Interactive Fiction and Text Generation

Lara J. Martin (she/they)

https://laramartin.net/interactive-fiction-class

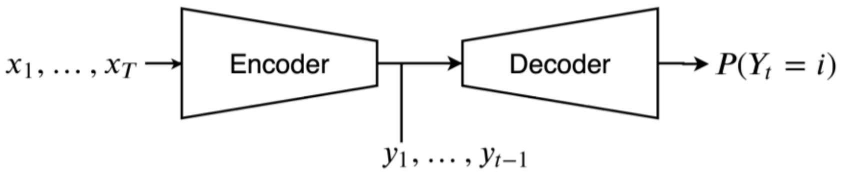
Slides modified from Dr. Daphne Ippolito

Learning Objectives

Compare sequence-to-sequence RNNs to transformers

Consider the strengths and weaknesses of LLMs/transformers

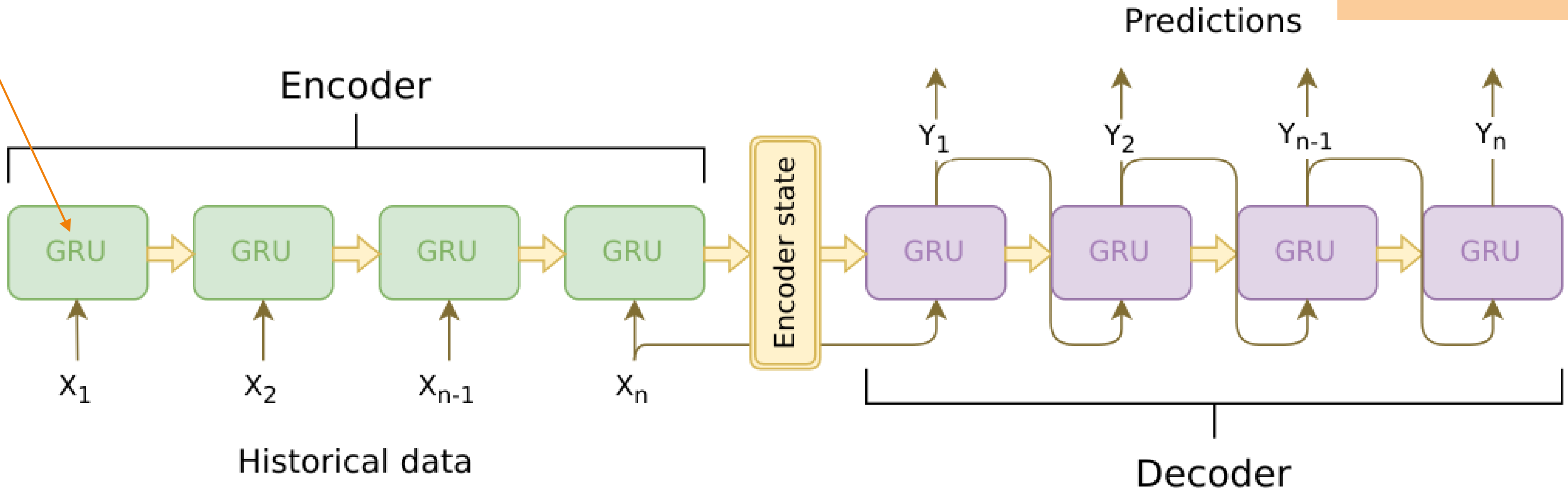
What is a language model?



Review: Sequence-to-Sequence / Encoder-Decoder Models

What are the inputs & outputs?

Can be LSTM



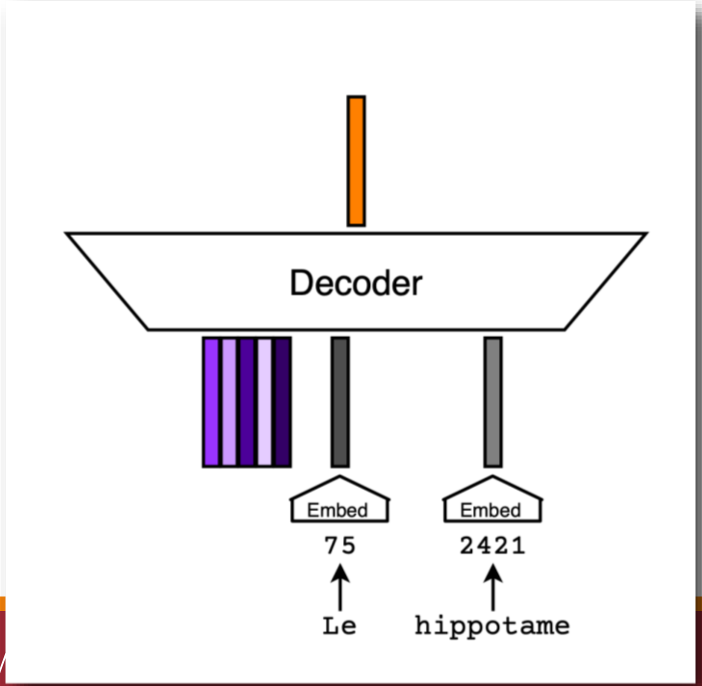
https://jeddy92.github.io/JEddy92.github.io/ts_seq2seq_intro/

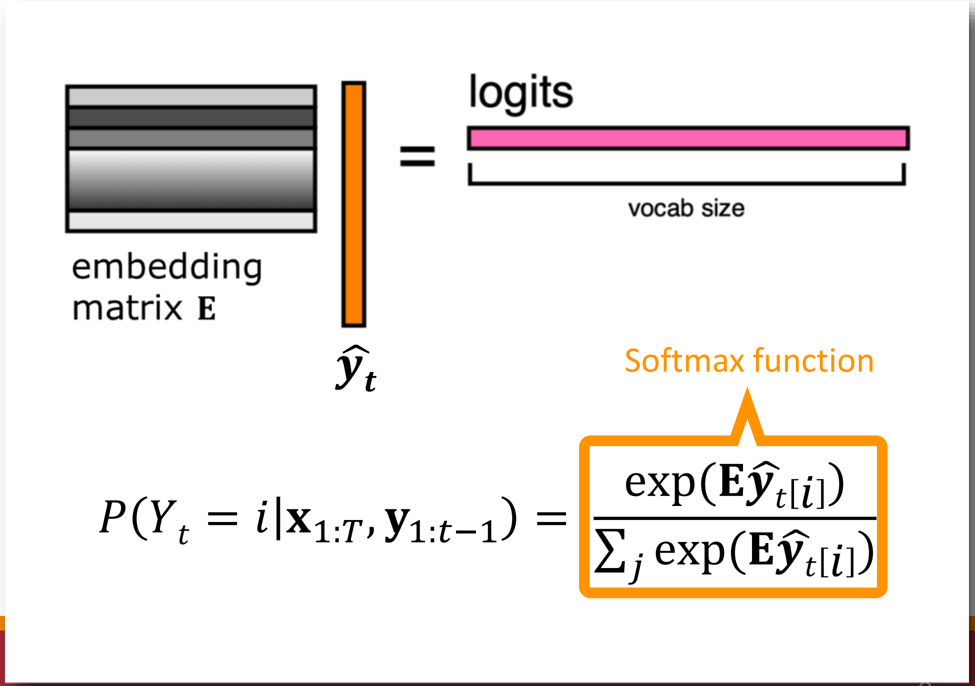
I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to Sequence Learning with Neural Networks,” in *Conference on Advances in Neural Information Processing Systems (NeurIPS)*, Montréal, Canada, 2014, pp. 3104–3112. https://proceedings.neurips.cc/paper_files/paper/2014/hash/a14ac55a4f27472c5d894ec1c3c743d2-Abstract.html

Review:
Turning $\widehat{yt}$ into a Probability Distribution

We can multiply the predicted embedding $\widehat{yt}$ by our vocabulary embedding matric to get a score for each vocabulary word. These scores are referred to as logits.

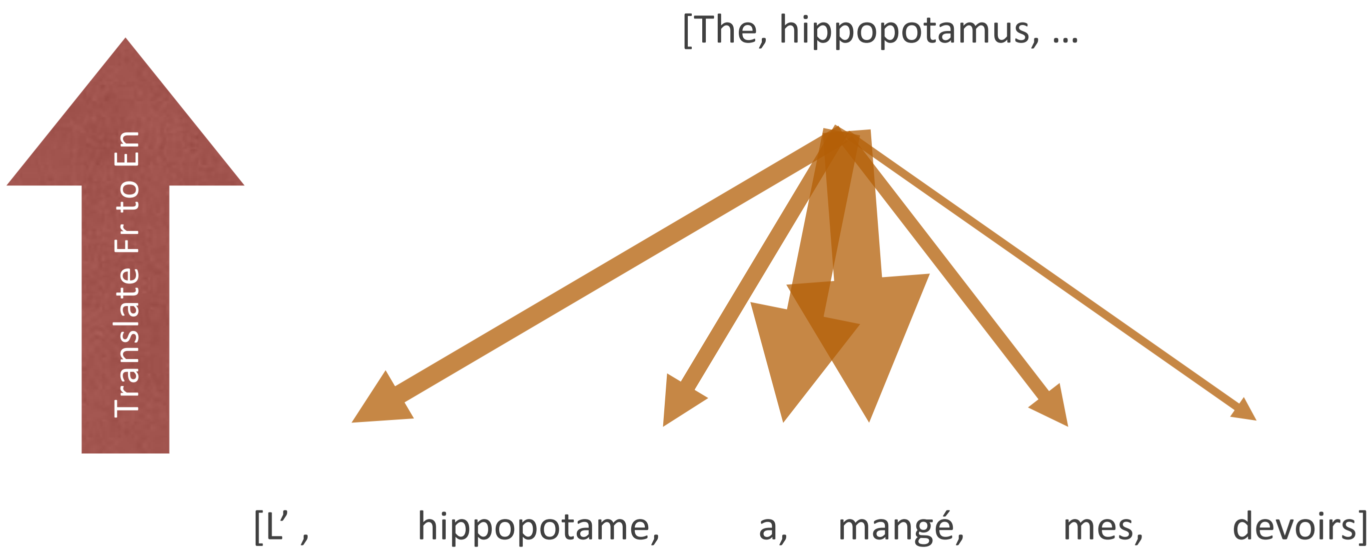
The softmax function then lets us turn the logits into probabilities.

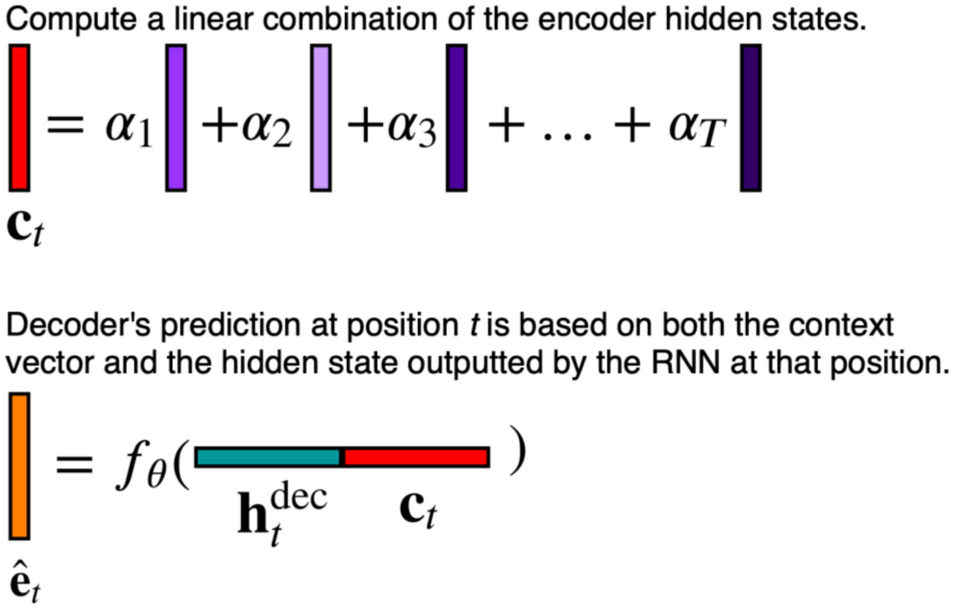




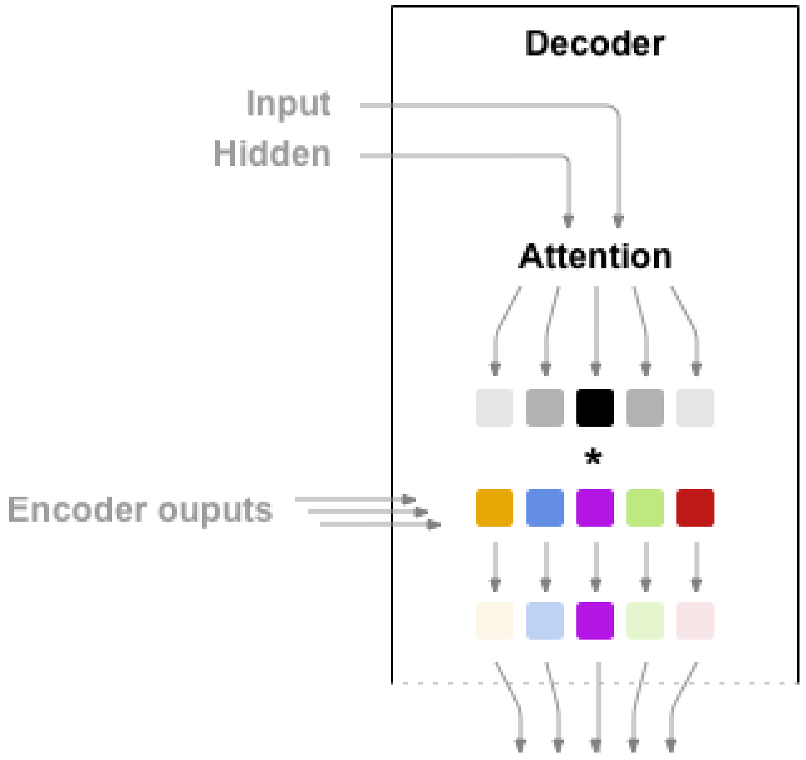
Review: Attention

Better approach: an attention mechanism





Review: Attention Decoder



https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

What are some of the limitations of RNNs?

Transformers

Since 2018, the field has rapidly standardized on the Transformer architecture

Attention Is All You Need

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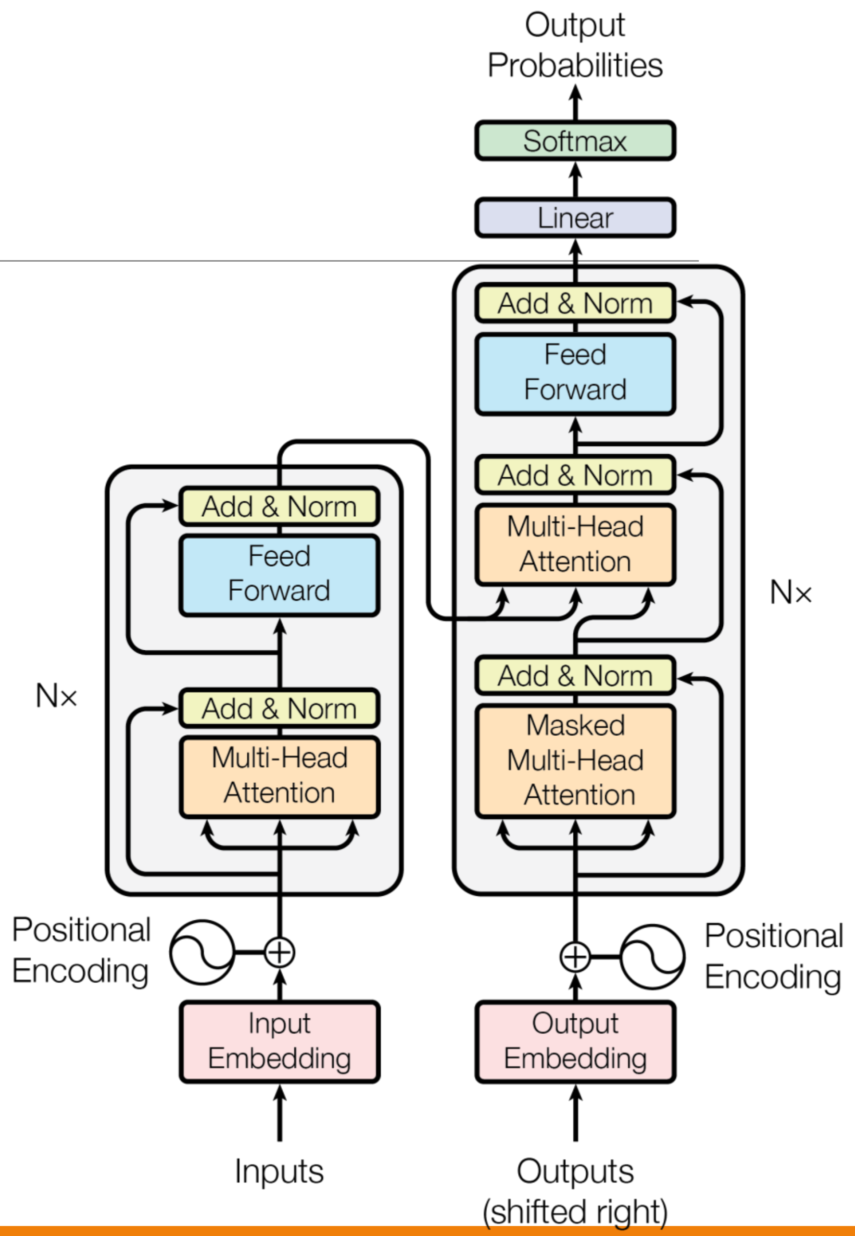
Abstract

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

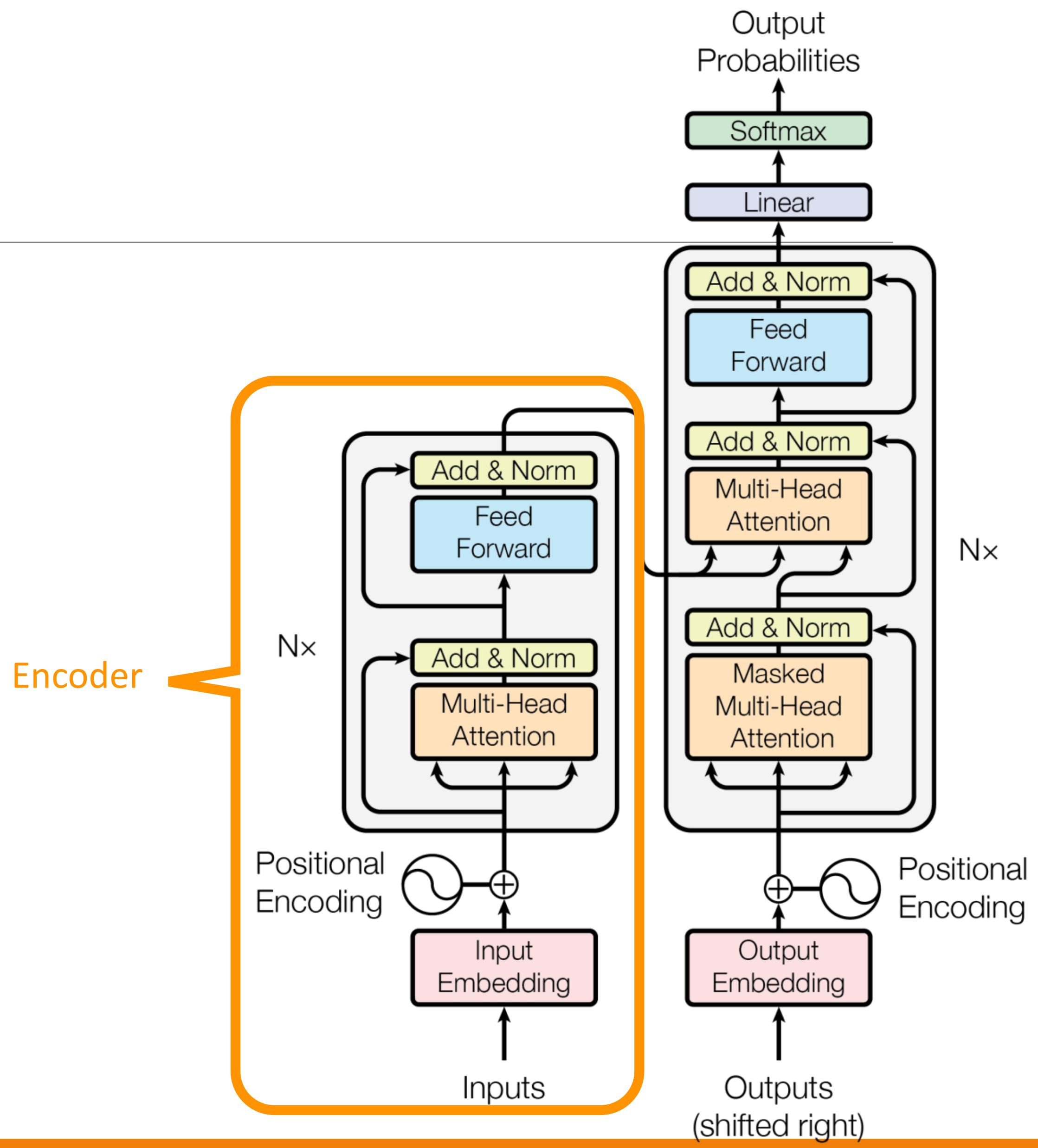
Transformers

The Transformer is a **non-recurrent** non-convolutional (feed-forward) neural network designed for language understanding

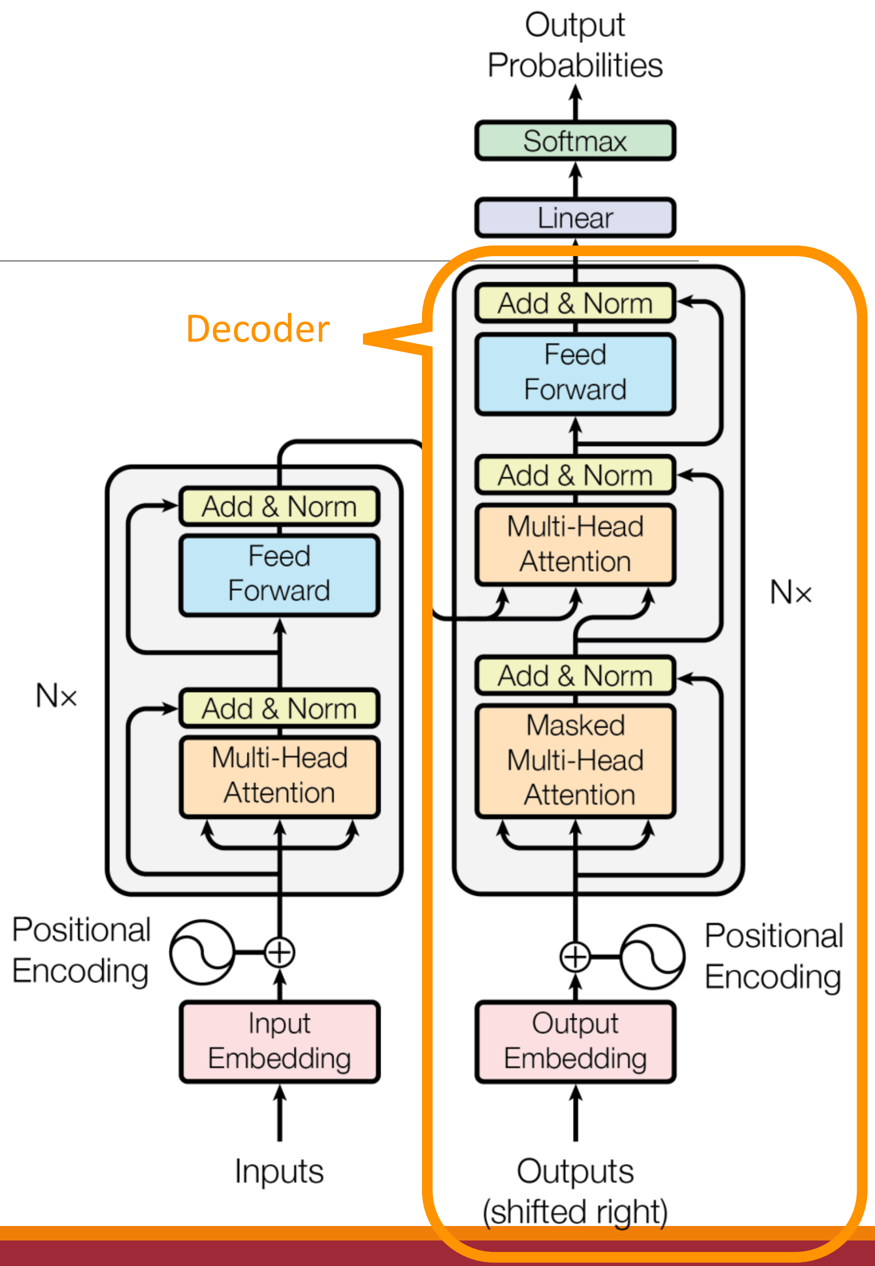
- introduces self-attention in addition to encoder-decoder attention



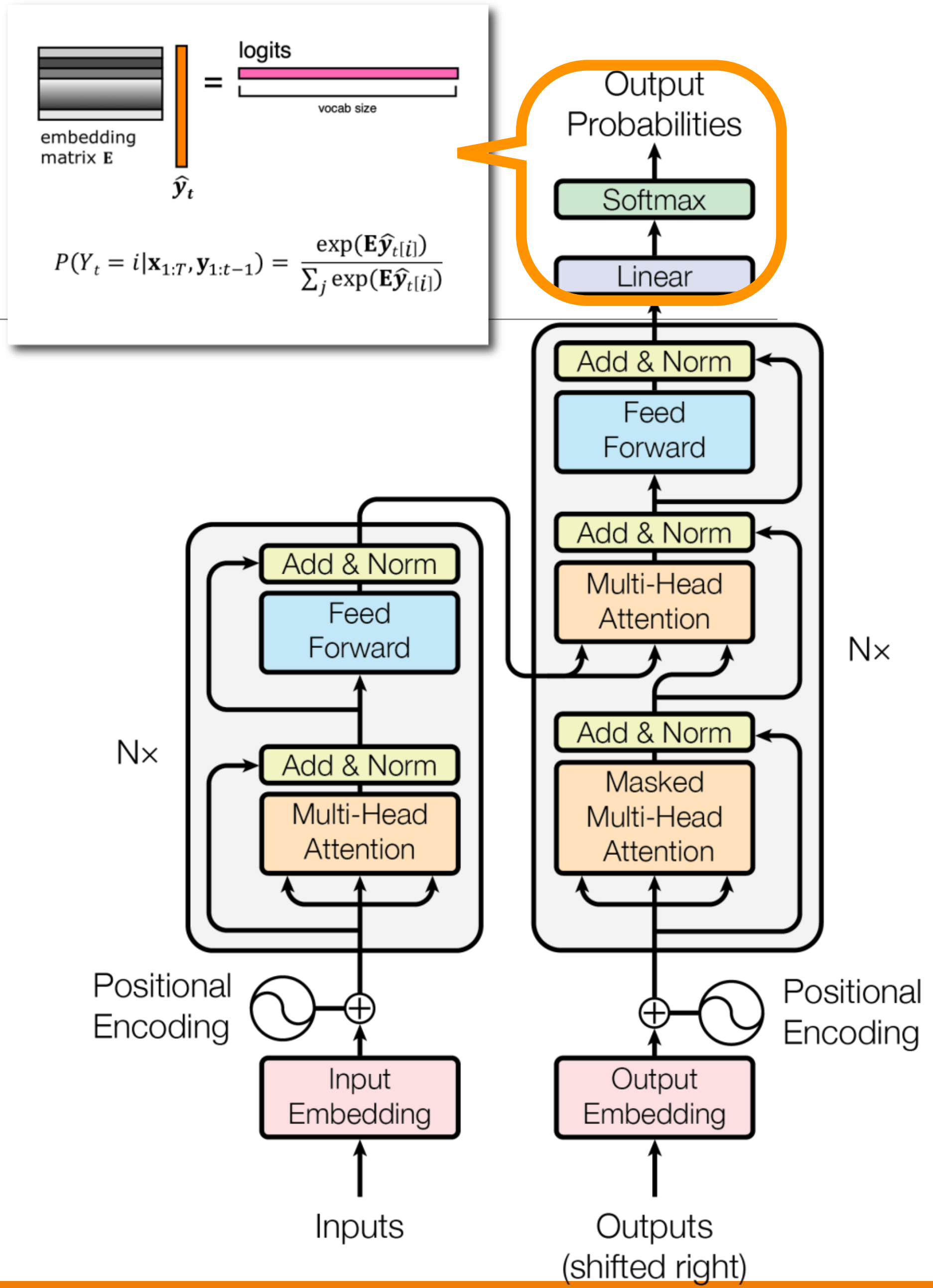
Transformers



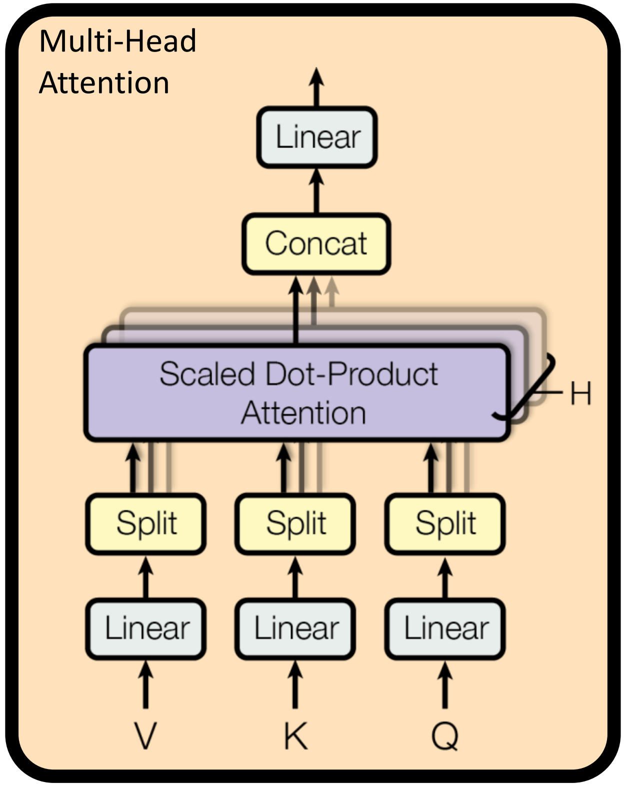
Transformers

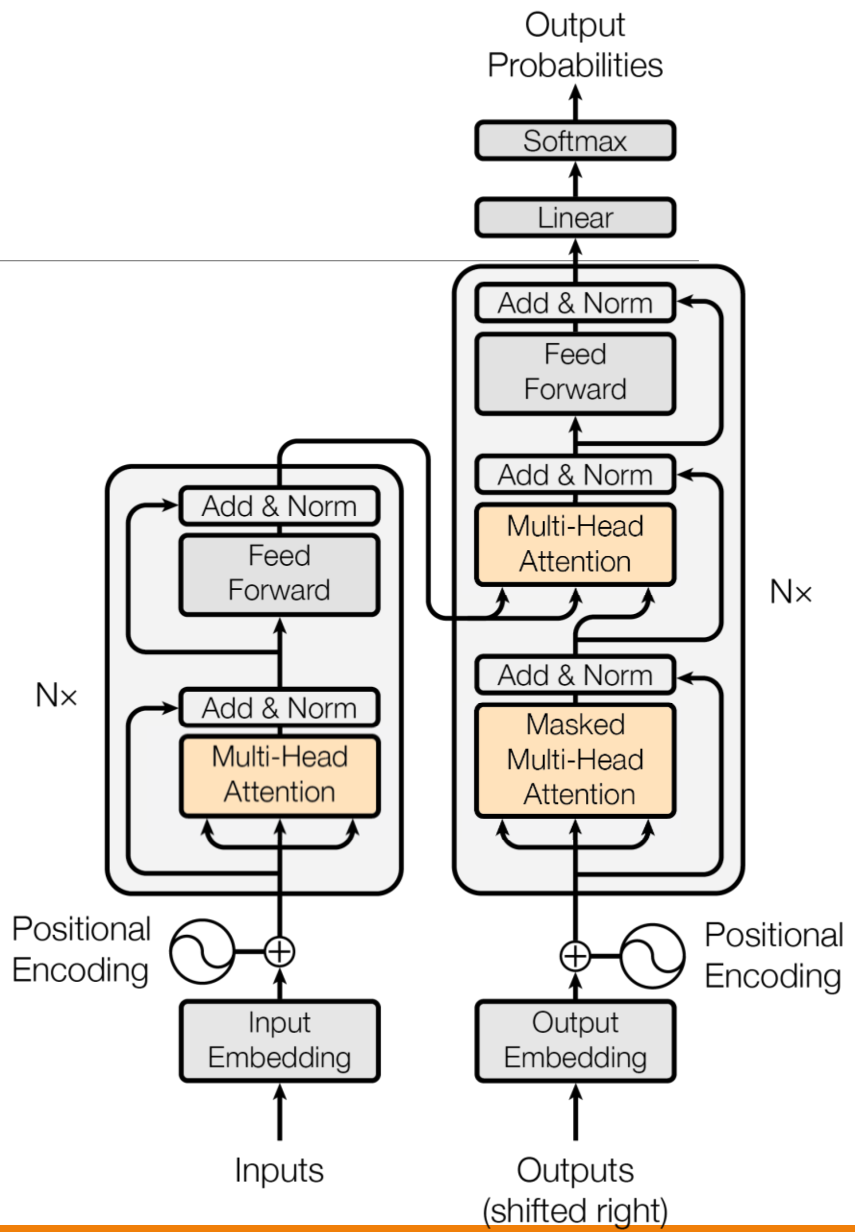


Transformers

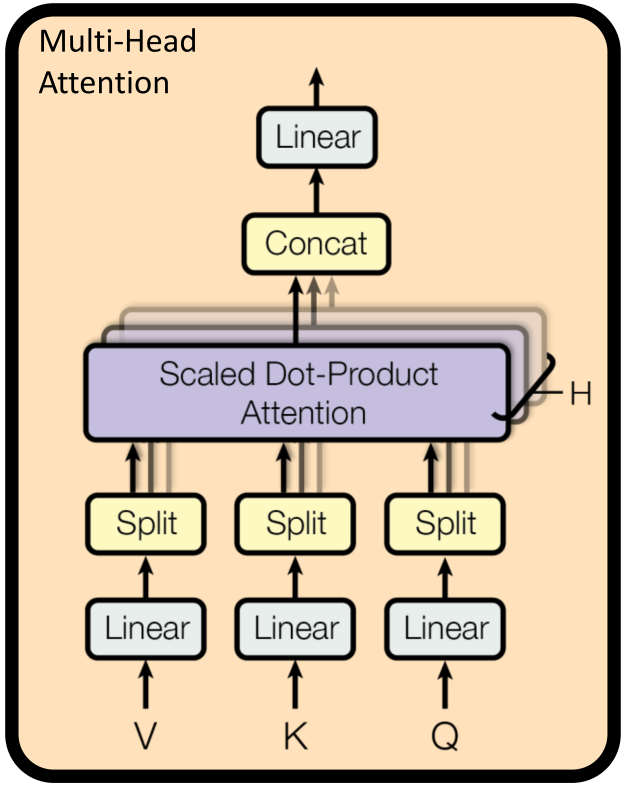


Attention Mechanism

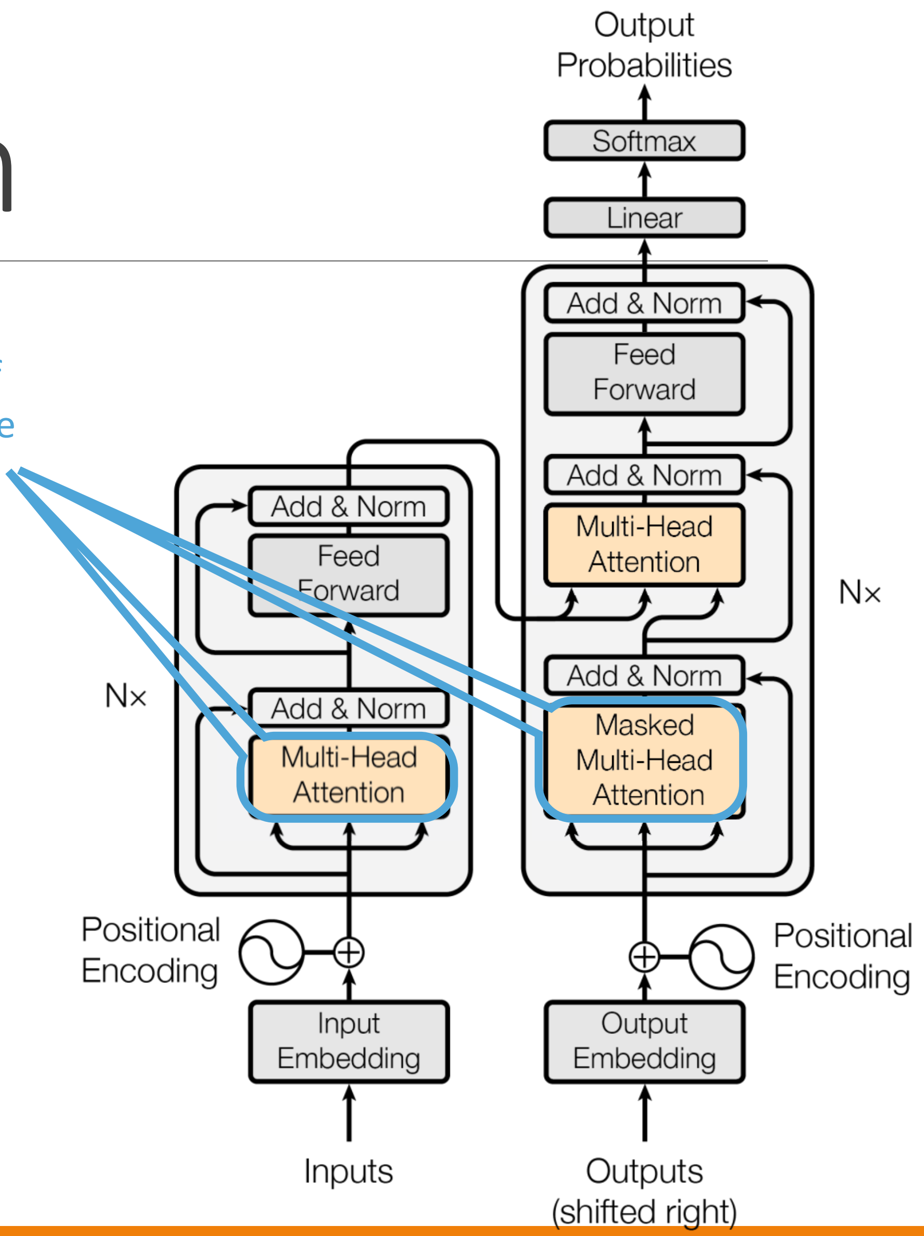




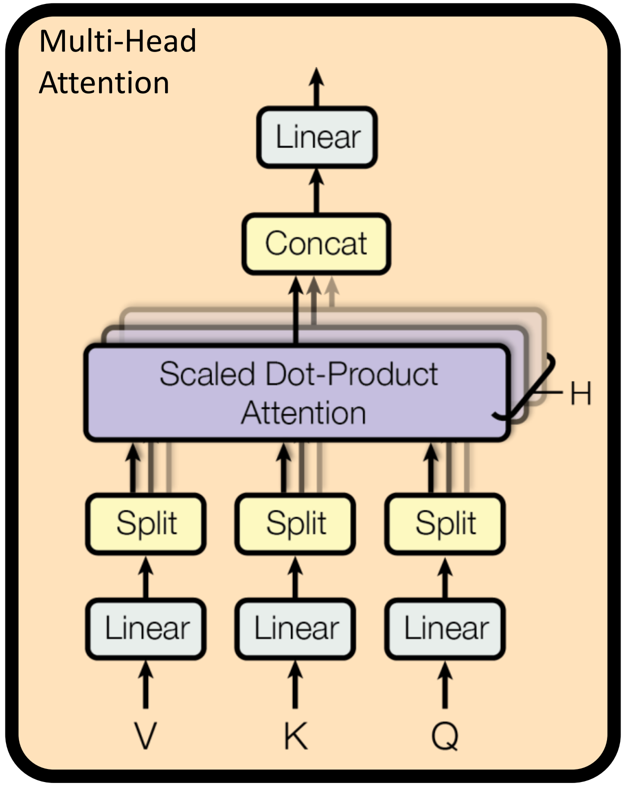
Multi-Head Attention



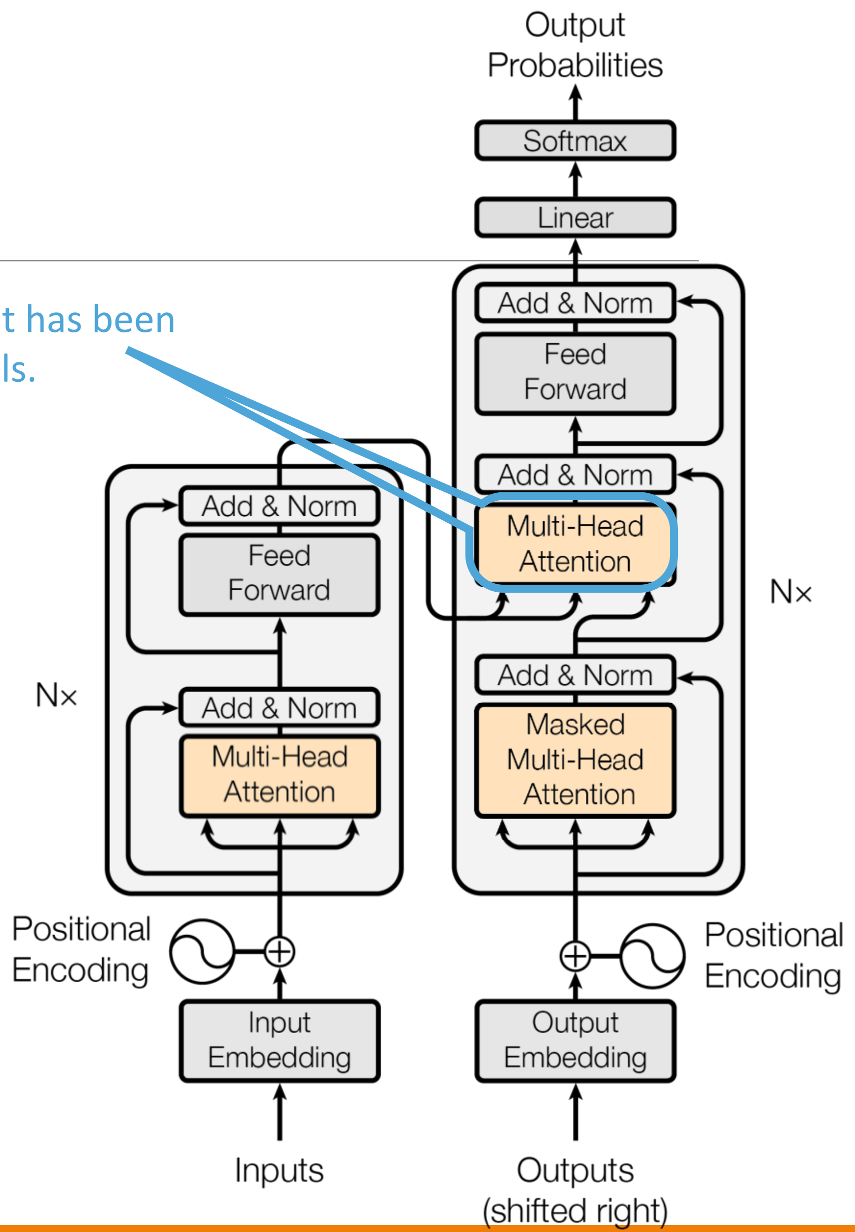
Self-attention between a sequence of hidden states and that same sequence of hidden states.



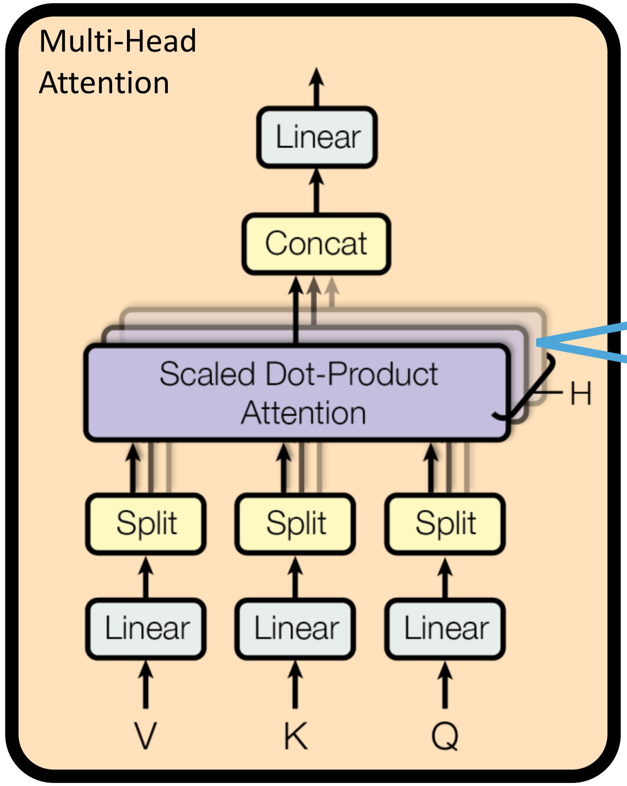
Multi-Head Attention

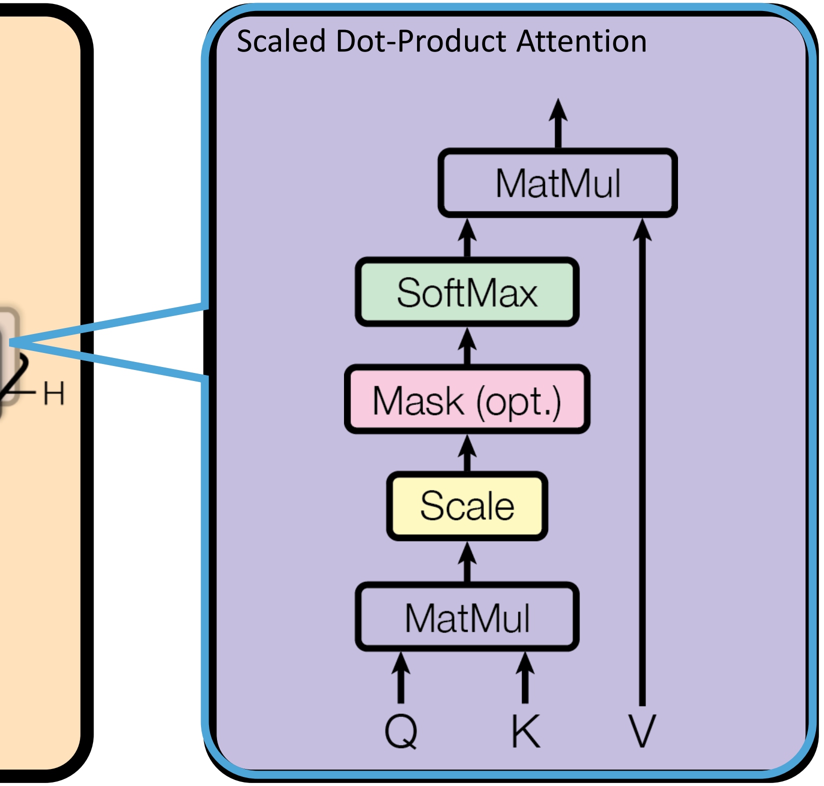


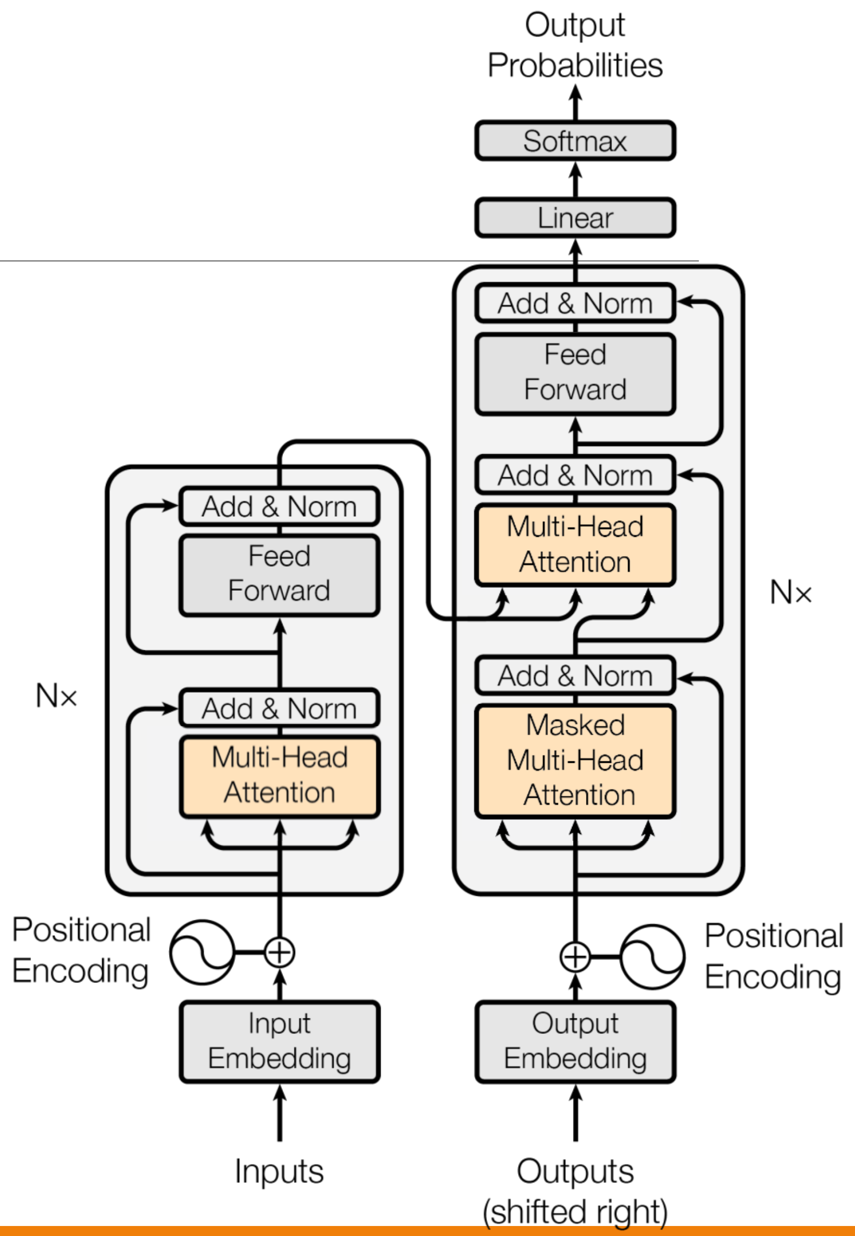
Encoder-decoder attention, like what has been standard in recurrent seq2seq models.



Attention Mechanism

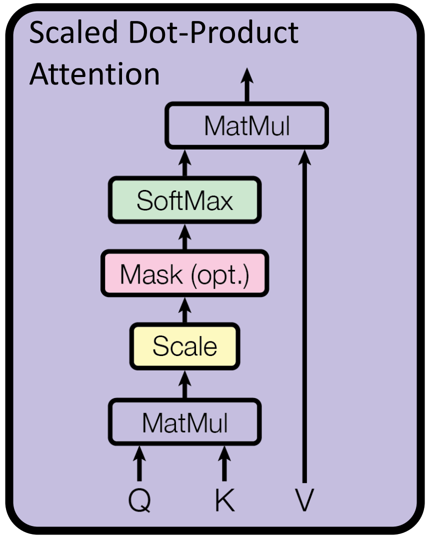






Scaled Dot-Product Attention

The scaled dot-product attention mechanism is almost identical to the one we looked at, but let's turn it into matrix multiplications.



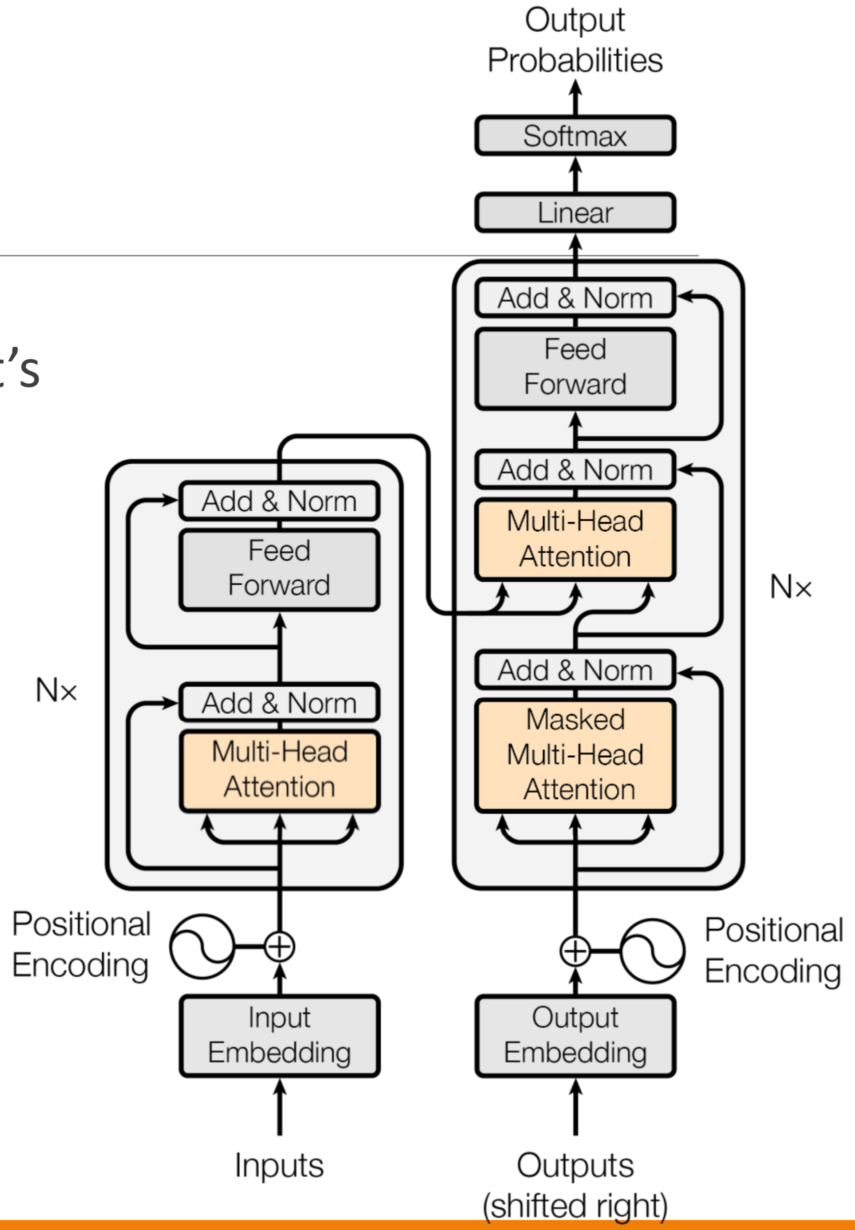
The query: Q ∈ R^{Txdk}

The key: K ∈ $R^{T'xdk}$

The value: V ∈ R^{Txdk}

This is the α vector we learned about before.

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



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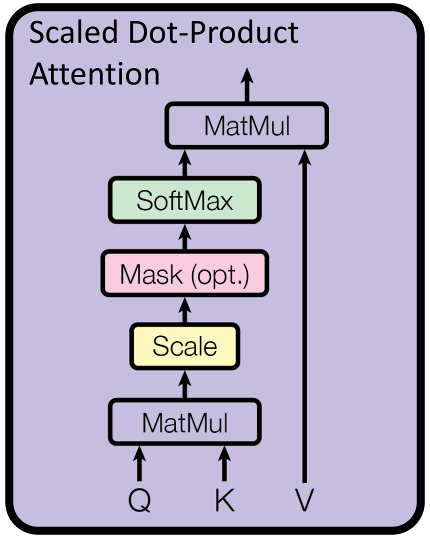


The query: Q ∈ R^{Txdk}

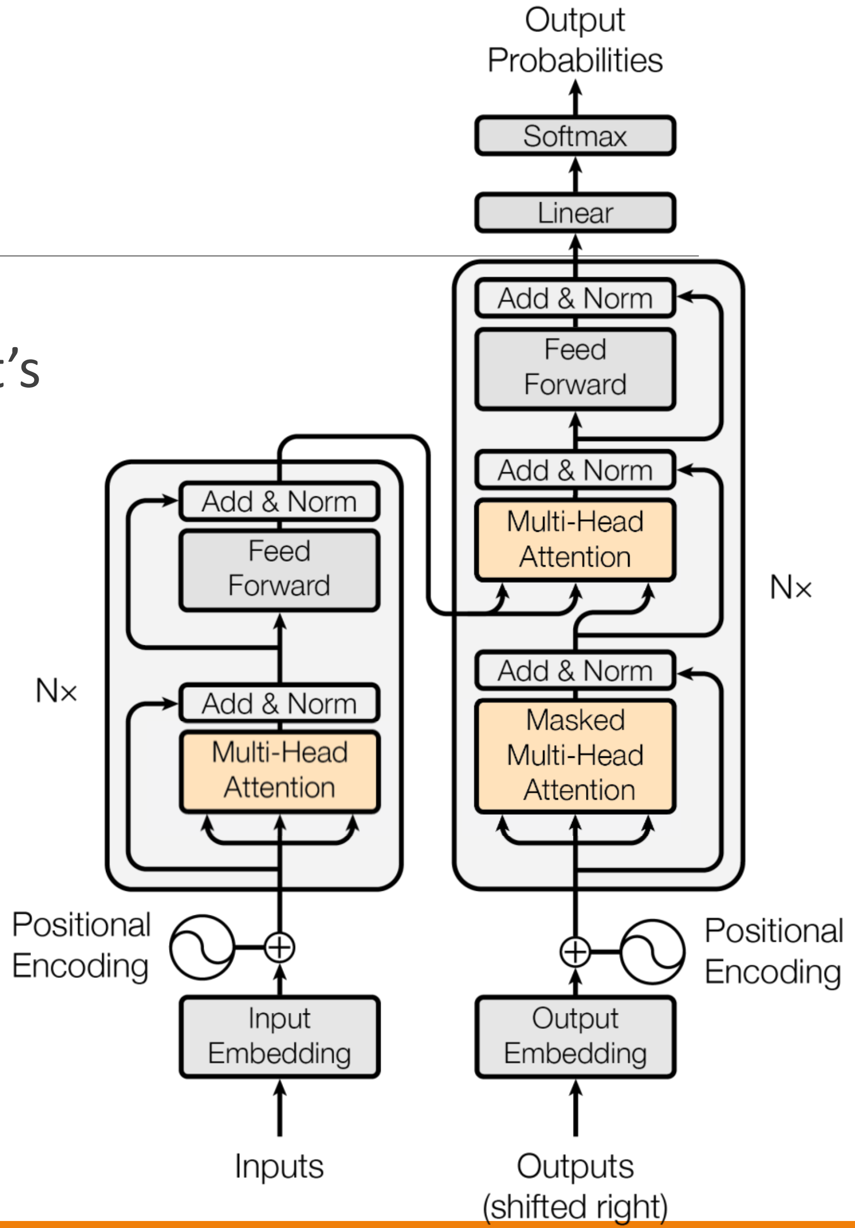
The key: K ∈ $R^{T'xdk}$

The value: V ∈ R^{Txdk}

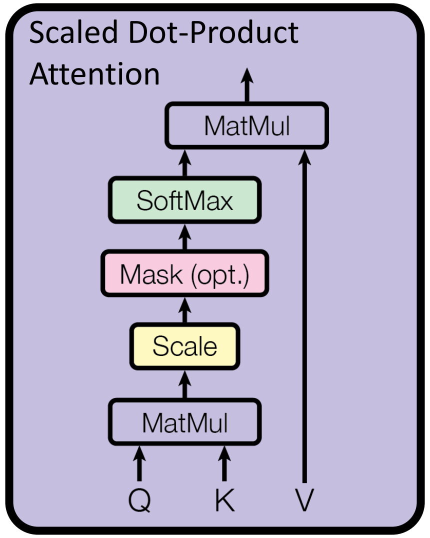
This is the dot-product scoring function from previous slides

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

The $\sqrt{d_k}$ in the denominator prevents the dot product from getting too big



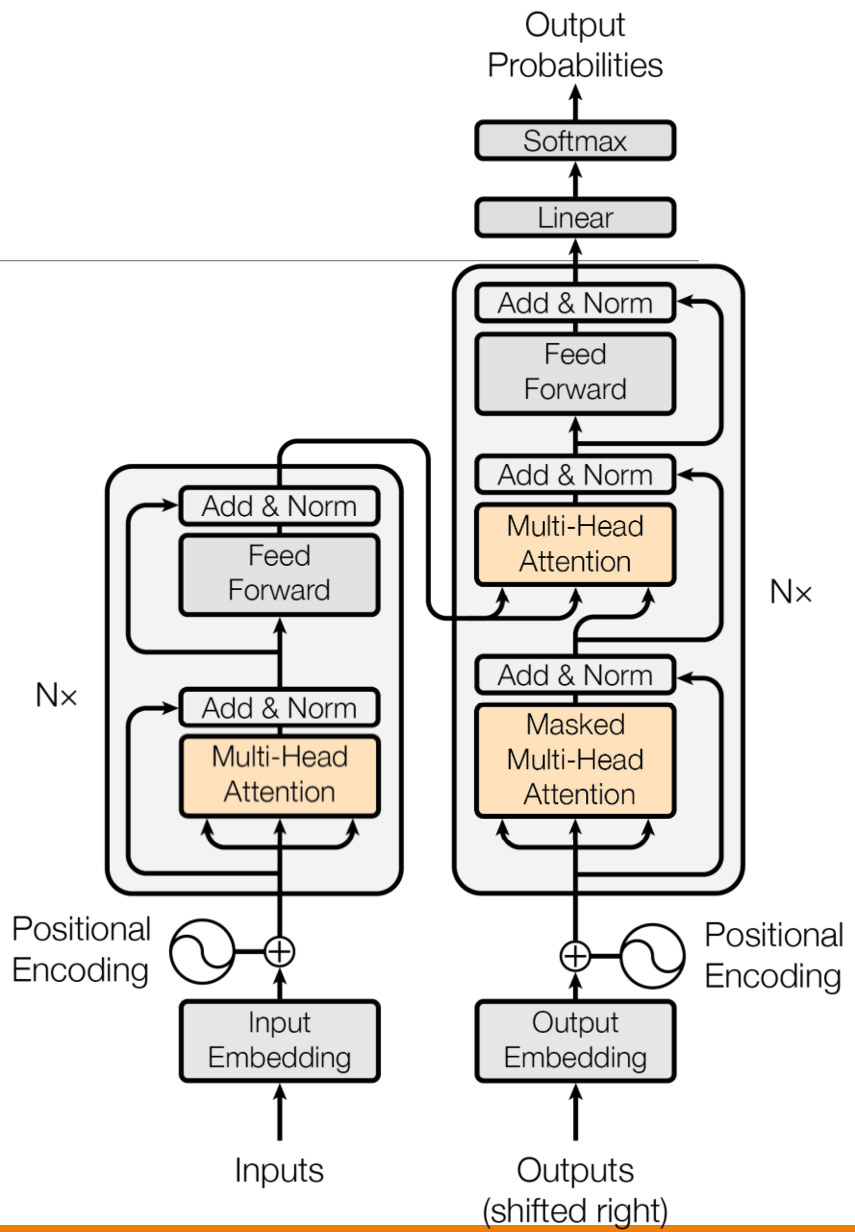
Scaled Dot-Product Attention



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

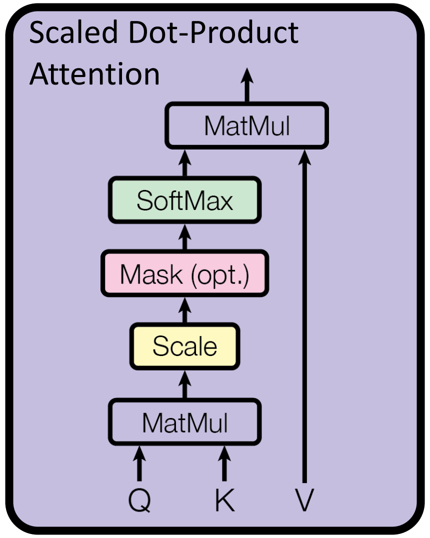
<u>The rough algorithm:</u>

- For each vector in Q (query matrix), take the linear sum of the vectors in V (value matrix)
- The amount to weigh each vector in V is dependent on how "similar" that vector is to the query vector
- "Similarity" is measured in terms of the dot product between the vectors



Scaled Dot-Product Attention

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

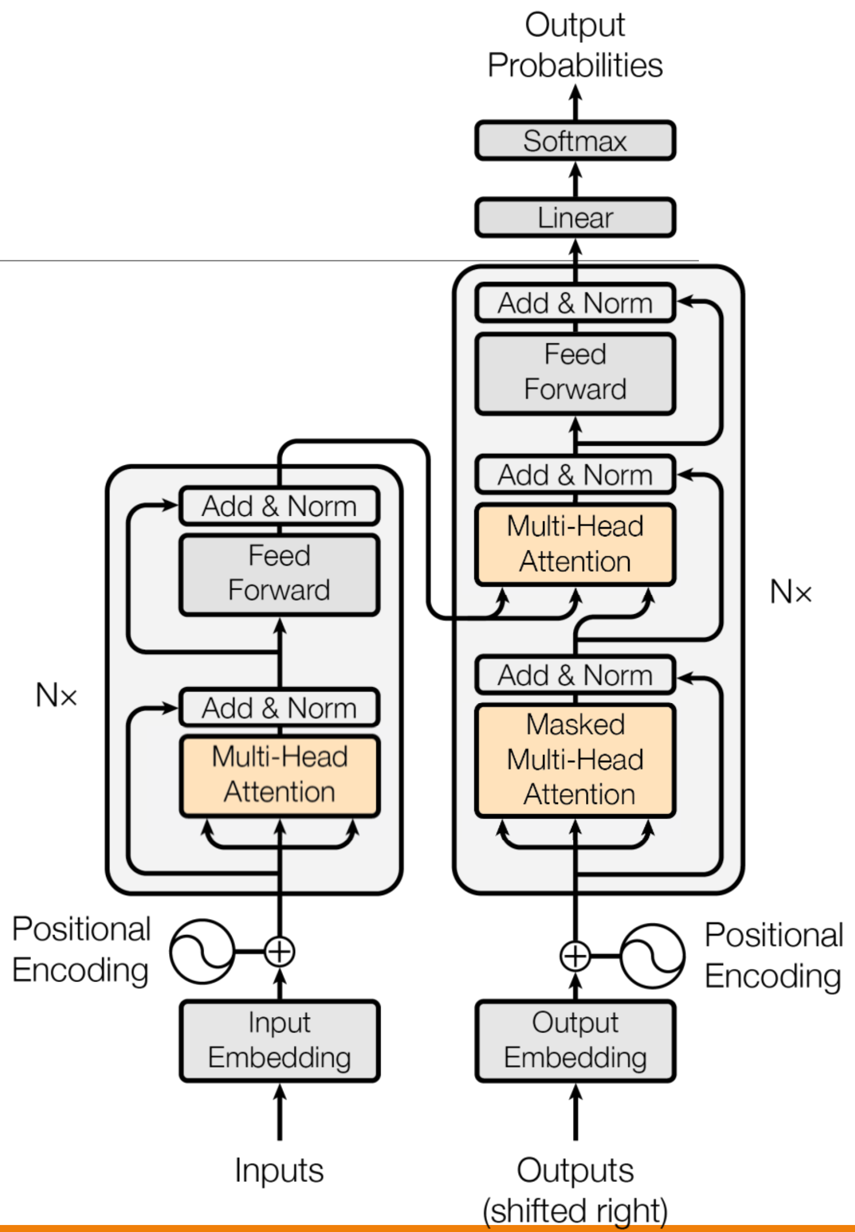


For self-attention:

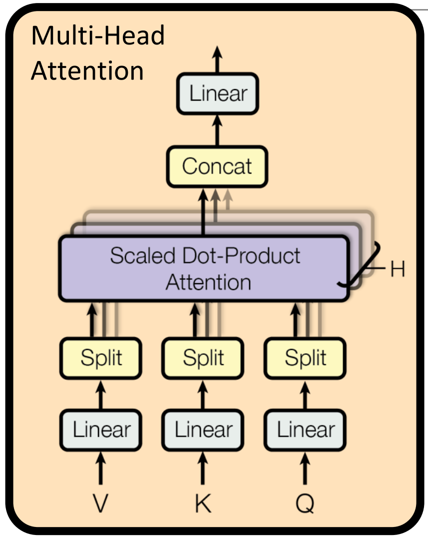
Keys, queries, and values all come from the outputs of the previous layer

For encoder-decoder attention:

Keys and values come from encoder's final output. Queries come from the previous decoder layer's outputs.



Multi-Head Attention



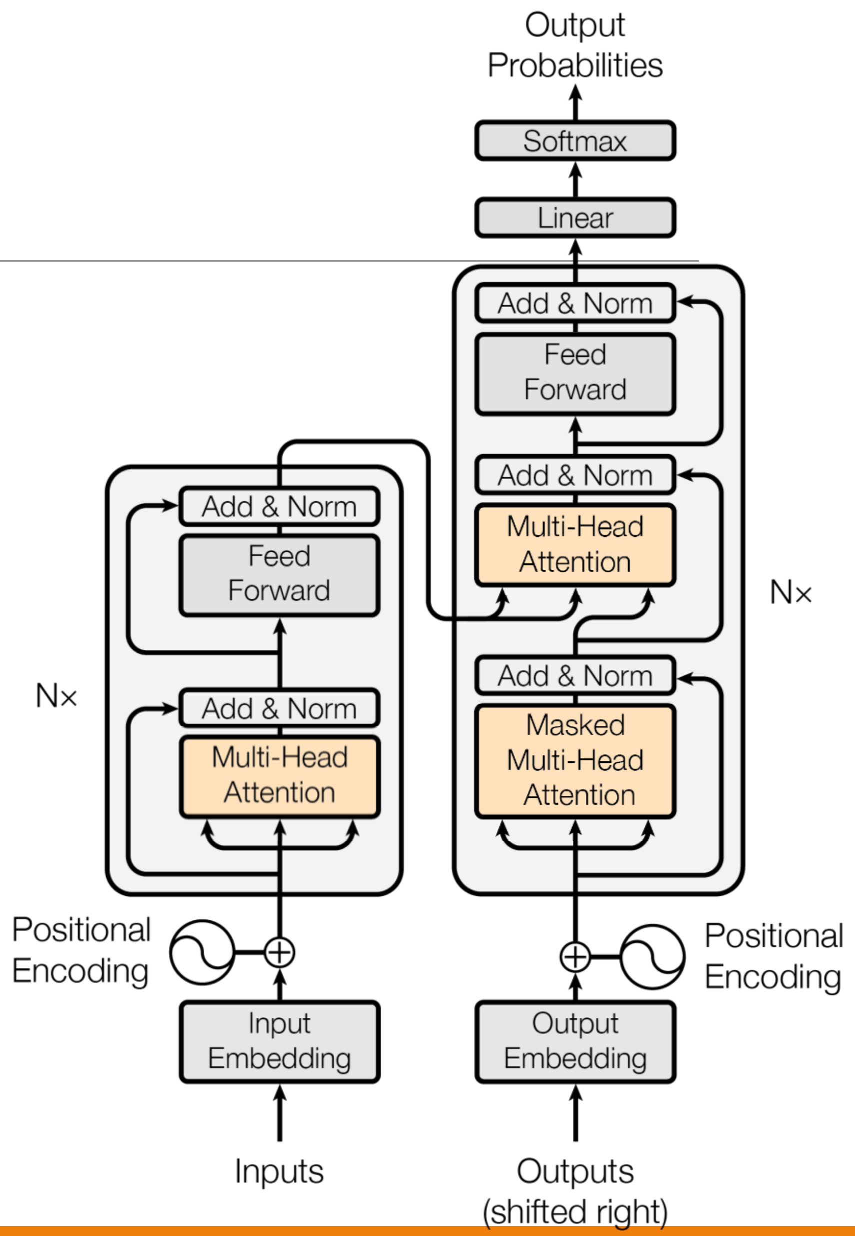
$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}$$

$$\text{MultiHeadAtt}(\mathbf{Q,K,V}) = \text{Concat}(\text{head}_1, \ldots \text{head}_h)\mathbf{W}^O$$

Instead of operating on **Q**, **K**, and **V** mechanism projects each input into a smaller dimension. This is done h times.

The attention operation is performed on each of these “heads,” and the results are concatenated.

Multi-head attention allows the model to jointly attend to information from different representation subspaces at different positions.

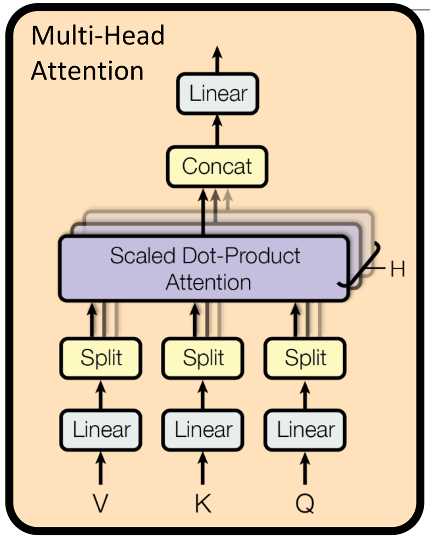


Think-Pair-Share

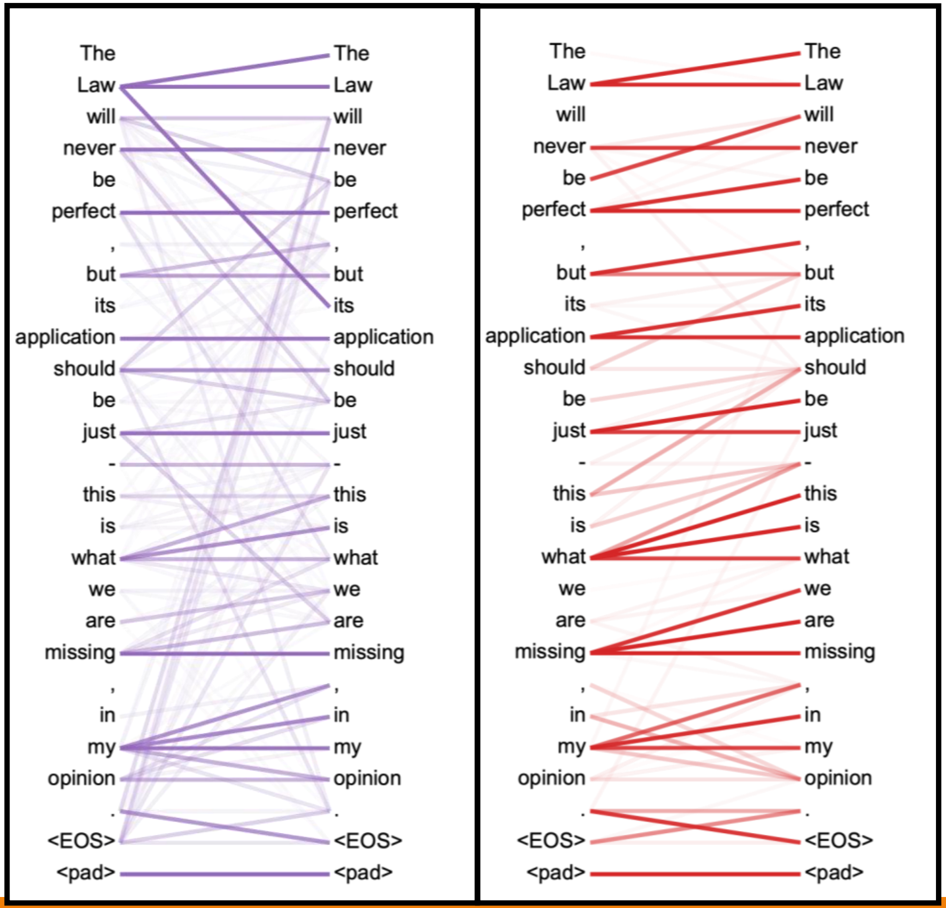
Why might **self-**attention be useful?

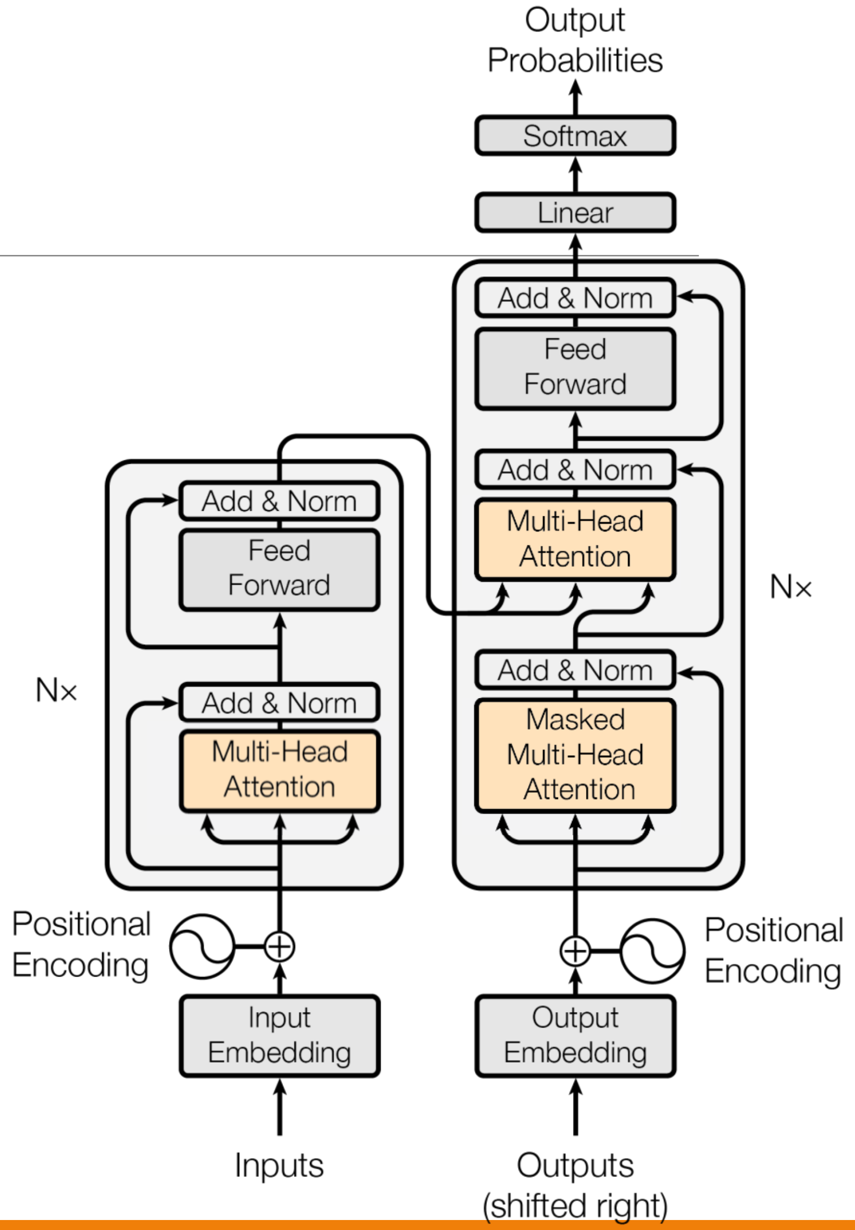
Why do you think we don’t need recurrence anymore (i.e., why is “attention all you need”)?

Multi-Head Attention



Two different self-attention heads:

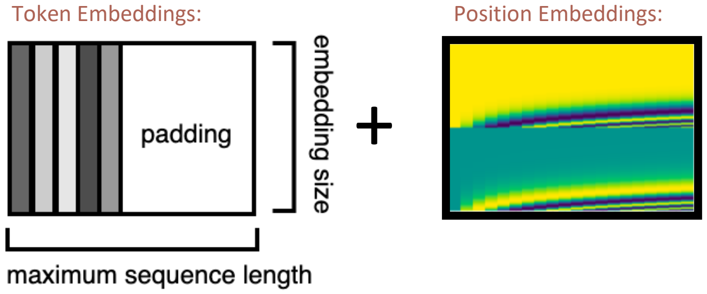




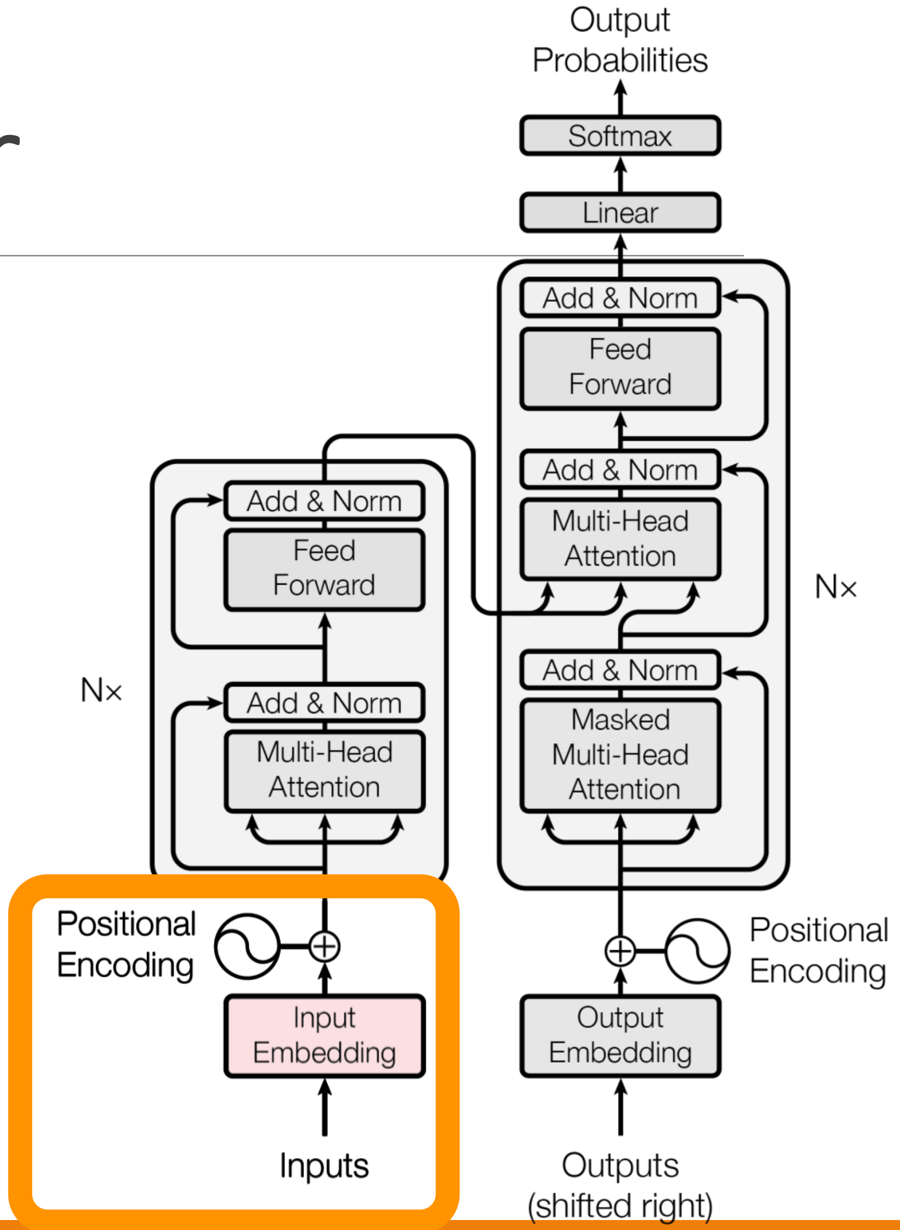
Inputs to the Encoder

The input into the encoder looks like:

$\mathbf{H}_0^{\text{enc}} =$

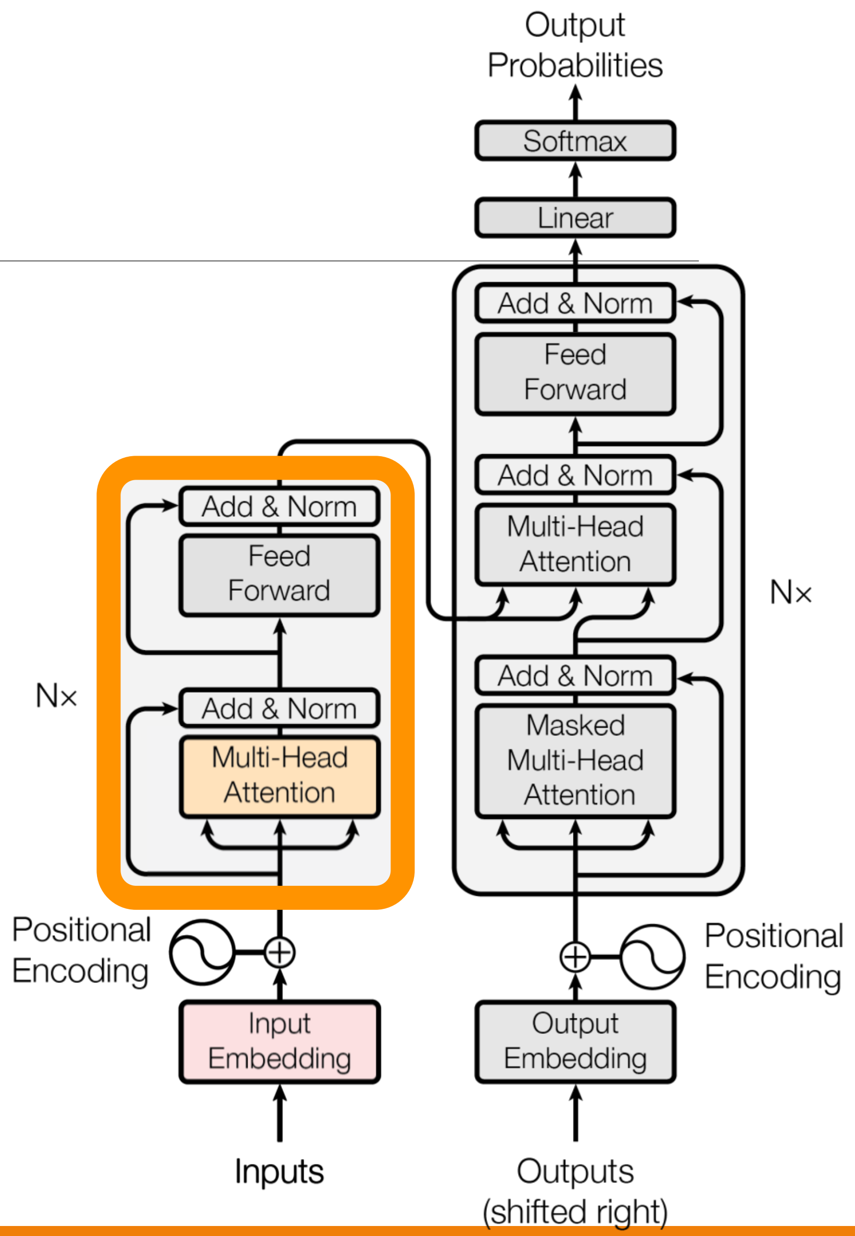


= token embeddings + position embeddings



The Encoder

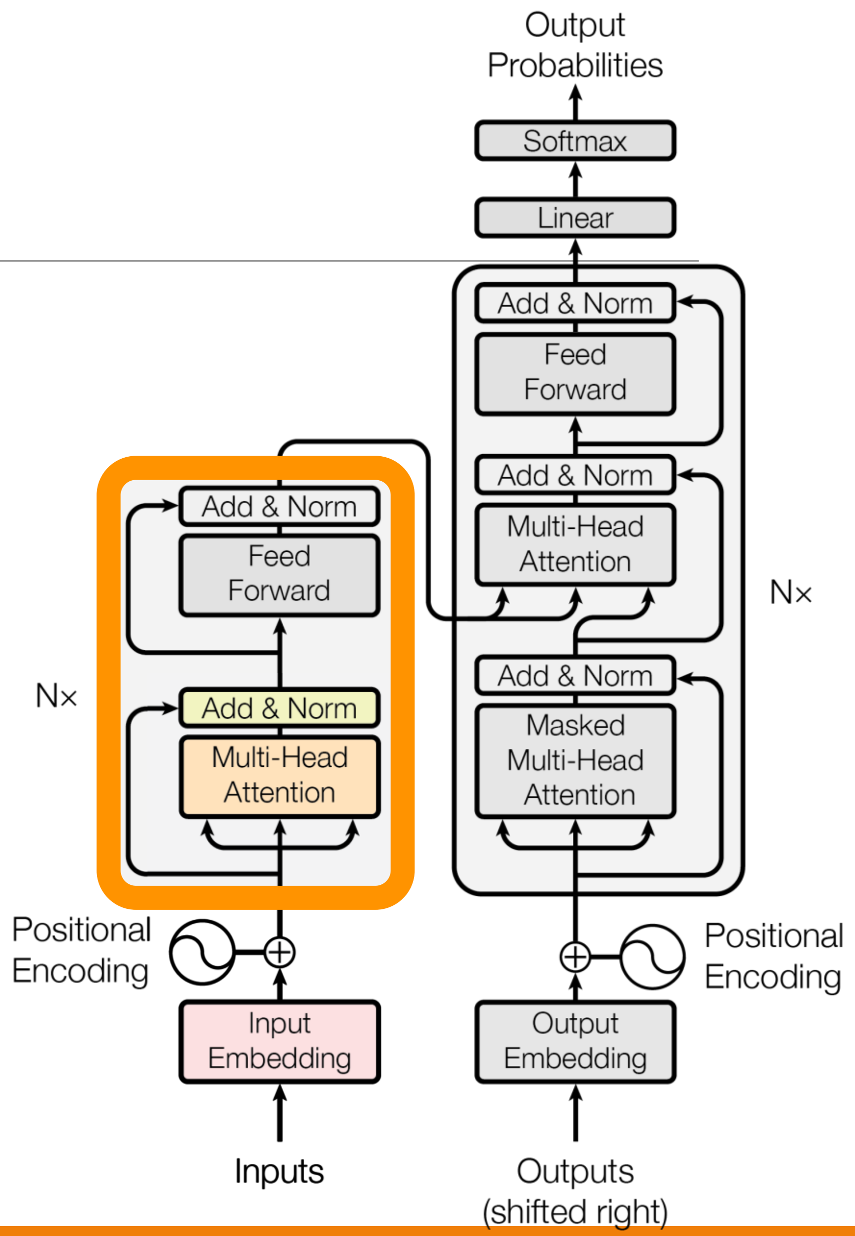
Multi-Head Attention $= \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$



The Encoder

$\boxed{\text{Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$

$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{enc})$

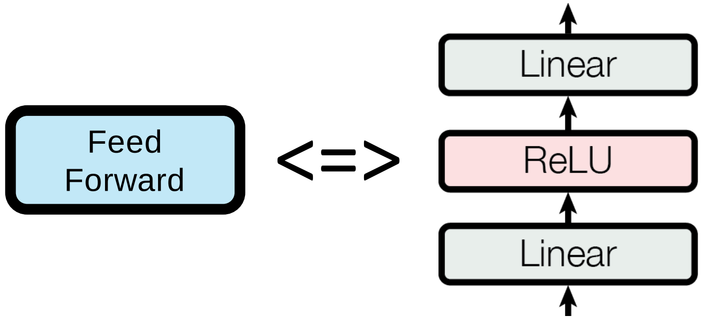


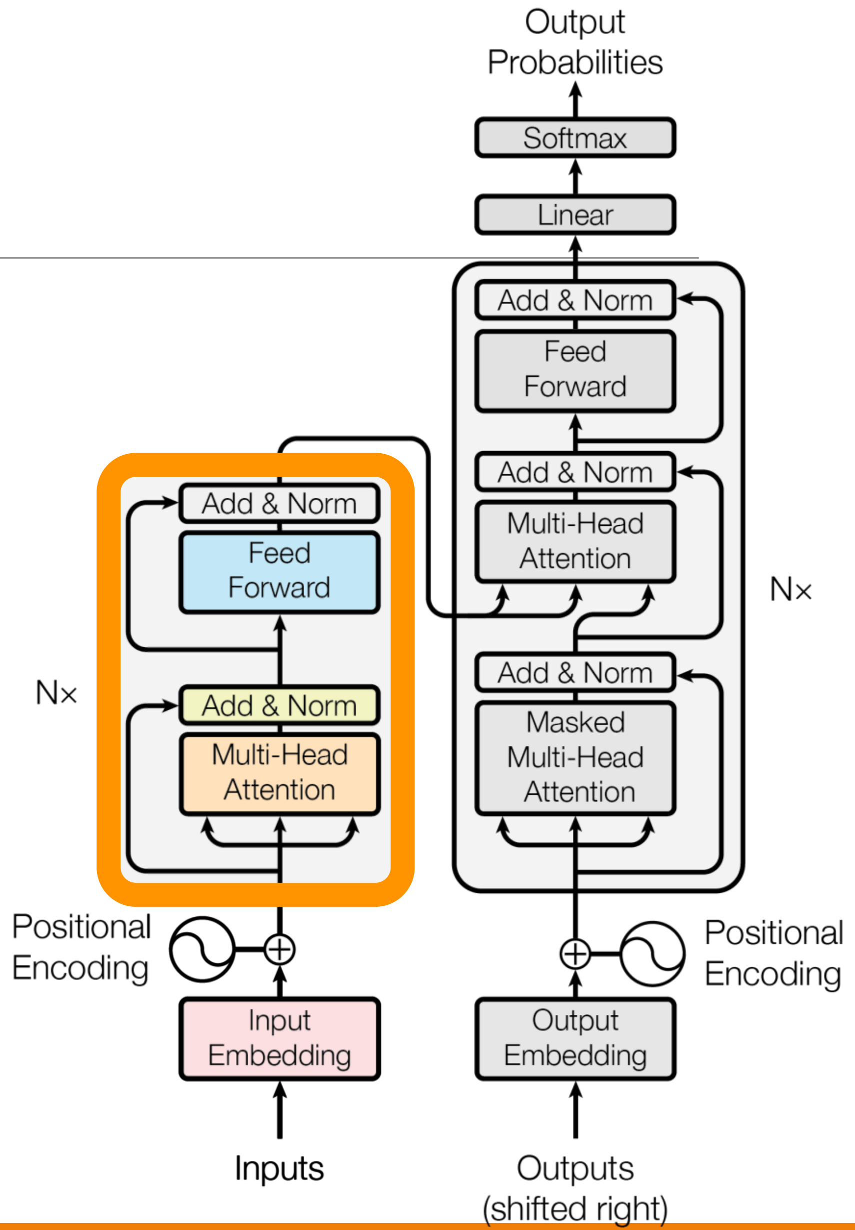
The Encoder

$\boxed{\text{Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$

$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{enc})$

$\boxed{\text{Feed Forward}} = max(0, \boxed{\text{Add \& Norm}}\mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$





The Encoder

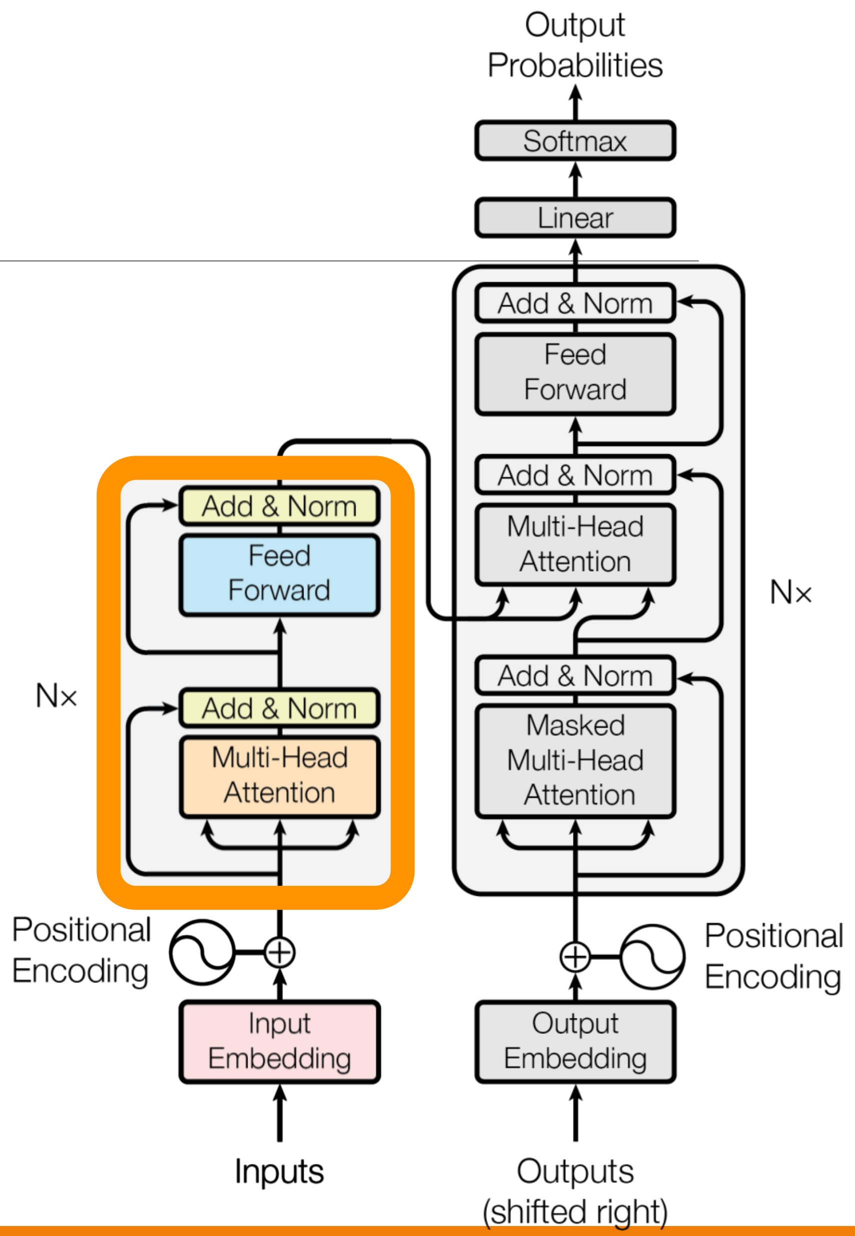
$$\boxed{\text{Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$$

$$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{enc})$$

$$\boxed{\text{Feed Forward}} = max(0, \boxed{\text{Add \& Norm}}\,\mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$$

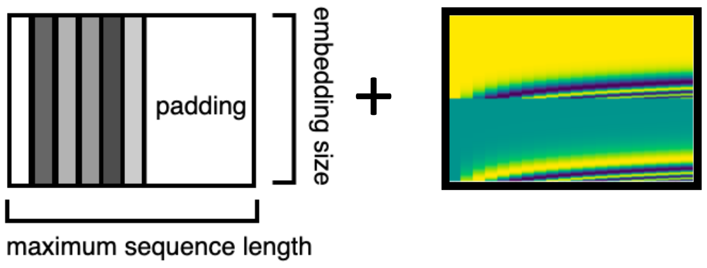
$$\boxed{\text{Add \& Norm (2)}} = \text{LayerNorm}(\boxed{\text{Feed Forward}} + \mathbf{H}_i^{enc})$$

$$\mathbf{H}_{i+1}^{enc} = \boxed{\text{Add \& Norm (2)}}$$

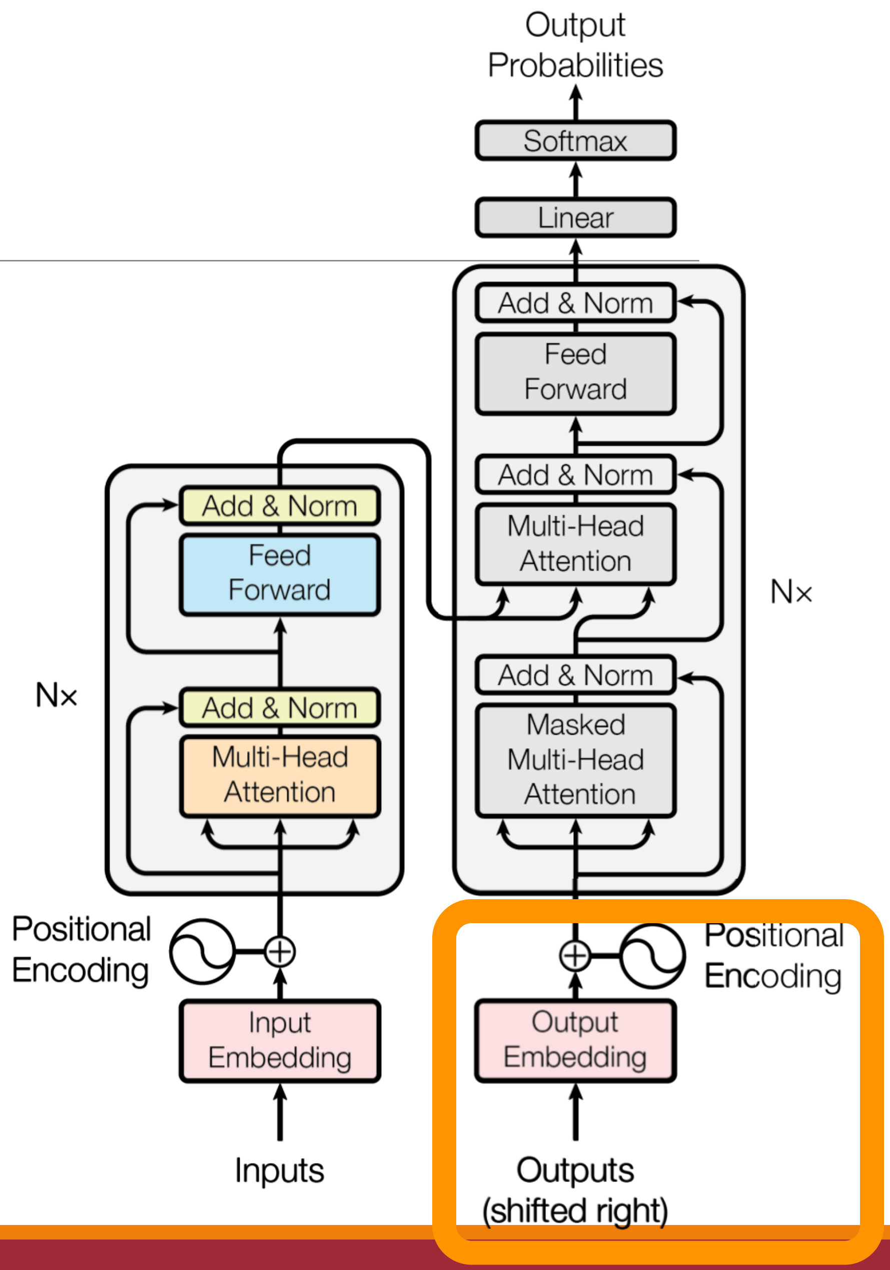


The Decoder

$\mathbf{H}_0^{\text{dec}} =$

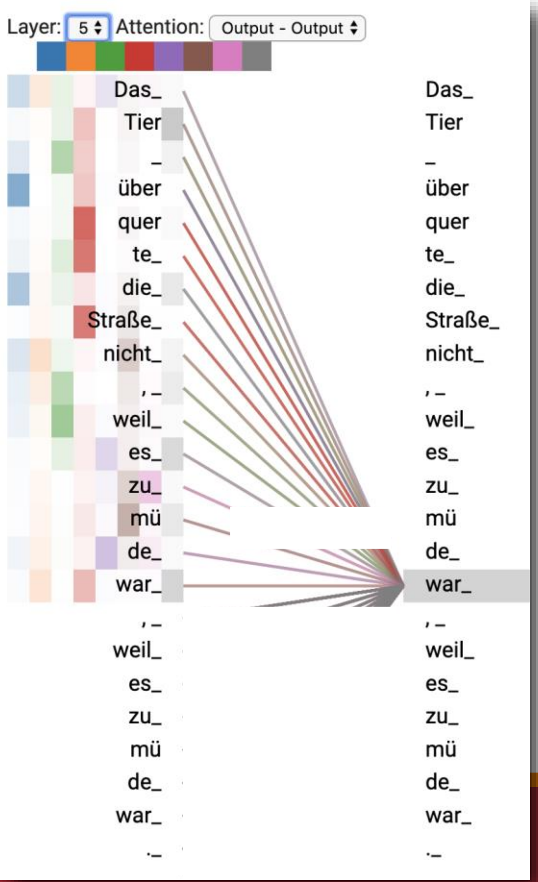


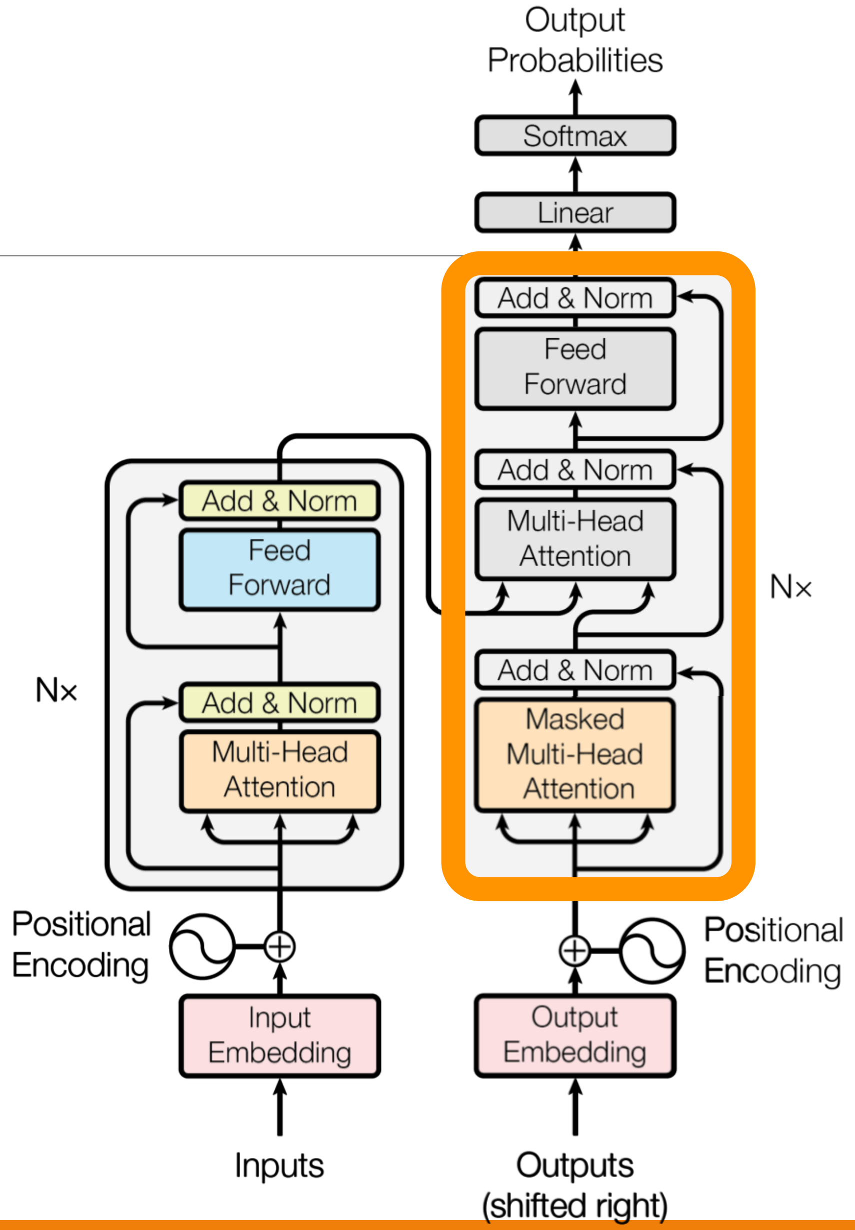
= token embeddings + position embeddings



The Decoder

Masked Multi-Head Attention $= \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$

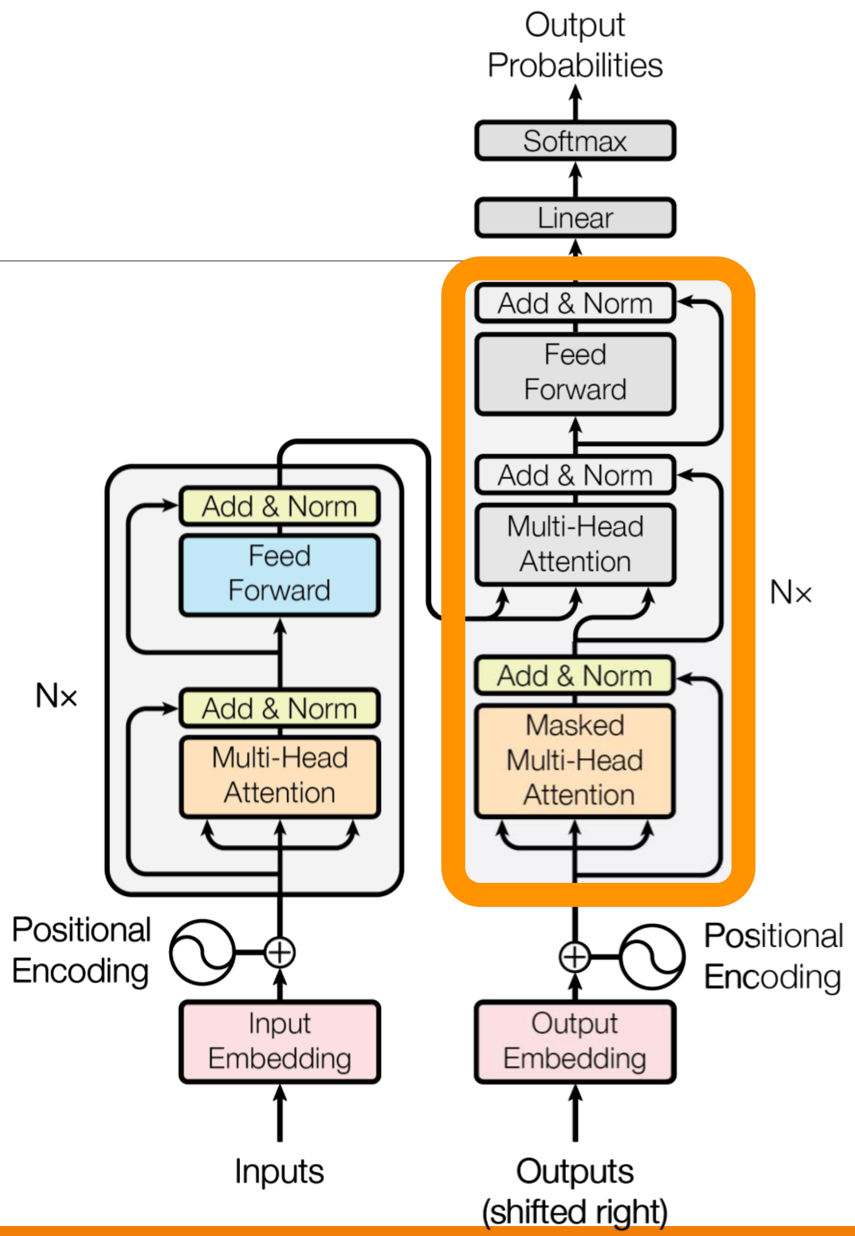




The Decoder

$\boxed{\text{Masked Multi-Head Attention}} = \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$

$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{dec})$

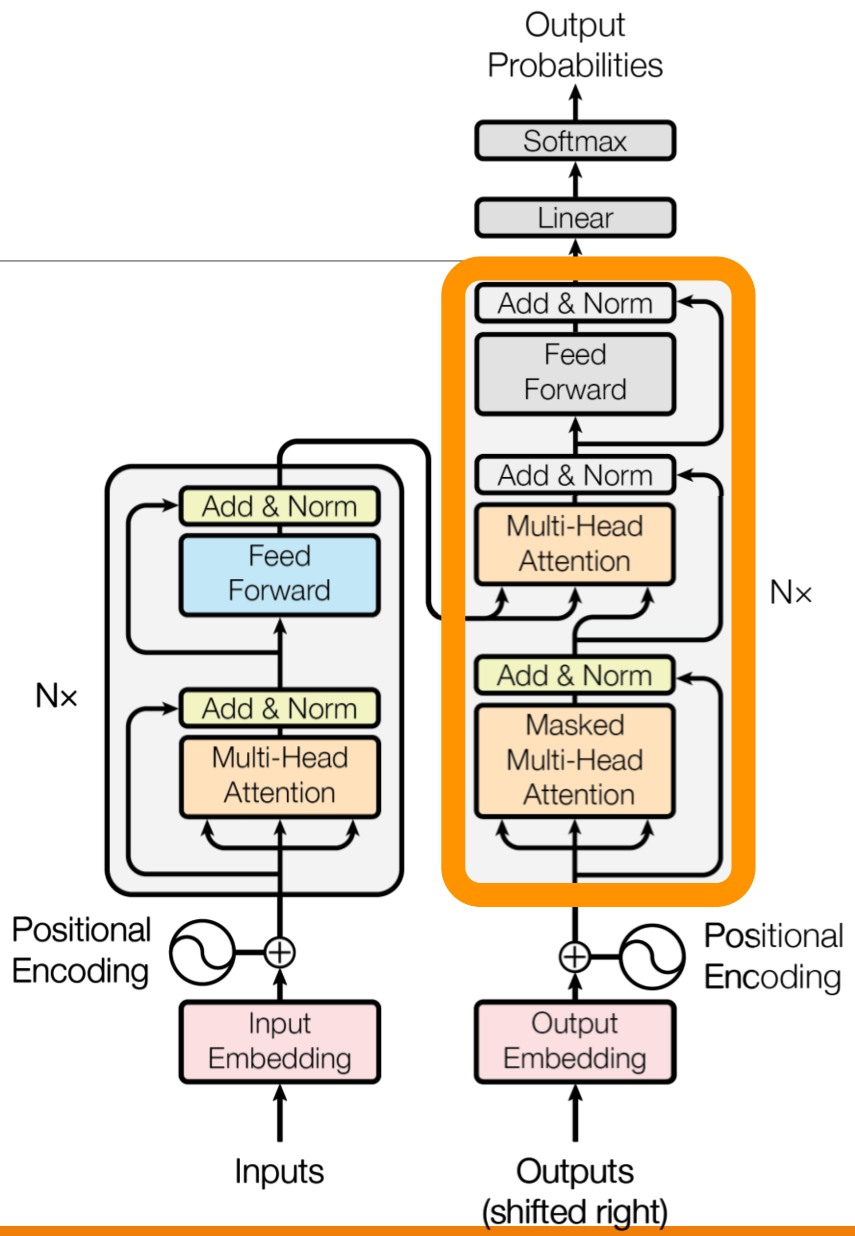


The Decoder

Masked Multi-Head Attention $= \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$

Add & Norm $= \text{LayerNorm}($ Multi-Head Attention $+ \mathbf{H}_i^{dec})$

Enc-Dec Multi-Head Attention $= \text{MultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$



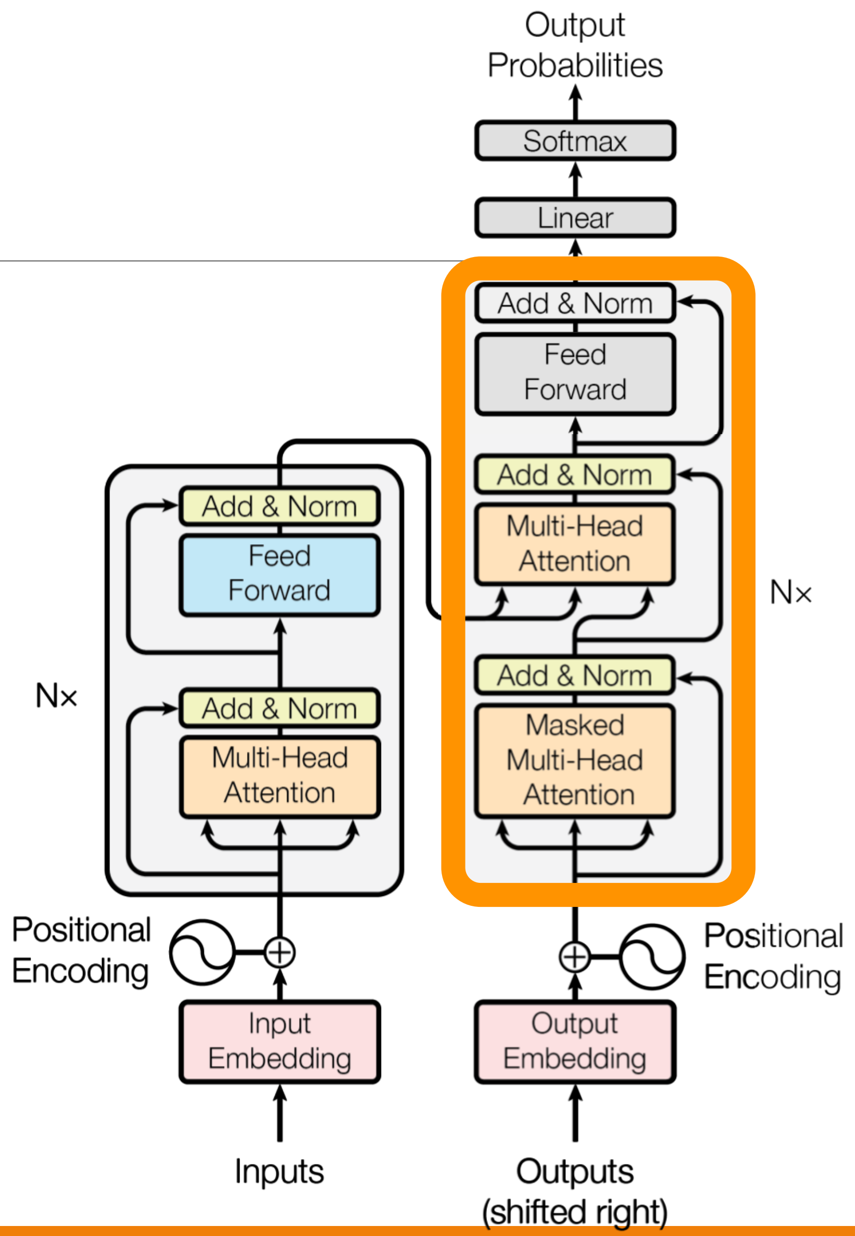
The Decoder

$$\boxed{\text{Masked Multi-Head Attention}} = \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$$

$$\boxed{\text{Add \& Norm}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \mathbf{H}_i^{dec})$$

$$\boxed{\text{Enc-Dec Multi-Head Attention}} = \text{MultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc})$$

$$\boxed{\text{Add \& Norm (2)}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \boxed{\text{Add \& Norm}})$$



The Decoder

$\boxed{\text{Masked Multi-Head Attention}} = \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$

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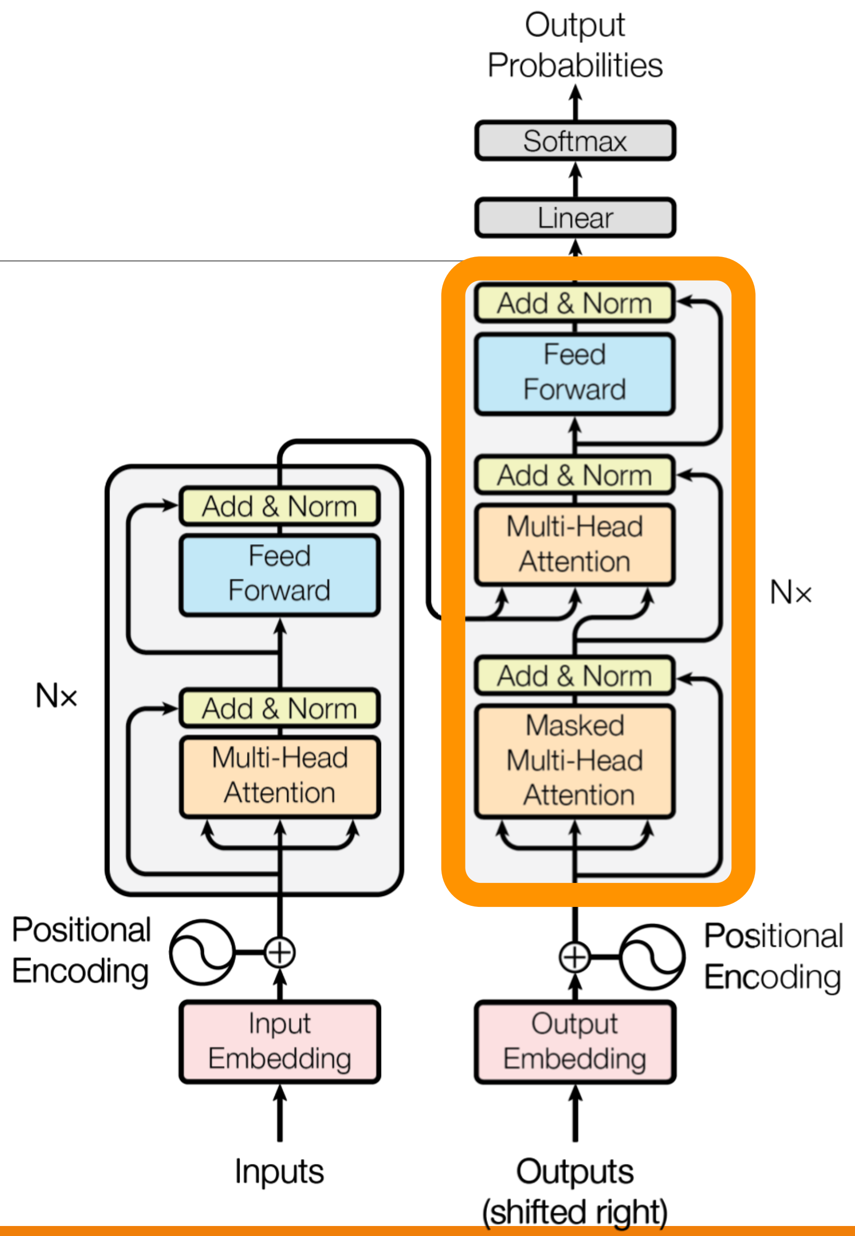
$\boxed{\text{Add \& Norm (2)}} = \text{LayerNorm}(\boxed{\text{Multi-Head Attention}} + \boxed{\text{Add \& Norm}})$

$\boxed{\text{Feed Forward}} = max(0, \boxed{\text{Add \& Norm (2)}}\ \mathbf{W}_1 + b_1)\mathbf{W}_2 + b_2$

$\boxed{\text{Add \& Norm (3)}} = \text{LayerNorm}(\boxed{\text{Feed Forward}} + \boxed{\text{Add \& Norm (2)}})$

$\mathbf{H}_{i+1}^{dec} = \boxed{\text{Add \& Norm (3)}}$



Strengths of the Transformer Architecture

Training is easily parallelizable

- Larger models can be trained efficiently.

Does not “forget” information from earlier in the sequence.

- Any position can attend to any position.

What are some of its weaknesses?

Neural Language Model Timeline

+attention
-recurrence

data++
parameters++

data++
parameters++

+RL

+???

Seq2Seq RNN (2014)

Transformers (2017)

GPT-2 (2019)

GPT-3 (2020)

ChatGPT (InstructGPT) (2022)

GPT-4 (2023)

Sequence to Sequence Learning with Neural Networks
Ilya Sutskever, Oriol Vinyals, & Quoc V. Le

Attention Is All You Need
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, & Illia Polosukhin

Language Models are Unsupervised Multitask Learners
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