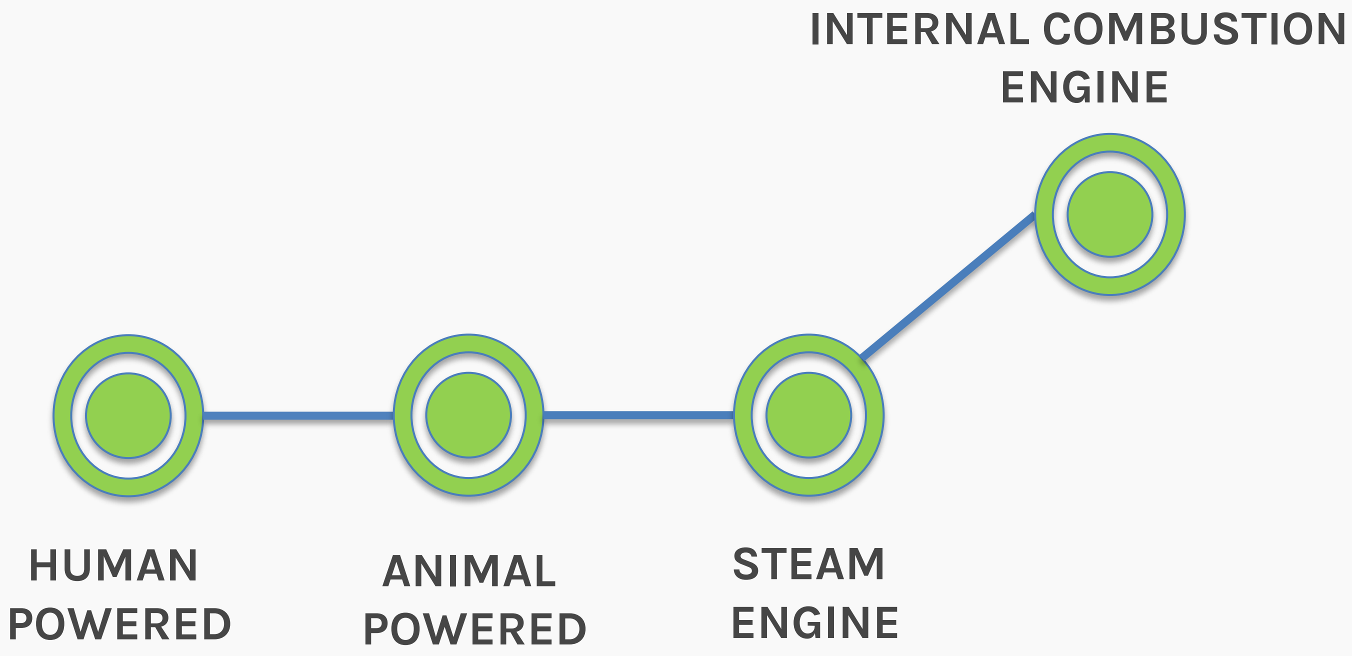
Self-Attention, Transformers, BERT

Pavlos Protopapas

Outline

- Motivation for Attention
  - Recap Seq2Seq
  - Limitations of RNNs
- Attention Basics
  - Issues with spatial attention models
  - Using cosine similarity as a tool for contextual relations
  - Self-Attention
- Building blocks of Transformers and BERT
  - Multi-head attention block
  - Positional Encoding
  - Bringing it all together

Electricity is all you need



A brief history of engines

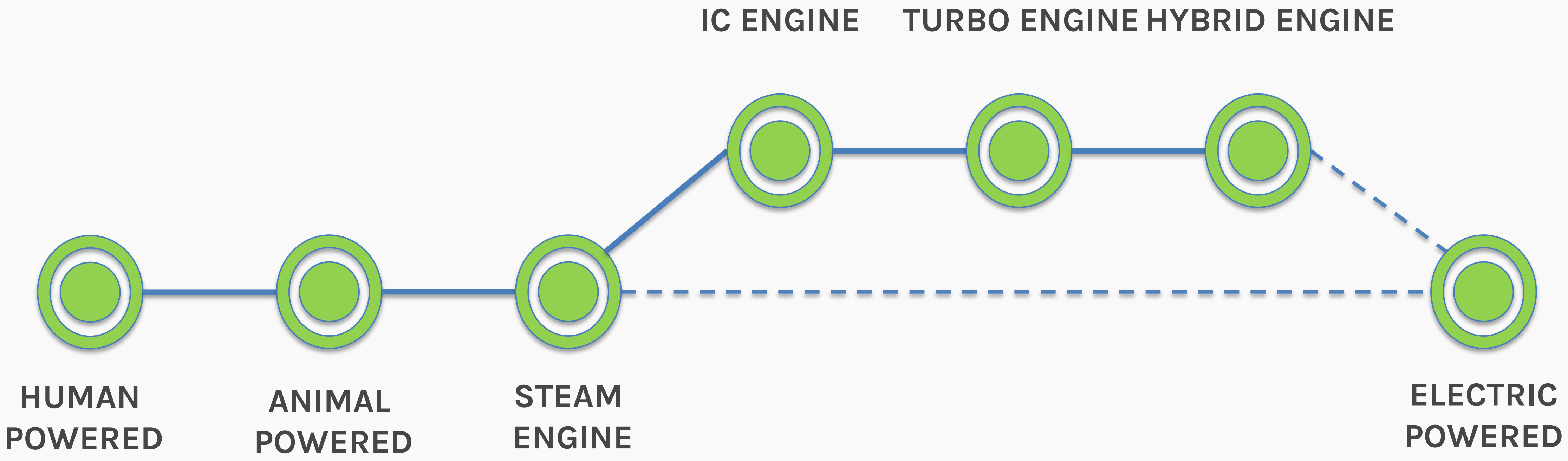
FLYWHEEL

IC COMBUSTION ENGINE

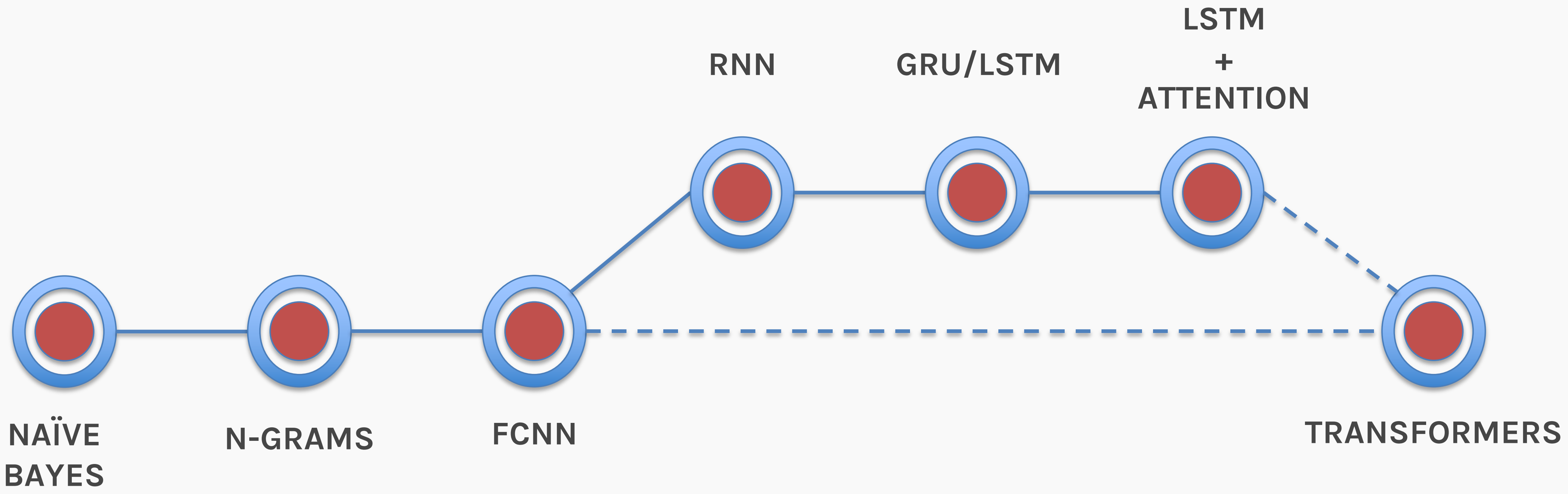
DC MOTOR

ALTERNATOR

Electricity is all you need



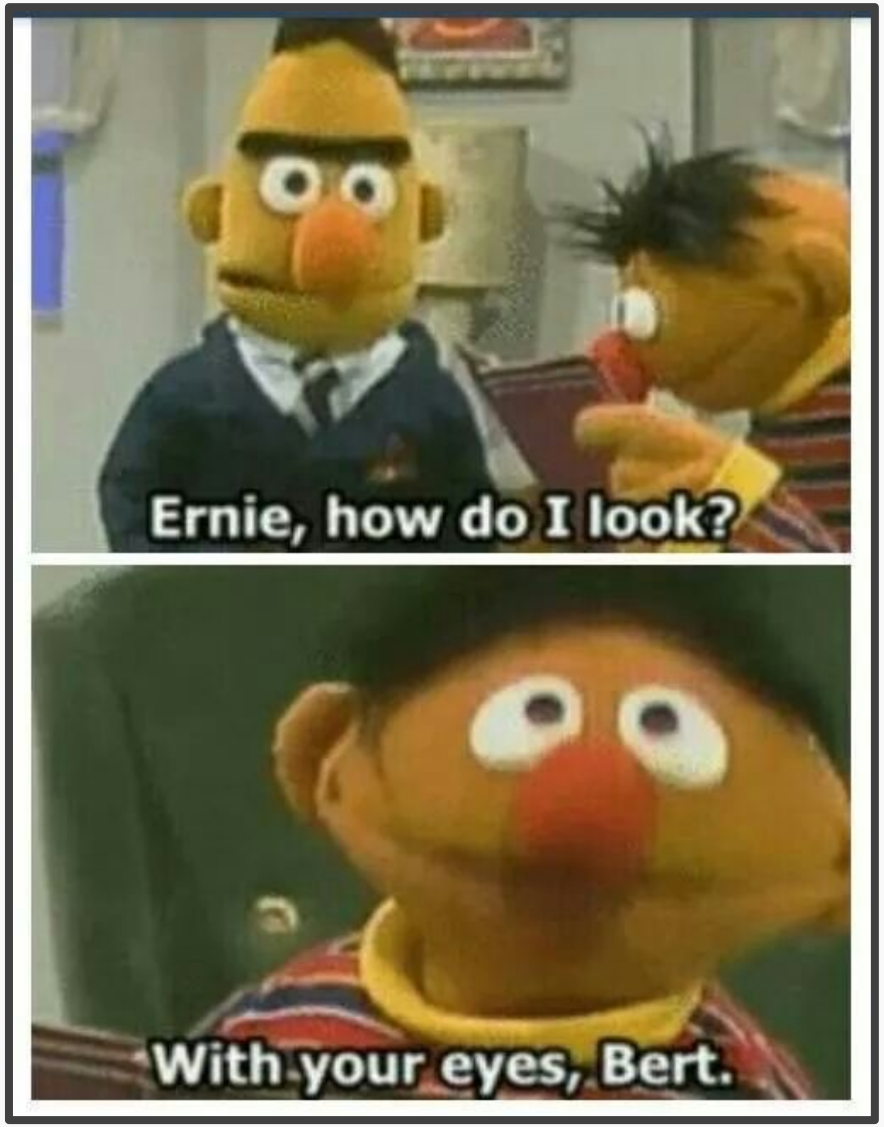
Language modeling



What we want

Language Model Wishlist?

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



We’ve already seen an approach of relative importance

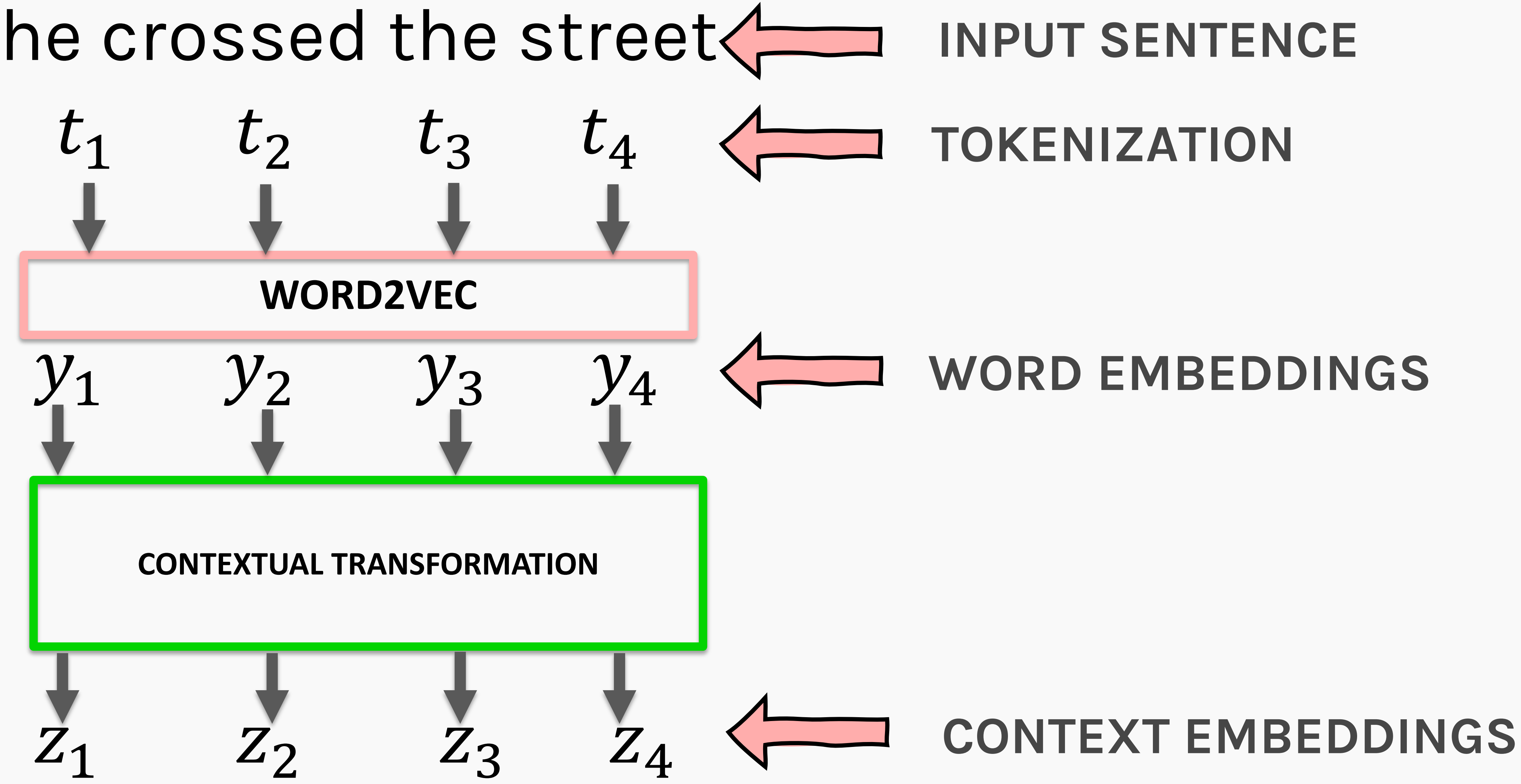
Attention

Attention: Example sentence

How do we find the context of the word ‘he’ in the sentence below?

Shivas was hit by a bus because $\boxed{\text{he}}$ crossed the street

Attention – Where to add weights?



💡 **IDEA #1:** Positional relationship

Shivas was hit by a bus because $\boxed{\text{he}}$ crossed the street

Attention: Example sentence

IDEA #1: Positional transformation

Shivas was hit by a bus because he crossed the street

True context

This idea does not work because context can be unevenly spread out in a sentence

Attention – The basics

- We can still use the idea of transforming the word embeddings to get more context

- However, the transformation matrix A must place some importance to the relative importance of words

$$y = [y_1, y_2, y_3, \ldots, y_n]$$

$$z = A\, y^T$$

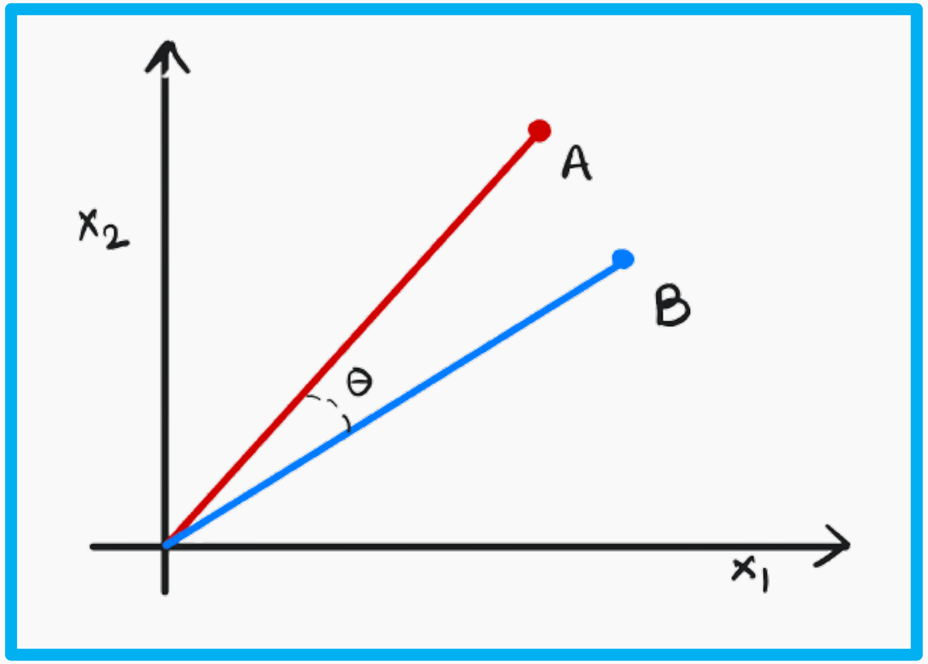
$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots a_{ij} & \cdots & a_{in} \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nn} \end{bmatrix}$$

a_{ij} must account for relative importance between word i & j

Attention – Text Data

But how can we do it?

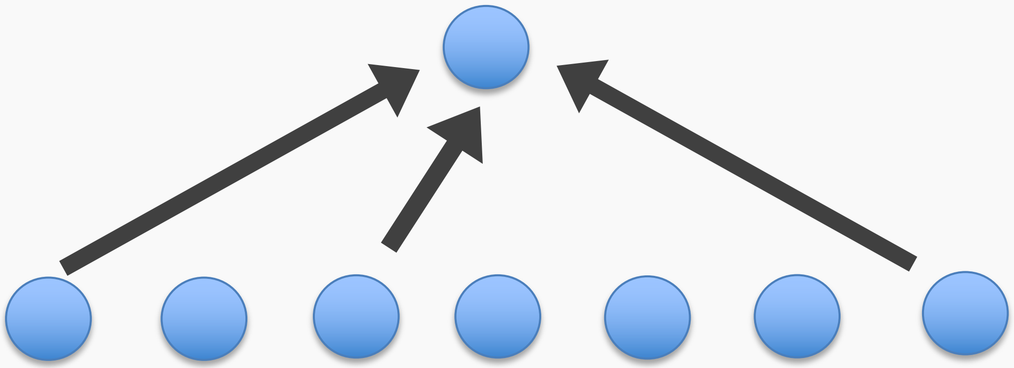
Yes! Let's use cosine similarity between words

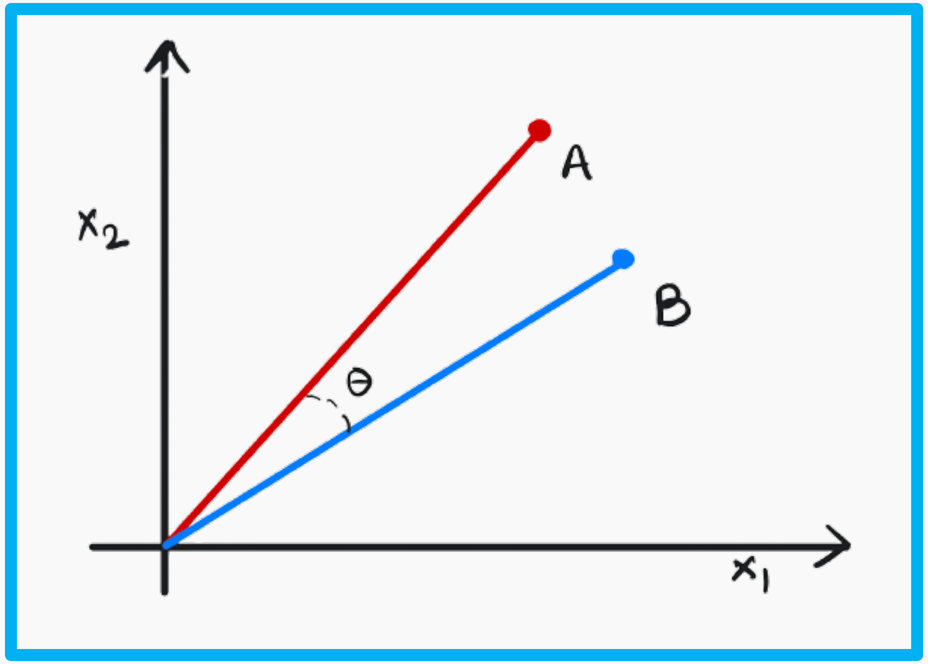


$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

RECAP: Cosine Similarity

For context, we could just take the cosine similarity of the target word with respect to every other word in the sentence





$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Where A_i & B_i are components of vector A & B respectively

How do we do it?

Attention: Example sentence #2

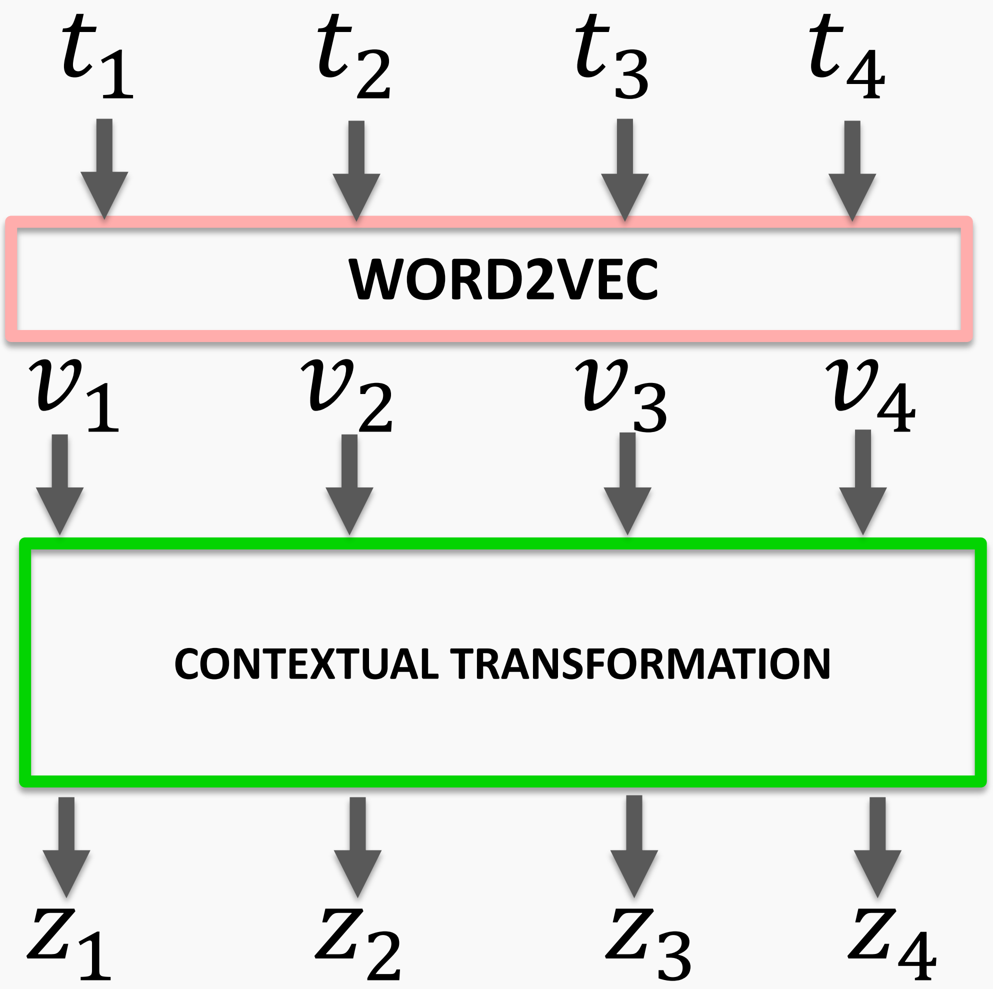
Ignacio was standing next to the bank of the river

Attention: Example sentence #2

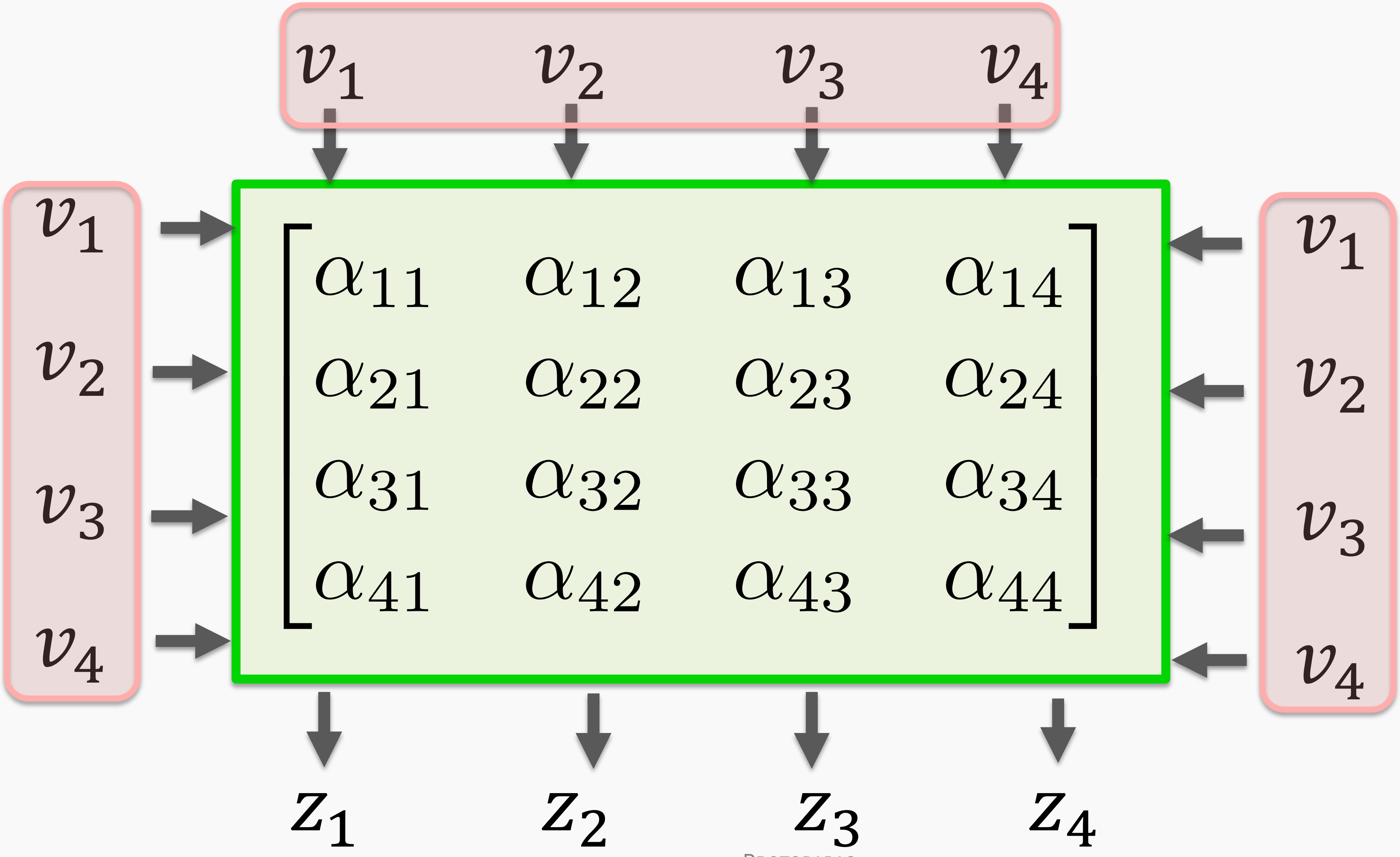
bank of the river

Attention – Cosine Similarity

bank of the river



Attention – Cosine Similarity



Attention: Example sentence #2

$v_1 \circ v_1 = a_{11}$

$v_1 \circ v_2 = a_{12}$

$v_1 \circ v_3 = a_{13}$

$v_1 \circ v_4 = a_{14}$

$\xrightarrow{\text{WEIGHTS NORMALIZATION}}$

α_{11}

α_{12}

α_{13}

α_{14}

$\boxed{\Sigma\alpha_{1i} = 1}$

Attention: Example sentence #2

$$\boxed{\Sigma\alpha_{1i} = 1}$$

$$z_1 = v_1\alpha_{11} + v_2\alpha_{12} + v_3\alpha_{13} + v_4\alpha_{14}$$

New contextual
word embedding

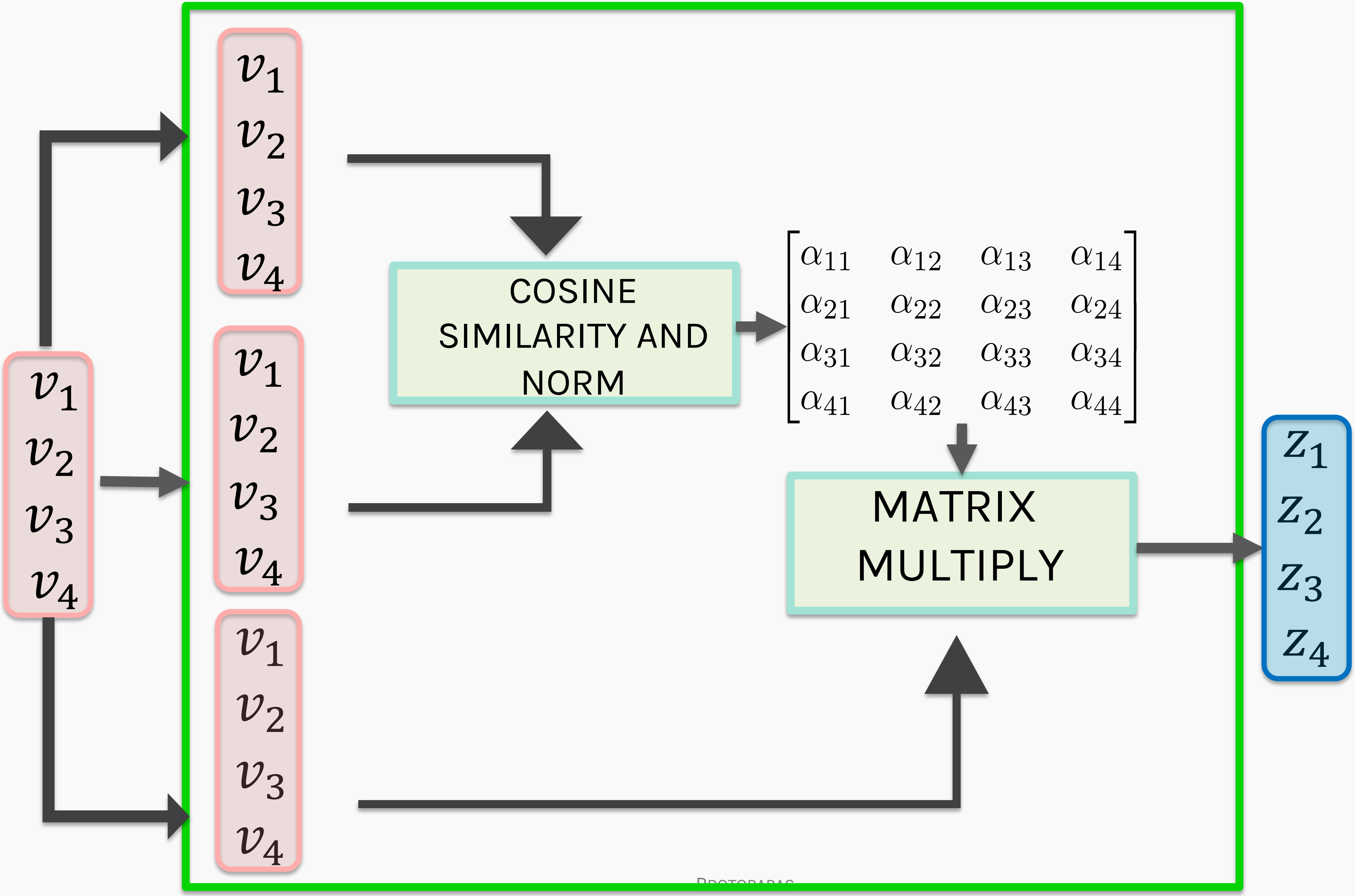
Similarly…

$$z_1 = v_1\alpha_{11} + v_2\alpha_{12} + v_3\alpha_{13} + v_4\alpha_{14}$$

$$z_2 = v_1\alpha_{21} + v_2\alpha_{22} + v_3\alpha_{23} + v_4\alpha_{24}$$

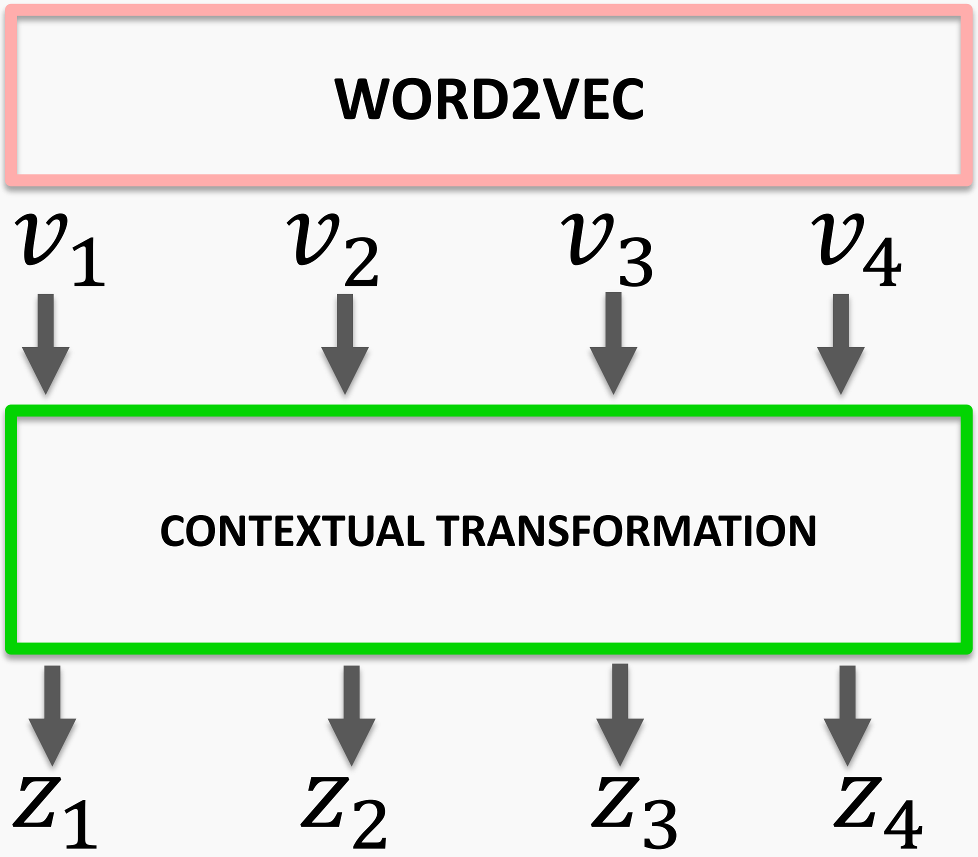
$$z_3 = v_1\alpha_{31} + v_2\alpha_{32} + v_3\alpha_{33} + v_4\alpha_{34}$$

$$z_4 = v_1\alpha_{41} + v_2\alpha_{42} + v_3\alpha_{43} + v_4\alpha_{44}$$


v_1 v_2 v_3 v_4
COSINE SIMILARITY AND NORM
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1 z_2 z_3 z_4

Attention: Example sentence #2

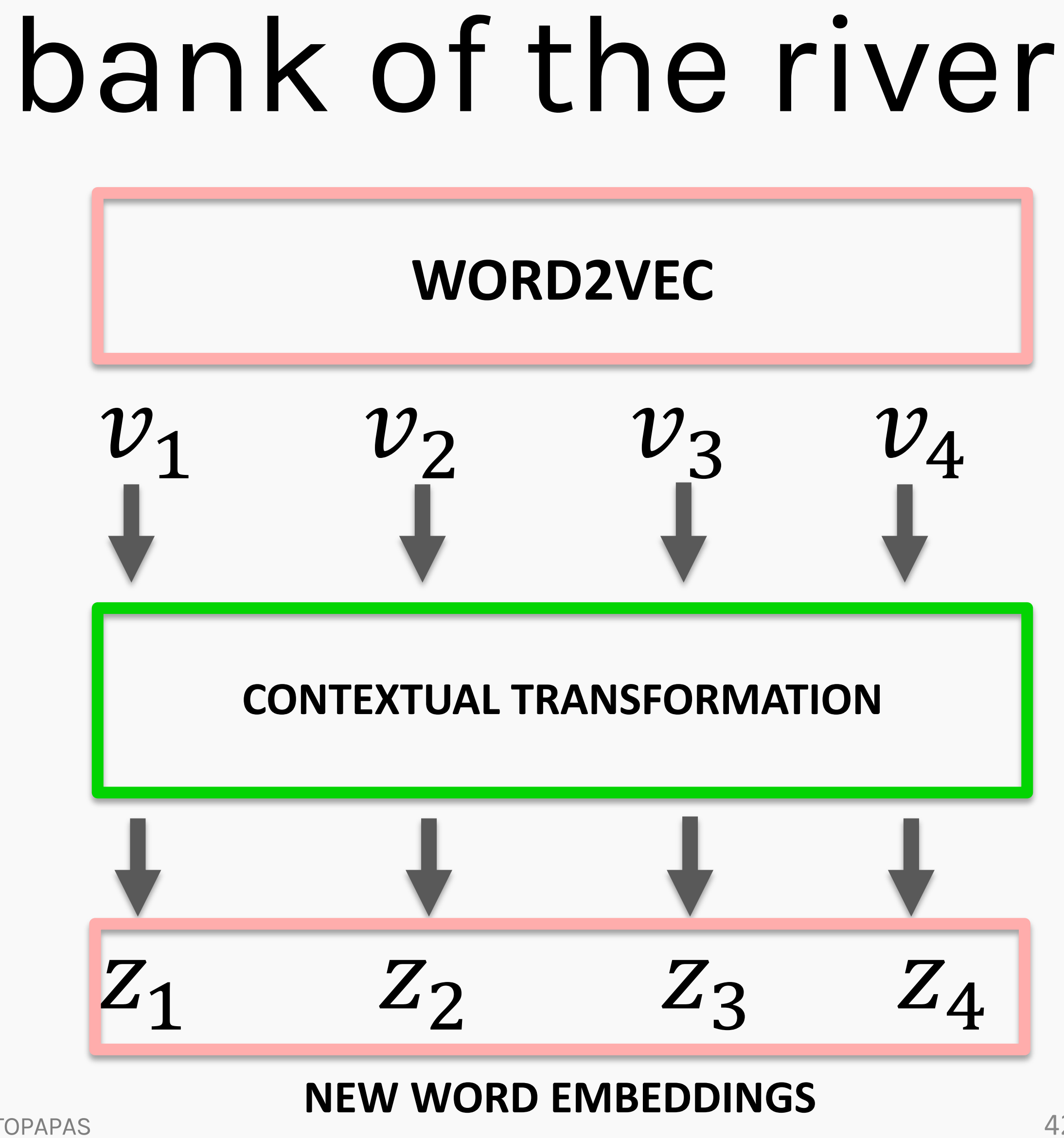
bank of the river



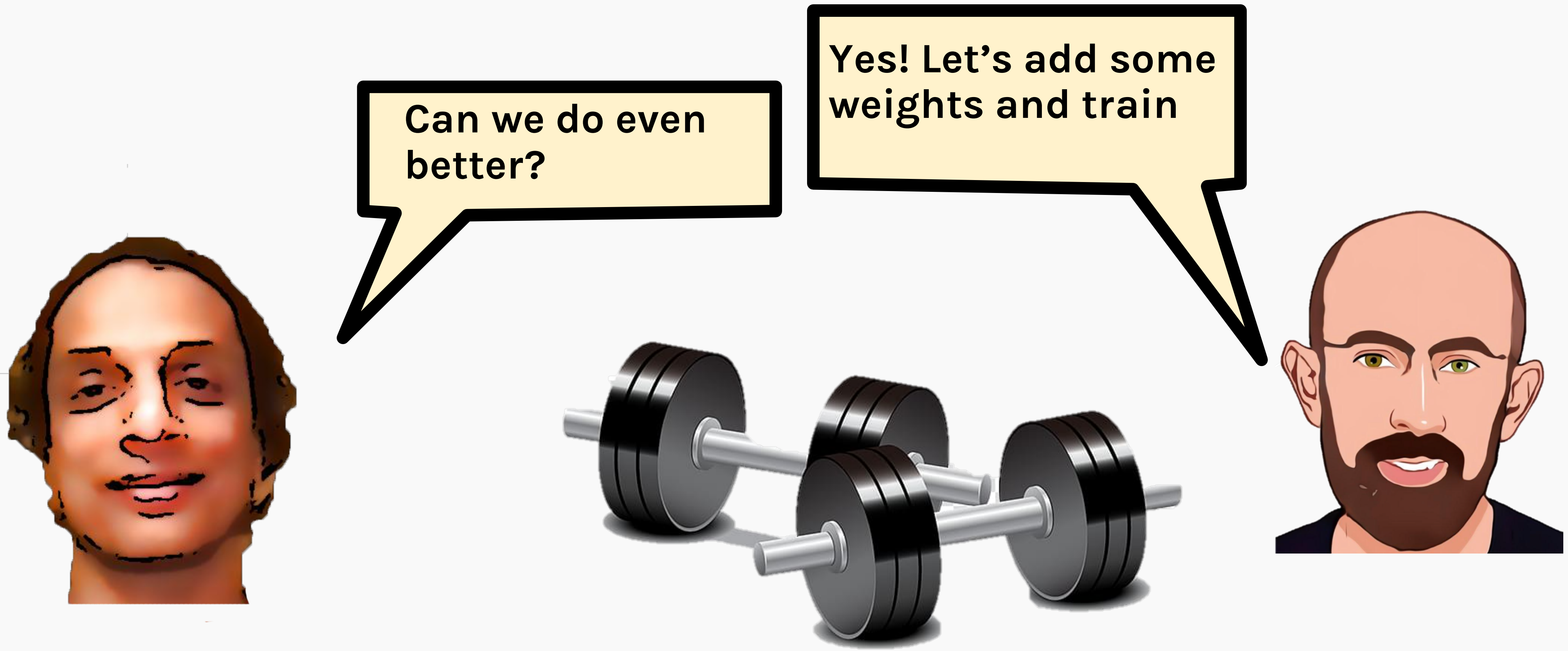
ATTENTION ISSUES?

This process gives us new embeddings with some context. However, we still have the following issues:

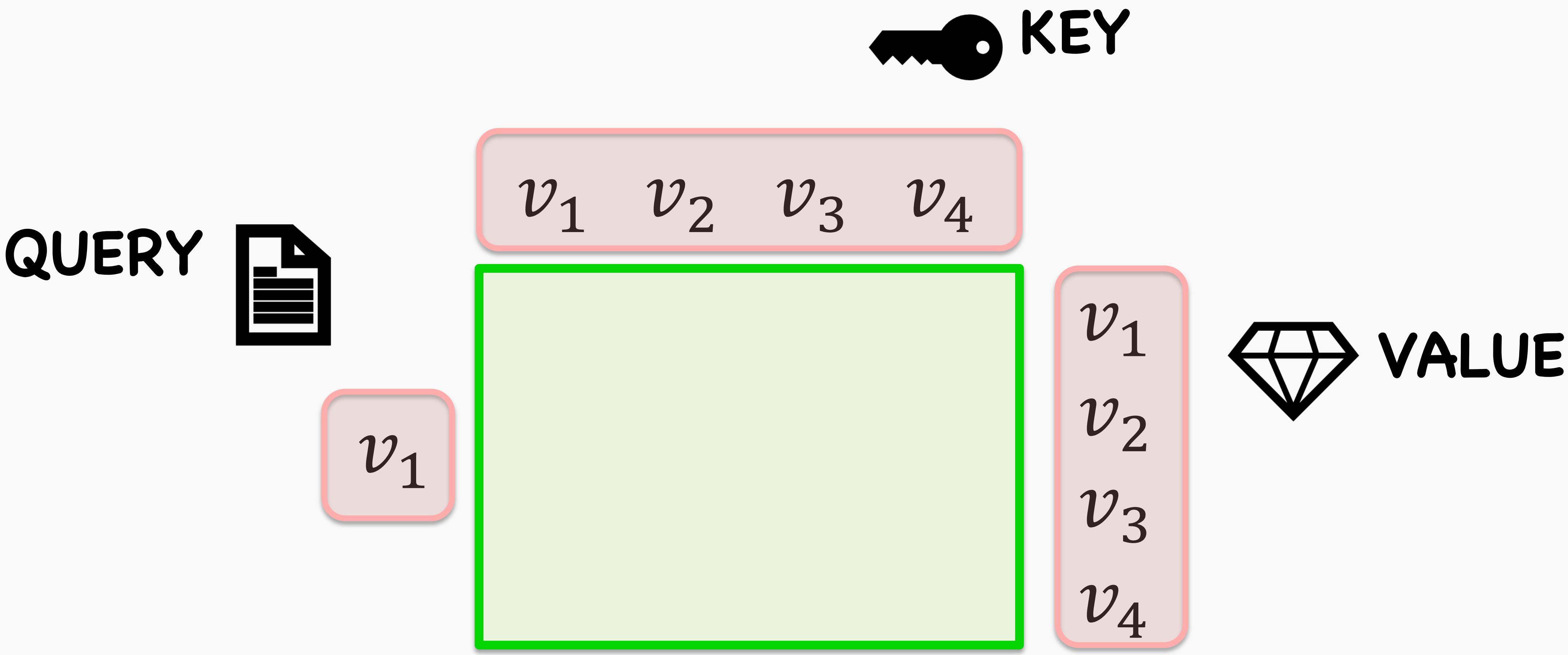
- No weights are trained in the process
- Attention as defined to be cosine similarity leads to fixed contextual mapping (two words will always have the same cosine similarity irrespective of the context)
- There is no positional information encoded



Attention – Text Data



Database Analogy



Database Analogy

For simplicity, we stick to our database analogy of **QUERY, KEY & VALUE**

KEY

$v_1 \quad v_2 \quad v_3 \quad v_4$

QUERY

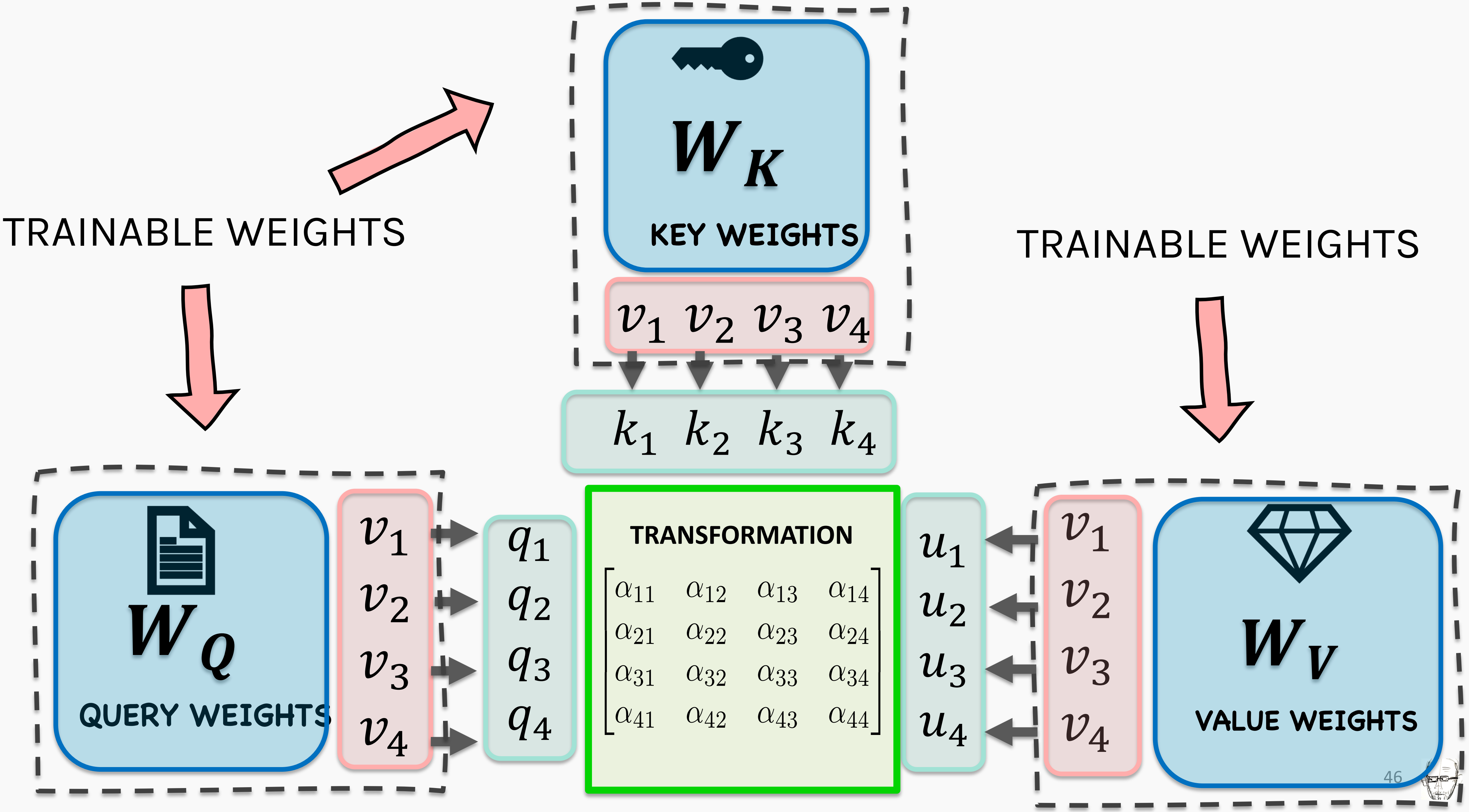
v_1
v_2
v_3
v_4

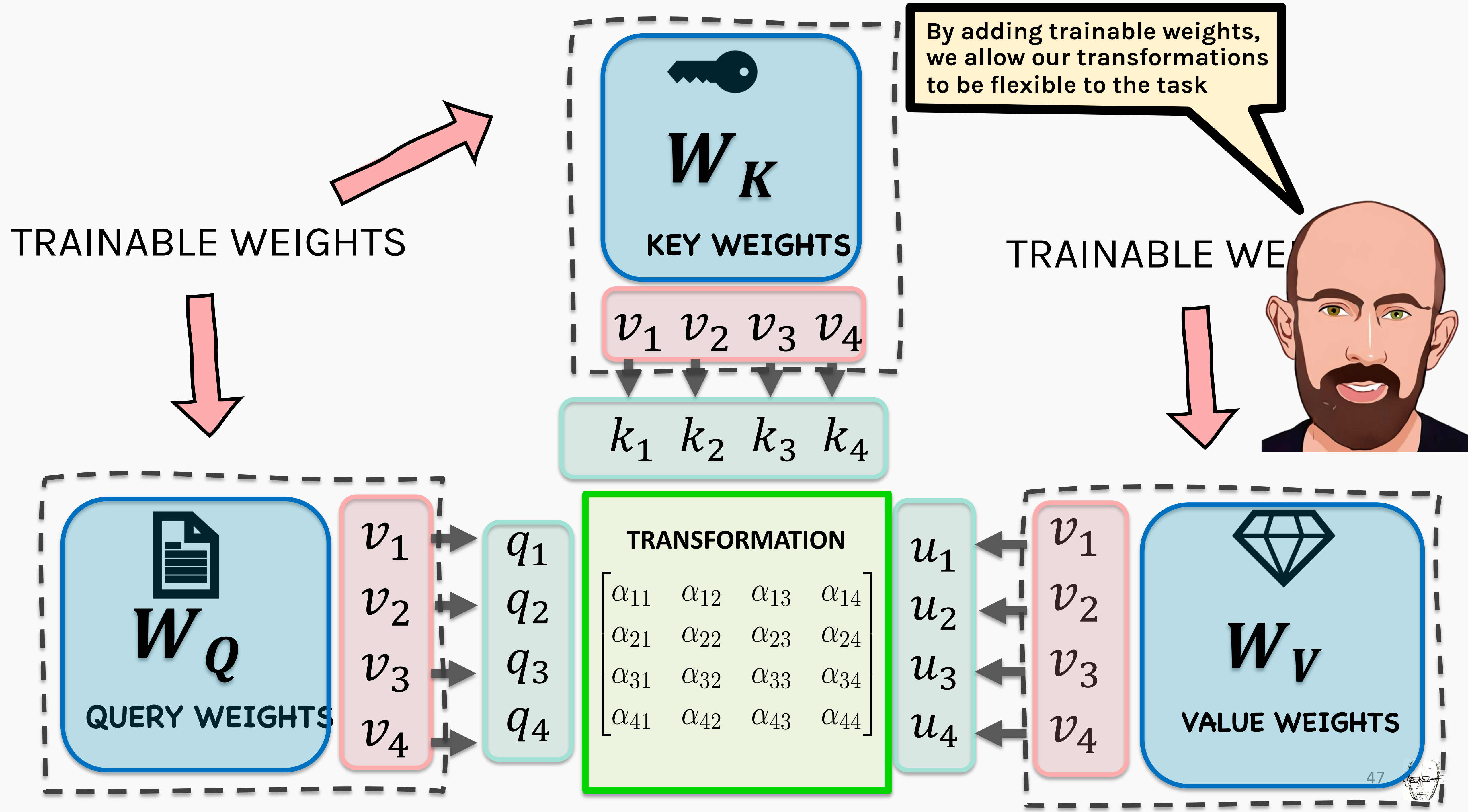
TRANSFORMATION

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

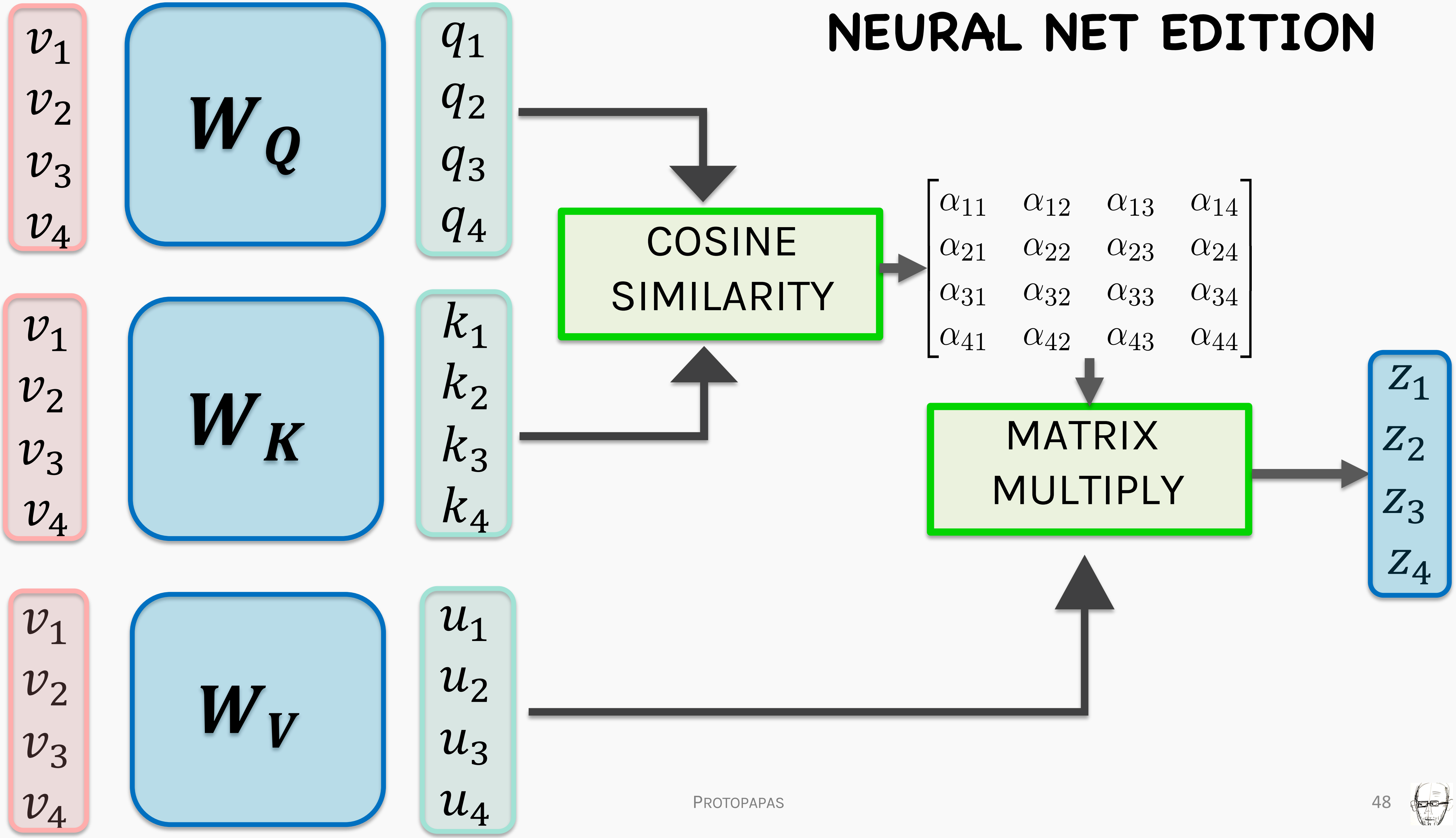
v_1
v_2
v_3
v_4

VALUE

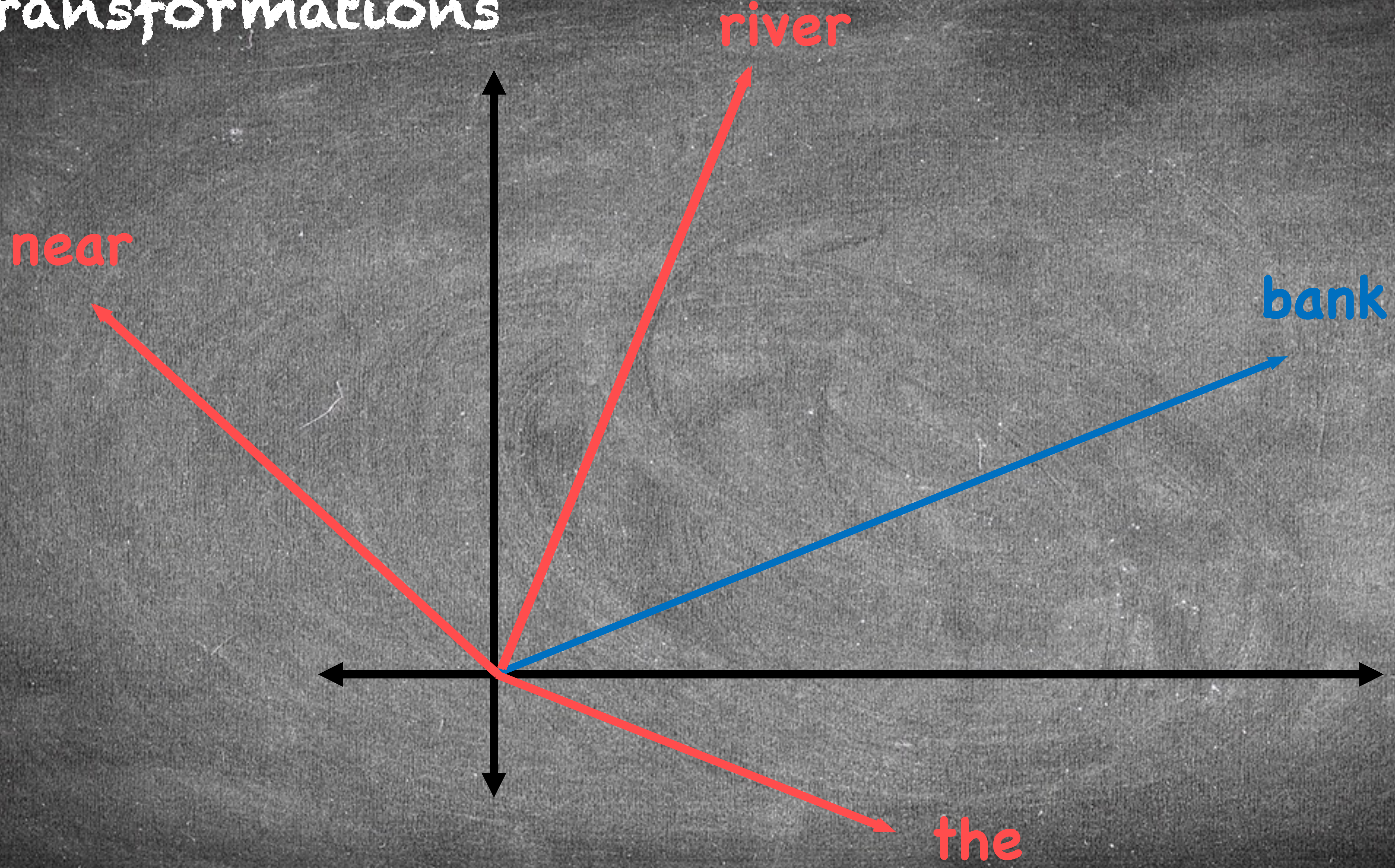

TRAINABLE WEIGHTS
W_K
KEY WEIGHTS
v_1 v_2 v_3 v_4
k_1 k_2 k_3 k_4
TRAINABLE WEIGHTS
W_Q
QUERY WEIGHTS
v_1 v_2 v_3 v_4
q_1 q_2 q_3 q_4
TRANSFORMATION
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
u_1 u_2 u_3 u_4
v_1 v_2 v_3 v_4
W_V
VALUE WEIGHTS


By adding trainable weights, we allow our transformations to be flexible to the task
TRAINABLE WEIGHTS
W_K
KEY WEIGHTS
v_1 v_2 v_3 v_4
k_1 k_2 k_3 k_4
TRAINABLE WE
W_Q
QUERY WEIGHTS
v_1 v_2 v_3 v_4
q_1 q_2 q_3 q_4
TRANSFORMATION
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
u_1 u_2 u_3 u_4
v_1 v_2 v_3 v_4
W_V
VALUE WEIGHTS

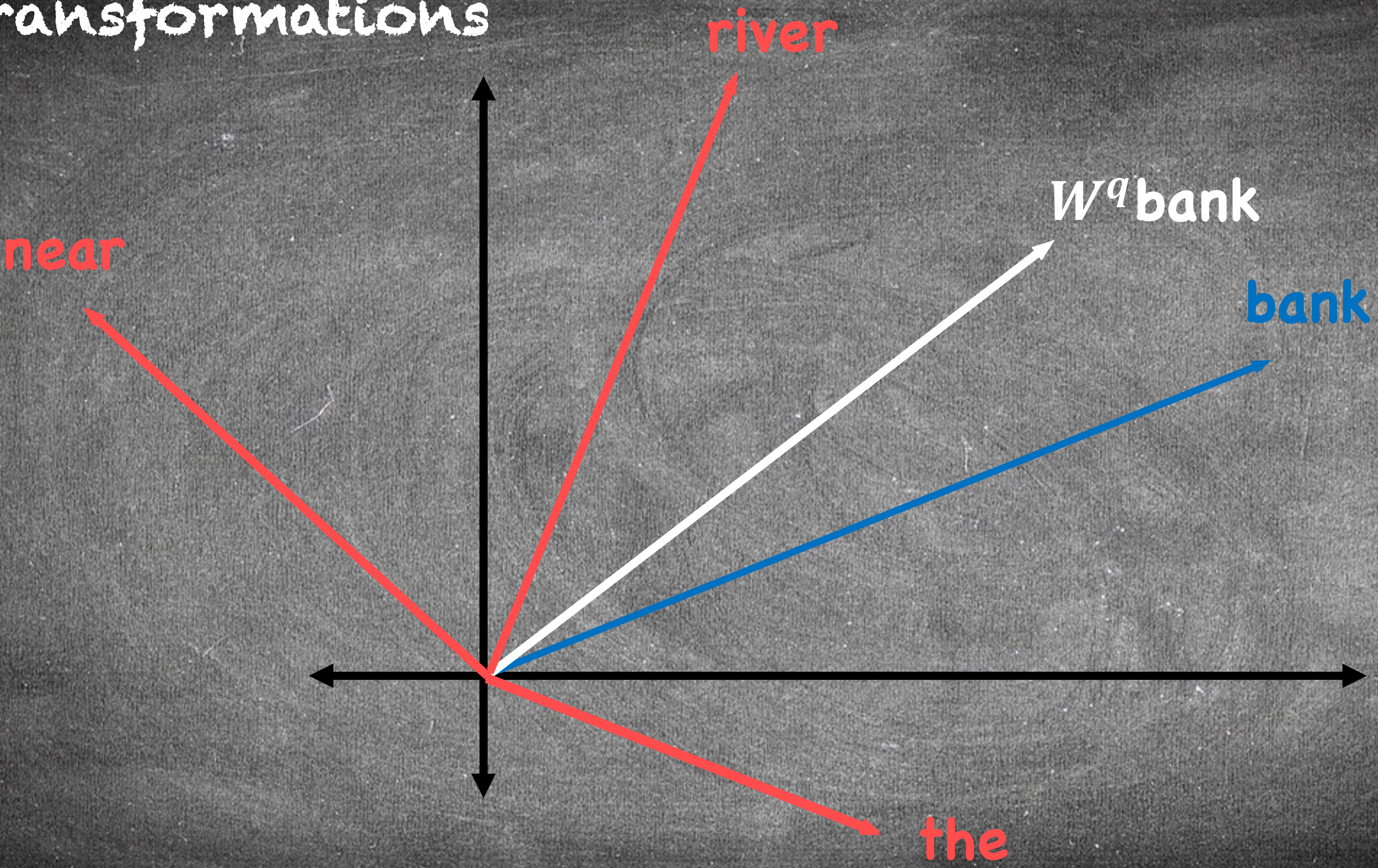
NEURAL NET EDITION



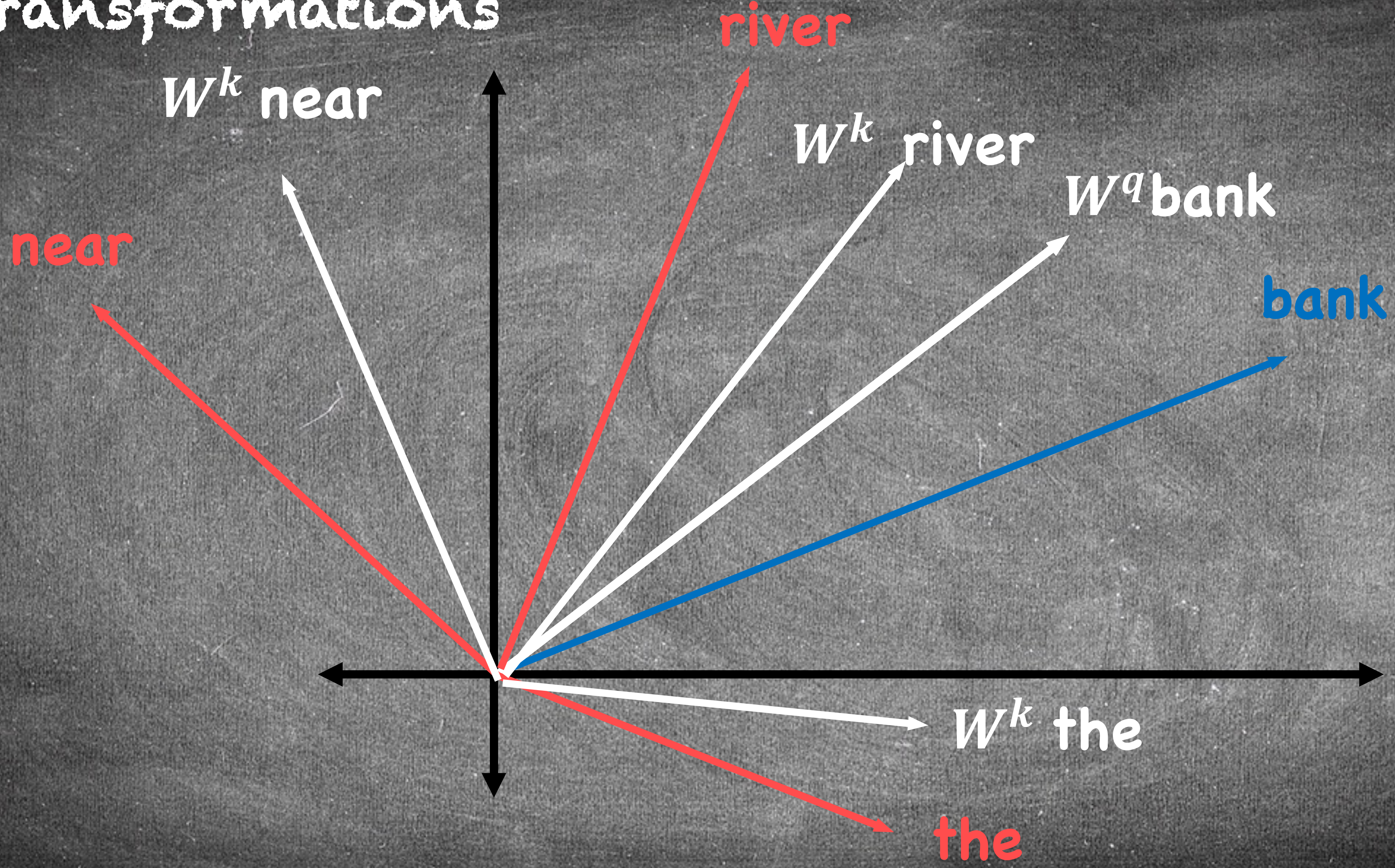
Transformations

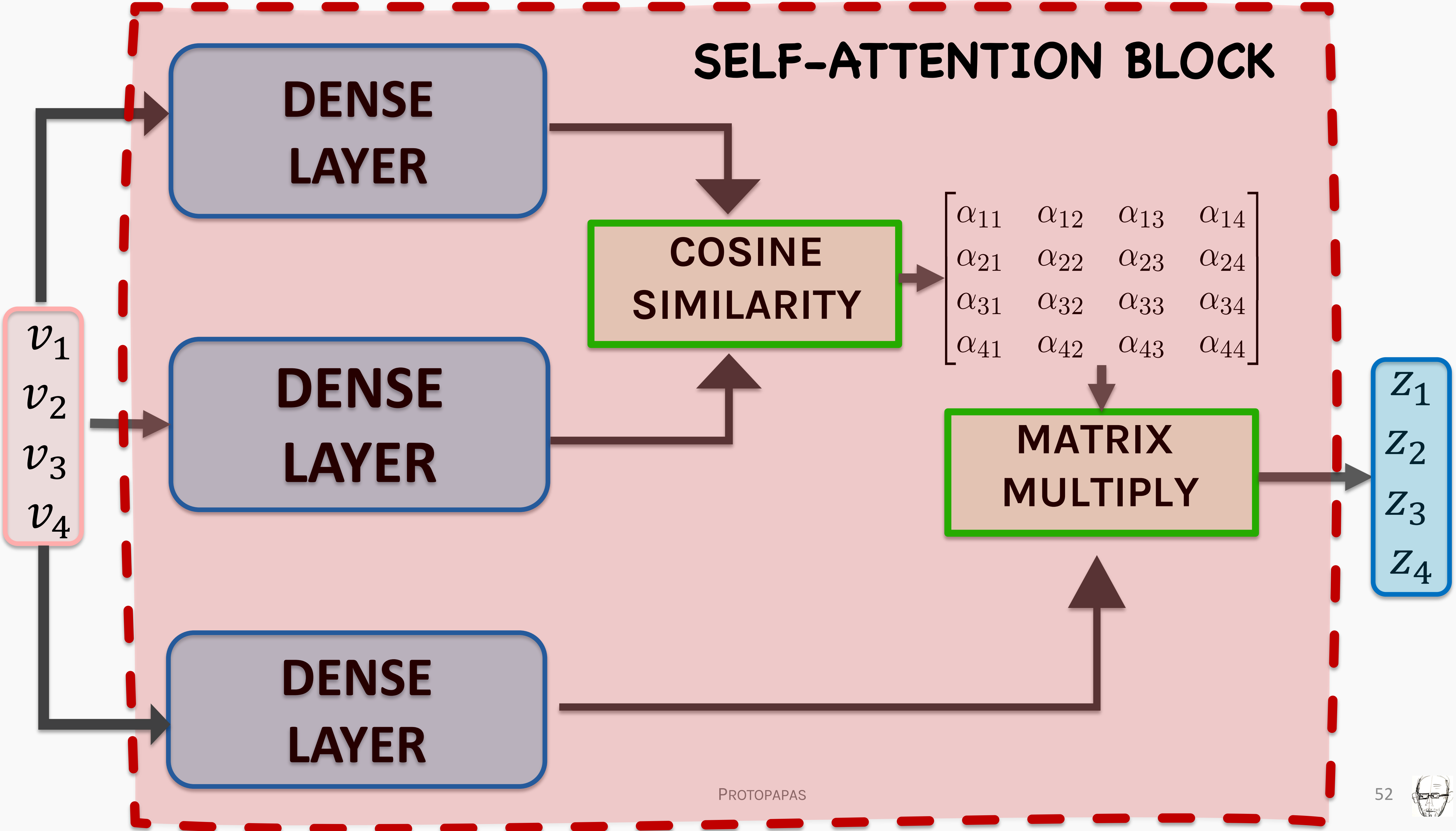


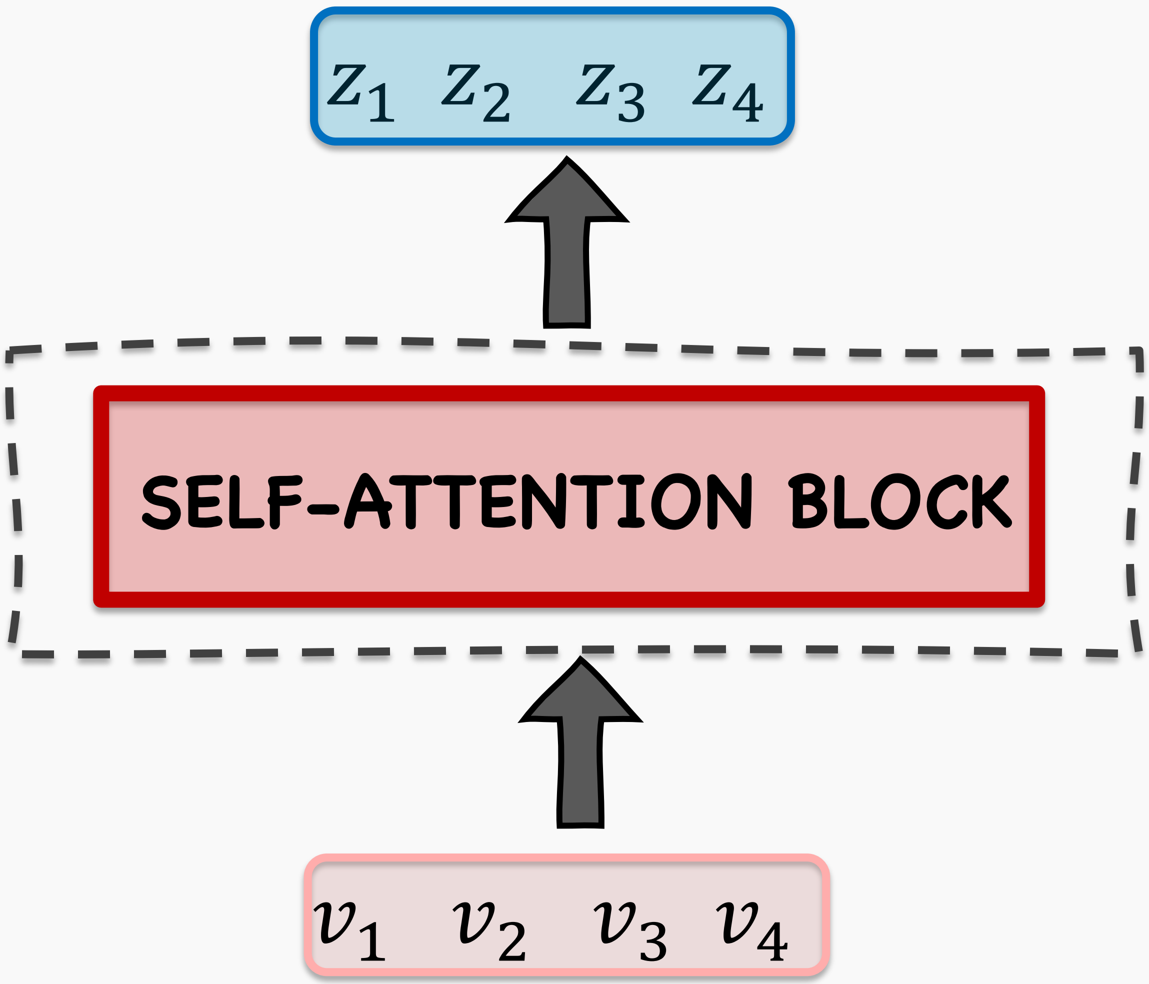
Transformations



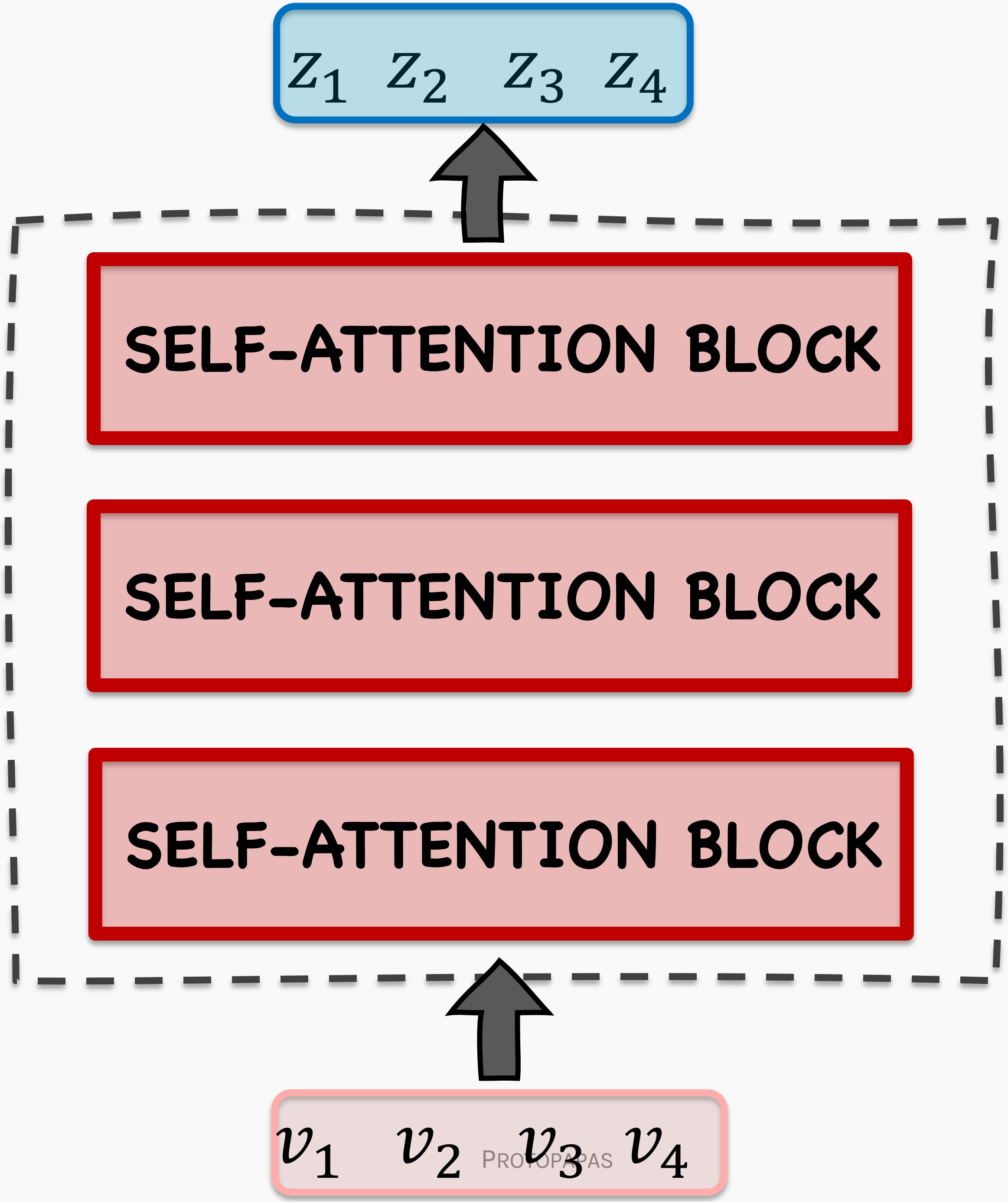
Transformations

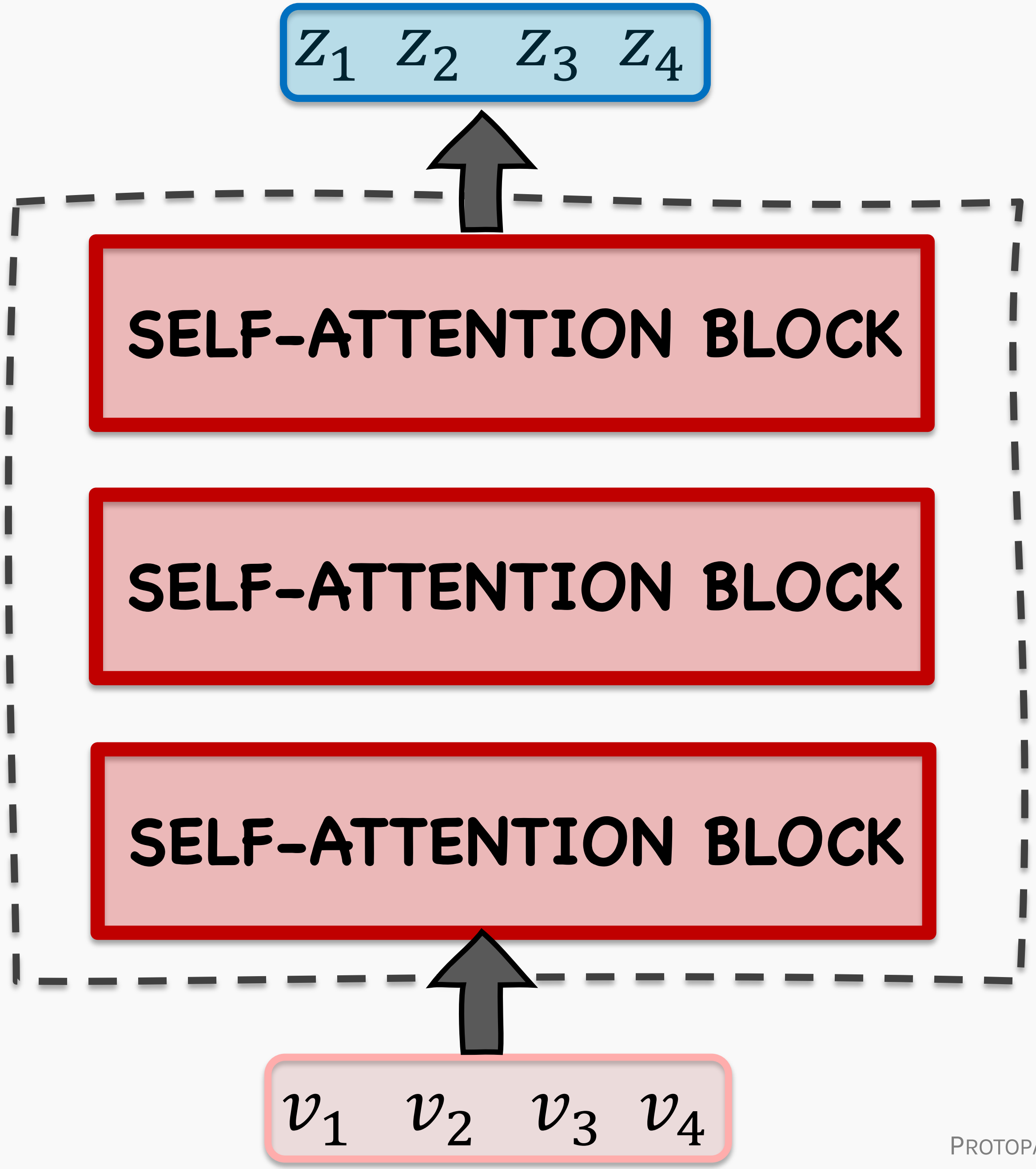


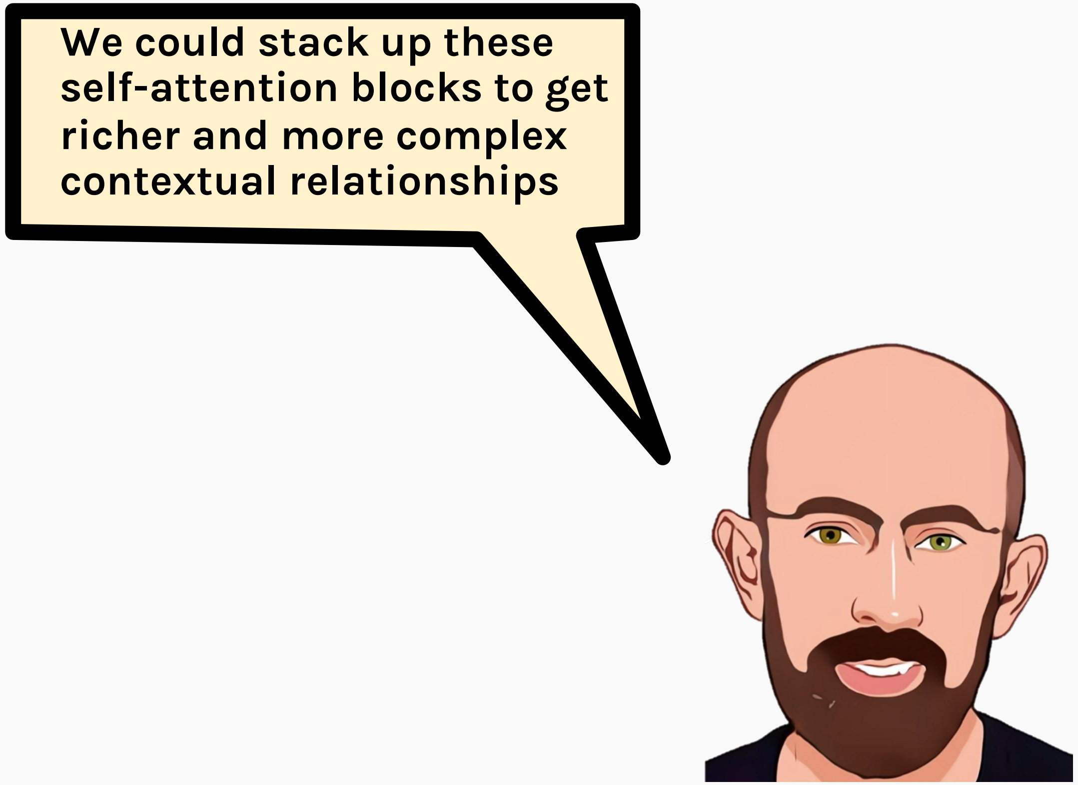

SELF-ATTENTION BLOCK
v_1 v_2 v_3 v_4
DENSE LAYER
DENSE LAYER
DENSE LAYER
COSINE SIMILARITY
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1 z_2 z_3 z_4



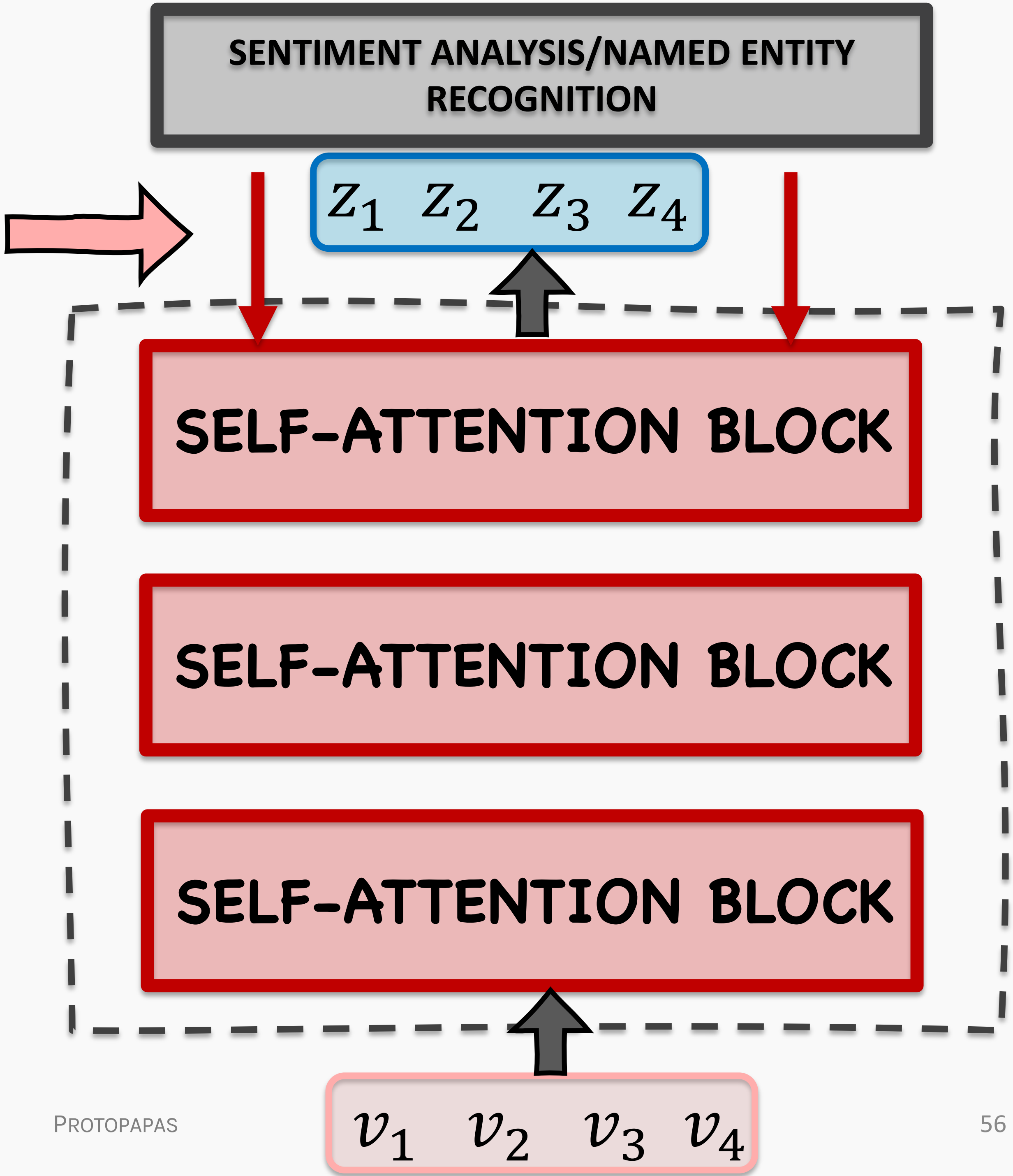
z_1 z_2 z_3 z_4
SELF-ATTENTION BLOCK
v_1 v_2 v_3 v_4


z_1 z_2 z_3 z_4
SELF-ATTENTION BLOCK
SELF-ATTENTION BLOCK
SELF-ATTENTION BLOCK
v_1 v_2 v_3 v_4

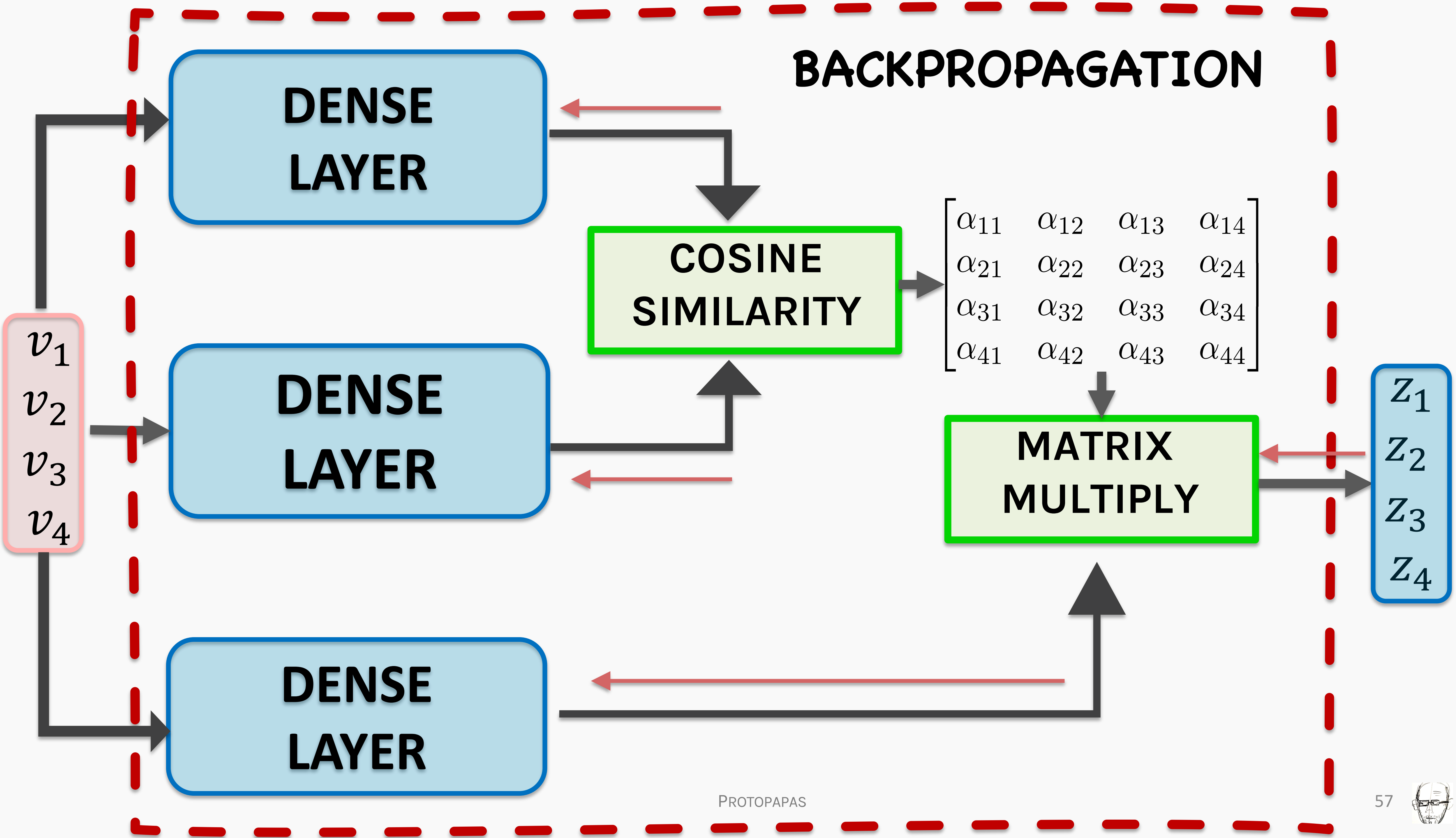

$z_1 \quad z_2 \quad z_3 \quad z_4$
SELF-ATTENTION BLOCK
SELF-ATTENTION BLOCK
SELF-ATTENTION BLOCK
$v_1 \quad v_2 \quad v_3 \quad v_4$


We could stack up these self-attention blocks to get richer and more complex contextual relationships

Flow of gradients

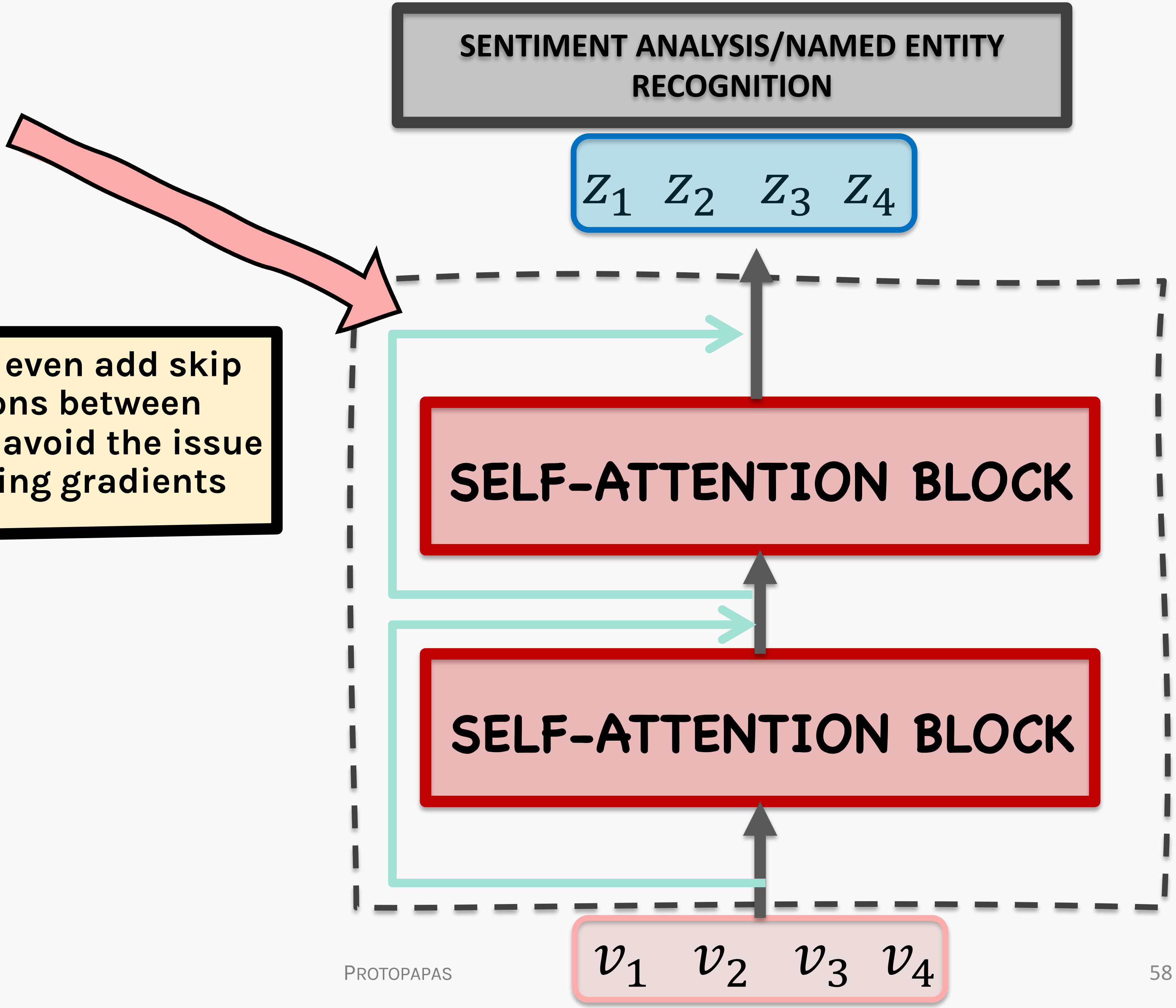


And we could train these weights by using backpropagation using masked words or a task like sentiment analysis


BACKPROPAGATION
DENSE LAYER
DENSE LAYER
DENSE LAYER
COSINE SIMILARITY
MATRIX MULTIPLY
v_1 v_2 v_3 v_4
z_1 z_2 z_3 z_4
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$

Skip connections

We could even add skip connections between blocks to avoid the issue of vanishing gradients



Attention

ATTENTION STRENGTHS?

- Unlike RNNs, each input is in direct context of every other input $O(1)$, hence vanishing gradients are not a significant issue with the attention block

- Unlike RNNs, the operations are not sequentially dependent (Non-Markovian)

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(\log_k(n))$

d: Dimension of embedding
n: Length of input sequence

Non-Markovian

Full context

Attention

ATTENTION ISSUES?

- **Optimization using attention leads to limited contextual mapping**
- There is no positional information encoded

Shivas spoke to Pavlos about attention

Attention: Do we have enough attention?

ATTENTION MECHANISM #1

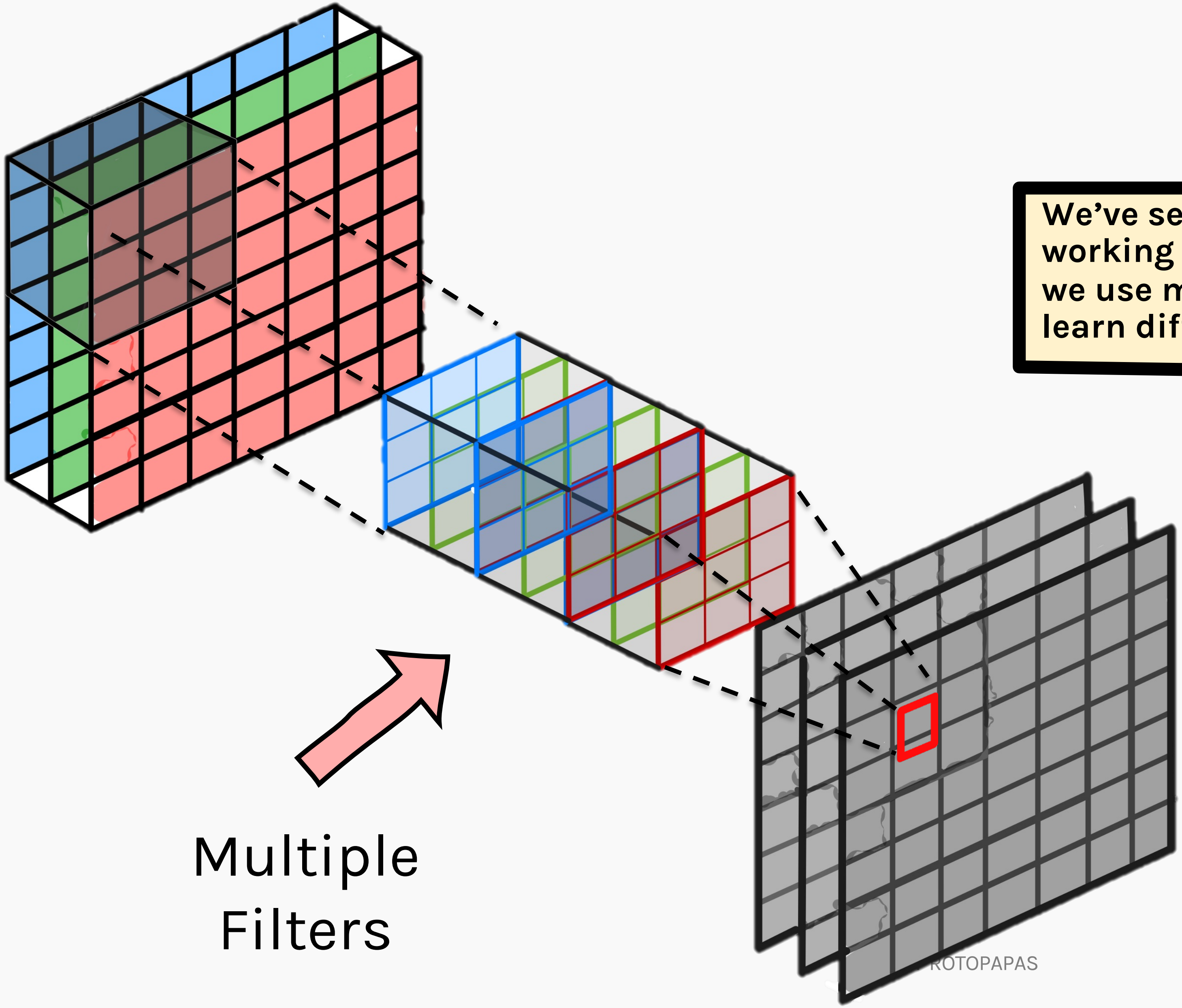
ATTENTION MECHANISM #2

Shivas $\boxed{\text{spoke}}$ to Pavlos about attention

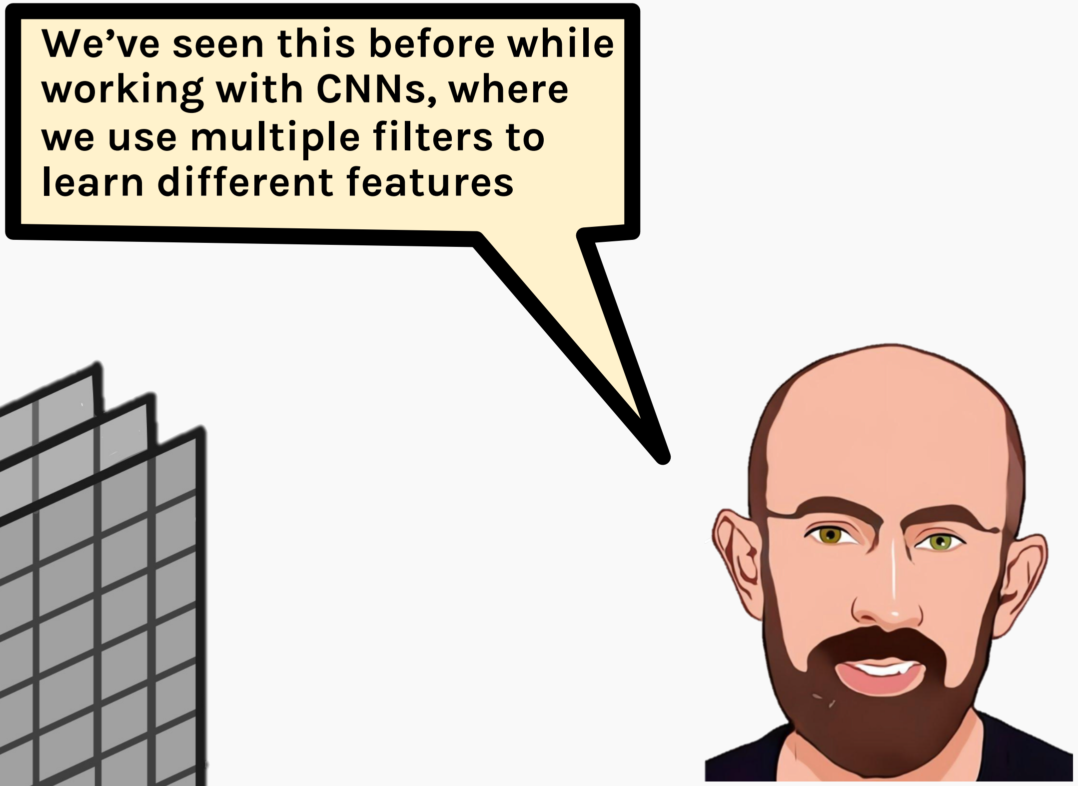
ATTENTION MECHANISM #3

We need to have multiple attention mechanisms to look for different relations

Analogy - CNN Filters



Multiple Filters



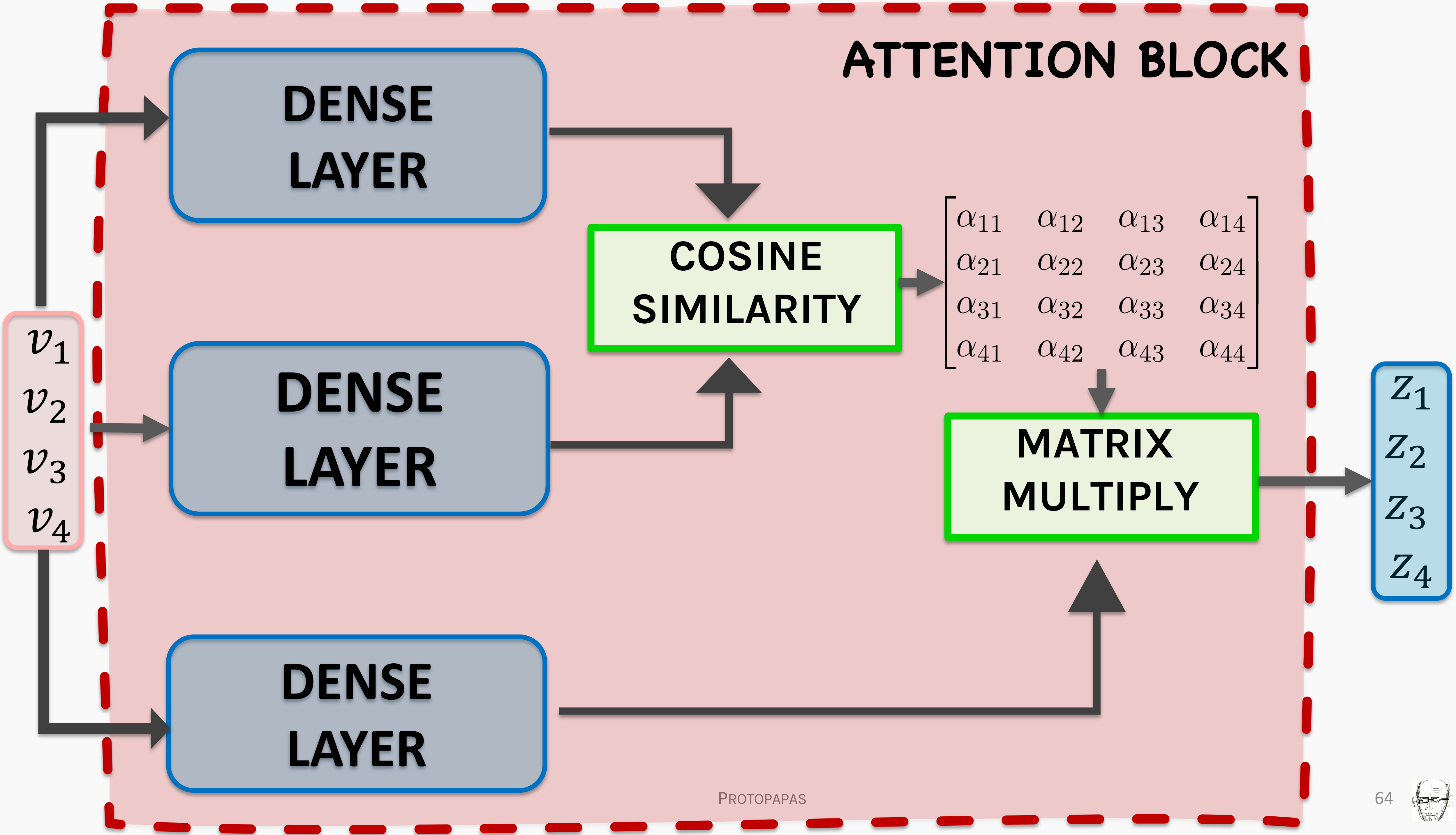
RECAP: CNNs

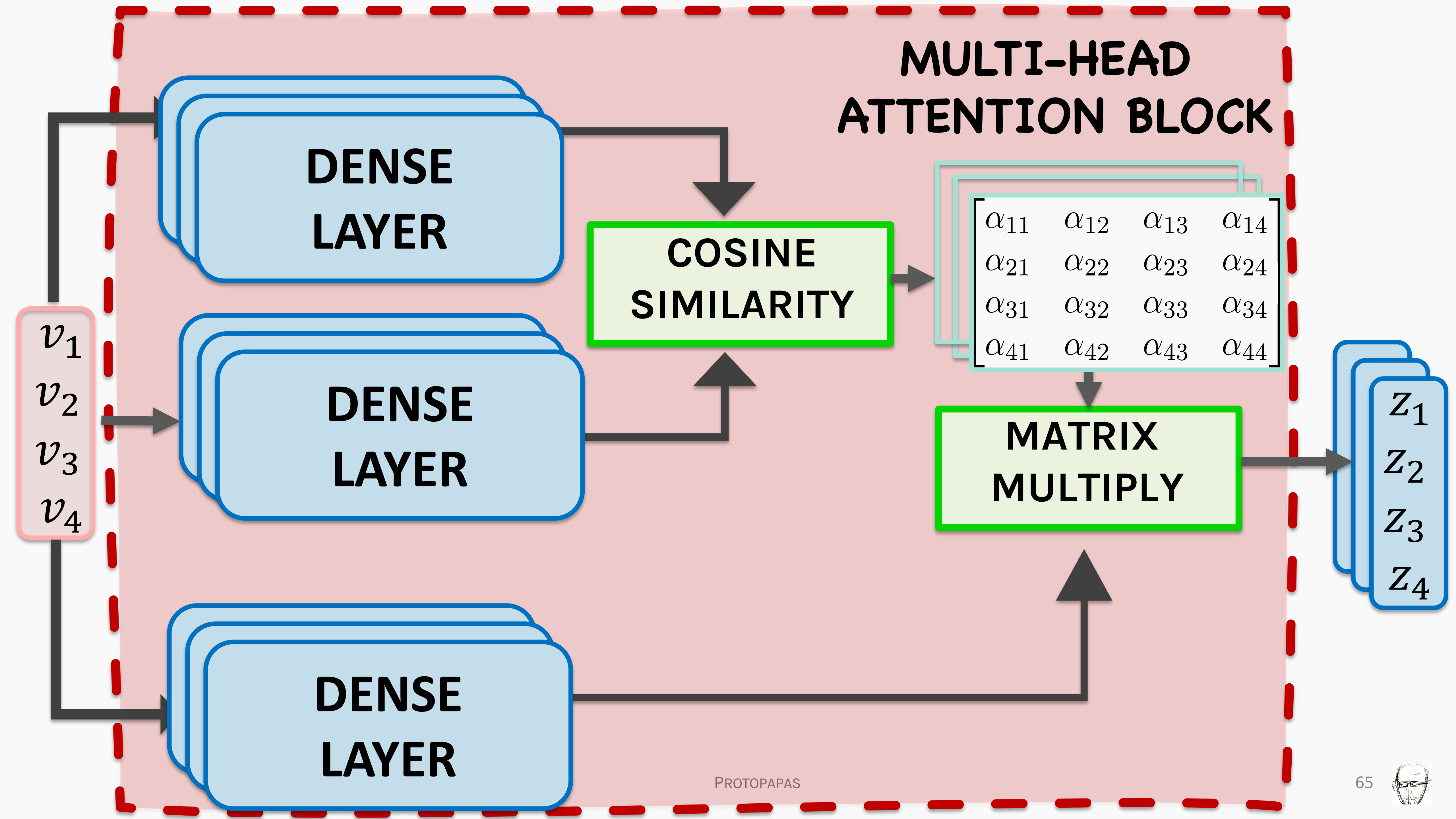
Imagine that we want to recognize swans in an image:

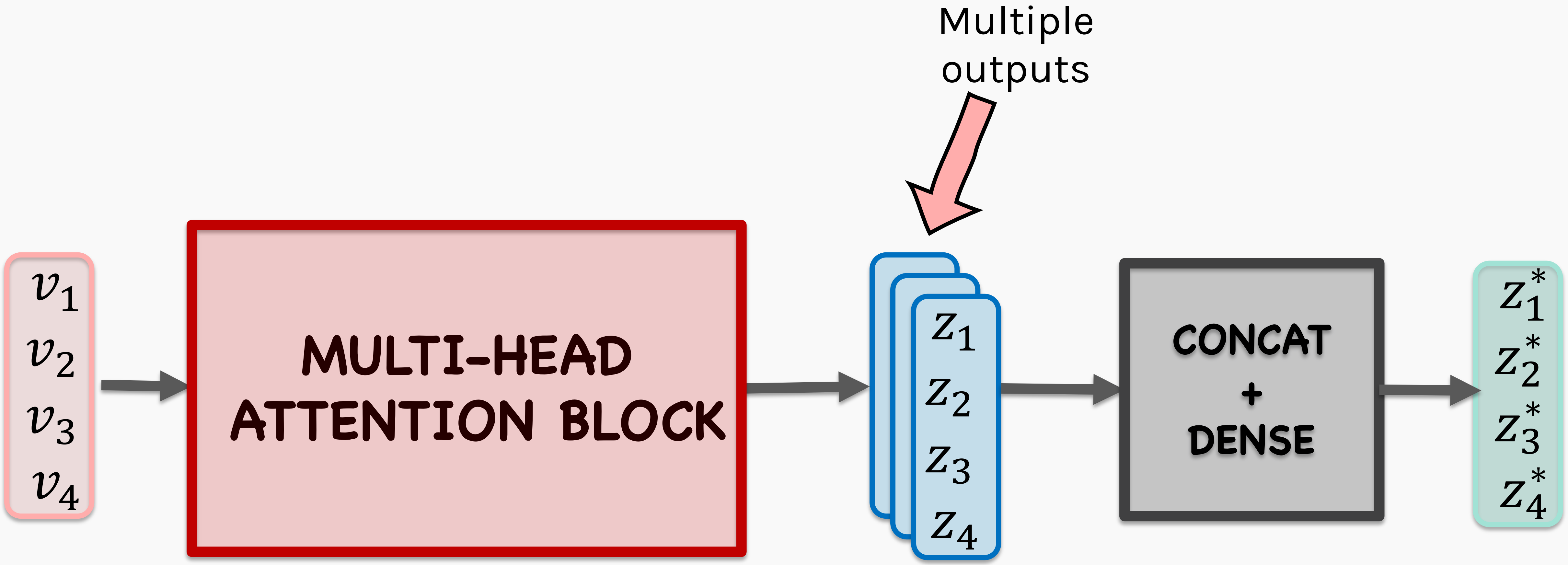
Oval-shaped white blob (body)

Round, elongated oval with orange protuberance

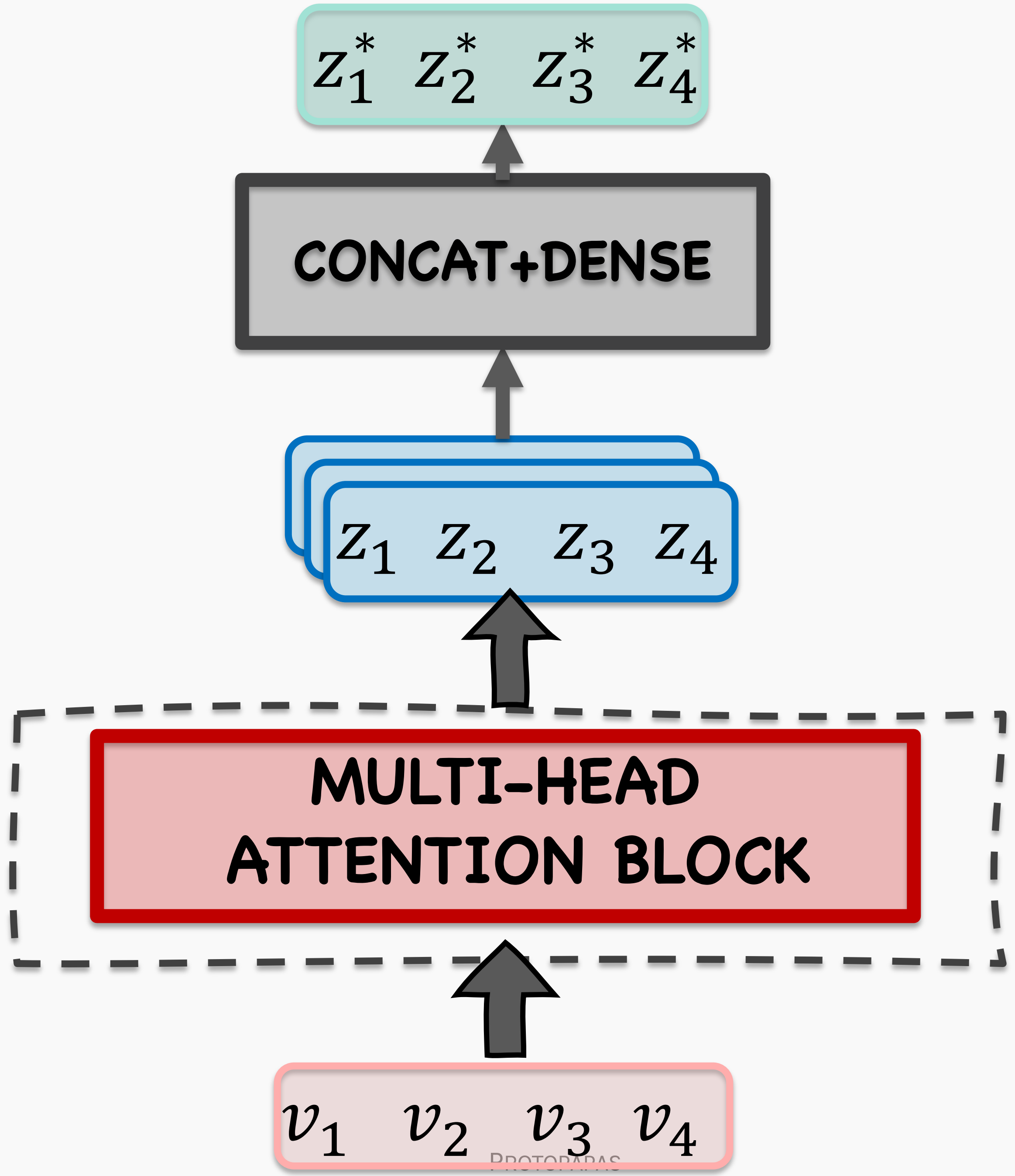
Long white rectangular shape (neck)

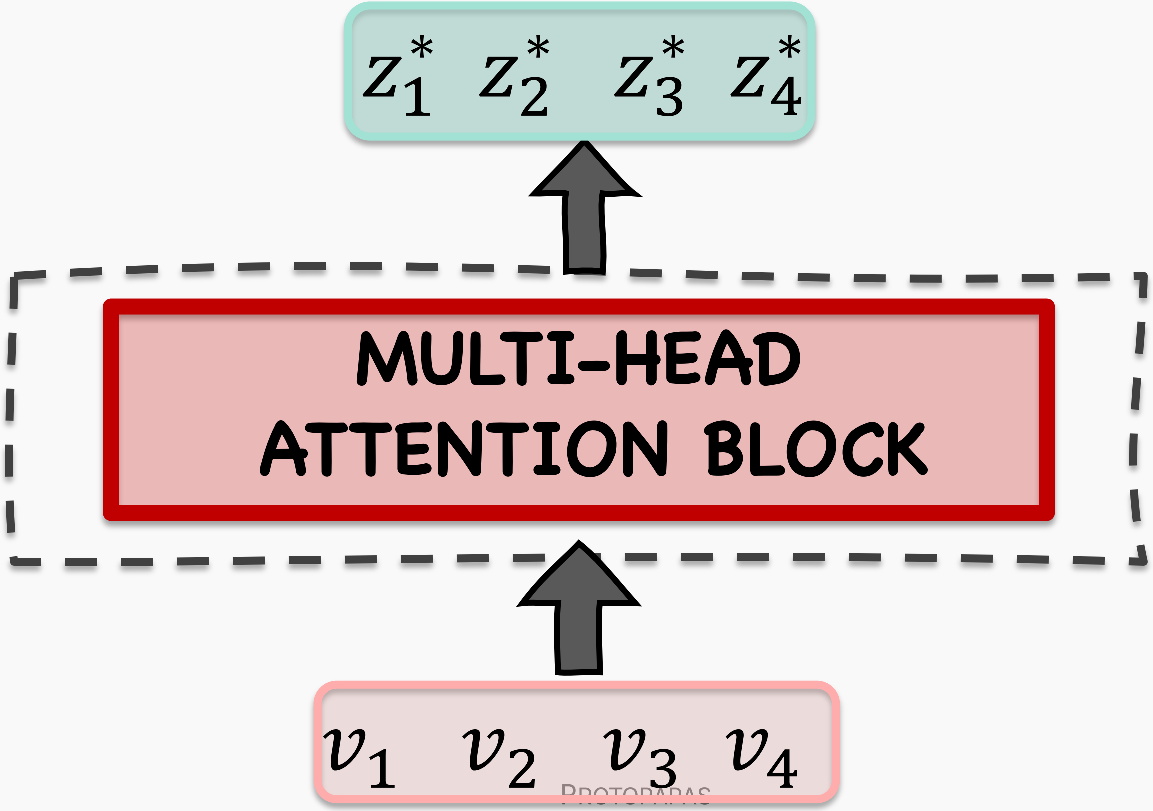

ATTENTION BLOCK
v_1 v_2 v_3 v_4
DENSE LAYER
DENSE LAYER
DENSE LAYER
COSINE SIMILARITY
$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix}$
MATRIX MULTIPLY
z_1 z_2 z_3 z_4

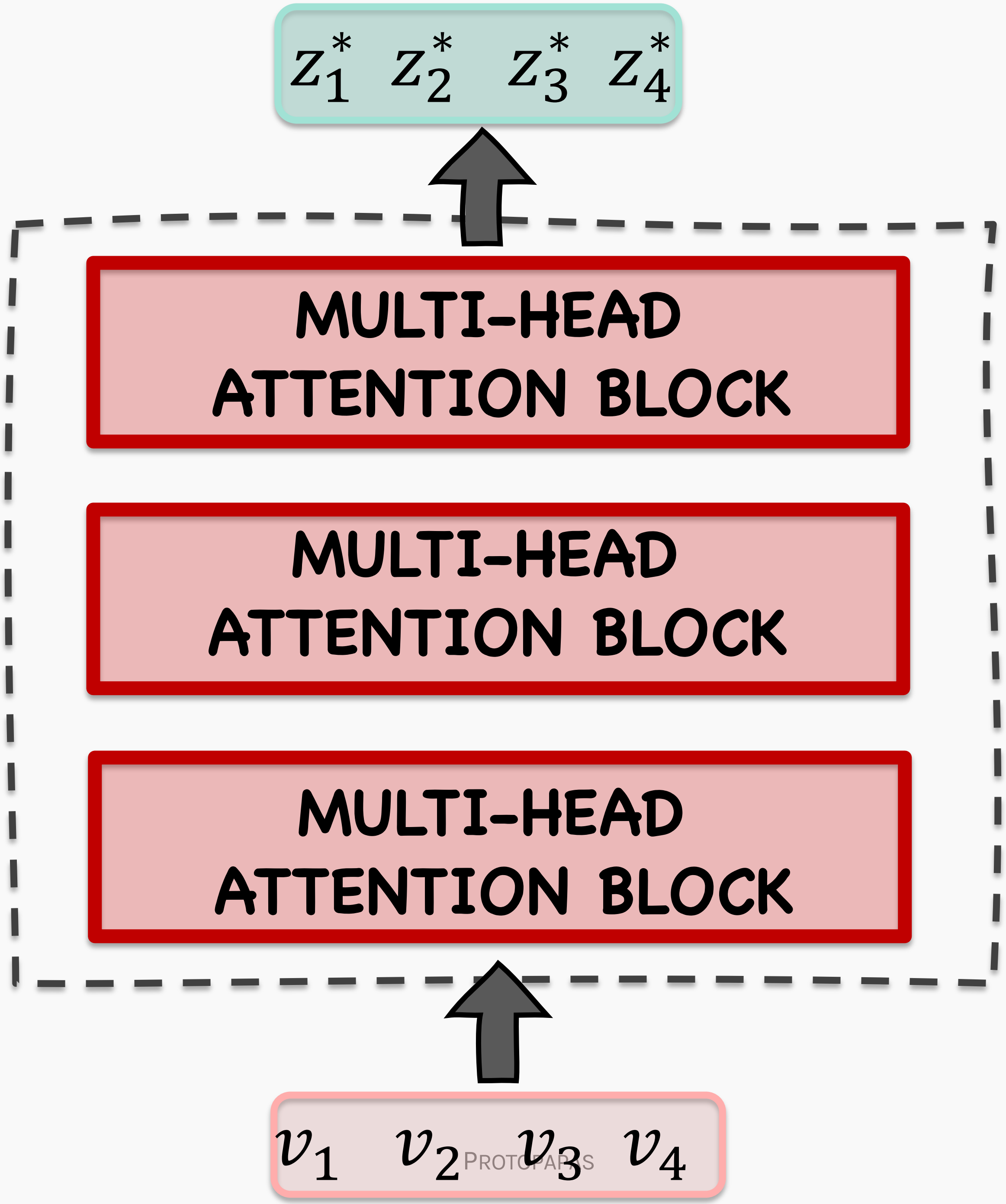

MULTI-HEAD ATTENTION BLOCK
v_1 v_2 v_3 v_4
DENSE LAYER
DENSE LAYER
DENSE LAYER
COSINE SIMILARITY
α_{11} α_{12} α_{13} α_{14}
α_{21} α_{22} α_{23} α_{24}
α_{31} α_{32} α_{33} α_{34}
α_{41} α_{42} α_{43} α_{44}
MATRIX MULTIPLY
z_1 z_2 z_3 z_4

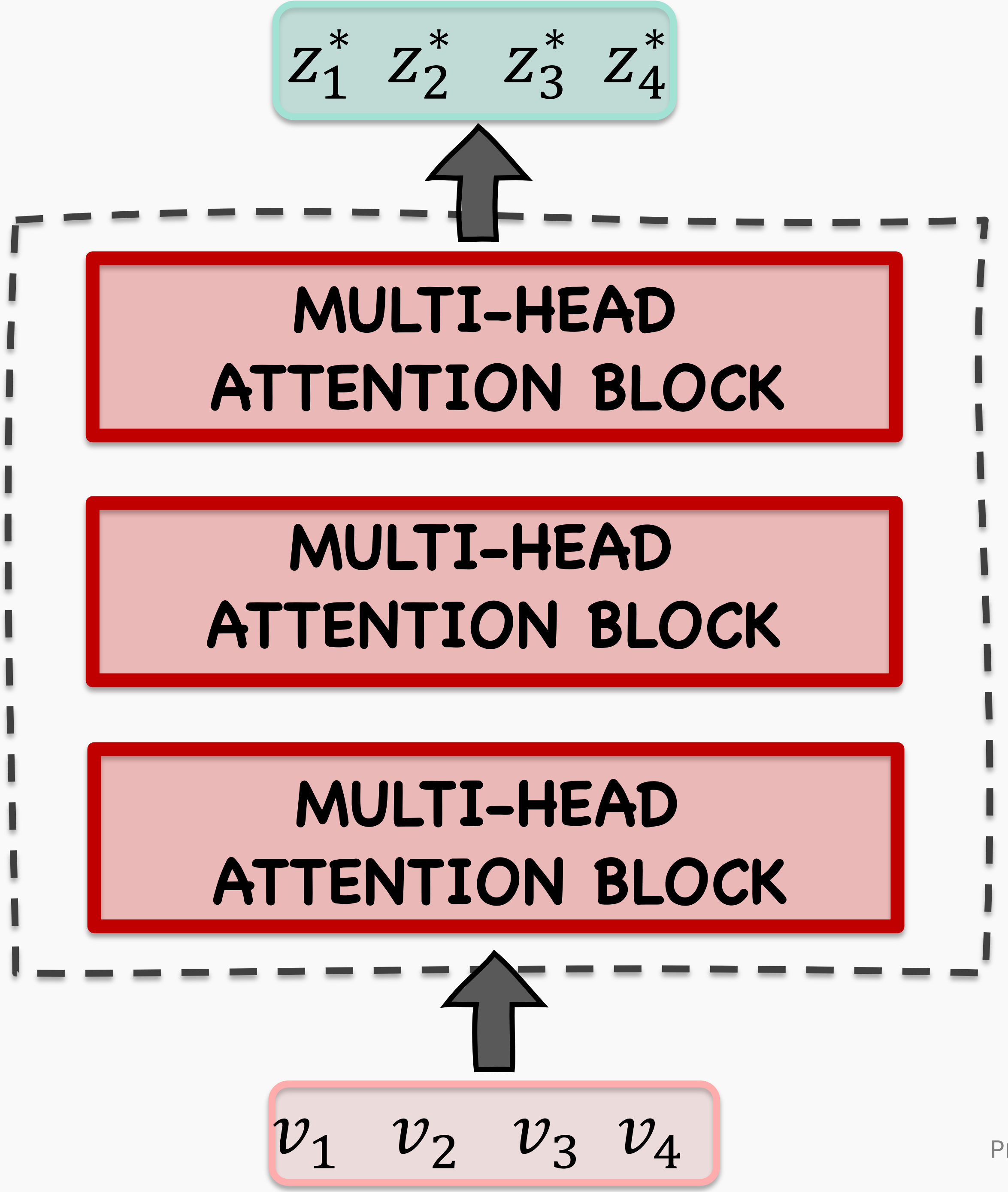


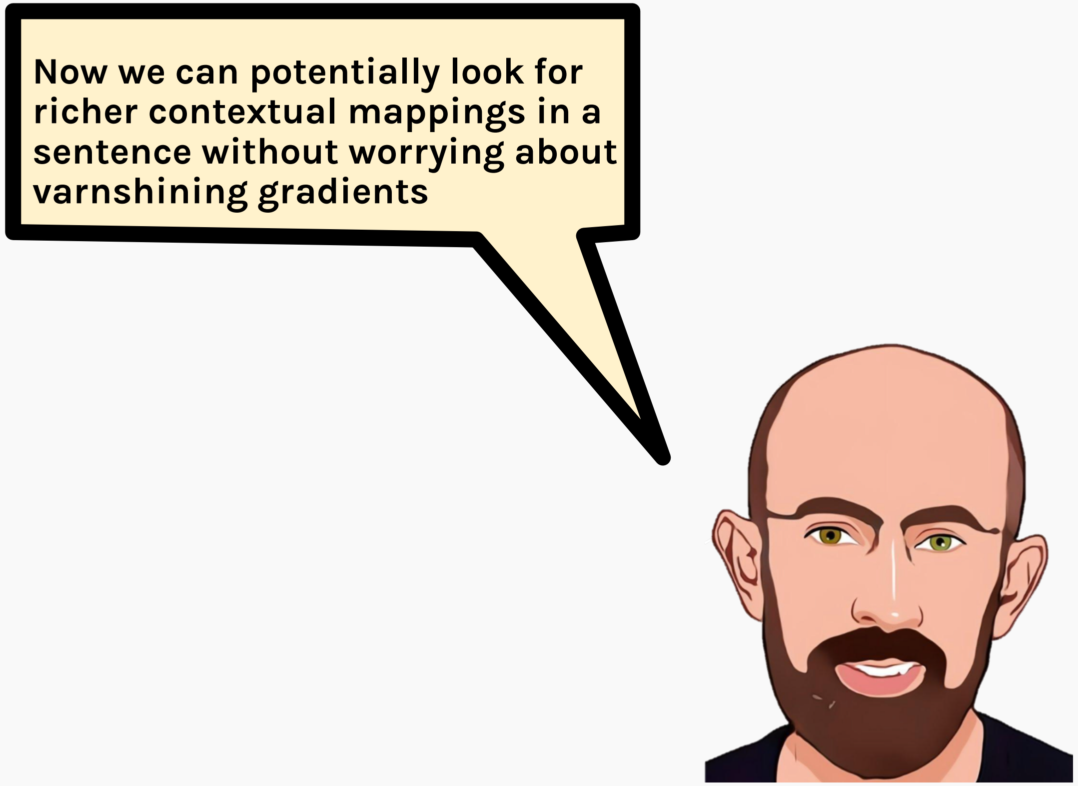
Multiple outputs
v_1
v_2
v_3
v_4
MULTI-HEAD ATTENTION BLOCK
z_1
z_2
z_3
z_4
CONCAT + DENSE
z_1^*
z_2^*
z_3^*
z_4^*


z_1^* z_2^* z_3^* z_4^*
CONCAT+DENSE
z_1 z_2 z_3 z_4
MULTI-HEAD ATTENTION BLOCK
v_1 v_2 v_3 v_4
PROTOPAPAS


z_1^* z_2^* z_3^* z_4^*
MULTI-HEAD
ATTENTION BLOCK
v_1 v_2 v_3 v_4


$z_1^* \quad z_2^* \quad z_3^* \quad z_4^*$
MULTI-HEAD ATTENTION BLOCK
MULTI-HEAD ATTENTION BLOCK
MULTI-HEAD ATTENTION BLOCK
$v_1 \quad v_2 \quad v_3 \quad v_4$


$z_1^* \quad z_2^* \quad z_3^* \quad z_4^*$
MULTI-HEAD ATTENTION BLOCK
MULTI-HEAD ATTENTION BLOCK
MULTI-HEAD ATTENTION BLOCK
$v_1 \quad v_2 \quad v_3 \quad v_4$


Now we can potentially look for richer contextual mappings in a sentence without worrying about varnshining gradients

Attention

MULTI-HEAD ATTENTION ISSUES?

- ~~No weights trained in the process~~
- ~~Optimization using attention leads to limited contextual mapping~~
- There is no positional information encoded

Shivas spoke to Pavlos about attention

Attention

MULTI-HEAD ATTENTION ISSUES?

- ~~No weights trained in the process~~
- ~~Optimization using attention leads to limited contextual mapping~~
- There is no positional information encoded

Pavlos spoke to Shivas about attention

What we want

LANGUAGE MODEL WISHLIST

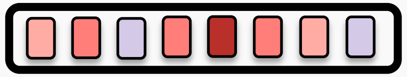
- Position and order of words are the essential parts of any language
- Recurrent Neural Networks (RNNs) inherently take the order of word into account
- Multi-head attention blocks do not take such an order by design, so there's the need to incorporate the order of the words separately

💡 **IDEA #255:** Positional Encoding

Positional Encoding

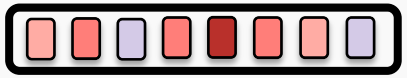
Assume an input embedding v_i of some dimension for the word 'Shivas' at the position *i* in the sentence

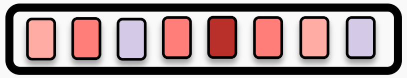
v_i

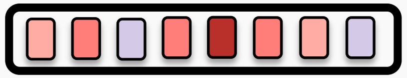


This input embedding will be the same for any position in the sentence

v_1 v_2 v_3





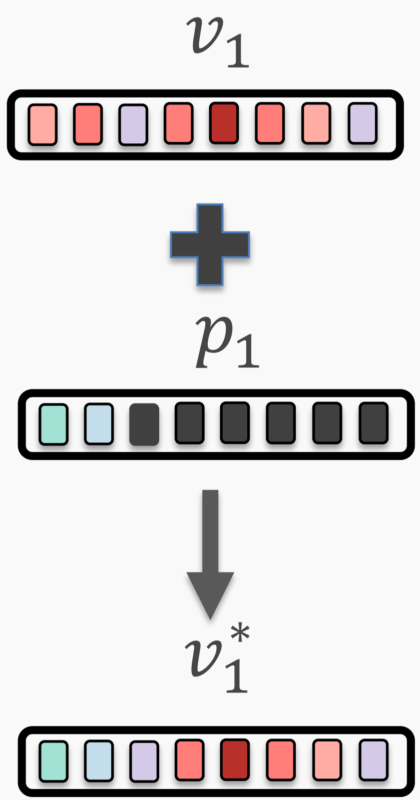


We hope to modify the embedding with some positional information

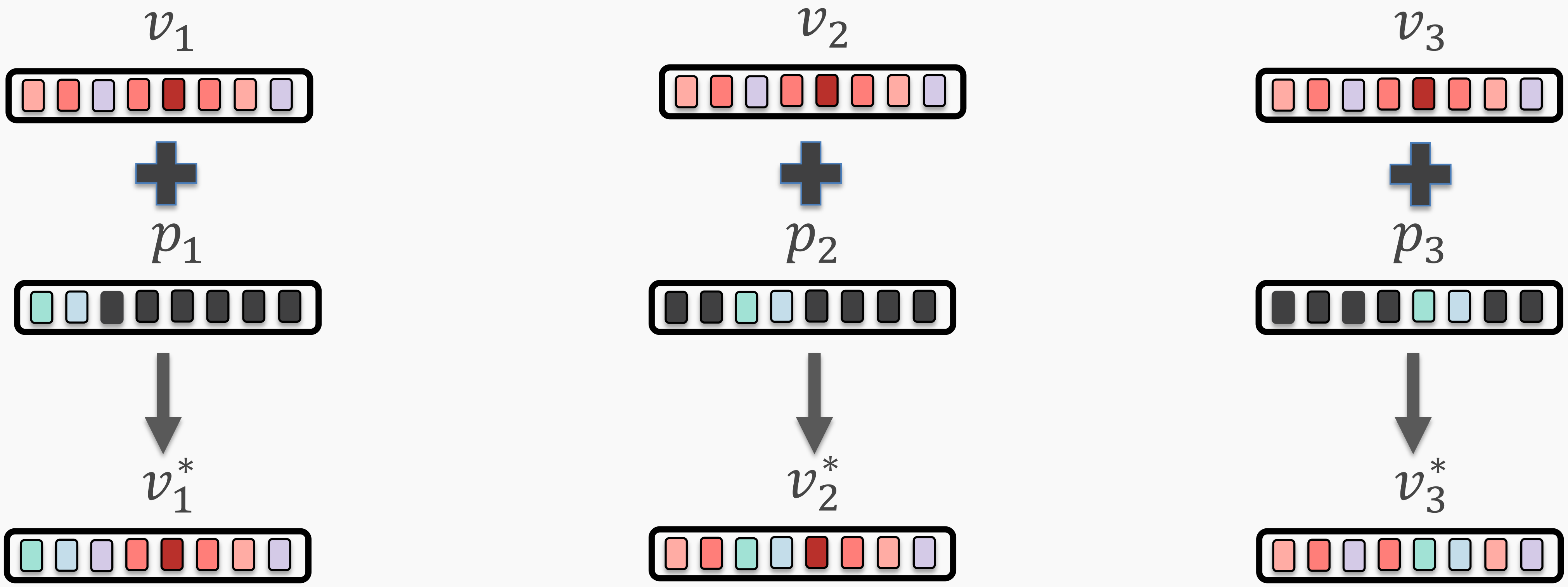
Positional Encoding

- A very simple way to do this would be to modify the input embedding v_i with a positional vector p_i which encodes some information of the position of the input embedding

- Thus, the same input embedding v_i will be a different value v_i^* depending on the position of the embedding in the sentence

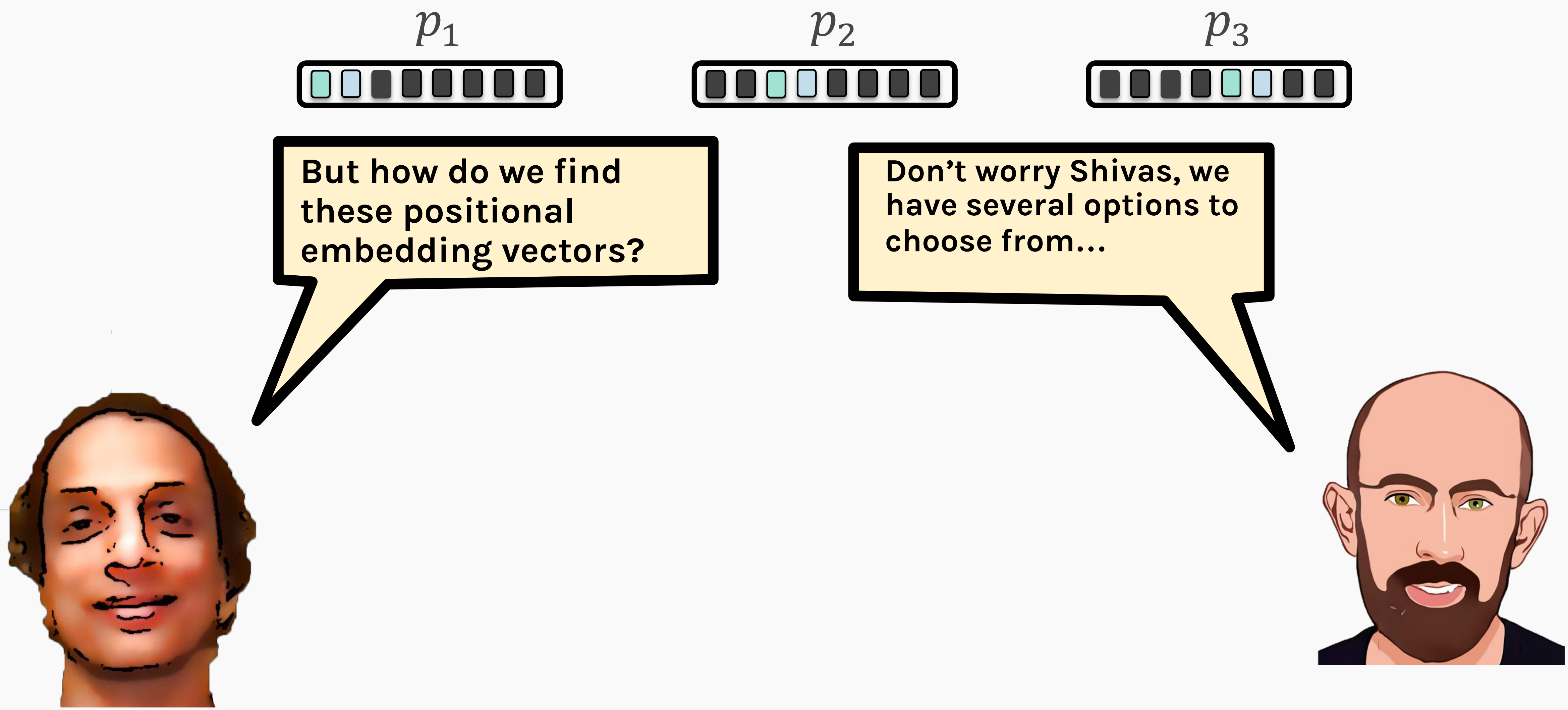


Positional Encoding



In the above case, although $v_1 = v_2 = v_3$, $v_1^* \neq v_2^* \neq v_3^*$

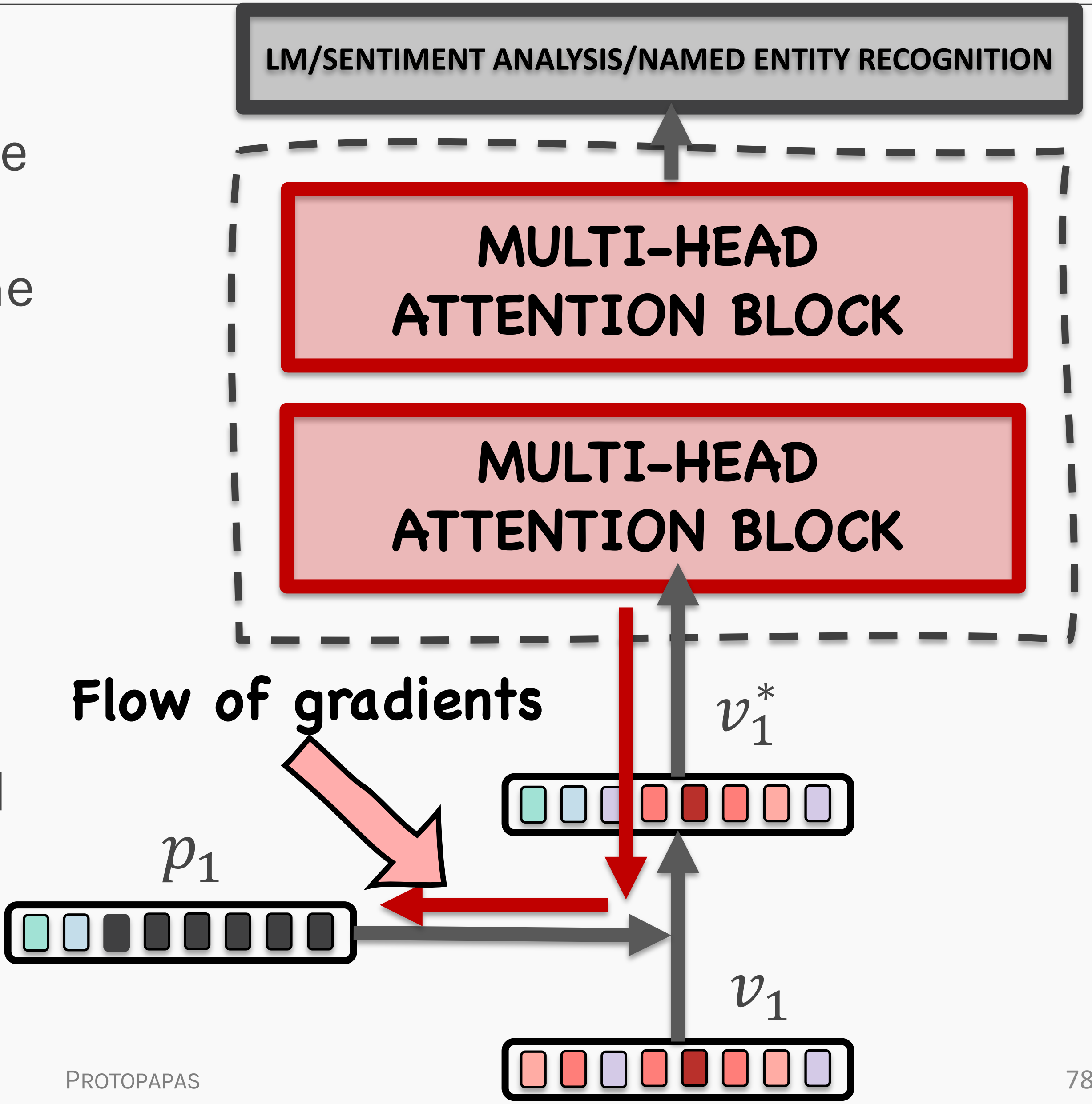
Positional Encoding



Positional Encoding

- The no-nonsense way to find these positional encodings would be to *learn* them during training (like the Query, Key & Value transformations)

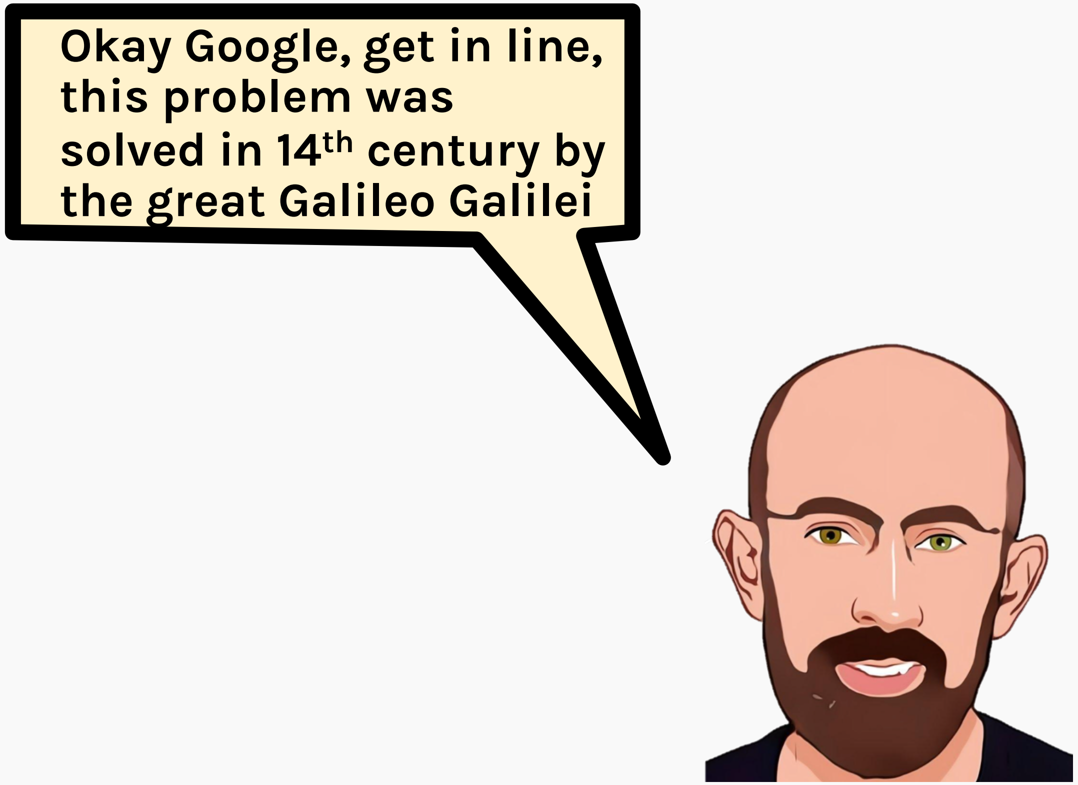
- But the number of learnable parameters in a stacked multi-head attention block can massively grow, and this can lead to poor training



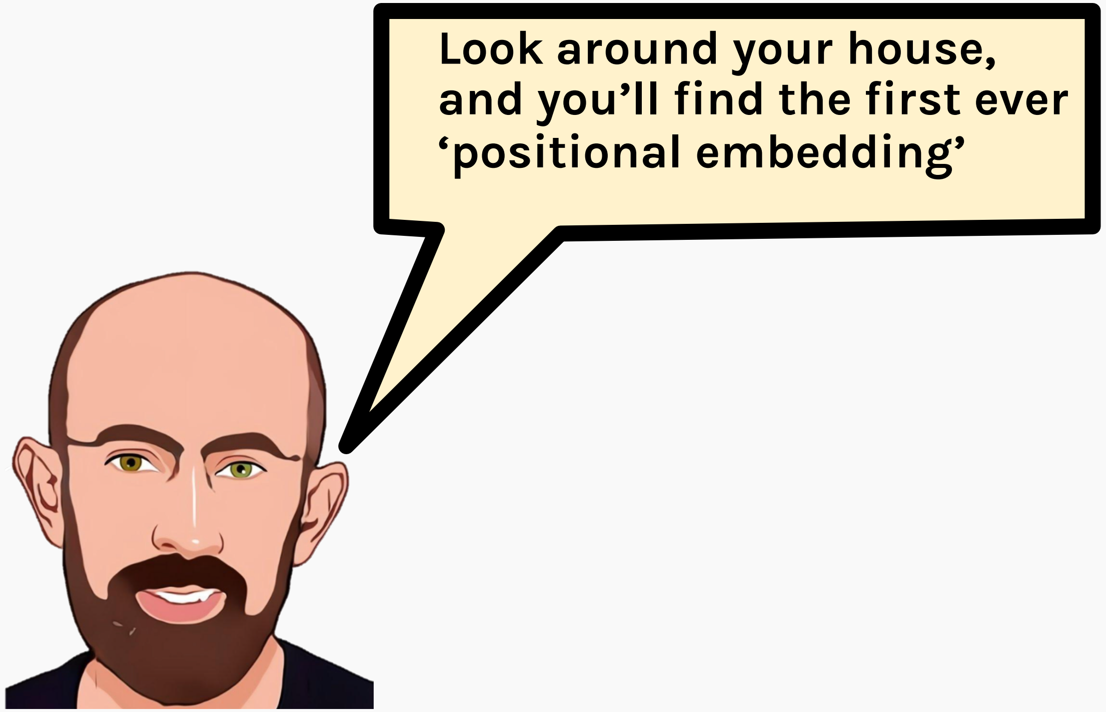
Positional Encoding

POSITIONAL EMBEDDING WISHLIST

- It should be a unique embedding for each timestep
- Relative encodings must remain consistent across sentences of different lengths
- It should generalize to longer sentences
- It should be bounded & deterministic



Positional Embedding – Motivation



Positional Embedding – Motivation

- The clock was an ingenious, compact solution to keep time
- Using the H:M:S system for hour, minute and second, we actually read a tuple of three numbers (H,M,S), with each dimension representing a **unique** time of the day
- We achieve this by setting separate frequencies for the hour, minute & second

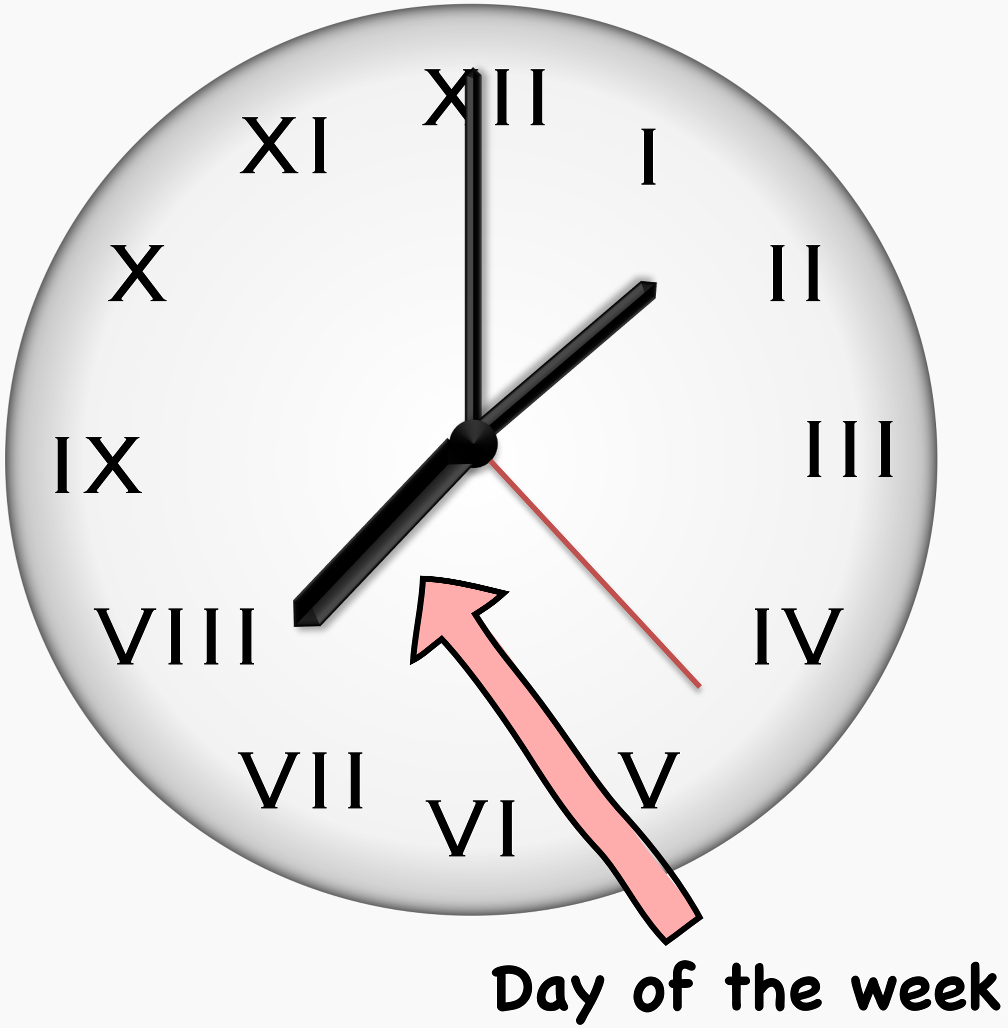
The mechanical clock

Positional Embedding – Motivation

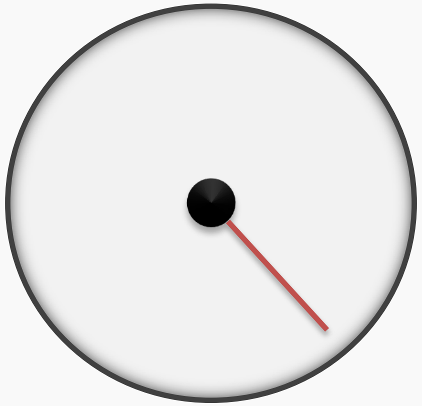
Even though the *seconds* hand repeats every minute, the overall tuple is unique

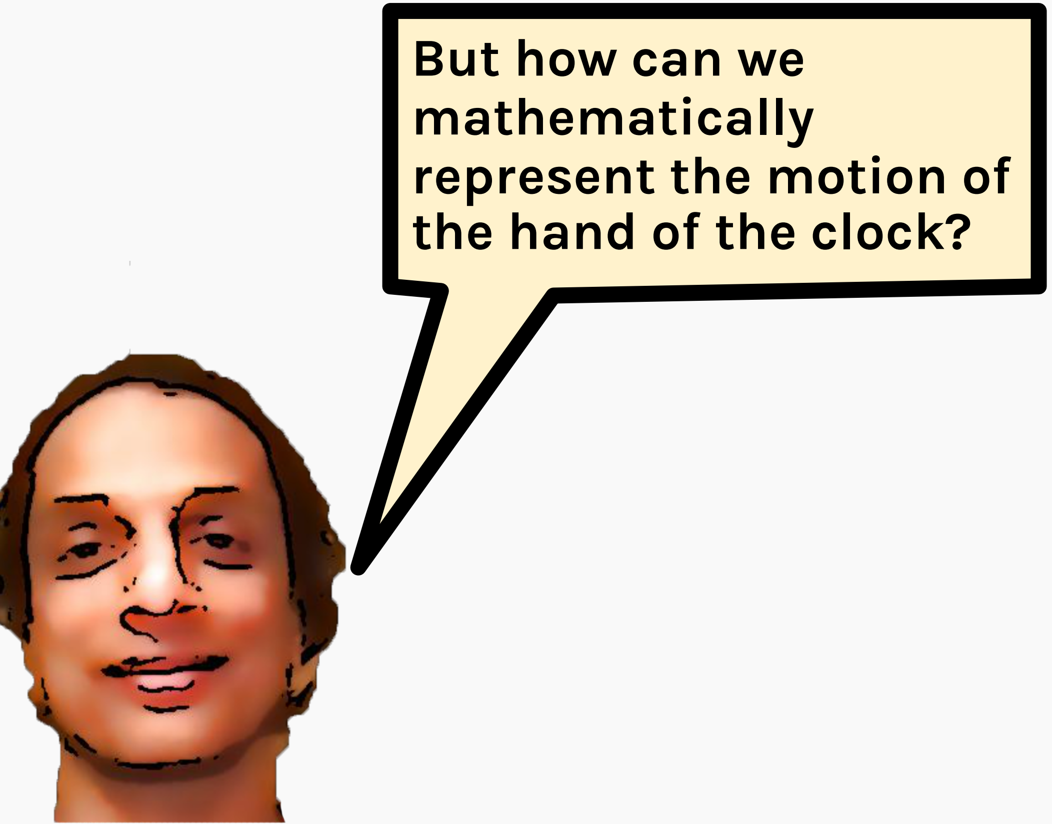
Positional Embedding – Motivation

- In principle, we could add more *hands* to the clock, for days of the week, week of the month, month of the year etc.
- With enough *hands,* we could uniquely represent any time series from the start of the universe to the end
- This powerful idea can be used to generate scale independent positional encodings



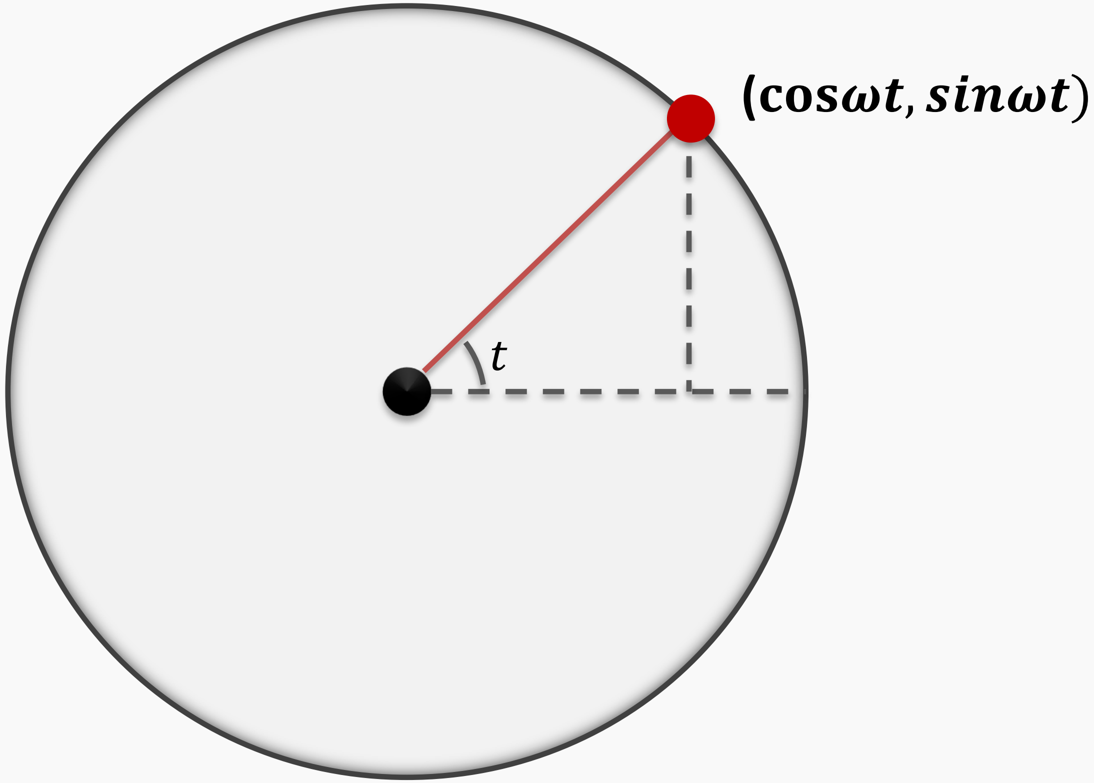
Positional Embedding - Motivation



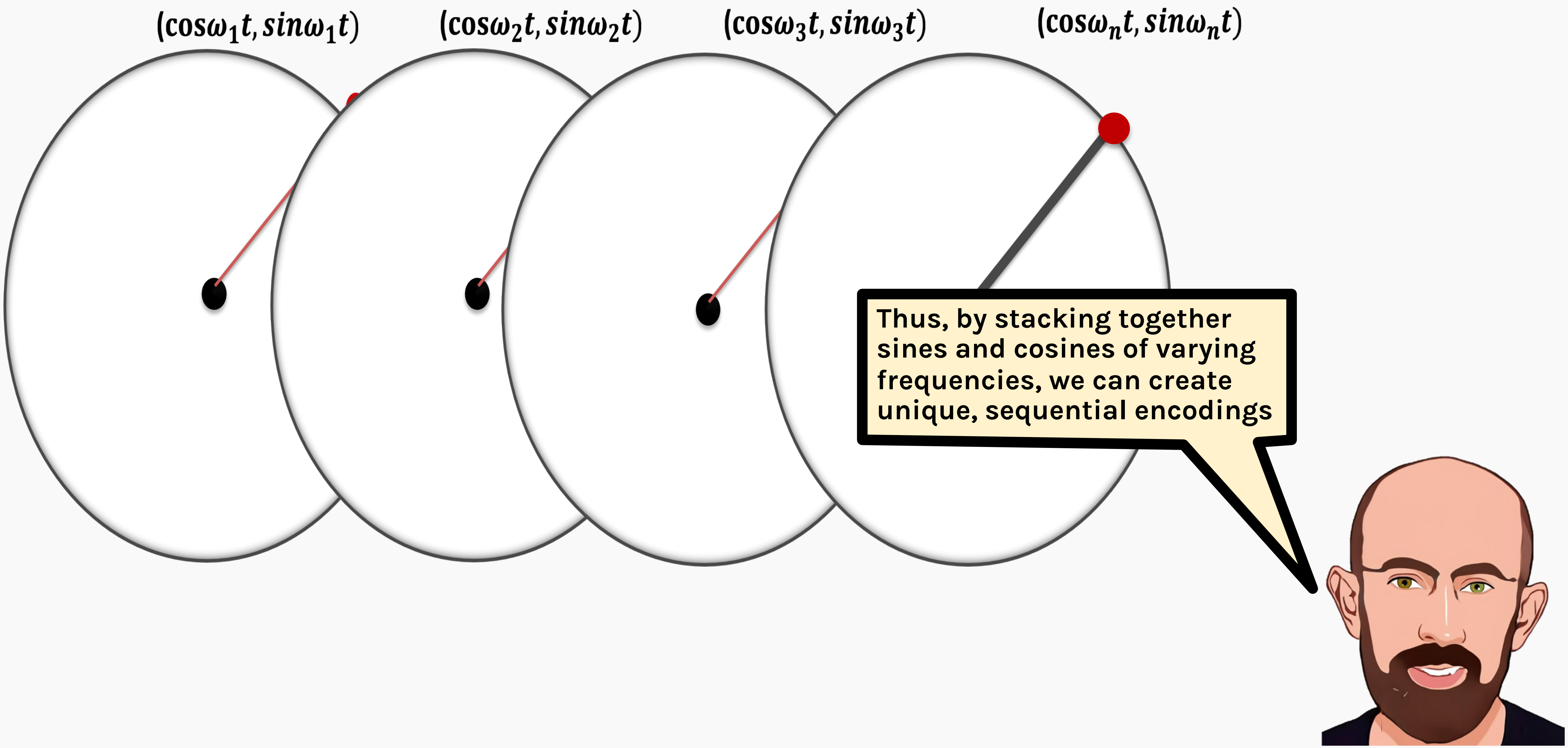


Positional Embedding - Motivation

- We can sufficiently define the path of a unit length around a circle by two hyperparameters
  - Angle of rotation $\boldsymbol{t}$
  - Frequency of rotation $\boldsymbol{\omega}$
- The combination the sine and the cosine together can completely define the unit circle



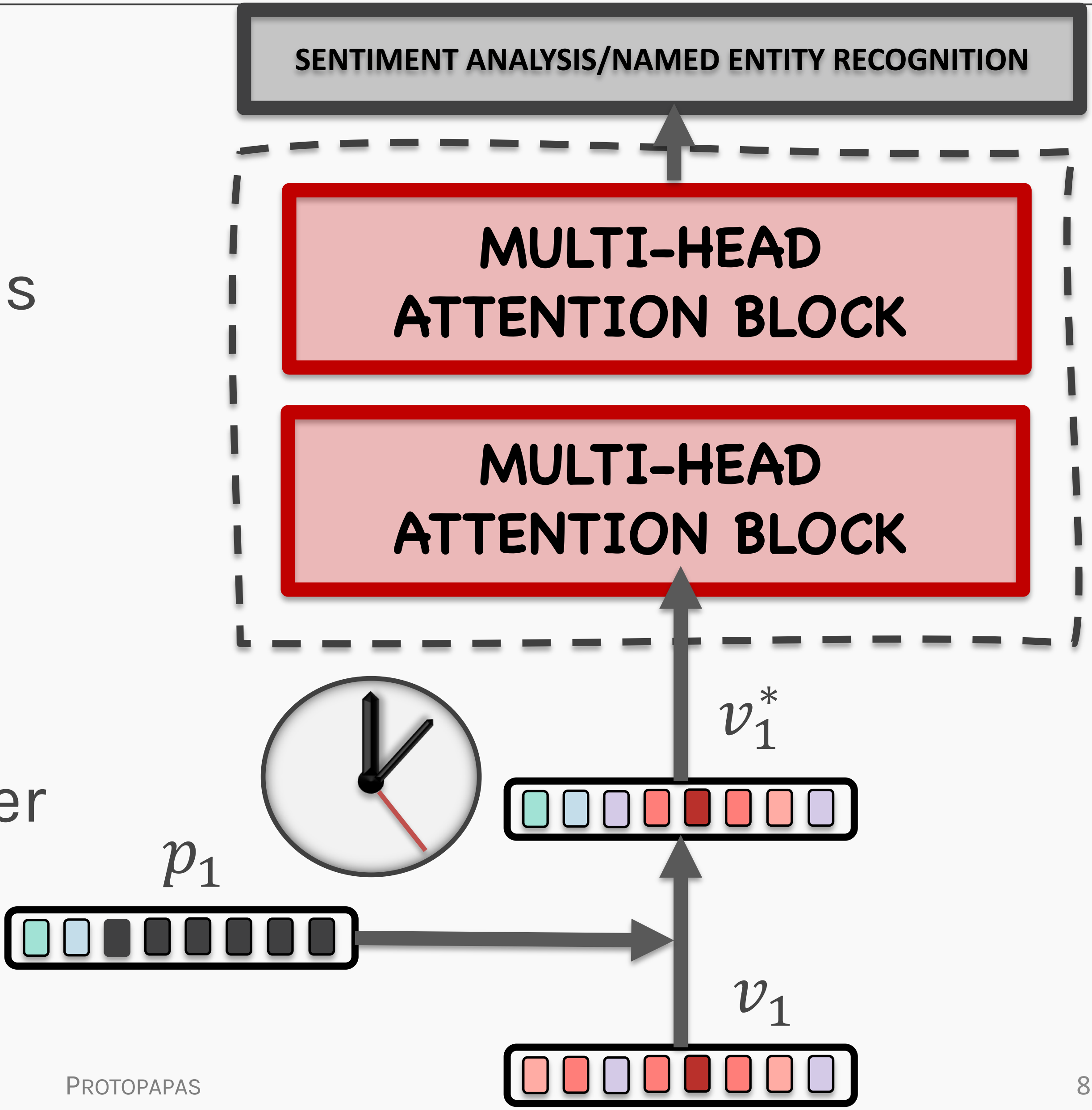
Positional Embedding - Motivation



Positional Encoding

- In the experimental results, the positional encodings using deterministic functions were found to be as effective as those learned using backpropagation

- However, since this method more general and much faster to implement, it is usually preferred



Positional Embedding

TECHNICAL DETAILS

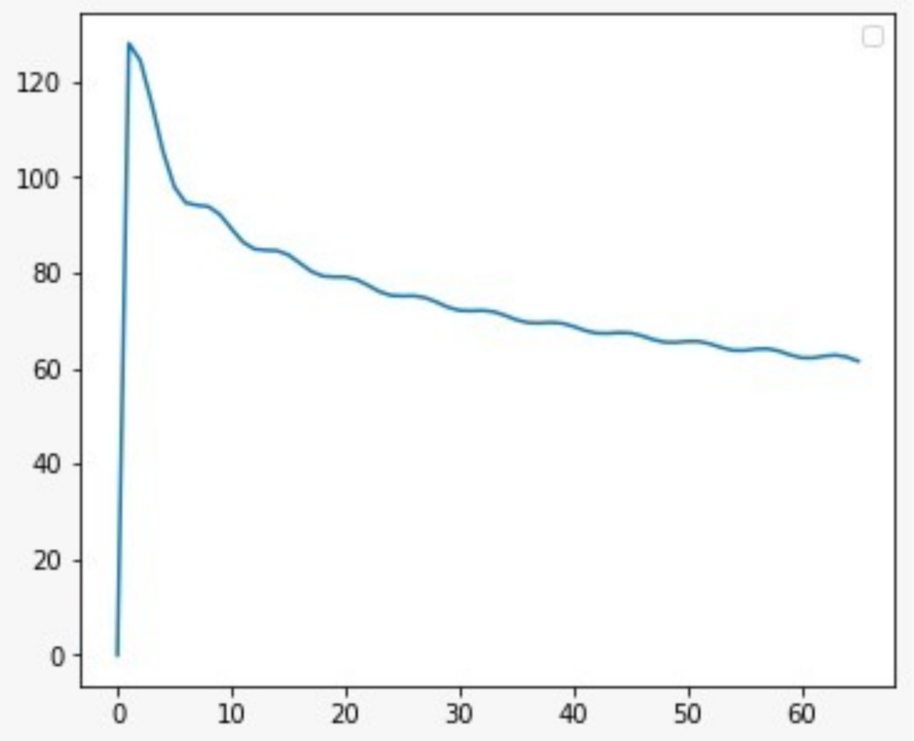
Let t be the desired position in an input sentence, $\vec{\mathrm{p}}_t \in \mathbb{R}^d$ be it's corresponding encoding and d be the encoding dimension.

Then $f : \mathbb{N} \rightarrow \mathbb{R}^d$ is the function that produces $\vec{\mathrm{p}}_t$ and is defined as:

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

Where,

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

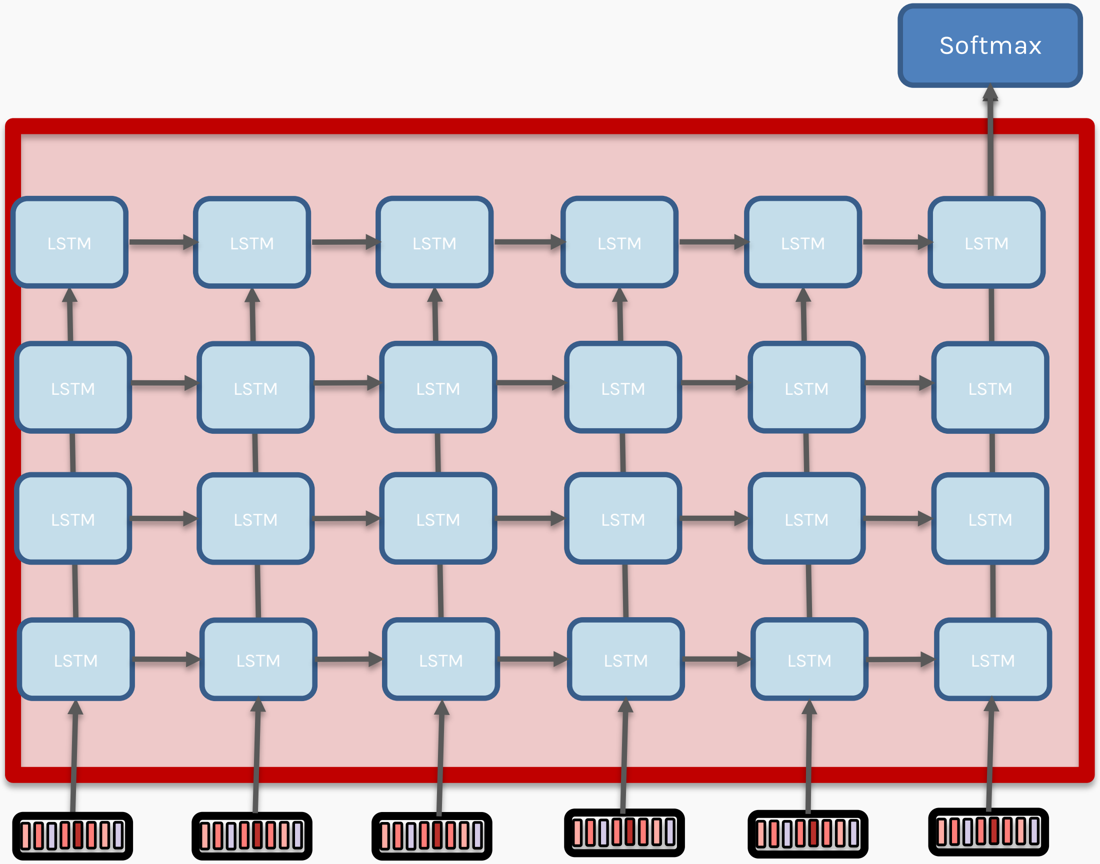


X-axis is time (position), y-axis is w_k

Bringing it all together

Comparison – RNN v/s Transformer

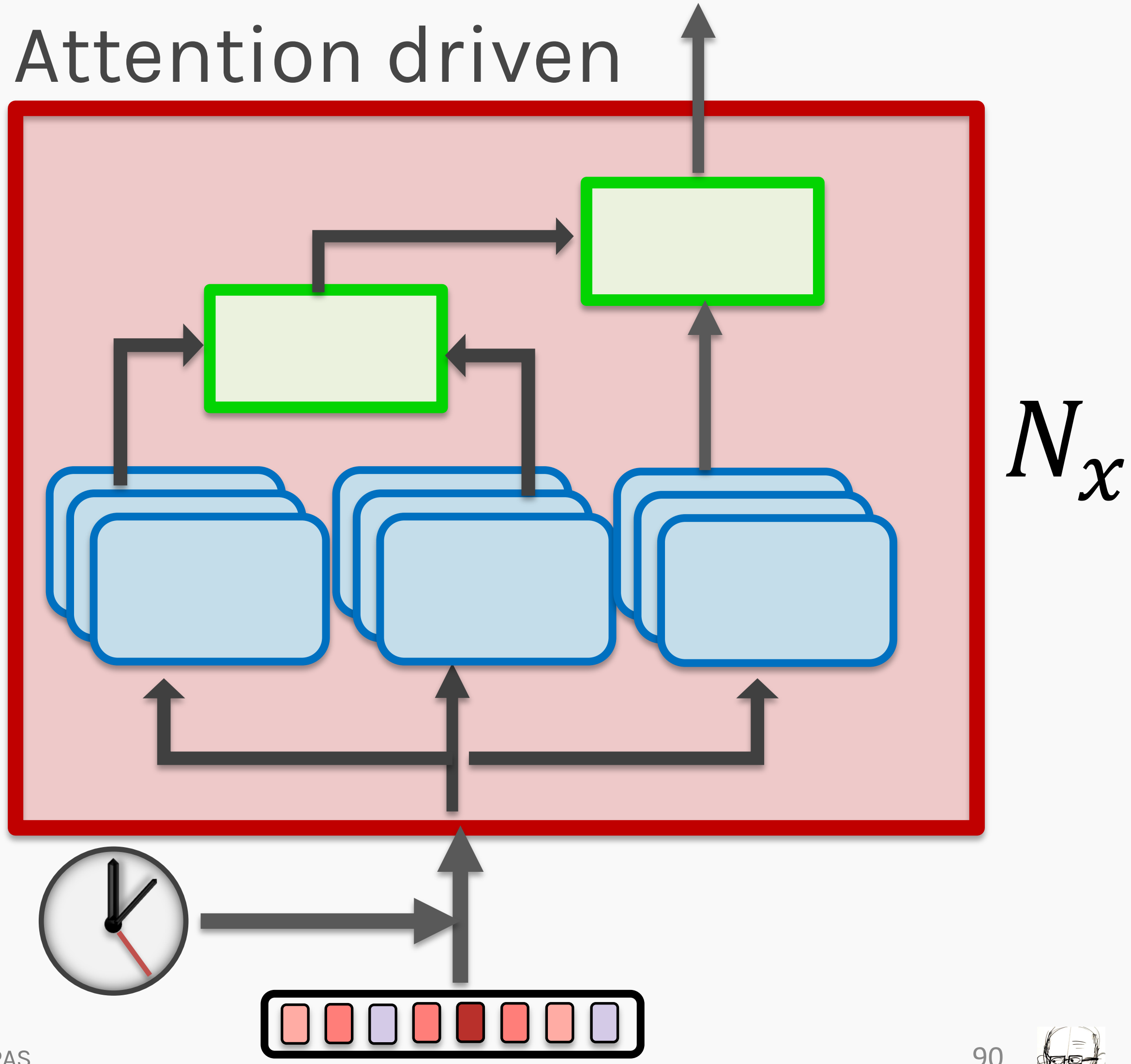
BEFORE



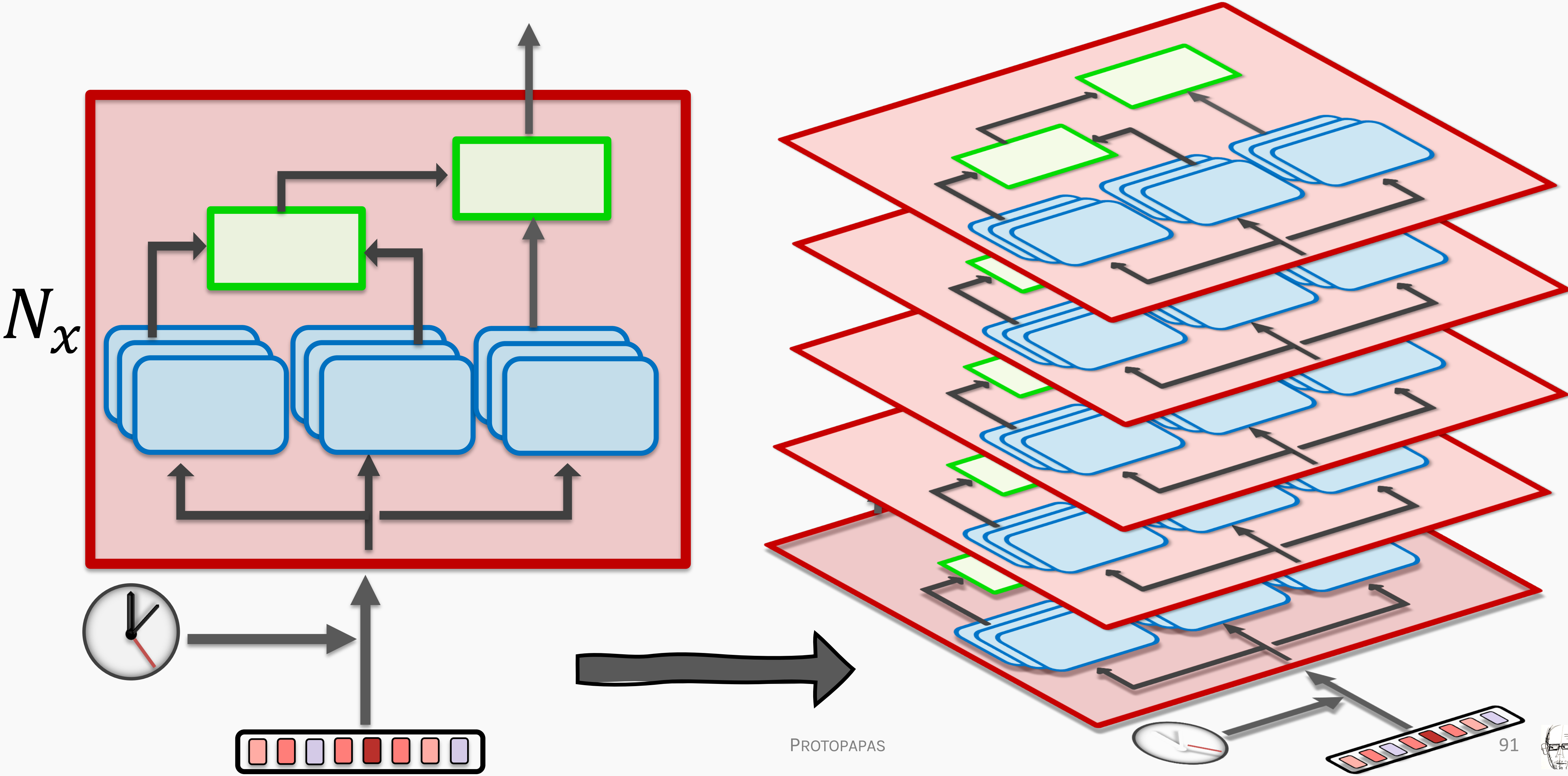
Recurrent units

AFTER

Attention driven



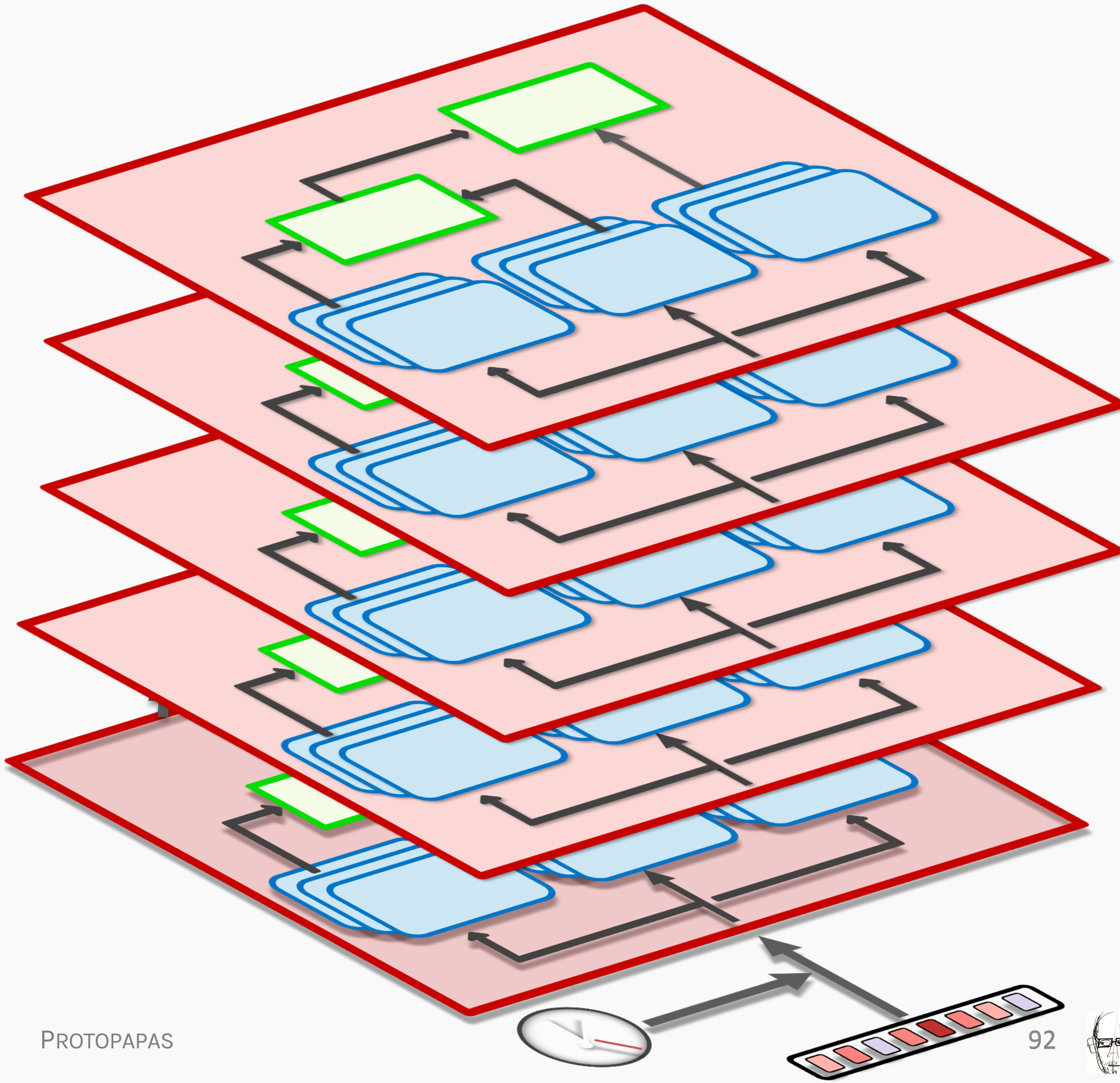
Transformer as a 3-D model



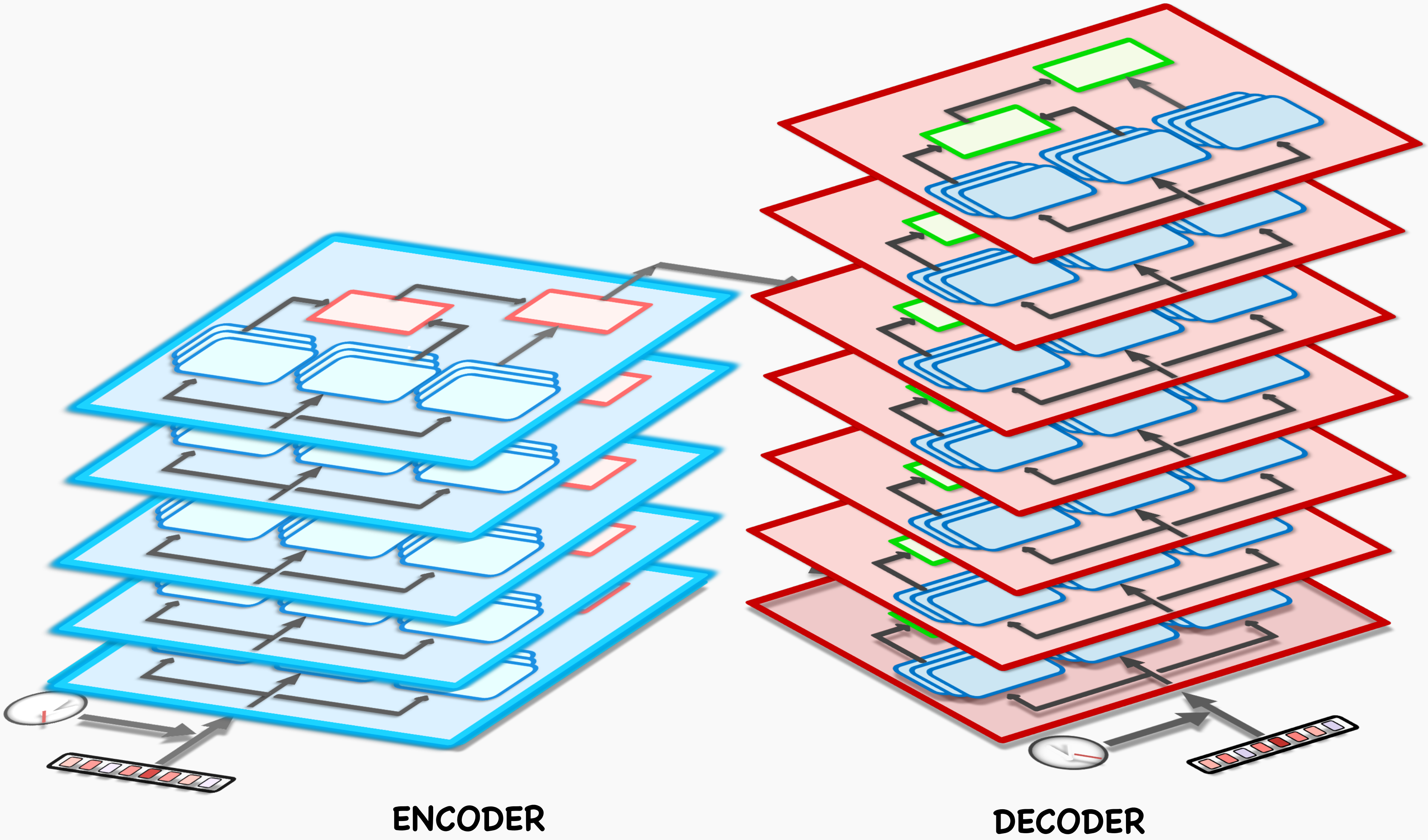
Transformers - Summary

Language Model Wishlist?

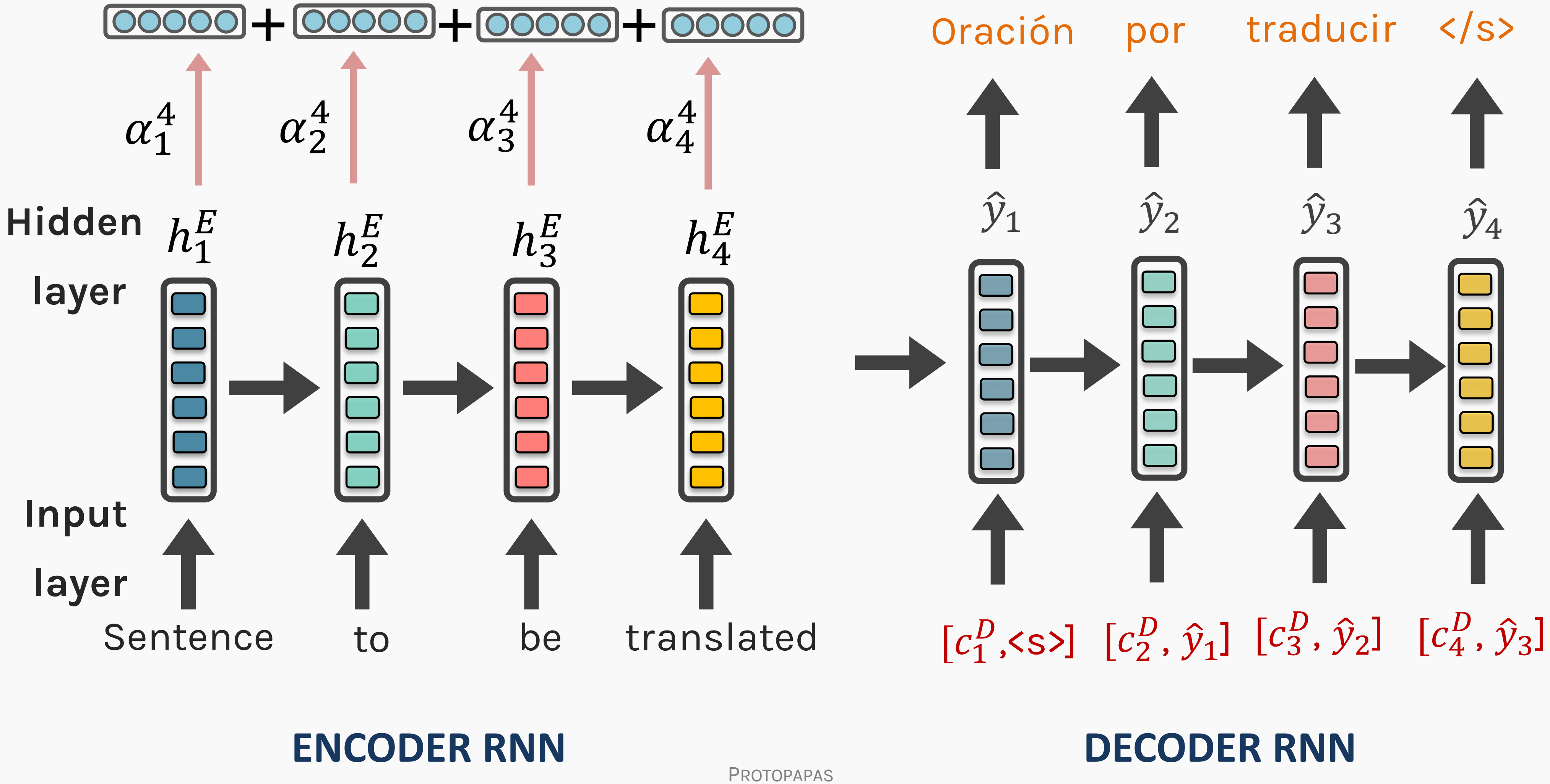
- ☑ We want to have strong contextual relations between words - **DONE**
- ☑ We want words to have sequential information - **DONE**
- ☑ We need an architecture that can be trained in parallel (non-Markovian property) - **DONE**



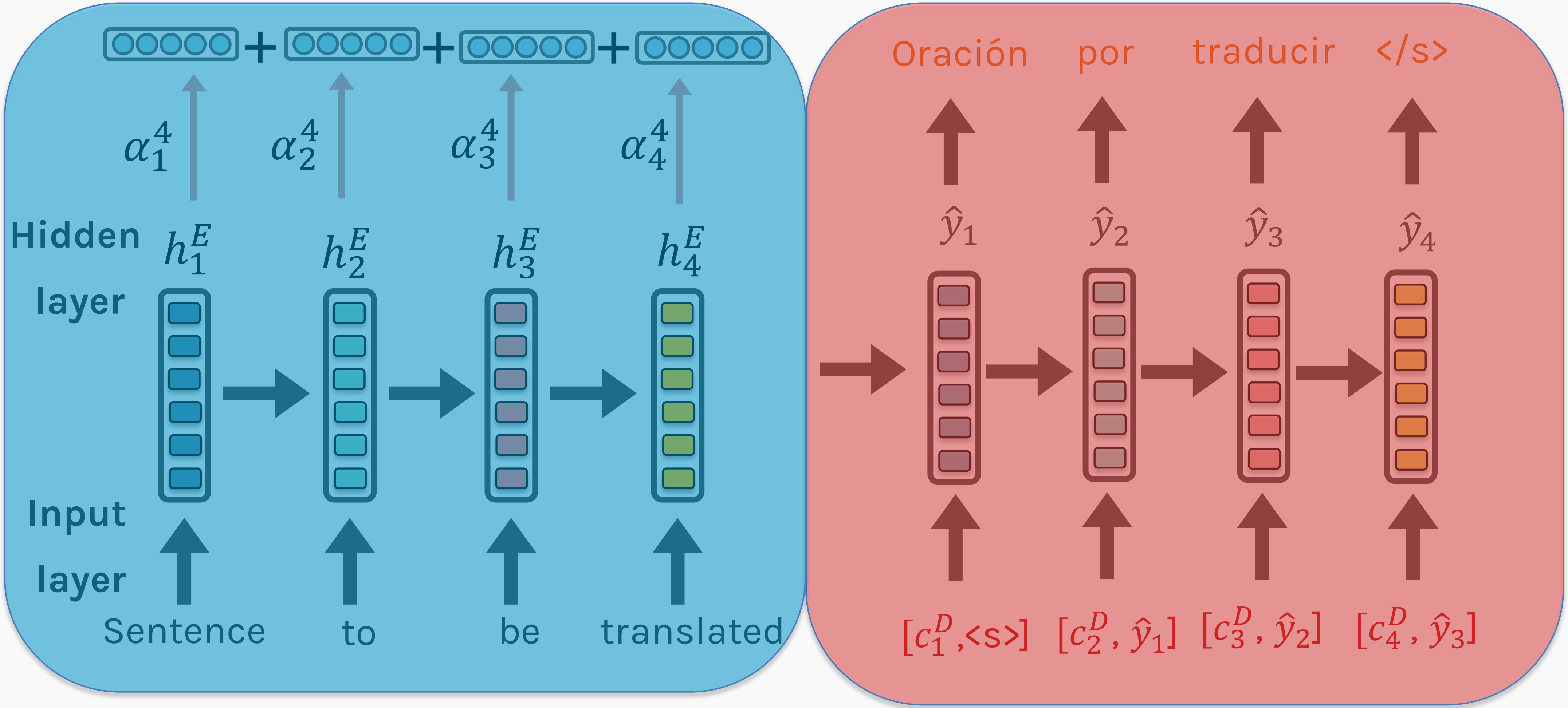
Transformers - Summary



RECAP: Seq2Seq + Attention



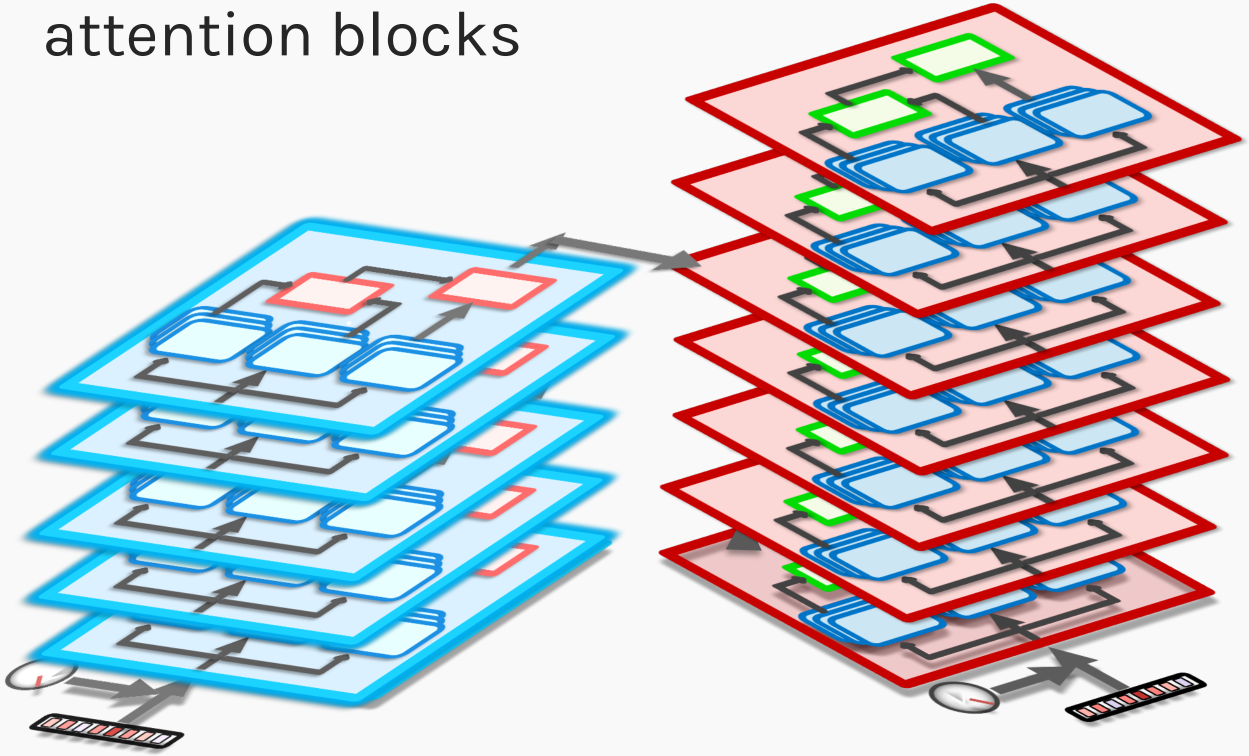
RECAP: Seq2Seq + Attention

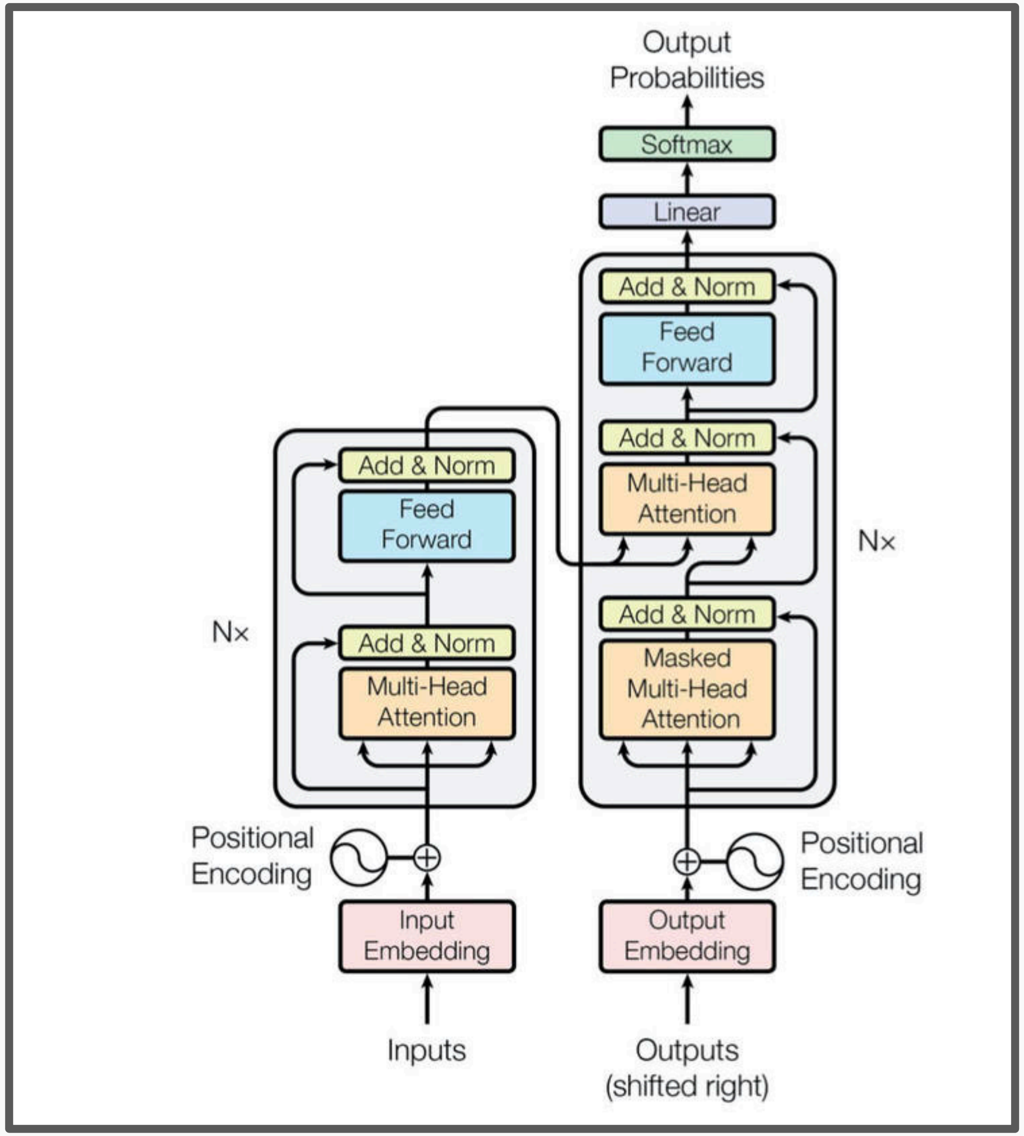


ENCODER RNN **DECODER RNN**

Transformers - Summary

Transformers consist of an Encoder-Decoder architecture, but instead of using RNNs, we use stacked multi-head attention blocks

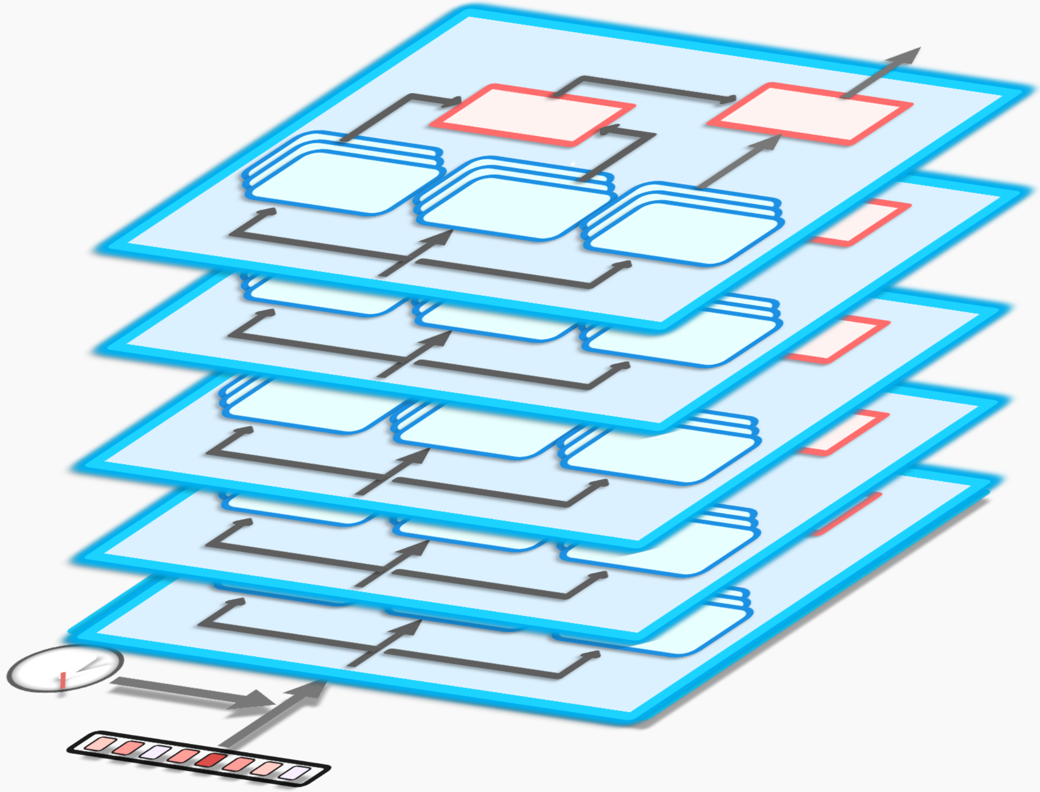




From Transformers to BERT

- Instead of an **Encoder-Decoder** architecture for machine translation, what if we just use the encoder for Language Model and other NLP tasks

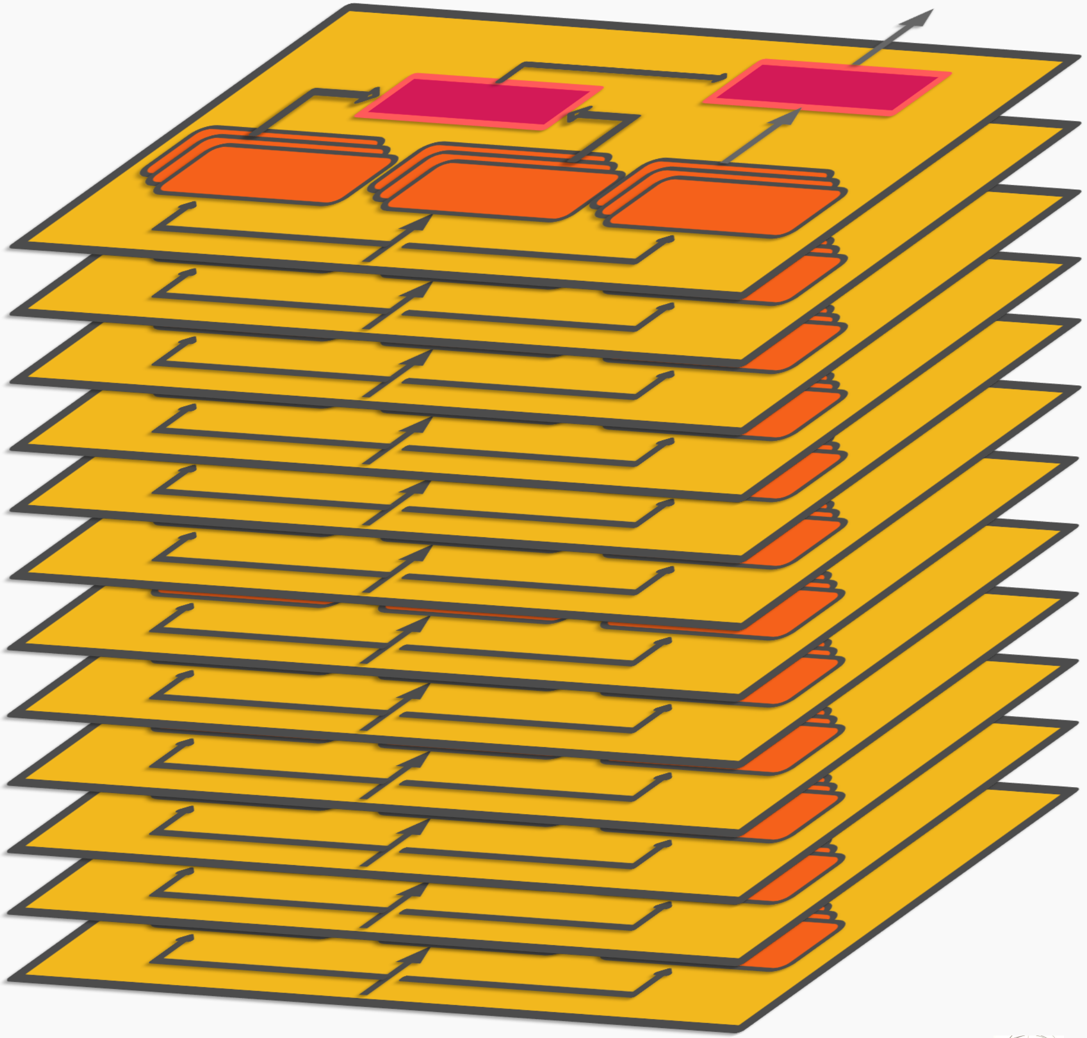
- This led to the new architecture called Bidirectional Encoder Representations from Transformers, or more commonly known as BERT



Bidirectional Encoder Representations from Transformers (BERT)

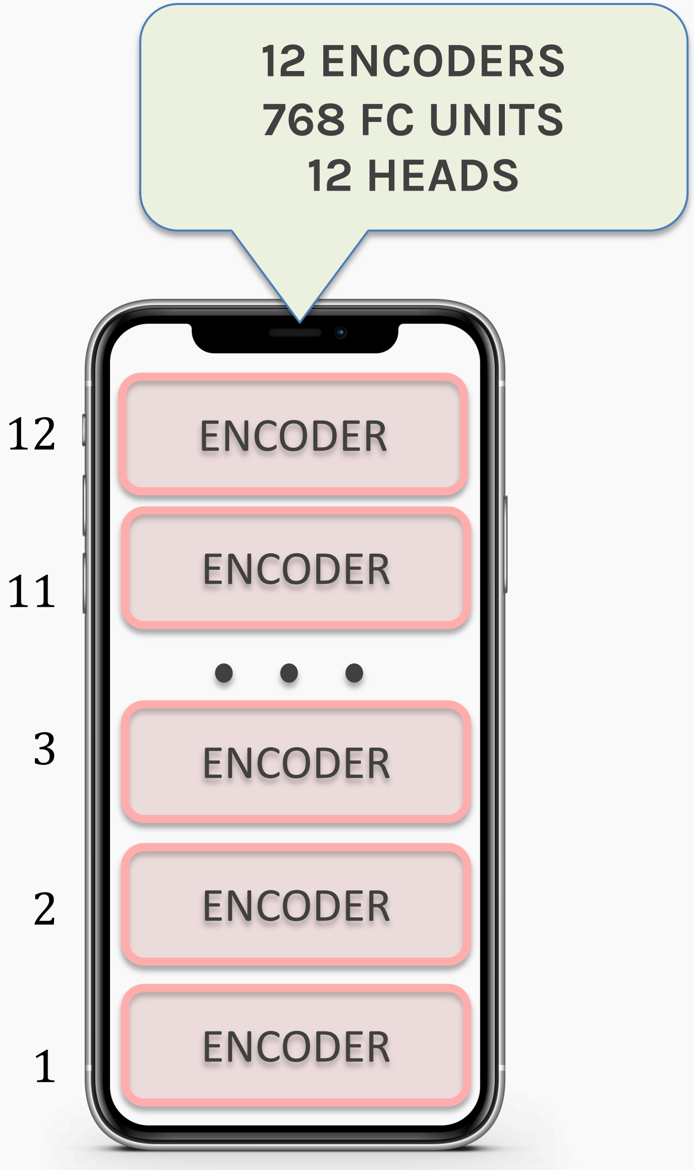
BERT

- The BERT model broke several records across various language model tasks
- The source-code and pre-trained BERT models are all open-source and can be easily adapted to individual tasks
- This makes BERT a prime candidate for transfer learning applications

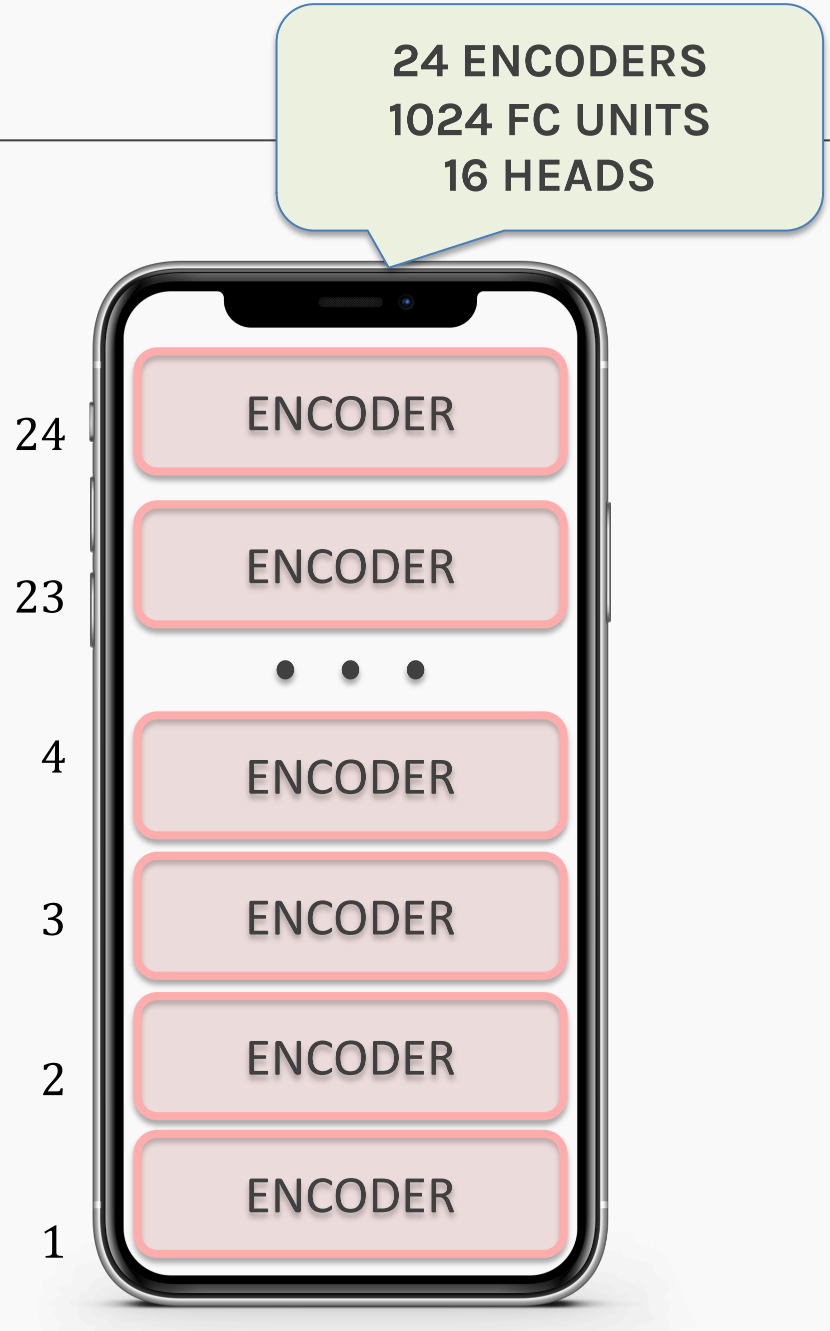


Flavors of BERT

Flavors of BERT



BERT BASE



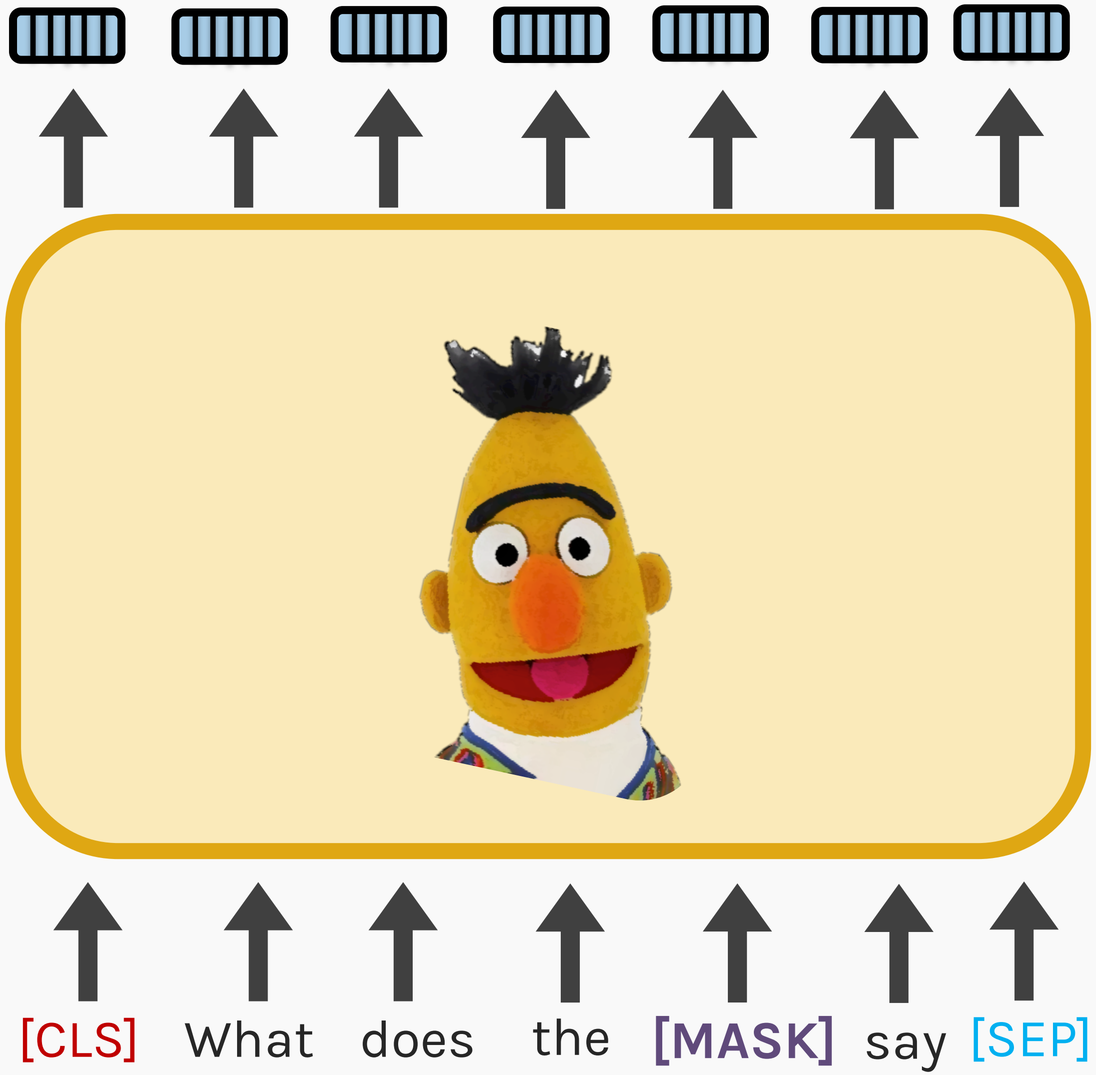
BERT LARGE

BERT

TECHNICAL DETAILS

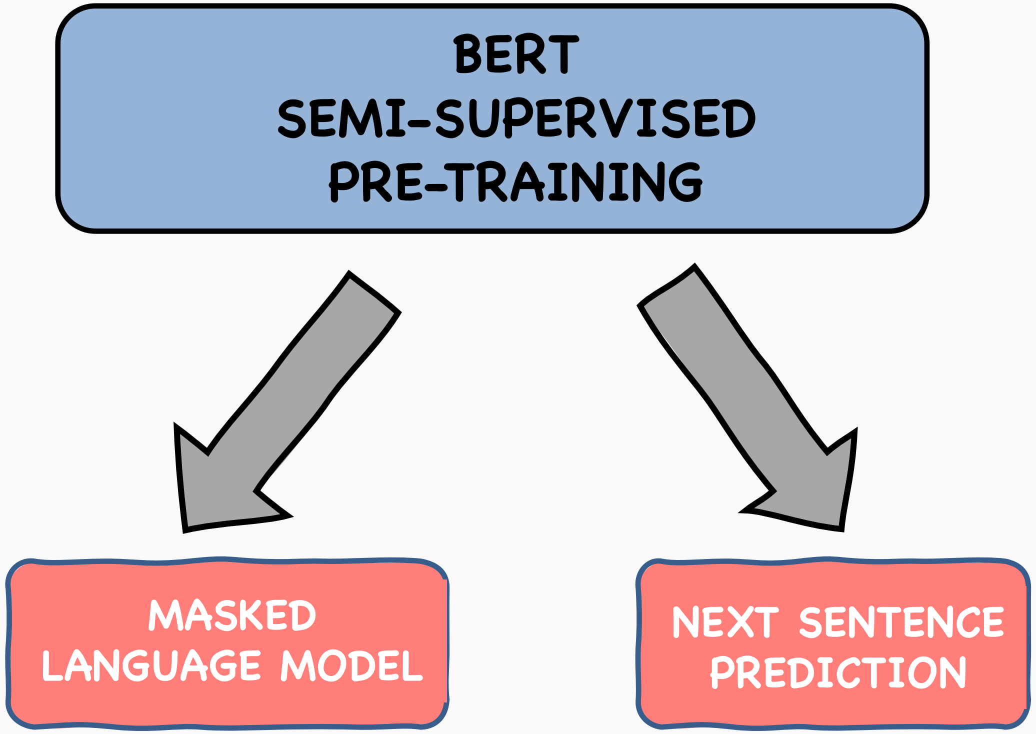
- Input sequences to BERT must have the following special tokens:
  - [MASK] – Masking token
  - [SEP] – Separator token
  - [CLS] – Classifier Token

What are these new tokens you ask? Hold on!



How to train a BERT?

How to train a BERT



How to train a BERT?

TRAINING ISSUES?

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

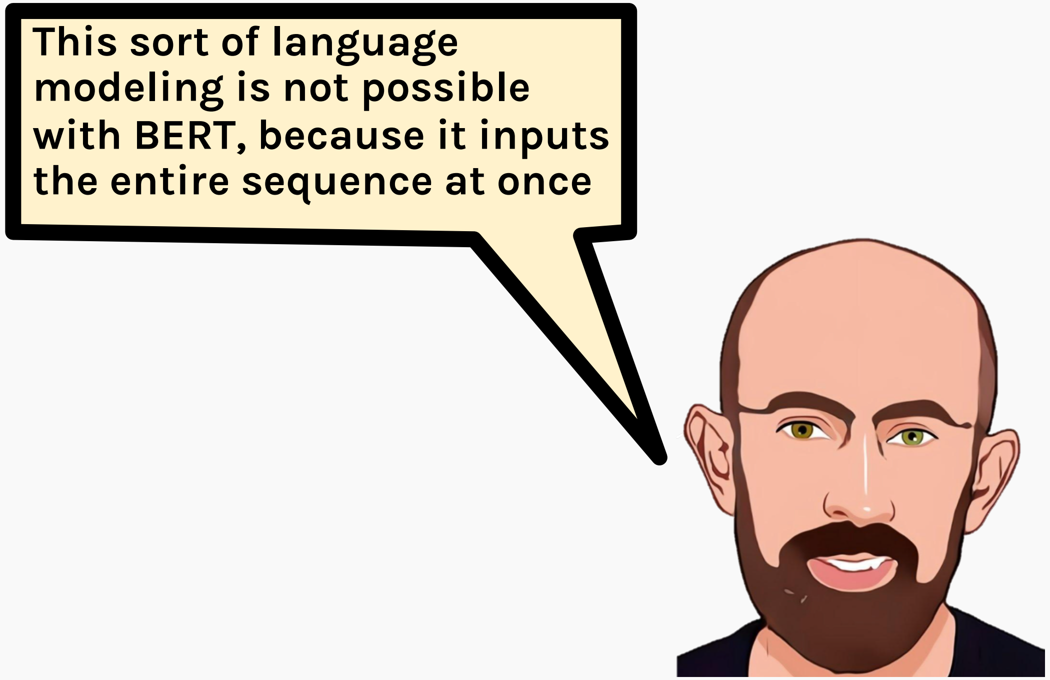
- How could we classify if two chosen sentences follow each other or are out of place if the output is also a sequence of tokens?

MASKED LANGUAGE MODELING

RECAP: Language Model

Shivas was hit by a bus as he was crossing the street

Shivas was hit by a ___

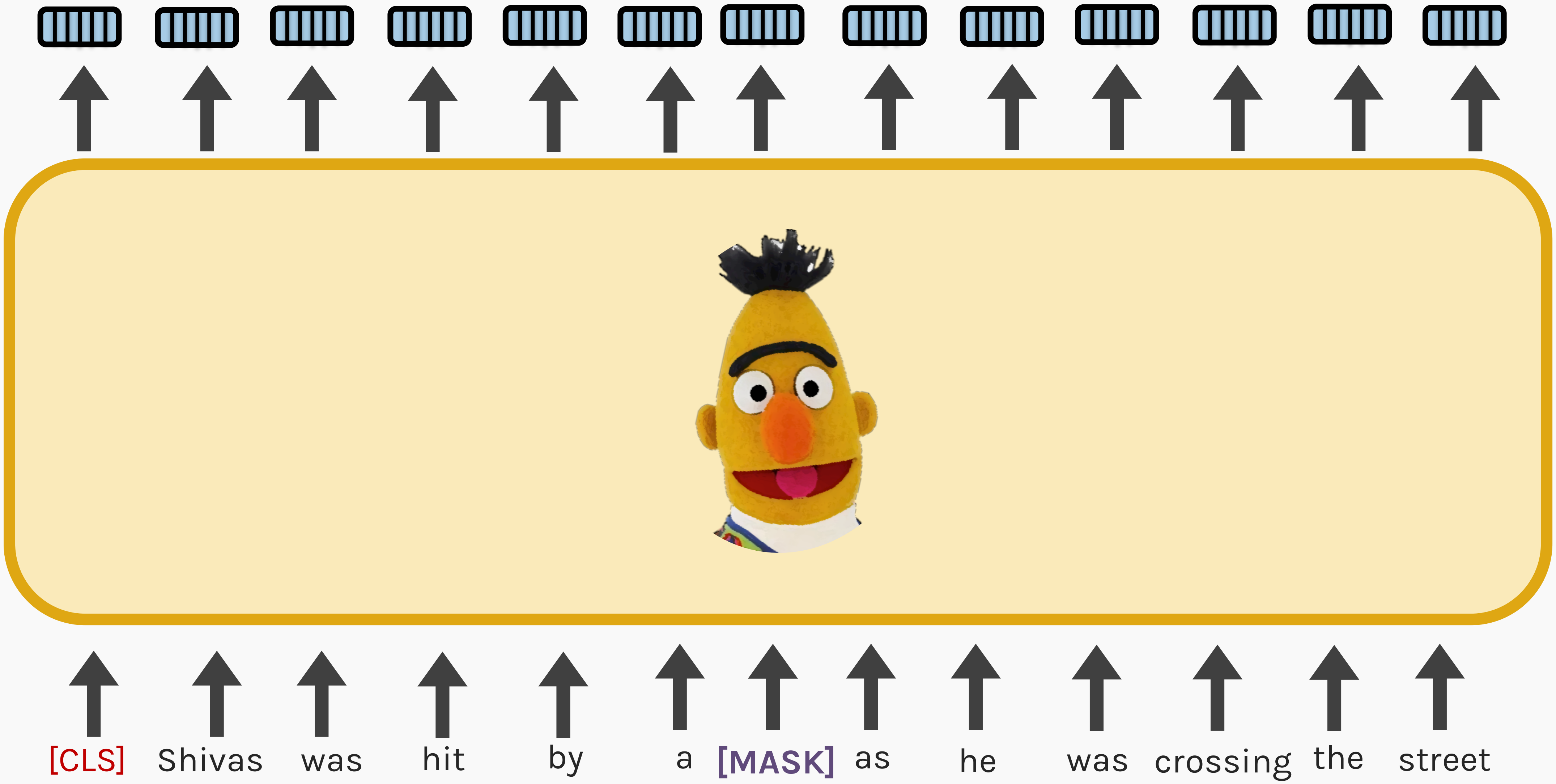


Masked Language Model

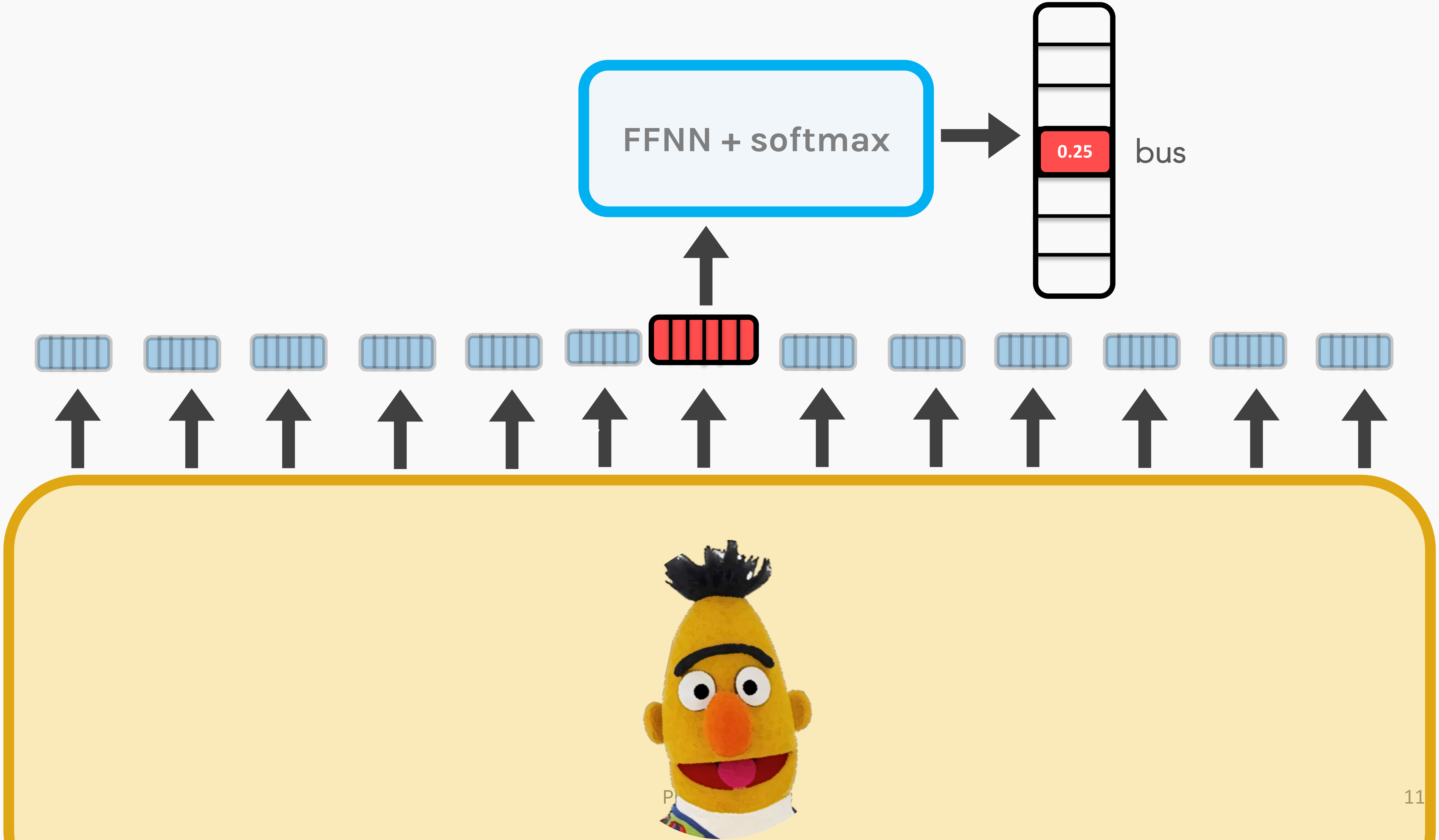
Shivas was hit by a bus as he was crossing the street

Shivas was hit by a [MASK] as he was ...

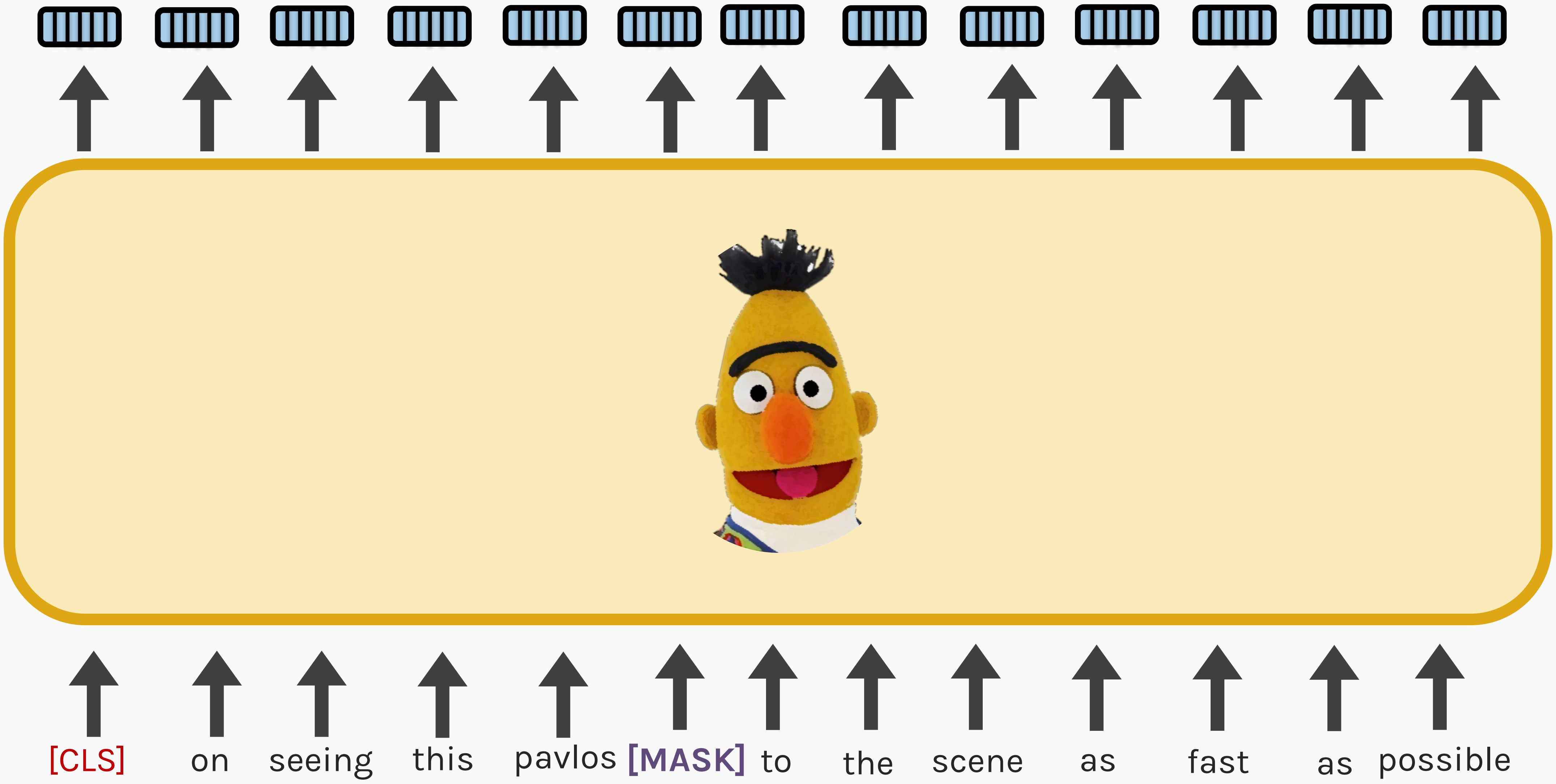
Shivas was hit by a **bus** as he was crossing the street



Shivas was hit by a bus as he was crossing the street



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



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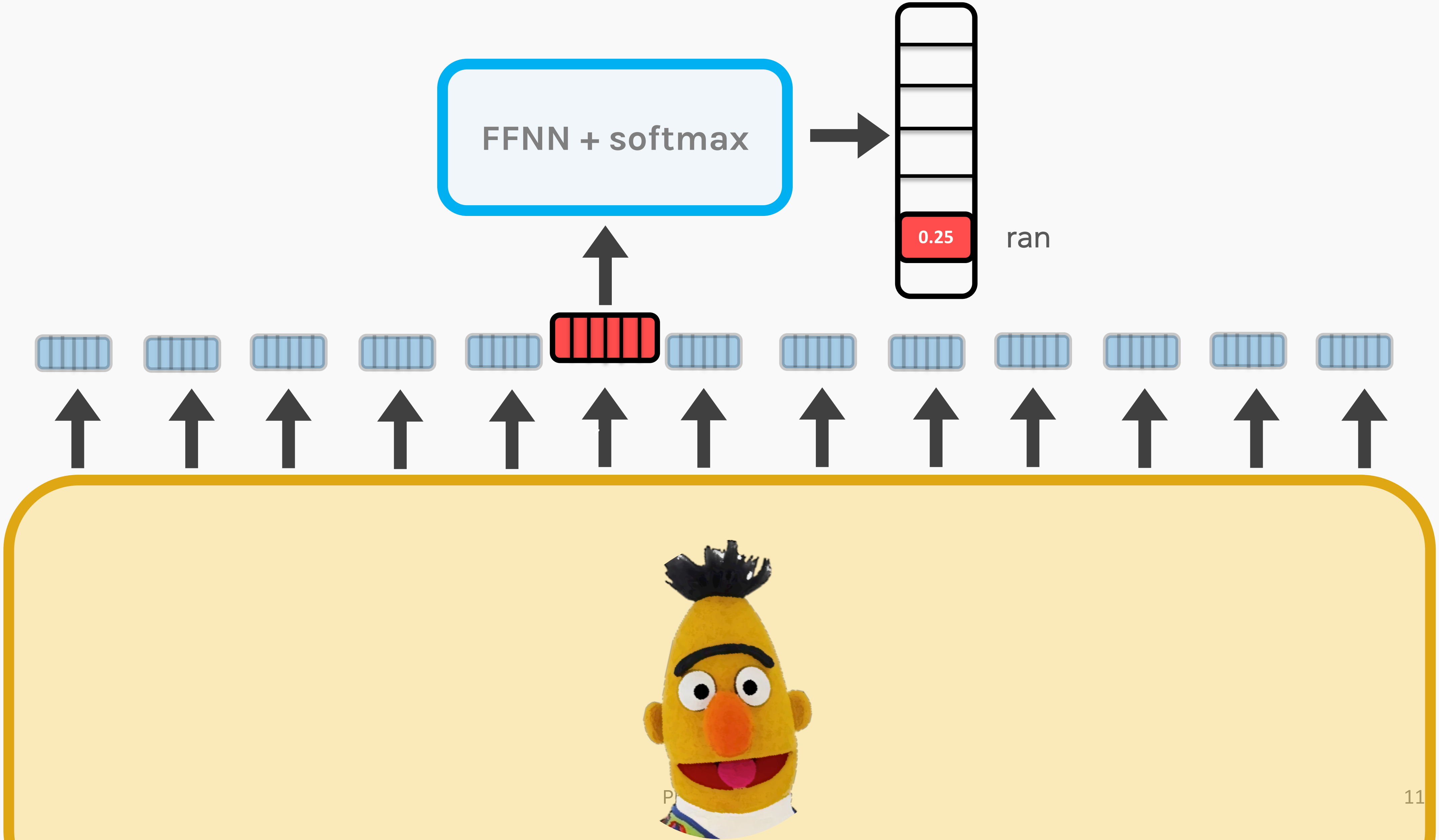
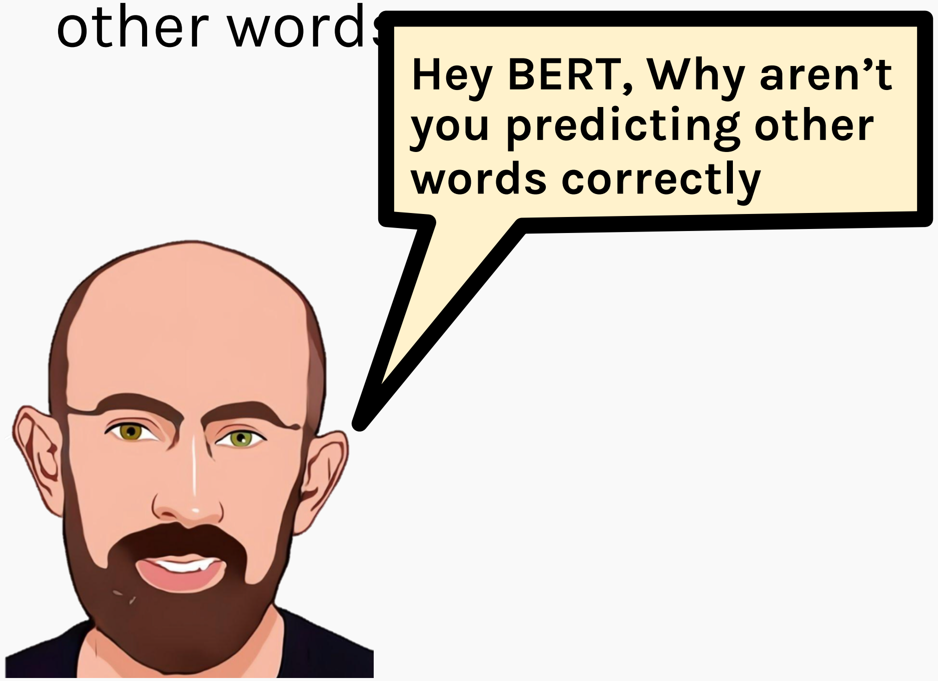
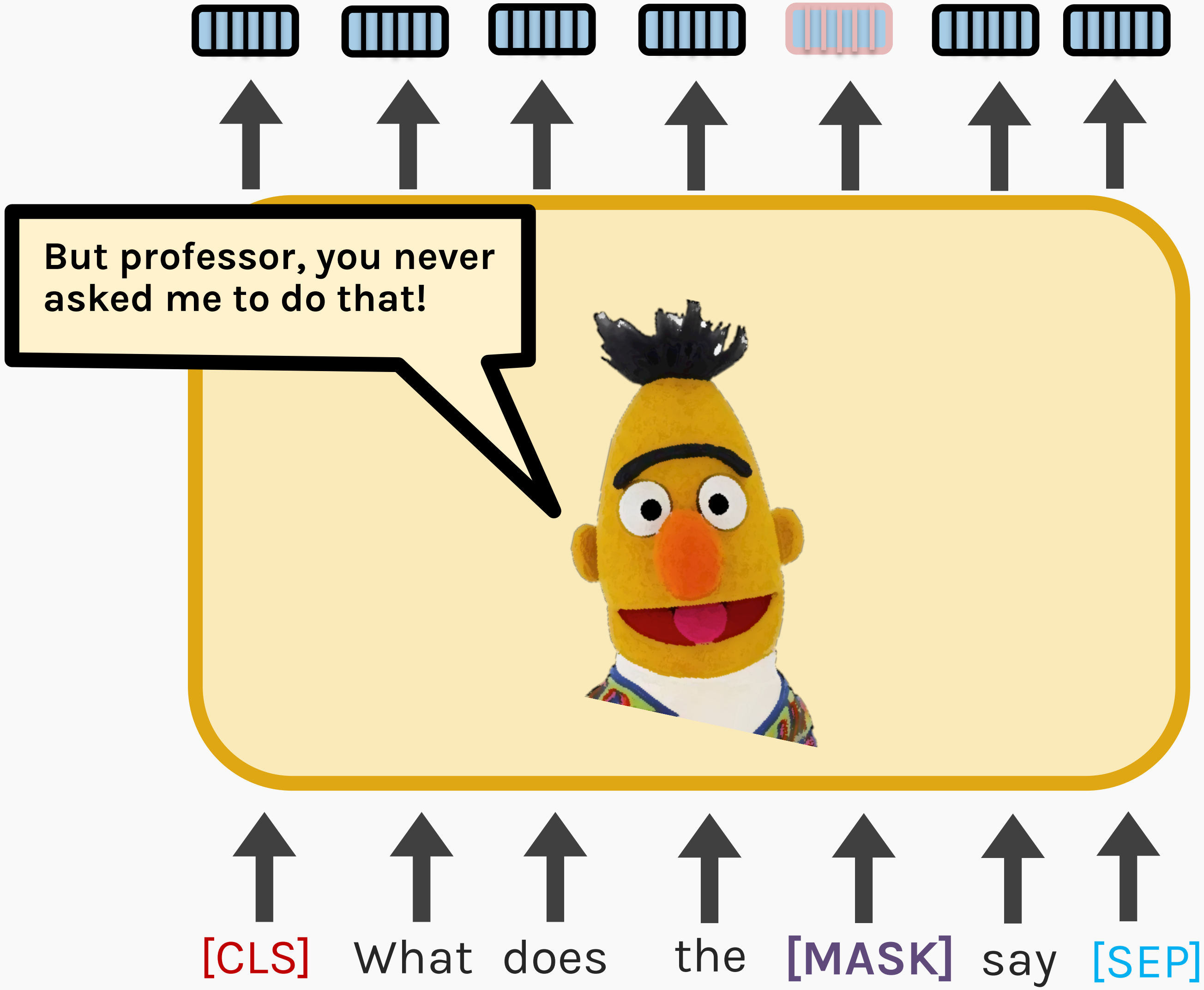


BERT

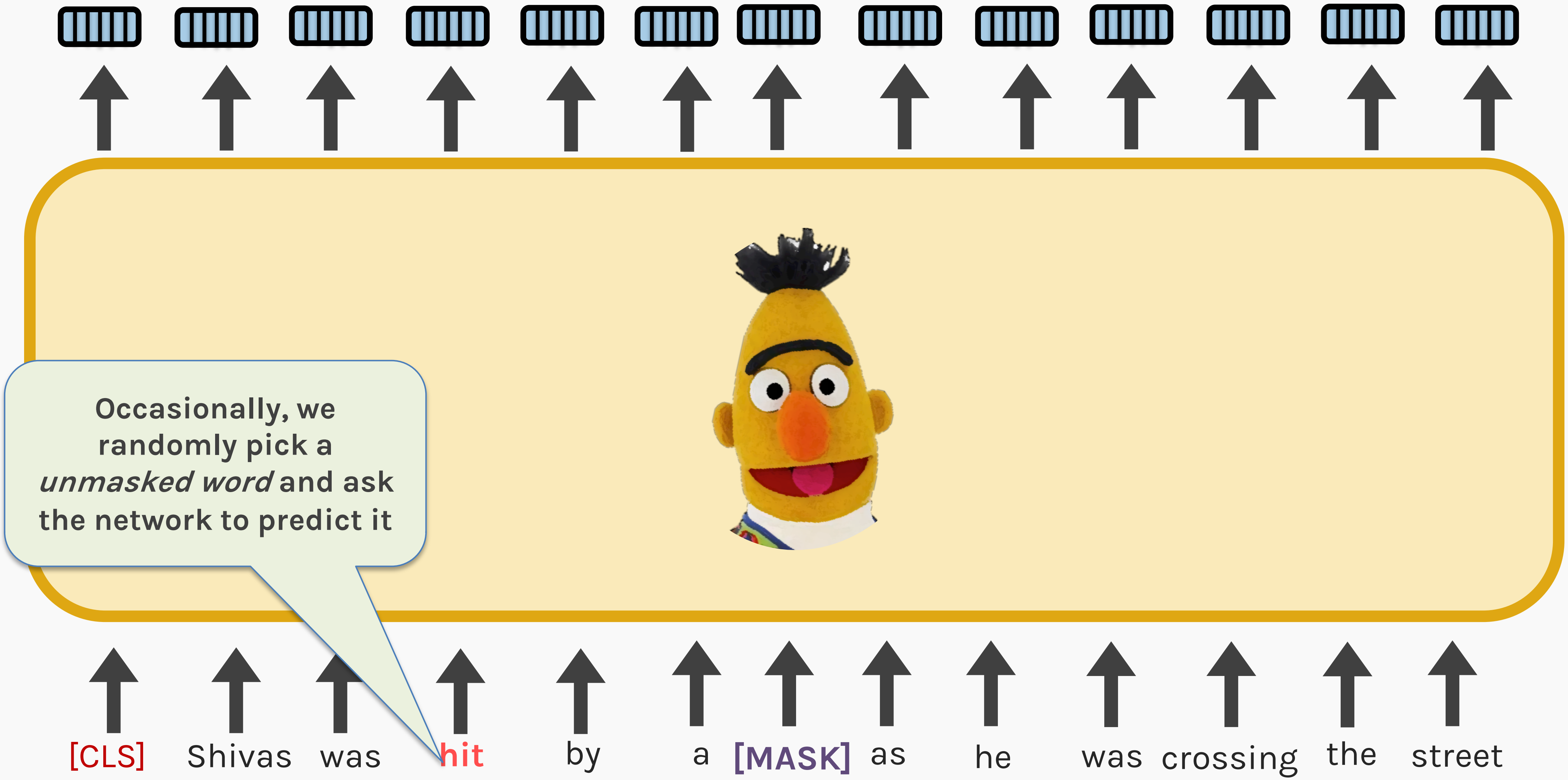
MASKING ISSUES?

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

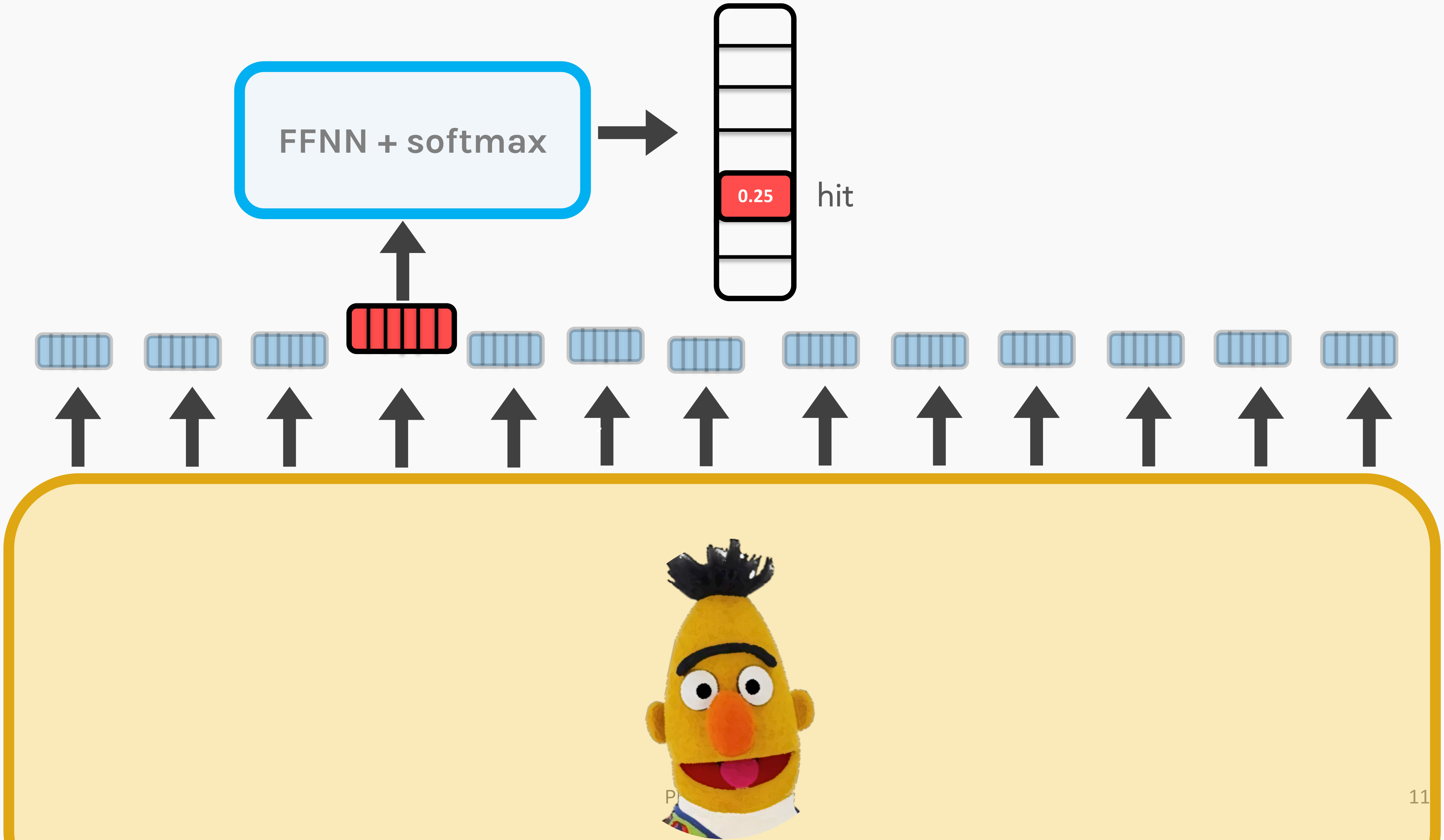




Shivas was **hit** by a bus as he was crossing the street

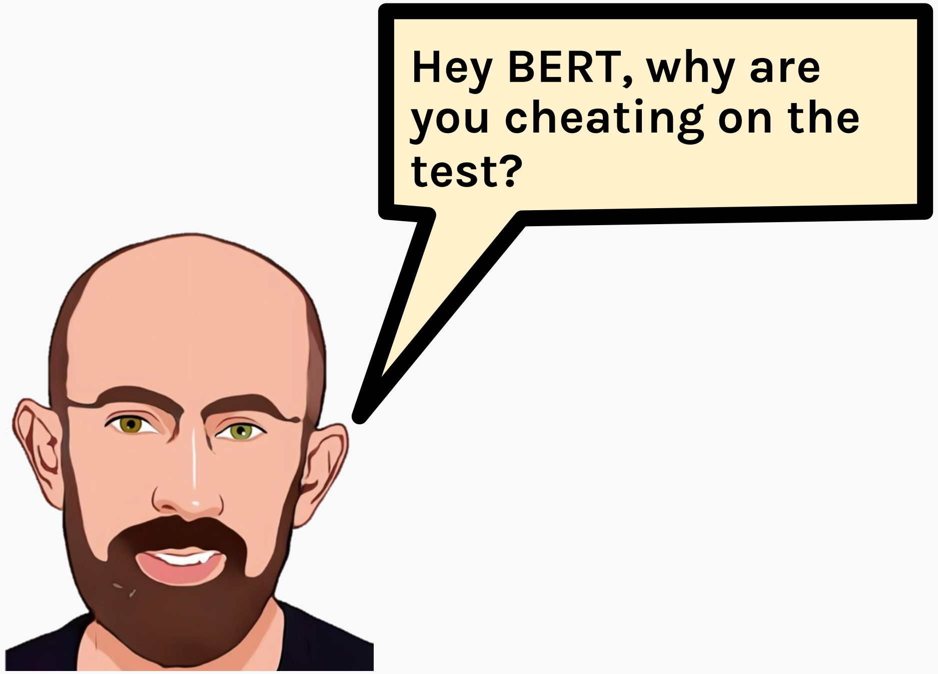


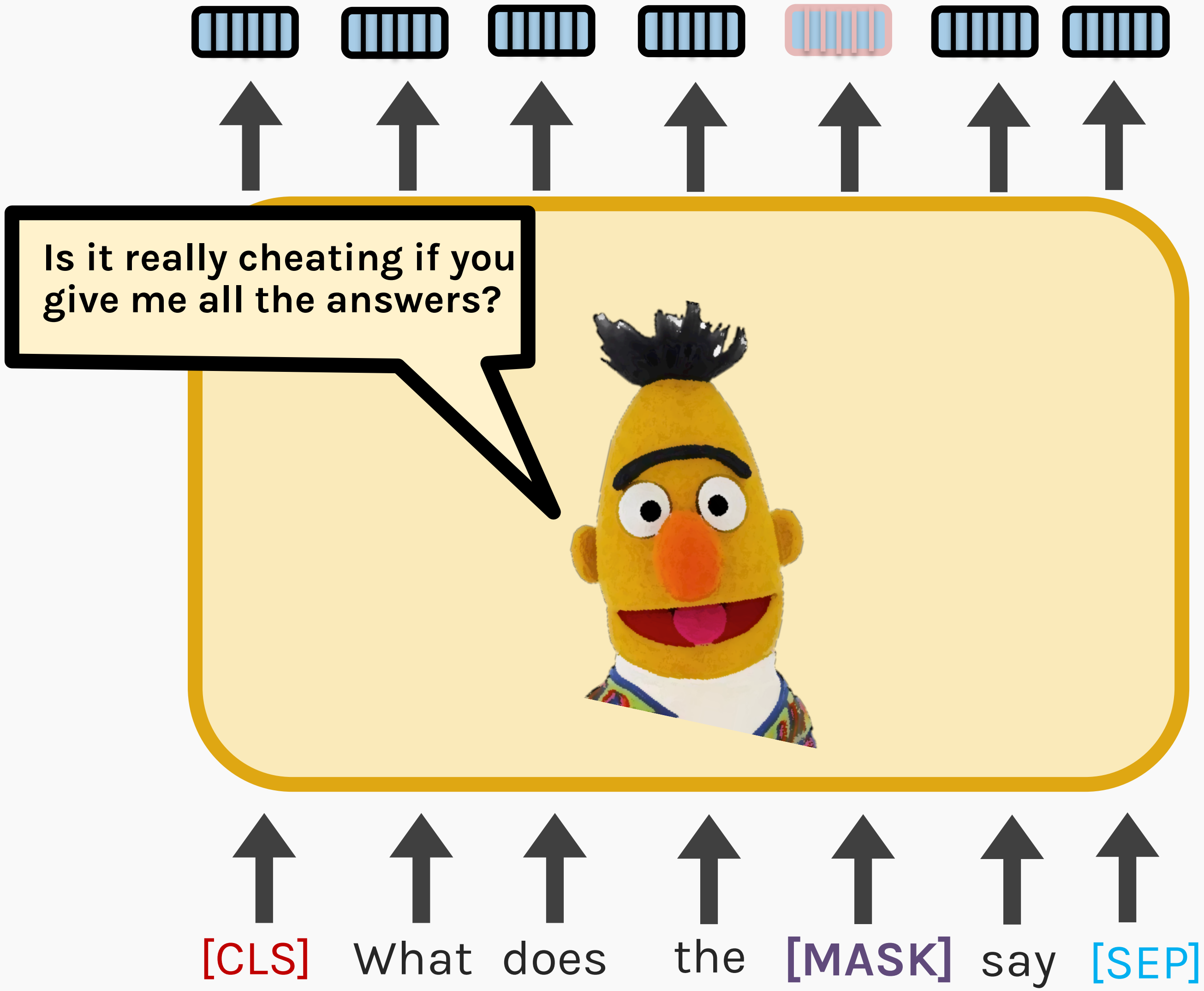
Shivas was hit by a bus as he was crossing the street



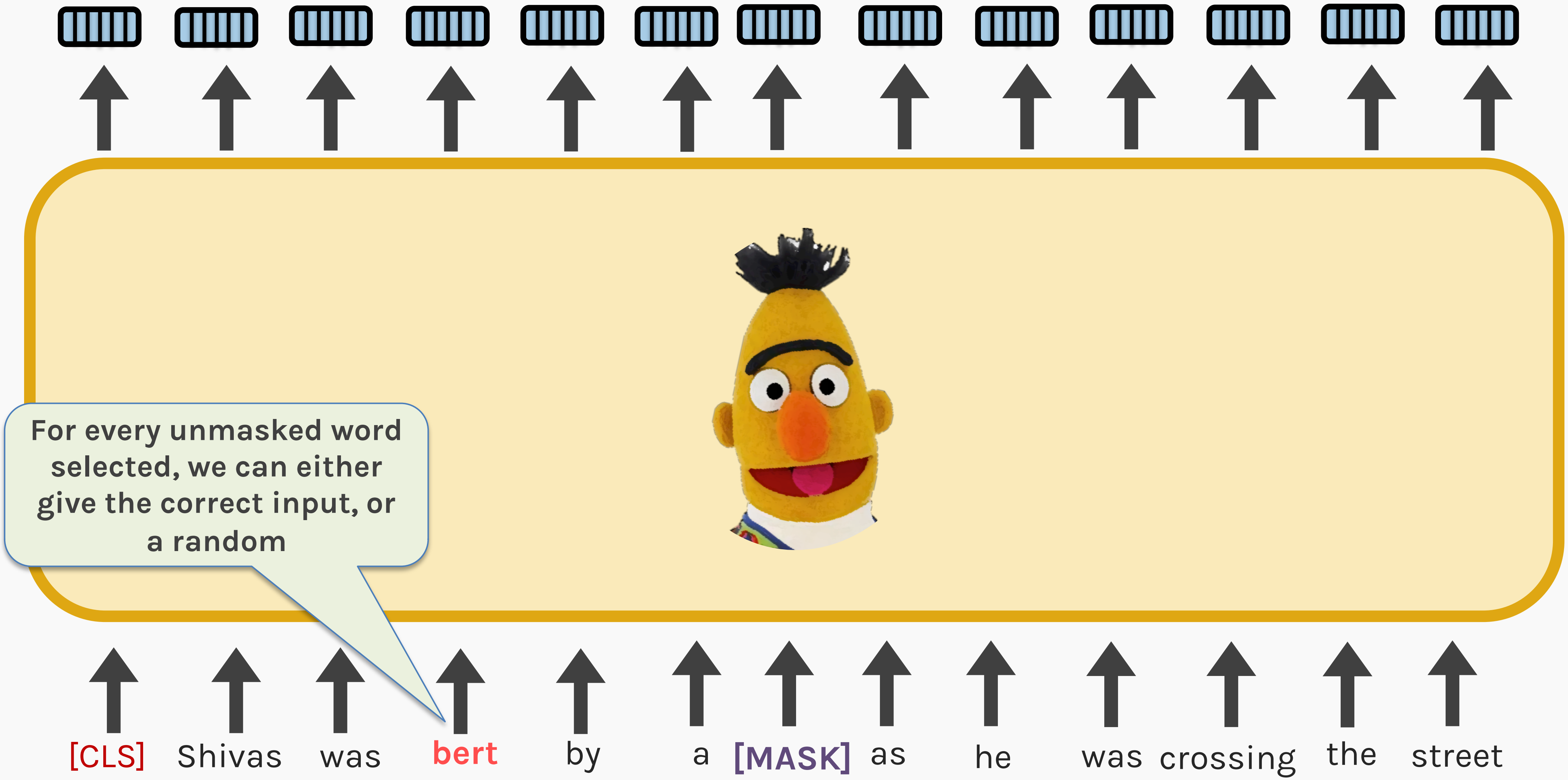
ISSUES?

- The model uses an identity mapping to return unmasked words

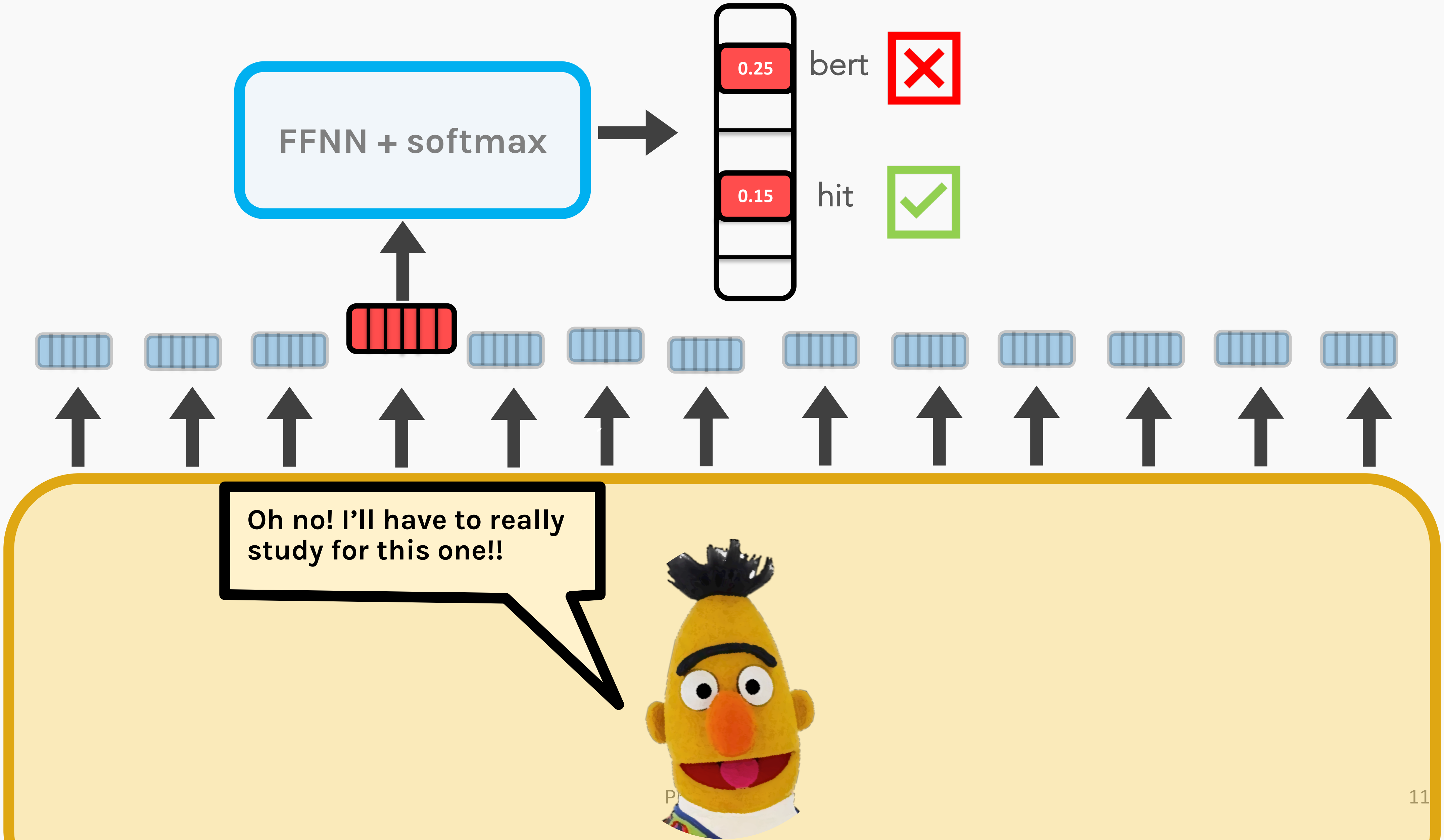




Shivas was **hit** by a bus as he was crossing the street



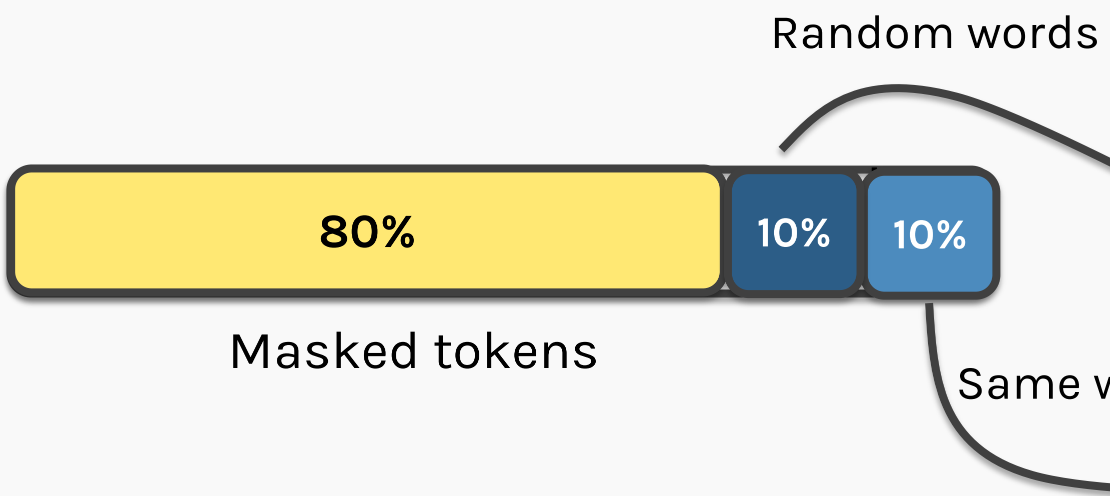
Shivas was hit by a bus as he was crossing the street

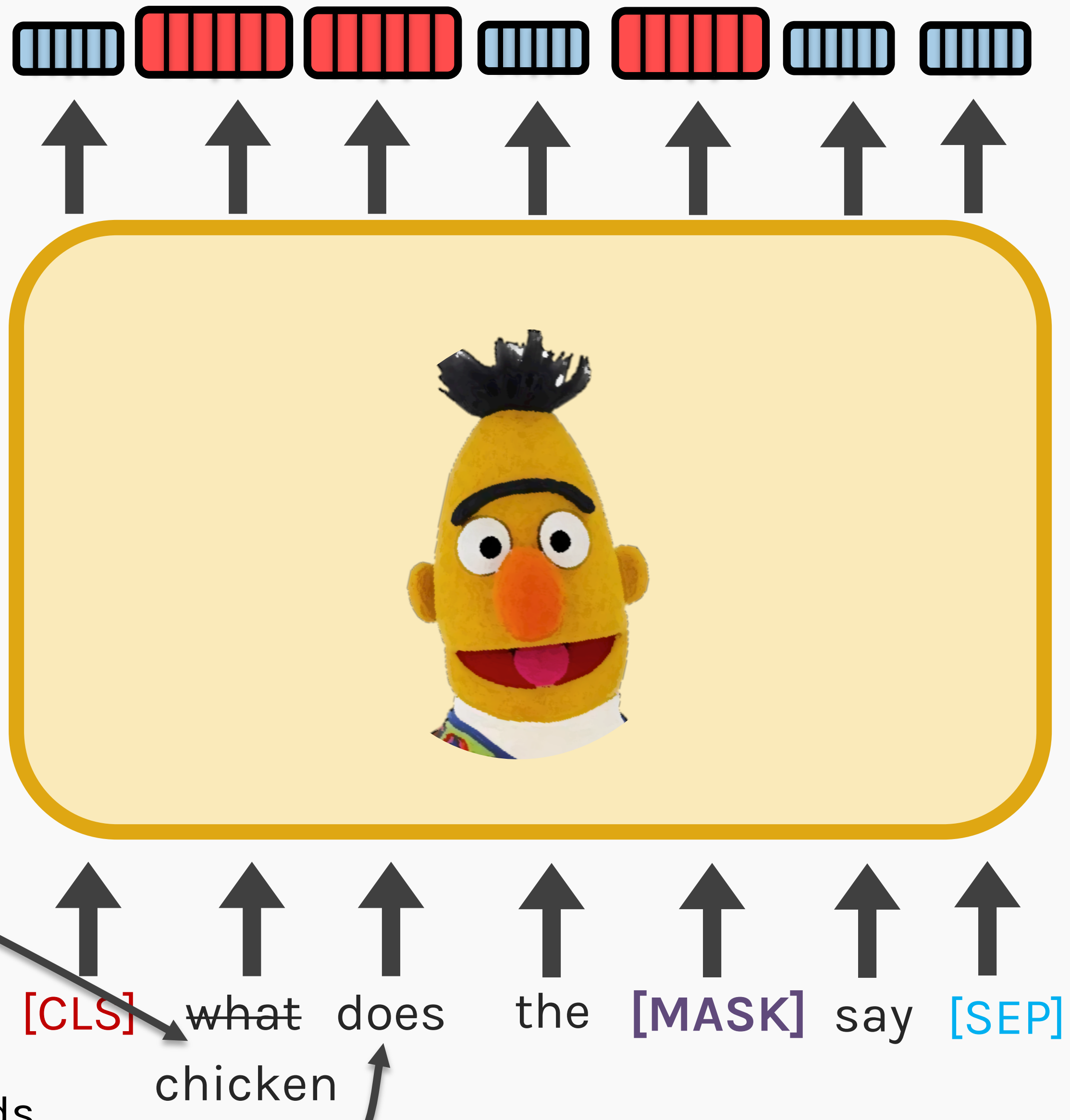


BERT

MASKING DETAILS

- BERT's language modeling task masks 15% of the input and asks the model to predict the missing word
- 80% of the selected tokens are masked, 10% are the same words and 10% are randomly replaced words





NEXT SENTENCE PREDICTION

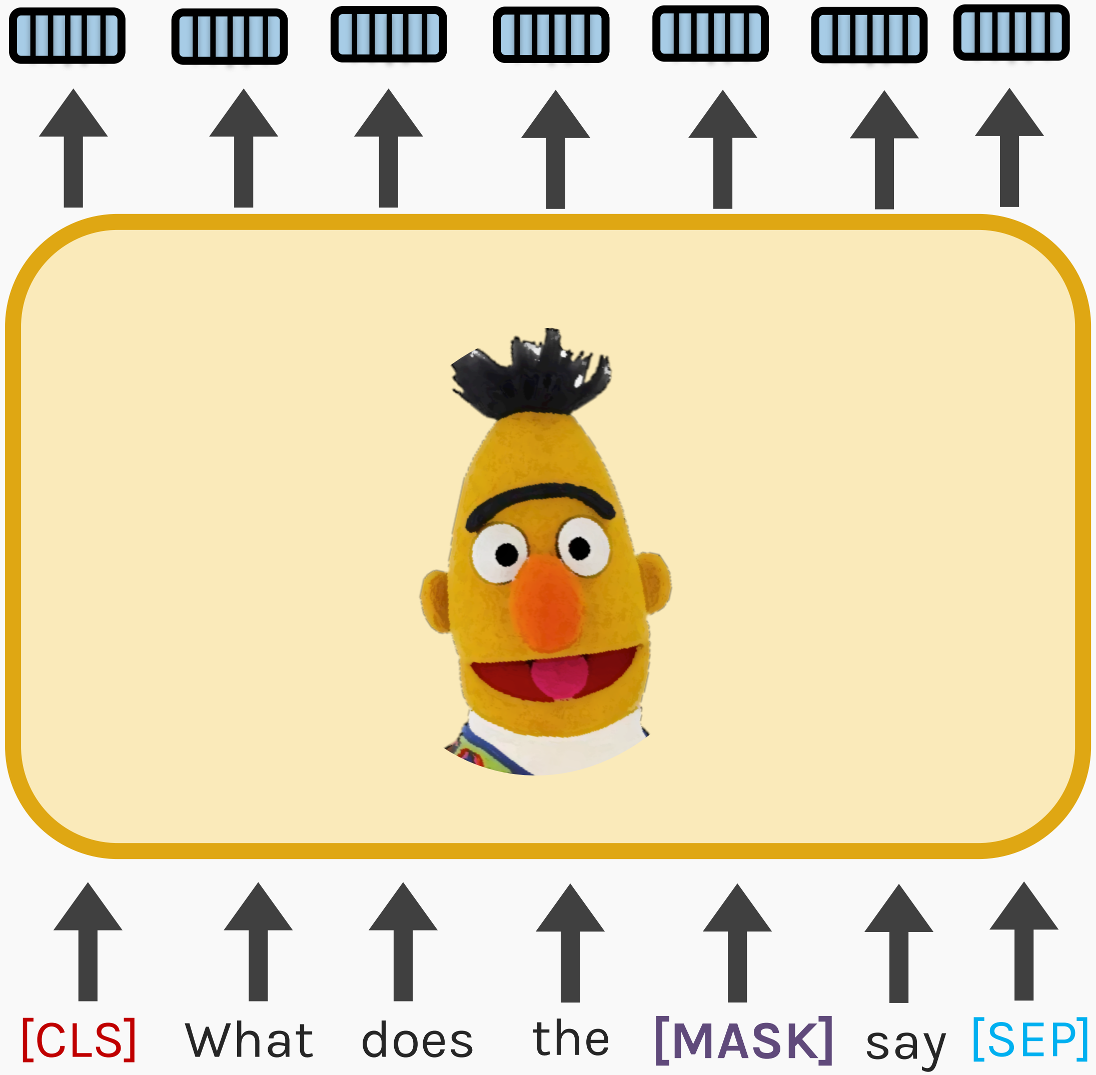
Two sentence task

TECHNICAL DETAILS

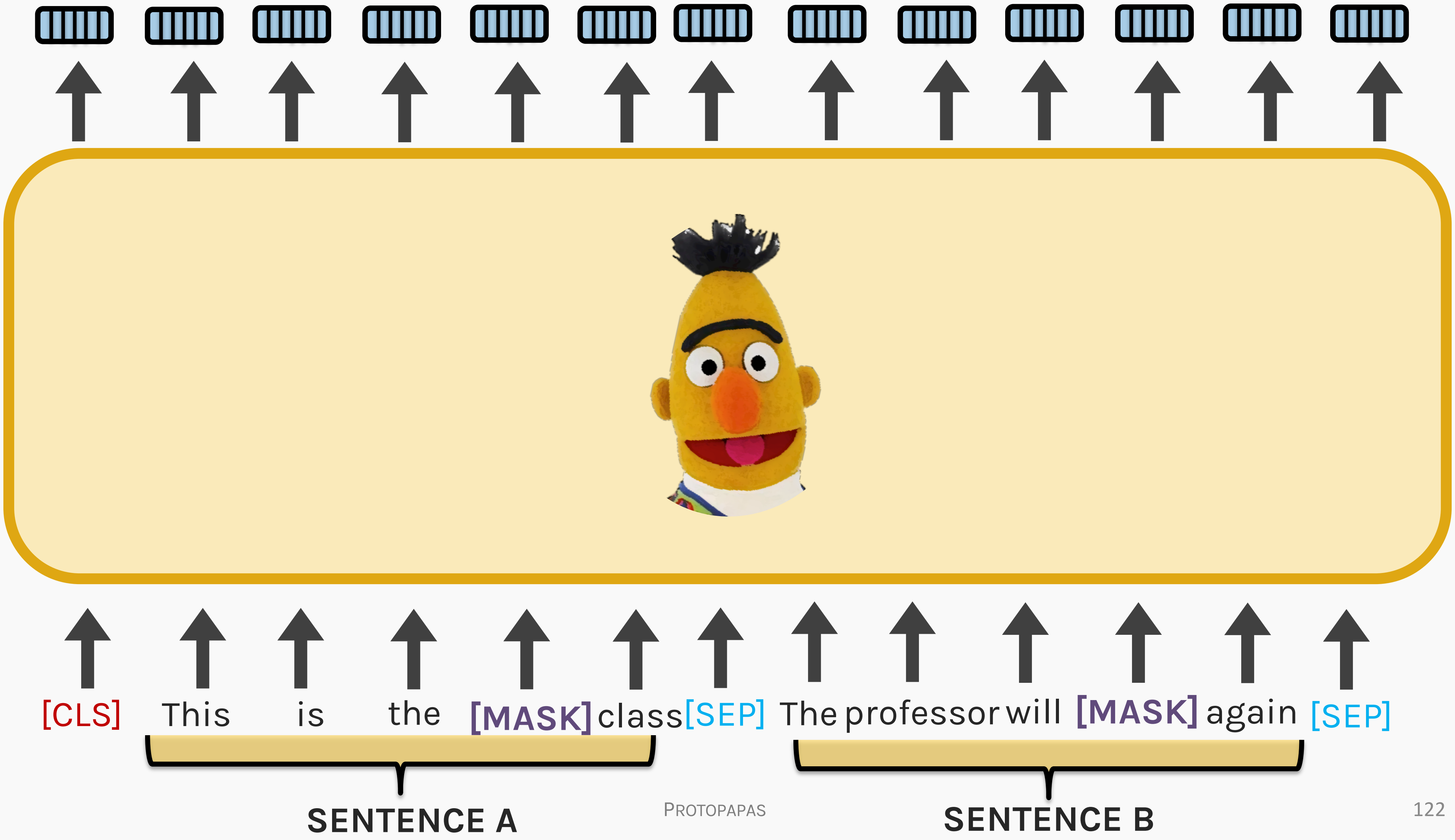
- To make BERT better at handling relationships between multiple sentences, the pre-training process includes an additional task:

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

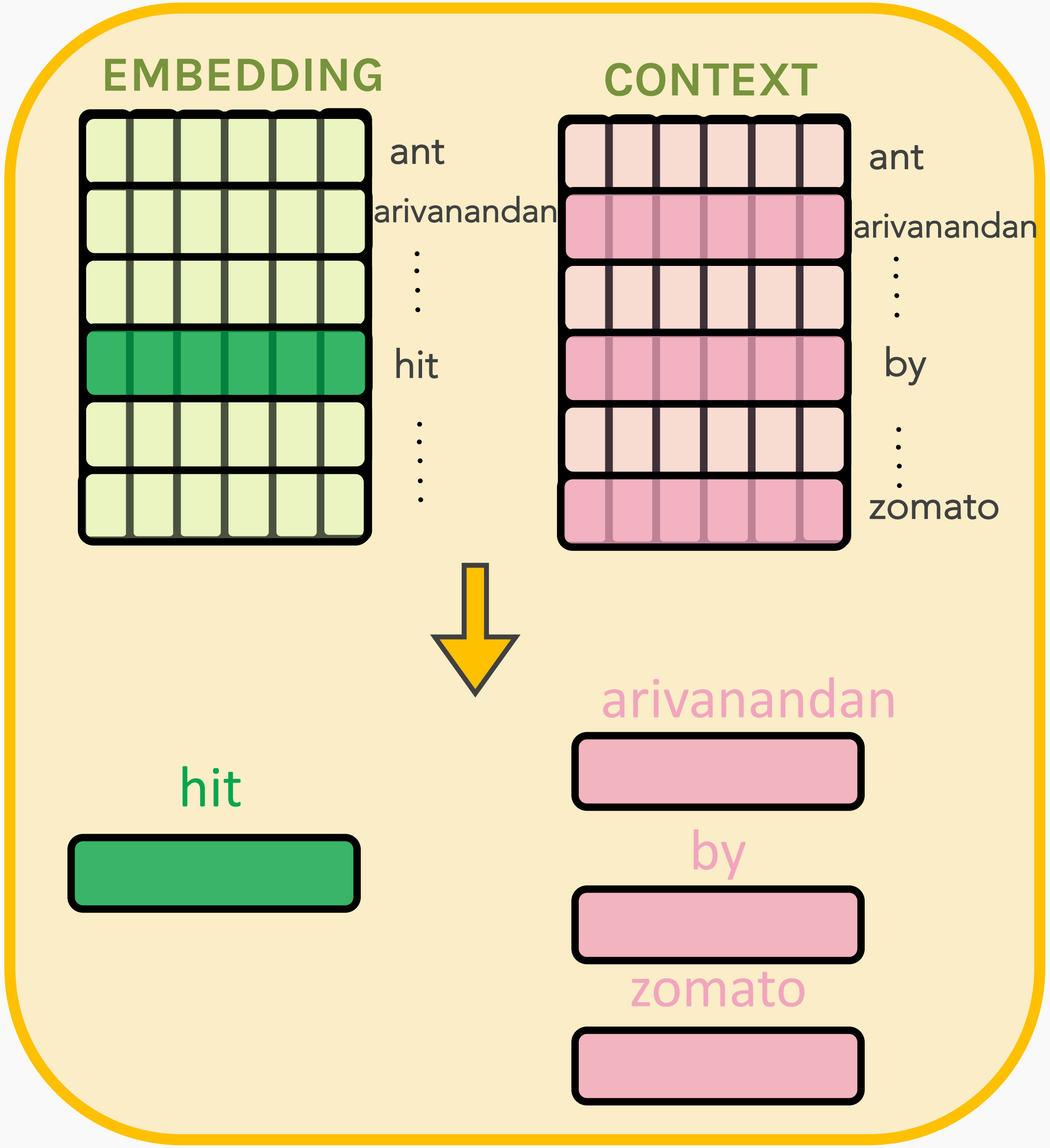
The individual sentences are separated by the **[SEP]** tag mentioned before



Two sentence task



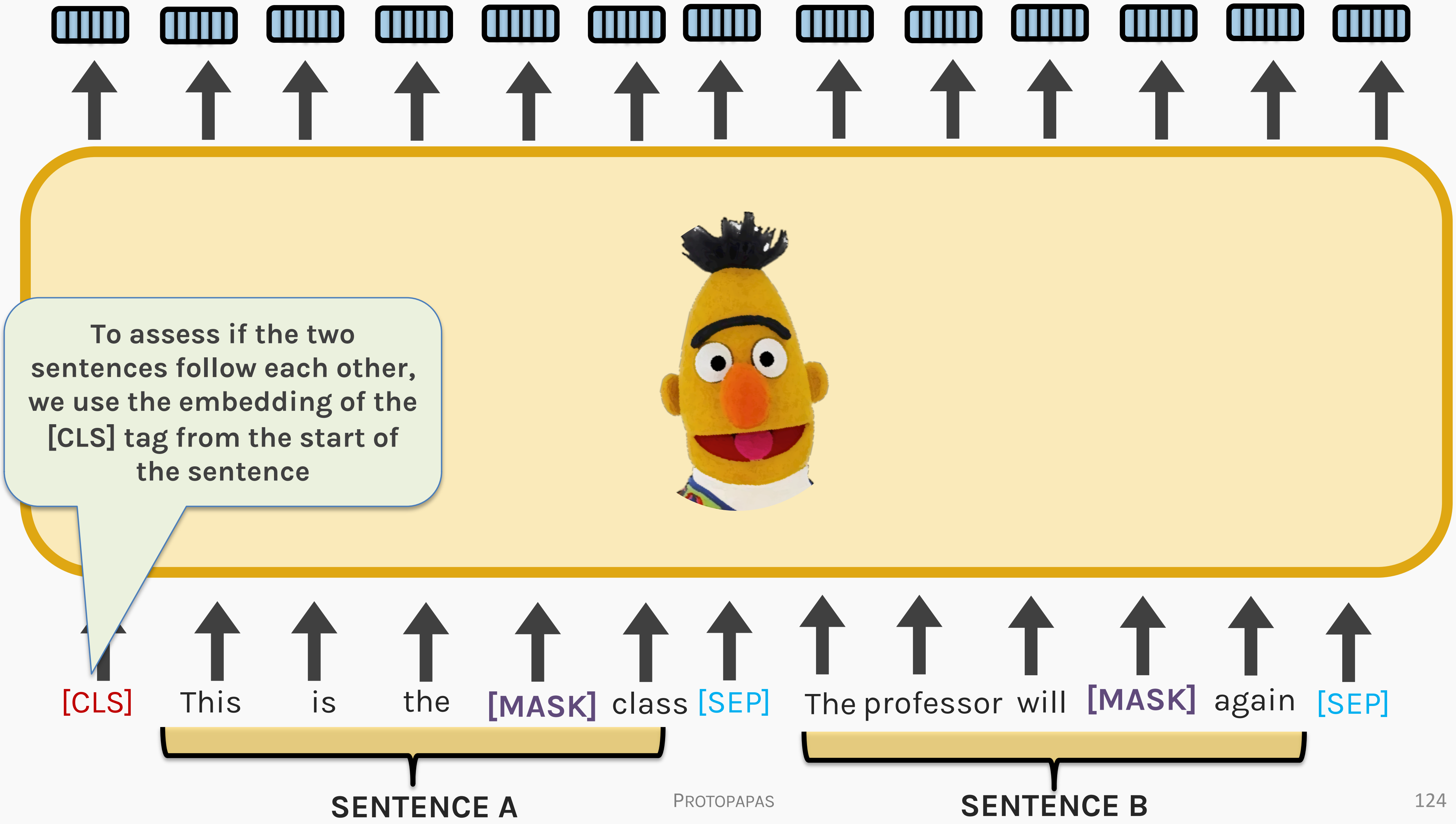
RECAP: Negative Sampling



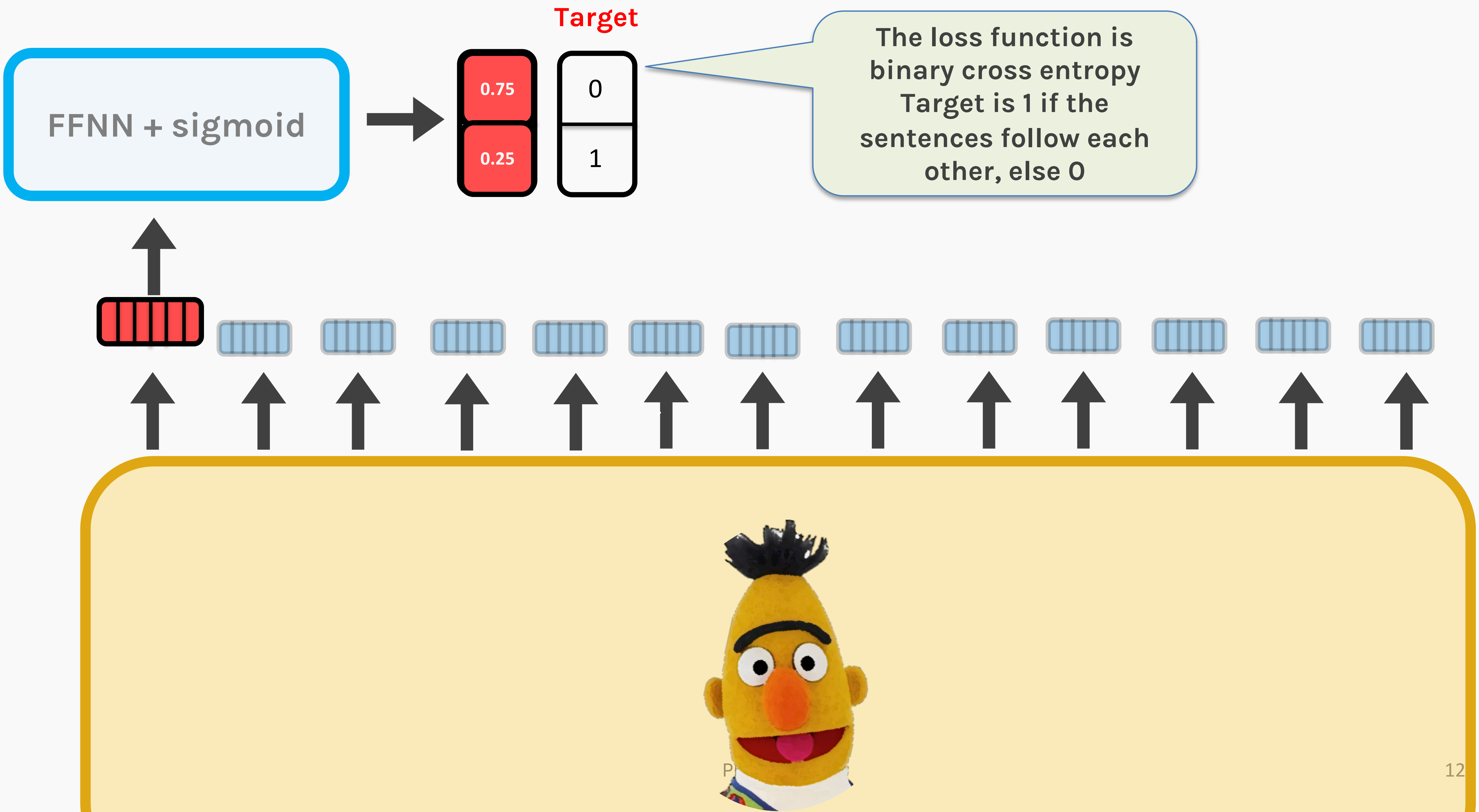
input (centre) word, w_c	output word, w_o	Input · Output	Sigmoid()	Target
hit	was	-0.91	0.25	1
hit	arivanandan	-1.11	0.25	0
hit	by	0.2	0.55	1
hit	zomato	0.74	0.68	0

- Just as in word2vec training, we generate ***negative samples*** of sentences
- These sentences could follow each other ($TARGET = 1$) or can be selected at random ($TARGET = 0$)
- The training will be using a simple classifier

This is the last class. The professor will explain again



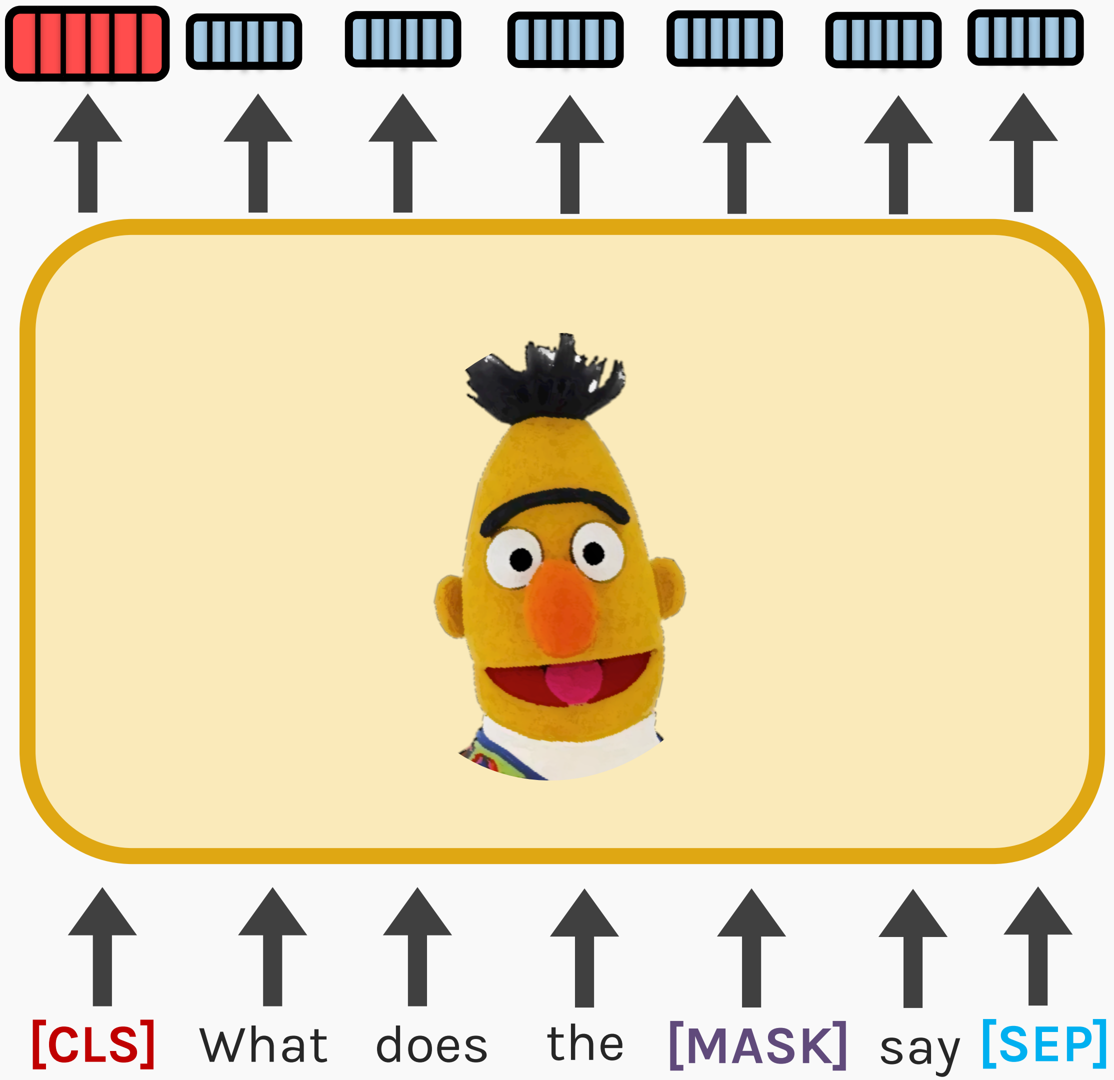
This is the last class. The professor will explain again



How to train BERT?

CLIFF NOTES

- Using a large corpus (e.g. wikipedia texts), we *pre-train* a BERT model for two tasks:
    - *Masked* word prediction
    - *Next sentence* prediction
- We train BERT with the two tasks *simultaneously* with a goal of minimizing the combined loss function
- The [MASK] tag is used for the language model task, and the [CLS] and [SEP] tag helps to train the sentence



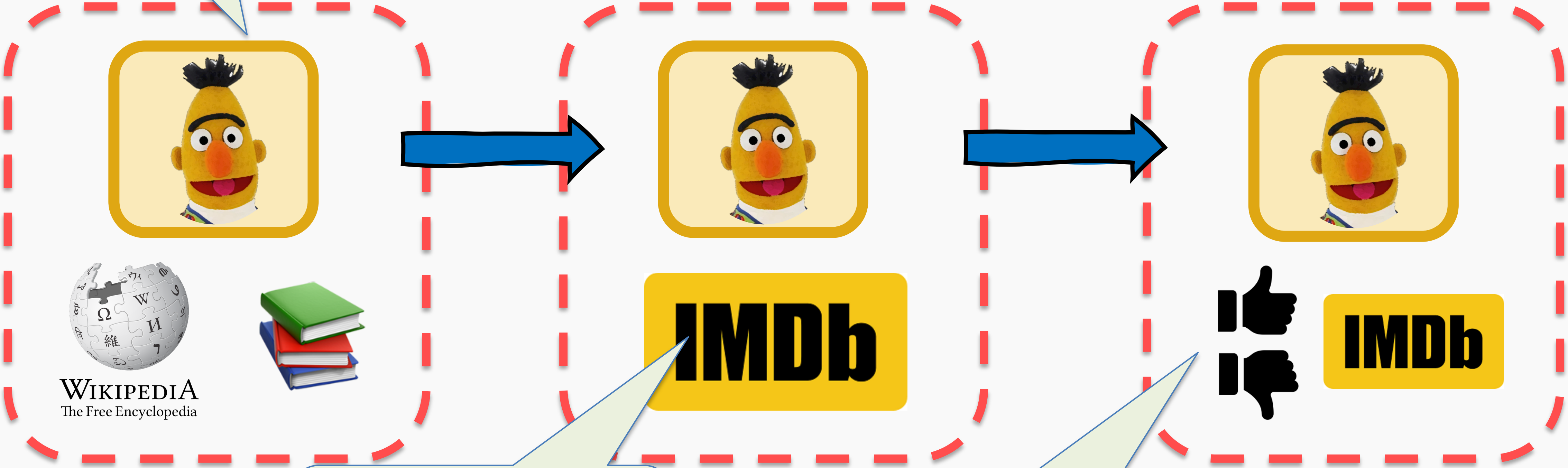
How to *use* a BERT?

How to use a BERT?

You will (almost) never train a BERT from scratch

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

Pre-training — Fine-tuning — Language tasks



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

The final step is the supervised learning using labels

How to use BERT?

BERT can be used for a wide variety of language tasks

Classification tasks (e.g. Sentiment analysis):

Done by adding a classification layer on top of the Transformer output for the [CLS] token.

Named Entity Recognition (NER)

Using BERT, a NER model can be trained by fe oken into a classification layer that predicts the NER lab

Question Answering tasks

Using BERT, a Q&A model can be trained by learning two extra vectors that ma k and the end of the answer.

Concluding remarks

BERT ISSUES?

- The vanilla BERT (base) has **109,482,240** trainable parameters; with such a massive size, it can only trained by large corporations with massive resources.
- The sheer size also makes it extremely slow to train.
- The fine-tuning is not straight-forward and requires lots of tweaks and experimentation (for e.g. you must use the *same* tokenizer used during pre-training).

Hey! I never said that I was perfect!

Vanilla BERT cannot be used for natural language generation
(GPT can be used instead)

THANK YOU