Attention is All You Need

overview of the transformer architecture, applications and established improvements

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Learning Goals

- Gain familiarity with the transformer architecture and understand how it works
- Understand Tokens and Embeddings
- Comprehend how Attention works
- Become aware of common compression techniques
- Recognize limitations

Key Takeaway: Transformers can be powerful, it might be worth trying to use them.

Ask if you have questions
or anything is unclear

Overview

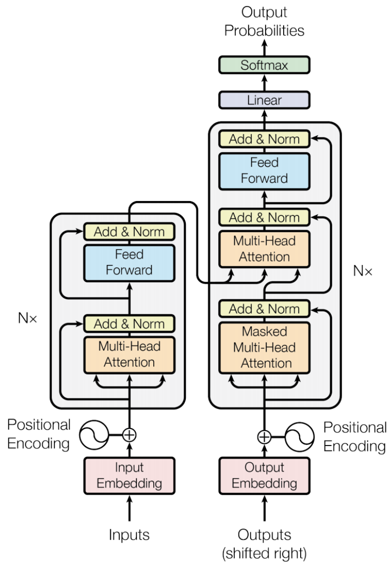


Image Source: [1]

Background

Multi-Layer Perceptron

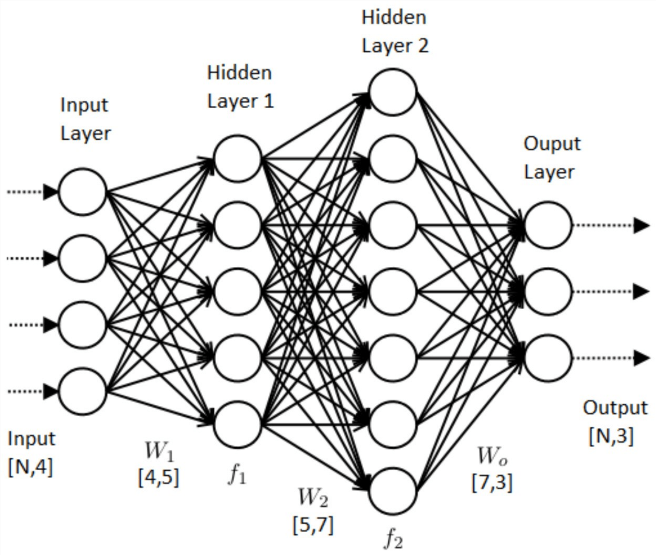


Image Source: Public Domain

Background

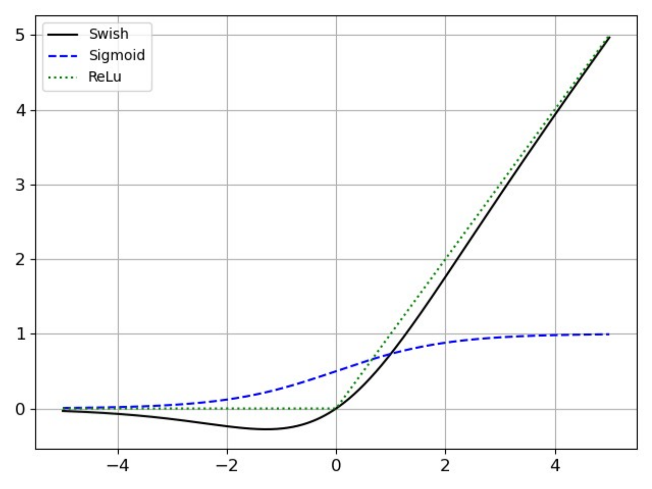
Multi-Layer Perceptron

Activation Functions

Missing Connections

Going Deeper

Common Activation Functions



$swish(x) := x * sigmoid(x)$

Image Source: [2] SwiGLU introduced by [3]

Background

Problem: neural network training results in highly specialized feature adaptations (overfitting)

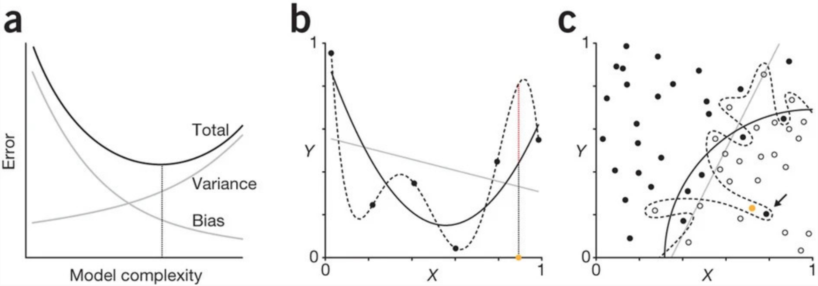


Image Source: [4]

Dropout II

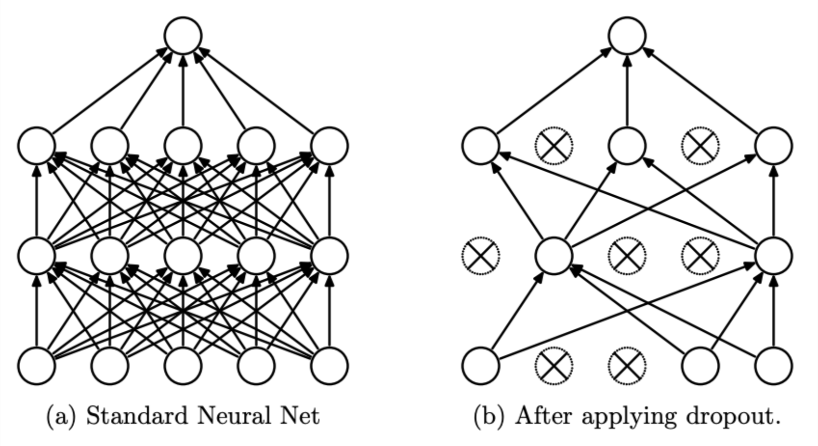


Image Source: [5]

Background

Residual Connections

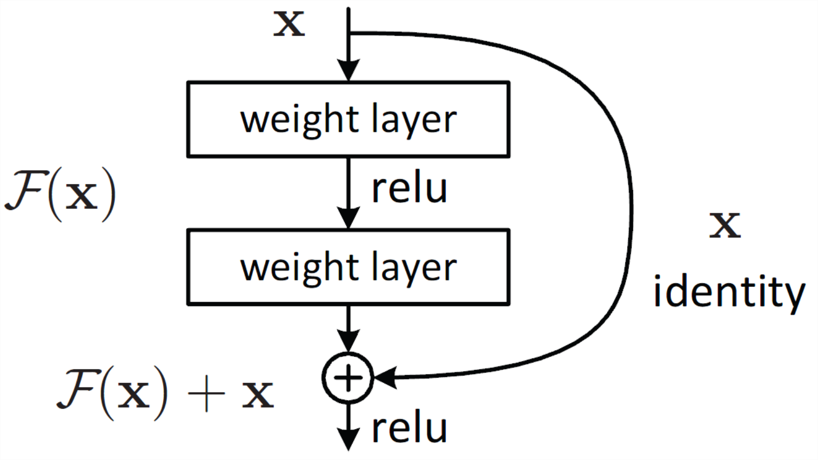


Image Source: [6]

Embedding

We are here

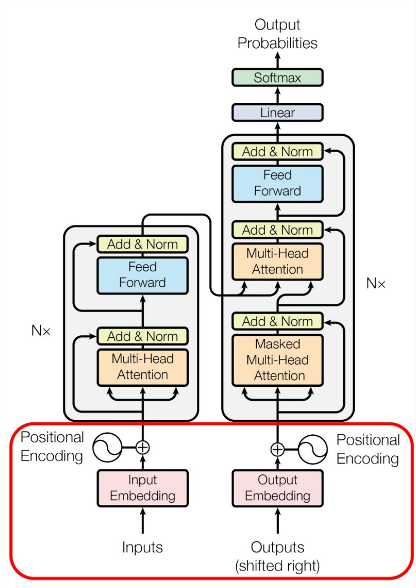


Image Adapted from [1]

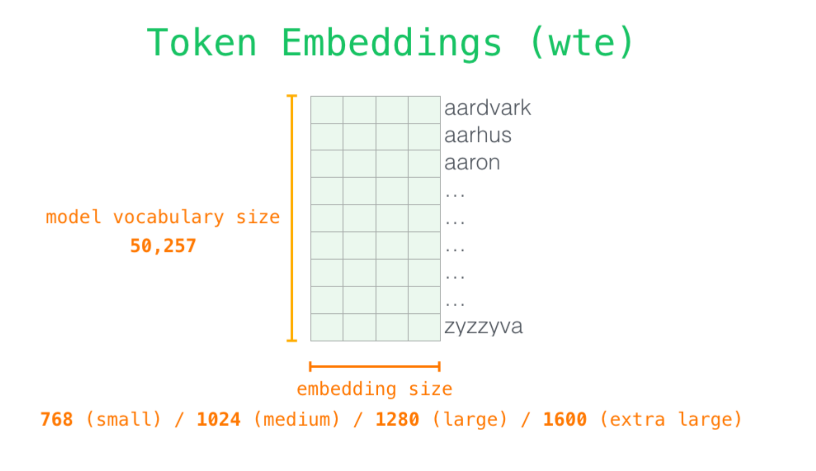
Definitions

- **Vocabulary:** List of tokens available to the tokenizer, that can be recognized and generated
- **Tokenizer:** Split the input apart using the available tokens in vocabulary
- **Embedding:** Internal high-dimensional representation of given set of tokens (learned)

The Vocabulary / Tokens are commonly learned via Byte Pair Encoding (BPE) [7].

Embedding

Input Embedding



Exemplary token to embedding encoding in GPT2.

Image Source: [8]

In Code

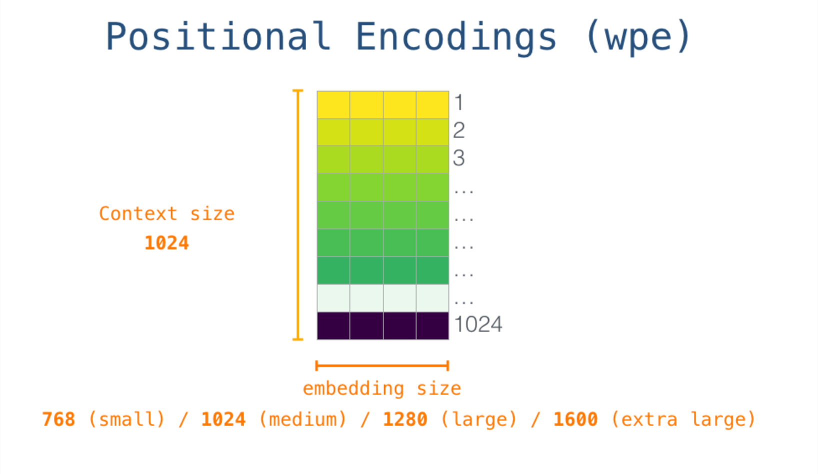
```
>>> ids = encoder.encode("Not all heroes wear capes.")
>>> ids
[3673, 477, 10281, 5806, 1451, 274, 13]

>>> encoder.decode(ids)
"Not all heroes wear capes."

>>> [encoder.decode([i]) for i in ids]
['Not', ' all', ' heroes', ' wear', ' cap', 'es', '.']
```

Embedding

Positional Encoding



Exemplary positional encoding in GPT2.

Image Source: [8]

Positional Encoding II

Visualization of a sinusoidal position encoding for the first 128 positions in 512 dimensions.

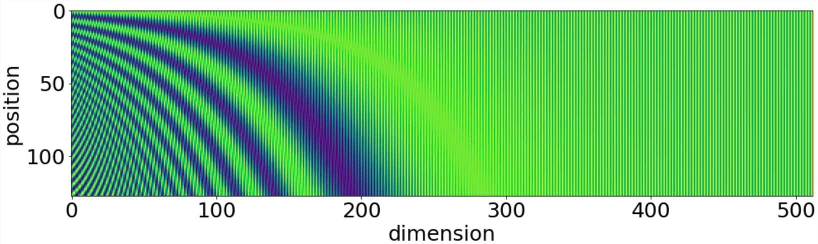


Image source: Public Domain

RoPE: Rotary Positional Encoding

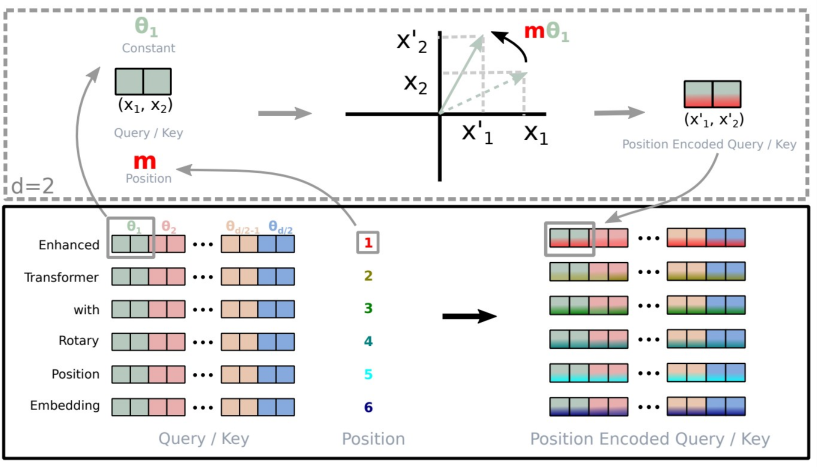


Image Source: [9]

Embedding

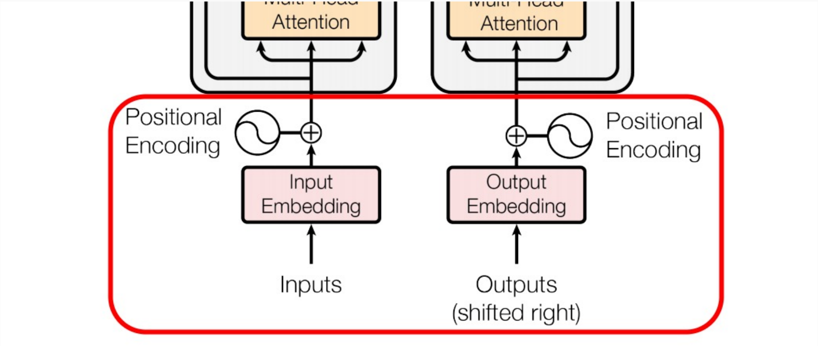
Overview

Input Embedding

Positional Encoding

Full Input Embedding

Full Input Embedding



Simple Addition. Works well due to sparse high dimensional spaces.

Image Adapted from [1]

Attention in Transformer

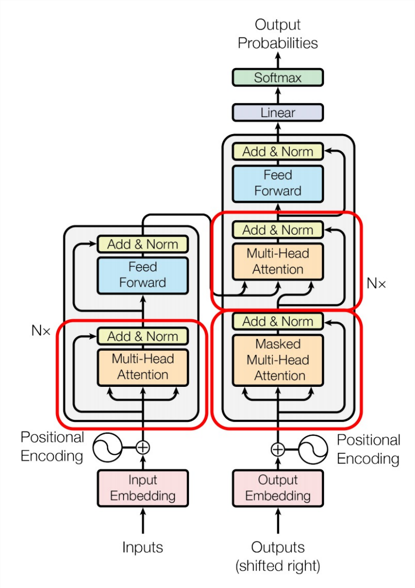


Image Adapted from [1]

Attention

Basic Attention

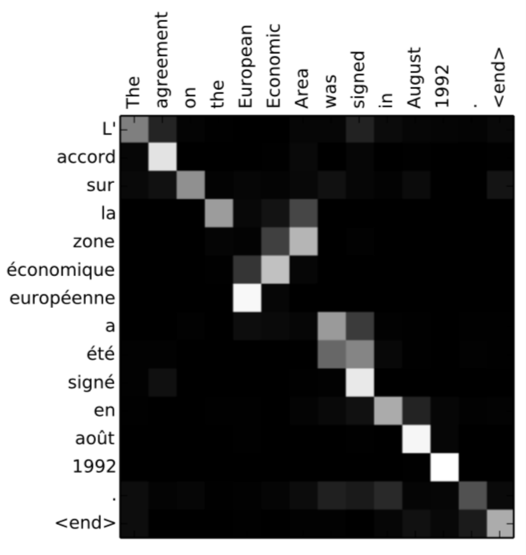


Image Source: [10]

Attention Mechanism

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

where

$Q = W_Q x, K = W_K x, V = W_V x,$ and d_k query-size

for self-attention and

$$Q = W_Q x, K = W_K y, V = W_V y$$

for encoder-decoder cross-attention

Scaled Dot-Product Attention

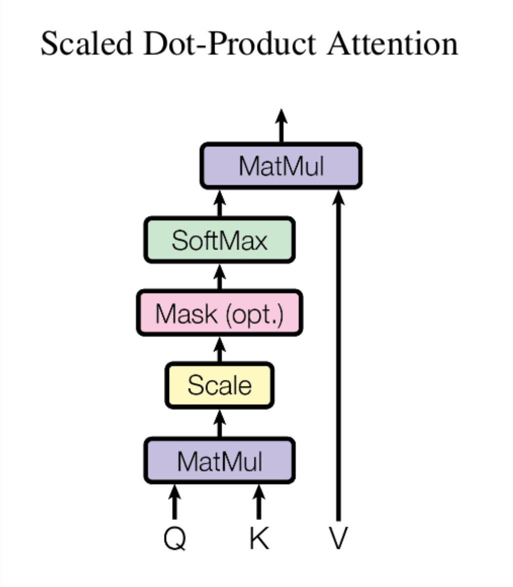


Image Source: [1]

Attention

Basic Attention

Multi-Head Attention

Masked Attention

Multi-Head Attention

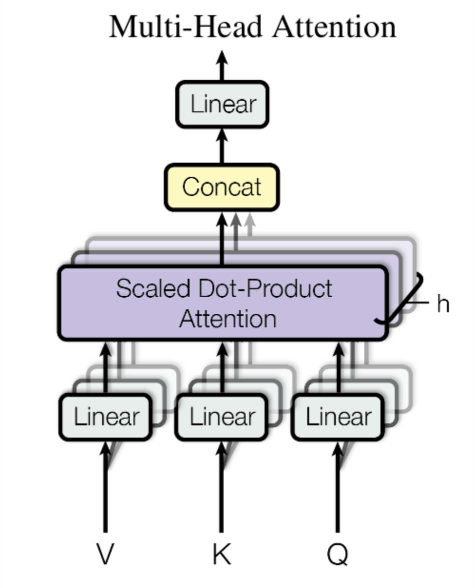


Image Source: [1]

Attention

Basic Attention

Multi-Head Attention

Masked Attention

Masked Attention

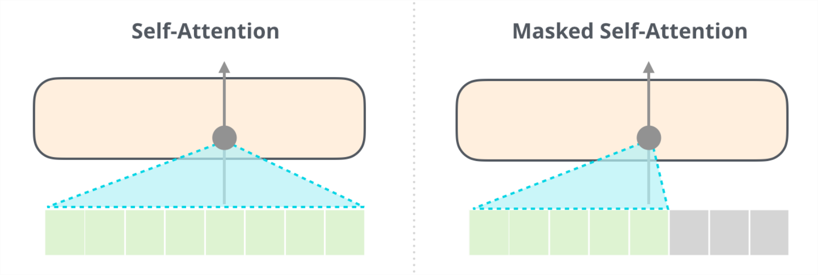
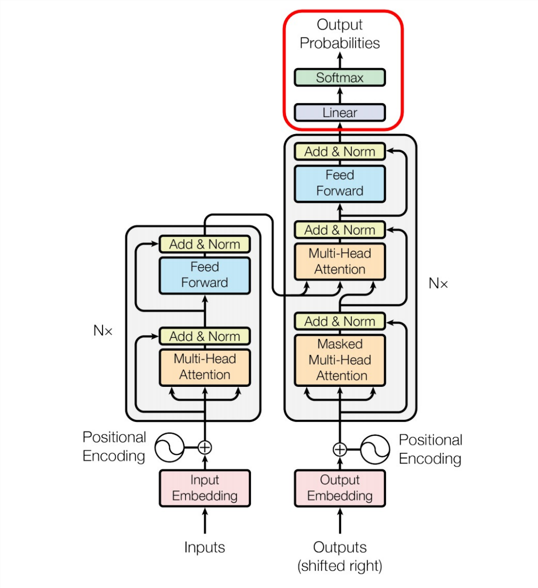


Image Source: [8]

Transformer

Output


Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

Parameters

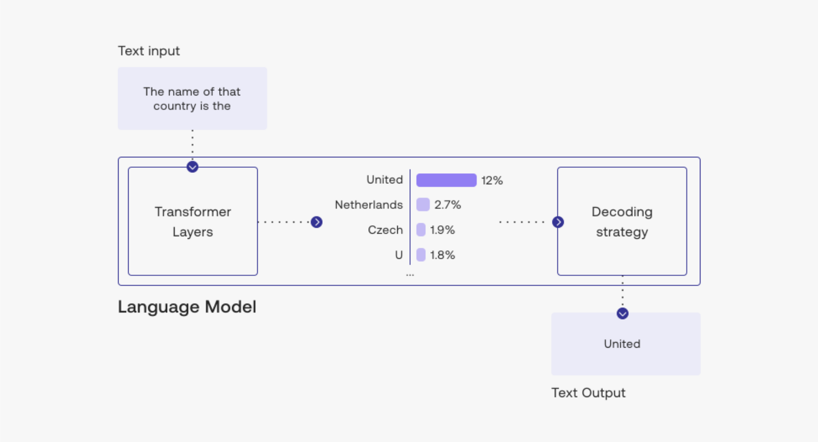


Image Source: [11]

Temperature, Top-k and Top-p

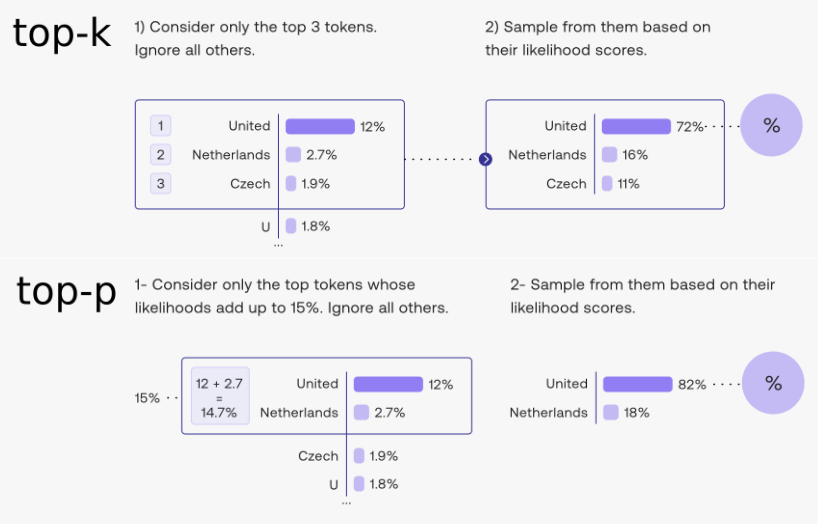


Image Source: [11]

Transformer

Dimensions

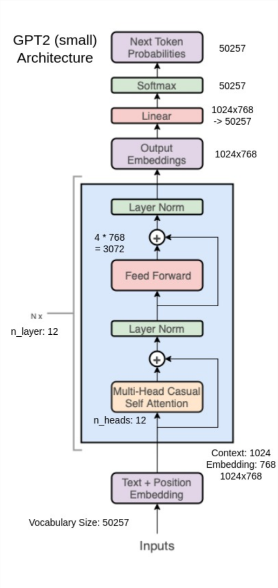


Image Adapted from: [12]

Dimensions II

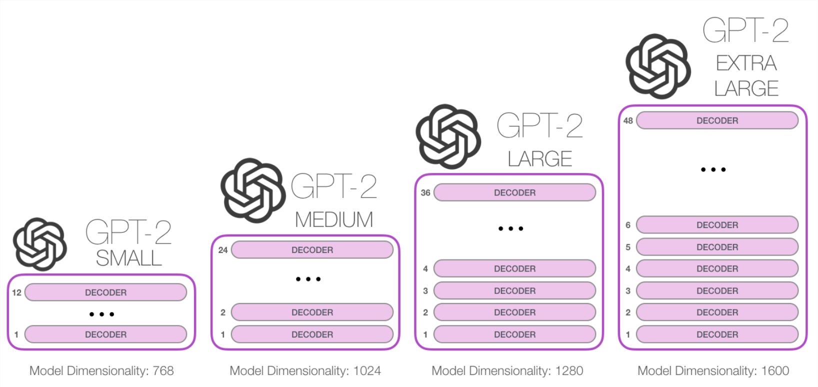


Image Source: [8]

Transformer

Full Architecture

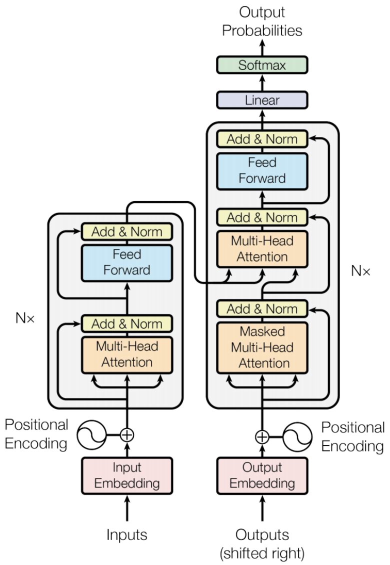


Image Source: [1]

Transformer

Output

Dimensions

Putting it all Together

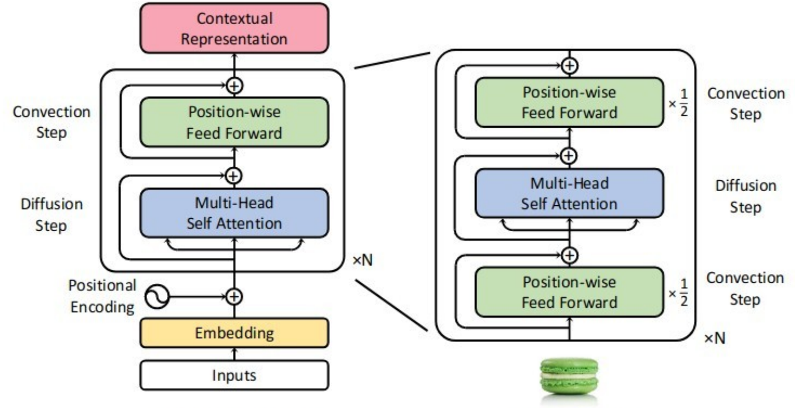
Interpretation

Architecture Improvements

One Prevalent Interpretation: Solving ODEs

'... the Transformer can be mathematically interpreted as a *numerical Ordinary Differential Equation (ODE) solver for a convection-diffusion equation in a multi-particle dynamic system.*' Lu et al., 2019 [13]

A Better ODE Solver



(a) Original Transformer (b) Macaron Layers

For solving, use a Strang-Marchuk Splitting scheme instead of Lie-Trotter

Image Source: [13] For details on solving methods see [14]

As High-Order Nonlinearity

'However, we find only a weak consistency exists between the attention weights of features and their importance. We verify the feature map multiplication that brings about **high-order non-linearity into CNNs is crucial for the effectiveness** *of attention mechanism.'* Ye et al. 2023, Towards ... [15]

In-Context Optimization

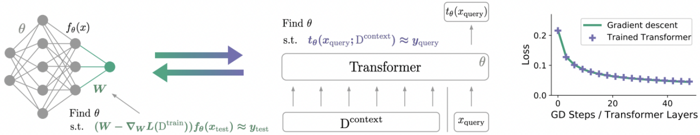


Figure 1: **Illustration of our hypothesis: gradient-based optimization and attention-based in-context learning are equivalent.** *Left*: Learning a neural network output layer by gradient descent on a dataset $\mathrm{D}^{\text{train}}$. The task-shared meta-parameters θ are obtained by meta-learning with the common goal that after adjusting the neural network output layer, the model generalizes well on unseen data. *Center*: Illustration of a Transformer that adjusts its query prediction on the data given in-context i.e. $t_\theta(x_{\text{query}}; \mathrm{D}^{\text{context}})$. The weights of the Transformer are optimized to predict the next token y_{query}. *Right*: Our results confirm the hypothesis that learning with K gradient descent steps matches trained Transformers with K linear self-attention layers.

Image Source: [16]

> *'... training Transformers ... can be closely related to well-known gradient-based meta-learning formulations.'* Transformers Learn In-Context [16]

Transformer

Sparse Transformer: $O(n\sqrt{n})$ instead of $O(n^2)$

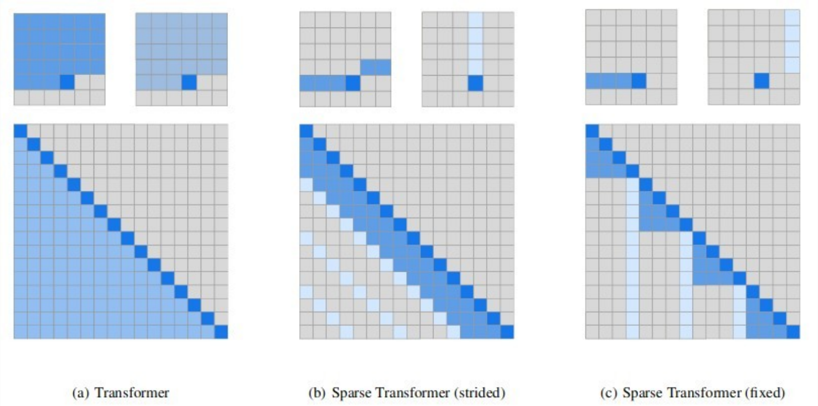


Image Source: [17]

FlashAttention

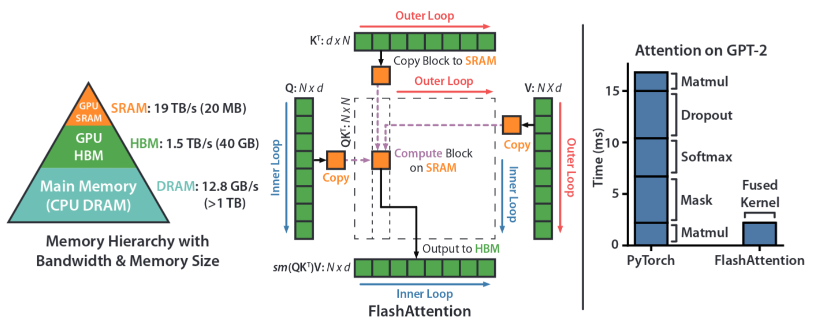


Image Source: [18]

FlashAttention Benchmarks

Attention	Standard	FlashAttention	Ratio
GFLOPs	66.6	75.2	0.89
HBM R/W	40.3	4.4	9.16
Runtime (ms)	41.7	7.3	5.71

Table from [18]

Compression

Quantization

Distillation

Rank Reduction

Quantization

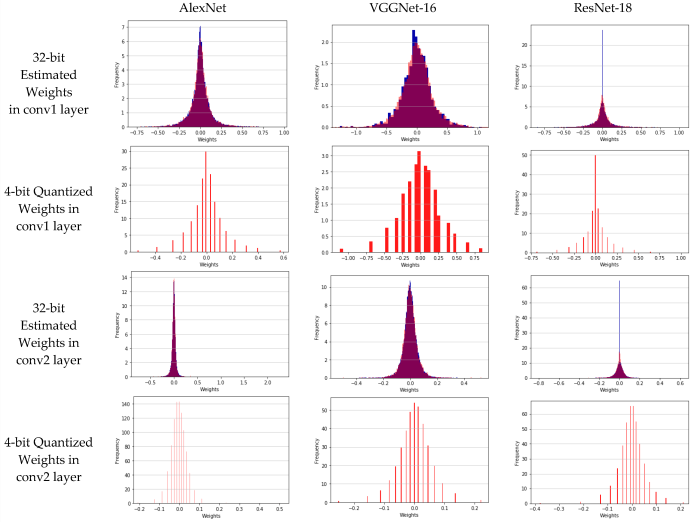


Image Source: [19] Current SOTA is GPTQ [20]

Compression

Quantization

Distillation

Rank Reduction

Knowledge Distillation

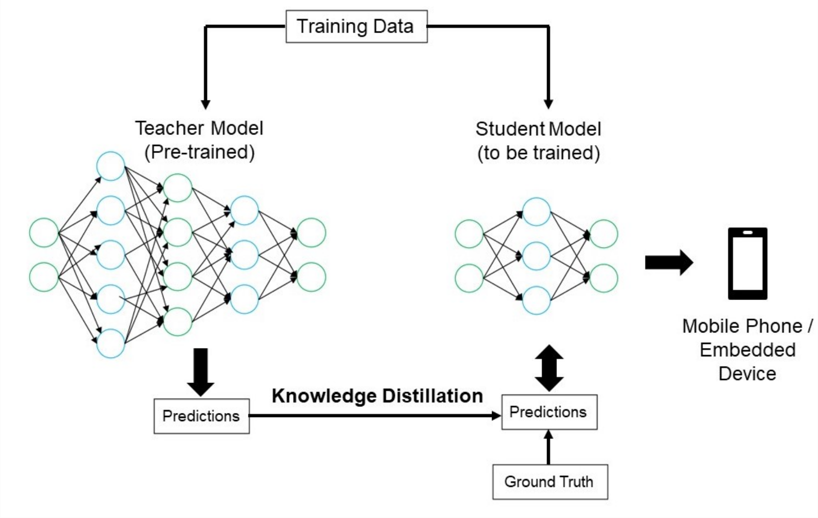
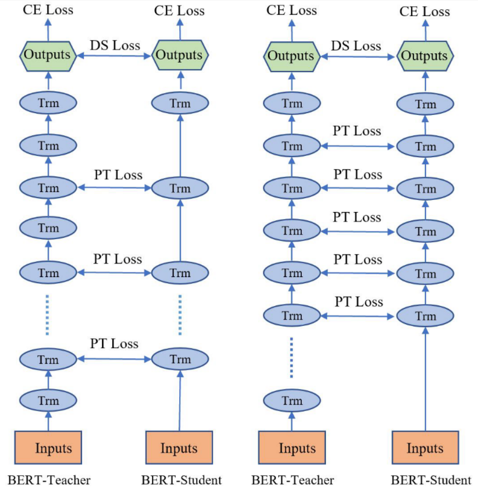


Image Source: [21]

Patient Knowledge Distillation



(a) PKD-*Skip* (b) PKD-*Last*

Distillation compression is often 2-80x with inference speedups of 1.5-10x while keeping $1 - \epsilon$ accuracy (often 97%)

Image Source: [22]

Compression

- Quantization
- Distillation
- **Rank Reduction**

LoRA: Low-Rank Adaptation

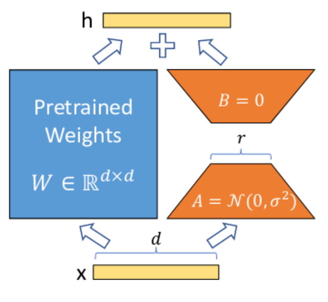


Figure 1: Our reparametrization. We only train A and B.

Image Source: [23]

'LoRA can reduce the number of trainable parameters by 10,000 times and the GPU memory requirement by 3 times ... despite having ... no additional inference latency.'

LoRA [23]

Honorable Mentions

- Transformer-XL [24]: Attentive Language Models beyond a Fixed-Length Context
- Compressive Transformer [25]: Long-Range Sequence Modelling by Compressing Past Memories
- Memorizing Transformer [26]: kNN-augmented attention layer, can reduce parameter count 5x while keeping perplexity
- Adaptive Attention Span [27]: varying attention distances
- Reflexion [28]: Asking the model if the answer is correct

Successes

- BERT
- GPT
- CLIP
- Latent Diffusion Models
- Reinforcement Learning
- Physics Simulation

BERT: Bidirectional Encoder Representations

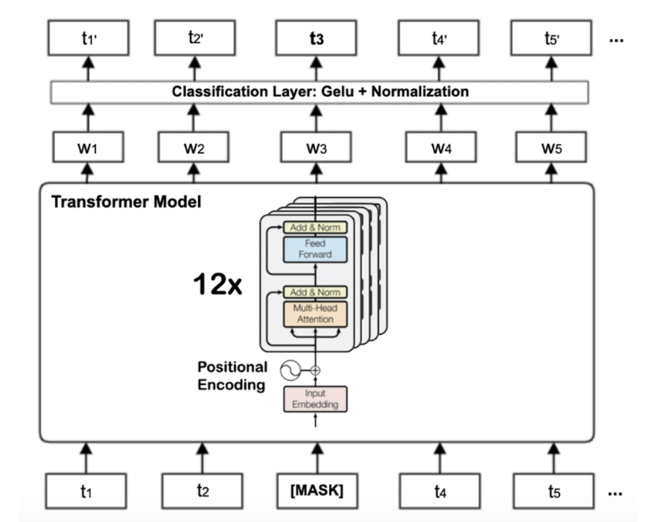


Image Source: [29] Original BERT [30]

Successes

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GPT: Pure Decoder Architecture

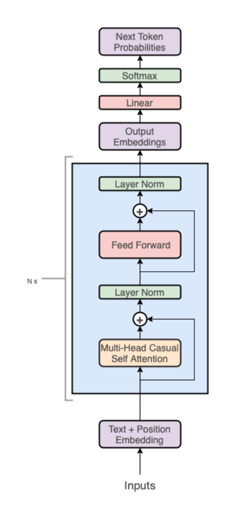

Image Source: [12]

Examples:

- GPT [31]
- GPT2 [32]
- GPT3? [33]
- GPT4? [34]
- LlaMa [35]
- Bloom [36]
- OPT [37]
- PaLM [38]

Successes

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- GPT
- CLIP
- Latent Diffusion Models
- Reinforcement Learning
- Physics Simulation

CLIP: Multimodal Embedding Spaces

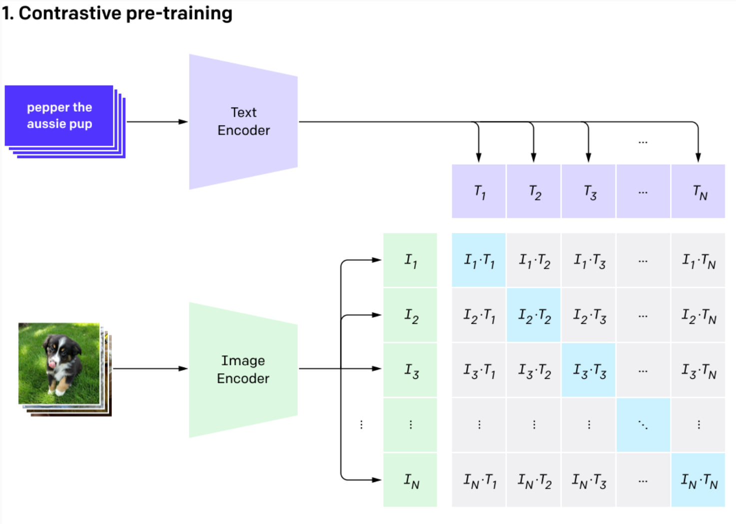

Image Source: [39]

Successes

- BERT
- GPT
- CLIP
- **Latent Diffusion Models**
- Reinforcement Learning
- Physics Simulation

Latent Diffusion Models

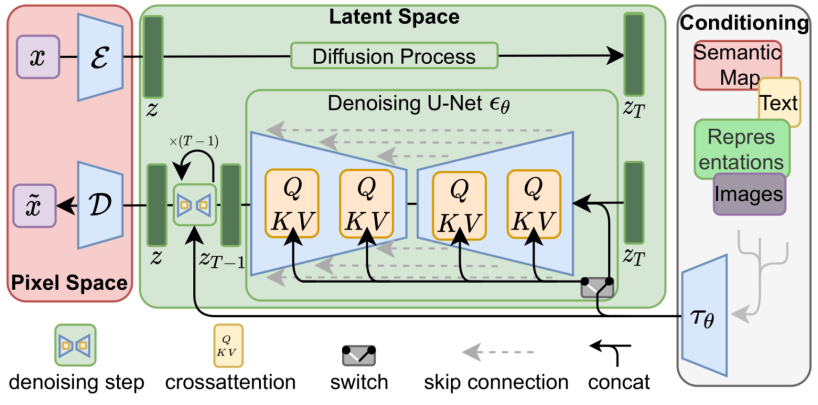

Image Source: [40]

Successes

- BERT
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- CLIP
- Latent Diffusion Models
- **Reinforcement Learning**
- Physics Simulation

GATO: A Generalist Agent

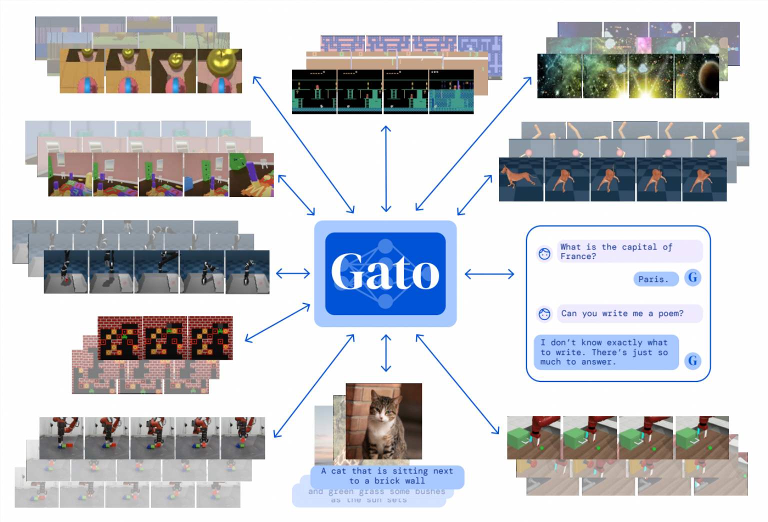

Image Source: [41]

Successes

- BERT
- GPT
- CLIP
- Latent Diffusion Models
- Reinforcement Learning
- **Physics Simulation**

Physics Simulation in Latent Spaces

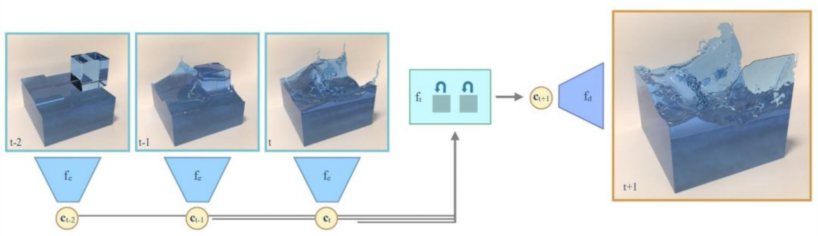

Image Source: [42]

> *'... we arrive at a data-driven solver that yields practical speed-ups, and at its core is more than 150x faster than a regular pressure solver.'* Latent Space Physics [42]

Limitations

- Hallucination: Output could be plain wrong
- Spatial Reasoning: Difficult from text alone
- Planning beyond the next step

A list of failures: [43]

Overview

Background

Embedding

Attention

Transformer

Compression

Successes

Limitations

Recap

Recap: Learning Goals

- Gain familiarity with the transformer architecture and understand how it works
- Understand Tokens and Embeddings
- Comprehend how Attention works
- Become aware of common compression techniques
- Recognize limitations

Key Takeaway: Transformers can be powerful, it might be worth trying to use them.

What are your Questions?

Sources i

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End

Thesis content

- Using a large language model
- (planned: OPT [37], but currently using LlaMa [35])
- Fine-tuning it for data extraction tasks on a specialized domain
- (probably trying a LoRA-version for that [23])
- If time permits, see how much I can reduce model size by Compression