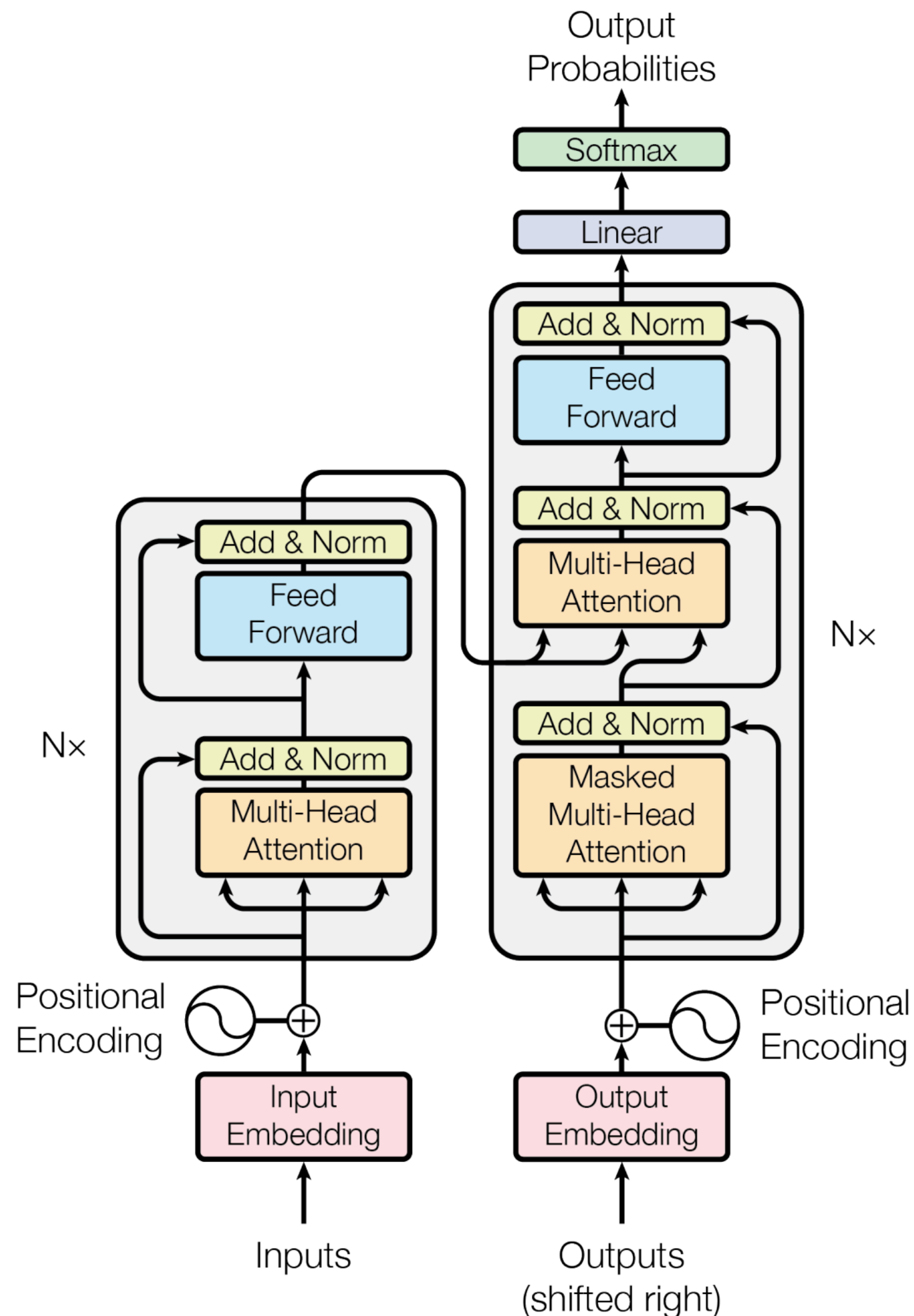


# Transformers for MT



# Transformers



- ▶ Encoder and decoder are both transformers
- ▶ Decoder consumes the previous generated token (and attends to input), but has *no recurrent state*



# Transformers

- ▶ If we let self attention look at the whole sentence, can access anything in  $O(1)$
- ▶ Quadratic in sentence length

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types.  $n$  is the sequence length,  $d$  is the representation dimension,  $k$  is the kernel size of convolutions and  $r$  the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(\log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$



# Transformers

Model	BLEU	
	EN-DE	EN-FR
ByteNet [18]	23.75	
Deep-Att + PosUnk [39]		39.2
GNMT + RL [38]	24.6	39.92
ConvS2S [9]	25.16	40.46
MoE [32]	26.03	40.56
Deep-Att + PosUnk Ensemble [39]		40.4
GNMT + RL Ensemble [38]	26.30	41.16
ConvS2S Ensemble [9]	26.36	<b>41.29</b>
Transformer (base model)	27.3	38.1
Transformer (big)	<b>28.4</b>	<b>41.8</b>

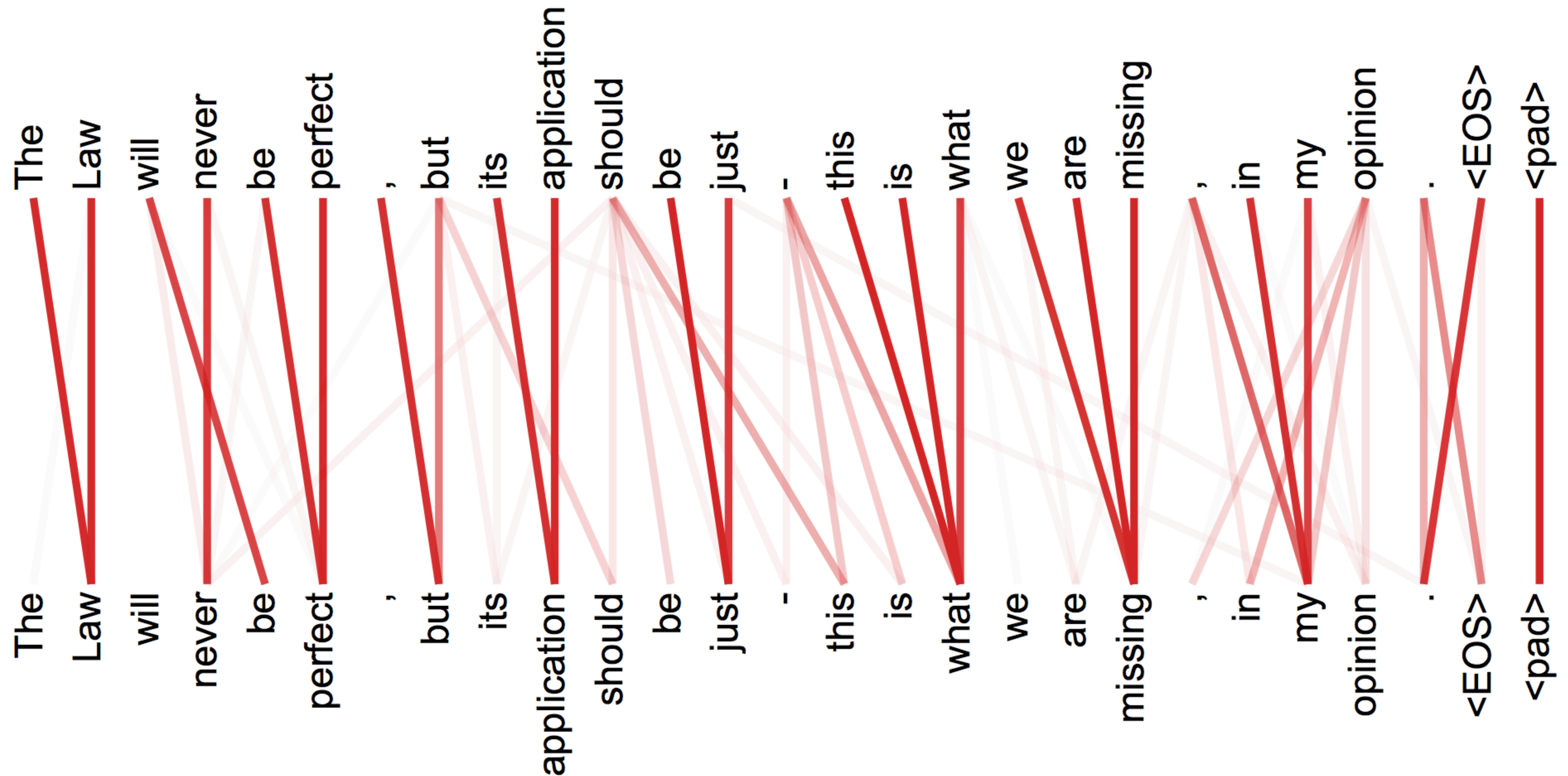
- Big = 6 layers, 1000 dim for each token, 16 heads, base = 6 layers + other params halved

Vaswani et al. (2017)



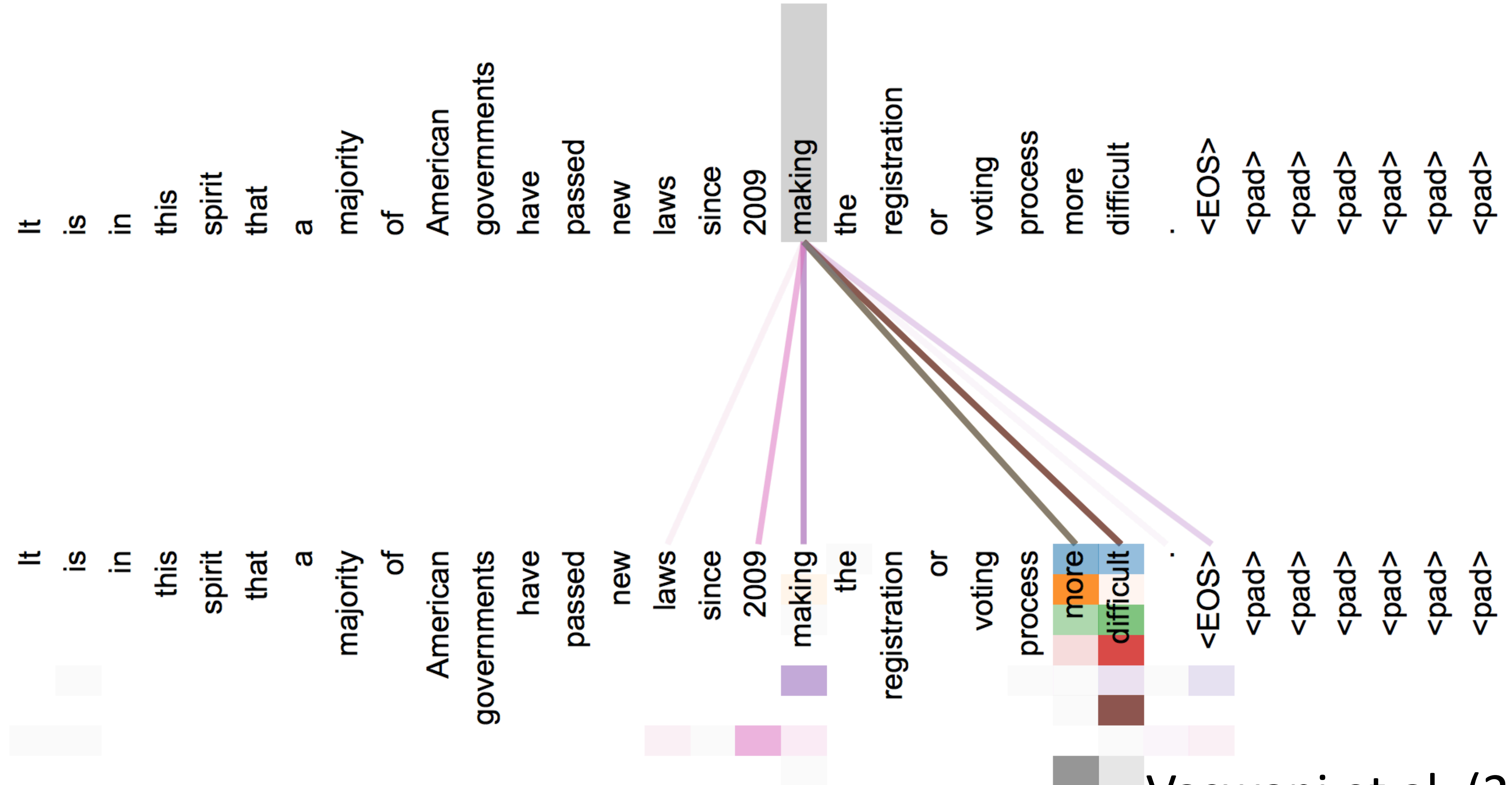


# Visualization: low layer (one head)





# Visualization: high layer (several heads)



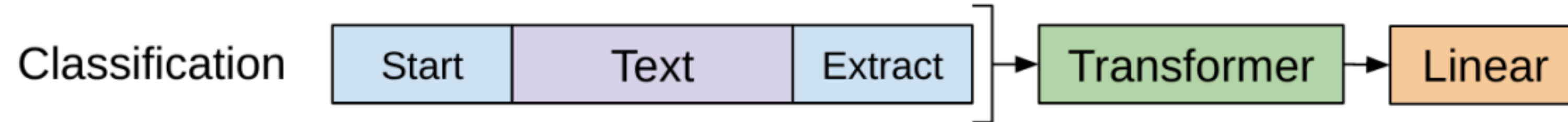
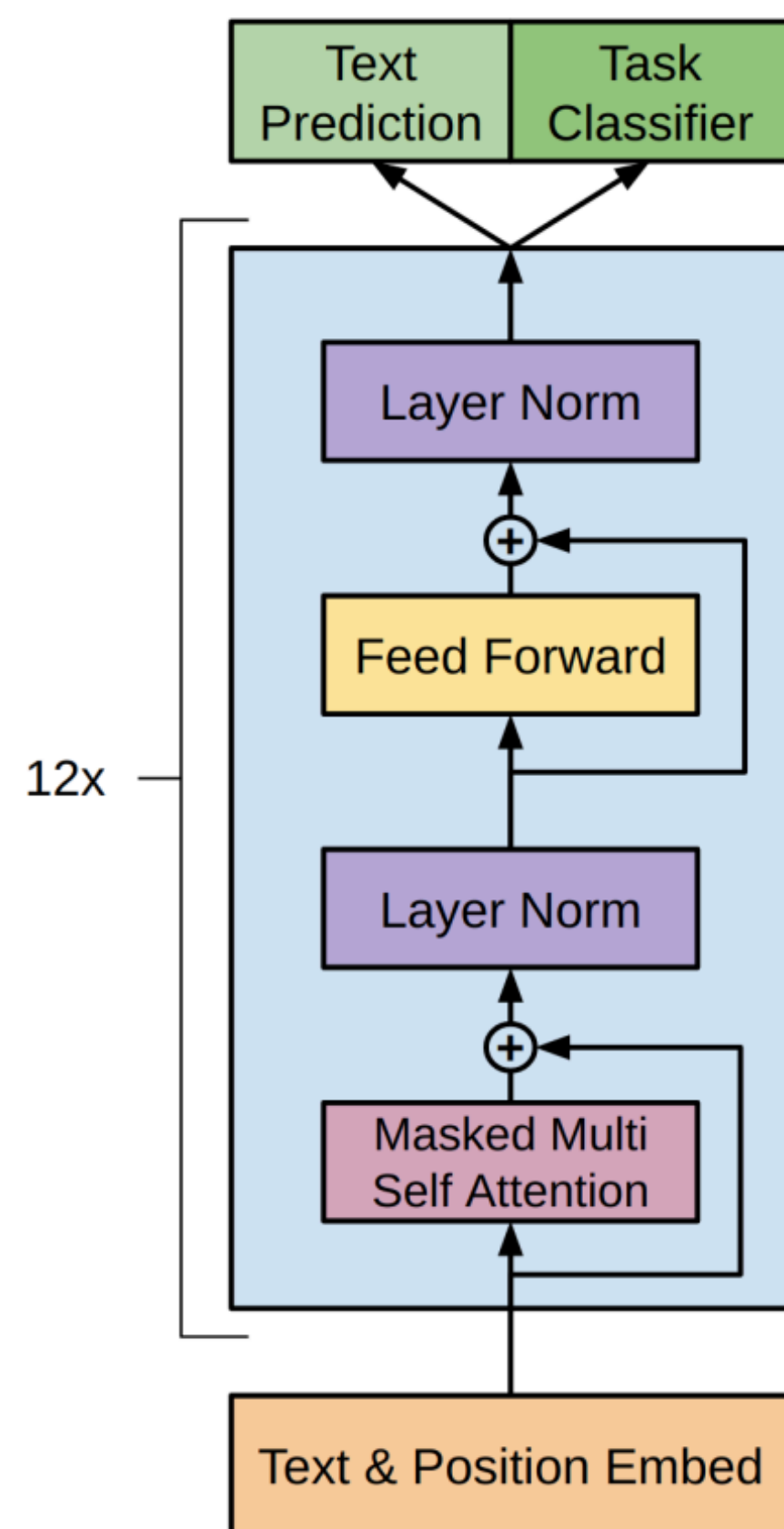
Vaswani et al. (2017)

GPT/BERT



# OpenAI GPT

- ▶ “ELMo with transformers”
- ▶ Fine-tune transformer parameters on the end task



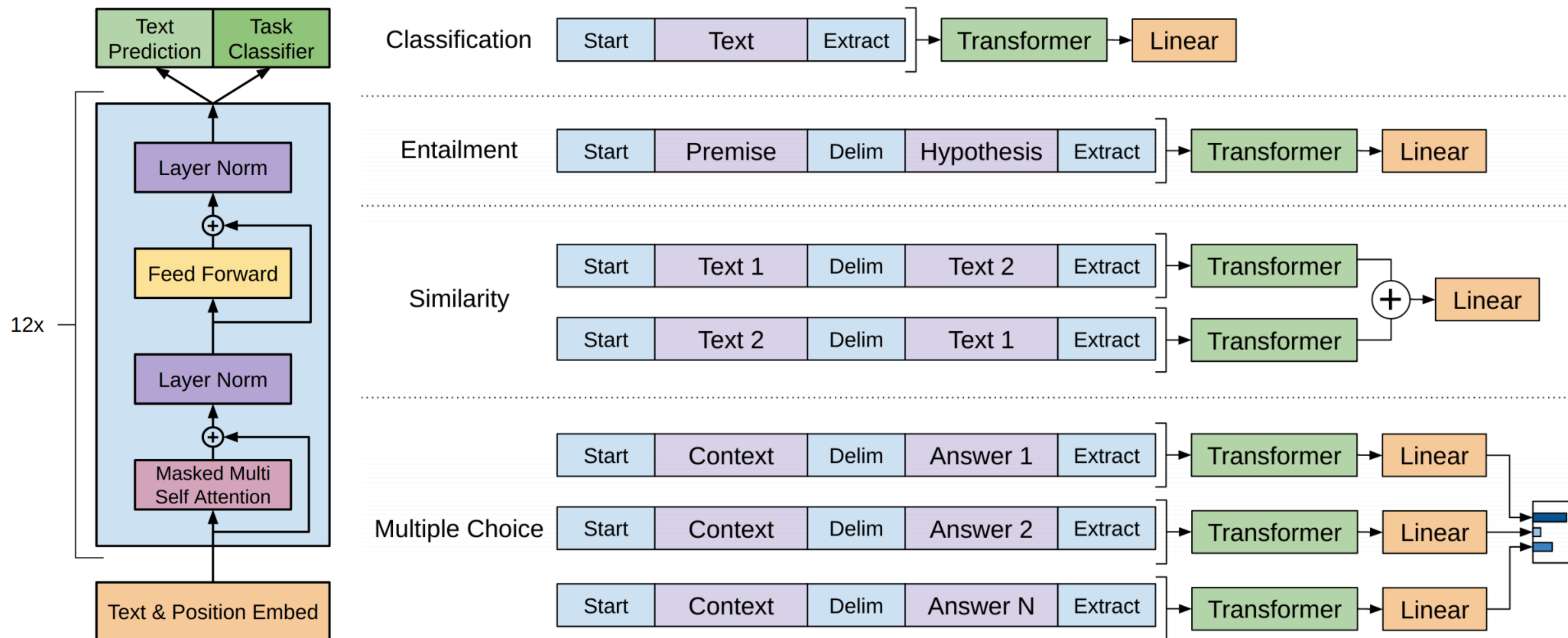
- ▶ Assignment 4 architecture but with a pretrained transformer model





# OpenAI GPT

- ▶ “ELMo with transformers”
- ▶ Fine-tune transformer parameters on the end task



Radford et al. (2018)



# OpenAI GPT

Method	Classification		Semantic Similarity			GLUE
	CoLA (mc)	SST2 (acc)	MRPC (F1)	STSB (pc)	QQP (F1)	
Sparse byte mLSTM [16]	-	<b>93.2</b>	-	-	-	-
TF-KLD [23]	-	-	<b>86.0</b>	-	-	-
ECNU (mixed ensemble) [60]	-	-	-	<u>81.0</u>	-	-
Single-task BiLSTM + ELMo + Attn [64]	<u>35.0</u>	90.2	80.2	55.5	<u>66.1</u>	64.8
Multi-task BiLSTM + ELMo + Attn [64]	18.9	91.6	83.5	72.8	63.3	<u>68.9</u>
Finetuned Transformer LM (ours)	<b>45.4</b>	91.3	82.3	<b>82.0</b>	<b>70.3</b>	<b>72.8</b>

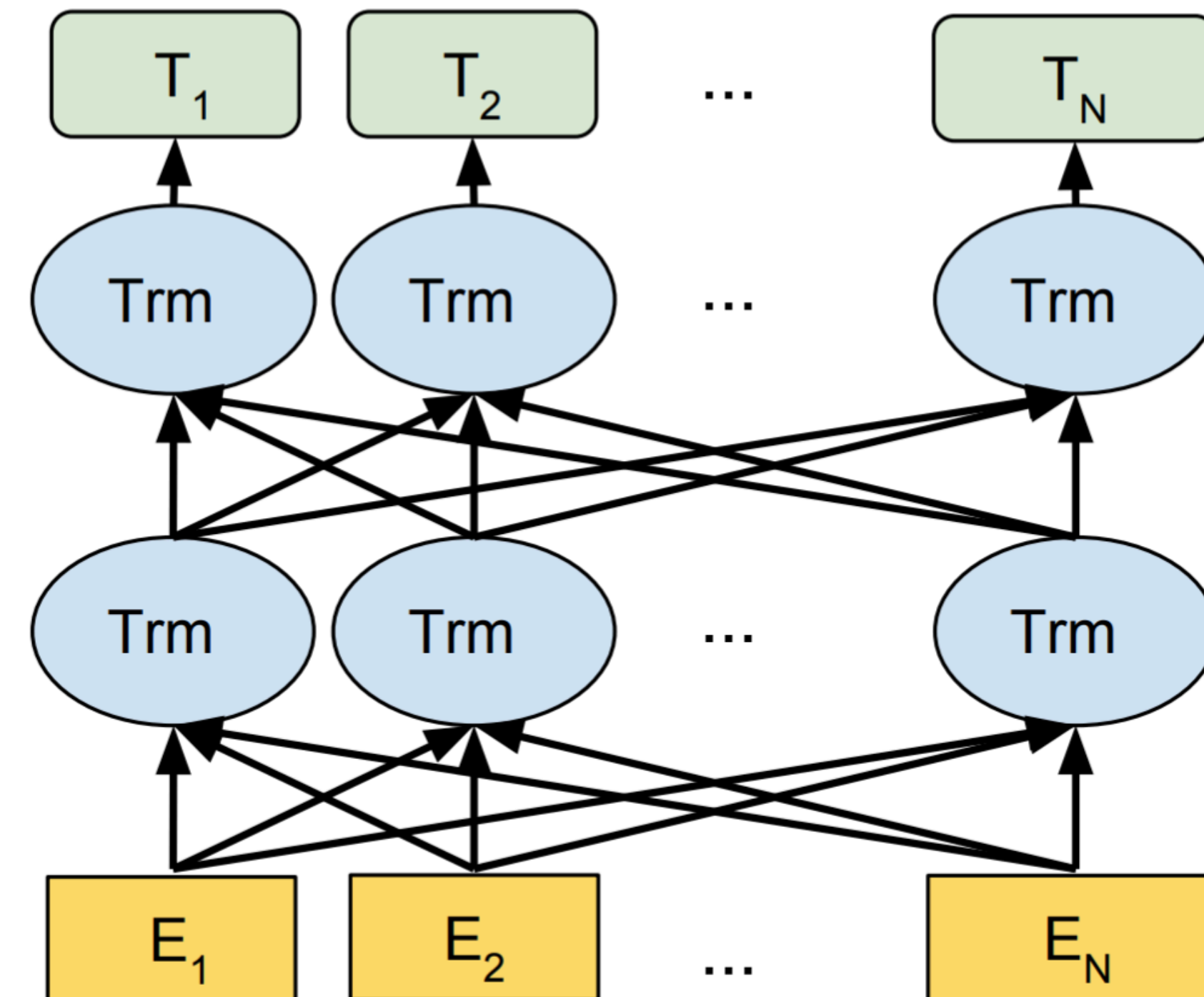
► Better than ELMo

Radford et al. (2018)



# BERT

- ▶ Two-sided Transformer model
- ▶ Big model: 24 layers, word dims of 1024, 16 heads
- ▶ Small model: 3/4 of this
- ▶ Problem: how to do LM when you look at the whole input?  
Predicting T's from E's is trivial

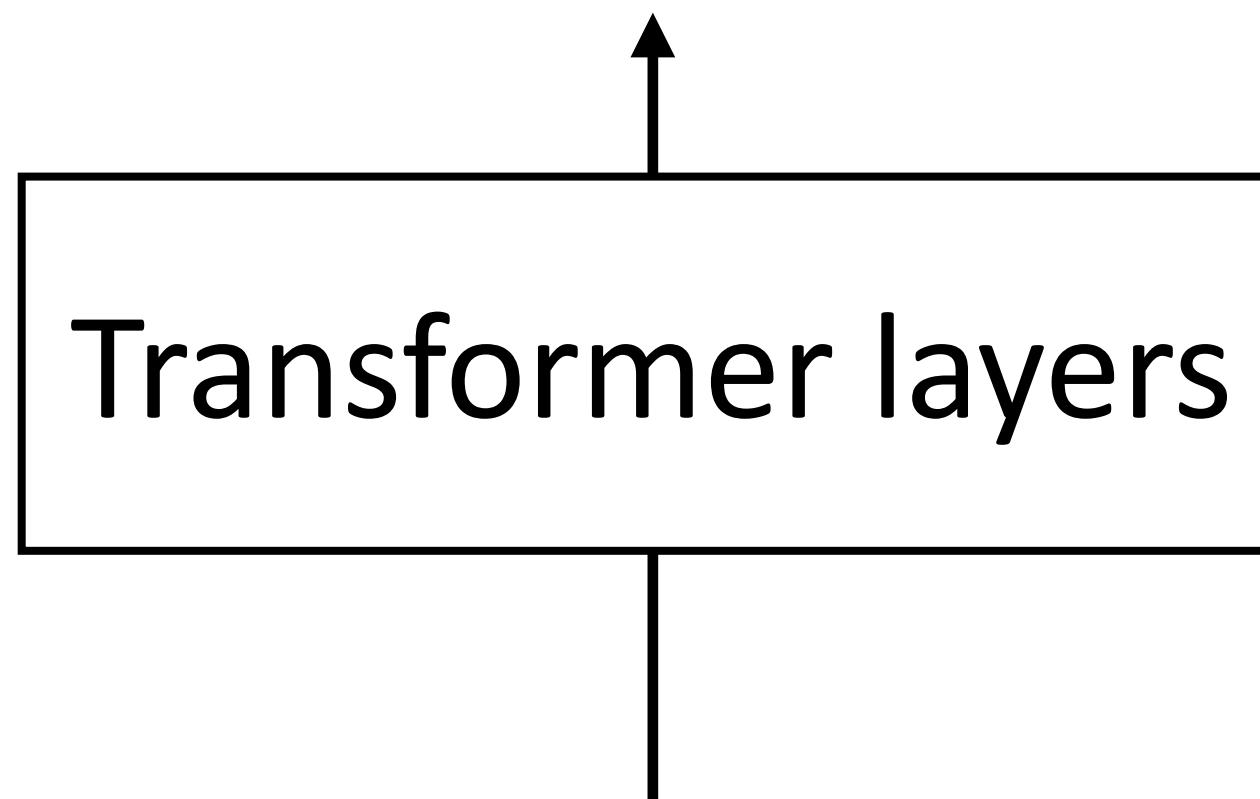




# BERT

## ► Text “infilling” task

I went to the **store** and bought **some milk**



I went to the [MASK] and bought [MASK] [MASK]

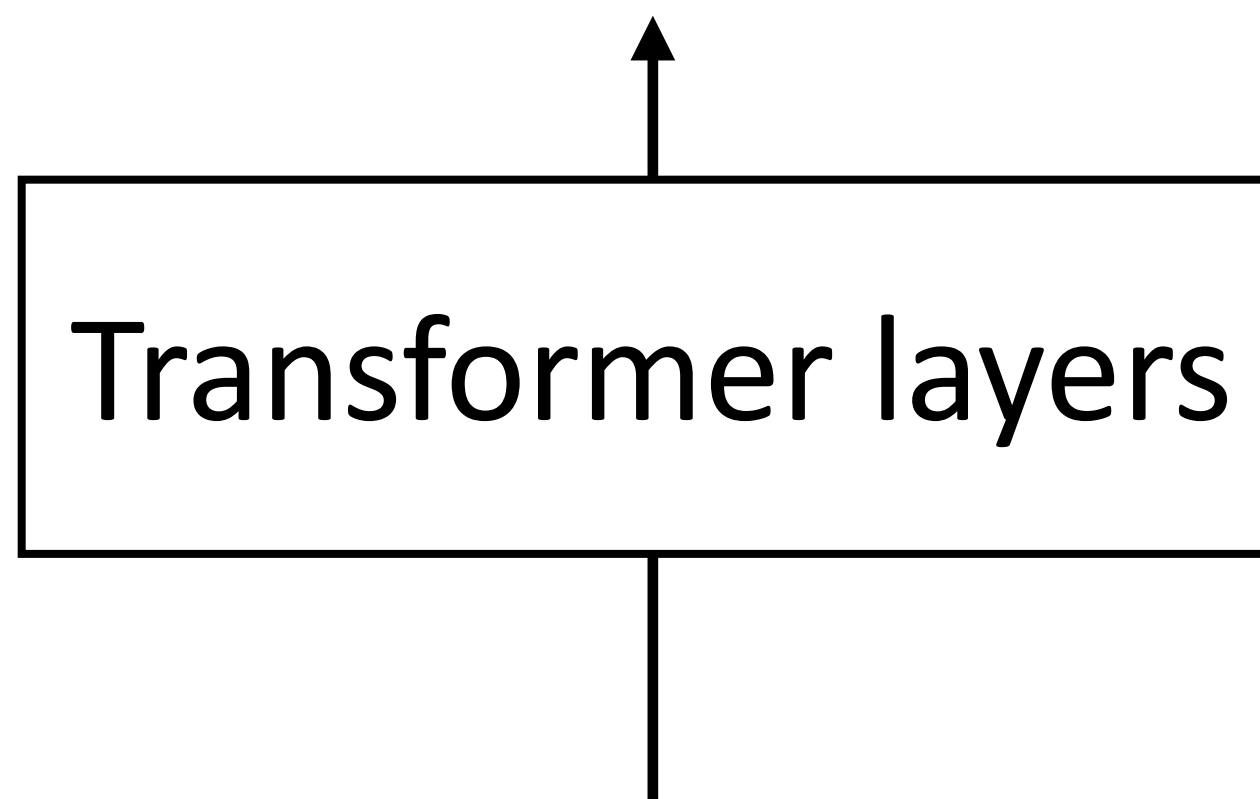




# BERT

- ▶ Next sentence prediction: predict a true/false label from a [CLS] (classification) input

**TRUE** I went to the **store** and bought **some milk** | | **It was tasty** .



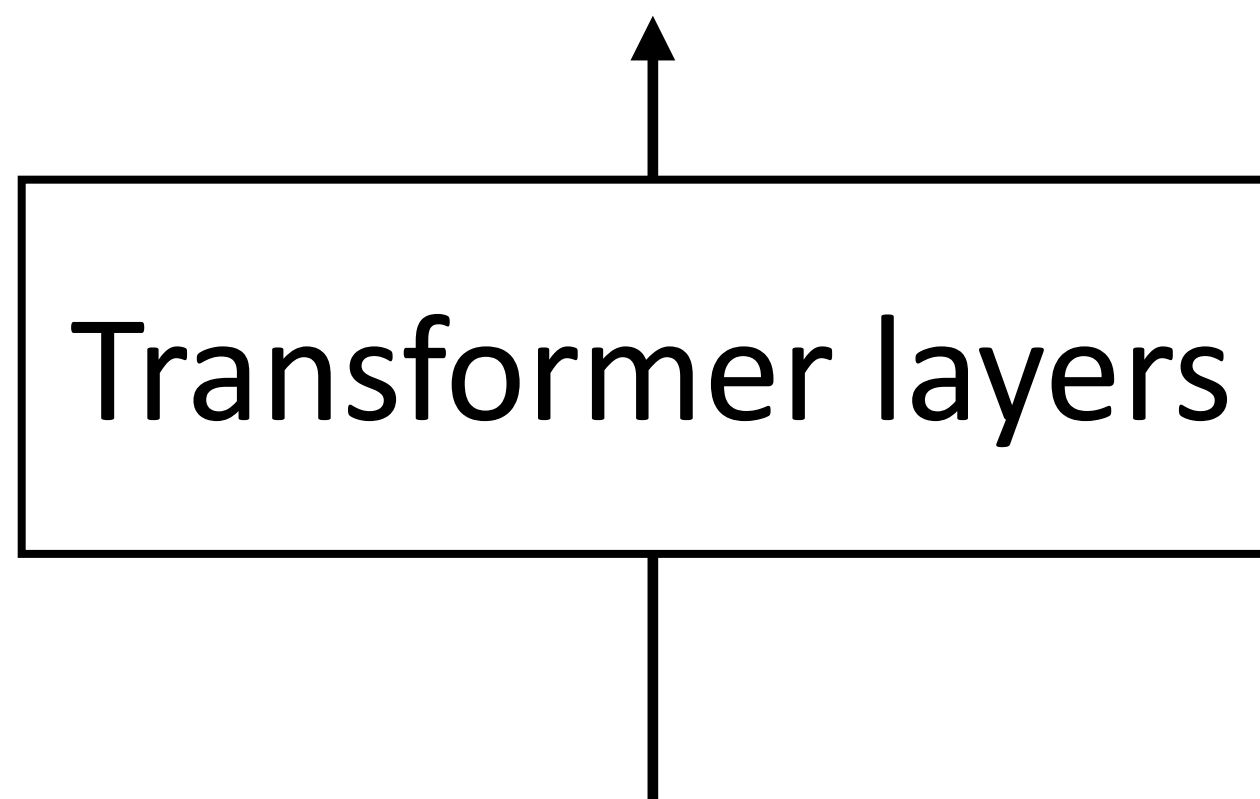
[CLS] I went to the [MASK] and bought [MASK] [MASK] | | [MASK] was tasty .



# BERT

- ▶ Next sentence prediction: predict a true/false label from a [CLS] (classification) input

**FALSE** I went to the **store** and bought **some milk** | | **I flew to Paris**

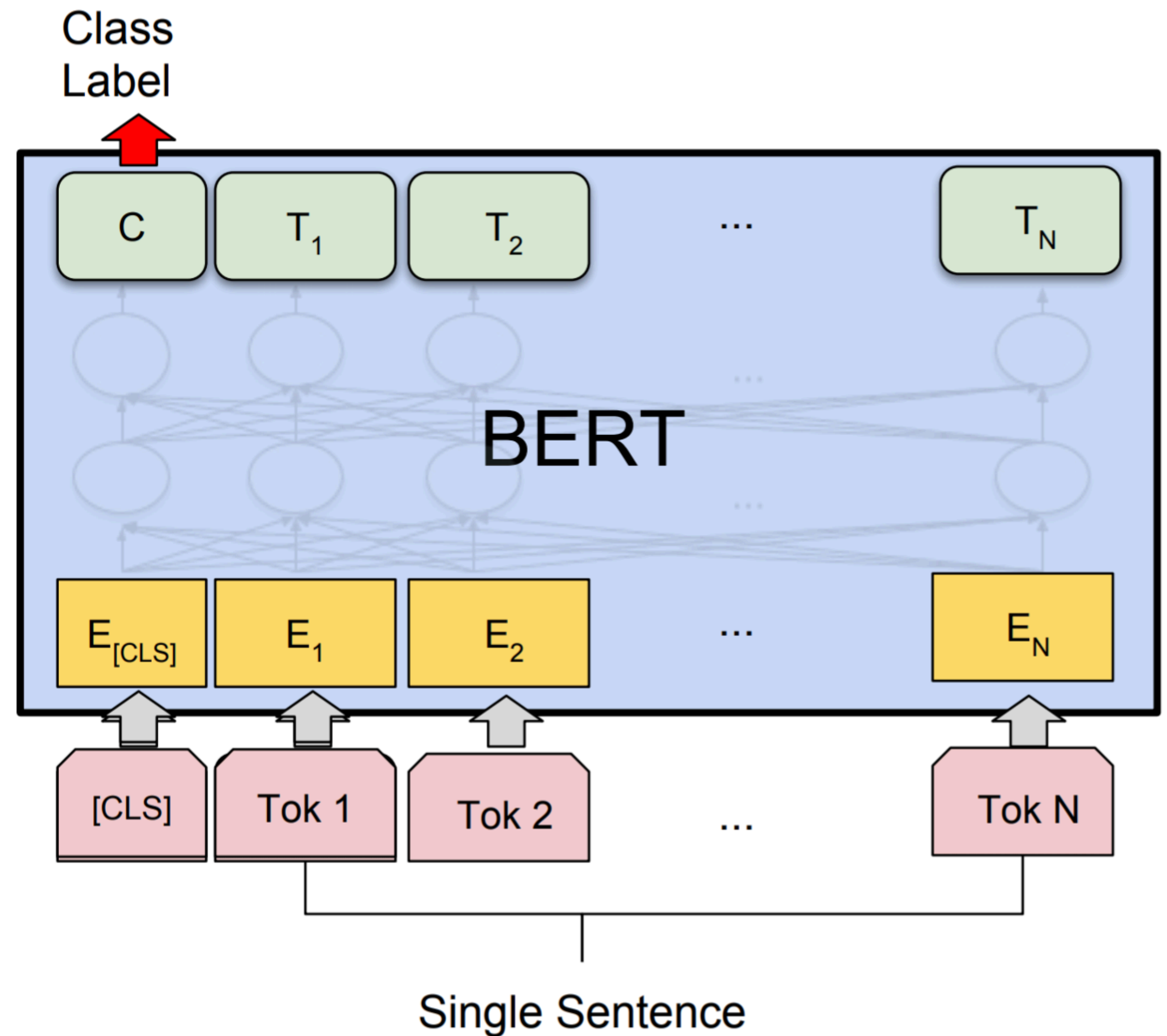


[CLS] I went to the [MASK] and bought [MASK] [MASK] | | [MASK] flew to Paris



# BERT

- ▶ Can use this like ELMo and just produce embeddings
- ▶ Again, works better to fine-tune the whole model on the end task
- ▶ “Rewires” the class label output to do the right thing



Devlin et al. (2018)



# BERT

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average -
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	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
BERT <sub>BASE</sub>	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
BERT <sub>LARGE</sub>	<b>86.7/85.9</b>	<b>72.1</b>	<b>91.1</b>	<b>94.9</b>	<b>60.5</b>	<b>86.5</b>	<b>89.3</b>	<b>70.1</b>	<b>81.9</b>

- ▶ Huge improvements over prior work (even compared to ELMo)
- ▶ Effective at “sentence pair” tasks: textual entailment (does sentence A imply sentence B), paraphrase detection

Devlin et al. (2018)





# Open AI GPT2

- ▶ GPT2: even bigger GPT
- ▶ Trained on 40GB of text collected from upvoted links from reddit
- ▶ 1.5B parameters — by far the largest of these models trained to date

Parameters	Layers	$d_{model}$
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600



# Open AI GPT2

SYSTEM PROMPT  
(HUMAN-WRITTEN)

*Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today.*

MODEL COMPLETION  
(MACHINE-WRITTEN,  
SECOND TRY)

The 19-year-old singer was caught on camera being escorted out of the store by security guards.

The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back.

Scroll down for video

Shoplifting: Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today (pictured)

The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back

The singer was also wearing a pair of black-rimmed glasses, a black jacket, black jeans and black sandals.

She was carrying a pair of black and white striped gloves and a small black bag.

slide credit:  
OpenAI