Amirkabir University of Technology
(Tehran Polytechnic)

Natural Language Processing

Lecture 13: Contextualized Representation (Pre-trained Models)

Amirkabir University of Technology

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Outline

- **Introduction**
- ELMO
- BERT

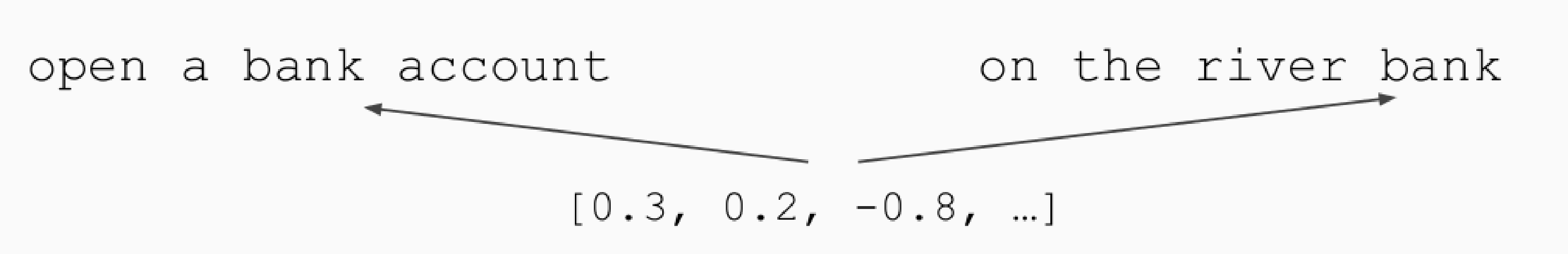
Pre-training in NLP

- Word embeddings are the basis of deep learning for NLP

- Word embeddings (word2vec, GloVe) are often *pre-trained* on text corpus from co-occurrence statistics

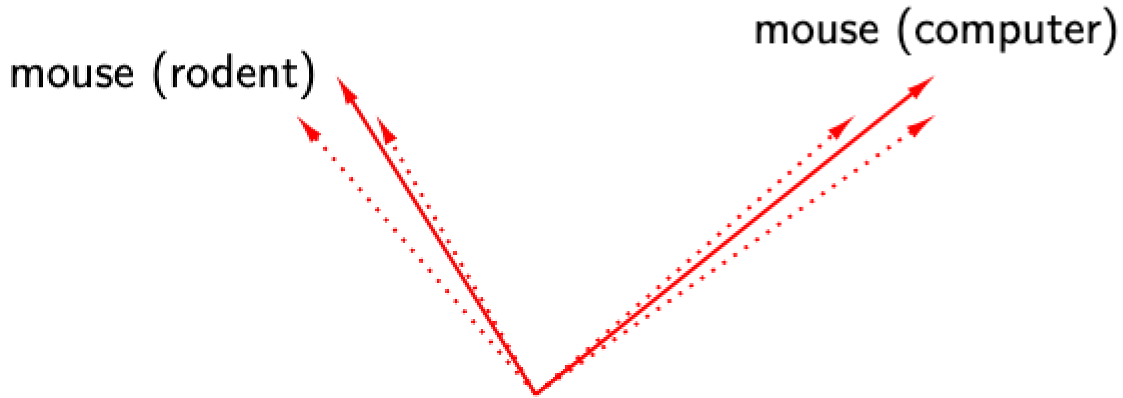
Contextual Representations

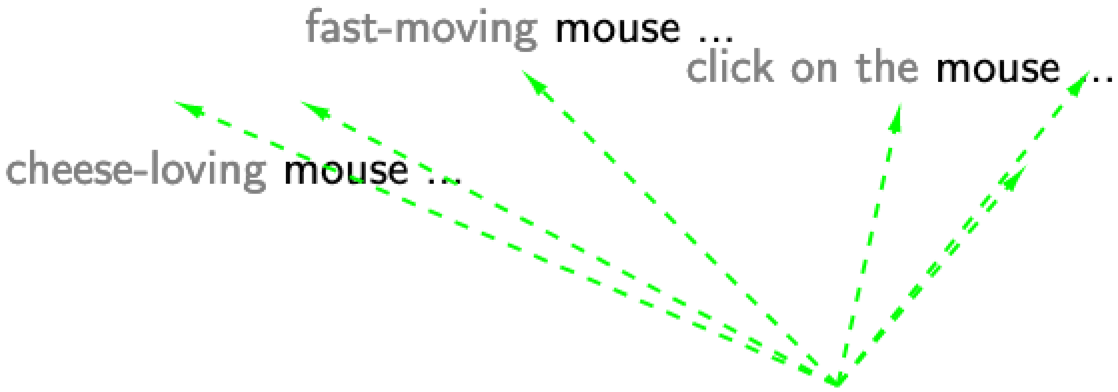
- **Problem**: Word embeddings are applied in a context free manner



- **Solution**: Train *contextual* representations on text corpus

Static vs Contextualized Representation



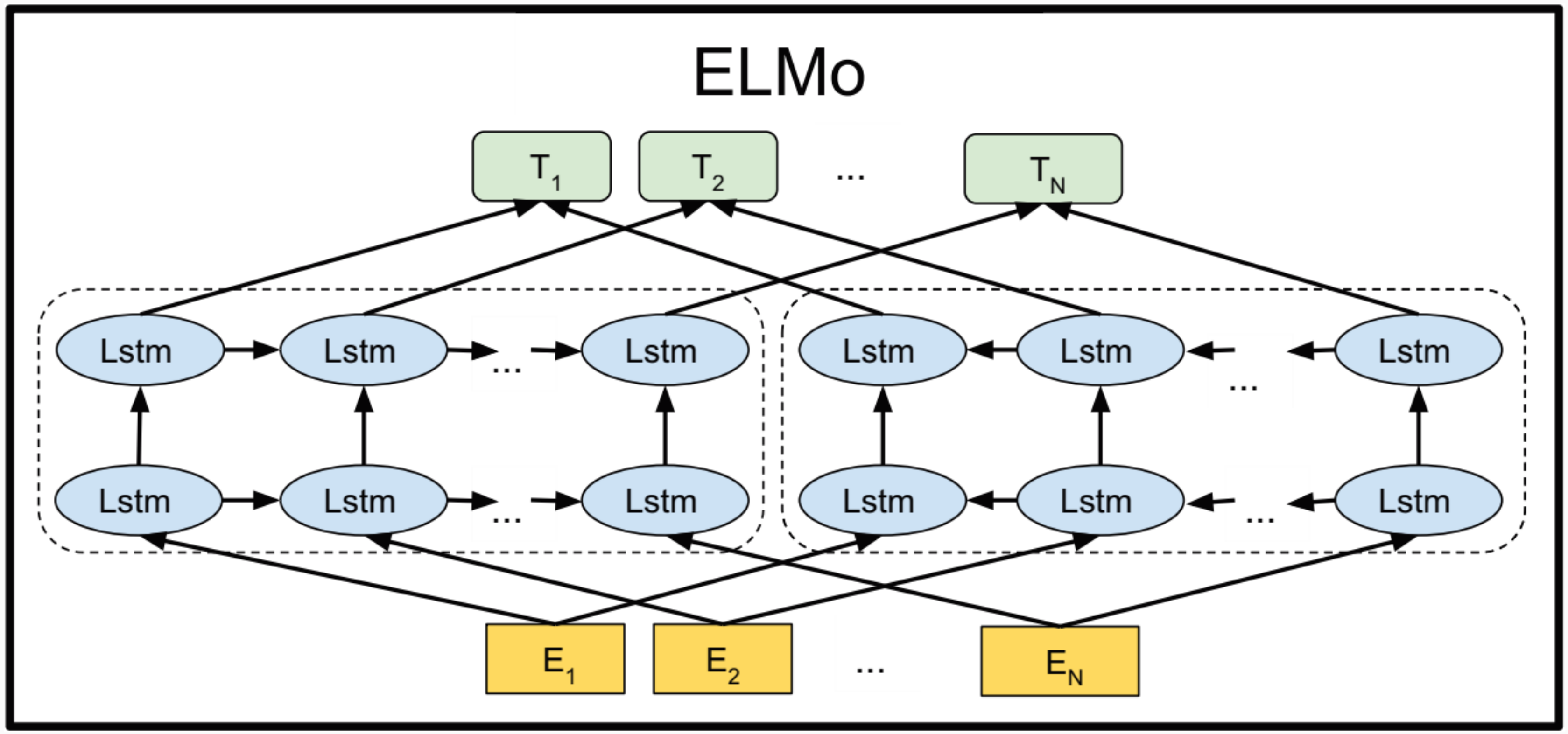


Outline

- Introduction
- **ELMO**
- BERT

ELMO

- Bidirectional language model
- Train Separate Left-to-Right and Right-to-Left LMs



ELMO

- Bidirectional training

- Forward language model

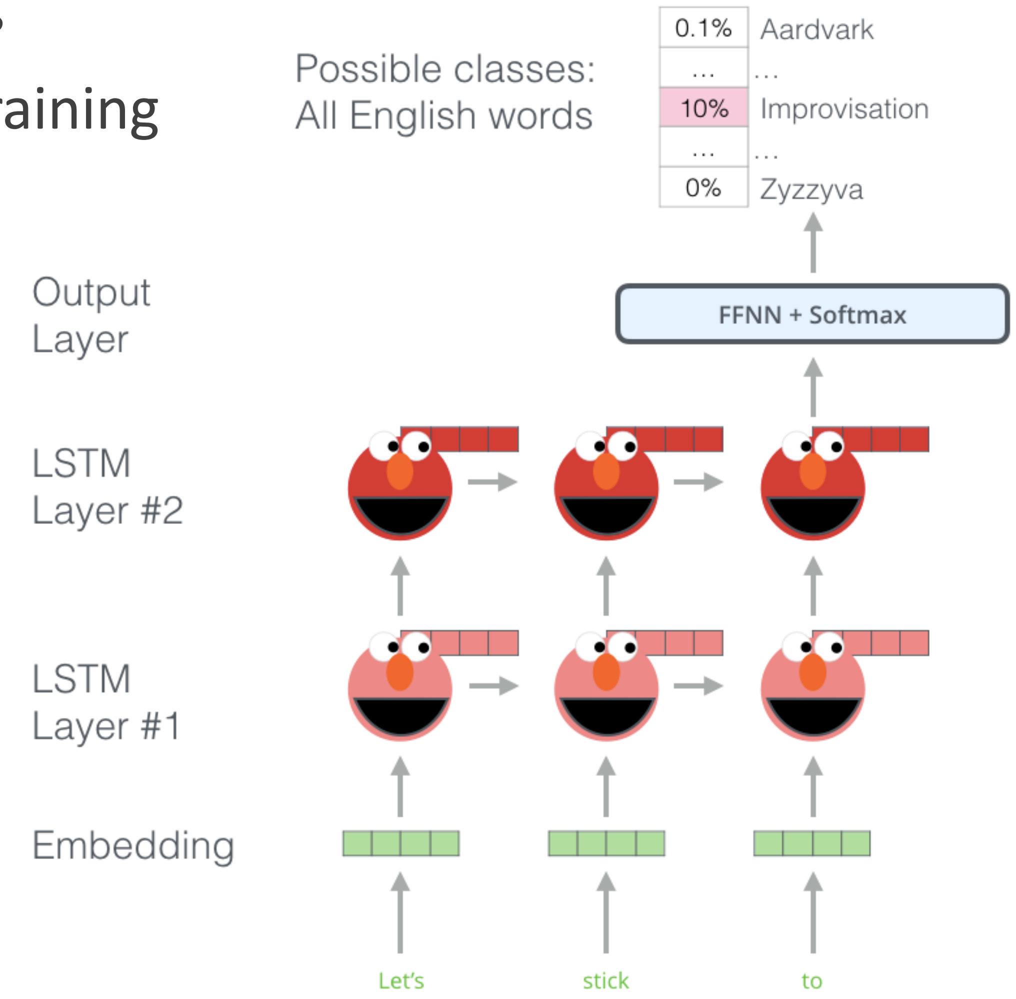
$$p(t_1, t_2;, \ldots, t_N) = \prod_{k=1}^{N} p(t_k | t_1, t_2;, \ldots, t_{k-1})$$

- Backward language model

$$p(t_1, t_2;, \ldots, t_N) = \prod_{k=1}^{N} p(t_k | t_{k+1}, t_{k+2};, \ldots, t_N)$$

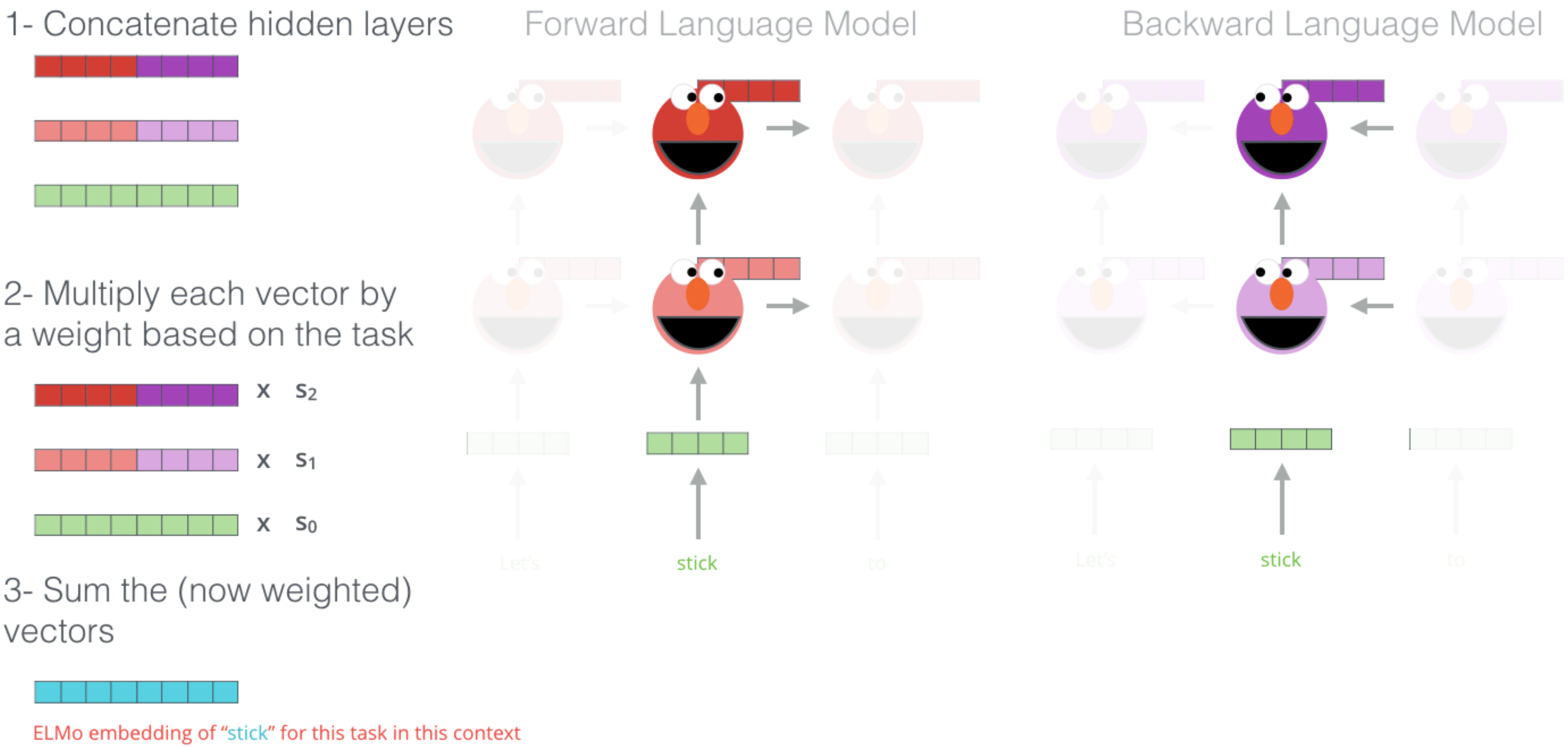
ELMO

- Predicting the next word in forward training
- Predicting the previous word in backward training



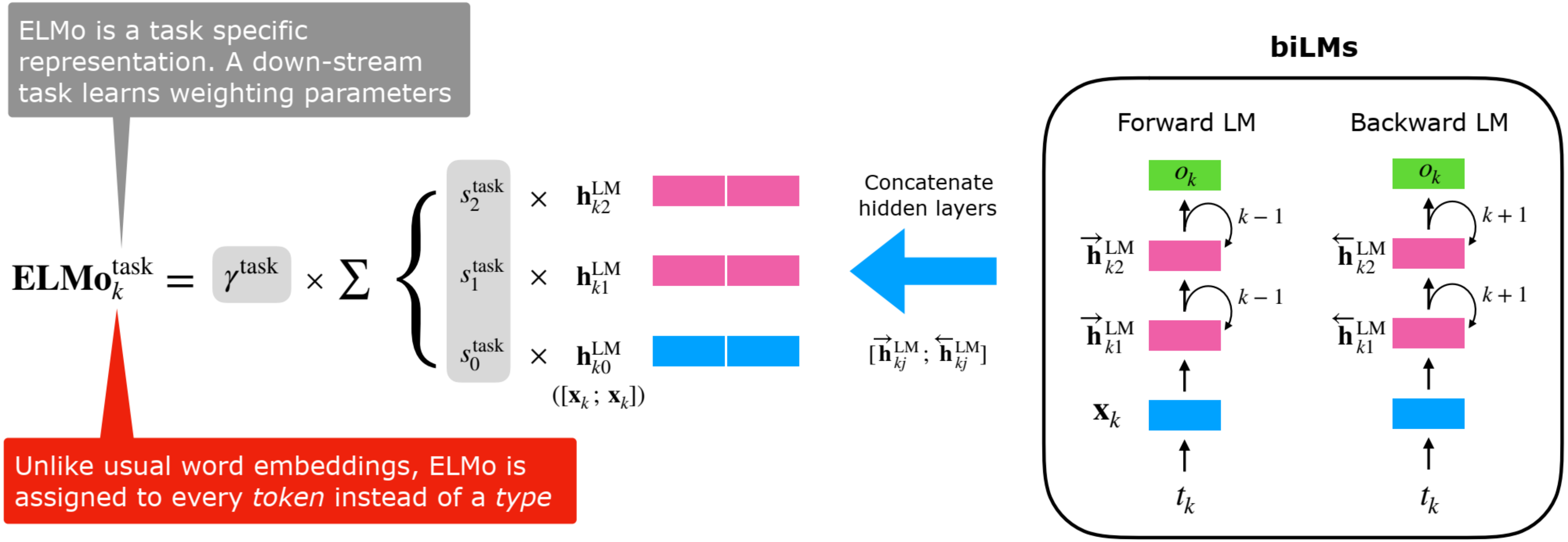
ELMO

- Extracting embedding



ELMO

- Extracting embedding

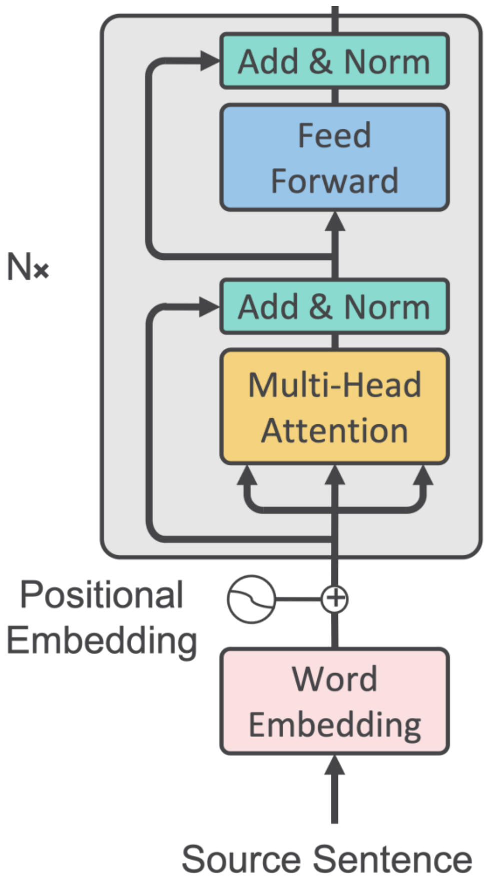


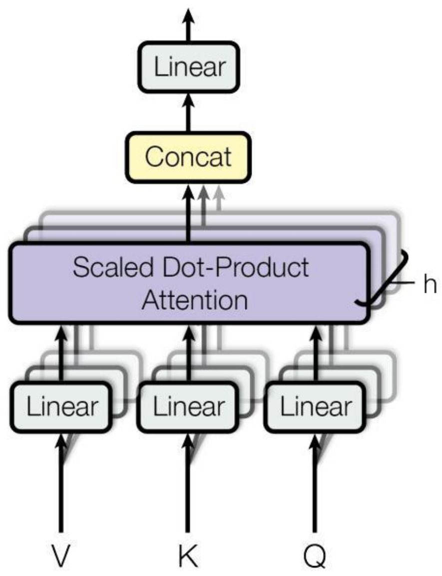
Outline

- Introduction
- ELMO
- **BERT**

Model Architecture

- Multi-headed self attention
  - Models context
- Feed-forward layers
  - Computes non-linear hierarchical features
- Layer norm and residuals
  - Makes training deep networks healthy
- Positional embeddings
  - Allows model to learn relative positioning





Model Architecture

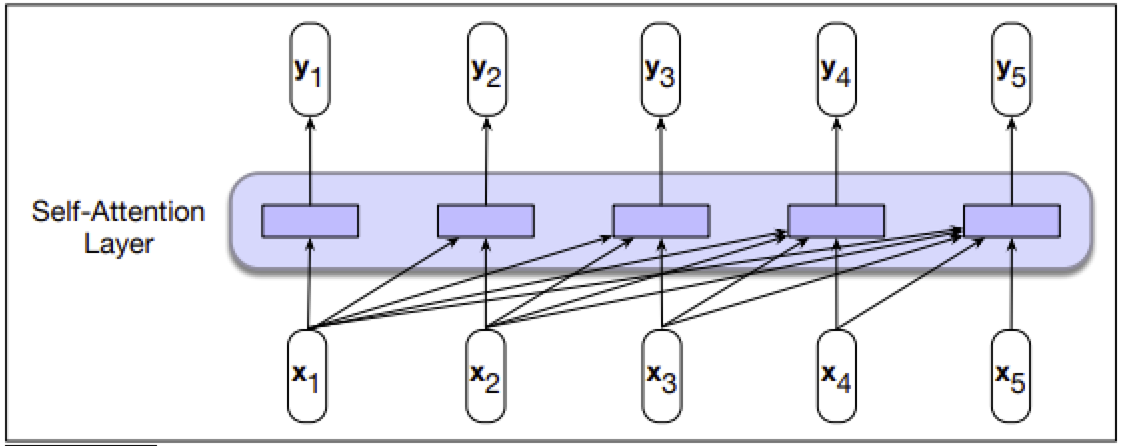
- Empirical advantages of Transformer vs. LSTM:
  - Self-attention == no locality bias
    - Long-distance context has “equal opportunity”
  - Single multiplication per layer == efficiency on TPU
    - Effective batch size is number of *words*, not *sequences*

Problem with Previous Methods

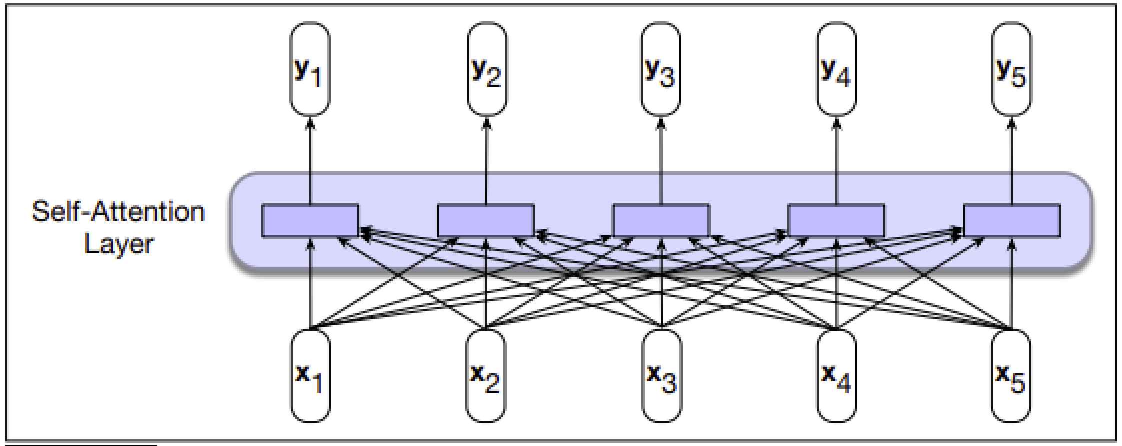
- **Problem**: Language models only use left context *or* right context, but language understanding is bidirectional.
- Why are LMs unidirectional?
- Reason 1: Directionality is needed to generate a well-formed probability distribution.
  - We don't care about this.
- Reason 2: Words can "see themselves" in a bidirectional encoder.

Bidirectional Transformer

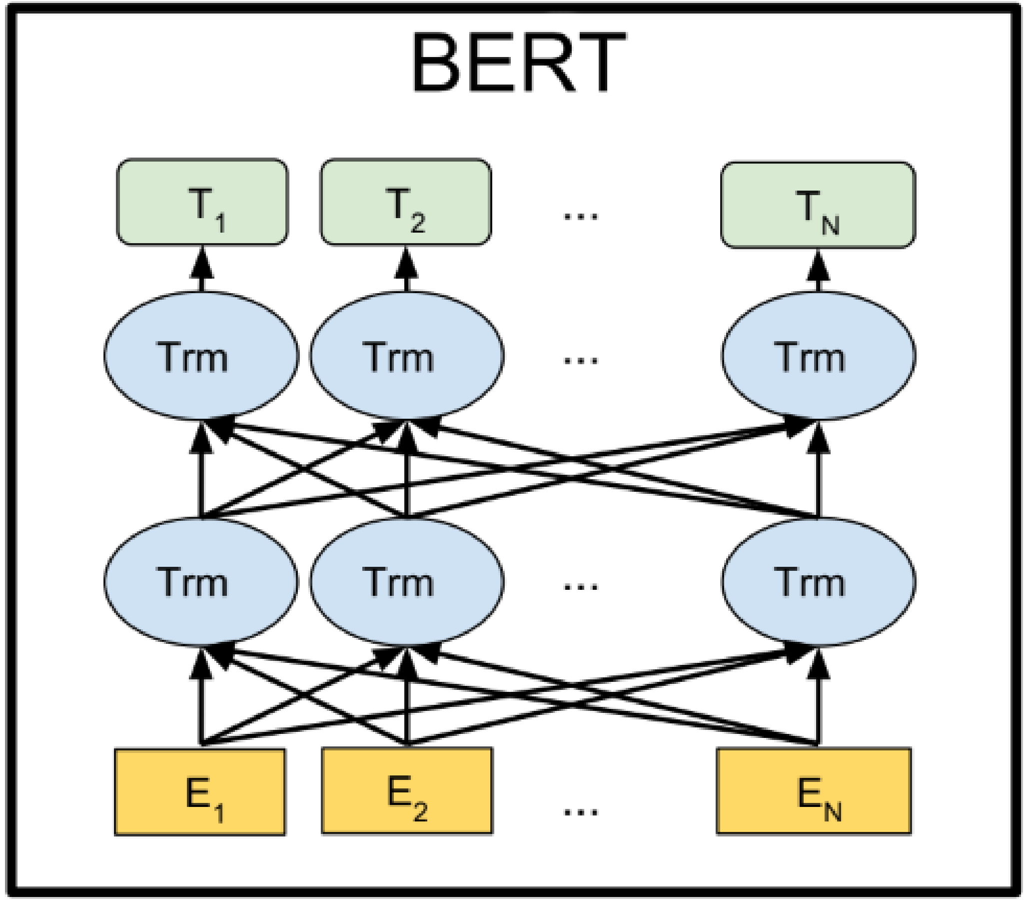
- A causal backward looking transformer



- A bidirectional transformer



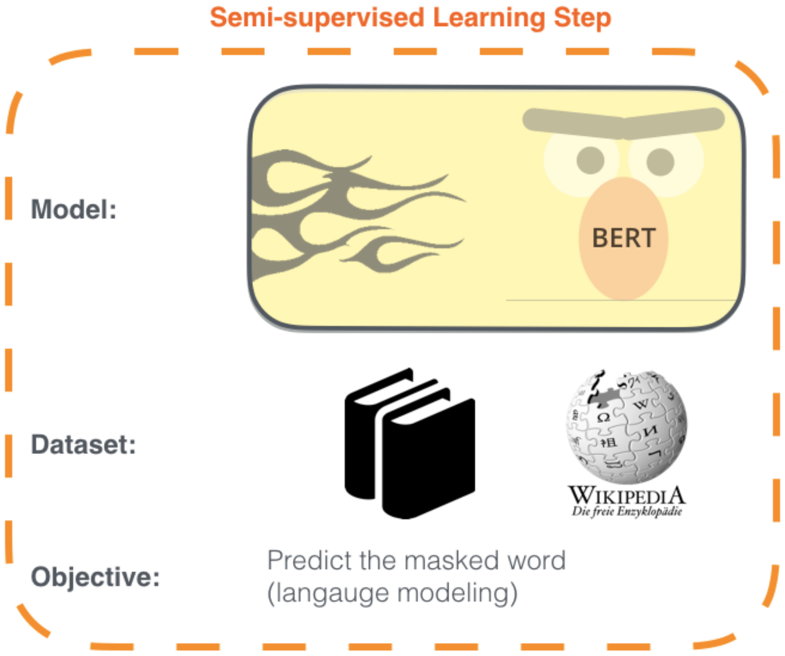
BERT



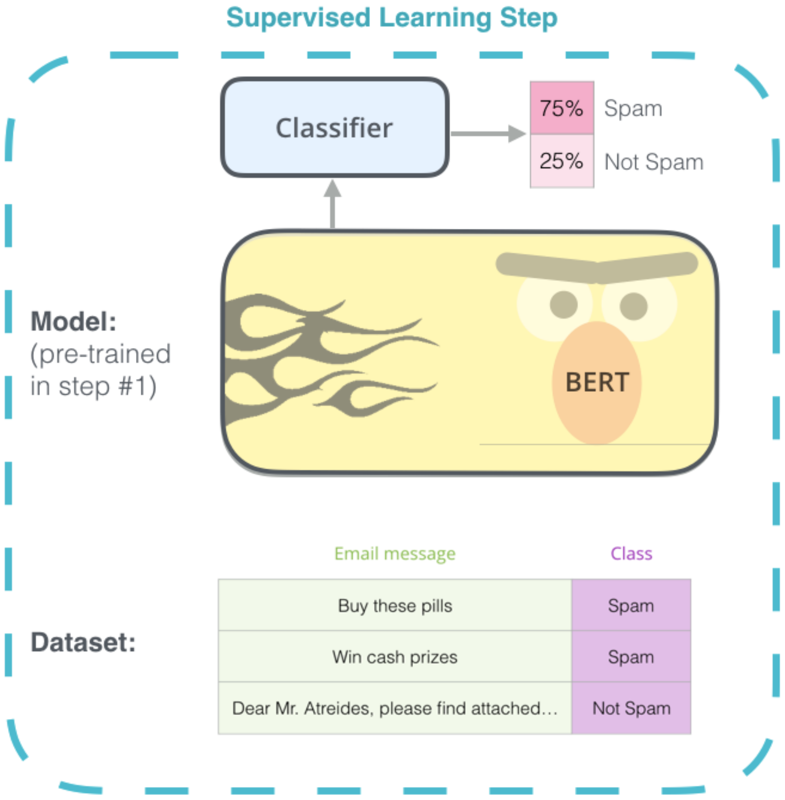
BERT

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.

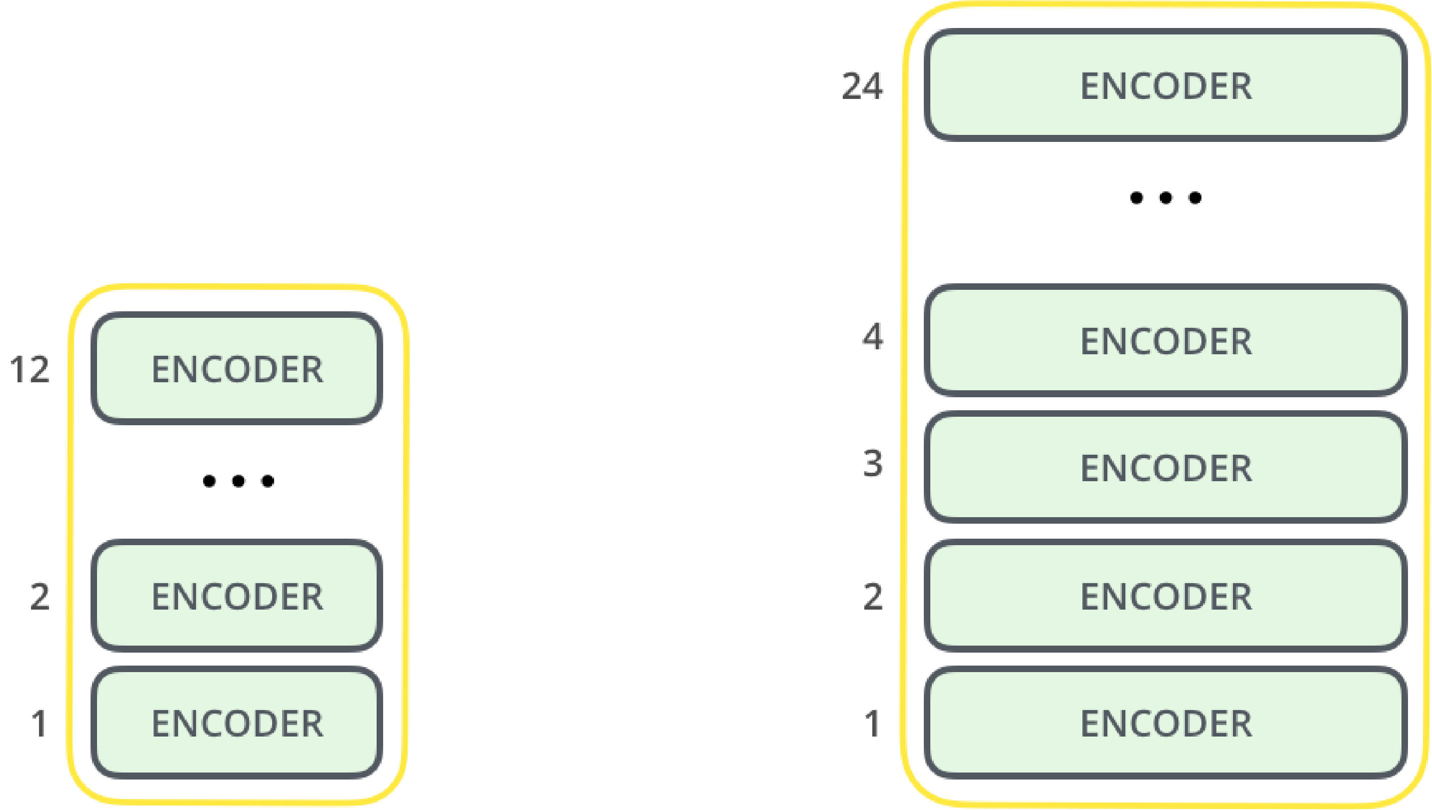


2 - Supervised training on a specific task with a labeled dataset.



BERT

- BERT Base
- BERT Large

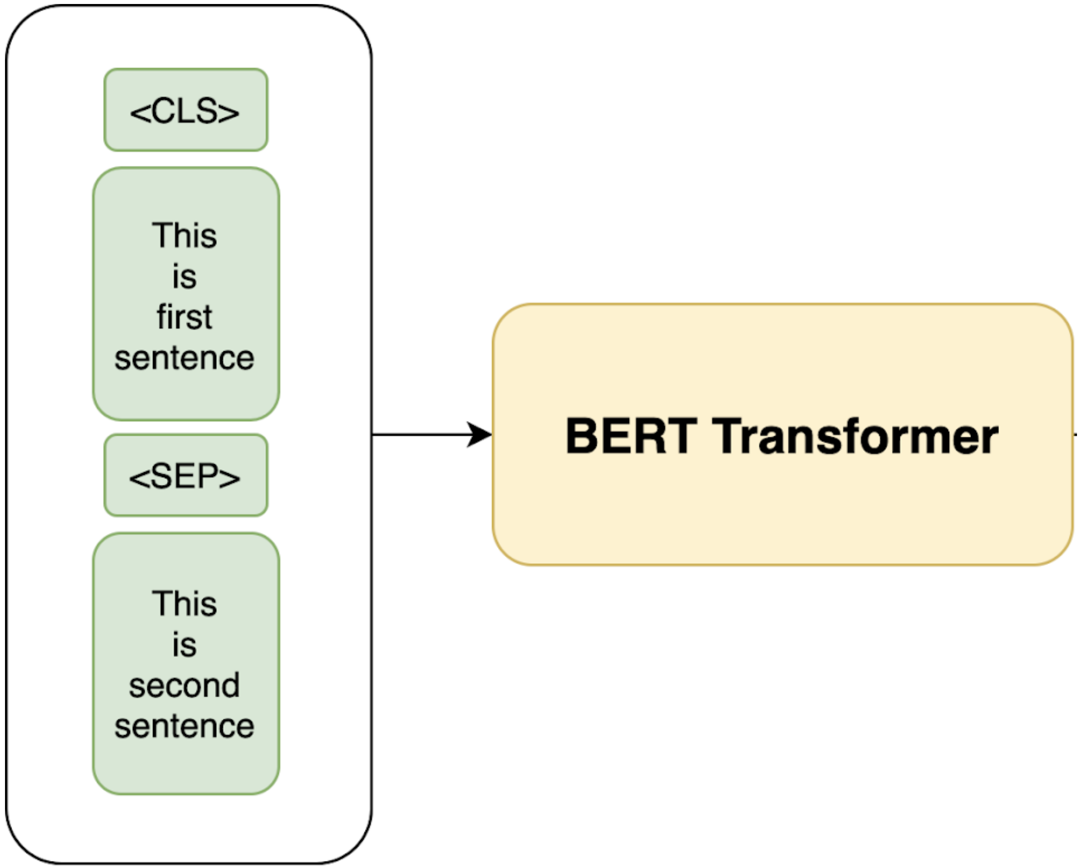


$\text{BERT}_{\text{BASE}}$ $\text{BERT}_{\text{LARGE}}$

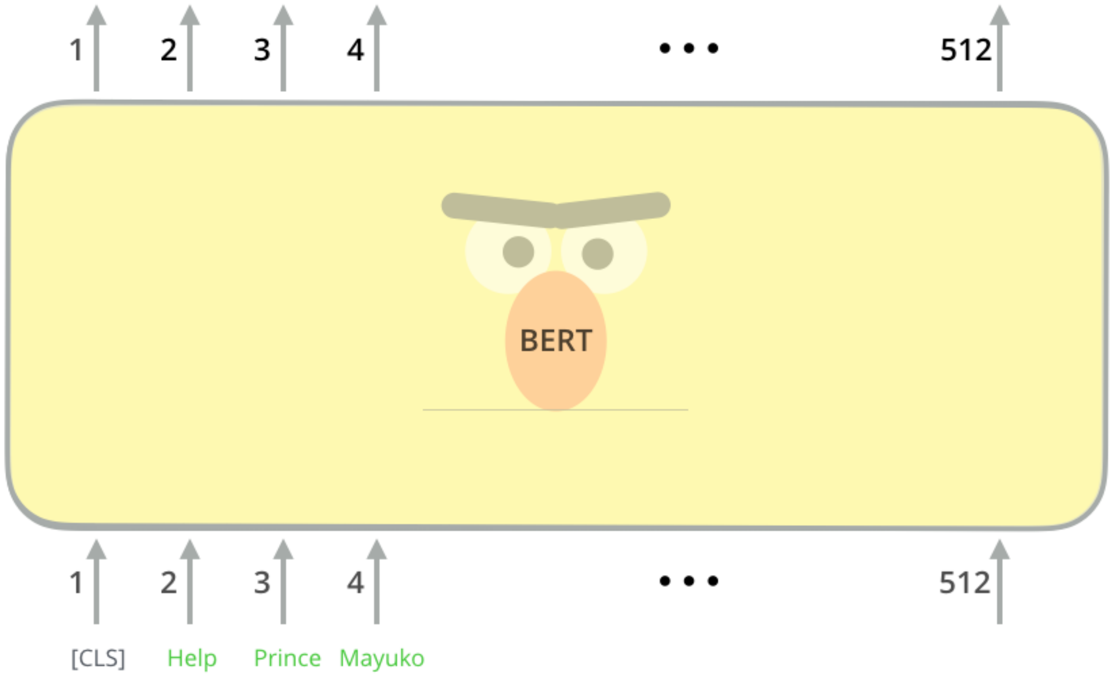
BERT

- Training type
  - Masked language model
  - Next sentence prediction

- Input
  - First token [CLS]
  - Delimiter token [SEP]
  - Masked token [MASK]



BERT



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• • •
512
BERT
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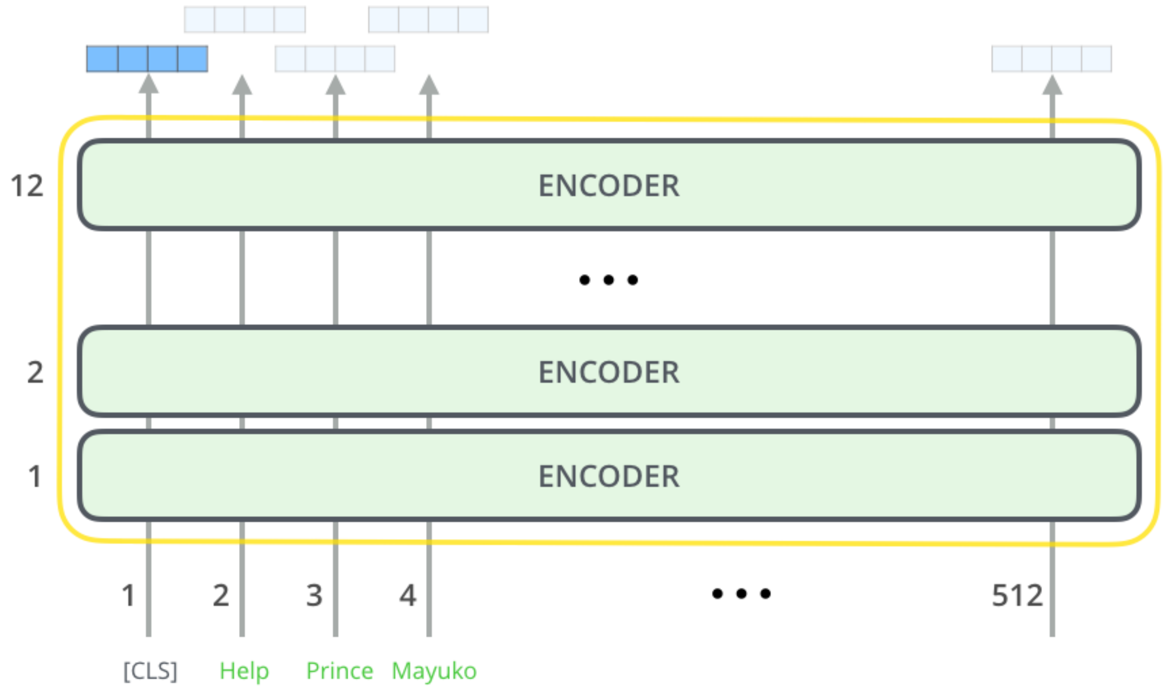
512
[CLS]
Help
Prince
Mayuko



12
ENCODER
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Help
Prince
Mayuko

BERT

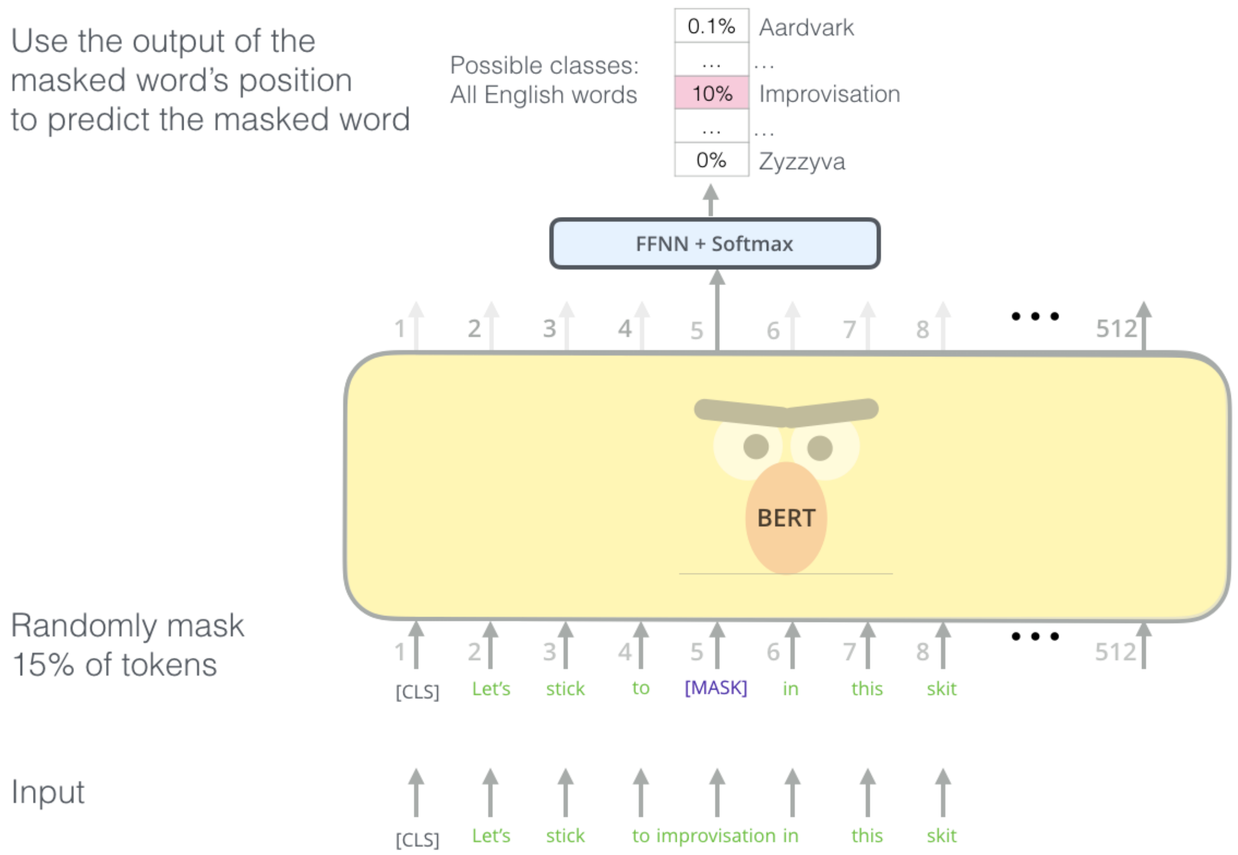
- Masked language model
- **Solution**: Mask out *k*% of the input words, and then predict the masked words
  - We always use $k = 15\%$

```
                                  store                    gallon
                                    ↑                        ↑
the man went to the [MASK] to buy a [MASK] of milk
```

- Too little masking: Too expensive to train
- Too much masking: Not enough context

BERT

- Masked language model



BERT

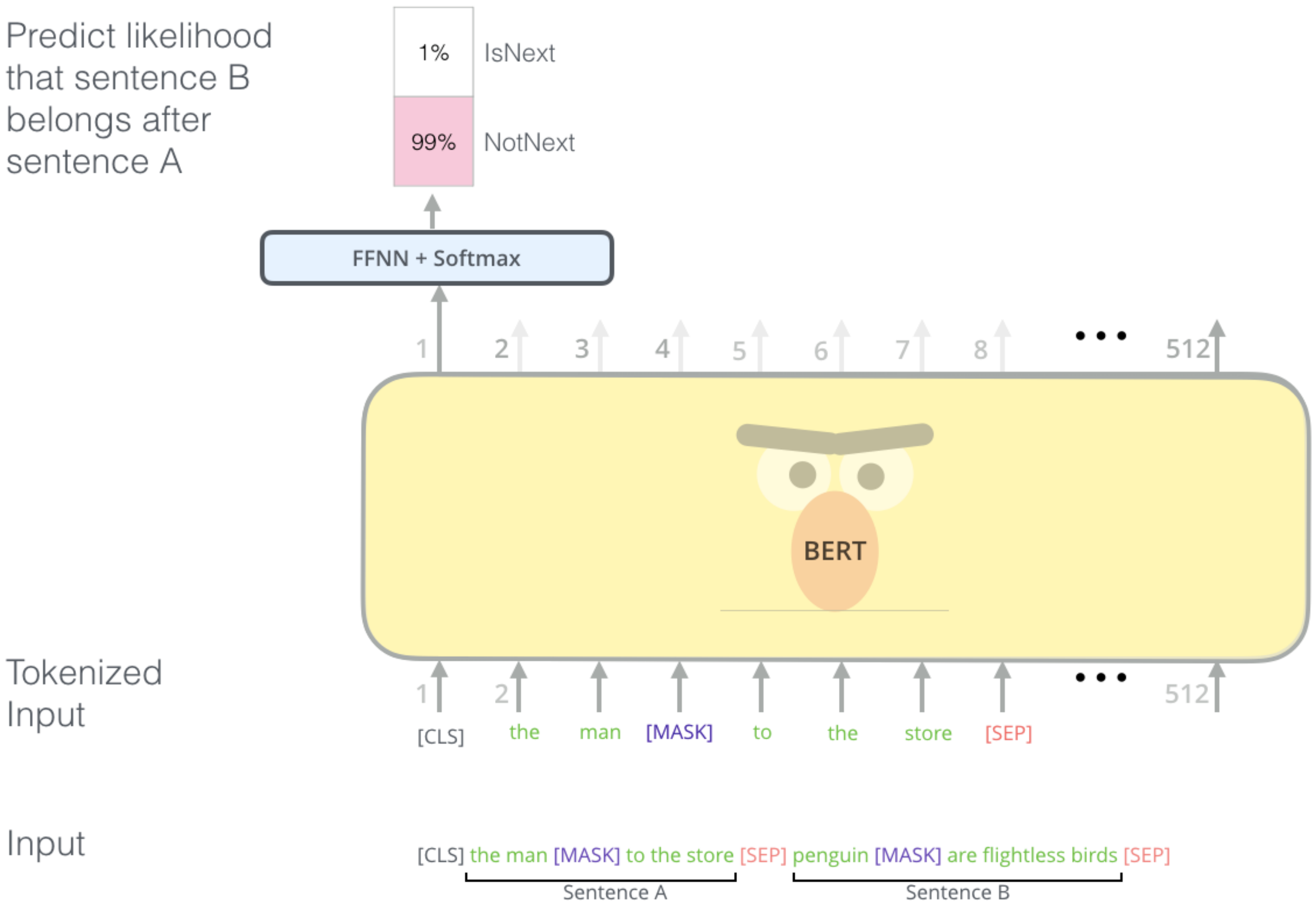
- Next sentence prediction
- To learn *relationships* between sentences, predict whether Sentence B is actual sentence that proceeds Sentence A, or a random sentence

Sentence A = `The man went to the store.`
Sentence B = `He bought a gallon of milk.`
Label = `IsNextSentence`

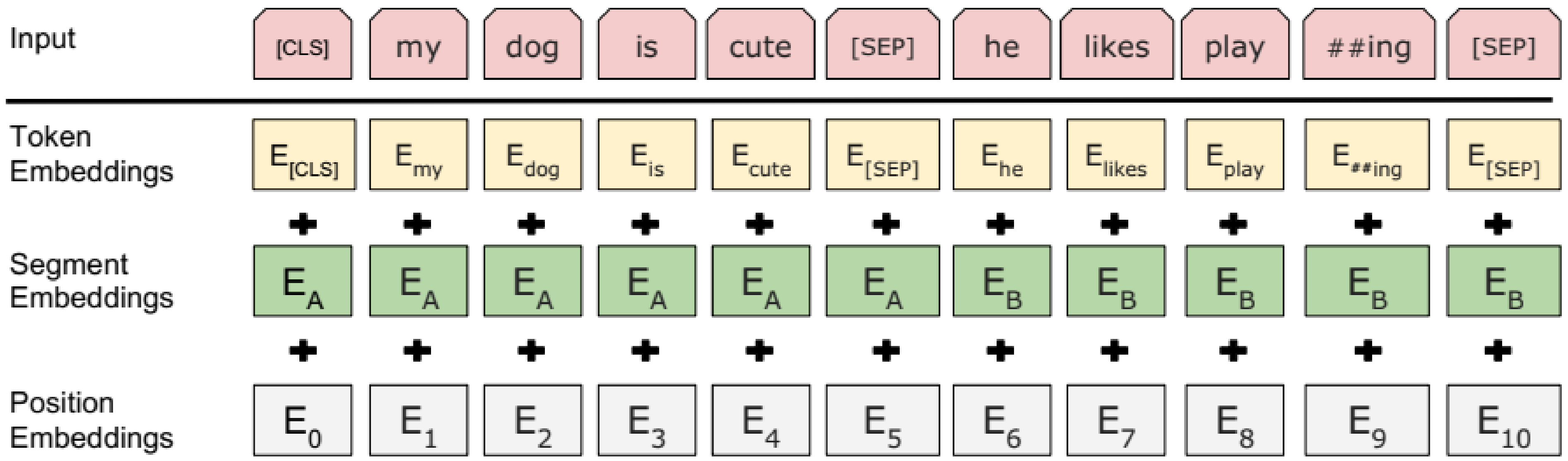
Sentence A = `The man went to the store.`
Sentence B = `Penguins are flightless.`
Label = `NotNextSentence`

BERT

- Next sentence prediction

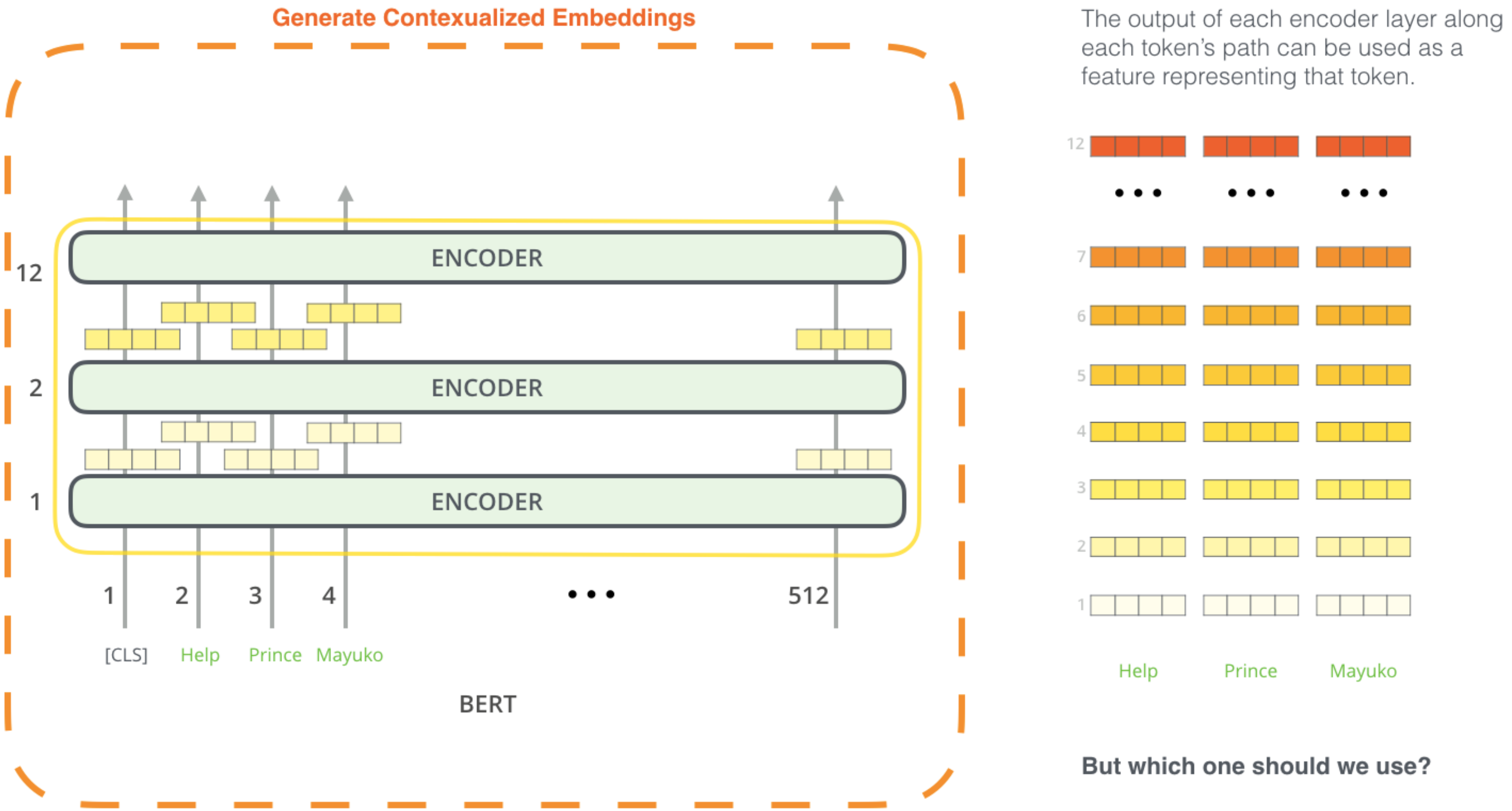


BERT


Input
[CLS]
my
dog
is
cute
[SEP]
he
likes
play
##ing
[SEP]
Token Embeddings
$E_{[CLS]}$ E_{my} E_{dog} E_{is} E_{cute} $E_{[SEP]}$ E_{he} E_{likes} E_{play} $E_{\#\#ing}$ $E_{[SEP]}$
Segment Embeddings
E_A E_A E_A E_A E_A E_A E_B E_B E_B E_B E_B
Position Embeddings
E_0 E_1 E_2 E_3 E_4 E_5 E_6 E_7 E_8 E_9 E_{10}

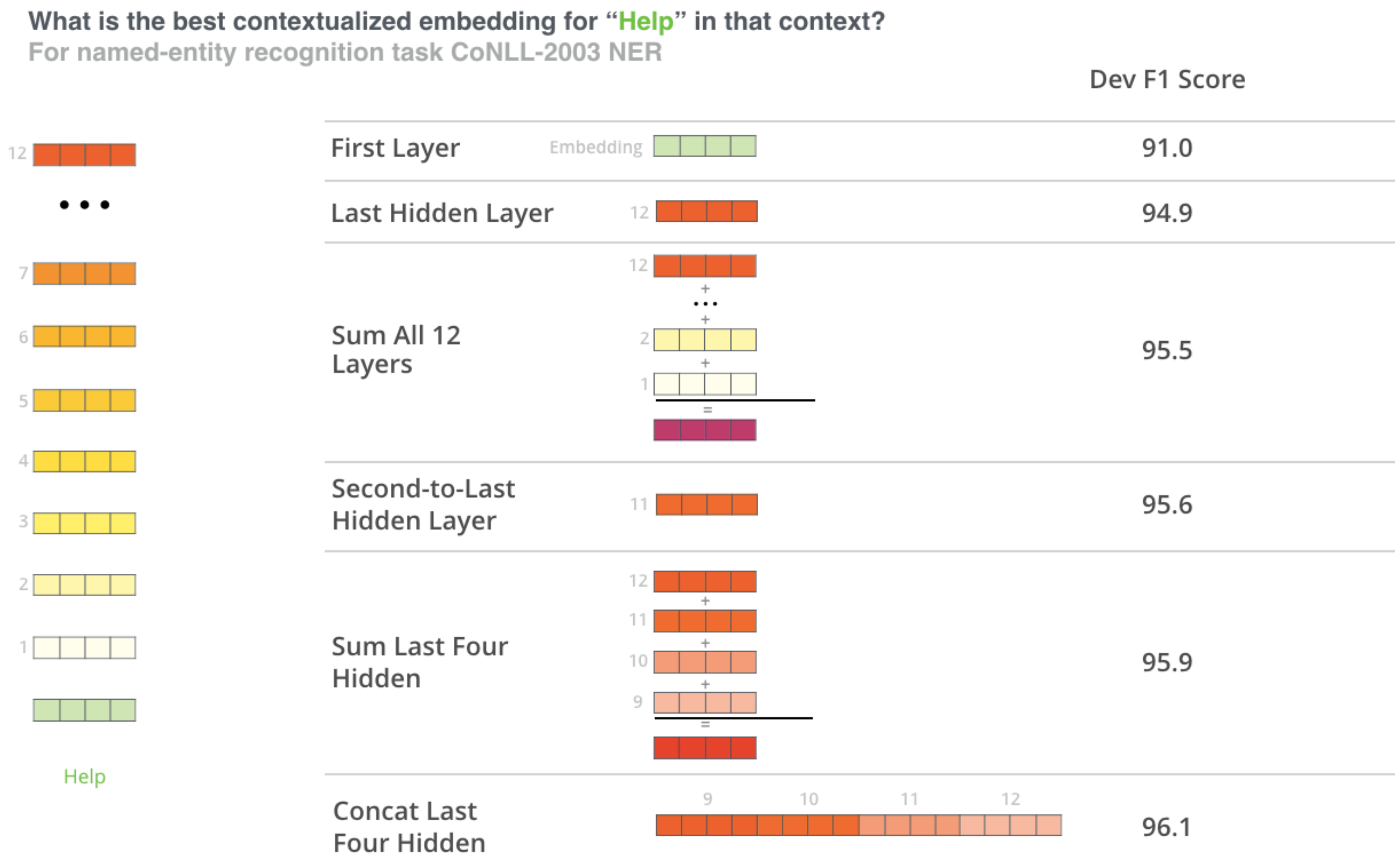
BERT

- Extracting embedding

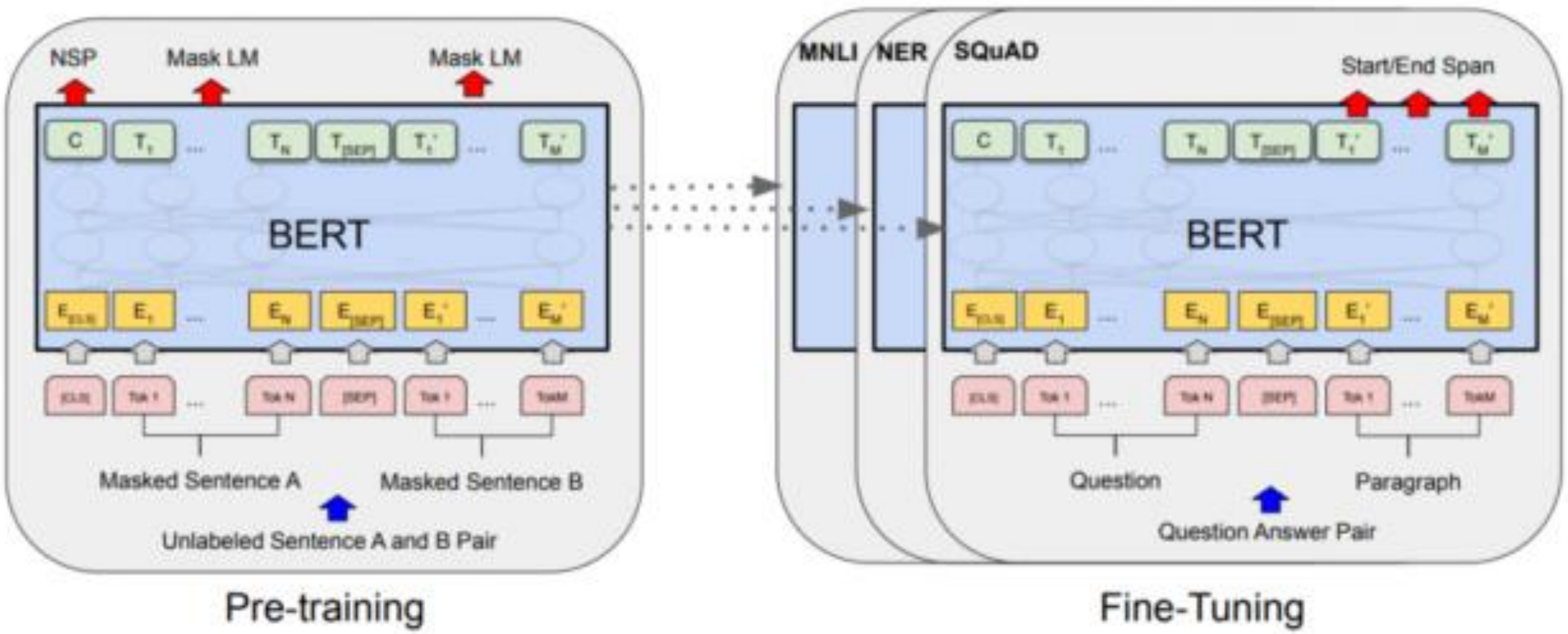


BERT

- Extracting embedding

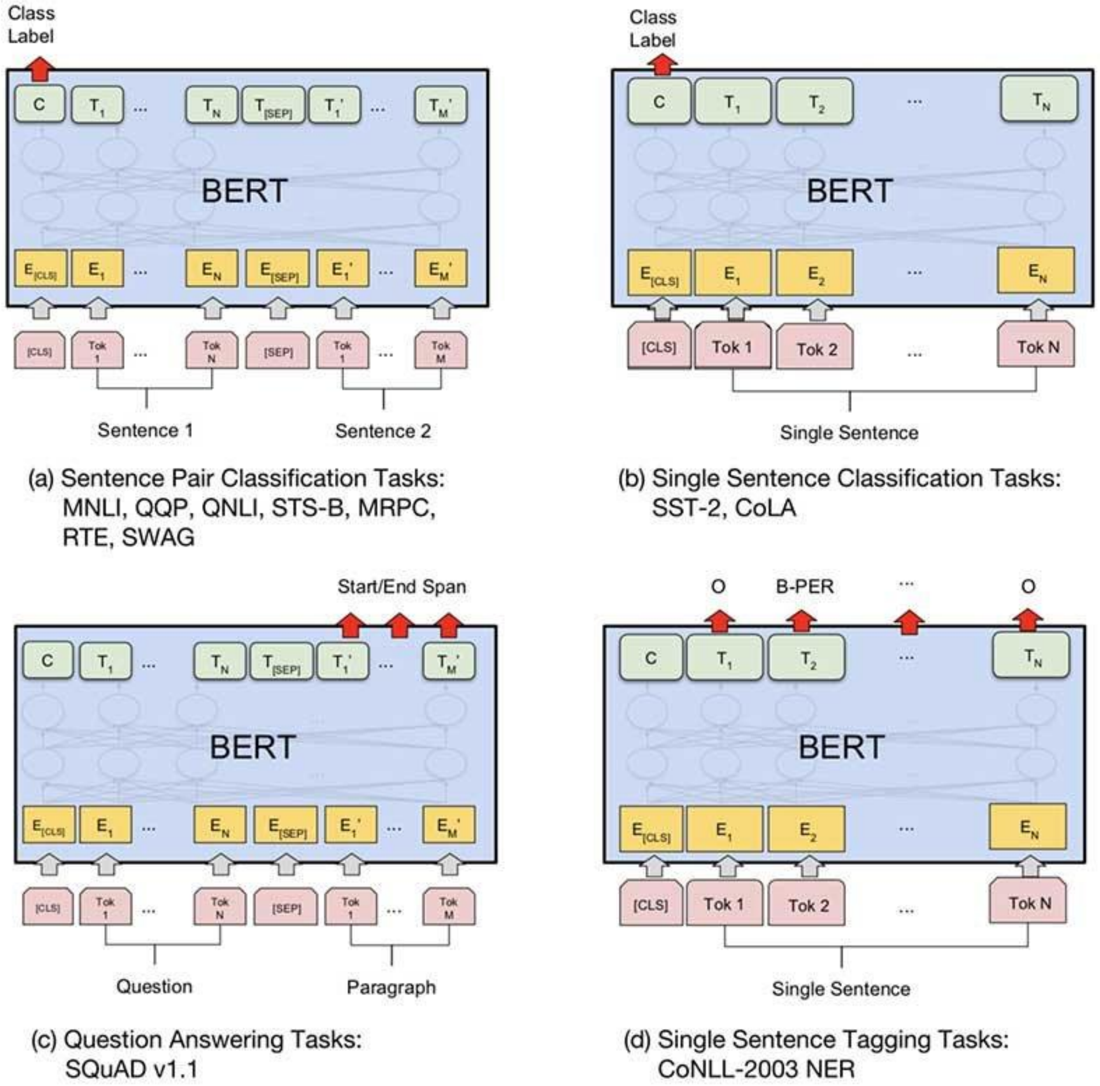


Fine-Tuning Procedure



Fine-Tuning Procedure

- Sentence pair classification
- Single sentence classification
- Question answering
- Single sentence sequence labeling



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

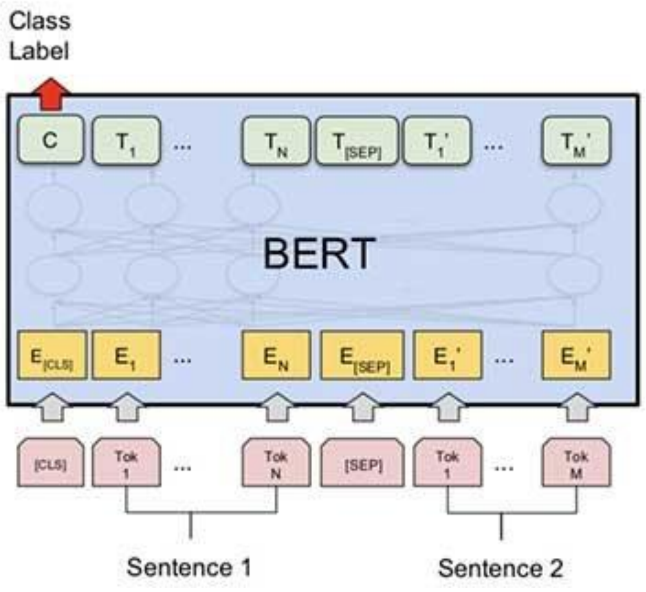
(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

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

Fine-Tuning Procedure

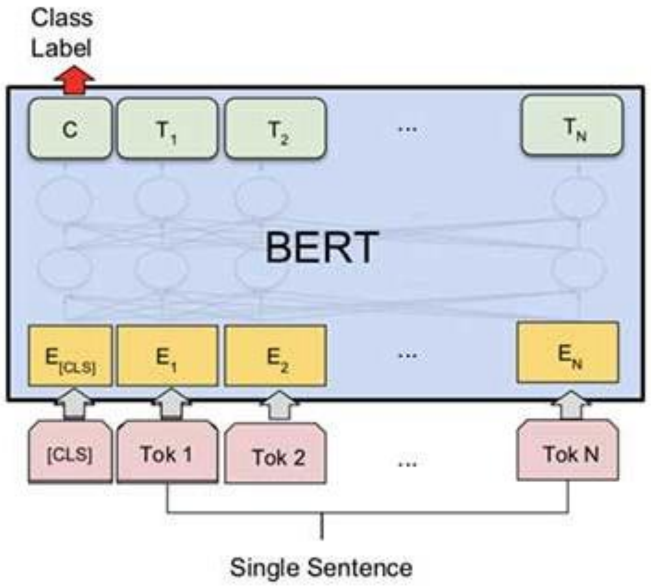
- Sentence pair classification tasks
  - Paraphrase identification
  - Answer retrieval
  - Textual entailment



- Datasets:
  - MNLI
  - QQP
  - QNLI
  - STS-B
  - MRPC
  - RTE
  - SWAG

Fine-Tuning Procedure

- Single sentence classification tasks:
  - Spam detection
  - Sentiment analysis
  - News categorization



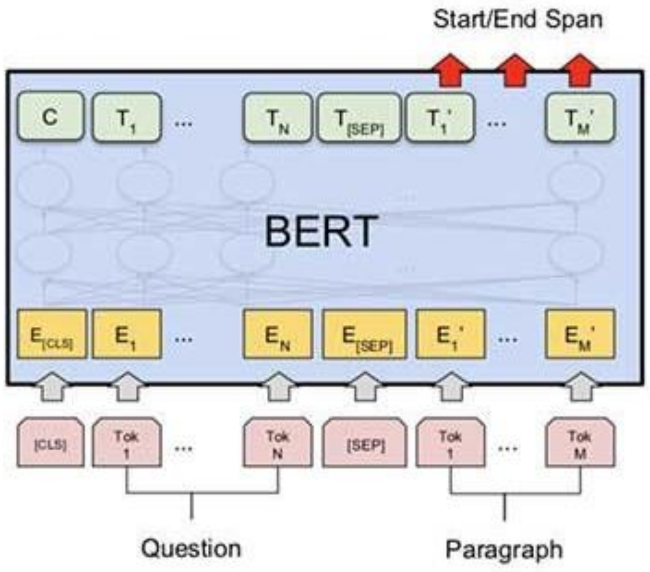
- Datasets:
  - SST-2
  - CoLA

Fine-Tuning Procedure

- Question answering tasks

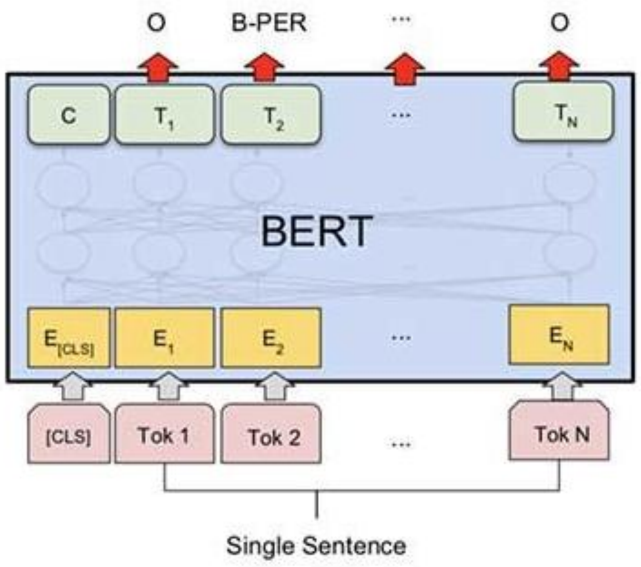
  (finding answer span)

- Dataset:
  - SQuAD



Fine-Tuning Procedure

- Single sentence sequence labeling tasks:
  - NER
  - POS tagging
  - Slot filing



- Datasets:
  - CoNLL-2003 NER

Motivations for Improving BERT

- Accuracy
- Large
- Slow
- Hard to train

	BERT
Size (millions)	**Base**: 110 **Large**: 340
Training Time	**Base**: 8 x V100 x 12 days* **Large:** 64 TPU Chips x 4 days (or 280 x V100 x 1 days*)
Performance	Outperforms state-of-the-art in Oct 2018
Data	16 GB BERT data (Books Corpus + Wikipedia). 3.3 Billion words.
Method	BERT (Bidirectional Transformer with MLM and NSP)

Model Improvement Methods

- Larger with more data
- Quantization
  - Quantization-aware training
- Distillation
- Pruning
- Specialization

Further Reading

- Speech and Language Processing (3rd ed. draft)
  - Chapter 11