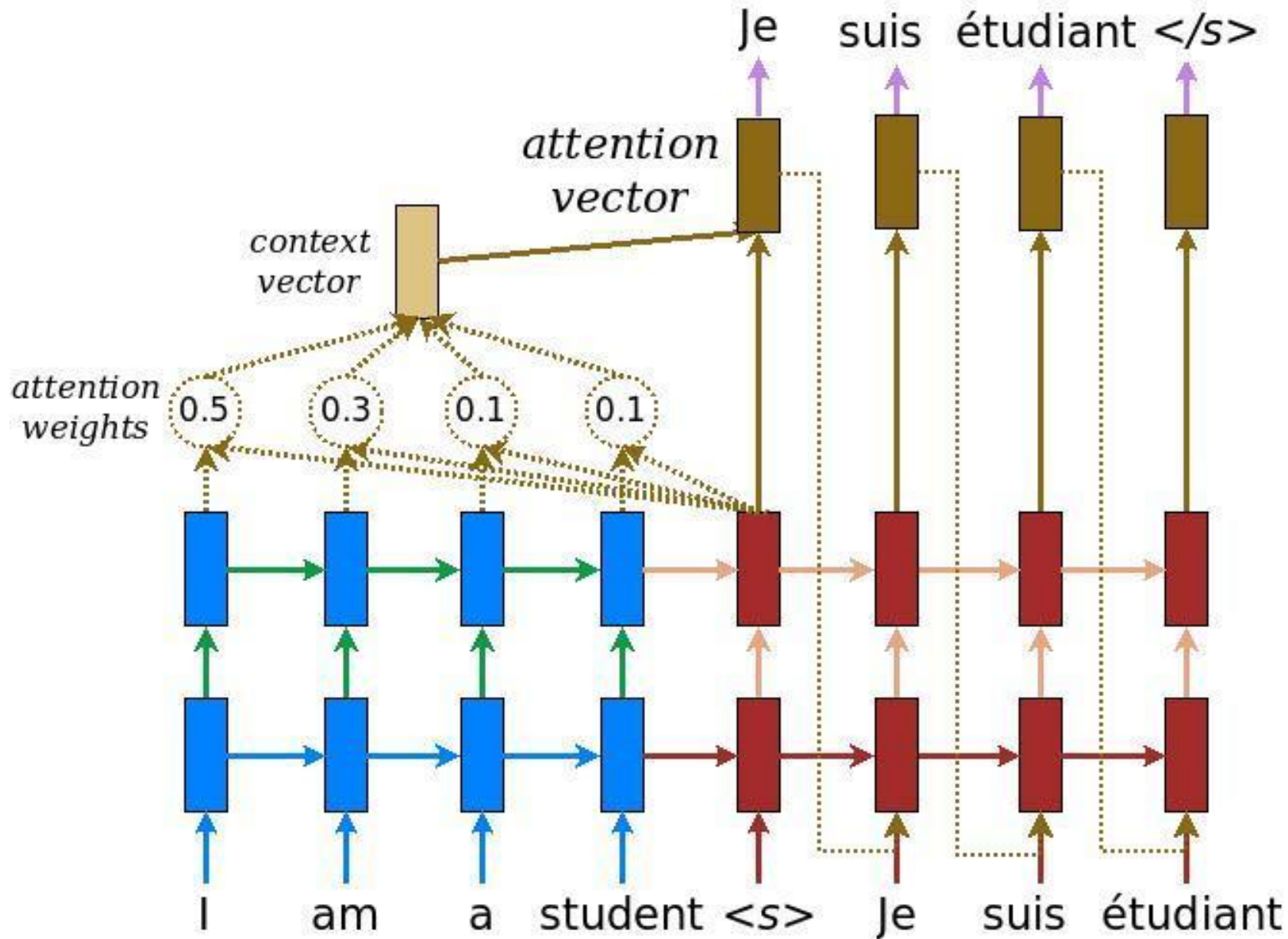
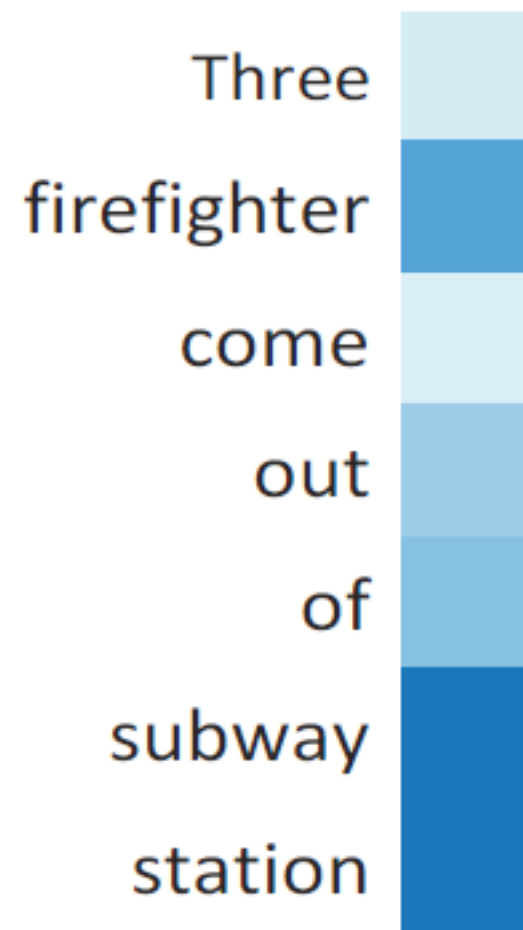
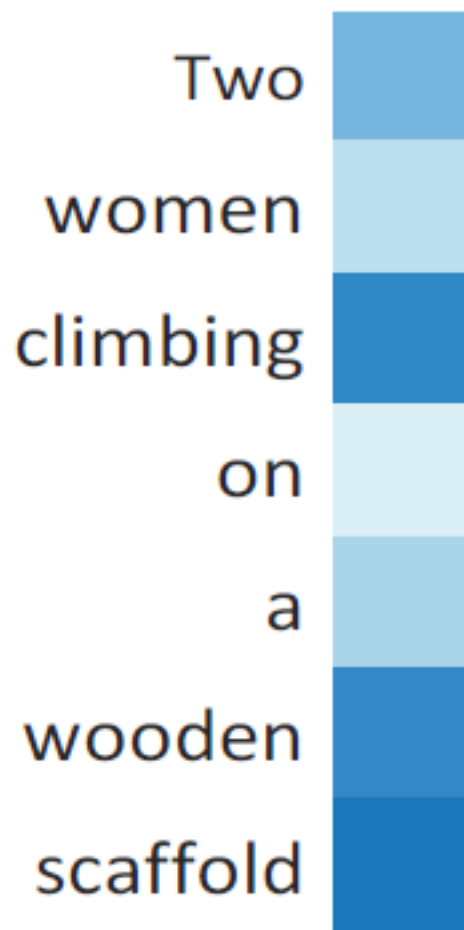
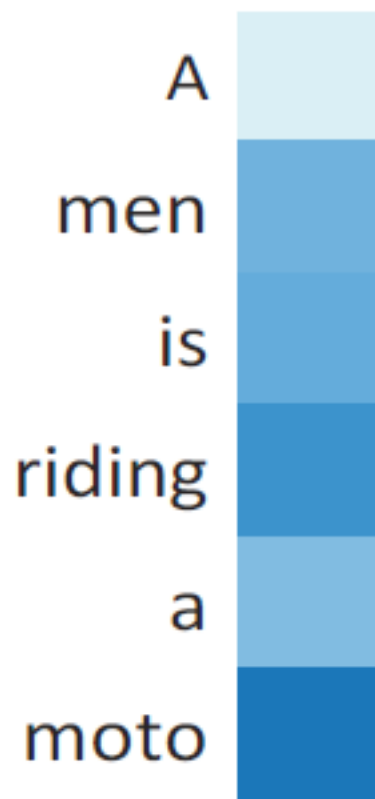


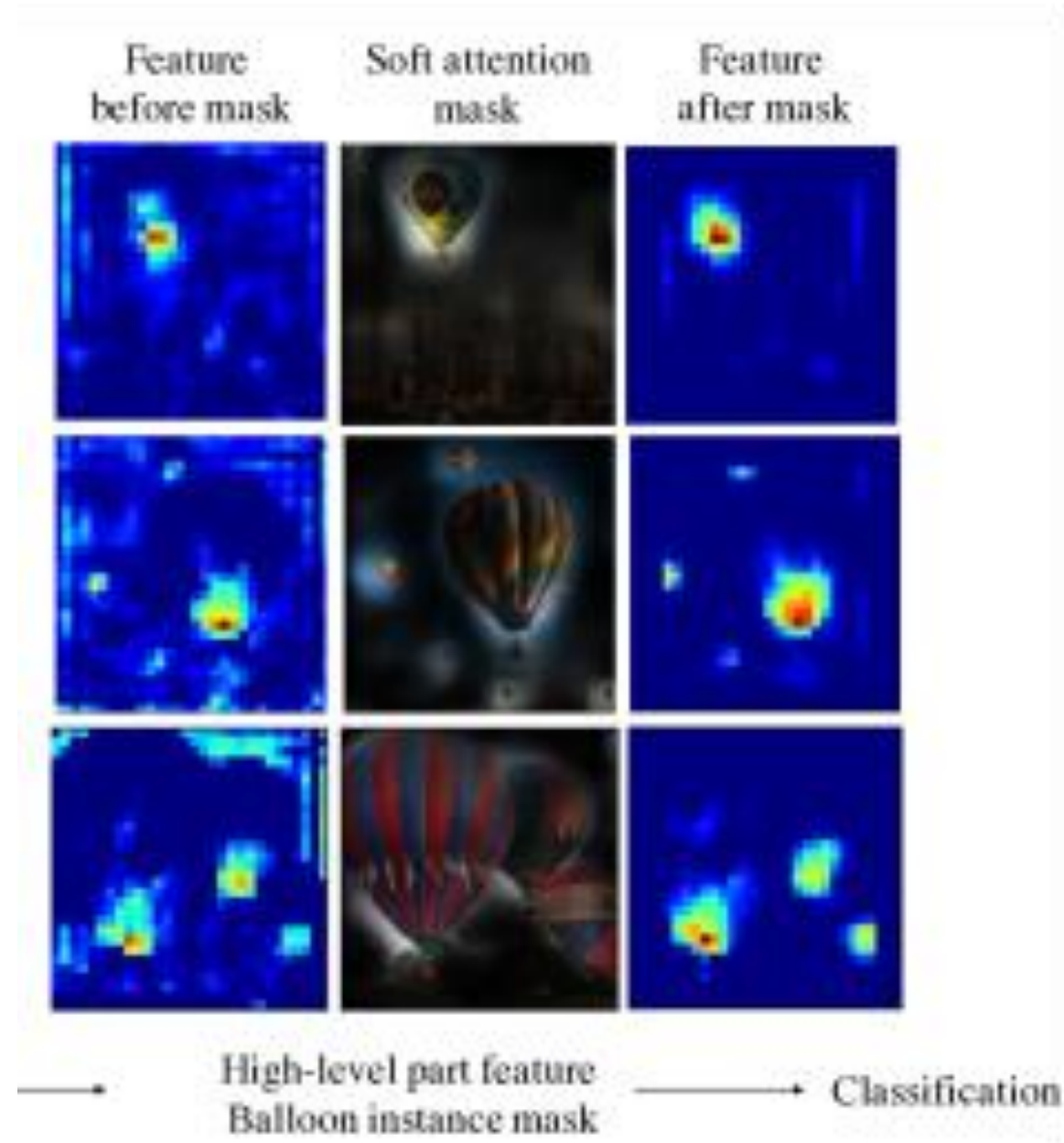
Attention



Attention



Visual attention



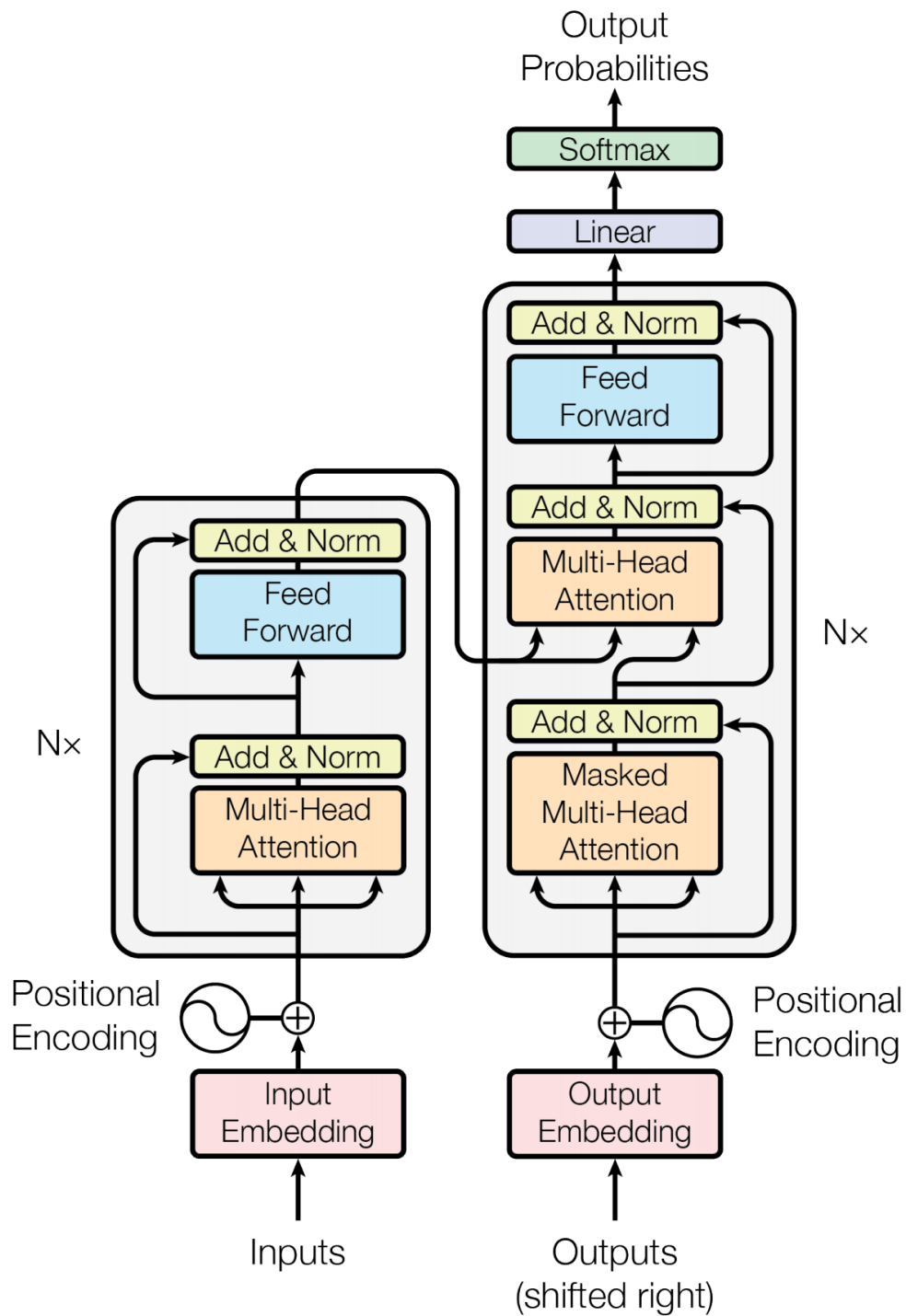
SQuAD1

Rank	Model	EM	F1
	Human Performance <i>Stanford University</i> (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Sep 13, 2018	nlnet (single model) <i>Microsoft Research Asia</i>	74.238	77.022
2 Sep 17, 2018	Unet (ensemble) <i>Fudan University & Liulishuo Lab</i>	71.553	75.011
2 Aug 15, 2018	Reinforced Mnemonic Reader + Answer Verifier (single model) <i>NUDT</i> https://arxiv.org/abs/1808.05759	71.699	74.238
2 Aug 28, 2018	SLQA+ (single model) <i>Alibaba DAMO NLP</i> http://www.aclweb.org/anthology/P18-1158	71.451	74.422
3 Sep 14, 2018	SAN (ensemble model) <i>Microsoft Business Applications Research Group</i> https://arxiv.org/abs/1712.03556	71.282	73.658

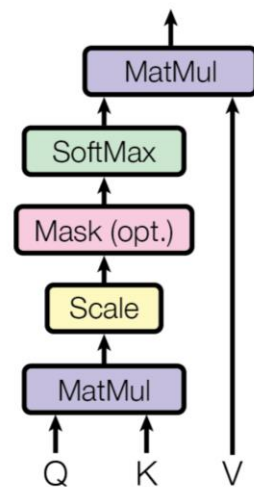
SQuAD2

Rank	Model	EM	F1
	Human Performance <i>Stanford University</i> (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Jul 22, 2019	XLNet + DAAF + Verifier (ensemble) <i>PINGAN Omni-Sinitic</i>	88.592	90.859
2 Jul 19, 2019	XLNet + SG-Net Verifier (ensemble) <i>Shanghai Jiao Tong University & CloudWalk</i>	88.050	90.645
3 Jul 23, 2019	XLNet + SG-Net Verifier (single model) <i>Shanghai Jiao Tong University & CloudWalk</i>	87.046	89.899
3 Mar 20, 2019	BERT + DAE + AoA (ensemble) <i>Joint Laboratory of HIT and iFLYTEK Research</i>	87.147	89.474
3 Jul 20, 2019	RoBERTa (single model) <i>Facebook AI</i>	86.820	89.795
4 Mar 15, 2019	BERT + ConvLSTM + MTL + Verifier (ensemble) <i>Layer 6 AI</i>	86.730	89.286
5 Mar 05, 2019	BERT + N-Gram Masking + Synthetic Self-Training (ensemble) <i>Google AI Language</i> https://github.com/google-research/bert	86.673	89.147

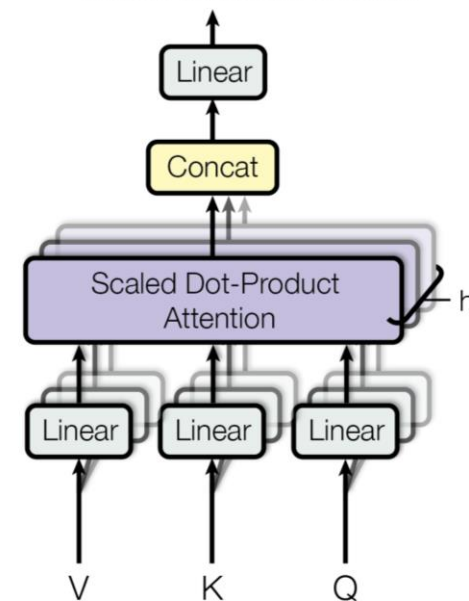
Multi-Head Attention Transformer



Scaled Dot-Product Attention



Multi-Head Attention

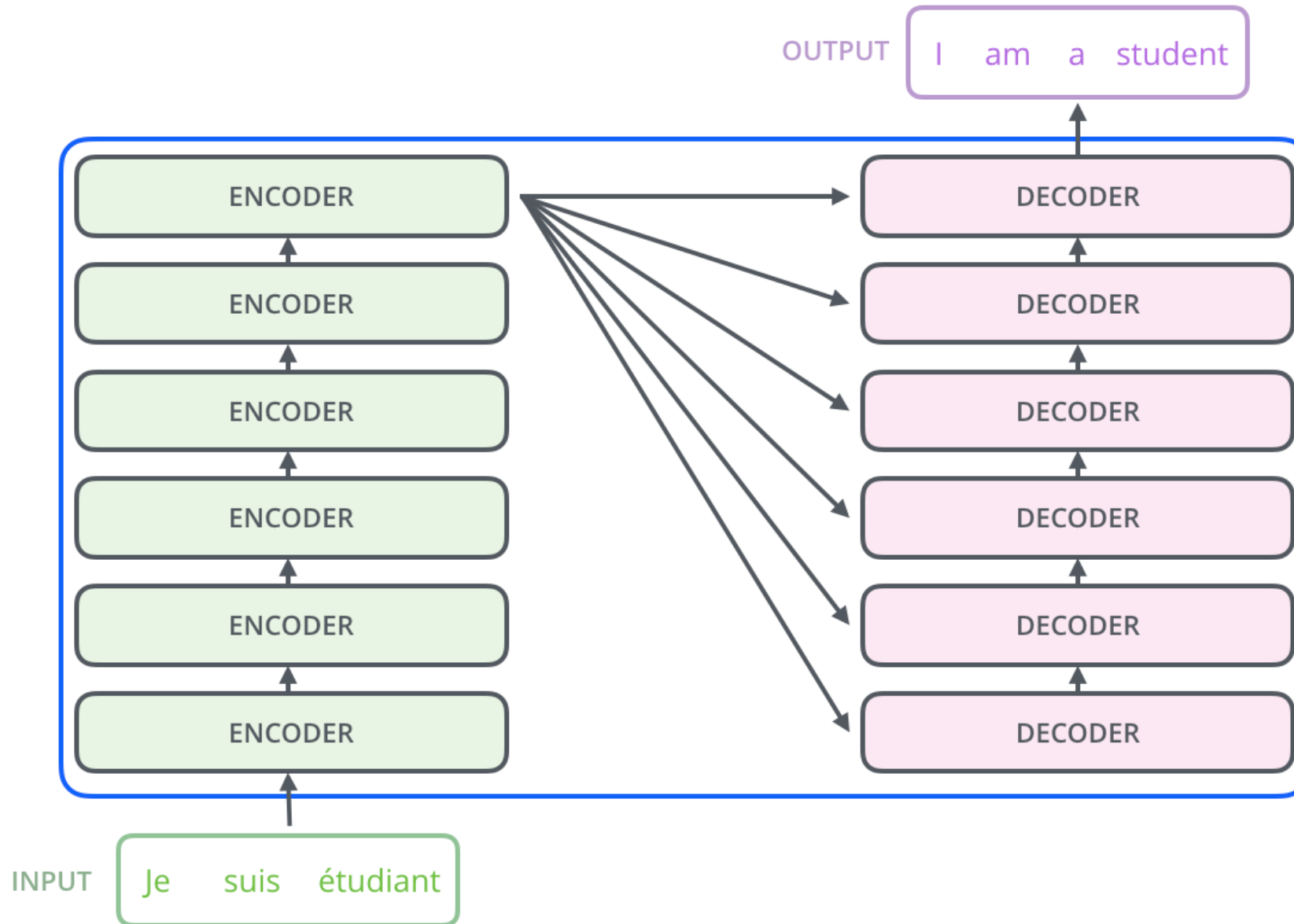


The Illustrated Transformer

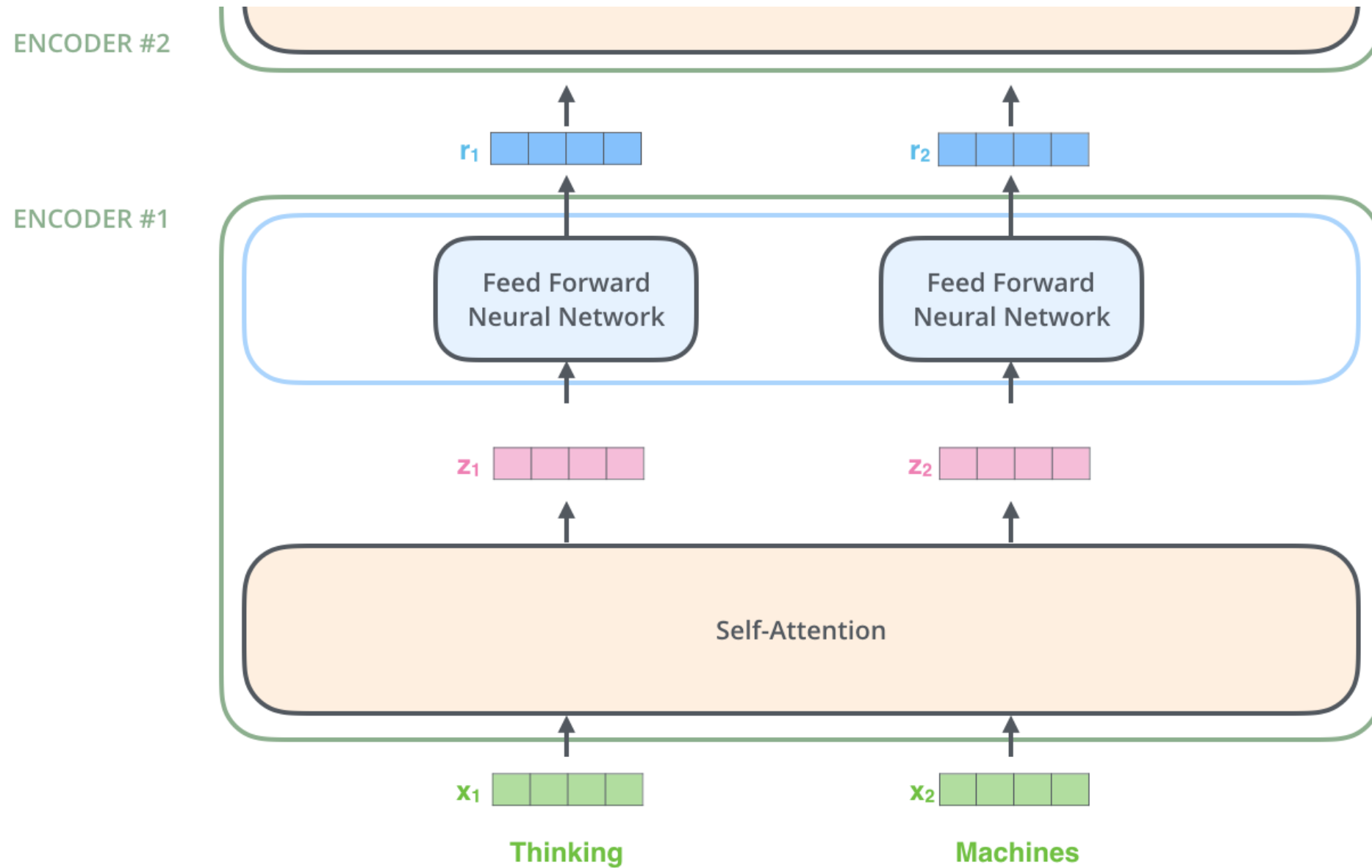
<http://jalammar.github.io/illustrated-transformer/>



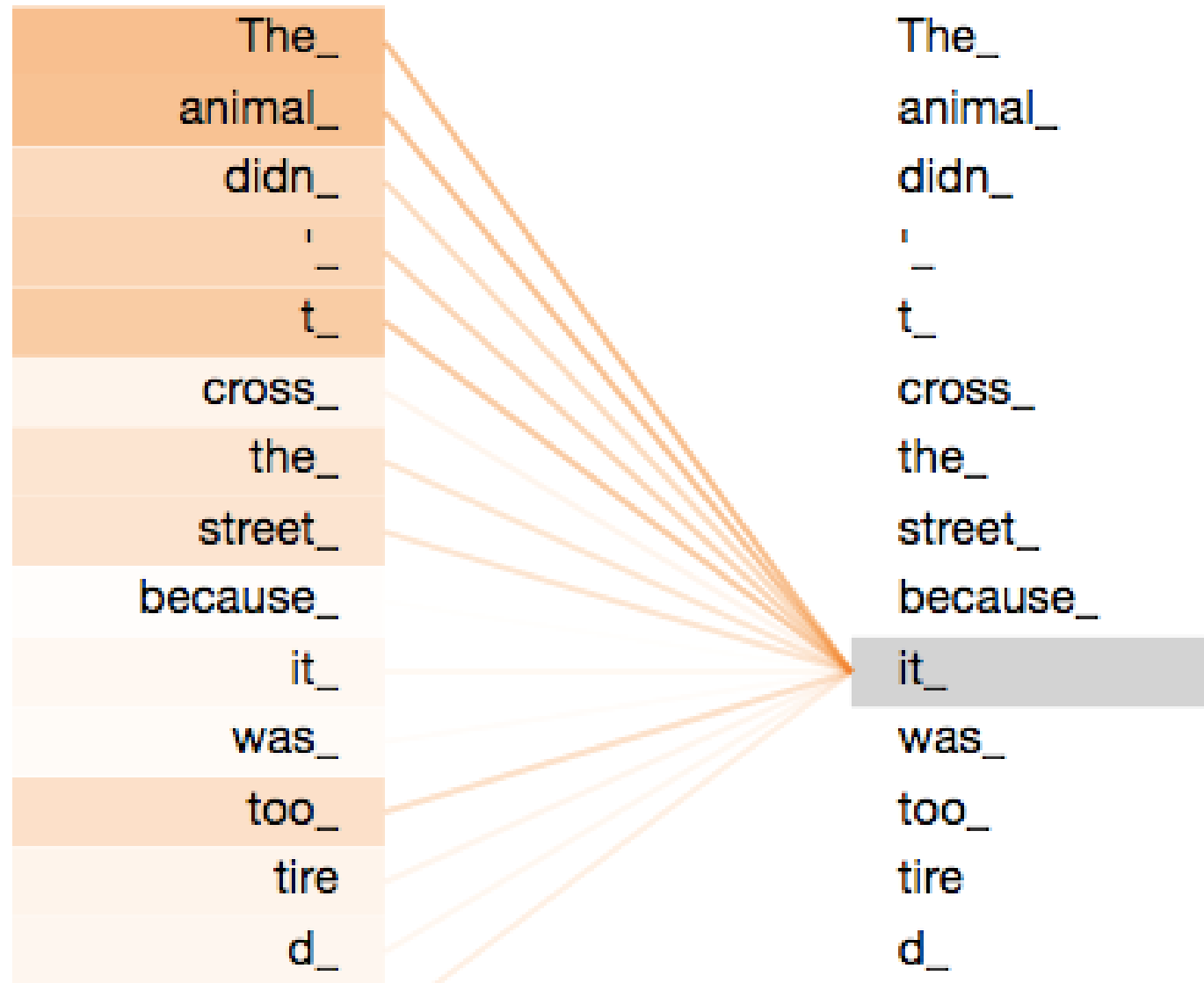
Transformer



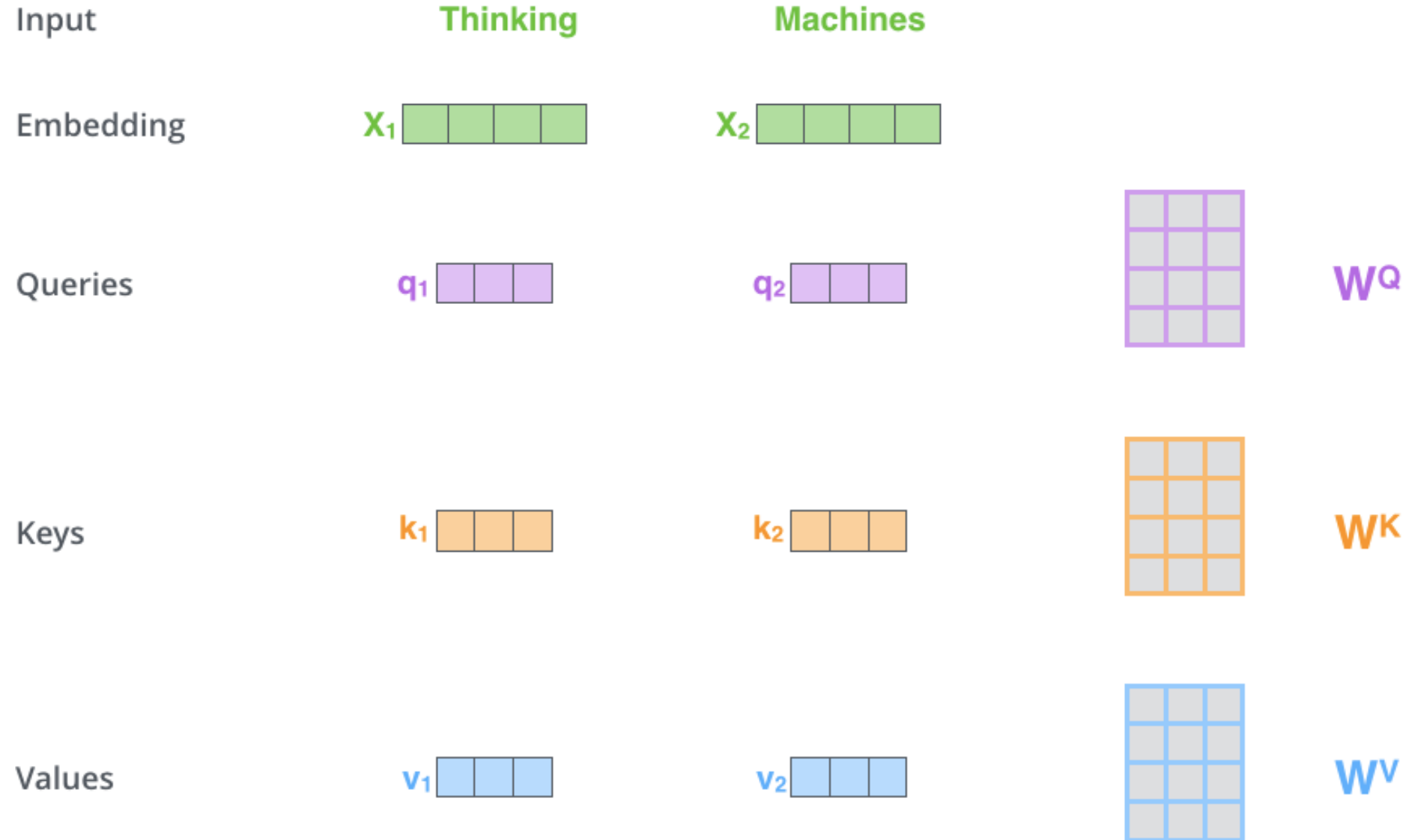
Transformer



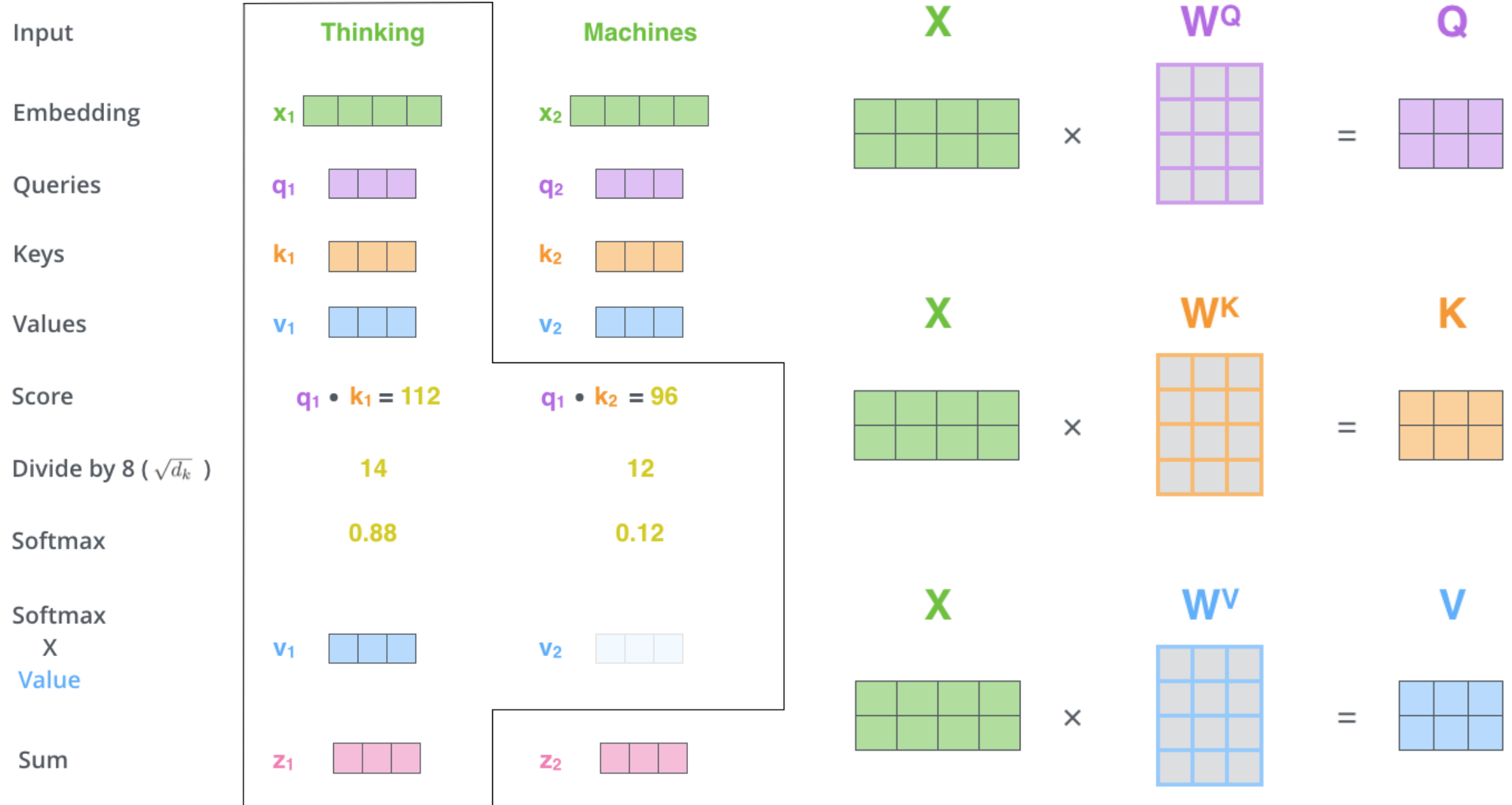
Self-attention



Queries, Keys and Values



Self attention

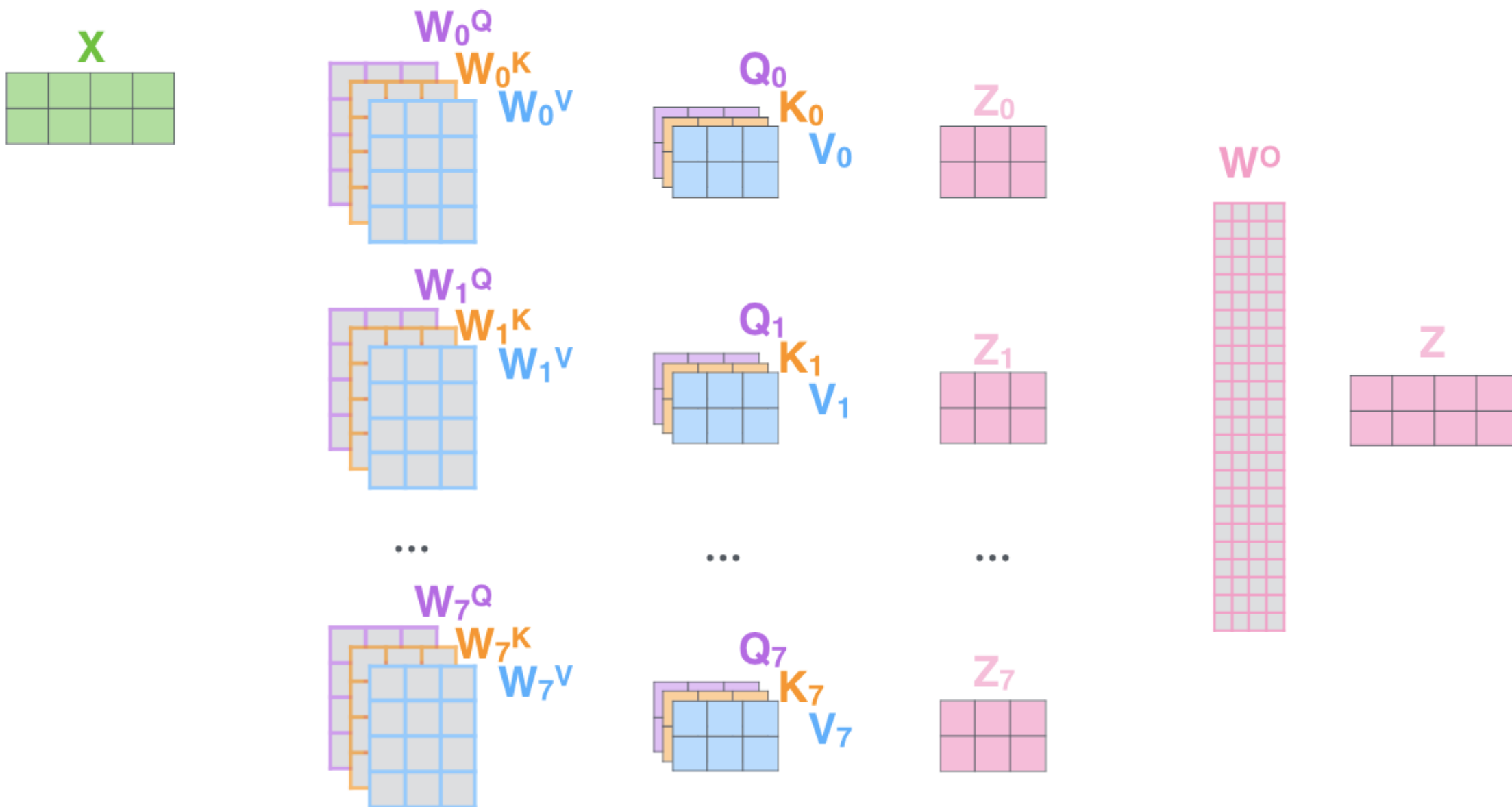


Transformer formula

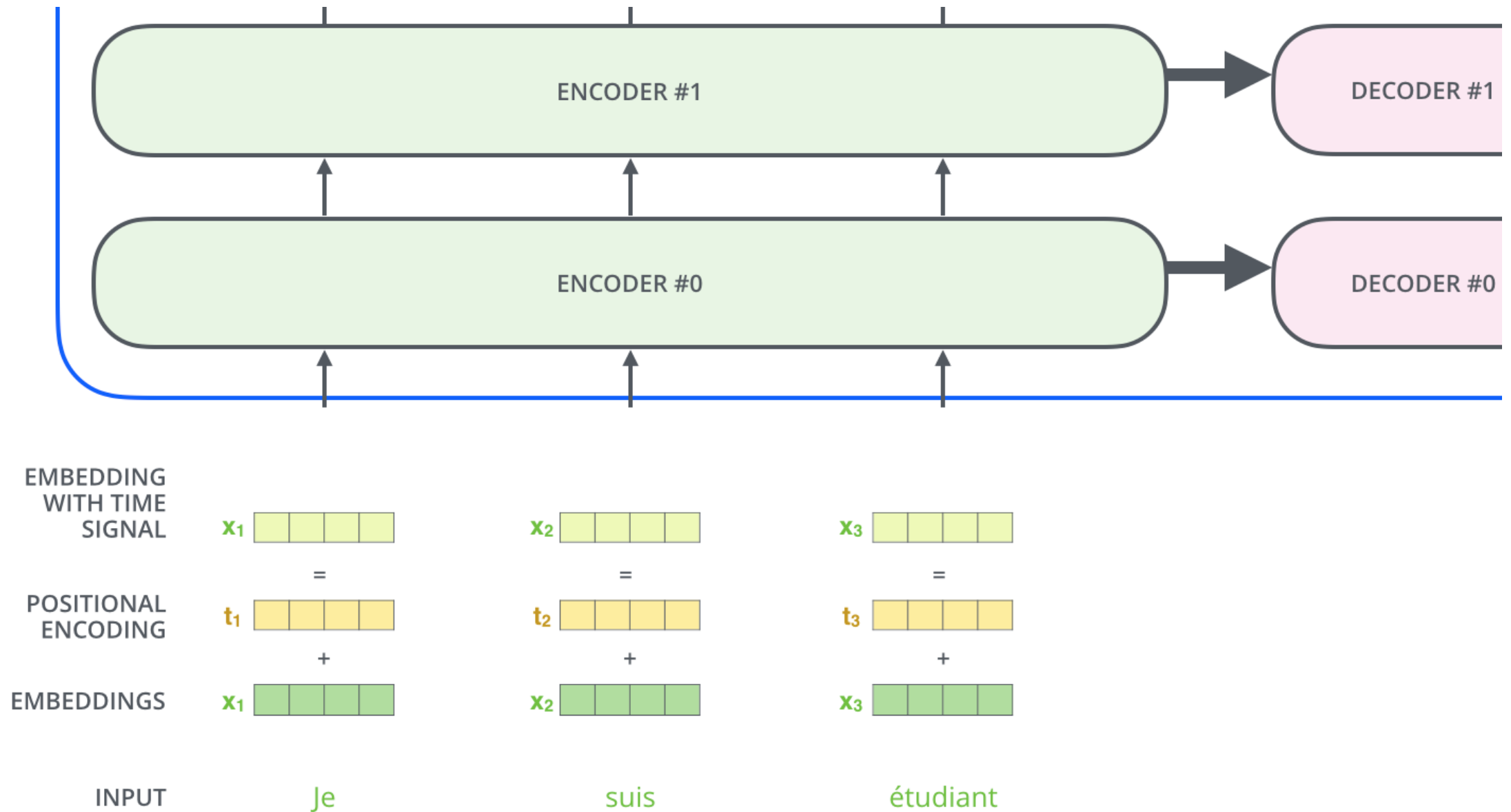
$$\text{softmax}\left(\frac{\begin{matrix} \text{Q} \\ \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} \end{matrix} \times \begin{matrix} \text{K}^T \\ \begin{array}{|c|c|} \hline \square & \square \\ \hline \square & \square \\ \hline \square & \square \\ \hline \end{array} \end{matrix}\right) \begin{matrix} \text{V} \\ \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} \end{matrix} = \begin{matrix} \text{Z} \\ \begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & \square & \square \\ \hline \end{array} \end{matrix}$$

The diagram illustrates the Transformer formula for calculating the output Z. It shows the softmax function applied to the scaled dot product of the Query (Q) and Key (K^T) matrices, followed by multiplication with the Value (V) matrix. The matrices are represented as grids of colored squares: Q is a 2x3 purple grid, K^T is a 3x2 orange grid, V is a 2x3 blue grid, and Z is a 2x3 pink grid. The scaling factor is $\sqrt{d_k}$.

Multi-headed attention



Positional encoding



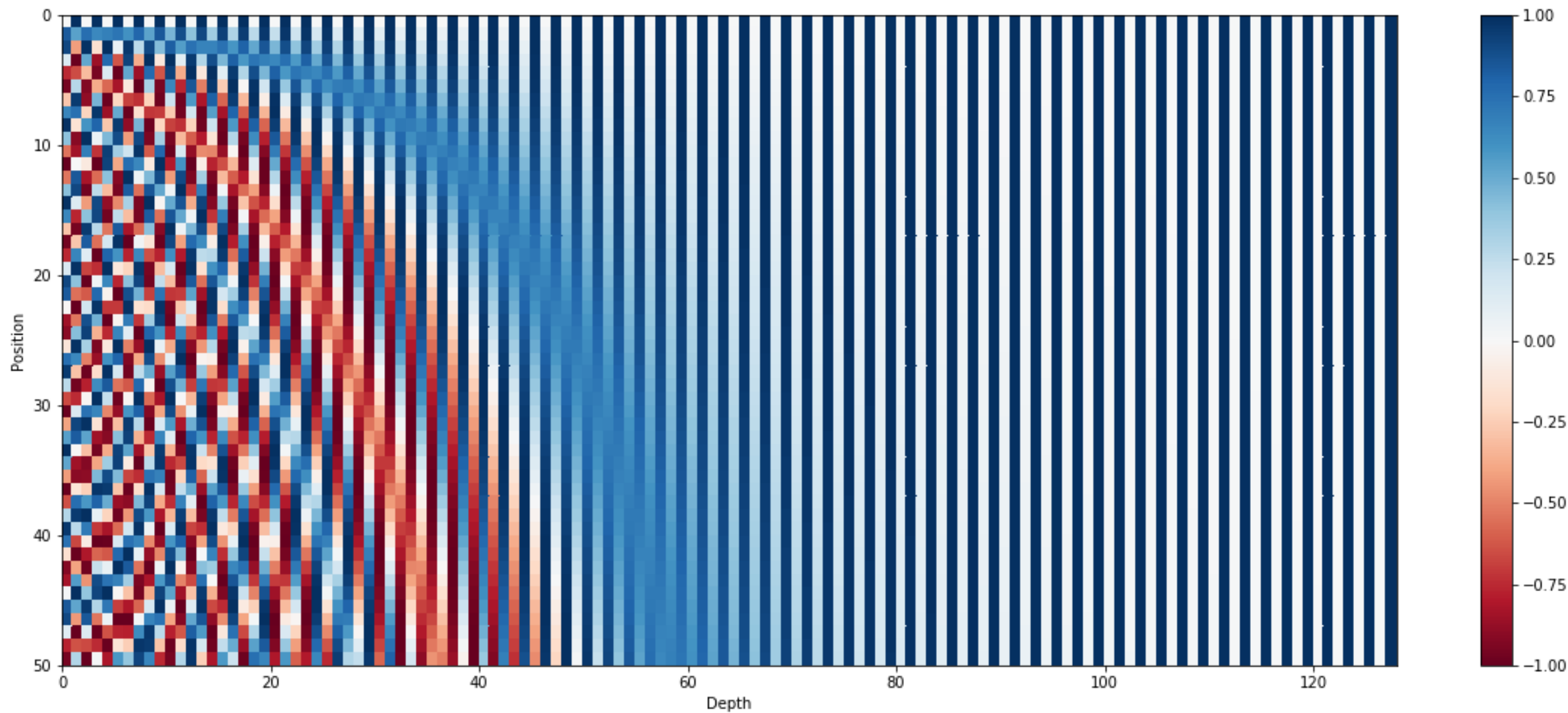
Positional encoding

- It should output a unique encoding for each time-step (word's position in a sentence)
- Distance between any two time-steps should be consistent across sentences with different lengths.
- Our model should generalize to longer sentences without any efforts. Its values should be bounded.
- It must be deterministic.

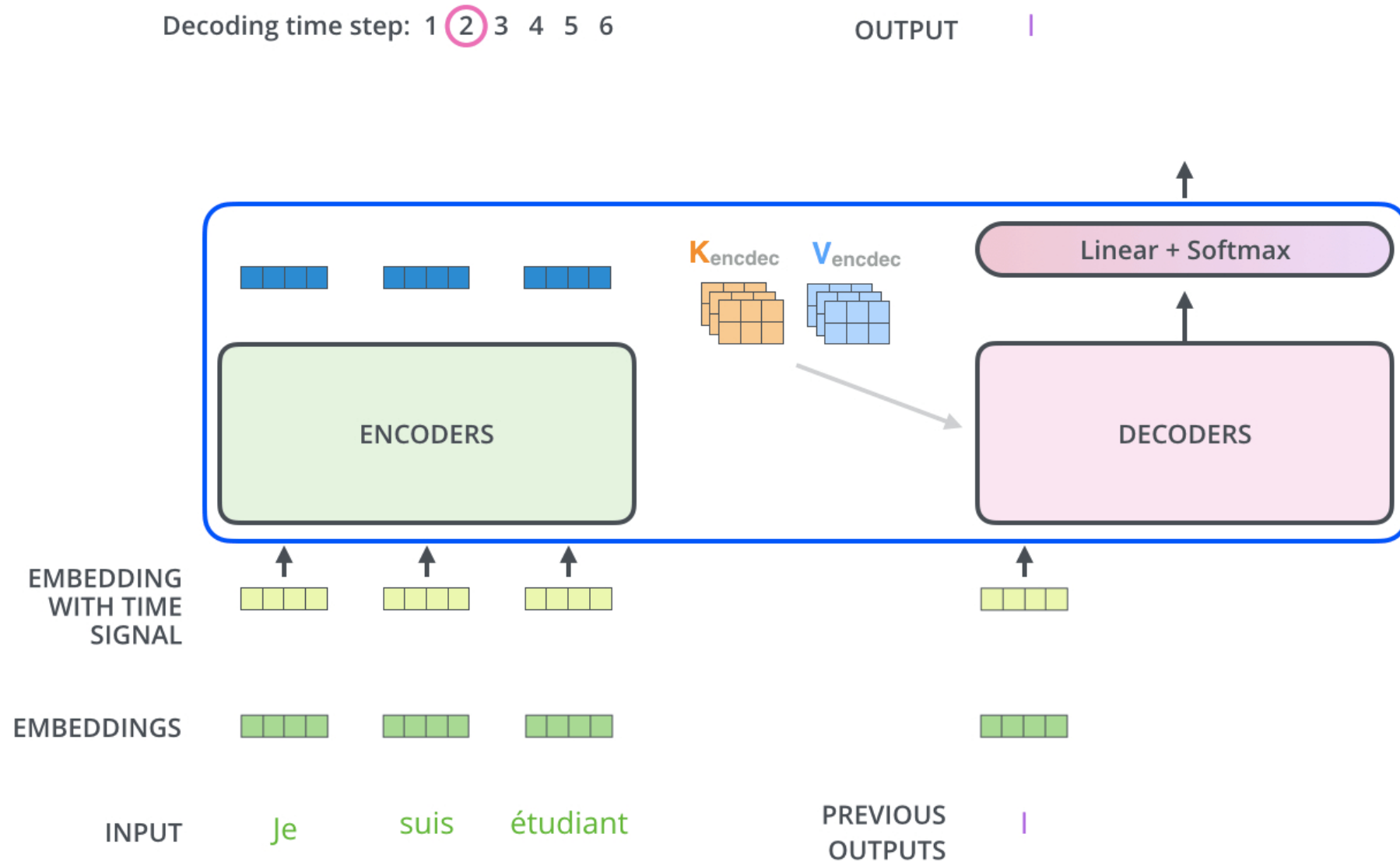
$$PE_{(pos, 2i)} = \sin(pos/10000^{2i/d_{\text{model}}})$$

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

Positional encoding



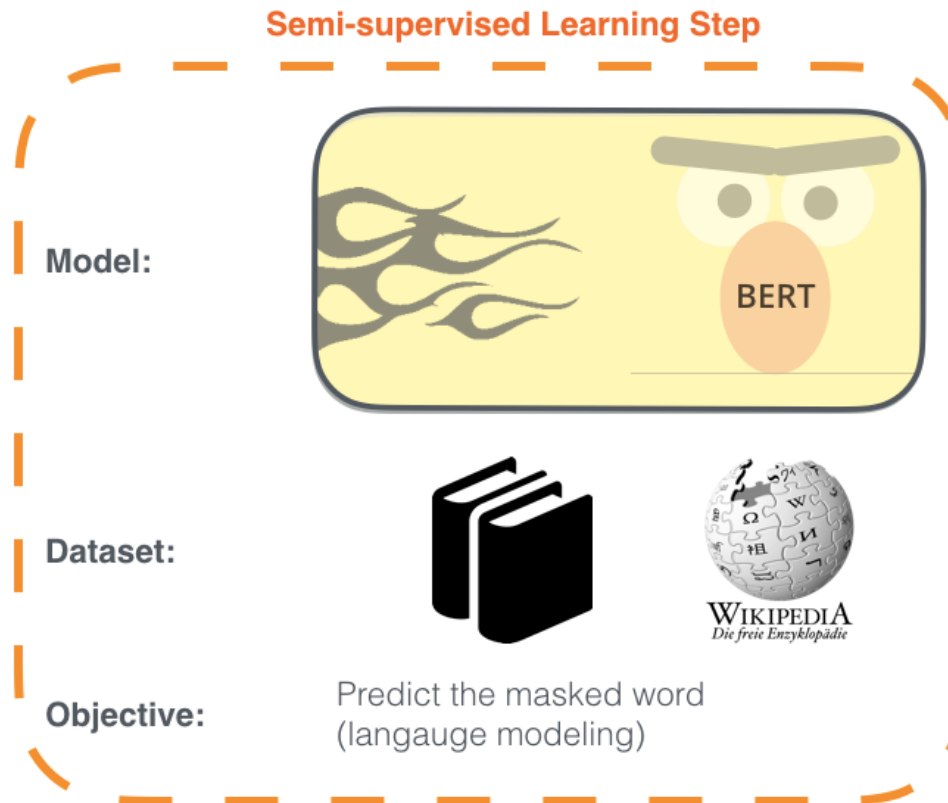
Encoder - decoder



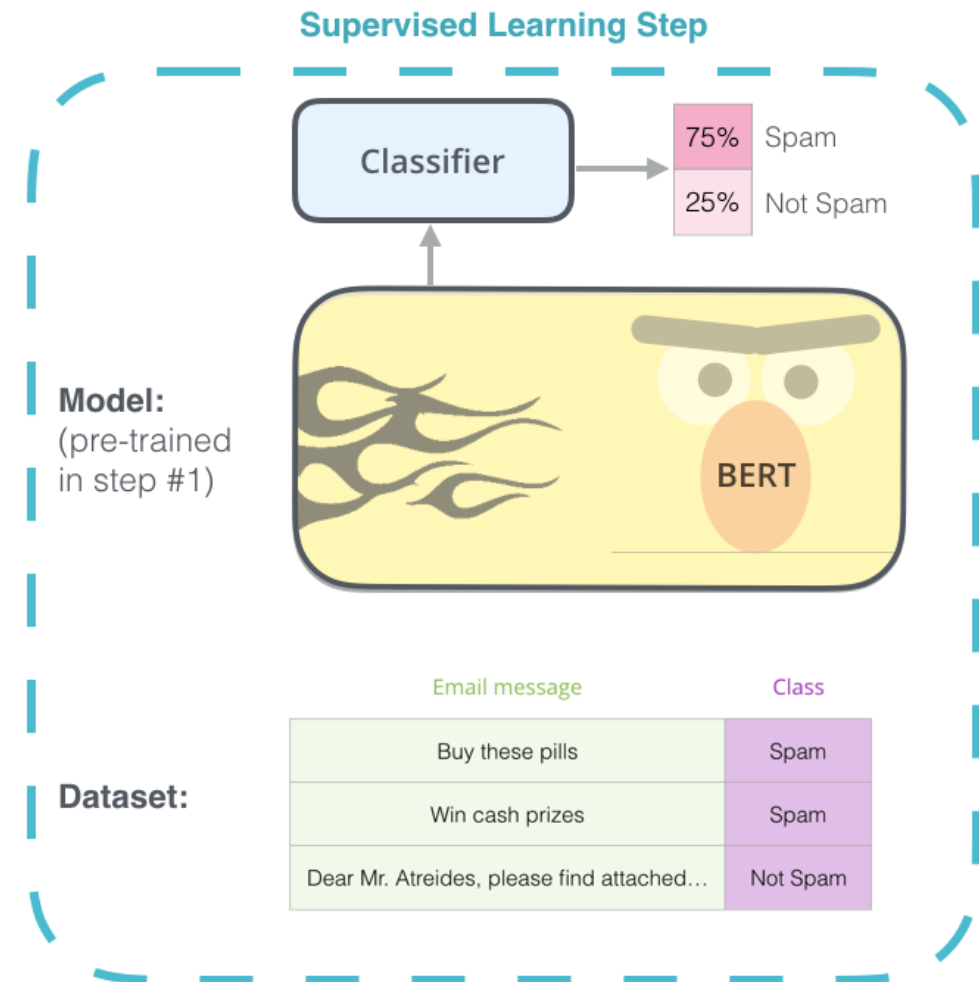
Bidirectional Encoder Representations from Transformers (**BERT**)

1 - **Semi-supervised** training on large amounts of text (books, wikipedia..etc).

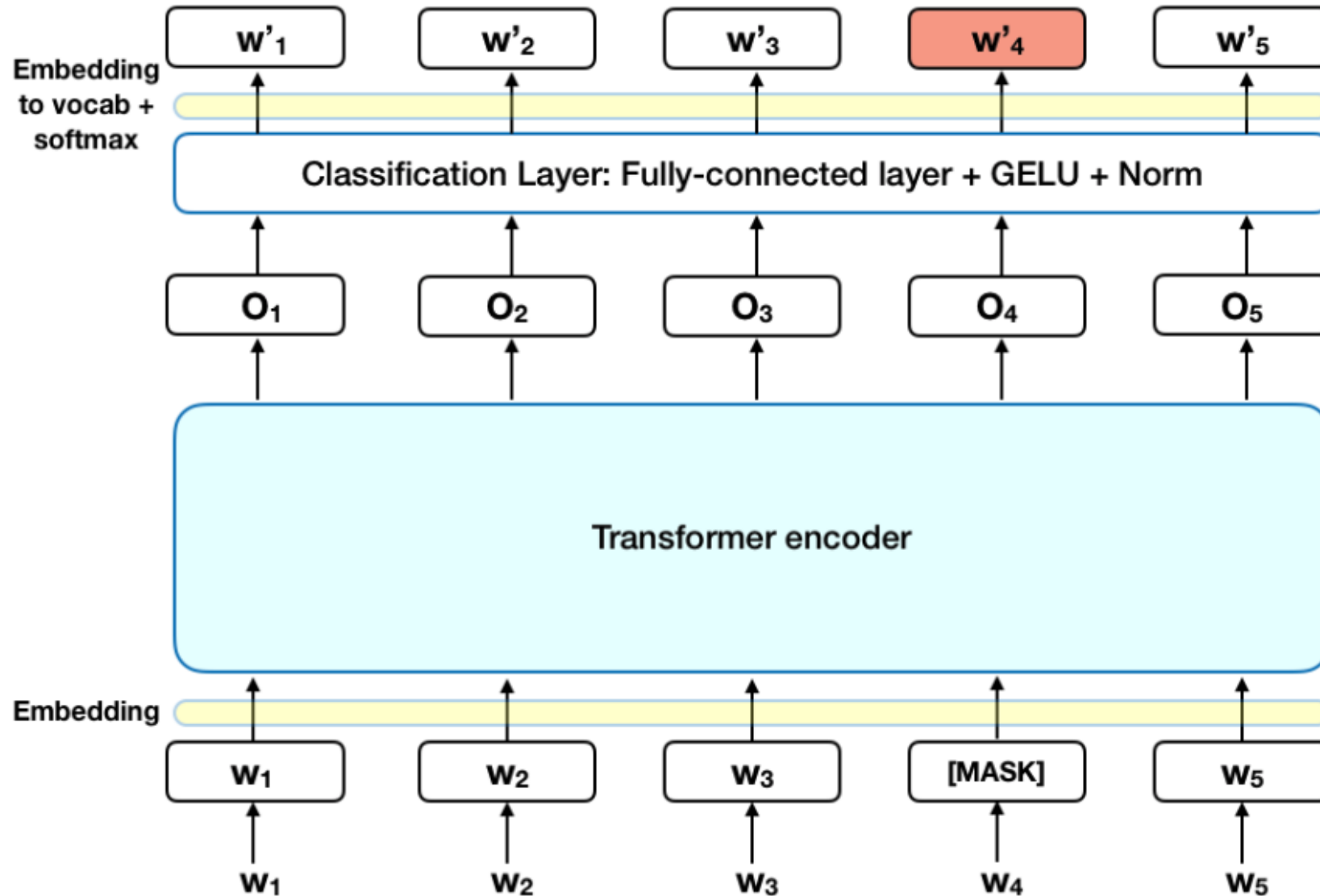
The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.



2 - **Supervised** training on a specific task with a labeled dataset.



Bidirectional Encoder Representations from Transformers (**BERT**)



ChatGPT

