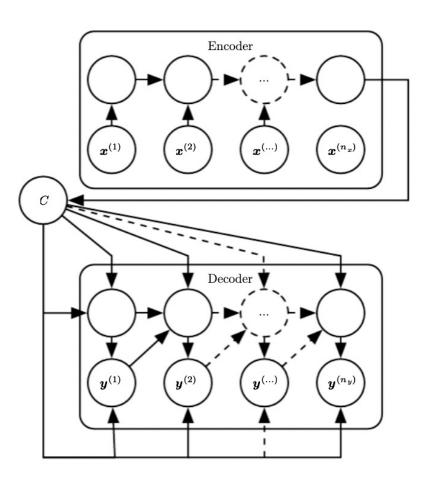
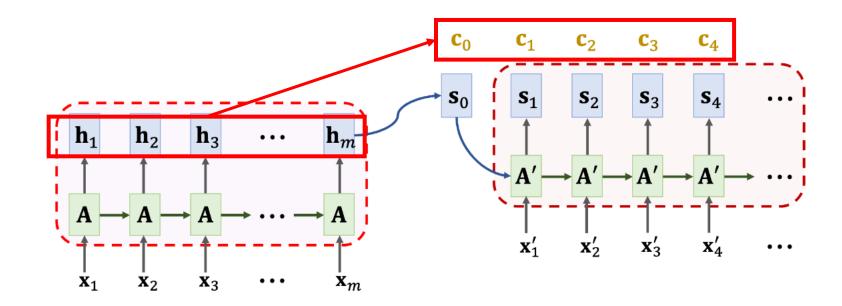
# Transformer

Neural Networks Design And Application

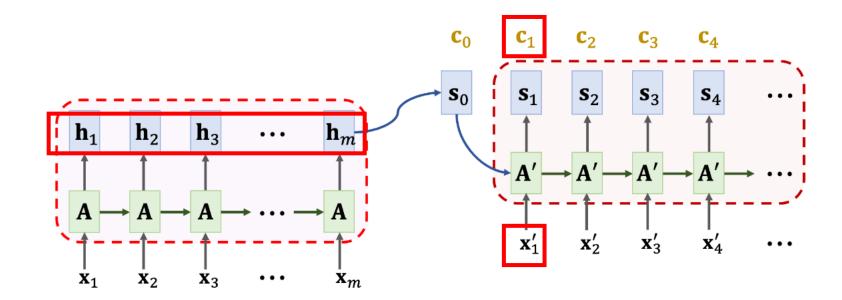
## Encoder-decoder for seq2seq



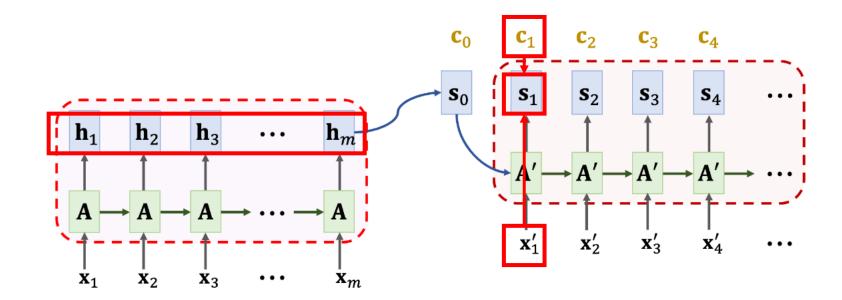
## Attention mechanism

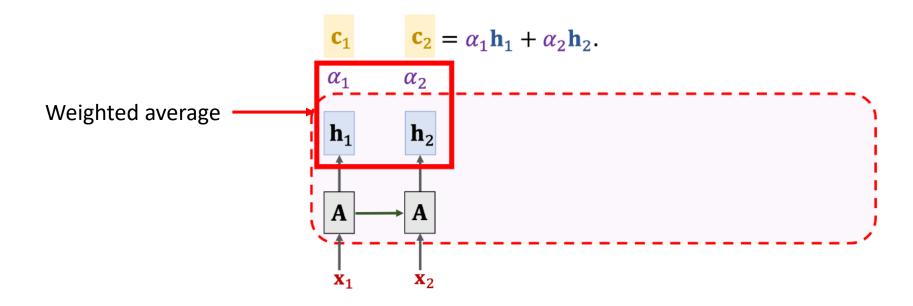


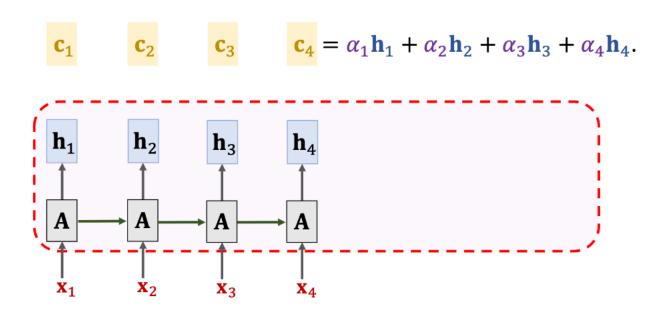
## Attention mechanism

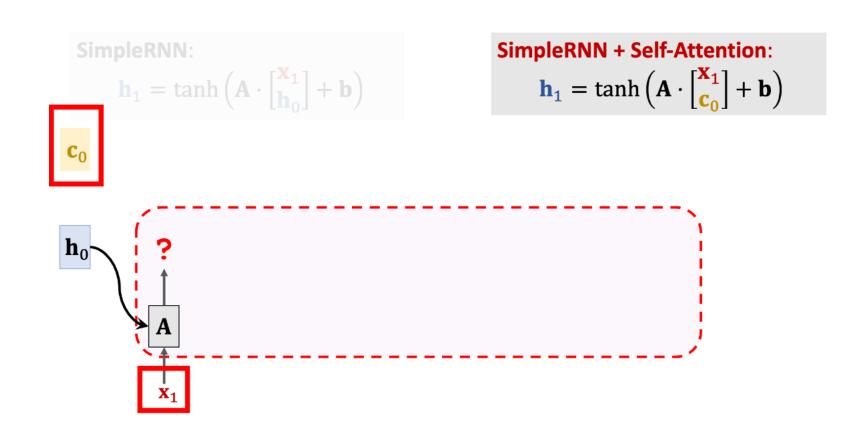


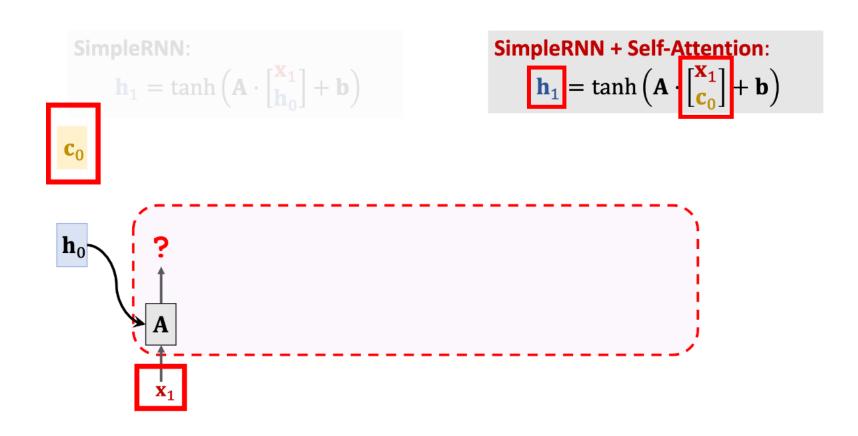
## Attention mechanism

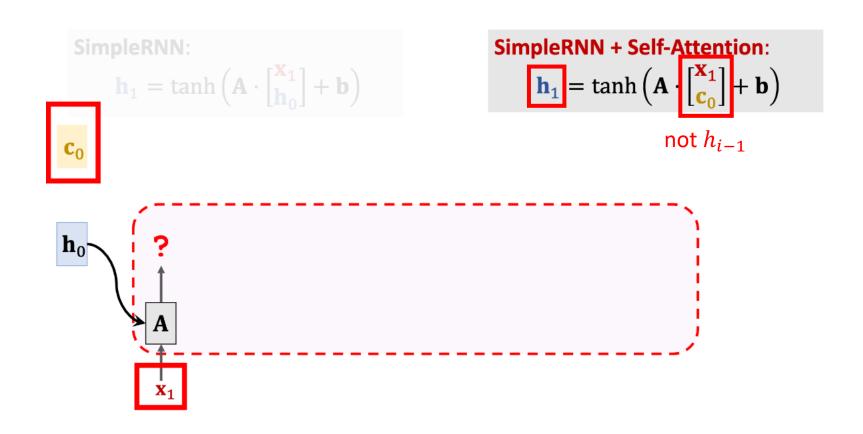


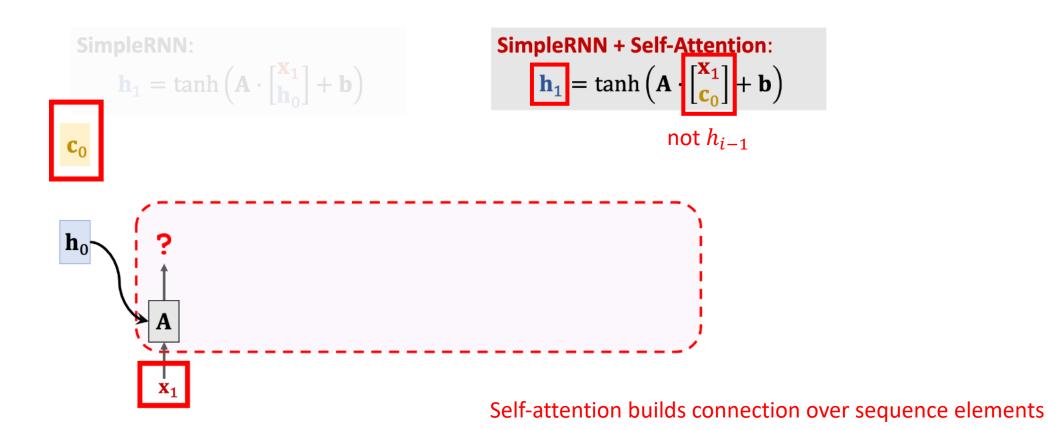


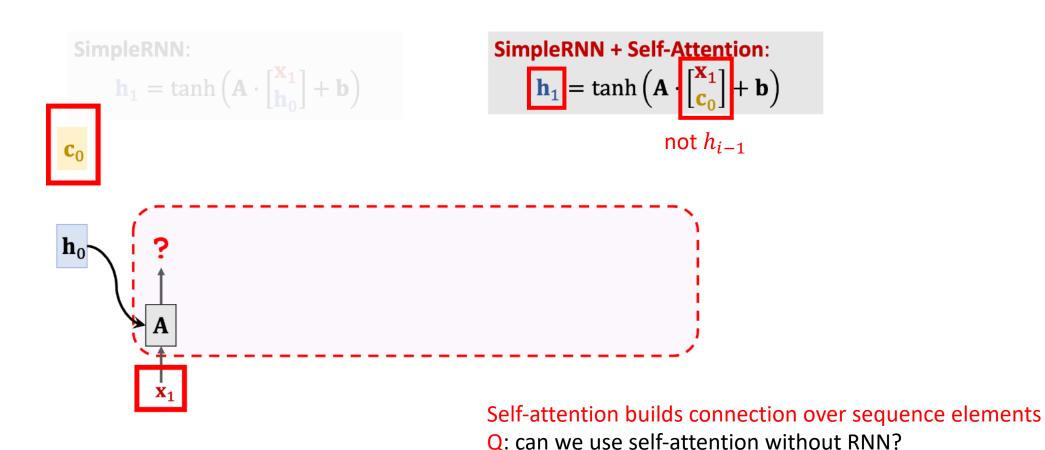












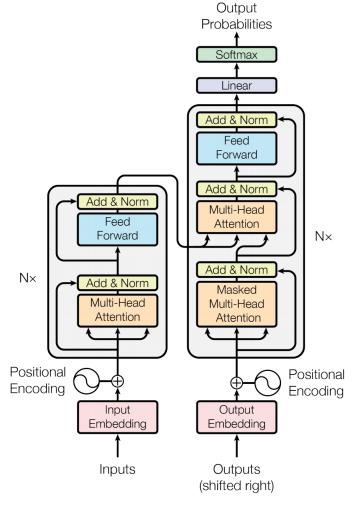


Figure 1: The Transformer - model architecture.

Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. "Attention is all you need." *arXiv preprint arXiv:1706.03762* (2017).

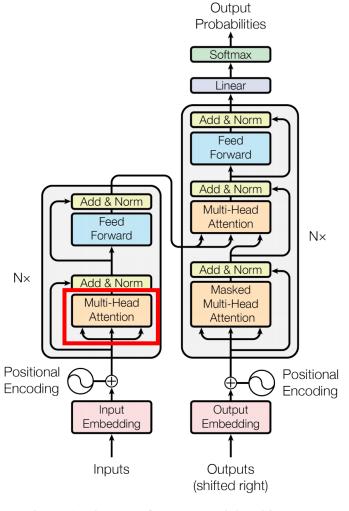


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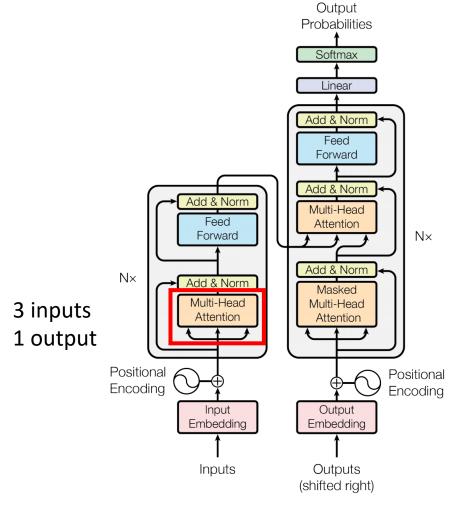
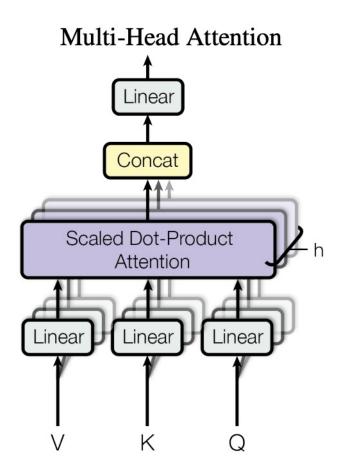
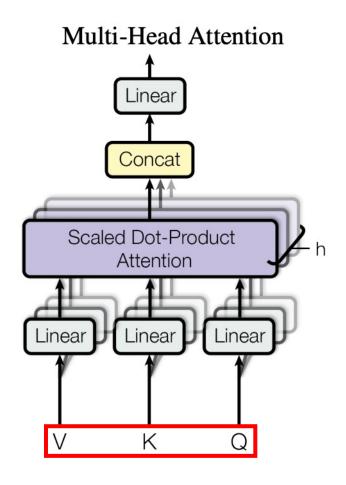


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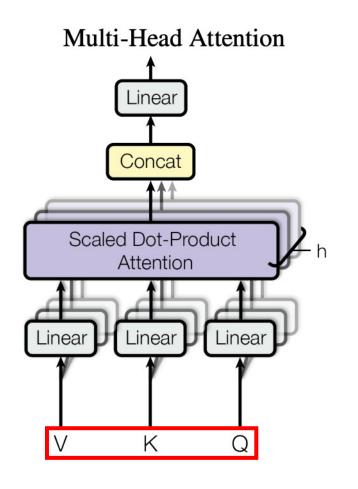




V: value

K: key

Q: query



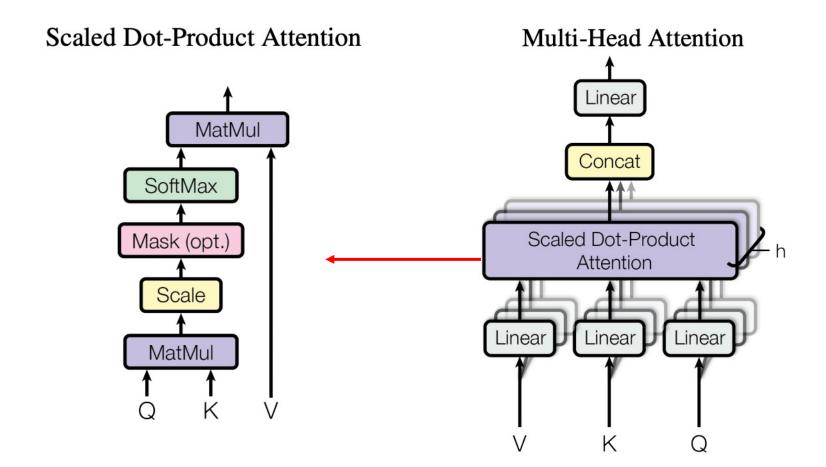
V: value

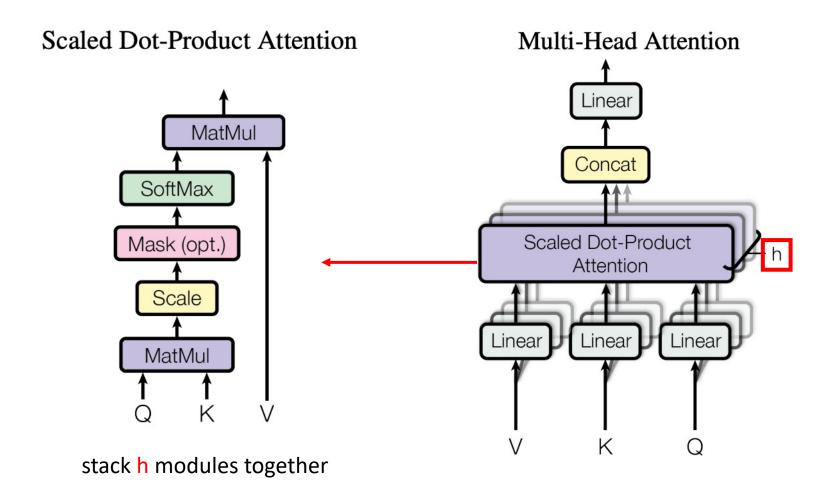
K: key

Q: query

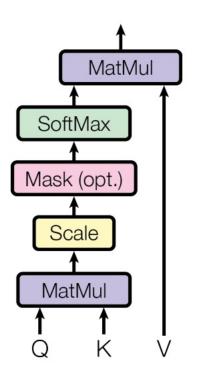
Interpreted from information retrieval systems:

https://stats.stackexchange.com/questio ns/421935/what-exactly-are-keysqueries-and-values-in-attentionmechanisms



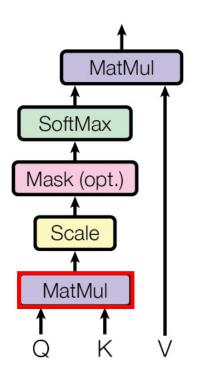


#### Scaled Dot-Product Attention



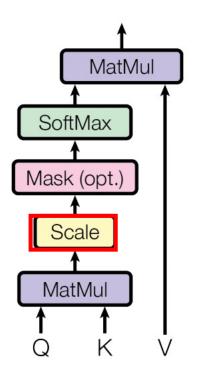
$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

#### Scaled Dot-Product Attention



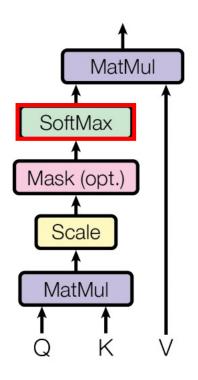
Attention
$$(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

#### Scaled Dot-Product Attention



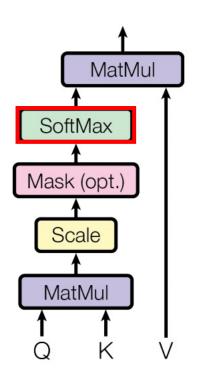
$$\operatorname{Attention}(Q,K,V) = \operatorname{softmax}(QK^T)V$$
 Dimension of keys

#### Scaled Dot-Product Attention



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

#### Scaled Dot-Product Attention

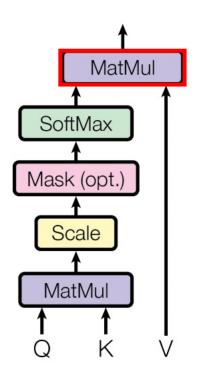


weights for selection (keys in a retrieval system)

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

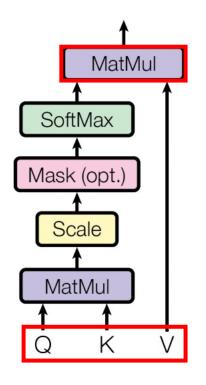
An example: one-hot format

#### Scaled Dot-Product Attention



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

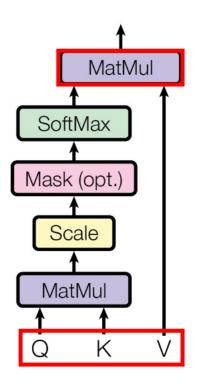
#### Scaled Dot-Product Attention



How to generate

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

#### Scaled Dot-Product Attention

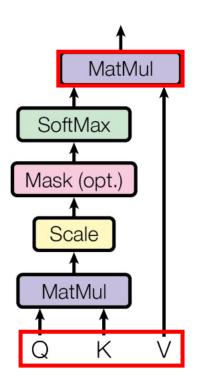


In addition to attention sub-layers, each of the layers in our encoder and decoder contains a fully connected feed-forward network, which is applied to each position separately and identically. This consists of two linear transformations with a ReLU activation in between.

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$
(2)

While the linear transformations are the same across different positions, they use different parameters from layer to layer. Another way of describing this is as two convolutions with kernel size 1. The dimensionality of input and output is  $d_{\rm model}=512$ , and the inner-layer has dimensionality  $d_{ff}=2048$ .

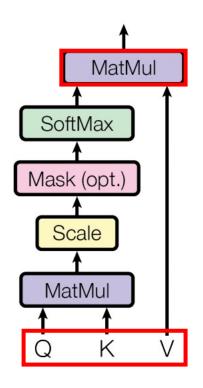
#### Scaled Dot-Product Attention



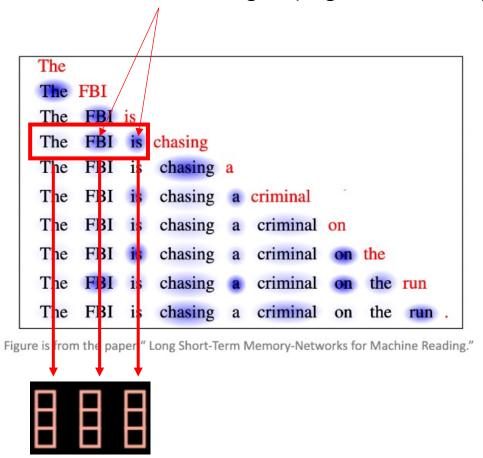
```
The FBI
The FBI is
The FBI is chasing
The FBI is chasing a
The FBI is chasing a criminal
The FBI is chasing a criminal on
The FBI is chasing a criminal on the
The FBI is chasing a criminal on the run
The FBI is chasing a criminal on the run
The FBI is chasing a criminal on the run.
```

Figure is from the paper "Long Short-Term Memory-Networks for Machine Reading."

#### Scaled Dot-Product Attention



Greater weights (larger Softmax output)



Embedding feature vectors (a matrix)

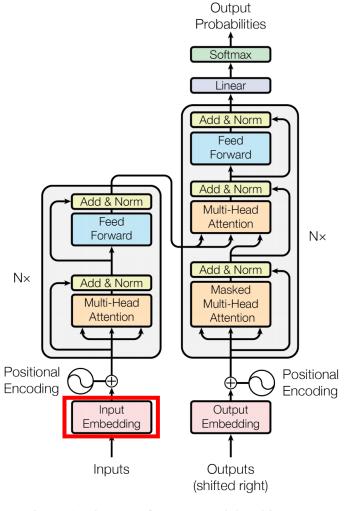


Figure 1: The Transformer - model architecture.

Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. "Attention is all you need." *arXiv preprint arXiv:1706.03762* (2017).

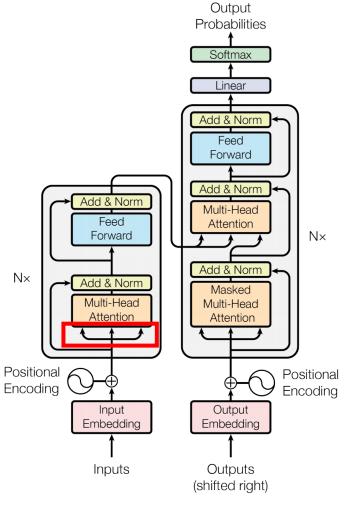


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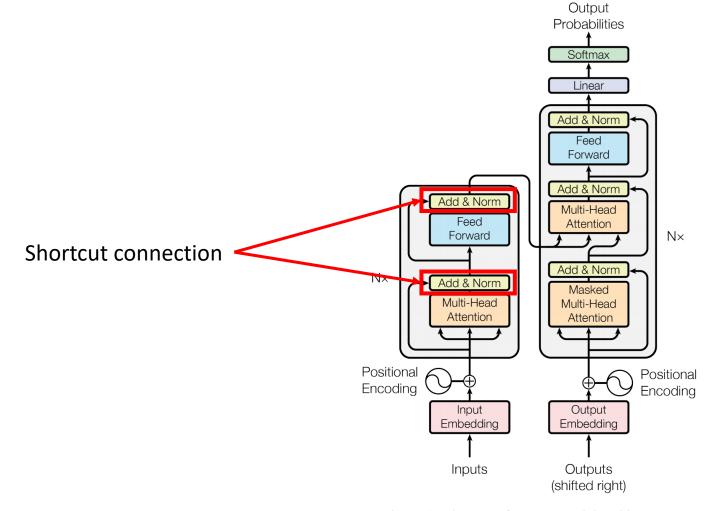


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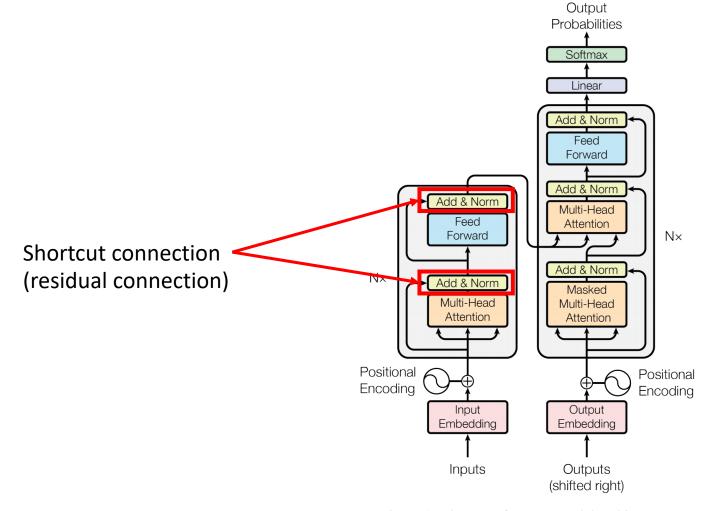
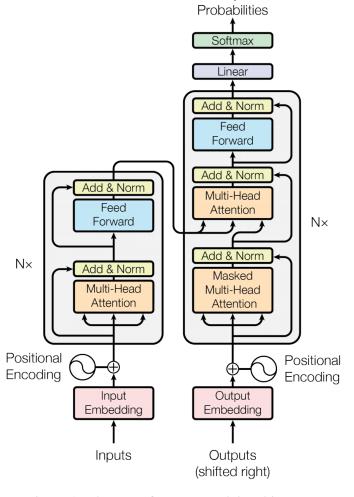


Figure 1: The Transformer - model architecture.

No recurrent structure  $\rightarrow$  not RNN



Output

Figure 1: The Transformer - model architecture.

No recurrent structure → not RNN Q: any benefit?

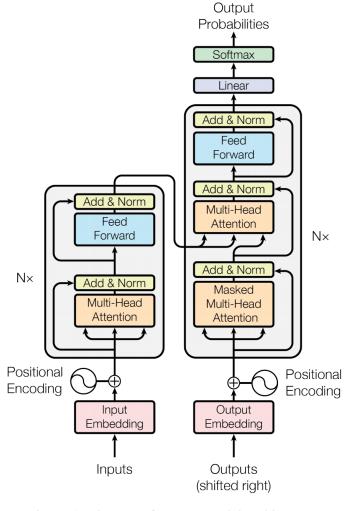


Figure 1: The Transformer - model architecture.

No recurrent structure → not RNN Q: any benefit?

1. No sequential dependence

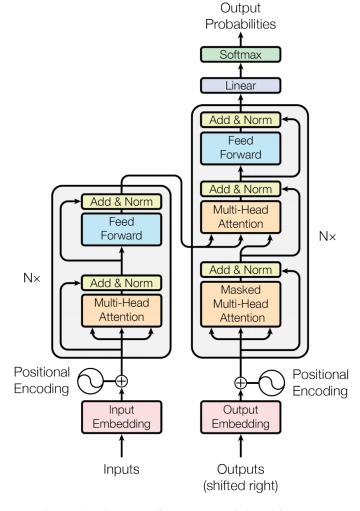


Figure 1: The Transformer - model architecture.

No recurrent structure → not RNN Q: any benefit?

- 1. No sequential dependence
- 2. Parallel processing

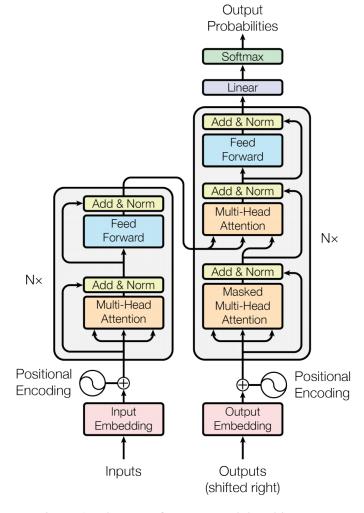


Figure 1: The Transformer - model architecture.

No recurrent structure → not RNN Q: any benefit?

- 1. No sequential dependence
- 2. Parallel processing
- 3. ...

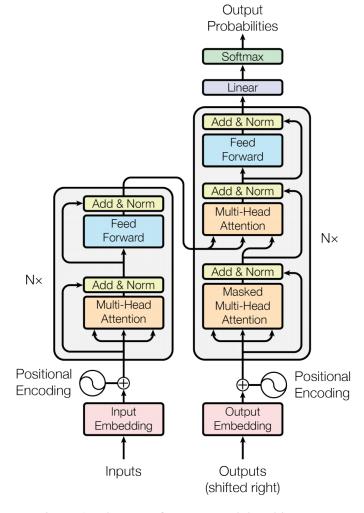


Figure 1: The Transformer - model architecture.