Deep Learning

16 Self-Attention & Transformers

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Motivation

1. Why does one need to think beyond LSTMs?

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2. Sequential processing doesn't allow parallelization
3. Despite the LSTM/GRU, RNNs need attention to deal with long-range dependencies
4. Since attention enables accesses to any state, do we need RNNs?

Transformers

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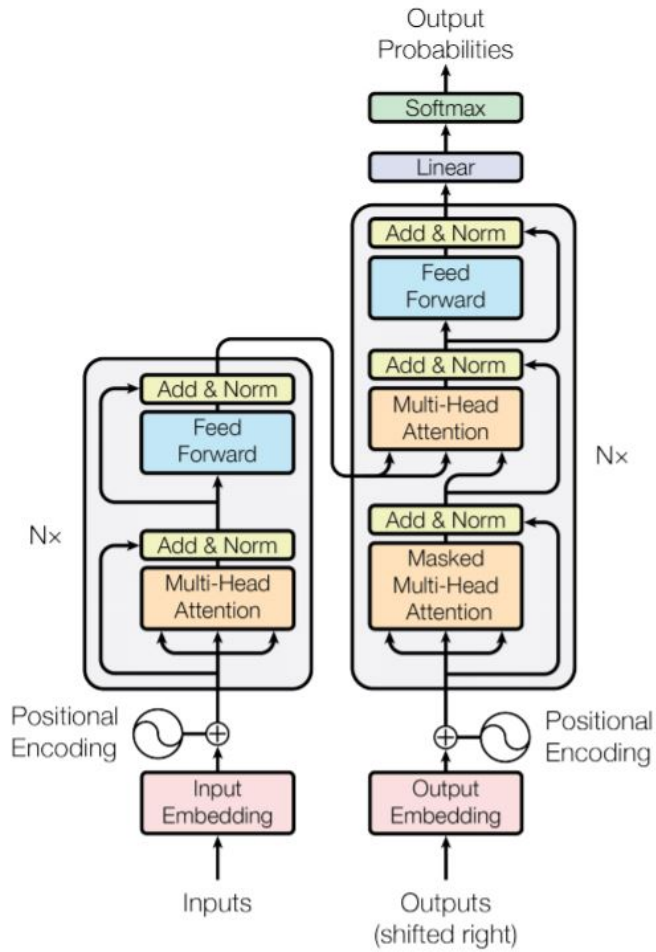

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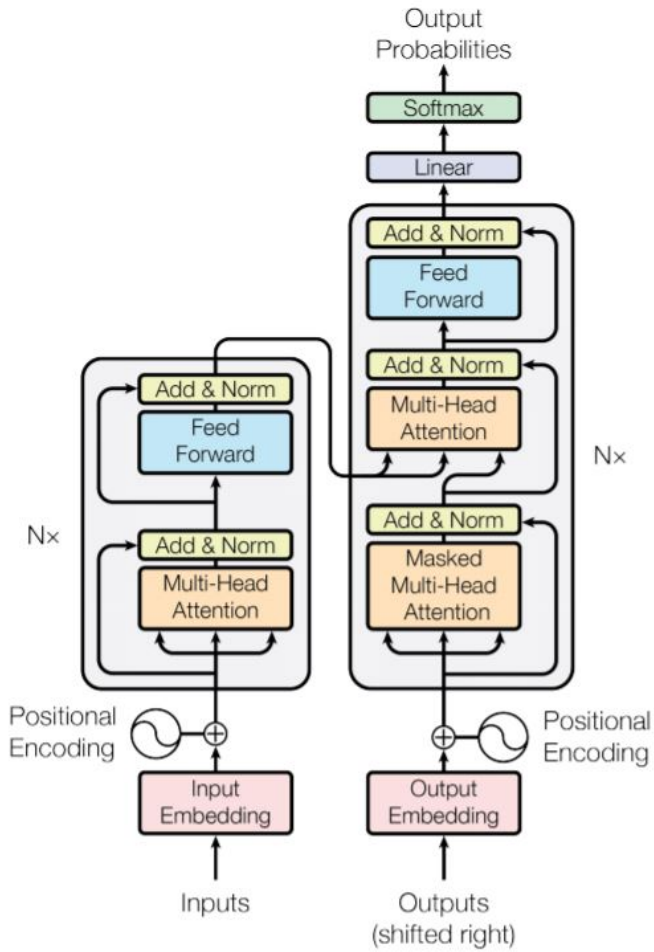

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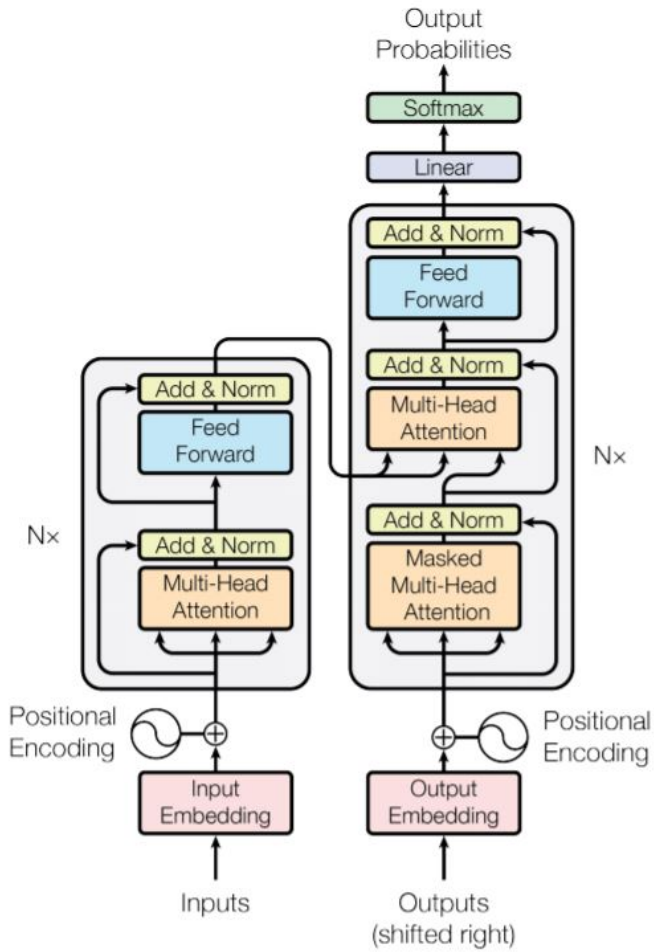
2. Sequnce to sequence modelling without RNNs
3. Transformer model is built on self-attention (no recurrent architectures!)



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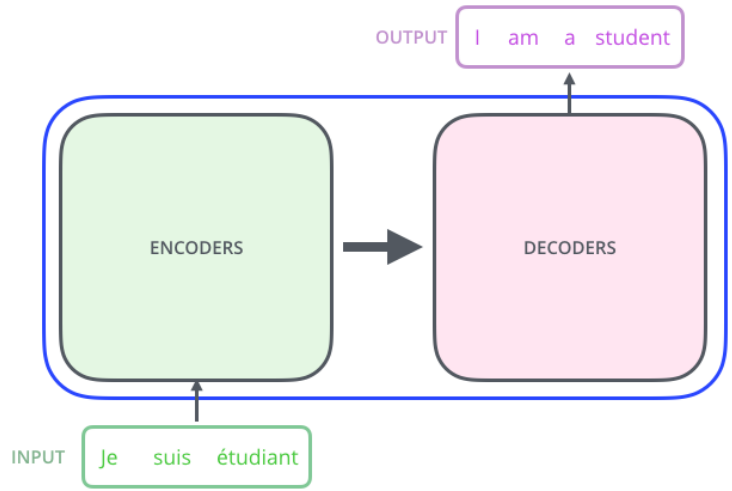

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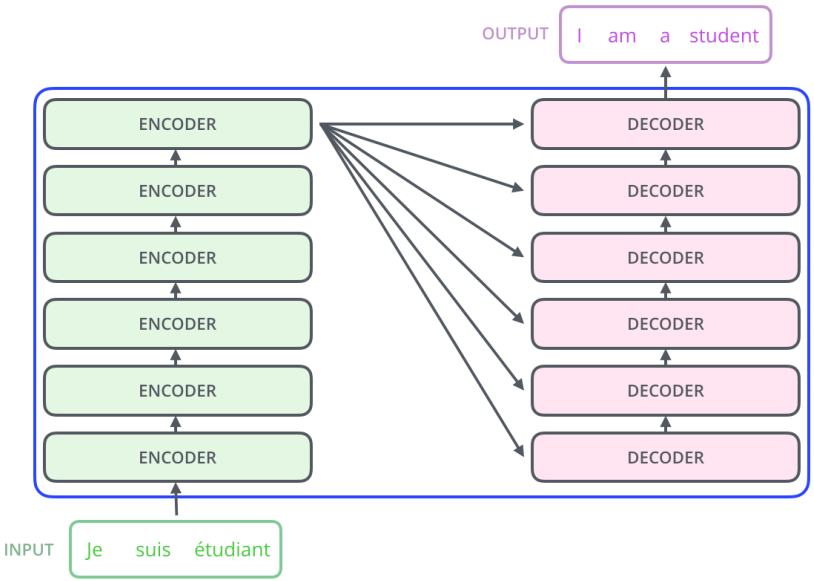

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1. Encoding module has a stack of encoders

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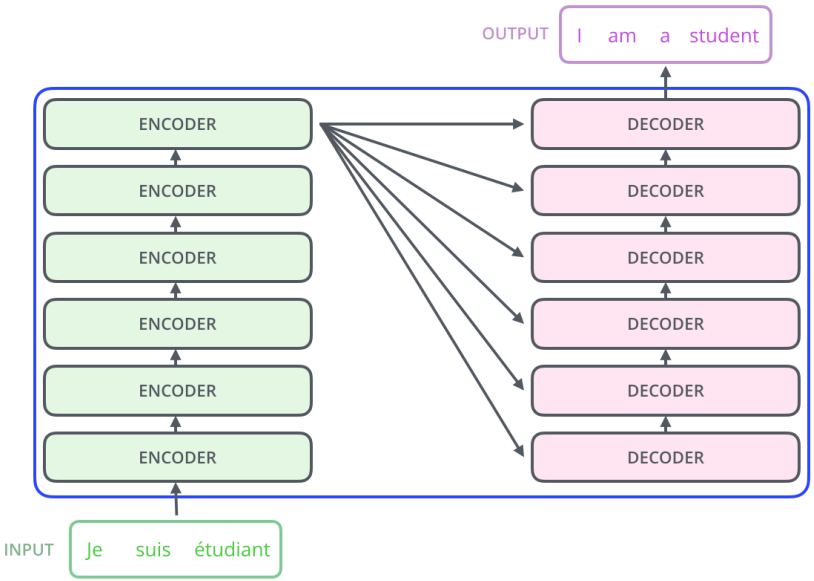

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2. Same structure different parameters

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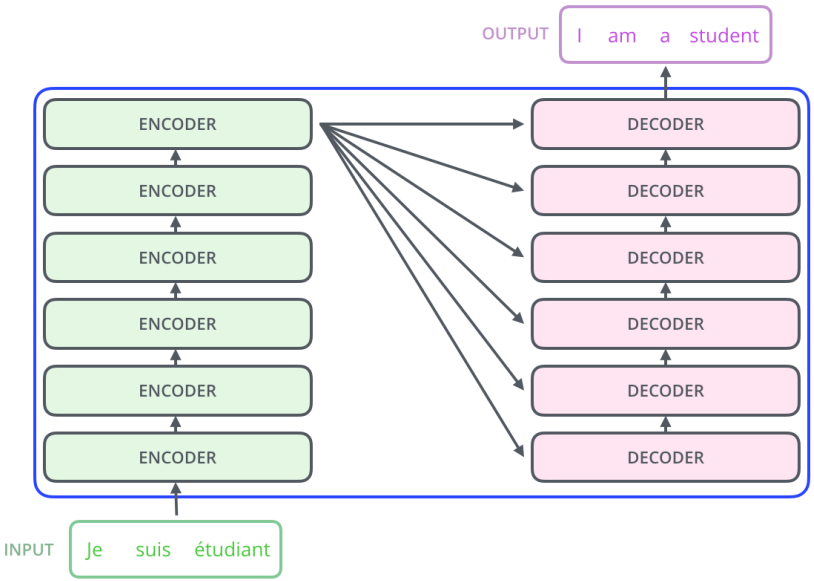

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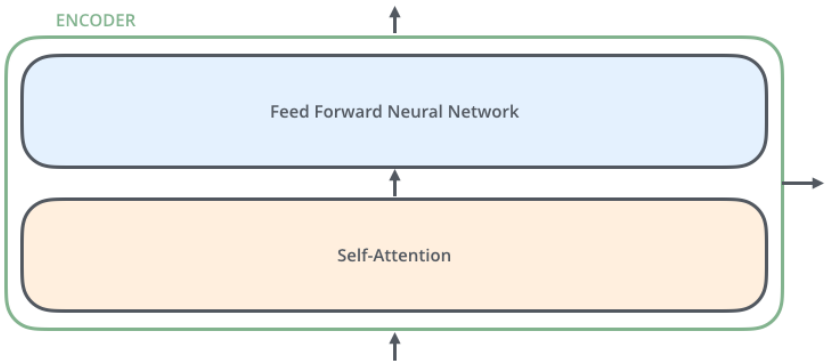
1. Encoding module has a stack of encoders
2. Same structure different parameters
3. Similarly the decoding module (same number of components in the stack as encoder)

Transformers



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1. Encoder first has a self-attention layer

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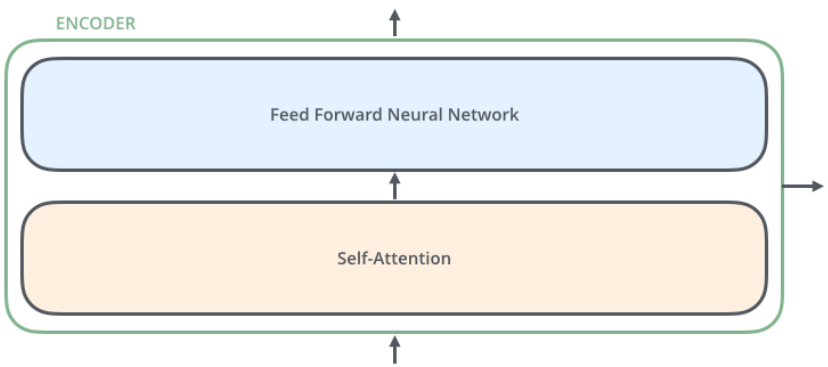

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1. Encoder first has a self-attention layer
2. Looks at the other words while encoding a specific word

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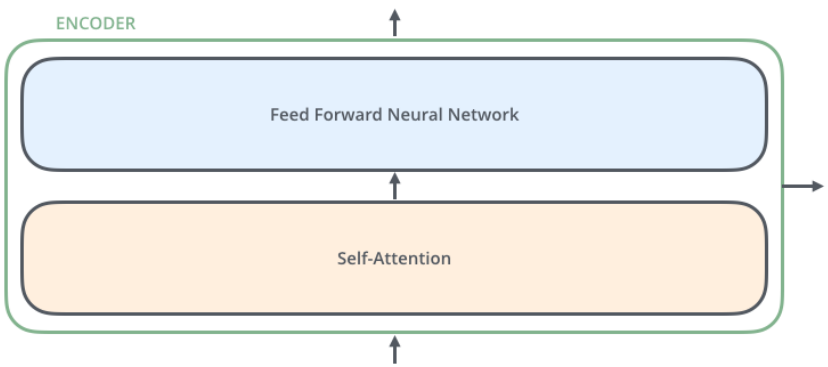

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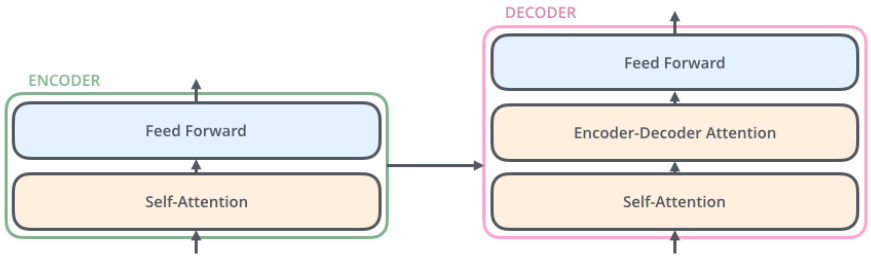
1. Encoder first has a self-attention layer
2. Looks at the other words while encoding a specific word
3. Next a (same) feed-forward NN is applied at all positions

Transformers



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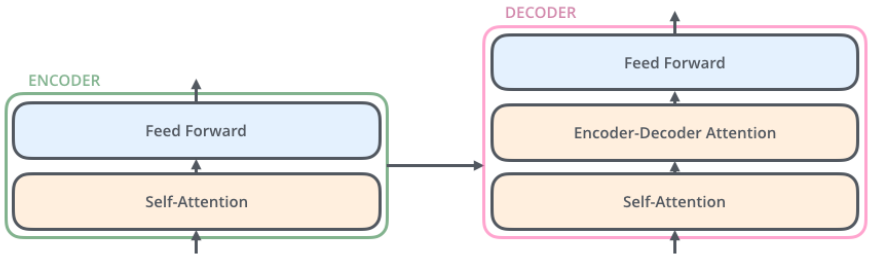
1. Decoder also has both the layers

Transformers



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1. Decoder also has both the layers
2. But, in the middle it has an encoder-decoder attention layer

Transformers-Encoding

1. Start with turning each word into a vector at the bottom-most encoder

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Transformers-Encoding

1. Start with turning each word into a vector at the bottom-most encoder
2. Others receive a list of vectors from the encoder immediately below

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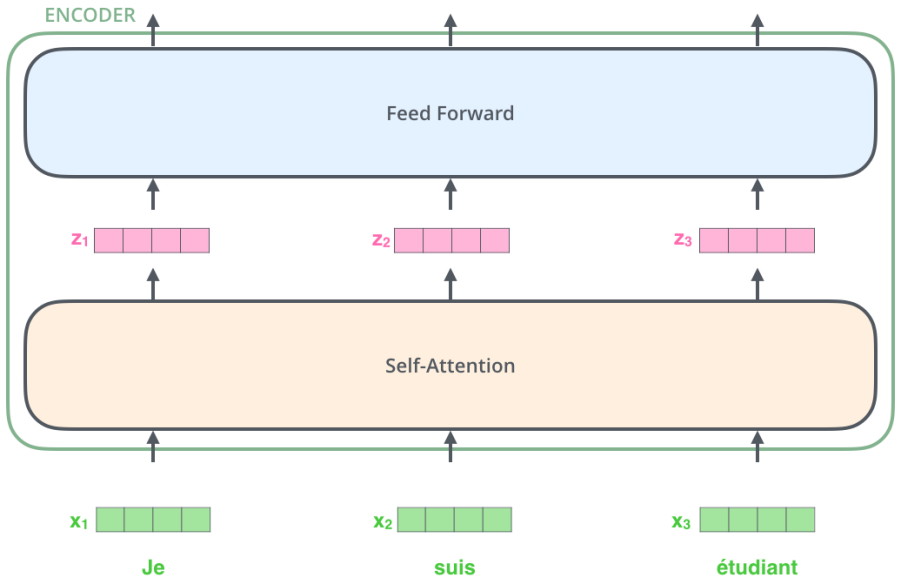
Transformers-Encoding

1. Each word flows through the two layers of the encoder through its own path



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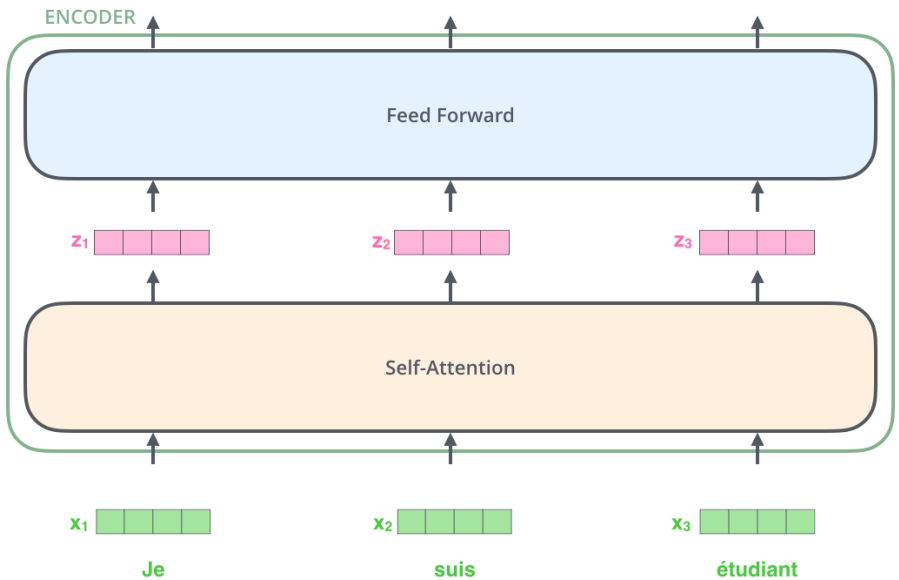
Transformers-Encoding

1. Each word flows through the two layers of the encoder through its own path
2. Self-attention layer has dependencies among them, but not the feed-forward layer (which can be parallelized)



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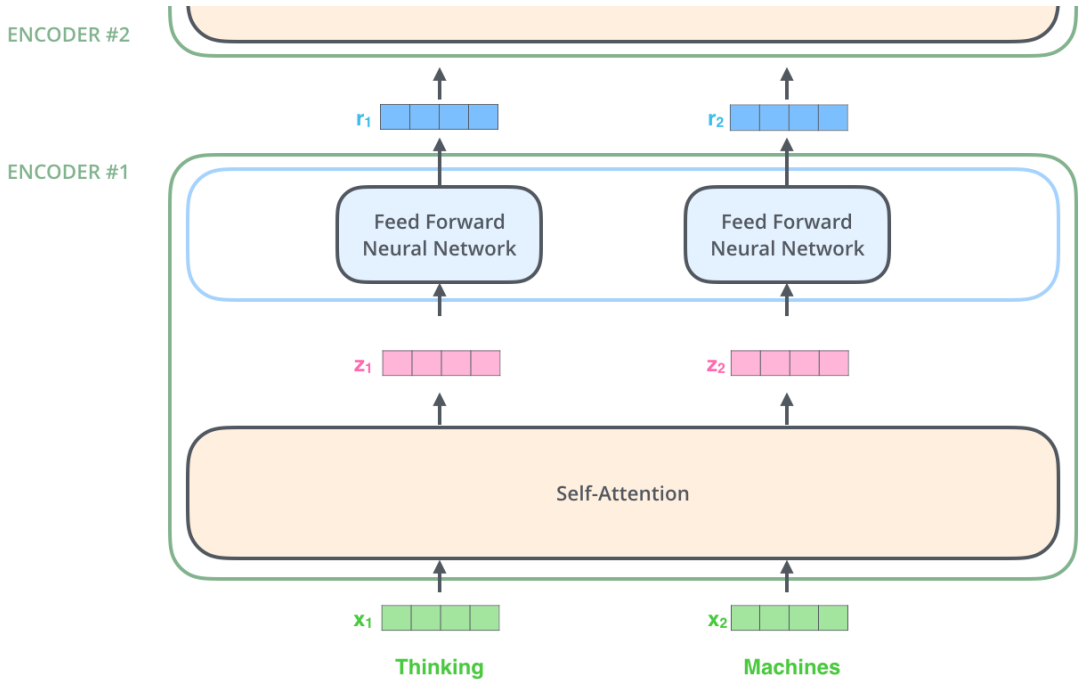

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Self-Attention

1. The animal didn't cross the street because it was too tired
2. The animal didn't cross the street because it was too wide

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3. What does 'it' refers to?

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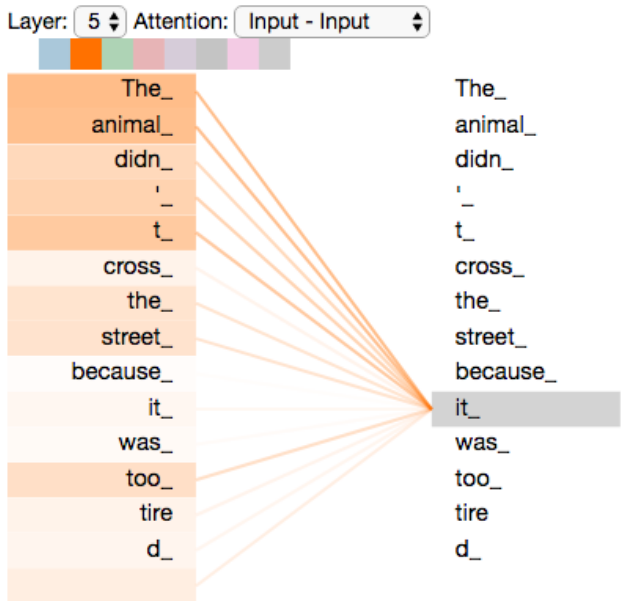
1. `The animal didn't cross the street because it was too tired`
2. `The animal didn't cross the street because it was too wide`
3. What does 'it' refers to?
4. Easy for humans, but not so much for the traditional Seq2Seq models

Self-Attention

1. As the model processes each word, self-attention attends other positions in the i/p sequence to encoder better



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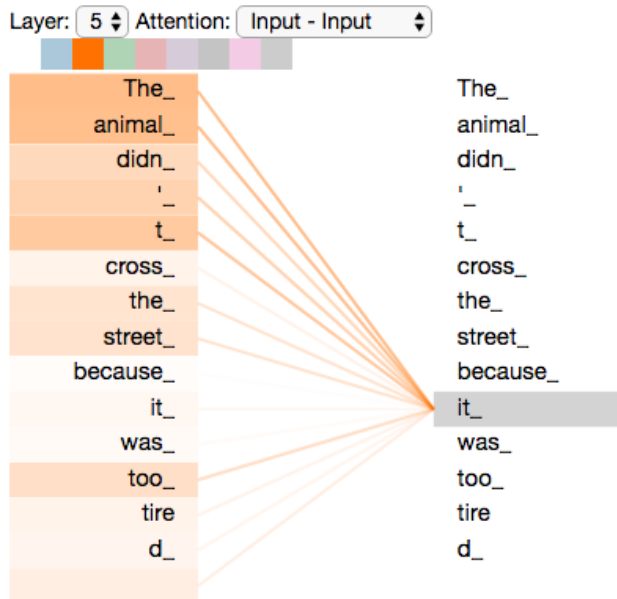
1. As the model processes each word, self-attention attends other positions in the i/p sequence to encoder better
2. Unlike RNNs, here we don't keep hidden states from previous positions!



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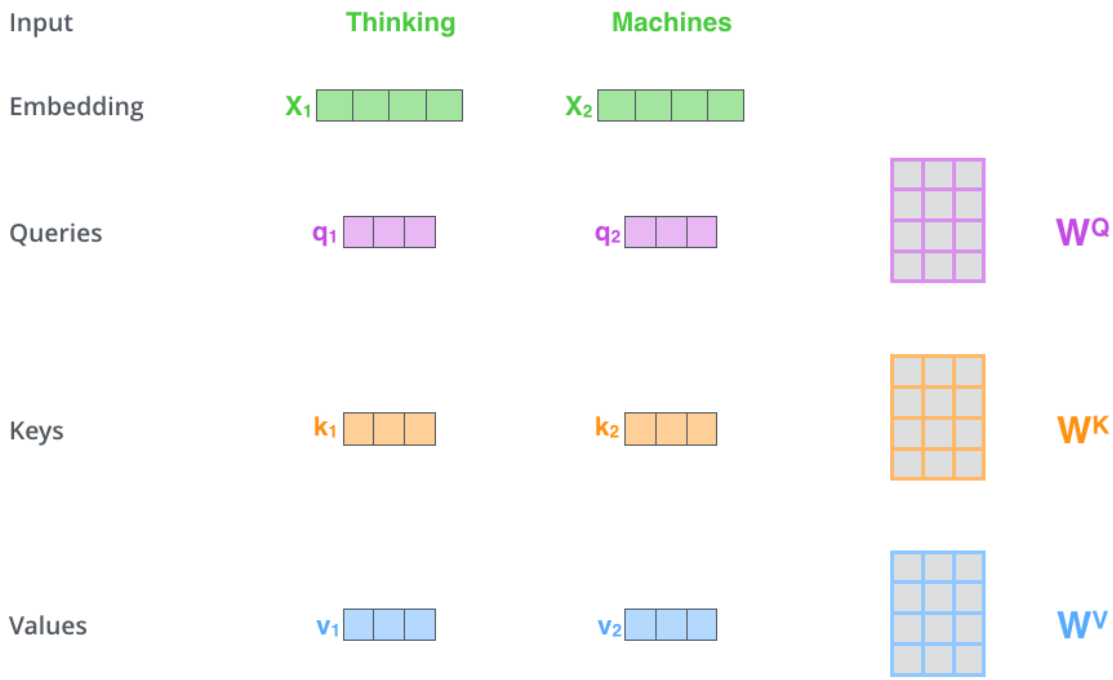

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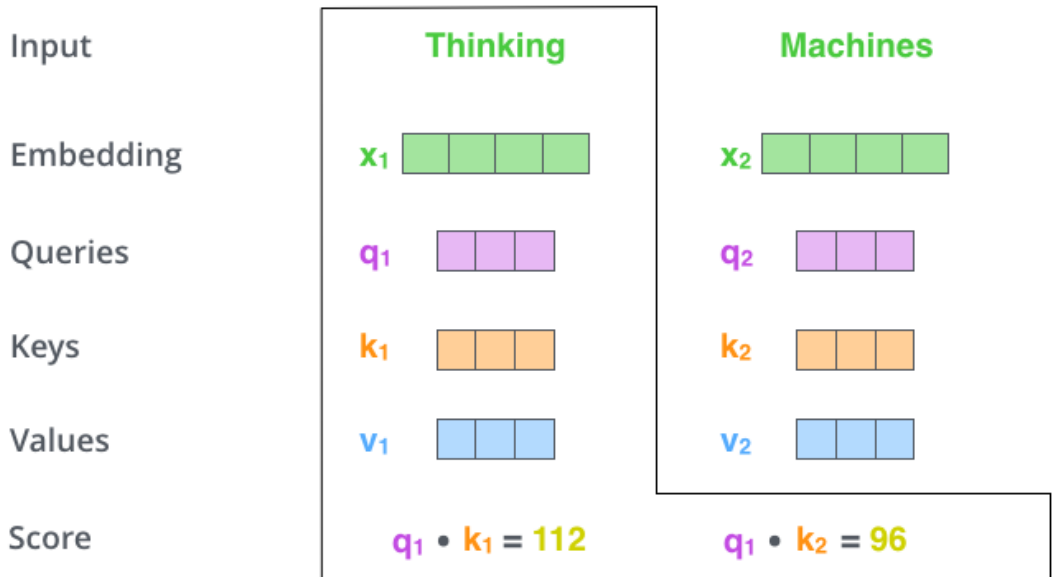

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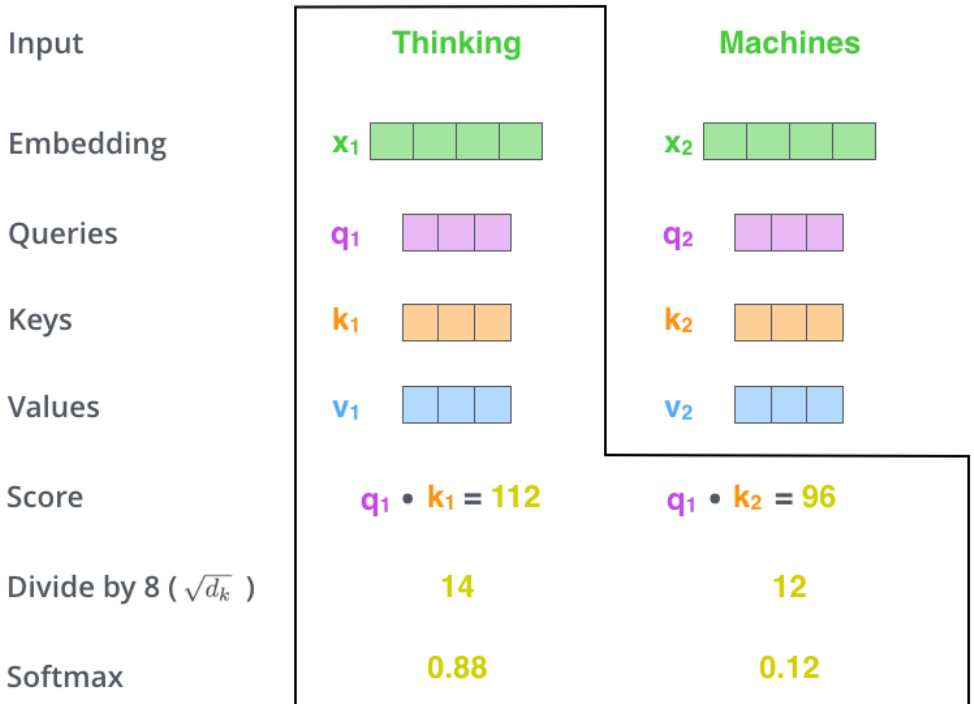

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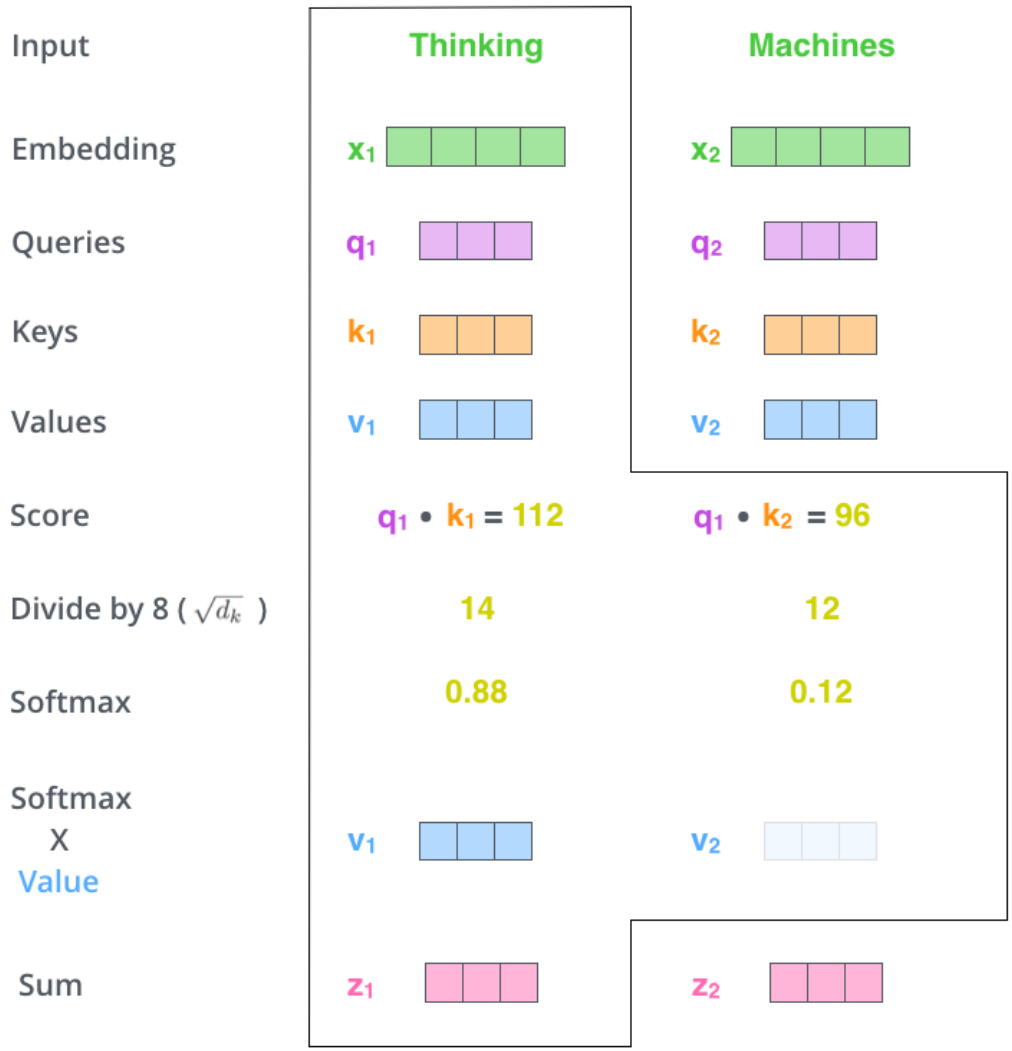

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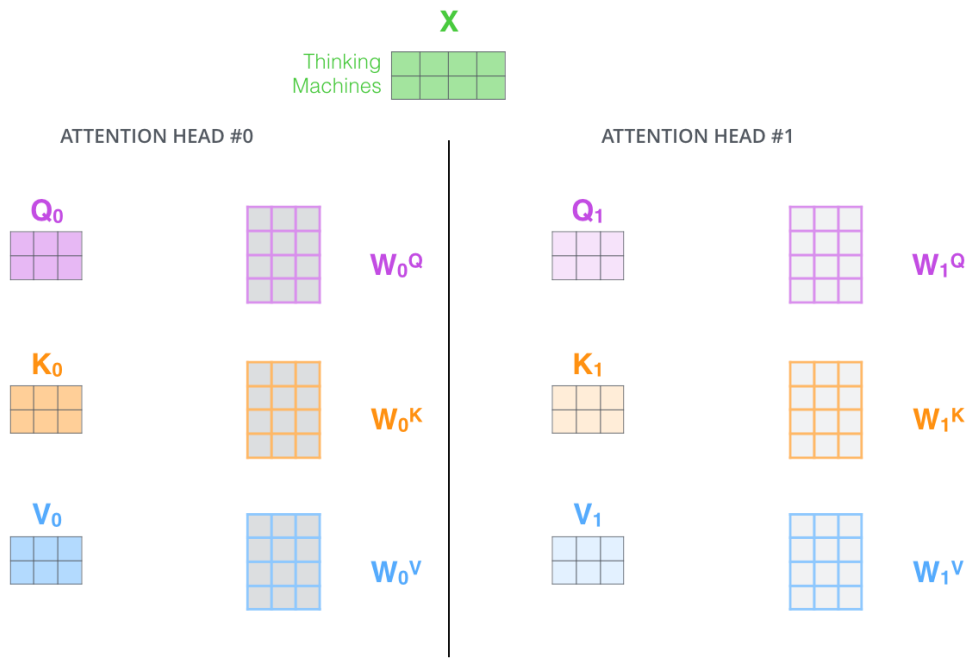
Multi-headed Self-Attention



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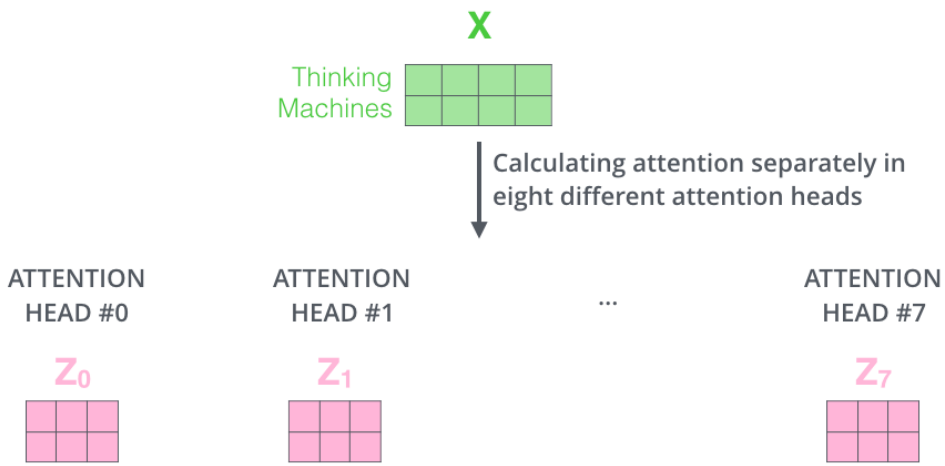

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2. Enables different 'representational subspace'

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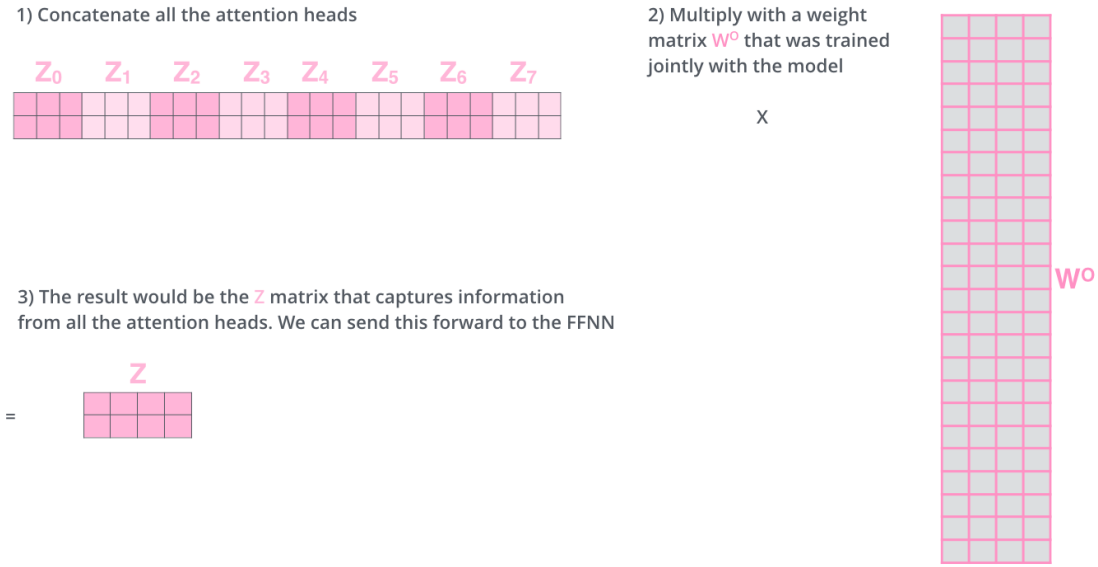

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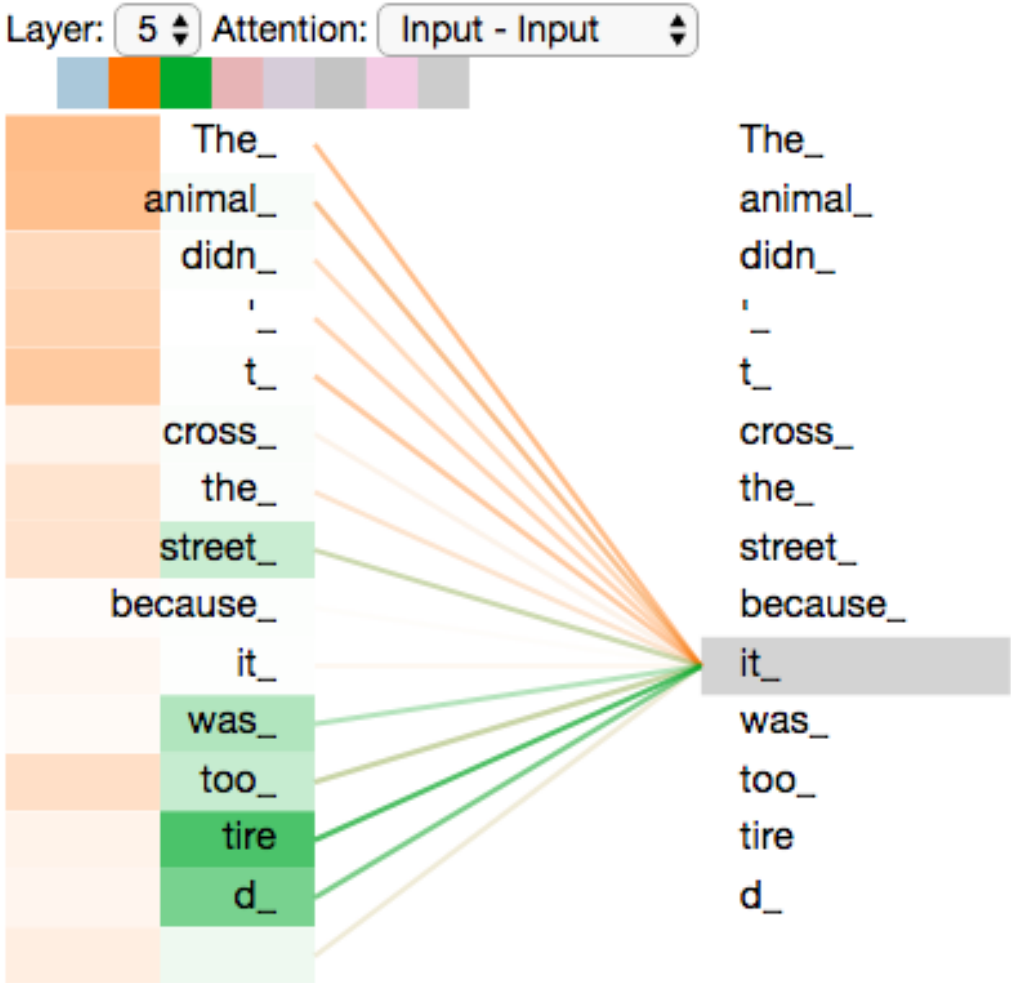

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3. Solution: Add positional information of the i/p words into their embedding vectors

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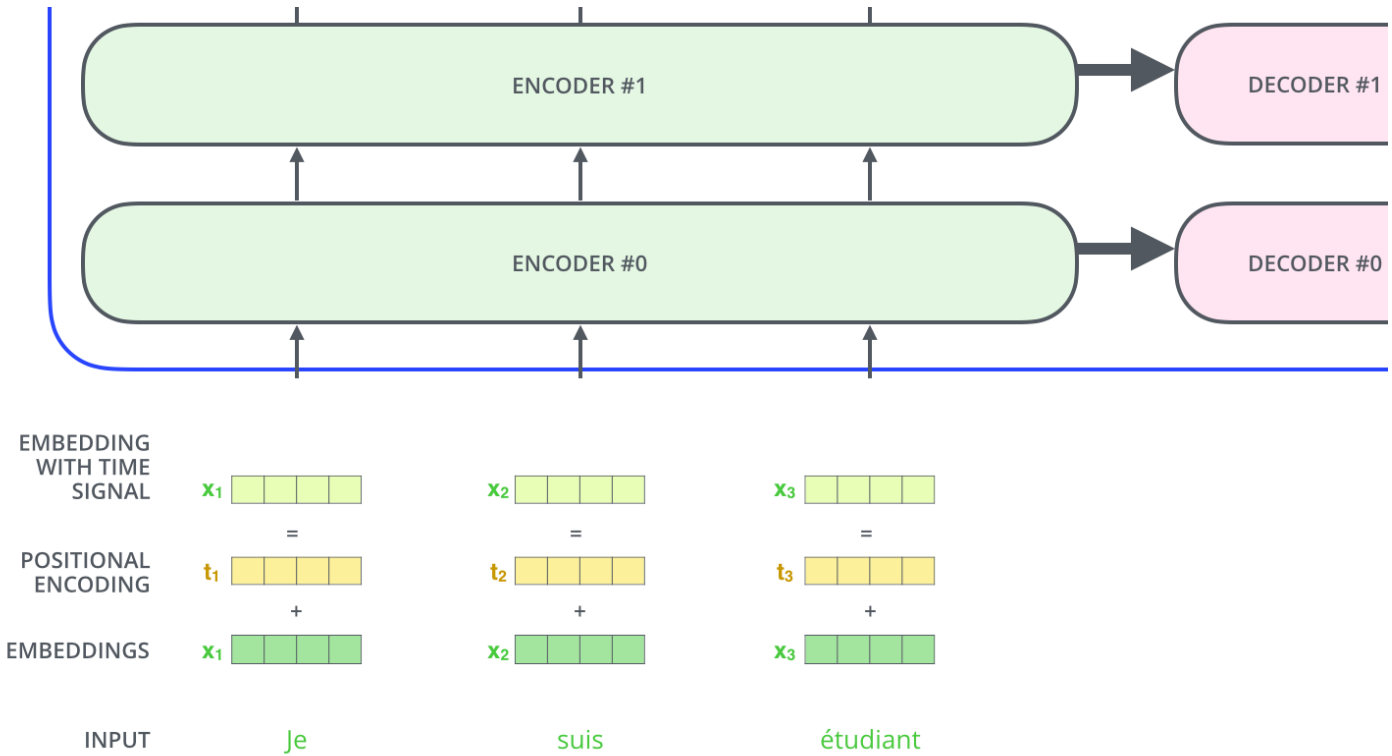

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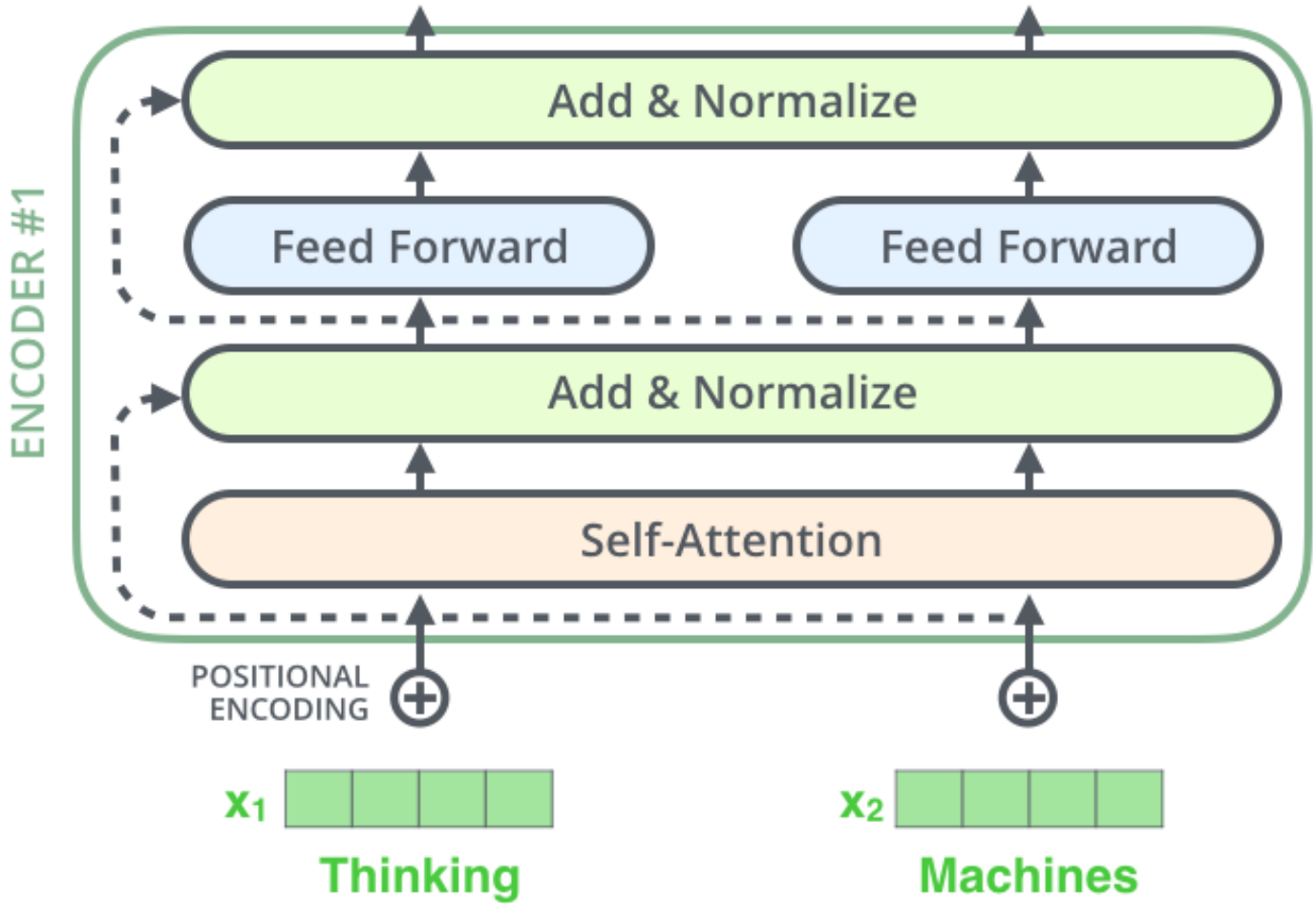
Residuals in the Encoder



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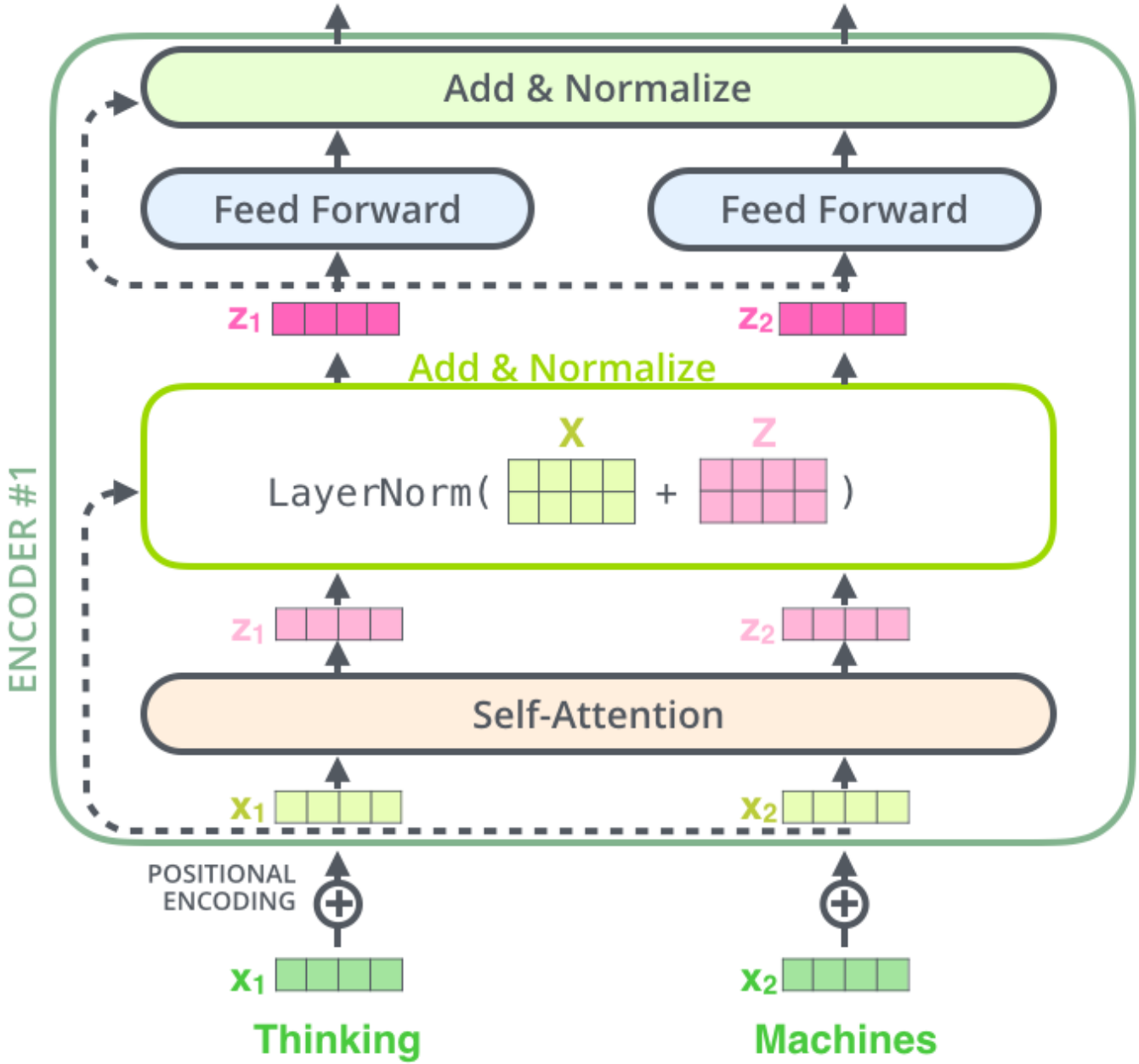

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2. Self-attention here works in a slightly different way $\rightarrow$ masks the future positions
3. Encoder-decoder attention layer borrows the queries from the layer below it