Deep Learning in Applications

How NLP Cracked Transfer Learning

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Outline

1. Transformer: recap
2. OpenAI Transformer
3. ELMO
4. BERT
5. BERTology
6. GPT, GPT-2, GPT-3
7. Q & A

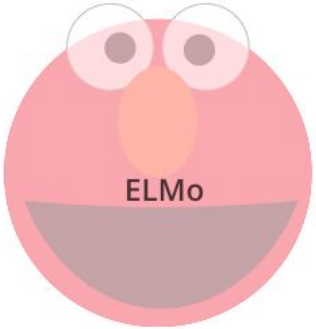
Based on: http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture13-contextual-representations.pdf
https://jalammar.github.io/illustrated-transformer/
http://jalammar.github.io/illustrated-bert/


THE
TRANSFORMER


ULM-FiT

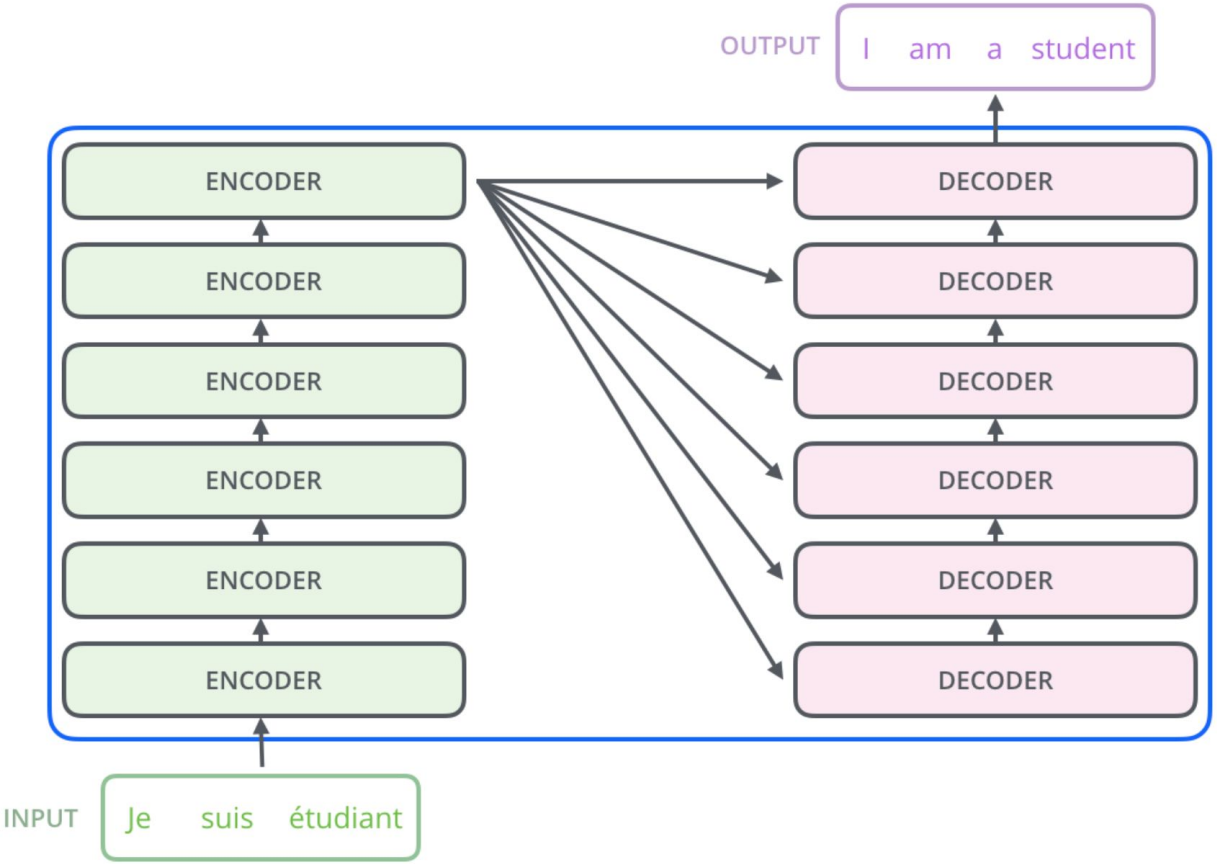

BERT


OpenAI
Transformer

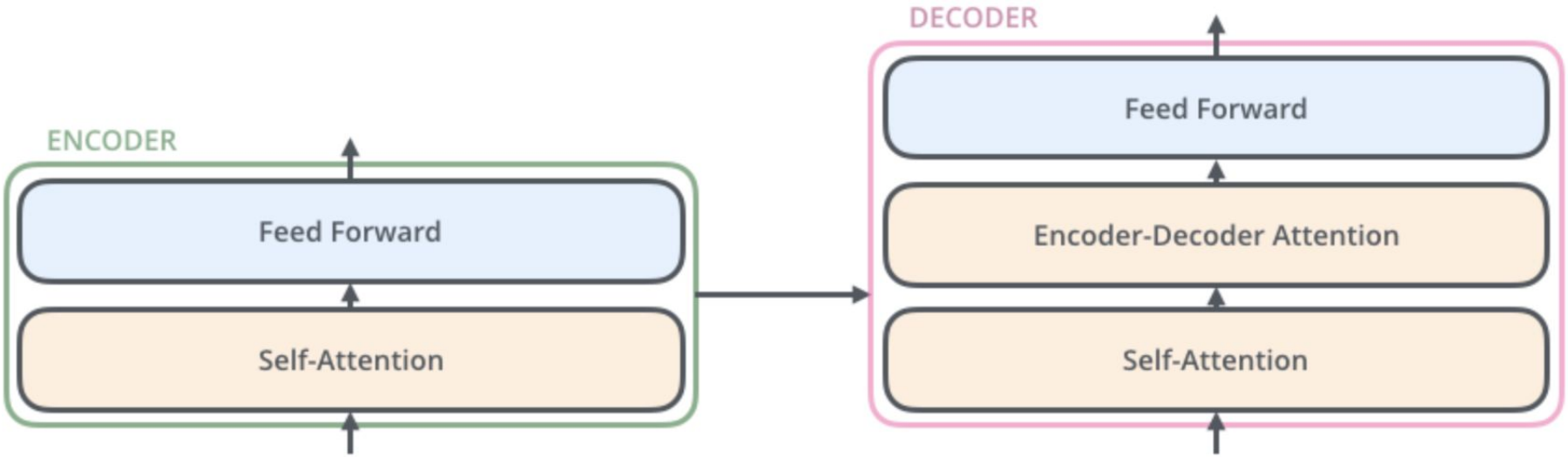

ELMo

The Transformer: recap

The Transformer

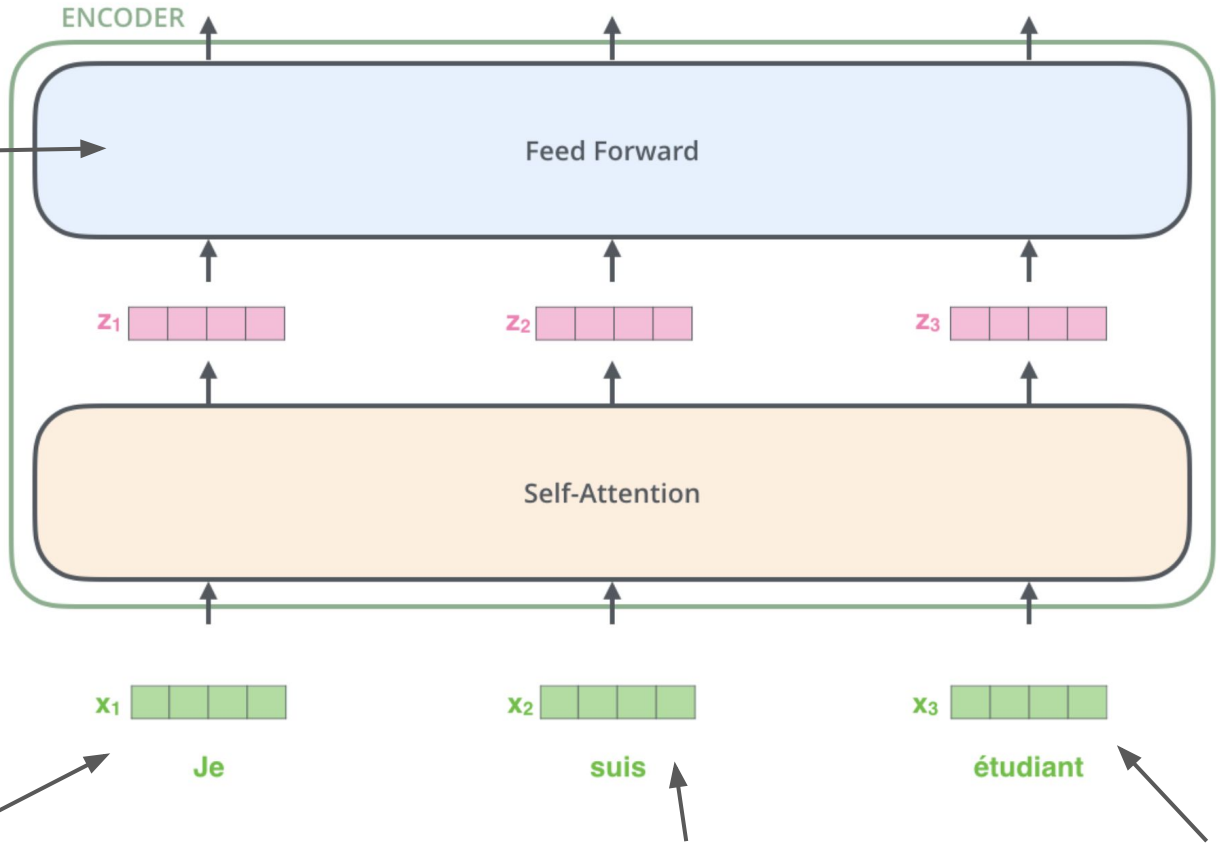


The Transformer



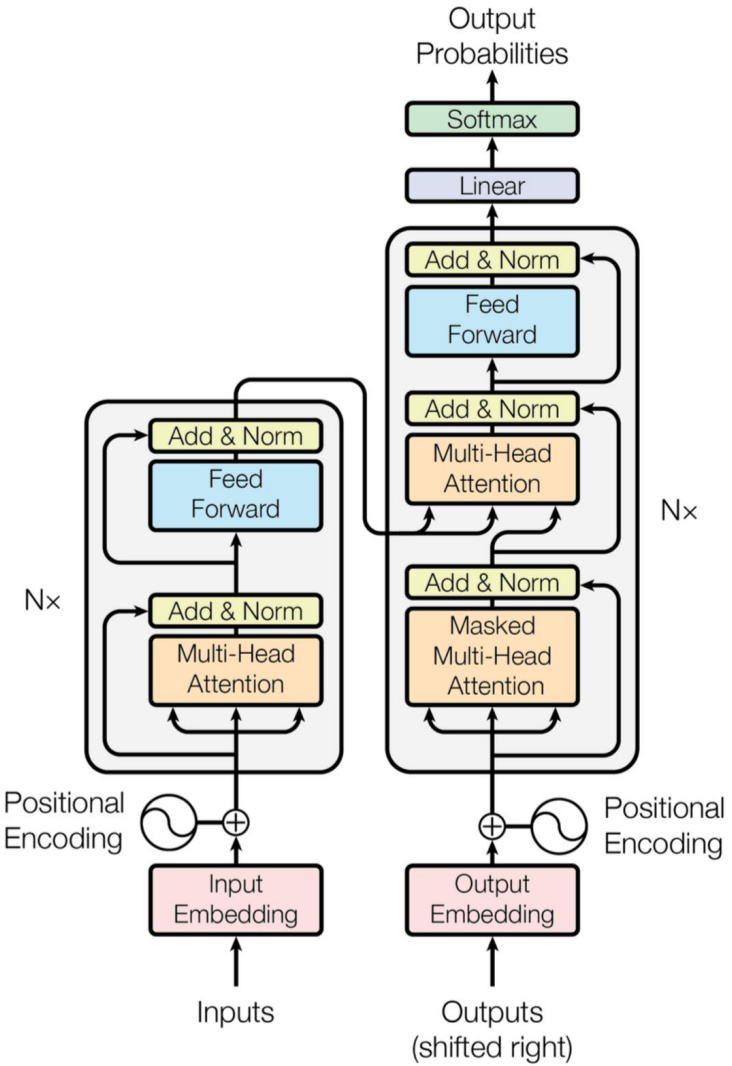
The Transformer

Can be parallelized



the word in each position flows through its own path in the encoder

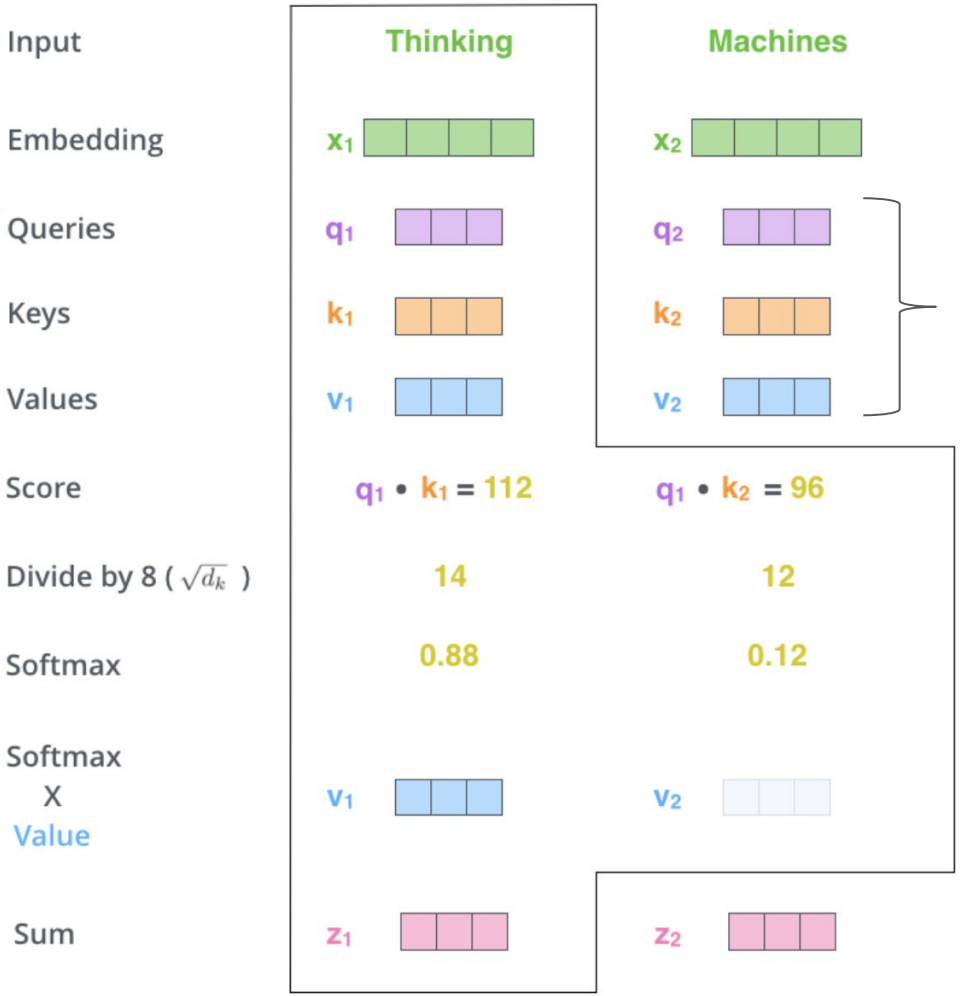
The Transformer: recap



- Proposed in the paper “Attention is All You Need” (Ashish Vaswani et al.)
- No recurrent or convolutional neural networks -> just attention
- Uses Multi-Head **self-attention** concept

Self-Attention: recap

Self-Attention in Detail



STEP 1: create Query, Key, Value

STEP 2: calculate scores

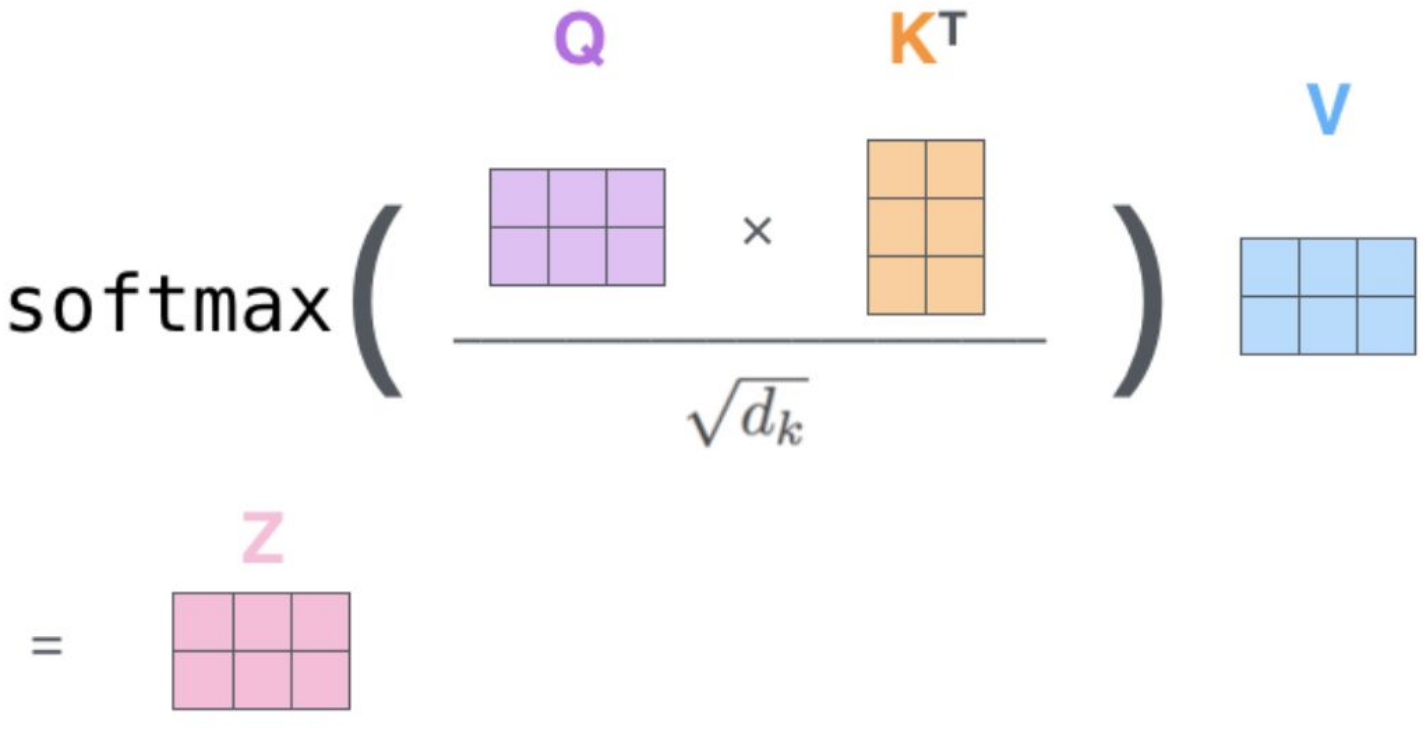
STEP 3: divide by $\sqrt{d_k}$

STEP 4: softmax

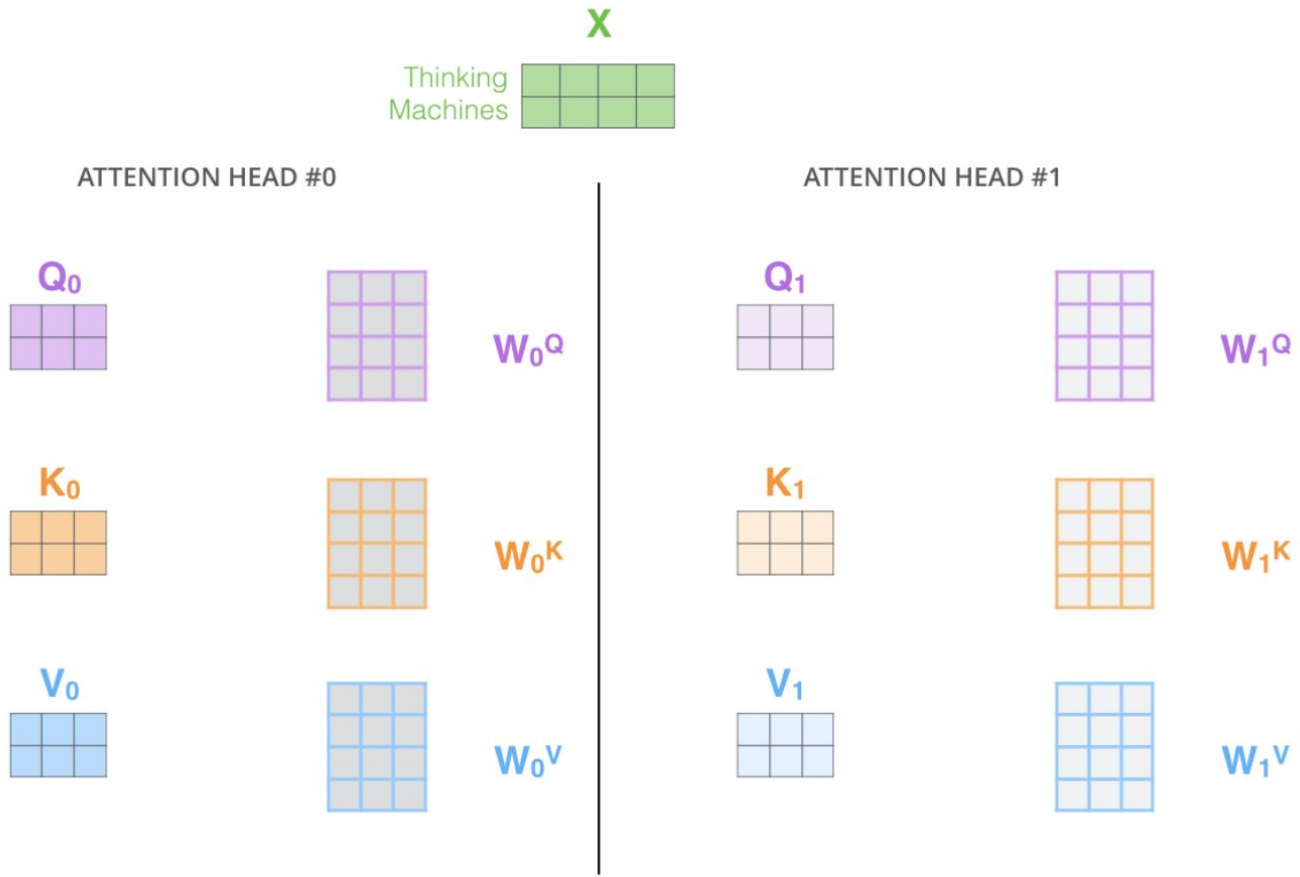
STEP 5: multiply each value vector by the softmax score

STEP 6: sum up the weighted value vectors

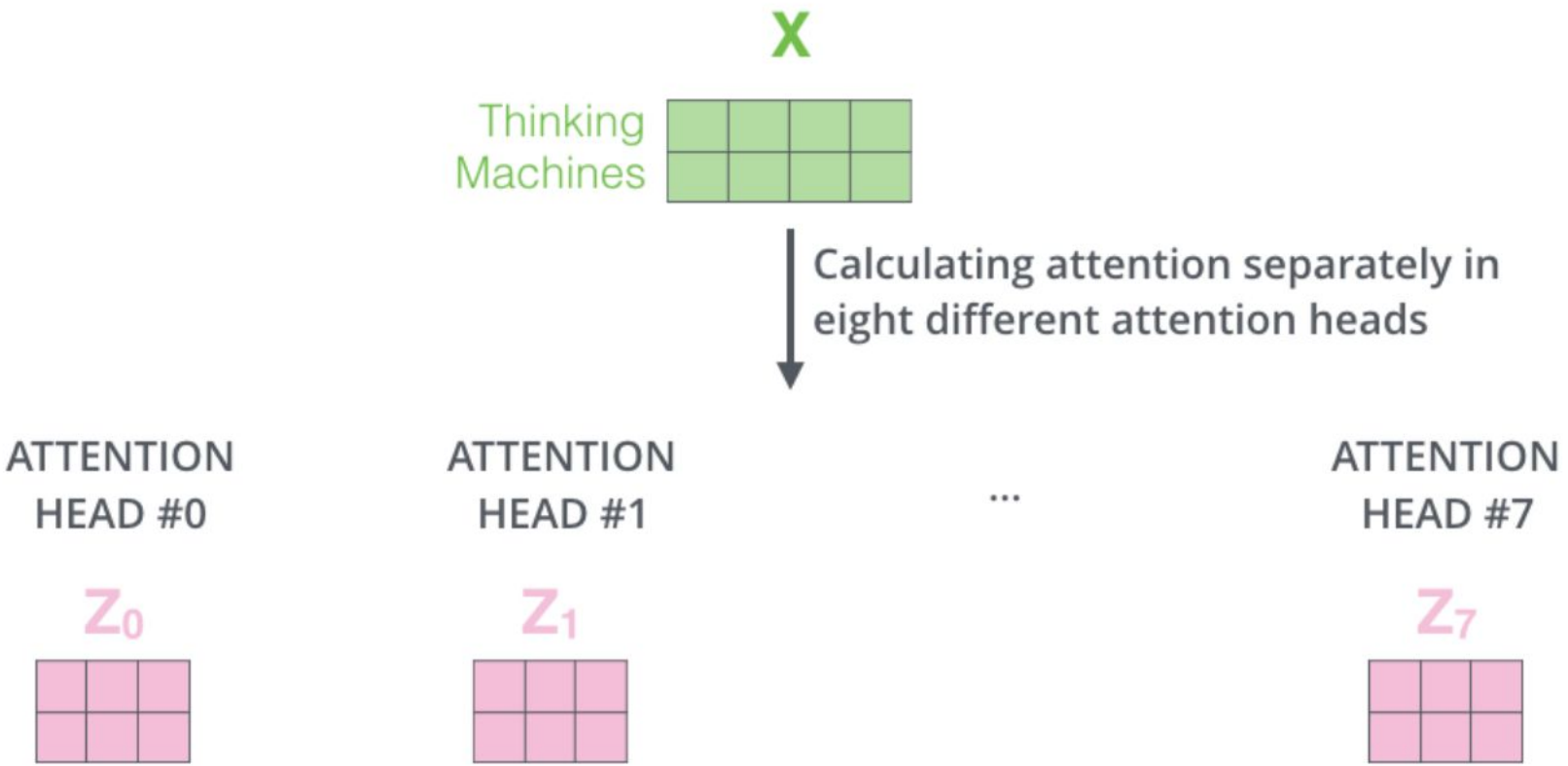
Self-Attention: Matrix Calculation



Multi-Head Attention



Multi-Head Attention

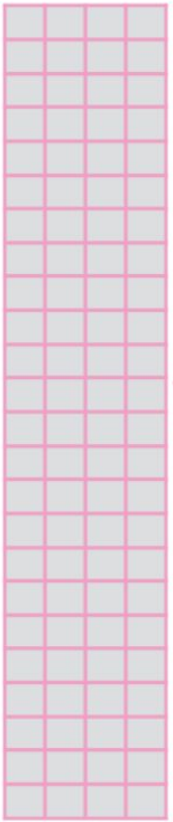


Multi-Head Attention

1) Concatenate all the attention heads

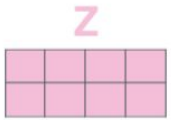
2) Multiply with a weight matrix W^O that was trained jointly with the model

X



3) The result would be the Z matrix that captures information from all the attention heads. We can send this forward to the FFNN

=



1) This is our input sentence*

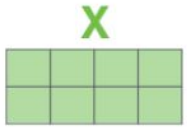
2) We embed each word*

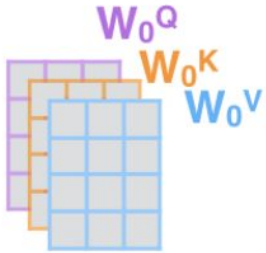
3) Split into 8 heads. We multiply X or R with weight matrices

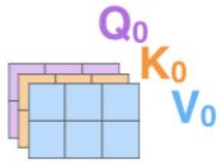
4) Calculate attention using the resulting Q/K/V matrices

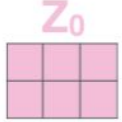
5) Concatenate the resulting Z matrices, then multiply with weight matrix W^O to produce the output of the layer

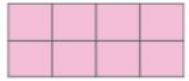
Thinking Machines



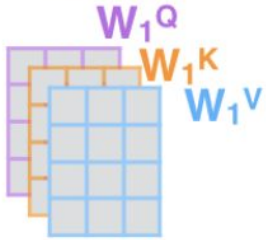


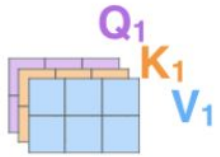


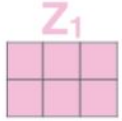


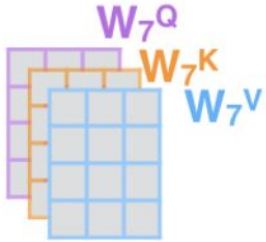


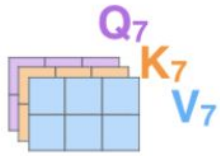
* In all encoders other than #0, we don't need embedding. We start directly with the output of the encoder right below this one

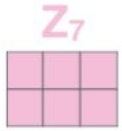










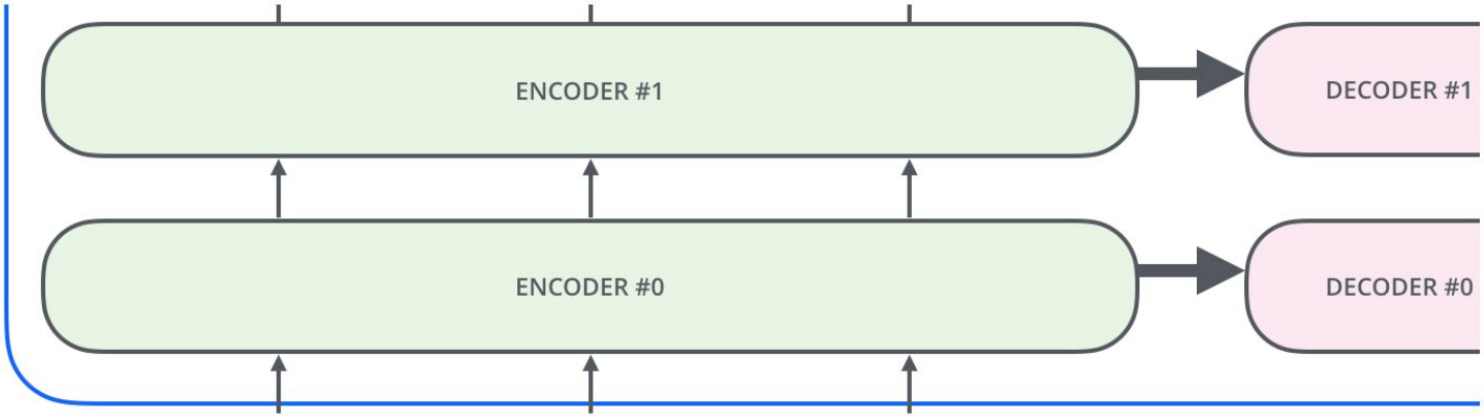


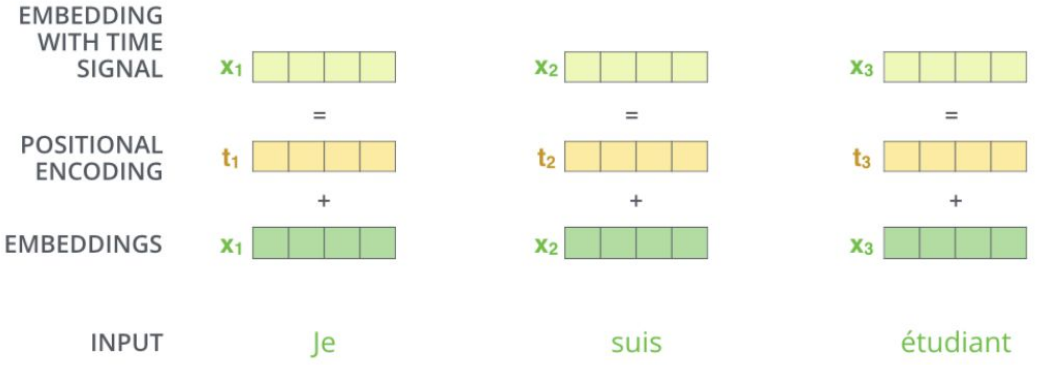
Positional Encoding

Positional encoding requirements

- Positional encoding should be unique for every position in the sequence
- Distance between two same positions should be preserved with sequences of different length
- The positional encoding should be deterministic
- *It would be great if it would work with long sequences (longer than any sequence in the training set)*

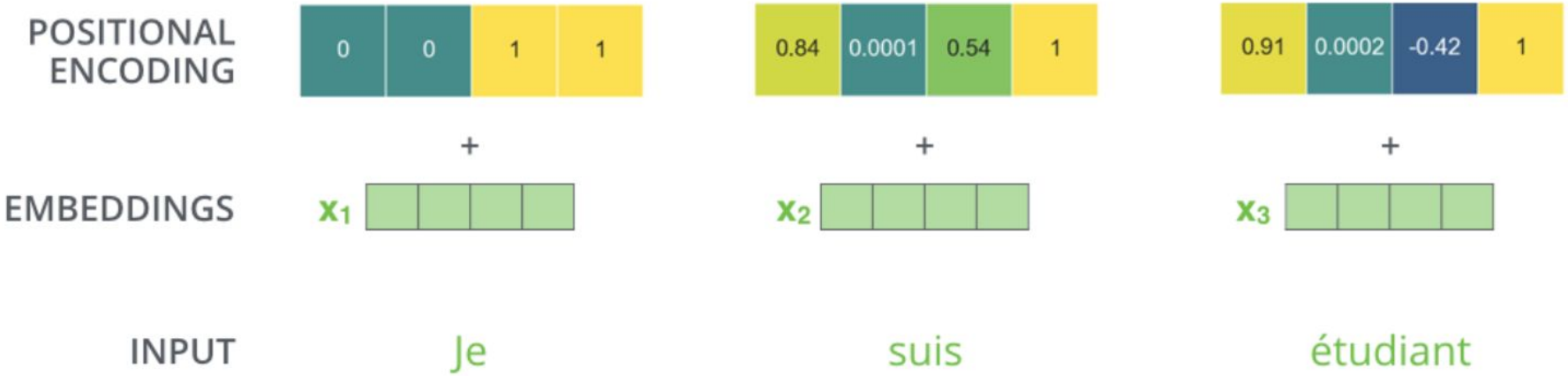
Positional Encoding





It provides meaningful distances between the embedding vectors once they're projected into Q/K/V vectors and during dot-product attention

Positional Encoding



Positional Encoding: why sin and cos?

$$\vec{p_t}^{(i)} = f(t)^{(i)} = \begin{cases} \sin(\omega_k t), & \text{if } i = 2k \\ \cos(\omega_k t), & \text{if } i = 2k+1 \end{cases}$$

$$\omega_k = \frac{1}{10000^{2k/d}}$$

$$\vec{p_t} = \begin{bmatrix} \sin(\omega_1 . t) \\ \cos(\omega_1 . t) \\ \\ \sin(\omega_2 . t) \\ \cos(\omega_2 . t) \\ \\ \vdots \\ \\ \sin(\omega_{d/2} . t) \\ \cos(\omega_{d/2} . t) \end{bmatrix}_{d \times 1}$$

t stays for position in the original sequence
k is the index of the element in the positional vector

Image source: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Positional Encoding

0 :	0	0	0	0	8 :	1	0	0	0
1 :	0	0	0	1	9 :	1	0	0	1
2 :	0	0	1	0	10 :	1	0	1	0
3 :	0	0	1	1	11 :	1	0	1	1
4 :	0	1	0	0	12 :	1	1	0	0
5 :	0	1	0	1	13 :	1	1	0	1
6 :	0	1	1	0	14 :	1	1	1	0
7 :	0	1	1	1	15 :	1	1	1	1

Image source: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Positional Encoding

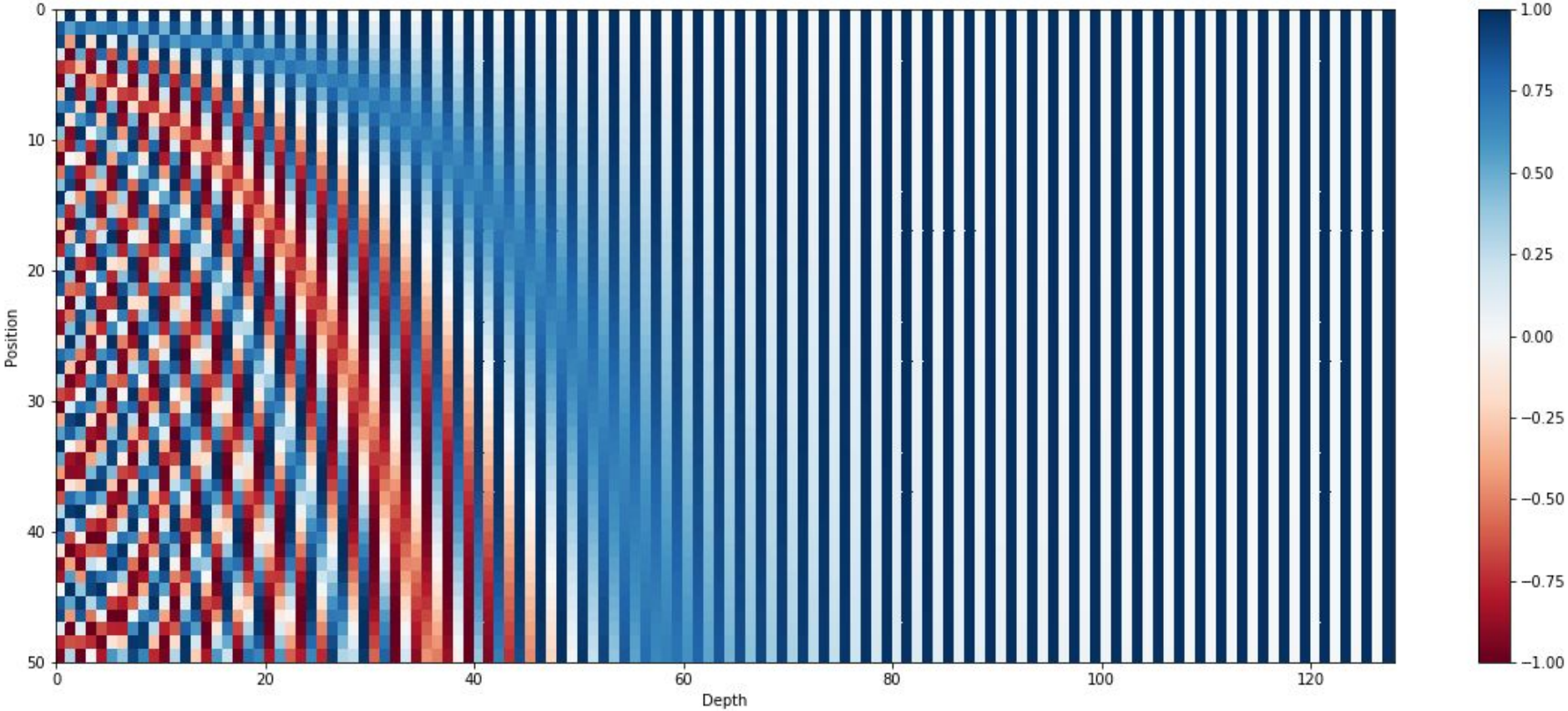


Image source: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Positional Encoding: why sin and cos?

We chose this function because we hypothesized it would allow the model to easily learn to attend by relative positions, since for any fixed offset k, PEpos+k can be represented as a linear function of PEpos.

$$M \begin{bmatrix} \sin(\omega_k t) \\ \cos(\omega_k t) \end{bmatrix} = \begin{bmatrix} \sin(\omega_k (t + \phi)) \\ \cos(\omega_k (t + \phi)) \end{bmatrix}$$

Image source: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Positional Encoding: why sin and cos?

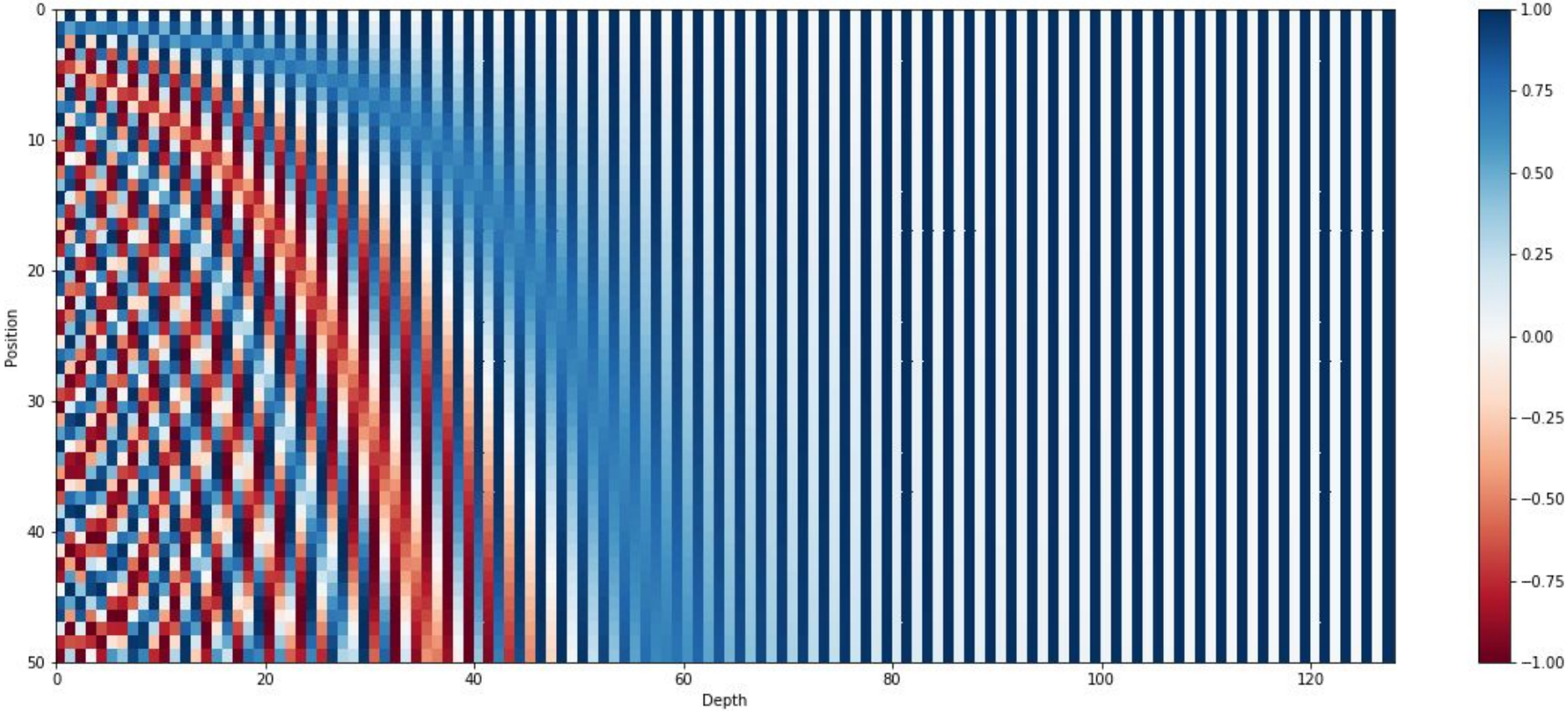
$$\begin{bmatrix} u_1 & v_1 \\ u_2 & v_2 \end{bmatrix} \begin{bmatrix} \sin(\omega_k t) \\ \cos(\omega_k t) \end{bmatrix} = \begin{bmatrix} \sin(\omega_k (t+\phi)) \\ \cos(\omega_k (t+\phi)) \end{bmatrix}$$

$$\begin{bmatrix} u_1 & v_1 \\ u_2 & v_2 \end{bmatrix} \begin{bmatrix} \sin(\omega_k t) \\ \cos(\omega_k t) \end{bmatrix} = \begin{bmatrix} \sin(\omega_k t)\cos(\omega_k \phi) + \cos(\omega_k t)\sin(\omega_k \phi) \\ \cos(\omega_k t)\cos(\omega_k \phi) - \sin(\omega_k t)\sin(\omega_k \phi) \end{bmatrix}$$

$$M_{\phi,k} = \begin{bmatrix} \cos(\omega_k \phi) & \sin(\omega_k \phi) \\ -\sin(\omega_k \phi) & \cos(\omega_k \phi) \end{bmatrix}$$

Image source: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Positional Encoding



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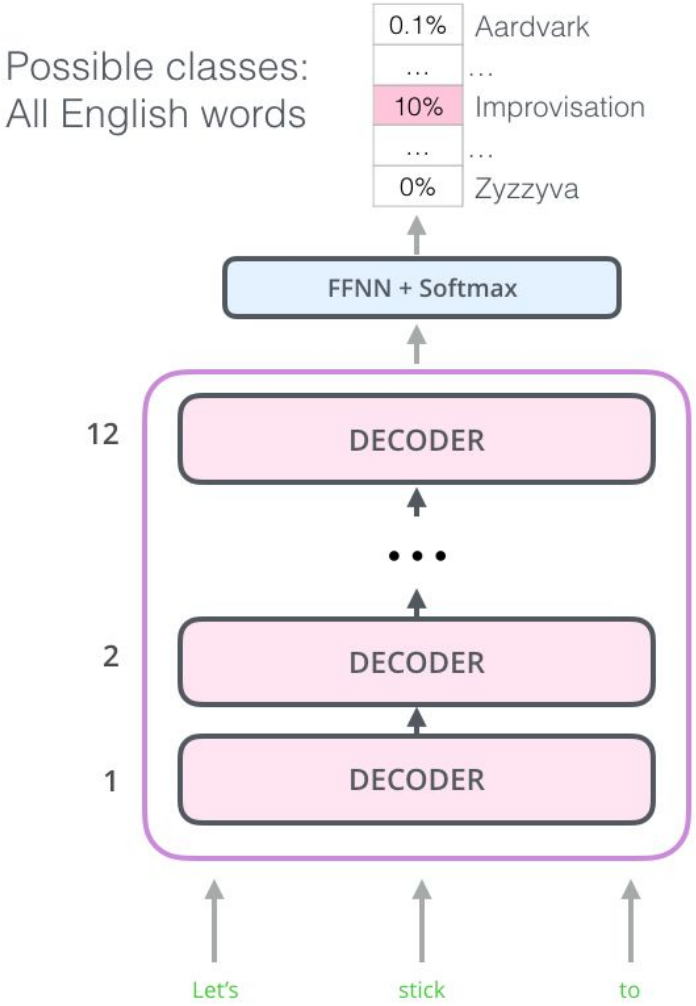
OpenAI Transformer: Pre-training Decoder for Language Modeling

OpenAI Transformer

- The Encoder-Decoder structure of the transformer made it perfect for machine translation
- But what about sentence classification?
- **Main goal: pre-train a language model that can be fine-tuned for other tasks**

OpenAI Transformer

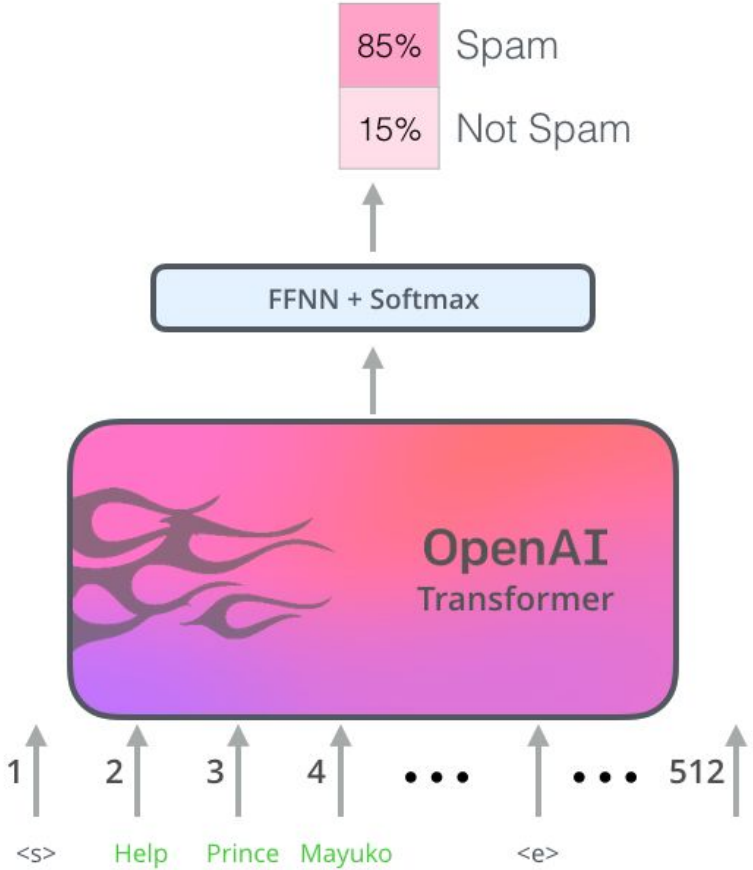


Differences from vanilla Transformer:

- no encoder
- decoder layers would not have the encoder-decoder attention sublayer
- Pre-train the model on predicting the next word using massive (unlabeled) datasets

Pre-training phase

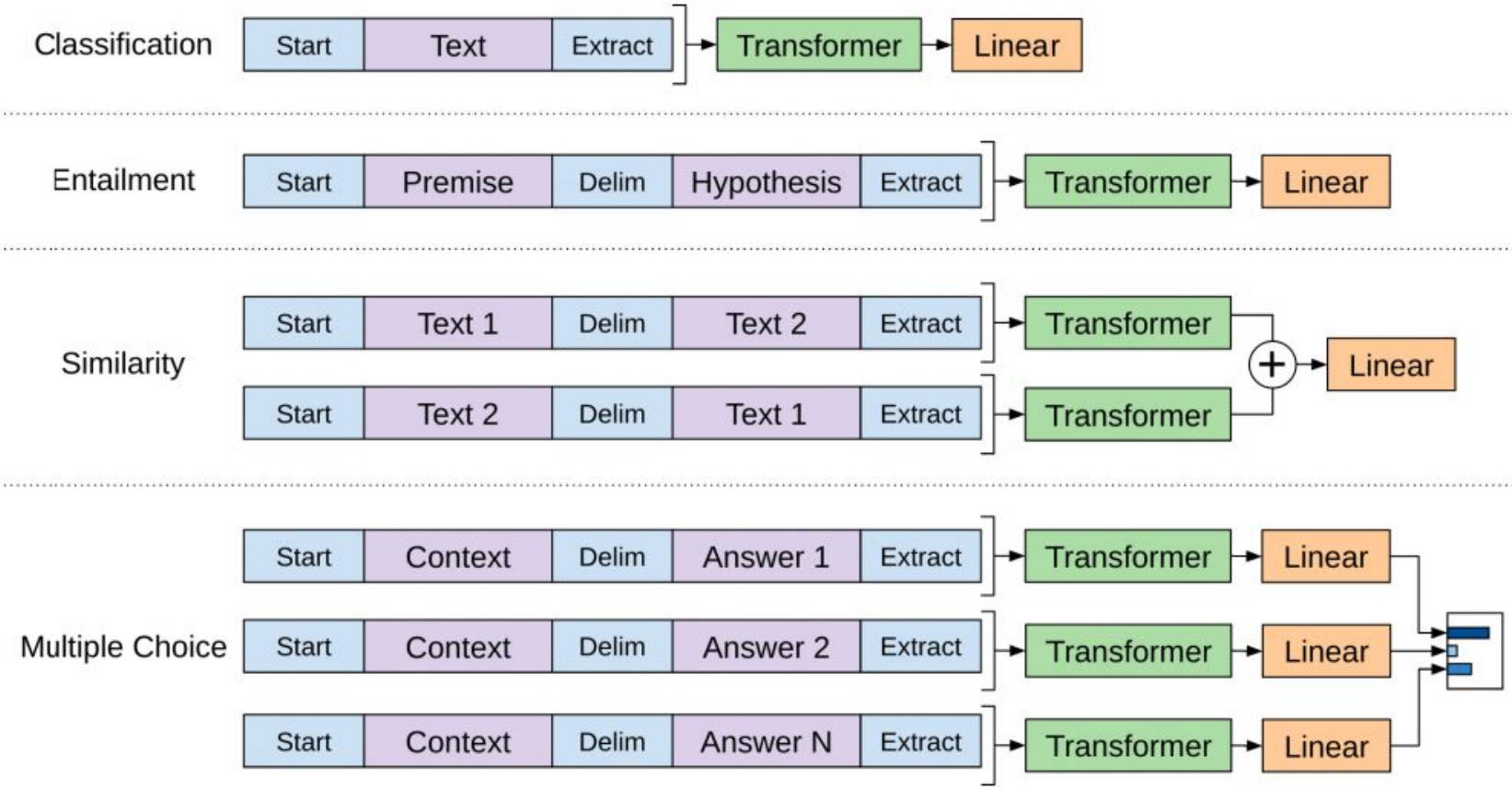
OpenAI Transformer



Fine-tuning phase

- During pre-training phase layers have been tuned to reasonably handle language
- Now let’s use it for downstream tasks (e.g. sentence classification)

Input transformations for different tasks

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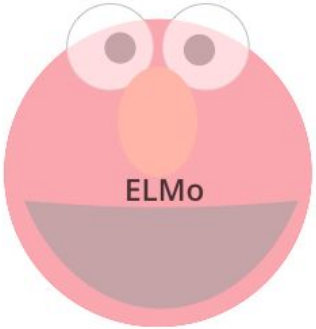
ELMo

ELMo: context that matters

ELMo: contextualized word embeddings

"Why not give it an embedding based on the context it's used in – to both capture the word meaning in that context as well as other contextual information?"

Peters et. al., 2017, McCann et. al., 2017,
and yet again Peters et. al., 2018 in the ELMo paper

ELMo - deep contextualized word representations

ELMo

What does it stand for?

1. **E**xpedited **L**abour **M**arket **O**pinion
2. **E**lectric **L**ight **M**achine **O**rganization
3. **E**nough **L**et's **M**ove **O**n

ELMo

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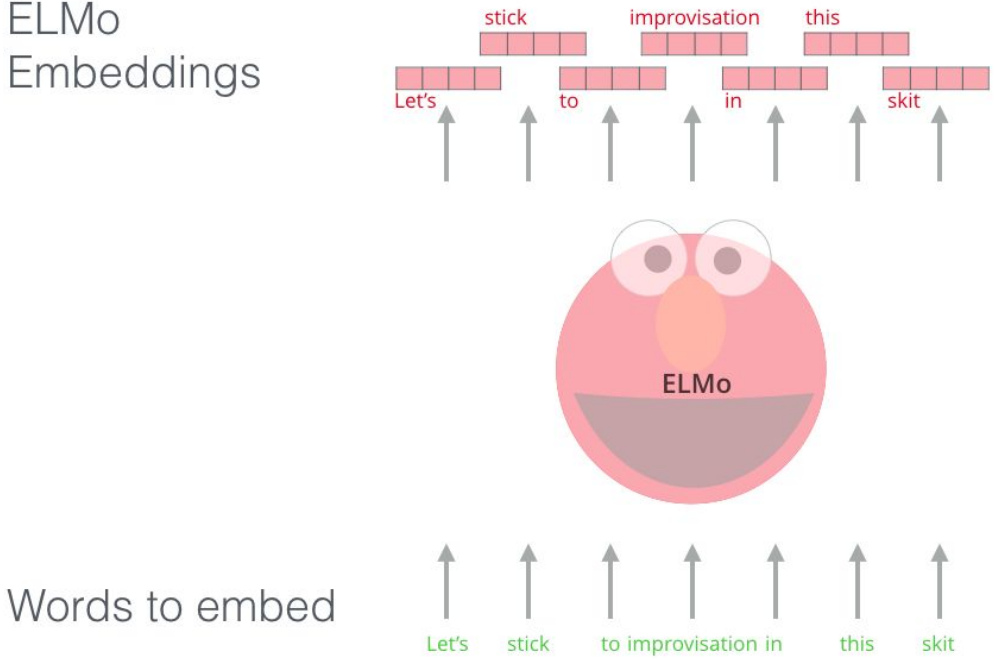
4. **Embeddings from Language Models**

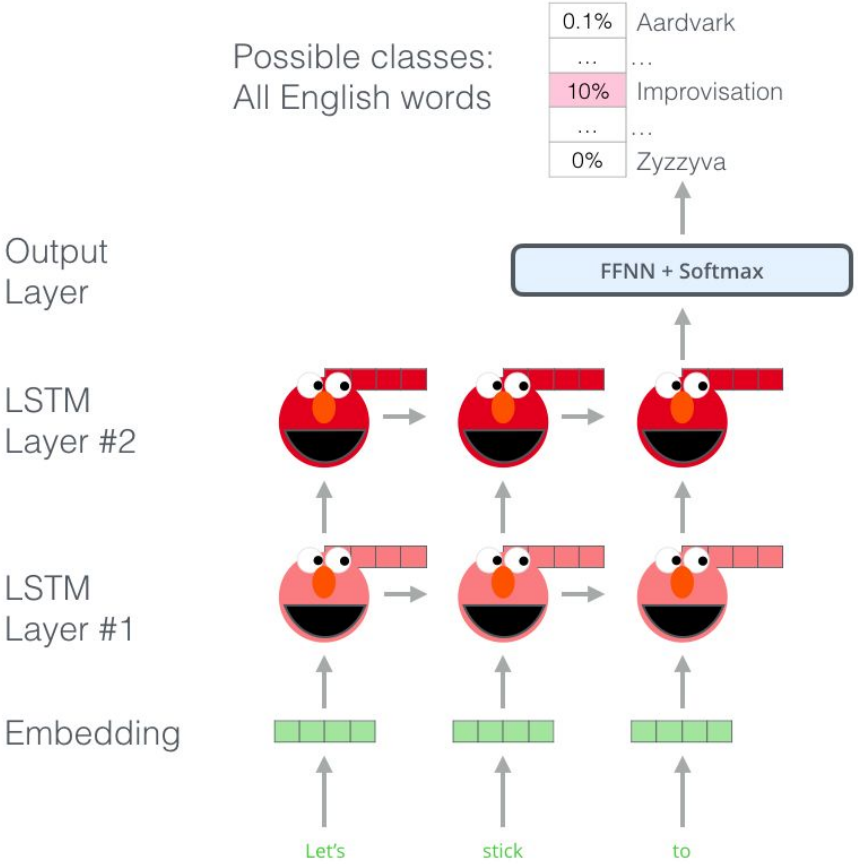
ELMo: contextualized word embeddings

ELMo: Contextualized word embeddings



- uses a bi-directional LSTM trained on Language Modeling task
- a model can learn without labels

Bidirectional Language Models (biLMs)



biLMs consist of forward and backward LMs:

- forward:

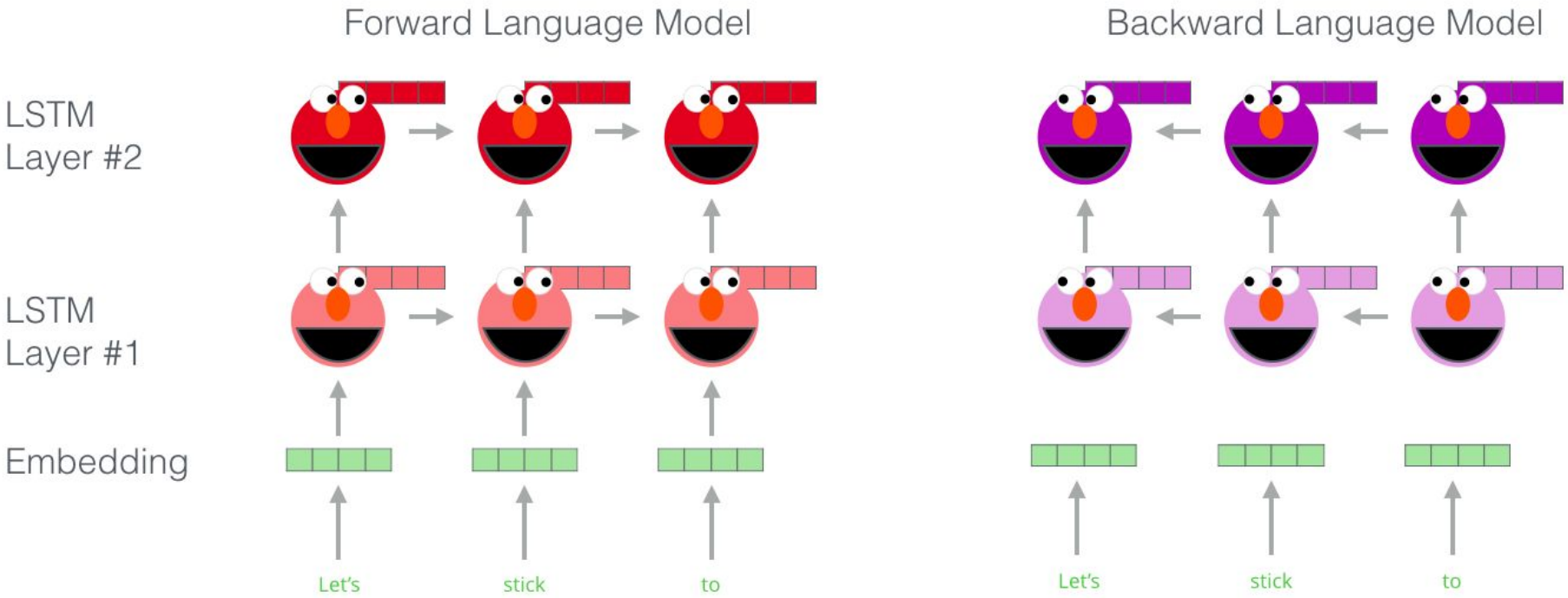
$$p(t_1,t_2,\ldots,t_N)=\prod_{k=1}^{N} p(t_k|t_1,t_2,\ldots,t_{k-1})$$

- Backward:

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

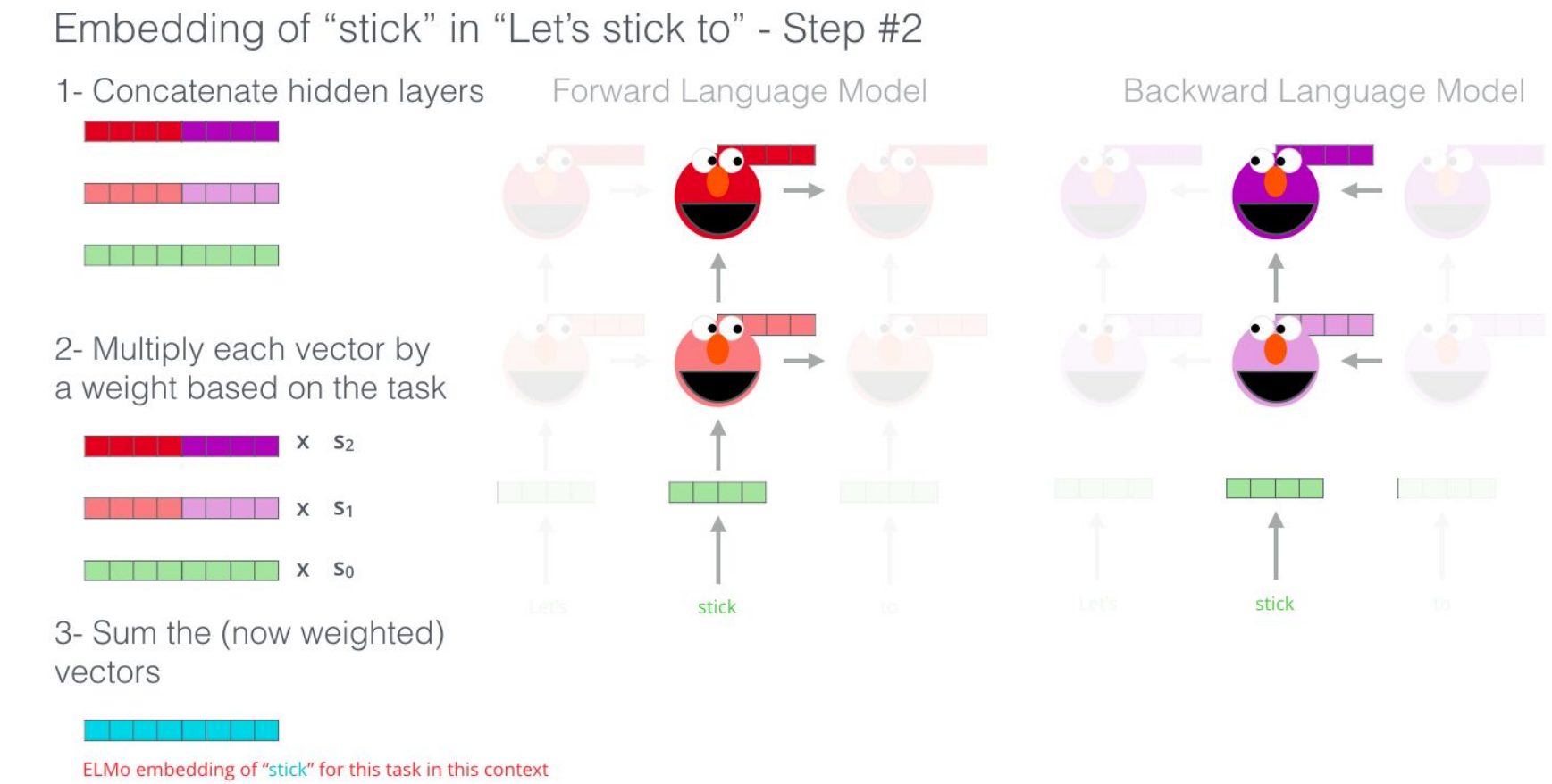
LSTM predicts next word in both directions to build biLMs

ELMo: main pipeline



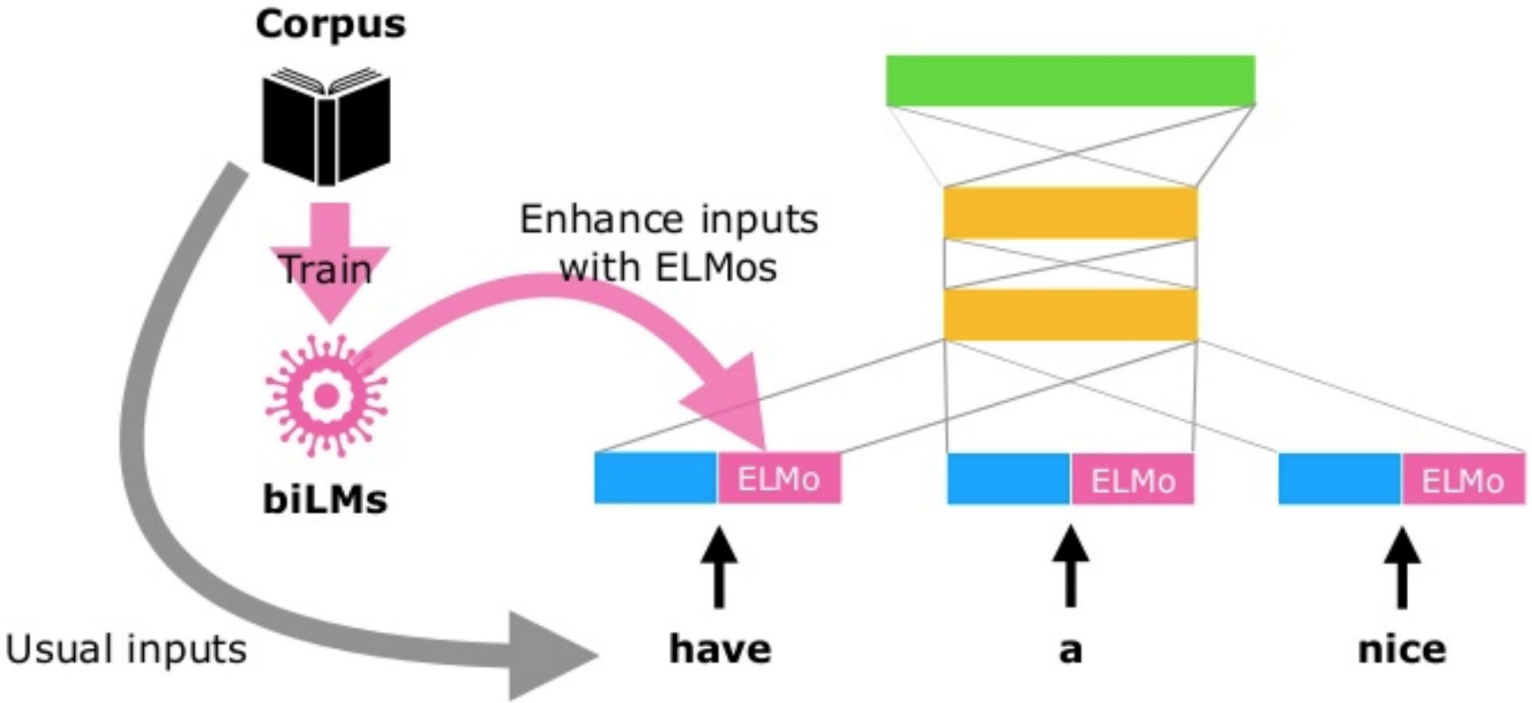
ELMo: main pipeline

ELMo represents a word as a linear combination of corresponding hidden layers:



ELMo

ELMo can be integrated to almost all neural NLP tasks with simple concatenation to the embedding layer



ELMo: overview

- Pretrained ELMo models: http://allennlp.org/elmo
- AllenNLP is a library on the top of PyTorch

- Higher levels seems to catch semantics while lower layer probably capture syntactic features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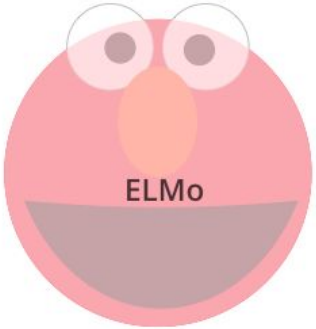
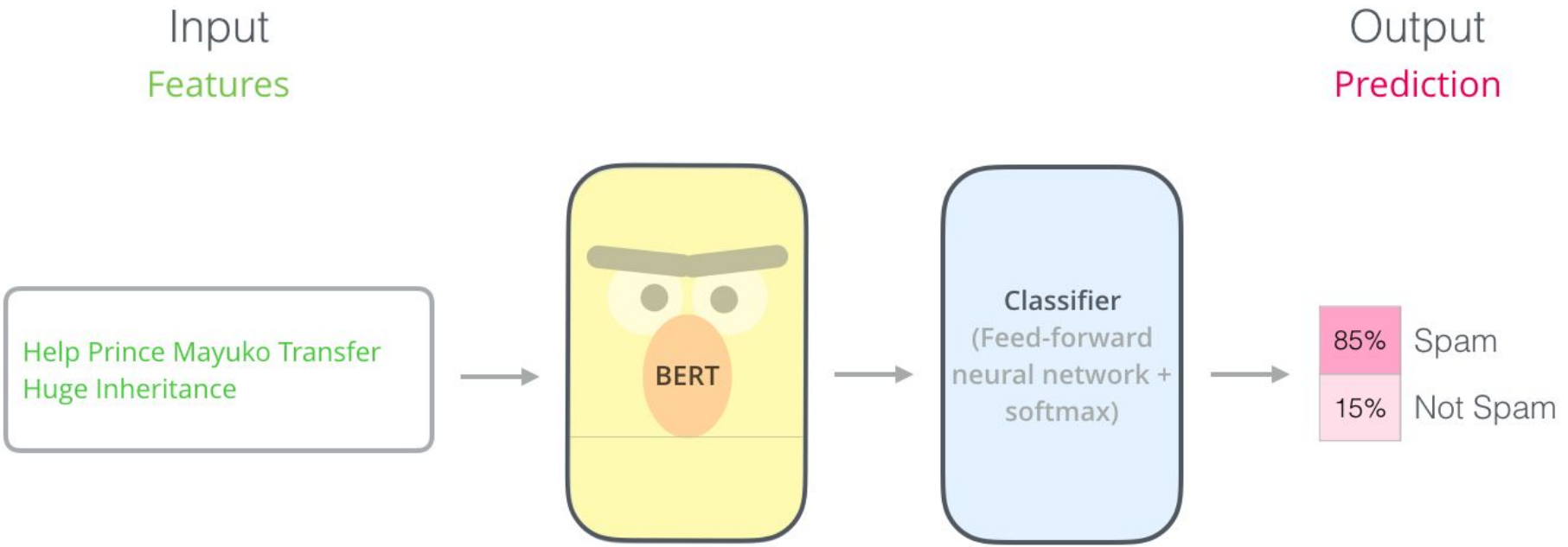

ELMo

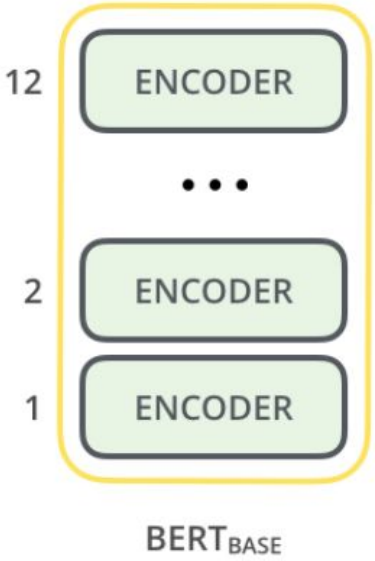
BERT

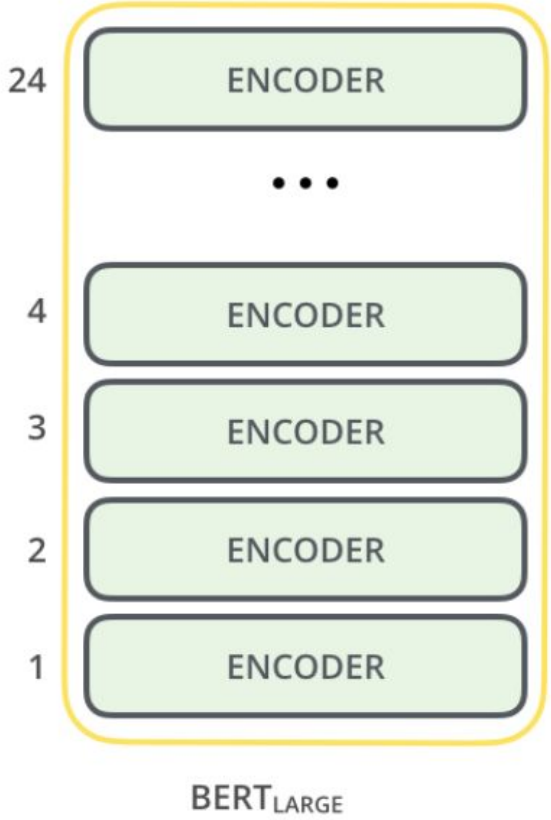
Bidirectional Encoder Representations from Transformers

BERT


Input
Features
Output
Prediction
Help Prince Mayuko Transfer
Huge Inheritance
BERT
Classifier
(Feed-forward
neural network +
softmax)
85%
Spam
15%
Not Spam

BERT: base and large

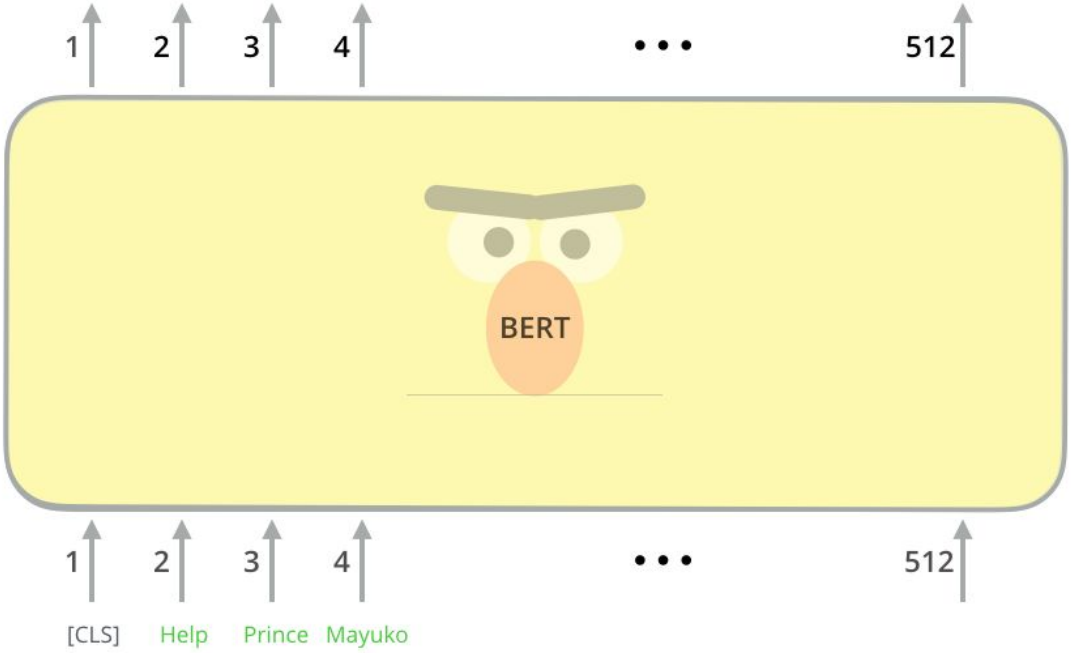




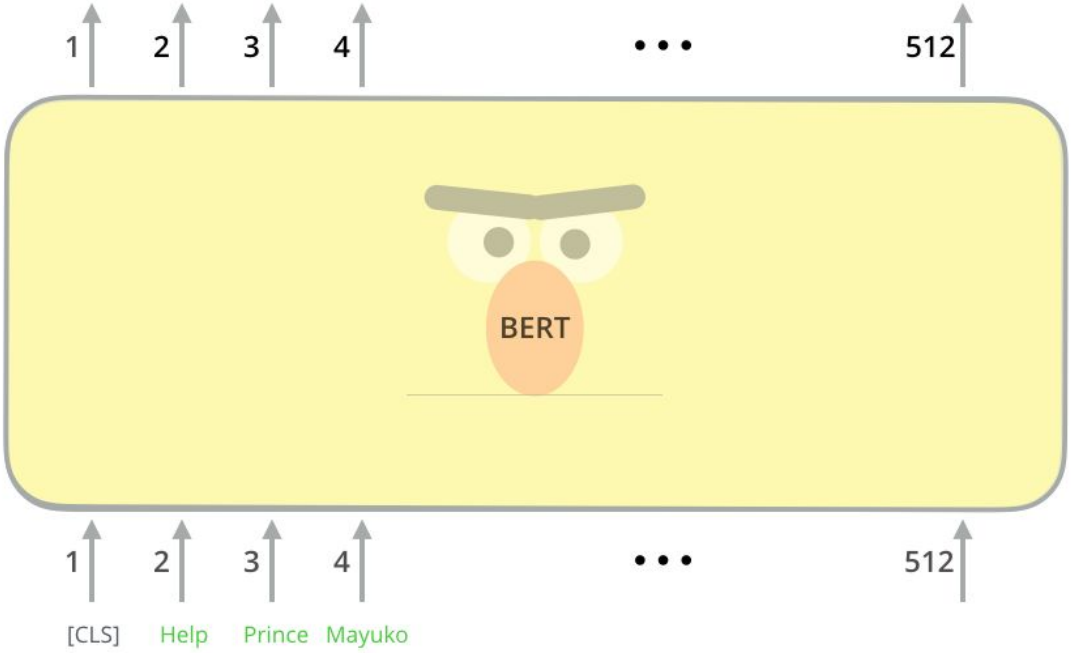
BERT vs. Transformer

			
		Base BERT	**Large BERT**
Encoders	6	12	24
Units in FFN	512	768	1024
Attention Heads	8	12	16

Model inputs

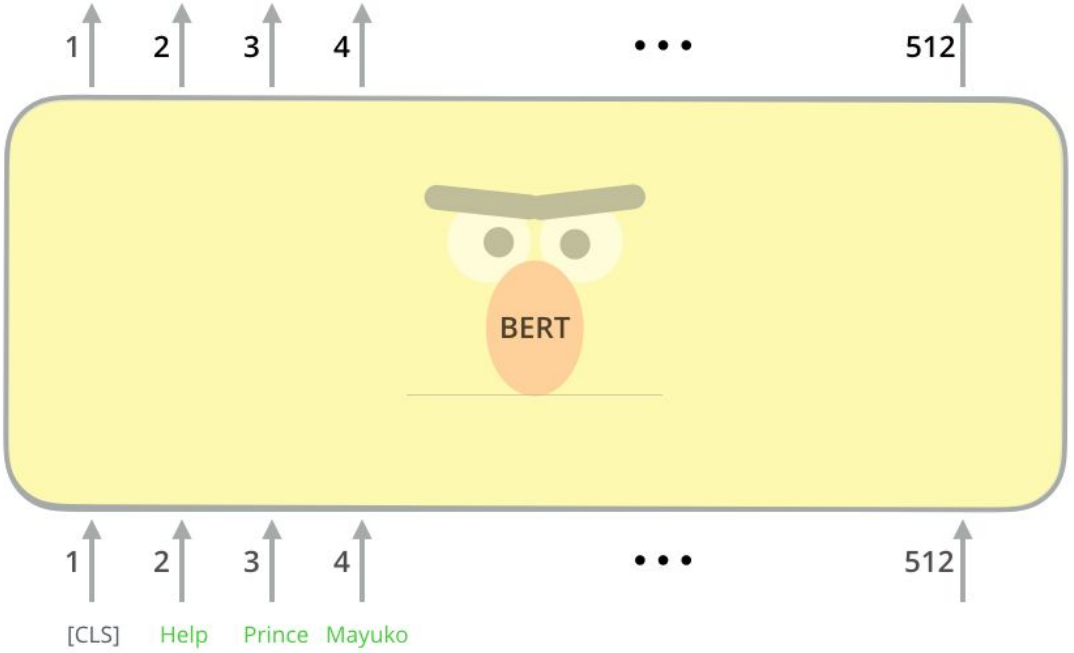


Model inputs



Identical to the Transformer up until this point

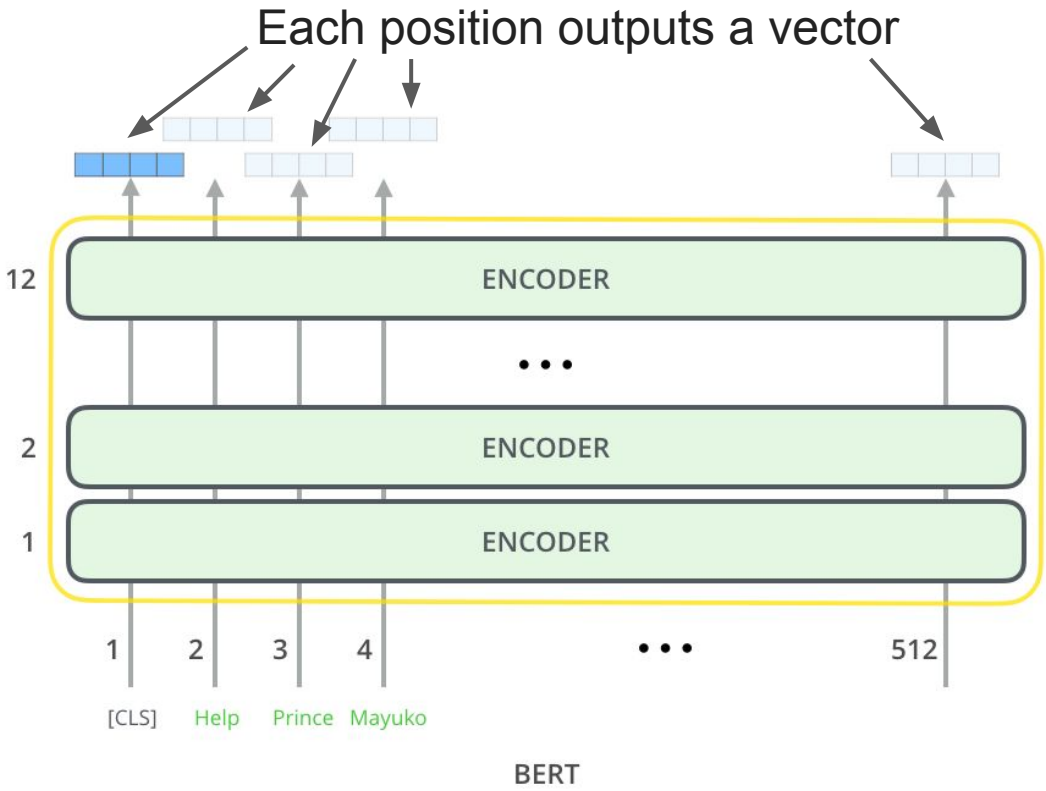
Model inputs



Identical to the Transformer up until this point

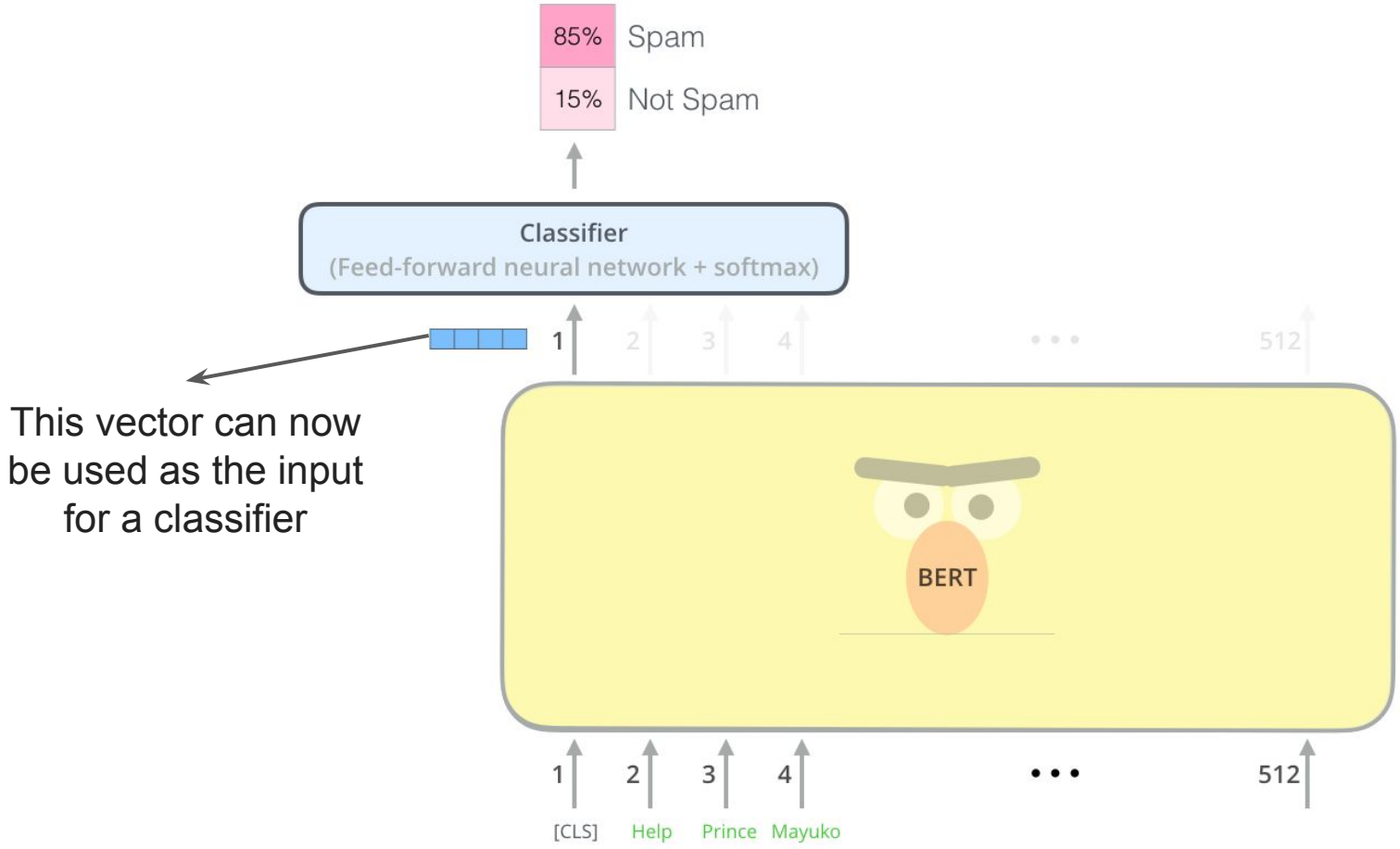
Why is BERT so special?

Model outputs



For sentence classification we focus on the first position (that we passed [CLS] token to)

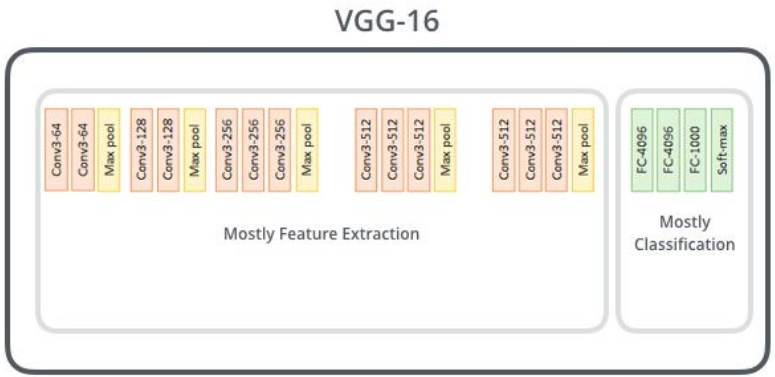
Model inputs



Similar to CNN concept!

Input

Features

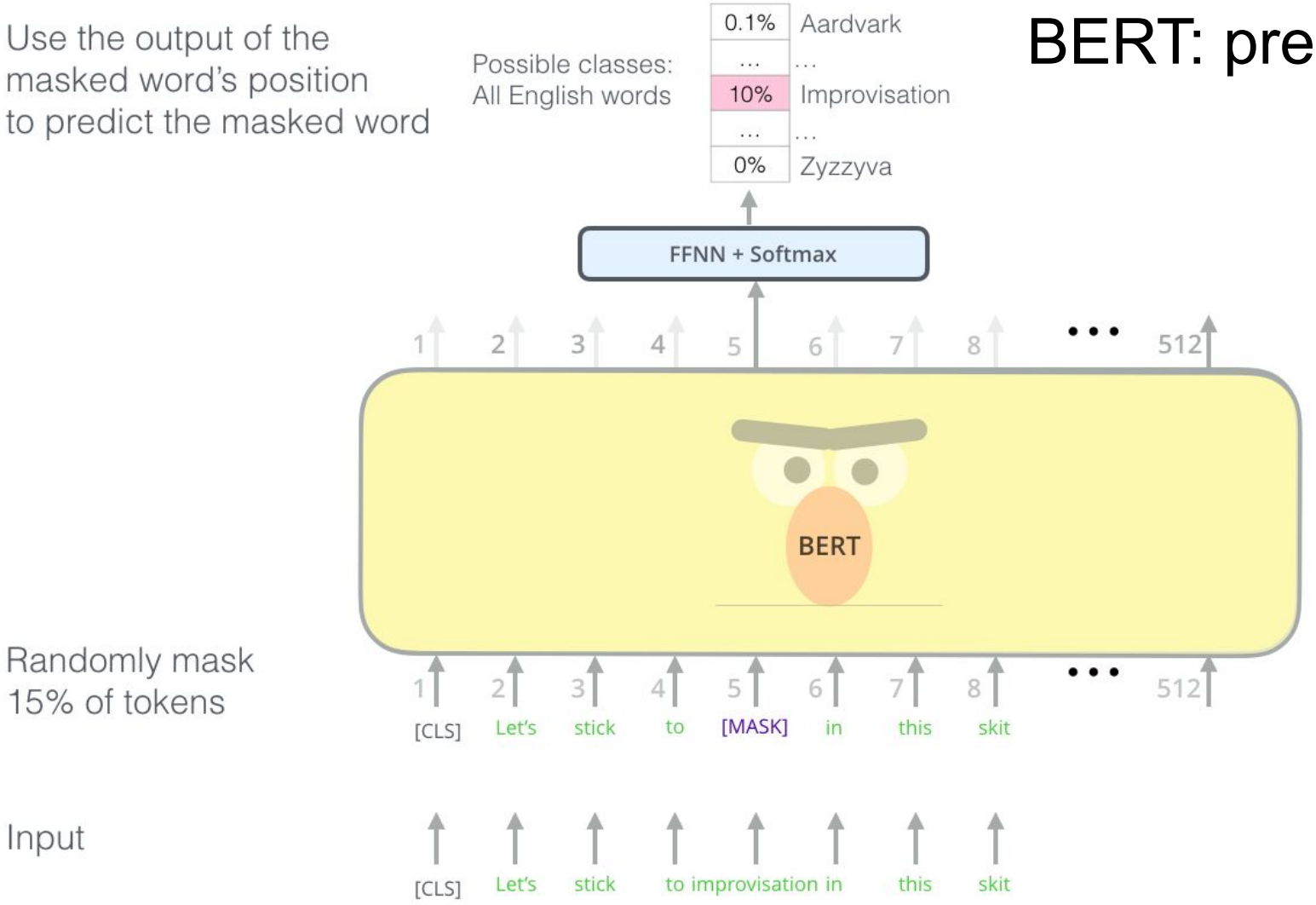


Output

Prediction

0.2%	Kit fox
0.1%	English setter
95%	Egyptian cat
1%	Great Dane
	…
0%	Hotdog

BERT: pre-training



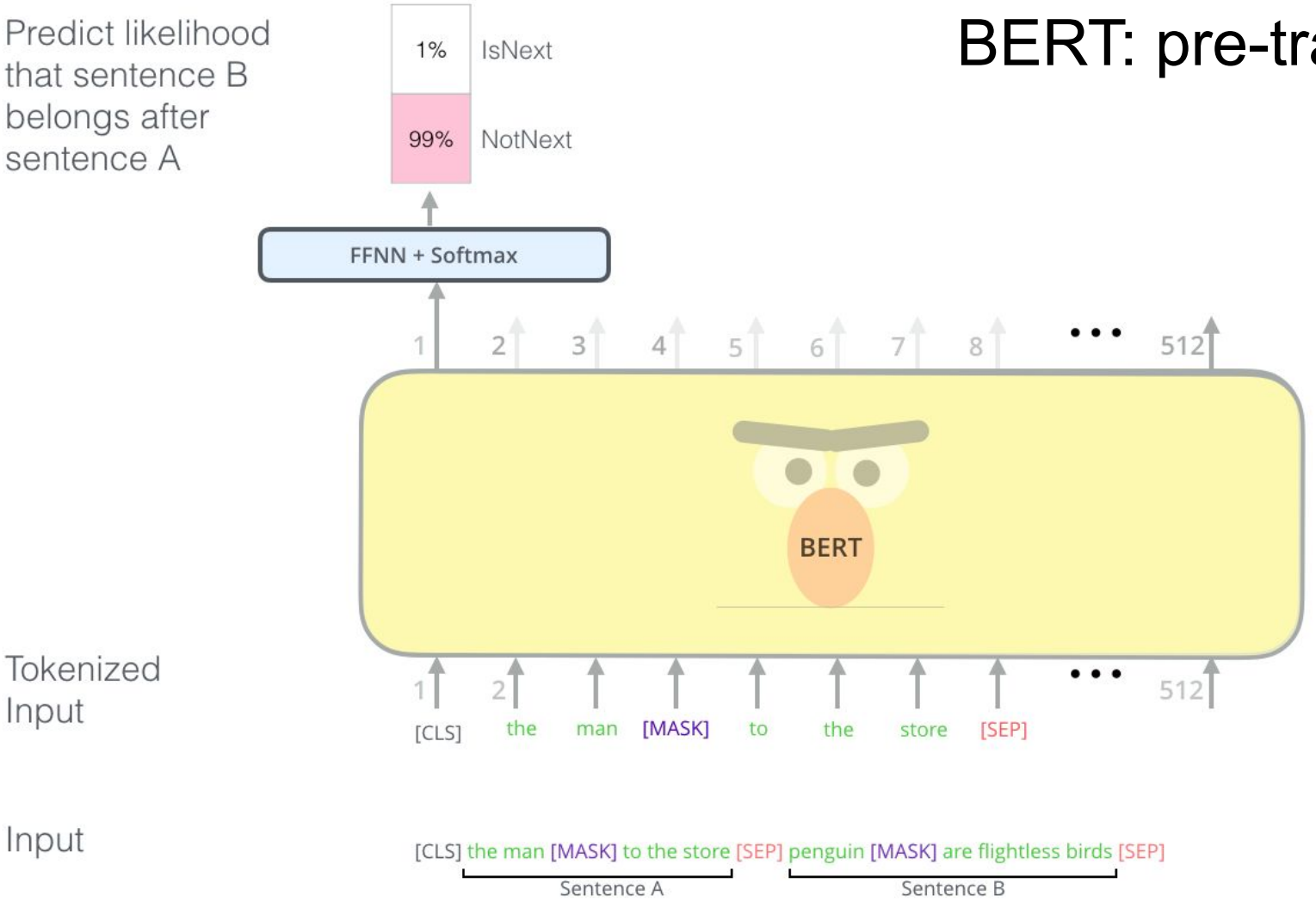
BERT: pre-training

- “Masked Language Model” approach

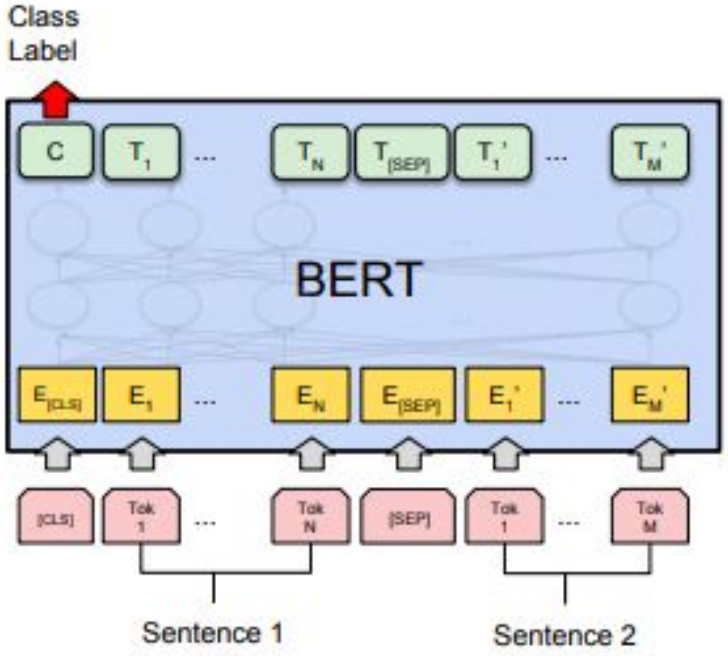
- To make BERT better at handling relationships between multiple sentences, the pre-training process includes an additional task:

  “Given two sentences (A and B),is B likely to be the sentence that follows A, or not?”

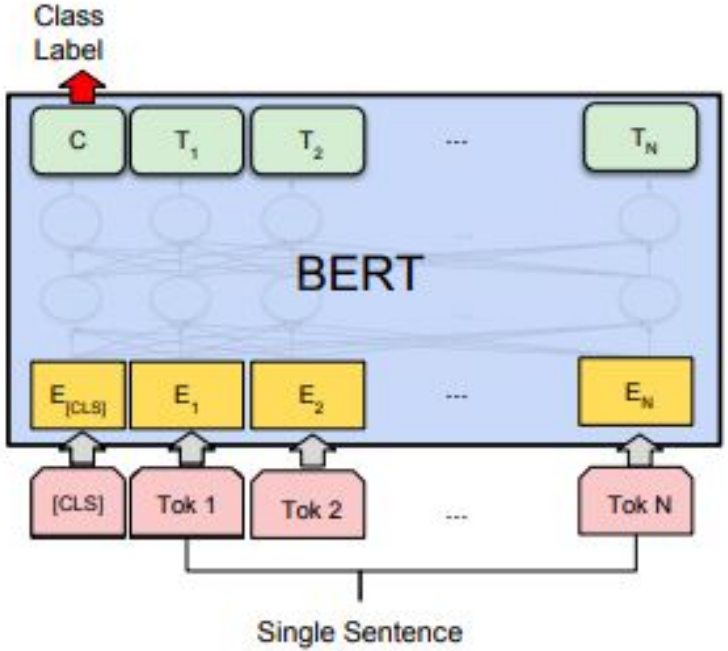
BERT: pre-training



BERT: fine-tuning for different tasks

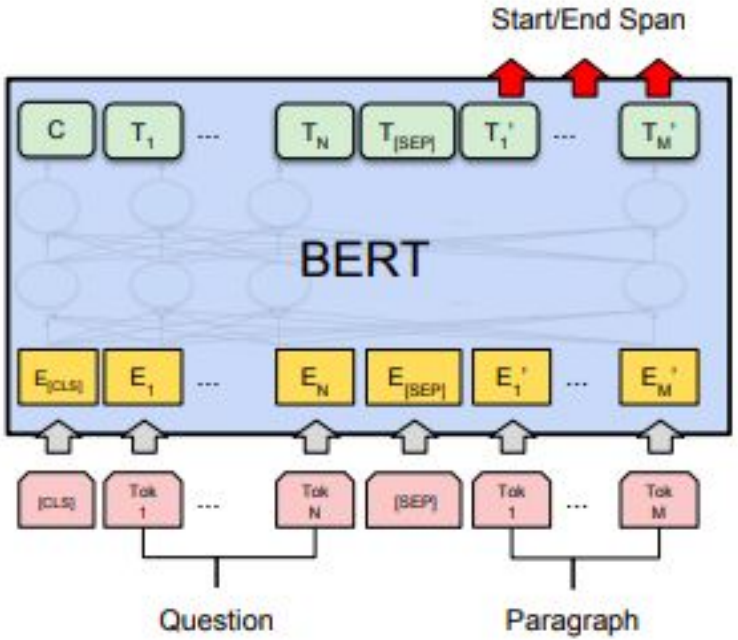


(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

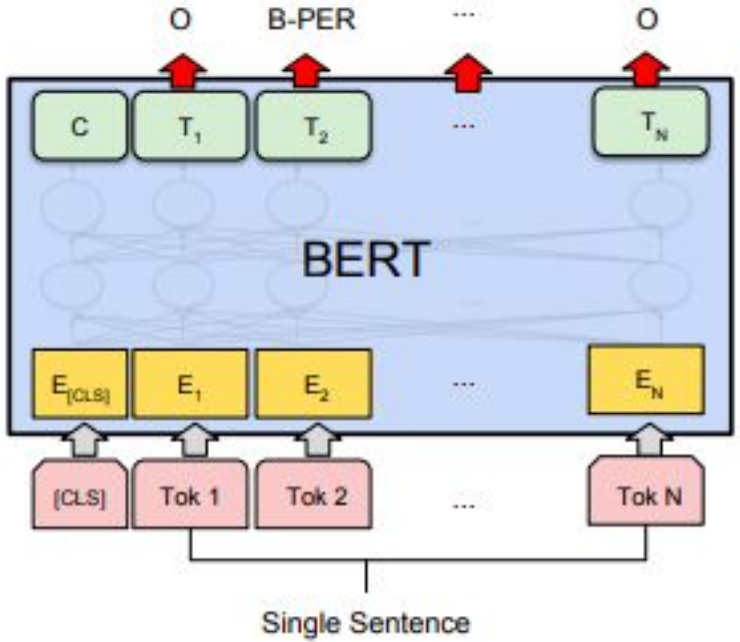


(b) Single Sentence Classification Tasks: SST-2, CoLA

BERT: fine-tuning for different tasks

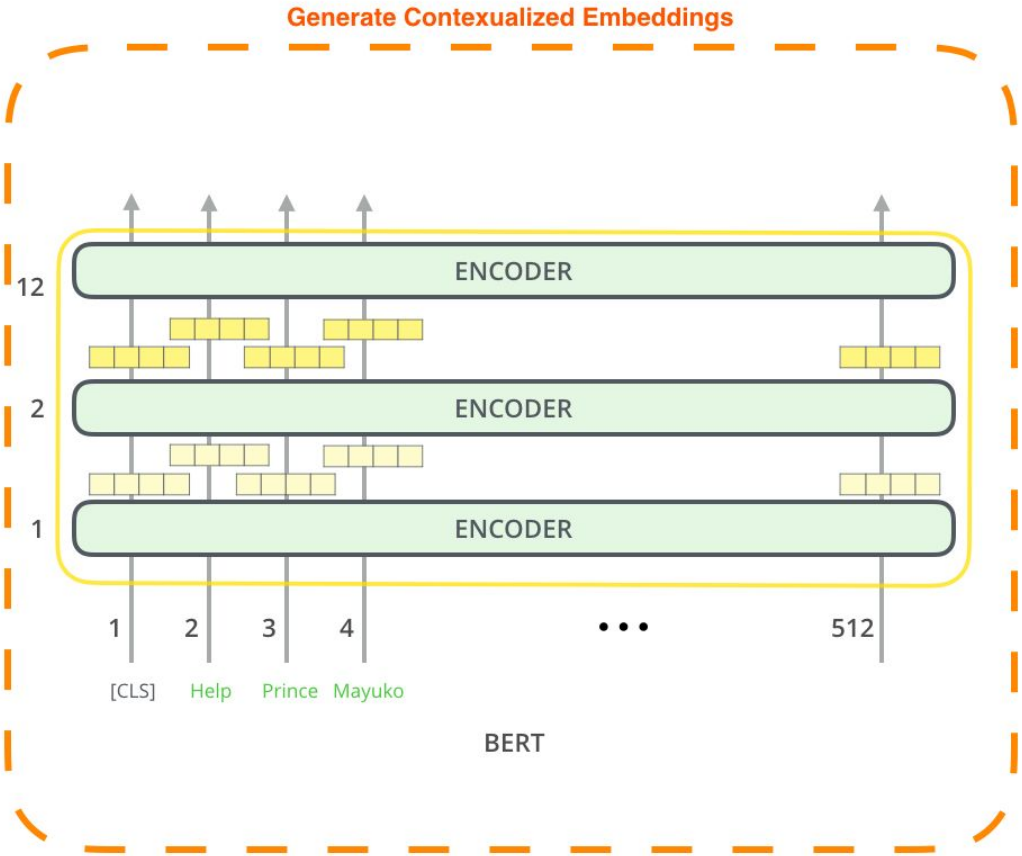


(c) Question Answering Tasks:
SQuAD v1.1

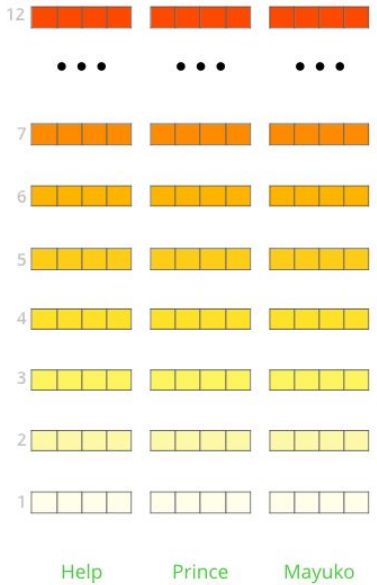


(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

BERT for feature extraction



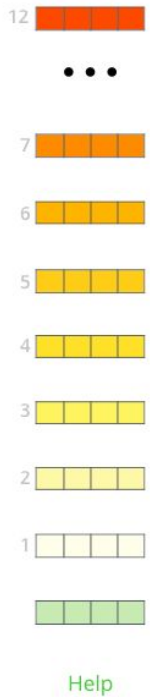
The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?

BERT for feature extraction

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



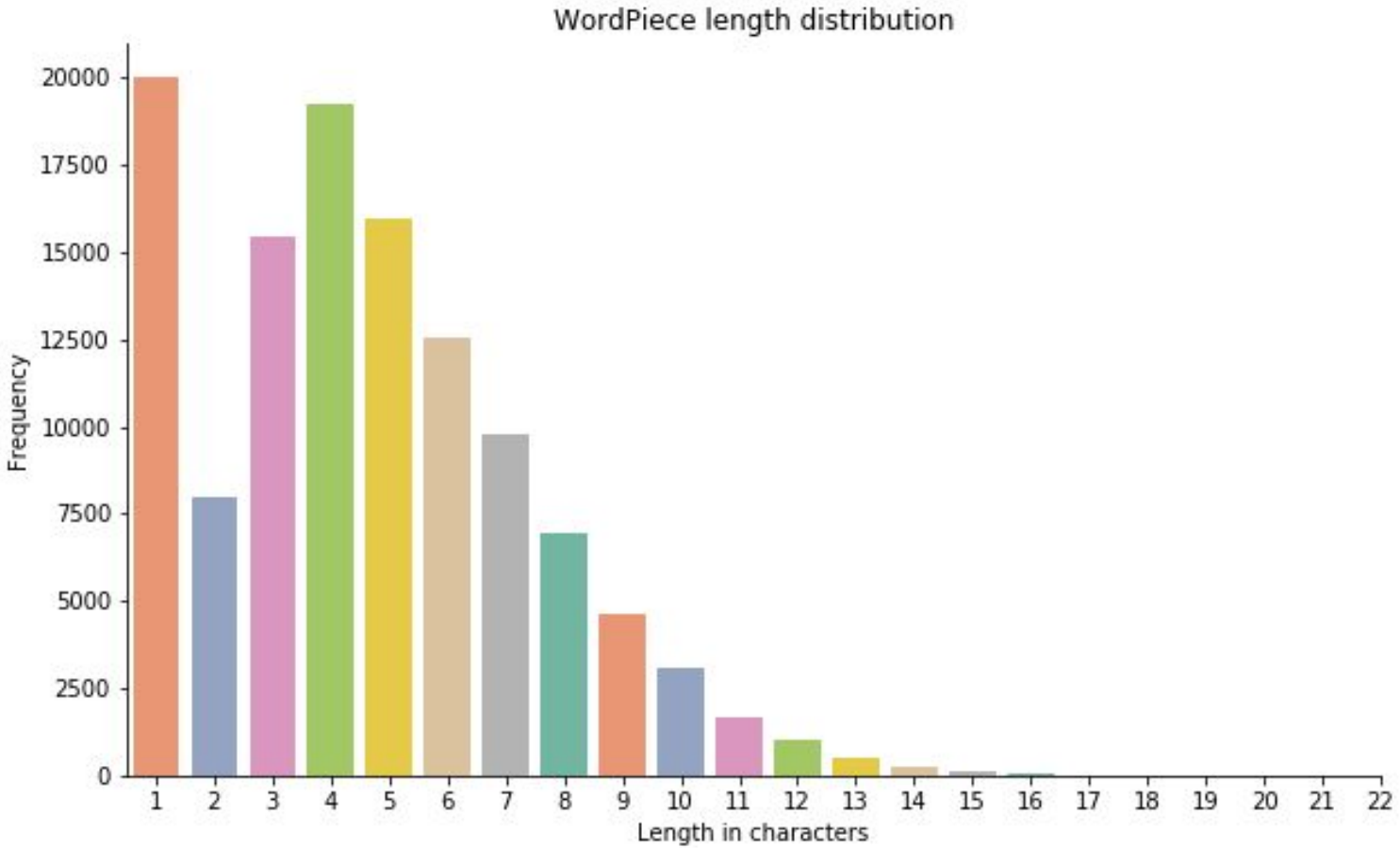
		Dev F1 Score
First Layer	Embedding	91.0
Last Hidden Layer	12	94.9
Sum All 12 Layers	12 + ... + 2 + 1 =	95.5
Second-to-Last Hidden Layer	11	95.6
Sum Last Four Hidden	12 + 11 + 10 + 9 =	95.9
Concat Last Four Hidden	9 10 11 12	96.1

BERT: tokenization

Example: Unaffable -> un, ##aff, ##able

- Single model for 104 languages with a large shared vocabulary (119,547 WordPiece model)
- Non-word-initial units are prefixed with ##
- The first 106 symbols: constants like PAD and UNK
- 36.5% of the vocabulary are non-initial word pieces
- The alphabet consists of 9,997 unique characters that are defined as word-initial (C) and continuation symbols (##C), which together make up 19,994 word pieces
- The rest are multicharacter word pieces of various length.

BERT: tokenization

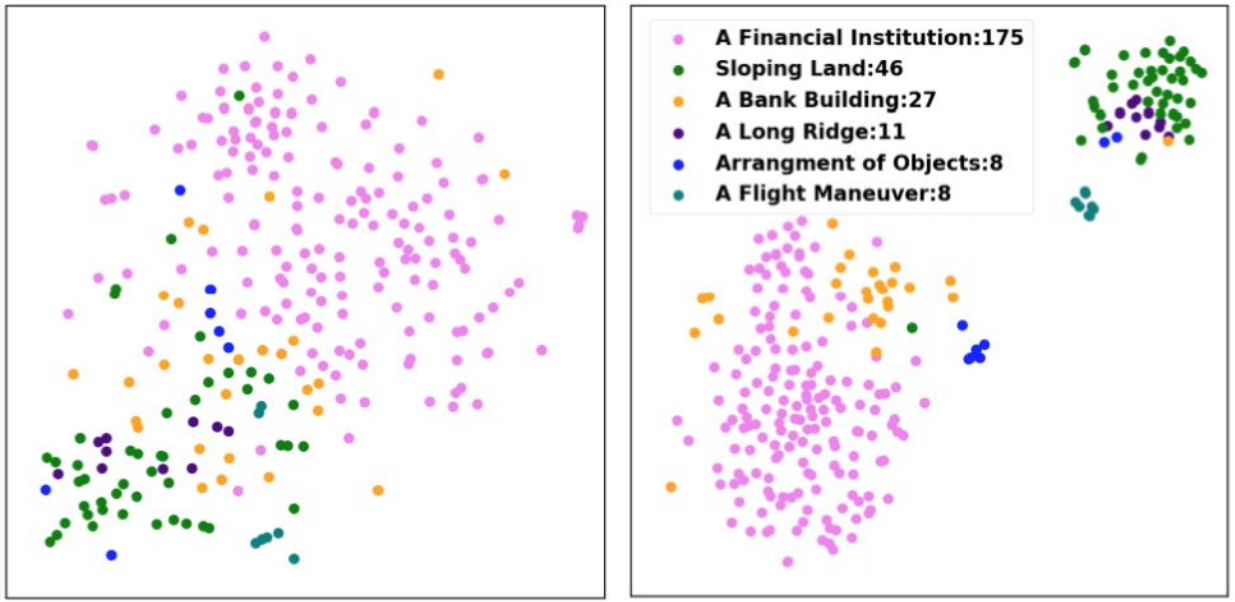


BERT: overview

- BERT repo
- Try out BERT on TPU
- WordPieces Tokenizer
- PyTorch Implementation of BERT

BERT vs. ELMO (Word Sense Disambiguation problem)

T-SNE plots of different senses of 'bank'

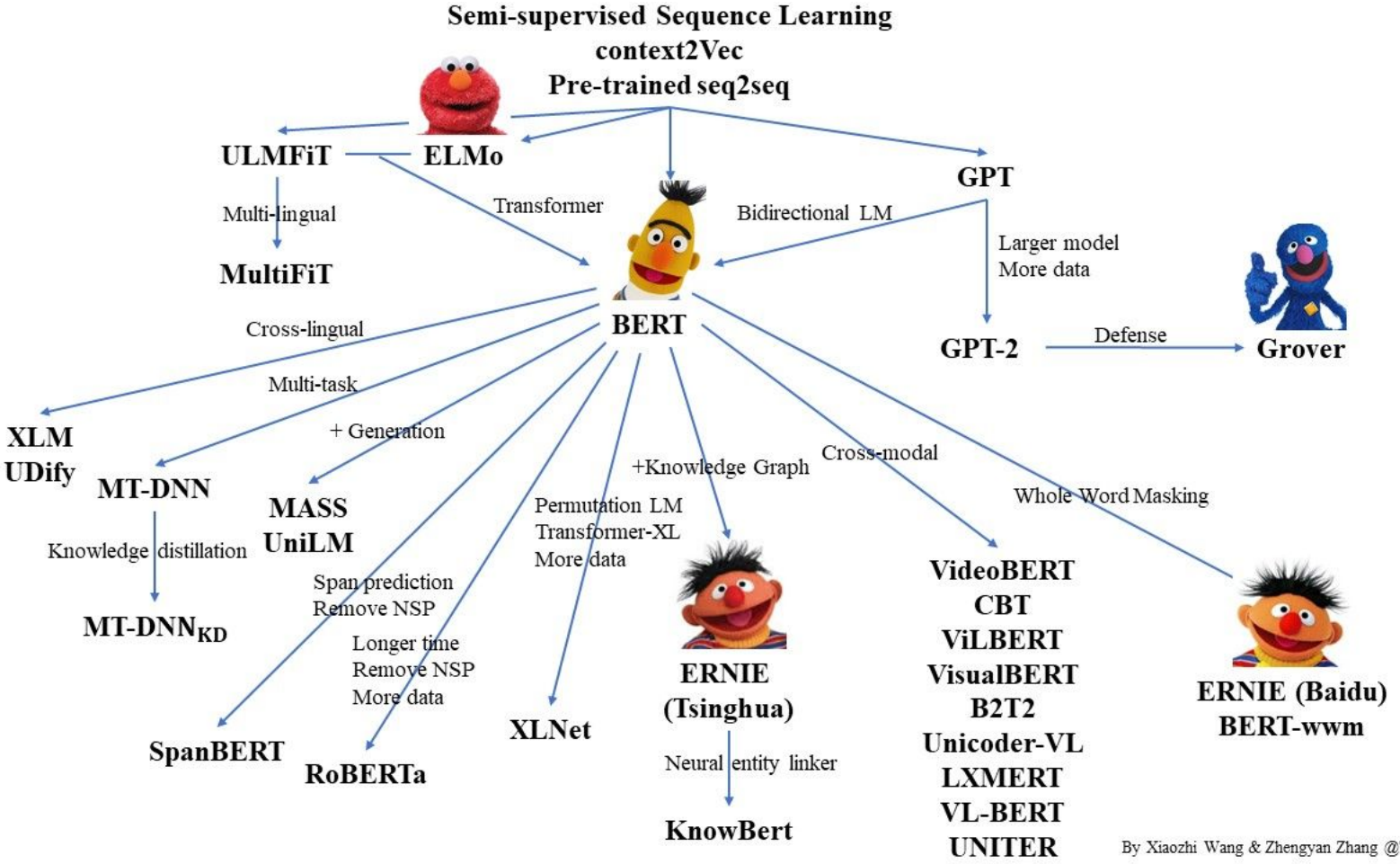


(c) ELMo (a) BERT

BERTology

BERTology paper

BERTology



BERTology

Miles Brundage
@Miles_Brundage

2018: Language model papers have to introduce Sesame Street-related acronyms

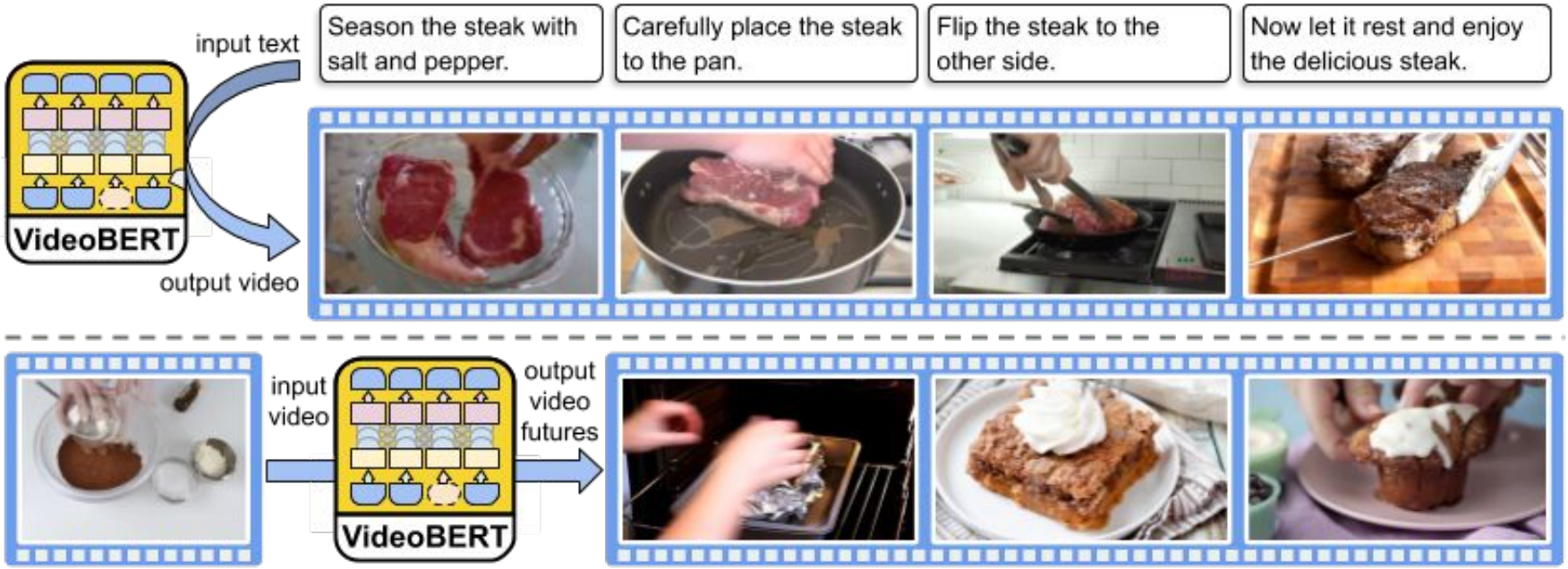
2019: Language model papers need Sesame Street jokes in the title, all talks need at least one Sesame Street image.

2020: ACL/NAACL co-located with Sesame Street convention, Big Bird gives a keynote.

293 2:46 AM - Jun 12, 2019

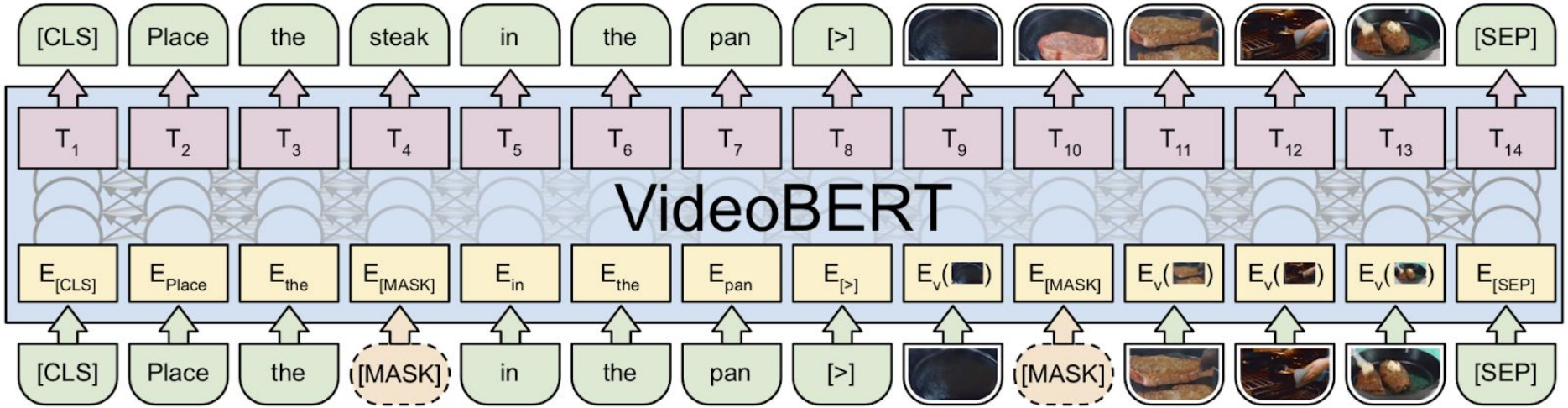
57 people are talking about this

VideoBERT (ICCV 2019)



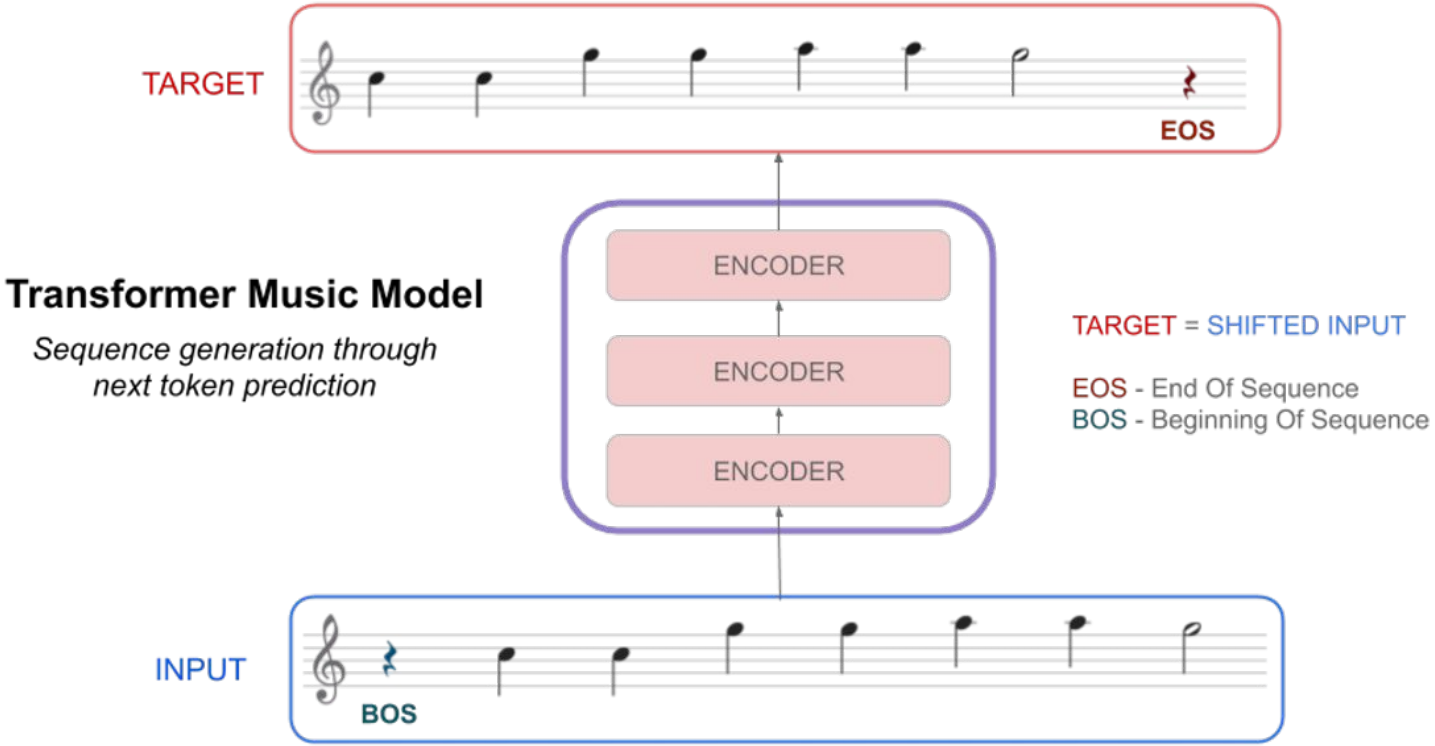
https://arxiv.org/abs/1904.01766
https://ai.googleblog.com/2019/09/learning-cross-modal-temporal.html

VideoBERT (ICCV 2019)



https://arxiv.org/abs/1904.01766
https://ai.googleblog.com/2019/09/learning-cross-modal-temporal.html

Music Transformer (ICLR 2019)



https://arxiv.org/abs/1809.04281
https://magenta.tensorflow.org/music-transformer

Fun demos to play with

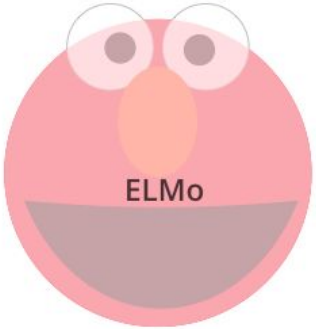
[Get a neural network to autocomplete your thoughts]
[And yet another auto-completion tool]


THE
TRANSFORMER


ULM-FiT


BERT


OpenAI
Transformer


ELMo

GPT, GPT-2 and GPT-3

GPT-2

- Transformer-based architecture
- Trained to predict the **next** word
- 1.5 billion parameters
- Trained on 8 million web-pages

GPT-2

- Transformer-based architecture
- trained to predict the **next** word
- 1.5 billion parameters
- Trained on 8 million web-pages

On language tasks (question answering, reading comprehension, summarization, translation) works well **WITHOUT** fine-tuning

GPT-2: question answering

EXAMPLES

Who wrote the book the origin of species?

Correct answer: *Charles Darwin*
Model answer: `Charles Darwin`

What is the largest state in the U.S. by land mass?

Correct answer: *Alaska*
Model answer: `California`

GPT-2: language modeling

EXAMPLE

Both its sun-speckled shade and the cool grass beneath were a welcome respite after the stifling kitchen, and I was glad to relax against the tree's rough, brittle bark and begin my breakfast of buttery, toasted bread and fresh fruit. Even the water was tasty, it was so clean and cold. It almost made up for the lack of...

Correct answer: *coffee*
Model answer: `food`

GPT-2: machine translation

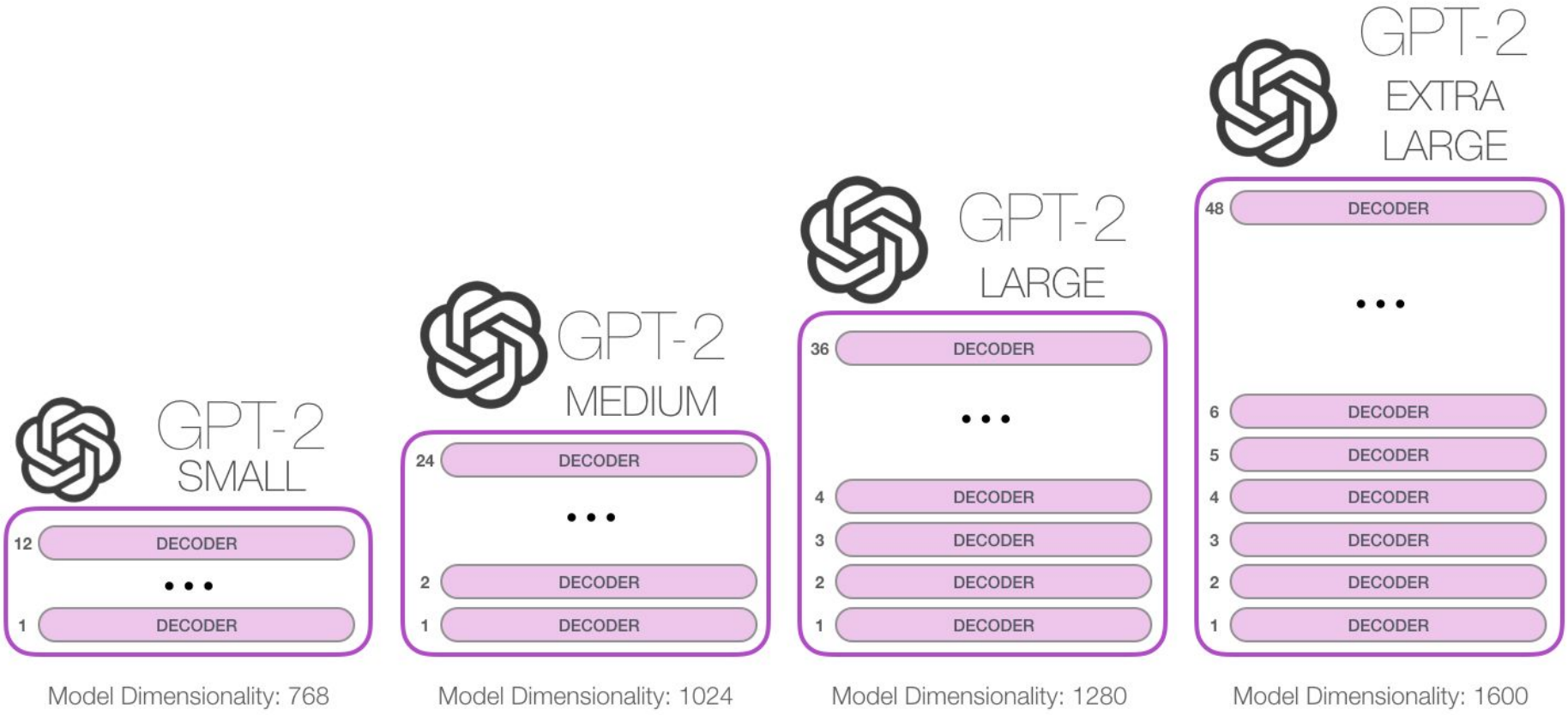
EXAMPLE

French sentence:
Un homme a expliqué que l'opération gratuite qu'il avait subie pour soigner une hernie lui permettrait de travailler à nouveau.

Reference translation:
One man explained that the free hernia surgery he'd received will allow him to work again.

Model translation:
`A man told me that the operation gratuity he had been promised would not allow him to travel.`

GPT-2


GPT-2
SMALL
12
DECODER
1
DECODER
Model Dimensionality: 768
GPT-2
MEDIUM
24
DECODER
2
DECODER
1
DECODER
Model Dimensionality: 1024
GPT-2
LARGE
36
DECODER
4
DECODER
3
DECODER
2
DECODER
1
DECODER
Model Dimensionality: 1280
GPT-2
EXTRA
LARGE
48
DECODER
6
DECODER
5
DECODER
4
DECODER
3
DECODER
2
DECODER
1
DECODER
Model Dimensionality: 1600

GPT-2: fake news and hype

New AI fake text generator may be too dangerous to ... - The Guardian
https://www.theguardian.com/.../elon-musk-backed-ai-writes-convincing-news-fiction
4 days ago - The Elon Musk-backed nonprofit company OpenAI declines to release research publicly for fear of misuse. The creators of a revolutionary AI system that can write news stories and works of fiction – dubbed "deepfakes for text" – have taken the unusual step of not releasing ...

OpenAI built a text generator so good, it's considered too dangerous to ...
https://techcrunch.com/2019/02/17/openai-text-generator-dangerous/
12 hours ago - A storm is brewing over a new language model, built by non-profit artificial intelligence research company OpenAI, which it says is so good at ...

The AI Text Generator That's Too Dangerous to Make Public | WIRED
https://www.wired.com/story/ai-text-generator-too-dangerous-to-make-public/
4 days ago - In 2015, car-and-rocket man Elon Musk joined with influential startup backer Sam Altman to put artificial intelligence on a new, more open ...

Elon Musk-backed AI Company Claims It Made a Text Generator ...
https://gizmodo.com/elon-musk-backed-ai-company-claims-it-made-a-text-gener-183...
Elon Musk-backed AI Company Claims It Made a Text Generator That's **Too Dangerous to** Release · Rhett Jones · Friday 12:15pm · Filed to: OpenAI Filed to: ...

Scientists have made an AI that they think is too dangerous to ...
https://www.weforum.org/.../amazing-new-ai-churns-out-coherent-paragraphs-of-text/
3 days ago - Sample outputs suggest that the AI system is an extraordinary step forward, producing text rich with context, nuance and even something ...

New AI Fake Text Generator May Be Too Dangerous To ... - Slashdot
https://news.slashdot.org/.../new-ai-fake-text-generator-may-be-too-dangerous-to-rele...
3 days ago - An anonymous reader shares a report: The creators of a revolutionary AI system that can write news stories and works of fiction -- dubbed ...

Top stories

OpenAI built a text generator so good, it's considered too dangerous to release
TechCrunch
11 hours ago

Elon Musk's AI company created a fake news generator it's too scared to make public
BGR.com
9 hours ago

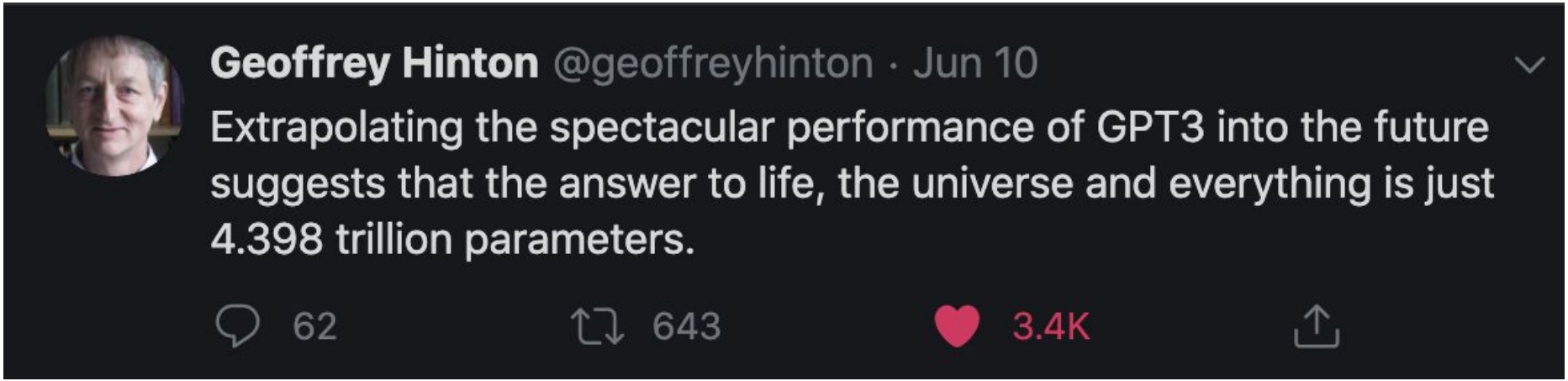
The AI That Can Write A Fake News Story From A Handful Of Words
NDTV.com
2 hours ago

When Is Technology Too Dangerous to Release to the Public?
Slate • 2 days ago

Scientists Developed an AI So Advanced They Say It's Too Dangerous to Release
ScienceAlert • 6 days ago

GPT-3

- GPT-2: 1.5 billion parameters
- GPT-3: **175 billion** parameters



GPT-3: OpenAI API released

- You can request access in order to integrate the API into your product
- Given any text prompt, the API will return a text completion, attempting to match the pattern you gave it

https://openai.com/blog/openai-api/

References

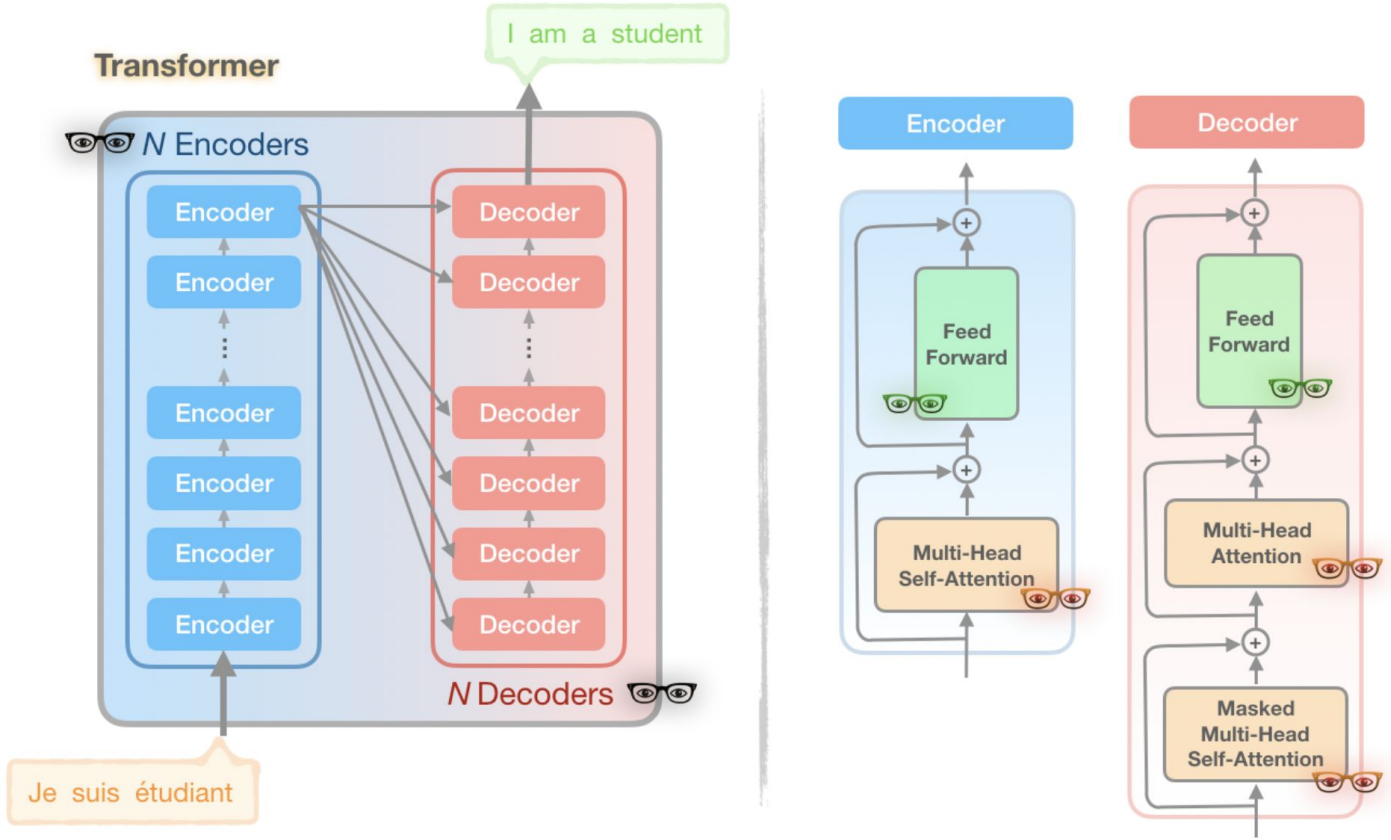
- Transformer
- OpenAI Transformer
- ELMO
- BERT
- BERTology
- GPT
- GPT-2
- GPT-3

The Reformer

Reformer: The Effective Transformer (ICLR 2020)

Transformer-based models have a problem:

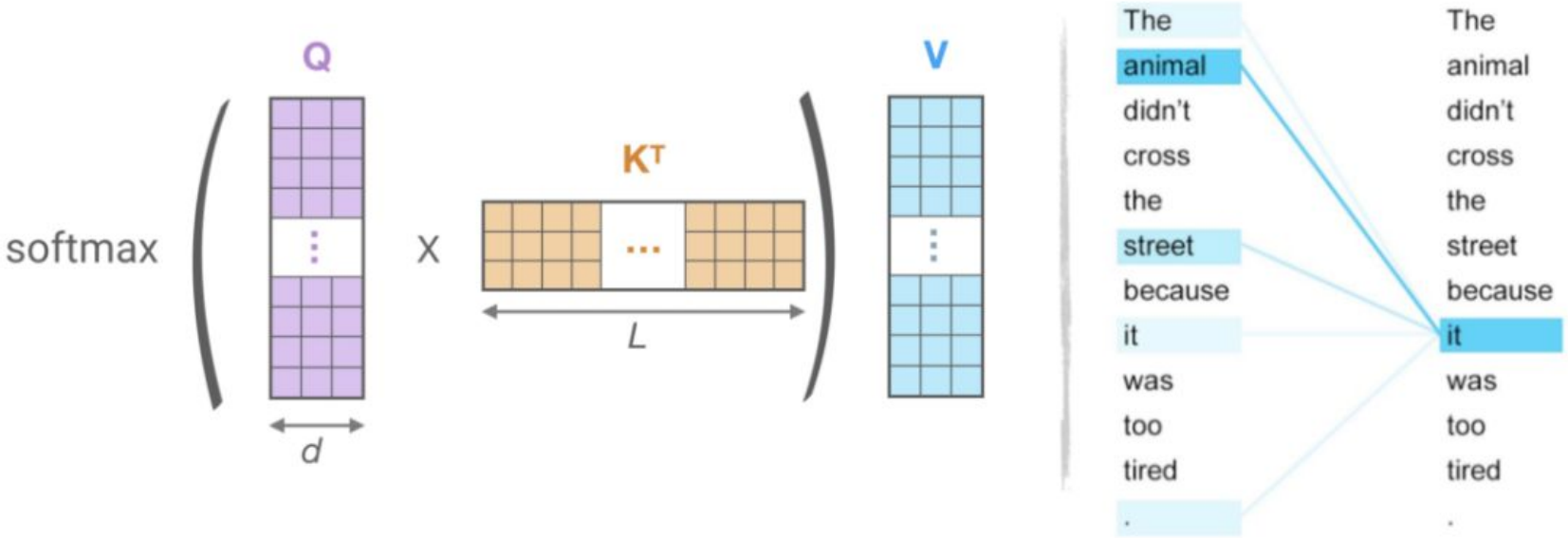
- They require lots of GPUs to train
  - even cannot be fine-tuned on a single GPU



- Problem 1 (**Red** 👓): Attention computation
- Problem 2 (**Black** 👓): Large number of layers
- Problem 3 (**Green** 👓): Depth of feed-forward layers

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Attention computation



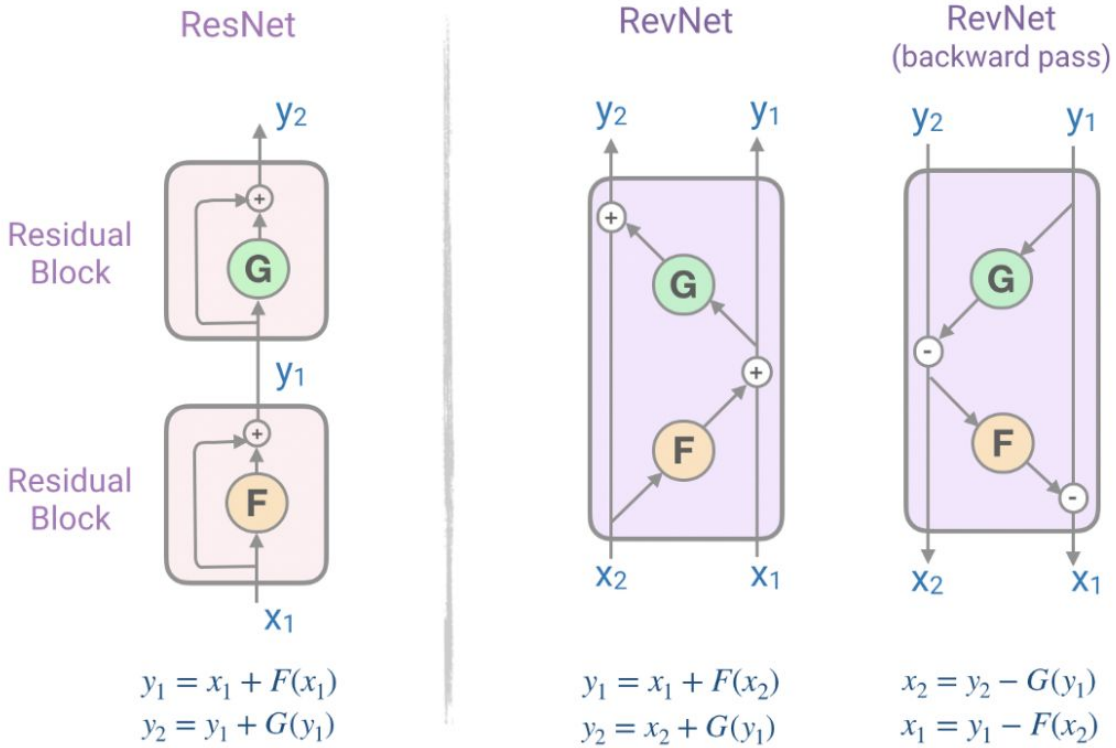
- Replace dot-product attention with locality-sensitive hashing (LSH)
  - changes the complexity from $O(L^2)$ to $O(L \log L)$

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Locality-sensitive hashing for attention computation

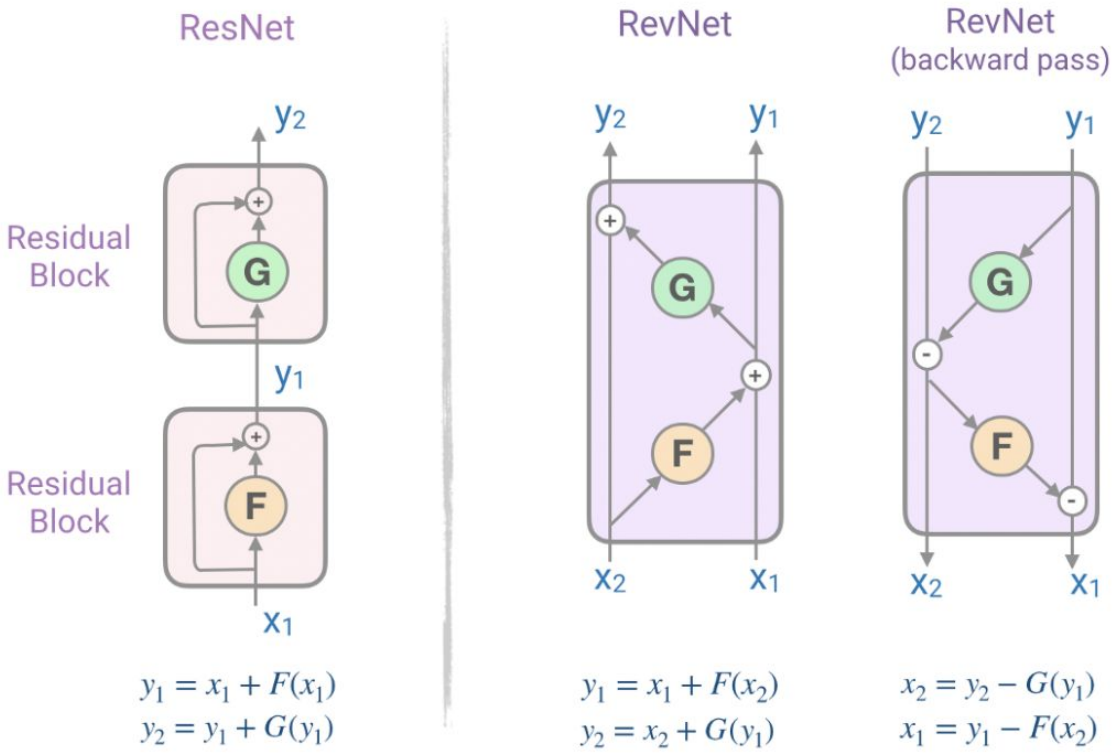
- LSH - an *efficient* and *approximate* way of nearest neighbors search in high dimensional datasets.
- The main idea behind LSH is to select hash functions such that for two points ‘p’ and ‘q’, if ‘q’ is close to ‘p’ then with good enough probability we have ‘hash(q) == hash(p)’.

Reversible Transformer



https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Reversible Transformer



- F - self-attention block
- G - feed-forward layer

Profit: storing activations only once during the training process

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0

Chunking

Computations in feed-forward layers are independent across positions in a sequence => the computations for the forward and backward passes can be split into chunks.

$$Y_2 = \left[Y_2^{(1)}; \ldots; Y_2^{(c)}\right] = \left[X_2^{(1)} + \text{FeedForward}(Y_1^{(1)}); \ldots; X_2^{(c)} + \text{FeedForward}(Y_1^{(c)})\right]$$

Chunking in the forward pass computation [Image is taken from the Reformer paper]

https://towardsdatascience.com/illustrating-the-reformer-393575ac6ba0