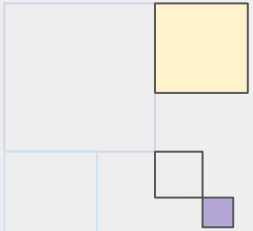
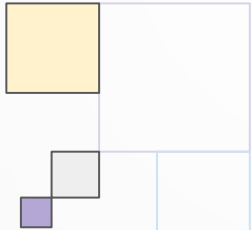
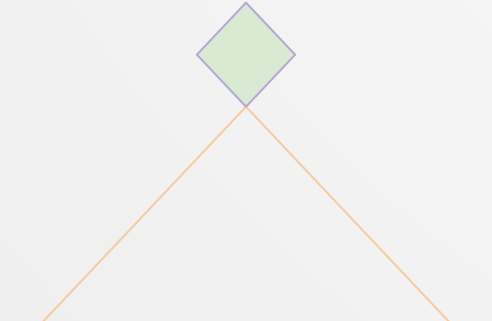




Deep Learning

Language Modelling



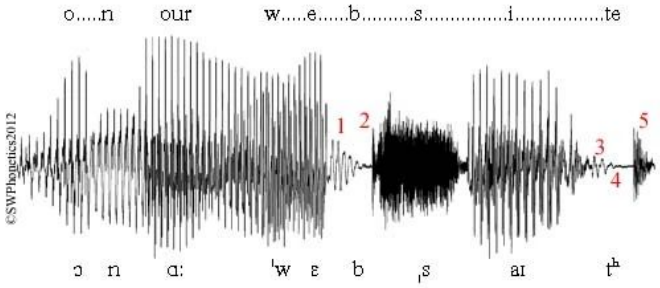
Bryan Cardenas
Caspar van Leeuwen
Monica Rotulo
Robert Jan Schlimbach

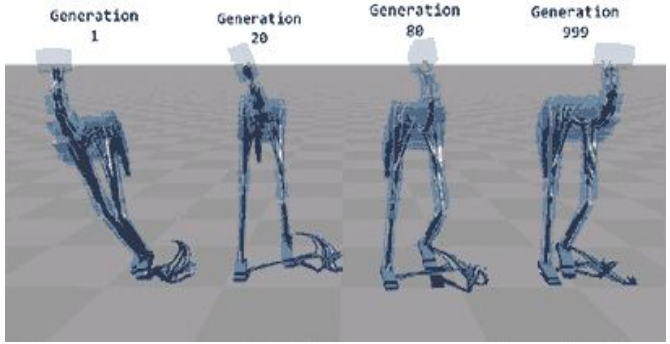
SURF

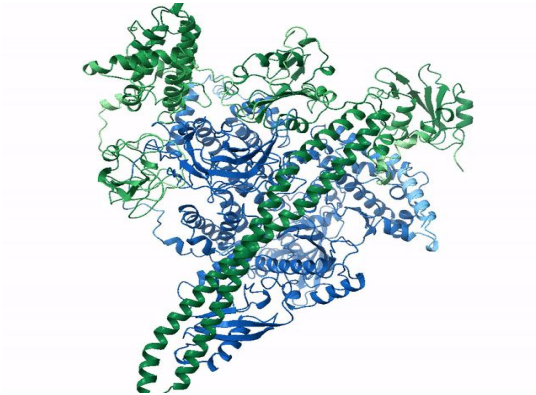
Sequential Data

Universe seems to be inherently sequential

We follow the arrow of time (no entropy reversals)



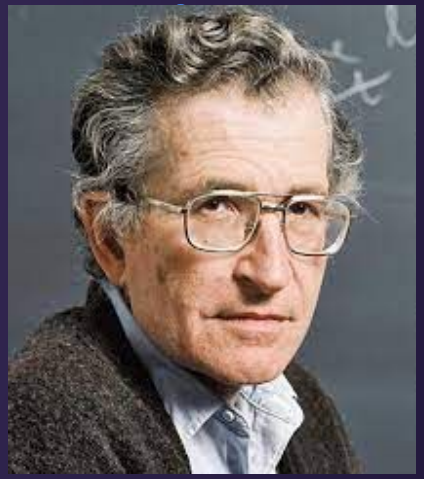




How Can we model this?

Is there one (sequential) model to rule them all?

Is modeling language difficult?



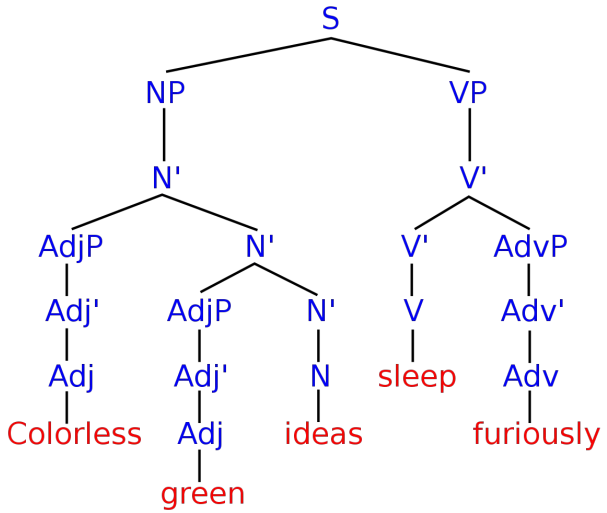
> Language is a process of free creation; its laws and principles are **fixed**, but the manner in which the principles of generation are used is free and **infinitely varied.**
>
> ~ Noam Chomsky

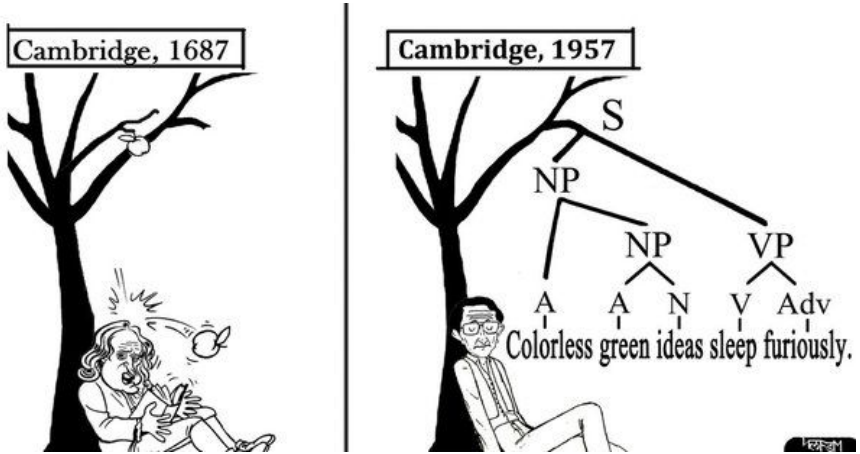
Sequential Data

Natural Language Modelling

Syntactic Structures

(**Chomsky**, N. 1957)





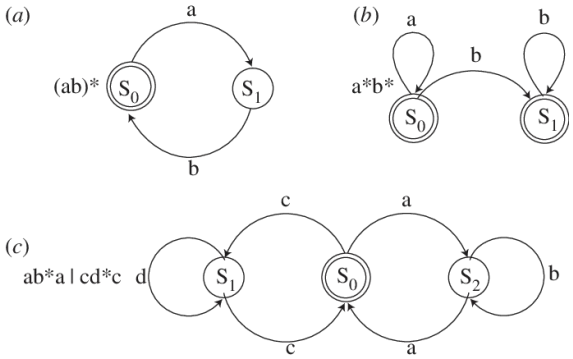
Sequential Data

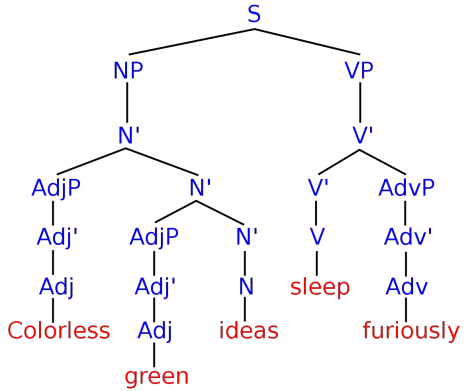
Natural Language Modelling

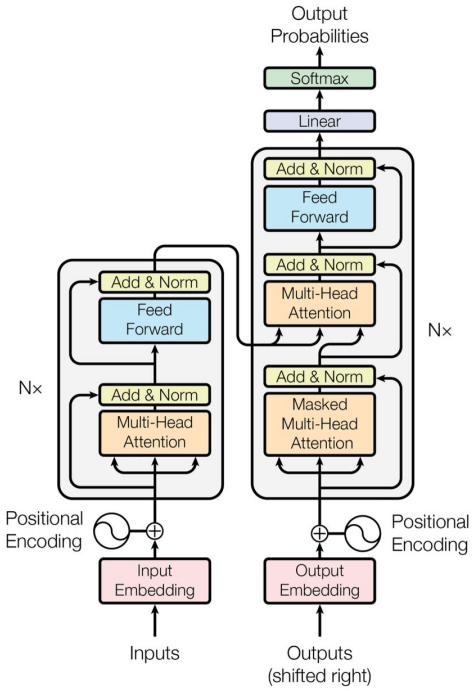
We have the innate ability for language (Universal Grammar)

Different ways to model language

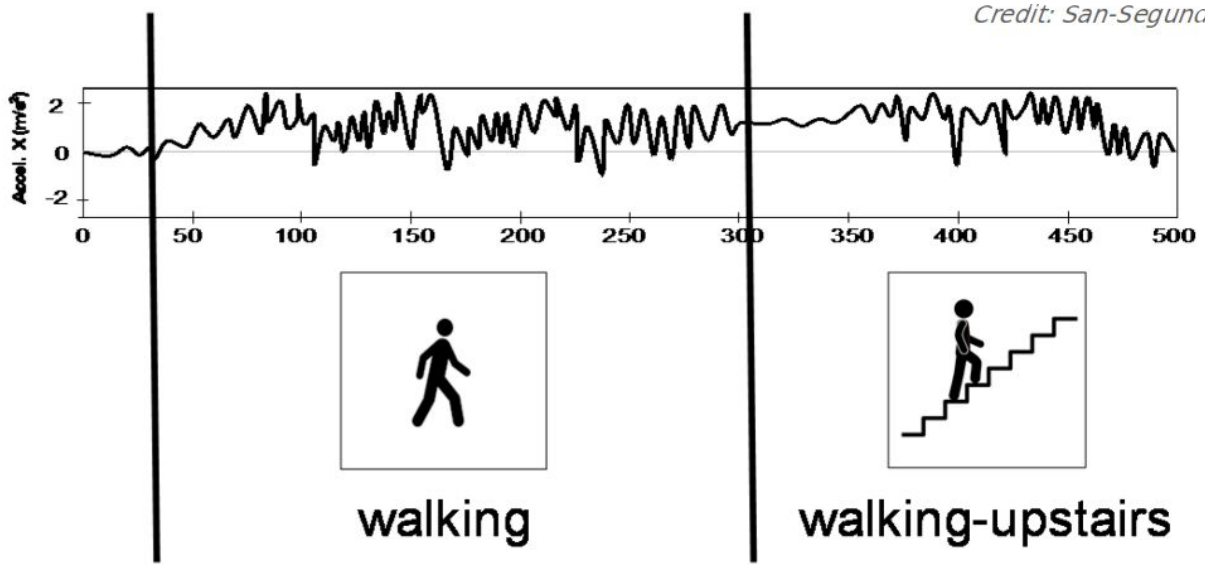
1. Finite State Automata
2. Generative Grammars
3. Deep Learning + Data







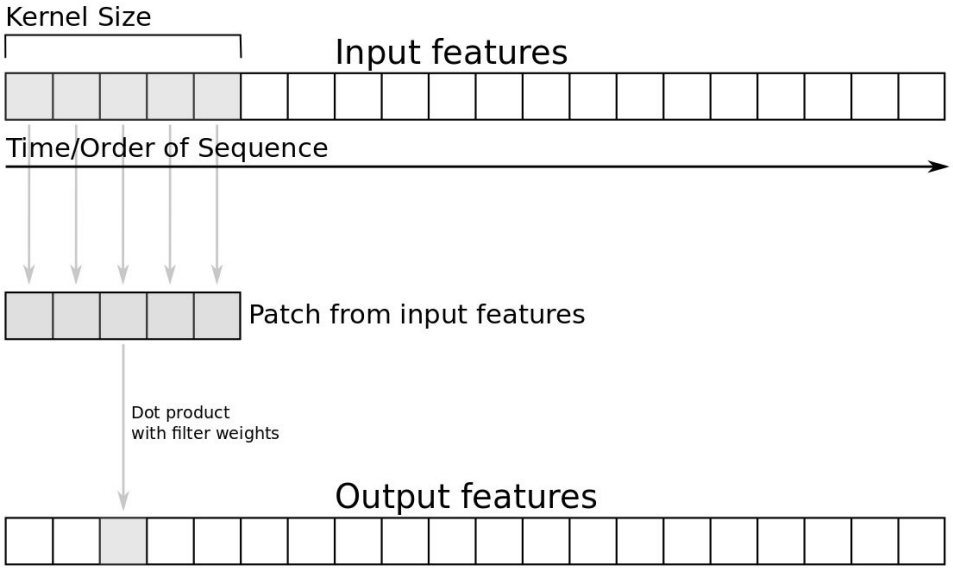
Human Activity Recognition



Human Activity Recognition

CNNs work here because they take into account **nearby** tokens

Use a CNN!



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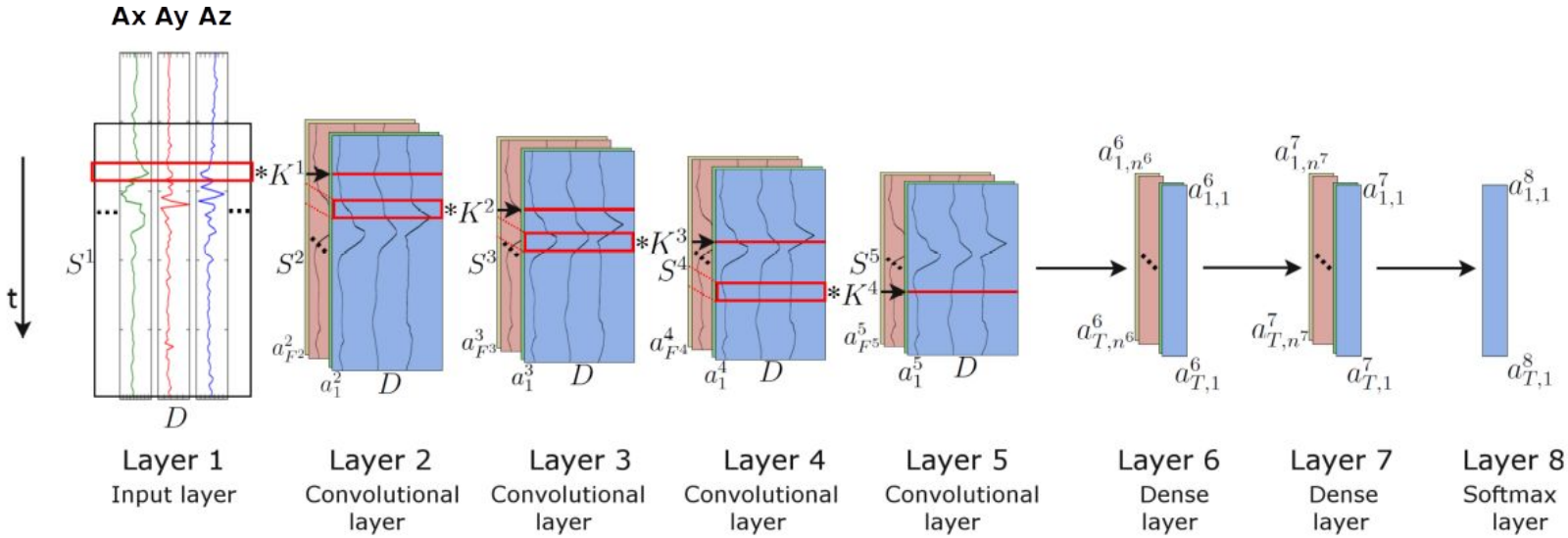

How to model Language?

$$P(w_1, w_2, \ \ldots \ w_n) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_1, w_2) \ \ldots \ P(w_n \mid w_1, \ \ldots \ w_{n-1})$$

LM objective:

Model the probability of the next word given the previous context

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SURF

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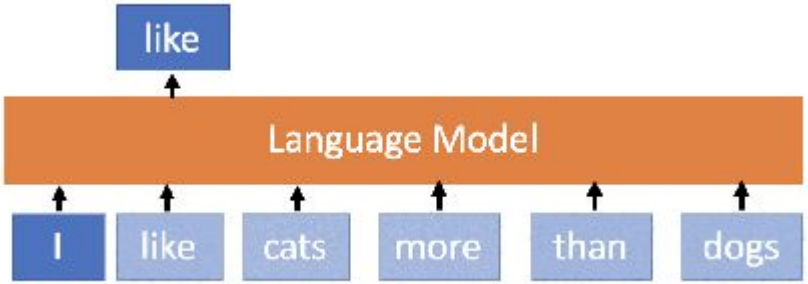

The cat

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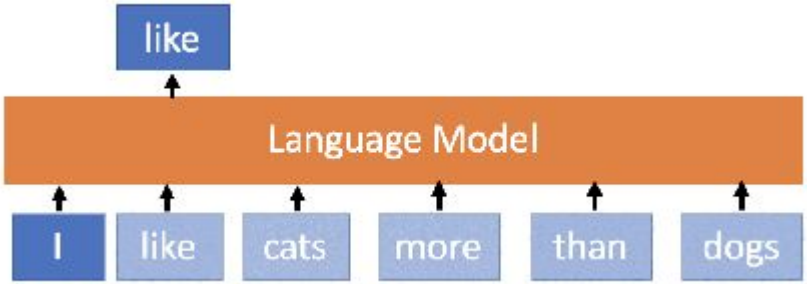
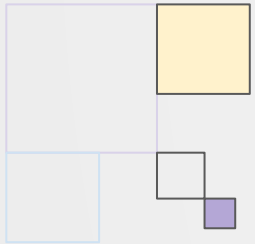


The cat

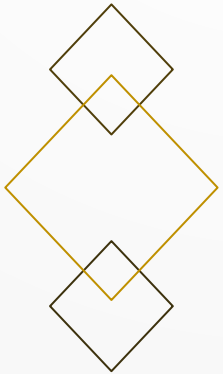
CNN's context size is too small and does **not *remember*** past context

How to even represent language as a continuous signal?

Language is very noise and heavily (long-distance) context dependent



The Transformer



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Transformers

Get rid of Recurrent Neural Networks

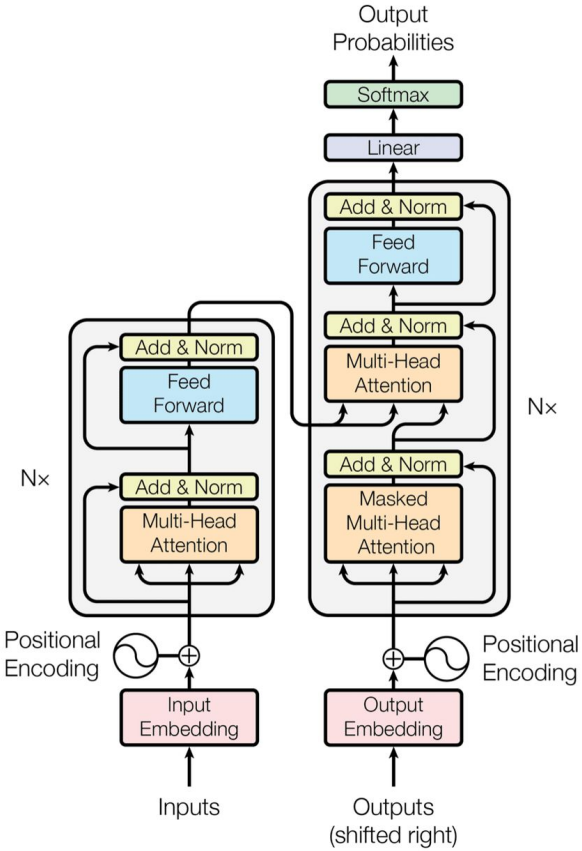
Instead of keeping one hidden state, **keep track of multiple**

What is the **importance** of every element in the input sequence with respect to it**self?**

Every word connected to every other word

More parallelization!

Self Attention



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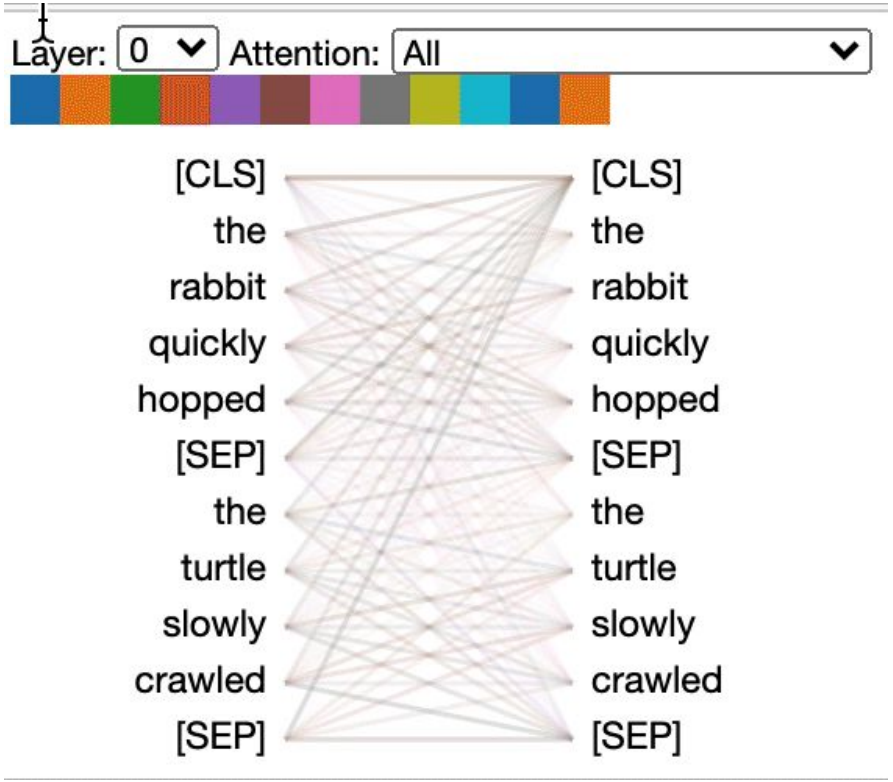
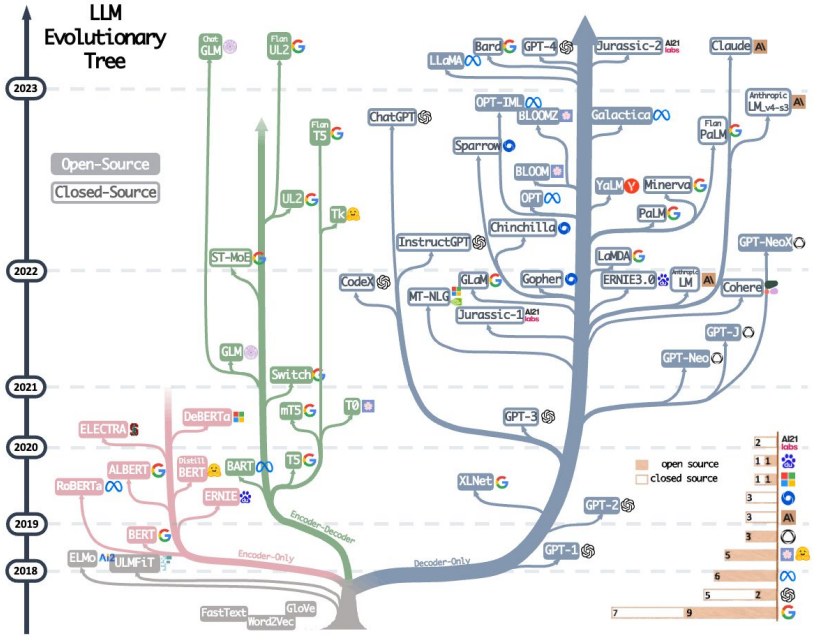
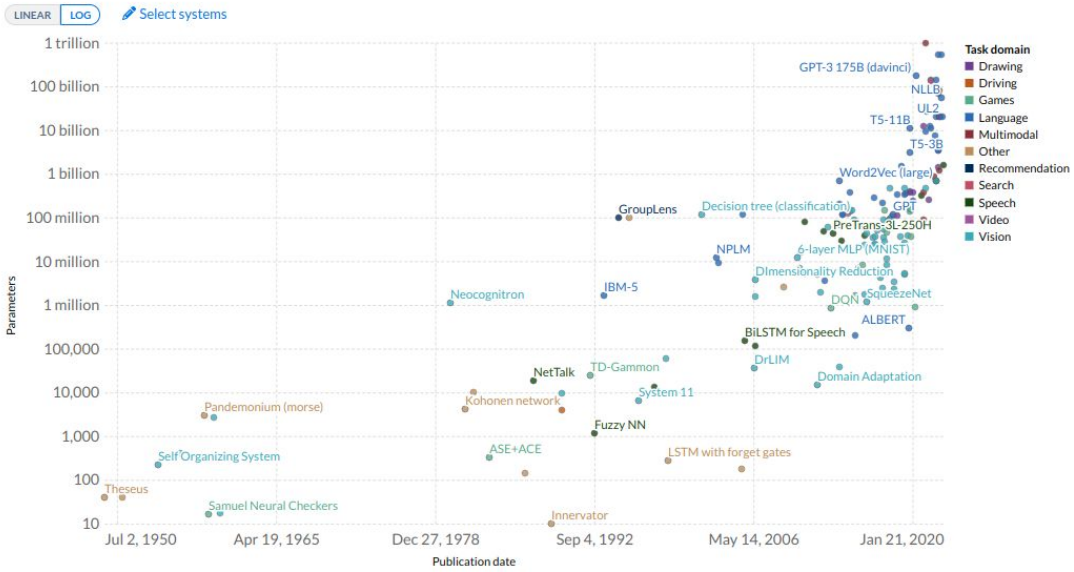
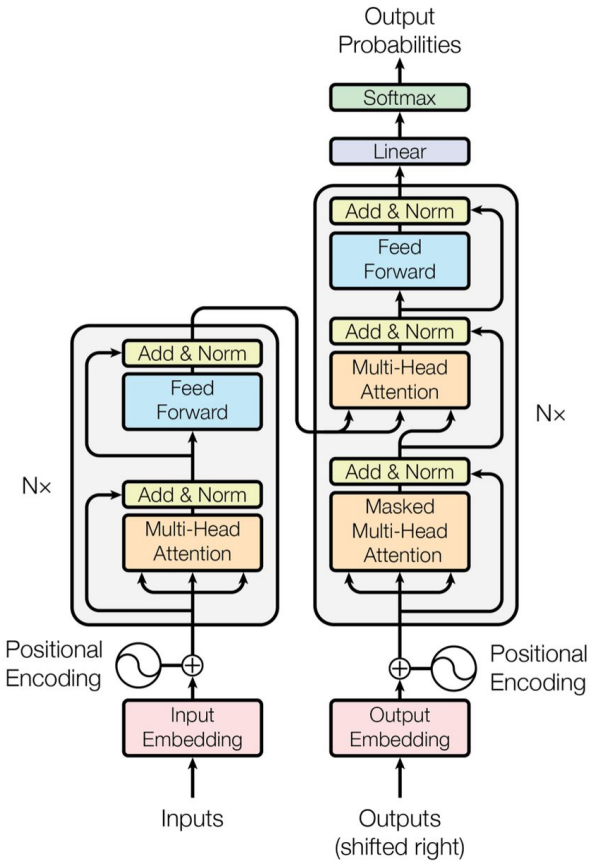


Cambrian Explosion of LMs

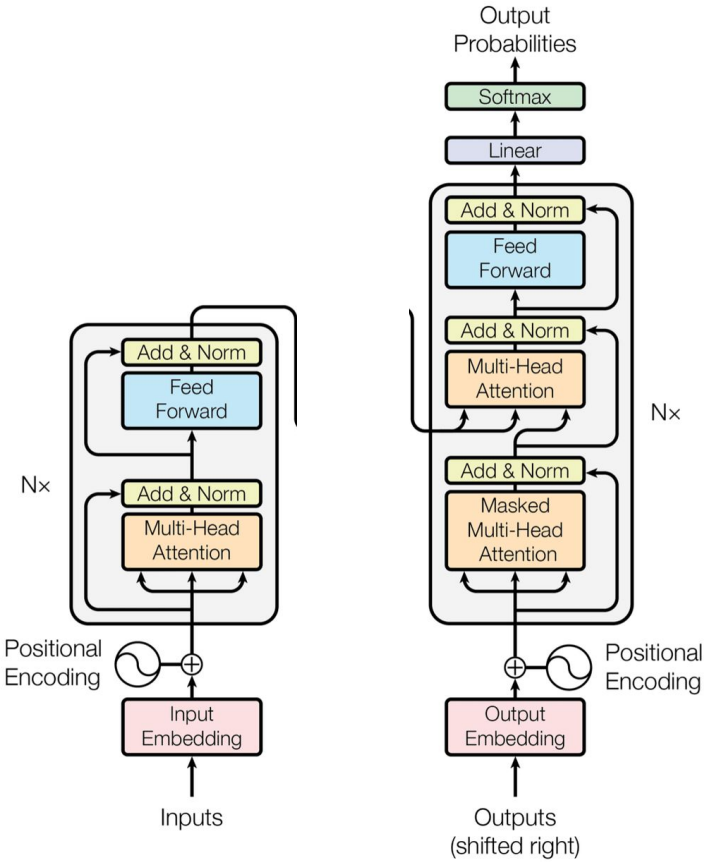




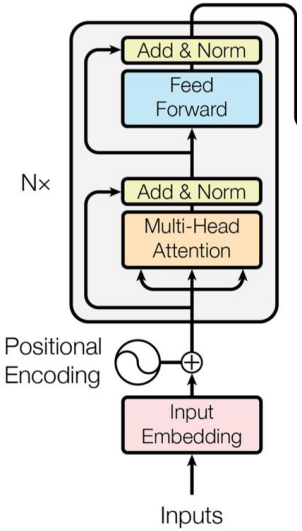
Dissection of the Transformer

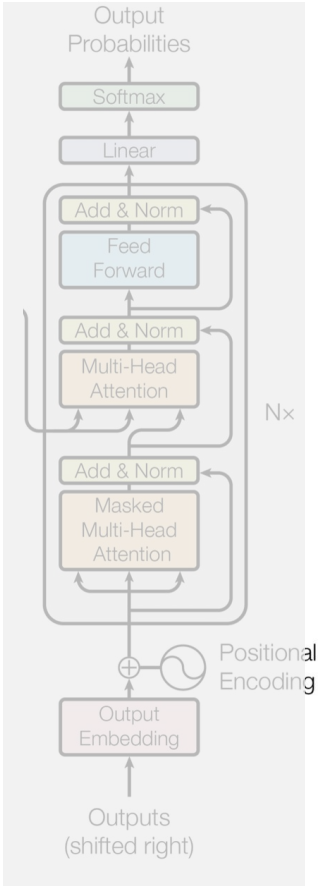


Dissection of the Transformer



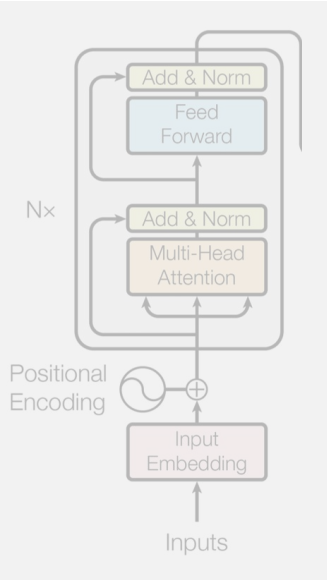
Dissection of the Transformer

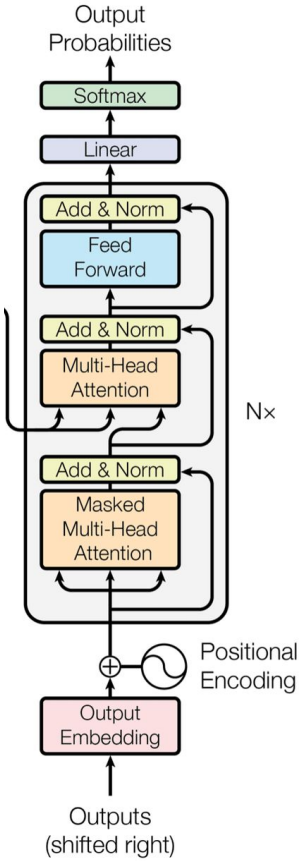




01. The Encoder

Dissection of the Transformer

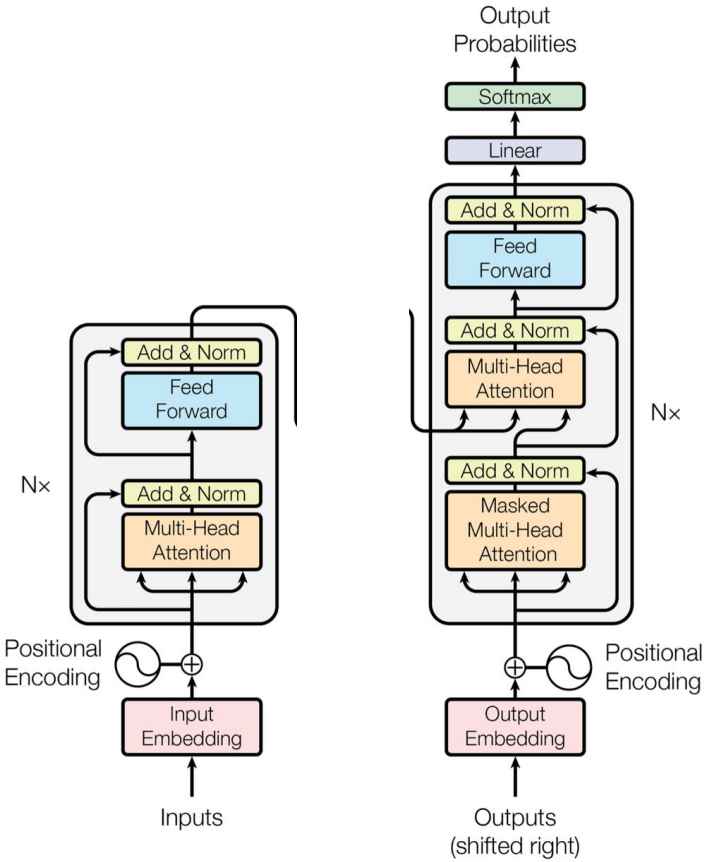




01. The Encoder

02. The Decoder

Dissection of the Transformer



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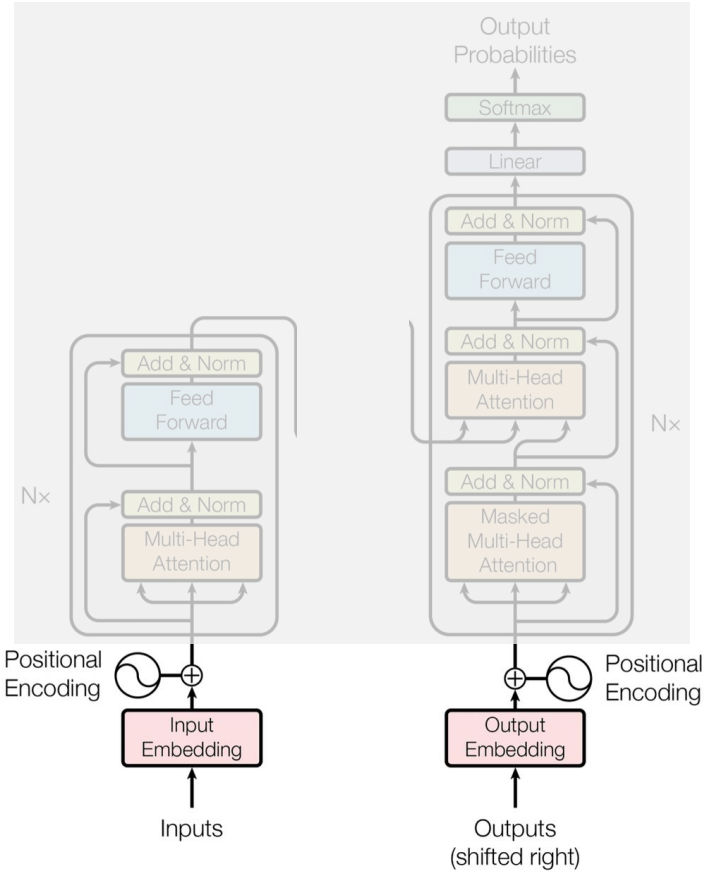
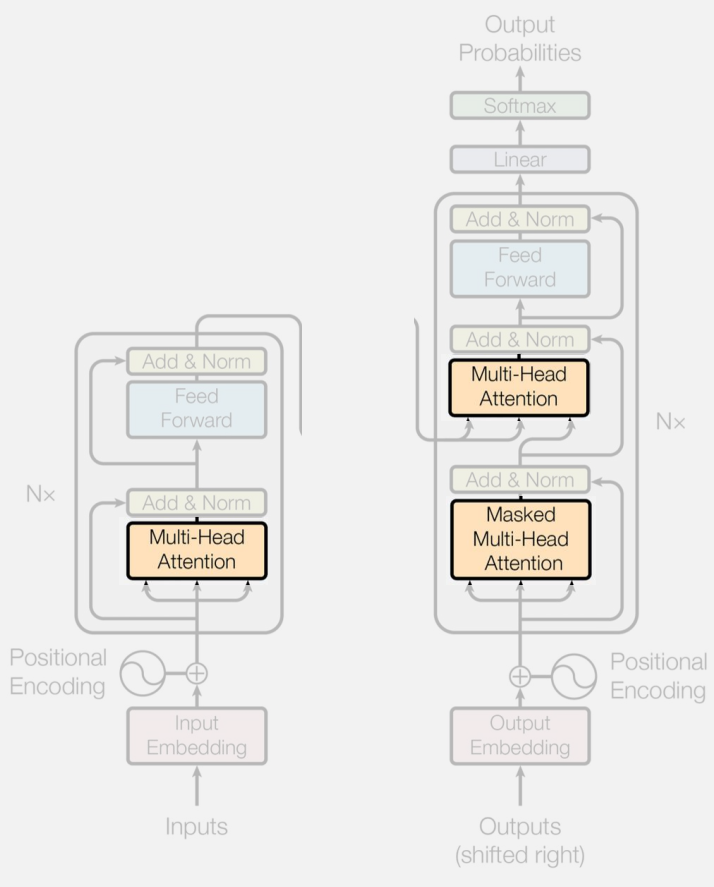


01. The Encoder

02. The Decoder

Input Embeddings

Dissection of the Transformer



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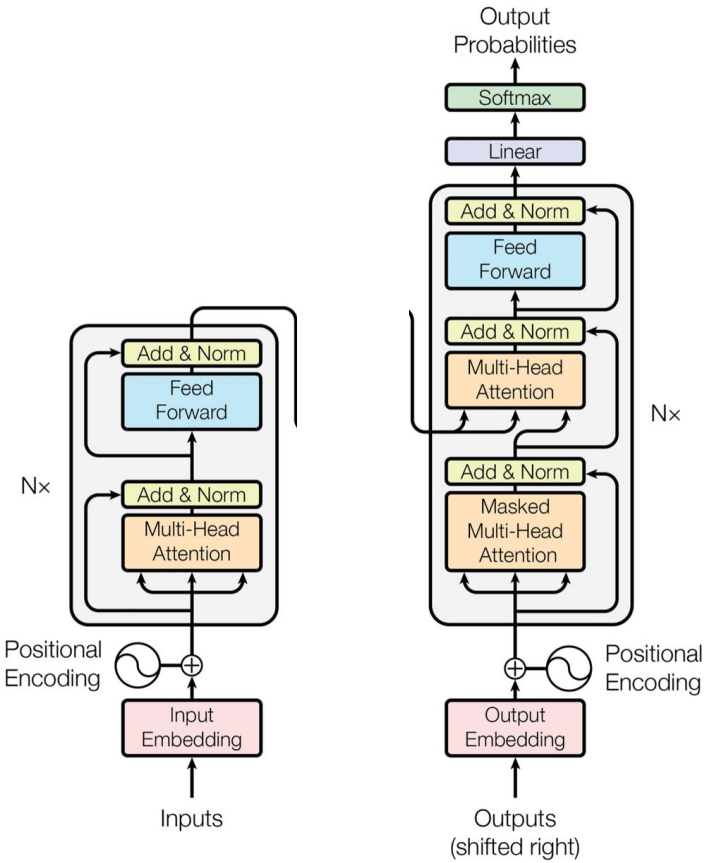
02. The Decoder

Self-Attention

Input Embeddings

Dissection of the Transformer



01. The Encoder

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Self-Attention

Input Embeddings

Layer Normalization

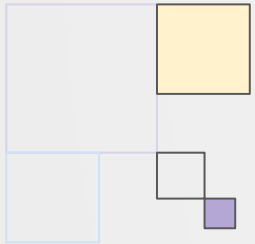
Skip Connections

Positional Encoding

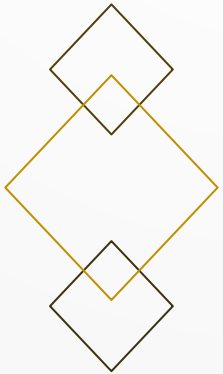
Byte Pair Encodings

Layer Stacking

Cross Attention



Neural Representations



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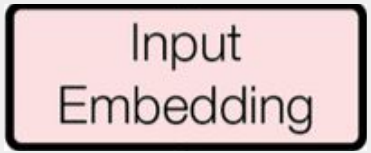
SURF

How do we represent words?

Language is **discrete**!

> One cat ate a tuna, one cat ate a chicken, one weird cat ate a human.



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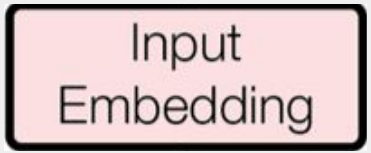

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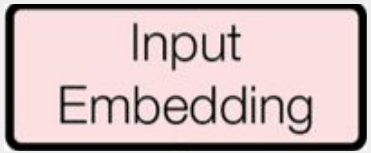

Vocabulary

A vocabulary is the set of unique tokens in your language (dataset)

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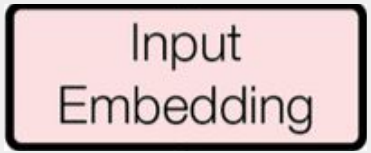

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one
cat
ate
tuna
chicken
weird
human
a

SURF

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ate	2
tuna	3
chicken	4
weird	5
human	6
a	7

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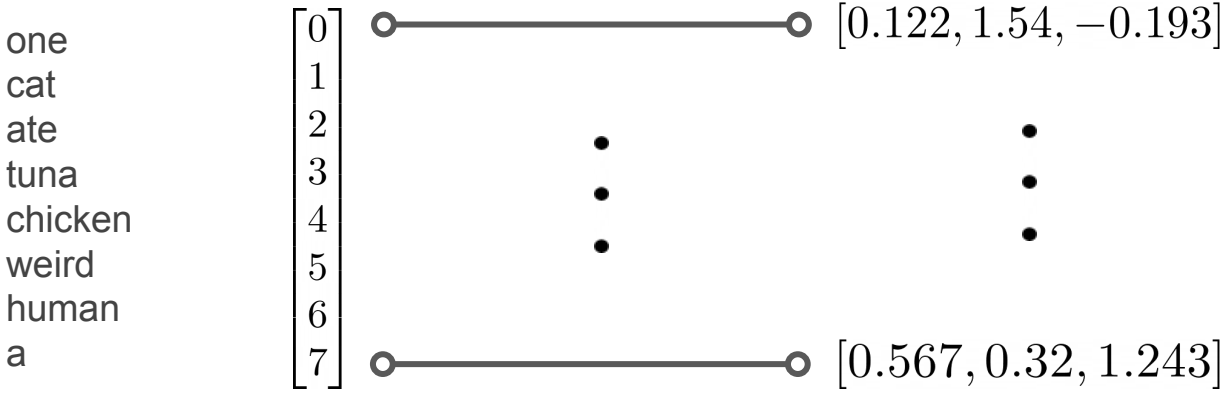


SURF

How do we represent words?

Language is **discrete**!

> One cat ate a tuna, one cat ate a chicken, one weird cat ate a human.

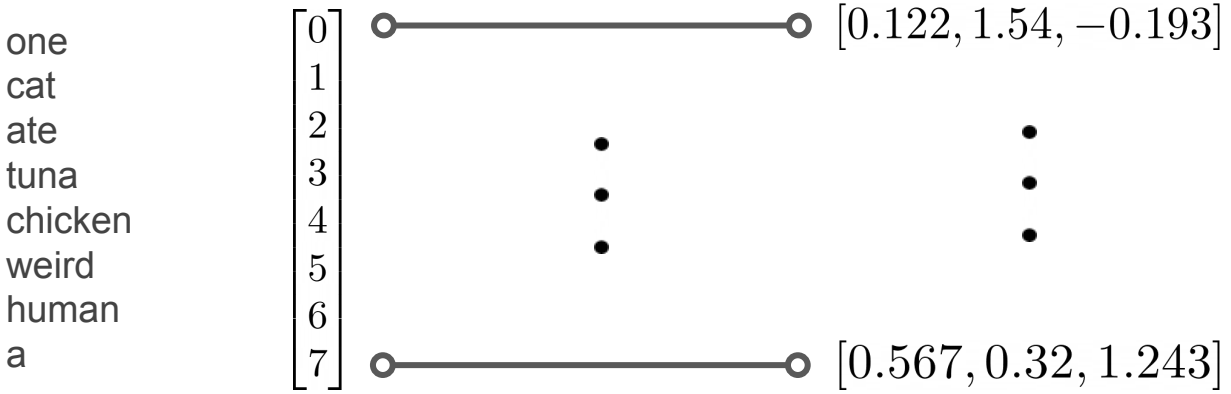
Easy to **compose** and easy to **vectorize**

Input Embedding

Vocabulary

A vocabulary is the set of unique tokens in your language (dataset)

Embedding



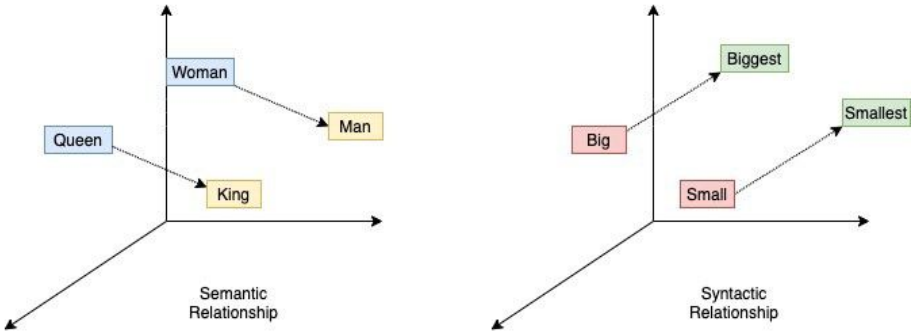
SURF

Neural Representation Learning

King $[0.122, 1.54, -0.193]$

Man $[0.567, 0.32, 1.243]$

Neural Representation Learning



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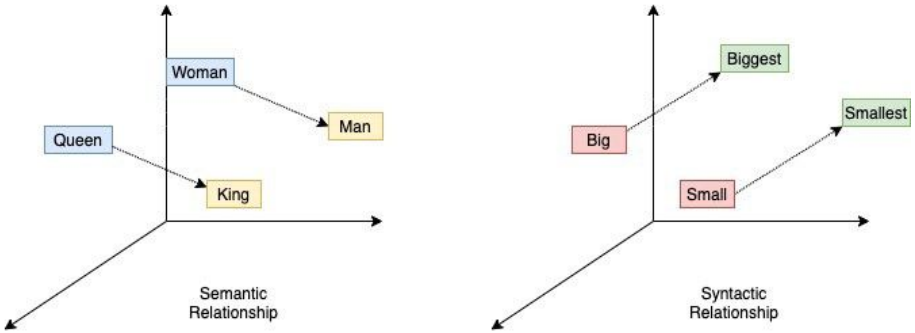


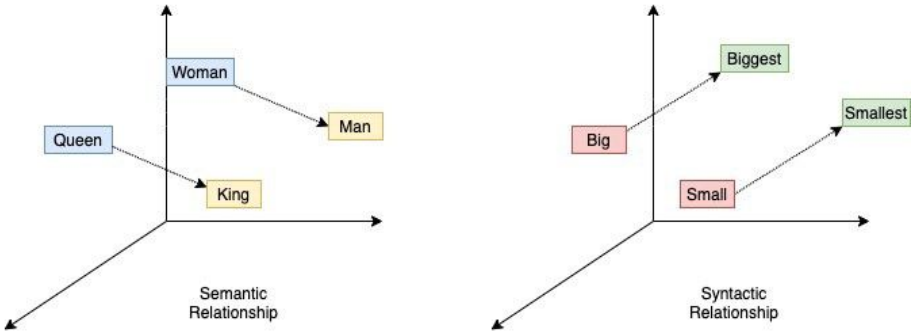
King $[0.122, 1.54, -0.193]$

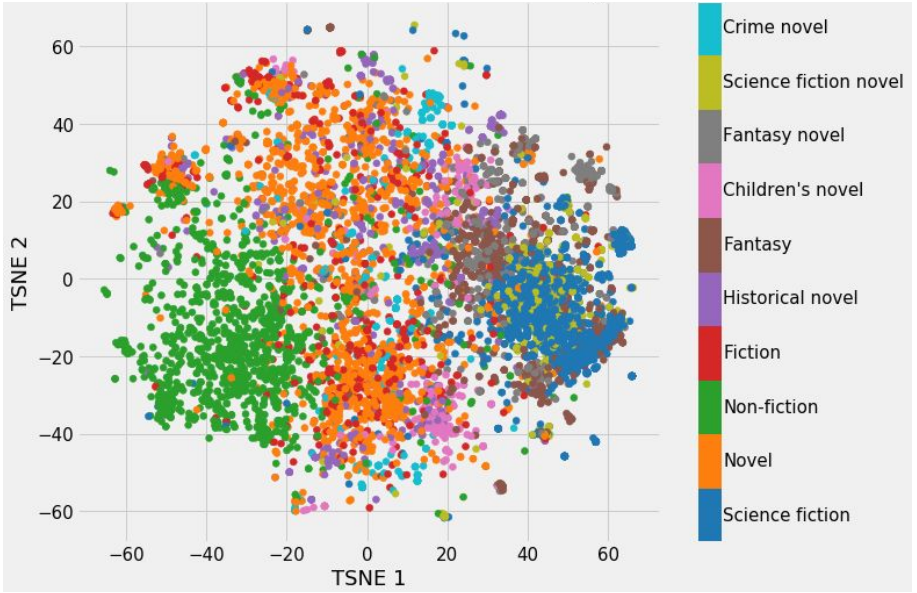
Man $[0.567, 0.32, 1.243]$

King - Man + Woman = Queen

Each word has a numerical vector representation learnt by a language model

Neural Representation Learning





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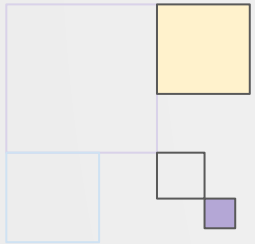
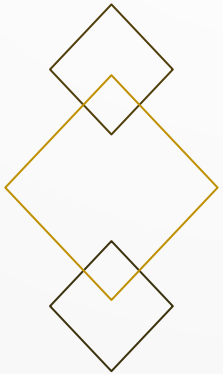


Self Attention



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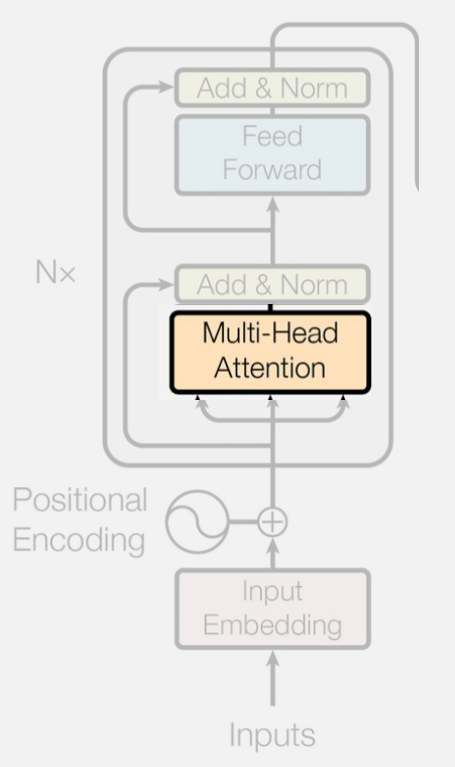
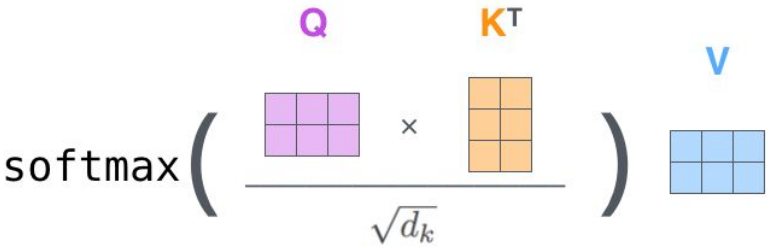
Self Attention



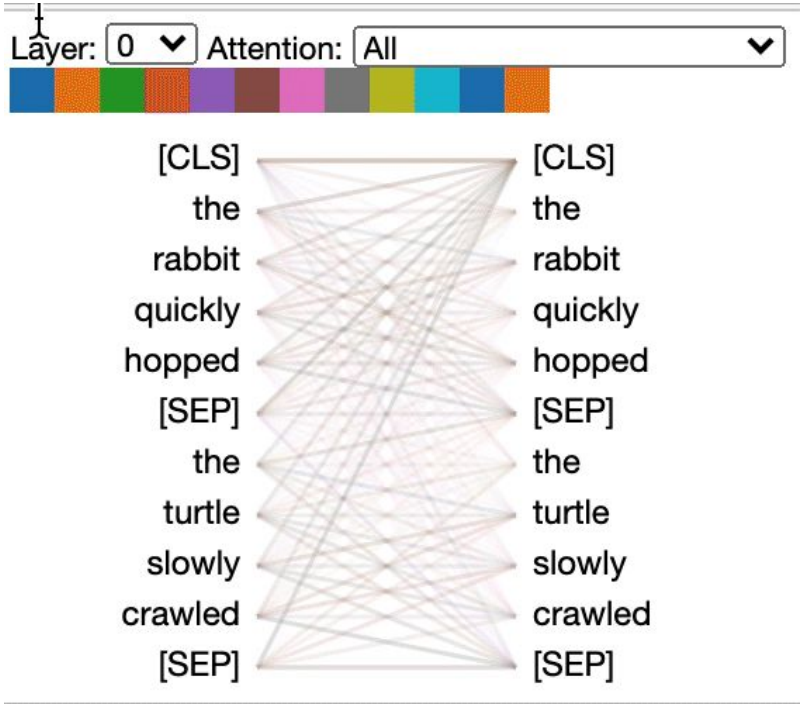
$$\text{softmax}\left(\frac{Q \times K^T}{\sqrt{d_k}}\right) V = Z$$

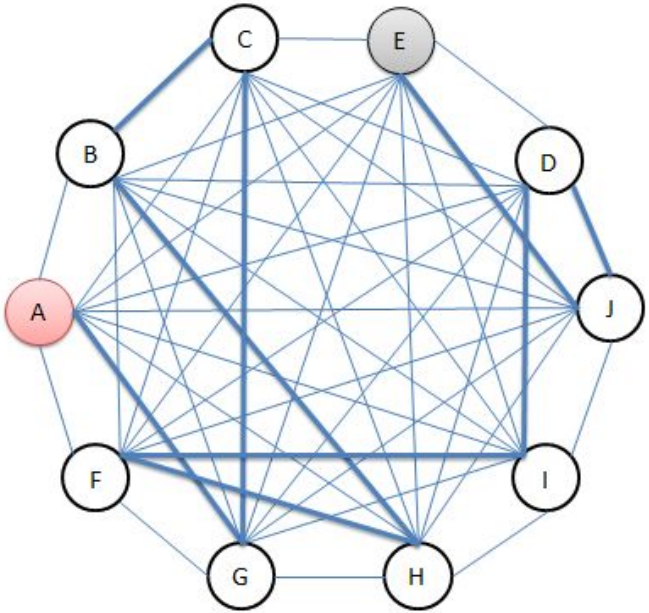
Self Attention



$$\text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Self Attention





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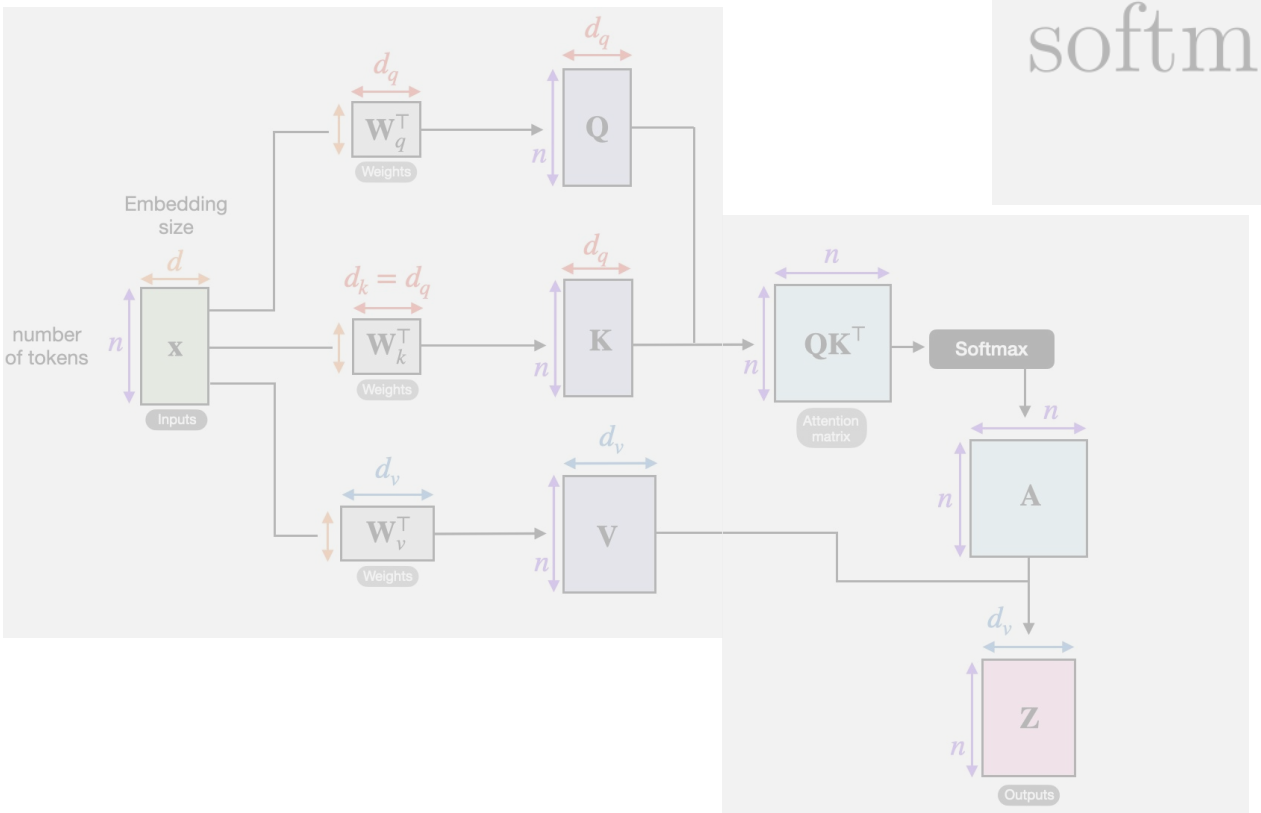

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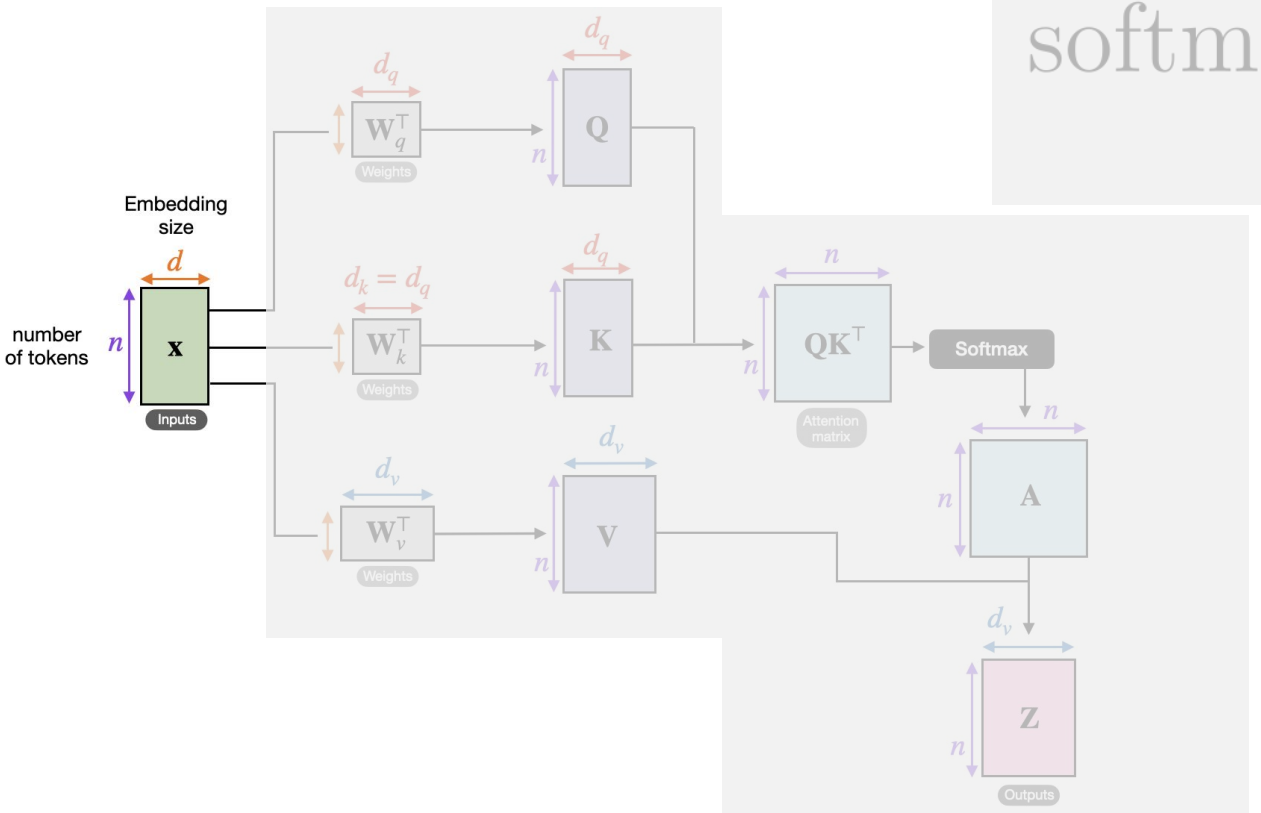
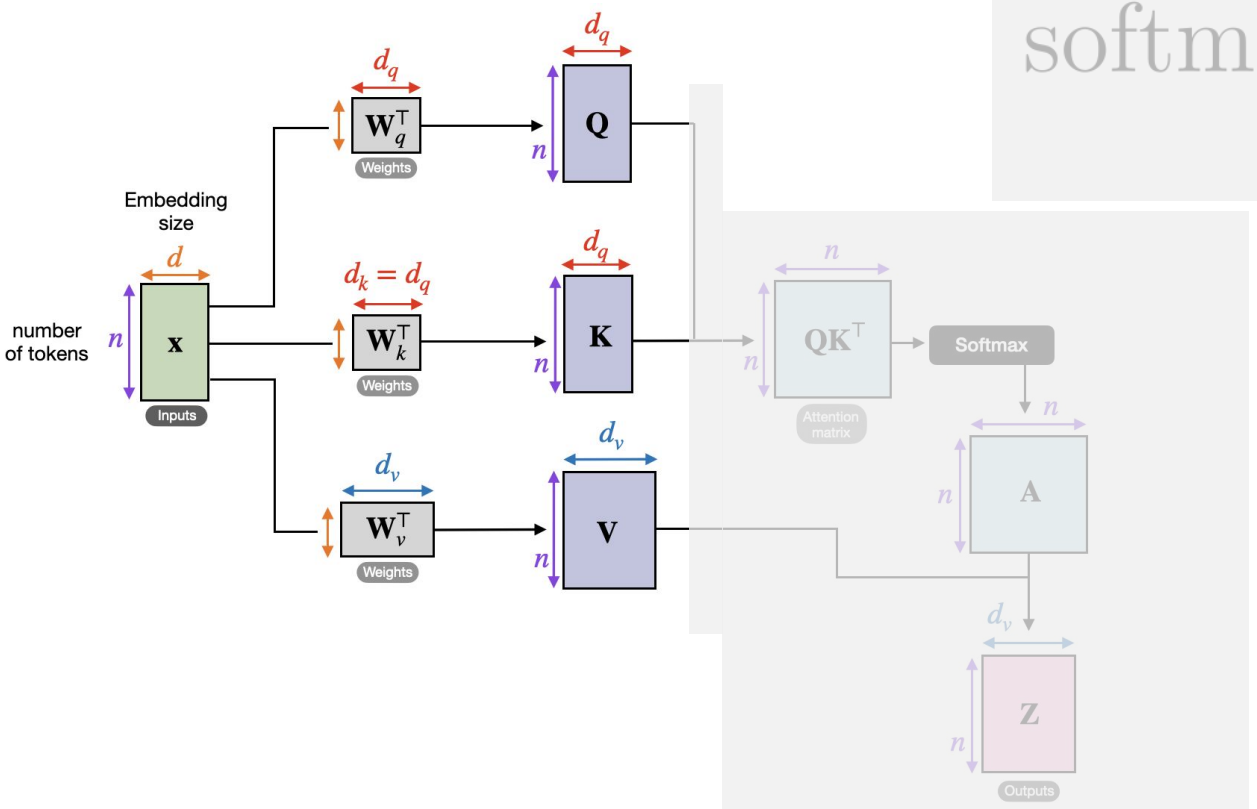


Self Attention

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



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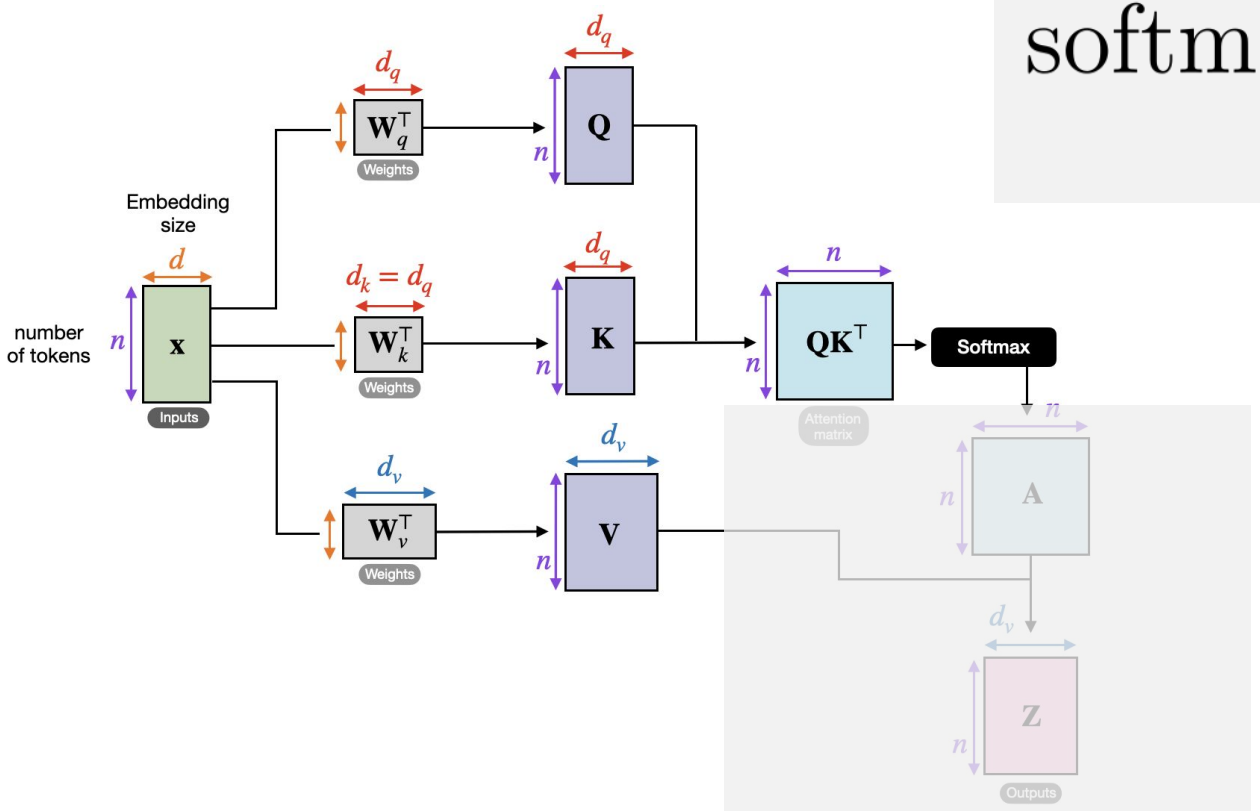

Self Attention

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$Softmax(x) = \frac{e^{x_i}}{\sum_{j=0}^{K} e^{x_j}}$$

Self Attention

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$\frac{e^{x_i}}{\sum_{j=0}^{K} e^{x_j}}$$

Self Attention

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$\begin{bmatrix} 1.3 \\ 5.1 \\ 2.2 \\ 0.7 \\ 1.1 \end{bmatrix}$$

$$\frac{e^{x_i}}{\sum_{j=0}^{K} e^{x_j}}$$

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Self Attention

$$\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$\begin{bmatrix} 1.3 \\ 5.1 \\ 2.2 \\ 0.7 \\ 1.1 \end{bmatrix}$$

$$\frac{e^{x_i}}{\sum_{j=0}^{K} e^{x_j}}$$

$$\begin{bmatrix} 0.02 \\ 0.90 \\ 0.05 \\ 0.01 \\ 0.02 \end{bmatrix}$$

SURF

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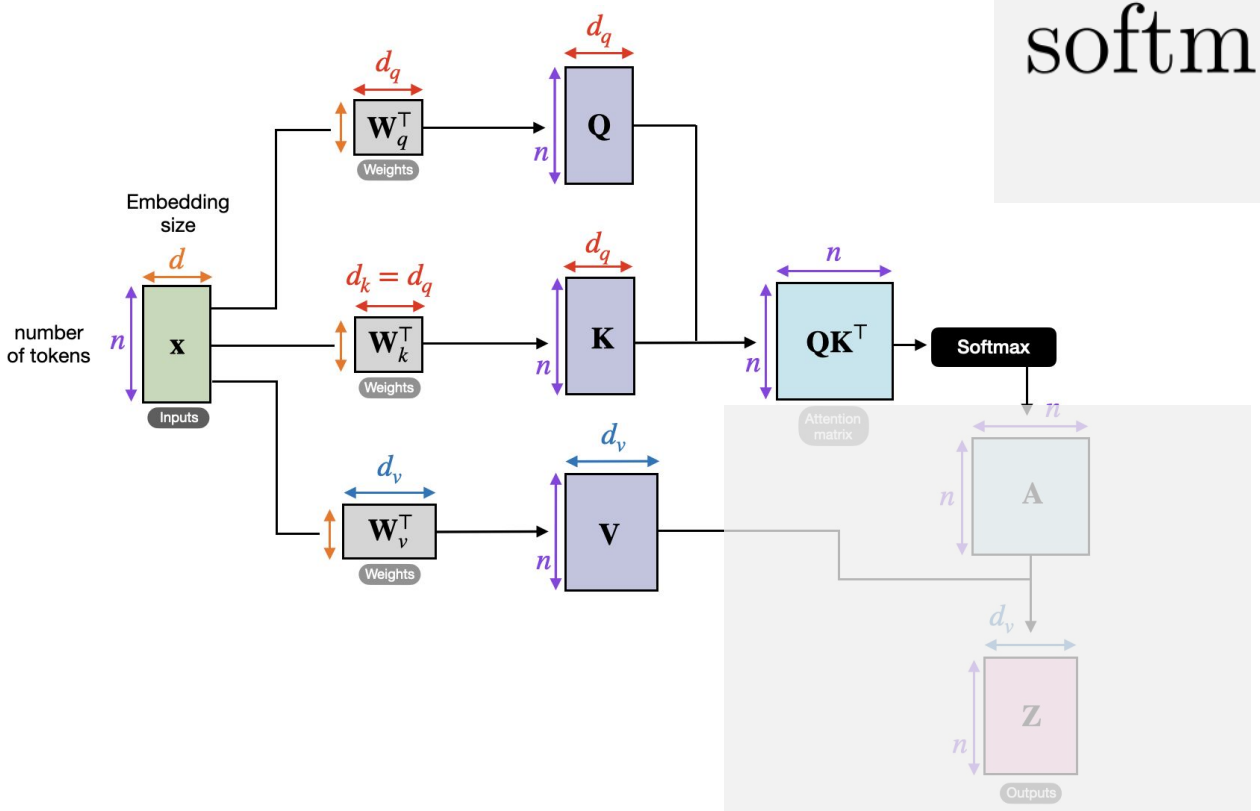

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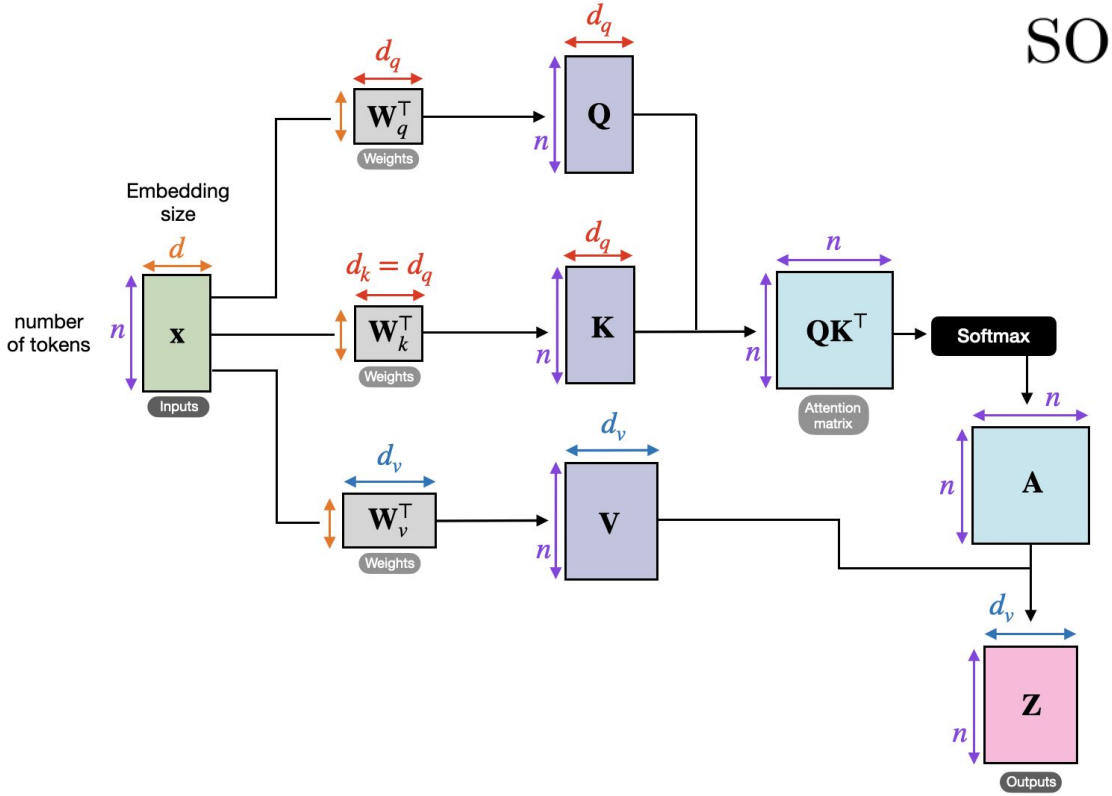
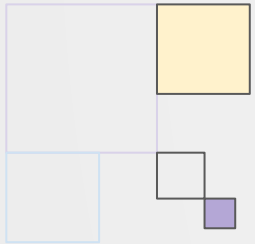
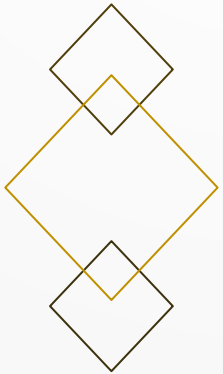




Multi-Head Attention



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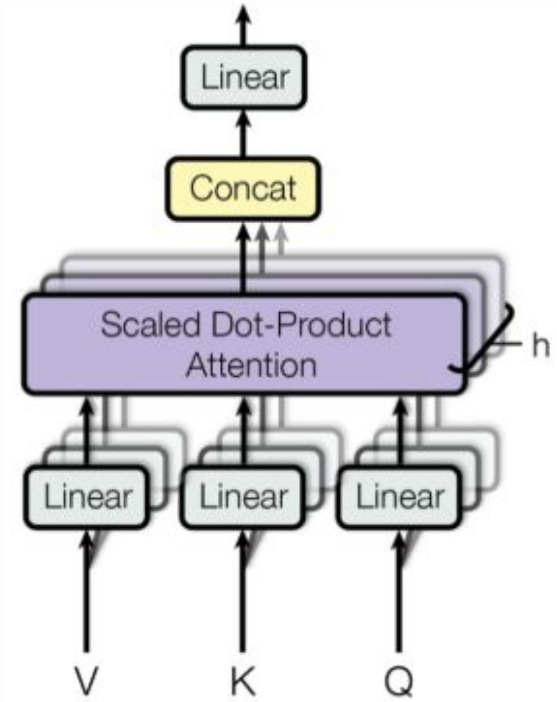
The Multi-Headed Beast

Stack Self-Attention **heads** to extract multiple features

Voita, Elena et al. “Analyzing Multi-Head Self-Attention: Specialized Heads Do the Heavy Lifting, the Rest Can Be Pruned.”



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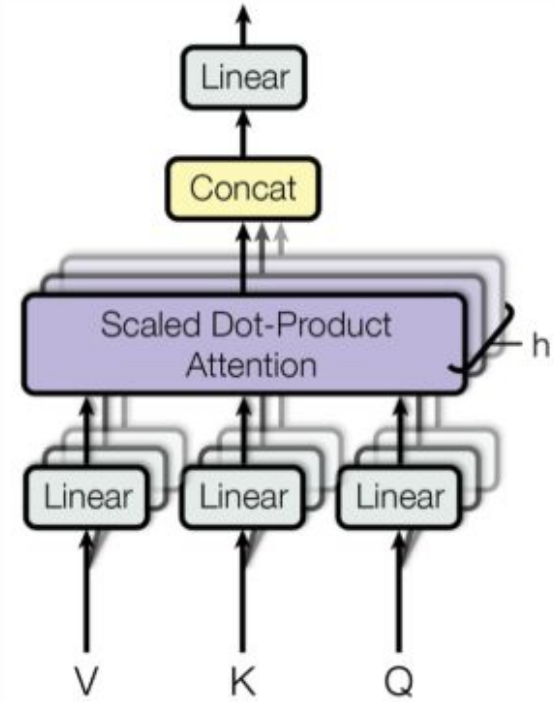

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Each head could focus on

1. Syntax
2. Positions
3. Rare words
4. Grammatical Errors
5. N-grams

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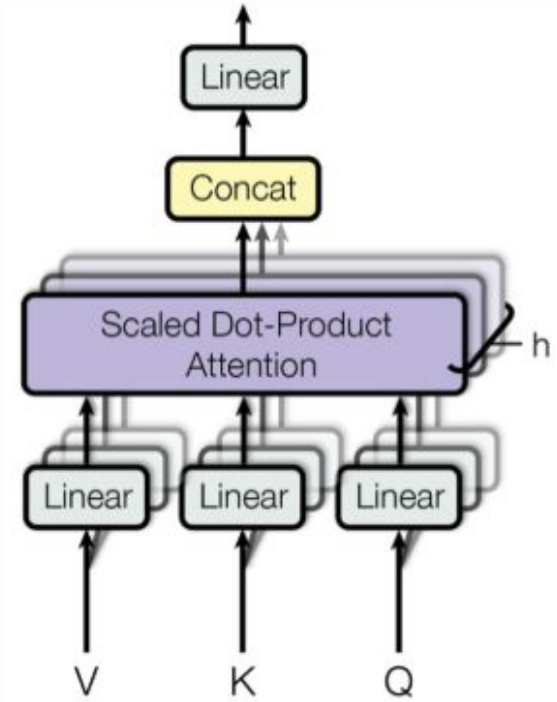

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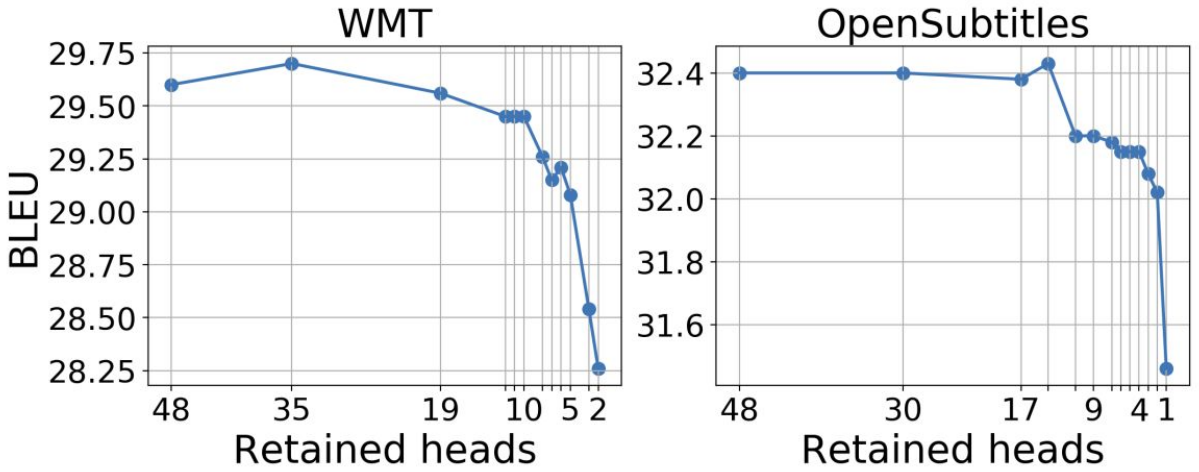

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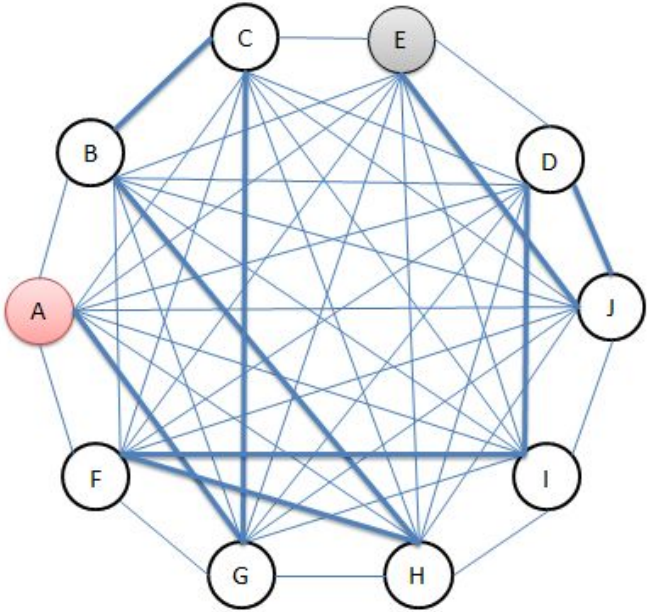
Transformers are **Permutation Invariant!**



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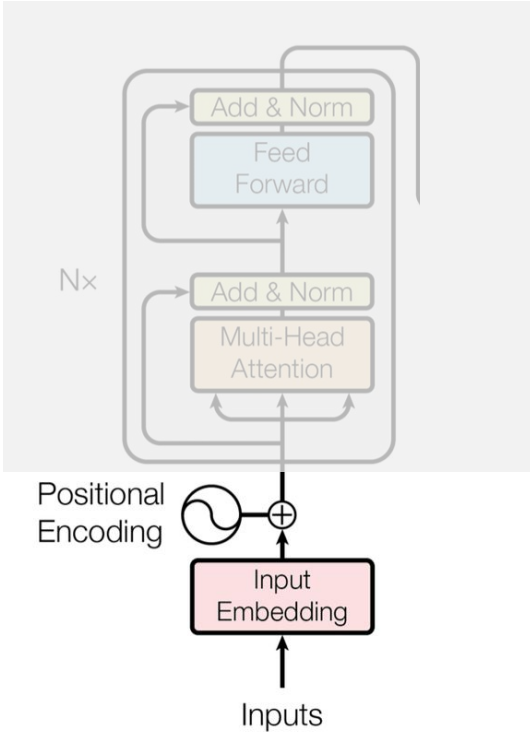

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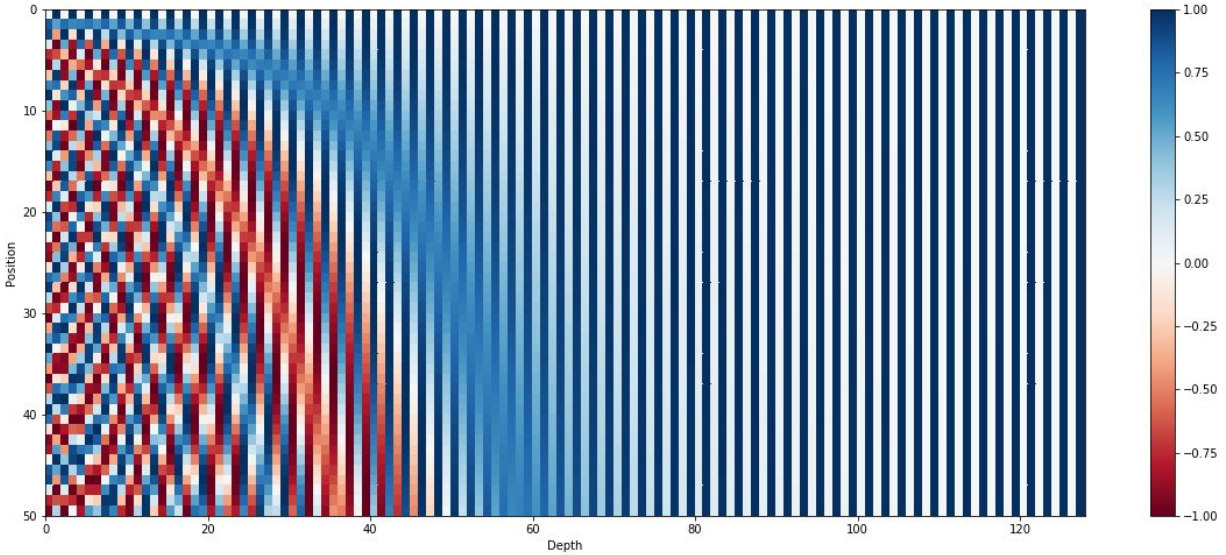

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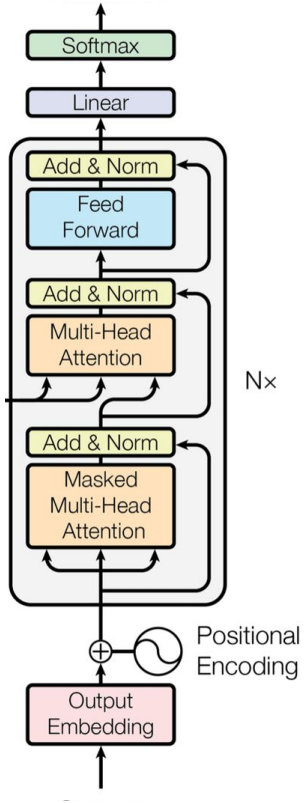

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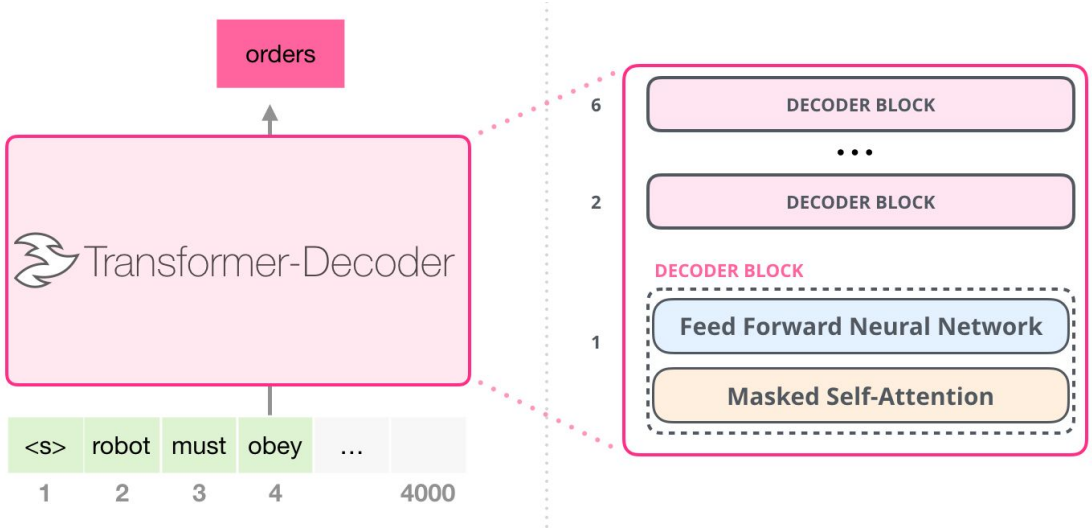

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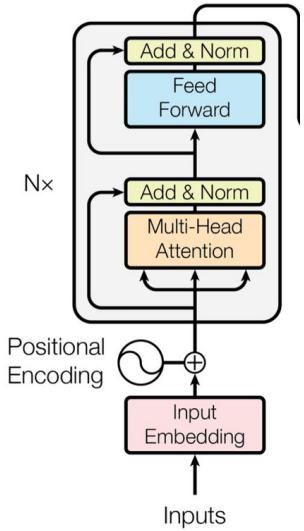
Dissection of the Transformer

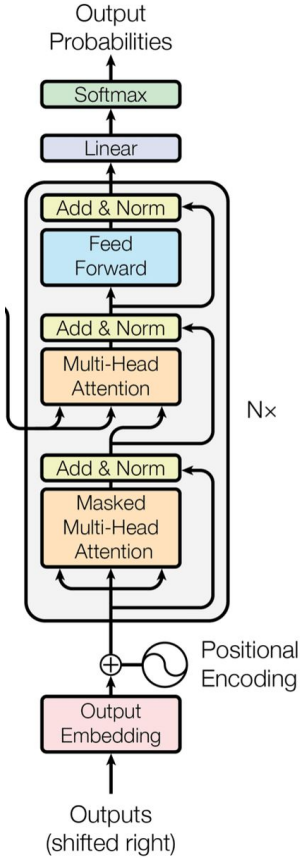
The Encoder

BERT

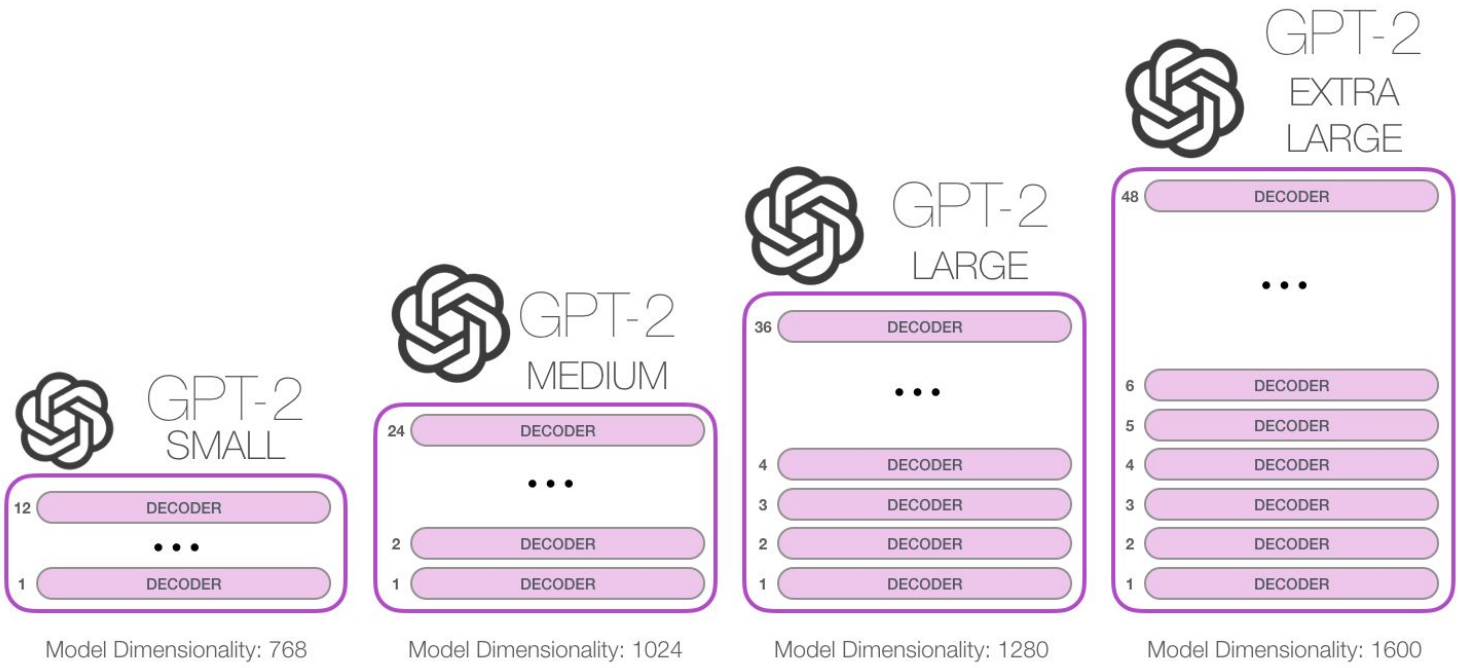


The Decoder

GPT



Generative Pre-Trained Transformers



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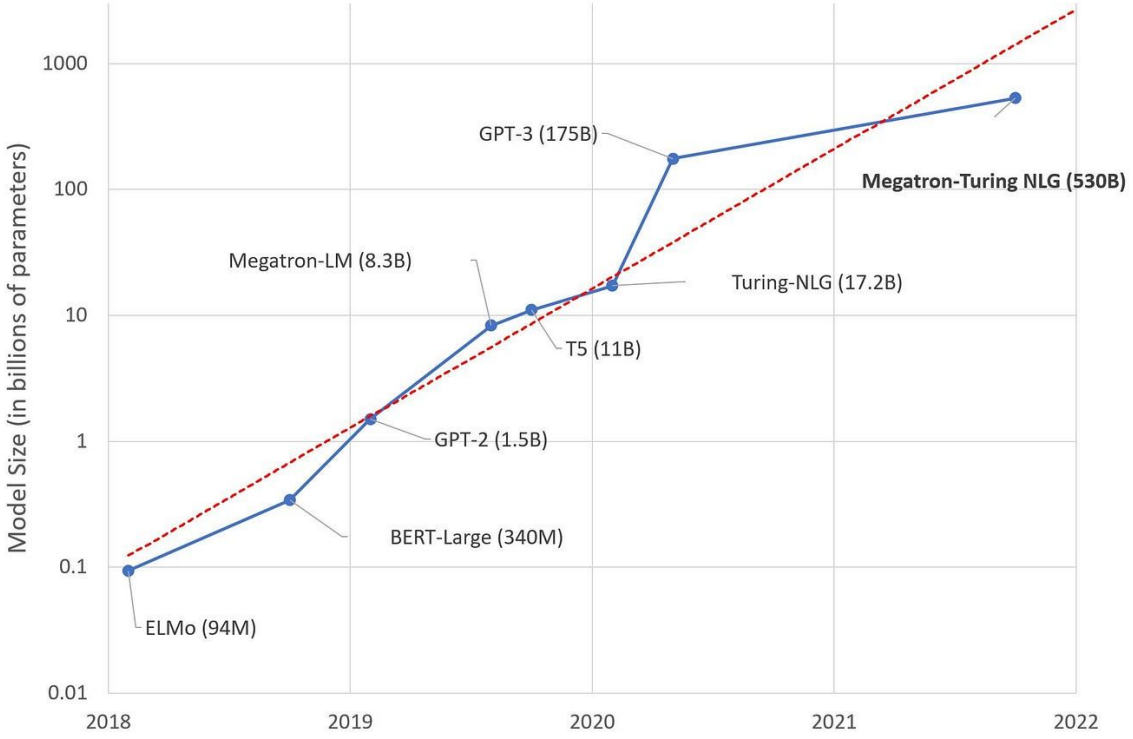
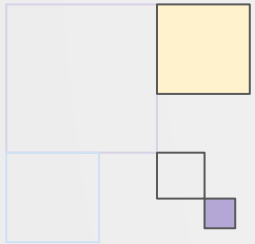
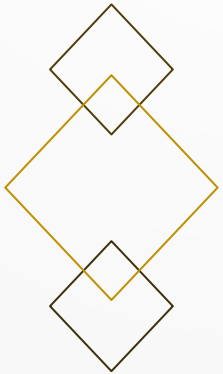




Transformer Cases



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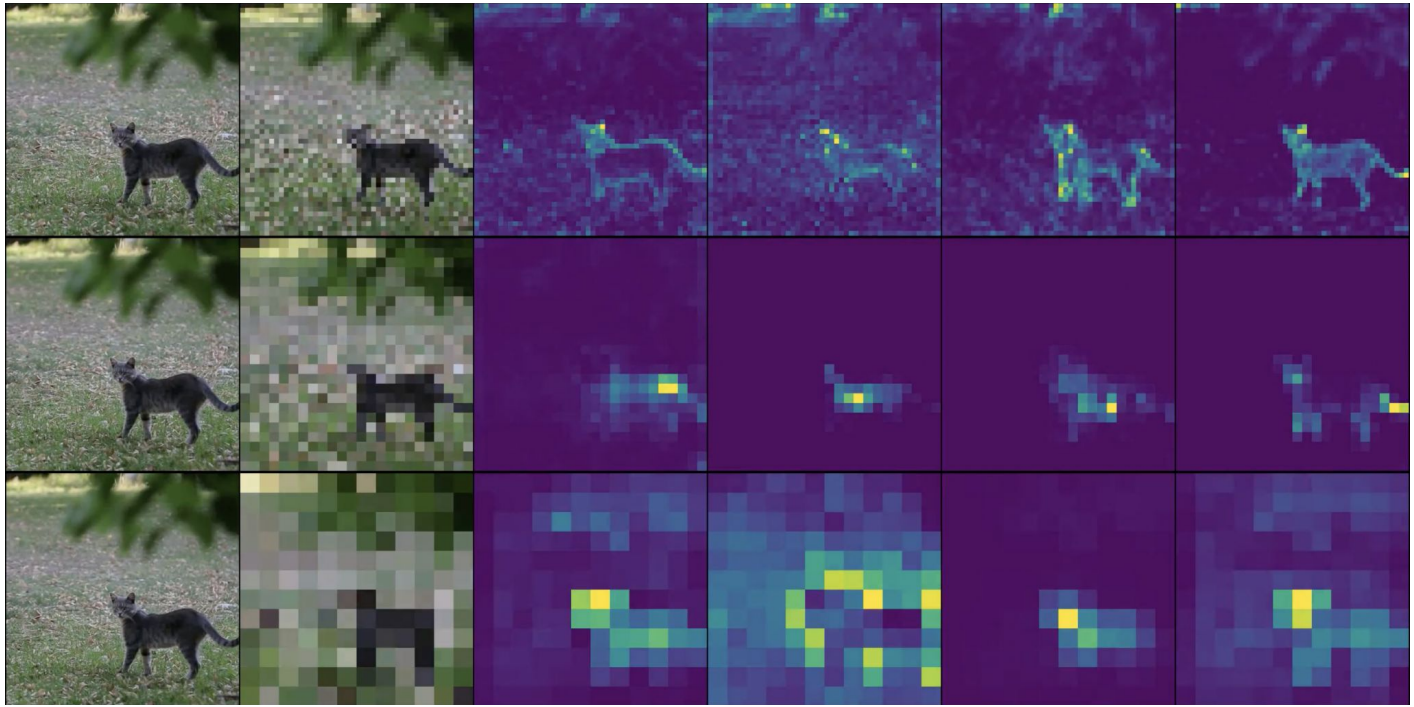
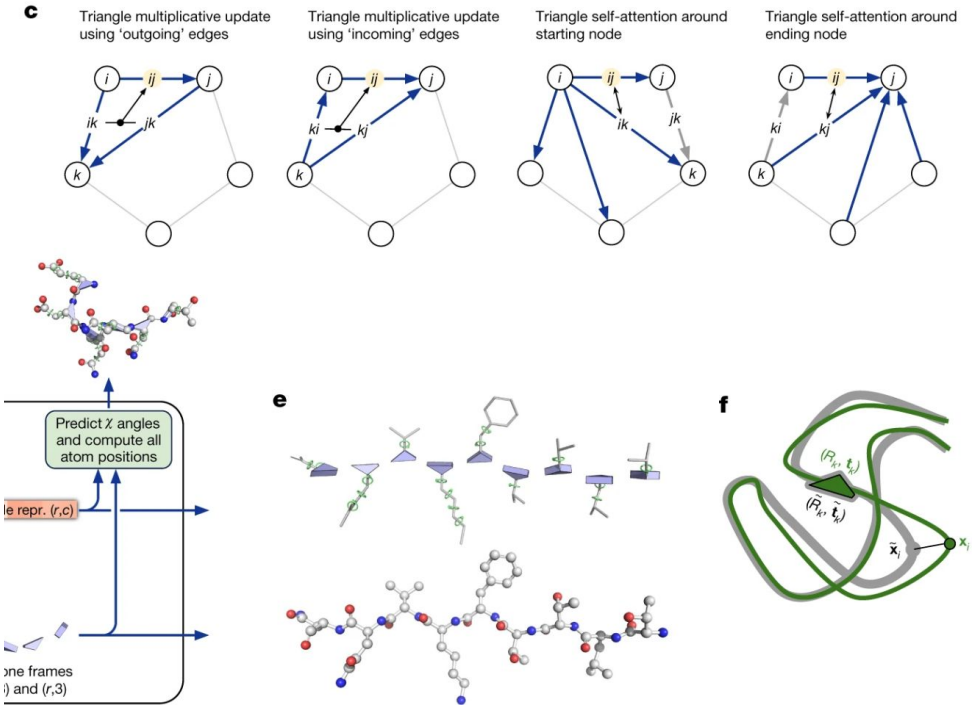
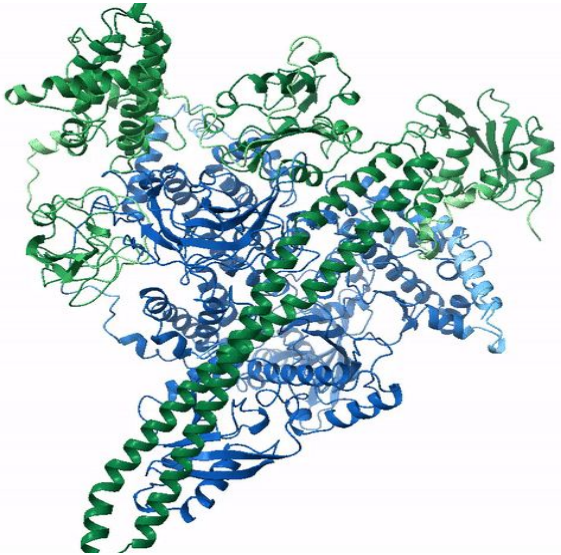
Transformers for other modalities: ViT



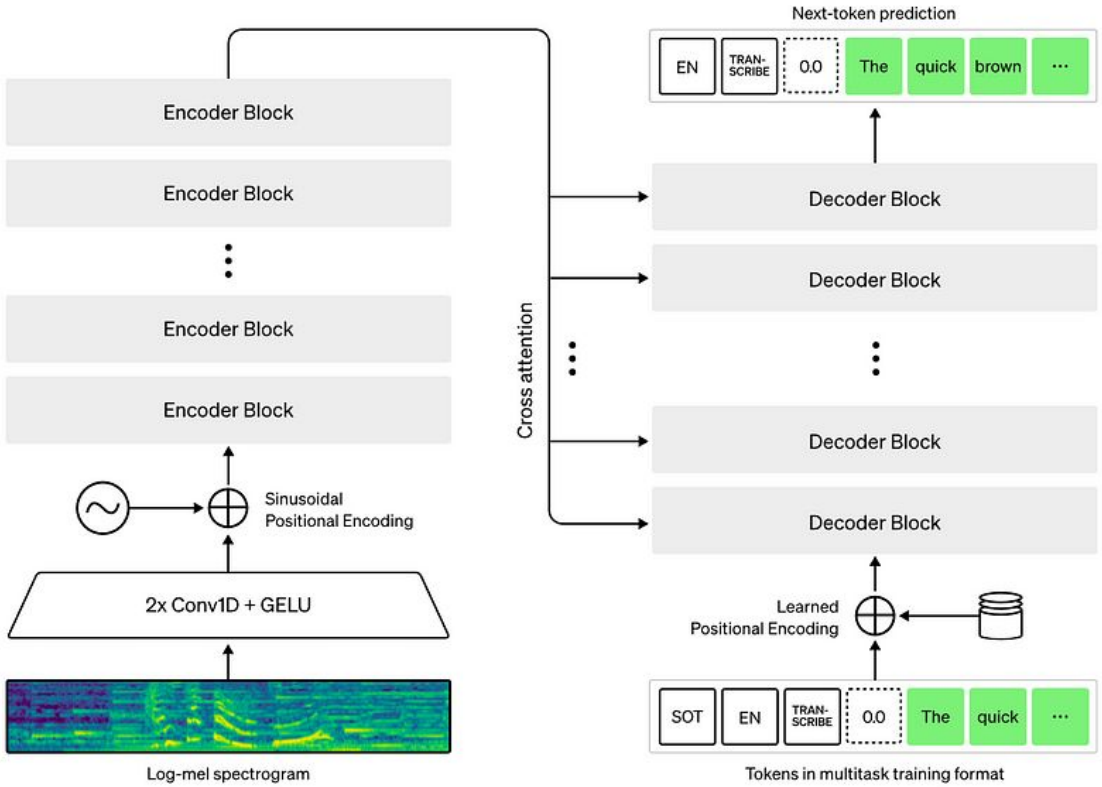
Transformers for other modalities: EvoFormer





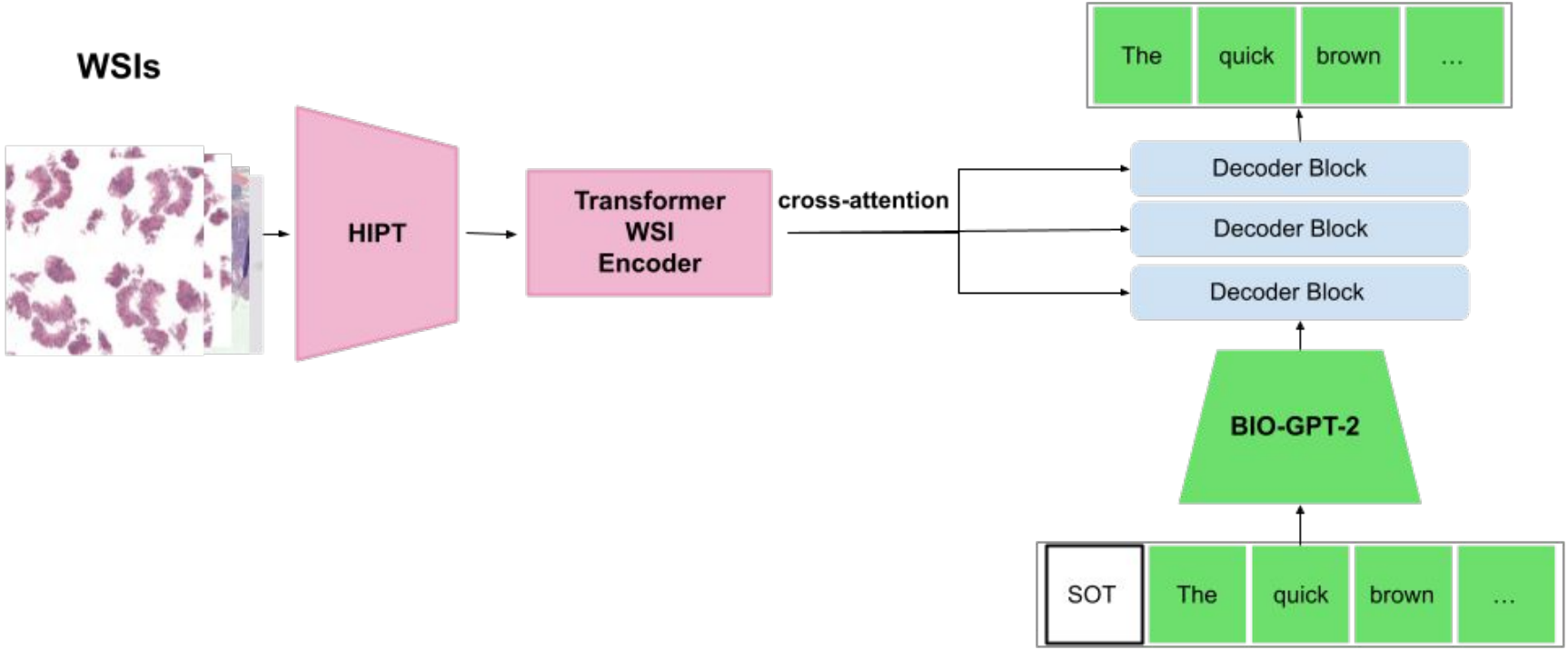
https://www.nature.com/articles/s41586-021-03819-2

Transformers for other modalities: Whisper

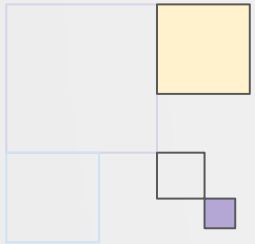


https://openai.com/research/whisper

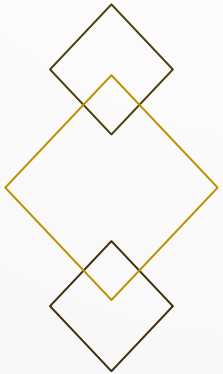
Transformers for other modalities: Multi-Modal Histopathology



Caption generation from histopathology whole-slide images using pre-trained transformers
BC Guevara, N Marini, S Marchesin, W Aswolinskiy, et al.



Transformer Interpretations



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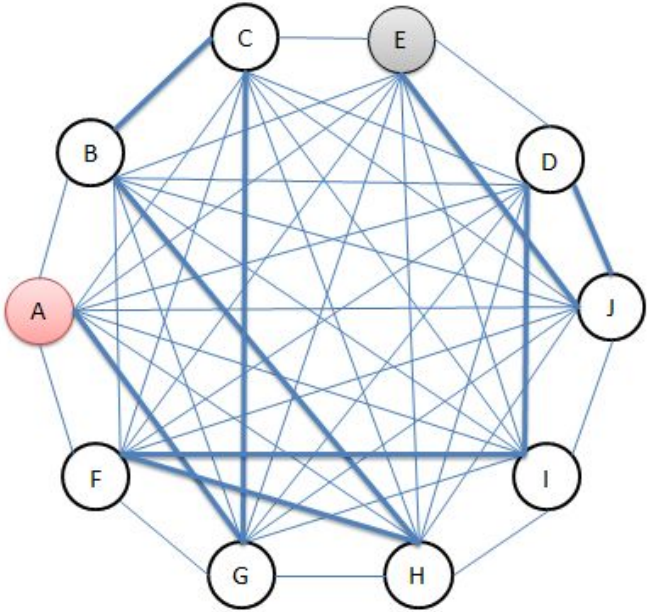
Fully Connected Weighted Graph

Lower the energy state that the network should ***remember***



Modify the input layer by layer

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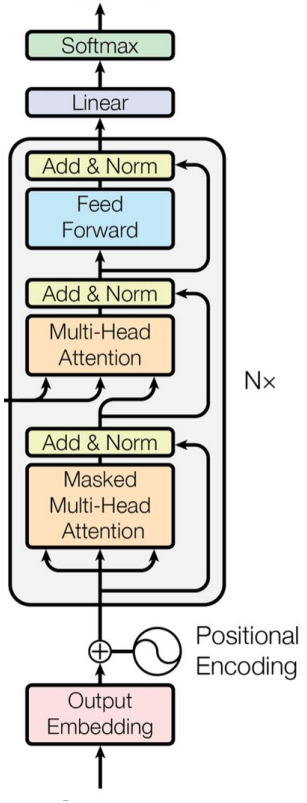

https://transformer-circuits.pub/2021/framework/index.html

Belrose, Nora et al. “Eliciting Latent Predictions from Transformers with the Tuned Lens.”

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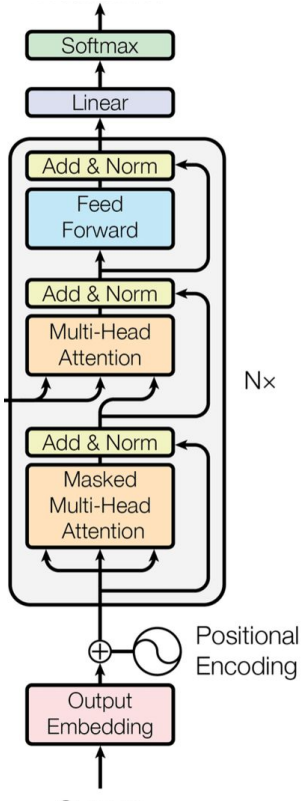
Lower the energy state that the network should ***remember***

Attention heads output a result added to the **residual stream.**

All components of a transformer **communicate** by **reading and writing** to different subspaces of the stream



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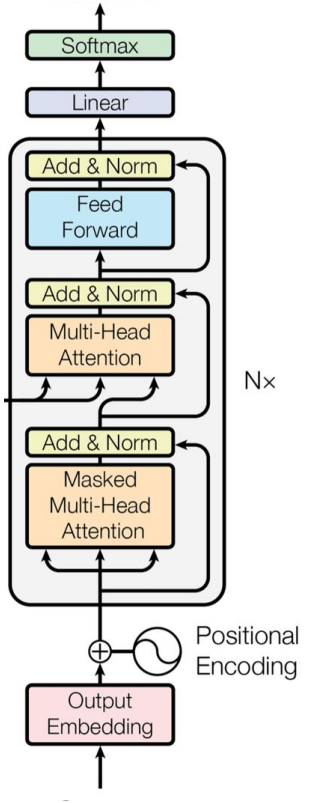
$$(T)$$



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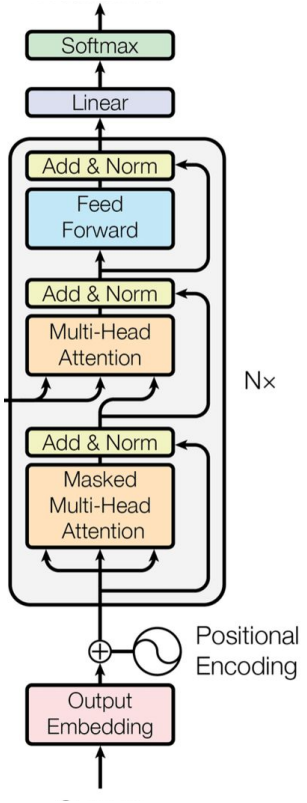

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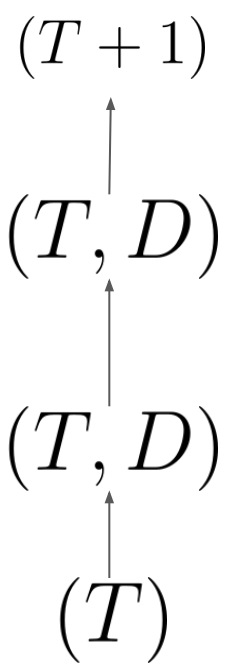

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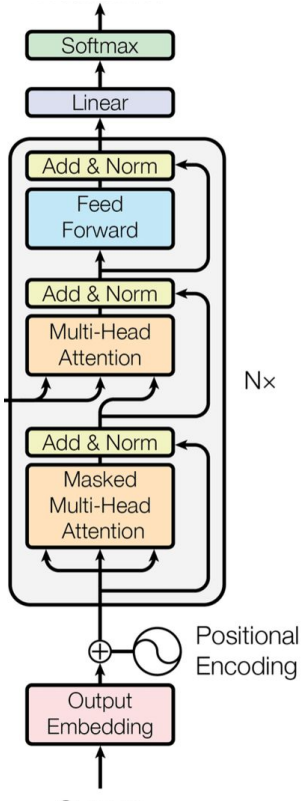

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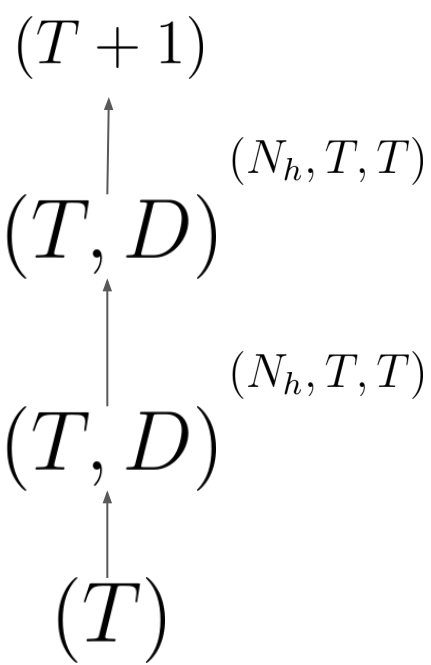

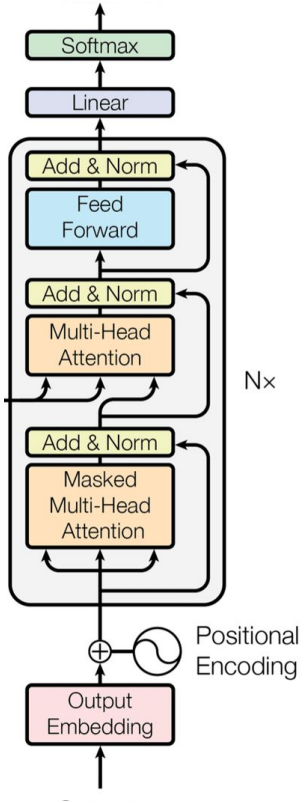

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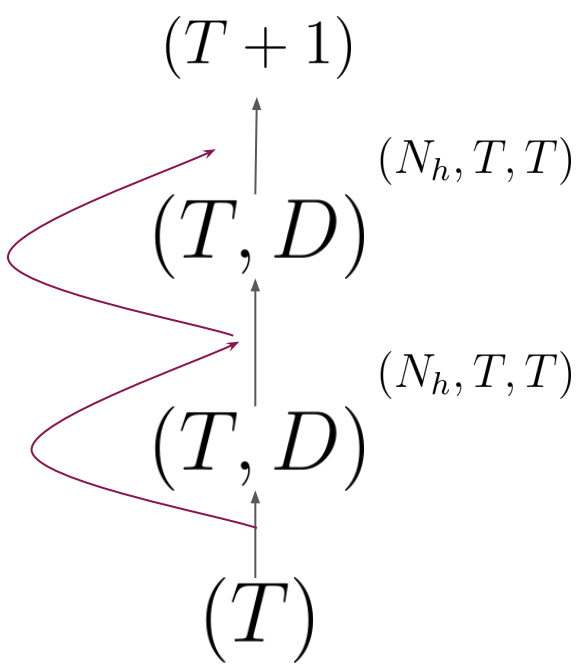

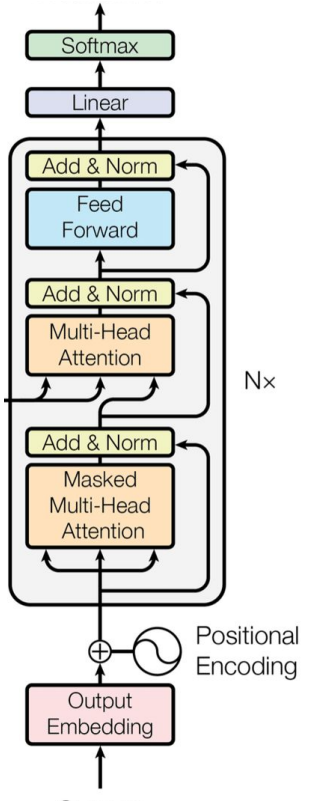

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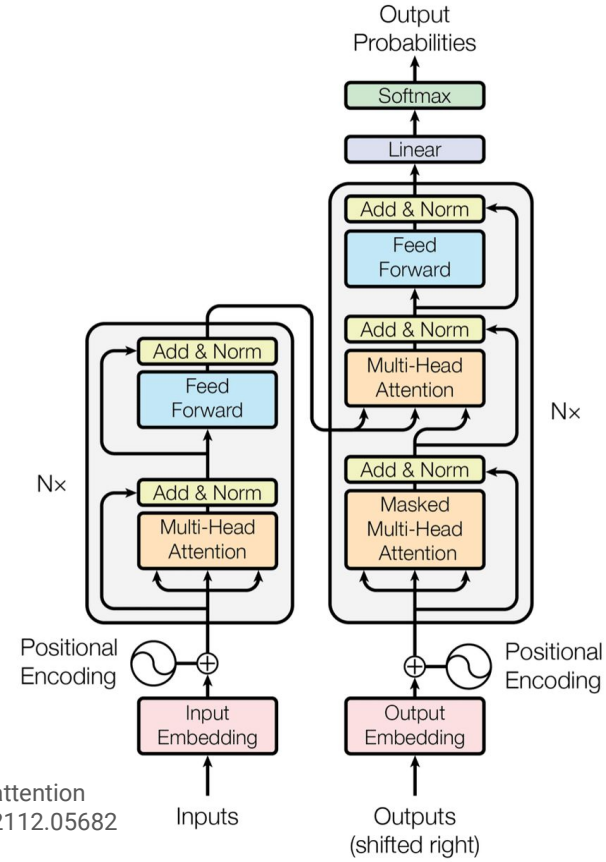
SURF

Final Words

Transformer training is quite slow

We need a lot of data

And **a lot** of parameters



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$O(N^2)$ in compute and memory

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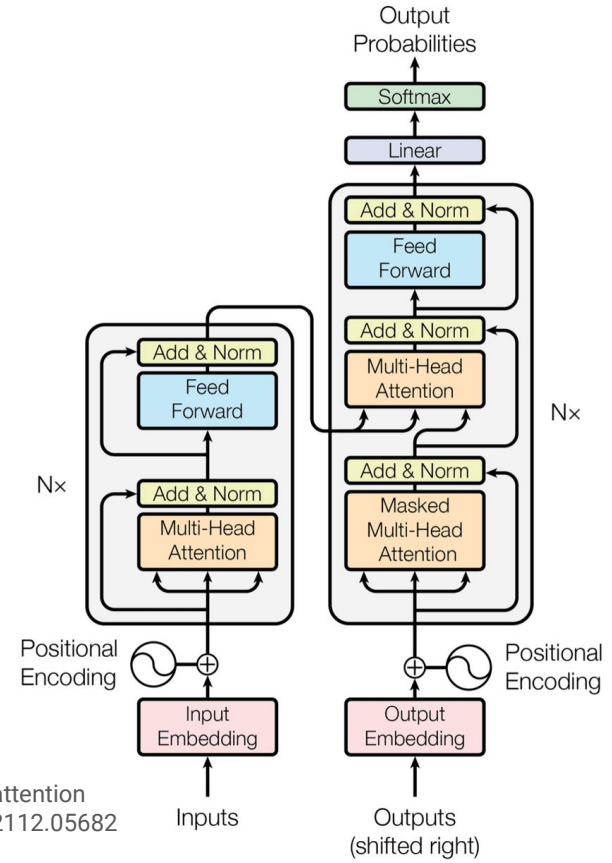

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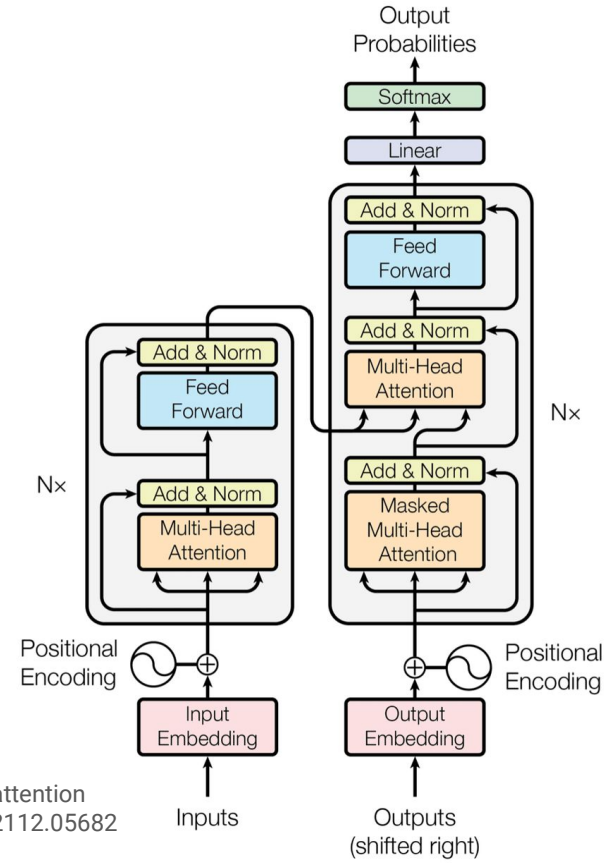
But, does not have to be $O(N^2)$
In memory!

$$O(N^2)$$



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And **a lot** of parameters

$O(N^2)$ in compute and memory

But, does not have to be $O(N^2)$ In memory!

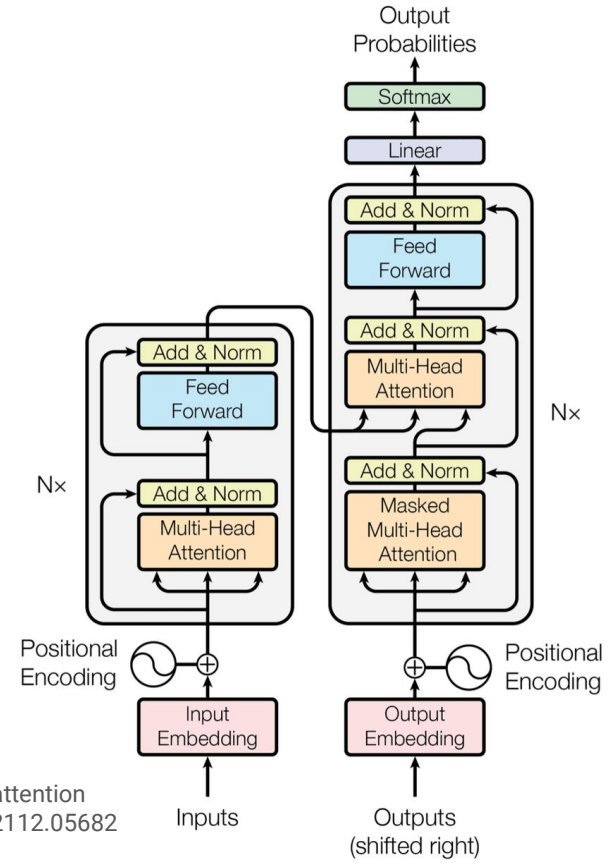
We can do $O(\sqrt{N})$

Partition the attention and compute it **chunk by chunk**

Uses more compute but orders of magnitude less memory usage

$$O(N^2)$$

$$O(\sqrt{N})$$



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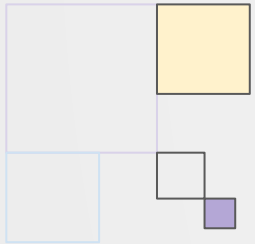
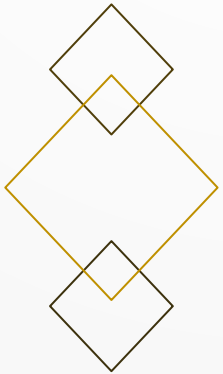


Chinchilla Scaling Laws



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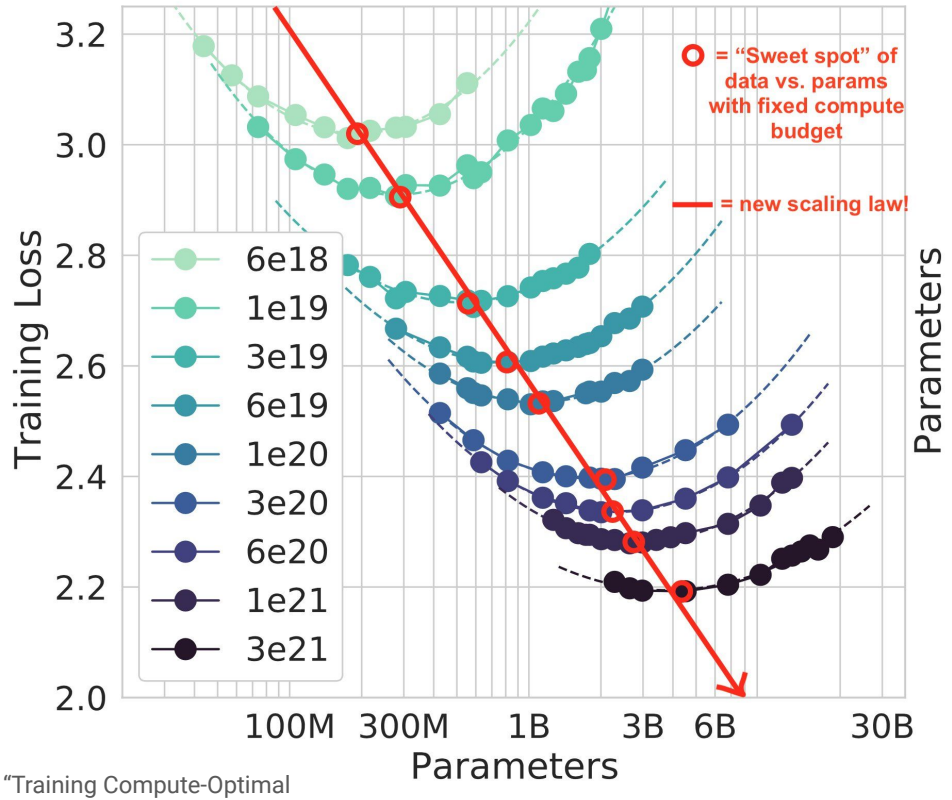

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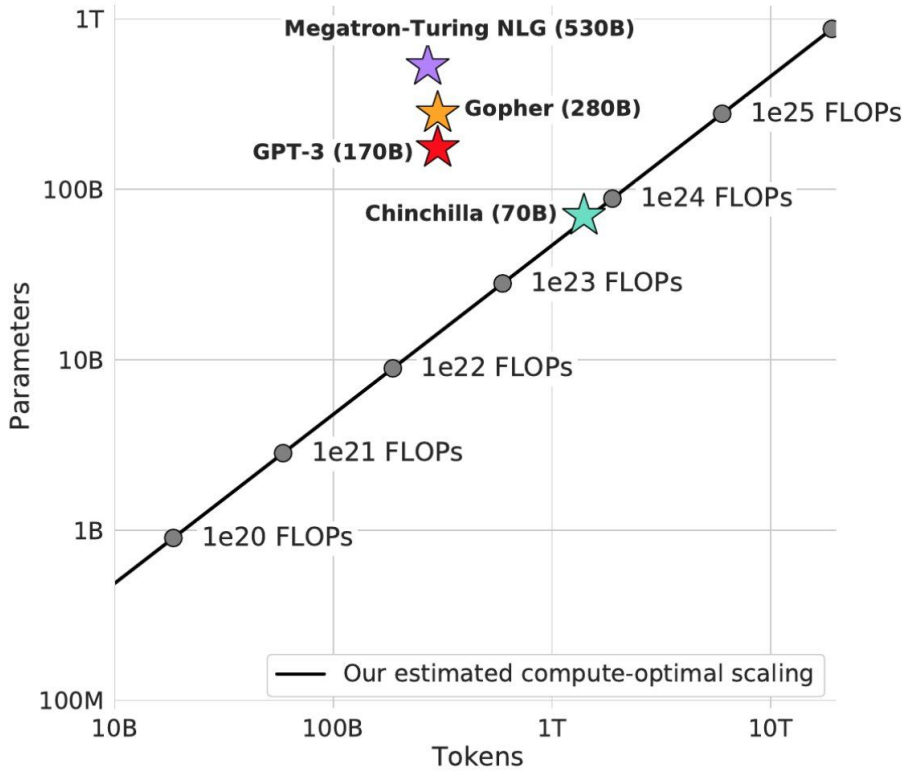

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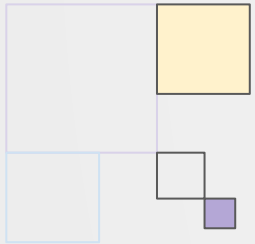
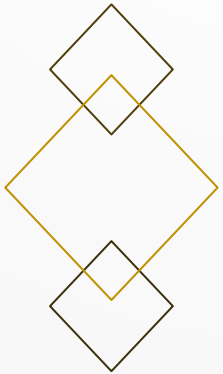


Transformer Demo



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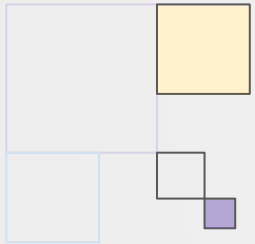
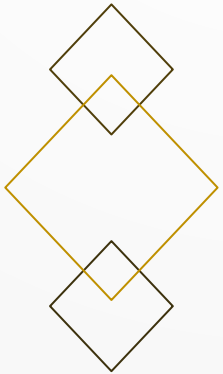


Scaling Transformers



High Performance Machine Learning Group

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Whose Revolution?

01.

Data Amount & Availability

Data generated by our devices continuously

02.

Compute Power

Easier available in the cloud
Frameworks to work with accelerated hardware

03.

Research & Funds

More funds to researchers to experiment without limits

04.

More Parameters

Make networks bigger
Feed more information

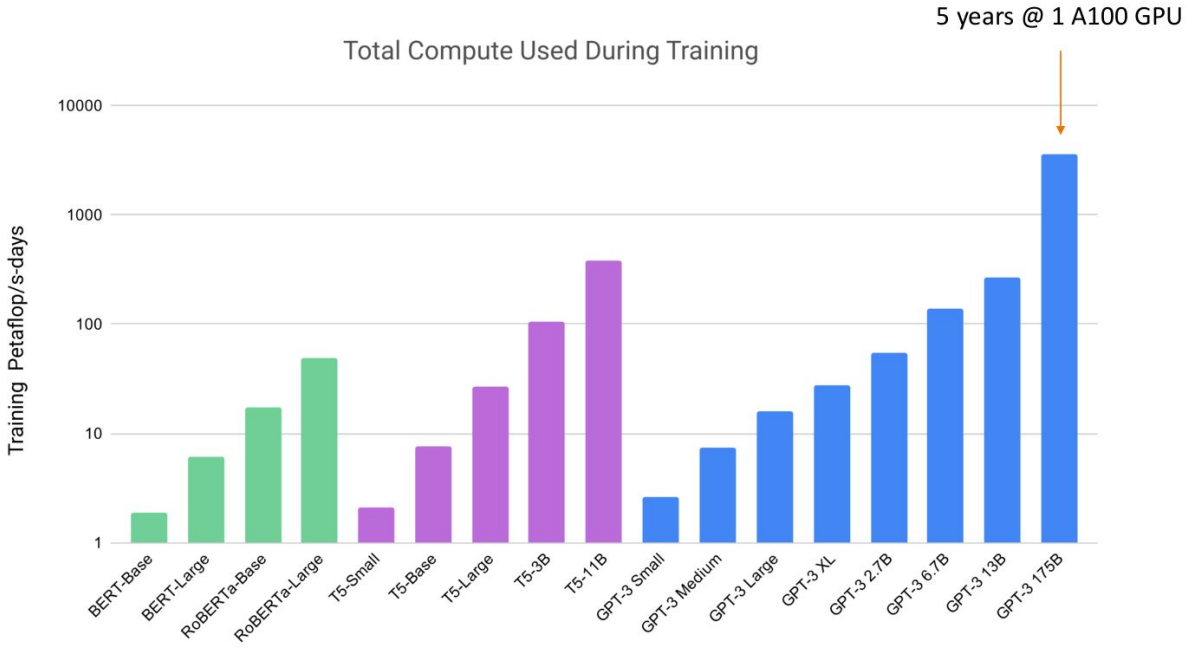
Transformer Explosion

GPT-3 Trained on ~350 Billion tokens

GPT-3 has 175B parameters!

OpenAI used a cluster of V100 GPUs

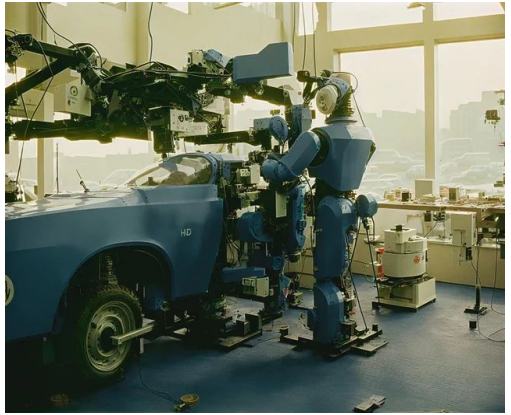
~Newest iterations trained on 1024 A100s for 34 days

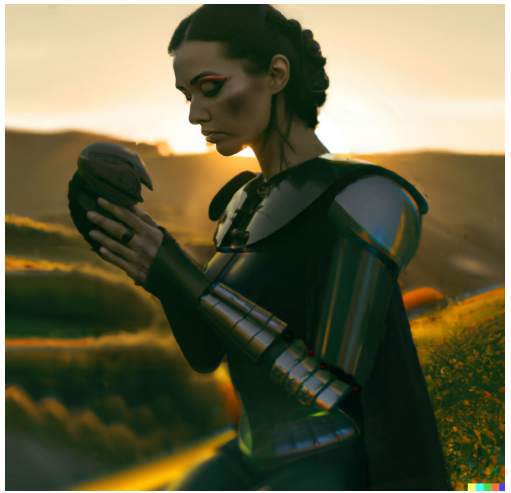


Stable Diffusion & DALLE

Trained on 500M+ image and text pairs

Stability AI used over 4000 A100 GPUs





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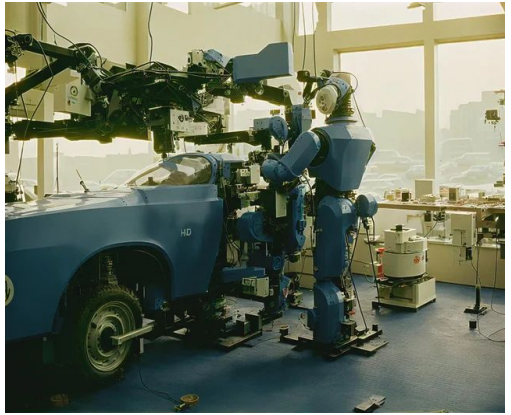
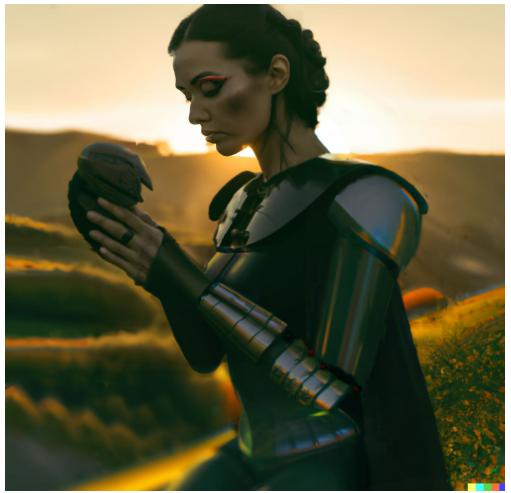
Training Large Language Models can consume a few hundreds or even thousands of MWh of energy

A GPU can consume around 400W at peak or more





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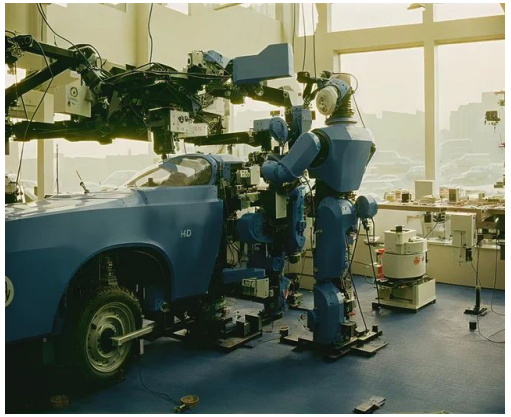
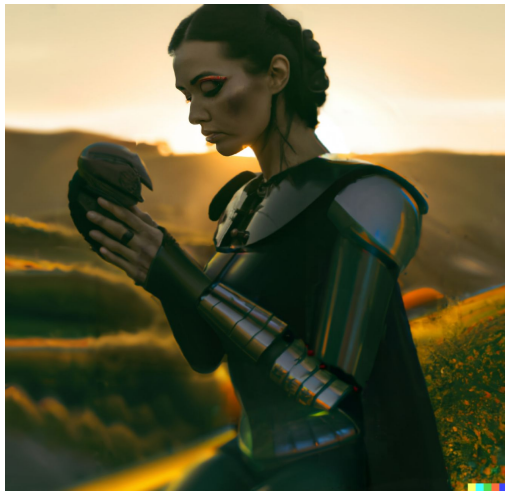
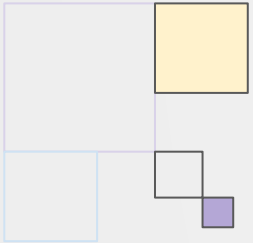
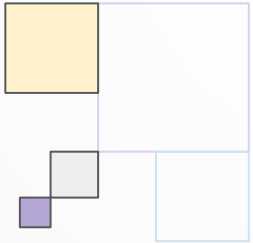
Brain is vastly more efficient consuming around 10W



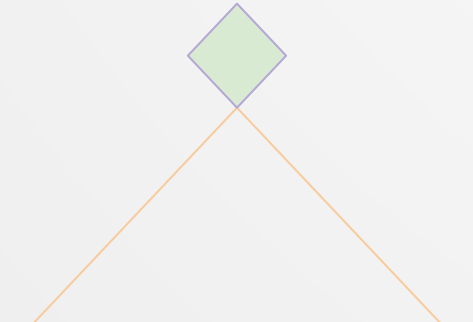






Fin

Introduction Series



Bryan Cardenas
Thomas van Osch

SURF