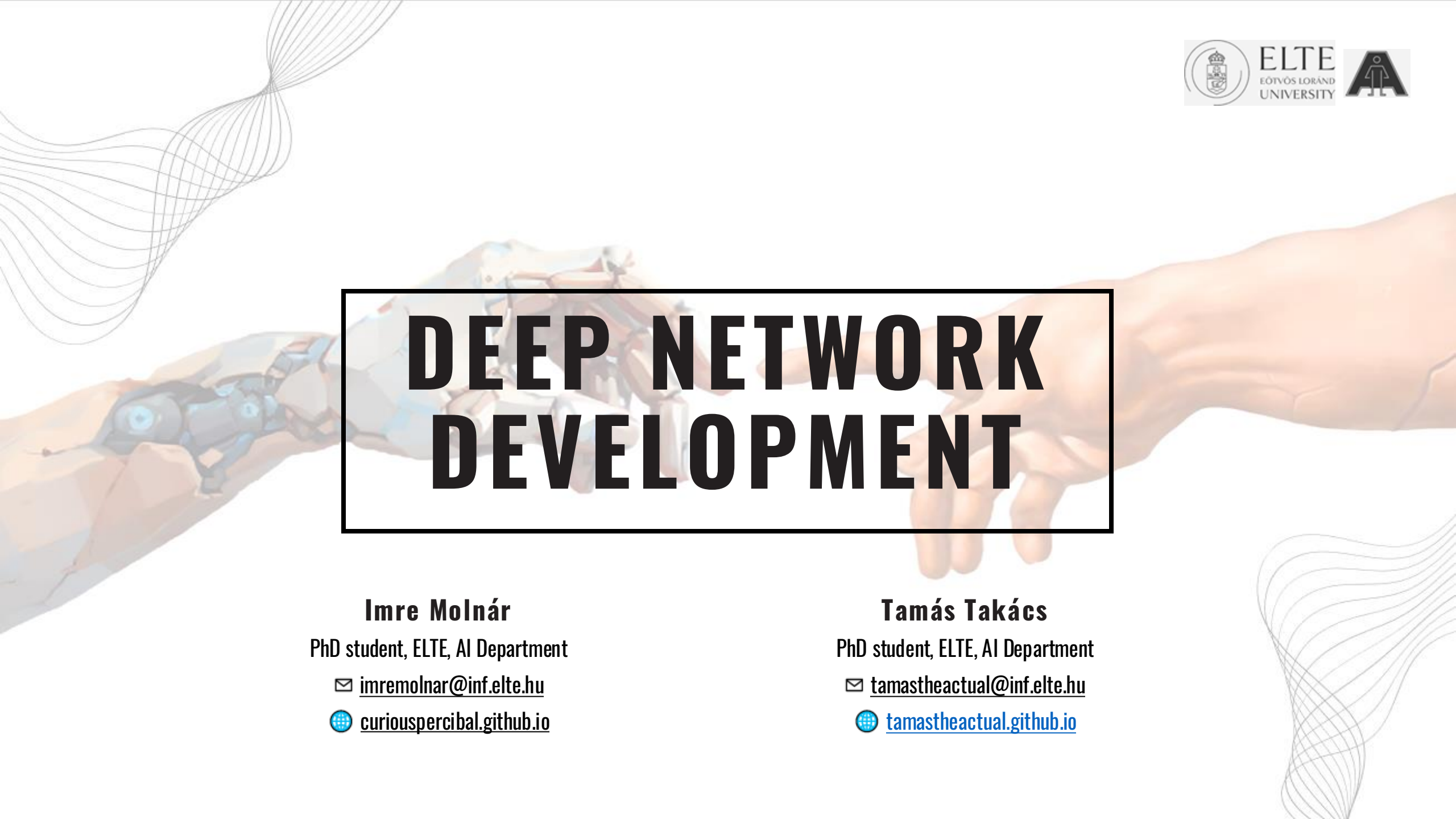

DEEP NETWORK DEVELOPMENT

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Deep Network Development

Lecture 8.

Transformer Networks

Budapest, 4th April 2025

1 Natural Language Understanding

2 Attention Mechanism

3 Transformer Architecture

Recap

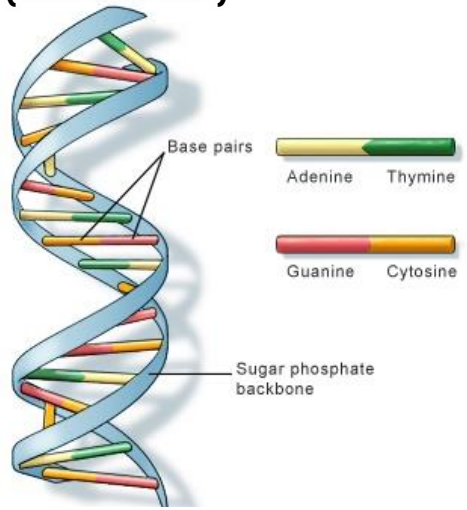
Sequential data

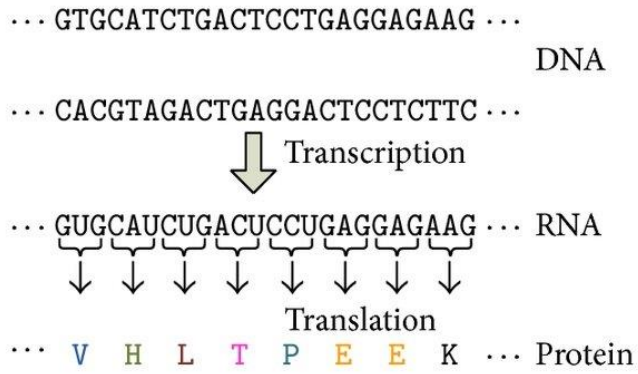
Text – sequence of words / characters

Speech – sequence of signals / acoustic features

Video – sequence of images (frames)

DNA – sequence of symbols (nucleotides)

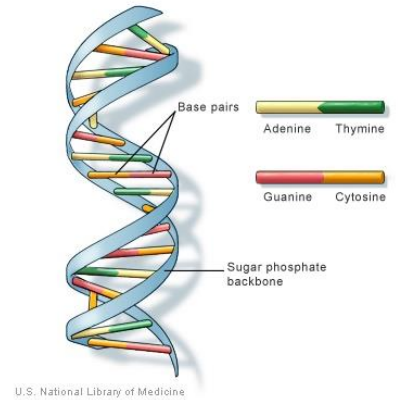




Recap

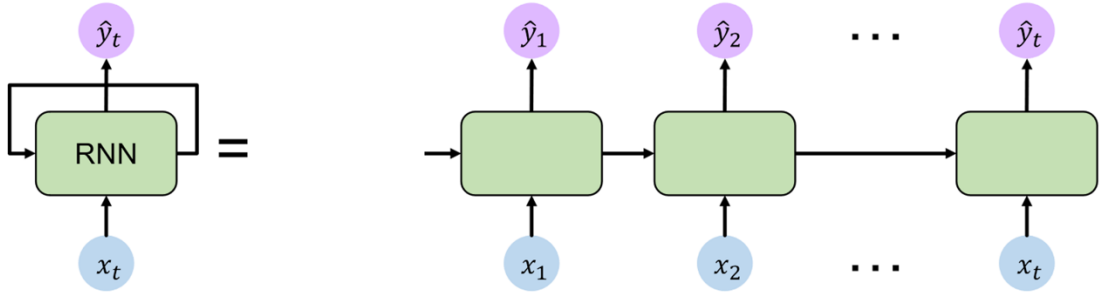
Key properties of sequential data

- Order
- Temporal information
- Context



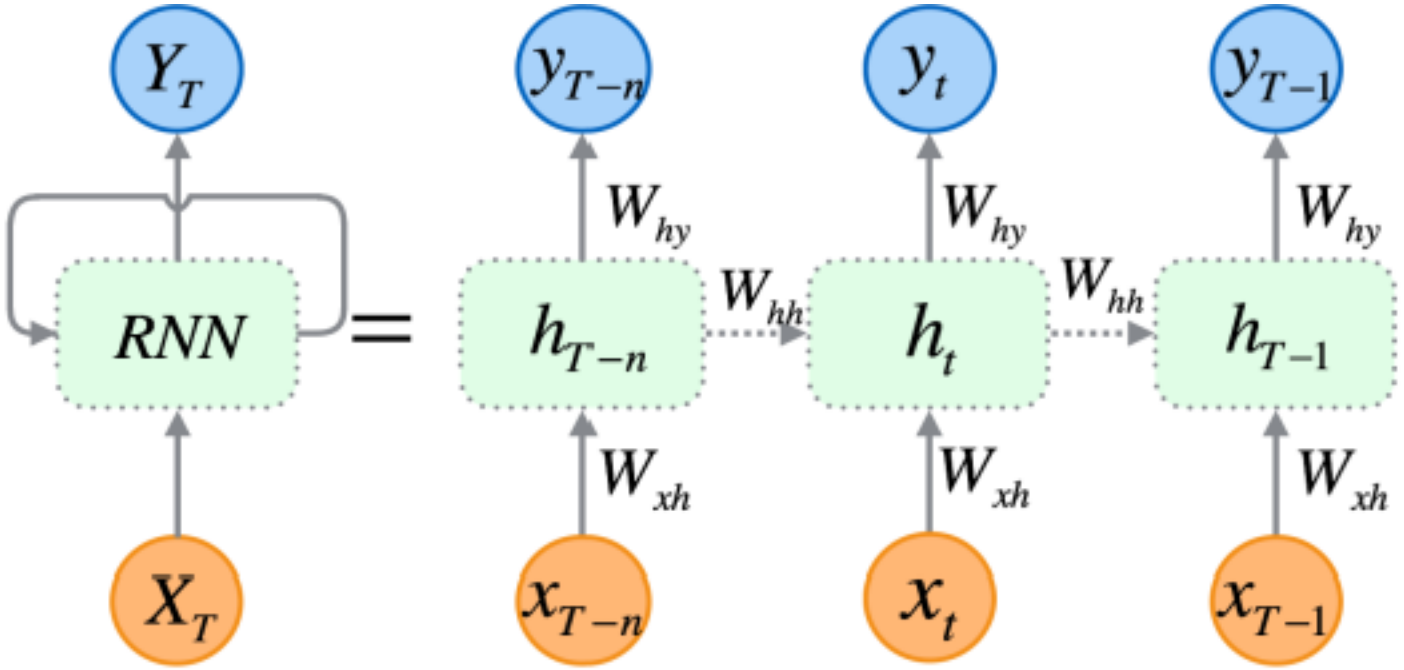
Key model properties:

- Handle variable length sequences
- Track long term dependencies
- Maintain the order of the input
- Share parameters across sequences



Recurrent Neural Network (review)

RNN (unrolled version)



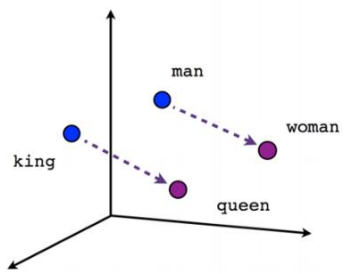
Embeddings: Word representation (review)

Featurized representation: Word Embedding

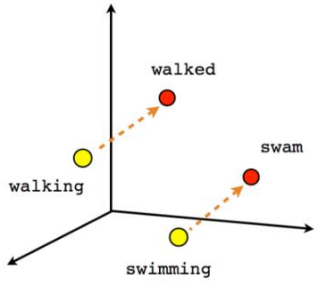
If we subtract man and woman, main difference is gender

We can compute word similarities

We can compute word analogies: man is to woman as king is to ___



Male-Female



Verb tense

	Man (5391)	Woman (9853)	King (4914)	Queen (7151)	Apple (456)	Orange (6257)
Gender	**-1**	**1**	**-0.95**	**0.97**	0.00	0.01
Royal	0.01	0.02	**0.93**	**0.95**	-0.01	0.00
Age	0.03	0.02	**0.7**	**0.68**	0.03	-0.02
Food	0.04	0.01	0.02	0.01	**0.95**	**0.97**
…	…	…	…	…	…	…

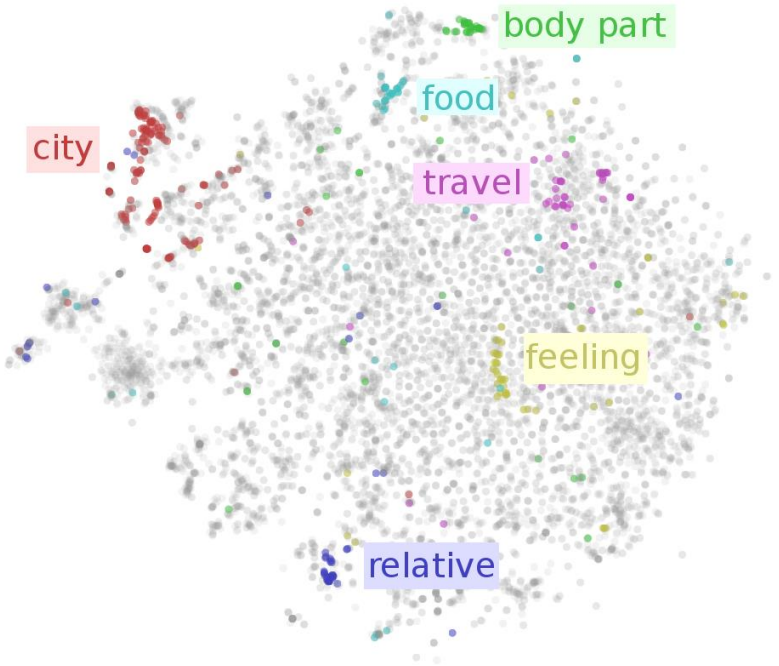
Embeddings: Word representation (review)

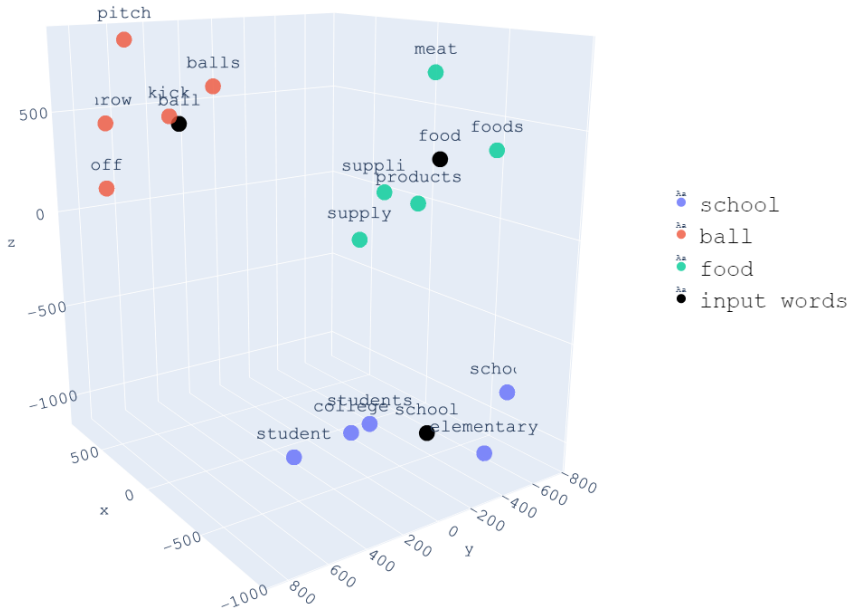
Featurized representation: Word Embedding

The word embeddings are learned with training.

Therefore, in practice, the features aren't that understandable.

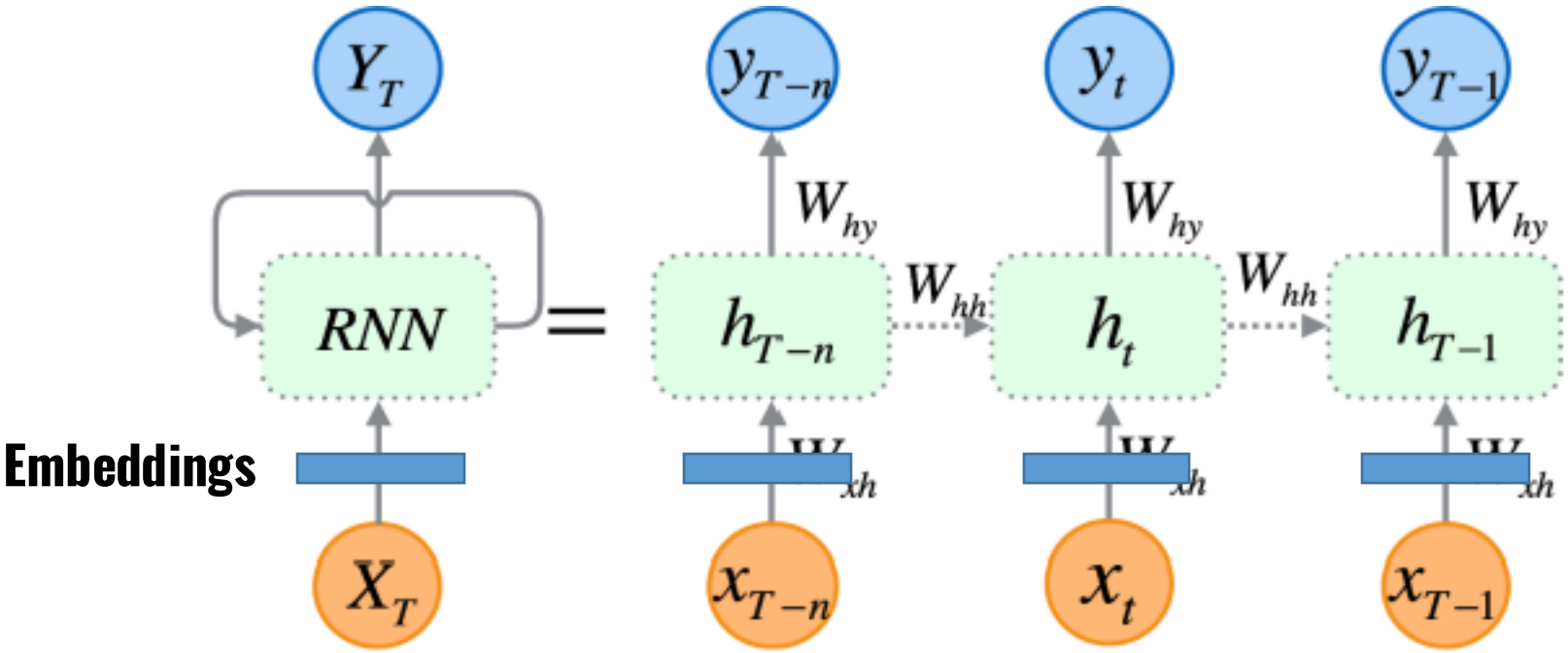
We can visualize lower representations of the embeddings with techniques such as T-SNE





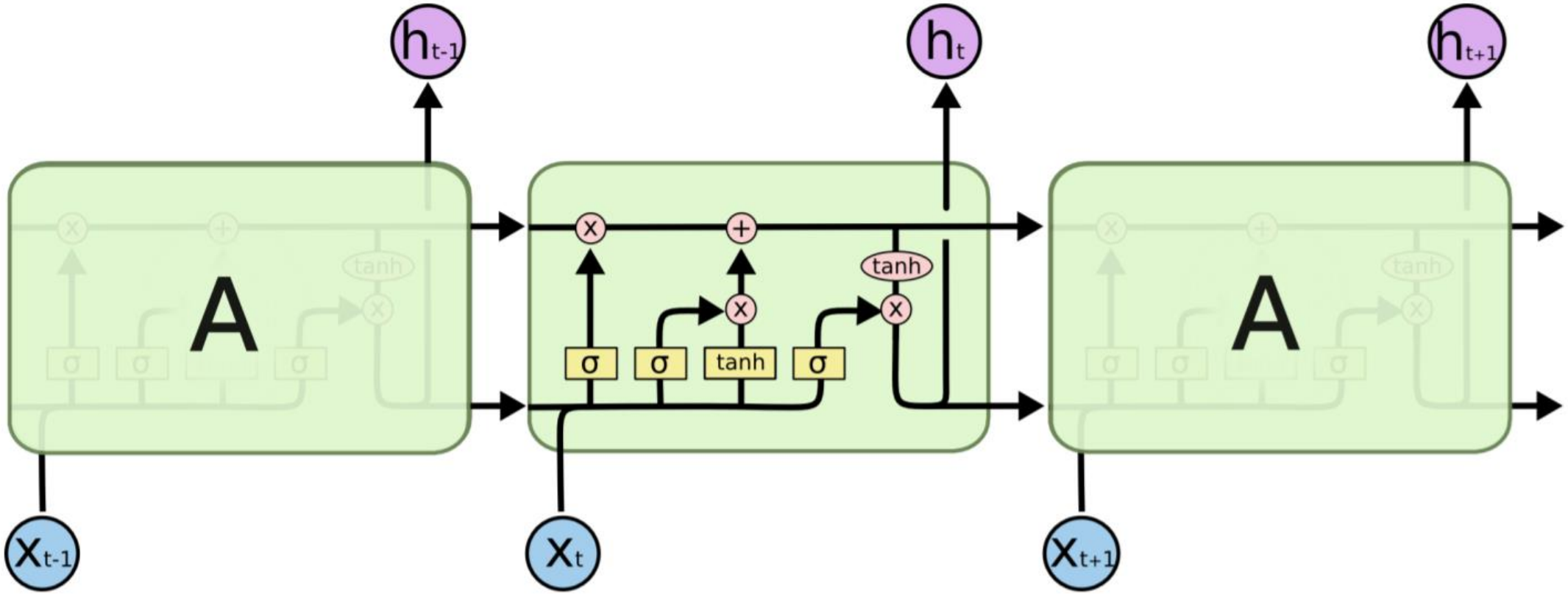
Embeddings: Word representation (review)

RNN (unrolled version)



Long Short-Term Memory (LSTM) (review)

LSTM – a more complex network



Long Short-Term Memory (LSTM) (review)

LSTM – a more complex network

Activations

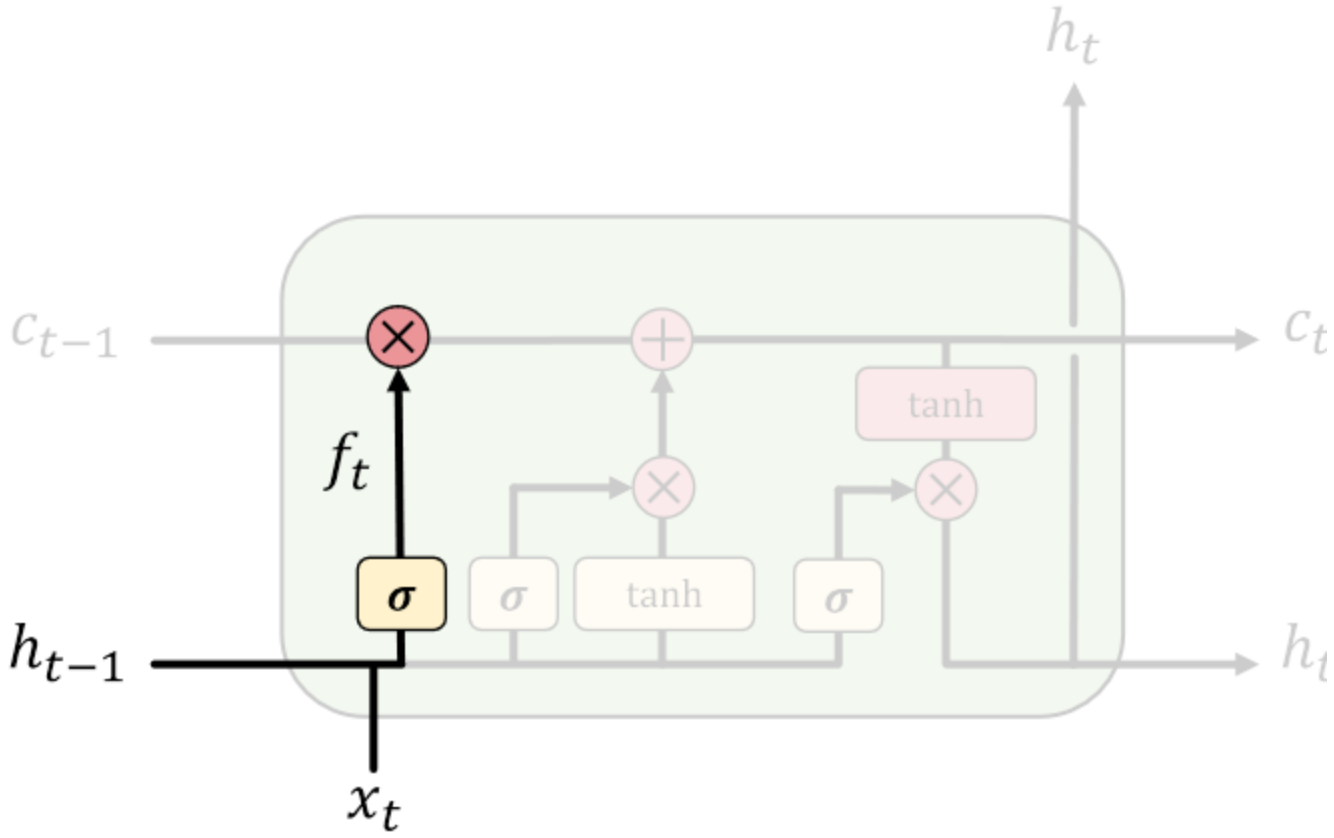
- $a = h$
- $a_t = h_t$

Cell state (memory)

- C
- $C\sim$

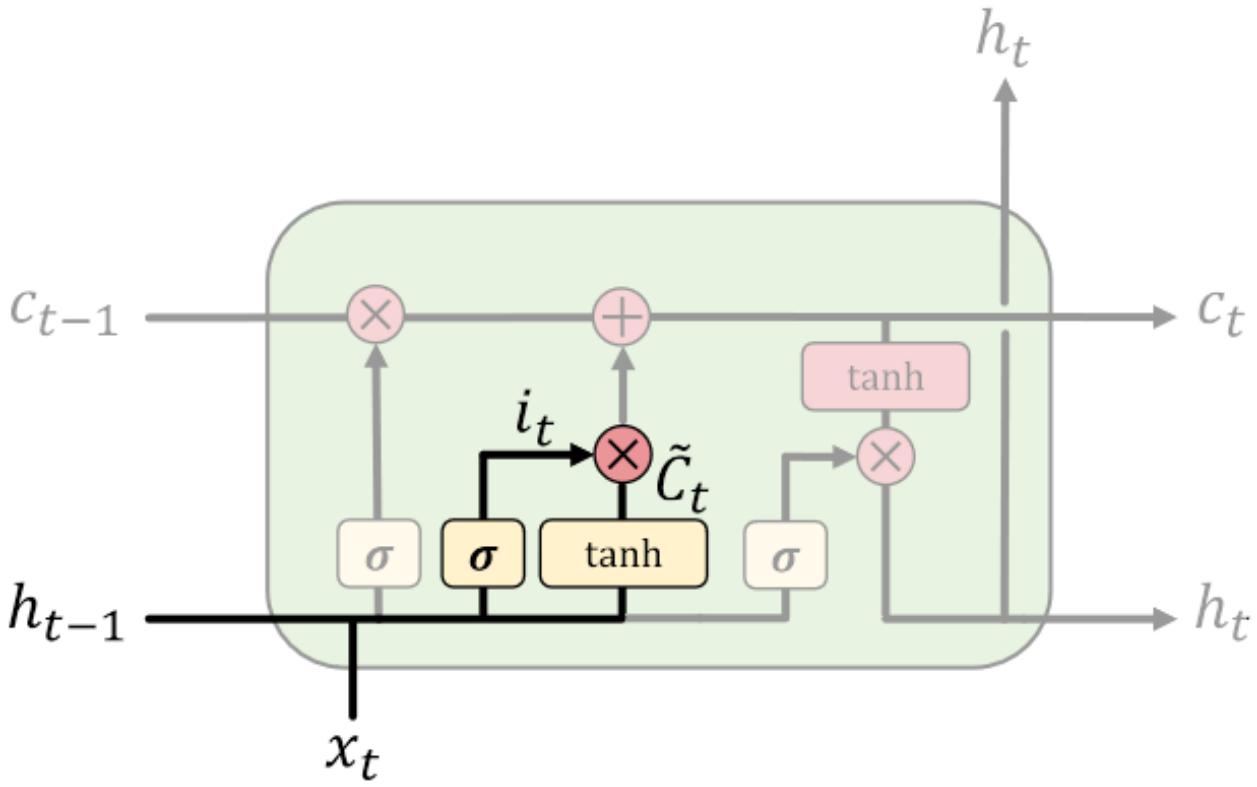
Long Short-Term Memory (LSTM) (review)

LSTM – Forget Gate



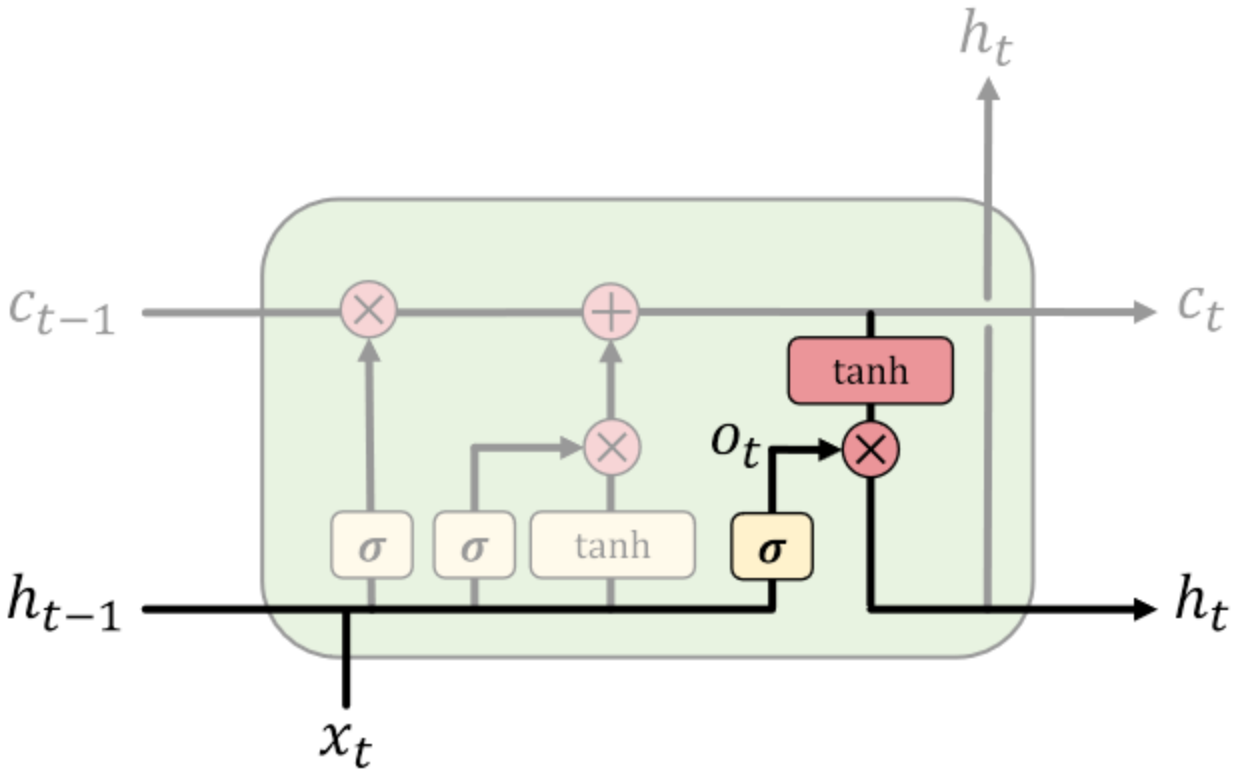
Long Short-Term Memory (LSTM) (review)

LSTM – Input / Ignore Gate

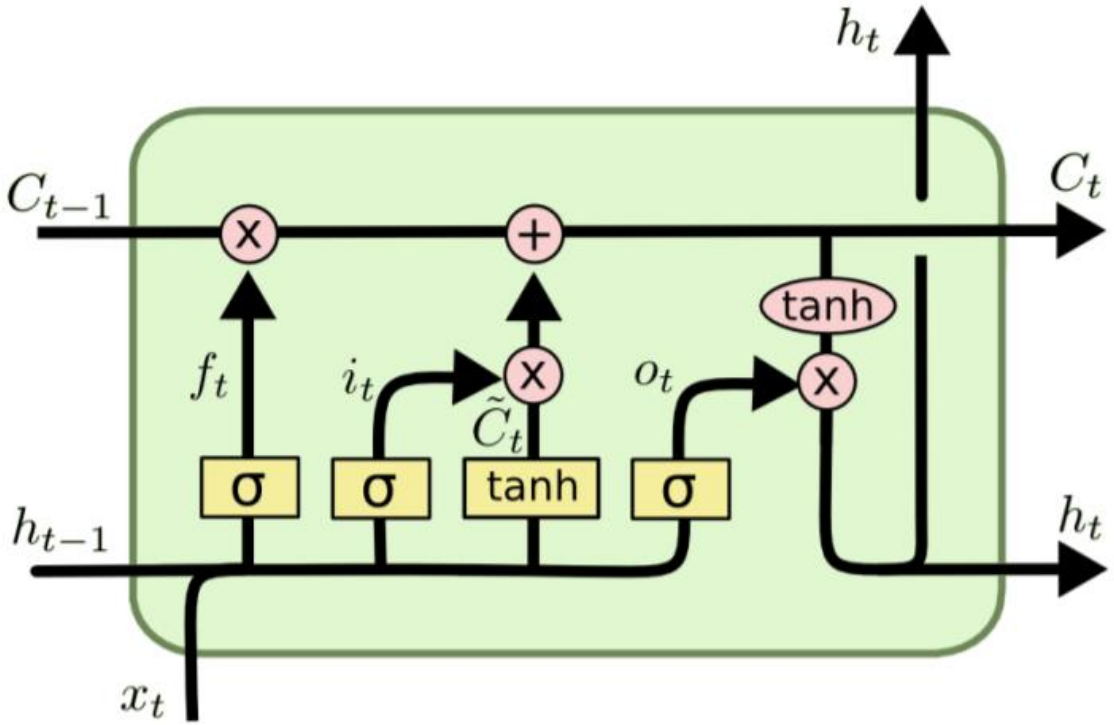


Long Short-Term Memory (LSTM) (review)

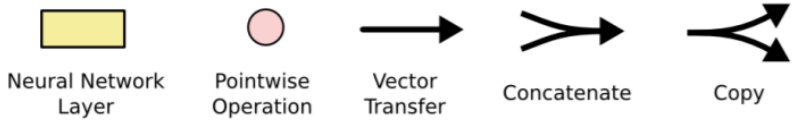
LSTM – Output Gate



Long Short-Term Memory (LSTM)



f – forget gate: Whether to erase cell
i – ignore gate: Whether to write to cell
c̃ – "vanilla RNN": How much to write to cell
o – output gate: How much to reveal cell



Gates:

$$i_t = \sigma(W_{hi}h_{t-1} + W_{xi}x_t + b_i)$$

$$f_t = \sigma(W_{hf}h_{t-1} + W_{xf}x_t + b_f)$$

$$o_t = \sigma(W_{ho}h_{t-1} + W_{xo}x_t + b_o)$$

$$\tilde{C}_t = \tanh(W_{hc}h_{t-1} + W_{xc}x_t + b_c)$$

Outputs:

$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t$$

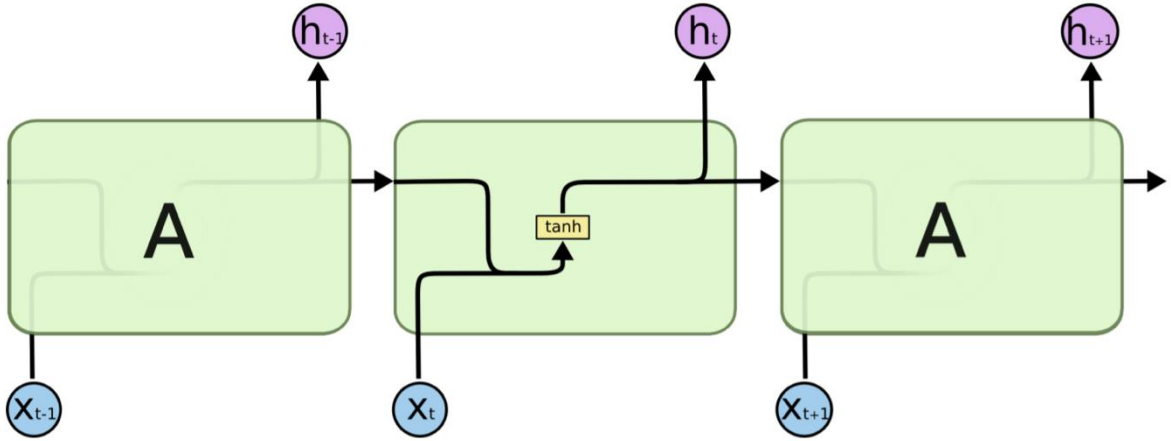
$$h_t = o_t \circ \tanh(\tilde{C}_t)$$

where $\circ$ is element-wise multiplication operation

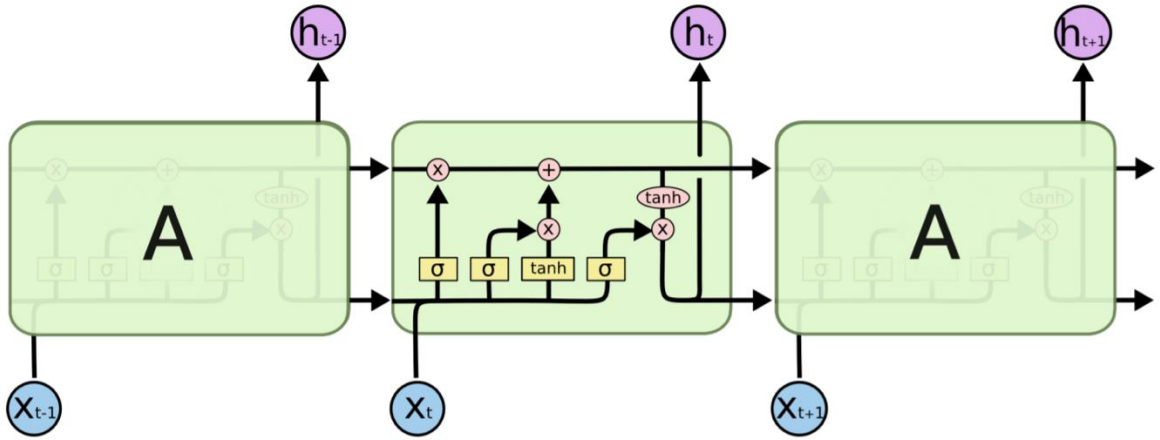
Long Short-Term Memory (LSTM) (review)

LSTM – a more complex network

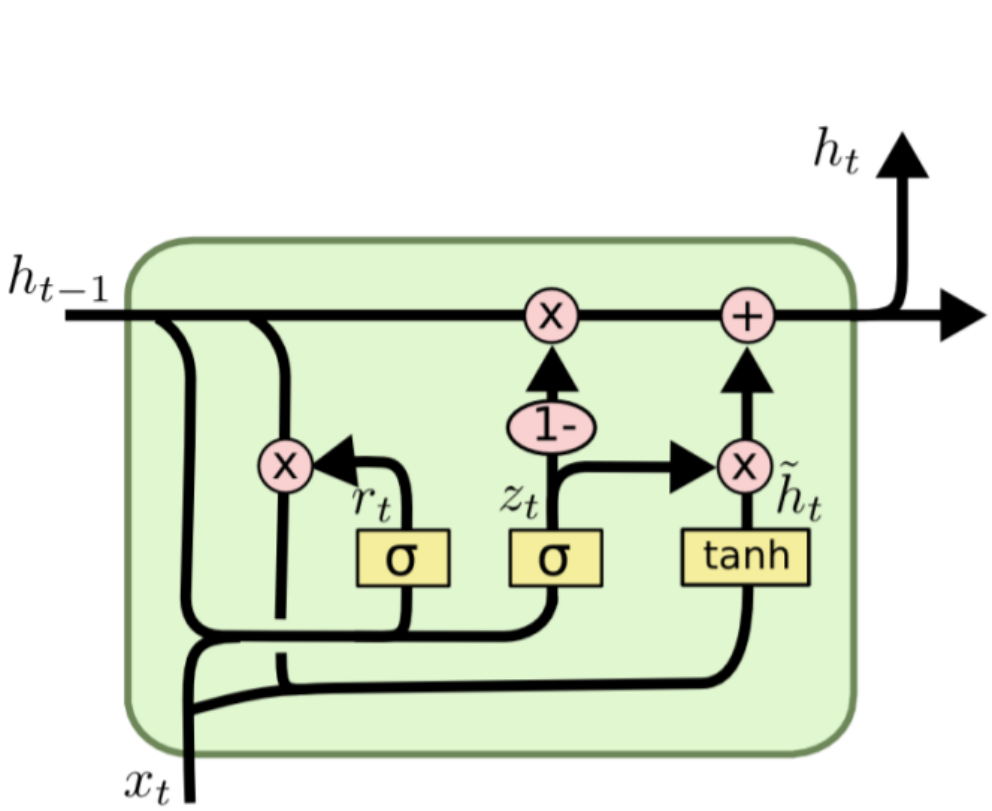
Vanilla RNN:

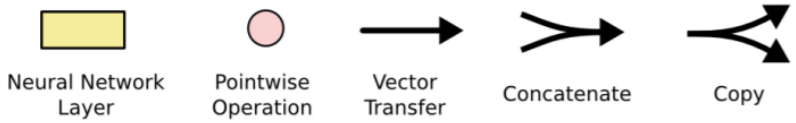


LSTM:



Gated Recurrent Unit (GRU) (review)





$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

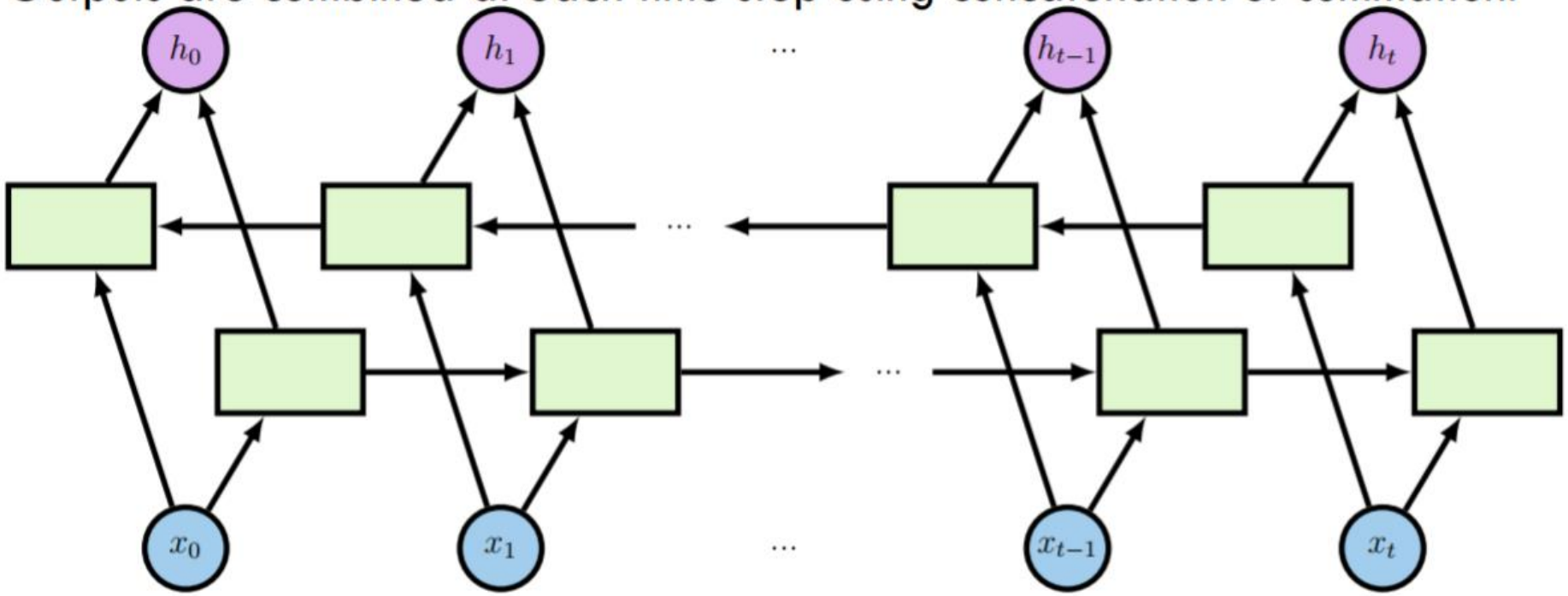
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Bidirectional RNN (review)

Idea: use 2 independent recurrent models together.

- Input is fed in the proper time order to the first one, and in reverse time order to the second one.
- Outputs are combined at each time step using concatenation or summation.



Bidirectional RNN (review)

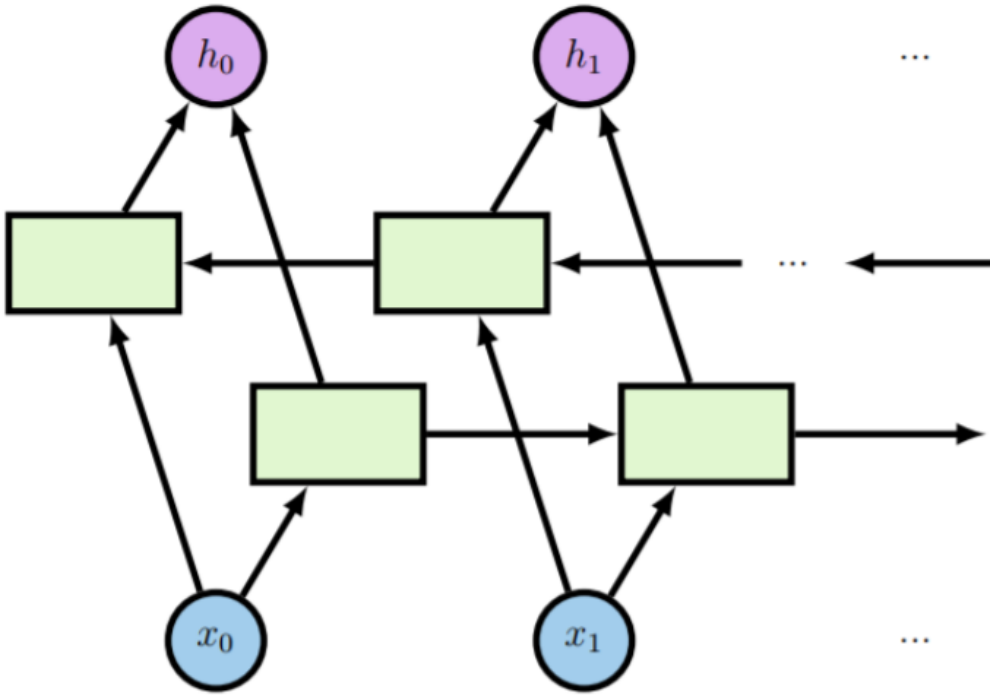
BIDIRECTIONAL RNN (BRNN)

A BRNN layer:

$$\overrightarrow{\boldsymbol{h}_{d,t}^{(n)}} = \overrightarrow{g_d}\left(\overrightarrow{\boldsymbol{W}_d^h}\overrightarrow{\boldsymbol{h}_{d,t-1}^{(n)}} + \overrightarrow{\boldsymbol{W}_d^x}\overrightarrow{\boldsymbol{h}_{d-1,t}^{(n)}} + \overrightarrow{\boldsymbol{b}_d}\right)$$

$$\overleftarrow{\boldsymbol{h}_{d,t}^{(n)}} = \overleftarrow{g_d}\left(\overleftarrow{\boldsymbol{W}_d^h}\overleftarrow{\boldsymbol{h}_{d,t+1}^{(n)}} + \overleftarrow{\boldsymbol{W}_d^x}\overleftarrow{\boldsymbol{h}_{d-1,t}^{(n)}} + \overleftarrow{\boldsymbol{b}_d}\right)$$

$$\boldsymbol{h}_{d,t}^{(n)} = g_d\left(\overrightarrow{\boldsymbol{W}_d}\overrightarrow{\boldsymbol{h}_{d,t}^{(n)}} + \overleftarrow{\boldsymbol{W}_d}\overleftarrow{\boldsymbol{h}_{d,t}^{(n)}} + \boldsymbol{b}_d\right)$$



Where

- "→" means normal time order, while "←" is associated with reverse time order
- $t = 1, \ldots, T_n$;
- $\boldsymbol{\theta}_d = \left\{\overrightarrow{\boldsymbol{W}_d^h}, \overrightarrow{\boldsymbol{W}_d^x}, \overrightarrow{\boldsymbol{b}_d}, \overleftarrow{\boldsymbol{W}_d^h}, \overleftarrow{\boldsymbol{W}_d^x}, \overleftarrow{\boldsymbol{b}_d}, \overrightarrow{\boldsymbol{W}_d}, \overleftarrow{\boldsymbol{W}_d}, \boldsymbol{b}_d\right\}$

Deep Network Development

Lecture 8.

Transformer Networks

Budapest, 4th April 2025

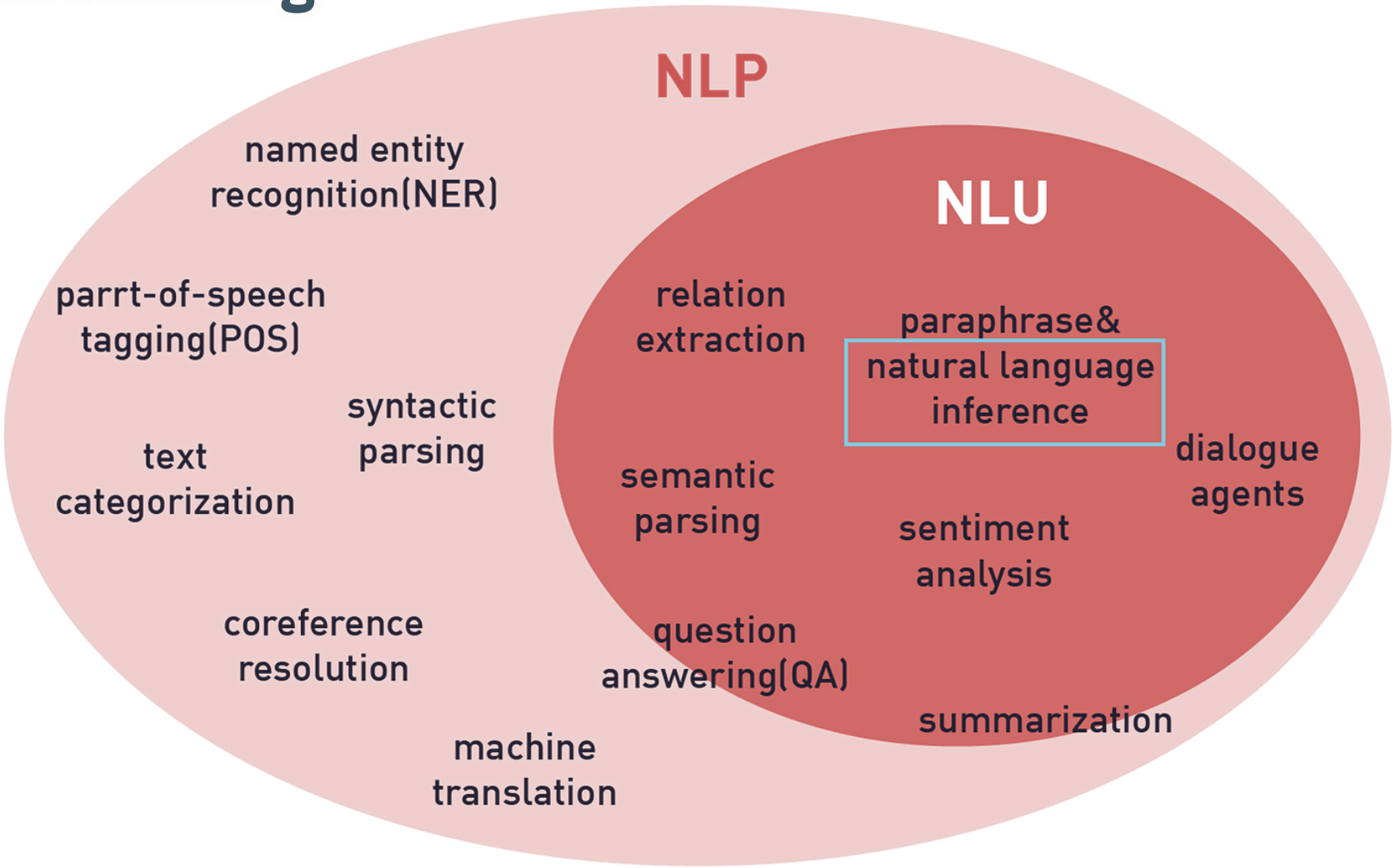
1 Natural Language Understanding

2 Attention Mechanism

3 Transformer Architecture

Natural Language Understanding

- Neural Machine Translation
- Textual entailment
- Question answering
- Semantic similarity assessment
- Text classification
- Etc...



Machine Translation

- Most of the proposed neural machine translation models belog to the a family of **encode-decoders**
- From probabilistic perspective:

$$argmax_y p(y \mid x)$$

- Which means finding a target **y** that maximizes the conditional probability of **y** given a source sentence **x**

Machine Translation

Machine Translation

- In the **encoder-decoder** framework an **encoder** reads and reduces the input sentence (a sequence of vectors $\mathbf{x} = (x_1, \dots, x_T)$) into a vector c
- The approach for RNNs:

$$h_t = f(x_t, h_{t-1})$$
$$c = q(\{h_1, \dots, h_{T_x}\})$$

- Where q is a nonlinear function, h_t is the hidden state at time t
- If we choose f as an LSTM then $q(\{h_1, \dots, h_{T_x}\}) = h_{T_x}$
- The decoder then predicts the next word y_t given the context vector c and all the previously predicted words $\{y_1, \dots, y_{t-1}\}$

Machine Translation

Machine Translation

- The **decoder** then predicts the next word y_t given the context vector c and all the previously predicted words $\{y_1, \dots, y_{t-1}\}$
- The predicted translation $\mathbf{y}$ can be expressed as the joint probability of:

$$p(\mathbf{y}) = \prod_{t=1}^{T} p(y_t \mid \{y_1, \dots, y_{t-1}\}, c)$$

- where $\mathbf{y} = \{y_1, \dots, y_{T_y}\}$
- Whit and RNN this is modelled as:

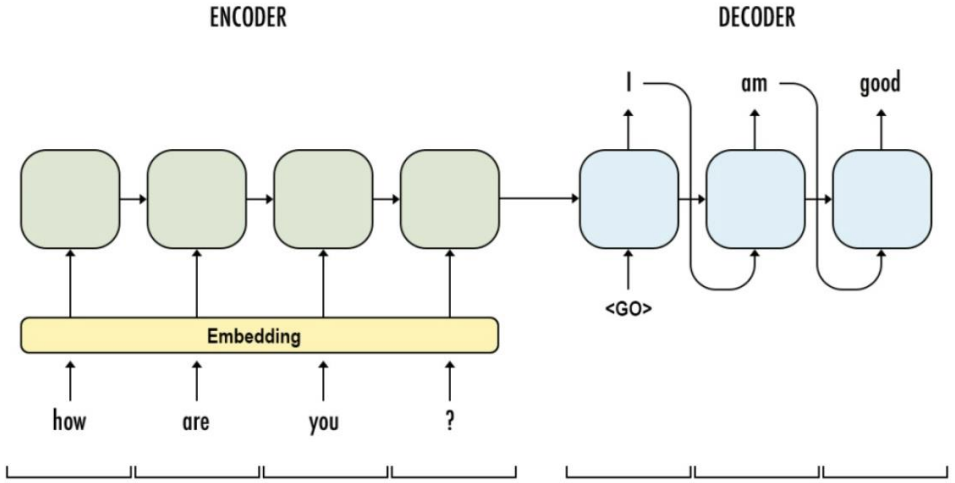
$$p(y_t \mid \{y_1, \dots, y_{t-1}\}, c) = g(y_{t-1}, s_t, c)$$

- Where g nonlinear multi layered function and s_t is the hidden state

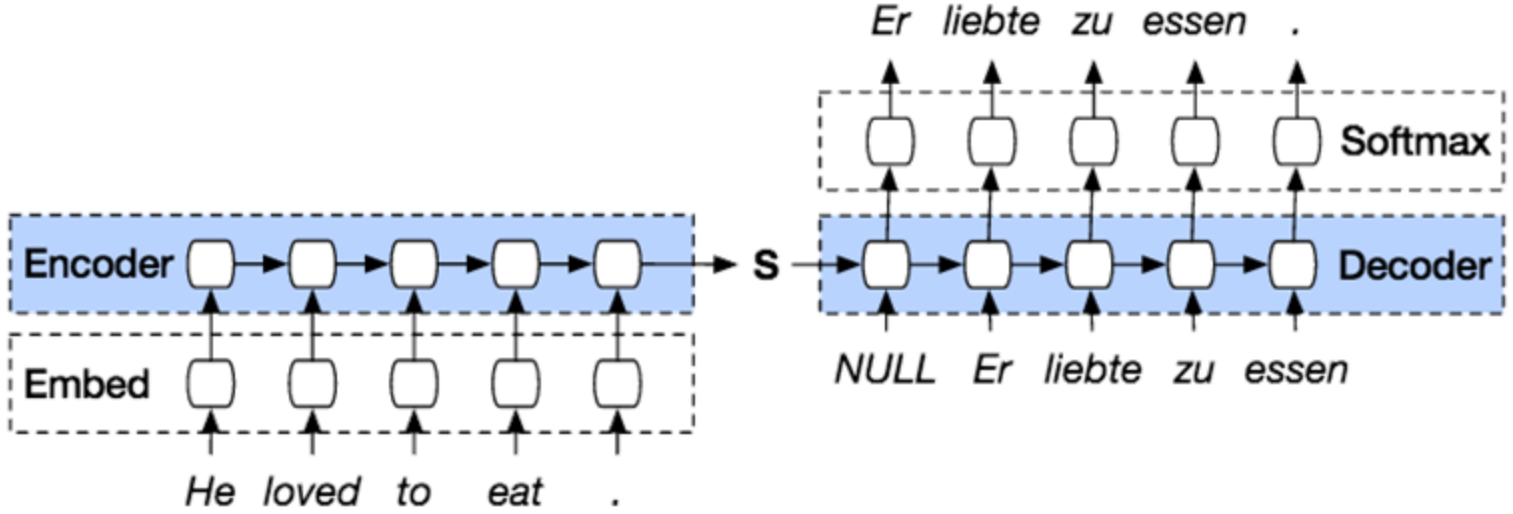
Machine Translation

Encoder – Decoder (Seq2Seq)

Question : Answer
(sequence) : (sequence)

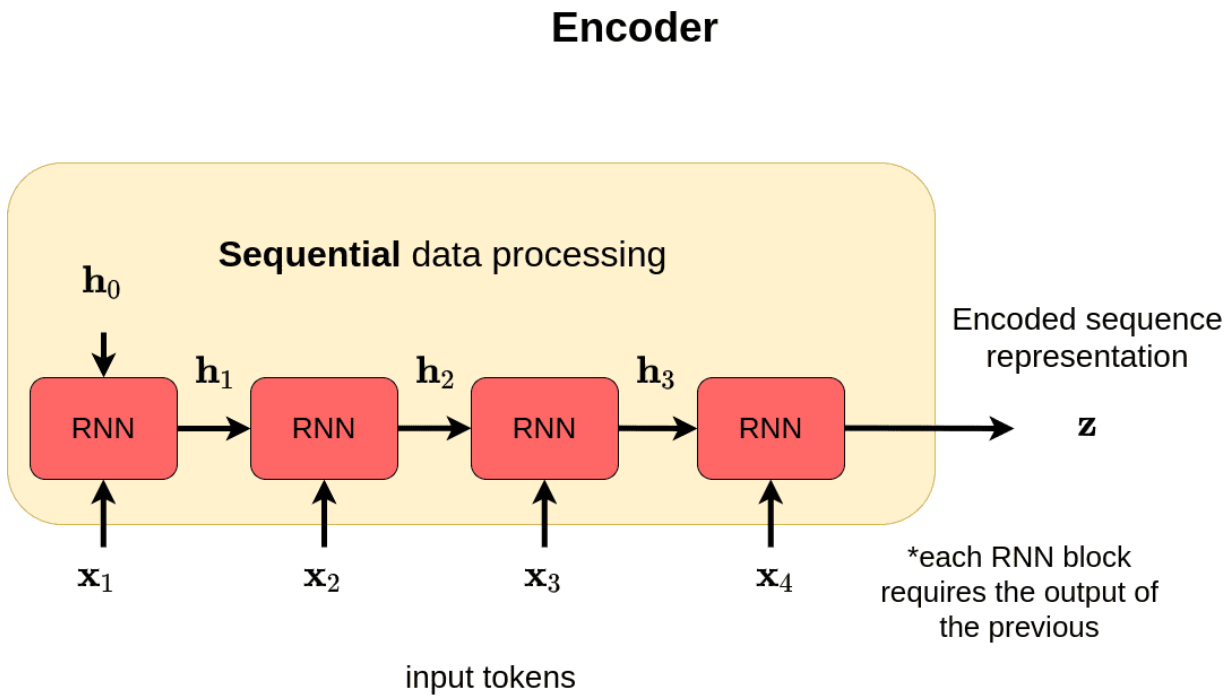


Machine Translation
English : German
(sequence) : (sequence)



Encoder – Decoder (Seq2Seq)

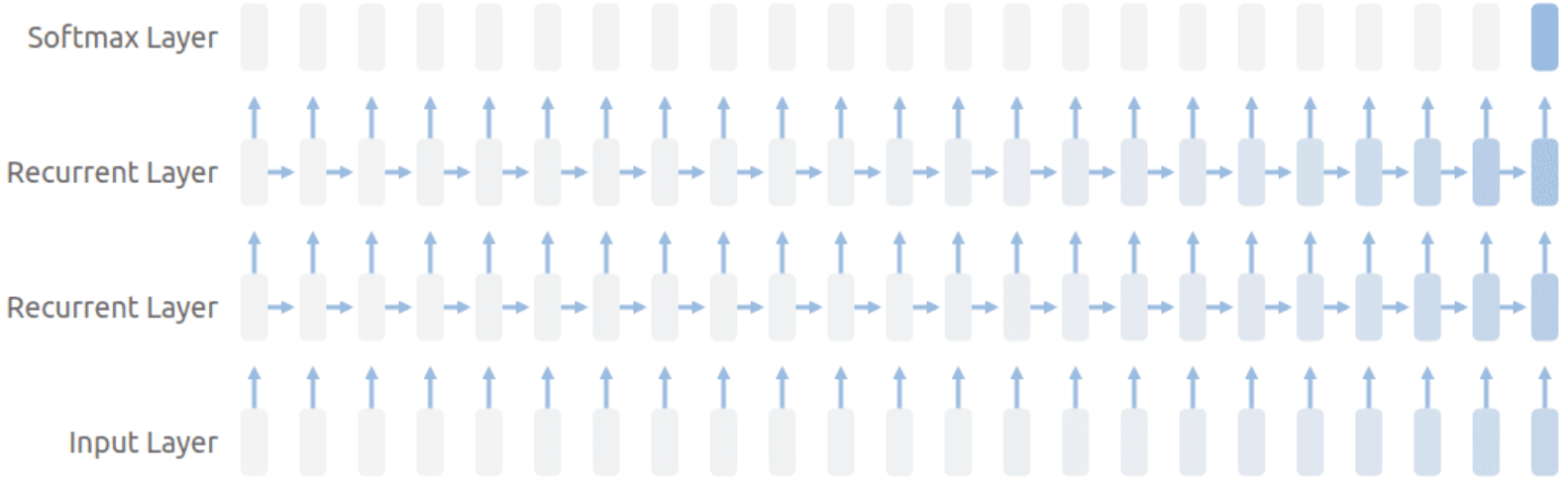
- The encoder and decoder are nothing more than stacked RNN layers, such as LSTM's. The encoder processes the input and produces one compact representation, called z, from all the input timesteps. It can be regarded as a compressed format of the input.



Encoder – Decoder (Seq2Seq)

Problems with this approach

- The intermediate representation **z** cannot encode information from all the input timesteps. This is commonly known as the **bottleneck problem**. The vector z needs to capture all the information about the source sentence.
- In practice, how far we can see in the past (the so-called reference window) is finite. RNN's tend to **forget information** from timesteps that are far behind.



Vanishing Gradient: where the contribution from the earlier steps becomes insignificant in the gradient for the vanilla RNN unit.

BLEU (bilingual evaluation understudy) [1]

- **BLEU** is an algorithm for evaluating the **quality of text** which has been machine-translated from one natural language to another.
- It's a metric, that measures the **precision** of **n-grams** (such as bigrams or trigrams) between the **predicted translation** and the **reference translations**

The children are sitting with their shoes off .

A man wearing a long white robe and a white cap , stands over a group of seated people .

A man in a white robe stands and talks to people who are sitting .

A man in a long white robe and white head cap is pointing to a group of people sitting on a blanket .

A man dressed in all white is talking to the people seated on the dirt floor .

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

N-gram

- It is just a fancy way of describing "a set **of 'n' consecutive words in a sentence**".
- For instance, in the sentence **"The ball is blue"**, we could have n-grams such as:
  - **1-gram (unigram):** "The", "ball", "is", "blue"
  - **2-gram (bigram):** "The ball", "ball is", "is blue"
  - **3-gram (trigram):** "The ball is", "ball is blue"
  - **4-gram:** "The ball is blue"

The children are sitting with their shoes off .

A man wearing a long white robe and a white cap , stands over a group of seated people .

A man in a white robe stands and talks to people who are sitting .

A man in a long white robe and white head cap is pointing to a group of people sitting on a blanket .

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[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

Precision

- Let's say, that we have:
  - **Target Sentence:** He eats an apple
  - **Predicted Sentence:** He ate an apple
- We would normally compute the Precision using the formula:

$$\textbf{Precision} = \frac{\textbf{Number of correct predicted words}}{\textbf{Number of total predicted words}}$$

- Here **eats** and **ate** count as different words
- Precision = 3 / 4

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

Precision

- The issue is that only using precision allow us to cheat:
    - **Target Sentence:** He eats an apple
    - **Predicted Sentence:** He he he
- Precision = 3 / 3

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

Clipped Precision

- **Target Sentence 1: He eats a sweet apple**
- **Target Sentence 2: He is eating a tasty apple**
- **Predicted Sentence: He He He eats tasty fruit**

$$\text{Clipped Precision} = \frac{\text{Clipped \# of correct predicted words}}{\text{\# of total predicted words}}$$

1. We compare each word from the predicted sentence with all of the target sentences.
2. If the word matches any target sentence, it is considered to be correct.
3. We limit the count for each correct word to the maximum number of times that that word occurs in the Target Sentence.

Word	*Matching Sentence*	*Matched Predicted Count*	*Clipped Count*
He	*Both*	*3*	*1*
eats	*Target 1*	*1*	*1*
tasty	*Target 2*	*1*	*1*
fruit	*None*	*0*	*0*
Total		*5*	*3*

Clipped Precision = **3** / **6**

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

How is BLEU score calculated?

- **Target Sentence:** The guard arrived late because it was raining
- **Predicted Sentence:** The guard arrived late because of the rain

Precision 1-gram: $p_1 = \frac{5}{8}$

Target Sentence: The guard arrived late because ~~it was raining~~

Predicted Sentence: The guard arrived late because of the rain

Precision 2-gram: $p_2 = \frac{4}{7}$

Target Sentence: The guard arrived late because it was raining

Predicted Sentence: The guard arrived late because of the rain

Precision 3-gram: $p_3 = \frac{3}{6}$

Target Sentence: The guard arrived late because it was raining

Predicted Sentence: The guard arrived late because of the rain

Precision 4-gram: $p_2 = \frac{2}{5}$

Target Sentence: The guard arrived late because it was raining

Predicted Sentence: The guard arrived late because of the rain

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

How is BLEU score calculated?

Geometric Average Precision (GAP)

- We combine these precision scores using the following formula

$$\mathbf{GAP}(N) = \prod_{n=1}^{N} p_n^w$$

- We usually use $N = 4$ and uniform weights $w = \frac{1}{N}$
- In case of $N = 4$ the Geometric Average Precision:

$$\mathbf{GAP}(N) = (p_1)^{\frac{1}{4}} \cdot (p_2)^{\frac{1}{4}} \cdot (p_3)^{\frac{1}{4}} \cdot (p_1)^{\frac{1}{4}}$$

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

How is BLEU score calculated?

Brevity Penalty

- The Brevity Penalty penalizes sentences that are too short.

$$\textbf{BrevityPenalty} = \begin{cases} 1, & \text{if } c > r \\ e^{(1-\frac{r}{c})}, & \text{if } c \leq r \end{cases}$$

- c is the predicted length -> number of words in the predicted sentence
- r is the target length -> number of words in the target sentence (length closes to prediction length)

- In the previous example $c = 8$ and $r = 8$

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

How is BLEU score calculated?

- To get the BLEU score we multiply the **Brevity Penalty** with the **Geometric Average** of the **Precision Scores**

$$\mathbf{BLEU}(N) = \mathbf{BrevityPenalty} \cdot \mathbf{GAP}(N)$$

- **BLEU** Score can be computed for different values of N.
  - **BLEU-1** uses the **unigram** Precision score
  - **BLEU-2** uses the geometric average of **unigram** and **bigram** precision
  - **BLEU-3** uses the geometric average of **unigram**, **bigram**, and **trigram** precision
  - and so on.

[1] https://towardsdatascience.com/foundations-of-nlp-explained-bleu-score-and-wer-metrics-1a5ba06d812b/

Deep Network Development

Lecture 8.

Attention Mechanism

Budapest, 4th April 2025

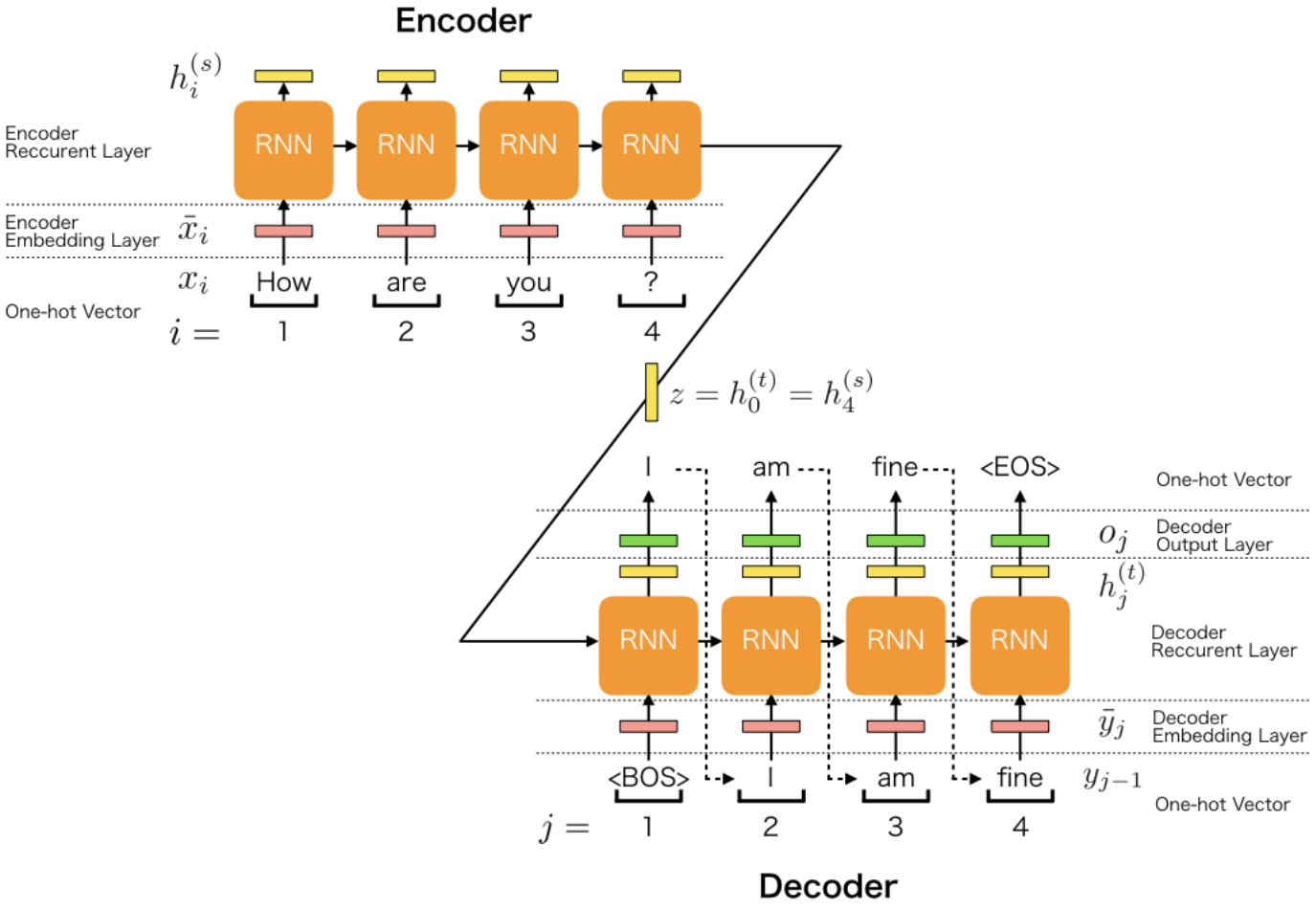
1 Natural Language Understanding

2 Attention Mechanism

3 Transformer Architecture

Introduction to Attention Mechanism

- All the information from the encoder is represented in the z vector (context)
- However, as seen previously, information from earlier timestamps is not preserved
- Can we create a better context vector?



Introduction to Attention Mechanism

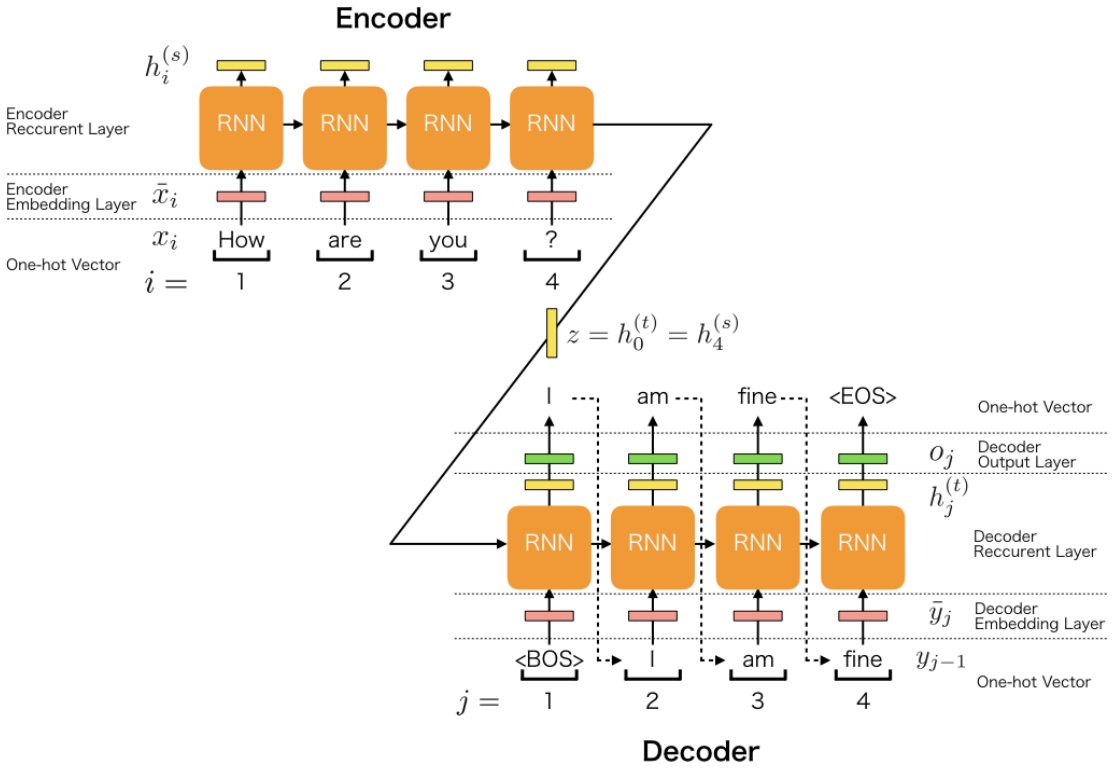
- In the new approach, we define each conditional probability as:

$$p(y_i \mid \{y_1, \ldots, y_{i-1}\}, c) = g(y_{i-1}, s_i, c_i)$$

- Where s_i is an RNN hidden state for time i, computed by

$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$

- Note that here we produce a distinct context vector c_i for each target word y_i



Introduction to Attention Mechanism (review)

- The core idea is that the context vector c_i should have access to all parts of the input sequence instead of just the last one.
- In other words, we need to form a **direct connection** with each timestamp. We can look at all the different words at the same time and learn to "pay attention" to the correct ones depending on the task at hand.
- In the encoder-decoder:
  - Given the hidden states of the encoder at each time step $h = \{h_1, \dots, h_{T_x}\}$
  - Given the previous state in the decoder y_{i-1}
  - We define an attention network that gives the attention scores for the current state of the decoder

$$e_{ij} = \text{attention}_{\text{net}}(y_{i-1}, \mathbf{h}) \in \mathbb{R}^n$$

  - We convert this scores into probabilities

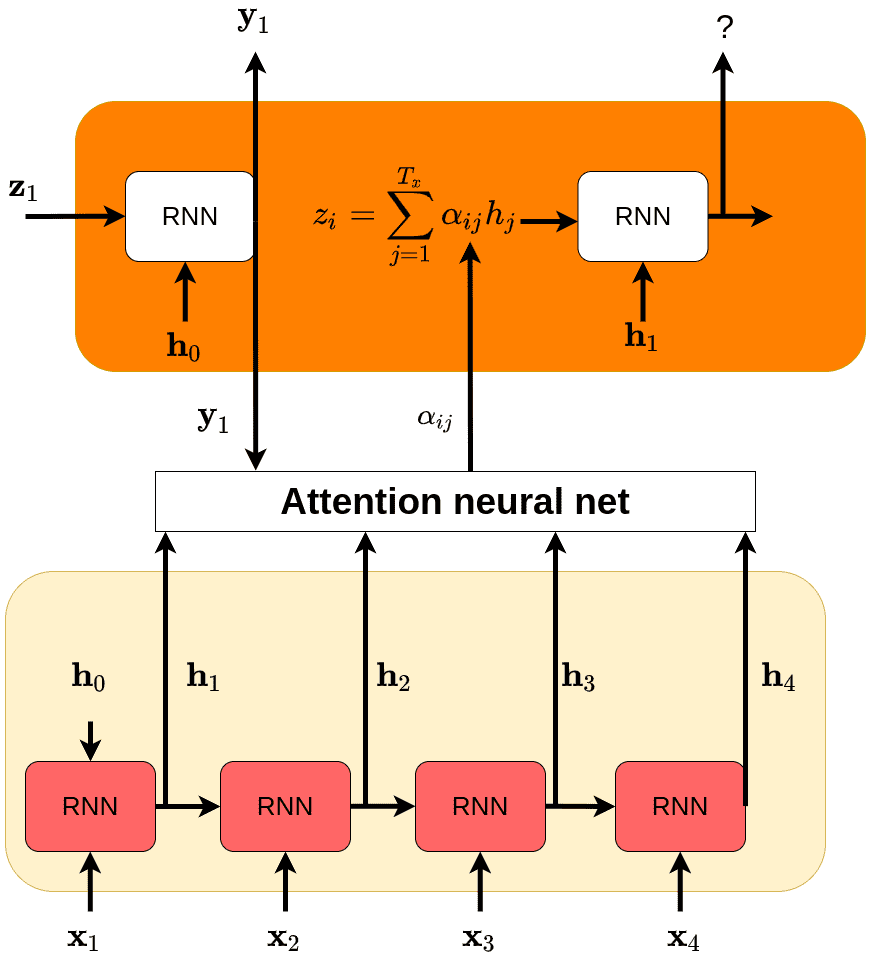
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

  - Finally, we get our new context vector z:

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

Introduction to Attention Mechanism (review)

- Attention mechanism helps creating a better context vector
- It learns which information from the encoder is relevant for the decoder



Introduction to Attention Mechanism (review)

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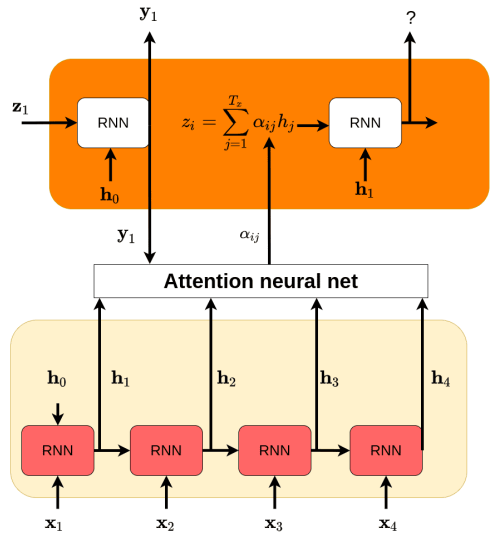
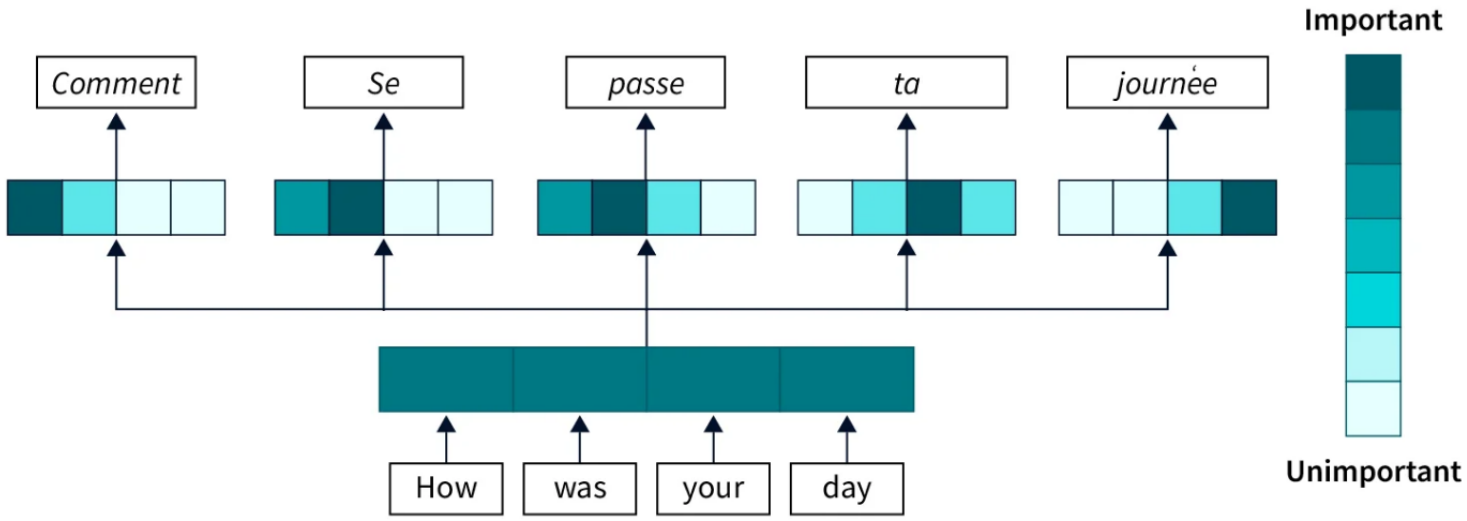
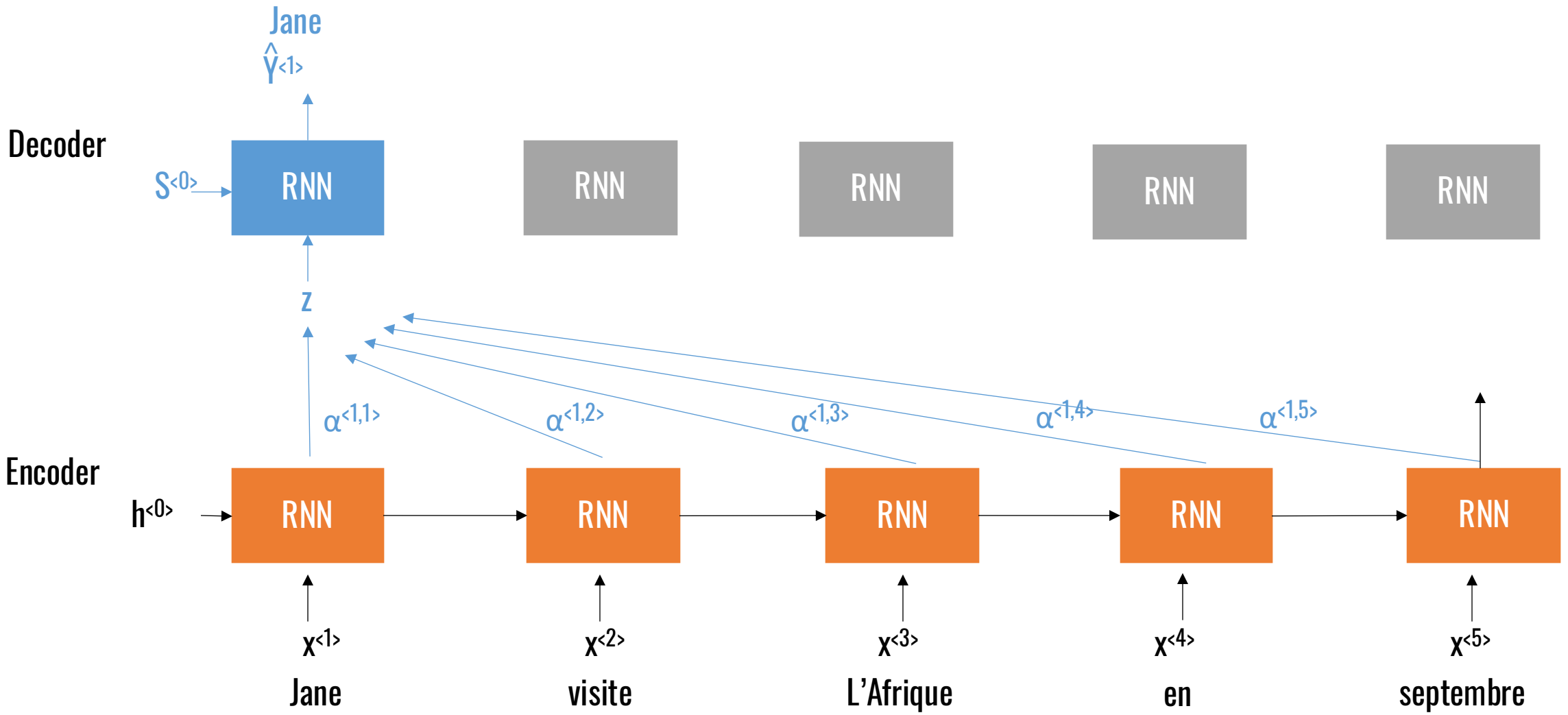




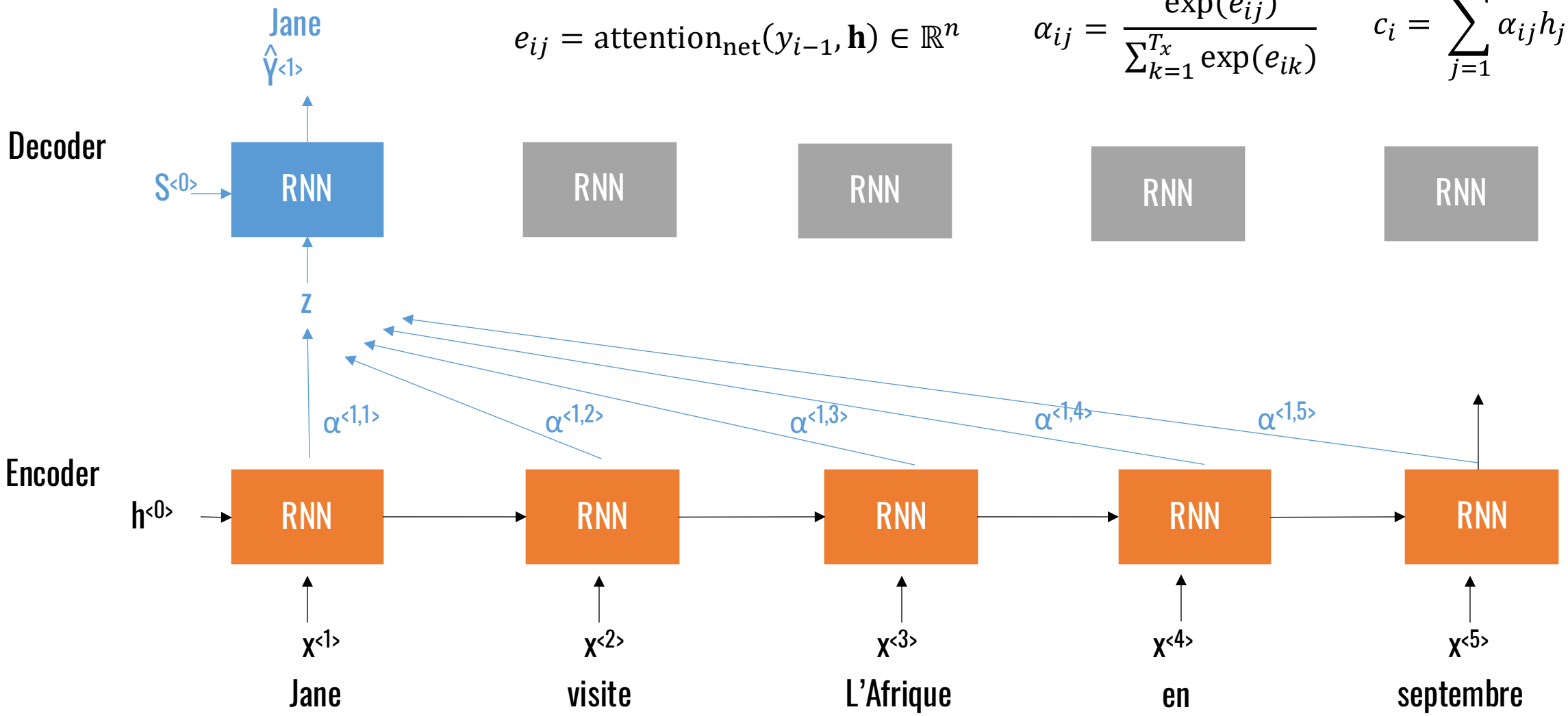
Attention Mechanism (review)



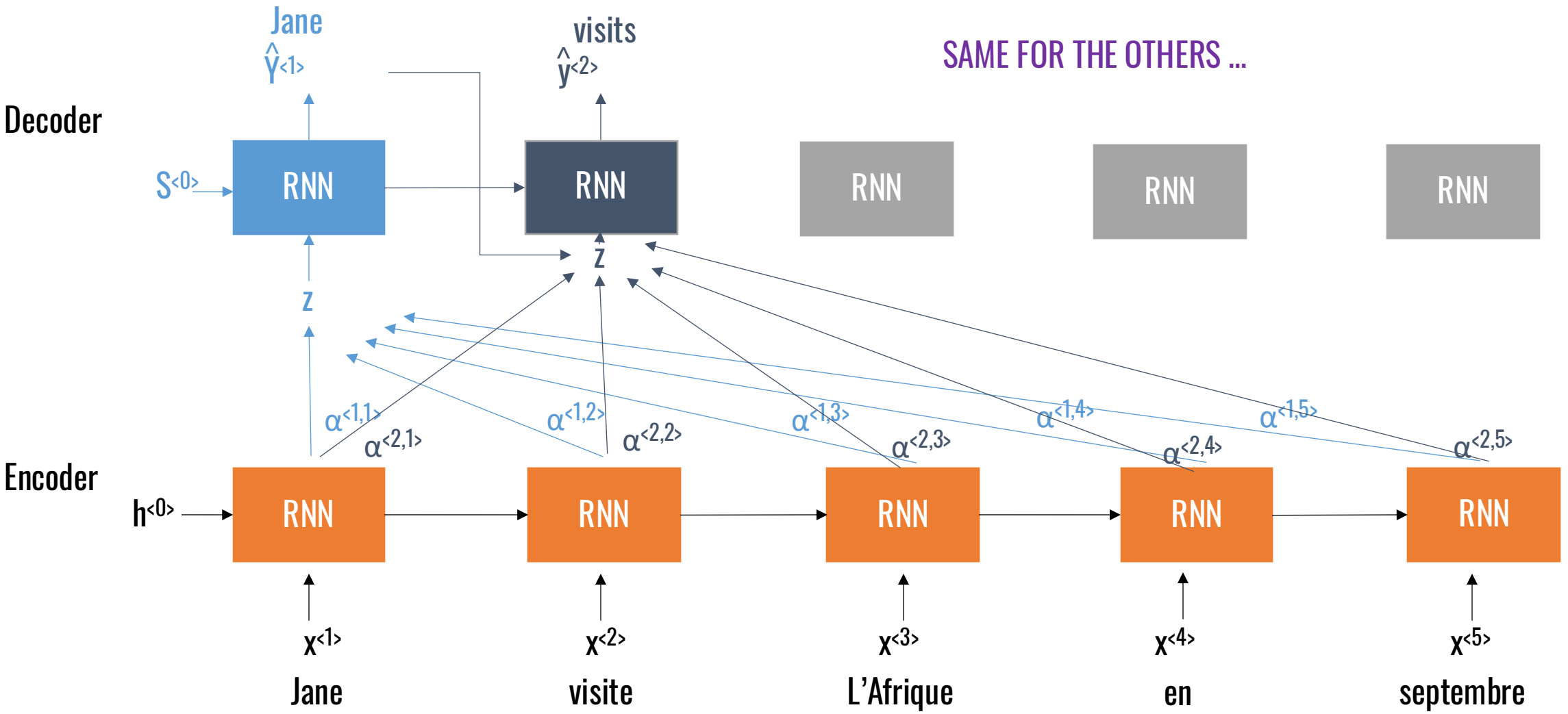
α_{ij} = amount of "attention" y_i should pay to h_*

Attention Mechanism (review)

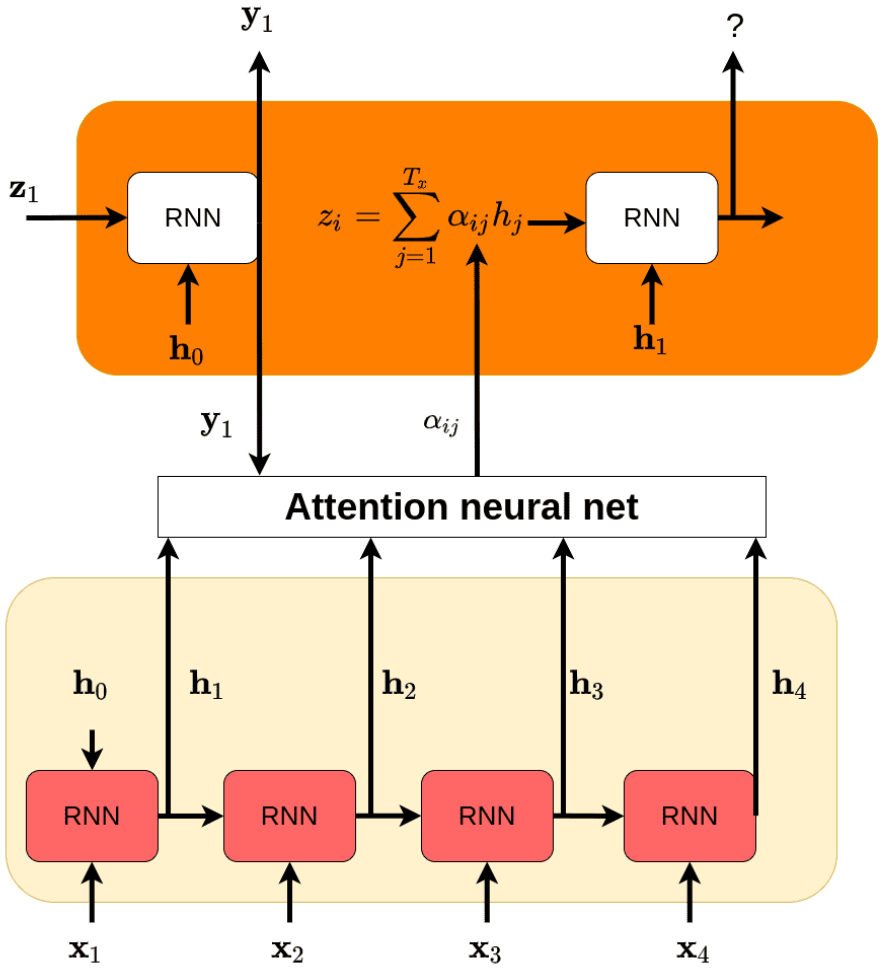
$$e_{ij} = \text{attention}_{\text{net}}(y_{i-1}, \mathbf{h}) \in \mathbb{R}^n \qquad \alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})} \qquad c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

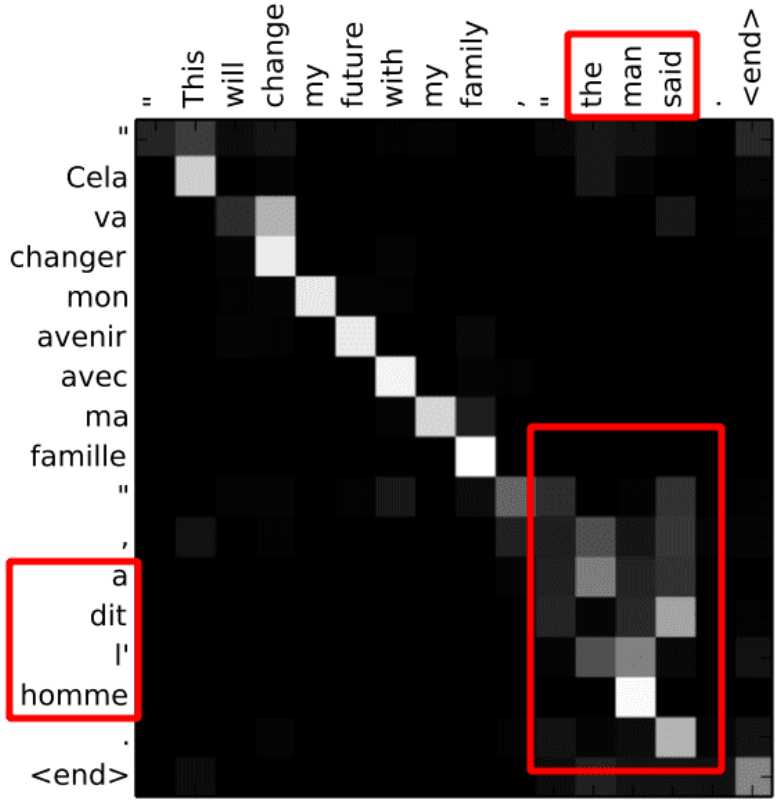


Attention Mechanism (review)

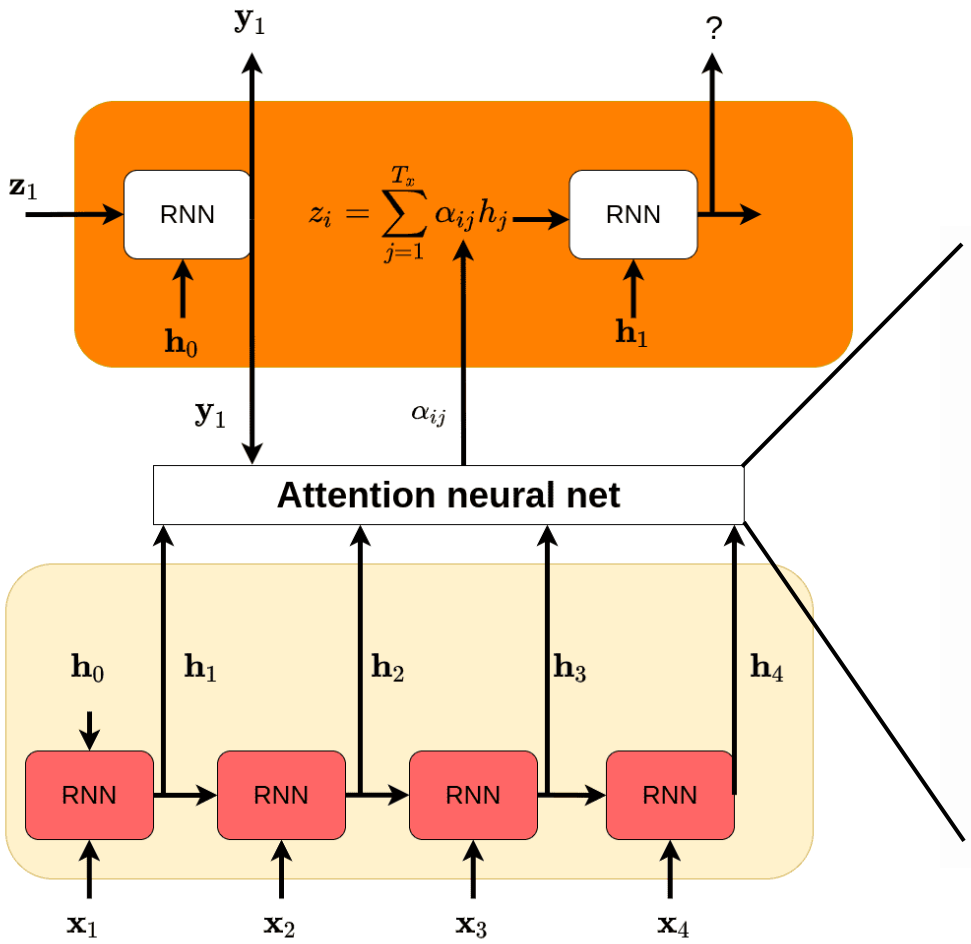


How does Attention work?





Attention Mechanism



Several ways to calculate the scores

Name	Alignment score function	Citation
Content-base attention	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \text{cosine}[\boldsymbol{s}_t, \boldsymbol{h}_i]$	Graves2014
Additive(*)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \mathbf{v}_a^\top \tanh(\mathbf{W}_a[\boldsymbol{s}_t; \boldsymbol{h}_i])$	Bahdanau2015
Location-Base	$\alpha_{t,i} = \text{softmax}(\mathbf{W}_a \boldsymbol{s}_t)$ Note: This simplifies the softmax alignment to only depend on the target position.	Luong2015
General	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \mathbf{W}_a \boldsymbol{h}_i$ where $\mathbf{W}_a$ is a trainable weight matrix in the attention layer.	Luong2015
Dot-Product	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \boldsymbol{h}_i$	Luong2015
Scaled Dot-Product(^)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \frac{\boldsymbol{s}_t^\top \boldsymbol{h}_i}{\sqrt{n}}$ Note: very similar to the dot-product attention except for a scaling factor; where n is the dimension of the source hidden state.	Vaswani2017

Deep Network Development

Lecture 8.

Transformer Architecture

Budapest, 4th April 2025

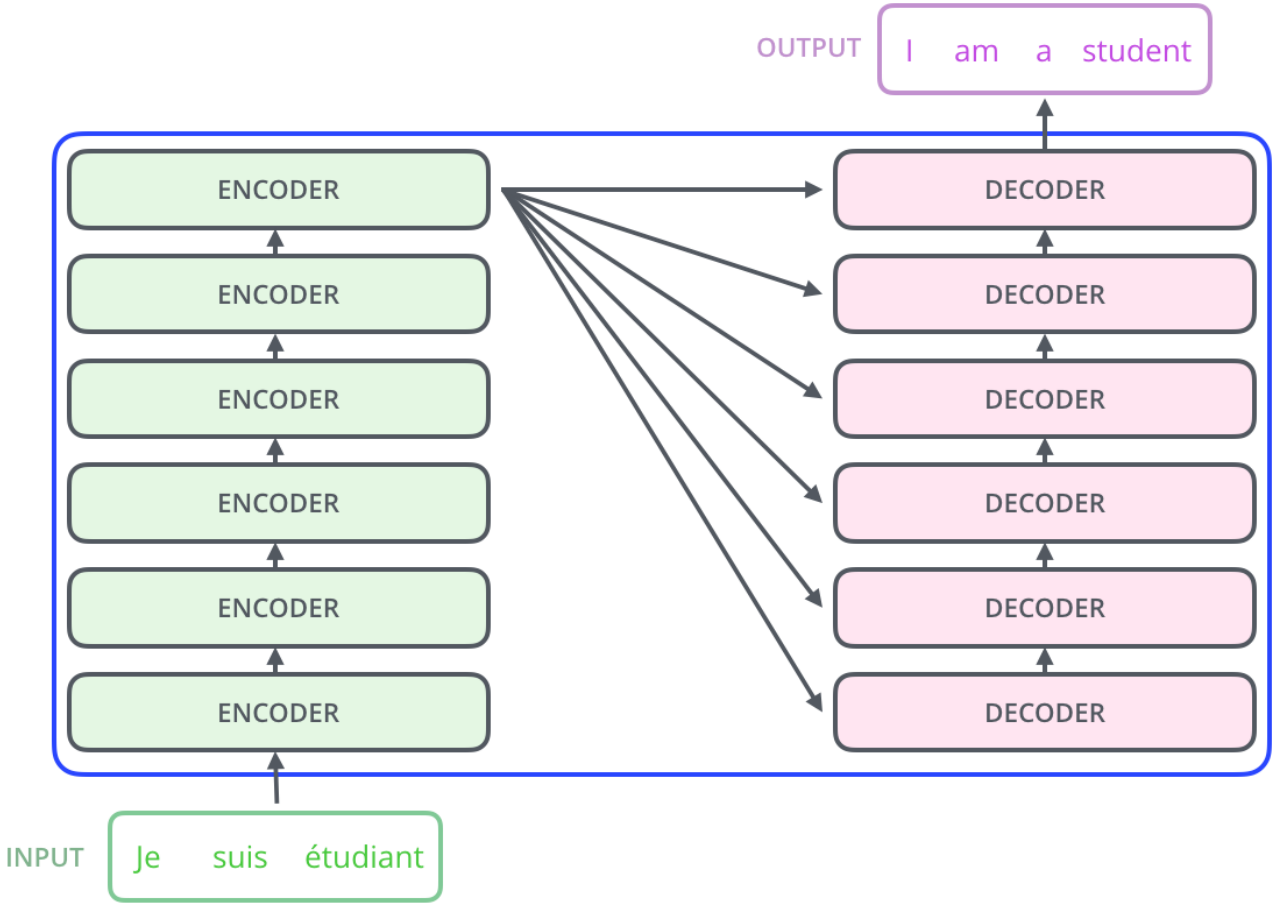
1 Natural Language Understanding

2 Attention Mechanism

3 Transformer Architecture

Transformers [1]

- Multi-Head Attention
- Self-Attention

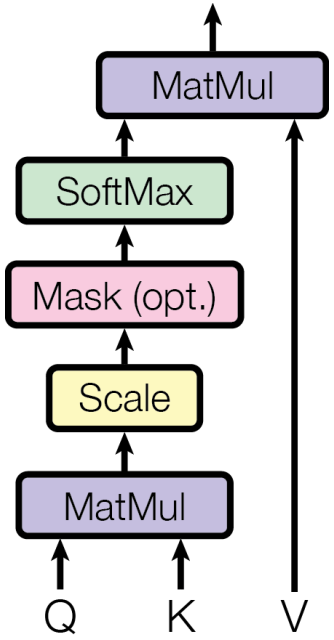


[1] Vaswani, Ashish et al. "Attention is All you Need." (2017)

Transformer Attention

- **Feature-based attention: The Key, Value, and Query**
- Key-value-query concepts come from **information retrieval systems**.
- Example of searching for a video on YouTube:
  - When you search (**query**) for a particular video, the search engine will map your **query** against a set of **keys** (video title, description, etc.) associated with possible stored videos. Then the algorithm will present you the best-matched videos (**values**). This is the foundation of content/**feature-based lookup**.
- Bringing this idea closer to the transformer's attention we have something like this:

Transformer Attention



$$\text{softmax}\left(\frac{Q \times K^T}{\sqrt{d_k}}\right) V = Z$$

Self-Attention

Self-attention: the key component of the Transformer architecture

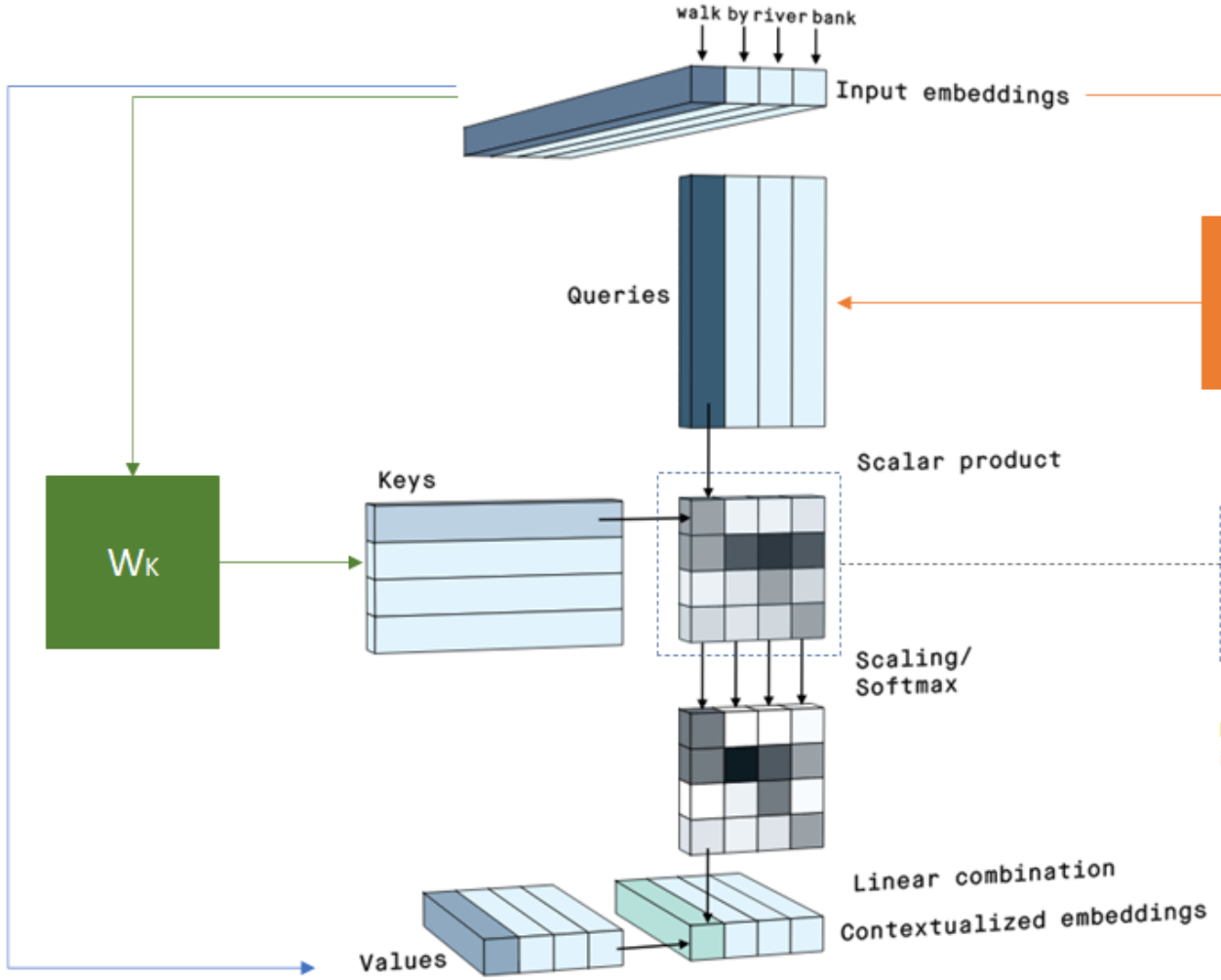
- We can also define the attention of the same sequence, called self-attention. Instead of looking for an input-output sequence association/alignment, **we are now looking for scores between the elements of the sequence**

Self-attention
Probability score matrix

	Hello	I	love	you
Hello	0.8	0.1	0.05	0.05
I	0.1	0.6	0.2	0.1
love	0.05	0.2	0.65	0.1
you	0.2	0.1	0.1	0.6

Softmax(Attention)
equation

Visualizing Self-Attention



Transformers Attention

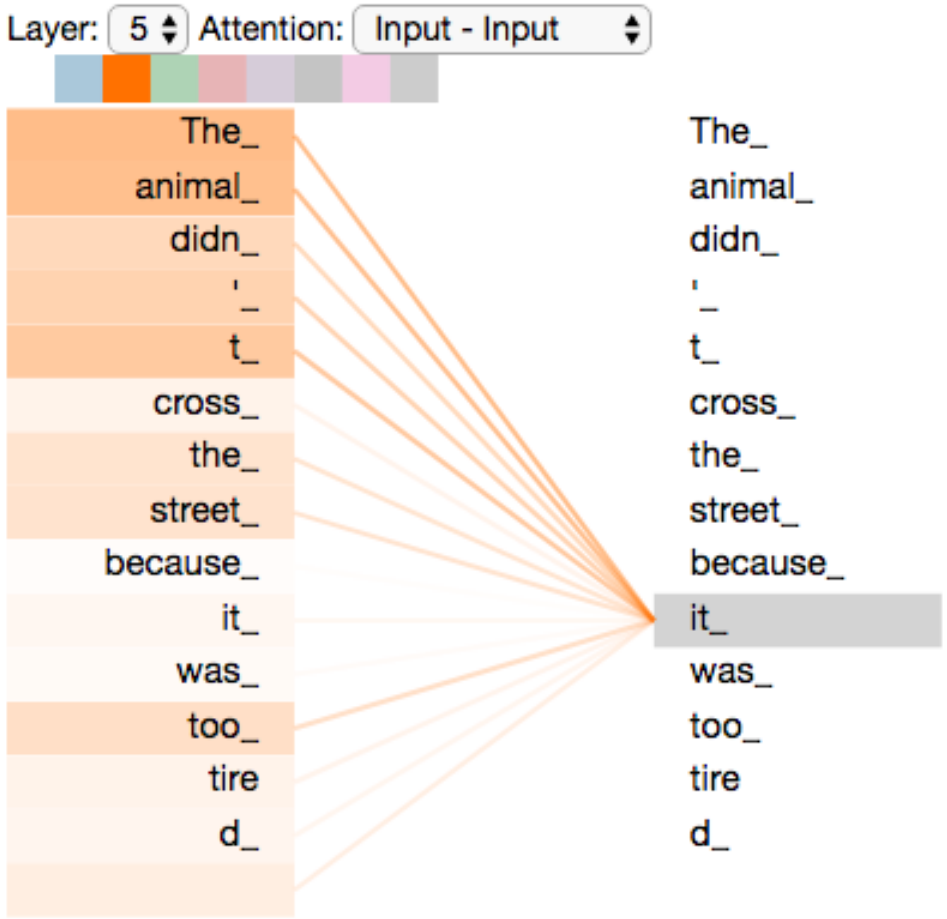
$$A(q,K,V)=\sum_i \frac{\exp(q\cdot k^{<i>})}{\sum_j \exp(q\cdot k^{<j>})} v^{<i>}$$

Embedded tensor in Q space

Self Attention	walk	by	river	bank
walk	0.88	0.1	0.21	0.12
by	0.08	0.8	0.12	0.14
river	0.03	0.14	0.83	0.7
bank	0.01	0.01	0.4	0.77

Embedded tensor in K space

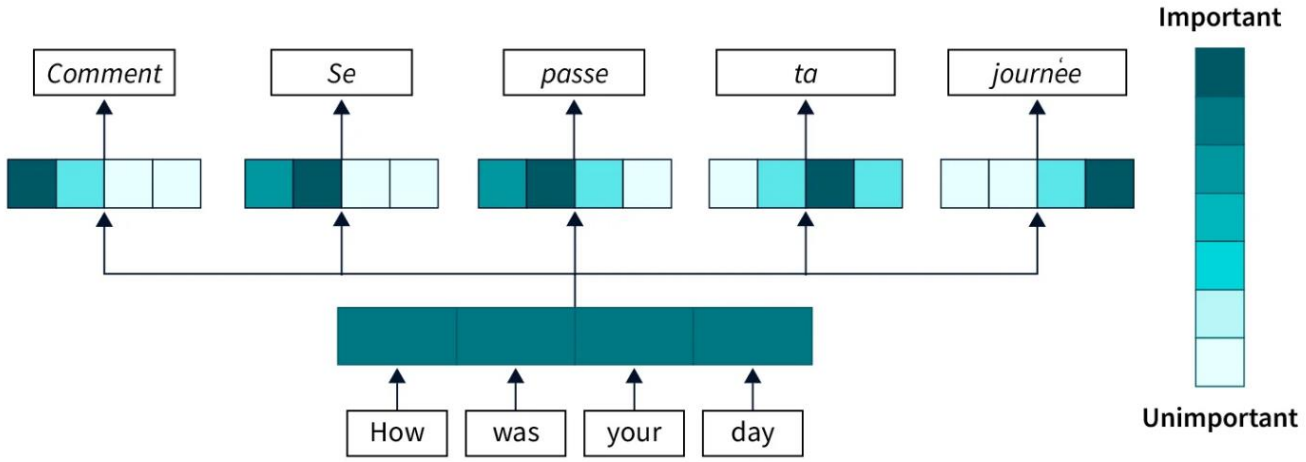
Self-Attention



Summary

1. Attention

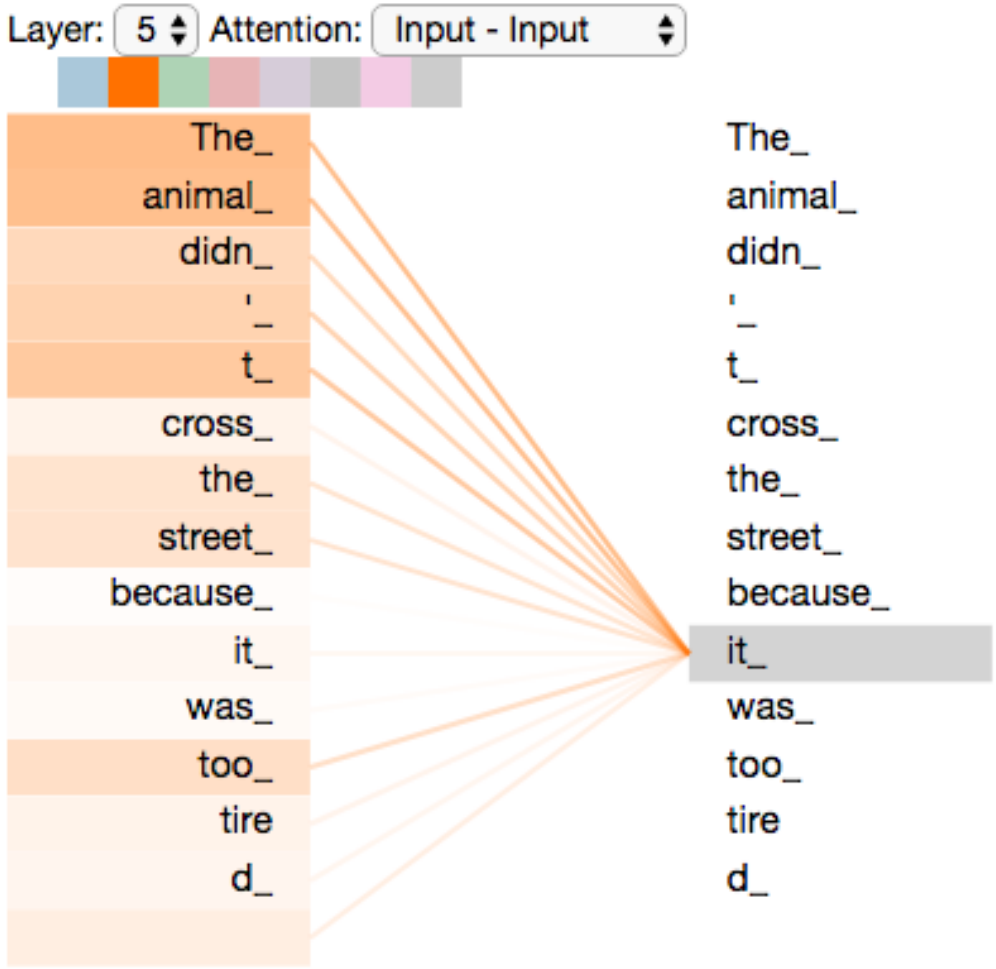
- How does the input elements relate to the output (what part of the input is relevant for the output)
  - Helps the model in focusing on the most relevant information



Summary

2. Self-Attention

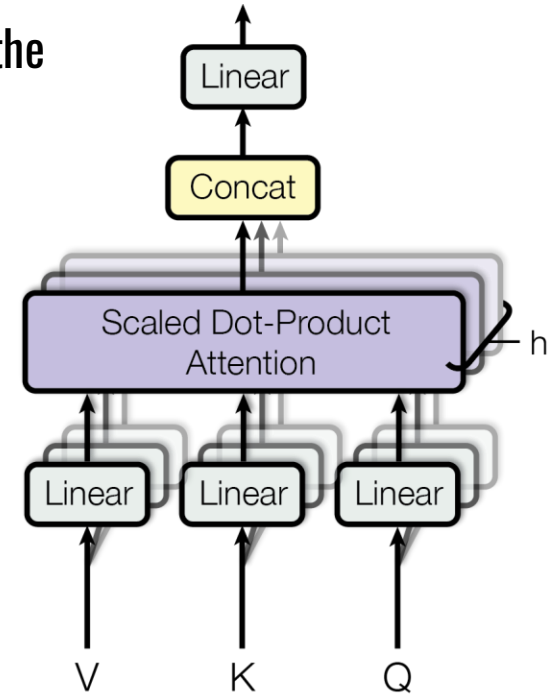
- How do the different elements of the input relate to each other (what part of the input is relevant in understanding the other parts of the input)
  - Helps in capturing dependencies and contextual information within the input

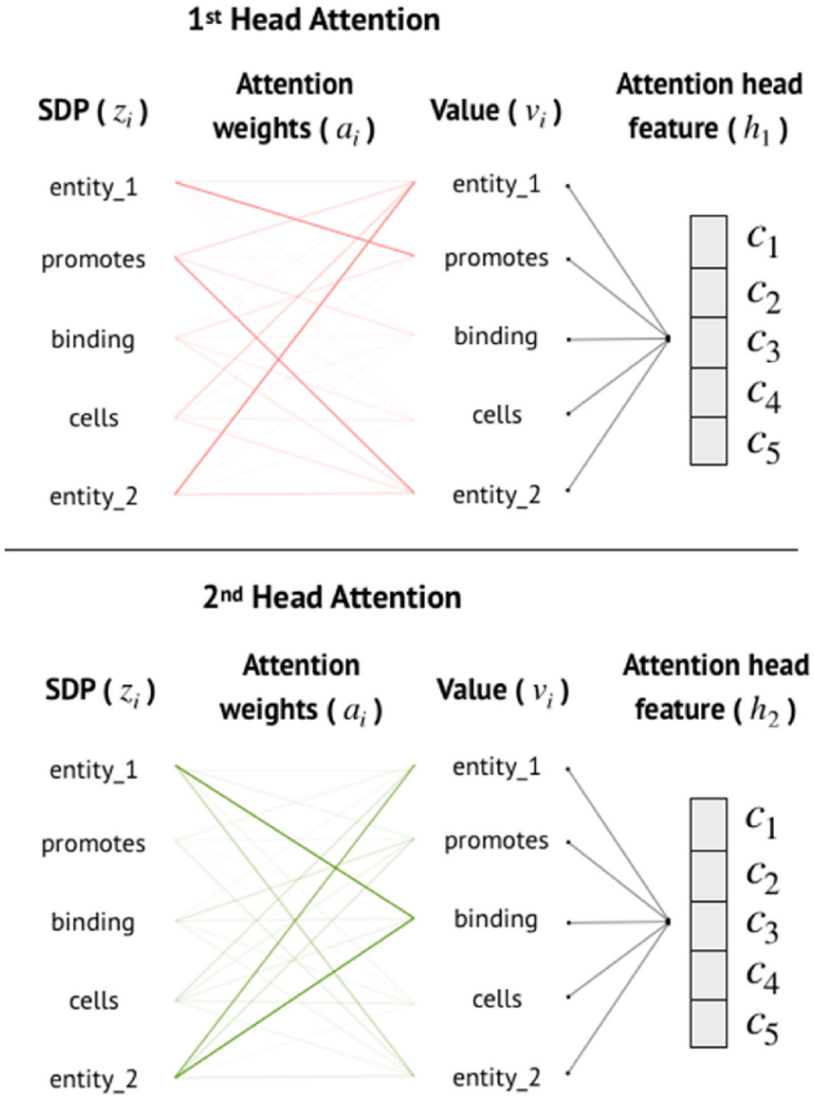


Summary

3. Multi-Head Attention

- Repeating self-attention multiple times to better understand the input (multiple ways of deciding the relationship between the parts of the input)
  - Looks at the input from different perspectives



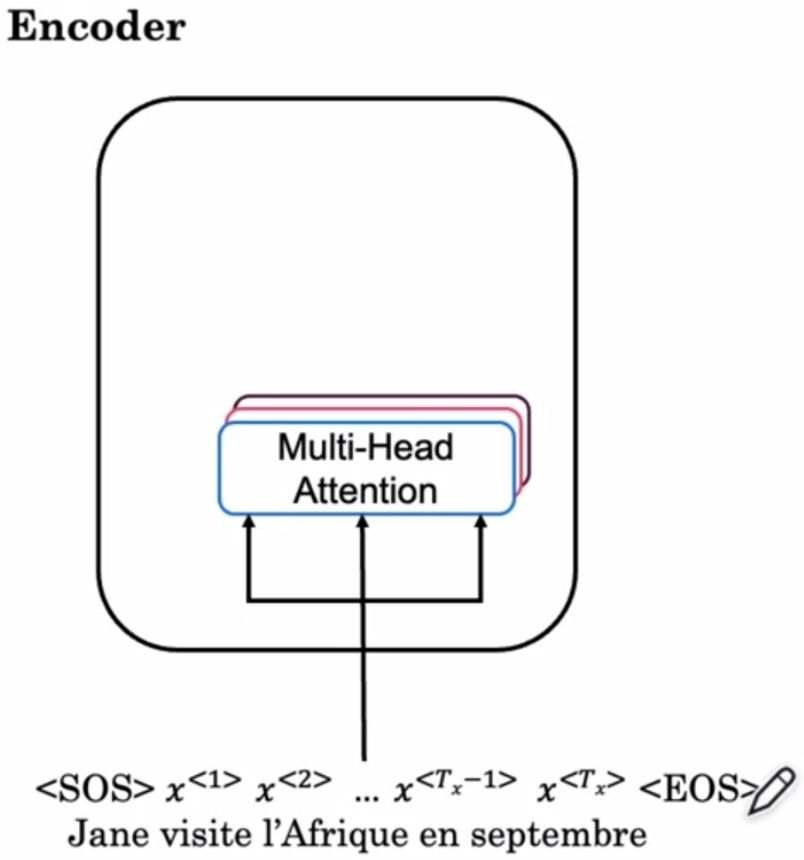


Transformer

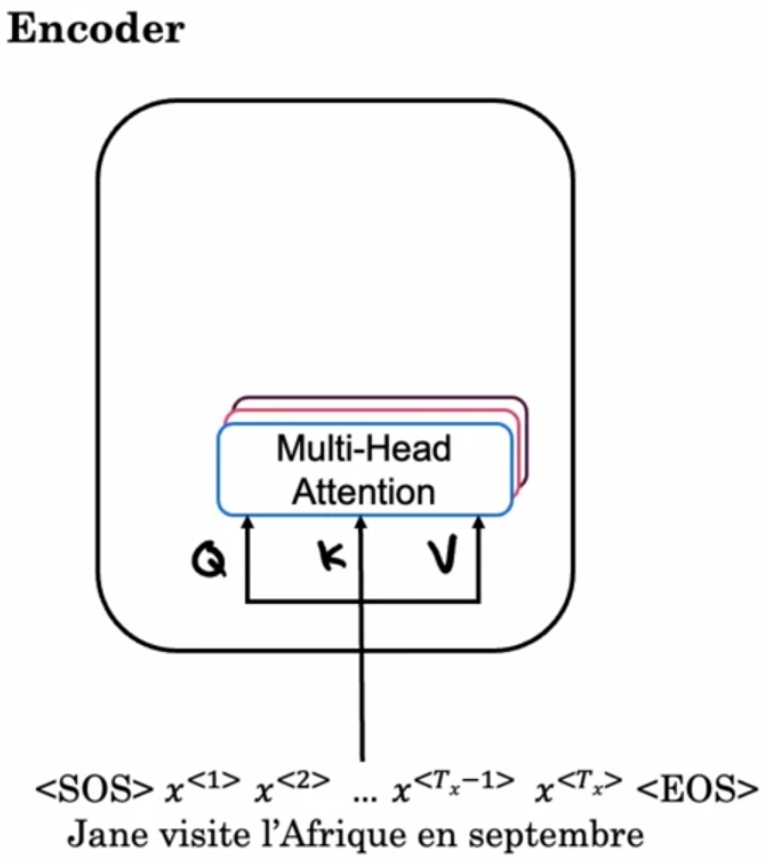
<SOS> $x^{<1>}$ $x^{<2>}$ ... $x^{<T_x-1>}$ $x^{<T_x>}$ <EOS>

Jane visite l'Afrique en septembre

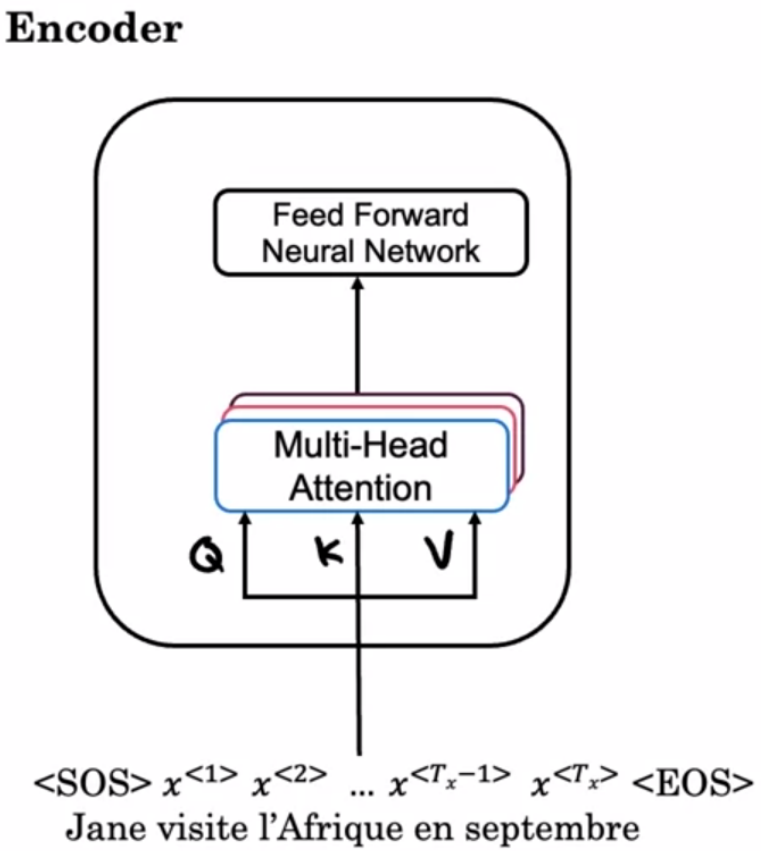
Transformer



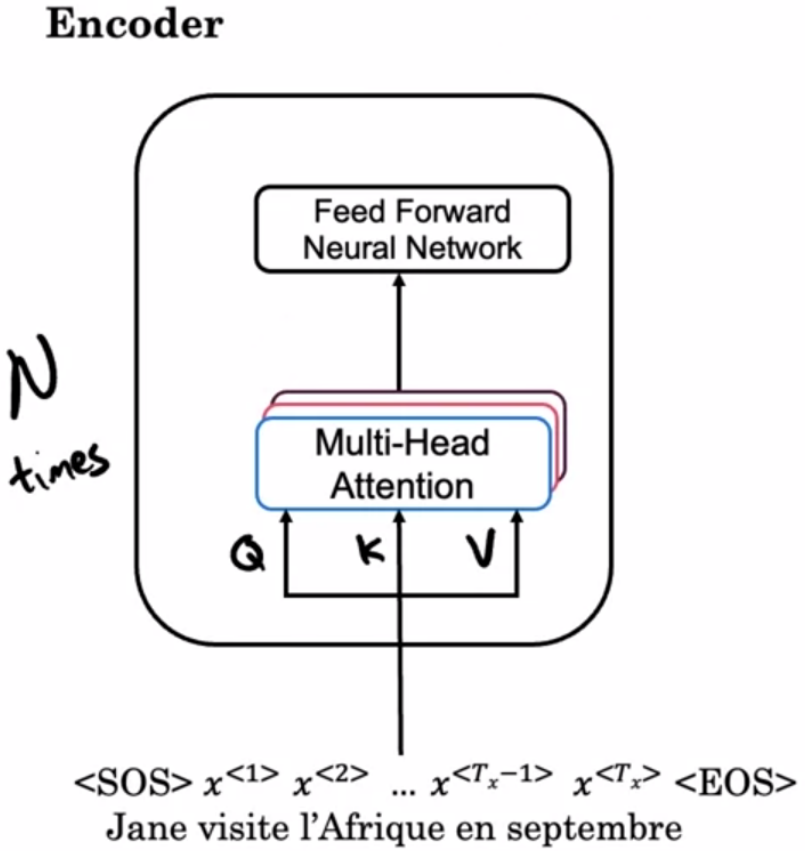
Transformer



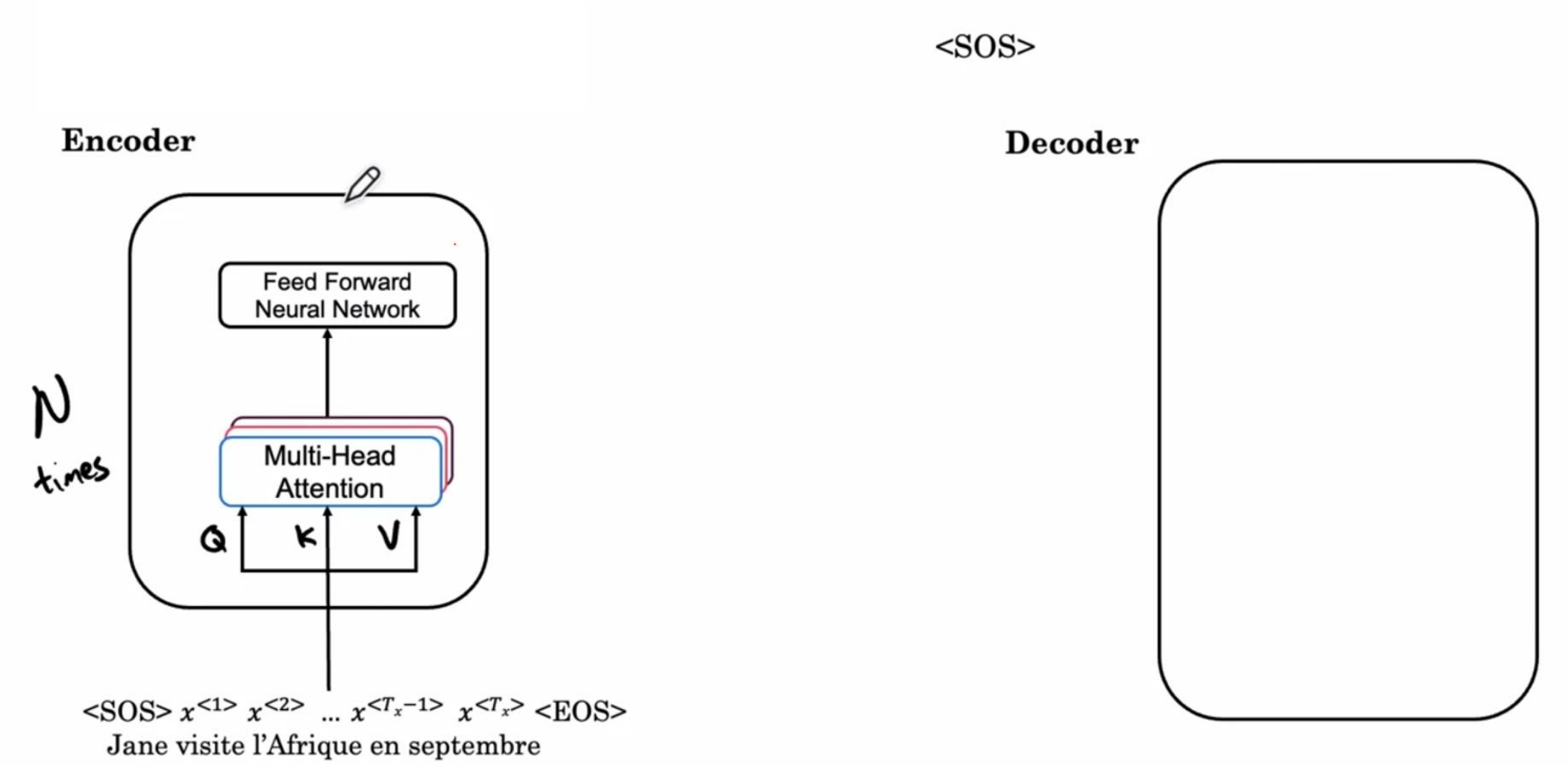
Transformer



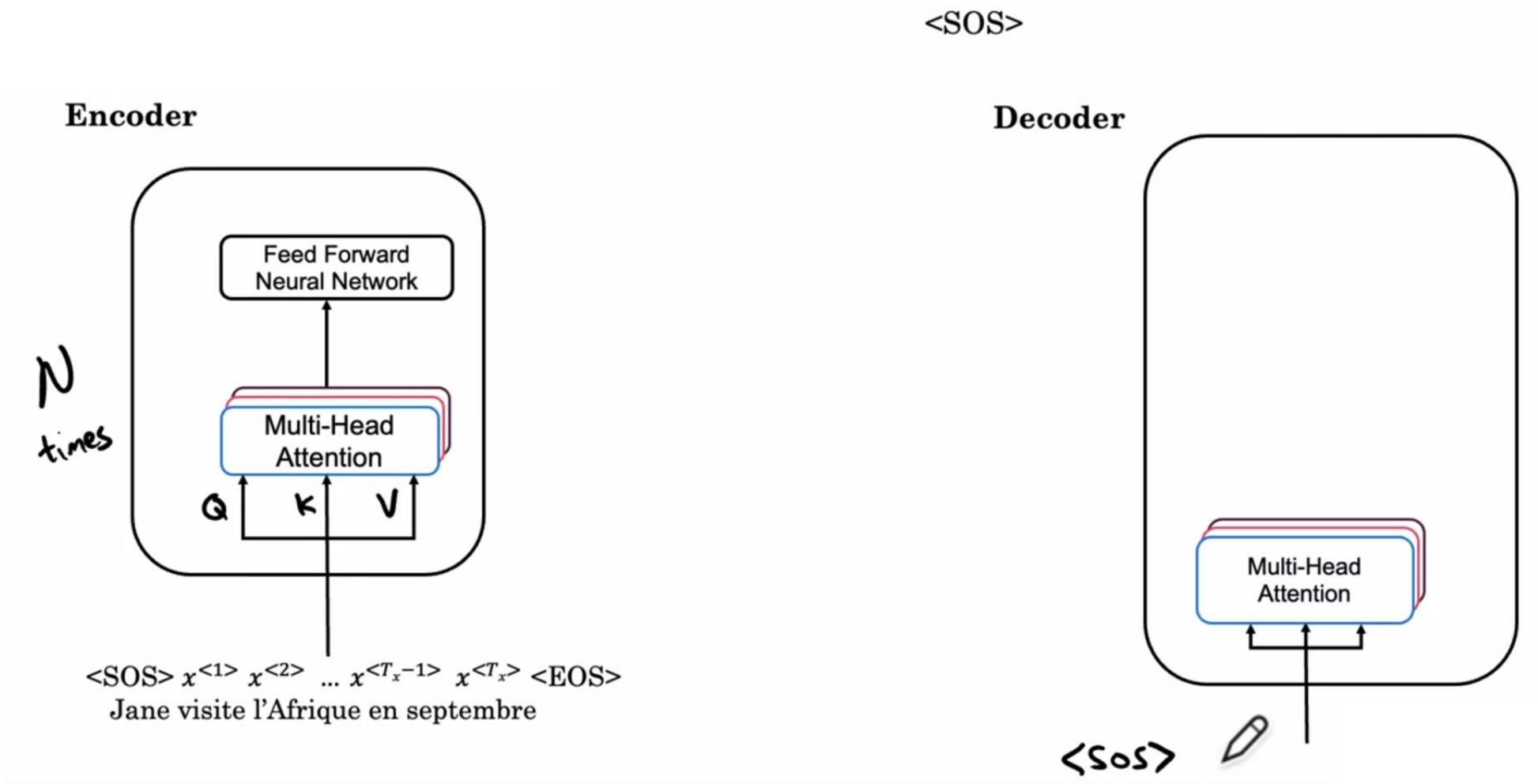
Transformer



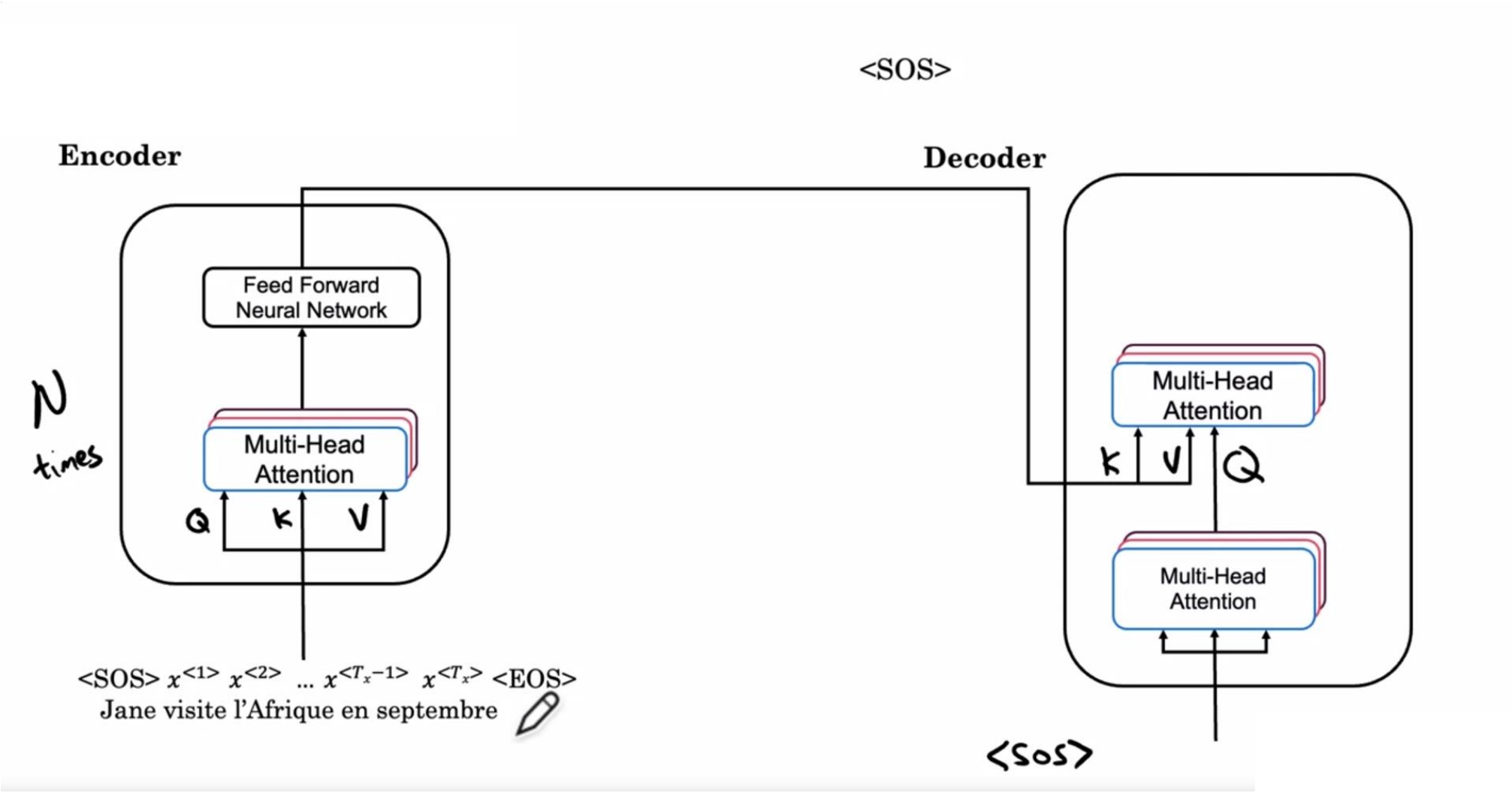
Transformer



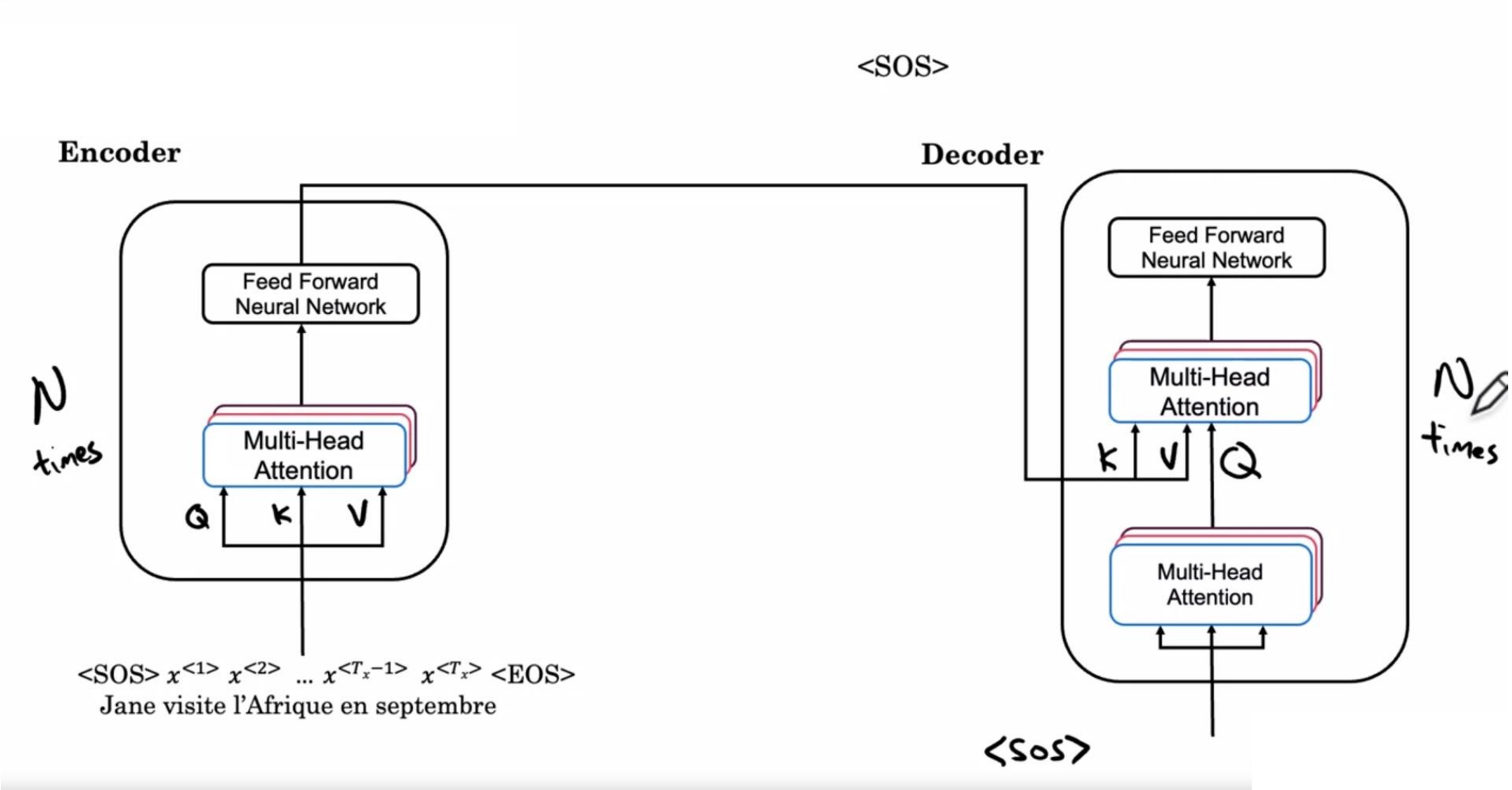
Transformer



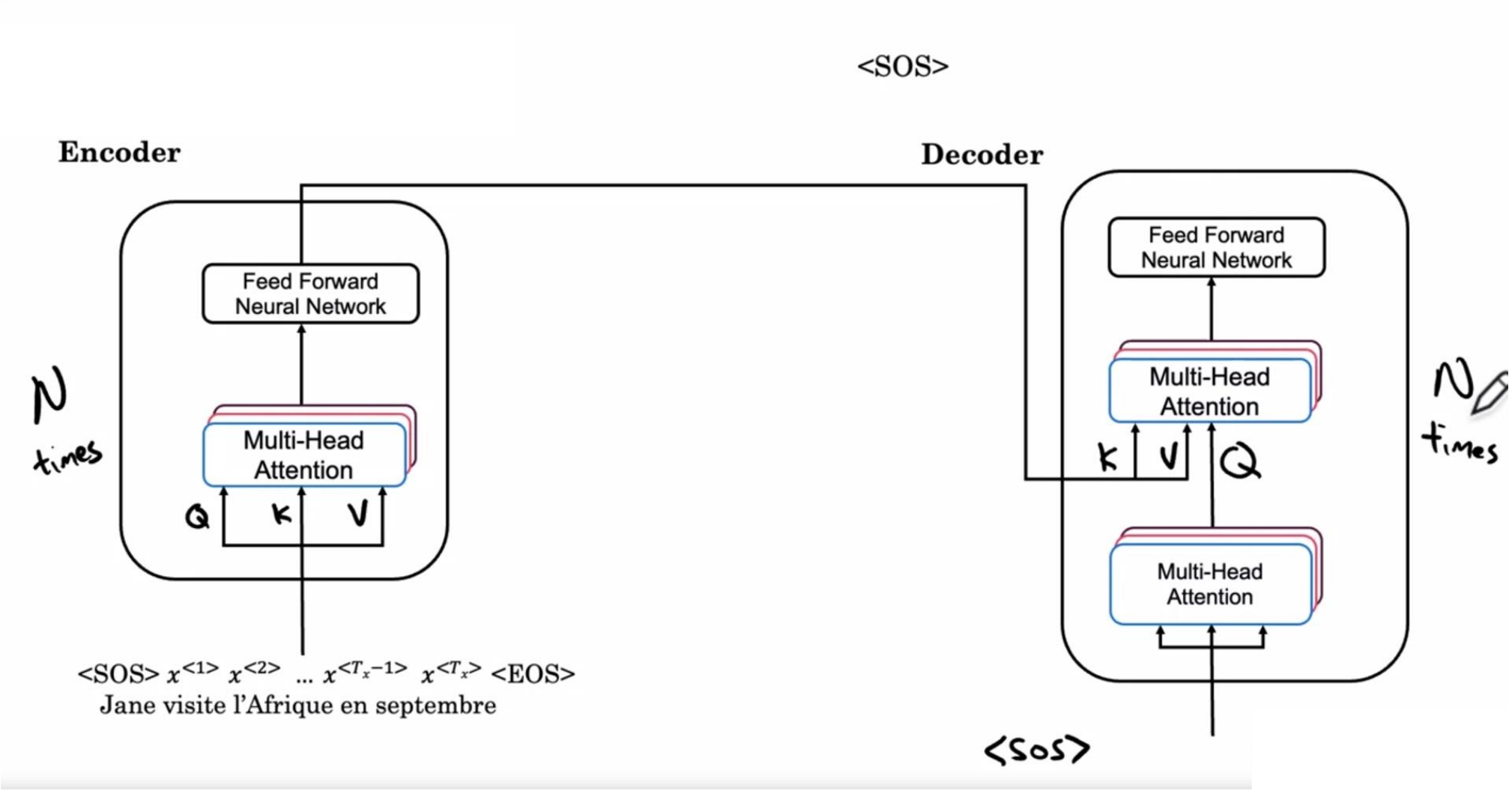
Transformer



Transformer



Transformer



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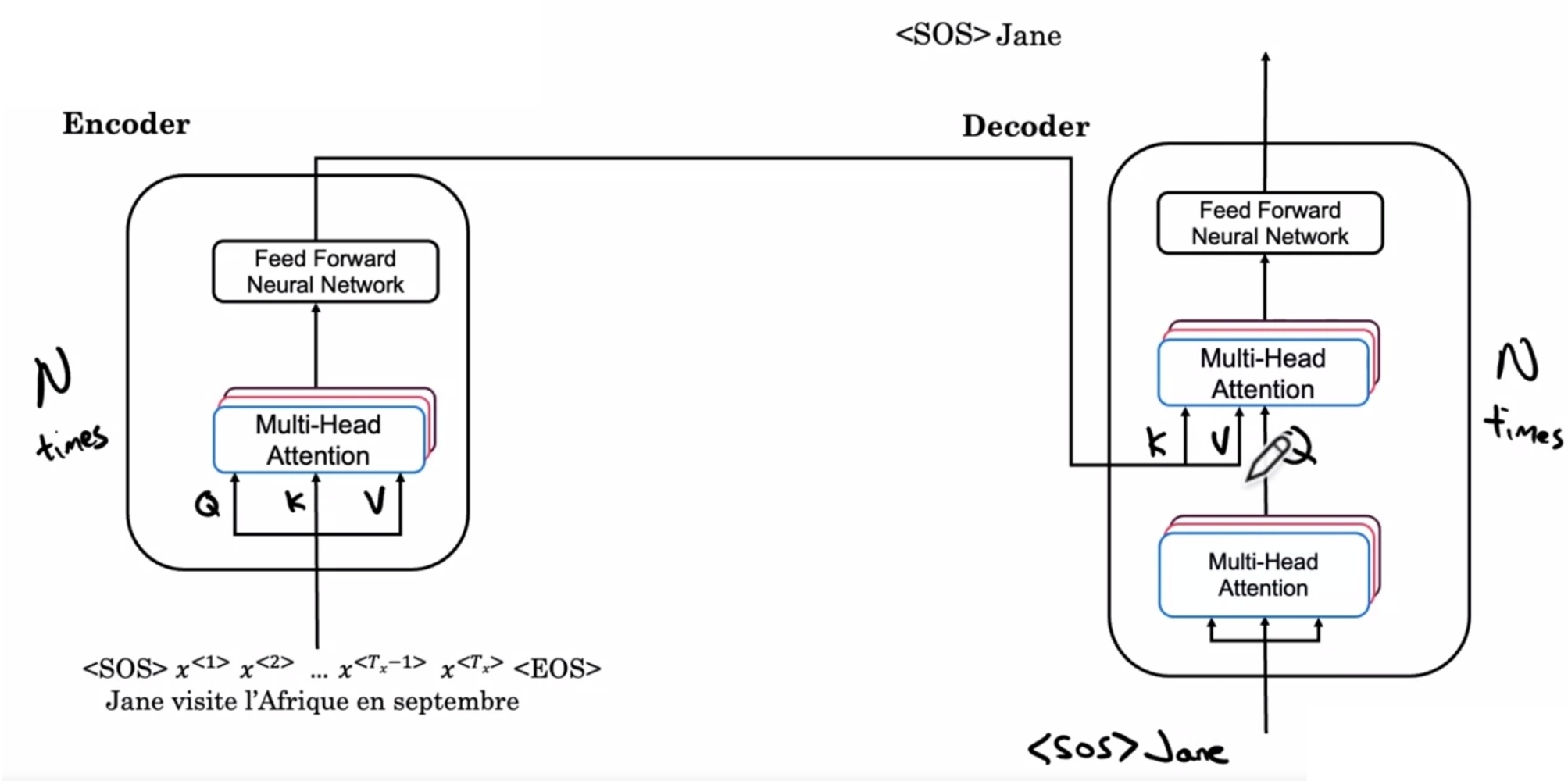
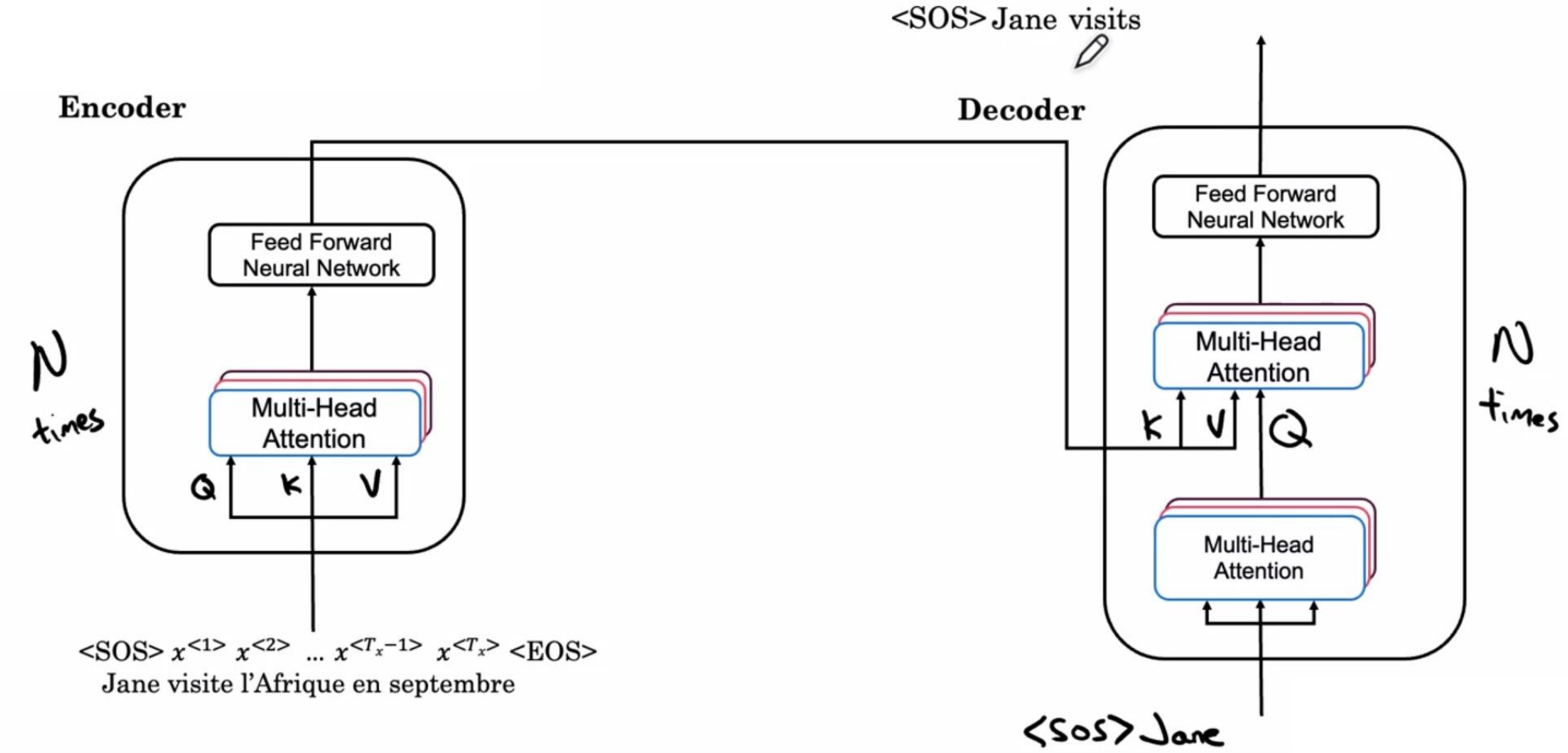
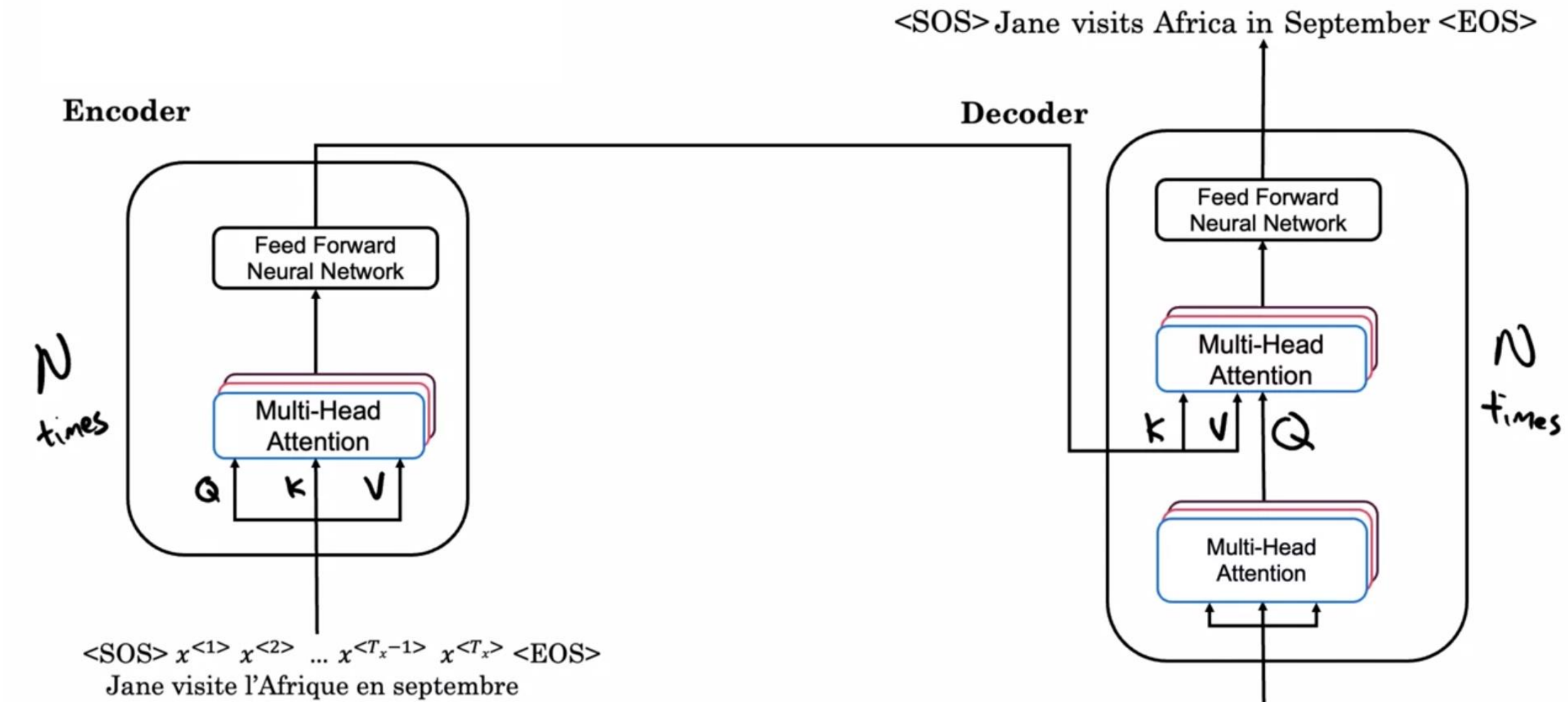


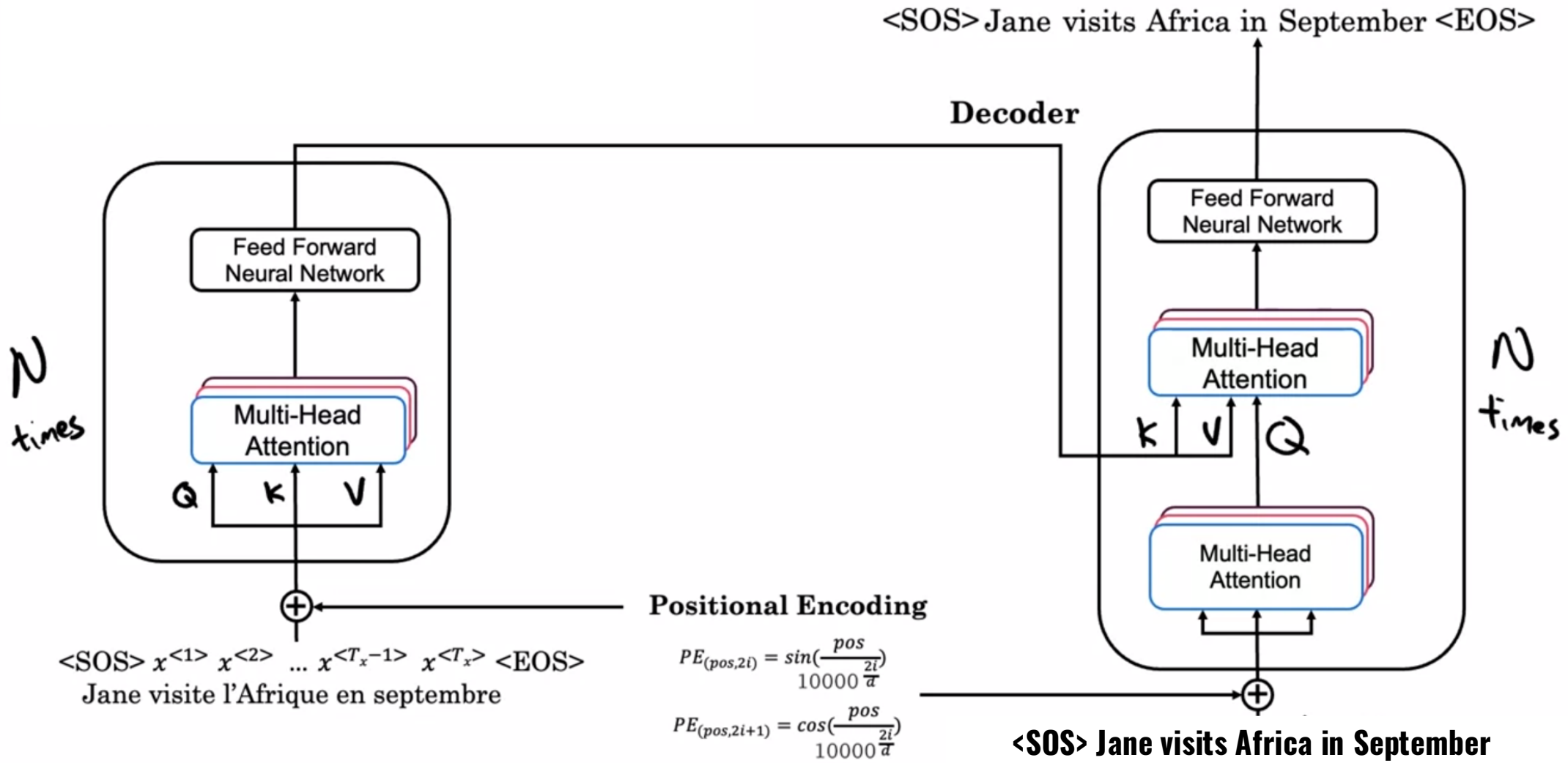
Transformer



Transformer

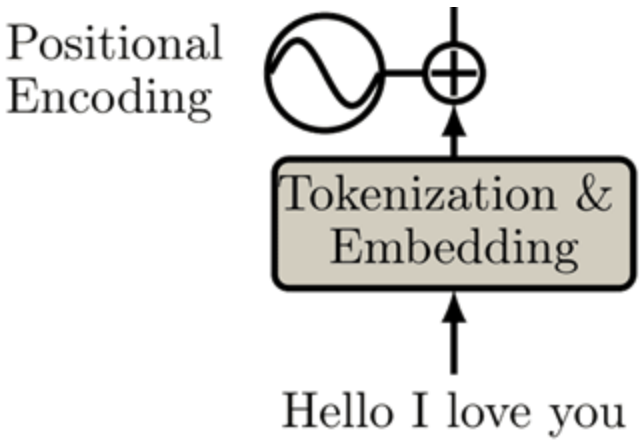


Transformer

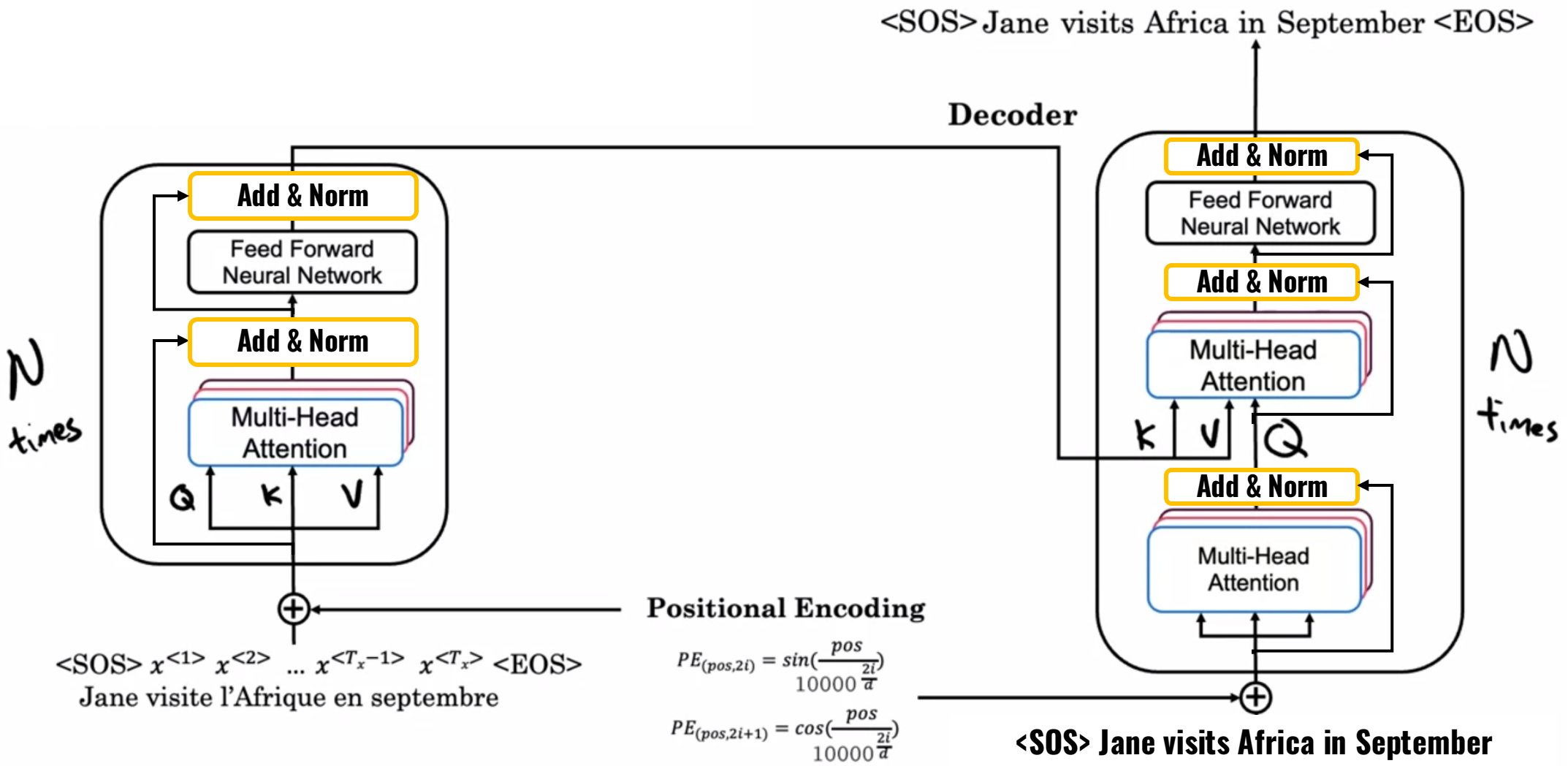


Transformer

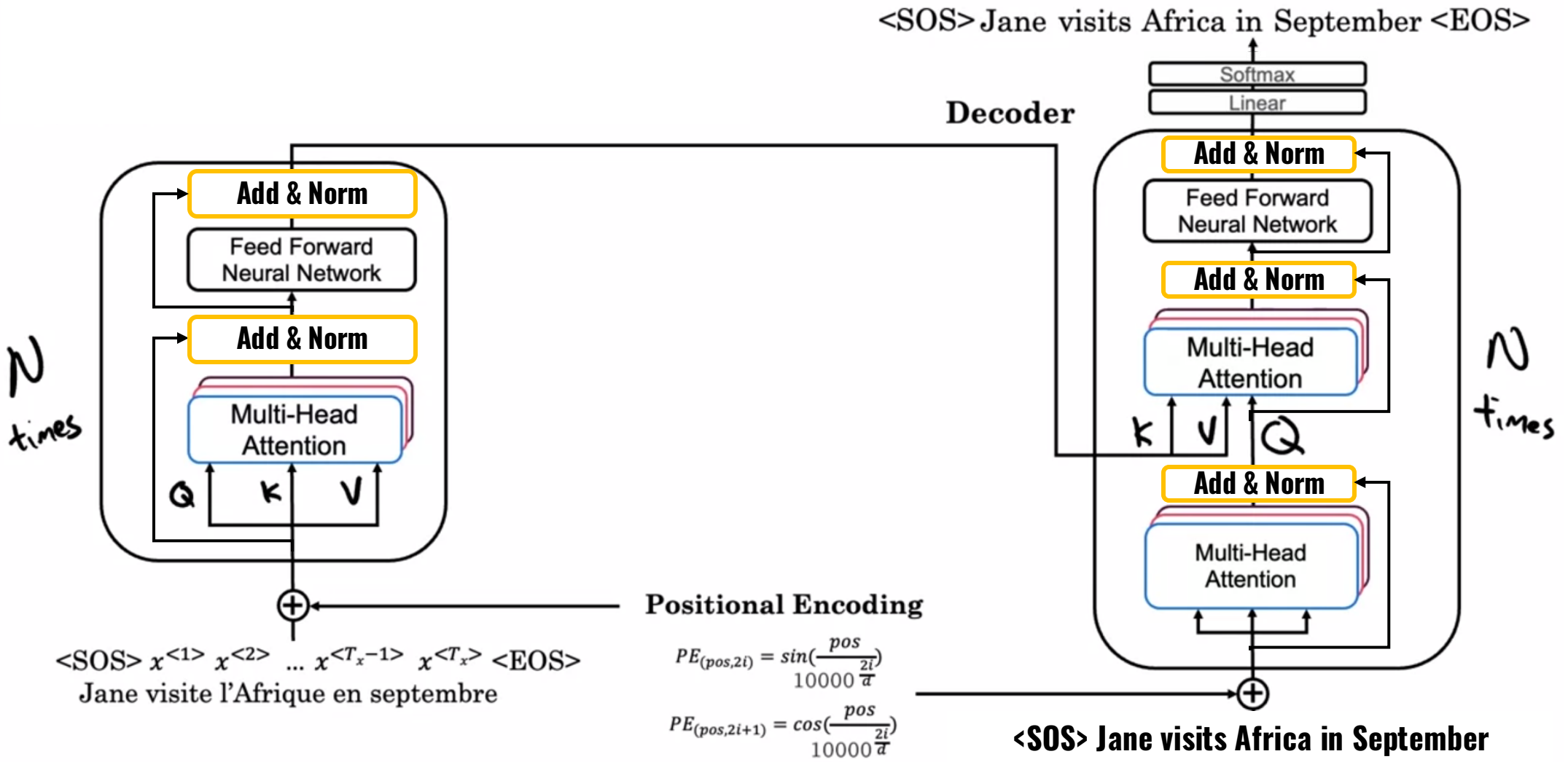
- When you convert a sequence into a set (**tokenization**), you lose the notion of order.
- **Positional encoding** is a set of small constants, which are added to the word embedding vector before the first self-attention layer.
- So if the same word appears in a different position, the actual representation will be slightly different, **depending on where it appears in the input sentence**.
- They use a sinusoidal function for the positional encoding. The sine function tells the model to pay attention to a particular wavelength.



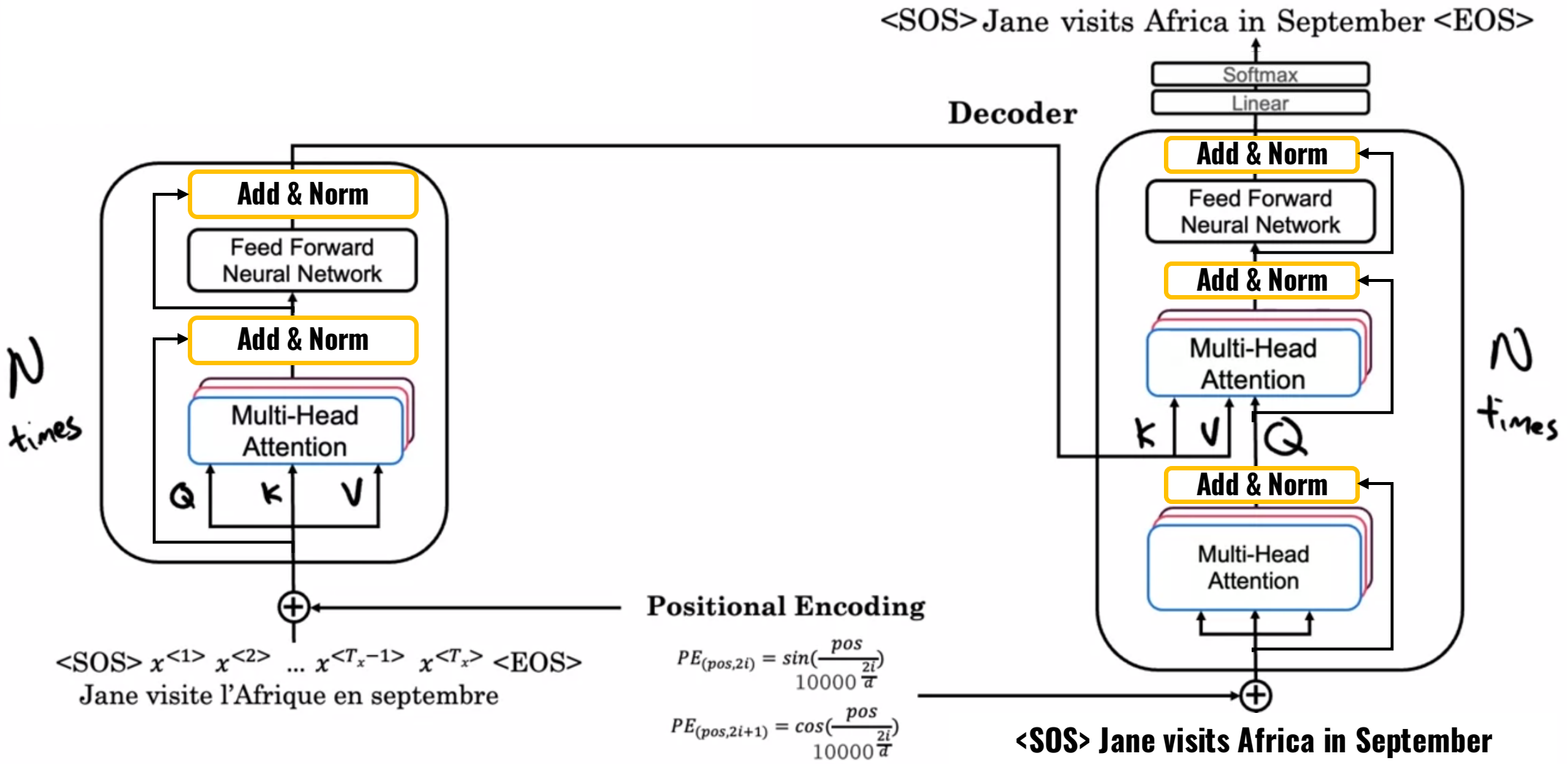
Transformer



Transformer



Transformer

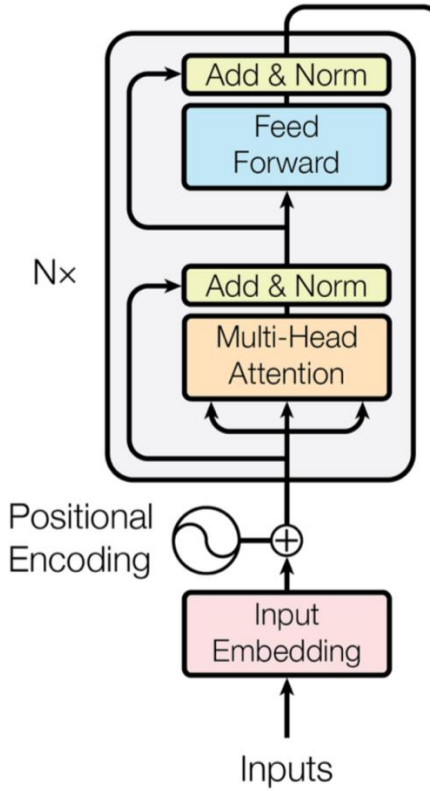


Transformer Encoder

Summary: the Transformer encoder

To process a sentence, we need these 3 steps:

1. Word embeddings of the input sentence are computed simultaneously.
2. Positional encodings are then applied to each embedding resulting in word vectors that also include positional information.
3. The word vectors are passed to the first encoder block.



Each block consists of the following layers in the same order:

1. A multi-head self-attention layer to find correlations between each word
2. A normalization layer
3. A residual connection around the previous two sublayers
4. A linear layer
5. A second normalization layer
6. A second residual connection

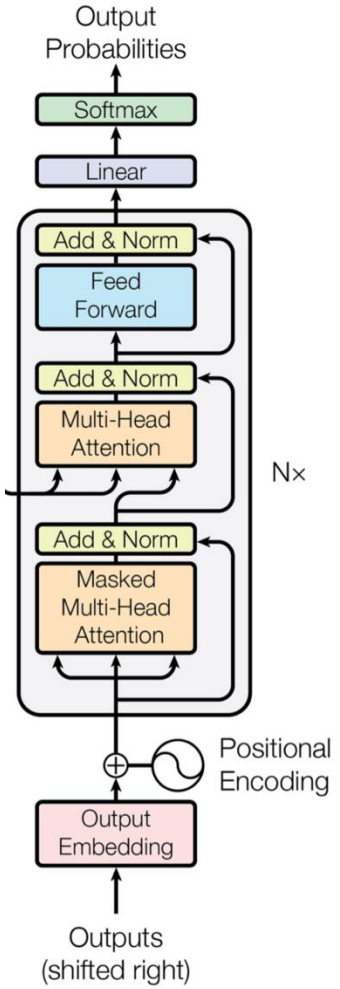
Note that the above block can be replicated several times to form the Encoder. In the original paper, the encoder composed of 6 identical blocks.

Transformer Decoder

Transformer decoder: what is different?

The decoder consists of all the aforementioned components plus two novel ones. As before:

1. The output sequence is fed in its entirety and word embeddings are computed
2. Positional encoding are again applied
3. And the vectors are passed to the first Decoder block

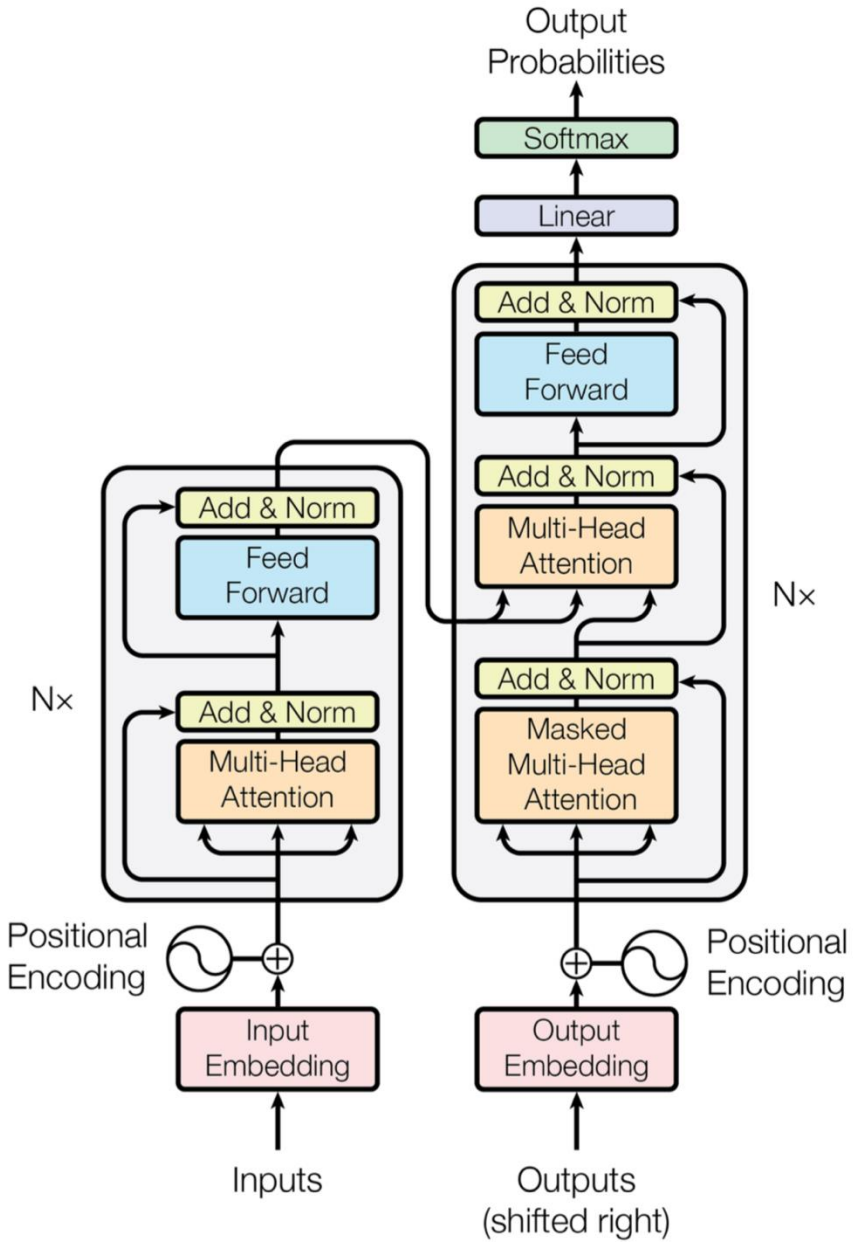


Each decoder block includes:

1. A **Masked** multi-head self-attention layer
2. A normalization layer followed by a residual connection
3. A new multi-head attention layer (known as **Encoder-Decoder attention**)
4. A second normalization layer and a residual connection
5. A linear layer and a third residual connection

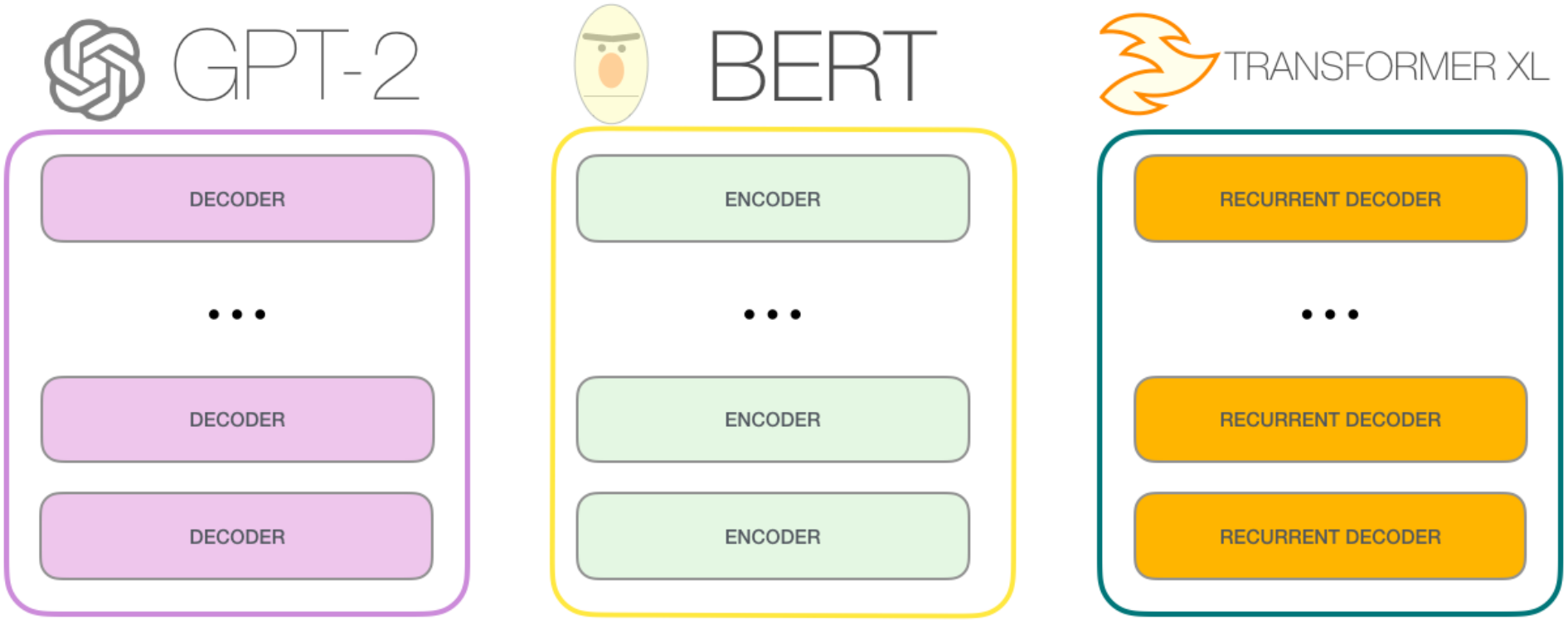
The decoder block appears again 6 times. The final output is transformed through a final linear layer and the output probabilities are calculated with the standard softmax function.

Transformer [1]

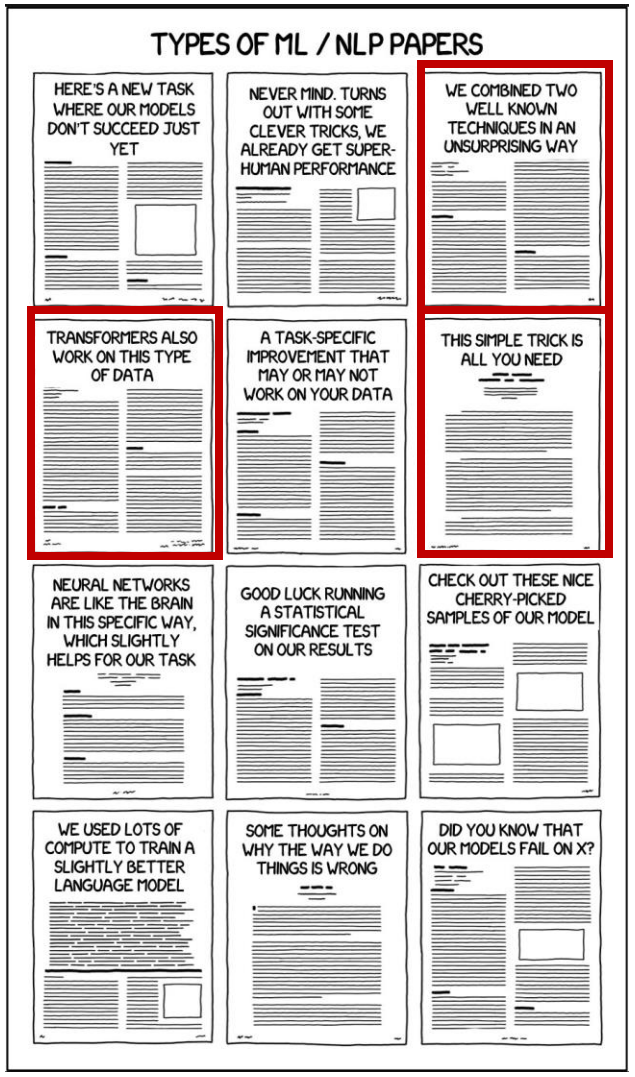


[1] Vaswani, Ashish et al. "Attention is All you Need." (2017)

Transformer Architectures



Transformer Networks



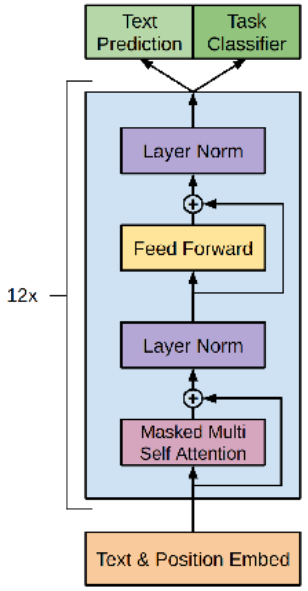
Generative Pre-trained Transformer (GPT) – June 2018

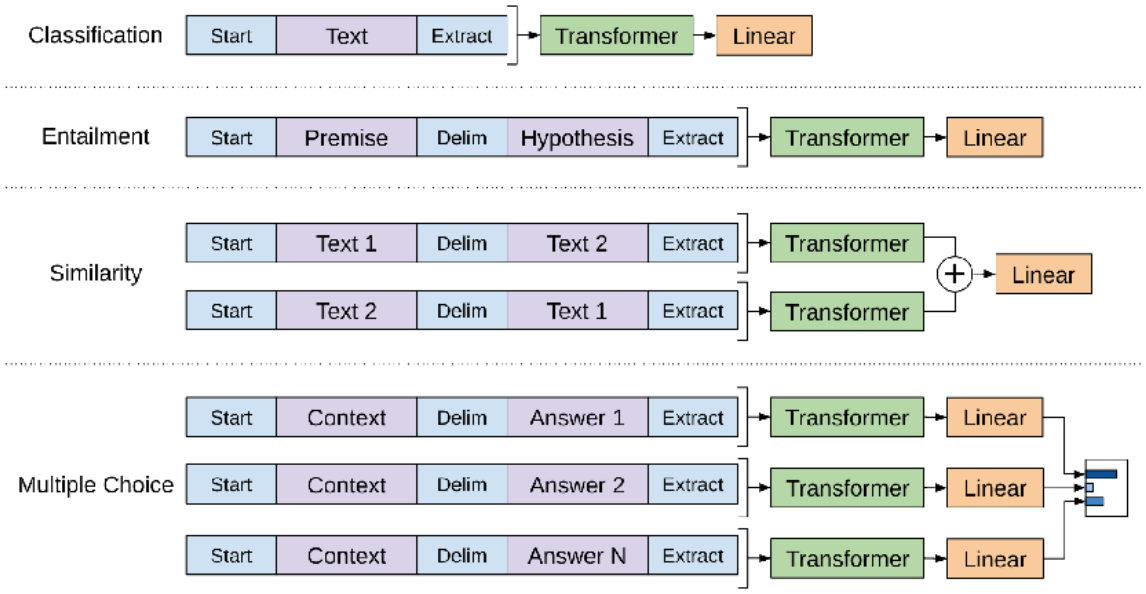
The original goal is Language Modelling (LM)

Uses Masked Self-Attention to limit the attention to the previous tokens only (left-to-right)

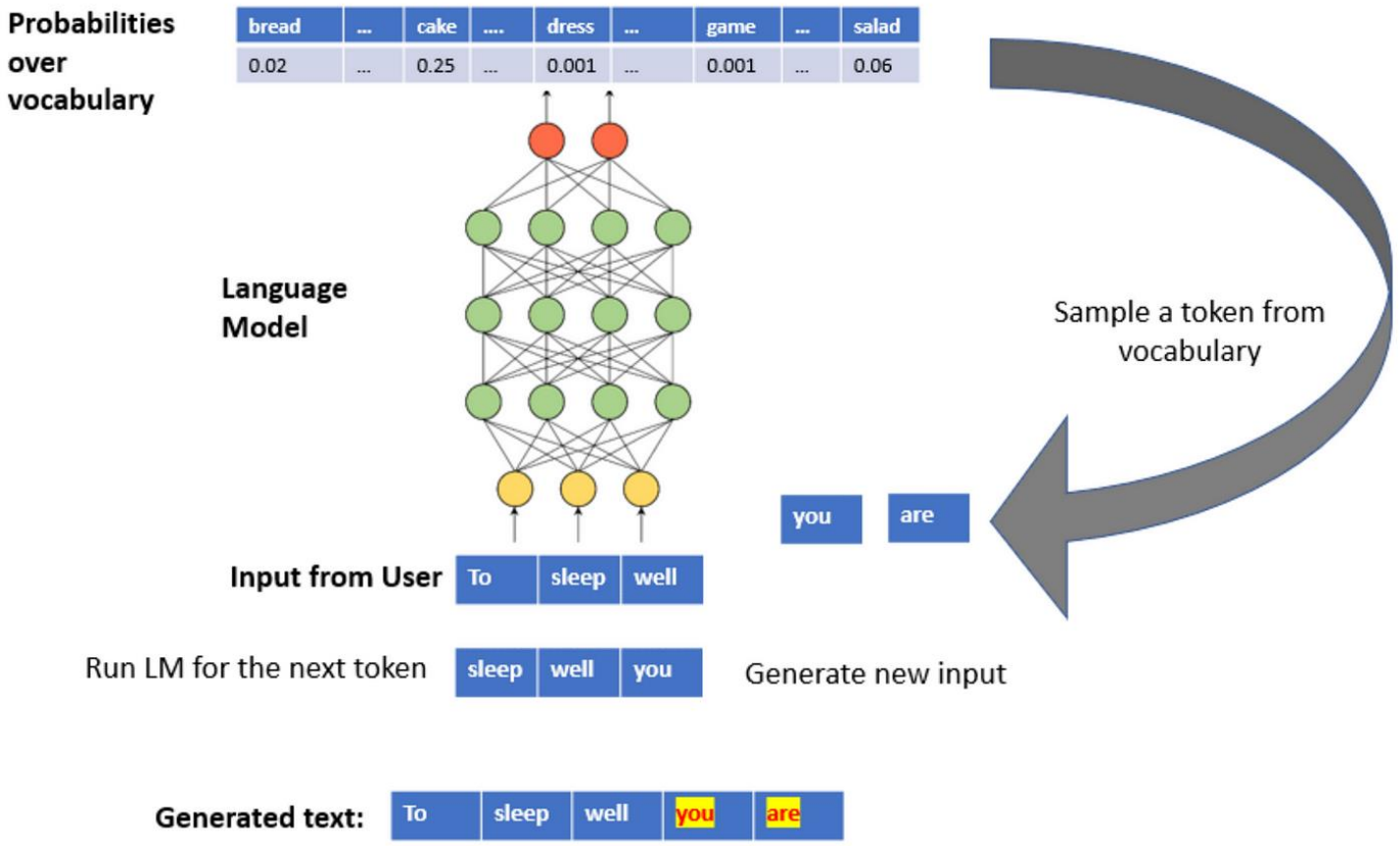
Two stage training:

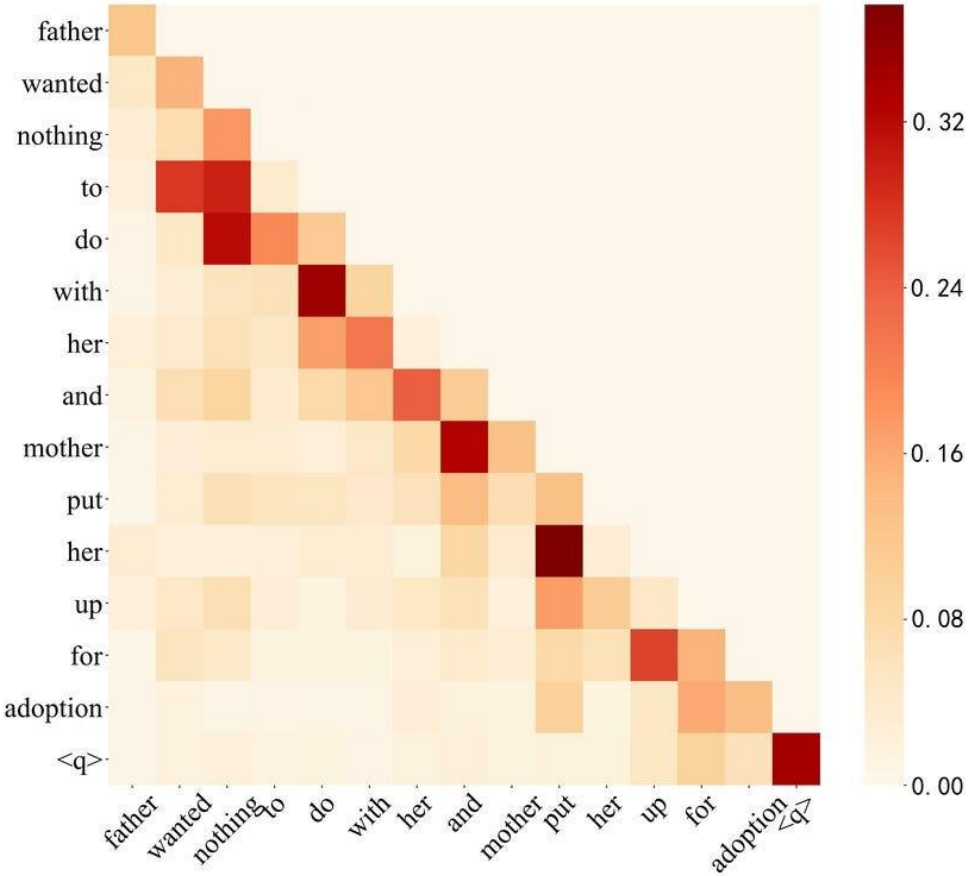
1. Unsupervised pre-training:
   - The goal is to predict the next token based on the previous tokens.
2. Supervised fine-tuning:
   - Predict the label (y) based on the input tokens





Generative Pre-trained Transformer (GPT) – June 2018

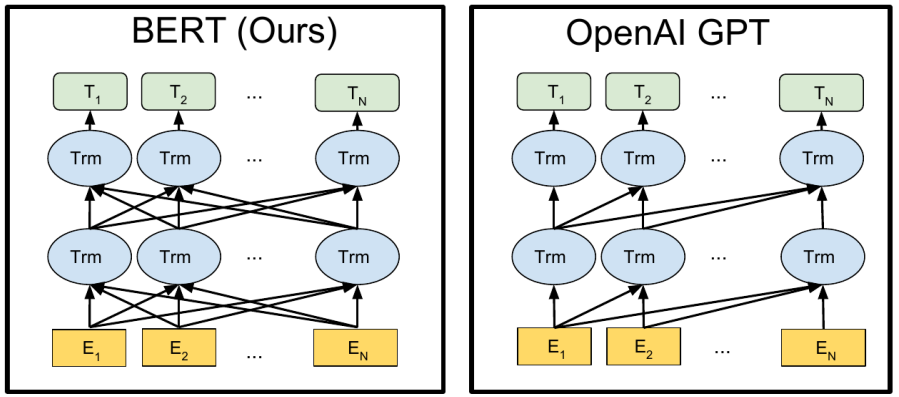


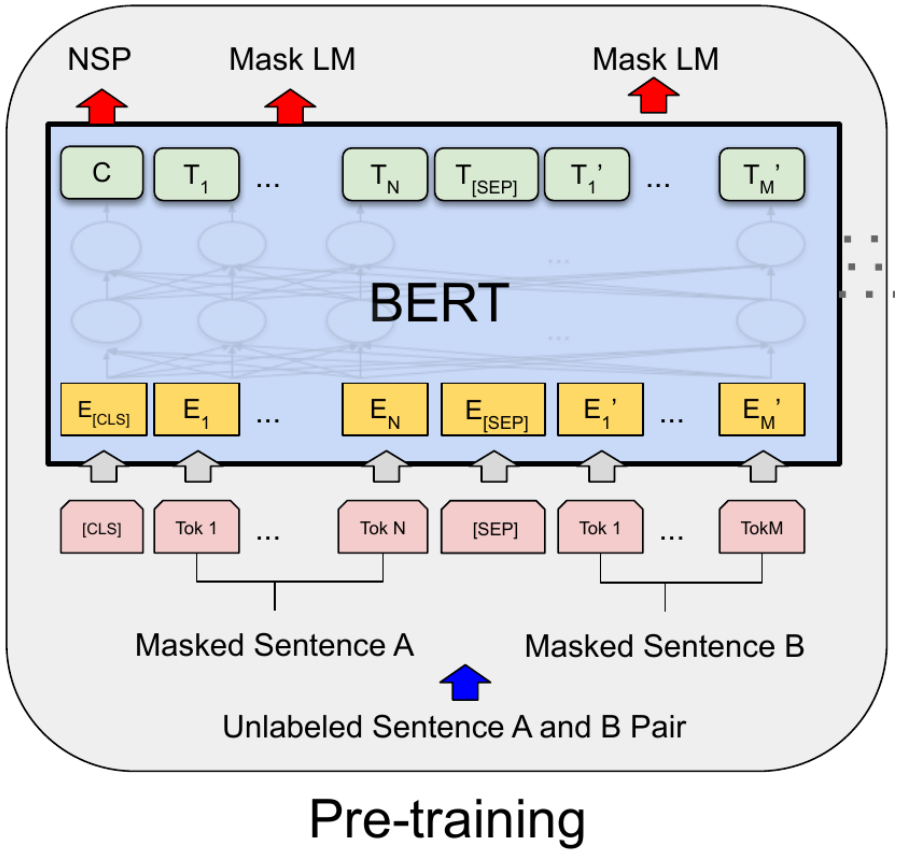


Bidirectional Encoder Representations from Transformers (BERT) – May 2019

- Compared to OpenAI GPT it uses a bidirectional self-attention
- Trained on 2 tasks at the same time during pre-training
  1. Masked LM (15% of the tokens are masked)
  2. Next Sentence Prediction

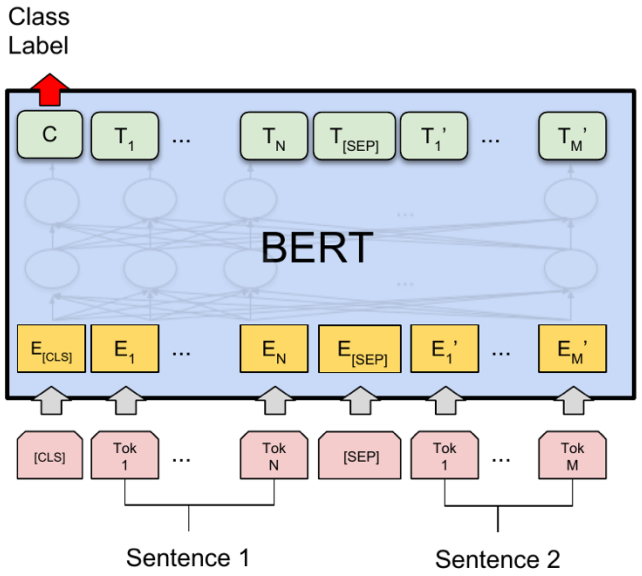
- A special [CLS] token is introduced at the beginning of each sequence.



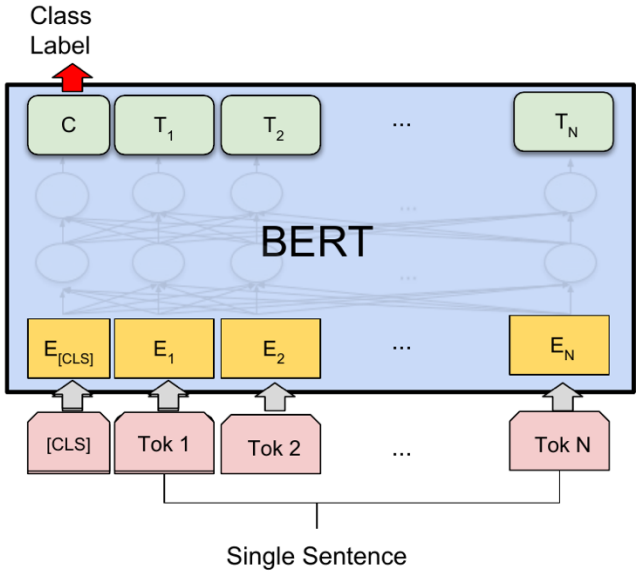


Pre-training

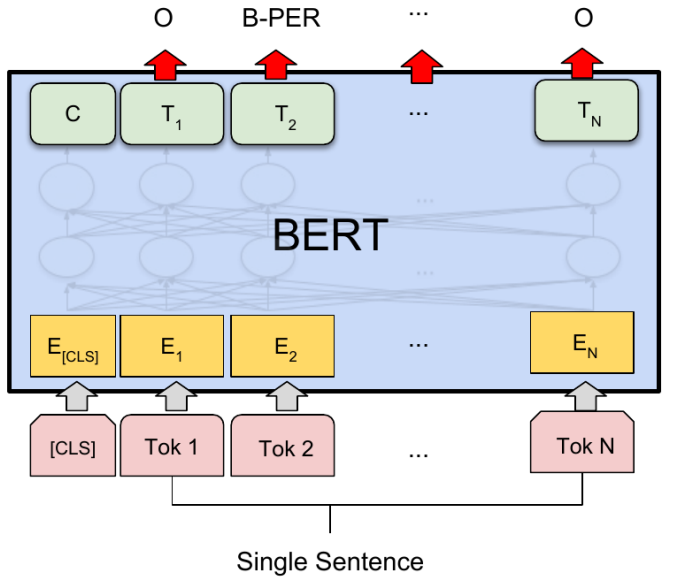
Bidirectional Encoder Representations from Transformers (BERT) – May 2019



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(b) Single Sentence Classification Tasks: SST-2, CoLA



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Further Links + Resources

- https://theaisummer.com/attention/
- https://theaisummer.com/transformer/
- https://jalammar.github.io/illustrated-transformer/
- https://nlp.seas.harvard.edu/annotated-transformer/ !!!!
- https://www.youtube.com/watch?v=bCz4OMemCcA
- Coursera Deep Learning Specialization

Please read this:

- Beam search: https://towardsdatascience.com/foundations-of-nlp-explained-visually-beam-search-how-it-works-1586b9849a24
- BLEU score: https://cloud.google.com/translate/automl/docs/evaluate#bleu

Resources

Books:

- Courville, Goodfellow, Bengio: Deep Learning
  Freely available: https://www.deeplearningbook.org/
- Zhang, Aston and Lipton, Zachary C. and Li, Mu and Smola, Alexander J.: Dive into Deep Learning
  Freely available: https://d2l.ai/

Courses:

- Deep Learning specialization by Andrew NG
- https://www.coursera.org/specializations/deep-learning

That’s all for today!