MICAS913 : Deep Learning

Transformers, prepared for Prof. Yousefi MANSOOR

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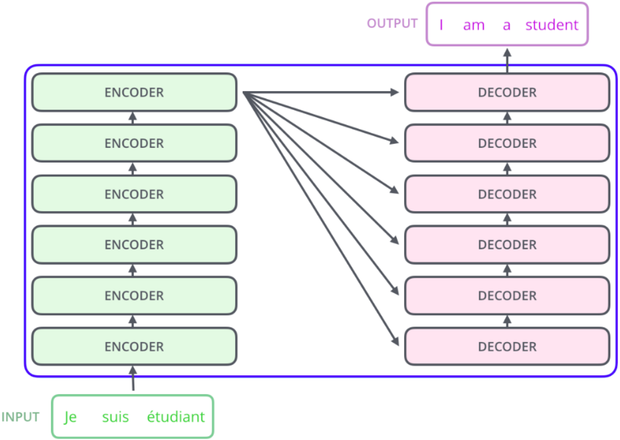
Introduction

Attention is All you Need (Google Brain 2017)

- Machine translation
- Attention Mechanism
- Encoder , Decoder
- Embedding
- Residual Connections
- Stack encoding decoding

Introduction - Global Concept



A very important note :

The number of encoder and decoders should be the same.

Outline

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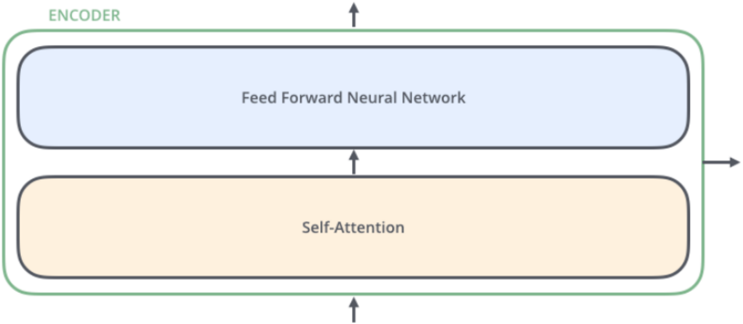
Encoder

Each encoder consists of :

- Self attention layer
- Feed Forward Network



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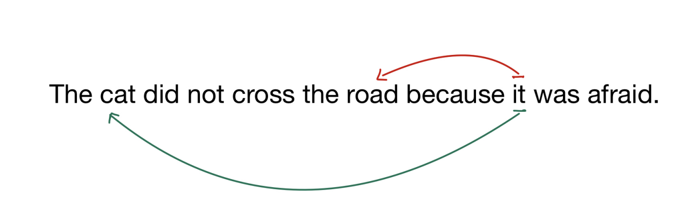
Self Attention Mechanism

Motivation

Its job is to look at other words in the input sentence while it encodes a specific word of that sentence.

Example



- Human's answer : "it" refers to "cat"
- Computer's answer : "it" can refer to "road"

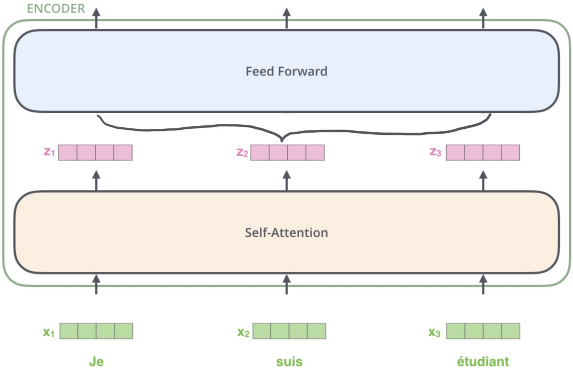
Self Attention Mechanism - Analogy with Human brain

Self Attention Mechanism - Embedding

Similar to any NLP procedure , we embed our input words.

Each word is embedded into a vector of size 512. We'll represent those vectors with these simple boxes.

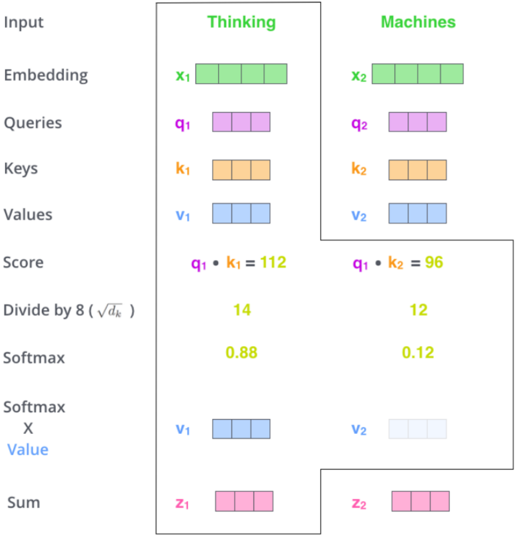
Self Attention Mechanism - Transformers Properties



2 properties :

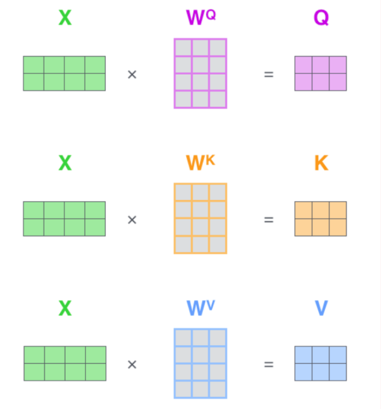
- Path dependencies in self attention
- Path independencies in feed forward network

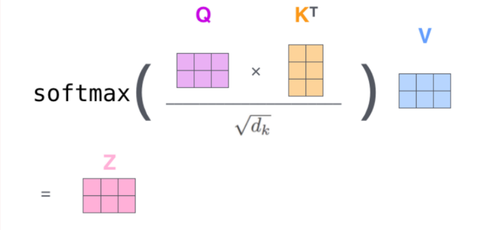
Self Attention Mechanism - In detail



Self Attention Mechanism - In detail (2)

Of course we use MATRICES





The self-attention calculation in matrix form

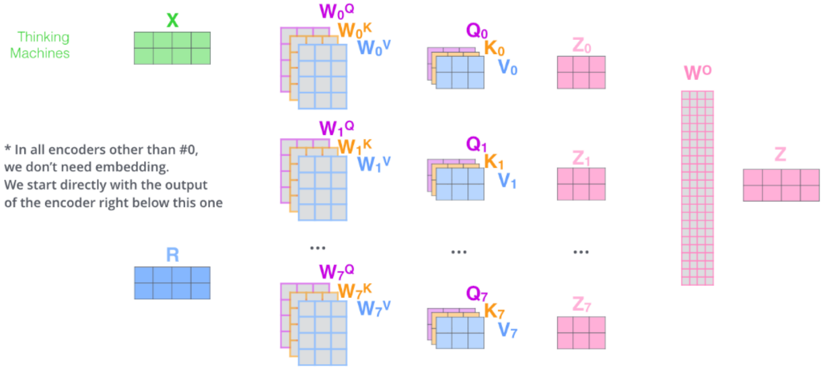
Remark

The complexity of the self-attention mechanism is $O(n^2.d)$

Self Attention Mechanism - Multi Head Attention

Motivation

- It expends the model's ability to focus on different positions.
- It gives the attention layer multiple representation subspaces.



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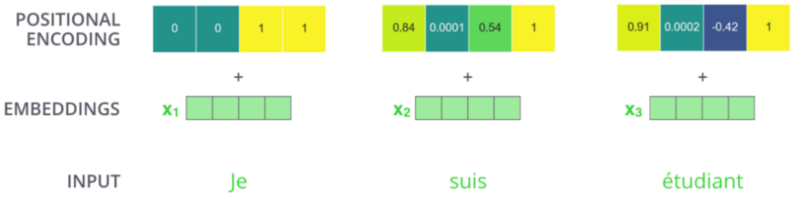
Positional Encoding



A real example of positional encoding with a toy embedding size of 4

Function of PE used in Attention is all you need :

$$PE(pos, i) = \begin{cases} \sin(\omega_k.pos) & \text{if } i = 2k \\ \cos(\omega_k.pos) & \text{if } i = 2k+1 \\ s.t. \quad w_k = 10000^{-2k/d} \end{cases}$$

d is the size of the embeddings, *pos* is the position of the word in the sentence and i is the position of the embedding of the word *pos*.

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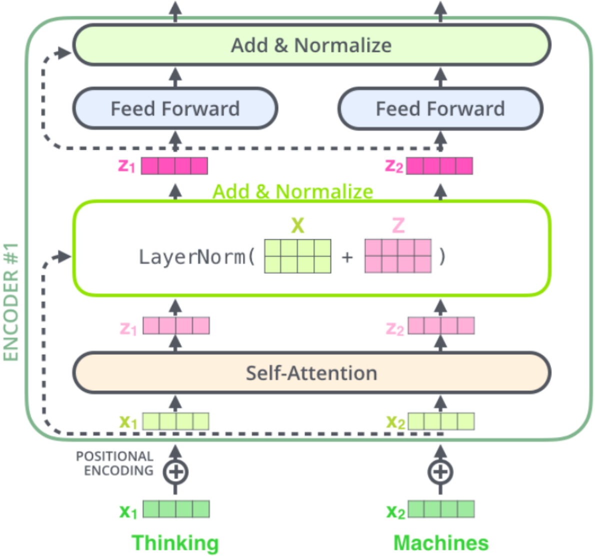
Residual Connections - Recap Encoder



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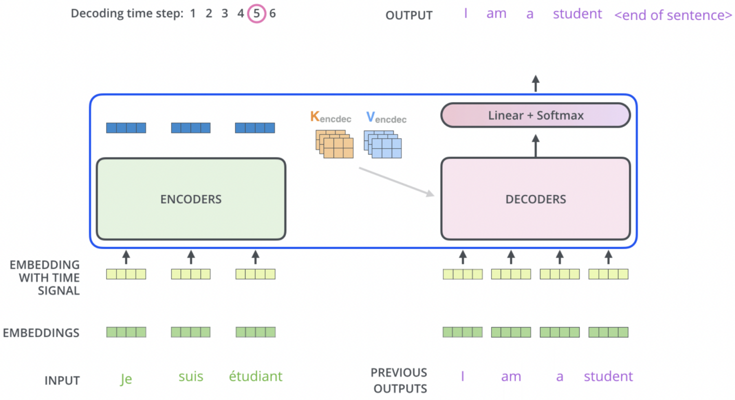
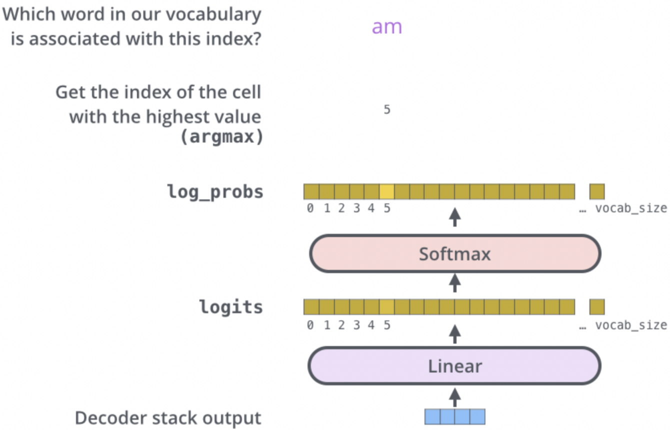
Decoders



Masking in self-attention calculation

The decoded embedding at position i can only see the decoded words from position 0 to i-1. We attribute $-\infty$ value to none visible positions before the Softmax.

Decoders - The Final Layer



This figure starts from the bottom with the vector produced as the output of the decoder stack. It is then turned into an output word.

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Conclusion

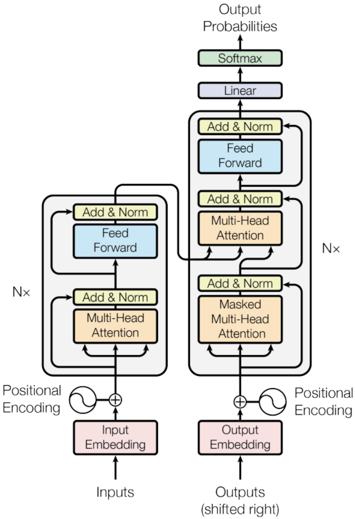

Figure 1: The Transformer - model architecture.

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Implementation

Now we go to our notebook ...

Appendix - Proof of positional encoding

We want to proove that For every sine-cosine pair corresponding to frequency ω_i, there is a linear transformation $M \in \mathbb{R}^{2x2}$ (indep of t) where the following equation holds:

$$M.\begin{pmatrix} sin(\omega_k.pos) \\ cos(\omega_k.pos) \end{pmatrix} = \begin{pmatrix} sin(\omega_k(pos+\alpha)) \\ cos(\omega_k(pos+\alpha)) \end{pmatrix}$$

Proof :

We can extend the sinus and cosinus :

$$\begin{pmatrix} sin(\omega_k(pos+\alpha)) \\ cos(\omega_k(pos+\alpha)) \end{pmatrix} = \begin{pmatrix} sin(\omega_k.pos)cos(\omega_k.\alpha) + cos(\omega_i.pos)sin(\omega_k.\alpha) \\ cos(\omega_k.pos)cos(\omega_k.\alpha) - sin(\omega_k.pos)sin(\omega_k.\alpha) \end{pmatrix}$$

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}.\begin{pmatrix} sin(\omega_k.pos) \\ cos(\omega_k.pos) \end{pmatrix} = \begin{pmatrix} sin(\omega_k.pos)cos(\omega_k.\alpha) + cos(\omega_k.pos)sin(\omega_k.\alpha) \\ cos(\omega_k.pos)cos(\omega_k.\alpha) - sin(\omega_k.pos)sin(\omega_k.\alpha) \end{pmatrix}$$

By identification :

$\mathrm{a} = \mathrm{cos}(\omega_k.\alpha), b = sin(\omega_k.\alpha), c = -sin(\omega_k.\alpha), d = cos(\omega_k.\alpha)$

References

- Ashish Vaswaniet al. *Attention Is All You Need*, 12 Jun 2017
- Qiang Wang et al., *Learning Deep Transformer Models for Machine Translation*
- Bryan Lim et al., *Temporal Fusion Transformers for interpretable multi-horizon time series forecasting*
- Jay Alammar, The Illustrated Transformer
- Amirhossein Kazemnejad, Blog