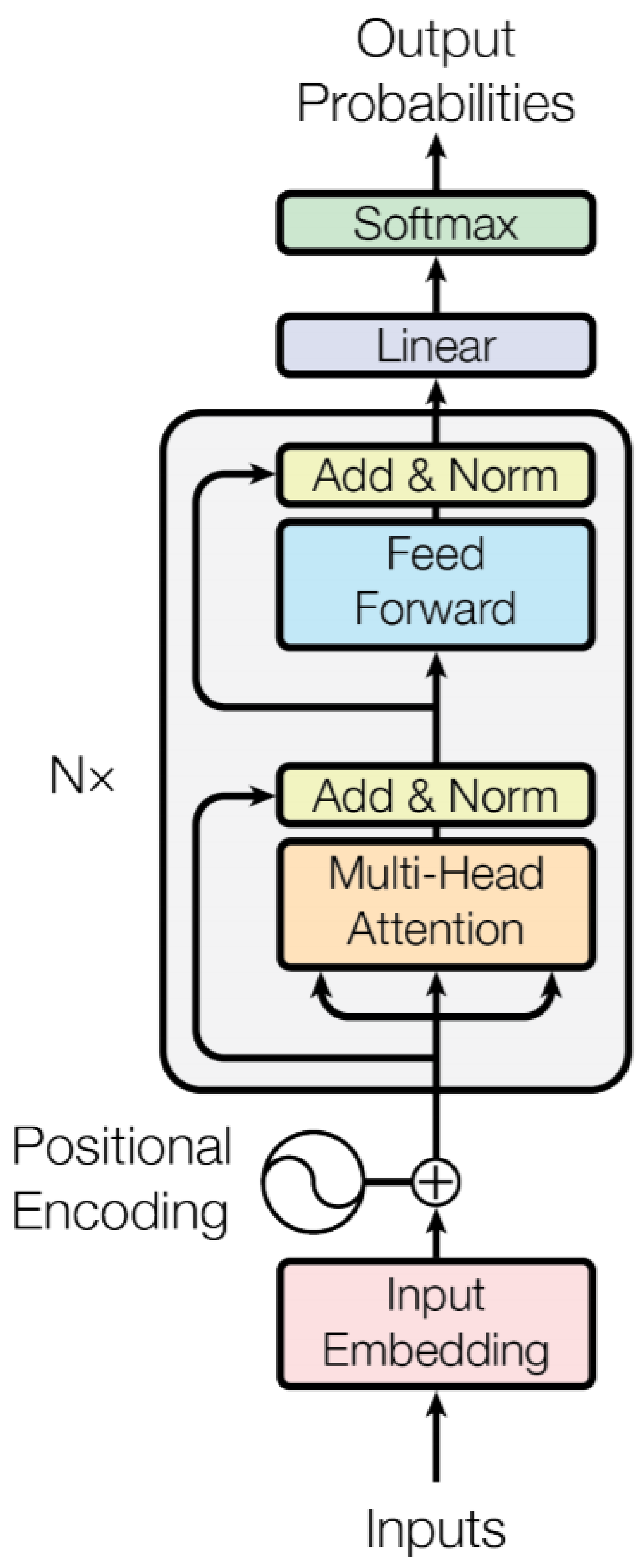
台灣人工智慧學校 × MIULAB

Contextualized Word Embeddings
BERT

國立臺灣大學 資訊工程學系
陳縕儂 助理教授
http://vivianchen.idv.tw

BERT: Bidirectional Encoder Representations from Transformers

- Idea: contextualized word representations
  - Learn word vectors using long contexts using Transformer instead of LSTM

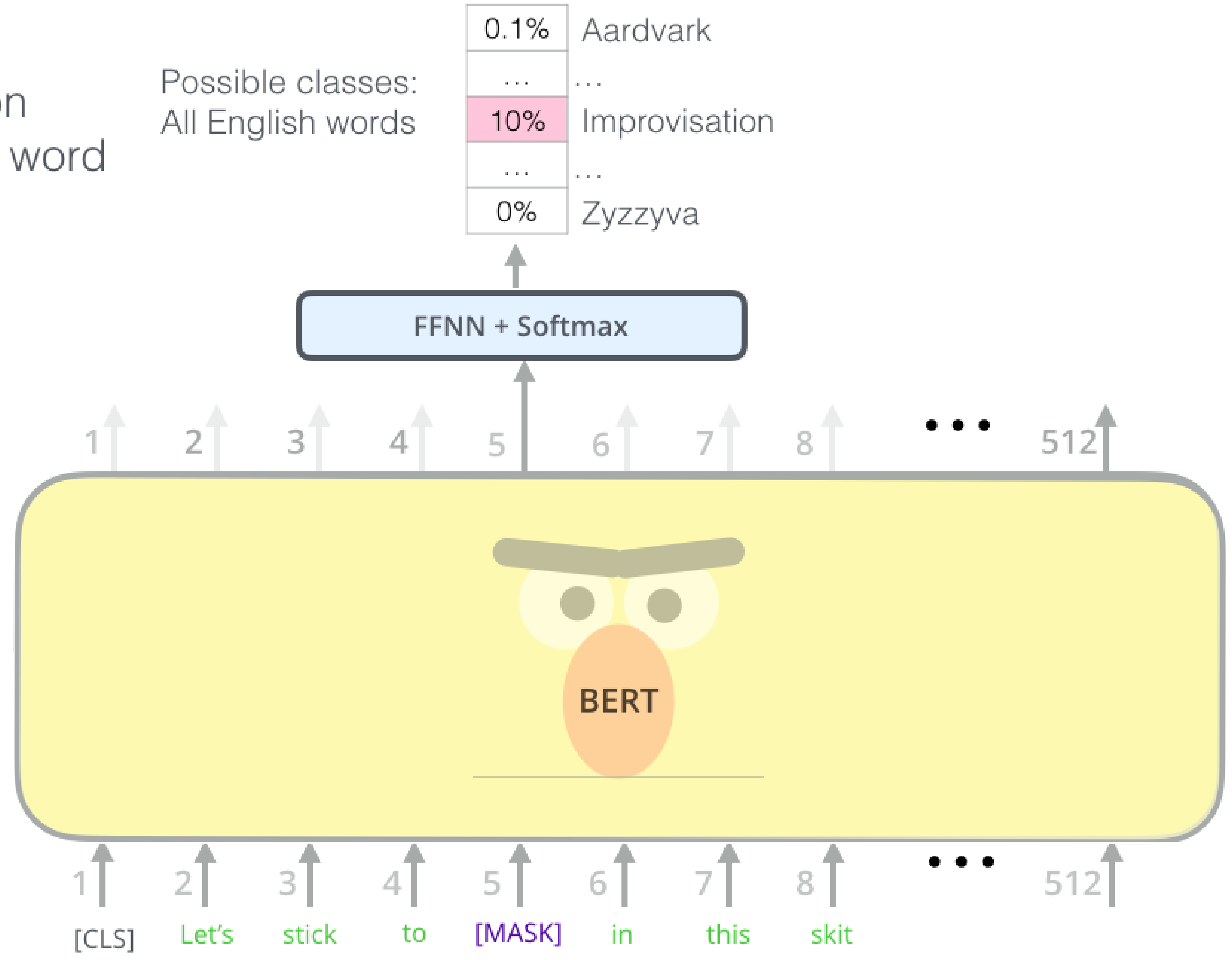


Devlin et al., “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”, in *NAACL-HLT*, 2019.

BERT #1 – Masked Language Model

- Idea: language understanding is **bidirectional** while LM only uses *left* or *right* context

Use the output of the masked word's position to predict the masked word

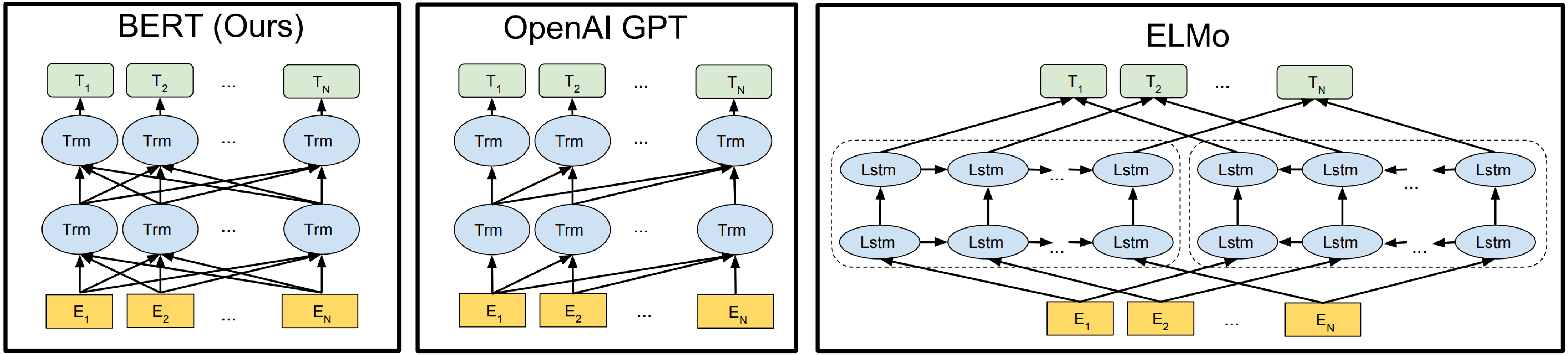


Randomly mask 15% of tokens

- Too little: expensive to train
- Too much: not enough context

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

BERT #1 – Masked Language Model



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BERT #2 – Next Sentence Prediction

- Idea: modeling ***relationship*** between sentences
  - QA, NLI etc. are based on understanding inter-sentence relationship

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

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

Label = `IsNext`

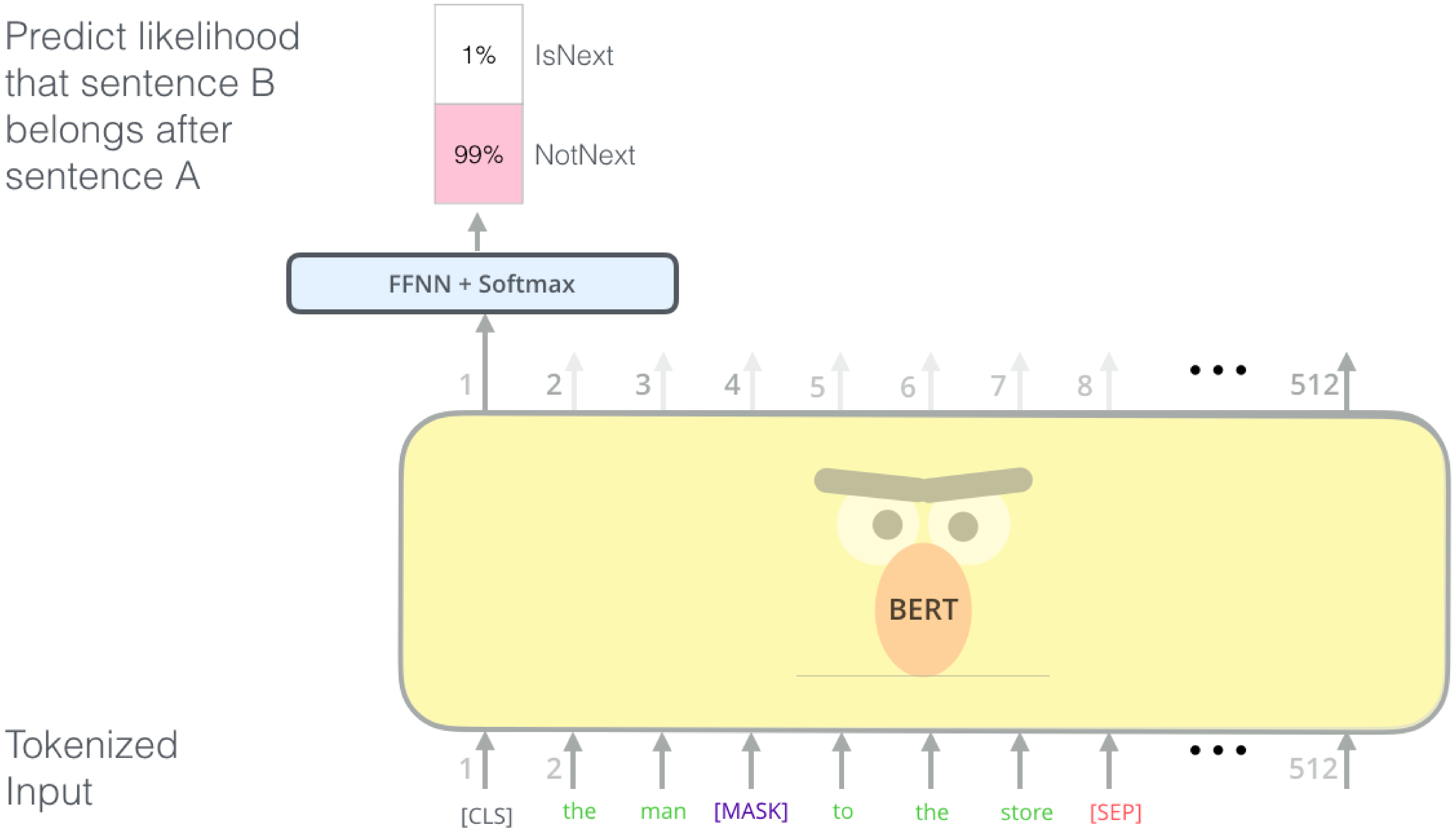
Input = `[CLS] the man [MASK] to the store [SEP]`

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

Label = `NotNext`

BERT #2 – Next Sentence Prediction

- Idea: modeling relationship between sentences



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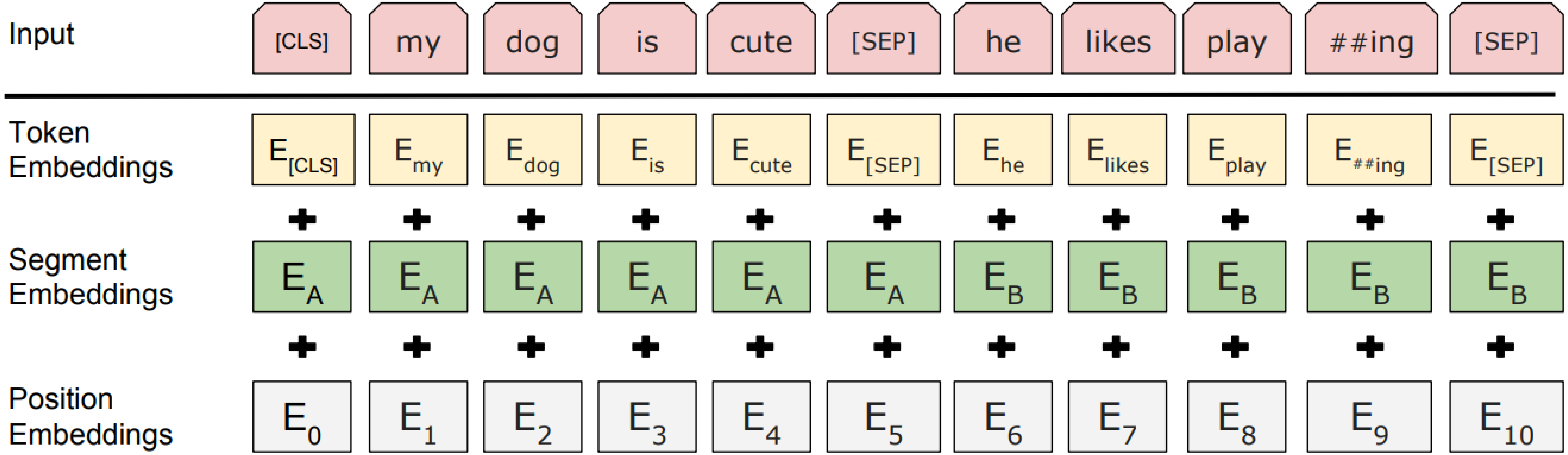
BERT – Input Representation

- Input embeddings contain
  - Word-level token embeddings
  - Sentence-level segment embeddings
  - Position embeddings



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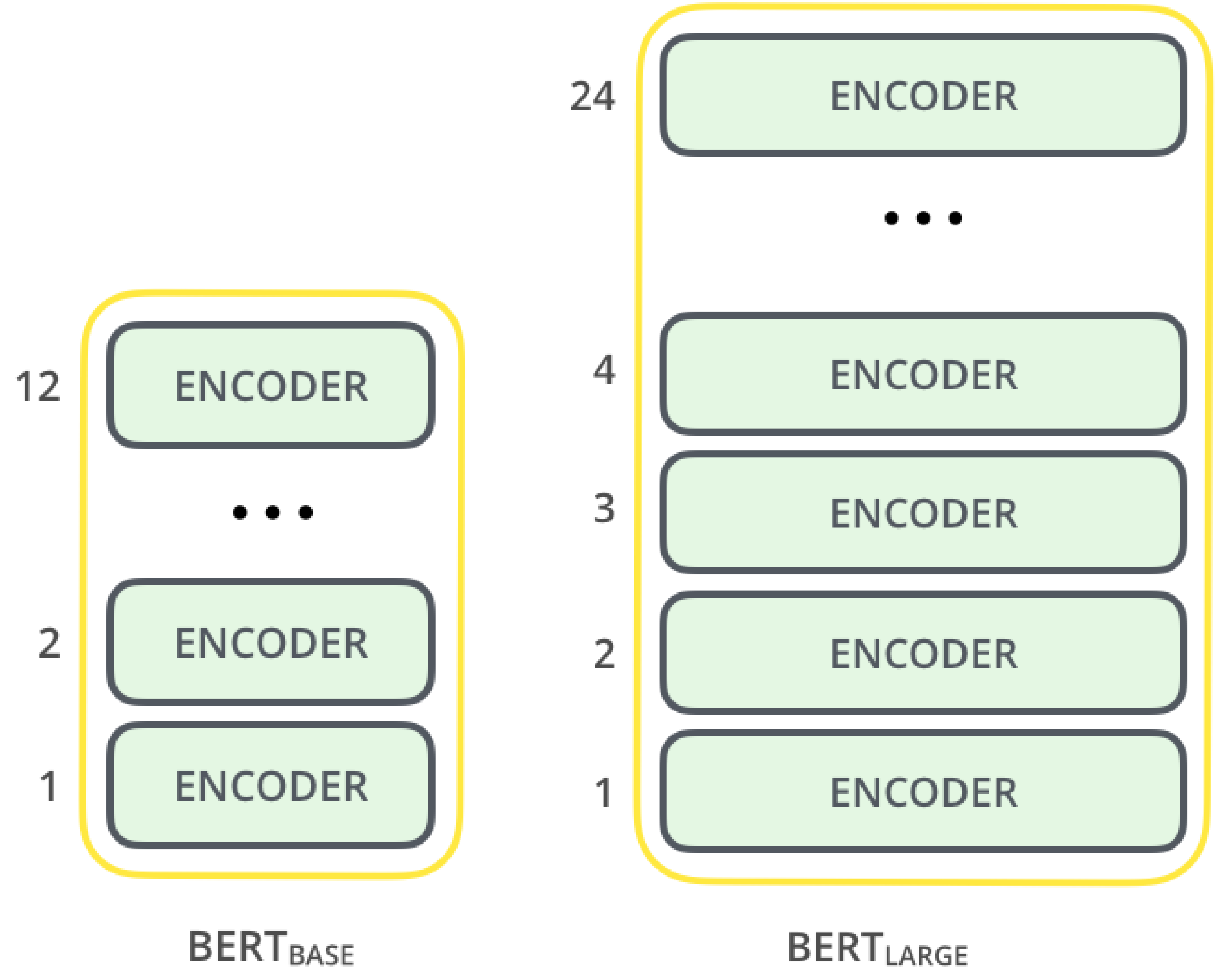
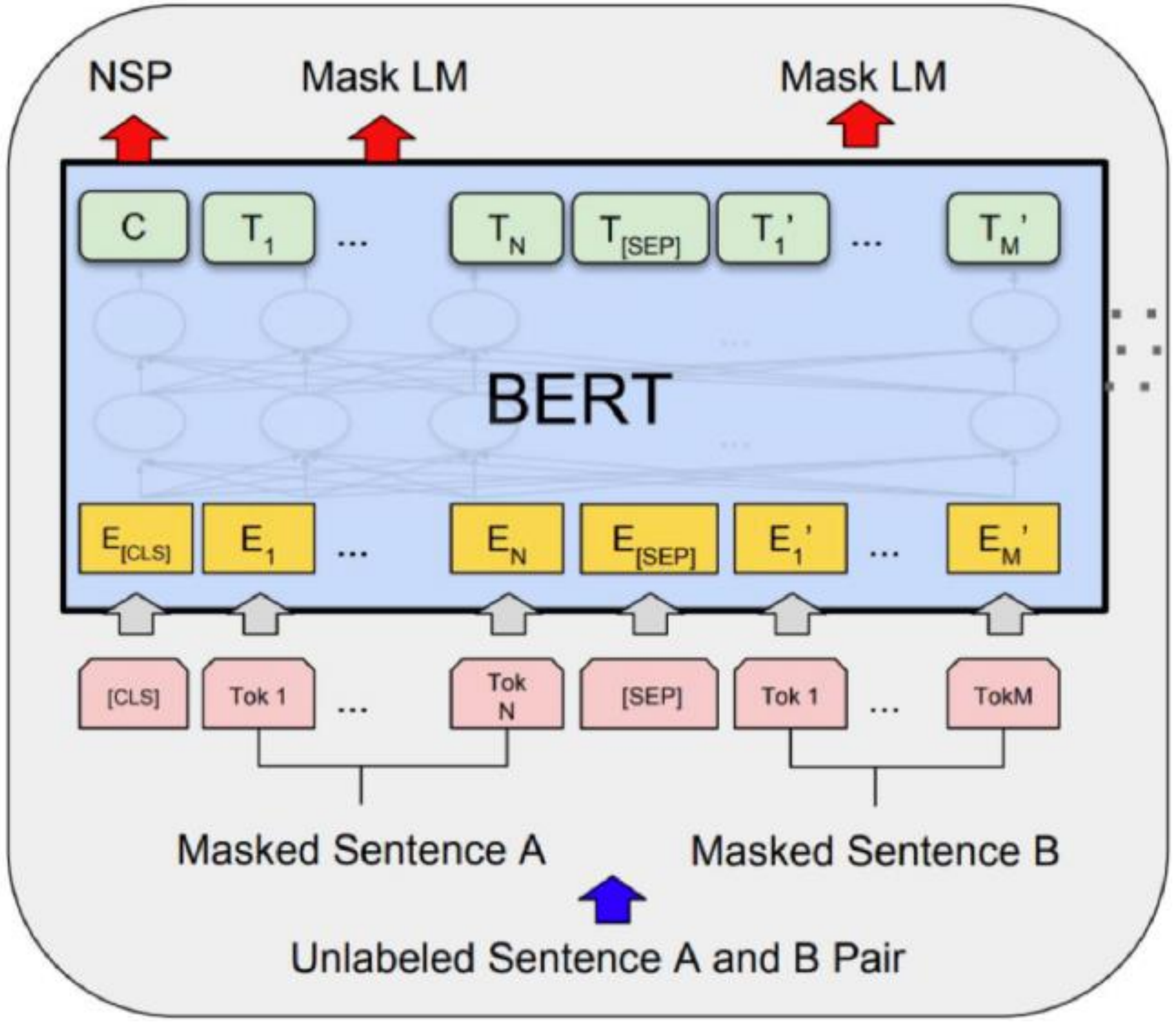
BERT Training

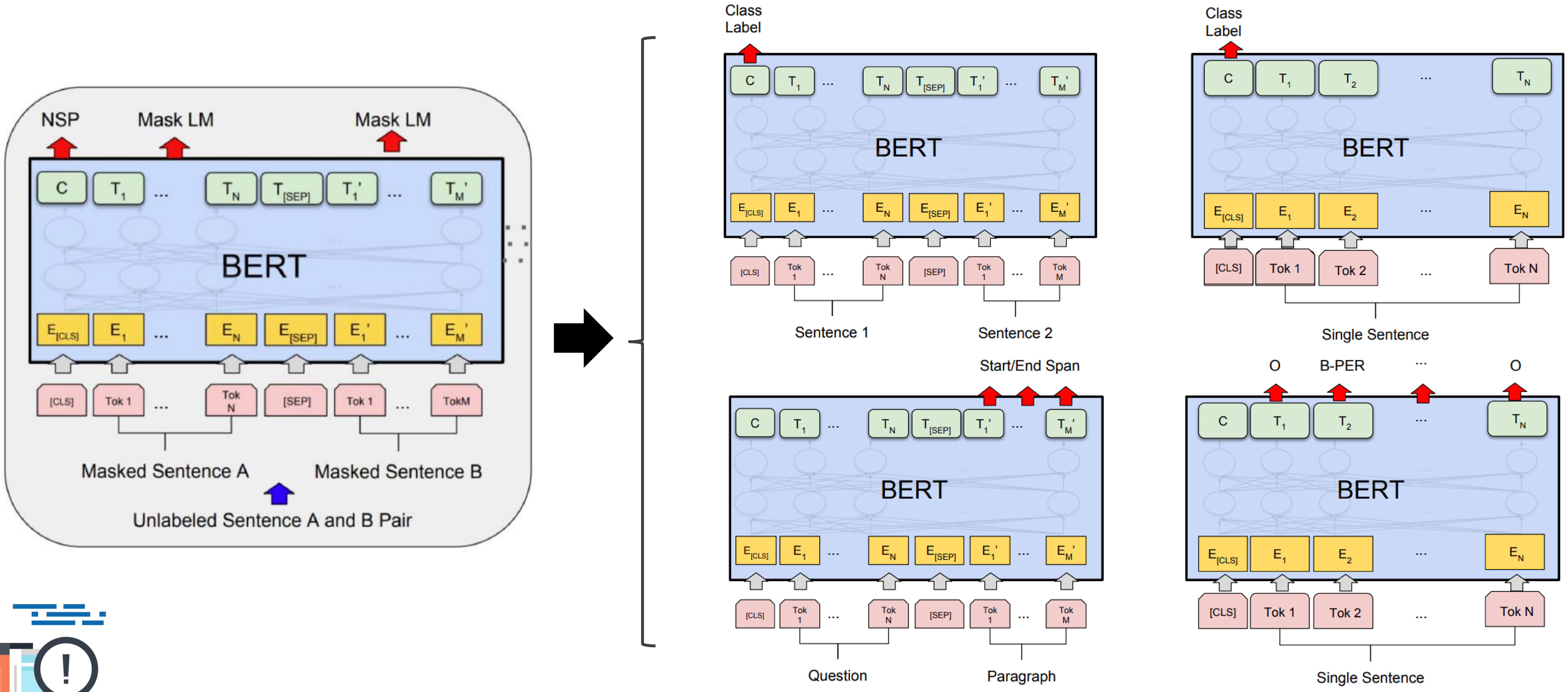
- Training data: Wikipedia + BookCorpus
- 2 BERT models
  - BERT-Base: 12-layer, 768-hidden, 12-head
  - BERT-Large: 24-layer, 1024-hidden, 16-head





BERT Fine-Tuning for Understanding Tasks

- Idea: simply learn a classifier/tagger built on the top layer for each target task



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BERT Overview

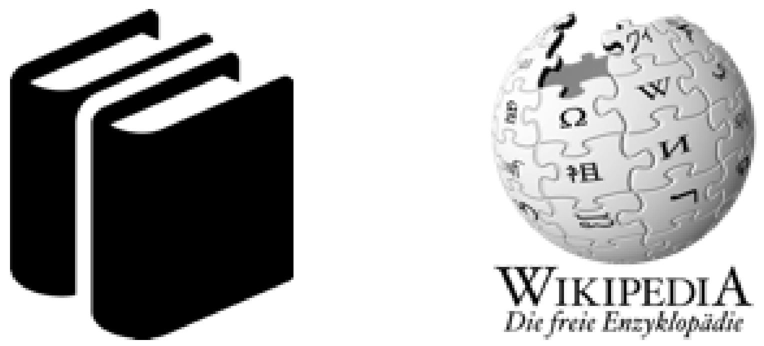
1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step

Model:

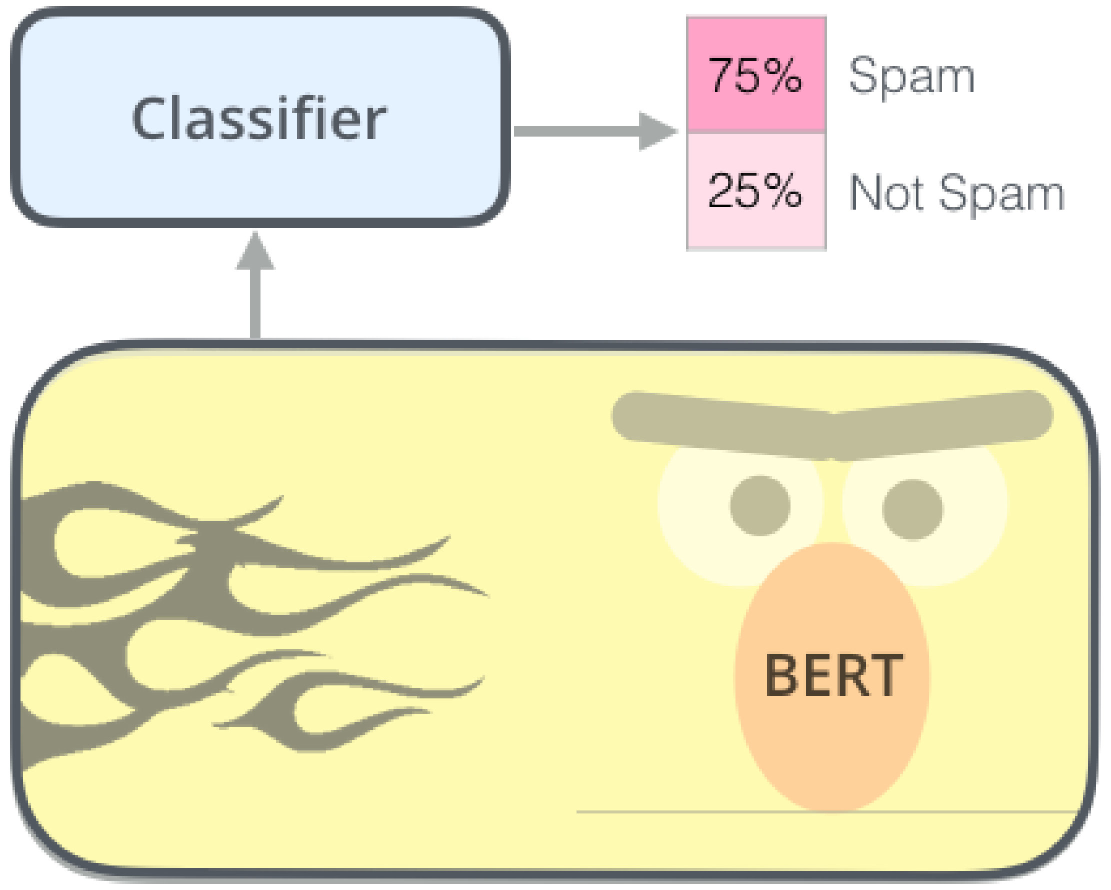
Dataset:



Objective: Predict the masked word (langauge modeling)

2 - Supervised training on a specific task with a labeled dataset.

Supervised Learning Step



Model: (pre-trained in step #1)

Dataset:

Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached…	Not Spam

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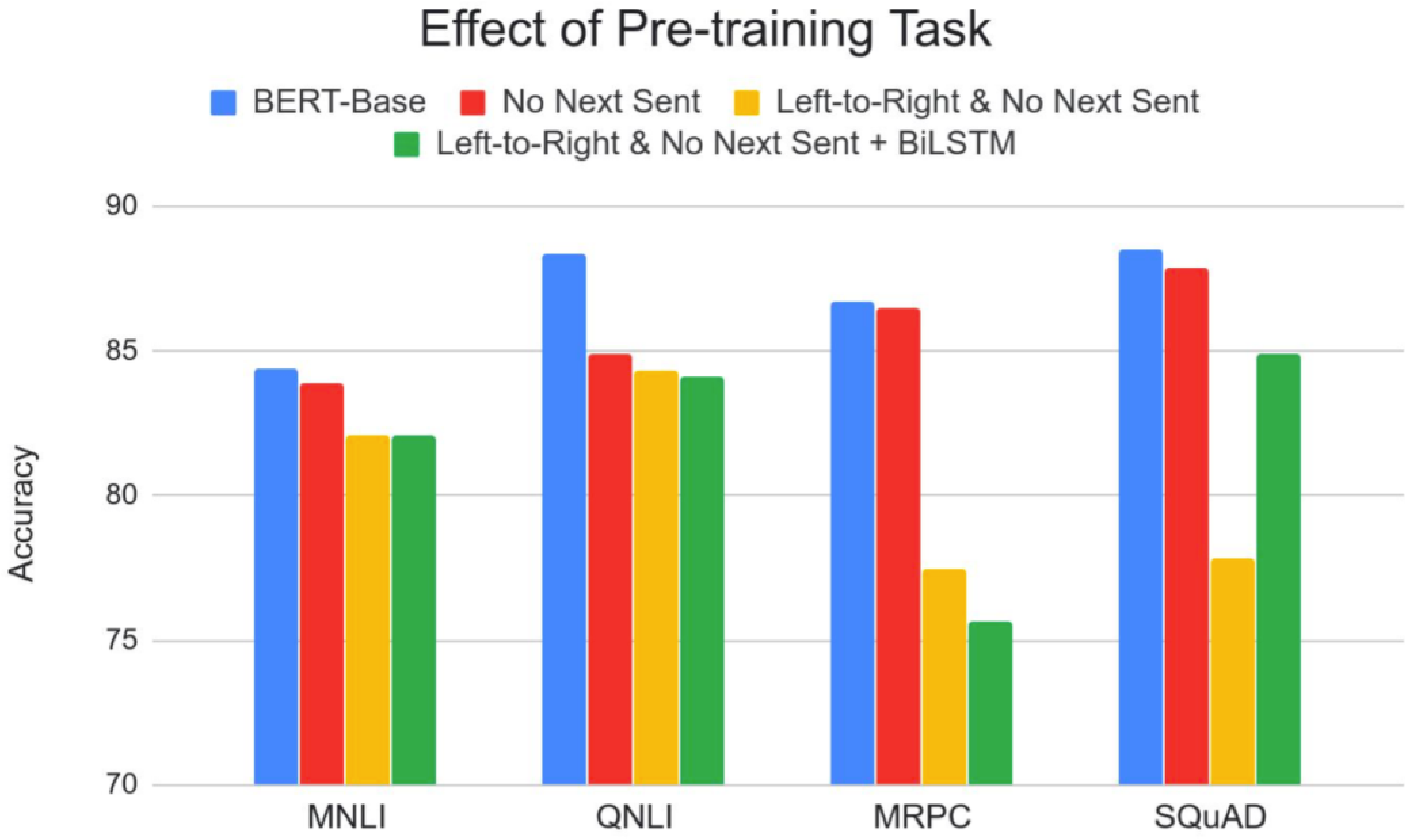
BERT Fine-Tuning Results



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BERT Results on QA

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Mar 20, 2019	BERT + DAE + AoA (ensemble) *Joint Laboratory of HIT and iFLYTEK Research*	**87.147**	**89.474**
2 Mar 15, 2019	BERT + ConvLSTM + MTL + Verifier (ensemble) *Layer 6 AI*	86.730	89.286
3 Mar 05, 2019	BERT + N-Gram Masking + Synthetic Self-Training (ensemble) *Google AI Language* https://github.com/google-research/bert	86.673	89.147
4 May 21, 2019	XLNet (single model) *Google Brain & CMU*	86.346	89.133
5 Apr 13, 2019	SemBERT(ensemble) *Shanghai Jiao Tong University*	86.166	88.886
5 May 14, 2019	SG-Net (ensemble) *Anonymous*	86.211	88.848
6 Mar 16, 2019	BERT + DAE + AoA (single model) *Joint Laboratory of HIT and iFLYTEK Research*	85.884	88.621
7 Jun 22, 2019	BNDVnet (ensemble model) *PAOS*	85.850	88.449
8 Mar 13, 2019	BERT + ConvLSTM + MTL + Verifier (single model) *Layer 6 AI*	84.924	88.204
8 May 14, 2019	SG-Net (single model) *Anonymous*	85.229	87.926
8 Jun 10, 2019	Unnamed submission by null	85.240	87.901
9 Mar 05, 2019	BERT + N-Gram Masking + Synthetic Self-Training (single model) *Google AI Language* https://github.com/google-research/bert	85.150	87.715
10 Jan 15, 2019	BERT + MMFT + ADA (ensemble) *Microsoft Research Asia*	85.082	87.615
10 Jun 19, 2019	BNDVnet (single model) *PAOS*	85.003	87.833

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BERT Results on NER

Model	Description	CONLL 2003 F1
TagLM (Peters+, 2017)	LSTM BiLM in BLSTM Tagger	91.93
ELMo (Peters+, 2018)	ELMo in BLSTM	92.22
BERT-Base (Devlin+, 2019)	Transformer LM + fine-tune	92.4
CVT Clark	Cross-view training + multitask learn	92.61
BERT-Large (Devlin+, 2019)	Transformer LM + fine-tune	92.8
Flair	Character-level language model	93.09

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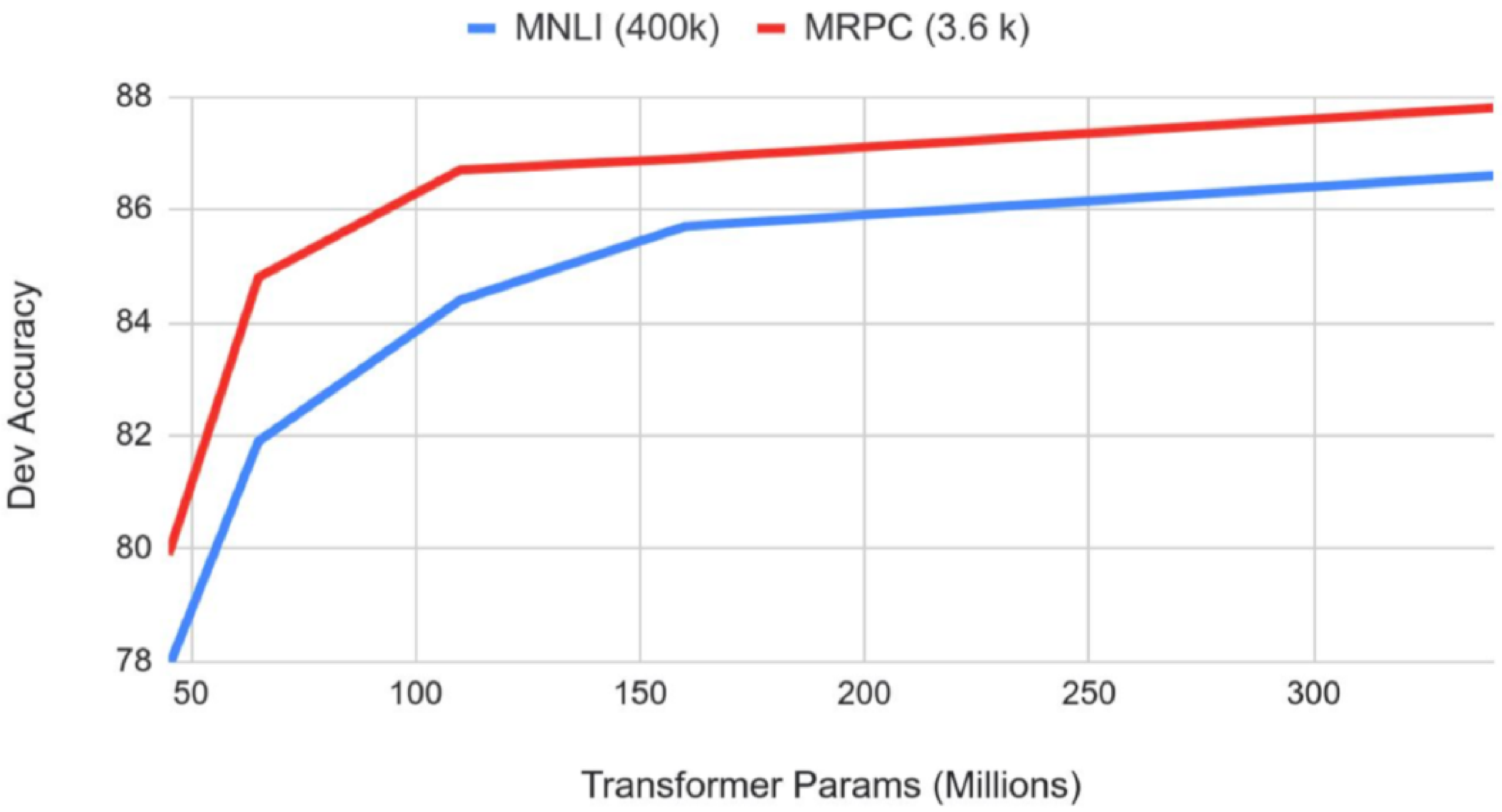
BERT Results with Different Model Sizes

- Improving performance by increasing model size



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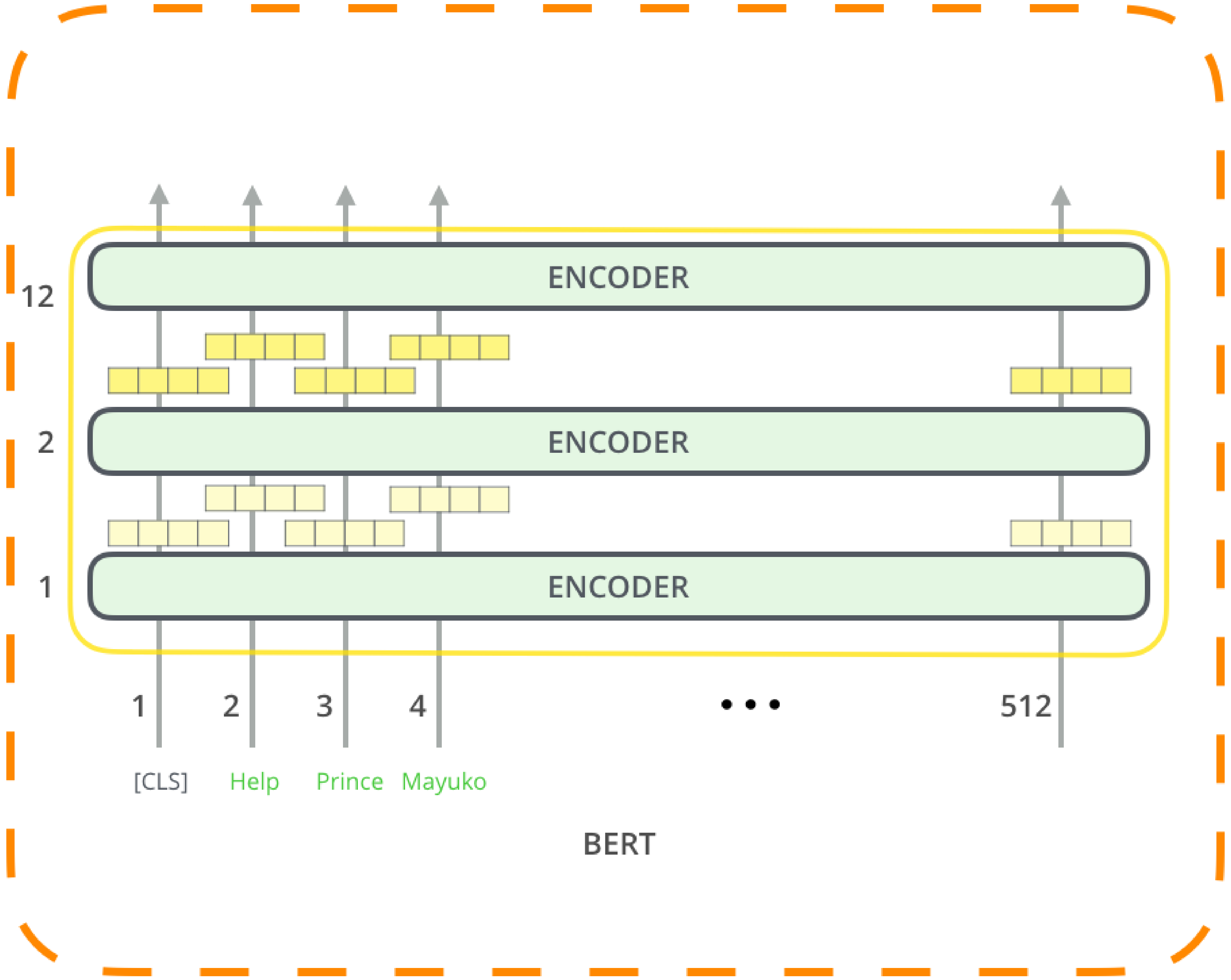
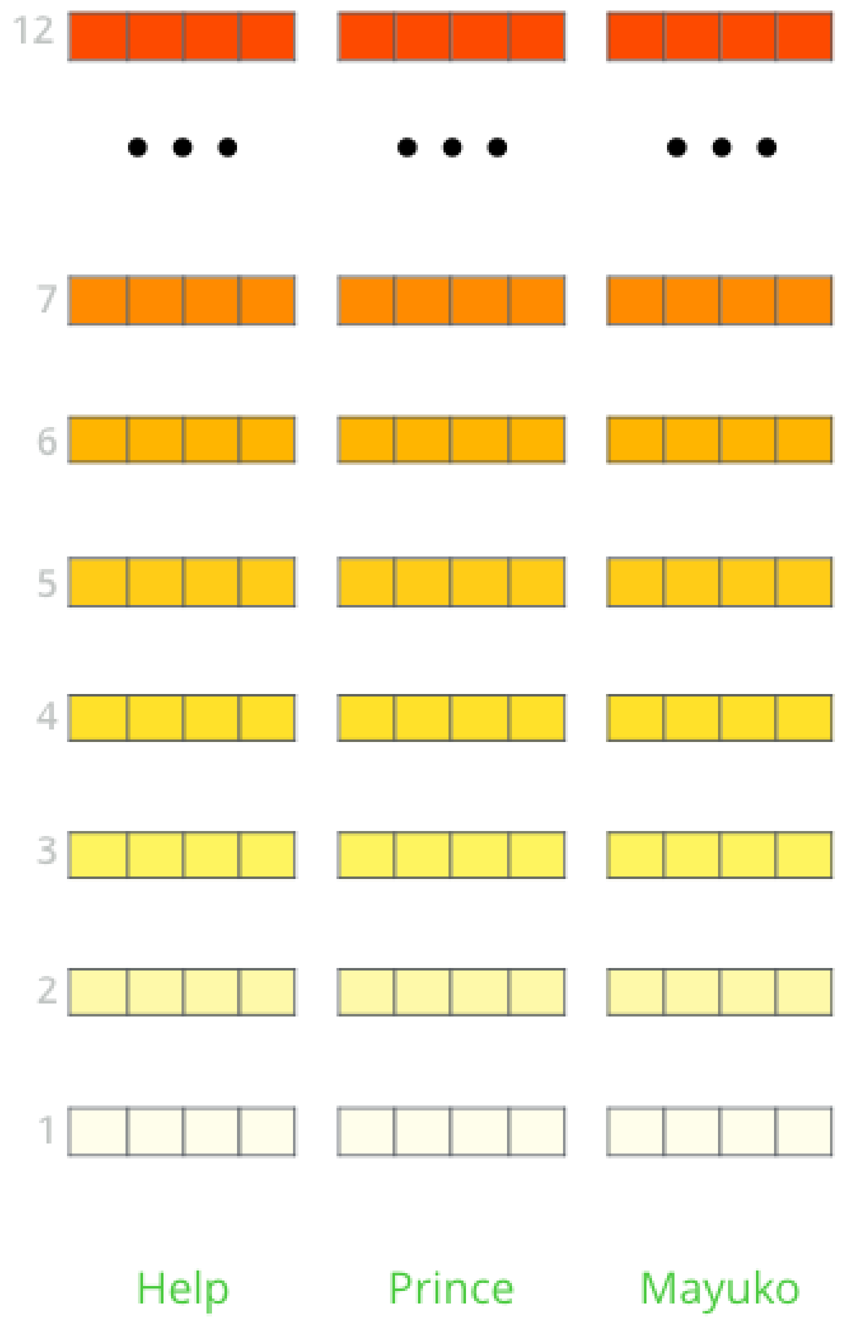
BERT for Contextual Embeddings

- Idea: use pre-trained BERT to get contextualized word embeddings and feed them into the task-specific models

Generate Contexualized Embeddings



The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?

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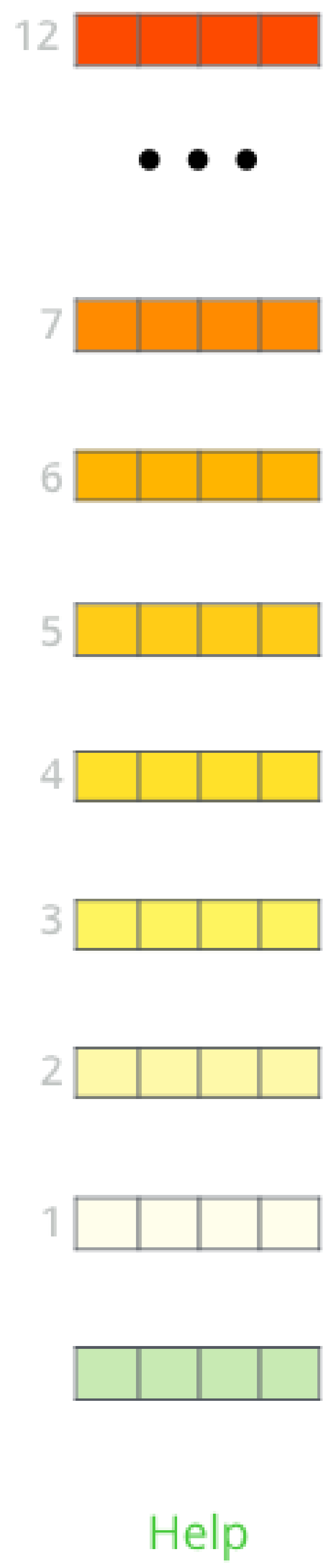
BERT Contextual Embeddings Results on NER

What is the best contextualized embedding for "Help" in that context?
For named-entity recognition task CoNLL-2003 NER



		Dev F1 Score
First Layer	Embedding	91.0
Last Hidden Layer	12	94.9
Sum All 12 Layers	12 + … + 2 + 1 =	95.5
Second-to-Last Hidden Layer	11	95.6
Sum Last Four Hidden	12 + 11 + 10 + 9 =	95.9
Concat Last Four Hidden	9 10 11 12	96.1 **fine-tune = 96.4**

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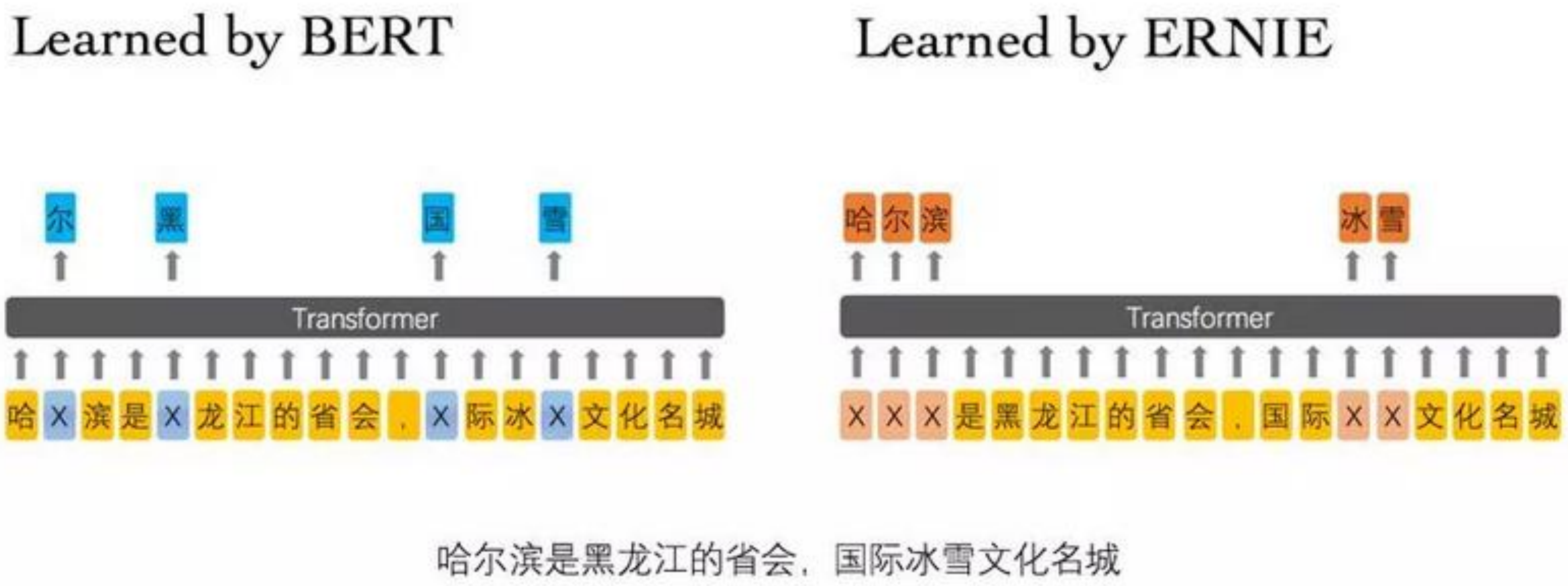
ERNIE: **E**nhanced **R**epresentation through k**N**owledge **I**nt**E**gration

- BERT models local cooccurrence between tokens, while characters are modeled independently
  - 哈(ha), 爾(er), 濱(bin) instead 哈爾濱(Harbin)
- ERNIE incorporates knowledge by masking semantic units/entities



Concluding Remarks

- Contextualized embeddings learned from masked LM via Transformers provide informative cues for **transfer learning**
- BERT – a general approach for learning contextual representations from Transformers and benefiting language understanding
  - ✓Pre-trained BERT: https://github.com/google-research/bert