Attention

- a visual tour

Martin Stoffel

Transformer

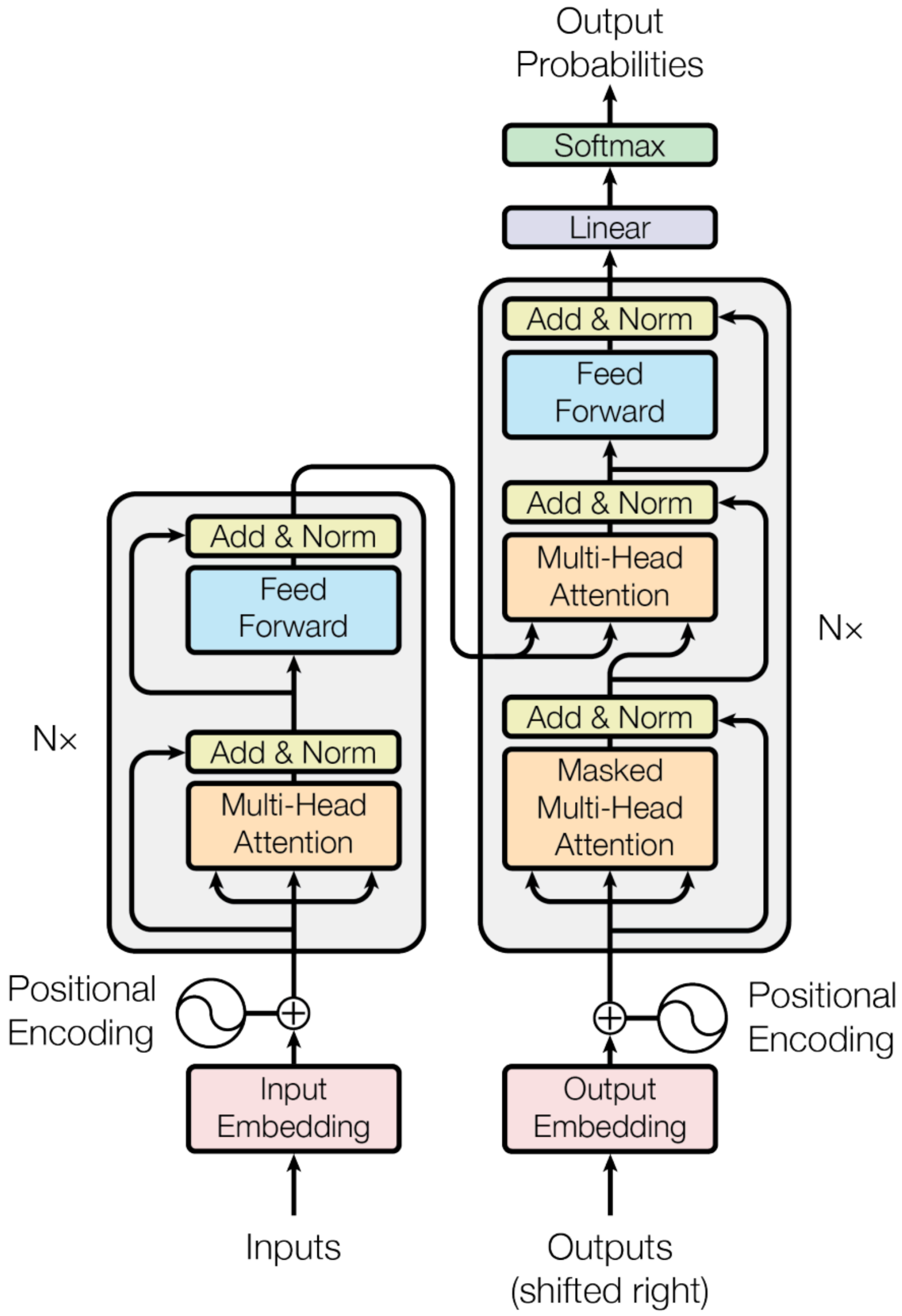
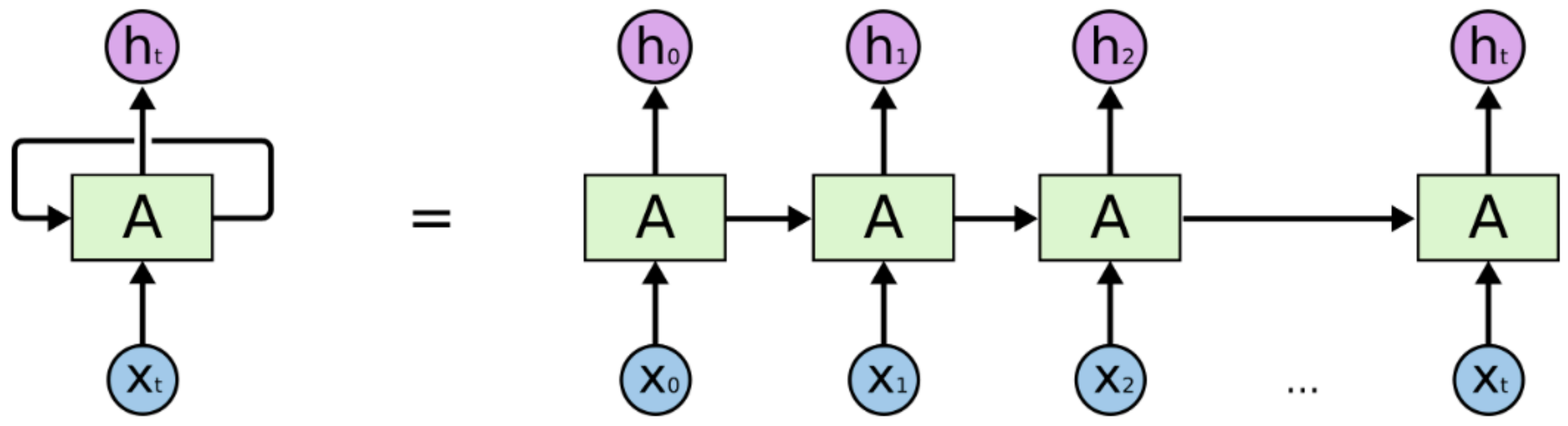


Figure 1: The Transformer - model architecture.

Vaswani et al. (2017) Attention is all you need

Why attention?



An unrolled recurrent neural network.

- Recurrence in RNNs and LSTMs has two fundamental weaknesses:
  - **Capturing long-range dependencies:** exploding/vanishing gradients
  - **Sequential computation:** makes parallelisation hard

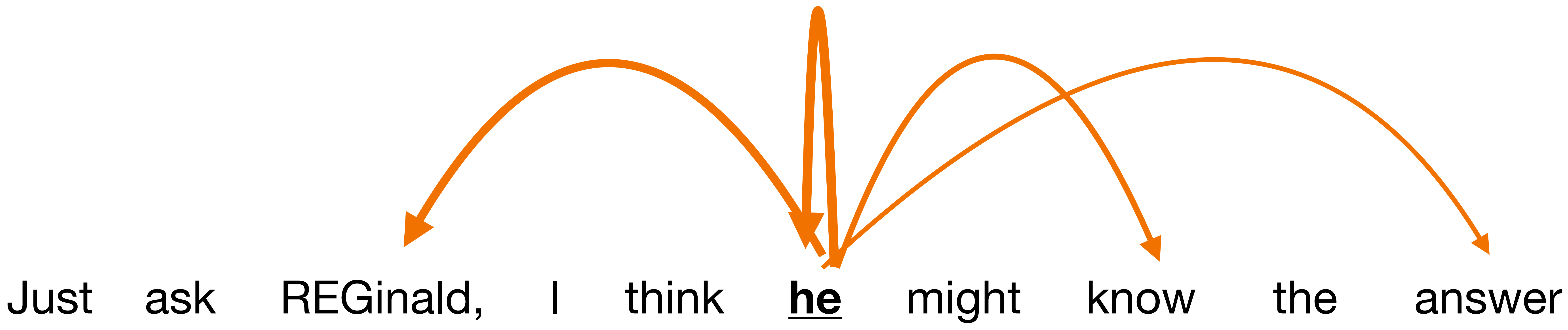
  - Also: attention seems to be a bit more *interpretable*

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Attention: Goal

Just ask REGinald, I think **he** might know the answer

Attention: Goal



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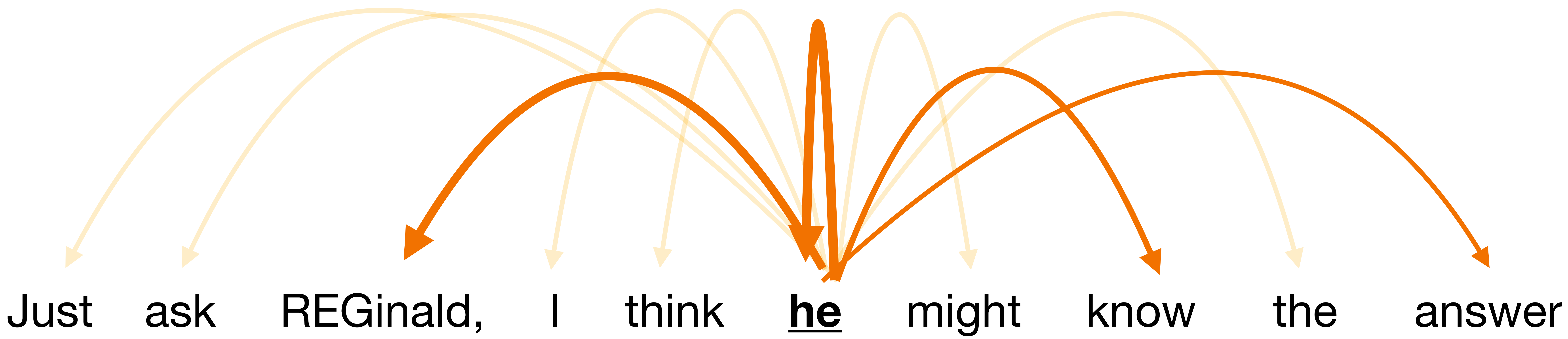

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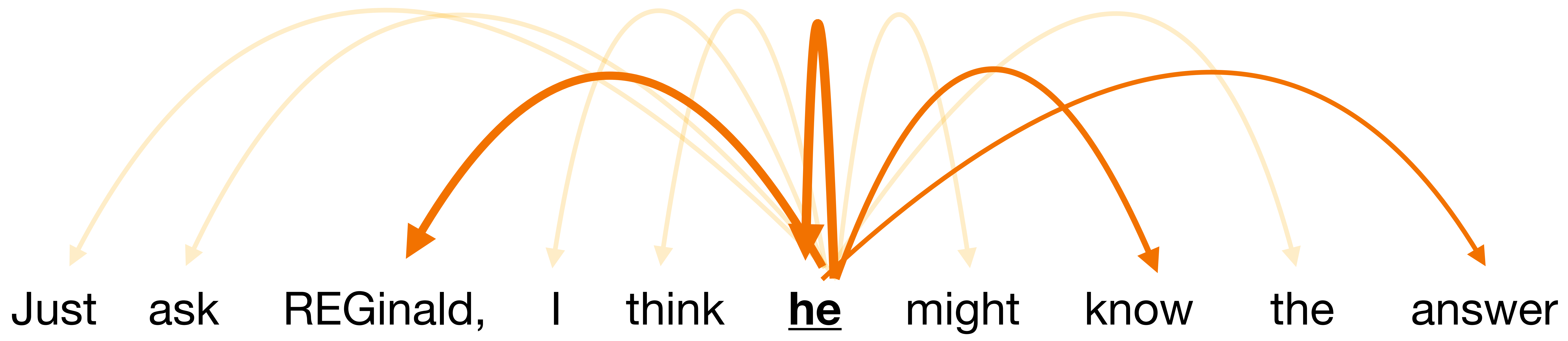

Me: What's the goal of the attention mechanism in transformers, in one illuminating sentence?

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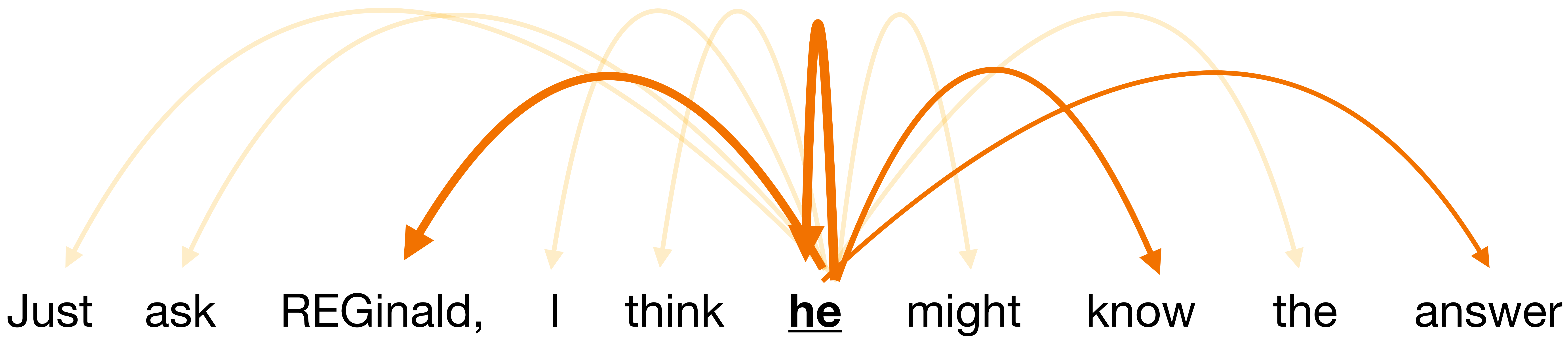

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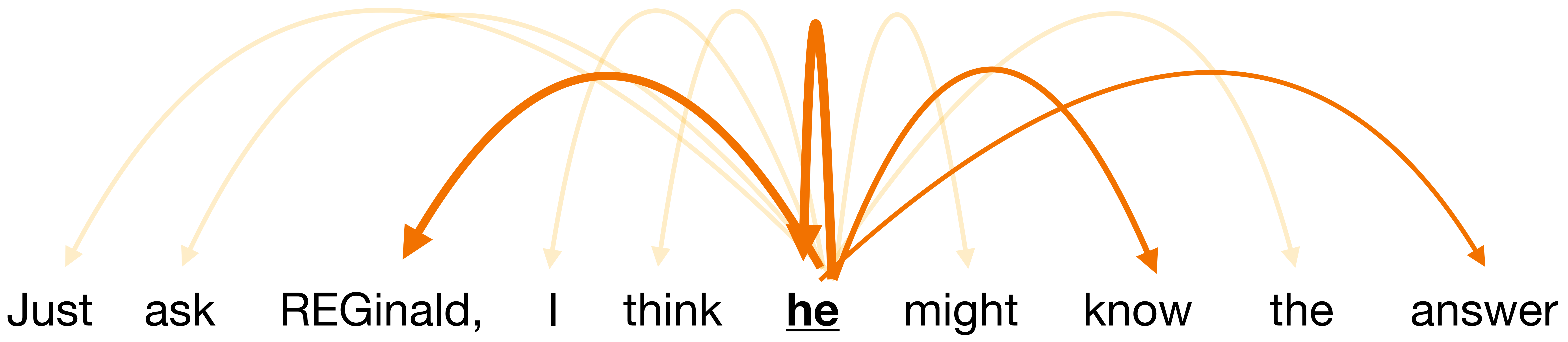
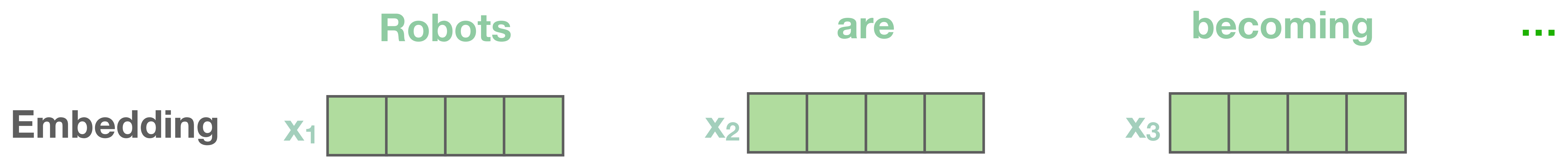


Me: What's the goal of the attention mechanism in transformers, in one illuminating sentence? Imagine you're not an AI, but a technologically advanced alien species, which doesn't use language to communicate.

ChatGP The attention mechanism in Transformers is akin to our advanced pattern recognition systems, **scanning and selectively amplifying** pertinent signals from a sea of information, regardless of their temporal sequence, to understand the **intricate dance of human symbolic sequences**, analogous to how we decipher cosmic vibrations.

Attention 1)

Keys, Queries, Values



Based on https://jalammar.github.io/illustrated-transformer/

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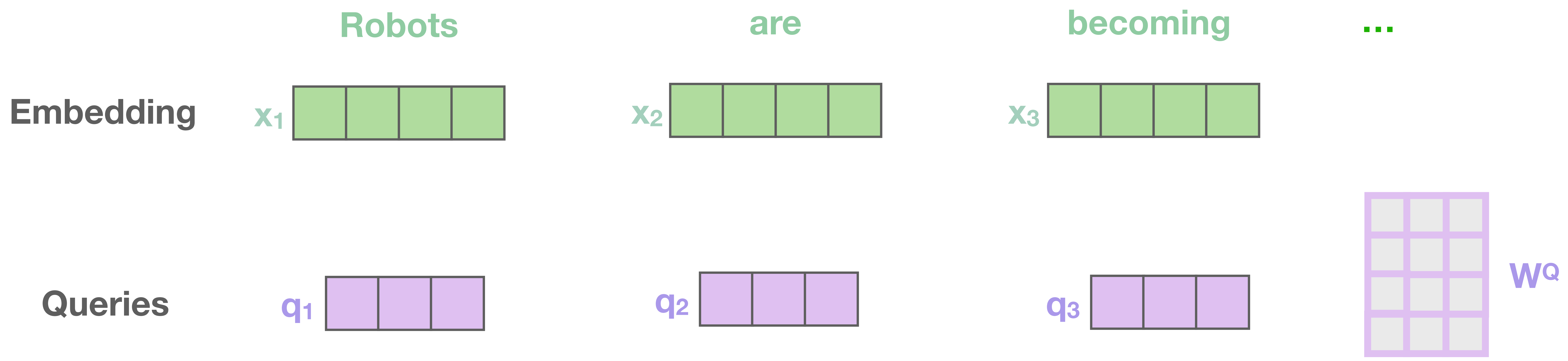

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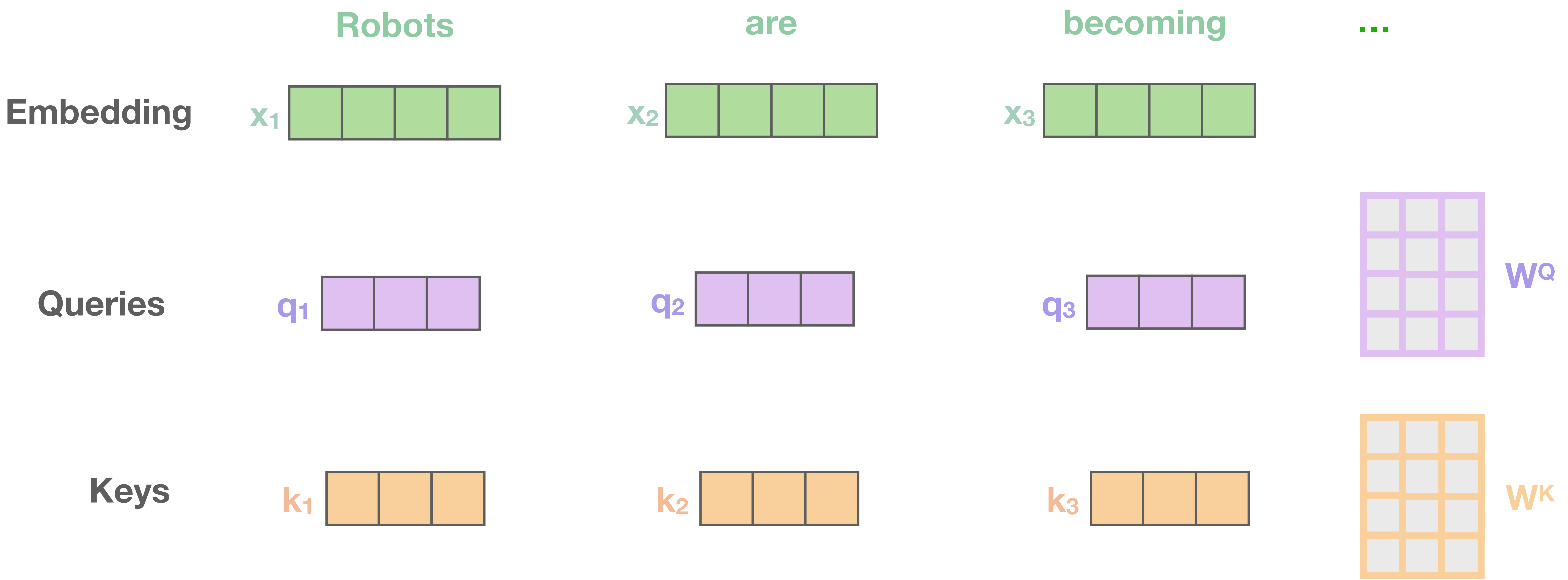

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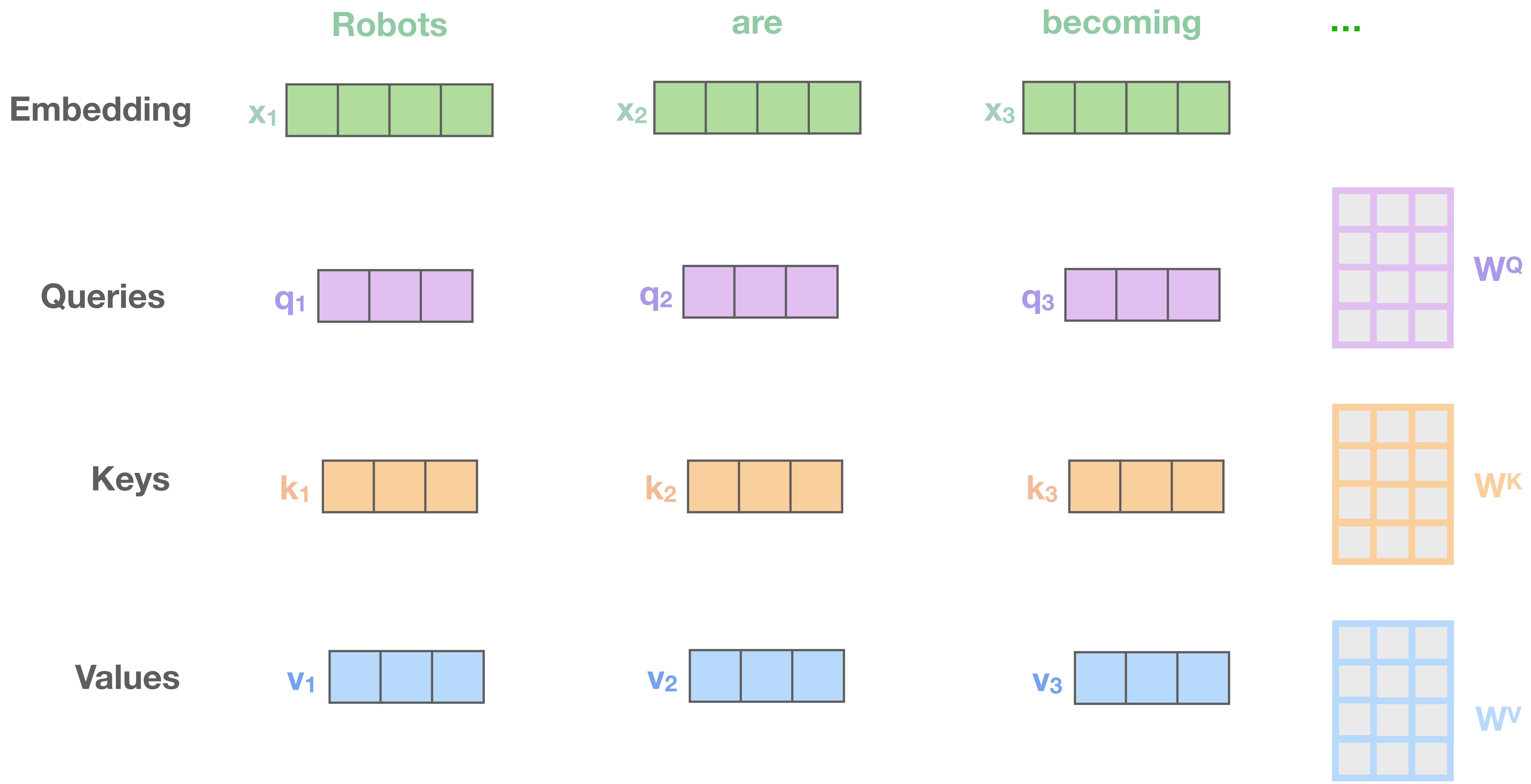

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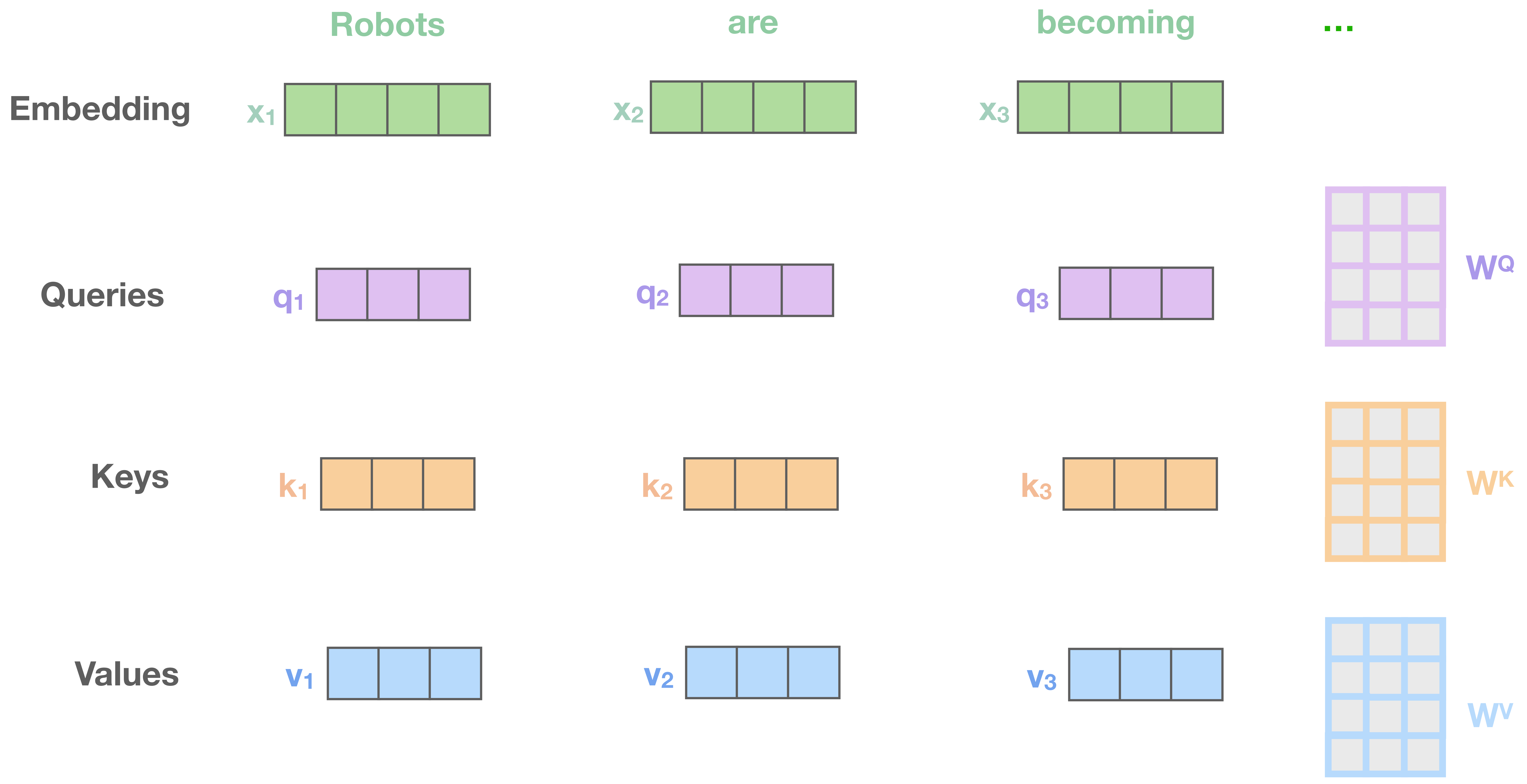

-> Linear projection of each input vector x into a query, key and value vector

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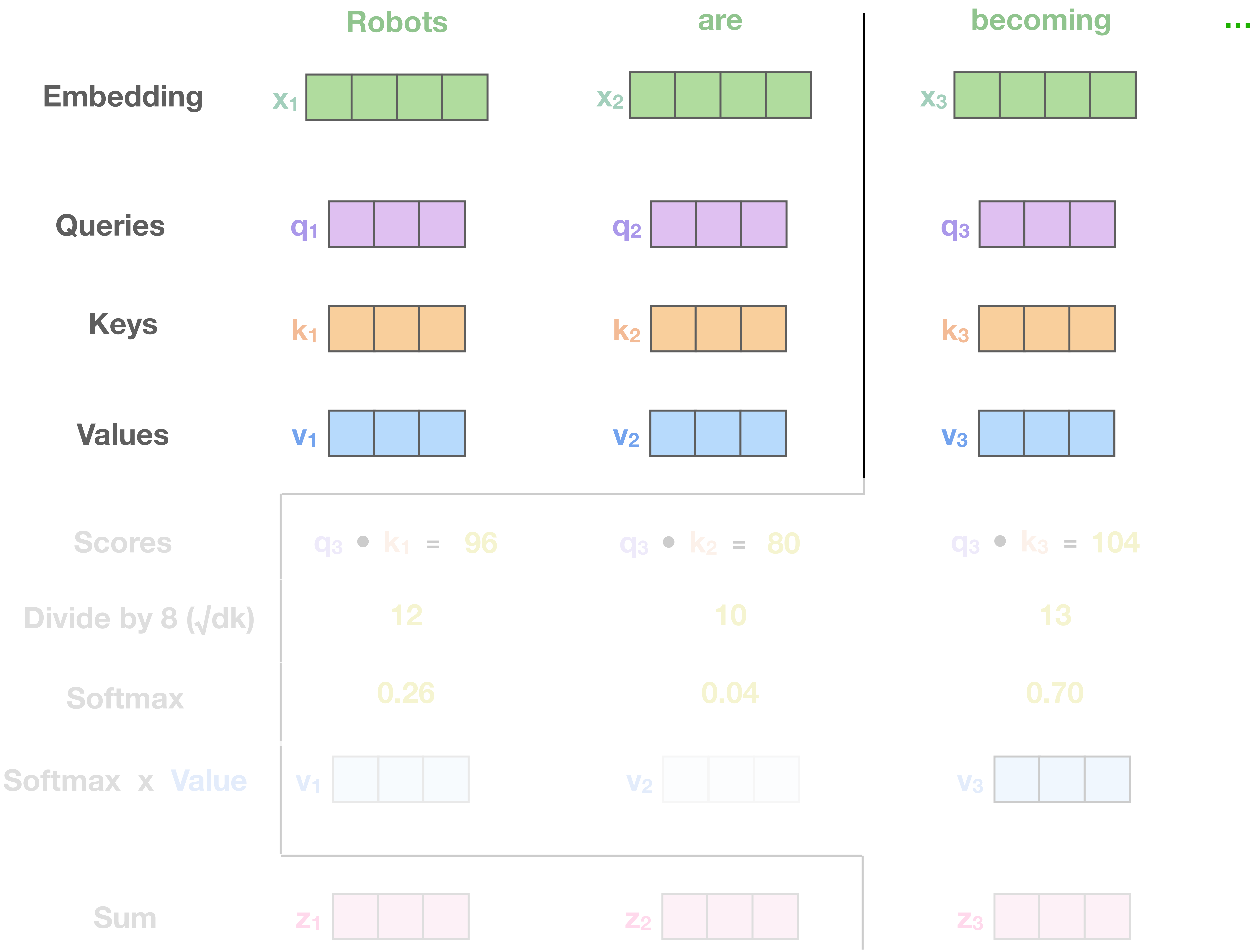
Attention 2)
Calculations



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Attention 2)
Calculations

	Robots	are	becoming	...
Embedding	x_1	x_2	x_3	
Queries	q_1	q_2	q_3	
Keys	k_1	k_2	k_3	
Values	v_1	v_2	v_3	
Scores	$q_3 \bullet k_1 = 96$	$q_3 \bullet k_2 = 80$	$q_3 \bullet k_3 = 104$	
Divide by 8 ($\sqrt{dk}$)	12	10	13	
Softmax	0.26	0.04	0.70	
Softmax x Value	v_1	v_2	v_3	
Sum	z_1	z_2	z_3	

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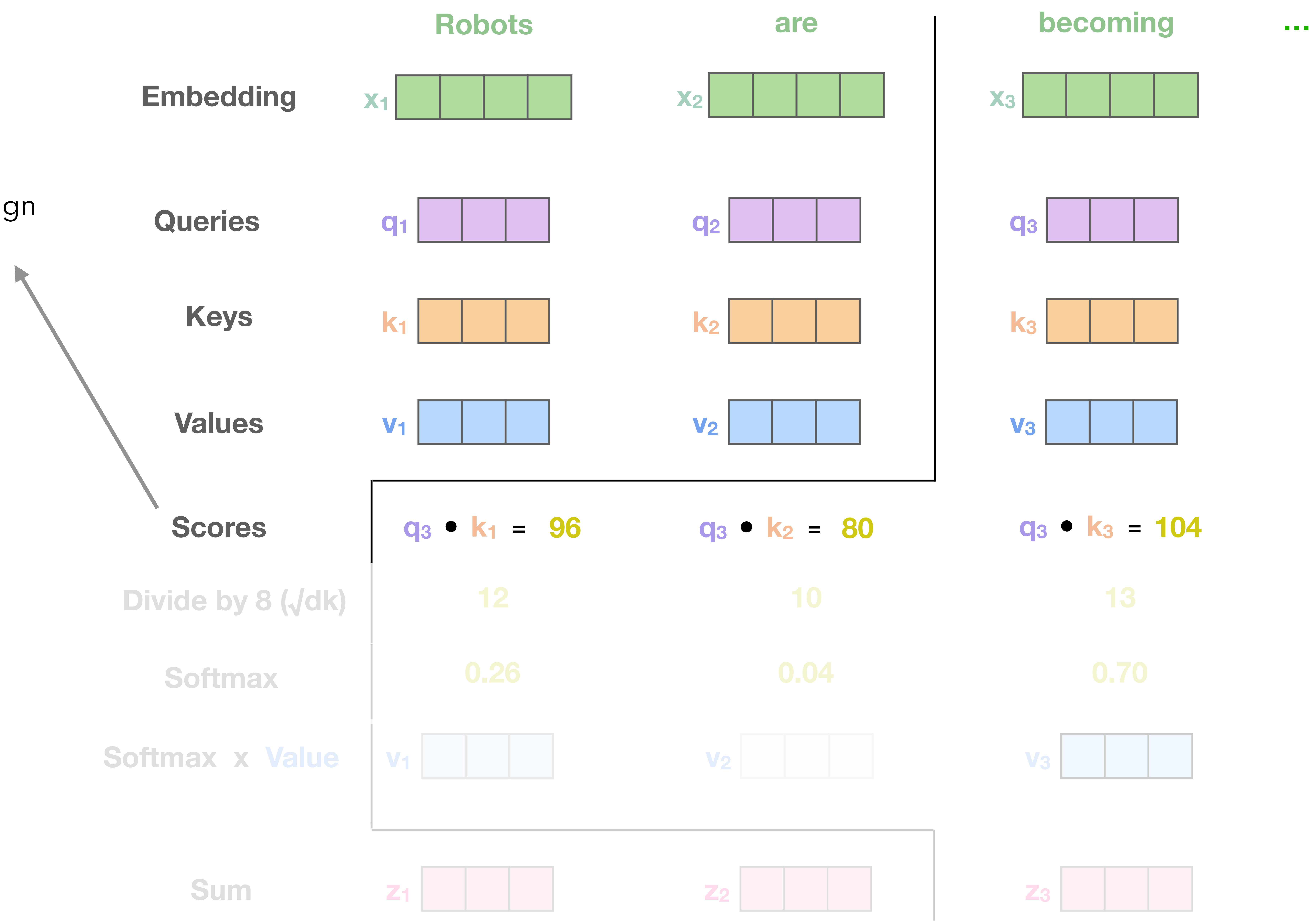
Calculations

Scores:

How well does the current **query** align with all the **keys** in the sequence?
(*raw attention scores*)



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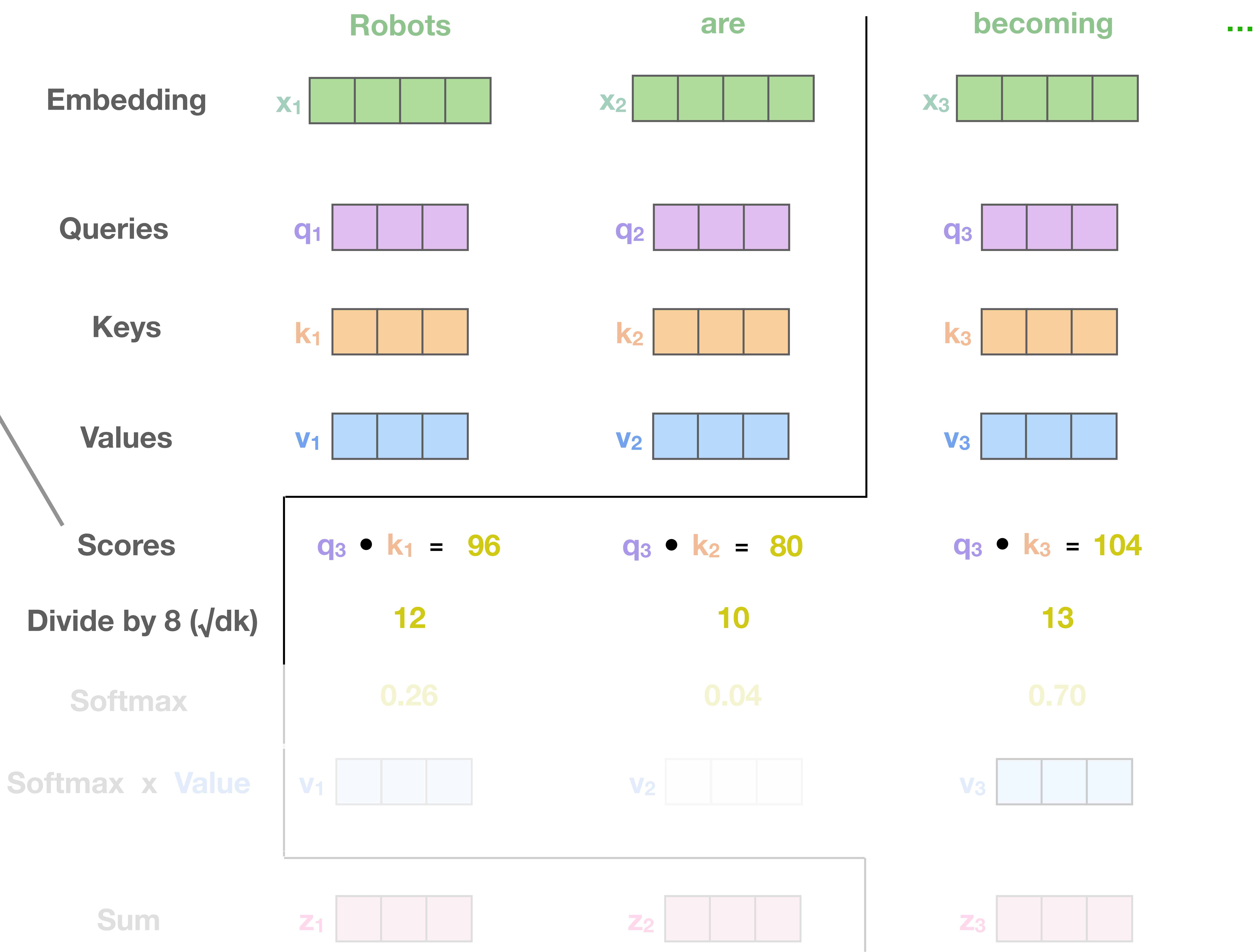

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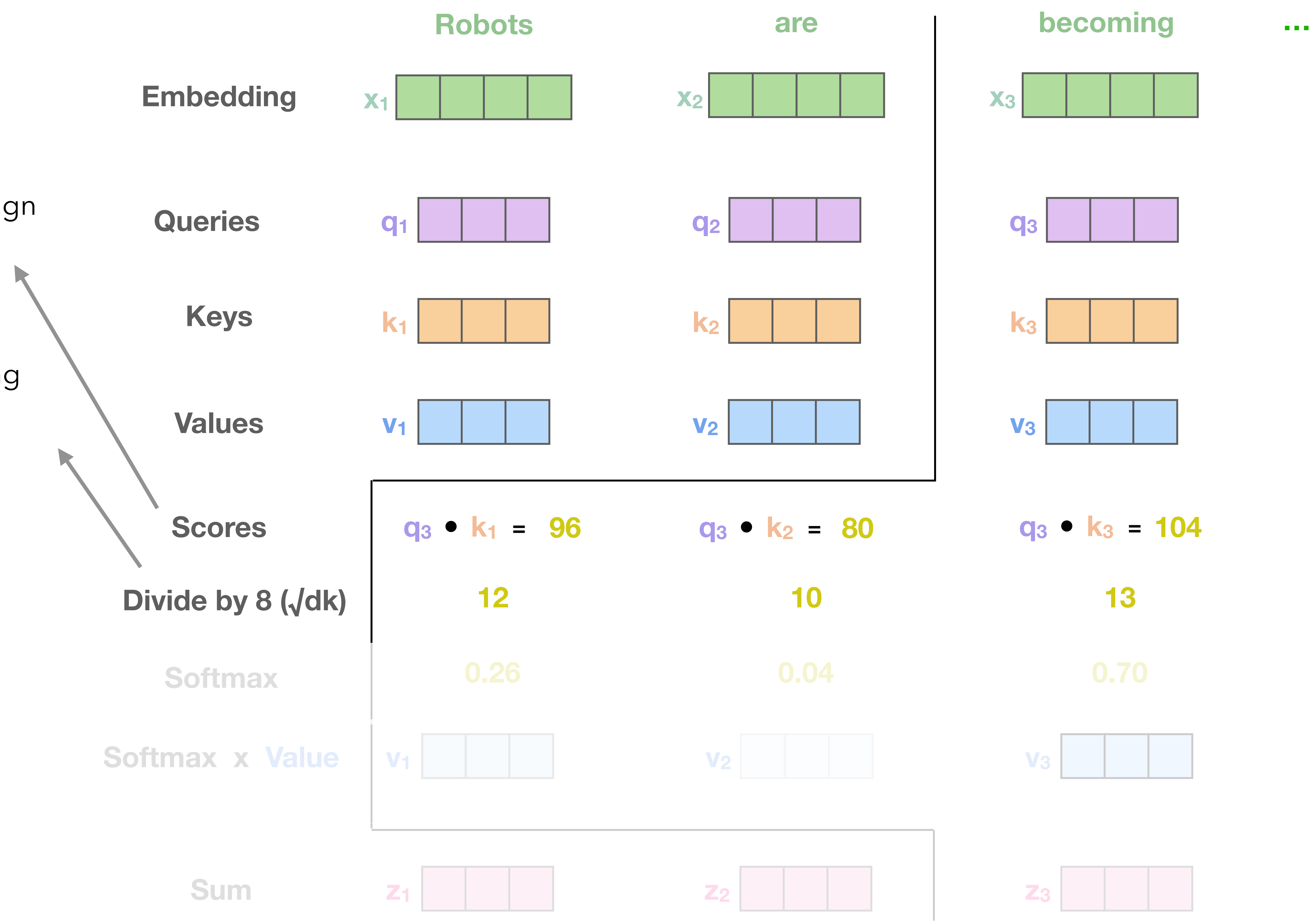
Prevent dot-products from becoming too large and gradients too small.



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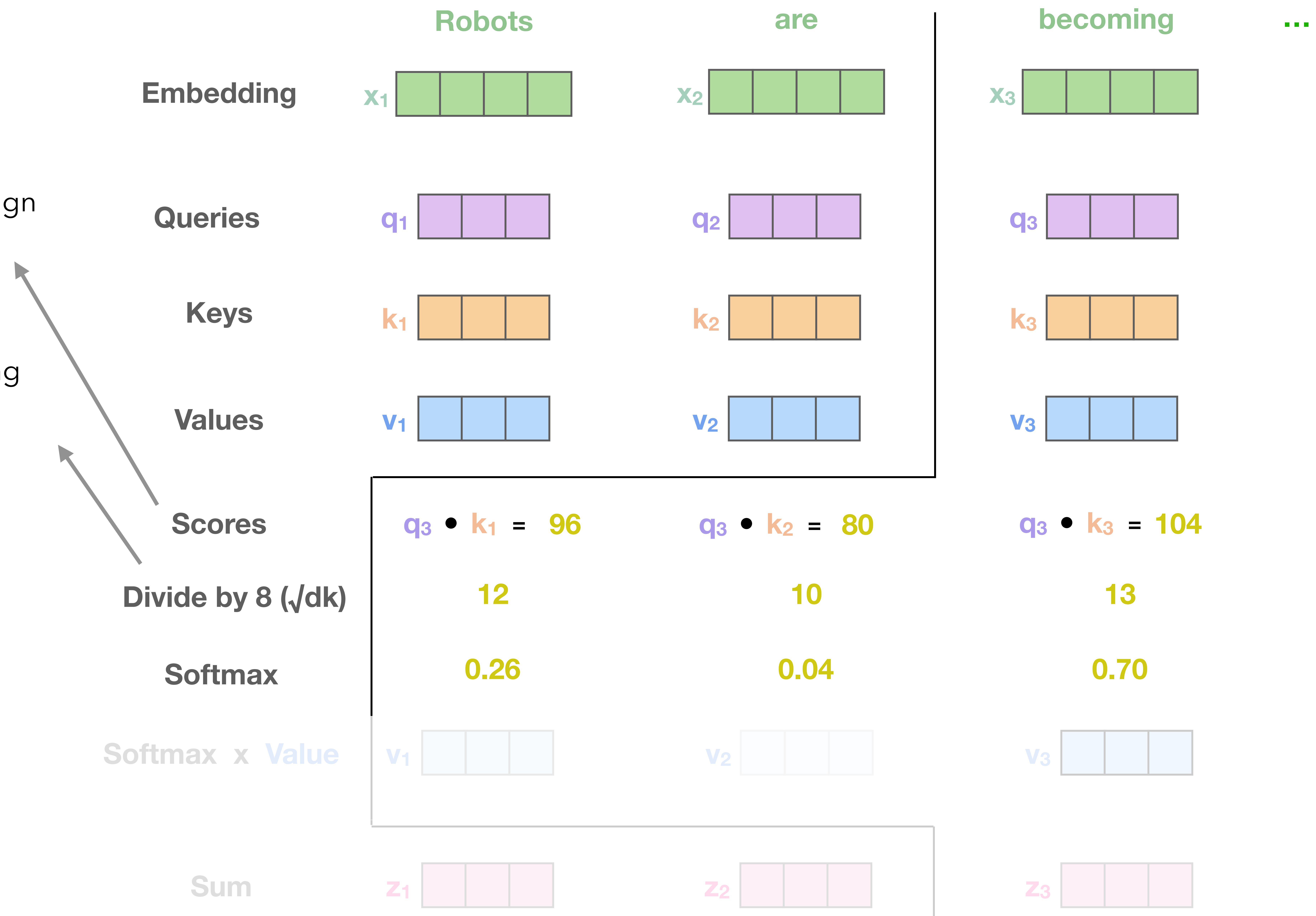

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Probability distribution (summing to 1)
How much *attention* to pay to each token?
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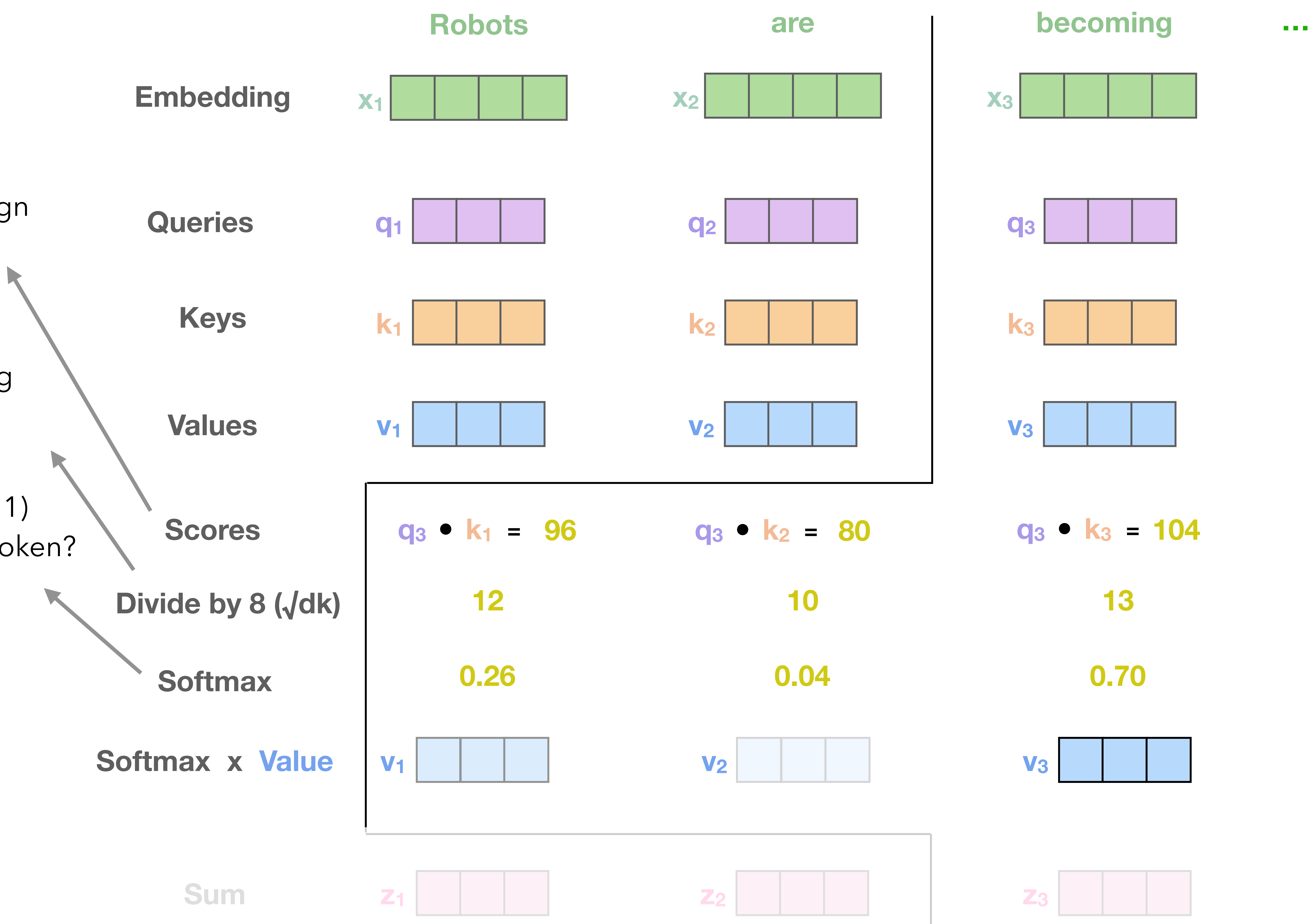

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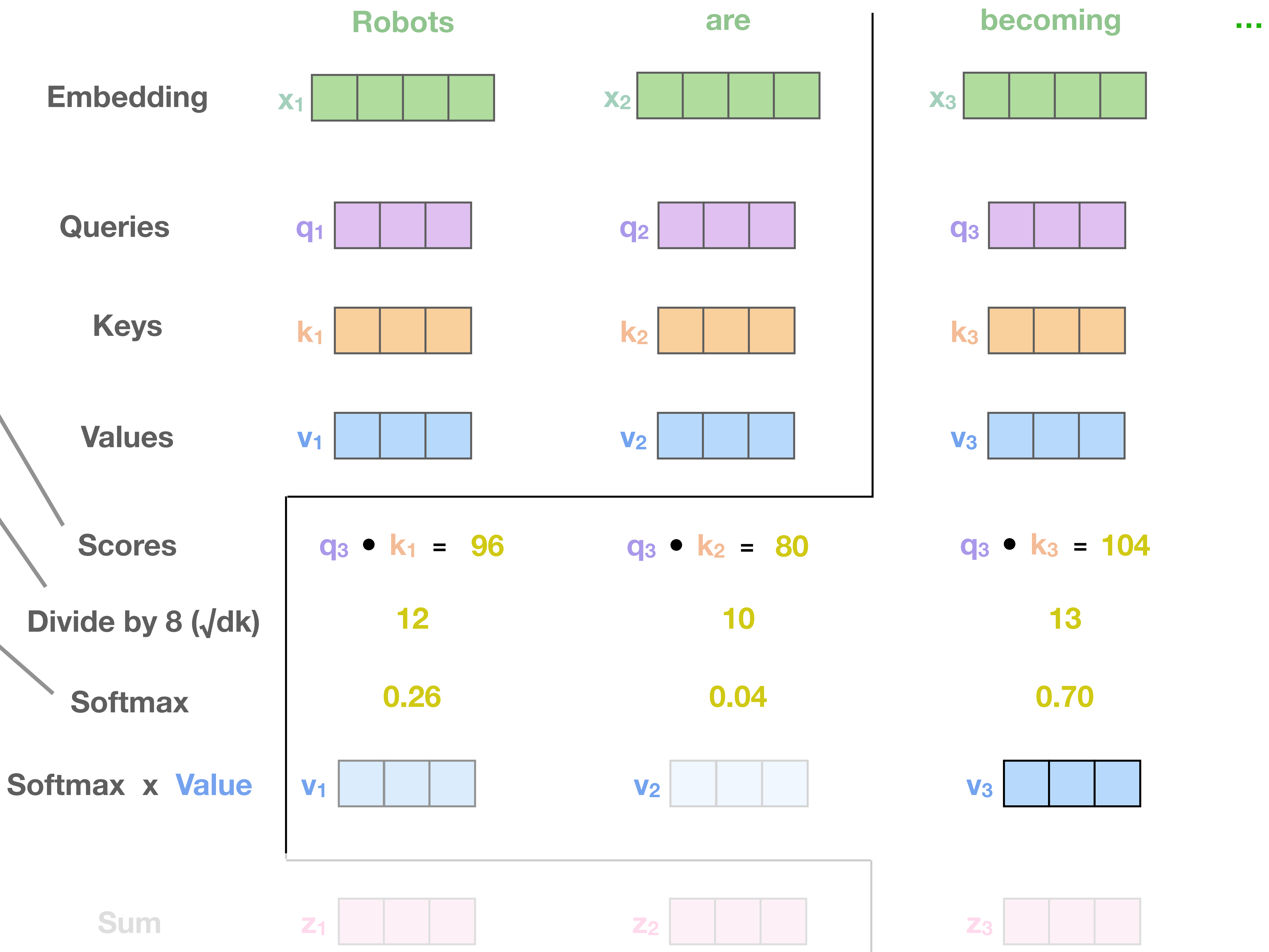
Attention-weighted values
Focus on relevant tokens, drown out irrelevant tokens.



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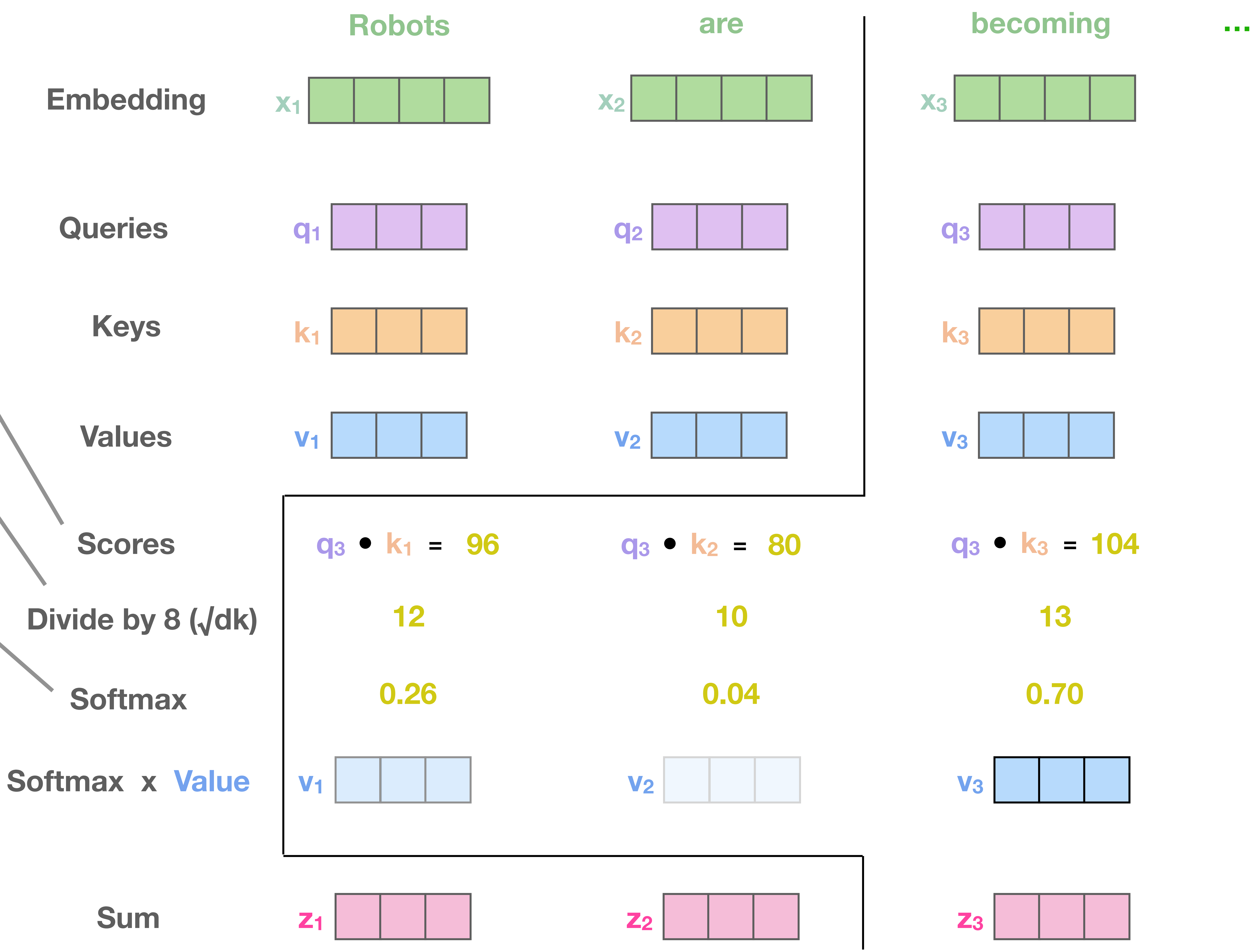

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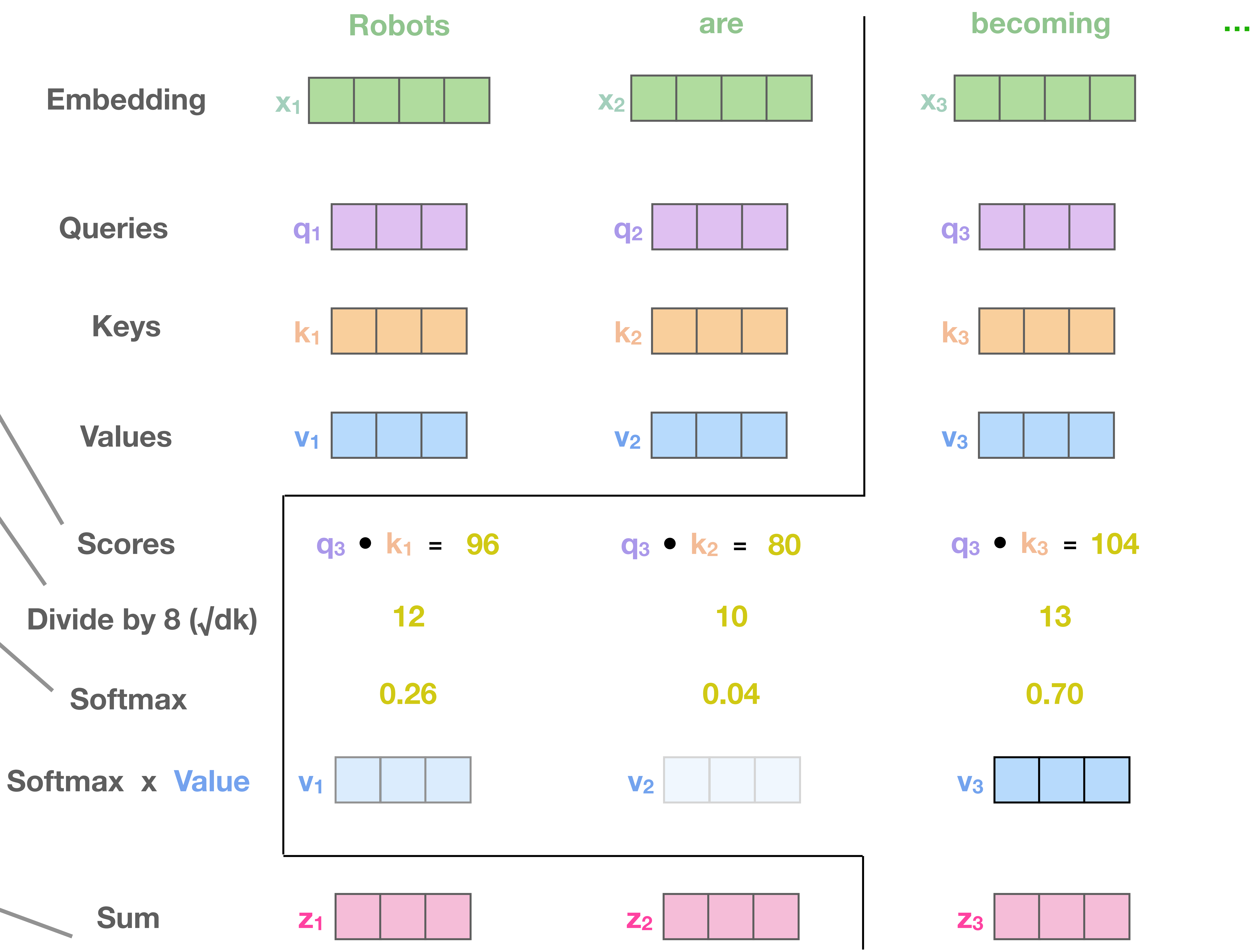
Sum:
Aggregate attention-weighted **value** vectors into an output vector **z**



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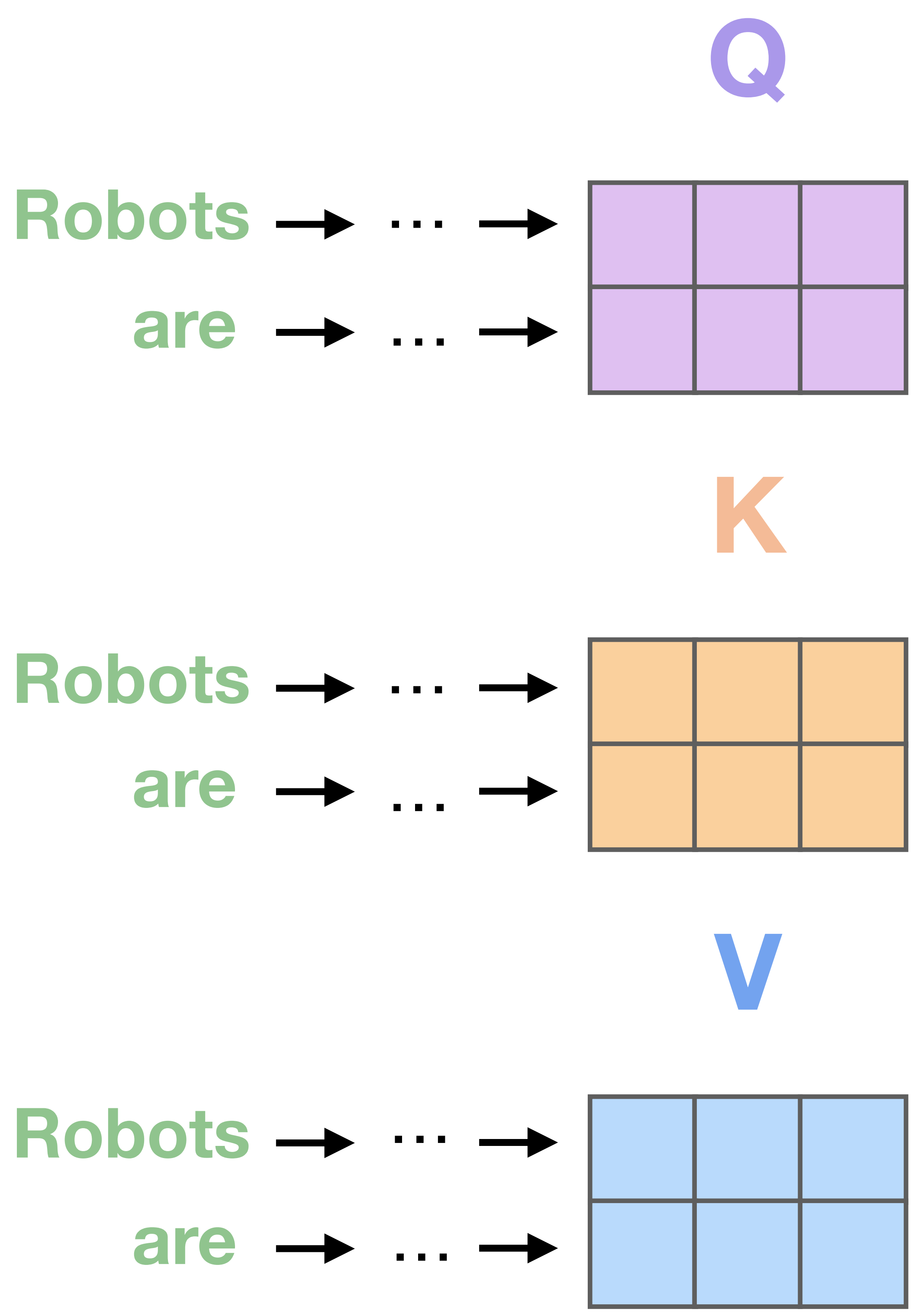
Attention 3)

Matrix form

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



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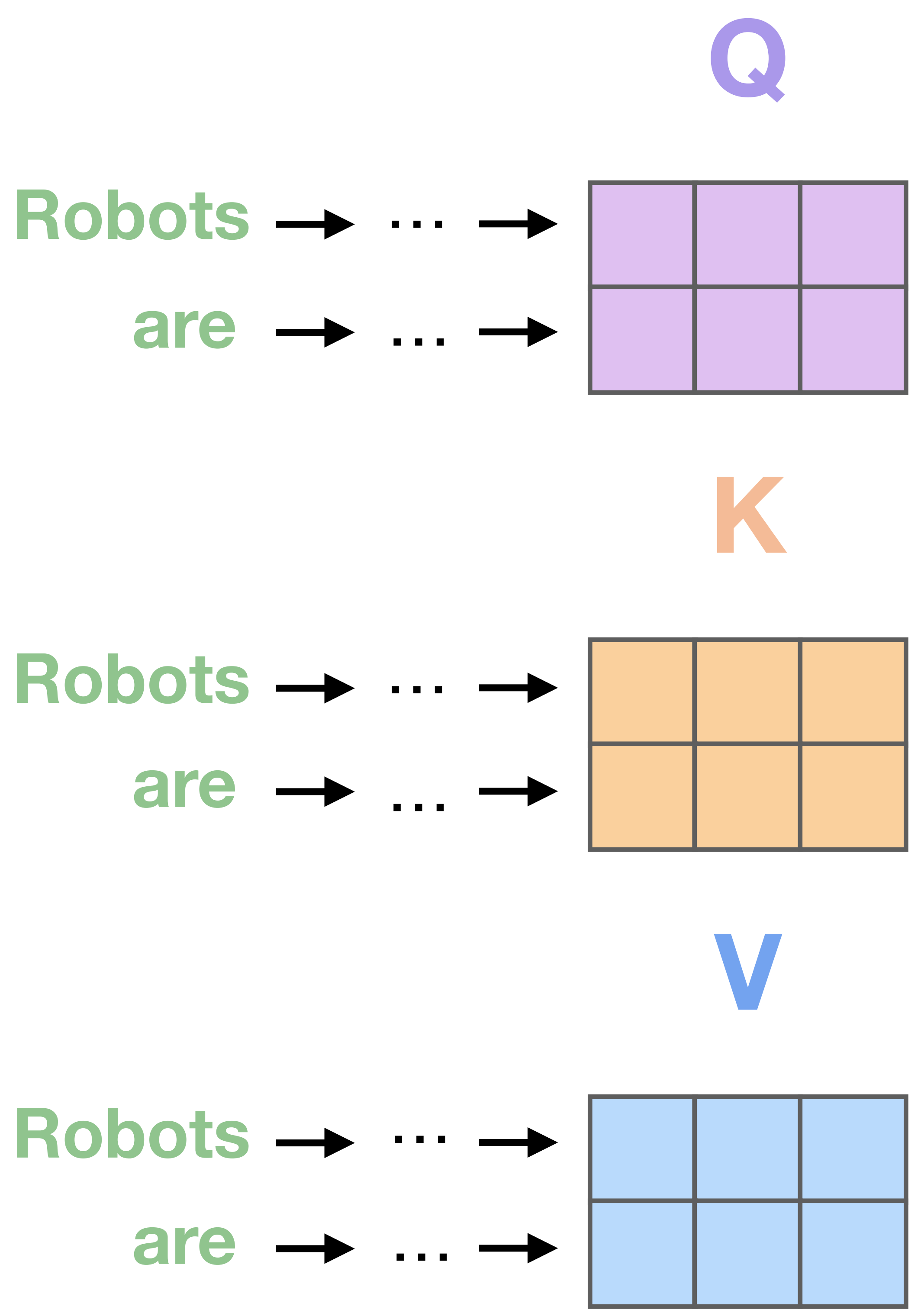

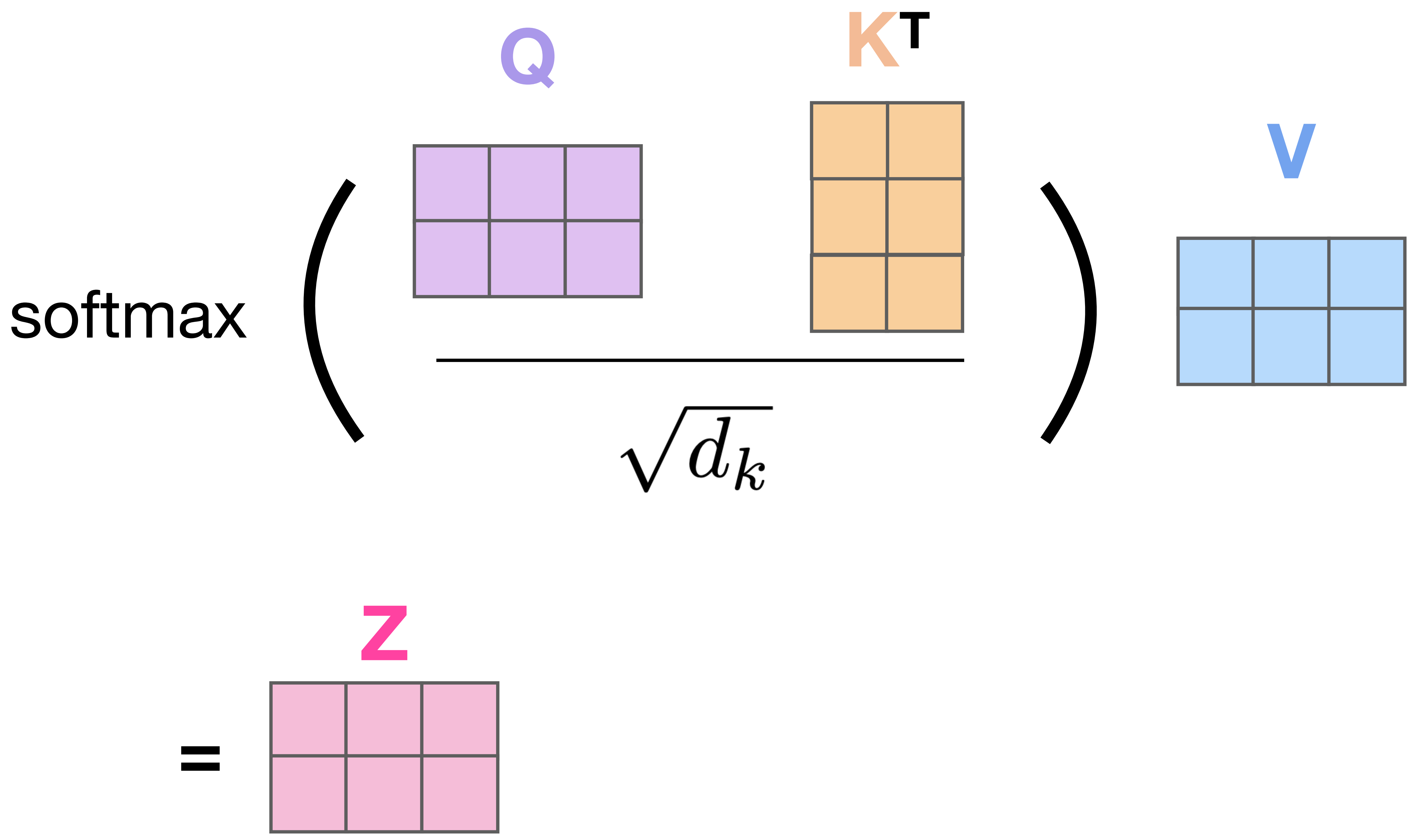

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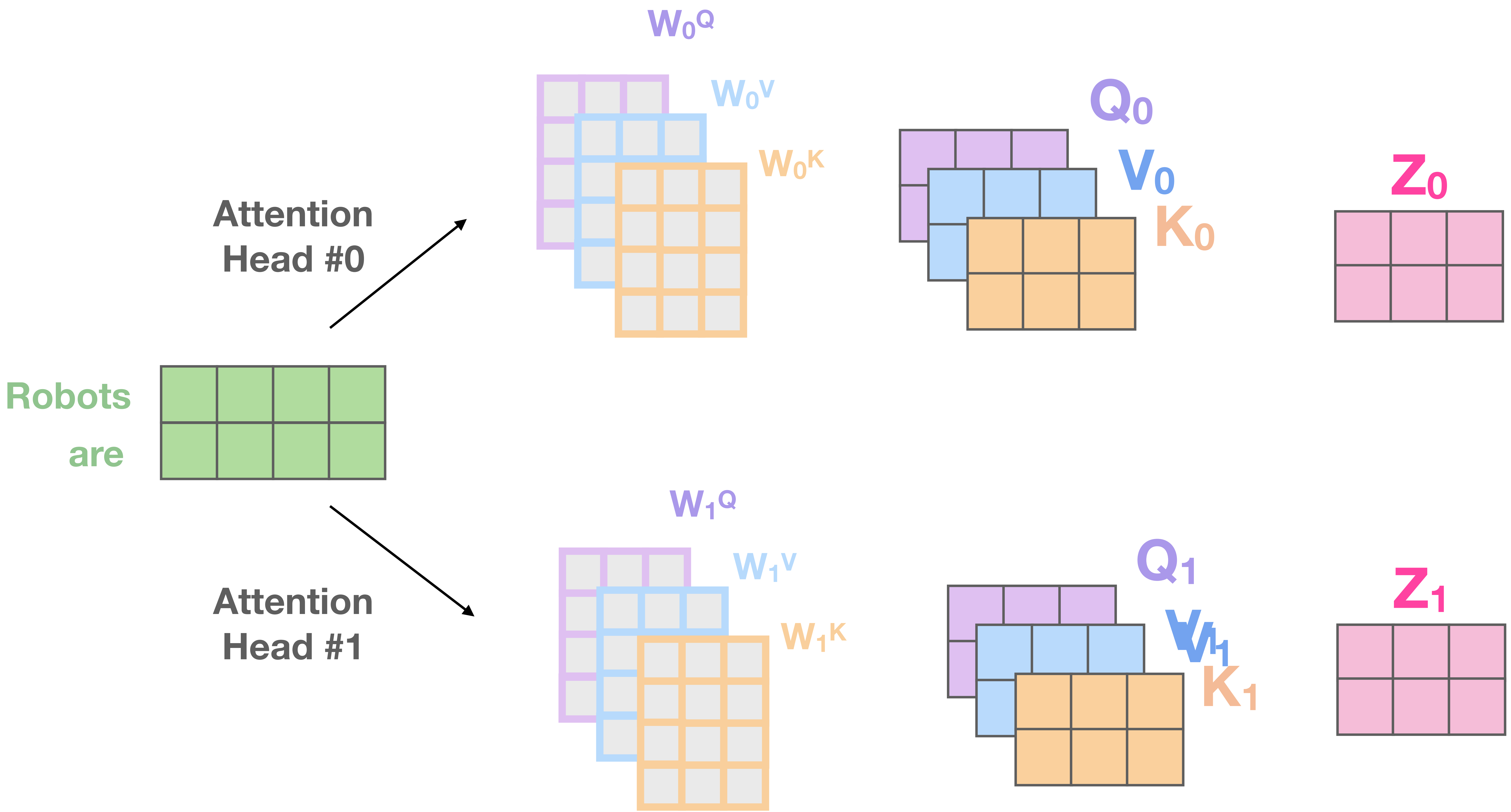
Attention 4)

Multiple heads



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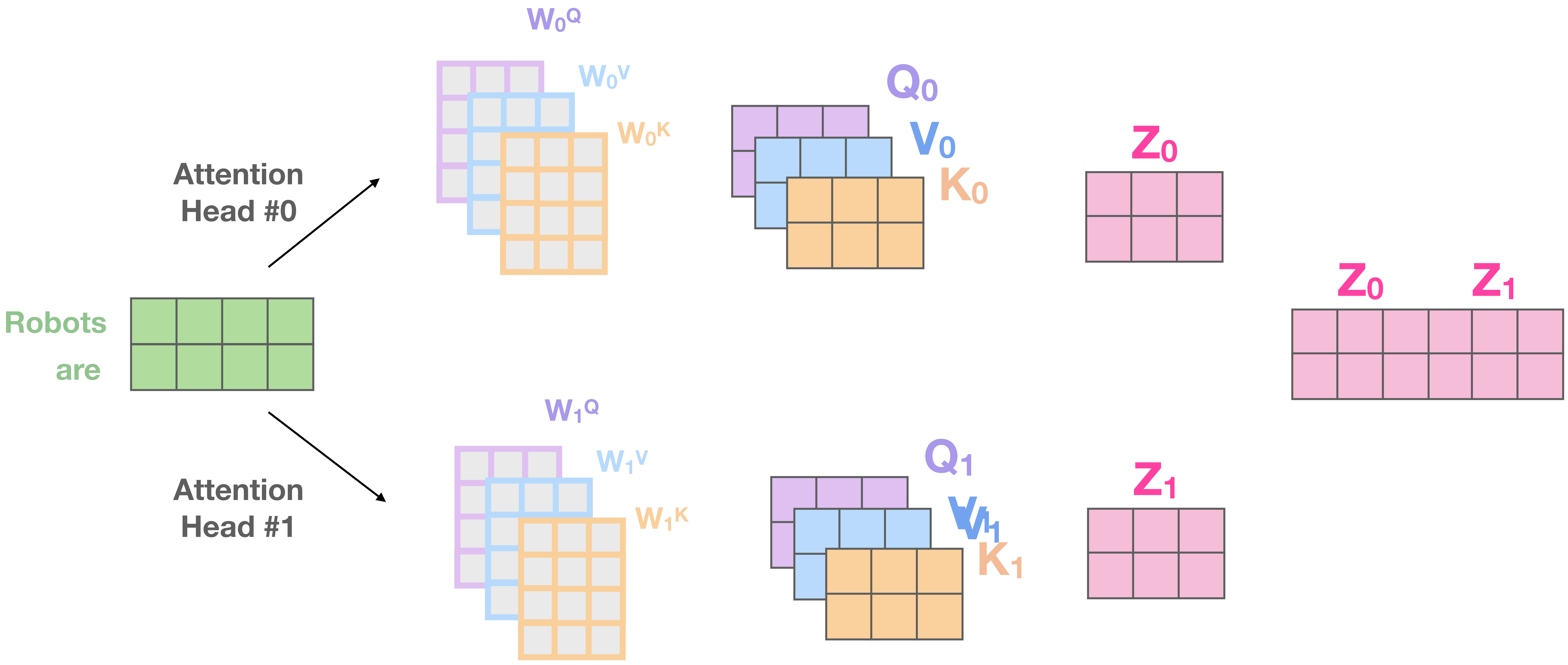

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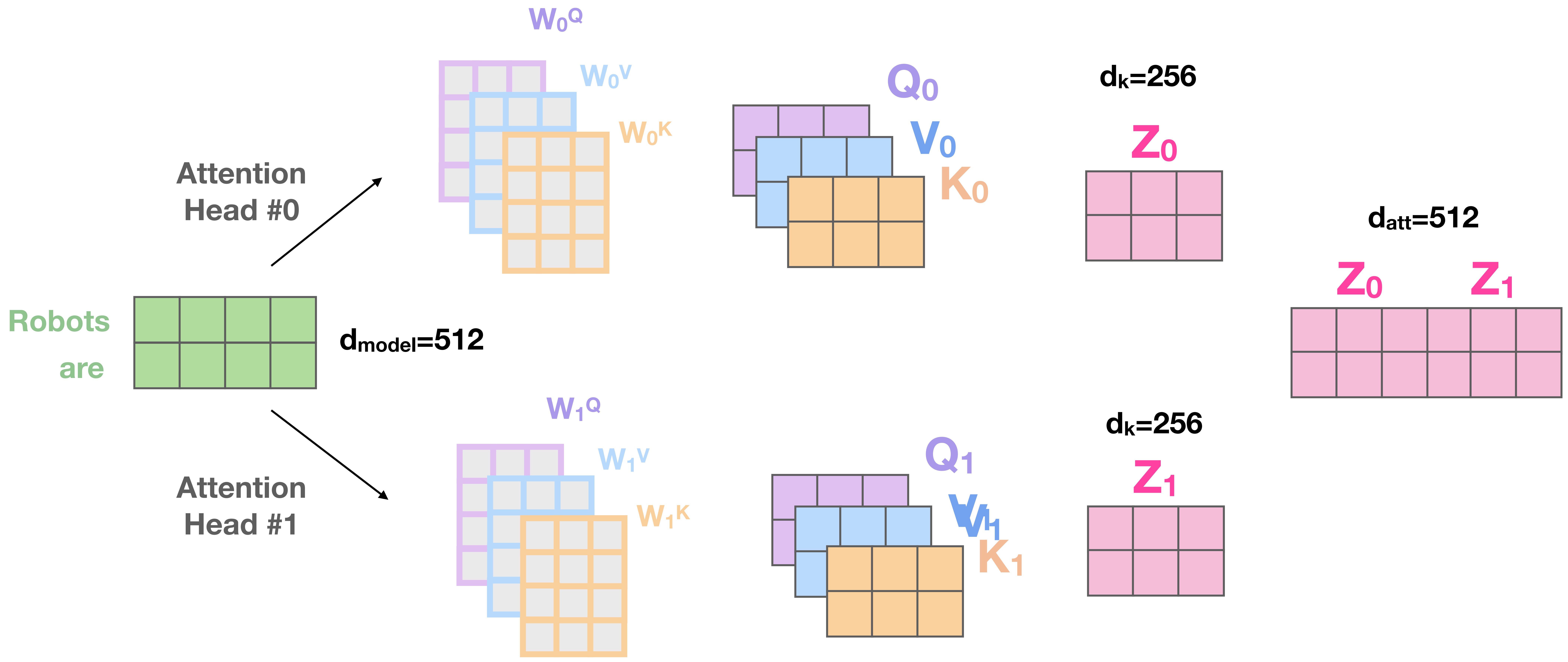

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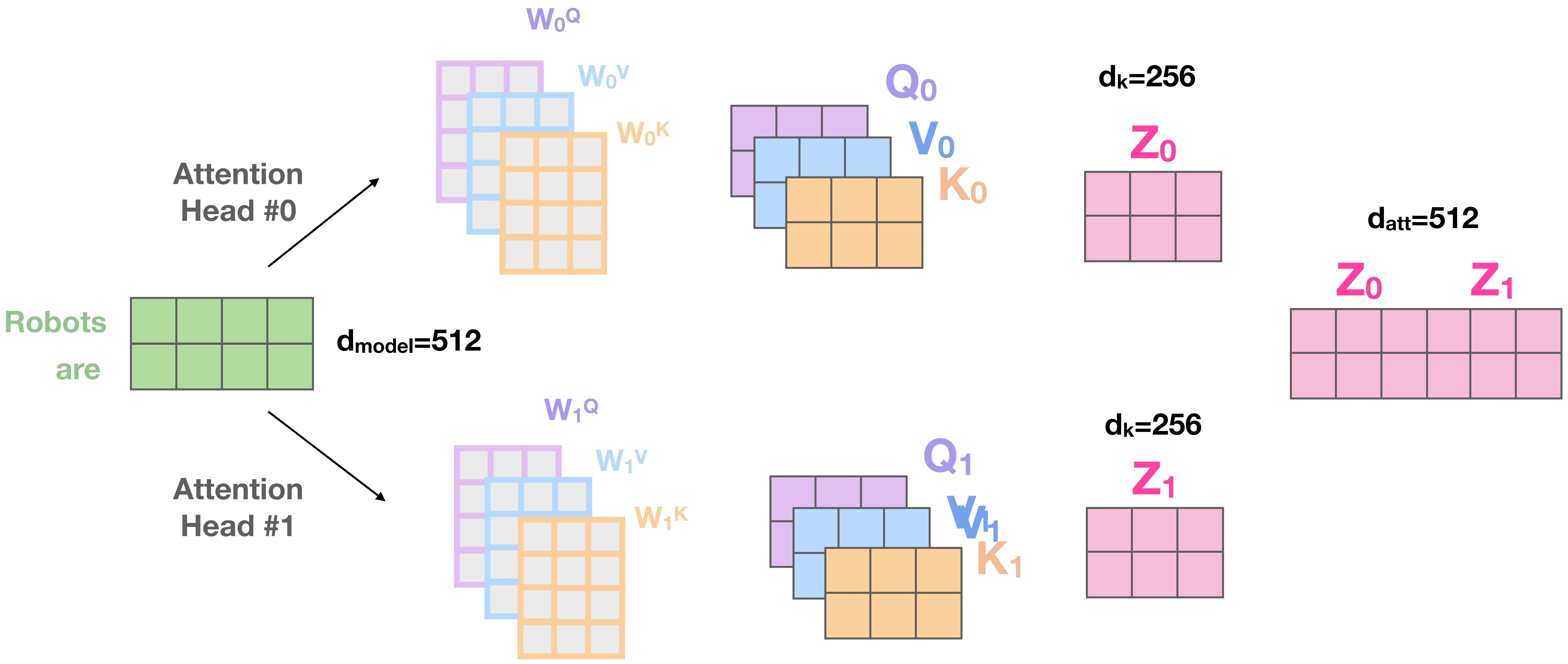


-> Allows the model to focus on different positions at each head

Three variants of Attention

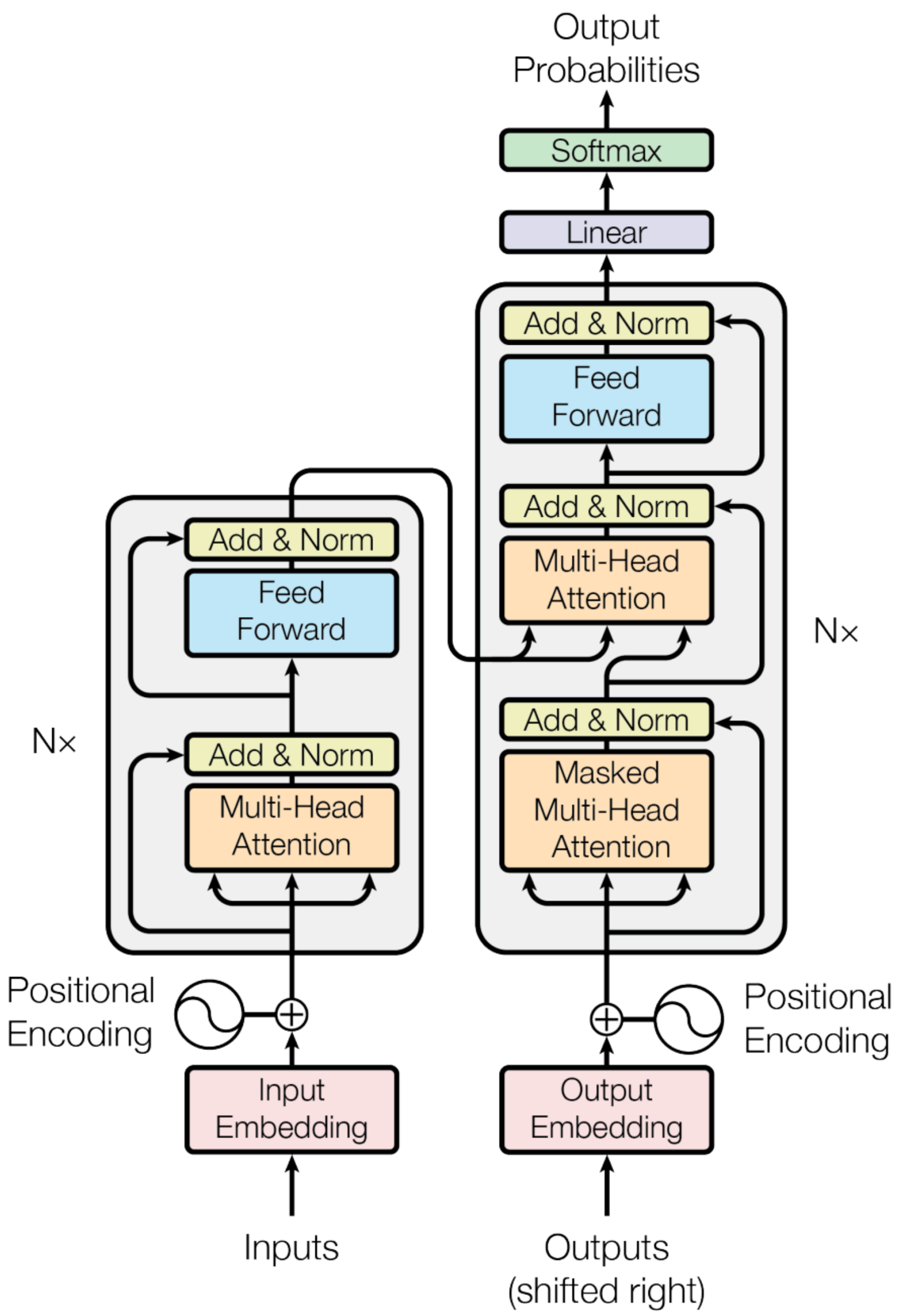


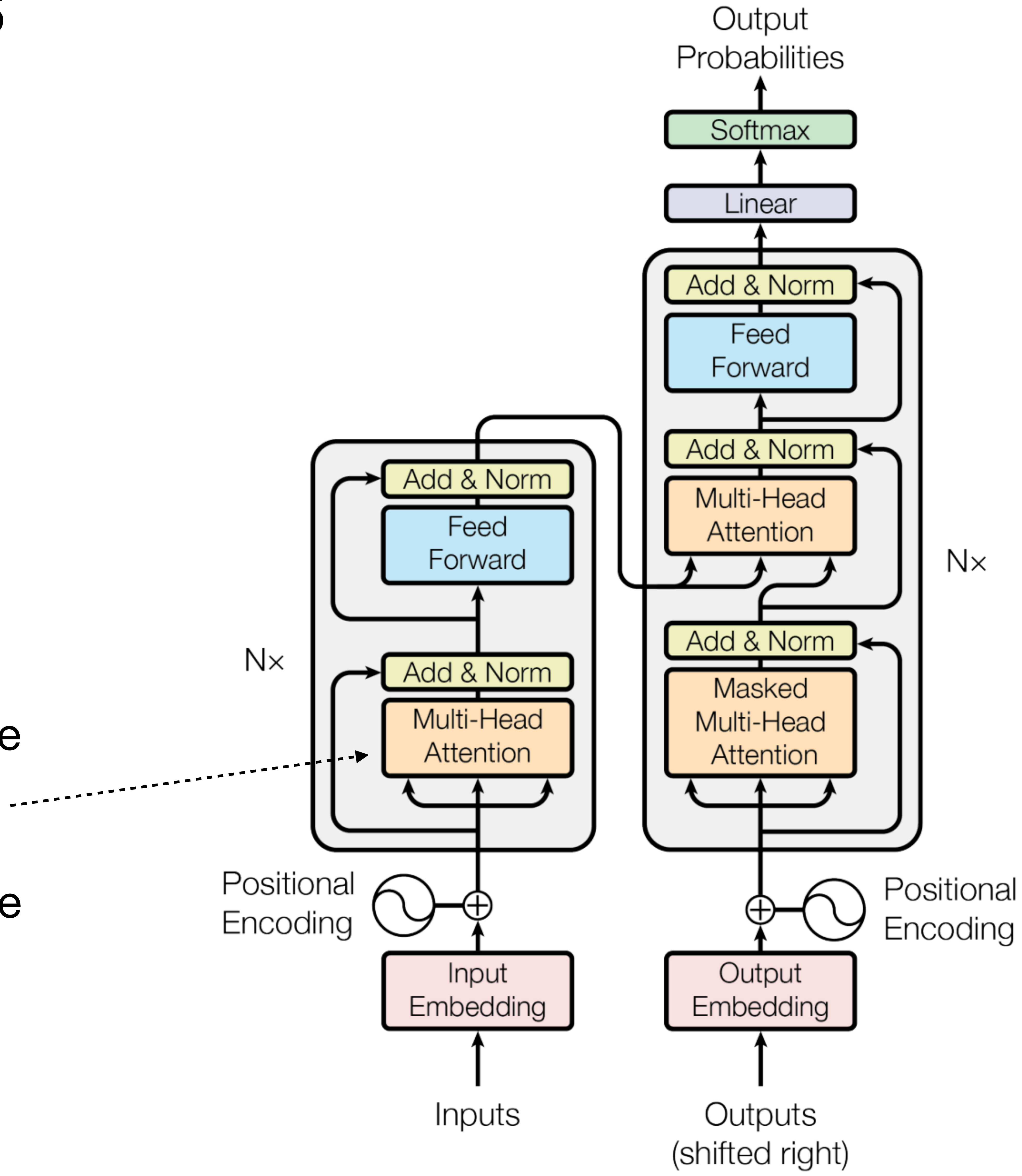
Figure 1: The Transformer - model architecture.

Three variants of Attention

Self-attention

- keys, queries, values come from the *same source x*
- each token attends to *all tokens* in the input sequence

-> e.g. sentiment analysis



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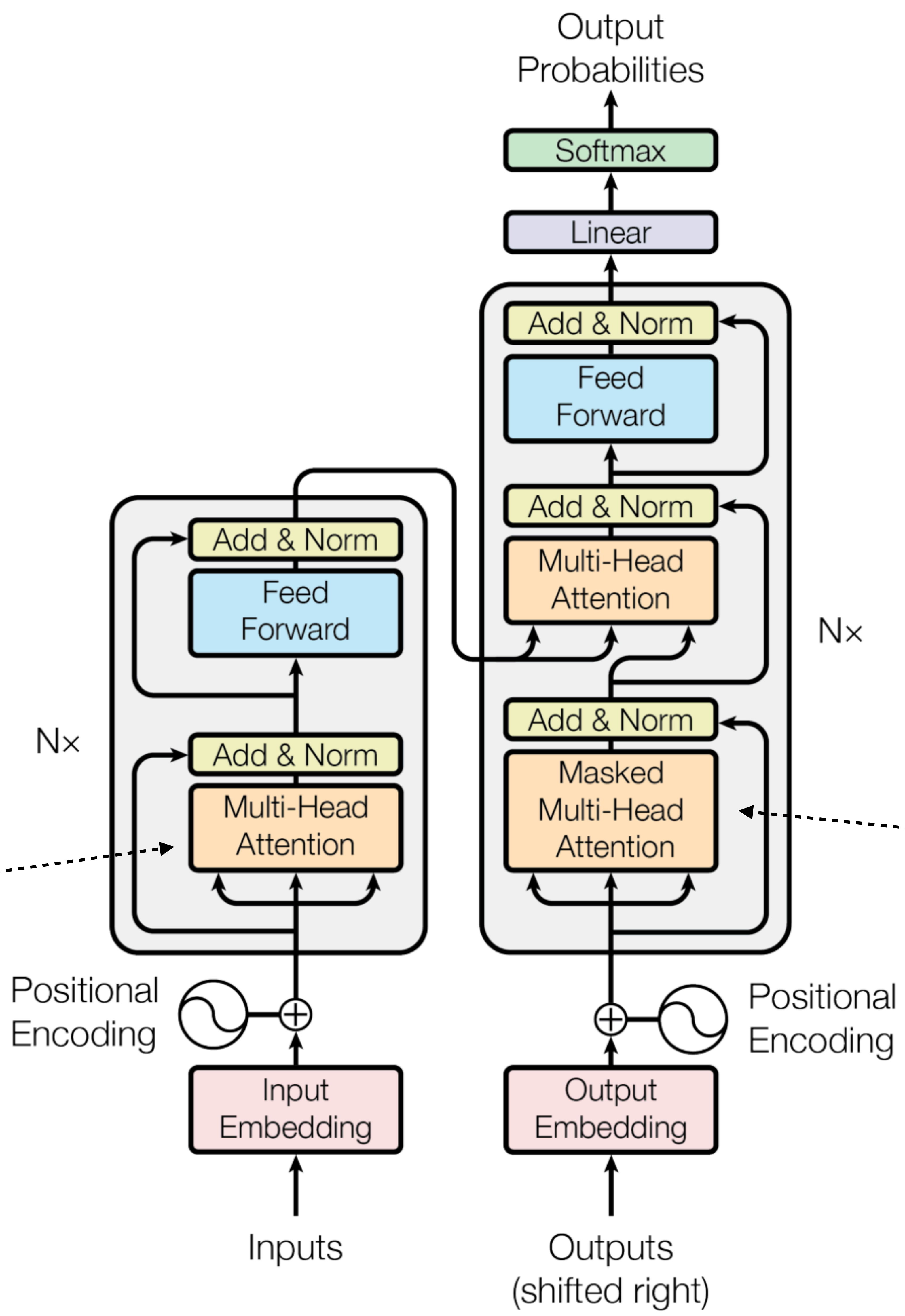

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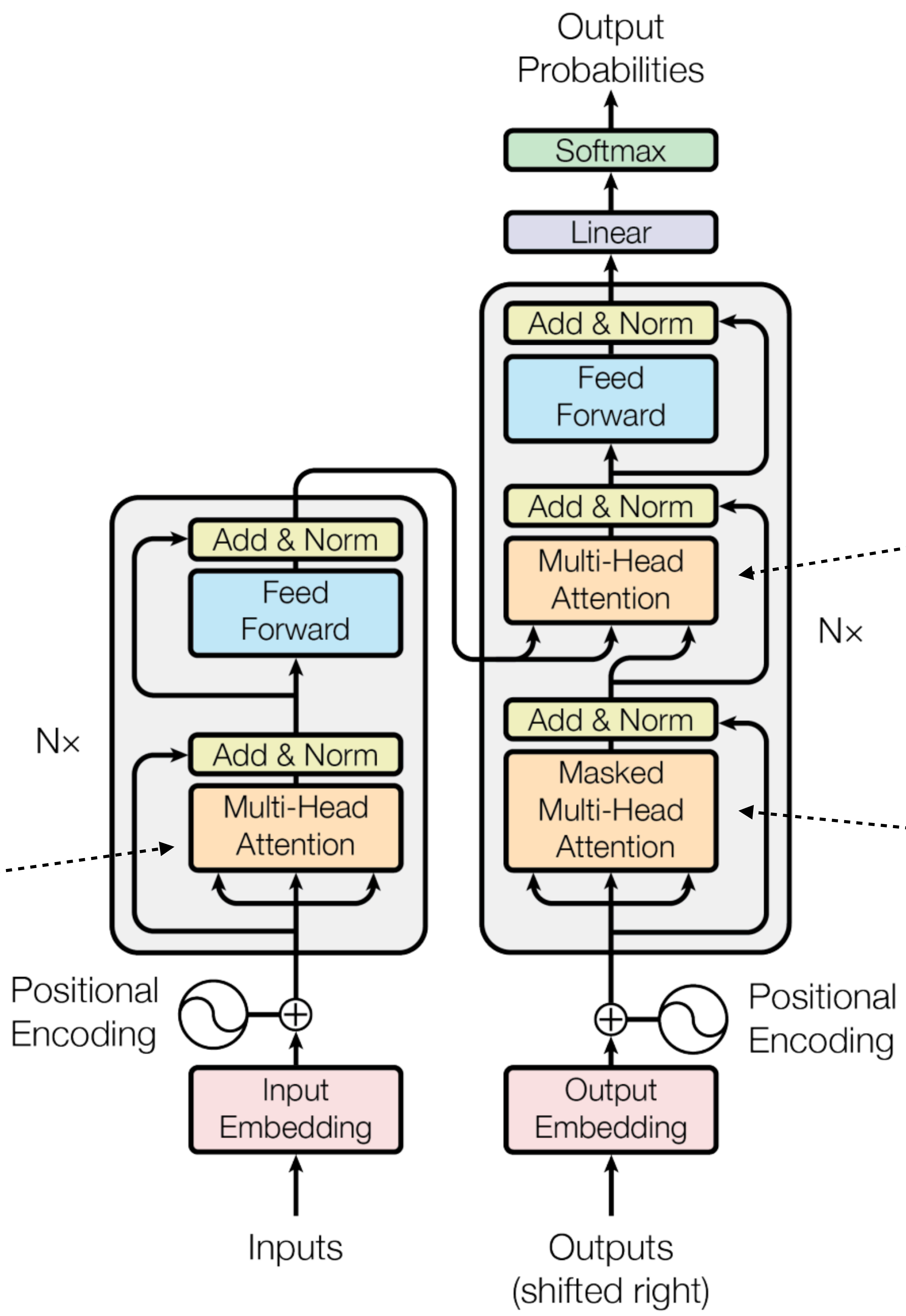

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Cross-attention

- query from decoder, keys/values from encoder
- Each token attends to *all tokens* in sequence

Masked Self-attention

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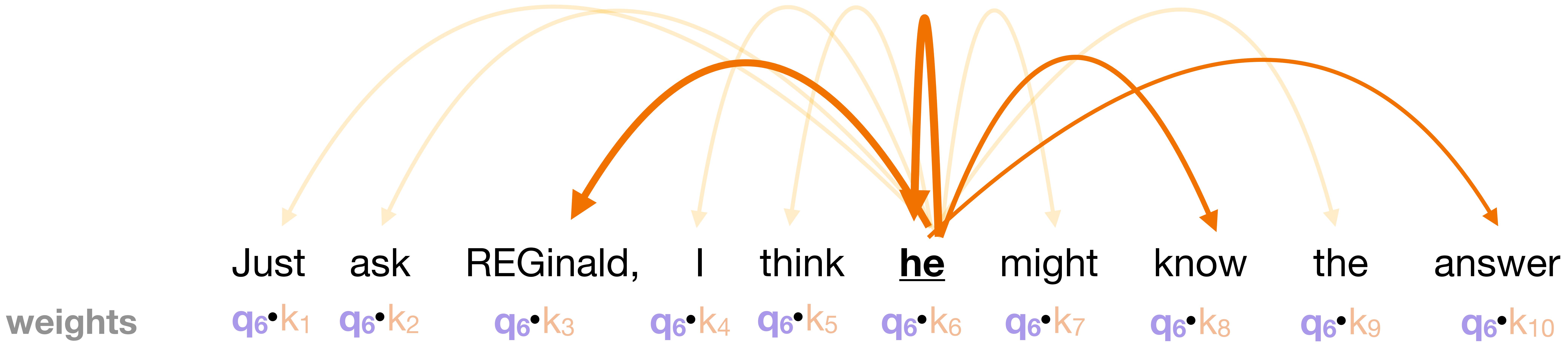

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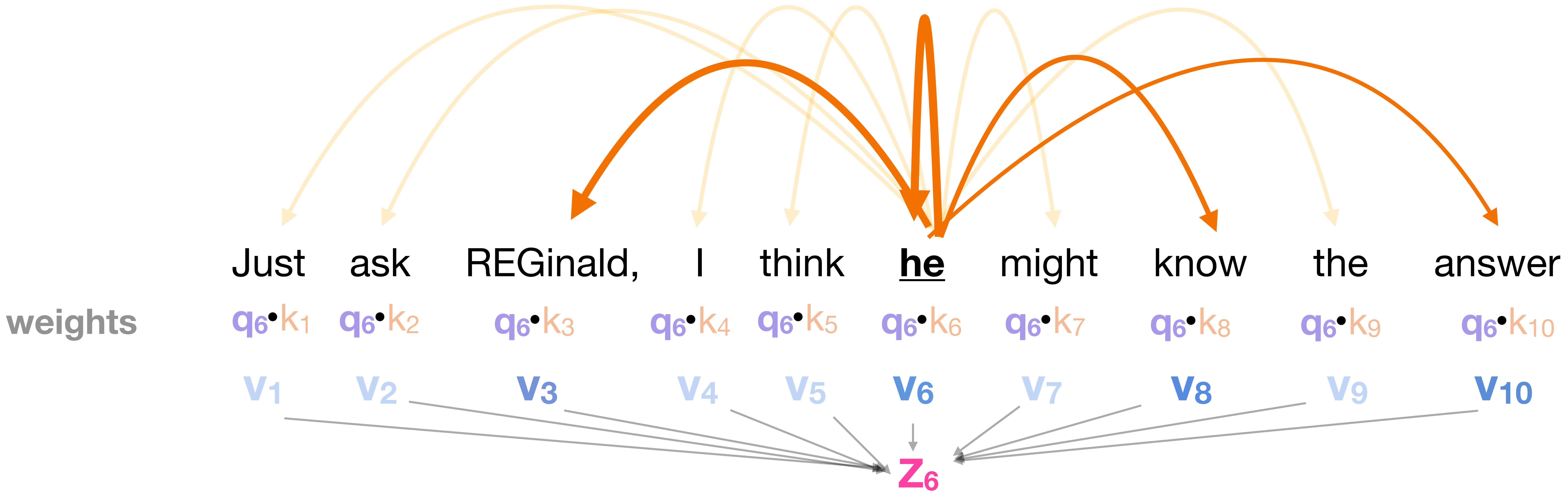
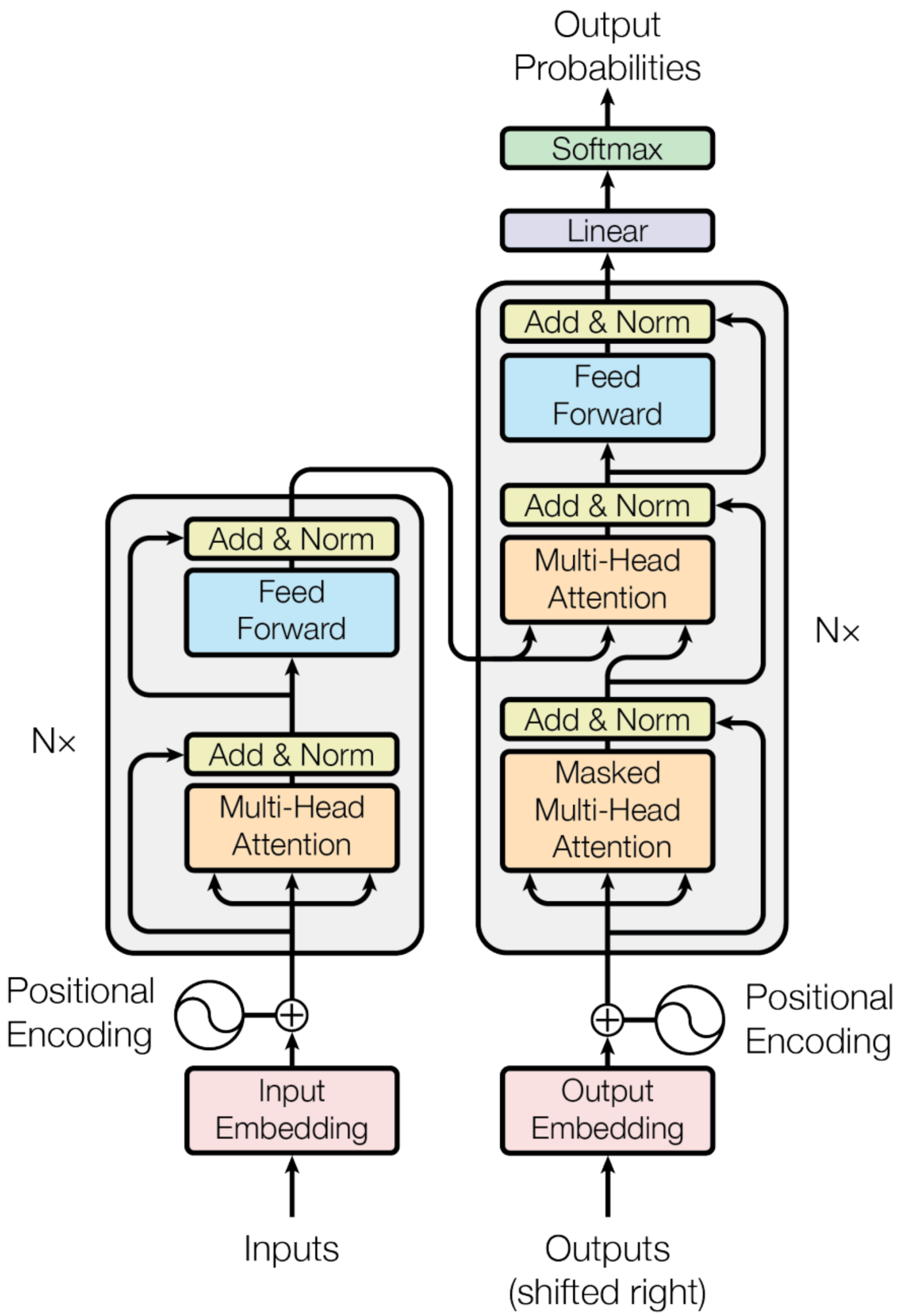


- Attention output **z** is a sum of weighted **values**

Notes



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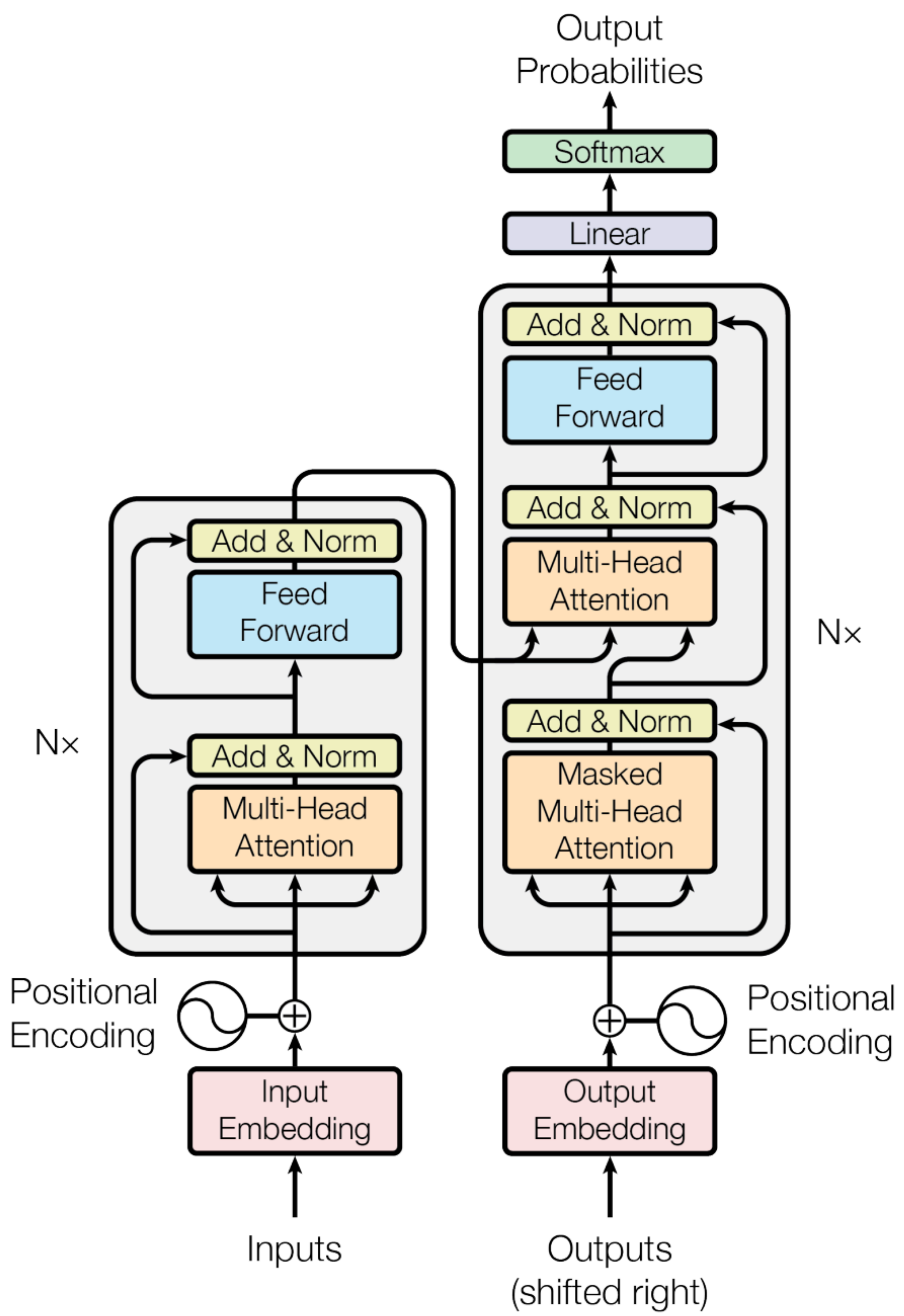

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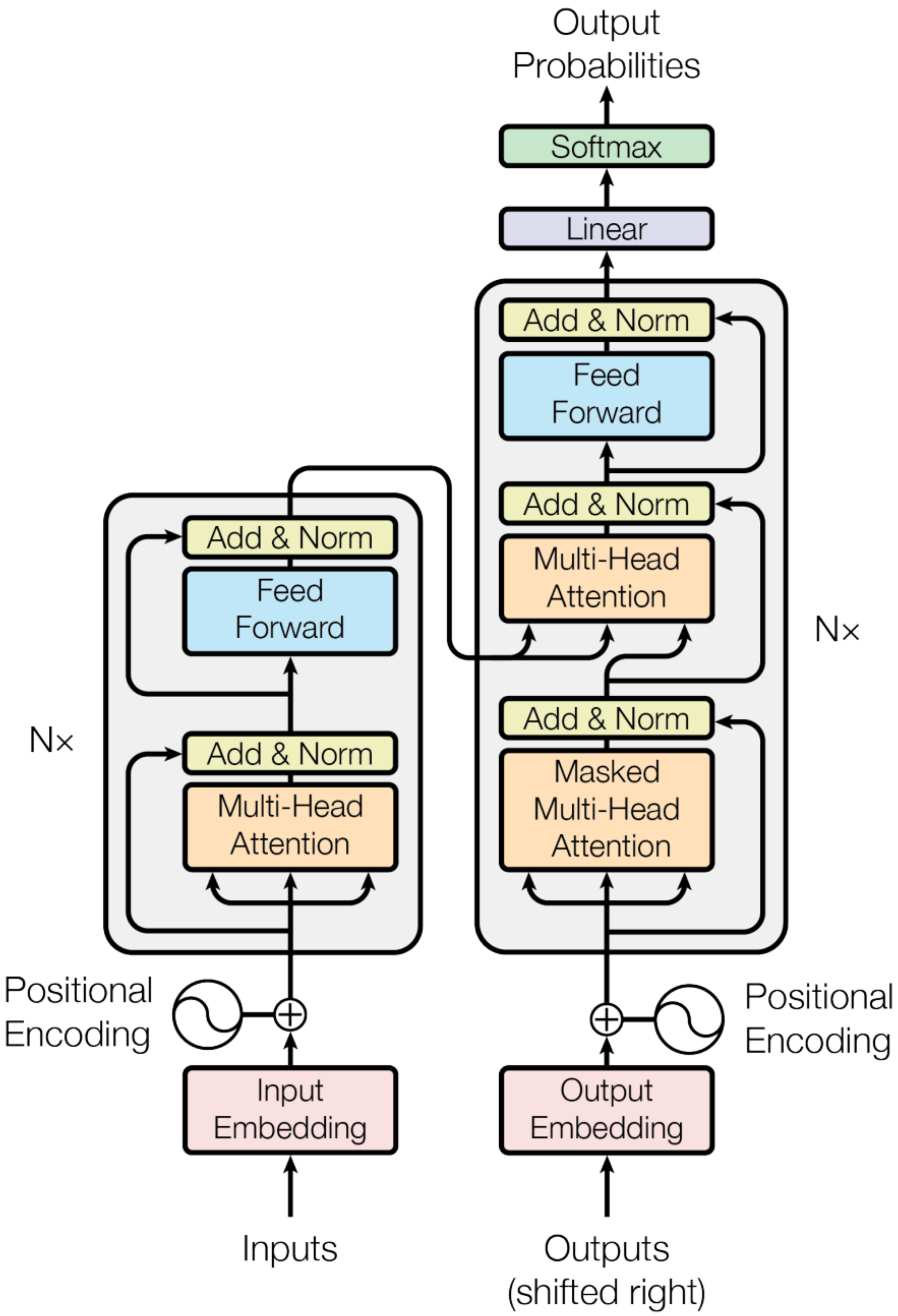

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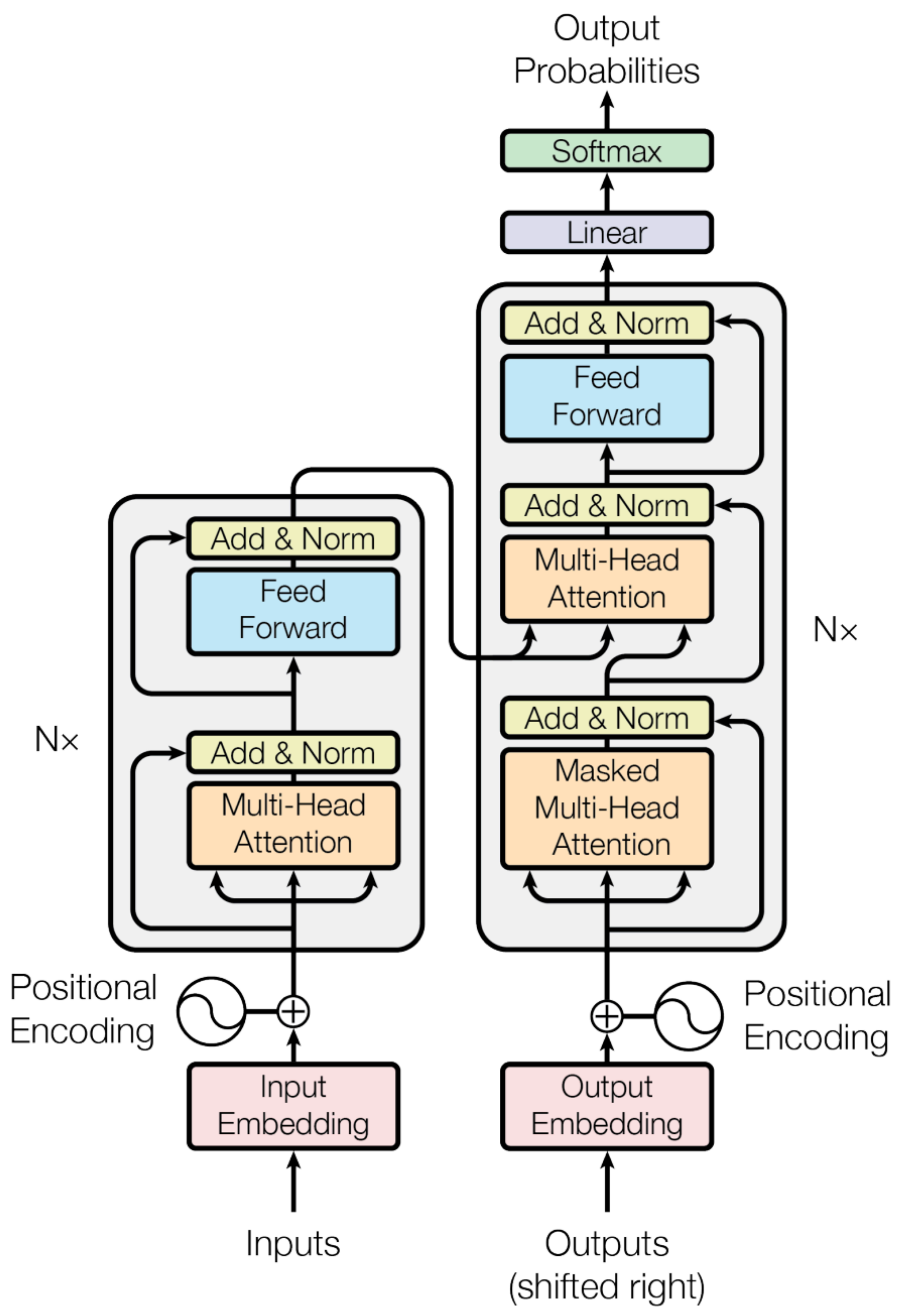

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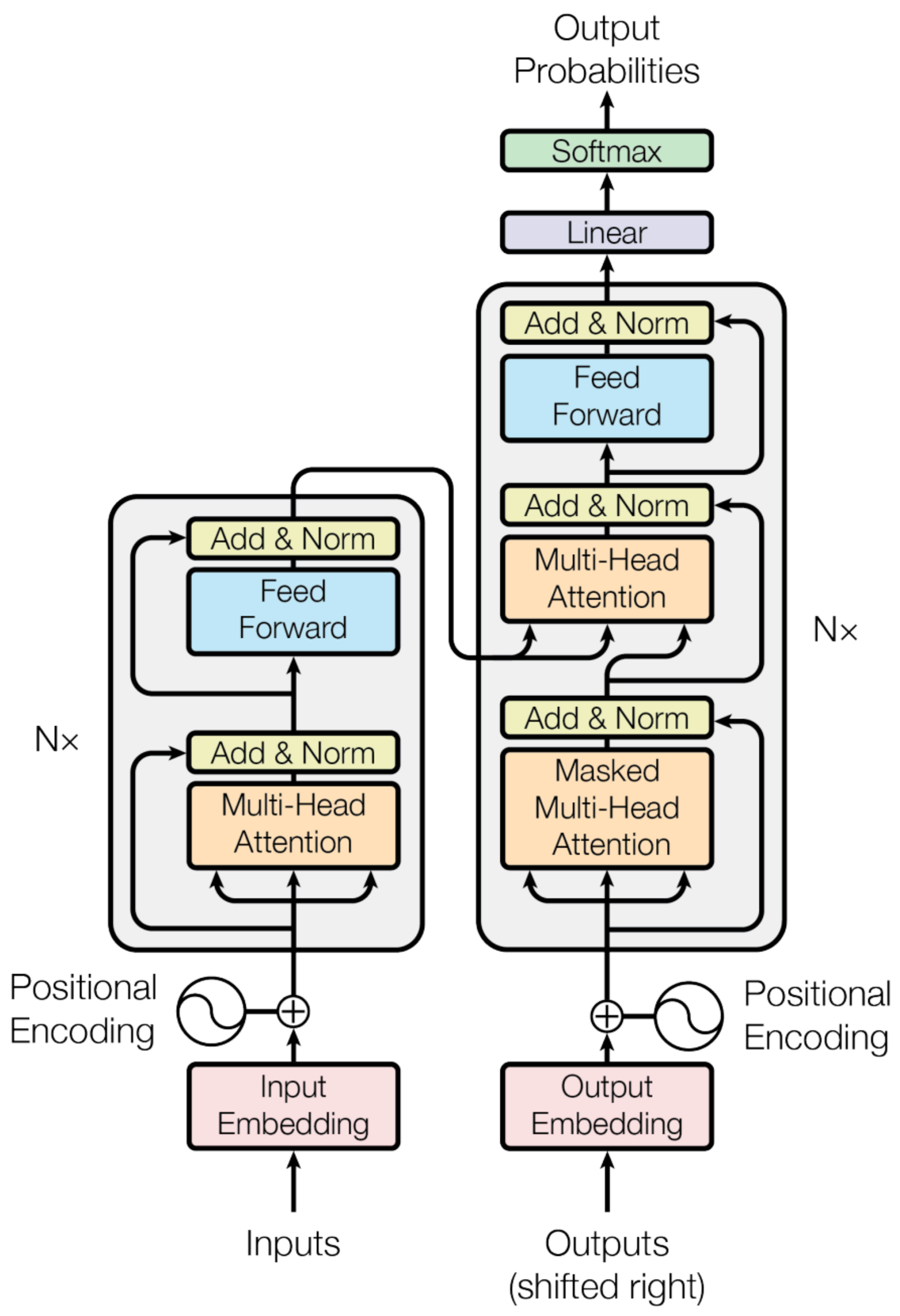

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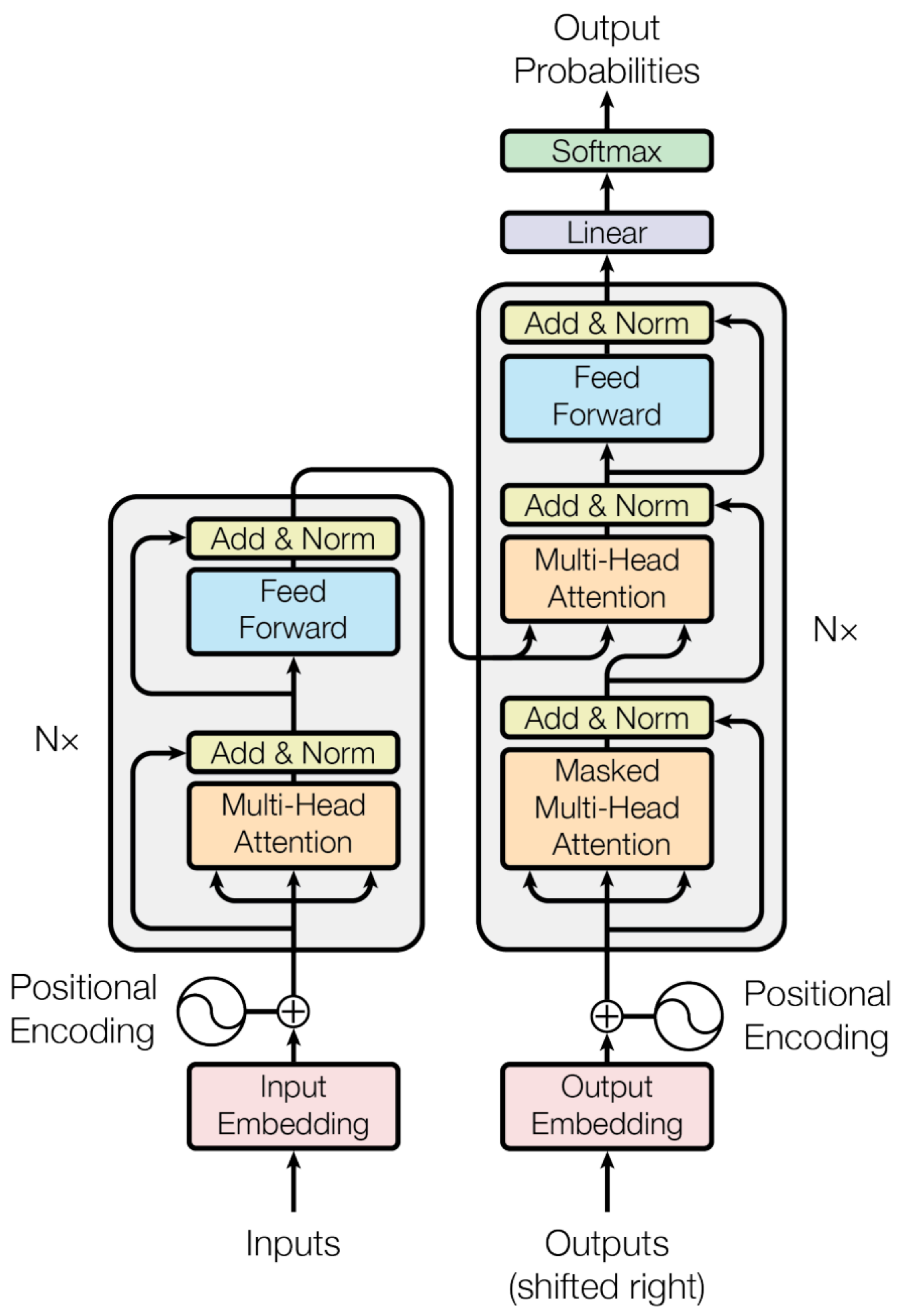
  - -> Needs positional encoders
- Attention weights are data-dependent and *change during runtime* (unlike Feed Forward NNs / MLPs)
- No communication *between batches* of data
- Attention is a general communication mechanism, tokens can be seen as nodes in a directed graph*



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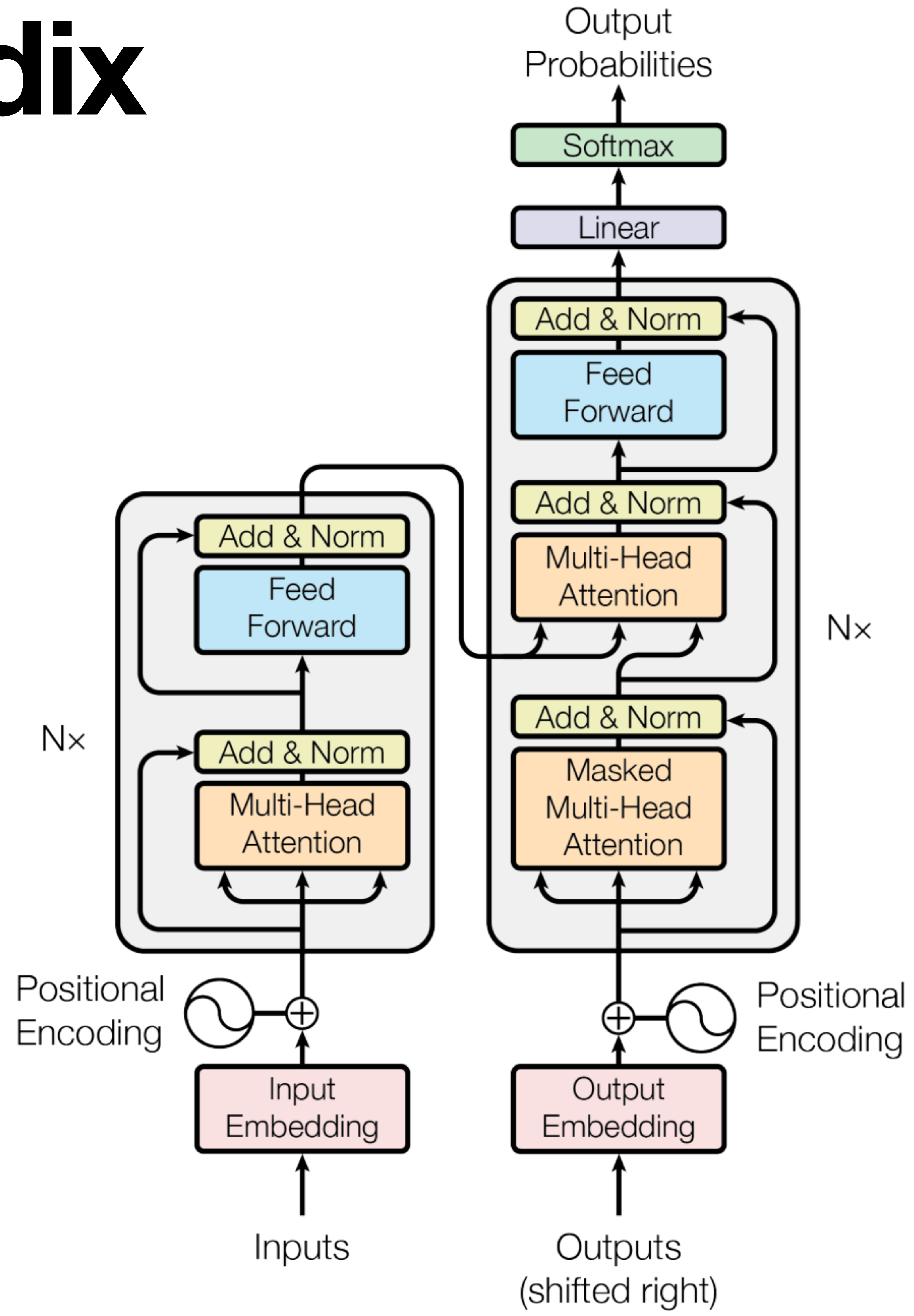
Appendix



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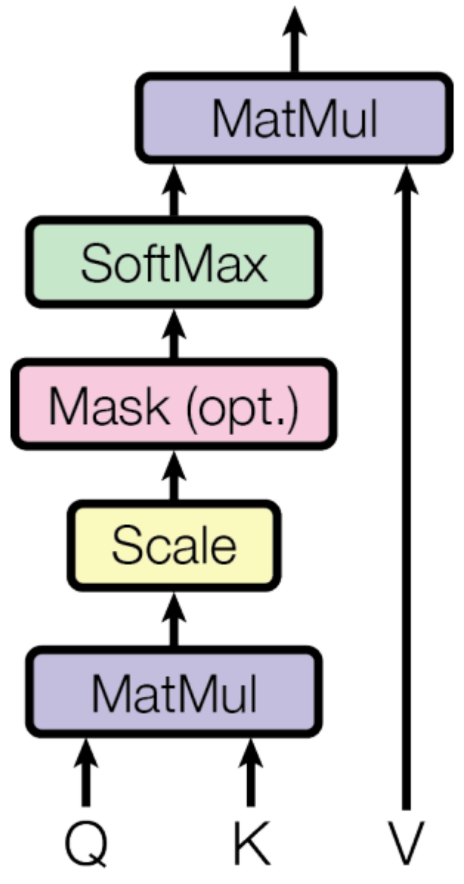
Scaled Dot-Product Attention



Multi-Head Attention