Attention & Transformers

Ivo Verhoeven | Advanced Topics in Computational Semantics

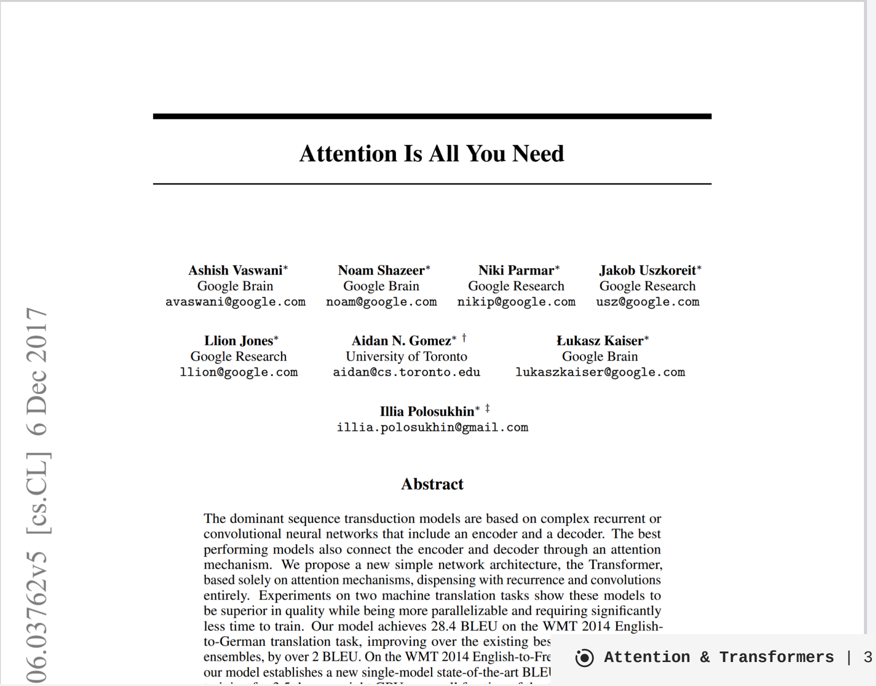
About Me

- 2017 - 2020: BSc. Liberal Arts & Sciences
- 2020 – 2022: MSc. AI at University of Amsterdam
  - Thesis on meta-learning, morphology and NMT
  - Took ATCS in 2021
- 2022 - ???: PhD at ILLC
  - Misinformation detection and generalisation with Katia Shutova

Vaswani et al.: Attention is All You Need

- Introduces the Transformer architecture in late 2017
  - Google Brain/Google Research collab

`Vaswani et al. (2017). Attention is all you need. Advances`
`neural information processing systems, 30.`



06.03762v5 [cs.CL] 6 Dec 2017

Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing bes ensembles, by over 2 BLEU. On the WMT 2014 English-to-Fre our model establishes a new single-model state-of-the-art BLE

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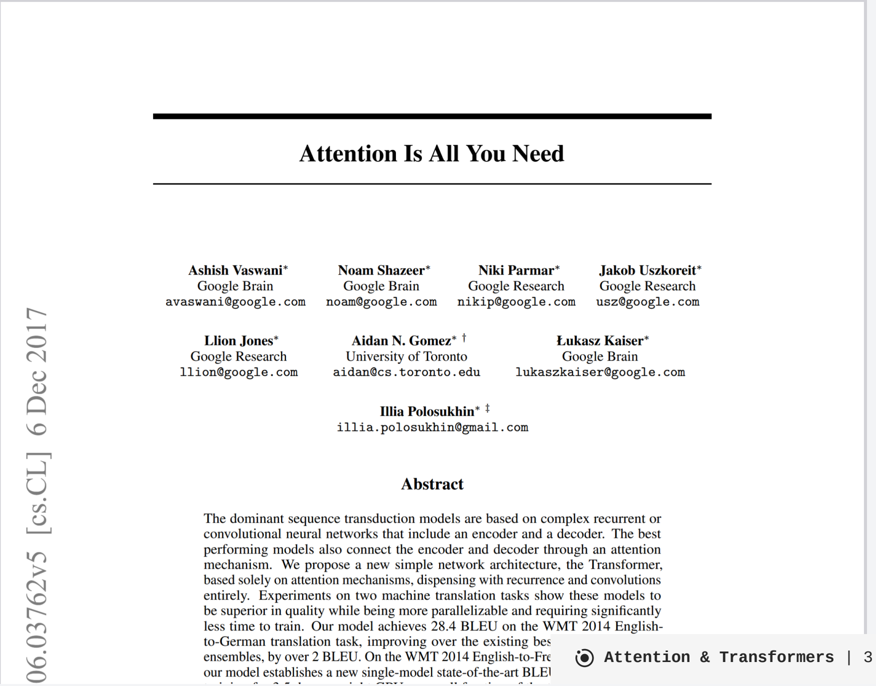

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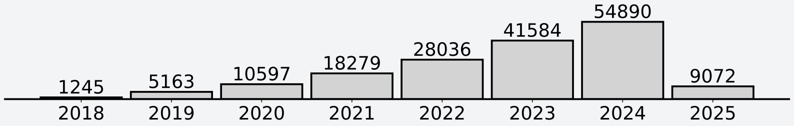

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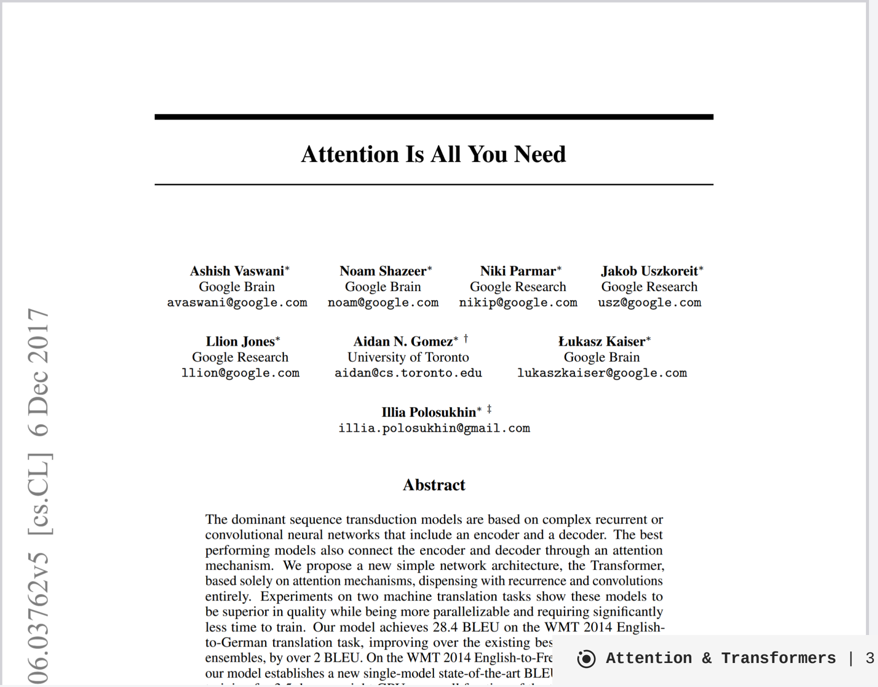

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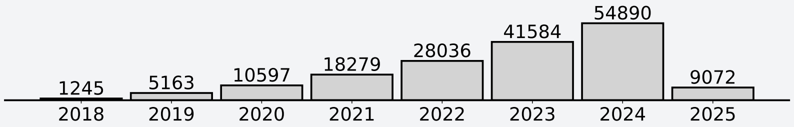

- Most cited paper ever has **233 829** citations

  `Lowry et al. (1951) Protein measurement with the folin phenol reagent.`

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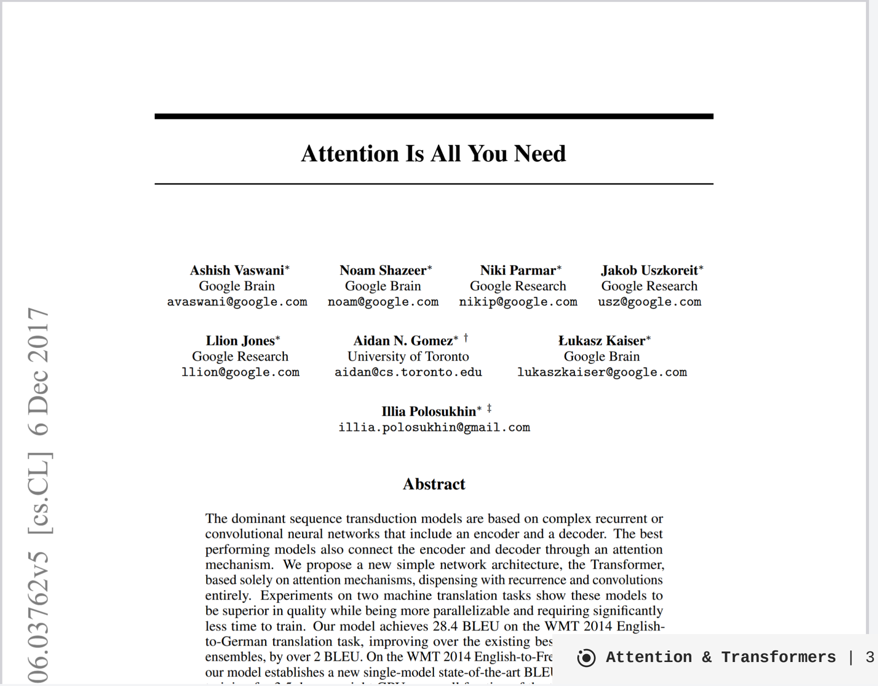

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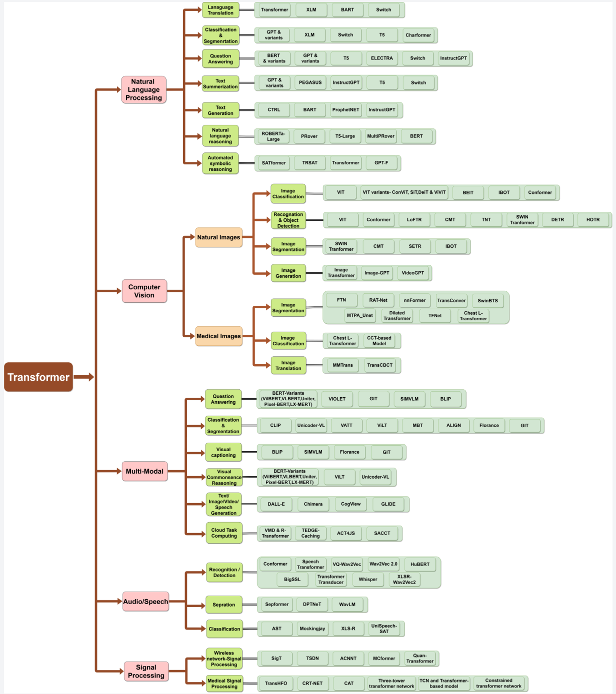
Vaswani et al.: Attention is All You Need

- It’s hard to think of an AI area that hasn’t been affected by the Transformer



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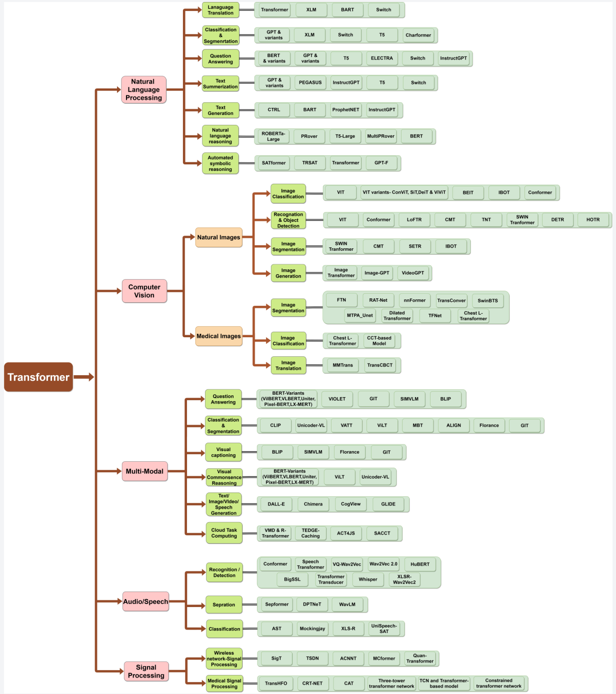
  - **NLP:** Transformer > RNN
    - Seq-to-seq: what it was designed for
    - Classification: encoder-only transformers
    - Generation: decoder-only transformers



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    - Classification: encoder-only transformers
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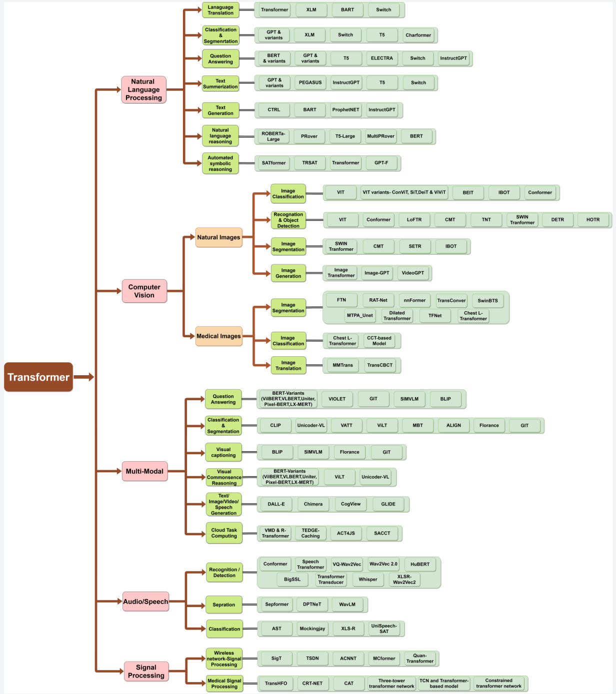
  - **CV:** ViT > CNN
  - **Multi-modal:** Transformer > different architectures
  - **Speech:** Transformer > CNN
  - **Graphs:** Transformer/Attention > GCN



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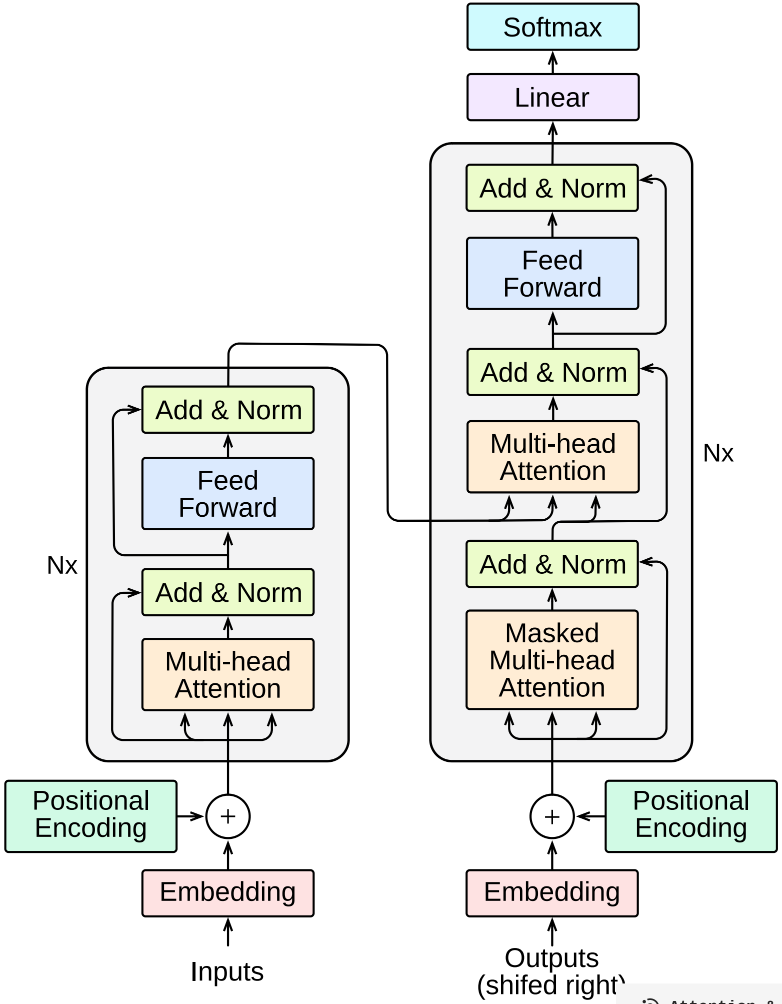
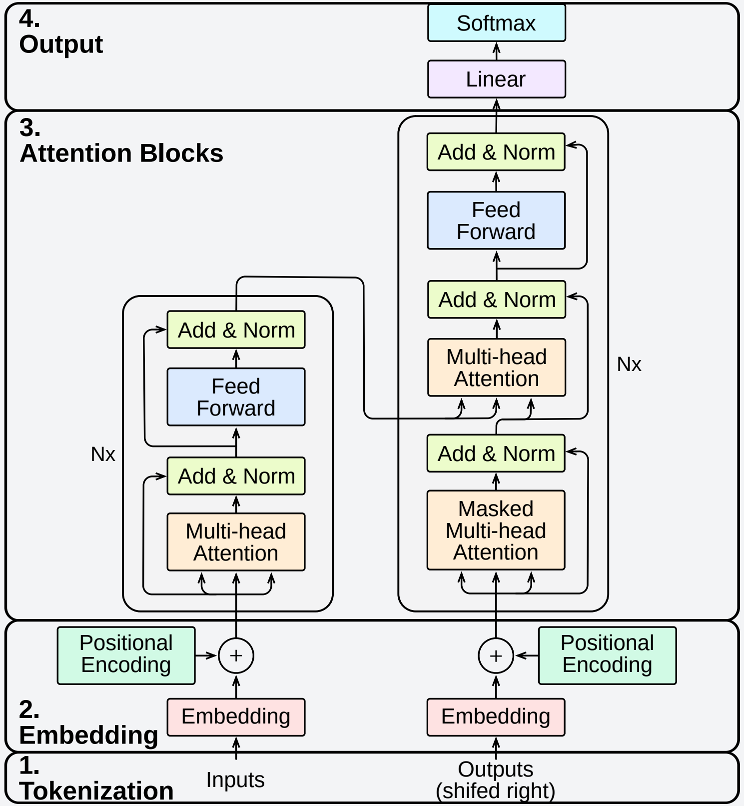
The Transformer

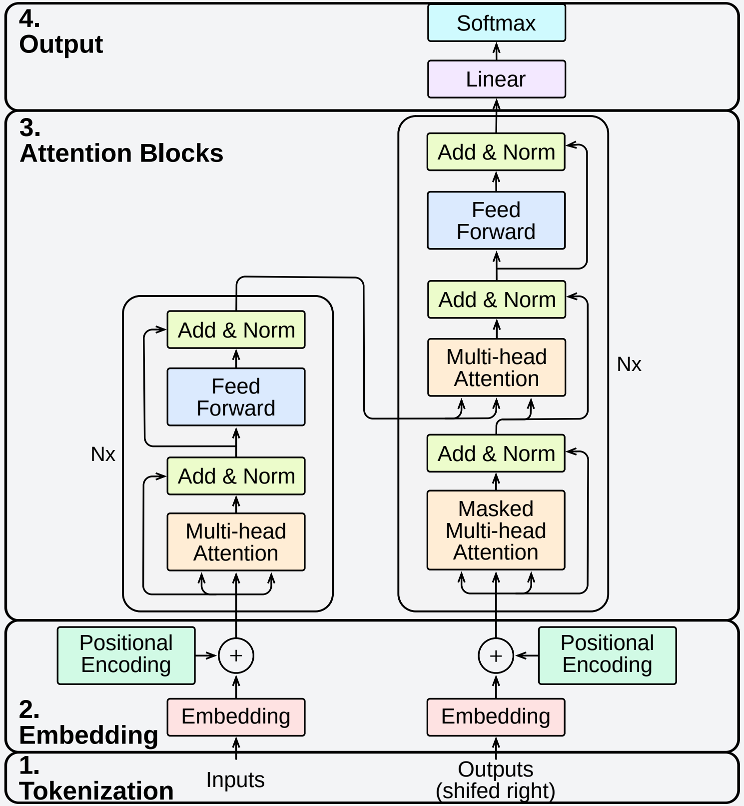


Breaking the Transformer into modules



Breaking the Transformer into modules

4. Output
   - Softmax
   - Linear



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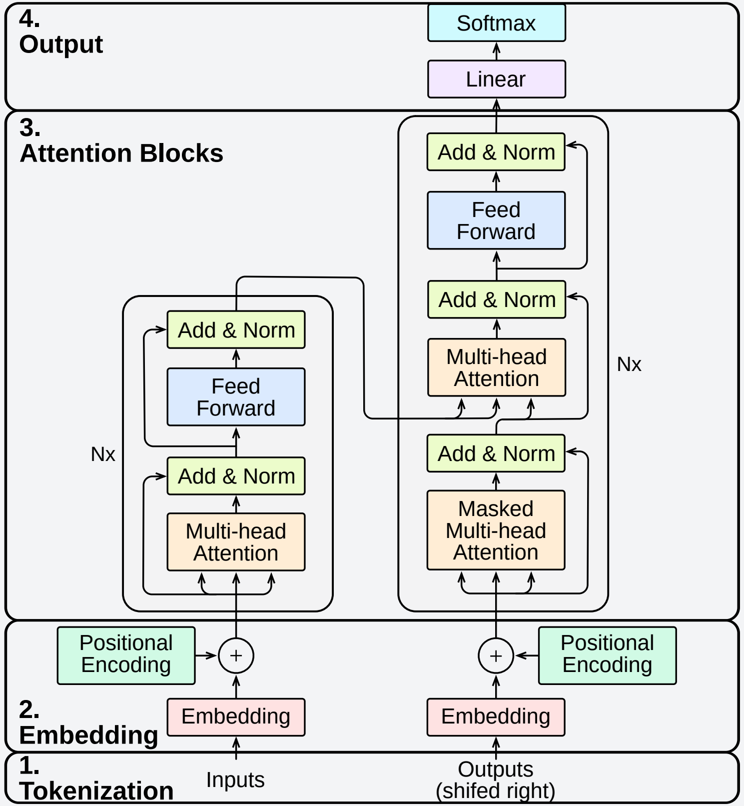
3. Attention Blocks
   - Multi-head Attention
   - Add & Norm
   - Feed Forward



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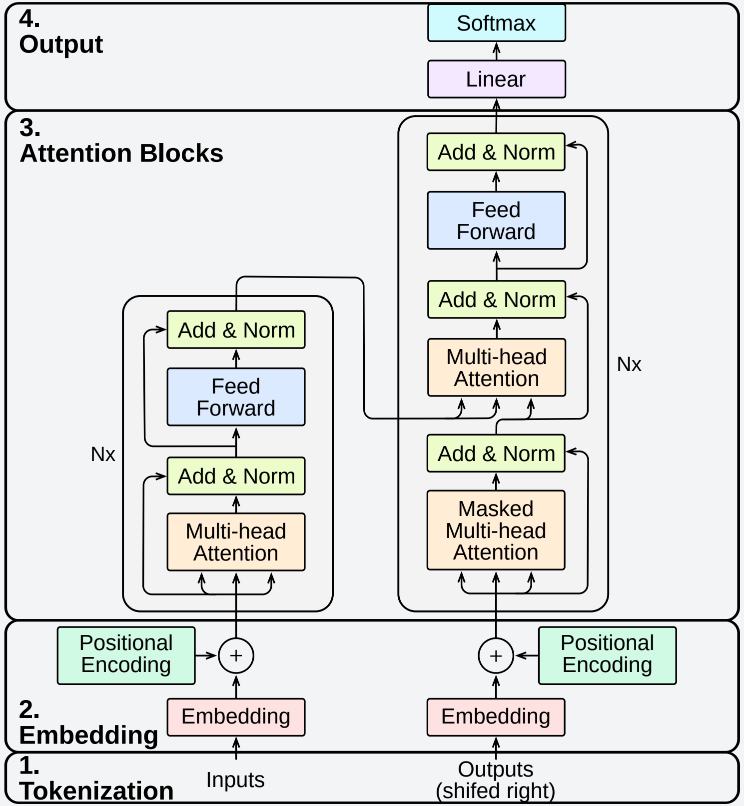
2. Embedding
   - Token Embedding
   - Positional Encoding



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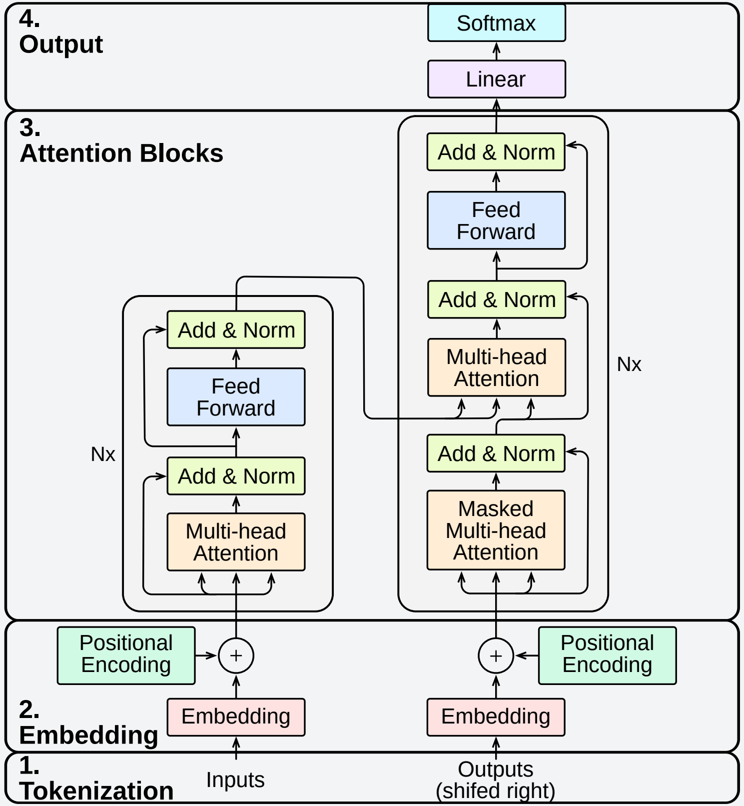

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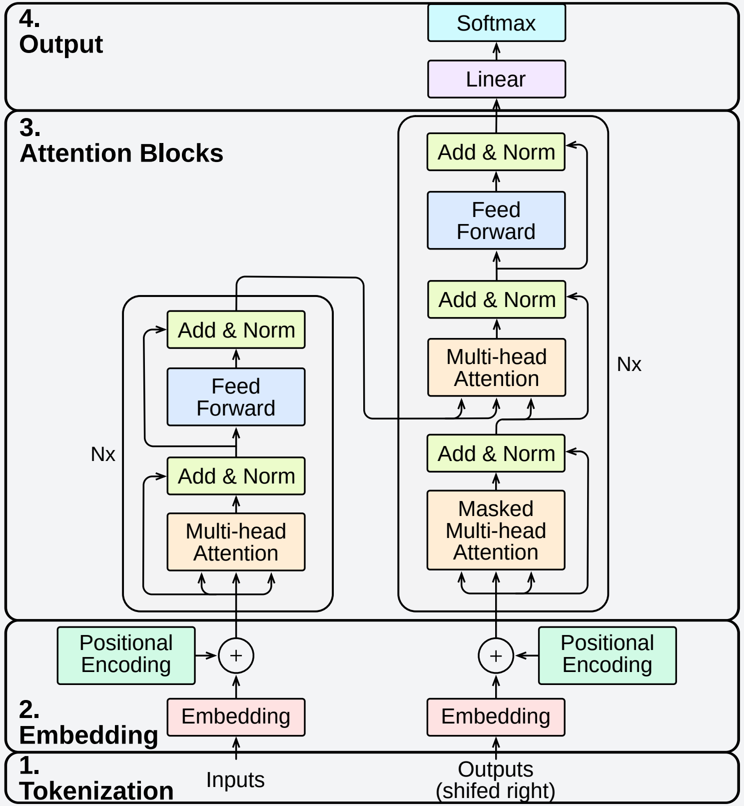
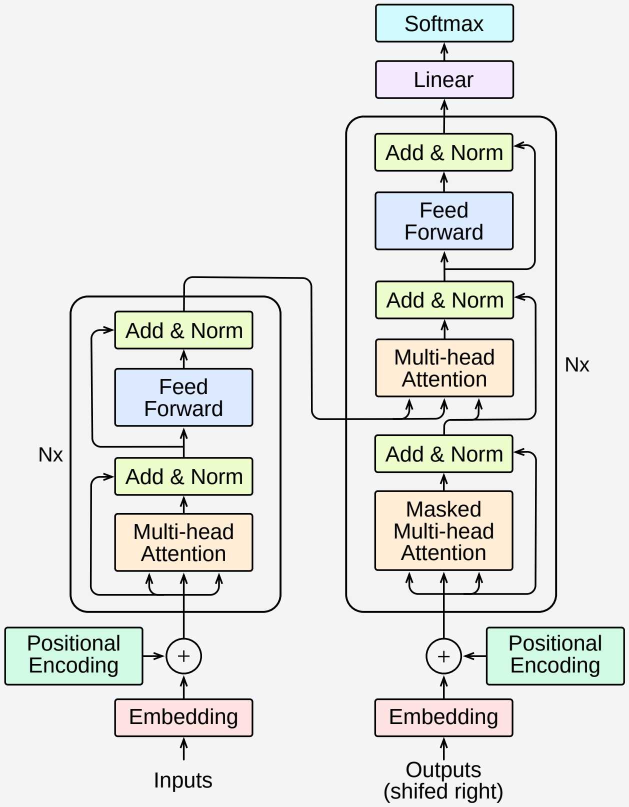


Table of Contents



Encoders & Decoders

Text comes in, text goes out

Jakob Uszkoreit (August 31, 2017). Transformer: A Novel Neural Network Architecture for Language Understanding. https://research.google/blog/transformer-a-novel-neural-network-architecture-for-language-understanding/

Attention Blocks

What makes the Transformer what it is — and where it came from

Multi-head Attention

$$\nabla \cdot \vec{E} = \frac{\rho}{\varepsilon_0}$$

$$\nabla \cdot \vec{B} = 0$$

$$\nabla \times \vec{E} = -\frac{\partial \vec{B}}{\partial t}$$

$$\nabla \times \vec{B} = \mu_0 \vec{J} + \mu_0 \varepsilon_0 \frac{\partial \vec{E}}{\partial t}$$

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Definition & Properties

Multi-head Attention

Non-Transformer Examples

Multi-head Attention

Attention in Transformers

Multi-head Attention

Multi-head Attention

Multi-head Attention

Add & Norm

Residual Connections

Add & Norm

LayerNorm

Add & Norm

These are the equations

$$\begin{aligned}\mathbf{X}_l \;=\; & \texttt{LayerNorm}(\\ & \quad \mathbf{X}_{l-1} + \texttt{SubLayer}\left(\mathbf{X}_{l-1}\right) \\ &)\end{aligned}$$

Feed Forward

Embedding

Position Encoding

Tokenization

Training Transformers

The End