Language Understanding

05 - Transformers

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Introduction

- Assume we have a fixed size sequence, so sequence modeling is a problem of:

$$f:\quad \mathbb{R}^d \longrightarrow \mathbb{R}$$

  where the input is a fixed size vector.
- But, documents have variable lengths. We should somehow encode a document in a fixed size vector.
- Typical ways to do this:

Bag of Words | RNN | LSTM | Attention | Transformer

Introduction

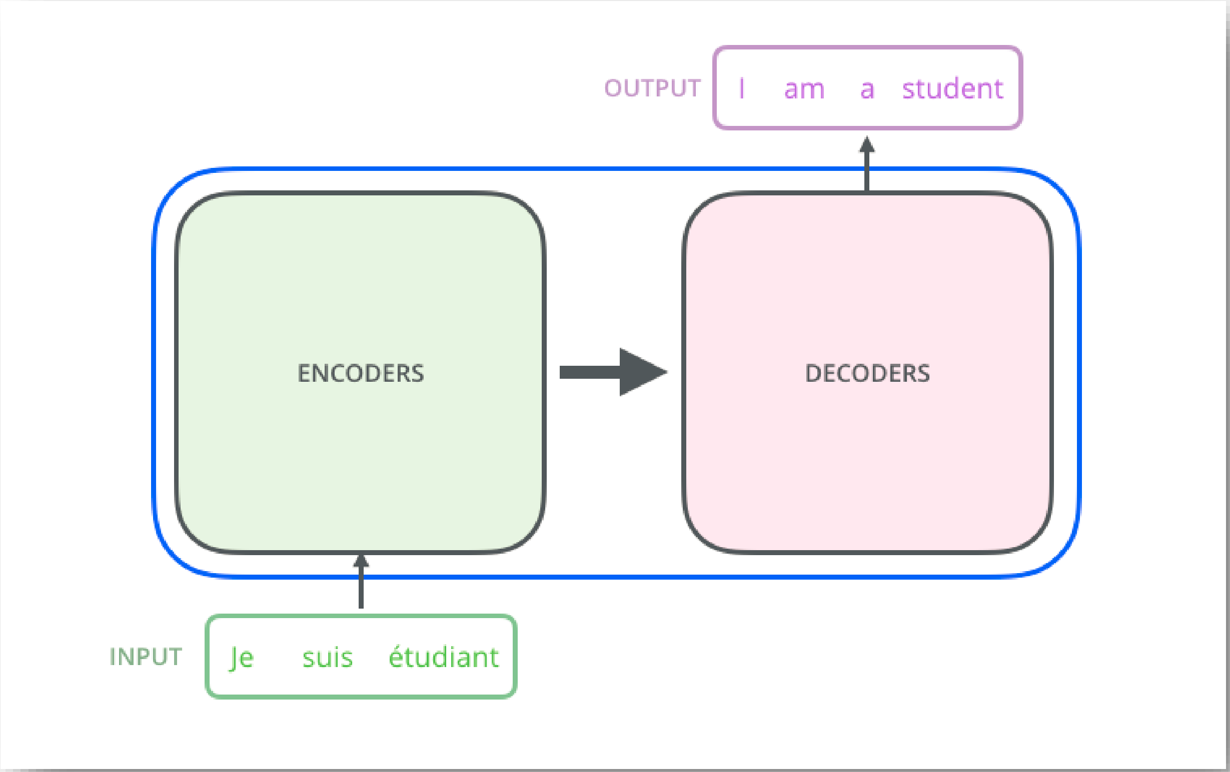
- Bag of Words:
  - One dimension per word in vocabulary ($d \approx 100{,}000$)
  - Almost all values are zero
    - Can use sparse data and only store non-zero data
  - Cannot preserve word order while order matters in our tasks.
    - E.g. "work to live" vs. "live to work"
  - N-grams as a solution:
    - The dimensionality is d^N
- RNN:
  - We saw how we can use RNN for sequence modeling
  - Main problem: Vanishing & Exploding Gradients
  - It is practical for only very short segments

Introduction

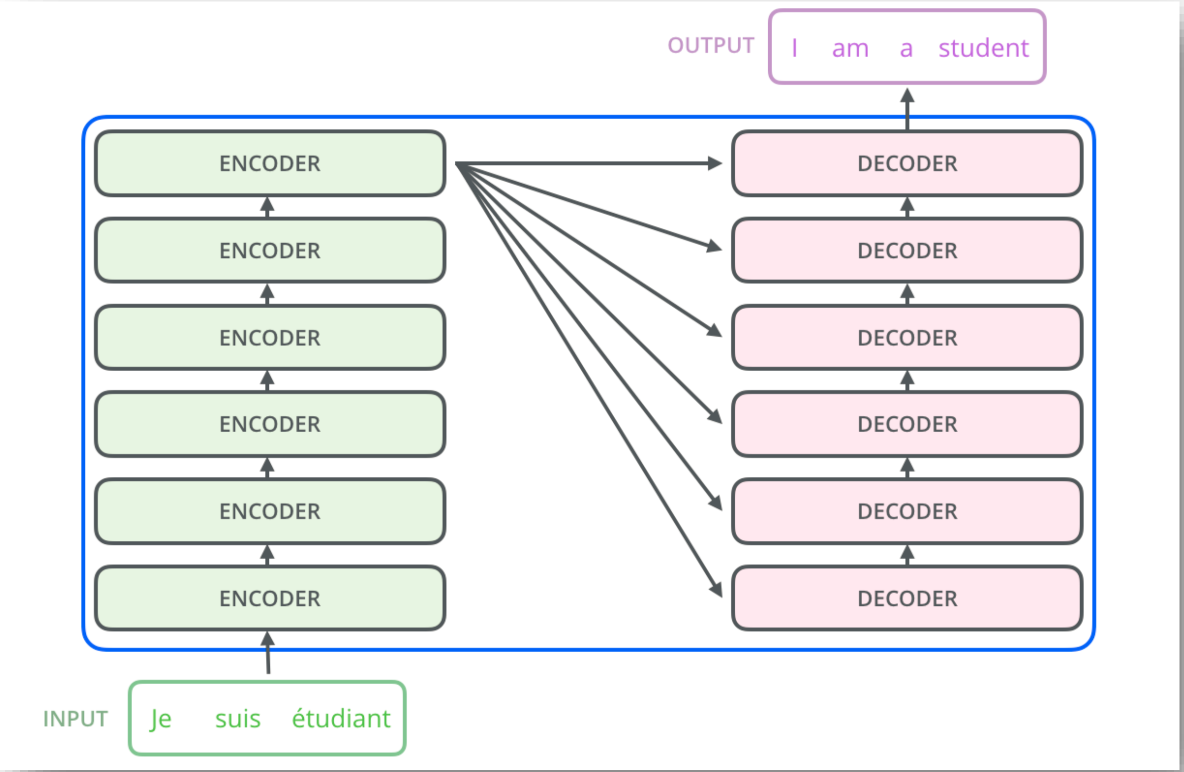
- LSTM:
  - Again, we saw how LSTM can be used for sequence modeling
  - Difficult to train
    - Forward pass is not parallelizable like RNN
  - Very long gradients paths for long sequences
    - Vanishing gradient, even with a forget gate
  - Transfer learning never really worked
    - Finetuning a pre-trained network with small labeled training data
      - It needs lots of labeled data to train the network from scratch
- Seq2seq models with attentions:
  - Has better performance because it uses a combination of encoder hidden states.
    - Allows modeling of dependencies without regard to their distance in the input or output sequences
  - But, in all but a few cases, encoder and decoder are still RNN/LSTM.

Transformer

Transformer Topology

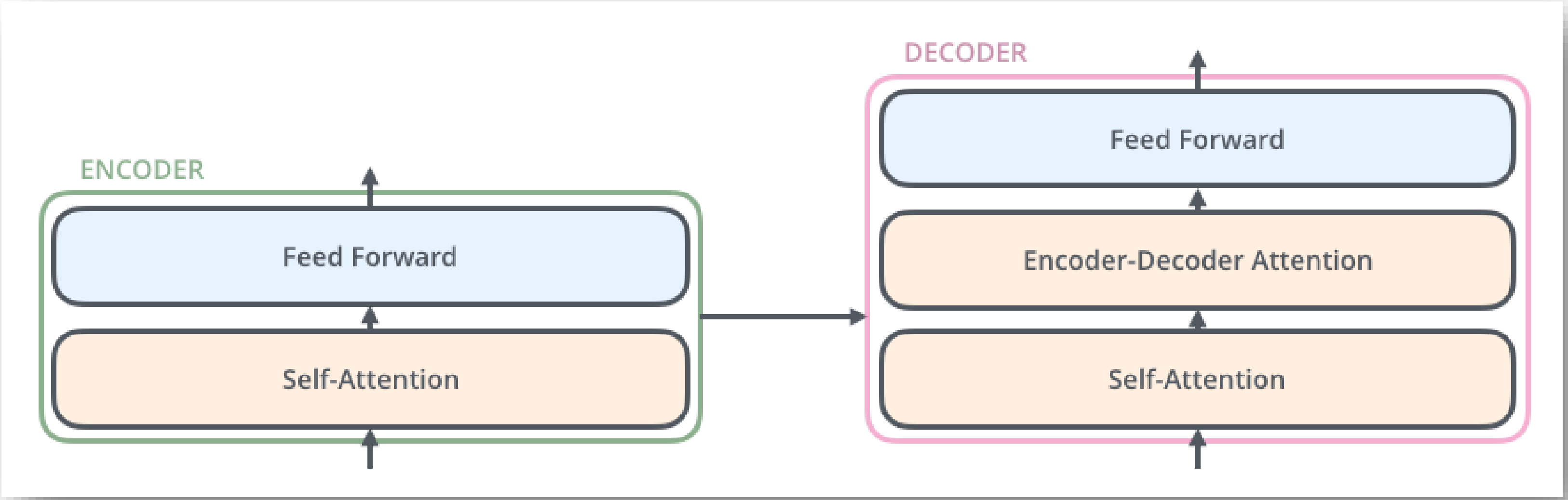


Transformer Topology

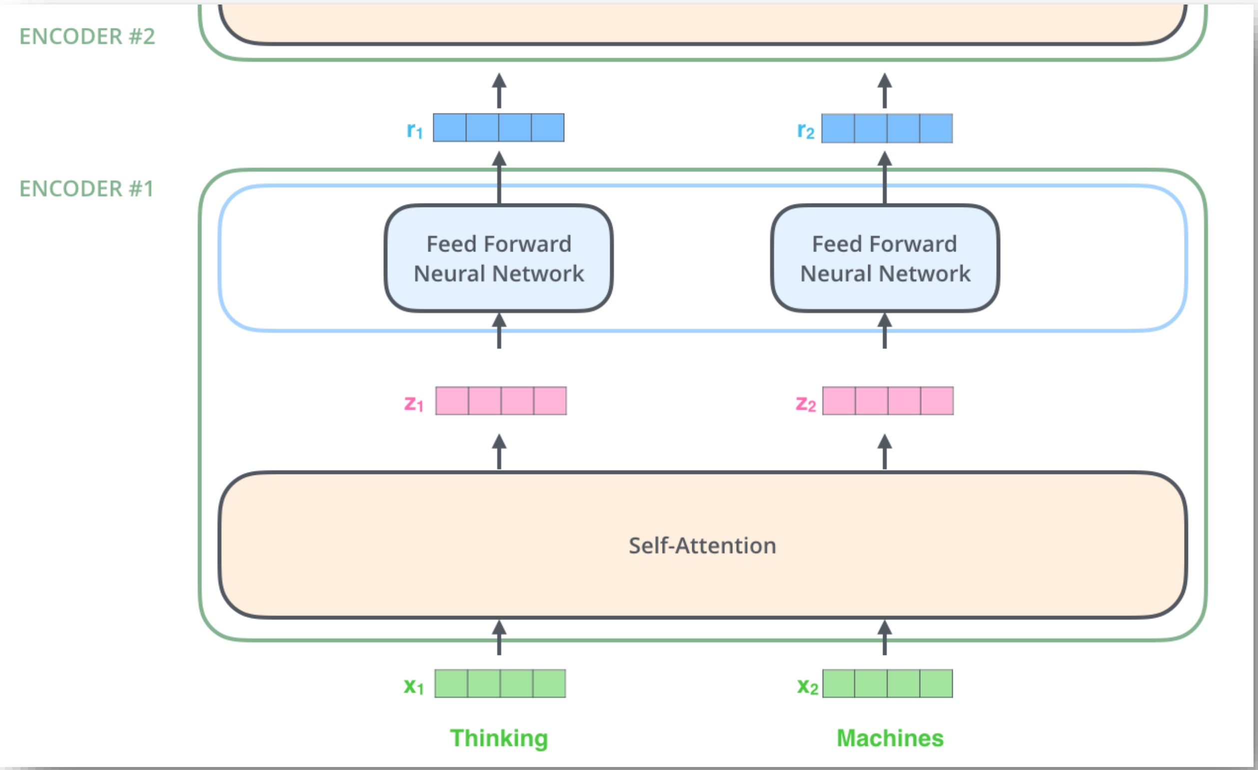


Transformer Topology

- The encoders (decoders) are all identical in structure, but they do not share weights.

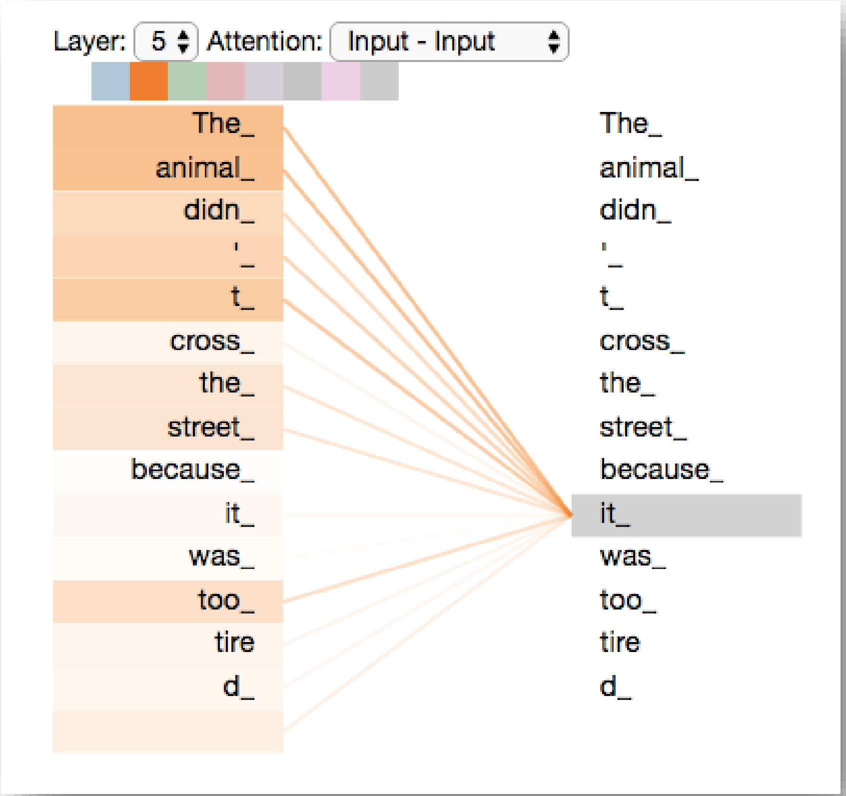


Encoder Topology

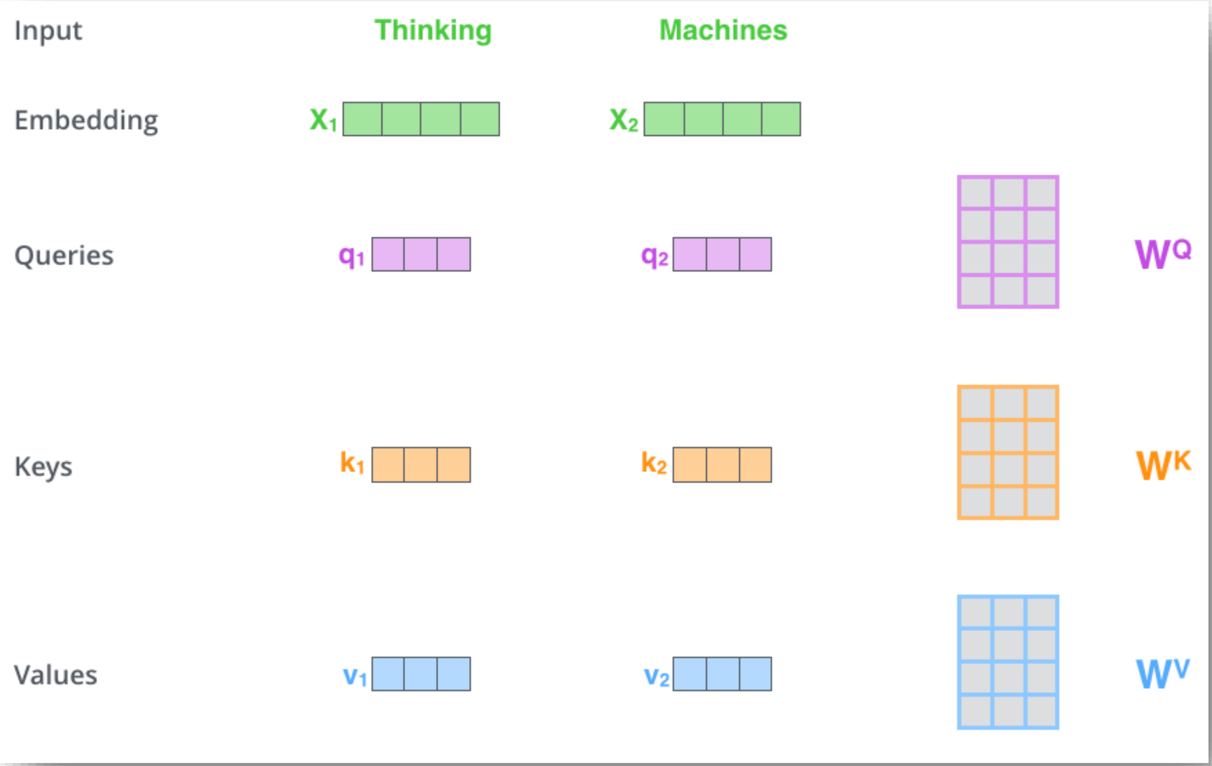


Self-Attention Layer

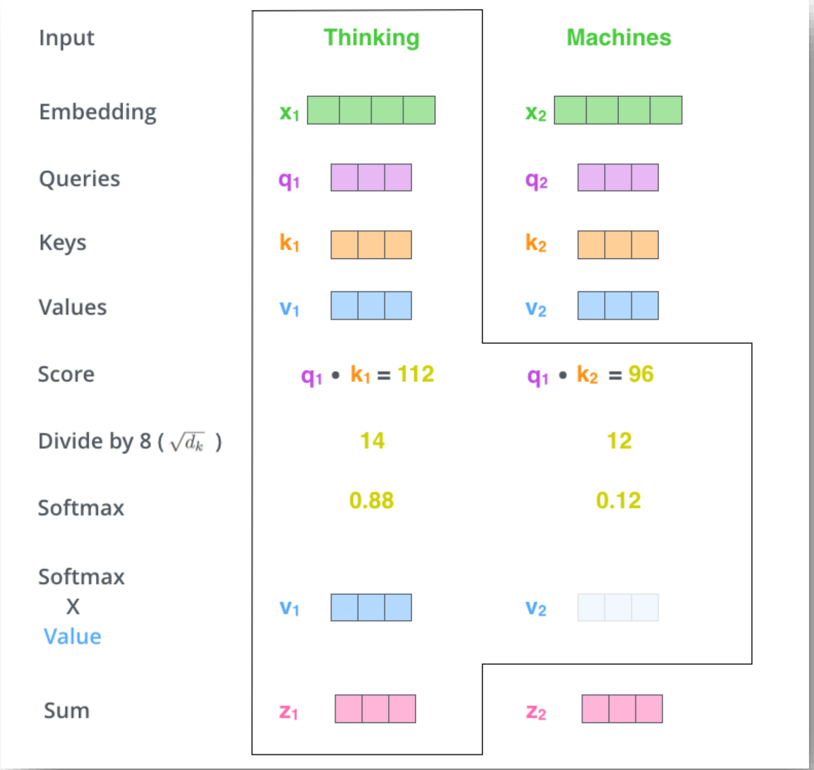
- Input: “The animal didn't cross the street because it was too tired”



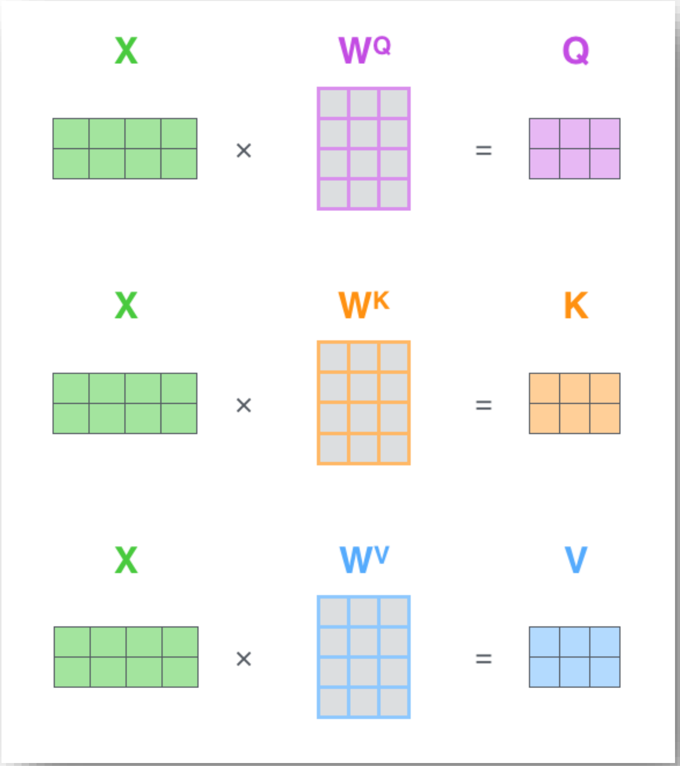
Self-Attention Layer

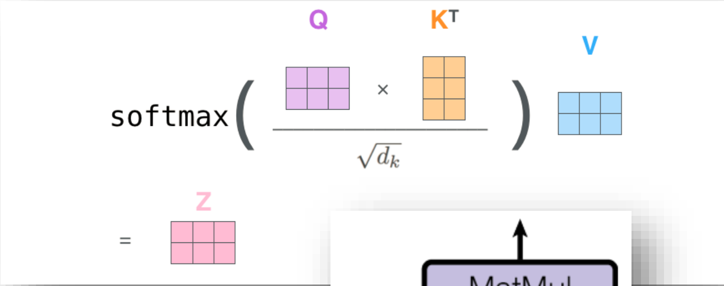


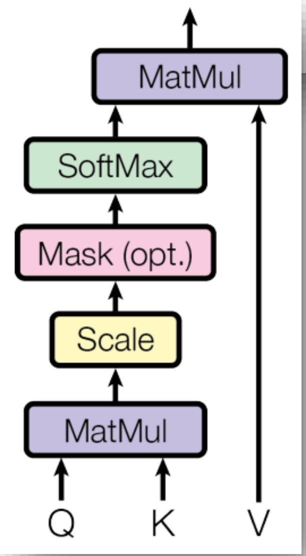
Scaled Dot-Product Attention



Scaled Dot-Product Attention

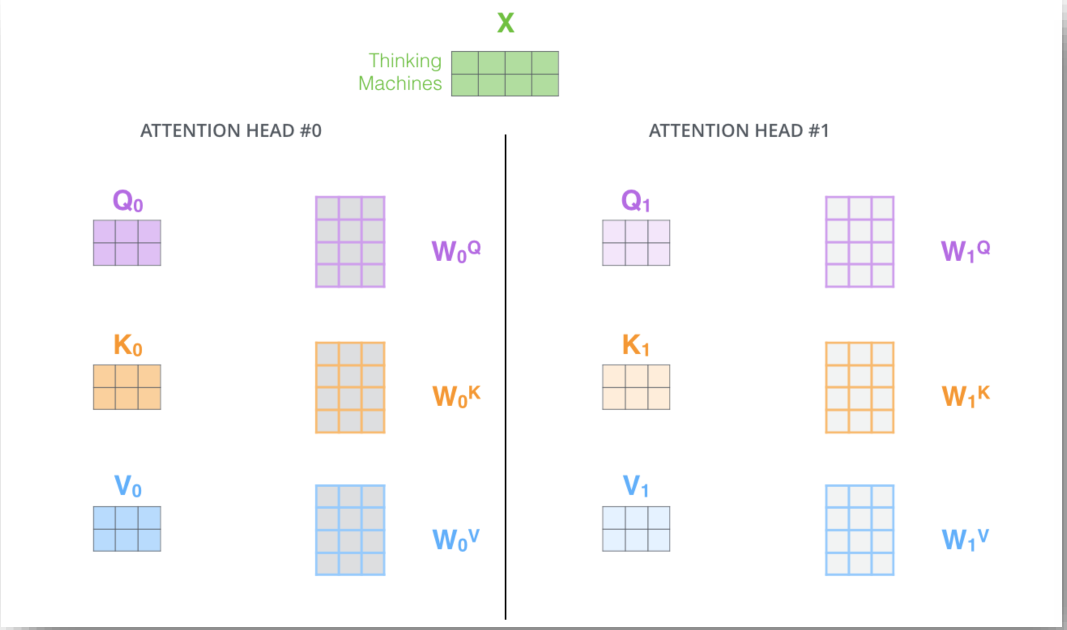


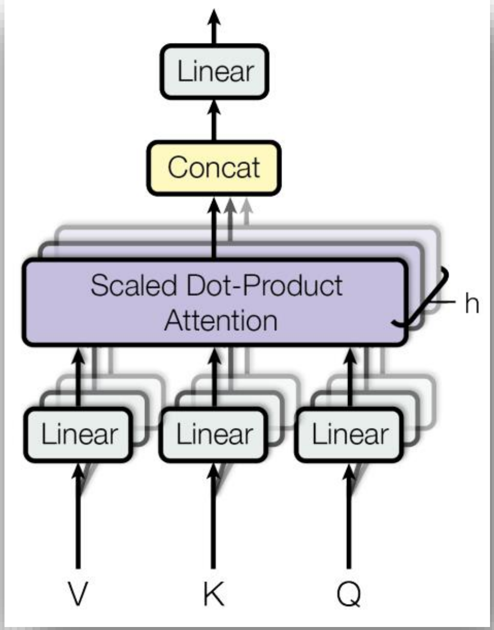




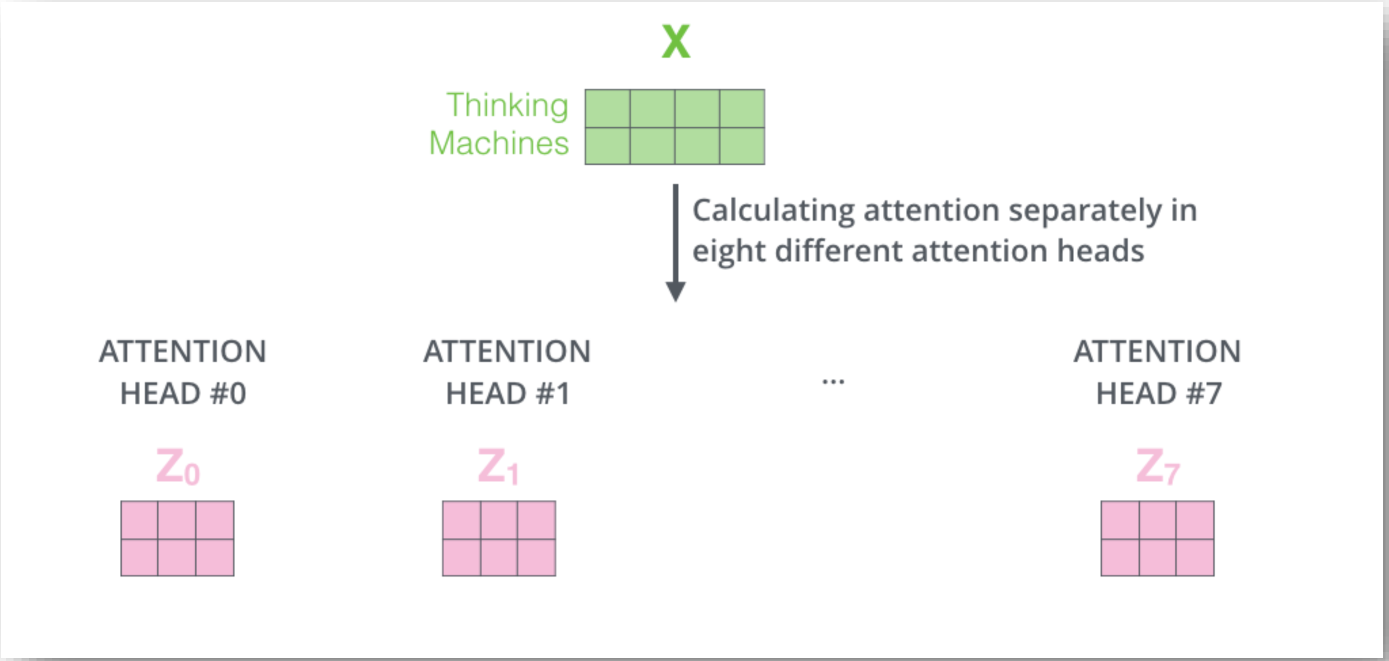
Multi-Head Attention

- Multi-head attention expands the model's ability to focus on different positions simultaneously.

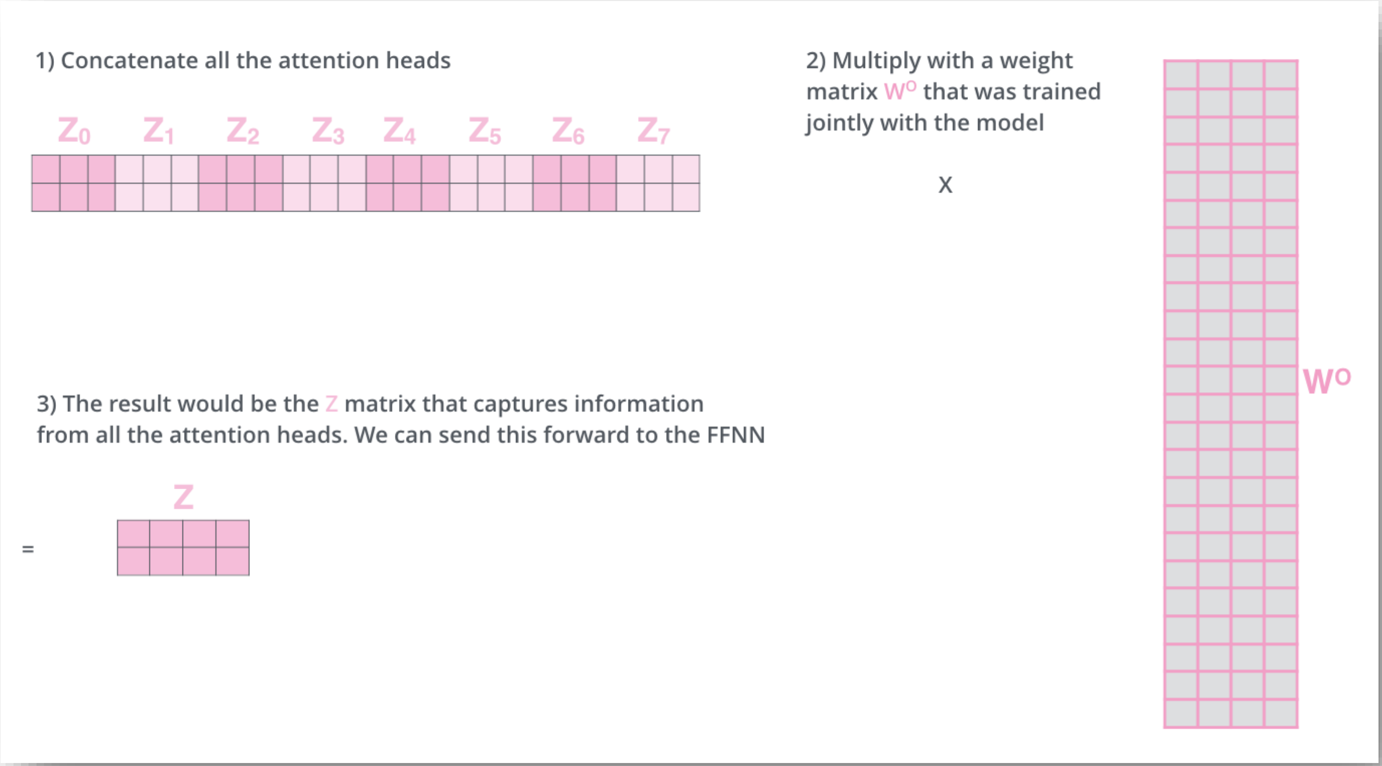




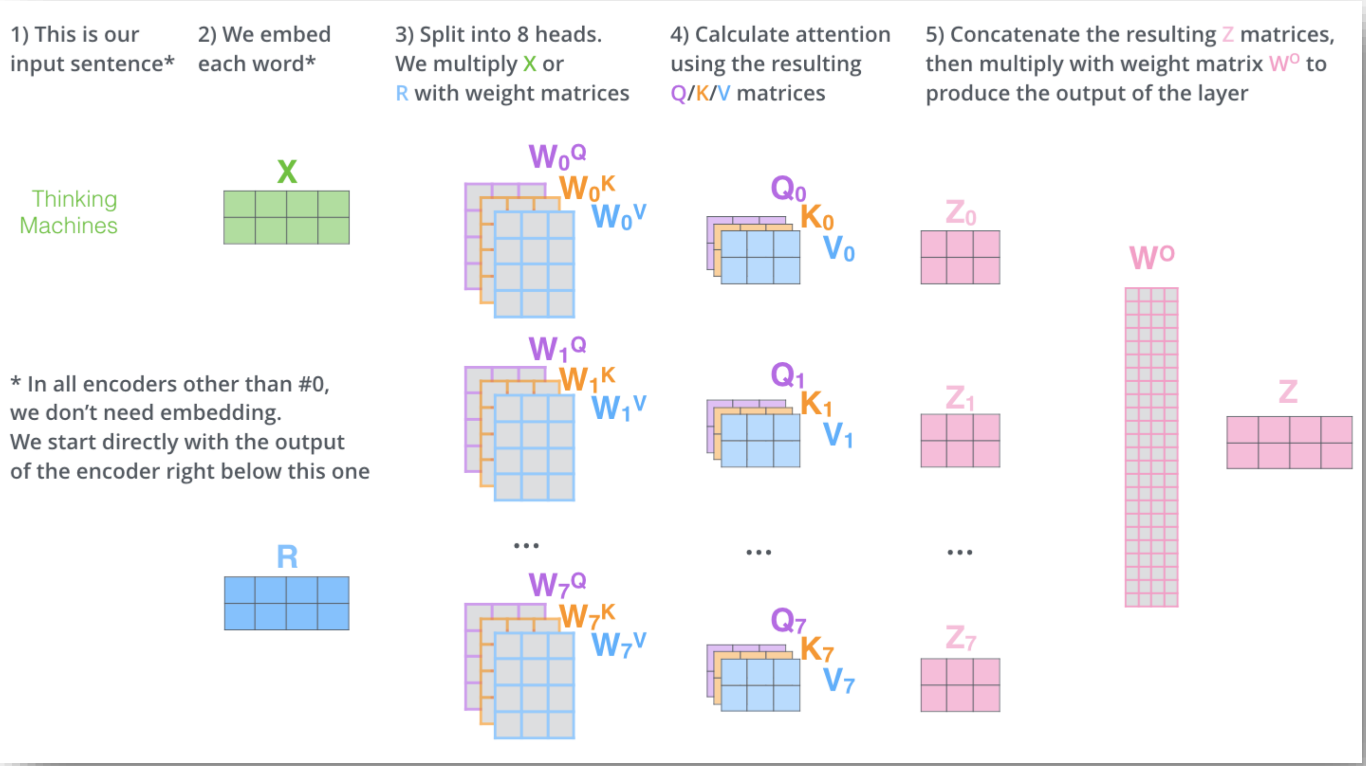
Multi-Head Attention



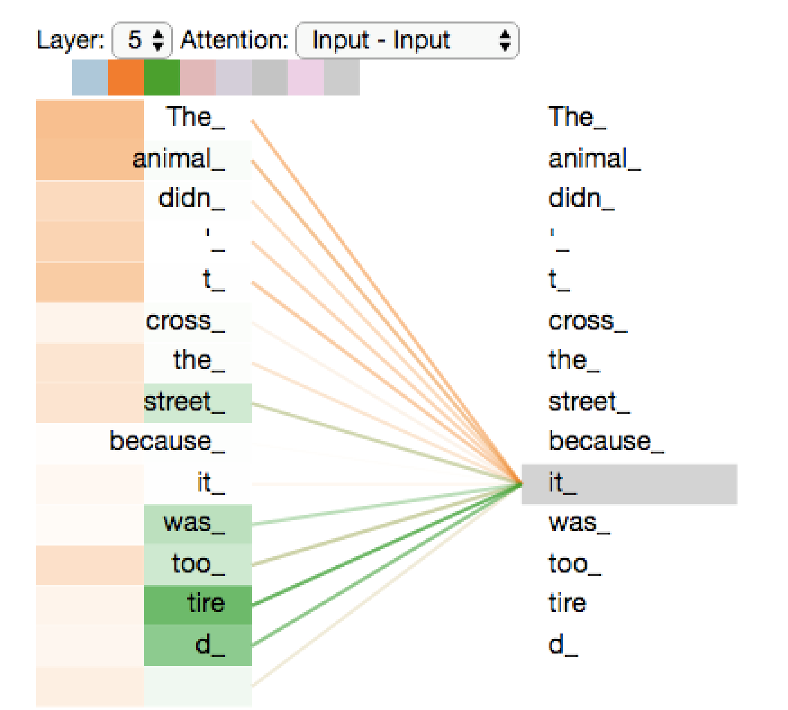
Multi-Head Attention

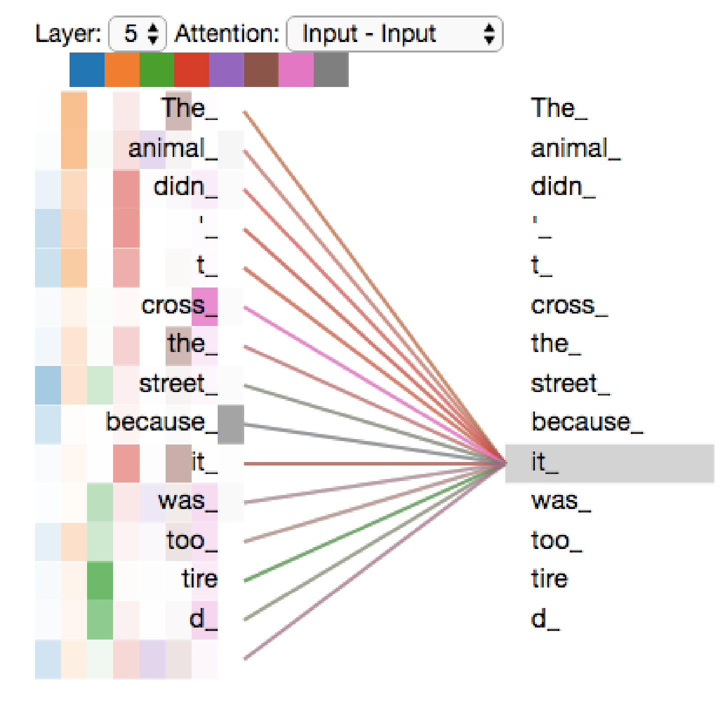


Multi-Head Attention: All-in-One!



Multi-Head Attention





Position-wise Feed-Forward Networks

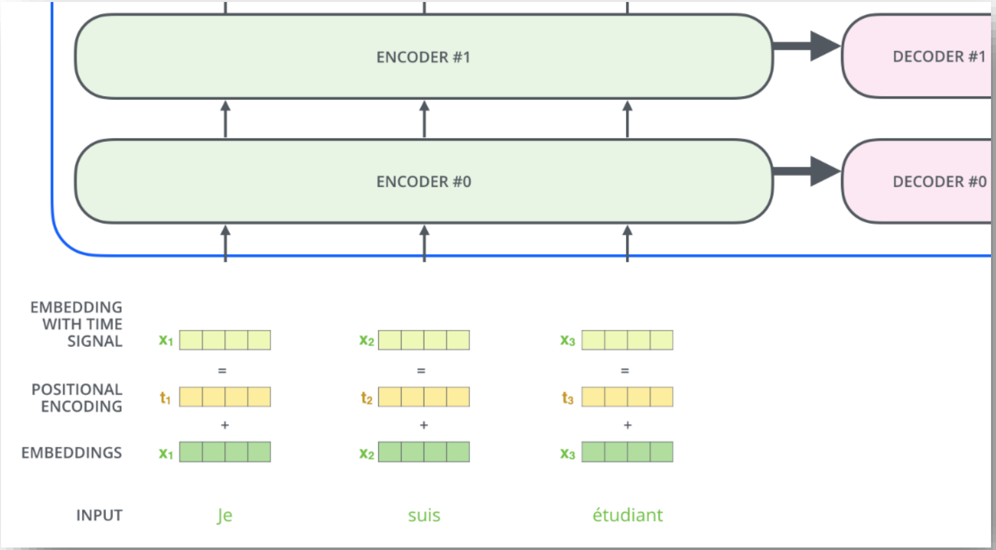
- There is a fully connected feed-forward network (FFN) in each layer of encoder and decoder, which is applied to each position separately and identically.
- This FFN consists of two linear transformations with a ReLU activation in between:

$$FFN(x) = max(0, xW_1 + b_1)W_2 + b_2$$

- The dimensionality of input and output is $d_{model} = 512$, and the inner-layer has dimensionality $d_{FF} = 2048$.

Positional Encoding

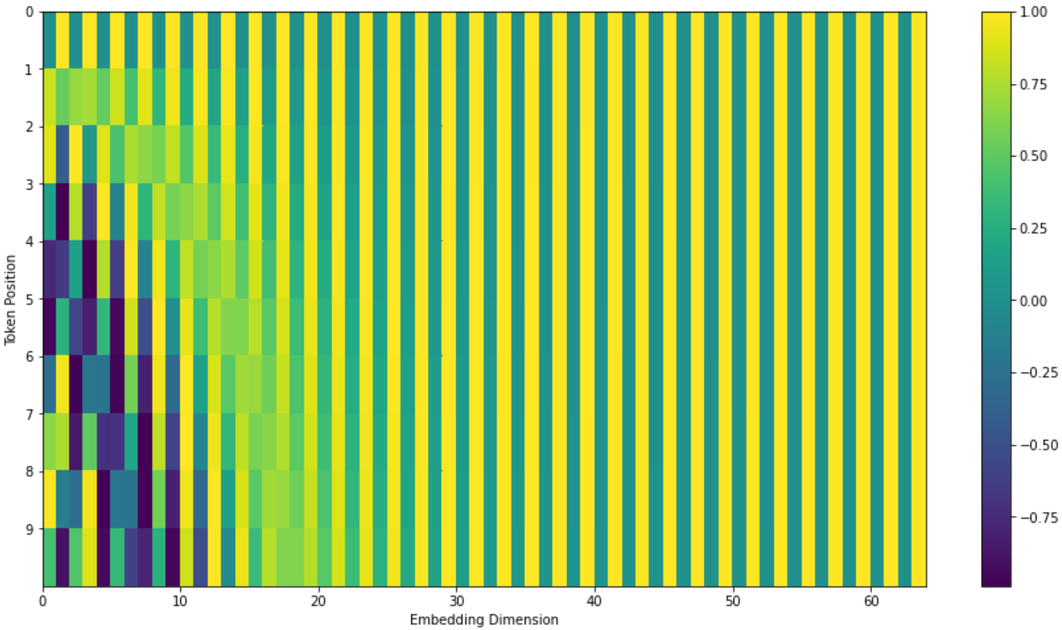
- To preserve the order of the words in the input sequence, the transformer adds a vector to each input embedding.
  - Determine the position of each word, or the distance between different words



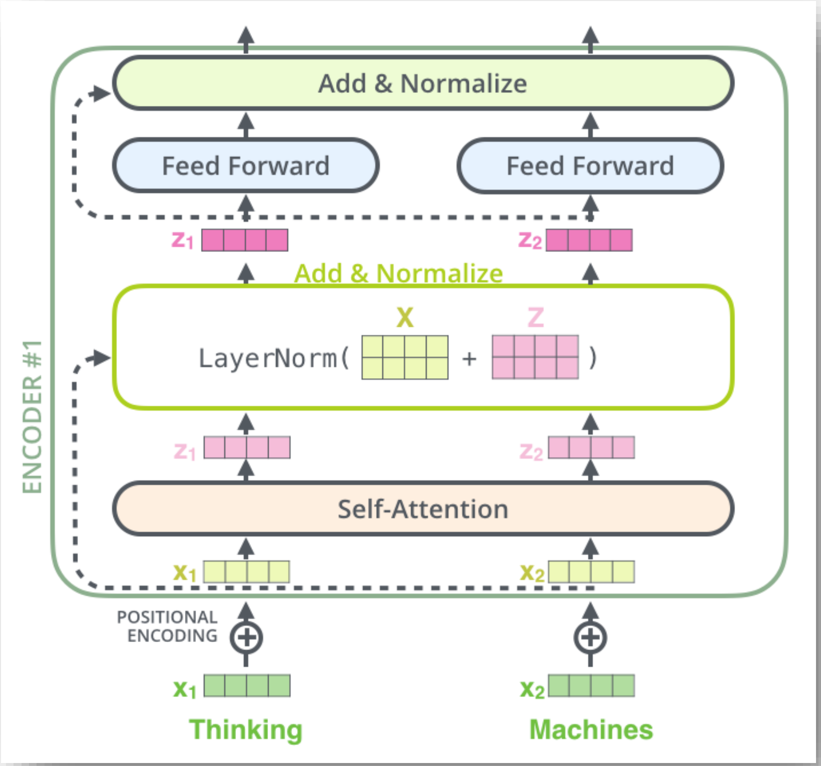
Positional Encoding

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

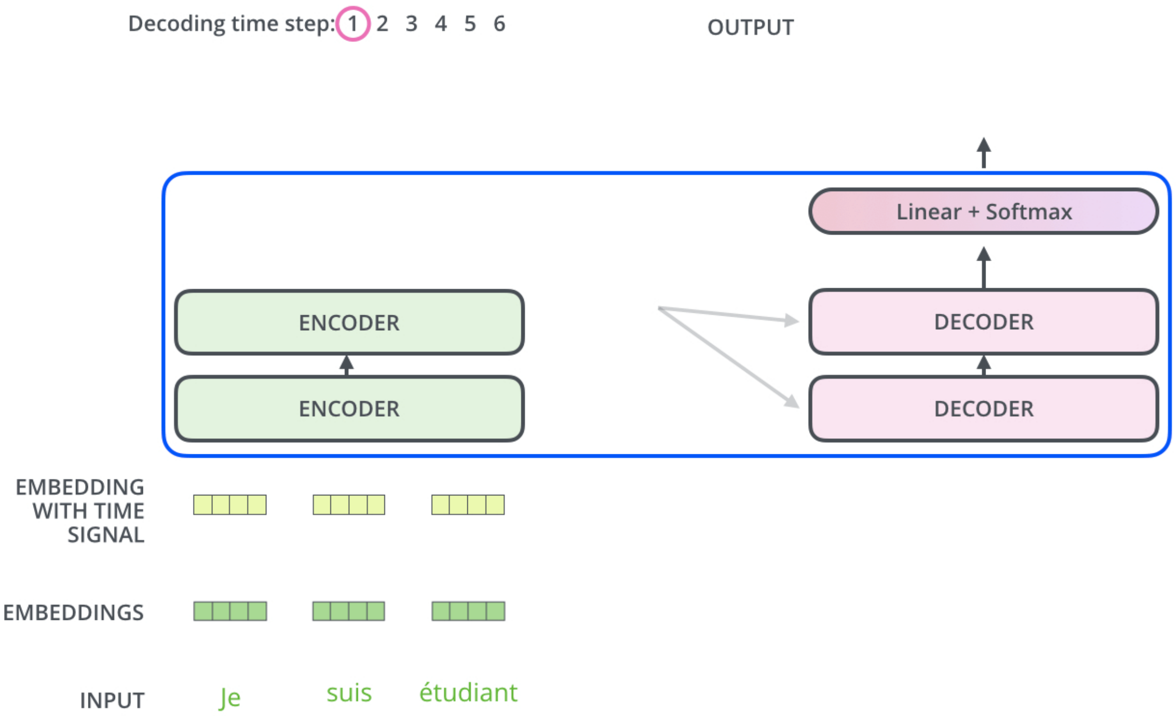
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$



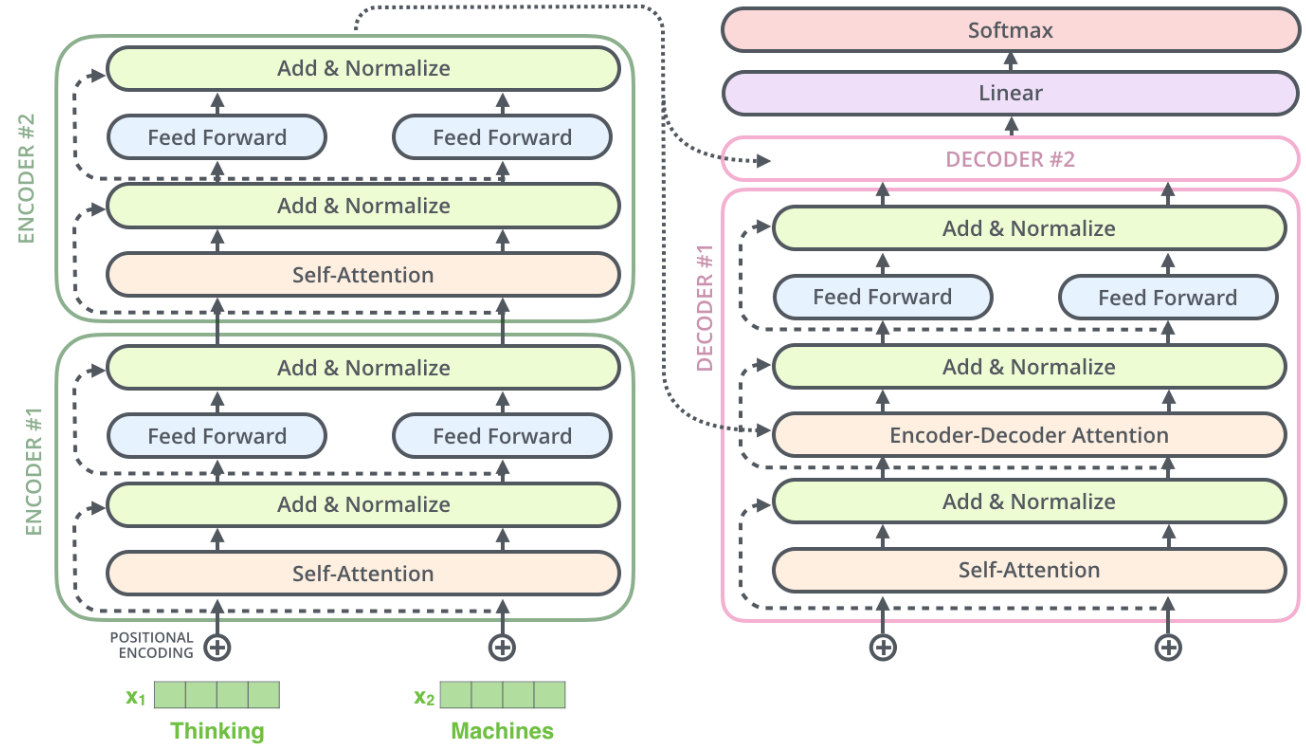
The Residuals and Layer-norm



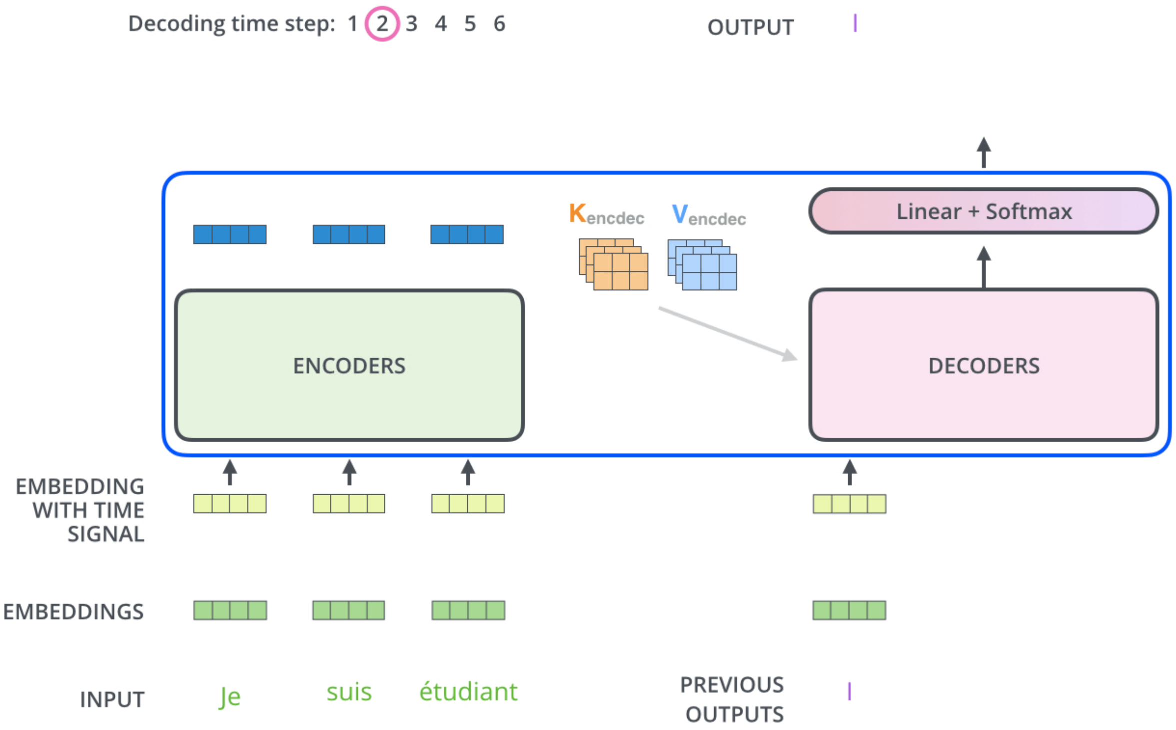
The Decoder Side



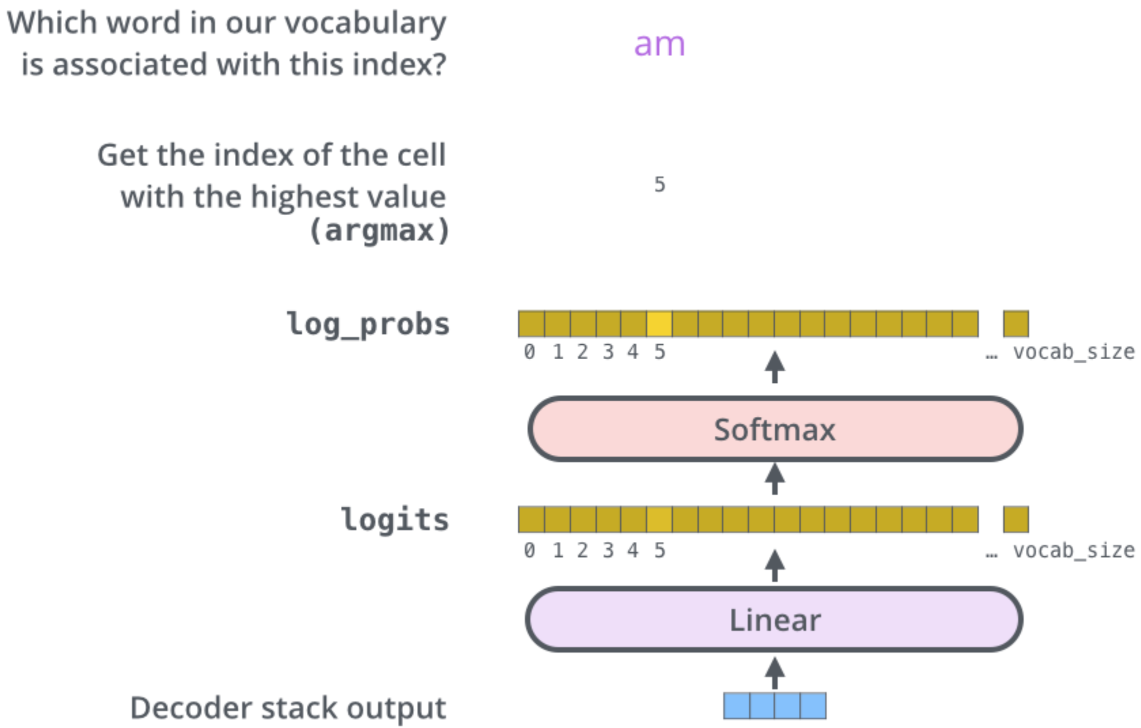
The Decoder Side



The Decoder Side

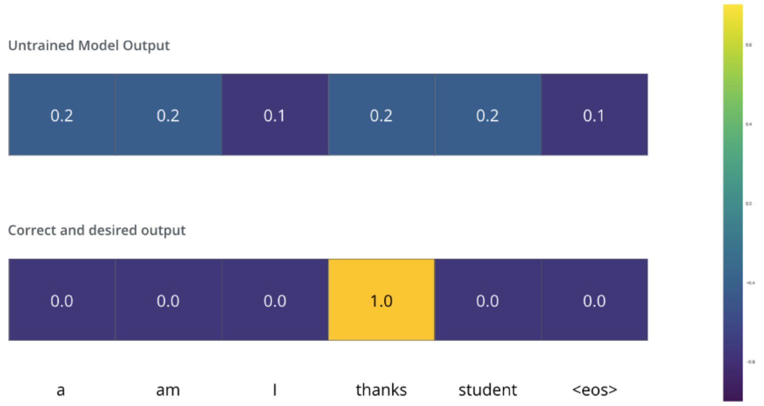


The Final Linear and Softmax Layer

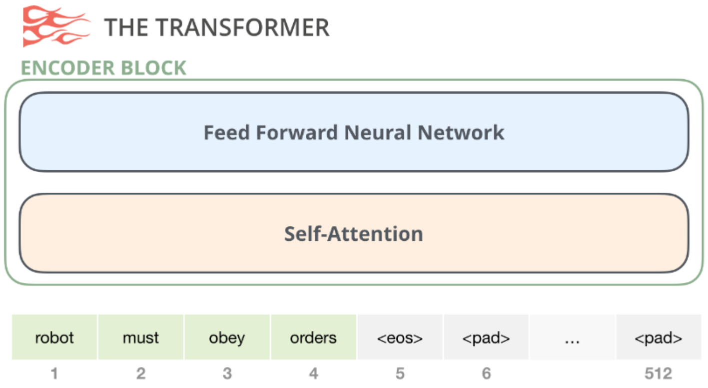


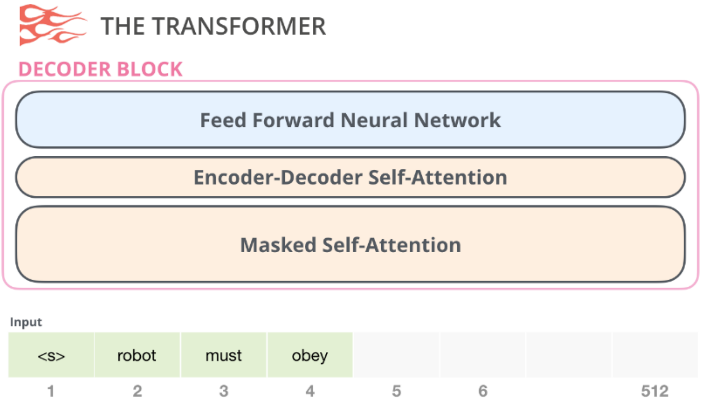
The Loss Function and Training

- One-hot encoding is used to encode the output vocabulary
- Cross-entropy loss is used for training the network

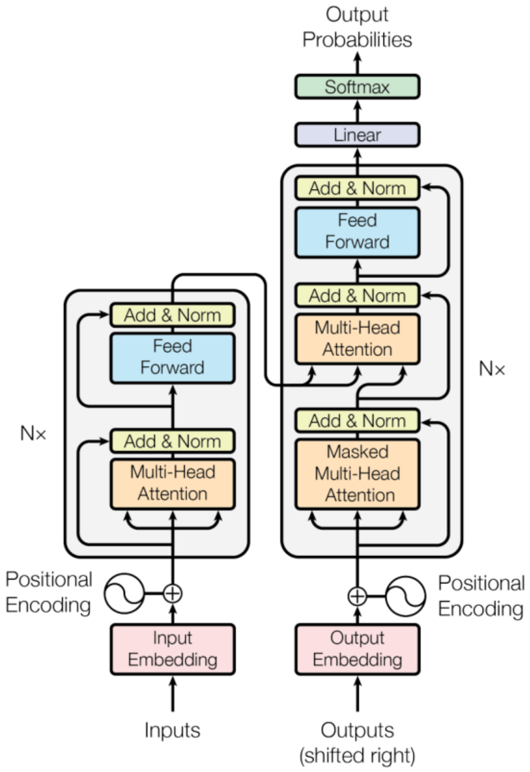


The Decoder and Encoder Blocks





The Whole Transformer Model



New Related Papers

- Child, Rewon, et al. "Generating long sequences with sparse transformers." *arXiv preprint arXiv:1904.10509* (2019).
- Kitaev, Nikita, Łukasz Kaiser, and Anselm Levskaya. "Reformer: The efficient transformer." *arXiv preprint arXiv:2001.04451* (2020).
- Making Transformer networks simpler and more efficient
  - https://ai.facebook.com/blog/making-transformer-networks-simpler-and-more-efficient/

Thanks for your attention

References and IP Notice

- [1] Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems*. 2017.

- Most of the figures are selected from https://jalammar.github.io web site.