Contextualized Word Representations

CS 490A, Fall 2021

Applications of Natural Language Processing
https://people.cs.umass.edu/~brenocon/cs490a_f21

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Administrivia

- Project Progress Report due **Monday**, 11/22
- Hugging Face (transformers) virtual tutorial this Friday, 11/19
- HW4 will be released next week

Recall Word Embeddings

So far, we've talked about **vocabulary-level** word embeddings

Other adjectives: **static**, **type**, **noncontextual**

Idea: Each word **type** is represented by a *k*-dimensional vector
where **distance** reflects **semantic** relationships

Q: What are their pros and cons?

fastText: Dealing with out-of-vocabulary terms

Idea: Consider a word to be a **bag of n-grams**

Instead of learning representations for each word, learn the representations of their n-grams

Note: the full word is also included (no matter its length)!

Bojanowski et al. 2017

fastText: Dealing with out-of-vocabulary terms

Formally, a word representation is the sum of its n-grams' learned representations

$$w = \sum_{g \in G_w} vec_g$$

Bojanowski et al. 2017

fastText: Dealing with out-of-vocabulary terms

Word: **making**

3-grams: `<ma mak aki kin ing ng>`
4-grams: `<mak maki akin king ing>`
5-grams: `<maki makin aking king>`
6-grams: `<makin making aking>`
Full sequence: `<making>`

Bojanowski et al. 2017

Contextual Word Representations

Idea: Represent each word **token** as a *k*-dimensional vector
that reflects the token's **local context**

Contextual Word Representations

Idea: Represent each word **token** as a *k*-dimensional vector
that reflects the token's **local context**

1. She lived off the ***land***
2. She had just enough fuel to ***land***

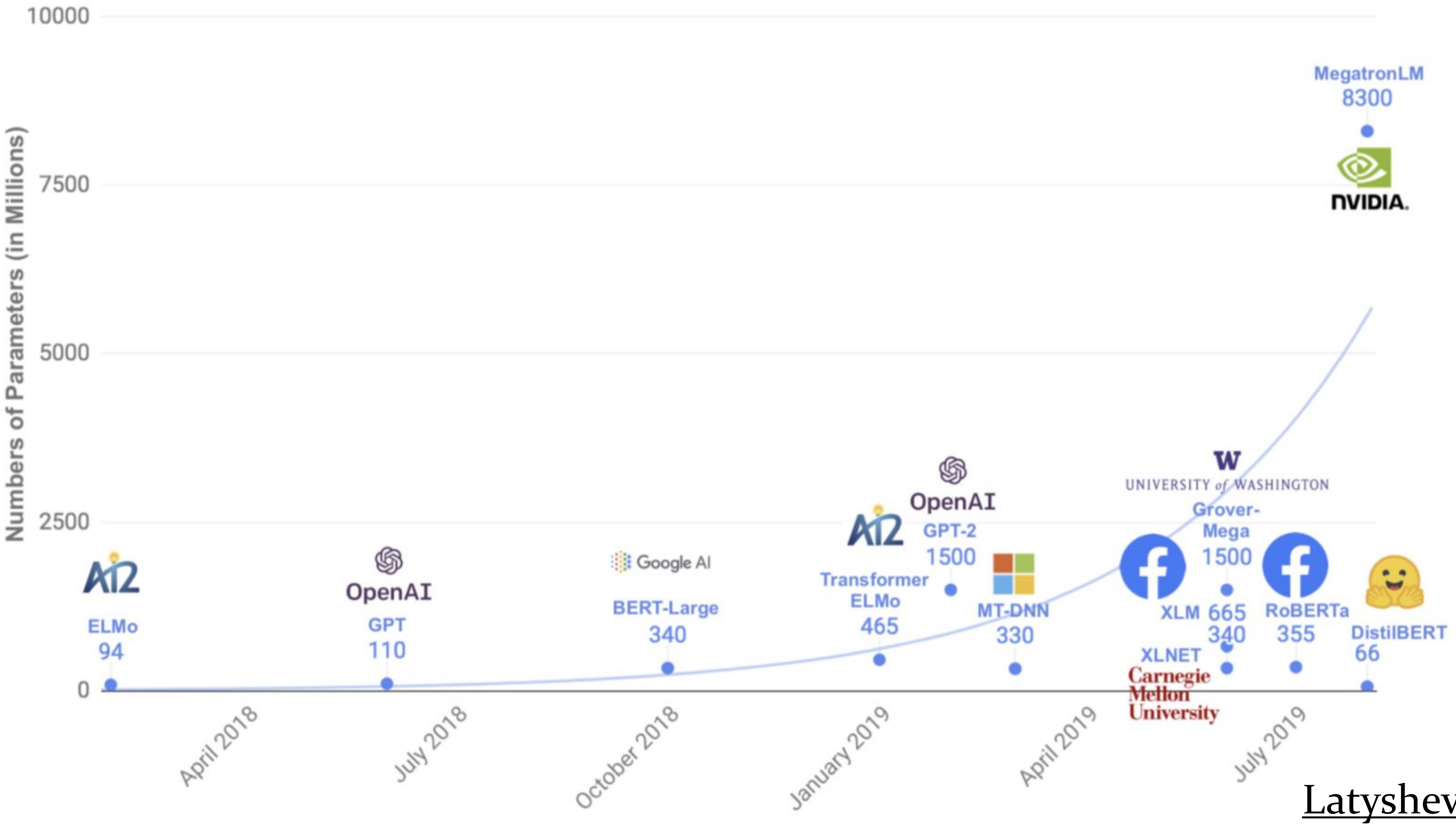
Contextual Word Representations

Idea: Represent each word **token** as a *k*-dimensional vector
that reflects the token's **local context**

1. Caesium is the most reactive alkali ***metal***
2. Folk ***metal*** is a fusion of music genres

Large Pretrained Language Models

Large Pretrained Language Models



Latysheva 2019

<u>Large</u> Pretrained Language Models

- Large model size (millions of parameters)
- Large (pre)training corpus

Model	Size	Data Sources
BERT	16 GB	BookCorpus, Wikipedia (en)
RoBERTa	161GB	BookCorpus, Wikipedia (en), Stories, CommonCrawl News, OpenWebText
GPT-3	570 GB	CommonCrawl (filtered), WebText2, Books1, Books2, Wikipedia (en)
T5	750 GB	C4: Colossal Clean Crawled Corpus

Large <u>**Pretrained**</u> Language Models

Paradigm Shift:

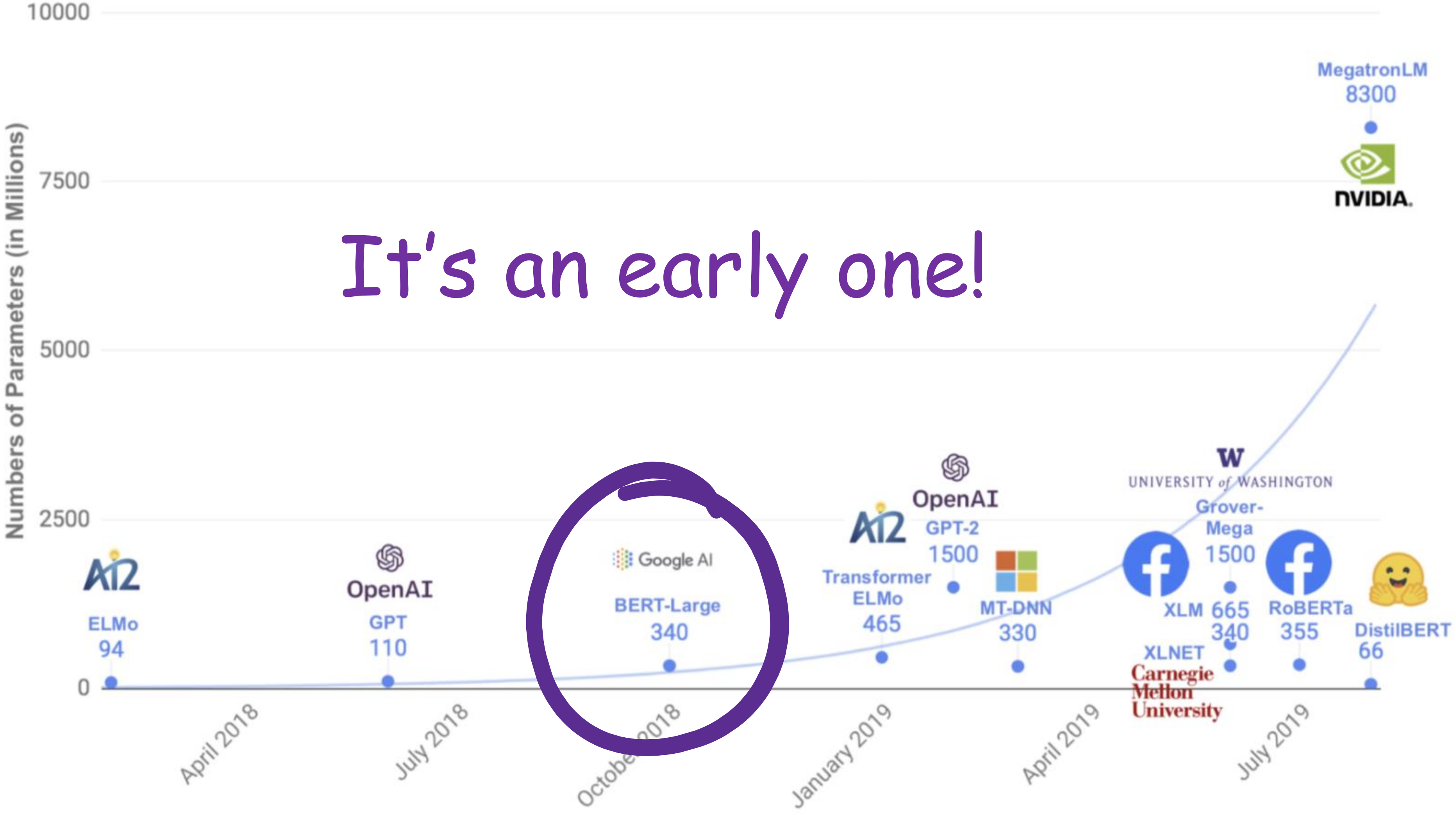
(a) **Pretrain** a model on general tasks where labels can easily be generated for massive text corpora

(b) **Fine-tune** the pretrained model (as needed) for a more specialized, harder task

BERT: **B**idirectional **E**ncoder **R**epresentations for **T**ransformers

Devlin et al. 2019

Why BERT?



It's an early one!

Why BERT?

Highly influential!

25,048 Citations

Highly Influential Citations	7,670
Background Citations	10,124
Methods Citations	13,635
Results Citations	463

View All

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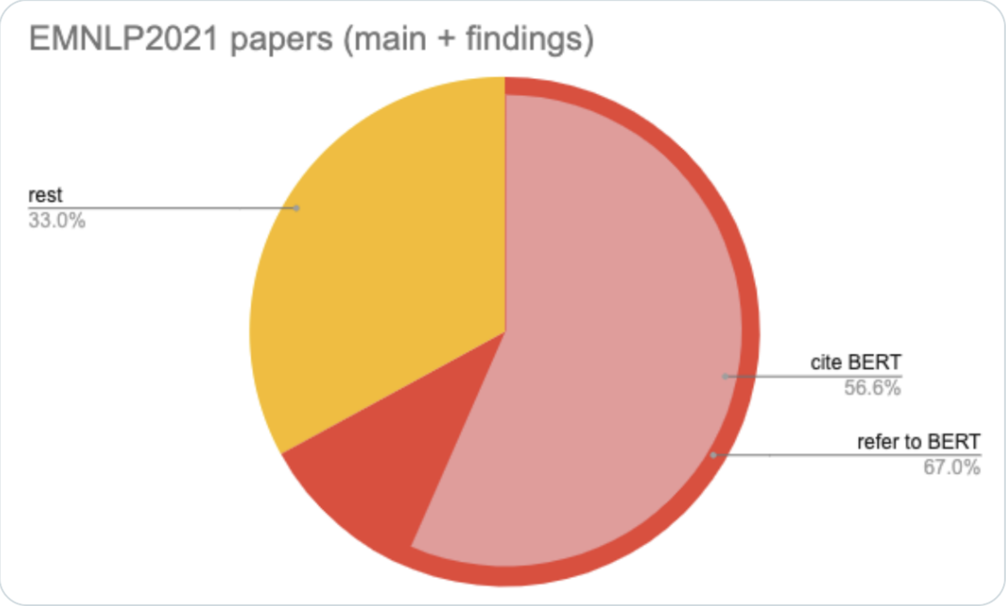
View All

Gabriel Stanovsky
@GabiStanovsky

I skimmed through many papers from @emnlpmeeting, which got me thinking - what % of papers refer to BERT, and out of those, how many cite it?
Here's the answer*: 67% of papers refer to BERT (!), and 56% cite it.

*computed automatically, exact #'s may vary
#EMNLP2021 #NLProc



12:21 PM · Nov 9, 2021 · Twitter Web App

BERT is a **Transformer**-based model.

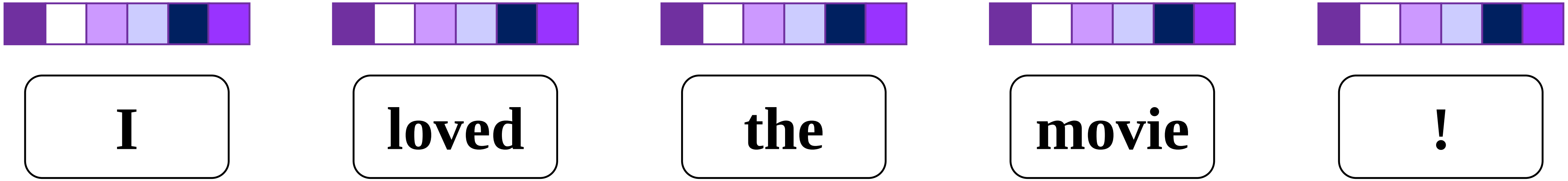
What's a Transformer?

Let’s talk about ***attention***

How do we use word embeddings for document classification?

<u>Adapted from the slides by Bamman (2021)</u>

How do we use word embeddings for document classification?



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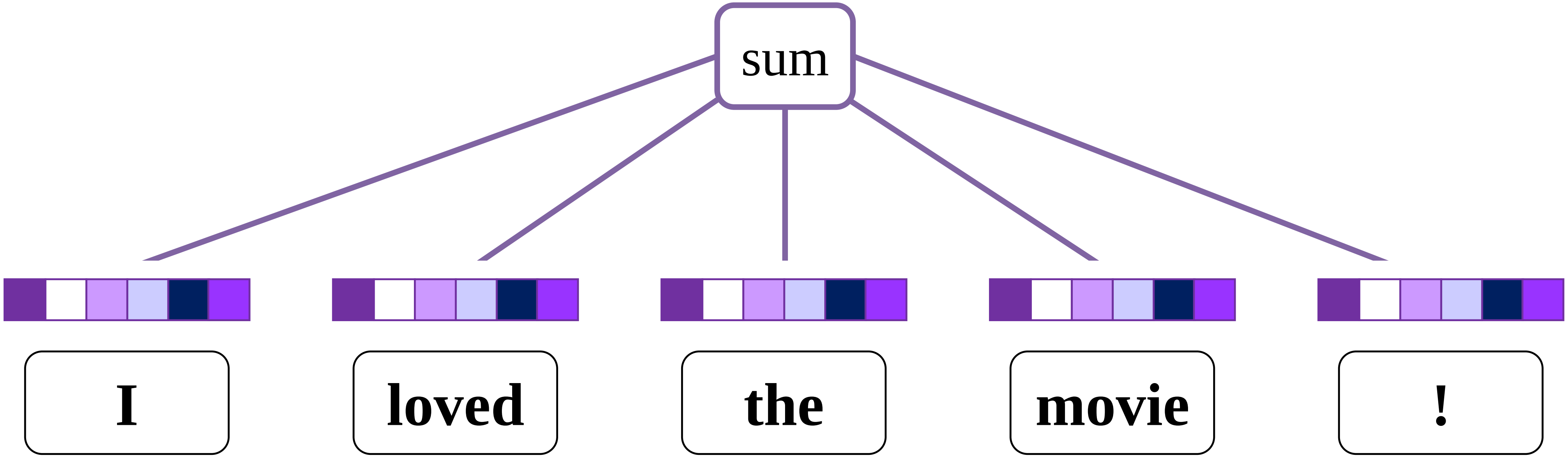
How do we use word embeddings for document classification?



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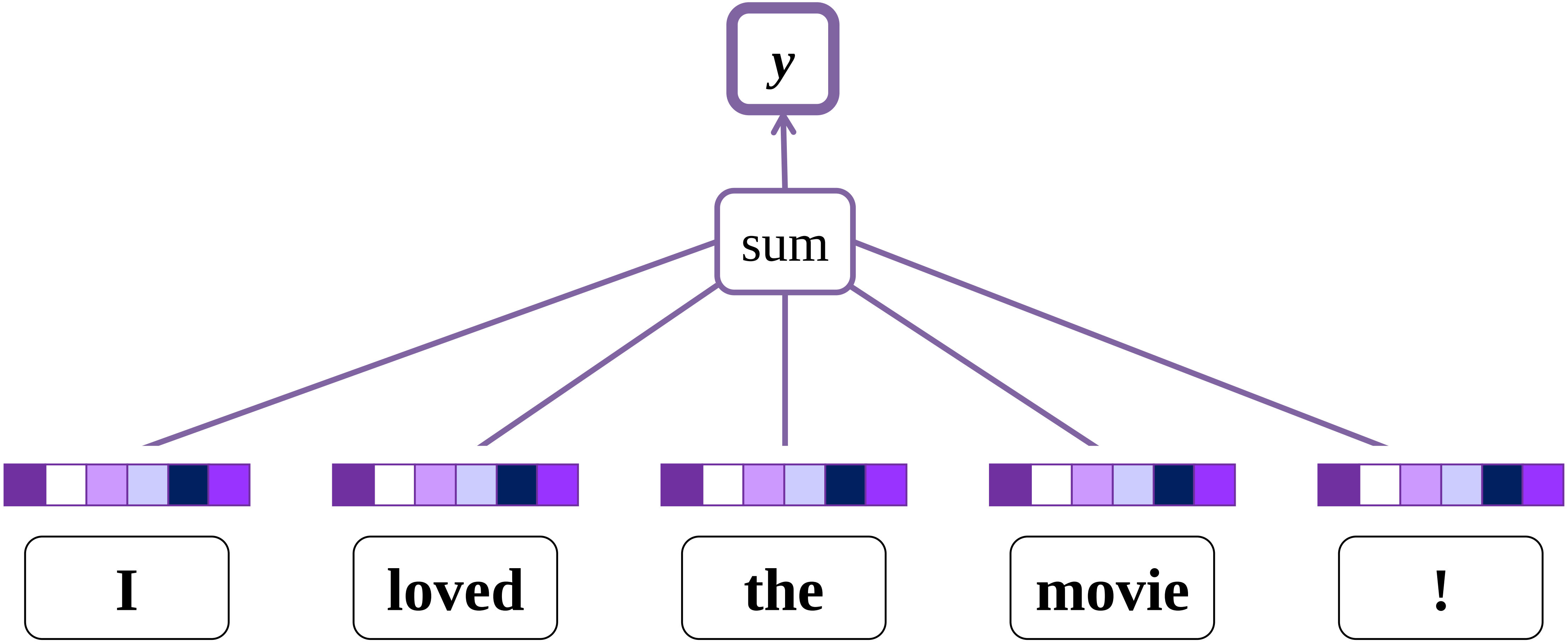
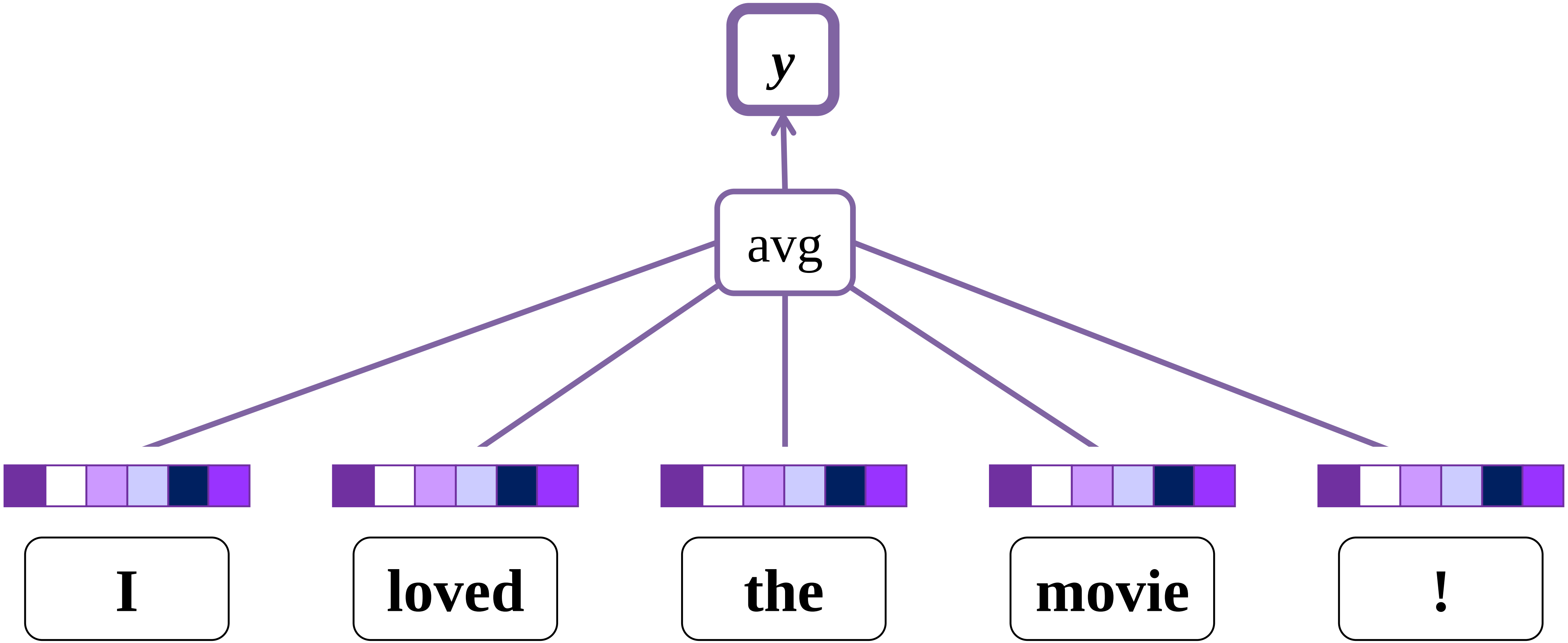
How do we use word embeddings for document classification?



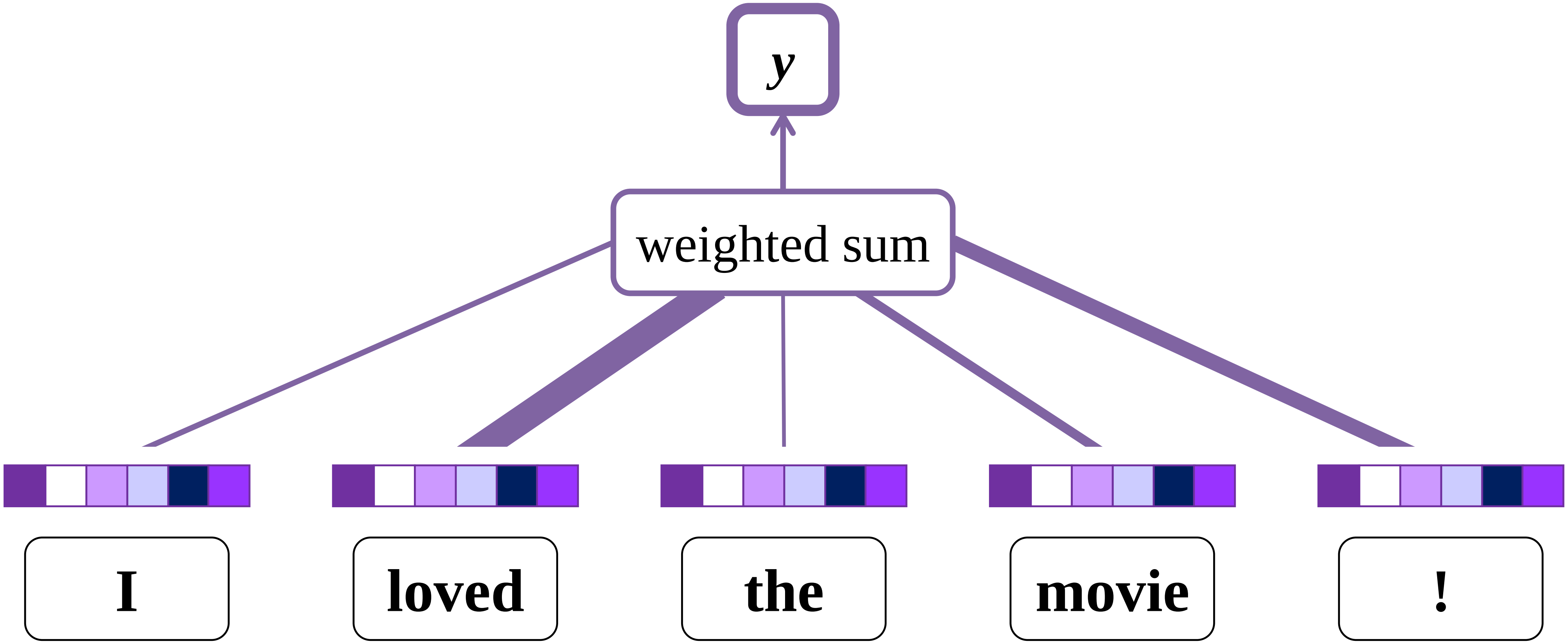
Adapted from the slides by Bamman (2021)

…or we could average them



Adapted from the slides by Bamman (2021); Iyyer et al. 2015

...or take a weighted sum



Adapted from the slides by Bamman (2021)

What is attention?

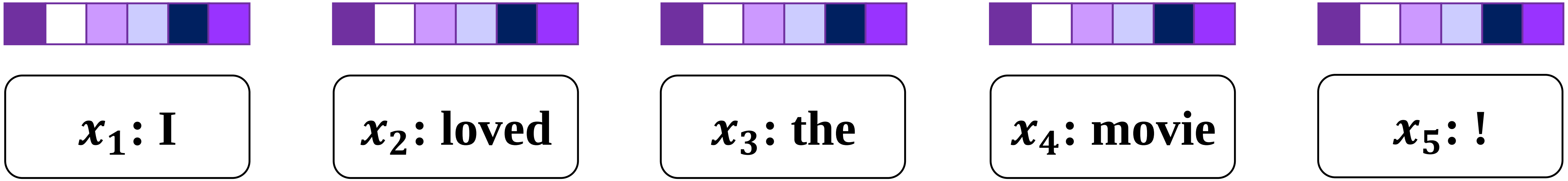
Idea: Give neural networks structure (and parameter) to learn which input elements we should **attend** to and which we can ignore

Adapted from the slides by Bamman (2021)

What is attention?

Let’s learn a task-specific vector ***v***

Intuition: think of ***v*** like an “**important word**” vector

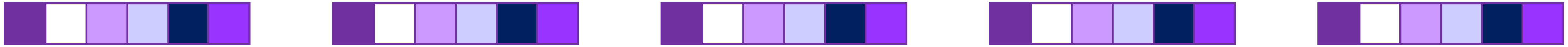


Adapted from the slides by Bamman (2021)

What is attention?

We'll measure the "**importance**" of each input vector $\boldsymbol{x}$ by its similarity (dot product) to $\boldsymbol{v}$

$\boldsymbol{r_1 = v \cdot x_1}$ $\boldsymbol{r_2 = v \cdot x_2}$ $\boldsymbol{r_3 = v \cdot x_3}$ $\boldsymbol{r_4 = v \cdot x_4}$ $\boldsymbol{r_5 = v \cdot x_5}$



$\boldsymbol{x_1}$**: I** $\boldsymbol{x_2}$**: loved** $\boldsymbol{x_3}$**: the** $\boldsymbol{x_4}$**: movie** $\boldsymbol{x_5}$**: !**

Adapted from the slides by Bamman (2021)

What is attention?

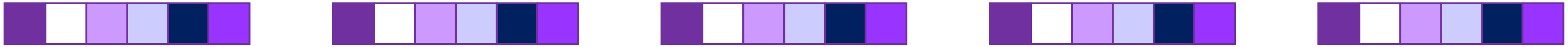
-3.4	2.4	-0.8	-1.2	1.7
$\boldsymbol{r_1 = v \cdot x_1}$	$\boldsymbol{r_2 = v \cdot x_2}$	$\boldsymbol{r_3 = v \cdot x_3}$	$\boldsymbol{r_4 = v \cdot x_4}$	$\boldsymbol{r_5 = v \cdot x_5}$
$\boldsymbol{x_1}$: **I**	$\boldsymbol{x_2}$: **loved**	$\boldsymbol{x_3}$: **the**	$\boldsymbol{x_4}$: **movie**	$\boldsymbol{x_5}$: **!**

Adapted from the slides by Bamman (2021)

What is attention?

$$a = \mathrm{softmax}(r)$$

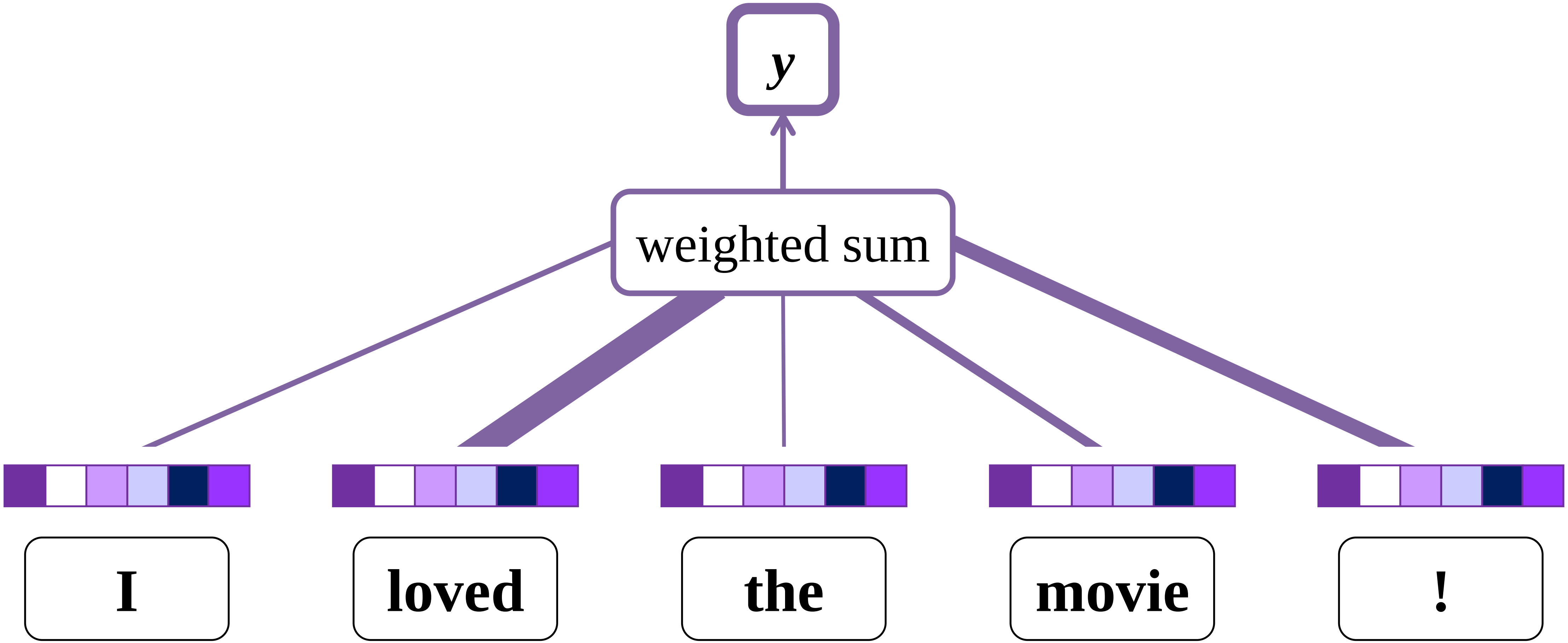
0	0.64	0.02	0.02	0.32
-3.4	2.4	-0.8	-1.2	1.7
$\boldsymbol{r_1 = v \cdot x_1}$	$\boldsymbol{r_2 = v \cdot x_2}$	$\boldsymbol{r_3 = v \cdot x_3}$	$\boldsymbol{r_4 = v \cdot x_4}$	$\boldsymbol{r_5 = v \cdot x_5}$



$\boldsymbol{x_1}$: **I**	$\boldsymbol{x_2}$: **loved**	$\boldsymbol{x_3}$: **the**	$\boldsymbol{x_4}$: **movie**	$\boldsymbol{x_5}$: **!**

Adapted from the slides by Bamman (2021)

...this seems familiar



Adapted from the slides by Bamman (2021)

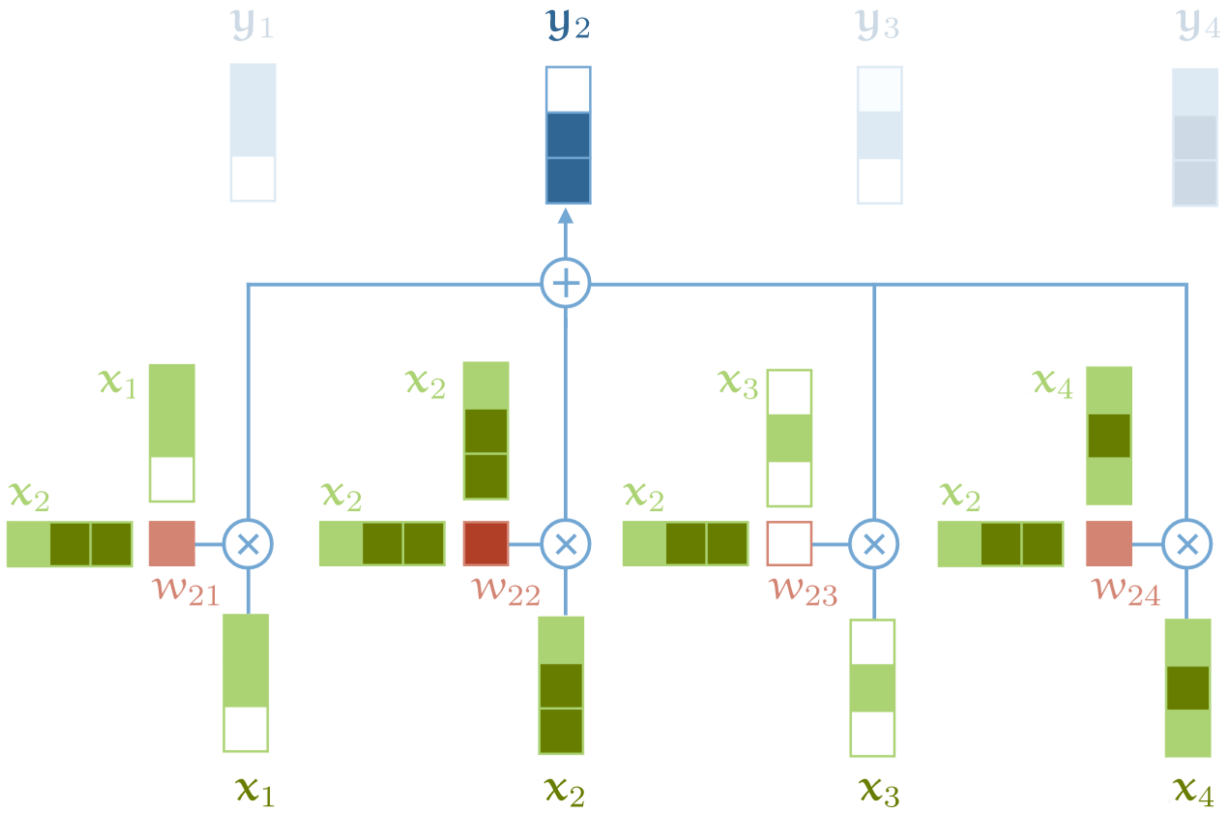
Transformers rely on a specific kind of attention

Self-Attention Operation

Sequence-to-sequence operation

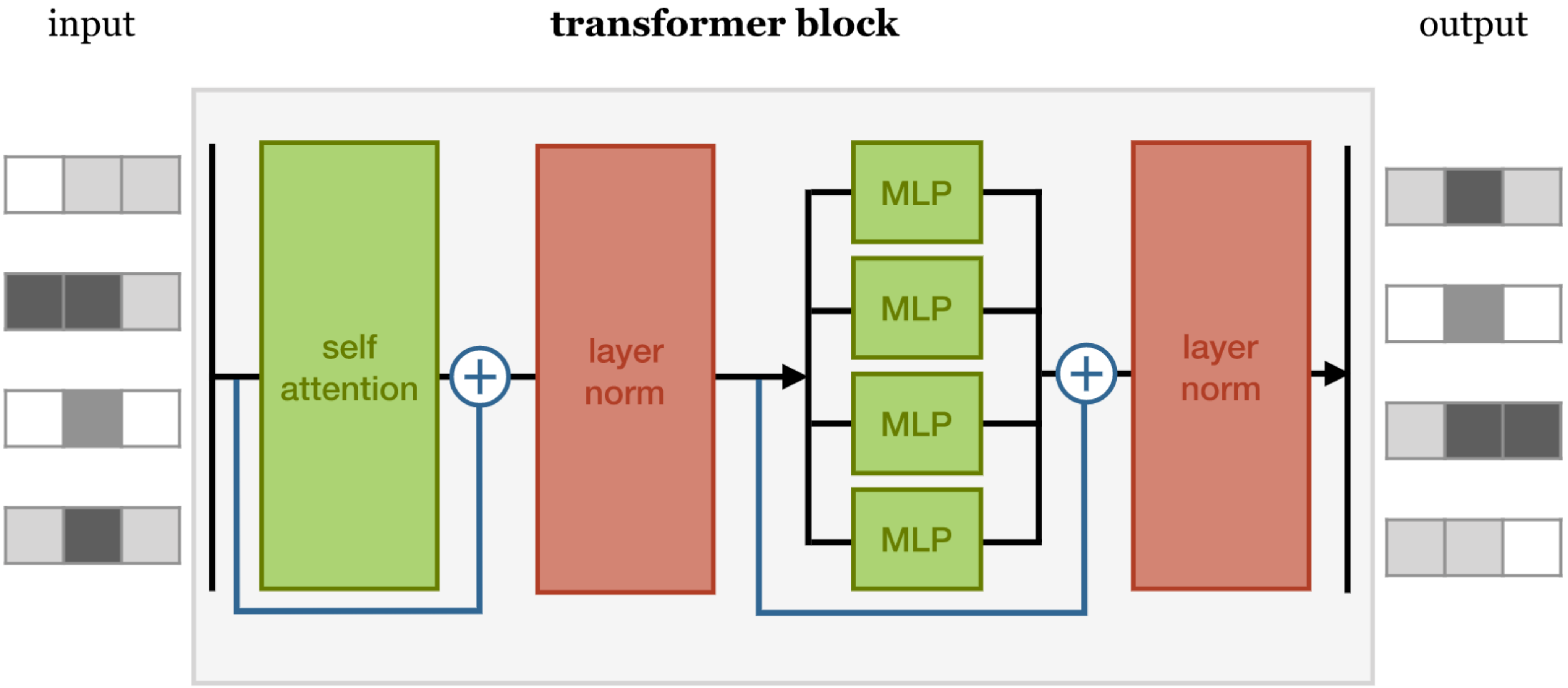
Self-Attention Operation

Outputs are **weighted average** of all input vectors



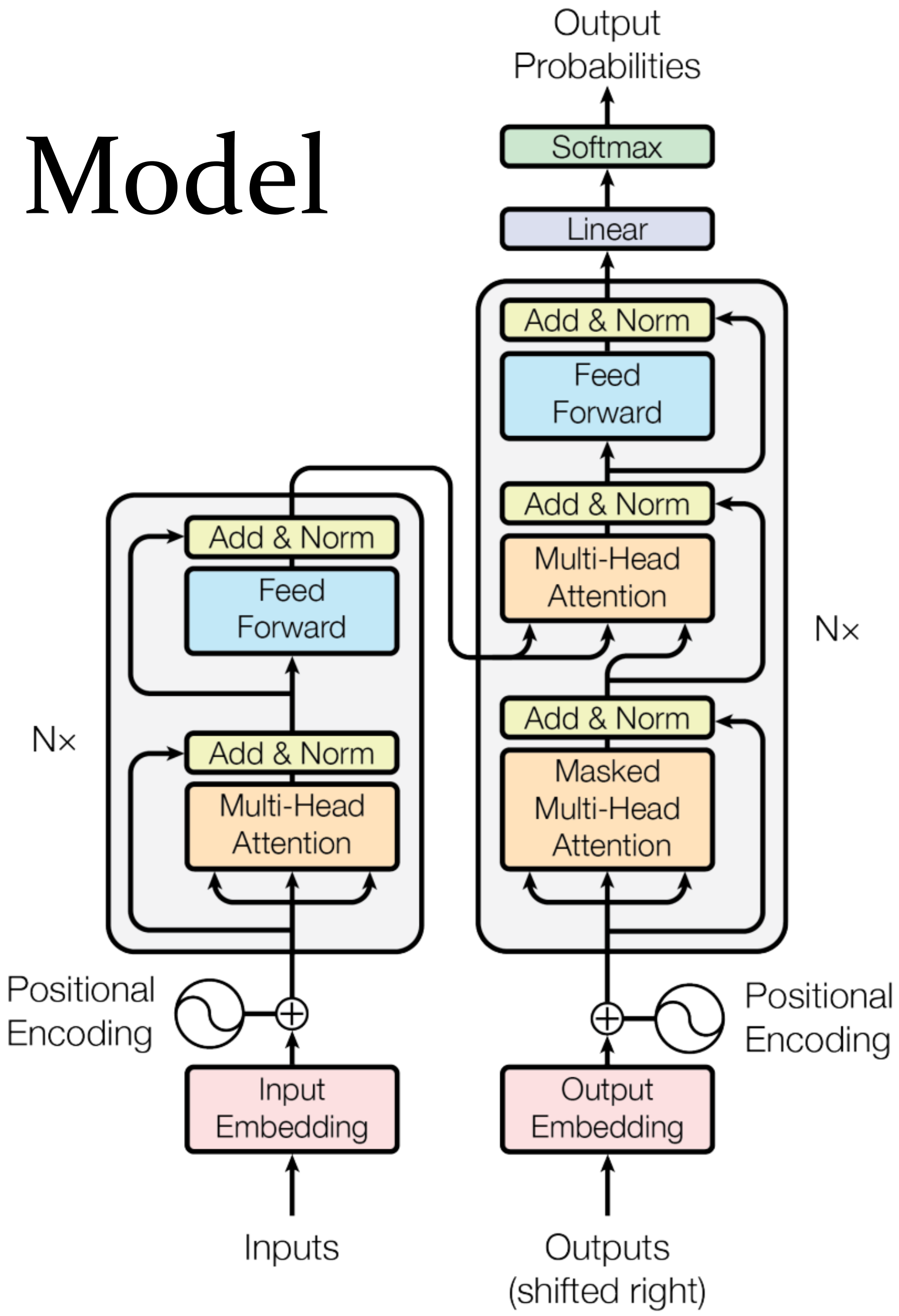
Bloem (2019)

Transformer Block



Bloem (2019)

Transformer Model

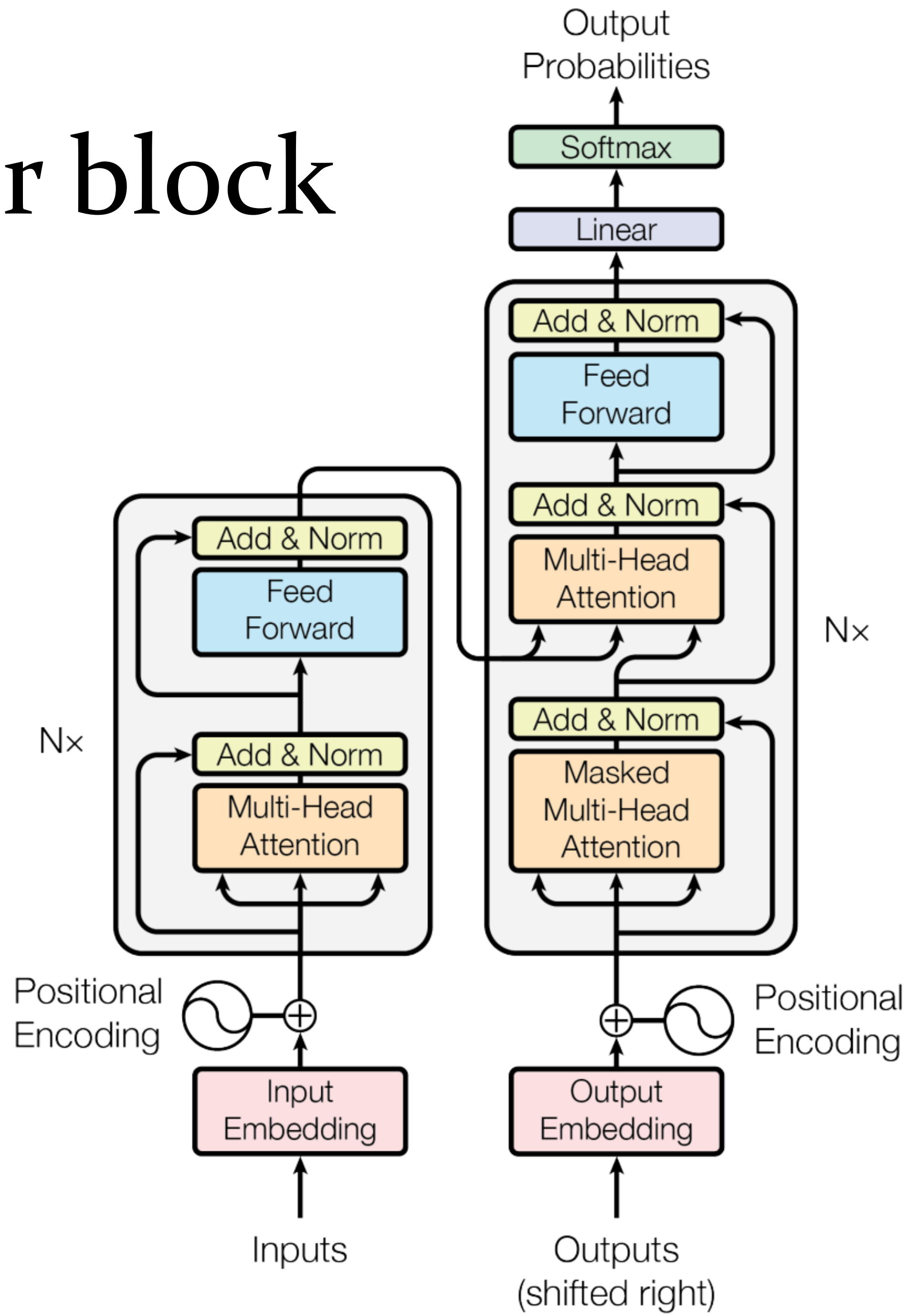


Vaswani et al. (2017)

…and back to BERT

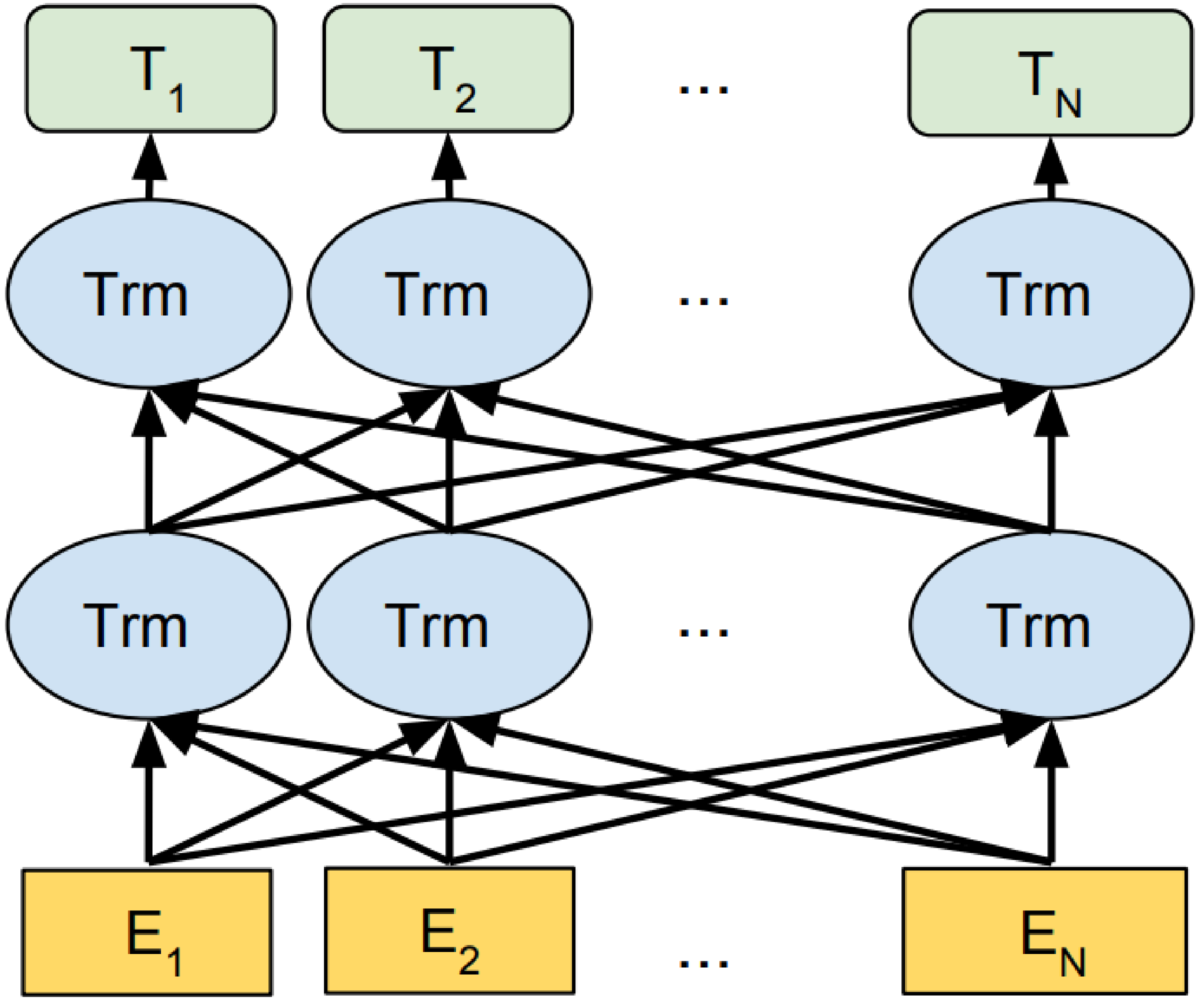
Devlin et al. 2019

Uses encoder block



Vaswani et al. (2017)

BERT



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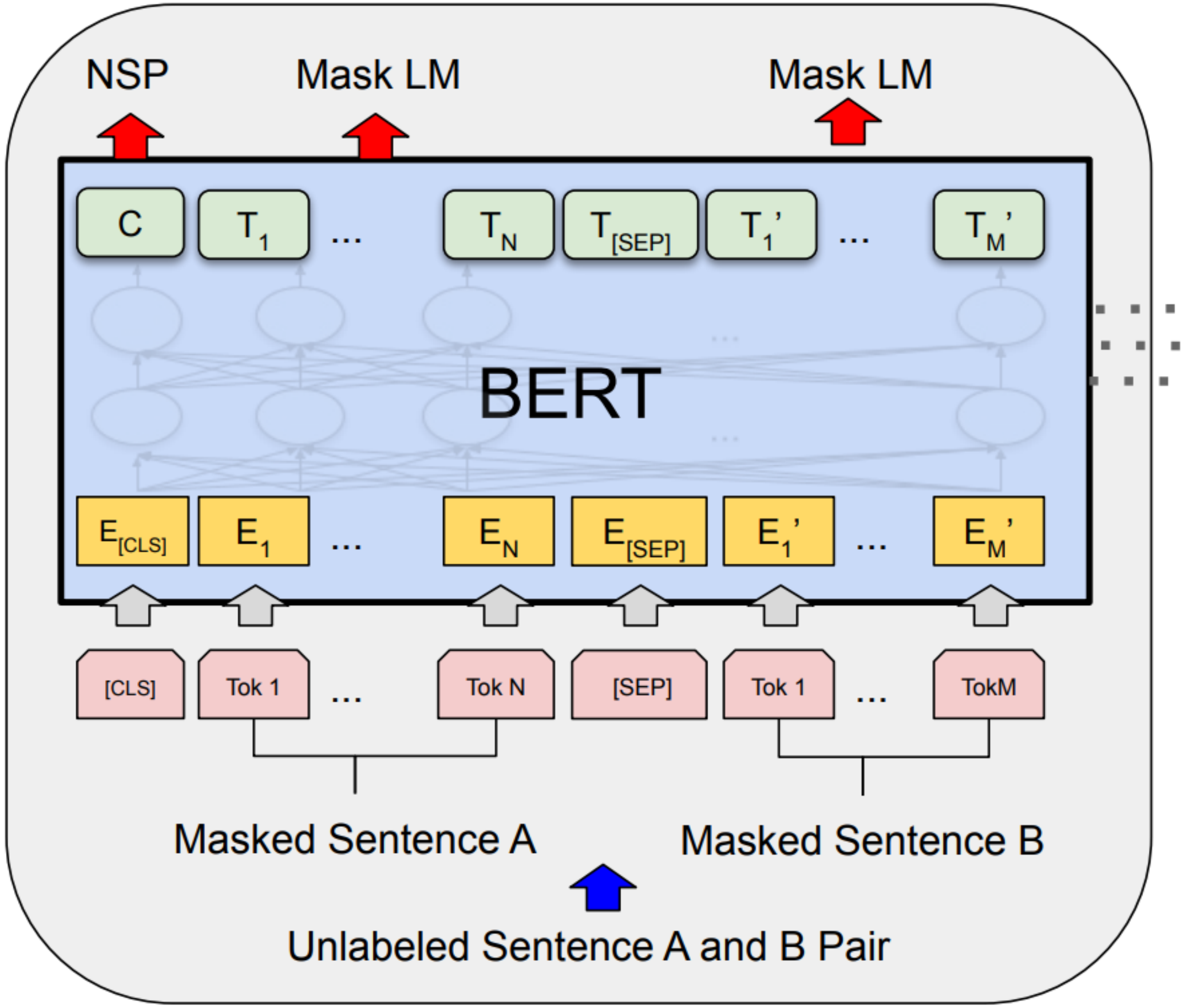
Pre-Training



Devlin et al. 2019

Pre-Training Tasks

1. Masked Language Model (MLM)
2. Next Sentence Prediction (NSP)

Devlin et al. 2019

Masked Language Model

Setting: Randomly mask some tokens of the input

Objective: Predict the original word types of each masked token based solely on its context

Masked Language Model Procedure

Apply procedure to 15% of tokens

- 80% of the time: Replace the word with the [MASK] token
- 10% of the time: Replace the word with a random word
- 10% of the time: Keep the word unchanged

Devlin et al. 2019

Masked Language Model Procedure

Example: `my dog is hairy`

- 80% of the time: Replace the word with the [MASK] token

  `my dog is [MASK]`

- 10% of the time: Replace the word with a random word

  `my dog is apple`

- 10% of the time: Keep the word unchanged

  `my dog is hairy`

Devlin et al. 2019

Next Sentence Prediction

Input = `[CLS] the man went to [MASK] store [SEP]`

`he bought a gallon [MASK] milk [SEP]`

Label = `IsNext`

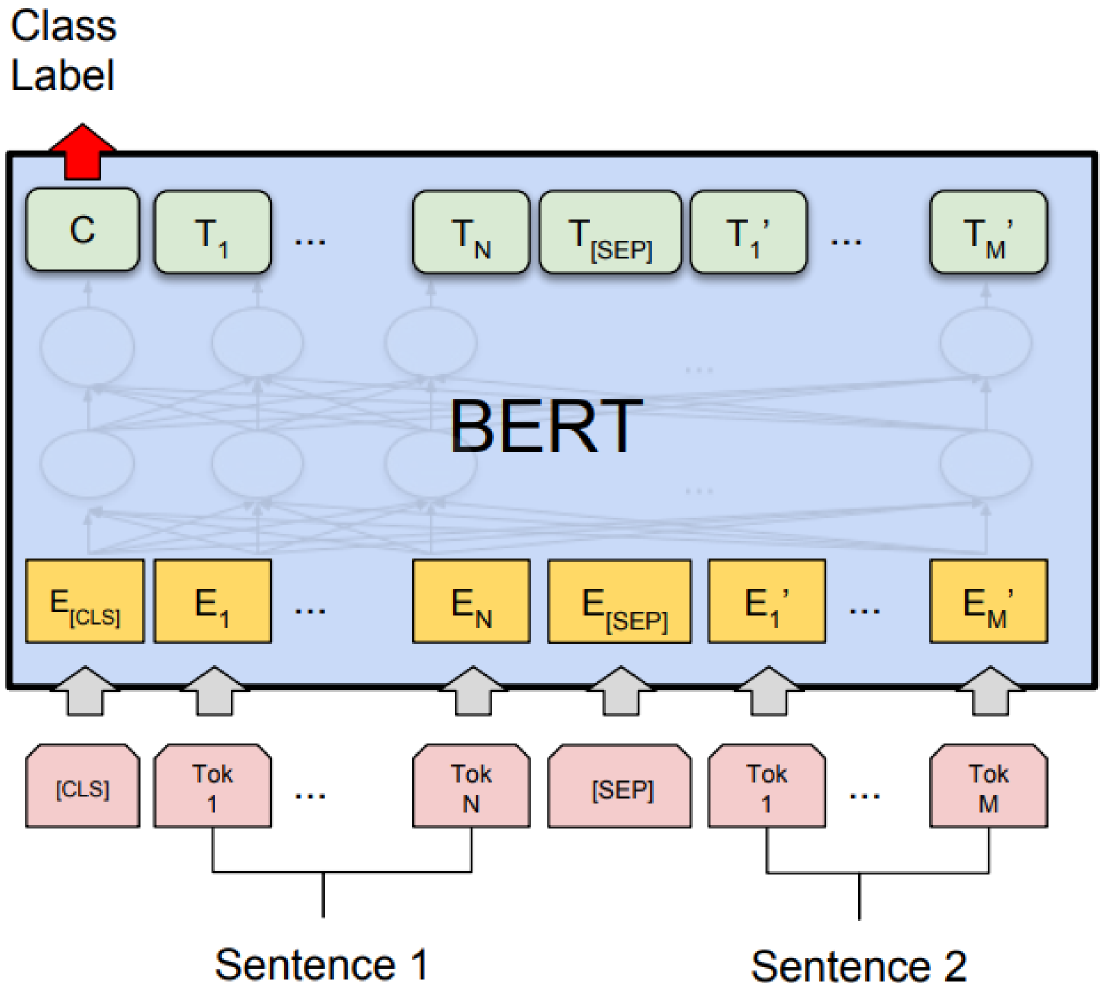
Input = `[CLS] the man [MASK] to the store [SEP]`

`penguin [MASK] are flight ##less birds [SEP]`

Label = `NotNext`

Devlin et al. 2019

Fine-Tuning: Sentence Pair Classification



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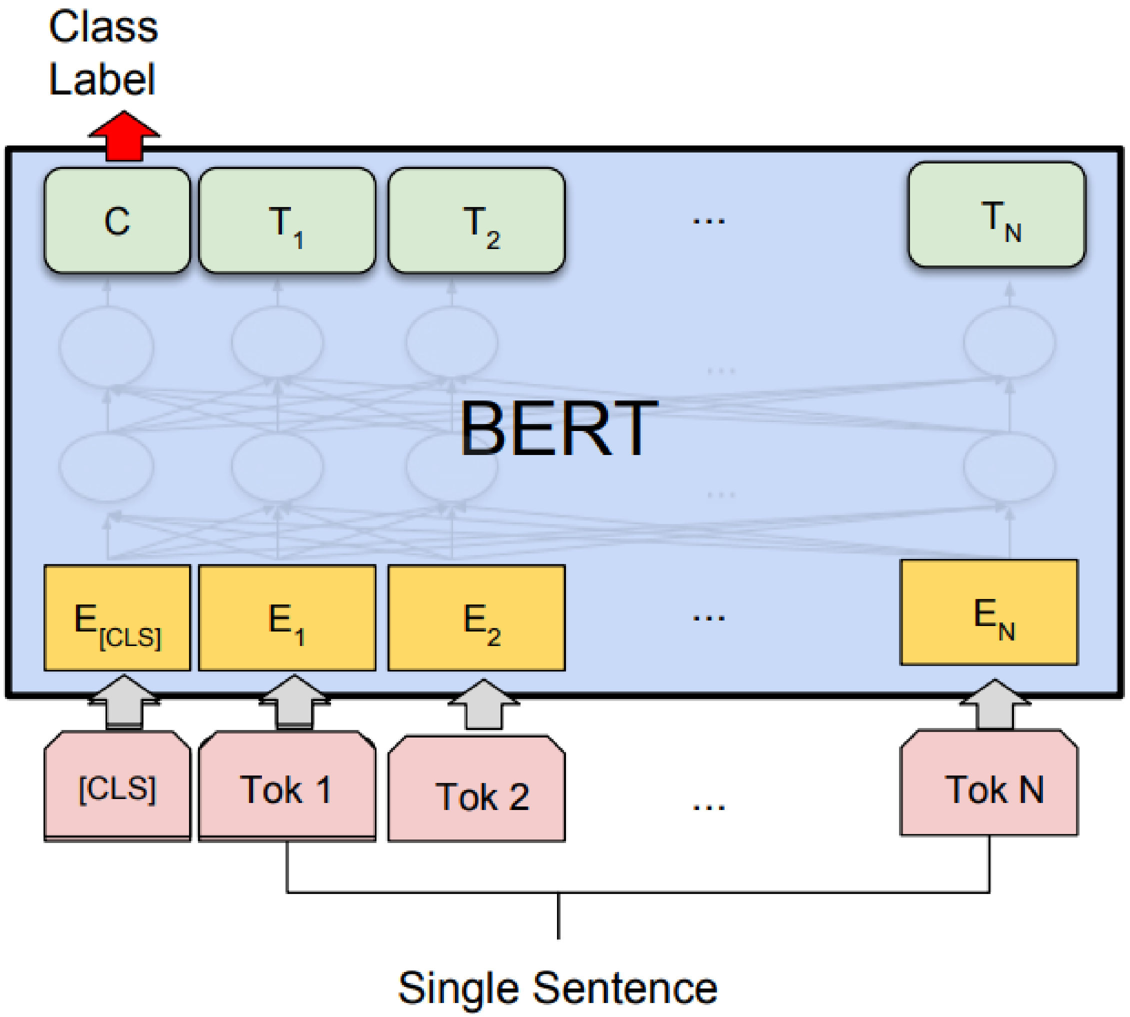
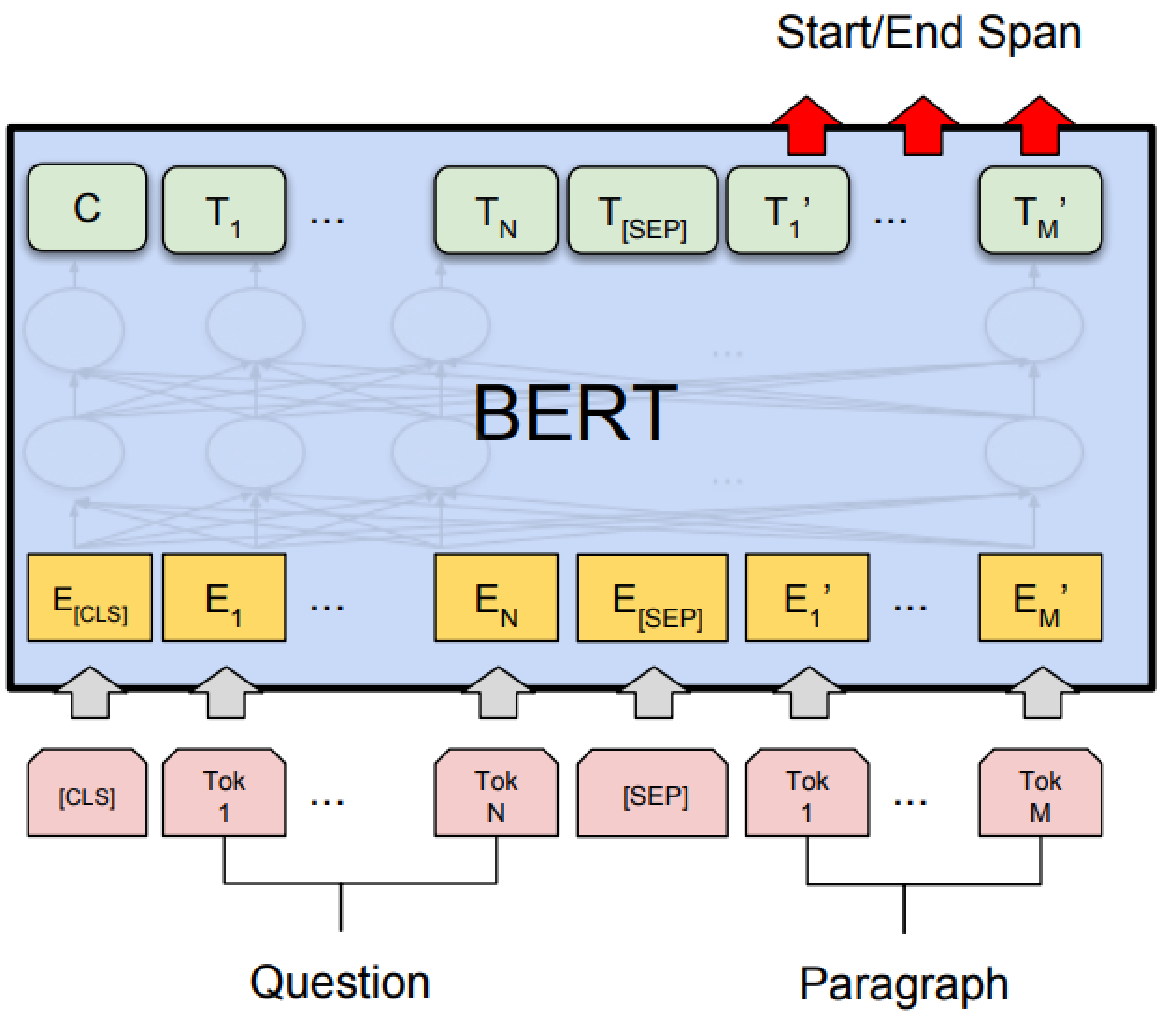
Fine-Tuning: Single Sentence Classification



Devlin et al. 2019

Fine-Tuning: Question Answering



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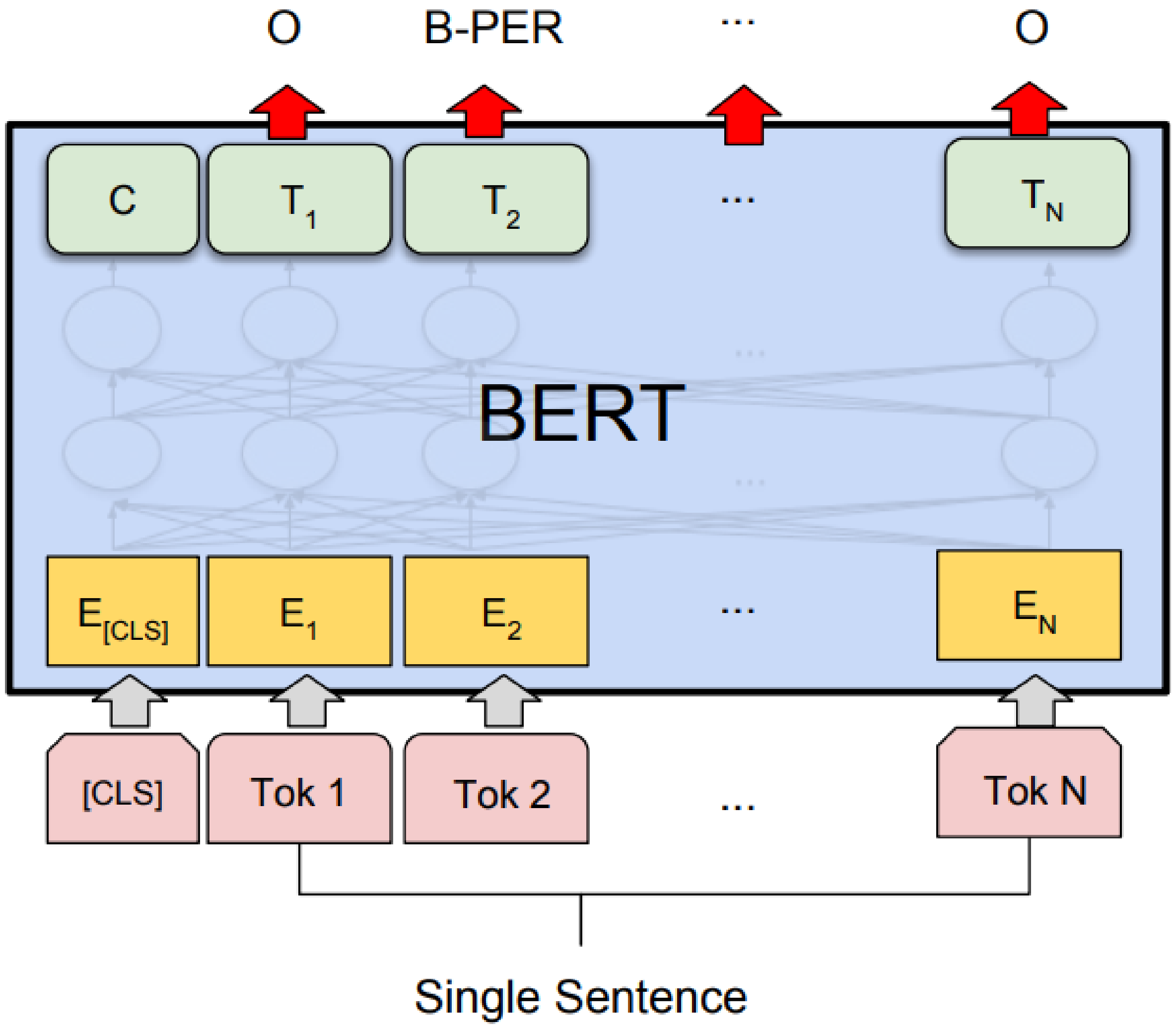
Fine-Tuning: Single Sentence Tagging



Devlin et al. 2019

Huge gains for many 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**

Devlin et al. 2019

Still visible in leaderboards today

Rank	Name	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	MNLI-
1	ERNIE Team - Baidu	ERNIE		91.1	75.5	97.8	93.9/91.8	93.0/92.6	75.2/90.9	92.3	[illegible]
2	AliceMind & DIRL	StructBERT + CLEVER		91.0	75.3	97.7	93.9/91.9	93.5/93.1	75.6/90.8	91.7	[illegible]
3	liangzhu ge	DEBERTa + CLEVER		90.9	73.9	97.5	92.8/90.4	93.2/92.9	76.4/90.9	92.1	[illegible]
4	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.8	71.5	97.5	94.0/92.0	92.9/92.6	76.2/90.8	91.9	[illegible]
5	HFL iFLYTEK	MacALBERT + DKM		90.7	74.8	97.0	94.5/92.6	92.8/92.6	74.7/90.6	91.3	[illegible]
6	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS		90.6	73.5	97.2	94.0/92.0	93.0/92.4	76.1/91.0	91.6	[illegible]
7	T5 Team - Google	T5		90.3	71.6	97.5	92.8/90.4	93.1/92.8	75.1/90.6	92.2	[illegible]
8	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART		89.9	69.5	97.5	93.7/91.6	92.9/92.5	73.9/90.2	91.0	[illegible]
9	Huawei Noah's Ark Lab	NEZHA-Large		89.8	71.7	97.3	93.3/91.0	92.4/91.9	75.2/90.7	91.5	[illegible]
10	Zihang Dai	Funnel-Transformer (Ensemble B10-10-10H1024)		89.7	70.5	97.5	93.4/91.2	92.6/92.3	75.4/90.7	91.4	[illegible]

GLUE leaderboard