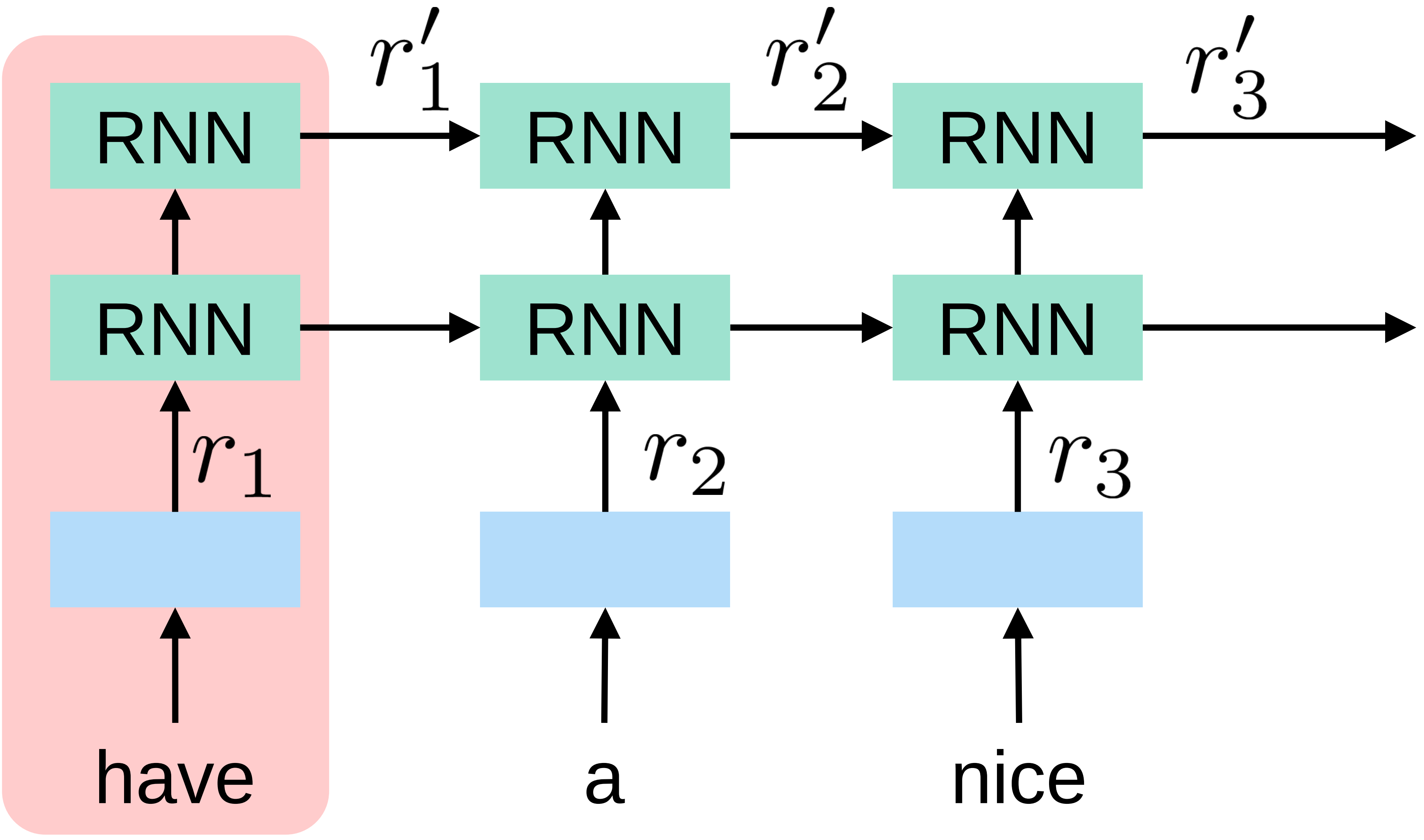
3 Representations of Variable Length Data

- Input: word sequence, image pixels, audio signal, click logs
- Property: continuity, temporal, importance distribution
- Example
  - ✓ Basic combination: average, sum
  - ✓ Neural combination: network architectures should consider input domain properties
    - – CNN (convolutional neural network)
    - – RNN (recurrent neural network): temporal information

Network architectures should consider the input domain properties

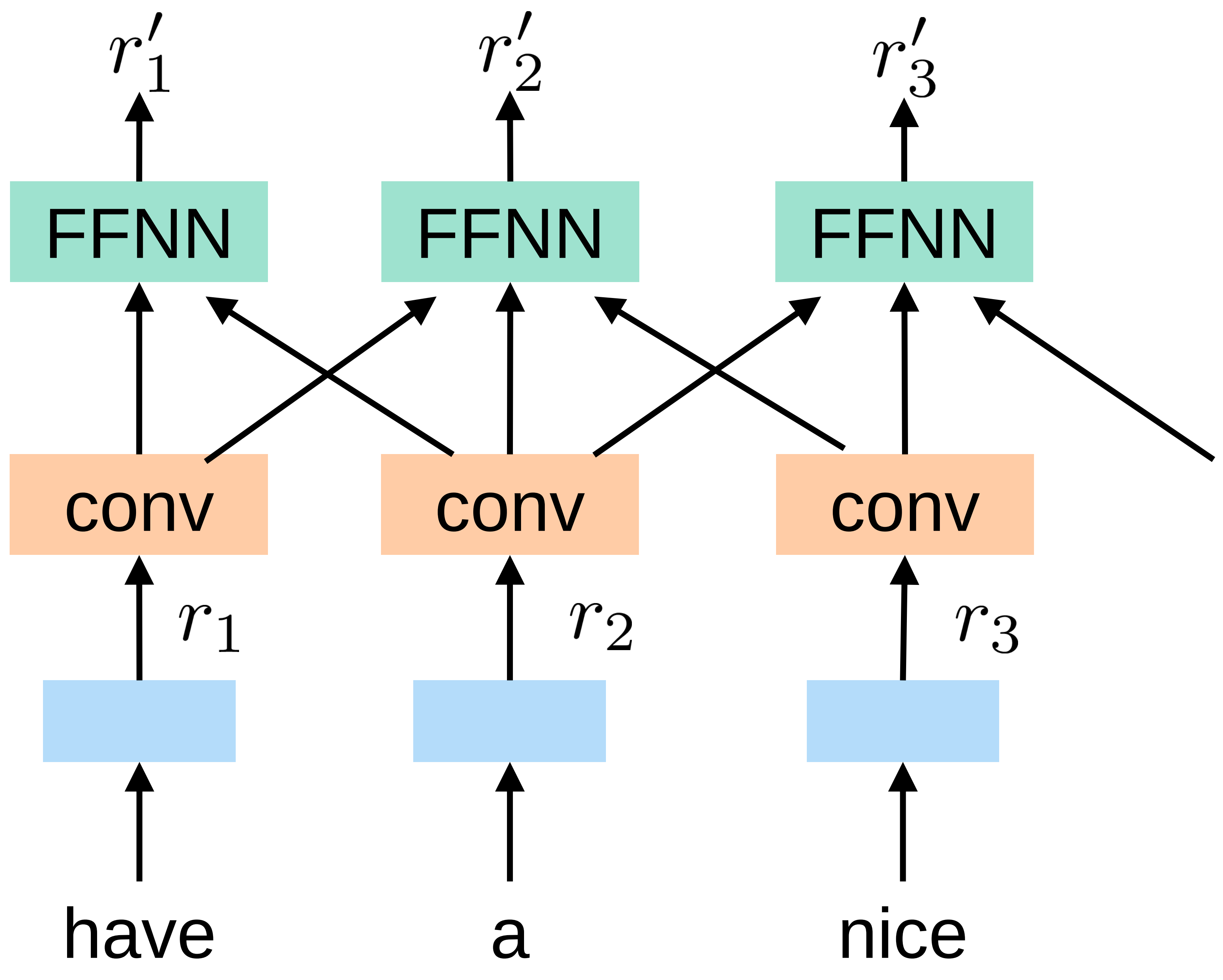
Recurrent Neural Networks

- Learning variable-length representations
  - ✓ Fit for sentences and sequences of values
- Sequential computation makes parallelization difficult
- No explicit modeling of long and short range dependencies



5 Convolutional Neural Networks

- Easy to parallelize
- Exploit local dependencies
  - ✓ **Long-distance** dependencies require many layers



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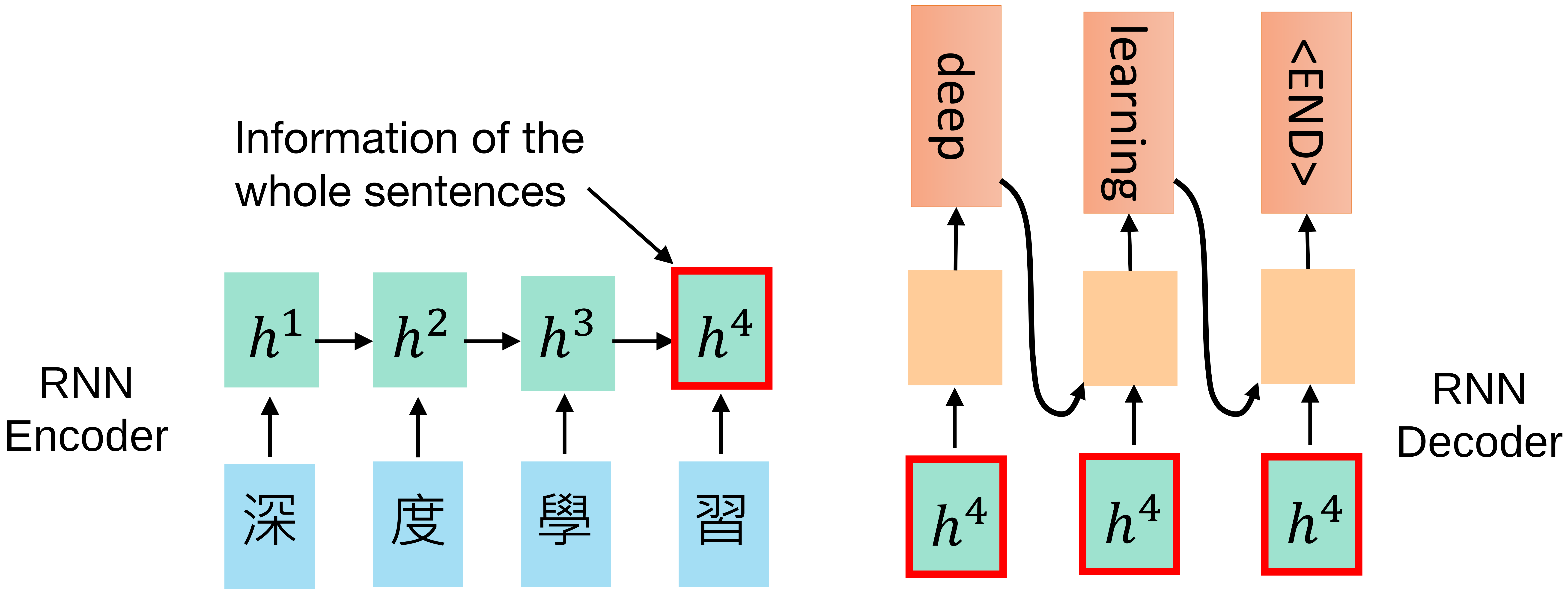
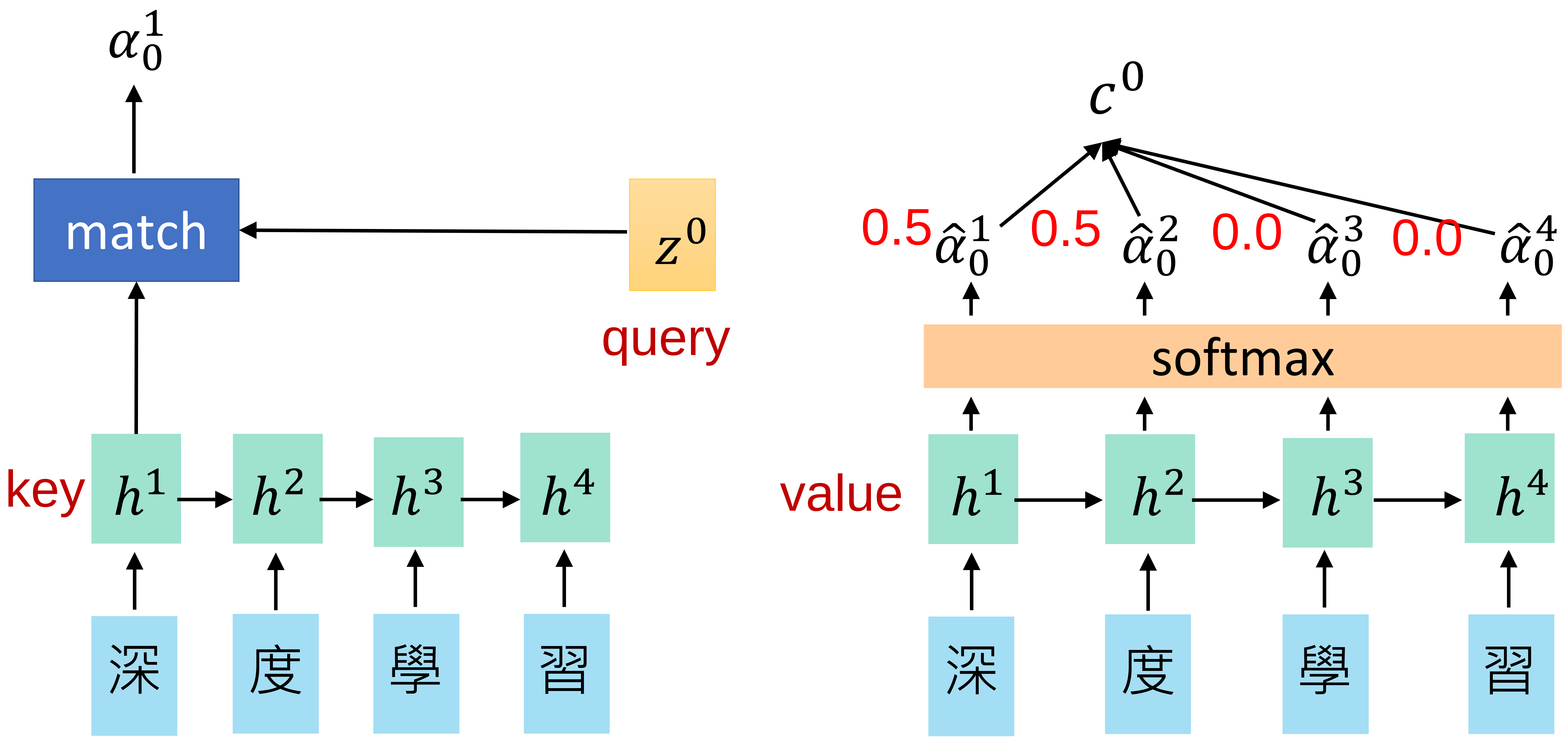
Attention

- Encoder-decoder model is important in NMT
- RNNs need **attention mechanism** to handle long dependencies
- Attention allows us to access any state



Machine Translation with Attention



Dot-Product Attention

- Input: a query q and a set of key-value (k-v) pairs to an output
- Output: weighted sum of values

Inner product of
query and corresponding key

$$A(q, K, V) = \sum_i \boxed{\frac{\exp(q \cdot k_i)}{\sum_j \exp(q \cdot k_j)}} v_i$$

- ✓ Query q is a d_k-dim vector
- ✓ Key k is a d_k-dim vector
- ✓ Value v is a d_v-dim vector

Dot-Product Attention in Matrix

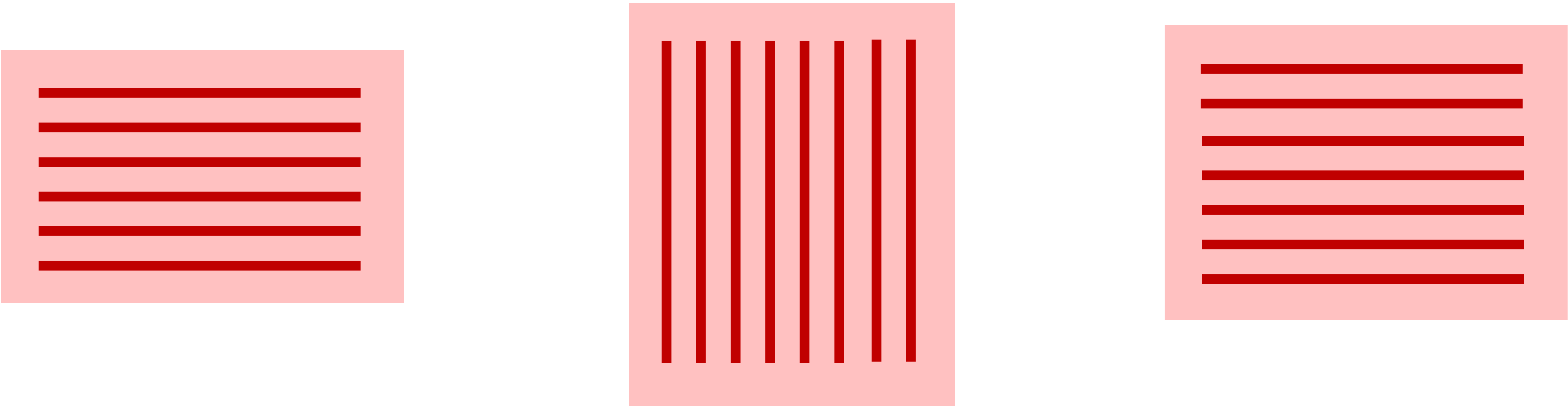
- Input: *multiple* queries q and a set of key-value (k-v) pairs to an output
- Output: a set of weighted sum of values

$$A(q, K, V) = \sum_i \frac{\exp(q \cdot k_i)}{\sum_j \exp(q \cdot k_j)} v_i$$

$$A(Q, K, V) = \mathrm{softmax}(QK^T)V$$

$$[|Q| \times d_k] \times [d_k \times |K|] \times [|K| \times d_v]$$

softmax
row-wise



$$= [|Q| \times d_v]$$

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Sequence Encoding

Self-Attention

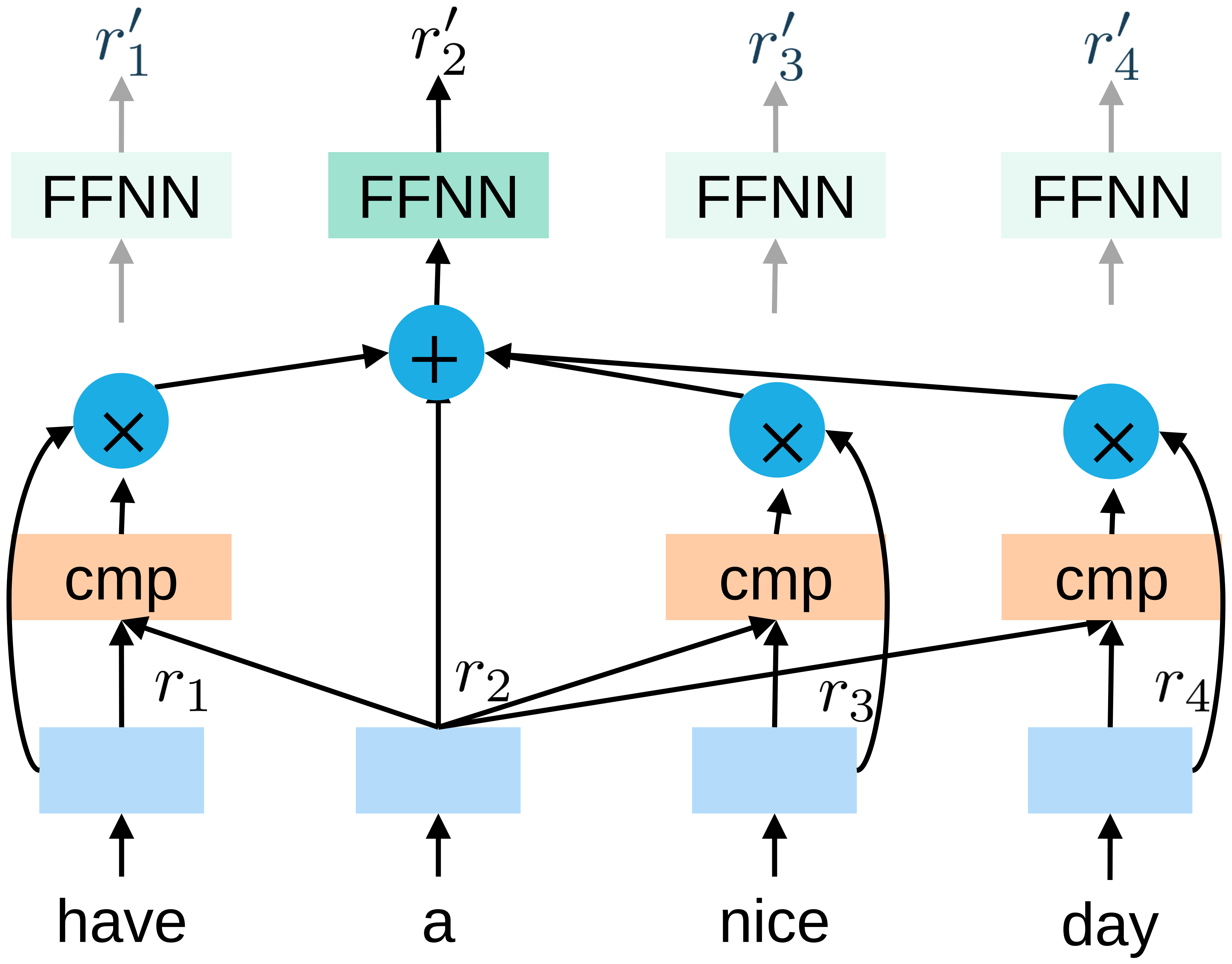
Attention

- Encoder-decoder model is important in NMT
- RNNs need **attention mechanism** to handle long dependencies
- Attention allows us to access any state

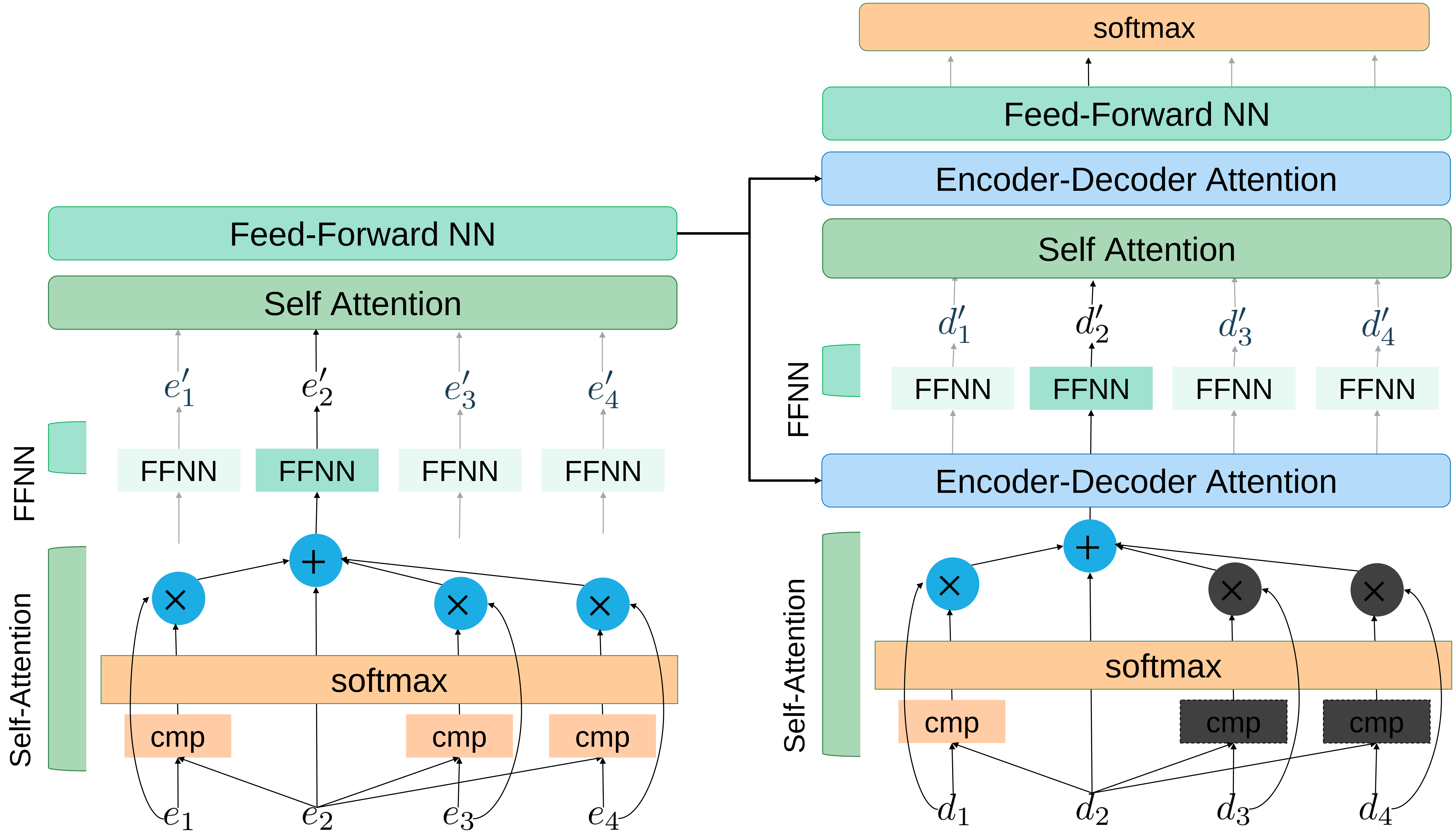
Using attention to replace recurrence architectures

Self-Attention

- Constant “path length” between two positions
- Easy to parallelize

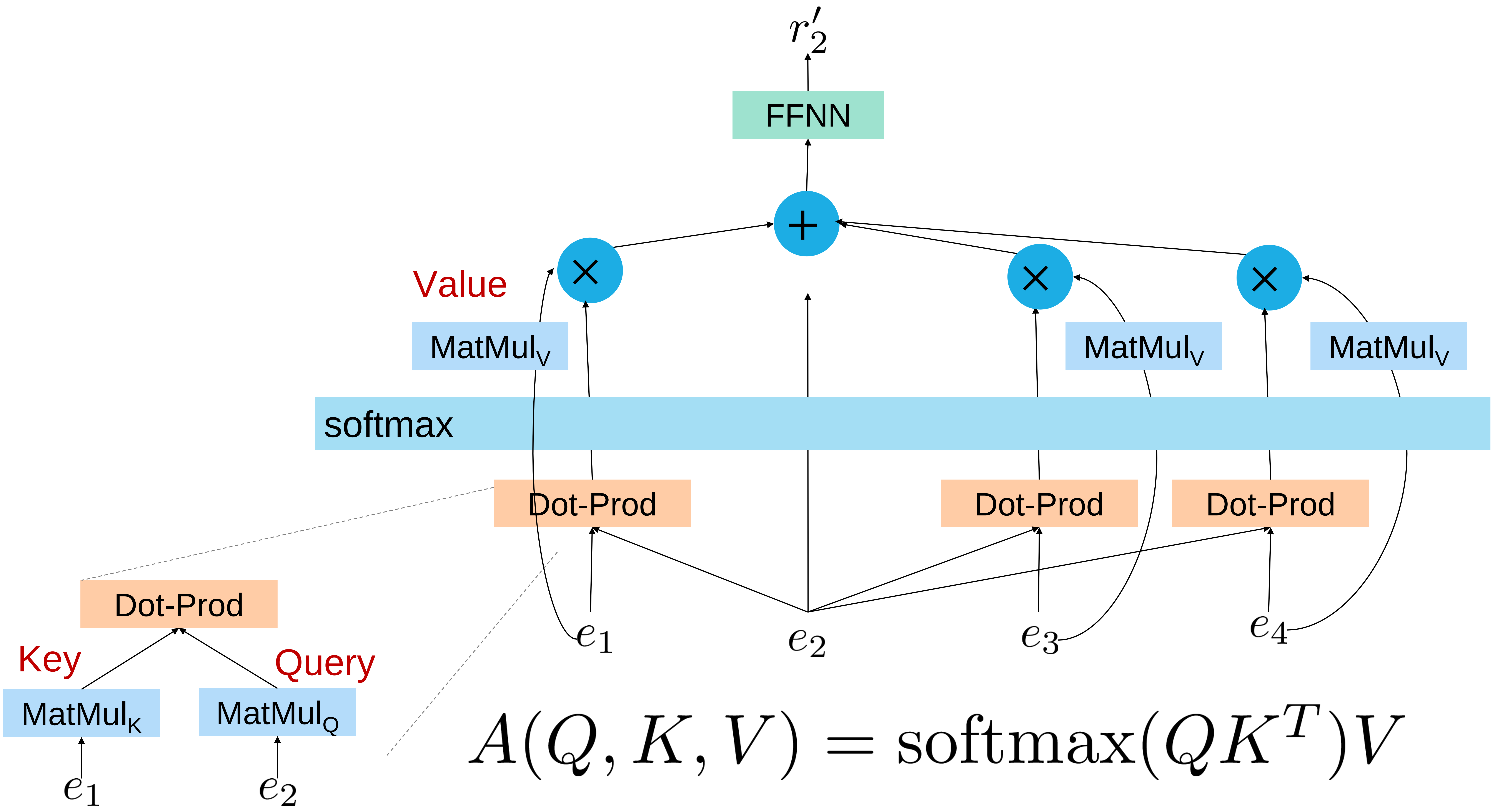


Transformer Idea



Vaswani et al., “Attention Is All You Need”, in *NIPS*, 2017.

Encoder Self-Attention (Vaswani+, 2017)



$$A(Q, K, V) = \mathrm{softmax}(QK^T)V$$

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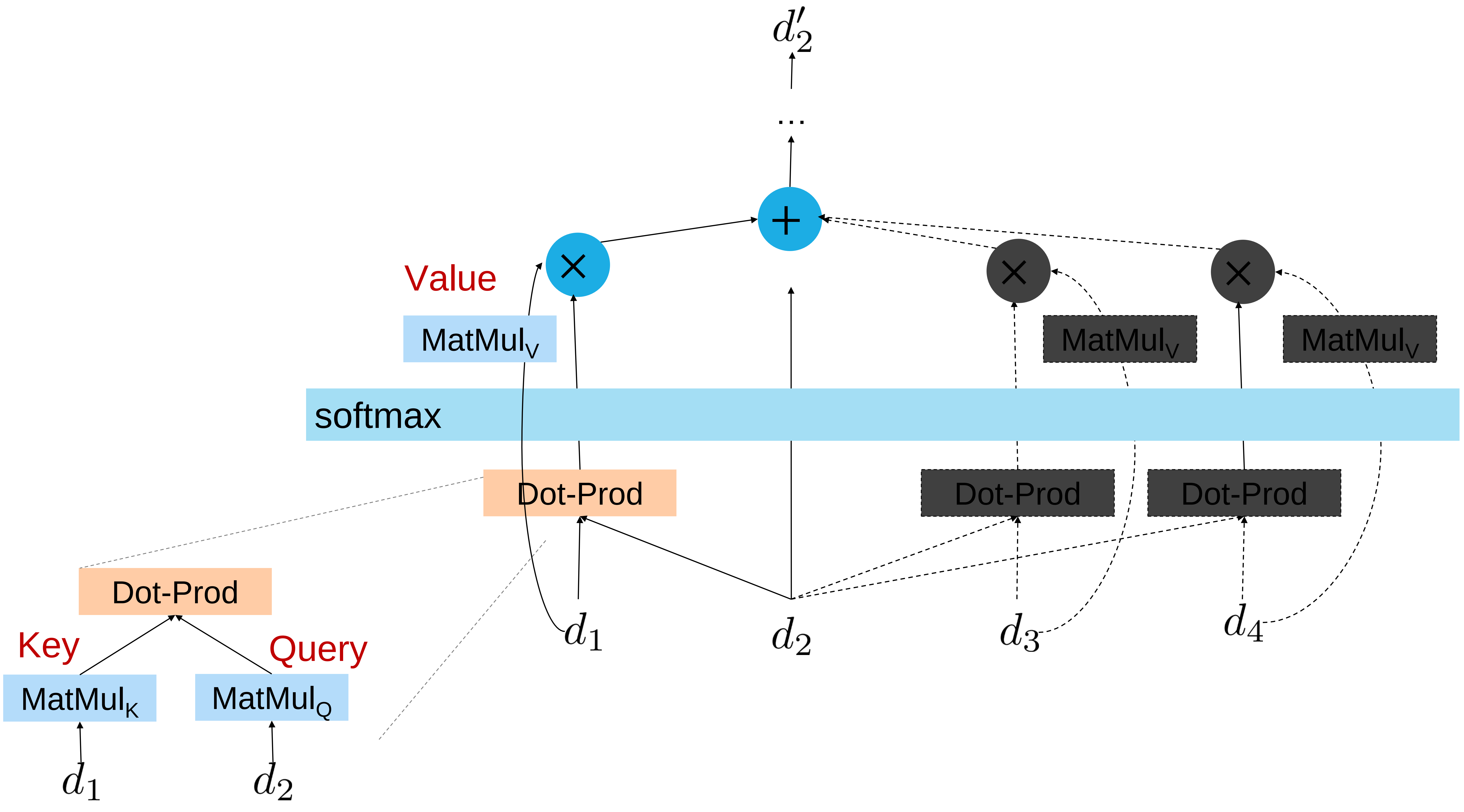
Decoder Self-Attention (Vaswani+, 2017)



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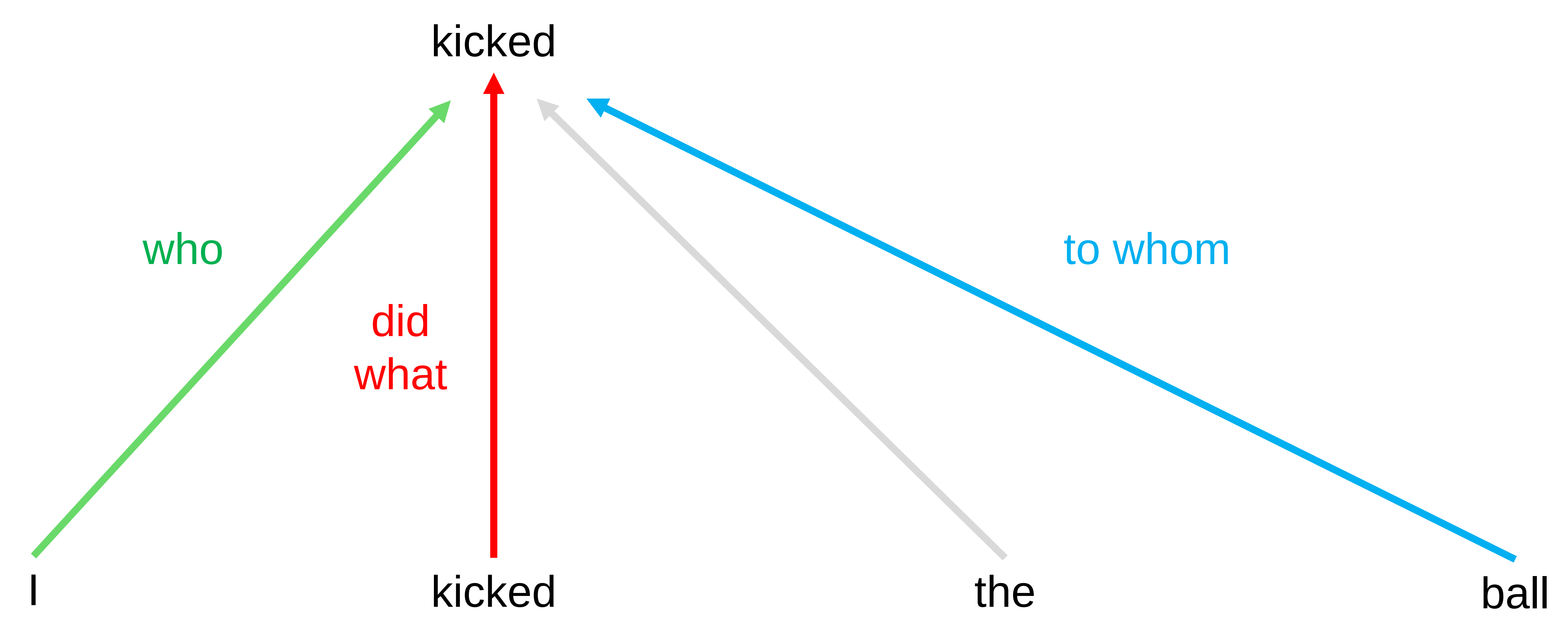
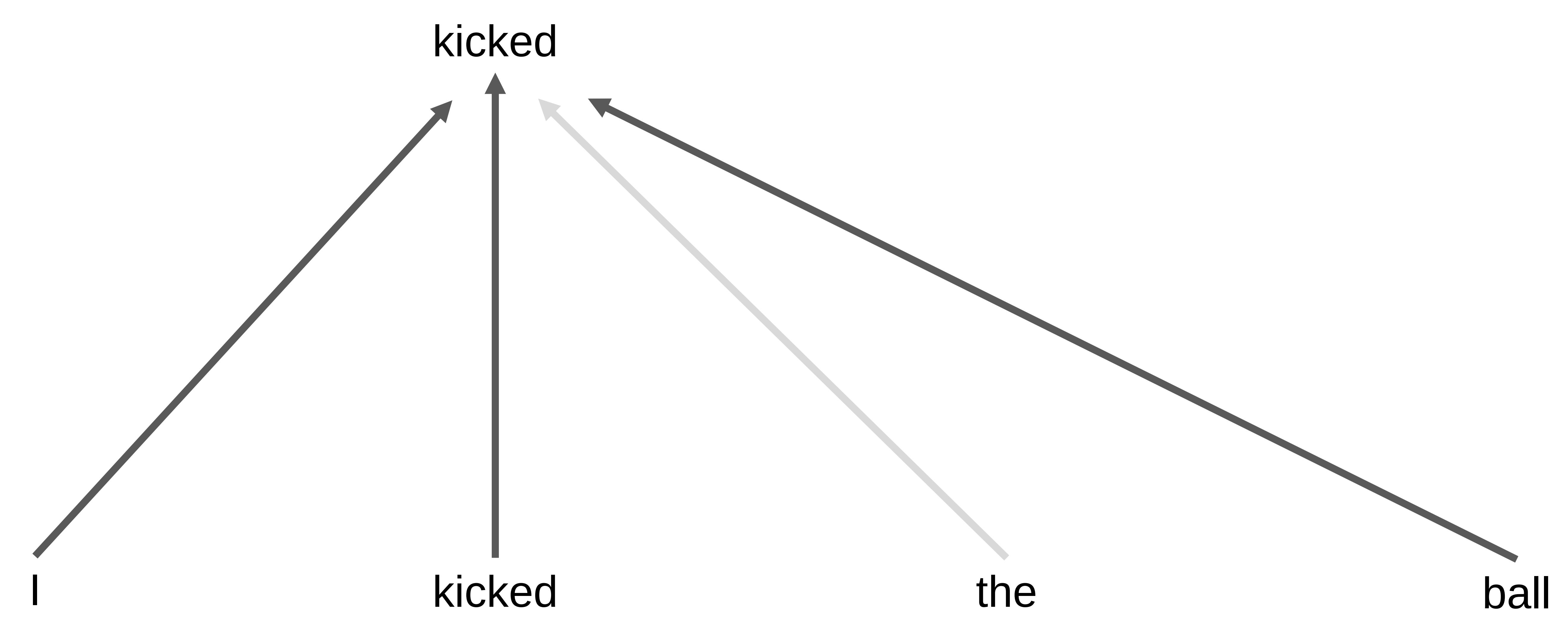
Sequence Encoding

Multi-Head Attention

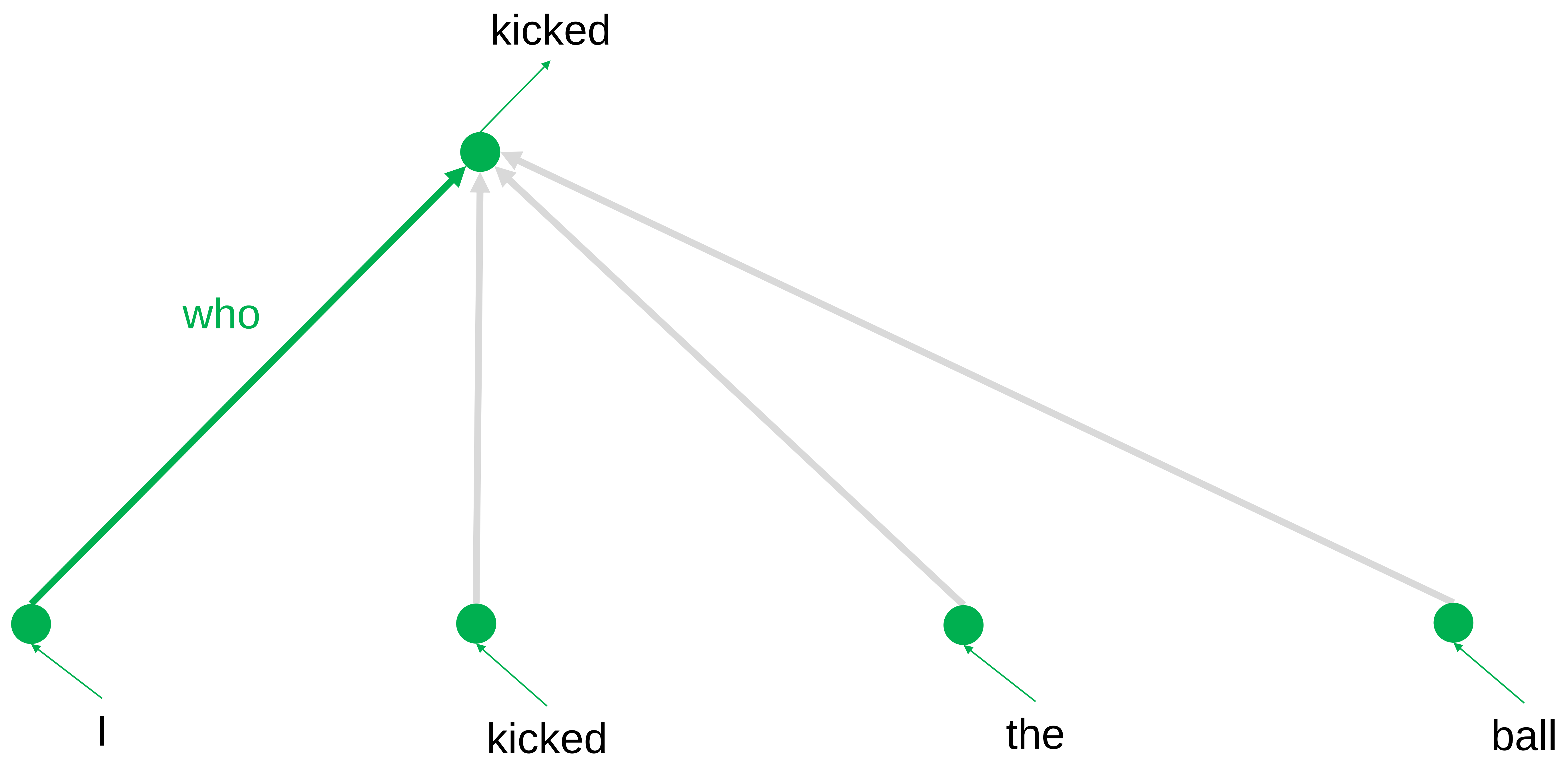
Convolutions



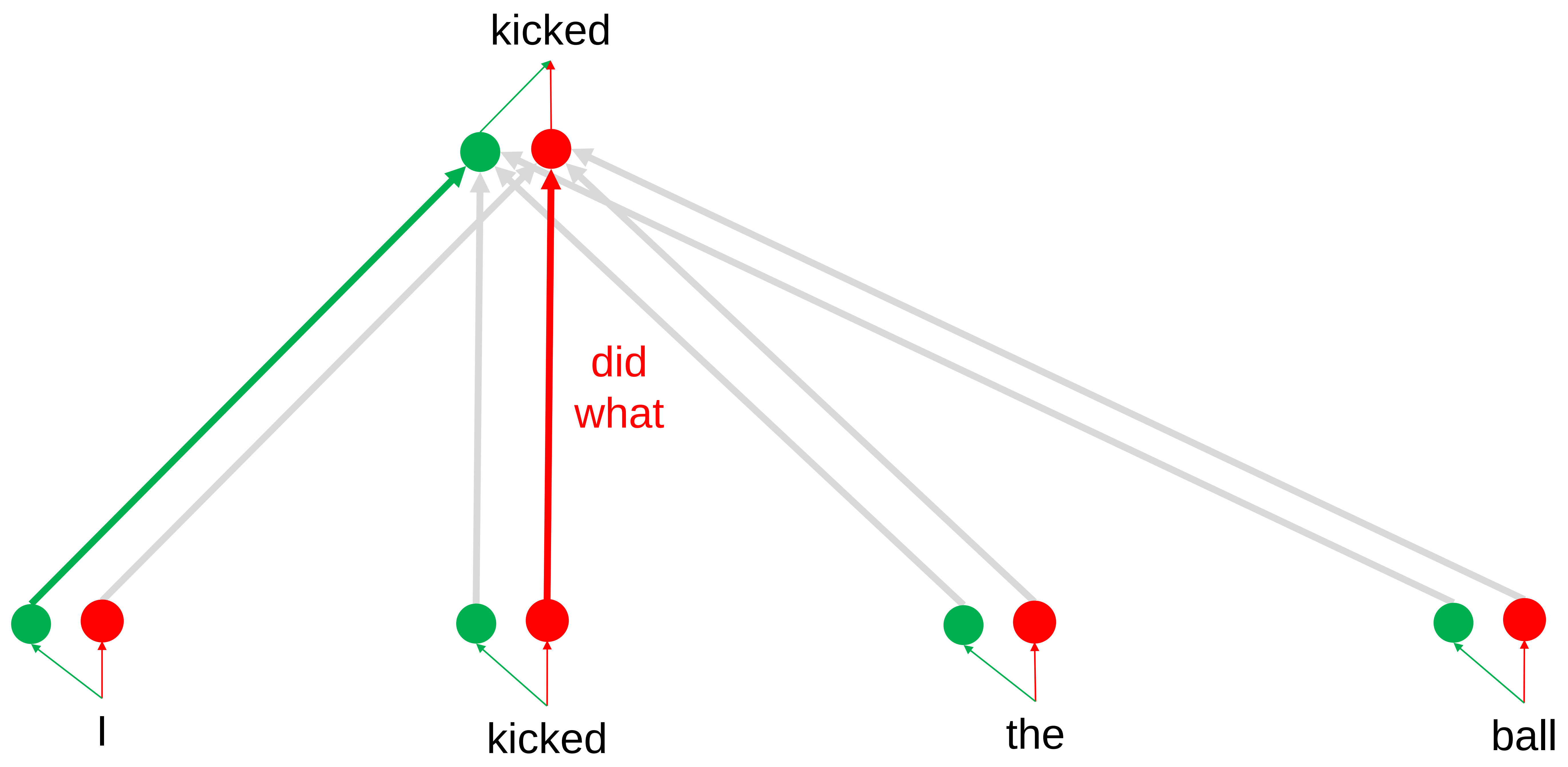
Self-Attention



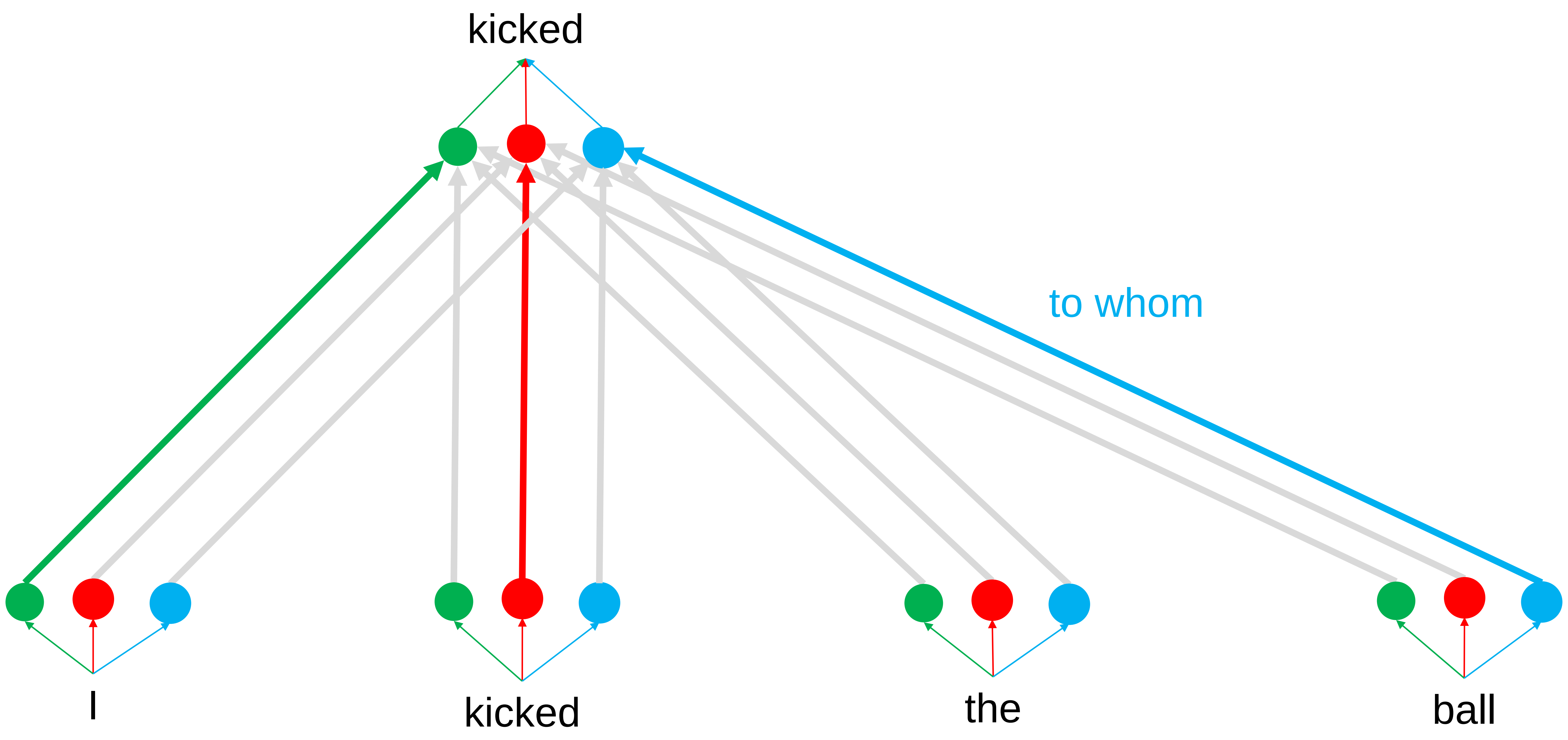
Attention Head: who



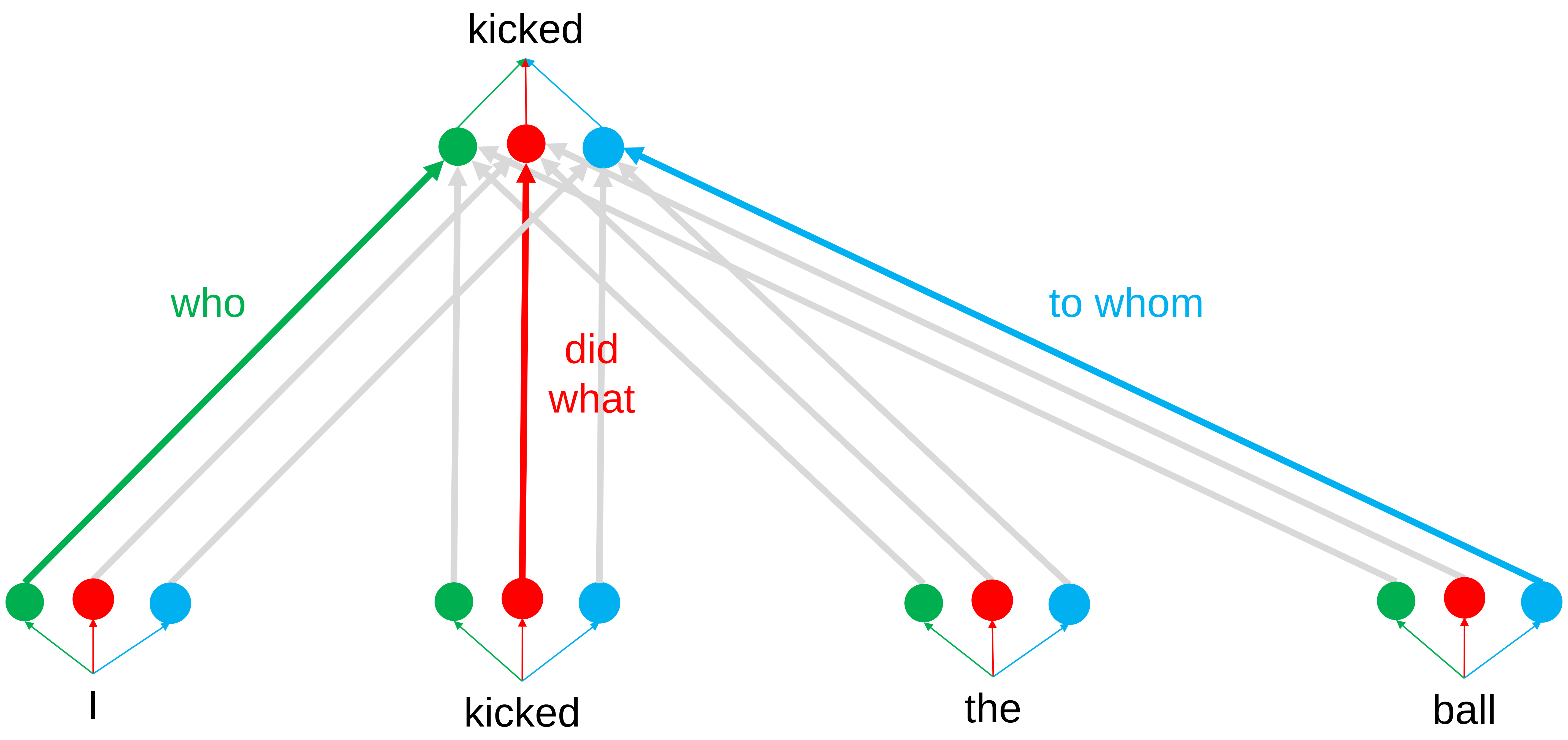
Attention Head: did what



Attention Head: to whom

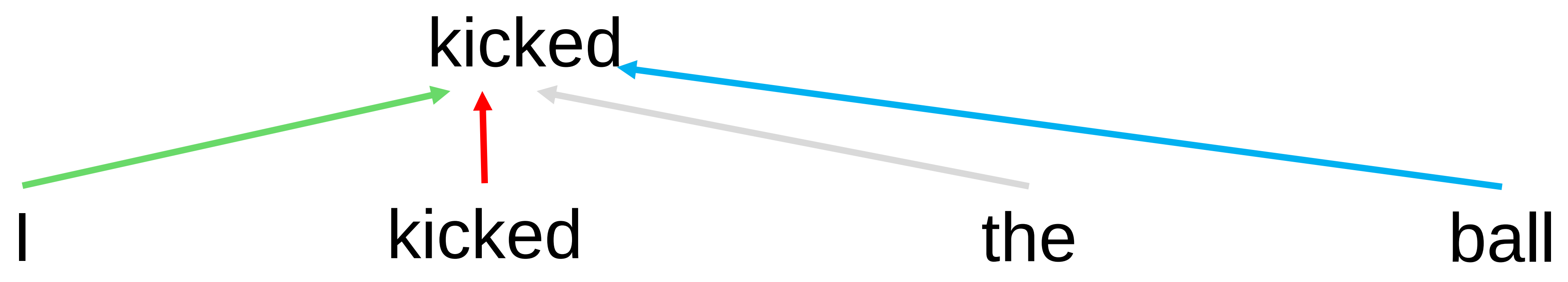


Multi-Head Attention



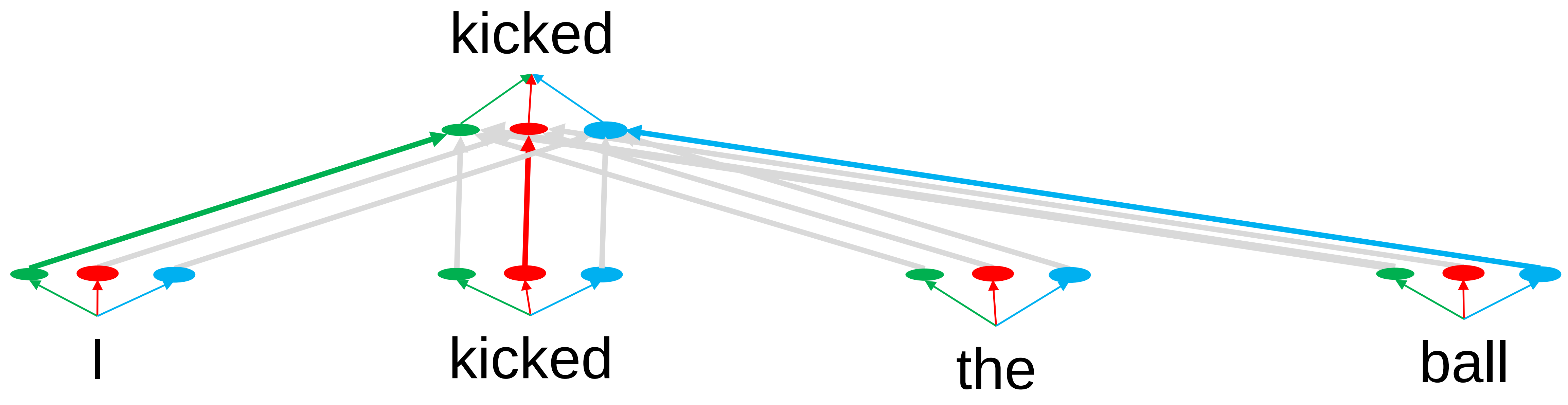
Comparison

- Convolution: different linear transformations by relative positions



- Attention: a weighted average

- Multi-Head Attention: parallel attention layers with different linear transformations on input/output



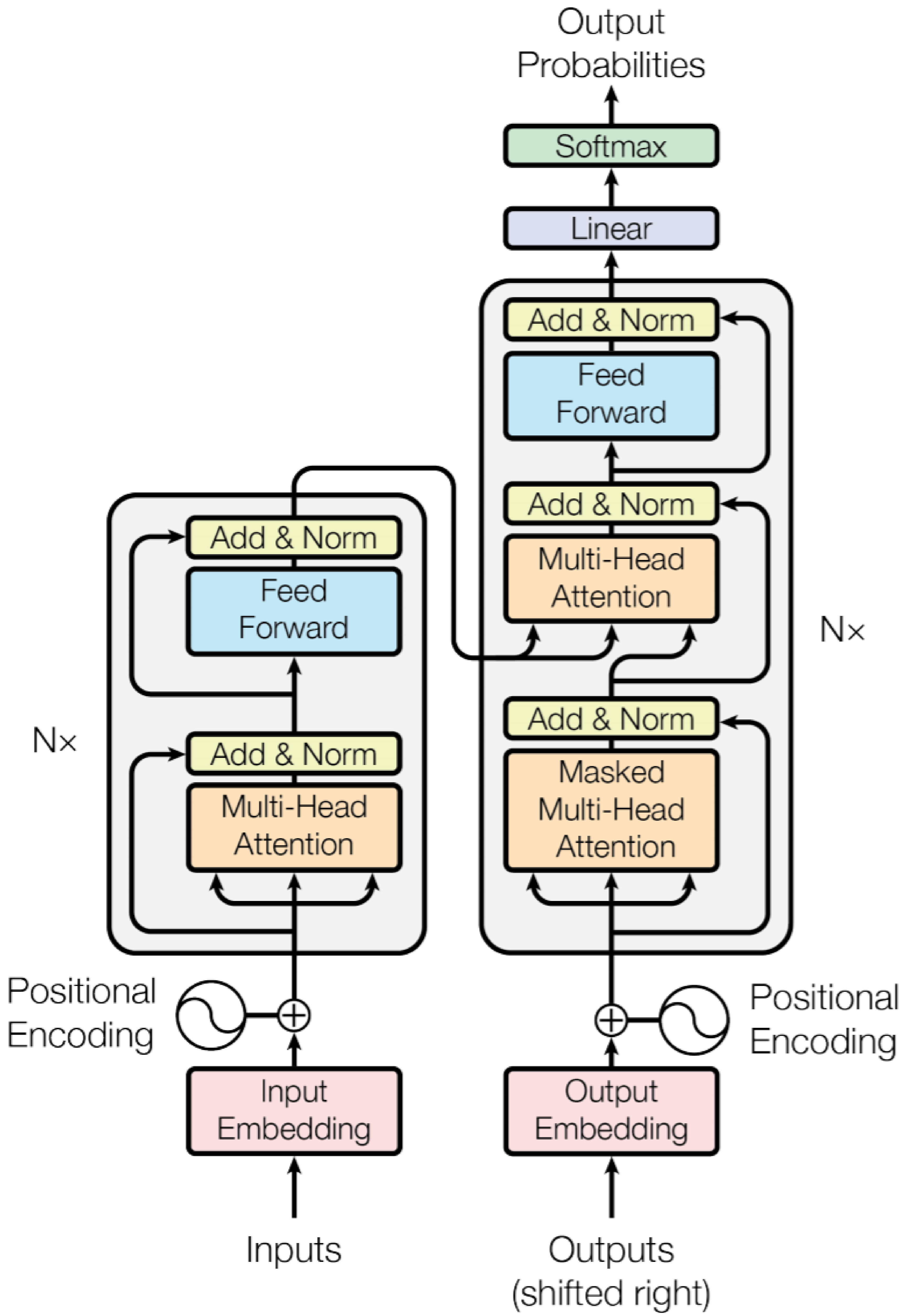
Sequence Encoding

Transformer

Transformer Overview

- Non-recurrent encoder-decoder for MT
- PyTorch explanation by Sasha Rush

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



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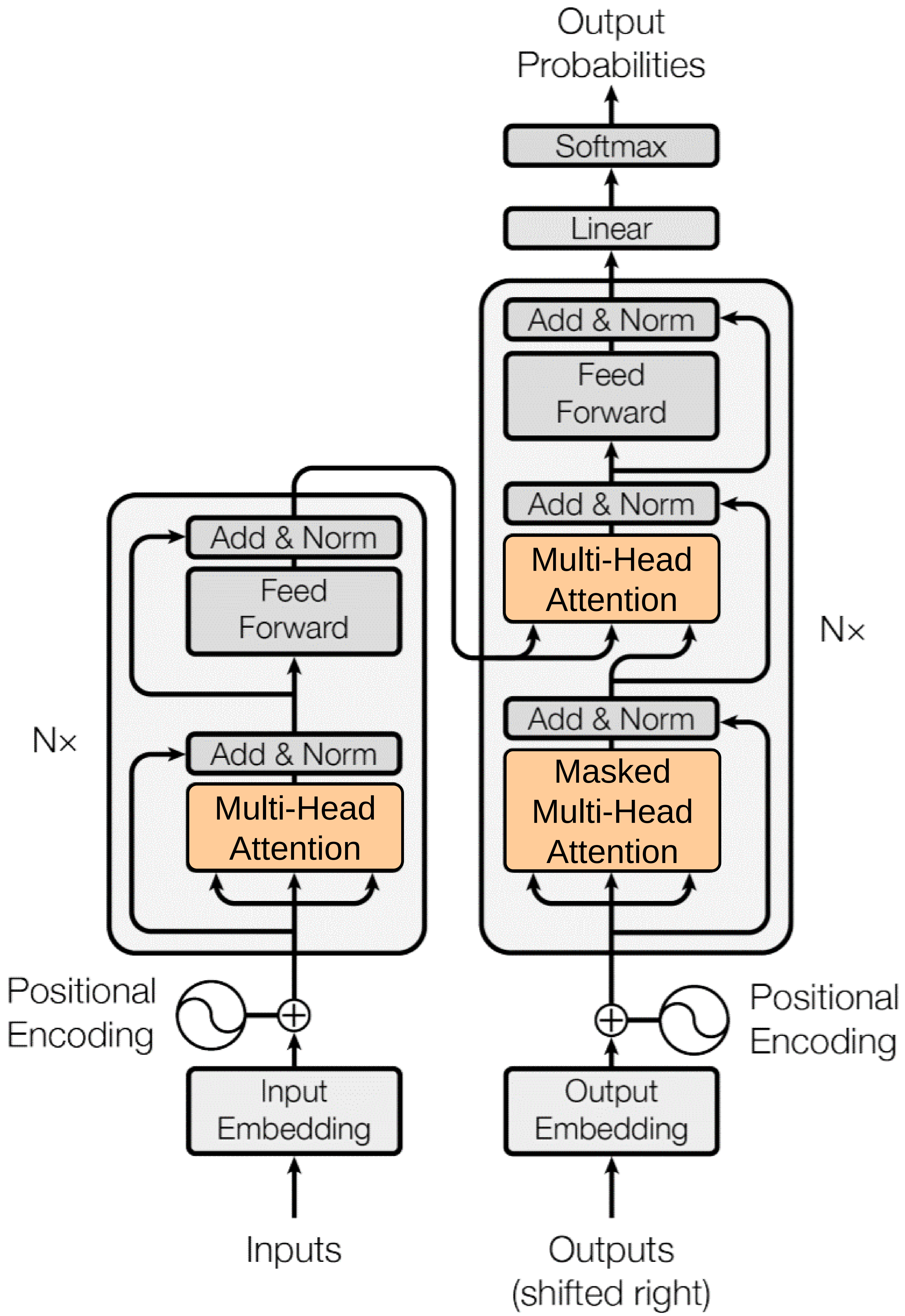

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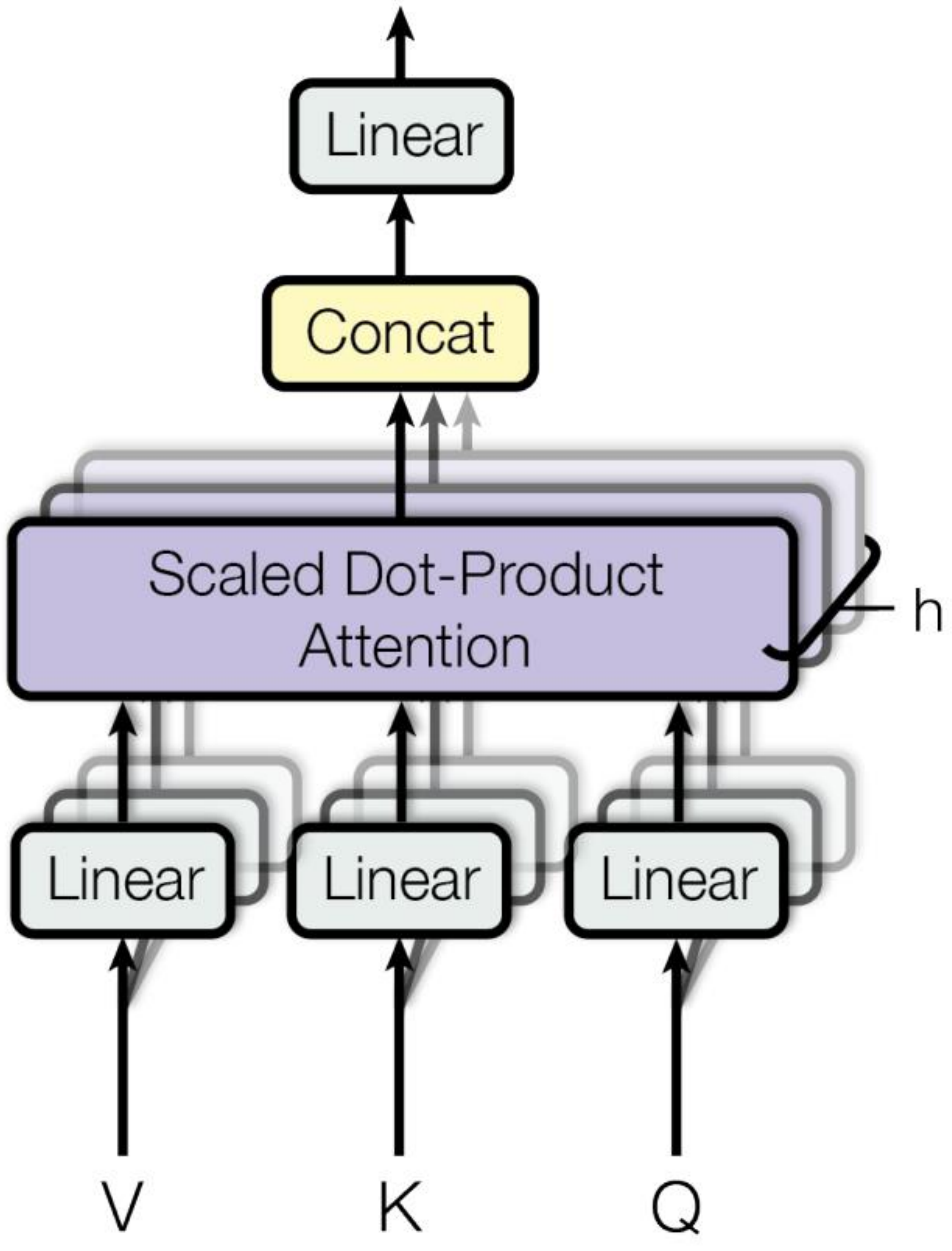
Multi-Head Attention

- Idea: allow words to interact with one another
- Model
  - Map V, K, Q to lower dimensional spaces
  - Apply attention, concatenate outputs
  - Linear transformation

$$\begin{aligned}\mathrm{MultiHead}(Q,K,V)\\&=\mathrm{Concat}(\mathrm{head}_1,\cdots,\mathrm{head}_h)W^O\end{aligned}$$

$$\mathrm{head}_i=\mathrm{Attention}(QW_i^Q,KW_i^K,VW_i^V)$$



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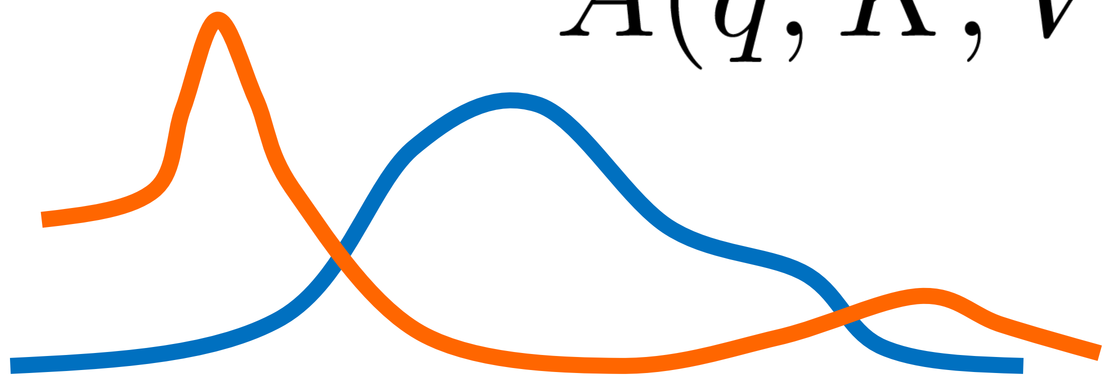
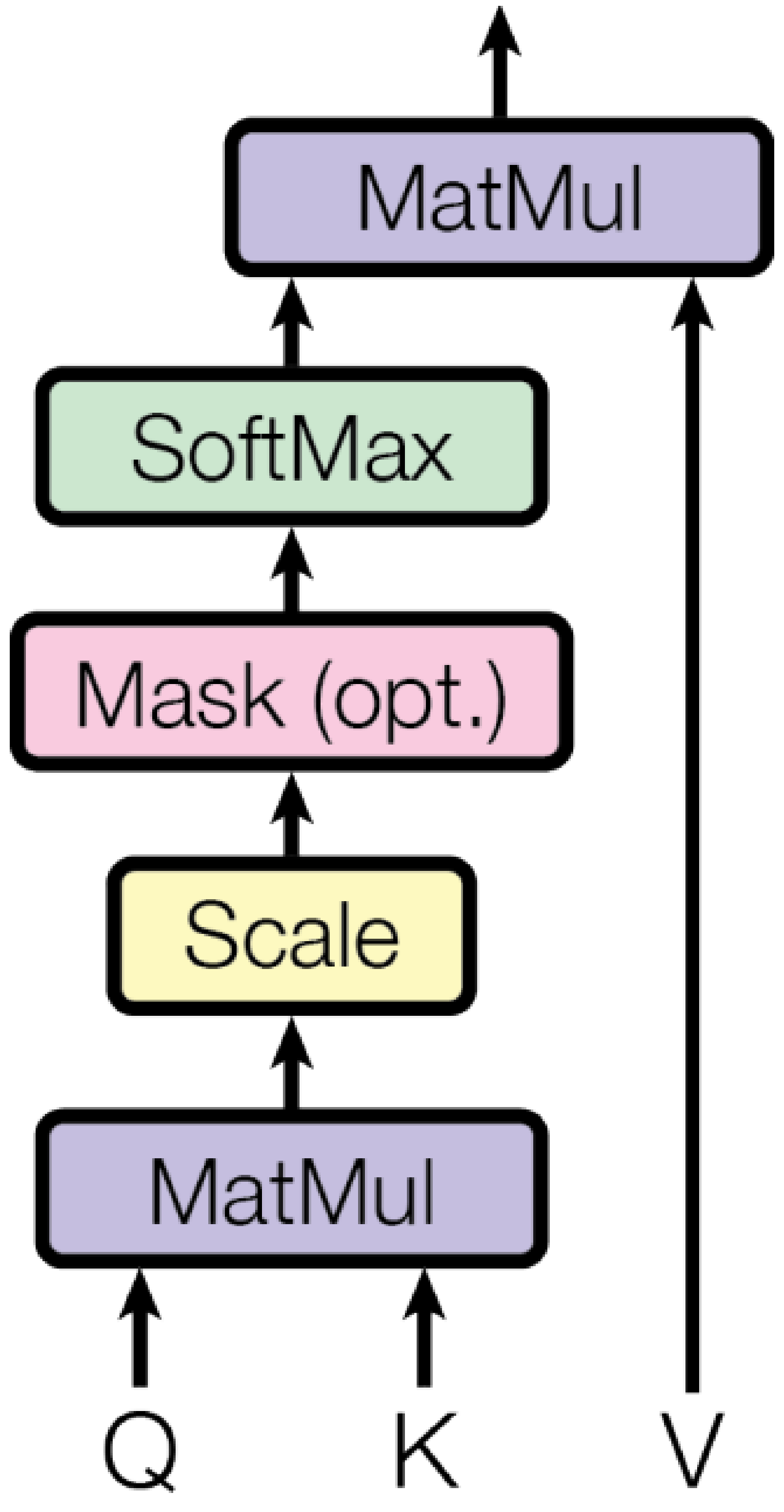
Scaled Dot-Product Attention

- Problem: when d_k gets large, the variance of $q^T k$ increases
  → some values inside softmax get large
  → the softmax gets very peaked
  → hence its gradient gets smaller
- Solution: scale by length of query/key vectors

$$A(q, K, V) = \sum_i \frac{\exp(q \cdot k_i)}{\sum_j \exp(q \cdot k_j)} v_i$$



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



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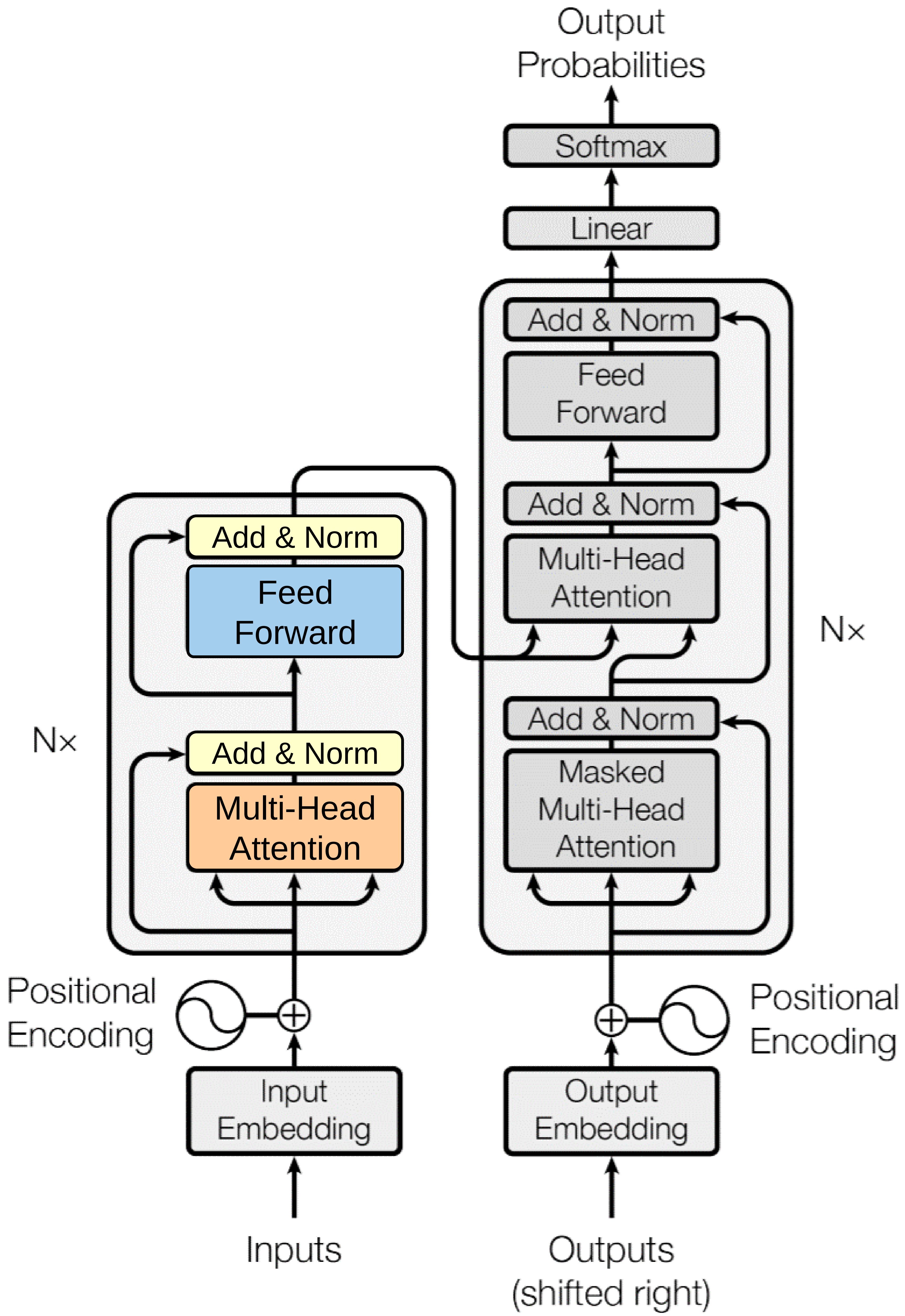

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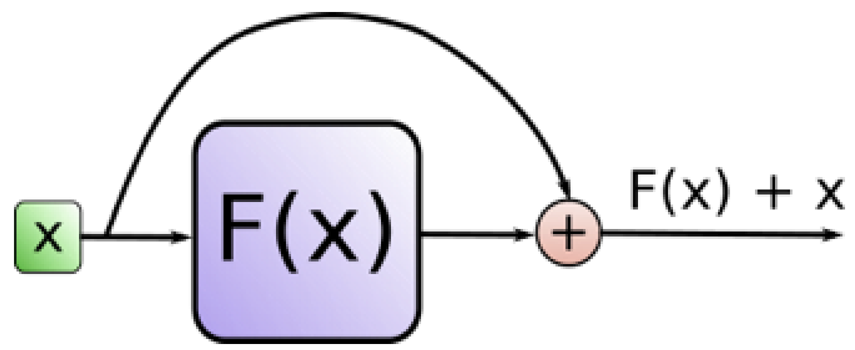
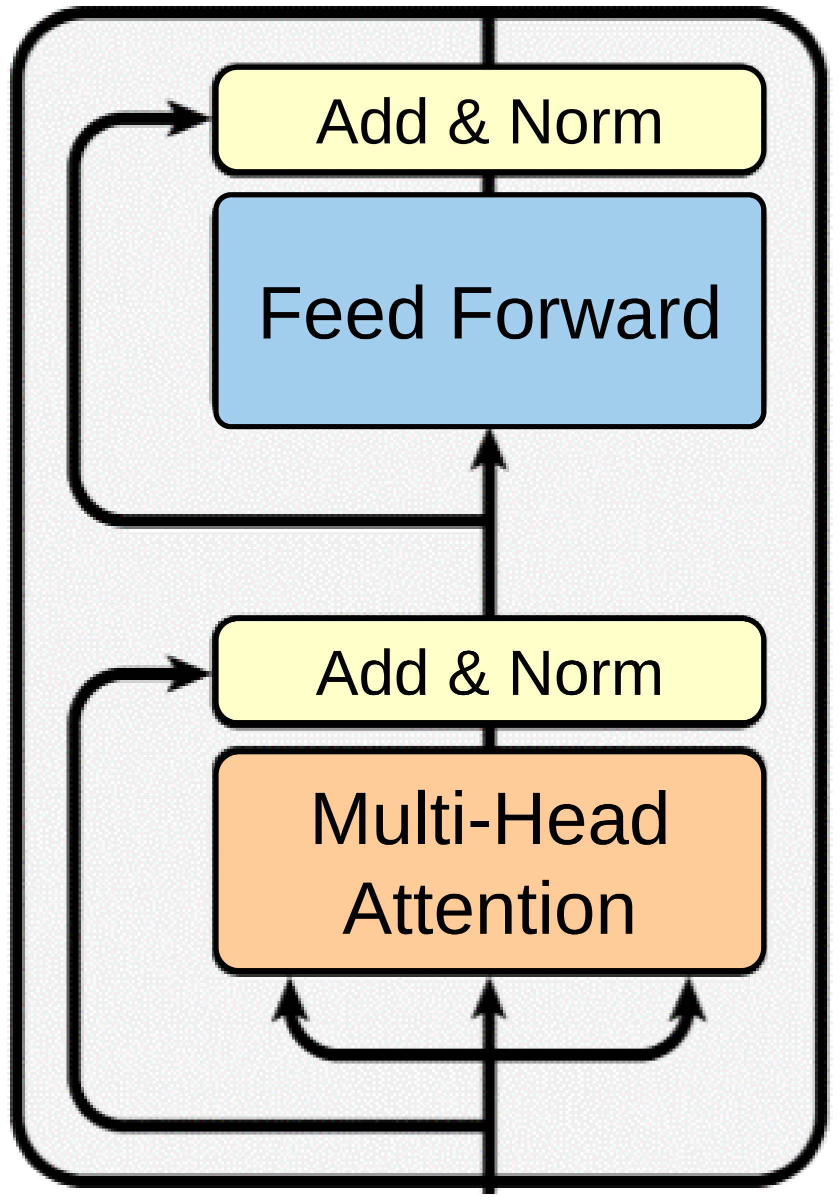
Transformer Encoder Block

- Each block has
  - multi-head attention
  - 2-layer feed-forward NN (w/ ReLU)
- Both parts contain
  - Residual connection
  - Layer normalization (LayerNorm)

$$H(x) = g(x) = x + F(x)$$

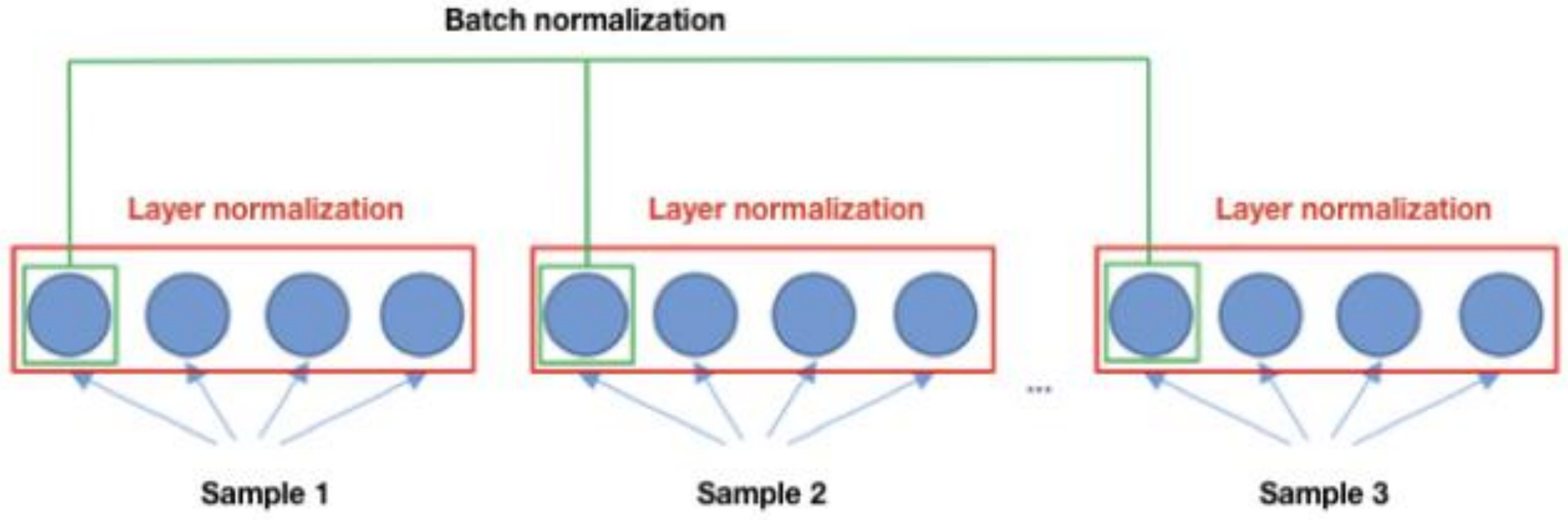




Change input to have 0 mean and 1 variance per layer & per training point

→ LayerNorm(x + sublayer(x))

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \quad \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i^l - \mu^l)^2} \quad h_i = f\left(\frac{g_i}{\sigma_i}(a_i - \mu_i) + b_i\right)$$



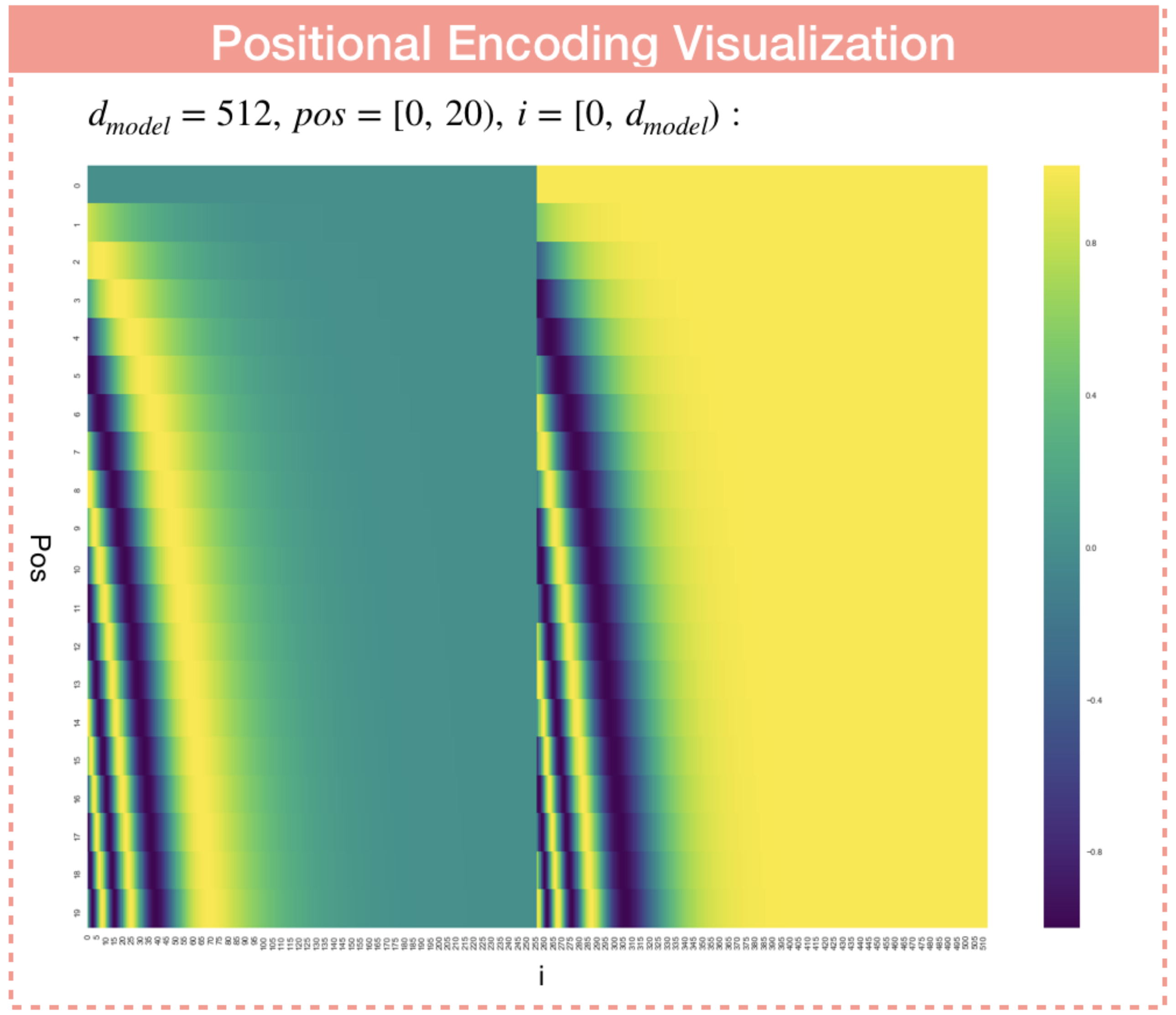
https://medium.com/@bgg/seq2seq-pay-attention-to-self-attention-part-2-中文版-ef2ddf8597a4

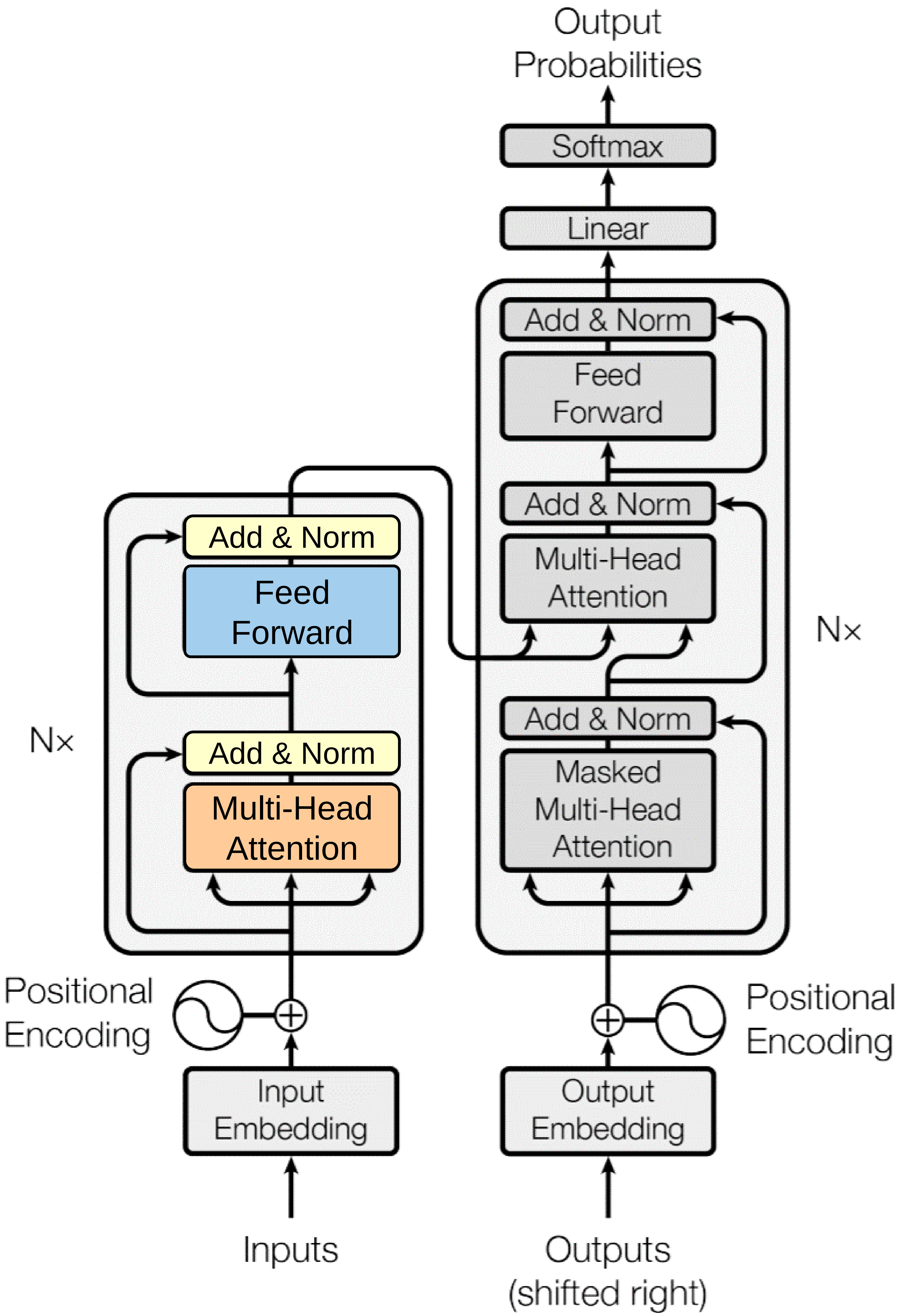
Encoder Input

- Problem: temporal information is missing
- Solution: **positional encoding** allows words at diffi different embeddings with fixed dimensions

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

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





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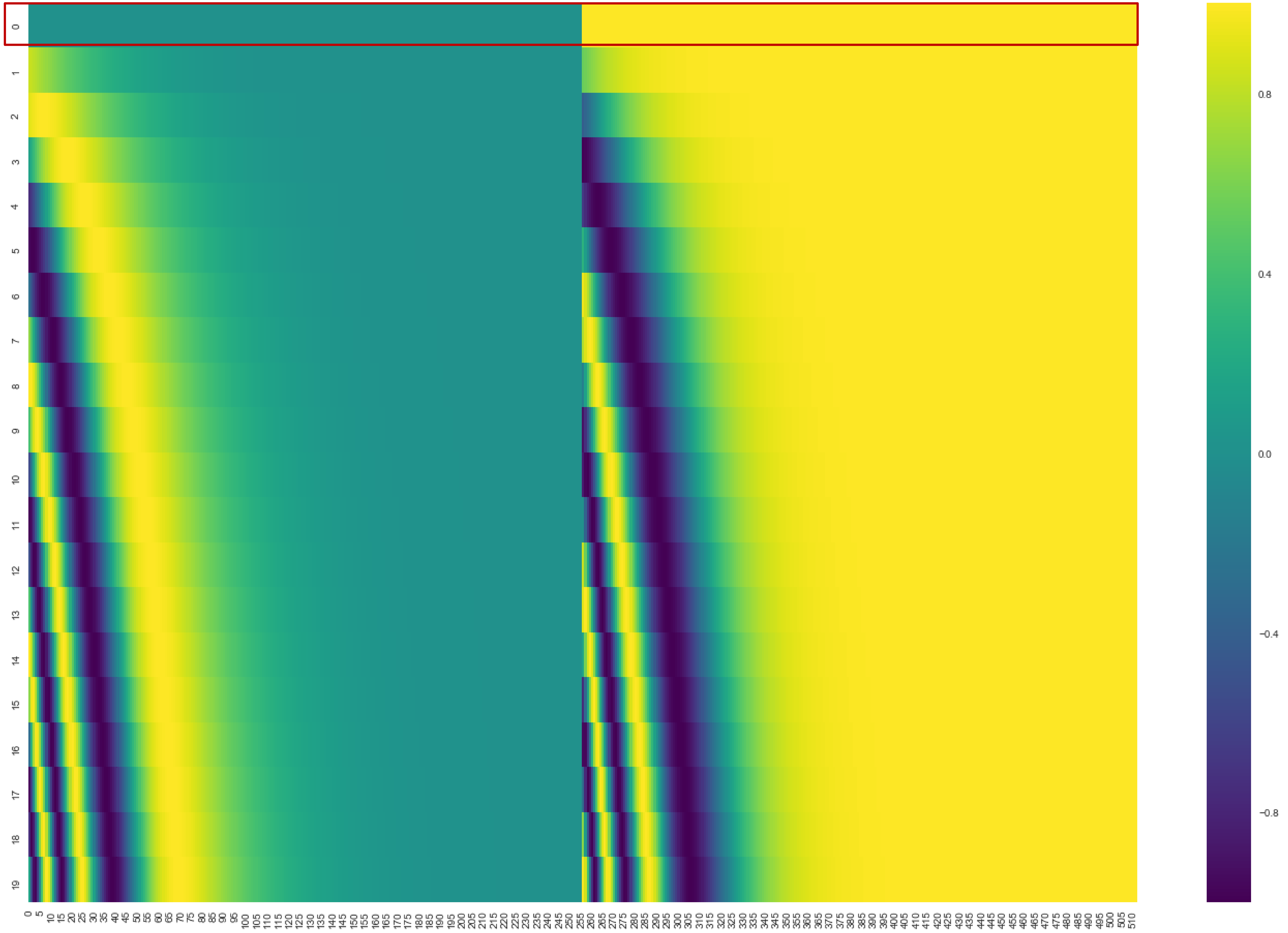

0.8
0.4
0.0
−0.4
−0.8

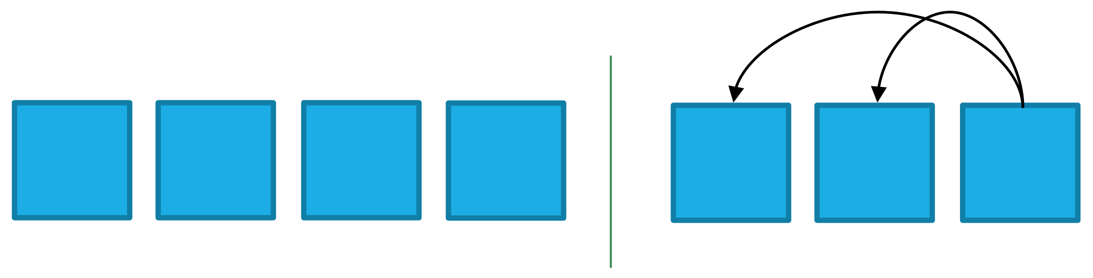
Multi-Head Attention Details

encoder self attention

1. **Multi-head Attention**
2. **Query=Key=Value**

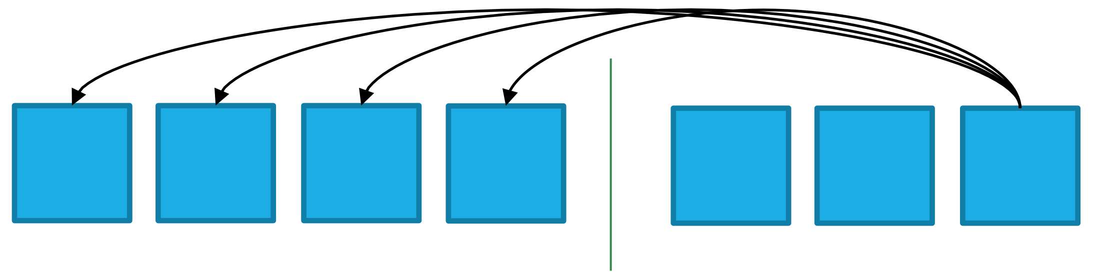
decoder self attention

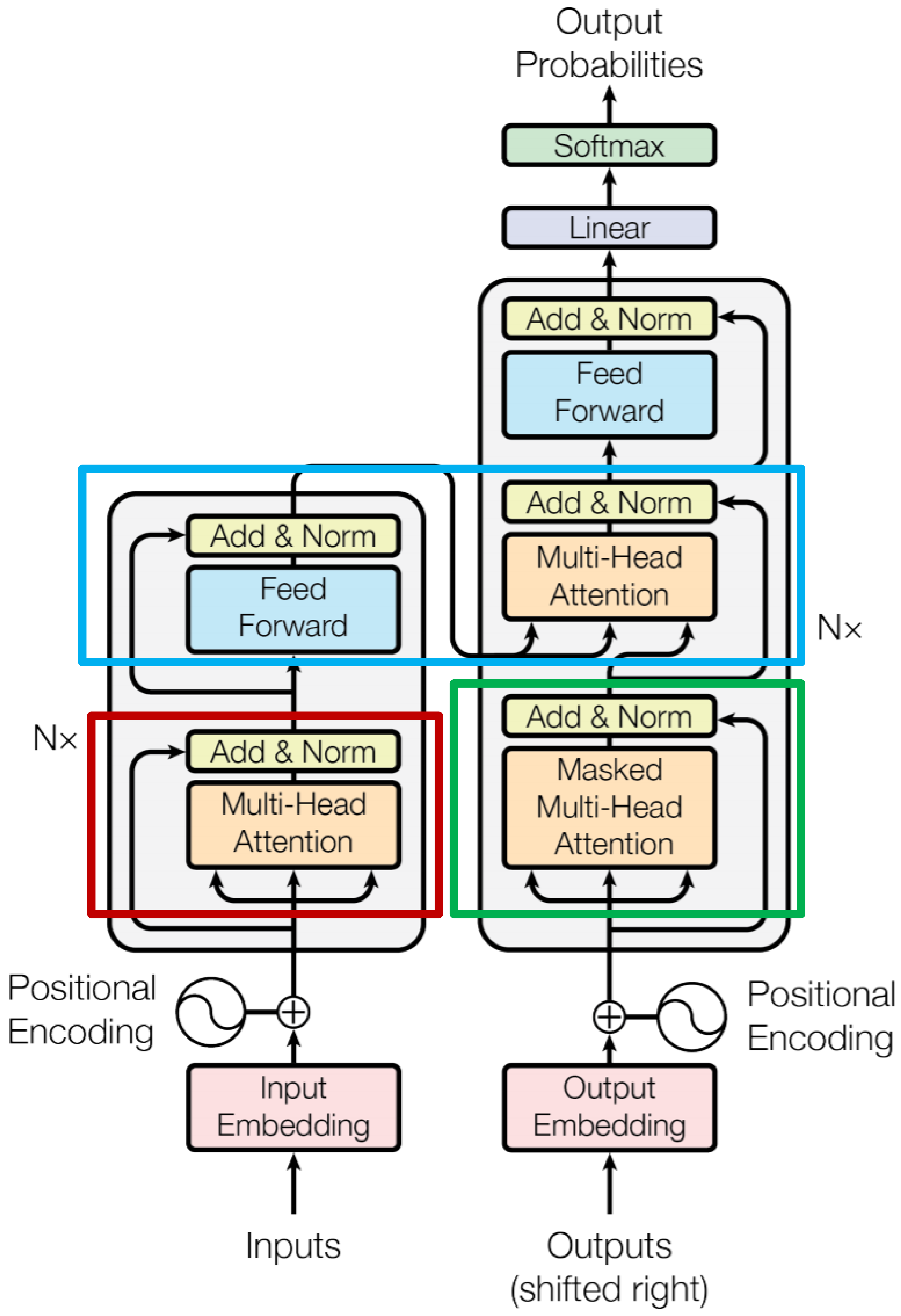
1. **Masked Multi-head Attention**
2. **Query=Key=Value**



encoder-decoder attention

1. **Multi-head Attention**
2. **Encoder Self attention=Key=Value**
3. **Decoder Self attention=Query**





Training Tips

- Byte-pair encodings (BPE)
- Checkpoint averaging
- ADAM optimizer with learning rate changes
- Dropout during training at every layer just before adding residual
- Label smoothing
- Auto-regressive decoding with beam search and length penalties

MT Experiments

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

Vaswani et al., "Attention Is All You Need", in *NIPS*, 2017.

Parsing Experiments

Parser	Training	WSJ 23 F1
Vinyals & Kaiser el al. (2014) [37]	WSJ only, discriminative	88.3
Petrov et al. (2006) [29]	WSJ only, discriminative	90.4
Zhu et al. (2013) [40]	WSJ only, discriminative	90.4
Dyer et al. (2016) [8]	WSJ only, discriminative	91.7
Transformer (4 layers)	WSJ only, discriminative	91.3
Zhu et al. (2013) [40]	semi-supervised	91.3
Huang & Harper (2009) [14]	semi-supervised	91.3
McClosky et al. (2006) [26]	semi-supervised	92.1
Vinyals & Kaiser el al. (2014) [37]	semi-supervised	92.1
Transformer (4 layers)	semi-supervised	92.7
Luong et al. (2015) [23]	multi-task	93.0
Dyer et al. (2016) [8]	generative	93.3

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Concluding Remarks

- **Non-recurrence** model is easy to parallelize
- **Multi-head attention** captures different aspects by interacting between words
- **Positional encoding** captures location information
- Each transformer block can be applied to diverse tasks