Contextual Representation

COMP90042

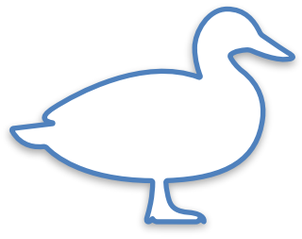
Natural Language Processing

Lecture 11

THE UNIVERSITY OF MELBOURNE

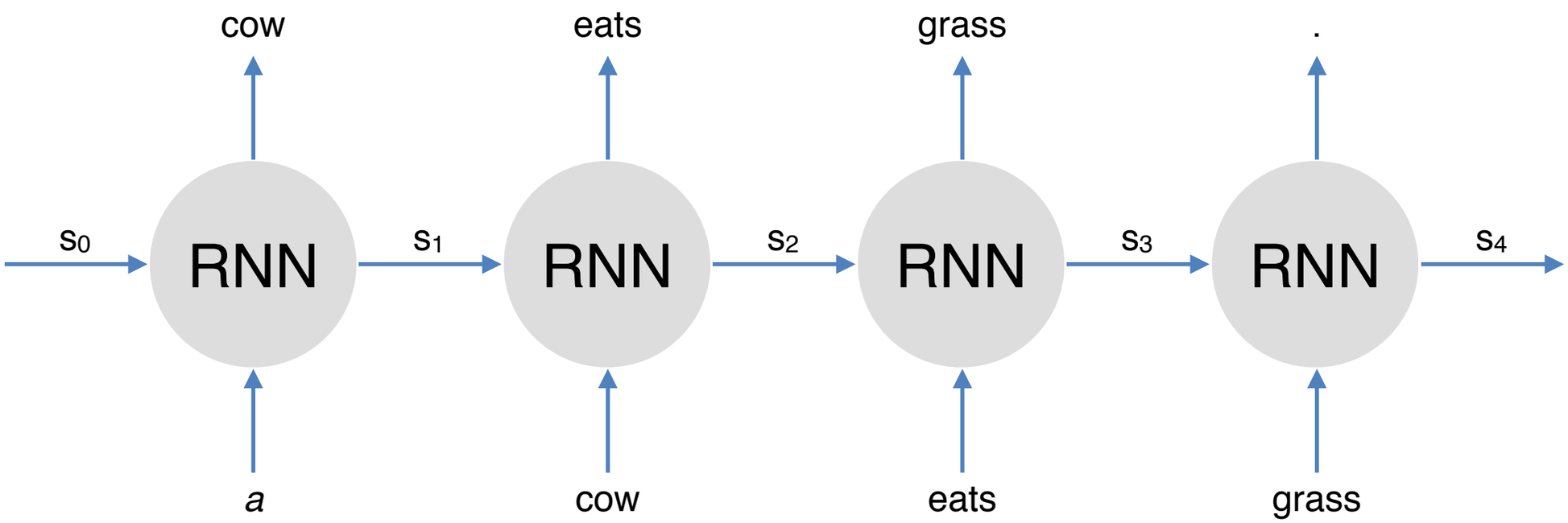
Word Vectors/Embeddings

- Each word type has one representation
  - Word2Vec
- Always the same representation regardless of the context of the word
- Does not capture multiple senses of words

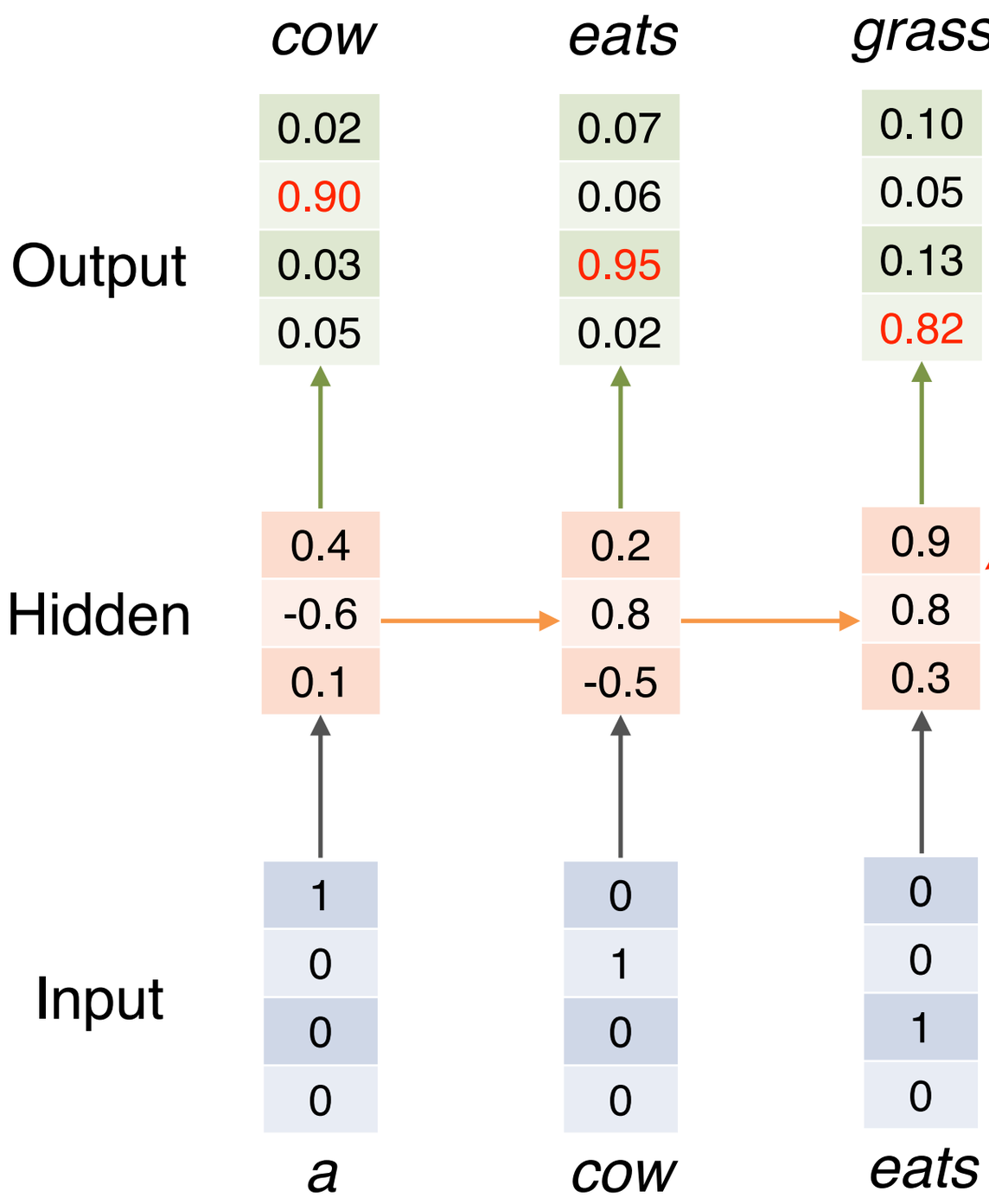


- Contextual representation = representation of words based on context
- Pre-trained contextual representations work *really well* for downstream applications!

RNN Language Model



RNN Language Model



Contextual Word Embedding!

Word Embedding

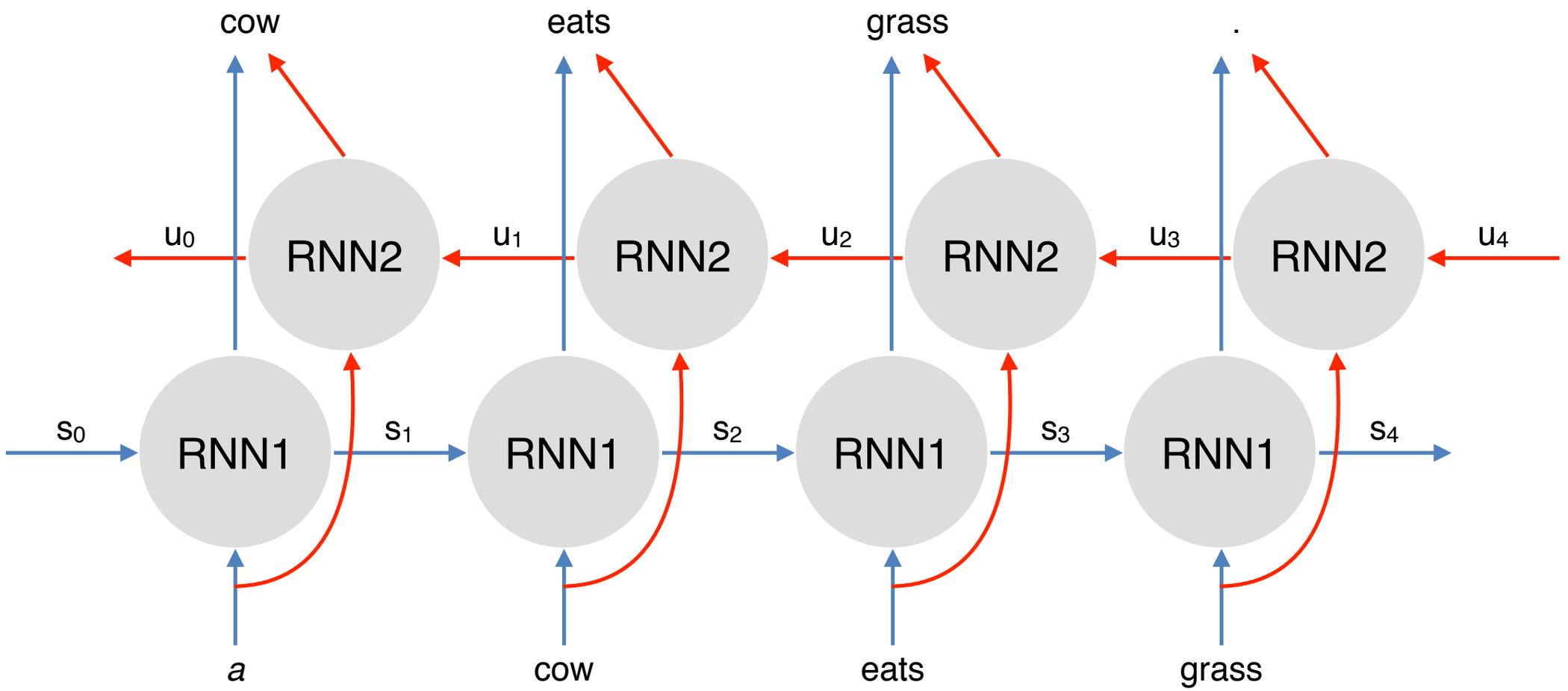
$$s_i = \tanh(W_s s_{i-1} + W_x x_i + b)$$

$$y_i = \text{softmax}(s_i)$$

Solved?

- Almost, but the contextual representation only captures context to the left
- Solution: use a bidirectional RNN instead!

Bidirectional RNN



$$y_i = \text{softmax}([s_i, u_i])$$

Contextual Word Embedding!

ELMo

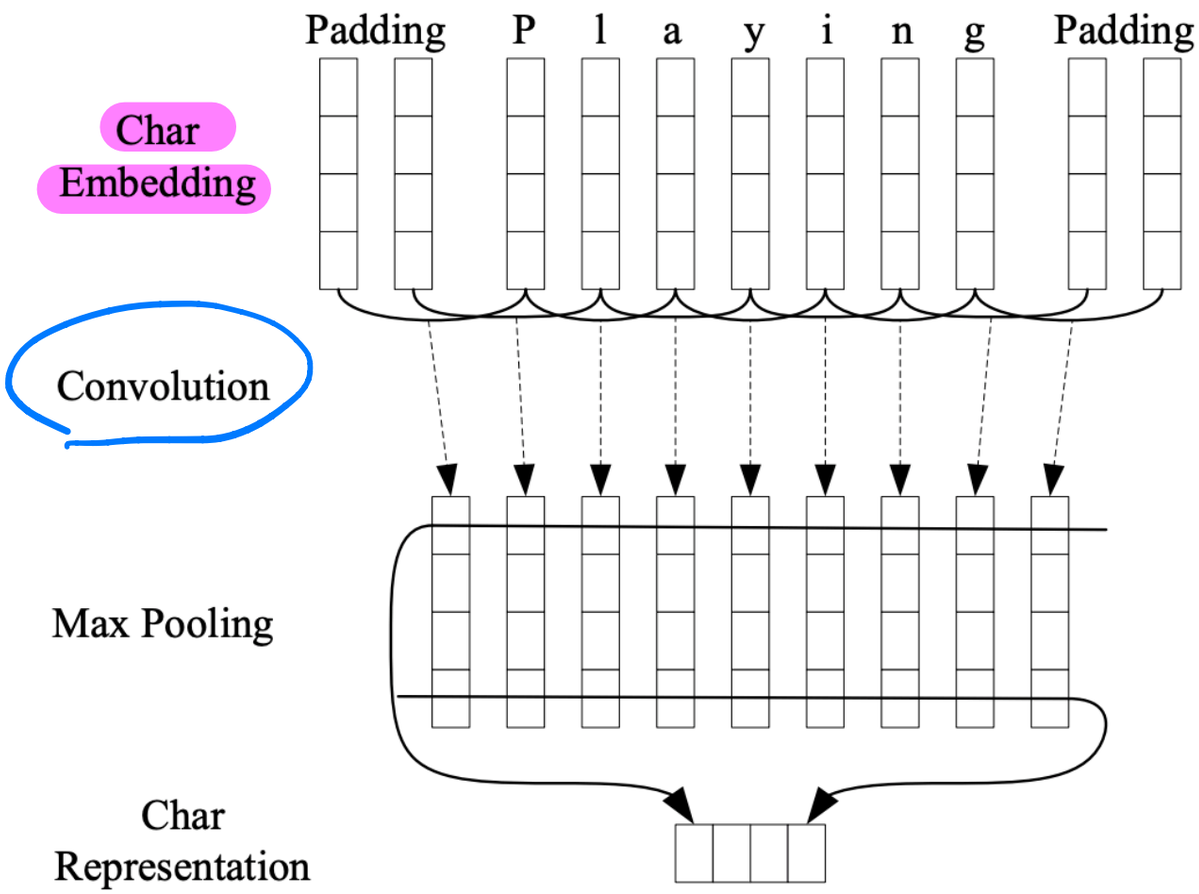
ELMo: **E**mbeddings from **L**anguage **Mo**dels

- Peters et al. (2018): https://arxiv.org/abs/1802.05365v2
- Trains a bidirectional, multi-layer LSTM language model over 1B word corpus
- Combine hidden states from **multiple layers** of LSTM for downstream tasks
  - Prior studies use only top layer information
- Improves task performance significantly!

ELMo

- Number of LSTM layers = 2
- LSTM hidden dimension = 4096
- Character convolutional networks (CNN) to create word embeddings
  - No unknown words

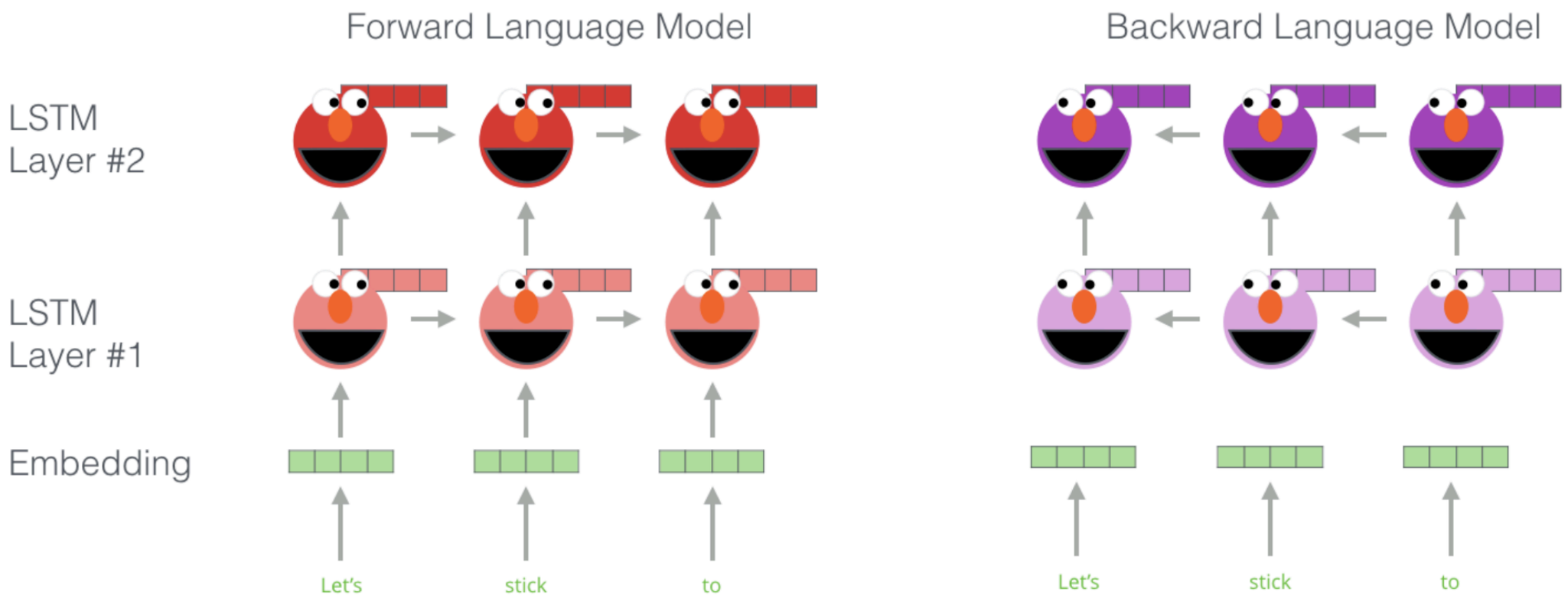
Still capture the characters of char.



https://www.aclweb.org/anthology/P16-1101.pdf

Extracting Contextual Representation

Embedding of “stick” in “Let’s stick to” - Step #1

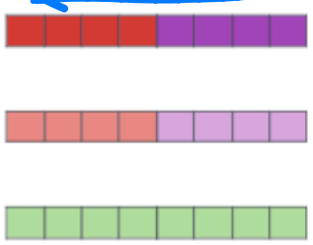


http://jalammar.github.io/illustrated-bert/

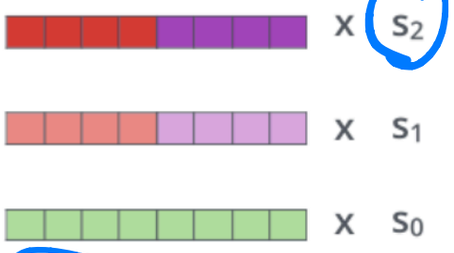
Extracting Contextual Representation

Embedding of "stick" in "Let's stick to" - Step #2

1- Concatenate hidden layers

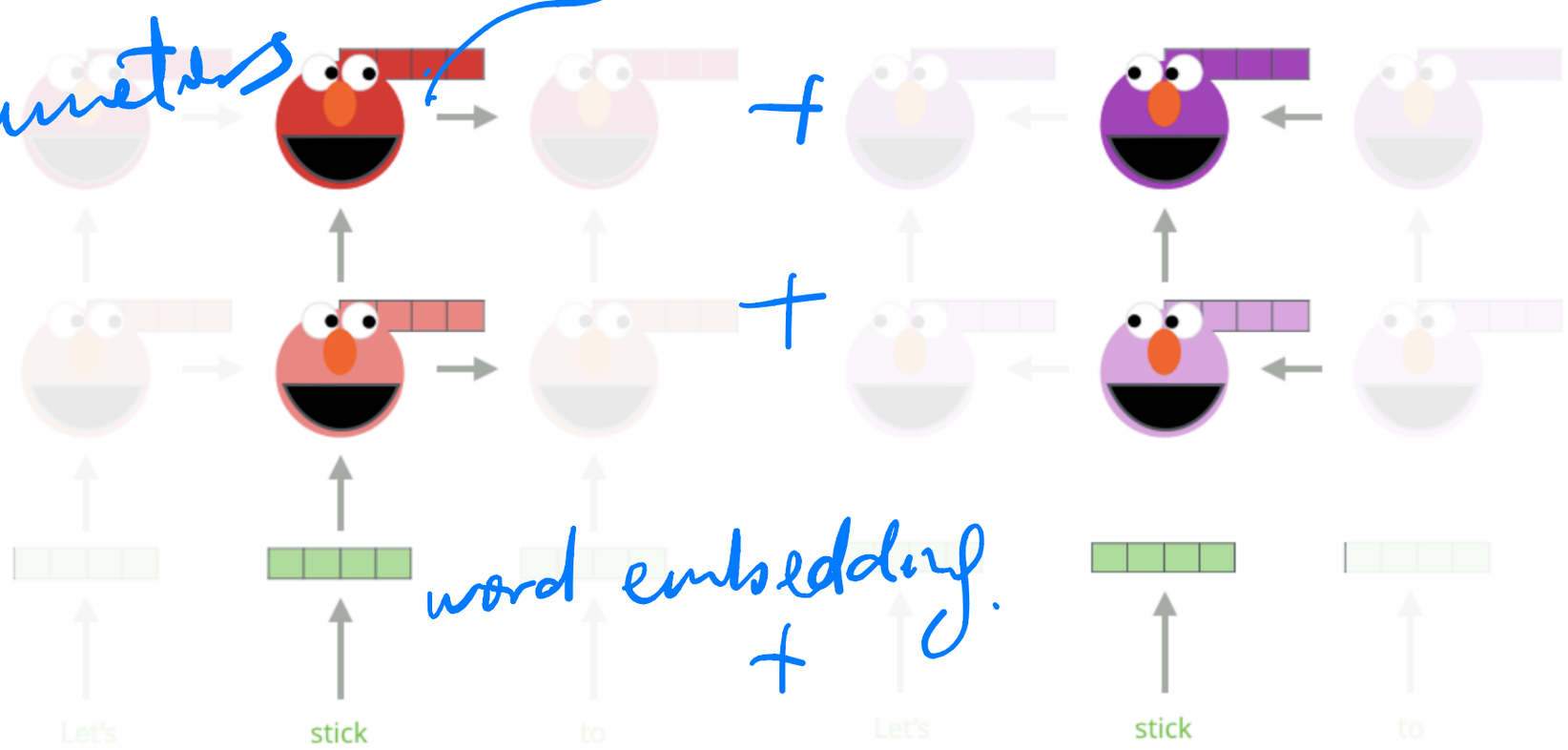


2- Multiply each vector by a weight based on the task



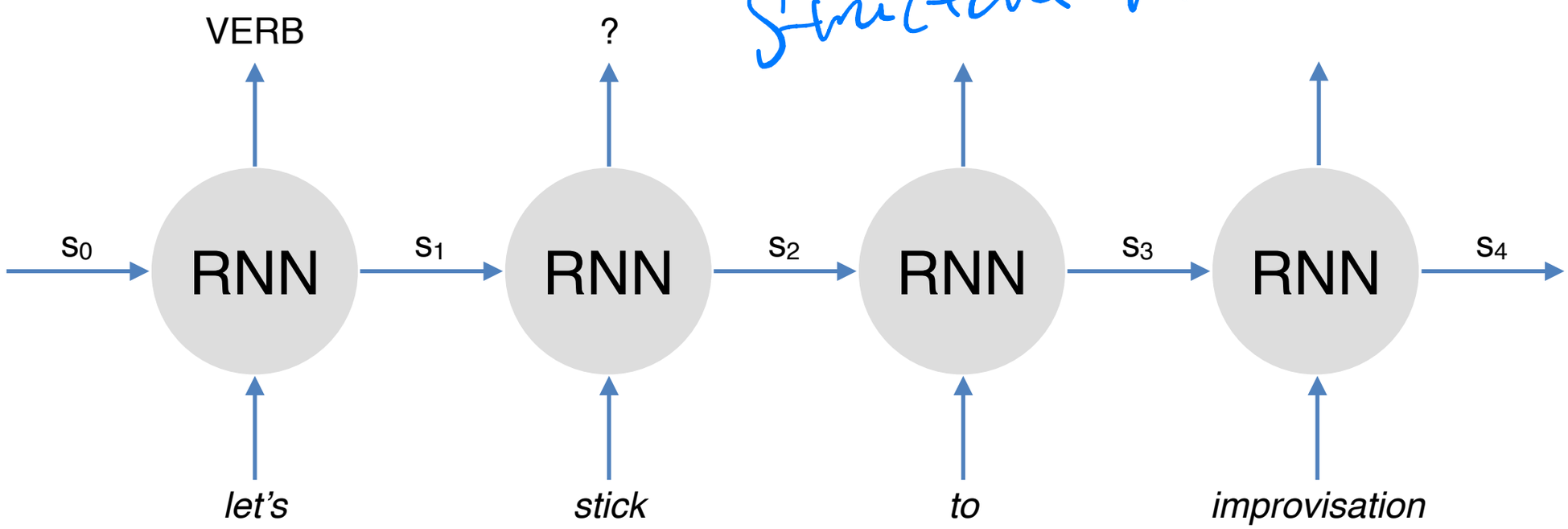
3- Sum the (now weighted) vectors

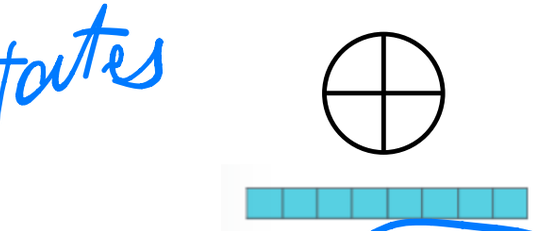
ELMo embedding of "stick" for this task in this context



Downstream Task: POS Tagging

Add extra Elmo ~~Embedding~~. Structure remains. Reps...





fix hidden states learn the concatenation coefficient.

$$s_i = \tanh(W_s s_{i-1} + (W_x x_i \oplus e_i) + b)$$

ELMo embedding

word embedding matrix

How Good is ELMo?

TASK	PREVIOUS SOTA		OUR BASELINE	ELMO + BASELINE	INCREASE (ABSOLUTE/ RELATIVE)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

- SQuAD: QA
- SNLI: textual entailment
- SRL: semantic role labelling
- Coref: coreference resolution
- NER: named entity recognition
- SST-5: sentiment analysis

Other Findings

- Lower layer representation = captures syntax
  - good for POS tagging, NER
- Higher layer representation = captures semantics
  - good for QA, textual entailment, sentiment analysis

second & high layer.

Contextual vs. Non-contextual

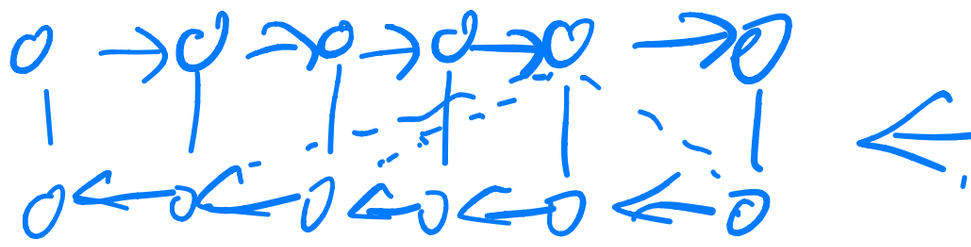
Base on context

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular play on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , and had talent enough to fill the roles competently , with nice understatement .

Table 4: Nearest neighbors to "play" using GloVe and the context embeddings from a biLM.

Disadvantages of RNNs

- Sequential processing: difficult to scale to very large corpus or models
- RNN language models run left to right (captures only one side of context) Uni direction
  - Produces well-formed sentence probability
- Bidirectional RNNs help, but they only capture surface bidirectional representations

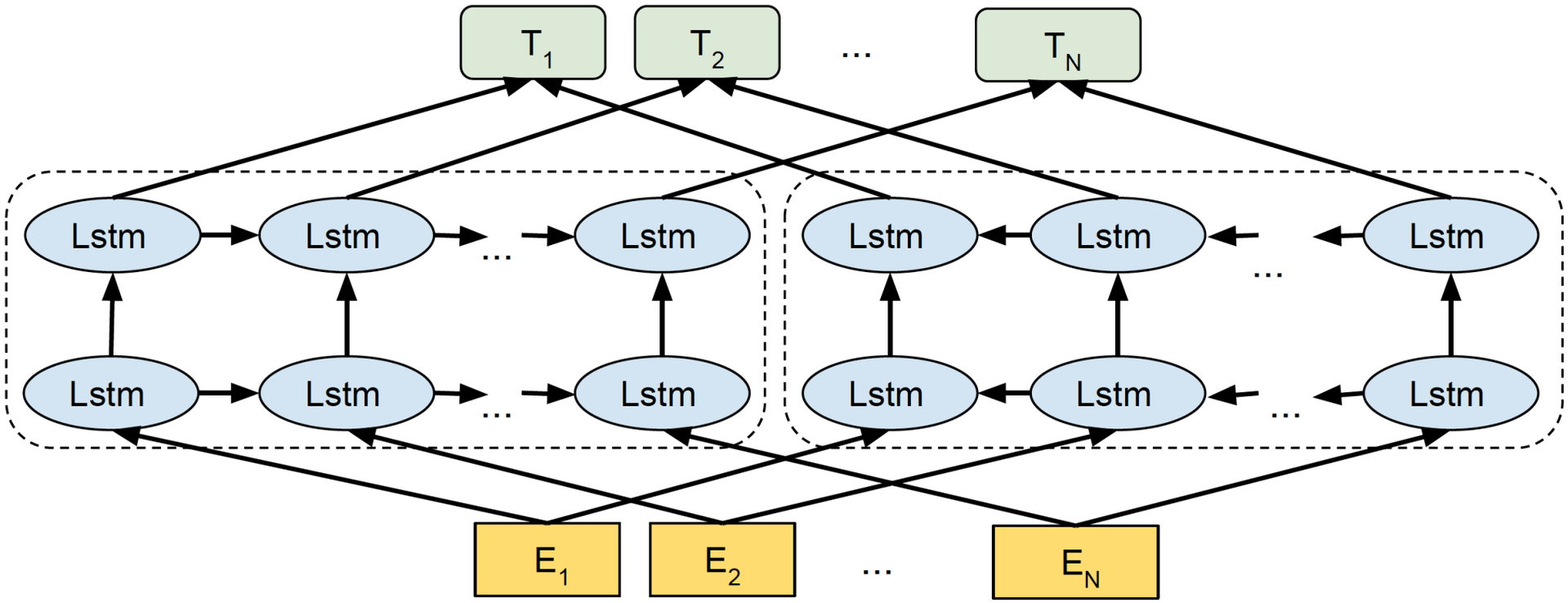


BERT

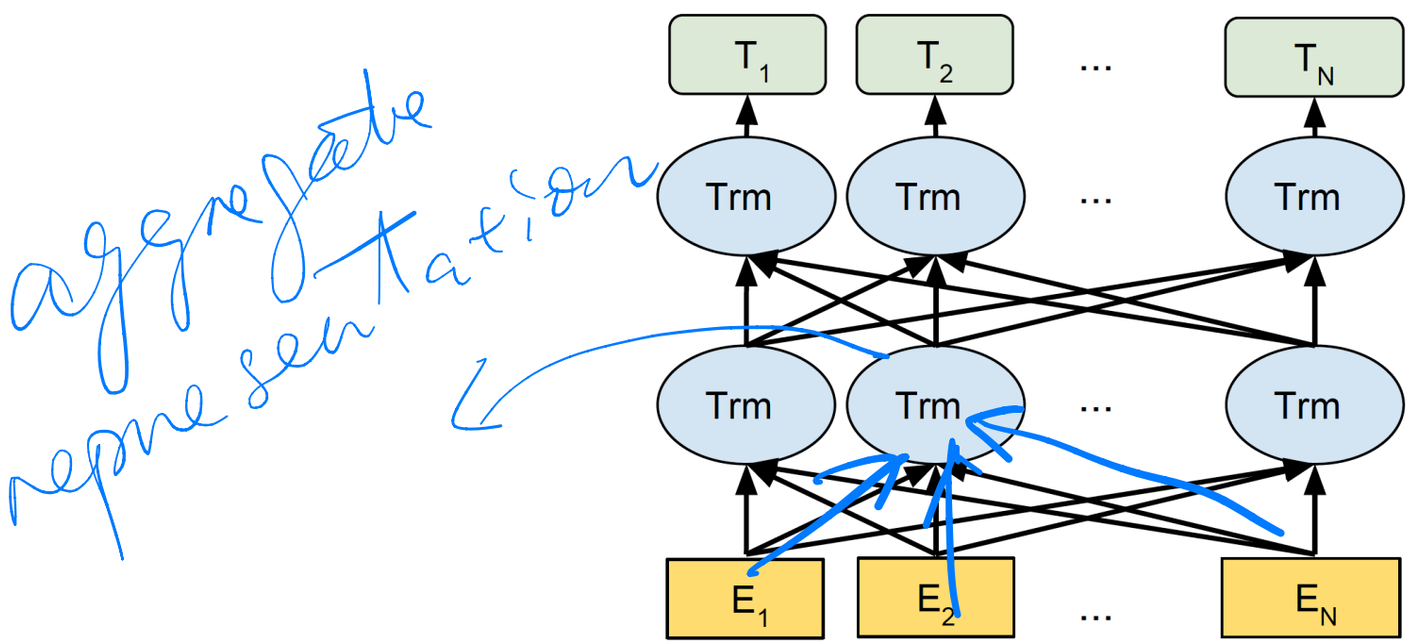
BERT: **B**idirectional **E**ncoder **R**epresentations from **T**ransformers

- Devlin et al. (2019): https://arxiv.org/abs/1810.04805
- Uses self-attention networks (aka **Transformers**) to capture dependencies between words
  - No sequential processing
- **Masked language model** objective to capture deep bidirectional representations
- Loses the ability to generate language
- Not an issue if the goal is to learn contextual representations

ELMo

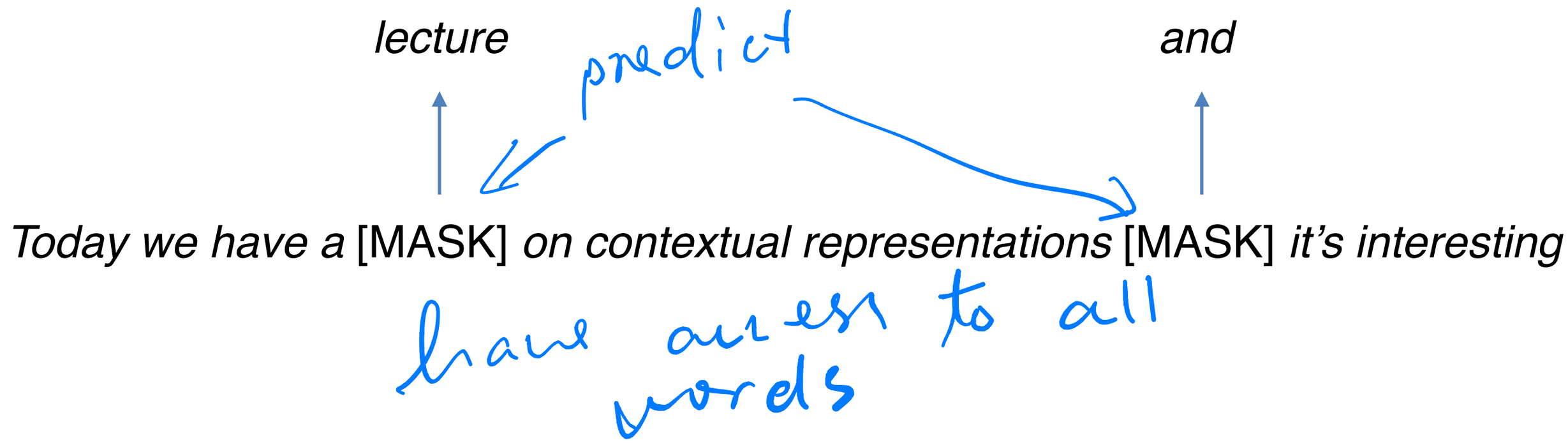

T1
T2
...
TN
Lstm
Lstm
...
Lstm
Lstm
Lstm
...
Lstm
Lstm
Lstm
...
Lstm
Lstm
Lstm
...
Lstm
E1
E2
...
EN

BERT


aggregate representation
T1
T2
...
TN
Trm
Trm
...
Trm
Trm
Trm
...
Trm
E1
E2
...
EN

Objective 1: Masked Language Model

- 'Mask' out k% of tokens at random
- Objective: predict the masked words



Objective 2: Next Sentence Prediction

- Learn relationships between sentences
- Predicts whether sentence B follows sentence A
- Useful pre-training objective for downstream applications that analyse sentence pairs (e.g. textual entailment)

analyse a pair of sentences

Sentence A: *Today we have a lecture on NLP.*
Sentence B: *It is an interesting lecture.*
Label: IsNextSentence

Sentence A: *Today we have a lecture on NLP.*
Sentence B: *Polar bears are white.*
Label: NotNextSentence

Training/Model Details

BPE similar.

- WordPiece (subword) Tokenisation
- Multiple layers of transformers to learn contextual representations

whole text.

- Train models trained on Wikipedia+BookCorpus
- Training takes multiple GPUs over several days

Fine-Tuning for 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.

Semi-supervised Learning Step

Model:

Dataset:

Objective:

Predict the masked word (langauge modeling)

pretrain

Fine-Tuning for BERT

add a classification layer

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)

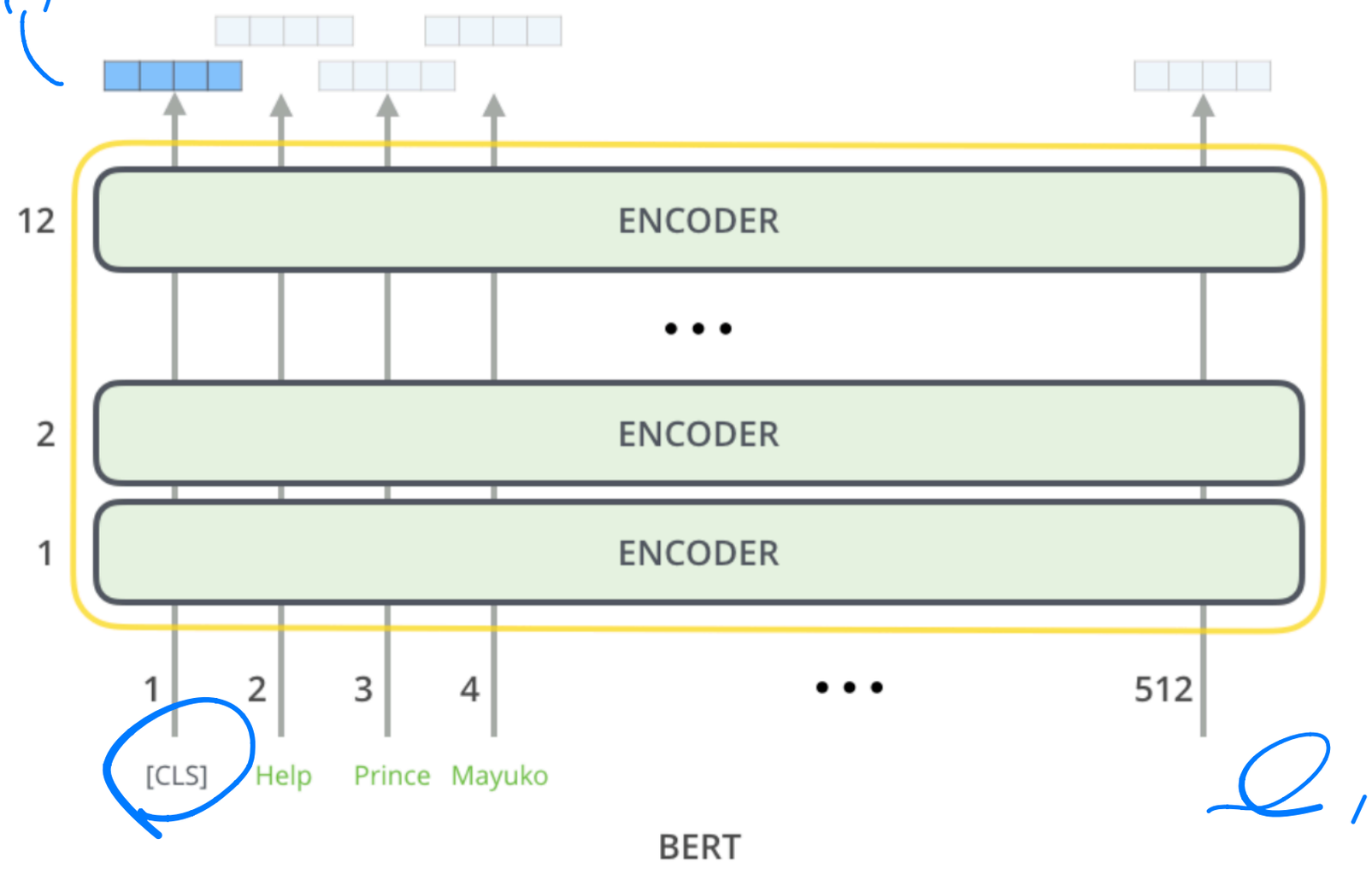
Dataset:

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

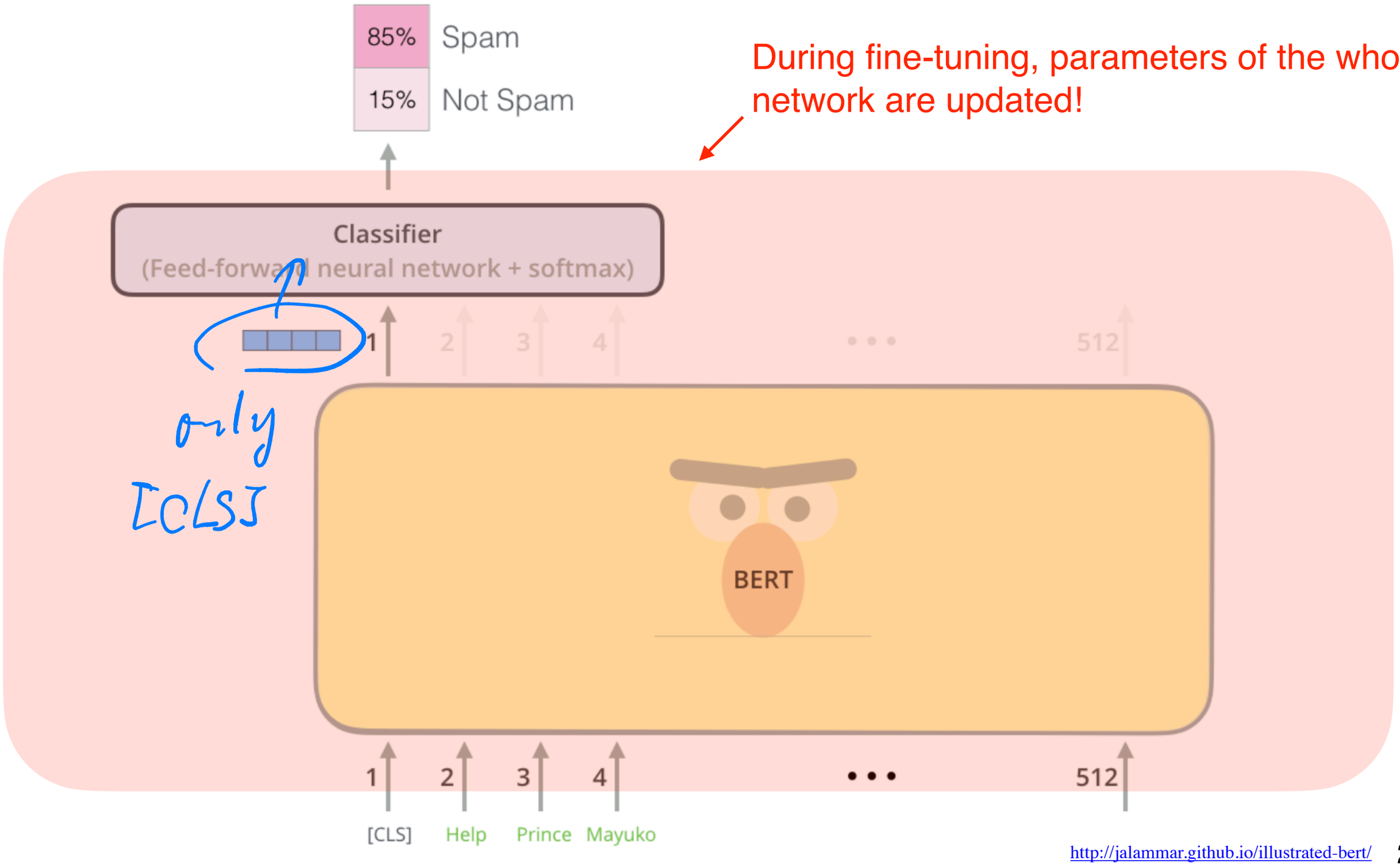
http://jalammar.github.io/illustrated-bert/

Example: Spam Detection

Contextual Repr.



Example: Spam Detection



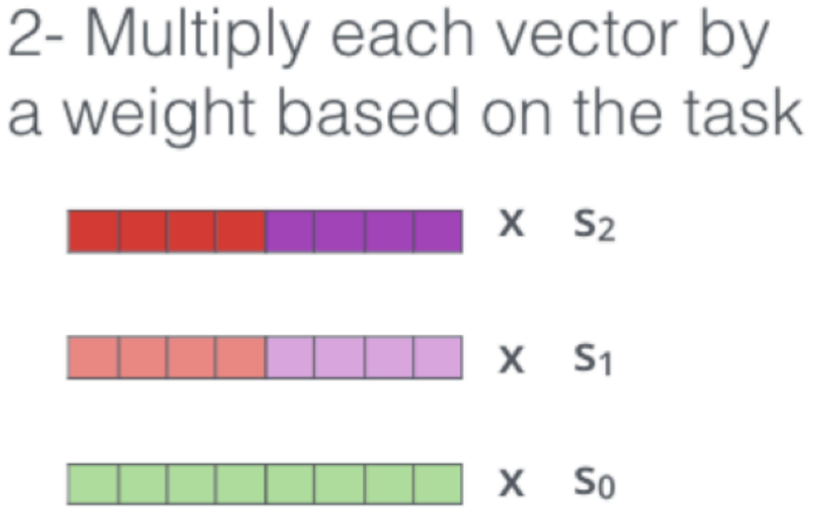
http://jalammar.github.io/illustrated-bert/

BERT vs. ELMo

ELMO requires

- ELMo provides only the contextual representations
- Downstream applications has their own network architecture

- ELMo parameters are fixed when applied to downstream applications
  - Only the weights to combine states from different LSTM layers are learned



concatenate

BERT vs. ELMo

- BERT adds a classification layer for downstream tasks

add classification layer.

  - No task-specific model needed

- BERT updates all parameters during fine-tuning

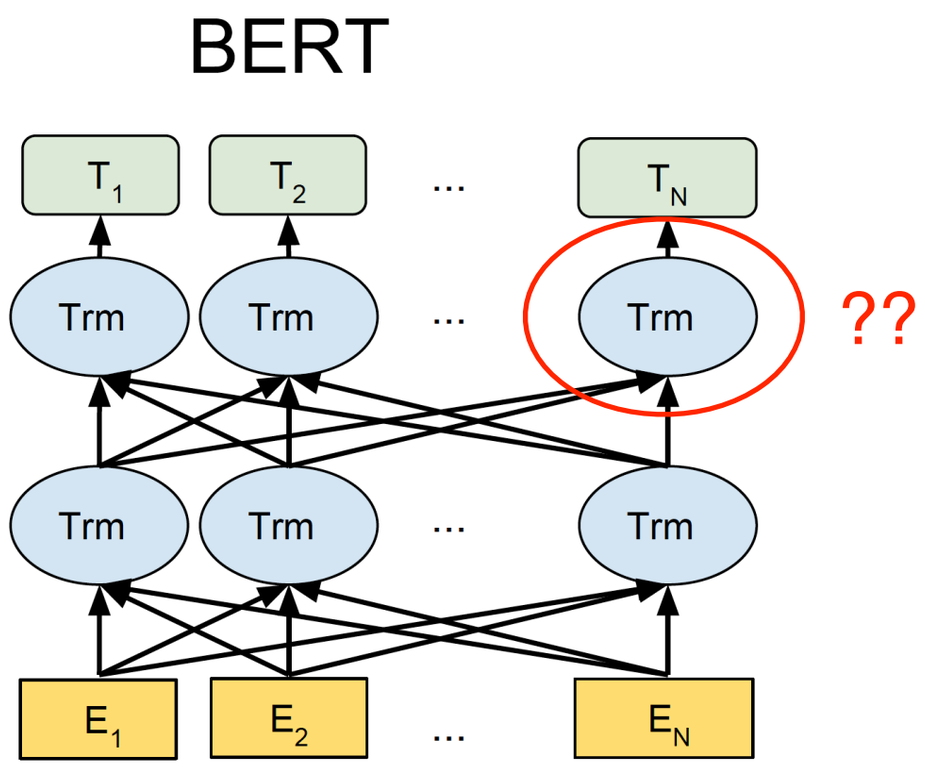
How Good is BERT?

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
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

- MNLI, RTE: textual entailment
- QQP, STS-B, MRPC: sentence similarity
- QNLP: answerability prediction
- SST: sentiment analysis
- COLA: sentence acceptability prediction

Transformers

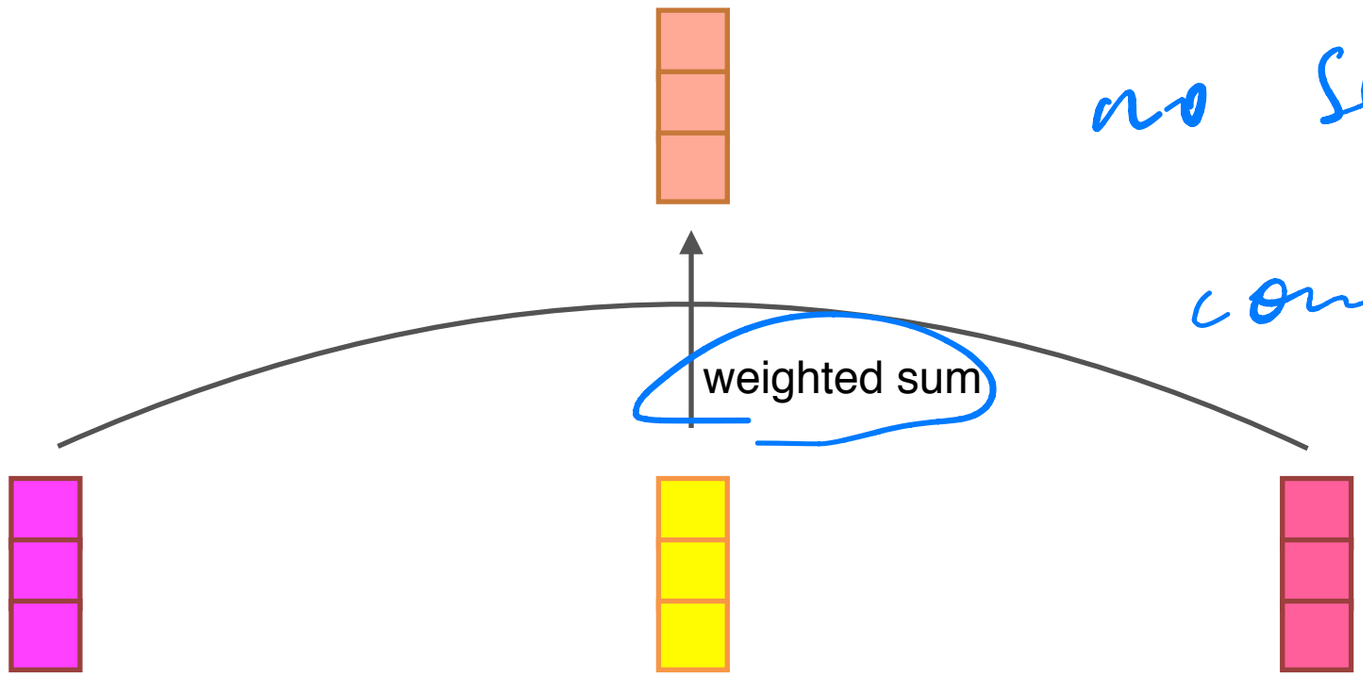
- What are transformers, and how do they work?



Attention is All You Need

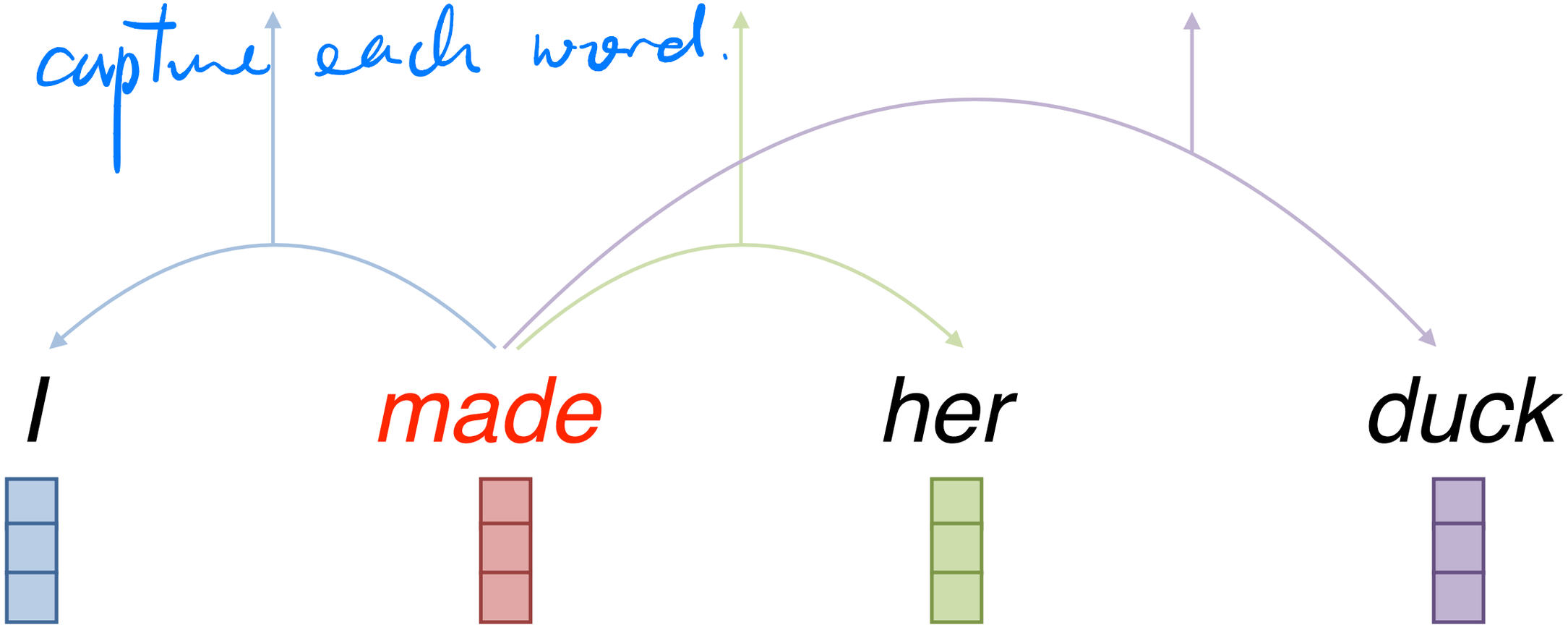
- Vaswani et al. (2017): https://arxiv.org/abs/1706.03762
- Use **attention** instead of using RNNs (or CNNs) to capture dependencies between words

contextual representation for *made*



no sequential computation

capture each word.



Self-Attention: Implementation

- Input:
  - query q (e.g. *made*)
  - key k and value v (e.g. *her*)
- Query, key and value are all **vectors**
  - linear projections from embeddings

$$A(q, K, V) = \sum_i \frac{e^{q \cdot k_i}}{\sum_j e^{q \cdot k_j}} \times v_i$$

$$c_{\text{made}} = 0.1 v_{\text{I}} + 0.6 v_{\text{her}} + 0.3 v_{\text{duck}}$$

Self-Attention: Implementation

$$A(q, K, V) = \sum_i \frac{e^{q \cdot k_i}}{\sum_j e^{q \cdot k_j}} \times v_i$$

- Multiple queries, stack them in a matrix

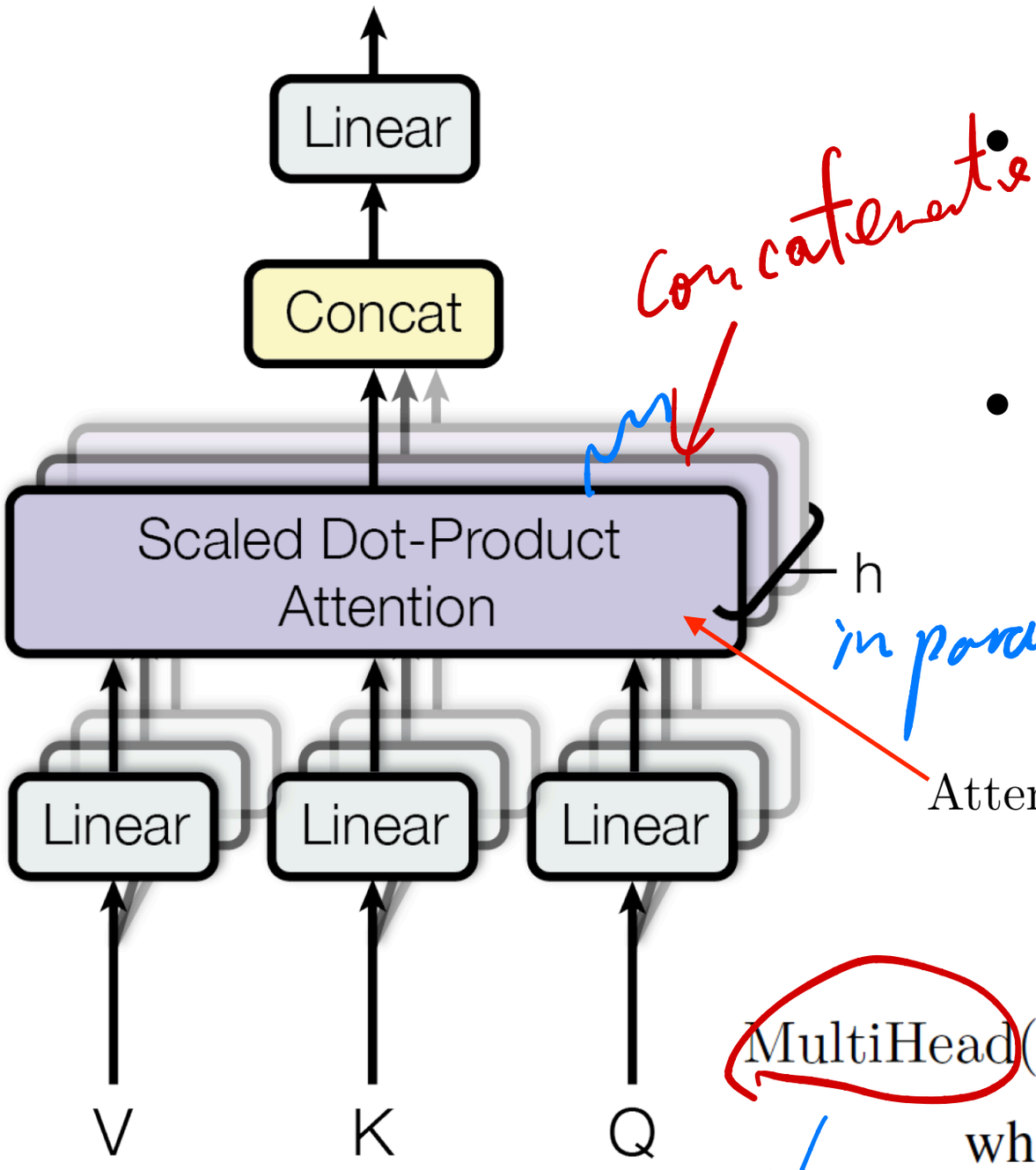
$$A(Q, K, V) = \text{softmax}(QK^\top)V$$

- Uses **scaled dot-product** to prevent values from growing too large

$$A(Q, K, V) = \text{softmax}(\frac{QK^\top}{\sqrt{d_k}})V$$

dimension of query and key vectors

prevent grow too large.

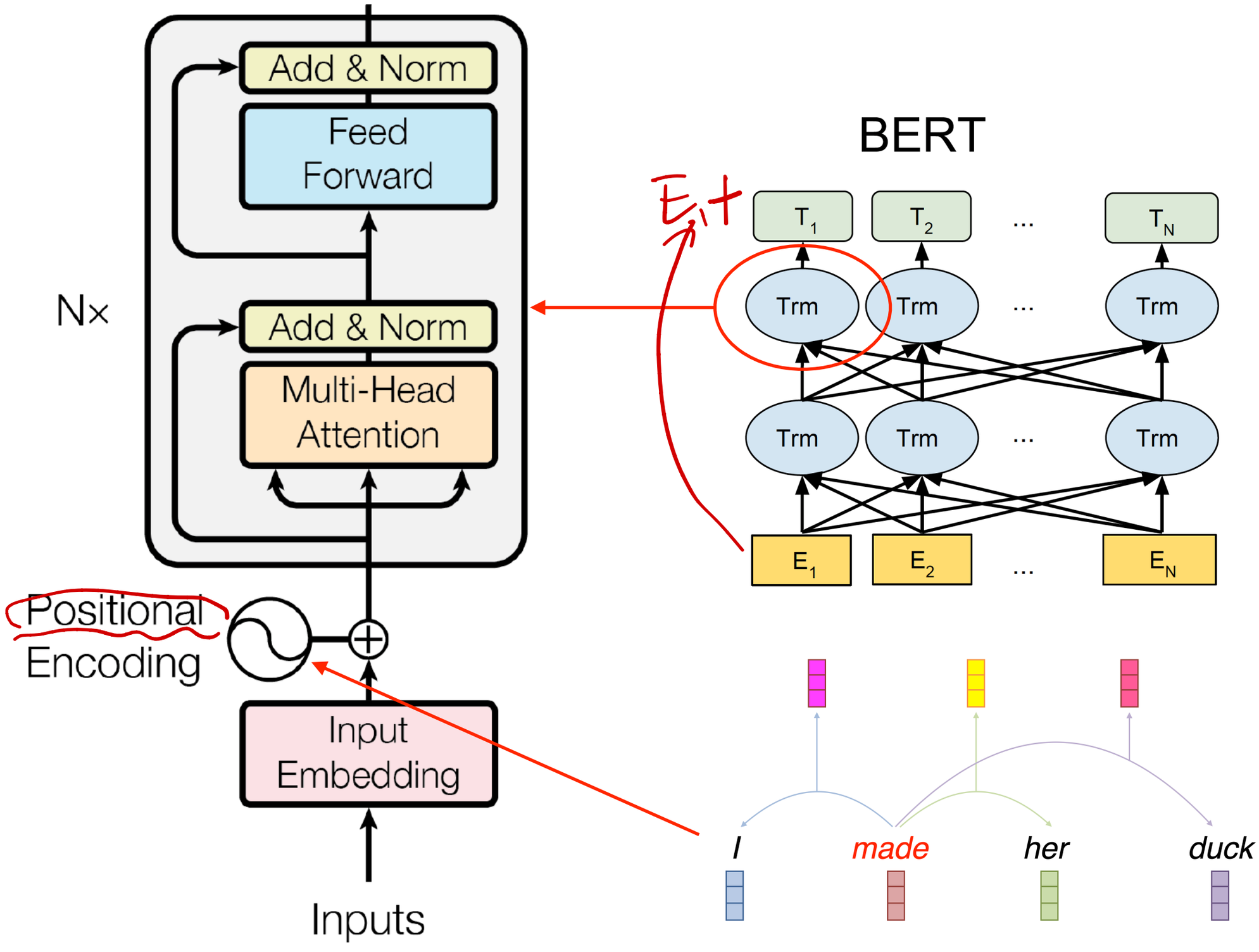


- Only one attention for each word pair
- Uses multi-head attention to allow multiple interactions

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Transformer Block



A Final Word

- Contextual representations are very useful
- Pre-trained on very very large corpus
  - Builds up some knowledge about language
  - Uses unsupervised objectives
- When we use them for downstream tasks, we are no longer starting from “scratch”

Further Reading

- ELMo: https://arxiv.org/abs/1802.05365v2
- BERT: https://arxiv.org/abs/1810.04805
- Transformer: http://nlp.seas.harvard.edu/2018/04/03/attention.html