# Attention & Transformers

Ivo Verhoeven | Advanced Topics in Computational Semantics

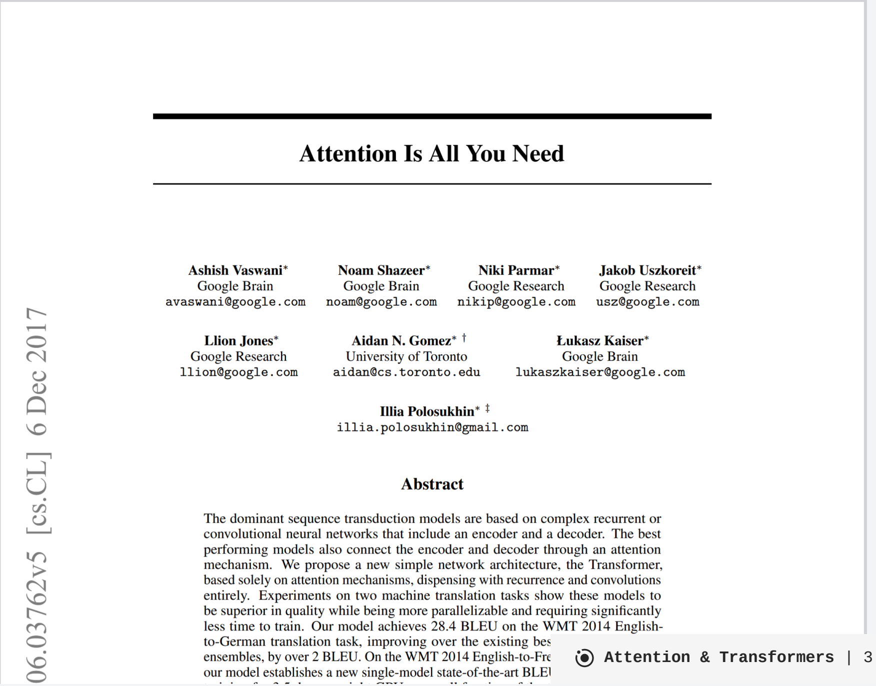
# About Me


- 2017 - 2020: BSc. Liberal Arts & Sciences
- 2020 – 2022: MSc. AI at University of Amsterdam
  - Thesis on meta-learning, morphology and translation
  - 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.



# Attention Is All You Need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06.03762v5 [cs.CL] 6 Dec 2017


## 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
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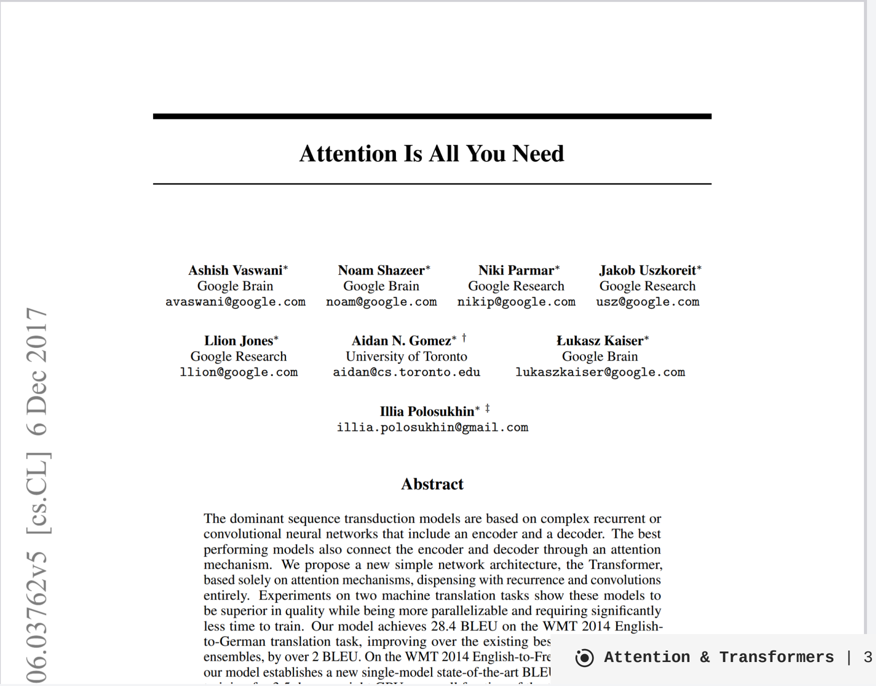

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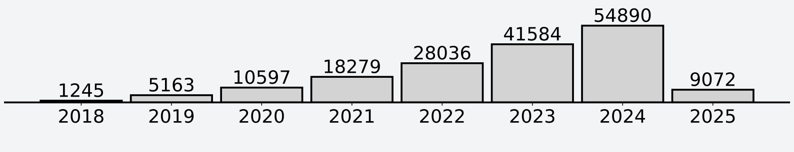


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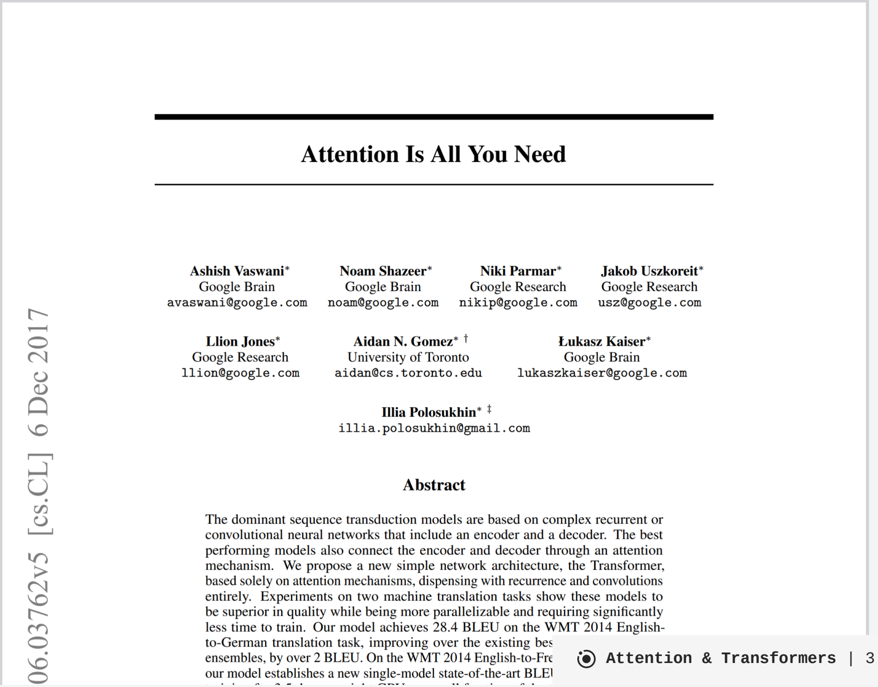

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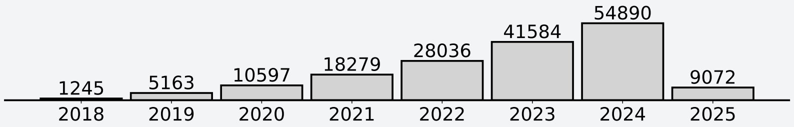


- Most cited paper ever has **233 829** citations

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

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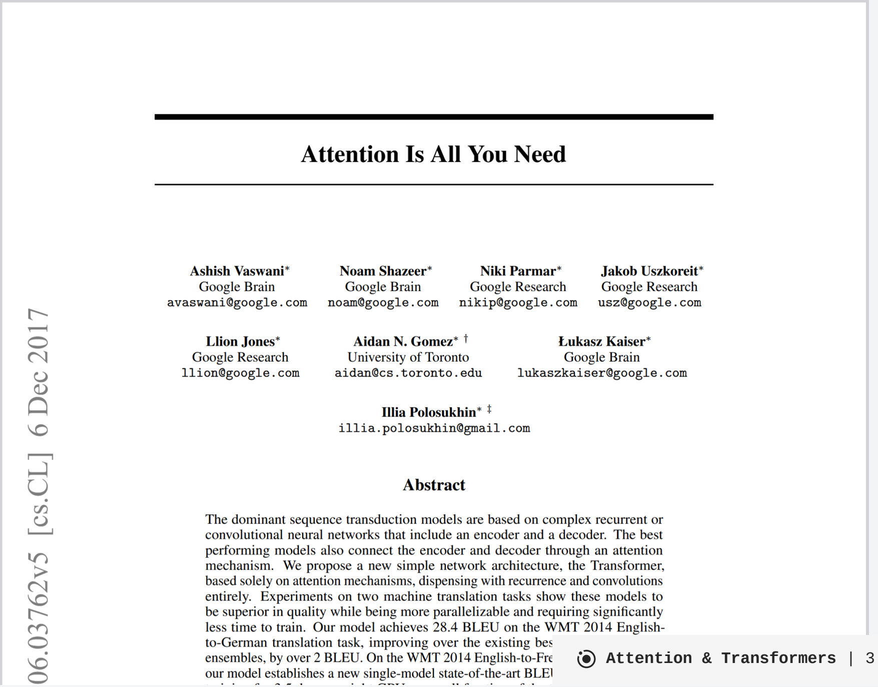

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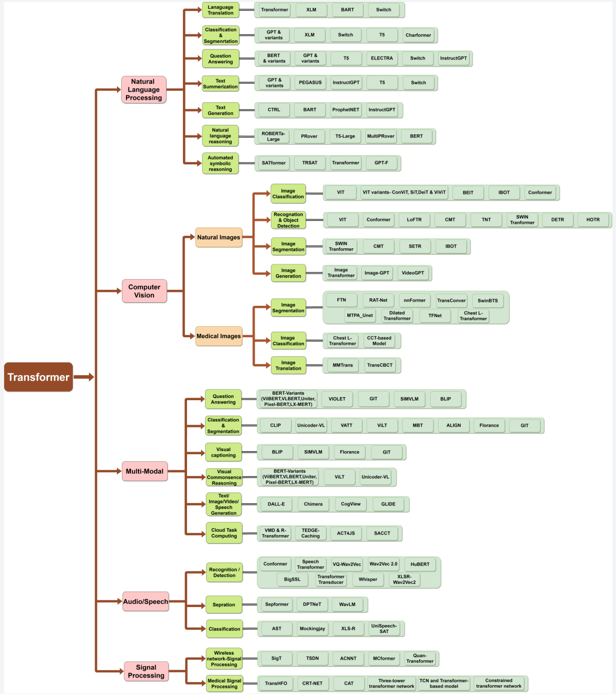
- It’s hard to think of an AI area that hasn’t been affected by the Transformer

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    - Seq-to-seq: what it was designed for
    - Classification: encoder-only transformers
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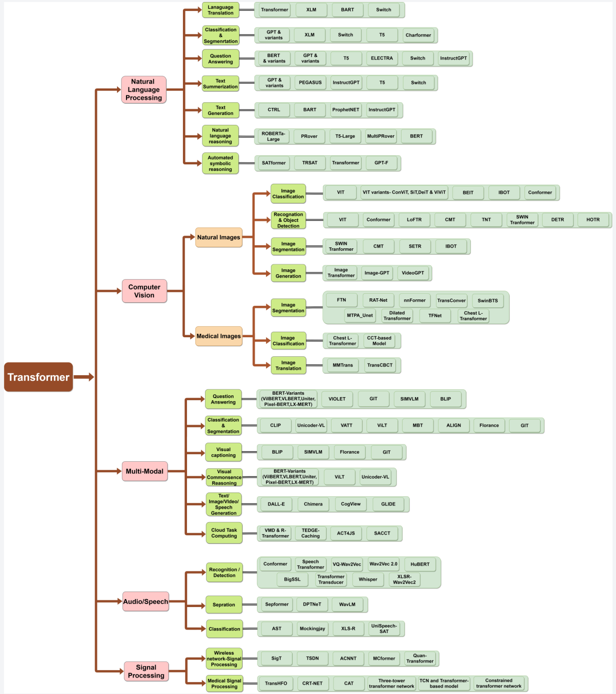


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    - Classification: encoder-only transformers
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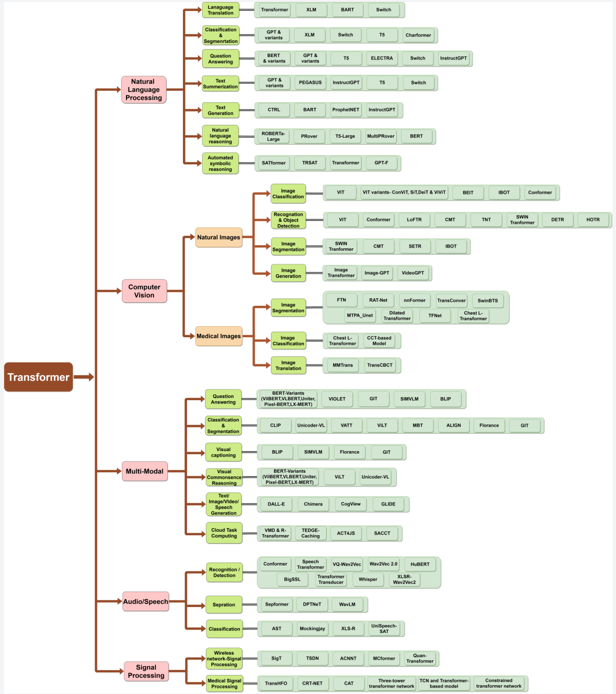
  - **CV:** ViT > CNN
  - **Multi-modal:** Transformer > different architectures
  - **Speech:** Transformer > CNN
  - **Graphs:** Transformer/Attention > GCN

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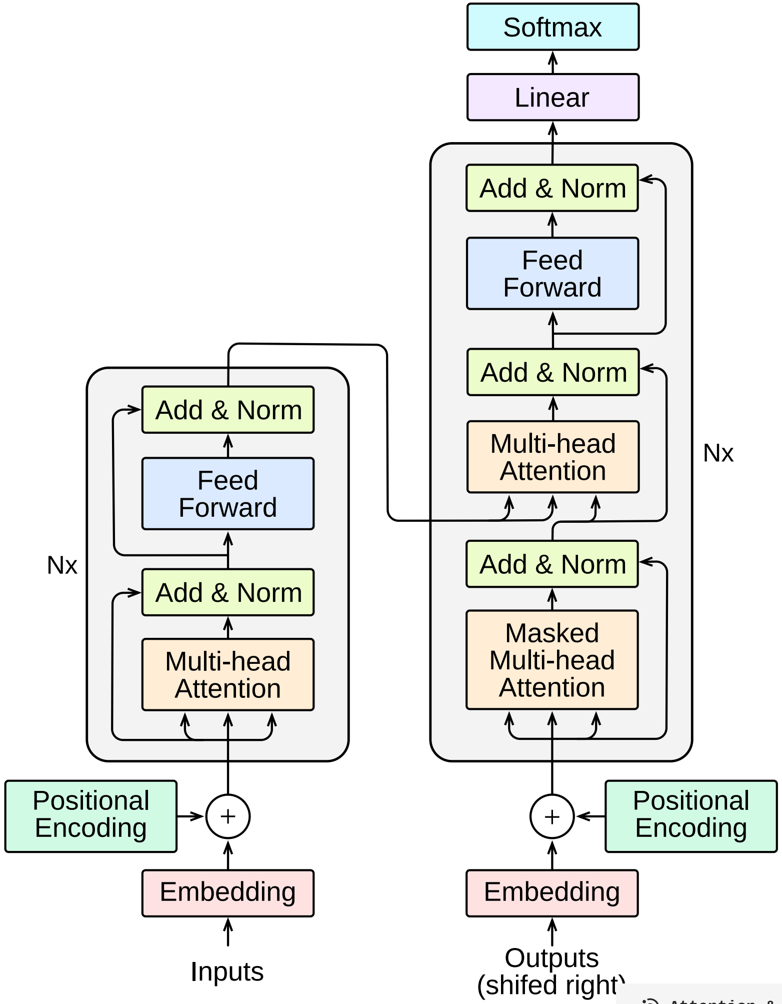
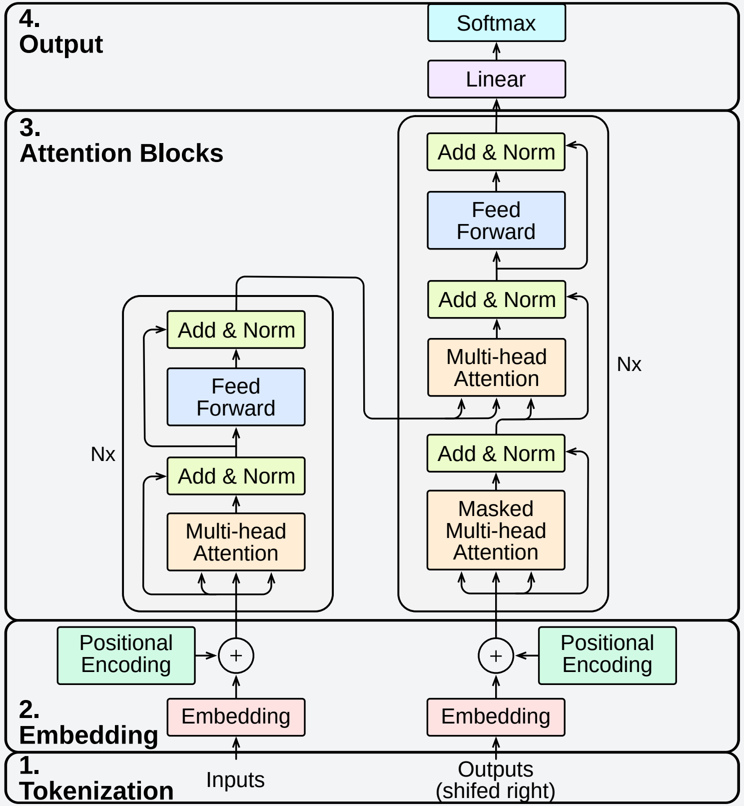
# The Transformer



# Breaking the Transformer into modules



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4. Output
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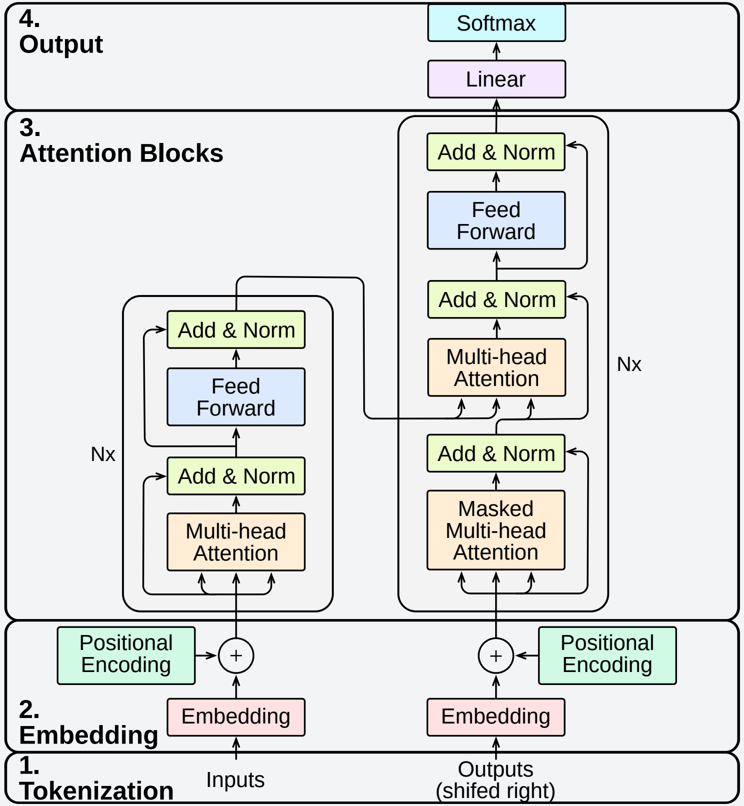

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    - Multi-head Attention
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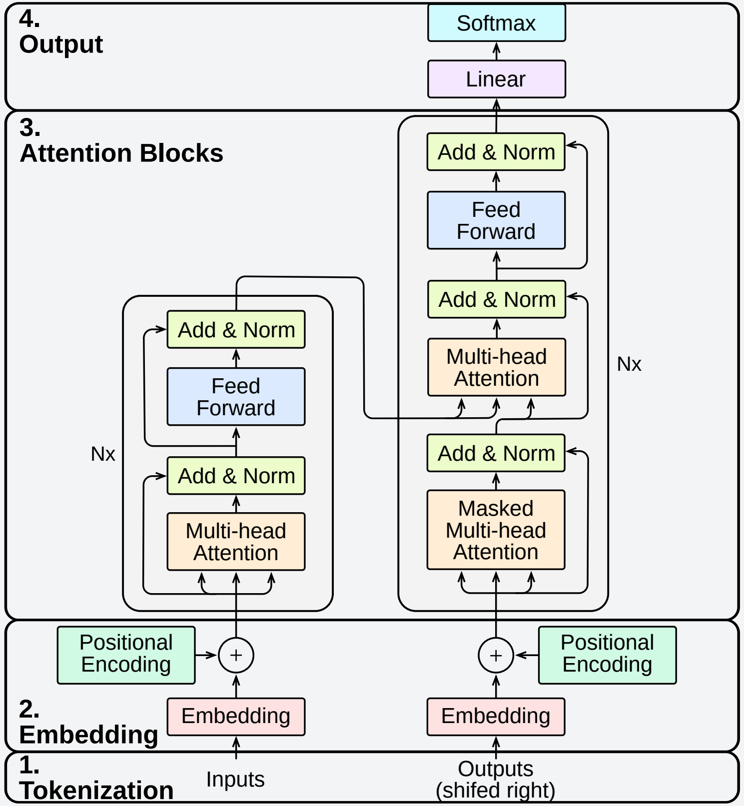
    - Feed Forward



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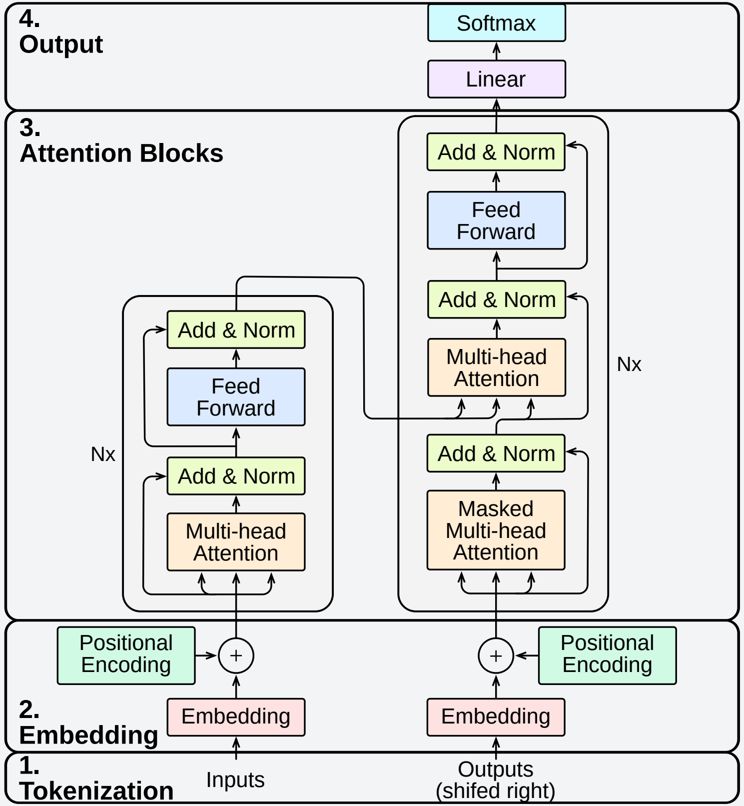

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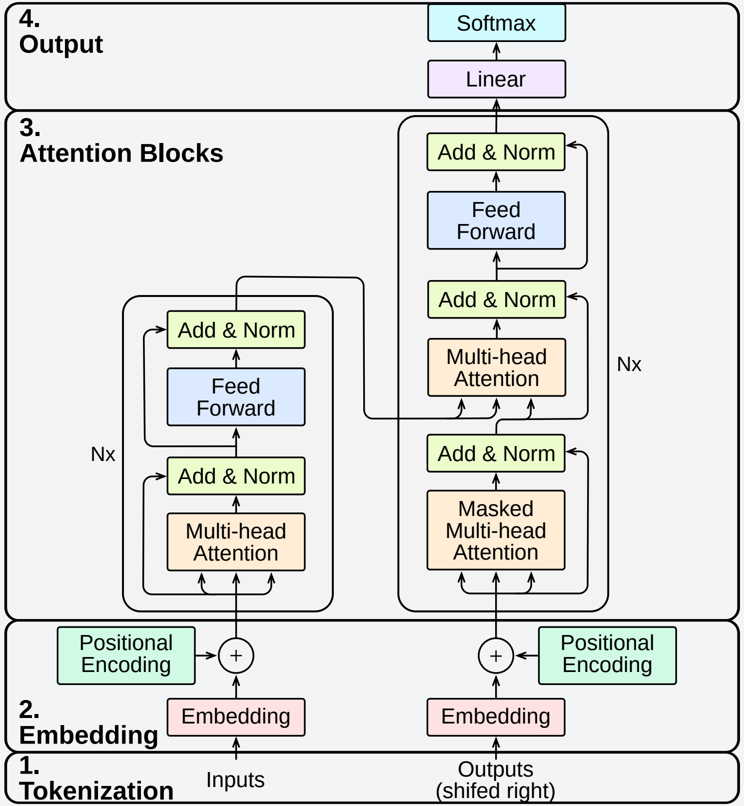

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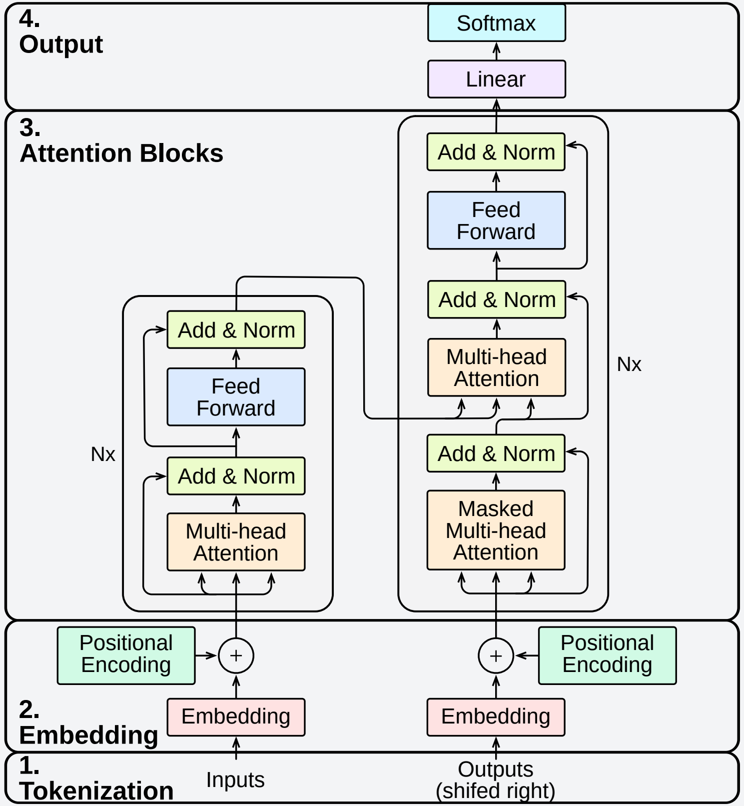

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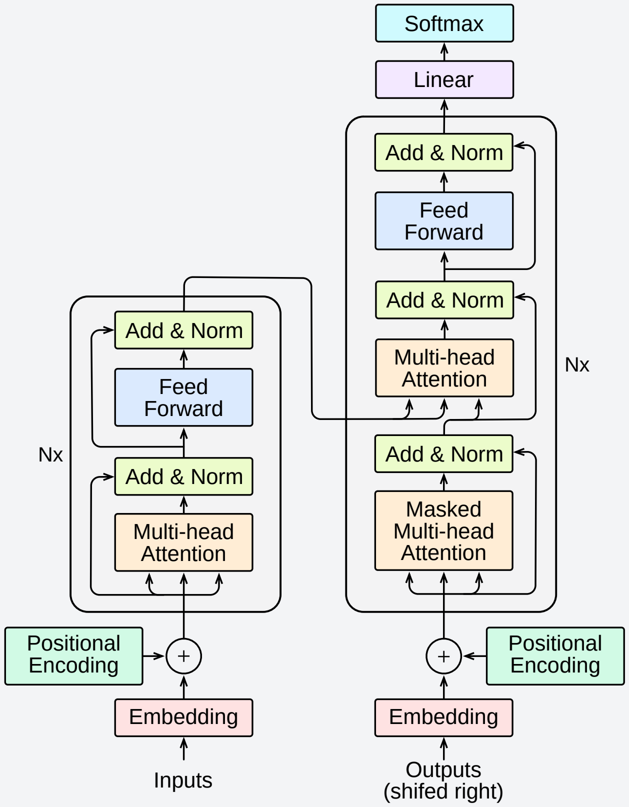


# Encoders & Decoders

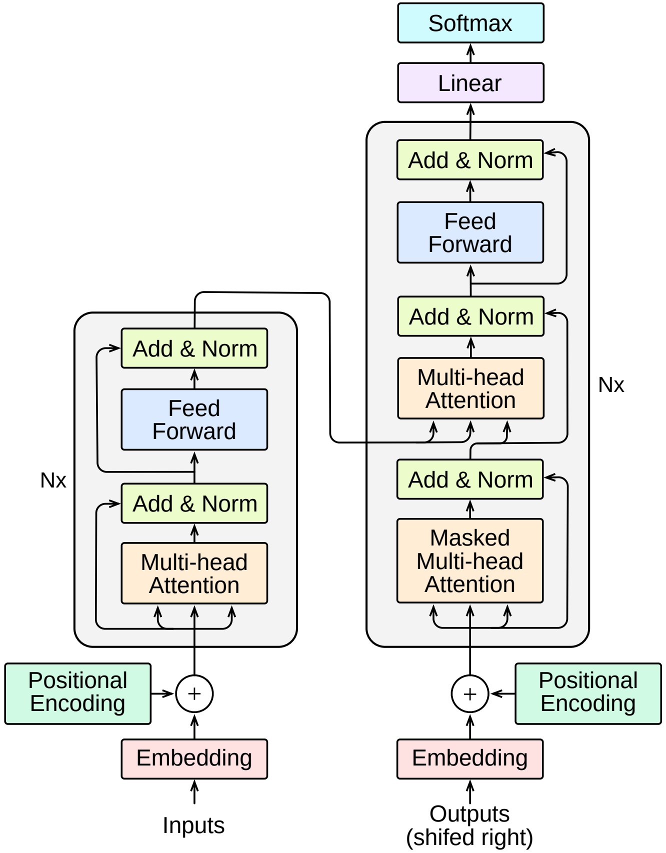
Text comes in, text goes out

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



# Definition & Properties

Multi-head Attention

- Let $\mathbf{V}$ be a matrix of (word) vectors
  - It has a sequence length of $T_V$
  - It has a dimensionality of $D$

$$\texttt{Attention}(?, ?, \mathbf{V}) = \mathbf{A}\mathbf{V}$$

$$\mathbf{A} \in (0, 1)^{[T_V \times T_V]}$$

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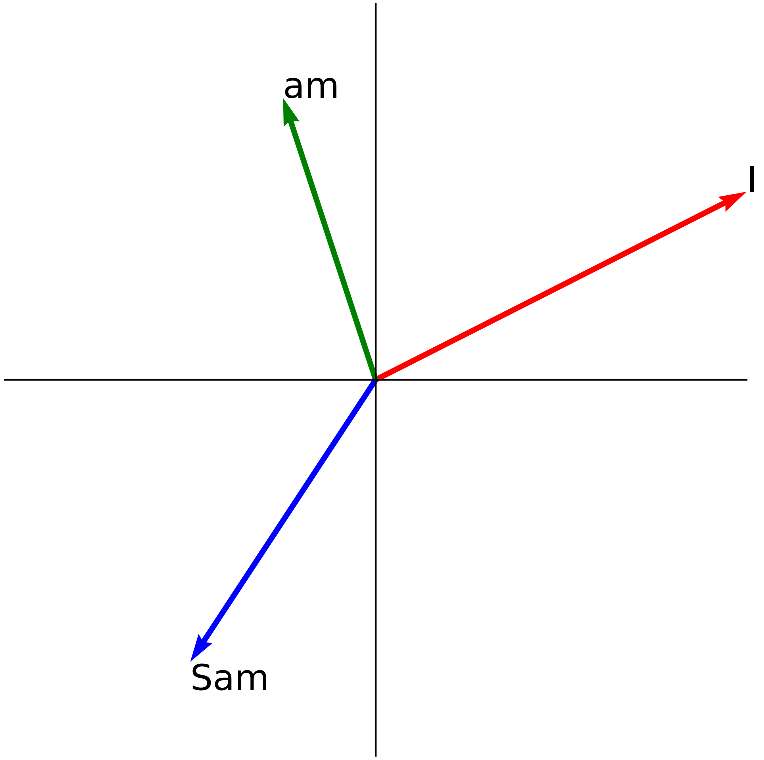
- The result of **`Attention`** is just a convex combination of $\mathbf{V}$

$$\overset{\mathbf{A}}{\begin{bmatrix} 0.6 & 0.1 & 0.3 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.1 & 0.7 \end{bmatrix}} \overset{\mathbf{V}}{\begin{bmatrix} 2.0 & 1.0 \\ -0.5 & 2.0 \\ -1.0 & -0.5 \end{bmatrix}} \begin{array}{c} \color{red}{\mathrm{I}} \\ \color{green}{\mathrm{am}} \\ \color{blue}{\mathrm{Sam}} \end{array}$$



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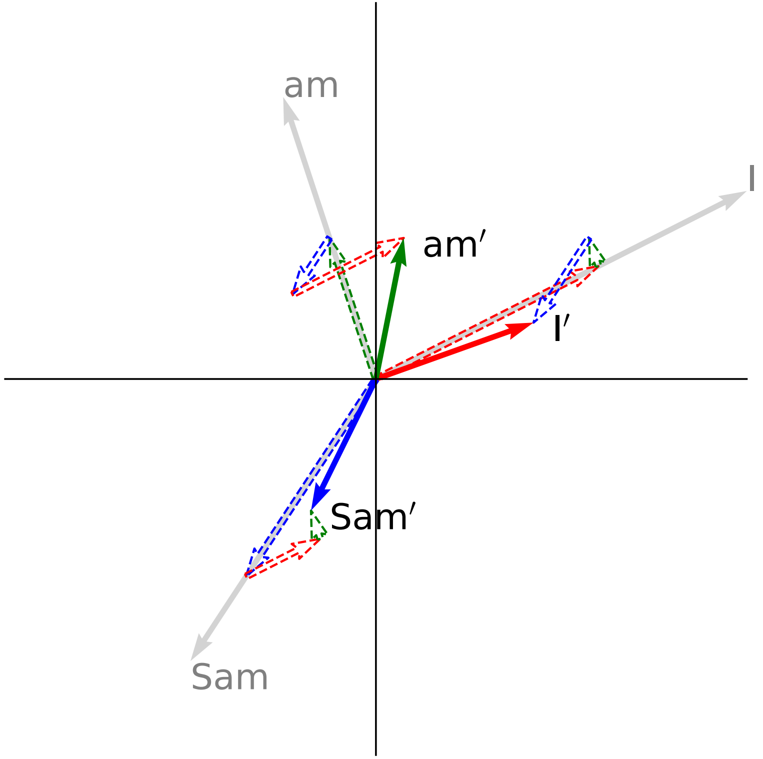
$$= \begin{bmatrix} 0.6 * \color{red}{\mathrm{I}} + 0.1 * \color{green}{\mathrm{am}} + 0.3 * \color{blue}{\mathrm{Sam}} \\ 0.3 * \color{red}{\mathrm{I}} + 0.5 * \color{green}{\mathrm{am}} + 0.2 * \color{blue}{\mathrm{Sam}} \\ 0.2 * \color{red}{\mathrm{I}} + 0.1 * \color{green}{\mathrm{am}} + 0.7 * \color{blue}{\mathrm{Sam}} \end{bmatrix}$$



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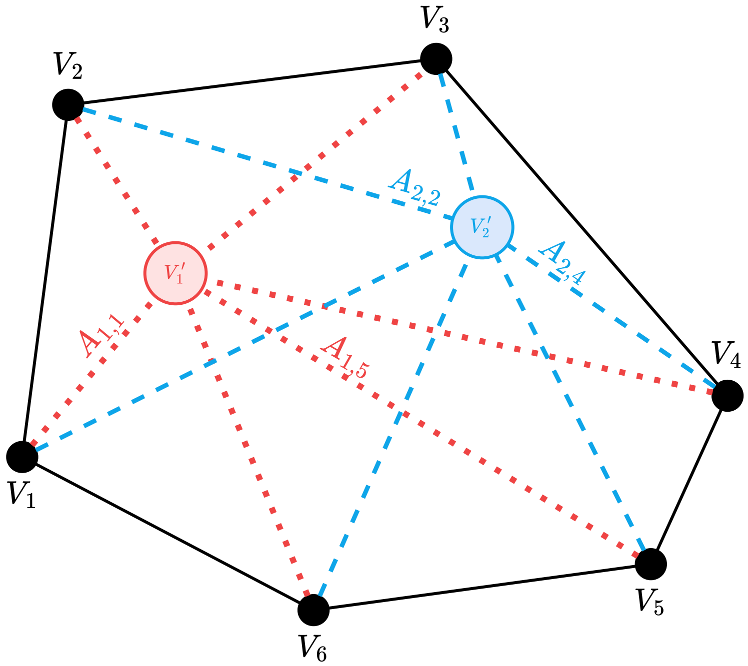
**Convex Combination**

The elements of $V'$ will lie inside the convex hull of all of the elements in $V$



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## Multi-head Attention

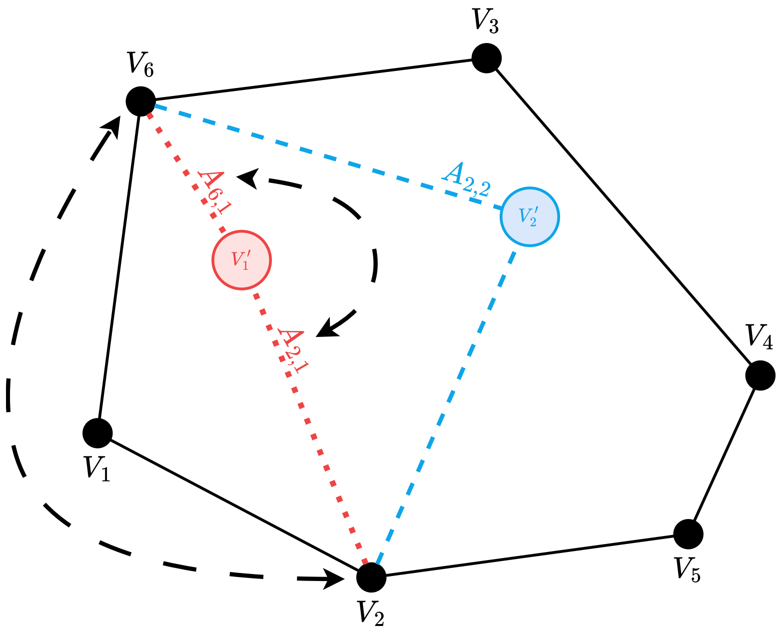
### Convex Combination

The elements of $V'$ will lie inside the convex hull of all of the elements in $V$

### Permutation Equivariance

The elements of $V'$ are *equivariant* to a change in the order of the rows of $\mathbf{A}$

- Attention does not care about word order



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So is `Attention` just a linear map?

- Not quite

Linear maps are:

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- Inflexible in terms of sequence length
- Parameter inefficient
- Invariant to the input content

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- Let $\mathbf{K}$ be a matrix of **key** vectors
  - It has a sequence length of $T_V$
  - It has a dimensionality of $D_Q$
- Let $\mathbf{Q}$ be a matrix of **query** vectors
  - It has a sequence length of $T_Q$
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$$\mathtt{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \underbrace{\mathtt{softmax}\left(f\left(\mathbf{Q}, \mathbf{K}\right)\right)}_{\mathbf{A}}\mathbf{V}$$

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- Let $\mathbf{Q}$ be a matrix of **query** vectors
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- Let $f(\mathbf{Q}, \mathbf{K})$ be some kernel function
  - Read: similarity function

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# Non-Transformer Examples

Multi-head Attention

- $\mathbf{V}$ contains information
- $\mathbf{K}$ contains information about information (i.e, metadata)
- $\mathbf{Q}$ contains metadata about what we want from $\mathbf{V}$
- $f(\mathbf{Q}, \mathbf{K})$ is high when $\mathbf{Q}$ is similar to $\mathbf{K}$

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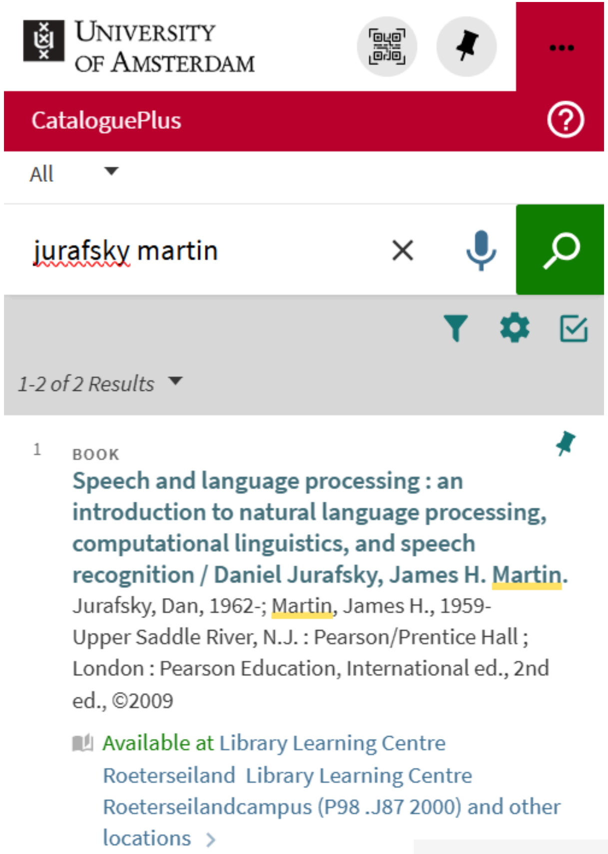
**E Soft lookup**

We want to find a textbook about NLP in the library $(\mathbf{V})$. We search for titles $(\mathbf{K})$ with "jurafsky" and "martin" as authors $(\mathbf{Q})$. The computer returns books with similar titles $(f)$



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- The output of $f$ must a matrix of size $\mathbf{A} \in (0,1)^{[T_Q \times T_V]}$

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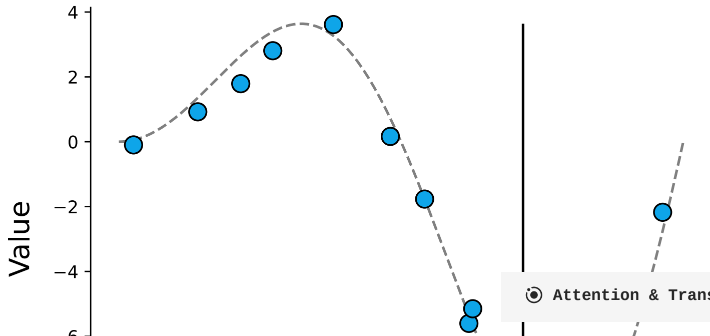
**E Nadaraya-Watson Kernel Regression**

We have some sequence of values
$\mathcal{D} = [(1.36, 1.79), (3.40, -1.77) \ldots, (6.05, -2.17)]$

We want to predict a new sample at $x = 4.21$

We compute the negative Euclidean distance of our new sample with all training samples ($f$). We normalize the outputs to lie between $(0,1)$

We compute our predicted value as the mean of the seen values, weighted by the computed similarities



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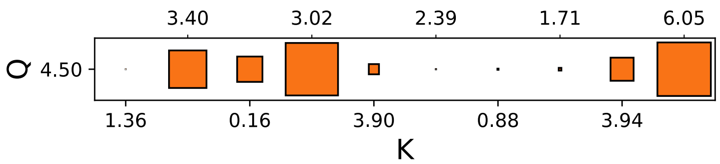
- The output of $f$ must a matrix of size $\mathbf{A} \in (0,1)^{[T_Q \times T_V]}$



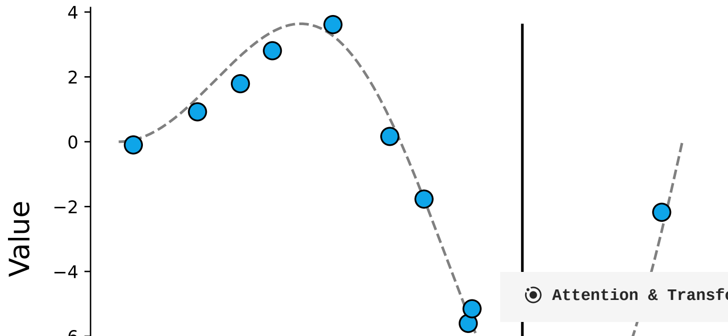

**E Nadaraya-Watson Kernel Regression**

We have some sequence of values
$\mathcal{D} = [(1.36, 1.79), (3.40, -1.77) \dots, (6.05, -2.17)]$

We want to predict a new sample at $x = 4.21$

We compute the negative Euclidean distance of our new sample with all training samples ($f$). We normalize the outputs to lie between $(0, 1)$

We compute our predicted value as the mean of the seen values, weighted by the computed similarities



# Non-Transformer Examples

Multi-head Attention

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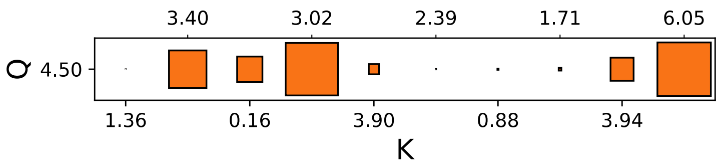


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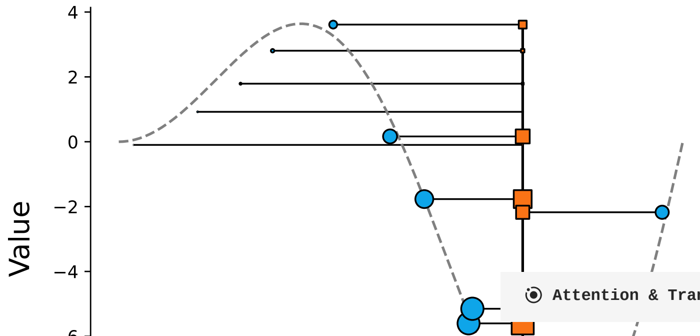

# Non-Transformer Examples

Multi-head Attention

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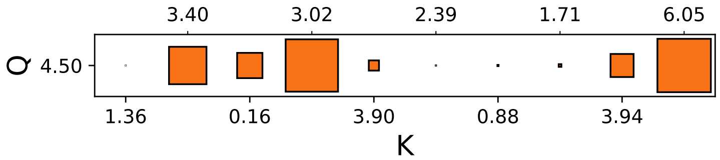


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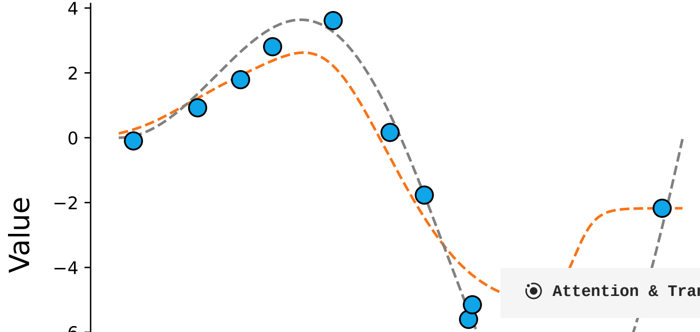

# Non-Transformer Examples

## 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