

Transformer Network Encoders

An overview

What are Transformer Networks?

- Transformer Networks are a type of neural network architecture designed to handle sequential data

- Examples:

- Chatbots



You

What is a Large Language Model?



ChatGPT

A Large Language Model (LLM) like me, ChatGPT, is a type of artificial intelligence system designed to understand, generate, and respond to human language in a way that is both coherent and contextually relevant. Here are the key characteristics of a Large Language Model:

⋮

- Translator

Englisch



Deutsch

The cat sat on the mat.



Die Katze saß auf der Matte.

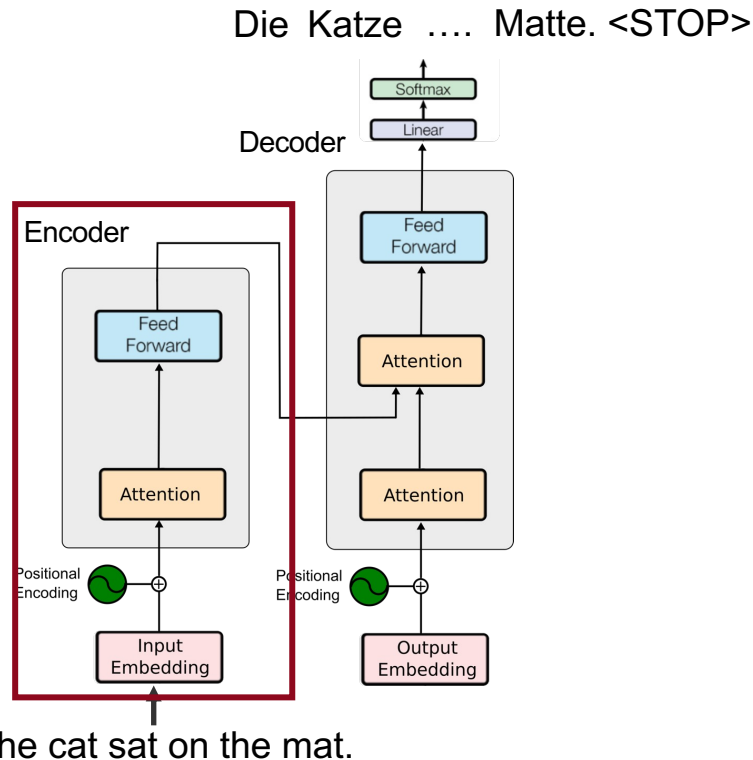


Überprüft

Transformer Network Architecture

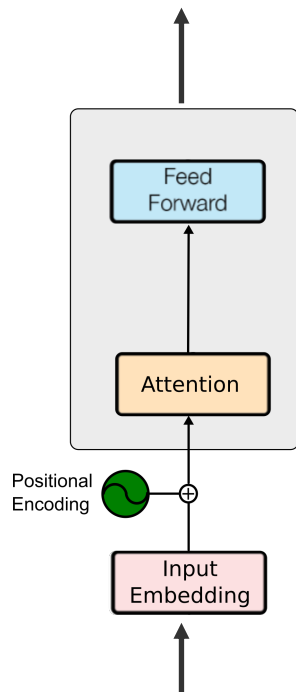
■ Transformer Network

- Encoder: Encodes the input sequence into numerical vectors
- Decoder: Uses the numerically encoded input sequence as its input and produces an output sequence.



Encoder

2.71	2.1	0.22	...	2.17
0.18	-0.34	1.85		0.16
⋮	⋮	⋮		⋮
1.43	0.67	-0.42		0.29

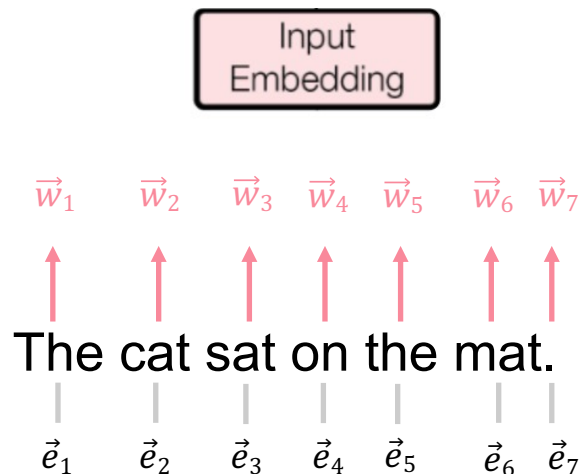
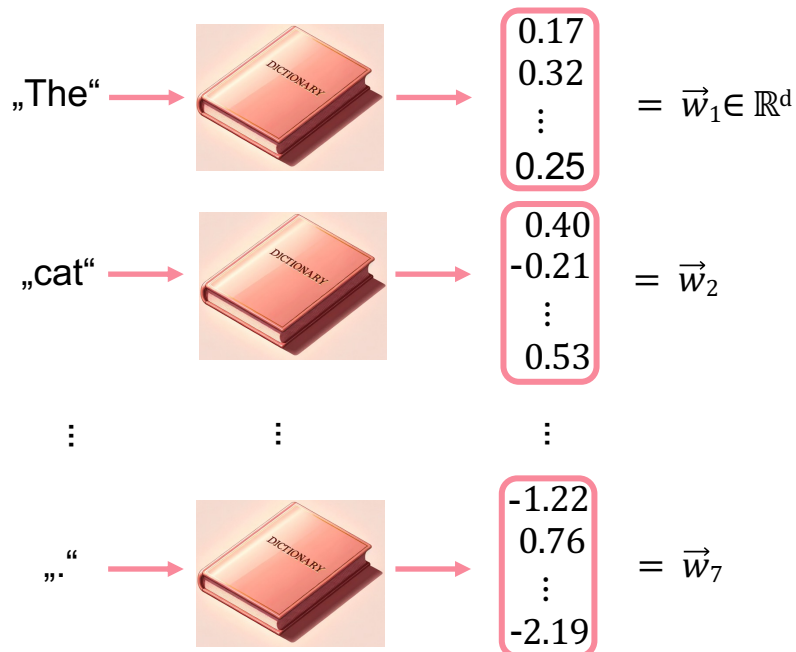


1. Input Embedding & Positional Encoding
2. Attention
3. Feed Forward Neural Network

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Input Embedding

- For every word, we have a specific vector representing this word

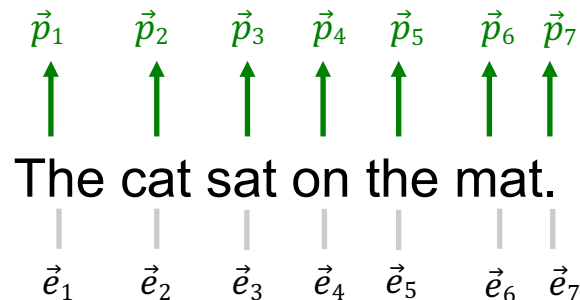


Positional Encoding

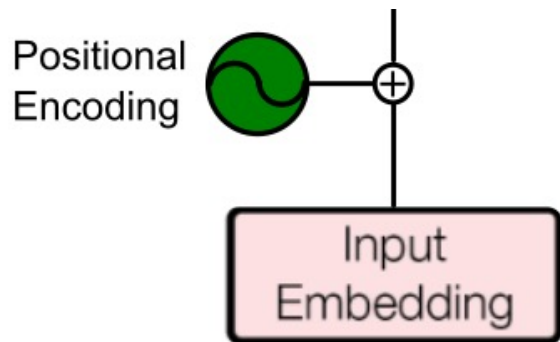
Positional Encoding: $\vec{p}_1 = \begin{bmatrix} 0.00 \\ 0.84 \\ \vdots \\ 0.14 \end{bmatrix}$ $\vec{p}_2 = \begin{bmatrix} 1.00 \\ 0.54 \\ \vdots \\ -0.99 \end{bmatrix}$... $\vec{p}_7 = \begin{bmatrix} 0.00 \\ 1.00 \\ \vdots \\ 0.96 \end{bmatrix} \in \mathbb{R}^d$

- The same positional encoding is used for every input sequence!

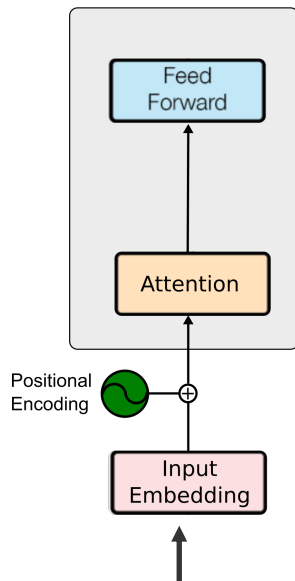
Positional
Encoding



Input Embedding & Positional Encoding



$$\begin{array}{ccccccc} \begin{array}{c} \boxed{\begin{array}{c} 0.00 + 0.17 \\ 0.84 + 0.32 \\ \vdots \\ 0.14 + 0.25 \end{array}} & \dots & \dots & \dots & \dots & \dots & \boxed{\begin{array}{c} 0.00 - 1.22 \\ 1.00 + 0.76 \\ \vdots \\ 0.96 - 2.19 \end{array}} \\ \text{= } \vec{e}_1 & & & & & & \text{= } \vec{e}_7 \\ \begin{array}{c} \vec{p}_1 \\ + \\ \vec{w}_1 \end{array} & \begin{array}{c} \vec{p}_2 \\ + \\ \vec{w}_2 \end{array} & \begin{array}{c} \vec{p}_3 \\ + \\ \vec{w}_3 \end{array} & \begin{array}{c} \vec{p}_4 \\ + \\ \vec{w}_4 \end{array} & \begin{array}{c} \vec{p}_5 \\ + \\ \vec{w}_5 \end{array} & \begin{array}{c} \vec{p}_6 \\ + \\ \vec{w}_6 \end{array} & \begin{array}{c} \vec{p}_7 \\ + \\ \vec{w}_7 \end{array} \\ \uparrow & \uparrow & \uparrow & \uparrow & \uparrow & \uparrow & \uparrow \\ \text{The cat sat on the mat.} & & & & & & \\ \vec{e}_1 & \vec{e}_2 & \vec{e}_3 & \vec{e}_4 & \vec{e}_5 & \vec{e}_6 & \vec{e}_7 \end{array} \in \mathbb{R}^d$$



1. Input Embedding & Positional Encoding
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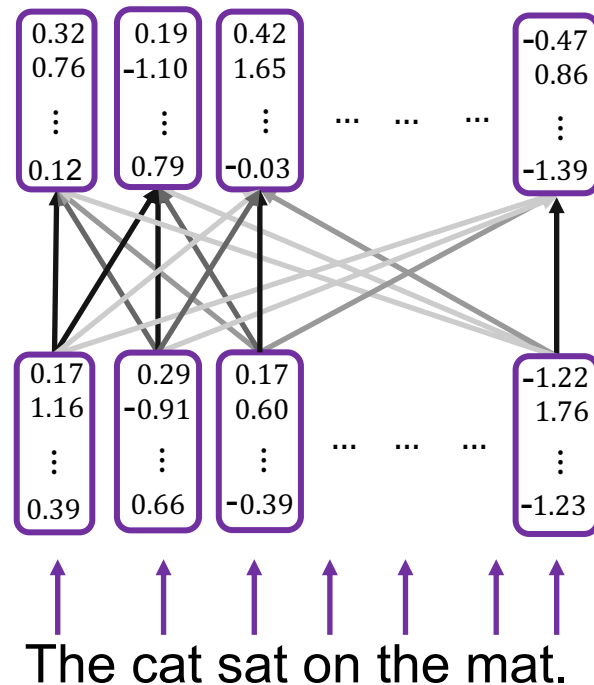
The cat sat on the mat.

$$\text{Attention}(\vec{e}_i, K, V) = \text{softmax}\left(\frac{\vec{e}_i^T \cdot K}{\sqrt{d}}\right) \cdot V^T$$

$$K = (\vec{e}_1, \vec{e}_2, \dots, \vec{e}_7), \quad V^T = \begin{pmatrix} \vec{e}_1 \\ \vec{e}_2 \\ \vdots \\ \vec{e}_7 \end{pmatrix}$$

Example for $i = 1$:

$$\begin{aligned} \vec{e}_1 = & 0.45 \cdot \vec{e}_1 + 0.25 \cdot \vec{e}_2 + 0.14 \cdot \vec{e}_3 + 0.05 \cdot \vec{e}_4 \\ & + 0.03 \cdot \vec{e}_5 + 0.06 \cdot \vec{e}_6 + 0.02 \cdot \vec{e}_7 \end{aligned}$$



$$\text{Attention}(\vec{e}_i, K, V) = \text{softmax}\left(\frac{\vec{e}_i^T \cdot K}{\sqrt{d}}\right) \cdot V^T$$

$$K = (\vec{e}_1, \vec{e}_2, \dots, \vec{e}_7), \quad V^T = \begin{pmatrix} \vec{e}_1^T \\ \vec{e}_2^T \\ \vdots \\ \vec{e}_7^T \end{pmatrix}$$

Example for $i = 2$:

$$\text{Attention}(\vec{e}_2, K, V)$$

$$\begin{aligned} 1. \vec{e}_2^T \cdot K &= \vec{e}_2^T \cdot K = \\ &= (\vec{e}_2^T \cdot \vec{e}_1, \vec{e}_2^T \cdot \vec{e}_2, \dots, \vec{e}_2^T \cdot \vec{e}_7) \\ &= (23.2, 70.8, 33.7, 5.7, -12.4, 27.8, -22.4) \end{aligned}$$

$$2. \frac{\vec{e}_2^T \cdot K}{\sqrt{d}} = (0.8, 2.6, 1.2, 0.2, -0.4, 1.0, -0.8)$$

$$3. \text{softmax}\left(\frac{\vec{e}_2^T \cdot K}{\sqrt{d}}\right) = (0.1, 0.55, 0.14, 0.05, 0.03, 0.12, 0.02)$$

$$4. \text{softmax}\left(\frac{\vec{e}_2^T \cdot K}{\sqrt{d}}\right) \cdot V^T = (0.1 \cdot \vec{e}_1 + 0.55 \cdot \vec{e}_2 + 0.14 \cdot \vec{e}_3 + 0.05 \cdot \vec{e}_4 + 0.03 \cdot \vec{e}_5 + 0.12 \cdot \vec{e}_6 + 0.02 \cdot \vec{e}_7)^T$$

\vec{e}_1	\vec{e}_2	\vec{e}_3	\vec{e}_7
0.7	0.2	0.1				-0.1
0.4	-0.9	0.6				0.8
\vdots	\vdots	\vdots				\vdots
2.1	0.6	-0.3				-1.6

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Attention (2)

$$\text{Attention}(\vec{e}_i, K, V) = \text{softmax}\left(\frac{\vec{e}_i^T \cdot K}{\sqrt{d}}\right) \cdot V^T$$

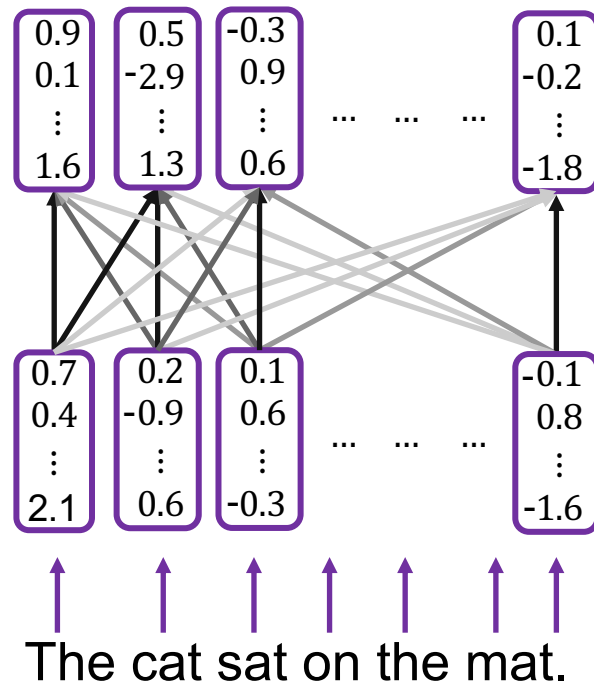


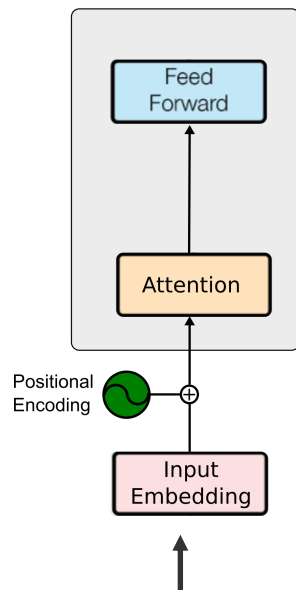
$$\begin{aligned} \text{Attention}(W_E \cdot \vec{e}_i, W_K \cdot K, W_V \cdot V) \\ = \text{Attention}(\vec{\tilde{e}}_i, \tilde{K}, \tilde{V}) \end{aligned}$$

$$\tilde{K} = W_K \cdot K = (W_K \cdot \vec{e}_1, W_K \cdot \vec{e}_2, \dots, W_K \cdot \vec{e}_7),$$

$$\tilde{V} = W_V \cdot V = (W_V \cdot \vec{e}_1, W_V \cdot \vec{e}_2, \dots, W_V \cdot \vec{e}_7)$$

$$\text{softmax}(\vec{x})_j = \frac{e^{x_j}}{\sum_{k=1}^n e^{x_k}}, \quad \vec{x} \in \mathbb{R}^N$$



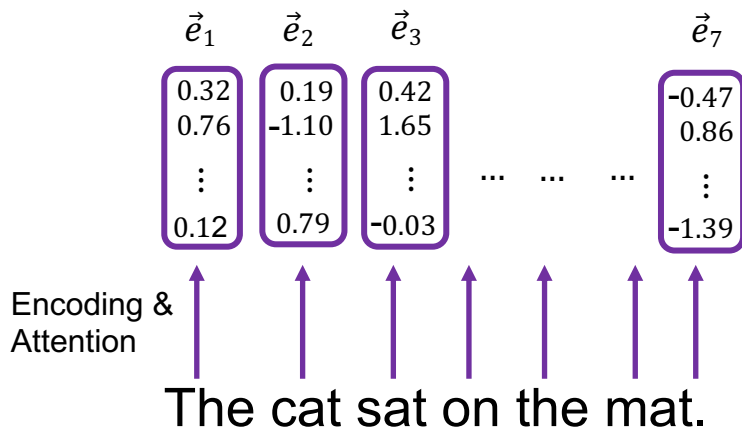


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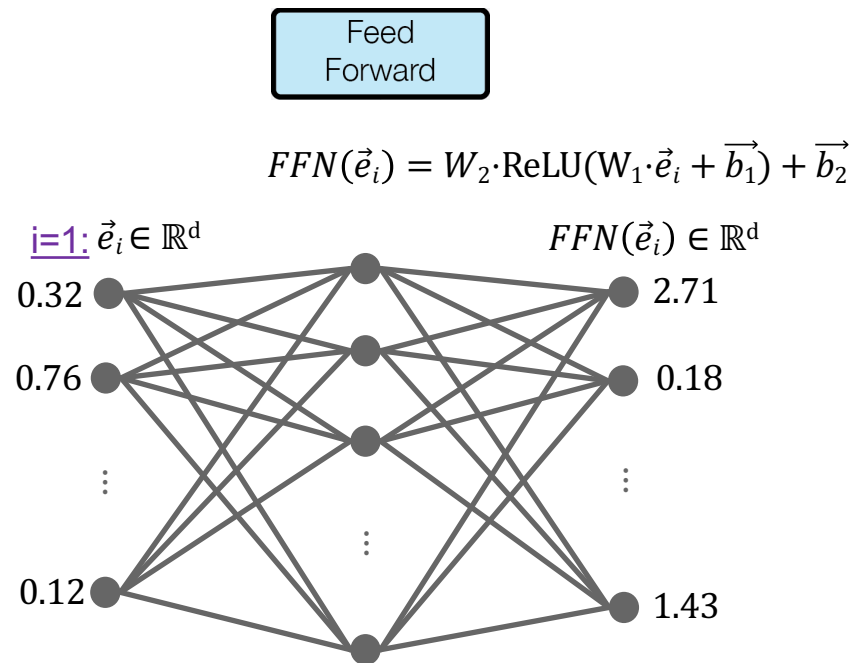
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Feed Forward Neural Network

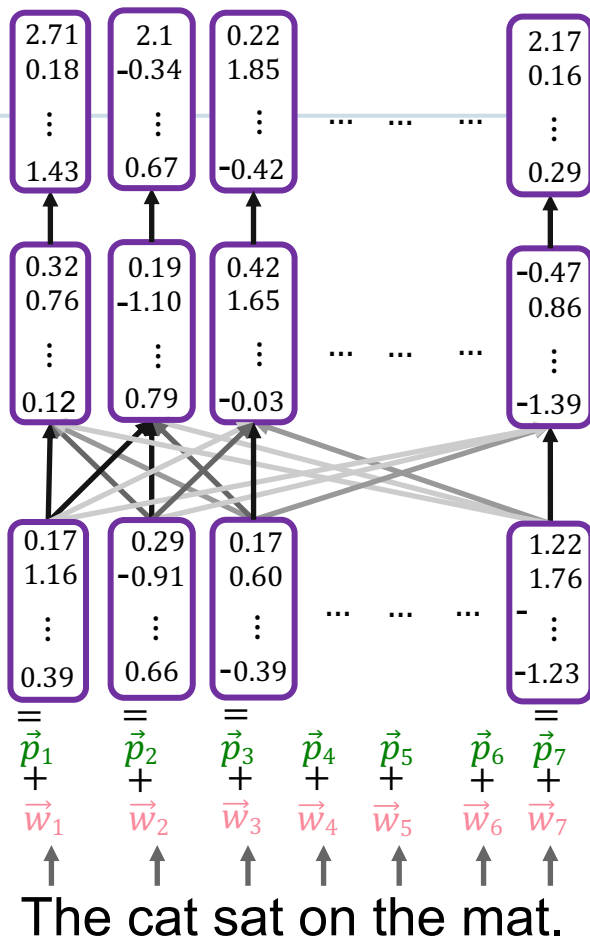
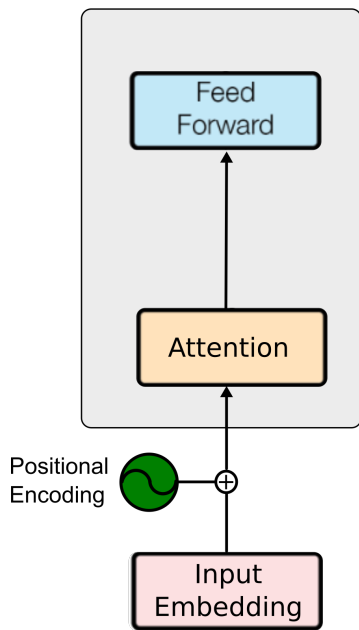
■ Mapping through Encoding and Attention:



■ Feed Forward Neural Network:



Encoder



Applying Encoders to Protein Sequences

