
? Resources

Article:

[Google Brain, Attention is All You Need](#)

Web:

- [Transformer: A Novel Neural Network Architecture for Language Understanding](#)
- [Visualizing A Neural Machine Translation Model \(Mechanics of Seq2seq Models With Attention\)](#)
- 3Blue1Brown:
 - [Deep Learning Chapter 05: What is a GPT?](#)
 - [Deep Learning Chapter 06: Attention in Transformers](#)
- [The AI Hacker, Illustrated Guide to Transformers](#)
- [StatQuest, Transformer Neural Networks](#)
- [Campus X, 100 Days of Deep Learning](#) Video 68 - 77

Introduction

Recurrent Neural Networks

- [Long Short-Term Memory \(LSTM\)](#)
- [Gated Recurrent Unit \(GRU\)](#)

Working and Disadvantages

- Generate sequence of hidden states, $h_{t-1} \rightarrow h_t \rightarrow \dots$, for input position t
- Cannot parallelize training, RNNs need to train *in order*. This becomes critical at longer sequence lengths, **memory constraints** limit *batching* across examples.

Improvements

- Conditional computation
- Factorization tricks

Conclusion

Although [Improvements](#) have been made to the efficiency of RNNs, the fundamental problems discussed, remain.

Attention Mechanisms

- Become an essential part of **sequence modelling**
- They allow the model to consider how **different parts of the input or output relate to each other**, *regardless of how far apart they are*. This is a big improvement over RNNs, which process things step-by-step.
- Used to be implemented in conjunction with a recurrent network

Transformers

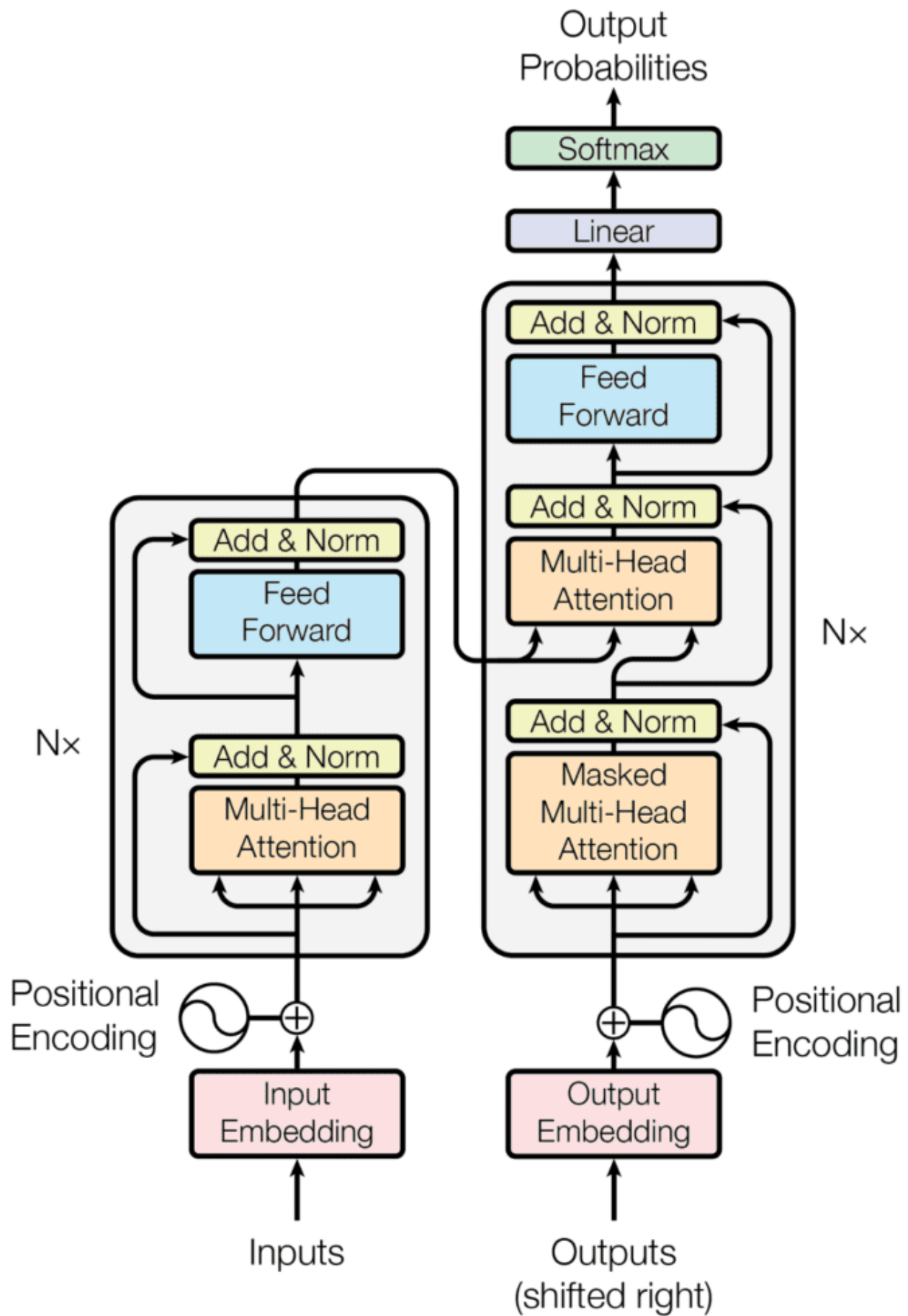
[Attention is All You Need](#) introduces the **Transformer** architecture, which

- Rejects recurrence
- Relies entirely on the **Attention** mechanism to figure out *how much the output depends on the input*
- Allows for parallelization

The Transformer allows for significantly more parallelization and can reach a new state of the art in translation quality after being trained for as little as twelve hours on eight P100 GPUs.

[Attention-Is-All-You-Need_Google-Brain.,page 2](#)

Transformer Model Architecture



Encoder-Decoder Stacks

Transformers follow the *Encoder-Decoder* structure as described in the figure.

- The **encoder** maps the input sequence of symbol representations $\vec{x} = (x_1, x_2, \dots, x_n)$ to a sequence of continuous representations $\vec{z} = (z_1, z_2, \dots, z_n)$
- Given \vec{z} , the **decoder** generates an output sequence $\vec{y} = (y_1, y_2, \dots, y_m)$ of symbols, *one element at a time*.
- At each time step the model is **auto-regressive** - consuming the **previously generated symbols** as **additional input** when *generating the next*.