

Transformers

Lara J. Martin (she/they)

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

Slides modified from Dr. Daphne Ippolito

Learning Objectives

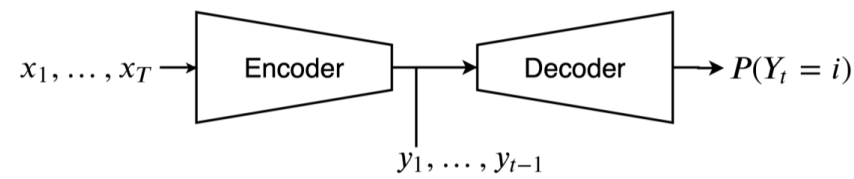
Intuit what query, key, and value components are in the transformer algorithm

Distinguish encoder-decoder attention from self-attention

Investigate what information self-attention might capture

Compare sequence-to-sequence RNNs to transformers

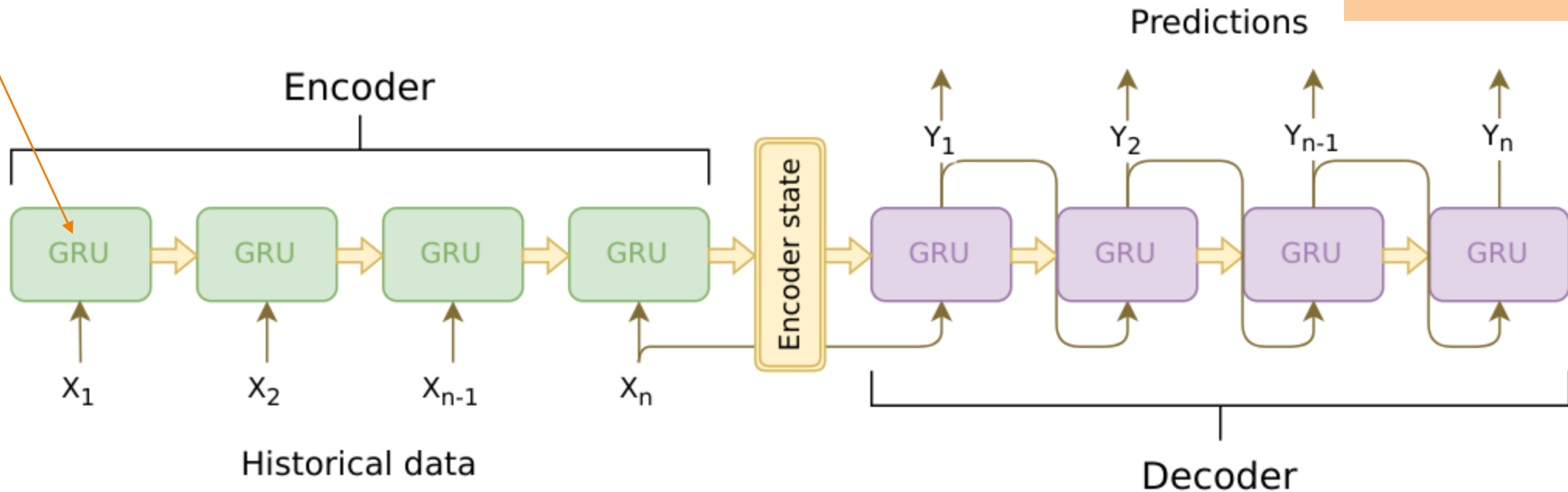
What is a language model?



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/

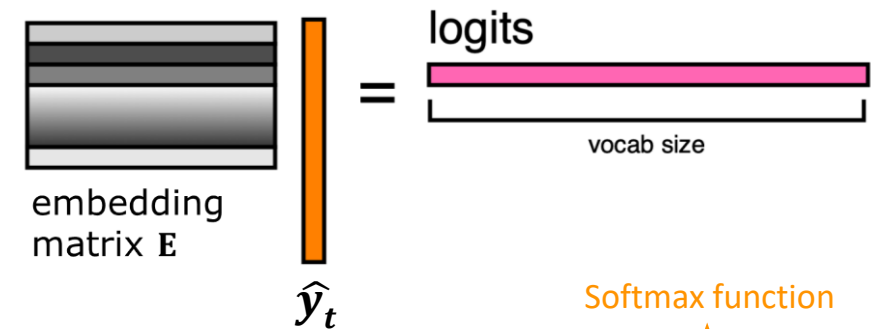
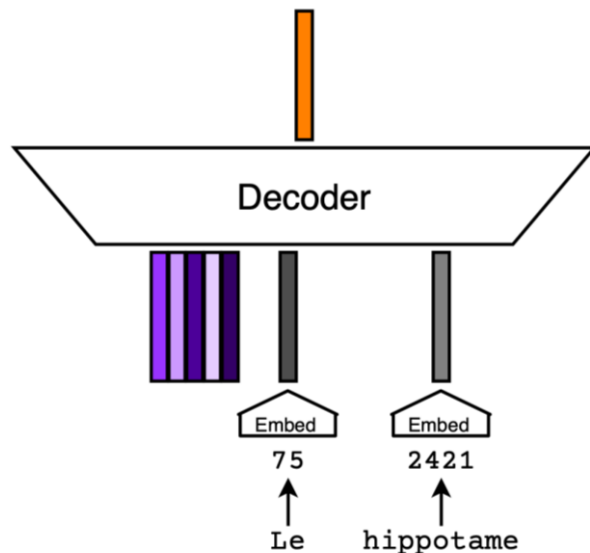
I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to Sequence Learning with Neural Networks," in *Conference on Advances in Neural Information Processing Systems (NeurIPS)*, Montréal, Canada, 2014, pp. 3104–3112. https://proceedings.neurips.cc/paper_files/paper/2014/hash/a14ac55a4f27472c5d894ec1c3c743d2-Abstract.html

Review:

Turning $\hat{\mathbf{y}}_t$ into a Probability Distribution

We can multiply the predicted embedding $\hat{\mathbf{y}}_t$ by our vocabulary embedding matrix 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.

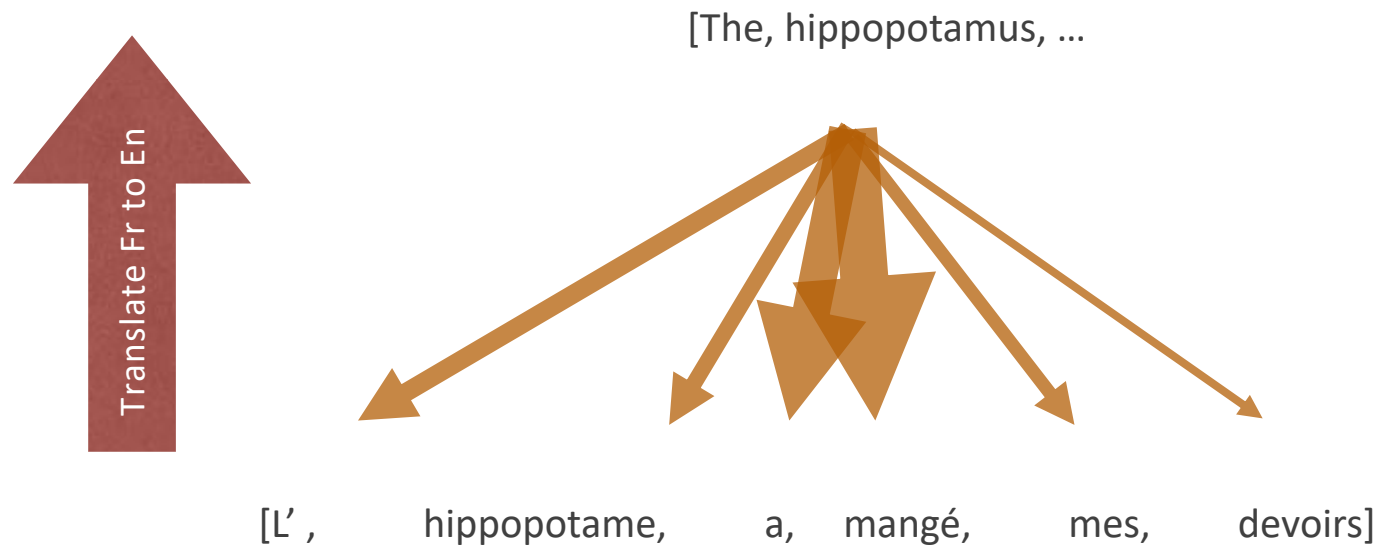


Softmax function

$$P(Y_t = i | \mathbf{x}_{1:T}, \mathbf{y}_{1:t-1}) = \frac{\exp(\mathbf{E}\hat{\mathbf{y}}_{t[i]})}{\sum_j \exp(\mathbf{E}\hat{\mathbf{y}}_{t[i]})}$$

Review: Attention

Better approach: an attention mechanism



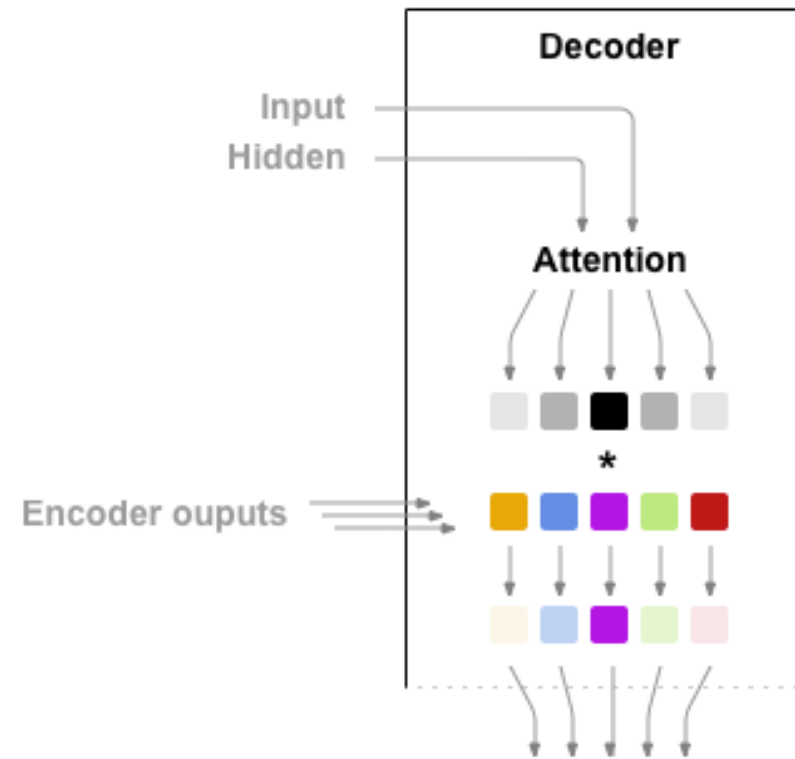
Compute a linear combination of the encoder hidden states.

$$\mathbf{c}_t = \alpha_1 \mathbf{h}_1 + \alpha_2 \mathbf{h}_2 + \alpha_3 \mathbf{h}_3 + \dots + \alpha_T \mathbf{h}_T$$

Decoder's prediction at position t is based on both the context vector and the hidden state outputted by the RNN at that position.

$$\hat{\mathbf{e}}_t = f_{\theta}(\mathbf{h}_t^{\text{dec}} \parallel \mathbf{c}_t)$$

Review: Attention Decoder



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

Review: 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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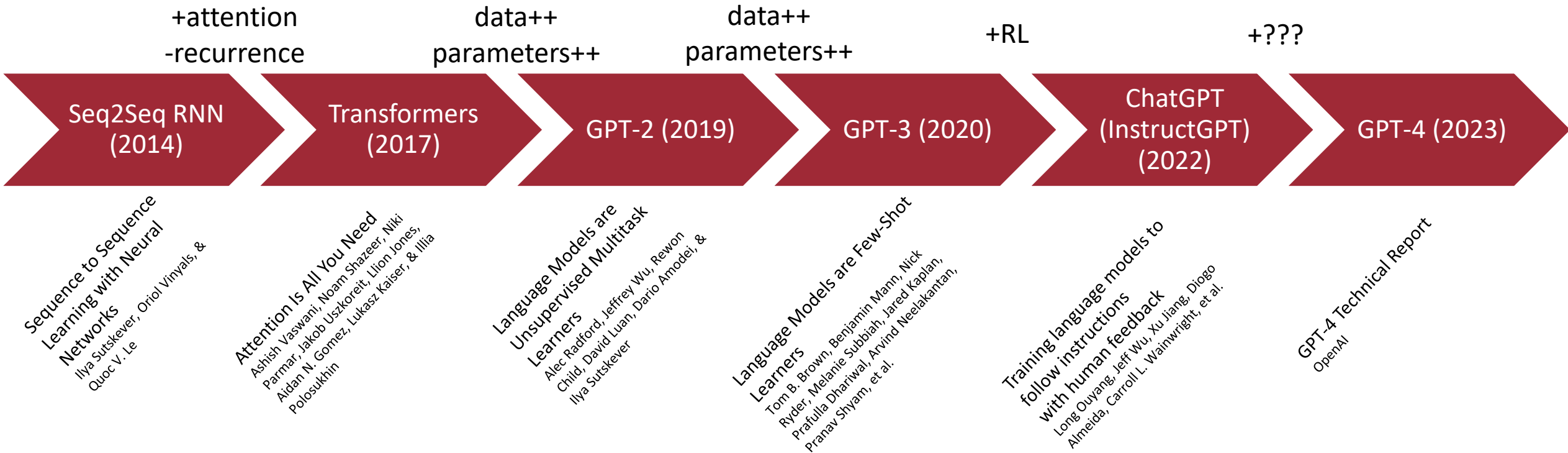
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Abstract

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

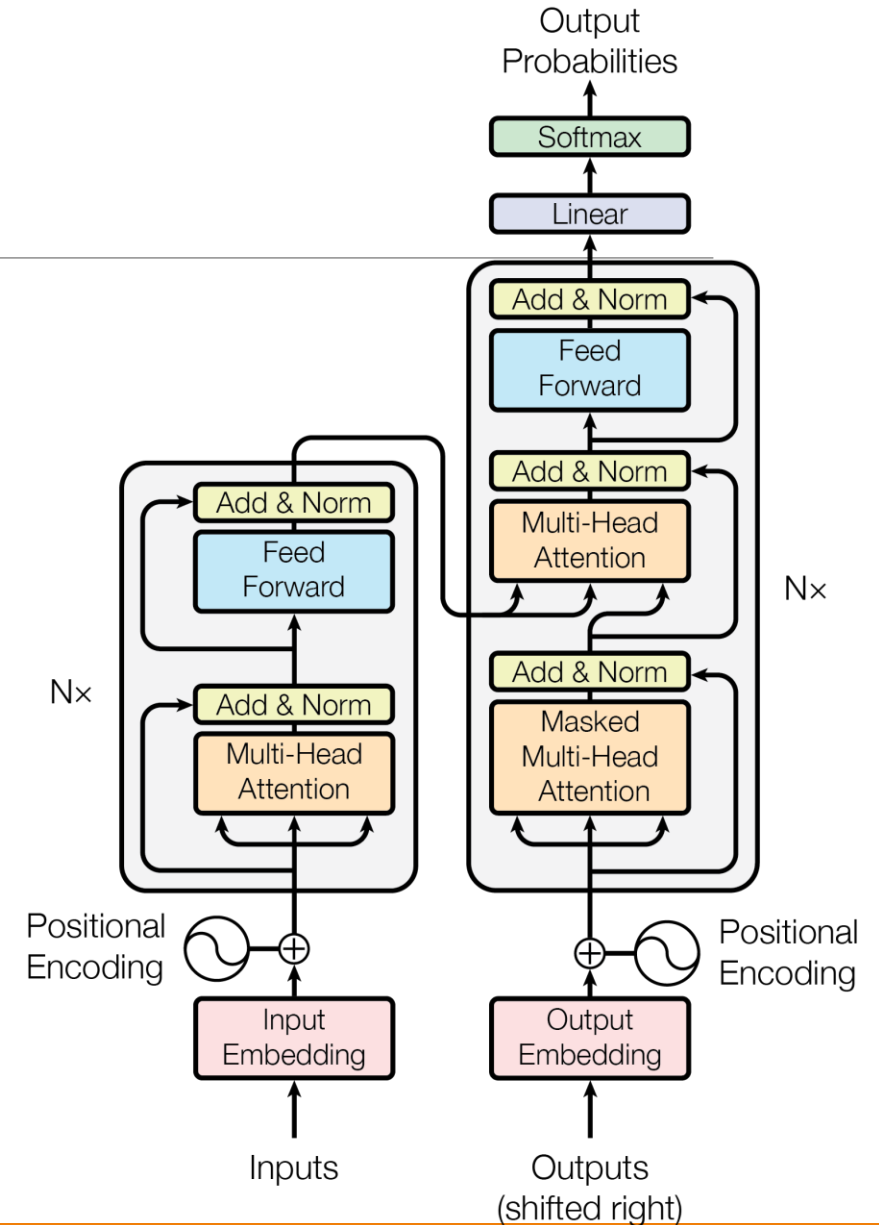
Neural Language Model Timeline



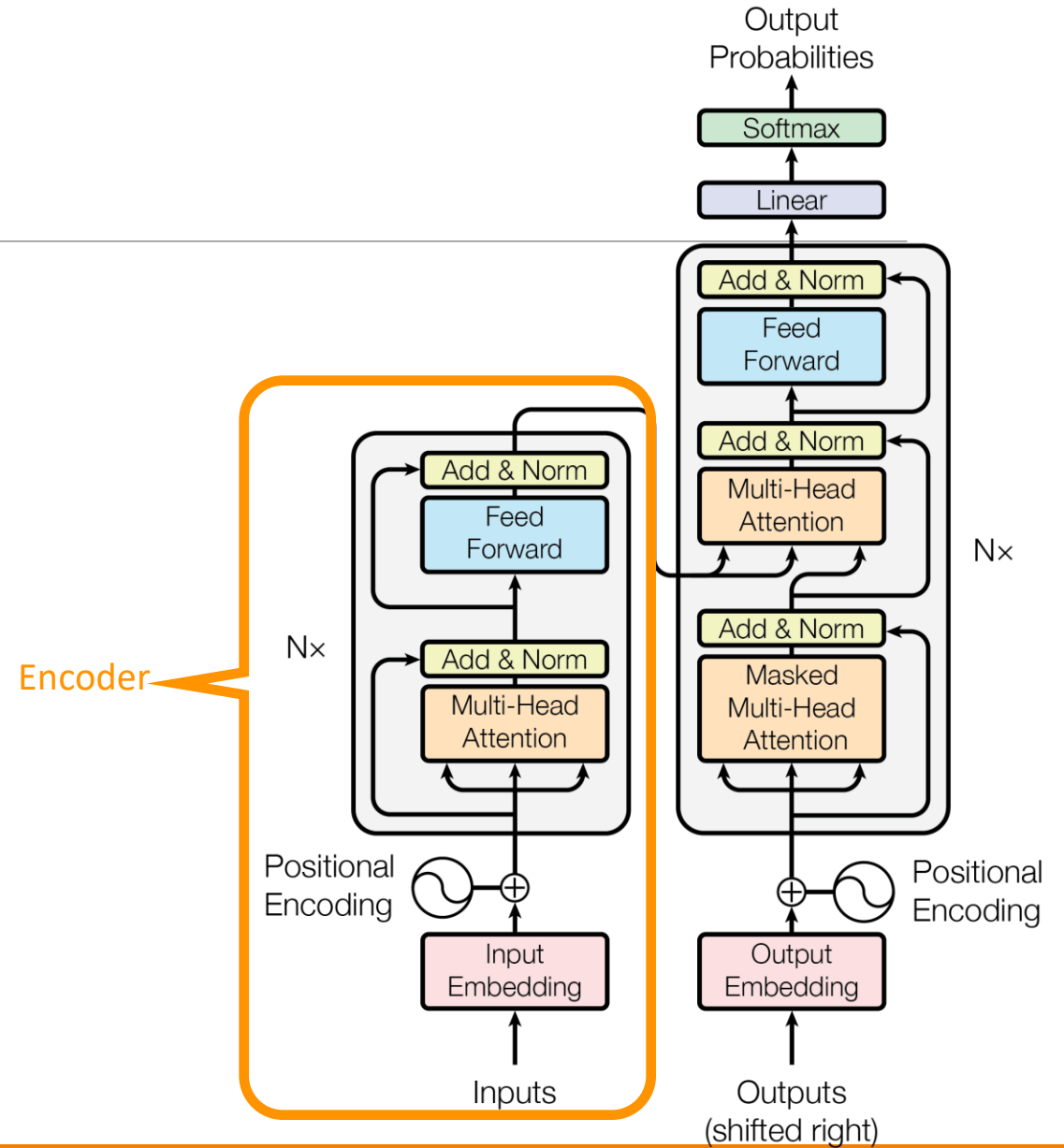
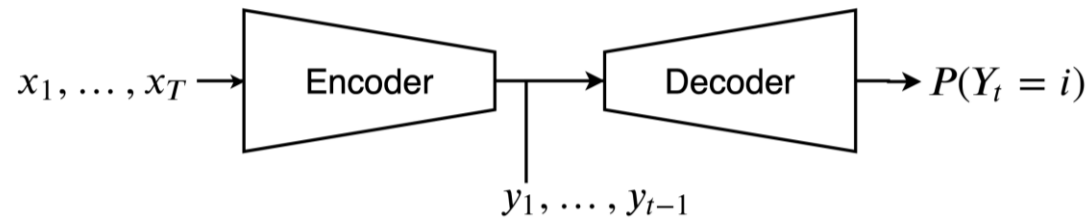
Transformers

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

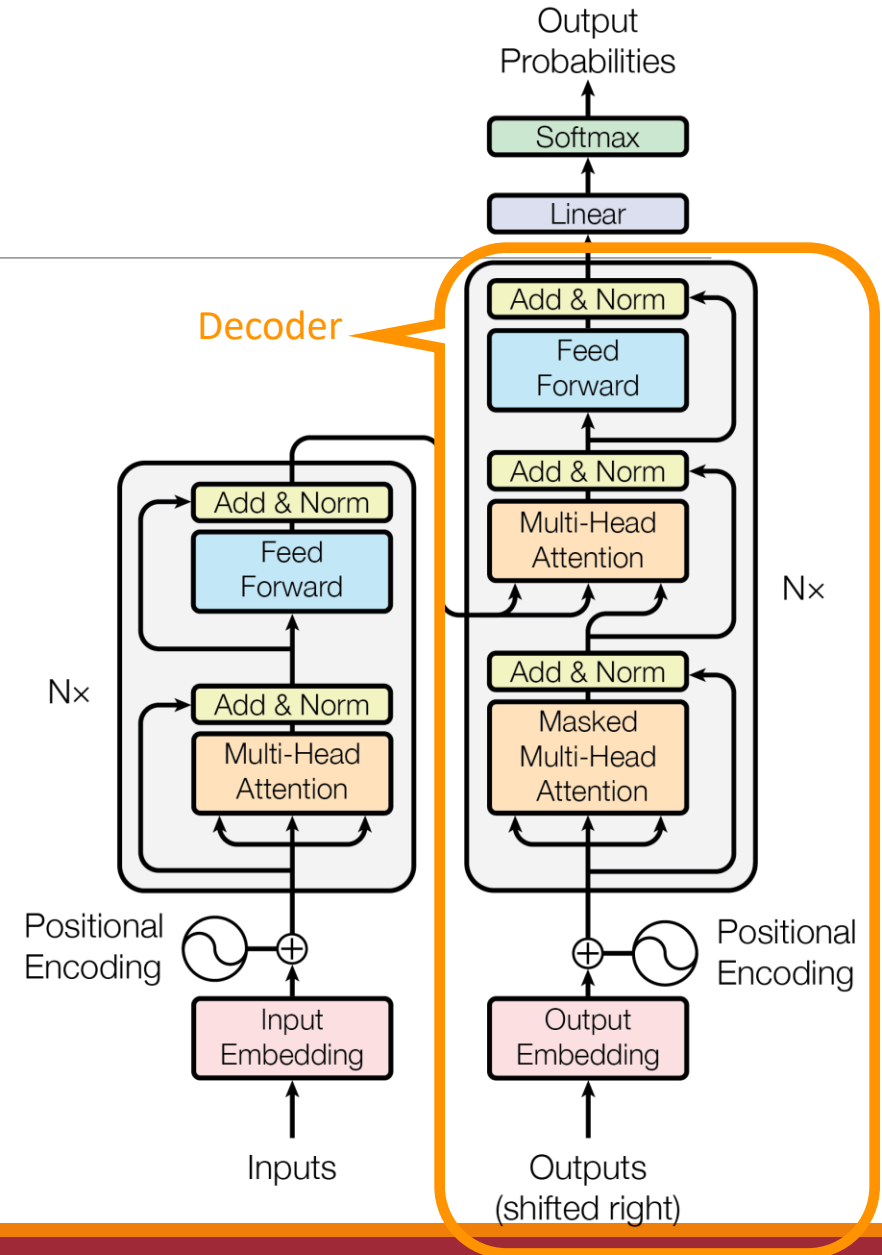
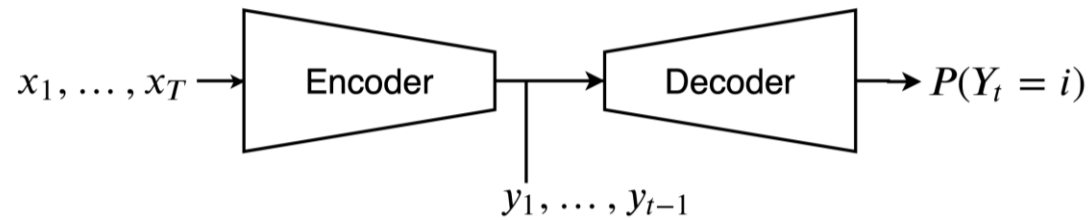
- introduces self-attention in addition to encoder-decoder attention



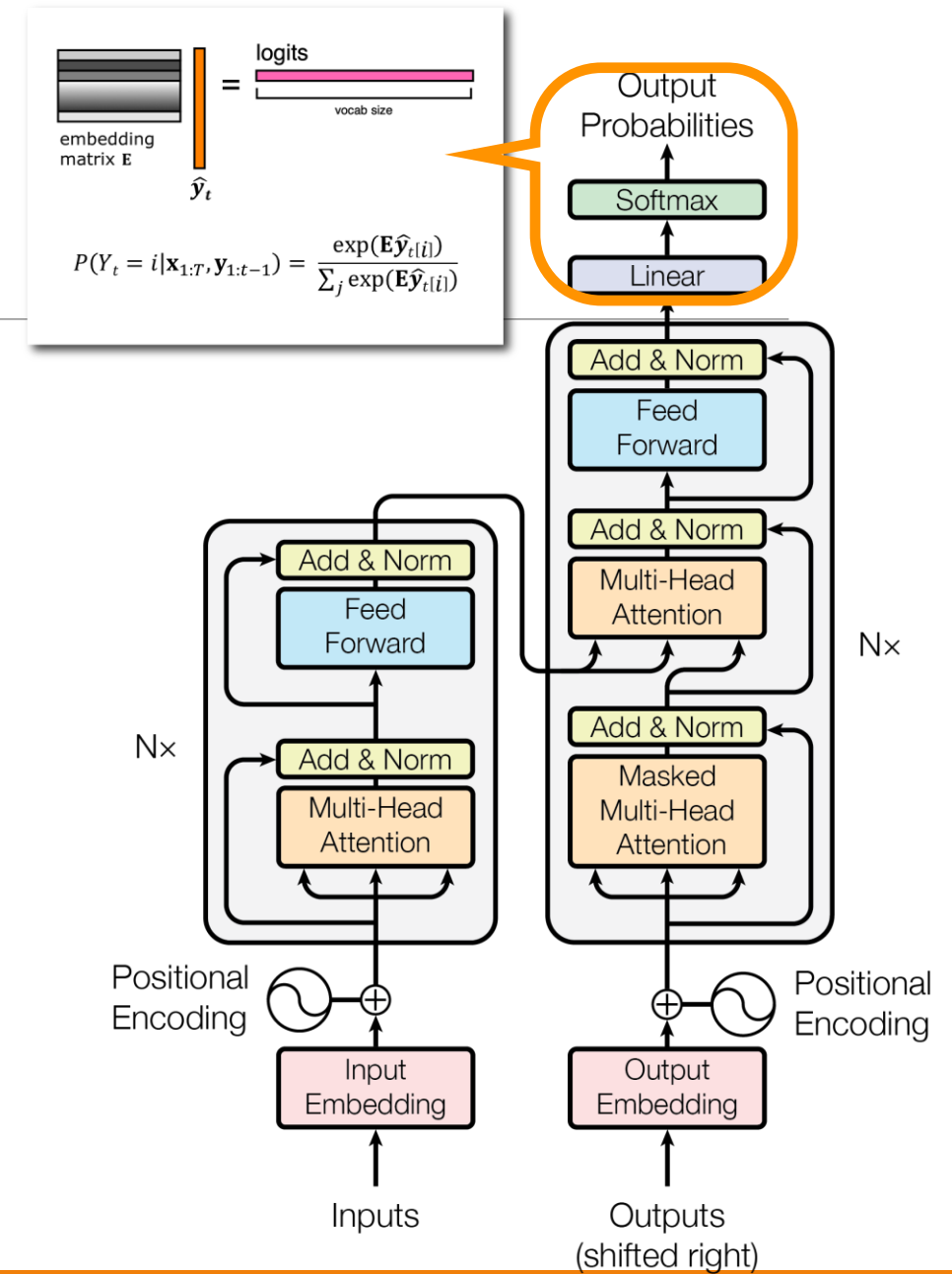
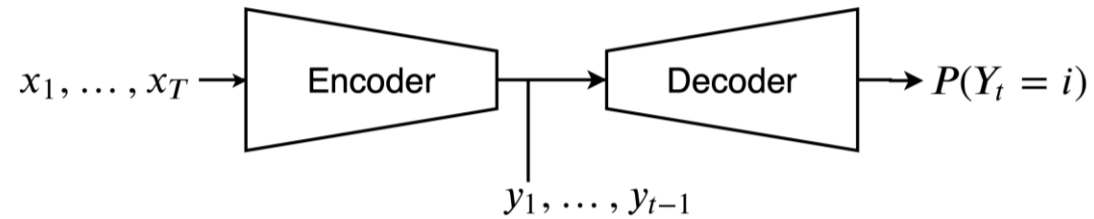
Transformers



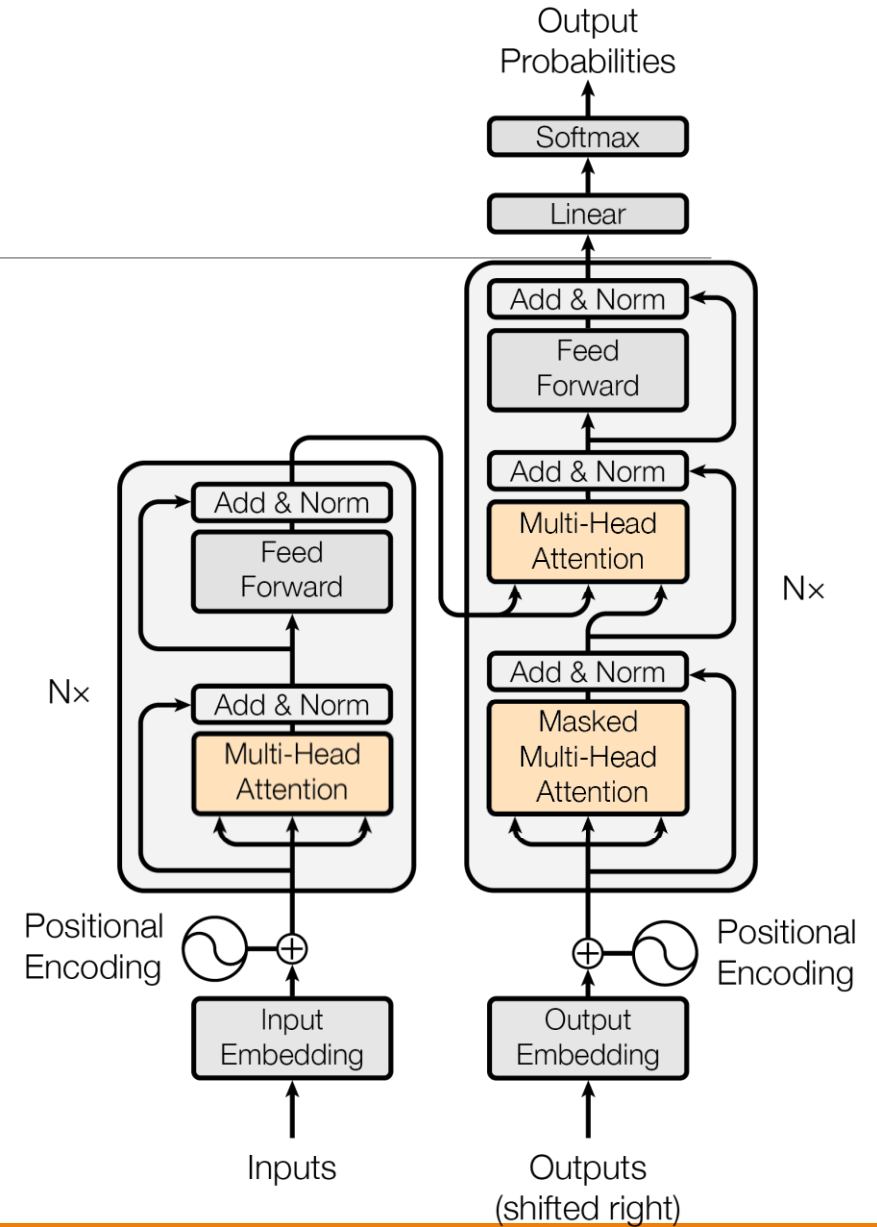
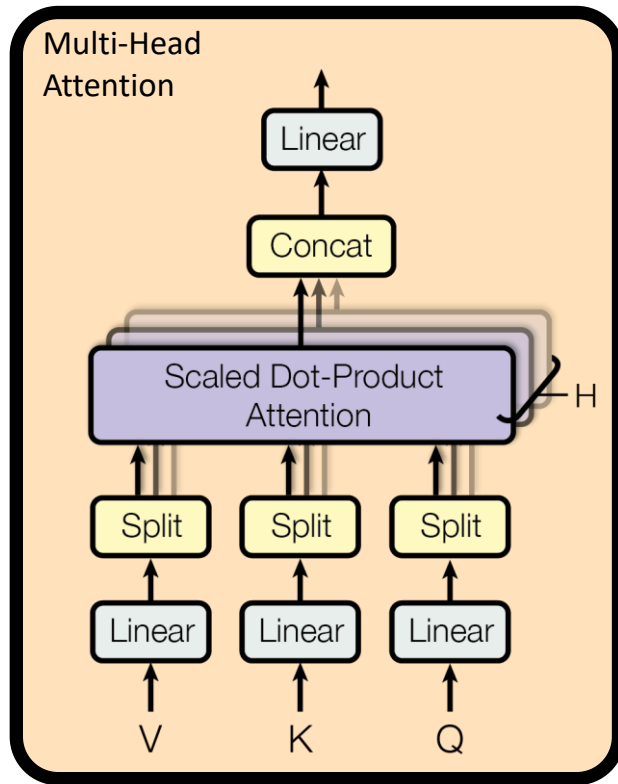
Transformers



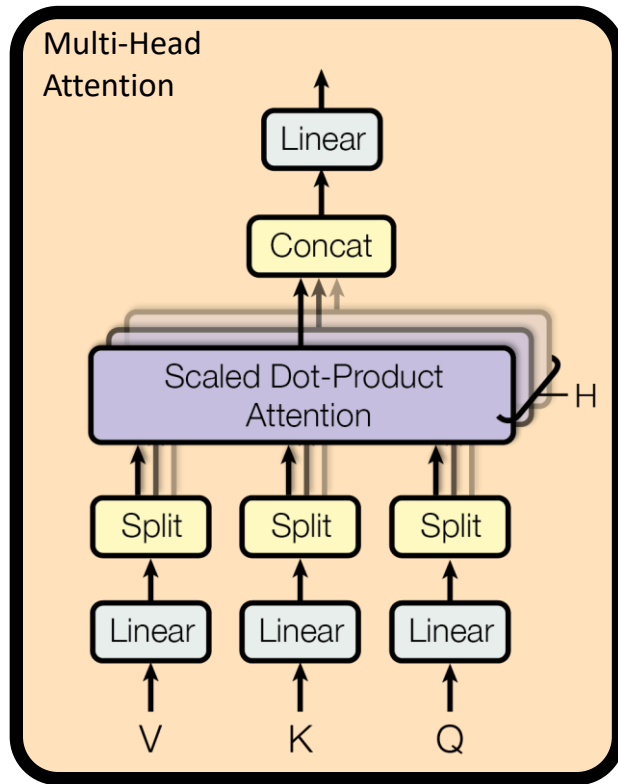
Transformers



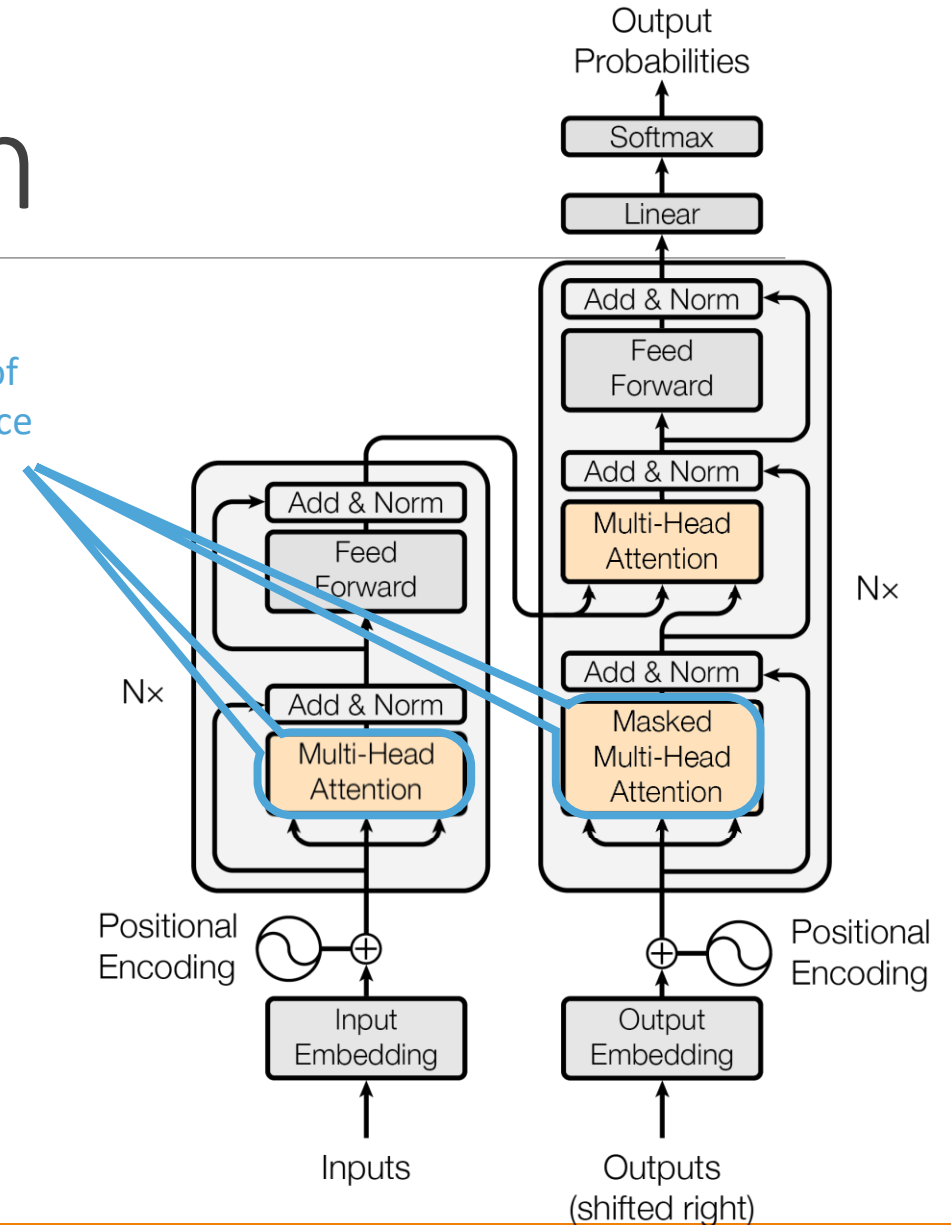
Attention Mechanism



Multi-Head Attention

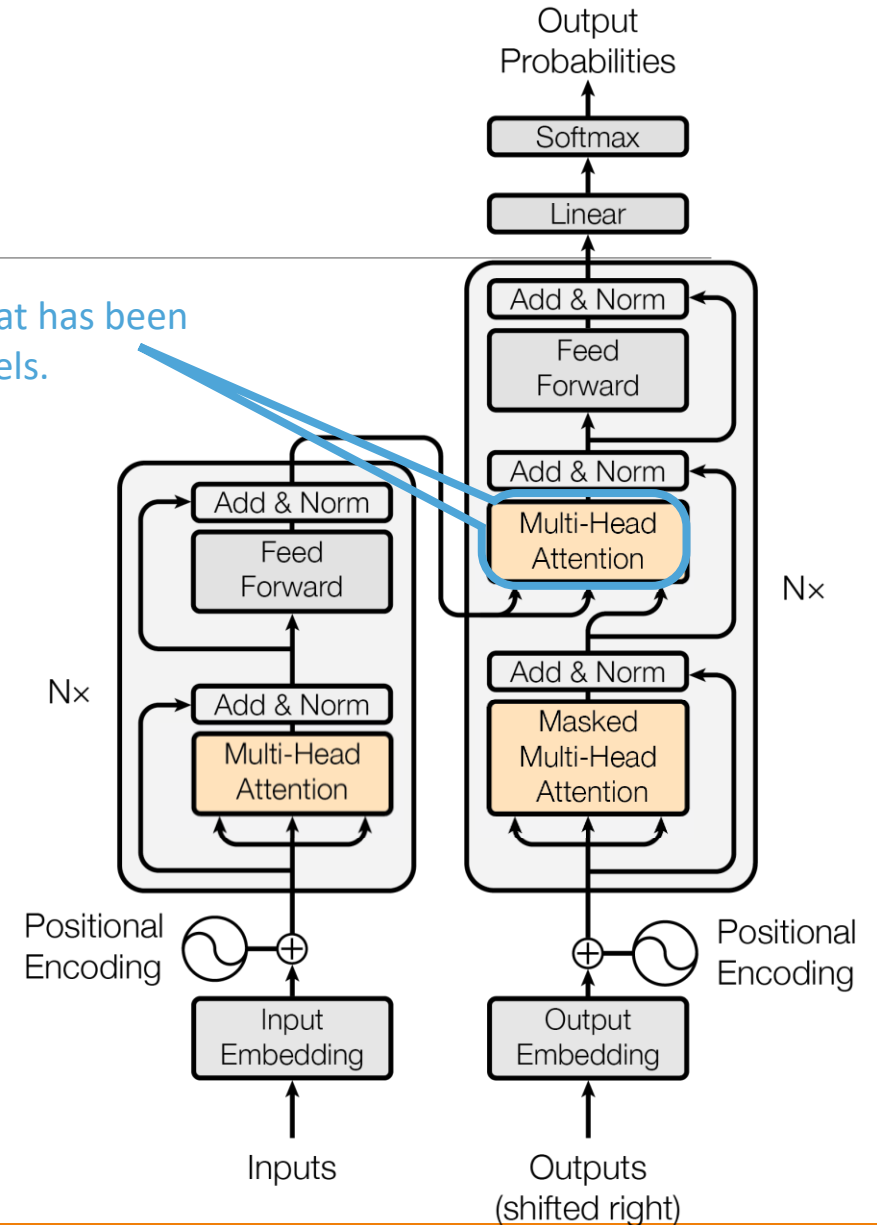
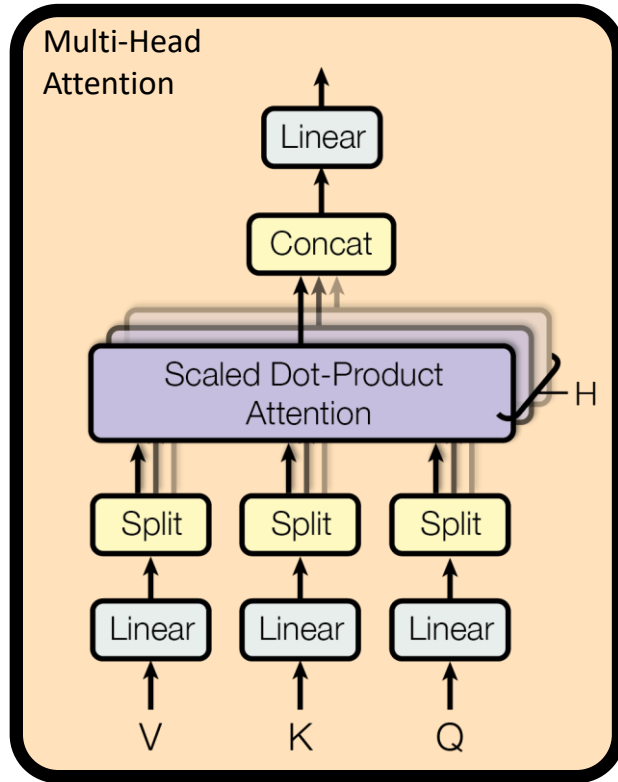


Self-attention between a sequence of hidden states and that same sequence of hidden states.

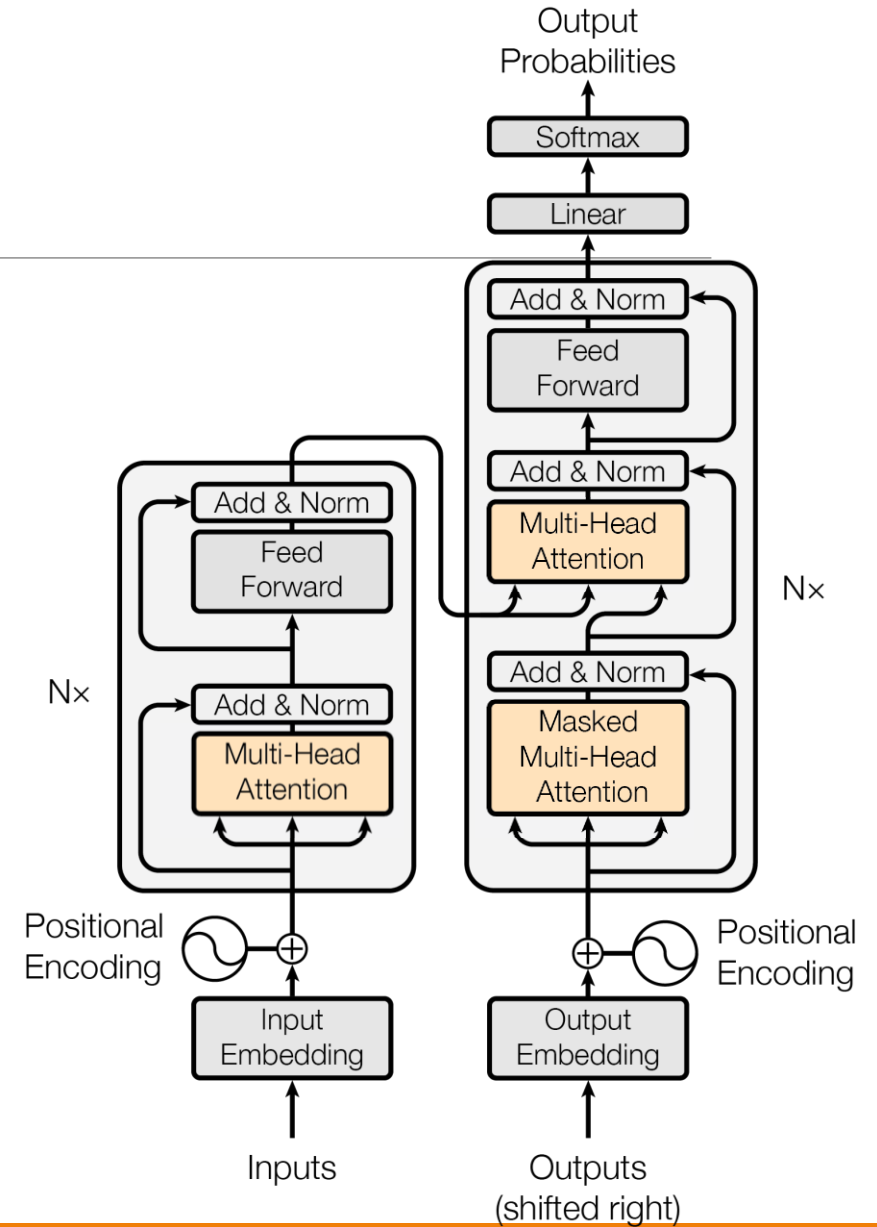
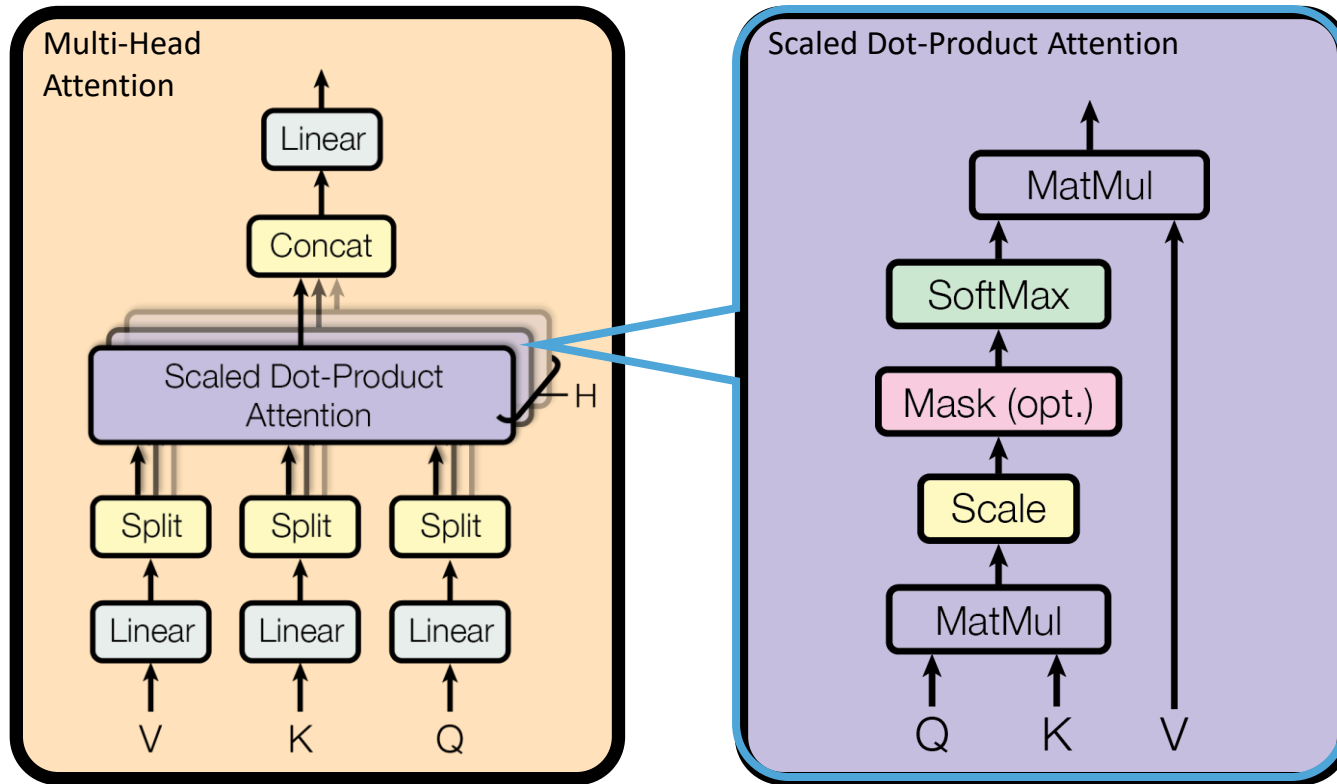


Multi-Head Attention

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

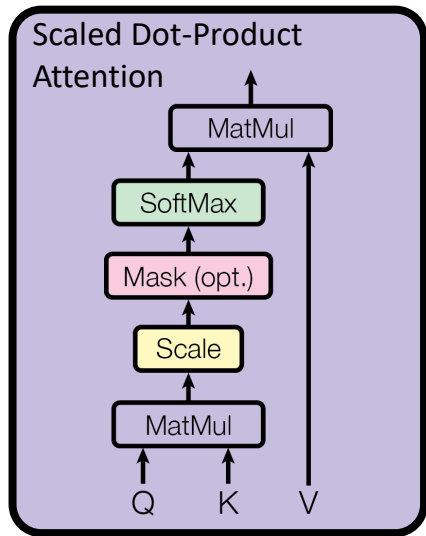


Attention Mechanism



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.

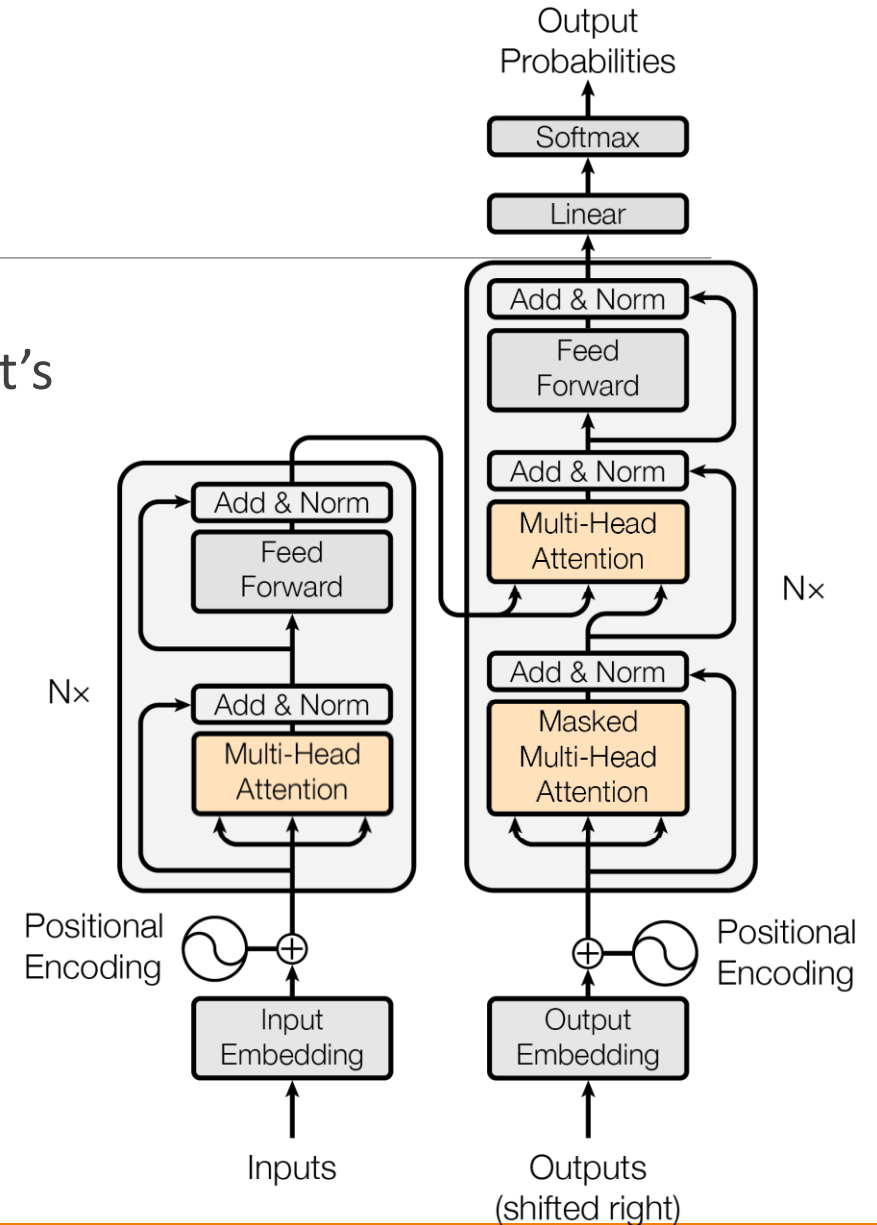


The query: $Q \in R^{T \times d_k}$

The key: $K \in R^{T' \times d_k}$

The value: $V \in R^{T \times d_k}$

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



An analogy...

Google

What is a transformer?

People also ask :

What is a transformer in simple terms?

What happens when a transformer blows?

What is the purpose of the transformer?

Is transformer in AC or DC?

Query

Value

Feedback



Wikipedia

<https://en.wikipedia.org/wiki/Transformer>

Transformer

A transformer is a passive component that transfers electrical energy from one electrical circuit to another circuit, or multiple circuits.

Transformer types

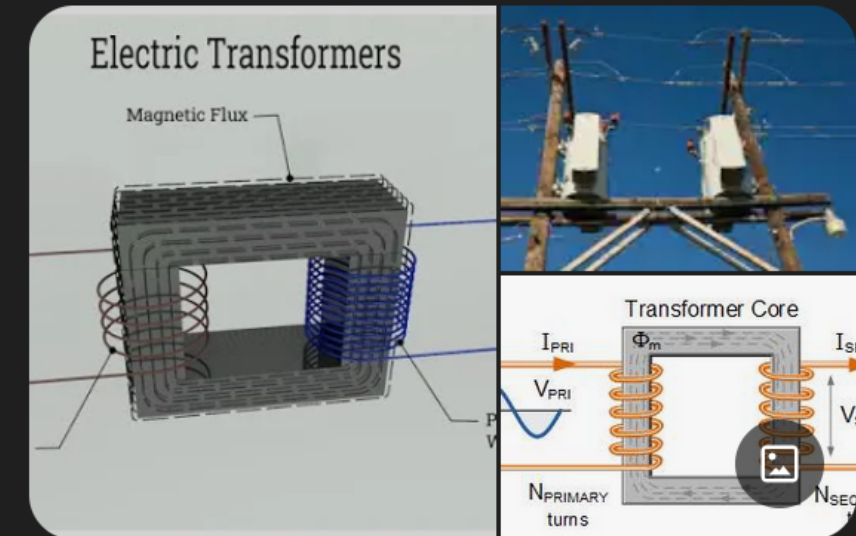
Transformer oil

Flyback transformer

Isolation transformer

Key

Transformer



In electrical engineering, a transformer is a passive component that transfers electrical energy from one electrical circuit to another circuit, or multiple circuits.

Source: [Wikipedia](#)

3Blue1Brown Explanation of Q,K,V (~6 minutes)

<https://youtu.be/eMlx5fFNoYc?si=1sXvOHytbTUPqnE8&t=366>

6:06 - 9:28 = 3:22

And then skip ahead to values

<https://youtu.be/eMlx5fFNoYc?t=790&si=uNLE2TOpFtxkdDEj>

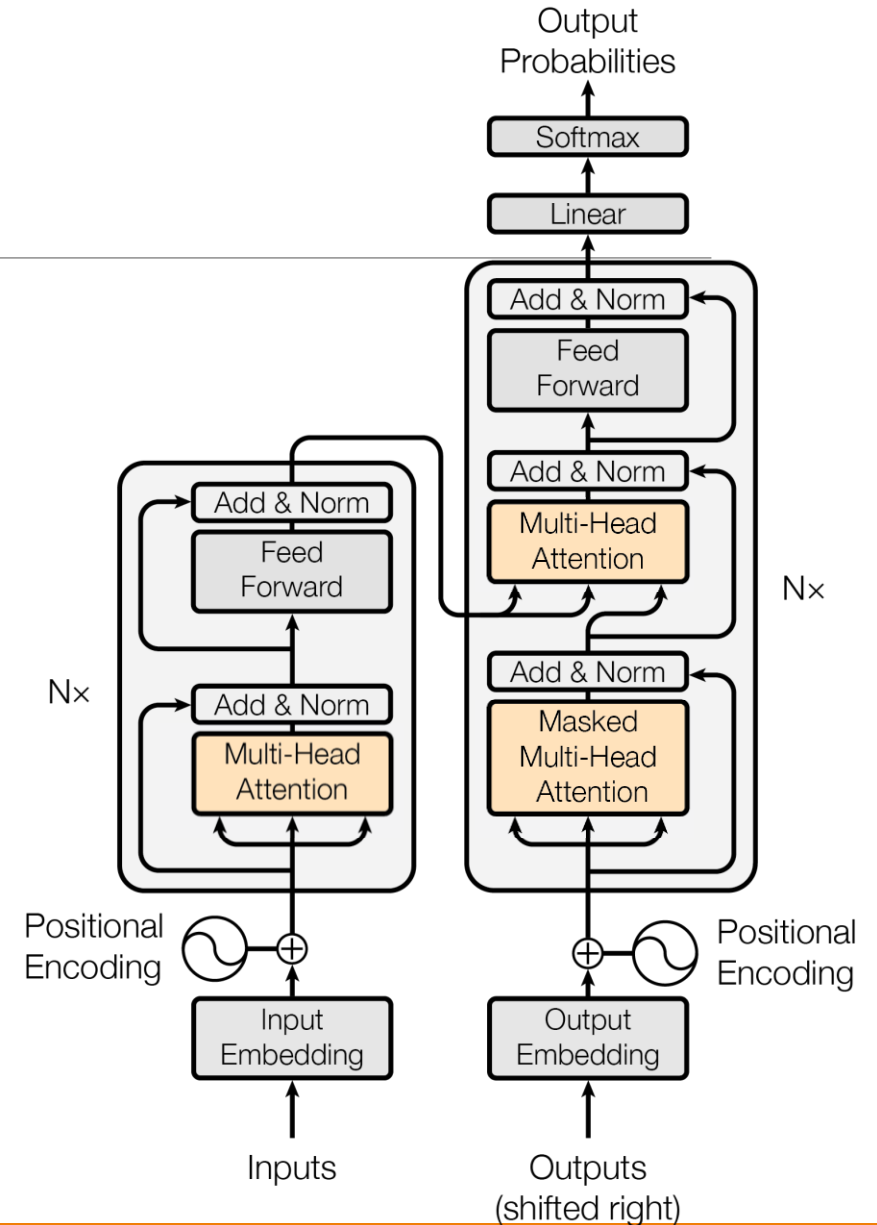
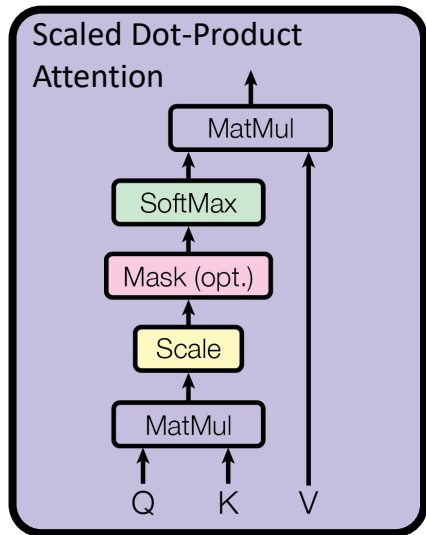
13:10 – 15:43

Scaled Dot-Product Attention

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

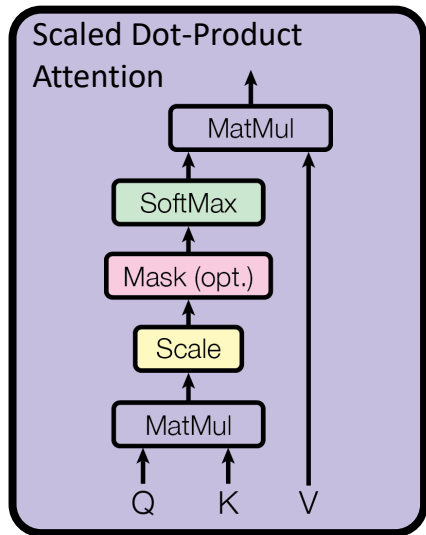
The rough algorithm:

- 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

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

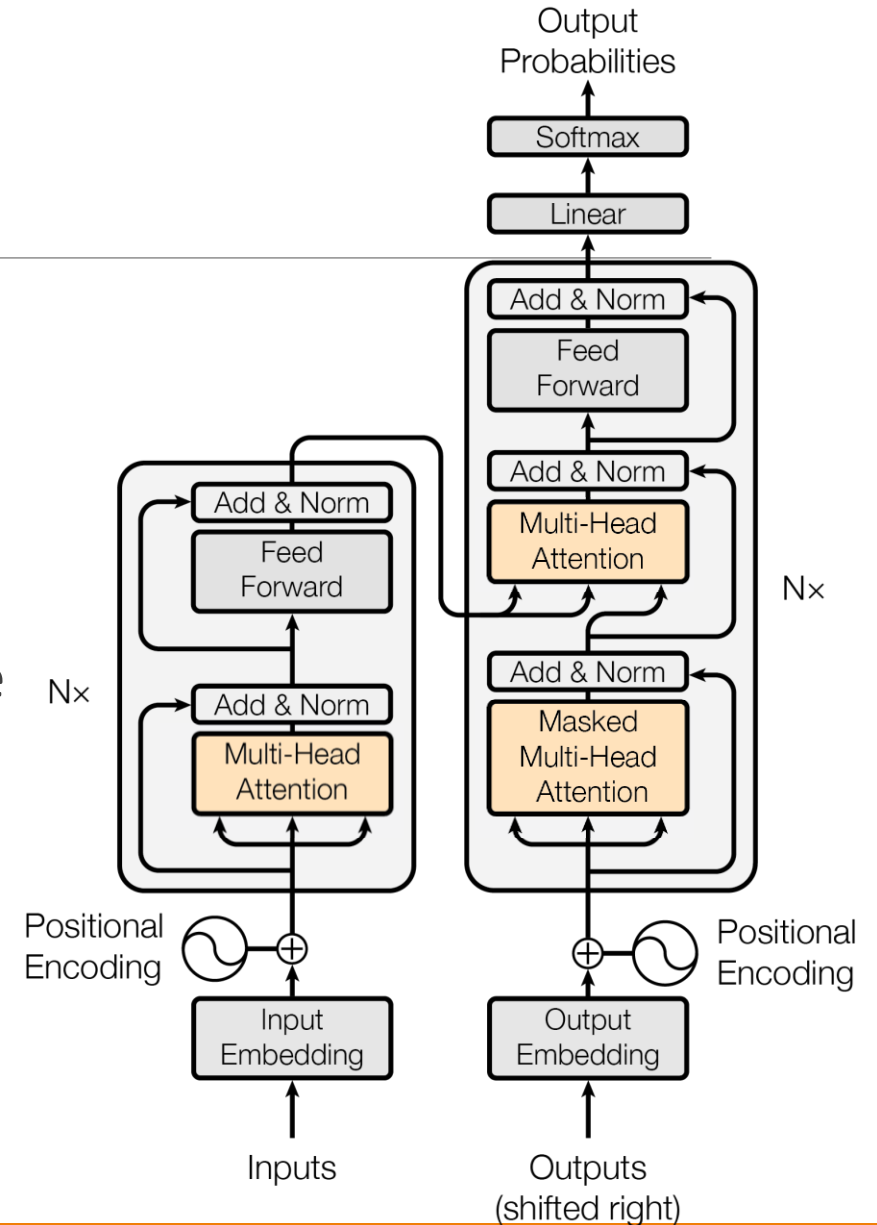


For self-attention:

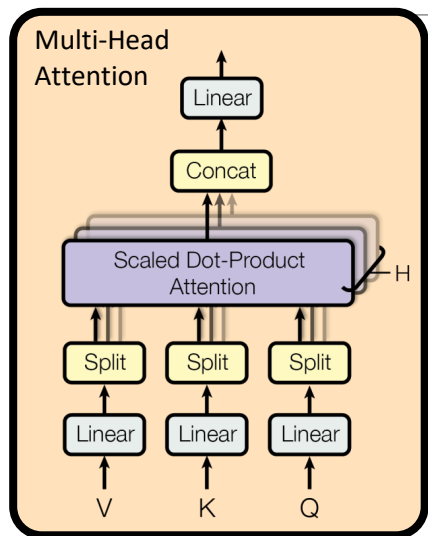
Keys, queries, and values all come from the outputs of the previous layer

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



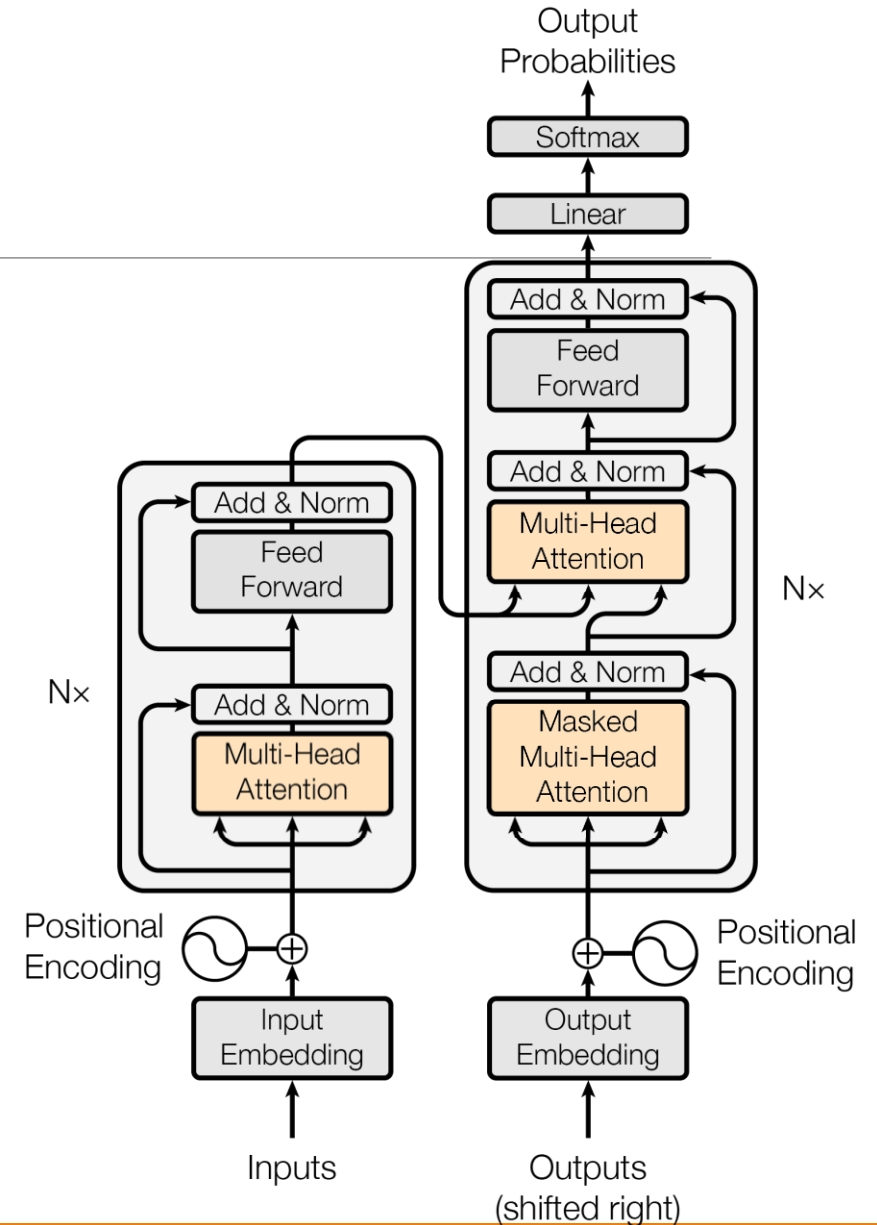
$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right) \mathbf{V}$$

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

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.



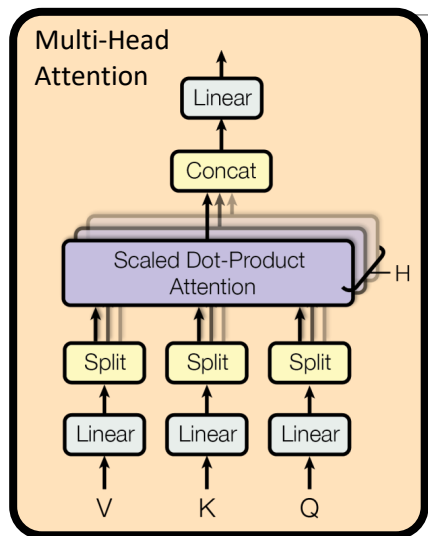
Knowledge Check

Run first three cells.

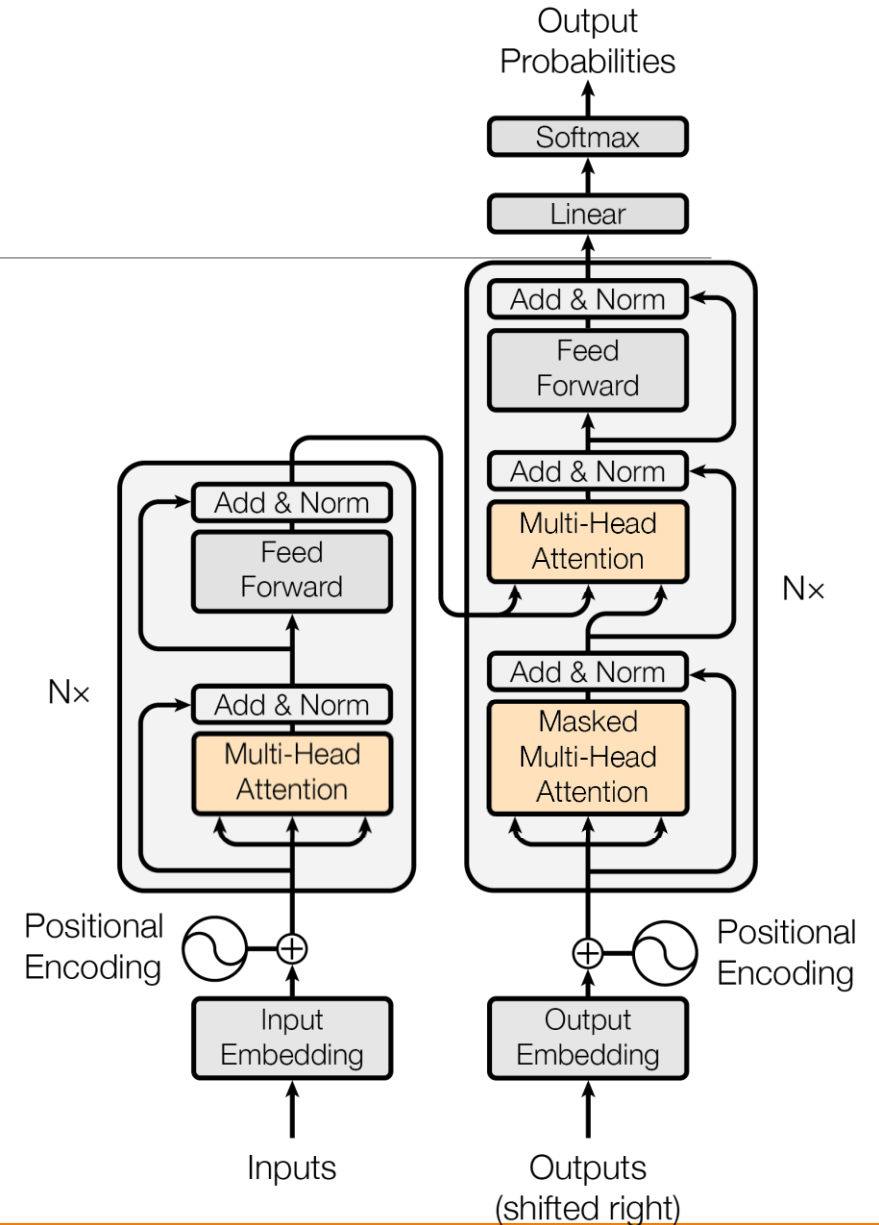
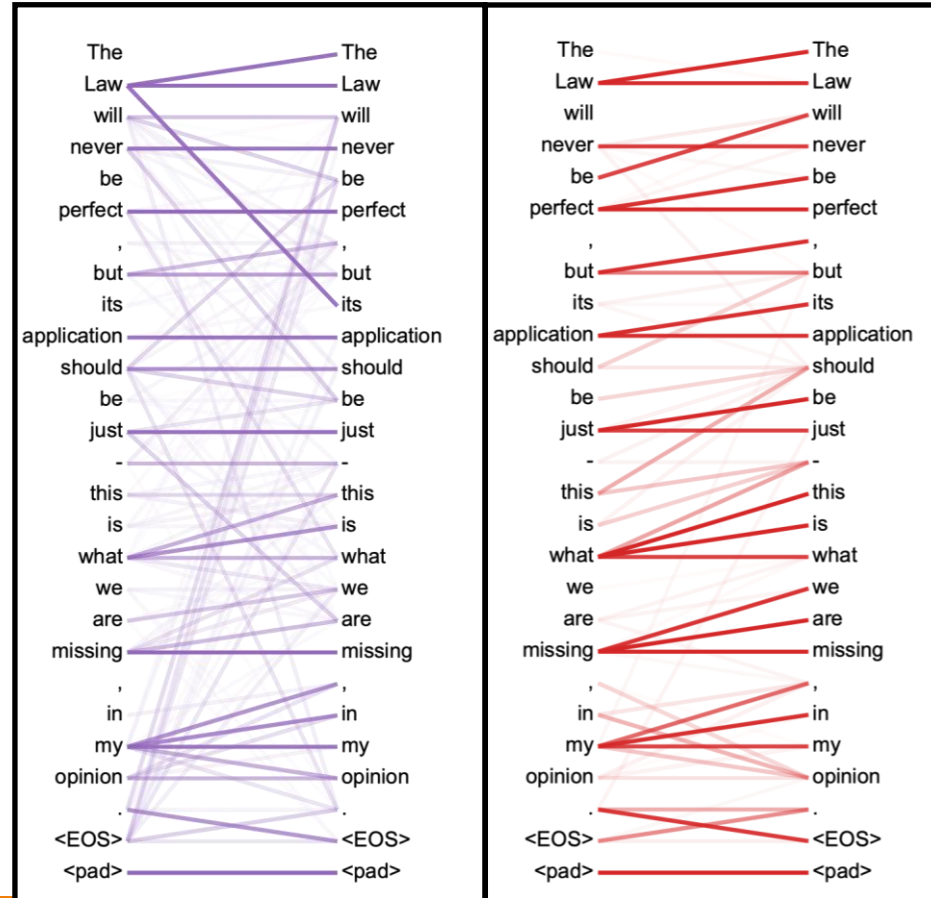
For the cell visualizing the “cat sentence”, look at the different layers of attention. (You can change the layer using the drop-down menu next to “Layer”).

1. Are there any patterns that you see between the layers? (e.g., What words are connected to what other words for each layer?)
2. Come up with a guess for what type of information each layer could be capturing.
3. Change the sentence on the `inputs = tokenizer.encode()` line and run the cell again. Does this break what you thought for question #2? Explain.

Multi-Head Attention



Two different self-attention heads:

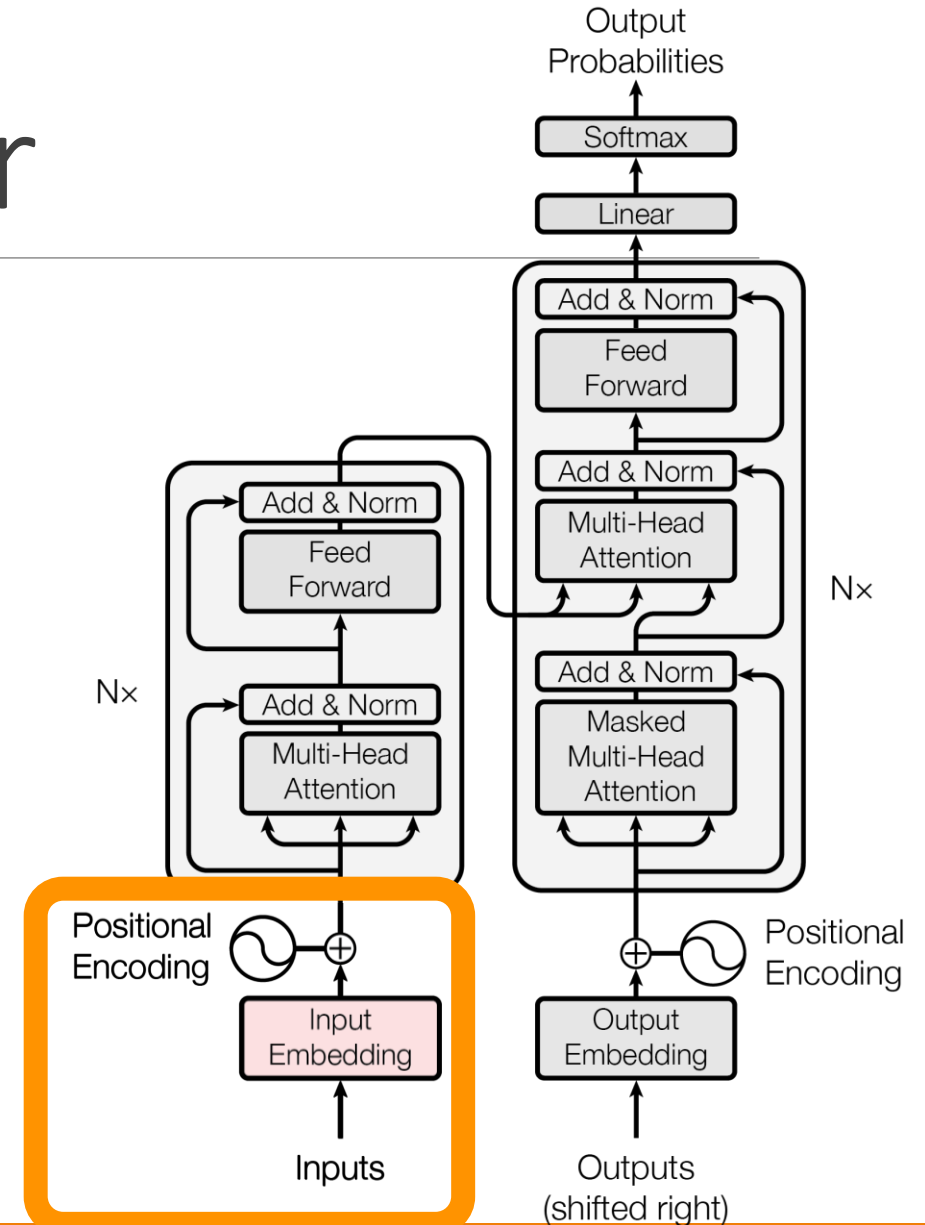


Inputs to the Encoder

The input into the encoder looks like:

$$\mathbf{H}_0^{\text{enc}} = \begin{array}{c} \text{Token Embeddings:} \\ \begin{array}{|c|c|c|c|c|c|} \hline \text{padding} \\ \hline \end{array} \\ \text{maximum sequence length} \end{array} \begin{array}{c} \text{embedding size} \\ + \\ \end{array} \begin{array}{c} \text{Position Embeddings:} \\ \text{[Heatmap]} \end{array}$$

= token embeddings + position embeddings



How does the transformer compare to the seq2seq RNN?

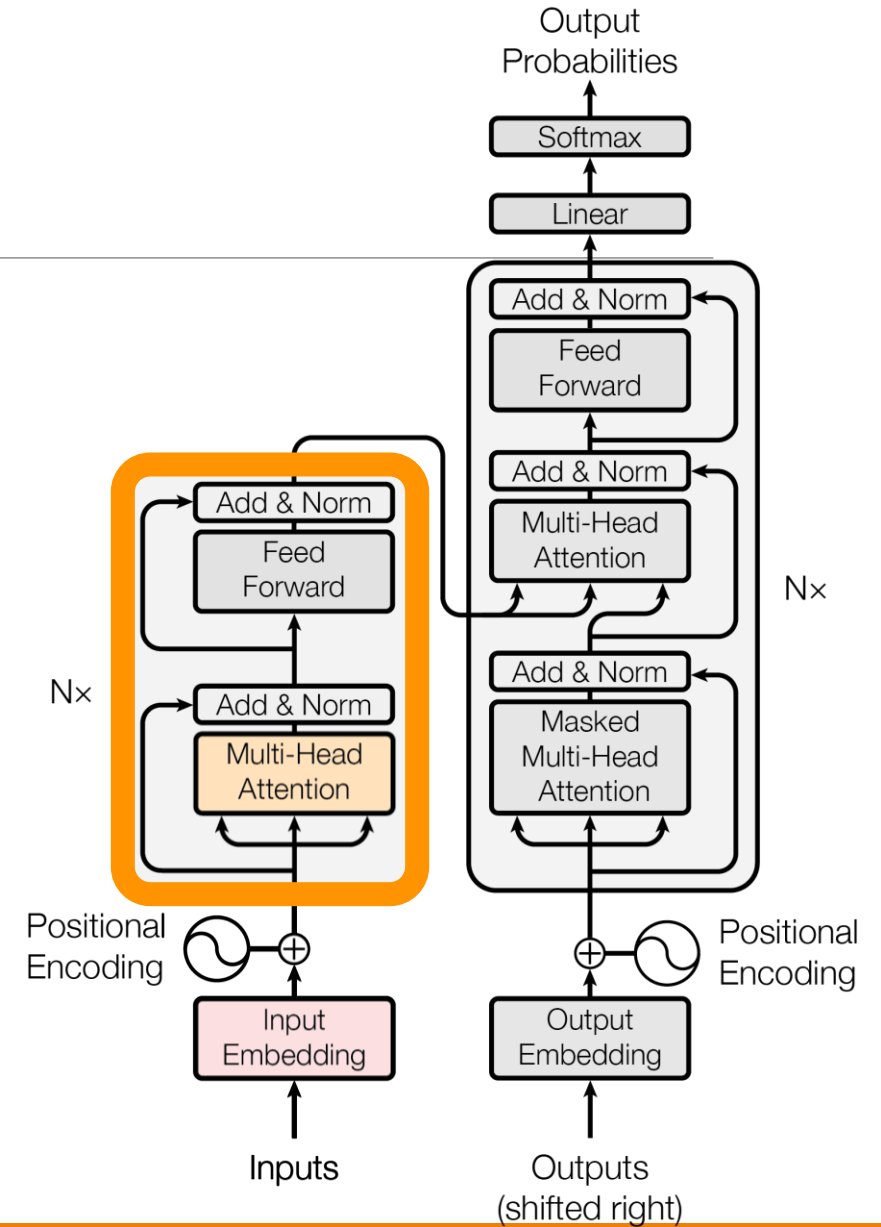
Think-Pair-Share

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

If you want more details, check out the following slides

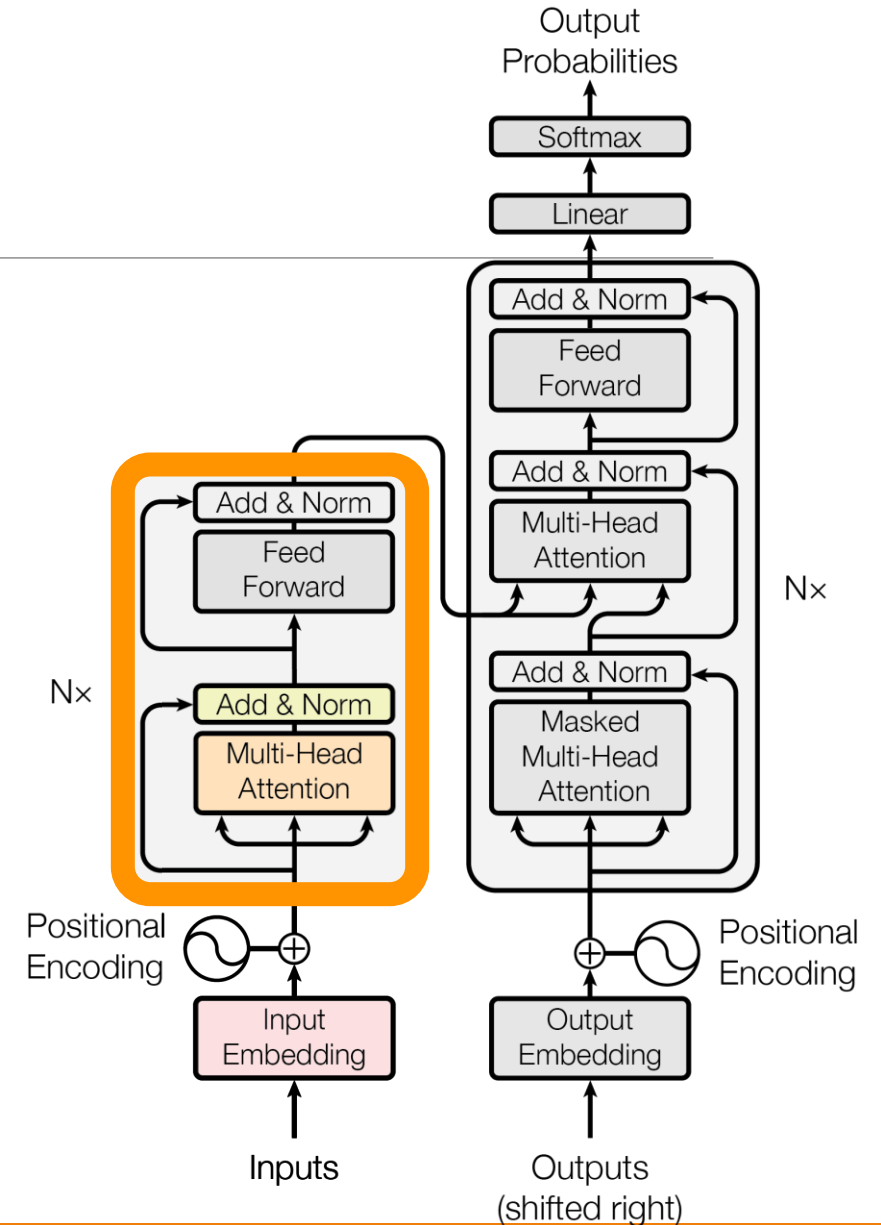
The Encoder

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



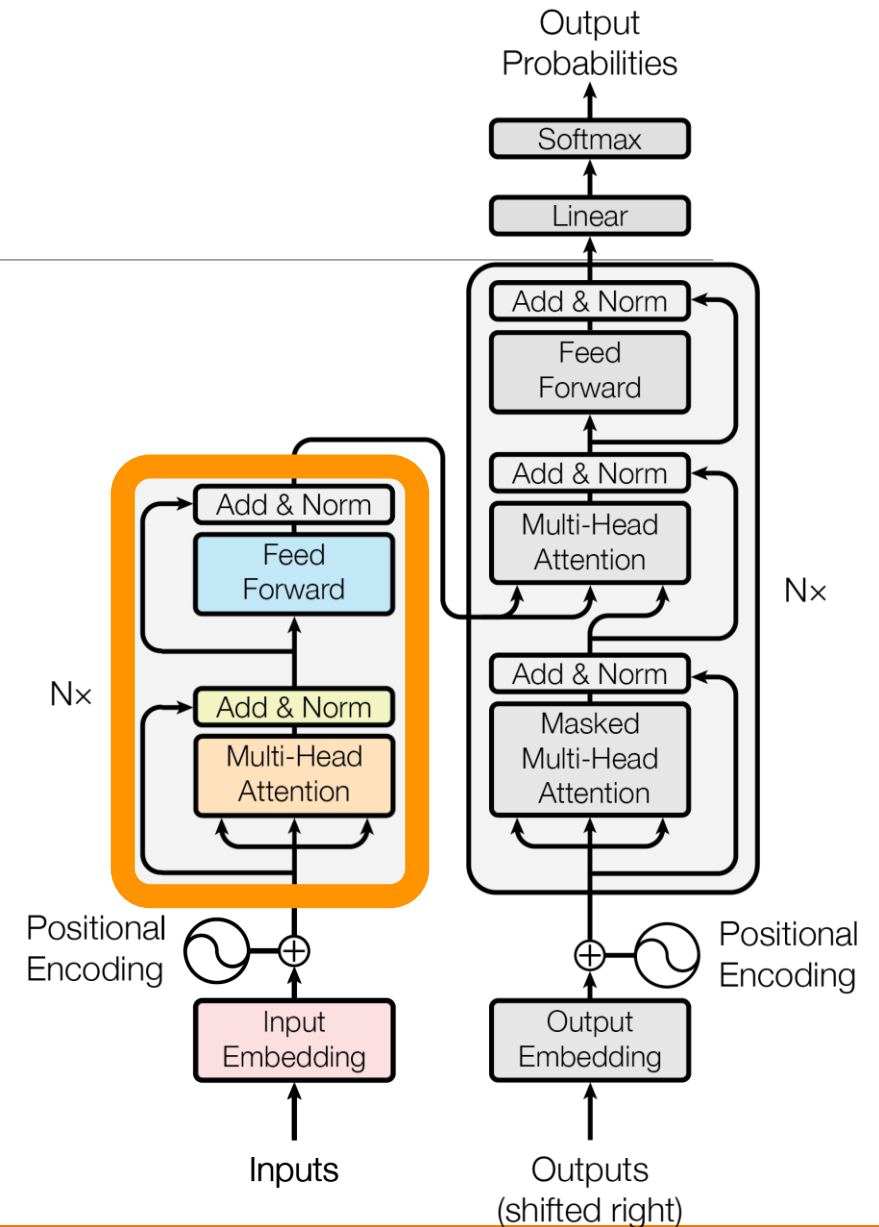
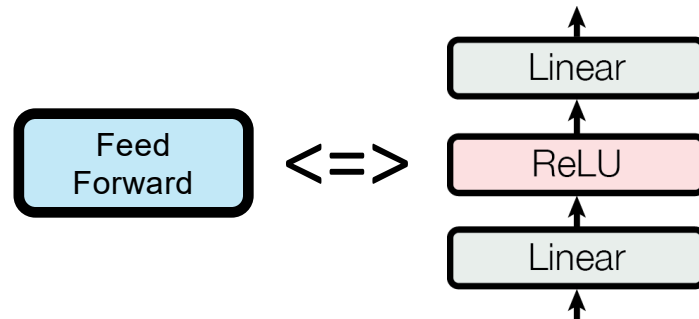
The Encoder

$$\begin{aligned} \text{Multi-Head Attention} &= \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}) \\ \text{Add \& Norm} &= \text{LayerNorm}(\text{Multi-Head Attention} + \mathbf{H}_i^{enc}) \end{aligned}$$



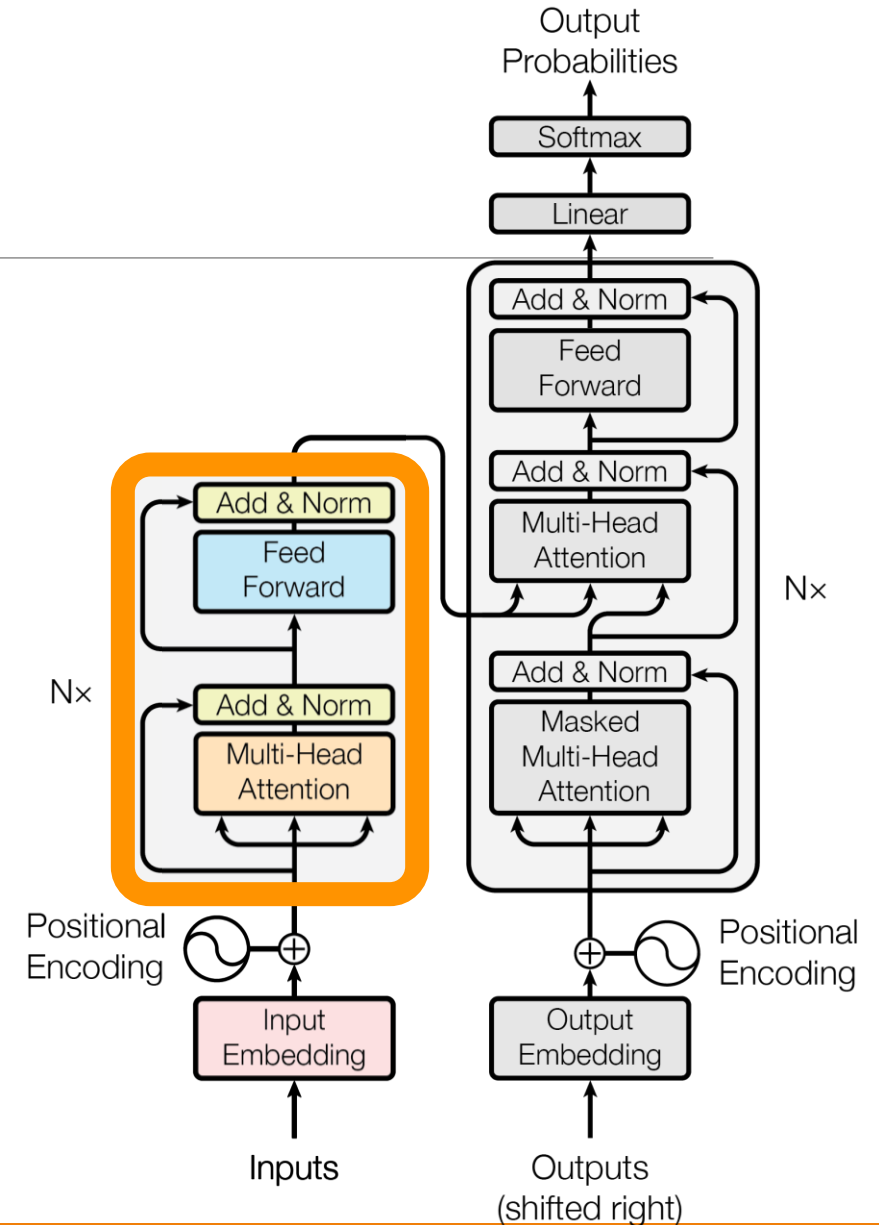
The Encoder

$$\begin{aligned}
 \text{Multi-Head Attention} &= \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}) \\
 \text{Add \& Norm} &= \text{LayerNorm}(\text{Multi-Head Attention} + \mathbf{H}_i^{enc}) \\
 \text{Feed Forward} &= \max(0, \text{Add \& Norm} \mathbf{W}_1 + b_1) \mathbf{W}_2 + b_2
 \end{aligned}$$



The Encoder

$$\begin{aligned}
 \text{Multi-Head Attention} &= \text{MultiHeadAtt}(\mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}, \mathbf{H}_i^{enc}) \\
 \text{Add \& Norm} &= \text{LayerNorm}(\text{Multi-Head Attention} + \mathbf{H}_i^{enc}) \\
 \text{Feed Forward} &= \max(0, \text{Add \& Norm} \mathbf{W}_1 + b_1) \mathbf{W}_2 + b_2 \\
 \text{Add \& Norm (2)} &= \text{LayerNorm}(\text{Feed Forward} + \mathbf{H}_i^{enc}) \\
 \mathbf{H}_{i+1}^{enc} &= \text{Add \& Norm (2)}
 \end{aligned}$$

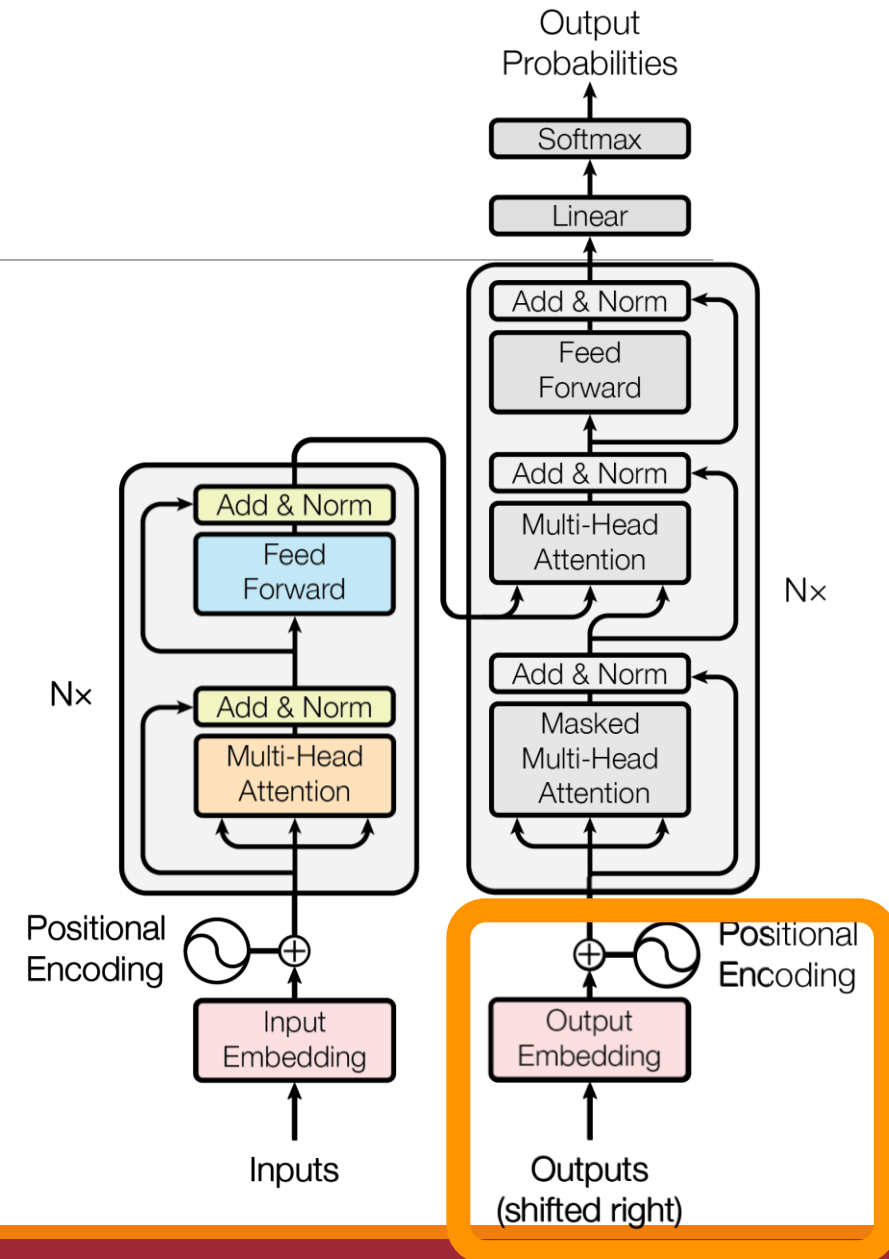


The Decoder

$$\mathbf{H}_0^{\text{dec}} = \begin{array}{|c|} \hline \text{padding} \\ \hline \end{array} + \begin{array}{|c|} \hline \text{embedding size} \\ \hline \end{array}$$

maximum sequence length

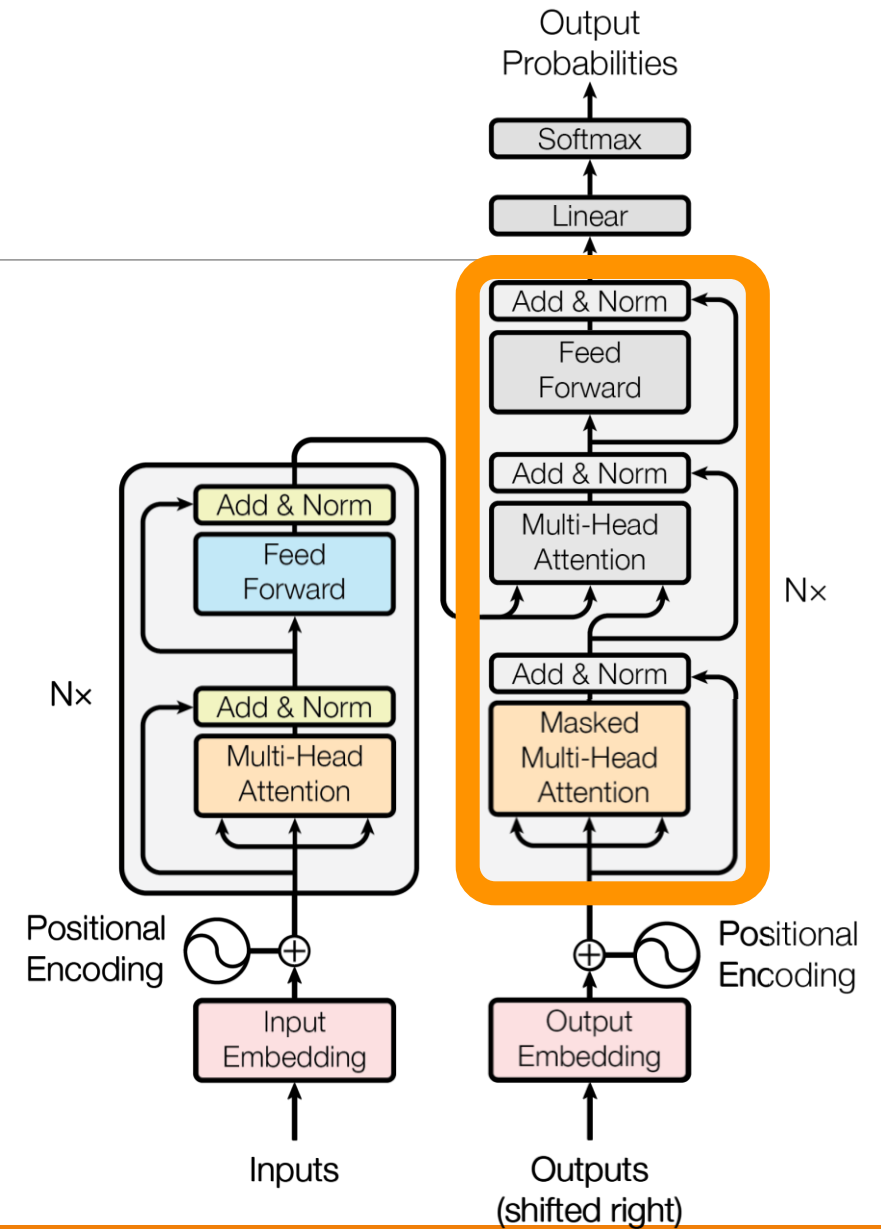
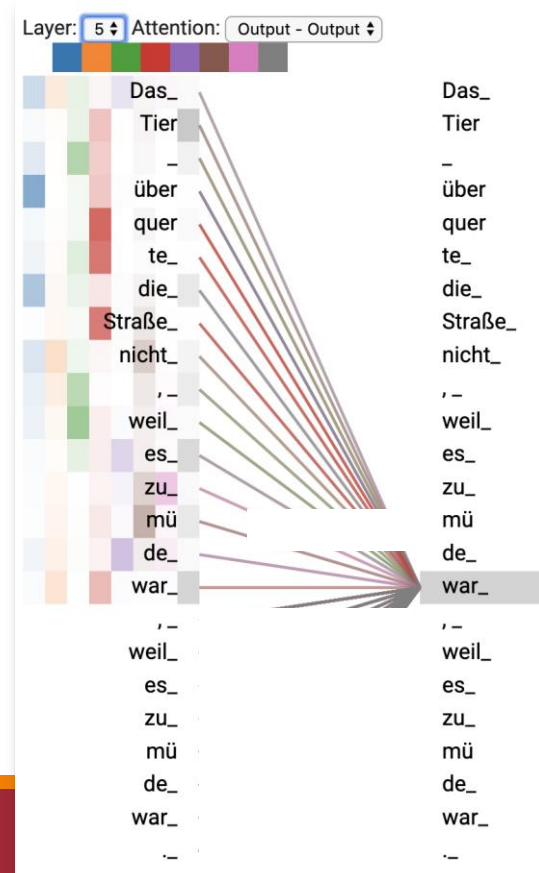
= token embeddings + position embeddings



The Decoder

Masked Multi-Head Attention

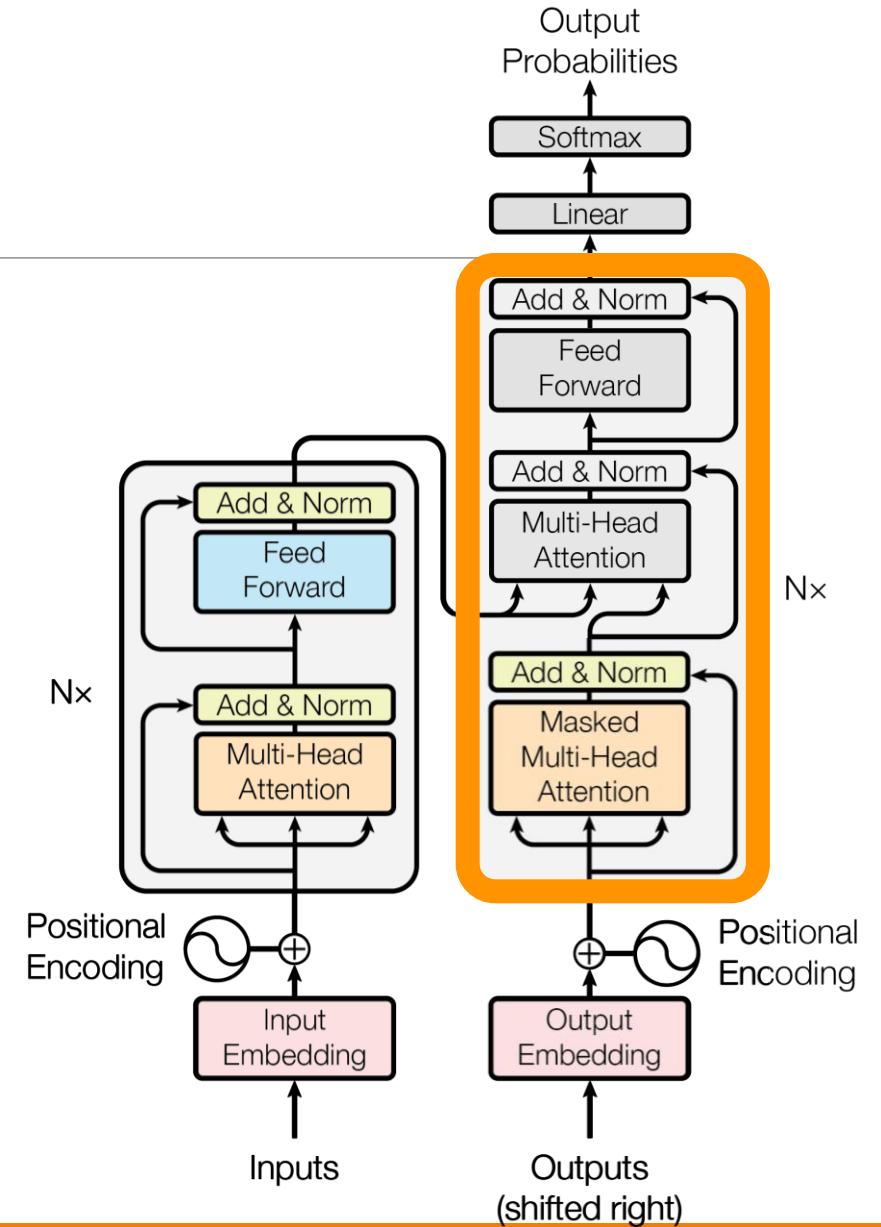
$$= \text{MaskedMultiHeadAtt}(\mathbf{H}_i^{dec}, \mathbf{H}_i^{dec}, \mathbf{H}_i^{dec})$$



The Decoder

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

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

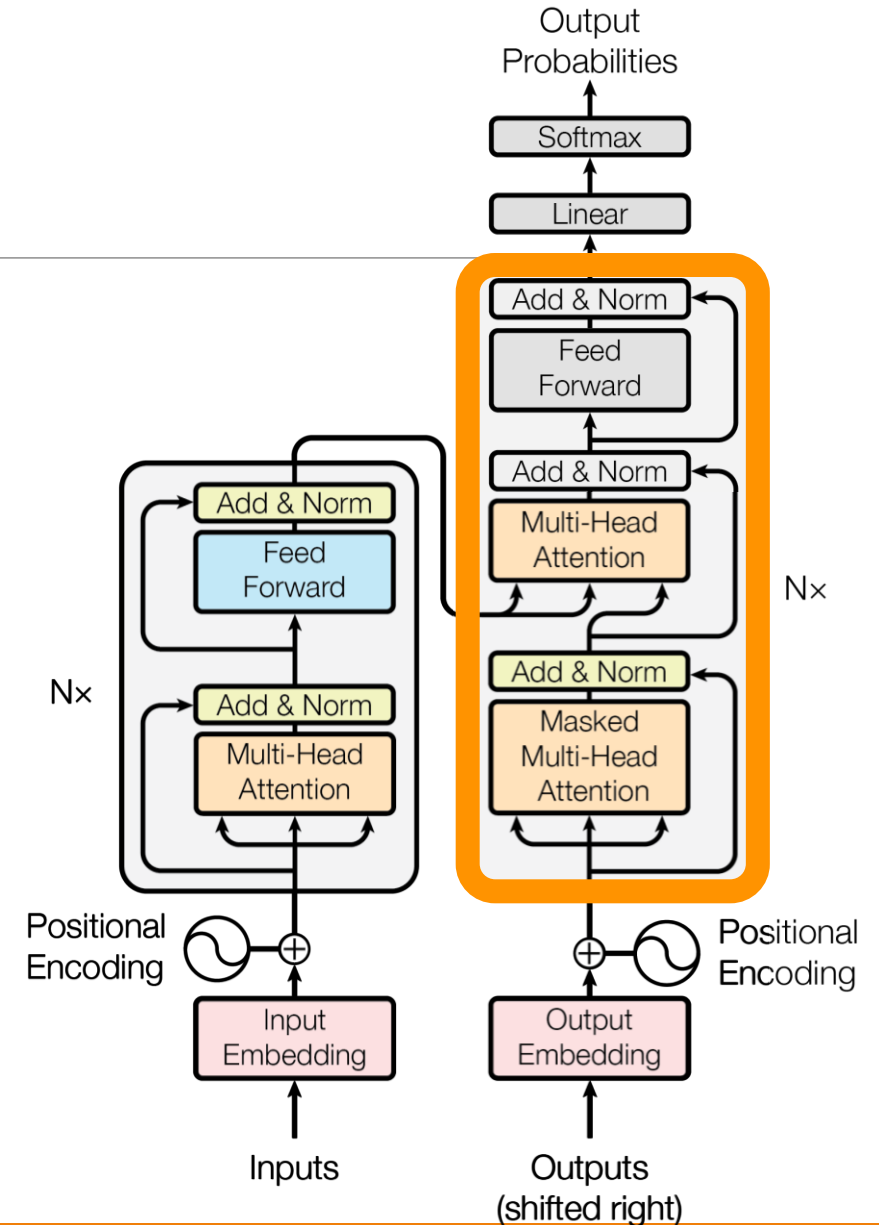


The Decoder

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

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

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



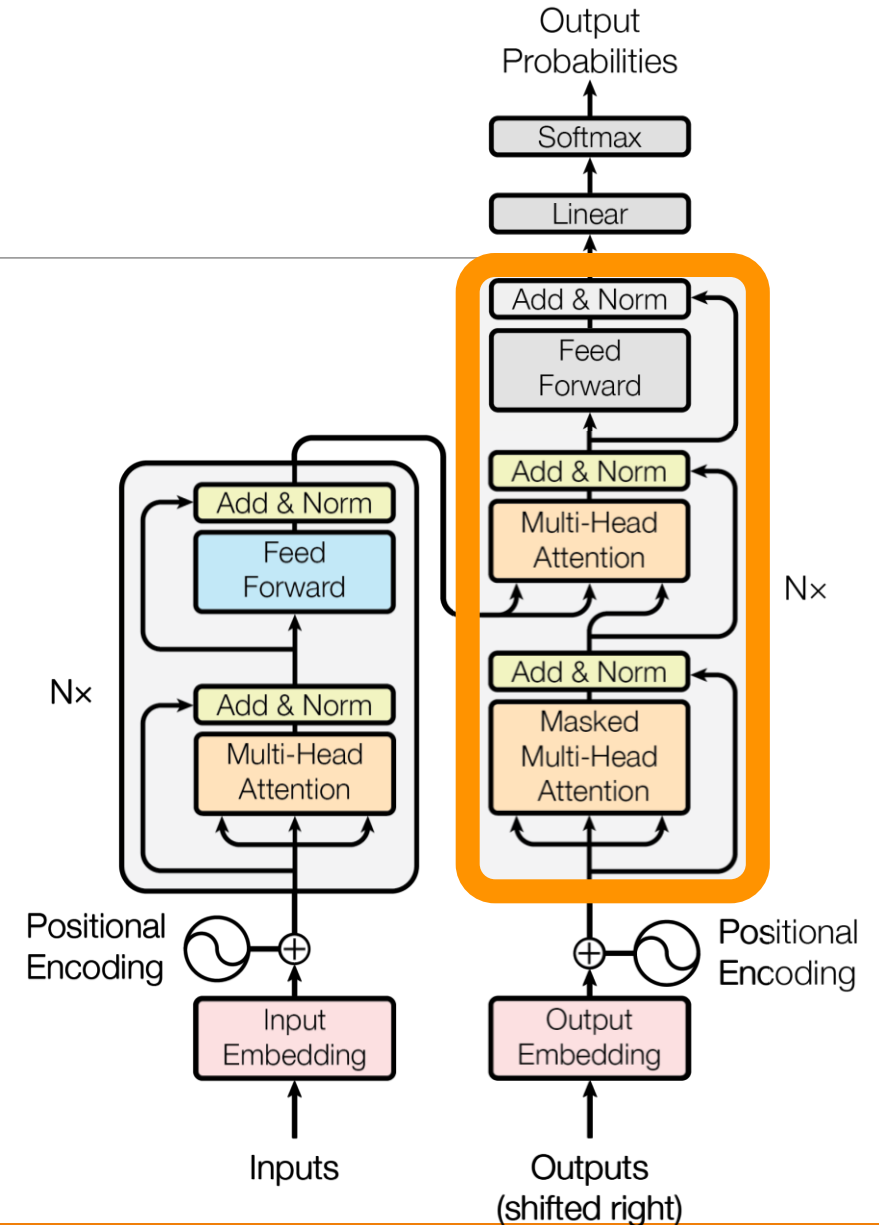
The Decoder

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

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

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

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



The Decoder

