Natural Language Processing

LLMs, Transformer, PEFT, RAG, LLMs Project Life Cycle

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Most illustrations in these slides are from the internet, will be used for an educational purpose.

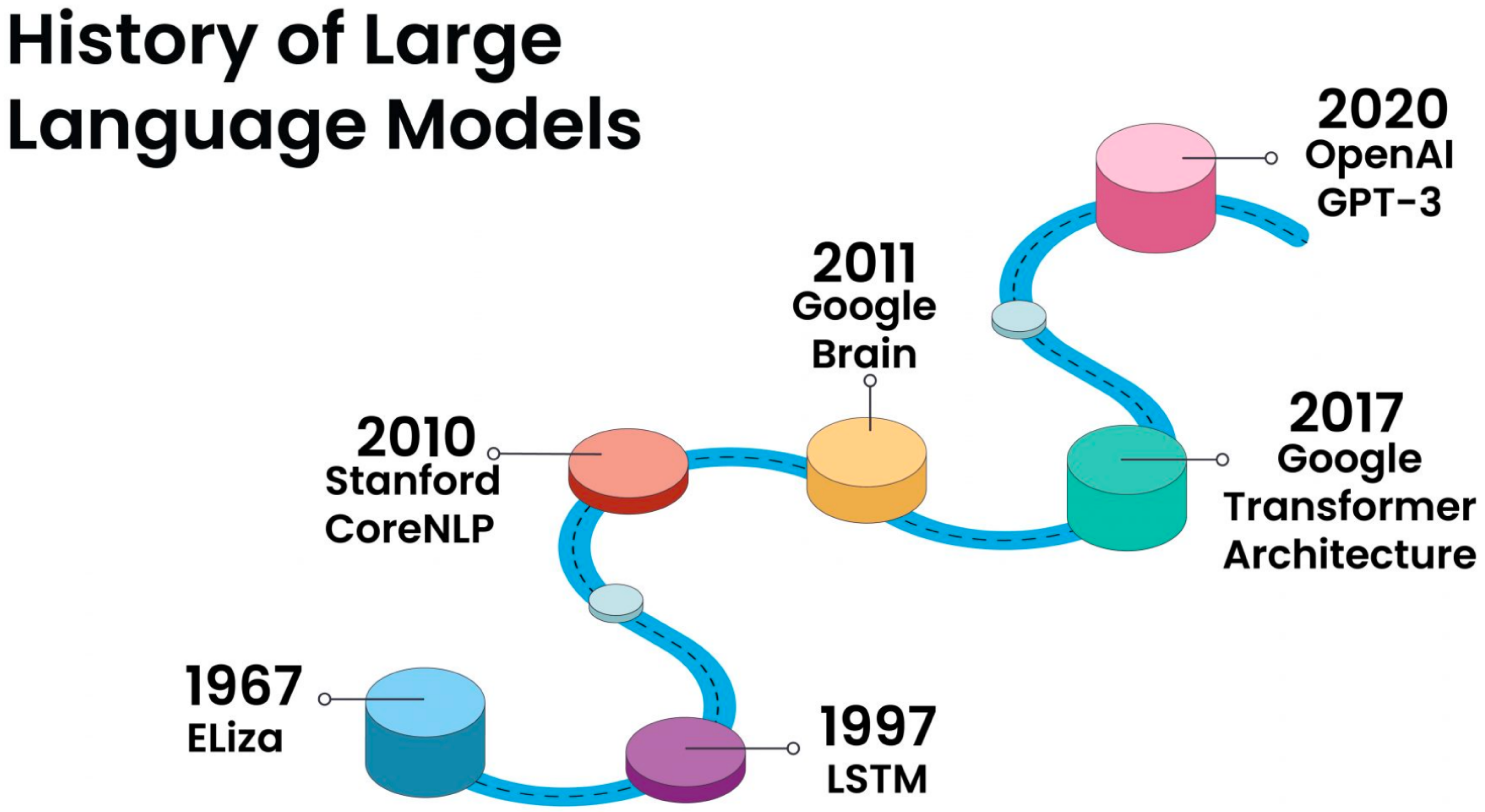


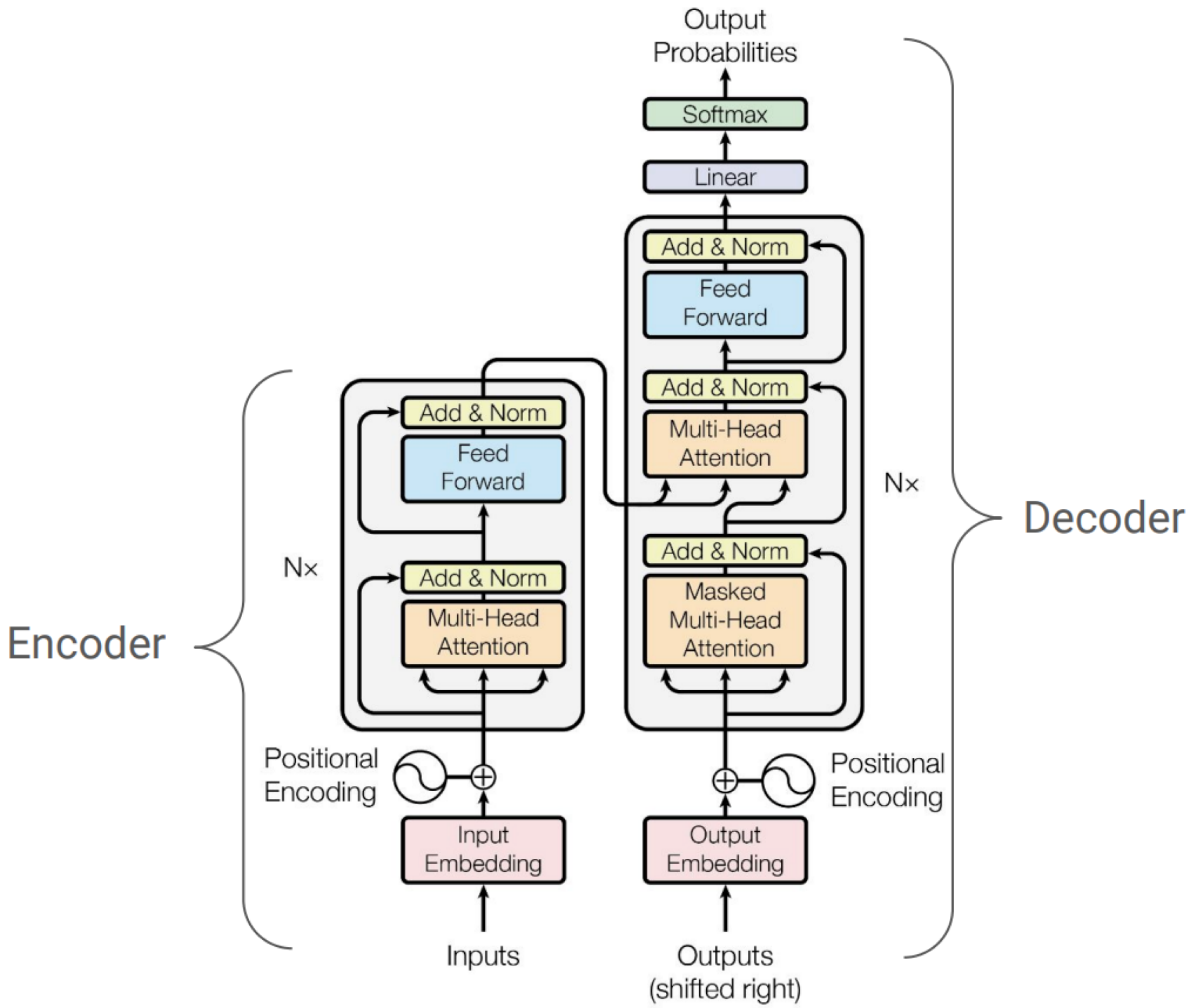
Fig. 1. History of Large Language Models from [2]

Transformer Block

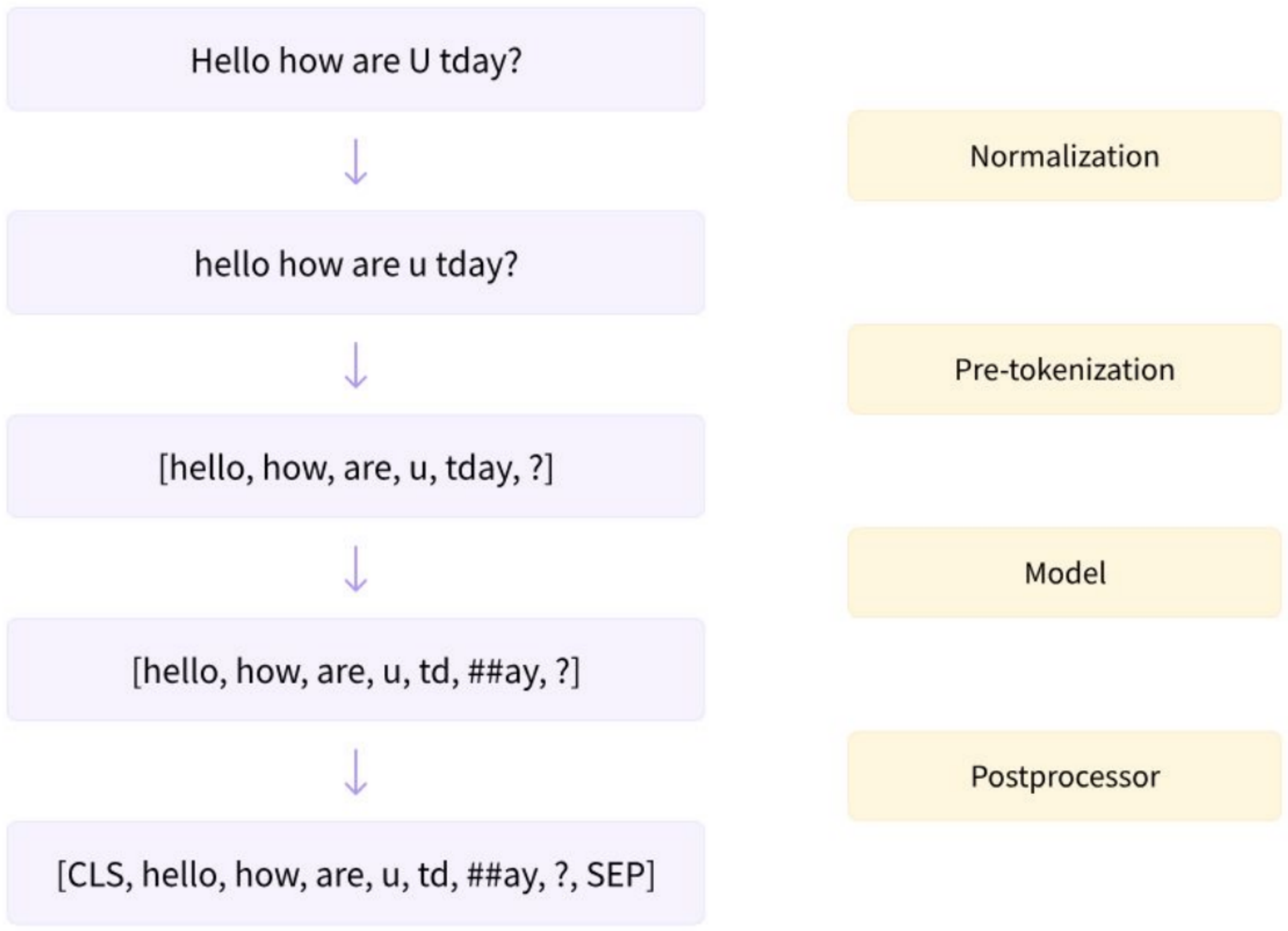
Next, we will learn exactly how the Transformer architecture works:

First, we will talk about the Encoder!

Next, we will go through the Decoder (which is quite similar)!



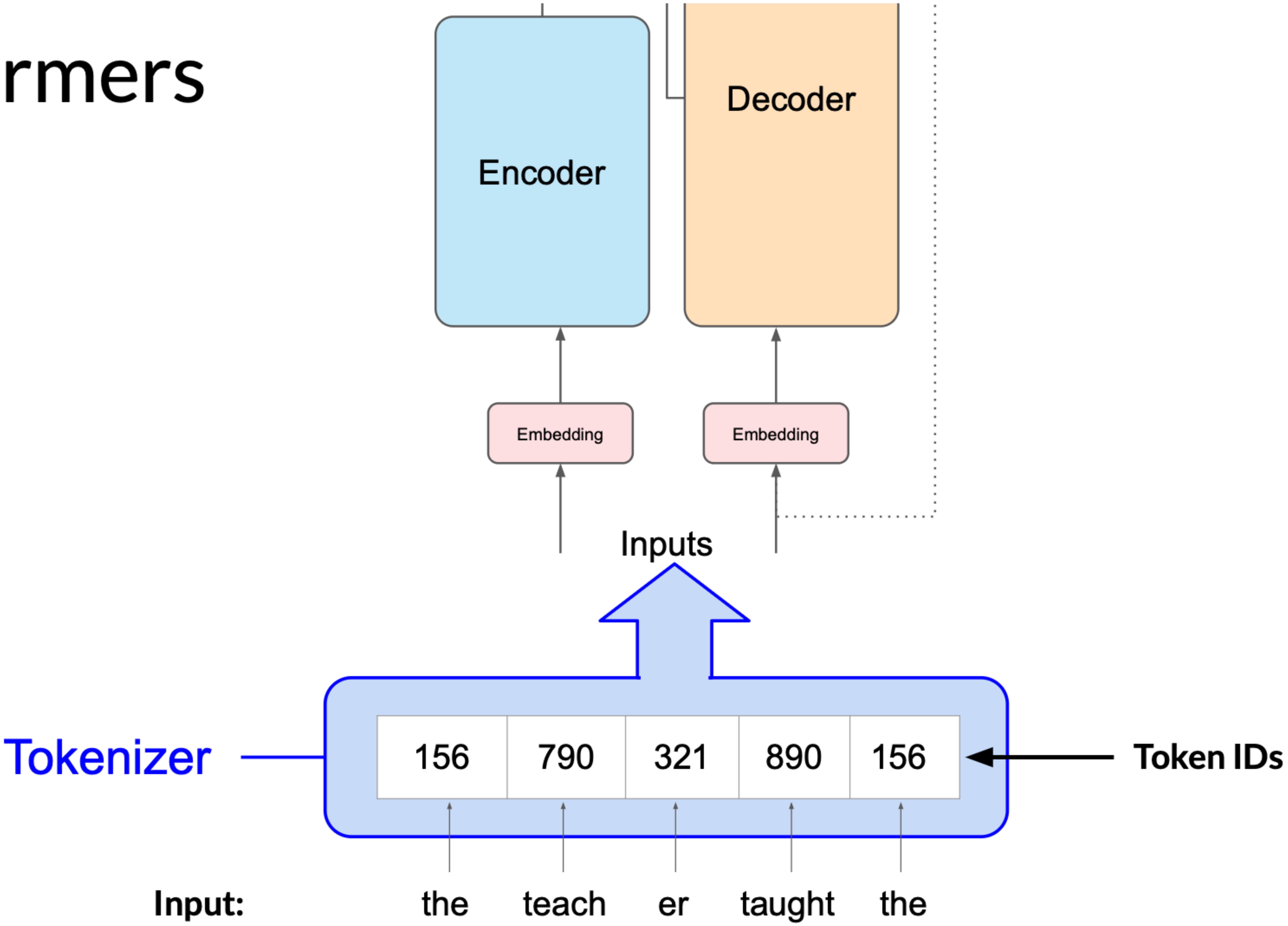
Tokenization: decomposing a sentence into a sequence of tokens



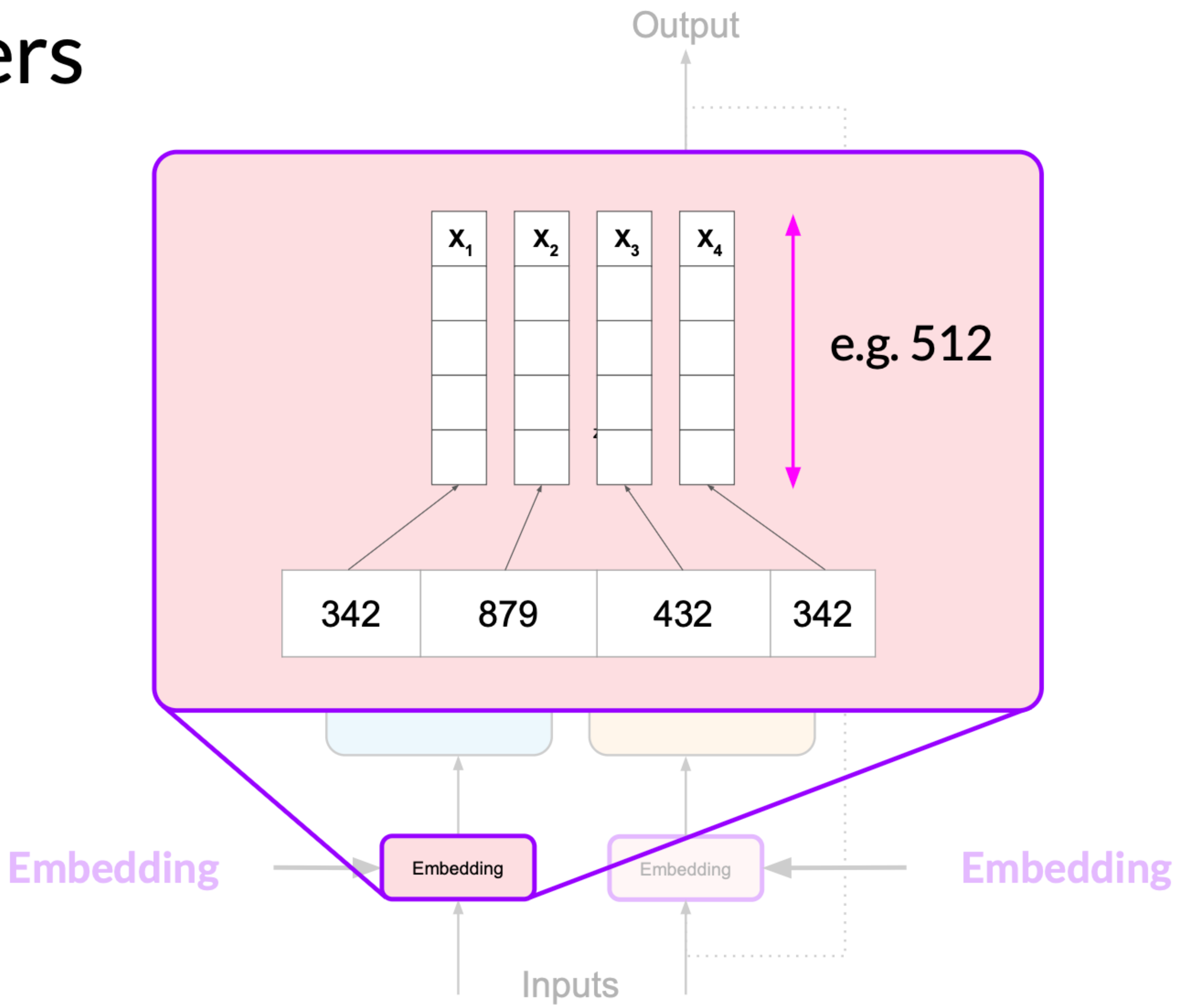
Every single explanation you will ever see about Language Models use **words**, **BUT** in reality the unit object is **tokens**

Words != Tokens

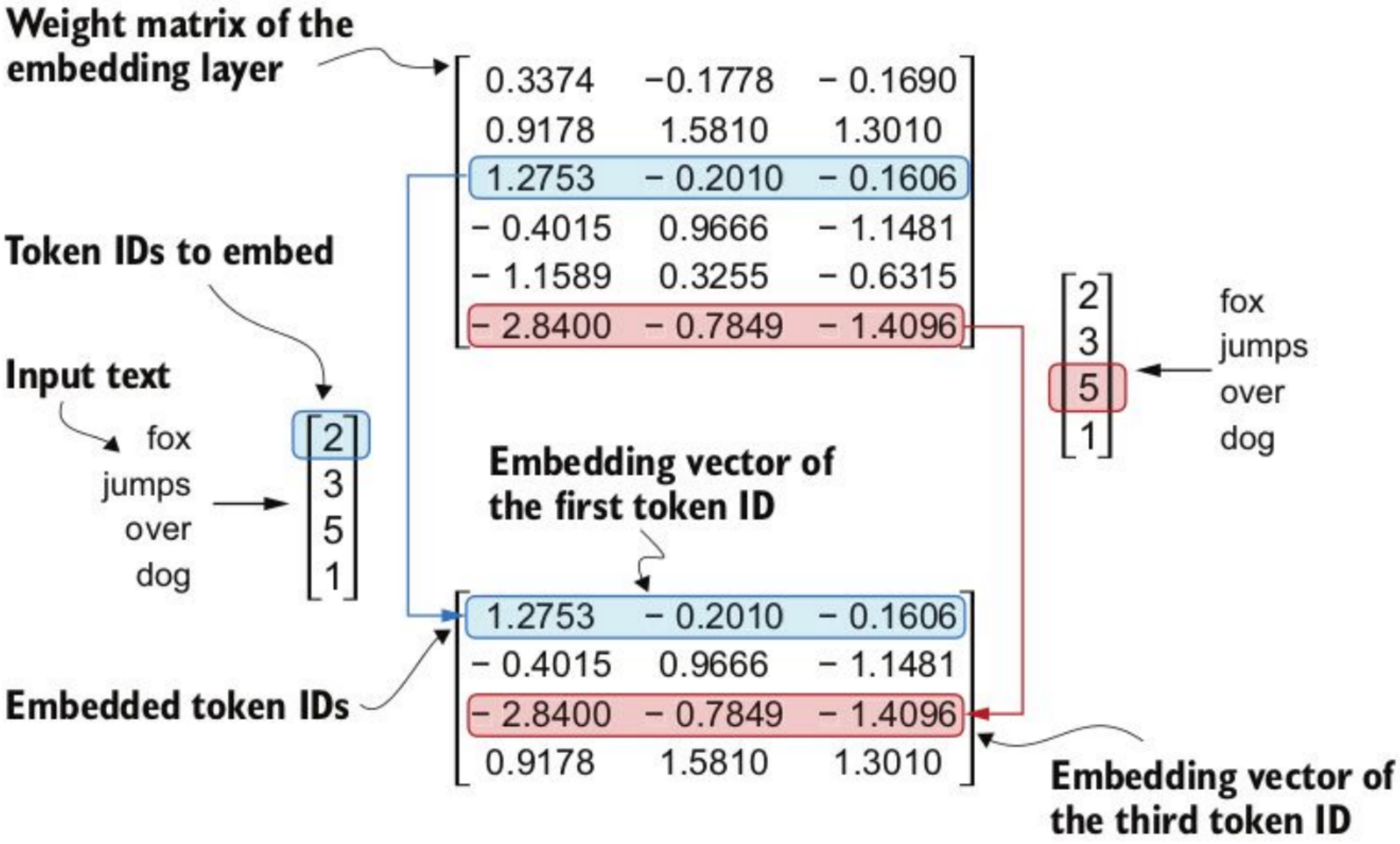
Transformers



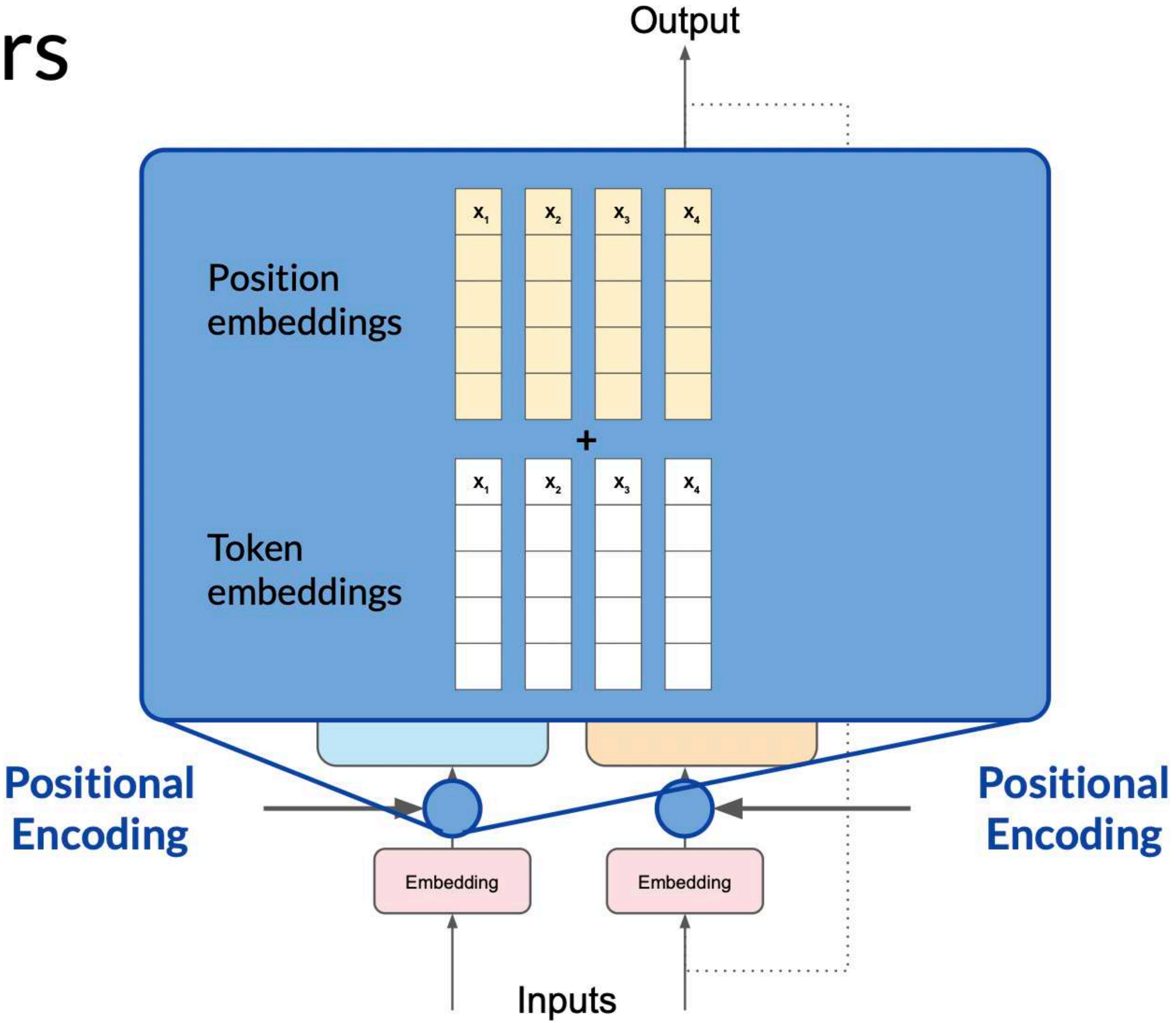
Transformers

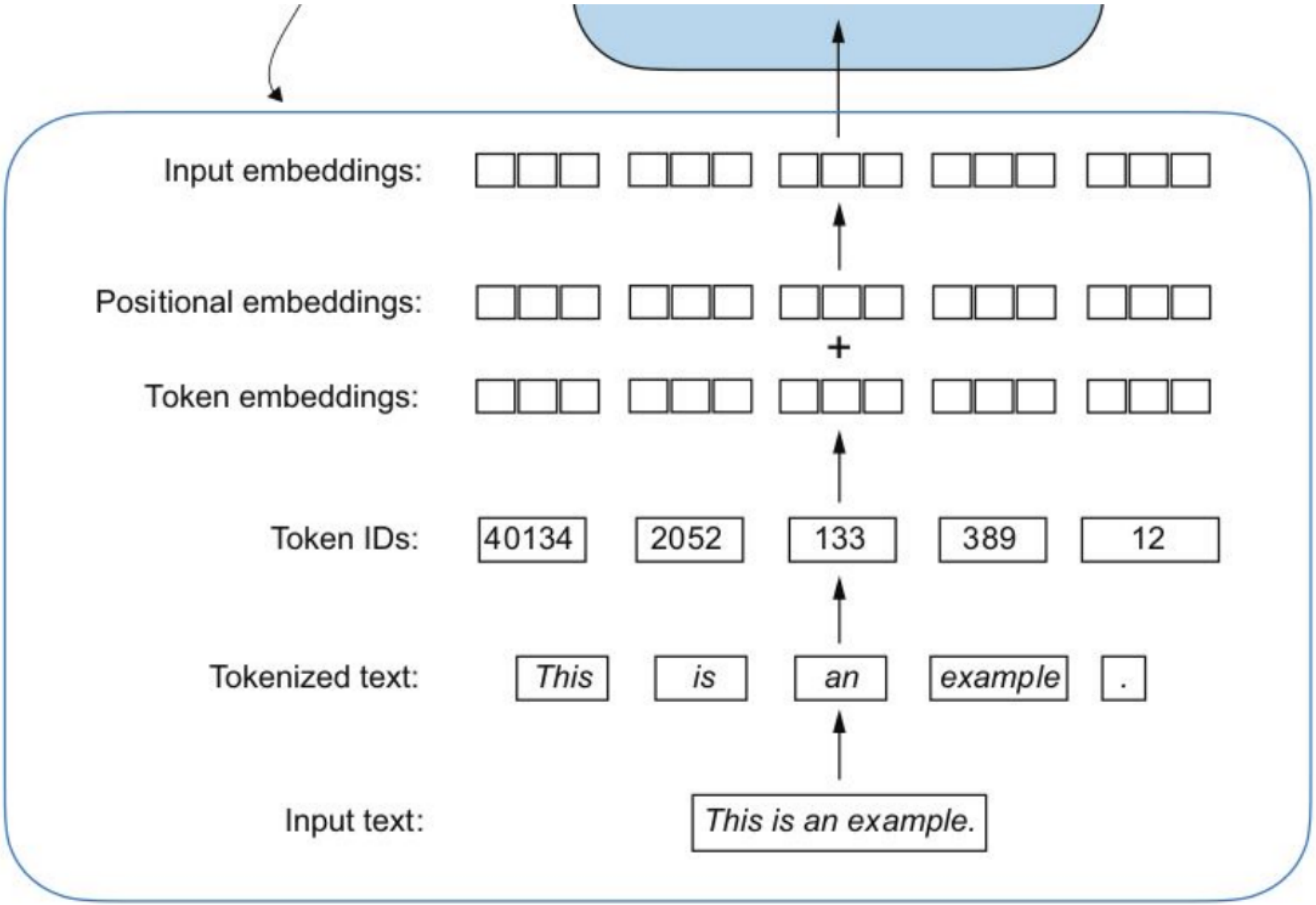


From text to vectors



Transformers





Input embeddings:
Positional embeddings:
+
Token embeddings:
Token IDs:
40134
2052
133
389
12
Tokenized text:
This
is
an
example
.
Input text:
This is an example.

Statistics

The smallest GPT-2 models (117M and 125M parameters) use an embedding size of 768 dimensions.

The largest GPT-3 model (175B parameters) uses an embedding size of 12,288 dimensions.

A self-attention head

Input: an embedding vector x(i) for each token i

Output: a context vector z(i) for each token i

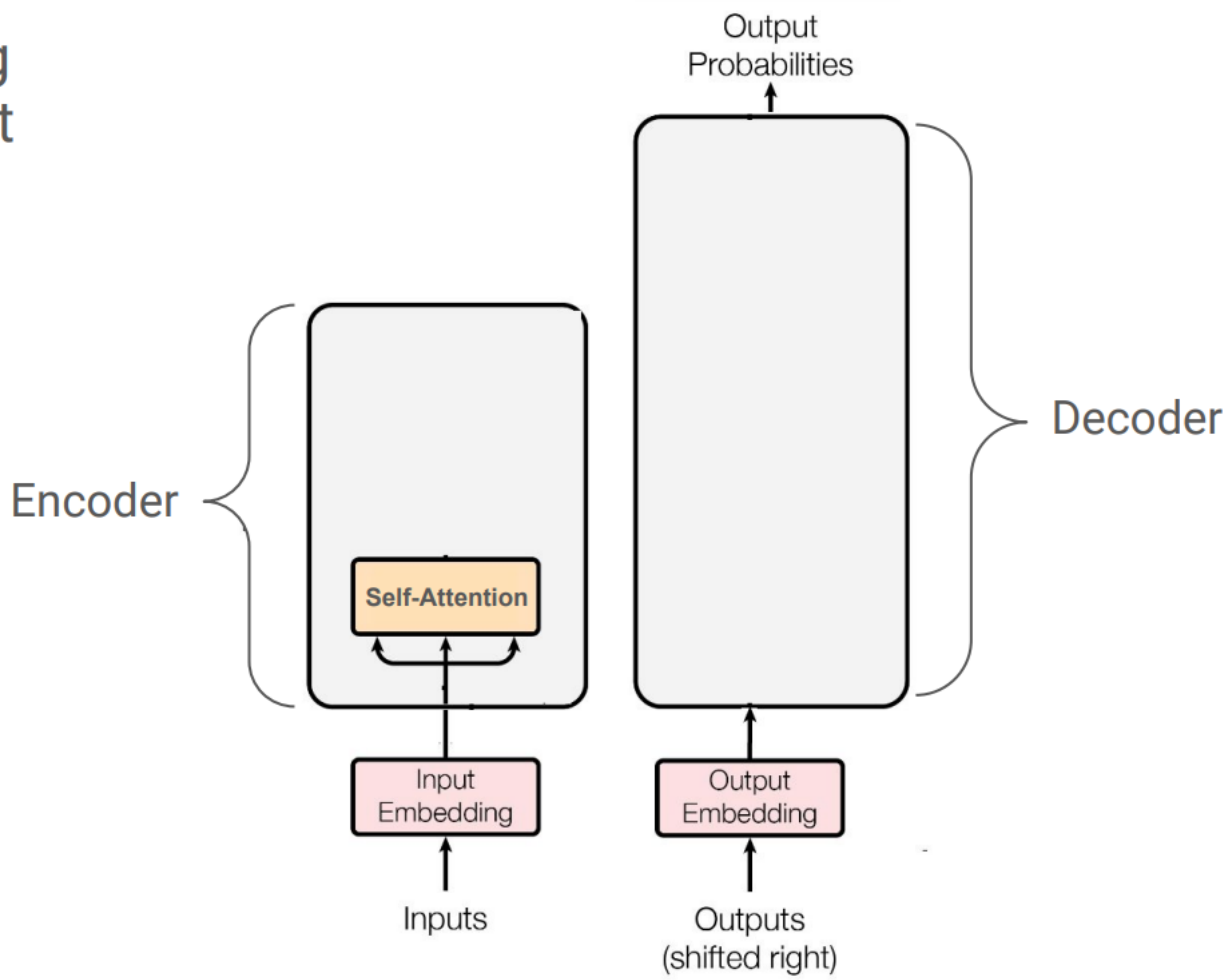
Intuition: z(i) gathers *contextual* information

Computing context vectors

Computing context vectors is very easy assuming we have computed **attention weights**: alpha(i,j) describes the importance of token j for token i.

Encoder: Self-Attention

Self-Attention is the core building block of Transformer, so let's first focus on that!



Keys, queries, and values

Input: an embedding vector x(i) for each token i

Output: for each token i:

- A *query* vector q(i), describing the information token i is interested in,
- A *key* vector k(i), whose goal is to match the relevant queries for token i,
- A *value* vector v(i), describing the information contained by token i.

Recipe for (Vectorized) Self-Attention in the Transformer Encoder

- Step 1: With embeddings stacked in X, calculate queries, keys, and values.

$$Q = XW^Q \qquad K = XW^K \qquad V = XW^V$$

- Step 2: Calculate attention score between query and keys.

$$E = QK^T$$

- Step 3: Take the softmax to normalize attention scores.

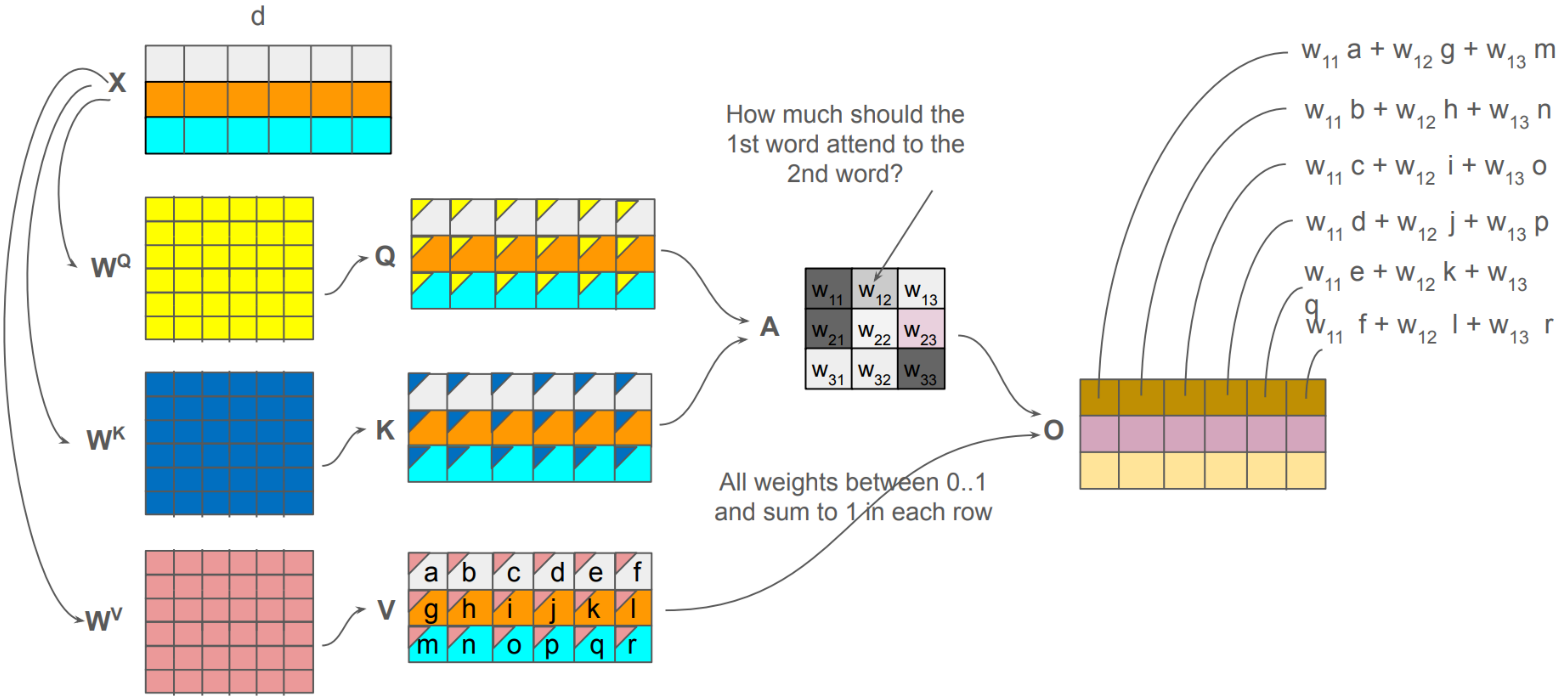
$$A = softmax(E)$$

- Step 4: Take a weighted sum of values.

$$Output = AV$$

$$\boxed{Output = softmax\left(QK^T\right)V}$$

In Pictures (N = 3, d = 6, h = 1)



Computing attention scores and weights

Now we focus on the core computation: attention scores and weights.

We first compute **attention scores**, and then normalise them into **attention weights**.