BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

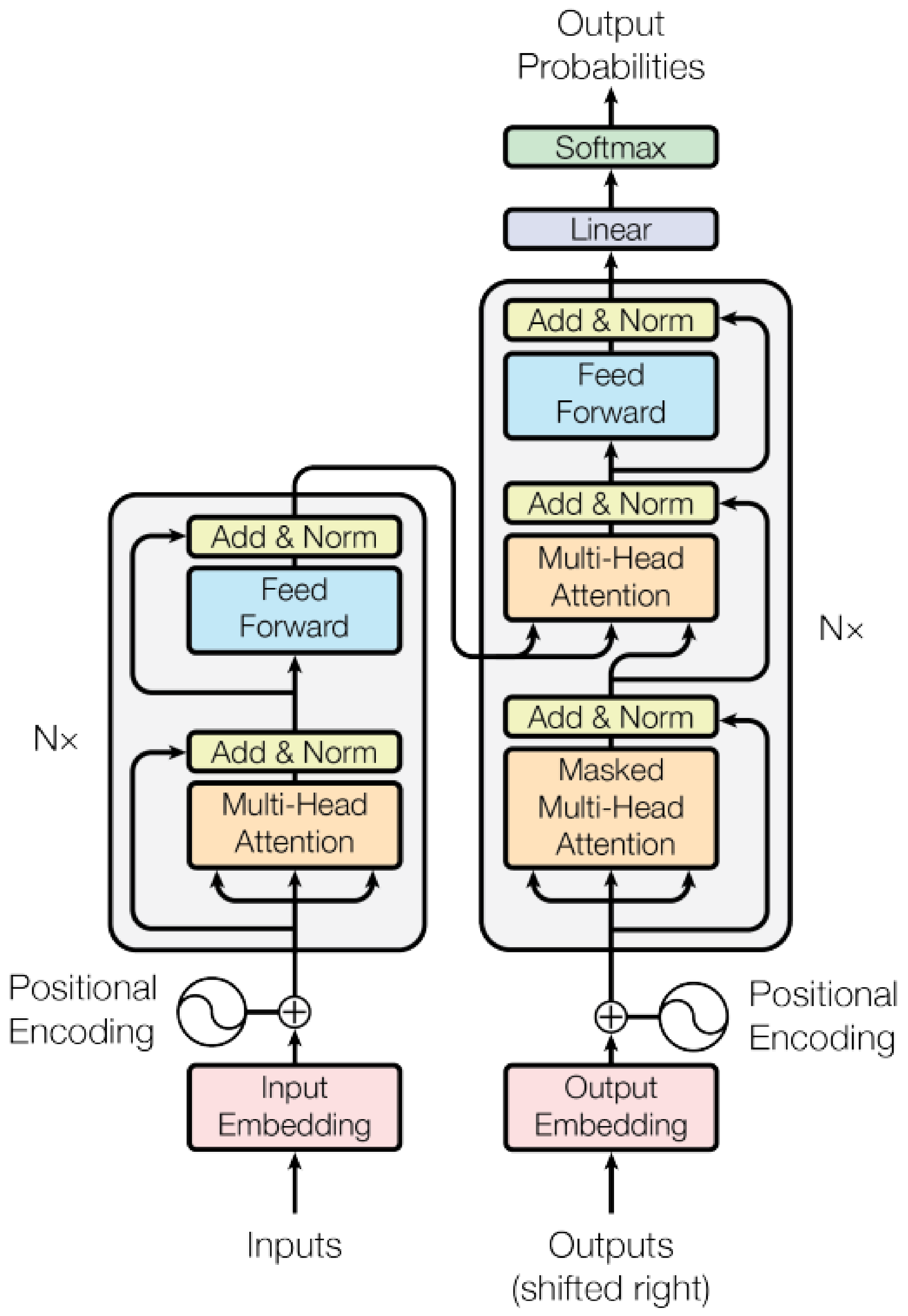
with a quick introduction to transformers

Mateusz Pach

December 14, 2022

Transformer

"Attention Is All You Need" Vaswani et al. 2017



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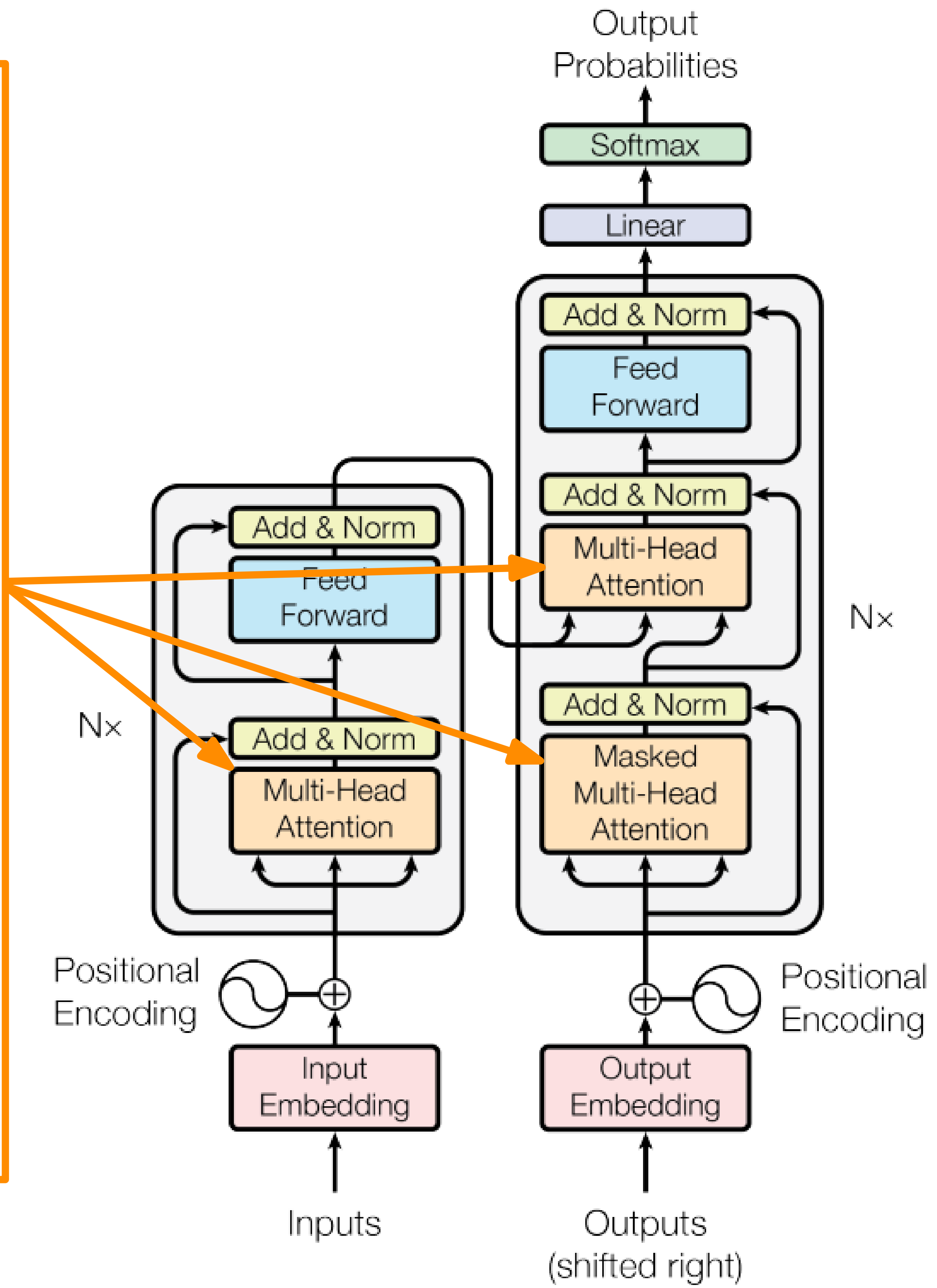
For each query $q \in Q$ assign sum of values $v \in V$ weighted by similarity of corresponding keys $k \in K$

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



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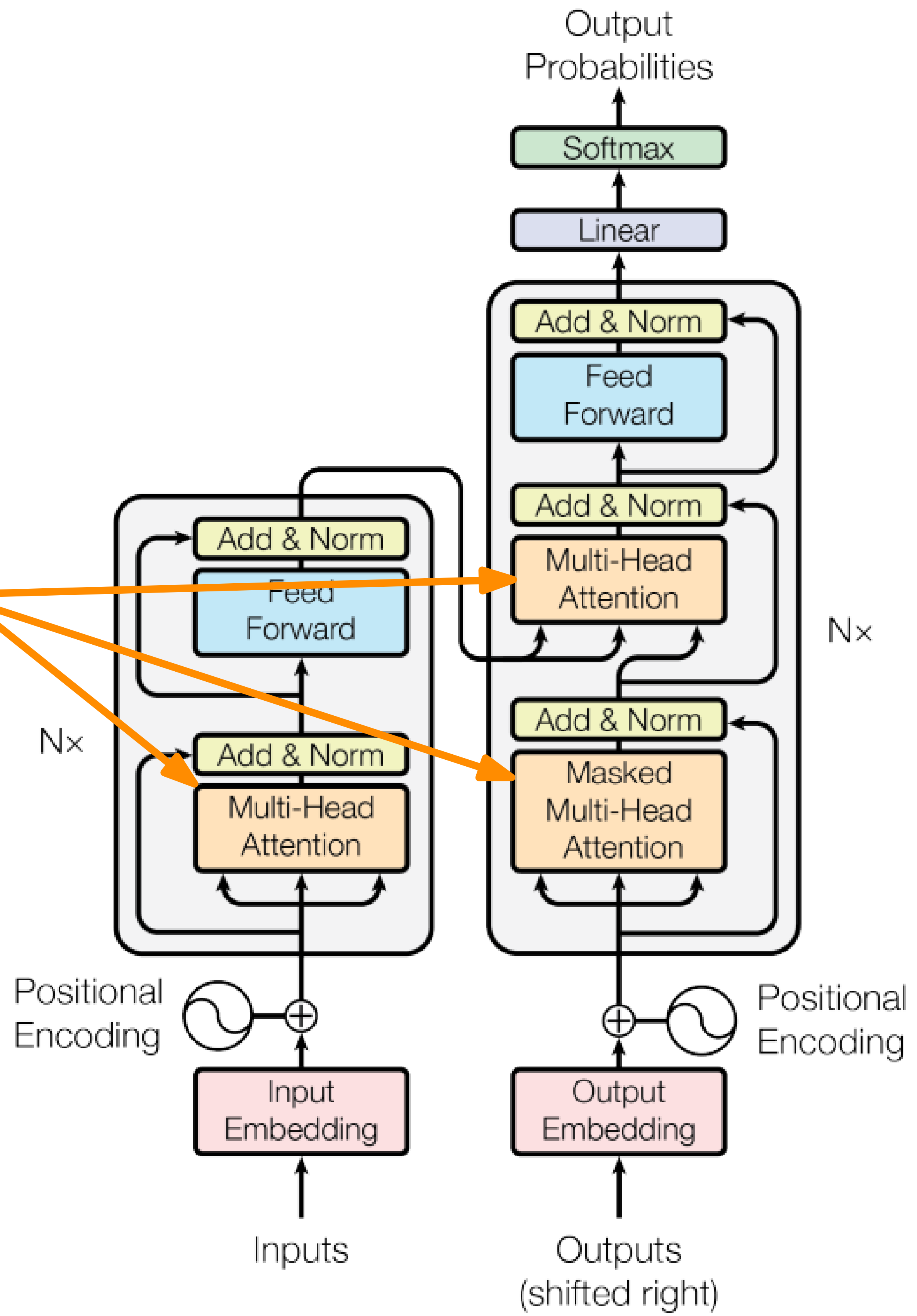
Q	K	V	Attention(Q, K, V)
cat	pies	pies	$0.10 \times$ pies $+ 0.01 \times$ jajko $+ 0.89 \times$ kot
dog	jajko	jajko	$0.89 \times$ pies $+ 0.01 \times$ jajko $+ 0.10 \times$ kot
egg	kot	kot	$0.01 \times$ pies $+ 0.98 \times$ jajko $+ 0.01 \times$ kot



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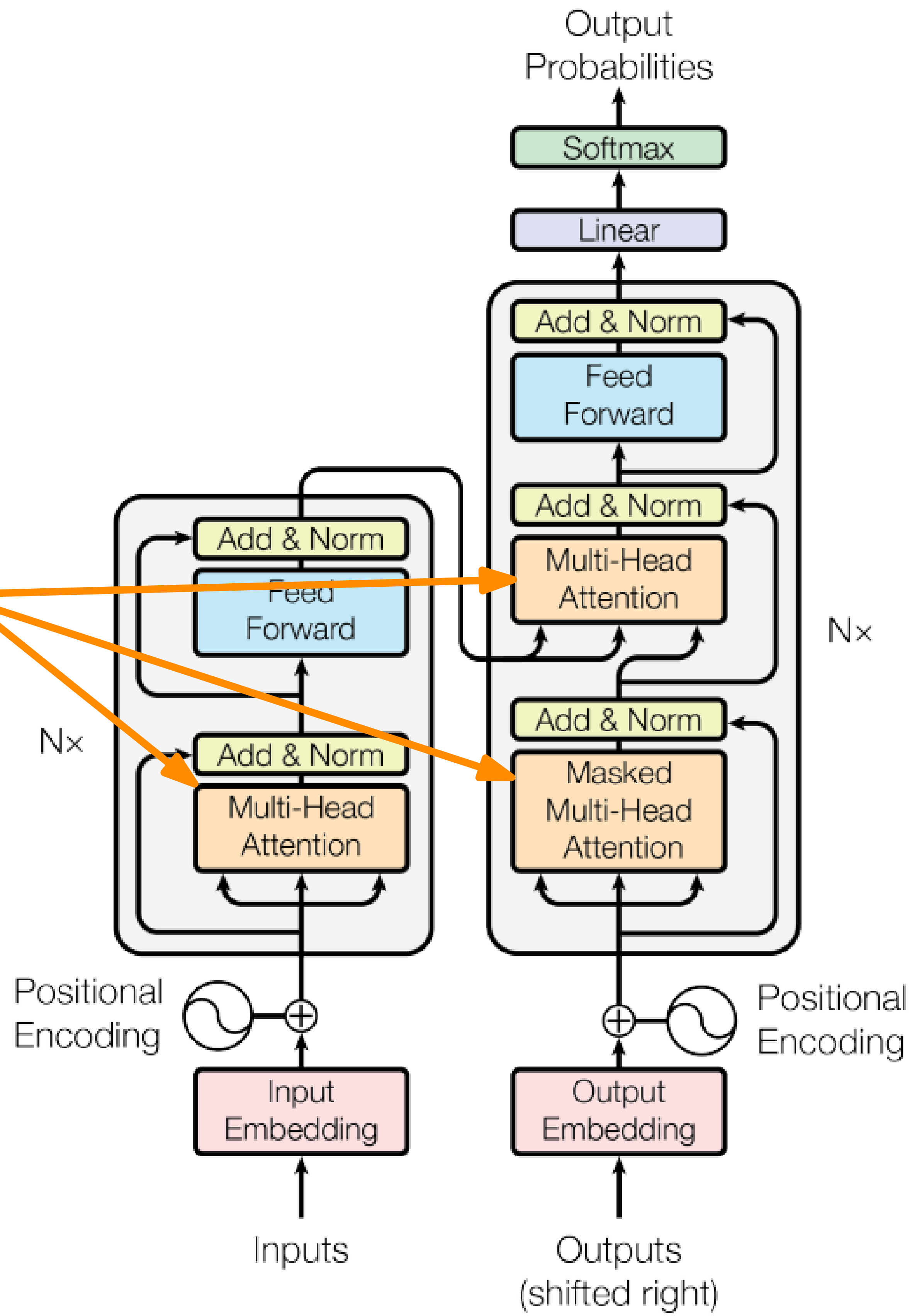
Q	K	V	Self Attention(Q, K, V)
to	to	to	$0.60 \times$ to $+ 0.10 \times$ jest $+ 0.30 \times$ kot
jest	jest	jest	$0.10 \times$ to $+ 0.70 \times$ jest $+ 0.20 \times$ kot
kot	kot	kot	$0.30 \times$ to $+ 0.10 \times$ jest $+ 0.60 \times$ kot



Transformer

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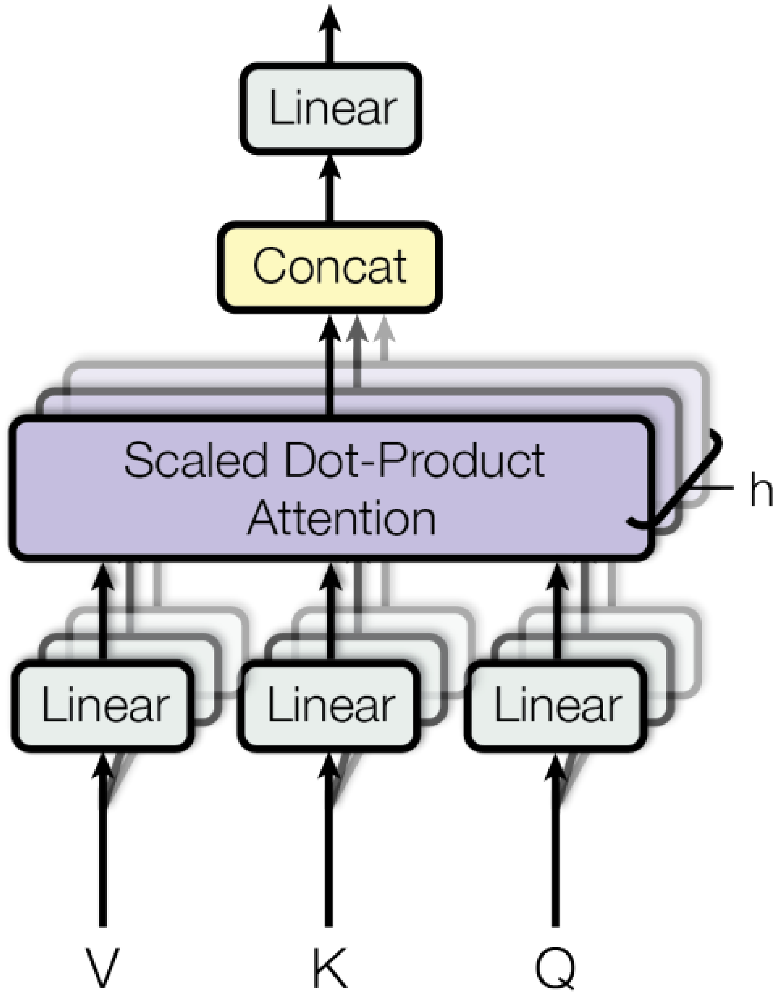
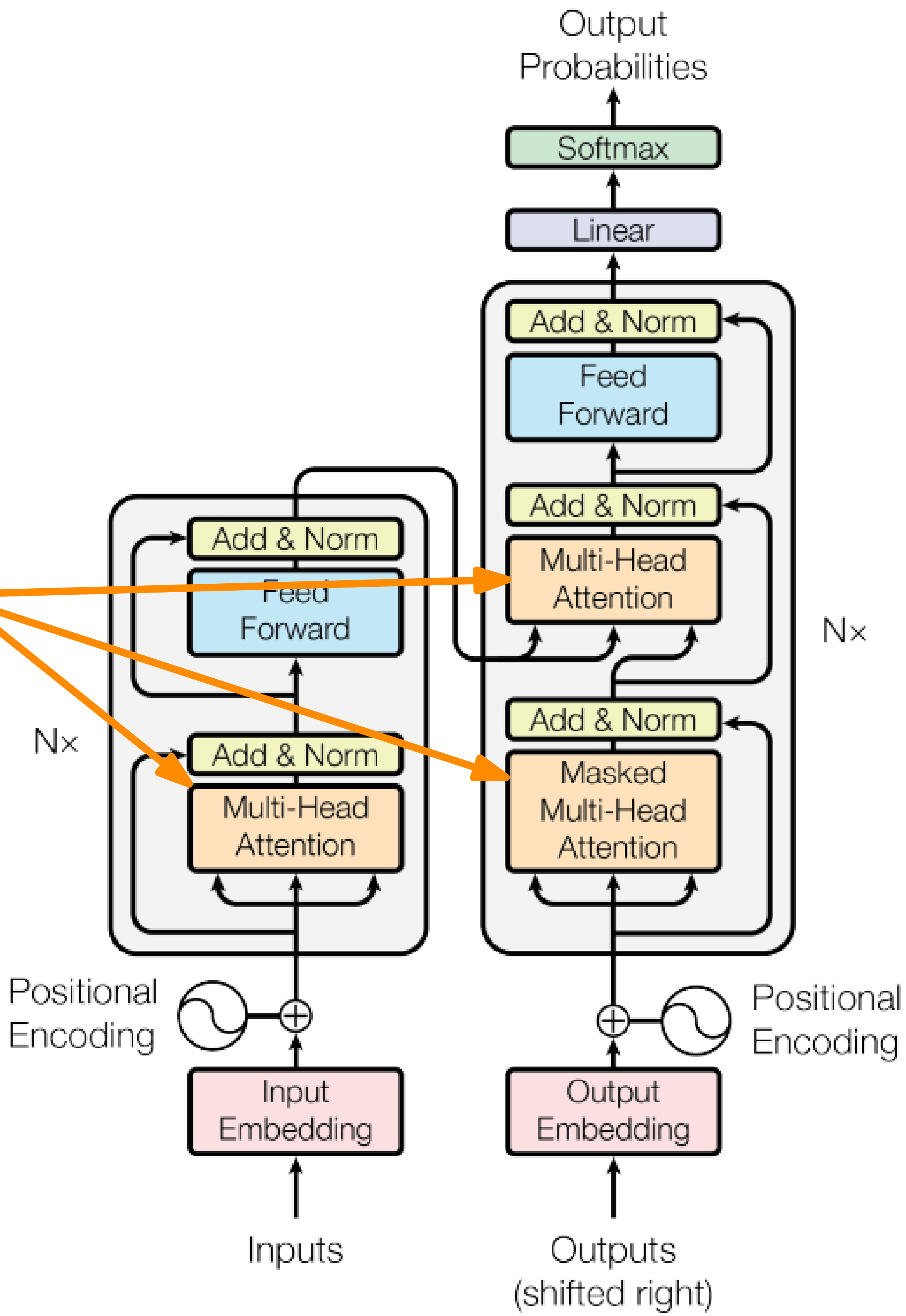
Multi-Head as we project to different representations

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h)$$

$$\text{where } \mathrm{head}_i = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$





Transformer

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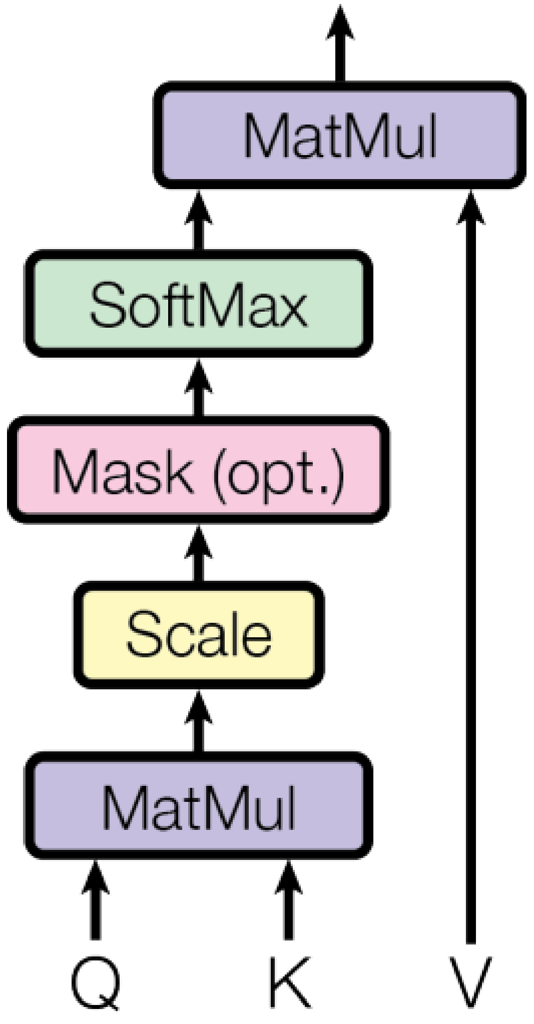
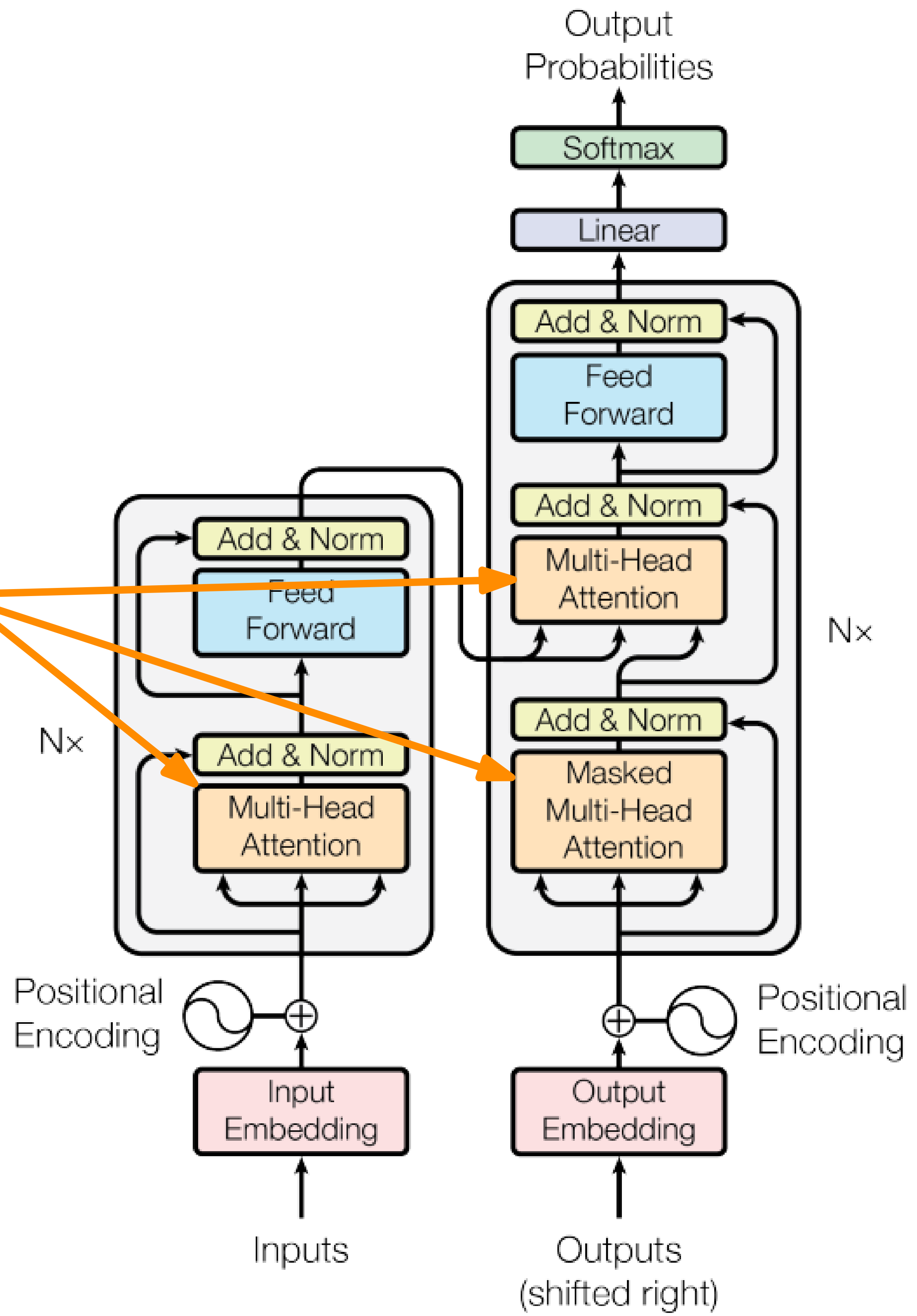
Masked as we don't want to attend words to the right

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$





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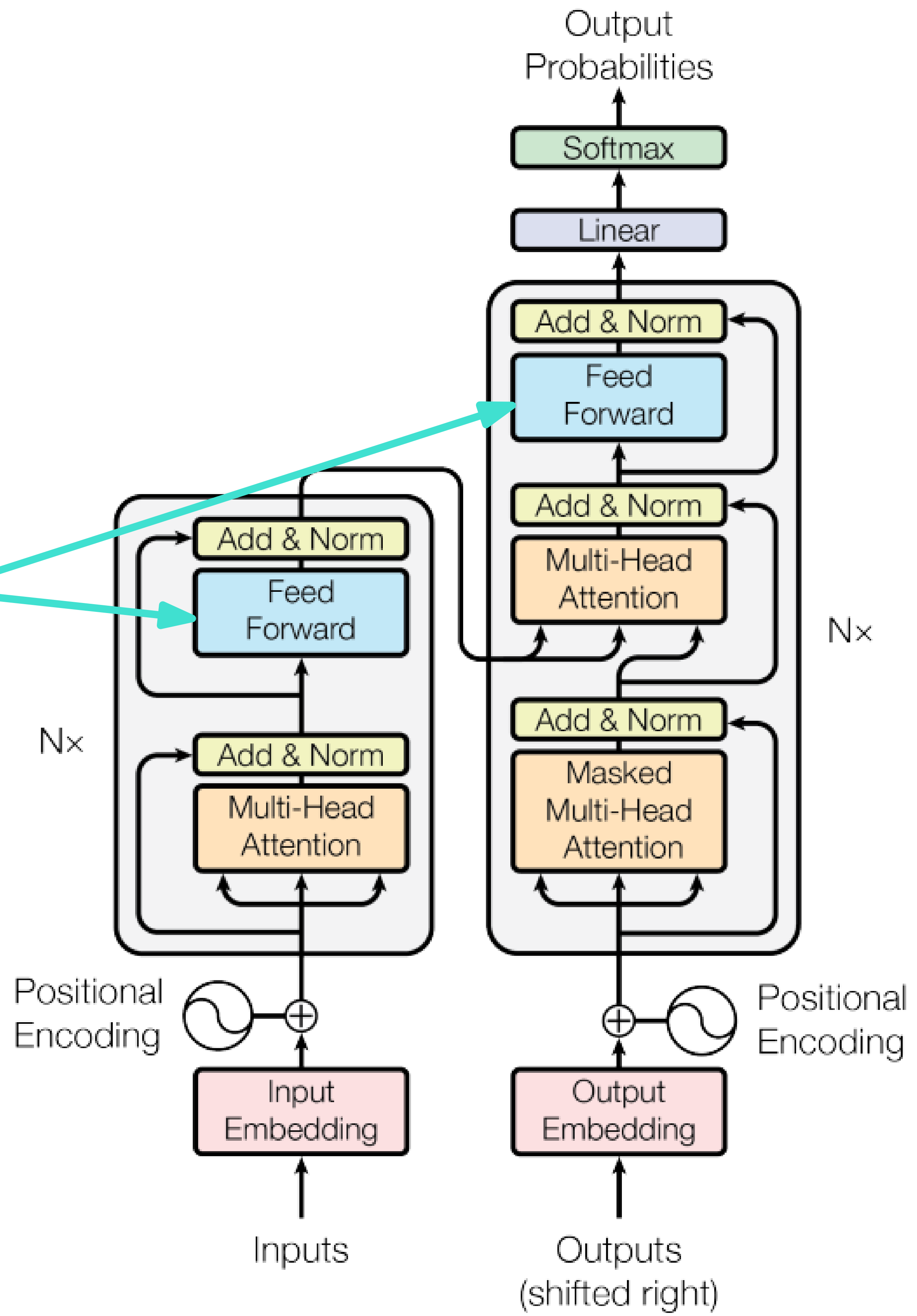
Feed Forward are two convolutions with kernel size 1

$$\mathsf{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$



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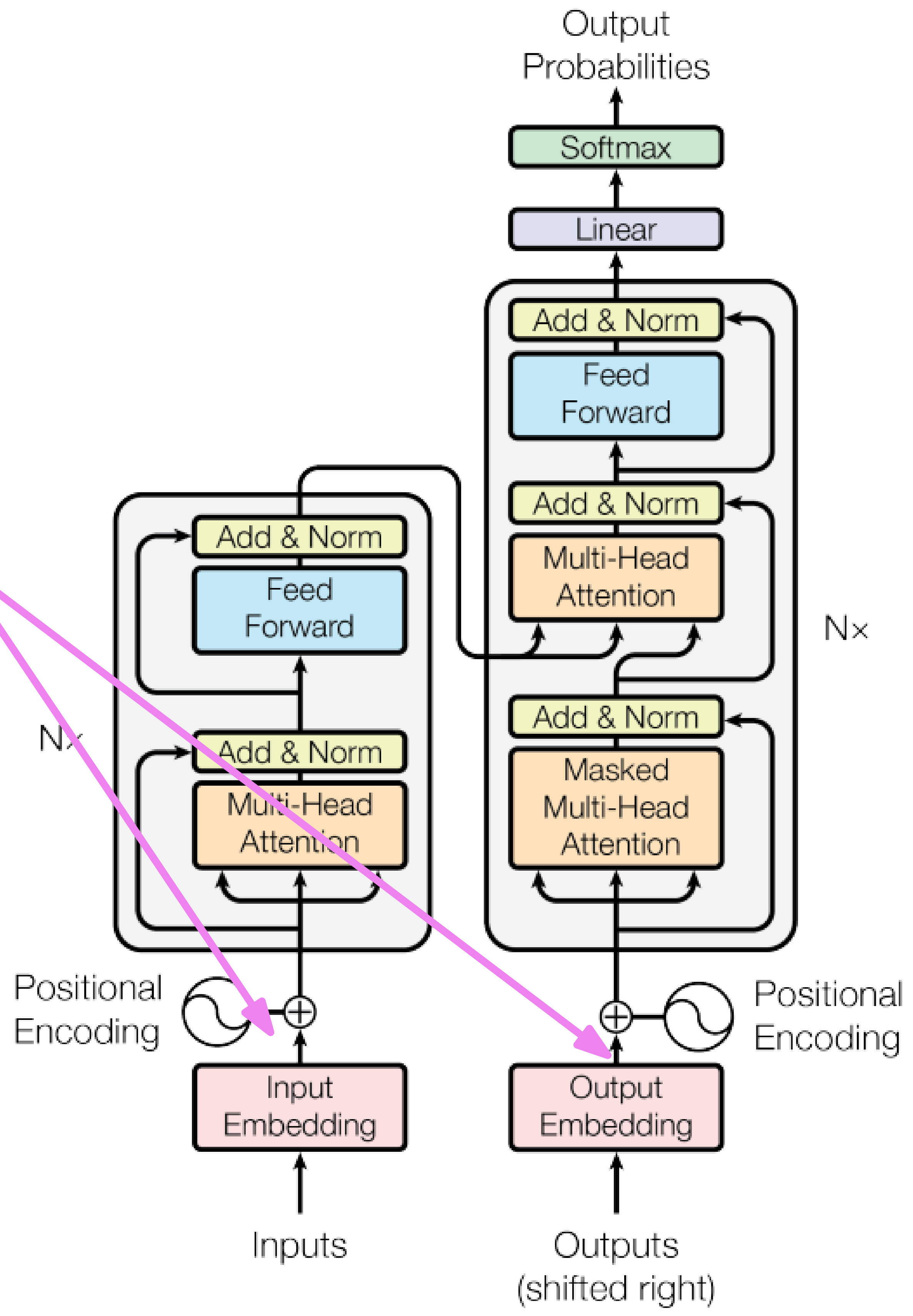
Embedding transforms input tokens into vector representations



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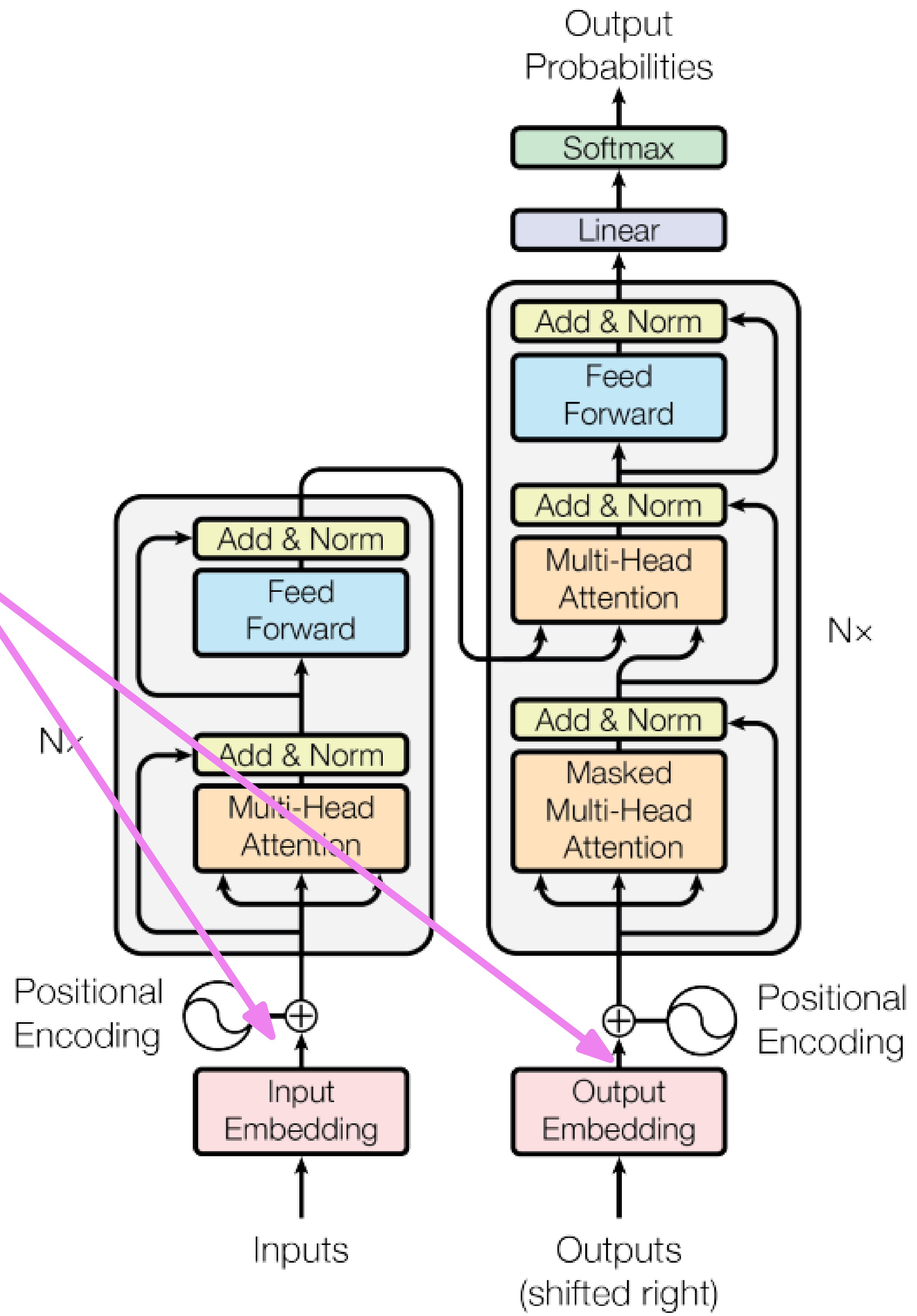
Embedding transforms input tokens into vector representations

Positional Encoding adds information about position

$$PE(pos, 2i) = \sin(pos/10000^{2i/d_{model}})$$
$$PE(pos, 2i+1) = \cos(pos/10000^{2i/d_{model}})$$



Transformer

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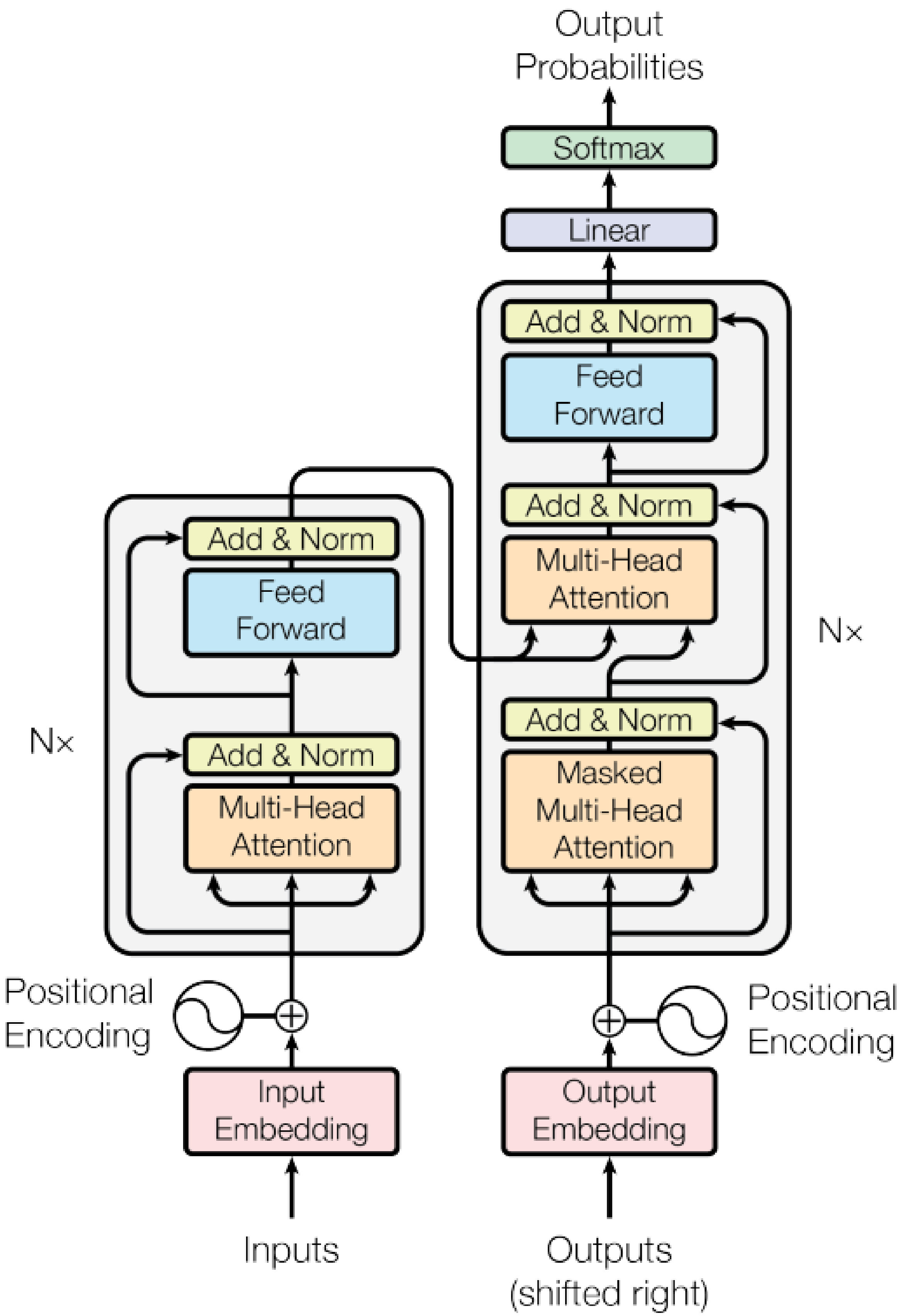
Intuition behind translation with transformers:

1. Embed k input words + encode position
2. Self-attend input words i.e. enrich them with context
3. Adjust for the next layer in a learned way
4. Embed already translated words + encode position
5. Self-attend l translated words i.e. enrich them with context (from the left)
6. Attend words to translate from translated words i.e enrich with original context
7. Adjust for the next layer in a learned way
8. Output $l + 1$ translated words

Note that steps 2-3 and 6-7 are repeated N times to boost the effect



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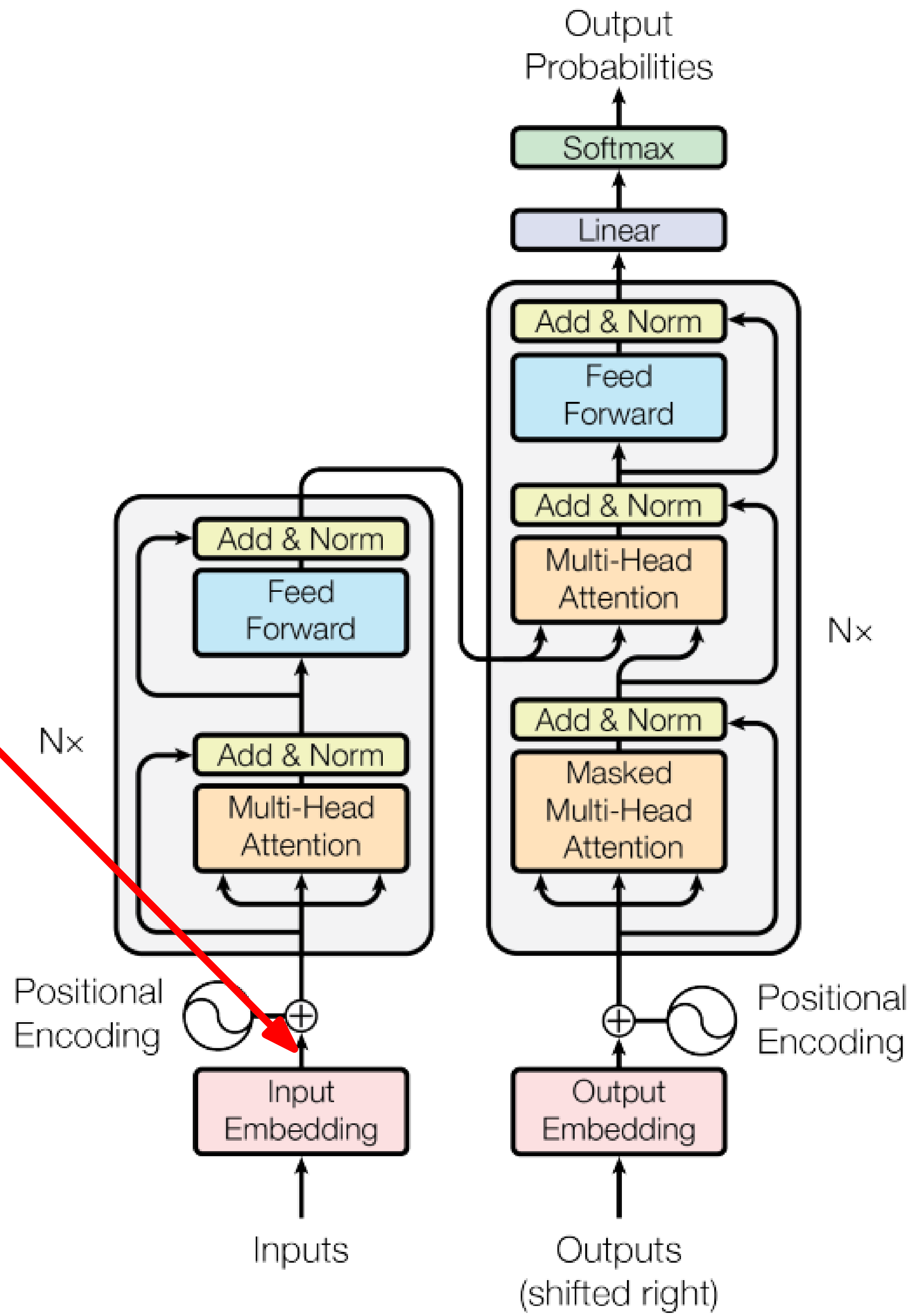

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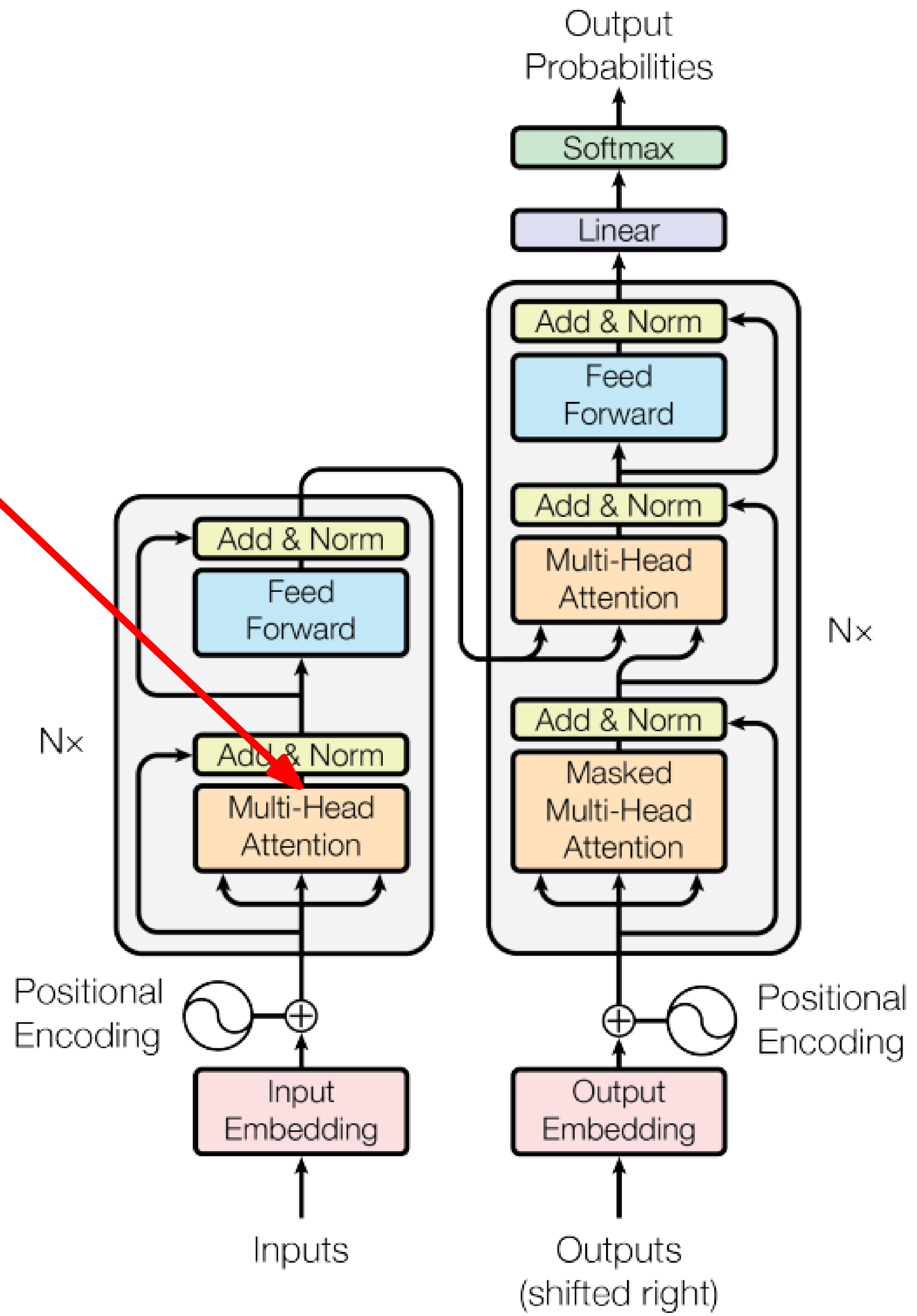

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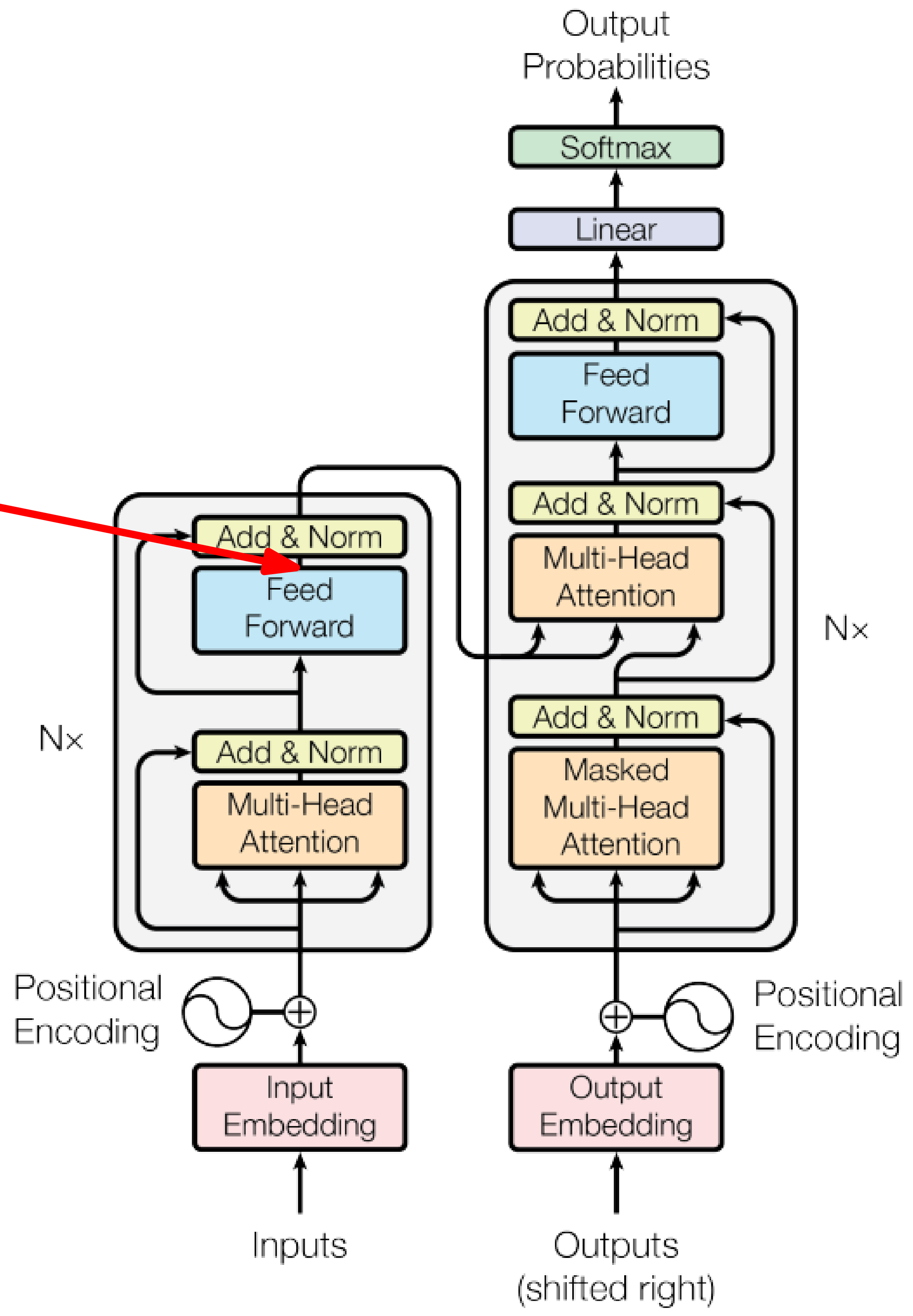

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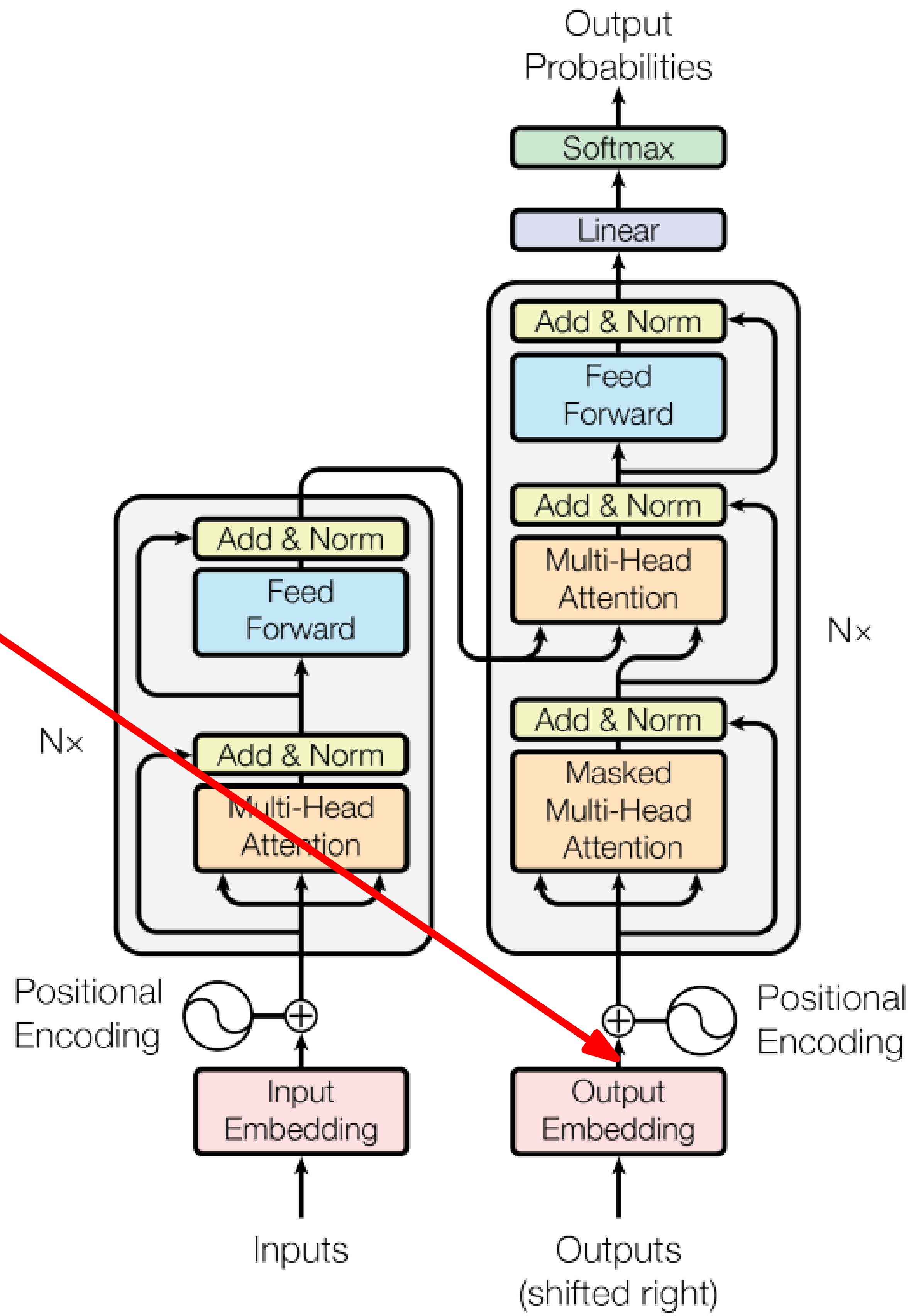

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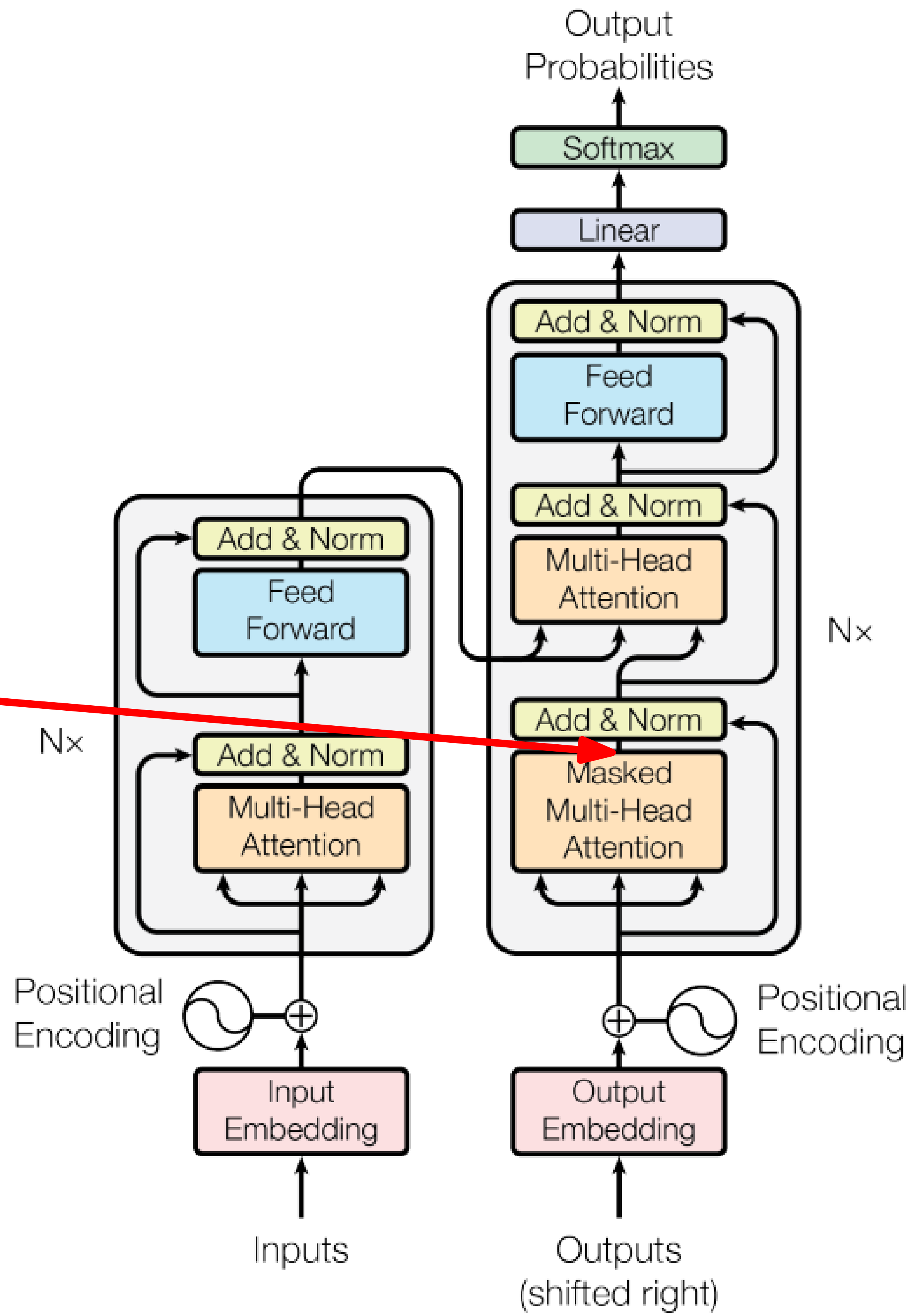

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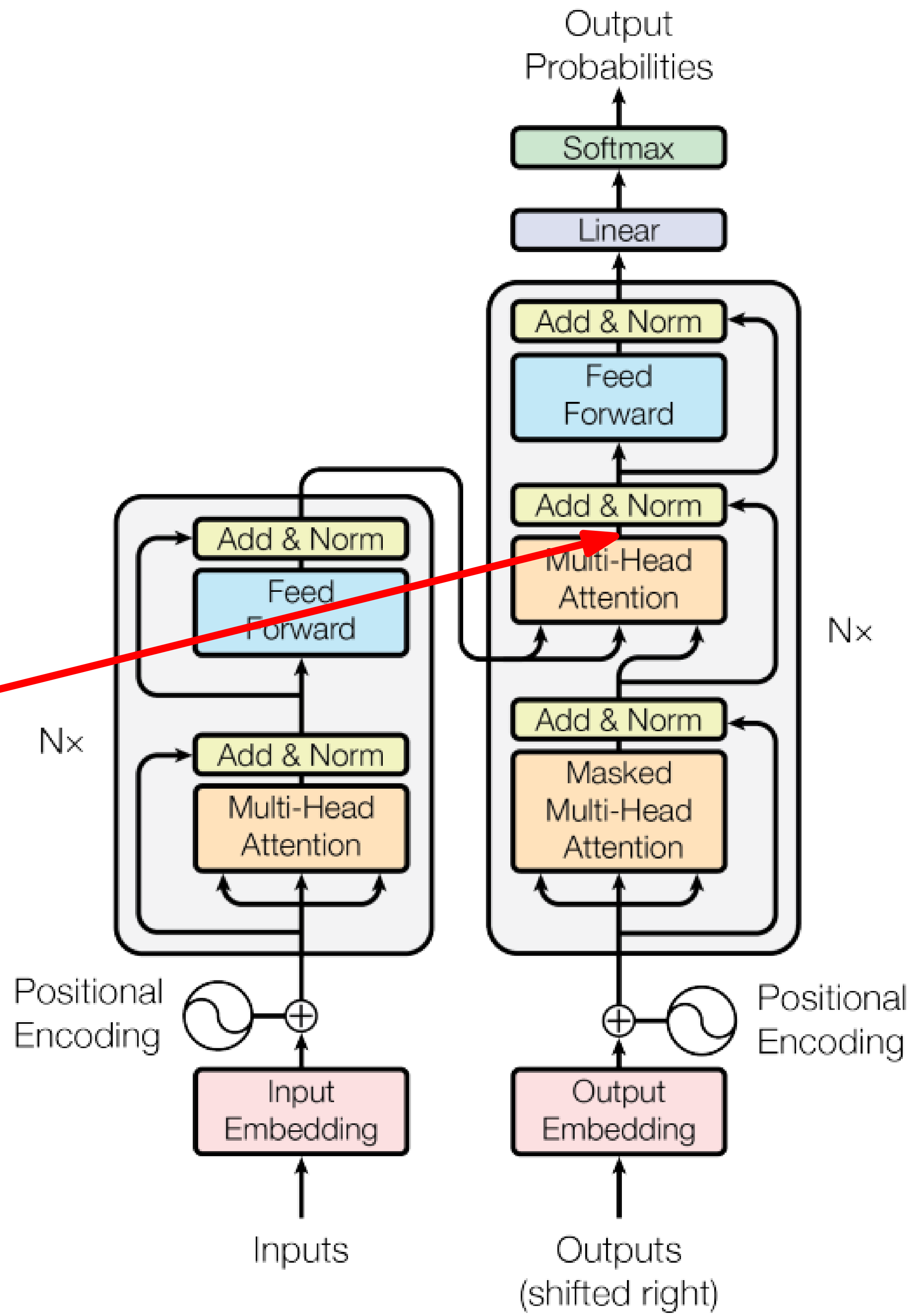

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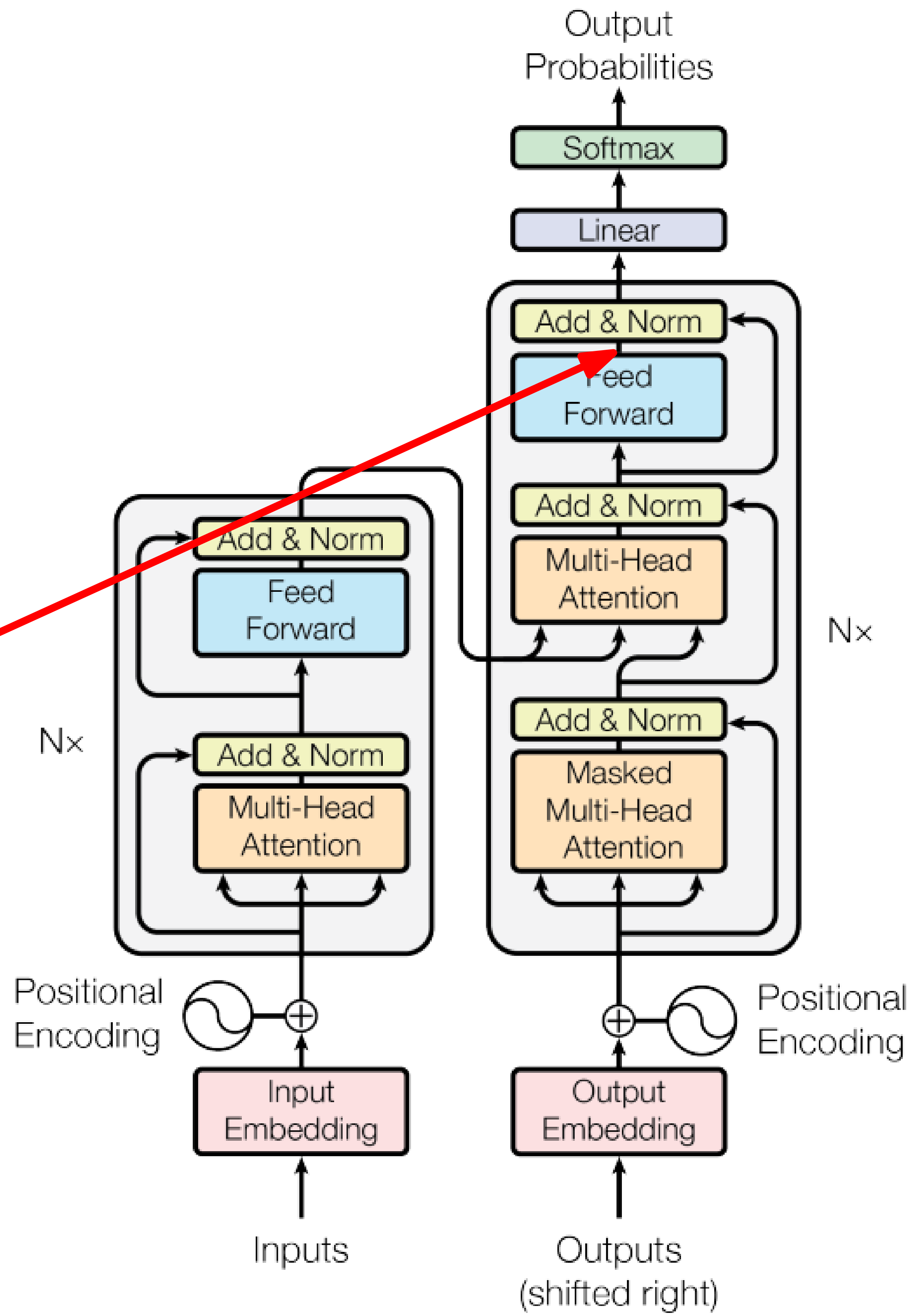

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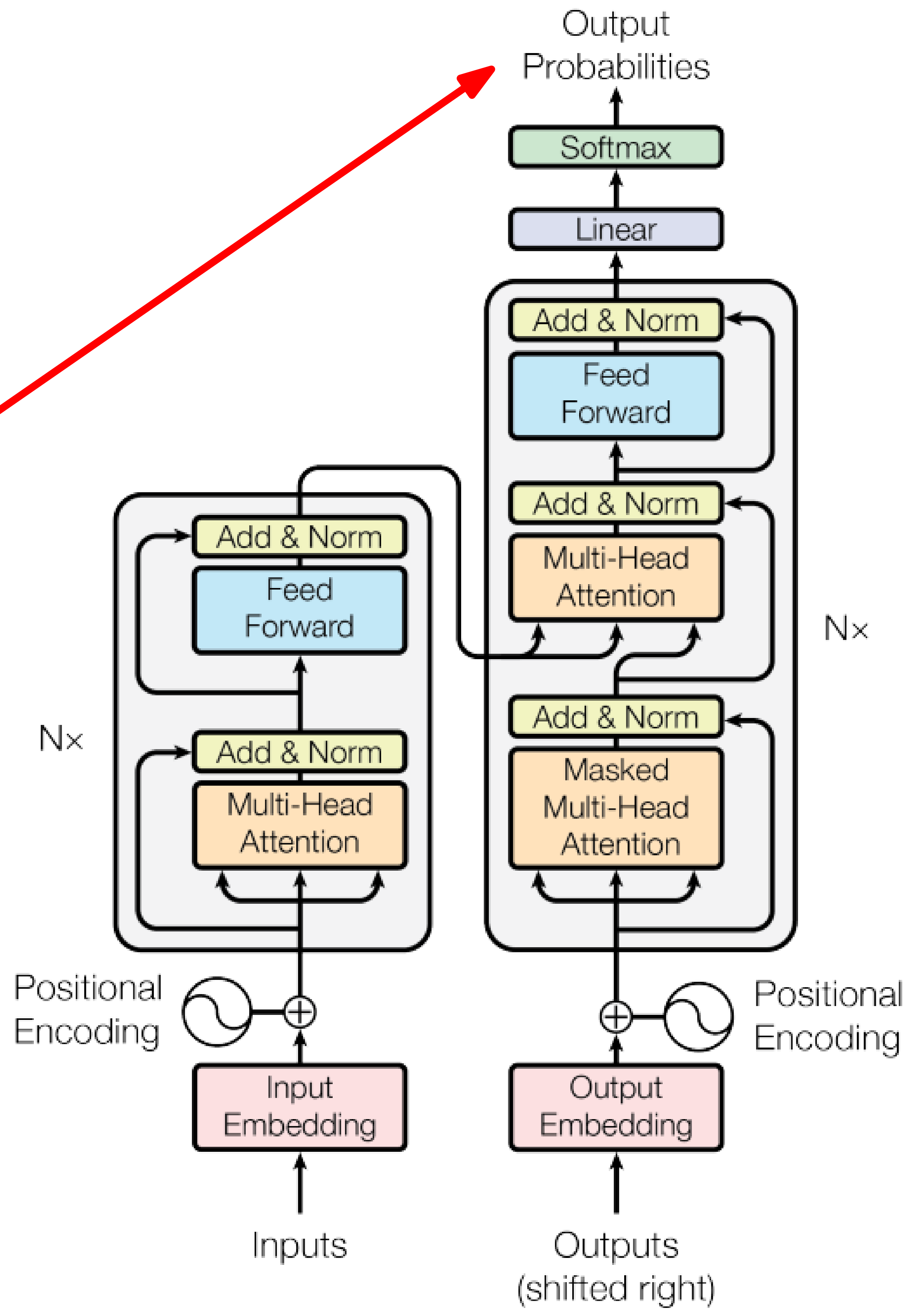

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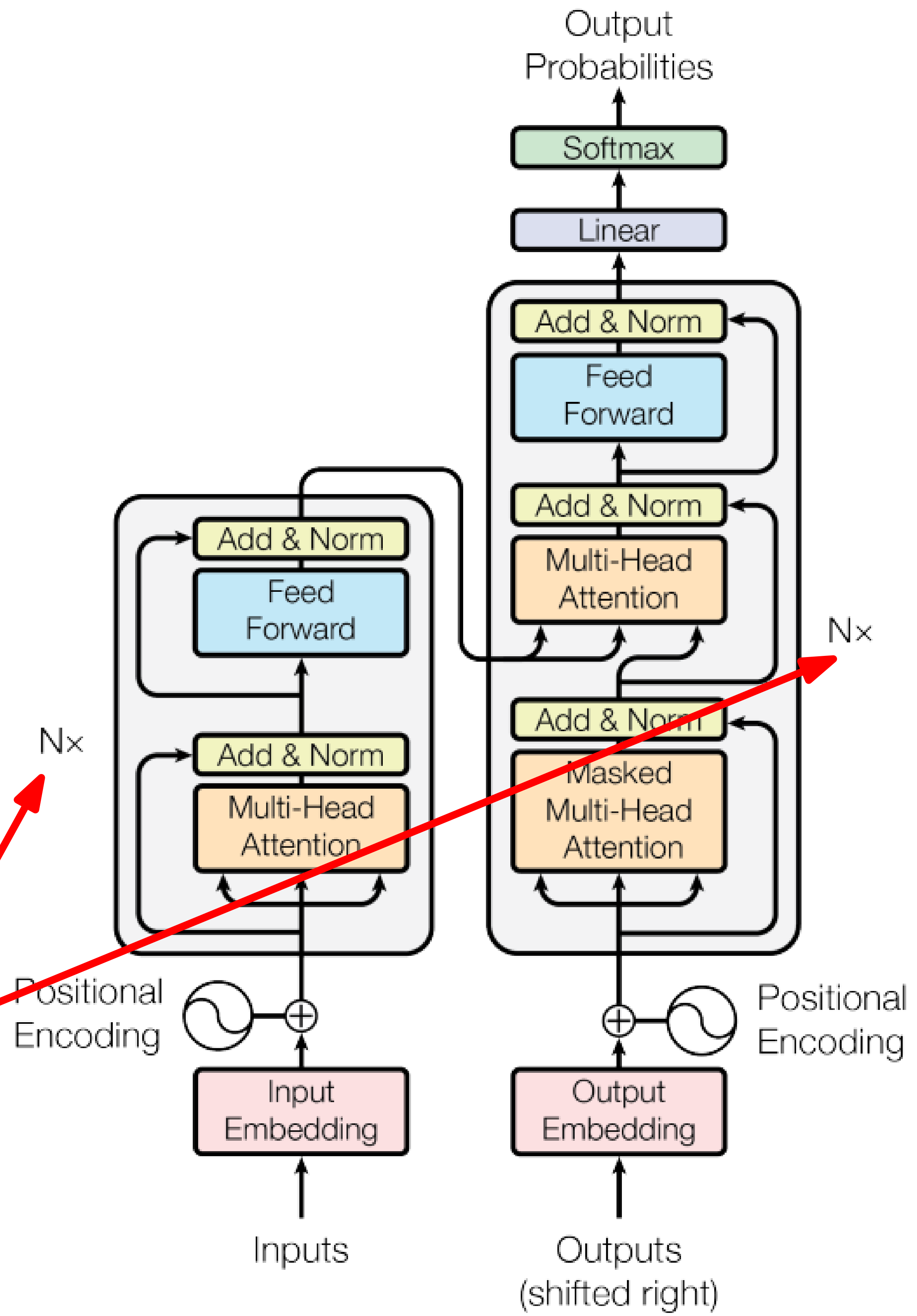
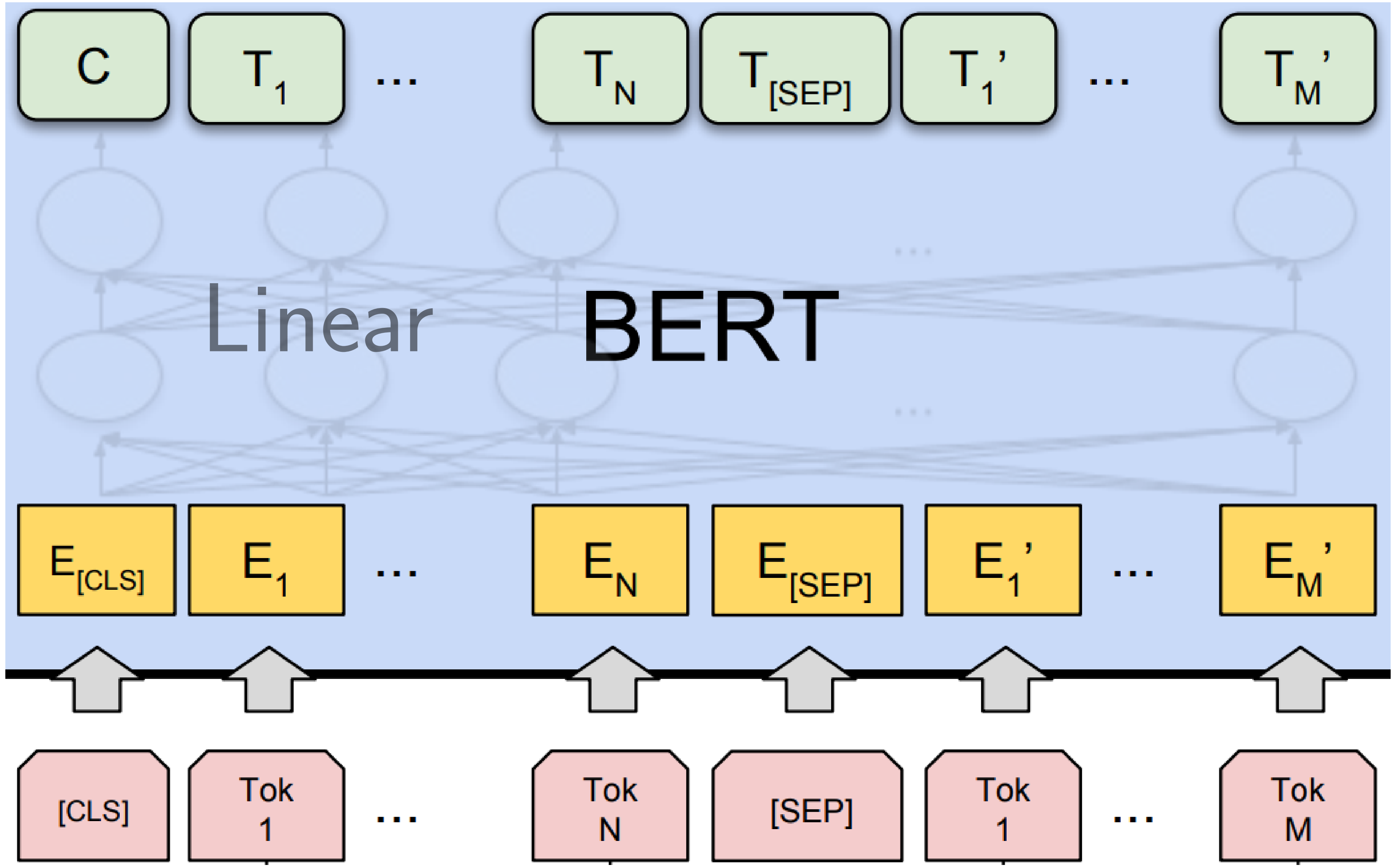


BERT

"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" Devlin et al. 2018



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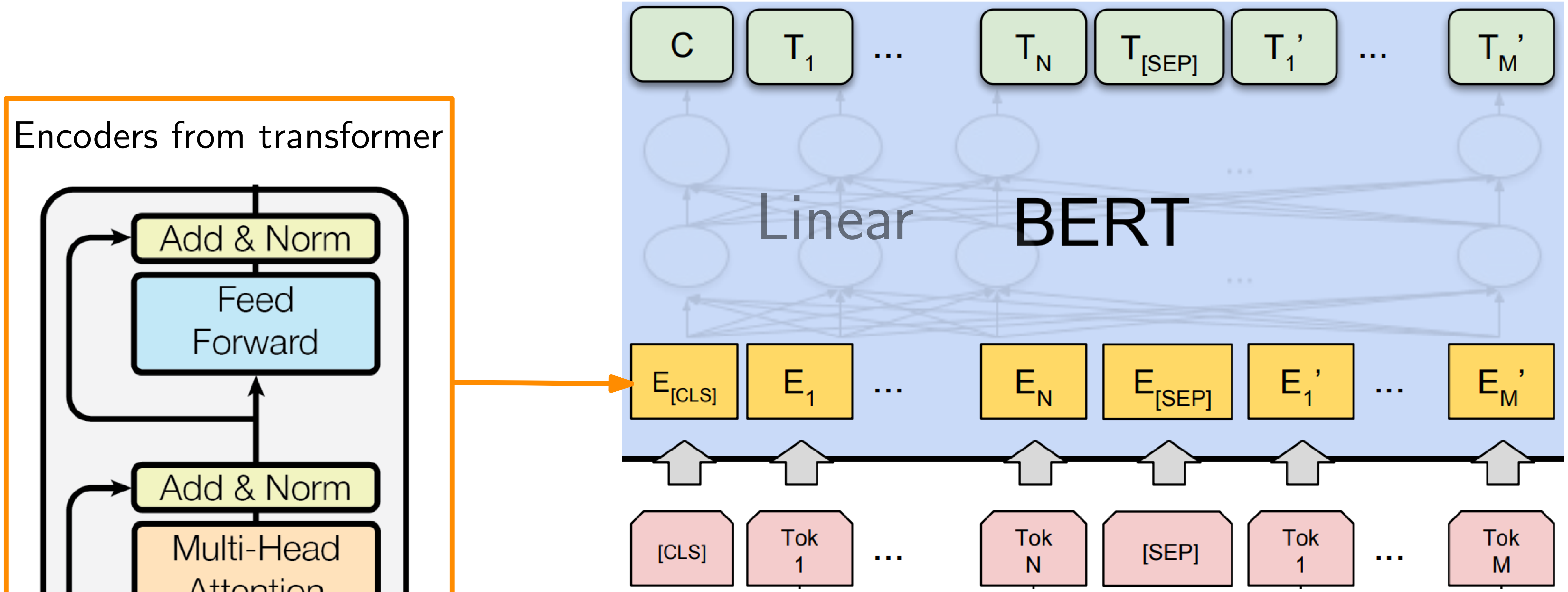

Bidirectional
Encoder
Representations from
Transformers

BERT

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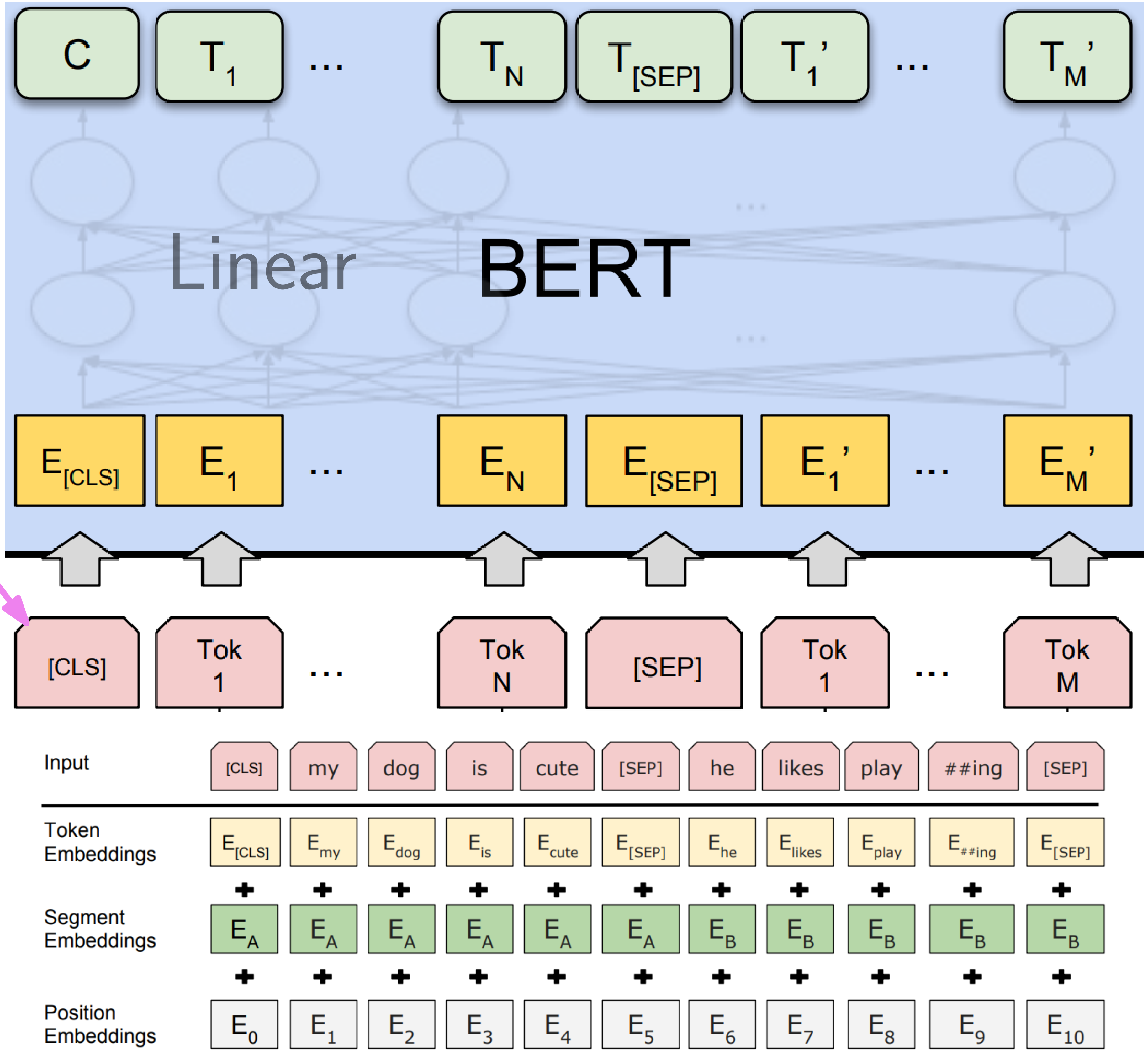
The input embeddings are the sum of the token, segment and position embeddings

There are two special tokens:
[SEP] – it's used to seperate sentences
[CLS] – its corresponding output token is used as agregate representation



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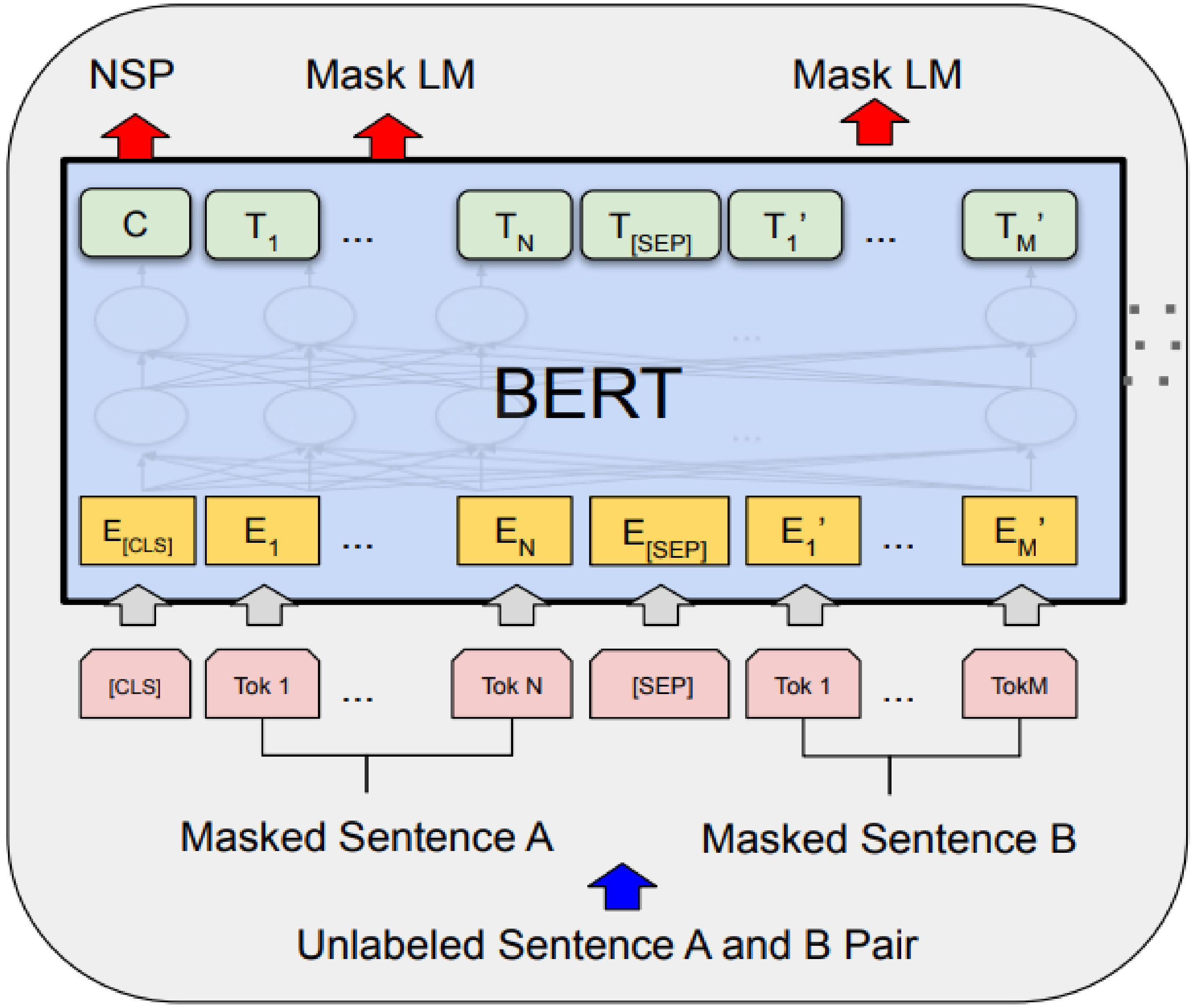

Pre-training

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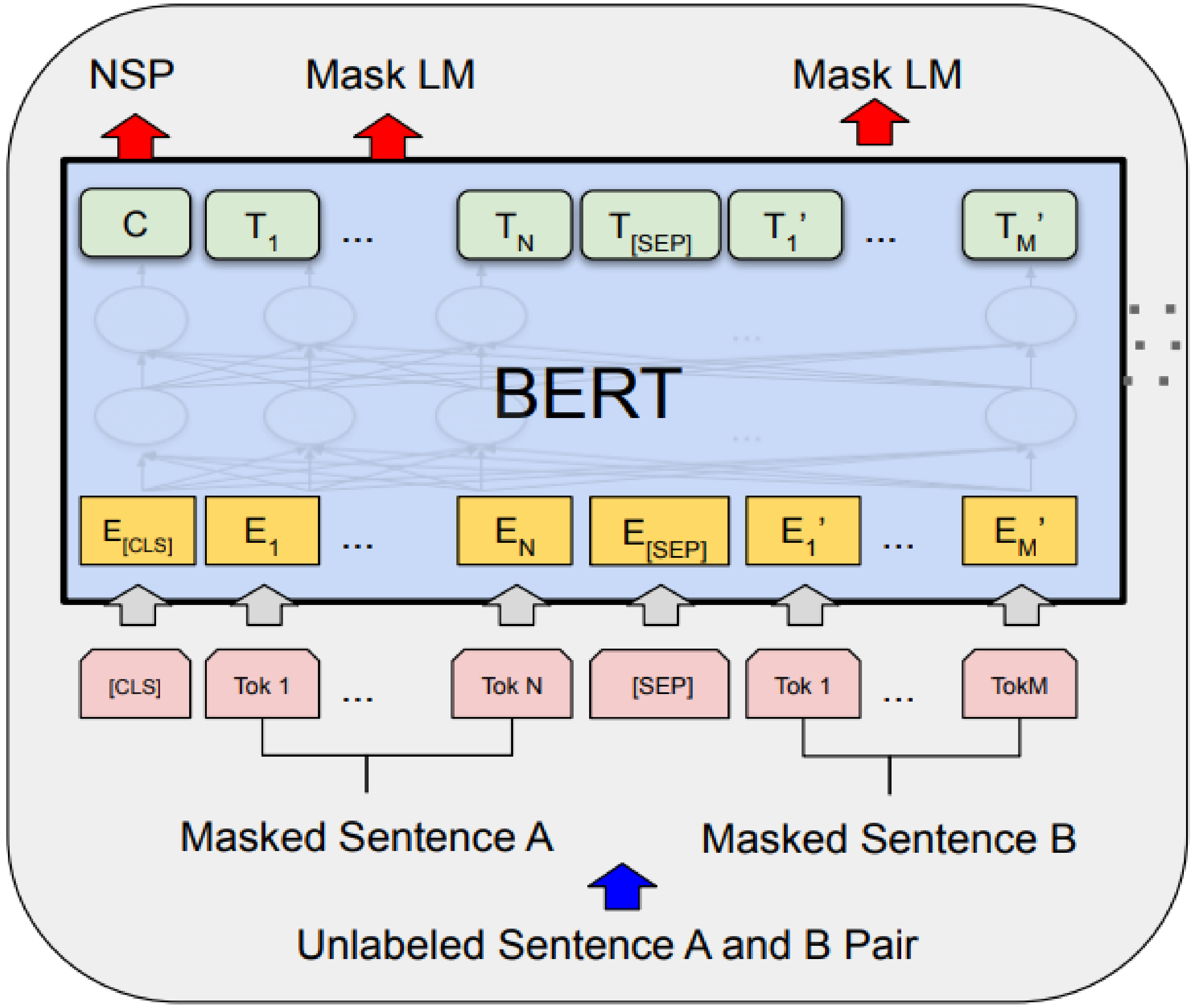

Pre-training

We pre-train the model using two unsupervised tasks.

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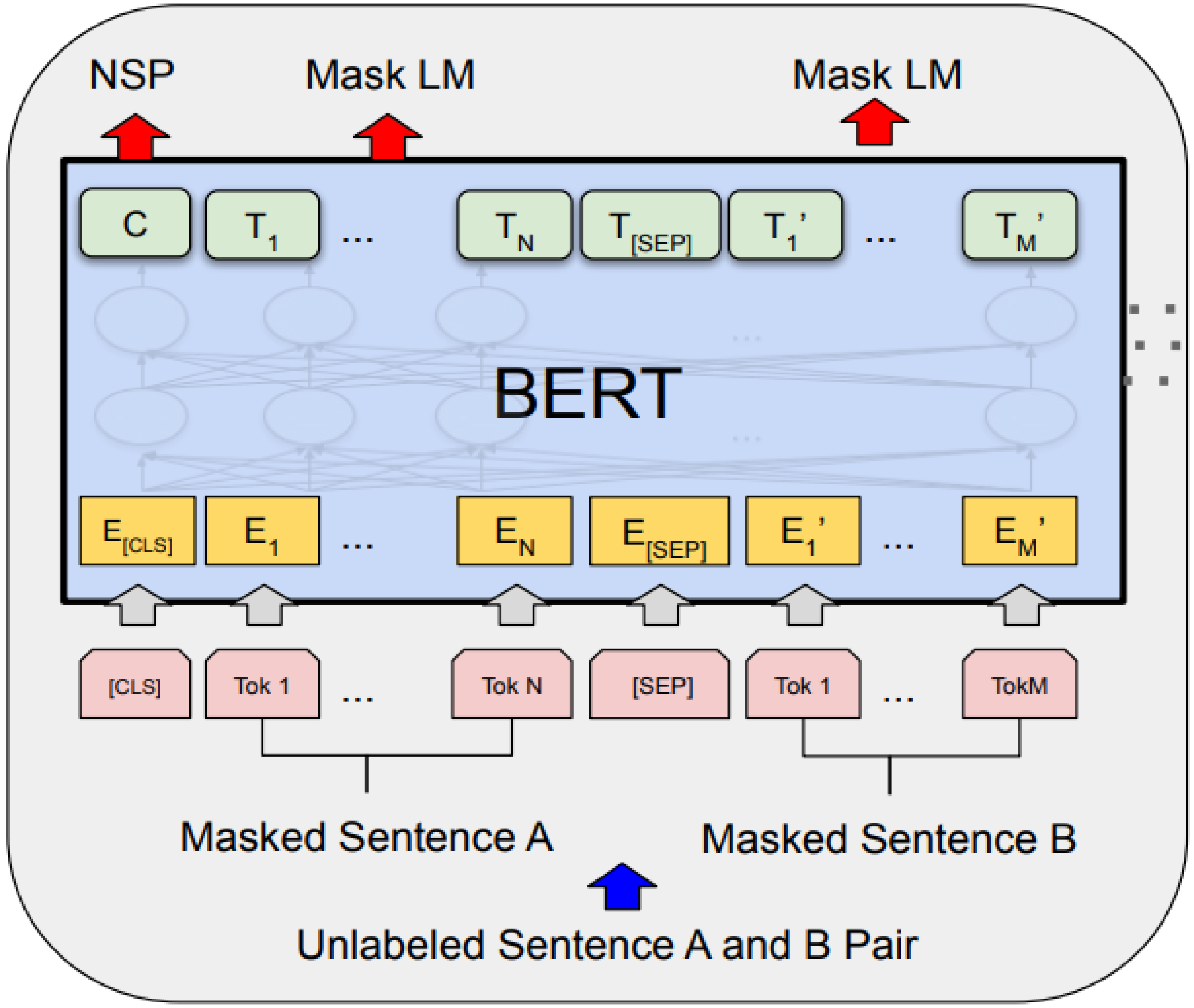

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We pre-train the model using two unsupervised tasks.

Task 1: Masked LM

Mask some percentage of the input tokens at random, and then predict those masked tokens.

To mitigate mismatch between pre-training and fine-tuning replace some `[MASK]` tokens with random tokens.

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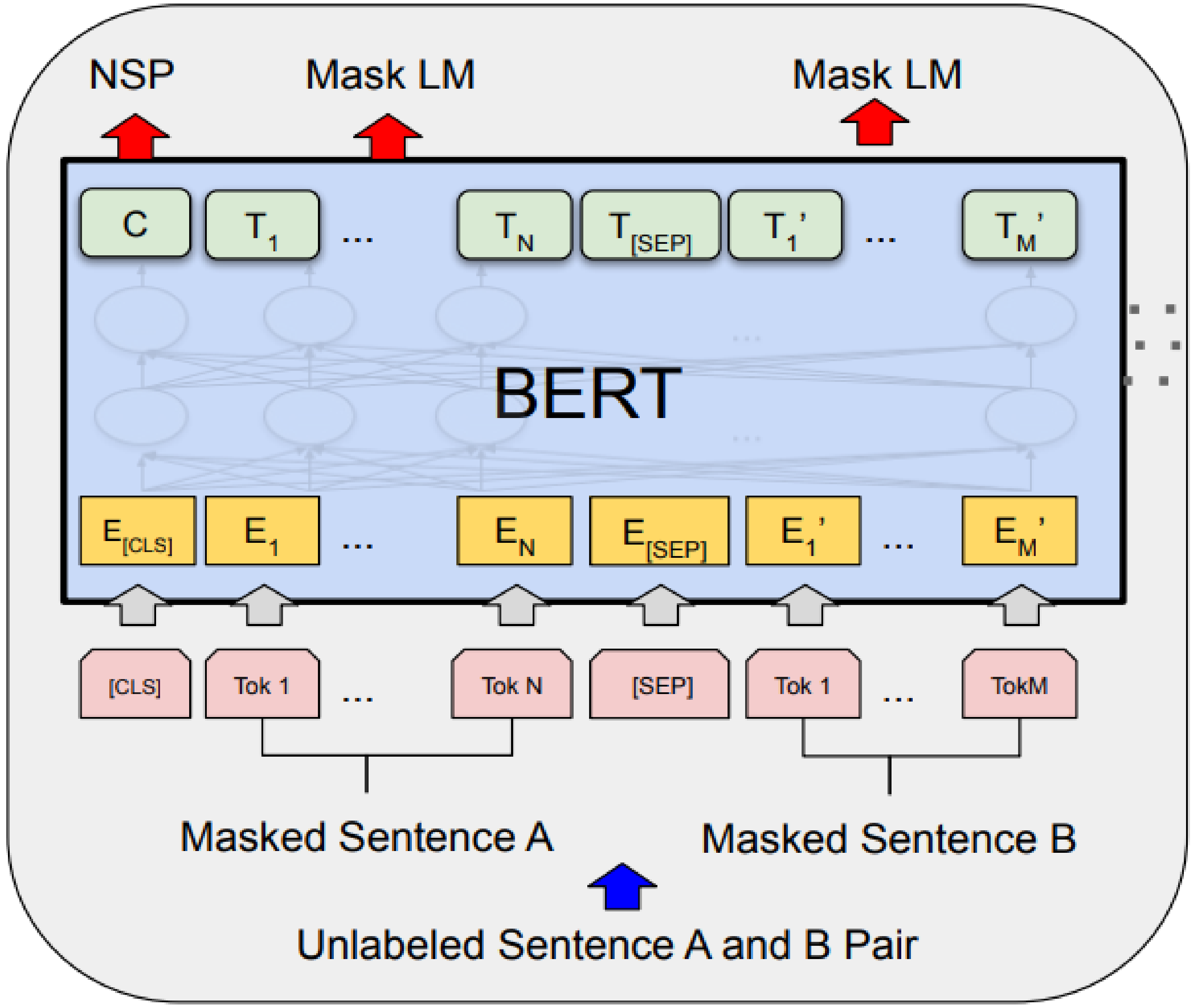

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Task 2: Next Sentence Prediction (NSP)

Let the sentence `B` be the actual next sentence that follows `A` 50% of the time and a random sentence from the corpus another 50% of the time.

Use C to output prediction if `B` follows `A`.

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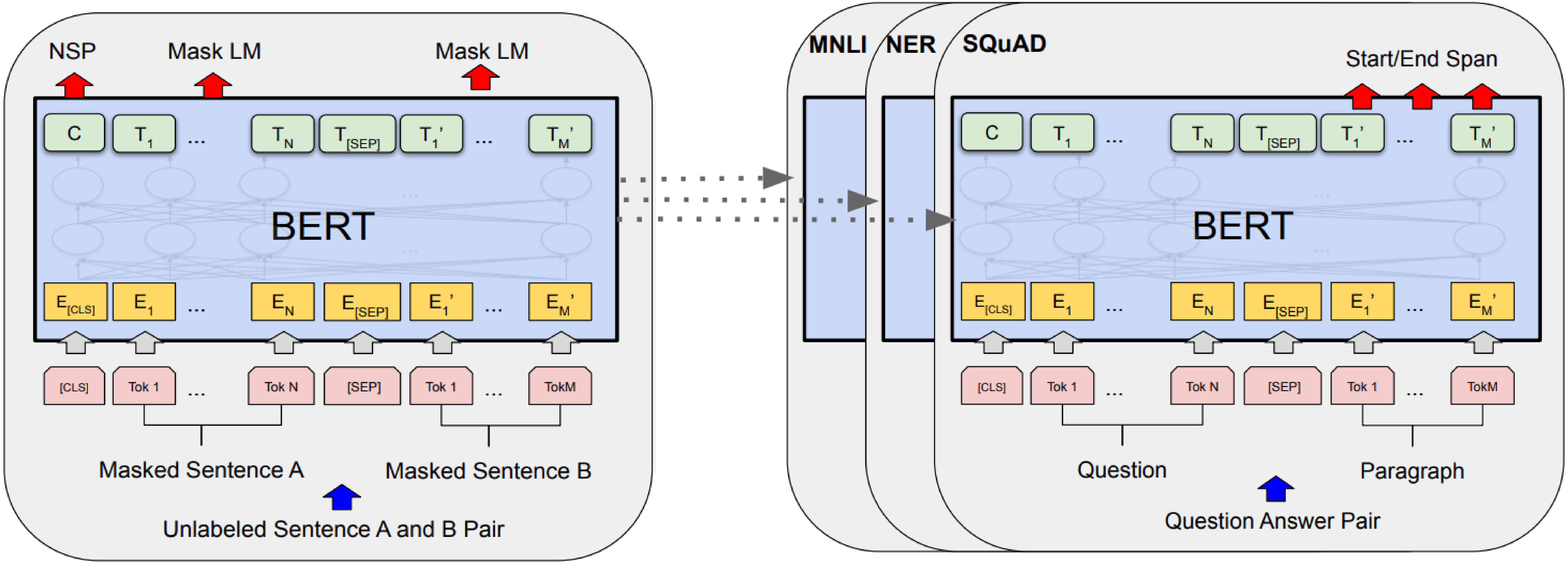

Pre-training

Fine-Tuning

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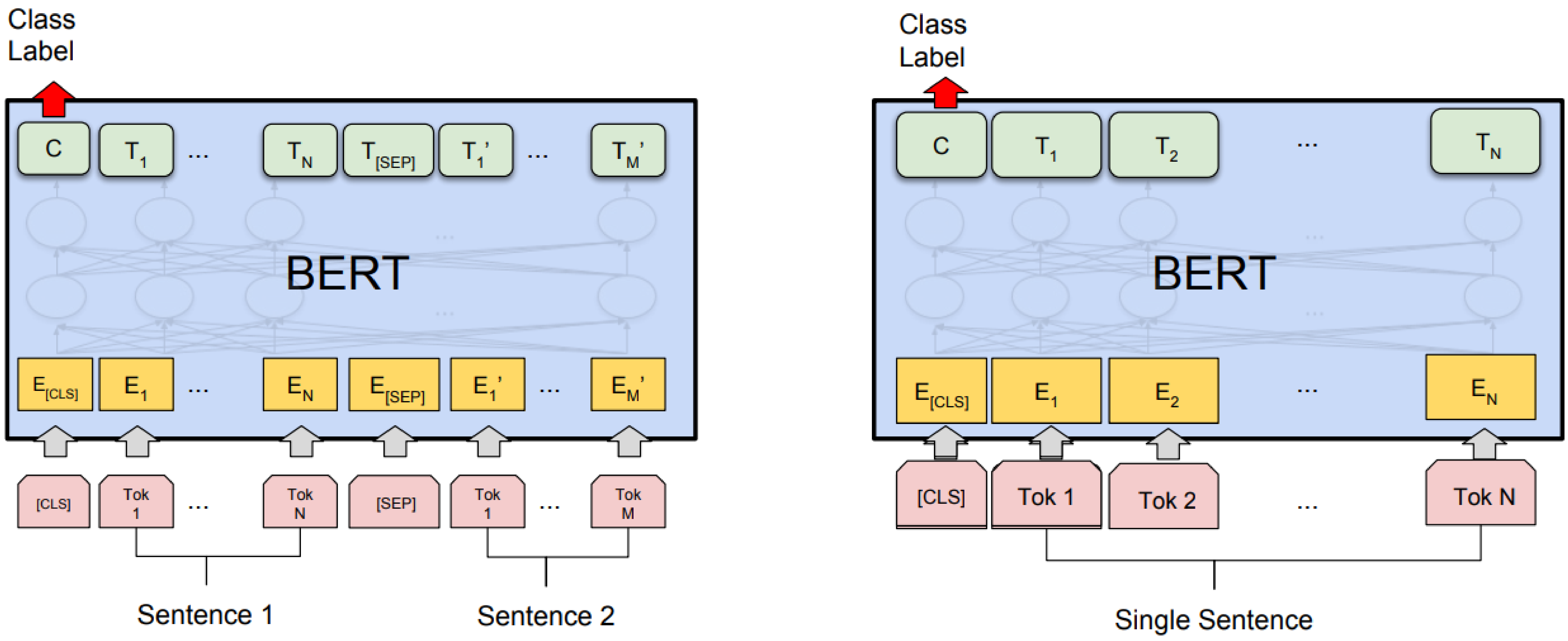

(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

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

BERT

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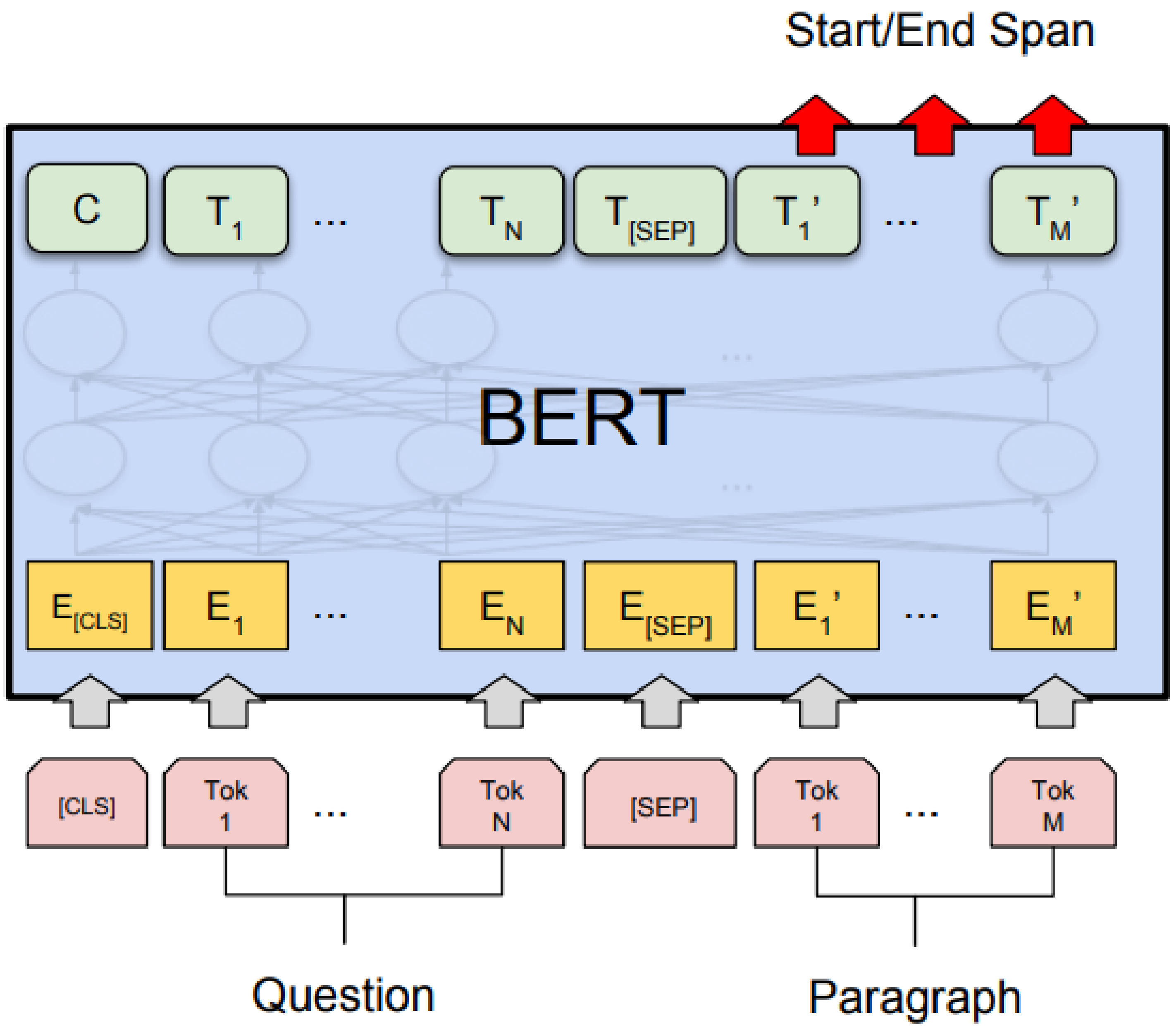
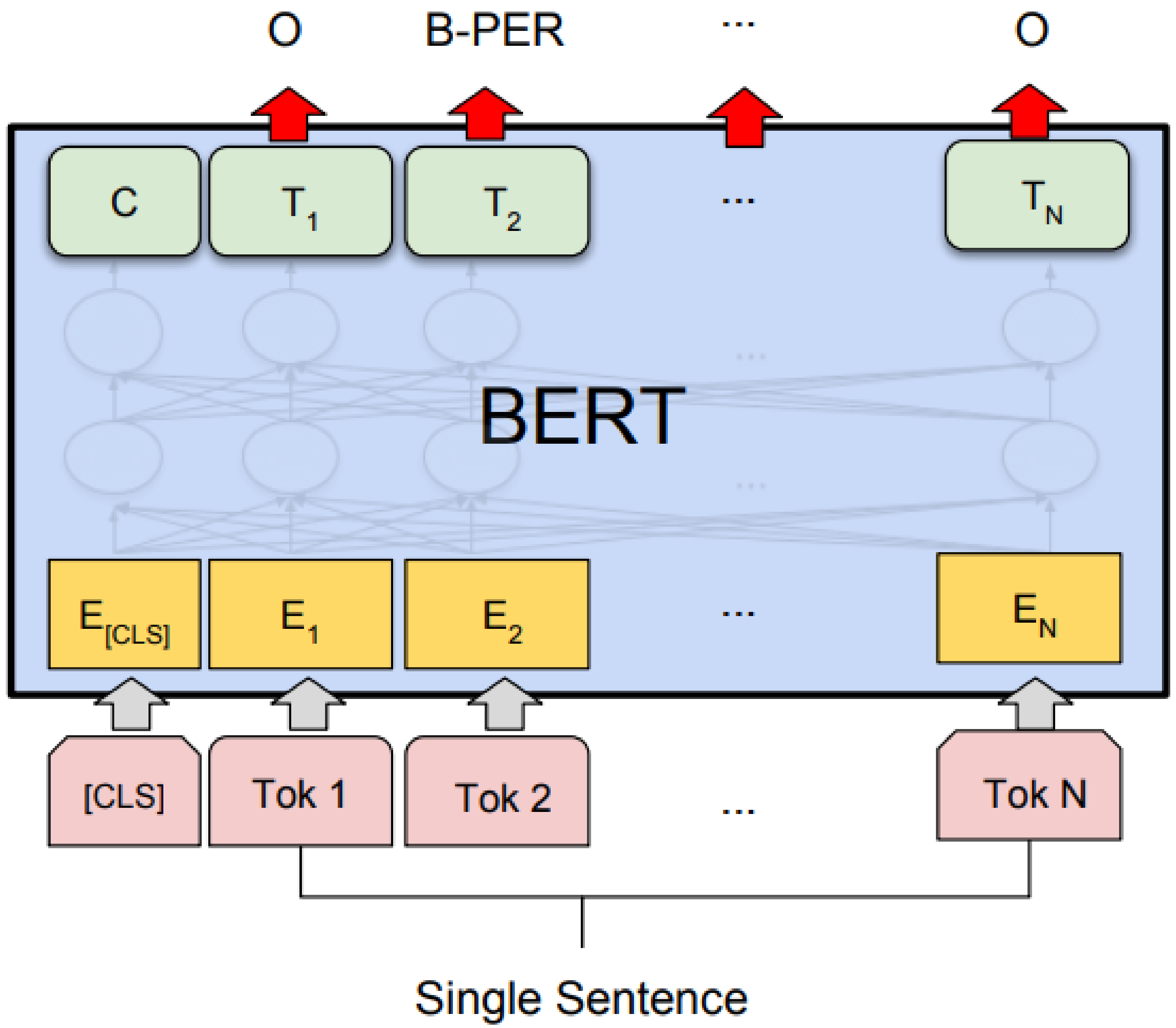


(c) Question Answering Tasks:
SQuAD v1.1



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

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New state-of-the-art results on 11 NLP tasks

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different

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System	Dev EM	Dev F1	Test EM	Test F1
Top Leaderboard Systems (Dec 10th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.5
Published				
BiDAF+ELMo (Single)	-	85.6	-	85.8
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$\text{BERT}_{\text{BASE}}$ (Single)	80.8	88.5	-	-
$\text{BERT}_{\text{LARGE}}$ (Single)	84.1	90.9	-	-
$\text{BERT}_{\text{LARGE}}$ (Ensemble)	85.8	91.8	-	-
$\text{BERT}_{\text{LARGE}}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
$\text{BERT}_{\text{LARGE}}$ (Ens.+TriviaQA)	**86.2**	**92.2**	**87.4**	**93.2**

Table 2: SQuAD 1.1 results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

System	Dev EM	Dev F1	Test EM	Test F1
Top Leaderboard Systems (Dec 10th, 2018)				
Human	86.3	89.0	86.9	89.5
#1 Single - MIR-MRC (F-Net)	-	-	74.8	78.0
#2 Single - nlnet	-	-	74.2	77.1
Published				
unet (Ensemble)	-	-	71.4	74.9
SLQA+ (Single)	-		71.4	74.4
Ours				
$\text{BERT}_{\text{LARGE}}$ (Single)	78.7	81.9	80.0	83.1

Table 3: SQuAD 2.0 results. We exclude entries that use BERT as one of their components.

System	Dev	Test
ESIM+GloVe	51.9	52.7
ESIM+ELMo	59.1	59.2
OpenAI GPT	-	78.0
$\text{BERT}_{\text{BASE}}$	81.6	-
$\text{BERT}_{\text{LARGE}}$	**86.6**	**86.3**
Human (expert)†	-	85.0
Human (5 annotations)†	-	88.0

: SWAG Dev and Test accuracies. †Human per-
ce is measured with 100 samples, as reported in
the SWAG paper.

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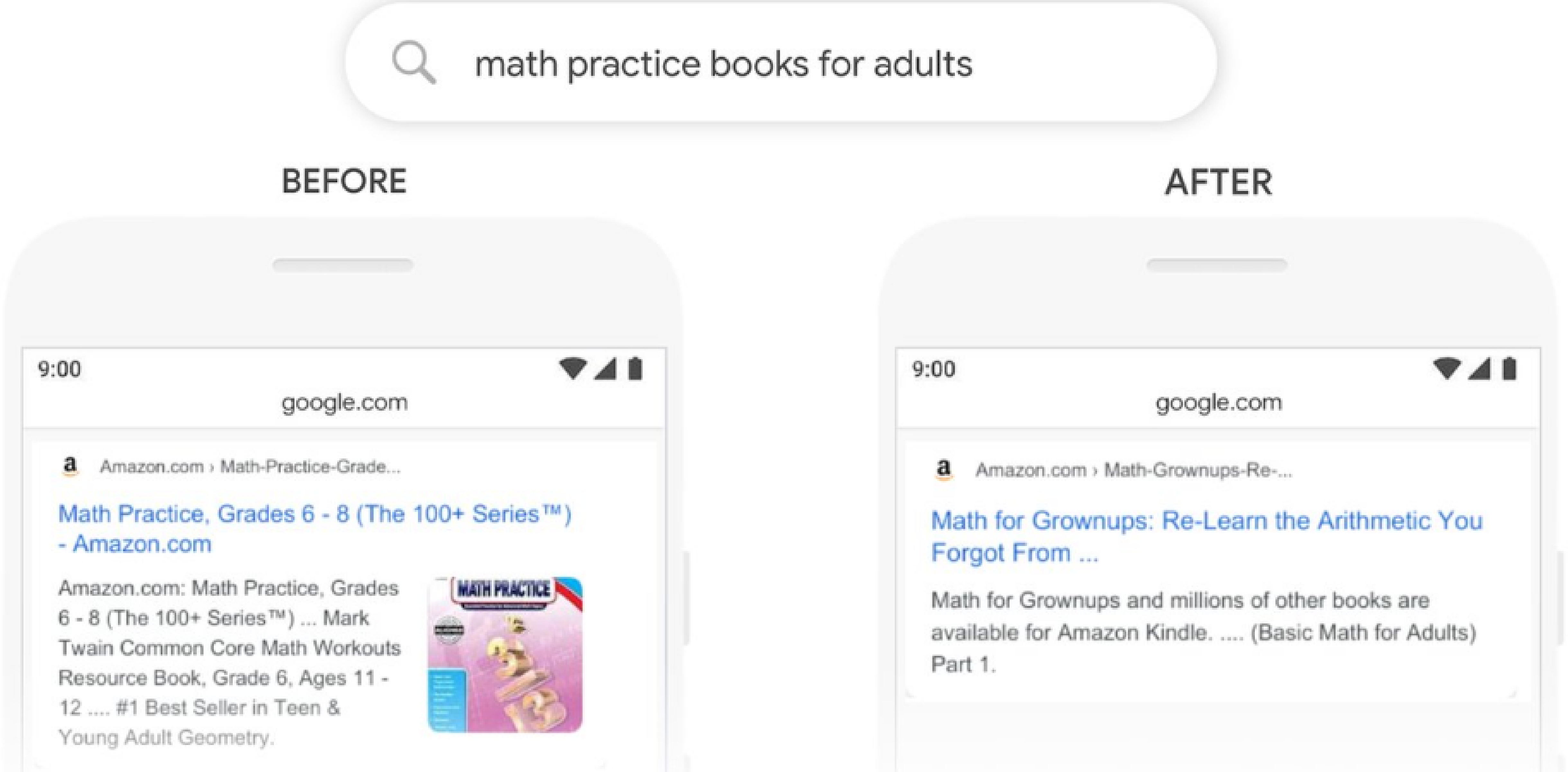
Tasks	Dev Set MNLI-m (Acc)	QNLI (Acc)	MRPC (Acc)	SST-2 (Acc)	SQuAD (F1)
$\text{BERT}_{\text{BASE}}$	84.4	88.4	86.7	92.7	88.5
No NSP	83.9	84.9	86.5	92.6	87.9
LTR & No NSP	82.1	84.3	77.5	92.1	77.8
+ BiLSTM	82.1	84.1	75.7	91.6	84.9

Table 5: Ablation over the pre-training tasks using the $\text{BERT}_{\text{BASE}}$ architecture. "No NSP" is trained without the next sentence prediction task. "LTR & No NSP" is trained as a left-to-right LM without the next sentence prediction, like OpenAI GPT. "+ BiLSTM" adds a randomly initialized BiLSTM on top of the "LTR + No NSP" model during fine-tuning.

BERT

"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" Devlin et al. 2018



"While the previous results page included a book in the 'Young Adult' category, BERT can better understand that 'adult' is being matched out of context, and pick out a more helpful result."

https://blog.google/products/search/search-language-understanding-bert/

Questions