BERT & GPT

Pavlos Protopapas

Christopher Montall

Outline

- Transformers Recap
- BERT
- Practical problems in Large Language Models
- GPT
- Hugging Face

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- **Transformers Recap**
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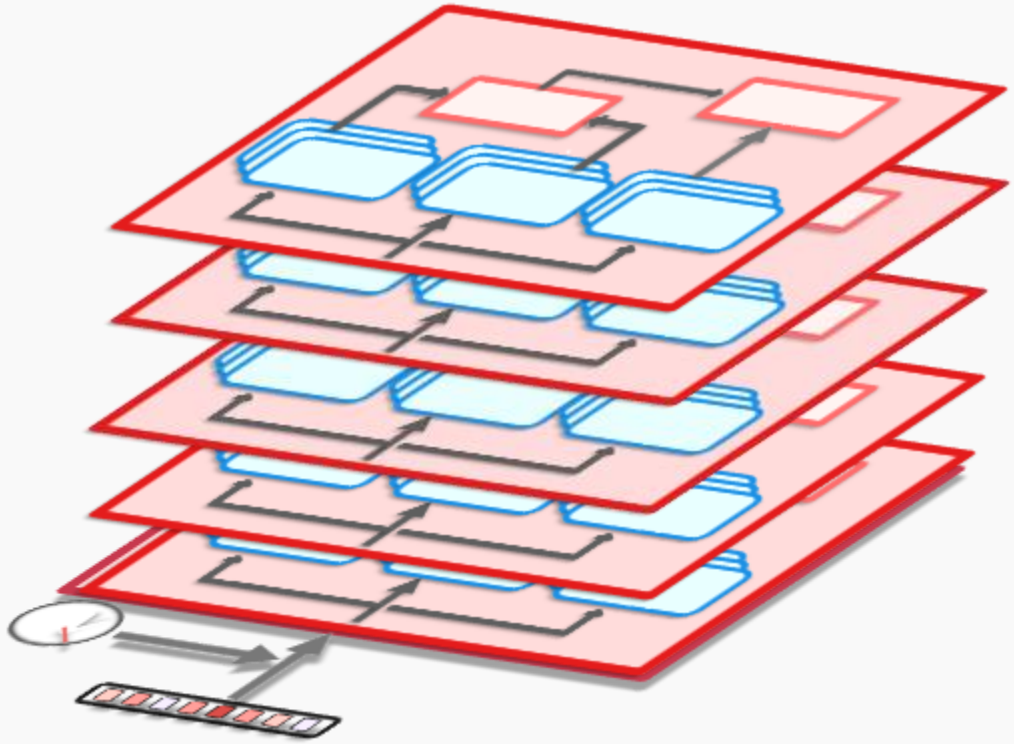
Recap: Encoder

Language Model Wishlist?

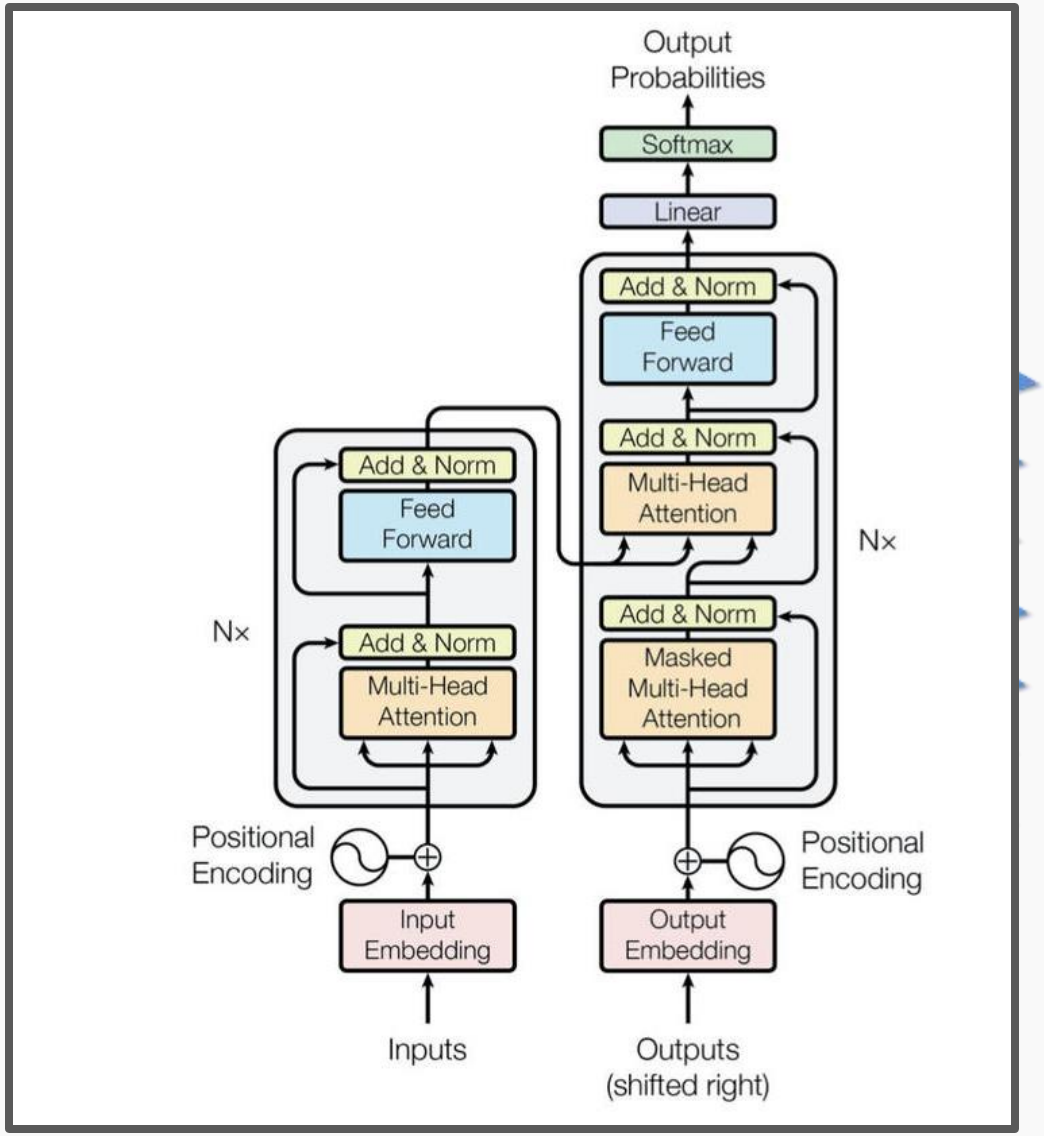
- ☑ We want to have strong contextual relations between words - **DONE**
- ☑ We want words to have sequential information - **DONE**
- ☑ We need an architecture that can be trained in parallel (non-Markovian property) - **DONE**



Recap: Transformers

Transformers were originally devised to help with neural machine translation.

They consist of an encoder-decoder architecture, using stacked multi-head attention blocks.



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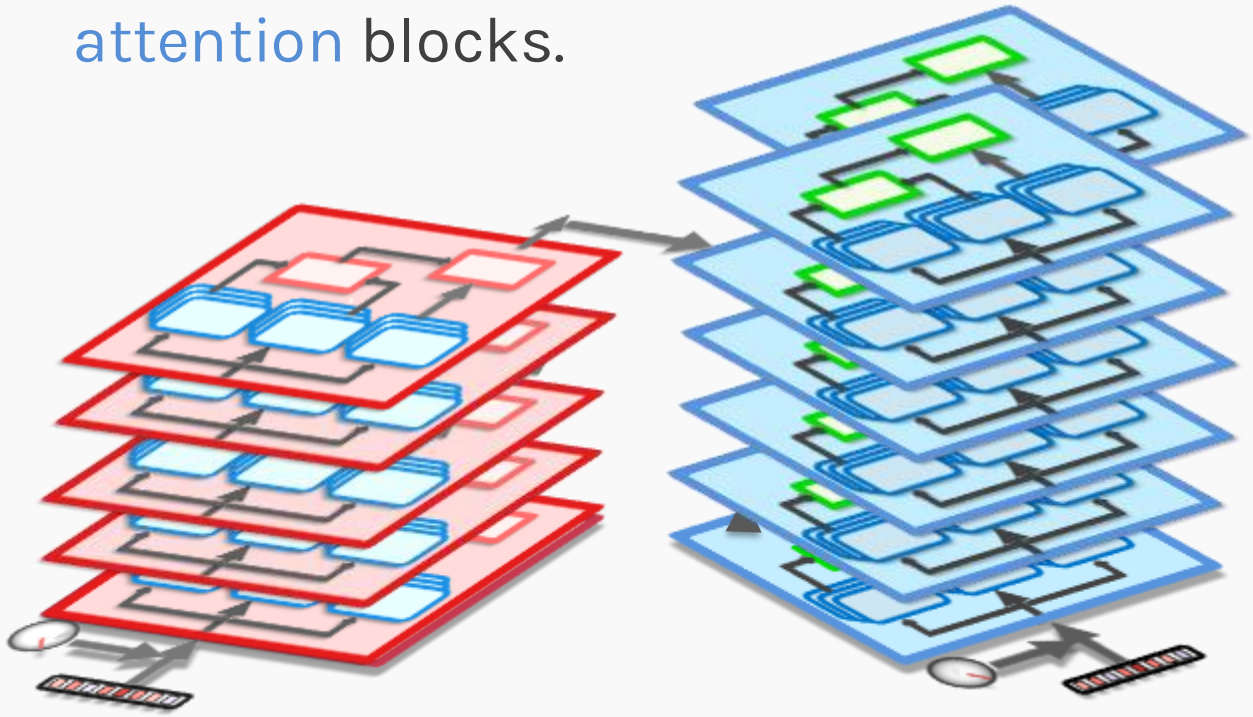
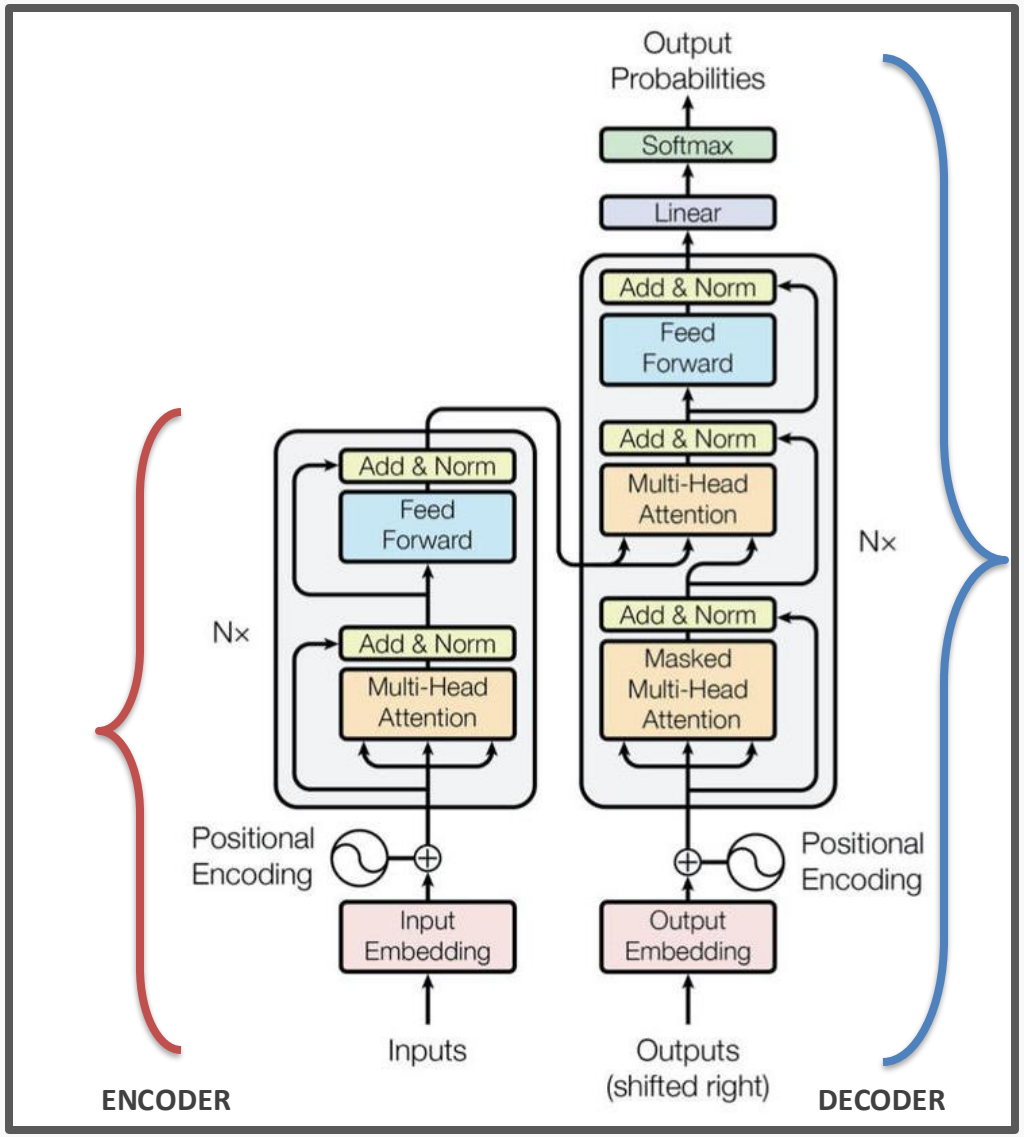


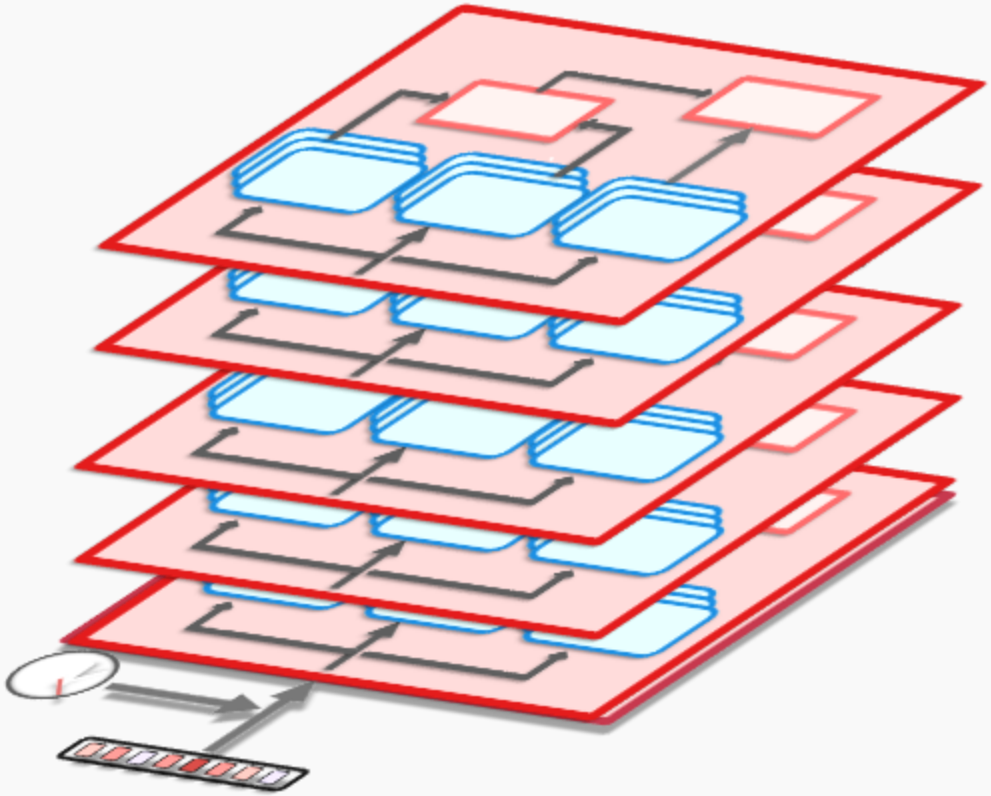
ENCODER DECODER



From Transformers to BERT

- Instead of an **encoder-decoder** architecture for machine translation, what if we just use the encoder as a language model?

- This led to the new architecture called **B**idirectional **E**ncoder **R**epresentations from **T**ransformers, or more commonly known as BERT



ENCODER

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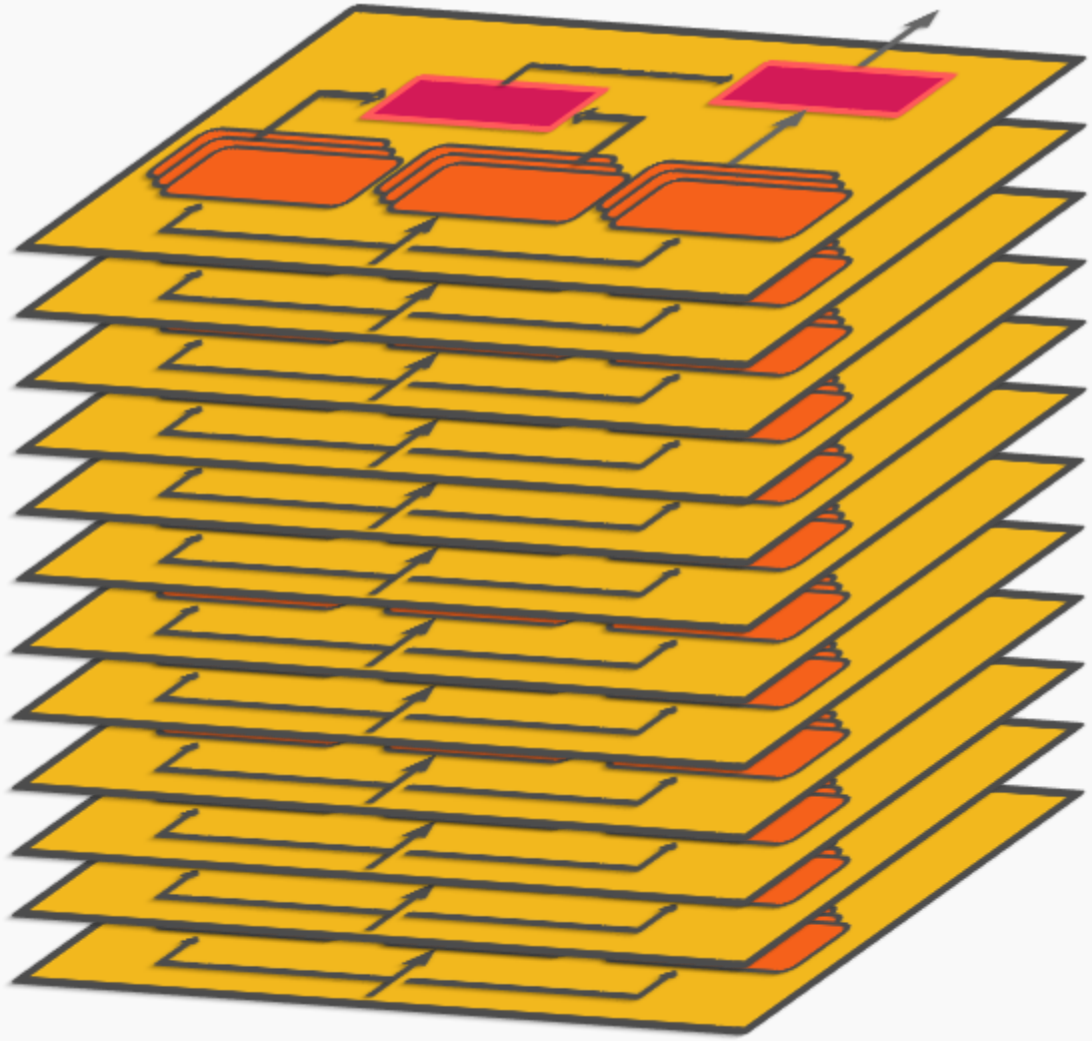
Bidirectional Encoder Representations from Transformers (BERT)

BERT

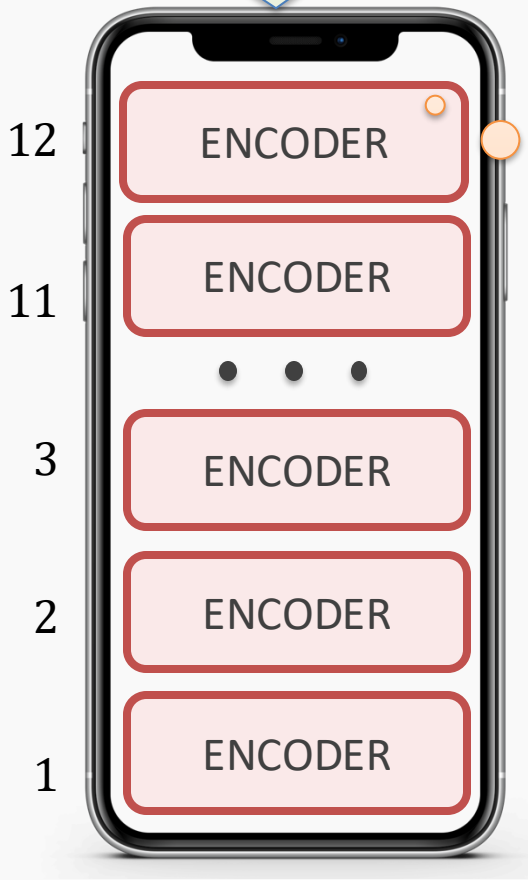
- BERT set new records in language model tasks.
- BERT's code and models are open-source and adaptable.
- BERT is ideal for transfer learning.



Flavors of BERT

Flavors of BERT

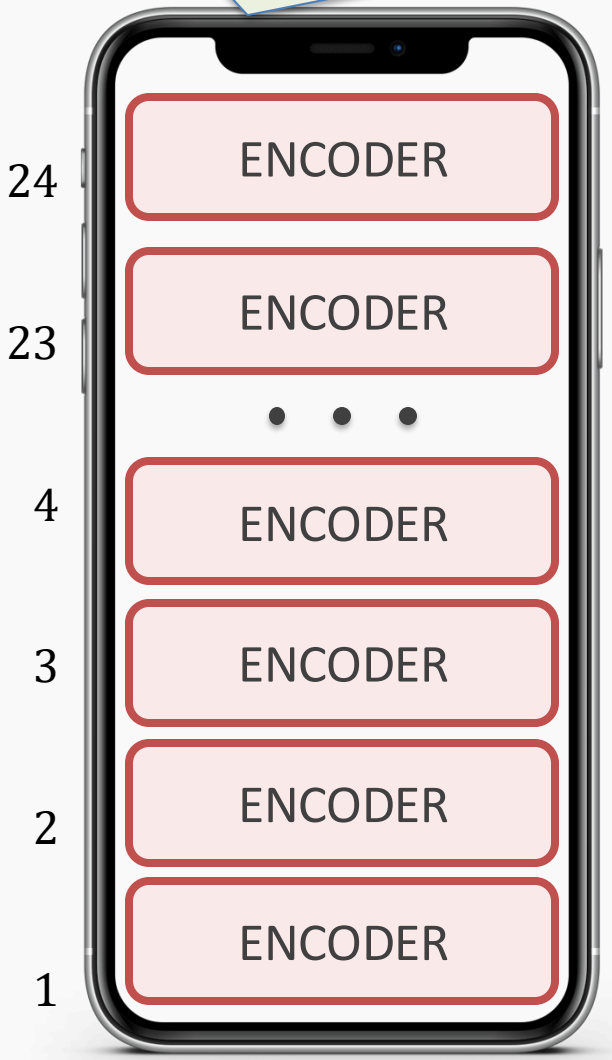
12 ENCODERS
768 HIDDEN UNITS
12 MULTIHEAD ATTENTION LAYERS



BERT BASE

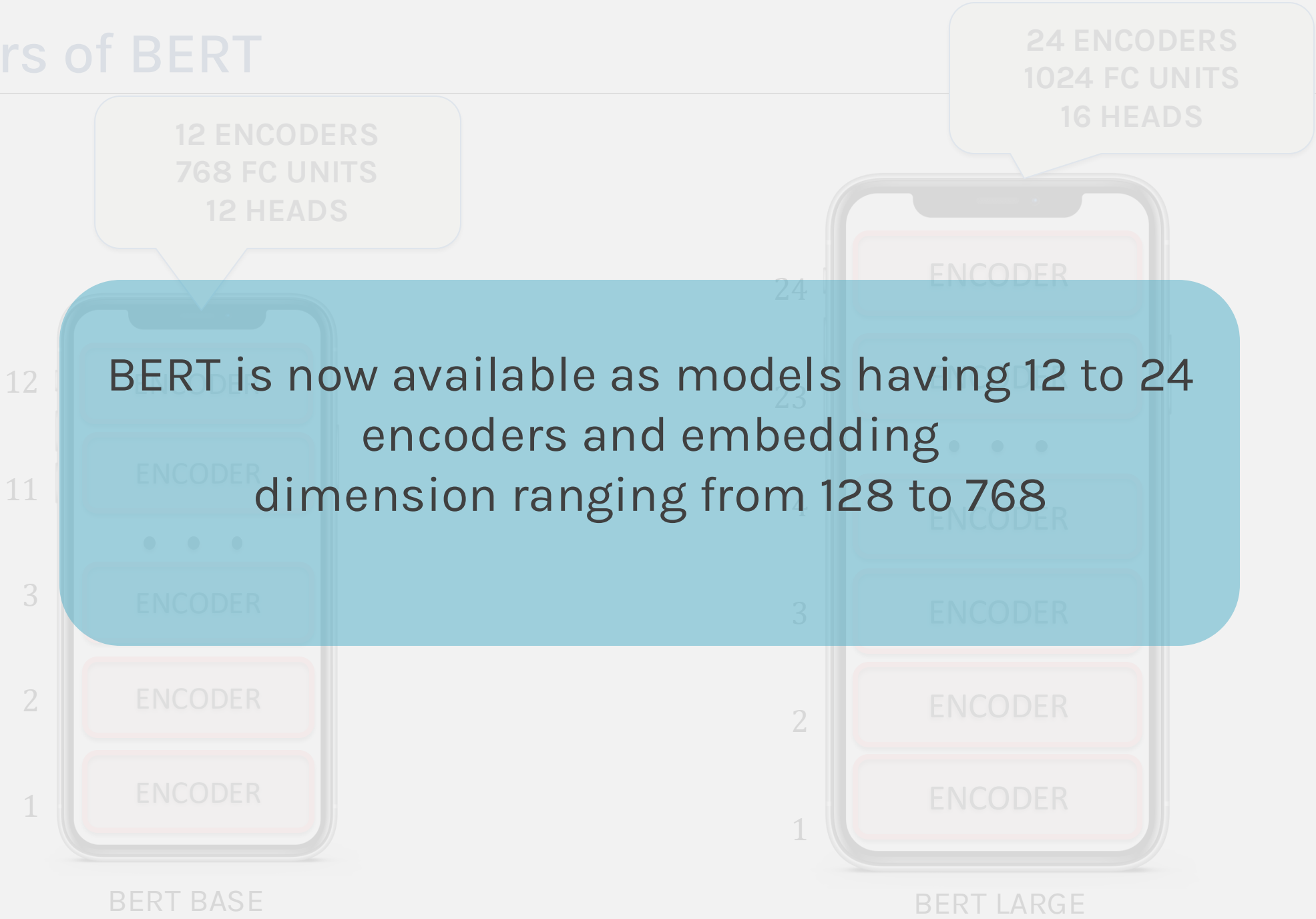
These are the same as the 'transformer layers' mentioned in the last lesson!

24 ENCODERS
1024 HIDDEN UNITS
16 MULTI HEAD ATTENTION LAYERS



BERT LARGE

Flavors of BERT

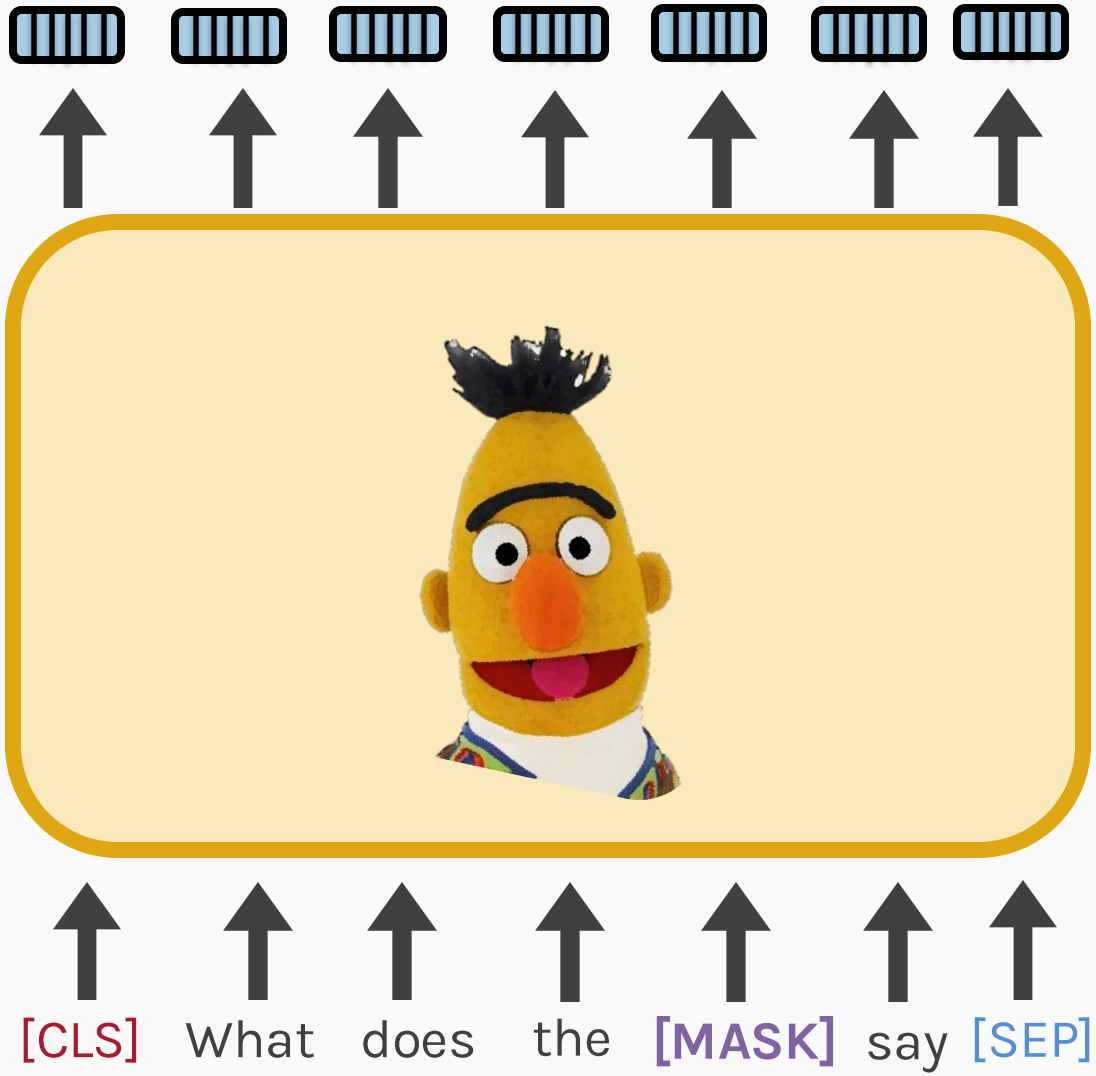


BERT is now available as models having 12 to 24 encoders and embedding dimension ranging from 128 to 768

BERT

TECHNICAL DETAILS

- Input sequences to BERT must have the following special tokens:
  - [CLS] – Classifier Token
  - **[MASK]** – Masking token
  - [SEP] – Separator token



How to train a BERT?

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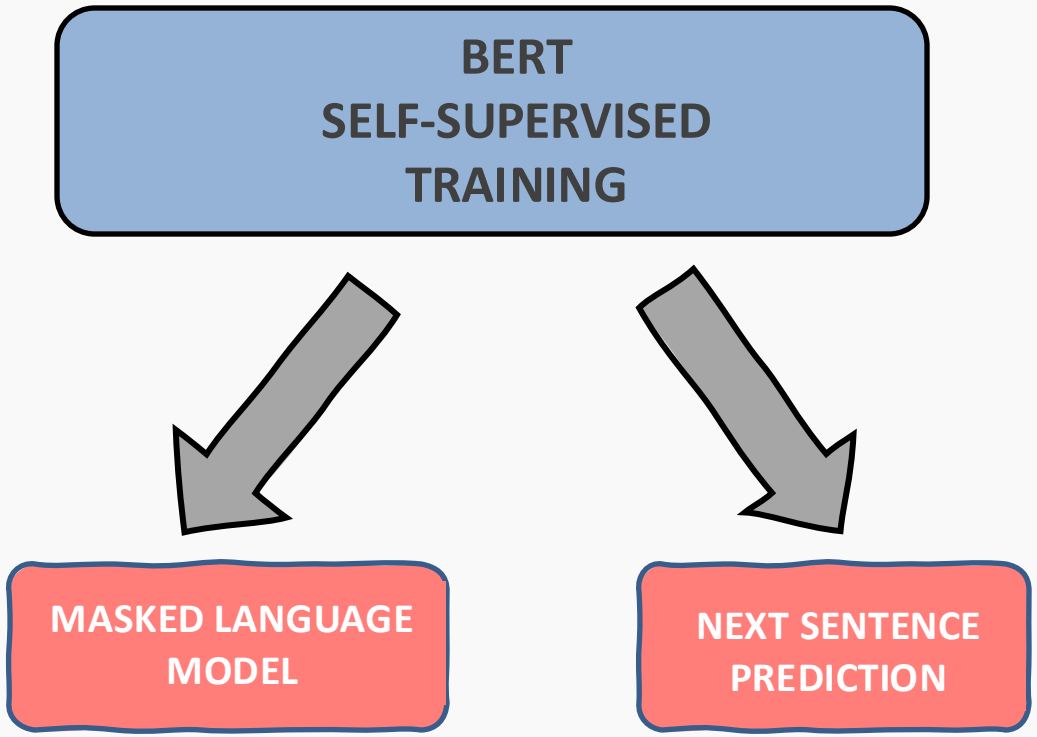

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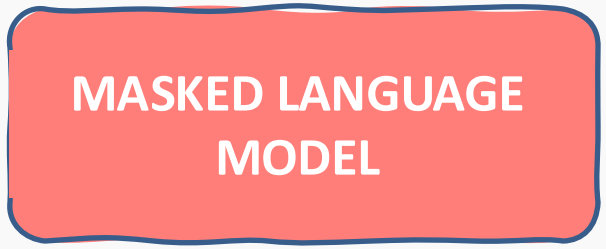

Challenges on training BERT as a language model

TRAINING ISSUES?

- If BERT takes the entire sequence as an input, how can we train it as a language model?

- How could we classify if two chosen sentences follow each other or are out of place if the output is also a sequence of tokens?

RECAP: Language Model

Amelia was hit by a bus as she was crossing the street

Amelia was hit by a ___

So, how do we do this with self-attention?

This sort of language modeling is not possible with self-attention, because it inputs the entire sequence at once

Masked Language Model

Amelia was hit by a bus as she was crossing the street

Amelia was hit by a [MASK] as he was …

Great! We SHALL call this a masked language model

Let's use my "favorite" trick, MASKING!

Amelia was hit by a **bus** as she was crossing the street

[CLS] Amelia was hit by a **bus** as she was crossing the street

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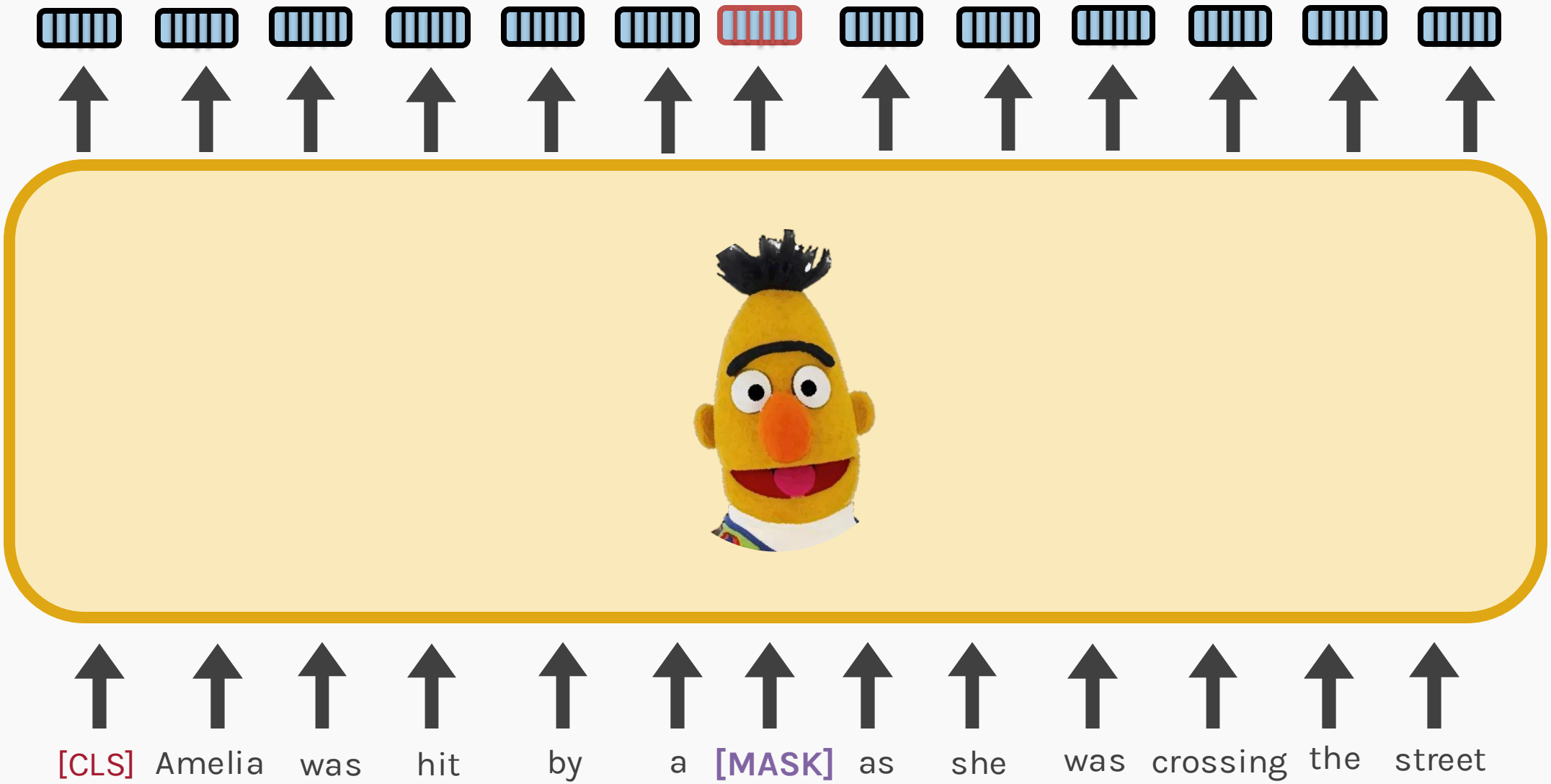

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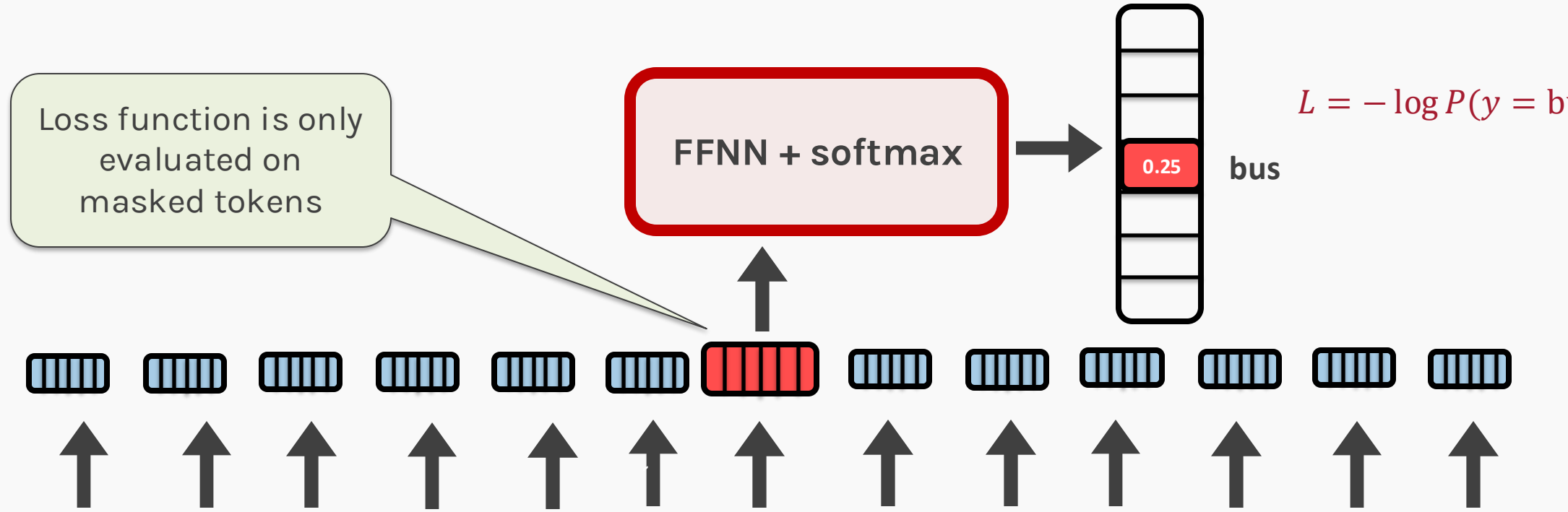
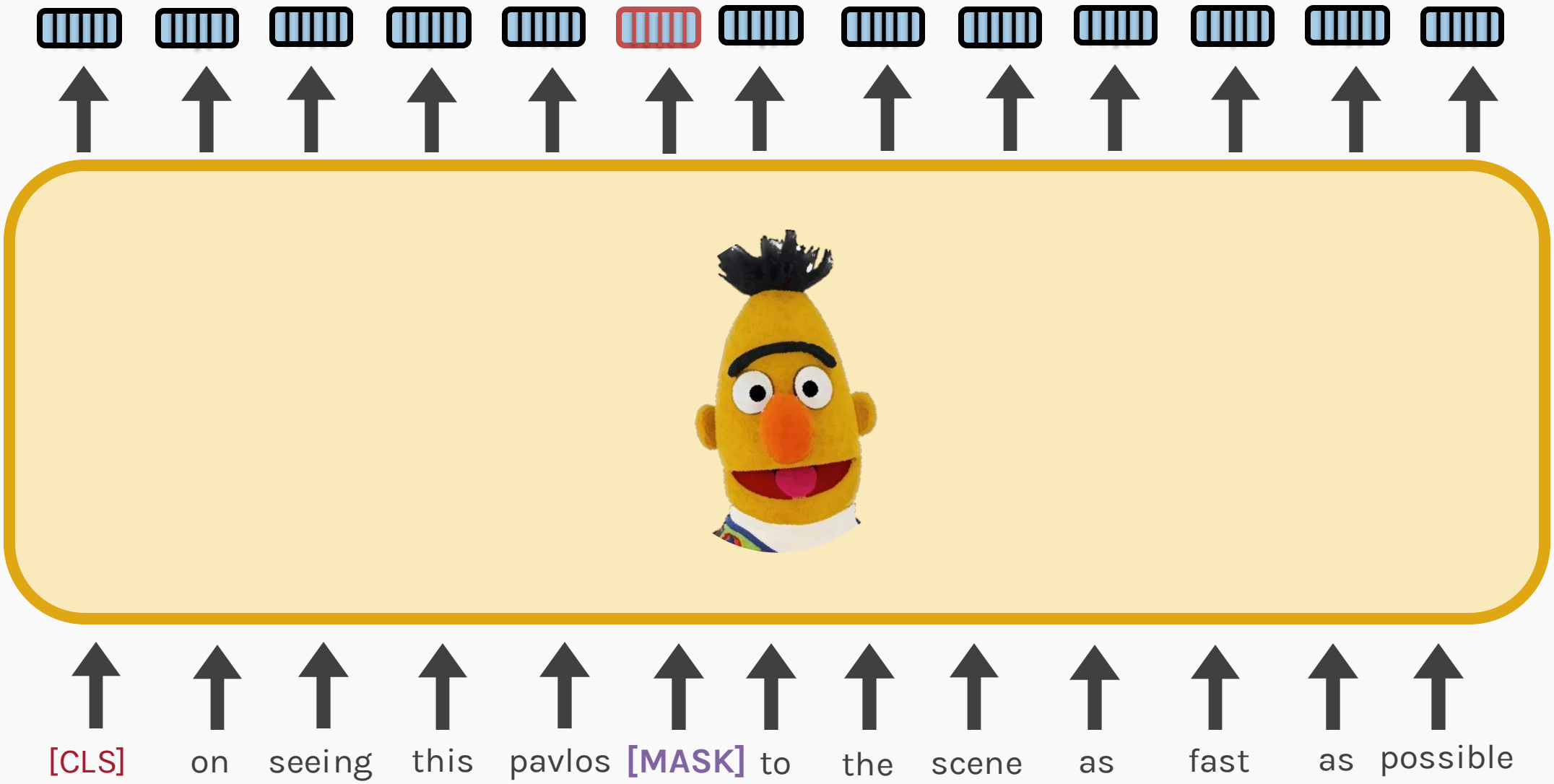


On seeing this, Pavlos **ran** to the scene as fast as possible



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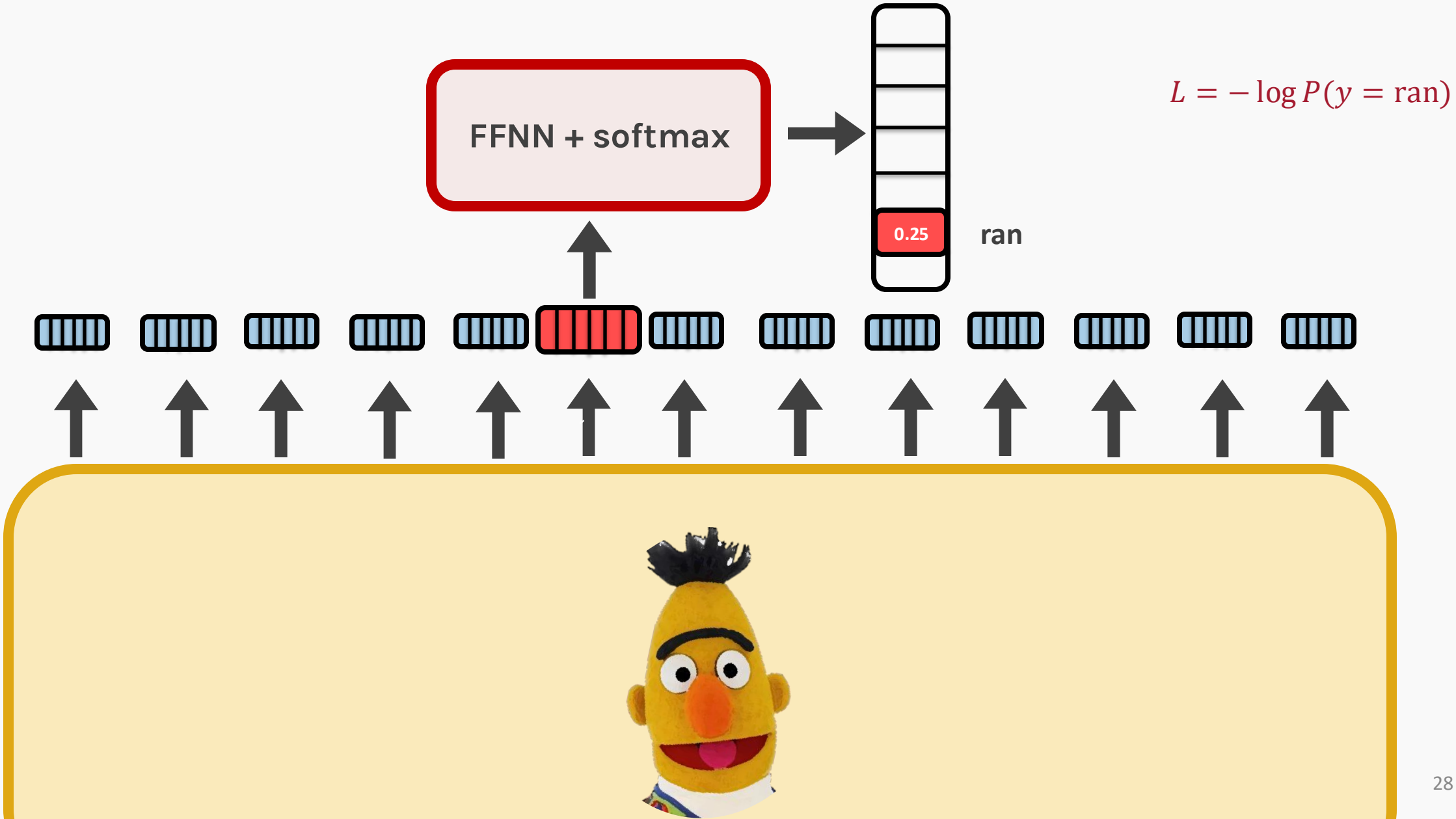
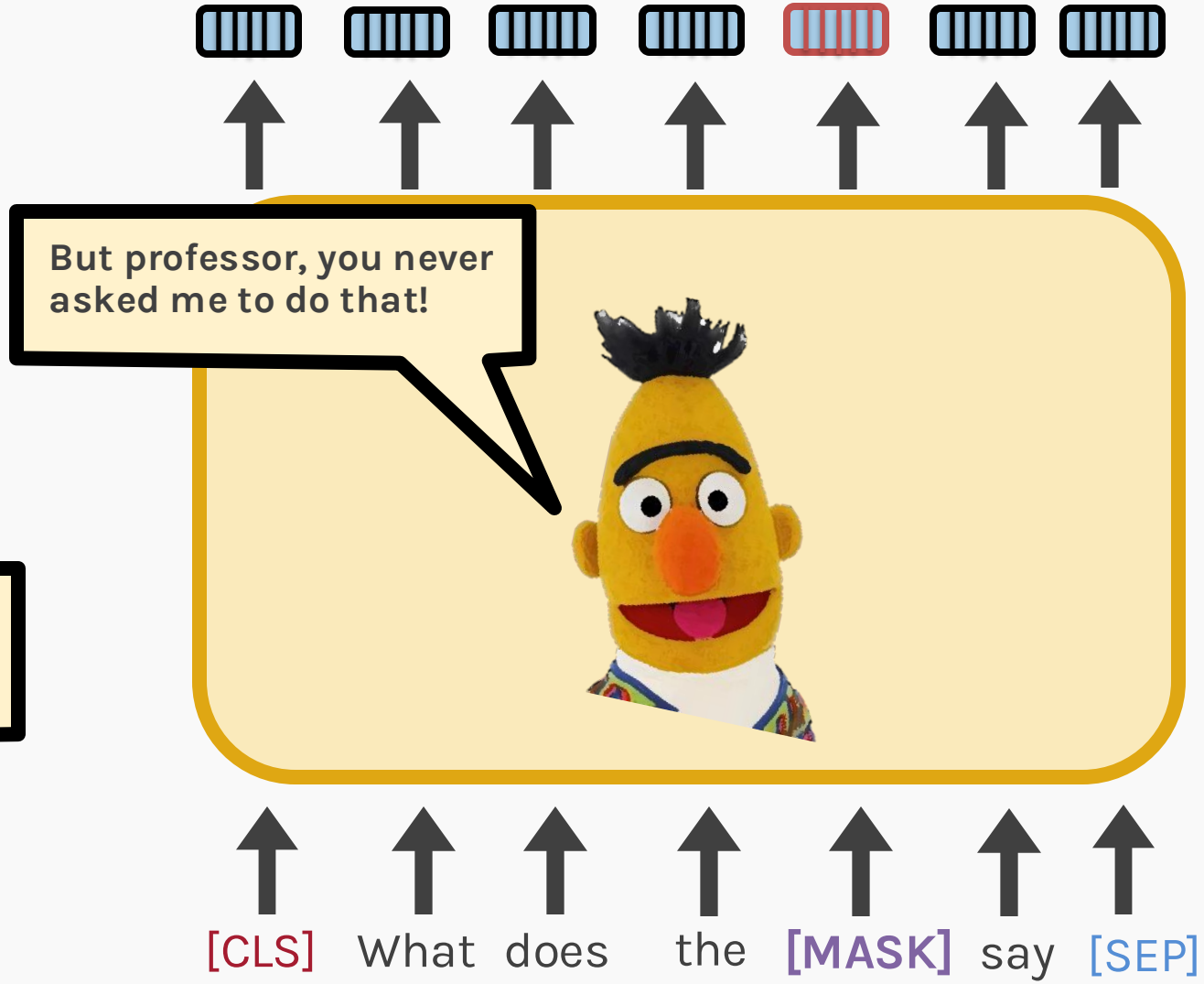


BERT

MASKING ISSUES?

- The model learns how to correctly predict the masked words but completely ignores other words.

Hey BERT, why aren't you predicting other words correctly?



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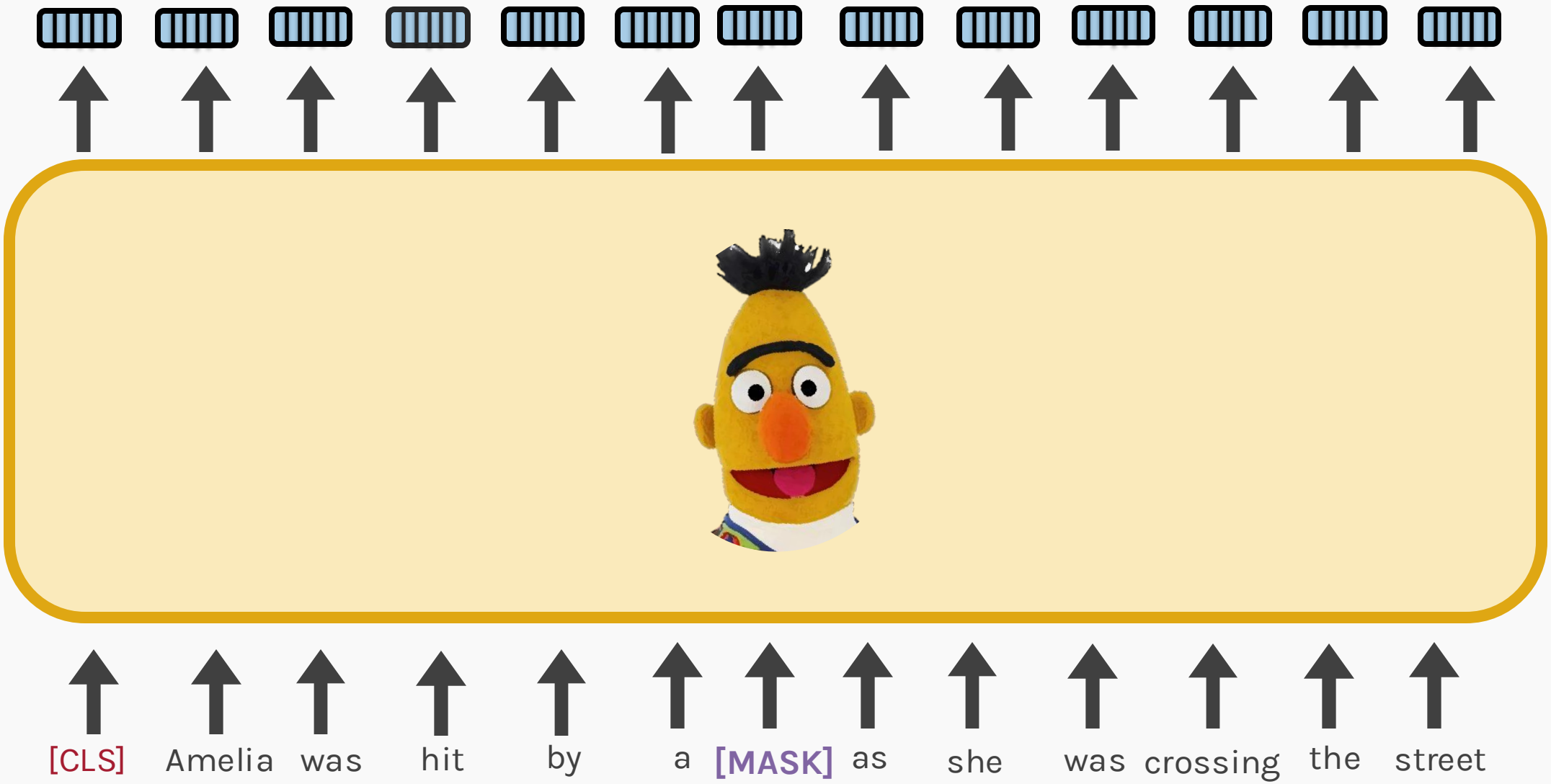

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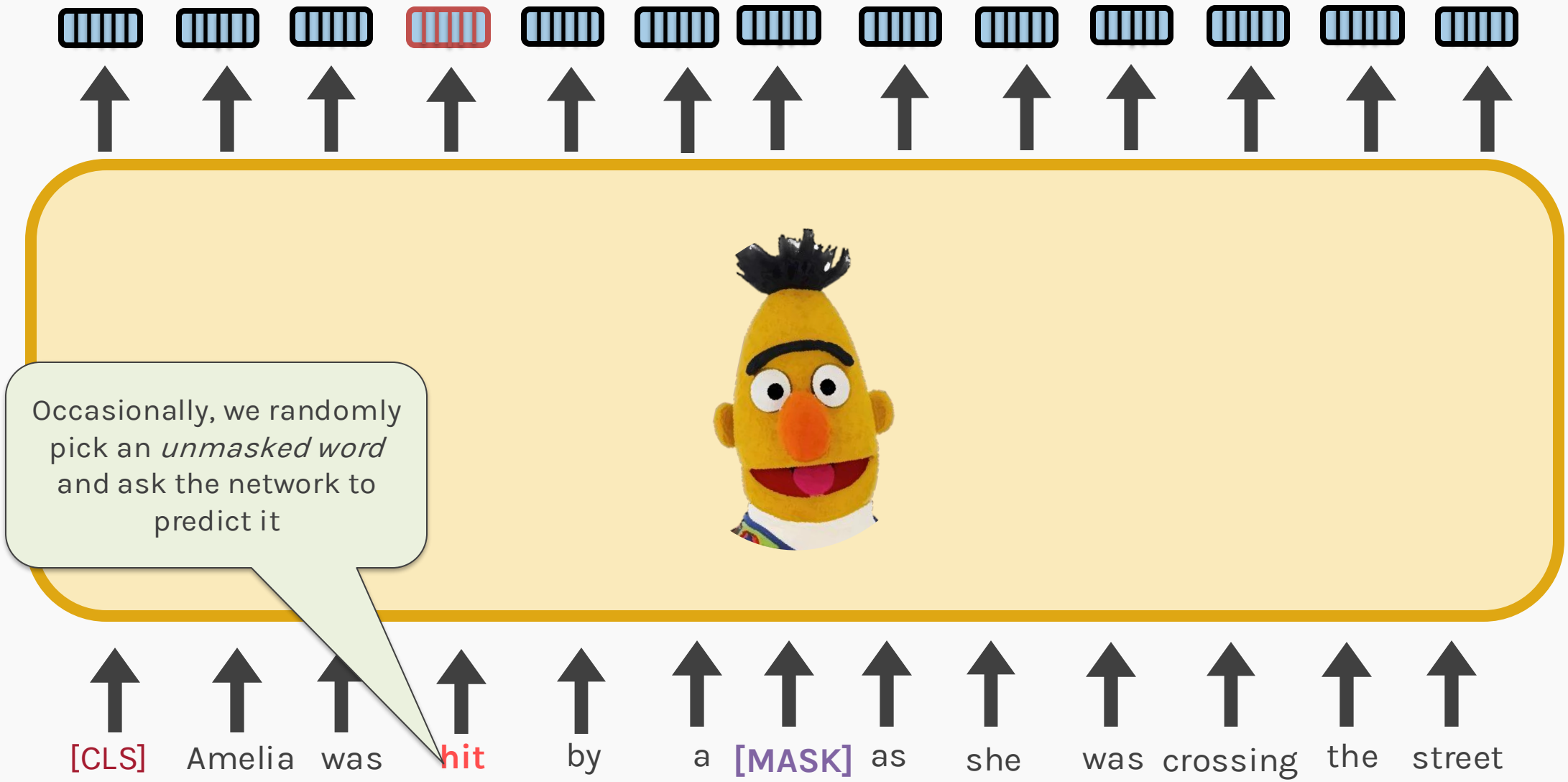

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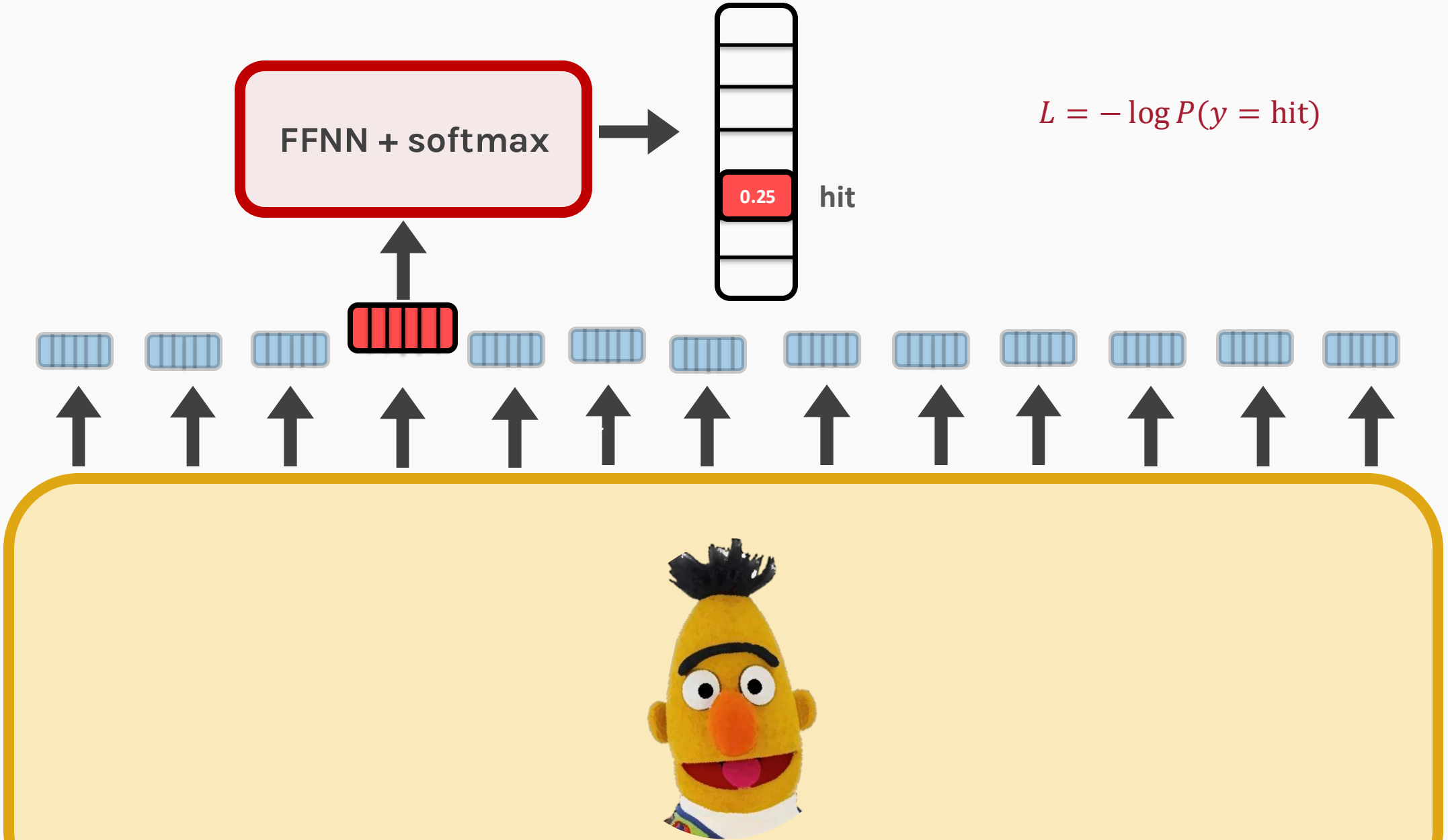


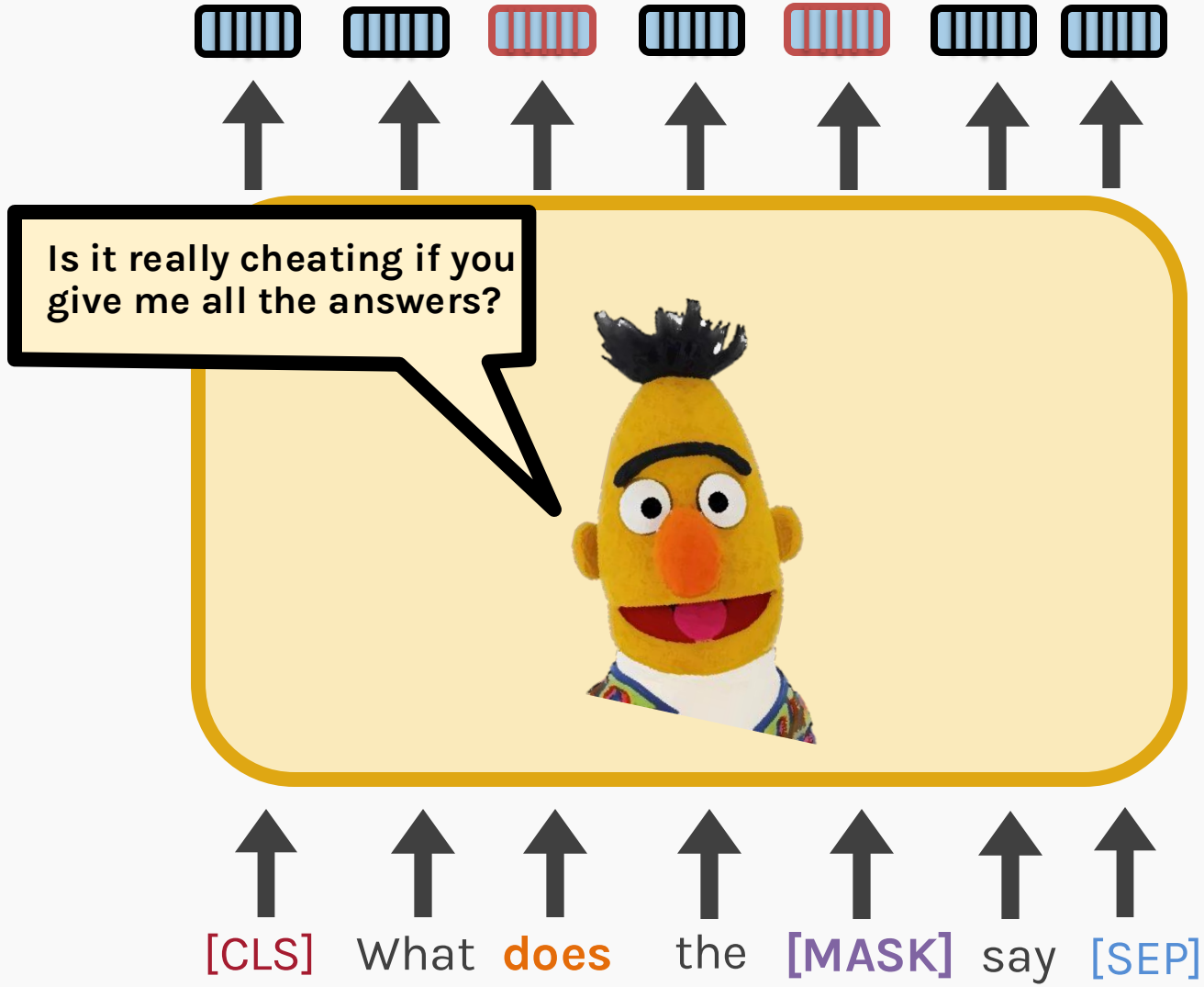
$$L = -\log P(y = \text{hit})$$

BERT

ISSUES?

- The model could use an identity mapping to return unmasked words.

Hey BERT, why are you cheating on the test?



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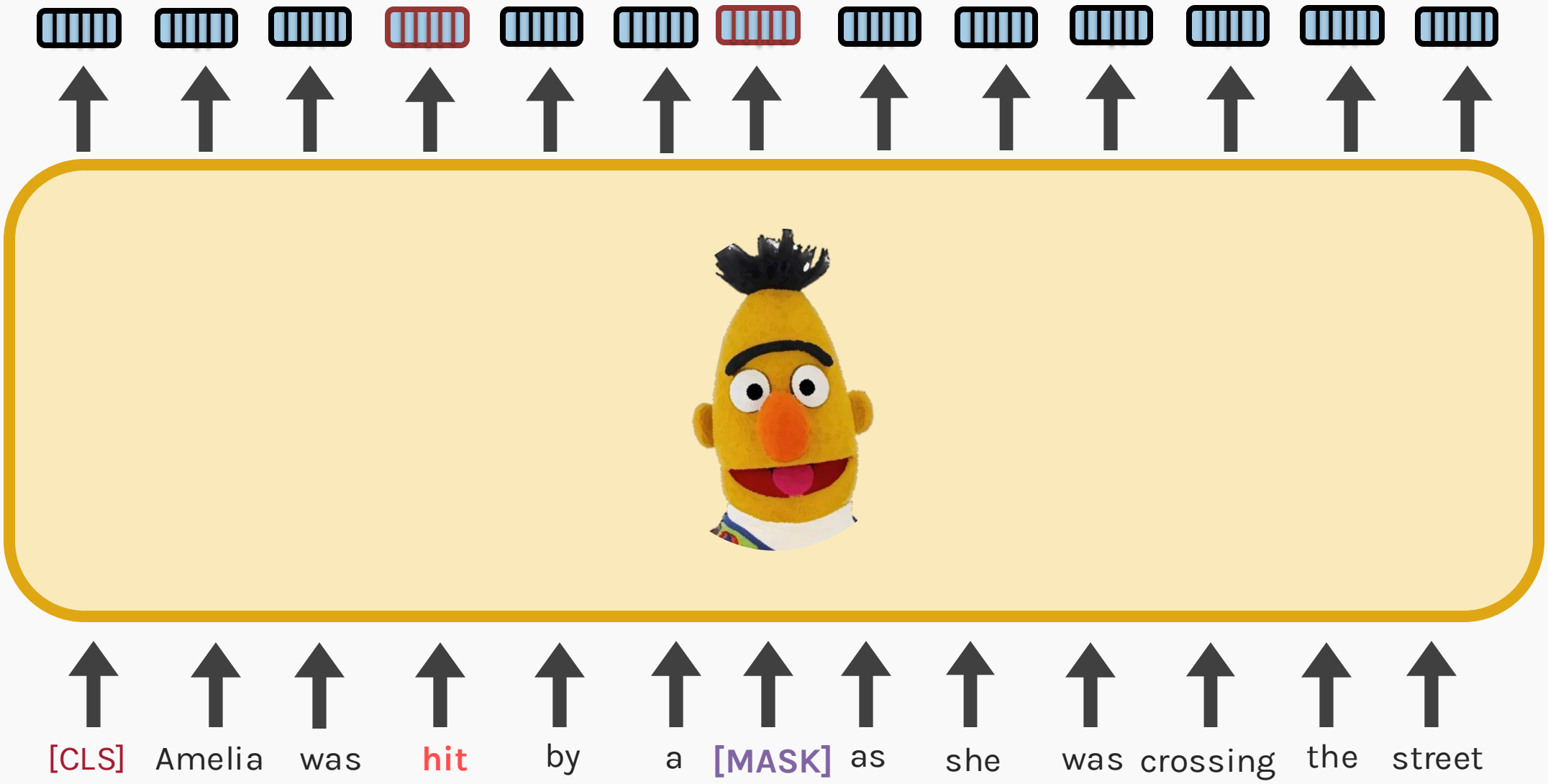

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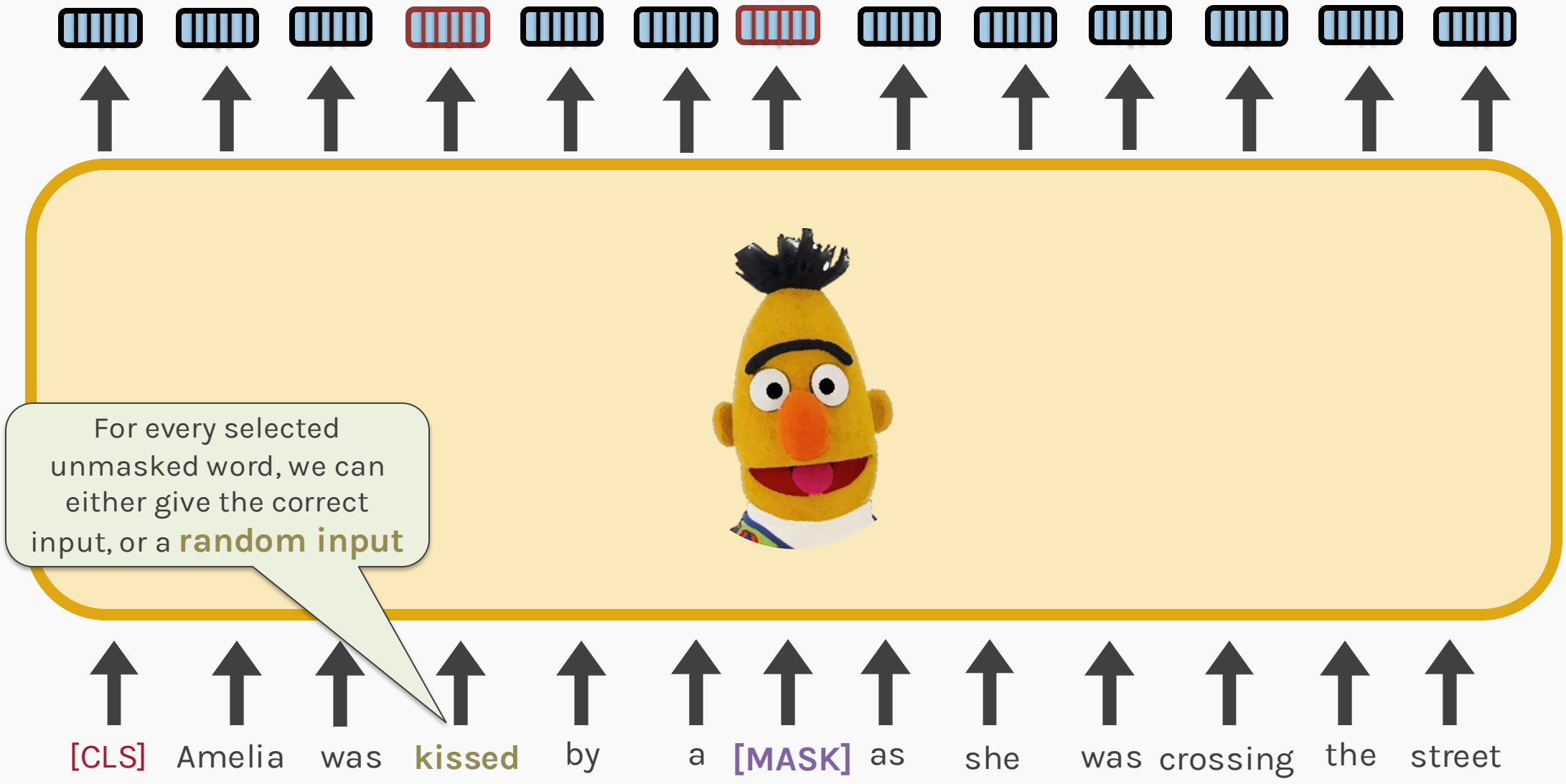

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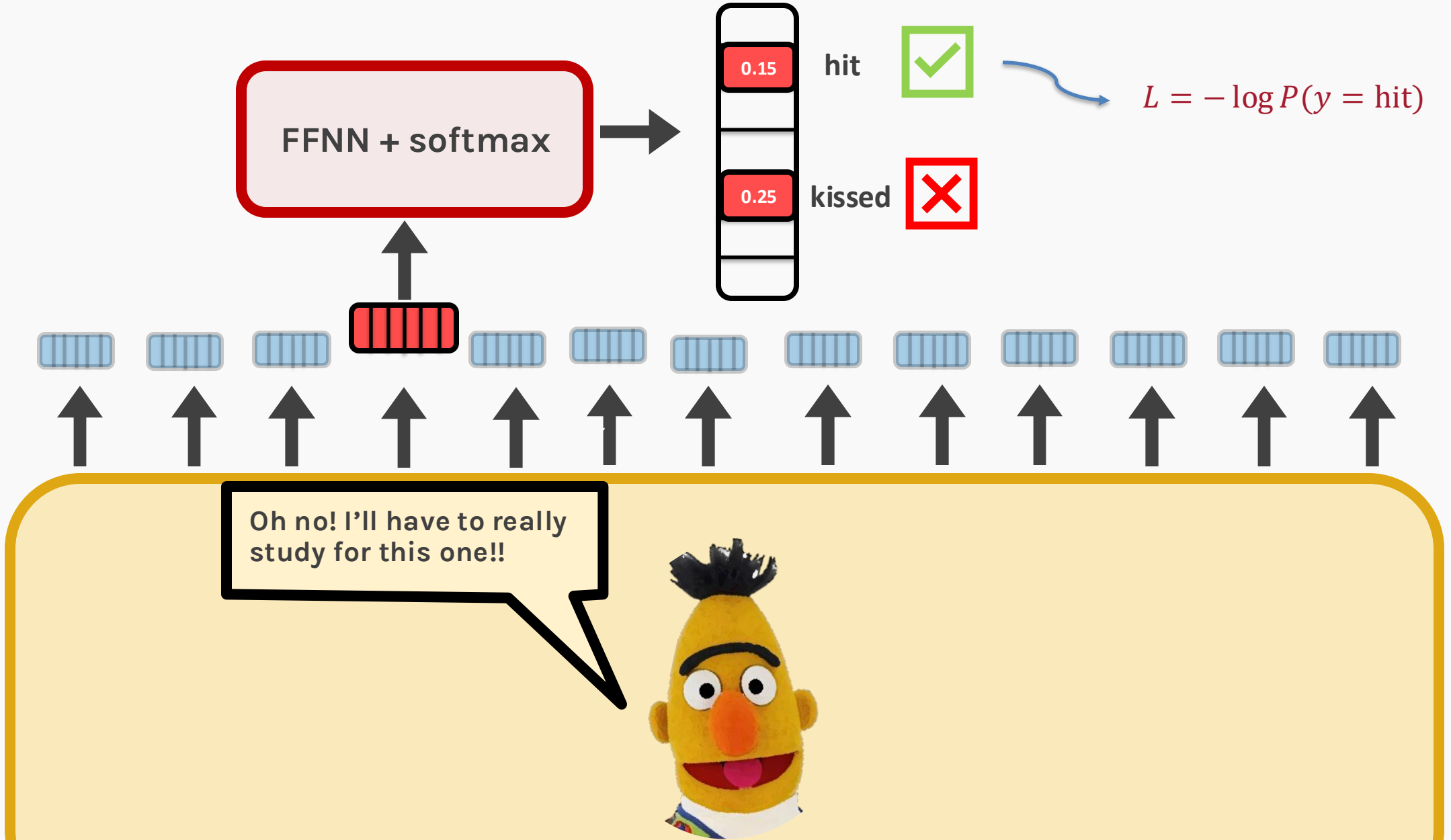
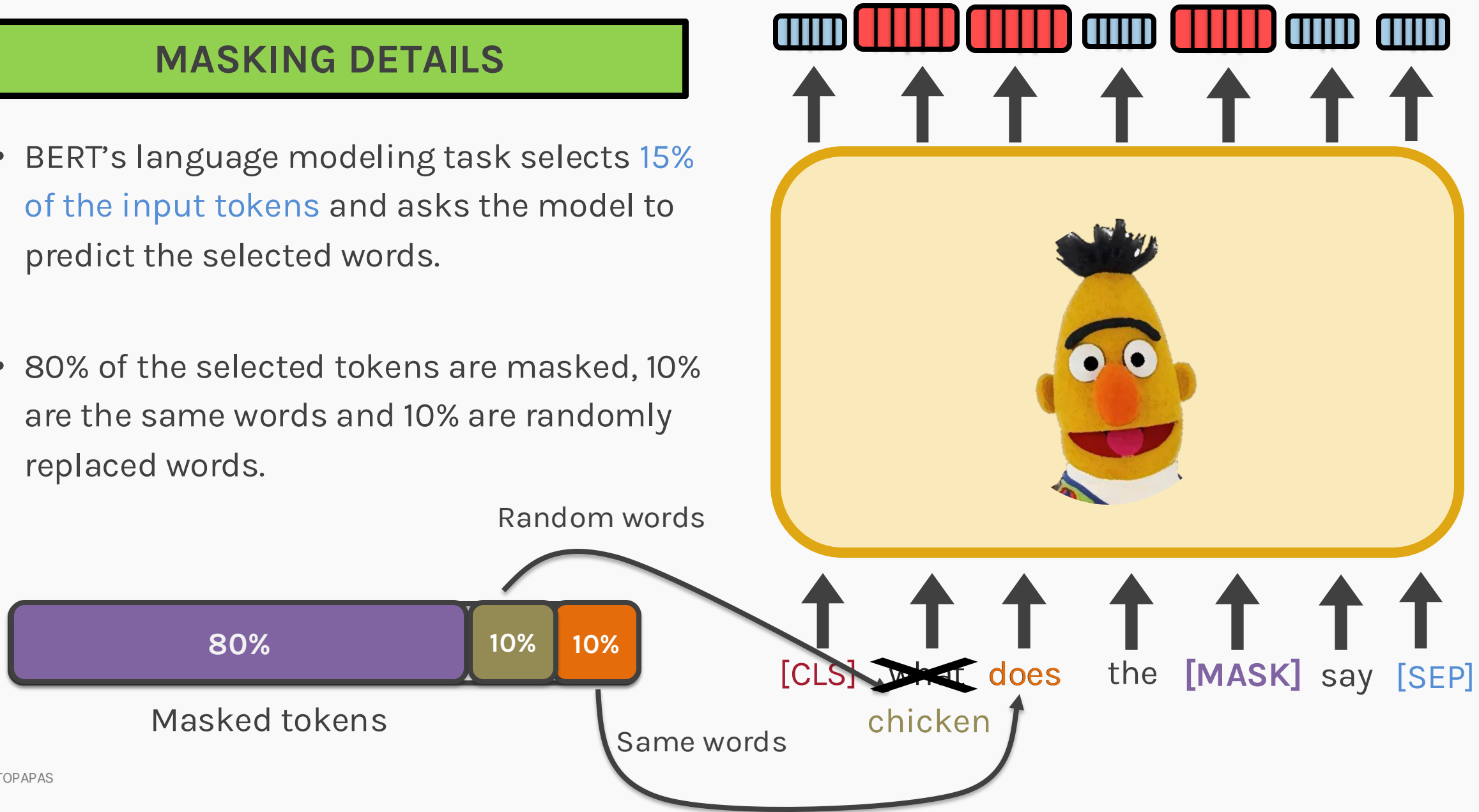


BERT

MASKING DETAILS

- BERT's language modeling task selects 15% of the input tokens and asks the model to predict the selected words.

- 80% of the selected tokens are masked, 10% are the same words and 10% are randomly replaced words.



NEXT SENTENCE PREDICTION

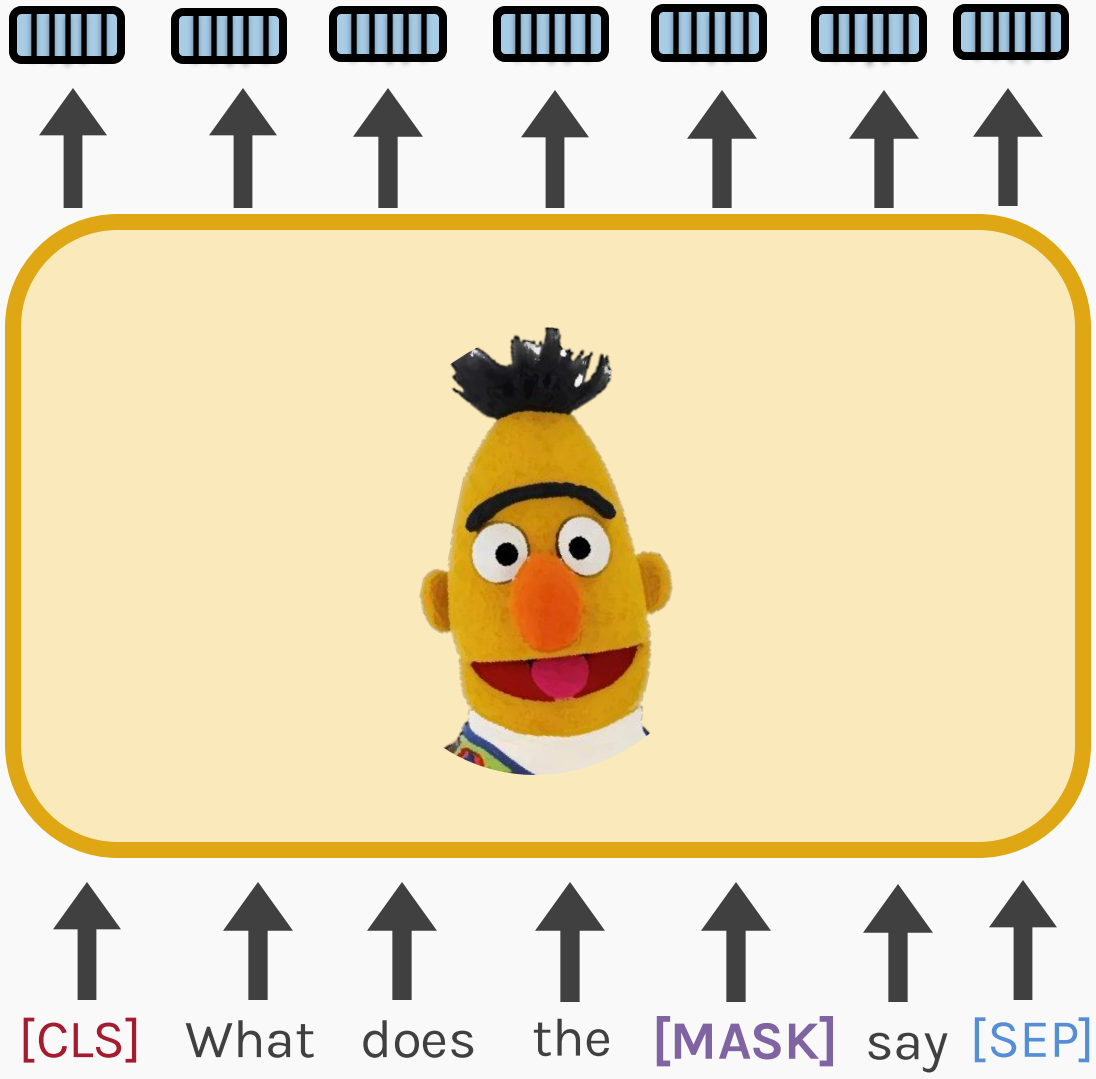
Two sentence task

TECHNICAL DETAILS

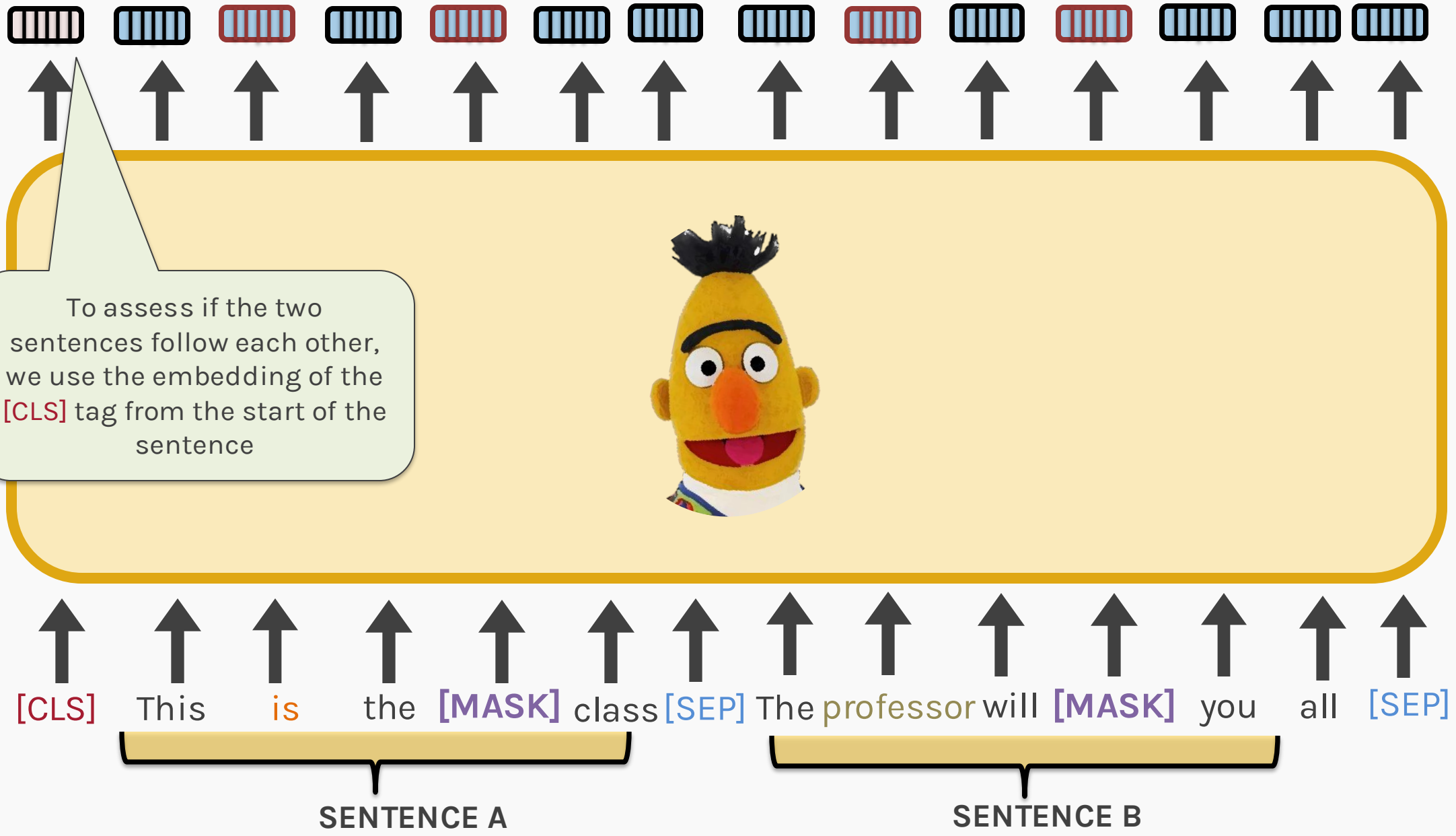
- To make BERT better at handling relationships between multiple sentences, the training process includes an additional task:

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

The individual sentences are separated by the **[SEP]** tag mentioned before.



This is the **last** class. The professor will **miss** you all



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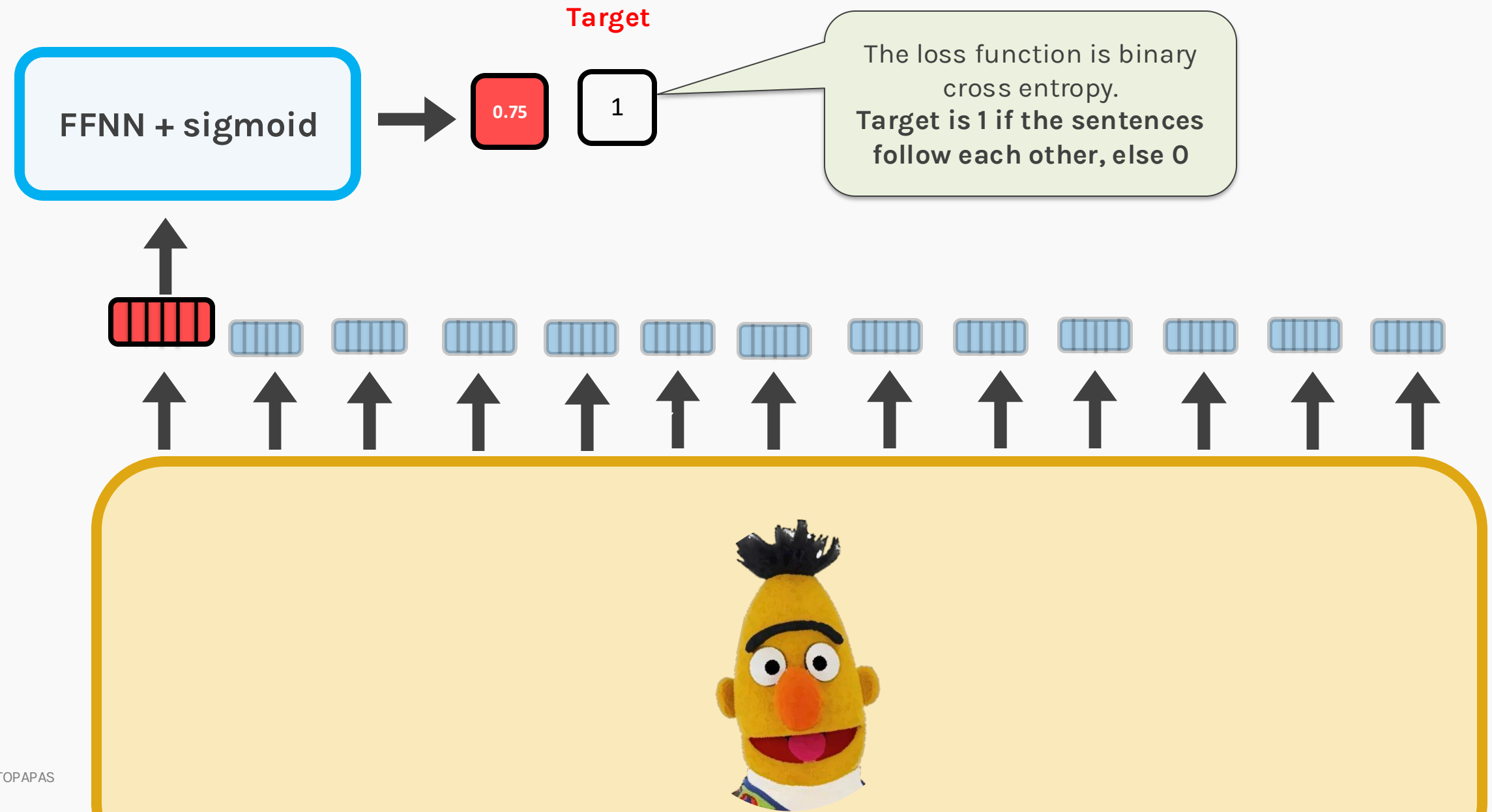
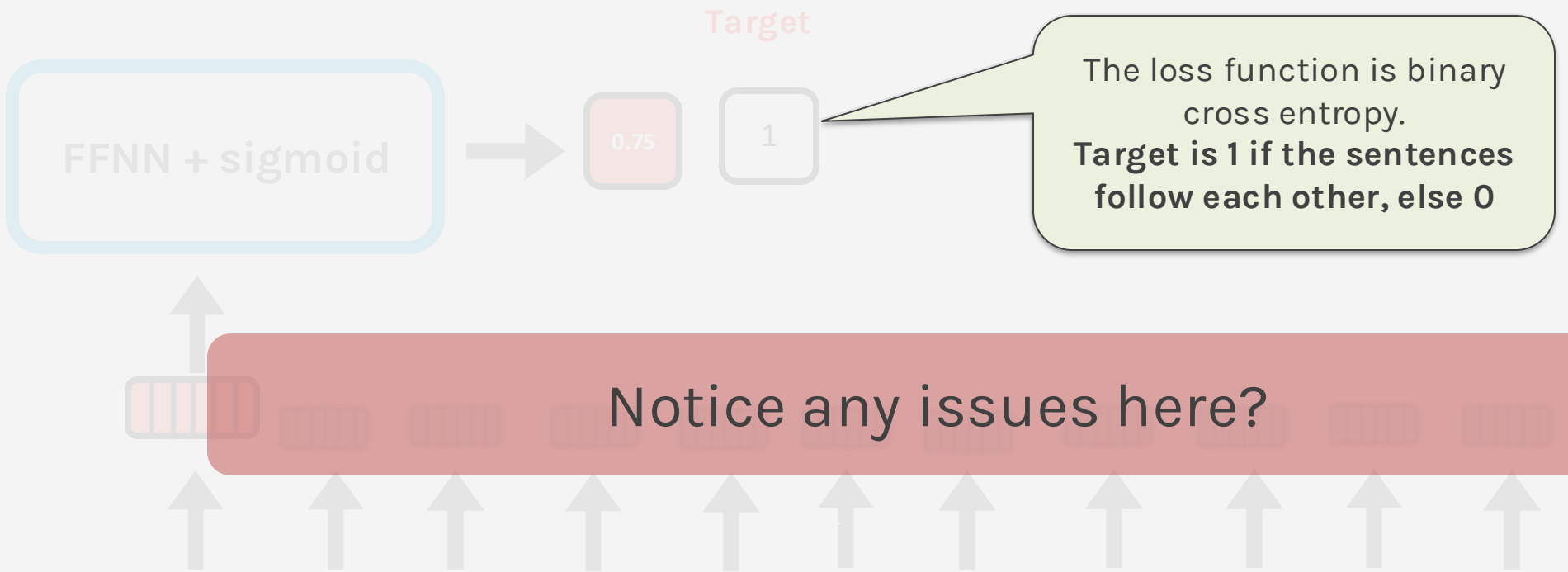
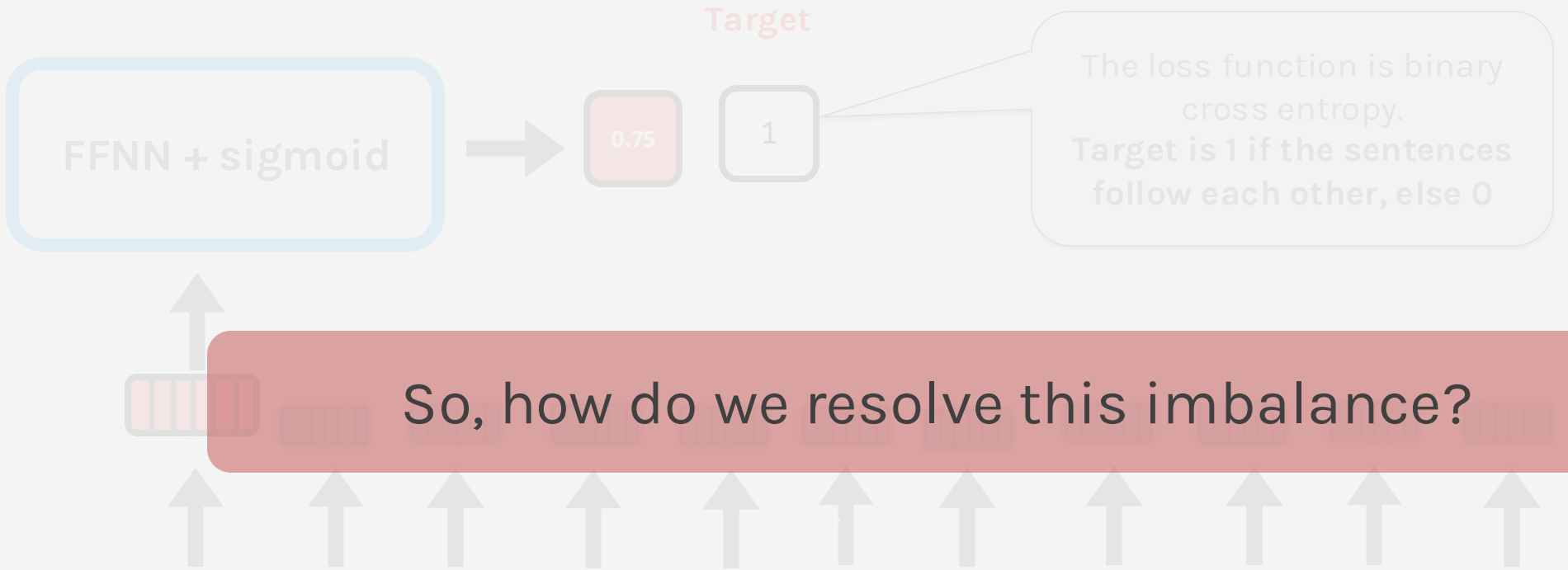




The texts used for training have continuous sentences that follow each other. Therefore, all of the examples for training would be labelled 1!

This is the last class. The professor will miss you all



So, how do we resolve this imbalance?

Let us first take a quick class poll!

Class Poll - Negative Sampling

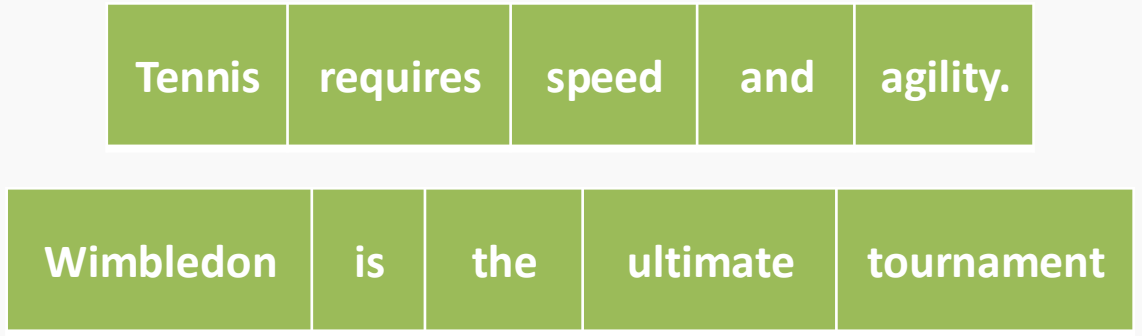
Do you think these two sentences belong together?

Tennis	requires	speed	and	agility.

Wimbledon	is	the	ultimate	tournament

Class Poll - Negative Sampling

CORRECT!



Class Poll - Negative Sampling

How about now?

Tennis	requires	speed	and	agility.

Brown	butter	is	the	secret	ingredient

Class Poll - Negative Sampling

CORRECT AGAIN, Humans!

Brown	butter	is	the	secret	ingredient

Tennis	requires	speed	and	agility.

Wimbledon	is	the	ultimate	tournament

Negative Sampling

However, this understanding is not intuitive for a language model.

- We need to create 'synthetic' negative samples of sentences that don't belong together to 'teach' the model.

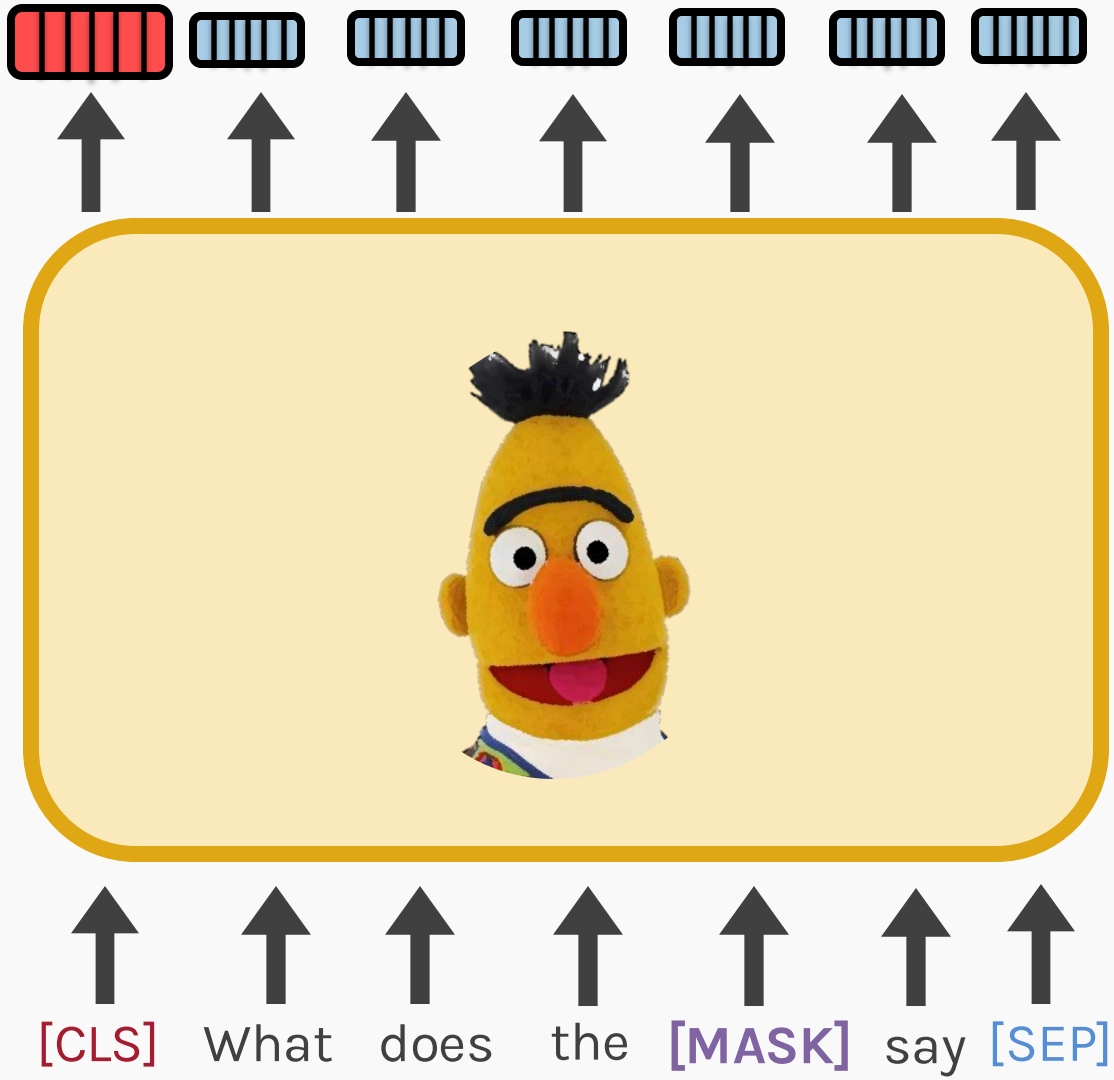
- We can use sample sentences from widely different sources and train a simple classifier.

Sentence A	Sentence B	Target
Tennis requires speed and agility.	Wimbledon is the ultimate tournament.	1
Tennis requires speed and agility.	Brown butter is the secret ingredient.	0
Brown butter is the secret ingredient	Grand Slam titles define tennis legends.	0
Brown butter is the secret ingredient.	It adds a rich, nutty flavor.	1

How to train BERT?

CLIFF NOTES

- Using a large corpus (e.g. Wikipedia), we *pre-train* a BERT model for two tasks:
  - ***Masked word*** prediction
  - ***Next sentence*** prediction
- The goal is minimizing the combined loss function.
- The selected ([MASK]/true/random) tags are used for the language model task, and the [CLS] and [SEP] tag helps to train the next sentence prediction task.



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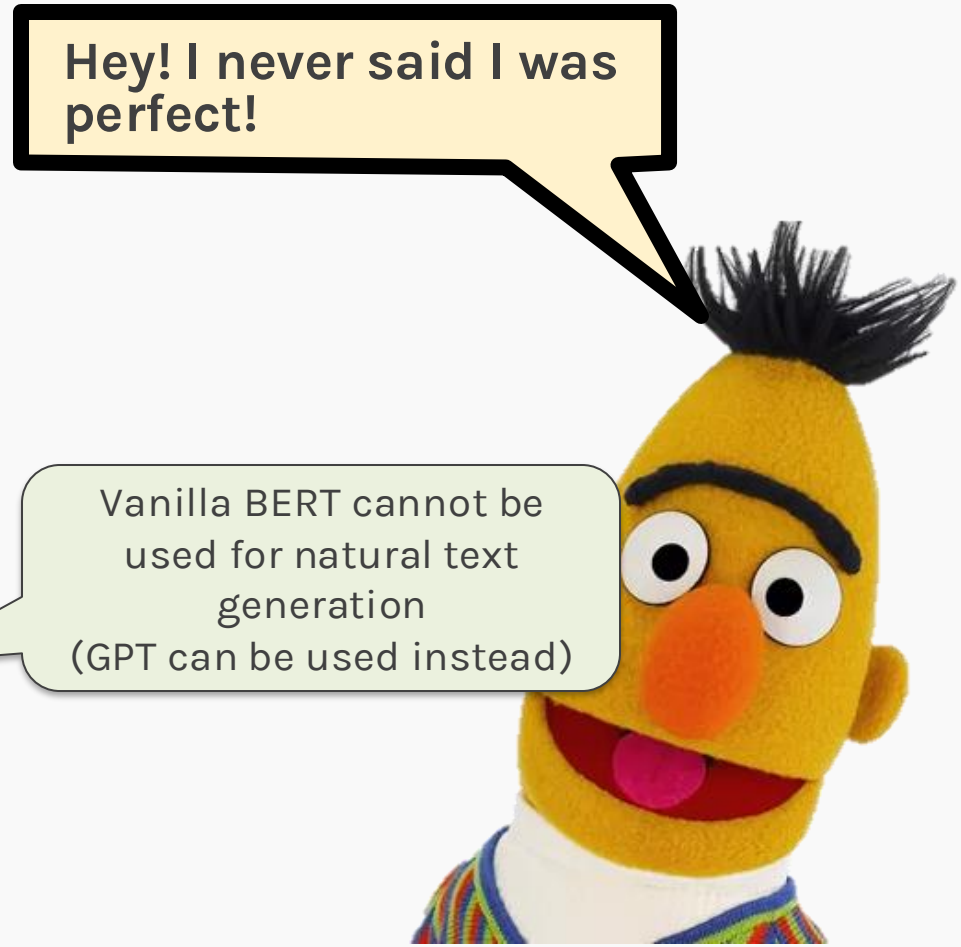
BERT ISSUES?

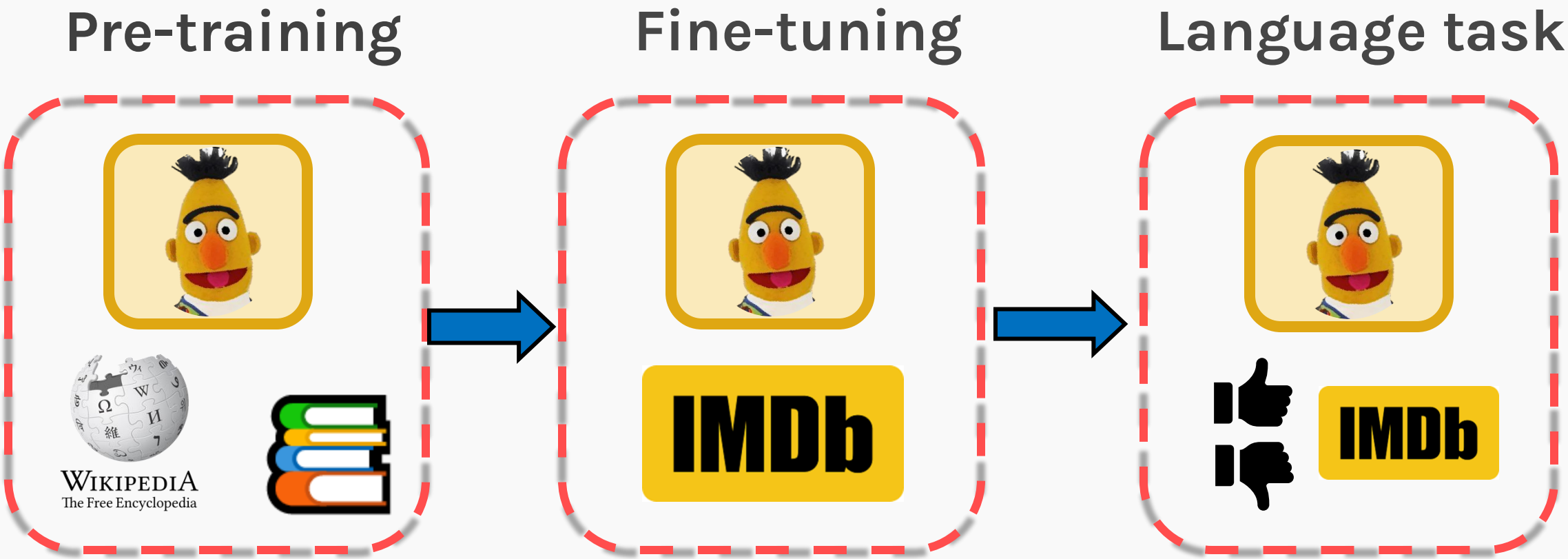
- The vanilla BERT (base) has **109,482,240** trainable parameters.
- An extremely large dataset is required to train such model sufficiently.
- The sheer size makes it extremely slow to train.
- The fine-tuning – we will explain later - requires lots of tweaks and experimentation (for e.g. you must use the *same* tokenizer used during pre-training).



How to *use* BERT?

How to use a BERT?

There are three main steps in using BERT for a given NLP task



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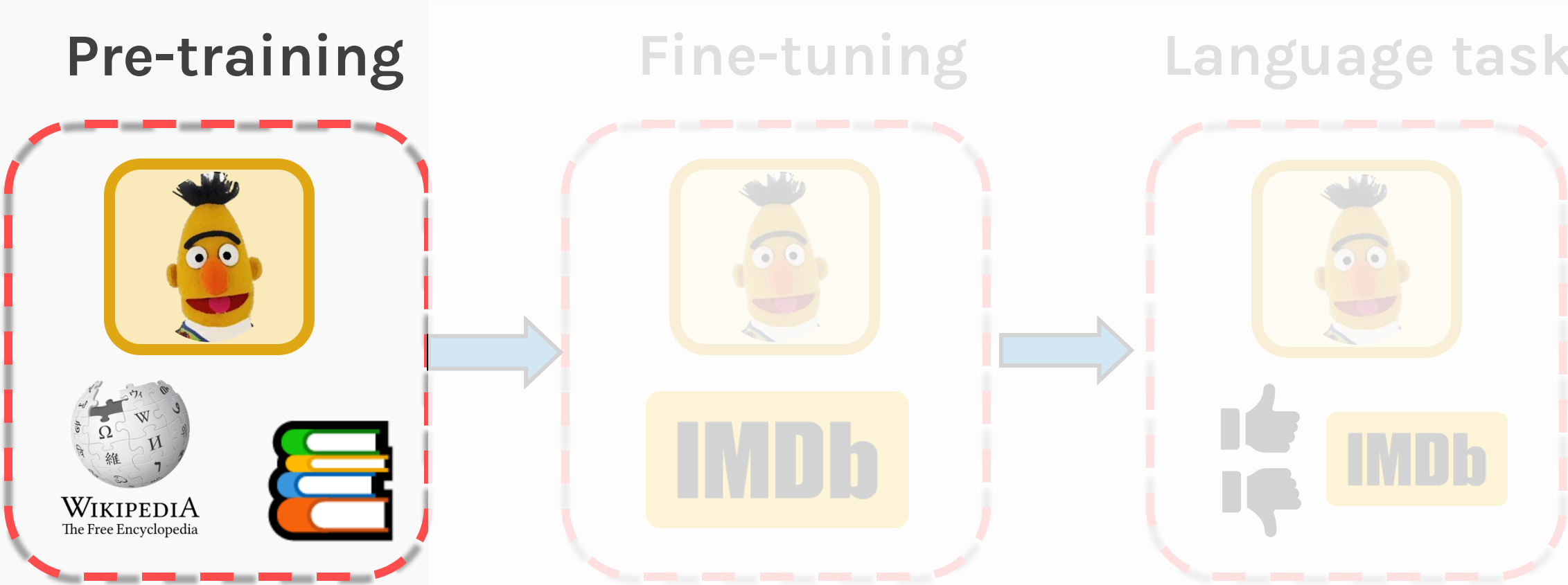

Pre-training

We train a Language Model on a large dataset!

For example, BERT Large was pretrained on BooksCorpus which contains 800 million words and Wikipedia which contains 2.5 billion words.

Note that these datasets contain a **broad range** of topics which helps in **generalization.**

Pre-training issues

Large dataset

Uncompressed, the total amount of data is roughly 40 TB.
That amount of storage is not unattainable but will imply an investment to store that much data.

Computational Complexity

BERT was trained for 40 epochs on 16 TPUs.

This pre-training takes around 4 days to complete and impacts the environment!

Assuming you don't have that hardware or resources at your disposal, the next solution is to use cloud resources. At a 12 USD an hour, for todays cost it would cost around 18000 USD.

Pre-training issues

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Let someone else do it for us (transfer learning!)

How to use a BERT?

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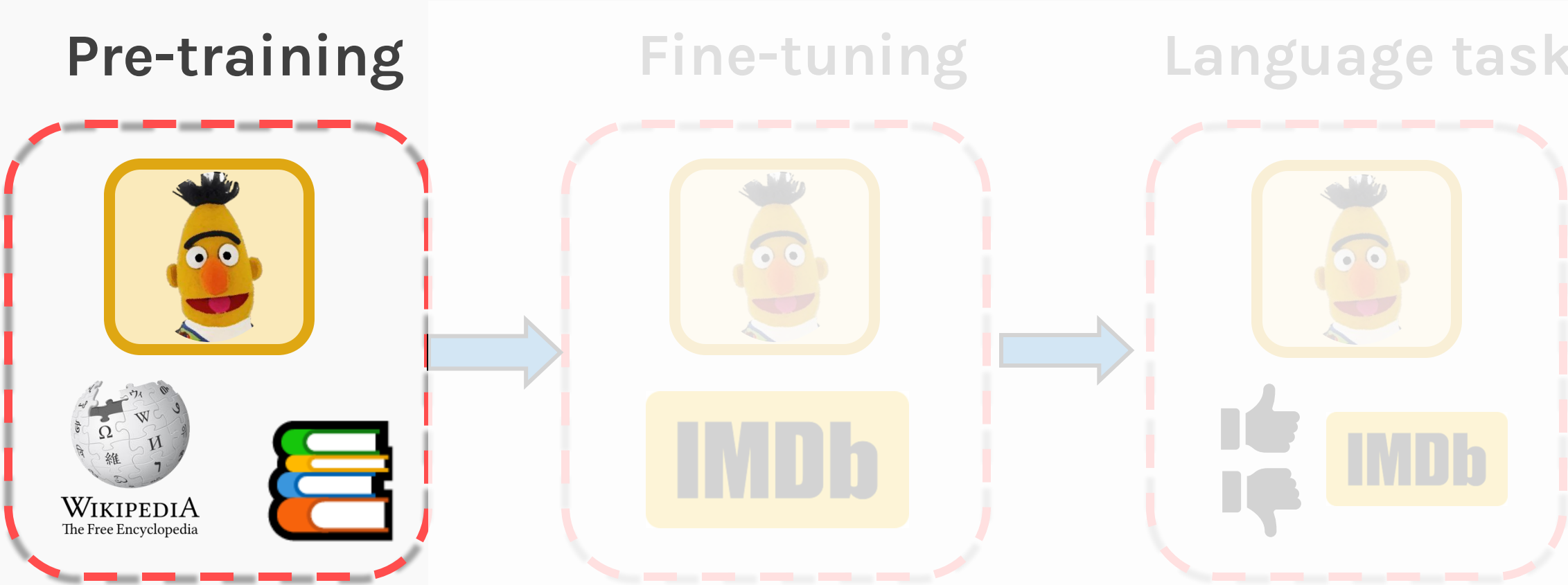

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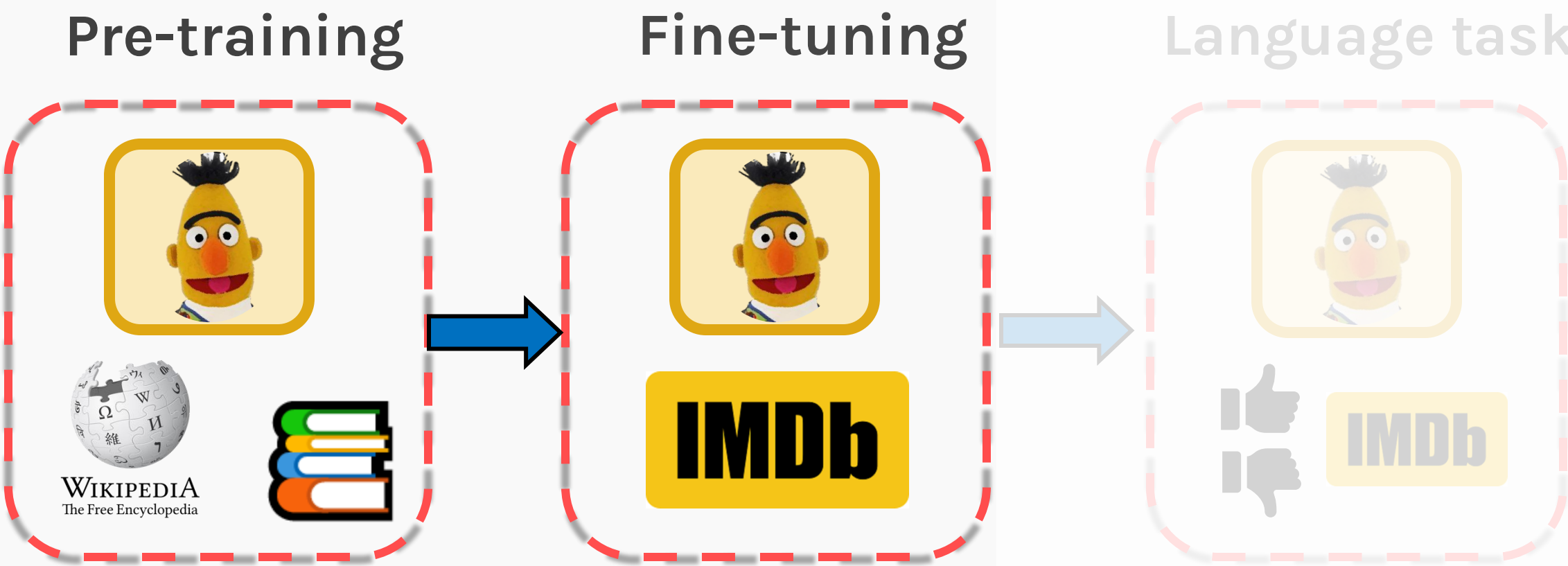


Why fine-tune?

What if our requirement is domain specific, like scientific journals or legal contracts?

By fine-tuning the language model on in-domain data, you can boost the performance of many downstream tasks.

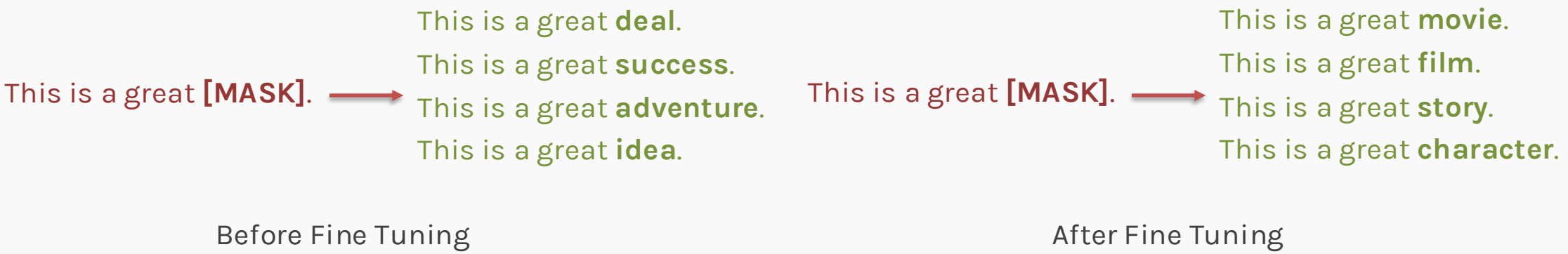
Fine-tuning is the process of providing a model with labelled examples to update its weight and improve performance on a specific task!

How to fine-tune?

We do Masked Language Modelling to fine-tune BERT.

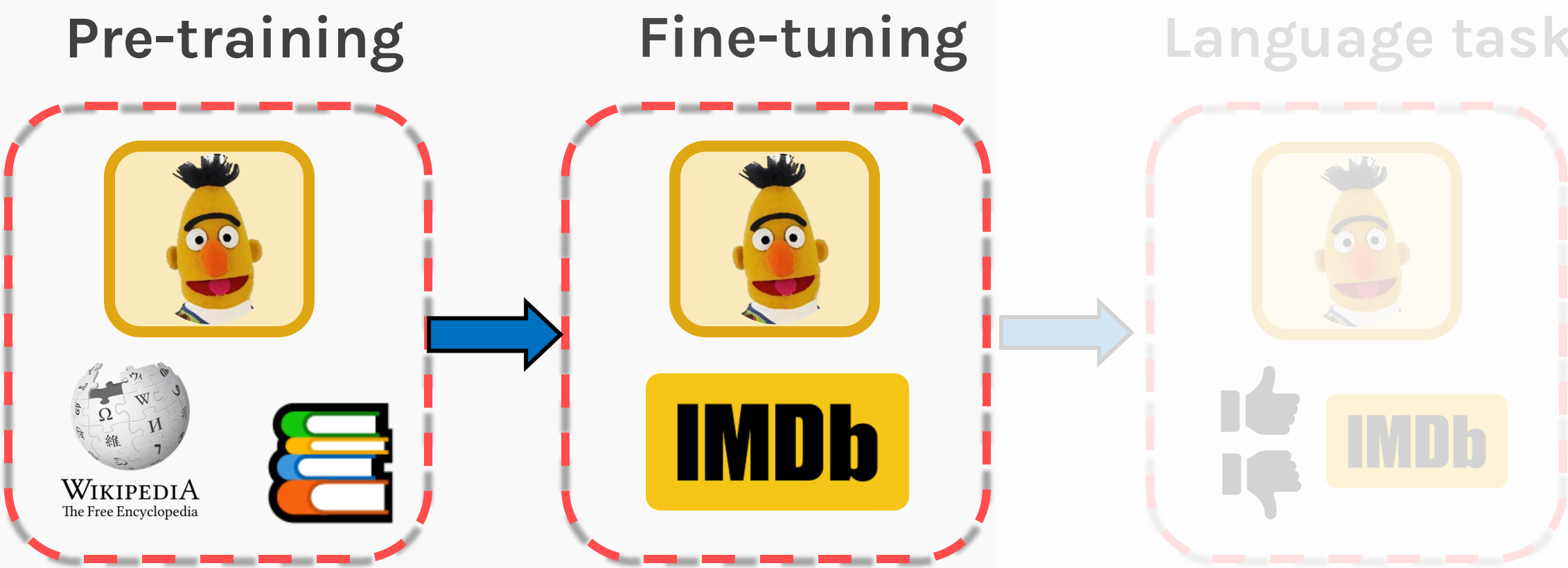
This is similar to what we do when we pretrain the model. The only difference is that we load pretrained weights trained on a very large corpus before fine-tuning it to a domain specific dataset.

For a movie dataset:



How to use a BERT?

There are three main steps in using BERT for a given NLP task



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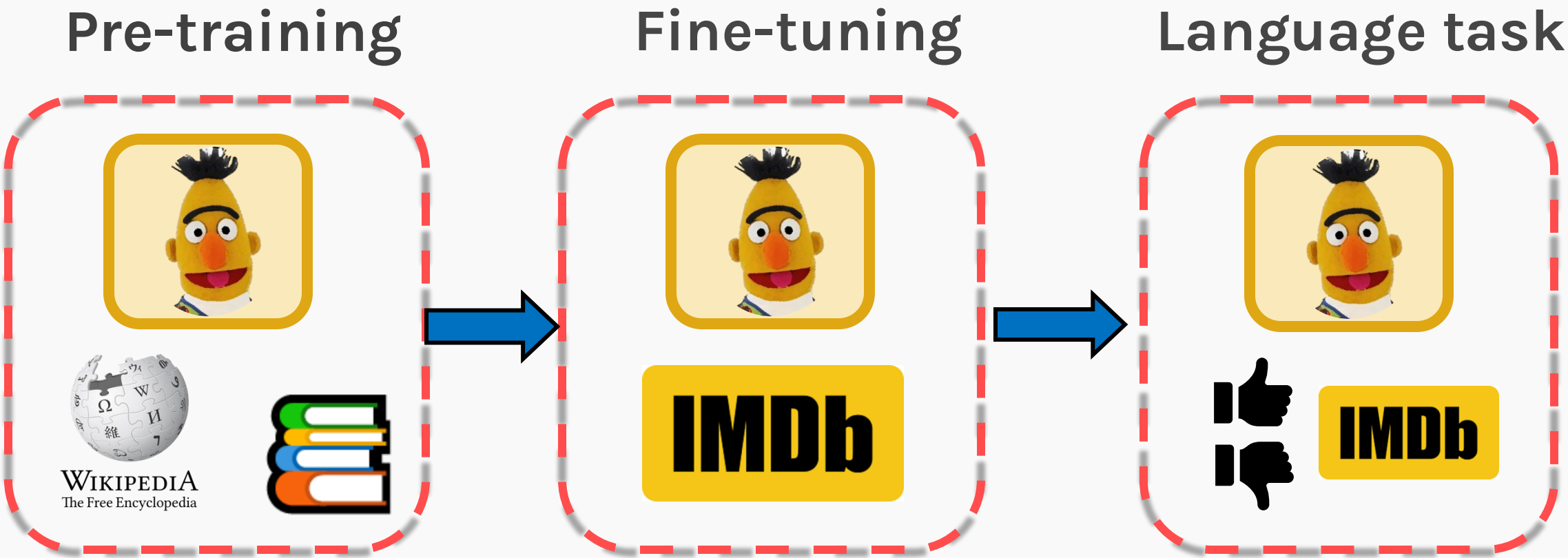
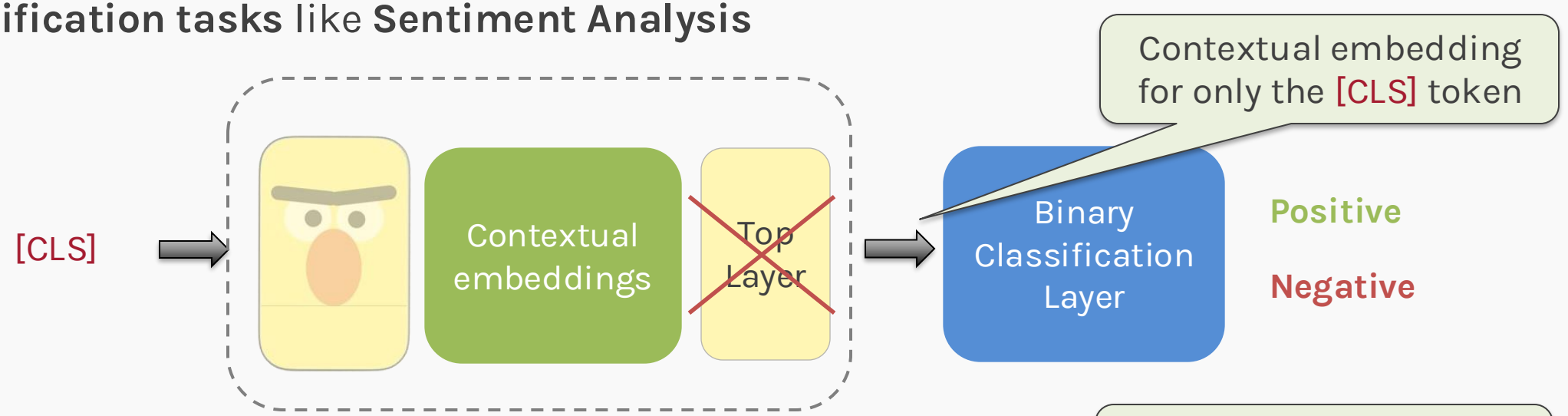


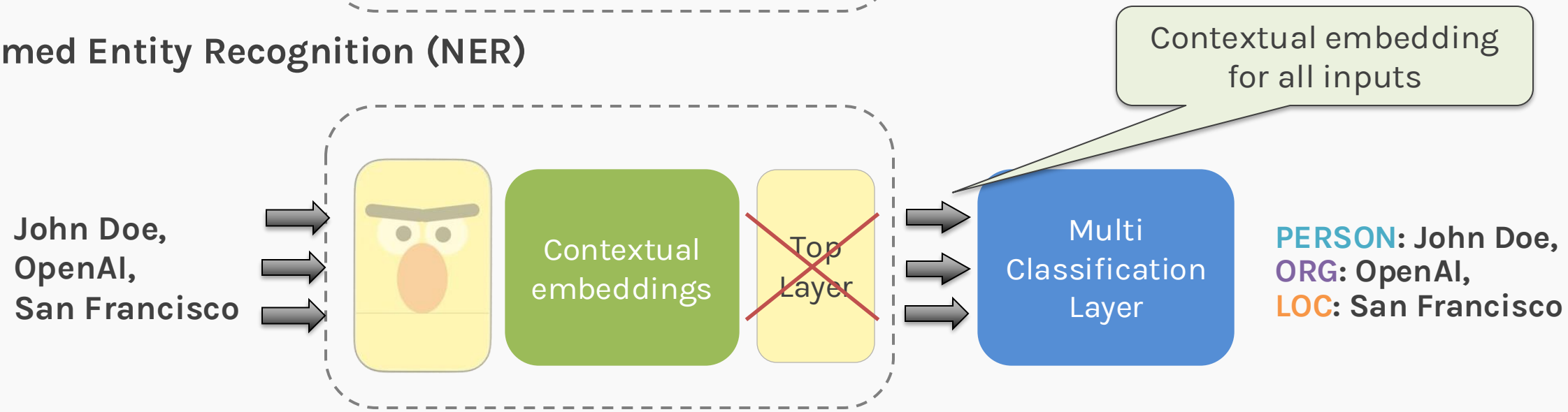
How to use BERT for NLP Tasks?

BERT can be used for a wide variety of language tasks, for example:

(A) Classification tasks like **Sentiment Analysis**

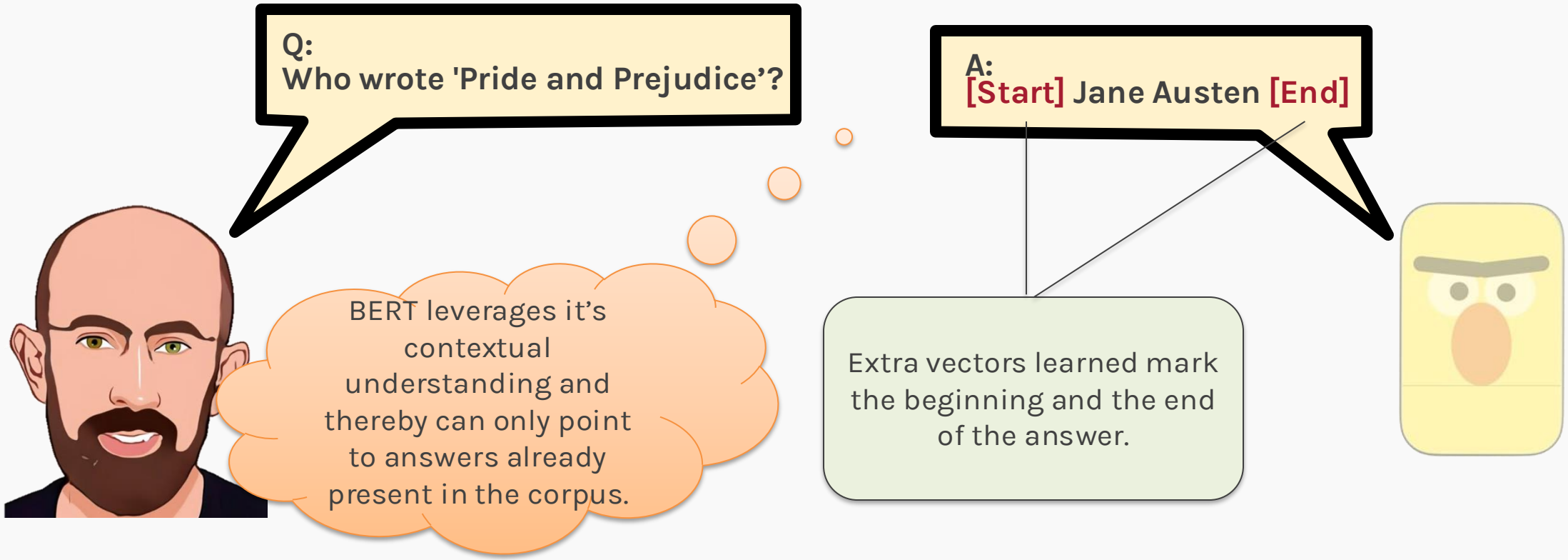


Named Entity Recognition (NER)



How to use BERT for NLP Tasks?

(B) Question Answering tasks

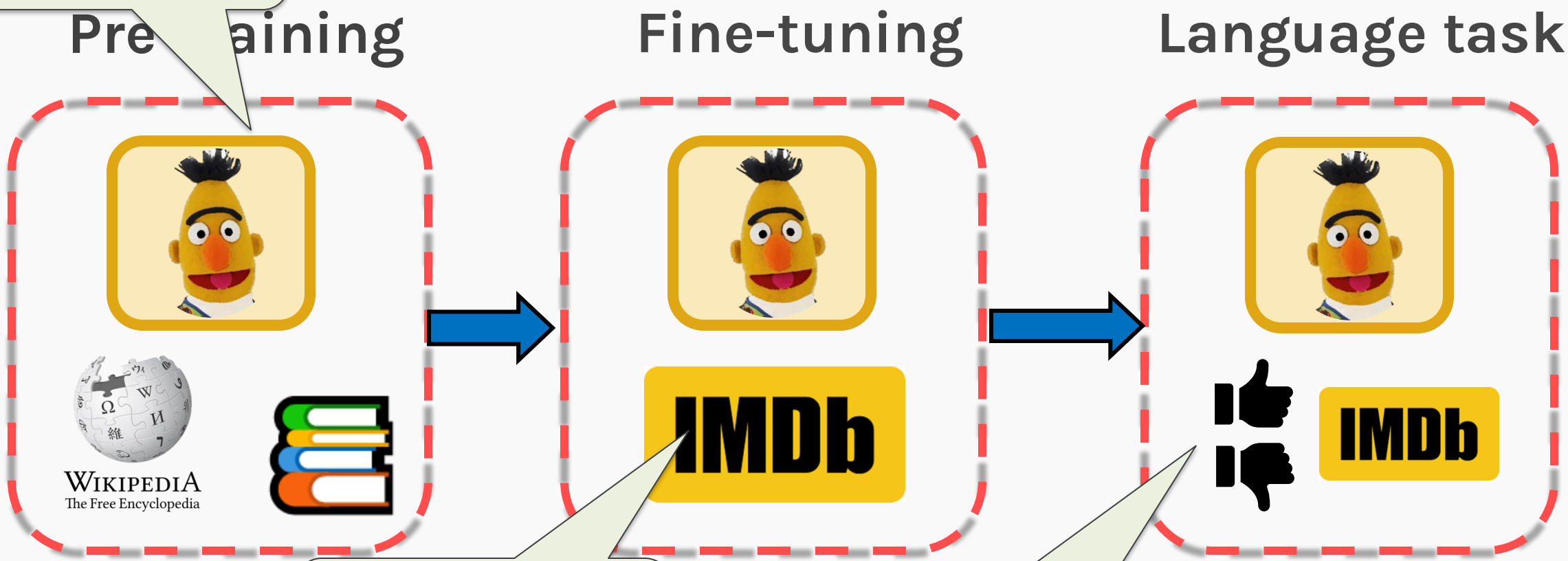


(C) various other tasks like language translation, semantic text similarity, search relevance, spell check and grammar check, etc.

How to use a BERT?

You will (almost) never train a BERT from scratch

re three main steps in using BERT for a given NLP task



We don't use the labels in the fine-tuning step

The final step is the supervised learning using labels

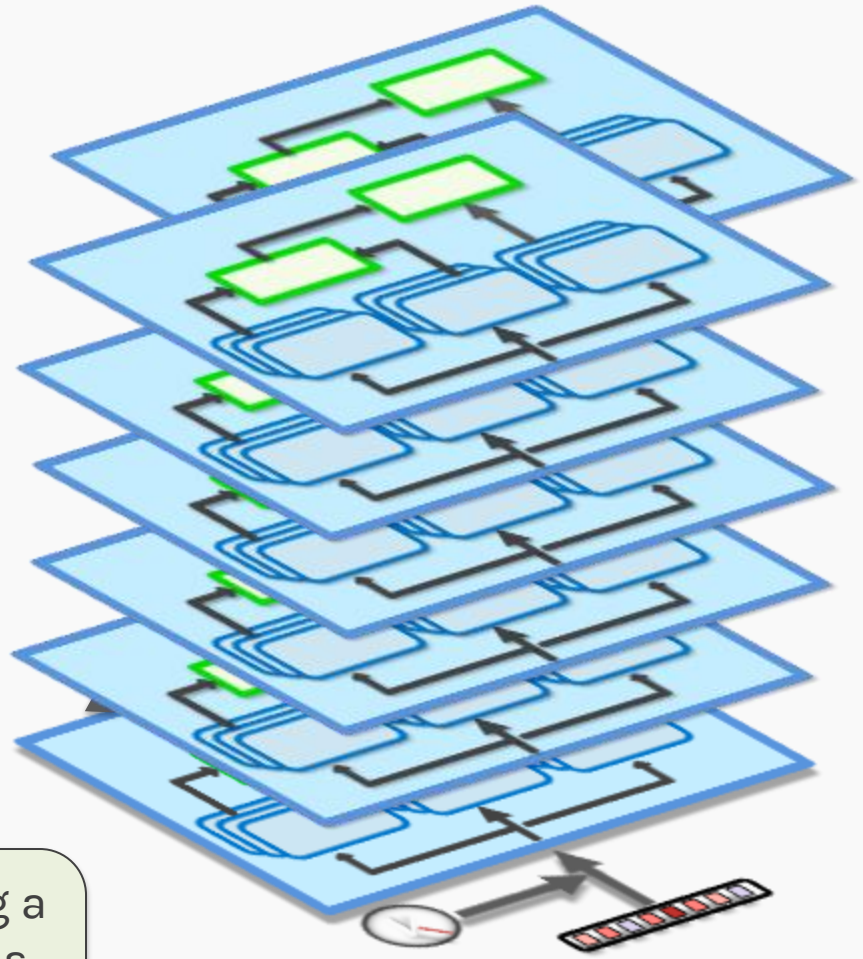
Outline

- Transformers Recap
- BERT
- Practical problems in Large Language Models
- **GPT**
- Hugging Face

From Transformers to GPT

- We saw how we can make use of the encoder blocks of the Transformers in BERT. Now, what if we use just the decoder blocks?

- Voilà, The Generative Pre-trained Transformer! Or GPT in short.



DECODER

Note that we are simply using a decoder like architecture. It is not essentially a decoder anymore!

BERT v/s GPT: Key Difference

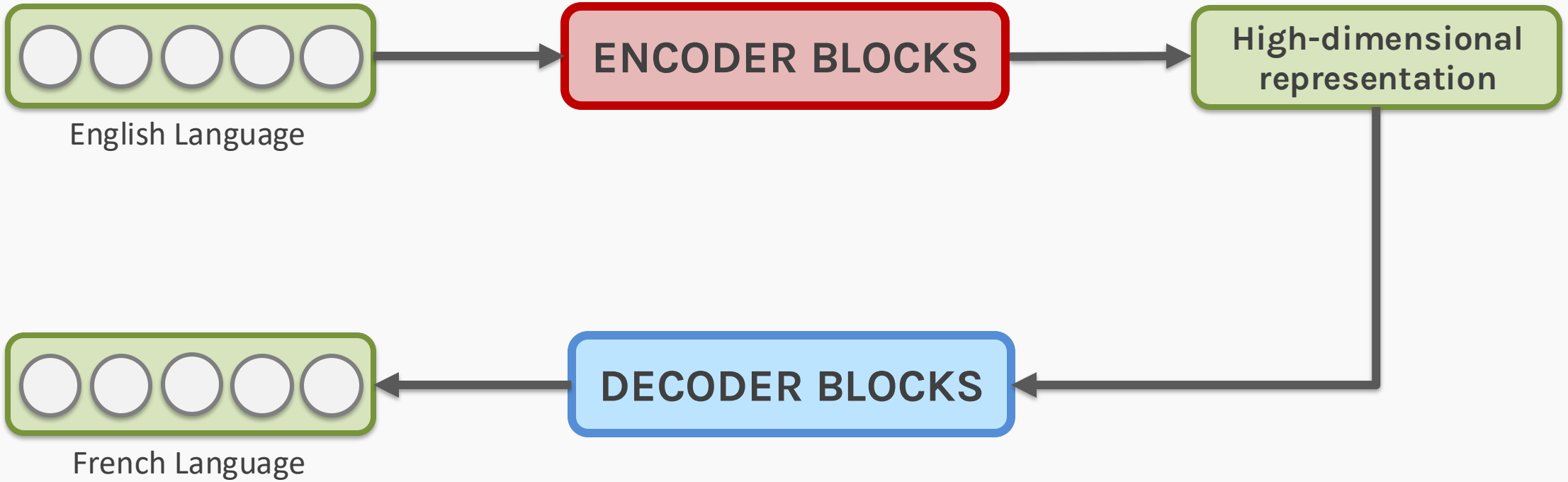
- Apart from the fact that GPT uses decoder like blocks of the transformer while BERT uses encoder like blocks, there is another key difference between the two models.

- BERT is auto-encoding, while GPT is auto-regressive.

But what do auto-encoding and auto-regressive mean?

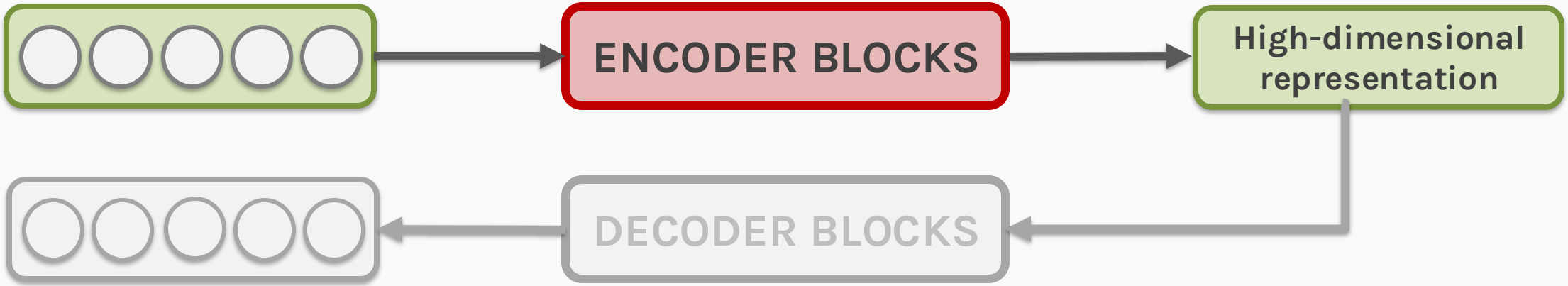
BERT v/s GPT: Key Difference

- Before we understand what those two terms mean, let's recap what the original transformer was tasked to do.



Auto-encoding Model

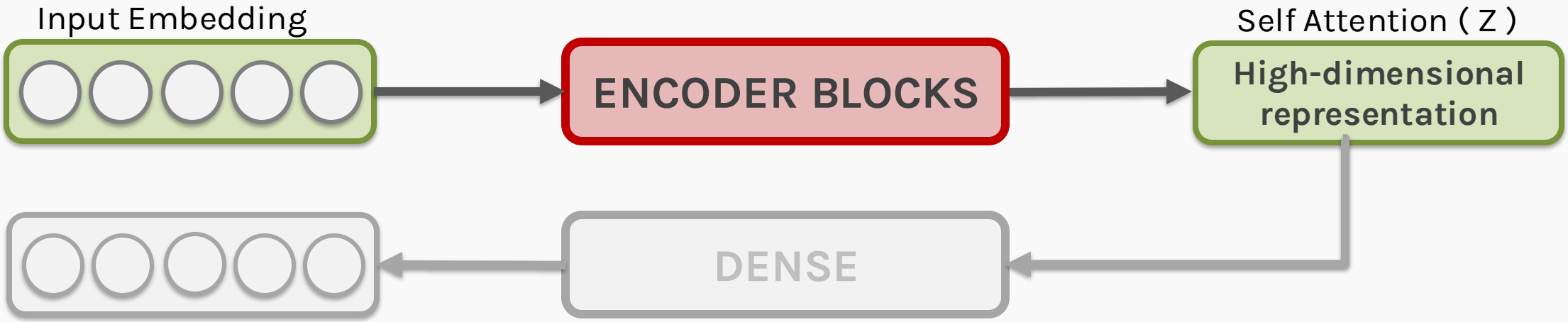
- Now if we take just the encoder blocks and train that part of the network separately, we have an auto-encoding model.



- The aim of an auto-encoding model is to learn a representation for a set of data. One way to do this can be to train the model on a reconstruction task.

Auto-encoding Model/BERT

- Now if we take just the encoder blocks and train that part of the network separately, we have an auto-encoding model.



- The aim of an auto-encoding model is to learn a representation for a set of data. One way to do this can be to train the model on a reconstruction task.

- For e.g. BERT

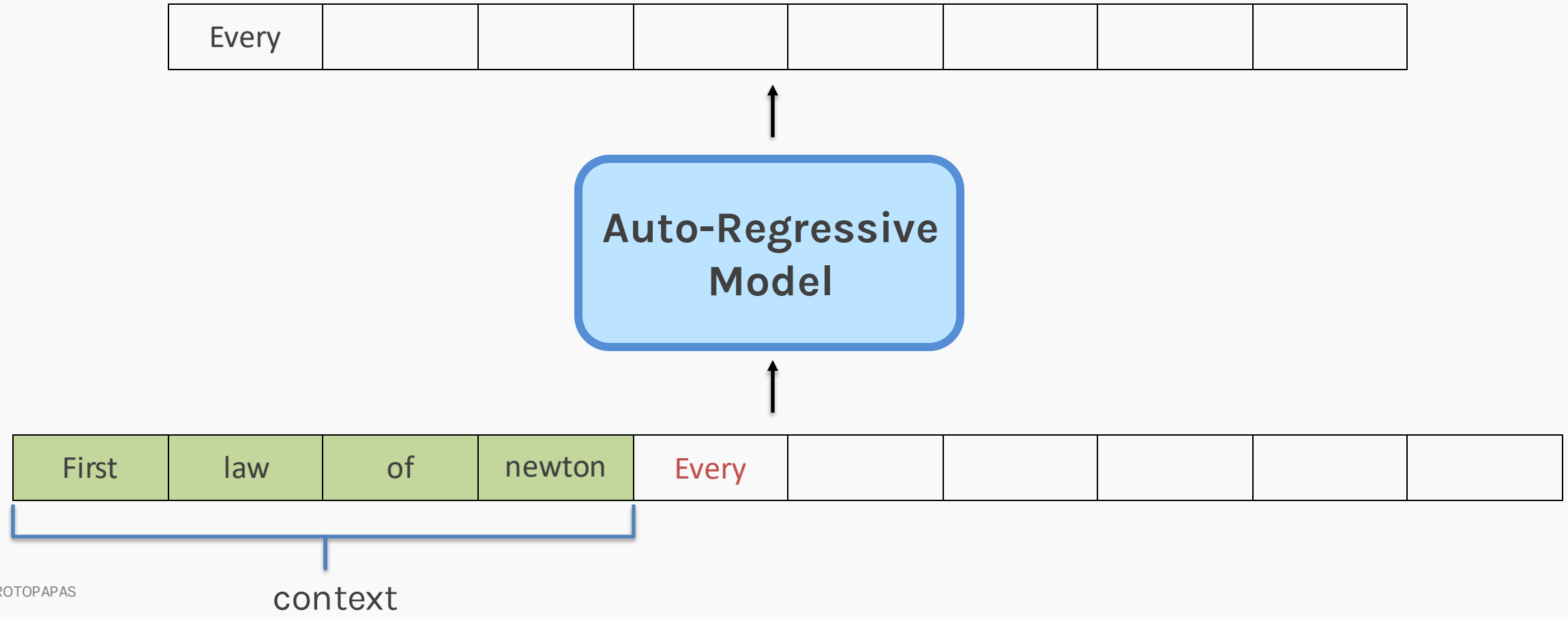
Auto-regressive Model

- Now if we take just the decoder blocks and train that part of the network separately, we have an auto-regressive model.

- A model is said to be auto-regressive if it predicts future values based on past values.

Auto-regressive Model

- Unidirectional processing and a fixed length sliding window are characteristic of a general auto-regressive model



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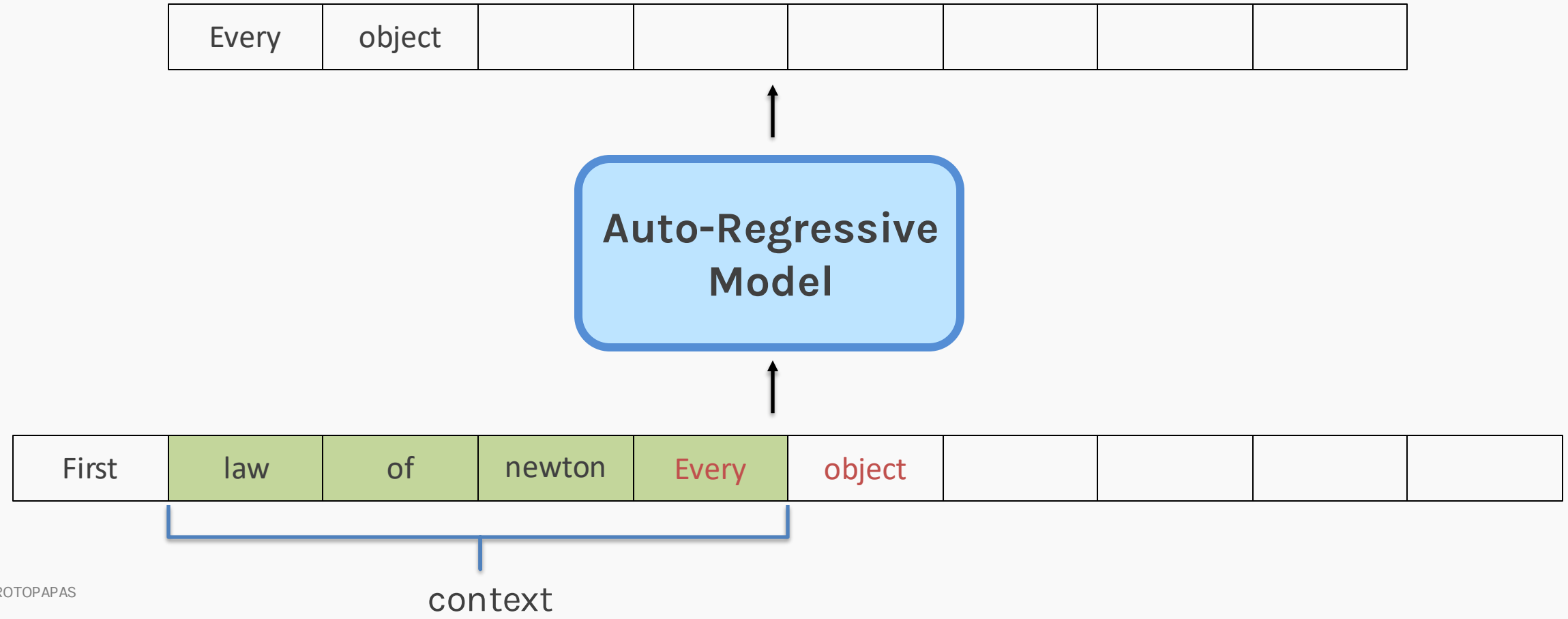

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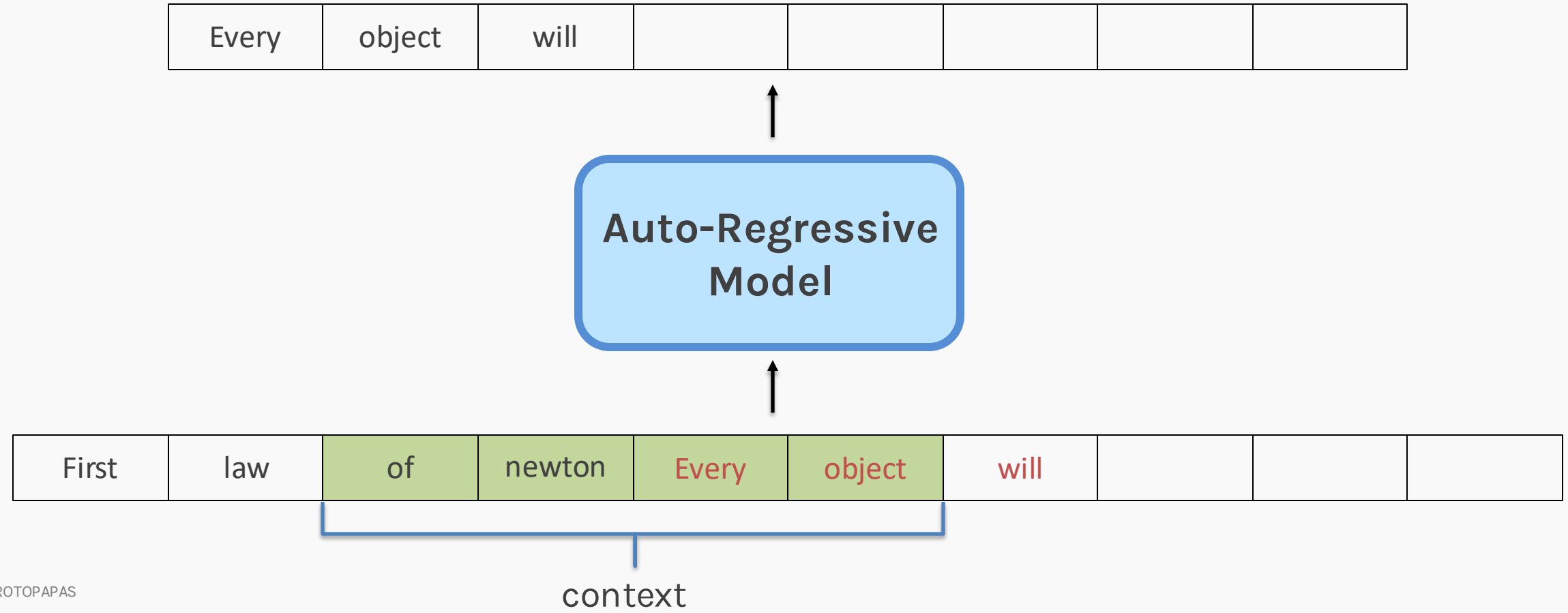

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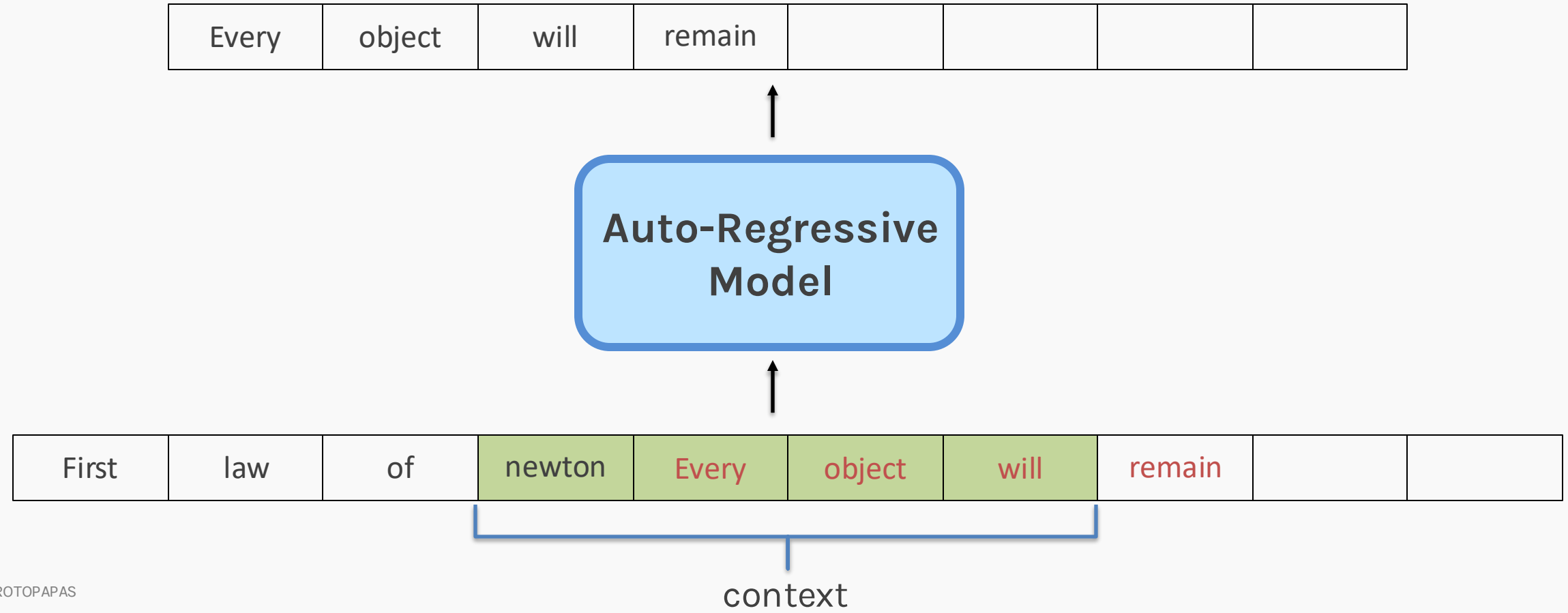

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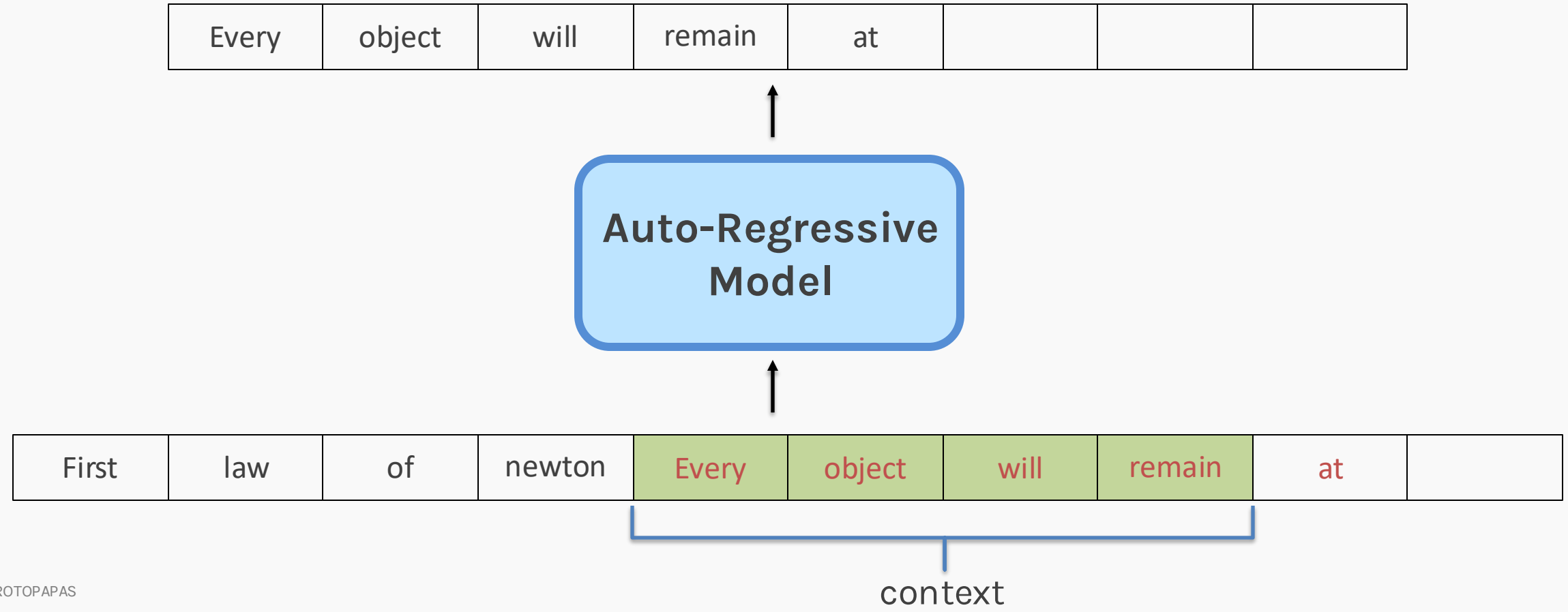

Auto-regressive Model

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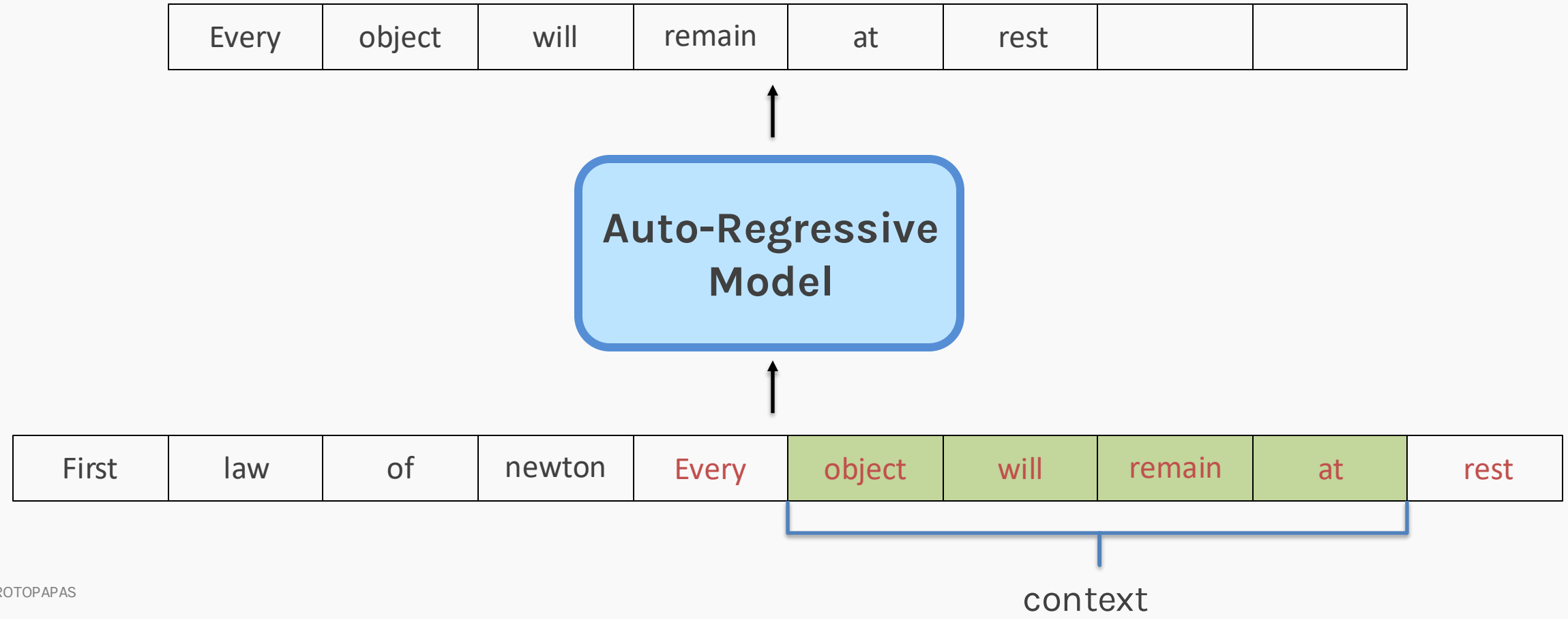


GPT

- GPT belongs to the auto-regressive family of models.

How do we train a GPT model?

GPT

- GPT belongs to the auto-regressive family of models.

How do we train a GPT model?

Since every next prediction is dependent on the previous one, don't we train this sequentially?

No, that will be very inefficient considering the increasing size of the transformer models

GPT

- GPT belongs to the auto-regressive family of models.

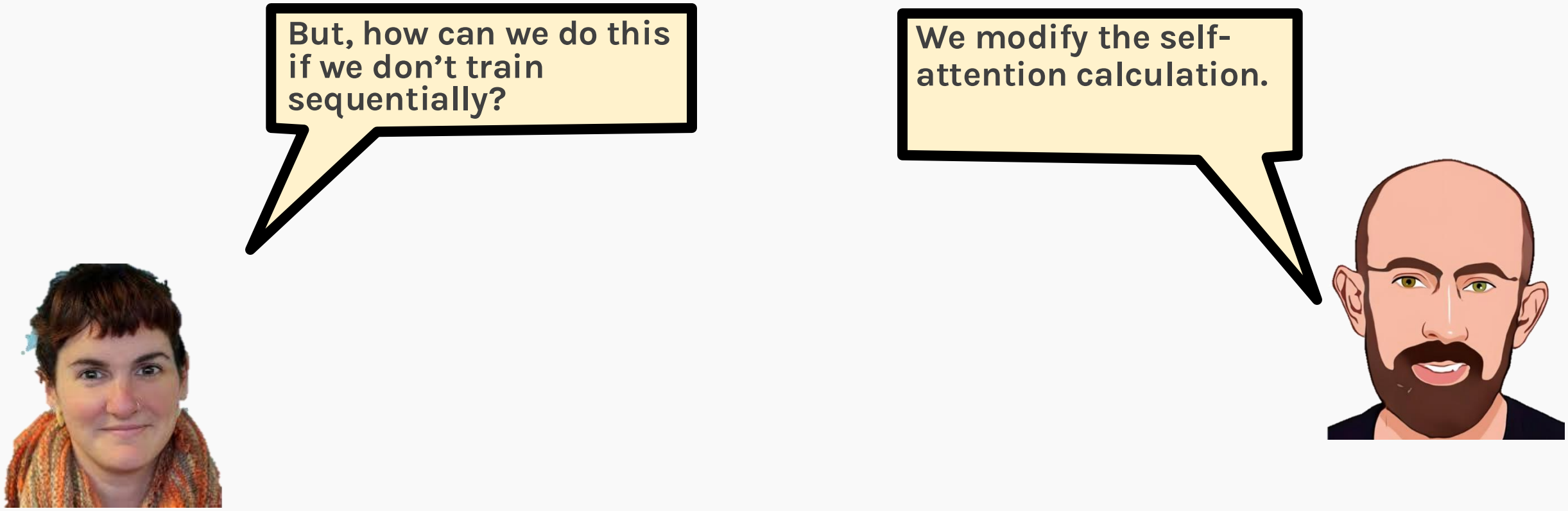
How do we train a GPT model?

Then how do we train this?

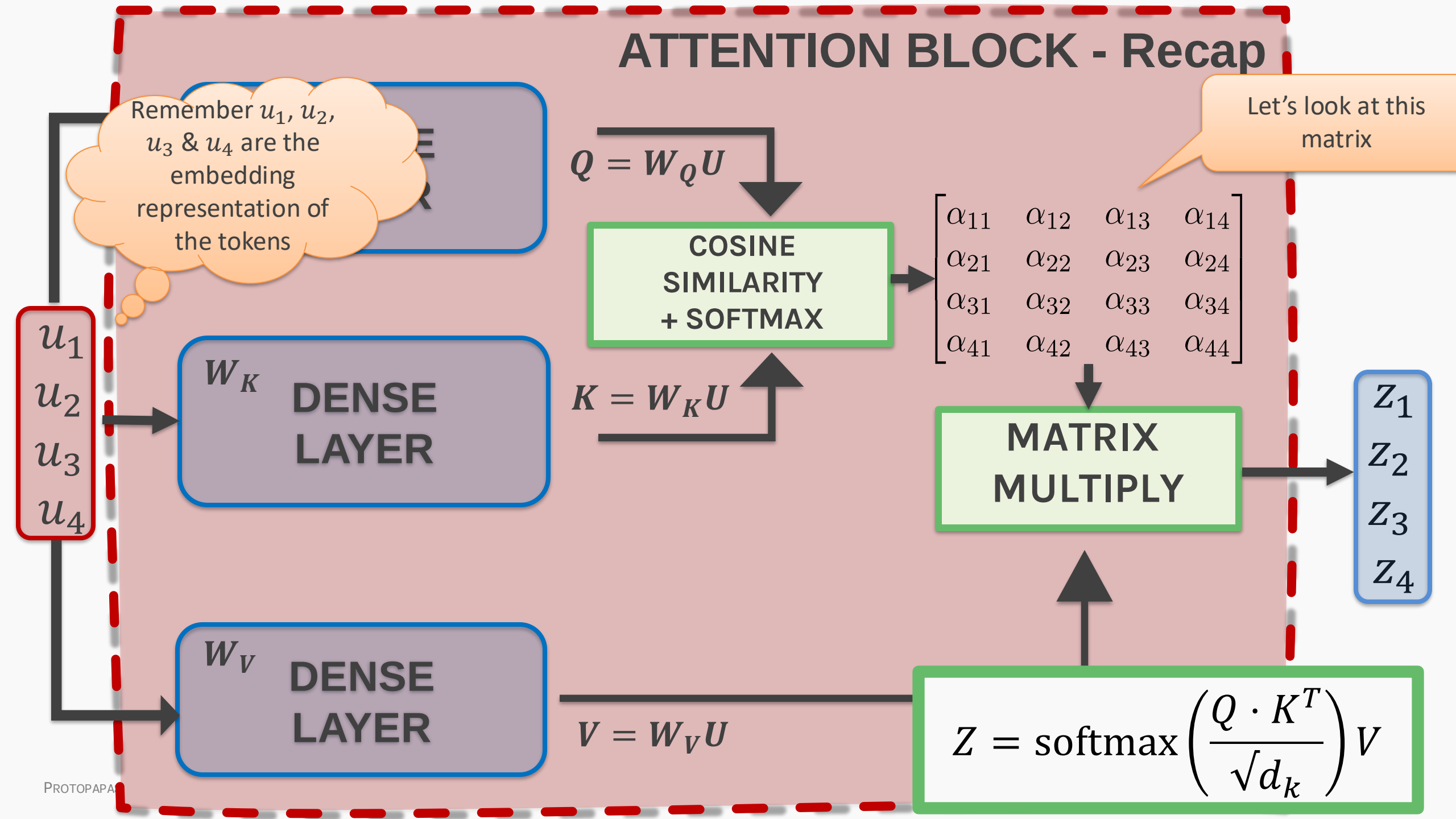
It's MAGIC! Let me show you.

GPT - Training

- The goal when training an auto-regressive model is to not let the model have a sneak peak into the future tokens when training.



ATTENTION BLOCK - Recap



Attention - Recap

Remember, α_{12} is the similarity score for the first transformed token with the second transformed token

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$$

Attention - Recap

But, doesn't this mean that model is looking at the future here if it is calculating the similarity score between first and the third transformed token?

α_{13} is the similarity score for the first transformed token with the third transformed token

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \end{bmatrix}$$

Exactly! How about we mask the problematic scores?

Masked Self-Attention

This has been simplified for demonstration purposes. (The softmax would also need to be modified)

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \times \underline{\text{Mask M}} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$$

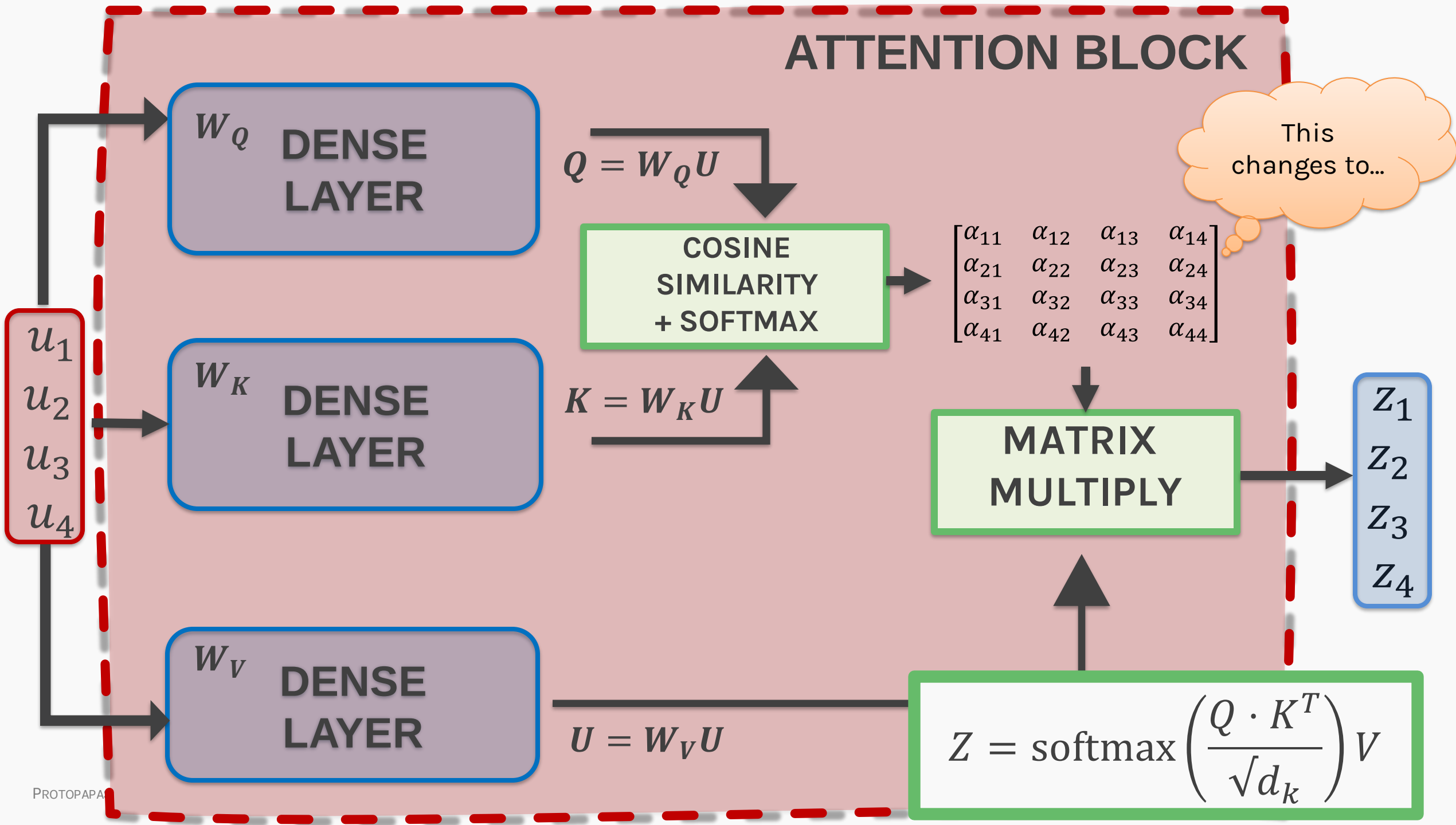
Masked Self-Attention

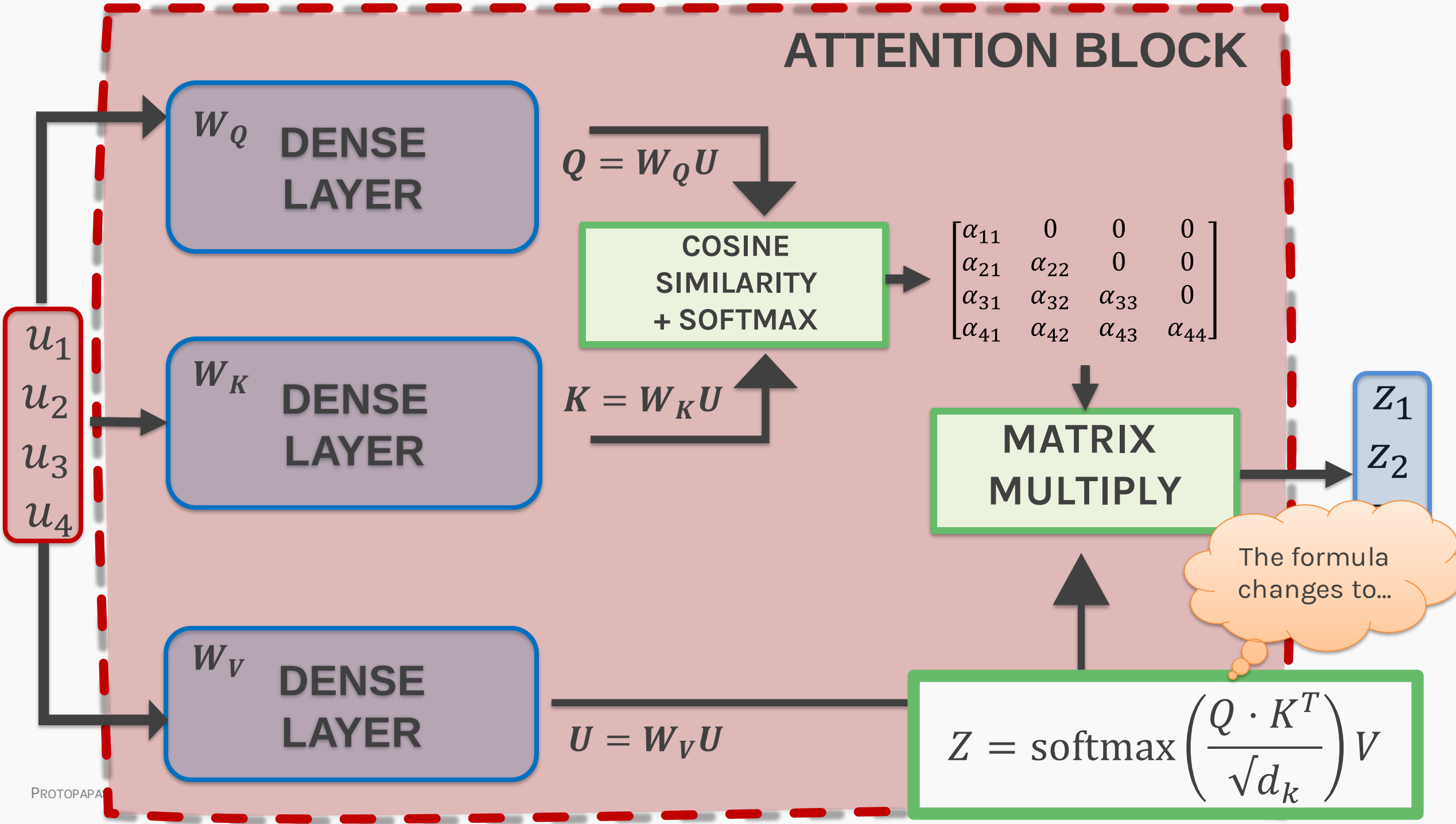
- Now when this is multiplie[illegible] we get the desired outcome.

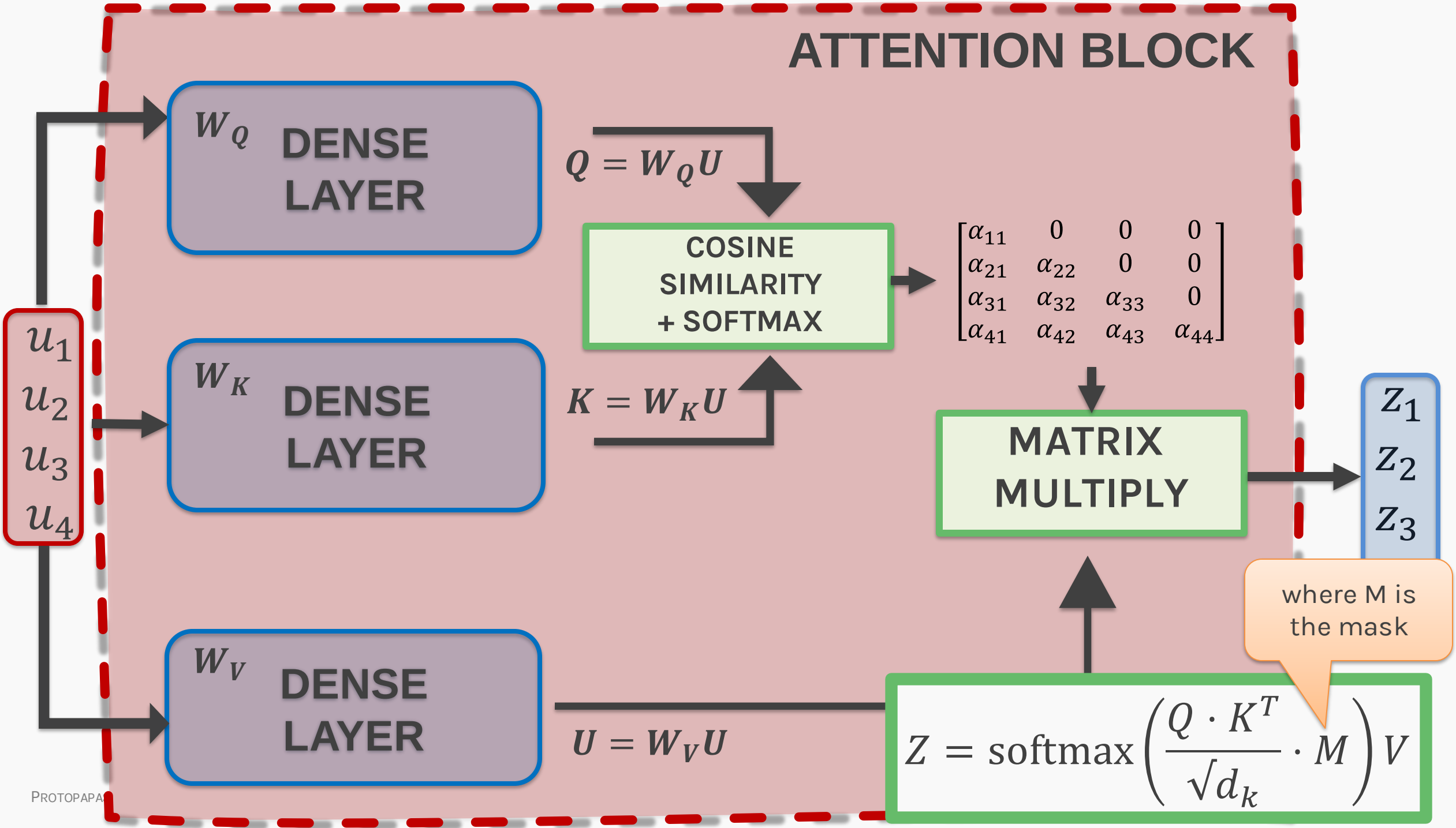
Remember, this is just another representation of the token embeddings, just like query and keys.

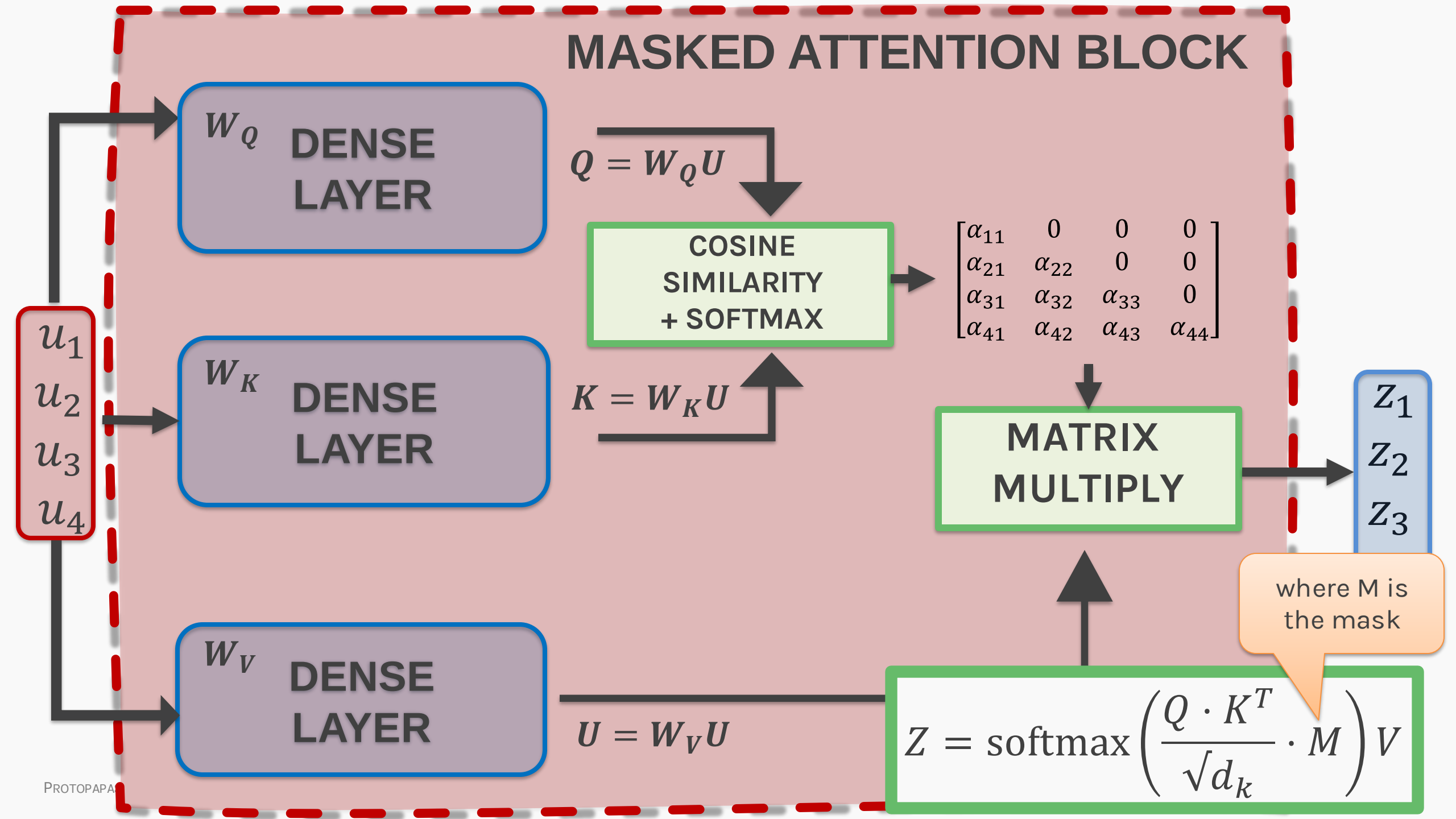
$$\begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \times \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{bmatrix} = \begin{bmatrix} \alpha_{11}V_1 \\ \alpha_{21}V_1 + \alpha_{22}V_2 \\ \alpha_{31}V_1 + \alpha_{32}V_2 + \alpha_{33}V_3 \\ \alpha_{41}V_1 + \alpha_{42}V_2 + \alpha_{43}V_3 + \alpha_{44}V_4 \end{bmatrix}$$

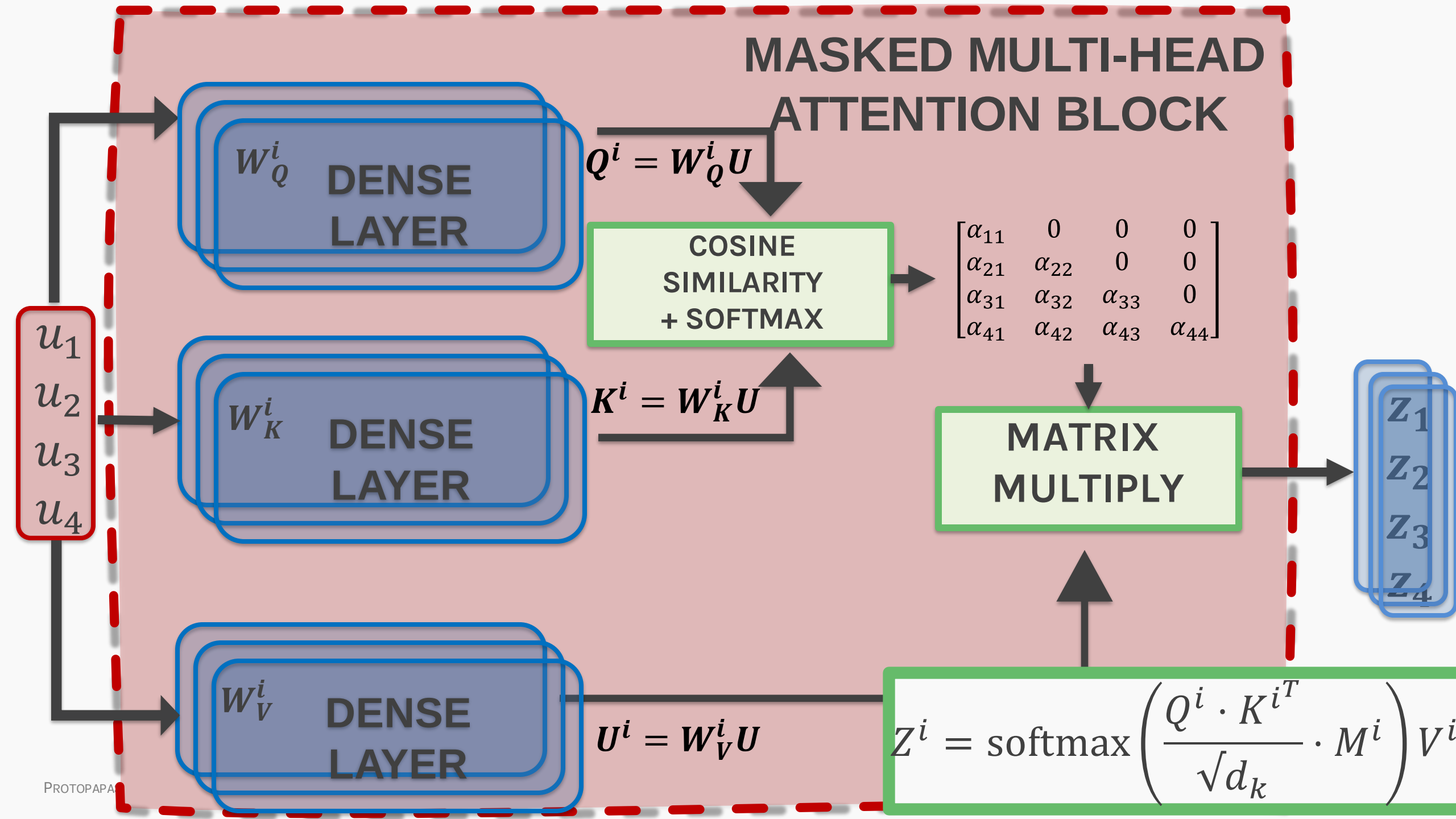
values


ATTENTION BLOCK
W_Q DENSE LAYER
W_K DENSE LAYER
W_V DENSE LAYER
u_1 u_2 u_3 u_4
$Q = W_Q U$
$K = W_K U$
$U = W_V U$
COSINE SIMILARITY + SOFTMAX
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
This changes to...
MATRIX MULTIPLY
z_1 z_2 z_3 z_4
$Z = \text{softmax}\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) V$

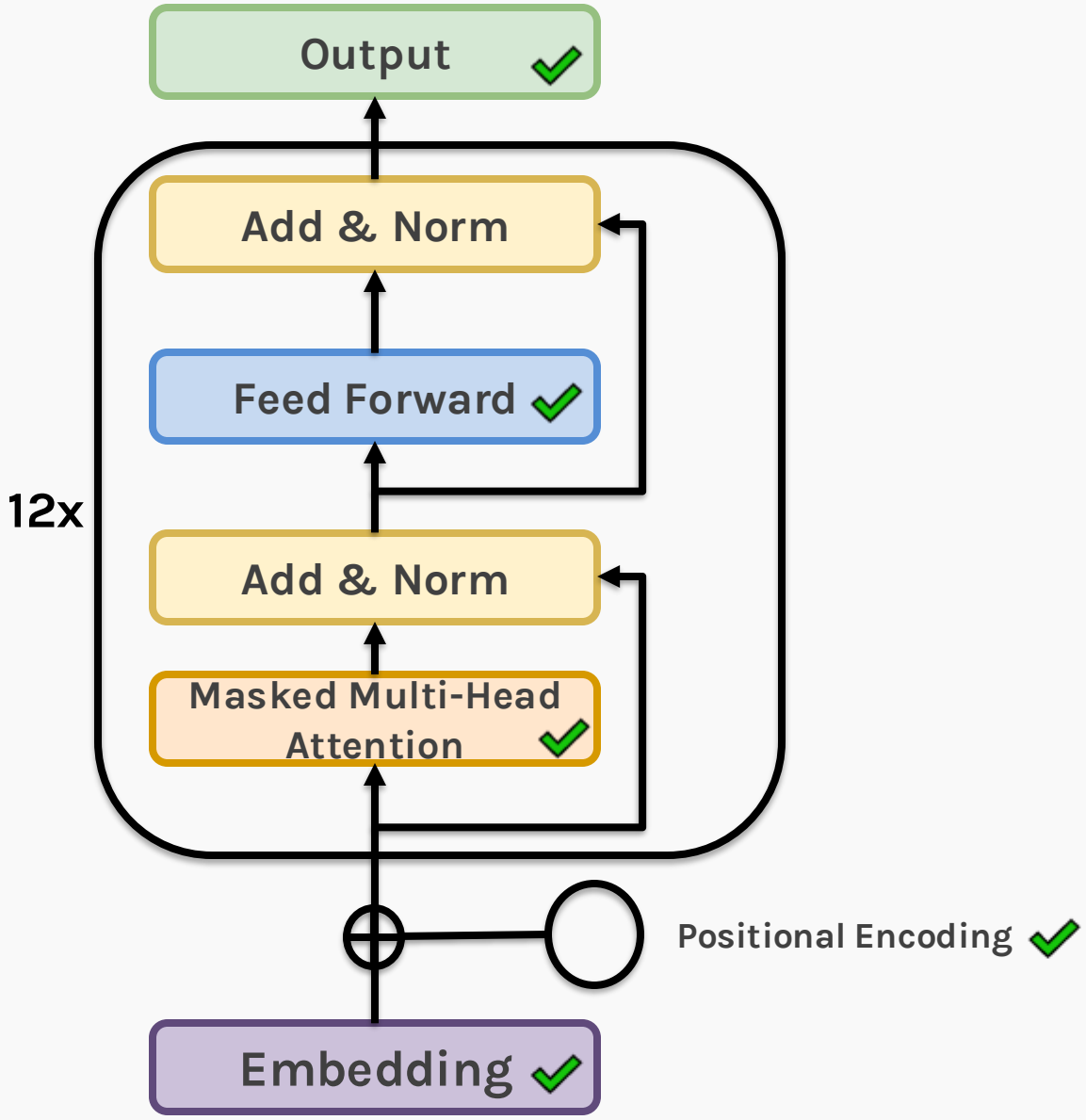

ATTENTION BLOCK
W_Q DENSE LAYER
W_K DENSE LAYER
W_V DENSE LAYER
u_1
u_2
u_3
u_4
$Q = W_Q U$
$K = W_K U$
$U = W_V U$
COSINE SIMILARITY + SOFTMAX
$\begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1
z_2
The formula changes to...
$Z = \text{softmax}\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) V$


ATTENTION BLOCK
W_Q DENSE LAYER
W_K DENSE LAYER
W_V DENSE LAYER
u_1
u_2
u_3
u_4
$Q = W_Q U$
$K = W_K U$
$U = W_V U$
COSINE SIMILARITY + SOFTMAX
$\begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1
z_2
z_3
where M is the mask
$Z = \text{softmax}\left(\frac{Q \cdot K^T}{\sqrt{d_k}} \cdot M\right) V$


MASKED ATTENTION BLOCK
W_Q DENSE LAYER
W_K DENSE LAYER
W_V DENSE LAYER
u_1
u_2
u_3
u_4
$Q = W_Q U$
$K = W_K U$
$U = W_V U$
COSINE SIMILARITY + SOFTMAX
$\begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1
z_2
z_3
where M is the mask
$Z = \text{softmax}\left(\frac{Q \cdot K^T}{\sqrt{d_k}} \cdot M\right) V$

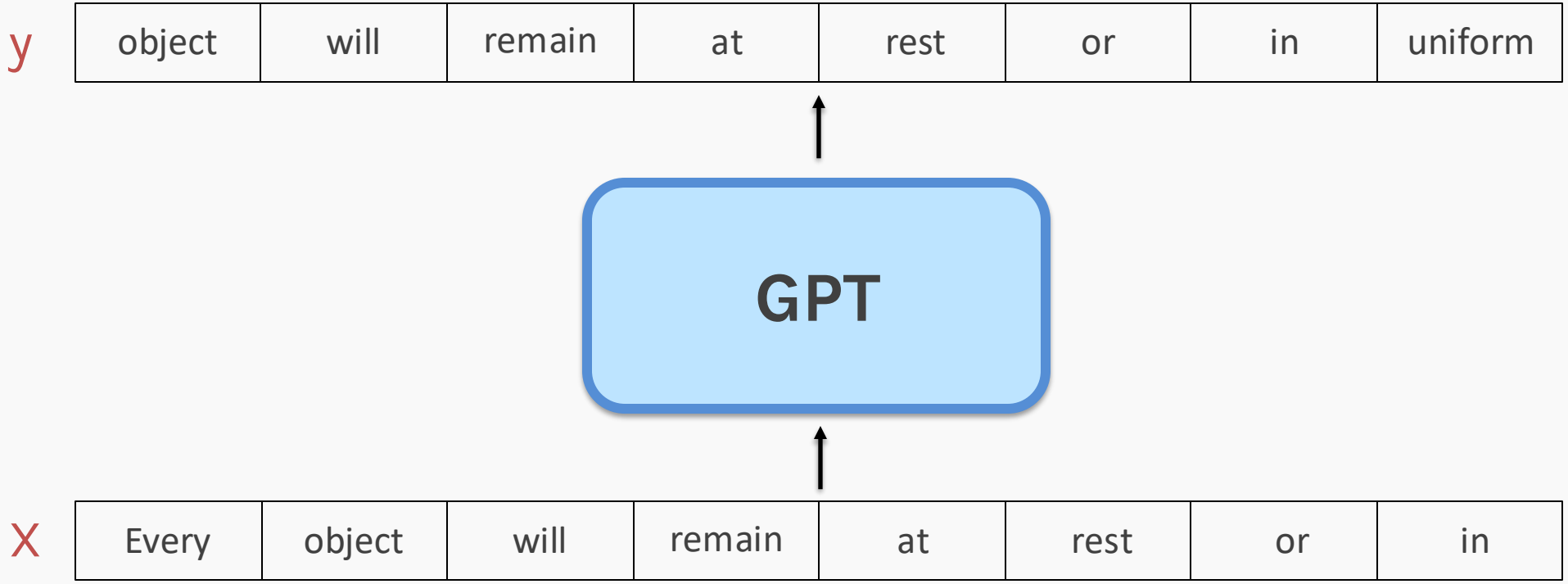

MASKED MULTI-HEAD ATTENTION BLOCK
W_Q^i
DENSE LAYER
W_K^i
DENSE LAYER
W_V^i
DENSE LAYER
u_1
u_2
u_3
u_4
$Q^i = W_Q^i U$
$K^i = W_K^i U$
$U^i = W_V^i U$
COSINE SIMILARITY + SOFTMAX
$\begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1
z_2
z_3
z_4
$Z^i = \text{softmax}\left(\frac{Q^i \cdot K^{iT}}{\sqrt{d_k}} \cdot M^i\right) V^i$

GPT – The Complete Picture



GPT - Training

- Now that we have figured out how to keep the model from extracting information from the future tokens, the model can be trained just like any other language model trained to do next word prediction.



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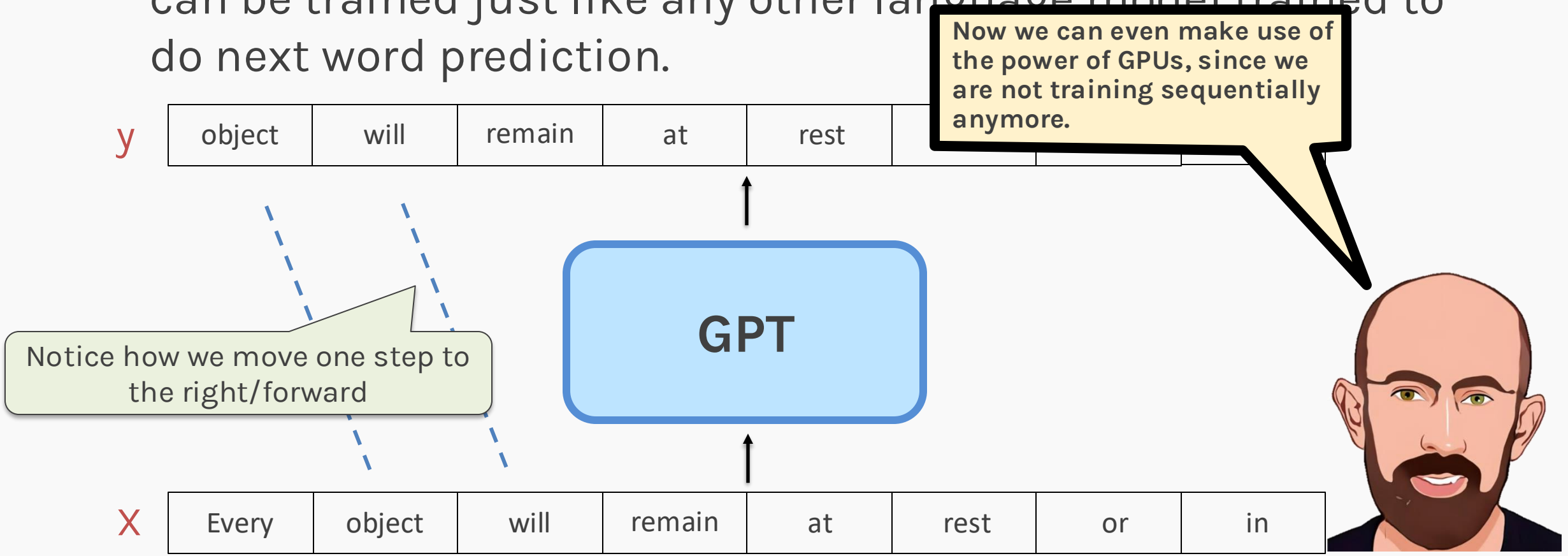
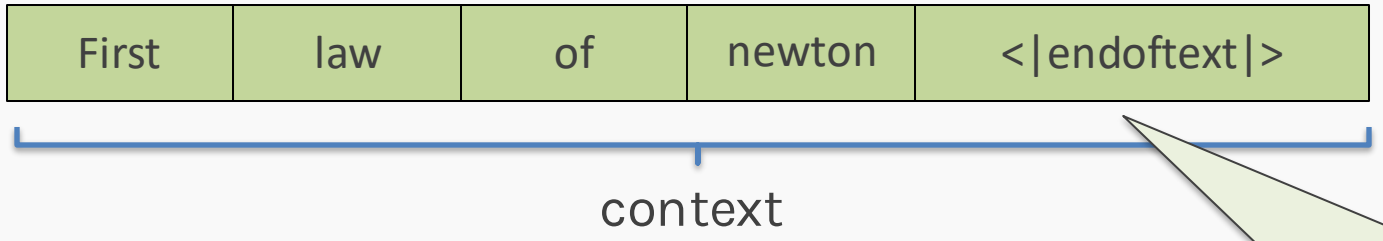


GPT - Inference

There are two ways GPT can generate text:

1. **<u>Conditional</u>:** We provide a starting prompt(context) and the model continues to generate text on that topic.



This is a special token used by the model to mark the end of the input or the starting point for predictions.

GPT uses a special implementation of the Conv1D layer in place of Dense layer that allows the model to input variable length sequences without the use of padding.

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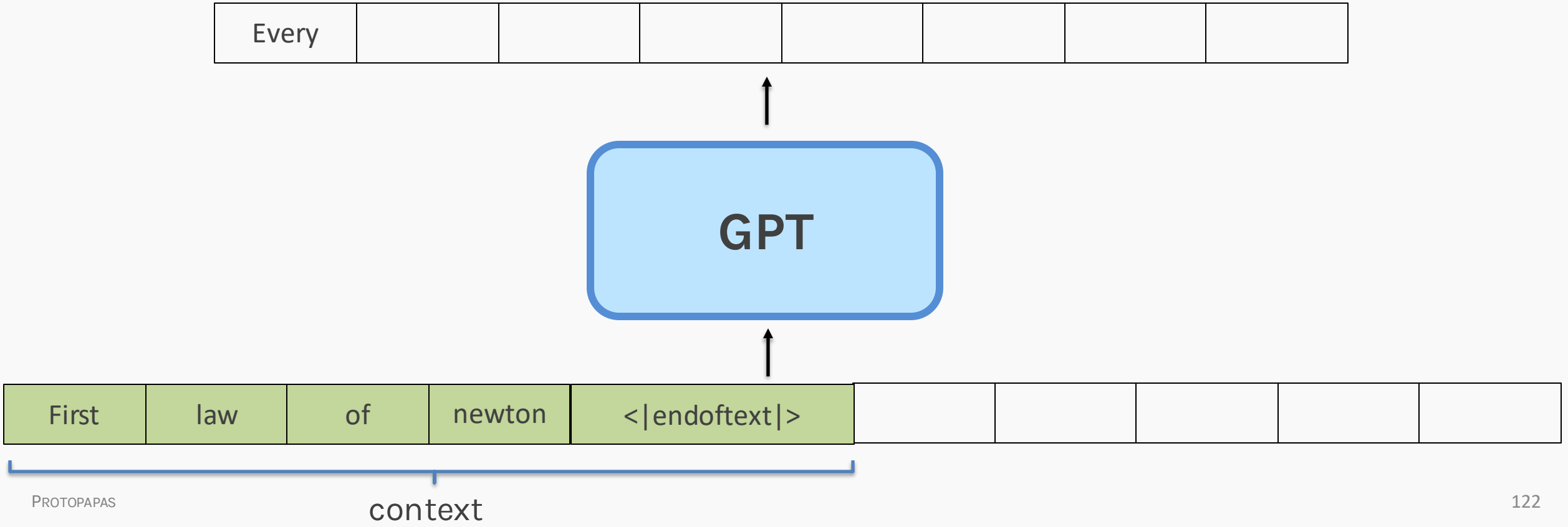

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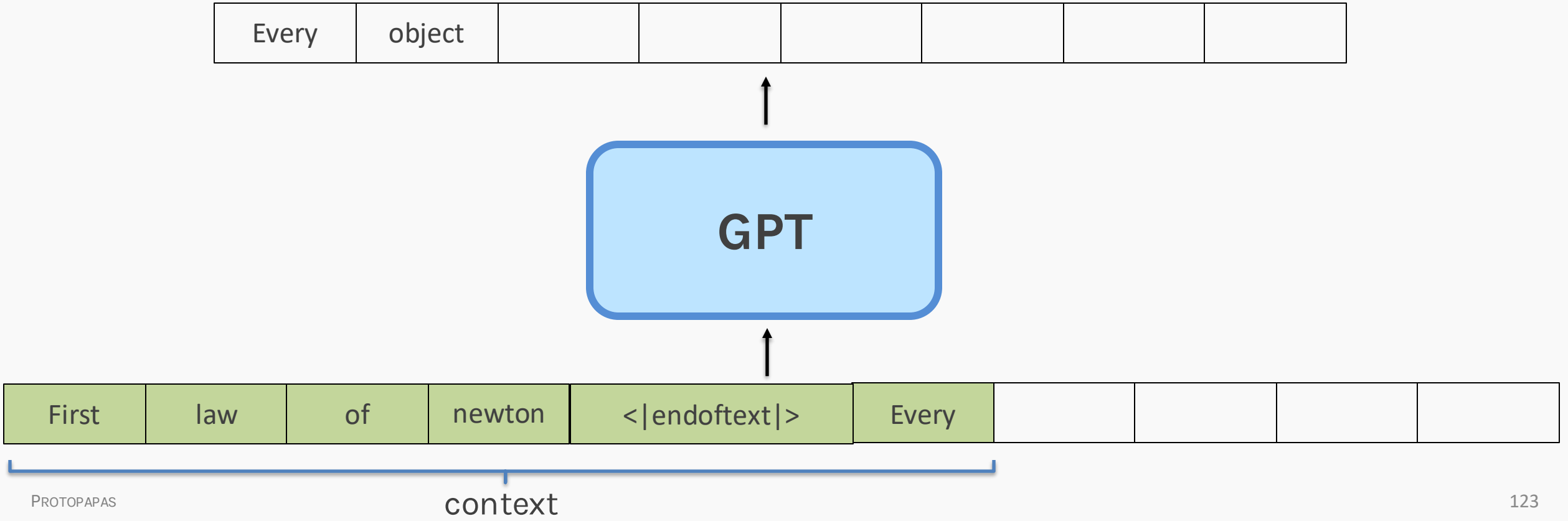

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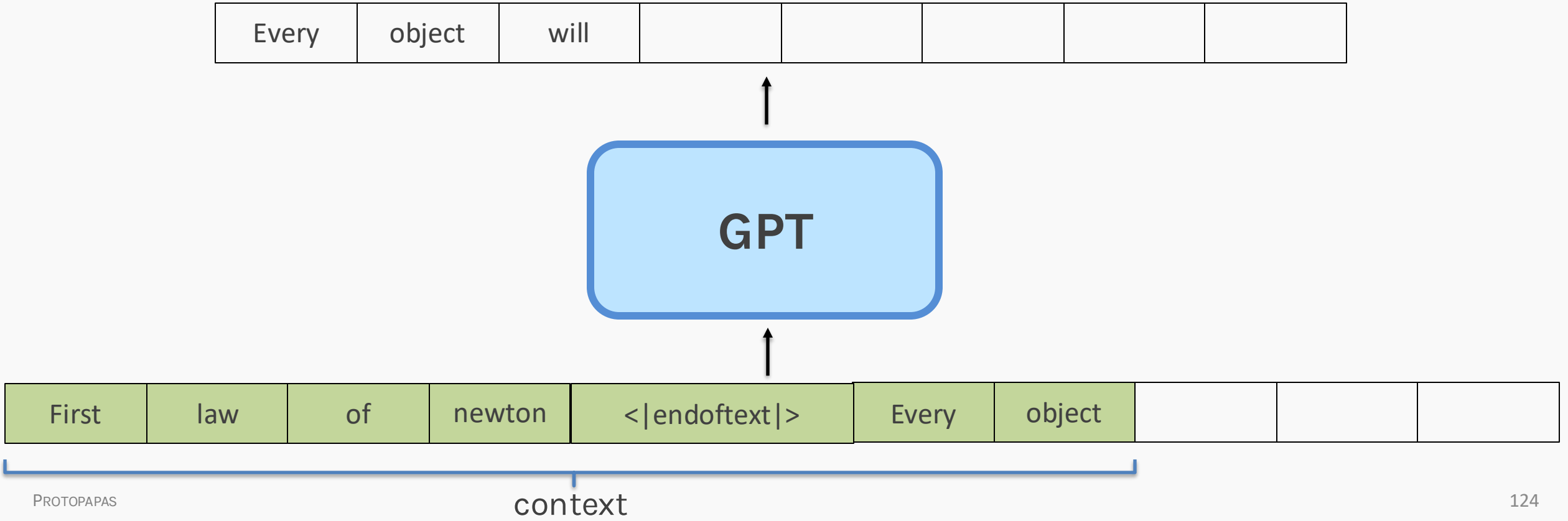

GPT - Inference

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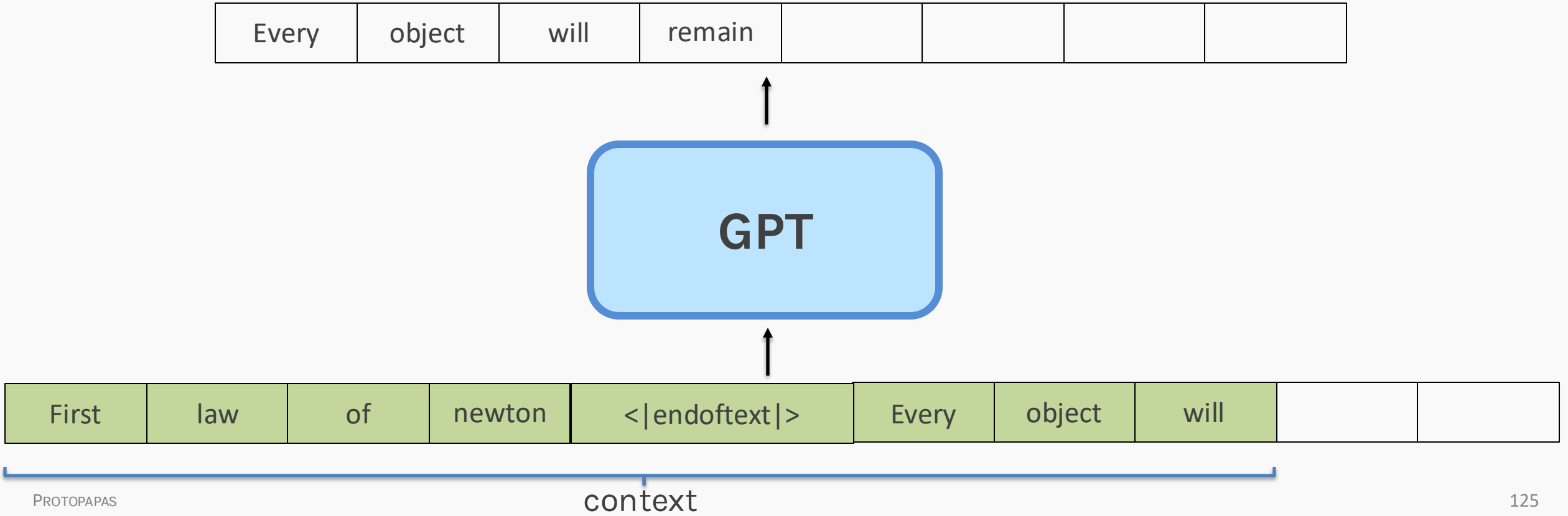

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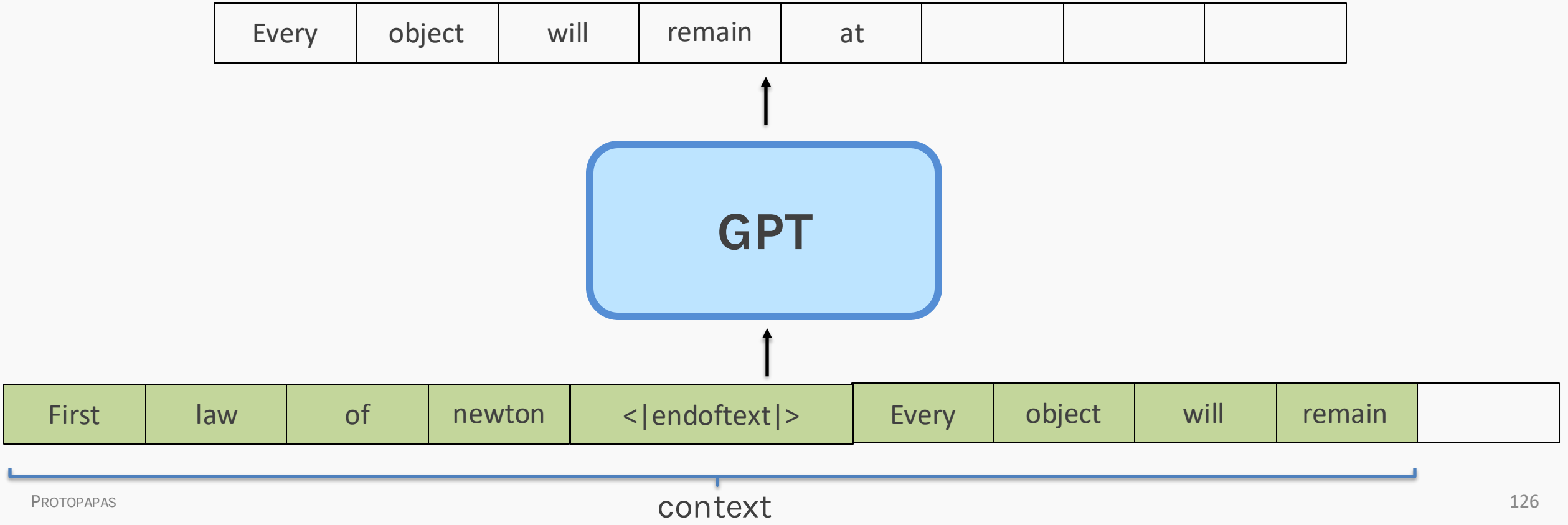

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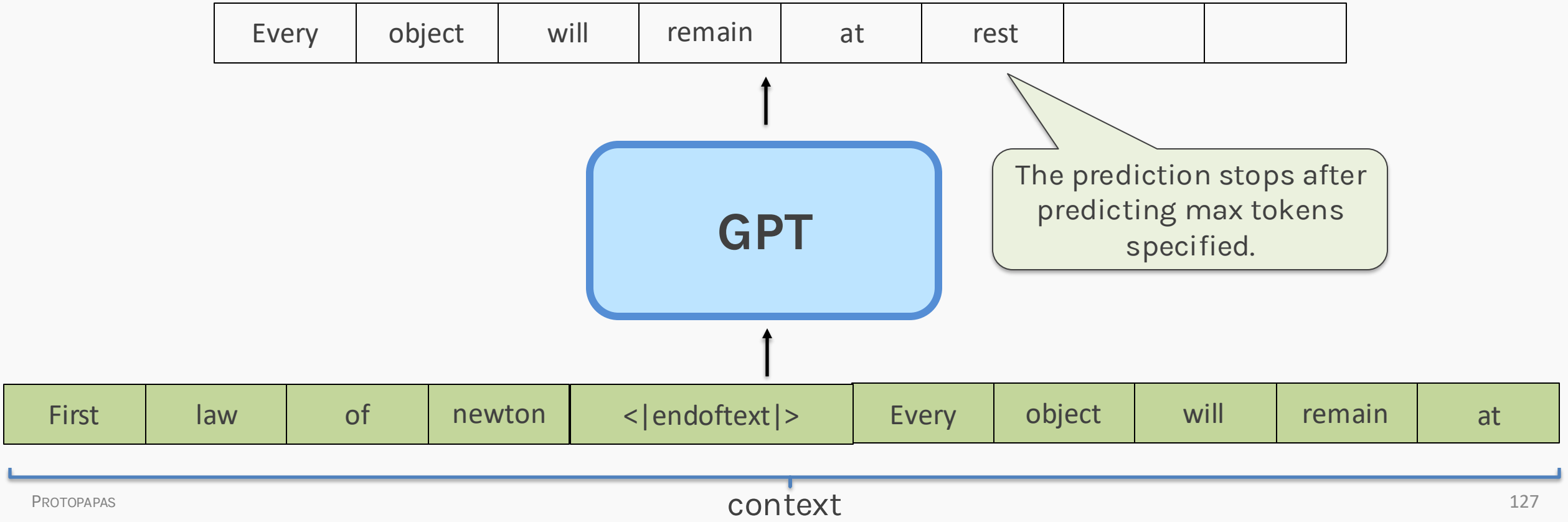
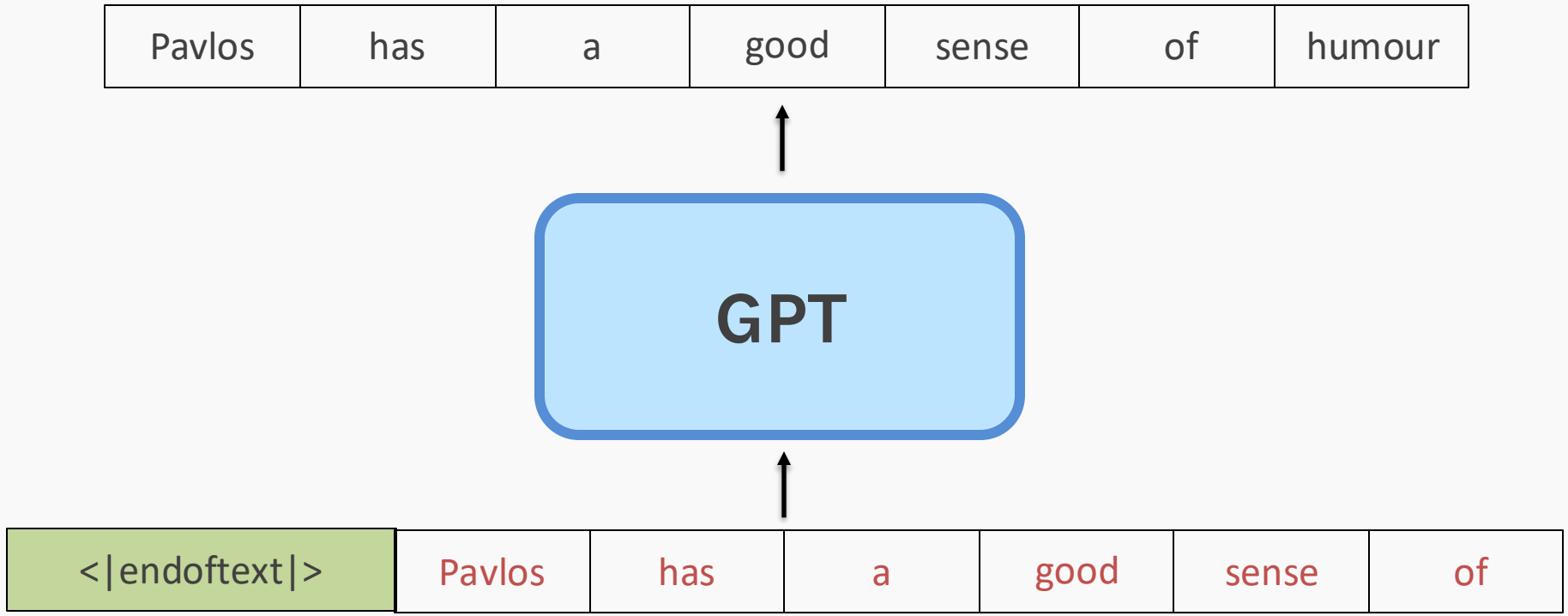


GPT - Inference

2. **<u>Unconditional</u>:** We start with *</endoftext/>* which acts as a special start token to have the model generate words on topic of its own choosing.

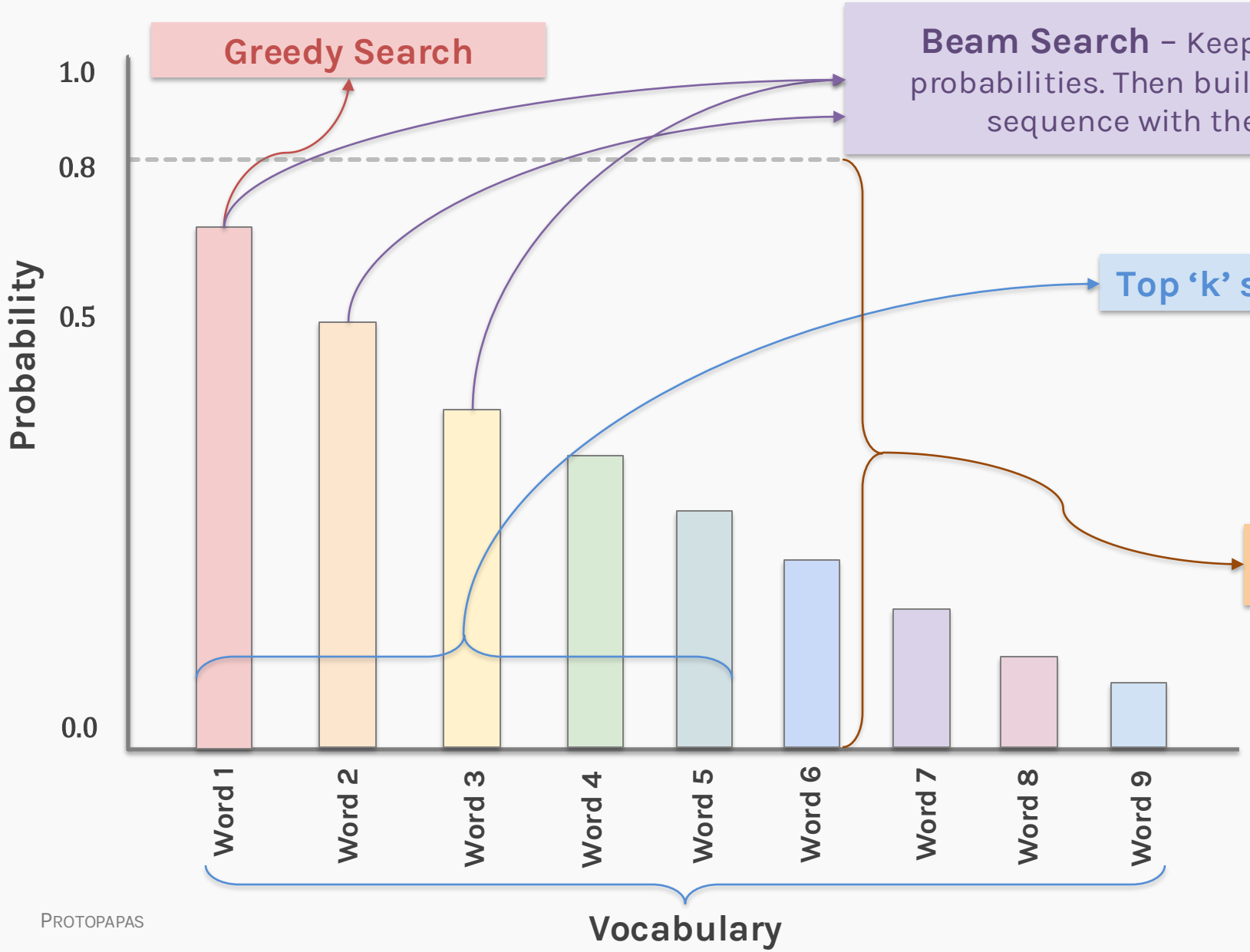


GPT - Inference

There are also different methods on how words are picked when generating text:

- Greedy Search
- Beam Search
- Top ‘k’ sampling
- Top ‘p’ sampling

GPT - Inference



Evolution of GPT

- Since its inception in 2018, GPT has received some major upgrades in terms of performance, thanks to the increasing number of parameters with each iteration.

	GPT - 1	GPT-2	GPT-3
Parameters	117 Million	1.5 Billion	175 Billion
Decoder Layers	12	48	96
Context Token Size	512	1024	2048
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Outline

- Transformers Recap
- BERT
- Practical problems in Large Language Models
- GPT
- **Hugging Face**

Hugging Face

Since the community is aware of difficulties in training language models from scratch, it has become standard to upload the trained weights and make them available to the community.

For the case of BERT, it is 340 million, or 1.4 GB assuming float32 format, which is much smaller than the dataset and can be stored in user-grade machines.

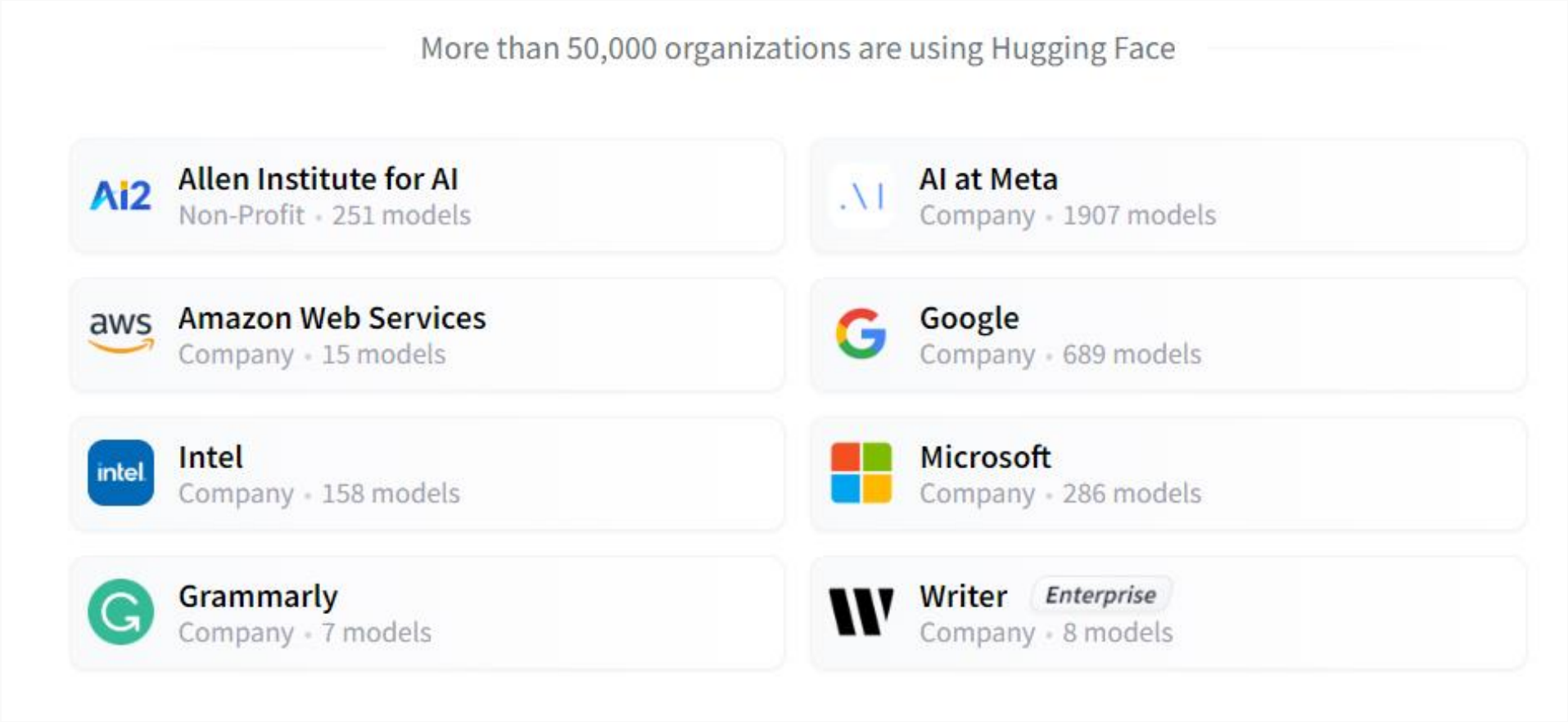
And can fit in most consumer-grade GPUs.

Hugging Face: What is it?

It is a service that enables you to download pre-trained models and datasets, free of charge.

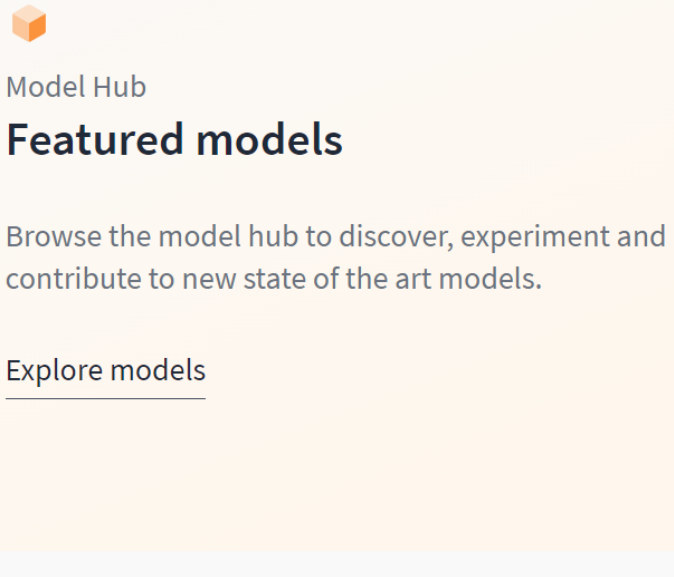
They also have a subscription model that enable you to train and serve NLP models. Aimed at labs or startups.

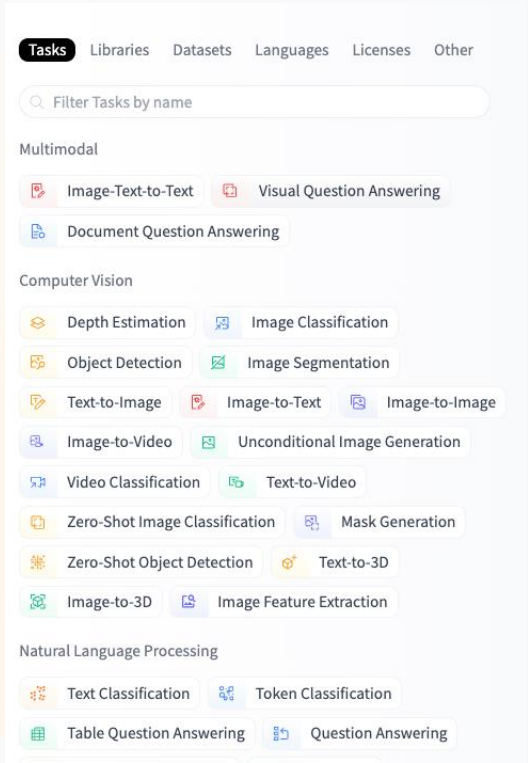
Hugging Face: Who use it?

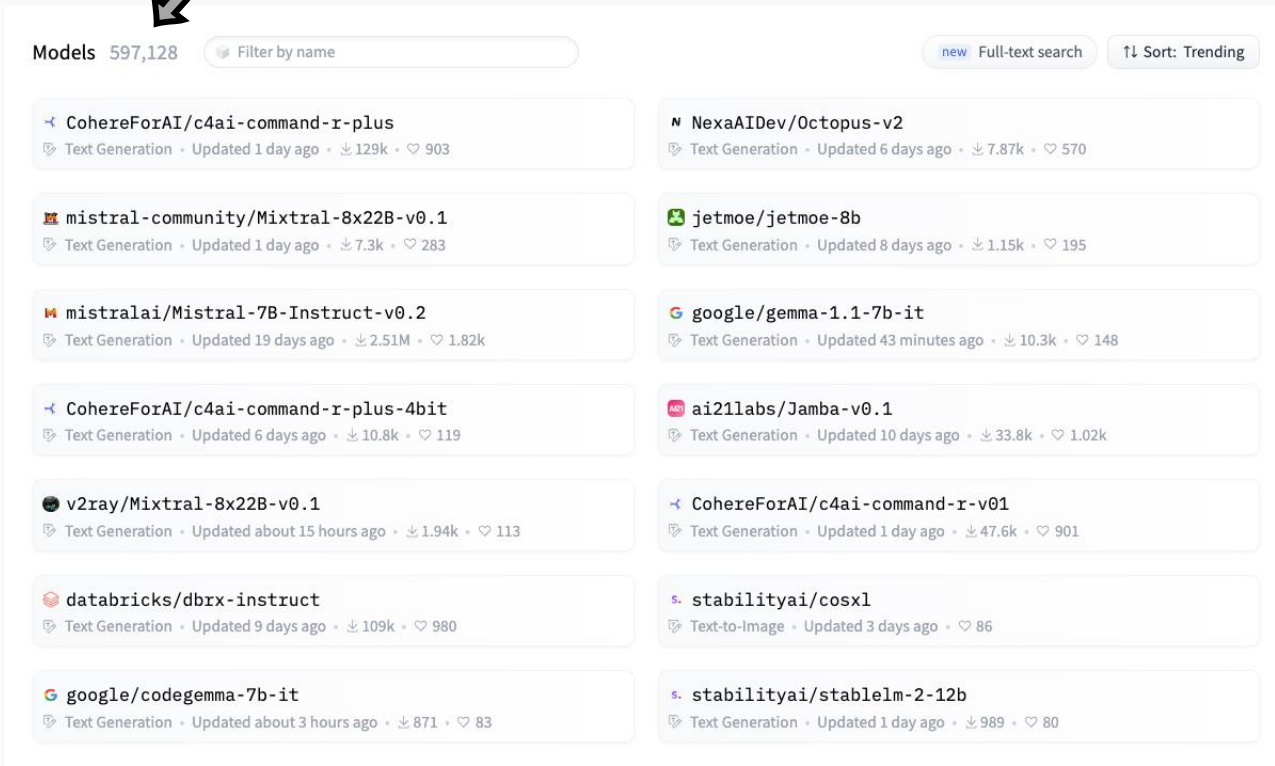


Hugging Face: What can you find?

This platform has available almost all the state-of-the-art models in NLP.







Hugging Face: What can you find?

You can explore the predictions using the hosted API.

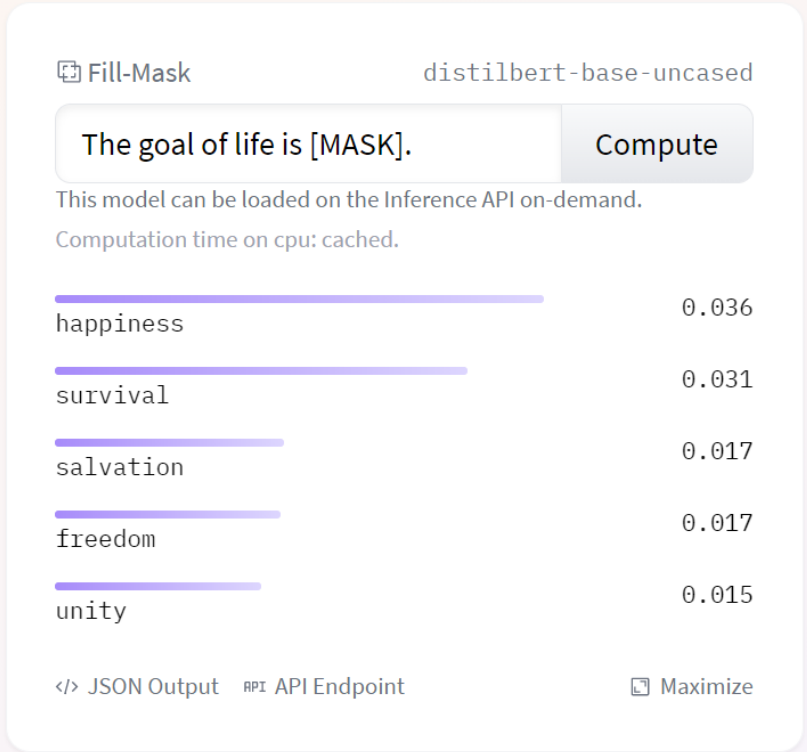
API

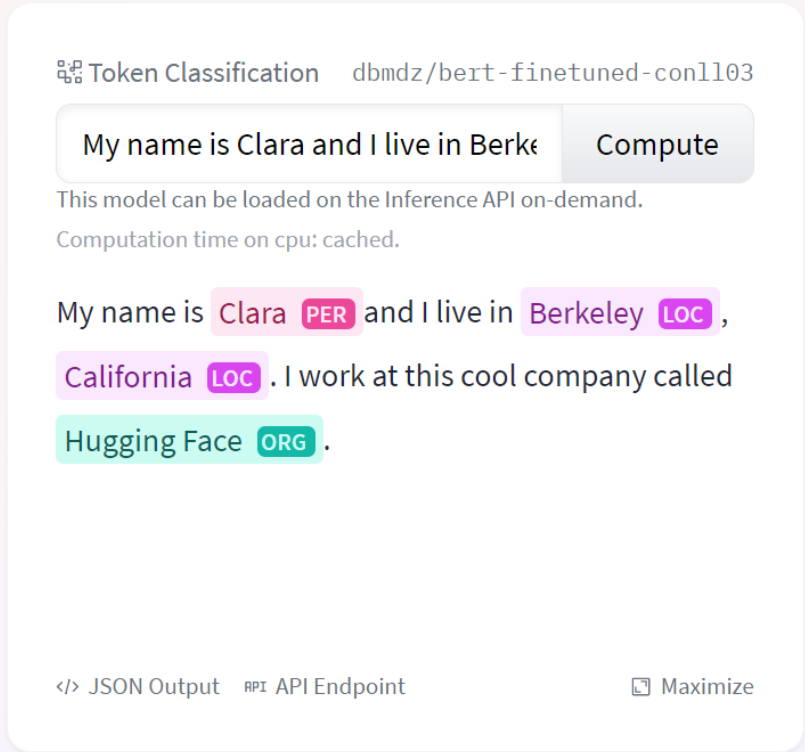
On demand

Inference API

Serve your models directly from Hugging Face infrastructure and run large scale NLP models in milliseconds with just a few lines of code.

See pricing

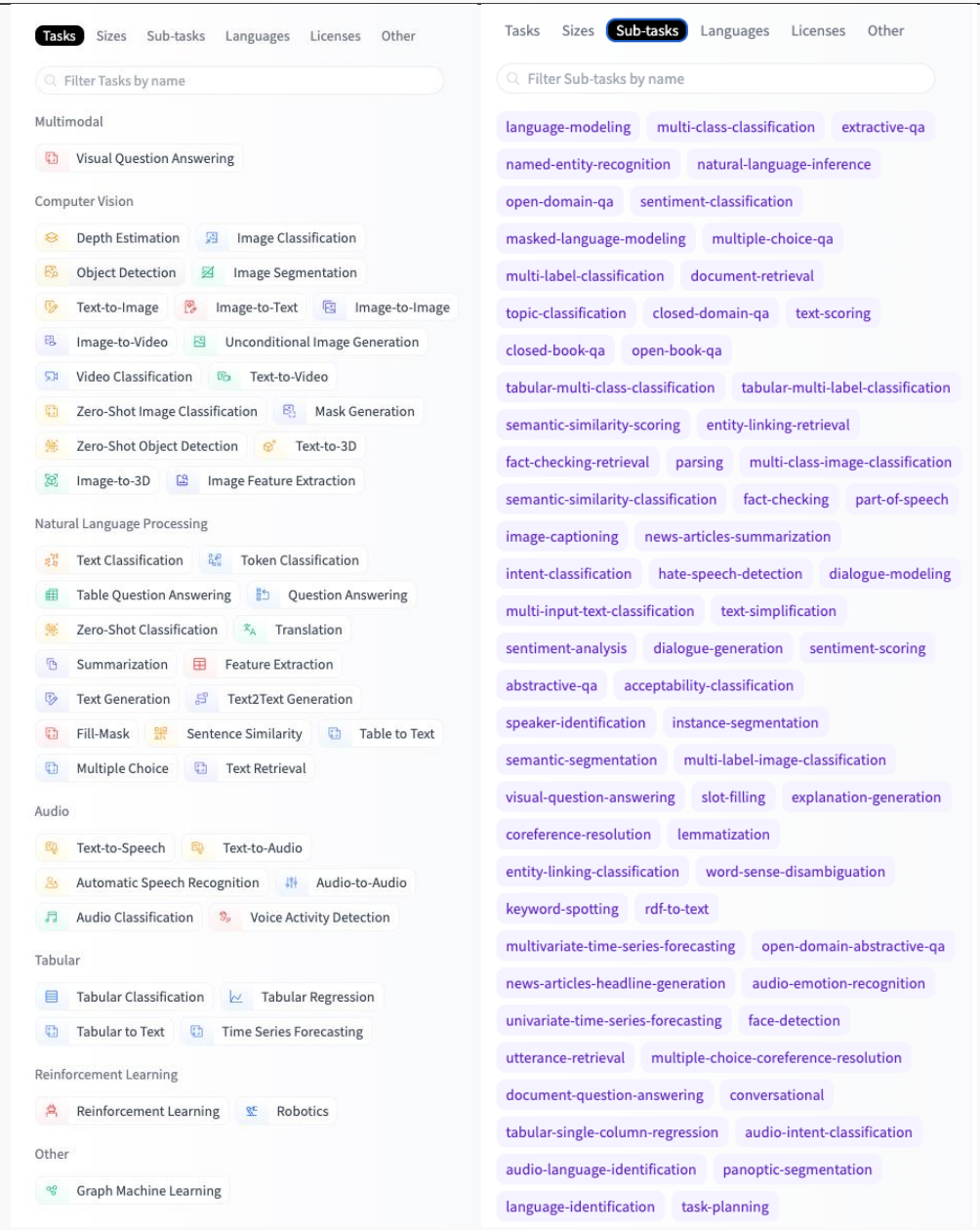




Hugging Face: What can you find?

You can also find datasets on HuggingFace that can be used to multiple downstream tasks.

The datasets can also be filtered on the basis of the task category and even subtask category.



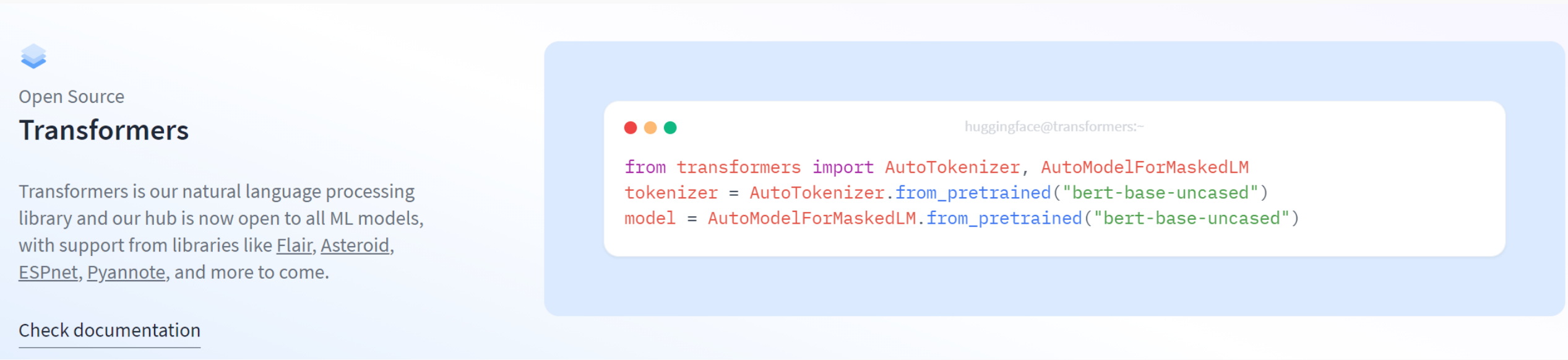
Hugging Face: What can you find?

It also provides licenses info, size and the metadata of the dataset.

There are roughly 133,136 such datasets available across 110+ languages!

Hugging Face: How to Use?

HuggingFace has an available Python API that gives access to datasets, tokenizers, and models. The models are available for PyTorch and Tensorflow.



Thank you!