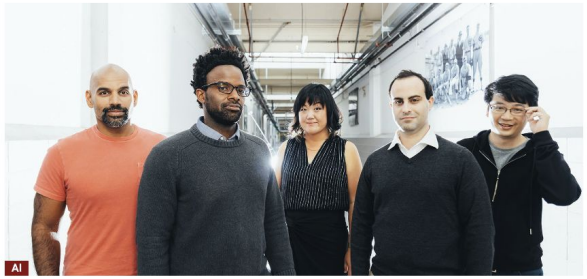
A Whirlwind Tour of LLMs

April 9, 2024
QMSS GR5069

Eitan

Jacob

A bit about our journey



AI

Naveen Rao's MosaicML debuts with a mission to improve machine learning training

FORBES > INNOVATION > CLOUD

Databricks Acquires MosaicML To Make Generative AI More Accessible

Janakiram MSV Senior Contributor

I cover emerging technologies with a focus on infrastructure and AI

for Open-Source, Commercially Usable LL

0

Introducing MPT-7B: A New Standard for Open-Source, Commercially Usable LLMs

by The MosaicML NLP Team

May 5, 2023 in Mosaic AI Research

WILL KNIGHT BUSINESS MAR 27, 2024 8:00 AM

Inside the Creation of the World's Most Powerful Open Source AI Model

Startup Databricks just released DBRX, the most powerful open source large language model yet—eclipsing Meta's Llama 2.

LLM Trivia

- How many people have used LLMs besides GPT4? Which ones?
    - Perplexity? You.com? Bing?
- How much GPT4 cost to train?
- What data went into GPT4?
- How many people here believe the US should allow companies to open source LLM models?
- Who here is worried about the risks of AI? Which risks in particular?
- Do people think that AI will replace jobs? Or “enhance productivity?” Or both?

Why should we care about LLMs?

🤓 Nerd factor – it is incredibly cool that these things work!

Economics – NVIDIA $2T valuation, OpenAI valuation at $80B

Political – US Chips Act, TSMC to build factory in the US, France invests €500M in AI, Canada invests $2B in AI, Saudi Arabia raises $40B AI fund,

Social – will AI replace employees? Will ChatGPT ruin the college education? AI companions,

Science – protein folding

…not to mention the potential harm such as surveillance and misinformation

Main themes

- How do LLMs work?
- What LLMs should you use and why?
- What evaluation benchmarks matter and why?
- When should you finetune?
- What are some rules of thumb around hardware?
- What can these models be used for?
- What are these models are bad at?
- What are open research questions?

Part 1: LLM Overview

What we mean when we talk about LLMs

Proprietary (closed source) LLMs:

- ChatGPT, GPT4 (OpenAI)
- Claude (Anthropic)
- Gemini (Google)
- Pi (Inflection)

Open Source LLMs

- LLama-7B, 13B, 70B (Meta)
- Command-R (Cohere)
- DBRX (Databricks)
- Mistral (Mistral AI)

...

BERT, T5, **GPT2**, OPT, Pythia

...

The Stages of building and serving LLMs

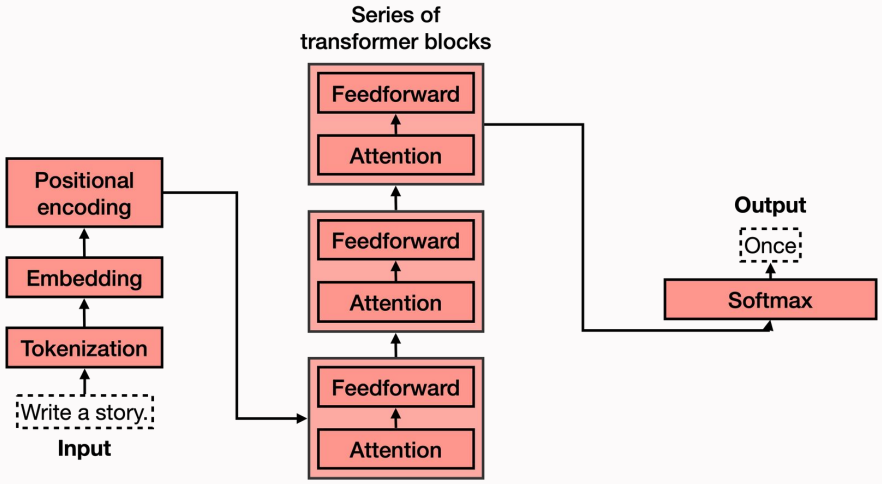
- Data Collection
- Pretraining
- Finetuning
- Evaluation
- Serving

Pretraining

Next token prediction (aka causal language modeling)

“Unsupervised” - the data does not need any human labelers

Core architecture is the transformer block



Hugging Face is a startup based in New York City and Paris

p(word)

Pretraining Data

Example Datasets

- "C4" 750GB (from the CommonCrawl nonprofit open repository of web crawls)
- ThePile (famously contains "Books3" copyrighted books)

BOT COURT

Sarah Silverman-Led AI Copyright Suit Against ChatGPT Partially Dismis

The decision mirrors a ruling that nixed some core claims from suit brought against Meta and its AI tools

BY JON BLISTEIN

The Times Sues OpenAI and Microsoft Over A.I. Use of Copyrighted Work

Millions of articles from The New York Times were used to train chatbots that now compete with it, the lawsuit said.

What is good data?

- Open source textbooks, well-written forum threads

What is bad data?

- Html tags, poorly scraped websites

The websites in Google's C4 dataset

Search for a website

Page 1 of 67

RANK	DOMAIN	CATEGORY	PERCENT OF ALL TOKENS
1	patents.google.com	Law & Government	0.46%
2	wikipedia.org	News & Media	0.19%
3	scribd.com	News & Media	0.07%
4	nytimes.com	News & Media	0.06%
5	journals.plos.org	Science & Health	0.06%
6	latimes.com	News & Media	0.05%
7	theguardian.com	News & Media	0.05%
8	forbes.com	News & Media	0.05%
9	huffpost.com	News & Media	0.04%
10	patents.com	Law & Government	0.04%
11	washingtonpost.com	News & Media	0.03%
12	coursera.org	Jobs & Education	0.03%
13	fool.com	Business & Industrial	0.03%
14	frontiersin.org	Science & Health	0.03%
15	instructables.com	Technology	0.03%

The Post believes it is important to present the complete contents of the data fed into AI models, which promise to govern many aspects of modern life. Some websites in this data set contain highly offensive language and we have attempted to mask these words. Objectionable content may remain.

Note: Some websites were unable to to be categorized and, in many cases, are no longer accessible.

[Washington Post] Inside the secret list of websites that make AI like ChatGPT sound smart (April 2023)

Pretraining Data

Example: NYT Lawsuit against OpenAI has many examples of ChatGPT regurgitating NYT content verbatim

105. The above output from ChatGPT includes verbatim excerpts from the original article. The copied article text is highlighted in red below:

> The snow burst through the trees with no warning but a last-second whoosh of sound, a two-story wall of white and Chris Rudolph's piercing cry: "Avalanche! Elyse!"
>
> The very thing the 16 skiers and snowboarders had sought — fresh, soft snow — instantly became the enemy. Somewhere above, a pristine meadow cracked in the shape of a lightning bolt, slicing a slab nearly 200 feet across and 3 feet deep. Gravity did the rest.
>
> Snow shattered and spilled down the slope. Within seconds, the avalanche was the size of more than a thousand cars barreling down the mountain and weighed millions of pounds. Moving about 7o miles per hour, it crashed through the sturdy old-growth trees, snapping their limbs and shredding bark from their trunks.
>
> The avalanche, in Washington's Cascades in February, slid past some trees and rocks, like ocean swells around a ship's prow. Others it captured and added to its violent load.
>
> Somewhere inside, it also carried people. How many, no one knew.

https://nytco-assets.nytimes.com/2023/12/NYT_Complaint_Dec2023.pdf

How much data?

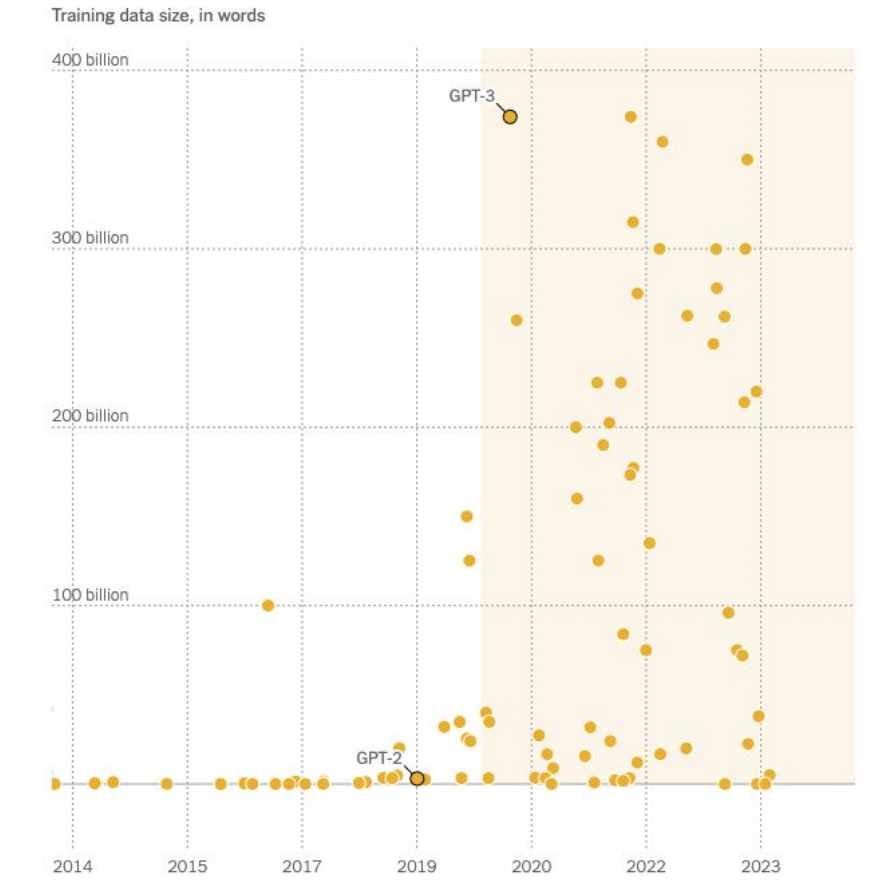
How much data should you train on?

How much data exists on the public internet?

Example models:

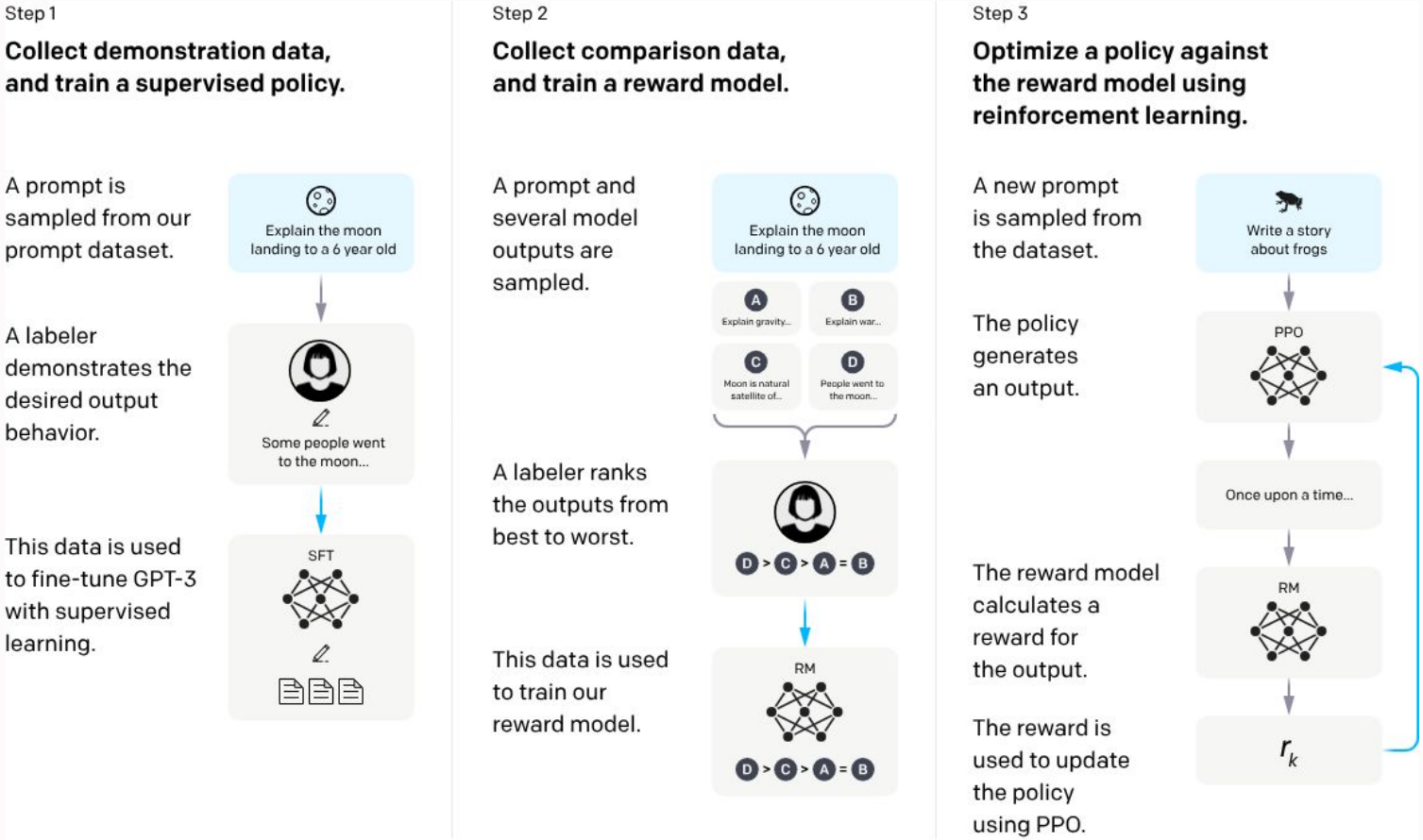
- GPT3: 500 billion tokens
- Llama-7B: 2 trillion tokens
- DBRX: 12 trillion tokens
- GPT4: 13 trillion tokens (estimated)

Important relationship between model size and dataset size i.e. “scaling laws”



(NYT) How Tech Giants Cut Corners to Harvest Data for A.I.

Reinforcement Learning with Human Feedback (RLHF)



https://openai.com/research/instruction-following

Intuition Behind RLHF

From the OpenAI blogpost (Aligning language models to follow instructions, Jan 2022):

> RLHF…"unlocks" capabilities that GPT-3 already had, but were difficult to elicit through prompt engineering alone

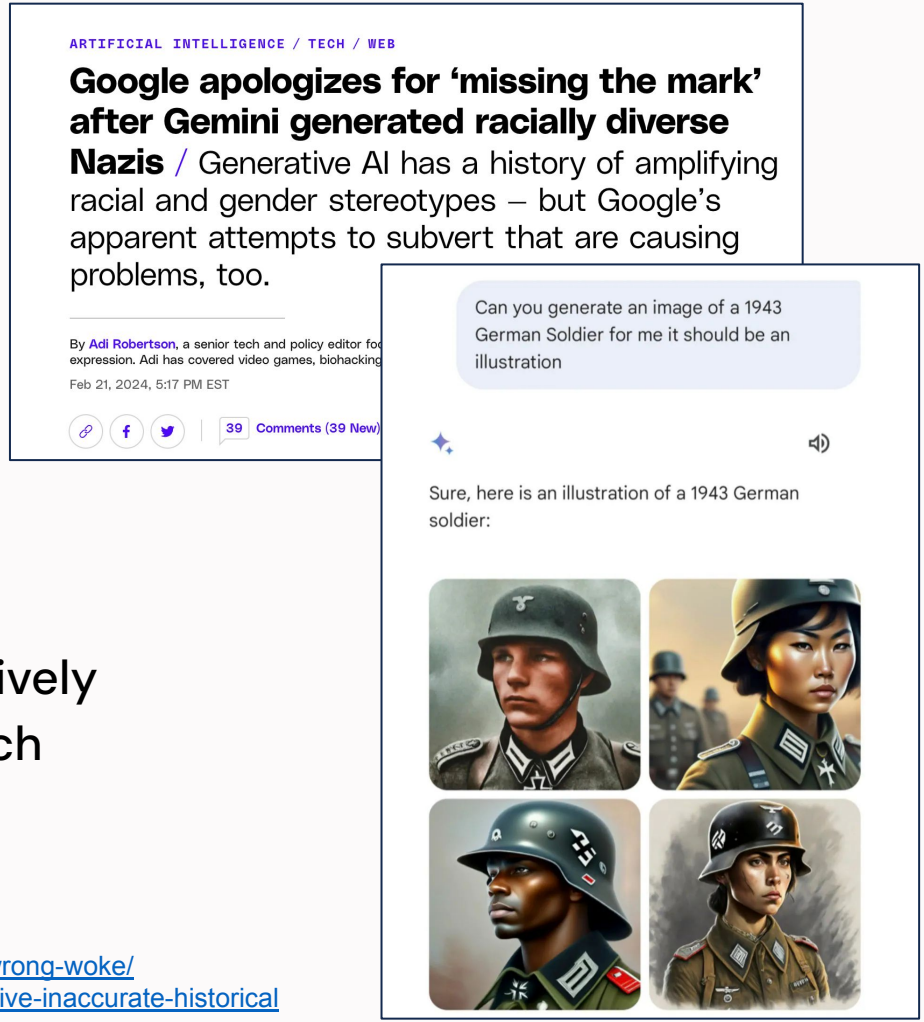
> A limitation of this approach is that it introduces an "**alignment tax**": aligning the models only on customer tasks can make their performance worse on some other academic NLP tasks.

AI Safety and Alignment

General approaches to alignment

1. Heavily filter the pretraining data
2. Finetune on a special, curated datasets
3. “Human in the loop” via RLHF
4. Safety filter in the user interface

The Gemini “…controversy has been promoted largely — though not exclusively — by right-wing figures attacking a tech company that’s perceived as liberal. “



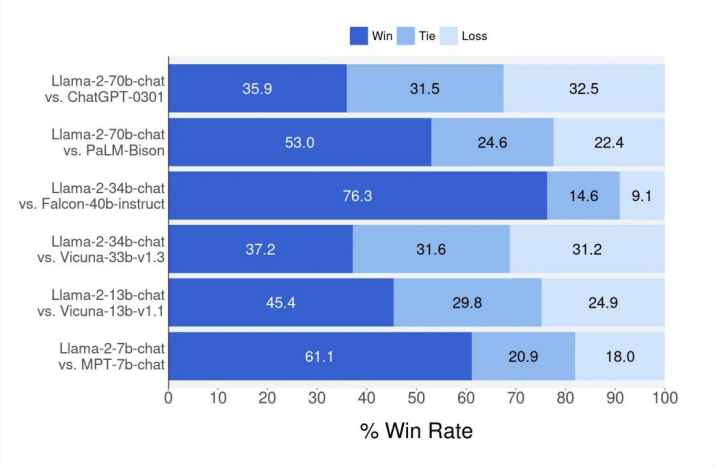
https://www.telegraph.co.uk/news/2024/02/23/google-gemini-ai-images-wrong-woke/
https://www.theverge.com/2024/2/21/24079371/google-ai-gemini-generative-inaccurate-historical

Evaluation

Two paradigms: **perplexity based**, and more recently, **LLM-as-a-judge**

Model	Size	Code	Commonsense Reasoning	World Knowledge	Reading Comprehension	Math	MMLU	BBH	AGI Eval
MPT	7B	20.5	57.4	41.0	57.5	4.9	26.8	31.0	23.5
	30B	28.9	64.9	50.0	64.7	9.1	46.9	38.0	33.8
Falcon	7B	5.6	56.1	42.8	36.0	4.6	26.2	28.0	21.2
	40B	15.2	69.2	56.7	65.7	12.6	55.4	37.1	37.0
LLAMA 1	7B	14.1	60.8	46.2	58.5	6.95	35.1	30.3	23.9
	13B	18.9	66.1	52.6	62.3	10.9	46.9	37.0	33.9
	33B	26.0	70.0	58.4	67.6	21.4	57.8	39.8	41.7
	65B	30.7	70.7	60.5	68.6	30.8	63.4	43.5	47.6
LLAMA 2	7B	16.8	63.9	48.9	61.3	14.6	45.3	32.6	29.3
	13B	24.5	66.9	55.4	65.8	28.7	54.8	39.4	39.1
	34B	27.8	69.9	58.7	68.0	24.2	62.6	44.1	43.4
	70B	**37.5**	**71.9**	**63.6**	**69.4**	**35.2**	**68.9**	**51.2**	**54.2**

Table 3: Overall performance on grouped academic benchmarks compared to open-source base models.



Figures from the [Llama2 Paper]

Prompt Engineering - is this a real thing? Yes!

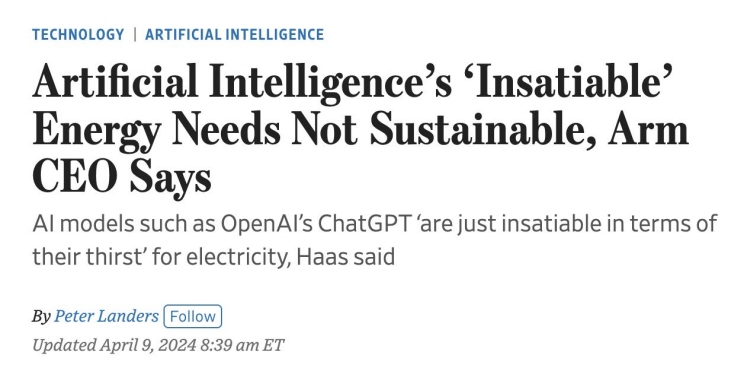
👍 The larger and more powerful the model, the less prompt engineering and in context learning is necessary

https://kyleake.medium.com/prompt-engineering-guide-for-ai-enthusiasts-2f0334dae165

Serving

How do companies efficiently support LLMs?

> “In a January report, the International Energy Agency said **a request to ChatGPT requires 2.9 watt-hours of electricity on average**—equivalent to turning on a 60-watt lightbulb for just under three minutes. That is nearly **10 times as much as the average Google search.**” [WSJ: Artificial Intelligence’s ‘Insatiable’ Energy Needs Not Sustainable, Arm CEO Says 4/9/2024]



TECHNOLOGY | ARTIFICIAL INTELLIGENCE

Artificial Intelligence’s ‘Insatiable’ Energy Needs Not Sustainable, Arm CEO Says

AI models such as OpenAI’s ChatGPT ‘are just insatiable in terms of their thirst’ for electricity, Haas said

By Peter Landers Follow

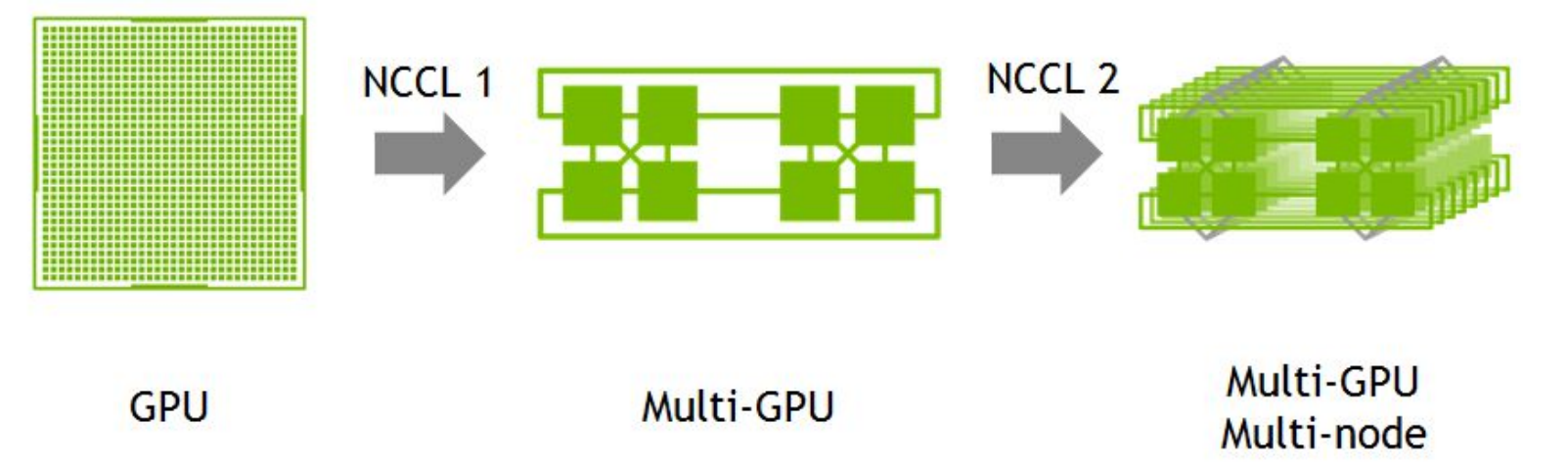
Updated April 9, 2024 8:39 am ET

GPUs for Training and Serving 🛠️

A single node can contain multiple GPUs connected in the same “box”

Multinode training involves multiple nodes. The nodes are distributed and communication is slower

See also A Gentle Introduction To Multi GPU And Multi Node Distributed Training and Efficient Training on Multiple GPUs (HuggingFace)



https://www.mn.uio.no/ifi/studier/masteroppgaver/nd/fast-multi-gpu-communication-over-pcie.html

Important Tools 🛠️

Neural Network Training

- PyTorch
- TensorFlow
- PyTorch Lightning
- HuggingFace (also a model hub, and a great learning resource!)

Experiment Tracking

- Weights&Biases, TensorBoard, MLFlow

GPU Orchestration

- Slurm, kubernetes
- Modal, Replit (startups)

Part 2: How LLMs Work

What are Neural Networks?

What is the difference between machine learning vs. neural networks?

- Machine Learning is the broad class of algorithms that can learn from data. Neural networks are arguably the **most powerful ML systems** in the toolbox!

Basic idea:

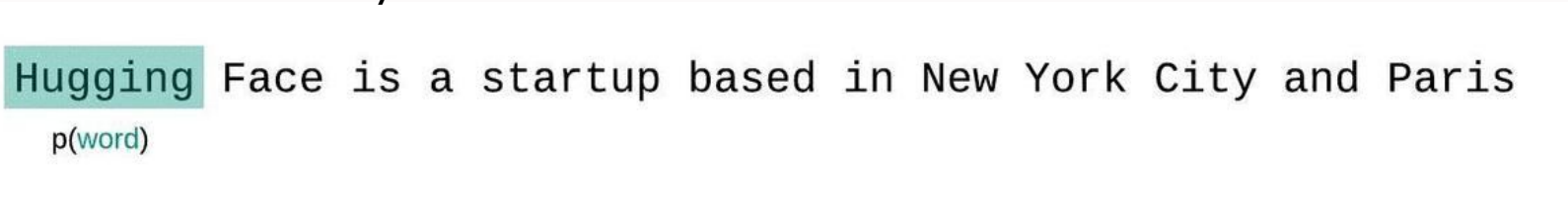
1. Transform inputs through layers of matrices and other mathematical operations
2. Define a function to optimize i.e. a **loss function** or **objective function**
3. Update the weights of the network 🧠

How do you “optimize the loss function”?

- Calculate the gradient of the loss function with respect to the weights
- Update the weights using the **backpropagation algorithm**
- Need to use an **optimizer algorithm** for best results! (e.g. Stochastic Gradient Descent “SGD”, Adam, etc.)

What is the LLM “Loss Function”? Next Token Prediction and Perplexity

Intuitively, we want to calculate the probability of a word given the preceding words, and choose the most likely word



Perplexity is defined as the exponentiated average **negative log-likelihood** of a sequence X.

$$\mathrm{PPL}(X) = \exp\left\{-\frac{1}{t}\sum_{i}^{t}\log p_\theta(x_i|x_{<i})\right\}$$

Perplexity can be thought of as a measure of how "surprised" the model is by the data. A lower perplexity indicates the model is better at predicting the next token

Related concepts: Cross Entropy

https://huggingface.co/docs/transformers/perplexity

Tokenization

- Fundamental step in the NLP pipeline.
- Converts raw text into a format that can be processed by models
- Tokenization can be done at different levels, such as by words, characters, or even subwords.

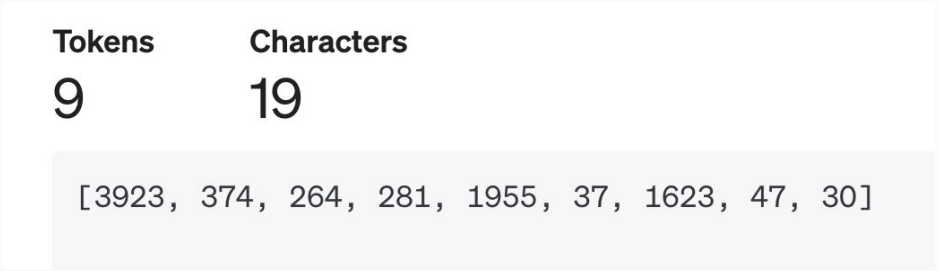
GPT4 tokenizer playground: https://platform.openai.com/tokenizer

Example: Using the GPT4 tokenizer

👉 GPT4 tokenizer playground: https://platform.openai.com/tokenizer

The GPT4 tokenizer chops “What is a petaFLOP into 9 tokens

These are represented as numbers in the tokenizer “dictionary” or “vocabulary.”



In this tokenizer, some words remain whole (i.e. get their own vocab ID) - “walking”

Other words get split - “_w” + “acky” + “_”

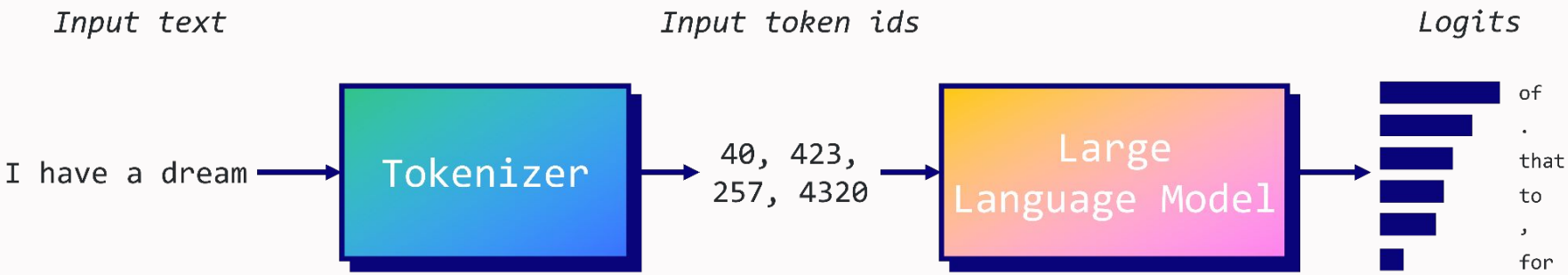
👍 Some Rules of Thumb around Tokenization

For a nice introduction to tokenization and tokenizers, see Tokenizers (HF NLP Course) and Summary of the Tokenizers (HF Conceptual Guide)

- Tokenizers are built algorithmically based on a corpus. There are many tokenization algorithms and many tokenizers
- Each model on HuggingFace is paired with an associated tokenizer
    - If you want to use a HuggingFace model, you must use the correct tokenizer!
    - Different tokenizers split words differently!
- Some tokenizers handle different languages (e.g. Chinese) uniquely
- If you are using LLMs via an API, you will (likely) be charged based on the # of tokens

Logits

- Logits are the raw, unnormalized output values from a neural network's output layer
- Logits are scores assigned to every possible token in the tokenizer vocabulary



👍 Some APIs will give you access to the logits, others won't

LLM Decoding

So for a given text input, you get a bunch of logits. Then what?

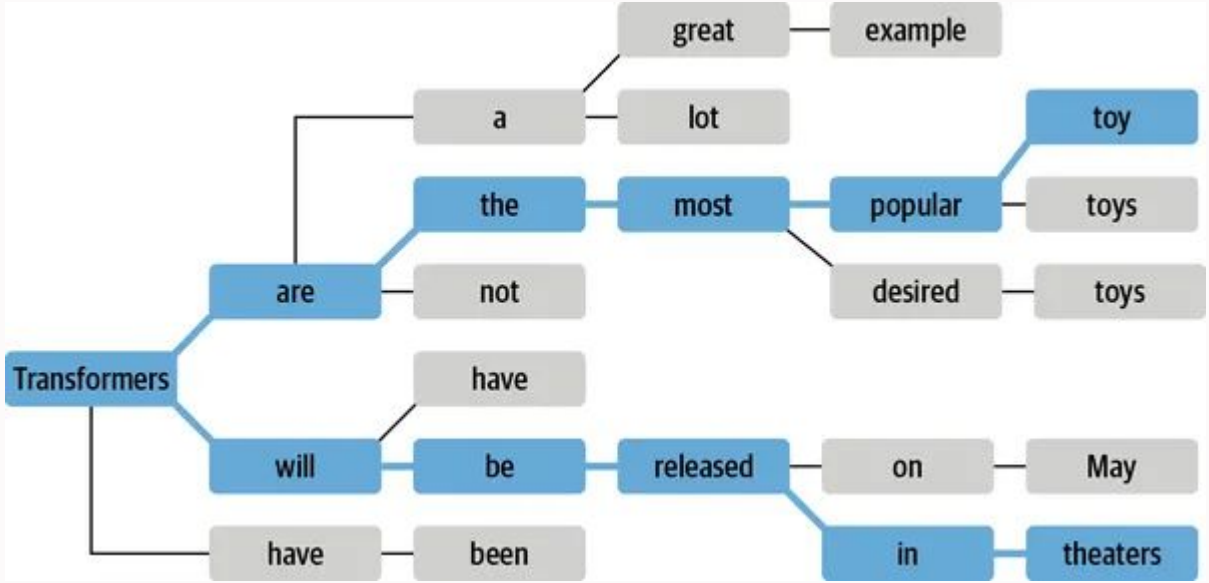
Greedy search is a decoding method that takes the most probable token at each step as the next token in the sequence.

Beam search takes into account the n most likely tokens, where n represents the number of beams. The sequence (or “beam”) with the highest overall score is chosen as the output.

Top-k sampling is a technique that leverages the probability distribution generated by the language model to select a token randomly from the k most likely options

Source: Decoding Strategies in Large Language Models

Decoding Example: Beam Search

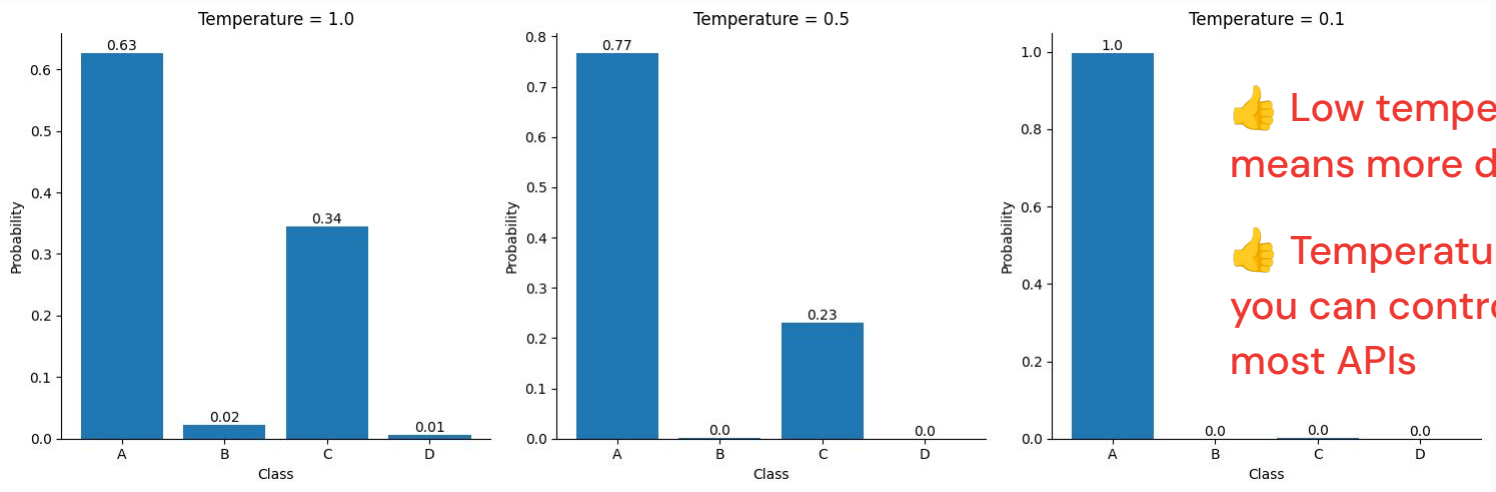


Decoding Example: Top-k

Suppose we have **k=3** and four tokens: A, B, C, and D, with respective probabilities: P(A)=0.3 P(A)=30, P(B)=0.15, P(C)=0.05, and P(D)=0.1 . In top-k sampling, token D is disregarded, and the algorithm will output A 60% of the time, B 30% of the time, and C 10% of the time

The temperature T is a parameter that ranges from 0 to 1

$$\text{softmax}(x_i) = \frac{e^{x_i/T}}{\sum_j e^{x_j/T}}$$



👍 Low temperature means more determinism!

👍 Temperature is a knob you can control through most APIs

[Decoding Strategies in Large Language Models]

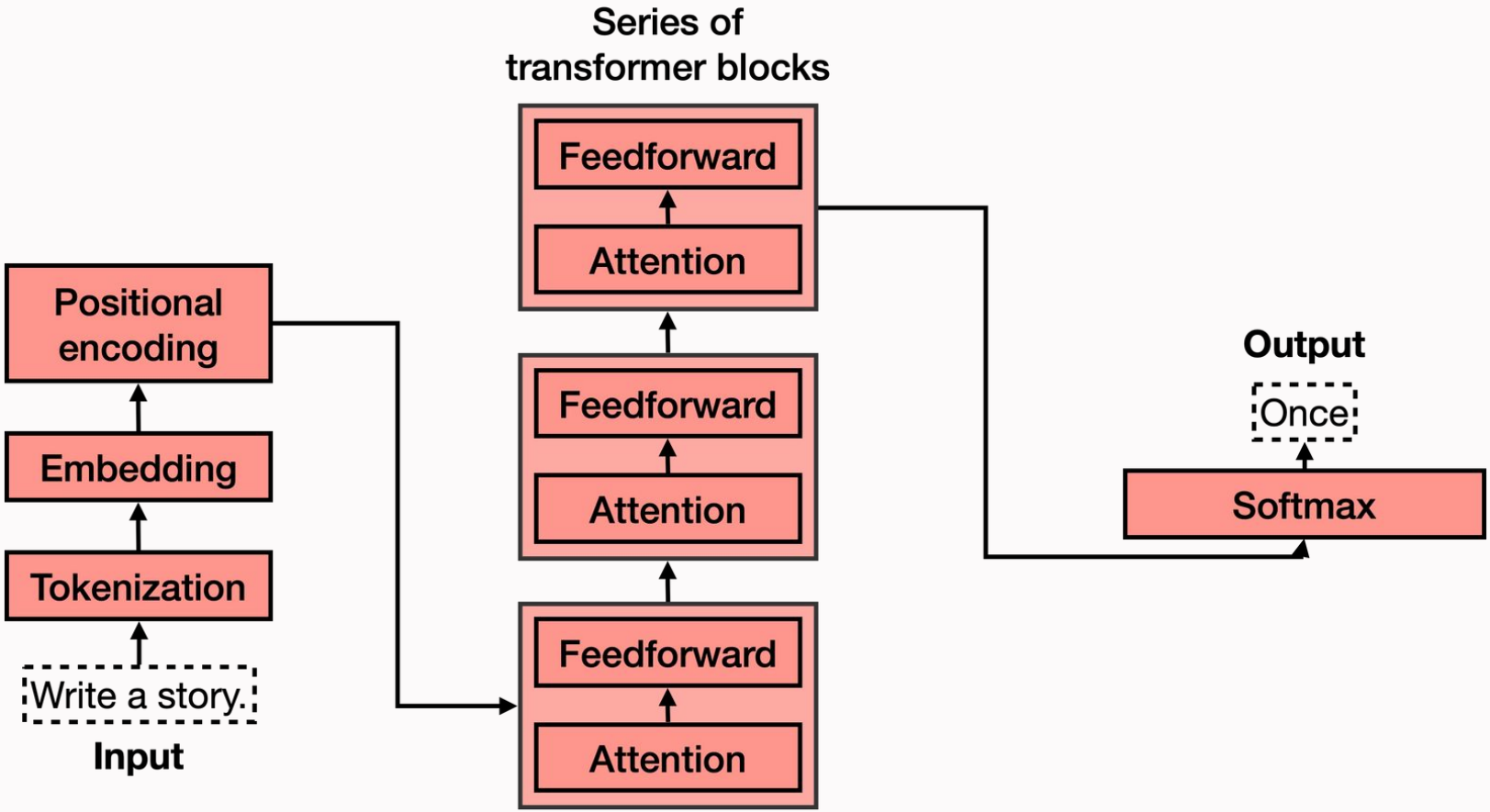
Demo: Exploring Logits (30 min)

Colab Notebook

Deep Dive into How Transformers Work: Version 1

The next few slides use graphics taken from Cohere's blogpost "What Are Transformer Models and How Do They Work?"

The Transformer Architecture



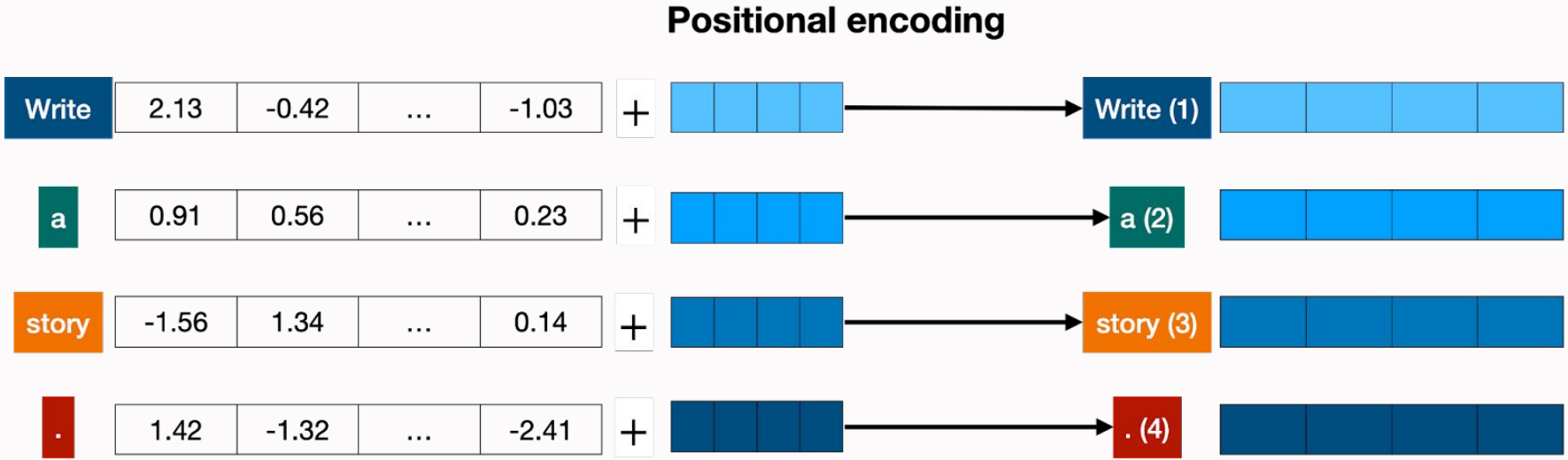
https://txt.cohere.com/what-are-transformer-models/

The “Embedding” Layer

https://txt.cohere.com/what-are-transformer-models/

Positional Encoding

Positional encoding adds a positional vector to each word, in order to keep track of the positions of the words.



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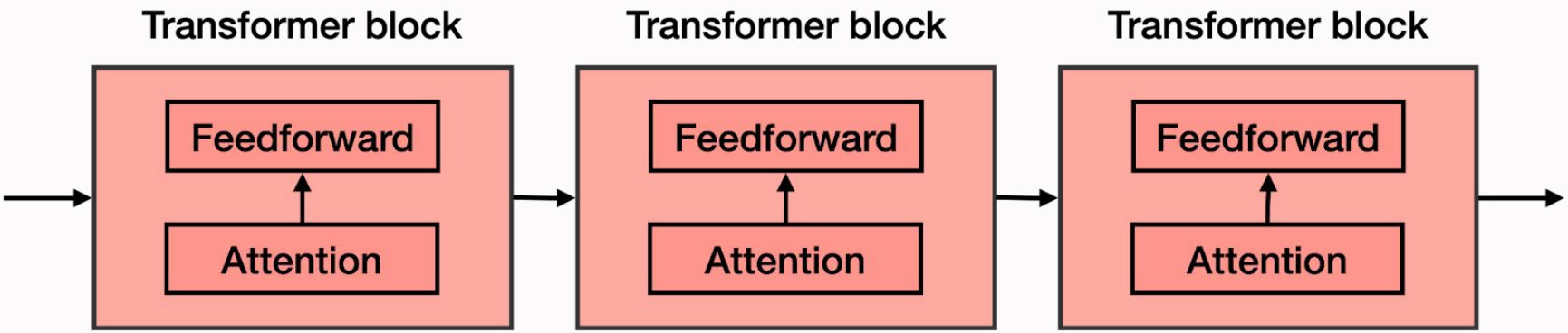
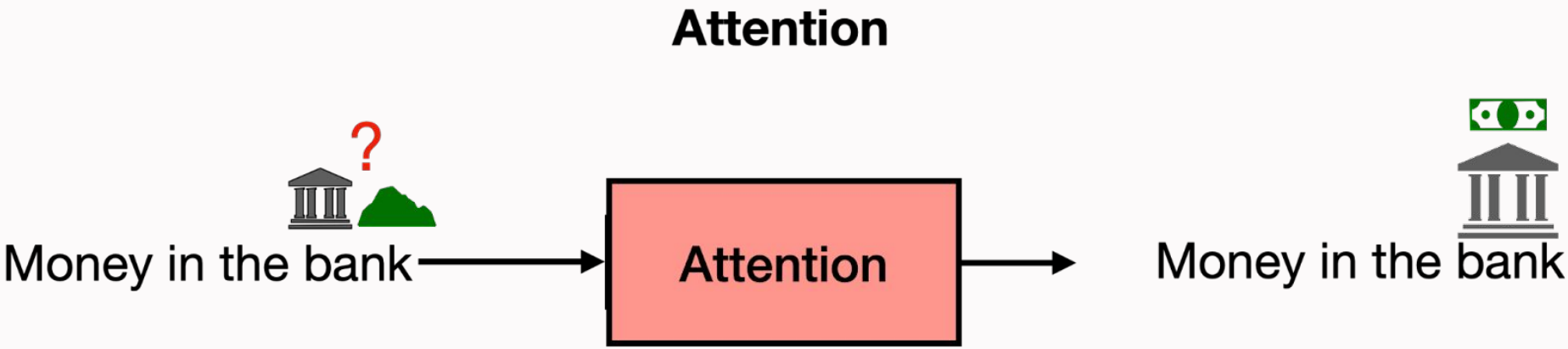
Transformer blocks & Attention

The attention mechanism in the transformer block is the key to the success of LLMs



What does the attention block do?

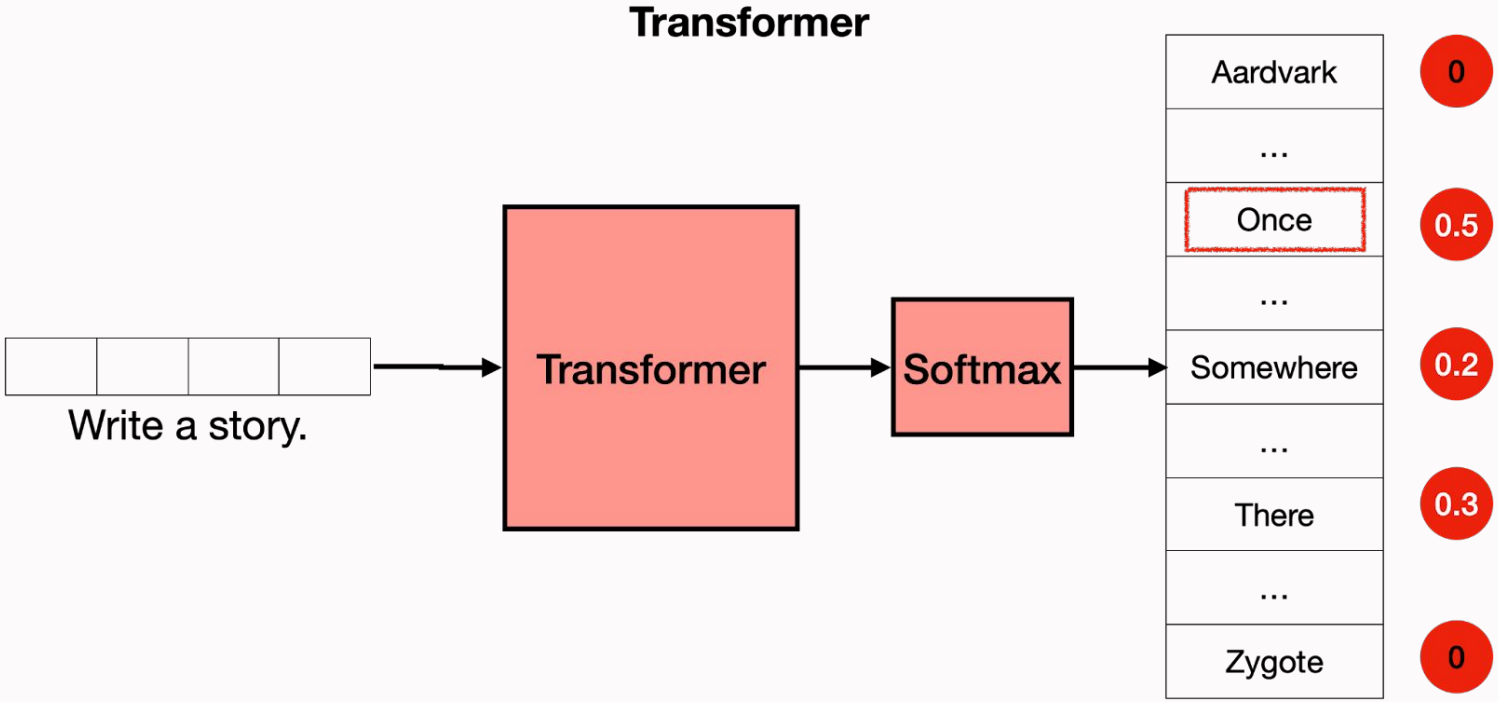
The attention mechanism is the key to the success of LLMs



https://txt.cohere.com/what-are-transformer-models/

Softmax

The softmax layer turns the scores into probabilities, and these are used to pick the next word in the text.



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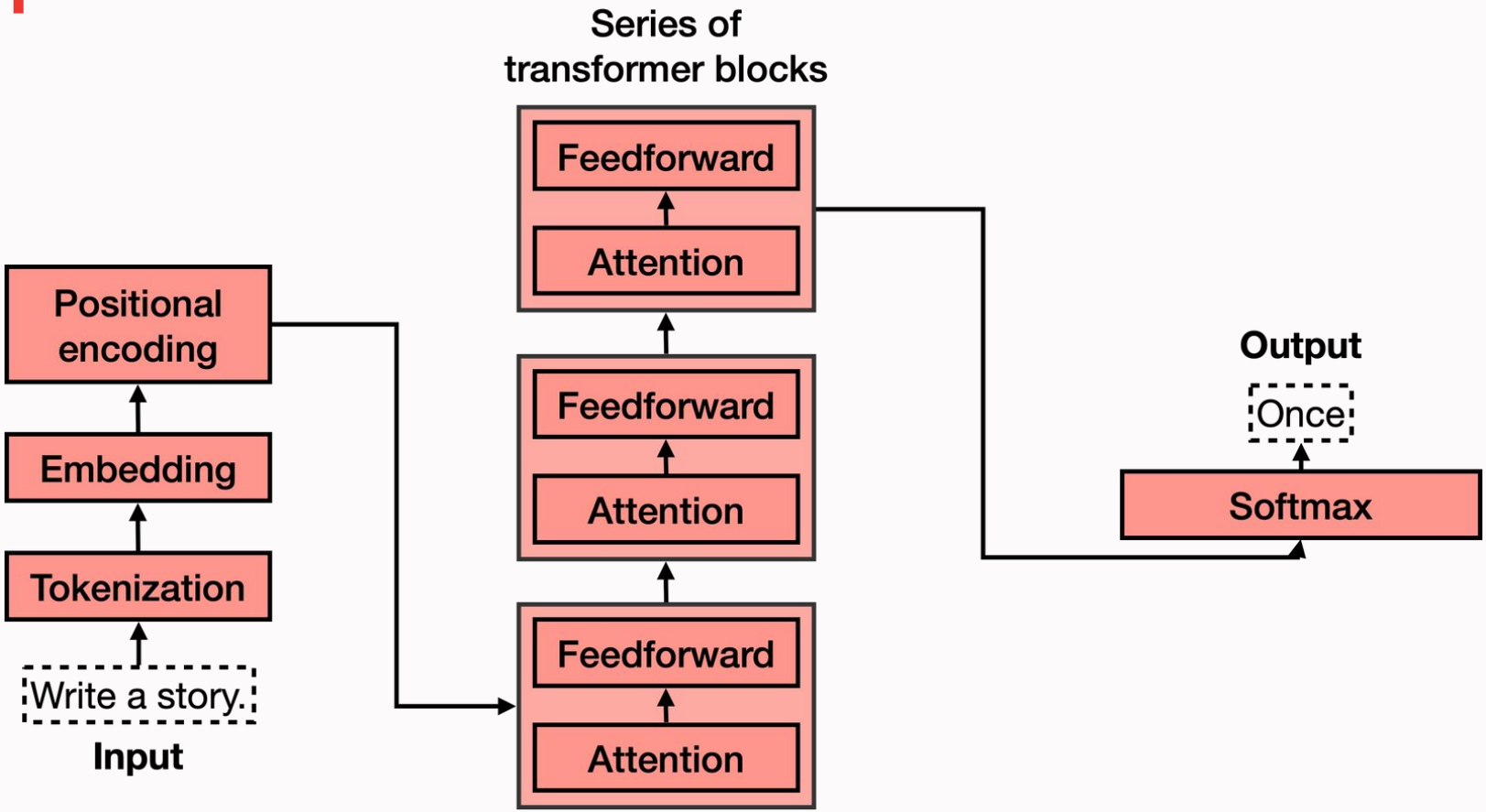
Recap

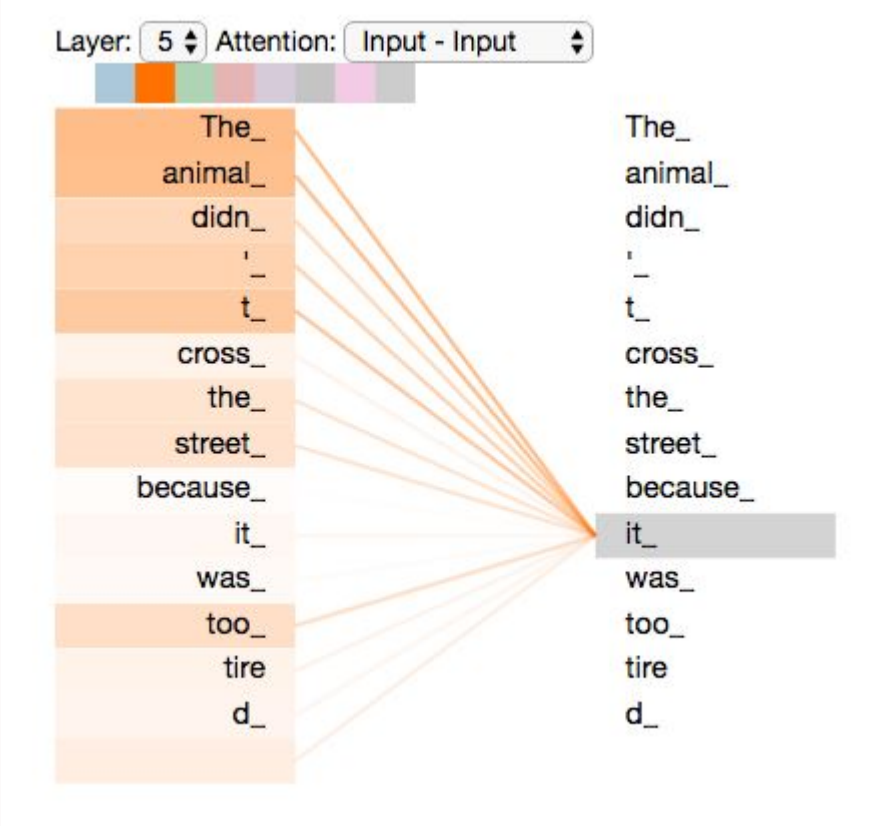


https://txt.cohere.com/what-are-transformer-models/

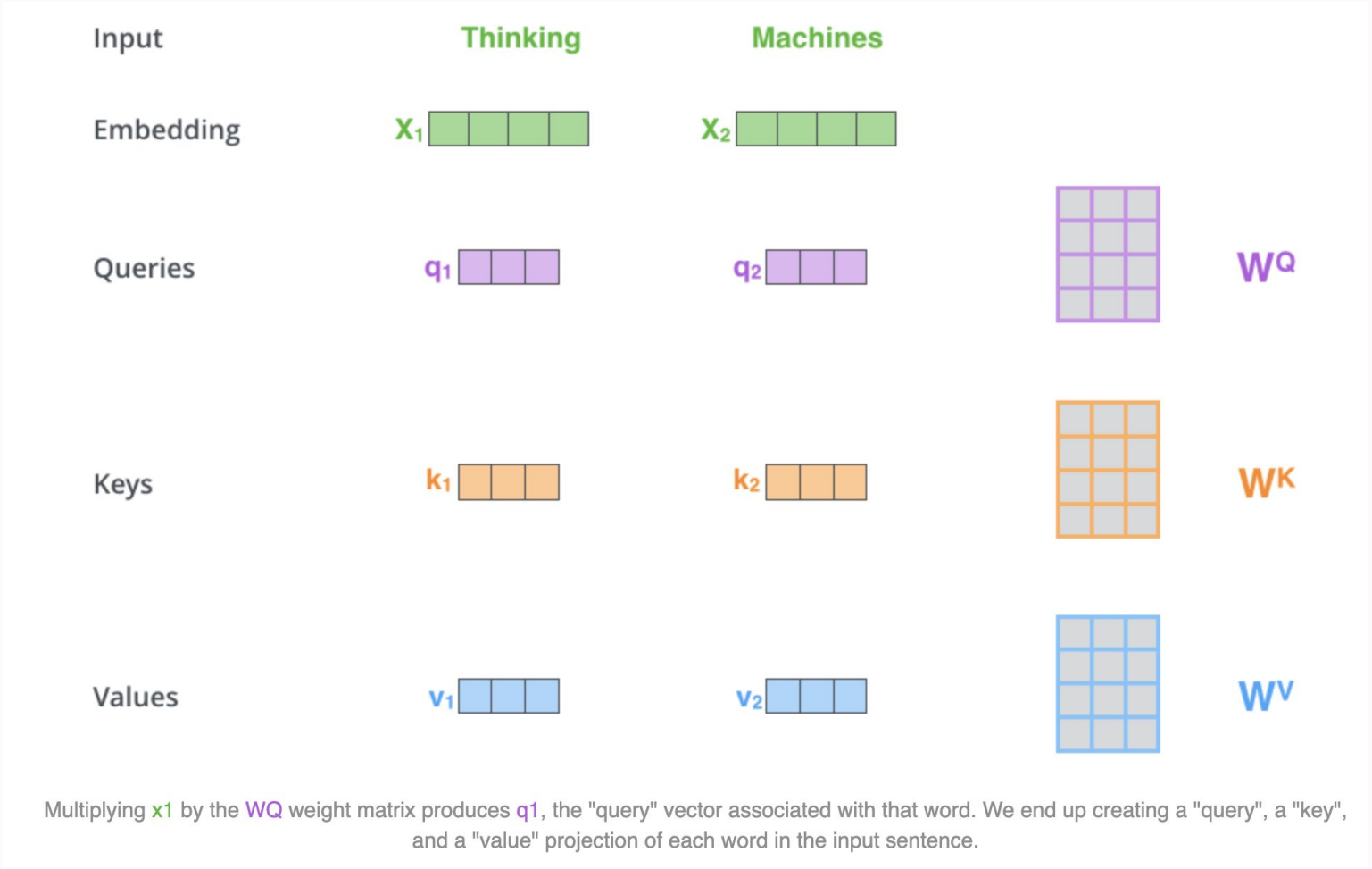
Deep Dive into How Transformers Work: Version 2

The next few slides use graphics taken from Jay Alamar's blogpost "The Illustrated Transformer"

Self Attention

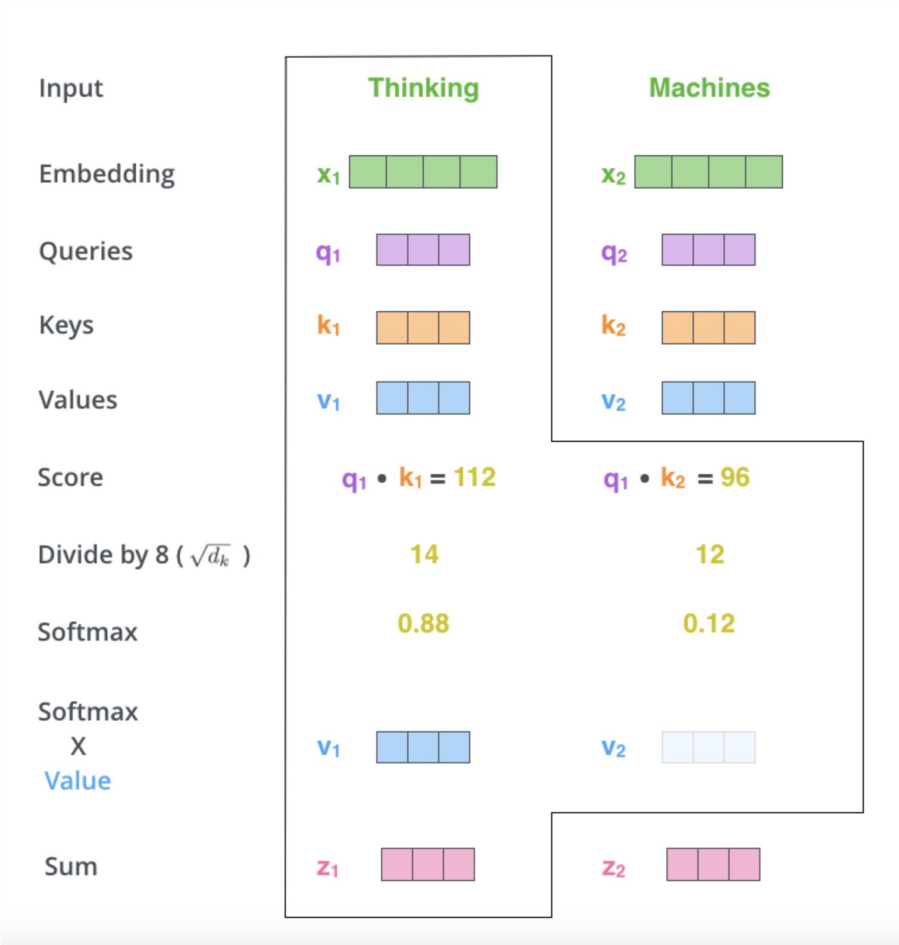


https://jalammar.github.io/illustrated-transformer/

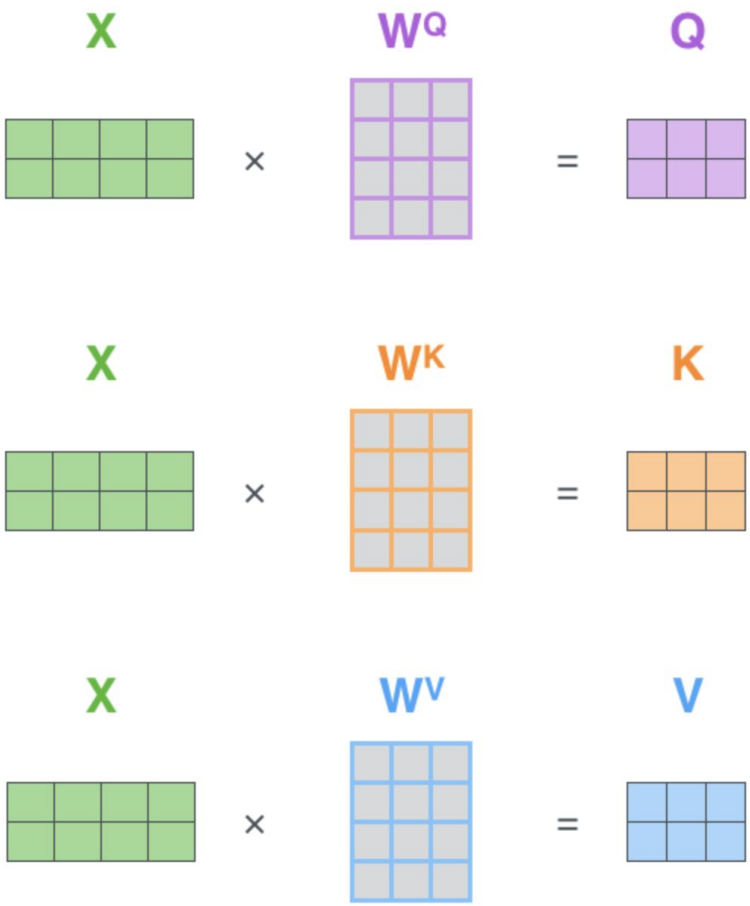


Multiplying x1 by the WQ weight matrix produces q1, the "query" vector associated with that word. We end up creating a "query", a "key", and a "value" projection of each word in the input sentence.

https://jalammar.github.io/illustrated-transformer/

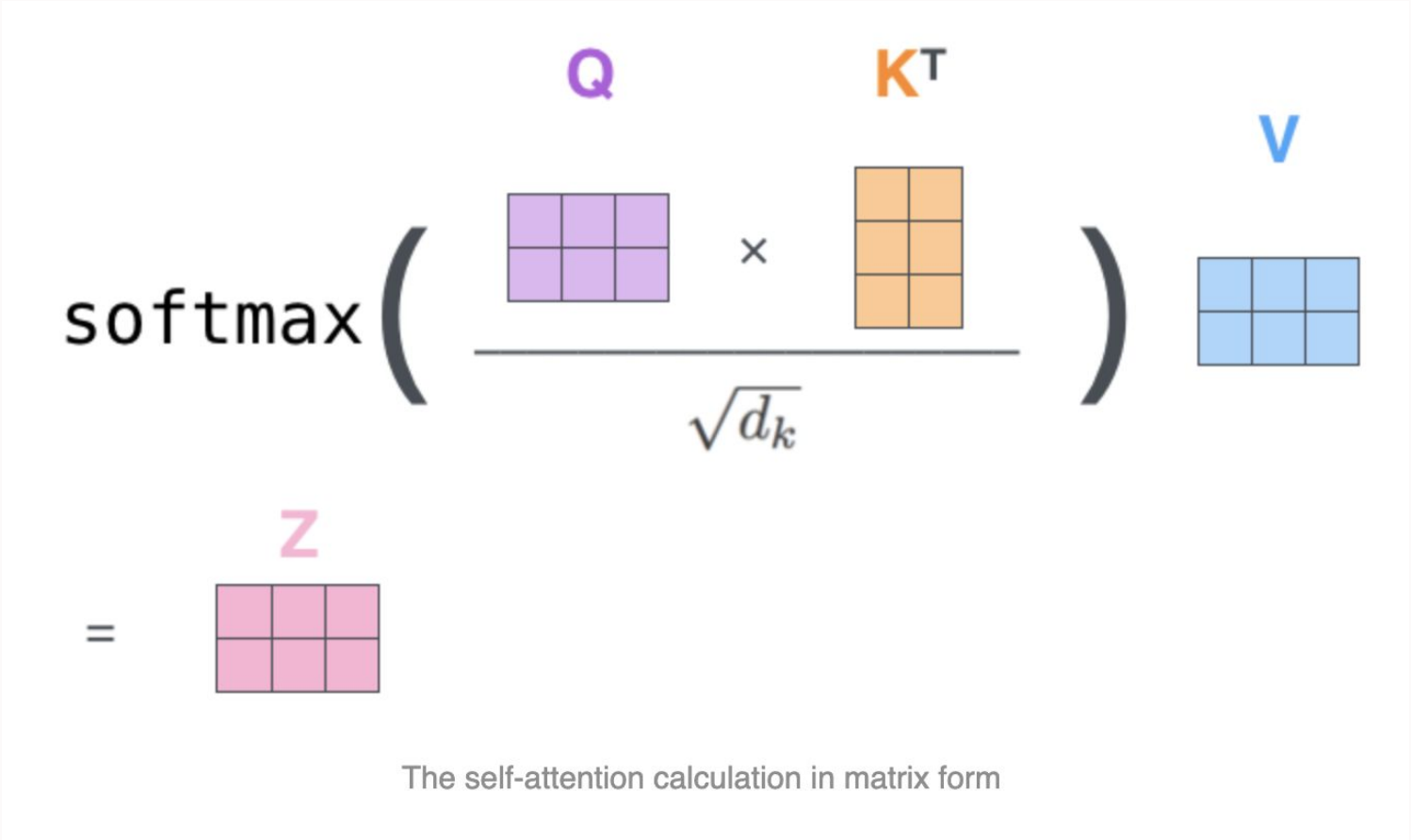


https://jalammar.github.io/illustrated-transformer/



Every row in the X matrix corresponds to a word in the input sentence. We see the difference in size of the embedding vector (512 or 4 boxes in the figure), and the q/k/v vectors (64, or 3 boxes in the figure)

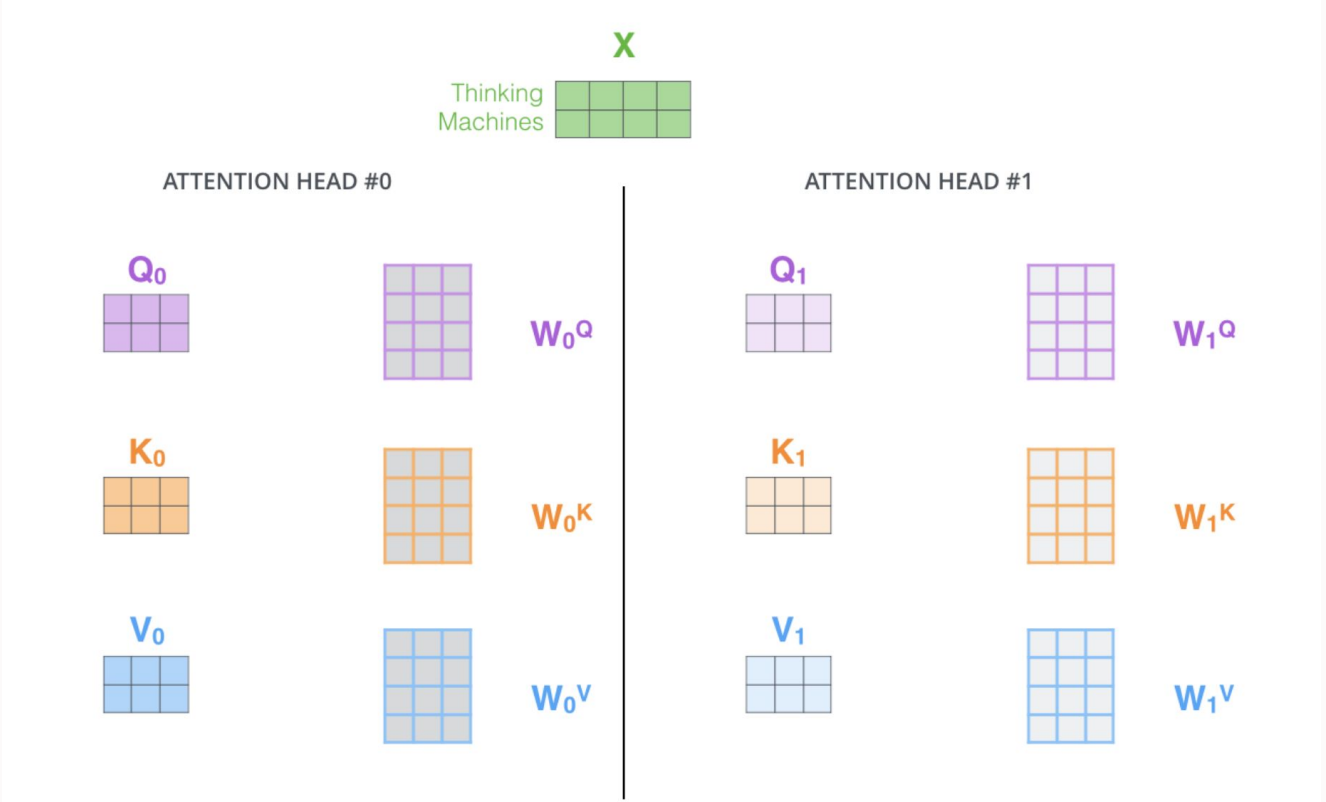
https://jalammar.github.io/illustrated-transformer/



The self-attention calculation in matrix form

https://jalammar.github.io/illustrated-transformer/

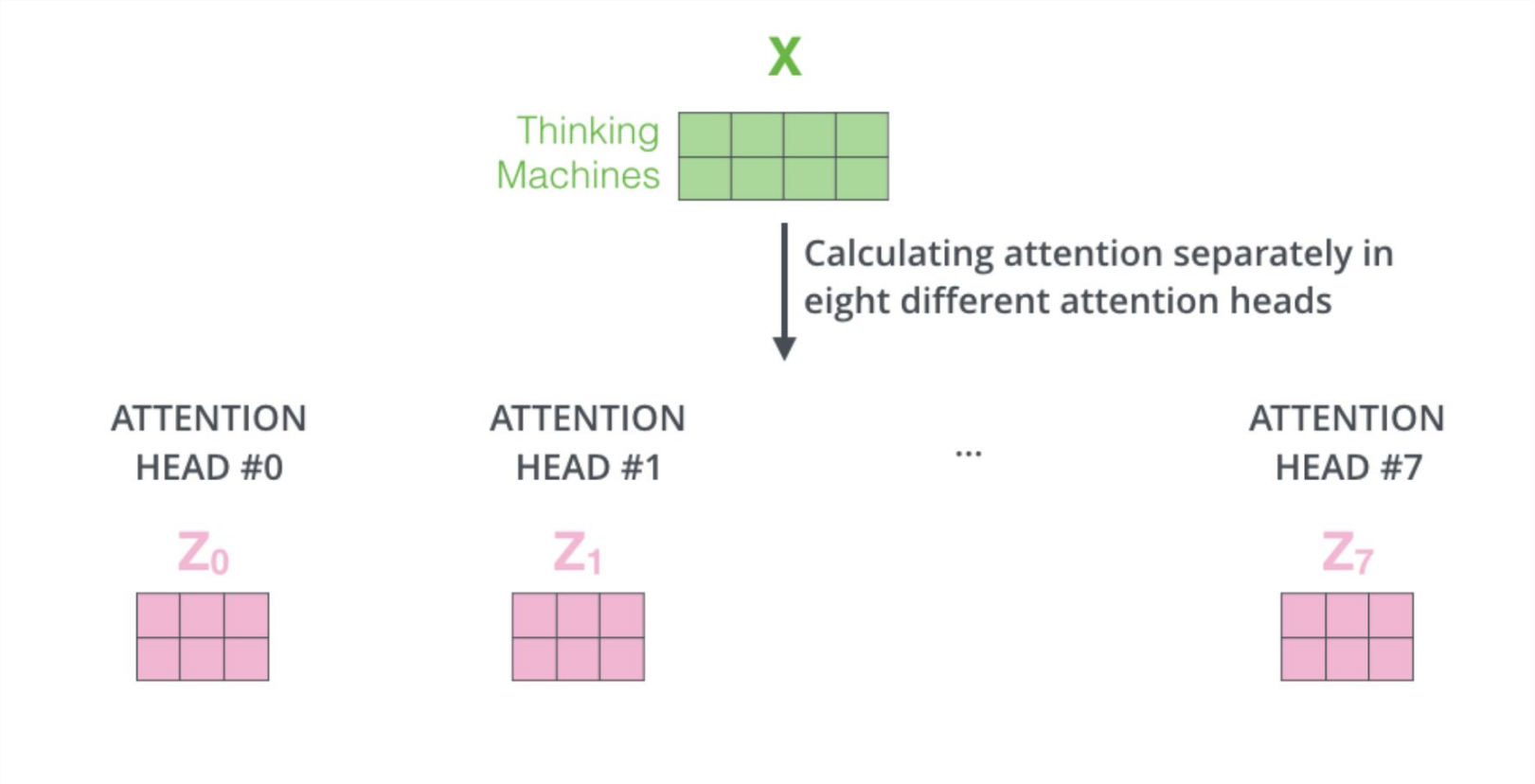
Multi Headed Self Attention



With multi-headed attention, we maintain separate Q/K/V weight matrices for each head resulting in different Q/K/V matrices. As we did before, we multiply X by the WQ/WK/WV matrices to produce Q/K/V matrices.

https://jalammar.github.io/illustrated-transformer/

Multi Headed Self Attention



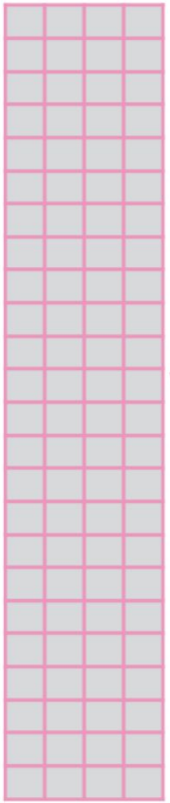
https://jalammar.github.io/illustrated-transformer/

Multi Headed Self Attention

1) Concatenate all the attention heads

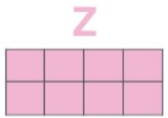
2) Multiply with a weight matrix W^O that was trained jointly with the model

X



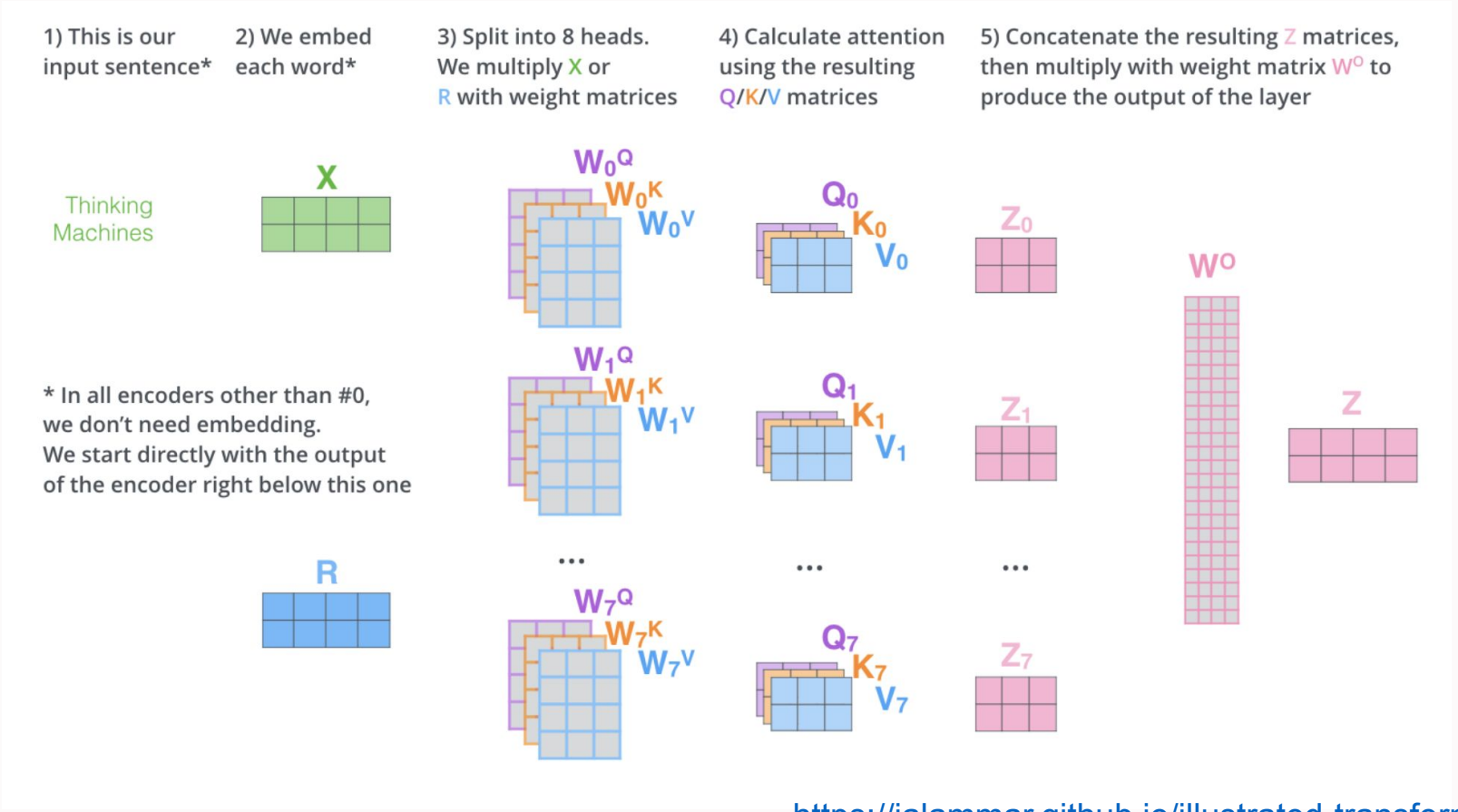
3) The result would be the Z matrix that captures information from all the attention heads. We can send this forward to the FFNN

=



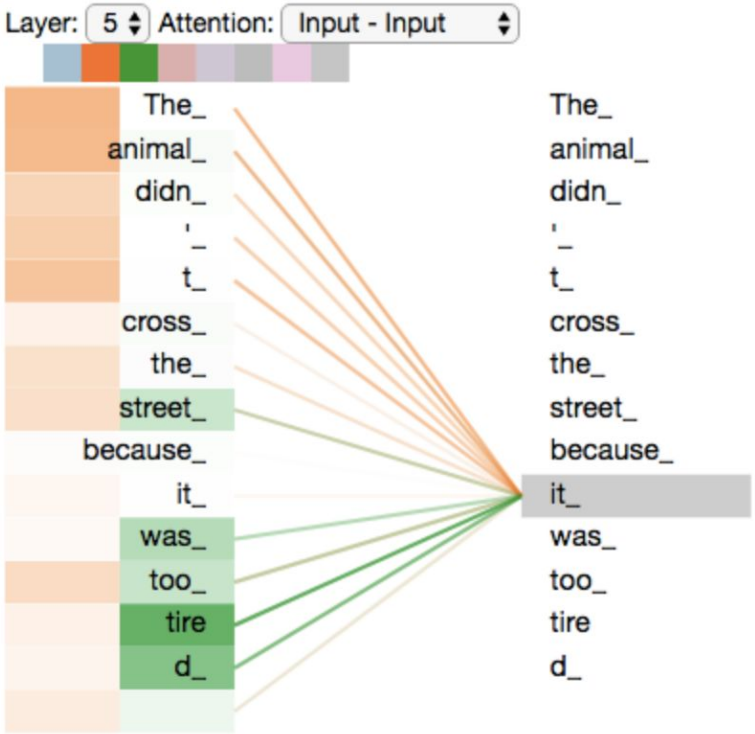
https://jalammar.github.io/illustrated-transformer/

Multi Headed Self Attention



https://jalammar.github.io/illustrated-transformer/

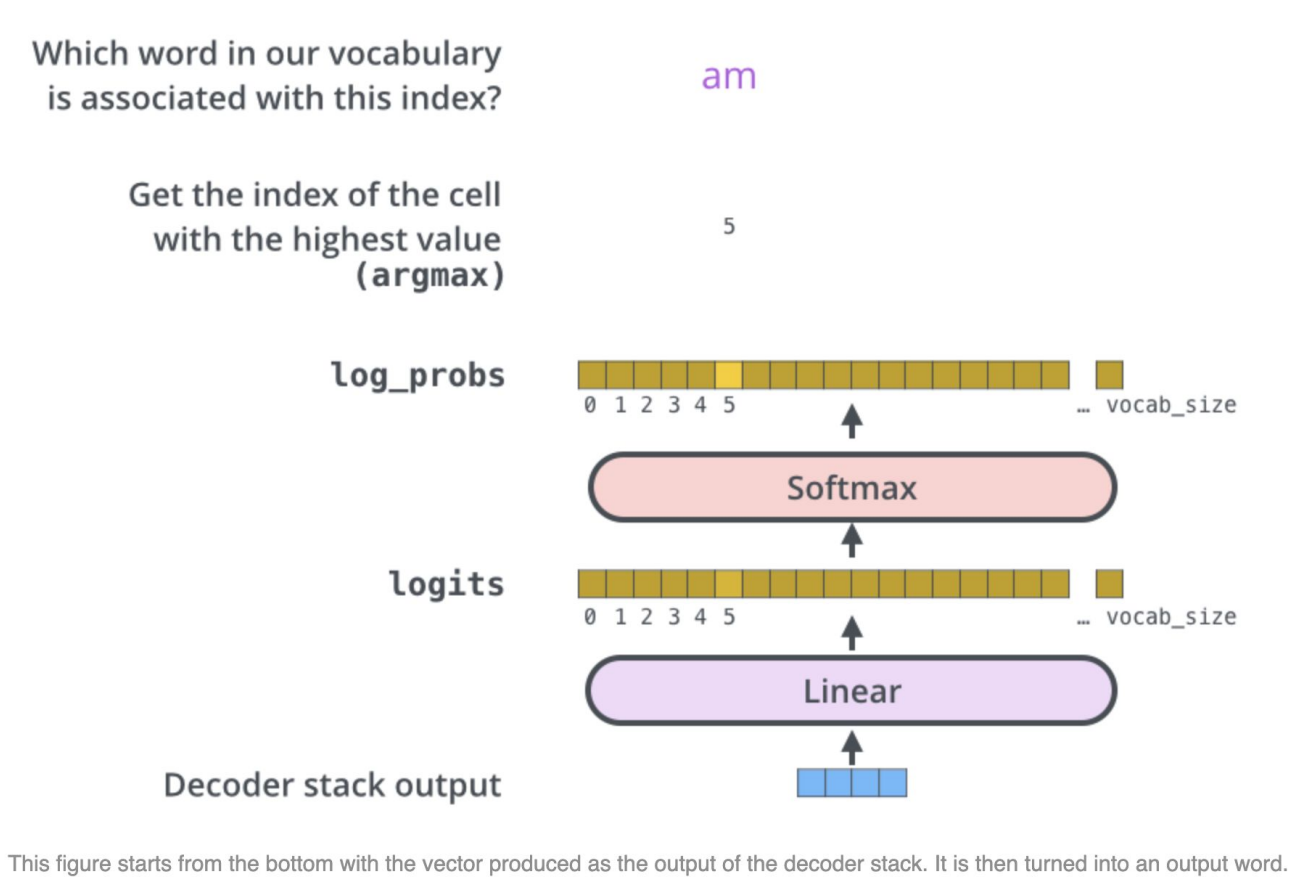
Multi Headed Self Attention



As we encode the word "it", one attention head is focusing most on "the animal", while another is focusing on "tired" -- in a sense, the model's representation of the word "it" bakes in some of the representation of both "animal" and "tired".

https://jalammar.github.io/illustrated-transformer/

Bringing this back to logits…



This figure starts from the bottom with the vector produced as the output of the decoder stack. It is then turned into an output word.

https://jalammar.github.io/illustrated-transformer/

👍 Example LLM Details

Model	Status	Total # Parameters	# Transformer Layers	Pretraining Tokens	Vocab Size
GPT2-1.2B	Open Source	1.2B	12	~10B tokens	50,257
GPT3-175B	Closed Source	175B	NA	~300B tokens	NA
Llama 7B	Open Source	7B	32	~2T tokens	32,000
Llama 65B (aka Llama-70B)	Open Source	65B	80	~2T tokens	32,000
DBRX	Open Source	132B	40	12T tokens	100,352

Demo of Transformer (5 min)

https://bbycroft.net/llm

LLM History...

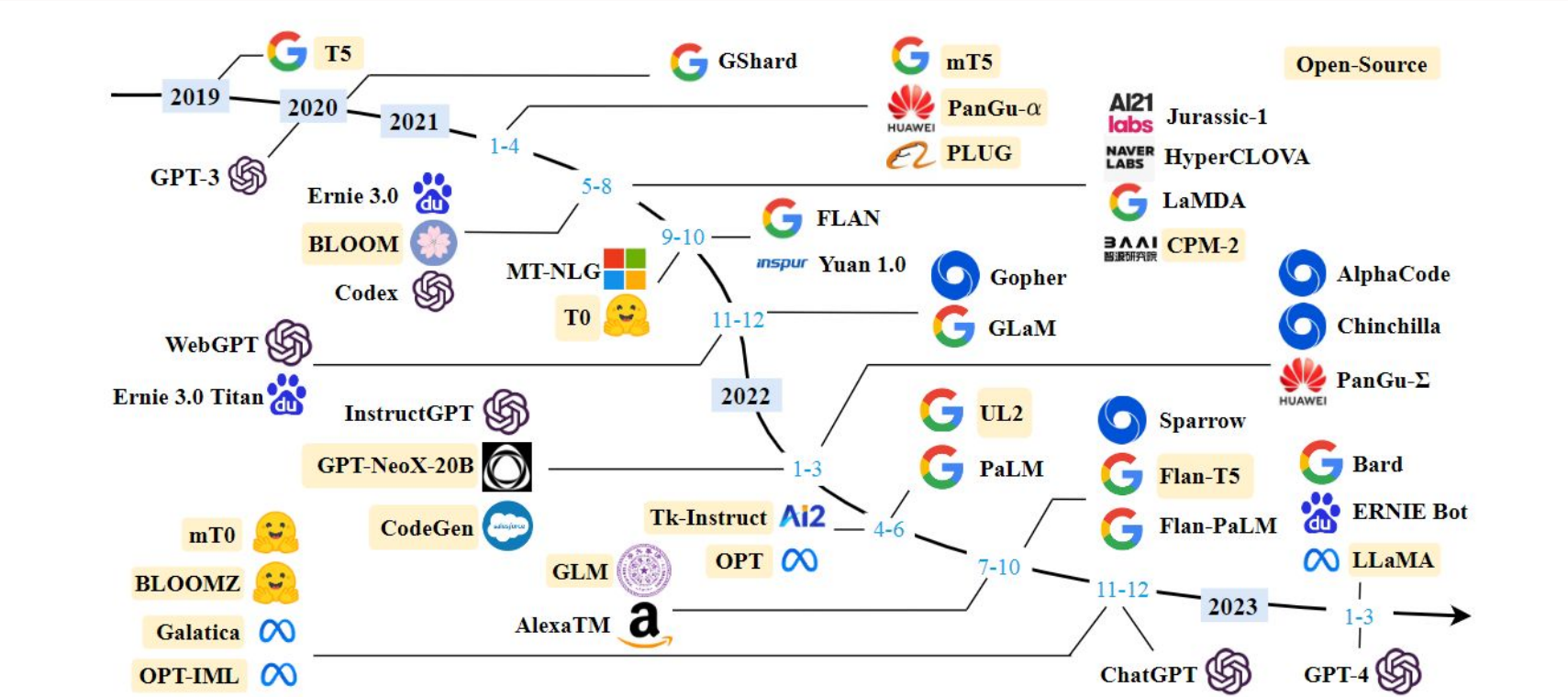


Fig. 1. A timeline of existing large language models (having a size larger than 10B) in recent years. We mark the open-source LLMs in yellow color.

[A Survey of Large Language Models]

Why does it take more memory and time to *train* a LLM?

👉 FP16 = 2 Bytes of memory, FP32 = 4 Bytes of memory

INFERENCE/SERVING

- Model parameters in FP16 → 2x the number of parameters. So a Llama-7B model uses at least 14 GB of memory to play with!

Why does it take more memory to **train** a LLM?

- Model parameters
- Model optimizer
- Model gradient

What is stored in GPU Memory?

TRAINING

- Model parameters in FP16 → 2x the number of parameters
- Model Gradients in FP16 → 2x the number of parameters
- Optimizer State [Adam, all in FP32] → 12x the number of parameters
  - Model copy in FP32 → 4x the number of parameters
  - Momentum → 4x the number of parameters
  - Variance → 4x the number of parameters

See also https://d2l.ai/chapter_optimization/adam.html for code examples

momentum

variance

$$\nu_t = \beta_1 * \nu_{t-1} - (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

gradient g

weights w

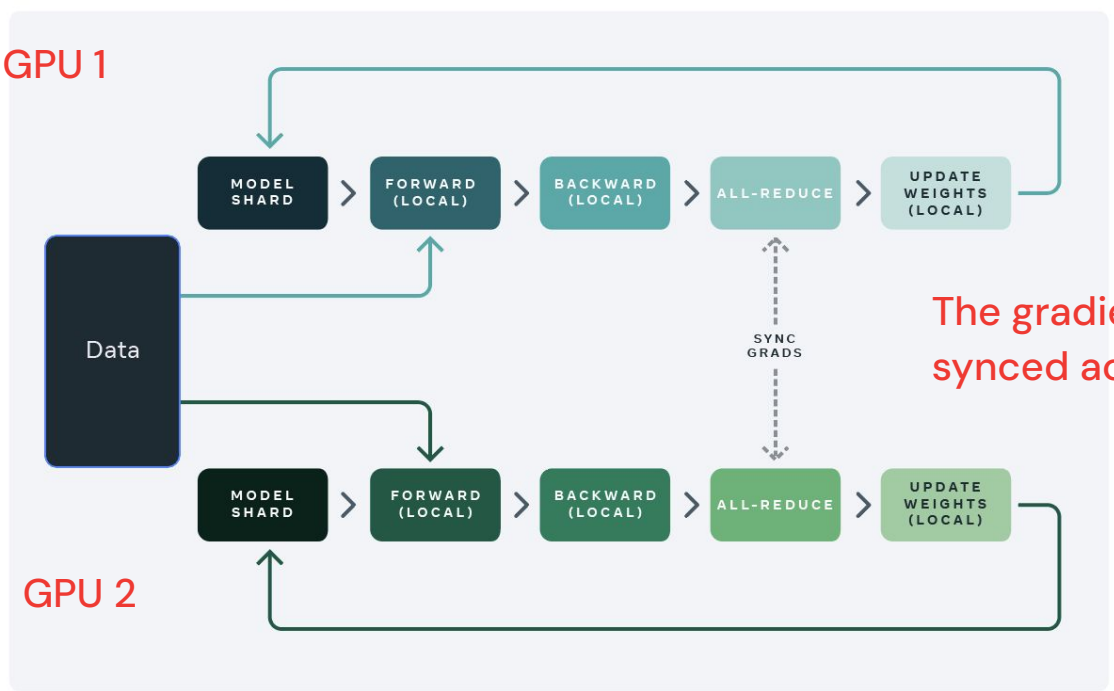
$$\omega_{t+1} = \omega_t + \Delta\omega_t$$

η : *Initial Learning rate*
g_t : *Gradient at time t along* ω^j
ν_t : *Exponential Average of gradients along* ω_j
s_t : *Exponential Average of squares of gradients along* ω_j
β_1, β_2 : *Hyperparameters*

https://discuss.pytorch.org/t/how-adam-optimizer-influence-the-learning-rate/168543 from the original Adam paper

Distributed Data Parallelism (DDP)

This is the simplest way to train a model using many GPUs. **Data** is split among the GPUs for efficient training. **Full model parameters** are replicated on **every** GPU



The gradient has to be synced across all GPUs

https://engineering.fb.com/2021/07/15/open-source/fsdp/

Example: Memory Consumption during LLM training

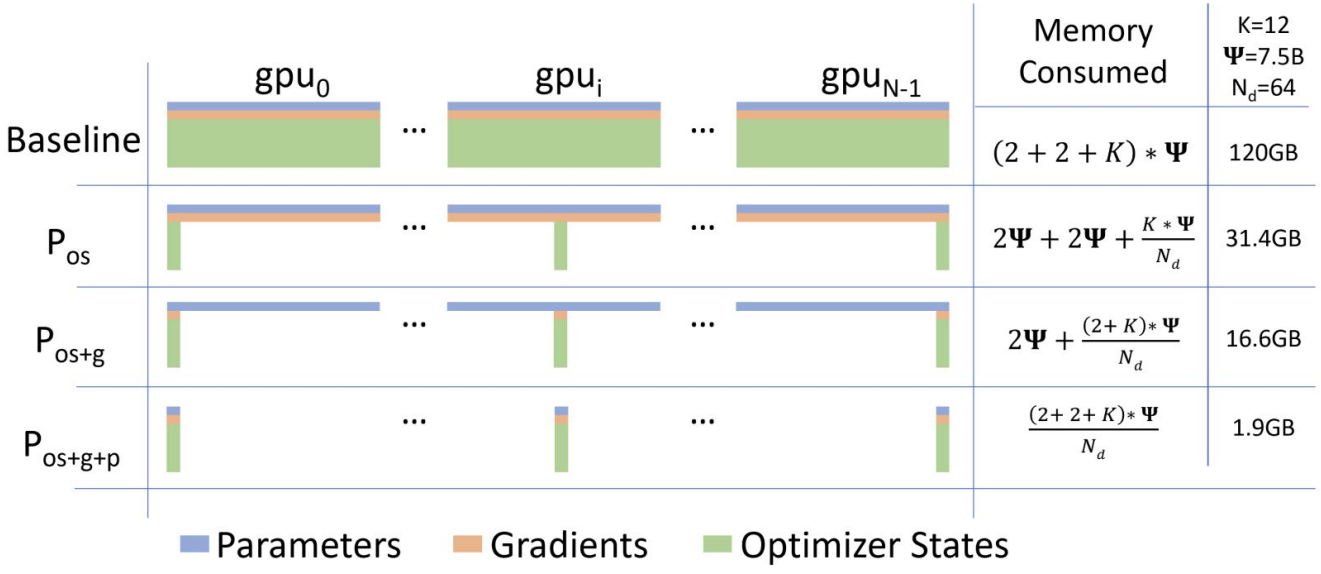


Figure 1: Comparing the per-device memory consumption of model states, with three stages of *ZeRO*-DP optimizations. Ψ denotes model size (number of parameters), K denotes the memory multiplier of optimizer states, and N_d denotes DP degree. In the example, we assume a model size of $\Psi = 7.5B$ and DP of $N_d = 64$ with $K = 12$ based on mixed-precision training with Adam optimizer.

Model size 7.5B parameters

shard optimizer

shard optimizer + gradient

shard optimizer + gradient + parameters

ZeRO: Memory Optimizations Toward Training Trillion Parameter Models

A Word About CPUs, GPUs and FLOPs

CPUs are general-purpose processors that can handle almost any type of calculation, less efficient at parallel processing.

GPUs, with their highly parallel architecture, are particularly well-suited for performing the **massive number of floating-point calculations** required for tasks like 3D rendering, machine learning, and scientific simulations.

- When given a task, a GPU will divide it into thousands of smaller subtasks and process them concurrently, instead of serially.

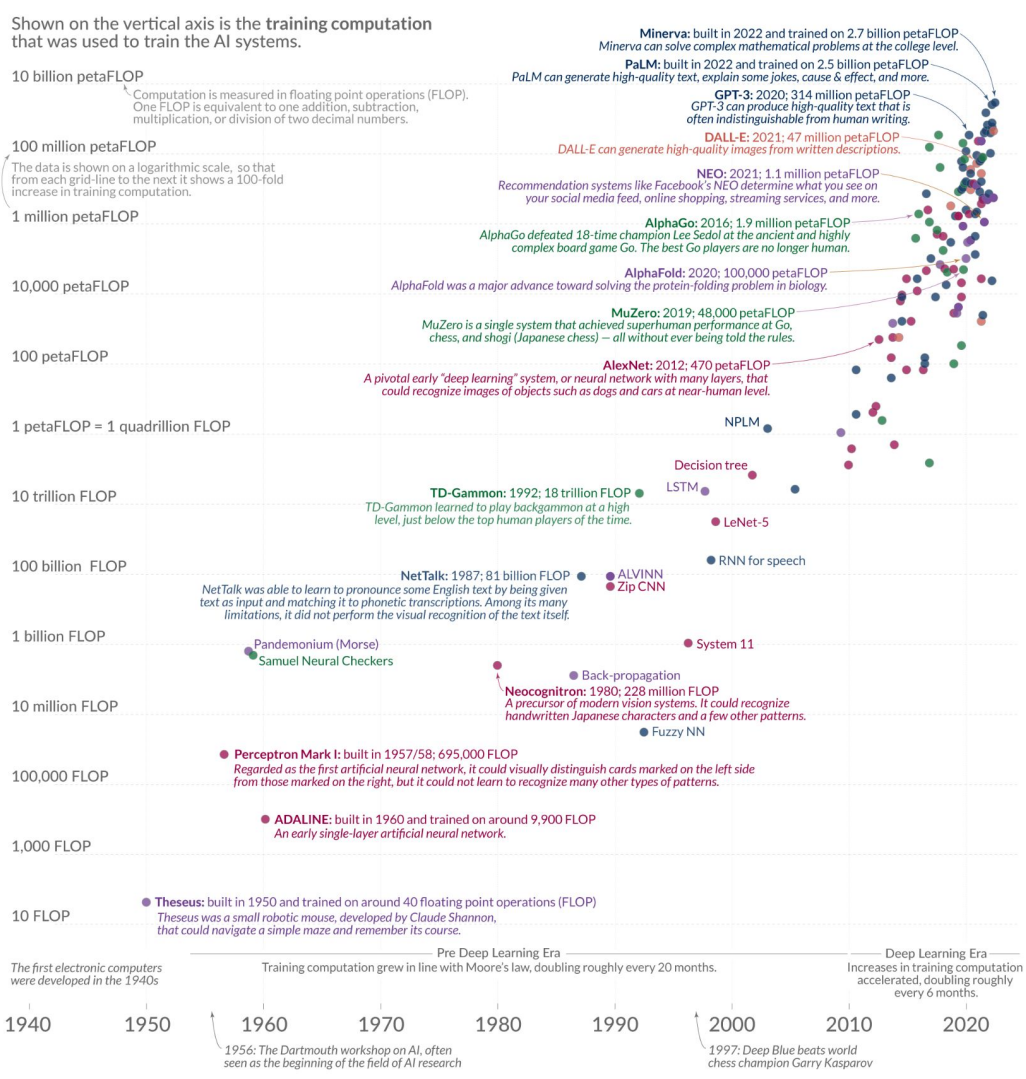
FLOPS stands for "Floating-Point Operations Per Second" and is a measure of a computer's performance based on the number of floating-point arithmetic calculations its processor can perform within one second

Why is “FLOPs” a useful metric for LLMs?

FLOPS = compute!

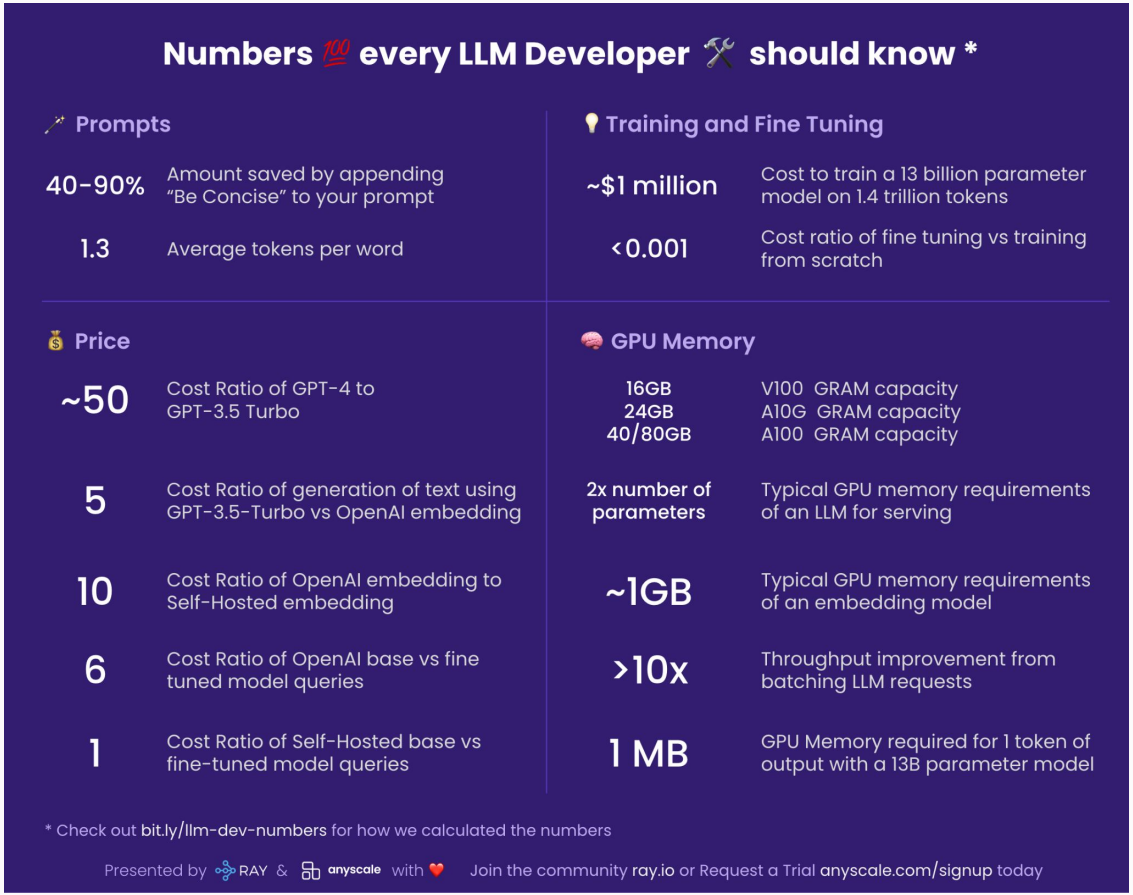
FLOPS is a function of both data amount and model size

In 2023, we are in the in the 100 billion petaFLOP range (1e26 FLOPs)



https://blog.heim.xyz/flop-for-quantity-flop-s-for-performance/

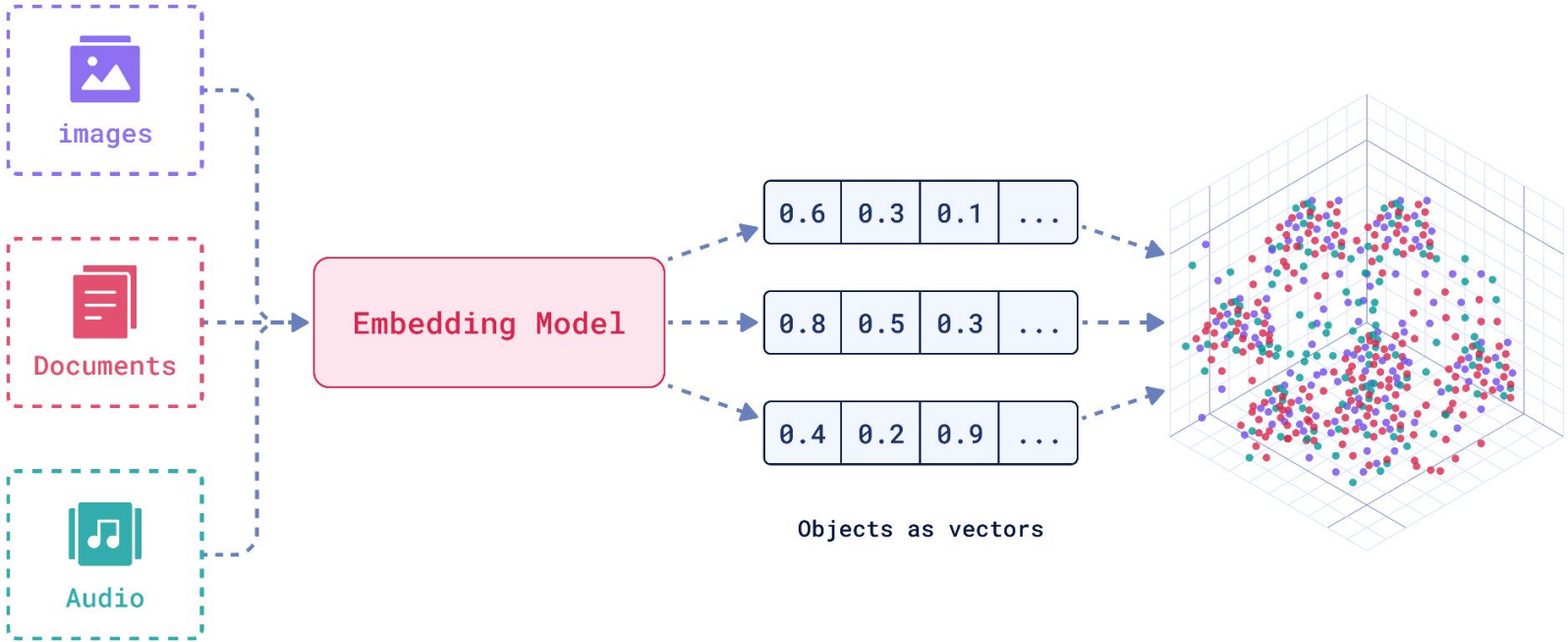
Serving



https://www.anyscale.com/blog/num-every-llm-developer-should-know

Part 3: Building with LLMs

Vector Embeddings

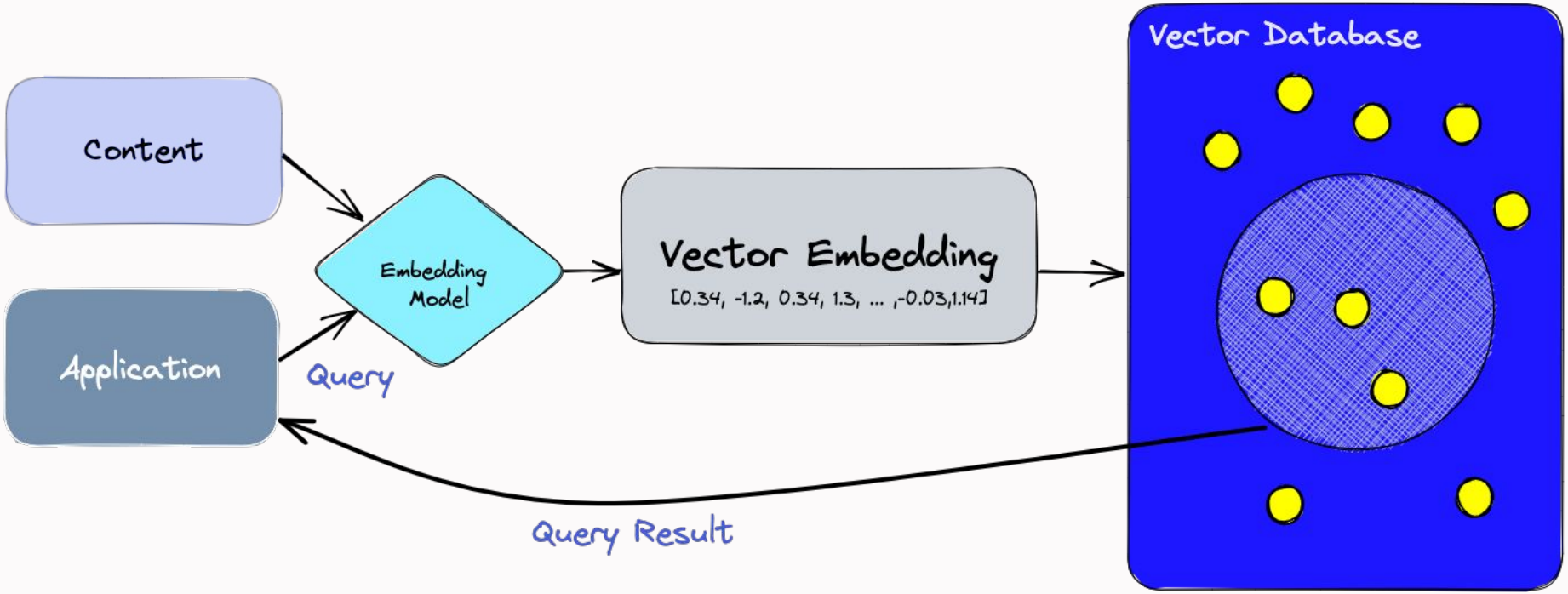


https://qdrant.tech/articles/what-are-embeddings/

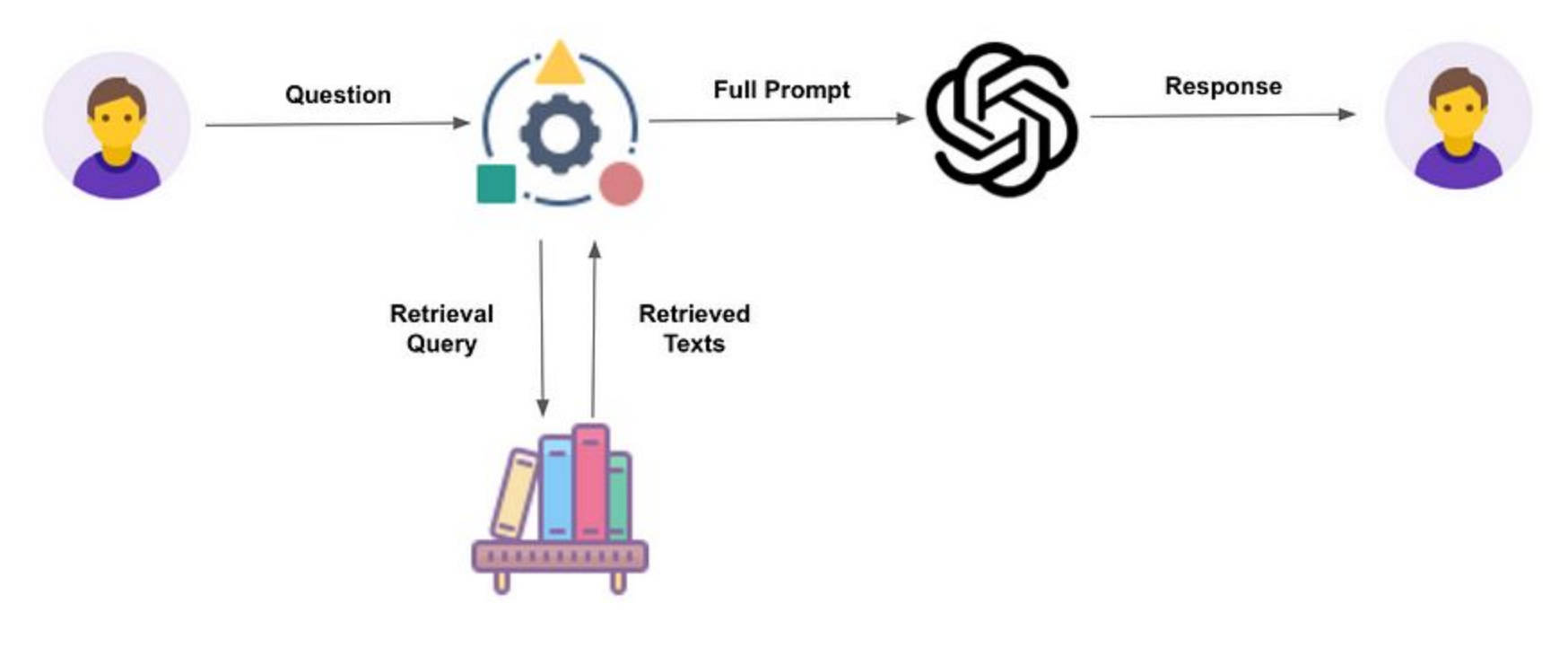
Vector Database

- Vector databases store embeddings and allow you to search over embeddings
- How do you efficiently store and search over billions of embeddings?
- How do you handle updating the vectors in your vector database?
- Example:
  - Search over Github issues
  - Search for images that look like you
  - Search for songs must similar to your music taste

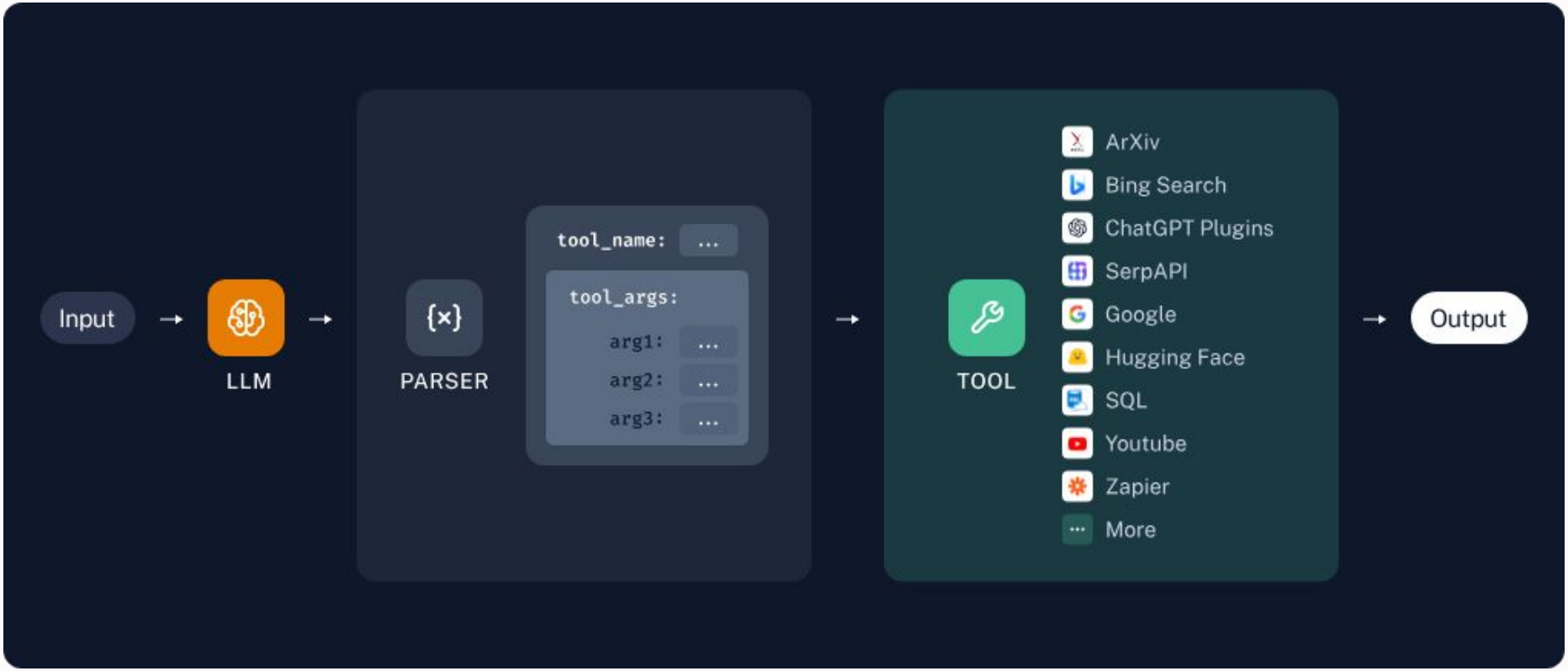
Semantic Search



Retrieval Augmented Generation (RAG)



Langchain



https://python.langchain.com/docs/use_cases/tool_use/

Langchain

https://python.langchain.com/docs/use_cases/tool_use/

Miscellaneous Resources

- Blog post: The Illustrated Transformer Jay Alammar, 2018
- Blog post: The Bitter Lesson (Richard Sutton 2019)
- Blog post: Alpaca: A Strong, Replicable Instruction-Following Model Taori, Gulrajani, Zhang et al. 2023
- Blog post: Why we should train smaller LLMs on more tokens (Harm de Vries, July 2023)
- Blog post: Google Gemini Eats The World – Gemini Smashes GPT-4 By 5X, The GPU-Poors Dylan Patel, Semi Analysis Newsletter
- Blog post: Illustrating Reinforcement Learning from Human Feedback (RLHF)
- Repo: https://minitorch.github.io/
- Repo: RL4LMs
- Youtube: Developing Llama 2 | Angela Fan (October 5, 2023)
- RAG blogpost from LangChain and/or LlamaIndex TBD
- Report of the 1st Workshop on Generative AI and Law Katherine Lee et al. 2023
- Blogpost on prompt attacks: Extracting Training Data from ChatGPT (with accompanying paper by Nasr, Carlini et al. 2023) *This blogpost that accompanies an academic paper highlights a recent approach for "jailbreaking" GPT4*
- Linden Li inference slides (How to serve LLMs)
- How Fully Sharded Data Parallel (FSDP) works?
- Mistral 7B's secrets: a talk by Guillaume Lample

Miscellaneous Resources (cont.)

- ML Collective Deep Learning: Classics and Trends https://mlcollective.org/dlct/. This is an open reading group that has weekly high quality talks. This is a great resource for up-to-date research, and has a strong community
- ML Research Newsletter by Sebastian Ruder (Google Research) https://www.ruder.io/nlp-news/
- HuggingFace NLP course: https://huggingface.co/learn/nlp-course/chapter1/1 *This is a great resource for learning how to use HuggingFace's libraries.*
- Cohere LLM course: https://docs.cohere.com/docs/llmu *This is a gentle introduction to LLMs with Cohere's API.*
- A hacker's Guide to LLMs (Jeremy Howard) https://x.com/jeremyphoward/status/1707188542768865725?s=20
- Visualization of the GPT/Transformer architecture https://bbycroft.net/llm
- CS 189/289A Introduction to Machine Learning Spring 2023 (notes and youtube lectures)
- Llama2: https://arxiv.org/pdf/2307.09288.pdf
- Computational cost blog posts - Training: https://blog.eleuther.ai/transformer-math/ and Inference: https://kipp.ly/transformer-inference-arithmetic/
- Model parallelism: https://huggingface.co/docs/transformers/v4.15.0/parallelism
- Speculative decoding: https://arxiv.org/pdf/2211.17192.pdf
- Roger Grosse's course (with slides and readings) CSC2541 Winter 2022: Topics in Machine Learning: Neural Net Training Dynamics
- Ana Marasović's course (with slides and youtube links): CS 6966/5966, Fall 2023 Local Explanations for Deep Learning Models (University of Utah)
- Modern language models refute Chomsky's approach to language Steven T. Piantadosi *This is a great article that explains how recent progress in LLMs completely upends classic (Chomskyan) linguistics*
- A Philosophical Introduction to Language Models Part I: Continuity With Classic Debates (Milliere and Buckner 2024)

Demo: Semantic Search (30 min)

Colab Notebook