# 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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1. (Despite the LSTM/GRU) RNNs need attention to deal with long-range dependencies
2. Since attention enables access to any state, do we need RNNs?

# Transformers

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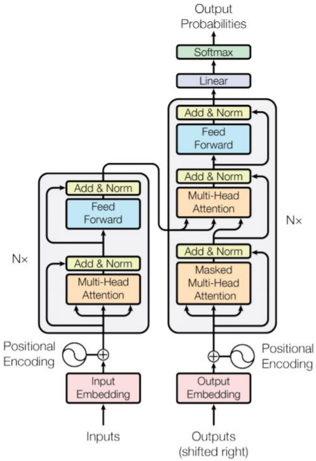

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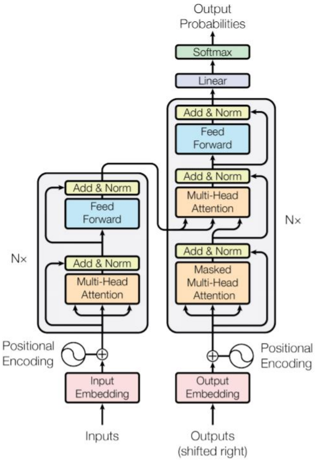

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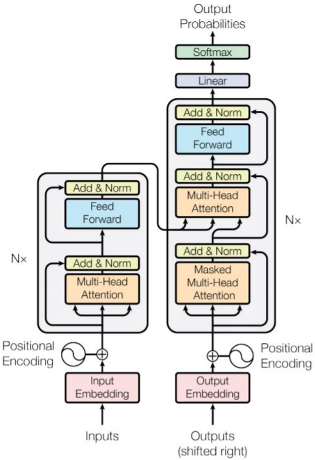
3. Transformer model is built on self-attention (no recurrence or convolutions)



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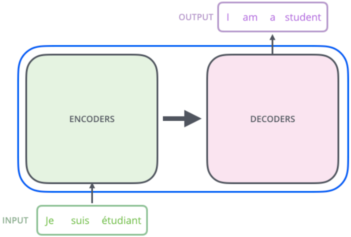


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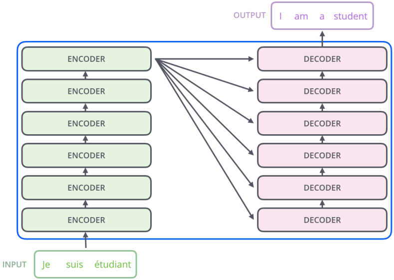


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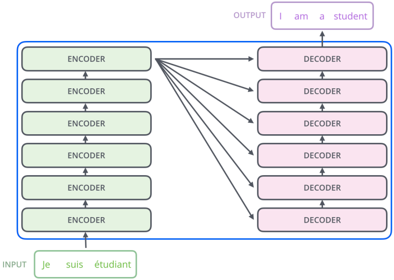


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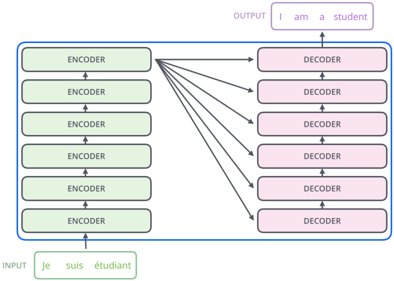


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3. Similarly, the decoding module

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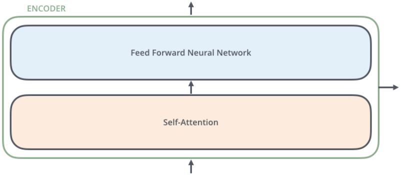


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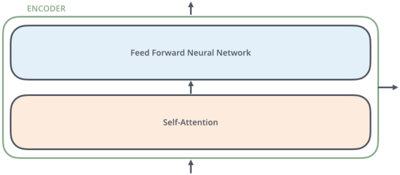


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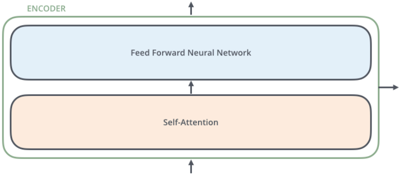


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1. Encoder first has a self-attention layer
2. Looks at the other words while encoding a specific word
3. Next a (same) feed-forward NN is applied at all positions

# Attention vs Self-attention

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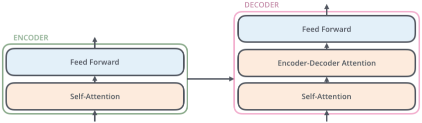


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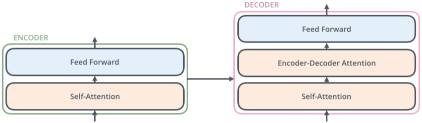


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1. Decoder has both the layers (self-attention and shared feed-forward)
2. But, in the middle it has an **encoder-decoder attention layer**

# 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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1. Transforms a set of vectors in some representation space into a corresponding set of vectors (same dimensionality) in some new space
2. Goal: new space will have a richer internal representation that is better suited to solve the downstream task

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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

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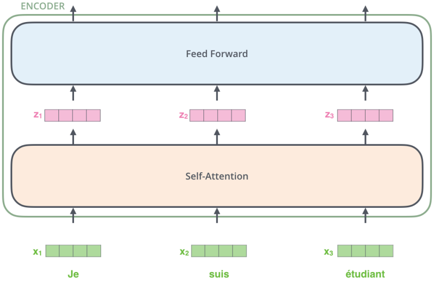


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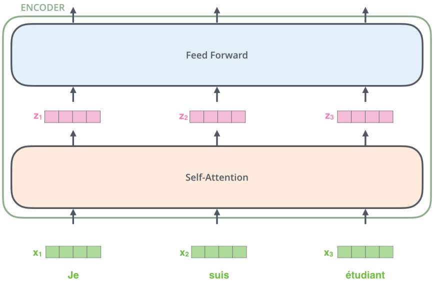
2. Self-attention layer has dependencies among them. However, the path length is $\mathbb{O}(1)$

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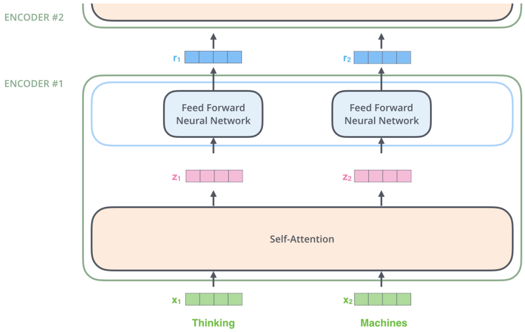


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# Self-Attention

1. The animal didn't cross the street because it was too tired
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4. Easy for humans, but not so much for the traditional Seq2Seq models

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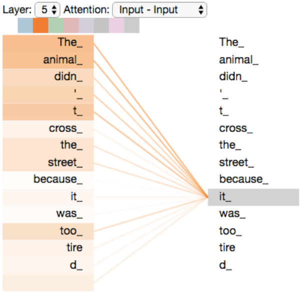
1. As the model processes each word, self-attention attends other positions in the i/p sequence to encode better

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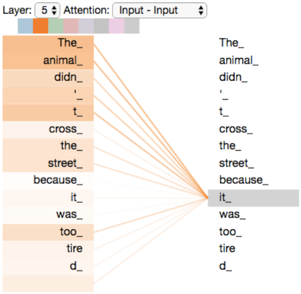
2. Unlike RNNs, we don't keep hidden states from previous positions here!

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# Attention weights

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

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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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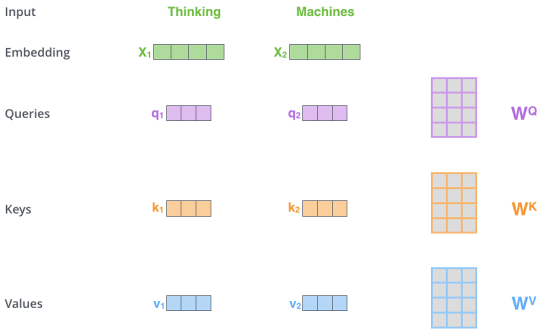


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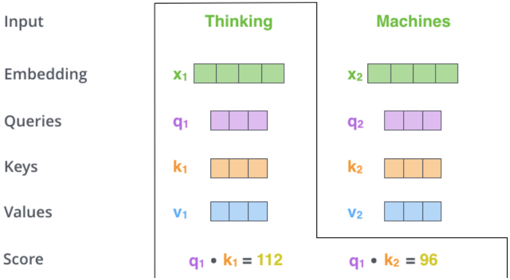


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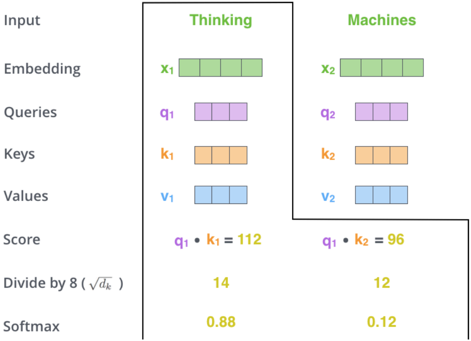


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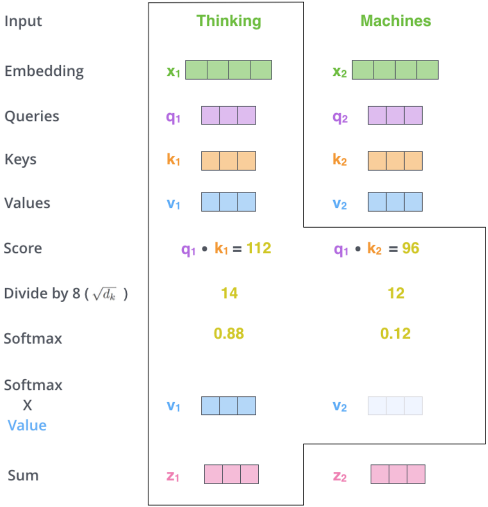


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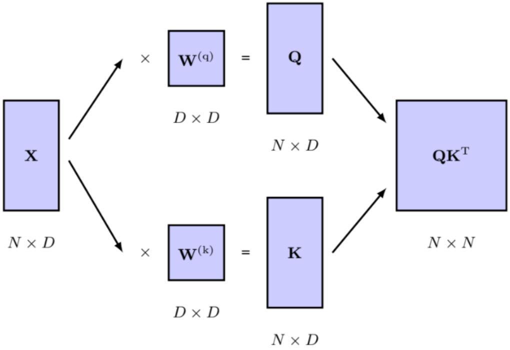


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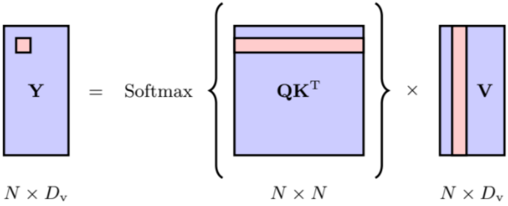


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# Scaled Self-Attention



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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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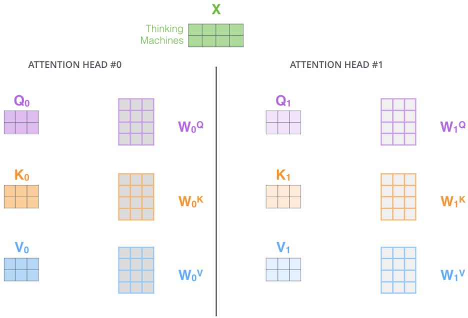


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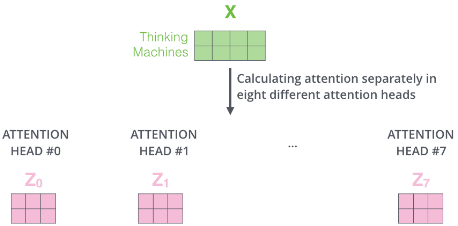


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2. Enables different 'representational subspace'

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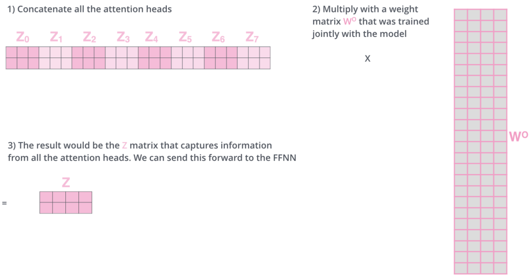


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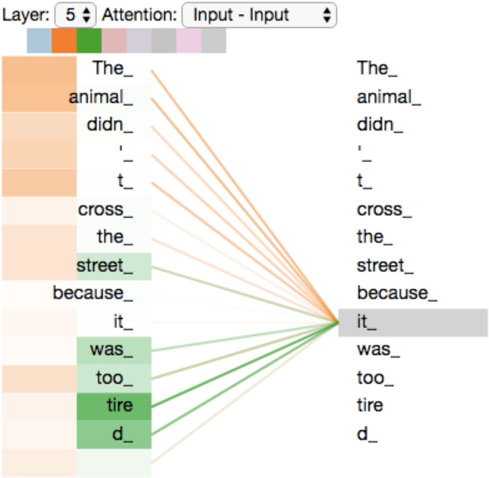


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2. $\rightarrow$ stack multiple self-attention layers
3. To improve the training efficiency, introduce residual connections (requires to maintain the dimensionality)
4. Followed by Layer normalization
   $\mathbf{Z} = \text{LayerNorm}[\mathbf{Y}(\mathbf{X}) + \mathbf{X}]$

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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)
   $\tilde{\mathbf{X}} = \textbf{LayerNorm}[\text{MLP}[\mathbf{Z}] + \mathbf{Z}]$