Transformers

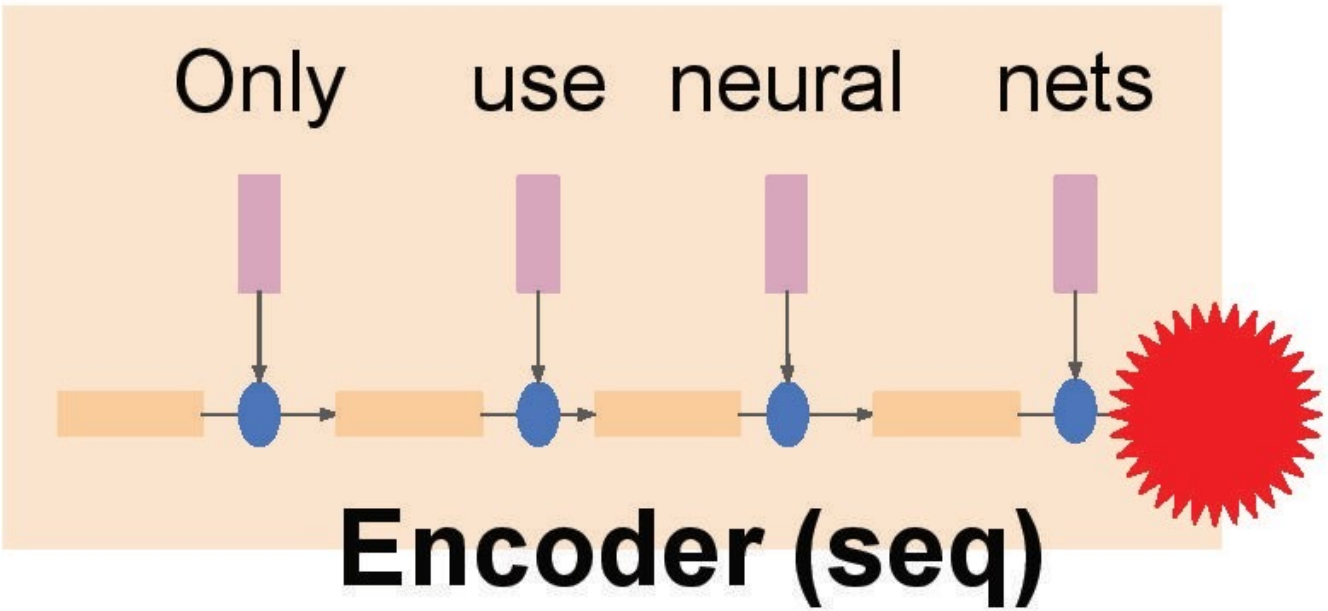
Attention is All You Need

Ashish Vaswani et. al., NeurIPS 2017

https://papers.nips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

The information bottleneck and latent structure

We are trying to encode *variable-length* structure (e.g., variable-length sentences) in a fixed-length memory (e.g., only the 300 dimensions of your hidden state.)

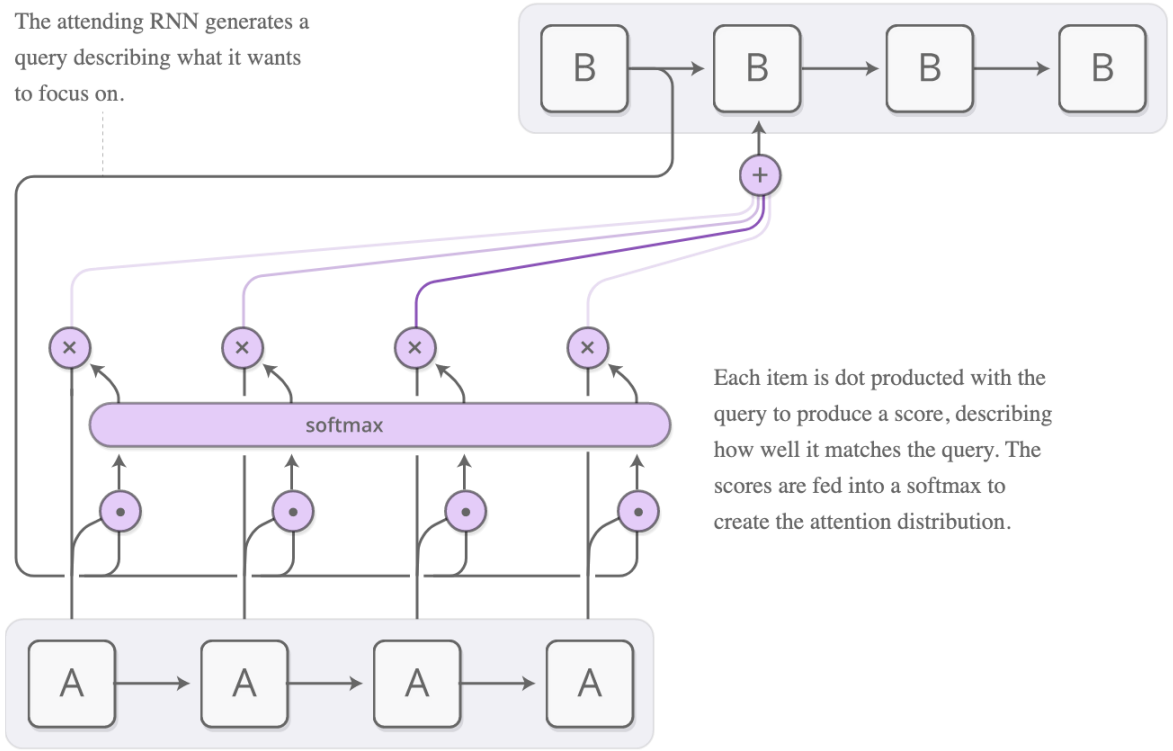


The last encoder hidden state is the bottleneck -- all information in the source sentence must pass through it to get to the decoder.

Finding a solution to this problem was the final advance that made neural MT competitive with previous approaches.

Attentional Interfaces

- When translating, pay attention to the word currently translated
- Attention == focusing on part of a subset of the given information



Attentional Interfaces

- One use of attention is translation
  - Traditional seq2seq model boils entire input into a single vector and then expands it back out
  - Attention allows RNN processing the input to pass along information about *each* word it sees. The RNN generating the output focuses on words as they become relevant

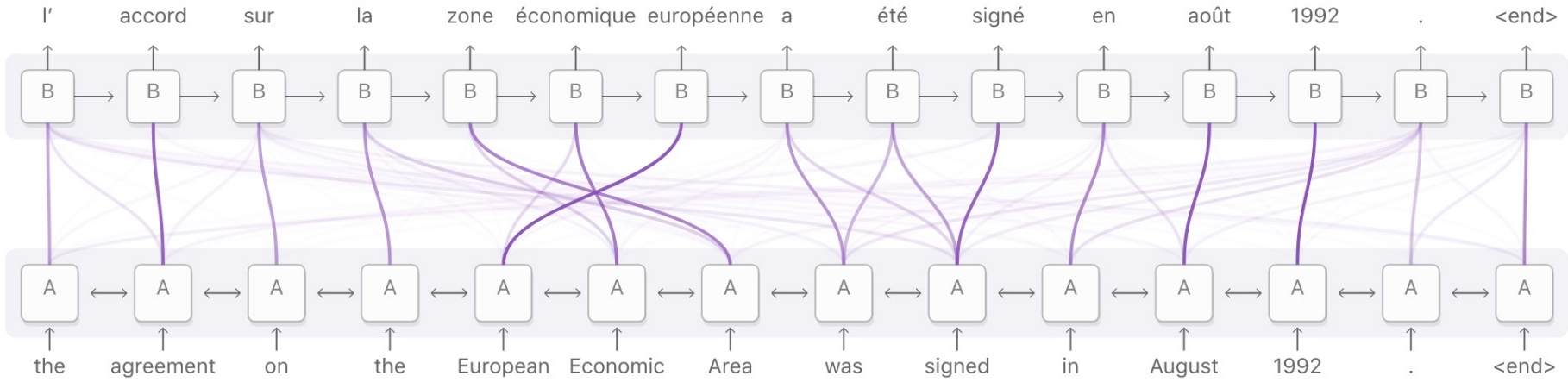


Diagram derived from Fig. 3 of Bahdanau, *et al.* 2014

Neural Machine Translation (NMT)

In two years, neural networks surpassed everything that had appeared in the past 20 years of translation. Neural translation contains 50% fewer word order mistakes, 17% fewer lexical mistakes, and 19% fewer grammar mistakes. The neural networks even learned to harmonize gender and case in different languages. And no one taught them to do so.

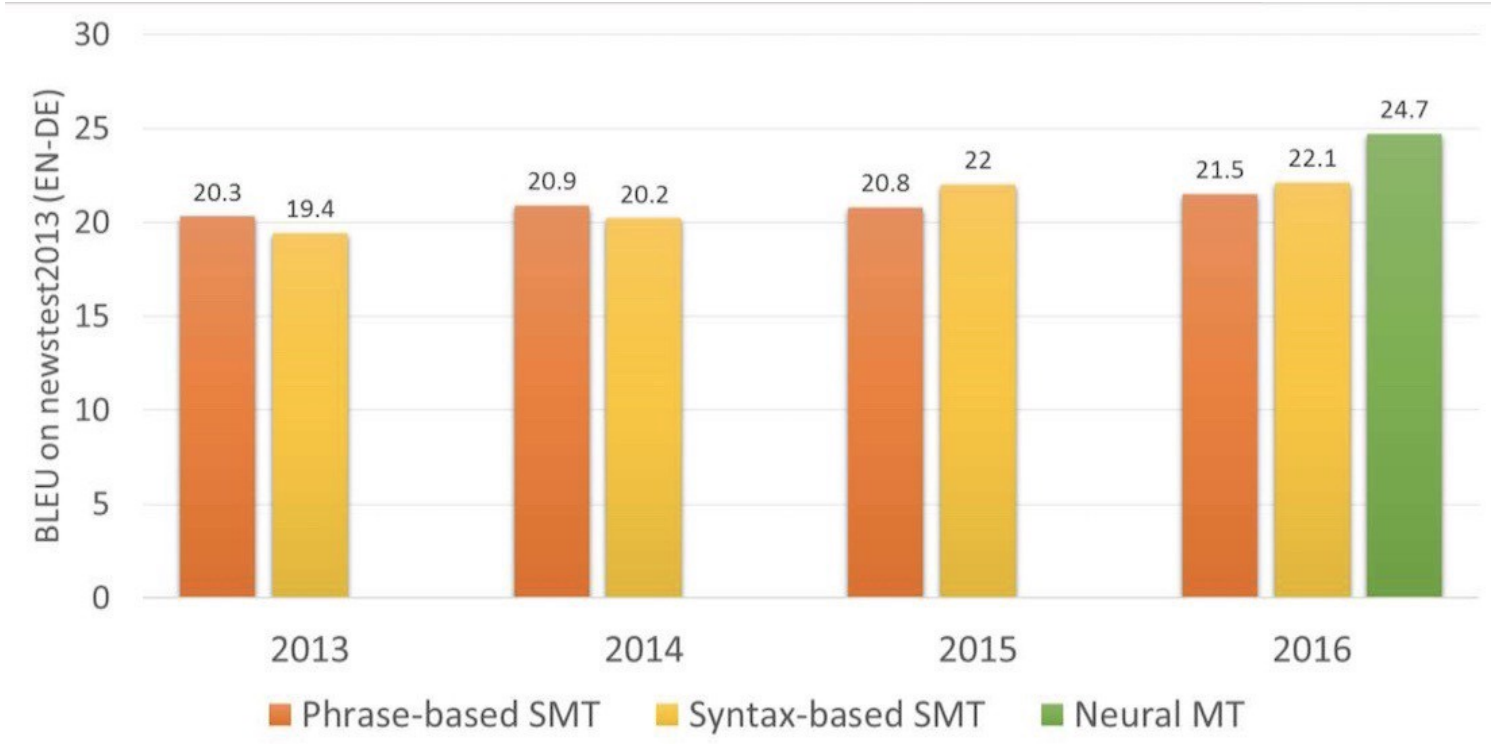


Figure from "A history of machine translation from the Cold War to deep learning" by Ilya Pestov

Attentional Interfaces

- Is also used in image captioning
  - On the interface between a CNN and an RNN
  - RNN will look at different position of an image as it generates each word
- Attention can be used whenever you want to interface with a NN that has a repeating structure in its output

A woman is throwing a frisbee in a park.

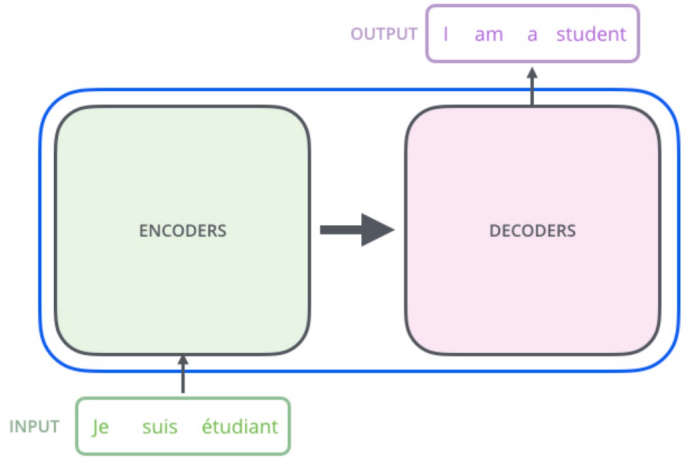
A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

Attention is all You Need

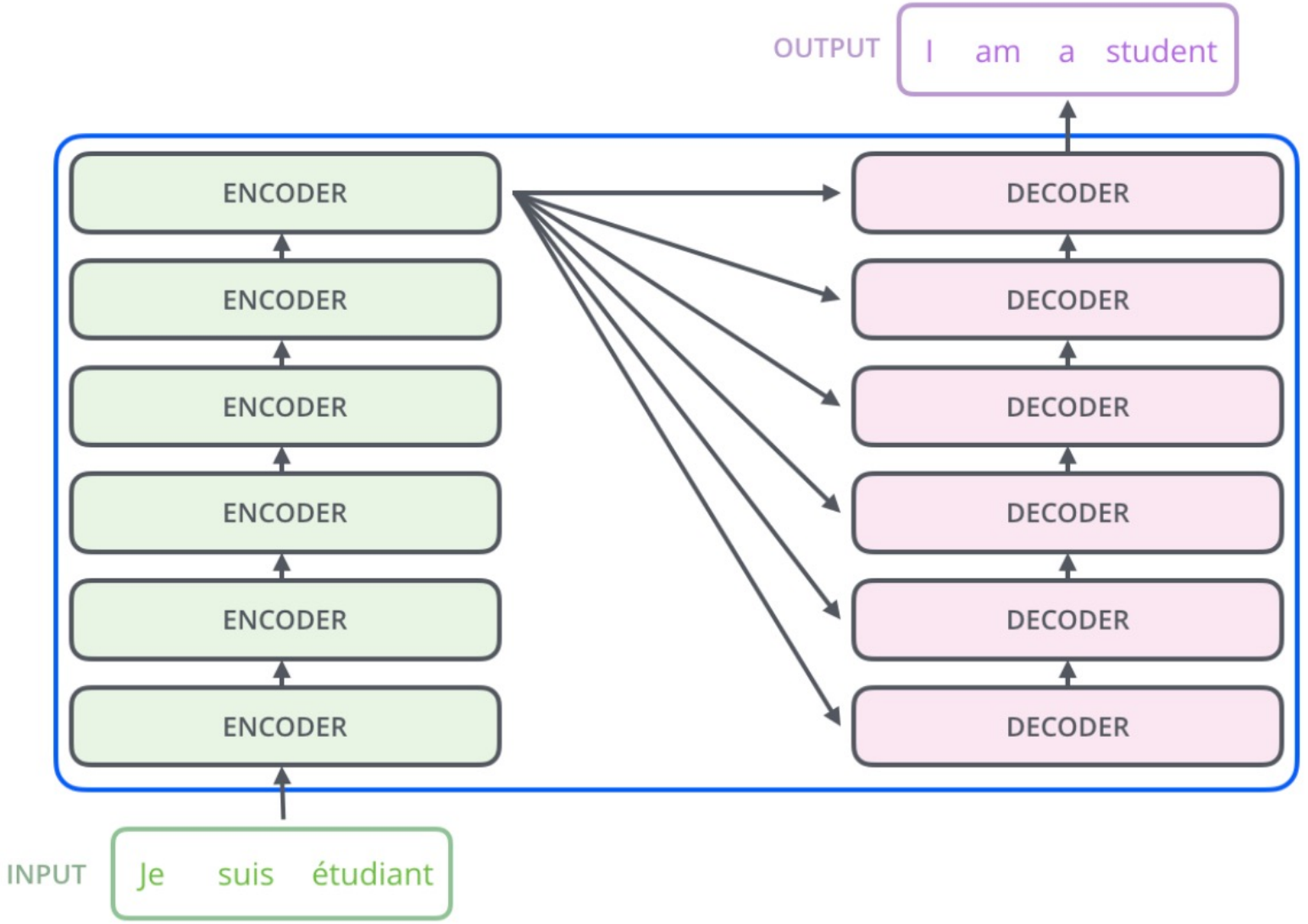
https://jalammar.github.io/illustrated-transformer/

- Improve NMT



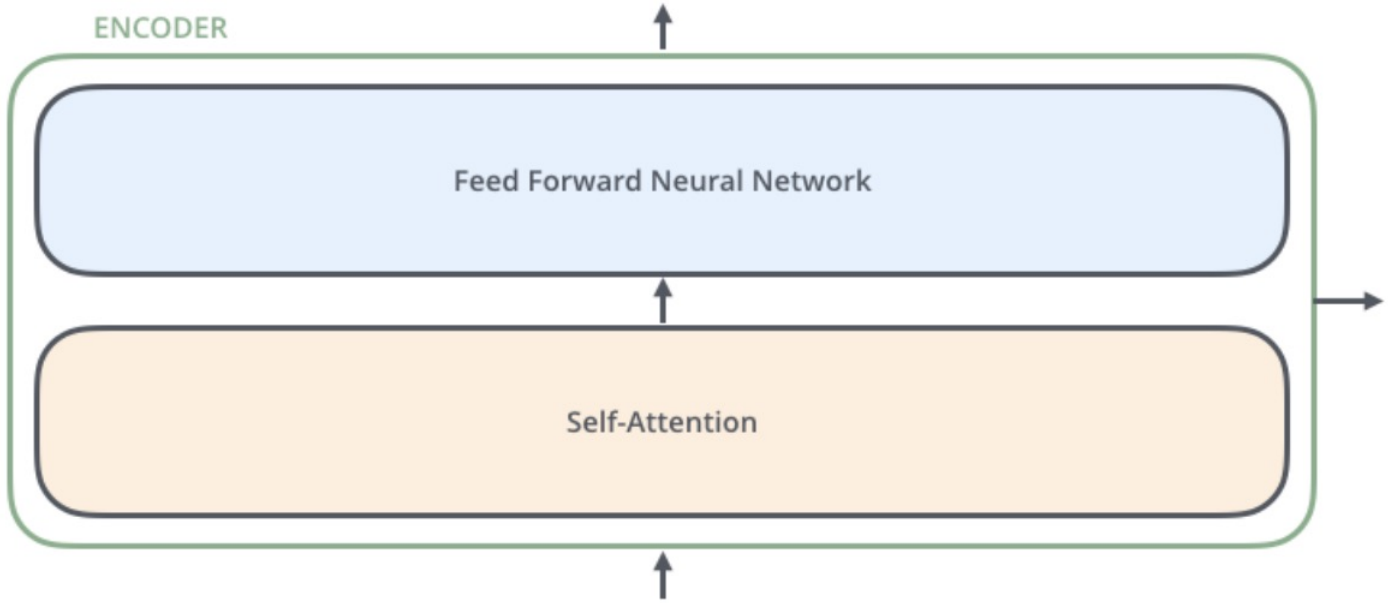
Attention is all You Need

- Transformer
  - Stack of Encoders
  - Stack of Decoders



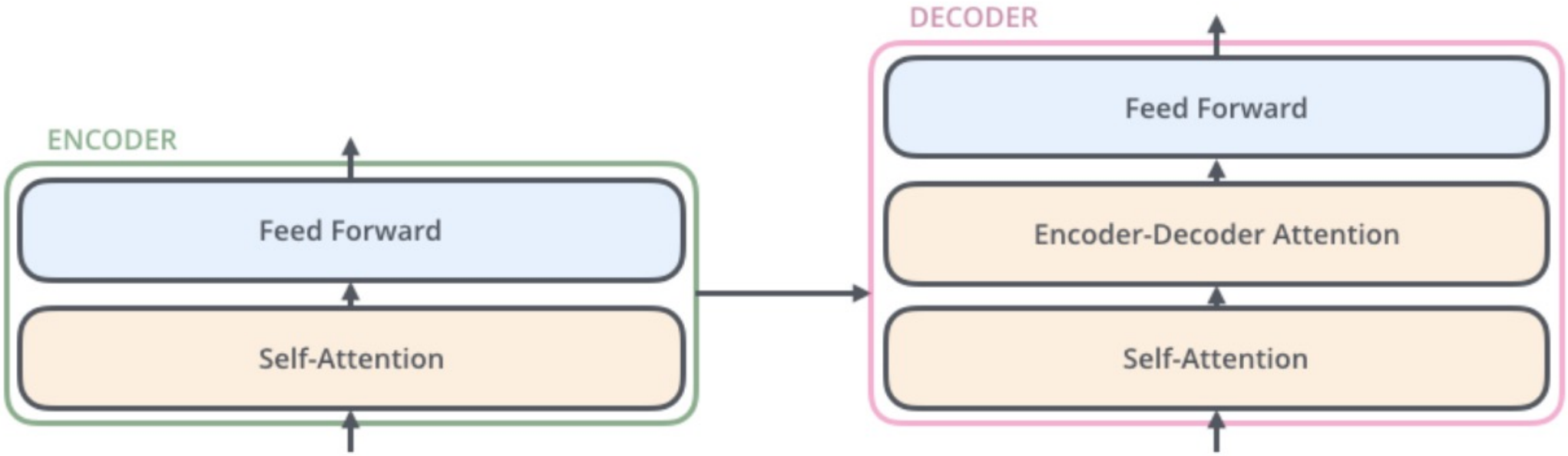
Attention is all You Need

- Each encoder:
  - Self-attention: look at other words in the input as it encodes a specific word
  - FFNN is independently applied to each position



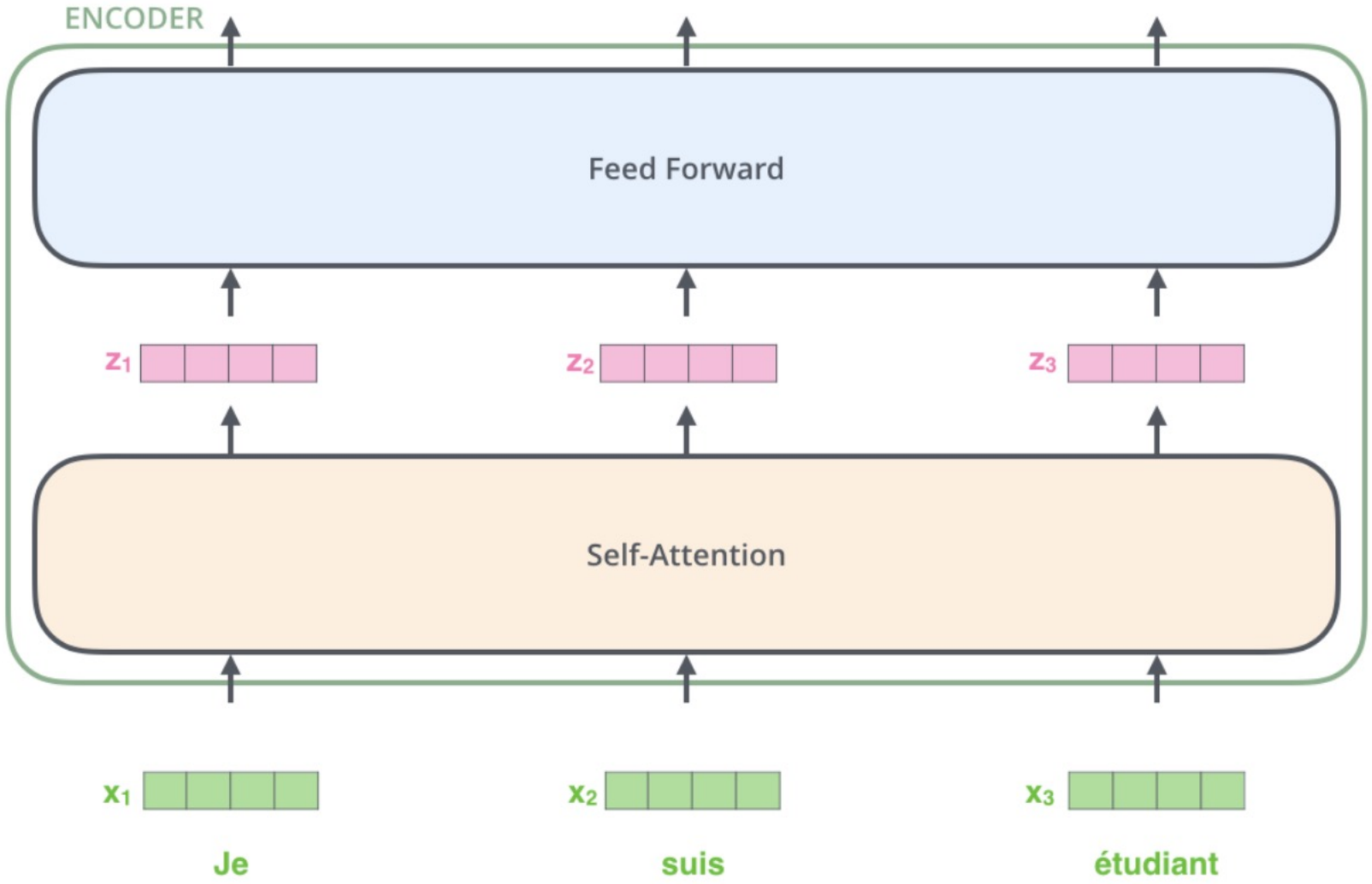
Attention is all You Need

- Each decoder:
  - Has attention layer that lets it focus on relevant parts of the input sentence



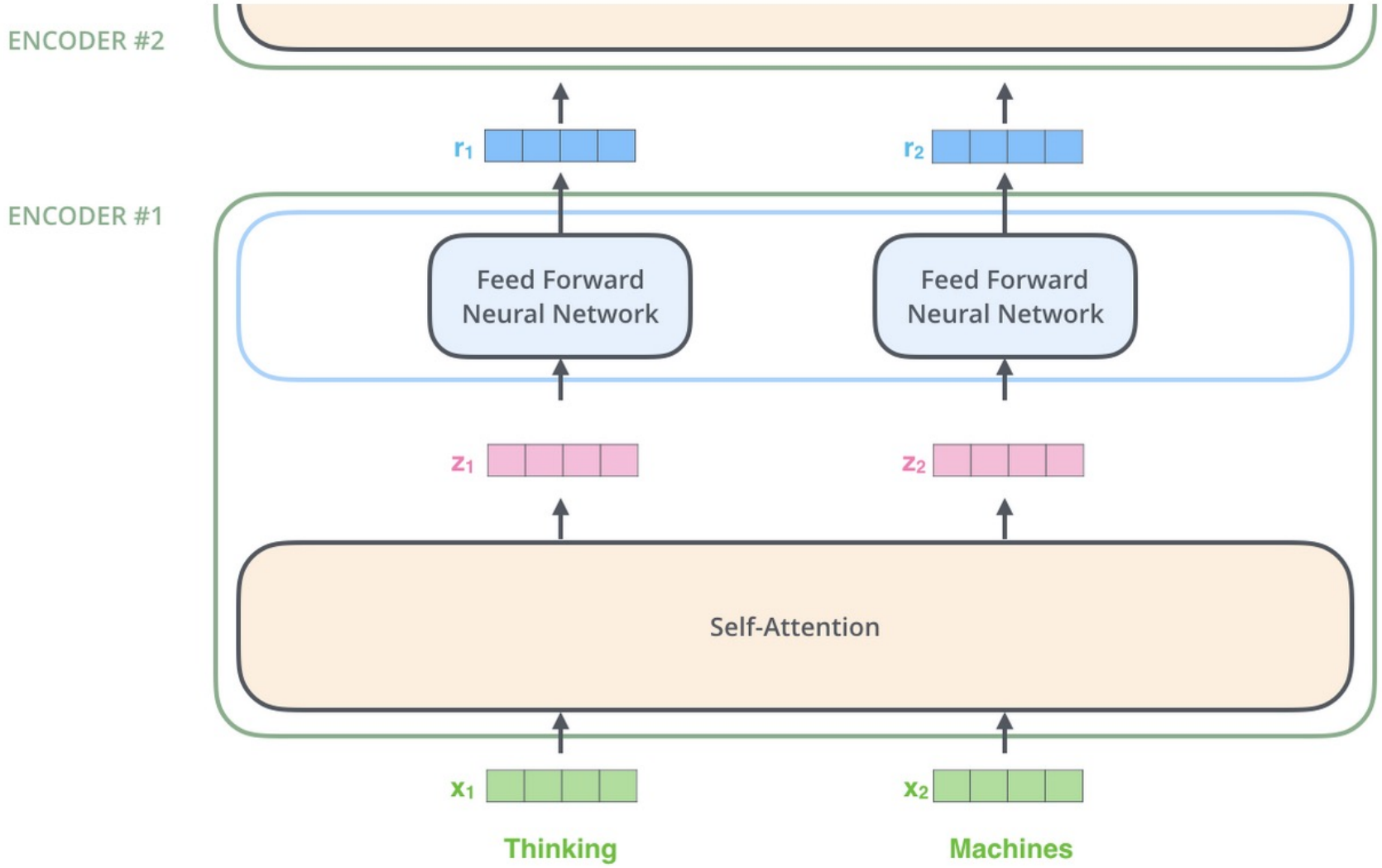
Attention is all You Need

- Input:
  - The encoder receives a list of vectors as input



Attention is all You Need

- Input:
  - The encoder receives a list of vectors as input
  - Word in each position flows through its own path in the encoder



Attention is all You Need

- Self attention:

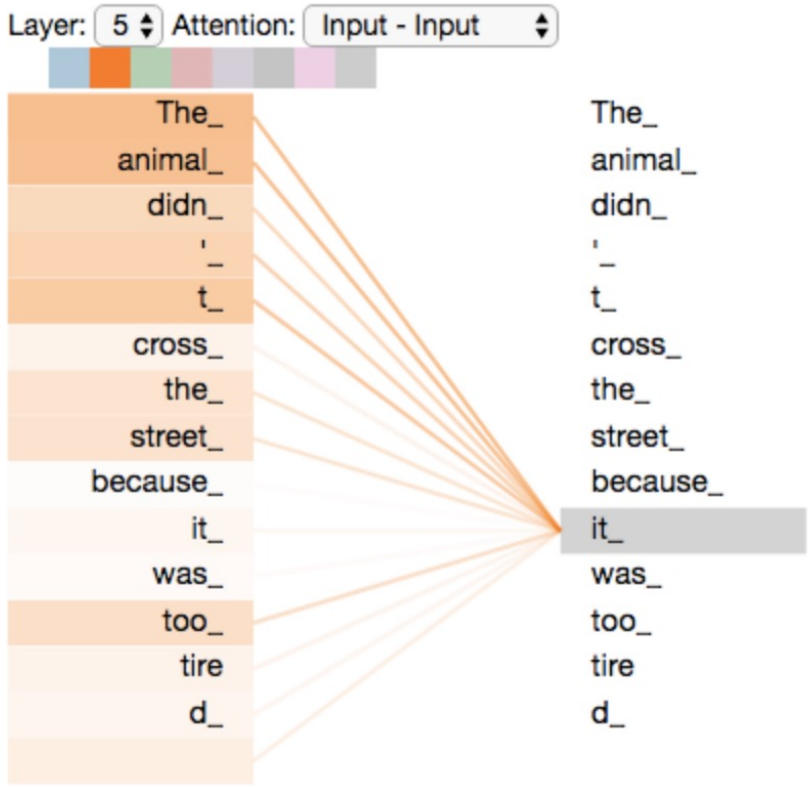
  “The animal didn't cross the street because it was too tired”

  allows to associate “it” with “animal” by allowing the model to look at other positions in the input sentence for clues that can help lead to a better encoding of the word “it”

Attention is all You Need

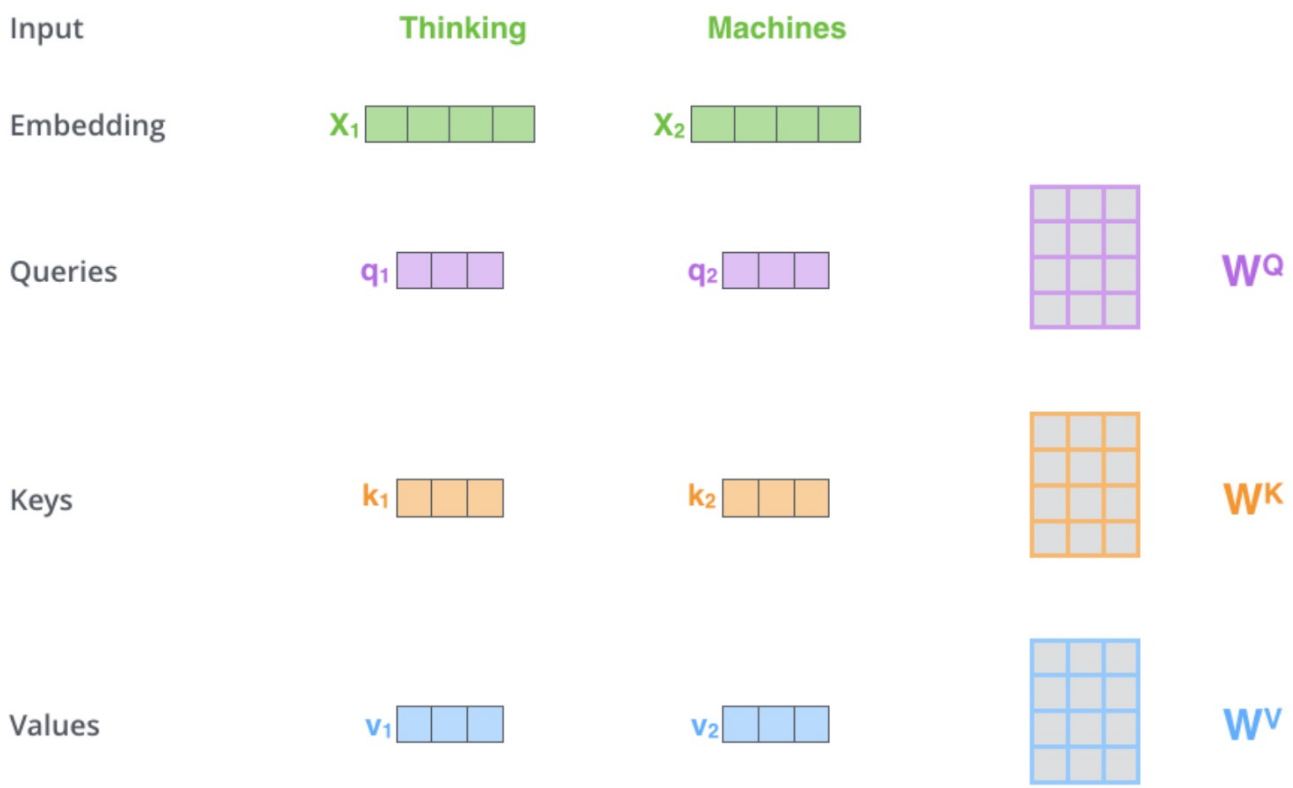
- Self attention:

"The animal didn't cross the street because it was too tired"



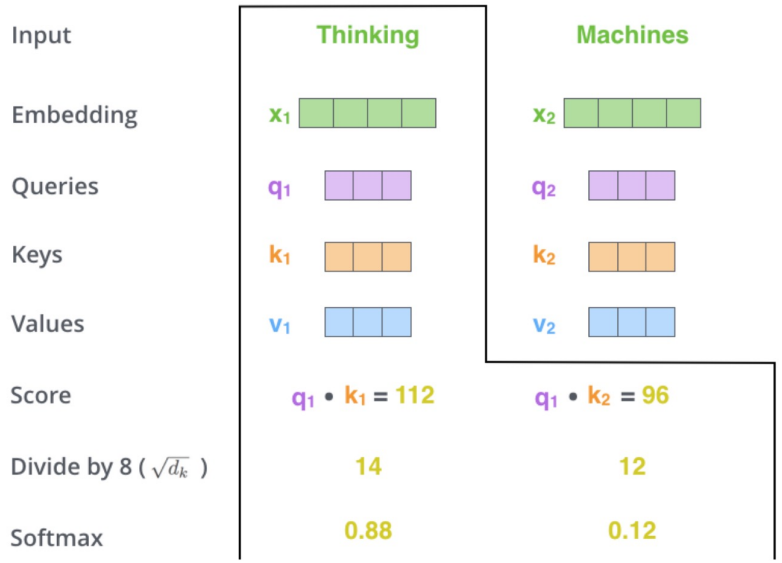
Attention is all You Need

- Calculating self attention:
  1. Create three vectors from each of the encoder's input vectors:
     - Query key
     - Key vector
     - Value vector



Attention is all You Need

- Calculating self attention:
  1. Create three vectors from each of the encoder's input vectors:
  2. Use the vectors to compute the attention score
     - Score each word of the input sentence against the word we're computing attention for
     - The score determines how much focus to place on other parts of the input sentence as we encode a word at a certain position



Attention is all You Need

- Calculating self attention:
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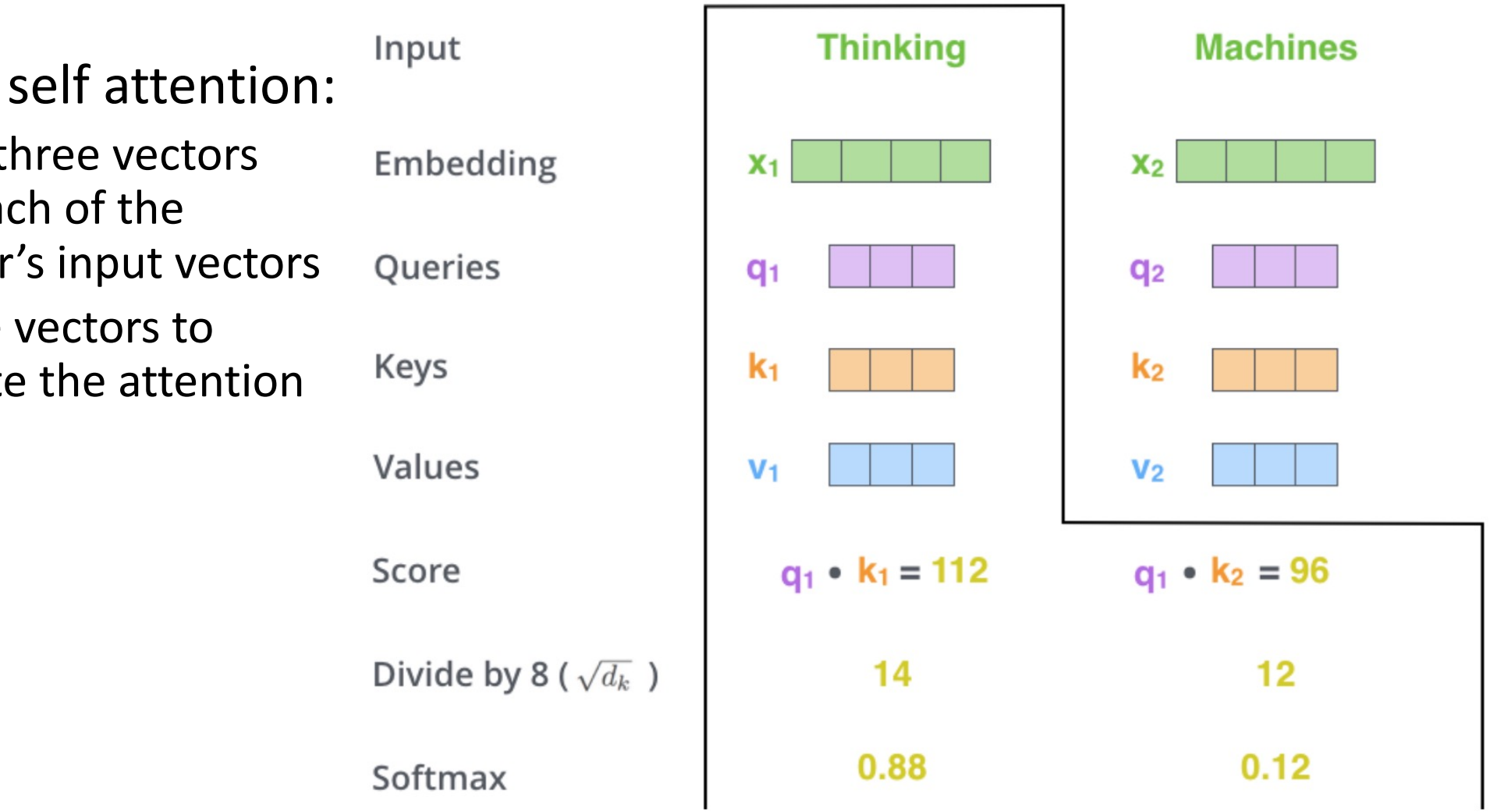
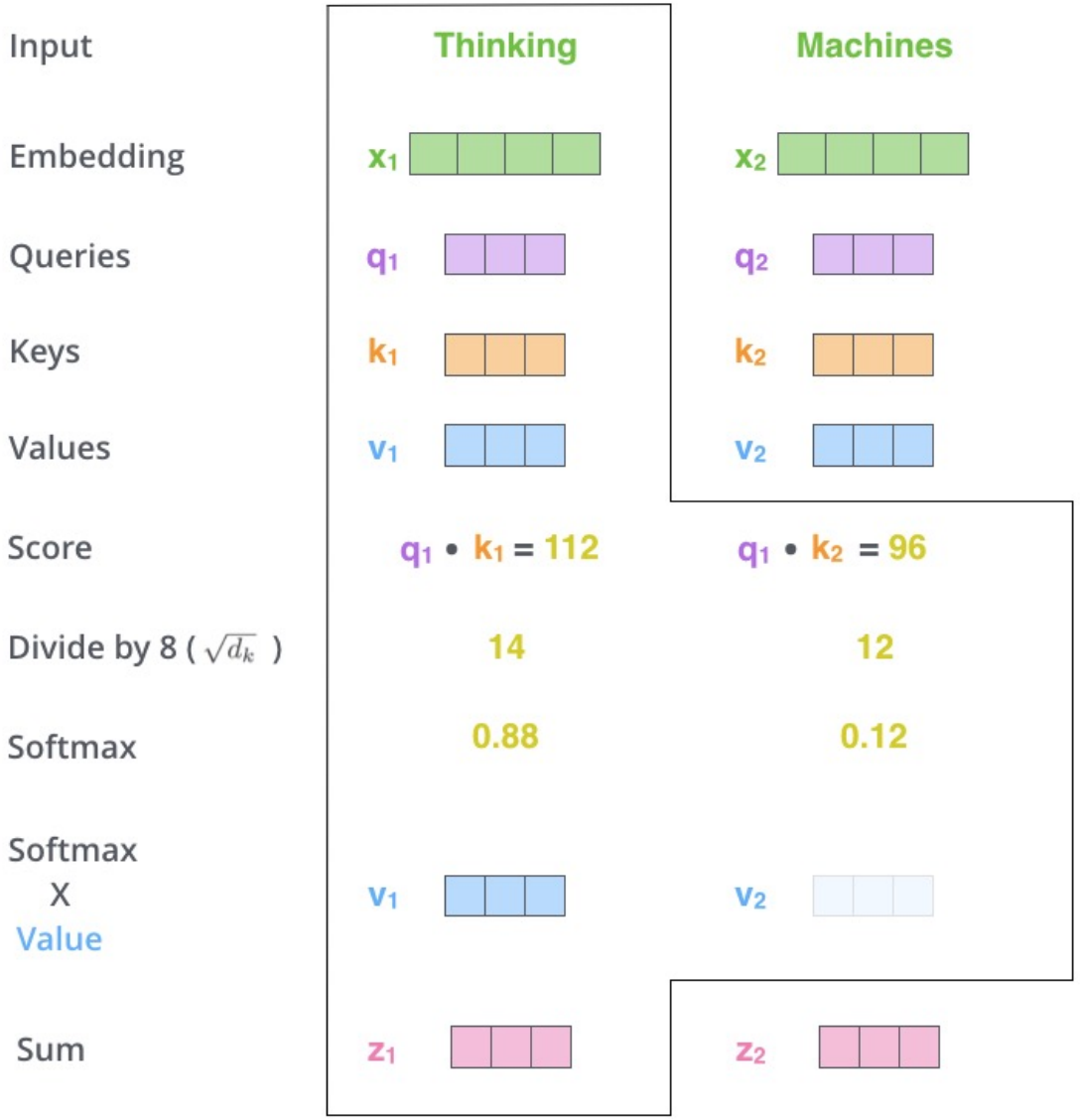


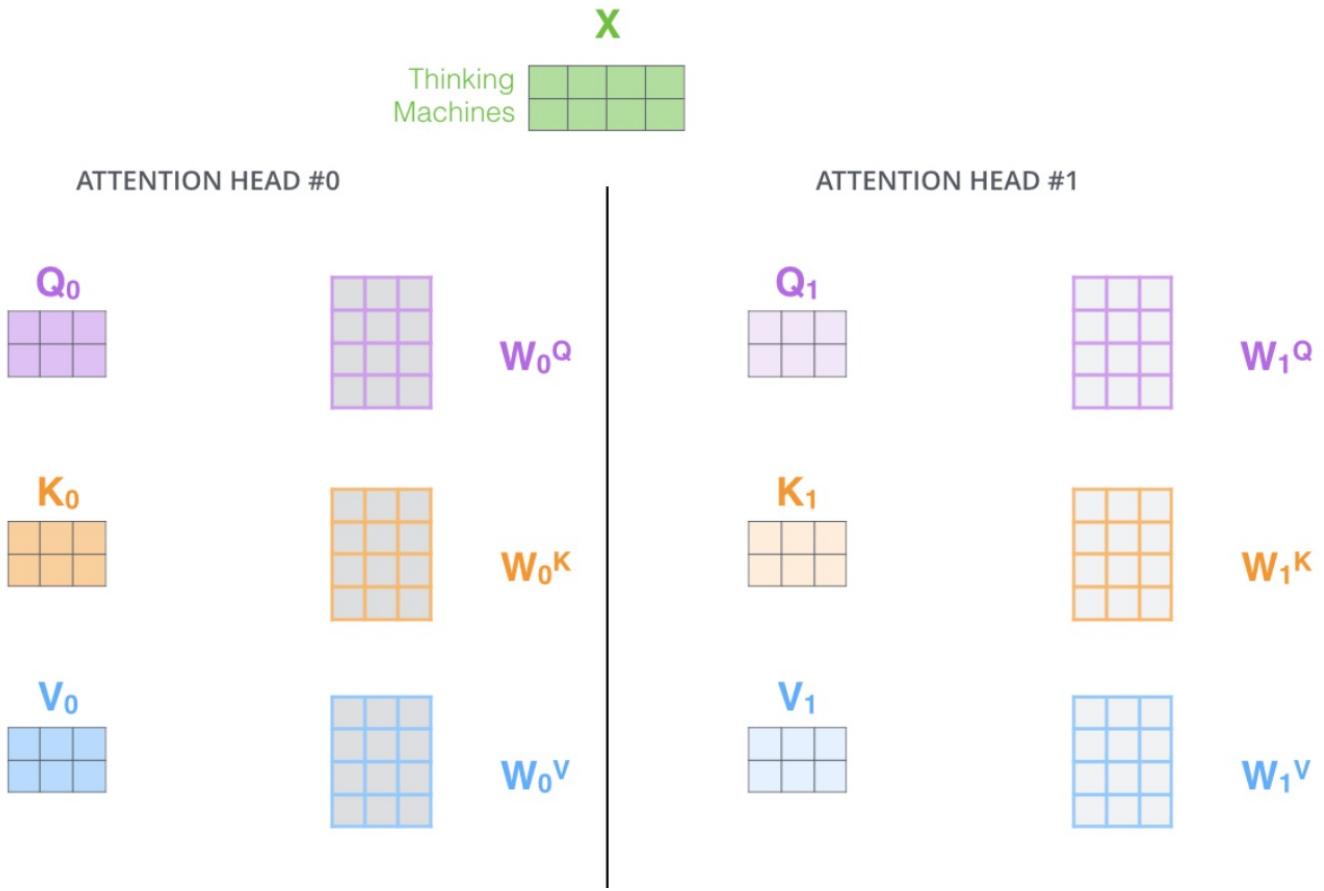
Attention is all You Need

- Calculating self attention:
  1. Create three vectors from each of the encoder's input vectors
  2. Use the vectors to compute the attention score
  3. Multiply each value vector by the softmax score and sum up the weighted value vectors to produce output of the self attention layer for this word



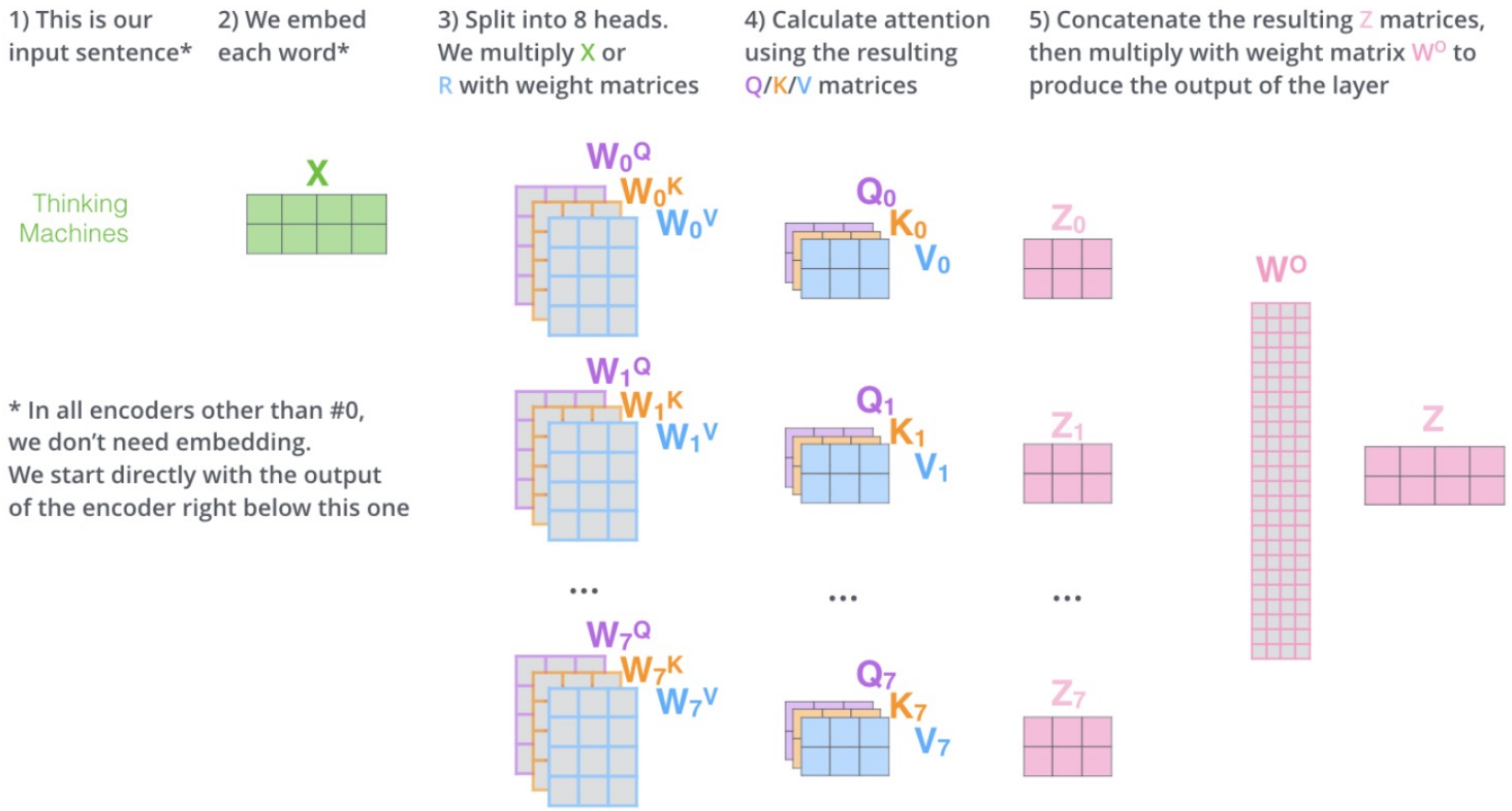
Attention is all You Need

- There are several attention heads on each layer
  - Gives the attention layer multiple ”representation subspaces”



Attention is all You Need

- Encoder summary

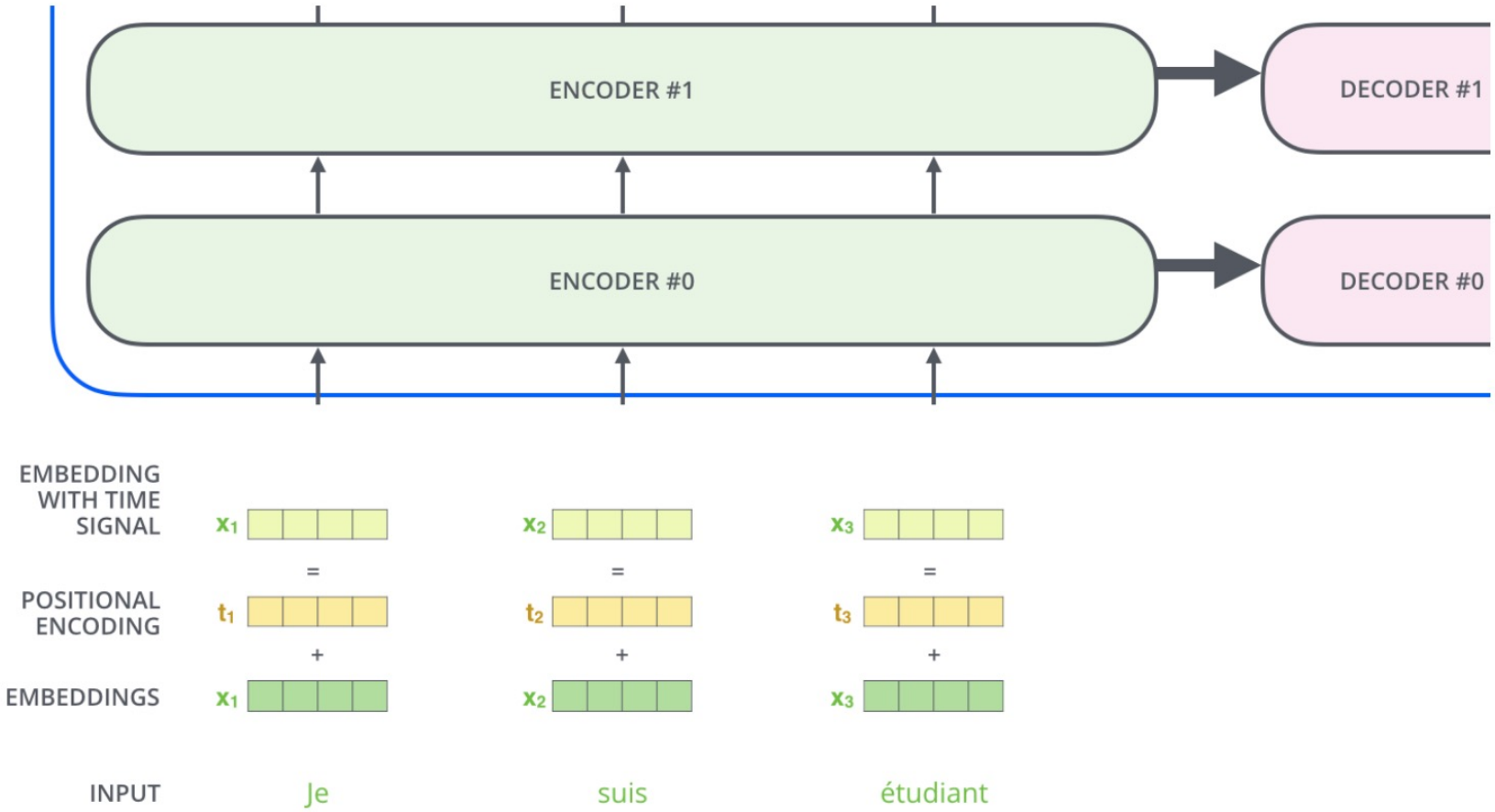


Attention is all You Need

- Positional encoding:
  - To account for the order of the words in the input sequence
  - Add a vector to each input embedding, the vector follows a specific pattern that helps the model determine the position of each word/distance between words in the sequence

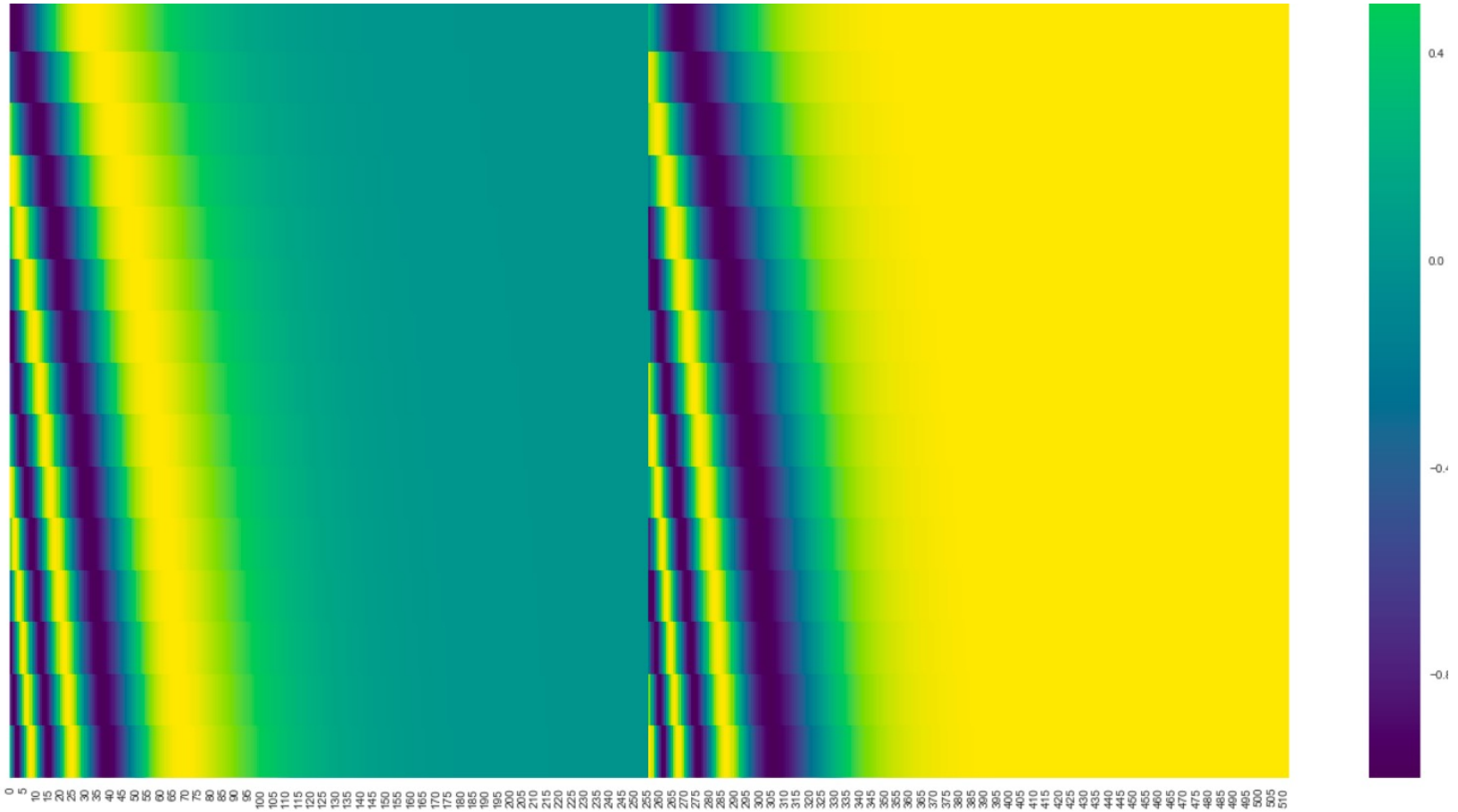
Attention is all You Need

- Positional encoding:



Attention is all You Need

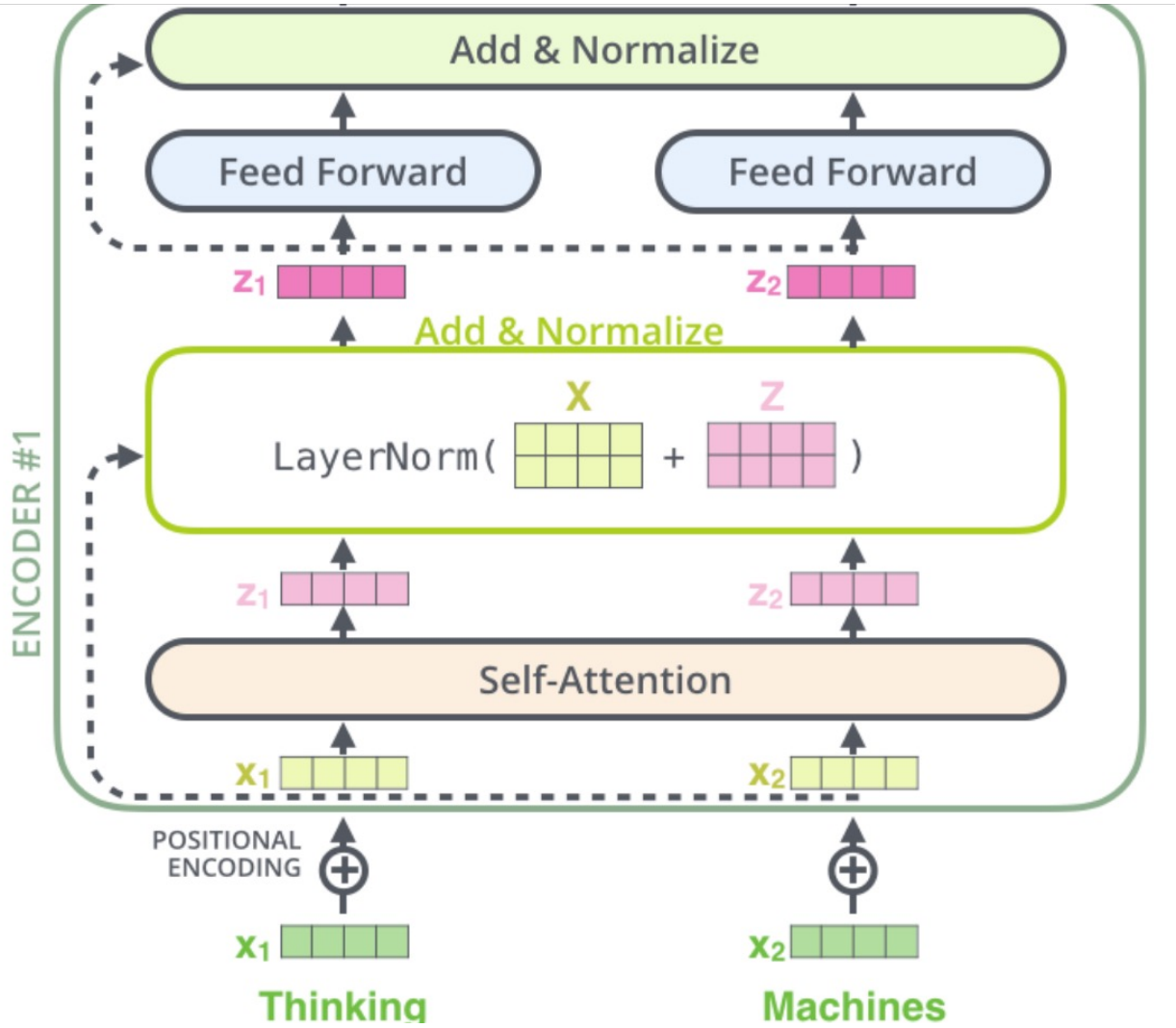
- Positional encoding:



A real example of positional encoding for 20 words (rows) with an embedding size of 512 (columns). You can see that it appears split in half down the center. That's because the values of the left half are generated by one function (which uses sine), and the right half is generated by another function (which uses cosine). They're then concatenated to form each of the positional encoding vectors.

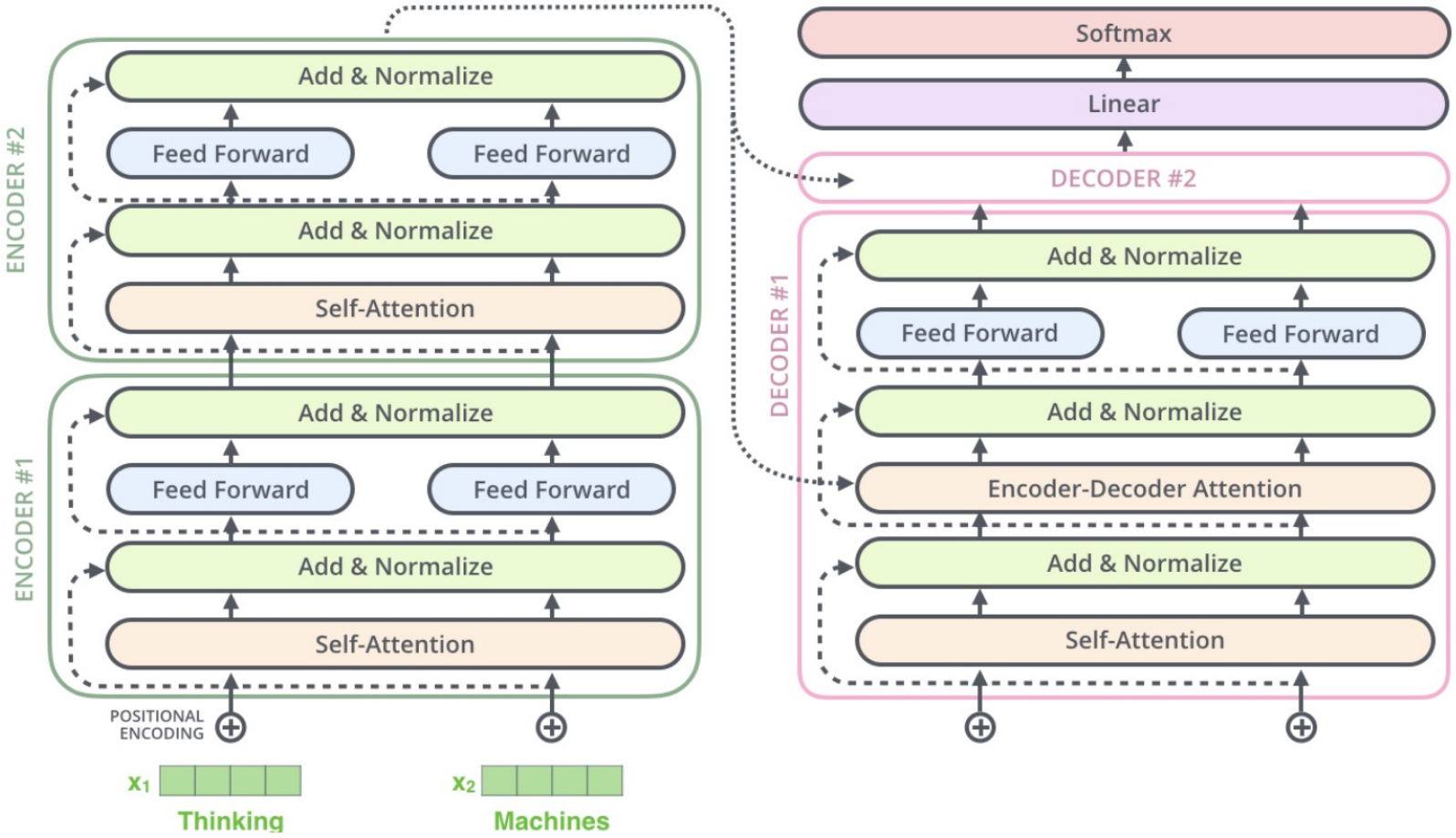
Residuals

- Each encoder has a residual connection followed by a layer-normalization step

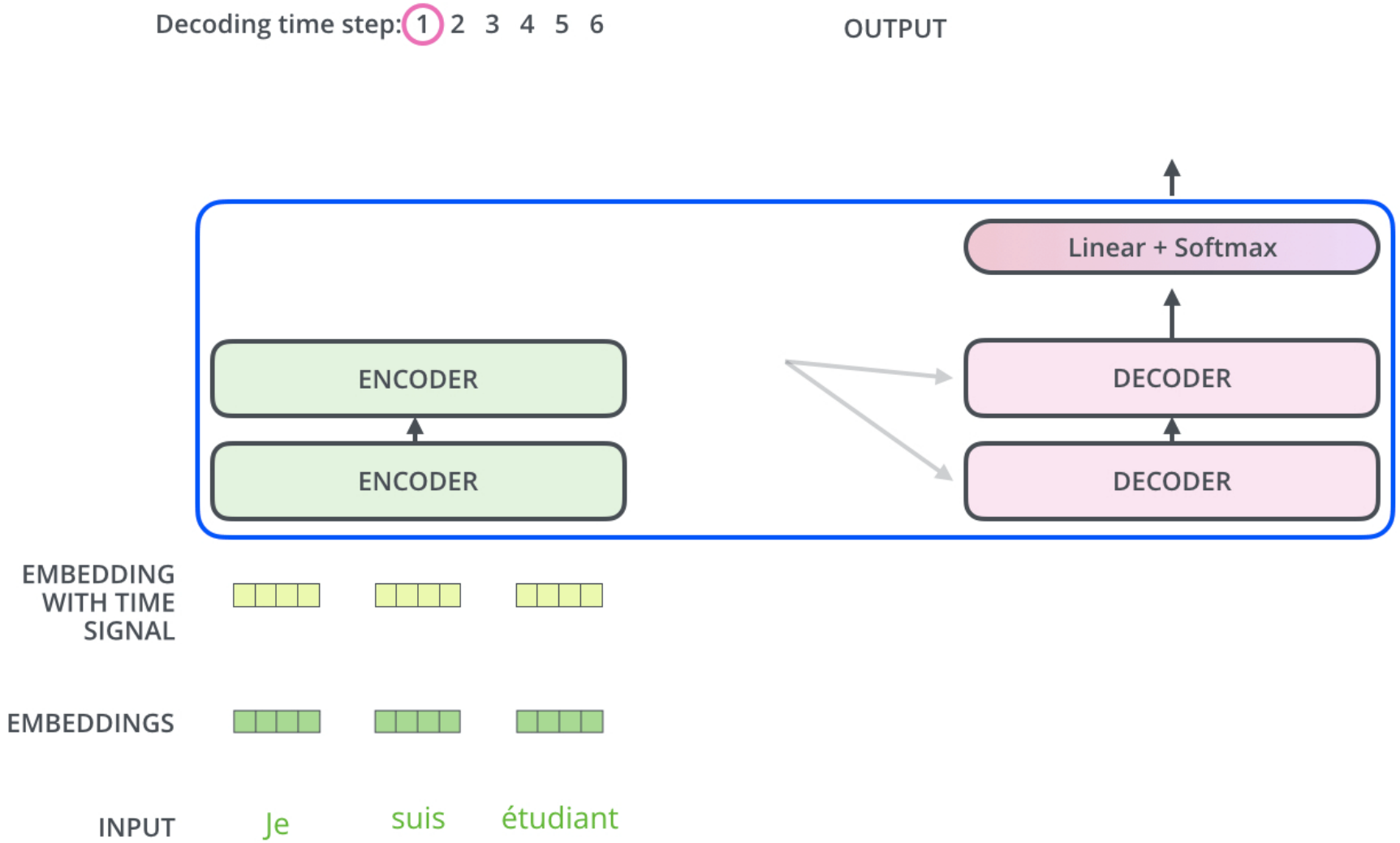


Residuals

- Goes for decoders as well

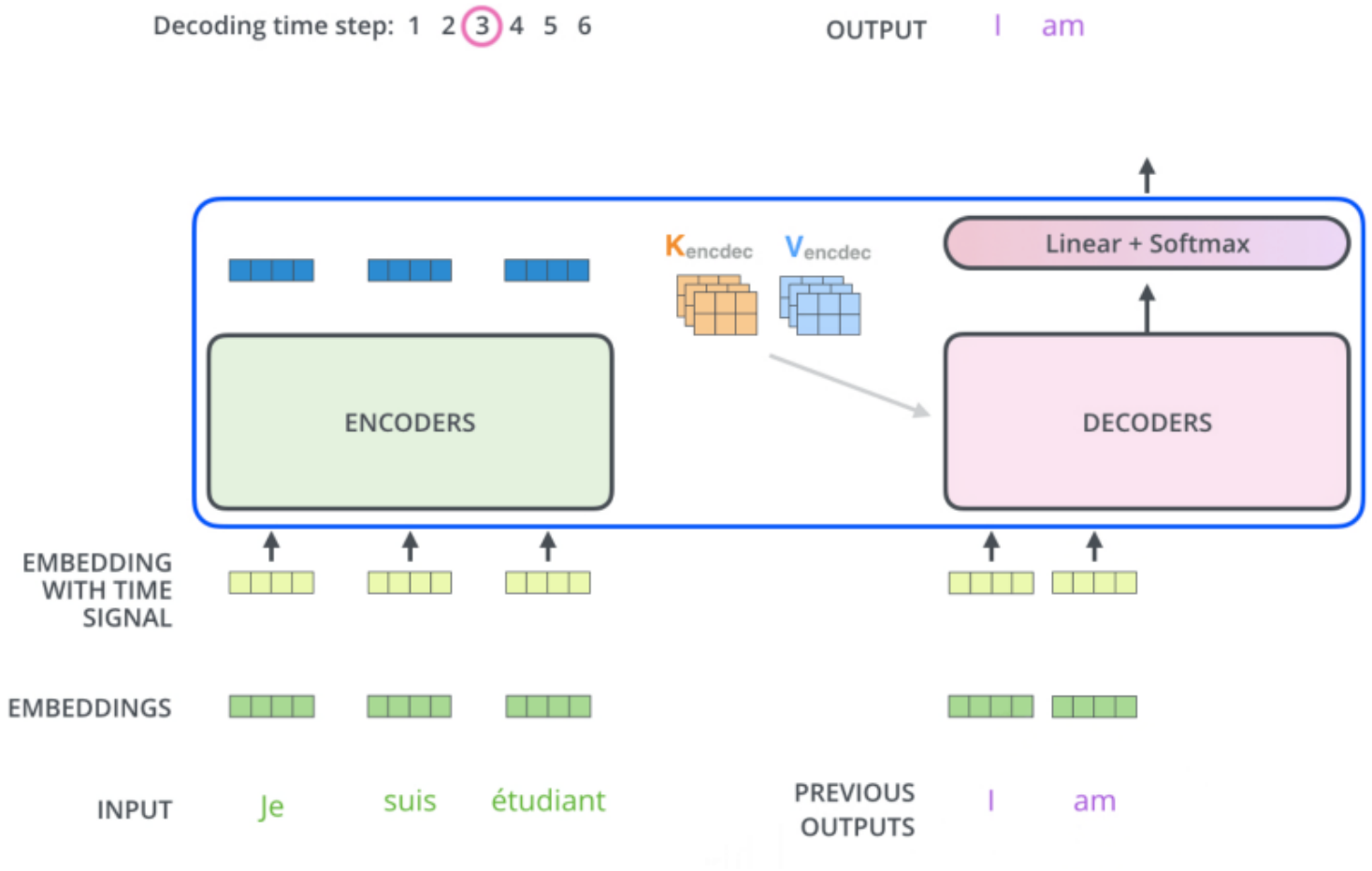


Encoder-Decoder



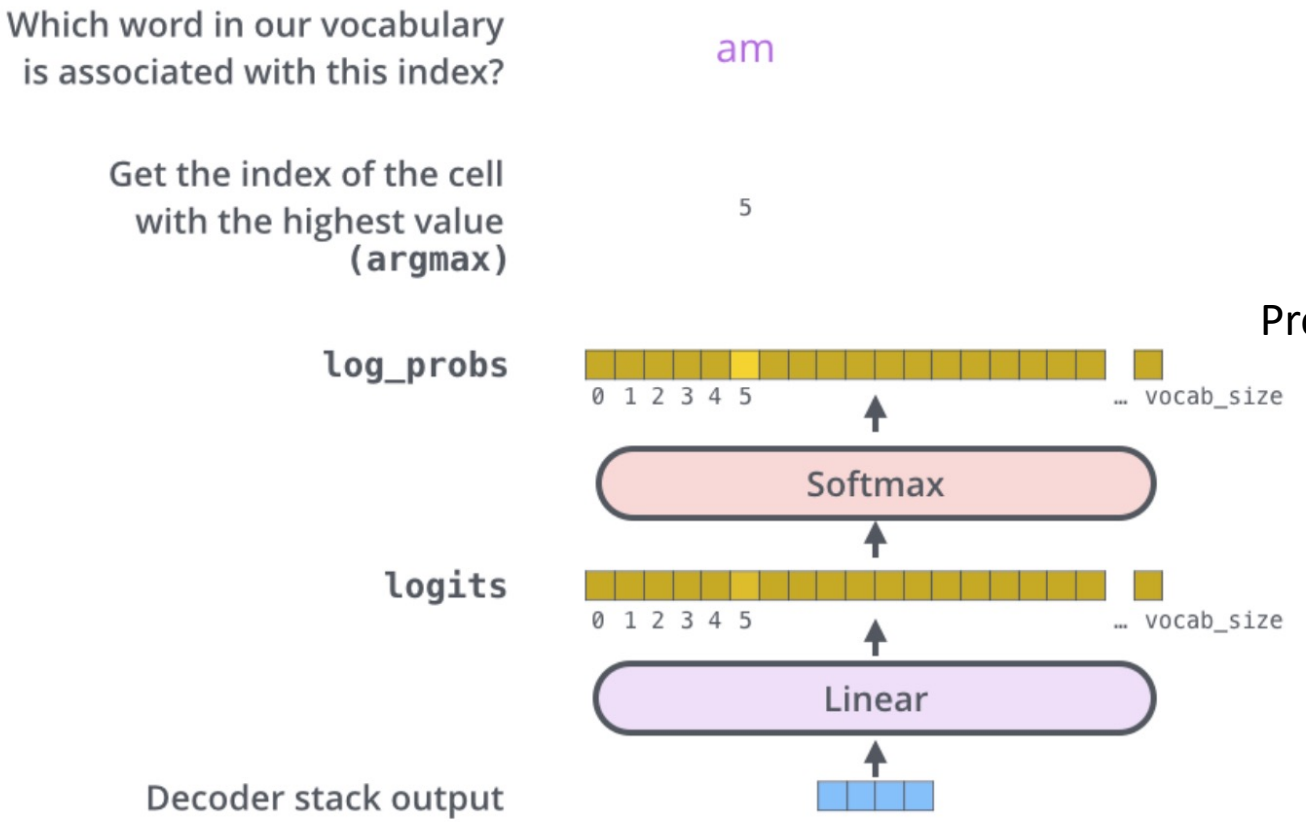
Encoder-Decoder

- The process repeats
  - Output of each step is fed to the bottom decoder in the next time step
  - Self-attention layer only attends to earlier positions in the input
  - Encoder-Decoder attention creates only Queries matrix from the layer below



Final Decoder Layer

- Output layer is turned into an output word

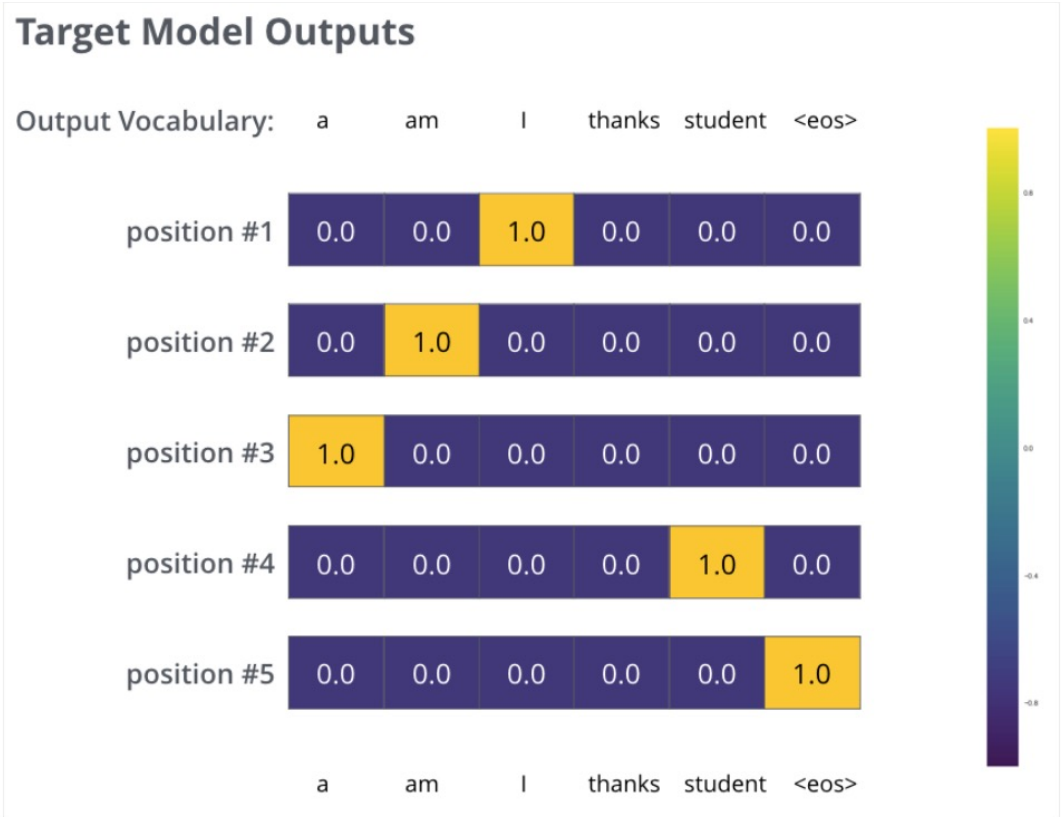


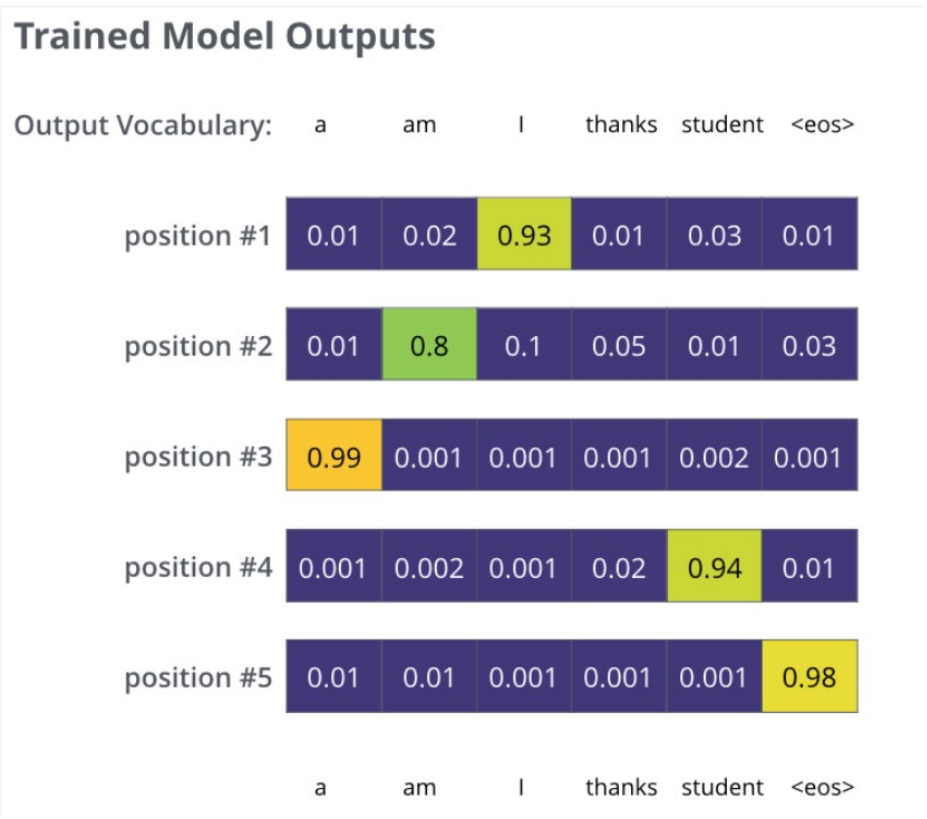
Probablity distribution over words

Final Decoder Layer

- Output layer is turned into an output word

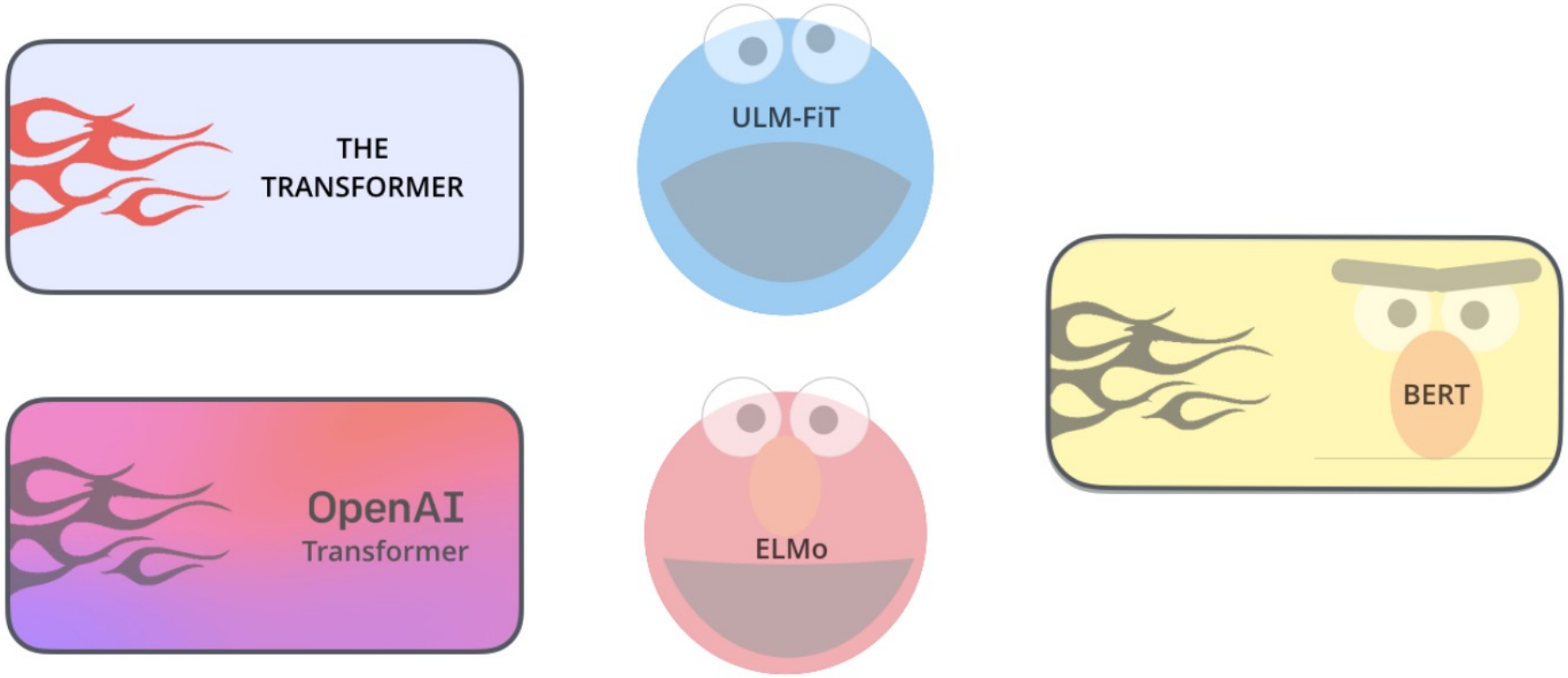
Compare probability distribution over words





Word and Sentence Representations

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



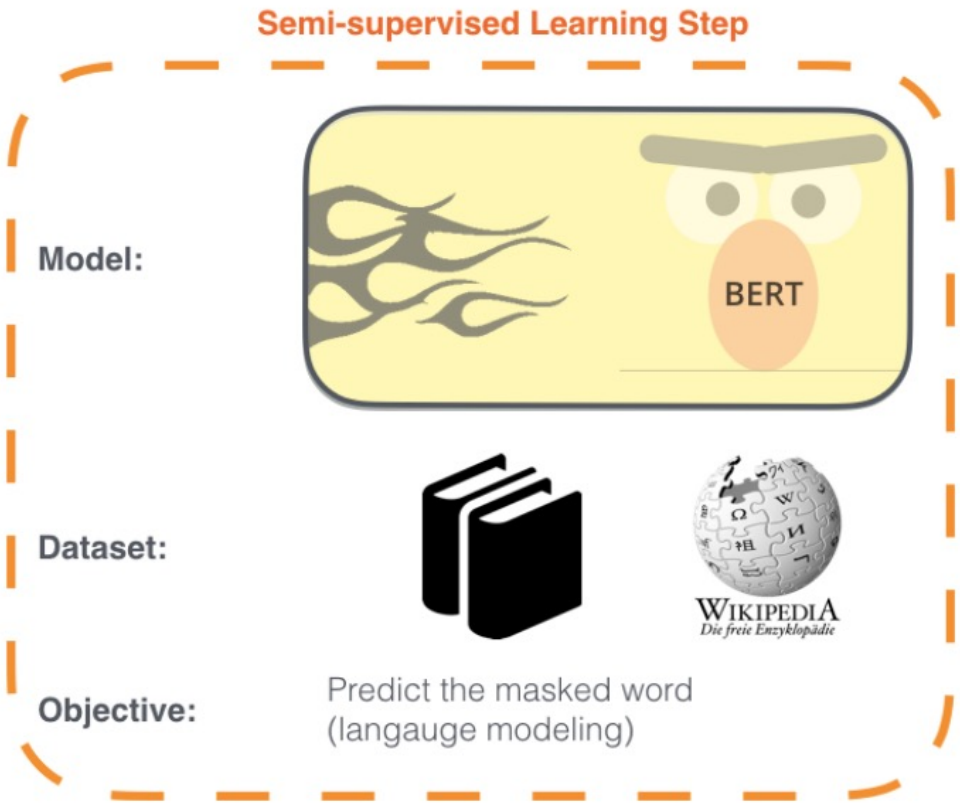
Milestone

- BERT: **B**idirectional **E**ncoder **R**epresentations from **T**ransformers
  - A new method for pre-training language representations
  - Achieve state-of-the-art results on a wide array of NLP tasks
  - https://github.com/google-research/bert
  - Enables anyone to use this pre-trained LM and fine tune the representations for their tasks, without needing to train LM model from scratch

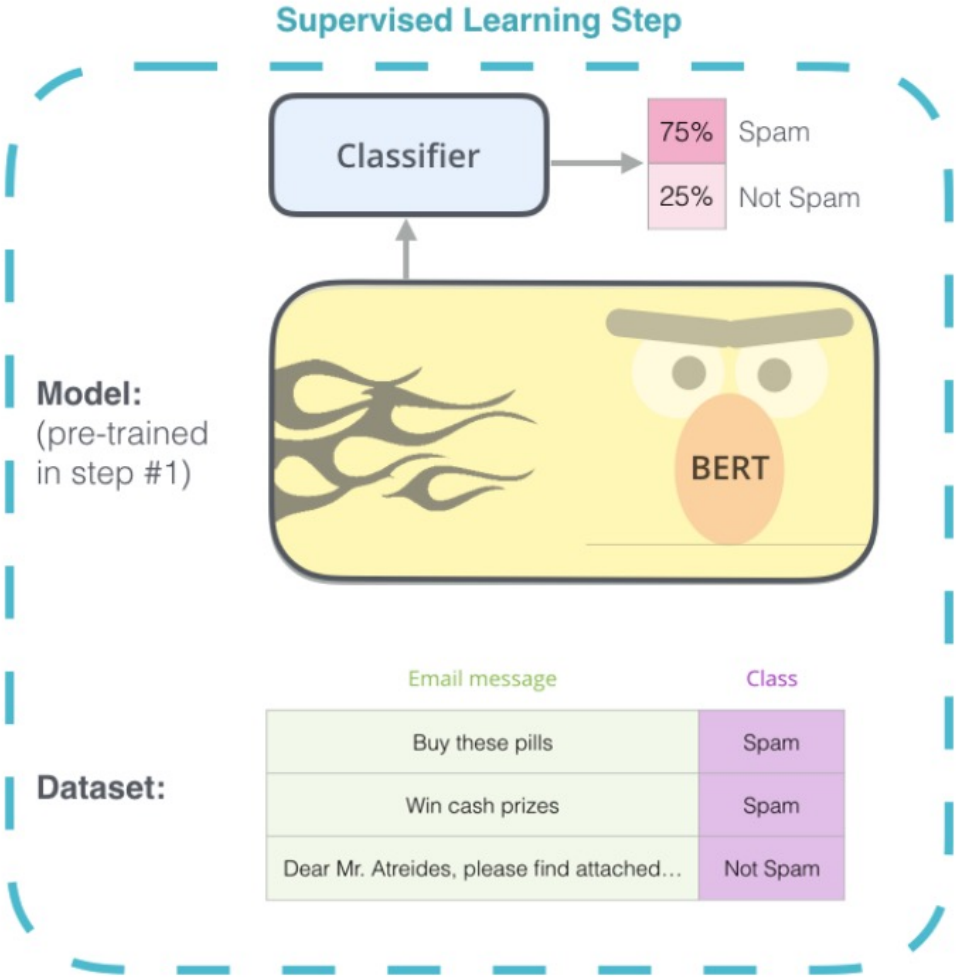
BERT

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.

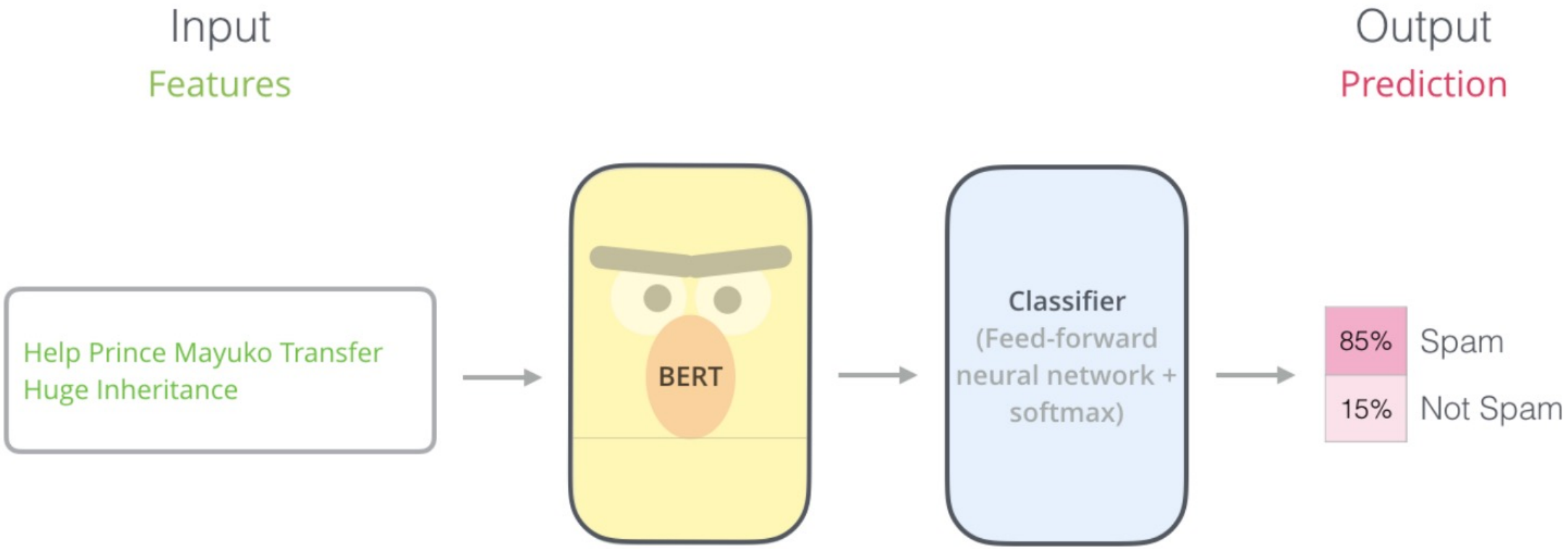


2 - Supervised training on a specific task with a labeled dataset.



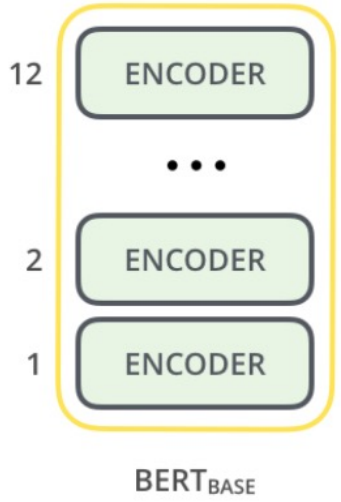
BERT

- Example: sentence classification

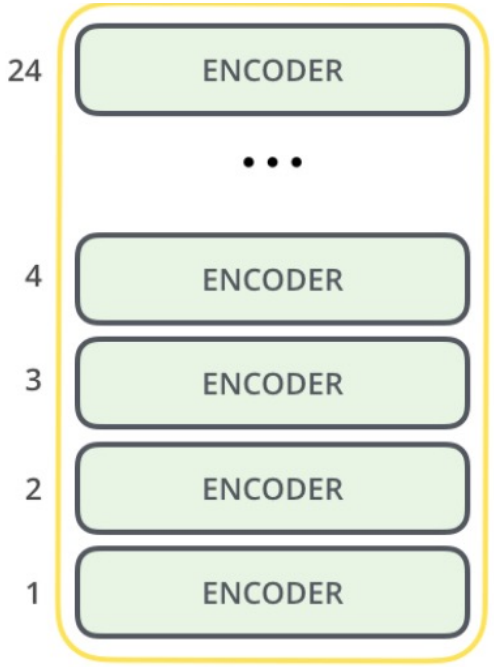


BERT

- Basically, a trained Transformed Encoder stack
- 12/24 layers
- 12/16 attention heads per layer
- 768/1024 hidden units in FFNN
- Initial transformer has:
  - 6 layers
  - 8 attention heads
  - 512 hidden units



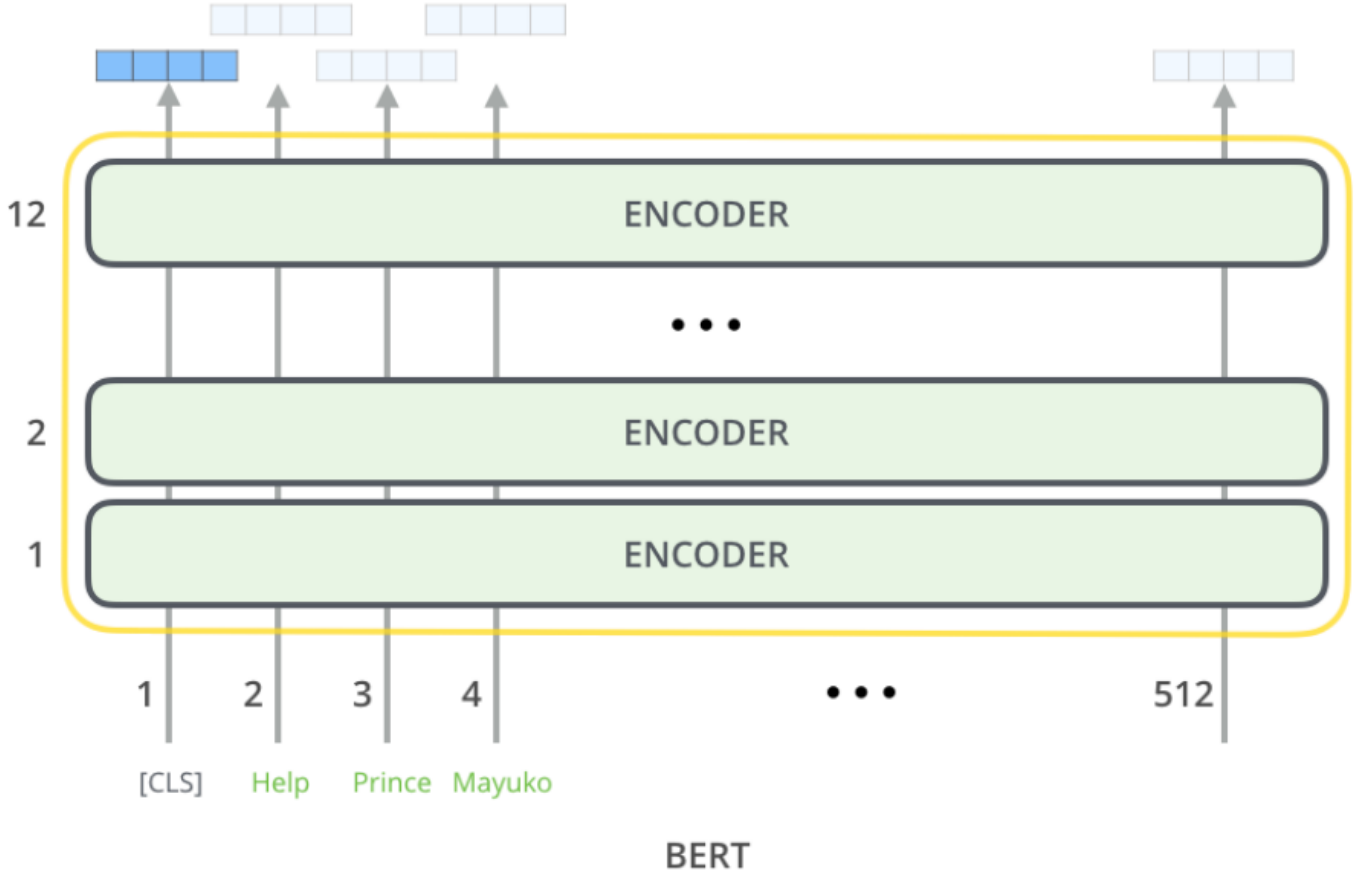
$BERT_{BASE}$



$BERT_{LARGE}$

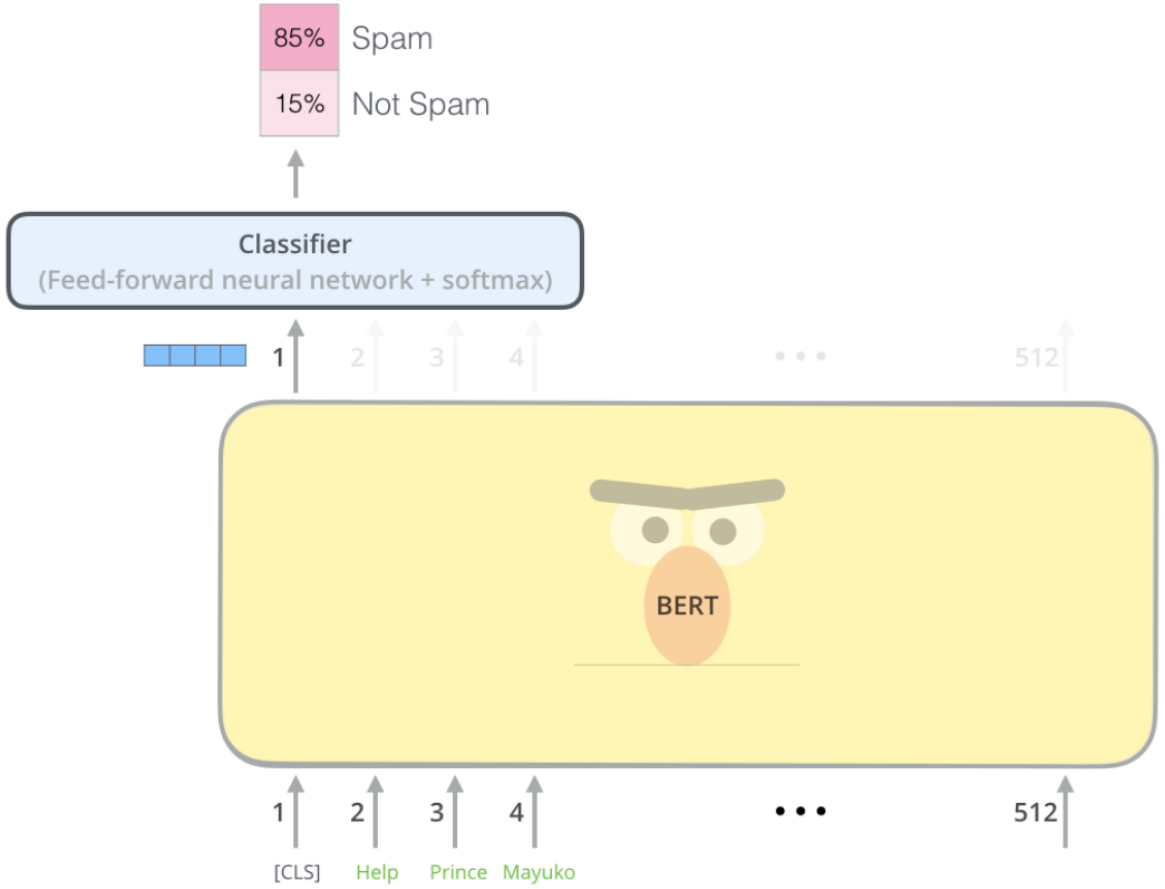
BERT

- Each position outputs a vector of size hidden_size (768/1024)



BERT

- The output vector can then be used as the input for a classifier of our choosing



Context Encoding

- Word2vec, Glove don’t really take context into consideration
  - The word “bank” has the same embedding no-matter what the context

Context Encoding

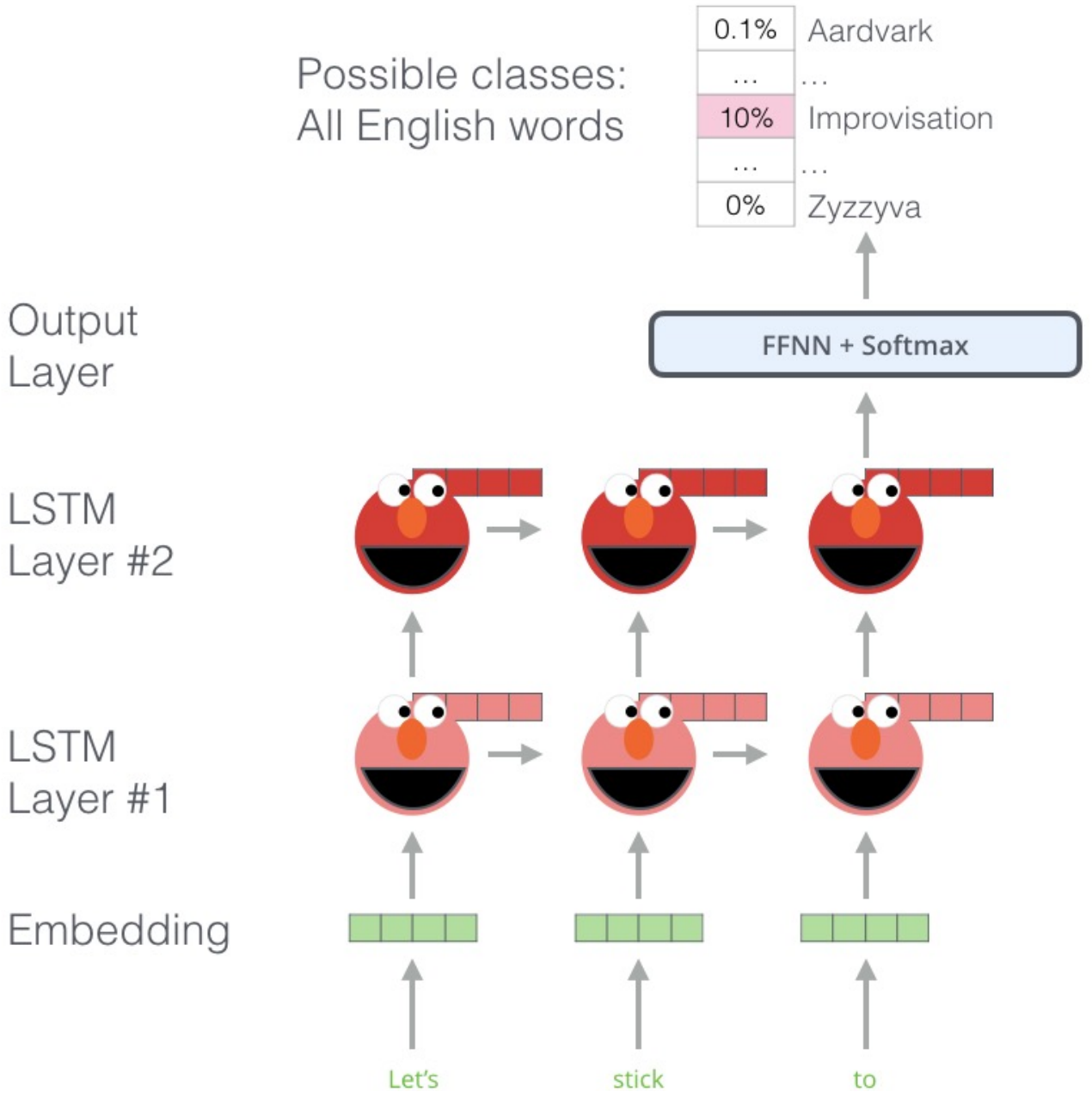
- Context2vec, ELMo were the start of the contextualized-word embeddings

ELMo

- Instead of using a fixed embedding for each word, ELMo looks at the entire sentence before assigning each word in it an embedding
  - It uses bi-directional LSTM to create those embeddings
  - Trained to predict the next word in a sequence of words – another way of saying doing “language modeling”

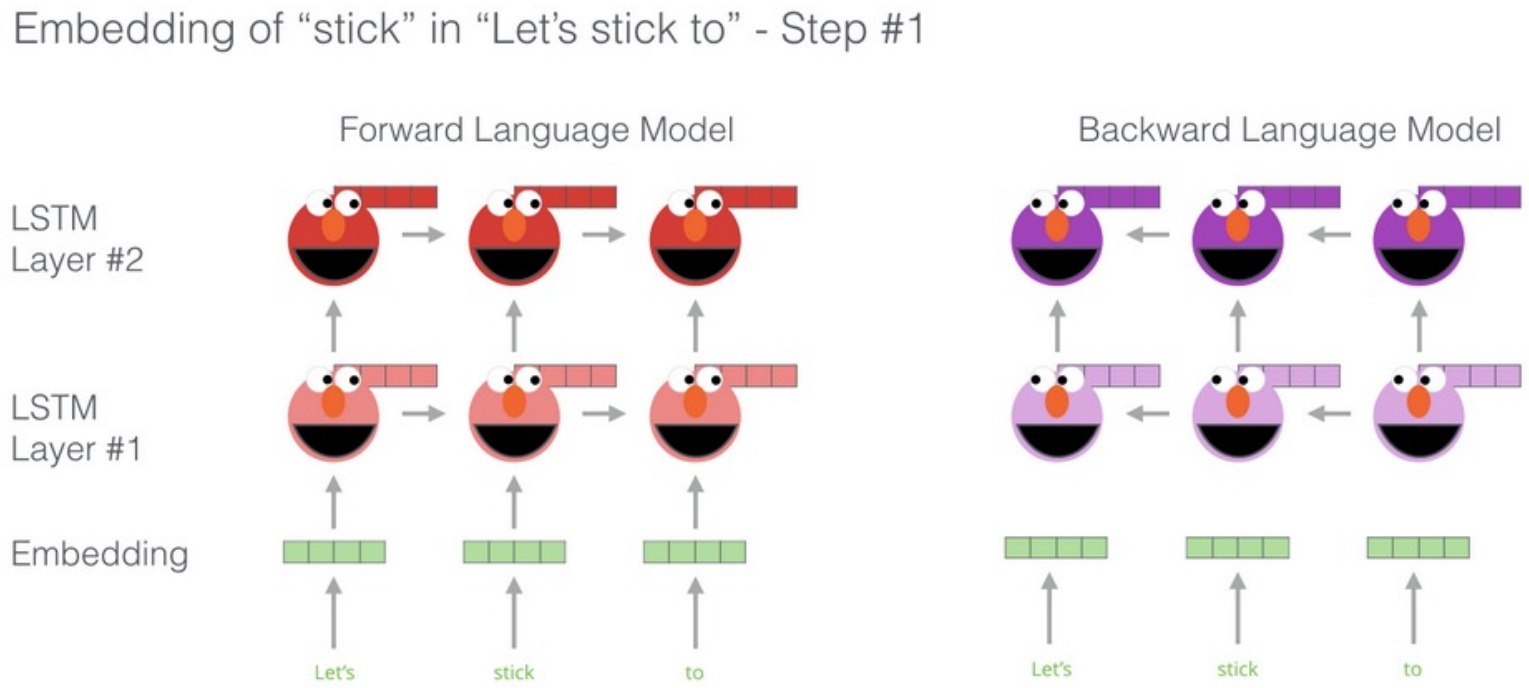
ELMo

- Trained to predict the next word in a sequence of words – a.k.a. LM



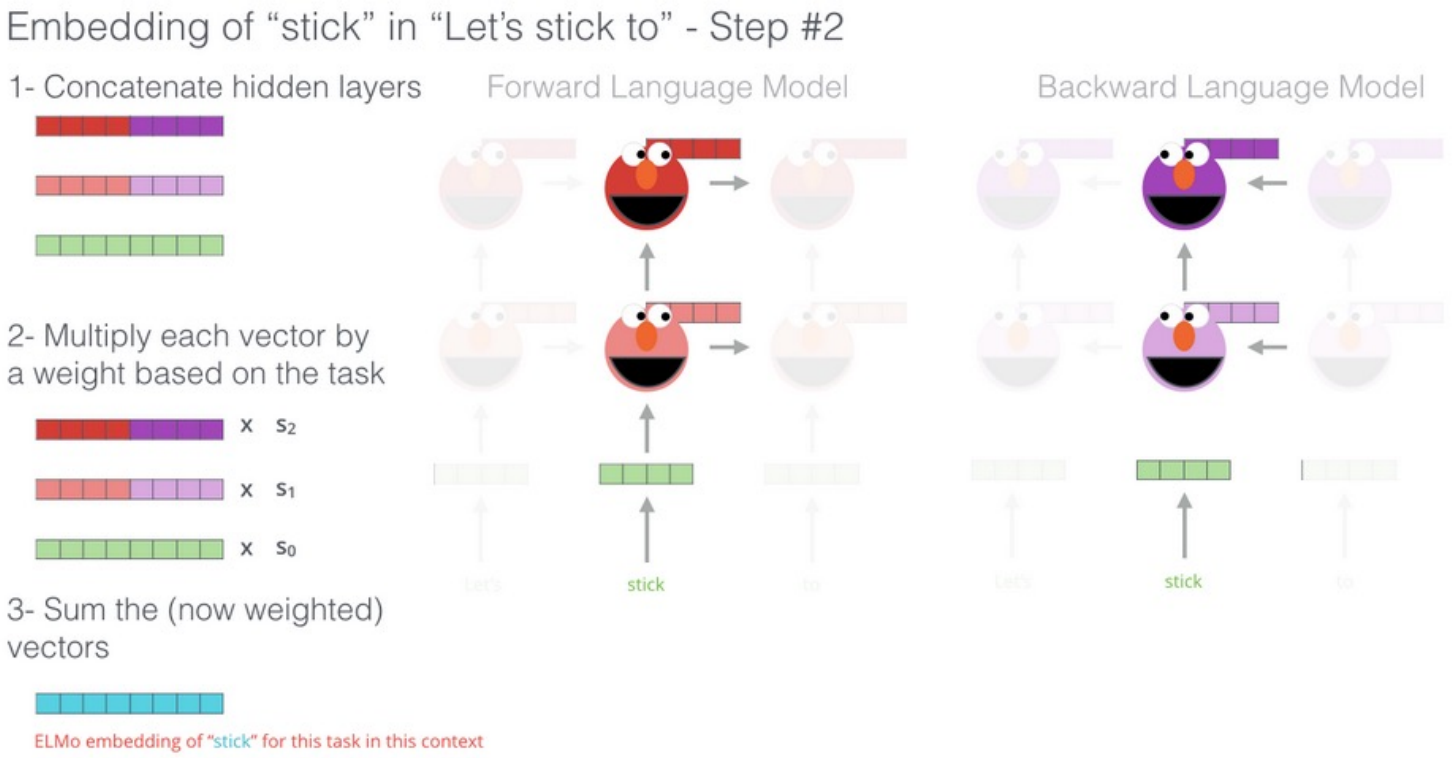
ELMo

- Use bi-directional LSTM, so that the representation of a word is informed by its next *and* previous word



ELMo

- Create a contextualized-embedding by grouping together the hidden states and initial embedding (concatenation followed by weighted summation)

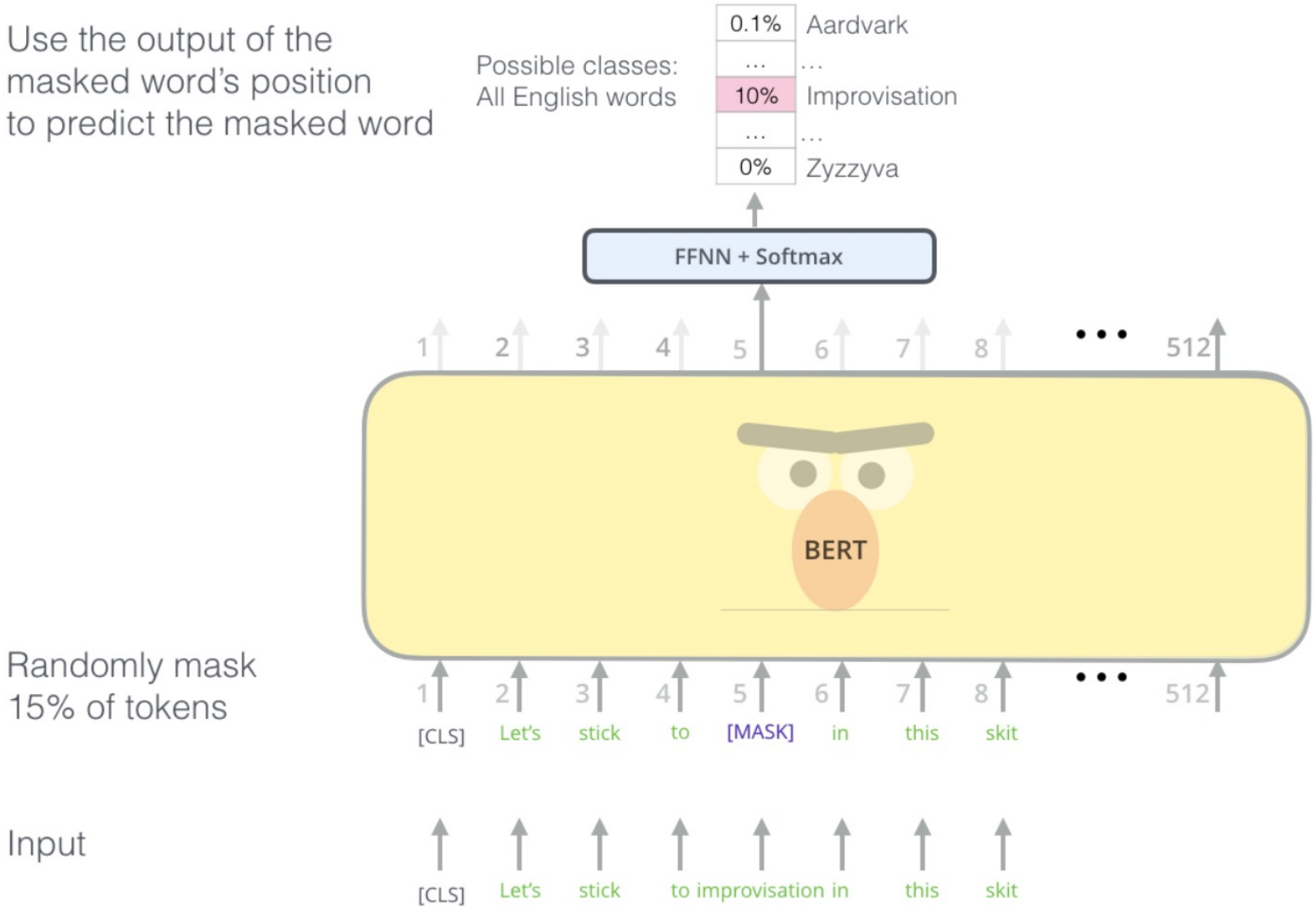


BERT

- Transformer-encoder model whose LM looks both forward and backward
  - Cannot be trained like other typical “predict the next word in the sequence” LM since transformer-encoder is multi layered and absorbs all parts of the input sentence at once
  - Using Masked LM

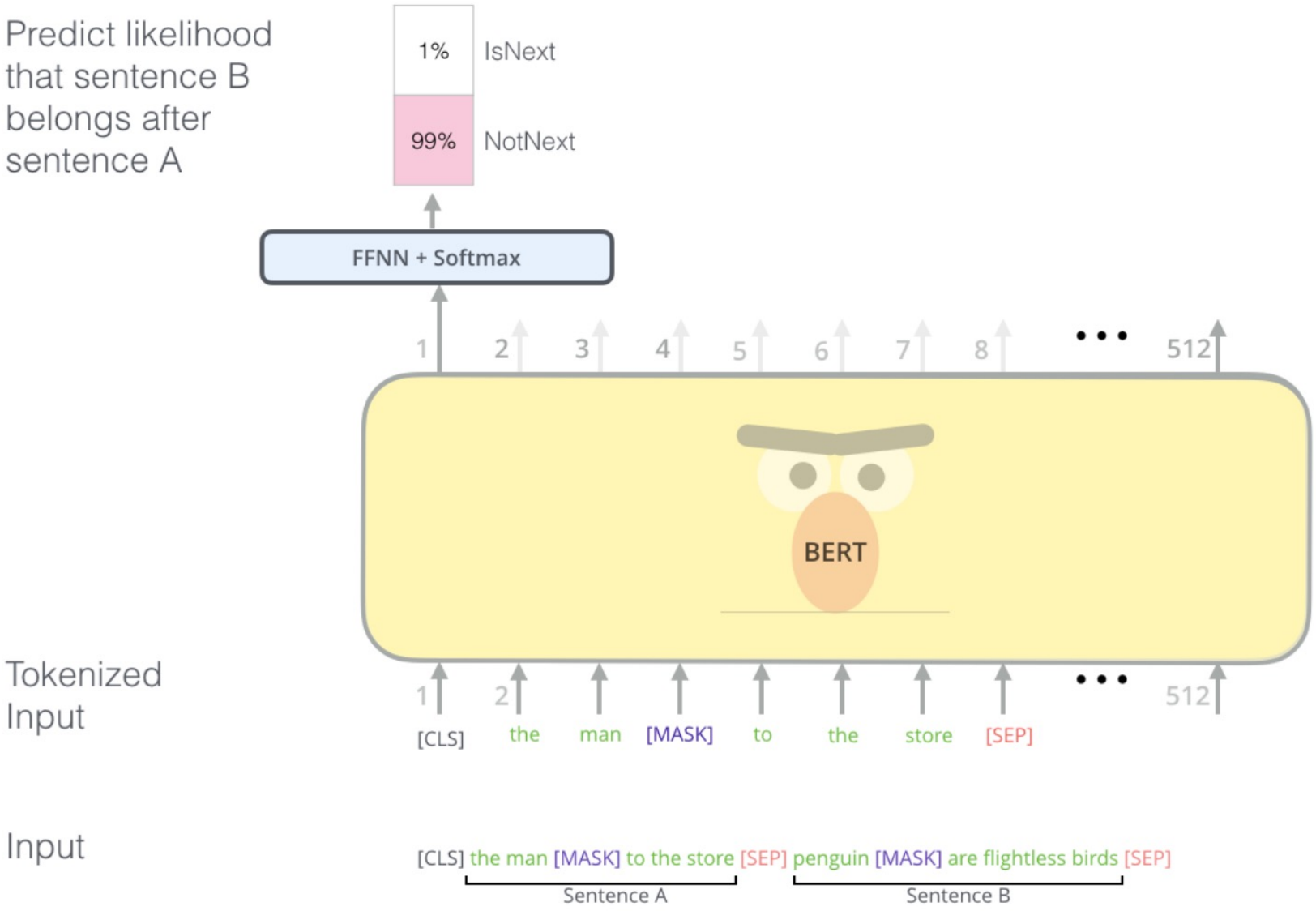
BERT

- Masked LM
  also called a Cloze task
- Also randomly replaces a word with another word and asks to predict the correct word



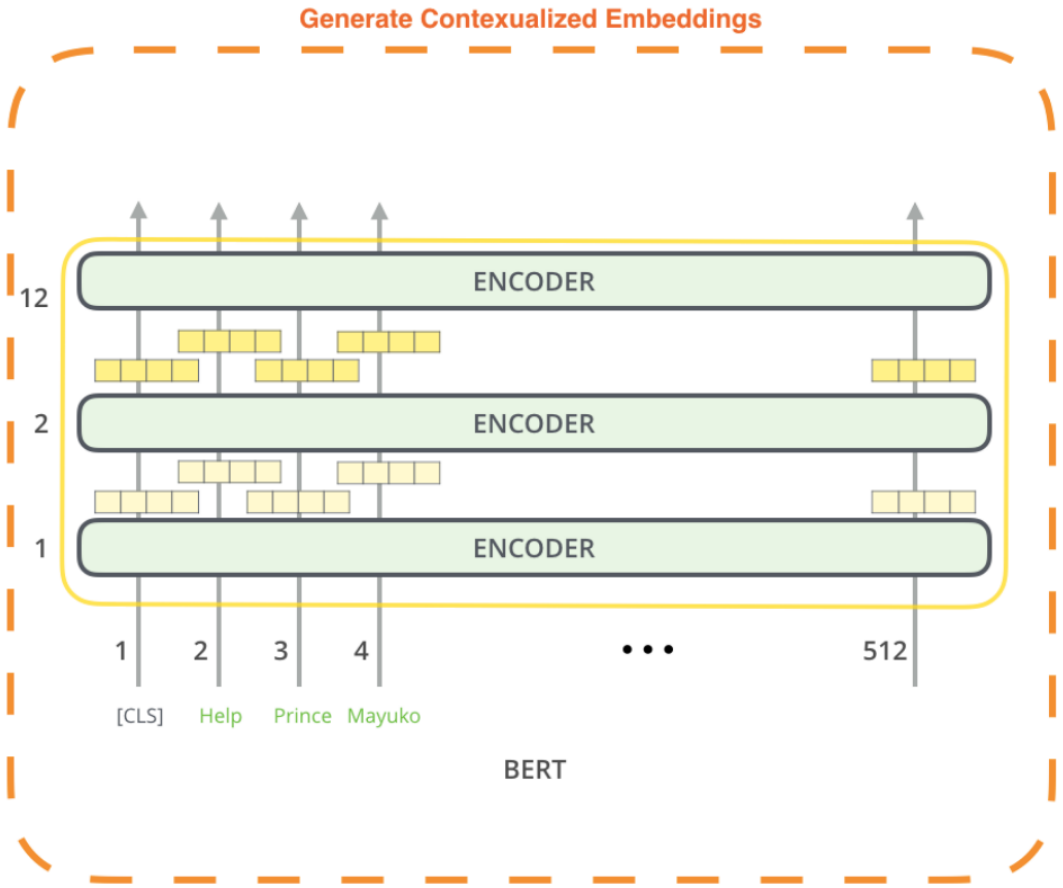
BERT

- Also trained on multiple sentences

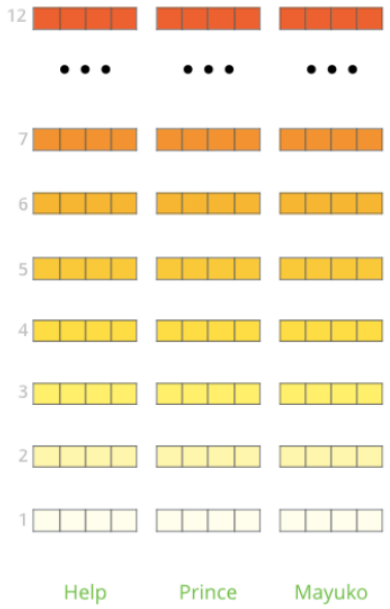


BERT

- Can also be used to create embeddings (without fine tuning)



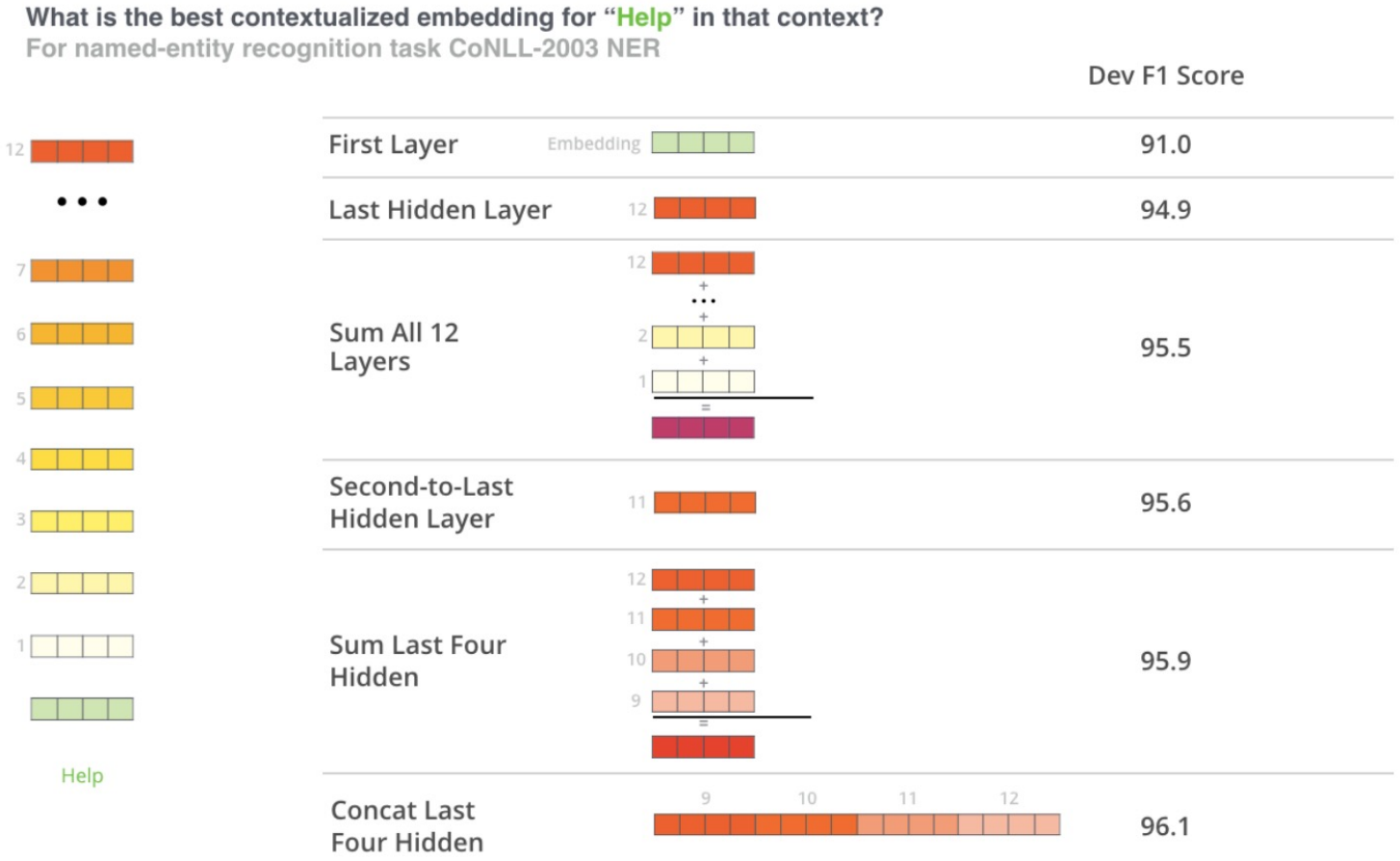
The output of each encoder layer along each token's path can be used as a feature representing that token.



But which one should we use?

BERT

- Can also be used to create embeddings (without fine tuning)



Try out BERT and other Transformers

- https://github.com/google-research/bert
- https://github.com/huggingface/transformers

GPT Language Models

The importance of being on twitter

by Jerome K. Jerome
London, Summer 1897

It is a curious fact that the last remaining form of social life in which the people of London are still interested is Twitter. I was struck with this curious fact when I went on one of my periodical holidays to the sea-side, and found the whole place twittering like a starling-cage. I called it an anomaly, and it is.

I spoke to the sexton, whose cottage, like all sexton's cottages, is full of antiquities and interesting relics of former centuries. I said to him, "My dear sexton, what does all this twittering mean?" And he replied, "Why, sir, of course it means Twitter."
"Ah!" I said, "I know about that. But what is Twitter?"

"It is a system of short and pithy sentences strung together in groups, for the purpose of conveying useful information to the initiated, and entertainment and the exercise of wits to the initiated, and entertainment and the exercise of wits to the rest of us."

"Very interesting," I said. "Has it a name?"
"It has," he said; "it is called Twitter.
"Yes," I said, "I know that, but what is it?"
"It is a system of information," he said.
"Oh, yes," I replied; "but what is it?"

"Why, sir," he said, "you can go up to any of the gentlemen you see twittering in the street, and say to him, 'You are a fool,' or 'Your wife is an adulteress,' or 'You have stolen that hat,' and if he is a member of the initiated he will answer you in the same form and tell you that you are a liar, or that your eyes resemble the eyes of a duck, or that you have stepped out of your part in the last charade you acted in, or that you were for a short time a statistician in a Government Office, and he will go on to tell you the whole story of your life, in language so exceedingly small and pointed that even you will be glad you can't understand it.

Mario Klingemann 🇺🇦 ✓
@quasimondo

Another attempt at a longer piece. An imaginary Jerome K. Jerome writes about Twitter. All I seeded was the title, the author's name and the first "It", the rest is done by #gpt3

Here is the full-length version as a PDF: drive.google.com/file/d/1qtPa1c...

11:25 AM · Jul 18, 2020 · Twitter Web App

400 Retweets **176** Quote Tweets

1,265 Likes

Tweet your reply

Reply

https://jalammar.github.io/illustrated-gpt2/

GPT Language Models

- Language model that is able to look at part of a sentence and predict the next word
  - Autocomplete
  - Larger, more sophisticated
    - GPT-2 is trained on 40GB WebText
    - Takes 500MBs for storage (smallest) to 6.5GB (largest)

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GPT Language Models

BERT 110M parameters

117M Parameters

345M Parameters

762M Parameters

1,542M Parameters

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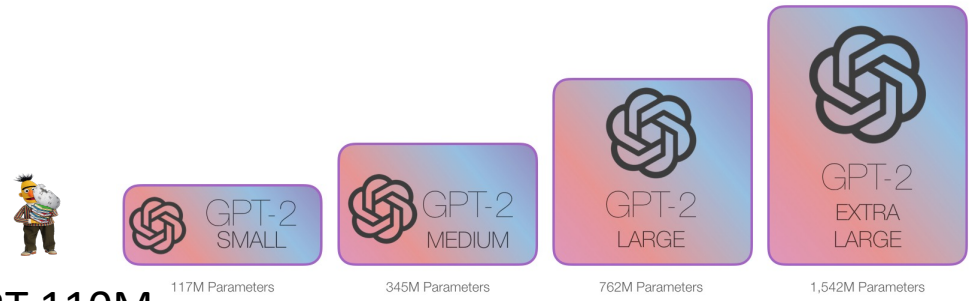
GPT Language Models



BERT 110M parameters

175B parameters

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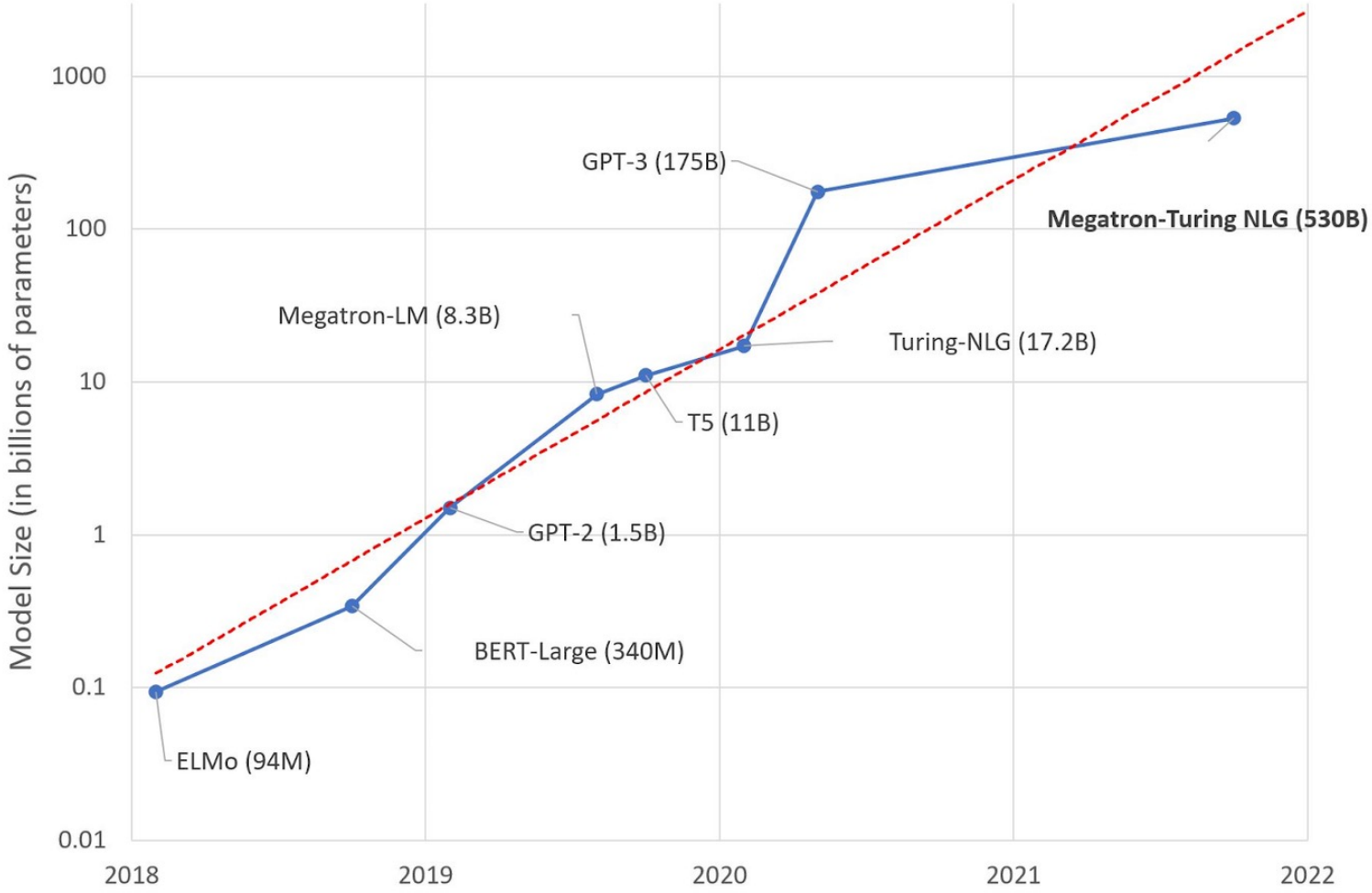
GPT Language Models



https://lastweekin.ai/p/gpt-3-is-no-longer-the-only-game?s=r

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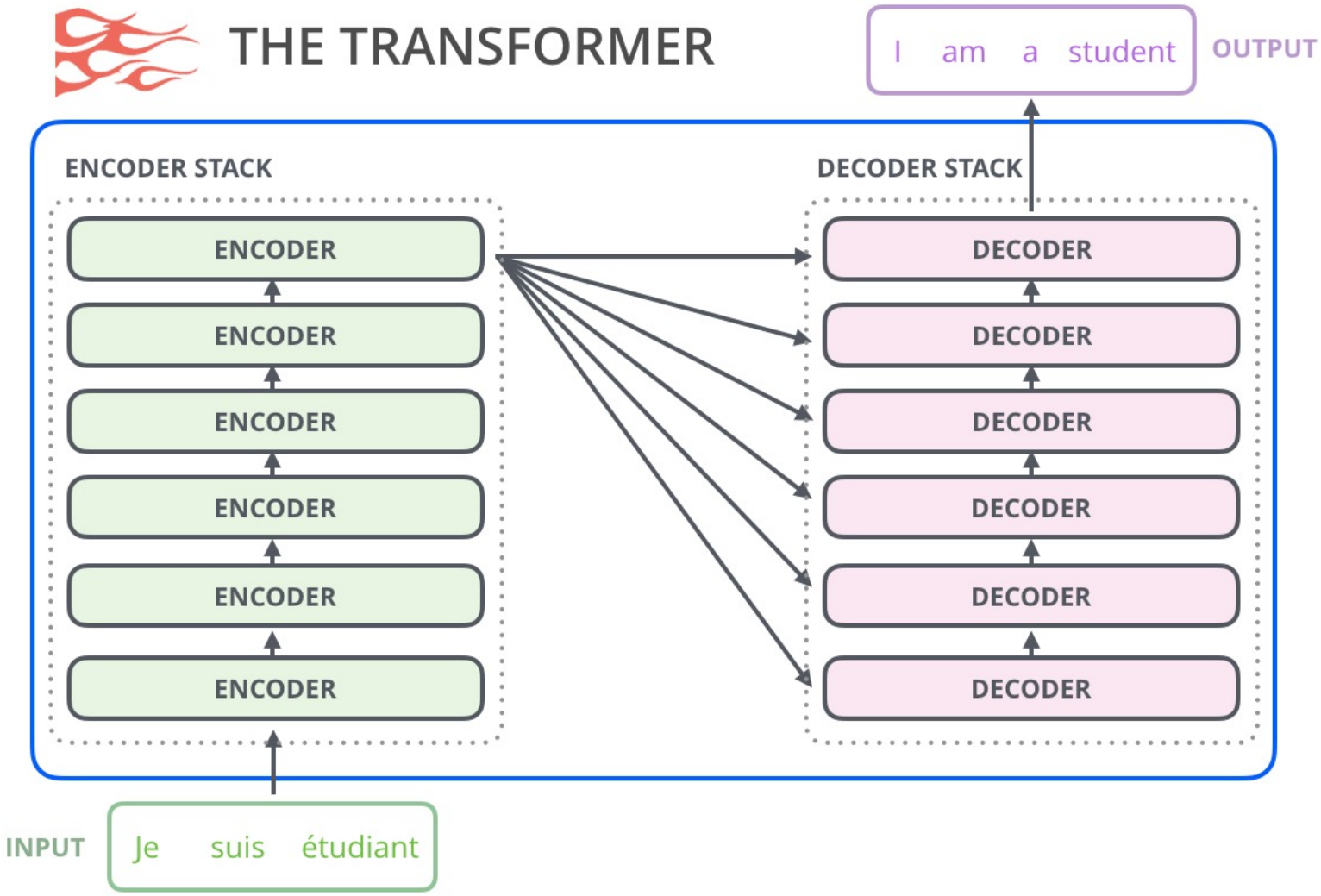
GPT Language Models



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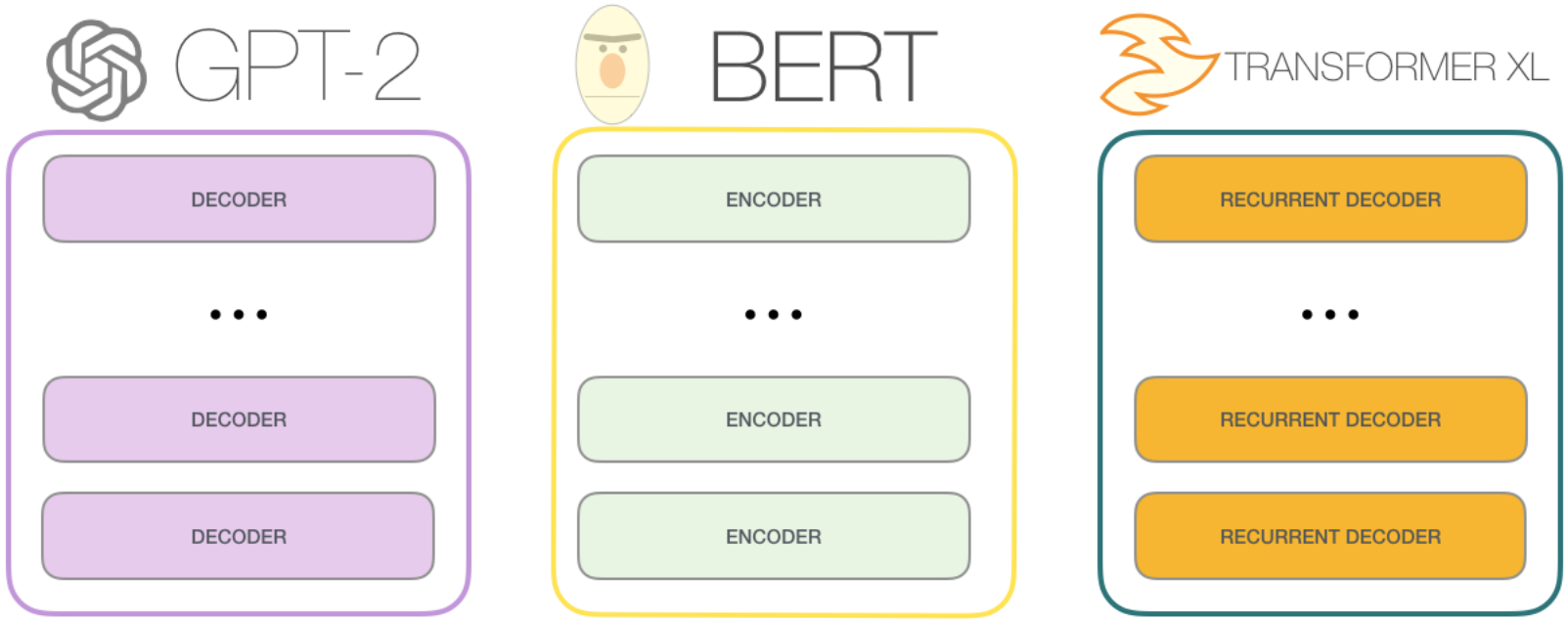
GPT Language Models



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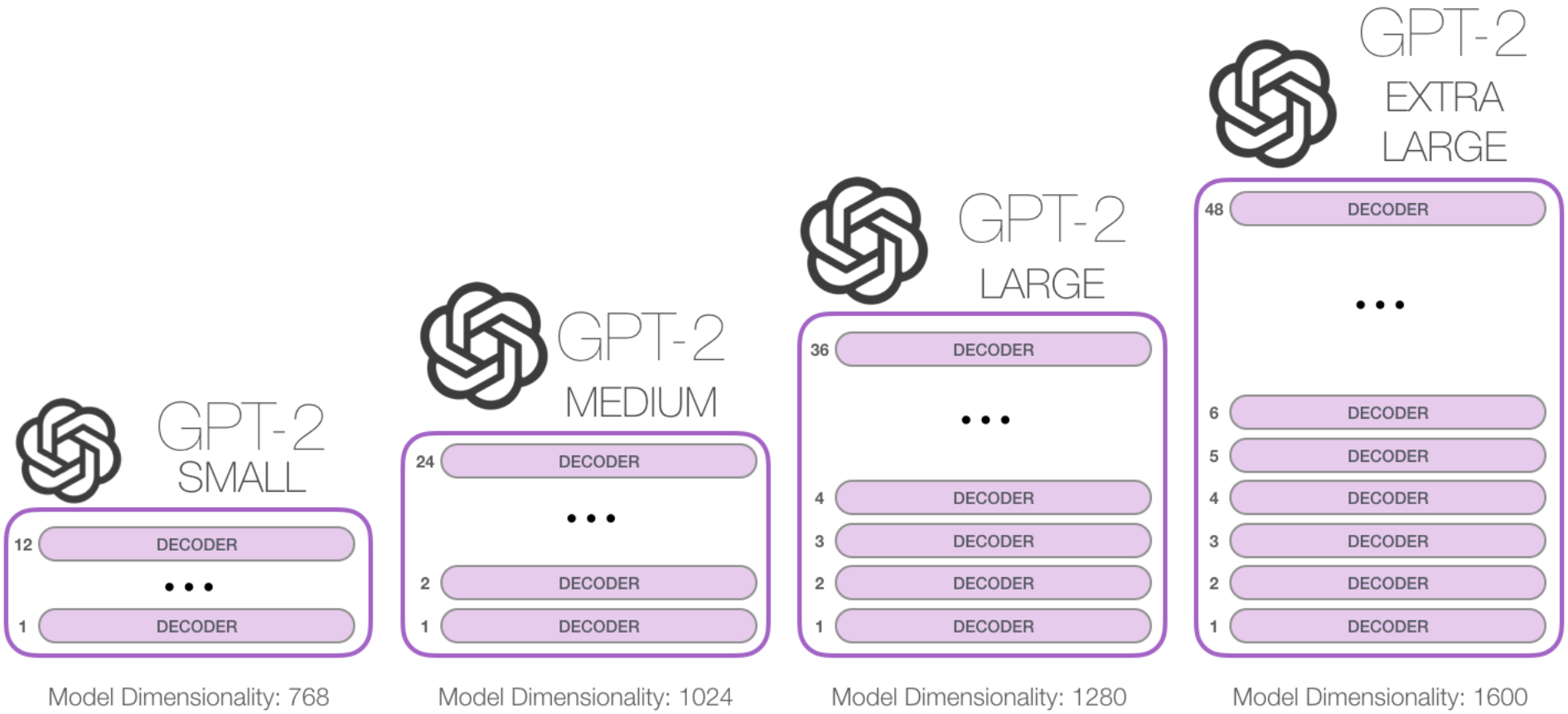
GPT Language Models



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GPT Language Models

- Only using transformer decoder blocks (BERT is using transformer encoder blocks)
- Outputs one token at a time:
  - “autoregression”: after each token is produced, that token is added to the sequence of inputs, and that new sequence becomes the input to the model in its next step

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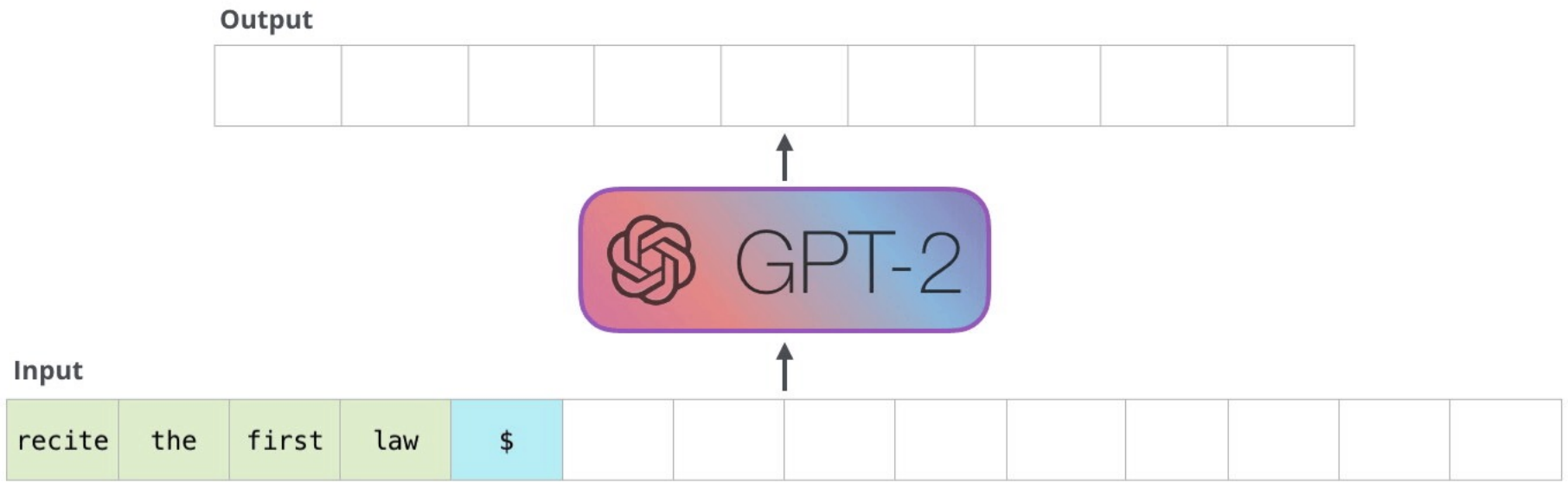
GPT Language Models



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GPT Language Models

- Only using transformer decoder blocks (BERT is using transformer encoder blocks)
- Outputs one token at a time:
  - “autoregression”: after each token is produced, that token is added to the sequence of inputs, and that new sequence becomes the input to the model in its next step
- Self-attention layer masks future tokens

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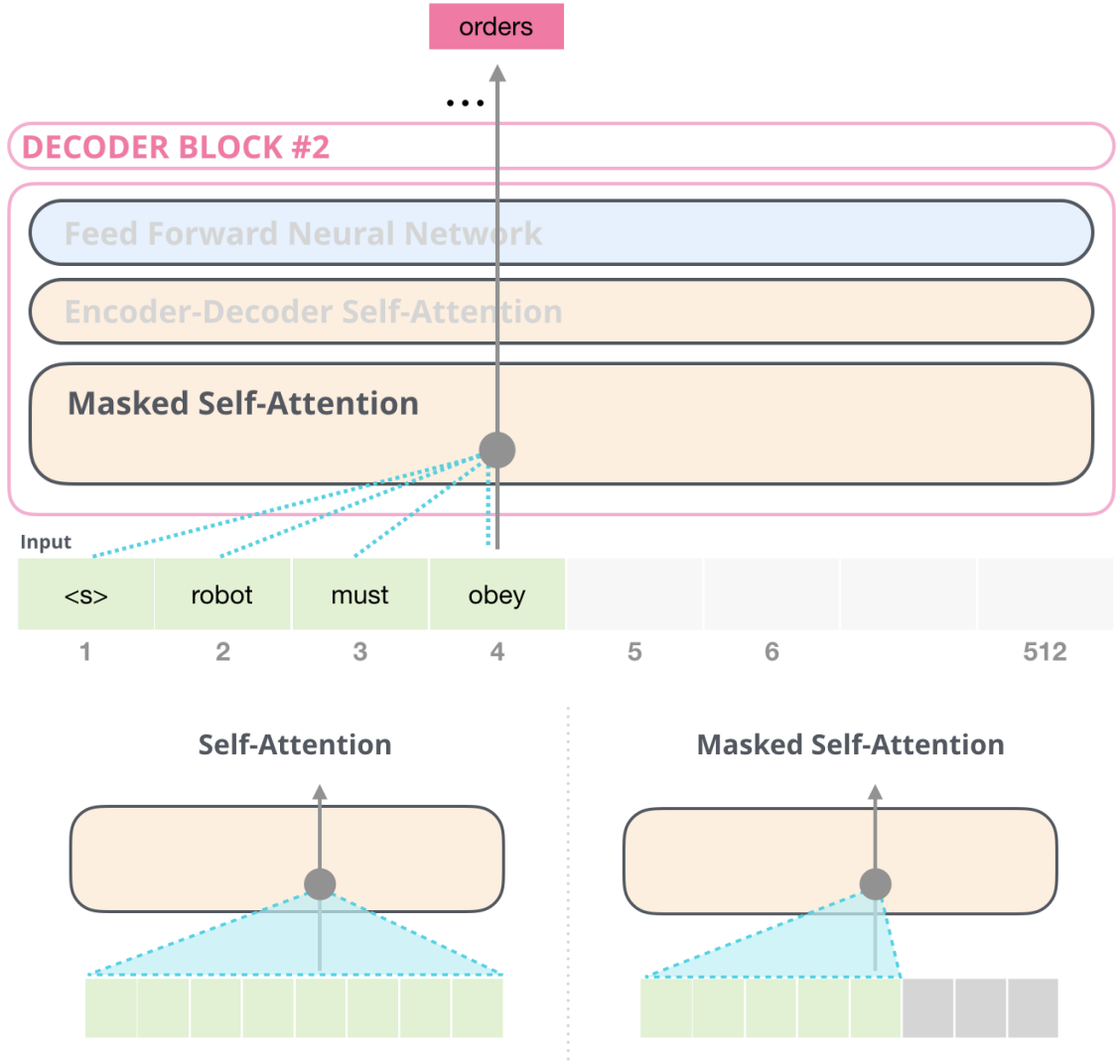
GPT Language Models



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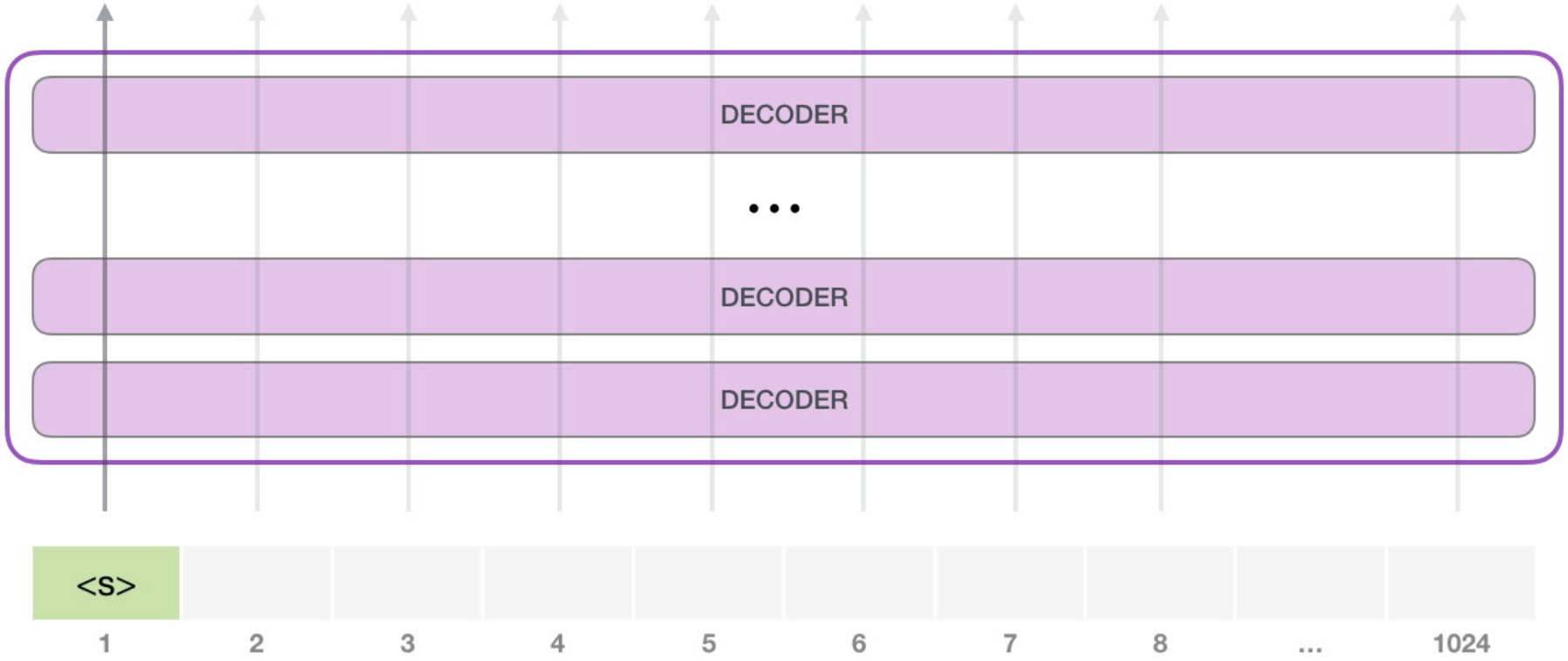
GPT Language Models



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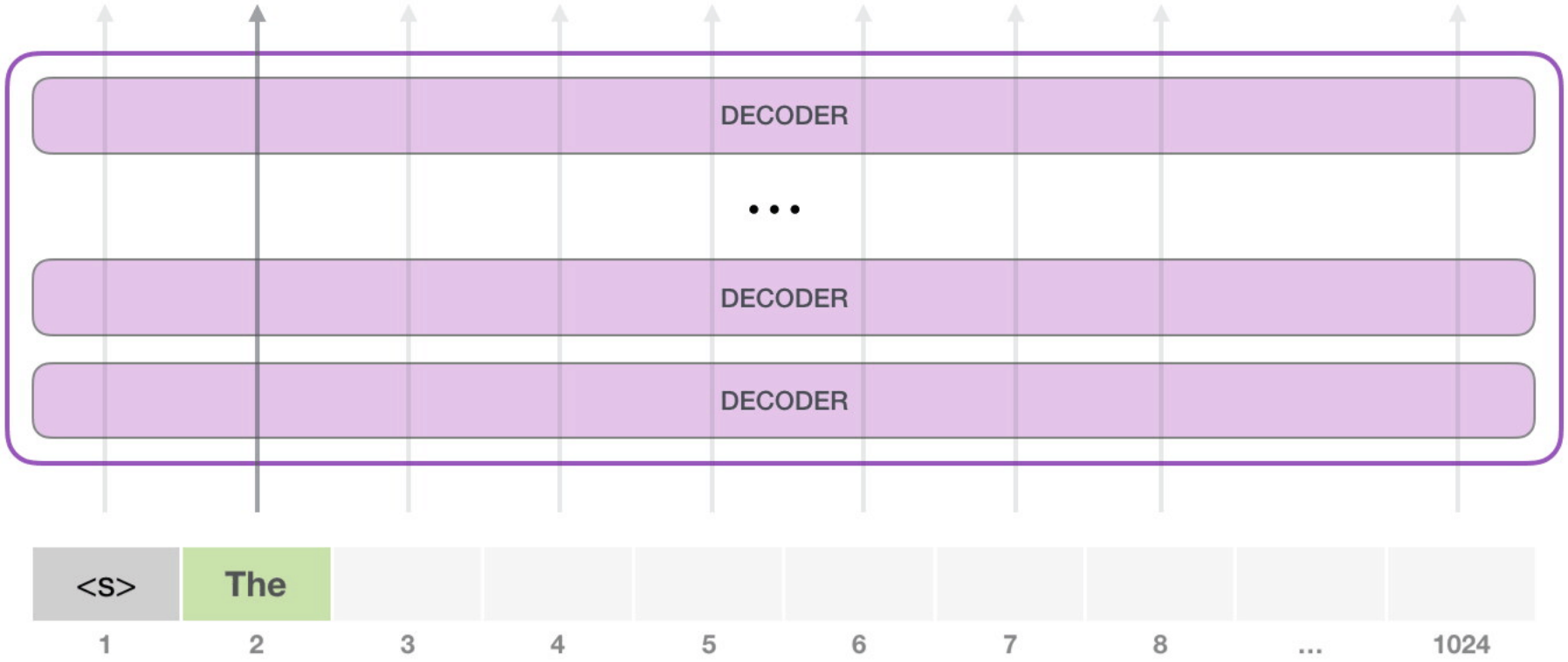
GPT Language Models



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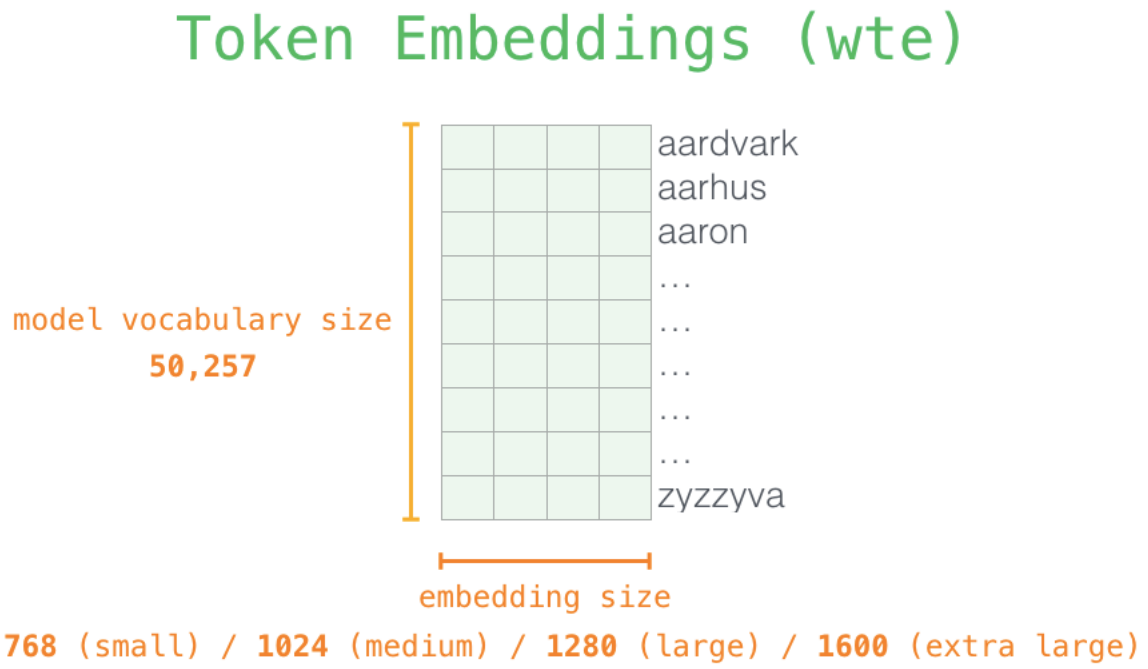
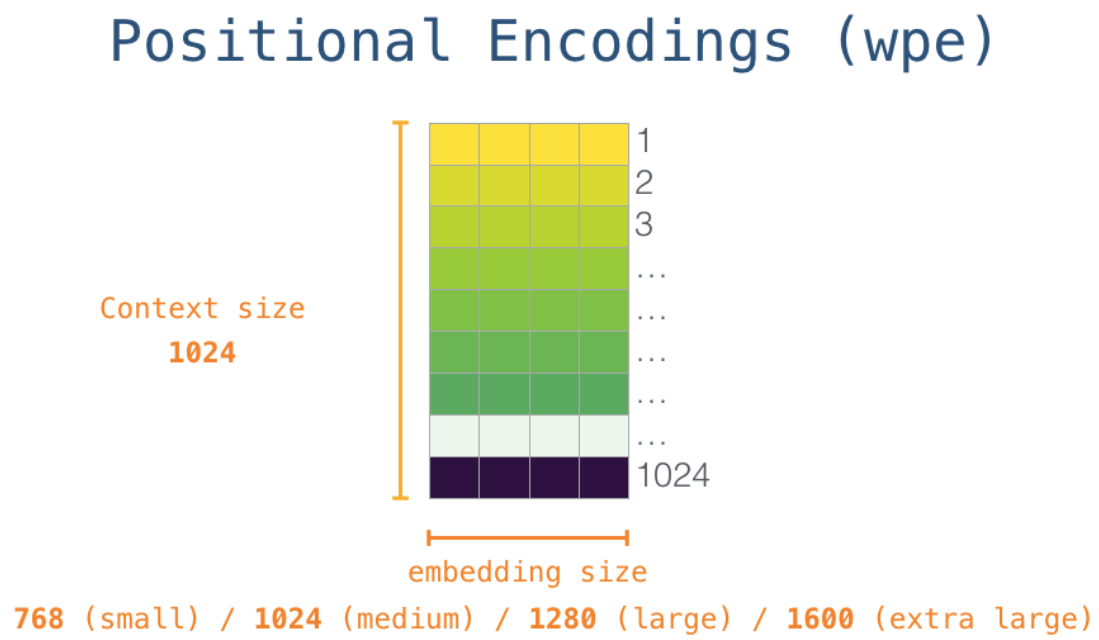
GPT Language Models – Inner Workings

- Inputs:





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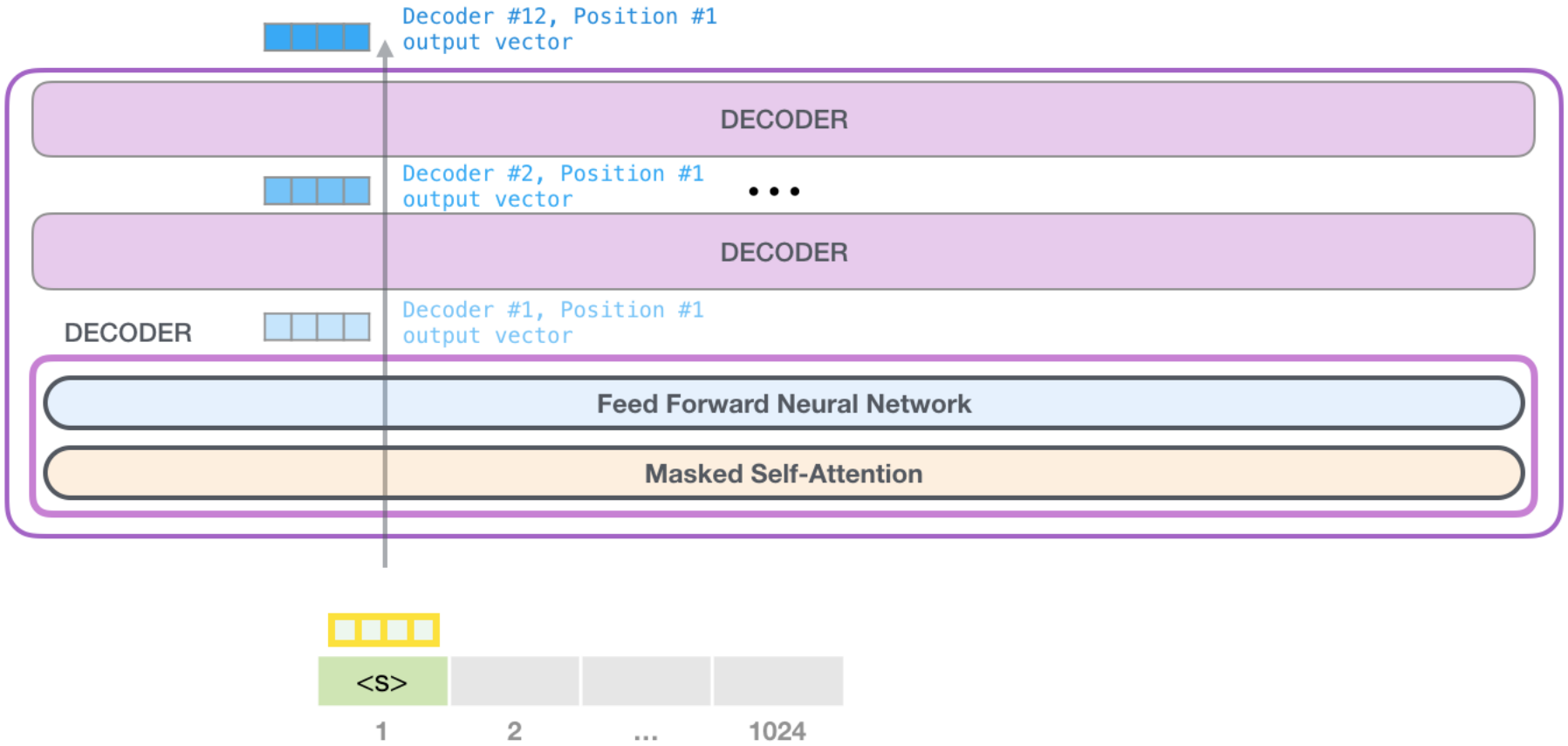
GPT Language Models – Inner Workings

- Inputs:

https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Inner Workings

- Up the stack:



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GPT Language Models – Inner Workings

- Self-attention:
  - Process words by incorporating the context they are referring to in the sentence
  - By assigning scores to how relevant each word in the sentence is and adding up their vector representation

> ***Second Law of Robotics***
> *A robot must obey the orders given **it** by human beings except where **such orders** would conflict with the **First Law**.*

  - **it** refers to the robot
  - **such orders** refers to the earlier part of the law, namely “the orders given it by human beings”
  - **The First Law** refers to the entire First Law

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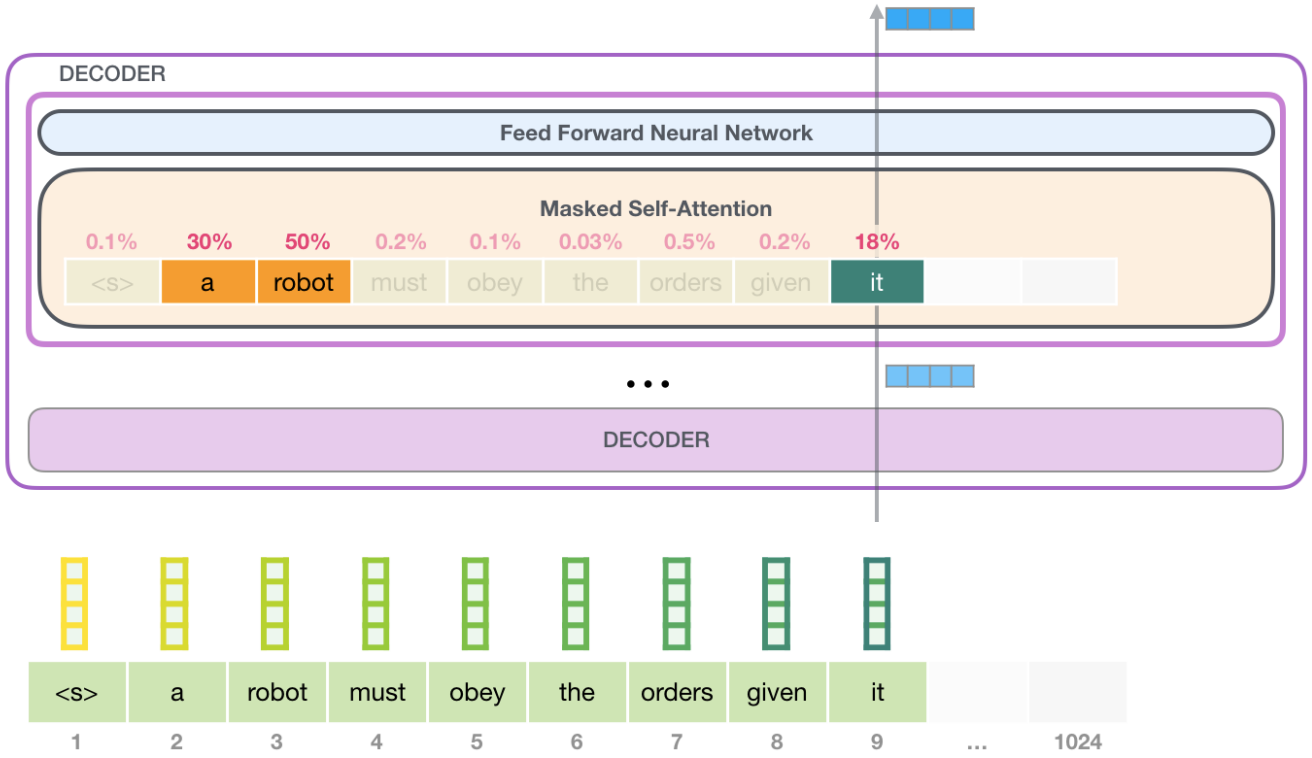
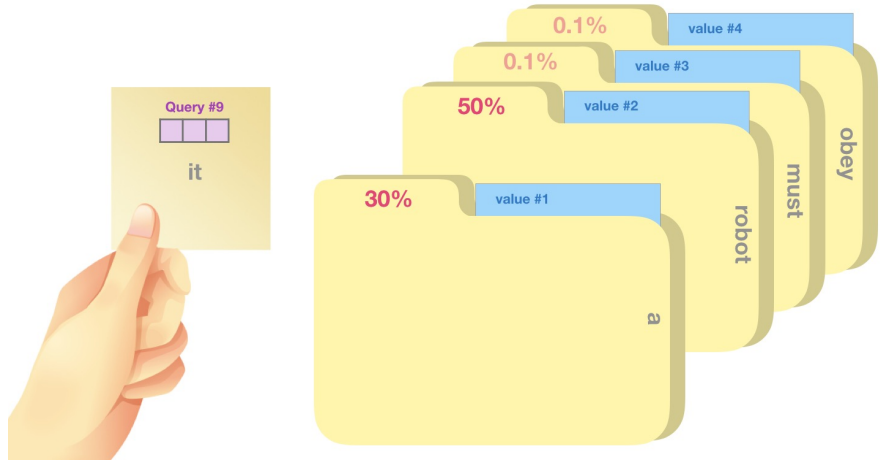
GPT Language Models – Inner Workings

- Self-attention:





Word	Value vector	Score	Value X Score
<s>		0.001	
a		0.3	
robot		0.5	
must		0.002	
obey		0.001	
the		0.0003	
orders		0.005	
given		0.002	
it		0.19	
		Sum:	

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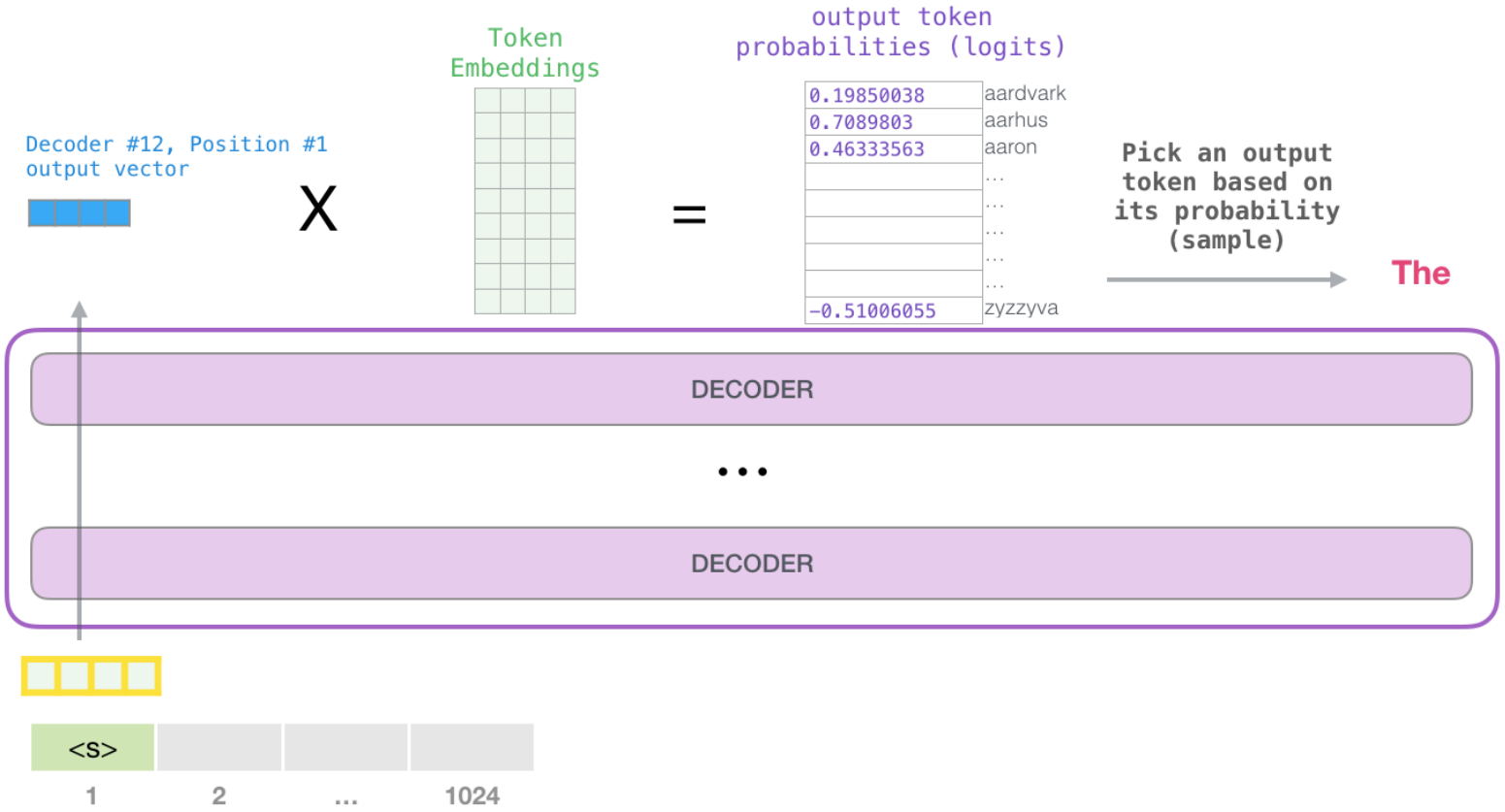
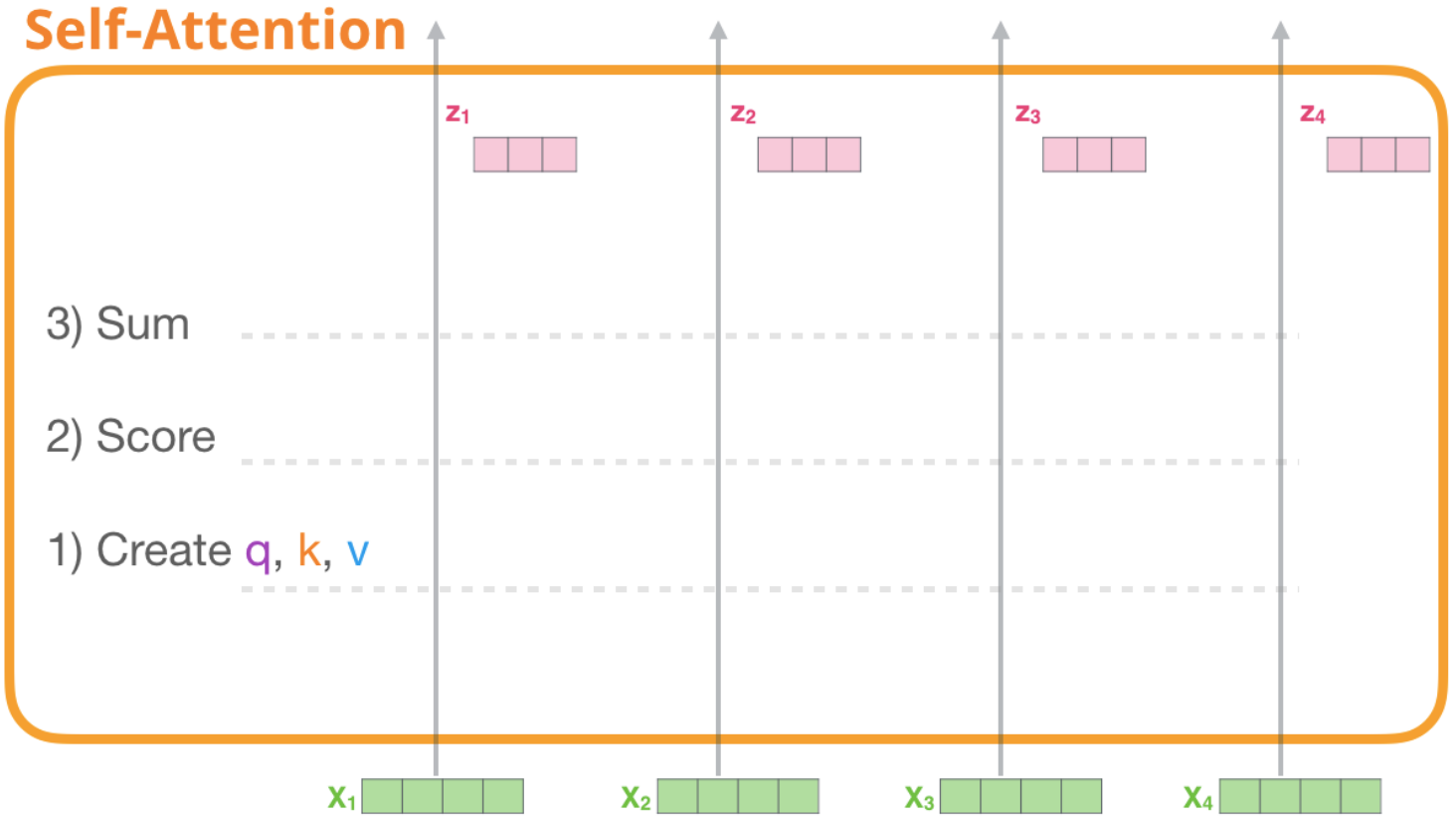
GPT Language Models – Inner Workings

- Output:



GPT Language Models – Going Deeper on Masked Self Attention



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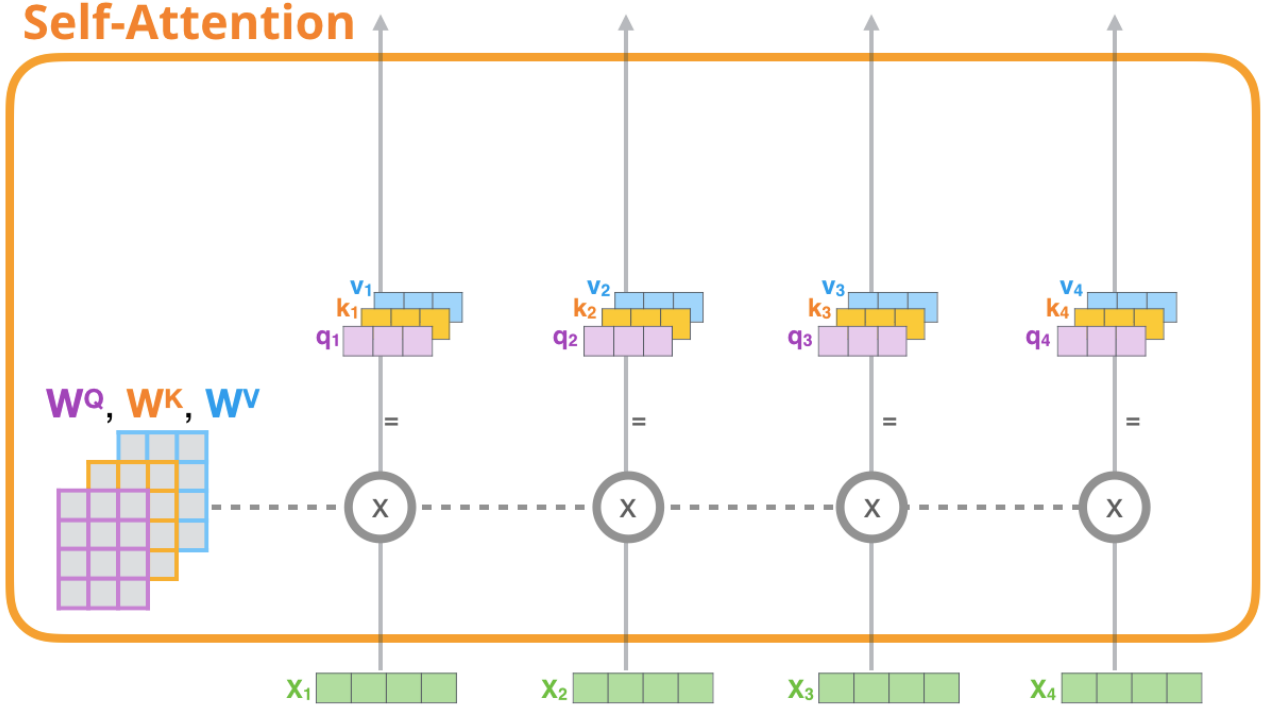
GPT Language Models – Going Deeper on Masked Self Attention

1) For each input token, create a query vector, a key vector, and a value vector by multiplying by weight Matrices W^Q, W^K, W^V



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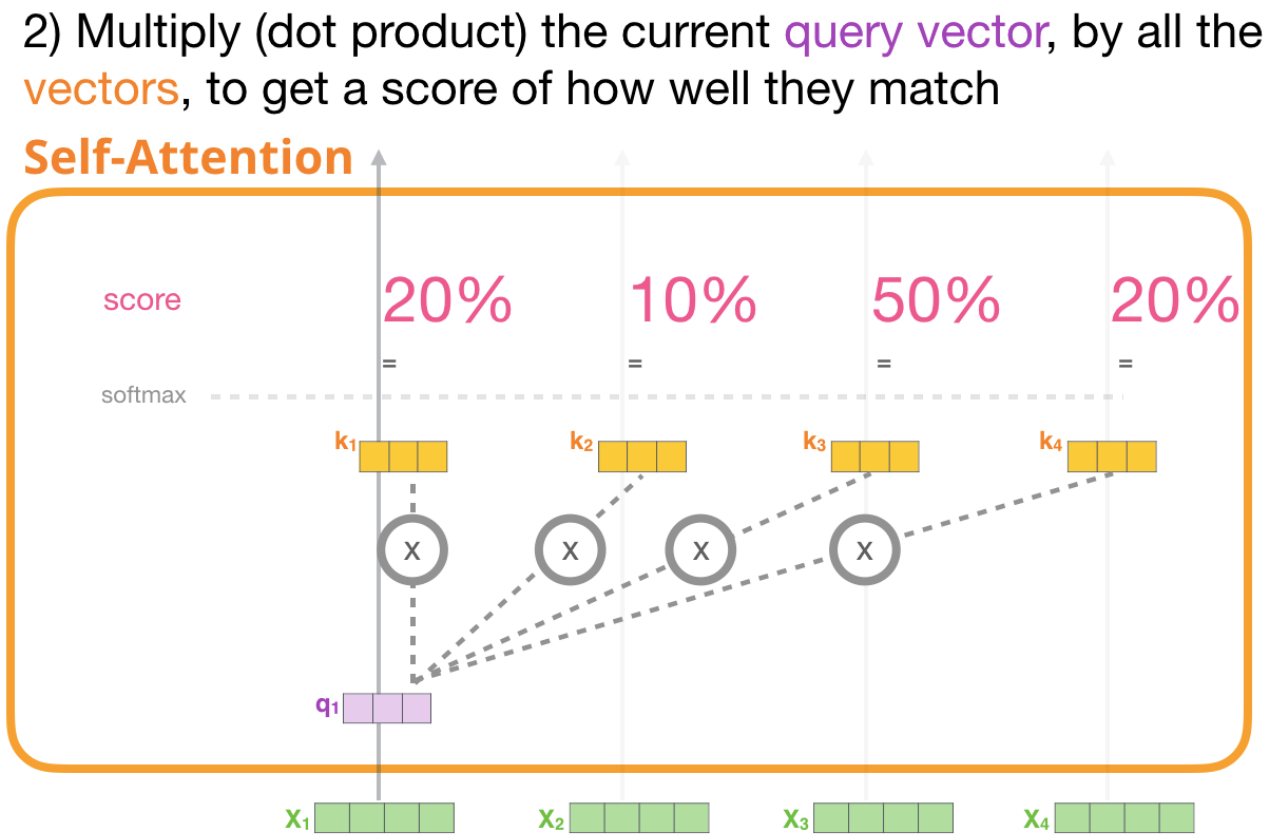
GPT Language Models – Going Deeper on Masked Self Attention



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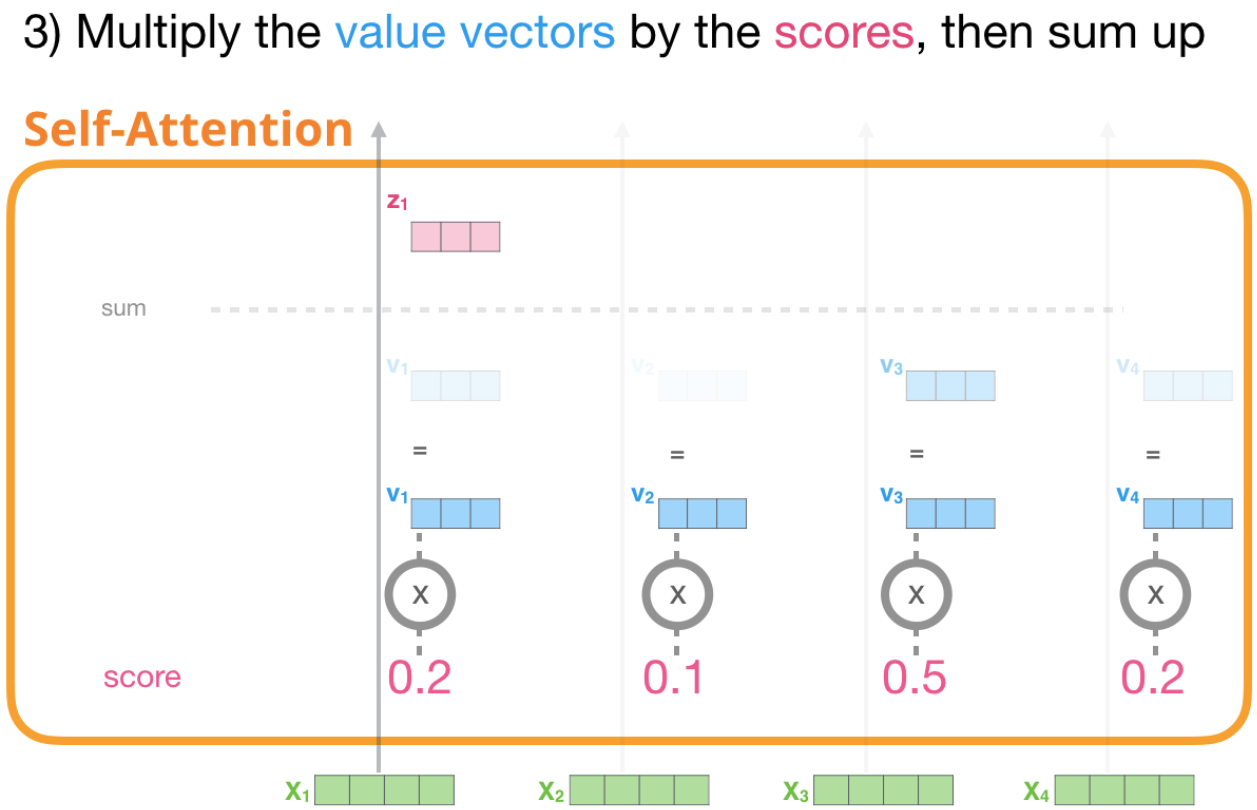
GPT Language Models – Going Deeper on Masked Self Attention



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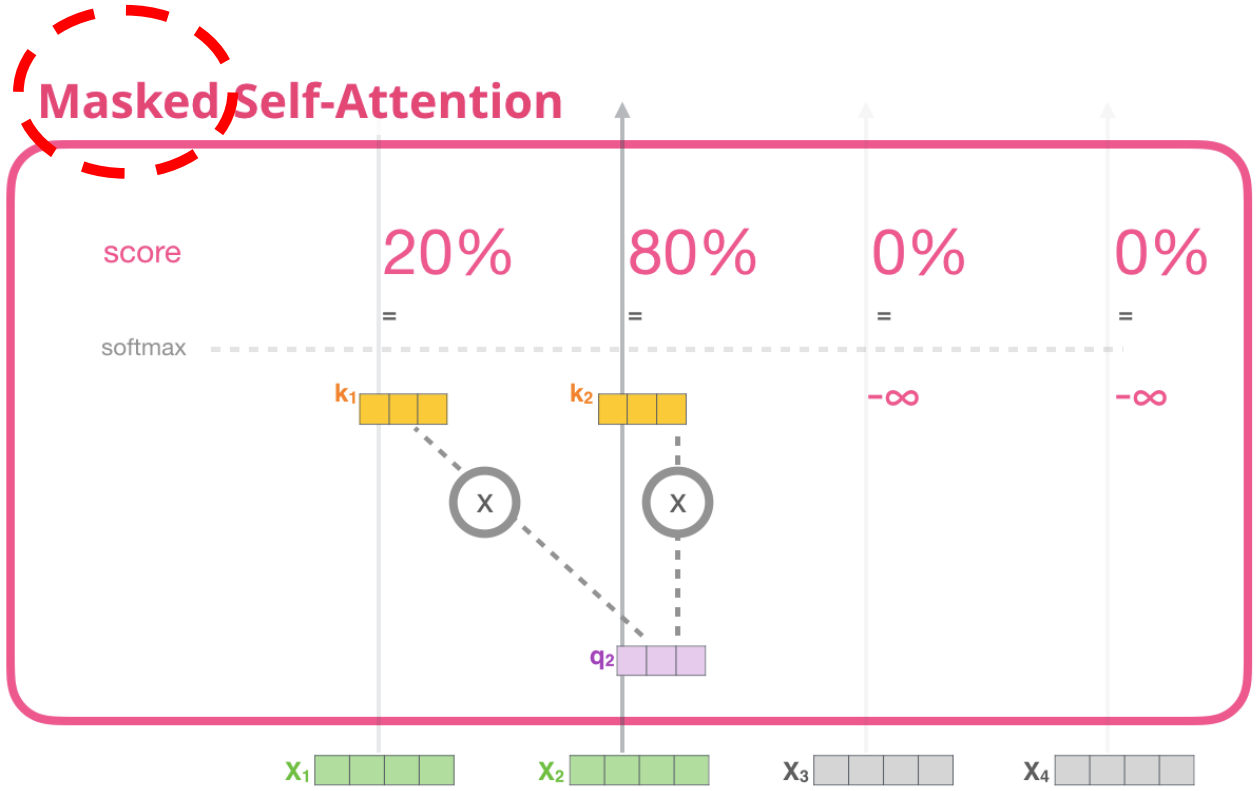
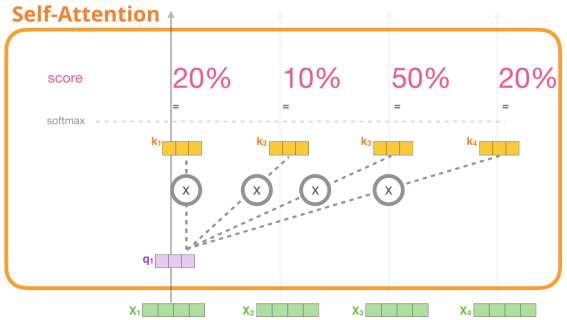
GPT Language Models – Going Deeper on Masked Self Attention





https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

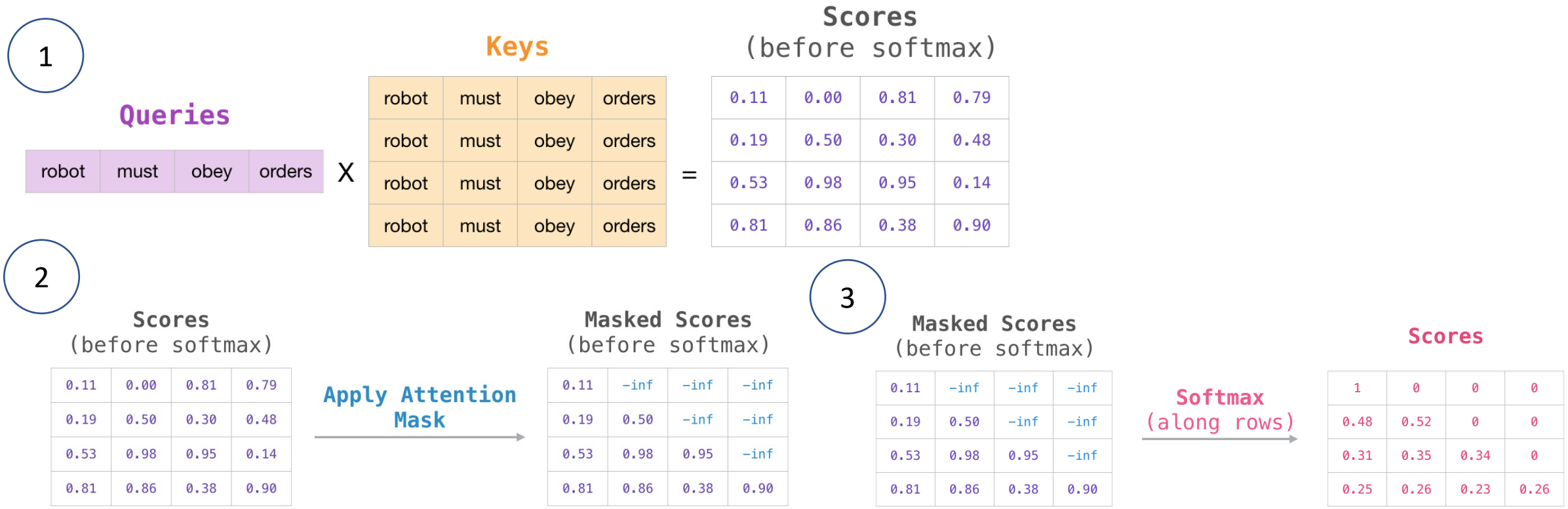
- During training: Batch processing of pairs of input and output

	Features				Labels
position:	1	2	3	4	
Example: 1	robot	must	obey	orders	must
2	robot	must	obey	orders	obey
3	robot	must	obey	orders	orders
4	robot	must	obey	orders	<eos>

https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

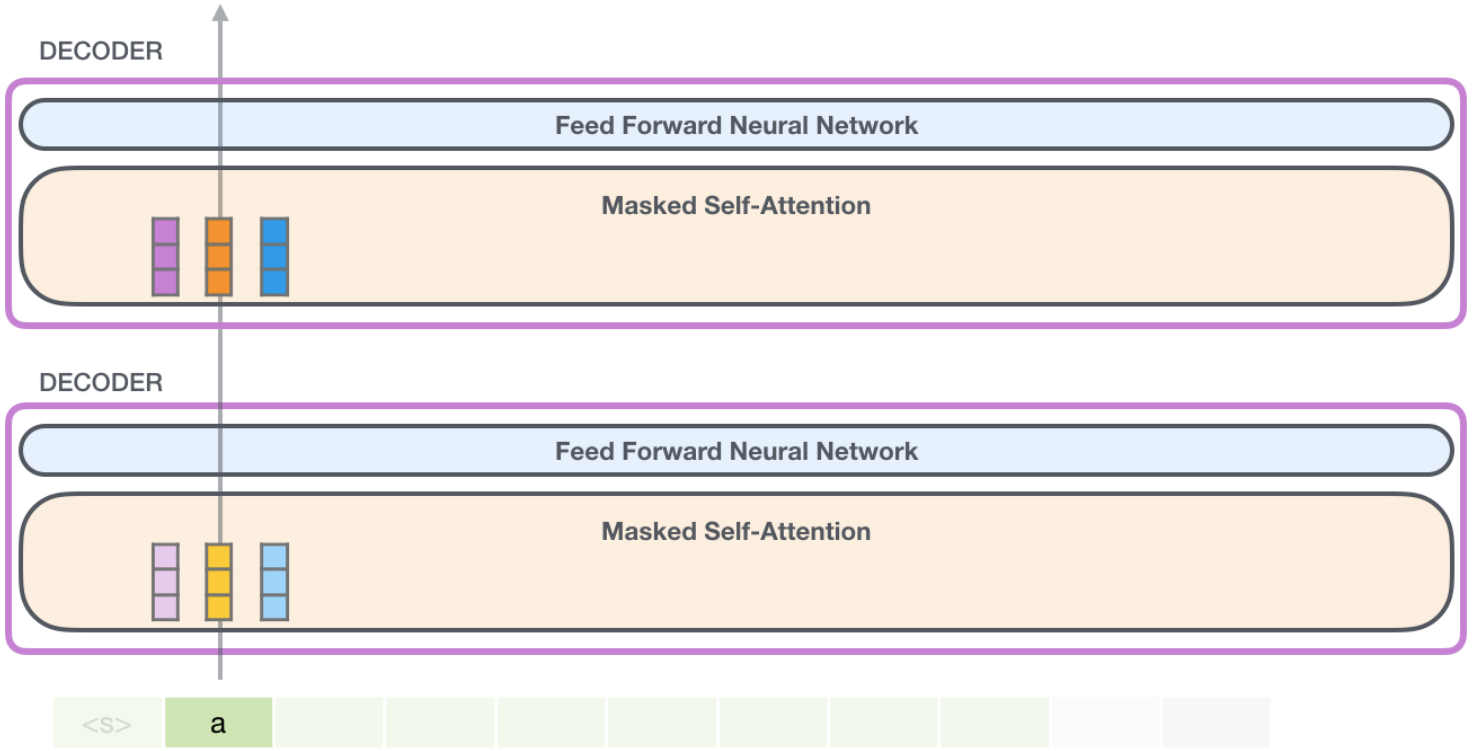
- During training: compute self attention scores



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

- During evaluation:



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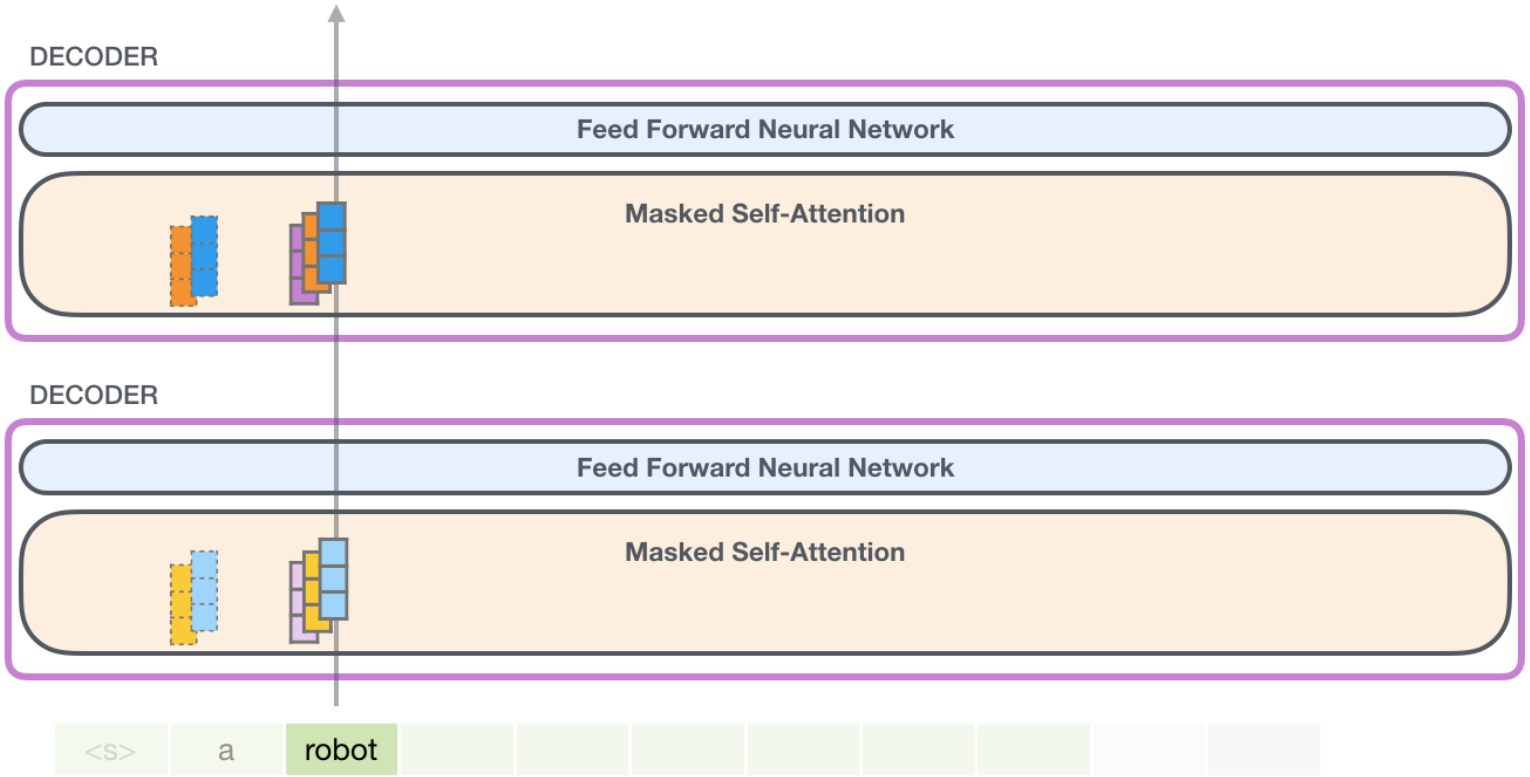
GPT Language Models – Going Deeper on Masked Self Attention

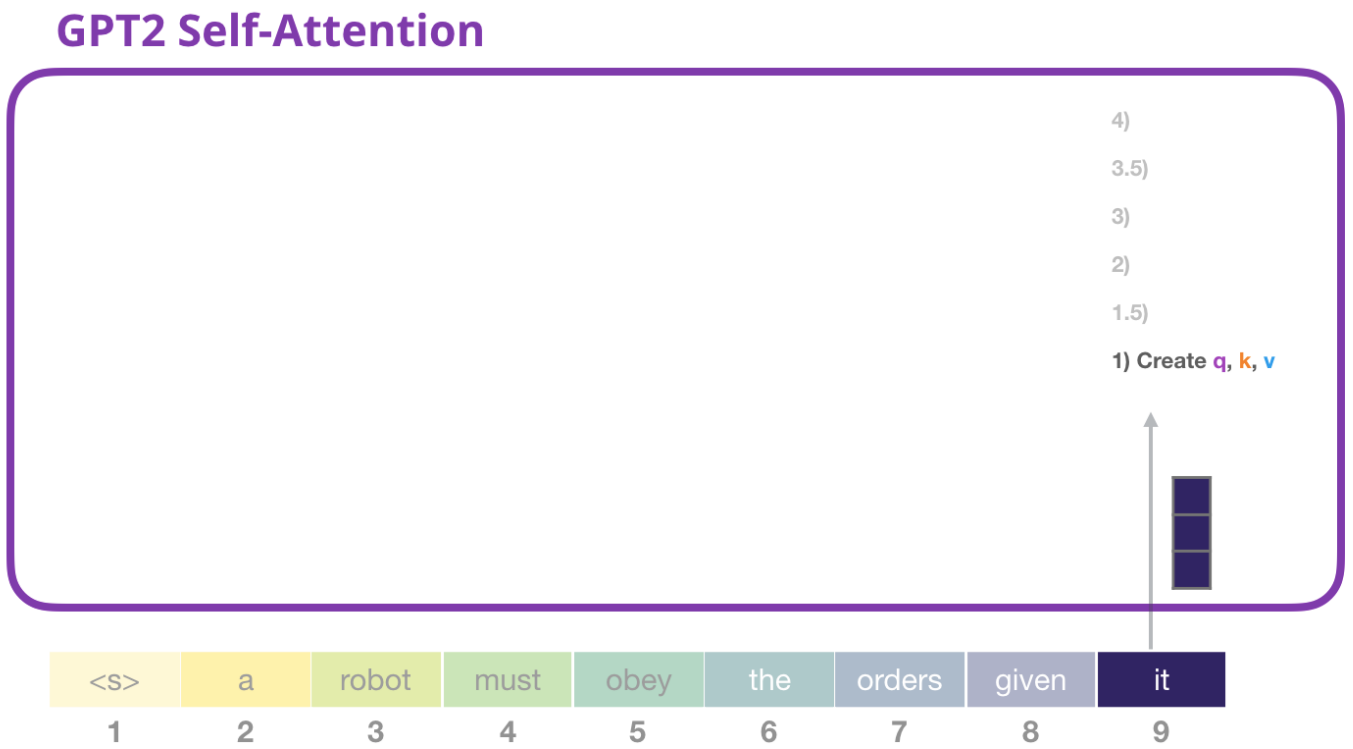
- During evaluation:



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

- Implementation: input (token embedding + positional embedding)



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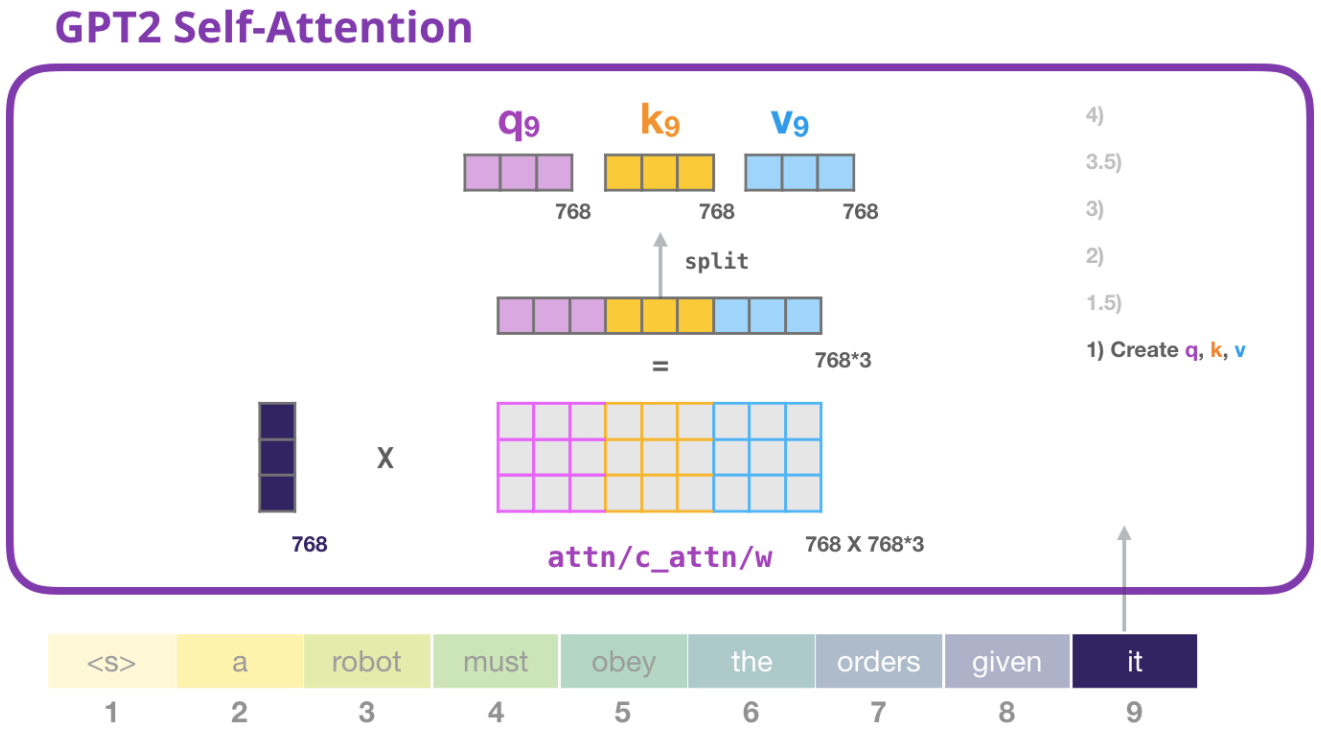
GPT Language Models – Going Deeper on Masked Self Attention

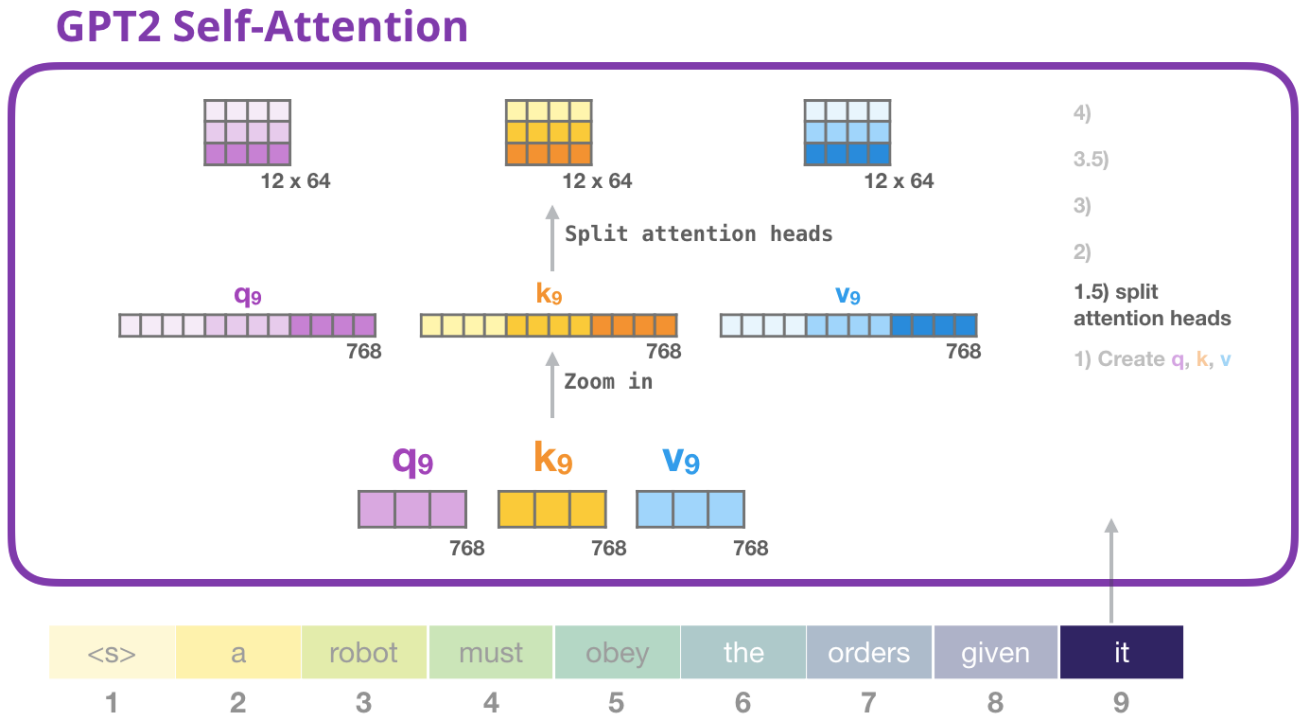
- Implementation: create query, key, value vectors



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

- Implementation: create query, key, value vectors for multiple attention heads



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GPT Language Models – Going Deeper on Masked Self Attention

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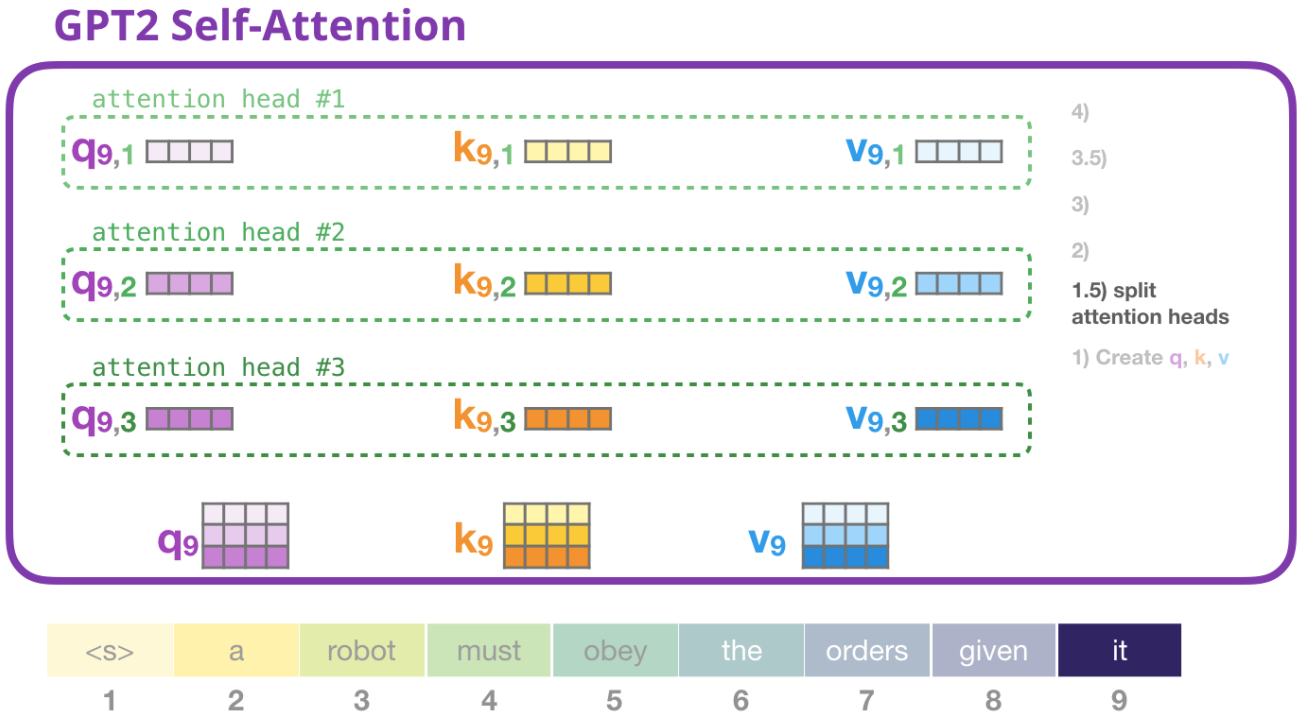

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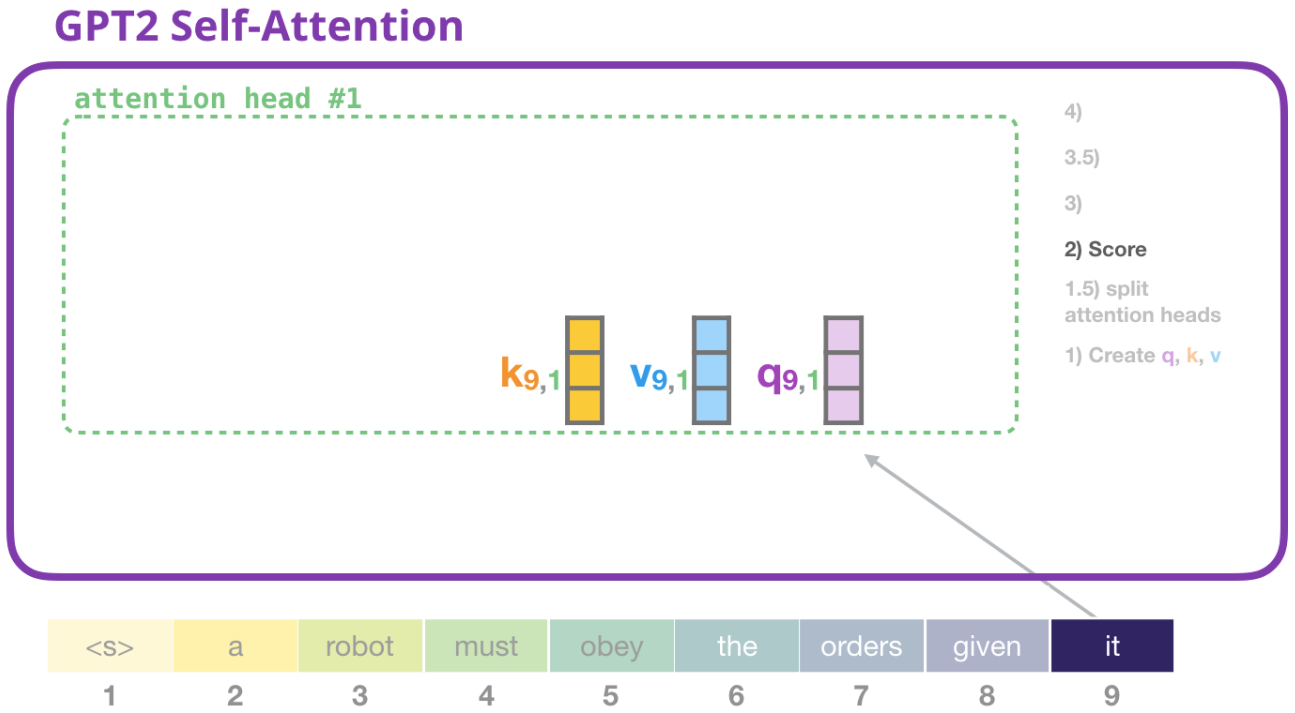
GPT Language Models – Going Deeper on Masked Self Attention

- Implementation: within each attention head, compute attention scores



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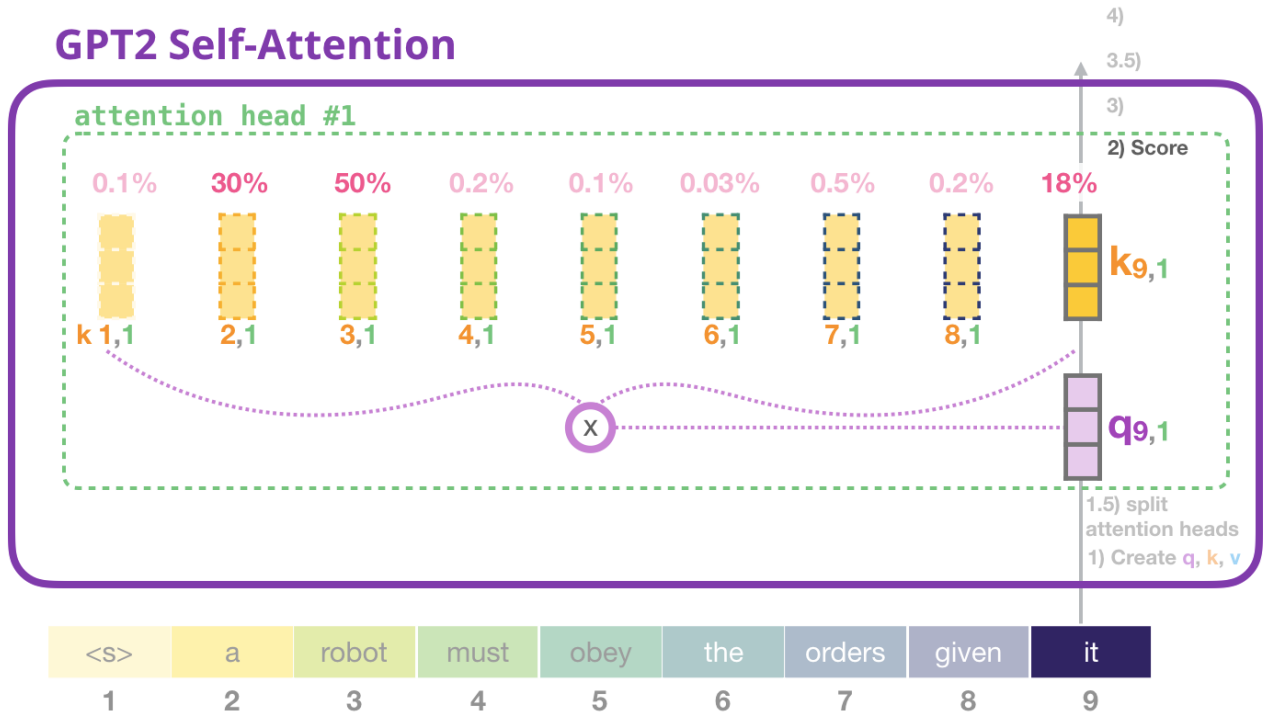
GPT Language Models – Going Deeper on Masked Self Attention

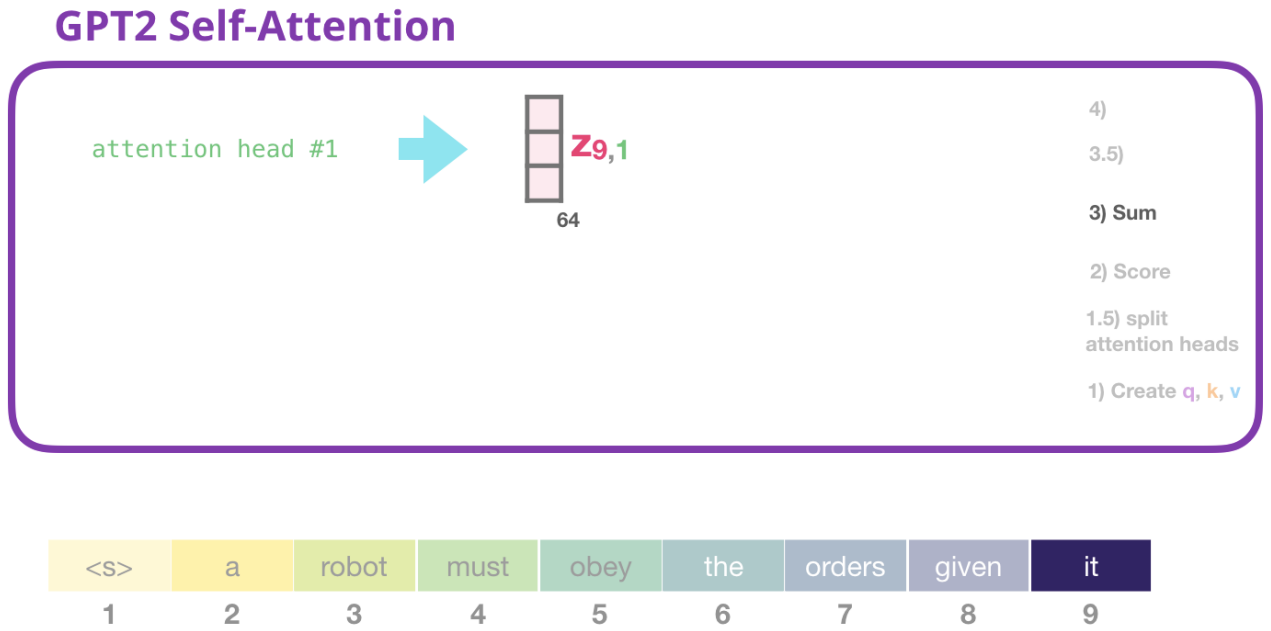
- Implementation: within each attention head, compute attention scores



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

- Implementation: within each attention head, compute attention scores, and create a weighted sum of value vectors



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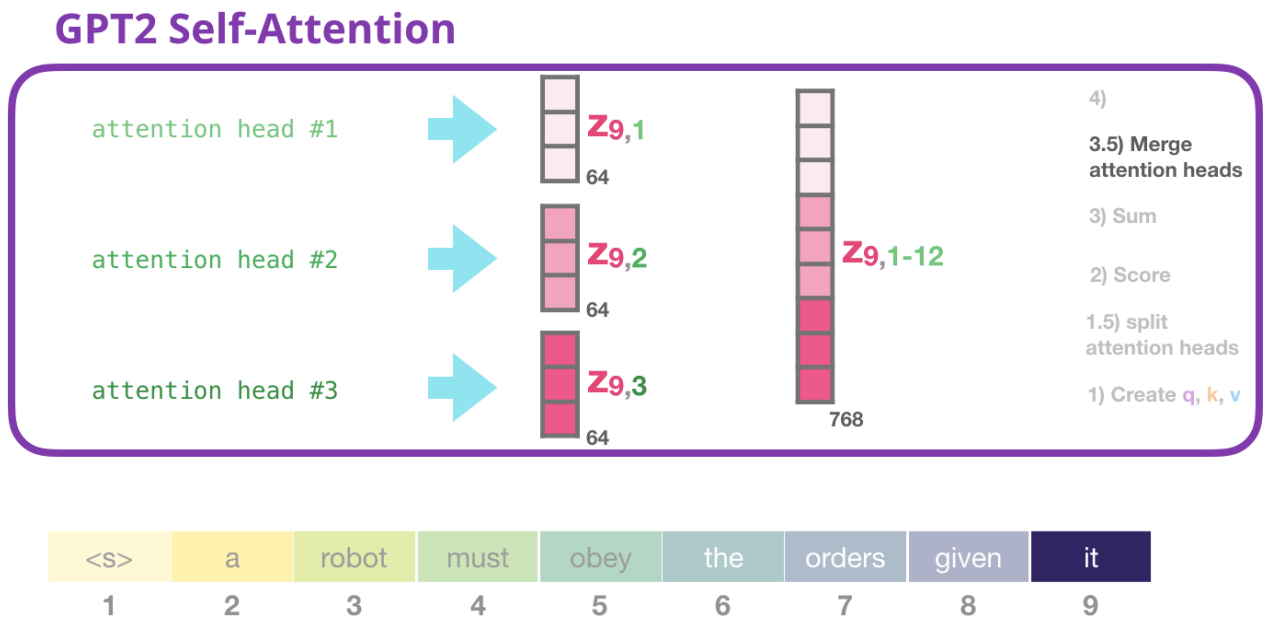
GPT Language Models – Going Deeper on Masked Self Attention

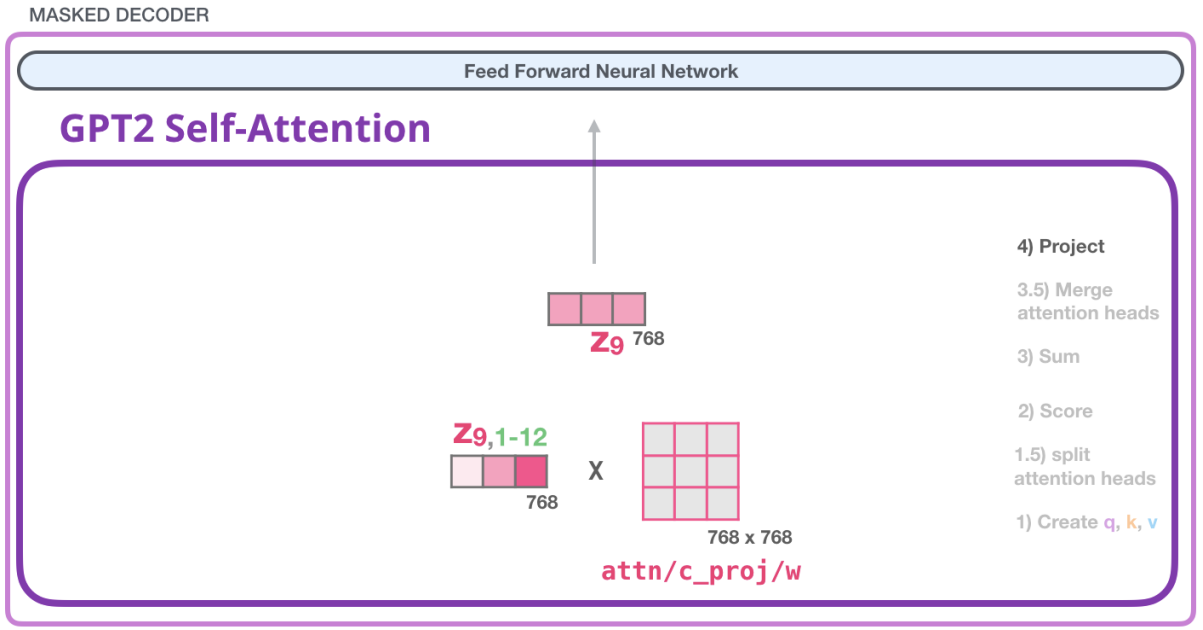
- Implementation: merge vectors from multiple heads



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

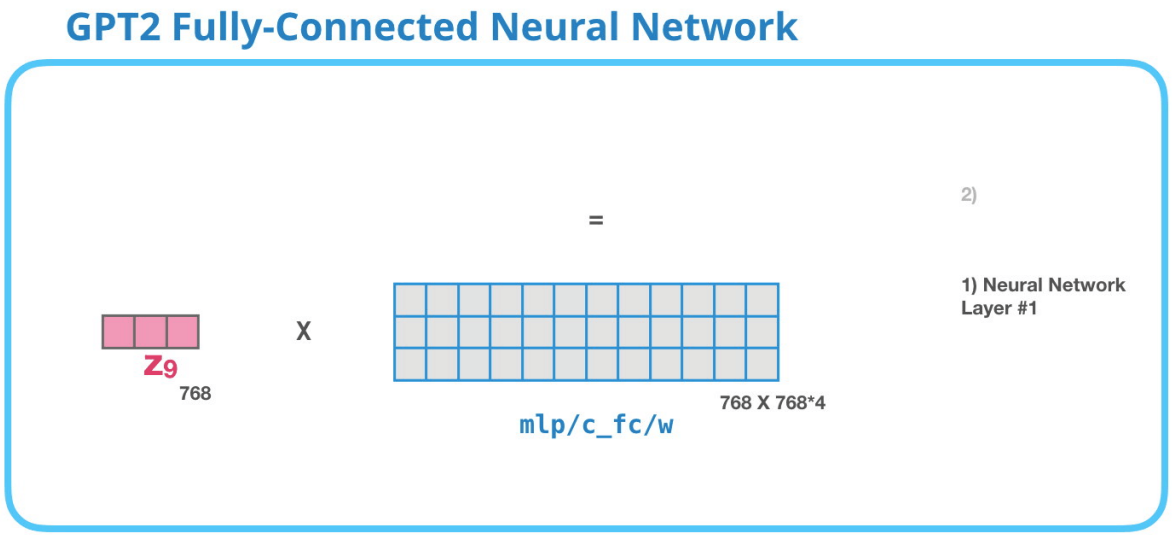
- Implementation: project the vectors and pass to the FFNN



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

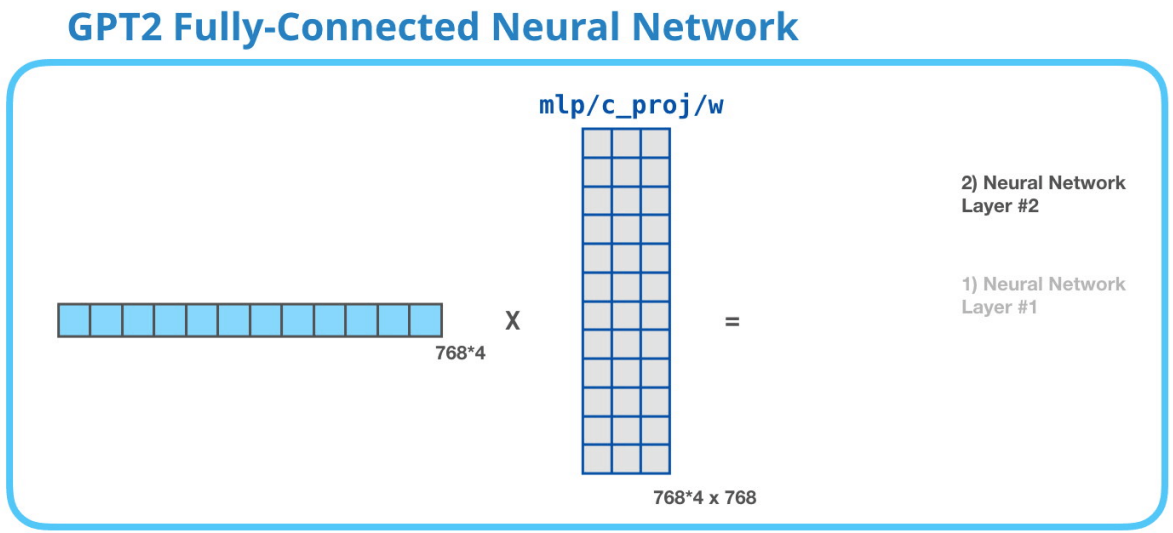
- Implementation: FFNN layer 1



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

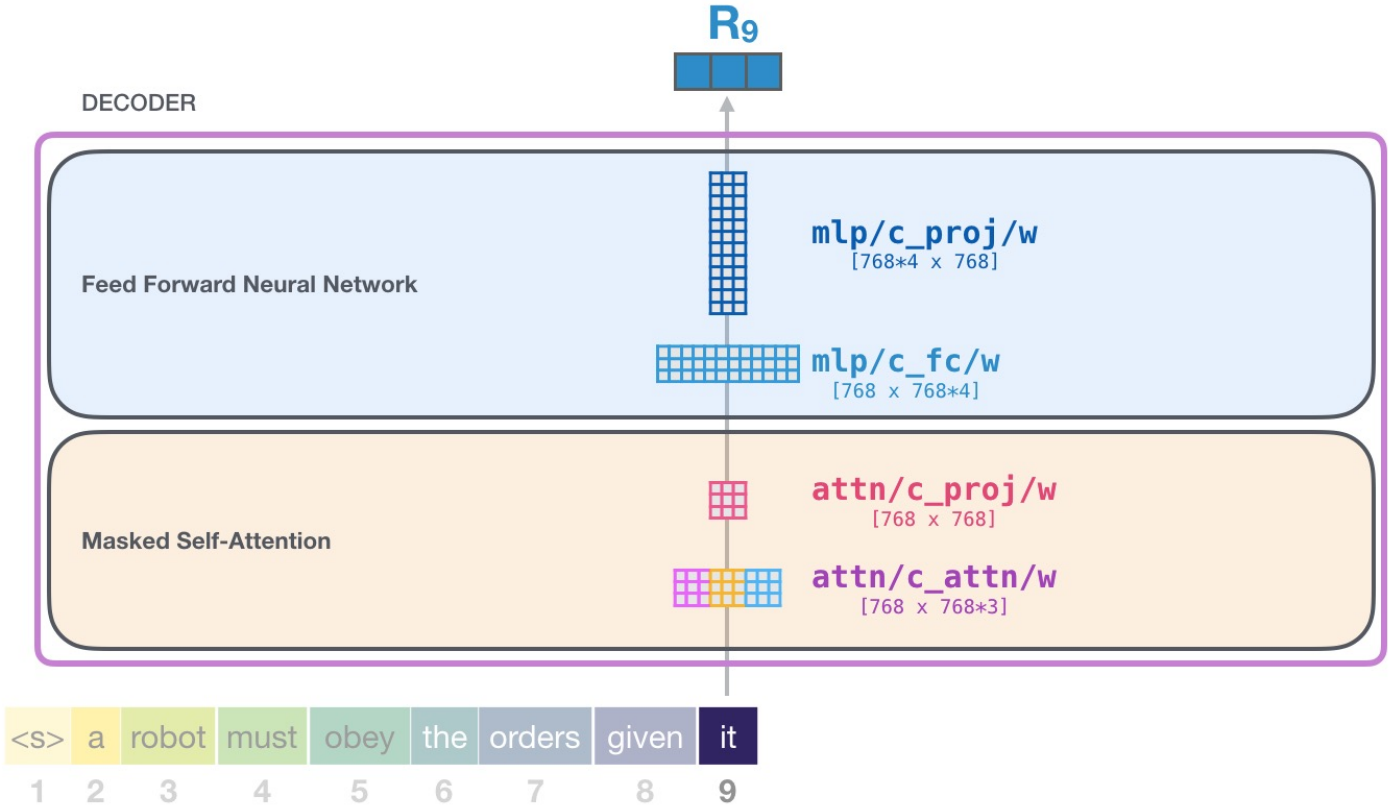
- Implementation: FFNN layer 2



https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Going Deeper on Masked Self Attention

- Implementation Recap



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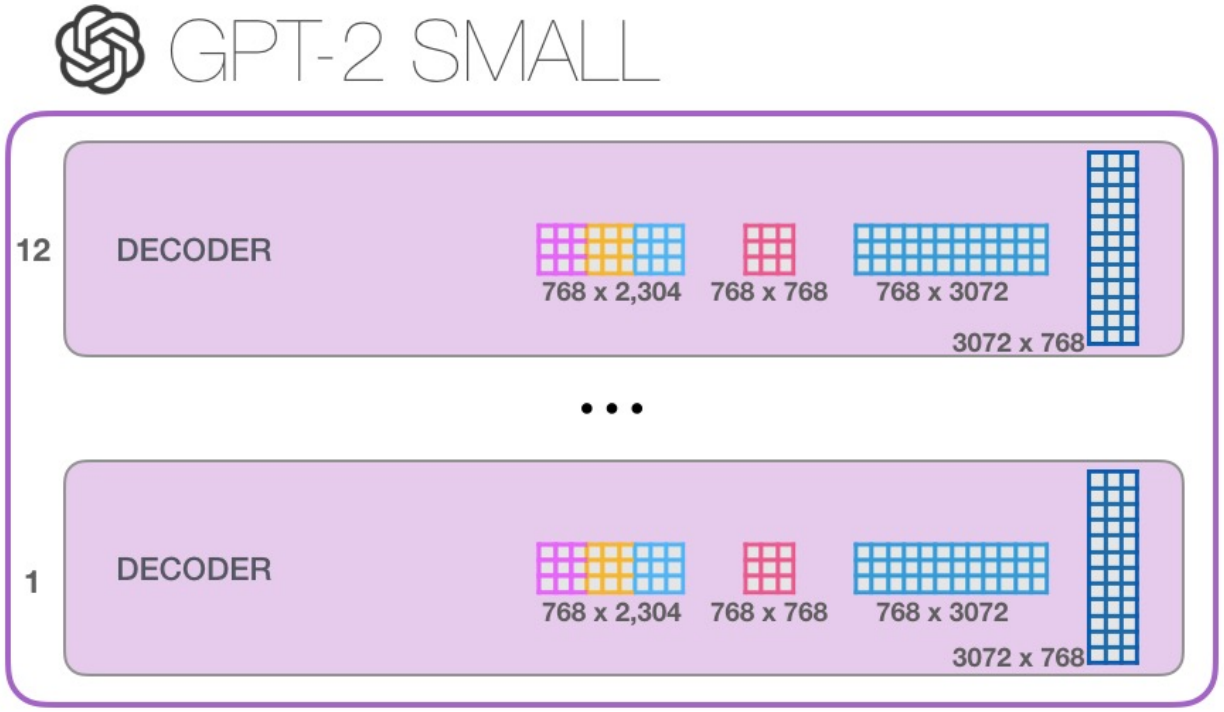
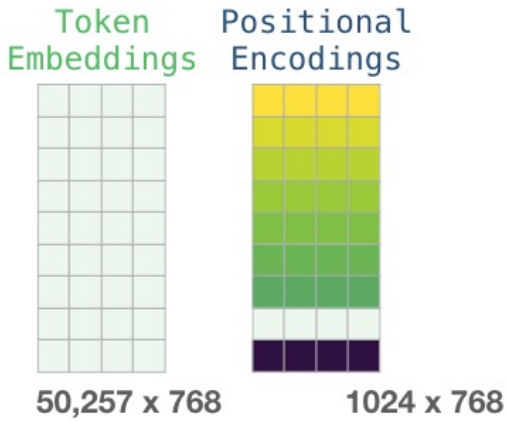
GPT Language Models – Going Deeper on Masked Self Attention

- Implementation Recap





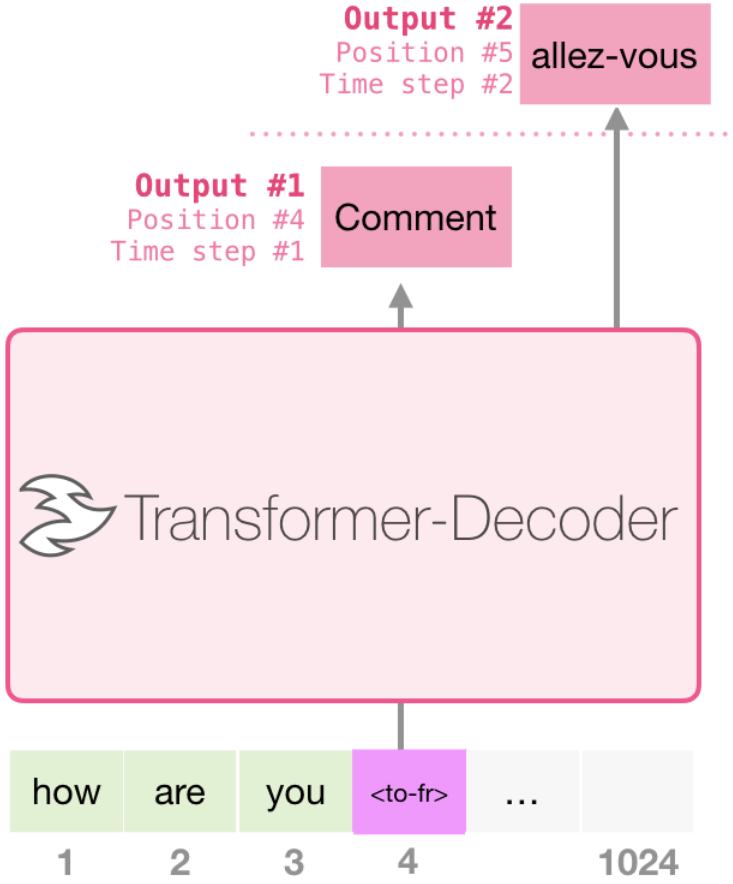
https://jalammar.github.io/illustrated-gpt2/

GPT Language Models – Application

- Machine translation (decoder only)

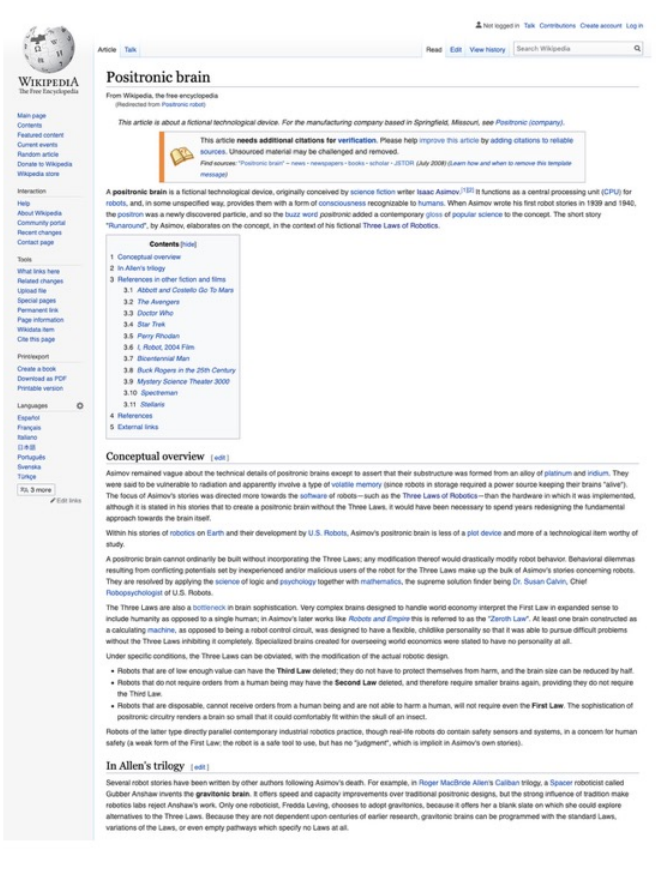
Training Dataset

I	am	a	student	<to-fr>	je	suis	étudiant
let	them	eat	cake	<to-fr>	Qu'ils	mangent	de
good	morning	<to-fr>	Bonjour				



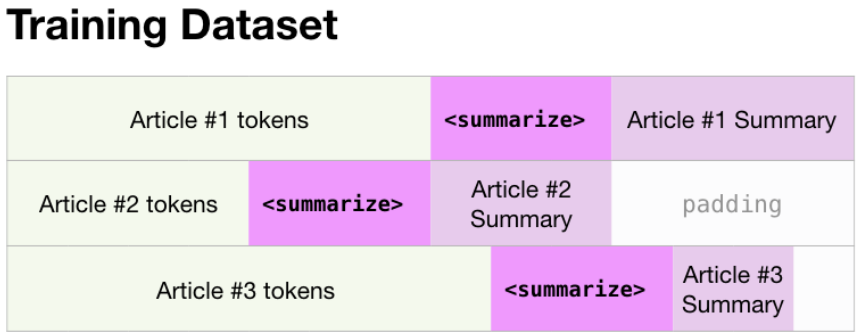
GPT Language Models – Application

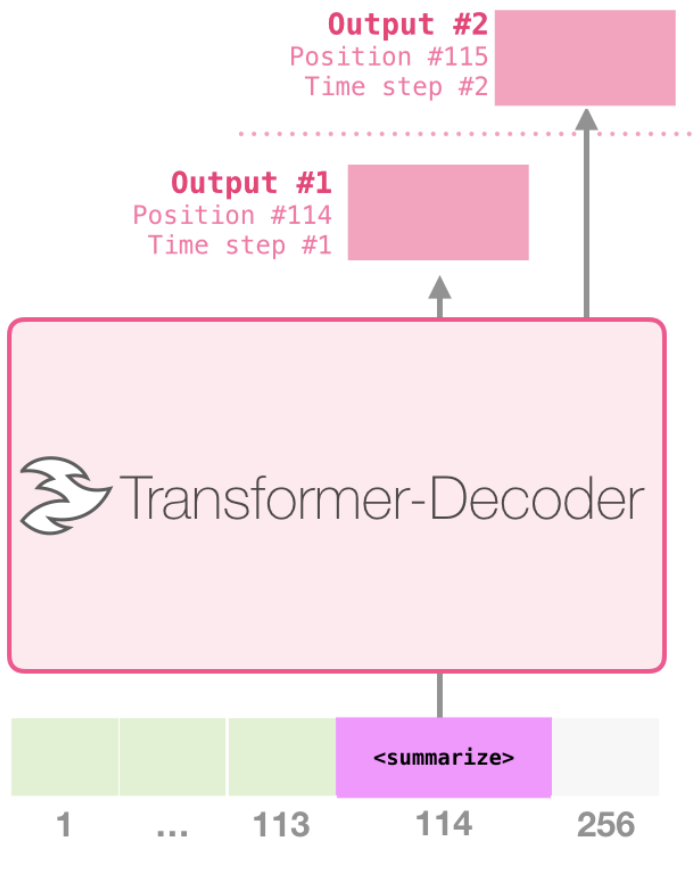
- Summarization



GPT Language Models – Application

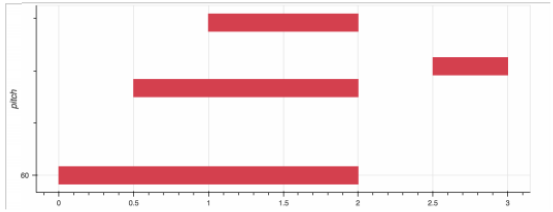
- Summarization





GPT Language Models – Application

- Music Transformer: https://magenta.tensorflow.org/music-transformer



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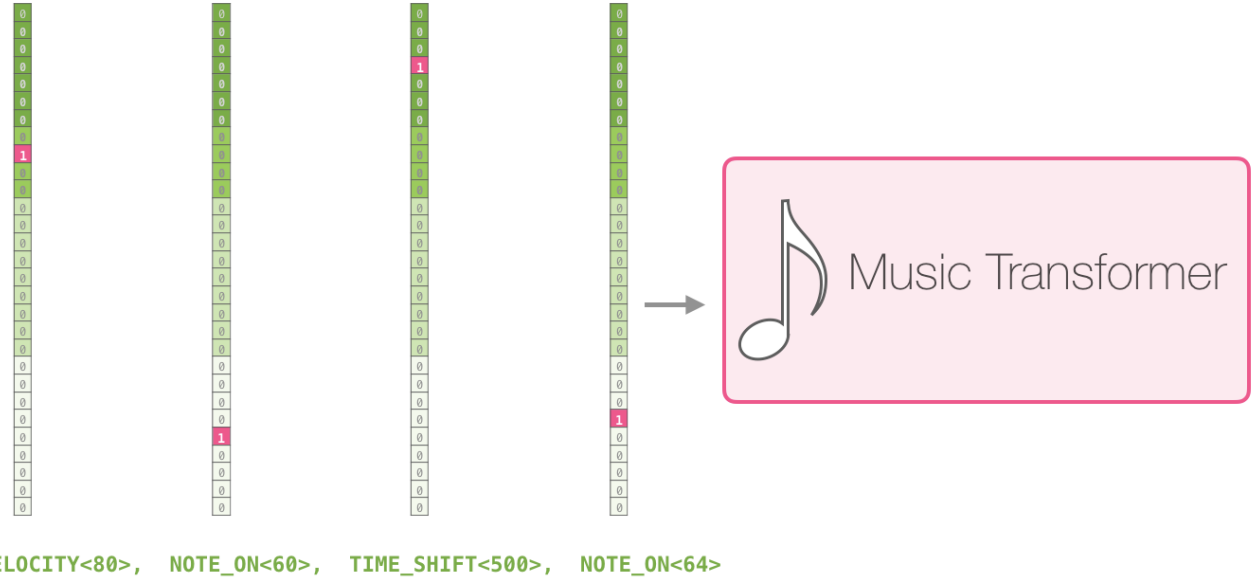
SET_VELOCITY<80>, NOTE_ON<60>
TIME_SHIFT<500>, NOTE_ON<64>
TIME_SHIFT<500>, NOTE_ON<67>
TIME_SHIFT<1000>, NOTE_OFF<60>, NOTE_OFF<64>,
NOTE_OFF<67>
TIME_SHIFT<500>, SET_VELOCITY<100>, NOTE_ON<65>
TIME_SHIFT<500>, NOTE_OFF<65>
```



Try out GPTs

- GPT2: Decoder only transformer http://jalammar.github.io/illustrated-gpt2/
- Try out GPT3 yourself: https://beta.openai.com/playground/ (requires signing up)