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
   - Path length $= \mathbb{O}(n)$
   - RNNs need at most $\mathbb{O}(n)$ sequential computations to access each element

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2. Since attention enables accesses to any state, do we need RNNs?

Transformers

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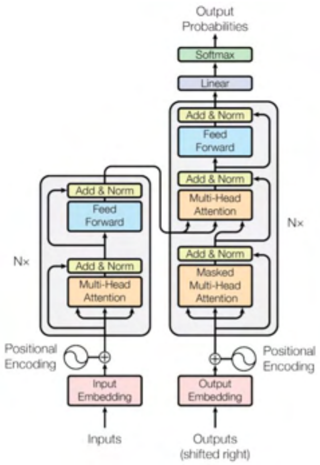

Transformers

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

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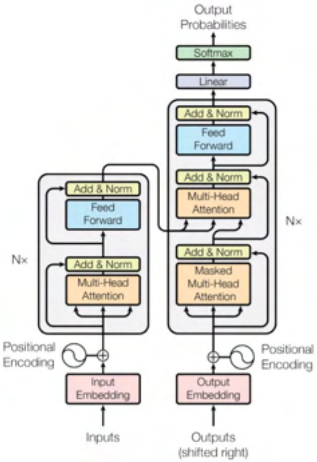
2. Sequnce to sequence modelling without RNNs



Transformers

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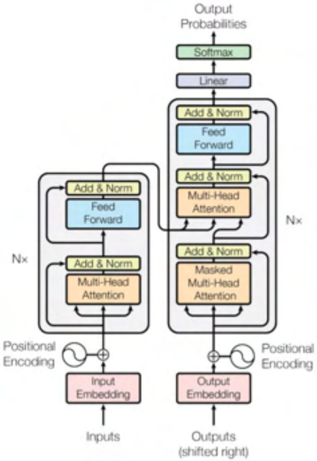
2. Sequnce to sequence modelling without RNNs
3. Transformer model is built on self-attention (no recurrent architectures!)



Transformers

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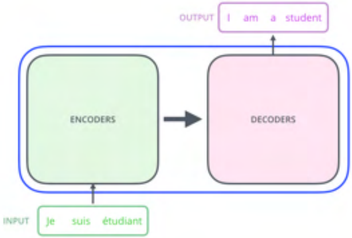

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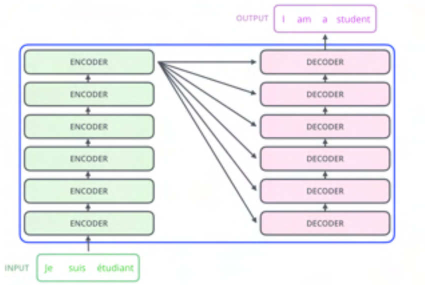
Transformers



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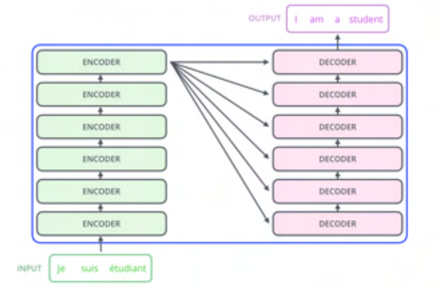
1. Encoding module has a stack of encoders

Transformers



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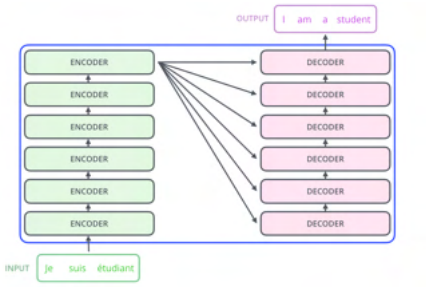
2. Same structure different parameters

Transformers



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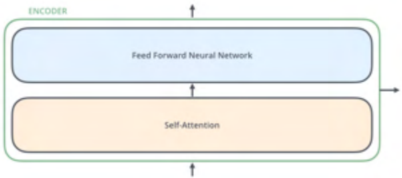
1. Encoding module has a stack of encoders
2. Same structure different parameters
3. Similarly the decoding module (same number of components in the stack as encoder)

Transformers



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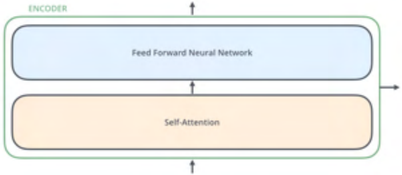
1. Encoder first has a self-attention layer

Transformers



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2. Looks at the other words while encoding a specific word

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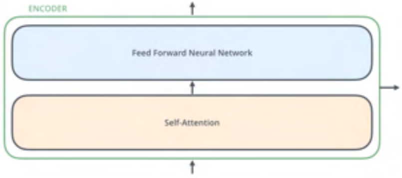

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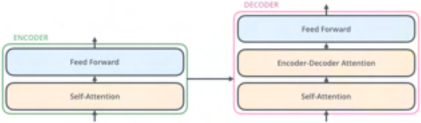
1. Encoder first has a self-attention layer
2. Looks at the other words while encoding a specific word
3. Next a (same) feed-forward NN is applied at all positions

Transformers



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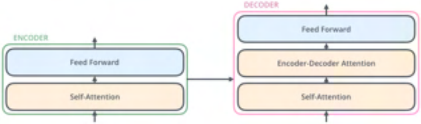
1. Decoder also has both the layers

Transformers



Credits: Jay Alammar

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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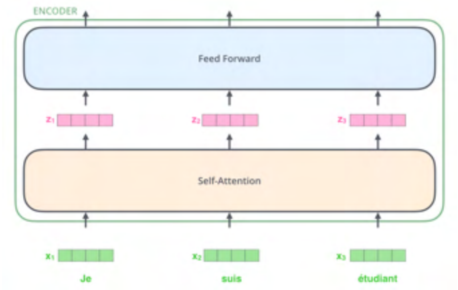
Transformers-Encoding

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



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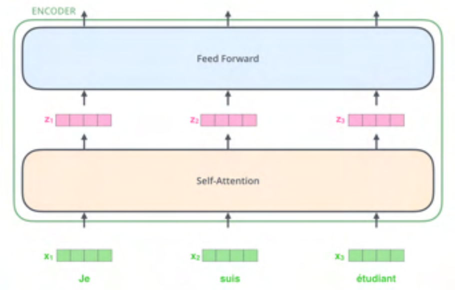
Transformers-Encoding

1. Each word flows through the two layers of the encoder through its own path
2. Self-attention layer has dependencies among them, however, the path length is $\mathbb{O}(1)$



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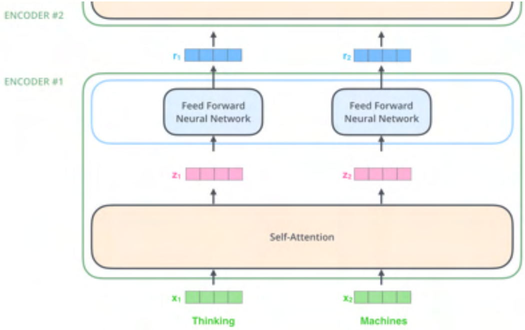
Transformers-Encoding



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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' refer to?

Self-Attention

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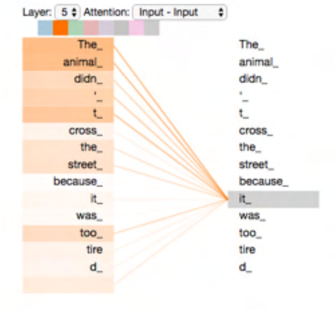
2. `The animal didn't cross the street because it was too wide`
3. What does 'it' refer to?
4. Easy for humans, but not so much for the traditional Seq2Seq models

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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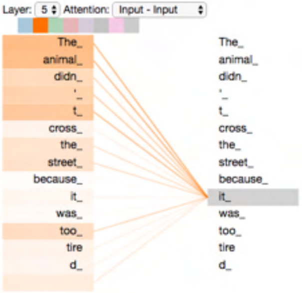
Self-Attention

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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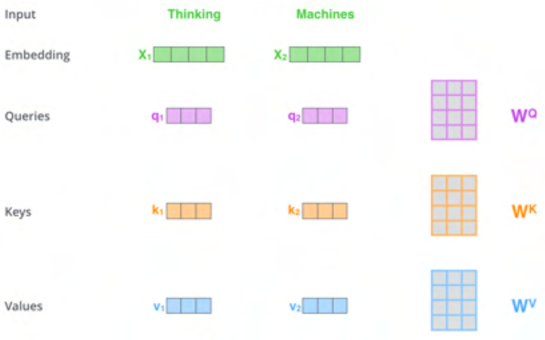
Self-Attention



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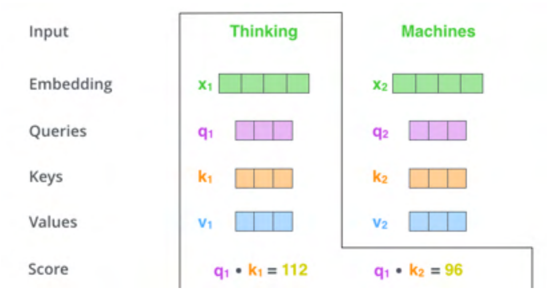

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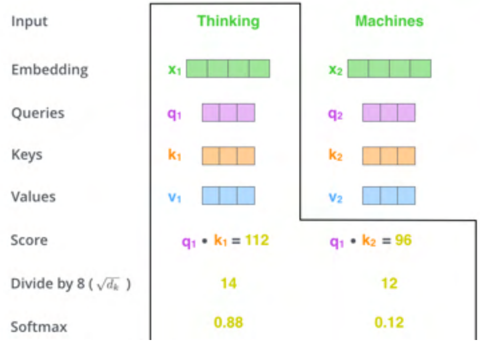

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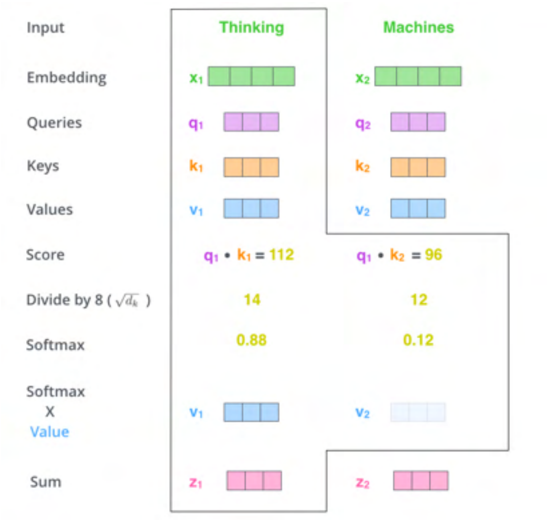

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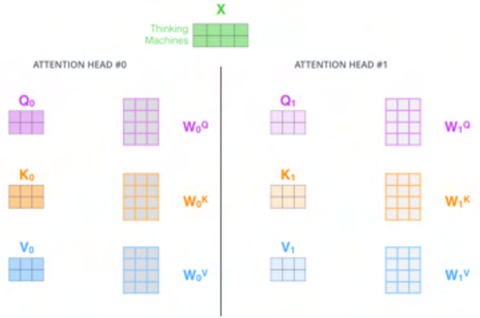
Multi-headed Self-Attention



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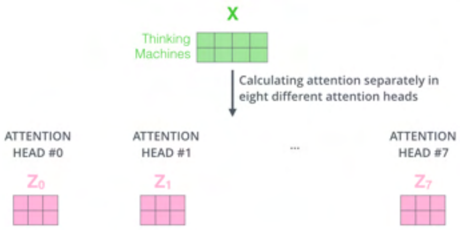
Multi-headed Self-Attention



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Multi-headed Self-Attention

1. Expands the model's ability to focus on different relevant positions in the i/p

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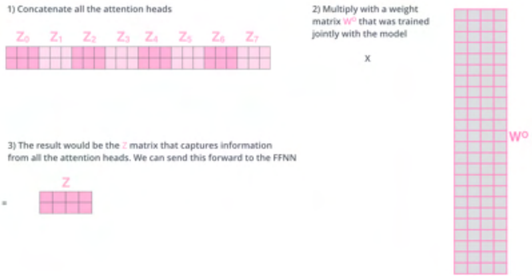
2. Enables different 'representational subspace'

Multi-headed Self-Attention



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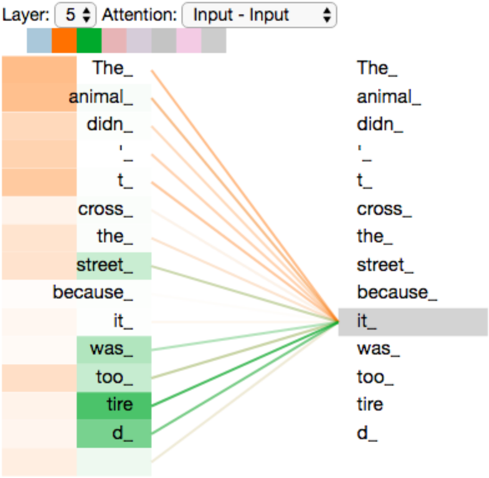
Multi-headed Self-Attention



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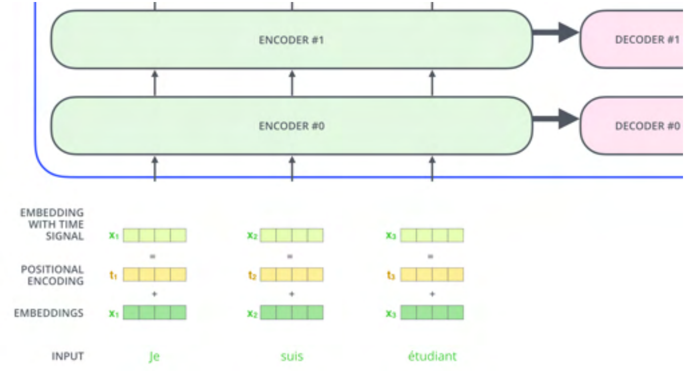
2. However, order the sequence conveys vital information in some applications
3. Solution: Add positional information of the i/p words into their embedding vectors

Positional Encoding



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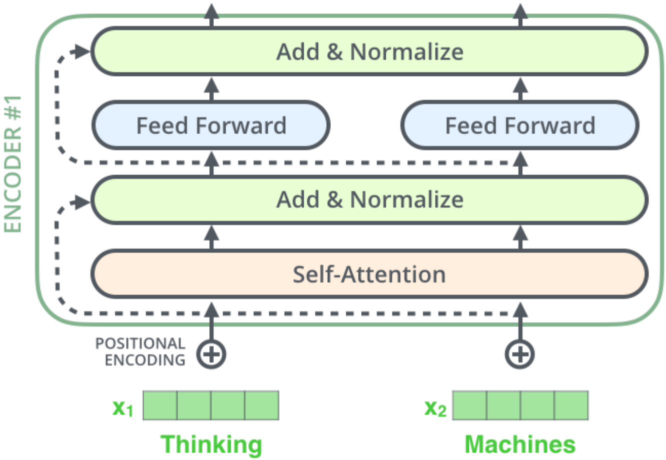
Residuals in the Encoder



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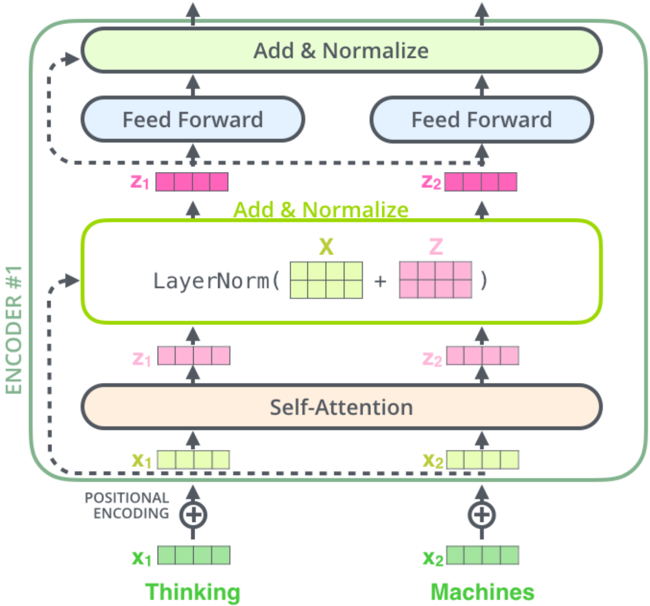
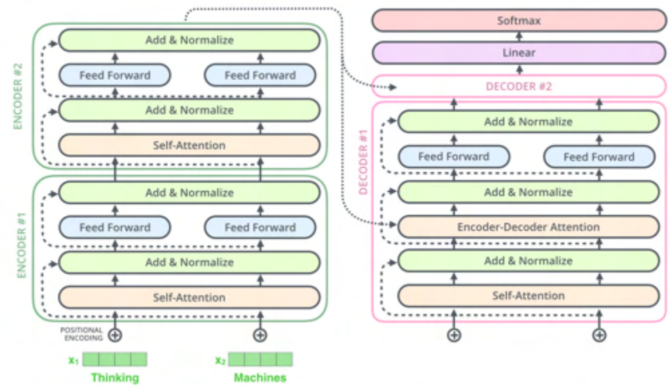


Tranformer-Decoder



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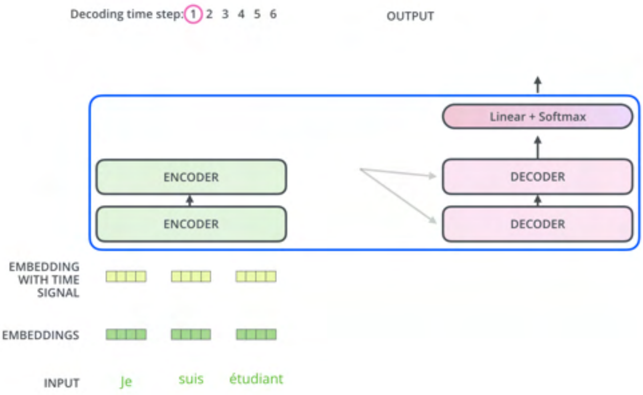
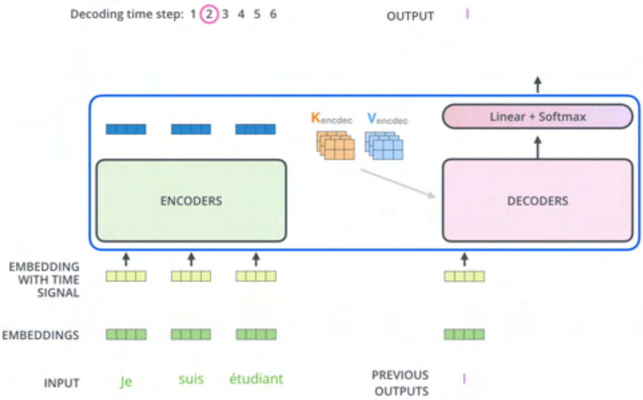
2. Uses the top encoder's K and V vectors for its' encoder-decoder attention
3. Encoder-decoder attention layer borrows the queries from the layer below it

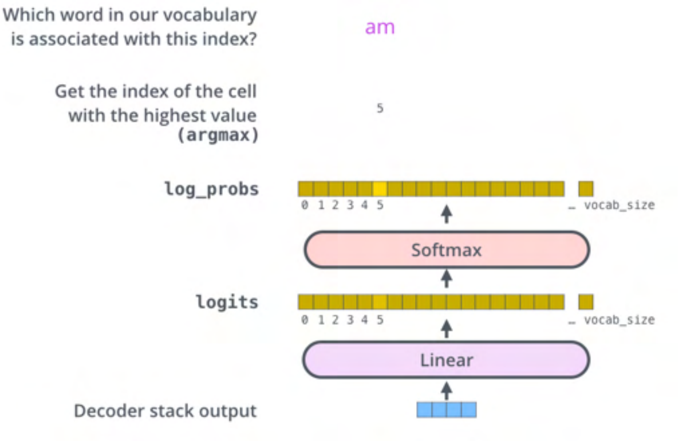
Transformer-Decoder



Transformer-Decoder



Final o/p



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