COMP 3361 Natural Language Processing

Lecture 11: Pre-training and large language models (LLMs)

Spring 2024

Many materials from COS484@Princeton and CSE447@UW (Liwei Jiang) with special thanks!

Announcements

- Again, get started on assignment 2 ASAP!
  - Join #assignment-2 Slack channel for discussion
  - Course reading materials

Lecture plan

- Traditional to modern NLP: recap
- Pretraining overview
- BERT pretraining
- T5 pretraining
- GPT pretraining

Traditional to modern NLP: training paradigm

Traditional		Modern
N-gram language models	→	Neural language models: BERT, GPT
Traditional models: Naive Bayes	→	Neural models: Transformers
Static embeddings: word2vec	→	Contextual embeddings: BERT, GPT
Traditional learning paradigm	→	New learning paradigm: Pretrain, ICL

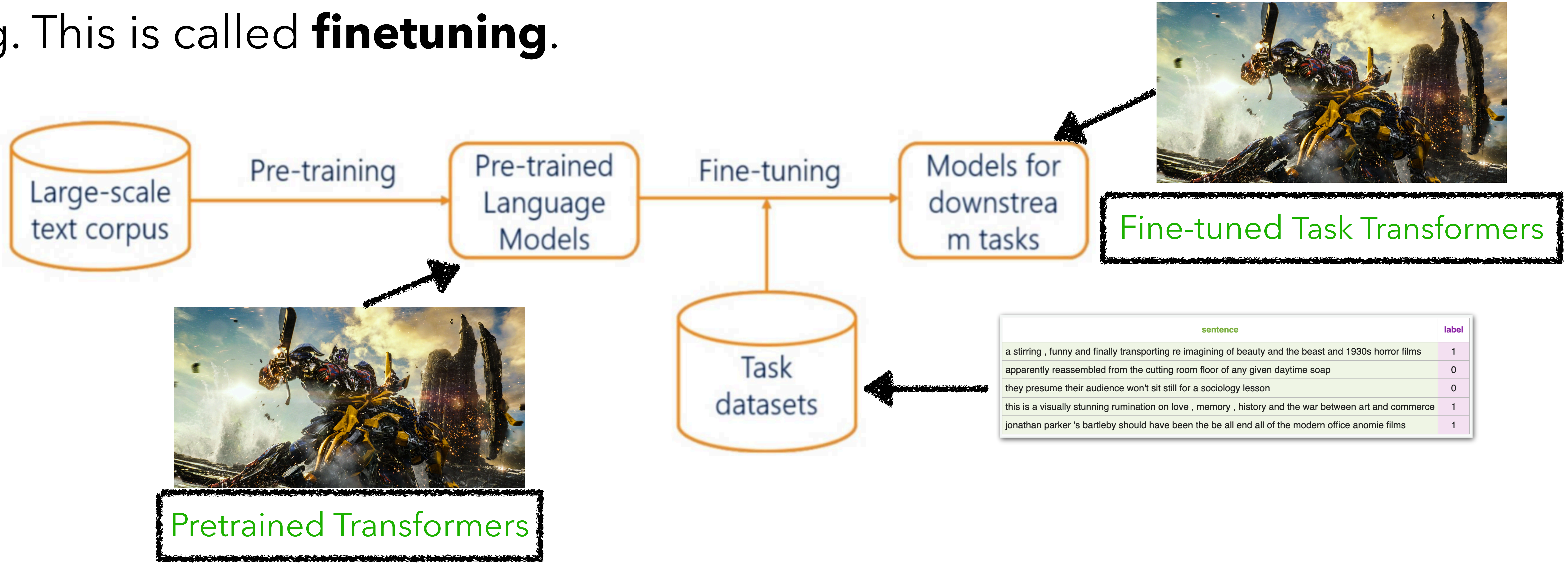
Traditional learning paradigm

- **Supervised training/fine-tuning only, NO pre-training**
  - Collect (x, y) task training pairs
  - Randomly initialize your models f(x) (e.g., vanilla Transformers)
  - Train f(x) on (x, y) pairs

Then you get a trained Transformers **ONLY** for sentiment analysis
The model can be: NB, LR, RNNs, LSTM too

Modern learning paradigm

- **Pre-training + supervised training/fine-tuning**
  - First train Transformer using a lot of general text using unsupervised learning. This is called **pretraining**.
  - Then train the pretrained Transformer for a specific task using supervised learning. This is called **finetuning**.



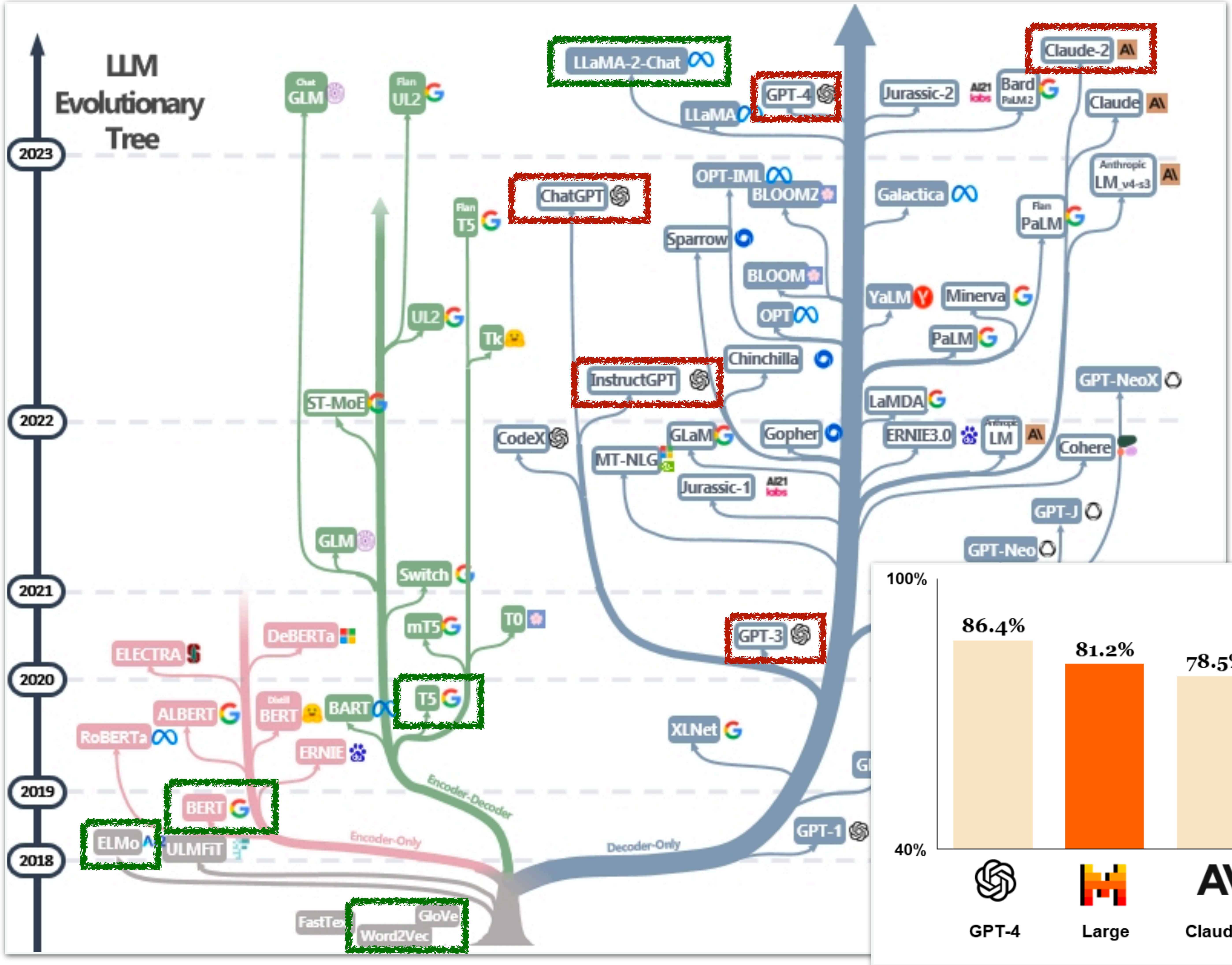
sentence	label
a stirring , funny and finally transporting re imagining of beauty and the beast and 1930s horror films	1
apparently reassembled from the cutting room floor of any given daytime soap	0
they presume their audience won't sit still for a sociology lesson	0
this is a visually stunning rumination on love , memory , history and the war between art and commerce	1
jonathan parker 's bartleby should have been the be all end all of the modern office anomie films	1

Evolution tree of pretrained LMs

~200 billion

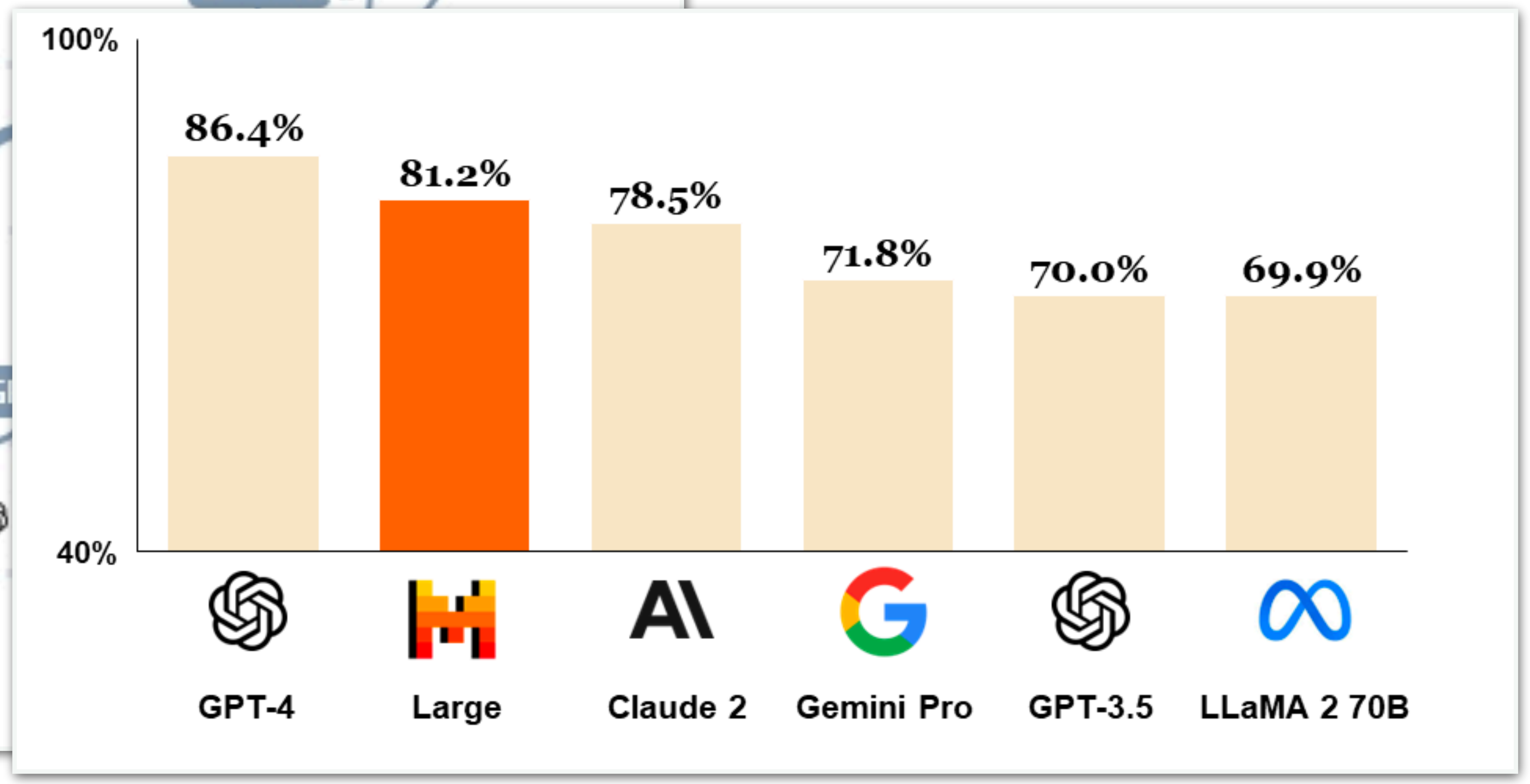
Model size
(# of parameters)
~1000 times larger

~300 million



Open-sourced

Close-sourced



https://github.com/Mooler0410/LLMsPracticalGuide
https://mistral.ai/news/mistral-large/

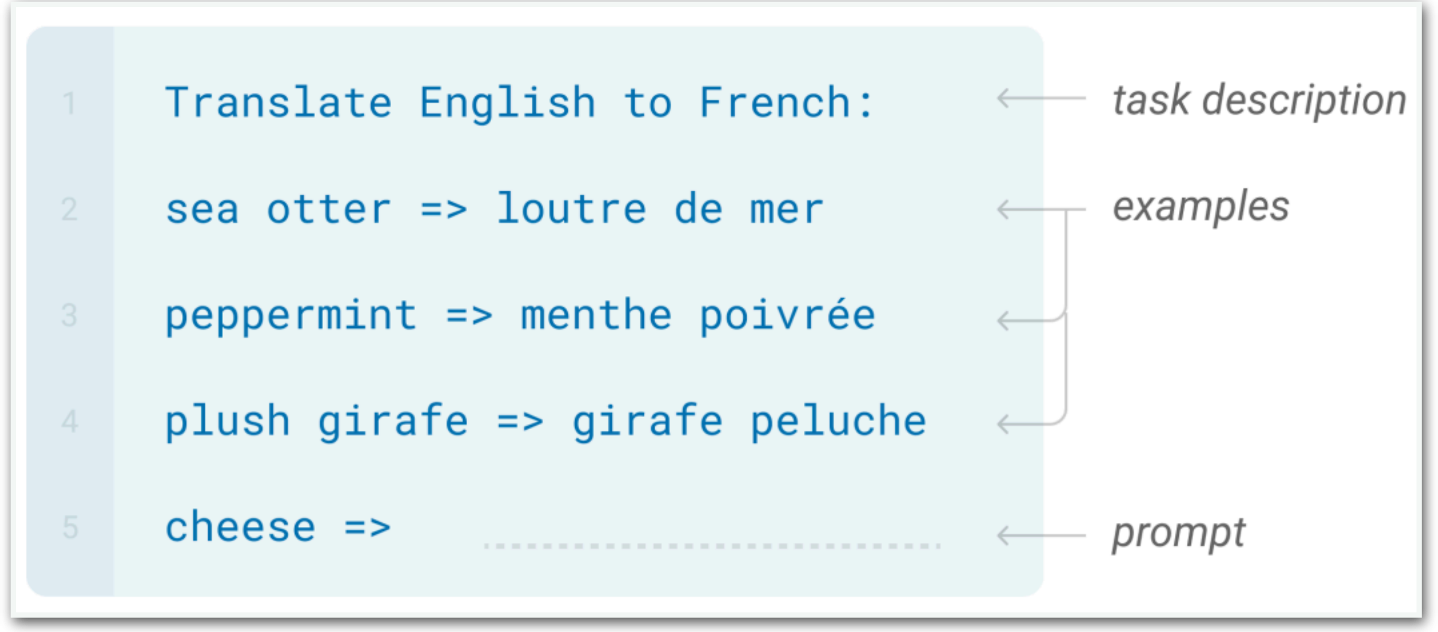
Latest learning paradigm with LLMs

- **Pre-training + prompting/in-context learning (no training this step)**
  - First train a **large (>7~175B)** Transformer using a lot of general text using unsupervised learning. This is called **large** language model **pretraining**.

Latest learning paradigm with LLMs

- **Pre-training + prompting/in-context learning (no training this step)**
  - First train a **large (>7~175B)** Transformer using a lot of general text using unsupervised learning. This is called **large** language model **pretraining**.
  - Then **directly use** the pretrained large Transformer (**no further finetuning/training**) for any different task given only a natural language description of the task or a few task (x, y) examples. This is called **prompting/in-context learning**.

Zero-shot prompting



Few-shot prompting/in-context learning

Example: Prompting ChatGPT for sentiment analysis

- **Pre-training + prompting/in-context learning (no training this step)**

TA **You**

what is the sentiment of "predictable with no fun"? just tell me: positive, negative, or neutral.

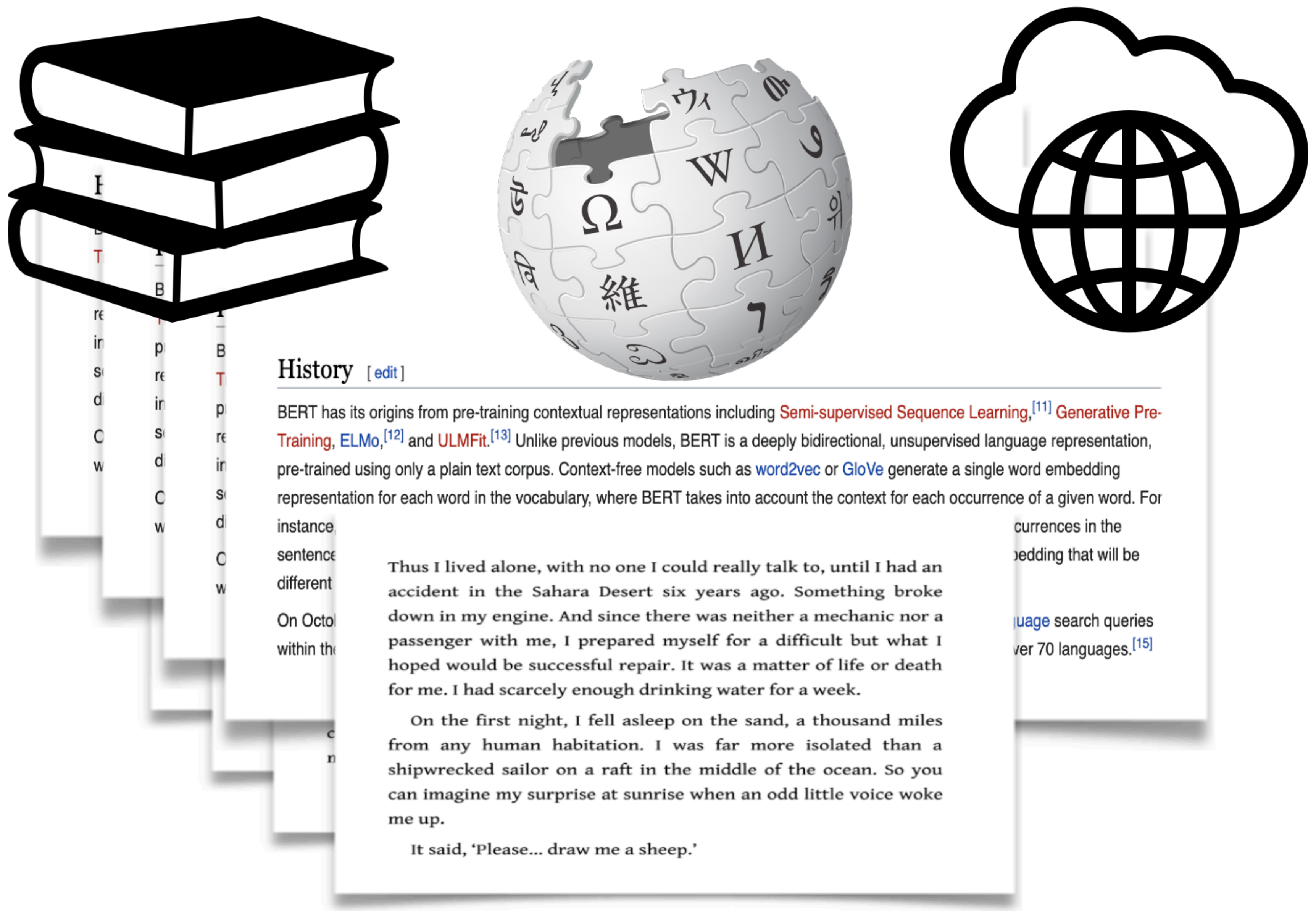
ChatGPT

Negative.

Already pretrained ChatGPT
No further training for sentiment analysis
Just prompting to conduct the task!

Pretraining: training objectives?

- During pretraining, we have a large text corpus (**no task labels**)
  - **Key question: what labels or objectives used to train the vanilla Transformers?**



Pretraining: training objectives?

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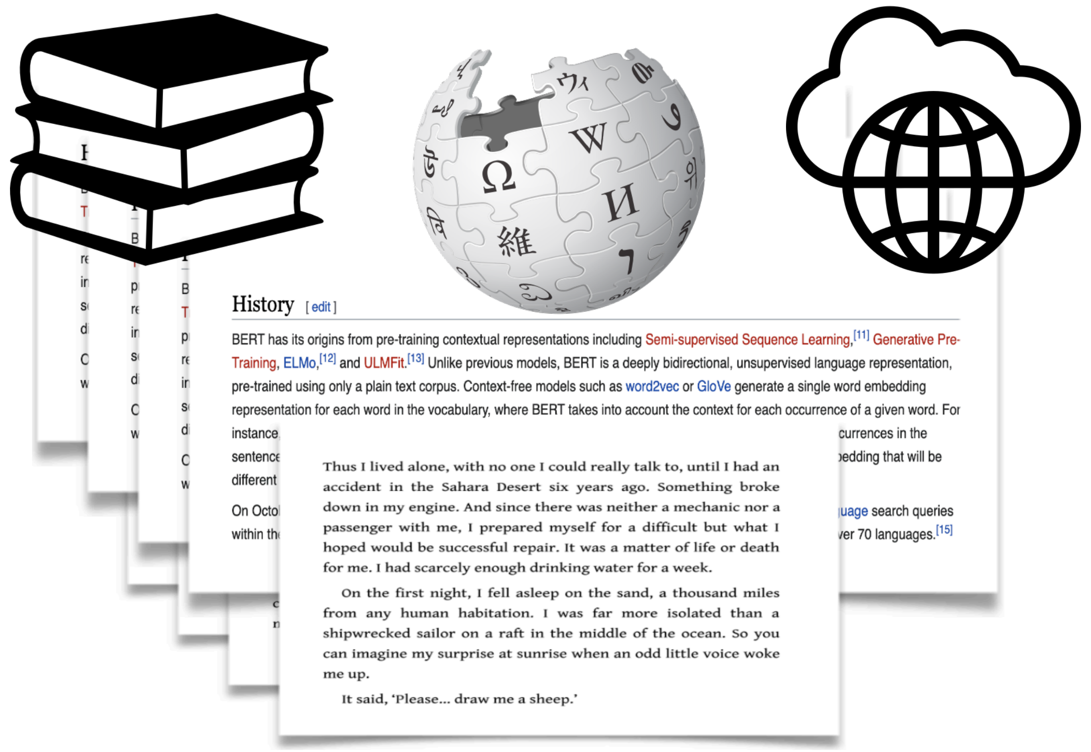


Pretraining Transformers

Training labels/objectives?

Pretraining: training objectives?

BERT (Encoder-only)

Devlin et al., 2018

```
The cabs ___ the same rates as those
___ by horse-drawn cabs and were ___
quite popular, ___ the Prince of
Wales (the ___ King Edward VII)
travelled in ___. The cabs quickly
___ known as "hummingbirds" for ___
noise made by their motors and their
distinctive black and ___ livery.
Passengers ___ ___ the interior
fittings were ___ when compared to
___ cabs but there ___ some
complaints ___ the ___ lighting made
them too ___ to those outside ___.
```

```
charged, used, initially, even,
future, became, the, yellow,
reported, that, luxurious,
horse-drawn, were that,
internal, conspicuous, cab
```

Masked token prediction

T5

T5 (Encoder-decoder)

Raffel et al., 2019

Original text

Thank you ~~for inviting~~ me to your party ~~last~~ week.

Inputs

Thank you <X> me to your party <Y> week.

Targets

<X> for inviting <Y> last <Z>

Denoising span-mask prediction

OpenAI

GPT - 4

Decoder-only

Text: Second Law of Robotics: A robot must obey the orders given it by human beings

Generated training examples

Example #	Input (features)	Correct output (labels)
1	Second law of robotics :	a
2	Second law of robotics : a	robot
3	Second law of robotics : a robot	must
...		

Next token prediction

https://github.com/manueldeprada/Pretraining-T5-PyTorch-Lightning

Advantages of pre-training

- **Leveraging rich underlying information** from abundant raw texts.
- **Reducing the reliance of task-specific labeled data** that is difficult or costly to obtain.
- **Initializing model parameters** for more **generalizable** NLP applications.
- **Saving training cost** by providing a reusable model checkpoints.
- **Providing robust representation** of language contexts.

Pre-training architectures

Encoder

- E.g., BERT, RoBERTa, DeBERTa, …
- **Autoencoder** model
- **Masked** language modeling

Encoder-Decoder

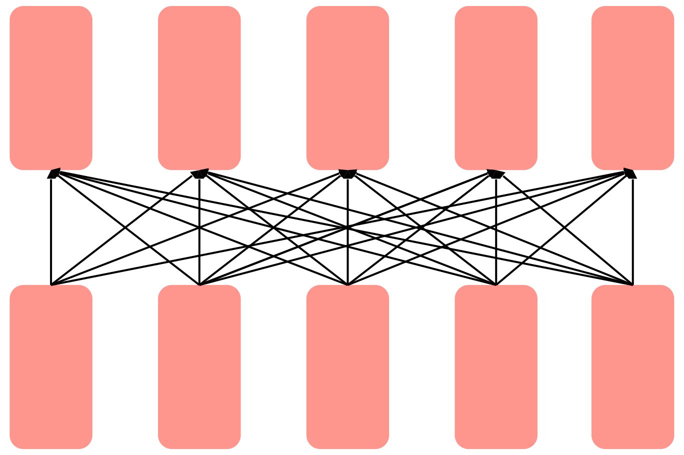
- E.g., T5, BART, …
- **seq2seq** model

Decoder

- E.g., GPT, GPT2, GPT3, …
- **Autoregressive** model
- **Left-to-right** language modeling

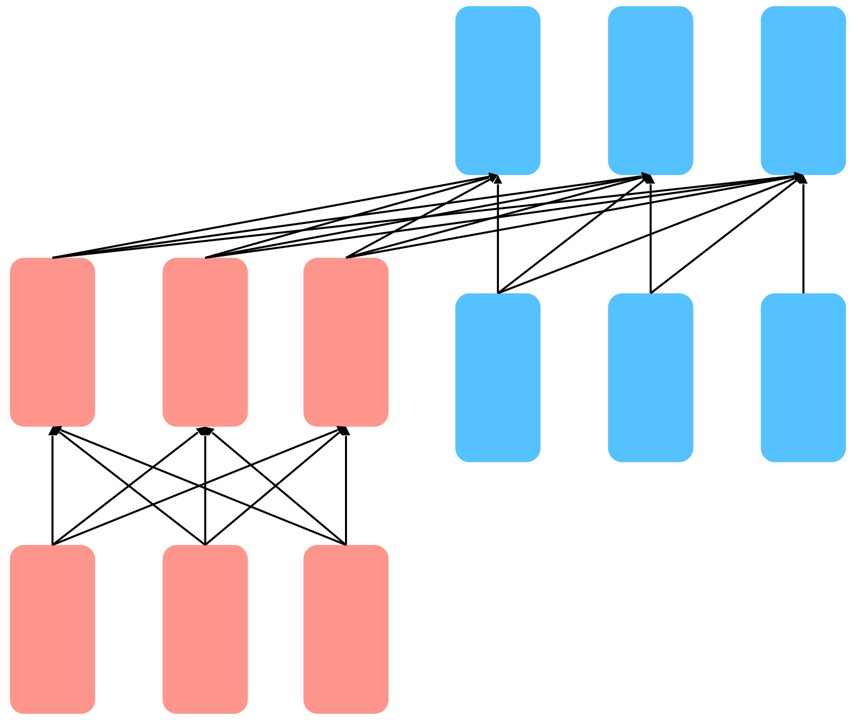
Pre-training architectures

Encoder



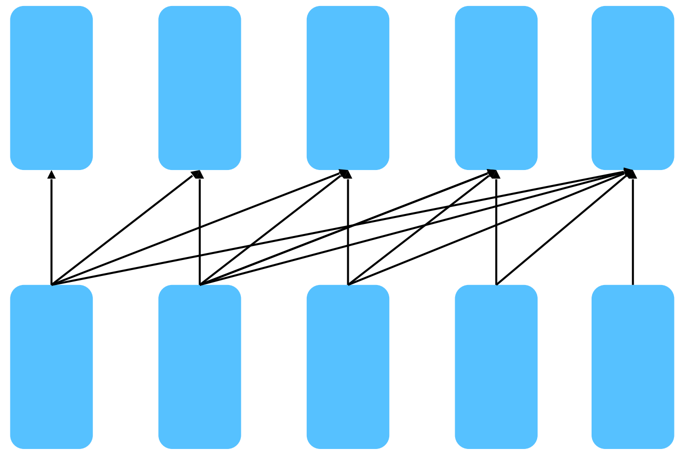
- Bidirectional; can condition on the future context

Encoder-Decoder



- Map two sequences of different length together

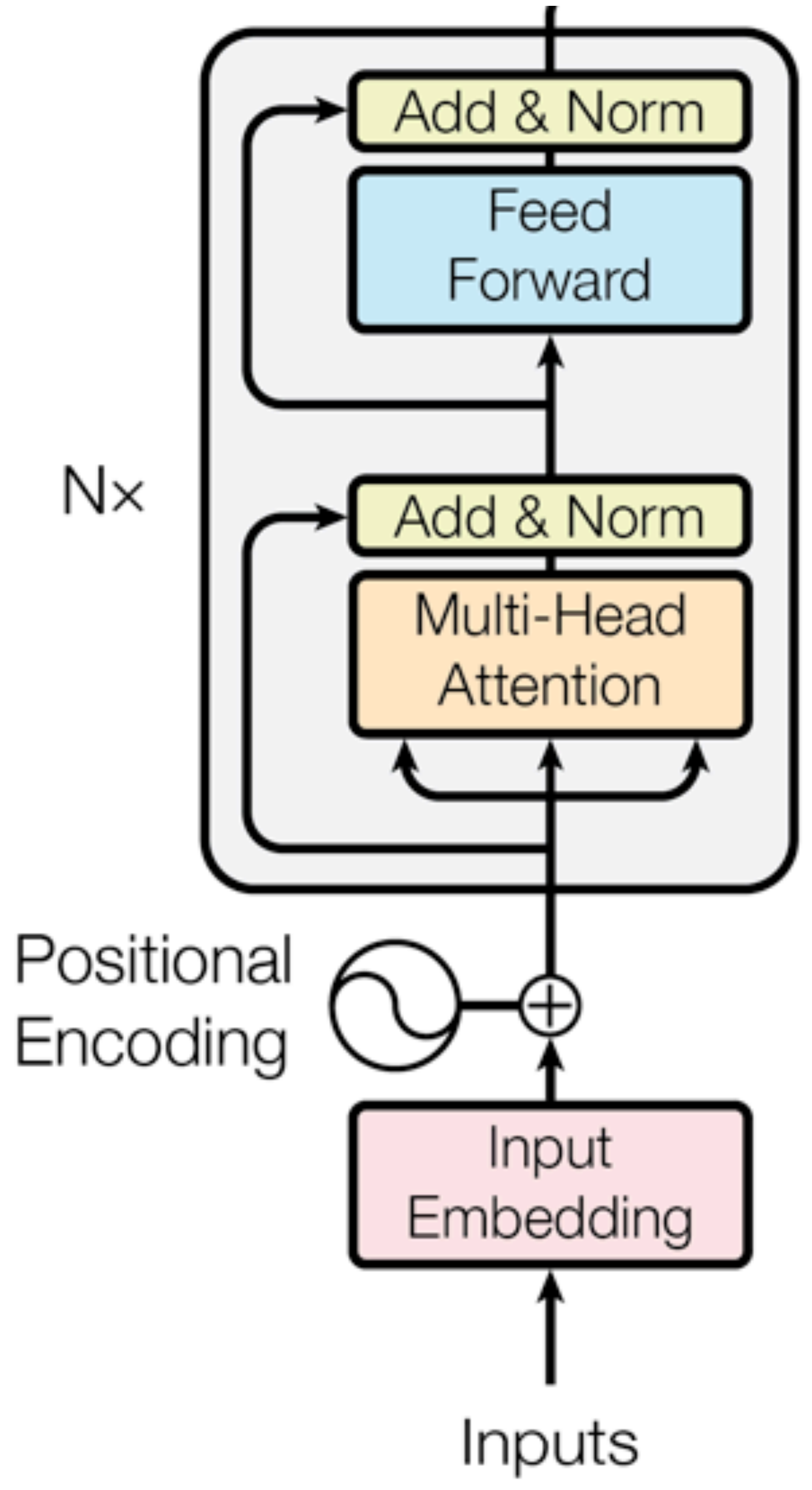
Decoder



- Language modeling; can only condition on the past context

BERT: Bidirectional Encoder Representations from Transformers

(Released in 2018/10)



- It is a fine-tuning approach based on a deep **bidirectional Transformer encoder** instead of a Transformer decoder
- The key: learn representations based on **bidirectional contexts**

Example #1: we went to the river bank.

Example #2: I need to go to bank to make a deposit.

- Two new pre-training objectives:
  - **Masked language modeling (MLM)**
  - Next sentence prediction (NSP) - Later work shows that NSP hurts performance though..

(Devlin et al, 2019): BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Masked Language Modeling (MLM)

- Q: Why we can't do language modeling with bidirectional models?

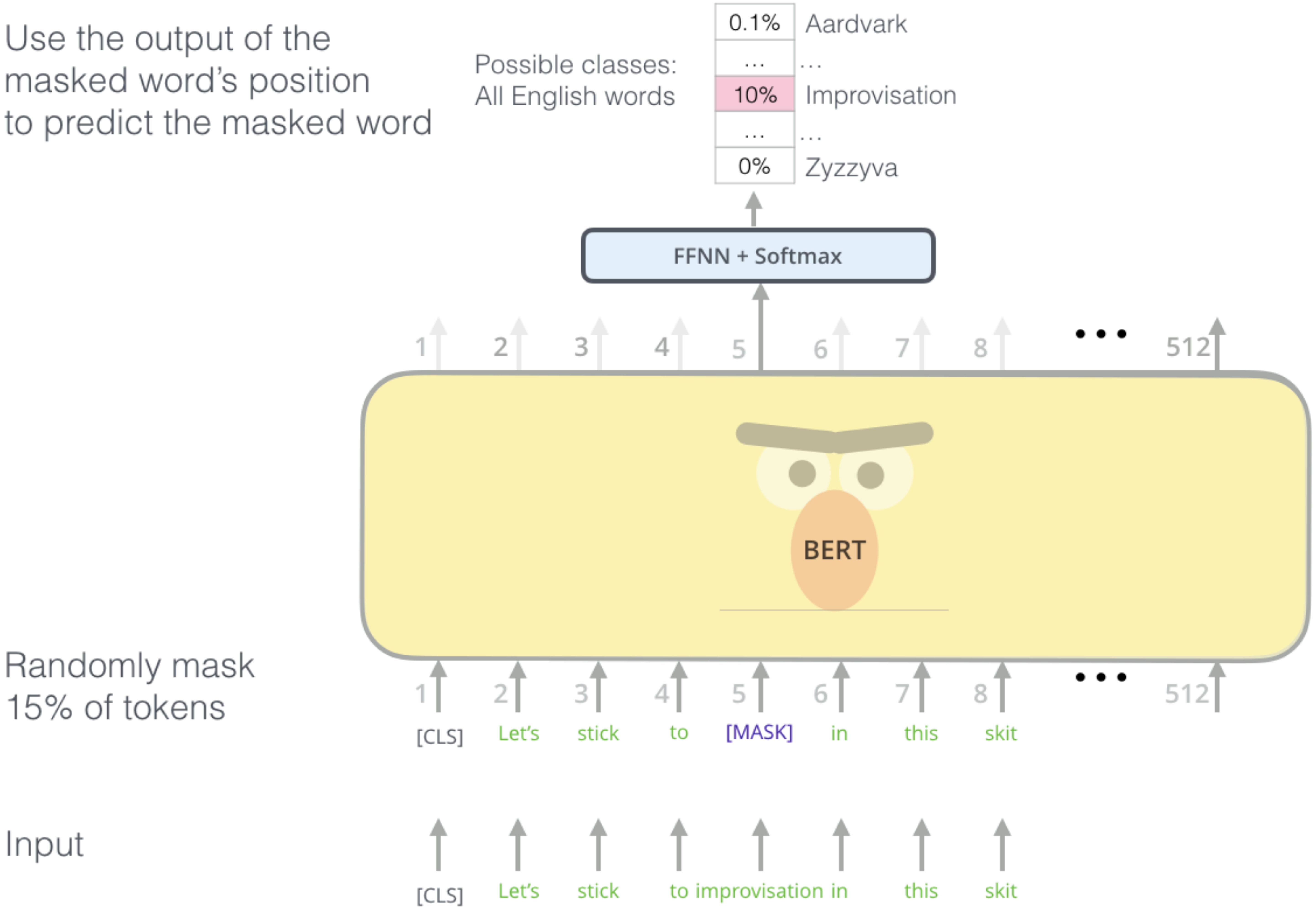
- Solution: Mask out k% of the input words, and then predict the masked words

store ↑ gallon ↑

the man went to [MASK] to buy a [MASK] of milk

k = 15% in practice

Masked Language Modeling (MLM)



http://jalammar.github.io/illustrated-bert/

MLM: 80-10-10 corruption

For the 15% predicted words,

- 80% of the time, they replace it with [MASK] token

went to the store $\longrightarrow$ went to the [MASK]

- 10% of the time, they replace it with a random word in the vocabulary

went to the store $\longrightarrow$ went to the running

- 10% of the time, they keep it unchanged

went to the store $\longrightarrow$ went to the store

Why? Because [MASK] tokens are never seen during fine-tuning

(See Table 8 of the paper for an ablation study)

Next Sentence Prediction (NSP)

- Motivation: many NLP downstream tasks require understanding the relationship between two sentences (natural language inference, paraphrase detection, QA)
- NSP is designed to reduce the gap between pre-training and fine-tuning

[CLS]: a special token always at the beginning

[SEP]: a special token used to separate two segments

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]

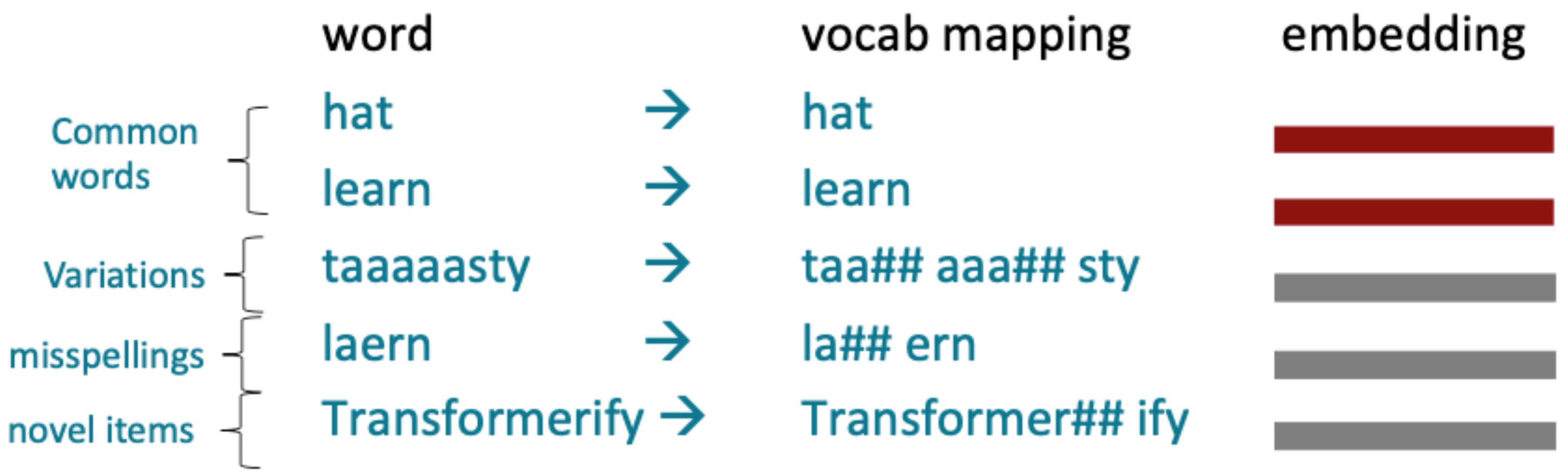
Label = NotNext

They sample two contiguous segments for 50% of the time and another random segment from the corpus for 50% of the time

This actually hurts model learning based on later work!

BERT pre-training

- Vocabulary size: 30,000 wordpieces (common sub-word units) (Wu et al., 2016)

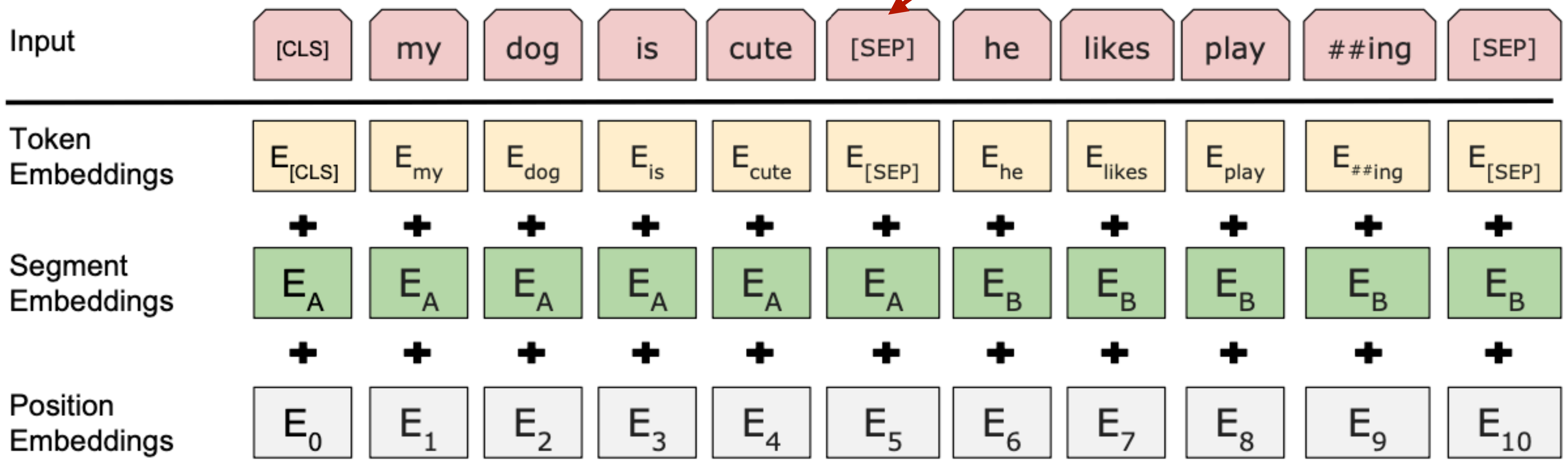


(Image: Stanford CS224N)

- Input embeddings:

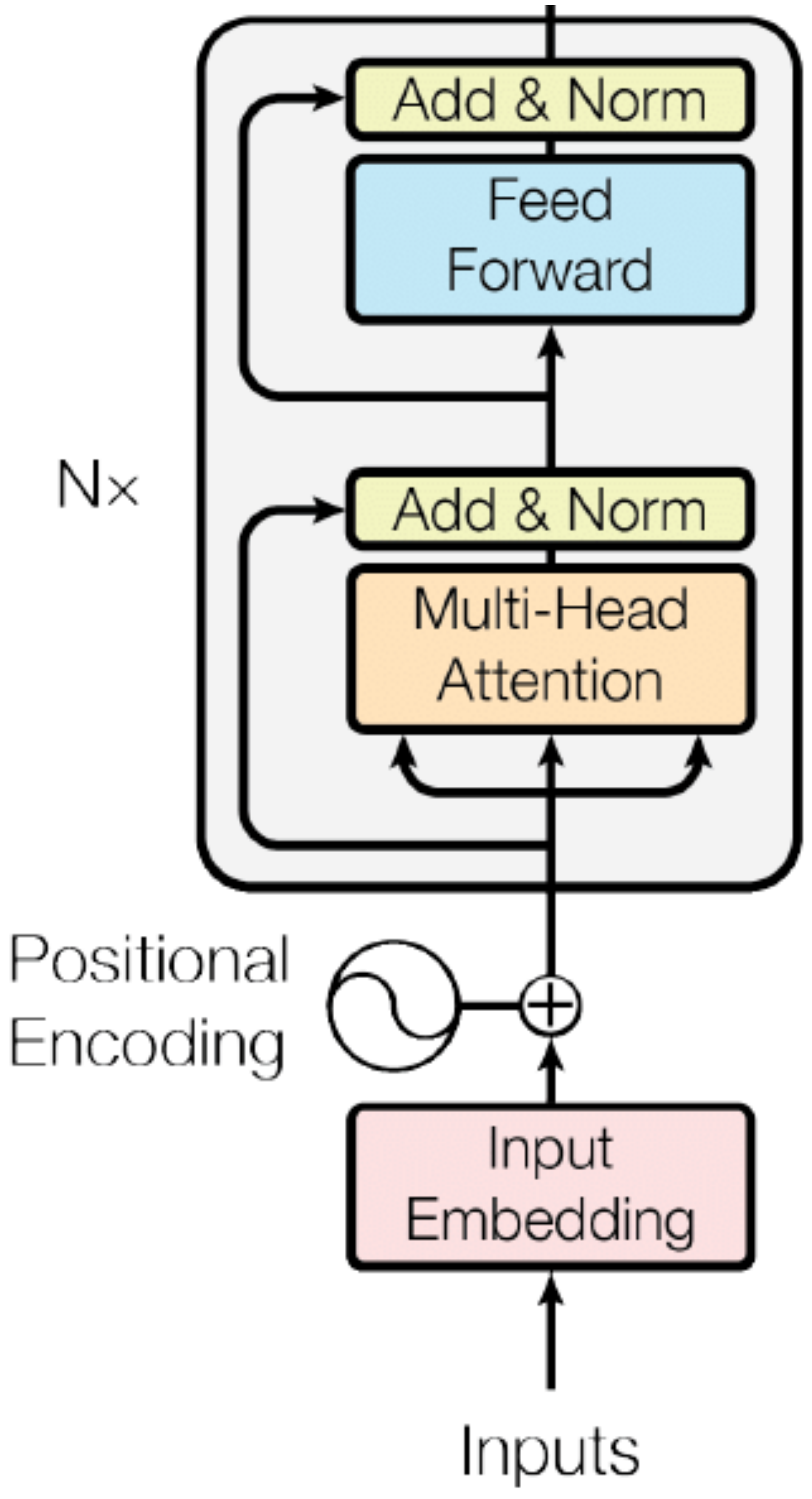
Special token added to the beginning of each input sequence

Special token to separate sentence A/B



Separate two segments

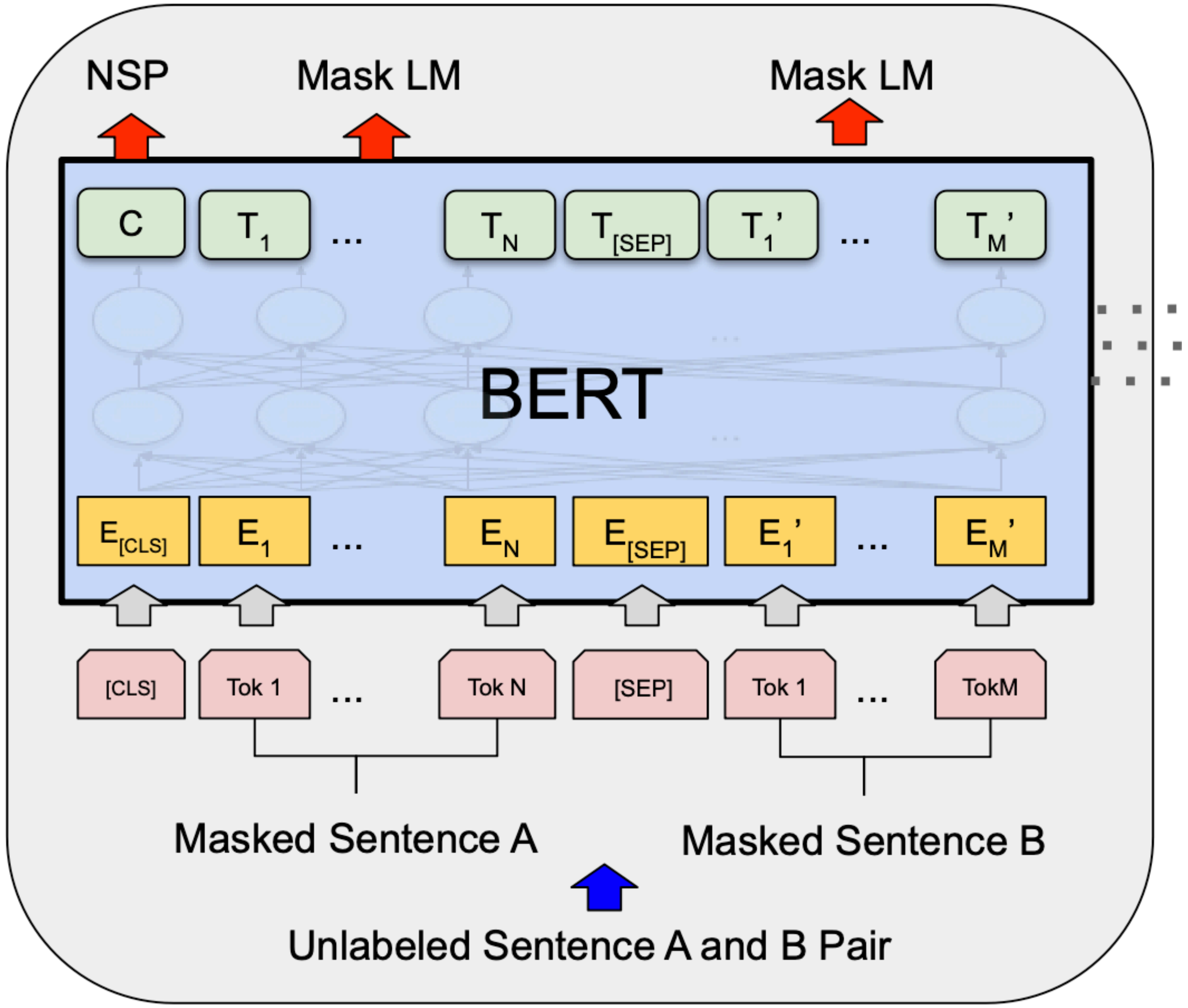
BERT pre-training



- BERT-base: 12 layers, 768 hidden size, 12 attention heads, 110M parameters
- BERT-large: 24 layers, 1024 hidden size, 16 attention heads, 340M parameters

- Training corpus: Wikipedia (2.5B) + BooksCorpus (0.8B)
- Max sequence size: 512 wordpiece tokens (roughly 256 and 256 for two non-contiguous sequences)
- Trained for 1M steps, batch size 128k

BERT pre-training

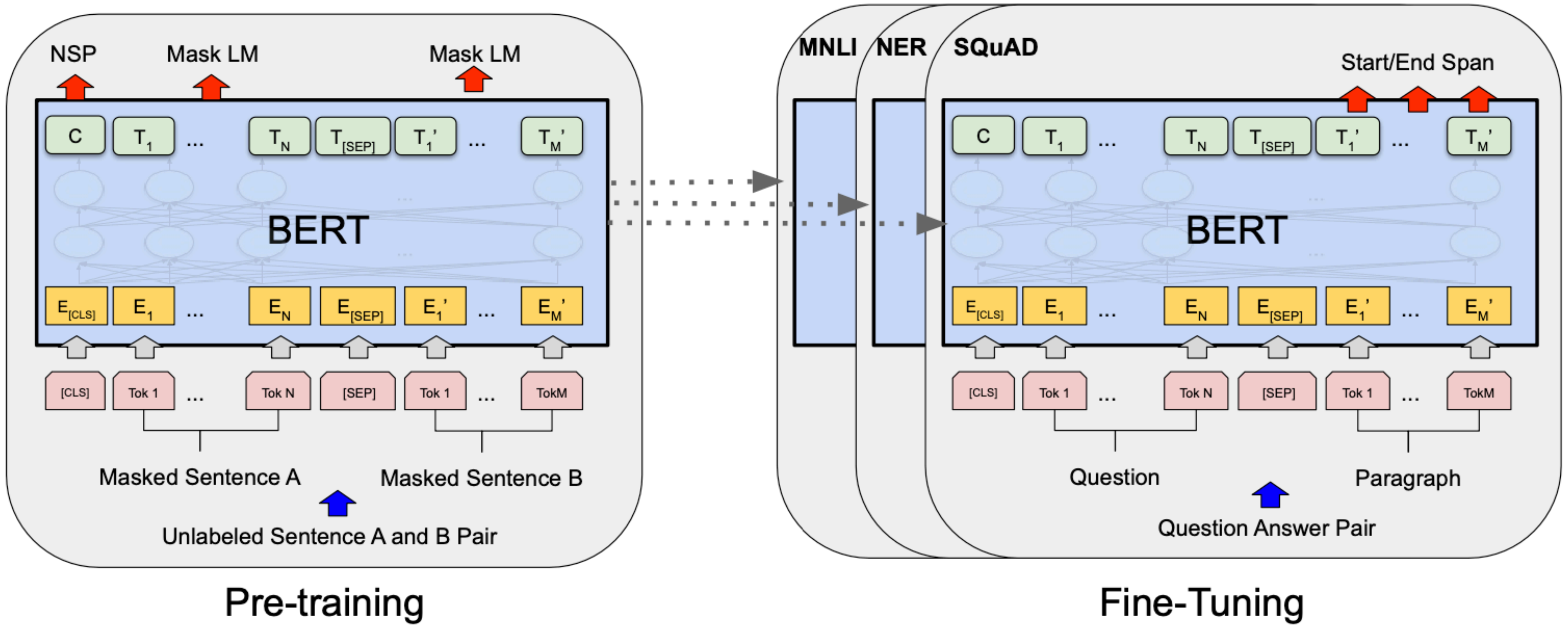


Pre-training

- MLM and NSP are trained together
- [CLS] is pre-trained for NSP
- Other token representations are trained for MLM

Pretraining / fine-tuning

"Pre-train" a model on a large dataset for task X, then "fine-tune" it on a dataset for task Y



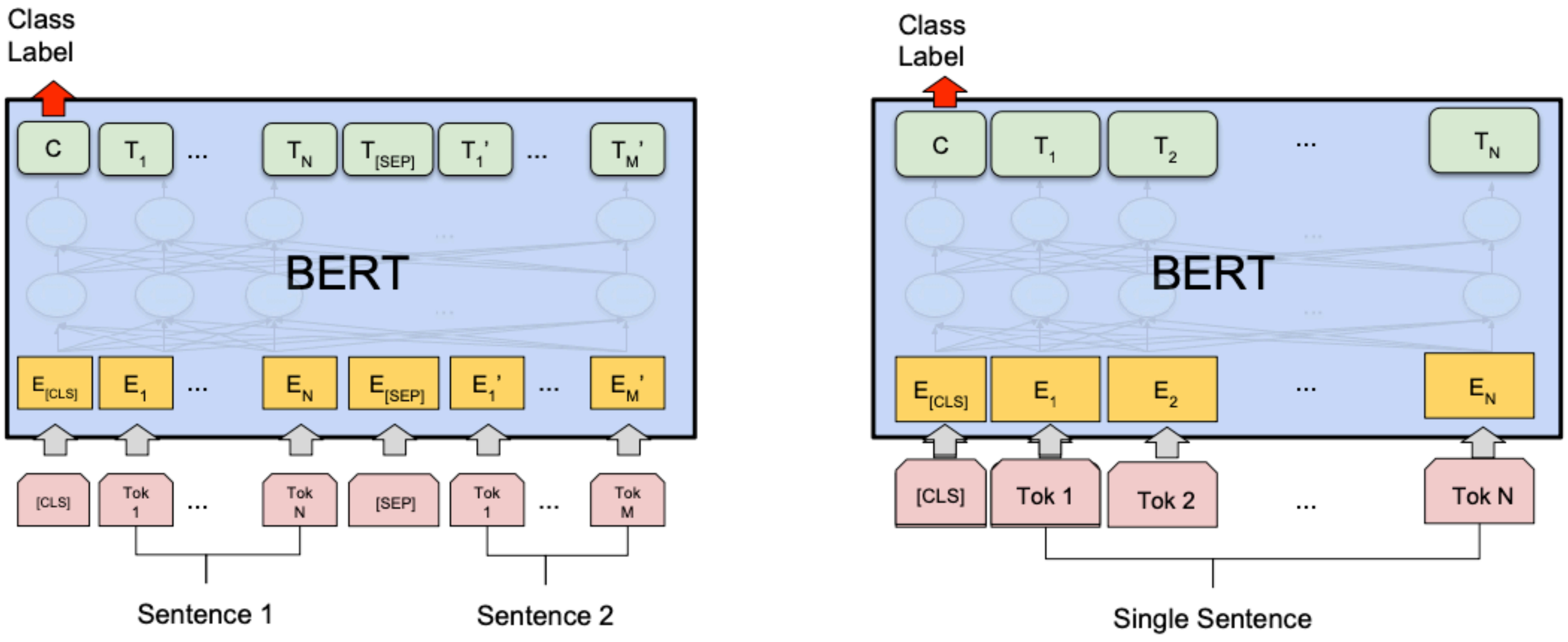
"**Fine-tuning** is the process of **taking the network learned by these pre-trained models**, and **further training the model**, often via an added neural net classifier that takes the top layer of the network as input, to perform some downstream task."

Fine-tuning is a training process and takes **gradient descent steps**!

BERT fine-tuning

“Pretrain once, finetune many times.”

sentence-level tasks



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

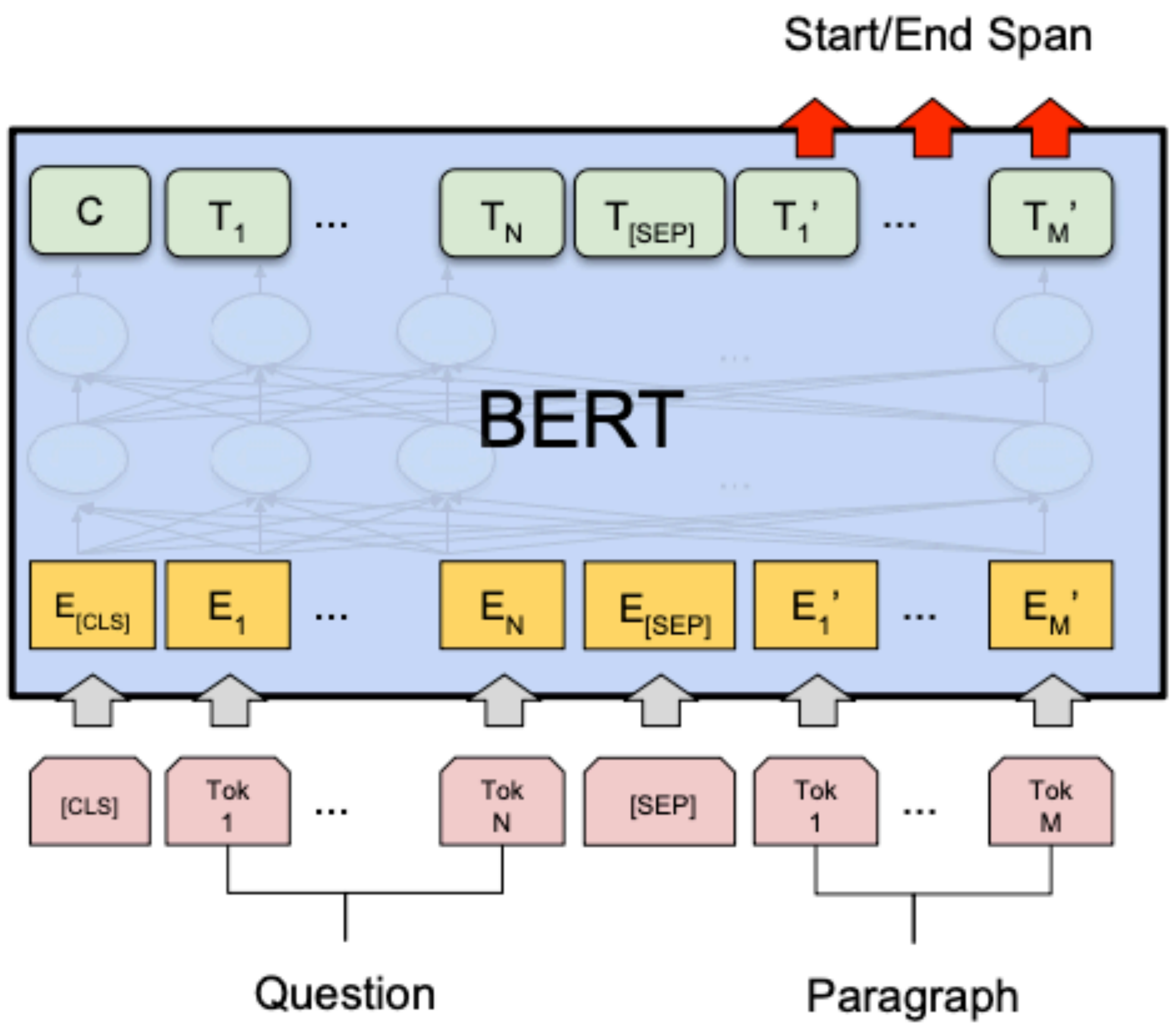
(b) Single Sentence Classification Tasks: SST-2, CoLA

- **QQP:** Quora Question Pairs (detect paraphrase questions)
- **QNLI:** natural language inference over question answering data
- **SST-2:** sentiment analysis

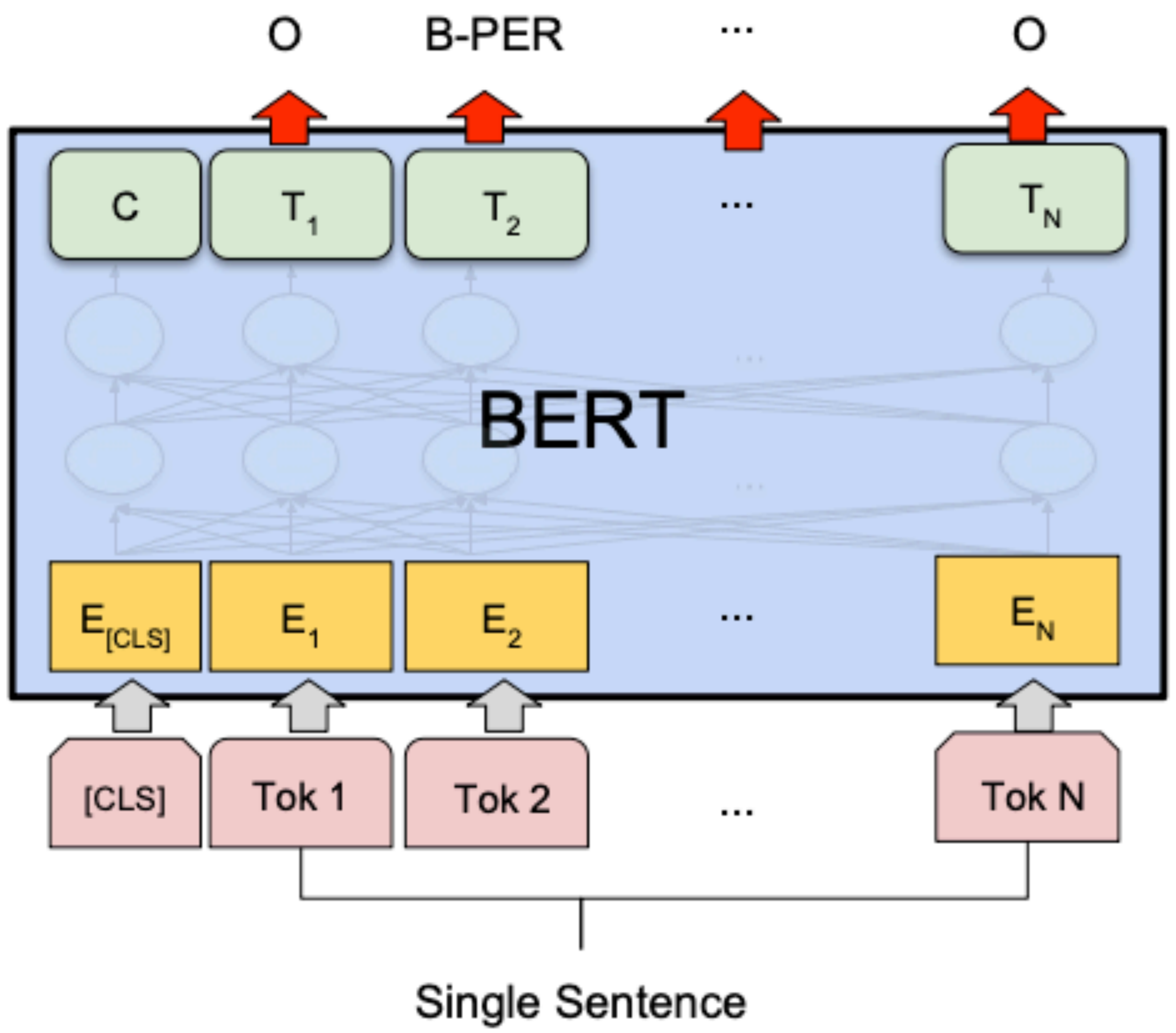
BERT fine-tuning

"Pretrain once, finetune many times."

token-level tasks



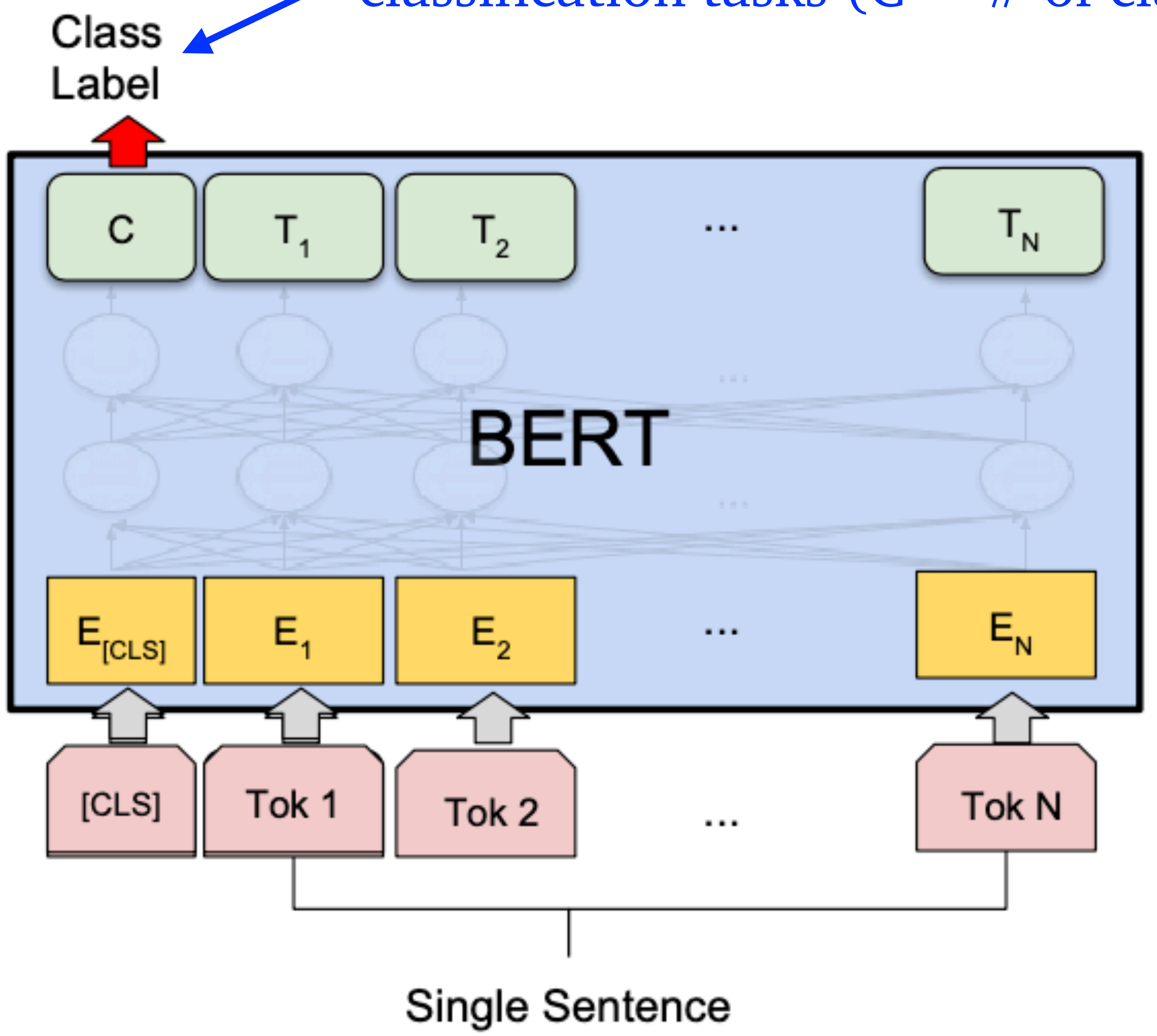
(c) Question Answering Tasks:
SQuAD v1.1



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

Example: sentiment classification

We just need to introduce $C \times h$ parameters for classification tasks (C = # of classes, h = hidden size)!



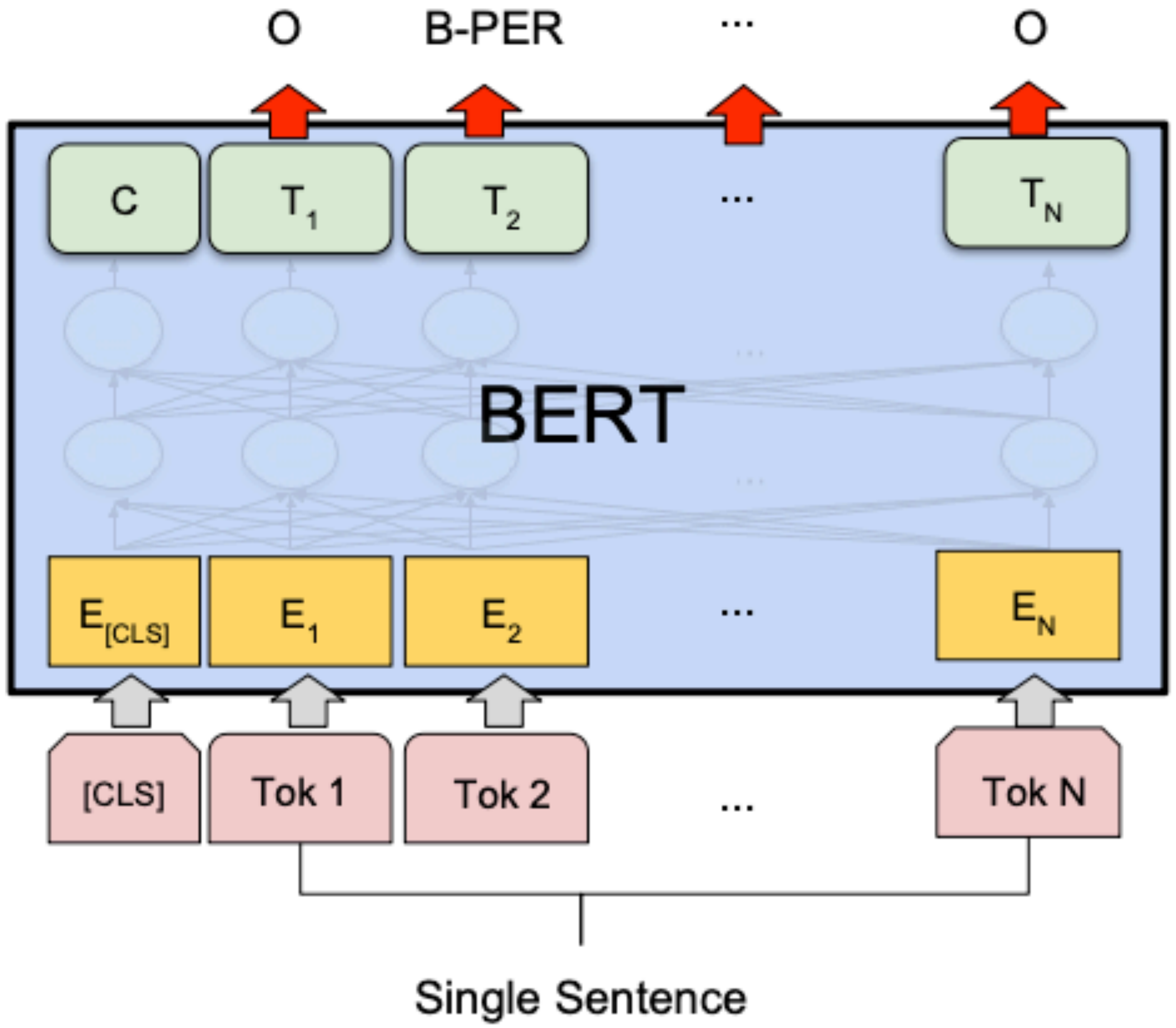
$$P(y = k) = softmax_k(\mathbf{W}_o \mathbf{h}_{[CLS]})$$

$$\mathbf{W}_o \in \mathbb{R}^{C \times h}$$

All the parameters will be learned together (original BERT parameters + new classifier parameters)

Example: named entity recognition (NER)

We just need to introduce $C \times h$ parameters for classification tasks (C = # of classes, h = hidden size)!



$$P(y_i = k) = softmax_k(\mathbf{W}_o \mathbf{h}_i)$$

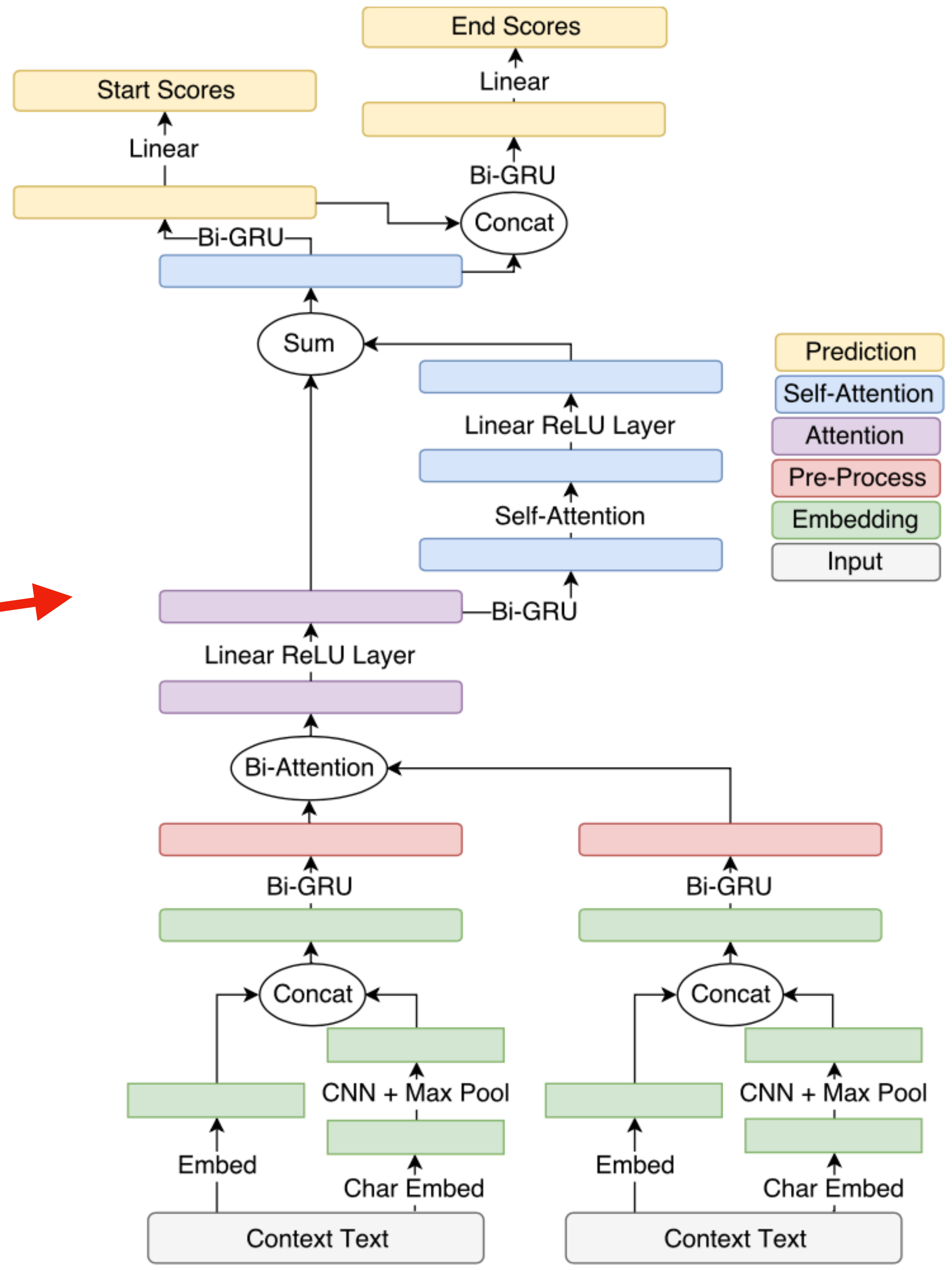
$$\mathbf{W}_o \in \mathbb{R}^{C \times h}$$

Experimental results: GLUE

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**

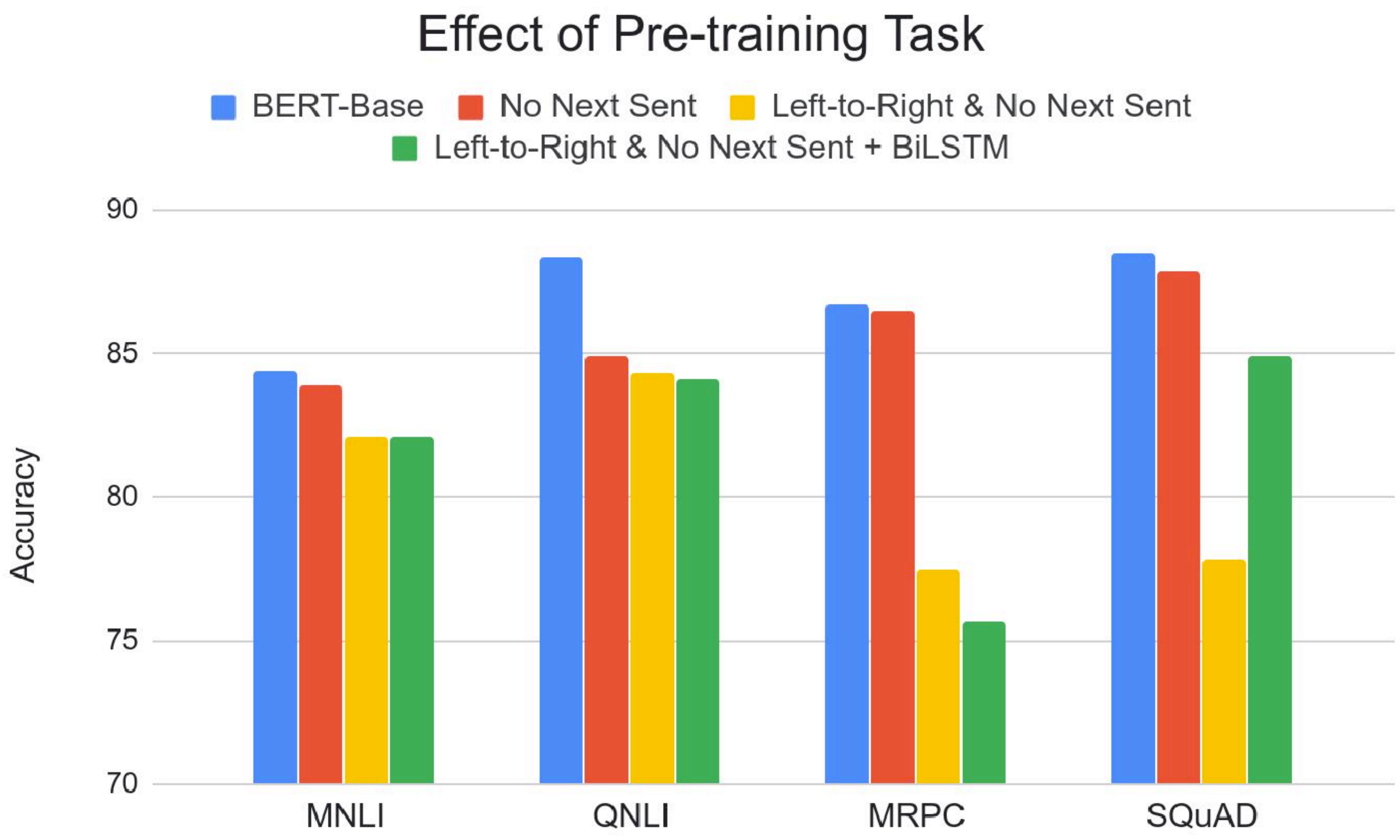
Experimental results: SQuAD

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**



SQuAD = Stanford Question Answering dataset

Ablation study: pre-training tasks



- MLM >> left-to-right LMs
- NSP improves on some tasks
- Note: later work (Joshi et al., 2020; Liu et al., 2019) argued that NSP is not useful

Ablation study: model sizes

layers hidden size # of heads

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

The bigger, the better!

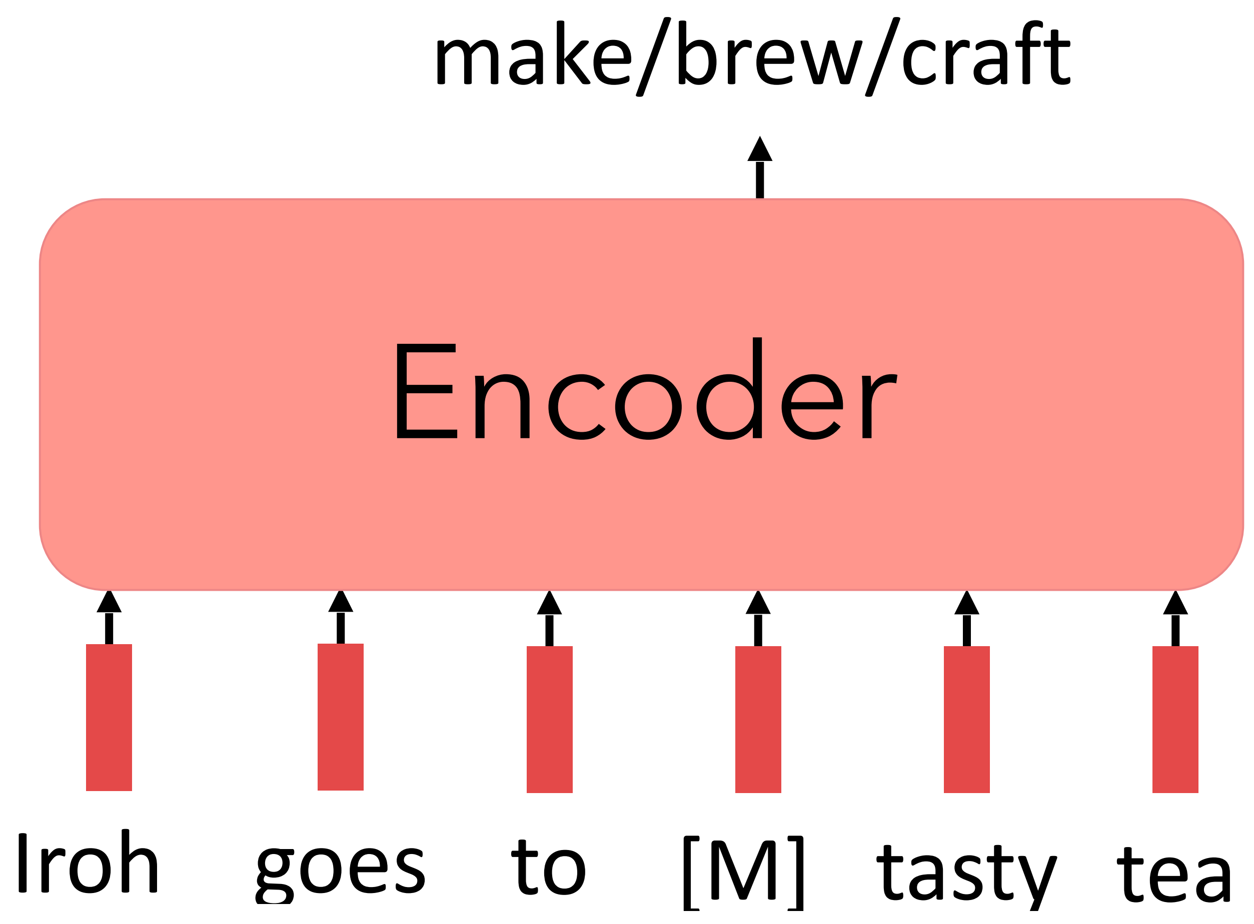
Encoder: other variations of BERT

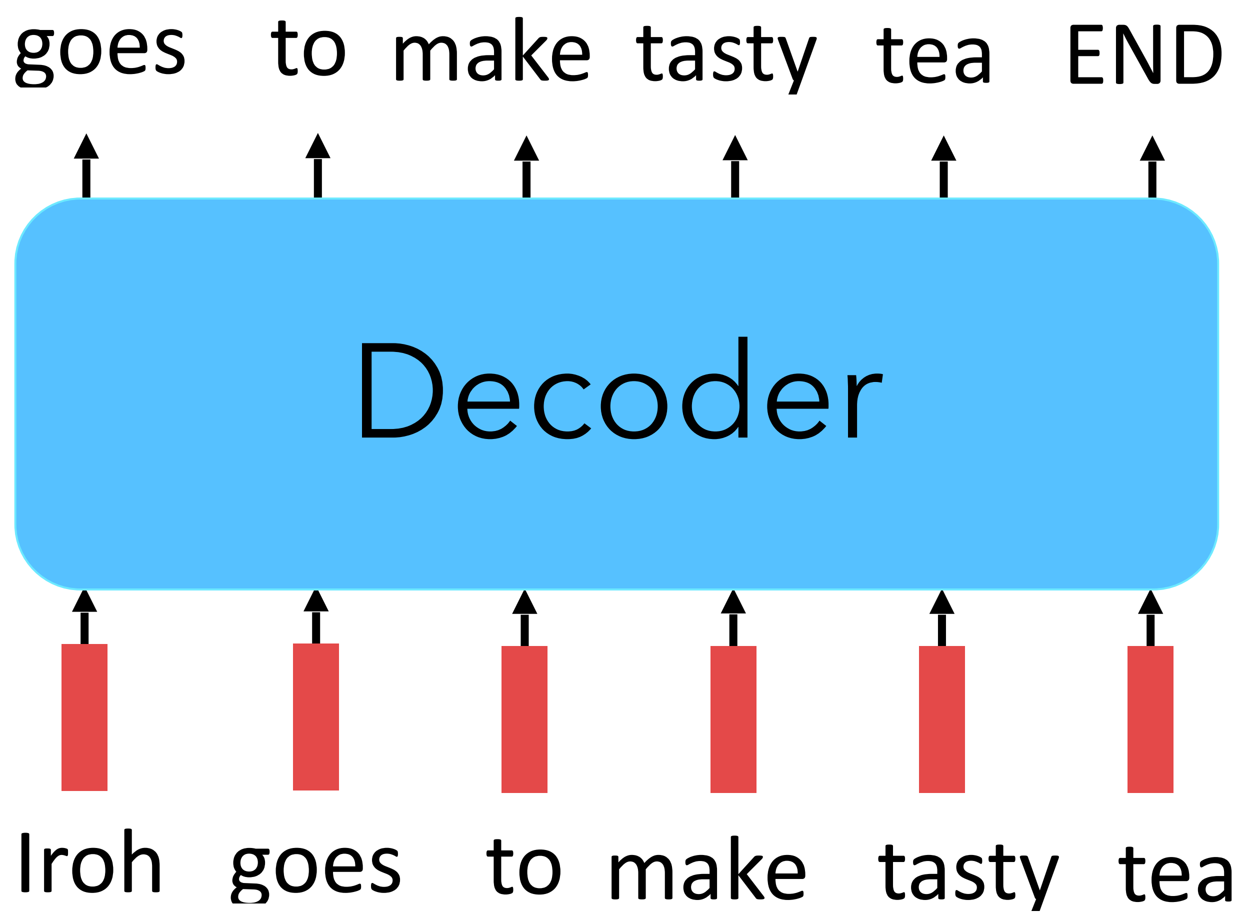
- **ALBERT [Lan et al., 2020]**: incorporates two parameter reduction techniques that lift the major obstacles in scaling pre-trained models
- **DeBERTa [He et al., 2021]:** decoding-enhanced BERT with disentangled attention
- **SpanBERT [Joshi et al., 2019]:** masking contiguous spans of words makes a harder, more useful pre-training task
- **ELECTRA [Clark et al., 2020]:** corrupts texts by replacing some tokens with plausible alternatives sampled from a small generator network, then train a discriminative model that predicts whether each token in the corrupted input was replaced by a generator sample or not.
- **DistilBERT [Sanh et al., 2019]:** distilled version of BERT that's 40% smaller
- **TinyBERT [Jiao et al., 2019]:** distill BERT for both pre-training & fine-tuning
- **...**

Encoder: pros & cons

- Consider both left and right context
- Capture intricate contextual relationships

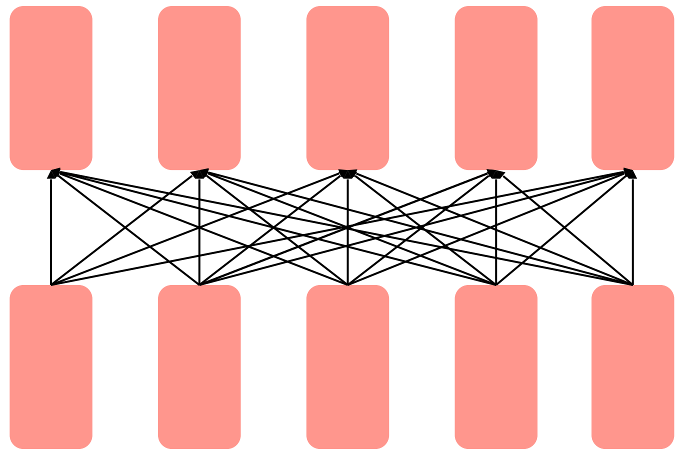
- Not good at generating open-text from left-to-right, one token at a time





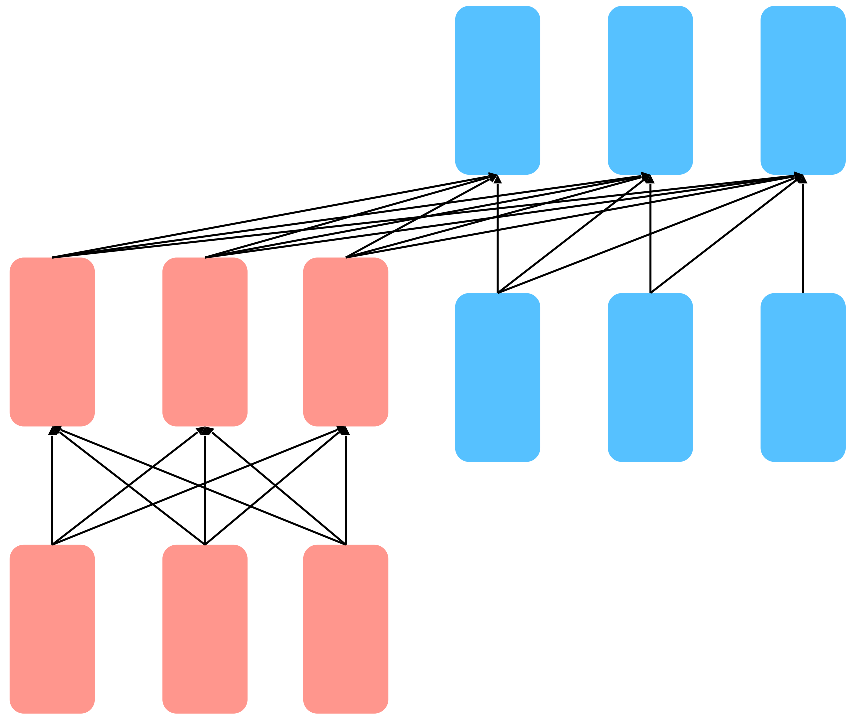
Pre-training architectures

Encoder



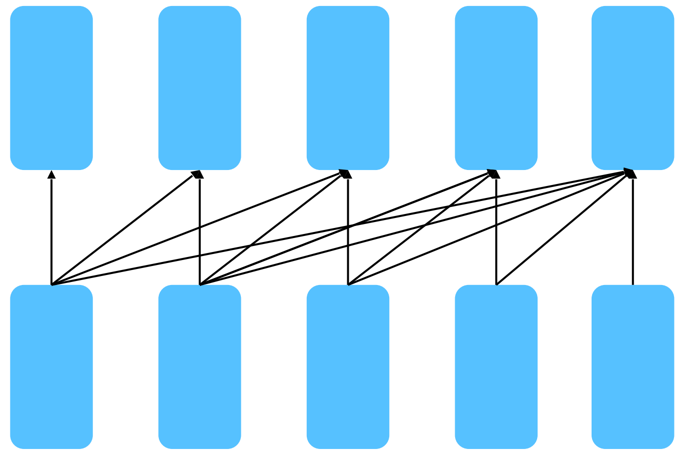
- Bidirectional; can condition on the future context

Encoder-Decoder



- Map two sequences of different length together

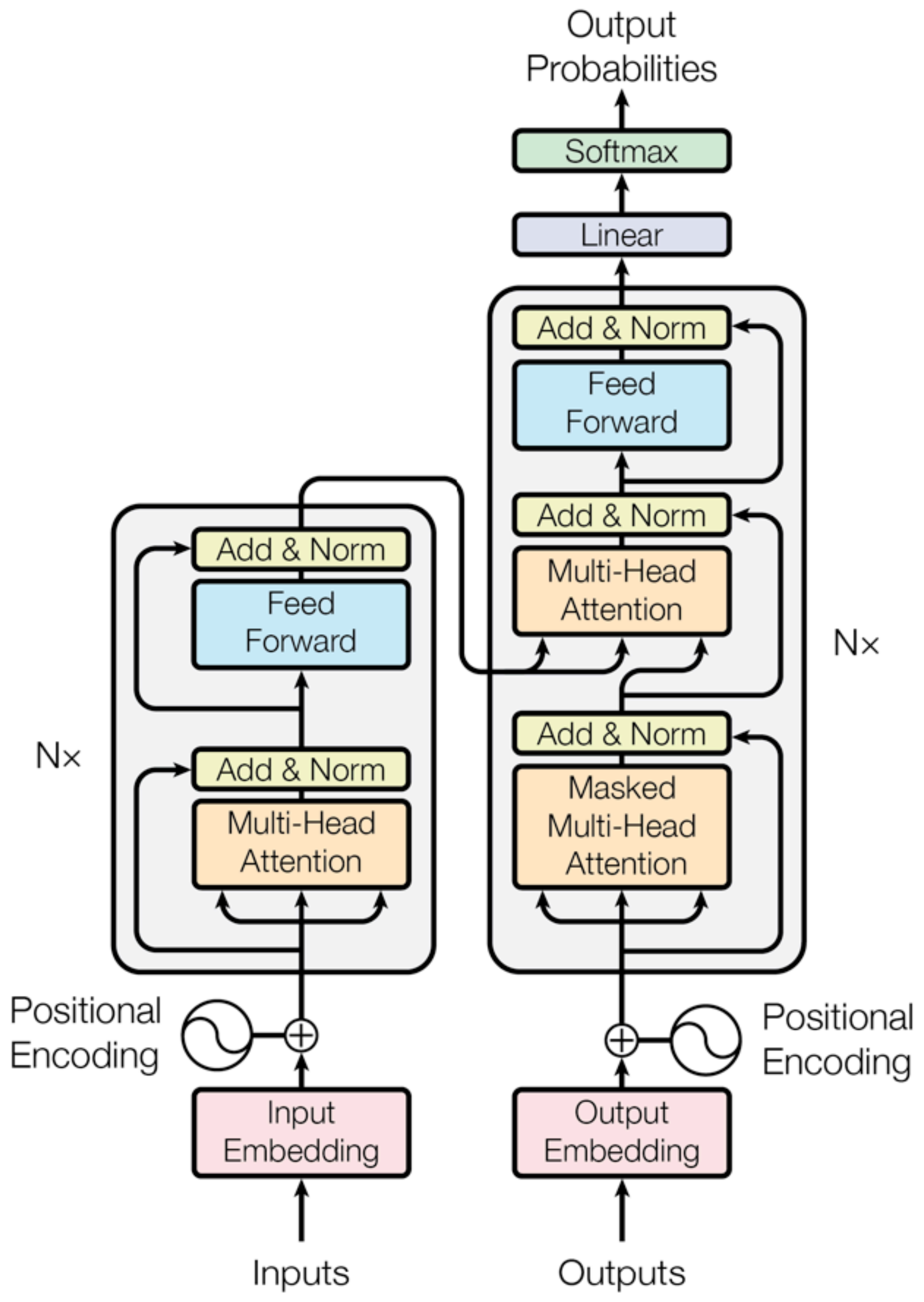
Decoder



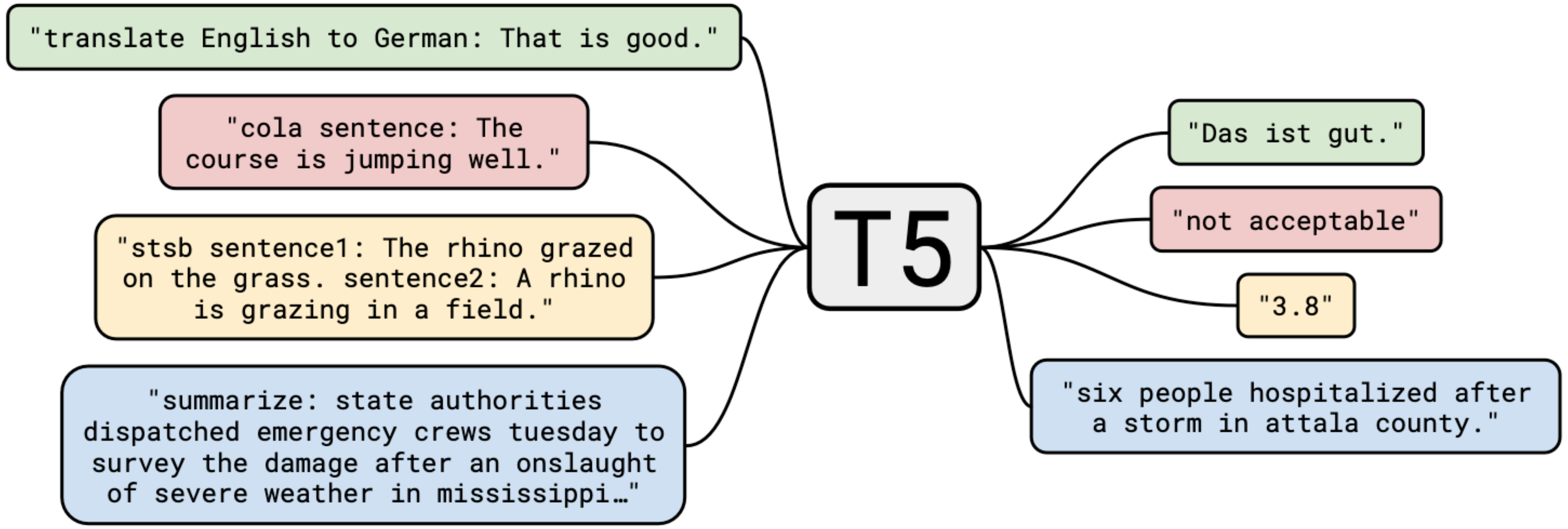
- Language modeling; can only condition on the past context

Text-to-text models: the best of both worlds

- So bar, **encoder-only models (e.g., BERT)** enjoy the benefits of **bidirectionality** but they can’t be used to generate text
- **Decoder-only models (e.g., GPT)** can do generation but they are left-to-right LMs..
- Text-to-text models combine the best of both worlds!



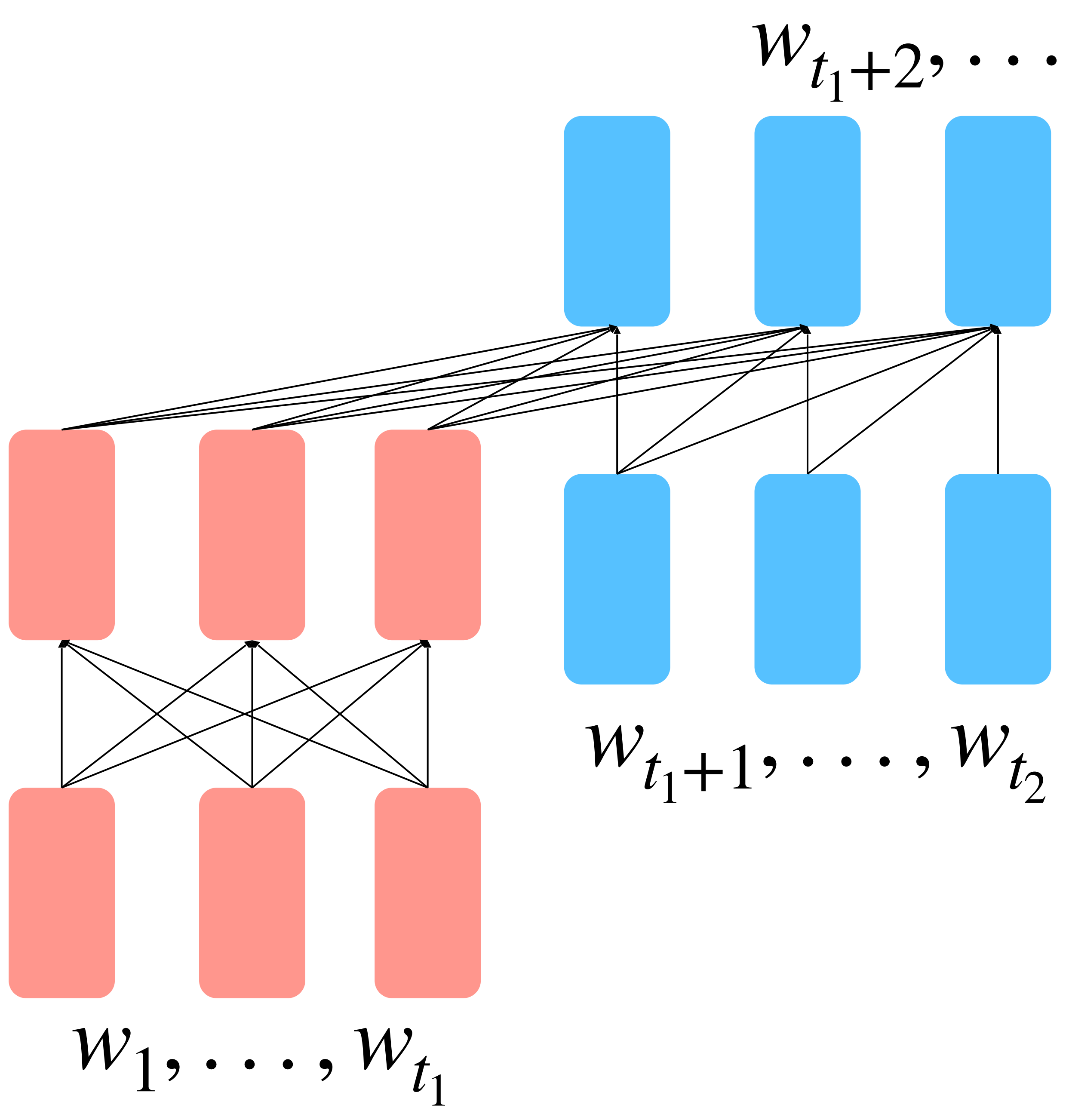
T5 = **T**ext-**t**o-**T**ext **T**ransfer **T**ransformer



(Raffel et al., 2020): Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

Encoder-decoder: architecture

- Moving towards **open-text generation**…
- **Encoder** builds a representation of the source and gives it to the **decoder**
- **Decoder** uses the source representation to generate the target sentence
- The **encoder** portion benefits from **bidirectional** context; the **decoder** portion is used to train the whole model through **language modeling**



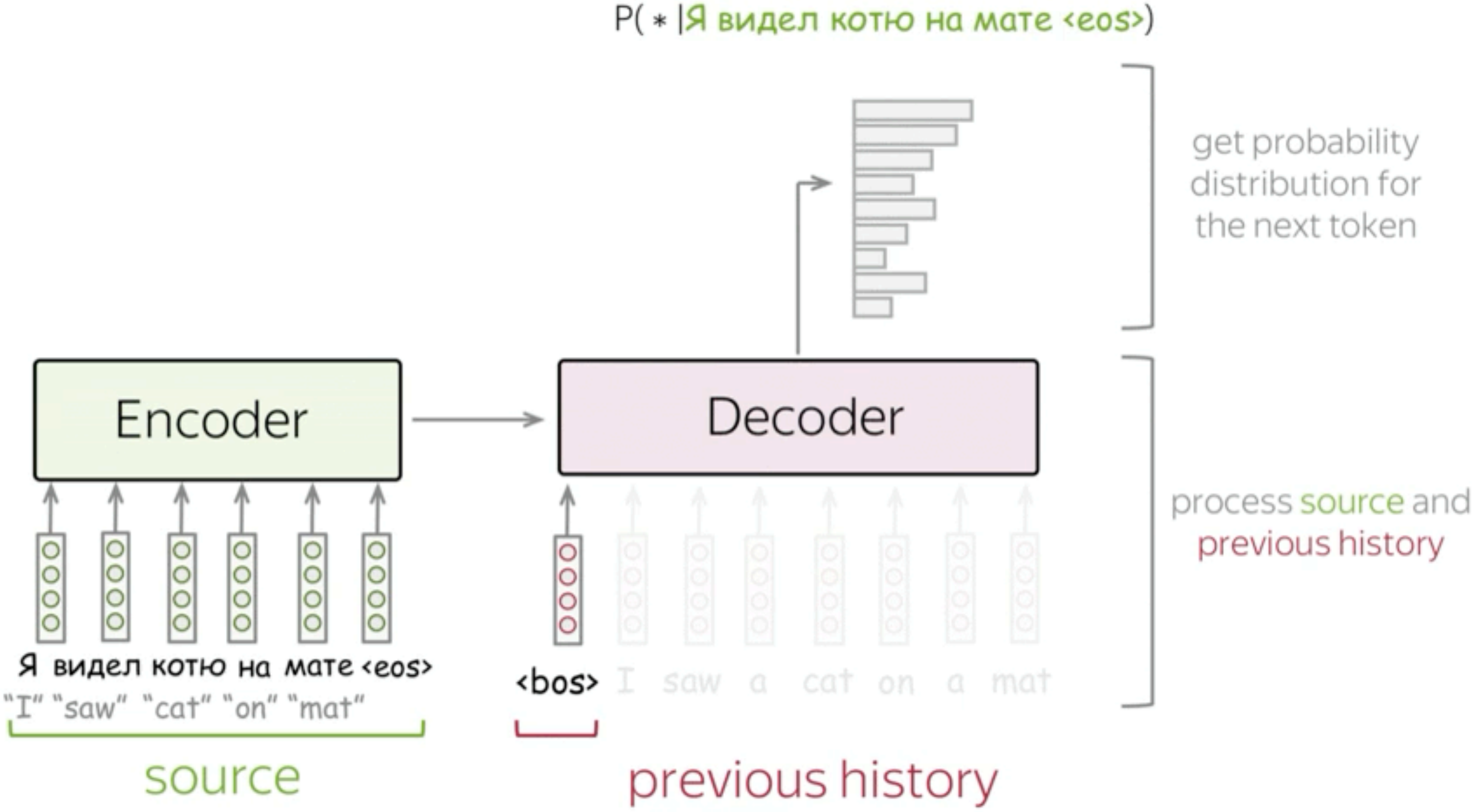
$$h_1, \ldots, h_{t_1} = \text{Encoder}(w_1, \ldots, w_{t_1})$$

$$h_{t_1+1}, \ldots, h_{t_2} = \text{Decoder}(w_{t_1+1}, \ldots, w_{t_2}, h_1, \ldots, h_{t_1})$$

$$y_i \sim Ah_i + b, i > t$$

[Raffel et al., 2018]

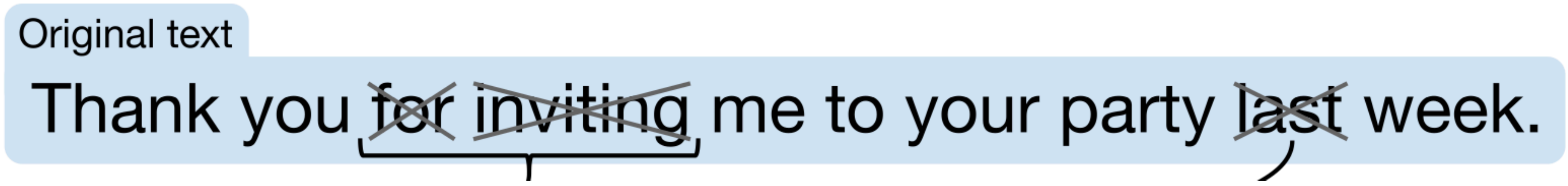
Encoder-decoder: machine translation example

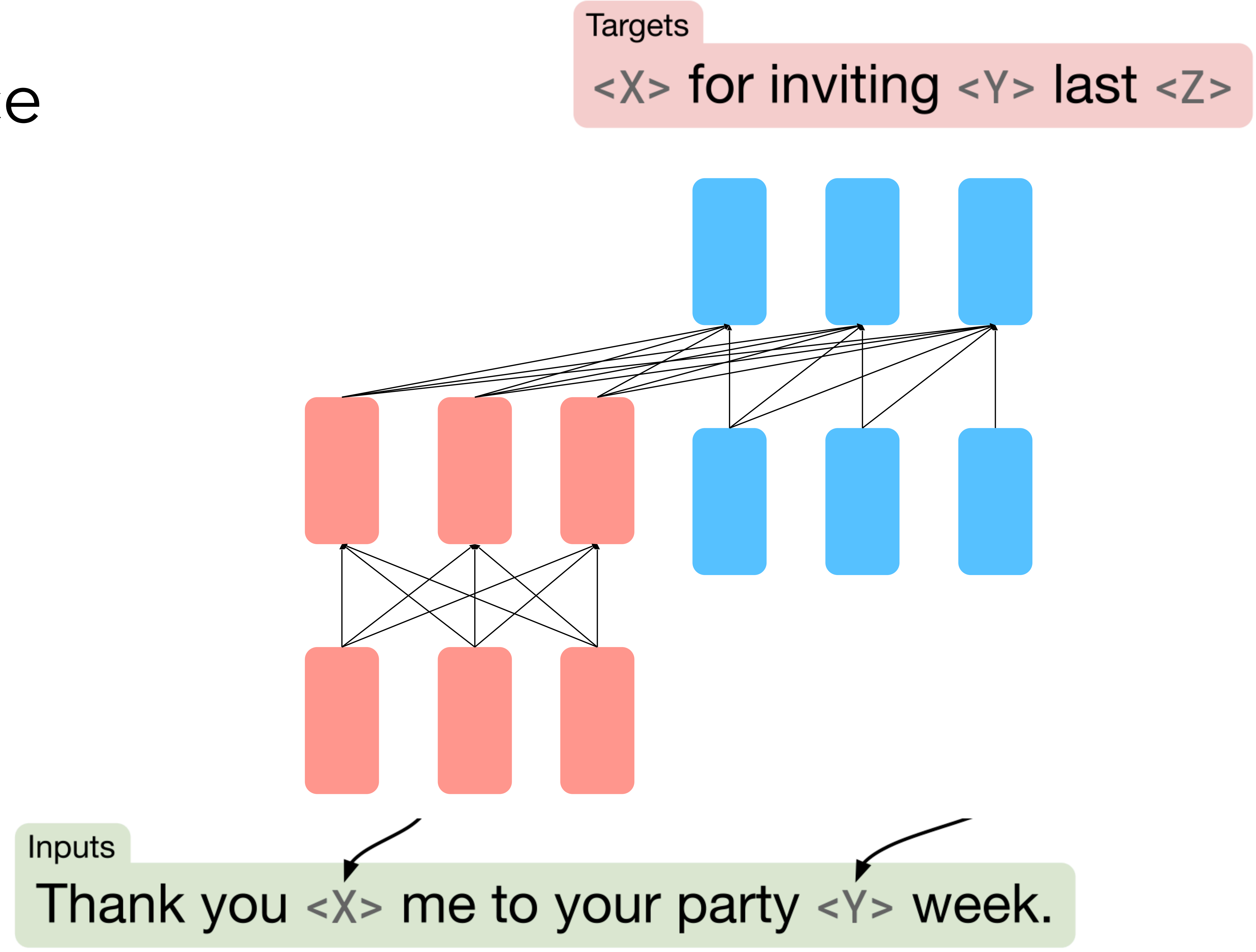


[Lena Viota Blog]

Encoder-decoder: training objective

- **T5 [Raffel et al., 2018]**
- **Text span corruption (denoising):** Replace different-length spans from the input with unique placeholders (e.g., <extra_id_0>); decode out the masked spans.
  - Done during **text preprocessing**: training uses **language modeling** objective at the decoder side





Encoder-decoder: T5

[Raffel et al., 2018]

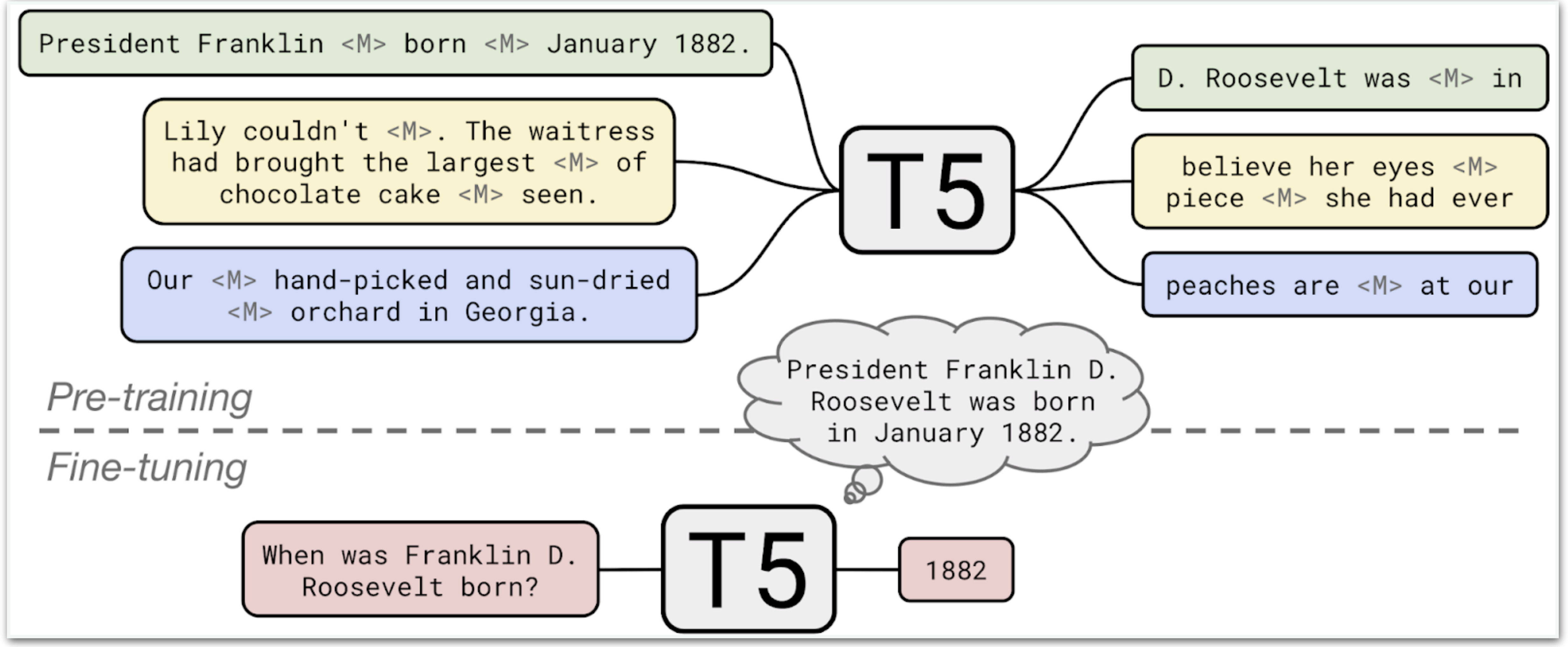
- **Encoder-decoders** works better than decoders
- **Span corruption (denoising)** objective works better than language modeling

Architecture	Objective	Params	Cost	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Encoder-decoder	Denoising	$2P$	M	**83.28**	**19.24**	**80.88**	**71.36**	**26.98**	**39.82**	**27.65**
Enc-dec, shared	Denoising	P	M	82.81	18.78	**80.63**	**70.73**	26.72	39.03	**27.46**
Enc-dec, 6 layers	Denoising	P	$M/2$	80.88	18.97	77.59	68.42	26.38	38.40	26.95
Language model	Denoising	P	M	74.70	17.93	61.14	55.02	25.09	35.28	25.86
Prefix LM	Denoising	P	M	81.82	18.61	78.94	68.11	26.43	37.98	27.39
Encoder-decoder	LM	$2P$	M	79.56	18.59	76.02	64.29	26.27	39.17	26.86
Enc-dec, shared	LM	P	M	79.60	18.13	76.35	63.50	26.62	39.17	27.05
Enc-dec, 6 layers	LM	P	$M/2$	78.67	18.26	75.32	64.06	26.13	38.42	26.89
Language model	LM	P	M	73.78	17.54	53.81	56.51	25.23	34.31	25.38
Prefix LM	LM	P	M	79.68	17.84	76.87	64.86	26.28	37.51	26.76

Encoder-decoder: T5

[Raffel et al., 2018]

- **Text-to-Text:** convert NLP tasks into input/output text sequences
- **Dataset:** Colossal Clean Crawled Corpus (C4), 750G text data!
- **Various Sized Models:**
  - Base (222M)
  - Small (60M)
  - Large (770M)
  - 3B
  - 11B
- **Achieved SOTA with scaling & purity of data**



[Google Blog]

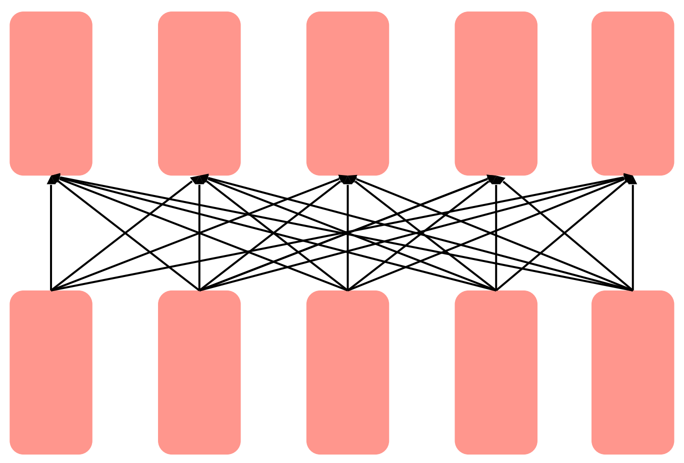
Encoder-decoder: pros & cons

- A nice middle ground between leveraging **bidirectional** contexts and **open-text** generation
- Good for **multi-task** fine-tuning

- Require more **text wrangling**
- **Harder to train**
- **Less flexible** for natural language generation

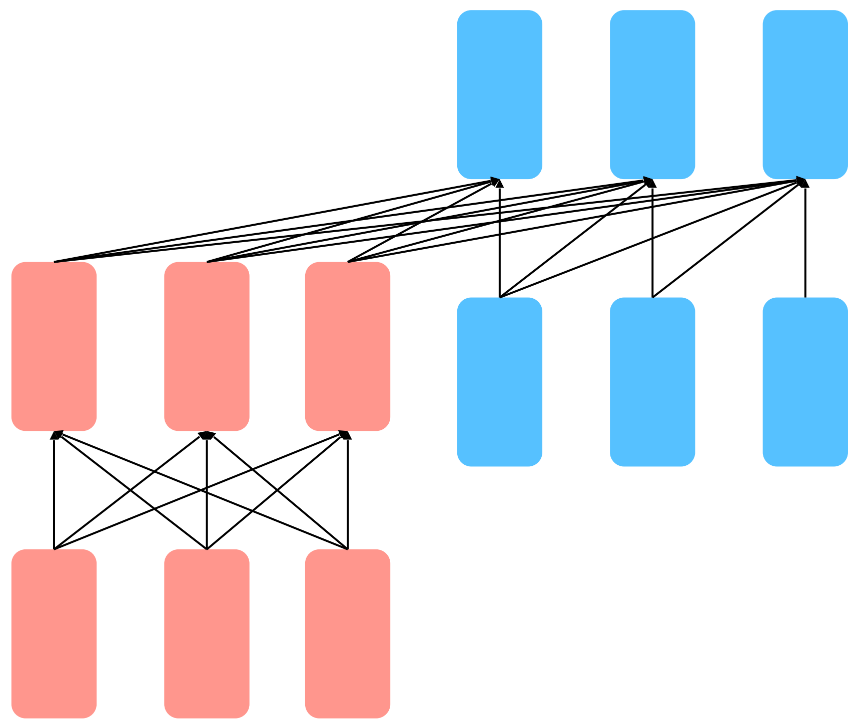
Pre-training architectures

Encoder



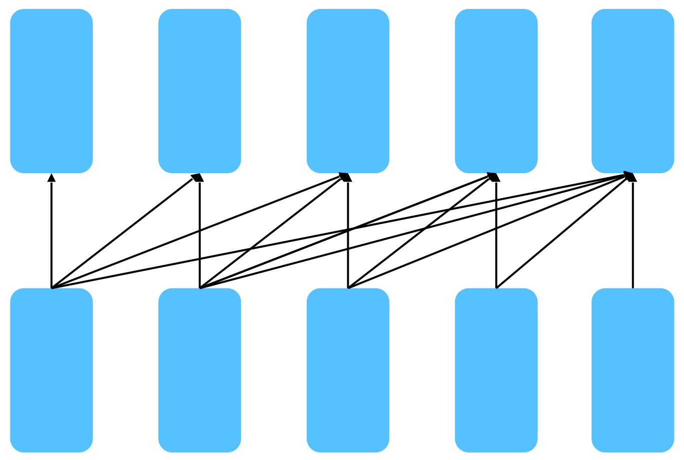
- Bidirectional; can condition on the future context

Encoder-Decoder



- Map two sequences of different length together

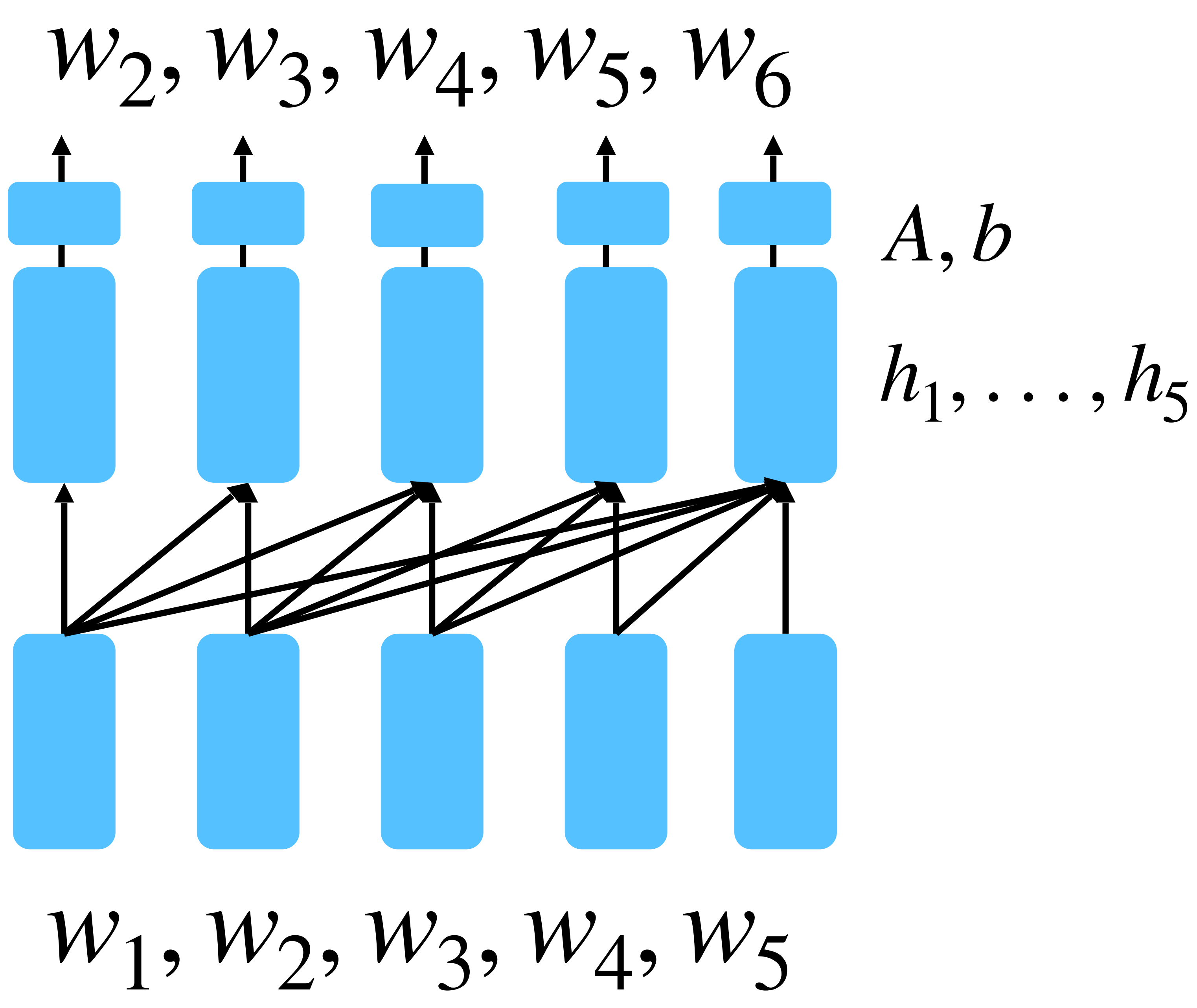
Decoder



- Language modeling; can only condition on the past context

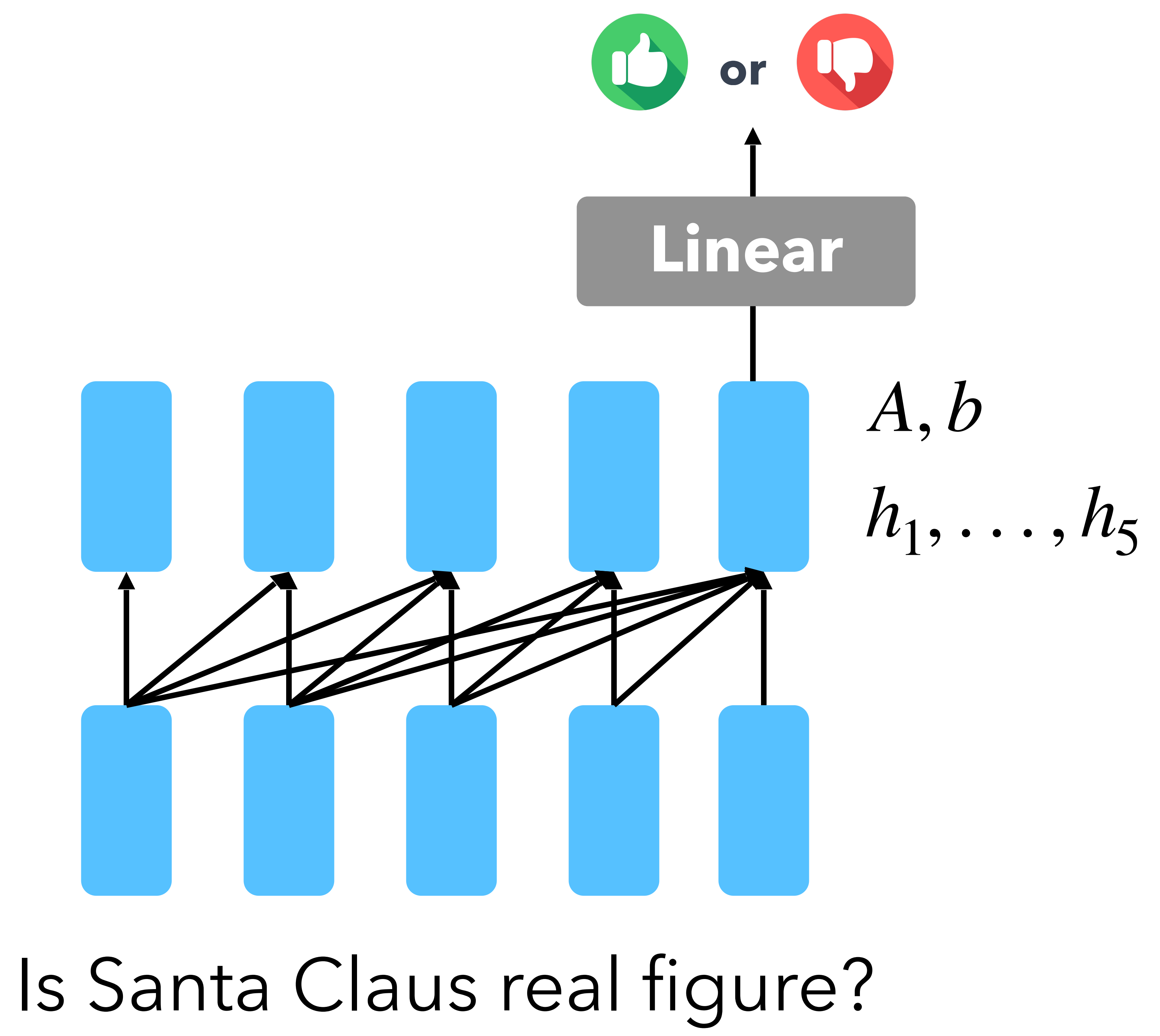
Decoder: training objective

- Many most famous generative LLMs are **decoder-only**
  - e.g., GPT1/2/3/4, Llama1/2
- **Language modeling!** Natural to be used for **open-text generation**
- **Conditional LM:** $p(w_t \mid w_1, \ldots, w_{t-1}, x)$
  - Conditioned on a source context x to generate from left-to-right
- Can be fine-tuned for **natural language generation (NLG)** tasks, e.g., dialogue, summarization.



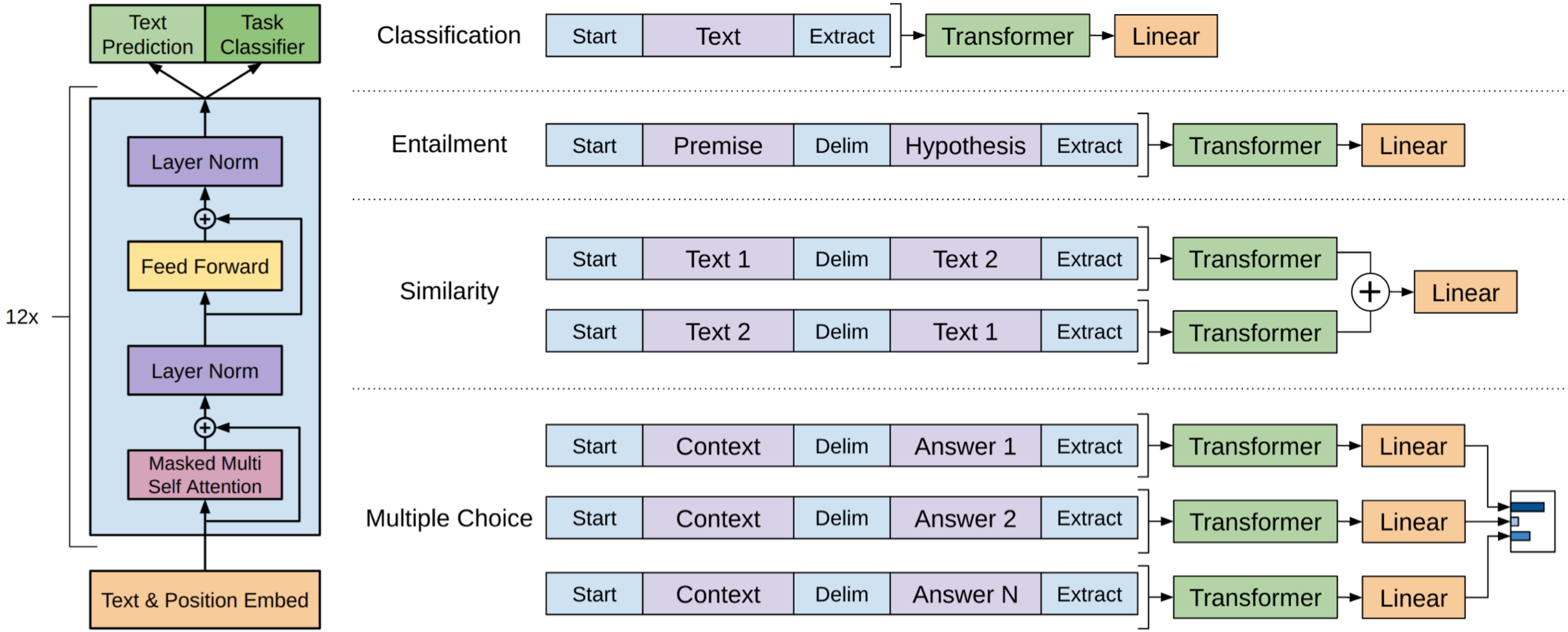
Decoder: training objective

- Customizing the pre-trained model for downstream tasks:
  - Add a **linear layer** on top of the last hidden layer to make it a classifier!
  - During fine-tuning, trained the randomly **initialized linear layer**, along with **all parameters** in the neural net.



Decoder: GPT

Generative **P**re-trained **T**ransformer [Radford et al., 2018]



How to use these pre-trained models?

Transformers

• **Transformers**

Search documentation ⌘K

V4.27.2 EN 92,354

- CANINE
- CodeGen
- ConvBERT
- CPM
- CTRL
- DeBERTa
- DeBERTa-v2
- DialoGPT
- **DistilBERT**
- DPR
- ELECTRA

DistilBERT

All model pages distilbert | Hugging Face Spaces

Overview

The DistilBERT model was proposed in the blog post Smaller, faster, cheaper, lighter: Introducing DistilBERT, a distilled version of BERT, and the paper DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. DistilBERT is a small, fast, cheap and light Transformer model trained by distilling BERT base. It has 40% less parameters than *bert-base-uncased*, runs 60% faster while preserving over 95% of BERT's performances as measured on the GLUE language understanding benchmark.

```
>>> from transformers import AutoTokenizer

>>> tokenizer = AutoTokenizer.from_pretrained("bert-base-cased")


>>> def tokenize_function(examples):
...     return tokenizer(examples["text"], padding="max_length", truncation=True)


>>> tokenized_datasets = dataset.map(tokenize_function, batched=True)
```

```
>>> from transformers import AutoModelForSequenceClassification

>>> model = AutoModelForSequenceClassification.from_pretrained("bert-base-cased", num_labels=5)
```

How to pick a proper architecture for a given task?

- Right now **decoder-only** models seem to dominant the field at the moment
    - e.g., GPT1/2/3/4, Mistral, Llama1/2
- T5 (seq2seq) works well with multi-tasking
- **Picking the best model architecture remains an open research question!**