الجامعة السورية الخاصة
SYRIAN PRIVATE UNIVERSITY

الذكاء الصنعي العملي | كلية الهندسة | المحاضرة الثالثة

Transformers:
Exploring Transformers Through BERT

د. رياض سنبل

BERT

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

2018

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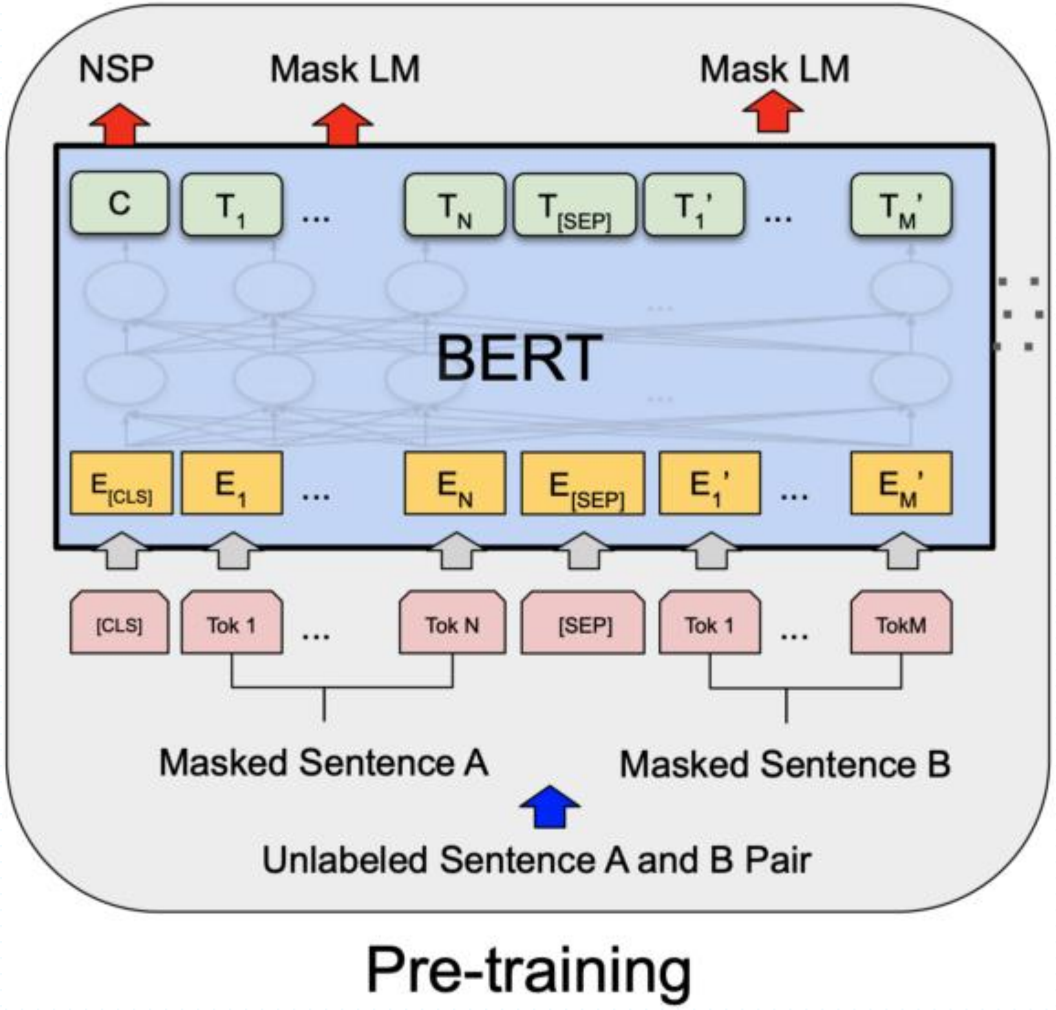
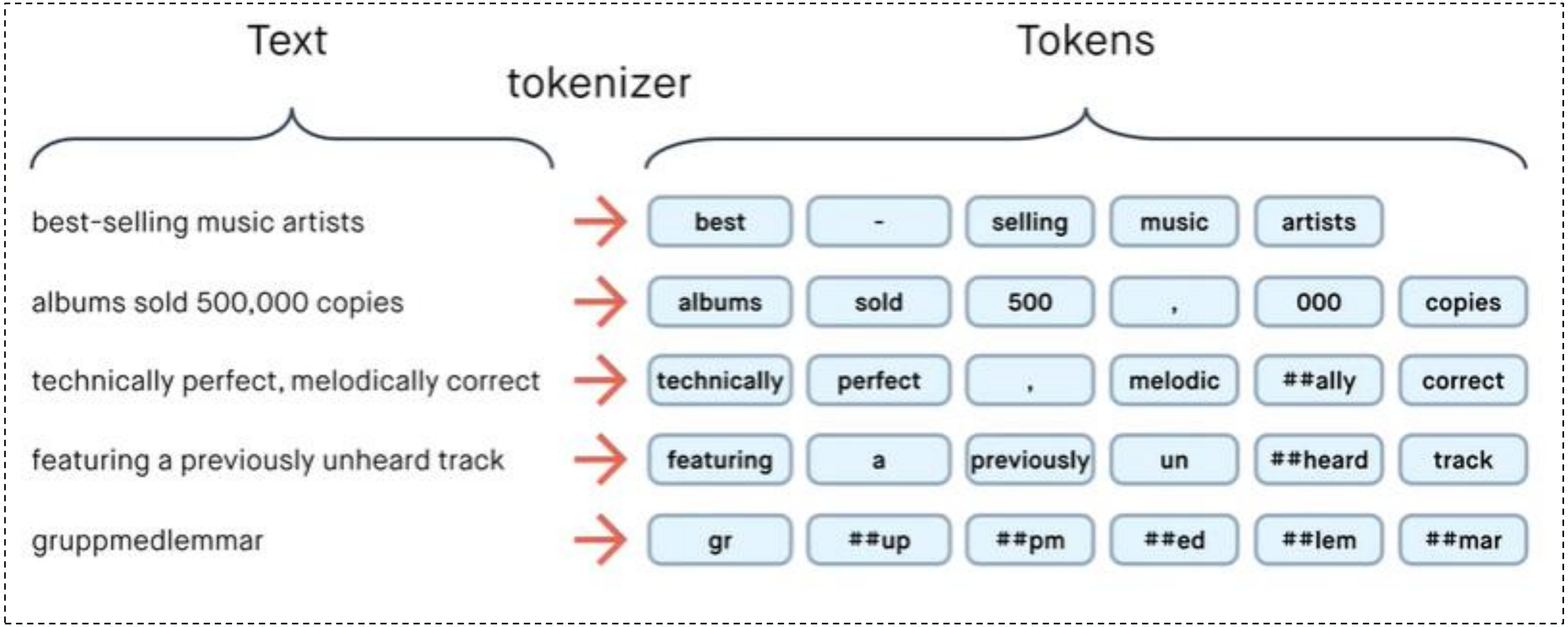
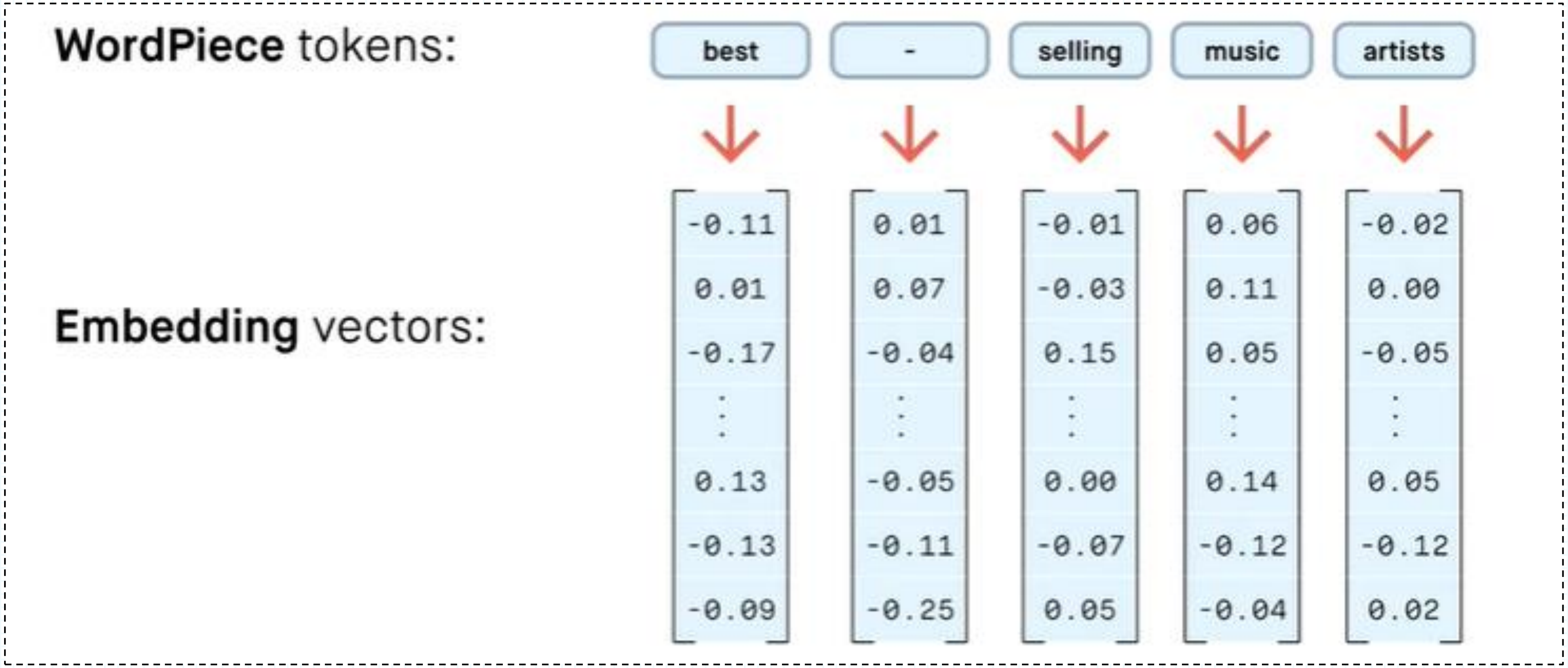
Next Sentence Prediction



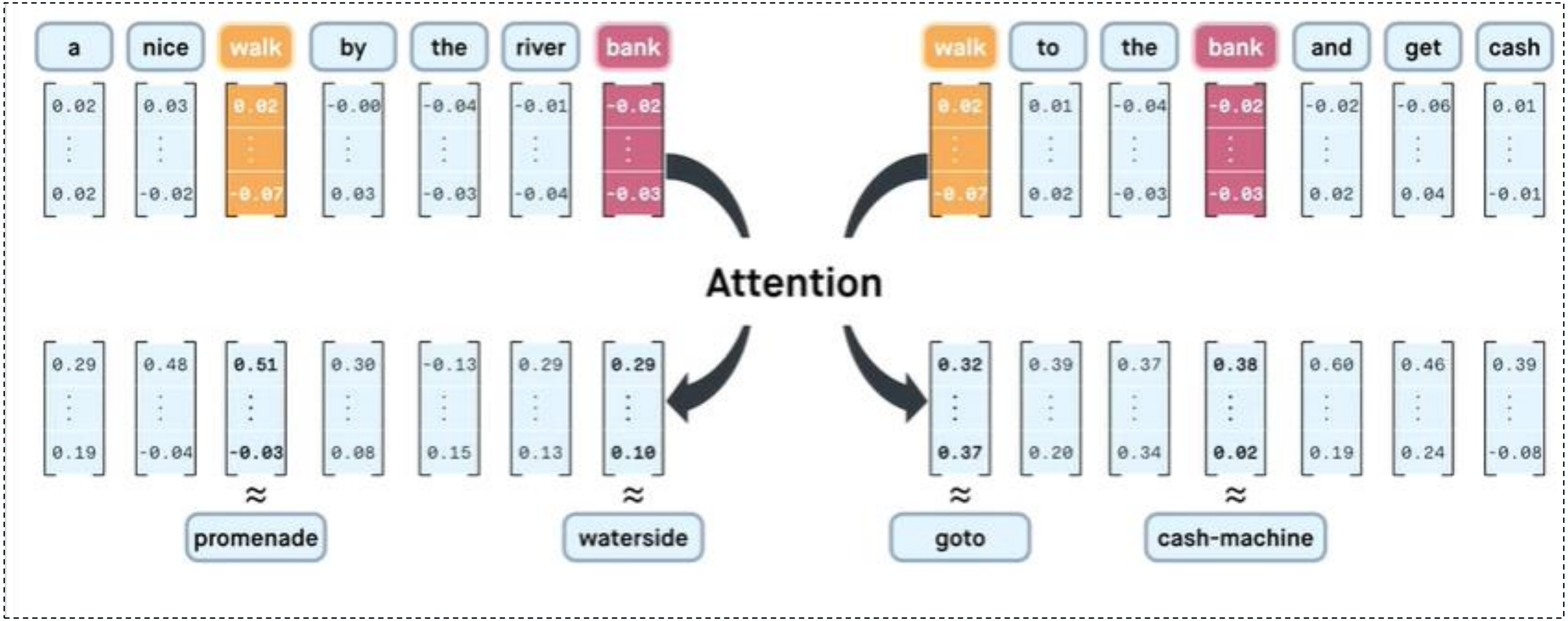
Tokenization

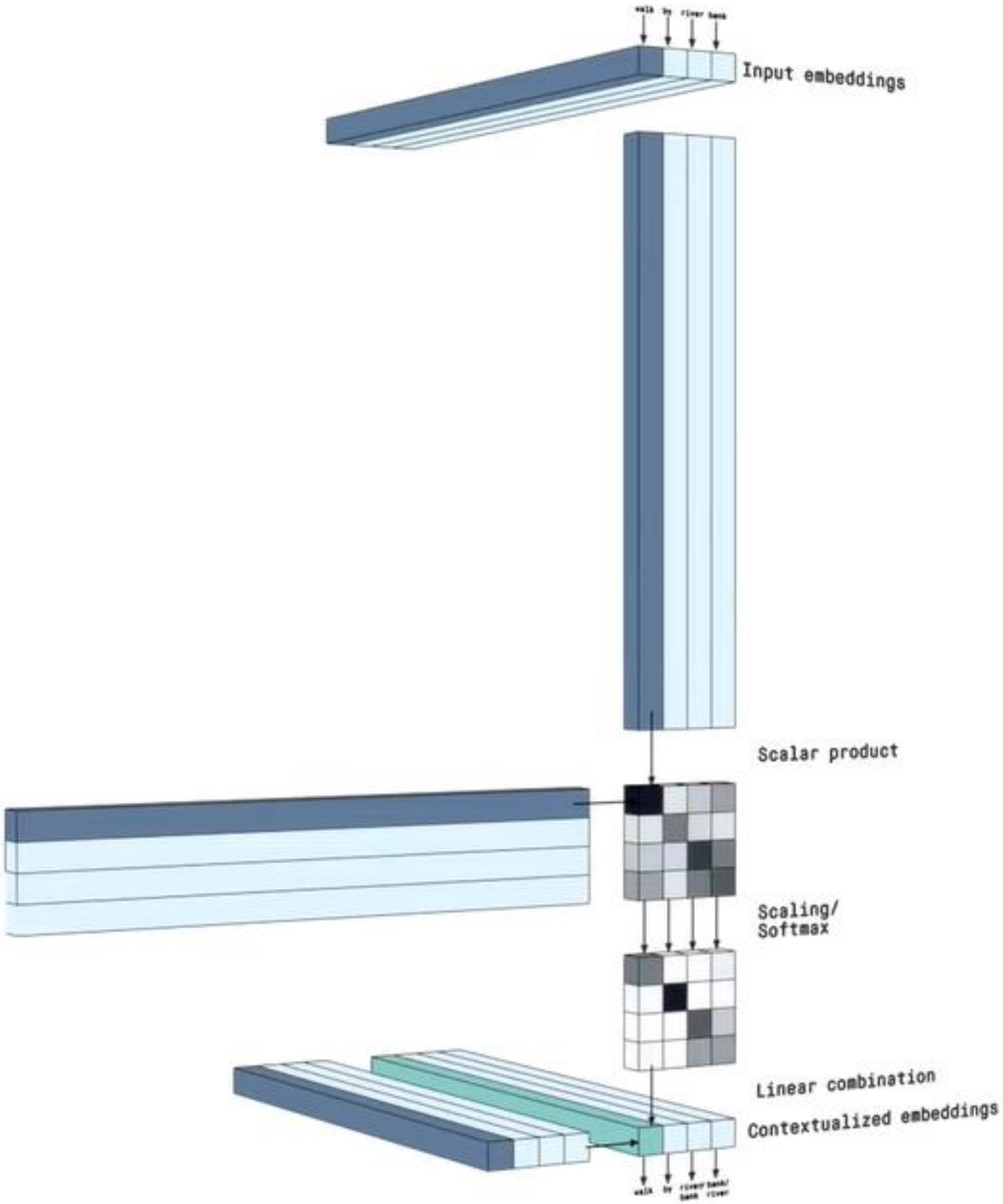


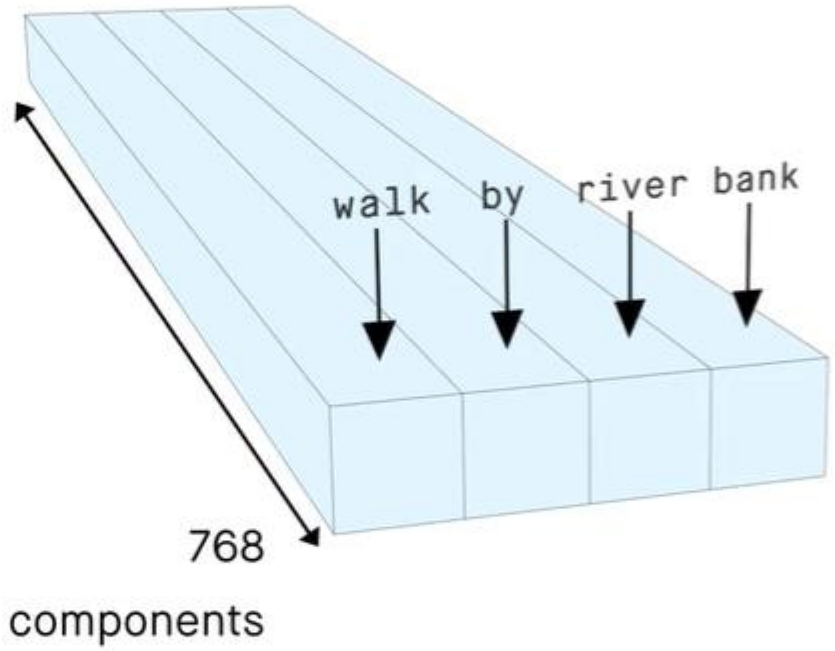
Initial Embedding

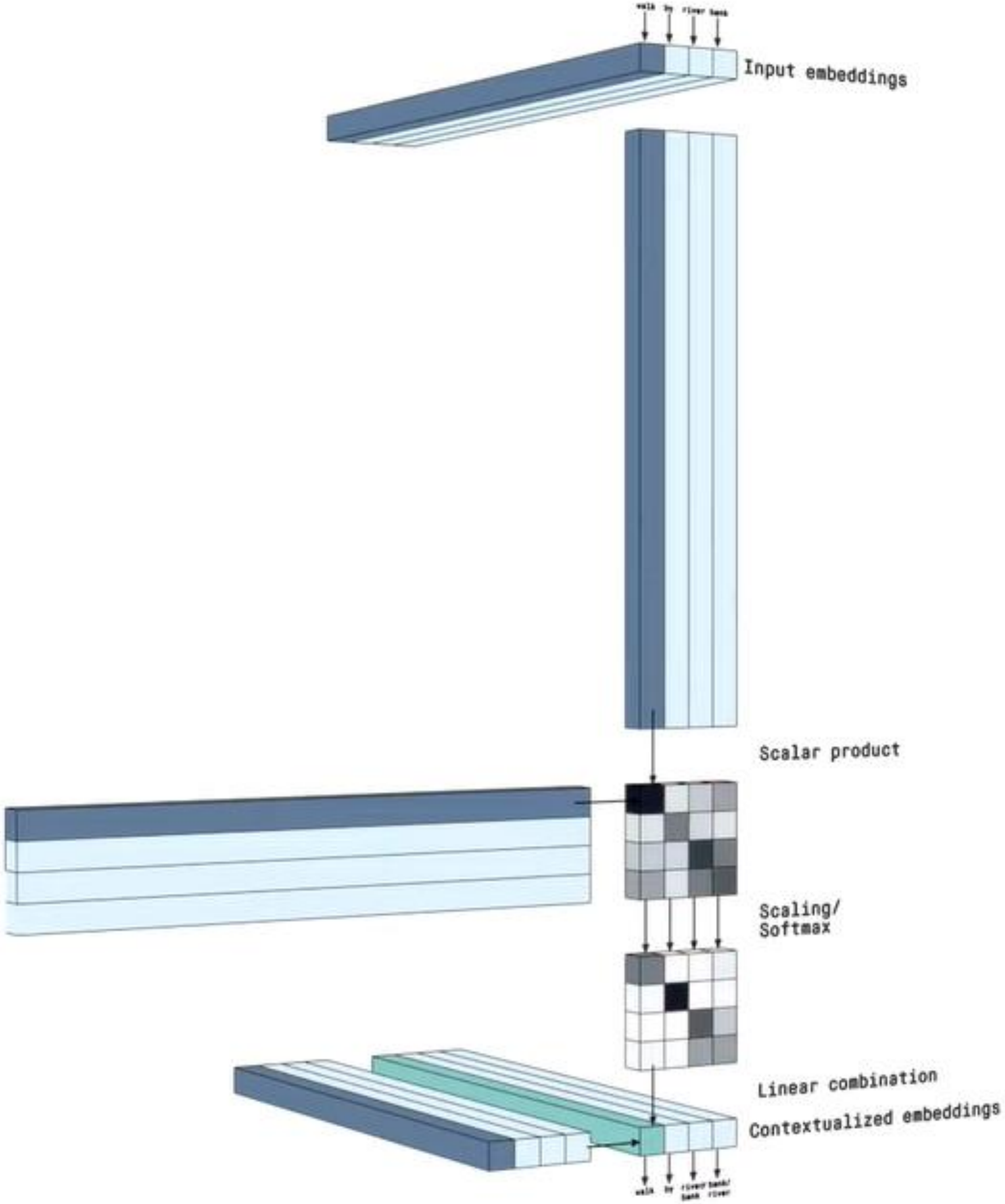


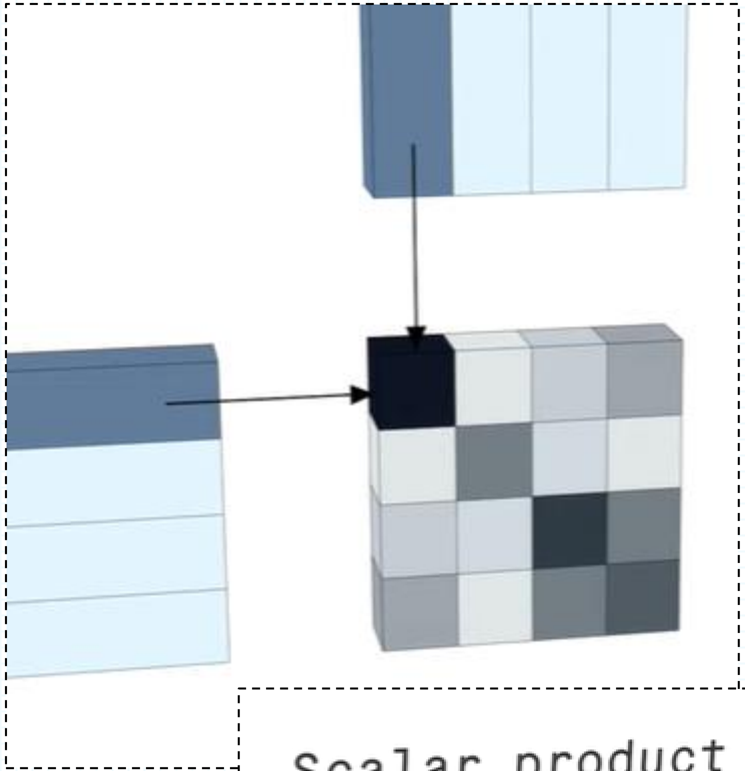
Contextual Embedding



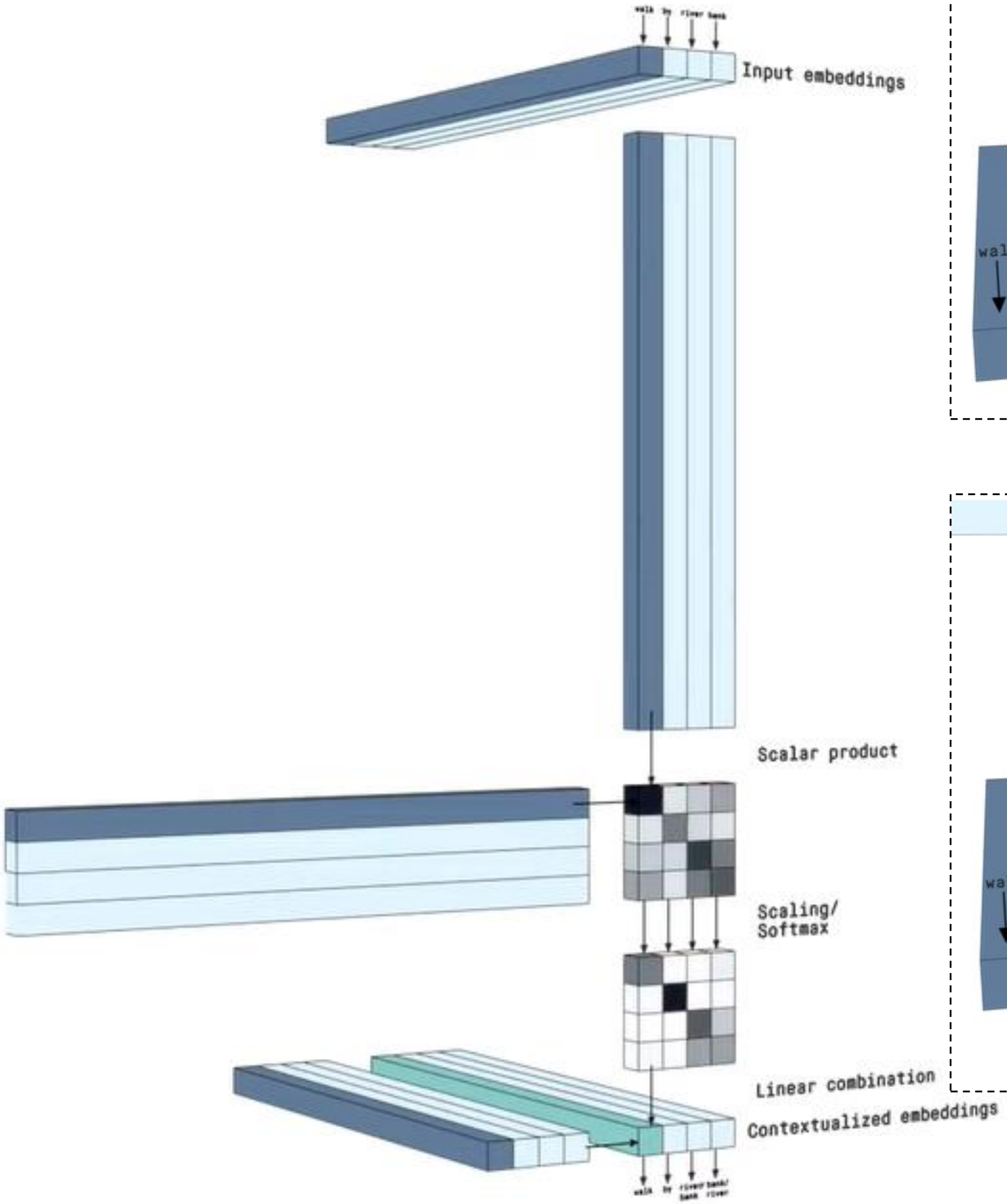

Input embeddings
Scalar product
Scaling/
Softmax
Linear combination
Contextualized embeddings

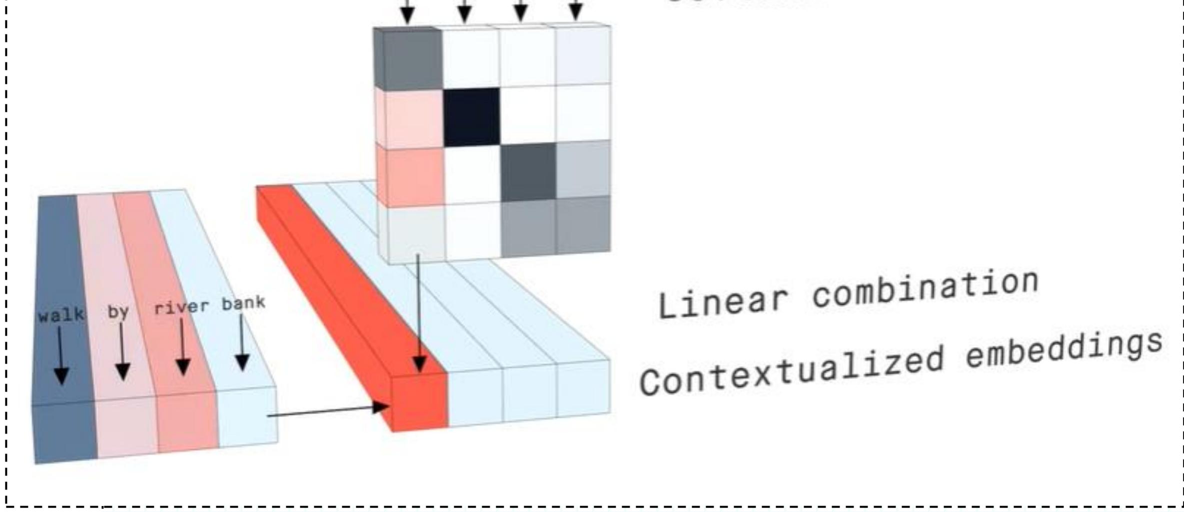

walk
by
river
bank
768
components

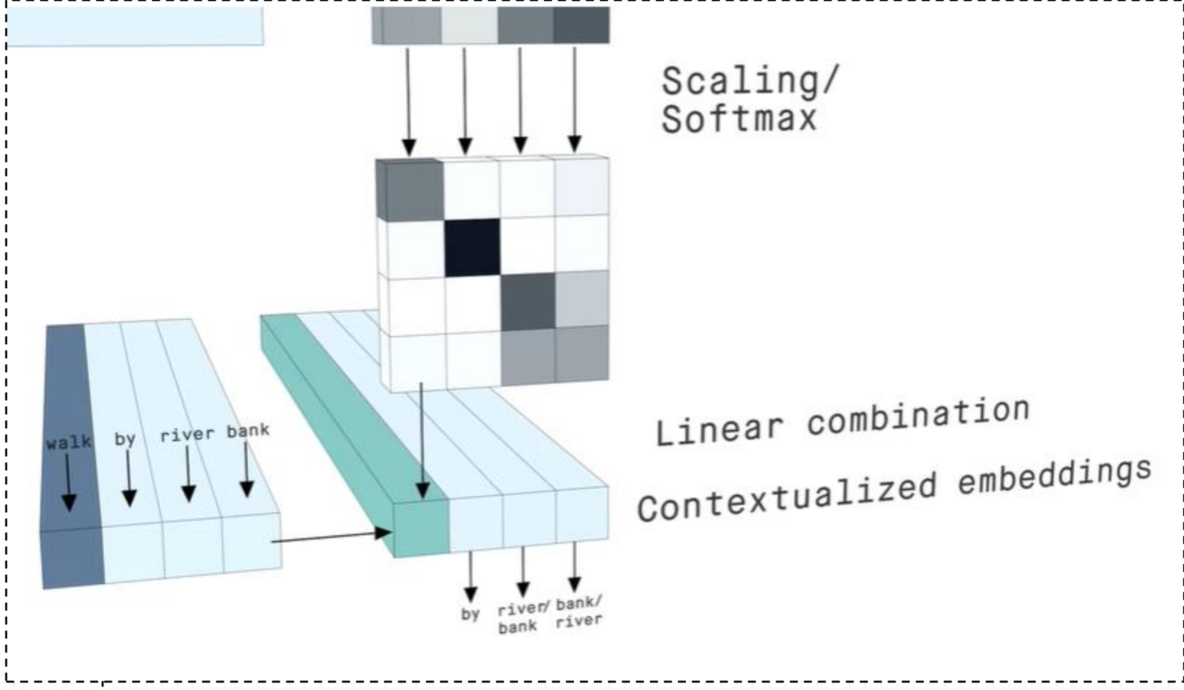




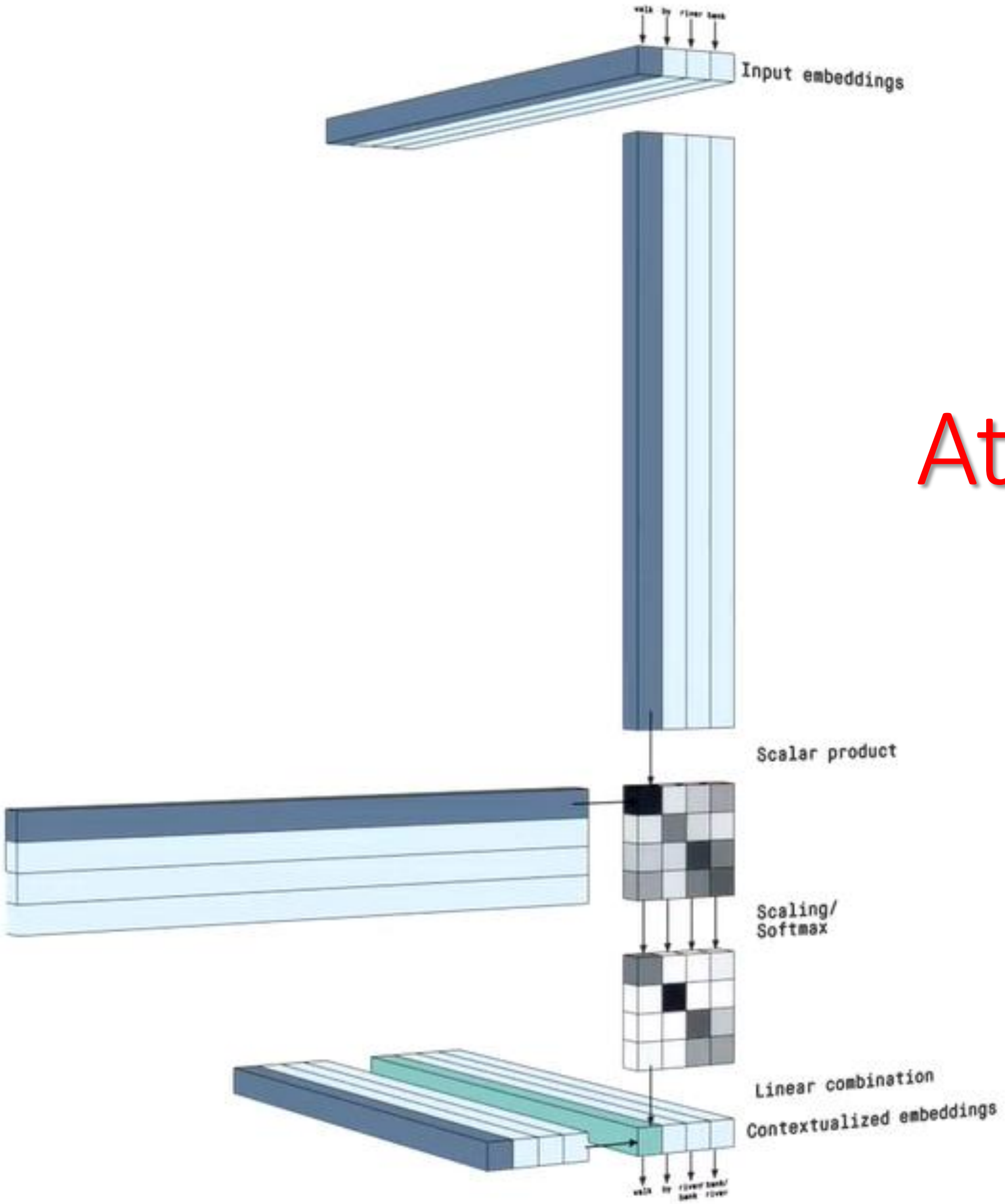
$$\frac{\text{Scalar product}}{\sqrt{\text{vector size}}}$$


Input embeddings
Scalar product
Scaling/
Softmax
Linear combination
Contextualized embeddings

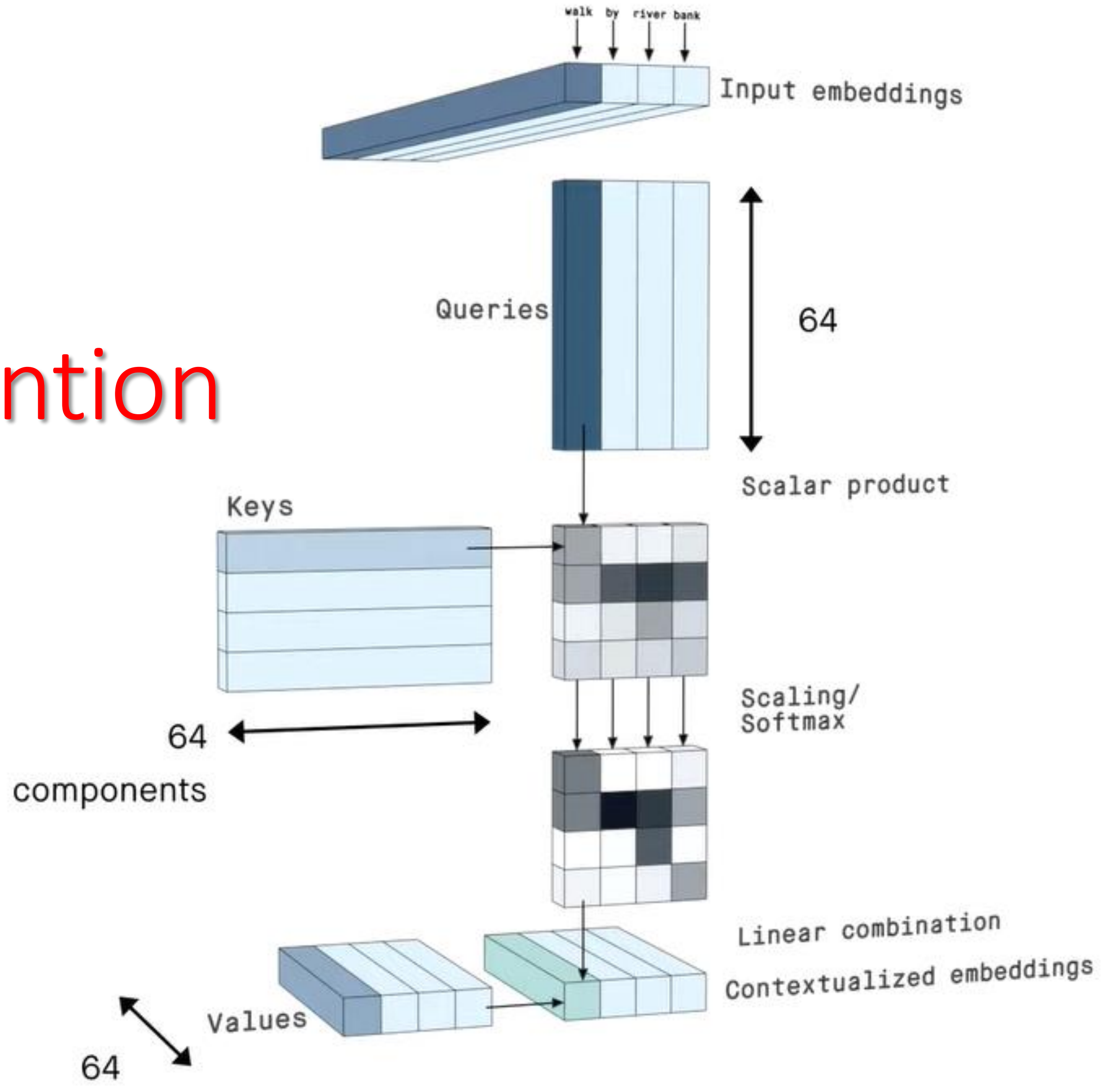

walk
by
river
bank
Linear combination
Contextualized embeddings


Scaling/
Softmax
walk
by
river
bank
Linear combination
Contextualized embeddings
by
river/
bank
bank/
river

Attention

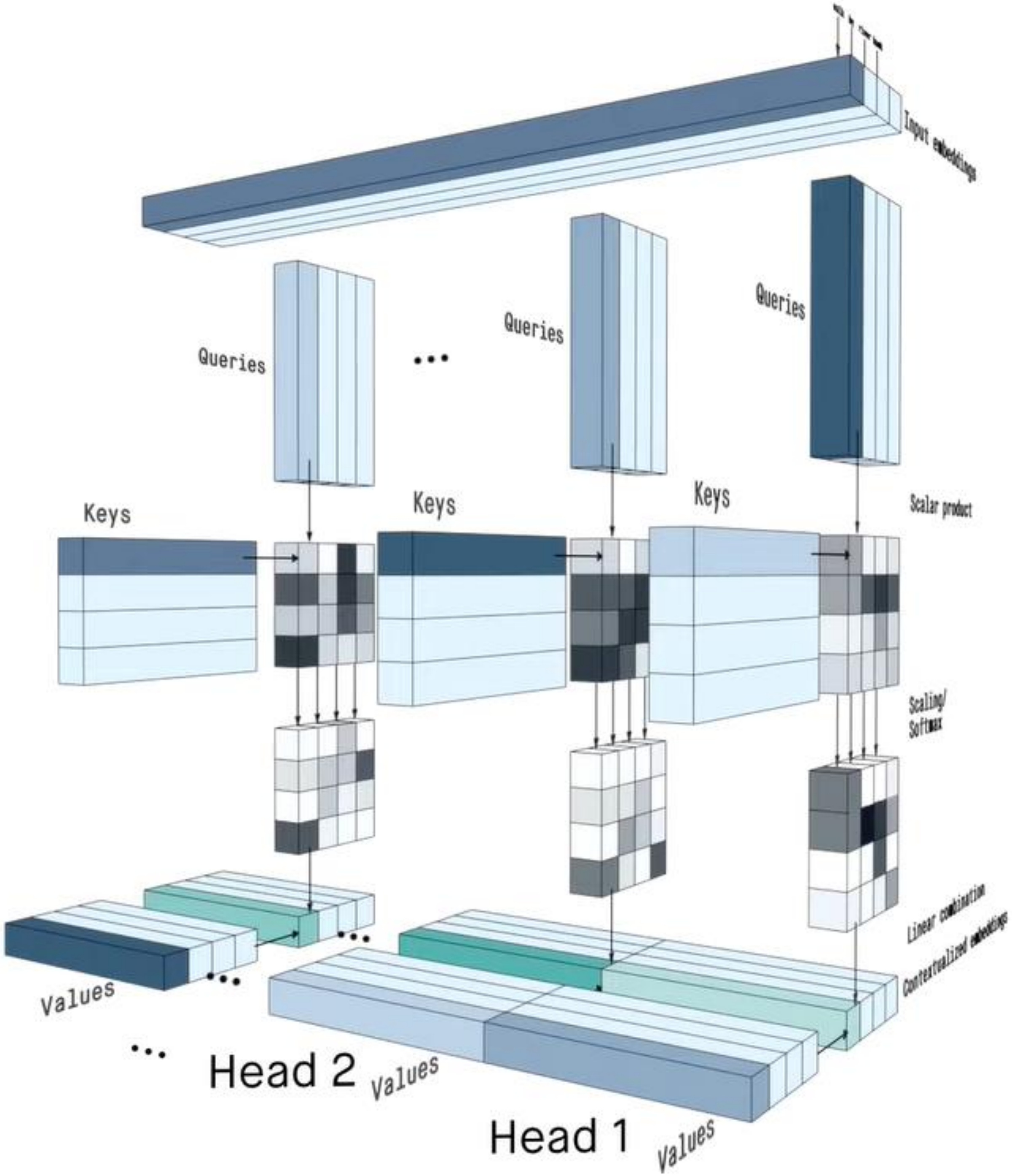


Input embeddings
Scalar product
Scaling/
Softmax
Linear combination
Contextualized embeddings

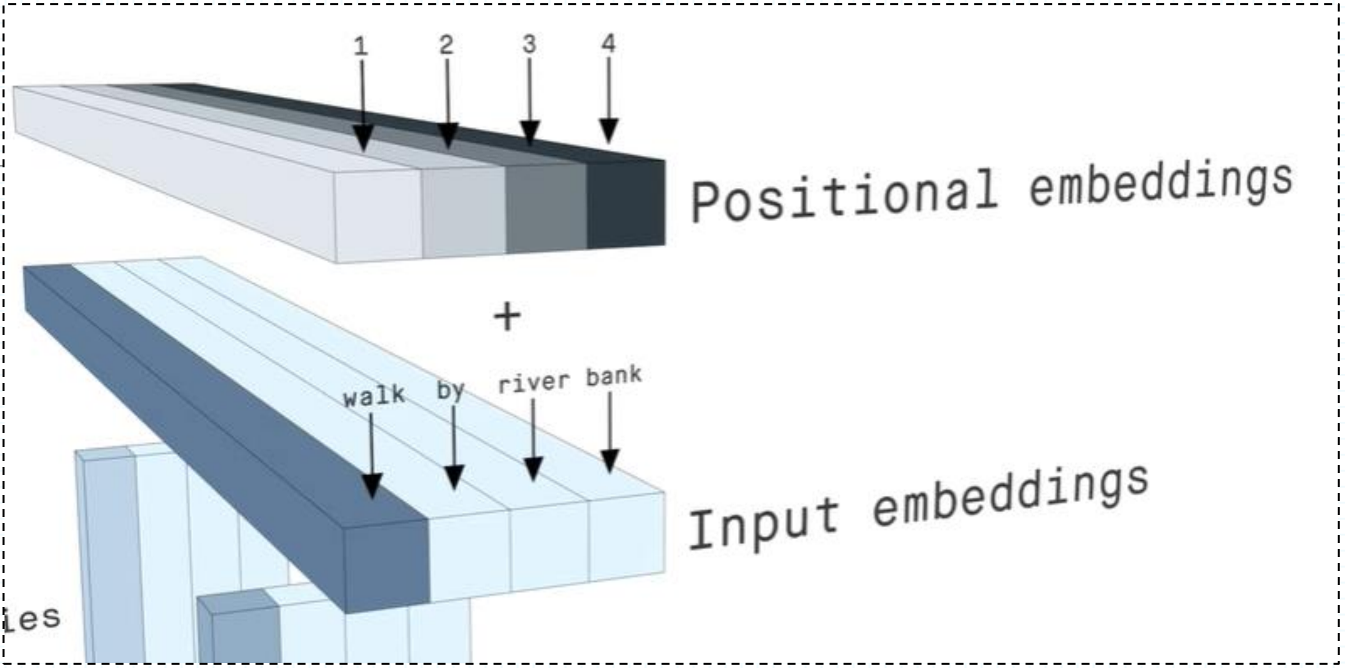


walk by river bank
Input embeddings
Queries
64
Scalar product
Keys
Scaling/
Softmax
64
components
Linear combination
Contextualized embeddings
Values
64

Multi-head attention



Enrich the input!



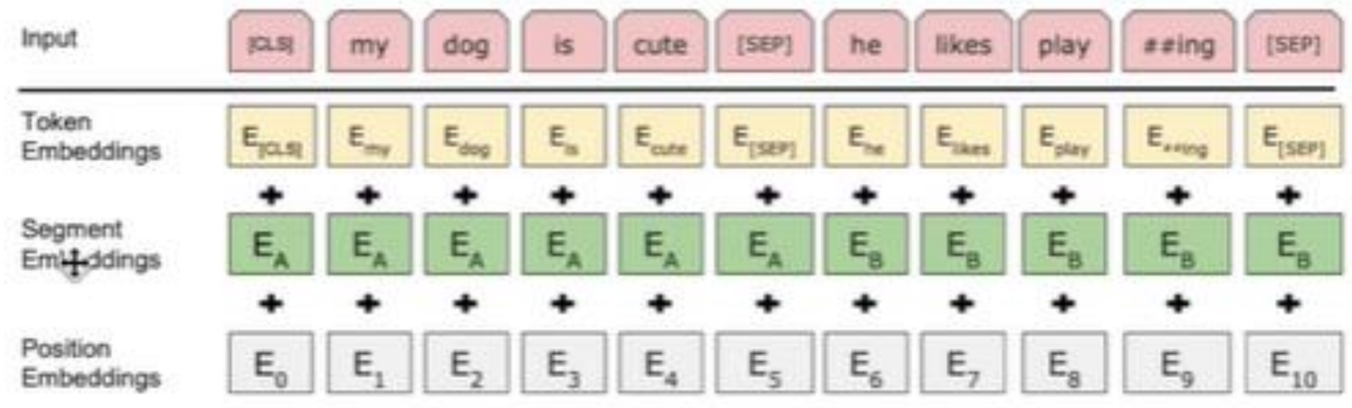
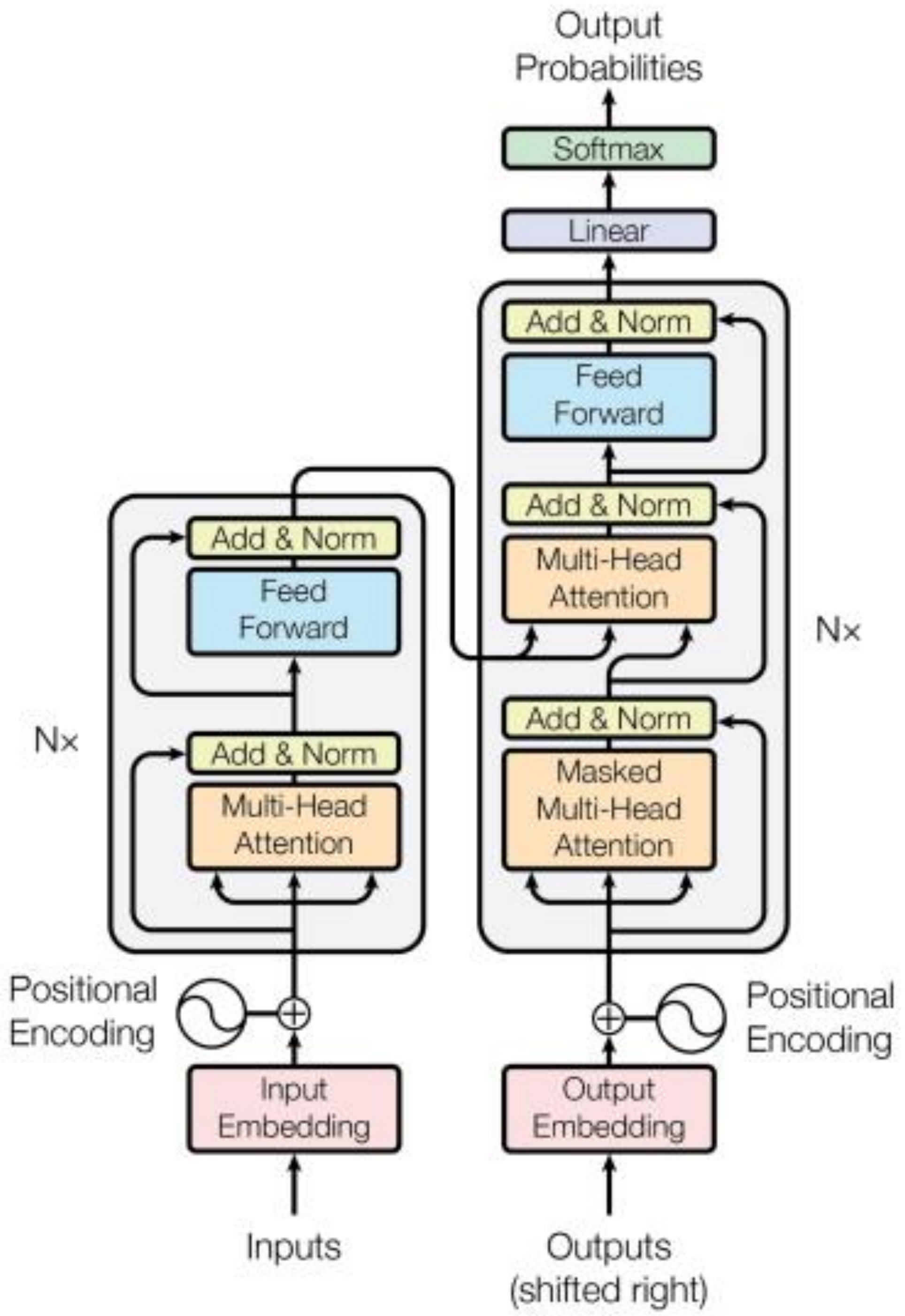


Figure 2: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

So.. What are Transformers in general!

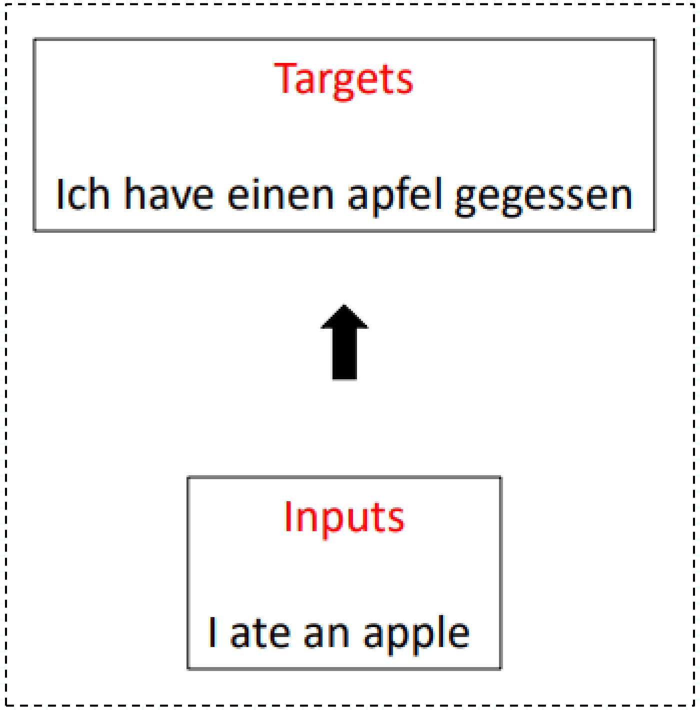
Transformers

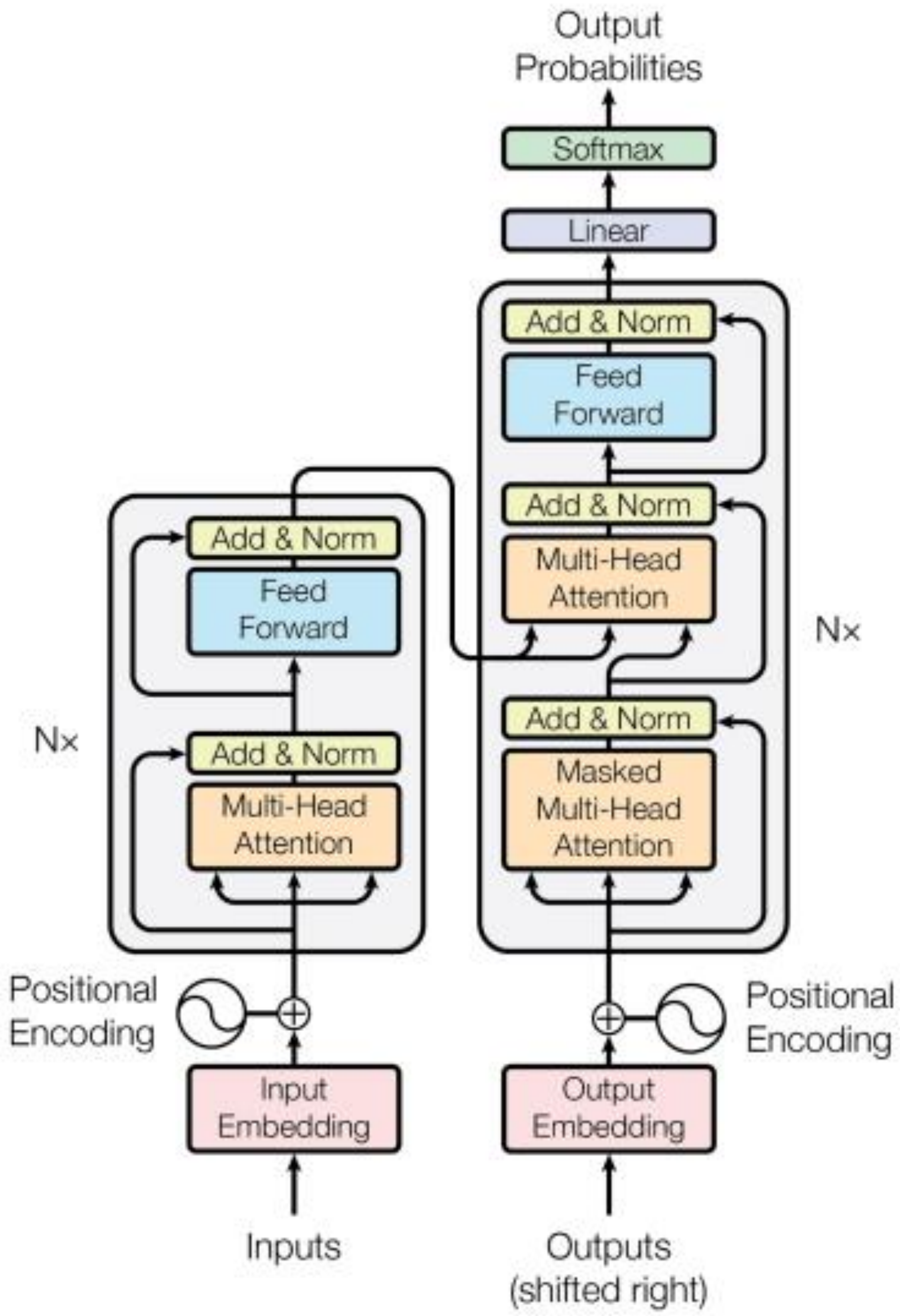
- Transformers are a type of neural network architecture that transforms or changes an input sequence into an output sequence.
- They do this by learning context and tracking relationships between sequence components.
- And break the problem into two parts:
  - An encoder (e.g., Bert)
  - A decoder (e.g., GPT)



Transformers

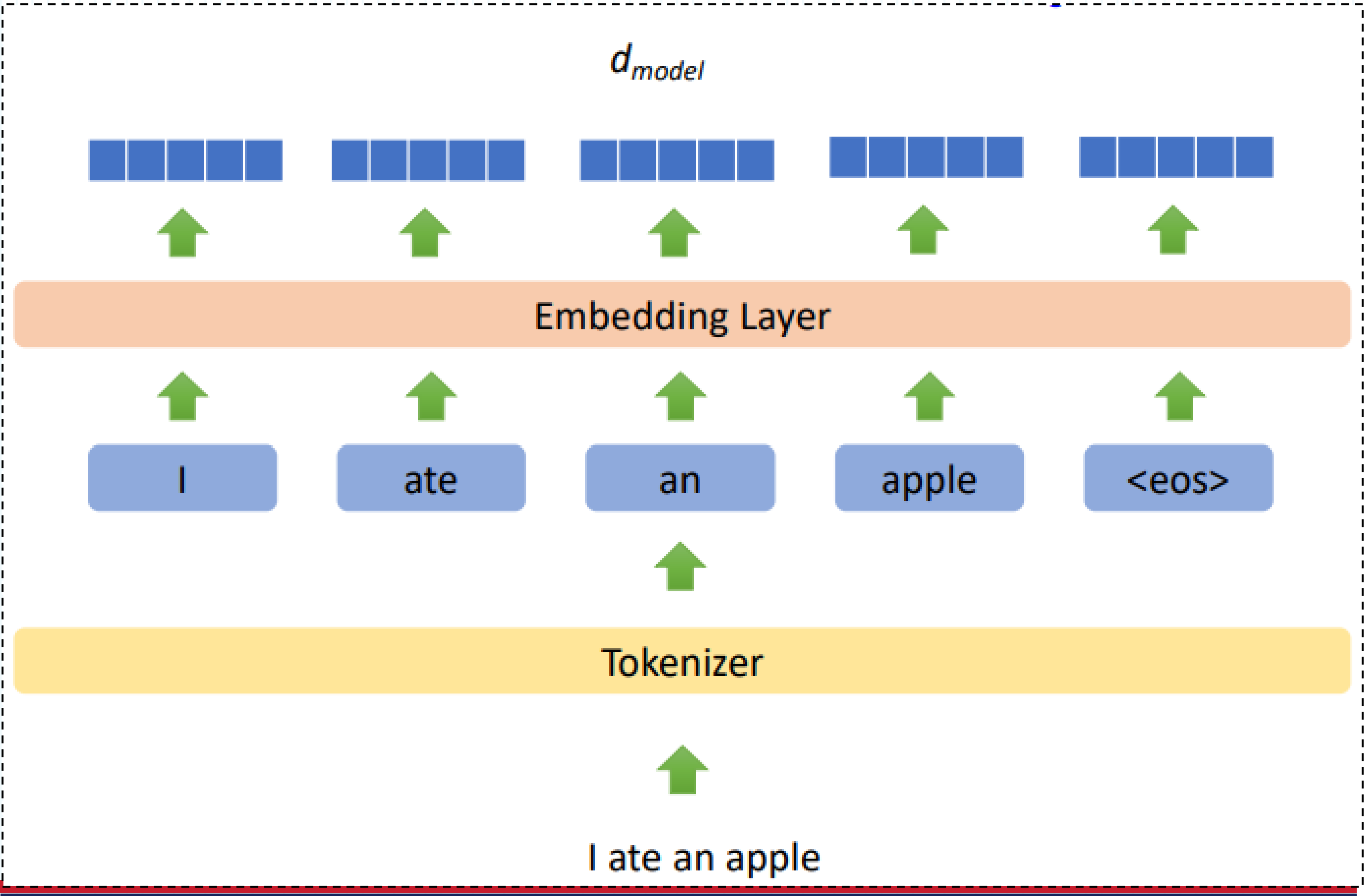
- Example: Machine Translation

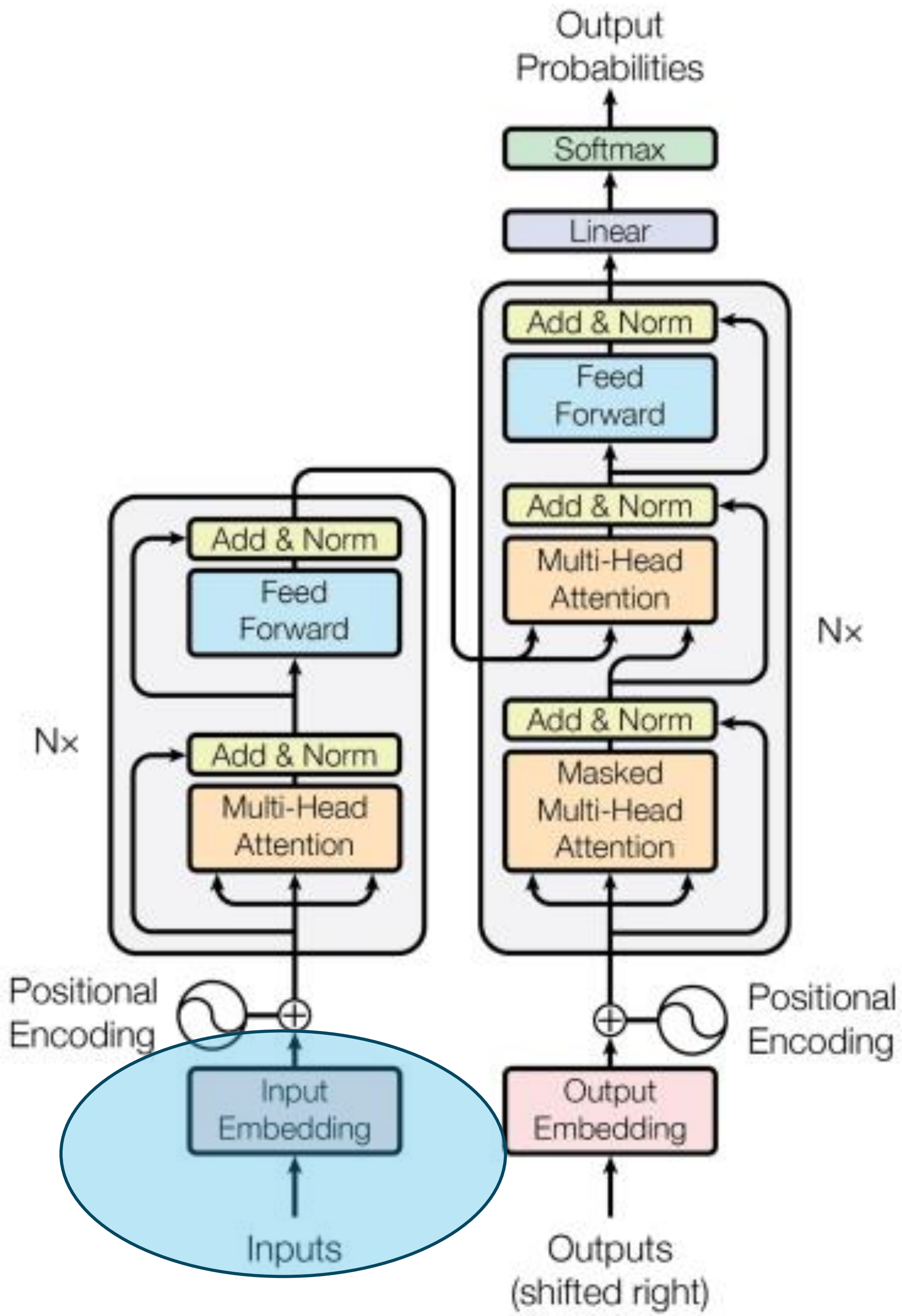




Transformers

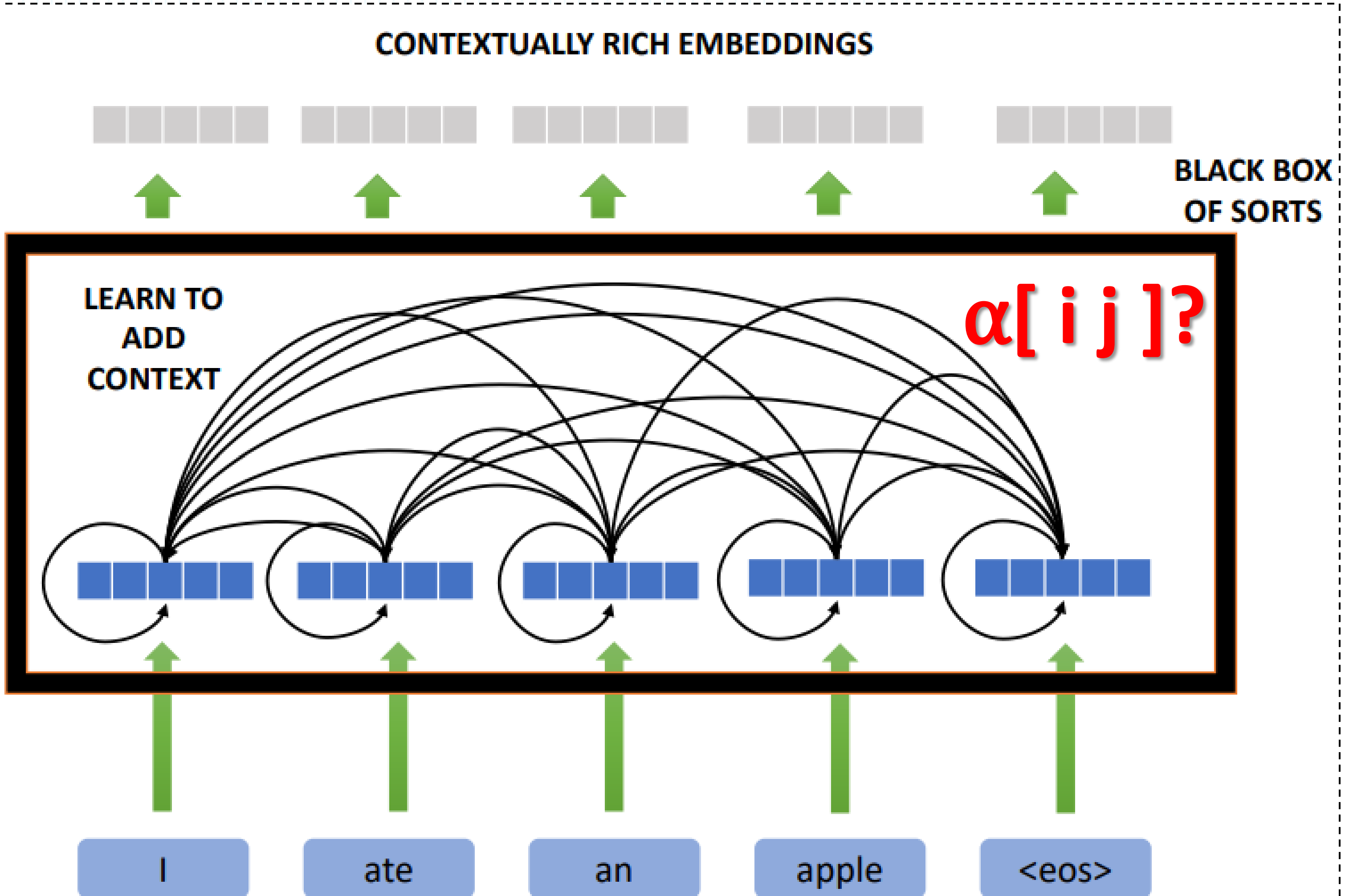
- Processing Input

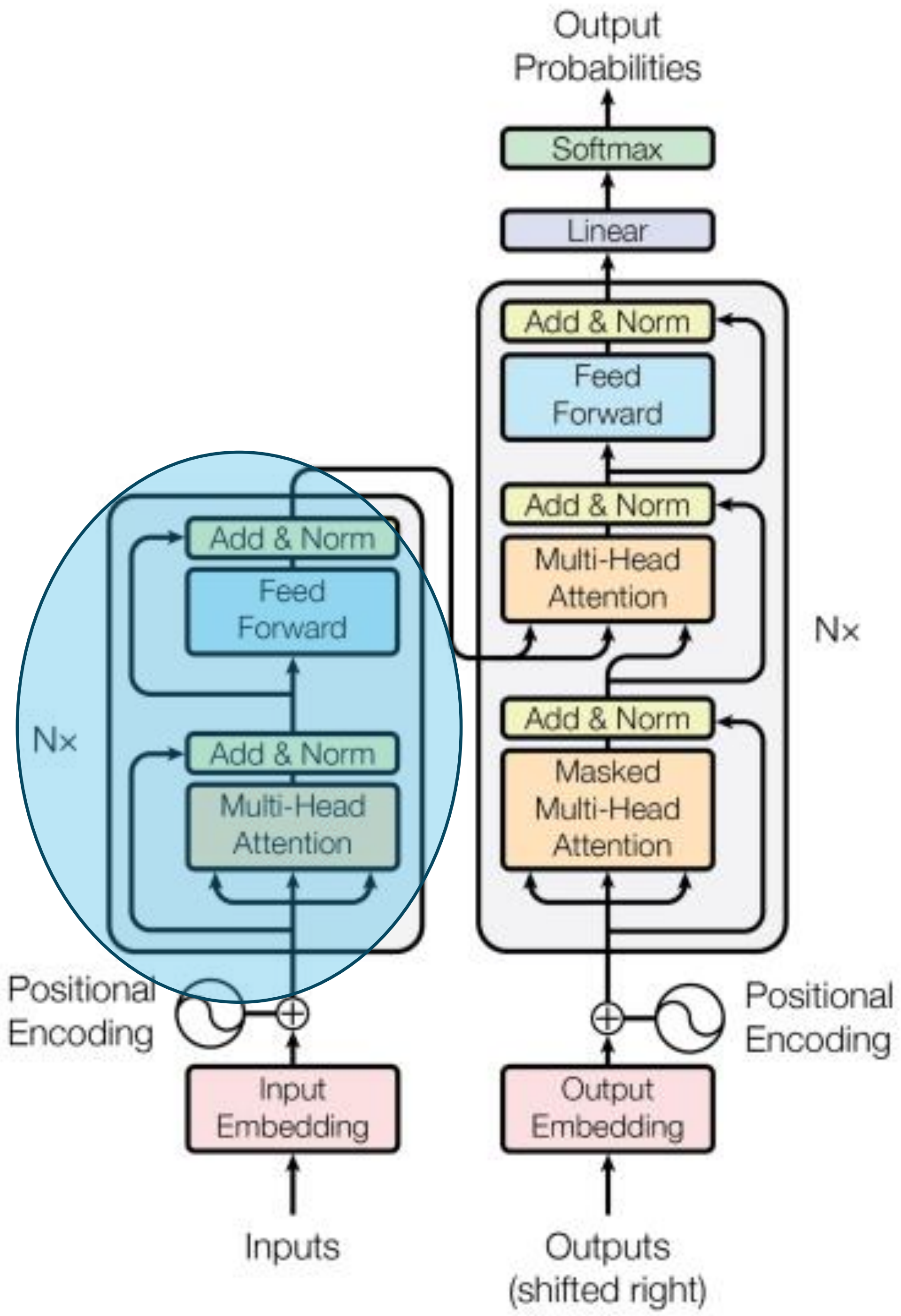




Transformers

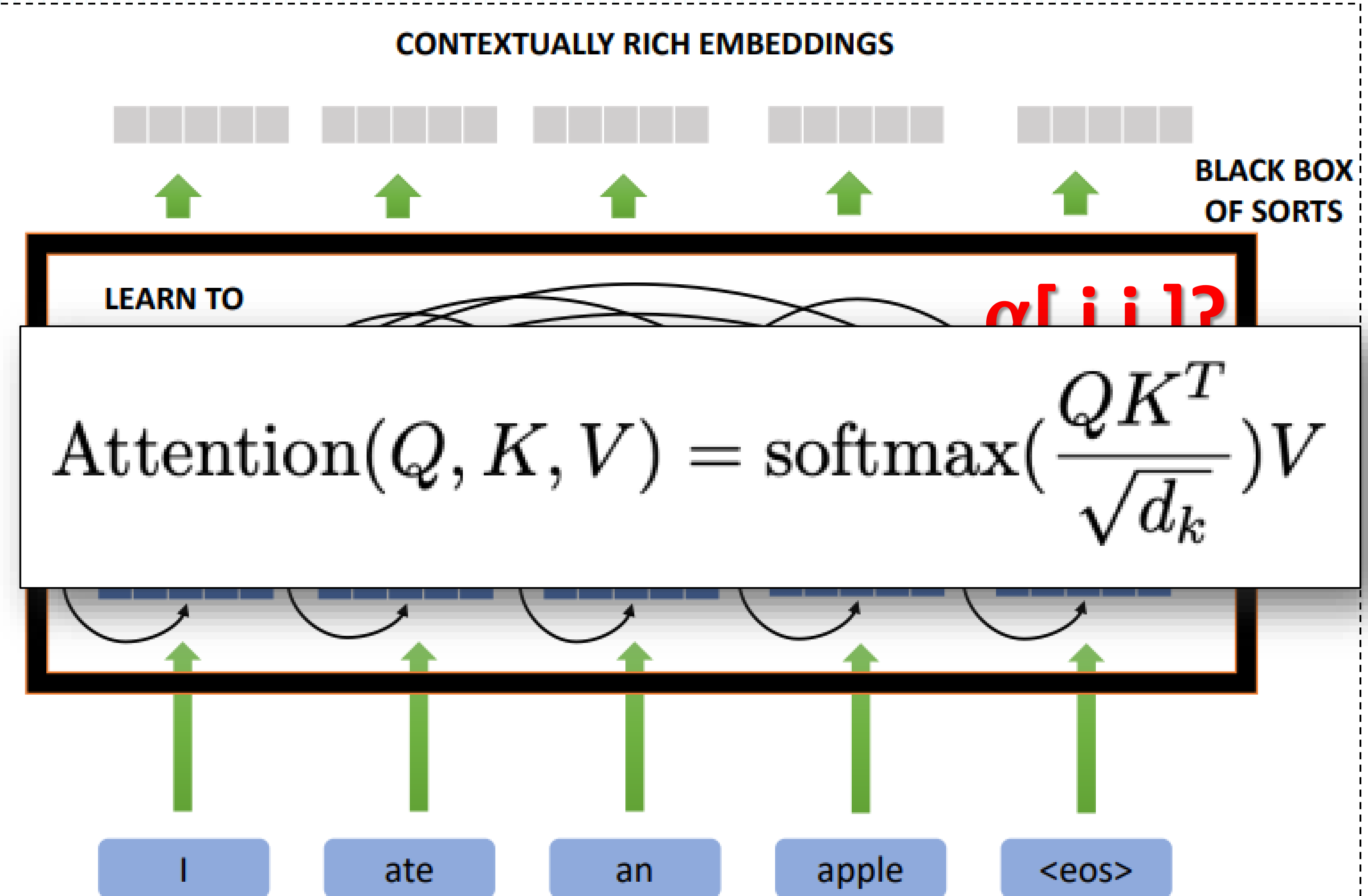
- Learn to add context



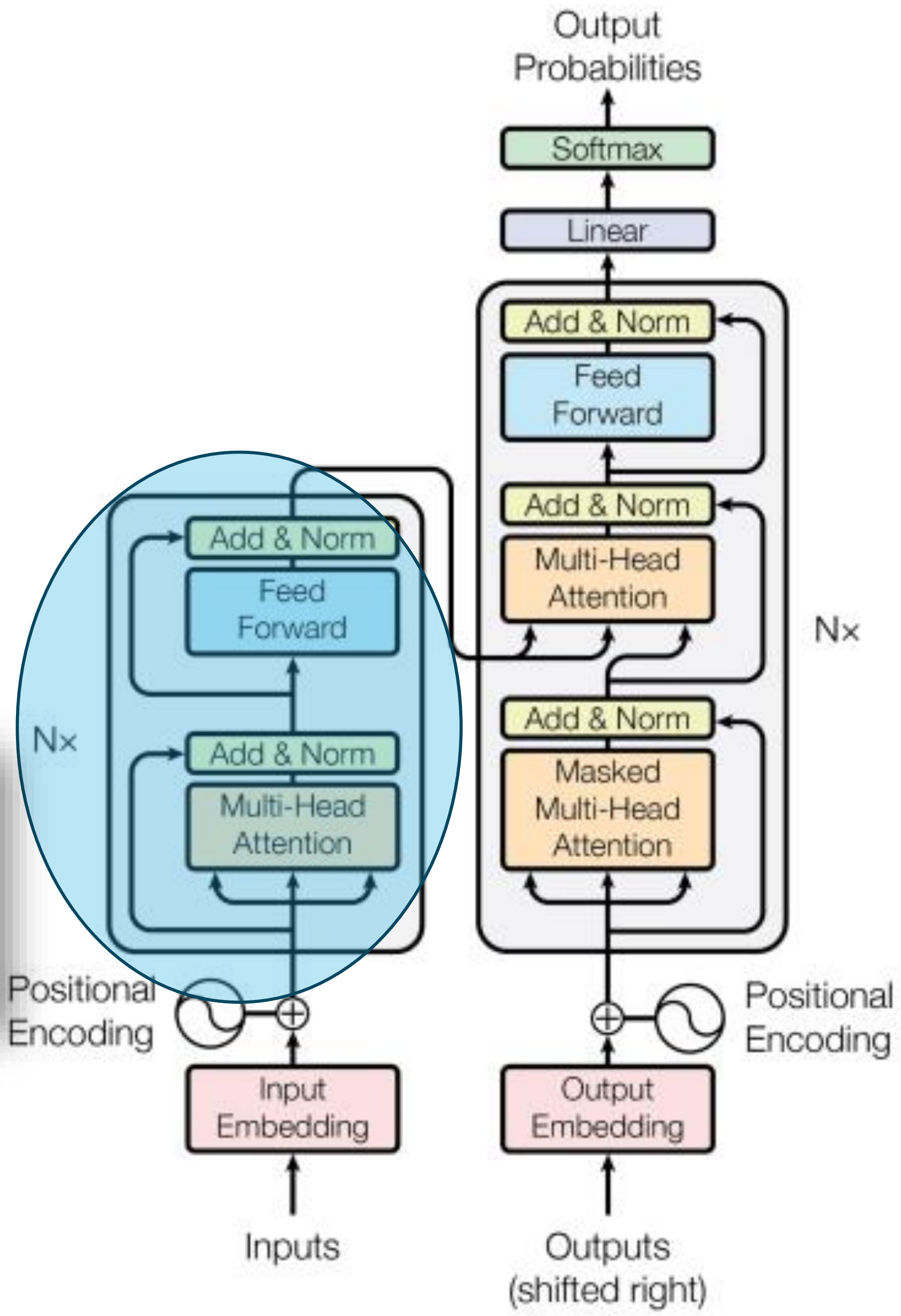


Transformers

- Learn to add context



$$\mathrm{Attention}(Q,K,V)=\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



Attention Concepts

- In the attention mechanism, we can draw an analogy to Information Retrieval (IR).

{Query: “Order details of order_104”}

OR

{Query: “Order details of order_106”}

A **query** (an embedding vector representing what we want to find more about — e.g., a specific token or position in a sequence)

A set of **keys** (representing the indexed or stored information — i.e., all other tokens in the context)

{Key, Value store}

```
{"order_100": {"items":"a1", "delivery_date":"a2", ...}},
{"order_101": {"items":"b1", "delivery_date":"b2", ...}},
{"order_102": {"items":"c1", "delivery_date":"c2", ...}},
{"order_103": {"items":"d1", "delivery_date":"d2", ...}},
{"order_104": {"items":"e1", "delivery_date":"e2", ...}},
{"order_105": {"items":"f1", "delivery_date":"f2", ...}},
{"order_106": {"items":"g1", "delivery_date":"g2", ...}},
{"order_107": {"items":"h1", "delivery_date":"h2", ...}},
{"order_108": {"items":"i1", "delivery_date":"i2", ...}},
{"order_109": {"items":"j1", "delivery_date":"j2", ...}},
{"order_110": {"items":"k1", "delivery_date":"k2", ...}}
```

And a set of **values** (the actual content or information associated with each key).

Attention Concepts

- In the attention mechanis
an analogy to Information

A set of **keys** (representing the ind ed

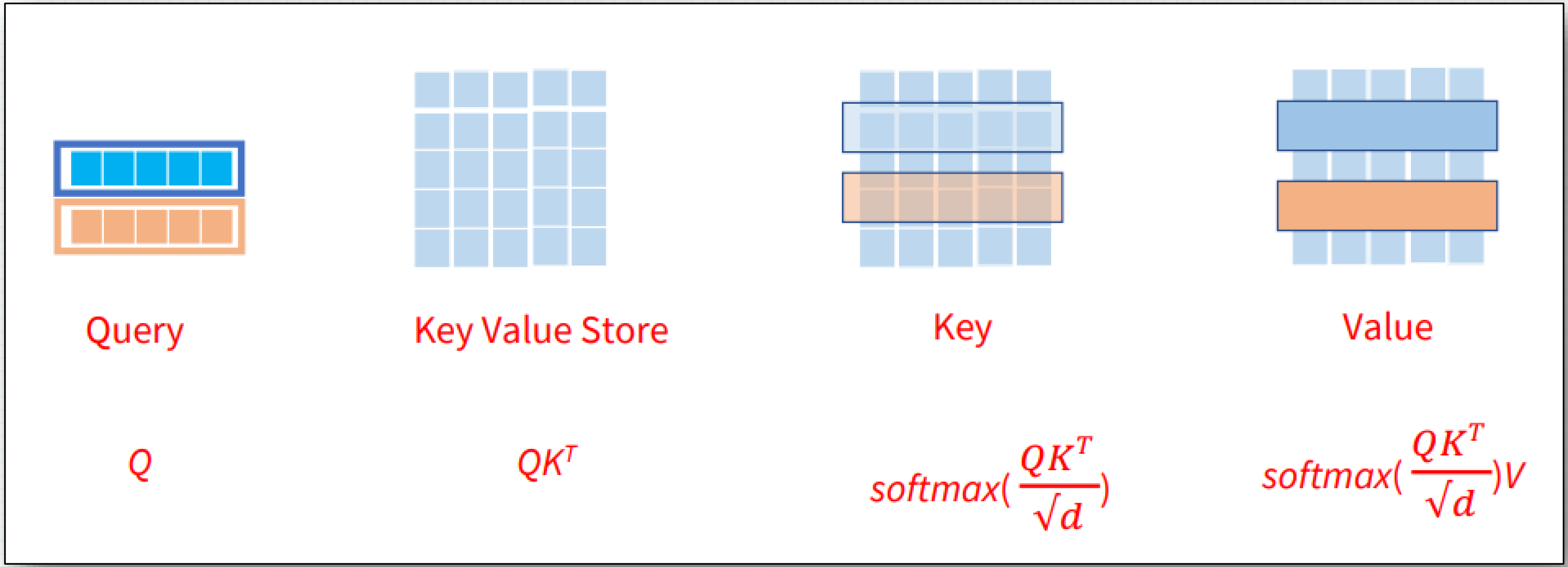
Attention allows the model to dynamically retrieve relevant information (values) from the context, based on how similar other tokens (keys) are to the current focus (query).

The attention process works as follows:

1. We compute the similarity between the query and each key (usually using a dot product).
2. This gives us a set of attention scores, indicating how much focus we should give to each position in the sequence.
3. We then apply a softmax to normalize the scores into a probability distribution.
4. Finally, we compute a weighted sum of the values based on these scores to produce the attention output.

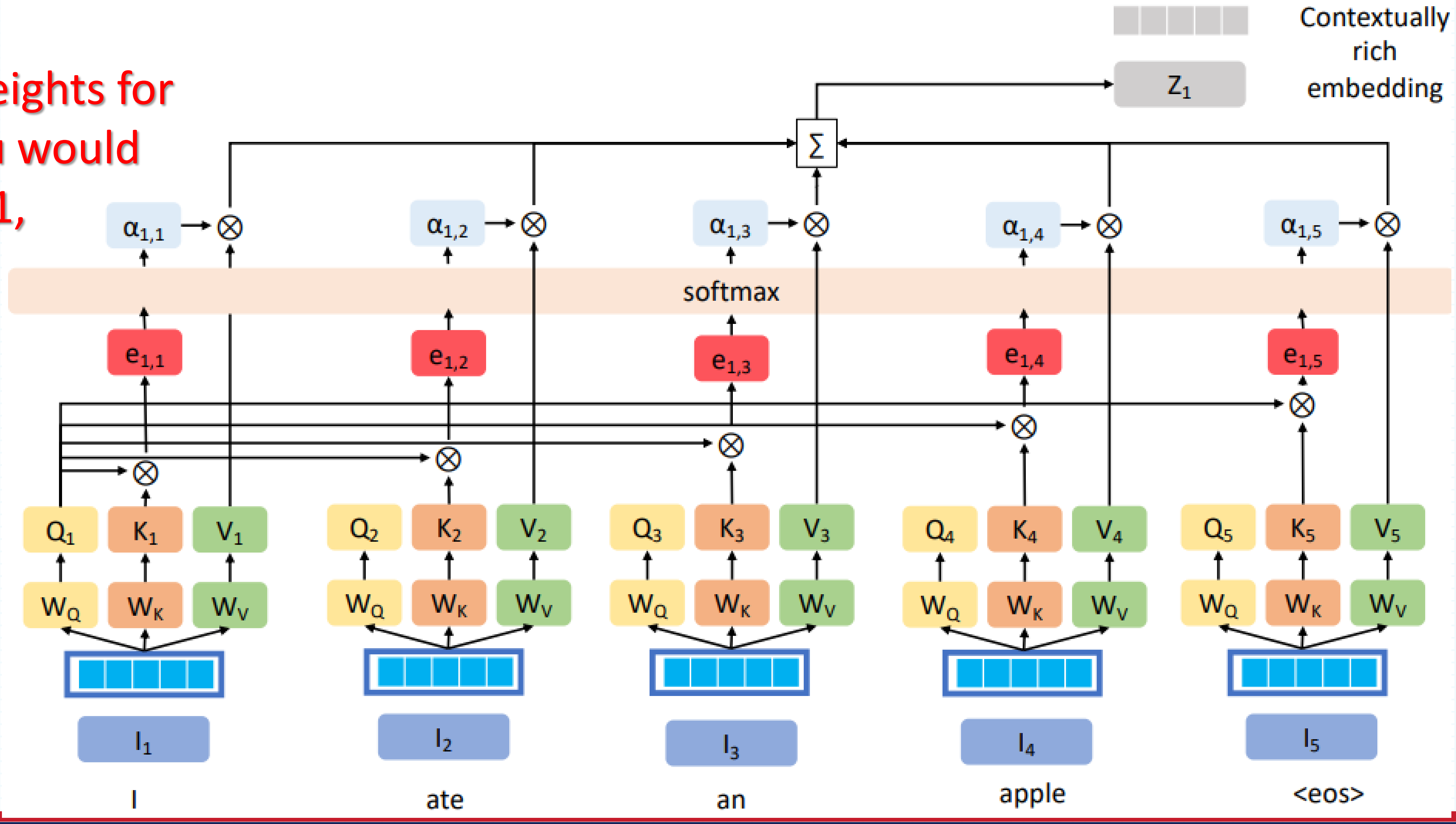
Attention

- More formal!



Attention

To calculate attention weights for input I1, you would use query q1, and all keys

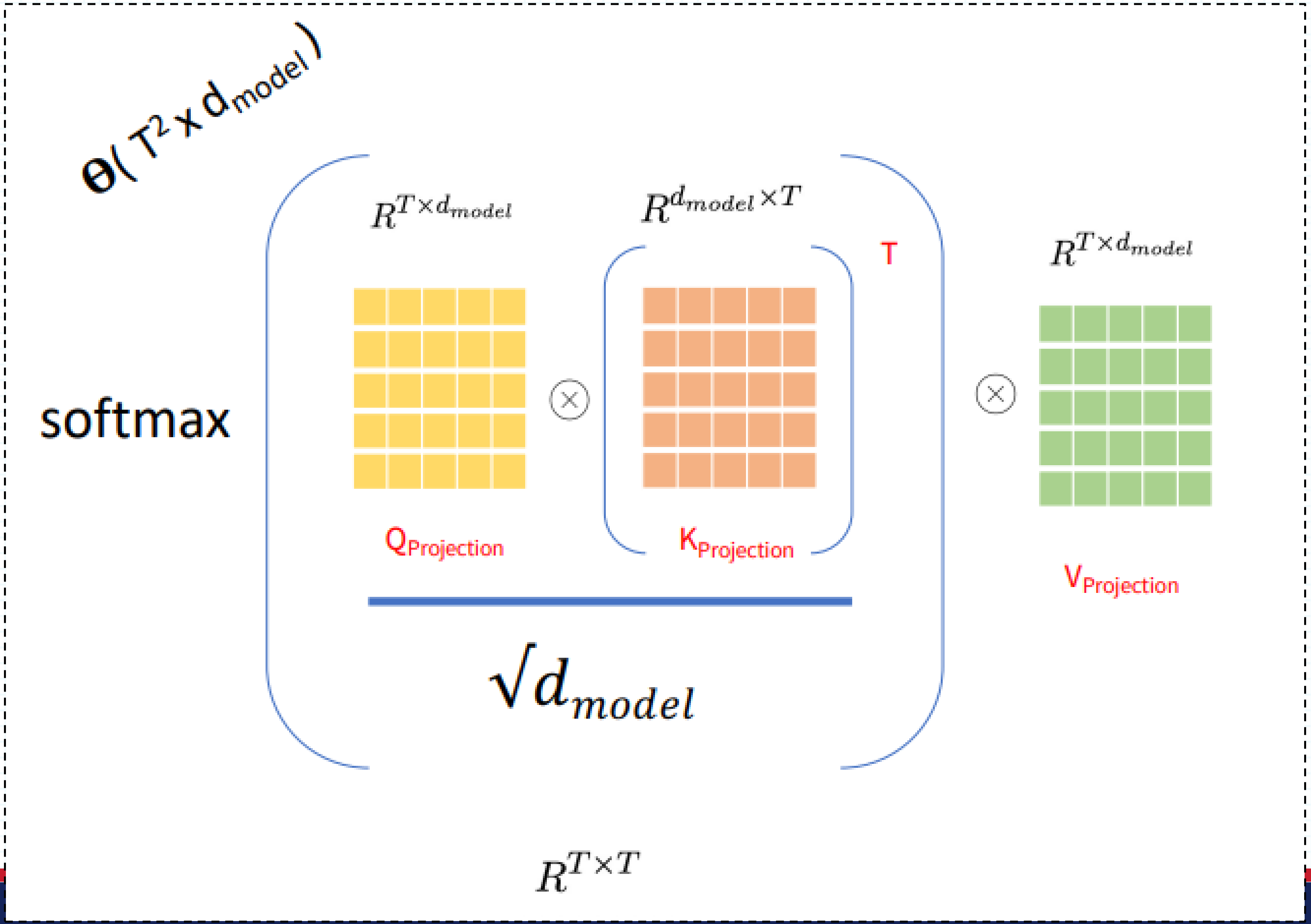


Of I1

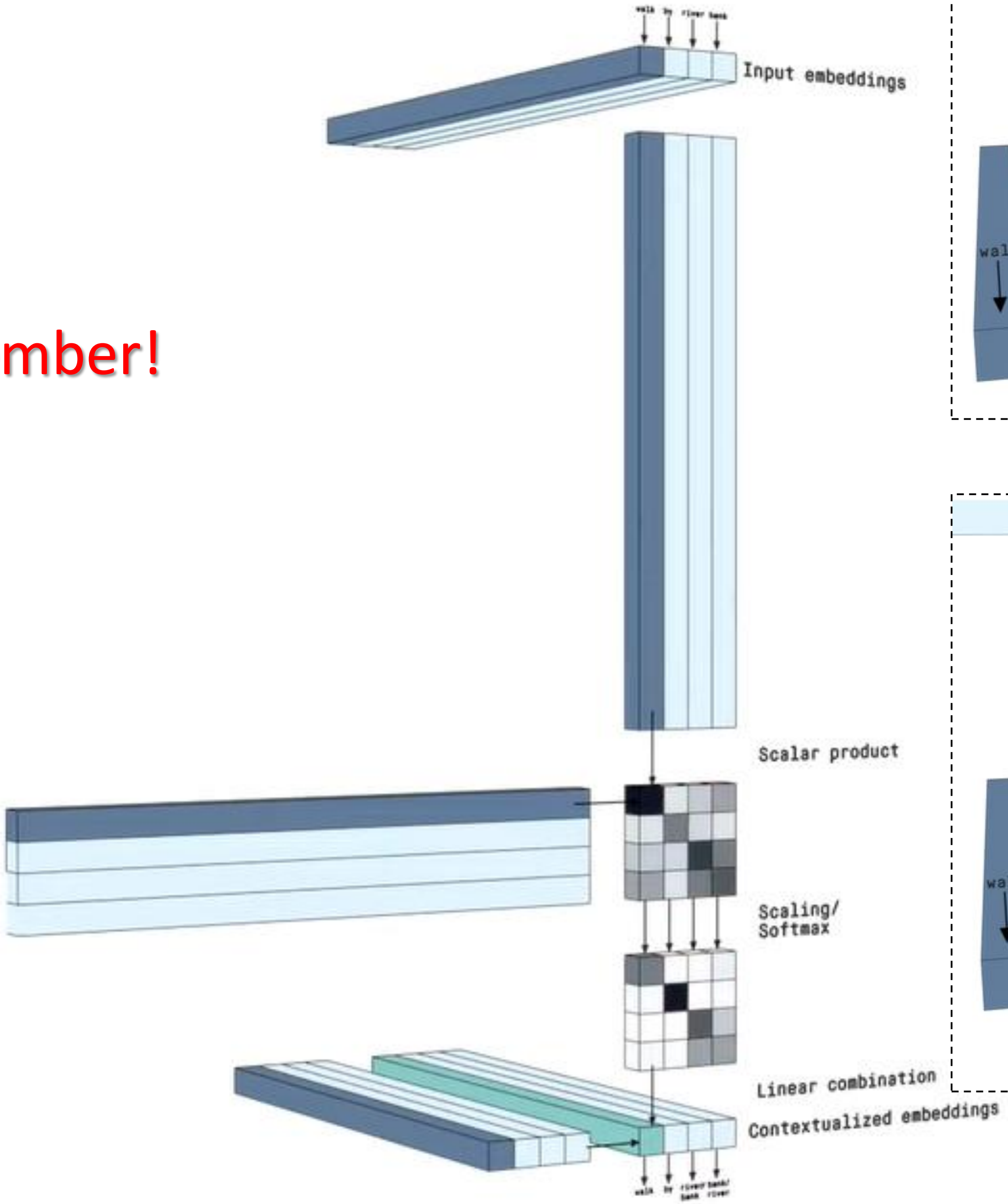
We do the same for I2, I3, etc

Self Attention

Query Inputs = Key Inputs = Value Inputs



Remember!



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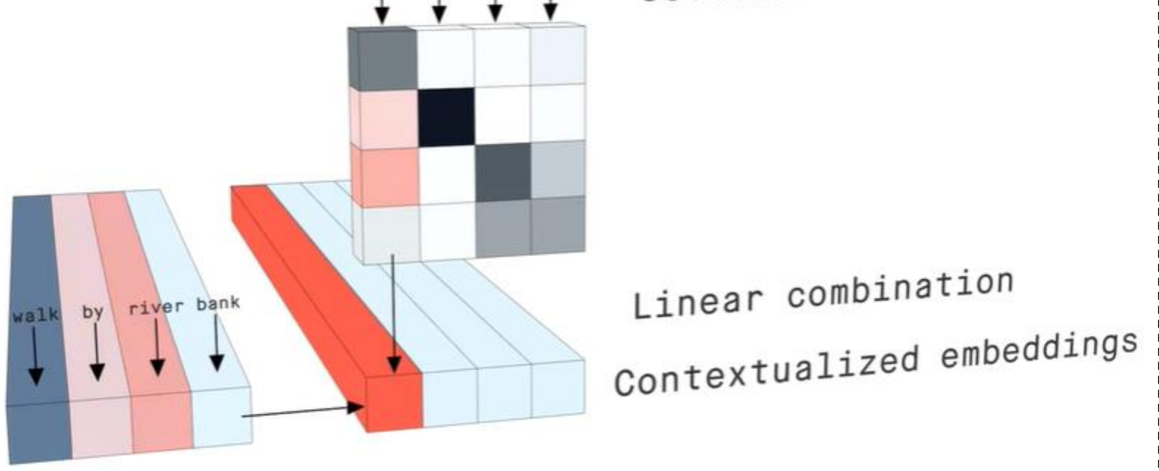
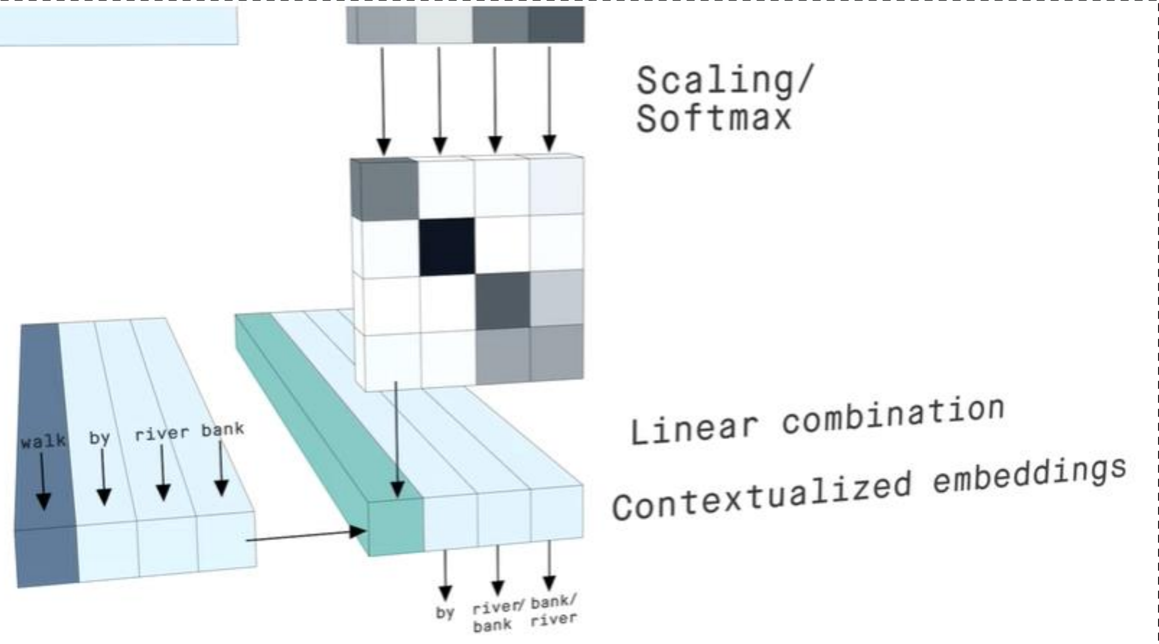
Linear combination
Contextualized embeddings



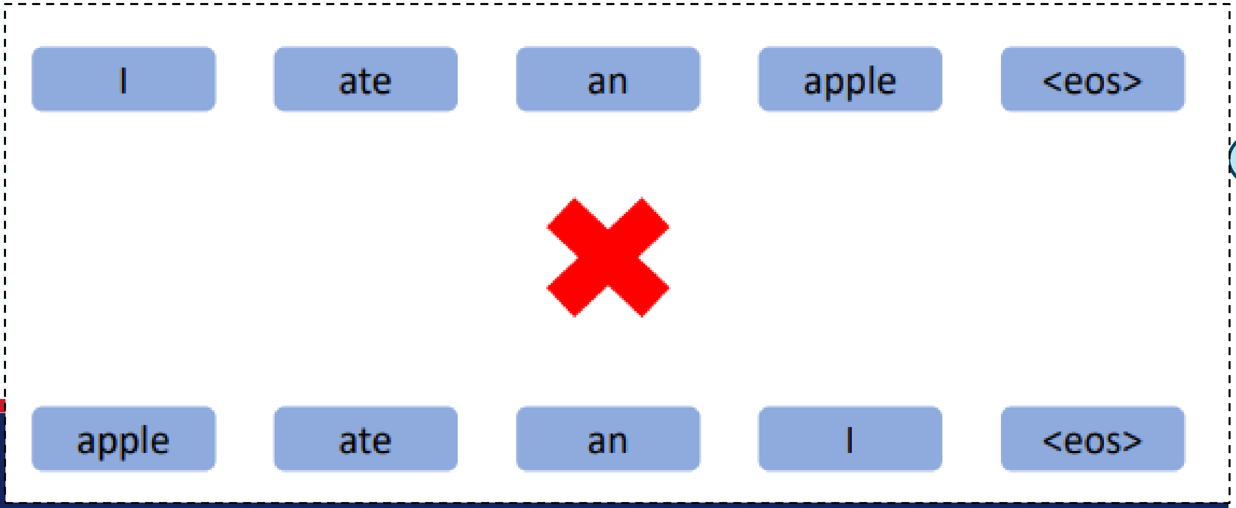
walk
by
river
bank
Linear combination
Contextualized embeddings

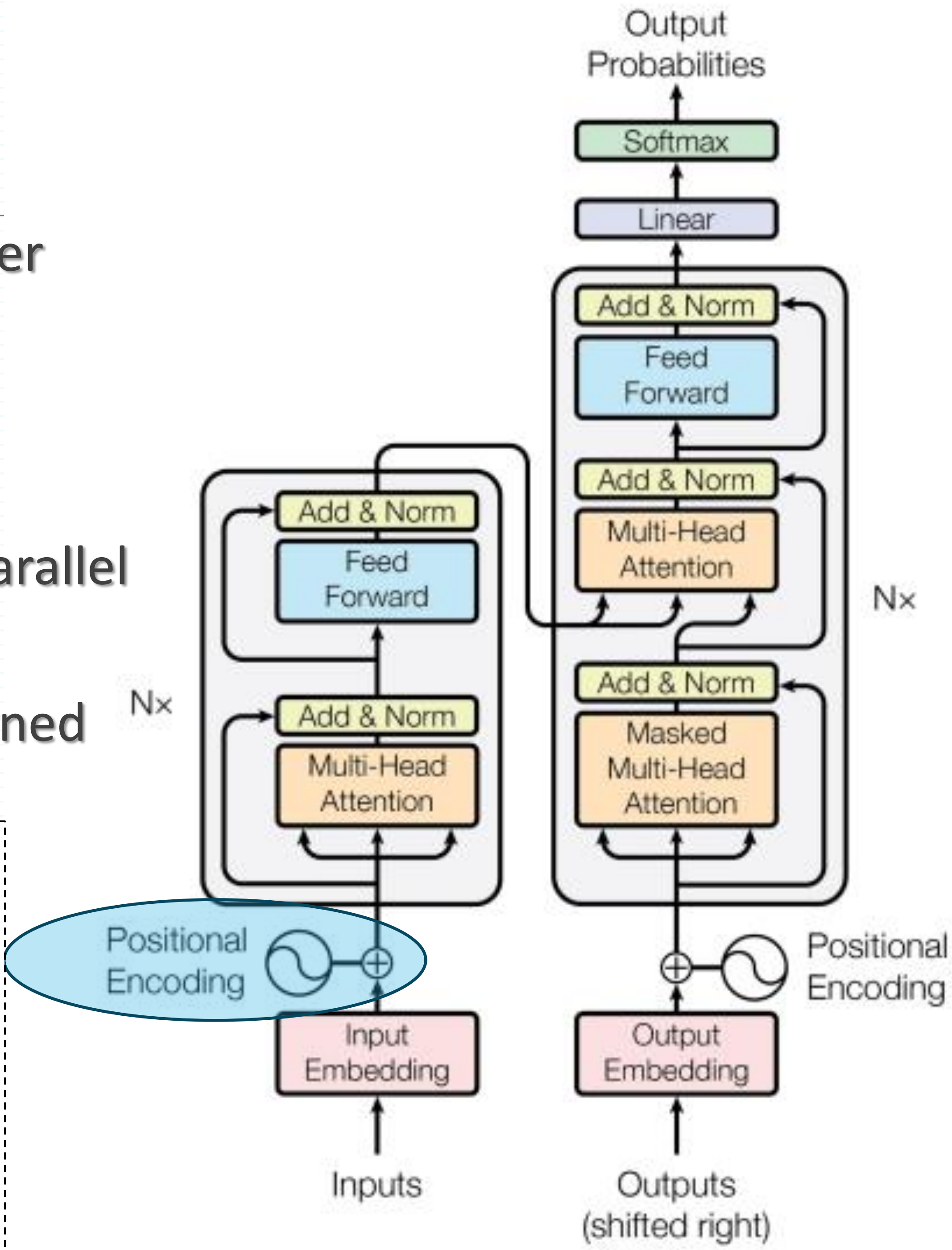


Scaling/
Softmax
walk
by
river
bank
Linear combination
Contextualized embeddings
by
river/
bank
bank/
river

Positional Encoding

- Injects sequence order information into transformer models.
- Added to token embeddings to help the model understand word positions.
- Needed because transformers process tokens in parallel and lack inherent order sensitivity.
- Can be fixed (e.g., sinusoidal – sine, cosine) or learned during training.





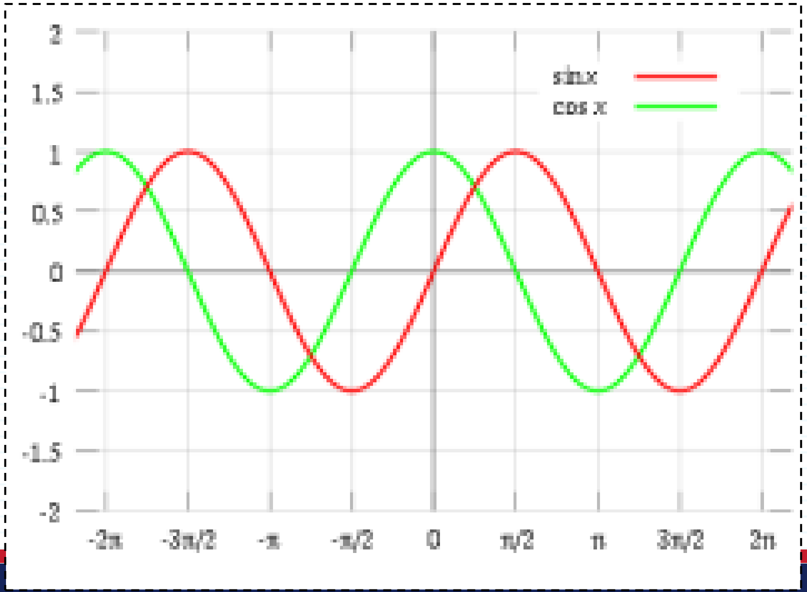
Positional Encoding

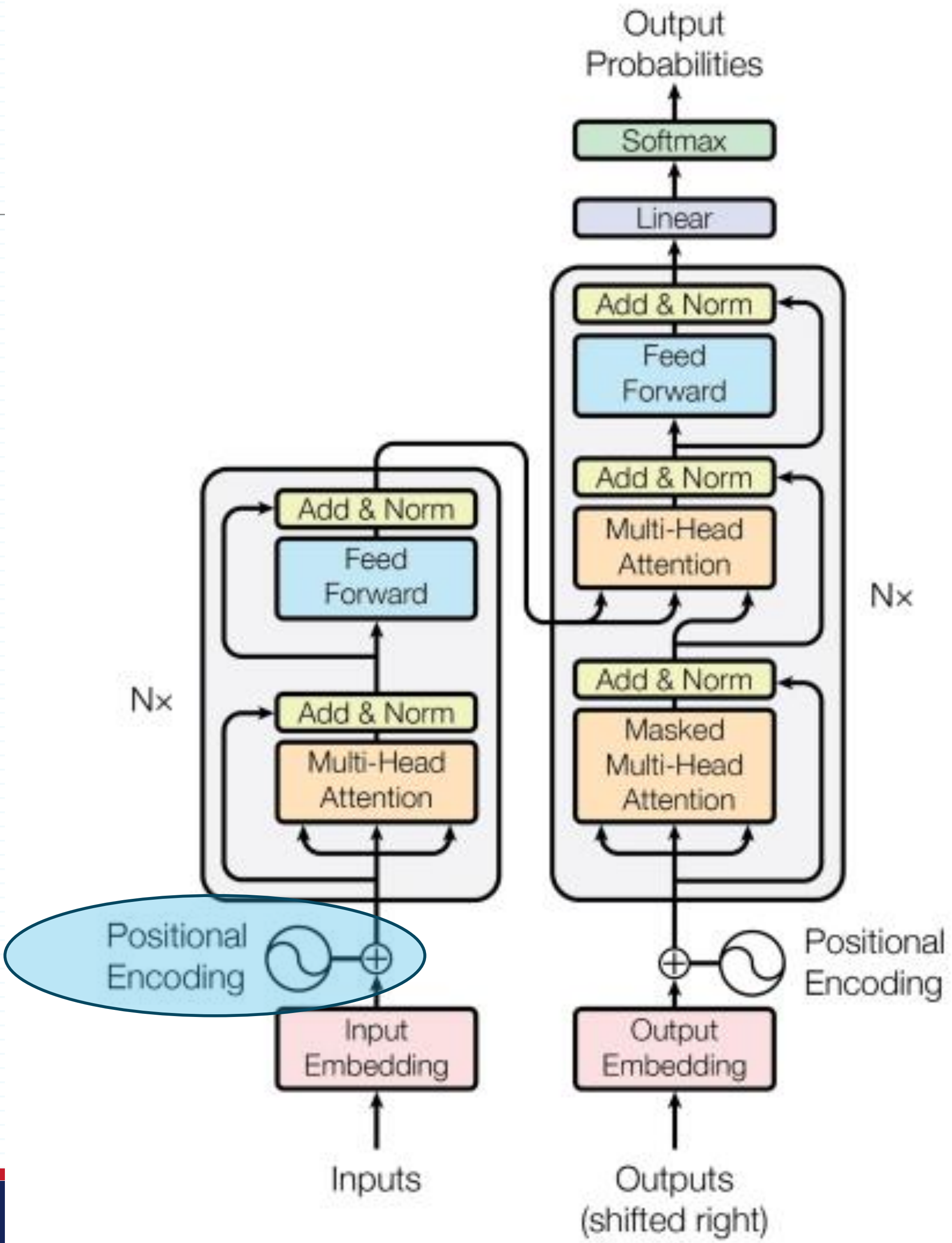
pos -> idx of the token in input sentence

i -> i^{th} dimension out of d

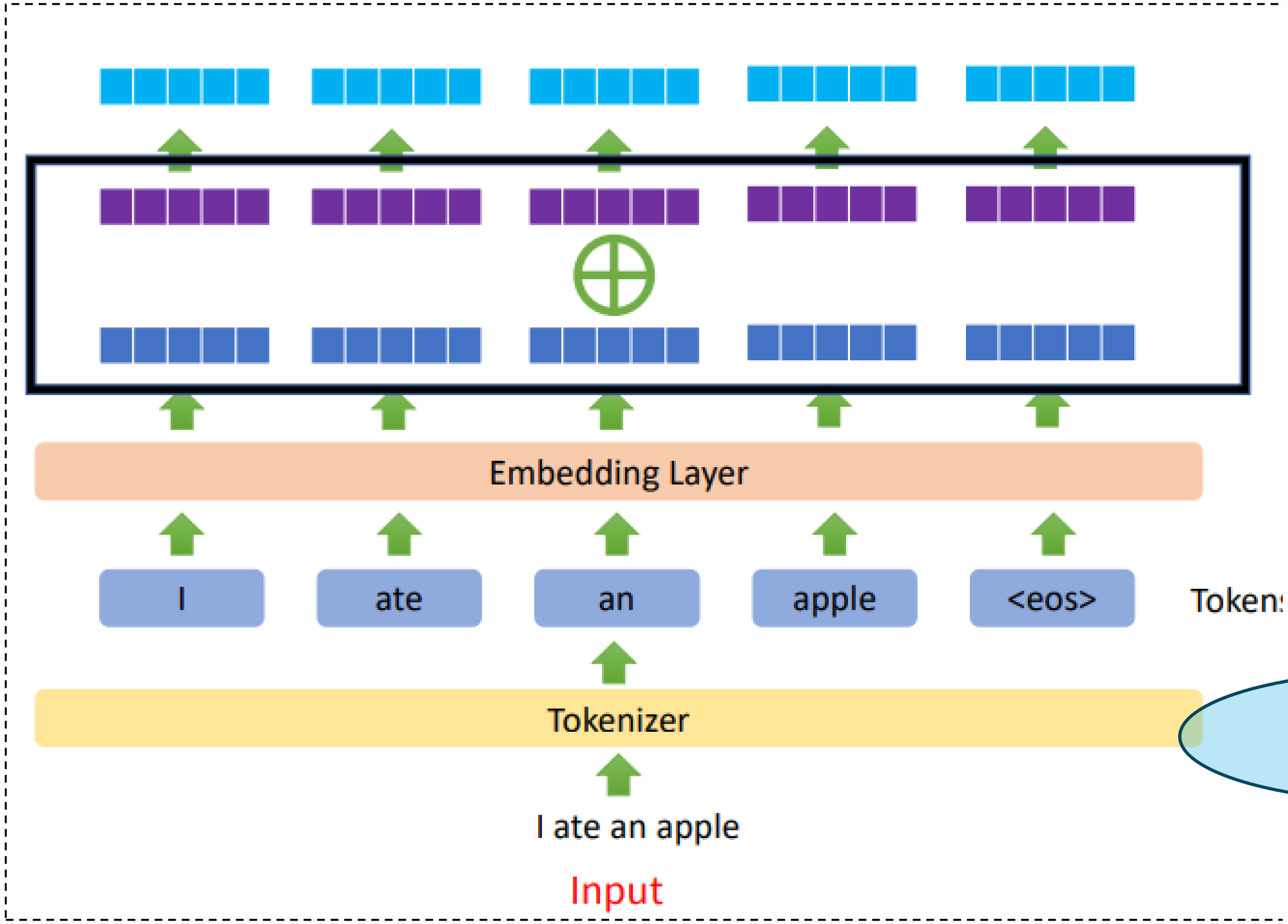
$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

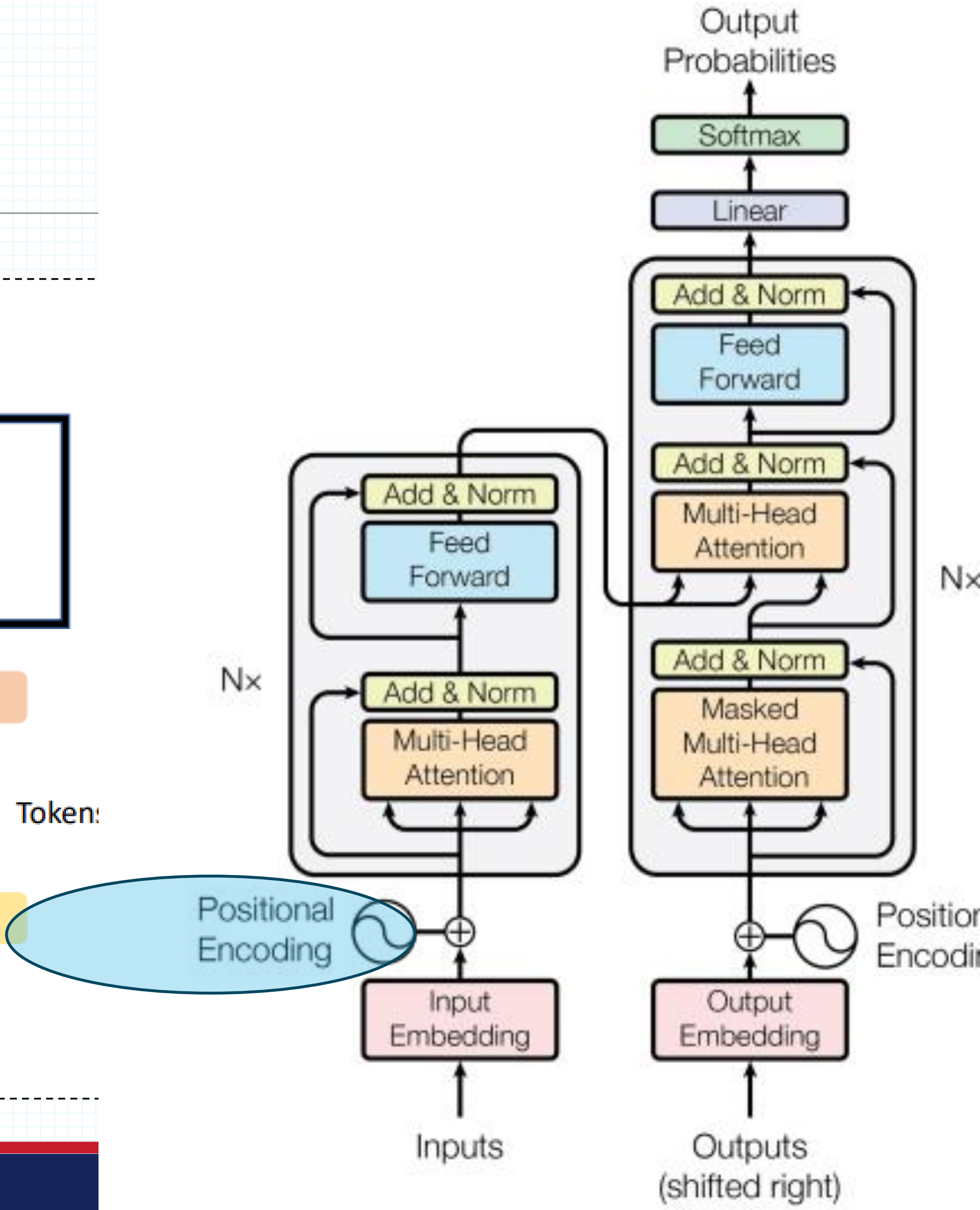
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$





Position Embedding





Next Lecture