NLP Advanced - 01

PRE-TRAINED LANGUAGE MODEL

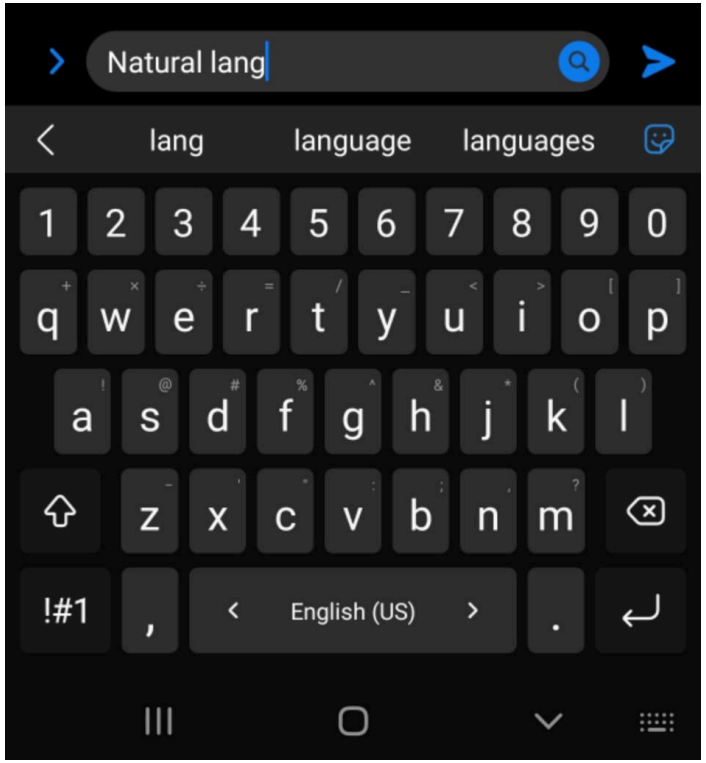
AI VIET NAM
Nguyen Quoc Thai

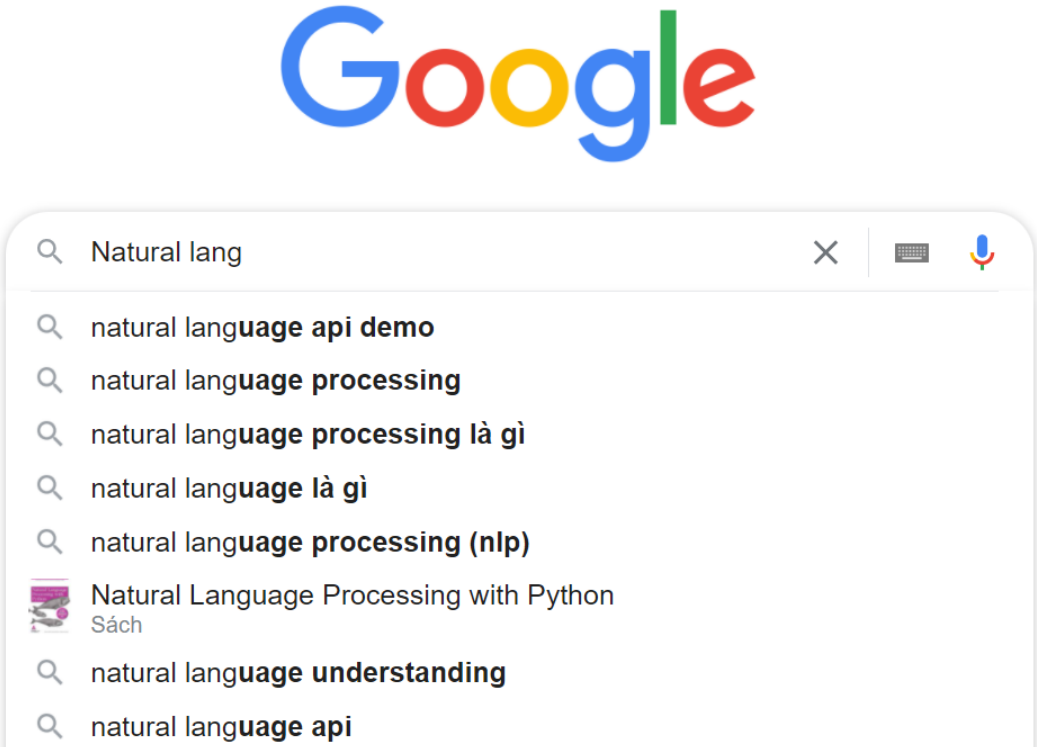
CONTENT

1 – Language Model

Language Model

- The task of predicting what word comes next





1 – Language Model

Language Model

- Assign a probability $P(w_1, w_2, \ldots, w_n)$ to every finite sequence $w_1, w_2, \ldots, w_n$
- Predict a next token based on history tokens

Completion

I am learning Natural Language …

Processing

P(Processing|I am learning Natural Language)

Conditional Probability

P(Handling|I am learning Natural Language)

Handling

1 – Language Model

Statistical Language Model

- The probability of a word depends only on some previous words

$$P(w_{1:n}) = \prod_{i=1}^{n} P(w_i | w_{i-N+1:i-1})$$

$$P(w_i | w_{1:i-1}) = P(w_i | w_{i-N+1:i-1})$$

- N-gram model with N = {1, 2,…}

1 – Language Model

Statistical Language Model

- Compute P(w|h)

P(w|h) = P(learning|I,am)

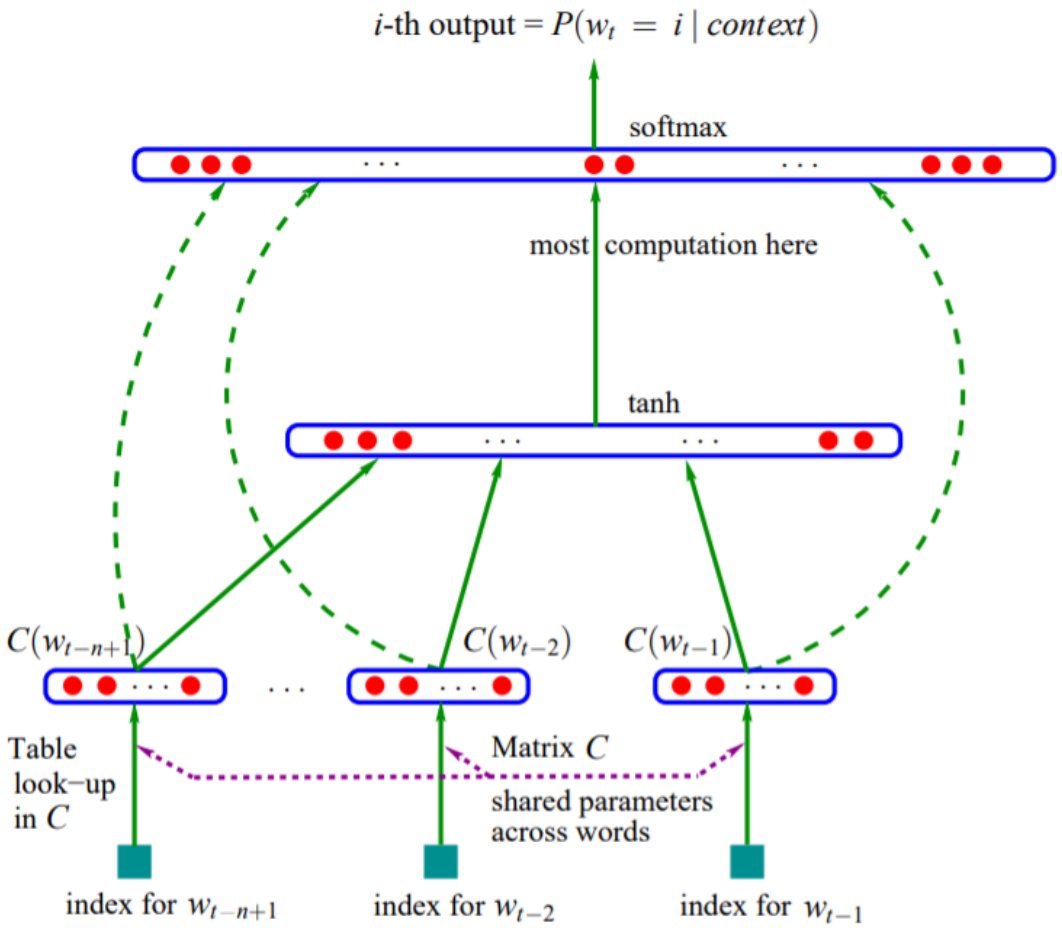
- w: token as word “learning”
- h: history tokens as “I,am”

$$P(w|h) = \frac{count(hw)}{count(h)}$$

$$P(school|i, go, to) = \frac{count(I, \text{am}, \text{learning})}{count(\text{I}, \text{am})}$$

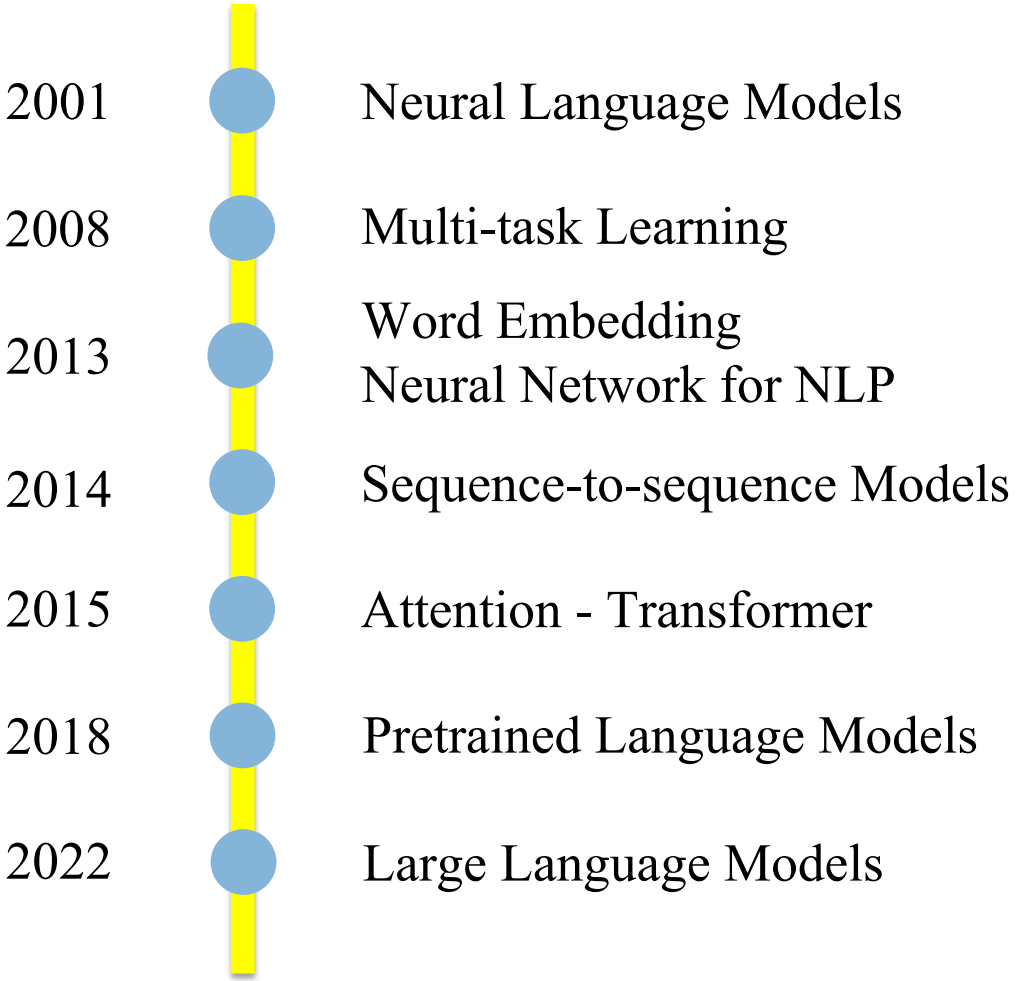
1 – Language Model

Neural Language Model



1 – Language Model

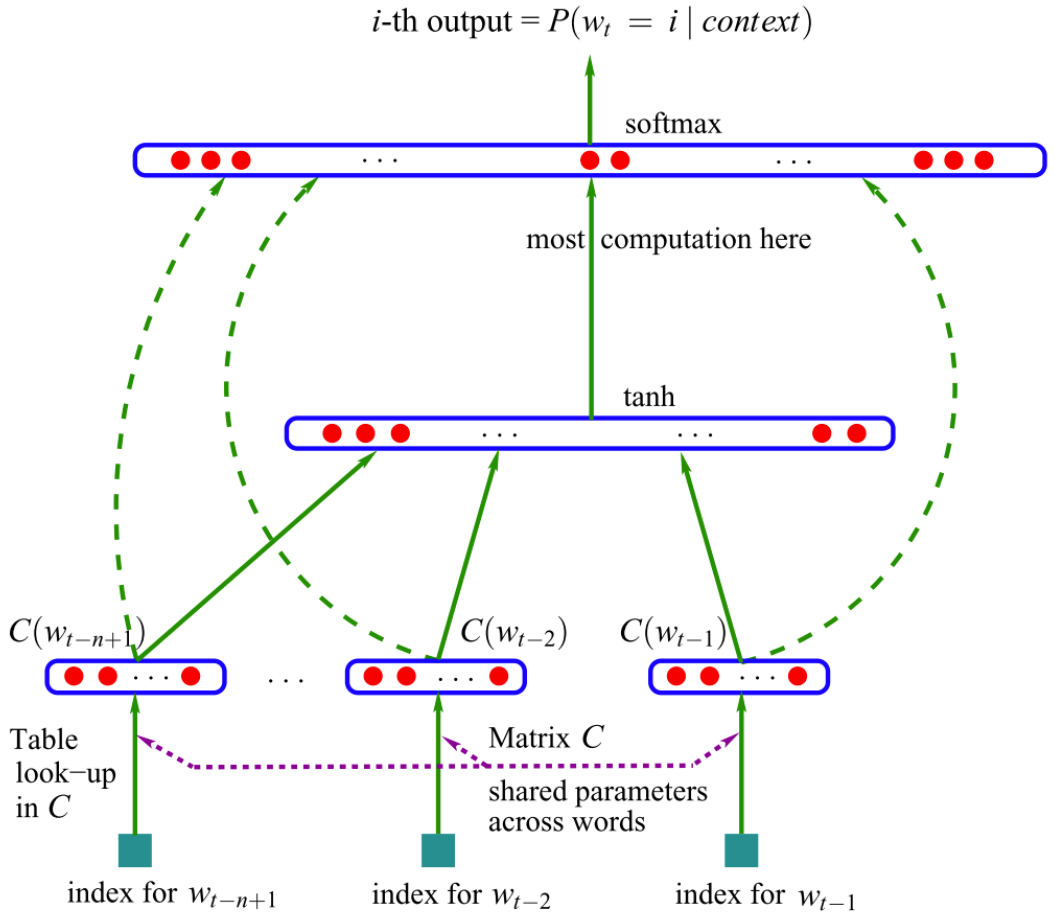
The neural history of NLP



1 – Language Model

The neural history of NLP

2001	Neural Language Models
2008	Multi-task Learning
2013	Word Embedding Neural Network for NLP
2014	Sequence-to-sequence Models
2015	Attention - Transformer
2018	Pretrained Language Models
2022	Large Language Models



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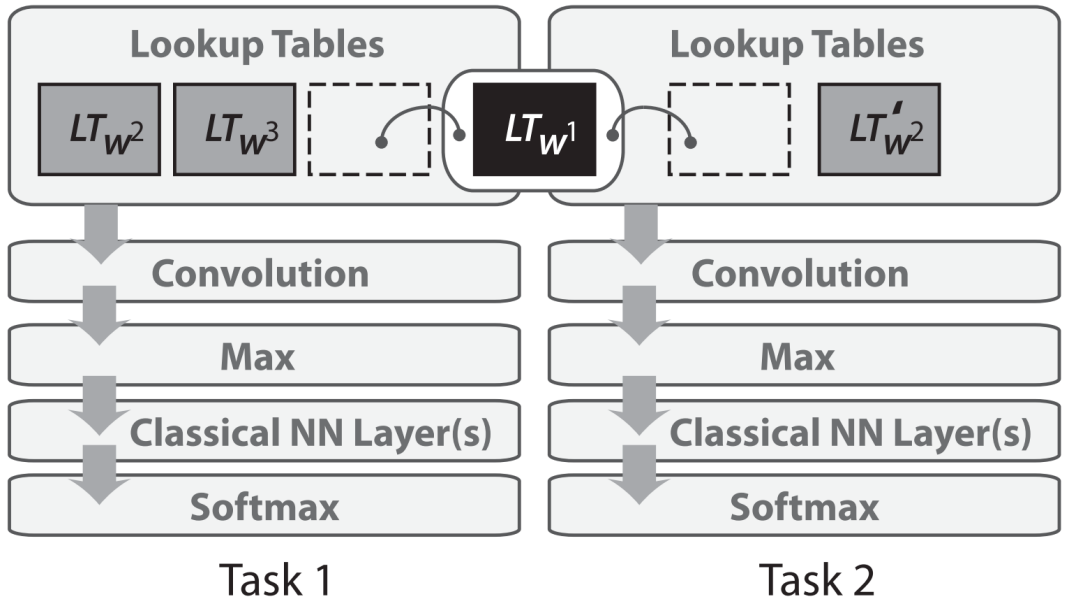

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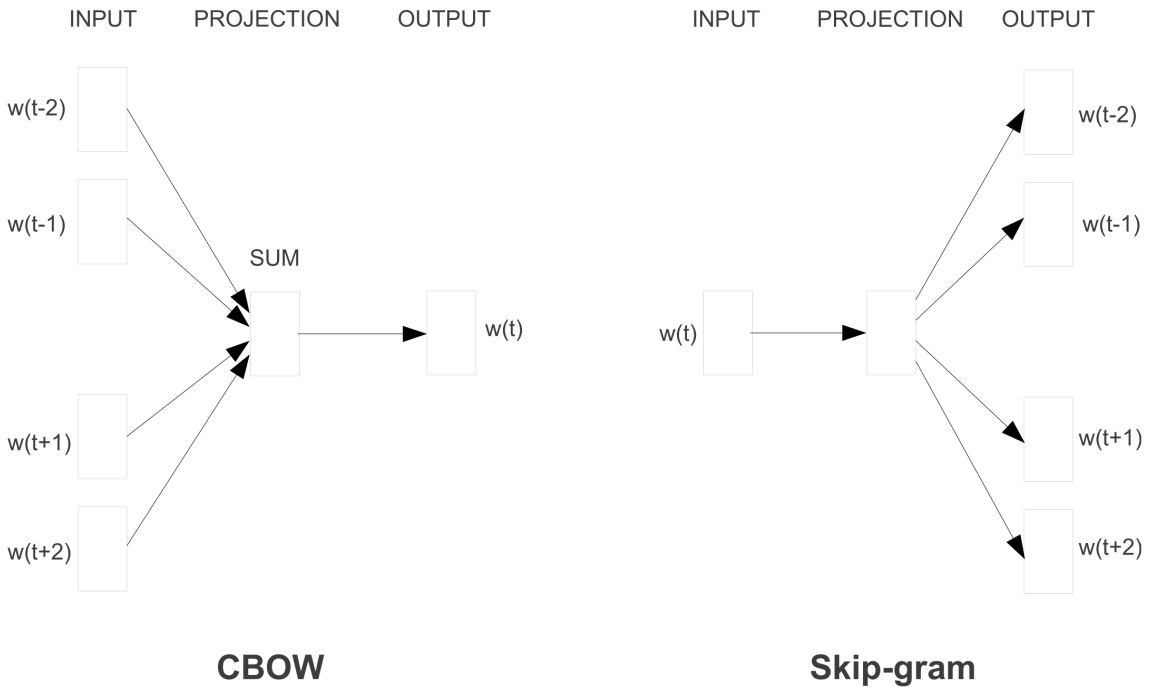

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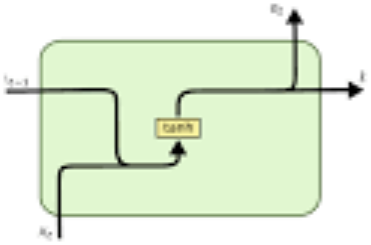
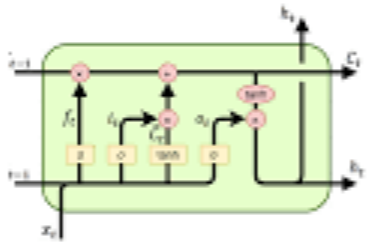
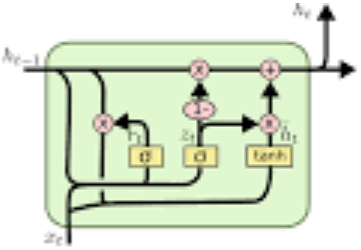
RNN



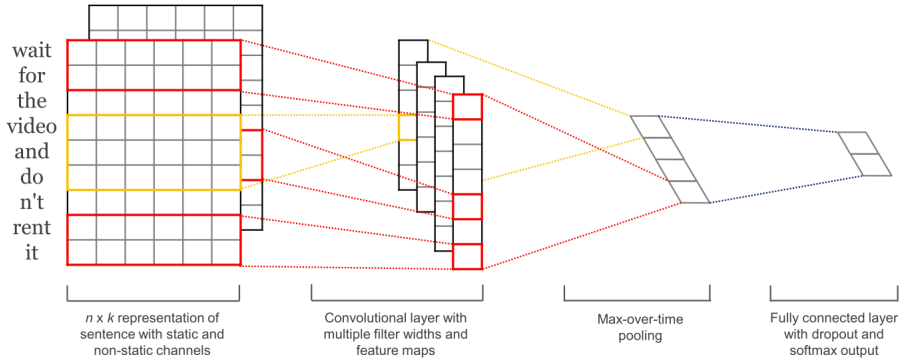
LSTM



GRU



CNN



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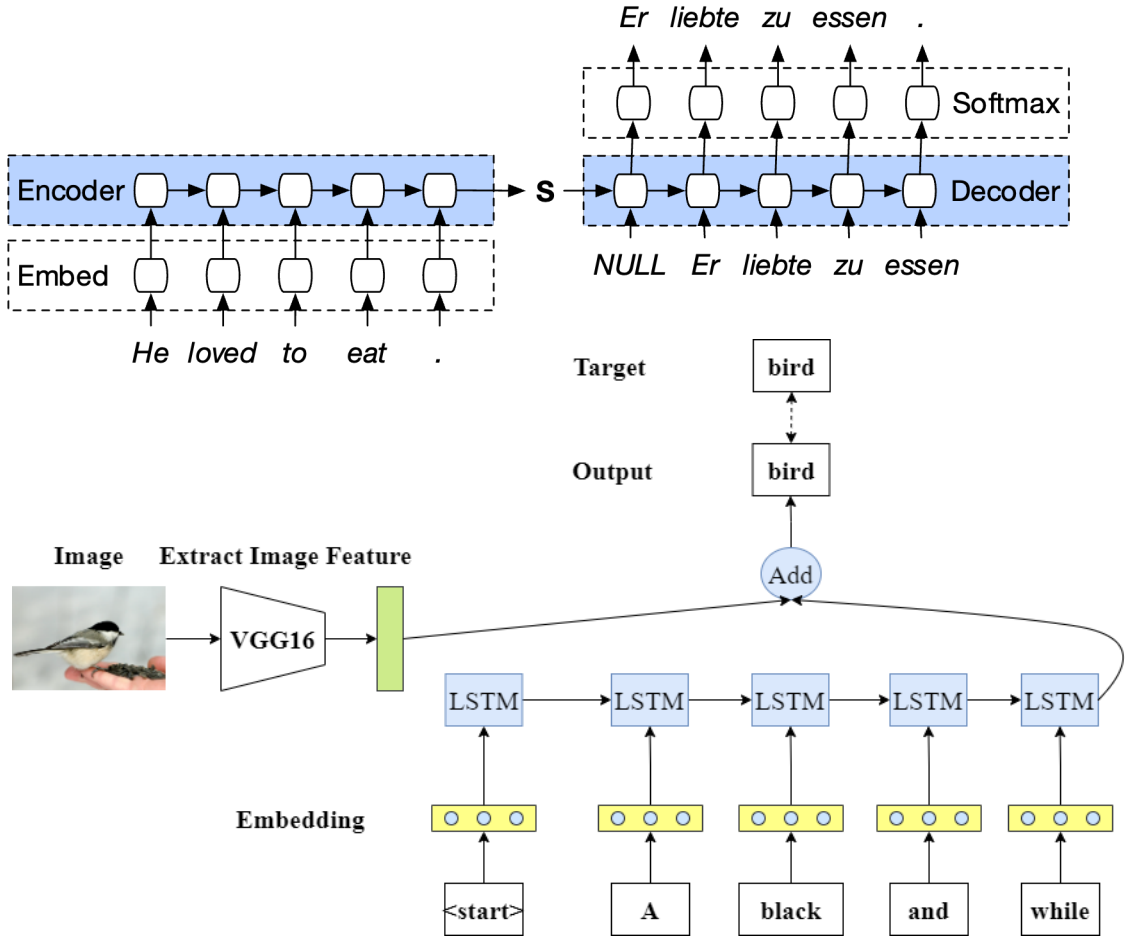

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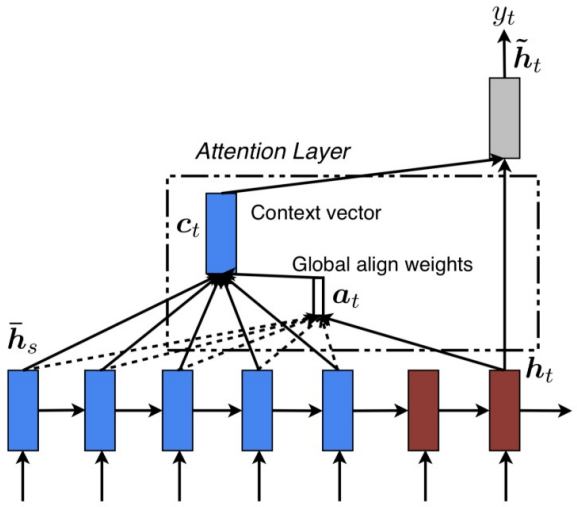
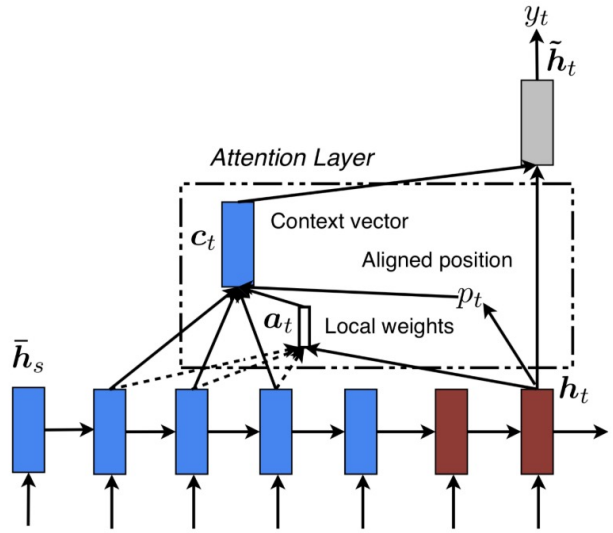


Global Attention Model



Local Attention Model

1 – Language Model

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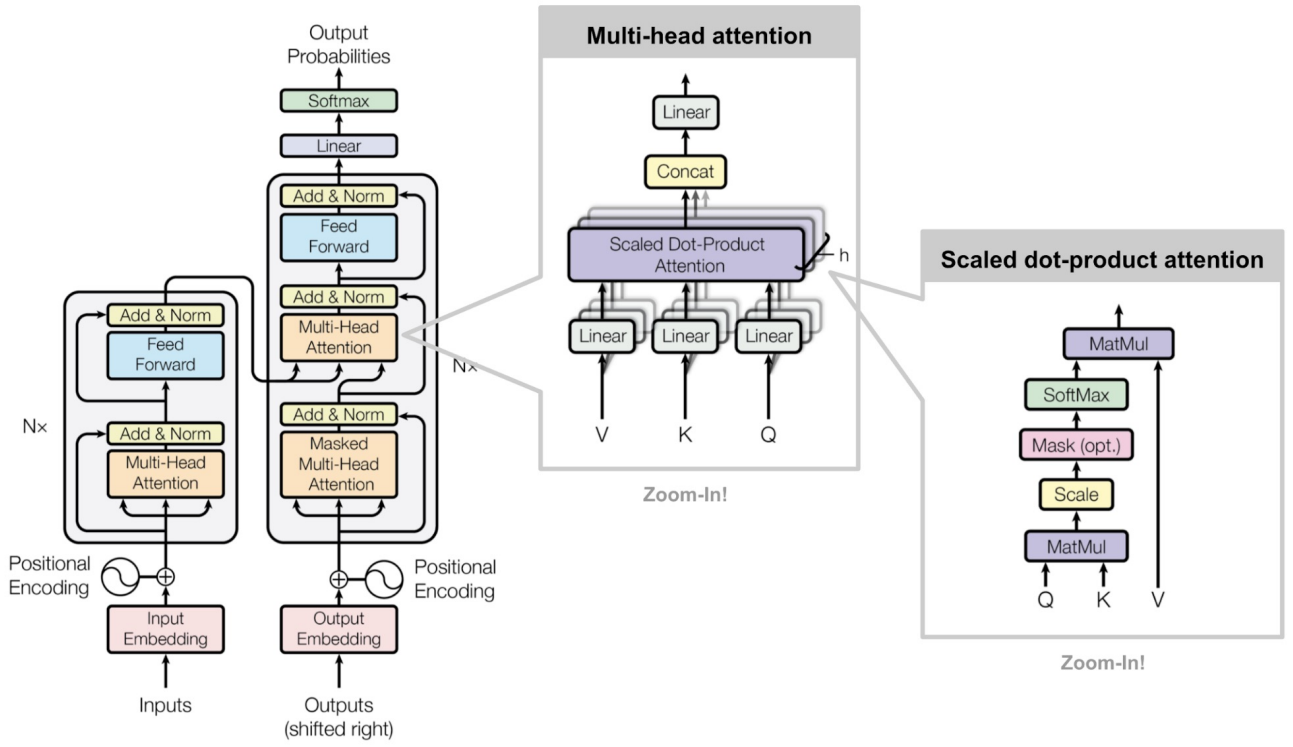

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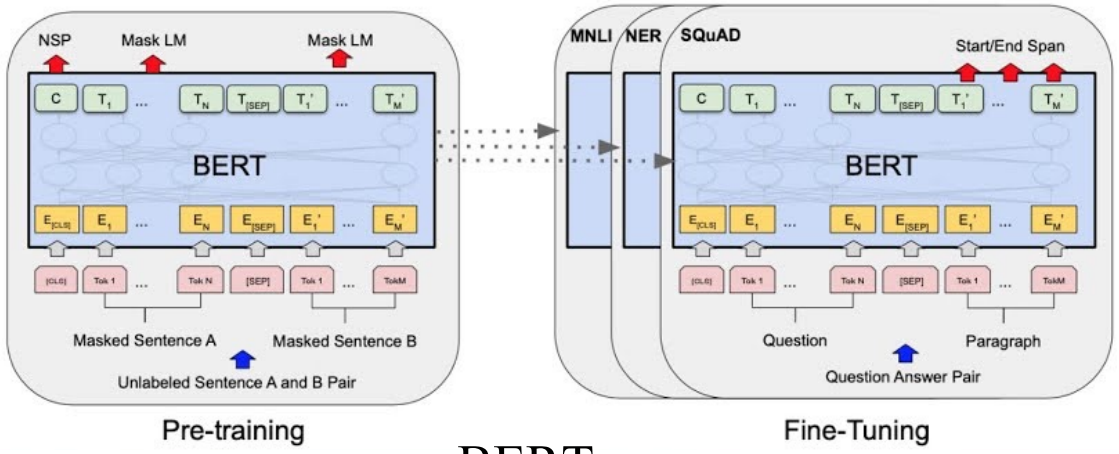
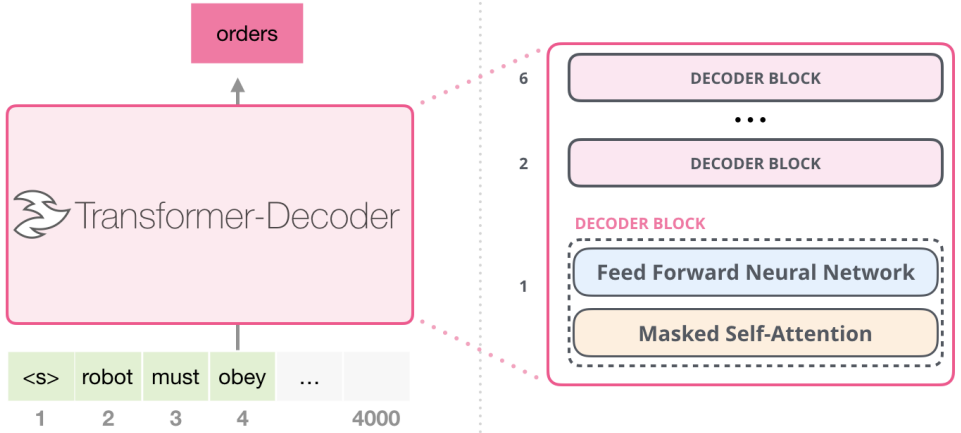


BERT



GPT

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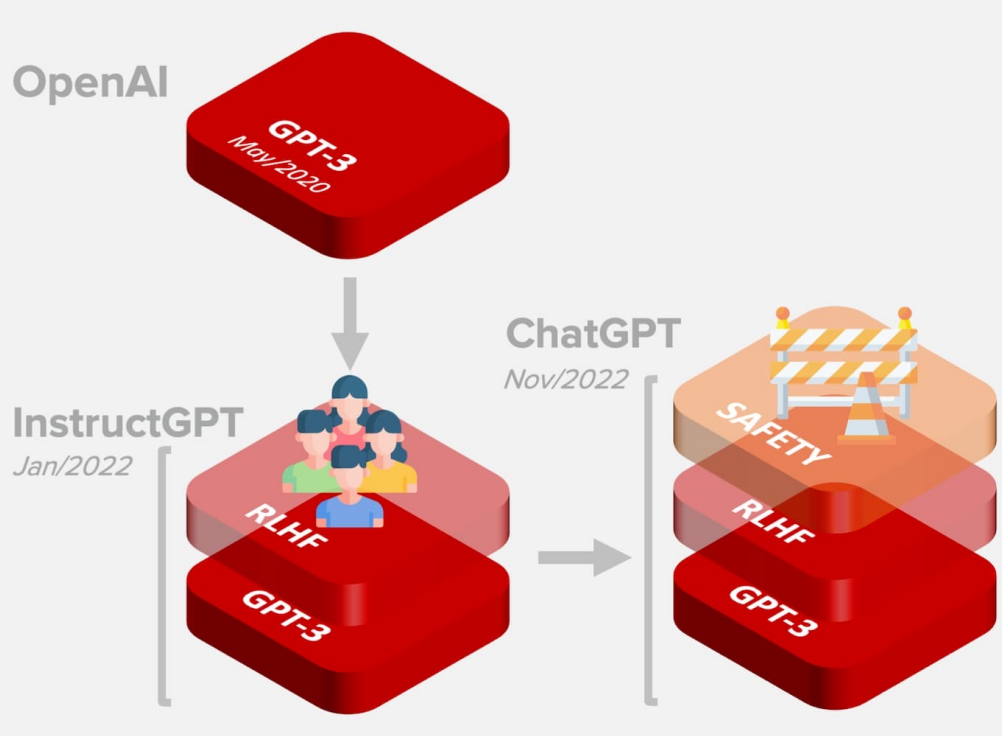


2 – Transformer

Machine Translation Task

- Translate a sentence $w^{(s)}$ in a **source language (input)** to a sentence $w^{(t)}$ in the **target language (output)**

2 – Transformer

Machine Translation Task

- Translate a sentence $w^{(s)}$ in a **source language (input)** to a sentence $w^{(t)}$ in the **target language (output)**
- Can be formulated as an optimization problem:

$$\hat{w}^{(t)} = \underset{w^{(t)}}{\operatorname{argmax}}\, \theta(w^{(s)}, w^{(t)})$$

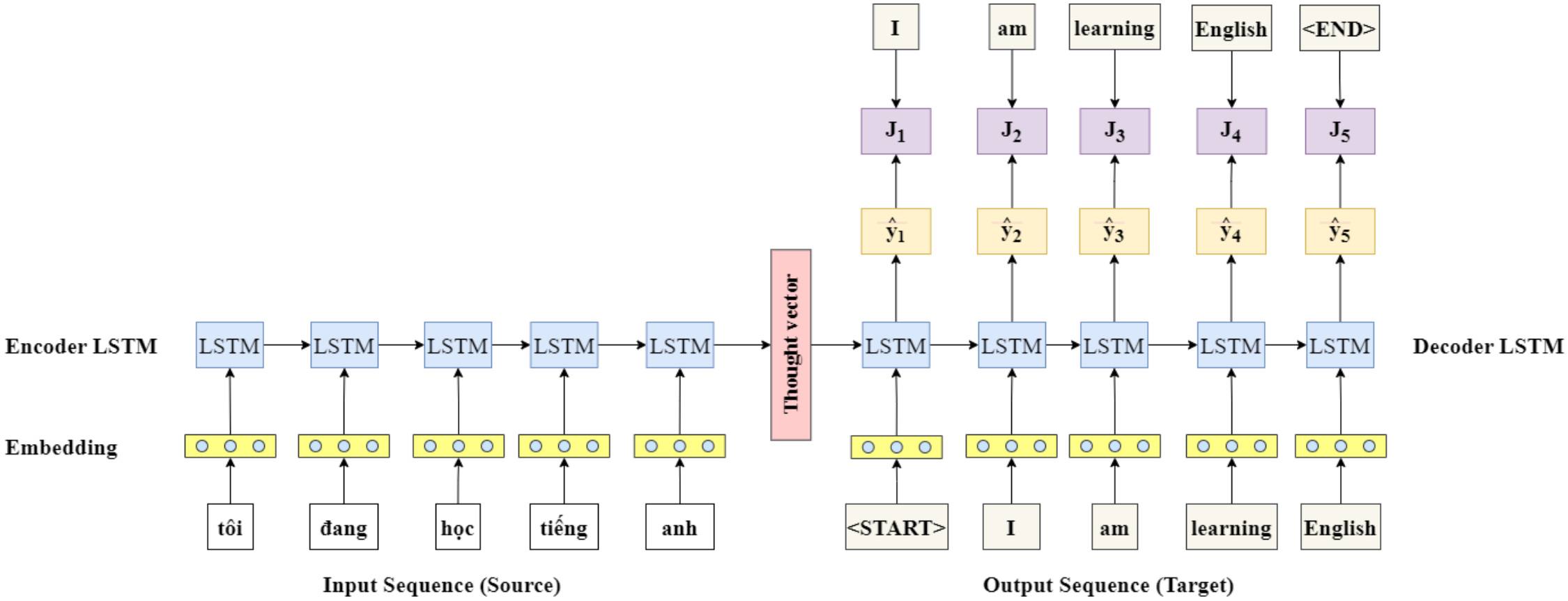
Where θ is a scoring function over source and target sentences

- Requires two components:
  - Learning algorithm to compute parameters of θ
  - Decoding algorithm for computing the best translation $\hat{w}^{(t)}$

2 – Transformer

Machine Translation Task

- Machine Translation using Sequence to Sequence (Seq2Seq) architecture



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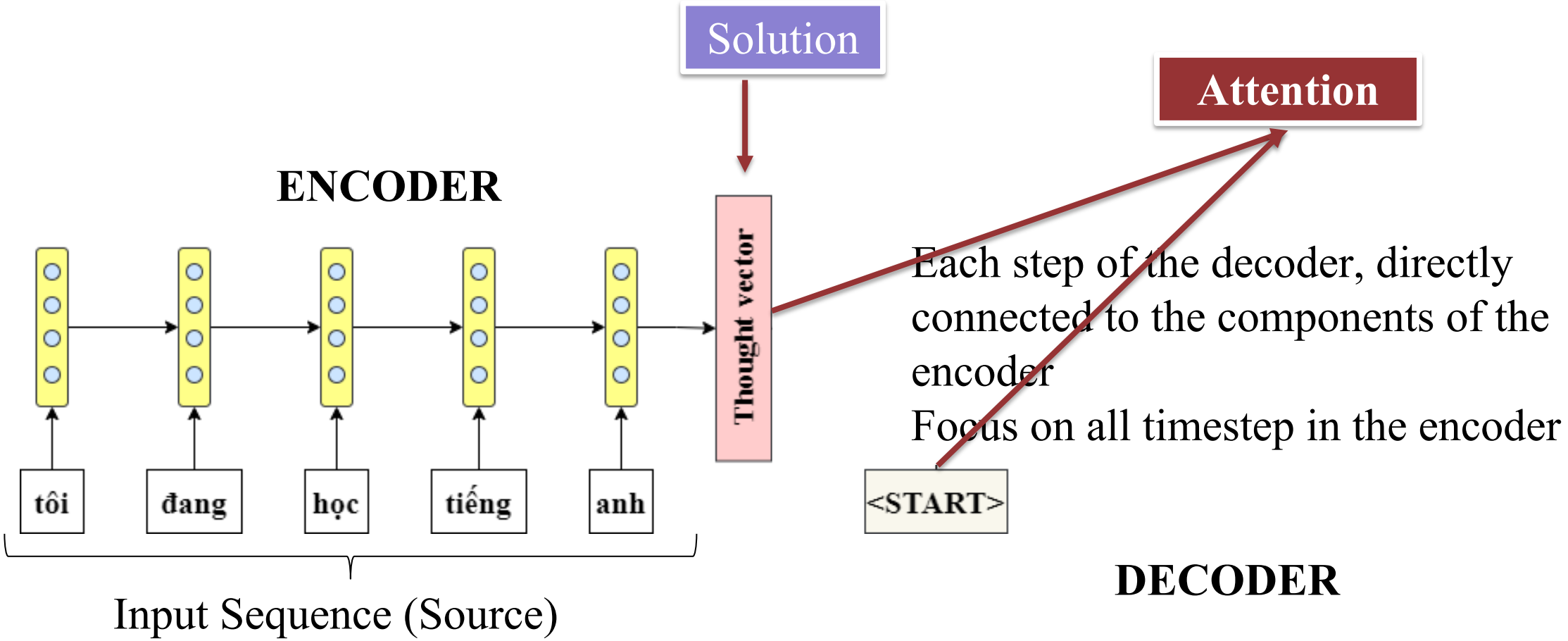
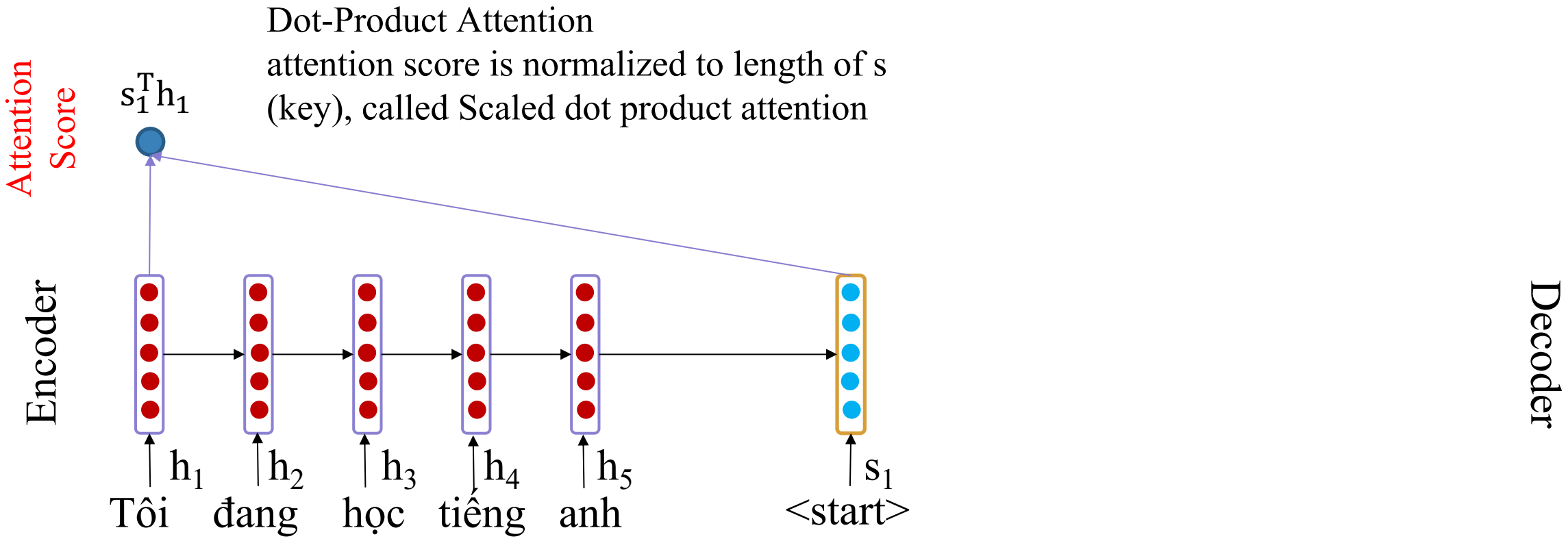


2 – Transformer

Seq2Seq with Attention



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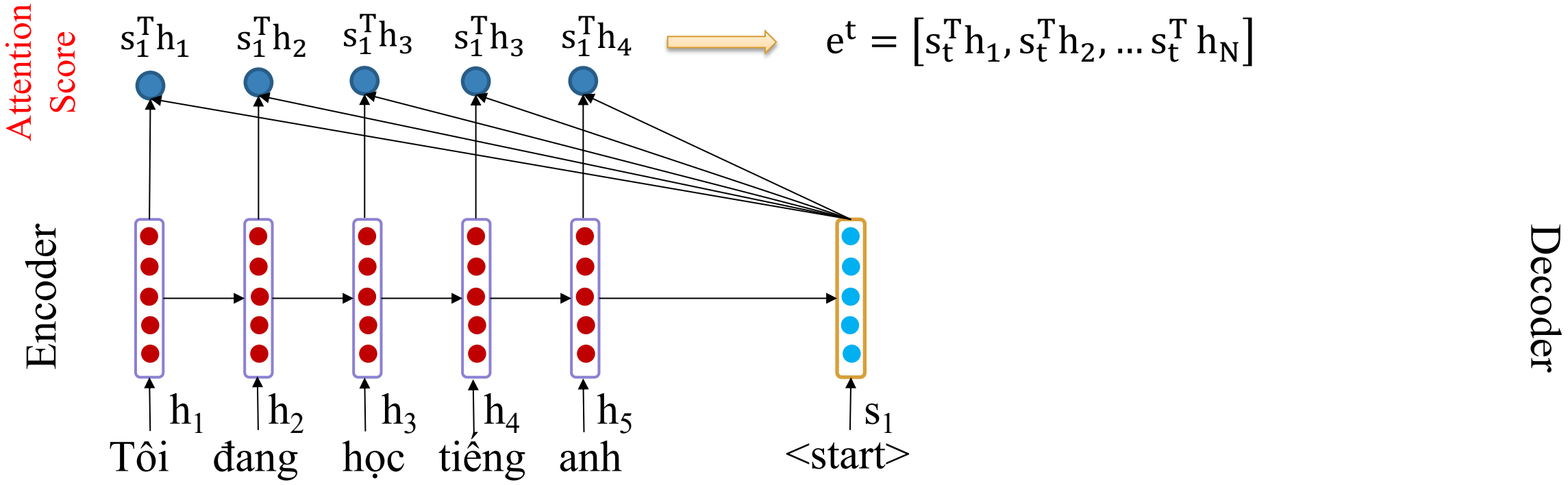

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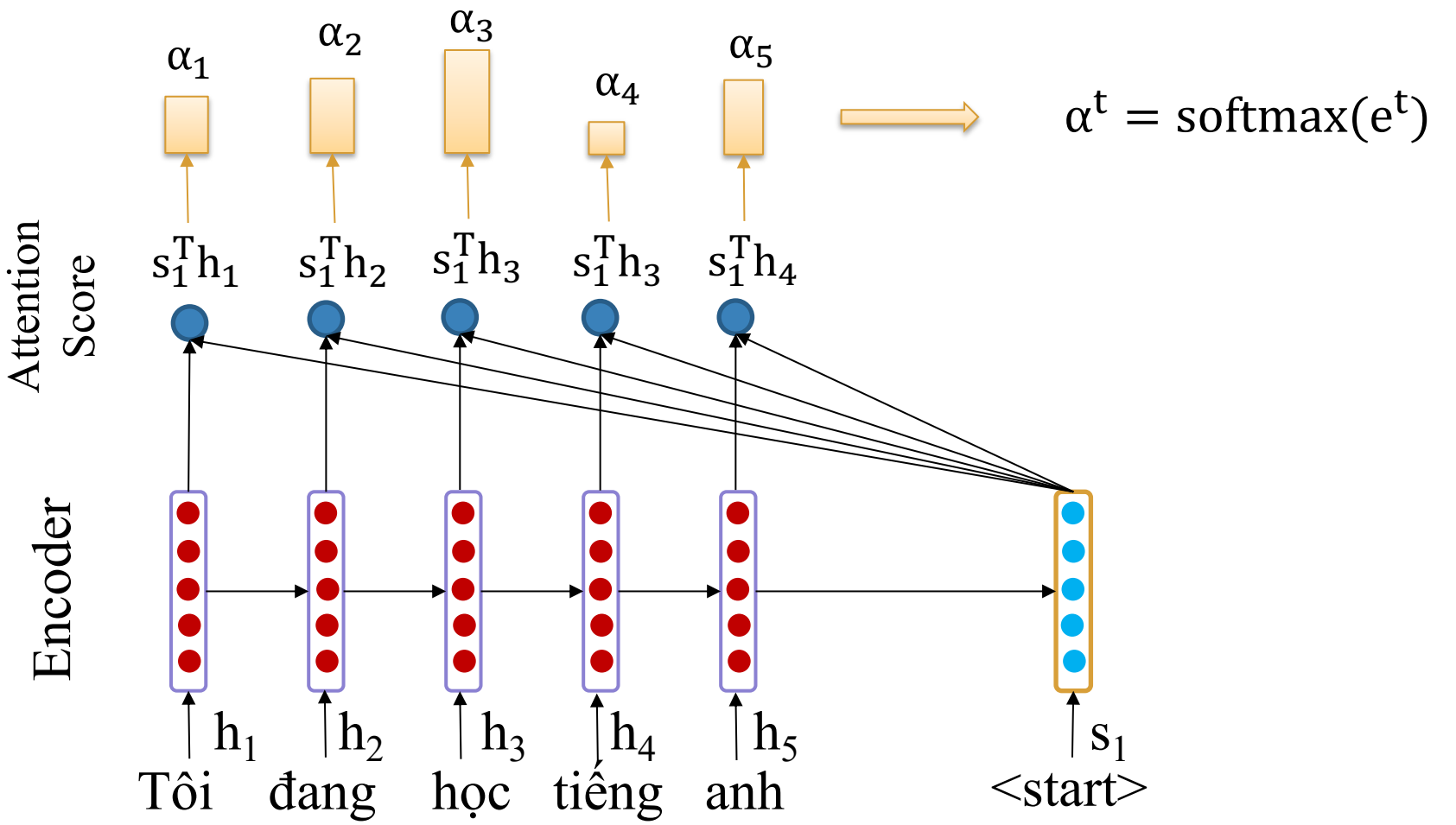
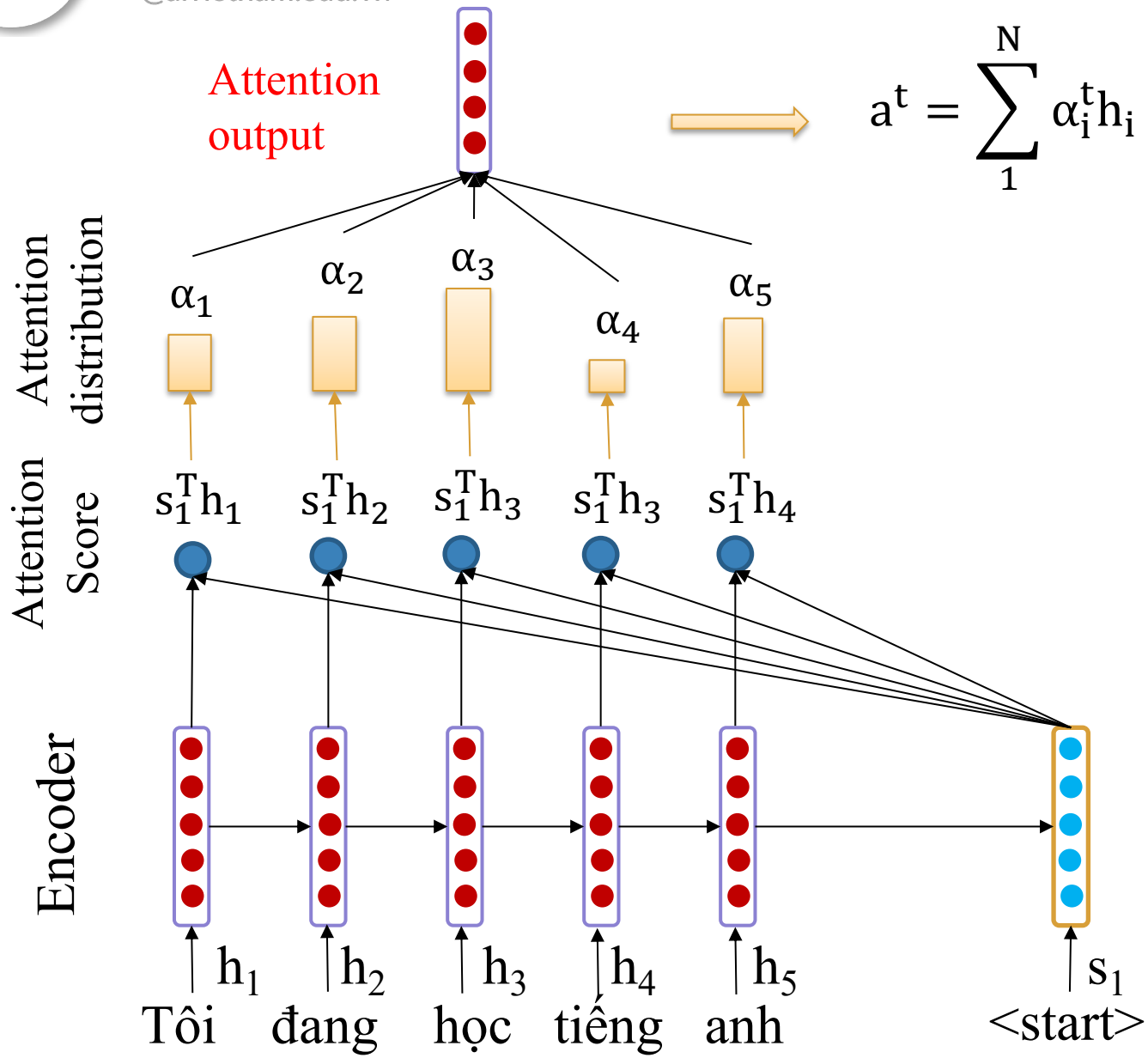


2 – Transformer

! Seq2Seq with Attention



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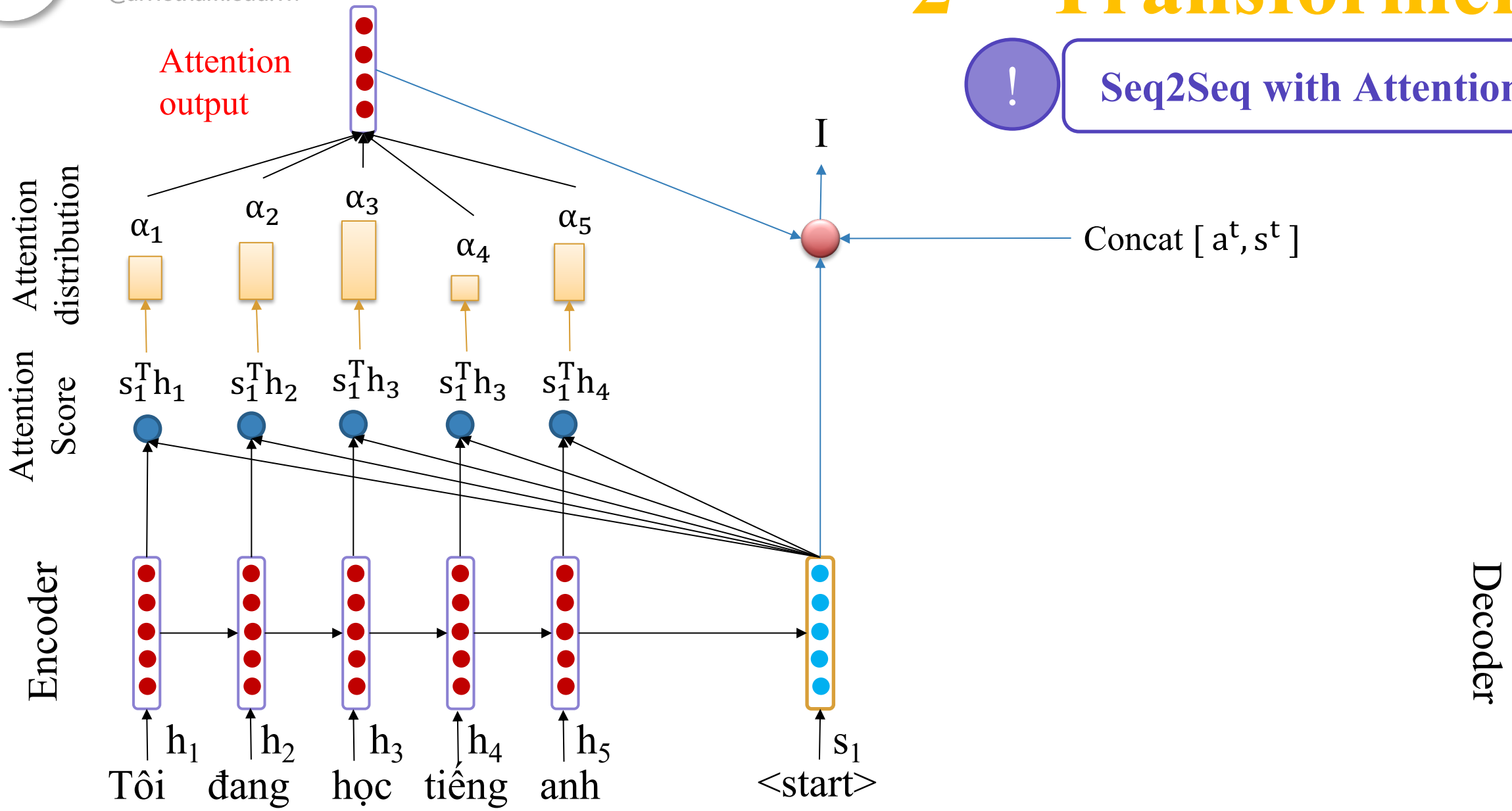

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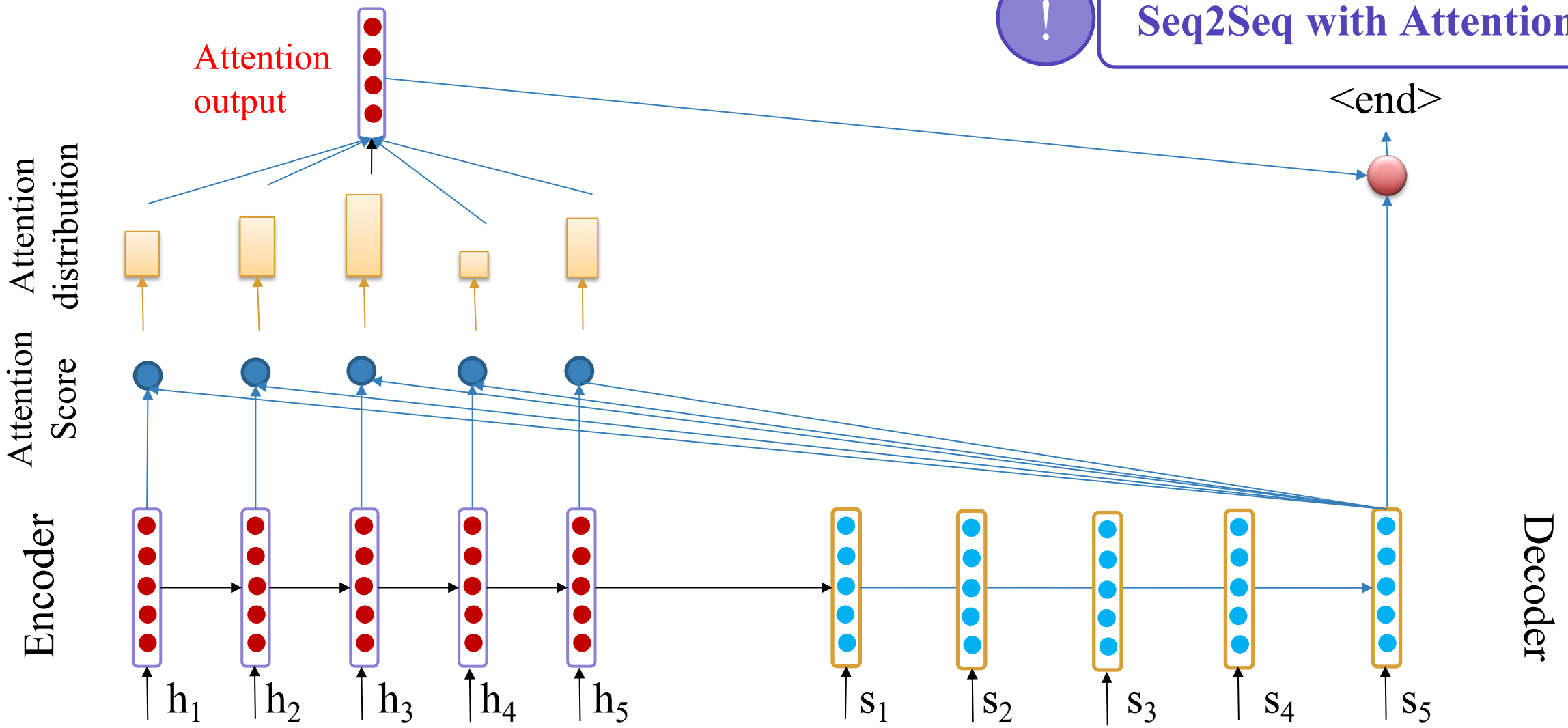


2 – Transformer

Seq2Seq with Attention

Compute $e \in \mathbb{R}^N$ from $h_1, h_2, \ldots, h_N \in \mathbb{R}^{d_1}$ and $s \in \mathbb{R}^{d_2}$

- Dot-product attention

$$e_i = s^T h_i;\ d_1 = d_2$$

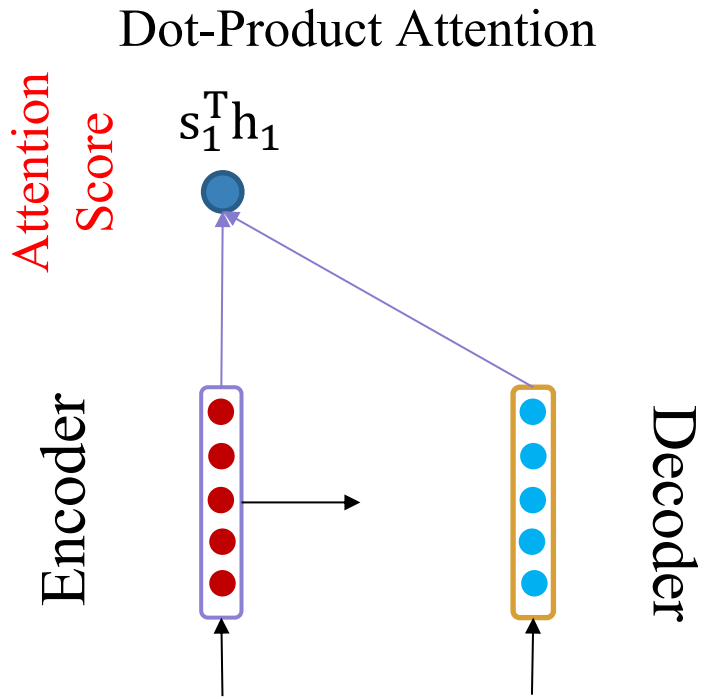
- Multiplicative attention

$$e_i = s^T W h_i;\ W \in \mathbb{R}^{d_2 \times d_1}$$

- Additive attention

$$e_i = v^T \tanh(W_1 h_i + W_2 s)$$

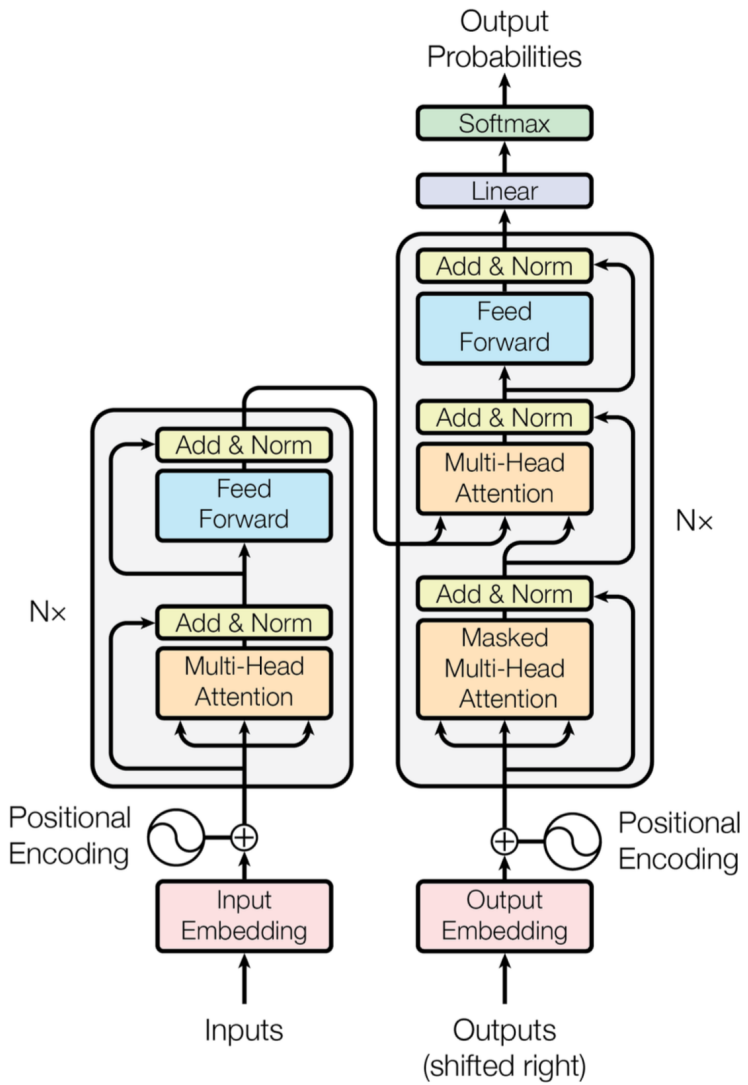
$$W_1 \in \mathbb{R}^{d_3 \times d_1}, W_2 \in \mathbb{R}^{d_3 \times d_2}, v \in \mathbb{R}^{d_3}$$



2 – Transformer

Transformer Architecture

- Architecture:
  - Token Embedding
  - Positional Embedding
  - N x Encoder Layer:
  - N x Decoder Layer
- Core technique: Self-Attention



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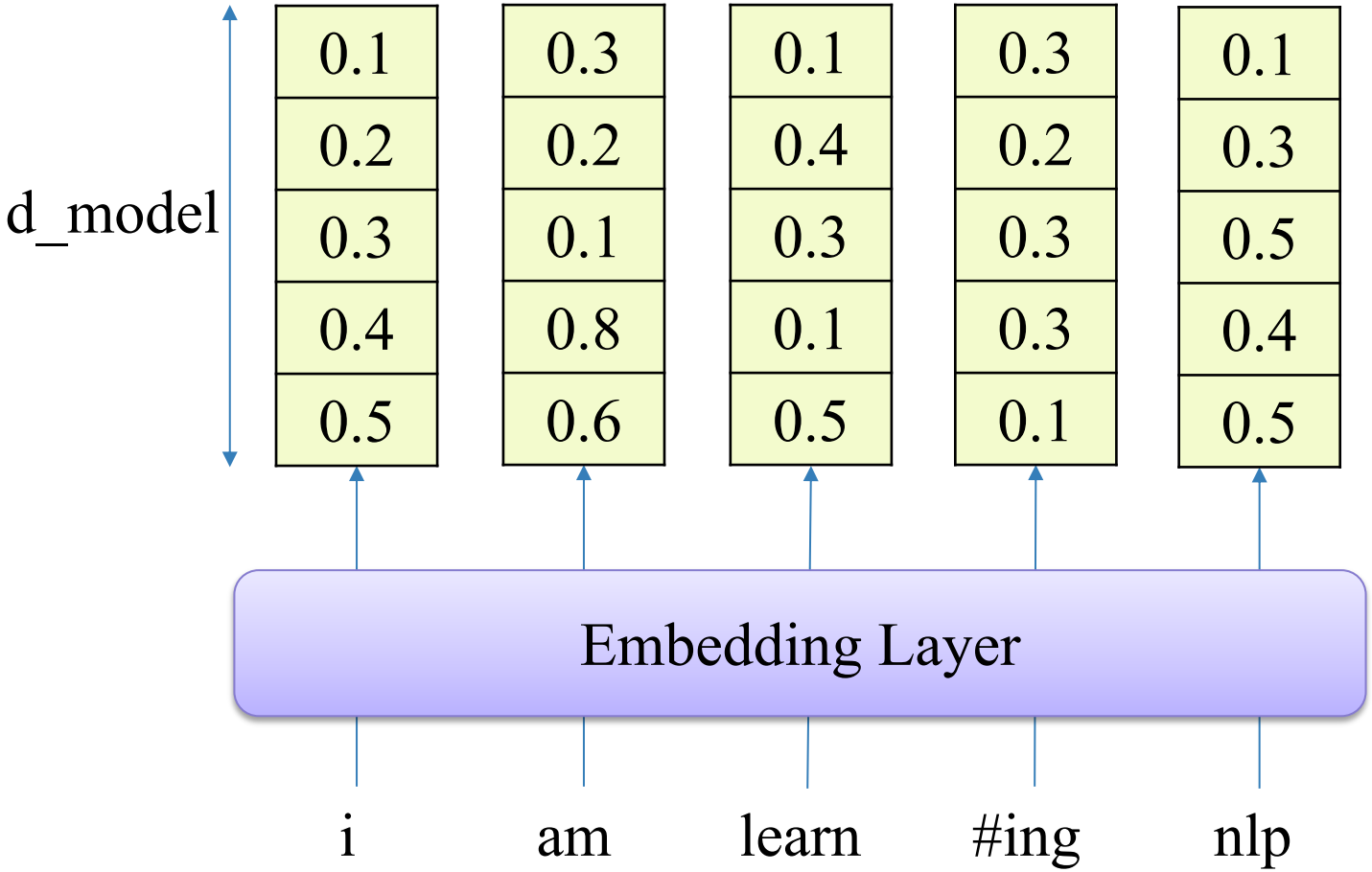
Transformer Architecture

- Token Embedding



2 – Transformer

Transformer Architecture

- Positional Embedding (Sinusoid)

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{n^{\frac{2i}{d_{model}}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{n^{\frac{2i}{d_{model}}}}\right)$$

pos: position of an entity in input sequence

d_{model}: dimension of the output embedding space

n = 1000 (recommend)

2 – Transformer

Transformer Architecture

- Positional Embedding (Sinusoid)
- Example: n = 100,

  $d_{model} = 5$

$$P_{00} = \sin\left(\frac{0}{100^{\frac{2*0}{5}}}\right)$$

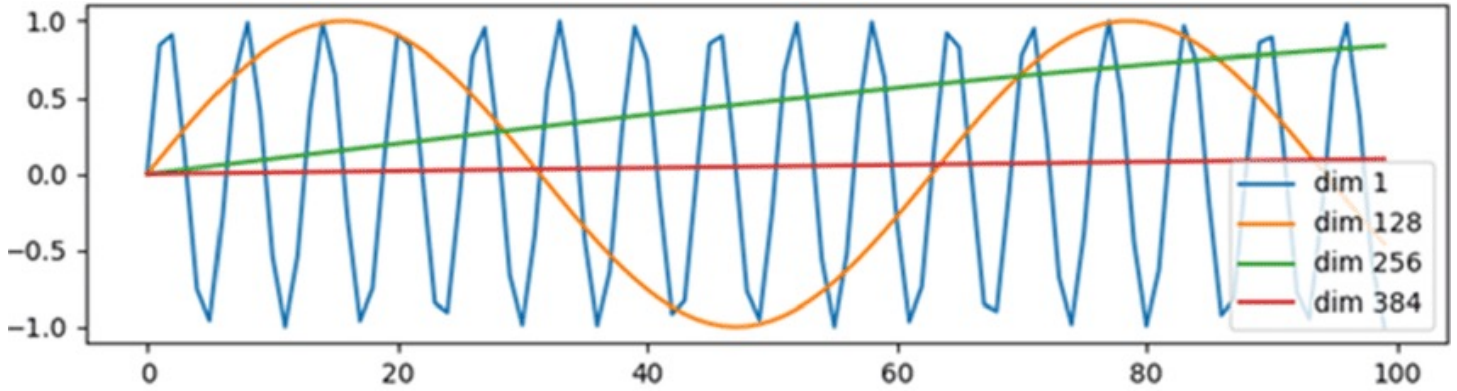
$$P_{01} = \cos\left(\frac{0}{100^{\frac{2*0}{5}}}\right)$$

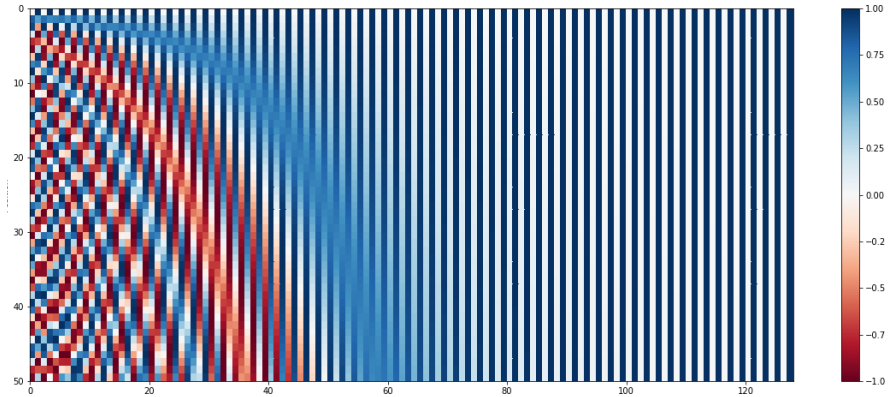
I	→	0	→	$P_{00}= 0$	$P_{01}= 1$	$P_{02}= 0$	$P_{03}= 1$	$P_{04}= 0$
am	→	1	→	$P_{10}= 0.84$	$P_{11}=0.54$	$P_{12}=0.16$	$P_{13}=0.99$	$P_{14}=0.025$
learn	→	2	→	$P_{20}= 0.91$	$P_{21}=-0.42$	$P_{22}=0.31$	$P_{23}=0.95$	$P_{24}=0.05$
#ing	→	3	→	$P_{30}= 0.14$	$P_{31}=-0.99$	$P_{32}=0.46$	$P_{33}=0.89$	$P_{34}=0.141$
nlp	→	4	→	$P_{40}= -0.76$	$P_{41}=-0.65$	$P_{42}=0.59$	$P_{43}=0.81$	$P_{4d}=0.1$

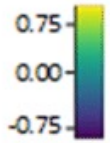
2 – Transformer

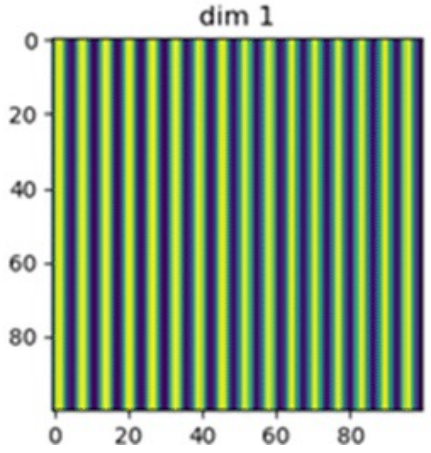
Transformer Architecture

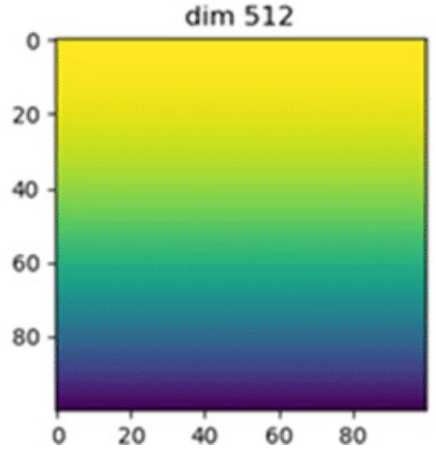
- Positional Embedding (Sinusoid)











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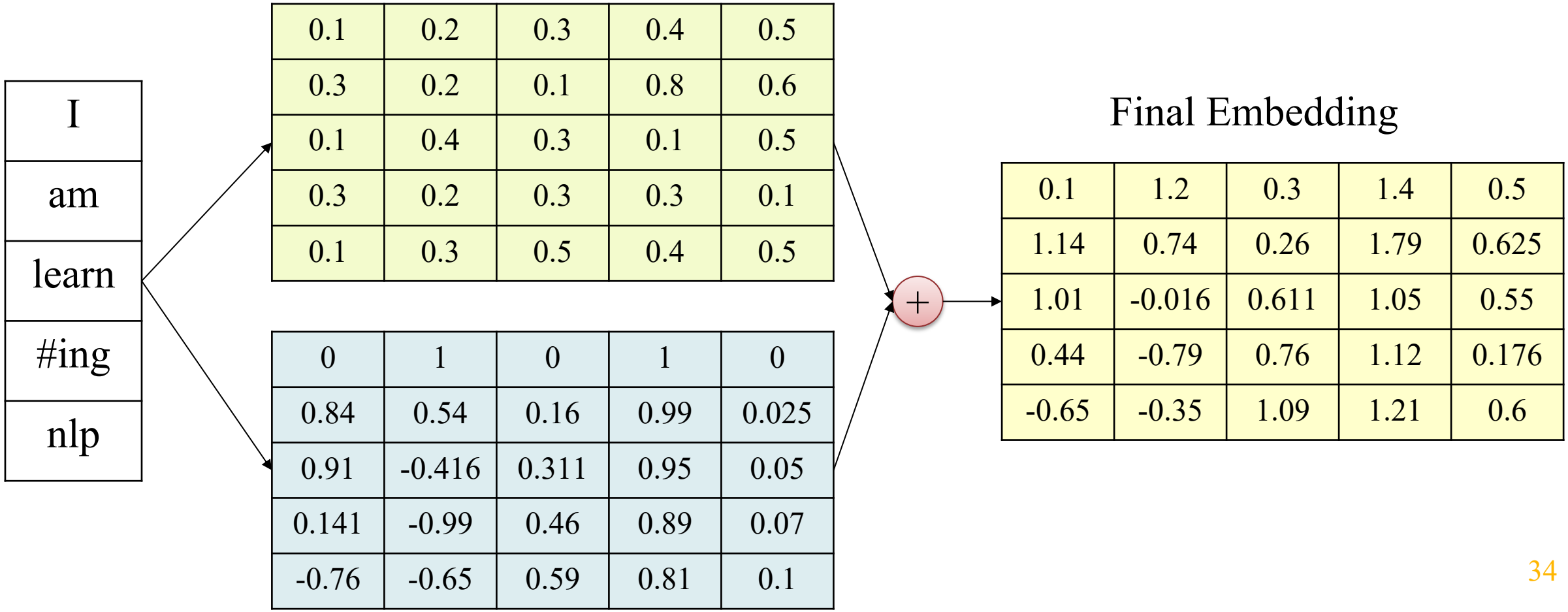
Transformer Architecture

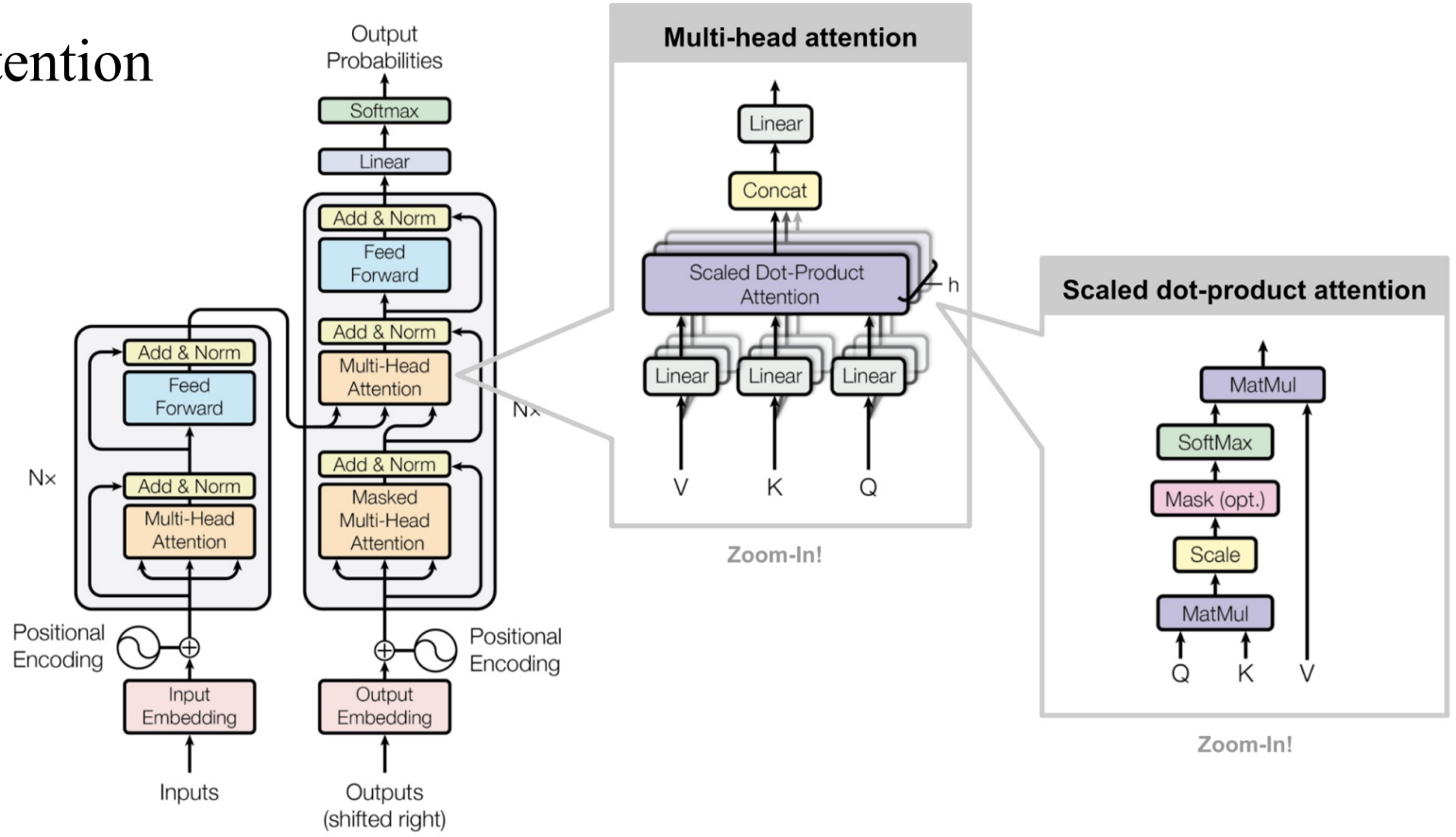
- Token embedding with positional embedding



2 – Transformer

Transformer Architecture

- Transformer-Encoder
- Multi-Head Attention



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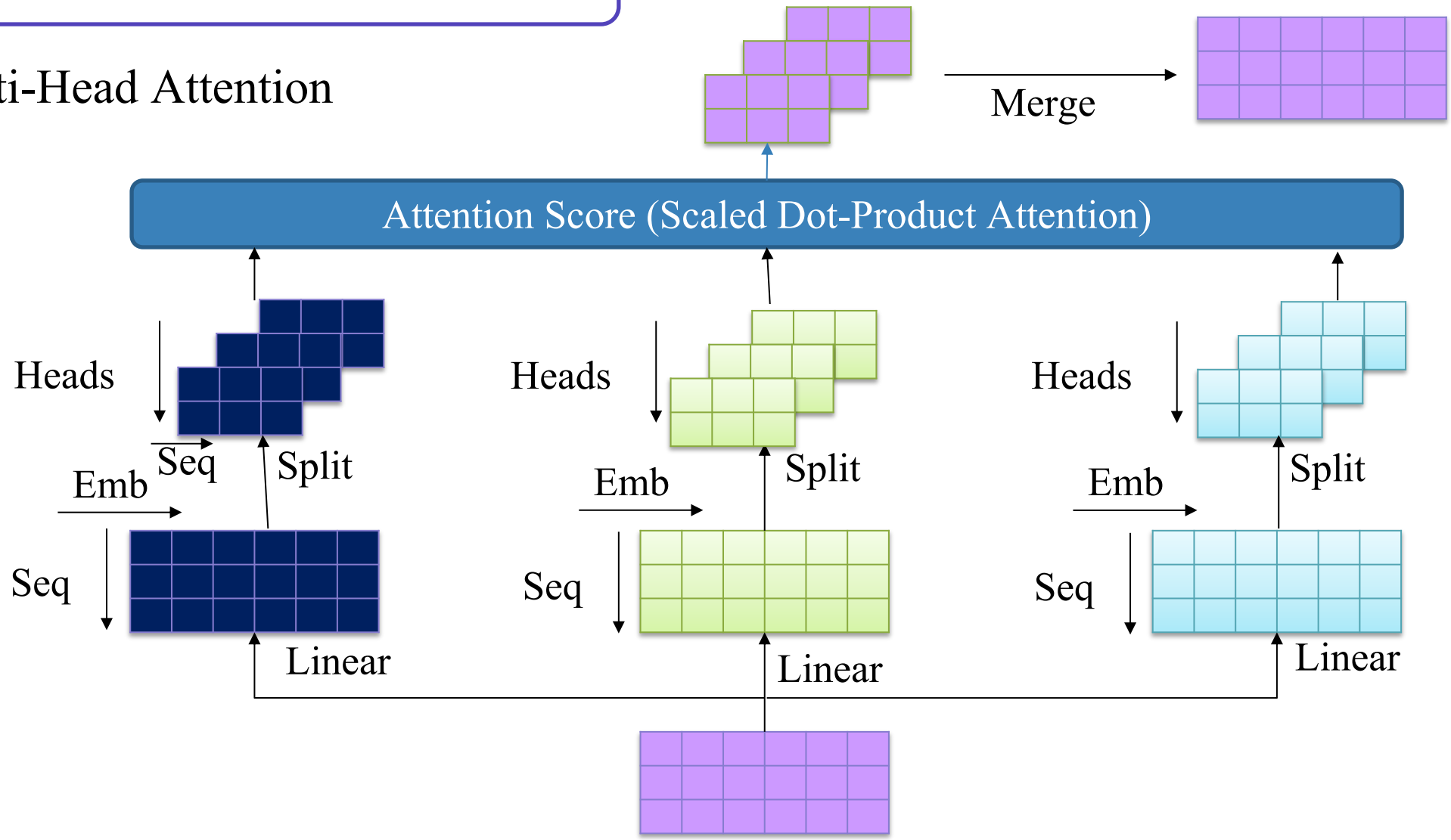
Transformer Architecture

- Multi-Head Attention



2 – Transformer

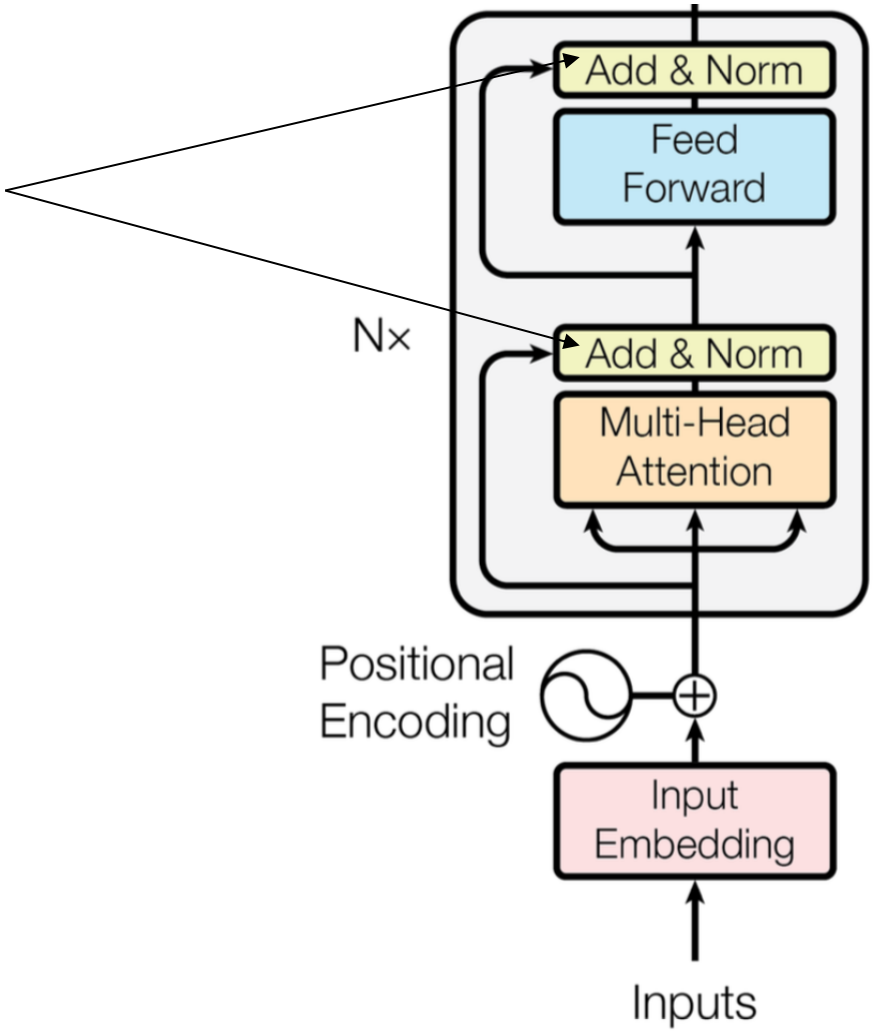
Transformer Architecture

- Transformer-Encoder
- Layer Normalization

$$\mu_i = \frac{1}{m}\sum_{j=1}^{m} x_{ij}$$

$$\sigma_i^2 = \frac{1}{m}\sum_{j=1}^{m}(x_{ij} - \mu_i)^2$$

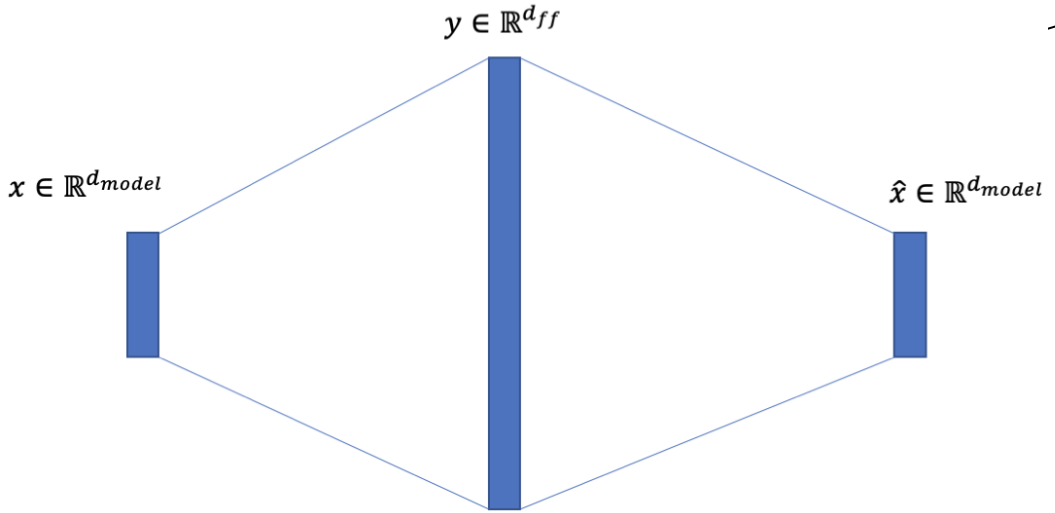
$$\hat{x}_{ij} = \frac{(x_{ij} - \mu_i)}{\sqrt{\sigma_i^2 + \epsilon}}$$

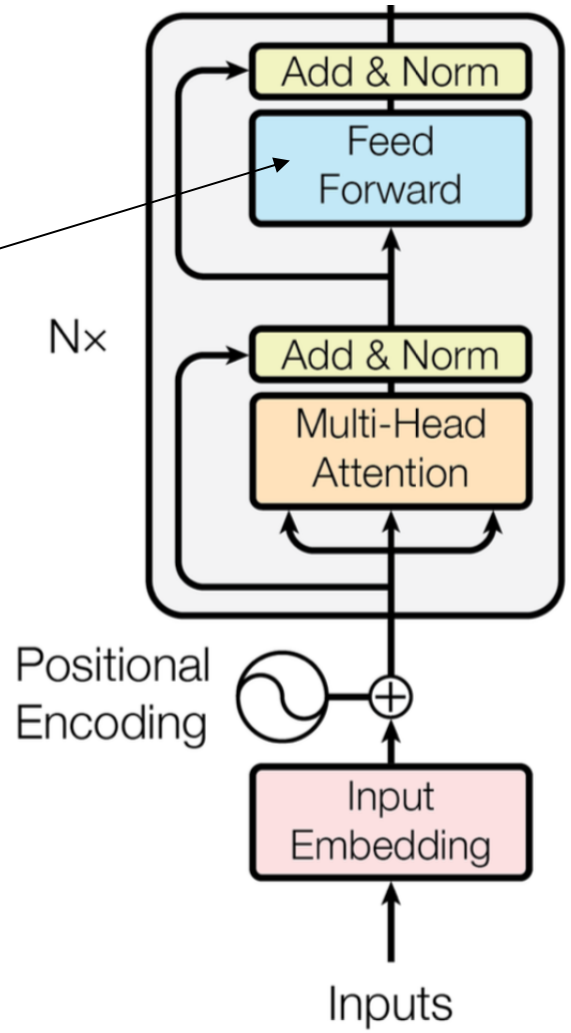


2 – Transformer

Transformer Architecture

- Transformer-Encoder
- Point Wise Feed Forward Network





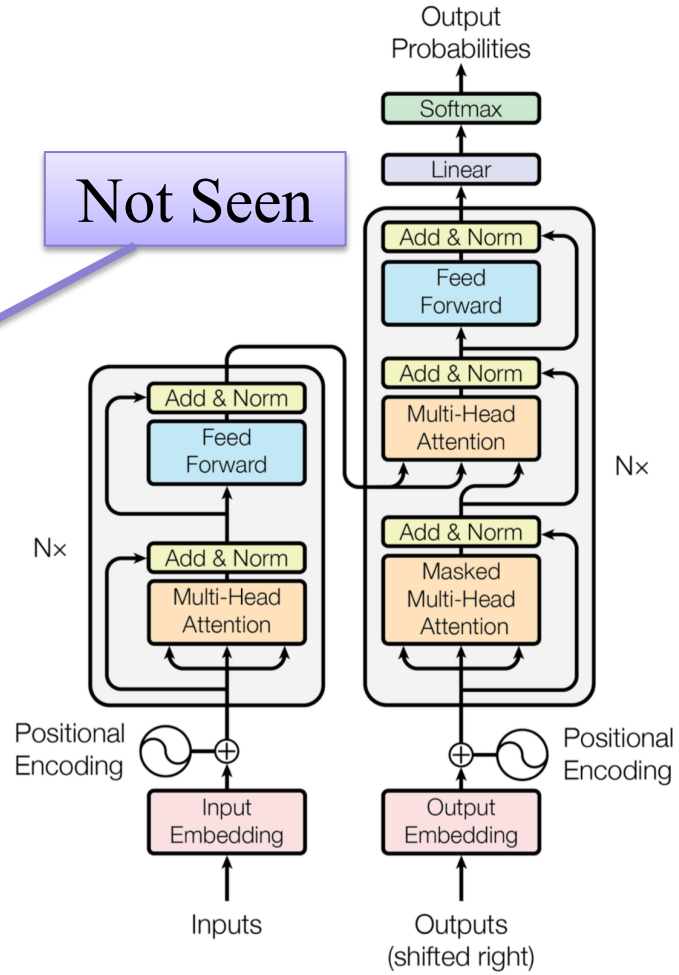
2 – Transformer

Transformer Architecture

- Transformer-Decoder
- Masked Multi-Head Attention
- Predict next token based on the history token

	I	am	learn	#ing	nlp
I	1.2	2.3	2.5	1.2	3.5
am	2.3	1.5	0.5	0.6	1.2
learn	0.5	1.4	1.6	0.3	4.8
#ing	0.6	1.8	2.4	0.3	1.2
nlp	2.1	2.3	0.2	2.0	2.5

Not Seen



2 – Transformer

Transformer Architecture

- Transformer-Decoder
- Masked Multi-Head Attention
- Predict next token based on the history to

	I	am	learn	#ing	nlp
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#ing	0.6	1.8	2.4	0.3	1.2
nlp	2.1	2.3	0.2	2.0	2.5

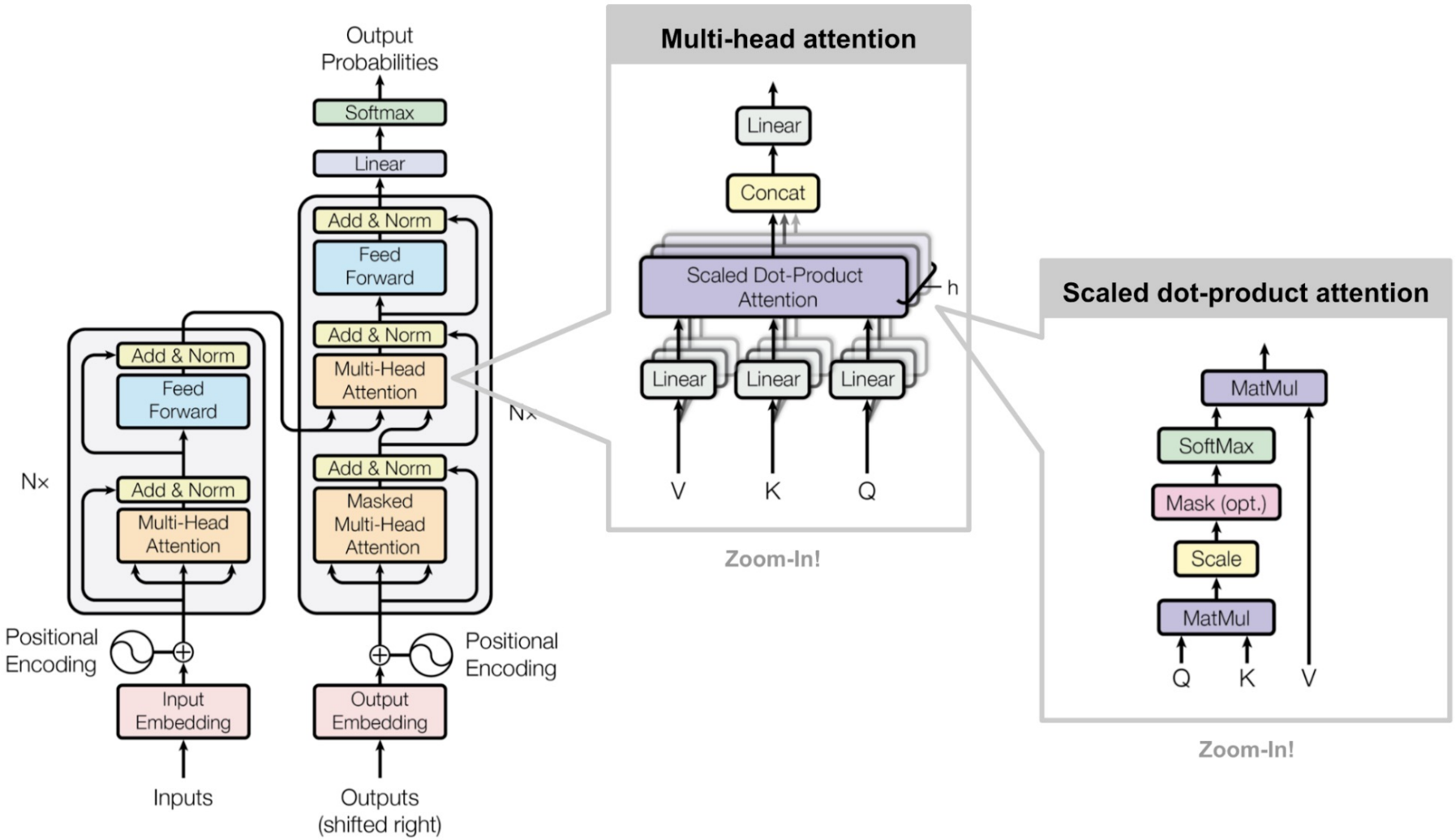
1.2	-inf	-inf	-inf	-inf
2.3	1.5	-inf	-inf	-inf
0.5	1.4	1.6	-inf	-inf
0.6	1.8	2.4	0.3	-inf
2.1	2.3	0.2	2.0	2.5

Softmax →

1.0	0.0	0.0	0.0	0.0
0.69	0.31	0.0	0.0	0.0
0.15	0.38	0.46	0.0	0.0
0.6	1.8	2.4	0.3	0.0
2.1	2.3	0.2	2.0	2.5

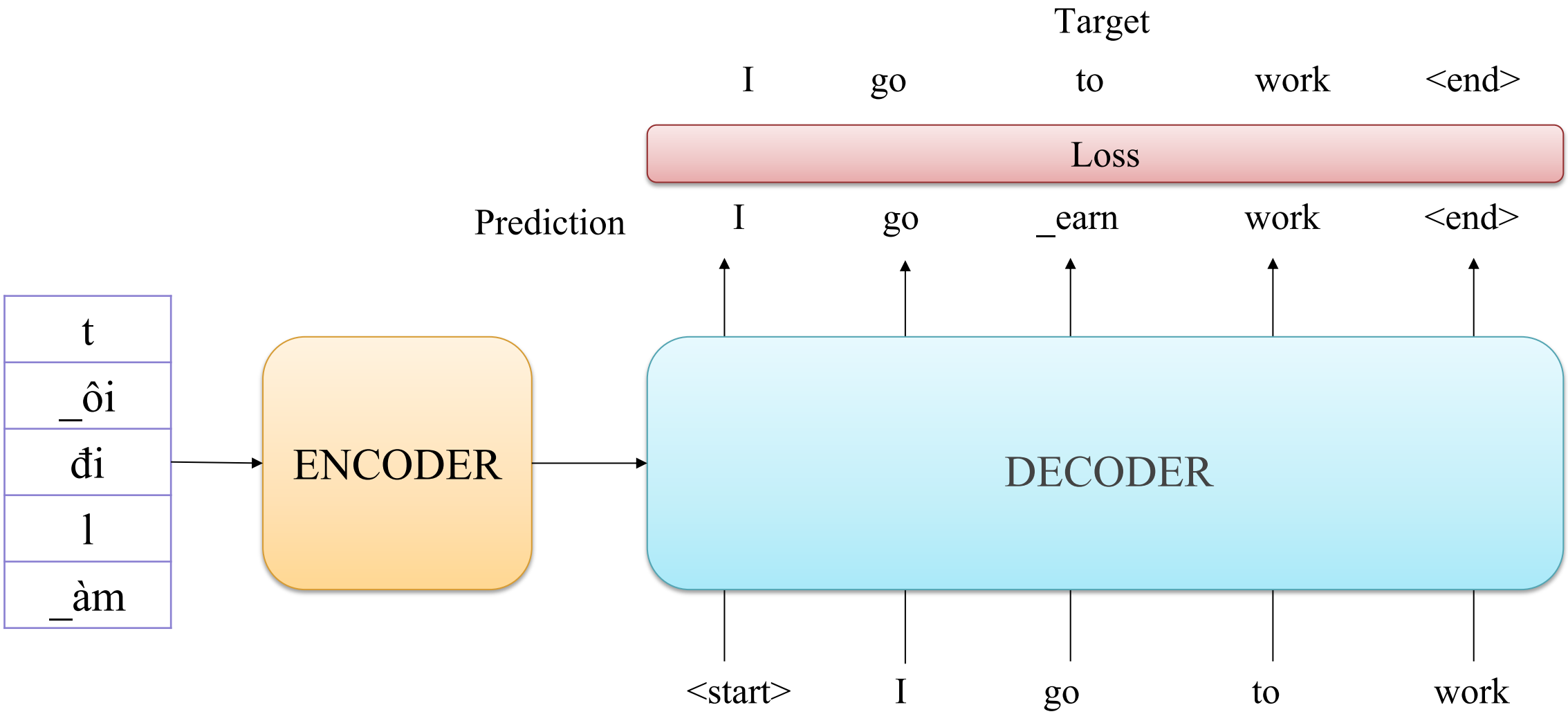
2 – Transformer

Transformer Architecture



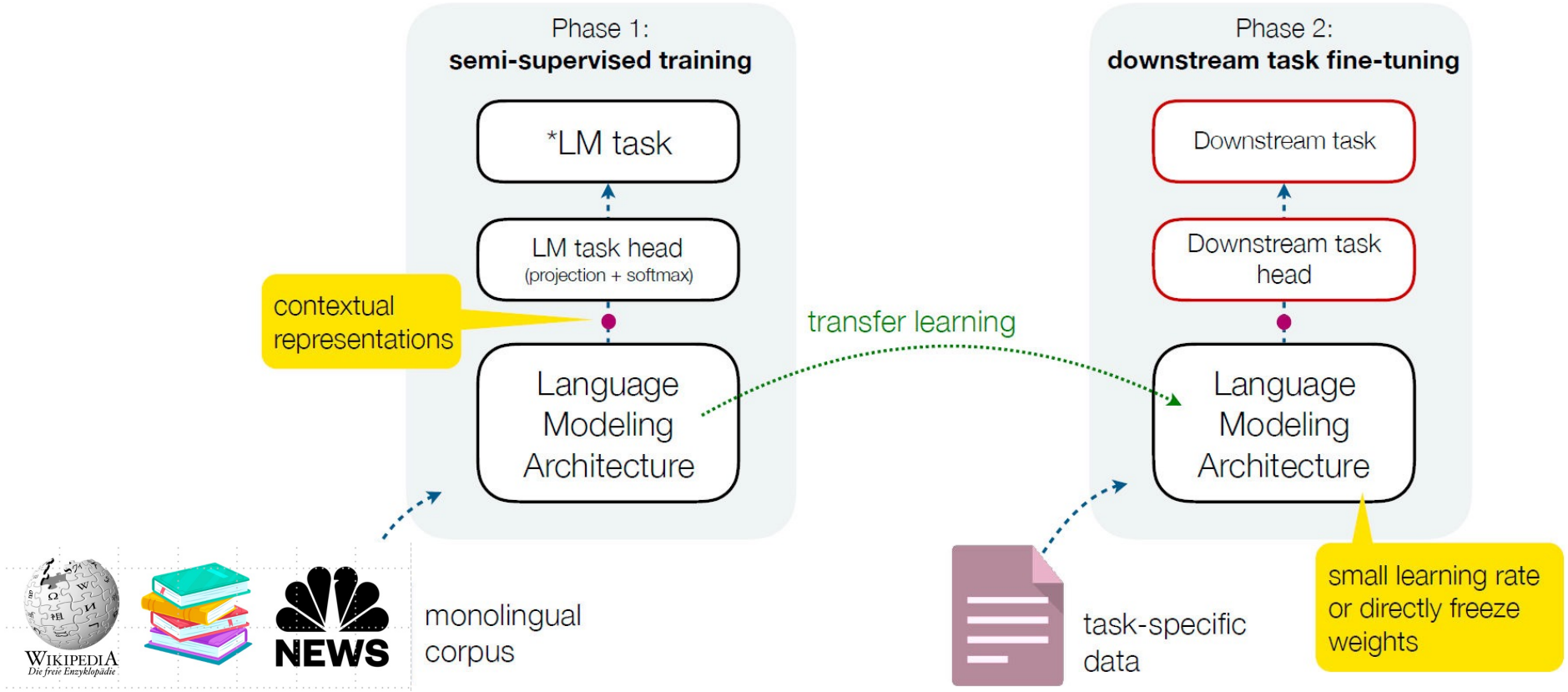
2 – Transformer

Transformer Architecture



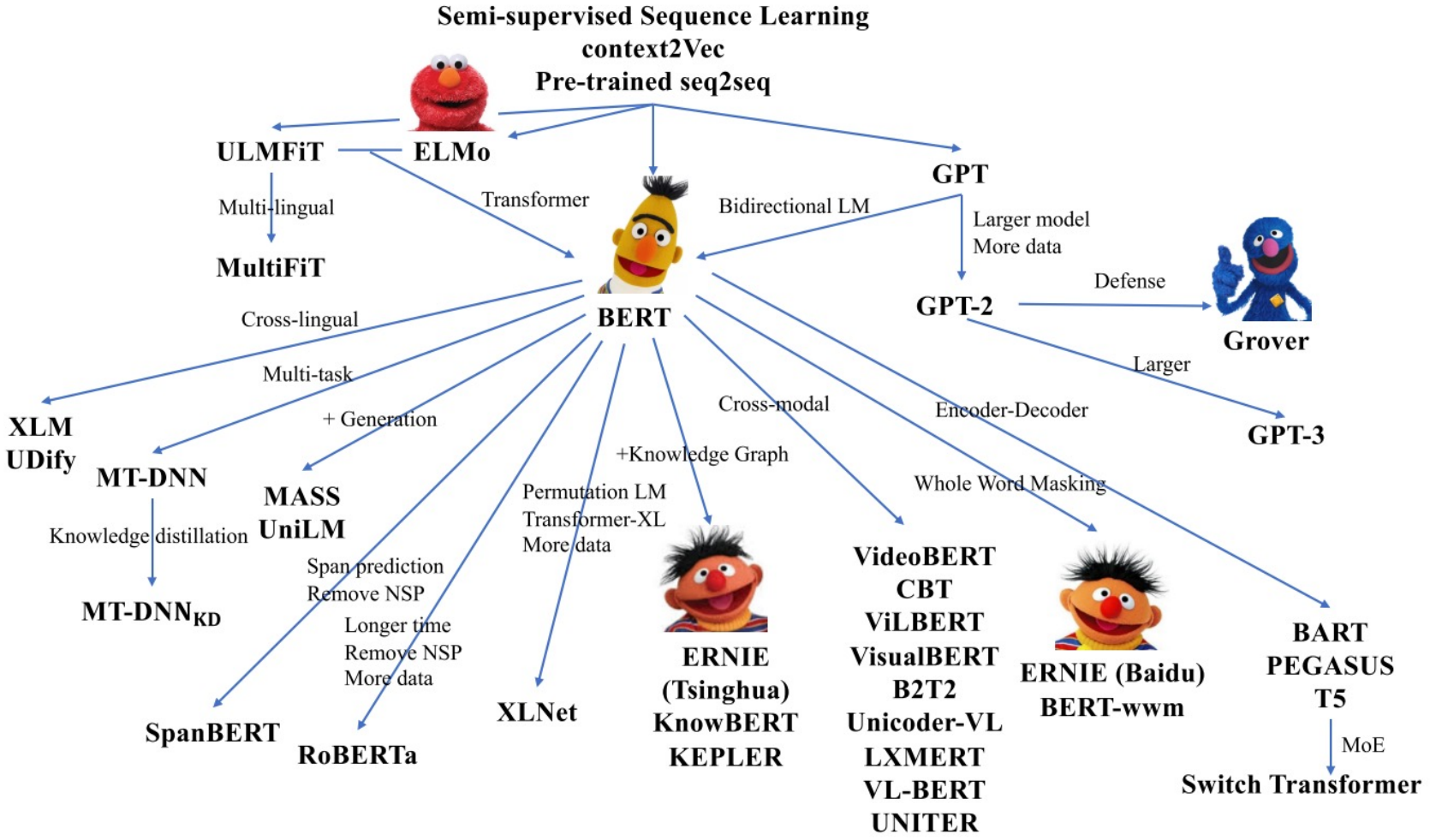
3 – Pre-trained LMs

Transfer Learning



3 – Pre-trained LMs

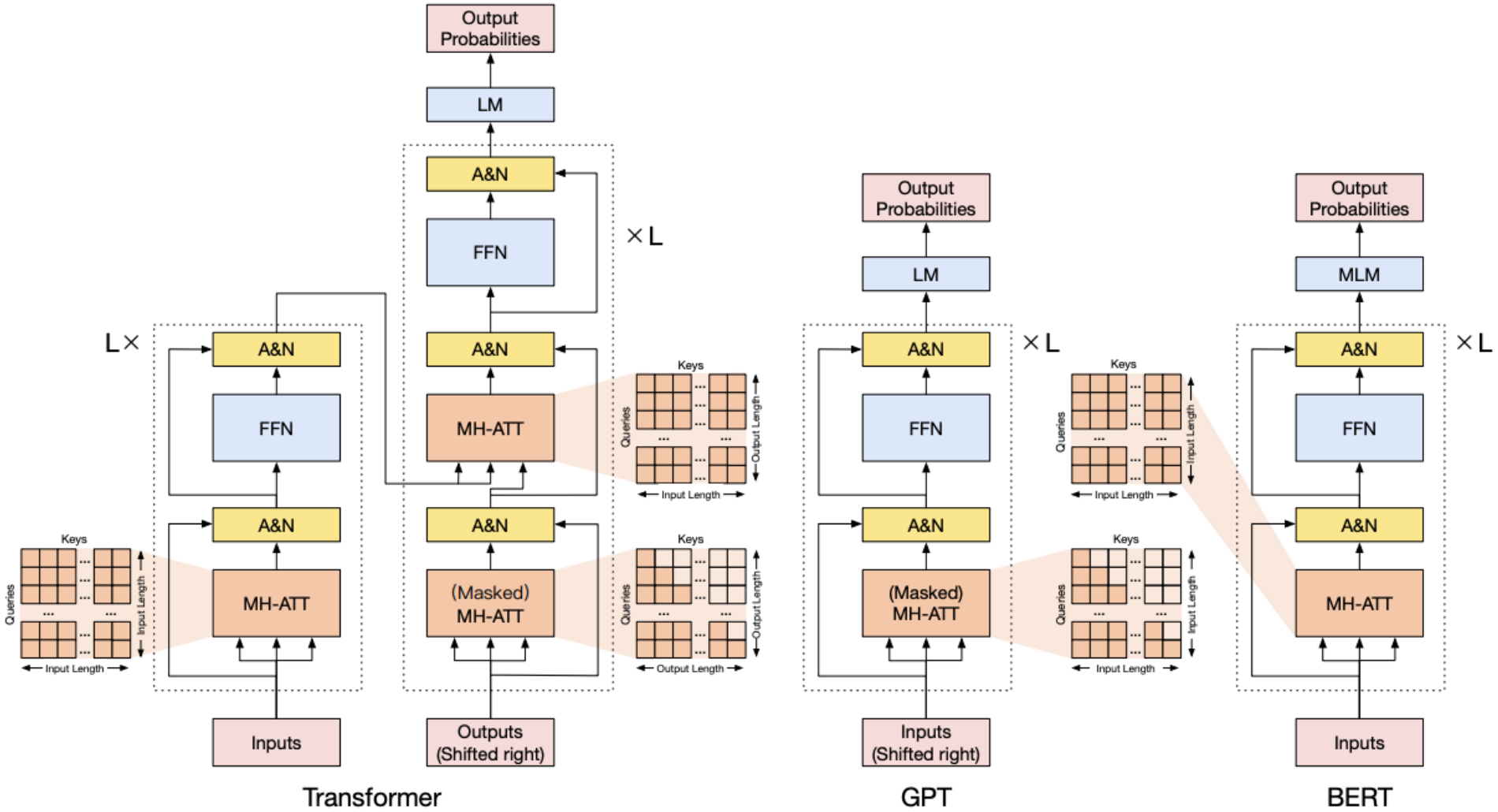
The family of recent typical pre-trained language models (PTMs)



Source

3 – Pre-trained LMs

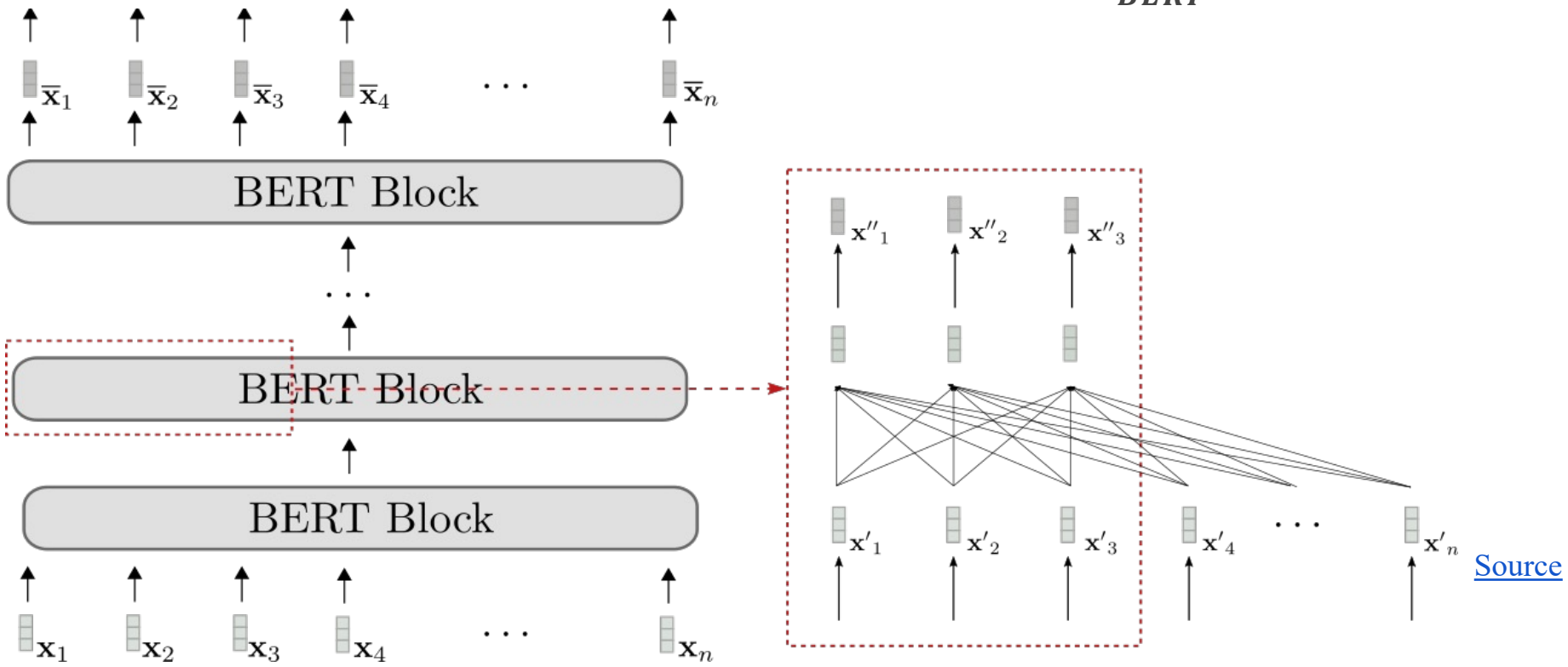
The architecture of Transformer, GPT and BERT



3 – Pre-trained LMs

BERT

- BERT: An encoder-only model
- Maps an input sequence to a contextualized sequence: $f_{\theta_{BERT}}: X_{1:n} \longrightarrow \overline{X}_{1:n}$



Source

3 – Pre-trained LMs

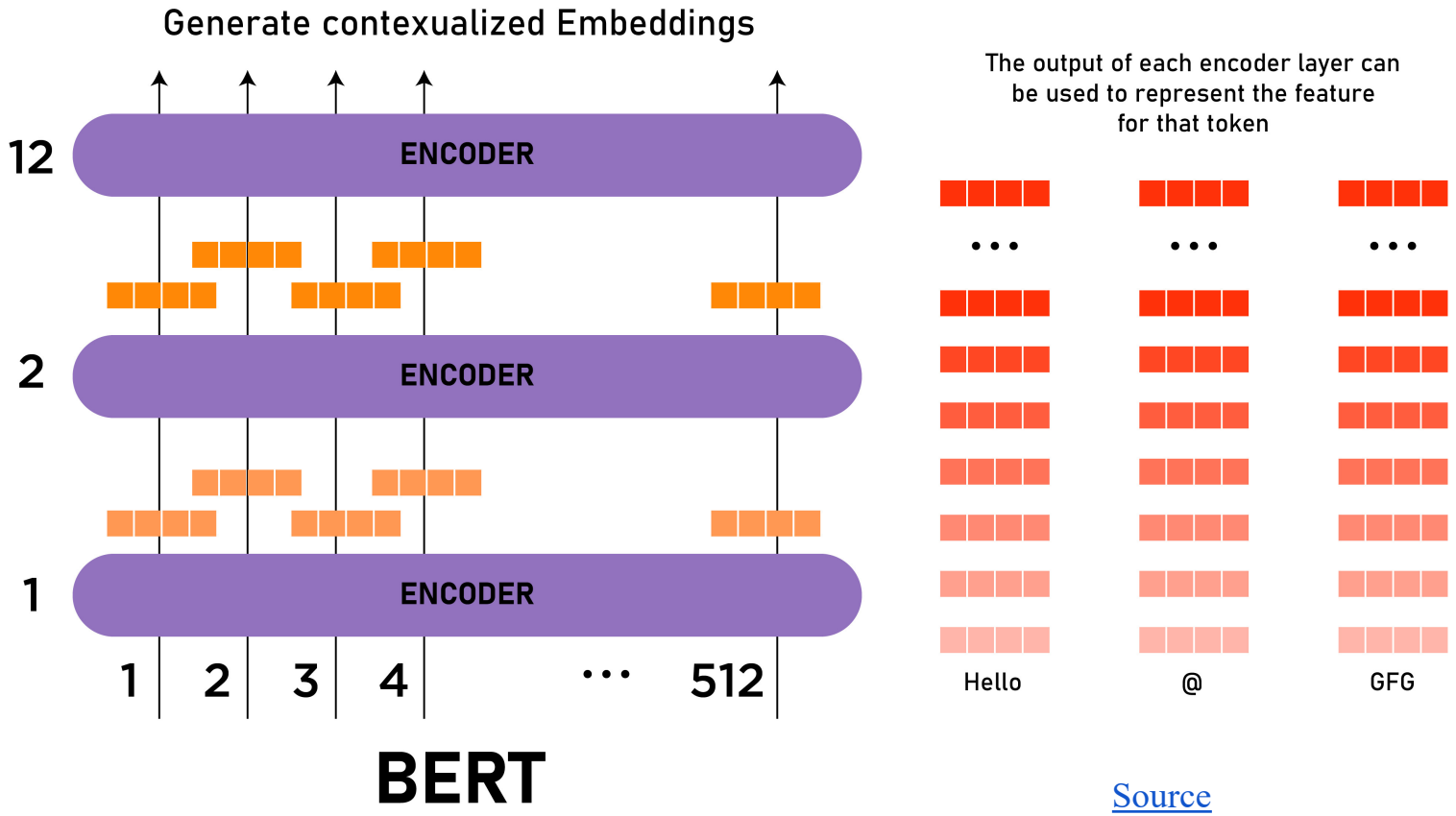
BERT

- BERT base:

L=12, H=768, A=12, P=110M

- BERT large:

L=24, H=1024, A=16, P=340M



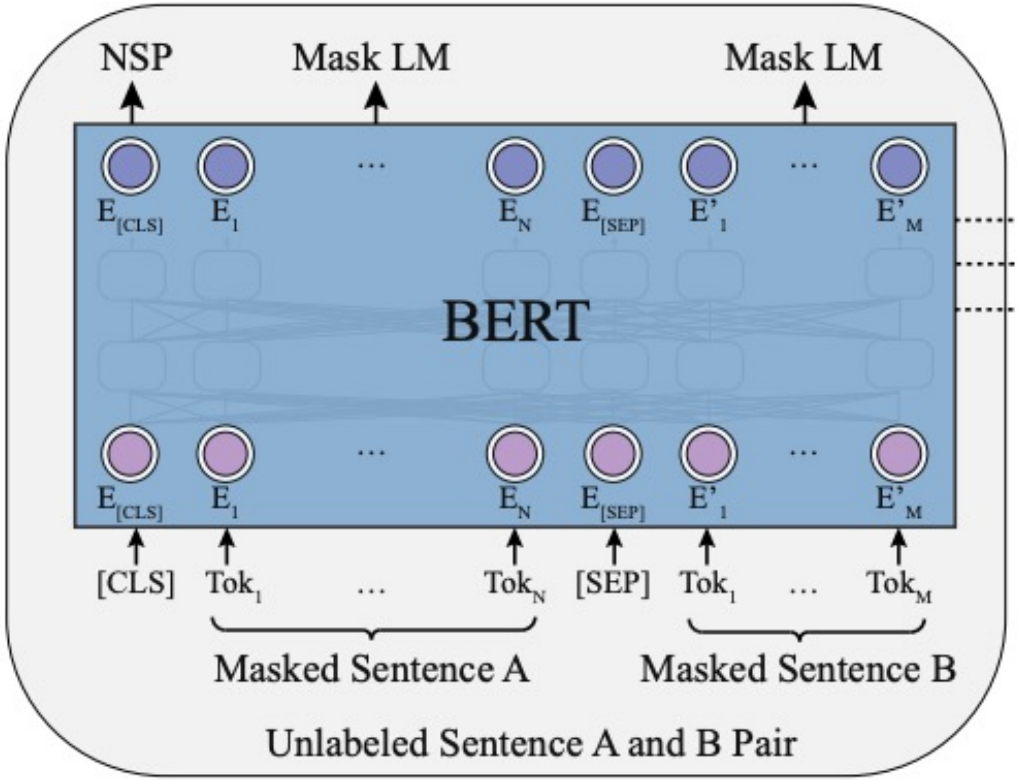
Source

3 – Pre-trained LMs

BERT

Objective Functions:

- Masked LM (15% token):
  - 80%: replace with [MASK]
  - 10%: replace with a random word
  - 10%: keep unchanged
- Next Sentence Prediction (NSP)
  - Classification Task
  - 2 Labels: IsNext and NotNext
  - Use [SEP] token



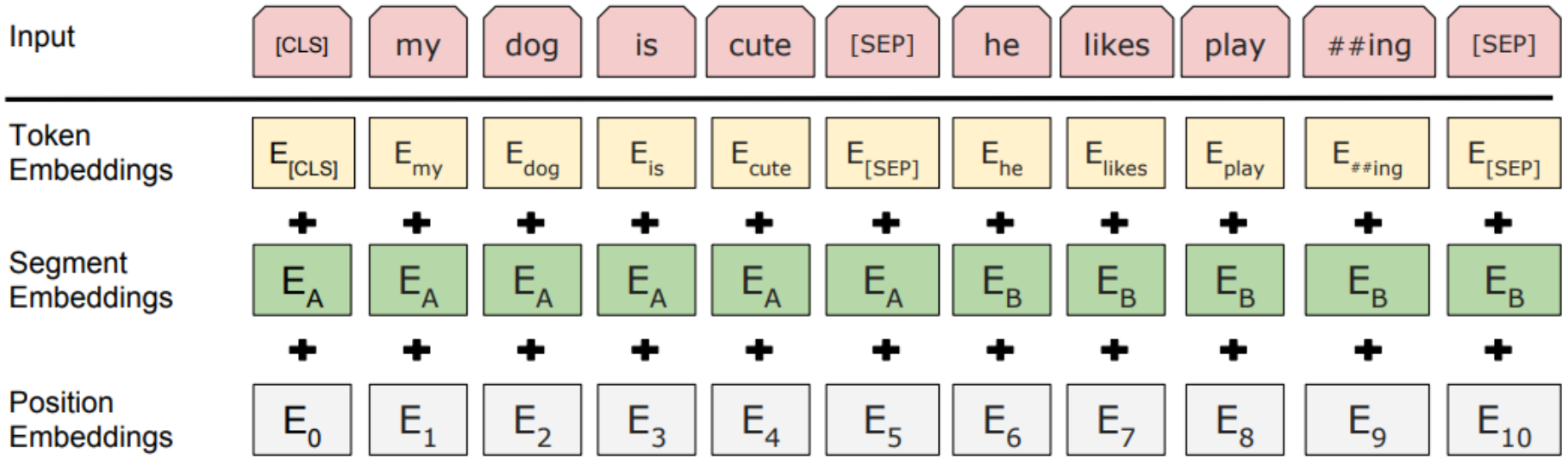
Pre-training

Source

3 – Pre-trained LMs

BERT

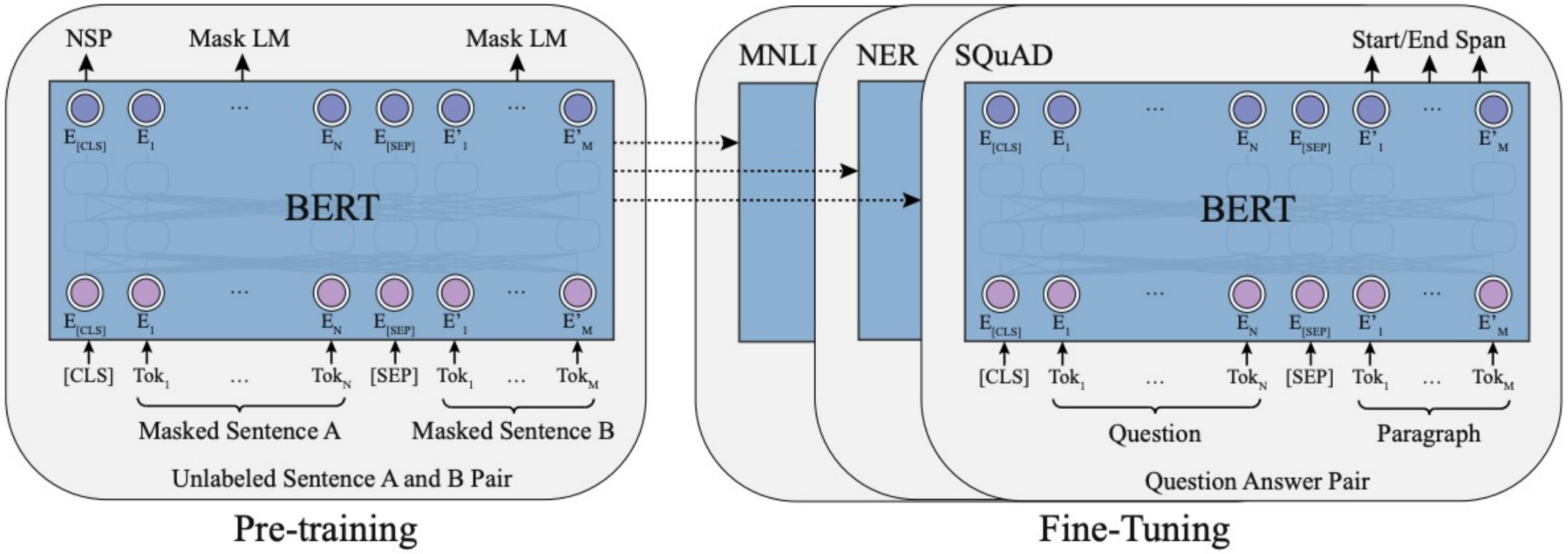
- BERT input representation



Source

3 – Pre-trained LMs

BERT



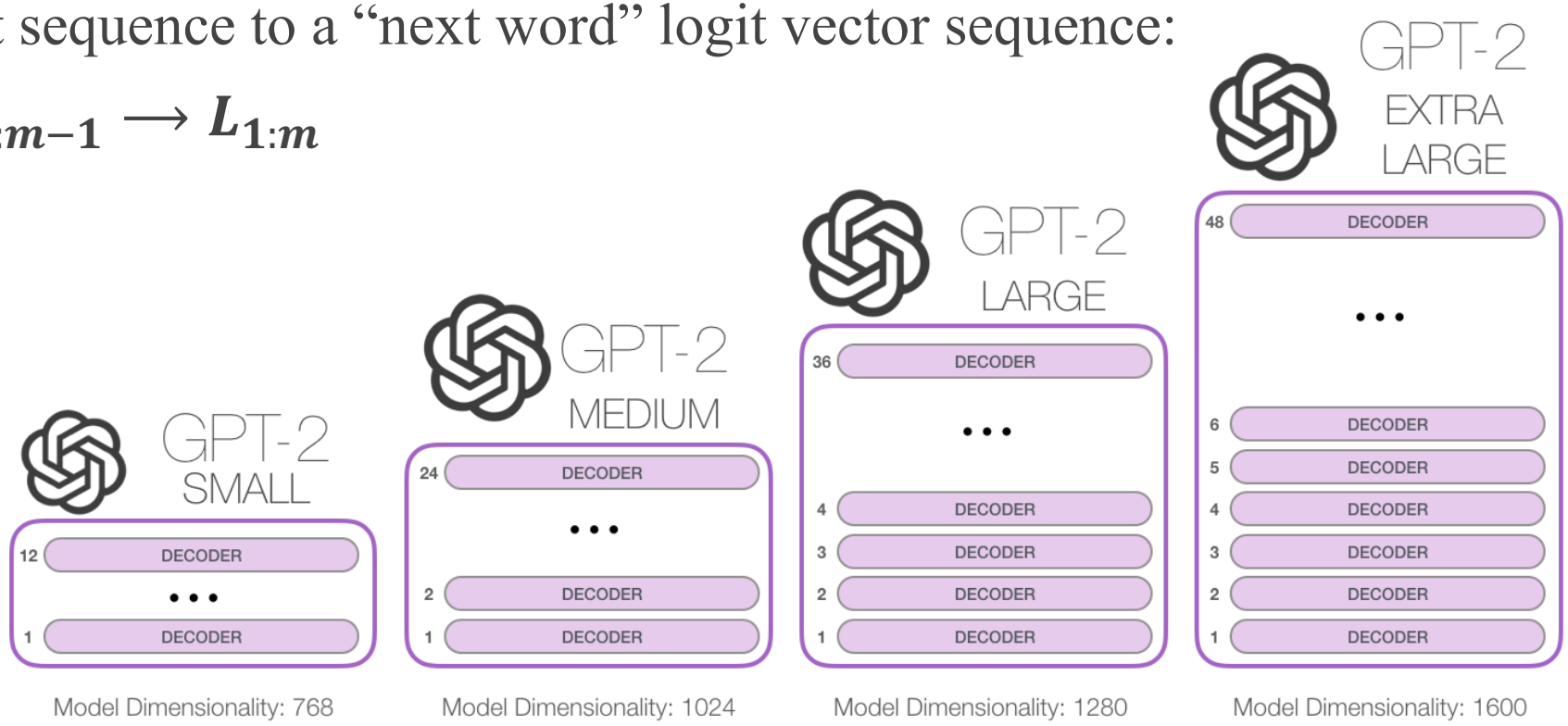
Source

3 – Pre-trained LMs

GPT (GPT2)

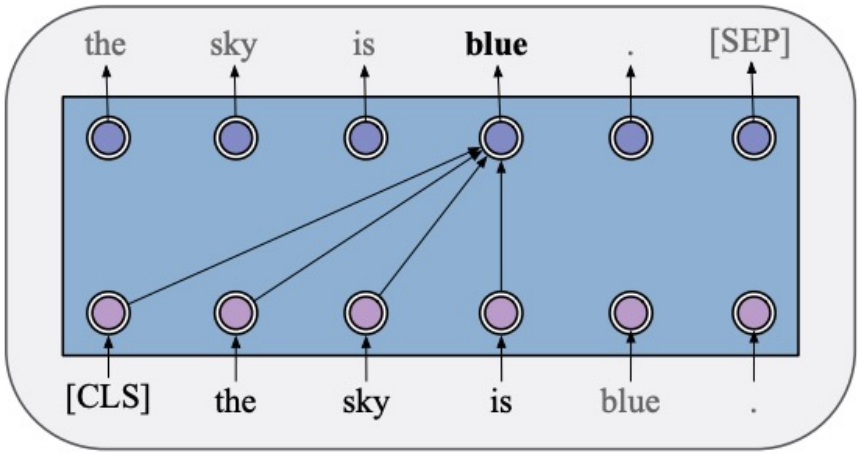
- GPT2: A decoder-only model, use uni-directional (causal) self-attention
- Maps an input sequence to a "next word" logit vector sequence:

$$f_{\theta_{GPY2}}: X_{0:m-1} \longrightarrow L_{1:m}$$

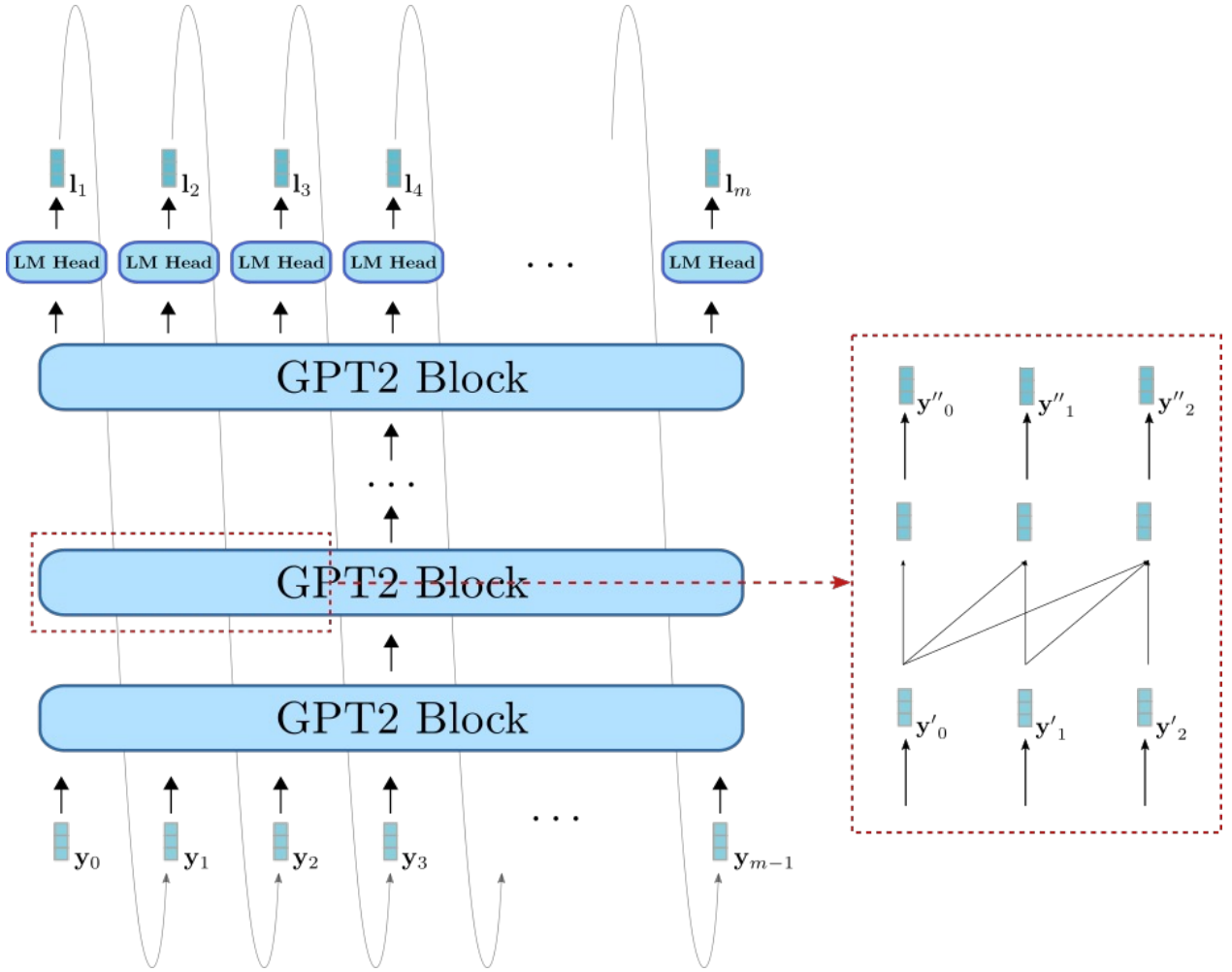


3 – Pre-trained LMs

GPT (GPT2)



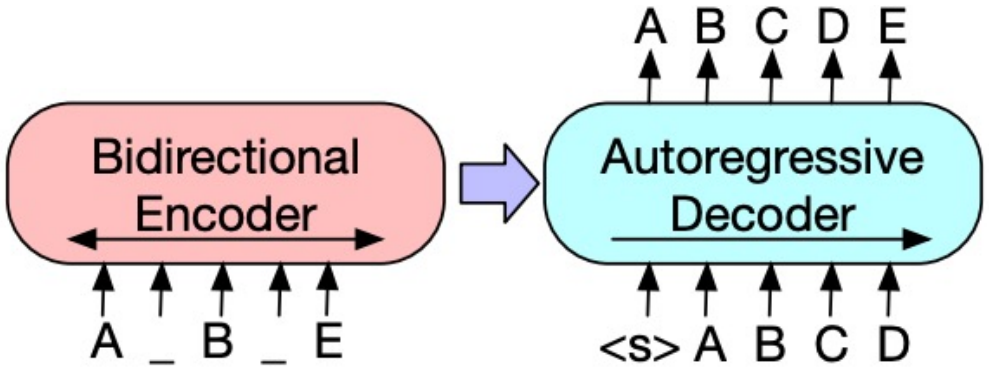
GPT

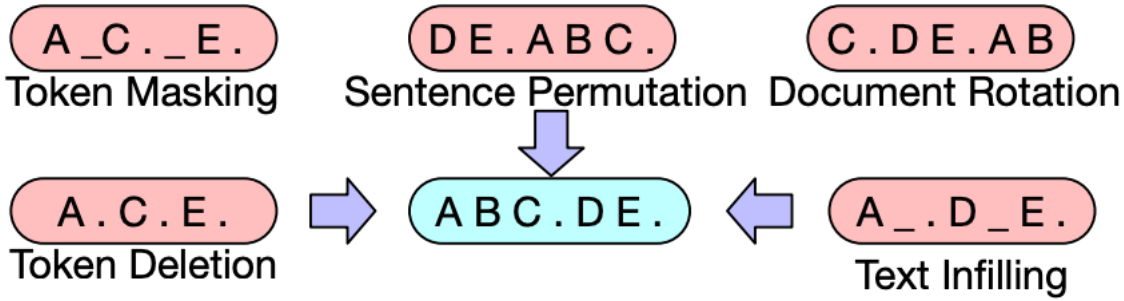


3 – Pre-trained LMs

BART

- **BART:** Denoising Sequence-to-Sequence Pre-Training for Natural Language Generation, Translation and Comprehension

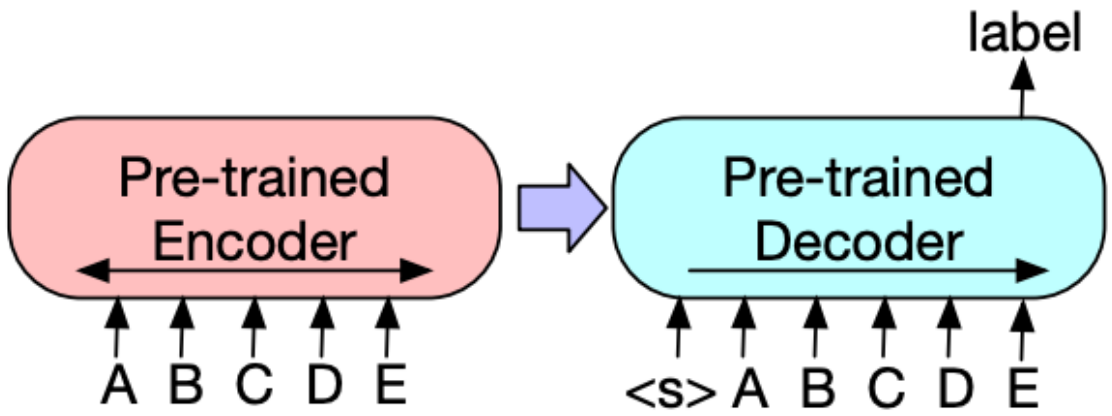




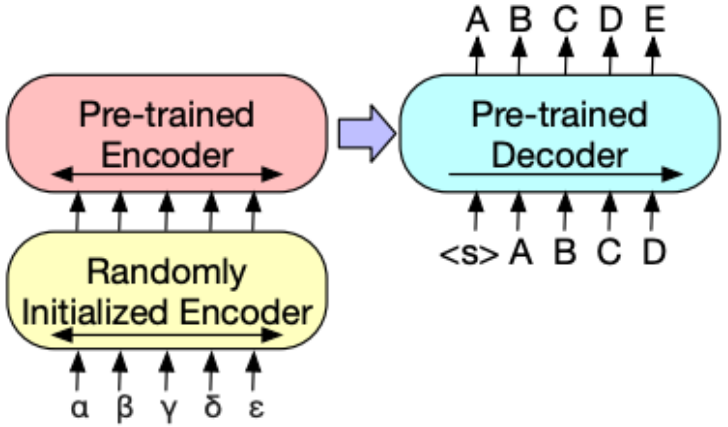
3 – Pre-trained LMs

BART

- **BART:** Denoising Sequence-to-Sequence Pre-Training for Natural Language Generation, Translation and Comprehension
- **Fine-tune BART**



Classification Task



Machine Translation Task

4 – Applications

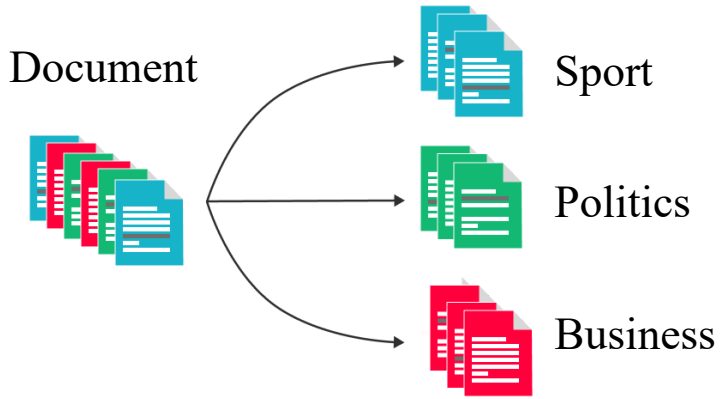
Text Classification

Input

- A document d
- A fixed set of classes $C=\{c_1, c_2, \ldots c_j\}$
- A training set of m hand-labeled documents: $(d_1, c_1), \ldots, (d_m, c_j)$

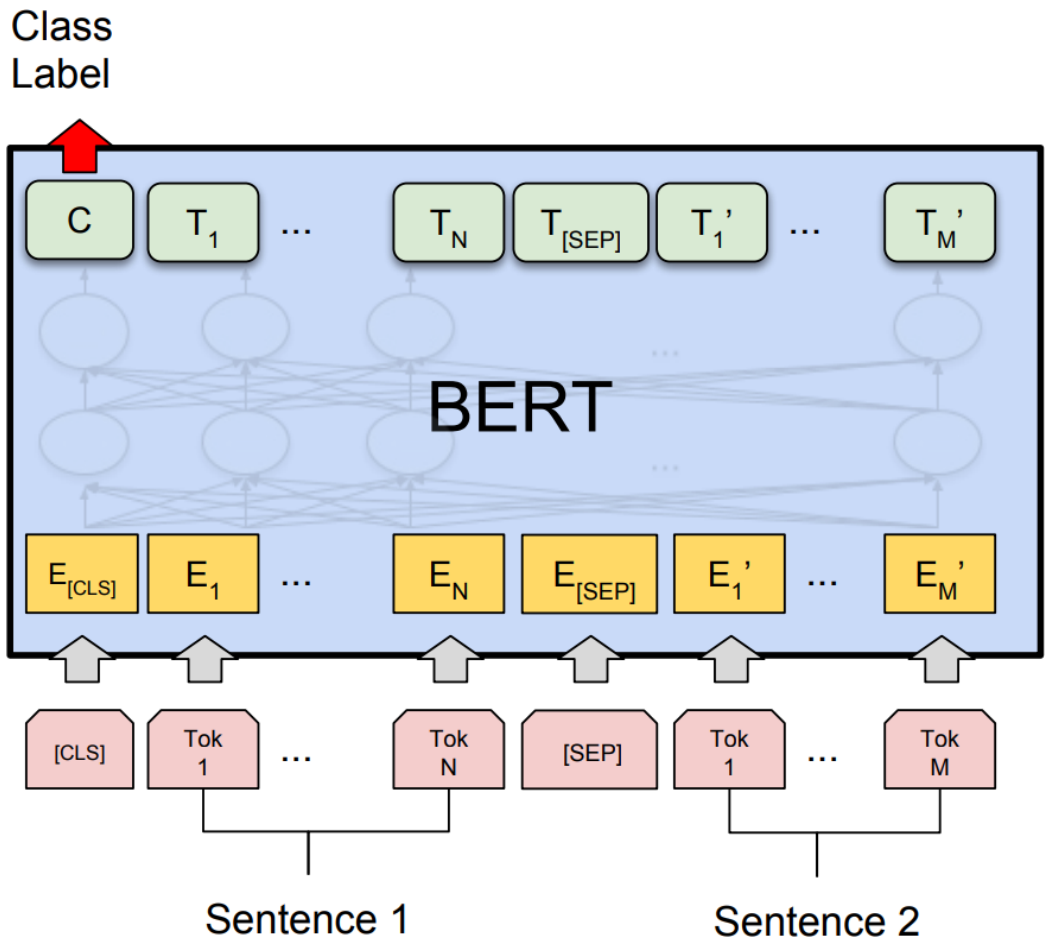
Output

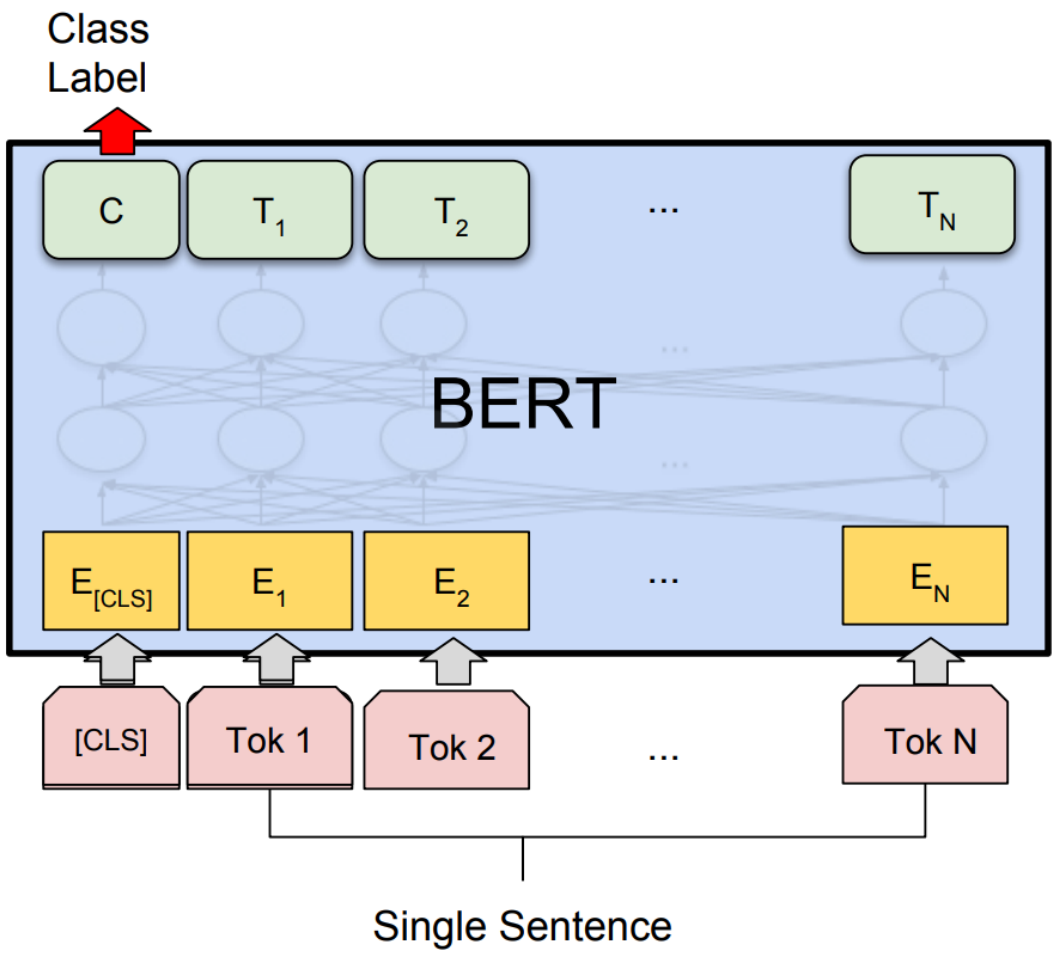
- A learned classifier $d => c$



4 – Applications

Text Classification using BERT

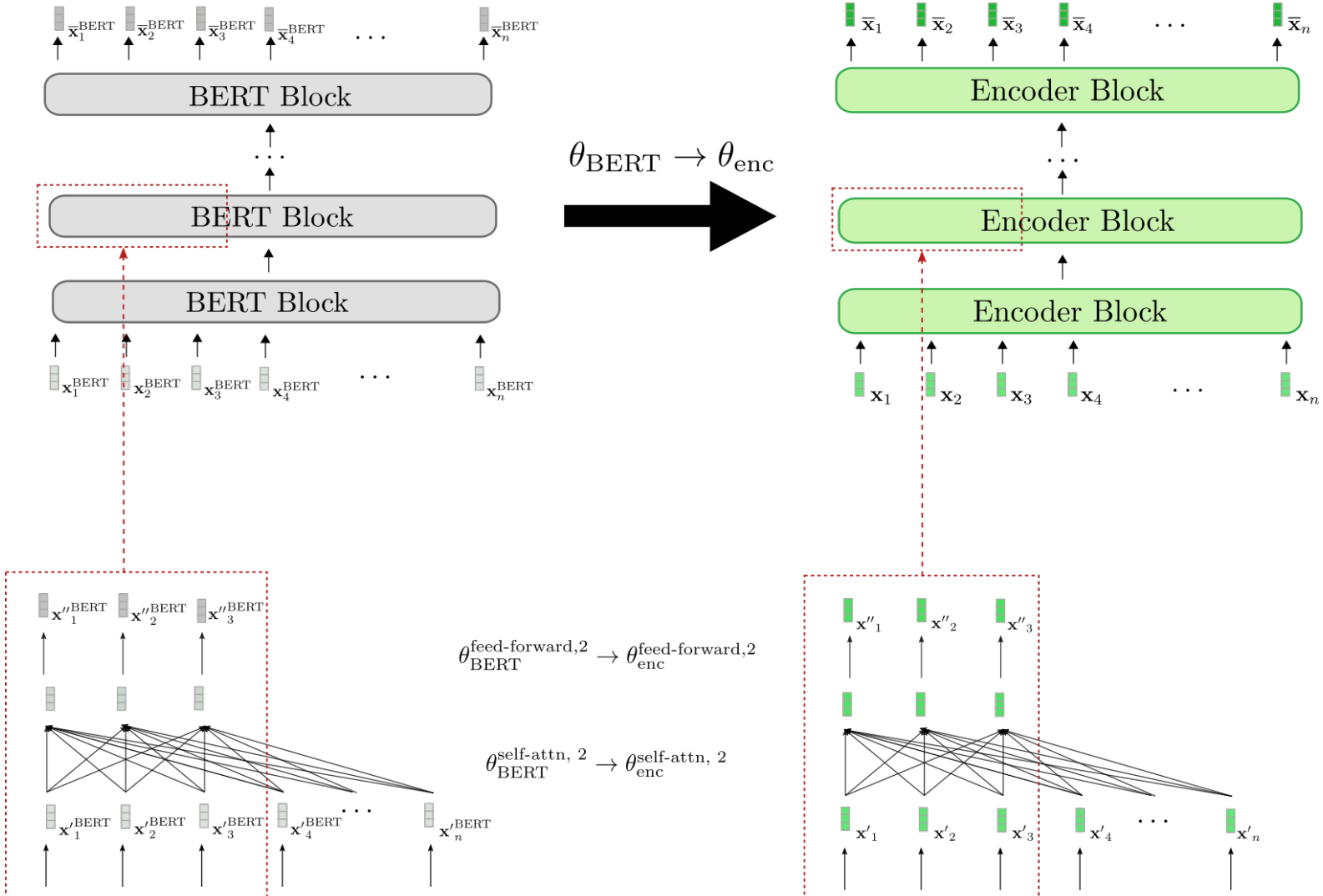




4 – Applications

Machine Translation using BERT-GPT2

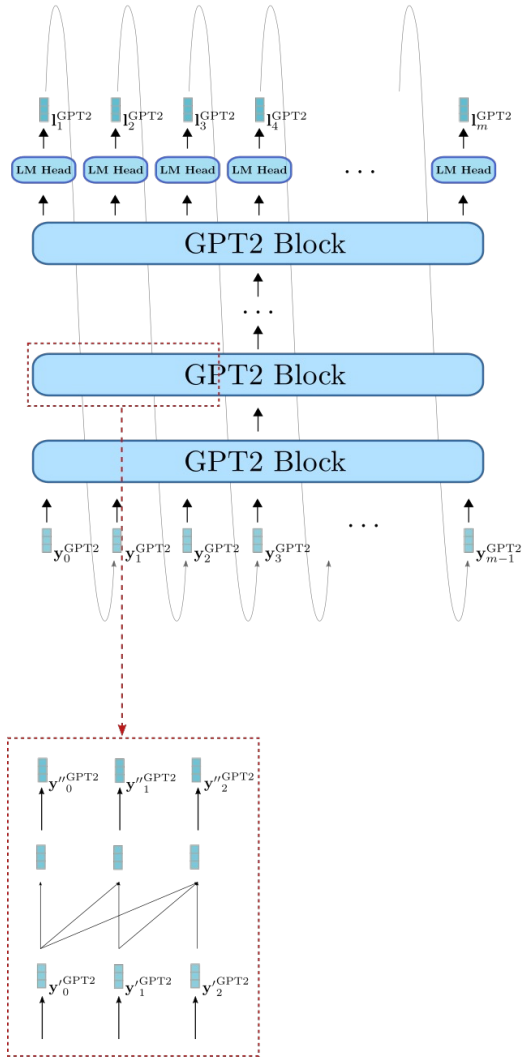
BERT for Encoder

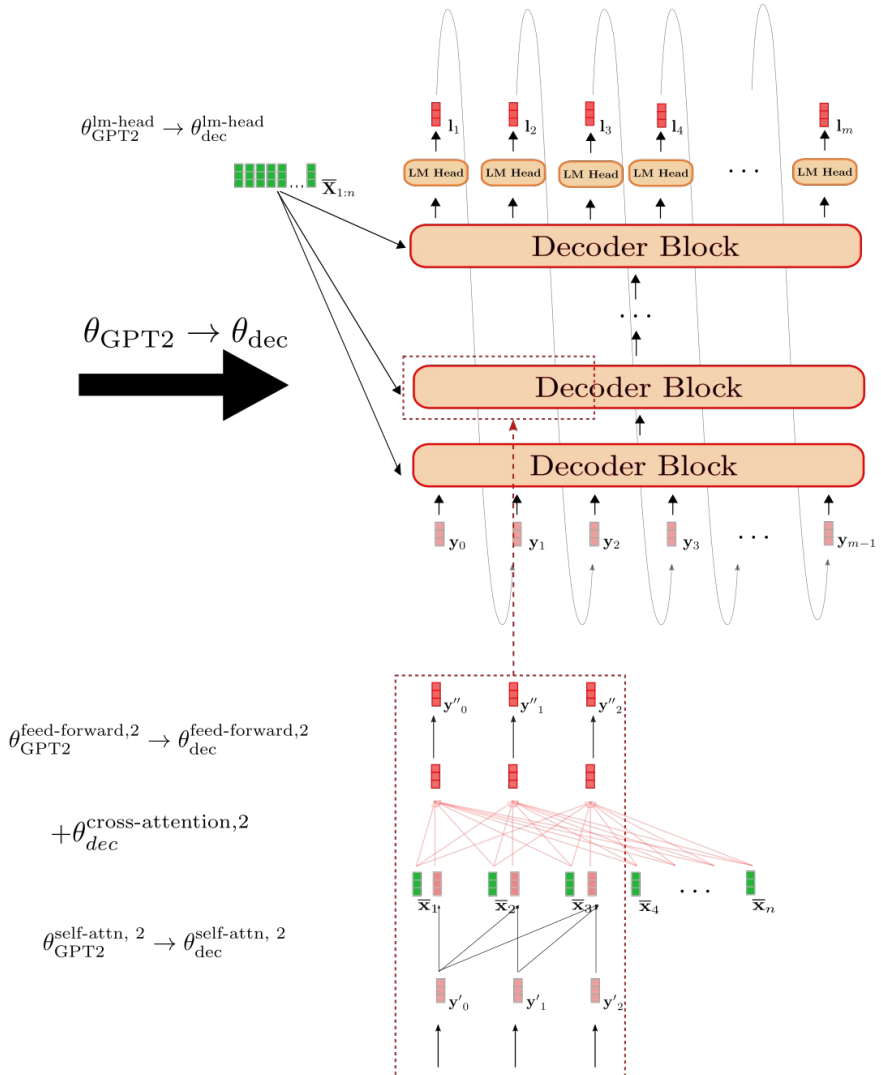


4 – Applications

Machine Translation using BERT-GPT2

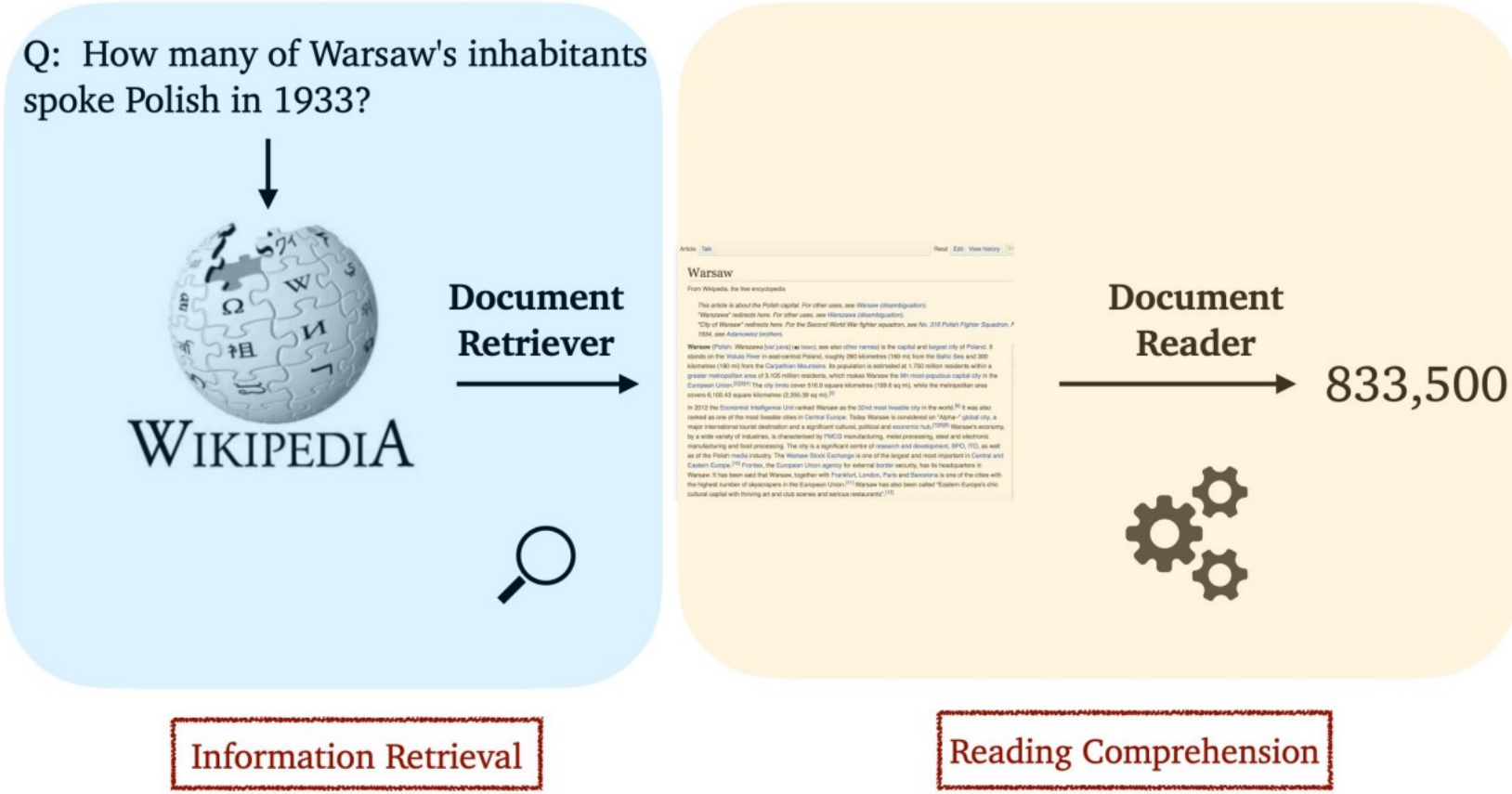
GPT2 for Decoder





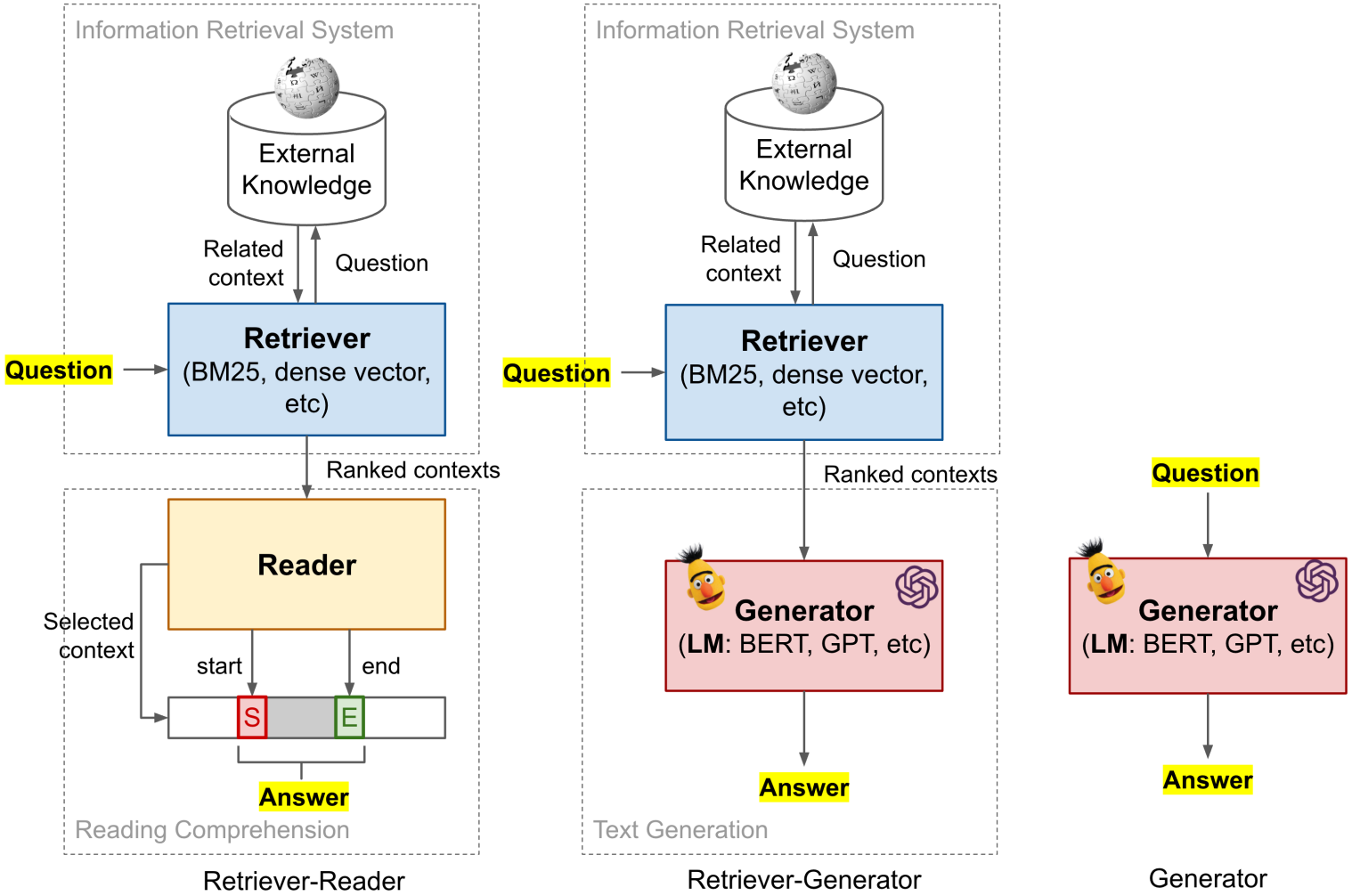
4 – Applications

Question Answering



4 – Applications

Question Answering



4 – Applications

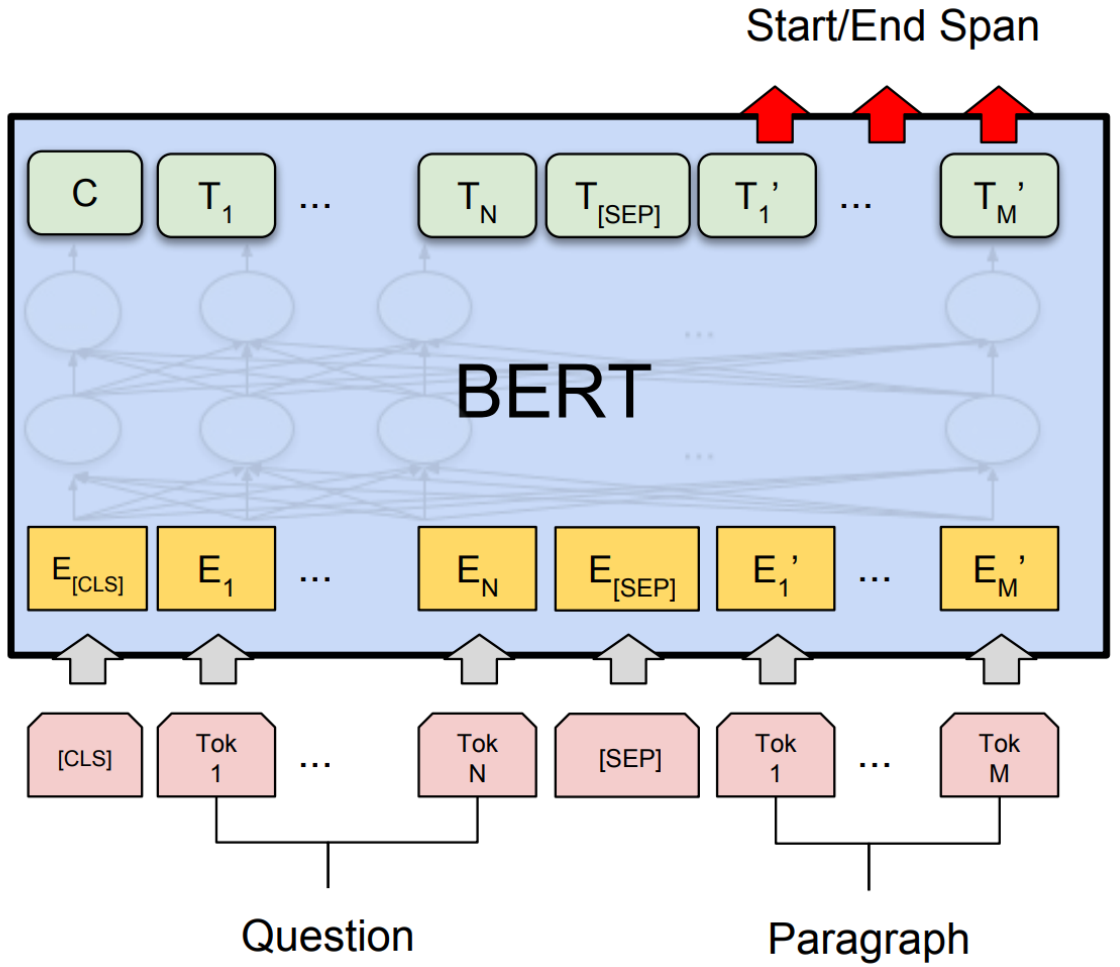
Question Answering using BERT

- Input: A passage P - content (paragraph, document,…) and a question Q
- Output: An answer A

Article: Endangered Species Act
Paragraph: " . . . *Other legislation followed, including the Migratory Bird Conservation Act of 1929, a 1937 treaty prohibiting the hunting of right and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little opposition was raised.*"

Question 1: "*Which laws faced significant opposition?*"
Plausible Answer: *later laws*

Question 2: "*What was the name of the 1937 treaty?*"
Plausible Answer: *Bald Eagle Protection Act*



4 – Applications

Experiment

- Source code + Checkpoint: Link

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Thanks!

Any questions?