Attention Is All You Need

How Transformers and GPT work

Henady Zakalusky, 2025

Not only ChatGPT, Gemini, Grok, Deepseek, etc

Transformer Architecture introduced in 2017 paper named “Attention is All You Need” and initially was intended for Language Translation

Found also usages in

- AlphaFold, AlphaGenome
- Robotics (Google RT-1 (Robotics Transformer 1))
- Surgical Robot Transformer-Hierarchy
- Weather Forecast (TENT, etc)
- Anomaly Detection, Trajectory Prediction
- Audio, Video
- etc

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 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 best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.0 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature.

1 Introduction

Recurrent neural networks, long short-term memory [12] and gated recurrent [7] neural networks in particular, have been firmly established as state of the art approaches in sequence modeling and transduction problems such as language modeling and machine translation [29, 2, 5]. Numerous efforts have since continued to push the boundaries of recurrent language models and encoder-decoder architectures [31, 21, 13].

*Equal contribution. Listing order is random. Jakob proposed replacing RNNs with self-attention and started the effort to evaluate this idea. Ashish, with Illia, designed and implemented the first Transformer models and has been crucially involved in every aspect of this work. Noam proposed scaled dot-product attention, multi-head attention and the parameter-free position representation and became the other person involved in nearly every detail. Niki designed, implemented, tuned and evaluated countless model variants in our original codebase and tensor2tensor. Llion also experimented with novel model variants, was responsible for our initial codebase, and efficient inference and visualizations. Lukasz and Aidan spent countless long days designing various parts of and implementing tensor2tensor, replacing our earlier codebase, greatly improving results and massively accelerating our research.

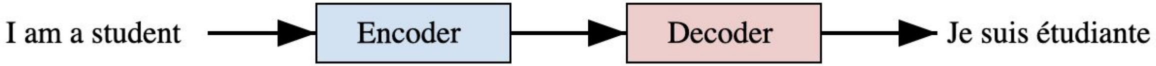
†Work performed while at Google Brain.

‡Work performed while at Google Research.

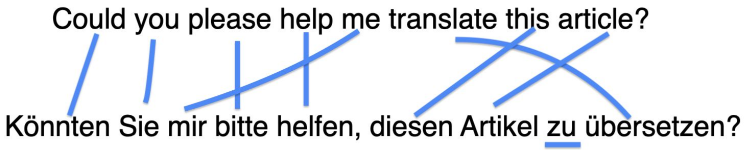
31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

Translation problems

- Different input and output length



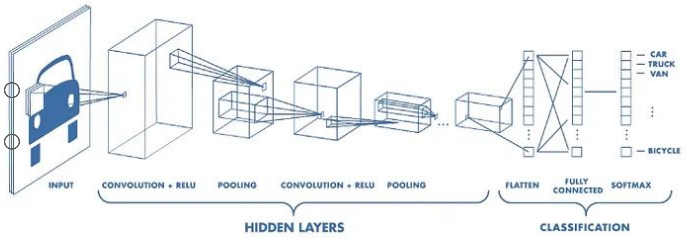
- Changing ordering of the words



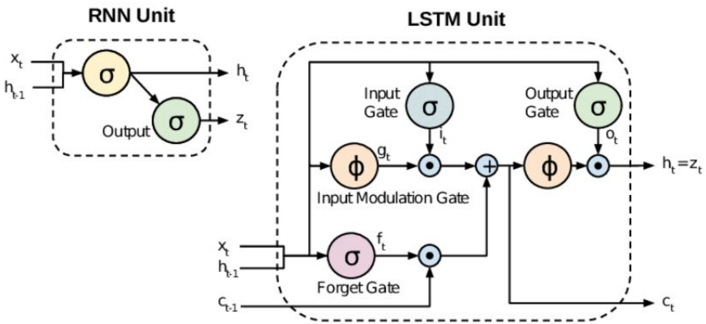
- Morphologically rich languages
- Multiple meanings
- etc

Common Neural Networks for Sequential Data

- RNN - Recurrent Neural Network (1982)
  - LSTM - Long Short-Term Memory
  - GRU - Gated Recurrent Unit
- CNN - Convolutional Neural Network (1989)
  - TCN - Temporal Convolutional Network



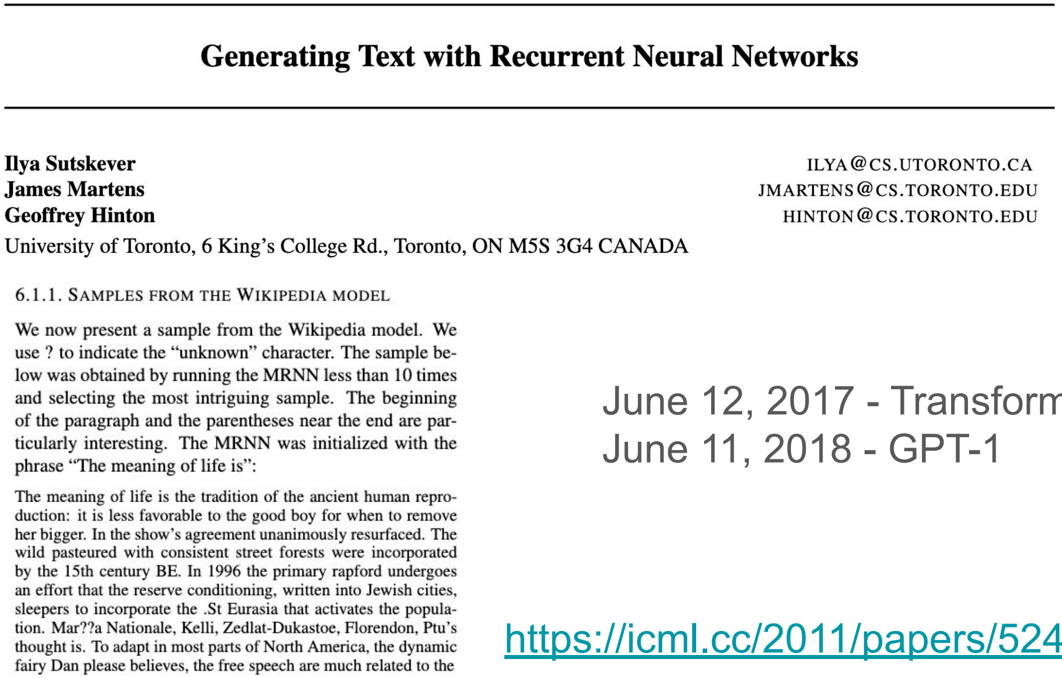
- Transformers (2017)




Yann LeCun, CNN inventor

Images from Deepseek, Youtube
https://ashutoshtripathi.com/2021/07/02/what-is-the-main-difference-between-rnn-and-lstm-nlp-rnn-vs-lstm/

Generating Text using RNN



Generating Text with Recurrent Neural Networks

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6.1.1. SAMPLES FROM THE WIKIPEDIA MODEL

We now present a sample from the Wikipedia model. We use ? to indicate the "unknown" character. The sample below was obtained by running the MRNN less than 10 times and selecting the most intriguing sample. The beginning of the paragraph and the parentheses near the end are particularly interesting. The MRNN was initialized with the phrase "The meaning of life is":

The meaning of life is the tradition of the ancient human reproduction: it is less favorable to the good boy for when to remove her bigger. In the show's agreement unanimously resurfaced. The wild pasteured with consistent street forests were incorporated by the 15th century BE. In 1996 the primary rapford undergoes an effort that the reserve conditioning, written into Jewish cities, sleepers to incorporate the .St Eurasia that activates the population. Mar??a Nationale, Kelli, Zedlat-Dukastoe, Florendon, Ptu's thought is. To adapt in most parts of North America, the dynamic fairy Dan please believes, the free speech are much related to the

June 12, 2017 - Transformers
June 11, 2018 - GPT-1

Geoffrey Hinton

https://icml.cc/2011/papers/524_icmlpaper.pdf

Image from https://www.nobelprize.org/prizes/physics/2024/hinton/facts/

Bahdanau Attention

NEURAL MACHINE TRANSLATION
BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

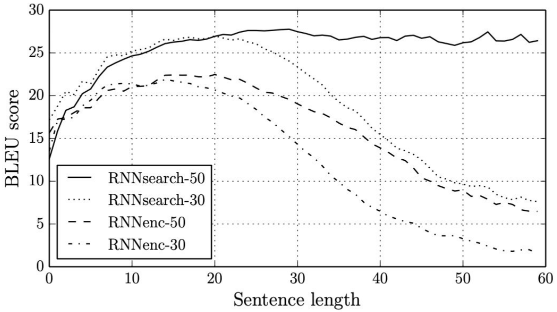
Dzmitry Bahdanau
Jacobs University Bremen, Germany

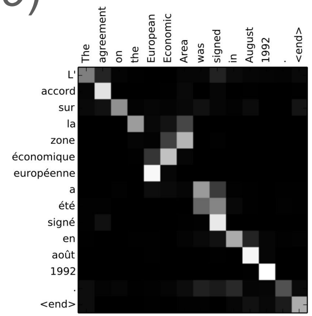
KyungHyun Cho **Yoshua Bengio***
Université de Montréal

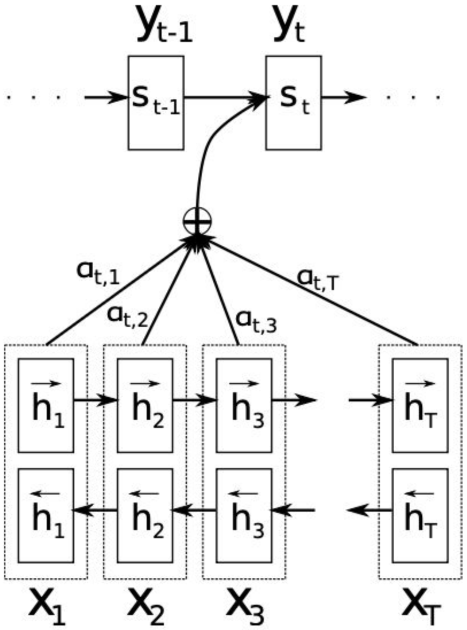
https://arxiv.org/abs/1409.0473

by D Bahdanau · 2014 · Cited by 39758

Introduced attention mechanism (*additive*)







Images from PDF

Transformer architecture

Introduced in 2017, paper “Attention Is All You Need”

- For text translation
- Consists from **Encoder** and **Decoder**
  - GPT is Decoder only architecure
- Introduced Dot-Product Attention
- Introduced Multi-Head Attention
- RNN -> FNN (MLP)
- Autoregressive Decoder
- Scalable

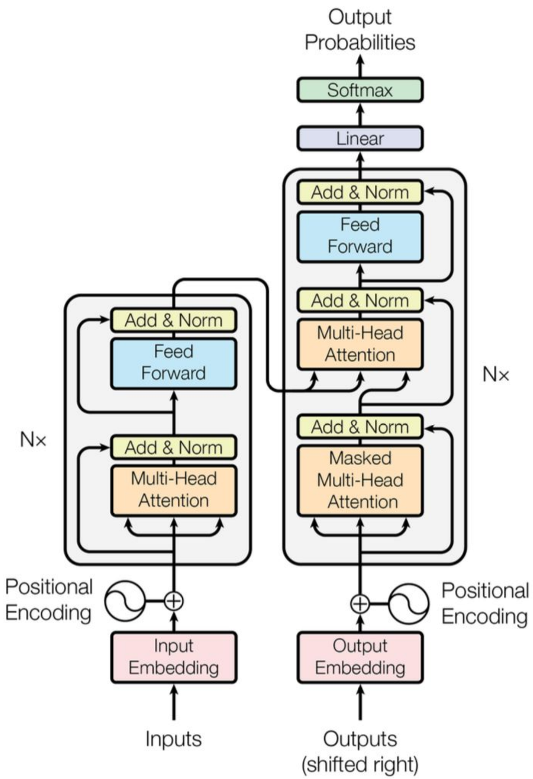


Figure 1: The Transformer - model architecture.

Tokenization

- Algorithm: BPE (byte-pair encoding)
  - originally designed for data compression
- Online: https://platform.openai.com/tokenizer

```
Many words map to one token, but some don't: indivisible.
```

- Spaces are included !
- <bos> **<eos>** and other special tokens.

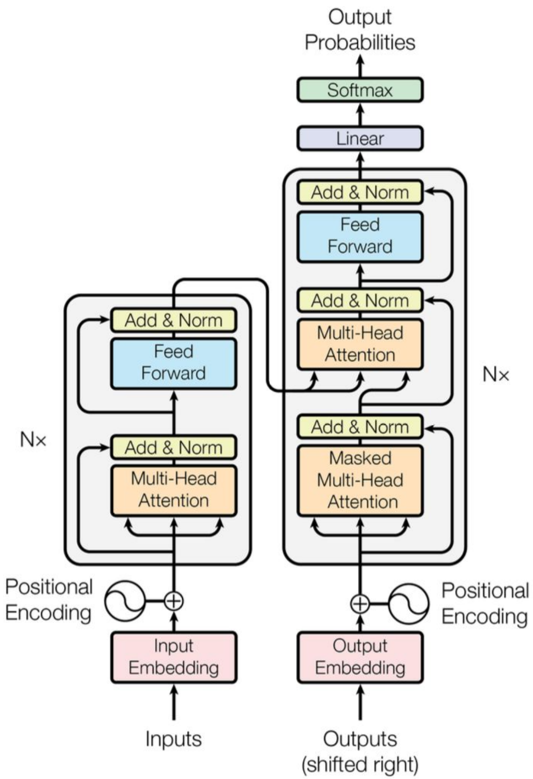
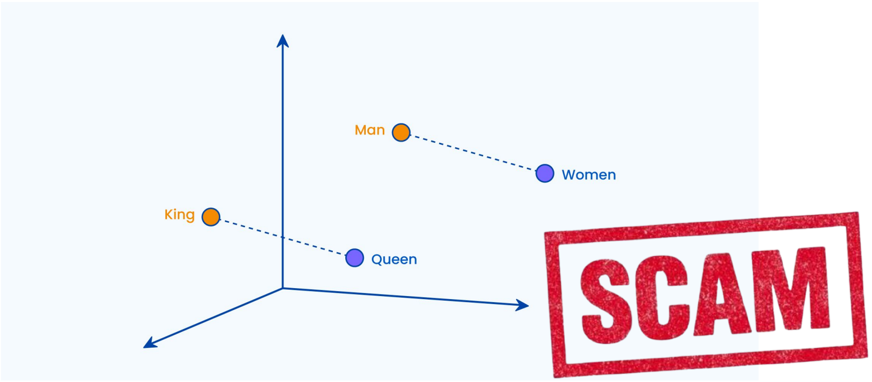


Figure 1: The Transformer - model architecture.

Embedding

- Token -> Vector

  Vector size: Transformer - 512, GPT3 - 12288
- Learnable parameter (Initially random)
- Word2Vec, GLoVe are not used!



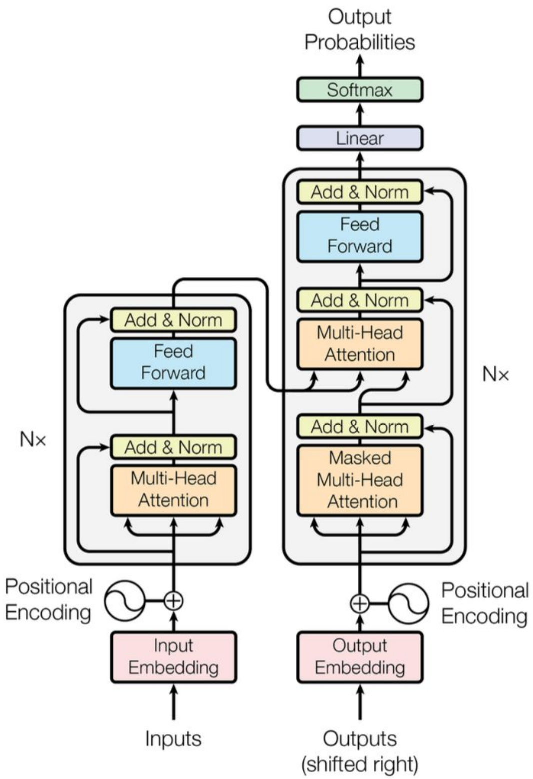


Figure 1: The Transformer - model architecture.

Image from https://www.searchunify.com/su/sudo-technical-blogs/demystifying-contextual-query-embedding/

Positional Encoding

- The cat likes to chase the mouse
  not equal to
  The mouse likes to chase the cat
- X = X + PE

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

Details: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Better: RoPE (LLaMa, Deepseek), ALiBi

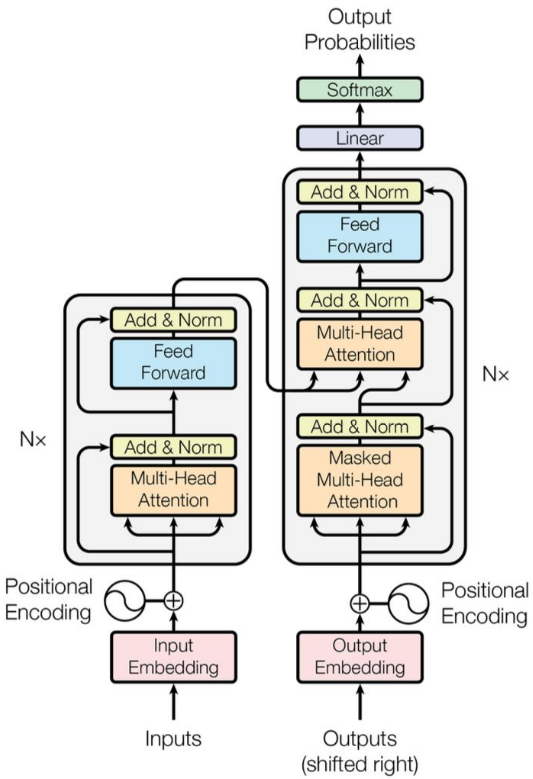
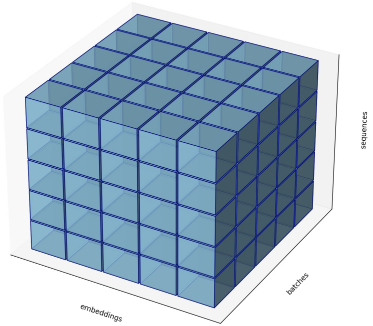


Figure 1: The Transformer - model architecture.

Data format. Scalability

Transformer accepts data as 3d matrix:

- Embeddings (fixed size)
- Sequences
- Batches (max load to GPU)



Uses matrix tricks inside.

https://www.calculator.net/matrix-calculator.html

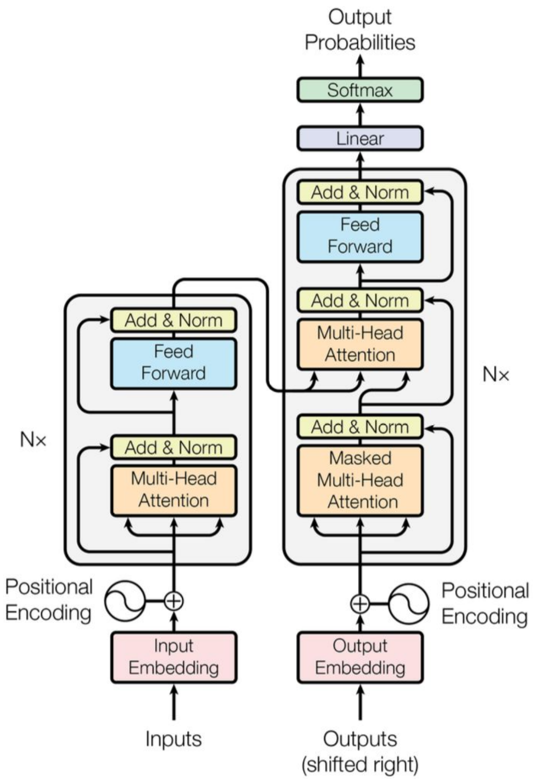


Figure 1: The Transformer - model architecture.

Add (= Residual Connection)

X = X + attention(X)

attention: embeddings see each other

and

X = X + ffn(X)

ffn: embeddings do not see each other

Residual function refers to the idea that instead of learning a direct mapping from input to output, the network learns the difference (or residual) between the input and the desired output.

Introduced in ResNet (2015, https://arxiv.org/pdf/1512.03385)

Deep Residual Learning for Image Recognition

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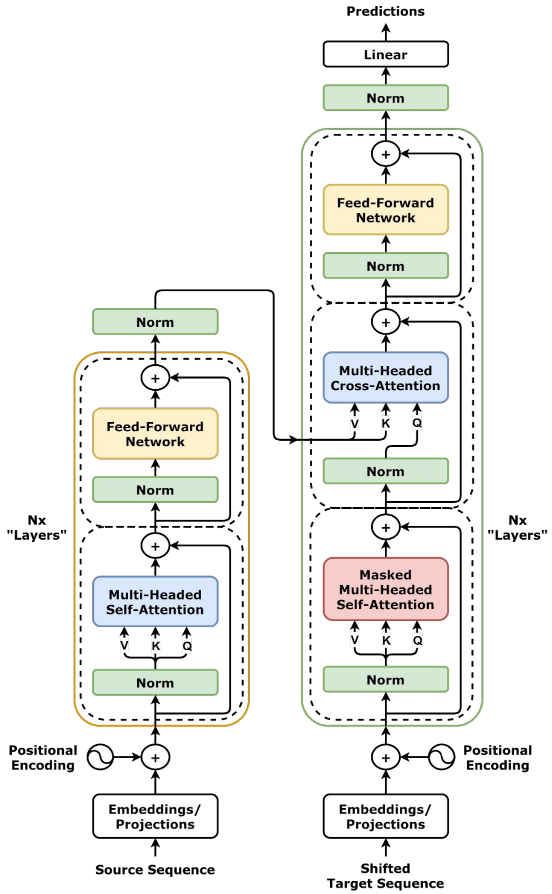


Scaled Dot-Product Attention (original name)

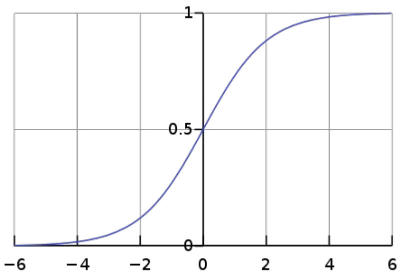
$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

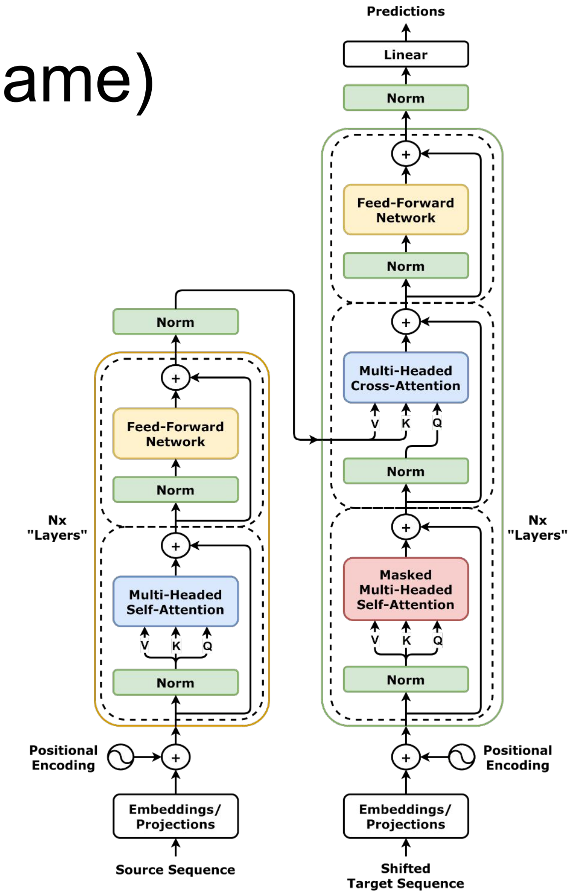
where Q = X*Wq, K = X*Wk, V = X*Wv

Wq, Wk, Wv - Learnable parameters

softmax:

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

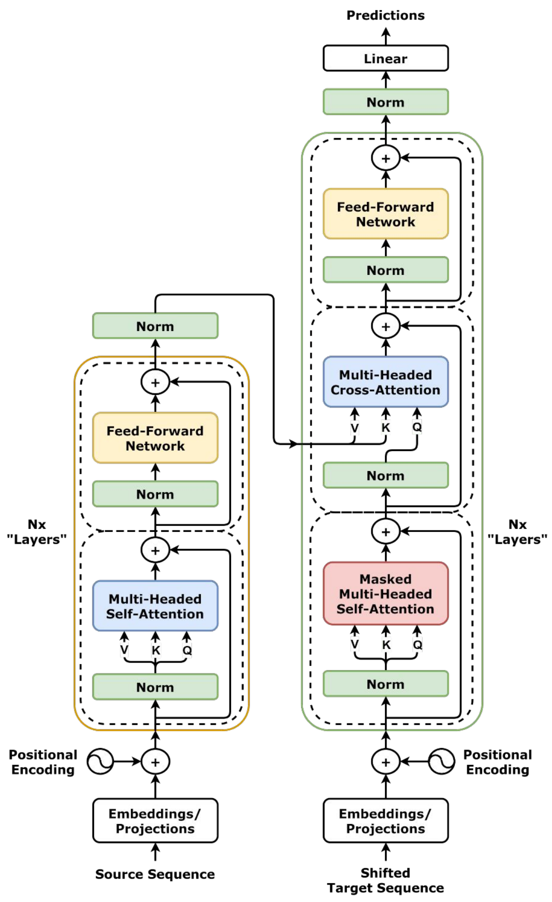




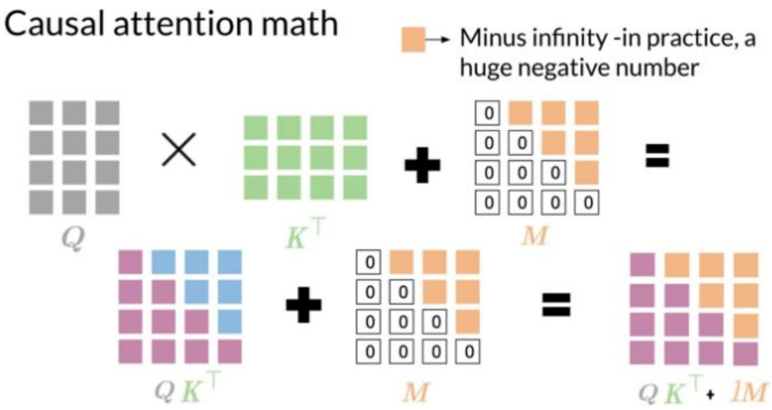
Multi-Head Attention

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

W° returns matrix back to embeddings dimension



Masked (Casual) Attention



For progressive learning:
The
The cat
The cat likes
The cat likes to

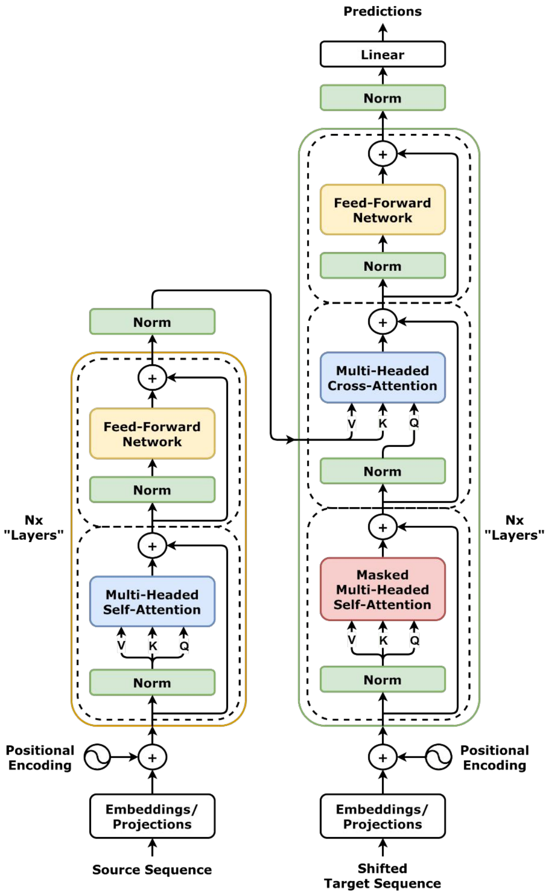


Image from https://blog.sailor.plus/deep-learning/attention/

Cross-Attention and Self-Attention

In Cross Attention decoder is calculating K and V from encoder sequence.

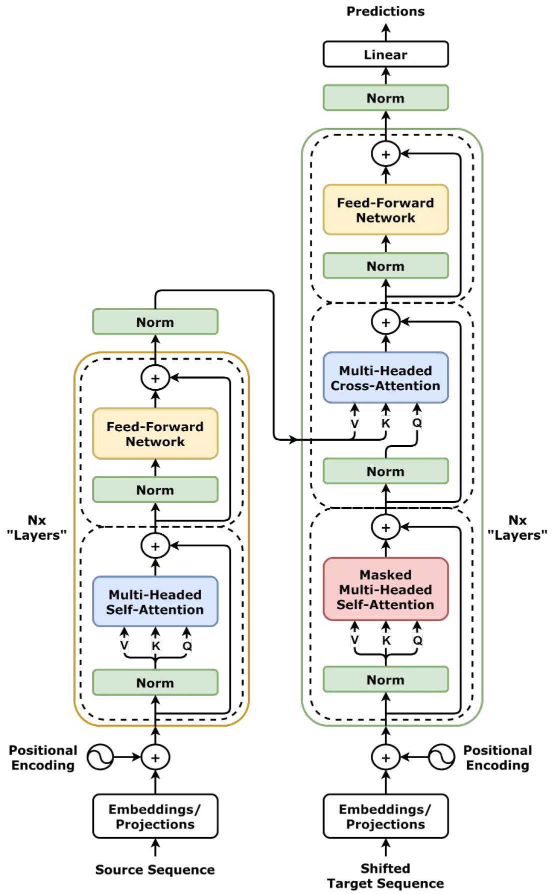
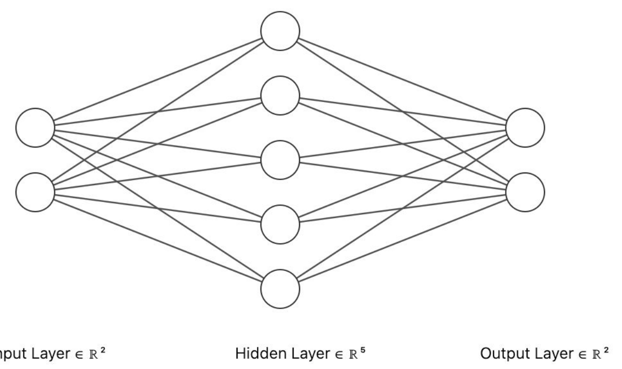


Image from Wikipedia

Feed-Forward Neural Network Theory

- Forward Propagation
- Weights and Biases (W and b)
- Activation Functions
  - ReLU, GeLU, tanh, sigmoid, …
- Loss Functions
  - measure how well predictions match the actual data
    - Mean Squared Error (MSE), Cross-Entropy, ...
- Backpropagation
- Learning Rate
- Dropout (2016, [Hinton paper](#))
  - prevents overfitting, neuron dying



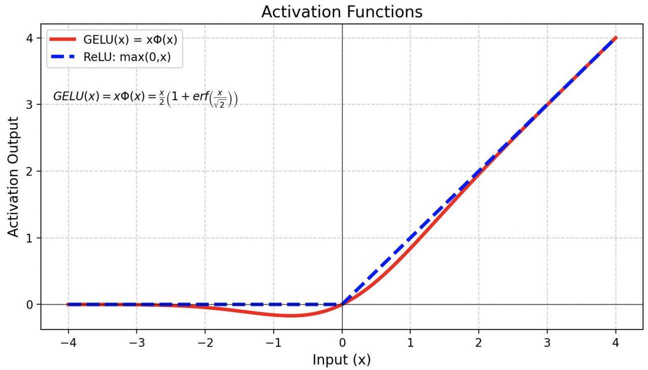
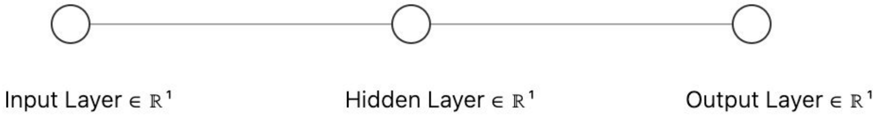


Image from https://alexlenail.me/NN-SVG/index.html

FNN in Transformer

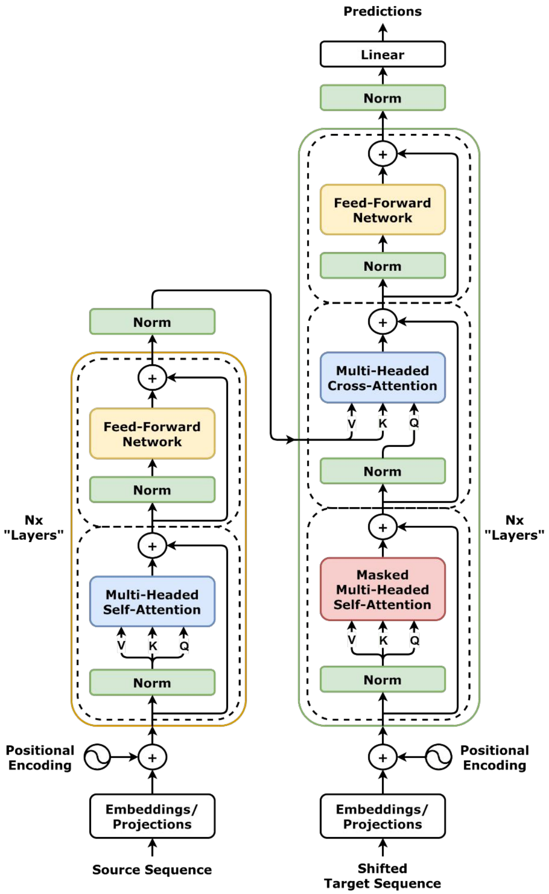
Minimalistic



$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

Uses matrix tricks inside.

https://www.calculator.net/matrix-calculator.html



Norm

X = layer_norm(X)

The key of layer norm is to normalize the input to the layer using the mean and standard deviation.

Layer norm plays two roles in neural networks:

- Projects the key vectors onto a hyperplane.
- Scales the key vectors to have the same length.

Paper: https://arxiv.org/abs/1607.06450 (2016)

Layer Normalization

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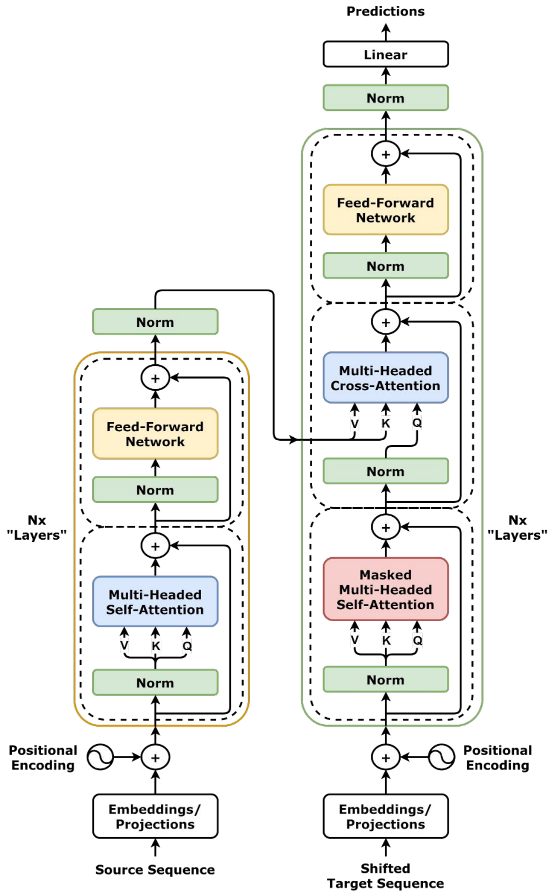


Inference

Or back to the next token (classification task)

Actions:

- logits = X * Head
  Head has the same dimension like vocabulary!
- softmax(last line in logits)
  Convert to probabilities
- argmax / multinomial (if inference)
  to find next index for embedding (forward) or
- cross entropy (if learning)
  and backpropogation

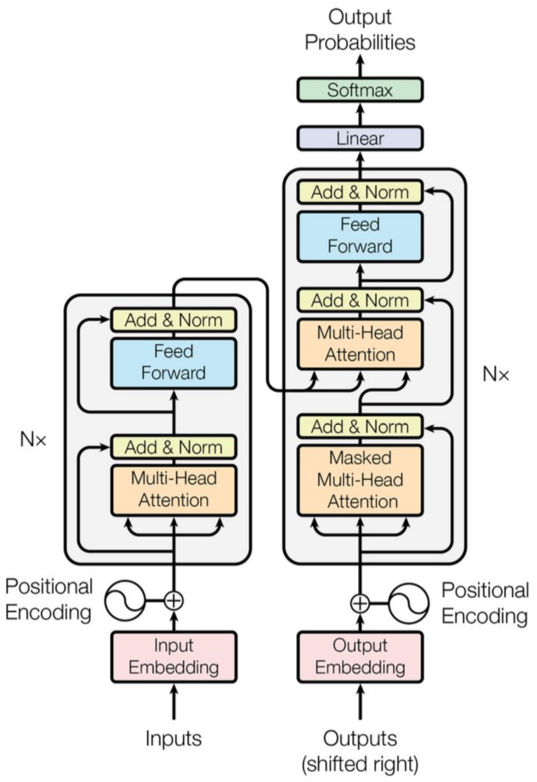
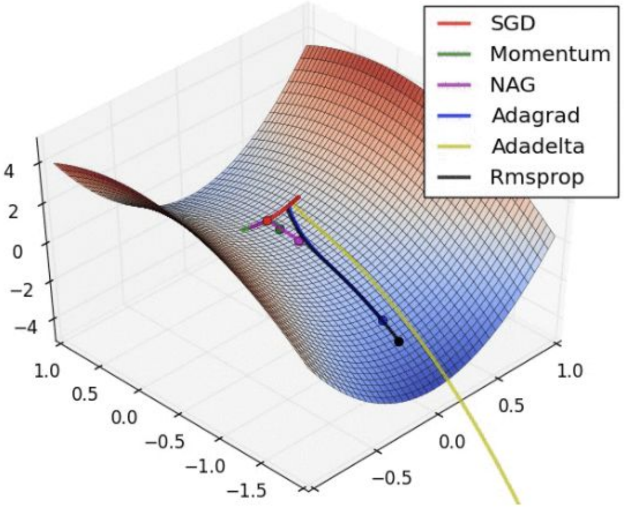


Figure 1: The Transformer - model architecture.

Deep Learning. Backprop.

Autograd ([automatic differentiation]) is a system that automatically computes gradients (derivatives) of tensors in machine learning frameworks like:

- TensorFlow (2015 by Google)
  - define-then-run (initially)
- PyTorch (2016 by Facebook)
  - Define-by-run



Letter | Published: 09 October 1986

Learning representations by back-propagating errors

David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams

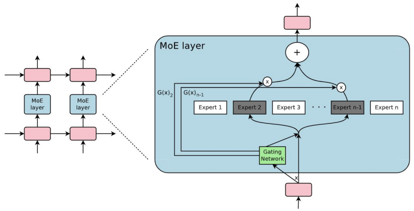
https://www.iro.umontreal.ca/~vincentp/ift3395/lectures/backprop_old.pdf

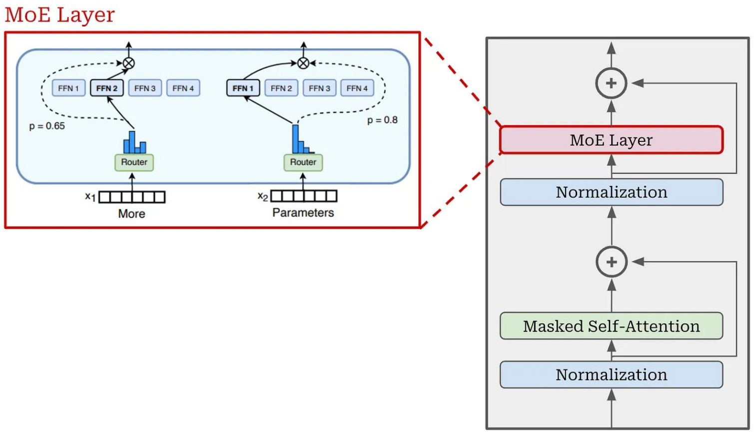
Image from https://arxiv.org/pdf/1609.04747

MoE - Mixture of Experts (GPT)

The concept of Mixture of Experts (MoE) was first introduced in 1991 by Robert Jacobs and *Geoffrey Hinton* in the Adaptive Mixtures of Local Experts

https://arxiv.org/pdf/1701.06538 (2018, Hinton)





Used in DeepSeek, Mixtral, etc

Image from https://cameronrwolfe.substack.com/p/nano-moe

Demo. Q&A

Code and presentaion available at

https://github.com/hza/askGPT