STOR566: Introduction to Deep Learning

Lecture 17: Transformer

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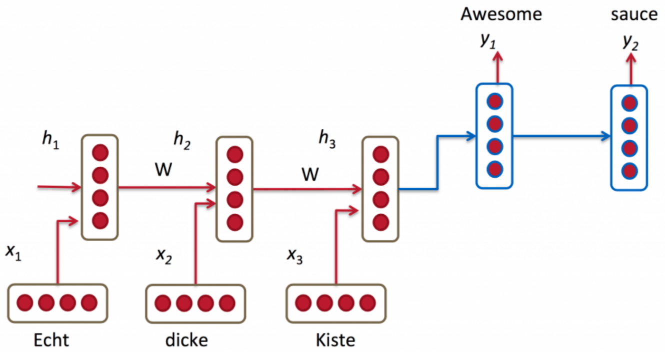
Materials are from *Deep Learning (UCLA)*

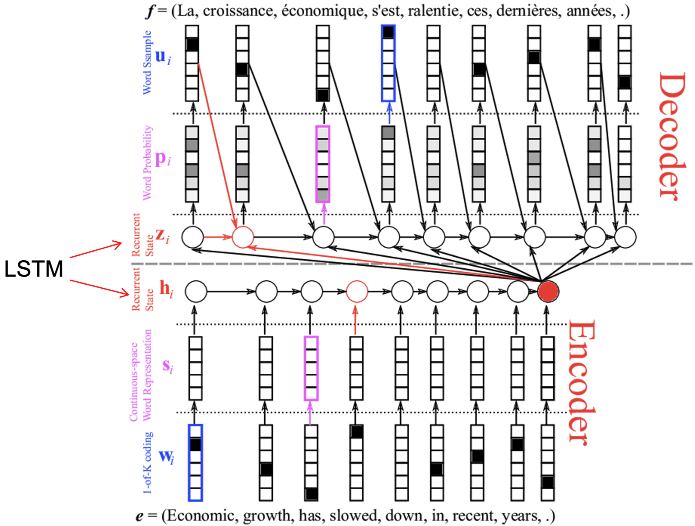
Neural Machine Translation

Neural Machine Translation (NMT)

- Out the translated sentence from an input sentence
- Training data: a set of input-output pairs (supervised setting)
- Encoder-decoder approach:
  - Encoder: Use (RNN/LSTM) to encode the input sentence input a latent vector
  - Decoder: Use (RNN/LSTM) to generate a sentence based on the latent vector

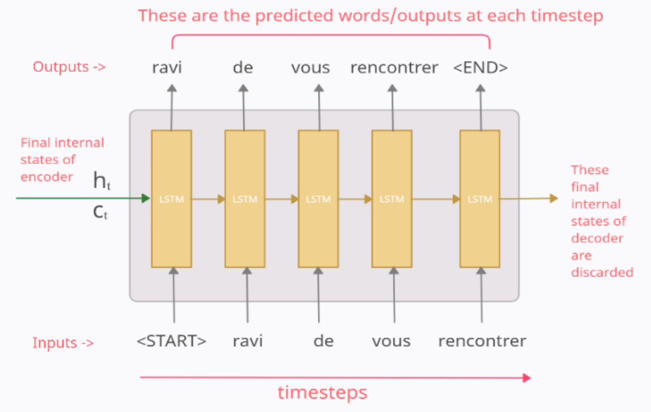


Neural Machine Translation



RNN: Neural Machine Translation

- Start input of the decoder?
- When to stop?



picture from https://medium.com/analytics-vidhya/encoder-decoder-seq2seq-models-clearly-explained-c34186fbf49b

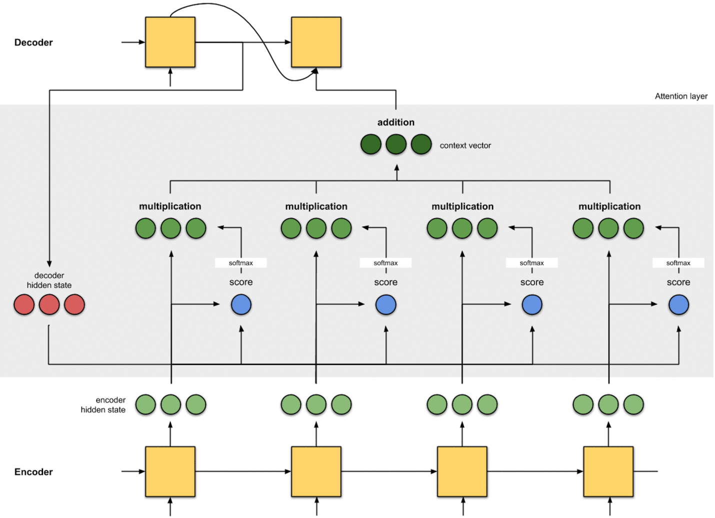
Attention in NMT

- Usually, each output word is only related to a subset of input words (e.g., for machine translation)
- Let $\boldsymbol{u}$ be the current decoder latent state
  $\boldsymbol{v}_1, \ldots, \boldsymbol{v}_n$ be the latent sate for each input word
- Compute the weight of each state by

$$\boldsymbol{p} = \text{Softmax}(\boldsymbol{u}^T \boldsymbol{v}_1, \ldots, \boldsymbol{u}^T \boldsymbol{v}_n)$$

- Compute the context vector by $V\boldsymbol{p} = p_1 \boldsymbol{v}_1 + \cdots + p_n \boldsymbol{v}_n$

Attention in NMT

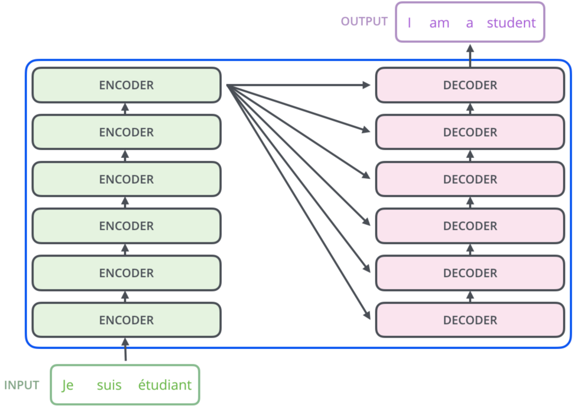


(Figure from `https://towardsdatascience.com/`

Transformer

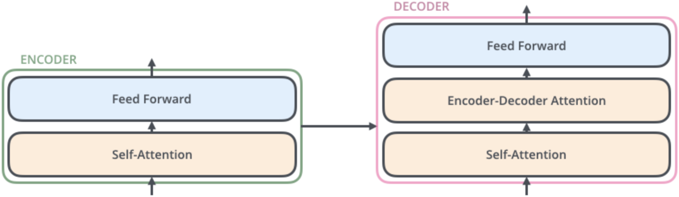
Transformer

- An architecture that relies entirely on attention without using CNN/RNN
- Proposed in "Attention Is All You Need" (Vaswani et al., 2017)
- Initially used for neural machine translation



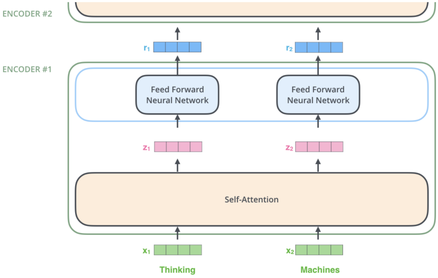
Encoder and Decoder

- Self attention layer: the main architecture used in Transformer
- Decoder: will have another attention layer to help it focuses on relevant parts of input sentences.



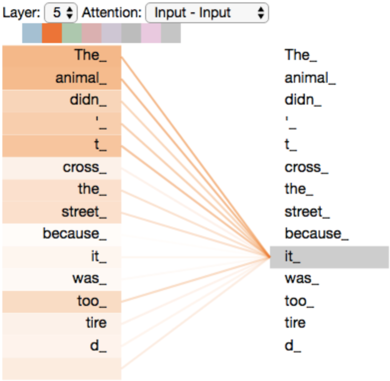
Encoder

- Each word has a corresponding “latent vector” (initially the word embedding for each word)
- Each layer of encoder:
  - Receive a list of vectors as input
  - Passing these vectors to a self-attention layer
  - Then passing them into a feed-foward layer
  - Output a list of vectors



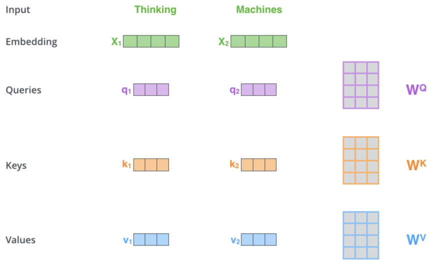
Self-attention layer

- Main idea: The actual meaning of each word may be related to other words in the sentence
- The actual meaning (latent vector) of each word is a weighted (attention) combination of other words (latent vectors) in the sentences



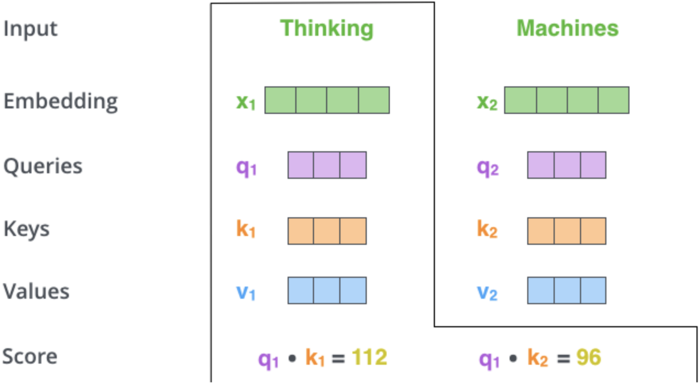
Self-attention layer

- Input latent vectors: $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$
- Self-attention parameters: W^Q, W^K, W^V (weights for query, key, value)
- For each word i, compute
  - Query vector: $\boldsymbol{q}_i = \boldsymbol{x}_i W^Q$
  - Key vector: $\boldsymbol{k}_i = \boldsymbol{x}_i W^K$
  - Value vector: $\boldsymbol{v}_i = \boldsymbol{x}_i W^V$



Self-attention layer

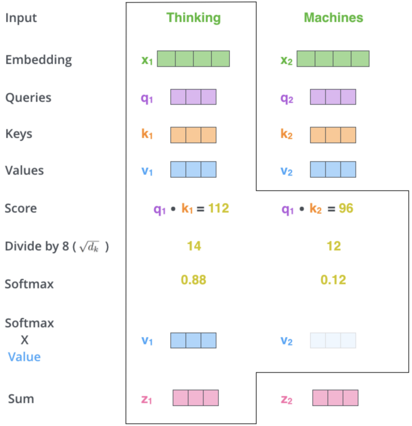
- For each word i, compute the scores to determine how much focus to place on other input words
  - The attention score for word j to word i: $\boldsymbol{q}_i^T \boldsymbol{k}_j$



Self-attention layer

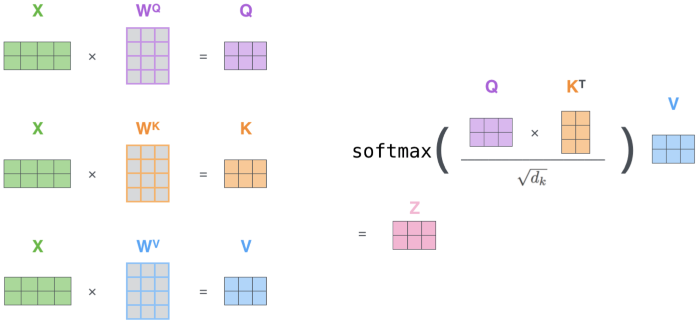
- For each word i, the output vector

$$\sum_j s_{ij} \boldsymbol{v}_j, \quad \boldsymbol{s}_i = \text{softmax}(\boldsymbol{q}_i^T \boldsymbol{k}_1, \dots, \boldsymbol{q}_i^T \boldsymbol{k}_n)$$



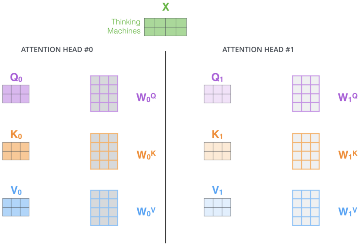
Matrix form

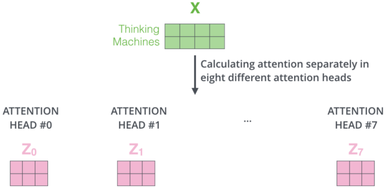
$$Q = XW^Q, \;\; K = XW^K, \;\; V = XW^V, \quad Z = \mathrm{softmax}(QK^T)V$$



Multiple heads

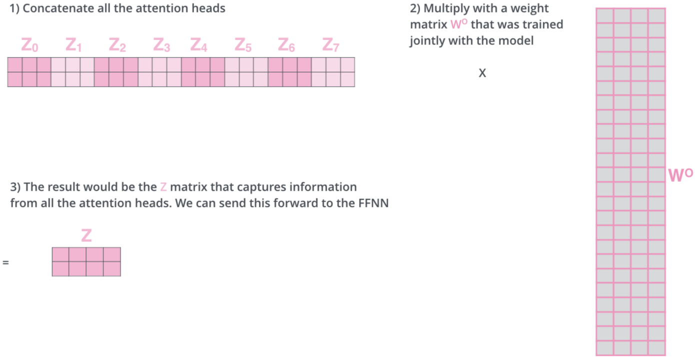
- Multi-headed attention: use multiple set of $(key, value, query)$ weights
- Each head will output a vector Z_i



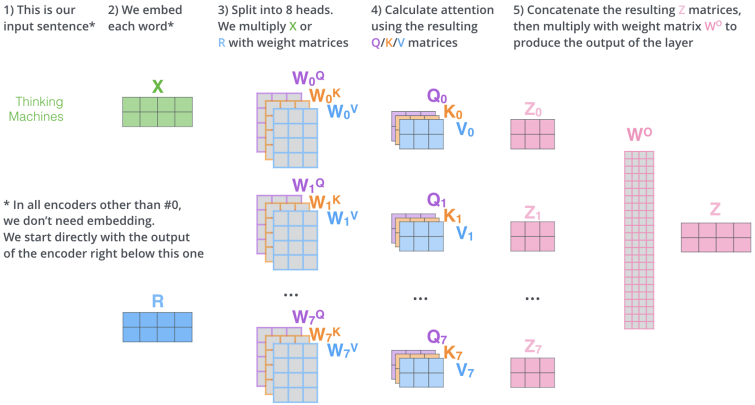


Multiply with weight matrix to reshape

- Gather all the outputs $Z_1, \ldots, Z_k$
- Multiply with a weight matrix to reshape
- Then pass to the next fully connected layer

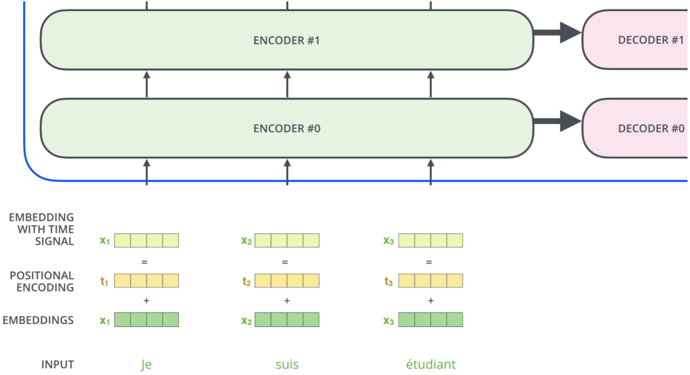


Overall architecture



Position encoding

- The above architecture ignores the sequential information
- Add a position encoding vector to each $\boldsymbol{x}_i$ (according to i)

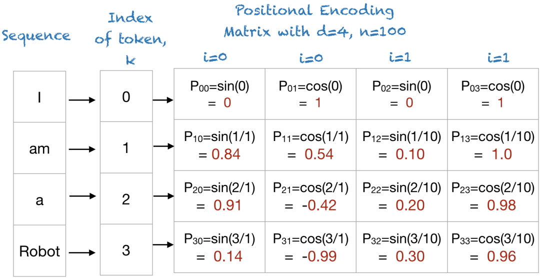


Position encoding

- Sin/cosine functions with different wavelengths (used in the original Transformer)

$$P(k,i) = \sin\left(\frac{k}{n^{2i/d}}\right), P(k,i) = \cos\left(\frac{k}{n^{2i/d}}\right)$$

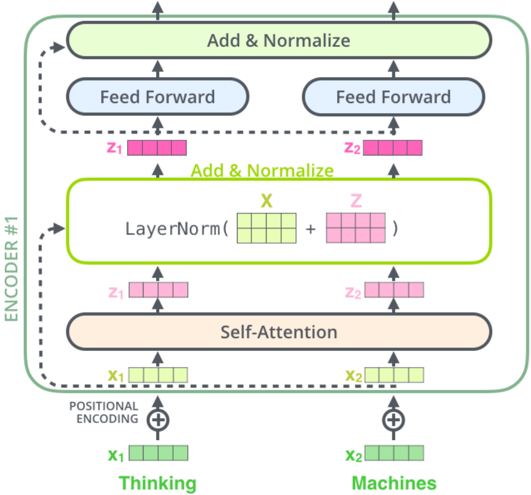
  - smooth, parameter-free, inductive
  - k: position, i: $0 < i < d/2$, n: user-defined scalar, 10,000 in the original paper



Positional Encoding Matrix for the sequence 'I am a robot'

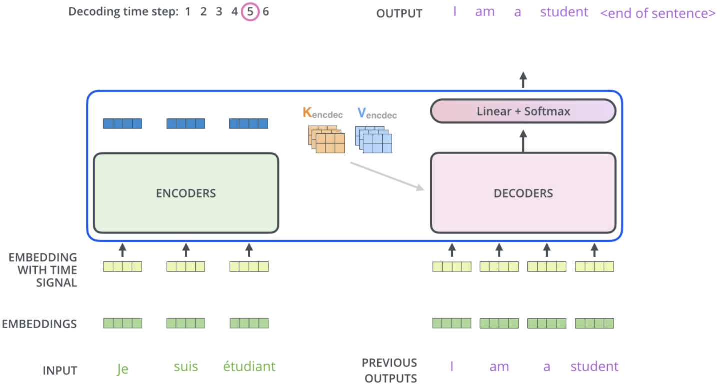
The Residuals

- Residual connection and Normalization



Decoder

- K and V from the final encoder layer used by all the encoder-decoder attention layers in the decoding part.
- Decoding sequentially not parallelly
- Attention layer only uses information from previous positions



Conclusions

- A review of RNN and NMT
- A brief introduction of Transformer.

Questions?