Natural Language Processing (CS-472)
Spring-2023

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Overview of this week's lecture

Transformers

- Rationale
- Positional Encoding
- Self Attention
- Encoder-Decoder Architecture

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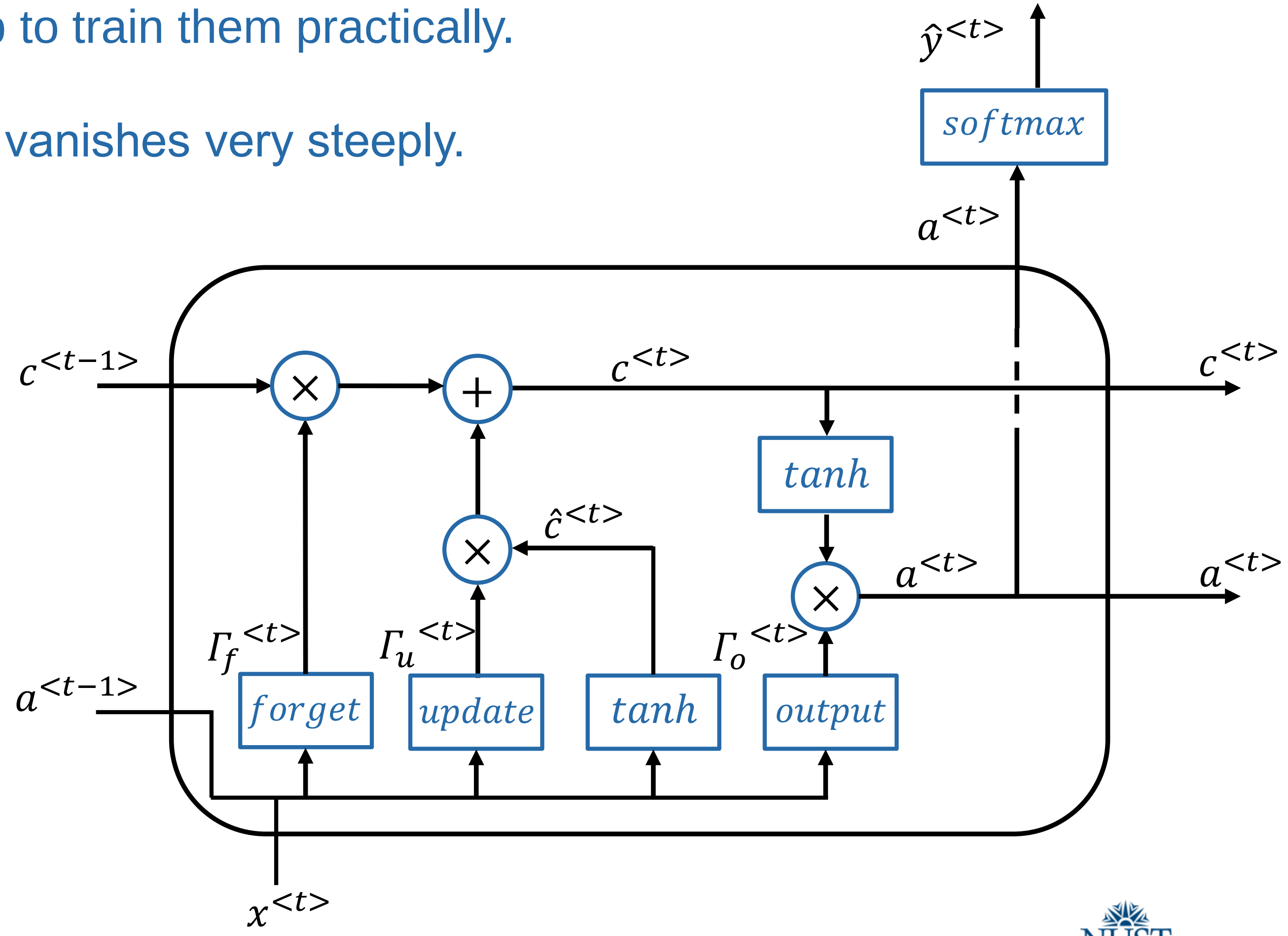

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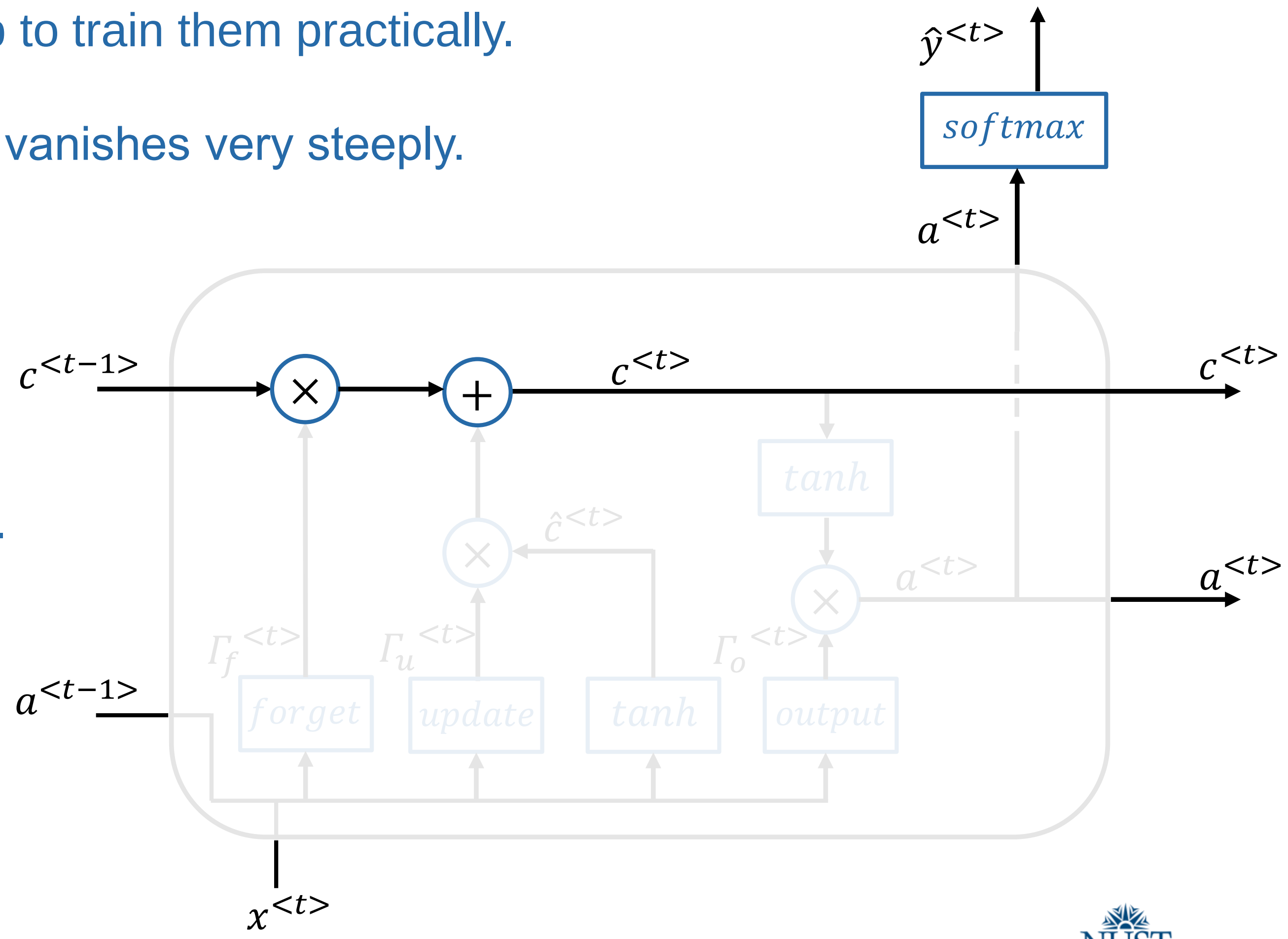
  - But they are even slower and more complex.



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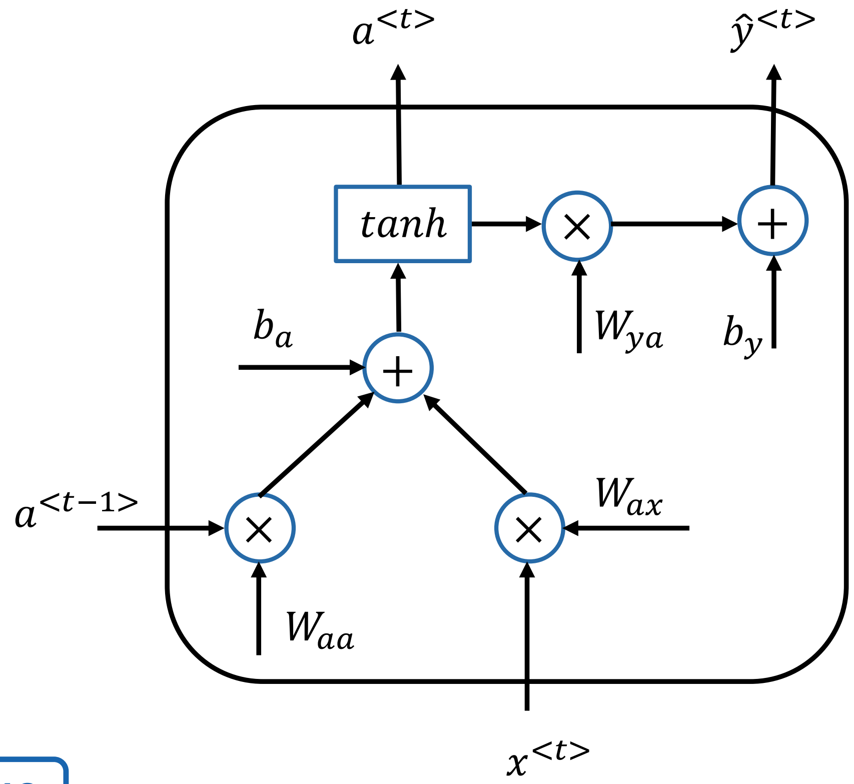

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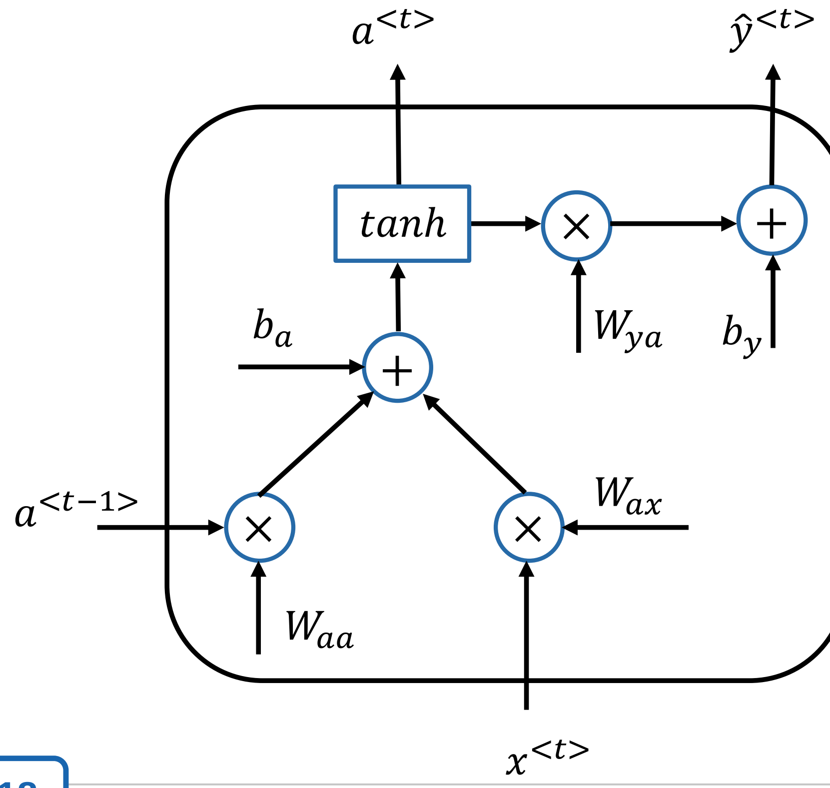
- GRUs are faster and can handle longer sequences.
    - Still not enough. **Need parallelisation.**



How can we achieve parallelisation for sequential data?

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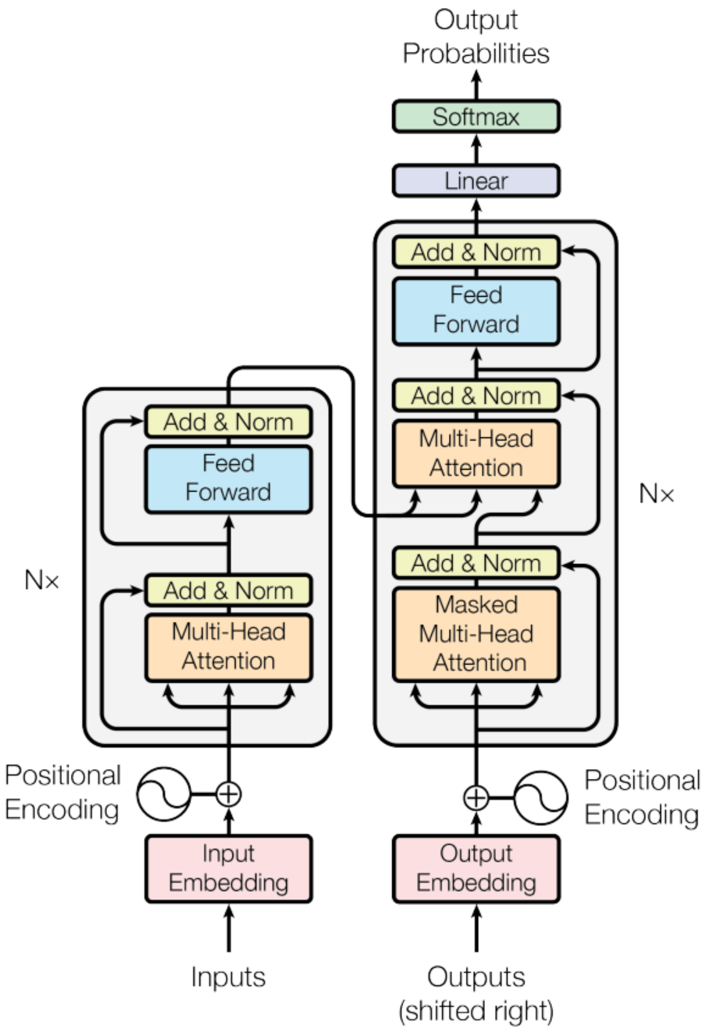
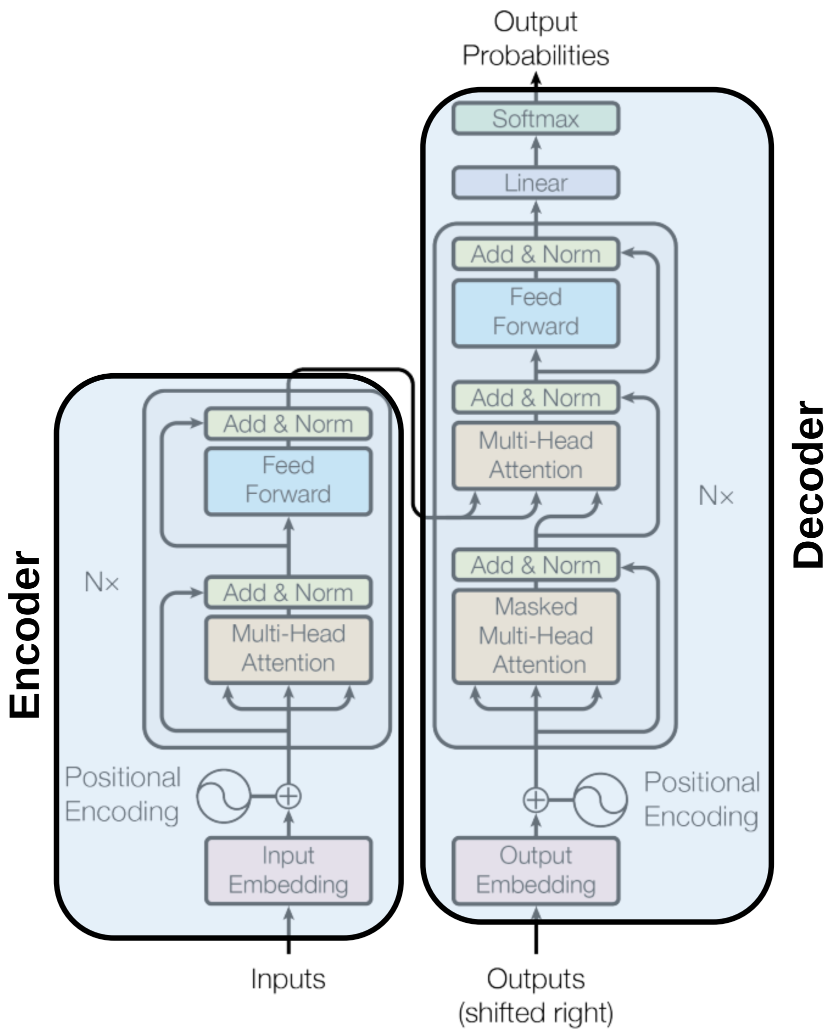


Figure 1: The Transformer - model architecture.

Transformers use encoder-decoder architecture without RNNs



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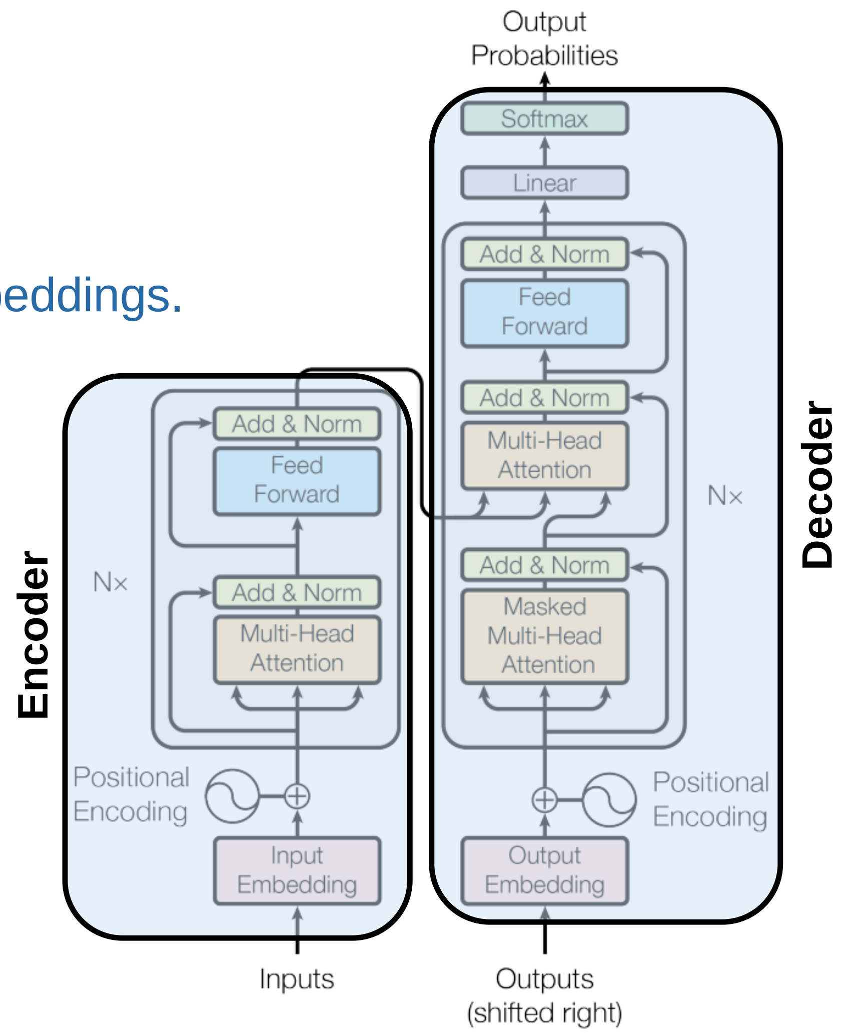
- **The Encoder**
  - Accepts input as text.
  - Gives output as word embeddings.
  - Uses Self-Attention.
  - Is bidirectional.



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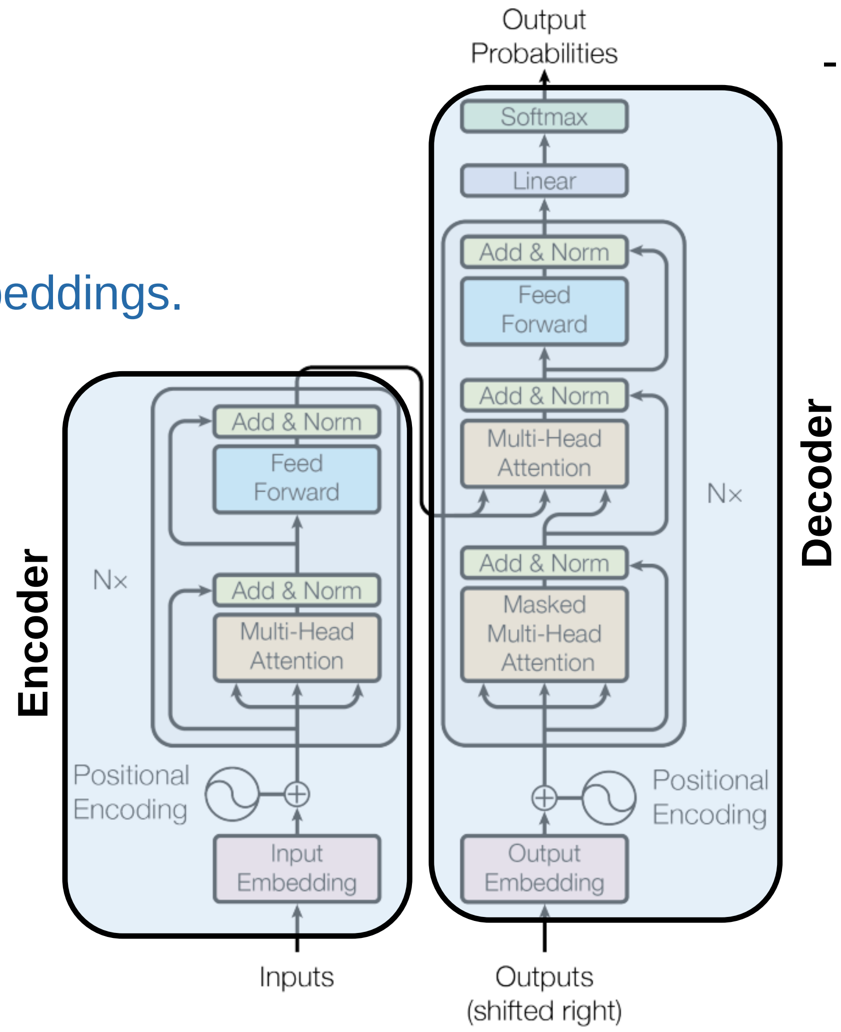
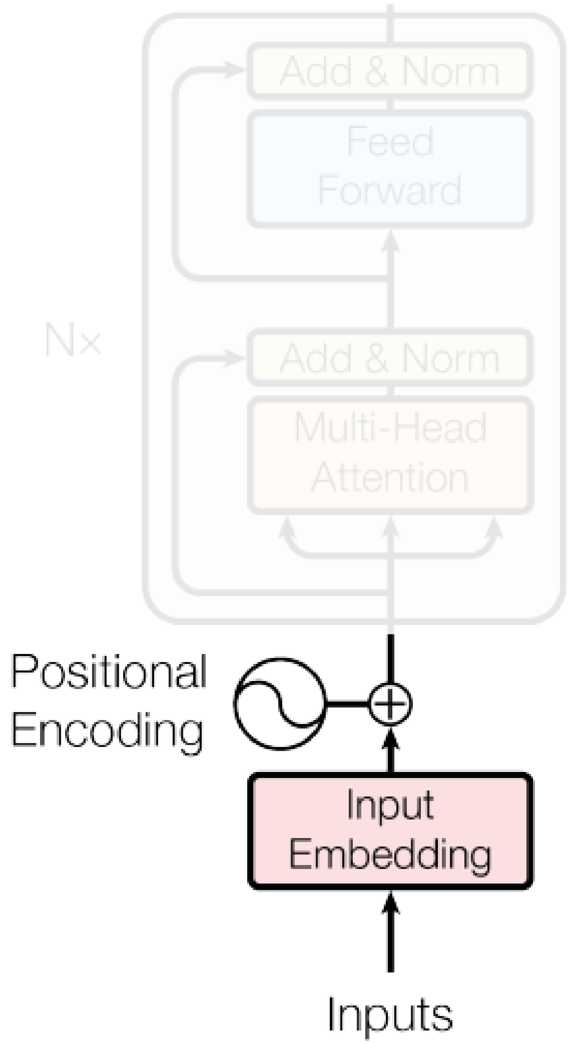


Figure 1: The Transformer - model architecture.

- **The Decoder**
  - Accepts input as word.
  - Gives output as sequence of words.
  - Uses Masked Self-Attention.
  - Is unidirectional.

Transformers use positional encoders to get position-aware embeddings

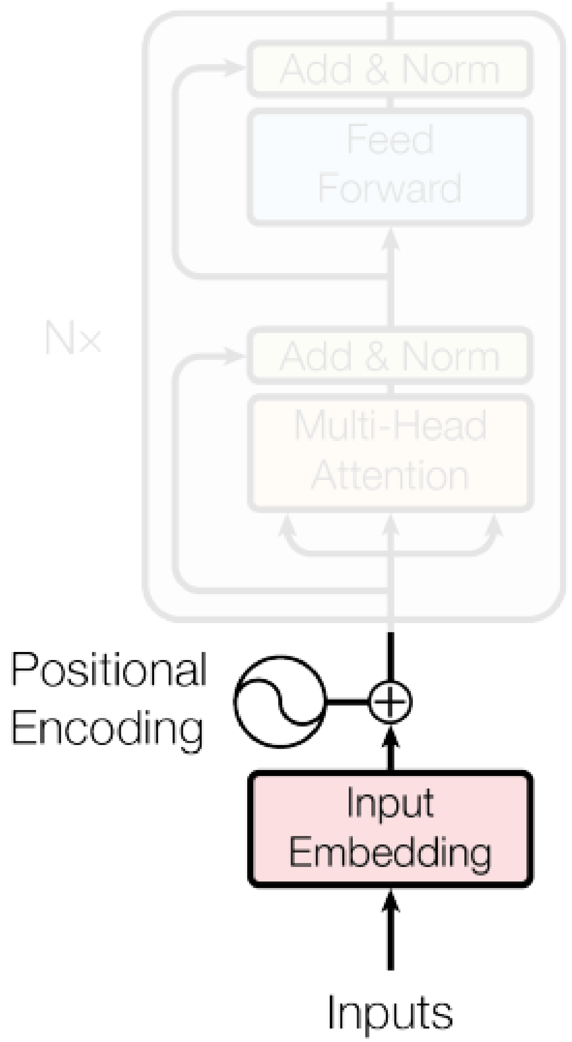
- Positional Encoder uses a vector that gives context based on position of words in a sentence.



Transformers use positional encoders to get position-aware embeddings

- Positional Encoder uses a vector that gives context based on position of words in a sentence.

- The vector has the same length as the embeddings to allow summation.



Transformers use positional encoders to get position-aware embeddings

- Positional Encoder uses a vector that gives context based on position of words in a sentence.

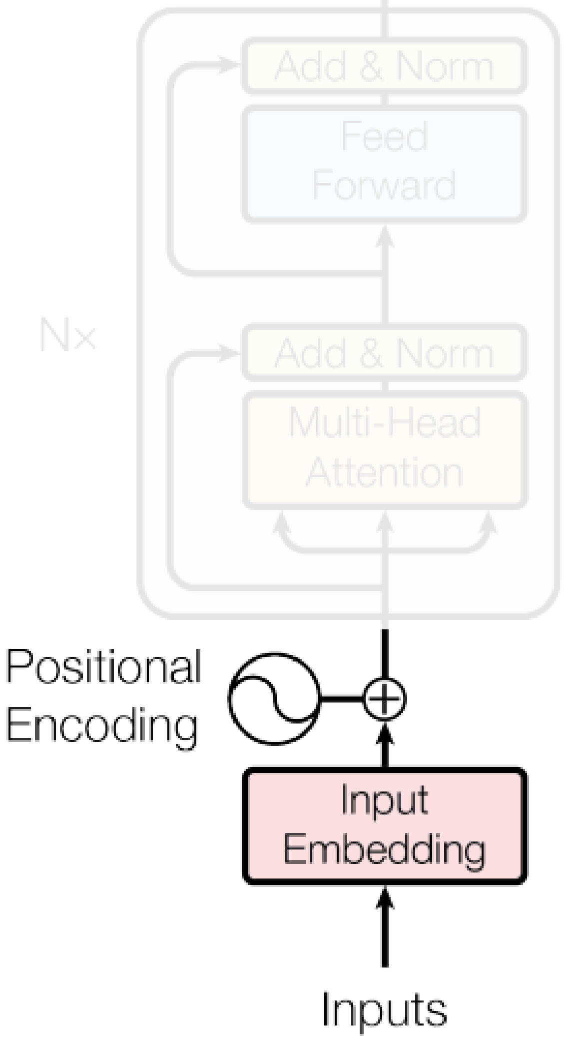
- The vector has the same length as the embeddings to allow summation.

- Positional encodings can be fixed or learned. In the original transformer paper, they used $sine$ and $cosine$ functions of different frequencies.

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\left(\frac{2i}{d_{model}}\right)}}\right)$$

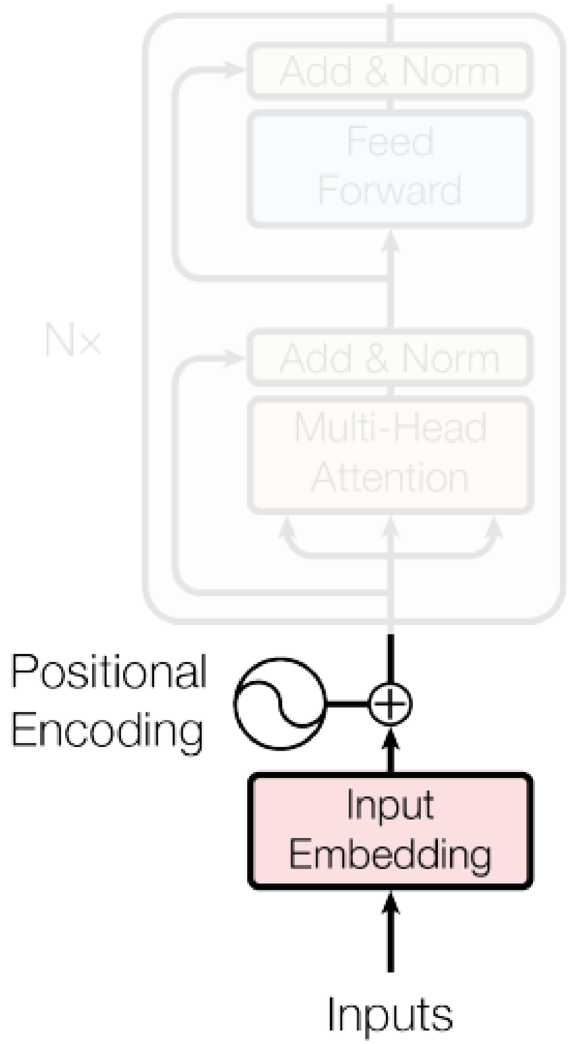
$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{\left(\frac{2i}{d_{model}}\right)}}\right)$$

  - Here pos is position, i represents dimension and d_{model} corresponds to the total length of input.



How Positional Encodings are calculated?

The		p0	Large		p1	Red		p2	Dog		p3
0.2		?	-0.9		?	0.5		?	0.6		?
-0.8		?	0.3		?	0.6		?	0.0		?
-0.6	+	?	0.4	+	?	-0.8	+	?	0.8	+	?
0.9		?	0.6		?	0.7		?	0.9		?
0.1		?	-0.1		?	0.7		?	0.4		?



https://kazemnejad.com/blog/transformer_architecture_positional_encoding/
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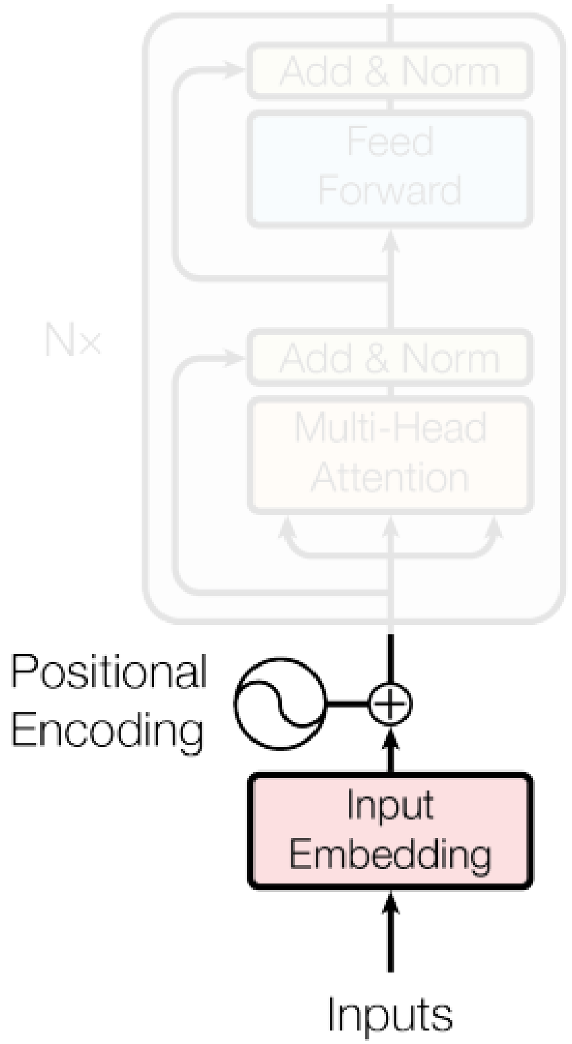
0.9		?	0.6		?	0.7		?	0.9		?
0.1		?	-0.1		?	0.7		?	0.4		?

The-p	Large-p	Red-p	Dog-p
0.2+?	-0.9+?	0.5+?	0.6+?
-0.8+?	0.3+?	0.6+?	0.0+?
-0.6+?	0.4+?	-0.8+?	0.8+?
0.9+?	0.6+?	0.7+?	0.9+?
0.1+?	-0.1+?	0.7+?	0.4+?



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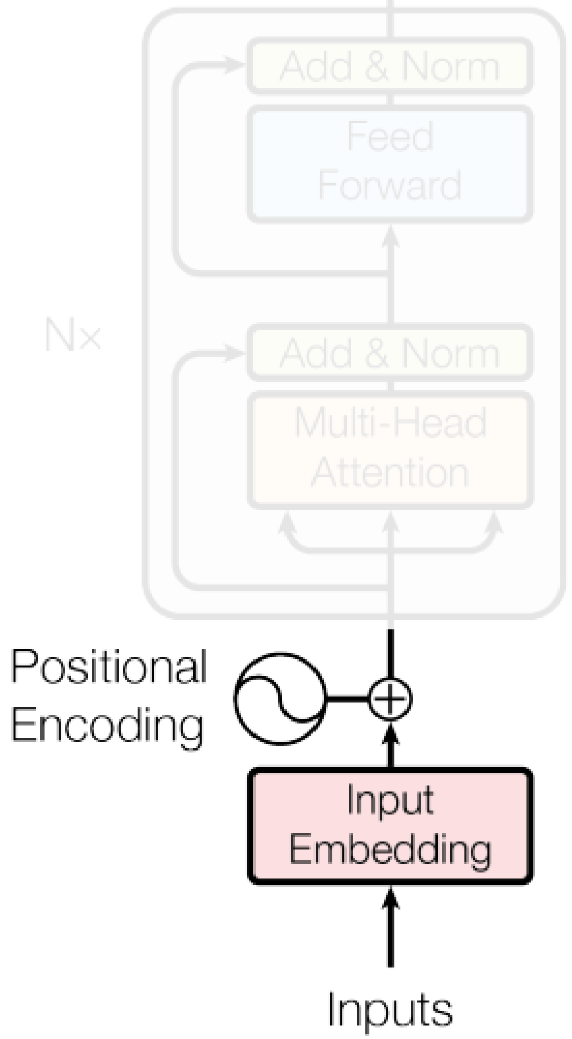
0.9		?	0.6		?	0.7		?	0.9		?
0.1		?	-0.1		?	0.7		?	0.4		?

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{\left(\frac{2i}{d_{model}}\right)}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{\left(\frac{2i}{d_{model}}\right)}}\right)$$

p0

$$\begin{bmatrix} PE_{(0,0)} \\ PE_{(0,1)} \\ PE_{(0,2)} \\ PE_{(0,3)} \\ PE_{(0,4)} \end{bmatrix} \quad \begin{bmatrix} \sin\left(\frac{0}{10000^{\left(\frac{2\times 0}{5}\right)}}\right) \\ \cos\left(\frac{0}{10000^{\left(\frac{2\times 0}{5}\right)}}\right) \\ \sin\left(\frac{0}{10000^{\left(\frac{2\times 1}{5}\right)}}\right) \\ \cos\left(\frac{0}{10000^{\left(\frac{2\times 1}{5}\right)}}\right) \\ \cos\left(\frac{0}{10000^{\left(\frac{2\times 1}{5}\right)}}\right) \end{bmatrix} \rightarrow \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$



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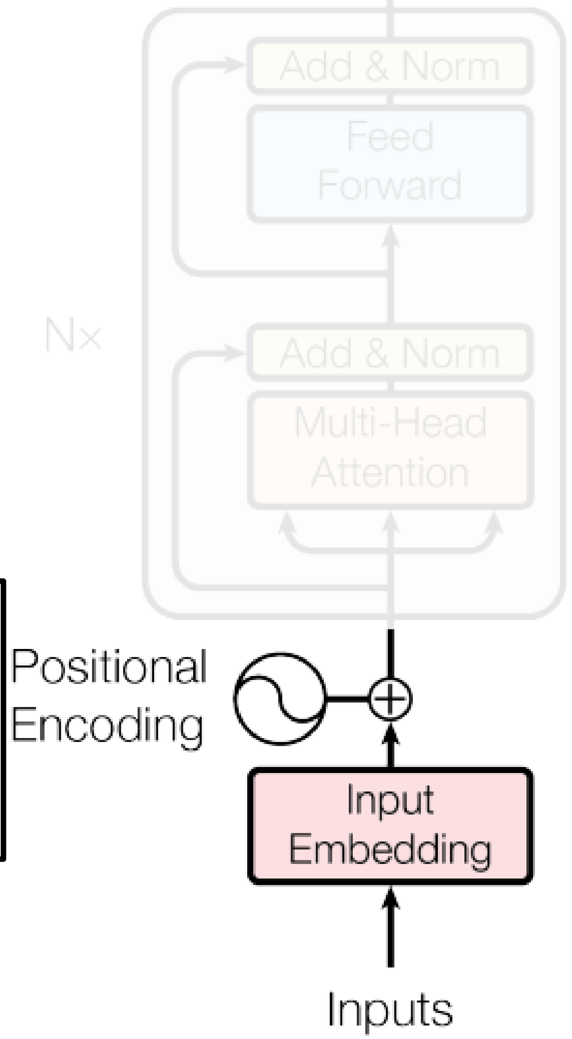
p1

$$\begin{bmatrix} PE_{(1,0)} \\ PE_{(1,1)} \\ PE_{(1,2)} \\ PE_{(1,3)} \\ PE_{(1,4)} \end{bmatrix} = \begin{bmatrix} \sin\left(\frac{1}{10000^{\left(\frac{2\times 0}{5}\right)}}\right) \\ \cos\left(\frac{1}{10000^{\left(\frac{2\times 0}{5}\right)}}\right) \\ \sin\left(\frac{1}{10000^{\left(\frac{2\times 1}{5}\right)}}\right) \\ \cos\left(\frac{1}{10000^{\left(\frac{2\times 1}{5}\right)}}\right) \\ \sin\left(\frac{1}{10000^{\left(\frac{2\times 2}{5}\right)}}\right) \end{bmatrix} \rightarrow \begin{bmatrix} 0.174000 \\ 0.999800 \\ 0.000174 \\ 0.999900 \\ 0.000631 \end{bmatrix}$$



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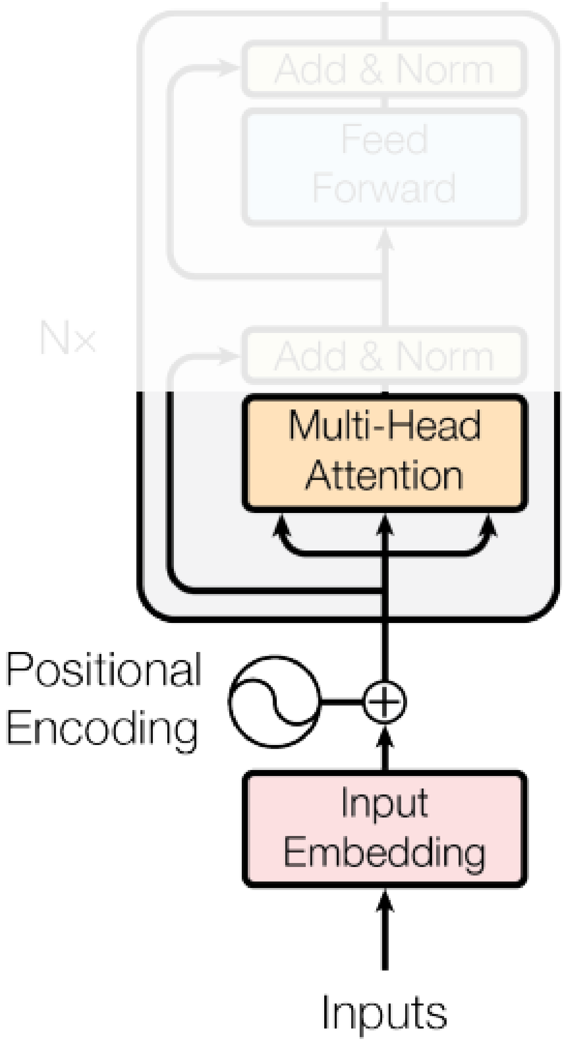
How Self Attention is calculated?



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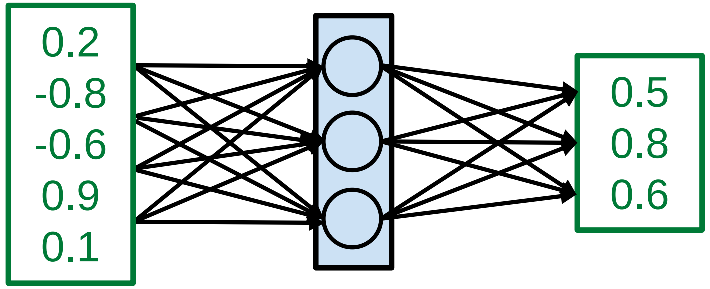
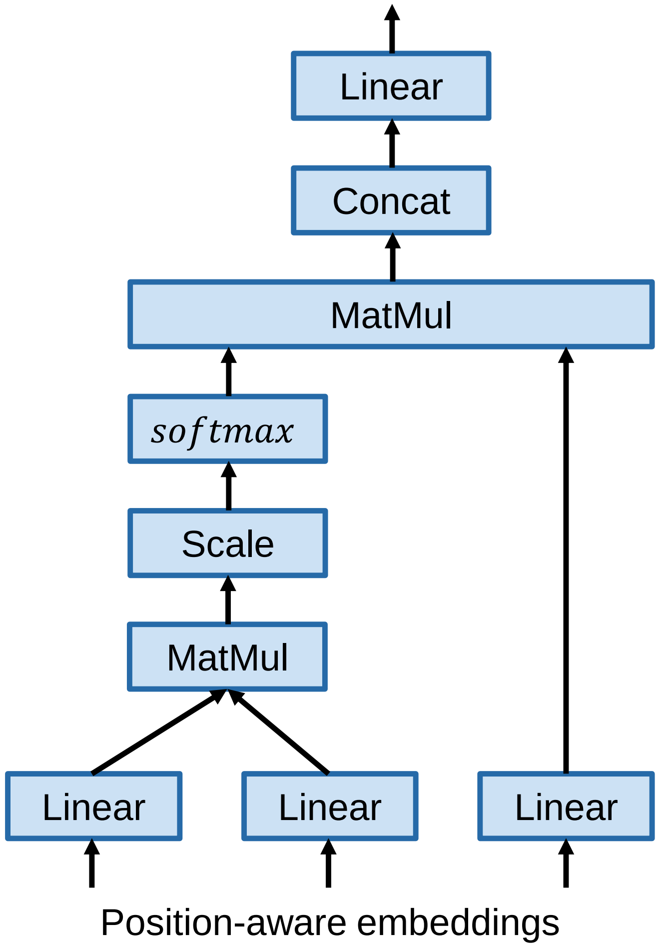
How Self Attention is calculated?

- A Linear layer is a fully connected layer without activation function.
  - Used to map input to the output.
  - Change dimensionality.





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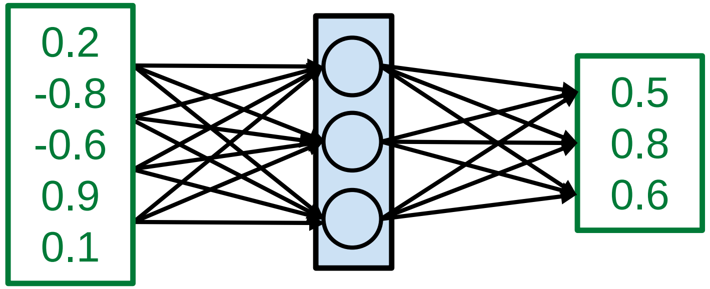
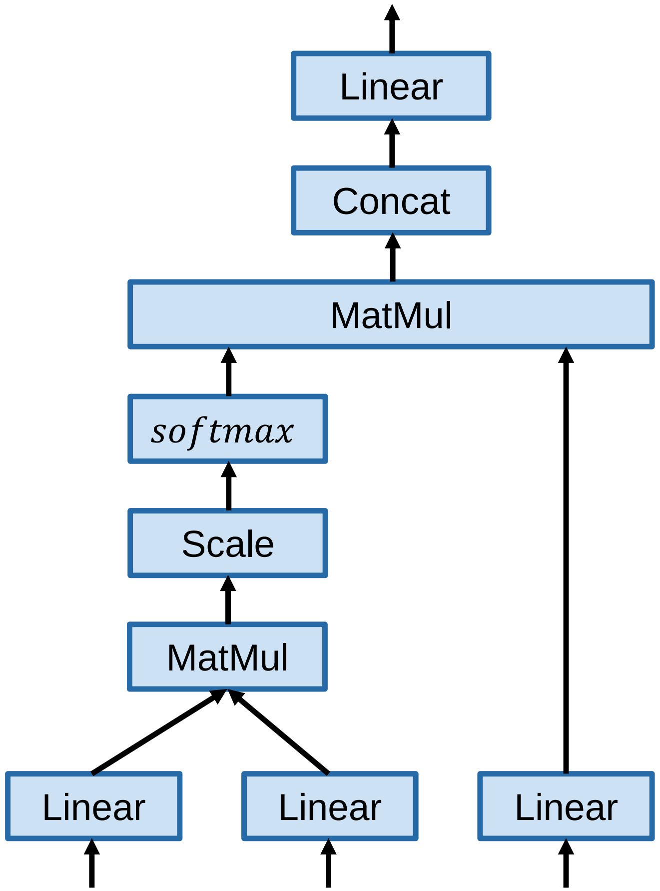


- Query, Key, Value Formulation is used to calculate Attention.



Position-aware embeddings

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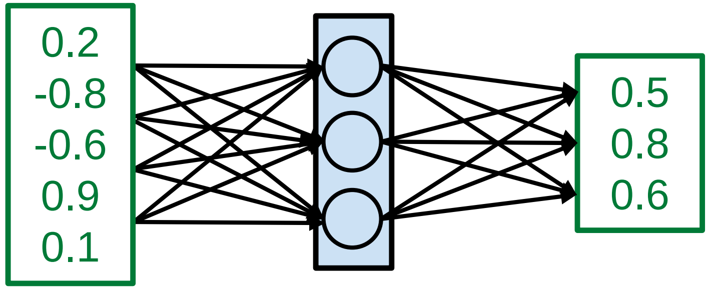
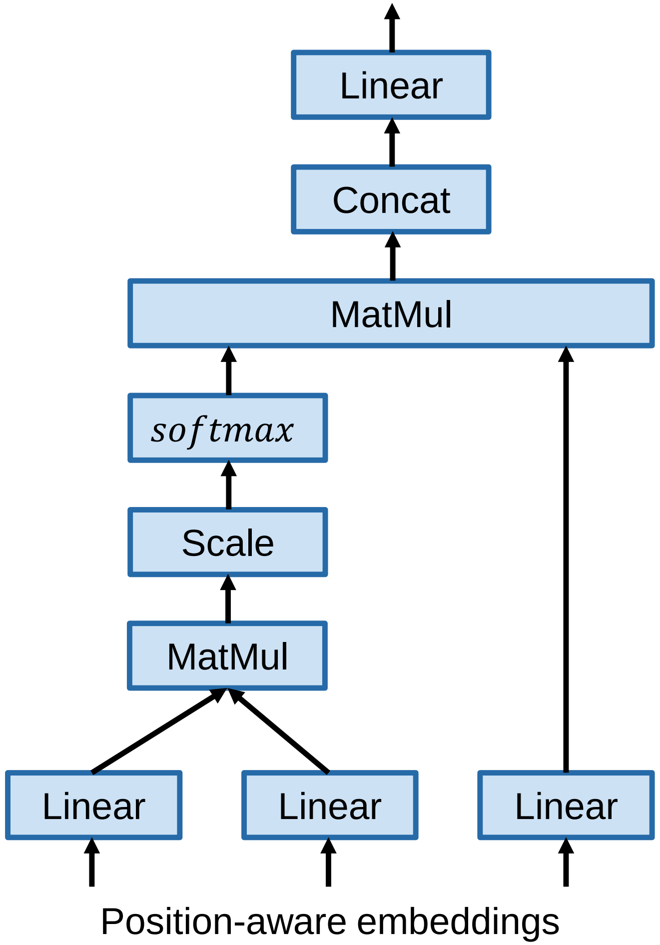


- Query, Key, Value Formulation is used to calculate Attention.
- Similarity between Query and Key can be considered as proxy to attention.
    - The similarity can be found using Cosine Similarity. (-1 to +1)

$$\cos(\boldsymbol{a}, \boldsymbol{b}) = \frac{\boldsymbol{a} \, . \, \boldsymbol{b}}{|\boldsymbol{a}||\boldsymbol{b}|}$$



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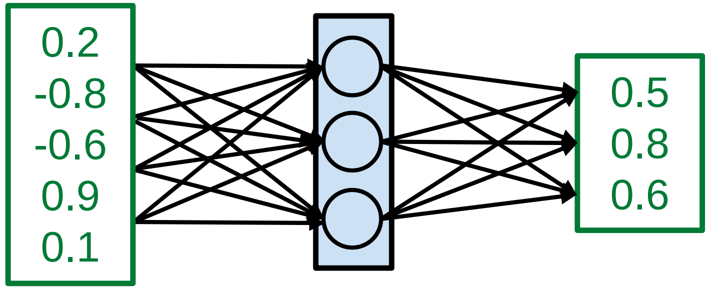

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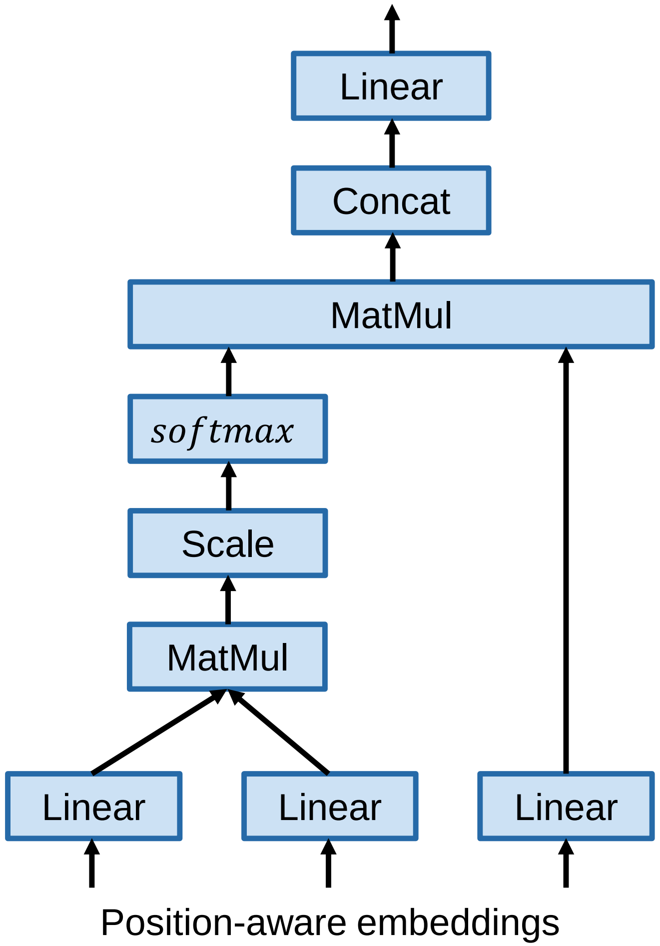
- What do Query, Key and Values consist of?



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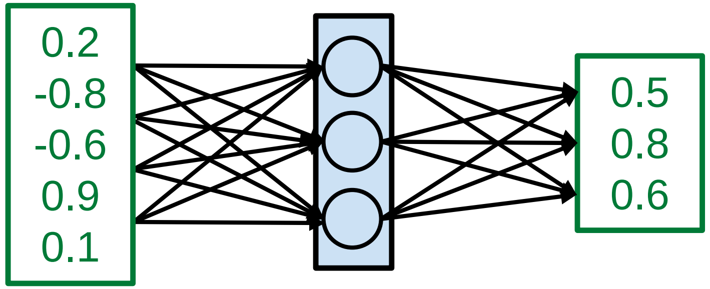

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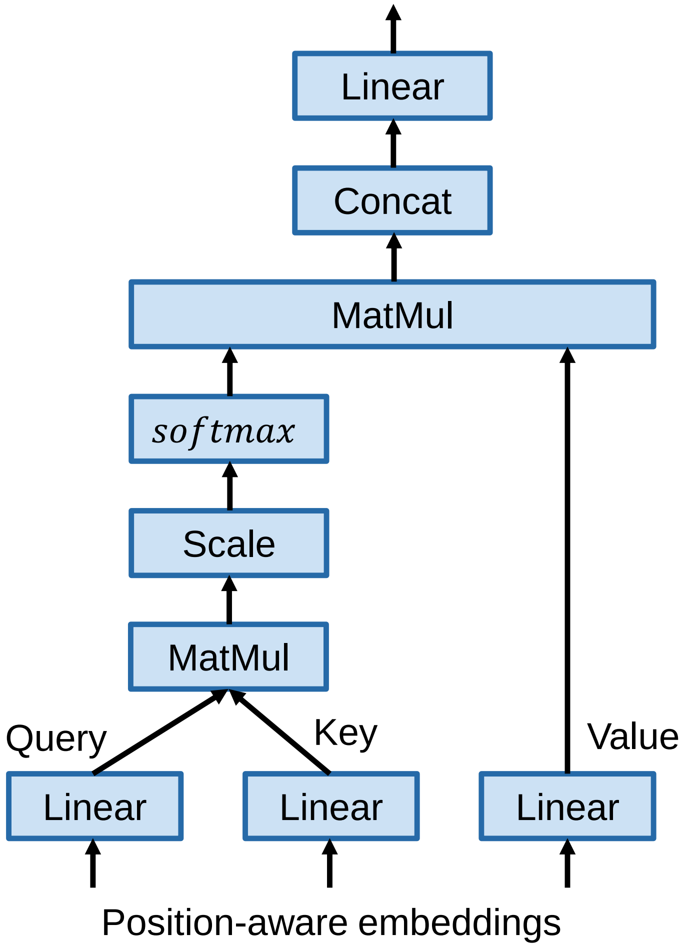
- What do Query, Key and Values consist of?
  - Position-aware embeddings processed by relevant linear layers.



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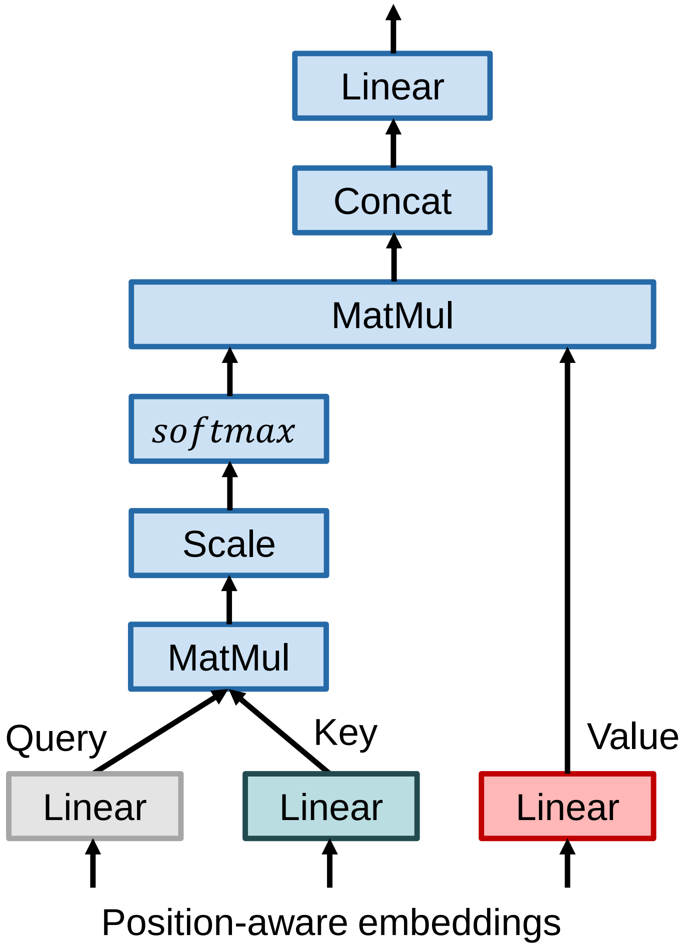
Values of Query, Kay and Value matrices are learnt

4x5 positional embeddings $\boldsymbol{W} \in \mathbb{R}^{5\times3}$ 4x3 Query

The	0.2	-0.8	-0.6	0.9	0.1
Large	-0.9	0.3	0.4	0.6	-0.1
Red	0.5	0.6	-0.8	0.7	0.7
Dog	0.6	0.0	0.8	0.9	0.4

0.7	0.5	0.2
-0.3	0.6	-0.1
0.1	0.2	-0.9
0.4	0.8	0.1



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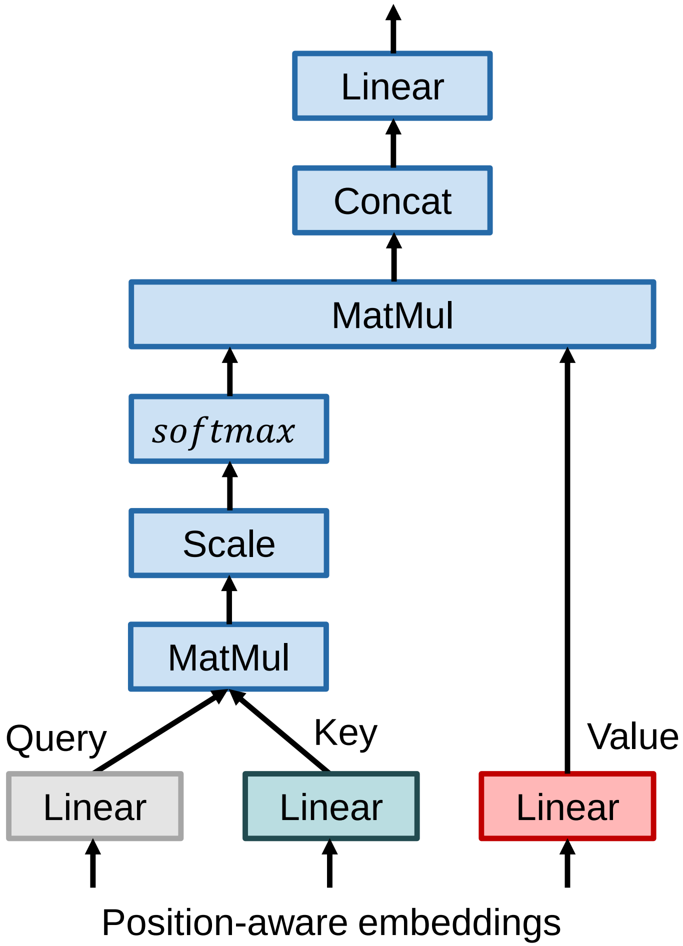
Red	0.5	0.6	-0.8	0.7	0.7	0.1	0.2	-0.9
Dog	0.6	0.0	0.8	0.9	0.4	0.4	0.8	0.1

4x5 positional embeddings $\boldsymbol{W} \in \mathbb{R}^{5\times3}$ 4x3 Key

The	0.2	-0.8	-0.6	0.9	0.1	0.7	0.5	0.2
Large	-0.9	0.3	0.4	0.6	-0.1	-0.3	0.6	-0.1
Red	0.5	0.6	-0.8	0.7	0.7	0.1	0.2	-0.9
Dog	0.6	0.0	0.8	0.9	0.4	0.4	0.8	0.1



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4x3 Query

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4x5 positional embeddings $\boldsymbol{W} \in \mathbb{R}^{5\times3}$

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4x3 Key

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4x5 positional embeddings $\boldsymbol{W} \in \mathbb{R}^{5\times3}$

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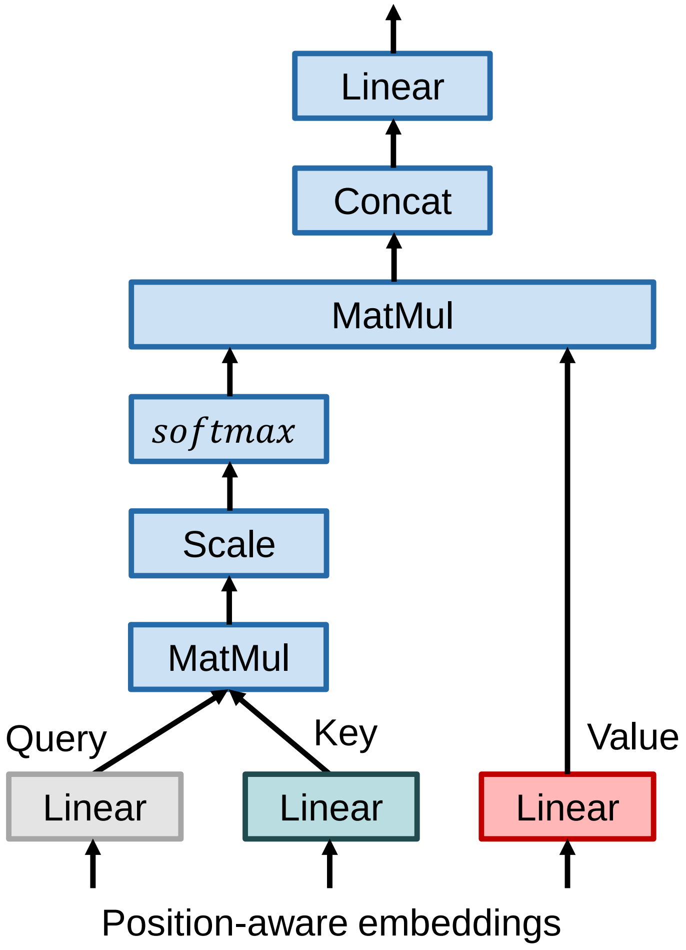
Dog	0.6	0.0	0.8	0.9	0.4

4x3 Value

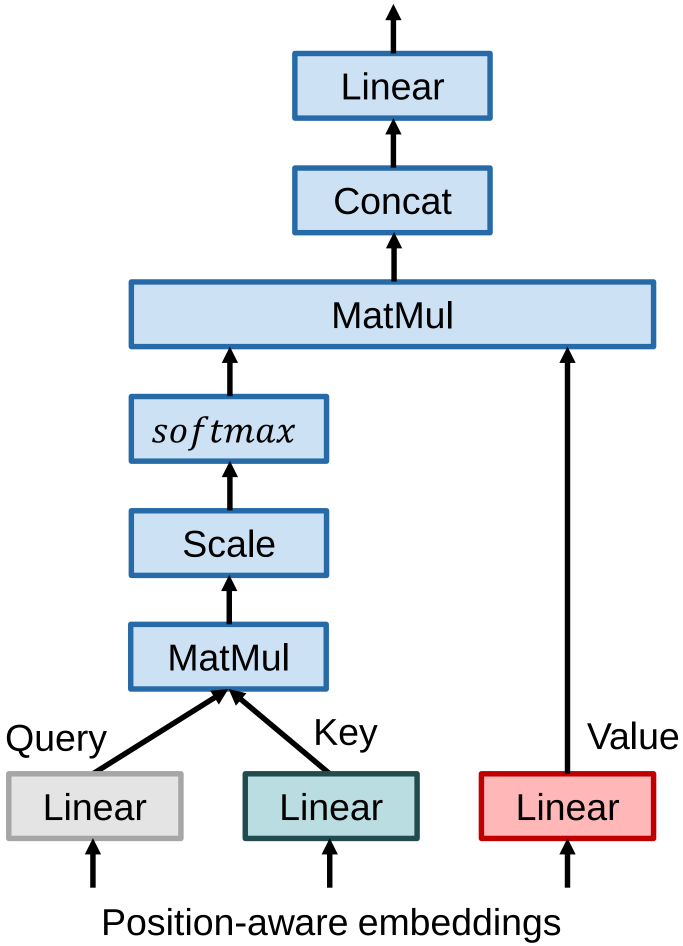
0.7	0.5	0.2
-0.3	0.6	-0.1
0.1	0.2	-0.9
0.4	0.8	0.1



Self Attention takes query and key from the same sequence

- Dot product of Query and Key gives attention scores.

$$\underset{4 \times 3\ Query}{\begin{bmatrix} 0.7 & 0.5 & 0.2 \\ -0.3 & 0.6 & -0.1 \\ 0.1 & 0.2 & -0.9 \\ 0.4 & 0.8 & 0.1 \end{bmatrix}} \times \underset{3 \times 4\ Key^T}{\begin{bmatrix} -0.1 & 0.8 & 0.3 & -0.3 \\ 0.2 & -0.4 & 0.5 & 0.9 \\ 0.1 & -0.8 & -0.7 & -0.6 \end{bmatrix}} = \underset{4 \times 4\ Attention\ Filter}{\begin{bmatrix} 0.5 & 0.2 & 0.3 & 0.1 \\ 0.1 & -0.4 & 0.3 & 0.7 \\ -0.1 & 0.7 & 0.8 & 0.7 \\ 0.1 & -0.1 & 0.4 & 0.5 \end{bmatrix}}$$



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$$\underset{4\times 3\ Query}{\begin{bmatrix} 0.7 & 0.5 & 0.2 \\ -0.3 & 0.6 & -0.1 \\ 0.1 & 0.2 & -0.9 \\ 0.4 & 0.8 & 0.1 \end{bmatrix}} \times \underset{3\times 4\ Key^T}{\begin{bmatrix} -0.1 & 0.8 & 0.3 & -0.3 \\ 0.2 & -0.4 & 0.5 & 0.9 \\ 0.1 & -0.8 & -0.7 & -0.6 \end{bmatrix}} = \underset{4\times 4\ Attention\ Filter}{\begin{bmatrix} 0.5 & 0.2 & 0.3 & 0.1 \\ 0.1 & -0.4 & 0.3 & 0.7 \\ -0.1 & 0.7 & 0.8 & 0.7 \\ 0.1 & -0.1 & 0.4 & 0.5 \end{bmatrix}}$$

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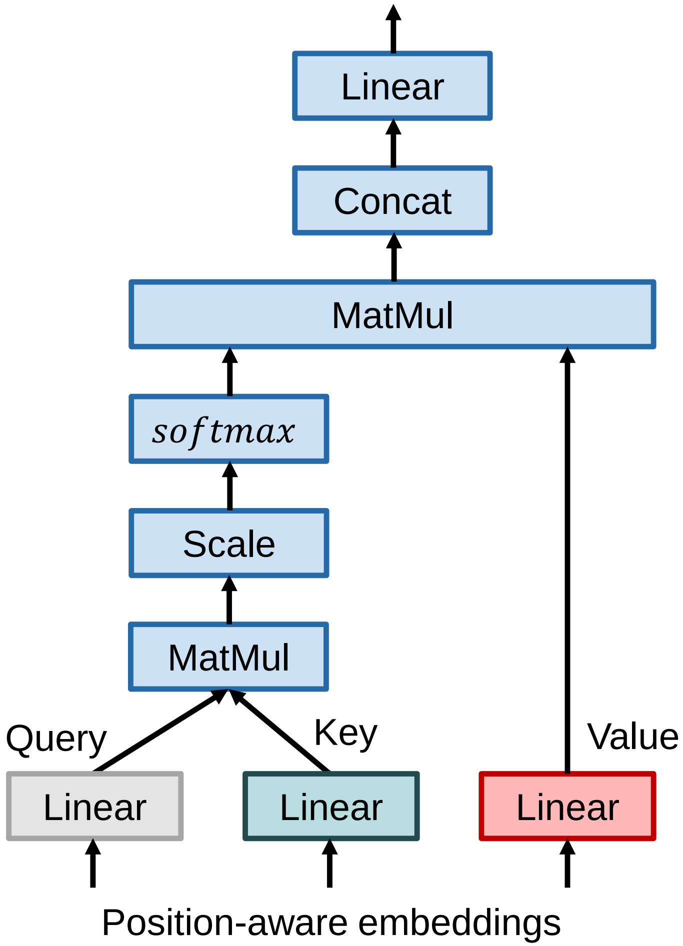

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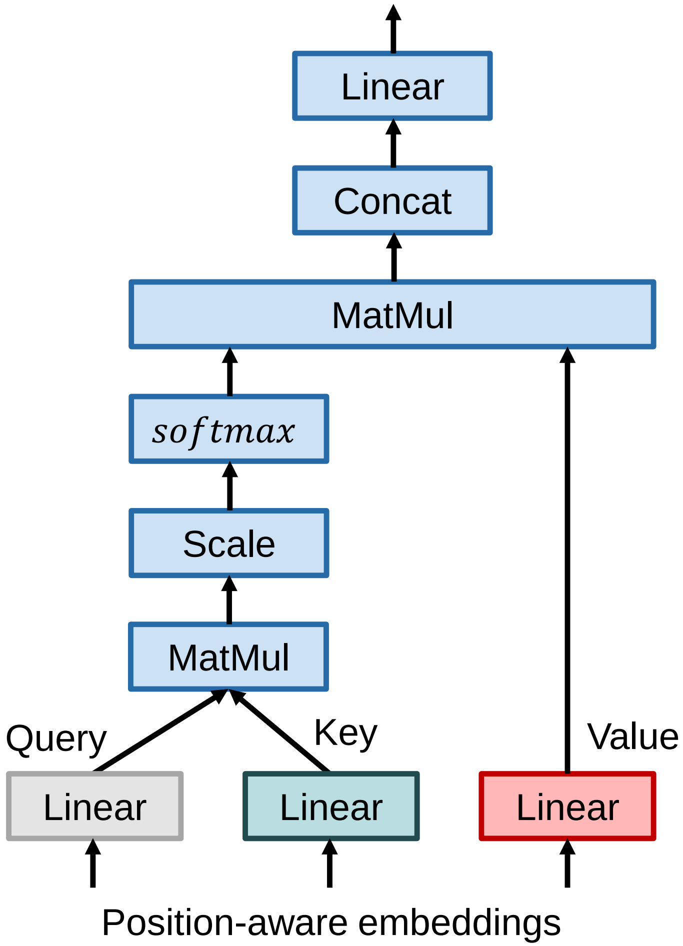
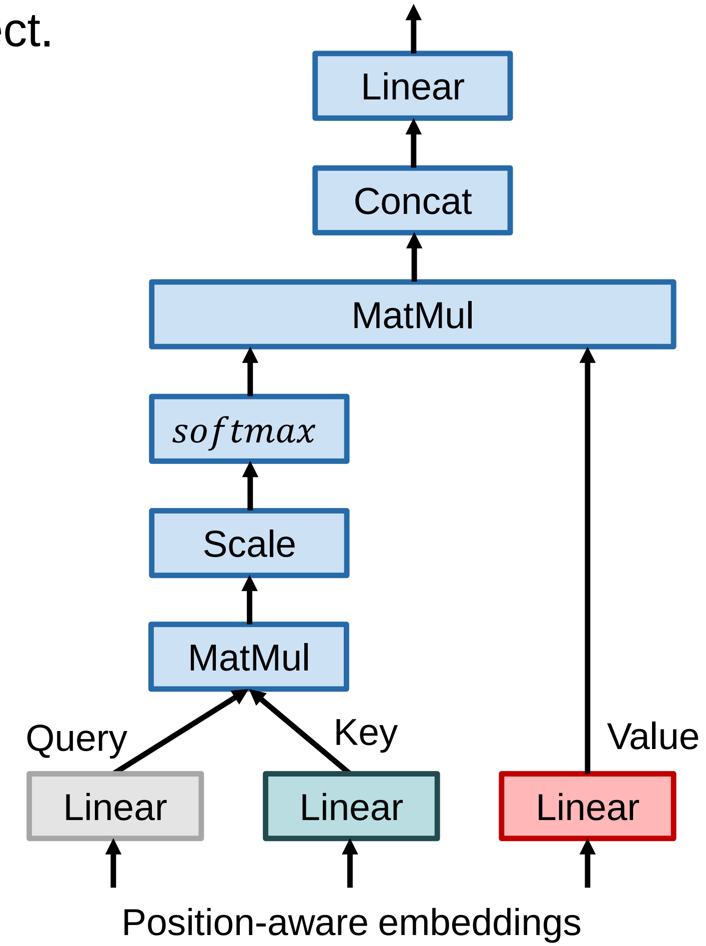


$$Attension\ (Q, K, V) = softmax\left(\frac{Q.K^T}{\sqrt{d_k}}\right).V$$

Transformers encoder uses a Multi-Headed Attention block

- Multiple attention filters are learnt each focusing on a particular linguistic aspect.



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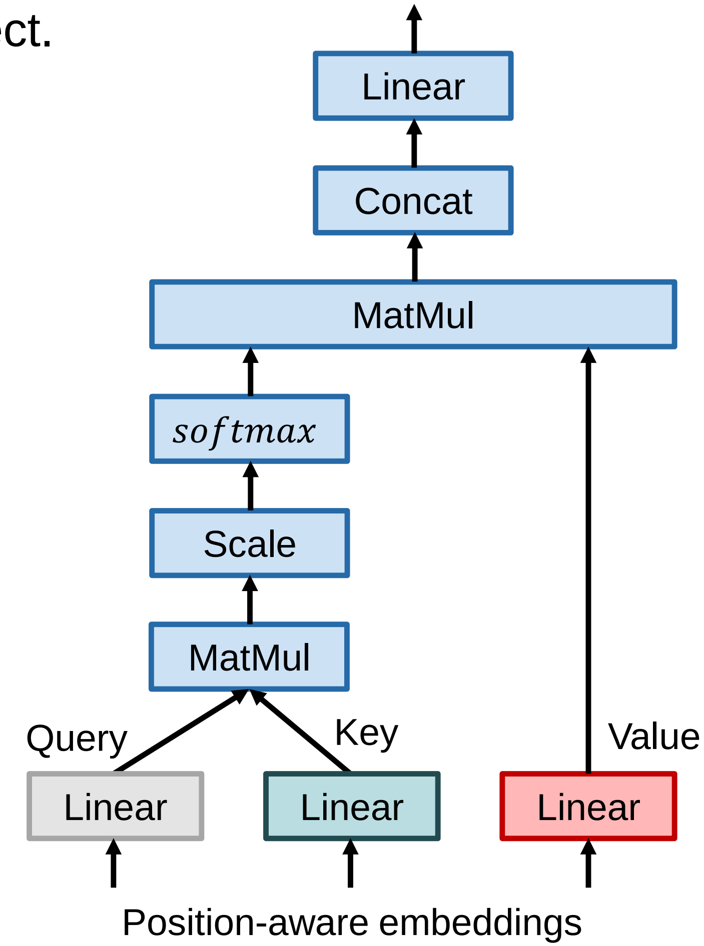
The original Transformer paper uses $h = 8$ attention heads and

$$d_k = d_v = \frac{d_{model}}{8} = 64$$



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-0.1	0.4	0.5
0.6	0.7	0.8
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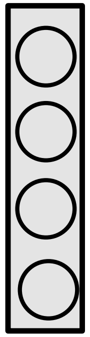
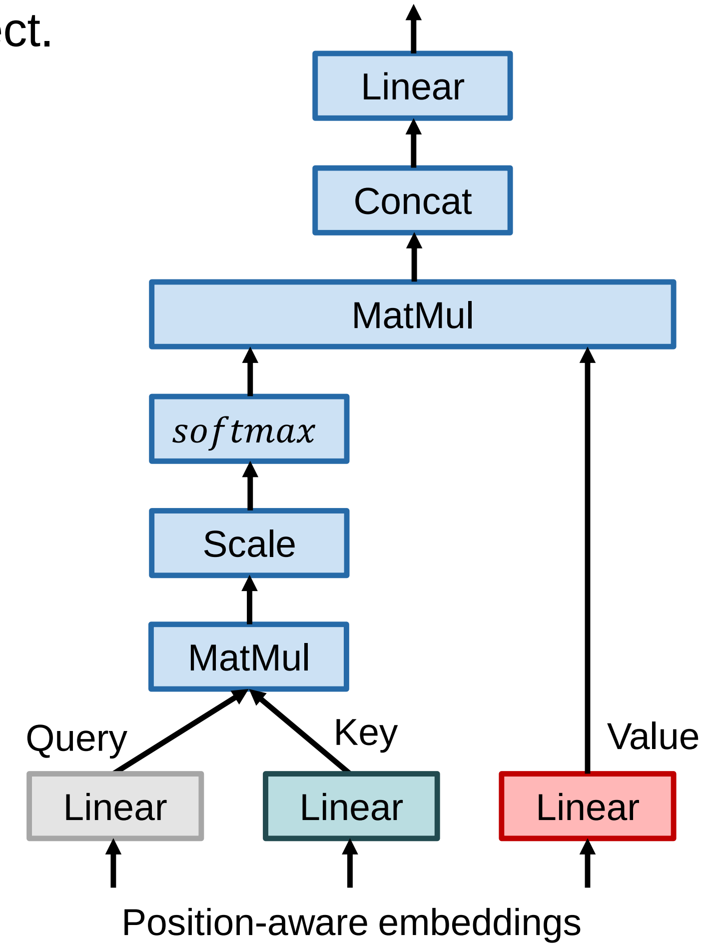


0.2	-0.6	0.9	0.1
-0.9	0.3	0.4	-0.1
0.5	0.6	-0.8	0.7
0.6	0.8	0.9	0.4
-0.8	0.6	0.1	-0.4



Add position-aware embedding to attention output and normalise

- Add Position-aware Embeddings and the output of Multi-head Attention Layer.

Skip Connection

0.1	-0.1	-0.3	0.8
0.8	-0.2	0.7	-0.9
-0.5	0.5	-0.6	0.3
0.7	-0.3	0.5	0.2
0.0	-0.3	0.4	0.1

+

MultiHead Attention Output

0.2	-0.6	0.9	0.1
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0.5	0.6	-0.8	0.7
0.6	0.8	0.9	0.4
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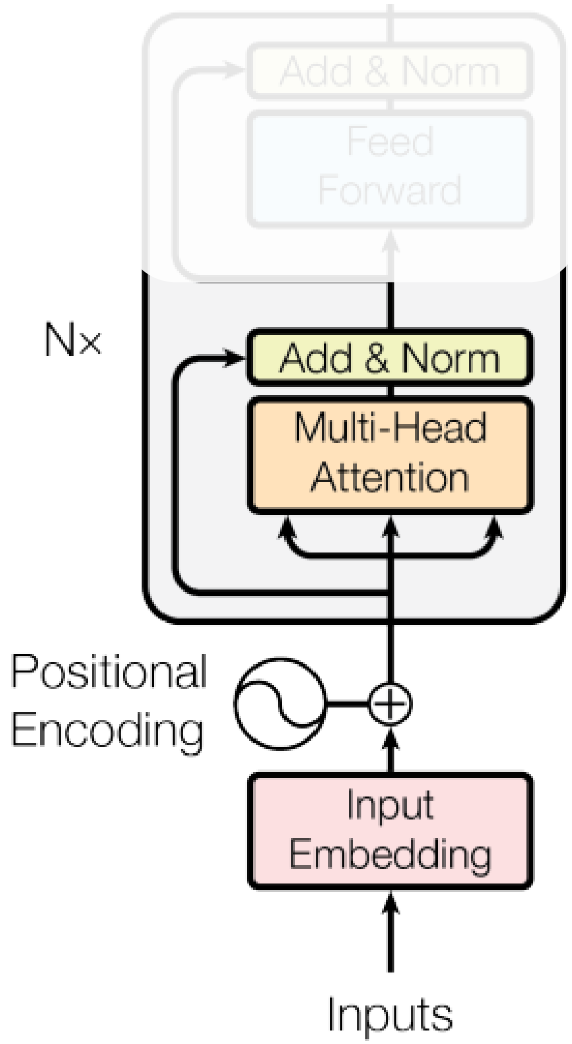

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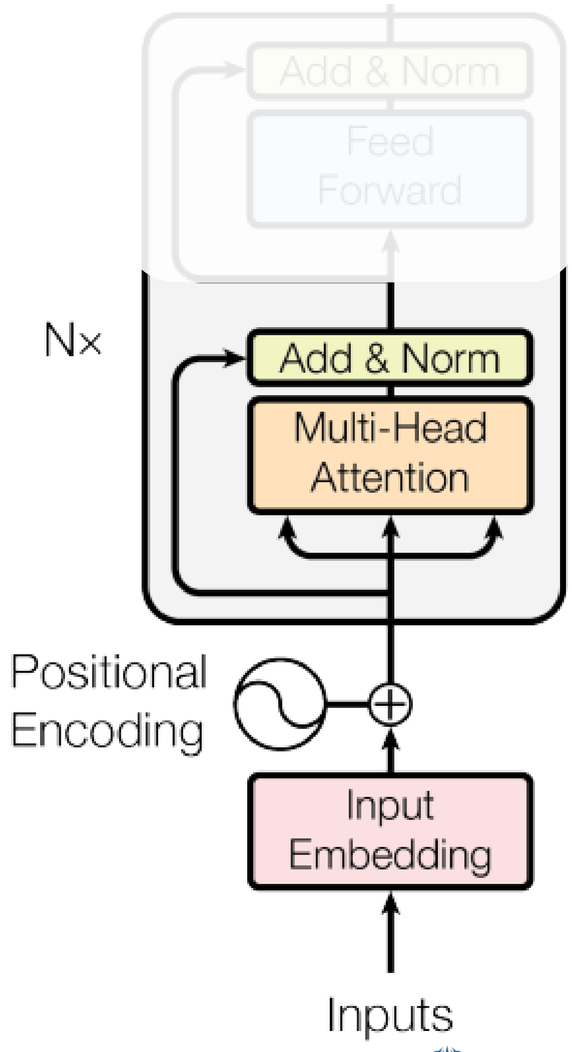
- Perform z-score standardisation across features.



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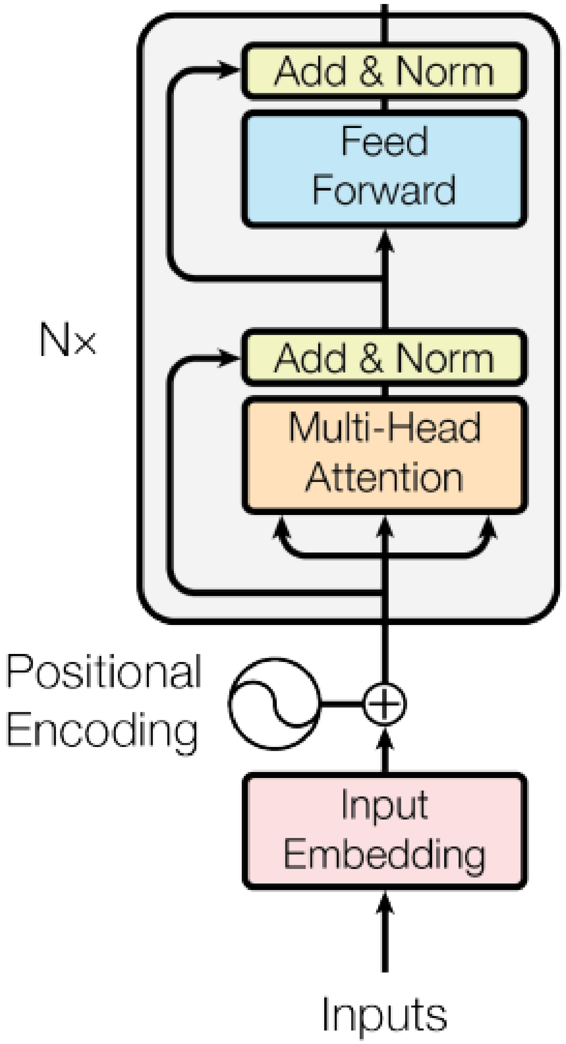
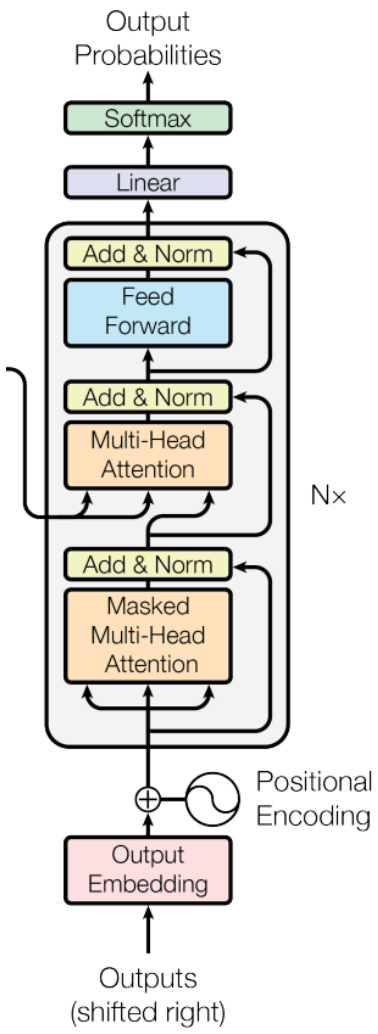
- Perform z-score standardisation across features.

- Pass through feedforward network and that's it.



Decoder uses masked self attention

- The output of encoder is given to the decoder as Q and K matrices.



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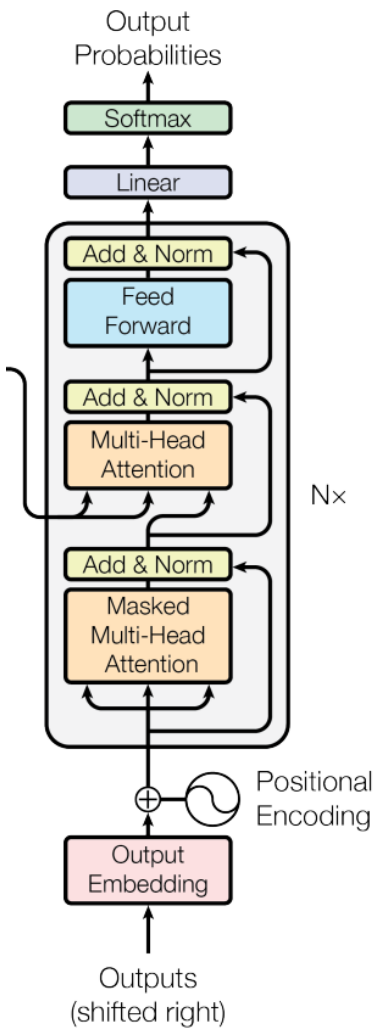

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$Attention\ Filter$

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0.1	-0.1	0.4	0.5

$Masked\ Attention\ Filter$

0.5	-inf	-inf	-inf
0.1	-0.4	-inf	-inf
-0.1	0.7	0.8	-inf
0.1	-0.1	0.4	0.5

$Softmax\ of$
$Masked\ Attention\ Filter$

0.5	0	0	0
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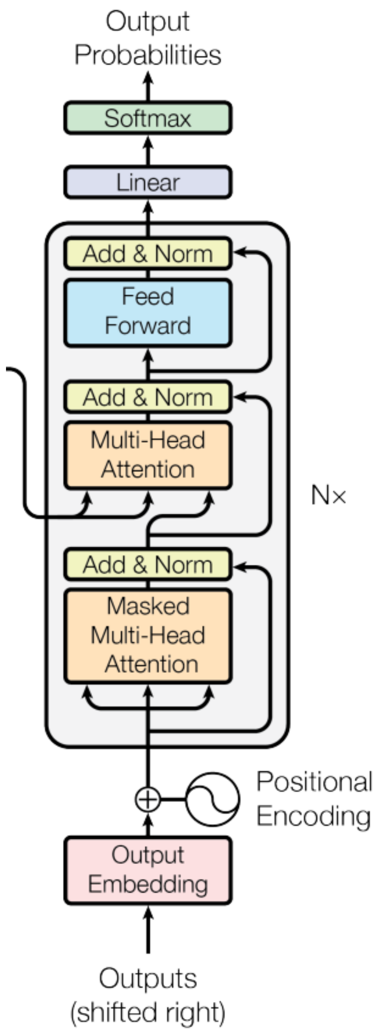

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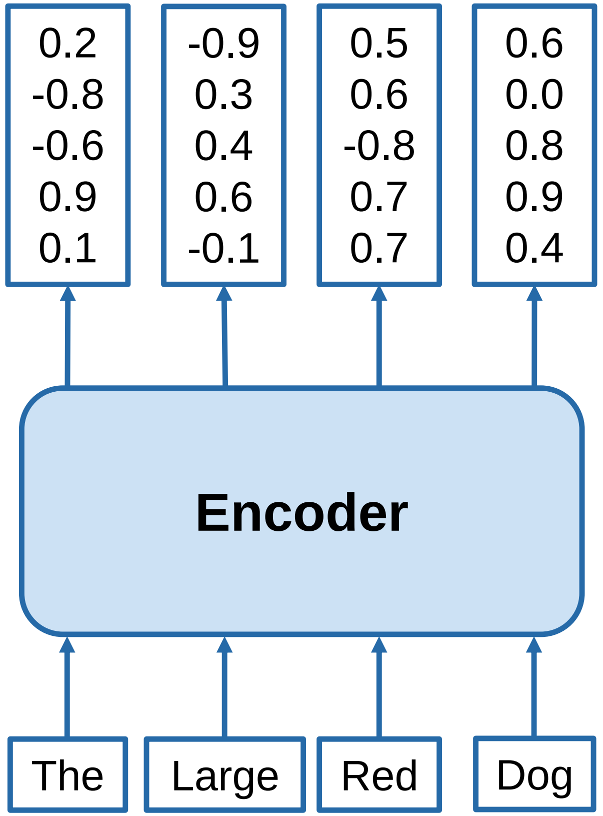
Encoder converts words into embeddings

- Dimension of word embeddings is defined by the model.
    - Base BERT used 768 dimensional embeddings.



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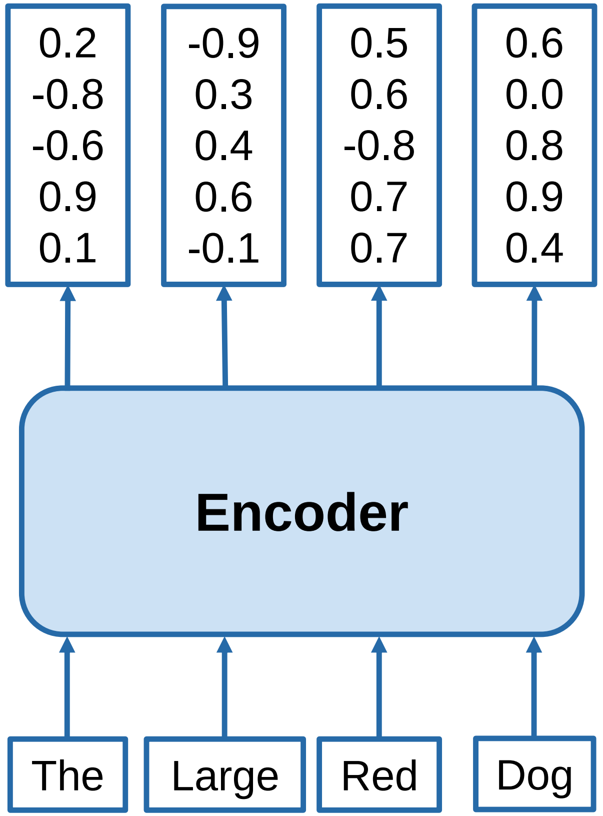

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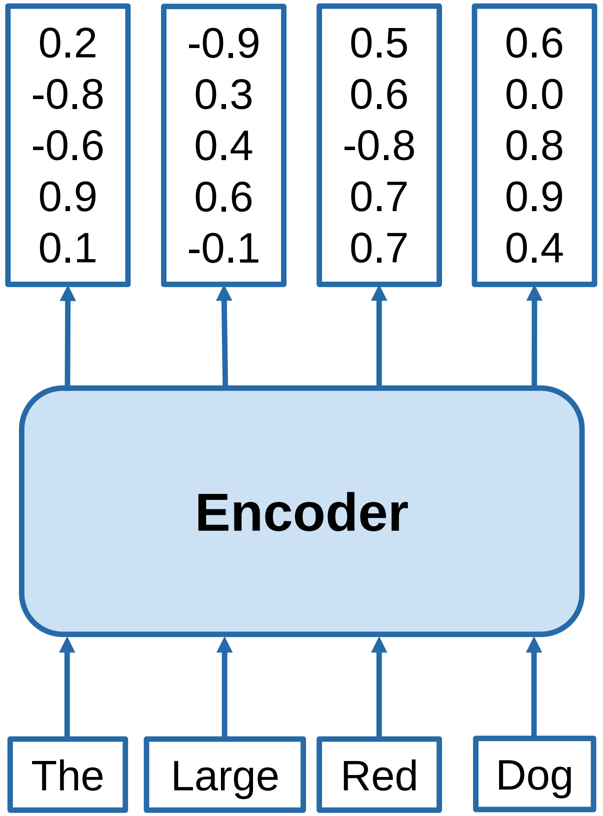

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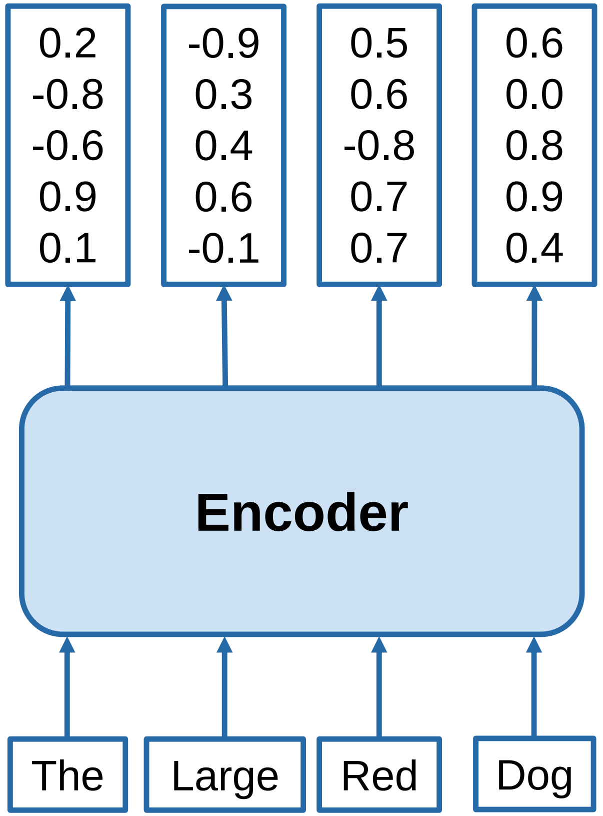
- Uses Self-Attention mechanism, which consults other words in the sequence to learn the meaning of a given word.



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- Common examples are BERT (SOTA of its time) and its variants RoERTa and ALBERT.

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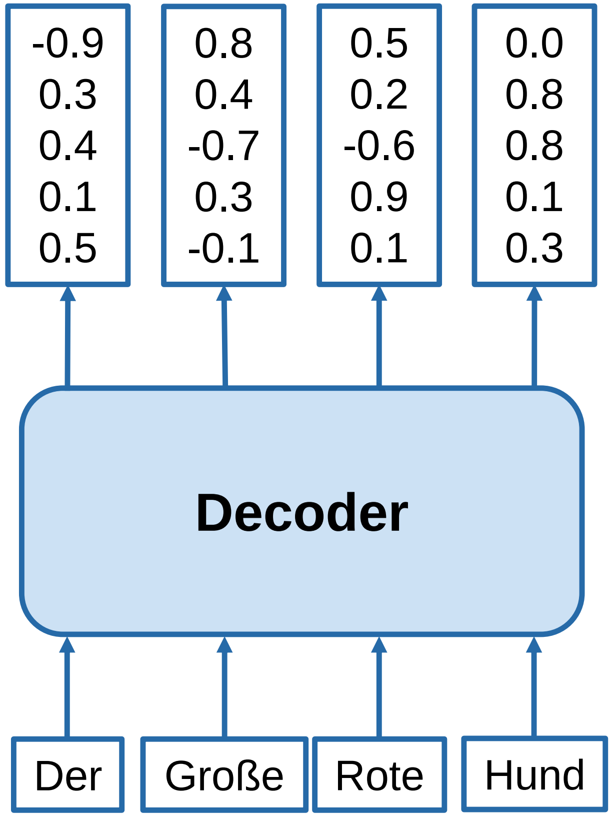
- Can be used to perform the same tasks as encoders (with reduced performance)



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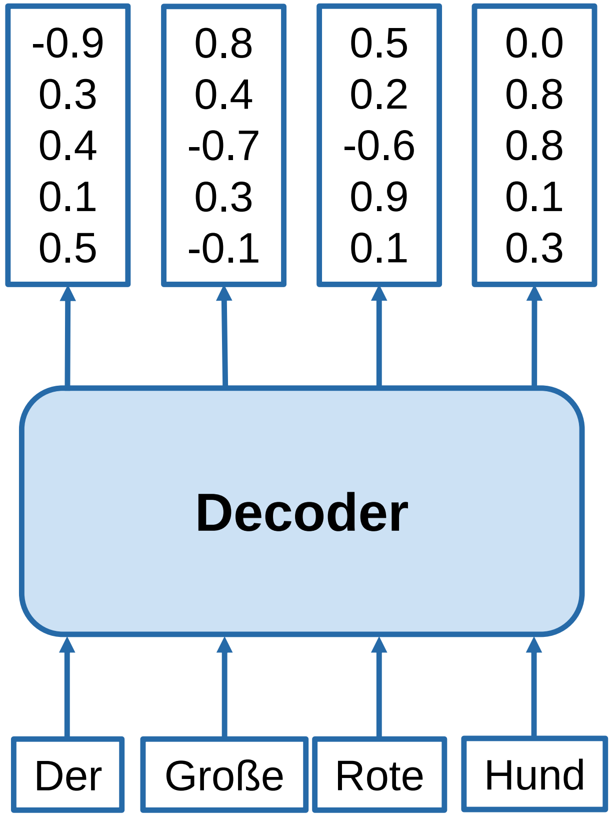

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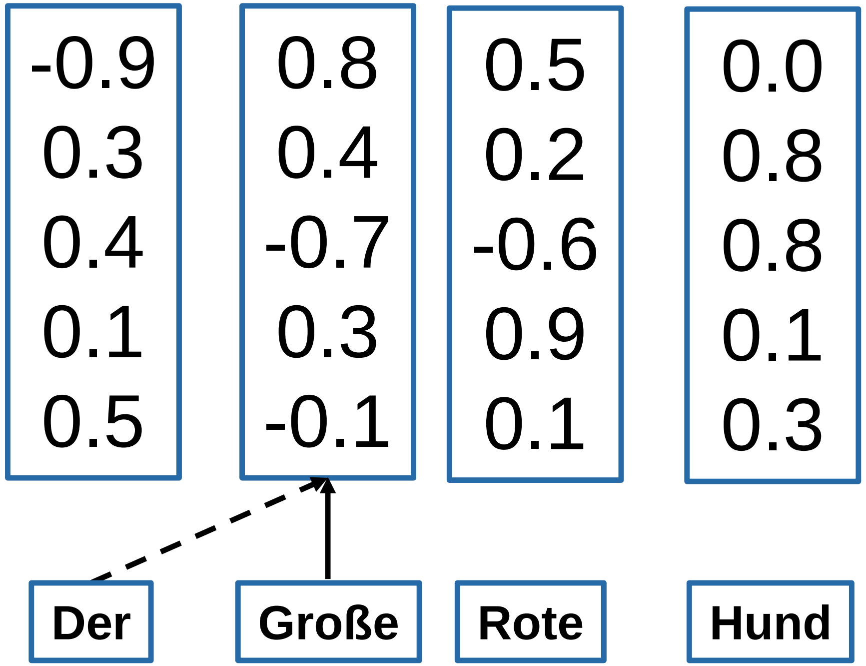
- Uses Masked Self-Attention mechanism, which consults only the previous or the following words in the sequence to learn the meaning of a given word.



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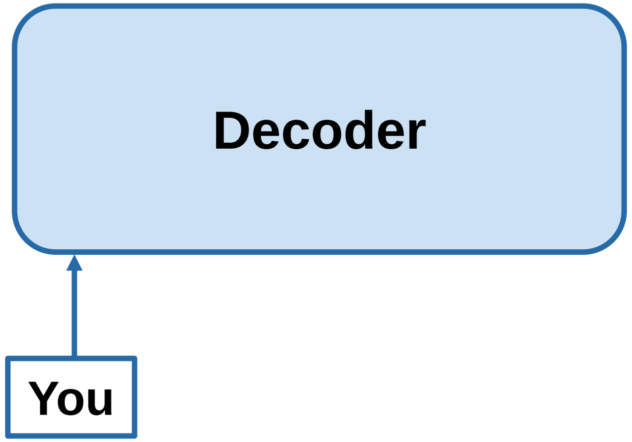

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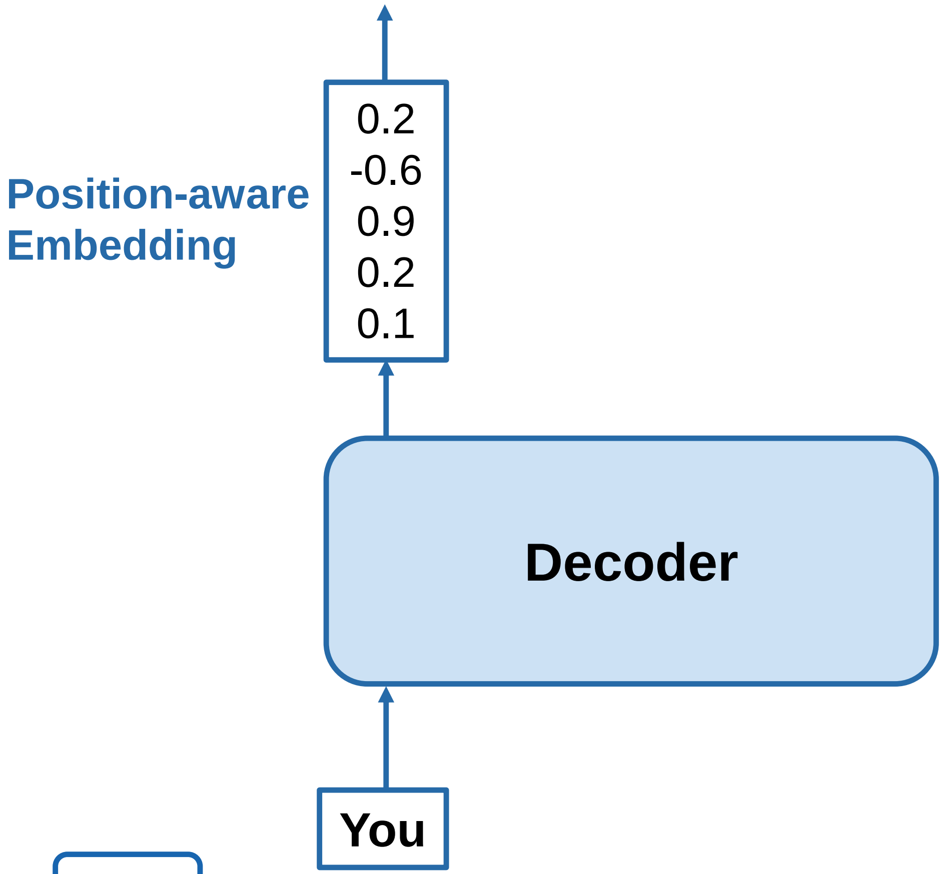

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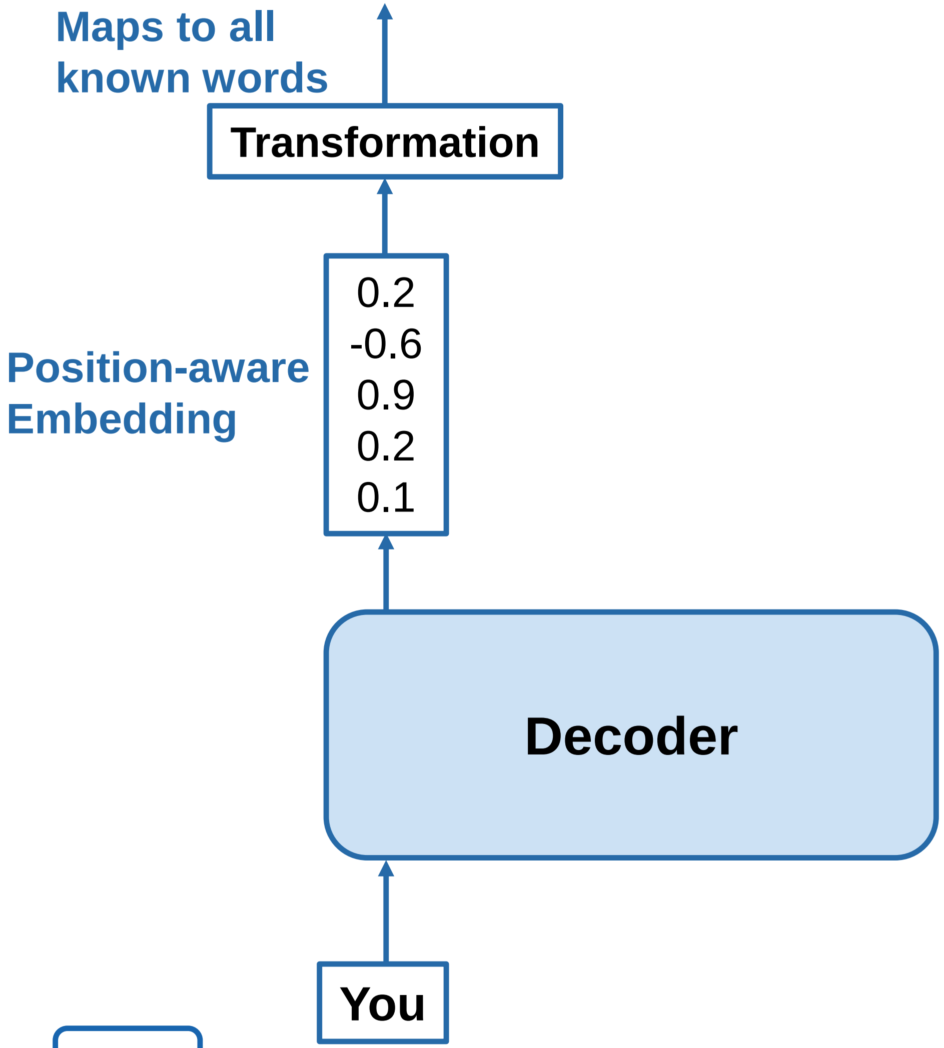

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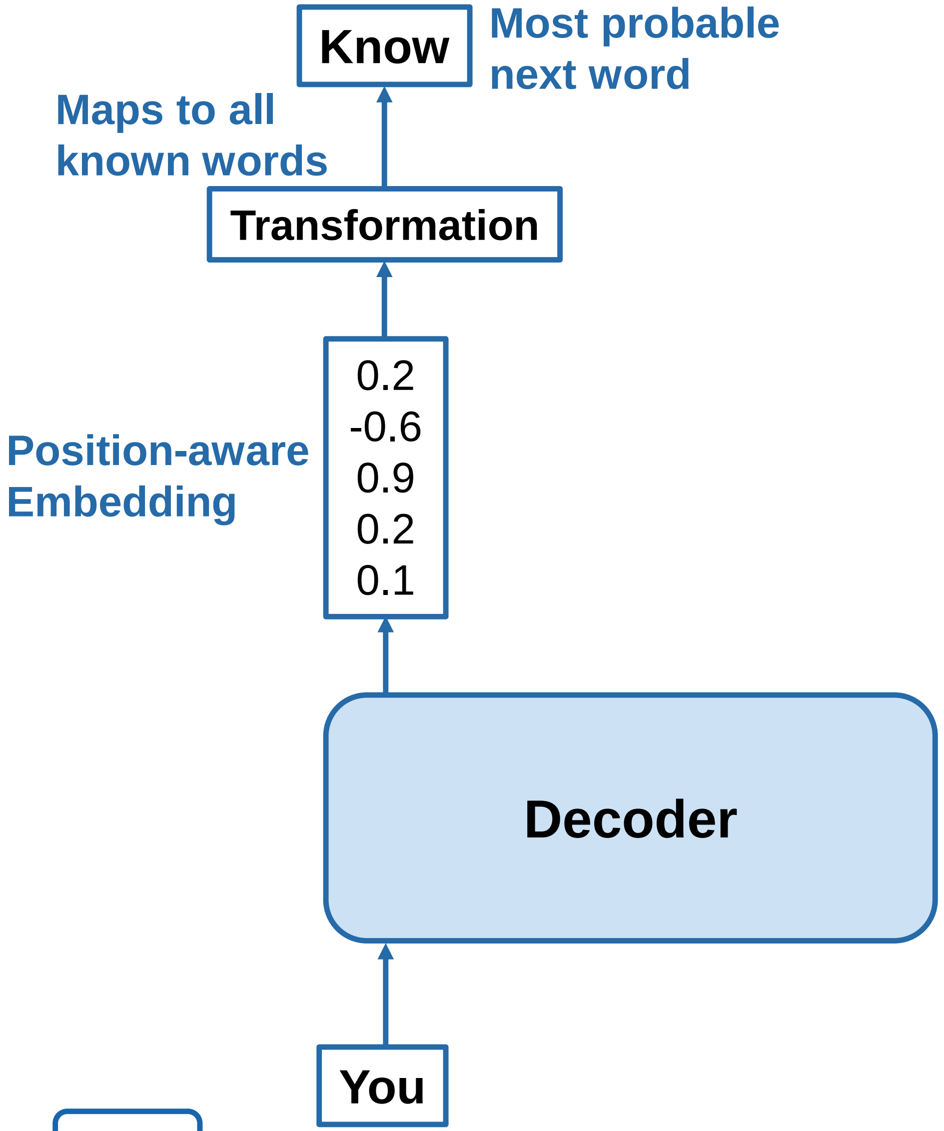

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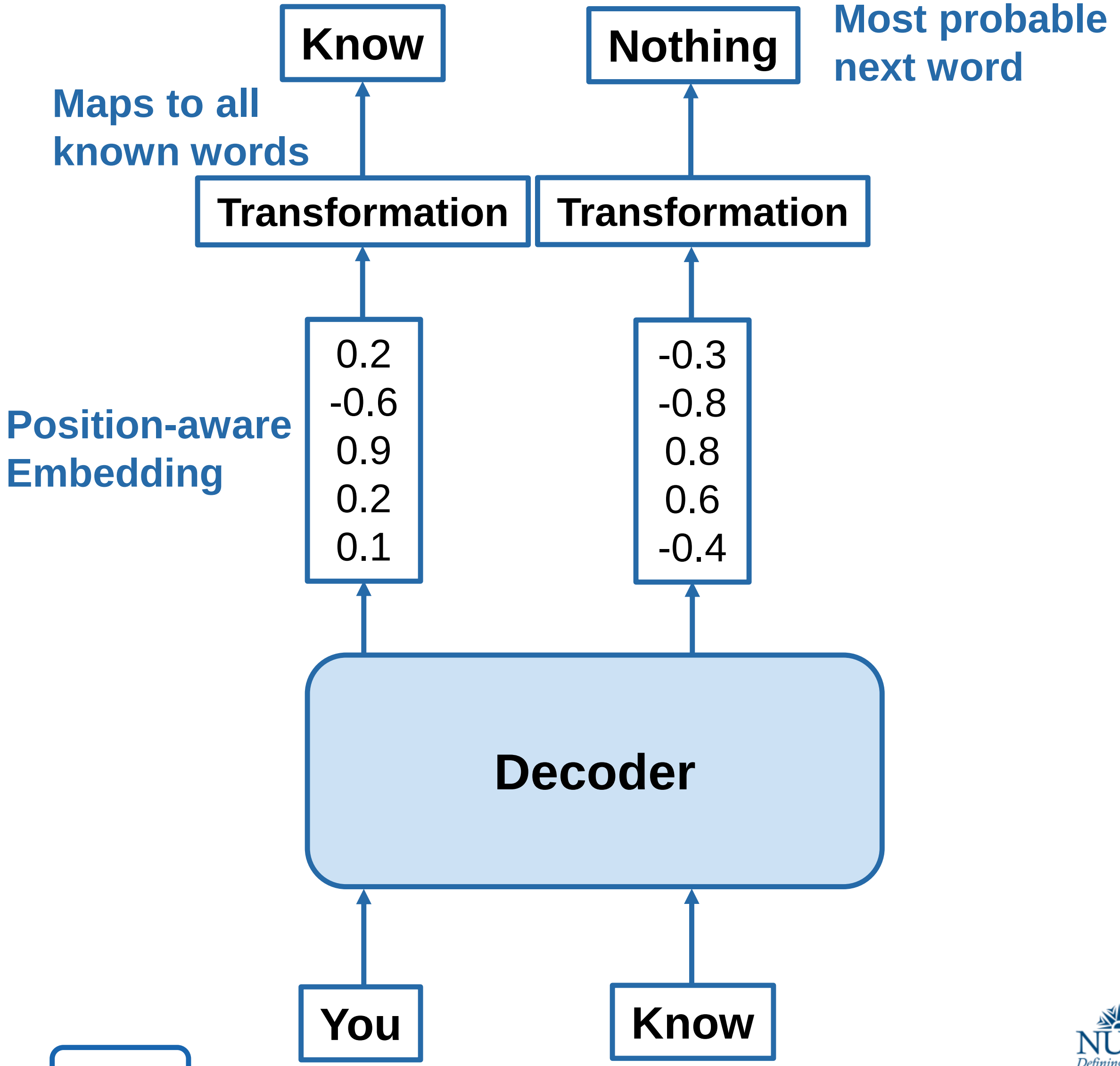

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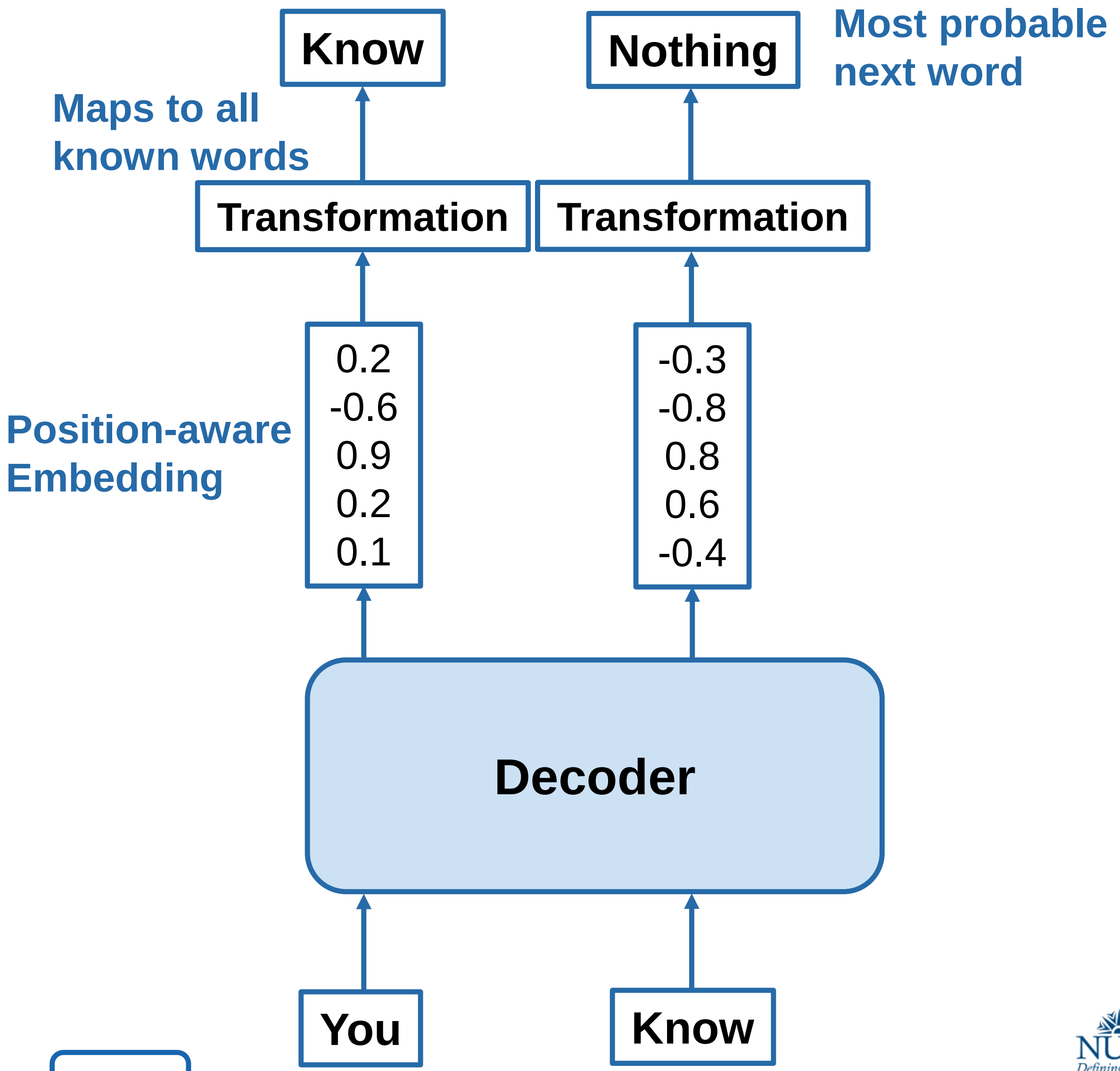
- Examples include GPT and GPT-2.

    - GPT-2 has a context of size 1024.



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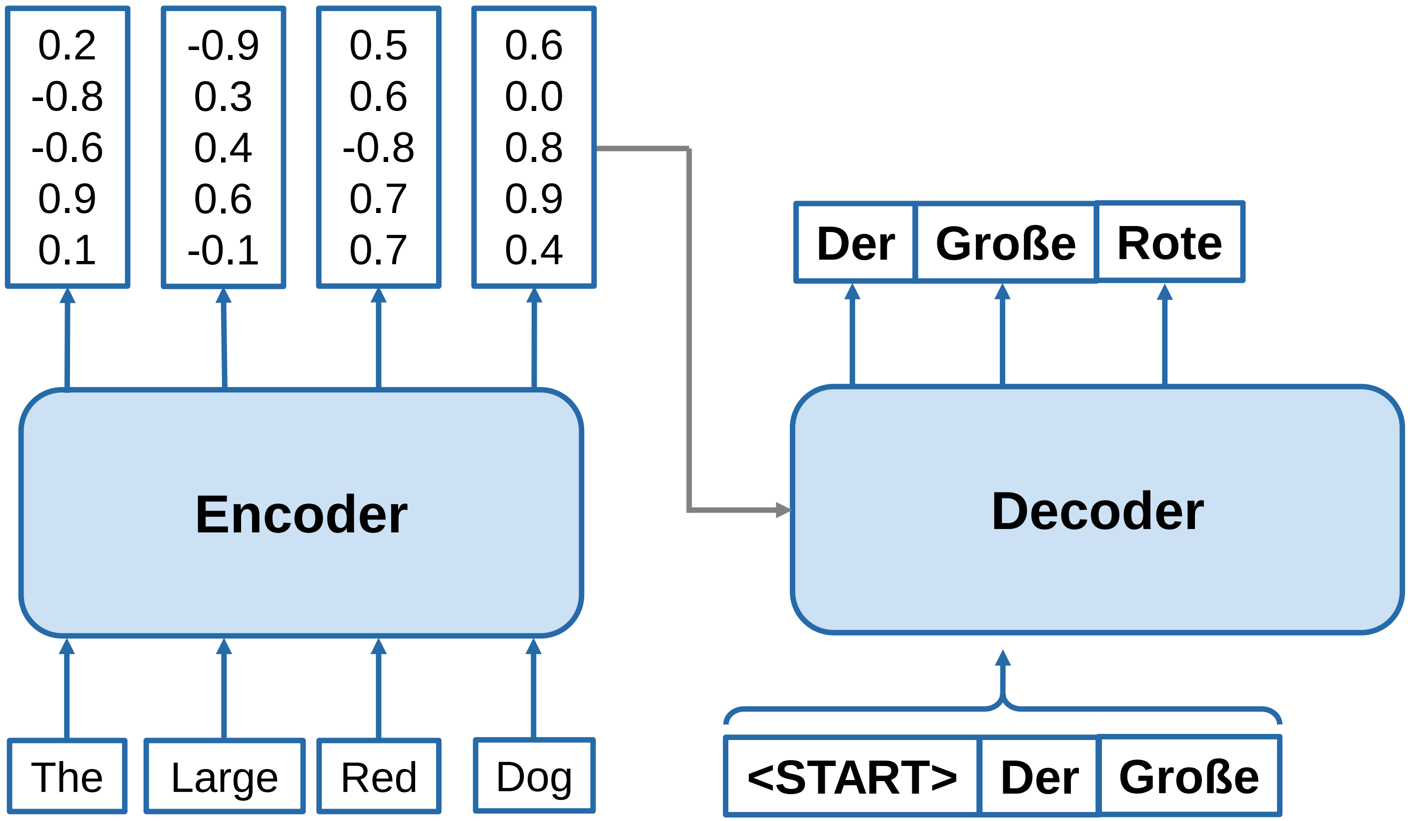
Encoder-Decoder architecture addresses *seq2seq* tasks

- Useful for translation and summarisation.



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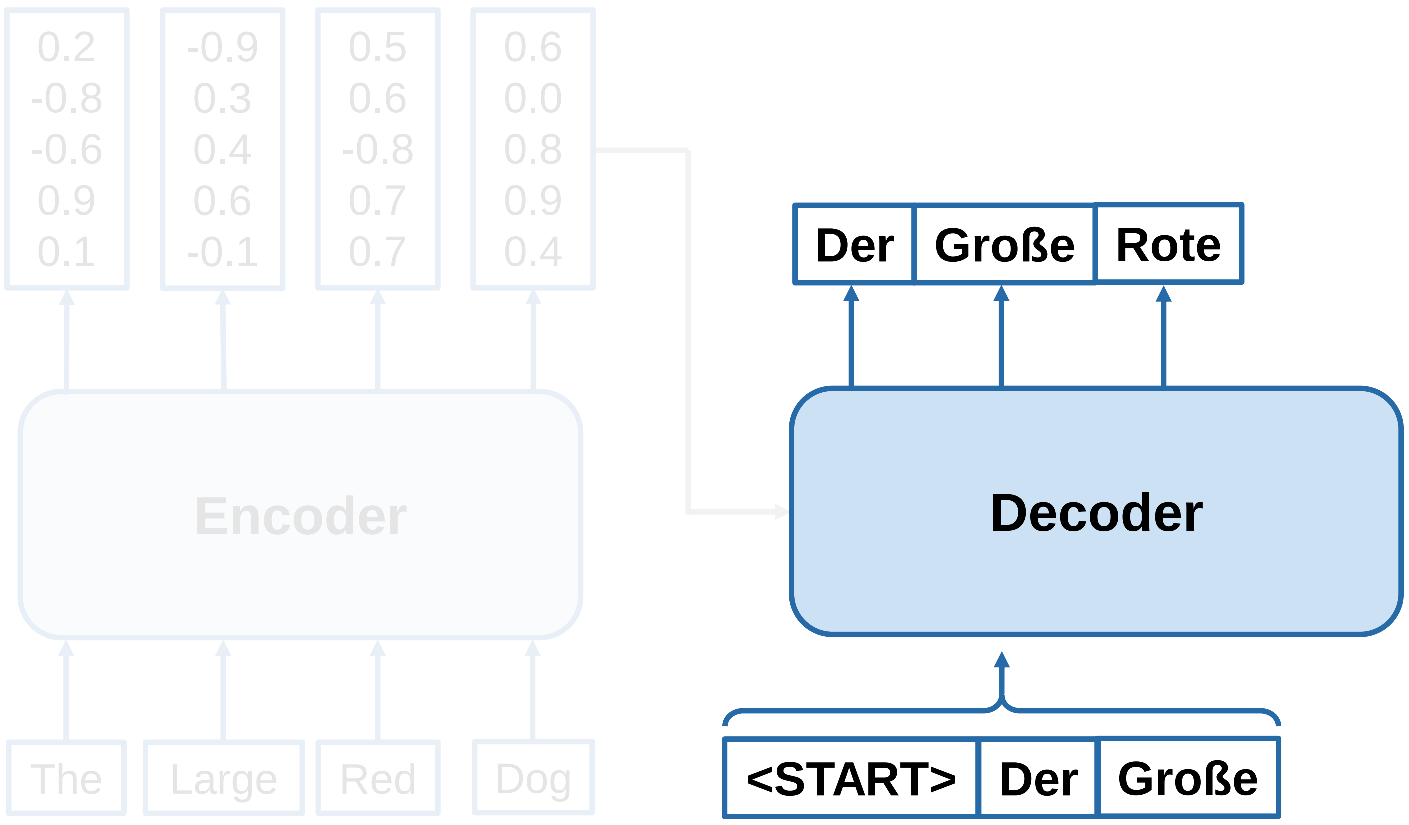

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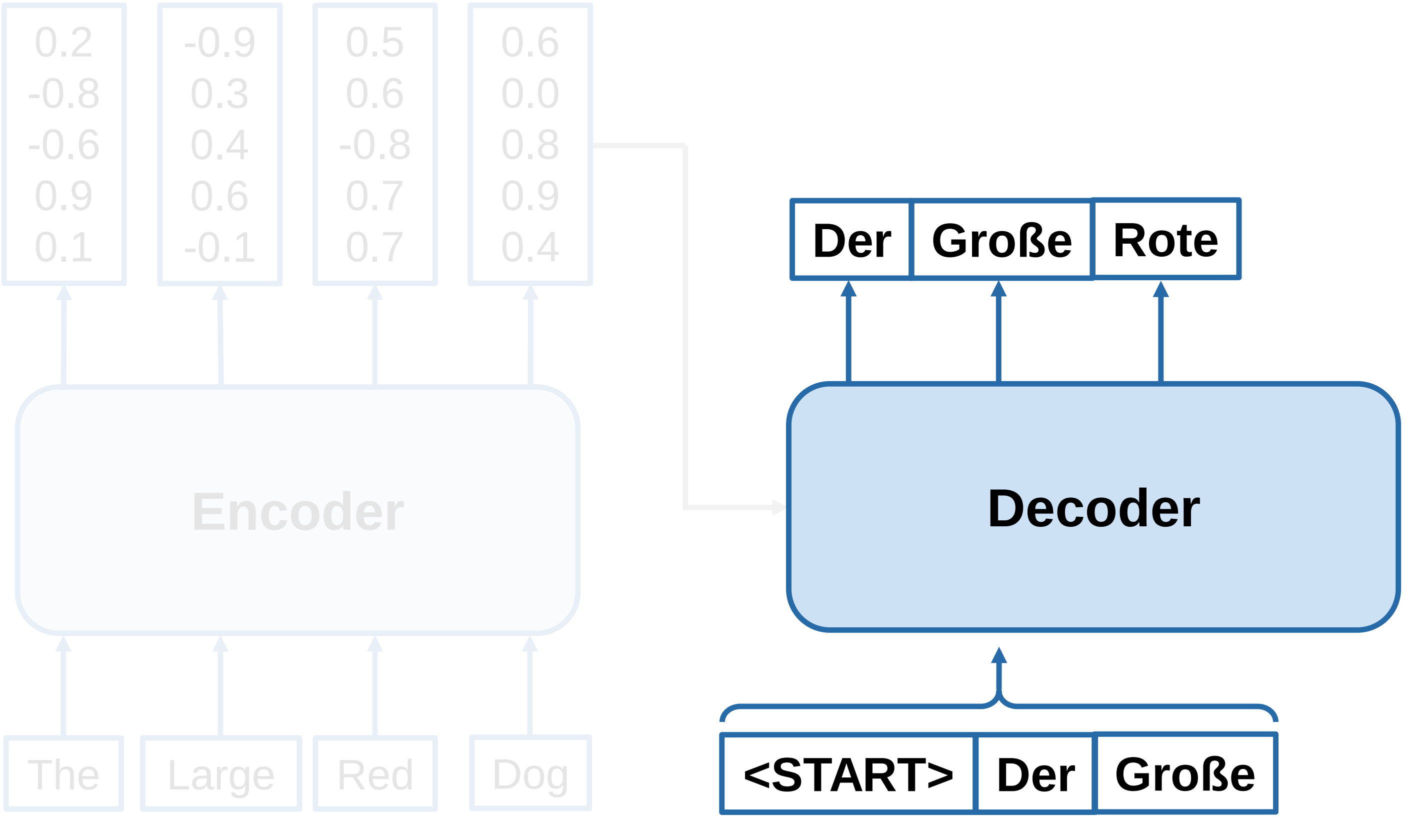

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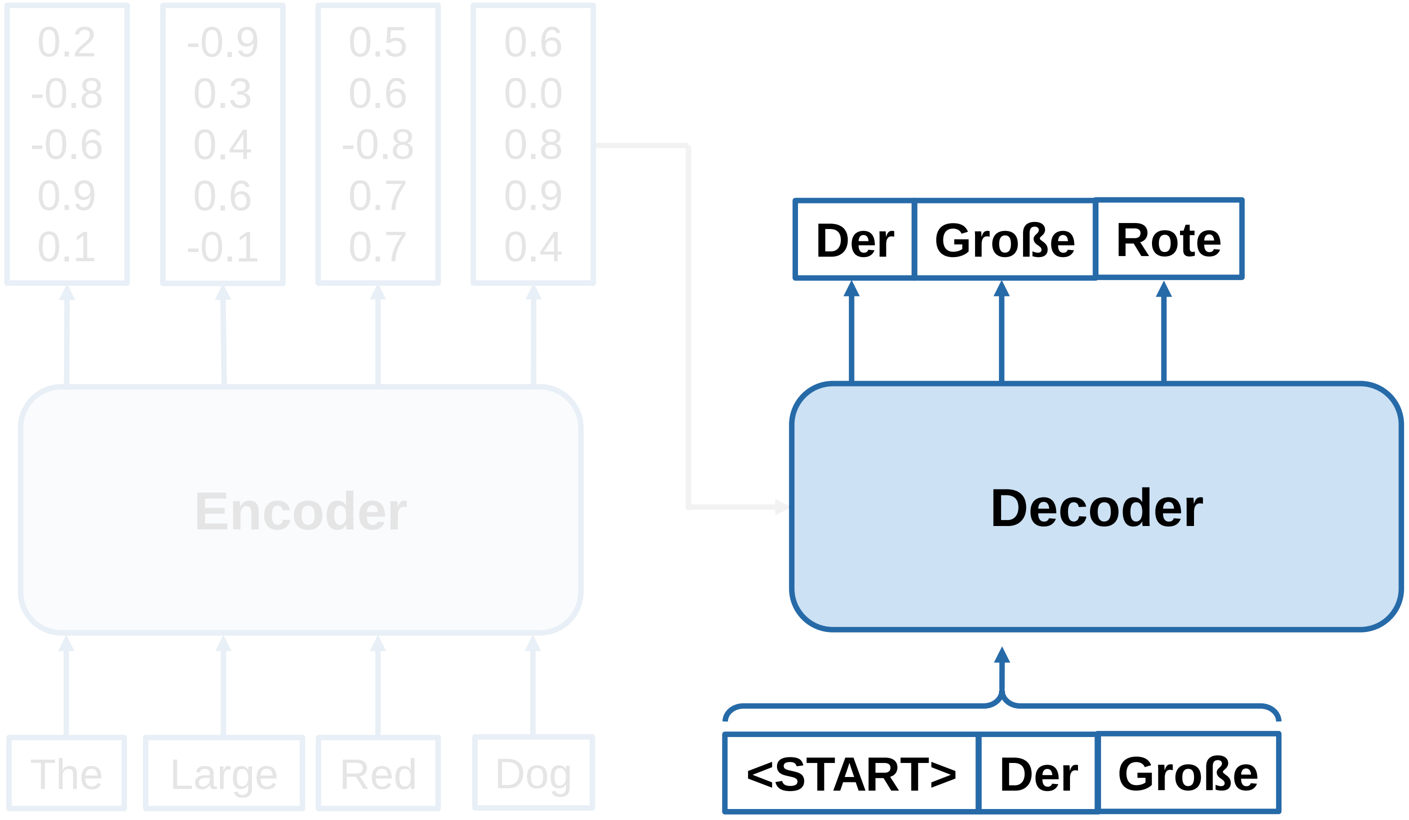

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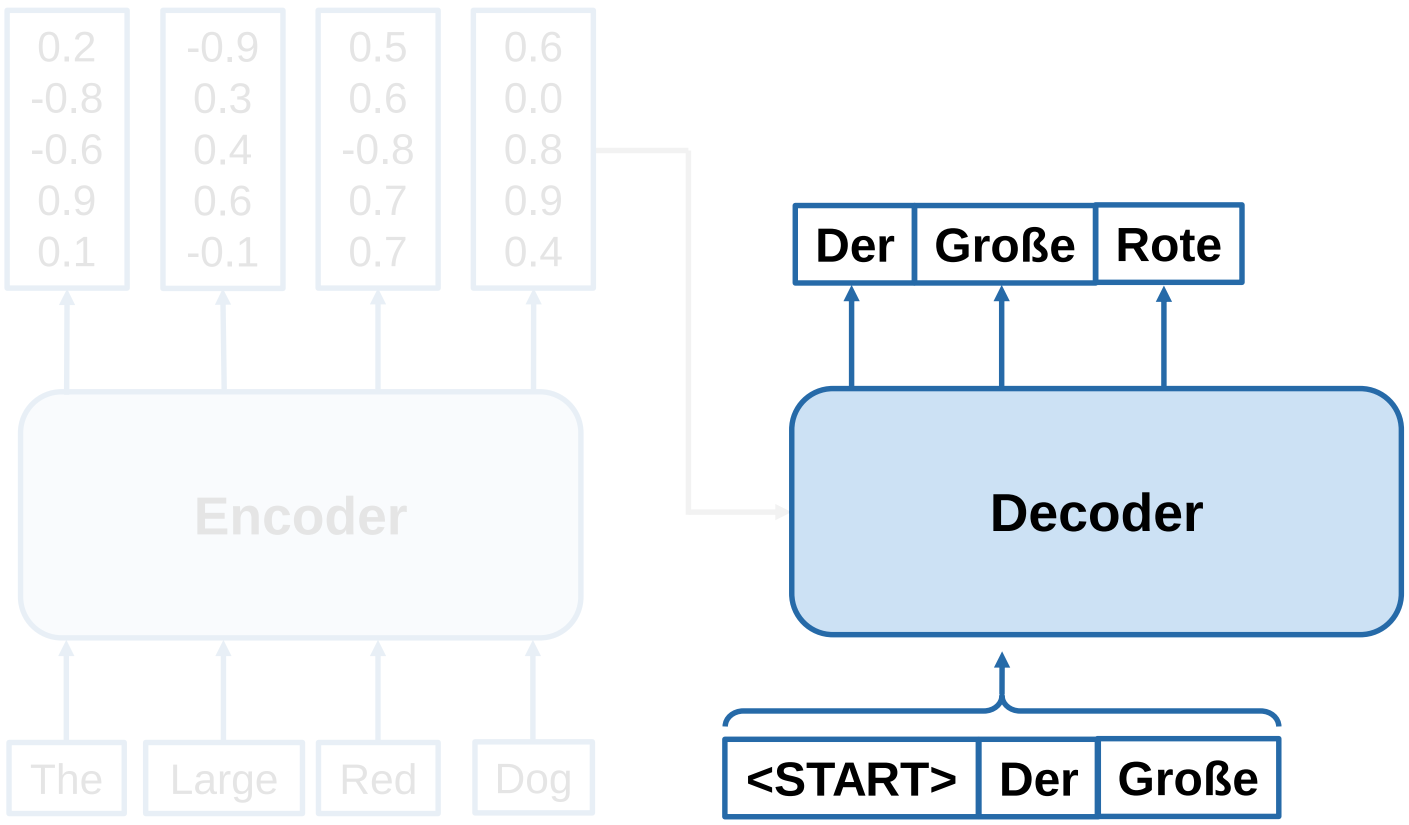

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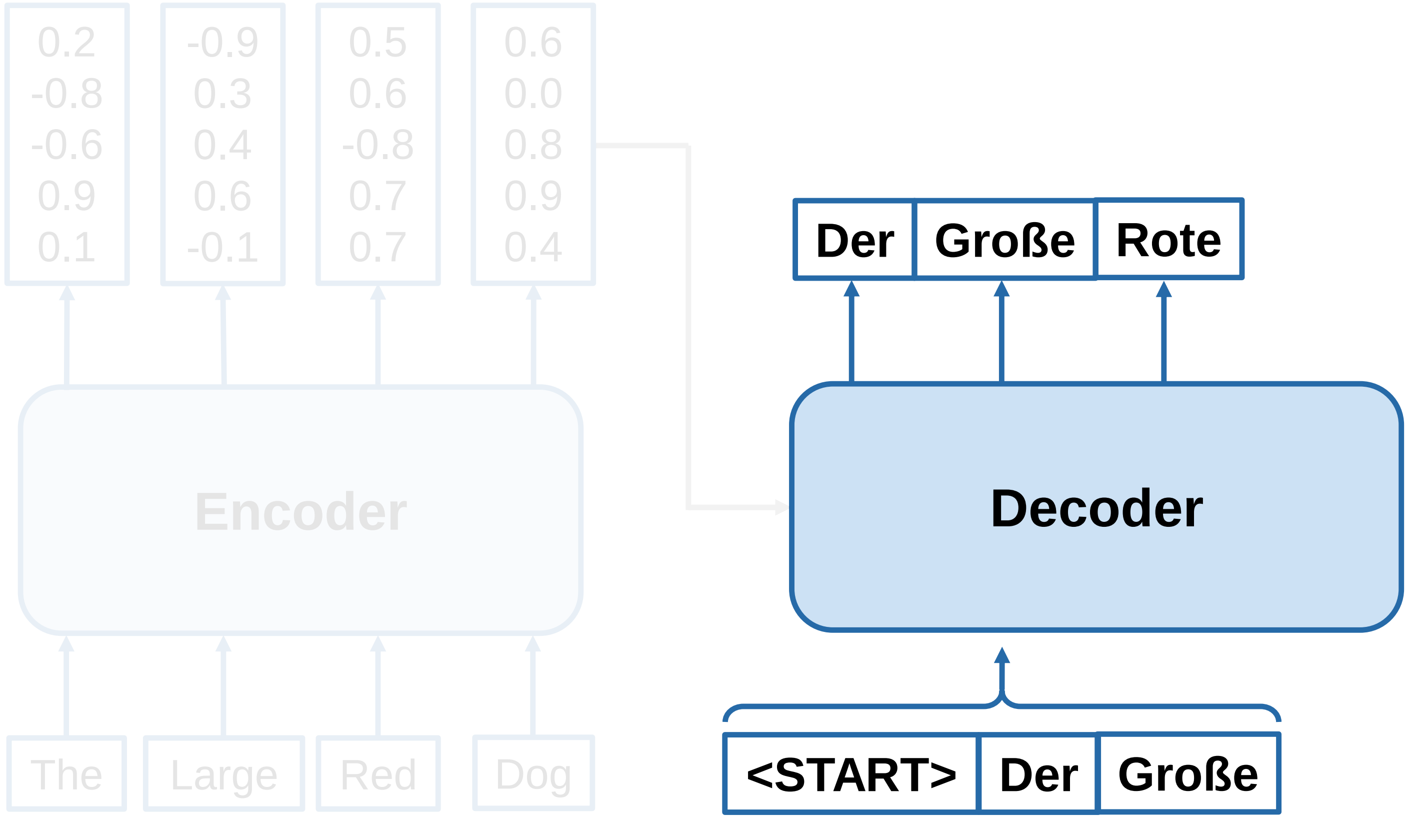
- Can mix-and-match different stand-along encoders and decoders.



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