Deep Learning

15 Self-Attention & Transformers - I

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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 $= \mathbb{O}(\mathrm{n})$
   - RNNs need $\mathbb{O}(\mathrm{n})$ steps to process a sentence of length n

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

Transformers

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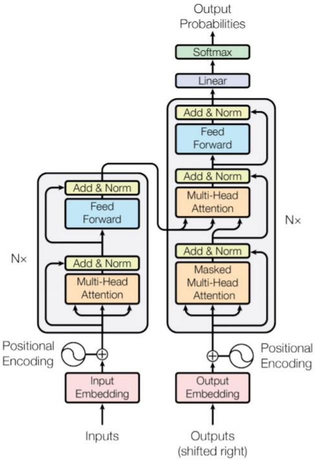

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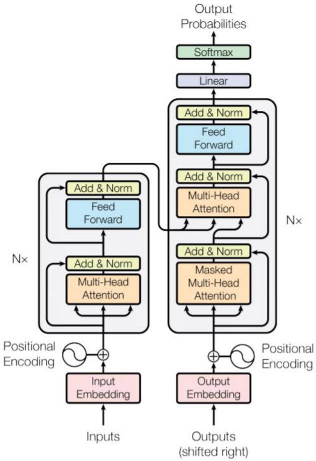

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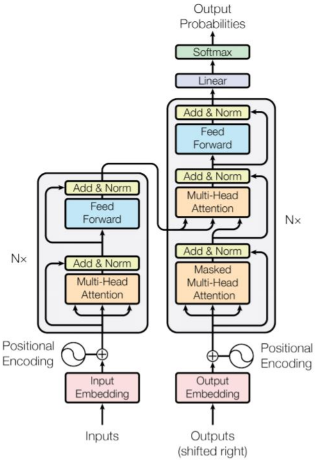
2. Sequnce to sequence modeling without RNNs
3. Transformer model is built on self-attention (no recurrence or convolutions)



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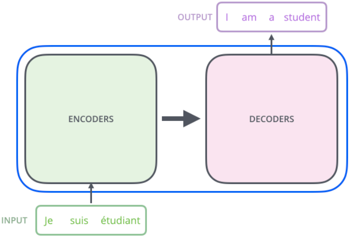

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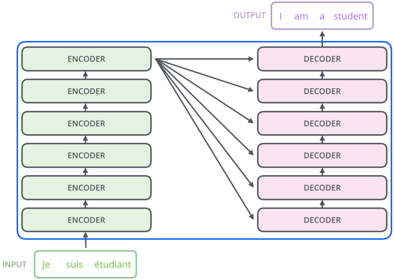

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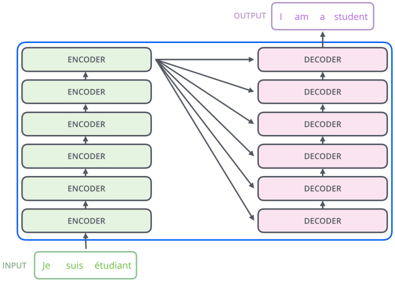

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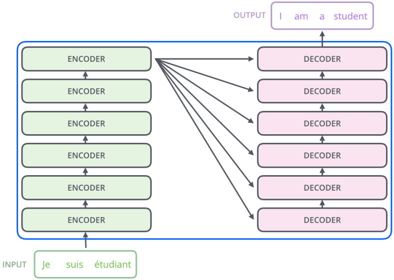

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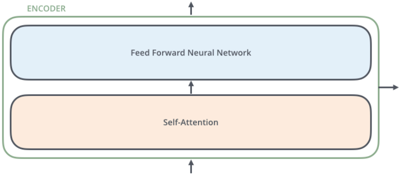
3. Similarly, the decoding module

Transformers



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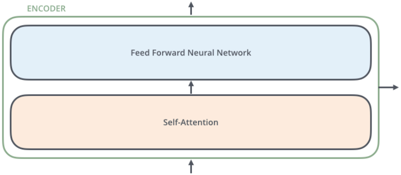

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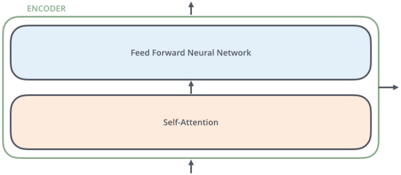

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1. Encoder first has a self-attention layer
2. Looks at the other words while encoding a specific word
3. Next a (same) feed-forward NN is applied at all positions

Attention vs Self-attention

1. Encoder-Decoder Attention
   looks

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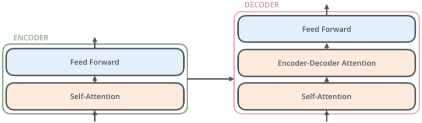

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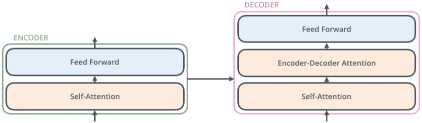

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1. Decoder has both the layers (self-attention and shared feed-forward)
2. But, in the middle it has an **encoder-decoder attention layer**

Why the name 'Transformer'?

1. Transforms a set of vectors in some representation space into a corresponding set of vectors (same dimensionality) in some new space

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2. Goal: new space will have a richer internal representation that is better suited to solve the downstream task

Transformers-Encoding

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

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2. Others receive a list of vectors from the encoder immediately below

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Self-attention in Encoder vs. Decoder

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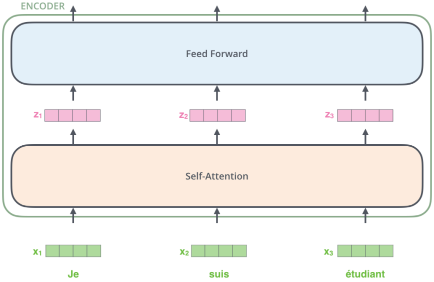
1. Decoder
2. Who is doing: target token at each time step
3. What are they doing (repeat)
   - looks at previous target tokens (self-attention)
   - looks at source representations (encoder-decoder attention)
   - update representation

Transformers-Encoding

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



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Transformers-Encoding

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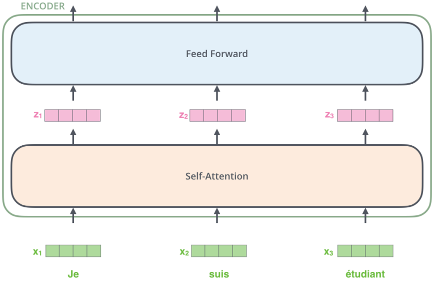
2. Self-attention layer has dependencies among them. However, the path length is $\mathbb{O}(1)$



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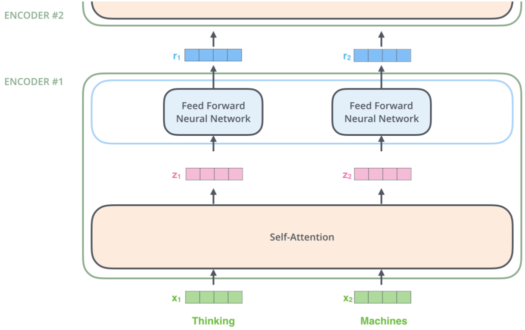

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Self-Attention

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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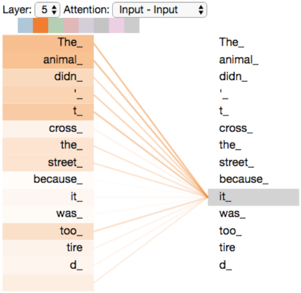
3. What does ‘it’ refer to?

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
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 encode better



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Self-Attention

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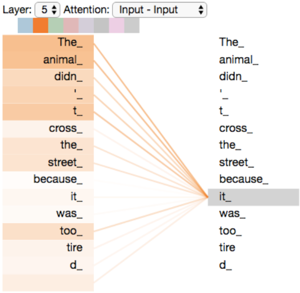
2. Unlike RNNs, we don't keep hidden states from previous positions here!



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3. $\mathbf{y_n} = \sum_{\mathbf{m=1}}^{\mathbf{N}} \mathbf{a_{nm}} \cdot \mathbf{x_m}$
4. $a_{mn} \geq 0$ and $\sum_{m=1}^{N} a_{mn} = 1$ Why?

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भारतीय प्रौद्योगिकी संस्थान हैदराबाद
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5. Each of the feature values in a token plays an equal role in determining the attention weights

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6. User's input of desired attributes $\rightarrow$ Query

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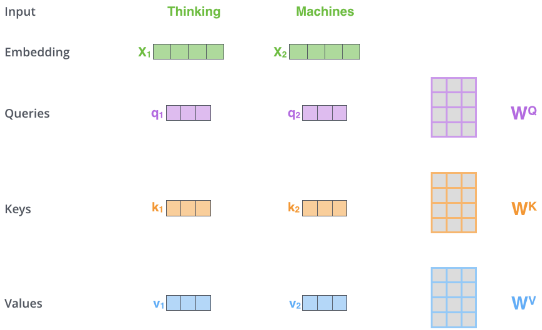

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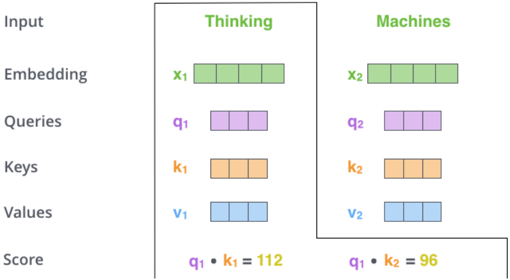

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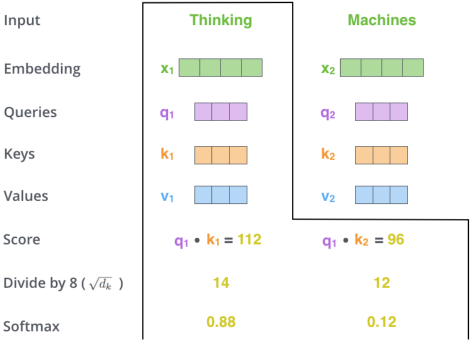

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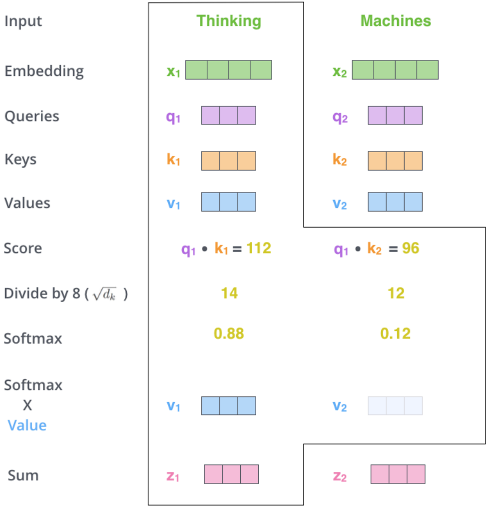

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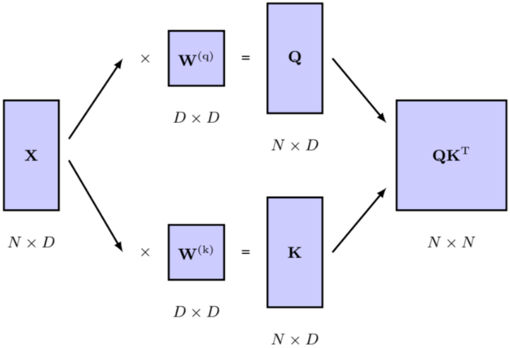

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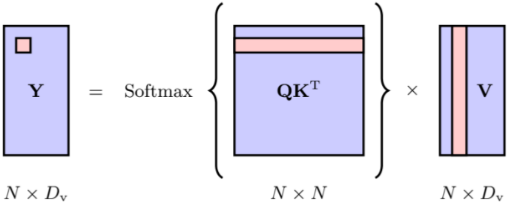

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2. To prevent this, the $\mathbf{QK^T}$ is scaled before the softmax
3. If the elements of q and v vectors are independent $N(0,1)$ distributed, the variance of the dot product $\rightarrow D_k$
4. Hence, normalize the product by the standard deviation
   $\mathbf{Y} = \text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Softmax}[\frac{\mathbf{QK^T}}{\sqrt{D_k}}]\mathbf{V}$

Multi-headed Self-Attention

1. There may be multiple patterns of attention that are relevant at the same time

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2. E.g., some patterns relevant to the 'tense' while others might be associated with the 'vocabulary.'

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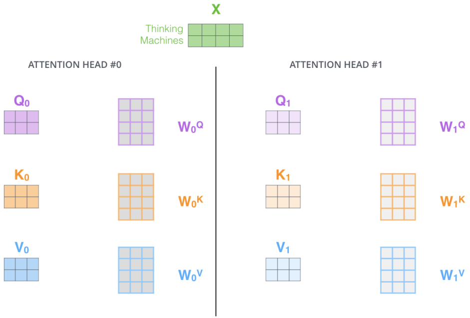

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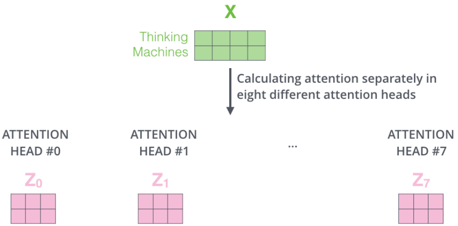

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2. Enables different 'representational subspace'

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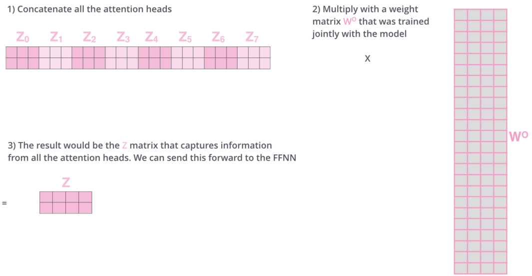

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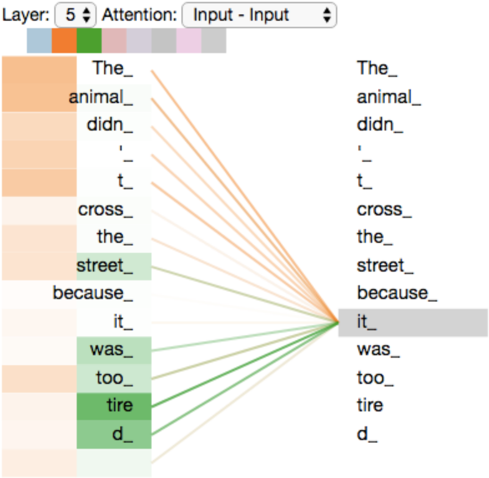

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4. Followed by Layer normalization
   $\mathbf{Z} = \text{LayerNorm}[\mathbf{Y}(\mathbf{X}) + \mathbf{X}]$

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2. Enhance the expressive capability/flexibility by post-processing using a nonlinear neural net (MLP)
3. This should not affect the transformer's ability to process variable length i/p
4. Same share net applies to all the o/p tokens (followed by residual connection and normalization)
   $\tilde{\mathbf{X}} = \textbf{LayerNorm}[\text{MLP}[\mathbf{Z}] + \mathbf{Z}]$